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Systematic Approach for Brain Tumor Detection Using Rough Sets on DICOM Images

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Abstract: This paper presents a systematic Automated way for diagnosing the human brain tumors (Astrocytoma tumors) using T_1-weighted Magnetic Resonance Images with contrast. The proposed image processing method has four distinct modules: Pre-processing, Segmentation, Feature Extraction, and Classification. We develop a fuzzy rule base by aggregating the existing filtering methods for Pre-processing step. For Segmentation step, we extend the Possibilistic Fuzzy method by using the Approximation, Lower and Upper, Roughness Index. Feature Extraction is done by Multi-Thresholding algorithm. Finally, we develop a Type-II Approximate Reasoning method to recognize the tumor grade in brain MRI. The proposed Type-II expert system has been tested and validated to show its accuracy in the real world. The results show that the proposed system is superior in recognizing the brain tumor and its grade than Type-I fuzzy expert systems.
Keywords: Roughness index, Image processing, Brain tumors diagnosis, MRI, DICOM

I. INTRODUCTION

The incidence of brain tumors has increased over the time and differs according to gender, age, race, and geography. Most of this increase probably is attributable to improvements in diagnostic imaging methods, increased availability of medical care and neurosurgeons, changing approaches in treatment of older patients, and changes in classifications of specific histologies of brain tumors. Survival time after brain tumor diagnosis varies greatly by histologic type and age at diagnosis. Moreover, some of malignant brain tumors such as Glioblastomas may develop suddenly or by way of malignant progression from lower grades. Therefore, diagnosing the brain tumors in an appropriate time is very essential for further treatments.
In recent years, neurology and basic neuroscience have been significantly advanced by imaging tools that enable in vivo monitoring of the brain. In particular, Magnetic Resonance Imaging (MRI) has proven to be a powerful and versatile brain imaging modality that allows noninvasive longitudinal and 3D assessment of tissue morphology, metabolism, physiology, and function. The information MRI provides, has greatly increased the knowledge of normal and diseased anatomy for medical research, and is a critical component in diagnosis and treatment planning .
The goal of this paper is to design, implement, and evaluate a Type-II Fuzzy Image Processing expert system to diagnose brain tumors, especially Astrocytoma tumors in T_1-weighted MR Images with contrast. The framework of fuzzy sets, systems, and relations is very useful to deal with the absence of sharp boundaries of the sets of symptoms, diagnoses, and phenomena of diseases. However, there are many uncertainties and vaguenesses in images, which are very difficult to handle with Type-I fuzzy sets. These fuzzy sets are not able to model such uncertainties directly because their membership functions are crisp. On the other hand, Type-II fuzzy sets are able to model such uncertainties as their membership functions are themselves fuzzy. Therefore, Type-II fuzzy logic systems have the potential to provide better performance. For these reasons, we have concentrated on Type-II fuzzy modeling.
The rest of this paper is organized as follows: Section 2 explains the brain tumors shortly. Section 3addresses the Brain tumors diagnosis. Section 4 presents the fundamentals of Type-II fuzzy logic. Image processing approaches are described in Section 5. Section 6 is dedicated to the proposed image processing approach. The experimental results are presented in Section 7. Conclusions and future works are presented in Section 8. Finally, the designed software, based on the proposed method, is presented in Appendix

A. Brain tumors

Gliomas are groups of tumors that arise in the Central Nervous System (CNS) and are divided into four major categories: Astrocytes, Oligodendrocytes, Ependymal Cells, and Microglia [29]. In addition, tumors of Glial origin can be divided into those that are infiltrated into normal brain structures (diffuse tumors) and those with more discrete boundaries (focal tumors).

II. PROPOSED IMAGE PROCESSING APPROACH

Developing an efficient diagnosing method may help physicians to diagnose tumors in an appropriate time. Designing an expert system for this purpose includes two main steps: designing strategy of building an automated system and applying this strategy to the application area.

Step 1—designing strategy of building Type-II fuzzy system: There are two methods for generating fuzzy systems, supervised and unsupervised learning [38]. For designing the Type-II image processing system, we use unsupervised learning method with the following steps:

Fig. 2. Proposed image processing algorithm

Step 1—pre-processing: The noises and artifacts of the image are reduced in pre-processing step by using the following Guassian rule base to combine the three common filters (Median Filter, Unsharp Masking, and Winner Filter). The presence of noise is common in all unprocessed medical images. So it becomes obvious that the noise components present in the MRI images are removed and supressed to the maximum possible extend to obtain accurate results after processing. In modern literature there are several techniques available for noise removal in images. One such technique is the use of pre-processing filters. Here we use a Gaussian filter for noise removal.

