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IMAGE & SIGNAL PROCESSING

Brain Tumor Detection Using Depth-First Search Tree Segmentation

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Abstract

With the advent of image processing technologies, the in-depth portion of human body can be epitomized visually to perceive abnormalities in human anatomy. Image processing is a tool for identifying the substances and obtaining information from them. Medical image processing is a stimulating area to diagnose diseases specifically, brain cancer, breast cancer, liver cancer, neuro- and cardio-diseases, etc. Image segmentation is an act of segregating the images into various parts to identify a particular substance and its margins. Brain tumor is the irregular and intense growth of tissues causing cancer. The most used technique to diagnose brain tumor is Magnetic Resonance Imaging (MRI). Precise information about the affected area is crucial for the appropriate treatment. As numerous data are created in MRI diagnosis, an automated segmentation technique is necessary to obtain precise information of tumor. In this paper we presented Depth-First Search (DFS) segmentation algorithm based on graph theory. Here the image pixels are arranged into a tree like structure based on their proximity in the image. The experimental results are compared with other existing systems. Also performance measures of ANFIS classifier and SVM classifier are compared. It distinguishes healthy cells from the cells affected by brain tumors. In the proposed method, the computational complexity is reduced and accuracy is enhanced.

Keywords ANFIS · SVM · Medical image processing

Introduction

In general the body cells develop and divide to create new cells, in a particular manner. The uncontrolled growth of cell leads to a tissue called tumor. It is also called as neoplasm. The development of abnormal tissue in brain is known as brain tumor or intracranial neoplasm. There are two major types of brain tumors namely, cancerous tumors and benign tumors. Benign brain tumors don't cause cancer and don't affect neighboring tissues. However they cannot be destroyed. According to WHO statistics Cancer is the second leading cause of death globally and is responsible for an estimate 9.6 million death in 2018. Globally, about 1 in 6 deaths is due to cancer. This year, an estimated 23,820 adults (13,410 men and 10,410 women) in the United States will be diagnosed with primary cancerous tumors of the brain and spinal cord. Brain tumors account for 85% to 90% of all primary CNS tumors. Also, about 3720 children under the age of 15 will be diagnosed with a brain tumor this year. This rest of this guide deals with adult primary brain tumors. It is estimated that 17,760 adults (9910 men and 7850 women) will die from primary cancerous brain.

Malignant brain tumors with rapid growth lead to cancer and also affect neighboring tissues [1]. Canceraffects many people in the world. The rate increases year by year. In a year roughly, 1.3 million people pass away due to brain cancer [2]. It is proved that for a year, about 13 thousand people die due to brain tumor [3]. Tumors are the second important reason for death of children and male above 20 years old [4]. So it becomes important to detect brain tumor at the beginning stage, which is difficult due to inaccurate measurement at the initial stage. Brain tumor detection turns out to be challenging by reason of different shape, size, and location of tumor.

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Treatments like chemotherapy, radiotherapy and surgery are given based on the tumors [5]. The most used technique for detecting brain tumor is Magnetic Resonance Imaging (MRI). Although X-ray, Computed Tomography (CT), Sputum Cytology are applicable for brain tumor detection [2].

MRI is widely used to detect and visually observe the inner parts of the human body. As it can able to differentiate abnormal tissue from the normal one, it is superior to CT scan. Single type MRI is not enough to give the entire data about the tumor. Segmentation is done by getting slices of head axially and the axial slices are represented by three weighted images. Segmentation task becomes more difficult as each tumor in brain may vary in terms of size, shape, intensities, place of appearance. Large amount of time is required to accomplish segmentation manually. As it is a difficult process, automatic segmentation is essential in detecting brain tumors [6]. Many digital image processing techniques are used to identify several attributes such as shape, boundaries, calcification and texture of tumor. Image processing is the most common technique to extract information from an image. It has several industrial and commercial applications. Image processing for detecting tumor can employ several algorithms to find the above mentioned attributes. One of the image processing tools is image segmentation which is used to separate an image into different segments which are not intersecting with each other. Each segment corresponds to a particular object of the image. In medical field, it is the basic tool to detect abnormal area of the human body with its boundaries. In MRI images contrast adjustment and threshold techniques are used to emphasize image attributes. As the medical images do not have linear characteristics, automatic segmentation becomes complex. Presence of noise, susceptance and sharp edges require suitable filtering method. Motion objects require suitable image restoration method. Partial volume effect and intensity in homogeneity requires special algorithms. There are several techniques for segmentation and classification proposed[5]. Brain tumor detection is done by Edge detection, Histogram, Segmentation and Morphological operations. Steps involved in MRI for brain tumor detection are preprocessing, feature extraction, segmentation, classification, post-processing [6].

This paper is structured as follows. In section 2, various works related to image processing of brain tumor are described. In section 3, proposed method is illustrated. In section 4, experimental results are evaluated and compared with existing methods.

Related works

There are several methods to detect brain tumor each works on different methodologies. In CT scan the images are represented as gray scale image. The cerebral part of head is represented in gray color. Veins and arteries are represented in white color. The damaged cells are represented in dark gray color. Ultimately the tumors are in white color whereas affected cells are in black color. In feature extraction process the images are converted into pixels. The binary values 0 and 1 are assigned to affected cells and tumors respectively [7].

