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BRAIN TUMOR CLASSIFICATION USING GUSTAFSON–KESSEL (G-K) FUZZY CLUSTERING ALGORITHM

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Abstract: Medical imaging has becoming as a transpire discipline in diversified medical diagnosis. It plays a vital role in automatic detection, which bestows information about abnormalities for further treatment. The traditional approach of detecting MRI is based on manual inspection, which has become inappropriate for vast volume of data. Automated tumor detection has gaining importance that conserves the time of radiologist.In this paper, brain tumor is detected from MRI images by utilizing classification technique based on Gustafson-Kessel (G-K) fuzzy clustering algorithm. Here feature extraction from MRI Images is done by Gray Level Coocurrence Matrix (GLCM).Finally, results prove that the proposed intelligent system improves accuracy rate and trim downthe error rate**.**

Keywords: MRI, G-K fuzzy, GLCM.

I. INTRODUCTION

The human body comprised of several types of cells with each cell has a precise function. The cells in the body grow and divide in an orderly manner which forms new cells to keep the human body in good physical condition. While few cells cease their capability to control their growth and they grow in an improper fashion which leads to extra cells formed form a mass of tissue which is called tumor. Brain tumors are a solid neoplasm inside the skull which usually they grow in the brain or grow in other places such as in lymphatic tissue, in blood vessels, in the cranial nerves, in the brain envelopes. Brain tumors may grow as a result of the spread of cancers primarily located in other parts of the body [1]. Brain tumors can be classified according to the tumor location or the type tissue which the tumor created or whether the tumor is malignant or benign, and other considerations [2]. The tumors may be either benign or malignant in which malignant tumors lead to cancer while benign tumors are not cancerous. In most cases, cancers that spread to the brain to cause secondary brain tumors arise in the kidney, lumy and breast or from melanomas in the skin [2].

Medical imaging techniques like X-ray, CT scan and MRI are the source of medical image data which is used in medical diagnosis. Magnetic field excitation and RF coil pulses produces MRI image [3]. On comparing with CT scan MRI seems to be powerful for diagnosis since it doesn’t utilize radiation. MRI images present a unique perception that determines whether brain tumor is present or not [4]. Manual examination of MRI image is a time consuming job, prone to error while manipulating huge scale of data. Moreover MRI accommodates noise results in flawed classification. In order to analyze large volume of MRI, automation is inevitable which results in economic analyzer. High accuracy of tumor detection is required, because human being is involved. Two common techniques used to classify the MR Images, they are supervised techniques such support vector machine, k-nearest neighbors, artificial neural networks, and unsupervised techniques such fuzzy c-means and self-organization map (SOM). Many research used both supervised and unsupervised techniques to classify MR Images either as normal or abnormal. [5].

The most significant procedure in the automated process is brain tumor classification. A few ordinary classifiers are accessible for classification yet the vast majority of the prior works rely on Artificial Intelligence (AI) systems which yield exceptionally precise results over the traditional classifiers. Ronald et al [6] have obviously represented utilization of Artificial Neural Networks (ANN) to enhance the exactness of the classifiers. This report depended on head and neck carcinoma discovery, and a similar examination was performed with the Linear Discriminant Classifier to demonstrate the unrivaled way of neural systems. Michael et al [7] have proposed an intuitive instrument to characterize the solid and the tumorous MR brain images. In any case, the precision proposed in this framework is low contrasted with the AI strategies. In spite of the fact that this methodology guaranteed a speedier union rate, it may not be much helpful due to its low exactness. This report predominantly focused on enhancing the union rate as it were.

The utilization of different ANN for image classification is investigated by Egmont et. al.,[8]. The absence of speedier union rate of the routine neural systems is likewise clarified in the report. This laid an accentuation on the prerequisite of adjusted neural systems with prevalent meeting rate for image grouping applications. Carles et al [9] have grouped four diverse sorts of tumor utilizing LDA system.

