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

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Abstract— **the brain is the anterior 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 formed 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 abnormal is done using 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 88.2% & 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 tumours 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

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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.

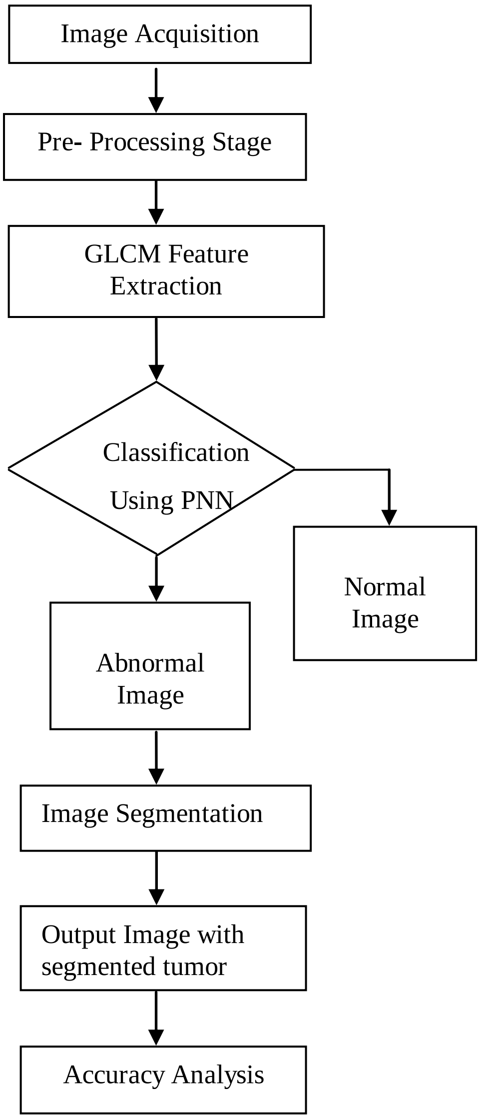

Fig 1 Flow chart of Proposed Methodology

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]. 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

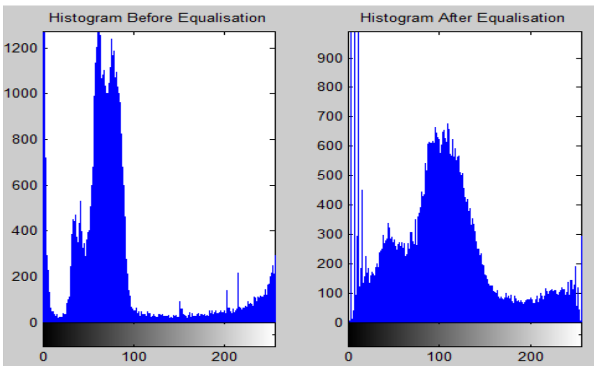

Fig 4 Adaptive Histogram Equalization

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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.

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 c_{ij}, 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 $C_{ij} = c_{ij}$ /Nh is the elements of the normalized GLCM, C. [7]

The probability measure can be defined as:

$$P_{r\,(x)} = \{C_{ij}|\delta, \theta|\} \quad (1)$$

Where Cij (the co-occurrence probability between grey levels i and j) is defined as:

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

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 the 12 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,

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

If there is 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

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

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

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

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 approach to generating texture features is to use local 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:

$$L_e = \sum_1^M \sum_1^N |C(i,j)| \quad (6)$$

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

5. Maximum Probability

This is simply the largest entry in the matrix, and corresponds to the strongest response. This could be the maximum in any of the matrices or the maximum overall.

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

6. Dissimilarity

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

7. *Autocorrelation*

Other statistical approaches include an autocorrelation function, which has been used for analysing 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

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indicates test image is of poor quality. Ideally it should be zero.

$$C(p,q) = \frac{MN}{(M-p)(N-q)} \frac{\sum_{i=1}^{M-p}\sum_{j=1}^{N-q} f(i,j)f(i+p,j+q)}{\sum_{i=1}^{M}\sum_{j=1}^{N} f^2(i,j)} \quad (9)$$

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 inhomogeneous areas. The result is a low IDM value for inhomogeneous images, and a relatively higher value for homogeneous images.

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

9. Entropy

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

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

10. Homogeneity

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

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

11. Cluster Prominence

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

12. Cluster Shade

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

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]

1) *Architecture of probabilistic neural network*

In the early 1990s, Donald F. Specht proposed a method to formulate the weighted-neighbor method in the form of a neural network. He called this a "Probabilistic Neural Network". Fig 2 shown below gives a diagrammatic representation of a PNN network.

