Detection of Brain Tumor MRI Image Using Probabilistic Neural Network and Image Segmentation

[1] S. Sabarinathan, M.E, [2]S.Indhumalini, M.E, [3]M.Prasanth, M.E., [4]S.Sivaprakasam, M.E
[1,2,3,4] Narasu's Sarathy Institute of Technology

Abstract- **The brain is the interior part of the central nervous system. Brain tumor is an unbalanced growth caused by cells reproducing themselves in an uncontrolled way. The seriousness of brain tumor is very high among all types of cancers because of space for me inside the skull. So, immediate detection and proper treatment can save a person's life. In this paper a system for brain tumor extraction is designed. It uses the MRI Scanned Images at input. In the pre-processing stage, noise is removed and the texture features are extracted from it with the help of Gray level co-occurrence matrix (GLCM). Then with the help of the obtained features classification of images into normal and abnormalised one uses Probabilistic Neural Network (PNN) classifier. Then using segmentation technique and morphological operations tumorous part is located from abnormal image. The accuracy of the proposed system is 86.2% & it is evaluated in terms of confusion matrix.**

Index Terms- **Brain Tumor, MRI, Probabilistic Neural Network, GLCM, Segmentation.**

I. INTRODUCTION

Tumor is defined as the irregular growth of the tissues. Brain tumor is an abnormal mass of tissue in which cells grow up and multiply uncontrollably. Brain tumors may be primary or metastatic, and either malignant or benign. A metastatic brain tumor is a cancer which has spread from anywhere in the body to the brain. MRI brain tumor segmentation provides useful information for medical diagnosis and surgical planning [1]. Generally treatments of Brain Tumor are determined by:

- Age of Patient
- Medical history
- Type of Tumor
- Location and
- Size of Tumor [9]

A. Types of Tumor

There are three general types of Tumor: 1. Benign 2. Pre-malignant 3. Malignant [2]

1. Benign Tumor: A benign tumor is a tumor which does not expand in an abrupt way; it doesn't affect its neighboring healthy tissues and also does not expand to non-adjacent tissues.
2. Pre-Malignant Tumor: Premalignant Tumor is a precancerous stage. It is considered as a disease, if not properly treated it may lead to cancer.
3. Malignant Tumor: Malignancy is the type of tumor, which grows worst with the passage of time and ultimately results in the death of a person. The term malignant tumor is typically used for the description of cancer.

Real time diagnosis of tumors by using more reliable algorithms has been the main focus of the latest developments in medical imaging and detection of brain tumor in MR images and CT scan images has been an active research area.

MRI is basically used in the biomedical to detect and visualize finer details in the internal structure of the body. This technique is basically used to detect the differences in the tissues having a better technique as compared to computed tomography (CT). So this makes the MRI technique as a very special one for the brain tumor detection and cancer imaging. [3] CT uses ionizing radiation but MRI uses strong magnetic field to align the nuclear magnetization then radio frequencies changes the alignment of the magnetization which can be detected by the scanner. That signal can be further processed to create the extra information of the body. MR image is safe as compared to CT scan image as it does not affect human body.

The main problems faced by most of the medical imagery diagnosis systems are the separation of the cells and their nuclei from the rest of the image content. The process of separation i.e. segmentation is most important in the construction of a robust and effective diagnosis system. Images Segmentation is performed on the input images. This enables easier analysis of the image thereby leading to better tumor detection efficiency. Hence image segmentation is the fundamental problem in tumor detection. But before image segmentation a major stage in image processing is classification. Classification algorithms are categorized into supervised and unsupervised; although each category has its basic principles and properties. Both categories have a common objective which is the detection and extraction of tumor [4].

A good classification process gives right decision and provides good and appropriate treatment. The classification of the given input image should be done under two classes' i.e. normal and abnormal class. Classification is done using the features of the tumor containing image and normal image. In feature extraction, the transformation of input image data into sets of features is done. If the accurate features are extracted from MRI then the further processing can be done quickly. Feature extraction plays a crucial role in determining the performance of the classifier. After classification the partitioning is performed on the tumorous image for extracting the tumor region.

II . PROPOSED METHODOLOGY

The proposed algorithm starts by reading the input brain MR image and converting it into grey scale image. There are four major steps in the proposed approach. The first step is pre-processing; the second step is feature extraction using GLCM; the third step is classification using PNN; and last step is segmentation. Fig 1 gives sequence of the proposed technique.

