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Medical Images Classification by using Artificial Intelligence Techniques

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Abstract: As known, the brain tumor is the most common fatality in the current scenario of health care society. Hence, a robust and more accurate detection system provides an efficient and fast way for diagnosis of the brain tumor is highly essential for treatment planning which can minimize the fatal results. Accurate results can be obtained only through computer aided automated systems to avoid the human error in manual interpretation of medical image content and to obtain high performance and efficiency**.** In this work, we proposed an artificial technique for automatic classification of the Magnetic Resonance Imaging (MRI) brain images as normal or abnormal. The proposed method consists of many stages, namely, image acquisition, image segmentation, features extraction, and classification. Modified K-means clustering algorithm that named weighted K-means used in segmentation stage to convert images into set of regions, the output of this stage will be input to features extraction stage. In features extraction stage multi extracted textural features using Gray Level Co-occurrence Matrix (GLCM) matrices in four directions, these features are used in classification stage. K-Nearest Neighbor classifier is used in decision making. In the experiment we test many MRI images and the results show that provides better output and the classification accuracy of our method is 86%.

Keywords: Brain Tumor, A.I Techniques; MRI; Weighted K-Means, GLCM, K-Nearest.

I. INTRODUCTION

The brain tumor is one of the major causes for the increase in mortality among children and adults. A tumor is any mass that results from abnormal growths of cells in the brain. It may affect any person at almost any age. Brain tumor effects may not be the same for each person. Tumors can directly destroy healthy brain cells[2]. They can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling, and pressure within the skull [1].Brain tumors are either malignant or benign. A malignant tumor, also called brain cancer, grows rapidly and often invades or crowds healthy areas of the brain. Benign brain tumors do not contain cancer cells and are usually slow growing [4]. There are many procedures and diagnostic imaging techniques can be performed for the early detection of any abnormal changes in tissues and organs such as Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRI), X-ray, and Ultrasound [8]. MRI is a primary medical imaging modality that is commonly used to visualize the structure and the function of human body. It provides rich information for excellent soft tissue contrast which is especially useful in neurological studies [10].

However, the important process is classifying MRI into normal and abnormal classes based on pattern recognition concept which can be defined as a quantitative description of an object, while pattern class can be defined as a set of patterns that share some properties in common. For this goal researchers have proposed a lot of approaches which fall into two categories containing supervised classification techniques such as neural network and support vector machine and others [3]. The other category has unsupervised classification techniques such as self-organization map and fuzzy c-means [5,9].Therefore the necessity of efficient and automated way for MRI analysis is continuously increasing.This work is to present an automated intelligent classification system that assists diagnosis of normal and abnormal MRI brain, to avoid the human error in manual interpretation of medical image content.

II. THE PROPOSED SYSTEM METHODOLOGY

As mentioned, the MRI is often the medical imaging method of choice when soft tissue delineation is necessary. This is especially true for any attempt to classify brain tissues. The use of computer technology in medical decision support is now widespread and pervasive across a wide range of medical area, such as cancer research, and brain tumors. Fully automatic normal and diseased human brain classification from MRI is of great importance for research and clinical studies.

A. Texture features used

There are many texture feature that can be used .In this work we used the following[6,7]:

Max Probability (F1): This statistic determines the most predominant pixel pair in an image**.**

$$F1 = Max\ (Cnorm(i,j)) \qquad (1)$$

Entropy (F2) : The Entropy indicator measures complexity of an image. The highest value of entropy is found when the values of Cnorm(i,j) are allocated quite uniformly throughout the matrix. This happens when the image has no pairs of grey-level, with particular preference over others. Entropy is strongly but inversely correlated to Energy.

$$F2 = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \mathrm{Cnorm}(i,j)\,\mathrm{Log}(\mathrm{Cnorm}(i,j)) \quad (2)$$

Contrast(F3): This statistic measures the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image.

$$F3 = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} (i-j)^2\,\mathrm{Cnorm}(i,j) \quad (3)$$

Inverse Difference Moment (IDM)(F4): This statistic measures the smoothness of an image.

