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COMPUTER AIDED DIAGNOSIS SYSTEM FOR BRAIN TUMOR DETECTION AND SEGMENTATION

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ABSTRACT

Abnormal cell growth leads to tumor in the brain cells. Earlier detection, diagnosis and proper treatment of brain tumor is essential to prevent human death. An effective brain tumor segmentation of MR image is an essential task in medical field. In this paper, a computer aided development of diagnosis system for brain tumor detection is proposed. The proposed work consists of four stages namely preprocessing, feature extraction, ANFIS Classifier and morphological operations to detect, segment and diagnose the brain tumor regions. Before going to segmentation the preprocessing is carried out since preprocessing makes the image ready for further segmentation. The performance of tumor segmentation are analyzed with the following factors similarity index (SI), extra fraction (EF), overlap fraction (OF) and accuracy, whose values are obtained as 0.78, 0.0098, 0.723 and 99.4% respectively. The results obtained in this paper shows that the proposed work is superior over the other state- of- art-techniques.

Keywords: *brain tumor, classifier, diagnosis system, similarity index, Extra fraction and overlap fraction.*

1. INTRODUCTION

Brain tumors are abnormal and uncontrolled growth of cells within brain structure. Brain tumors are one of the leading causes of cancer-related deaths in children and young adults. Although the causes of brain tumors are unknown, a few risk factors have been proposed. These include head injuries, hereditary disorder, immune suppression, prolonged exposure to ionizing radiation, cell phones, electromagnetic fields, or chemicals like formaldehyde and vinyl chloride. However, none of these is proven to actually cause the disease.

Brain tumors are mainly of two types, namely, primary and secondary. Those originating in the brain itself are termed primary tumors and others spreading to this location from somewhere else in the body are termed as secondary tumors. Primary brain tumors do not spread to other body sites and may be malignant (cancerous) or benign (non-cancerous). Secondary brain tumors spread to other parts of the body from its origin, i.e. lung cancer or breast cancer that spreads to the brain. Secondary brain tumors are also called metastatic brain tumors. Brain tumor is mostly treatable and curable if caught in the earliest stages of the disease. Untreated and/or advanced brain cancer can only spread inward because the skull will not let the brain tumor expand outward. This increases the pressure within the brain (intracranial pressure) and causes permanent brain damage and eventually death.

Magnetic resonance imaging (MRI) provides detailed information about brain tumor anatomy, cellular structure and vascular supply, making it an important tool for the effective diagnosis, treatment and monitoring of the disease. Since MRI does not use any ionization radiation its use is recommended in preference to CT when either modality could yield the same information. MRI provides a digital representation of tissue characteristic that can be obtained in any tissue plane. The images produced by an MRI scanner are best described as slices through the brain. MRI has the added advantage of being able to produce images which slice through the brain in both horizontal and vertical planes. This makes the MRI-scan images an ideal source for detecting, identifying and classifying the correct infected regions of the brain.

In this paper, we propose an algorithm to segment out the tumor from a given brain MR image using ANFIS classifier. The proposed method gives accurate tumor segmentation results and finally, normal and processed outputs, are compared for performance analysis.

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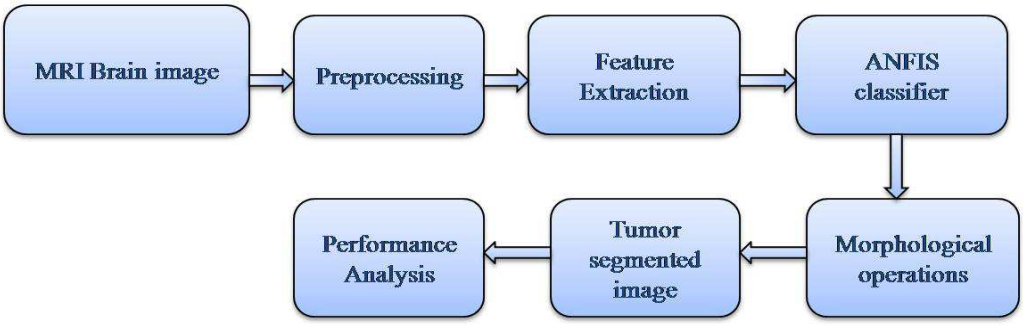

Figure 1: Process Flow of Proposed Tumor Segmentation Algorithm

2. RELATED WORKS

There are many approaches proposed for automatic and semiautomatic segmentation of the brain MRI into different tissues including tumor.

