ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 20, April 2016

Automated Detection and segmentation of Brain MRI

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Abstract-Image processing techniques have been widely used in medical imaging research. These techniques are useful for visualizing, enhancements segmentation and many such operations which are useful for processing medical images with MRI. In this paper a new method is suggested to detecting normal and abnormal brain images(DNABI). This method executes two processes, first, the MRI image must be preprocessed to detect and segment tumors in the brain. Next, their Feature extraction of brain tumors helps in knowing the exact size and shape of the tumor and the location using GLCM. Finaly, image enhancement techniques are enhance the contrast and normalize pixel value in the image,then applied to morphological operations to get the desired output. The proposed method has been used on different images of brain segment with tumor it has always given as the correct desired output.

Keywords: *Brain tumors,Segmentation, Gray level co occurrence matrix, DNABI*

1.Introduction

A mass of tissue that originates by a gradual growth of abnormal cells is called a tumor. Usually, in our body the cells get aged, die and then they are replaced by newly born cells. But in the case of cancers and tumors, this cycle gets interrupted a leads to the formation,of tumors have been categorized into primary and secondary areas. When the tumors emanate from the tissues of the brain itself,they are said to be primary tumors. Secondary brain tumors are those tumors that are caused from cancer that

arises from another part of the body.Segmentation of tumors in magnetic resonance images (MRI) is an important task. But it is quite time consuming when performed manually by experts. Projection images are useful in determining the primary location of tumors. Automating process is challenging task due to the high diversity in appearance of tumor tissue in different patients, and in many cases, similarity between tumor and normal tissues. this method is automatic and independent of the operator. It segments low contrast tumors without requiring exacta tissue boundaries. The segmentation results obtained by the proposed approach are compared with those of an expert radiologist. The images which are obtained through these modalities are in a standard format usable in digital imaging and communication for medicine(DICOM).This is the standard format for all medical images. It was developedbytheNationalElectronicManufacturesAssociation(NEMA) This standard format is mainly used for storing, printing and transmitting information in medical imaging. Many diagnostic imaging techniques can be performed for early detection of brain tumors such as Computed Tomography (CT), Positron Emission Tomography (PET) and Magnetic Resonance

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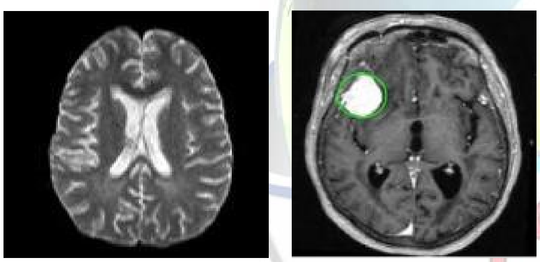
Imaging (MRI). Compared to all other imaging techniques, MRI is more efficient in brain tumor detection and identification,Mainly due to the high contrast of soft tissues, high spatial resolution and since it does not produce any harmful radiation, and is a non invasive technique.For the implementation of the proposed method of brain tumor classification, normal and brain tumor (benign and malignant) T2 weighted axial plane Magnetic Resonance images in DICOM format were collected from the patients of the National Institute of Mental Health and Neurosciences (NIMHANS), Bangalore. Figure 1(a), (b) shows the T2 weighted Magnetic Resonance image database considered for the implementation of textural feature extraction and classification. The collected T2 weighted Magnetic Resonance images are categorized into two distinct classes as normal, abnormal brain tumors, as shown in figure 2(a), (b) respectively.



(a) normal **(b) abnormal**

Fig. 1 MRI images taken from[12]

2.Related Work

The diagnostic process in grity unplated there are 2 stages-First pathologist observes tissues and recognize certain histological attributes related to the degree of tumor malignancy. In the second step interprets the histological findings and come up with a decision related to tumor grade. Pathologists are capable of verbalizing their impressions on particular features. For example, they can call mitosis and apoptosis as "present" or "absent" but they do not know how precisely these concepts have to be taken into account in the decision process. To this end, although the same set of features is recognized by different histopathologists, each one is likely to reach to a different diagnostic output.Karpagam, S.Gowri, in their work proposed detection of tumor growth by advanced diameter techniques using MRI data. To find the volume of brain tumor they proposed diameter and graphbased methods. The results show tumor growth and volume [8]. In this study a new and improved method is implemented by combining Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) for feature reduction and SVM (Support Vector Machine) is used for classification of MRI images. Compared to previous studies a higher accuracy is achieved in extraction.

