A Novel Fuzzy-C Means Image Segmentation Model for MRI Brain Tumor Diagnosis

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Abstract: *Accurate segmentation of brain tumor plays a key role in the diagnosis of brain tumor. Preset and precise diagnosis of Magnetic Resonance Imaging (MRI) brain tumor is enormously significant for medical analysis. During the last years many methods have been proposed. In this research, a novel fuzzy approach has been proposed to classify a given MRI brain image as normal or cancer label and the intensity of the disease. The applied method first employed feature selection algorithms to extract features from images, and then followed by applying a median filter to reduce the dimensions of features. The brain MRI offers a valuable method to perform pre-and-post surgical evaluations, which are keys to define procedures and to verify their effects. The reduced dimension was submitted to a diagnosis algorithm. We retrospectively investigated a total of 19 treatment plans, each of whom has CT simulation and MRI images acquired during pretreatment. The dose distributions of the same treatment plans were calculated on original CT simulation images as ground truth, as well as on pseudo CT images generated from MRI images. The simulation results demonstrate that the proposed algorithm is promising.*

Keywords: *Brain Tumor Diagnosis, Fuzzy Image Processing, Pattern Recognition, Medical Image Processing.*

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1. INTRODUCTION

Medical science has seen a radical development in the field of biomedical imaging in the last two decades. The advancements in the field of artificial intelligence and computer vision technologies have been effectively put into practice for medical applications such as diagnosis of various diseases like cancer. The growth of abnormal cells in the tissues of the brain called brain tumor. Brain tumors can classify to benign or malignant. Medical image classification is used as the basic theory for quantitative and qualitative analysis by extracting the interested regions. In last decades, most researches on image classification and segmentation have focused on diversity methods of feature extraction. In order to accomplish superior marks, approaches to extract and process the characteristics have become an area of interest. For example, gray level co-occurrence matrix has been widely used to extract image grain features, but does not suitably represent gray image features. Computer classification is sensed images involve the process of the computer program learning the association among the data and the information classes [1]. Supervised learning process intended to form a mapping from one set of variables or data to another set of variables or information classes. In supervised learning a teacher is elaborate in the learning process. In the other hand, unsupervised learning happens without a teacher exploration of the data space to discover the scientific laws underlying the data distribution.

The rest of the paper is organized as follows. Section II briefly presents the concept of brain image segmentation and concepts of fuzzy systems in the application of medical image processing. Moreover, this part is shown the research backgrounds. Section III briefly describes research methodology. Section IV has shown the experimental results. Section V reviews the conclusion of proposed methods and their benefits.

2. BACKGROUND AND LITERATURE REVIEW

In this paper fused images from CT and MRI imagers are used for detection of tumor. The fused images are obtained from multiple modality images like Computed Tomography (CT) and Magnetic Resonance Image (MRI) as shown in Fig.1 (left) and (right). These multiple modality images play a key role in medical image processing; CT images which are used to ascertain the difference in tissue density and MRI provide an excellent contrast between various tissues of the body. CT images signify the difference in tissue density depending upon the tissues ability to reflect the X-rays, while MRI images provide contrast between different soft tissues. The above features make CT and MRI more suitable for the detection of tumor. The complementary and redundant information of both the source images are retained in the fused image, these information including the tumor size and location, which enable better detection of tumor, when compared to the source images. [2]

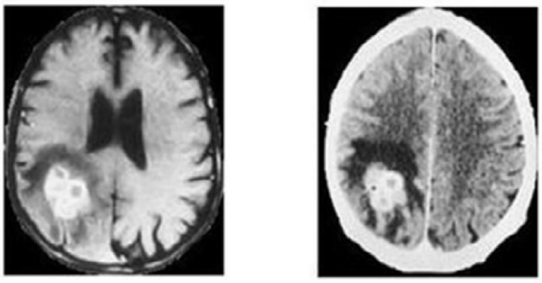

Fig.1: MR (Left) and CT scan Image (Right)

An application example of a more sophisticated segmentation method compared to intensity thresholding. In this case, we see an atlas-based segmentation method at work on a MR-image of the brain. Again, radiotherapists tried to delineate an organ-at-risk, a sensitive anatomical structure in the proximity of a tumor that must not be irradiated. A statistical shape model of the brain stem is adapted to the anatomy of the patient. The arrows in the upper left axial slice and in the lower right sagittal slice point at the contours of the brain stem. Based on these contours, a 3D model of the brain stem is derived. This model is visualized by means of surface rendering – see also Chapter 8. In the color version of this screenshot, which can be found on the accompanying CD, other structures such as the eye balls, the optical nerve and the cornea are also clearly visible as colored organs-at-risk. The screenshot shows the iPlan software suite, BrainLAB AG, Germany. [3]

Fig.2 iPlan software suite for Brain Tumor Diagnosis

Jainy Sachdeva et al. in [4] used two datasets of post-contrast T1-weighted MR images and proposed a CAD system with four modules for classifying brain tumors. First module use content-based active contour model (CBAC) which segments the tumor boundaries then the tumor regions is saved as segmented regions of interest (SROIs). The second module consists of feature extraction module in which intensity and texture features are extracted from the SROIs. Further, they proposed two hybrid models of Genetic algorithm - support vector machine (GA-SVM) and genetic algorithm - artificial neural network (GA-ANN) were in third module GA is used to select a set of salient features from input features for input of (GA-ANN) and (GA-SVM). in forth module (GA-SVM) and (GA-ANN) was used for the classification of tumors. Test results of the first dataset show that the GA optimization technique has enhanced the overall accuracy of SVM from 79.3% to 91.7% and of ANN from 75.6% to 94.9%.