Harati *et al*. [1] proposed a computer-assisted classification method which combines conventional MRI and perfusion MRI for differential diagnosis. Their method consists of several steps including ROI definition, feature extraction, feature selection and classification. The extracted features include tumor shape and intensity characteristics as well as rotation invariant texture features. Features subset selection is performed using support vector machines (SVMs) with recursive feature elimination. The binary SVM classification accuracy, sensitivity, and specificity, assessed by leave-one-out cross-validation on 102 brain tumors, were respectively 87%, 89%, and 79% for discrimination of metastases from gliomas, and 87%, 83%, and 96% for discrimination of high grade from low grade neoplasms.

Govindaraj *et al*. [2] used fuzzy algorithm for the detection and segmentation of brain tumors in MRI brain image. The average tumor segmentation time is 30seconds, which leads to high computational time.

Udupa, *et al*. [3] used Fuzzy connectedness algorithm for tumor object definition and analyzed its applications in image segmentation. Zacharaki et al. [4] proposed MRI-based classification of brain tumor type using SVM-RFE. The grades of brain tumor regions are analyzed and diagnosed in mild, moderate and severe. Wang et al. [5] has used Fluid Vector Flow and Applications in Brain Tumor Segmentation. The various brain tumor detection and segmentation algorithms were used [6]-[12].

Considering the above algorithms of tumor segmentation methods showed that human errors are involved and processing speed is very high. In the end of the section results of proposed method is given. The result showed that the proposed method is superior over the other state- of- art-techniques. This paper is structured as

- Proposed Tumor detection Algorithm
- Feature Extraction
- Morphological operation

3. PROPOSED TUMOR DETECTION ALGORITHM

The process flow of proposed tumor detection and segmentation algorithm is illustrated in figure 1.The modules in this proposed work flow is explained in the following sections.

3.1 Pre-Processing

Preprocessing is the initial step for brain tumor detection and diagnosis process. In this phase, the brain MR image is enhanced in such a way that, the fine details are further improved, noise is removed from the image and is resized for better analysis. Most commonly used enhancement and noise reduction techniques are implemented that can give best achievable results.

3.1.1 Image resizing and grey scale conversion

The acquired MRI scanned image is stored in database and then it is converted to grey scale image of size **255×255**. In our proposed method, the MRI scan images of a given patient are considered to be color intensity images with default size of **220×220**. This color image is converted to grey scale image by using a large matrix whose entries are numerical values between 0 and 255, where 0 corresponds to black pixels and 255 corresponds to white pixels.

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Color images are often stored as three separate image matrices; one storing the amount of red (R) in each pixel, one the amount of green (G) and one the amount of blue (B). Such a color image is termed as an RGB image. But, in a grayscale image, the total amount of emitted light for each pixel is considered. A little light gives dark pixels and much light is supposed as bright pixels. When converting an RGB image to grayscale, the RGB values for each pixel is taken and a single value output reflecting the brightness of that pixel is calculated, using, a weighted average, e.g. 0.3R + 0.59G + 0.11B.

4. FEATURE EXTRACTION

4.1 Wavelet Features

In order to differentiate benign and malignant tissues in MRI Brain image, features are used. This is a texture related feature which is formed by the construction of wavelets from the brain MRI. Wavelets are small waves and are mathematical functions that represent scaled and shifted copies of a finite-length waveform called the mother wavelet.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

where, *a* is the scaling parameter and *b* is the shifting parameter.

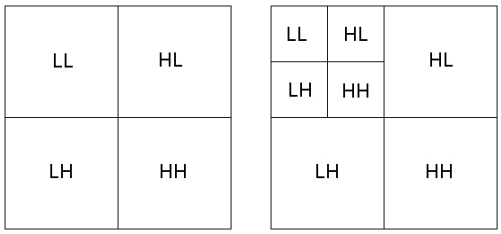
A wavelet transform (WT) entirely depends on wavelets. WT analyzes the image on different resolution scales and splits the image into various frequency components, i.e. multi-resolution image. This permits to view the spatial and frequency attributes of the image simultaneously.

The wavelet is discontinuous, and resembles a step function. For a function f, the Haar WT is defined as:

$$f \rightarrow (a^L \mid d^L) \quad (2)$$

where, L is the decomposition level, a is the approximation sub-band and d is the detail sub-band.

Firstly, wavelet transform is applied to each row and secondly to each column of the resulting image of the first operation. The resulting image is decomposed into four sub-bands: LL, HL, LH, and HH sub-bands. (L=Low, H=High). The LL-sub-band contains an approximation of the original image while the other sub-bands contain the missing details. The LL-sub-band output from any stage can be decomposed further. Figure 2 shows the result of pyramid decomposition.