2.1 Outline Work

In this paper a Brain tumor detection and segmentation system has been designed and developed for distinguishing different types of brain MRI into three classes such as Benign, Malignant and Normal. The imageprocessing techniques such as image acquisition, image segmentation,and morphological operations & feature extraction have been developed for detection of brain tumor.to obtain the features related to the Discrete Cosine Transform as well as Discrete Wavelet Transform. For segmentation of tumor region growing issued. The extraction of texture features in the detected tumor has been achieved by using Gray level co-occurrence matrix (GLCM) and Gabor Filters .

This Paper is organized as follows. Section 3 describes related research,Section 4 outlines the proposed method , feature extraction , classification. In section 5 Post Processing ,Morpological operations,Region growing algorithms and experimental results are discussed. The conclusion are given in section 6.

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3.Proposed Method:

The architecture of the proposed is illustrated in Figure 1.The major components are Brain tumor Database, Pre processing , Feature extraction and Classification.

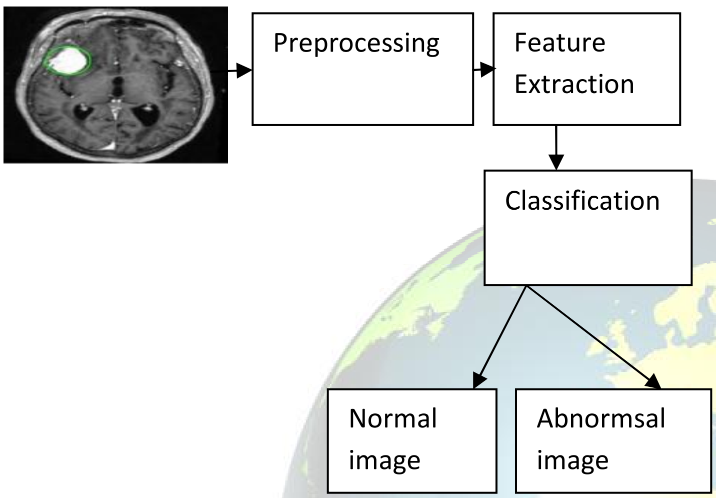

Fig 2.Outlined of the Proposed Method

3.1 Preprocessing

The prime objective of pre-processing is to improve the quality of the image data by enhacing the required image features for further processing. The redundancy in the image are eliminated using the pre-processing technique. it eliminates incomplete, noisy and inconsistent data from the image. In order to improve the quality of images taken from the brain MRI images and to make the feature extraction process more reliable and pre-processing is necessary. Image pre-processing includes

3.2 Feature Extraction

Gray-level co-occurrence matrix (GLCM) is a statistical method of finding the textures that consider 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 occur in a specified spatial relationship present in an image, [GLCM [3]]. This makes the extraction of statistical measures from this matrix possible. It is the most widely used and more generally applied method because of its high accuracy and less computation time. A gray level cooccurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values [10].The five features extracted in this paper are explained below.

(i) Mean:

The mean is defined as below

$$\text{Mean}(m)=\frac{1}{x+1}\sum_{i=1}^{x}\sum_{j=1}^{y}x(i,j) \qquad (1)$$

(ii) Variance:

It is square of Vaiance. The Variance is defined as below

$$\text{Variance}(v)=\frac{1}{x+1}\sum_{i=1}^{x}\sum_{j=1}^{y}(x(i,j)-m)^2 \qquad (2)$$

(iii) Entropy:

Entropy is a measure of the uncertainty in a random variable.

$$\text{Entropy}=\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\frac{(u(i,j))}{R}\right)log\frac{(u(i,j))}{R} \qquad (3)$$

(iv) Contrast:

Contrast is defined as the separation between the darkest and brightest area. Contrast=

$$\sum_{i=1}^{N}\sum_{j=1}^{N}(i-j)^2\left(\frac{p(i,j)}{R}\right) \qquad (4)$$

(v) Energy:

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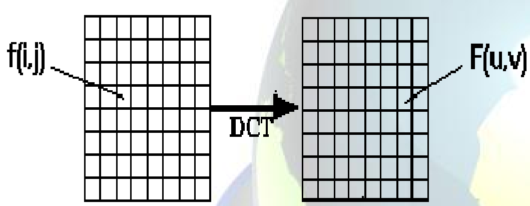
It provides the sum of squared elements in the GLCM. The uniformity or the angular second moment are also identified.

$$\text{Energy}=\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\frac{u(i,j)}{R}\right)^{2} \quad (5)$$

3.2.1 The Discrete Cosine Transform (DCT)

The discrete cosine transform (DCT) helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform: it transforms a signal or image from the spatial domain to the frequency domain.