Peck et al. used Eigen image analysis for image segmentation with the implementation of operator intervention [8]. Vasuda et al. [9] and Lawrence et al. [10] used artificial intelligence to develop fuzzy clustering technique to identify brain tumors from MRI. Fuzzy C-mean algorithm is used in this paper. However it consumes more time for the process. In paper [11] Thresholding method and histogram are used to detect the tumor. It also finds the area of affected tissue. But it fails when the image is of low intense. In paper [12], Sudharani et al. proposed an advanced morphological technique to accurately detect brain tumor. They provided mathematical calculation to find several parameters regarding tumor which helps in diagnosis. The proposed method is also useful to apply with ground truth images. Rajesh et al. [13] presented a method to extract brain tumor features from MRI based on Meyer's flooding Watershed algorithm.

In paper [14], Neuro fuzzy classifier is used for image segmentation in tumor detection. It can be adopted only to detect tumor cells, other abnormal tissues cannot be detected. Dubey et al. [15] presented a paper in which they compared three different semi-automatic segmentation methods. They are modified gradient magnitude region growing technique (MGMRGT), morphological marker controlled watershed approach and level set methods. MGMRGT agrees well with manual segmentation data in terms of area. Amer et al. [16] proposed k- Nearest Neighbor (k-NN) algorithm for image classification of MR images of brain tumor. Senthikumaran et al. [17] in their paper compared various histogram equalization methods. They proved that with Dynamic Histogram Equalization, good quality image was obtained.

Pereira et al. [18] proposed the application of Convolutional Neural Network for automatic image segmentation using small kernals. In addition they normalized the intensity of the image in preprocessing itself. Mokheld et al. [19] used Thresholding and Watershed segmentation, Gabor filter Auto enhancement for processing the image of brain tumor. Amutha et al. [20] used nonlocal neighborhood de-noising function to remove noise and Level set-active contour modeling was used for segmentation. In paper [2], CT image of the brain is processed by Otsu's thresholding and marker controlled Watershed segmentation. From the segmented image they identify the differences among various stages of disease. Pranitha et al. [5] used spatial relationship of pixel to avoid noise. In this method, preprocessing is not necessary. They obtained results on edge and local information of the image. The method is known as fuzzy C-means with edge and local information (FELICM). It provided good accuracy rate on edge detection as well as removed the problems associated with isolated and random distribution.

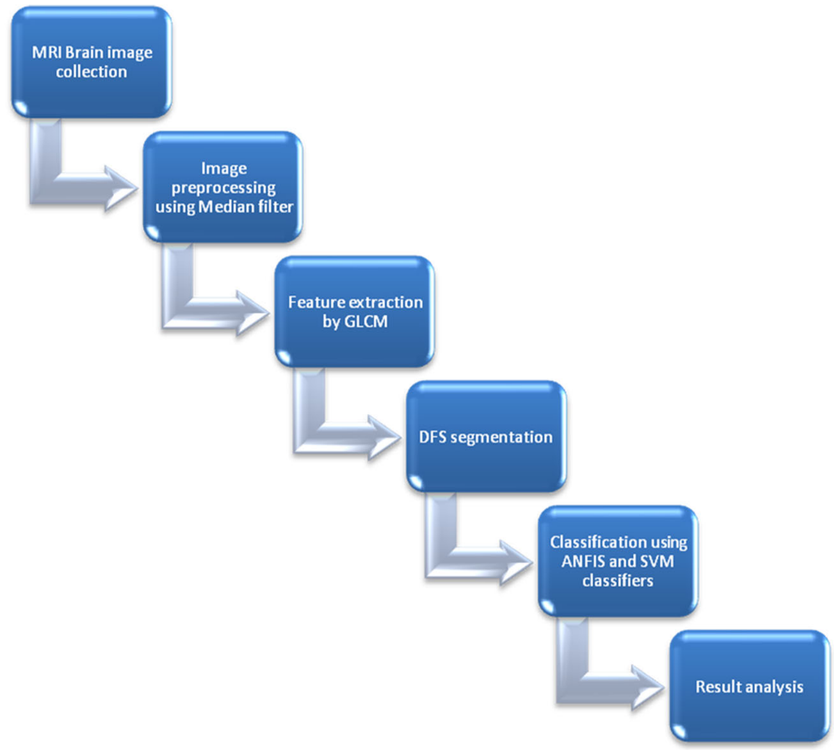

Fig. 1 Steps in image processing

In paper [21], Dual-Tree Complex wavelet transformation (DTCWT) for feature extraction, principal component analysis (PCA) for feature reduction, k-means clustering and Probabilistic neural network (PNN) for image classification. They obtained correction classification ratio 98.4% and 98.6% with PNN classifier and K-means clustering respectively. Santhakumar et al. [22], used adaptive neuro fuzzy inference system (ANFIS) based on automatic seed point selection range. They used GLCM matrix and Wavelet transformation for feature extraction. They find the variance between normal and affected brain tissues from the measurement of several features such as Similarity Index (SI), Overlap Fraction (OF), Extra Fraction (EF) and Positive Predictive Value (PPV). In paper [23], Artificial Neural Network Fuzzy Inference System (ANFIS) has been proposed for brain image classification and the results are validated from comparison of results of other methods like, Fuzzy C means (FCM) and K-Nearest Neighbor (K-NN). It has been proved that ANFIS classifier provided better result. Nazmy et al. [24] proposed ANFIS for ECG signal classification. Independent component analysis (ICA) method is used for feature extraction. These features and power spectrum are given as input to the ANFIS classifiers. It has been proved that the accuracy was increased more than 97%.Loganathan et al. [25] used ANFIS classifier for cancer classification. The proposed ANFIS classifier is designed with RungeKutta (RK) learning algorithm. The results are compared with conventional ANFIS classifier based on back propagation algorithm. Nan Zhag et al. [26] proposed multi kernal SVM classification on multi-image sources and relative multi-result was obtained. It enhances the region of tumor by measuring distance and maximum likelihood. In [27] a hybrid method has been proposed for image processing, based on SVM and modified FCM classifiers. Initially preprocessing has been done by median filter and GLCM was used for feature extraction. It has been proved that SVM techniques give high accuracy.