PNN is generally used in classification problems. When an input is present, the first layer computes the distance from the input vector to the training input vectors. This produces a vector whose elements indicate how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its total output as a vector of probabilities. Finally, a whole transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes. [9]

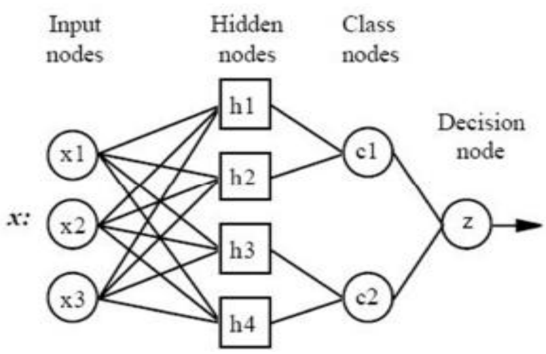

Fig 6 Architecture of Probabilistic Neural Network

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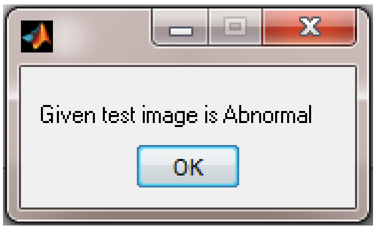

Fig 7 Decision of PNN Classifier

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 tumour & 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 tumour using edge detection & basic morphology.

Step 1: Read the input brain MRI image.

Step 2: The gradient image can be calculated and a threshold can be applied to create a binary mask containing the segmented cell. First, we use edge and the canny operator to calculate the threshold value. We then tune the threshold value and use edge again to obtain a binary mask that contains the segmented cell.

Step 3: Dilate the Image. The binary gradient mask shows lines of high contrast in the image. These lines do not quite delineate the outline of the object of interest. Compared to the original image, you can see gaps in the lines surrounding the object in the gradient mask. These linear gaps will disappear if the canny image is dilated using linear structuring elements, which we can create with the strel function. The binary gradient mask is dilated using the vertical structuring element followed by the horizontal structuring element. The imdilate function dilates the image.

Step 4: Fill Interior Gaps. The dilated gradient mask shows the outline of the cell quite nicely, but there are still holes in the interior of the cell. To fill these holes we use the imfill function.

Step 5: In some applications, it is helpful to be able to separate out the regions of the image corresponding to objects in which we are interested, from the regions of the image that correspond to background. Thresholding is an easy and suitable method to achieve this binarization on the basis of the different intensities or colours in the foreground and background regions of an image. For the binarization of equalized image a thresholding technique is used as shown below:

Binarized Image $b_{i,j} = 255$ if $e(i, j) > T$

Else $b_{i,j} = 0$

Where $e(i, j)$ is the equalized MRI image and T is threshold resultant for the equalized image.[11]

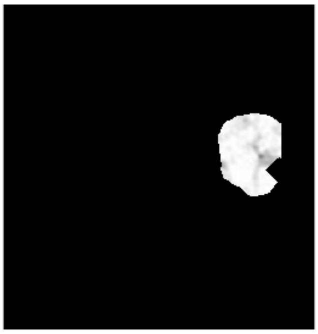

Fig 8 Threshold Segmentation Image
(White part indicates tumor)

F. *Accuracy Analysis*

Here in the proposed system a set of 32 Brain MRI-scan Gray-scale images is used. A group of 32 MRI images were used that were categorized into 2 classes 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.

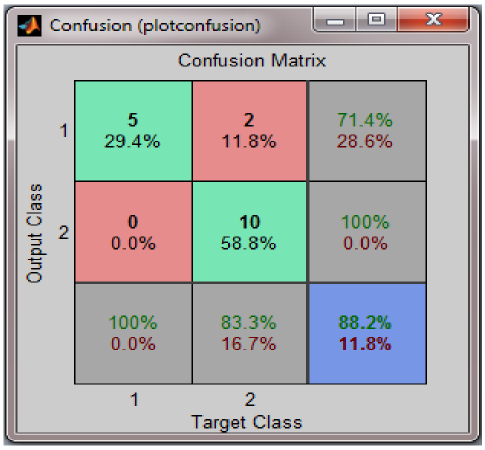

Fig 9 Confusion matrix

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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