

EARLY CLASSIFICATION OF BRAIN TUMOR BASED ON IMAGE HISTOGRAM USING FUZZY-GENETIC ALGORITHM

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Abstract

A Brain Tumor Classification Framework has been outlined and created. The framework uses computer based strategies to identify tumor blocks or lesions and classify the sort of tumor utilizing matching histogram in MRI images of different patients with brain tumors. The picture processing methods such as picture segmentation, picture enhancement. Several techniques can classify the tumor such as Support vector machine (SVM), artificial neural networks (ANN), and Naive Bayes, but they did not accomplish the required accuracy. The automatic classification of tumors requires high precision since the non-accurate conclusion would cause a rise within the predominance of more serious diseases. In this paper, the proposed method using fuzzy logic and genetic algorithm based on image histogram to enhance the brain tumor classification. The experimental result showed that our technique is more effective than the previous techniques, as well as the classification accuracy efficiency is 99.9%.

Keywords: Image Segmentation, Histogram, MRI, Fuzzy, membership and weight.

1. Introduction

Automated classification and discovery of tumors in several medical pictures requests high precision since it deals with human life. Too, computer help is highly looked for in medical institutions due to the reality that it seem improve the results. It has been proven that double reading of medical pictures may lead to way better tumor discovery. But the cost caused in reading is very high; hence great computer program to help people in medical institutions is of great interest these days.

Magnetic resonance images (MRI) combine a common advantage with CT - high spatial resolution pictures - but with no ionizing radiation presentation, which makes it a more secure method. MRI holds a really particular place among imaging modalities ,since it is highly flexible from particular centres of see ,and it offers flexibility of slice positioning at any point inside the three dimensional space, included to an really great soft tissue differentiate. Classification of brain tumors is a more difficult task due to frequent change of behavior for tumor region's texture, form, discontinuity, irregularity and uncertain boarder of gliomas. Analyzing the medical images manually gives more mistakes, as well as takes a long time. This problem significantly degrades the accuracy of the classifier and has a negative effect on computational time. The hvbrid classification technique to enhance the accuracy problem. The proposed methode consists of sub steps: FCM segmentation based on otsu's thresholding, the image histogram and fuzzy-genetic classifier. FCM segmentation is an unsupervised classification algorithm [14]. Otsu's Thresholding is used for removing the noise of the picture to get a high-quality image without losing any important information. It is a critical technique in medical picture preparing. The basic idea is to calculate the optimal threshold gray level value required to isolate the object region from the overall

image. This algorithm greatly improves the speed of thresholding and has superior resistance to salt and pepper noise [13].

In the area of medical diagnosis, some Artificial Intelligence (AI) methods including neural networks and fuzzy logic are successfully applied to a wide variety of decision-making problems. In the proposed method, the data set BRATS 2013 which is online available is used [8]. It comprises of low-grade gliomas (LGG) and high-grade gliomas (HGG).

MRI sequences are T1-weighted, T2weighted, and Fluid Attenuated Inversion Recovery (Flair) scans. Flair has a better resolution since it involves 1019 images for HGG type and 206 images for LGG type.

MRI images are converted into grayscale images, and then they are segmented using the FCM method biased on Otsu's thresholding. The proposed classification method generates fuzzy if-then rules based on image histogram, and then optimizes the matching accuracy using genetic algorithm.

The rest of this paper is organized as follows. Section 2 describes the related work for brain tumor classification. Section 3 presents the proposed model. The experimented results obtained by the proposed method and discussions are given in section 4. Finally, the conclusion.

2. Related work

Saumya Chauhan et al. [1] detect the tumor from MRI pictures utilizing Instance-based K-Nearest utilizing Log and Gaussian (IBKLG).Unimportant Weight Kernels information from the picture is evacuated utilizing median filtering. The input MRI pictures are Grayscale. HSV colour-map is utilized to change over the picture into an RGB picture, which makes a difference to imagine the colour contrasts. K-means clustering calculation is connected to make sections of the picture. Texture Features are extricated. This method achieves a better accuracy with 86.6% compared to Naïve Bays.