Methodologies

To incorporate image processing of brain tumor, data must be collected from hospitals, labs,MIAS data set(Mammographic Image Analysis Society) or database. The image might be obtained from X-ray, CT scan or MRI scan. Both CT and MRI images are appeared as 2-D matrixes with pixels as elements [2]. The dimension of CT image is 512 × 512 pixels. The dimension of MRI image is 256 × 256 pixels [5] (Figs. 1 and 2).

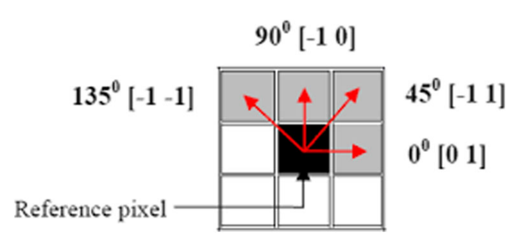

Fig. 2 Directions of GLCM for feature extraction of image subset

Table 1 Features obtained by GLCM matrix

SI.No	Parameter	Equation
1.	Contrast	$\sum_{n=0}^{Ng-i} n2 \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} g(i,j)$ where n = |i-j| (1)
2.	Homogeneity (HOM)	$\sum_i \sum_j g(i,j)/(1+n)$ (2)
3.	Correlation	$\{\sum_i \sum_j (ij)g(i,j) - \mu x \mu y\}/\sigma_x \sigma_y$ (3) μ_x, μ_y, σ_x, σ_y are mean and standard deviation of g_x, g_y.
4.	Energy	$\sum_i \sum_j g(i,j)2$ (4)
5.	Variance	$\sum_i \sum_j (i-\mu)2g(i,j)$ (5)
6.	Local Homogeneity or inverse difference moment	$\sum_i \sum_j 1/(1+(i-j)2)g(i,j)$ (6)
7.	ASM	$\sum_i \sum_j \{g(i,j)\}^2$ (7)
8.	Sum average	$\sum_{i=2}^{2Ng} i\, g_{x+y}(i)$ (8)
9.	Sum variance	$\sum_{i=2}^{2Ng} (i - sum\ entropy)^2 g_{x+y}(i)$ (9)
10.	Sum entropy	$-\sum_{i=2}^{2Ng} g_{x+y}(i) \log\{p(i,j)\}$ (10)
11.	Entropy	$-\sum_i \sum_j g(i,j)\log\{g(i,j)\}$ (11)
12.	Difference variance	variance of g_{x-y}
13.	Difference entropy	$-\sum_{i=0}^{Ng-1} g_{x-y}(i) \log\{g_{x-y}(i)\}$ (12)
14.	Maximal correlation coefficient	$\sum_k \frac{g(i,k)g(j,k)}{gx(i)gy(k)}$ (13)

Preprocessing method

As the CT and MRI images may contain various noises image preprocessing should be done to reduce these noises. Preprocessing is not only meant for reduction of noise, but also some attributes are improved. Image processing modifies the brightness of the image. Based on the surrounding pixel size, it is divided into two types. There are several filters available for eliminating noise preprocessing step[28]. Mean filter, Median filter, Wiener filter, Hybrid filter. Mean filter is a linear filter, eliminates Gaussian noise based on average value of pixels. Though it offers quick operation, it deforms the boundaries and edges. Median filter is a non-linear filter, removes salt, pepper and speckle noises at expense of time. It retains the boundary and edges. Weiner filter performs inverse filtering frequency. It eliminates blurred parts. However it doesn't take intense care on speckle noise and also consumes more time. The benefits of both median and Weiner filter are utilized to form a hybrid filter which eliminates noises as well as blurred parts. Also it incorporates demerits of both filters.

In this paper we employed median filter. Initially the pixel values of surrounding objects are arranged in ascending order depending on their intensity. Then the center value is taken as median.

Edge detection and threshold

Edge detection is performed for image segmentation and feature extraction. It detects boundaries of objects in CT and MRI image from the brightness gaps. Sobel, Canny, Prewitt, Log and Zero cross are available methods for edge detection. Thresholding is used for image segmentation that modifies gray level into binary level. This is suited for high contrast images. It separates image into foreground and background [28].

Image segmentation

Image segmentation is performed to obtain the simplest representation of image to make analysis straightforward. In segmentation the image is split up into many objects based on features like gray level, color, texture, brightness and contrast. MRI image is segmented to know about [5] the anatomy, to detect, tumor and abnormal tissues, to assist for proper treatment by measuring the volume of the tissue.

Fig. 3 DFS-Tree algorithm

Input: A graph with number of nodes and undirected edges between nodes.

Step-1: Initialize instance, i to be equal to zero and stack, S as empty.

Step-2: Select any node, n and mark it as root node, r.

Step-3: Increase i value by 1and the value of i is assigned to a (r).

Step-4: Insert root node r in stack, S.

Step-5: If stack contains elements, go to step-6.

Step-6: After increasing i value again, check the top element, x of stack

Step-7: Find x's neighboring node, y which does not exist in stack. If such a node presents, do as instep-8, otherwise do as in Step-9.

