BIOLOGICAL EARLY BRAIN CANCER DETECTION USING ARTIFICIAL NEURAL NETWORK

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Abstract

Computer aided diagnosis systems for detecting malignant texture in biological study have been investigated using several techniques. This paper presents an approach in computer-aided diagnosis for early prediction of brain cancer using Texture features and neuro classification logic.

The Tumor mass detection and Cluster micro classification is used as the processing method for cancer prediction. Nine distinct invariant features with calculation of minimum distance for the prediction of cancer are used for the prediction of tumor in a given MRI image. A neuro fuzzy approach is used for the recognition of the extracted region. The implementation is observed on various types of MRI images with different types of cancer regions.

Keyword: Brain cancer, Neuro Fuzzy Logic, recognition, MRI.

I. Introduction

Brain cancer can be counted among the most deadly and intractable diseases. Tumors may be embedded in regions of the brain that are critical to orchestrating the body's vital functions, while they shed cells to invade other parts of the brain, forming more tumors too small to detect using conventional imaging techniques. Brain cancer's location and ability to spread quickly makes treatment with surgery or radiation like fighting an enemy hiding out among minefields and caves.

In recent years, the occurrence of brain tumors has been on the rise. Unfortunately, many of these tumors will be detected too late, after symptoms appear. It is much easier and safer to remove a small tumor than a large one. About 60 percent of glioblastomas start out as a lower-grade tumor. But small tumors become big tumors. Low-grade gliomas become high-grade gliomas. Once symptoms appear, it is generally too late to treat the tumor. Computer-assisted surgical planning and advanced image-guided technology have become
Increasingly used in Neuro surgery [1][2][3][4][5]. The availability of accurate anatomic three-dimensional (3D) models substantially improves spatial information concerning the relationships of critical structures (eg, functionally significant cortical areas, vascular structures) and disease [6]. In daily clinical practice, however, commercially available intraoperative navigational systems provide the surgeon with only two-dimensional (2D) cross sections of the intensity-value images and a 3D model of the skin. The main limiting factor in the routine use of 3D models to identify (segment) important structures is the amount of time and effort that a trained operator must spend on the Preparation of the data [9].

A brain cancer is a disease in which cells grow uncontrollably in the brain. Brain tumors are of two main types : 1) Benign tumors 2) Malignant tumors
Benign tumors are incapable of spreading beyond the brain itself. Benign tumors in the brain usually do not need to be treated and their growth is self limited. Sometimes they cause problems because of their location and surgery or radiation can be helpful.

Malignant tumors are typically called brain cancer. These tumors can spread outside of the brain. Malignant tumors of the brain will always develop into a problem is left untreated and an aggressive approach is almost always warranted. Brain malignancies can be divided into two categories :
Primary brain cancer originated in the brain.
Secondary or metastatic brain cancer spreads to the brain from another site in the body.

Cancer occurs when cells in the body (in this case brain cells) divide without control or order. Normally, cells divide in a regulated manner. If cells keep dividing

uncontrollably when new cells are not needed, a mass of tissue forms, called a growth or tumor. The term cancer usually refers to malignant tumors, which can invade nearby tissues and can spread to other parts of the body.

II. Approach

The present work implements an efficient system for the detection of cancer from a given brain MRI and recognizes the extracted data for further applications. The implemented project work finds efficient usage under biomedical early cancer detection. The work can be efficiently used in the area of medical science such as Computer aided diagnosis & Mammography etc. The proposed work will be very useful under medicines for predicting early brain cancer cells using texture features and neuro classification.

Fig.1 shows a block diagram for the proposed algorithm.

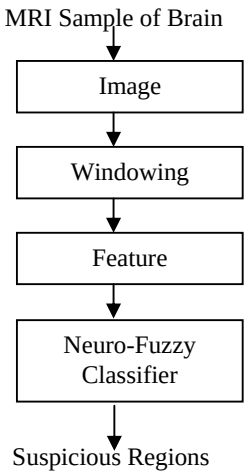

Fig.1. Operational flow chart for the proposed system

Image preprocessing consists mainly of two steps. Image Segmentation to isolate the cancer cells from the background image and Image enhancement to increase the contrast between the Cancer Cells and the Complete MRI of the brain.

1. Data Set

For the implementation of automated recognition system a data set collected from different source for various class of MRI image is considered. Figure shows the database considered for the implementation. The collected MRI images are categorized into four distinct classes with each as one type of cancer. The MRI scan are scanned and passed for implementation.

