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Classification of Brain Tumor using Neural Network

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Abstract— Due to uncontrolled cell devision within the brain abnormal tissue growth will occur this is known as the brain tumor. There are two types of brain tumors that is malignant(cancerous) and benign(non cancerous).Benign tumor increases with age but not malignant. About 25% of the total cancer deaths are due to this brain tumor.Hence,detection of brain tumor is a serious concern in the current scenario. Magnetic resonance imaging (MRI) is the widely used technique to detect Brain tumor. While diagnosing large amount of data by an expert the computational complexity and time consuming is more and it is prone to errors. To investigate an automated system which consists of two stages here? In the first stage, segment the tumor area from brain MRI using Multiracial analysis with RBF classifier. There are three features are considered that is intensity,fractal dimension and gray level co-occurrence matrix(GLCM).Here second stage classifies the segmented tumor area into benign or malignant using one of the best features (GLCM) in the wavelet domain along with a best classifier.

Index Terms—Magnetic Resonance Images, Multiracial analysis, Gray Level Co occurnace Matrix,radial basis function

I. INTRODUCTION

Brain tumour is the abnormal growth of brain cells which leads to the death of human. Tumour is the masses of abnormal cells in the brain. There are two types of brain tumours that is benign and malignant. Malignant is the cancerous tumour, it is very dangerous because they can spread to other body parts benign is the non-cancerous tumour which lacks the ability to invade neighbouring tissues. Benign tumour is sometimes fatal because they can destroy the normal brain tissue. So the early detection of brain tumour is brain tumour is very important. By early detection of brain tumour an expert neurologist can give proper treatment to the patient. The existing method to find out the segmented part of the brain tumour from MRI is very difficult that is it need the help of expert neurologist. It is impractical for large amount of data
and it takes hours of time and it may prone to errors. Apart from being time consuming, manual brain tumor delineation is
difficult and depends on the individual operator. Multimodal MRI images are used simultaneously by radiologists in segmenting brain tumor images since it provides various data
on tumors. Different MRI images are there T1 weighted images with contrast enhancement it highlights contrast– enhancing regions, where T2 weighted highlights edema regions. Brain tumor has different shapes,size and locations so
segmentation is very difficult.Tumor edges can be complex and visually vague.Noises in brain tumor images increases the difficulty when segmenting tumors.

II. METHEDOLOGY

A. Overview of the Proposed Method

The basic block diagram for tumor area segmentation and its classification is shown in fig. 1. The whole work is done in two stages, the segmentation stage and classification stage.The feature extraction methods, training and testing of classifiers employed in the work are explained below.

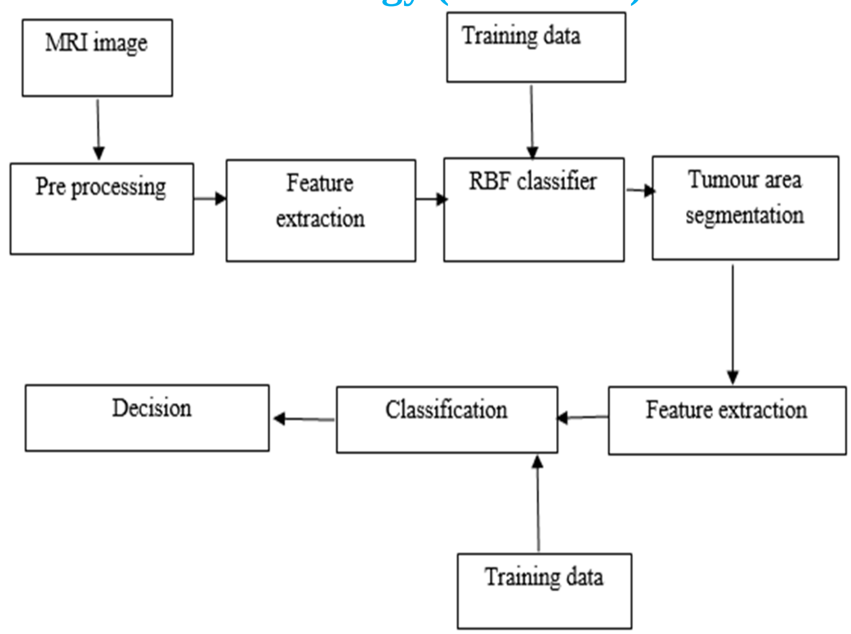

Figure.1 system block diagram

B. Database collection

MRI uses radio waves and magnetic fields to acquire a set of cross sectional images of the brain. That is anatomic details of the 3D tumor are presented as a set of 2D parallel cross sectional images. Brain tumor image data used in this work were obtained from the MICCAI 2012 Challenge on Multimodal Brain Tumor Segmentation(BRATS 2012) dataset. Since the dataset is of 3D structure, it has to be sliced into 2D cross sectional images for the proper identification of tumor affected area manually. The 2D images of size 256*256 is created for the entire process.