Step-8: Now set x as parent node of y and a(y) equal to i. Then insert y into stack.

Step-9: Set r (x) equal to i and pop x out of stack.

Step-10 Repeat step-6 until stack, S becomes empty.

Histogram and morphology

Histogram graphically denotes the relative frequency of different gray levels of the image depending on the individual frequencies [29]. In histogram clustering after fixing histogram values, threshold values of the image are plotted [4]. Morphology is a technique used to sharpen the image by examining the shape and structure of the image [28]. Morphology is performed on two images known as structuring image and input image. Structuring images are small mages used to investigate input image for certain given attributes. Structuring image transmits a section of input image. Mounting of this section is done by structural element based on the neighborhood window of structure element, which defines the input image section. When it is mounted geometric measures of the input image which are not present in neighborhood window are blocked out [30]. Morphology employsDilation and Erosion. There are two techniques known as opening-by-reconstruction and closing-by-reconstruction. In Opening technique first erosion is performed and then dilation is performed. In opening-by-reconstruction reconstruction is performed after erosion [4].

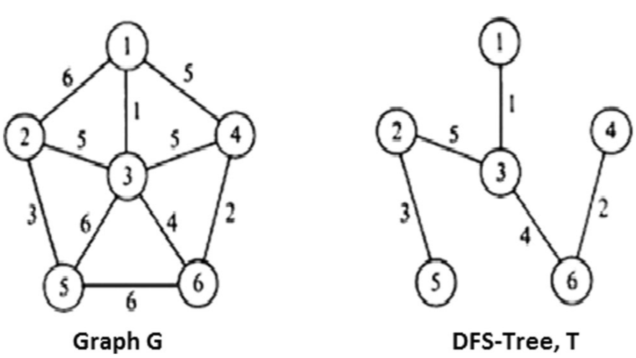

Fig. 4 Conversion of graph into DFS-tree

Feature extraction

Feature extraction is necessary before segmentation to extract some useful features of the image. It also enhances

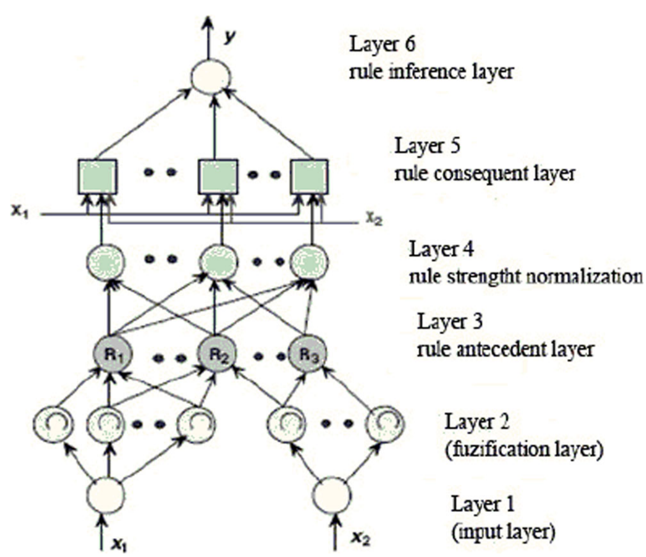

Fig. 5 Typical ANFIS architecture with x_1, x_2 as input and y as output

Table 2 Layers and their description

Layers	Description
Input layer	It is the first layer of the ANFIS architecture. The neurons of this layer send the input crisp values to the next layer
Fuzzification layer	It is the first hidden layer. It originates the fuzzy sets of fuzzy rules. It gets input signal from input layer and finds the amount of relation of signal with fuzzy set.
Fuzzy Ruleantecedent layer	It is the second hidden layer in which every neuron gets signal from fuzzification neurons. A product operator is used to find the conjunction of antecedents which originates fuzzy sets
Rule strength normalization layer	It is the third hidden layer which receives signal from all neurons of fuzzy rule layer estimates normalized firing strength of a given rule to denote the impact of fuzzy rule on the final result.
Defuzzificationor rule consequent layer	It is the fourth hidden layer in which each defuzification neuron receives initial input signals from normalization neuron and calculates 'weighted consequent value'
Summation or rule inference layer	It is the output layer and last layer of the architecture. it contains only one layer to evaluate the total output by adding the output of all neurons of defuziffication layer

image quality. Co-occurrence matrix shows distance and angular spatial relationship of a subset of image. Gray level Co-occurrence Matrix (GLCM) forms a matrix with number of rows and columns equal to number of different gray levels (N_g) of the subset. It illustrates about the co-occurrence of gray levels among them in a subset of an image. The intensity variation of the region of interest is estimated by the elements of GLCM. In general there are two parameters required to form co-occurrence matrix. They are the comparative distance between two pixels and the relative angle between them. The $(i, j)^{th}$ element of the matrix represented by g (i, j) gives relative frequency of the occurrence of i thandjth element in the region of interest. The angle in between the pixels is calculated in four directions, horizontal, vertical, diagonally in 45^{o} and in 135^{o}. The command glcms = graycomatrix(I) is used to create GLCM of image, I.

A set of 14 features such as Angular Second Momentum (ASM), contrast, correlation, variance, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, correlation measures, maximum correlation coefficient[31]. Among them we consider four parameters. They are contrast, homogeneity, correlation, energy.