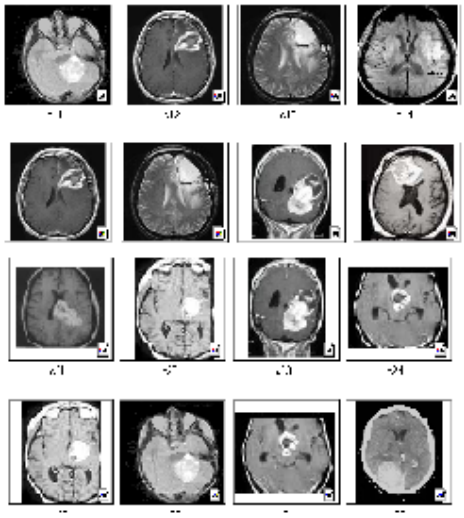

Fig.2 A typical example of the used MRI

2. Image Segmentation

The first step is to segment the MRI image. Segmentation subdivides an image into its constituent parts of objects, the level to which this subdivision is carried depends on the problem being solved, that is, the segmentation should stop when the edge of the tumor is able to be detected.i.e. the main interest is to isolate the tumor from its background.

The main problem in the edge detection process is that the cancer cells near the surface of the MRI is very fatty, thus appears very dark on the MRI, which is very confusing in the edge detection process. To overcome the problem, two steps were performed. First, histogram equalization has been applied to the image to enhance the gray level near the edge. Second, thresholding the equalized image in order to obtain a binarized MRI with gray level 1 representing the cancer cells and gray level 0 representing the background.

3. Histogram Equalization

The histogram of an image represents the relative frequency of occurrences of the various gray levels in the image. Histogram modeling techniques (e.g. histogram equalization) provide a sophisticated method for modifying the dynamic range and contrast of an image by altering that image such that its intensity histogram has a desired shape. Unlike contrast stretching, histogram modeling operators may employ non-linear and non-monotonic transfer functions to map between pixel intensity values in the input and output images. Histogram equalization employs a monotonic, non-linear mapping which re-assign the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities.

Fig. 3 shows the effect of histogram equalization on MRI.

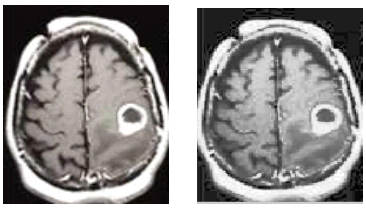

Fig. 3 a) The original MRI b) Histogram equalized MRI

4.Thresholding

In many vision applications, it is useful 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 often provides an easy and convenient way to perform this segmentation on the basis of the different intensities or colors in the foreground and background regions of an image.

The input to a Thresholding operation is typically a greyscale or color image. In the simplest implementation the output is a binary image representing the segmentation. Black pixels corresponds to background and white pixels correspond to foreground. In simple implementations, the segmentation is determined by a single parameter known as the intensity threshold. In a single pass, each pixel in the image is compared with this threshold. If the pixel's intensity is higher than the threshold, the pixel is set to white, in the output. If it is less than the threshold, it is set to black.

Segmentation is accomplished by scanning the whole image pixel by pixel and labeling each pixel as object or background according to its binarized gray level.

5. Image Enhancement

The fundamental enhancement needed in MRI is an increase in contrast. Contrast between the brain and the tumor region may be present on a MRI but below the threshold of human perception. Thus, to enhance contrast between the normal brain and tumor region, a sharpening filter is applied to the digitized MRI resulting in noticeable enhancement in image contrast.

6. Sharpening Filter

Sharpening filters work by increasing contrast at edges to highlight fine detail or enhance detail that has been blurred. It seeks to emphasize changes.

The most common sharpening filter uses a neighborhood of 3*3 pixel. For each output pixel it computes the weighted sum of the corresponding input pixel and its eight surrounding pixels. The weights are positive for the central pixel and negative for the surrounding pixels. By arranging the weights so that their sum is equal to one, the overall brightness of the image is unaffected. Weights can be adjusted as follows:

$$\begin{pmatrix} -1 & -1 & -1 \\ -1 & 0 & -1 \\ -1 & -1 & -1 \end{pmatrix}$$

7. Morphological operation

For the text region extraction, we use morphological operators and the logical operator to further remove the non-text regions. In text regions, vertical edges, Horizontal edges and diagonal edges are mingled together while they are distributed separately in non-text regions. Since text regions are composed of vertical edges, horizontal edges and diagonal edges, text regions can be determined to be the regions where those three kinds of edges are intermixed. Text edges are generally short and connected with each other in different orientation. Morphological dilation and Erosion operators are used to connect isolated candidate text edges in each detail component sub-band of the binary image. Figure 5 shows the Morphological operated scaled image.