R. Isola et al. resolute the knowledge mining in medical systems based on Differential Evolutionary (DE) Analysis, LAMSTAR, and k-NN. They proposed enormous repository of data so that analysis based on this historical information can be made. They focused on computing the probability of occurrence of a particular disease from the medical data by mining it using a unique algorithm which increases accuracy of such diagnosis by linking the key points of neural networks, large memory storage, and retrieval, k-NN, and differential diagnosis all integrated into one single algorithm [5].

S. Shah and S. Parikh deliberated disputes in medical diagnosis based on computational techniques. They give emphasis on a number of methods offered by researchers for medical diagnosis and their performance issues are discussed. Research has been carried out to diagnose medical images using techniques like Classification, Association Rule Mining, Clustering or combination of algorithms [6].

A. Padma and R. Sukanesh did their study on Super Vector Machines (SVM) based classification of Soft tissues in brain CT images based on wavelet based dominant gray level run length texture features. They focused on the procedure of medical CT imaging as one of the widely applied and reliable technique used for the recognition and position of pathological changes efficiently. Their study aimed on the methods of classifying and segmenting soft tissues in brain CT images [7].

P. Rajendran et al. introduced an improved pre-processing system with image mining methodology for the medical image classification. In their proposed method, they isolate the looked-for object from the image. On the other hand, they effort to apply association rule mining techniques to solve feature selection problems, and try to extract a small size feature subtypes that is acceptable for classification tasks. They applied the decision tree as main classification technique for their learning classifiers [8].

3. RESEARCH METHODOLOGY

As indicated in the c method, this method has a high sensitivity to noise. It has been tried to devise methods that are less susceptible to noise. One of the ideas about noise data is to consider a cluster for noise data and define the attribute of the characteristic (sample) vector xt to the noise cluster according to the following equation:

$$u_k = 1 - \sum_{i=1}^{c} u_{ik} \quad k = 1,\dots,n \qquad (1)$$

In the proposed model each instance will have a small or large membership to this cluster, and therefore the total membership grade of the samples will be less than 1 with the initial cluster, contrary to the original c method, which should be equal to 1:

$$\sum_{i=1}^{c} u_{ik} < 1 \quad \forall k \qquad (2)$$

The objective function defined for this clustering is follows:

δ is a fixed number equal to the distance of the center of the noise cluster with all the samples. Since the sentence added to the target function does not depend on Vi, the formula provided for the c-average algorithm can be used to compute the values of Vi. If the k is a sample, the second sentence of the above formula increases and the membership of this sample is reduced to the clusters and, as a result, the degree of belonging of the sample to the noise cluster increases.

$$J_m(U,V;X)=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}^{m}d^2(x_k,v_i)+\sum_{k=1}^{n}\delta^2\left(1-\sum_{i=1}^{c}u_{ik}\right)^m \tag{3}$$

4. EXPERIMENTAL RESEARCH DESIGN

The confusion matrix can be used to determine the performance of the proposed method. Here, two classification algorithms, Naive Bayesian and Decision Tree for learning procedure and FCM for the handling uncertainty associated in MRI images, have been implemented. This matrix describes all possible outcomes of a prediction results in table structure. The possible outcomes of a two class prediction be represented as True positive (TP), True negative (TN), False Positive (FP) and False Negative (FN). The normal and abnormal images are correctly classified as True Positive and True Negative respectively. A False Positive is when the outcome is incorrectly classified as positive when it is a negative. False Positive is the False alarm in the classification process. A false negative is when the outcome is incorrectly predicted as negative when it should have been in fact positive. In our system consider: [9]

TABLE.1: CONFUSION MATRIX DESCRIPTION

TP= Number of Abnormal images correctly classified
TN= Number of Normal images correctly classified
FP= Number of Normal images classified as Abnormal
FN= Number of Abnormal images classified as Normal.

TABLE.2: THE COMPARISON ERRORS BETWEEN THE SEGMENTED IMAGES AND PHANTOMS [10]

Tissue Type	White matter	CSF	Skull	Grey matter	Scalp	Background
MSE	2.638	1.825	0.649	3.742	1.384	4.219

Additional experiments were performed with the pixel's coordinates as extra inputs to the 10-fold cross validation. The results were reliable considering the additional complexity and training time as reasonable segmentation was available.