Table 3 Fuzzy rule table

SI. No	IF				THEN
	A=	B=	C=	D=	Output=
1	Contrast1	Homogeneity1	Correlation1	Energy1	$a_1A + b_1B + c_1C + d_1D + f_1$
2	Contrast2	Homogeneity2	Correlation2	Energy2	$a_2A + b_2B + c_2C + d_2D + f_2$
3	Contrast3	Homogeneity3	Correlation3	Energy3	$a_3A + b_3B + c_3C + d_3D + f_3$
4	Contrast4	Homogeneity4	Correlation4	Energy4	$a_4A + b_4B + c_4C + d_4D + f_4$
5	Contrast5	Homogeneity5	Correlation5	Energy5	$a_5A + b_5B + c_5C + d_5D + f_5$
6	Contrast6	Homogeneity6	Correlation6	Energy6	$a_6A + b_6B + c_6C + d_6D + f_6$
7	Contrast7	Homogeneity7	Correlation7	Energy7	$a_7A + b_7B + c_7C + d_7D + f_7$
8	Contrast8	Homogeneity8	Correlation8	Energy8	$a_8A + b_8B + c_8C + d_8D + f_8$
9	Contrast9	Homogeneity9	Correlation9	Energy9	$a_9A + b_9B + c_9C + d_9D + f_9$
10	Contrast10	Homogeneity10	Correlation10	Energy10	$a_{10}A + b_{10}B + c_{10}C + d_{10}D + f_{10}$
11	Contrast11	Homogeneity11	Correlation11	Energy11	$a_{10}A + b_{10}B + c_{10}C + d_{10}D + f_{10}$
12	Contrast12	Homogeneity12	Correlation12	Energy12	$a_{11}A + b_{11}B + c_{11}C + d_{11}D + f_{11}$
13	Contrast13	Homogeneity13	Correlation13	Energy13	$a_{12}A + b_{12}B + c_{12}C + d_{12}D + f_{12}$
14	Contrast14	Homogeneity14	Correlation14	Energy14	$a_{13}A + b_{13}B + c_{13}C + d_{13}D + f_{13}$
15	Contrast15	Homogeneity15	Correlation15	Energy15	$a_{14}A + b_{14}B + c_{14}C + d_{14}D + f_{14}$
16	Contrast16	Homogeneity16	Correlation16	Energy16	$a_{15}A + b_{15}B + c_{15}C + d_{15}D + f_{15}$

Based on these values we can detect whether the given brain image has normal or abnormal tissue. These features are given as input to an Artificial Neural Network Fuzzy Inference System (ANFIS) (Table 1).

Here $g_x(i)$, $g_y(j)$, $g_{x+y}(k)$, $g_{x-y}(k)$ are defined as follows,

$$\mathrm{gx(i)} = \sum_{j=1}^{Ng} g(i,j), \mathrm{gy(j)} = \sum_{i=1}^{Ng} g(i,j) \tag{14}$$

$$\mathrm{gx + y(k)} = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} g(i,j) \text{ where } \mathrm{k = i + j} \tag{15}$$

$$\mathrm{gx{-}y(k)} = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} g(i,j) \text{ where } \mathrm{k = i{-}j} \tag{16}$$

DFS-tree segmentation

In graph theorybased analysis has become a powerful and popular approach for analyzing brain imaging data, largely because of its potential to quantitatively illuminate the networks, the static architecture in structure and function, the organization of dynamic behavior over time and disease related brain changes a spanning tree (T) can be formed with a single root, r and many nodes, n. In Depth-First Search algorithm, each time a node which is nearer to the node, already appearing in the tree, is connected to the tree, T. In order to construct this DFS-tree we create a stack to provide information about neighboring nodes. In stack the last inserted element can be taken out first. Initially the Stack is empty. Each and every time, when a node is inserted in the tree, it should also be pushed into the stack. If the top element of the stack has any neighboring node which is not in stack, add that node as children node to the node presenting before it. If all the neighboring nodes of the top node appear in the stack, then remove the top node. Now its parent node becomes the top element of the stack. This process is repeated until the stack becomes empty. Each node of a graph is represented by two times:

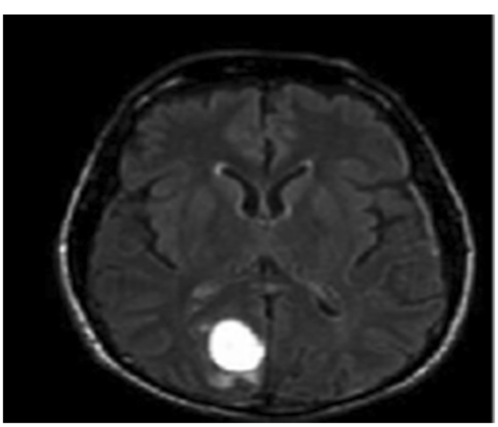

Fig. 6 Brain input image 1

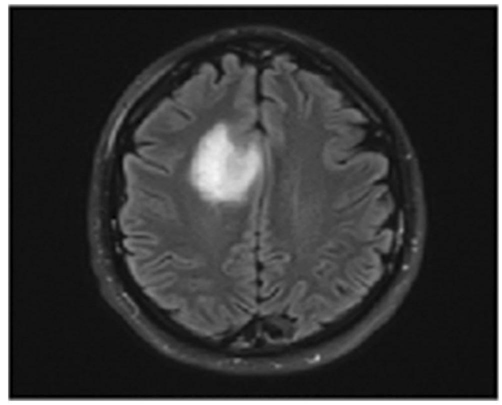

Fig. 7 Brain input image 2

1. a (n) - time when n is added in tree T
2. r (n) – time when n is removed from stack S

The formation of DFS-tree can be used for segmentation of texture of an image. Here the pixels of the subset are represented by nodes of graph. The steps involved in DFS tree is given in Figs. 3 and 4.