Garima Singh et al. [2] detect the brain tumors using K-Means Segmentation and Normalized Histogram. They classify using the Naïve Bayes method and SVM into normal and abnormal.

The results were not satisfactory and the classification of brain tumors was not accurate. However, G Rajesh Chandra et al. [3] make a segmentation method using soft thresholding Discrete Wavelet Transform (DWT) and genetic algorithm for enhancement of the image. This method achieved SNR (signal to noise ratio) value from 20 to 44 and segmentation accuracy from 82% to 97% based on ground truth MRI images.

Anitta Antony et al. [4] classify the tumor as meningioma or glioma. They segment the image into three clusters K=3 and extract 1024 features using weighted Neighbor Distance using Compound Hierarchy of Algorithms Representing Morphology (Wndchrm tool)with SVM classification. An 80% accuracy is achieved, however for 154 features with SVM classification, 93.33% accuracy is achieved.

Saddam H et al. [5] utilize cascade deep convolutional neural networks (CNN) design for tumor segmentation. This strategy joined both local and global features since is important for tumor segmentation. The utilize of max-pooling, max-out and drop-out complement the learning handle, progressing training and testing speed by decreasing highlights in a completely associated layer as well as decreasing the number of parameters, which decrease the chances of over-fitting.

Reema Mathew et al. [6] design a K-mean clustering algorithm for image segmentation and extracted from it GLCM, DWT and Gabor wavelet features. Since the vector gotten could be huge, it is decreased with the assistance of Principal component analysis (PCA). PCA output is the input for the SVM classifier. Their results appeared that the SVM method with a linear kernel achieves more precision for a large number of the data. Sudipta Roy et al, [7] develop a classifier system using ANFIS for brain tumor tissue. It got 98.25% precision on the Harvard benchmark dataset. Examination with a huge number of variables requires a huge amount of memory and computation control. Feature extraction may be a term for strategies of building combinations of the factors to get around these problems while portraying the information with adequate exactness.

3. Proposed Method

In this study the design of the proposed system provides the MRIs with accurate detection and classification into a benign and malignant .The proposed classification method consists of sub steps as shown in fig.1.

The image pre-processing has the objective of removing the noise and keeping the information for the tumor by thresholding. In the FCM segmentation, the tumor is extracted from the image with high accuracy. In the next stage, the histogram from the segmented image. The final stage is the classification based on the image histogram using fuzzy system. The matching accuracy is optimized using genetic algorithm.



Fig. 1 Flowchart of the proposed method for Brain Tumor Classification

3.1 Proposed Image Pre-processing

The goal of pre-processing is striding the image data that smother undesired distortions and improves image features that are pertinent for processing [9,10].

It includes sub steps such as thresholding and FCM segmentation [11, 12].

The flow chart of the proposed method is shown in fig.2. It has higher accuracy than other methods such as neural network or Kmean method. FCM clustering for brain tumor gives three clusters; CSF, WM, and GM (brain tissues) [15, 16].

The fuzzy partition should have two properties; homogeneity within the clusters and heterogeneity between clusters [17, 18]. Utilizing an averaging (Gaussian) filter and a median filter to remove salt and pepper noise from an image.



Fig. 2 Flowchart of the proposed methodforimage segmentation

3.2 Image Histogram

Histograms are an effective strategy to depict distributions of continuous factors. Histograms plot the frequency of event of an observation within the intervals. It can be respected as a sort of classification of information. Each sample is sorted into one of several "bins" agreeing to some property.

Firstly, we assess the number of bins 'S', used to build MRI image histograms, on the classification results. The main aim from our proposed system is to obtain a feature space, which may be utilized to discriminate between benign and malignant tumor.

