Automatic Brain Tumor Detection

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Abstract- *tumor is uncontrolled growth of the abnormal tissue in the body. If this phenomenon is present in brain, it is called brain tumor. A tumor may lead to cancer. Image processing techniques are applied to magnetic resonance (MR) images to detect tumor. The main objective of this is to present the automatic detection method which separates non-enhancing brain tumors from healthy tissues in MR images by locating tumor position in the brain and to give complete statistical analysis of the tumor. The knowledge of this information regarding tumor in the brain is important for diagnosis, planning and treatment. This will help the physicians in analyzing the brain tumors accurately and efficiently.*

I. INTRODUCTION

A brain tumor arises due to an abnormal growth of cells that have proliferated in an uncontrolled manner. Primary brain tumors can start from brain cells, the membrane around the nerves or glands. Tumor can directly destroy brain cells. They can also damage cells by producing swelling, increasing pressure within the skull.

Image processing is a method to convert an image into digital form and perform some operation on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is an image, like video frame or photograph and output may be an image or characteristics associated with that image. Usually image processing system includes treating images as two dimensional signals while applying already set signal processing methods for them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image processing forms core research area within computer science engineering and medical science disciplines too.

Image processing techniques are widely used to extract information from medical images. According to the target position, medical imaging can be classified into central imaging, cardiac imaging, thoracic imaging and vascular imaging. Medical imaging can be categorized as one of the following. Magnetic Resonance Imaging(MRI), Computed Tomography(CT), Positron Emission Tomography(PET), Single Photon Emission Computed Tomography(SPECT), Ultrasound, Diffusion Tensor Imaging(DTI).

1.1. Classification of brain tumor

a) Benign and malignant brain tumors

Benign tumors are composed of harmless cells and have clearly defined borders. They can usually be completely removed, and are unlikely to reoccur. Benign brain tumors do not infiltrate nearby tissues, but can cause severe pain, permanent brain damage, and death. Malignant brain tumors do not have distinct borders. They tend to grow rapidly, increasing pressure within the brain and can spread in the brain or spinal cord beyond the point where they originate. It is highly unusual for malignant brain tumors to spread beyond the CNS.

b) Primary and secondary brain tumors

Primary brain tumors originate in the brain. They represent about 1% of all cancers and 2.5% of all cancer deaths. Approximately 25% of all cancer patients develop secondary or metastatic brain tumors when cancer cells spread from another part of the body to the brain.

c) Normal and grading brain tumors

The name of the brain tumors describes where it originates, how it grows, and what kind of cells it contains. The tumor in an adult is graded or staged according to how malignant it is, how rapidly it is growing, how likely it is to invade other tissues and how closely its cells resemble normal cells.

d) Low grade brain tumors

It has well defined borders. Some low grade brain tumor forms are enclosed in cysts. Low grade brain tumors grow slowly, if at all. They may spread throughout the brain, but rarely metastasize to other parts of the body.

e) Mid grade and high grade brain tumors

It grows more rapidly than low grade brain tumors. Described as “truly malignant”, these tumors usually infiltrate healthy tissue. The growth pattern makes it difficult to remove the entire tumor, and these tumors re-occur more often than low-grade tumors. A single brain tumor can contain several different types of cells. The tumor’s grade is determined by the highest grade cell detected under a microscope, even if most of the cells in the tumor are less malignant. World Health Organization grading system classifies brain tumors on the basis of rate of growth into four categories, grade I, II, III, IV. Grade I tumors are the least malignant and grow slowly. But a grade I tumor may be life threatening if it is inaccessible for surgery. Grade II tumors grow slightly faster than grade I tumors and have a little abnormal microscopic appearance. These tumors may invade surrounding normal tissues, and may recur as a grade III or higher tumor. Grade III tumors are malignant. The chances of re-occurrences of the tumors are quite high. Grade IV tumors are the most malignant and invade wide areas of surrounding normal tissues.