A graph, G with six nodes is converted into DFS-Tree, T as shown in Fig. 5. The nodes correspond to pixel of the texture.

ANFIS classification

ANFIS system is carried out based on Tagaki-Sugeno fuzzy inference system. It is a multilayer feed-forward network with un-weighted links between the nodes. It has training dataset and testing data. The training is done by a back propagation algorithm. The algorithm continues until the anticipated error is obtained.

ANFIS has totally six layers in its architecture out of which, five are hidden layers. The six layers name and their details are listed in Table 2.

The first and fifth layers have adaptive nodes. The second, third and fourth layers have fixed nodes [32]. A typical ANFIS architecture with two inputs and one output is given in Fig. 5.

This system is given with four inputs. The output of ANFIS classifier is a single output obtained from the four inputs. Based on the features extracted from GLCM method, Fuzzy If-Then rules are formed. It has two membership functions as high and low. Thus $2^4 = 16$ fuzzy rules are framed for this classification. The 16 fuzzy rules are given in Table 3.

Table 4 Values of extracted features

Features	Image 1 (Low-High)	Image 2 (Low-High)
Contrast	**7.08e+01-6.89e+02**	**3.08e+01-2.89e+02**
Homogeneity	**8.09e-001-4.09e-001**	**2.19e-001-1.33e-001**
Correlation	**6.09e-001-2.22e-001**	**4.33e-001-2.55e-001**
Energy	**2.17e-001-1.01e-001**	**1.19e-001-0.97e-001**

Table 5 Comparison of performance measures with other classifiers

SI. No.	Classification method	SI	EF	OF	Sensitivity	Specificity	Accuracy	PPV
1	ANFIS + Wavelet + GLCM [34]	0.78	0.0098	0.723	72.39	99.98	99.40	99.06
2	Logistic Regression (LR) [35]	NR	NR	0.98	98	NR	NR	35
3	Support Vector Machine (SVM) [35]	NR	NR	0.98	98	NR	NR	44
4	Markov random field (MRF) [35]	NR	NR	0.87	87	NR	NR	61
5	Custom Random Field [35]	NR	NR	NR	98	NR	NR	67
6	ANFIS+ Seed point selection [22]	0.817	0.182	0.817	81.7	NR	87	NR
7	k-means+ PNN[21]	NR	NR	NR	NR	NR	98	NR
8	PCA + ANN[21]	NR	NR	NR	NR	NR	95	NR
9	SVM-REF [36]	NR	NR	0.827	82.7	95.5	86.5	NR
10	SVM-BFS [33]	NR	NR	NR	NR	NR	88.21	NR
11	FCM [23]	NR	NR	0.96	96	93.3	86.6	NR
12	k-means[23]	NR	NR	0.80	80	93.12	83.3	NR
13	ANFIS + GLCM [23]	NR	NR	0.96	96.6	95.3	98.67	NR
14	Proposed (ANFIS)	0.912	0.021	0.96	98.3	97.2	99.2	88
15	Proposed (SVM)	0.934	0.011	0.98	99.1	99.3	99.8	91

SVM classification

Guo-Zeng Li et al. [33] proposed SVM classification for brain tumor detection based on Backward floating search (BFS) algorithm. BFS algorithm is derived from sequential backward search (SBS) and sequential forward search (SFS). BFS creates subset of features. SVM based on BFS is called as SVM-BFS method. In BFS algorithm, the SBS process removes the least significant feature sequentially whereas SFS inserts the most significant feature sequentially. SVM-BFS method has five steps.

Step 1: It is called as initialization. SBS method decreases the least two significant features and sets the valuefor the present number and the target number of features. As the features fromthe maximum to 1 are to be removed, the target number is set 1.

Step 2: It is called as exclusion. Basic SBS method is used to remove the feature. In BFS this step is the mainmodule.

Step 3: It is called asConditional inclusion. It detects the most significant feature among the left out features. If it does not present in left out,the basic SFS is used to add it.

Step 4: It is called as Continuation of conditional inclusion. It continues to find the most significant feature amongthe excluded features with respect to the subset obtained in Step 2. If accuracy of the subset is notgreater thanthat of any other subset with the same number of feature, then go to Step 1; otherwise, go to Step 3.

Performance analyses

Performance parameters

Sometimes the segmentation and classification yields error, which may fail to detect abnormalities or detect the normal tissues as abnormal one by mistake. These errors are measured by true positive (TP), true negative (TN), false positive (FP) and false negative (FN). From these values, Similarity Index,

Table 6 Comparison of performance measures with other segmentation technique

SI. No.	Segmentation method	SI	EF	OF	Sensitivity	Specificity	Accuracy	PPV
1	Fuzzy connectedness [37]	0.750	0.107	0.706	70.6	NR	NR	NR
2	Improved Fuzzy connectedness [37]	0.928	0.0319	0.917	91.7	NR	NR	NR
3	Multivariate Bayesian Image Segmentation tool MBIS [38]	0.940	0.079	0.871	87.1	NR	NR	NR
4	Fast Automated Segmented Tool FAST [38]	0.874	0.163	0.710	71	NR	NR	NR
5	OTSU's thresholding [2]	NR	NR	1	100	83.3	90.909	NR
6	CNN [18]	0.84	NR	0.86	86	NR	NR	85
7	Morphological filters [12]	0.9302	NR	NR	88.9	90	89.2	NR
8	Proposed (DFS-tree)	0.971	0.011	0.98	99.1	99.3	99.8	91