A. Image Acquisition

Images are obtained using MRI scan & displayed in 2D having pixels as its elements. MRI scan were stored in database of images in JPEG image formats. These images are displayed as a gray scale images. The entries of gray scale images are ranging from 0 to 255, where o indicates total black color and 255 represents total white color.

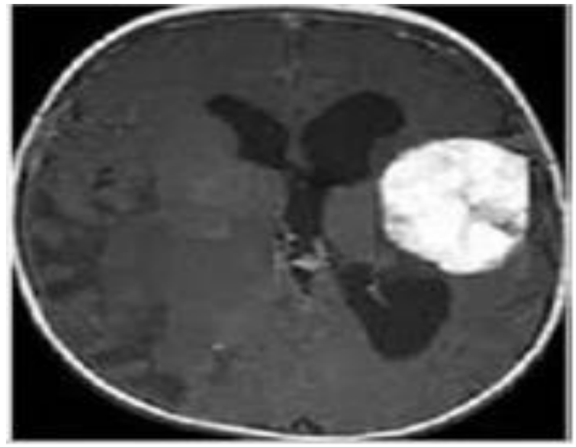

Fig 2 Input Brain MR Image

B. Pre-Processing Stage

Most of the imaging techniques are degraded by noise. In order to preserve the edges and contour information of the medical images, the efficient denoising and an improved enhancement technique is required [6].

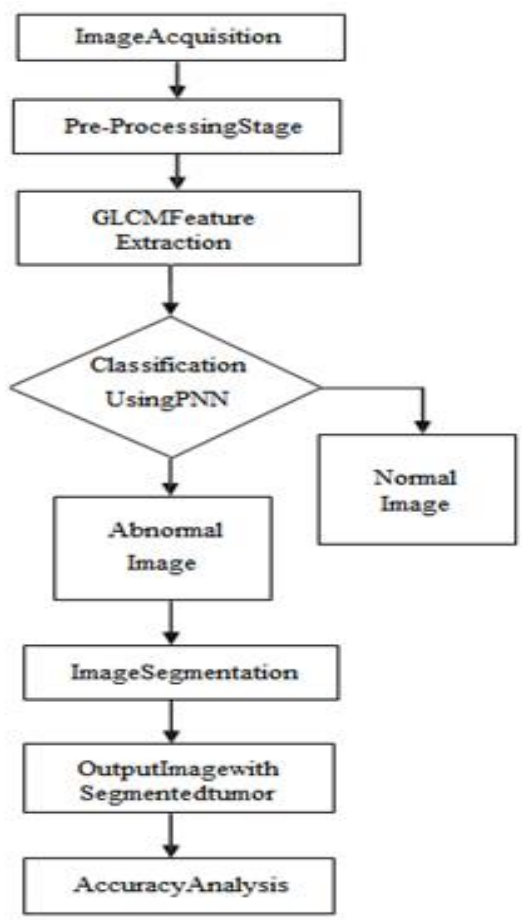

Fig 1. Flow chart of Proposed Methodology

The Contrast Limited Adaptive Histogram Equalization (CLAHE) is an enhanced version of adaptive histogram equalization. The contrast limited adaptive histogram equalization algorithm partitions the images into contextual regions and applies the histogram equalization to each region.

These evens out the distribution of used gray values and by using this make unknown features of the image more visible. The amount of contrast enhancement for some intensity is directly proportional to the slope of the Cumulative Distribution Function (CDF) at that intensity level. Therefore by limiting the slope of the CDF, contrast enhancement can also be limited. The slope of CDF at a bin location is evaluated by the height of the histogram for that bin. Therefore the height limitation of the histogram limits the slope of the CDF and that's why the amount of contrast enhancement.