(a) (b)

Figure 2. Pyramid Decomposition Using Discrete Wavelet Transform: (A) Decomposition At Level 1, (B) Decomposition At Level 2

4.2 GLCM Features

The gray level co-occurrence matrix (GLCM) is a feature to identify texture in an image, by modeling texture as a 2-Dimensional array gray level variation. This array is called Gray Level co-occurrence matrix. GLCM is a statistical method that considers the spatial relationship of pixels, hence it is also known as the gray-level spatial dependence matrix. GLCM features are calculated in four directions - 0°, 45°, 90° and 145° and four distances-(1, 2, 3, and 4). Four properties of GLCM namely, contrast, correlation, energy and homogeneity are computed using,

$$\text{Contrast} = \sum\left(|i-j|^2 \times p(i,j)\right) \quad (3)$$

$$\text{Energy} = \sum p(i,j)^2 \quad (4)$$

$$\text{Homogeneity} = \frac{\sum p(i,j)}{1+|i-j|} \quad (5)$$

$$\text{Correlation} = \sum (i-\mu i)(j-\mu j)\frac{p(i,j)}{[\sigma i.\sigma j]} \quad (6)$$

The number of gray levels in an image determines the size of GLCM. The matrix element P(i,j | Δx,Δy) is the relative frequency with two pixels separated by pixel distance (Δx,Δy), which occurs within a given neighborhood, one with intensity i and other with intensity j.

A gray level co-occurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values. A GLCM P[i,j] is defined by first specifying a displacement vector d = (dx,dy) and counting all pairs of pixels separated by d having gray levels i and j. The extracted GLCM features are depicted in Table 1.

4.3 Law's Energy Texture Features

In this feature set, the 1D kernels of the brain image are converted into 2D filter kernels at the first step. Then, the input mammogram image is filtered with Law's 2D kernels and the energy features of the image are calculated. The extracted Law's features are depicted in Table 2.

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4.4 Classifier

ANFIS is one of the widely used neuro- fuzzy systems. In this work, the neuro-fuzzy based approach namely adaptive neuro fuzzy inference system (ANFIS) is used for MR brain tumor classification. Advantages of ANFIS are,

- It refines fuzzy if-then rules for segmenting image.
- It does not require human expertise all time.
- Provide more choices of membership function to use.
- It provides fast convergent time.

The extracted features are trained using ANFIS classifier in training mode. In the same way, the features are extracted from test brain MRI image and these features are classified with trained features to classify the brain cells in to benign and malignant. The ANFIS architecture is shown in Figure 3. The circular nodes in the figure are fixed nodes and the square nodes have parameters to be trained.

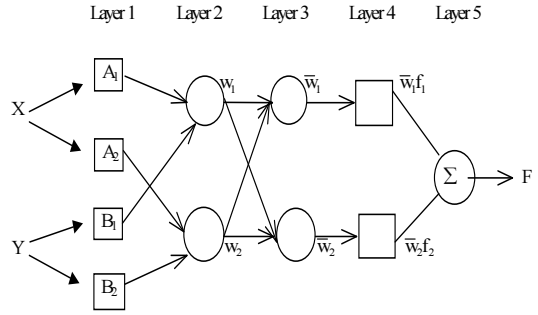

Figure 3. ANFIS architecture employed in proposed method

For an ANFIS adaptive network with fixed premise parameters, the output is linear in the consequent parameters. The total parameter can be categorized into three:

S= set of total parameters

S_1= set of premise parameters

S_2= set of consequent parameters

ANFIS employs a 2-pass supervised learning algorithm, which consists of, a Forward Pass and a Backward Pass. The steepest descent algorithm is used along with the least squares algorithm to adapt to the parameters in this ANFIS algorithm.

4.4.1 The Forward Pass

Here S_1 is fixed and S_2 is estimated using a Least Squares algorithm. The procedure is as follows:

Step 1: Feed the input vector

Step 2: Compute the output at each node and at each layer

Step 3: Repeat for all data →A until *y* is produced

Step 4: Find the parameters in S_2 using Least Squares

Step 5: Calculate the error for each training pair

4.4.2 The Backward Pass

Here S_2 is fixed and S_1 is estimated using back propagation. The parameters in S_1 are updated by back propagation for given fixed values of S_1 and these parameters are assured to be the global optimal point.