C. Preprocessing

A problem that occurs in texture analysis and quantitative analysis of magnetic resonance Simaging (MRI), is that the extracted results are not comparable between consecutive or repeated scans or within the same scan, between different anatomic regions. The reason is that there are intra-scan and inter-scan image intensity variations due to the MRI instrumentation. Therefore, image intensity normalization methods should be applied to magnetic resonance (MR) images prior to further image analysis. The normalization of an image consists of the correction of signal intensity inhomogeneities as well as the standardization of the image intensities to a given general intensity scale. Hence, these MRI images are normalized to gray level values from 0 to 1 and the features are extracted from the normalized images. Since normalization reduces the dynamic range of the intensity values, feature extraction is made much simpler.

D. Feature extraction

In image processing, feature extraction is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen, it is expected that the feature set will extract the relevant information from the input data in order to perform the desired task instead of using the full size input. Feature extraction is a method of capturing visual content of an image and it is the major aspect of any data classification system. It is performed for each image in the database and its feature vector is calculated. These feature vectors form the database images are stored as .xls file format. Later these feature vectors are used for the training of classifiers. In this work texture features, intensity features and fractal dimension are used.

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1) *Intensity Feature: The* mean is defined as the sum of the pixel values divided by the total number of pixels values.

$$Mean;M = 1/mn\sum_{i=1}^{m}\sum_{j=1}^{n} x(i,j) \qquad (1)$$

The variance of an image is a numerical value used to indicate how widely the pixevalues vary. If individual pixel value varies greatly from the image mean, the variance is big and vice versa.

$$Variance;\ \sigma 2 = 1/mn\sum_{i=1}^{m}\sum_{j=1}^{n}(x(i,j) - M) \qquad (2)$$

2) *Texture feature:* Texture analysis is an important task in computer image analysis for classification, detection or segmentation of images based on local spatial patterns of intensity. Textures are replications, symmetries and combinations of various basic patterns, usually with some random variation. The major task in texture analysis is the texture segmentation of an image, that is, to partition the image space into a set of sub regions each of which is homogeneously textured.
3) *Gray level co-occurance matrix:* Texture is one of the most important defining characteristics of an image. It is characterized by the spatial distribution of gray levels in a neighborhood. In order to capture the spatial dependence of gray level values which contribute to the perception of texture, a two dimensional dependence texture analysis matrix are discussed for texture consideration. Since texture shows its characteristics by both pixel values and its neighbourhood. There are many approaches used for texture classification. Among them the Gray-level co-occurrence matrix seems to be a well-known statistical technique for feature extraction. Gray-level co-occurrence matrix (GLCM) is the statistical method of examining the textures that considers the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The graycomatrix function in MATLAB creates a grey level co occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j.

Various texture features can be calculated from GLCM matrix are;

a) contrast can be calculated from this equation

$$\text{Contrast} = \Sigma\,(i - j)^2 \qquad (3)$$

b) Correlation can be calculated from this equation

$$\text{Correlation} = \Sigma \text{Pij}\ ((i - \mu)(j - \mu)/\sigma^2) \qquad (4)$$