The basic operation of the DCT is as follows:

- The input image is N by M;
- f(i,j) is the intensity of the pixel in row i and column j;
- F(u,v) is the DCT coefficient in row k1 and column k2 of the DCT matrix.
- For most images, much of the signal energy lies at low frequencies; these appear in the upper left corner of the DCT.
- Compression is achieved since the lower right values represent higher frequencies, and are often small - small enough to be neglected with little visible distortion.
- The DCT input is an 8 by 8 array of integers. This array contains each pixel's gray scale level;
- 8 bit pixels have levels from 0 to 255.
- Therefore an 8 point DCT would be:

where

$$A(\epsilon)=\begin{cases}\frac{1}{\sqrt{2}} & for\ \epsilon=0\\ 1 & otherwise\end{cases} \quad (6)$$

3.2.2 Discrete Wavelet Decomposition

The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficients from MR images. Discrete Wavelet Transform is an implementation of the WT using dyadic scales and positions. The basic fundamental principle of DWT is as follows: Suppose *x* (*t*) is a square-integrable function, then the continuous WT of *x* (*t*) relative to a given wavelet *Ψ* (*t*) is defined as, ∫ (1) where, the wavelet is calculated from the mother wavelet Ψ (t) by dilation and translation factor a and b respectively, which are real positive numbers. √ ( ) (2) Equation (1) can be discretized by restraining a and b to a discrete lattice (a=2b and a > 0) to give the discrete wavelet transform, which can be expressed as,[Σ] (3) [Σ] (4) where, the coefficients refer to the approximate and detailed components, respectively. The functions g (n) and h (n) denote the coefficients of the low-pass and high-pass filter, respectively. The subscripts *j* and *k* represent the wavelet scale and translation factors, respectively. The *DS* operator is used for down sampling. two dimensional DWT results in four sub bands LL (low-low), LH (low-high), HL (high-low), HH (high-high) at each scale. Sub band LL, is the approximation component of the image, which is used for the next two dimensional DWT. whereas, LH, HL, HH are the detailed components of the image along the horizontal, vertical and diagonal axis, respectively.

3.3 Classification:

The Proposed method is considered superior over SVM and other neural networks in terms of accuracy in classification.It is employed to implement an automatic MR image classification of brain tumors into normal, abnormal .It automatic Classification of

Brain MRI Using Region Growing method and SVM.

3.3.1Support Vector Machine

Support vector machines are a state of the art pattern recognition technique developed from statistical learning theory. The basic idea of applying SVMs for solving classification problems can be stated briefly as follows: a) Transform the input space to higher dimension feature space through a non-linear mapping function and b) Construct the separating hyperplane with maximum distance from the closest points of the training set. In the case of linear separable data, the SVM tries to find, among all hyperplanes that minimize the training error, the one that separates the training data with maximum distance from their closest points

$$w.x + b = 0 \tag{7}$$

when w and b are weight and bias parameters respectively.The optimization problem is solved using the MATLAB optimization toolbox the Support Vector Machine(SVM) is employed to implement an automated brain tumor classification. The performance of the SVM classifier is evaluated in terms of training performance and classification accuracies. Tumor area is calculated. Finally there is a comparison to the accuracy of Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) over 90 MRI of the brain. Simulation is performed by MATLAB software.

3.4 Post Processing

The major components of the system are Morpological operations,Erosion ,dilation and Region Growing Method, experimental results and performance analysis are discussed below.

3.4.1 Morphological Operations:

In this paper morphological operators are used for the tumor region extraction and to further remove the nontumor regions. In tumor regions, vertical edges, horizontal edges, and diagonal edges are mingled together while they are distributed separately in non tumor regions [9]. The dilation operator is used for filling the broken gaps and to have continuities at the boundaries. Binary Dilation and Erosion The set of black and white pixels constitute a description of a binary image. Assume that only black pixels are considered, and the others are treated as a background. The primary morphological operations are dilation and erosion, and from these two, more complex morphological operations such as opening, closing, and shape decomposition can be worked out. Dilation,Erosion.