3.3 Fuzzy classifier

In later decades utilizing fuzzy theory in administration and building has increased significantly. Fuzzy science is able to develop models which can handle qualitative data intelligently nearly like a human. Data input for the fuzzy system is the histogram from the segmented image. Fuzzy systems use the linguistic variables to create choices based on fuzzy rules and this is the reason why these systems get better results compared to those use crisp values [19-21]. Thus, fuzzy logic provides simple modeling, fast convergence, and noise reduction. The proposed fuzzy system could be illustrated through the following items: linguistic variables. fuzzification. knowledgebase, fuzzy logic operations, and defuzzification.

3.3.1 Fuzzification

In this phase, the input is the histogram from the segmented image and converts this crisp value to a fuzzy weight depending on the fuzzy membership. The membership functions have multiple types such as triangular, Gaussian, trapezoidal, piecewise linear and singleton. In the proposed fuzzy system, two output fuzzy sets are labeled "low" and "High". The MF is the triangular membership function. A triangular MF is indicated by three parameters $\{a, b, c\}$ as takes after: The parameters $\{a, b, c\}$ (with a < b < c) specify

the x coordinates of the three corners of the TMF. Triangular memberships function (a, b, c) by calculation in equation (1).

$$\mu_{A}(x) = \begin{bmatrix} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ \\ \frac{c-x}{c-b} & b < x < c \\ 0 & x \geq c \end{bmatrix}$$

3.3.2 Histogram Matching

Histogram-based picture coordinatin calculations attempt to measure the similarity in contents through their histograms between a model picture and any pictures in database, i.e., target images, in arrange to properly classify or recover images. Histogram intersection (HI) is calculated by equation (2).

(2)
$$HI = \sum_{i=1}^{n} \min(h_M(i), h_T(i))$$

Where,

 $\mathbf{h}_{\mathbf{M}}$ The histogram of a model image.

h_T The histogram of a target image.

n Number of bins

The intersection of two fuzzy sets High and Low has the triangular membership function. Applying a binary operation on the unit interval function [0, 1].

The shaded area from the intersection between the test histogram and the triangular membership

function is the μ_h or μ_l show in fig.3, and then apply the fuzzy rule base for μ_h and μ_l values. It is cleared from fig.3, that $\mu_h > \mu_l$. So that the image histogram belong to high and the tumor is malignant.



Fig.3 the histogram matching between the test histogram and fuzzy membership 3.3.3 Fuzzy Rule base

The proposed rule base for fuzzy system is shown in fig.4.



Fig.4 Flow chart of the proposed fuzzy rule

3.4 Genetic Algorithm

The proposed GFS (Genetic Fuzzy System) is a fuzzy system classifier improved by a genetic algorithm. In the proposed genetic algorithm, the parameters (a, b, c) for each fuzzy membership are optimized such that the classification accuracy is as maximum as possible [22]. The fitness function of the proposed Genetic algorithm is the classification accuracy that

could be calculated by equation (3).

$$AC = \frac{T_B + T_M}{T_B + T_M + F_B + F_M} * 100$$
(3)

Where,

T_B Number of true benign.

 T_M Number of true malignant.

 $\mathbf{F}_{\mathbf{B}}$ Number of false benign.

 $\mathbf{F}_{\mathbf{M}}$ Number of false malignant.

The parameters (a, b, c) defining the fuzzy membership functions are defined as a chromosome in the optimisation process as shown in fig.5. A group of chromosomes (a population) is created at random. A simulation evaluates the fitness of each chromosome. Then, based on the results of the simulation, the population evolves through three genetic operations: selection, crossover and mutation. The phase of assessment-evolution is repeated until a condition is reached. The false positive error rates and false negative error rates are used to determine the fitness of a chromosome when improving the fuzzy system used for

classification.



Fig.5 Fuzzy system optimization by combining a genetic algorithm

4. RESULTS

This section presents in details the simulation of the proposed methods that carried out on the BRATS2013 dataset. The proposed method is implemented in MATLAB R2016a and executed in a PC with AMB A8 -5545M APU processor with 1.70 GHz speed and 8 GB of RAM.