II. PROPOSED SYSTEM

Automated detection of brain tumor through MRI is basically called Computer Aided Diagnosis (CAD) system[1]. The CAD system can provide highly accurate reconstruction of the original image, i.e the valuable outlook and accuracy of earlier brain tumor detection. In the initial stage, pre-processing is required after that stages post-processing is performed, i.e. segmentation is required[2]. Then the detection strategies like feature extraction, classification are performed.

a) Pre-processing

Pre-processing techniques are used for improvement of image quality and remove noise for the accurate detection of the undesired regions in MR[4]I.

b) Post-processing

Post-processing is used to segment with different strategy the brain tumor from the MRI of brain image[5]s.

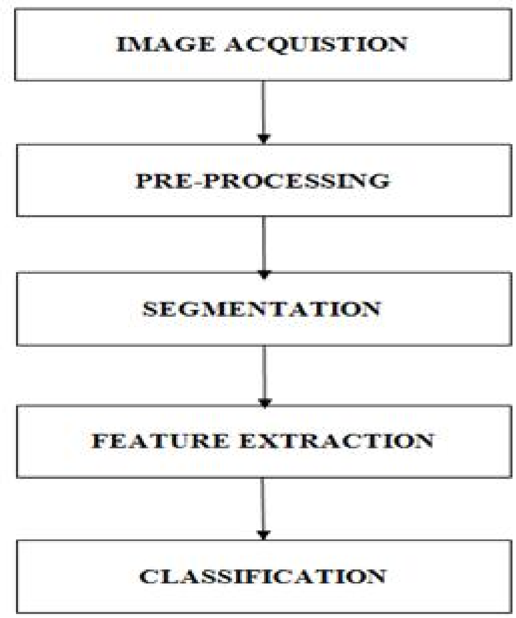


Fig. 1: Block Diagram

i) Image Acquisition

Images are acquired from the dataset. The images acquired are gray scale images. These are fed into the pre-processing stage to improve the contrast and adjust the image size.

ii) Pre-processing

The objective of the pre-processing phase is to apply possible image enhancement techniques to obtain the required visual quality of the brain image.

a) Contrast Adjustment

Image contrast is a measure of intensity after the image has been acquired. The proper contrast levels are of the utmost importance when processing an image. Contrast is the visual property of an object that separates it from other objects in an image. The contrast adjustment equation (1) is given as
Contrast adjustment: + (1)

Where S(x,y) is result of R(x,y) original image and S(x,y) is the result of corresponding technique.

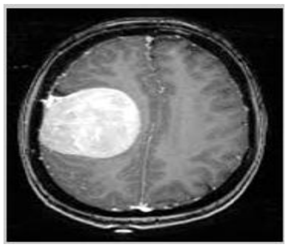


Fig. 2: Contrast adjustment image

b) Re-sampling of the image

Changing the dimensions of the image like width, height, and resolution through bilinear interpolation. Bilinear interpolation is a re-sampling method that uses the distances weighted average of the four nearest pixel values to estimate a new pixel value. Here, Height x Width = 250 x 250 pixels is considered as the re-sampling size.

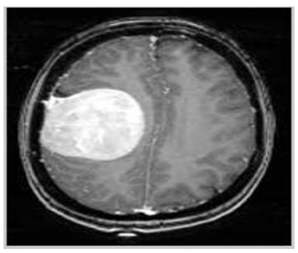


Fig. 3: Re-sampling image

c) Histogram Processing

An image histogram is a type of histogram that acts as a graphical representation in the lightness/color distribution in a digital image[6]. It plots the number of pixels for each value and equation (2) is given as

H(n)=▸ (2)

Where n=0,1,…,L-1

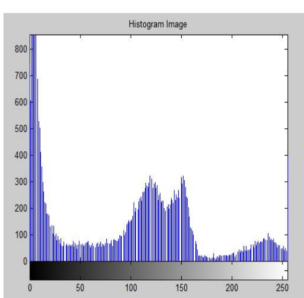


Fig. 4: Histogram image

2.1 Segmentation

Thresholding Method, FFT, Morphological Operation are various steps involved in segmentation.