Fig 3 Filtered Image

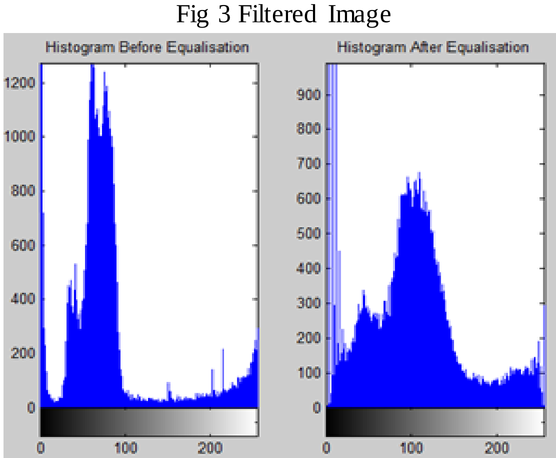

Fig 4 Adaptive Histogram Equalization

Gray level co-occurrence matrix

Haralick proposed two steps for texture feature extraction. First step is computing the co-occurrence matrix and the second step is calculating texture feature based on the co-occurrence matrix. This technique is useful in wide range of image analysis applications from biomedical to remote sensing techniques. 4.5.1 Working of GLCM Basic of GLCM texture considers the relation between two neighbouring pixels in one offset, as the second order texture. The gray value relationships in a target are transformed into the co-occurrence matrix space by a given kernel mask such as 3 3 , 5 5 , 7 7 and so forth. In the transformation from the image space into the co-occurrence matrix space, the neighboring pixels in one or some of the eight defined directions can be used; normally, four direction such as 0°, 45°, 90°, and 135° is initially regarded, and its reverse direction (negative direction) can be also counted into account. It contains information about the positions of the pixels having similar gray level values. Each element (i, j) in GLCM specifies the number of times that the pixel with value i occurred horizontally adjacent to a pixel with value j . In Figure 4.8, computation has been made in the manner where, element (1, 1) in the GLCM contains the value 1 because there is only one instance in the 103 image where two, horizontally adjacent pixels have the values 1 and 1. Element (1, 2) in the GLCM contains the value 2 because there are two instances in the image where two, horizontally adjacent pixels have the values 1 and 2. Figure 4.10 Creation of GLCM from image matrix Element (1, 2) in the GLCM contains the value 2 because there are two instances in the image where two, horizontally adjacent pixels have the values 1 and 2. The GLCM matrix has been extracted for input dataset imagery. Once after the GLCM is computed, texture features of the image are being extracted successively.

C. *Extraction of Texture Feature*

Gray-level co-occurrence matrix (GLCM) is the statistical method of finding the textures that considers the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by evaluating how frequently pairs of pixel with specific values and in a specified spatial relationship that present in an image, forms GLCM. This makes the extraction of statistical measures from this matrix.

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, ɵ) contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (ɵ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, ɵ). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in fig 2.1 for four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbor). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbor pixel) falls to the right of another pixel with grey level 0(reference pixel).

Here we are using Statistical approach to texture analysis among the four approaches (Structural, Statistical, model based and Transform). It is the most widely used and more generally applied method because of its high accuracy and less computation time.

A gray level co-occurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values. The GLCM, C, is defined with respect to given (row, column) displacement h. And element (i , j), denoted cij, is the number of times a point having gray level j occurs in position h relative to a point having gray level i.

Let Nh be the total number of pairs, then Cij = cij /Nh is the elements of the normalized GLCM, C. [7]

Gray Level Co-Occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Haralick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. In this paper four important features, Angular Second Moment (energy), (inertia moment), Correlation, Entropy, and the Inverse Difference Moment are selected for implementation using Xilinx ISE 13.4.

The probability measure can be defined as: Where Cij (the co occurrence probability between grey levels in a dj) is defined as:

$$C_{ij} = \frac{P_{ij}}{\sum_{i,j=1}^{G} P_{ij}} \qquad (2)$$

Where Pij represents the number of occurrences of grey levels i and j within the given window, given a certain (δ-inter pixel distance, θ-orientation) pair. G is the quantized number of grey levels.

The result of a texture calculation is a single number representing the entire window. This number is put in the place of the centre pixel of the window, then the window is moved one pixel and the process is repeated of calculating a new GLCM and a new texture measure. In this way an entire image is built up of texture values.

From the co-occurrence matrix obtained, we have to extract the12 different statistical features. These are given as follows:

1. Contrast

Contrast is a measure of the local variations present in an image. It is given as,

$$C(k,n) = \sum_i \sum_j (i-j)^k Pd[i,j]^n \qquad (3)$$

If the a large amount of variation in an image the P[i,j]'s will be concentrated away from the main diagonal and contrast will be high(typically k=2, n=1).

2. Sum of Squares, Variance

$$VARIANCE = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i-\mu)^2 P(i,j) \qquad (4)$$

This feature puts relatively high weights on the elements that differ from the average value of P(i,j).

3. Correlation

Correlation is a measure of image linearity

$$C_c = \frac{\sum_i \sum_j \left[C_{ij} Pd[i,j] \right] - \mu_{i\mu_j}}{\sigma_i \sigma j} \qquad (5)$$

Where

$$\mu_i = \sum i P_d[i,j] \; \sigma_i^{\,2} = \sum i^2 P_d[i,j] - \mu_i^{\,2}$$

4. Energy

One approaches to generating texture features is tousle cal kernels to detect various types of texture.