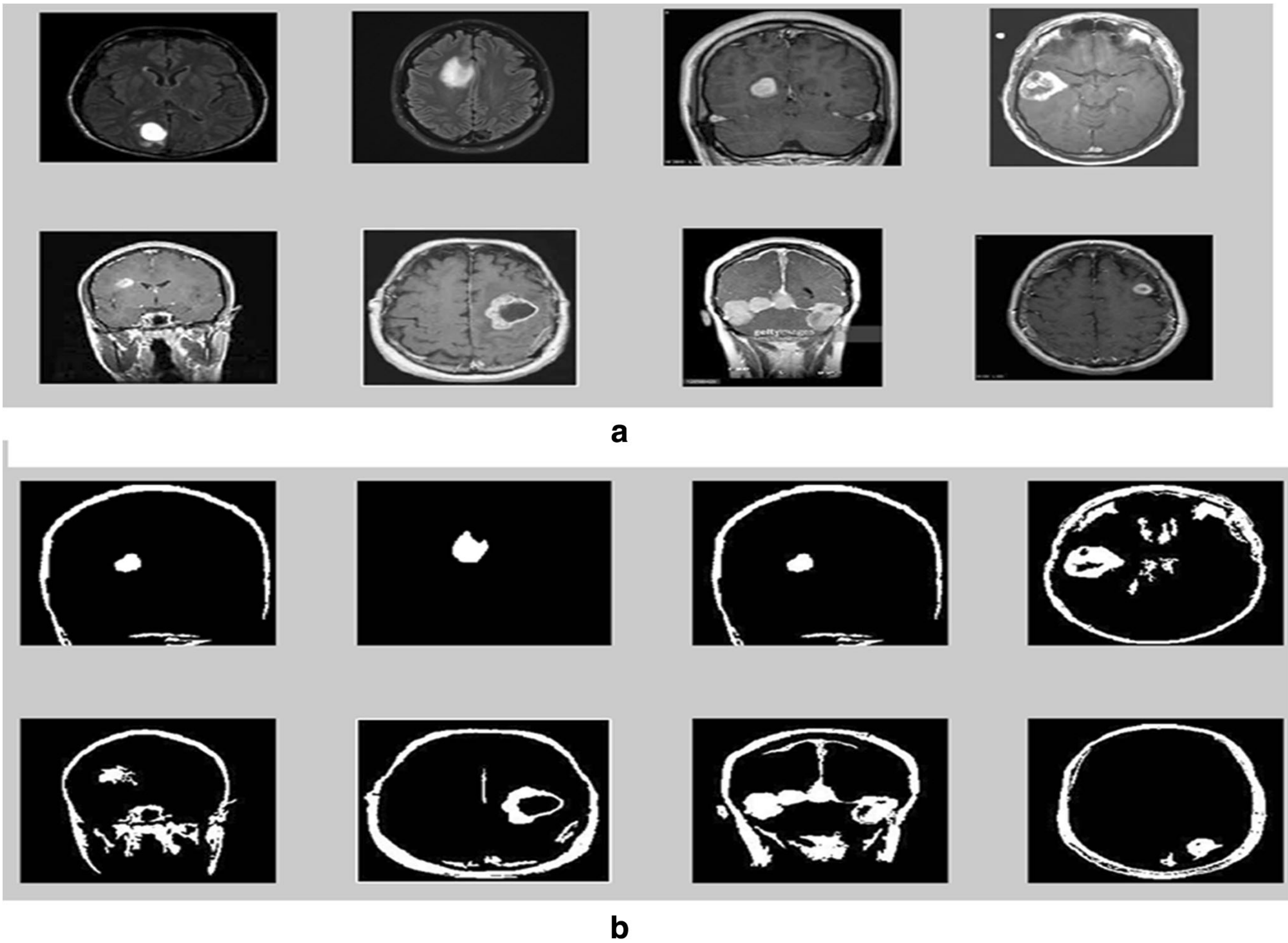

Fig. 8 a) Brain MR image of Benign tumor b) corresponding segmented output

Overlap Function, Extra Function, sensitivity, accuracy, positive predictive value (PPV) are calculated for performance analysis. Similarity index tells about the accuracy of segmentation concerning the total disintegrated region. Overlap and Extra function represents correct and incorrect classification. For an ideal segmentation, the values of SI and OF must be equal to 1 and EF must be equal to 0. But in general, good segmented results have SI as 0.7 and above.

$$\text{Similarity Index (SI)} = \frac{2TP}{2TP + FP + FN} \tag{17}$$

$$\text{Overlap Function (OF)} = \frac{TP}{TP + FN} \tag{18}$$

$$\text{Extra Function (EF)} = \frac{FP}{TP + FN} \tag{19}$$

$$\text{Sensitivity} = \text{OF} \times 100 \tag{20}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100 \tag{21}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{22}$$

$$\text{Positive Predictive Value (PPV)} = \frac{TP}{TP + FP} \times 100 \tag{23}$$

Image collection and feature extraction

Two brain images are collected from brain image database. The source MRI images of brain with tumor are given in Figs. 6 and 7. Moreover, brain MRI images with benign and malignant tumor are collected and given to train the ANFIS system.

Initially, the noises presenting in the image 1 and 2 are filtered using Median filter. Then their contrast, energy, homogeneity, correlation are extracted using GLCM matrix. The extracted values are listed in Table 4. These values are given as input to ANFIS and SVM classifier (Table 5).