Fig.3 Presentation of the input, Filtered, Stripped and segmented images

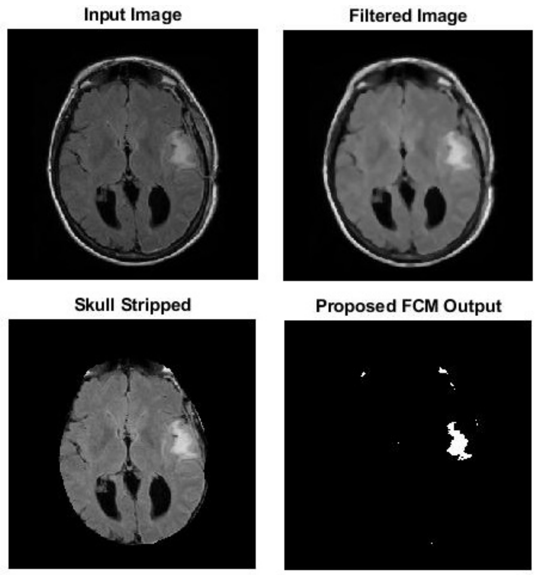

Fig.4 Comparison of NROI and ROI Segmented Image

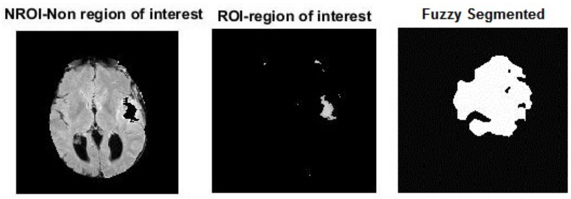

Fig.5 The brain MR image Phantoms [11]

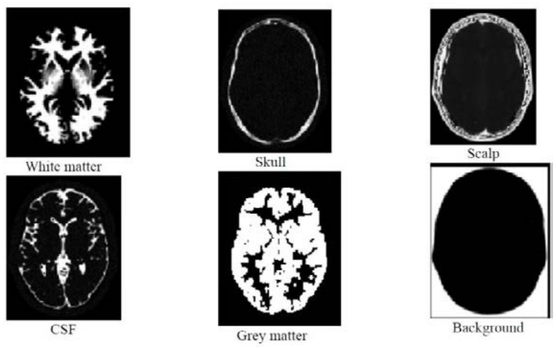

TABLE.3: Dataset Distribution of Brain Tumor Disease

Parameters	*Class A*	*Class B*	*Class C*
Age	10-39 *(14 Case)*	40-59 *(18 Case)*	60-79 *(6-Case)*
Tumor-Size	1-19 *(17 Case)*	20-34 *(16 Case)*	35-54 *(6 Case)*
Degree of Malignancy	Level 1 *(11 Case)*	Level 2 *(13 Case)*	Level 3 *(8 Case)*

TABLE.4: Applied confusion matrix for proposed method

Parameters	MEAN
Precision	91%
Sensitivity	92%
Specificity	90%
Accuracy	92%

Specificity: The prospect of the test finding the correct class among all classes: [12]

$$\frac{TN}{TN + FP} \tag{4}$$

Accuracy: The fraction of test results those are correct:

$$\frac{TP + TN}{TP + FN + TN + FP} \tag{5}$$

Precision: Precision or positive predictive value:

$$\frac{TP}{TP + FP} \tag{6}$$

Sensitivity (Recall): Hit rate

$$\frac{TP}{Total\ Positive} \quad for\ TP\ Rate \tag{7}$$

$$\frac{TP}{Total\ Negative} \quad for\ FP\ Rate \tag{8}$$

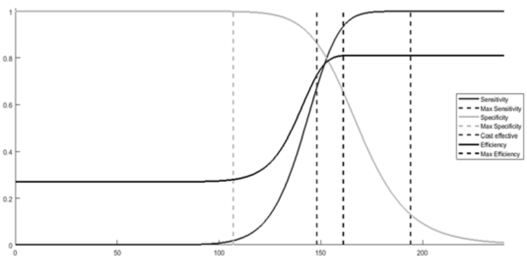

Fig.6: Performance Evaluation based on ROC model

TABLE.5 Comparison of the proposed method to the related works

Method	Features	Accuracy%	CI
Regression	8	90.80	NR
K-Means	9	92.07	[60-80]
K-Median	7	89.00	[80-95]
Watershed	7	91.20	[89-95]
Proposed FCM*	**7**	**92.80**	**[87-92]**

Proposed methods (*) and recent works, CI: Confidence Interval, NR: Not Reported

5. CONCLUSION

Tumor diagnosis and clustering using FCM in Brain MRI is used to get accurate and efficient result. Using proposed FCM model technique tumor has been found as well as classified in Normal or Abnormal class. Here we used a novel FCM model, to compare performance. After evaluating performance it can be obtained that the proposed model has been found to be performing well compared to the existing classifiers. This will produce result into normal or abnormal in efficient way. The developed brain tumor classification system is expected to provide valuable diagnosis techniques for the physicians.

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