In this paper, the G-K fuzzy is exploited for MRI image classification to detect whether the image is normal and abnormal. The proposed G-K fuzzy method is employed to brain image classification and segmentation is done by using Histogram based. The feature extraction from MRI Images is done by GLCM. The foremost objective of G-K fuzzy is to provide an excellent outcome of MRI brain cancer classification.

II. PROPOSED METHOD

It is most vital criteria to have best quality of images for accurate observations for the given application

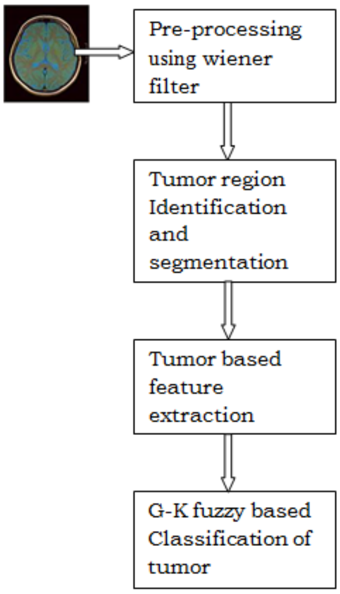

Fig.2 Proposed method

III. FEATURE EXTRACTION

In this paper, the texture features are attained from the statistical appropriation of examined blend of intensities at correct positions regarding each other. Based on the intensity pixels in all combinations, these measurements can be differentiated into first, second-and higher-request imminent. The GLCM is a technique for dividing the second order measurable texture features. The texture features are calculated using the following formulas.

Angular second moment

$$f_1 = \sum_i \sum_j \{p(i,j)\}^2 ,$$

Contrast

$$f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{\substack{j=1 \\ |i-1|=n}}^{N_g} p(i,j) \right\},$$

Correlation

$$f_3 = \frac{\sum_i \sum_j (i,j)\, p(i,j) - \mu_x, \mu_y}{\sigma_x, \sigma_y} ,$$

where μ_x, μ_y, σ_x and σ_y are the means and standard deviations of P_x, P_y

Sum of squares (Variance)

This feature puts relatively high weights on the elements that differ from the average value of P(i, j).

$$f_4 = \sum_i \sum_j (i-\mu)^2 p(i,j),$$

Inverse difference moment

Inverse Difference Moment (IDM) is the local homogeneity. It is high when local gray level is uniform and inverse GLCM is high

$$f_5 = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j),$$

Sum of average

$$f_6 = \sum_{i=2}^{2N_g} i p_{x+y}(i),$$

Sum of variance

$$f_7 = \sum_{i=2}^{2N_g} (i - f_8)^2 p_{x+y}(i),$$

Sum of entropy

$$f_8 = -\sum_{i=2}^{2N_g} p_{x+y}(i) \log\{p_{x+y}(i)\}$$

Entropy

$$f_9 = -\sum_i \sum_j p(i,j) \log(p(i,j)),$$

Difference variance

$$f_{10} = \text{variance} \quad of \quad p_{x-y},$$

Difference of entropy

$$f_{11} = -\sum_{i=0}^{N_{g-1}} p_{x-y}(i) \log\{p_{x-y}(i)\},$$

Maximal Correlation coefficient

$$f_{12} = (\text{Second largest eigen value of } Q)^{1/2}$$

$$\text{where } Q(i,j) = \sum_k \frac{p(i,k)p(j,k)}{p_x(i)p_y(j)}$$

Here, $p(i,j)$ is the $(i,j)^{th}$ entry in a normalized gray level spatial dependence. Matrix $p(i,j)/R$, $p_x(i)$ is the i^{th} entry in the marginal probability matrix obtained by summing the rows of $p(i,j) = \sum_{j=1}^{N_g} p(i,j)$ and N_g is the number of distinct gray levels in the quantized image.