3.5 Region Growing Method

There are a few important pointer to be considered when trying to segment an image. are must have regions that are disjointed because a single point cannot be contained in two different regions. The regions must span the entire image because each point has to belong to one region or another. To get regions,one must define some property that will be true for each region defined. To ensure that the regions are well defined and that they are indeed regions themselves and not several regions together or just a fraction of a single region, that property should not be true for any combination of two or more regions. If these criteria are met, then the image is truly segmented into regions. This paper discusses two different region determination techniques: one that focuses on edge detection as its main determination characteristic and another that uses region growing to locate separate areas of the image The region growing techniques take on a variety of aspects the potential sequences of processes that can lead to segmentation using region growing. Uniform Blocking, Merge-Split Blocking, Mean or Max-Min:Region, Dissolve.

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4.Experimental Results

4.1 MRI image data set

For the classification and segmentation of normal and abnormal brain images, data set is collected from different sources. One of the sources is the Harvard Medical School Website. [http://www.med.harvard.edu/aanlib/home.html] The types of brain images include Axial, T2-weighted, 256-256 pixels MR brain images. Figure 3 shows one of the databases considered for classification. The images are classified as normal and abnormal.

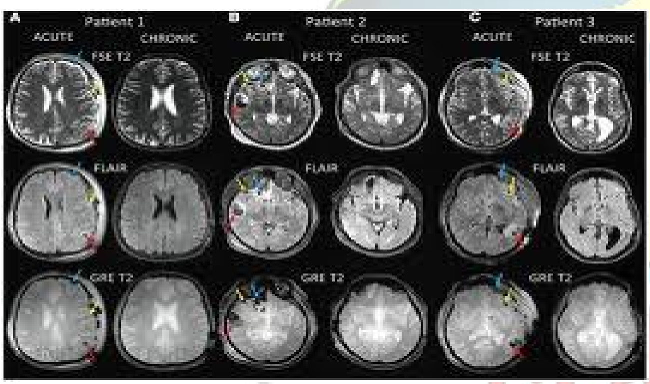

Fig 3.Sample MRI Brain images taken from[12]

4.2 Performance Evaluation

The comparison was done with testing techniques according to the following performance measures

$$True\ positive = \frac{\text{No.of results images having Brain Tumor}}{\text{Total No.of images}} \quad (8)$$

$$True\ Negative = \frac{\text{No.of images that haven't Brain Tumor}}{\text{Total No.of images}} \quad (9)$$

$$False\ positive = \frac{\text{no.of images that haven't tumor and detected positive}}{\text{total no of images}} \quad (10)$$

$$False\ negative = \frac{\text{no.of images have tumor and not detected}}{\text{total no of images}} \quad (11)$$

To compute *F*-measure,

$$F - measure = 2PR/(P+R) \quad (12)$$

where, P and R are precision and recall. The *F*-Measure computes the average information retrieval precision and recall metrics. Precision is calculated using following equation,

$$Precision = TP/(TP+FP) \quad (13)$$

where, TP and FP are True Positive and False Positive. Recall are calculated using the equation

$$Recall = TP/(TP+FN) \quad (14)$$

where, TP and FP is True Positive and False Positive. TP is the total number of correctly

detected Brain tumors. FP is total number of in-correctly detected Brain tumors. False Negative (FN) represents the total number false detections. using the equation

$$Specificity = TN/(TN+FP) \quad (15)$$

where, TN and FP are True Negative and False Positive. Specificity calculated using the equation

$$Accuracy = (TP+TN)/(TP+FP+FN+TN) \quad (16)$$

4.3 Experimental Results for tumor detection

The methodology of Region Growing was applied of MR brain tumor images of the head to obtained segmented regions of tumor. The performance was evaluated. The segmentation results are displayed below in Fig 3(a) and (b).The classification gets closer as the number of training samples increases; the pattern layer consists of a processing element corresponding to each input vector in the training set. All the output parameters in the pattern layer is tested and trained based on SVM values. An element is trained to return a high output value when an input vector matches the training vector.