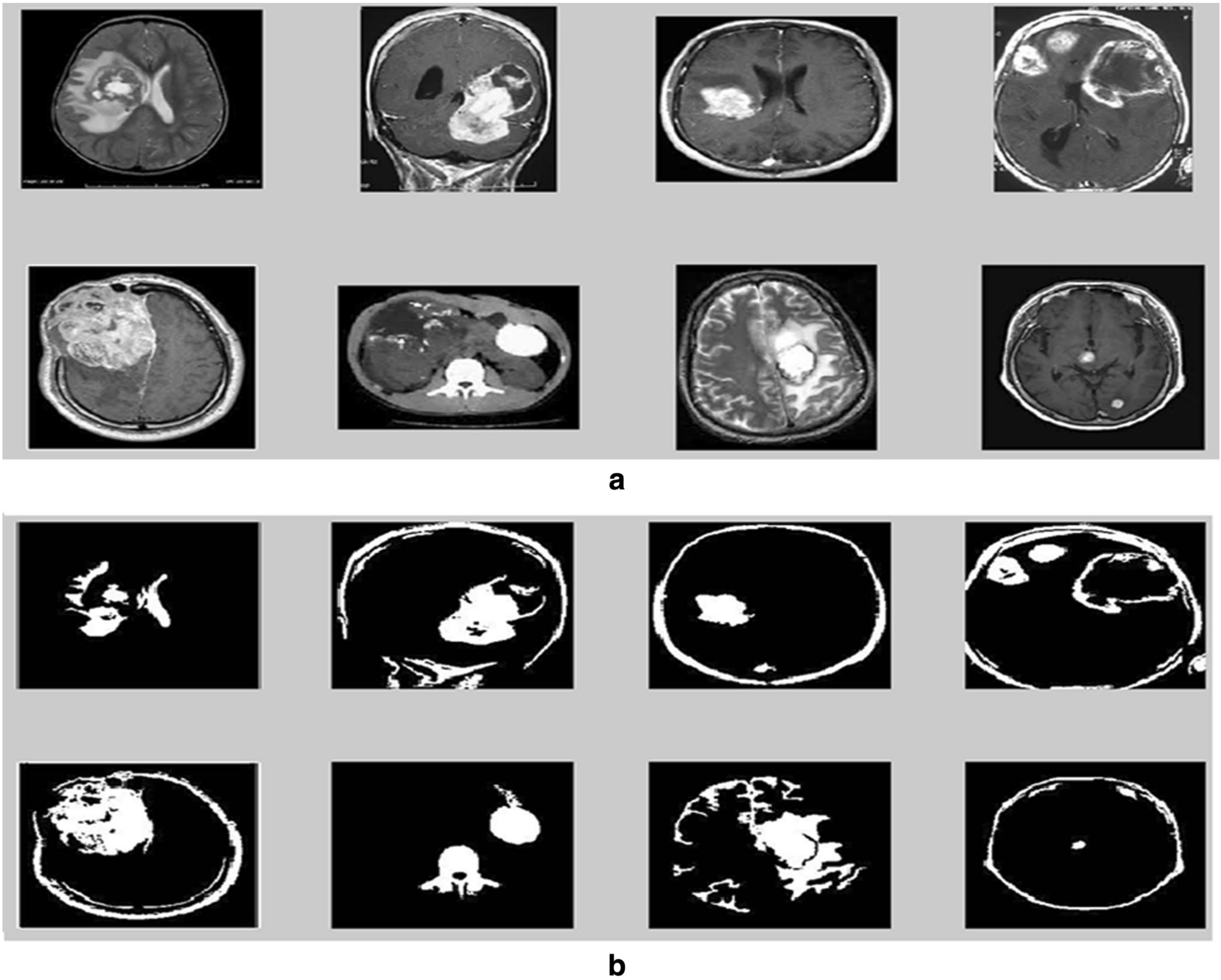

Fig. 9 a) Brain MR image of malignant tumor b) corresponding segmented output

Result analysis

The performance measures are calculated and compared with other existing methods. The results of proposed work are compared with that of other classifiers. The results of three recent works based on ANFIS classification is considered. Among them ANFIS mehtod when used with GLCM extraction shows good accuracy [34]. ANFIS yields better accuracy when compared with other classification (Figs. 8 and 9).

The segmented results of given input images of Figs. 6 and 7 are obtained using DFS-tree segmentation. The resultant images are shown in Figs. 10 and 11 respectively.

Fig. 10 Segmented result of image 1

Fig. 11 Segmented result of image 2

The values of sensitivity, specificity and accuracy are improved in proposed DFS-tree segmentation.

Conclusion

Brain tumor is a life threatening disease which is to be detected at initial stages. Digital image processing has a leading role in detection of brain tumor. For image processing of brain, the brain image is taken from either MRI or CT scan. It is then processed in various steps like noise filtering, feature extraction, segmentation, classification. Several researches are in progress to achieve better accuracy in tumor detection. Various segmentation, classification, feature extraction methods are available. Our work has mainly focused on segmentation technique. We have employed GLCM matrix for selecting features. ANFIS and SVM classifier are developed for classification, as they contribute for better accuracy. Further we proposed a novel segmentation tool based on Depth First Search Tree (DFS) algorithm. The results are obtained experimentally and comparisons have been made with other existing classification and segmentation methods. The SVM classifier offers good performance than ANFIS classifier by 0.5%. DFS-tree segmentation delivers accuracy of 99.8%.

Compliance with Ethical Standards

Conflict of Interest The authors have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants performed by any of the authors.

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