4.1 Results of proposed image processing 4.1.1 FCM segmentation based on

OTSU's thresholding

In this stage, there are two sub-steps are Otsu's

thresholding method and FCM segmentation. The obtained FCM parameters are shown in Table 1.

Table 1 FCM system parameters

	· · ·	
Max. No. of iteration	limited to100	
Min. improvement	1e-5 is an optional limit.	
No. of clusters	3	

4.1.2 Otsu's thresholding

Firstly, Original image is converted into gray scale image. Fig.6 shows both of the original images and enhanced one.



a) Original Image b) Enhanced Image Fig.6 a. Original, b. Enhanced Image

4.2 Image Histogram for the segmented image

Table 2 shows the histogram for each MRI image and its type.

Segmented images	Image type	Histogram of the image		
	Malignant			
	Benign			
	Malignant			
	Benign			

Table 2 the segmented images and image histogram.

4.1.3 Fuzzy c-means clustering

The FCM algorithm gives the best results.It divides the input image into 3 clusters and calculates the center for each cluster 3 Levels are: {0.2843, 0.1605, 0.5237}. Fig.7 shows the result from FCM segmentation and the tumor region.



Otsu,level=0.270588



FCM1,level=0.502500



Fig.7 the result of the proposed 3 class thresholding FCM Segmentation.

In this study, the counts and pixels value (ranges) for each histogram are the input for the classification stage.

4.3 Genetic Algorithm

GA is used to get the optimal fitness value and get higher accuracy value. The parameters of the proposed Genetic fuzzy system are shown in Table3.

Table 3. The proposed genetic Parameters

No. of genes	6
No. of Chromosomes	100
Crossover probability	0.6
mutation Probability	0.01
stopping crite	30

Table 4 shows the best parameters for TFN (triangular fuzzy numbers).

The proposed classification method using fuzzy logic and genetic algorithm is achieved accuracy 99.9%.

Table4. The results from Genetic Fuzzy system

Parameters	А	В	с
High	70	75	80
Low	88	93	98

5. Conclusion

The proposed system is performed on different MRI images without manual intervention. It achieves better results compared to other The pre-processing and FCM methods. segmentation are used to enhance the image and to separate the interested region (Tumor region) from the normal tissues GM, WM and CSF. Then calculates the histogram for each segmented image. Finally, the classification stage is implemented with fuzzy-genetic system. The proposed hybrid method achieved higher accuracy than the other methods such as: Support vector machine (SVM), artificial neural networks (ANN), and Naive Bayes. The classification accuracy obtained for this system is 99.9 %.

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التصنيف المبكر لورم الدماغ بناء على الرسم البيانى للصورة بأستخدام خوارزمة ضبابية وراثية

تم أنشاء نظام عمل لتصنيف ورم الدماغ و يستخدم هذا النظام أستراتيجات تعتمد على الكمبيوتر لتحديد كتلة الورم وتصنيف نوع هذا الورم بناء على الرسم البيانى المطابق لصور التصوير بالرنين المغناطيسي لمرضى مختلفيين يعانون من أورام الدماغ. طرق معالجة الصورة مثل تجزئة الصورة وتحسينها . نظام العمل المقترح يتكون من مراحل مختلفة فى البداية يتم إلتقاط صورة التصوير بالرنين المغناطيسى كبيانات أدخال وتتم المرحلة الثانية بتجزئة الصورة بأستخدام ملاحل مختلفة فى البداية يتم التقاط صورة التصوير استخراج الورم من الصورة . أخيرًا يُصنف الورم على أنه حميد أو خبيث باستخدام BRATS 2013 ثم يتم متت تجربة البحث واعتماده لإظهار تناسقه ودقته باستخدام صور مرضى مجموعة بيانات BRATS 2013. النتائج التجريبية حققت دقة تصنيف 100 %