Step 2—segmentation: The roughness based color image segmentation is employed in which upper and Lower approximations are correlated with Histon and Histogram respectively which allow more appropriate Peak and valley points so as to improve the quality of segmentation.

Step 3—feature extraction: Deducing the result and having an accurate diagnosis needs to recognize and extract the key features. This recognition is done in Feature Extraction step. Mass effect and hyper intense areas are two elements in MR Images, which helps physicians to diagnosis brain abnormalities. The system needs Cerebrospinal Fluid (CSF) cluster to determine the mass effect, and abnormality cluster to determine the tumor. Therefore, feature extraction is done in two stages:

Extracting the abnormalities. Extracting the features and characteristics of each extracted item.

After extracting the features, the Thresholding method is used to recognize the characteristics of pixels values belong to these two clusters (Section 6.3).

Step 4—approximate reasoning or Classification: Defining the diagnostic rules is one of the most important steps in diagnosis procedure. The power of inference engine is based on the accuracy of input data and the predefined rules. After defining the important characteristics of tumor, the proposed rule base must be able to recognize and to consider three parameters: Mass Effect existence, Tumor Shape (Cystic or Mass) and Patient's Age.

To diagnose *Mass Effect* existence, there are two parameters, which must be measured, Similarity and Dilation. Rule-1 measures the similarity and Rule-2 measures the dilation. By considering the results of Rule-1 and Rule-2 and firing Rule-3 (diagnostic rule), the system is able to diagnosis the mass effect existence in MRI.

The *Tumor Shape* (shape of enhanced area) is used to diagnose the tumor grade. If this area is cystic, then it could be Grade I or Grade IV and if it is mass, it could be Grade II or Grade III. This information is shown in Rule-4.

The *Patient's Age* is another important parameter to specify the grade of Astrocytoma. By considering the results of Rule-3, Rule-4, and Patient's Age, other rules could be defined (Section 6.4).

Experimental results: Two steps are used to validate the proposed approach, evaluating the performance of the proposed approach (by using 95 patient's information) and Comparing the results of the two type of fuzzy expert system: Type-II fuzzy expert system and Type-I fuzzy expert system.

The above strategy is explained in the following sections.

A. Pre-processing

In the literature, there are many Pre-processing techniques, which are applicable in different circumstances. However, as there is no sufficient information about the noises exists in MR Images, the usage of only one technique for Pre-processing seems inappropriate. Moreover, in the case of inappropriate usage of these methods, the noises may be increased or small details may be eliminated.

Image filtering is necessary to enhance edge and/or suppress noise. The general idea behind the filtering is to average a pixel using other pixel values from its neighborhood, but simultaneously to take care of important image structures such as edges. The main problem of filtering is the dilemma of occurring image properties, such as sharpness and smoothness. The fine details in an image are usually filtered out while the noises are removed, and while enhancing the edge and fine structures, the noise will also amplify.

B. Gaussian Filter

A Gaussian filter is a filter whose impulse response is a Gaussian function. Gaussian filters are created to shun overshoot of step function input while reducing the rise and fall time. Gaussian filter has the minimum possible group delay. In mathematical terms, a Gaussian filter changes the input signal by convolution with a Gaussian function and this change is also called as Weierstrass transform. The input image undergoes smoothing using Gaussian smoothing filter for elimination of noise. Gaussian filter is a linear spatial filter which is used for reducing the high frequency components of an image as a result it smooth's the edges of the input image.

Gaussian Smoothing is performed by convolving the input image with the Gaussian function i.e.

$$G_\sigma(x,y) * I(x,y)$$

$$G_\sigma(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where I(x, y) is the input image, G cr (x,y) is Gaussiansmoothing filter with standard deviation cr, x and y are the spatial coordinates, and * is the convolution operator.Gradient operator is then applied to the smoothened image to find edges in the image which have been suppressed by the Gaussian filter i.e. V(G,,(x,y)* J(x,y))

Where V is the gradient operator which calculates the directional changes in intensity values

Fig: Flow Diagram

Fig. 3(a) shows the input MRI to the system and Fig. 3(b) shows the effect of the proposed pre-processing method.