c) Energy can be calculated from this equation

$$\text{Energy} = \Sigma\ pij^{\ 2} \qquad (5)$$

d) Homegeneity can be calculated from this equation

$$\text{Homegeneity} = \Sigma\ pij\ /(1 + (i - j)/\sigma^{2}) \qquad (6)$$

e) Entropy can be calculated from this equation

$$\text{Entropy} = \Sigma(-\ln(\text{Pij})\text{Pij})) \qquad (7)$$

4) *Fractal diamention analysis:* Objects and phenomenon are described by using different measurements called dimensions. The most familiar dimension is the Euclidean and the second one is the topological dimension. They both can assume only the integer values. A point has a dimension of 0, a line has a dimension of 1 , an area has a dimension of 2 and volume has a dimension of 3 . From these elements points, lines, areas and volume the basic shapes of traditional geometry: triangles, squares, circles, cones, cubes and spheres are derived. The word fractal is used to describe the irregular structure of many natural objects and phenomenon. Fractal geometry exhibits a fundamental property generally known as self similarity. A fractal is an irregular geometric object with an infinite nesting of structure at all scales. Fractal texture can be quantified with the non integer FD. The brain MRI typically has a degree of randomness associated with it. This property of the image of brain is used for fractal analysis on it. Based on the fractal dimension obtained,the image is analyzed for abnormalities. It is a spectrum analysis, so the error of computation is very less.
5) *Fractal Brownian motion:* Brownian motion is defined as the random motion of particles suspended in a fluid resulting from their collision with quick atoms or molecules in the liquid. A continuous zero mean gaussian process with co-variance function r(t; s) = min(t; s) is a Brownian motion. Fractal brownian motion(fbm) process,on [0; T]; T_R,is a gaussian zero mean non

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stationary stochastic process starting at t = 0. It has the following covariance structure:

$$E[BH(t)BH(s)] = (1|2)((t^{2H} + s^{2H} - (t-s))^{2H} \qquad (8)$$

where H is a scalar parameter 0 < H < 1 known as Hurst parameter. The value of H determines the fbm process such that the curveBH(t) is very rough is H = 0:01, while for H = 0:99,the curve is very smooth. The FD is related to the Hurst coefficient.The parameter E is Euclidean dimension(2 for 2-D, 3 for 3-D and so on) of the space.

The fractional brownian motion has the following properties.

a) Self-similarity

b) Stationary increments

Hurst parameter: Hurst parameter is a measure of long memory of a series. Long memory/range dependence is a property characterized by self similar (or fractal) behavior. It means that similar statistical properties are preserved at different scale levels which are related by a constant known as the Hurst parameter (H)

0 < H < 0:5 indicates a series with -ve autocorelation

H > 0:5 indicates a series with +ve autocorelation

H = 0:5 indicates a perform walk(Brownian Motion)

The Hurst parameter can be estimated by using multiresolution wavelet analysis.

*Multiresolution wavelet analysis:*Tumor texture in magnetic resonance image exhibits the multifractal structure such as it varies with time.however in the fbm process the degree of H is same at all time variations.In the segmented tumor part we required finer as well as coarser resolution,in this situation multi resolution wavelet analysis is preferred. It gives complete idea about the extent of the details existing at different locations.We can't use Fourier and other transforms forthis purpose. Like other transforms such as DCT and DFT it don't use sinusoidal waves as basis function,which use wavelets as basis.It can be scaled, shifted according to our requirement.

E. Tumor classification

The segmented part is then processed to find out the benign tumor and malignant.to classify this ,we use radial basis function.The network is trained with GLCM feature in wavelet domain for classification. The wavelet domain is used for the dimensionality reduction.

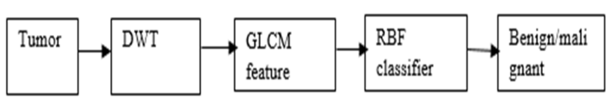

Figure. 2 Tumor Classifications

III. RESULT AND DISCUSSIONS

The input image from MICCAI 2012 is subdivided into 2D images and then this sliced image is used for the purpose of segmentation. For the segmentation RBF classifier is used ,before that features are extracted for diamentianality reduction.The segmented tumor is further classified into benign or malignent.

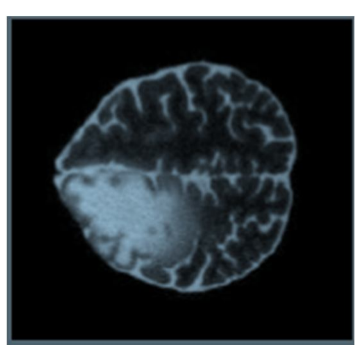

Figure. 3 Input Image

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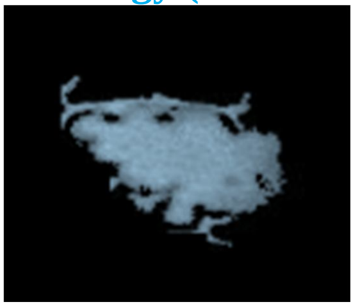

Figure. 4 Segmented Tumor

IV. CONCLUSION

In this work the automatic segmentation of brain tumor and its classification from cerebral magnetic resonance image is performed. In the segmentation stage the Neural network is trained with different features such as textural features,intensity features and fractal dimension and a comparative study of performance shown by the classifier with different feature vectors are analysed. Experimental results on various MRI images shows that among the features fractal dimension shows better result. The image is admitted to preprocessing and post processing which shapes the tumor with precise results. The tumor classification is performed using RBF classifier with an acceptable error rate.

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