$$F4 = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \mathrm{Cnorm}(i,j)}{1+(i-j)^2} \quad (4)$$

Angular second moment (ASM)(F5): This feature is a measure of local homogeneity in the image. Its value is high when the image has very good homogeneity. In a non homogenous image, there are many gray level transitions, the ASM assumes lower values.

$$F5 = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \mathrm{Cnorm}(i,j)^2 \quad (5)$$

Mean (F6):

$$F6 = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \mathrm{Cnorm}(i,j)}{L*L} \quad (6)$$

Dissimilarity (F7) :

$$F7 = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} (|i-j| * \mathrm{Cnorm}(i,j)) \quad (7)$$

Homogeneity (F8): It is a measure of image homogeneity.

$$F8 = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \mathrm{Cnorm}(i,j)}{1+|i-j|} \quad (8)$$

B. The System Stages

In the proposed classification system, the input to the system is a digital image of the brain with format BMP. Every image will pass through segmentation stage by using weighted k-means method. The output of previous stage will be input to features extraction stage, in this stage set of features extraction from images by using GLCM method. Finally, in classification stage K-NN classifier is used for decision making, which is one of the most commonly, used methods for pattern recognition.The block diagram of the proposed system of brain MRI classification is shown in figure1.

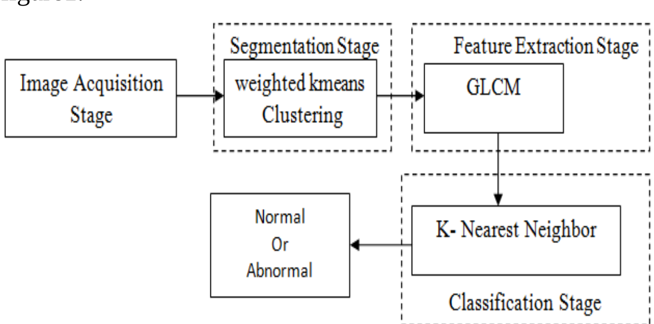


Figure1. The block diagram of the proposed system.

1. Image Acquisition Stage

Collect a set of the brain MRI images, and then the images will be converted into BMP format.

2. Segmentation Stage

The objective of the segmentation process is to partition an image into regions. In this work, concentrate on hard clustering or partition clustering. Particularly, weighted K-means algorithm is a variation of the classic K-means algorithm. In weighted K-means clustering algorithm, must specify the number of cluster that want (parameter k). The next step is to generate the center of each cluster (group) and this is done by randomly selected, and then will be used Euclidean distance to calculate the distance between each pixel of the image and the center of each cluster. Pixel goes to the cluster that gives minim distance. The center of each cluster is updated by dividing the summation of the pixels in the cluster on the number of pixels in the cluster. The weighted K-means clustering algorithm continues partition the image until the center of each cluster does not change. The algorithm for weighted K-means clustering algorithm is as follows:

Input: Image Data matrix I, number of cluster (K), height, width.

Output: Image Data matrix partition into set of region.

Begin

Step1: Generate center of each cluster randomly.

Step2: For ith=0 to height -1

Step3: For jw=0 to width-1

Step3-1 : Compute the distance between each pixel of the image(I(ith, jw)) with the center of each pixel.

Step3-2 : Pixel(I(ith, jw)) go to the cluster with minim distance.

Next jw

Next ith

Step4: Update the center of each cluster according to weight idea by divide the summation of pixels in each cluster on the number of the pixels in that cluster.

Step5: If the center of each cluster do not change stop else go to step2.

End

Figure2. Weighted K-means clustering algorithm.

3. Feature Extraction Stage

Features extraction is the process of analyzing and quantifying the texture within image. It analyzes images to extract the most prominent features that are representative of the various classes of objects. Features are used as inputs to classifier that assign them to the class that they represent. The features extracted in this work are based on gray-level co-occurrence matrix (GLCM). GLCM matrix is a second order statistical measure gives a number of textural characteristics which implement the features of a MRI brain images.