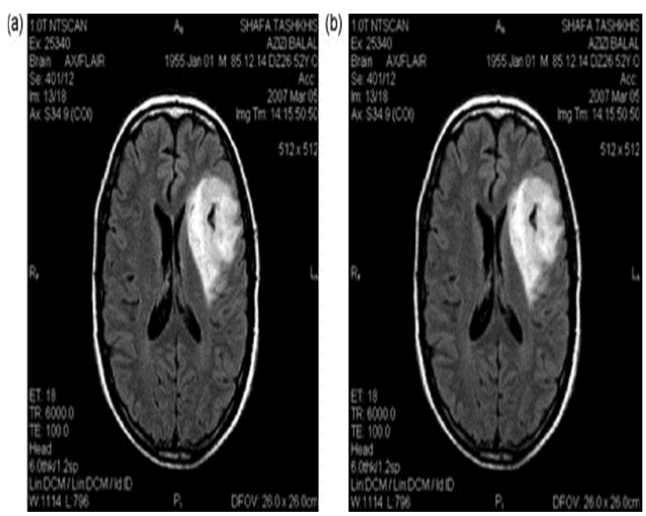

Fig. 3. (a) Input MR image and (b) proposed filtering of input MR image.

As shown in Fig. 3(a) and (b), the noises in the pre-processed image are reduced, the edges are sharpened, but it is also blurred.

However, the overall result is much better than using one filter alone.

C. Segmentation

Segmentation is an essential issue in image description and/or classification. It is based on a definition of uniformity, which usually depends on the particular task and its context. Currently, in many clinical studies, segmentation is still mainly manual or strongly supervised by a human expert. The level of operator supervision affects the performance of the segmentation method in terms of time consumption. Manual segmentation makes the segmentation irreproducible and deteriorating. Hence, there is a real need for automated MRI segmentation tools. Automated segmentation techniques can be categorized into four main categories:

1) *Thresholding:* Thresholding is one of the simplest methods to obtain a crisp segmentation. Thresholding generates a binary image in which the pixels belonging to the objects have the value 1 and pixels belonging to the background have the value 0.
2) *Edge detection:* Edge detection is an important topic in computer vision and image processing, and applied in many areas.
3) *Clustering*: Clustering is the most important methods in modern data mining, which is used in processing large databases. The general philosophy of clustering is to divide the initial set into homogenous groups and to reduce unnecessary data.
4) *Region extraction:* It contains three categories, Region Growing, Region-Based Segmentation and Contour Models.

The Image Segmentation is usually done by using a clustering method. In clustering, the partitioning structure is usually obtained as exclusive clusters (groups) of objects in the observation space with respect to attributes (or variables). However, such a partitioning structure is inadequate to explain the related features of attributes (or variables). Fuzzy clustering can solve this problem and obtain the degrees of belongingness of objects to the fuzzy clusters. That is, in a fuzzy clustering result, there exist objects that belong to several fuzzy clusters simultaneously with certain degrees. Fuzzy clustering has been shown to be advantageous over crisp clustering in that total commitment of a vector to a given class is not required in each iteration. Thus, this method is less prone to local minima.

Among the various methods in Rogh set theory based method which enhances the quality of choice of more appropriate peak and valley points from Histon and Histogram, may compensate some of other clustering method's shortcomings. The proposed model is the extended type of met. In this model, the membership functions are Type-II and the disods based on Fdinuzzy logic. A multi thresholding algorithm will be used using roughness index to get optimum threshold value for color image segmentation.

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Among the various methods in fuzzy clustering, Possibilistic C-mean (PCM) may compensate some of other clustering method's shortcomings. The proposed model is the extended type of Possibilistic C-mean (PCM) developed by Krishnapuram and Keller. In this model, the membership functions are Type-II and the distance function is Mahalanobis distance, computed based on Gustafson and Kessel (GK)[5] algorithm.

The proposed model can be represented as follows:

$$J_m(x, \tilde{\mu}, c) = \min \left[\sum_{i=1}^{c} \sum_{j=1}^{N} \tilde{\mu}_{ij}^{m} D_{ij} + \sum_{i=1}^{c} \eta_i \sum_{j=1}^{N} (1 - \tilde{\mu}_{ij})^m \right] \quad (1)$$

$$0 < \sum_{j=1}^{N} \tilde{\mu}_{ij} < N \quad (2)$$

$$S.T.: \quad \tilde{\mu}_{ij} \in [0, 1] \quad \forall i, j \quad (3)$$

$$\max(\tilde{\mu}_{ij}) > 0 \quad \forall j \tag{4}$$

where μij is Type-II Possibilistic membership values for the ith data in the jth cluster, Dij is the Mahalanobis distance of the ith data to the jth cluster's center, and ηi is positive numbers, c is the number of the clusters, and N is the number of input data. In Eq. (1), the first term makes the distance of the data to the cluster's center be as low as possible and the second term makes the membership values in a cluster to be as large as possible. The membership values for data in each cluster must lie in the interval [0,1], and their sum is restricted to be smaller than the number of input data, as shown in Eqs. (2), (3) and (4).