i) Thresholding Method

Thresholding can be applied to grayscale images or color images. In thresholding a pixel intensity value is adjusted, by taking the given value as reference the low intensity pixels will become 0 and the rest of the pixels will become 1. The result of the thresholding is a binary image containing black and white pixels, equation (3) is given as:

D(x,y) = (3)

D(x,y) is the result image after applying thresholding, J(x,y) is the image from the previous process and K is any constant intensity value.

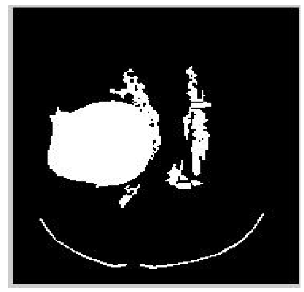


Fig. 5: Thresholding image

ii) FFT

Fourier Transform decomposes an image into its real and imaginary components which is a representation of the image in the frequency domain[3]. If the input signal is an image, then the number of frequencies in the frequency domain is equal to the number of pixels in the image or spatial domain. The FFT of a 2D image is given by the equation (4) as given below:

F(X,Y) = (4)

where f(n,m) is the pixel at coordinate (n,m), F(X,Y) is the value of the image in the frequency domain corresponding to the coordinates x and y, N and M are the dimensions of the image. The dimensions of the image are a power of two.

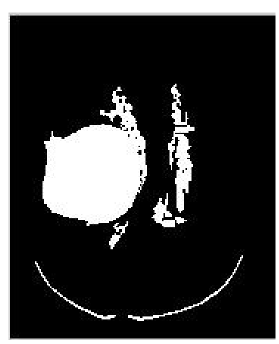


Fig. 6: FFT Transformed image

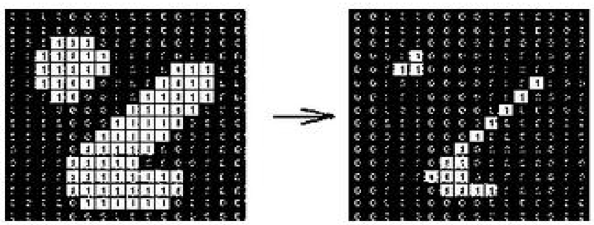
iii) Morphological operation

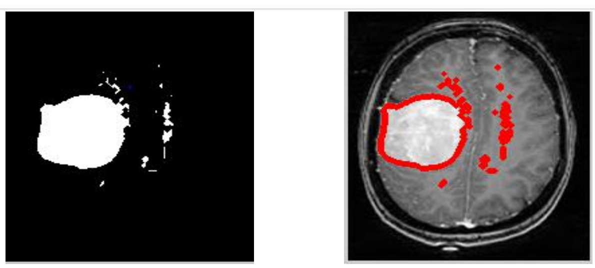
Morphology is a technique for extracting the information from an image it represents the description of region shape. Morphology operations are used in post processing mainly as a filter[7]. Morphological operations are erosion and dilation. Erosion shrinks the object in the binary image. Dilation grows or thickness the object in binary image.

a) Erosion

Reduces the noises in the background and also reduces the noise of the object region. Erosion of A by B is defined as

Where A is the image and B is the structural element.