Practically, the GLCM matrices that identify the probability of pairs connection of gray levels are implemented with distance d=1 and in four directions 0,45,90,135, each matrix with one of given directions is in size 256×256, whereas there exist 256 gray levels in the MRI brain image data. The algorithm for computing GLCM matrix with d=1 and in angle 0 (e.g.) is as follow:

```
Input: MRI Image Data matrix I, height, width,
no. of gray levels (G) in input image

Output: GLCM matrix in angle 0 with size G×G.

Begin

Step1: Set GLCM matrix elements to zero.

Step2: For ih= 0 to height-1

Step3: For jw= 0 to width-1

Step4: Get pixel value (let xx) from I(ih, jw).

Step5: Get pixel value (let yy) from
I(ih,jw+1).

Step6: Increment the value of GLCM(xx,yy).

Next jw

Next ih

End
```

Figure3. Computing GLCM matrix in direction 0.

```
Input: GLCM matrix, G.

Output: Normalized GLCM matrix.

Begin

Step1: Compute the summation of all elements in
GLCM matrix.

Step2: For i=0 to G-1

Step3: For j=0 to G-1

Step4: Divide each element of GLCM (i,j) by the
summation which was computed in step 1.

Step5: Replace the value of GLCM (i,j) with the
result of step 4.

Next j

Next i

End
```

Figure4. Normalizing GLCM matrix.

The same procedures are computed with other directions neighbors (i.e. θ = 45,90 and 135. Then each GLCM matrix is normalized using the following equation:

$$\text{Cnorm}(i,j) = \frac{C(i,j)}{\sum_{X=0}^{L-1}\sum_{Y=0}^{L-1} C(X,Y)} \qquad (9)$$

From the normalized GLCM matrix the texture features are extracted, they are eight features: max probability, contrast, entropy, ASM, IDM, dissimilarity, mean, and correlation. The algorithm for extraction those texture descriptors from a MRI image are as follows:

```
Input: MRI Image.

Output: Vector of Textural Features.

Begin

Step1: Call the Algorithm of Computing GLCM
matrix in four direction (0, 45, 90,135) with
distance d=1.

Step2: Call the Algorithm of normalizing
each GLCM matrix.

Step3: For each GLCM matrix in certain
angle:

Step3-1: Calculate textural features
according to their equations.

Step3-2: store computed features in a
vector.

End
```

Figure5. Texture Features extraction from GLCM matrices.

4. Classification Stage

This stage is used to classify the set of images in test stage. The classification method used in this work is K-nearest (K-NN) method. K-NN classifier is a supervised method which examines the k-nearest samples from the training set and classifies the test sample by using a voting scheme. The algorithm of K-NN (in figure (6) below) is used for classification MRI brain images. Where the distance between features vectors of test image and features vector of training images is calculated, then k value will be selected, and according to this, chosen k of the nearest samples to a test vector, and making voting to determine to which MRI brain a test class image belongs.

Input: Vector of training images features, Vector of test image features, k.

Output: Class of testimage.

Begin

Step1: For i = 1 to no. of images in test set

Step2: For j= 1 to no. of images in train set

Step2-1: Compute the distance between the features vector of test image and features vector of train image.

Step2-2: Store computed distance in a data structure.

Step3: Sort the images in train set according to the distancevalue.

Step4: Input the value of k parameter.

Step5: Select first k samples (they are with minimum distance to a test image).

Step6: Count the number of occurrence each class in selected k samples.

Step7: Choose the class who has the larger occurrence number.

Step8: Return the class which is selected in step7, this class will be considered as the class of a test image.

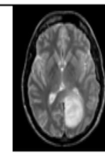
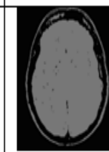
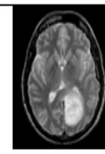
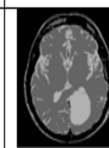
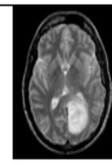
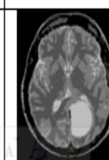
End

Figure6. K-NN Classifier.