5. MORPHOLOGICAL FILTERING

Morphological filtering is applied to extract image components from the binary image to represent the region shape, such as boundaries, skeletons, etc. To improve the tumor region segmentation accuracy, the morphological operations are used. Morphological opening and closing are the two functions in morphological operations.

The two principal morphological operations in image processing are dilation and erosion. Dilation allows the image to expand, thus probably fills in small holes and connects disjoints within the image. Erosion shrinks details in the image by etching away their boundaries. The dilation and erosion processes are performed by laying the structuring element B on the image A and sliding it across the image in a manner similar to convolution as represented in Eqs. 7 and 8,

$$A \oplus B \quad (7)$$

$$A \ominus B \quad (8)$$

5.1 Morphological Opening and Closing

The two basic operations, dilation and erosion, are further combined into more complex sequences, namely, opening and closing. Opening consists of an erosion followed by a dilation and is used in the elimination of pixels in regions that are too small to contain the structuring element. The structuring element probes the image looking for small objects to filter them out of the image. Morphological opening is given by,

$$A \circ B = (A \ominus B) \oplus B \quad (9)$$

Closing consists of a dilation followed by erosion and is used in filling up holes and small gaps in the image. We see that the closing operation has the effect of filling in holes and closing gaps. Closing and opening will generate different results even though both consist of erosion and dilation.

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$$A \bullet B = (A \oplus B) \ominus B \quad (10)$$

After converting the image in the binary format, some morphological operations are applied on the converted binary image. The purpose of the morphological operators is to separate the tumor part of the image. Now only the tumor portion of the image is visible, shown as white color figure 4. This portion has the highest intensity than other regions of the image.

6. RESULTS AND DISCUSSION

To analyze the performance of the proposed algorithm to detect the Tumors, the images obtained using the proposed methodology is compared with its corresponding ground truth images. The proposed technique is analyzed with the standard parameters such as similarity index (SI), overlap fraction (OF) and extra fraction (EF) to review its performance.

$$SI = \frac{2TP}{2TP+FP+FN} \quad (11)$$

$$OF = \frac{TP}{TP+FN} \quad (12)$$

$$EF = \frac{FP}{TP+FN} \quad (13)$$

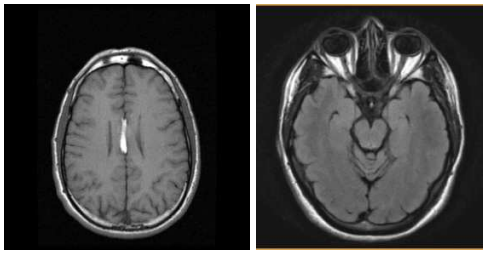
where, TP is the number of true-positive pixels detected correctly by the method, FP is the number of false- positive pixels detected falsely by the method, and FN is the number of false-negative pixels relative to the tumor region with manual segmentation. SI is a criterion for the correctly segmented region relative to the total segmented region, in both the manual segmentation and the segmented image by the proposed method. The OF and the EF specify the areas that have been correctly and falsely classified as tumor area, respectively, relative to the tumor area in manual segmentation. The performance parameters are calculated and tabulated as shown in Table 3.

Sensitivity(Se)=TP/(TP+FN)*100% (14)

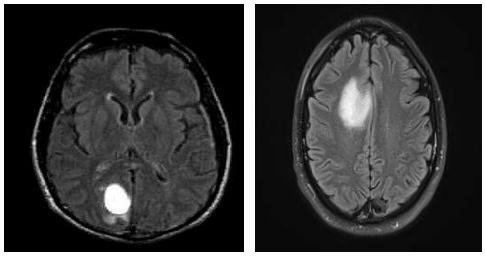
Specificity(Sp)=TN/(TN+FP)*100% (15)

Accuracy(Acc)=(TP+TN)/(TP+TN+FP+FN)*100%

By using the equation (14), (15) the parameters such as TP,FP,FN,TN are calculated and they are used to calculate SI, OF and EF using the formula mentioned in (11), (12) and (13). The parameters are compared with existing methodology and its comparison results are shown in Table 4 and 5, same is illustrated in Figure 6 and 7.



(a)



(b)

Figure 4: MRI Brain Images

(a).benign (b)malignant images

Table 1: GLCM Results.

