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Brain Cancer Detection using Neuro Fuzzy Logic

Laxmi Ghodke
Information Technology Department, TERNA Engineering College, Mumbai University,
lghodke@gmail.com

Apeksha Naik
Information Technology Department, TERNA Engineering College, Mumbai University,
naik.apeksha42@gmail.com

Rahul Konale
Information Technology Department, TERNA Engineering College, Mumbai University,
rahulkonale@yahoo.co.in

Suchit Mehta
Information Technology Department, TERNA Engineering College, Mumbai University,
suchitmehta@gmail.com

Available online at www.interscience.in

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[1]Laxmi Ghodke, [2]Apeksha Naik, [3]Rahul Konale, [4]Suchit Mehta

Information Technology Department, TERNA Engineering College, Mumbai University

Email: lghodke@gmail.com[1],naik.apeksha42@gmail.com[2], rahulkonale@yahoo.co.in[3],suchitmehta@gmail.com[4].

Abstract – This paper presents an approach of computer-aided diagnosis for early prediction of cancer cells in brain. It extracts the texture from the given brain MRI sample.It uses image processing techniques followed by neuro classification for prediction of Cancer for a given MRI sample. 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.

Keywords— Analysis, Tumor Detection, MRI Images.

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I. INTRODUCTION

Brain cancer begins at the microscopic cellular level, the first signs of a malignant (actively cancerous) growth are nearly impossible to detect without special tests and training. As the tumor becomes more organized, new blood vessels may form to feed it directly or older vessels may be diverted. Meanwhile, the host body may only experience a few symptoms which resemble many other conditions besides cancer.

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. 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.

Treatment for cancer(here brain cancer) ranges from rounds of powerful chemicals to focused burst of radiation to complete surgical removal of the tumor and surrounding tissue. Each treatment type brings a certain level of risk and pain to the patient, but cancerous cells left untreated will almost inevitably choke off vital organs and circulation. Chemotherapy introduces strong medicines which target fast-growing cells, but this also includes normal events such as hair growth and digestion. Radiation treatments use heat energy to literally burn off malignant cells, but healthy tissue is also damaged. Surgical removal can lead to a permanent recovery, but undetected malignant cells may have already metastasized to other organs or be jarred loose by the surgery itself.

A brain cancer is a disease in which cells grow uncontrollably in the brain. Brain tumors are of two main types : 1) Malignant tumors 2) Benign tumors

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:

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.

II. METHODOLOGY

The work involves processing of MRI images of brain, extracting the features of the brain and finally developing a suitable neuro fuzzy classifier to recognize the different types of brain cancers. Images of brain are obtained from MRI, and the textural features are extracted using image processing techniques. These features are used to train the neuro fuzzy classifier. The developed neuro fuzzy classifier is tested for classification of different brain MRI samples.

Thus, the proposed work emphasizes on development of Neural Network and Fuzzy logic based

method for prediction of brain cancer detection. The block schematic diagram shown in figure 1 is the proposed architecture for automated cancer recognition system.

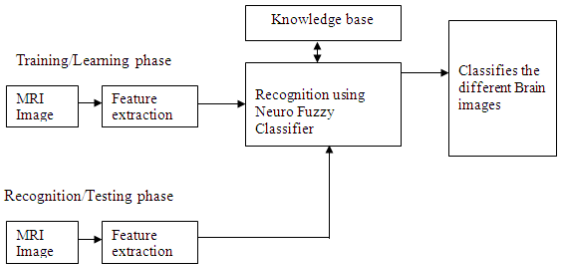

Fig 1 Proposed Methodology for automated cancer recognition system.

Operational flow of the proposed system is as follows:

MRI Image 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.

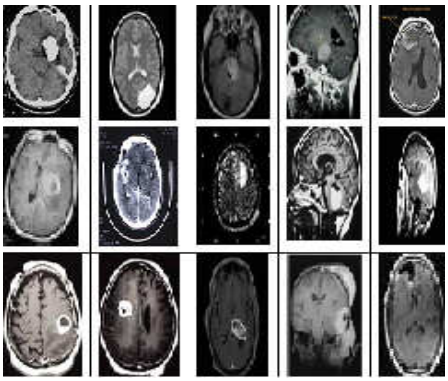

Fig.2 A typical example of the used MRI

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.

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. 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 Image.

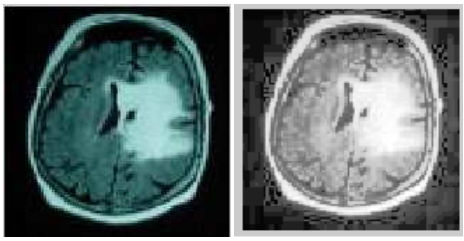

Fig. 3a) The original MRI b) Histogram equalized MRI

Thresholding

The input to a Thresholding operation is typically a grayscale 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. 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.

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. Weights can be adjusted as follows:

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

Morphological operation

For the text region extraction, we use morphological operators and the logical operator to further remove the non-text regions. 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.

Feature Extraction

The feature extracted image 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-features are extracted in different orientations for the training of the neuro-fuzzy model.

The following equations are used to detect the infected region in brain 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)

$$F4 = \sum_{i,j=0}^{N-1} P^2_{i,j}$$

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

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

Where

$$\mu_j = \sum_{i,j=0} j(P_{i,j})$$

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

9. Entropy

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

Neuro-Fuzzy Classifier

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.

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.

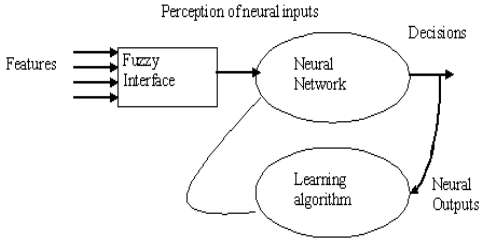

Fig. 4. Neuro fuzzy logic classification

III. RESULTS

Following 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. It shows the classification rate obtained during the matching of the query image.

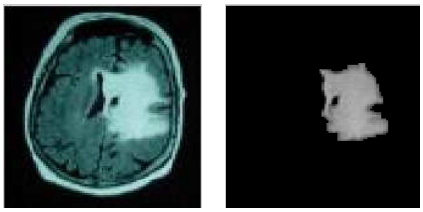

Fig. 2 a) Input image b) extracted tumor region

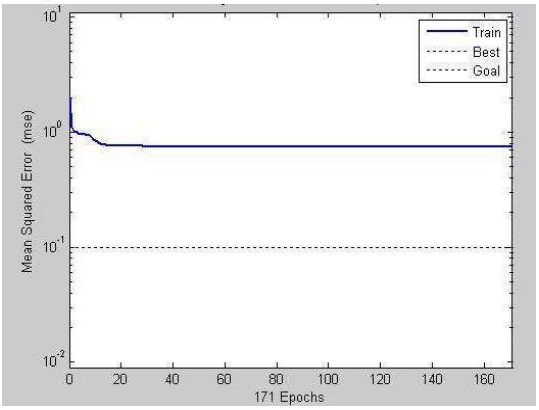

Fig. 3 Recognition plot

IV. CONCLUSION

The results in this paper show that neural network is able to distinguish between an abnormal and normal tumor regions, and classify them correctly as brain tumor and healthy patient respectively. This is possible with NNs and fuzzy logic since they are able learn the patterns in a normal and abnormal tumor regions. This technique can be extended to train neural networks with different types of brain disorder. The advantage of using NNs is that they will be consistent on their outputs provided sufficient training is given offline. Furthermore, they have the capability of making smart decisions on inputs that may be lightly different from ones they were trained on.

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