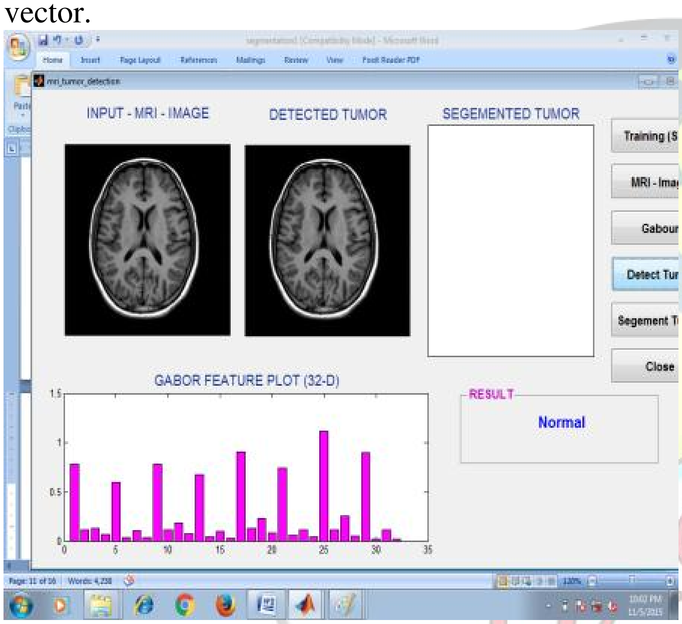

Fig4.ResultforNormalBrainimage

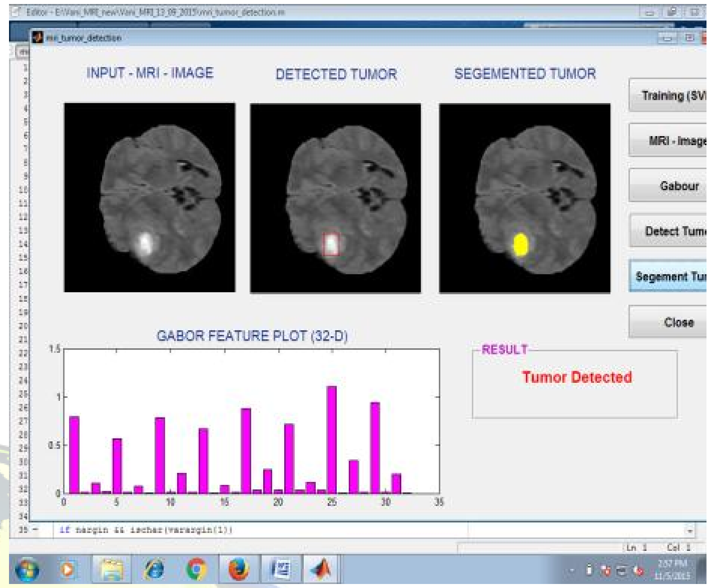

Fig 5. Result for Detect and Segmentation of Abnormal Brain images

The Data base consisted of MRI of the brain. Thus study Different images from different patients have been considered, analyzed and classified. The following Table shows Tumor Non tumor and assigned classes,the results after applying feature extraction by using DCT & DWT. Accuracy analyse are shown in the following figure:

	Normal	Tumor
Normal	38	7
Tumor	39	6

Table 1:Accuracy analysis for Assigned classes

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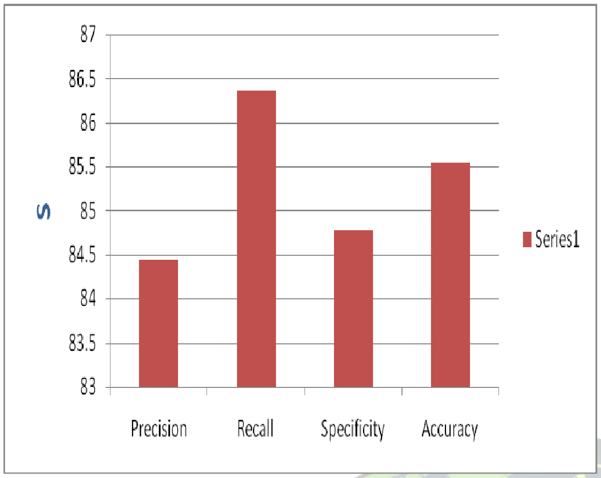

Fig. 6 Result for Performance analysis for Brain tumor

5.Conclusion and Future work

The study has developed an automatic tumor detection and segmentation algorithm using MRI.The preliminary results show 94% detection rate in all test sets including simulated and patient data with an average accuracy of segmentation about 90%. Quality results in the borders of tumor are relatively good due to the combination of local and global information. Future work would deal with classification of brain tumors into different grades by using advanced texture analysis methods, so that the accuracy of brain tumor diagnosis could be enhanced.

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