GLCM Texture features	Extracted feature values
Autocorrelation	2.040820087719930e+04
Contrast	5.470371210300043e+03
Correlation itself	-3.405268052407567e-04
Correlation of 2 adjacent pixels	-3.405268053619021e-04
Cluster Prominence	6.264694052405161e+07
Cluster Shade	-2.595015325872436e+04
Dissimilarity	6.252878413847216e+01
Energy	3.795029784845246e-05
Entropy	1.032712482091080e+01
Homogeneity	4.251937488880282e-02
Maximum probability	1.143704958207675e-04
Sum of squares	2.493899172236665e+04
Sum average	2.859639365158527e+02
Sum variance	8.389893762213402e+04
Sum entropy	5.658503299370912e+00
Difference variance	5.470371210299982e+03
Difference entropy	4.975384980632287e+00
Information measure of correlation1	-4.455008329591984e-02
Information measure of correlation2	6.128554855980177e-01
Inverse difference normalized (INN)	8.159638729510361e-01
Inverse difference moment normalized	9.283861606707303e-01

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Table 2: Laws Texture Features.

Laws Texture features	Estimated Results
Law's Energy feature1	5.154334105199678e+17
Law's Energy feature2	1.621271830601050e+15

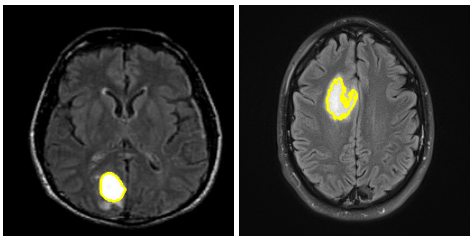

Figure 5: Tumor Segmented Images

Table 3: Performance Analysis.

Image Sequences	Se	Sp	Ppv	Npv	Acc
Image1	79.2	99.99	96.0	99.69	99.69
Image2	65.5	99.97	98.52	99.12	99.11
Average	72.39	99.98	99.06	99.41	99.40

Figure 6: Graphical Plot of Performance Analysis

Table 4: Performance Comparison In Terms Of Tumor Segmentation Time.

Work	Methodology	Tumor segmented time (s)
Proposed	Texture features and ANFIS classifier	0.441
Harati et al. (2011) [1]	Improved fuzzy connectedness algorithm	9.94
Govindaraj et al. (2013) [2]	Fuzzy logic	30

We have used images from open access web source [13], and evaluated the results as an average value in that source images. Hence, this proposed work is more suitable for all type of brain image sources.

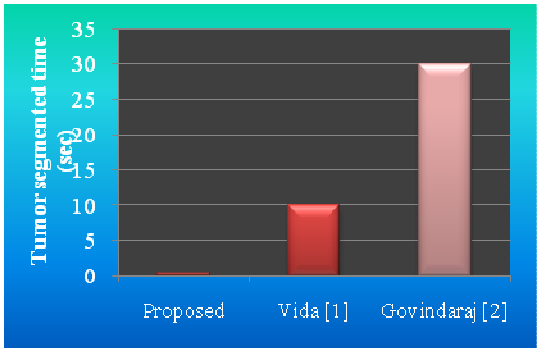

Figure 6: Graphical Illustration of Comparison In Terms Of Segmentation Time

Table 5: Performance Comparison In Terms Of SI, OF, EF.

Methodology	SI	OF	EF
Proposed work	0.78	0.723	0.0098
Udupa et al. [3]	0.75	0.706	0.107

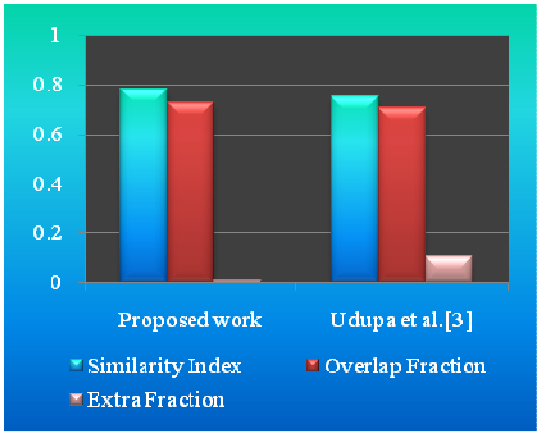

Figure 7: Graphical Illustration of Comparison In Terms Of SI, OF, EF

8. CONCLUSION

In this paper, a computer aided brain tumor detection and segmentation methodology is proposed. The ANFIS classifier is used to classify the brain tumor regions in to benign and malignant. The pixel level information features are extracted and trained for brain tumor diagnosis system. The algorithm proposed in this paper can be used by physicians in classifying complicated tumors at a reduced computational time. The performance comparison with other state of arts is done to show the superiority of our work. In future, this work can

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be extended for detecting and diagnosing brain stroke, which can be occurred in brain due to the blockage of blood vessels. However improvements can be made to this algorithm to make it more robust.

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