The extracted feature values for normal and abnormal images are given in Table 1 and Table 2 respectively. Features are extracted from the tumor regions of MRI images which involves in minimizing the quantity of data required to describe a large set of data accurately. The obtained features are used as inputs to classifiers which assign them to the class which they represent. The motto of feature extraction is to minimize the original data by measuring positive properties which discriminate one input sample from another sample. If the features are excessively used for classification it will lead to shoot the computation time and storage memory is also increases.

Classification of Tumor: G-K fuzzy is one of the classification technique applied on different fields such as face recognition [9], text categorization [10], cancer diagnosis [11], glaucoma diagnosis, microarray gene expression data analysis. G-K fuzzy utilizes binary classification of brain MR image as normal or tumor affected. G-K fuzzy divides the given data into subsets which are gradual. Dimensionality reduction and precise feature set given as input to the G-K fuzzy on the duration of training part as well as during the testing part.

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IV. SIMULATION RESULTS

Table 1 Observed GLCM texture features for Normal Data set

Features	Data set number			
	1	2	3	4
f_1	53.05051	50.72549	51.24476	41.46154
f_2	5.844444	6.124902	5.582517	4.611538
f_3	0.570532	0.593006	0.609933	0.75308
f_4	52.60378	53.36345	55.09159	43.83538
f_5	0.952819	0.956859	0.951454	0.958715
f_6	13.87949	13.6451	13.46245	11.81718
f_7	194.1419	184.0499	185.9767	153.205
f_8	0.662208	0.737747	0.720055	0.835605
f_9	0.73504	0.822593	0.789547	0.94204
f_{10}	5.64444	6.124902	5.972517	4.811538
f_{11}	0.346532	0.379273	0.355145	0.314349
f_{12}	-0.27284	-0.29809	-0.32303	-0.49761
f_{13}	0.456338	0.487363	0.5183	0.67888
f_{14}	0.938248	0.94581	0.942386	0.958128

Table 2 Observed GLCM texture features for Abnormal Data set

Features	Data set number			
	1	2	3	4
f_1	43.63333	42.5	42.68545	48.15513
f_2	6.883333	6.325	7.418182	5.449744
f_3	0.6559578	0.71114	0.642462	0.677783
f_4	47.81615	45.91587	46.40507	50.43204
f_5	0.943183	0.946796	0.935537	0.955246
f_6	12.32222	11.95833	12.03545	13.28333
f_7	162.8393	156.1366	157.7507	177.9915
f_8	0.849067	0.883296	0.894206	0.75541
f_9	0.949487	0.960561	0.986754	0.839657
f_{10}	0.857067	0.874196	0.893506	0.76431
f_{11}	6.543333	6.135	7.428182	5.449744
f_{12}	0.396674	0.36877	0.429881	0.356466
f_{13}	-0.34801	-0.38834	-0.33804	-0.37661
f_{14}	0.572321	0.624548	0.568267	0.569201

Table 3 shows the overall performance of G-K fuzzy clustering algorithm. From the results, G-K fuzzy has the most optimal performance.

Table 2 Performance Indices

	Accuracy of G-K fuzzy
Sample1	**95.13**
Sample 2	**95.67**
Sample 3	**95.42**
Sample 4	**95.23**

V. CONCLUSION

Brain tumor diagnosing has becoming a vital one in medical field because which are caused by abnormal and uncontrolled growing of the cells inside the brain. Moreover treatment of a brain tumor basically depends on its size and location. Automatic classification of MRI brain image eliminates the manual errors and accuracy of the test drastically. In this work, G-K fuzzy classification technique has been adopted for MRI brain image classification. This automated intelligent system results in the improved accuracy rate and the error rate get minimized. Automation of MRI image classification based on G-K fuzzy will be promising one which aids the physician to make the final decision without any hesitation. From the simulation results it is observed that G-K fuzzy based classification has been efficient for the classification of the human brain into normal and abnormal. It also achieves high degree of accurate classification (i.e. more than 95%). From the outcomes it has been concluded that this technique seems to be rapid, easy to operate, non-invasive and cost effective.

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