After the convolution with the specified kernel, the texture energy measure (TEM) is computed by summing the absolute values in a local neighborhood:

$$L_e = \sum_{1}^{M}\sum_{1}^{N} |C(i,j)| \qquad (6)$$

$$C_h = \sum_i \sum_j \frac{P_d[i,j]}{1+|i-j|} \qquad (12)$$

If n kernels are applied, the result is an n-dimensional feature vector a teach pixel of the image being analyzed.

5. Maximum Probability

This is simply the largest ten try in the matrix, and corresponds to the strongest response. This could be the maximum in any of the matrices or the maximum over all.

$$C_m = MAX\ Pd[i,j] \qquad (7)$$

6. Dissimilarity

$$\sum_{i,j=1}^{G} Cij\ |i-j| \qquad (8)$$

7. Autocorrelation

Other statistical approaches include an autocorrelation function, which has been used for analyzing the regularity and coarseness of texture by Keizer. This function evaluates the linear spatial relationships between primitives. The set of autocorrelation coefficients shown below are used as texture features large value of MD indicates test image is of poor quality. Ideally it should be zero.

$$C(p,q) = \frac{MN}{(M-p)(N-q)} \frac{\sum_{i=1}^{M-p}\sum_{j=1}^{N-q} f(i,j)f(i+p,j+q)}{\sum_{i=1}^{M}\sum_{j=1}^{N} f^2(i,j)}$$

8. Inverse different Moment

IDM is also influenced by the homogeneity of the image. Because of the weighting factor IDM will get small contributions from in homogeneous areas. The result is allowed IDM value for in homogeneous images, and a relatively higher value for homogeneous images.

$$IDM = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i,j) \qquad (10)$$

9. Entropy

Entropy is a measure of information content. It measures the randomness of intensity distribution.

$$C_e = -\sum_i \sum_j P_d[i,j] \ln P_d[i,j] \qquad (11)$$

10. Homogeneity

A homogeneous image will result in a *co-occurrence matrix* with a combination of high and low P[ij]'s.

11. Cluster Prominence

$$PROM = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \{i+j-\mu_x-\mu_y\}^4 \times P(i,j) \qquad (13)$$

12.Cluster Shade

$$SHADE = \sum_{i=0}^{2G-2} (i-2\mu)^3 H_s(i|\Delta x,\Delta y) \qquad (14)$$

Where

$$\mu = \frac{1}{2}\sum_{i=0}^{2G-2} iH_s(i|\Delta x,\Delta y)$$

	Value
Contrast	0.6752
Correlation	0.8837
ClusterProminence	370.1162
ClusterShade	14.7576
Dissimilarity	0.4354
Energy	0.0949
Entropy	2.8483
Homogeneity	0.8134
Homop	0.8051
Max.Prob	0.2227
Sosvh	16.5063
Autocorrelation	16.2493

Fig 5. Texture Feature Extraction

D. *Classification by using Probabilistic Neural Network (PNN)*

A probabilistic neural network (PNN) is a feed forward neural network, resulting from the Bayesian network and a statistical algorithm called Kernel. Fisher discriminate analysis. In a PNN, the operations are organized into a multilayered feed forward network with four layers as Input layer, Hidden layer, Pattern layer/Summation layer, Output layer.[8]

E. *Image Segmentation*

Image segmentation is the process of partitioning a digital image into several segments (sets of pixels, which are also called as super pixels). The main aim of segmentation is to make simpler or to change the representation of an image into something which is more significant & easy to recognize. [11]

In medical field image segmentation is typically used to study anatomical structure, to identify Region of interest (i.e. to locate tumor & other abnormalities), used in treatment planning etc.[10] There are various techniques of image segmentation such as thresholding, compression based methods, Region growing Techniques, Edge Detection Techniques, Clustering Methods, Watershed Segmentation etc. Here we detect tumor using edge detection & basic morphology.

F. Accuracy Analysis

Hereintheproposedsystemasetof32Brain MRI-scanGray-scaleimagesisused.Agroupof32 MRIimageswereusedthatwerecategorizedinto2classes Normal and Abnormal respectively.

Out of the 32 images a group of 17 random patients MRI images were selected as a test set which consists 5 normal images and 12 abnormal images, while the rest 15 images which consists 6 normal and 9 abnormal images are used for training. The accuracy of the proposed system in terms of the confusion matrix is shown in the Fig 9.

Fig 9 Confusion matrix

III. CONCLUSION

Percentage of Correct classification: 88.2%

Percentage of Incorrect classification: 11.8%

So the proposed system has 88.2% accuracy.

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