(a) (b)

Fig. 8: (a) Segmented image (b) Final Segmented image

2.2. Feature Extraction

Basically shaped based image retrieval consists of measuring the similarity between shapes represented by their features. They are not suitable to be stand alone shape descriptors. A shape can be described by different aspects. Some simple geometric feature can be used to describe shapes. These shape parameters are area, eccentricity, solidity, major axis length, perimeter.

a) Shape Features

1) Area – The area of the object is calculated using the total number of pixels which are present inside the object. Ex. Area=3524 pixels.
2) Eccentricity – It is the ratio of the distance between the foci of the ellipse and its major axis length. Ex. Eccentricity = 0.620
3) Solidity – Solidity describes the extent to which the shape is convex or concave. Ex. Solidity=0.459
4) Major axis length – It is calculated by using the maximum diameter of the shape, which holds the number of pixels in that longest diameter of the ellipse. Ex. 83.836
5) Perimeter – The perimeter is defined as the total length of the object boundary. It is calculated from the number of intercepts, formed by a series of parallel lines. Ex. 259.27

b) Texture feature

Texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. The Gray Level Co-occurrence Matrix(GLCM) method is a way of extracting the texture features. The approach has been used in number of applications. The texture features are contrast, correlation, energy, homogeneity. GLCM has proved to be a popular statistical method of extracting textural feature from images.

1) Contrast – It measures the intensity contrast between a pixel and its neighbor over the whole region. Ex. Contrast = 0.429.
2) Correlation – Return a measure of how correlated a pixel is to its neighbor over the whole image. Ex. Correlation = 0.946.
3) Energy – Returns the sum of squared elements in the GLCM. Ex. Energy = 0.827.
4) Homogeneity – Returns a value that measures the closeness of the distribution of elements in the GLCM to GLCM diagonal. Ex. Homogeneity = 0.992.

2.3 Classification

The classification process is done over the segmented images[9]. Random Forest classifier is applied over the segmented images and the classification is done. Random forest classifier is the simplest among classification algorithm, able to classify giant amount of information with accuracy[10].

a) Random Forest Algorithm

1) Let the number of training cases be N, and the number of variables in the classifier be M.

2) The number m of input variables are used to determine the decision at a node of the tree, m should be less than M.
3) Choose a training set for this tree by choosing N times with replacement from all N available training cases. Use the rest of the cases to estimate the error of the tree, by predicting their classes.
4) For each node of the tree, randomly choose m variables on which to base the decision at the node. Calculate the best split based on these m variables in the training set.
5) Each tree is fully grown and not pruned.

III. EXPERIMENTAL RESULTS

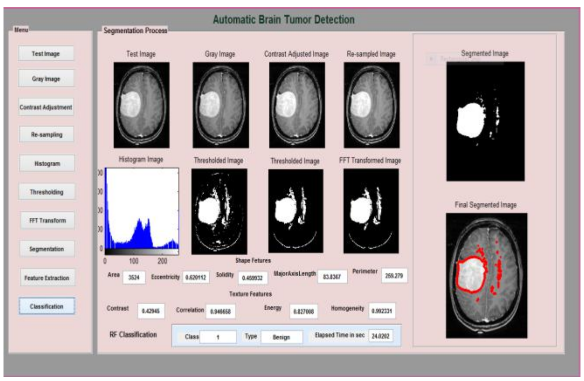


Fig. 10: Experimental Results

Figure 7 shows the GUI for loading a test image and adjusting contrast of that test image. In histogram the image has been derived using the graphical representation of the lightness in the digital image. Thresholding is applied to the grayscale image to highlight the pixels in the image. It also increases the pixel intensity value in the image. The low intensity pixels will be 0 and the rest of the pixels will be 1. Then the image is segmented using morphological operations. The segmented tumor is shown in red. In Feature extraction the shape based image retrieval consists of measuring the similarity between the shapes represented by their features. The shape can be described by different aspects. Some simple geometric features can be used to describe the shapes. The Gray Level Co-occurrence Matrix(GLCM) method is a way of extracting the texture features. The approach has been used in number of applications. The classification process is done over the segmented image. The Random Forest classifier is applied over the segmented images and the classification is done.

V. CONCLUSION

A new method has been proposed to find the tumor automatically with least amount of time. In pre-processing contrast adjustment, histogram, and re-sampling are done. In post-processing segmentation, feature extraction and classification are implemented.

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