Minimizing Eq. (1) with respect to μij, leads to Eq. (5) which satisfies Eqs. (2), (3) and (4) [39]:

$$\tilde{\mu}_{ij} = \frac{1}{1 + (D_{ij}/\eta_i)^{(1/m-1)}} \tag{5}$$

As mentioned in [48], the value of ηi determines the distance at which the membership value of a point in a cluster becomes 0.5. In general, it is desired that ηi be related to the ith cluster and be of the order

$$\eta_i = K \frac{\sum_{j=1}^{N} \tilde{\mu}_{ij}^{m} D_{ij}}{\sum_{j=1}^{N} \tilde{\mu}_{ij}^{m}} \tag{6}$$

where N is the number of input data, μij is Type-II fuzzy membership function, Dij is Mahalanobis distance function, and m is a degree of fuzziness.

The clustering method needs a validation index to recognize the structures in data and to define the number of clusters (c) and the degree of fuzziness (m). Therefore a Type-II Kwon Index is used, which is represented by Eq. (7):

$$\tilde{V}_k(c) = \frac{\sum_{i=1}^{c}\sum_{j=1}^{N}\tilde{\mu}_{ij}^{m}||x_j - \tilde{v}_i||^2 + 1/c\sum_{i=1}^{c}||v_i - \bar{\tilde{v}}||^2}{\min\limits_{i \neq j}||\tilde{v}_i - \tilde{v}_j||^2} \tag{7}$$

where μij is Type-II Possibilistic membership values for the ith data in the j th cluster, $\tilde{v}_i$ is the i th cluster center and $\bar{\tilde{v}}$ is the mean one, N is the number of input data, m is the degree of fuzziness and c is the number of the clusters. The first term in the numerator denotes the compactness by the sum of square distances within clusters and the second term denotes the separation between clusters, while denominator denotes the minimum separation between clusters. To assess the effectiveness of clustering algorithm, the smaller the $\tilde{V}_k(c)$, the better the performance.

D. Feature extraction

Recognizing the key features is very important to have an efficient expert system. Mass effect and hyper intense areas are two elements in MR Images help physicians to diagnosis brain abnormalities. Any changes in brain hemispheres, midline, ventricular shapes, and dilatation (or obstructive hydrocephalus) will guide the physicians to recognize mass effect. Existence of hyper-intensity areas in an image could also be the sign of abnormality. To determine the grade of Astrocytoma, the system must be able to 1determine the characteristics of tumor (intra or extra axial, shape of hyper intense areas) and must consider the age of patients.

By finishing the segmentation step, the input data is partitioned into the predefined clusters. The system needs Cerebrospinal Fluid (CSF) cluster to determine the mass effect, and abnormality cluster to determine the tumor in the input image. Therefore, feature extraction is done in two stages:

• Extracting the abnormalities.

• Extracting the features and characteristics of each extracted item.

The output of segmentation step is Type-II membership function for each pixel value. Therefore, the membership functions must be defuzzified and changed into crisp format. Then the thresholding method is used to recognize the characteristics of the pixels values, which belong to the abnormality and CSF clusters.

The *Patient's Age* is another important parameter to specify the grade of Astrocytoma. Usually both Grade I and Grade IV have a cystic shape, but Grade I occurs in youth and Grade IV occurs in adults. In addition, both Grade II and Grade III have a mass shape, but Grade II occurs between 20 and 40 years old patients and Grade III occurs between 36 and 60 years old patients. Fig. 9 shows these membership functions for each Grade of Astrocytoma, which are obtained by using elicitation method.