8. Feature Extraction

The feature extraction extracts the features of importance for image recognition. The feature extracted gives the property of the text character, which can be used for training in the database. The obtained trained feature is compared with the test sample feature obtained and classified as one of the extracted character.

Texture features or more precisely, Gray Level Co-occurrence Matrix (GLCM) features are used to distinguish between normal and abnormal brain tumors. Five co-occurrence matrices are constructed in four spatial orientations horizontal, right diagonal, vertical and left diagonal (0°, 45°, 90° , and 135°). A fifth matrix is constructed as the mean of the preceding four matrices.

Texture Features (Gray Level Co-occurrence Matrix Features)

From each co-occurrence matrix, a set of five-feautres are extracted in different orientations for the training of the neuro-fuzzy model.

Let P be the N*N co-occurrence matrix calculated for each sub-image, then the features as given by Byer are as follows :

1. **Maximum Probability**

$f^1=\max_{i,j} p(i,j)$

2. **Contrast**

$$f2 = \sum_{i,j=0}^{N-1} Pi,j(i-j)2$$

3.Inverse Difference Moment (Homogeneity)

$$f3 = \sum_{i,j=0}^{N-1} \frac{Pi,j}{1+(i-j)^2}$$

4. Angular Second Moment (ASM)

$$f^4 = \sum_{i,j=0}^{N-1} P^2_{i,j}$$

5.Dissimilarity

$$f^5 = \sum_{i,j=0}^{N-1} P_{i,j} \left| i - j \right|$$

6.Grey Level Co-occurrence Mean (GLCM)

$$f^6 = u_I = \sum_{i,j=0}^{N-1} i\,(P_{i,j})$$

7.Variance

$$f^7 = \sigma_i = \sum_{i,j=0}^{N-1} (P_{i,j}(i - \mu_i)^2$$

8.Correlation Coefficient

$$f^8 = \sum_{i,j=0}^{N-1} P_{i,j} \left(\frac{(i - \mu_i)(j - \mu_j)}{\sqrt{(\sigma_i^2)(\sigma_i^2)}} \right)$$

Where

$$\mu_j \quad \sigma_j = \sum_{i,j=0}^{N-1} j(P_{i,j}) \quad (P_{i,j}(j - \mu_j)^2$$

9. Entropy

$$f^9 = \sum_{i,j=0}^{N-1} P_{i,j}\,(-\ln P_{i,j})$$

9. Feature Selection

Feature selection concerns the reduction of the dimensionality of the pattern space and the identification of features that contain most of the essential information needed for discriminating between normal and abnormal cases. Selection of efficient features can reduce significantly the difficulty of the classifier design. Therefore feature selection based on the correlation coefficient between features is performed. The correlation matrix was calculated for the set of 9 texture features for both normal and abnormal spaces.

Any two features with correlation coefficient that exceeds 0.9 in both spaces can be combined together and thought as one feature reducing the dimensionality of the feature space by one. Therefore the maximum probability and contrast can be removed and the numbers of features are reduced to seven features.

10. Neuro-Fuzzy Classifier

A Neuro-fuzzy classifier is used to detect candidate-circumscribed tumor. Generally, the input layer consists of seven neurons corresponding to the seven features. The output layer consists of one neuron indicating whether the MRI is a candidate circumscribed tumor or not, and the hidden layer changes according to the number of rules that give best recognition rate for each group of features.

III. Results

Figure illustrates the recognition of the tumor from the given MRI image. The extracted region is passed to the recognition unit for the classification of the type of tumor and it's class. Figure shows the classification rate obtained during the matching of the query image.

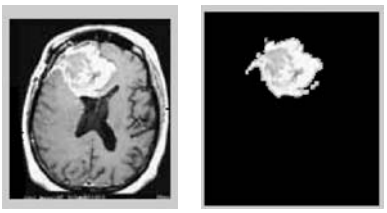

Fig. 4 a) Input image b) extracted tumor region

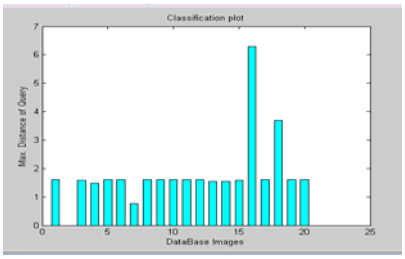

Fig. 5 Recognition plot

IV. Conclusion

This paper presents a automated recognition system for the MRI image using the neuro fuzzy logic. It is observed that the system result in better classification during the recognition process. The considerable iteration time and the accuracy level is found to be about 50-60% improved in recognition compared to the existing neuro classifier.

V. References

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