III. CONCLUSION AND FUTURE WORKS

In this research, an automated system for brain tumor image processing has been developed. The proposed system can help the physicians to better diagnosis the human brain tumors, for further treatment. The main contributions in this paper were the aggregation of the available image pre-processing methods, development of Rough Set Theory based cluster analysis for segmentation, and presenting a Feed Forward Neural Network based expert system for approximate reasoning and Classification . The presented system has been encoded and its main modules have been tested and validated in the real world problems. The results were impressing in terms of better diagnosing the brain tumors. It is shown that, this system can provide better results than Type-I fuzzy expert system according to the uncertainties in the real world.

This research has some potential future works. Development of an automated system for pre-processing needs further research. Moreover, in classification module, using parametric operators instead of standard ones may make the system more adaptive

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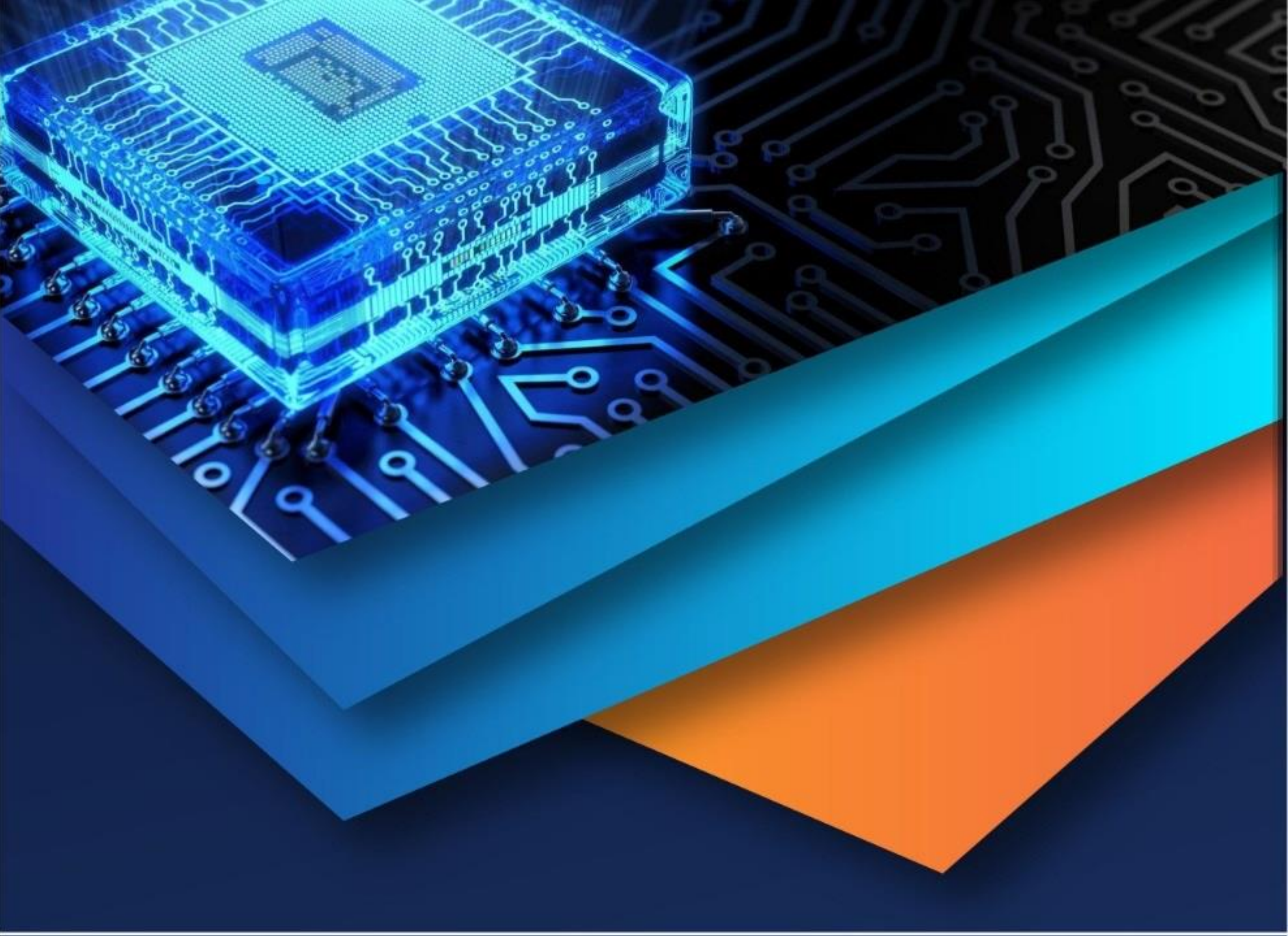

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