III. RESULTS AND DISCUSSION

As mentioned, segmentation stage is a primary stage. System as a whole depend on it, because of the importance of this stage which is used weighted k-means clustering mentioned previously necessary to determine the number of clusters. The value of k that is represented no of clusters will be chosen among the following three values: k= 2, k = 3, and k=4.The values of the k are not standard, anyone can try another values for k and choose the best from them. In this work, quality measure is used to measure the error rate for algorithms. The best value for k is chosen depending on the results provided by using quality measure. Table (1) shows weighted k-means algorithm applied on original image when k=2, k=3, k= 4. The results show that, best value for k is k=4. Therefore in this work=4 is chosen.

Table1.Weighted k-means applied on image when k=2,3,4

Original Image	No. of clusters	Quality measures	Segmented Image
	2	Sc= 1.15224308712002 IF= .860210152392896 NK= .878758866031109	
	3	Sc=1.0519764188673 IF=.942929379526034 NK= .954212875652043	
	4	Sc= 1.07055512668619 IF=.926432550839486 NK=.956084928309789	

The system is performed on MRI brain database with 100 images are used for training and 45 images for testing. All these images are converted to BMP format. The first step in this work is to applying weighted k-means on images of training and testing. The parameter used in weighted k -means is (no of cluster (k) = 4). This value is not standard, anyone can try other values. The output of previously stage will be input to features extraction stage, in this stage 32 extracted textural features using GLCM matrices in four directions 0,45, 90, and 135 respectively with distance equal 1(d=1). After features extracted from train images, next step is features extracted for test images that contain 45 images. Each image will extracted 32 features by using GLCM matrices in four directions 0, 45, 90, and 135 respectively with distance (d=1). In classification stage every image of training and testing is converted to a vector of 32 values (this vector represents the features that have been extracted, which was explained above). As mentioned earlier the classification method used in this work is K-NN. This method relies on computing the distance between each image of the test images with all of the training images, and then sorts the training images with ascending according to the distance. After that a value for the k is choose to make a decision, if the value of the k is equal to 1 then will be choose " class " the first image from train images ranked and put it as a class for image test, and so for the rest of the test images. The k values are not fixed may be (1, 3 , 5, 7, 9,...), the k value used here for making decision is 4.

In this work, a " 0" is used to indicate for images that have class normal and "1" to indicate for images that have class abnormal, Finally ,to evaluate the test stage performance, accuracy is defined as :

$$\text{Accuracy} = \frac{\text{Number of successful classification}}{\text{Total number of test images}} * 100$$

= 86% in our system

IV. CONCLUSIONS

From our work, the following conclusions are deduced:

- The proposed system is developed for classifying the brain tumor from brain MRI images. This system performs that in multiple stages. First stage is image acquisition. The second is image segmentation using weighted K-means algorithm .The texture feature extraction is the third stage that is used the second order texture features extraction. These extracted features are used for classification stage. In classification stage proposed system used k-nearest classifier for classifying brain images as benign and malignant.
- The use of GLCM method to extract features from images proved moreefficient when used compared to use histogram.
- Using K-Nearest Neighbor algorithm in classification stage gave good results in spite of its simplicity, but there is no scheme todetermineappropriate value of k. It works depending on experiment concept for k value selecting. In spite of this, it achieves good accuracy for classification.
- The selected value of k in k-nearest neighbor algorithm affects the system accuracy. In this work, the best results of the classification were obtained when k=4.
- All experiments show that the proposed system gives exceptionally good results as compared to the recently proposed techniques. We achieved accuracy of classification more than then 86%.

V. REFERENCES

[1] Ahmed K. et al, " A Hybrid Approach For Classification Of Brain MRI Using Genetic Algorithm And Support Vector Machine, Leonardo Journal of Sciences, Issue 17, Dec. 2010.

[2] Ahmed Kharrat et al," Automated Classification of Magnetic Resonance Brain Images Using Wavelet Genetic Algorithm and Support Vector Machine", Proc. 9th IEEE Int. Conf. on Cognitive Informatics (ICCI'10), 2010.

[3] Ali Ridho et al," A New Approach for Image Segmentation using Pillar-Kmeans Algorithm" , International Journal of Information and Communication Engineering, 2010.

[4] Bow S. et al, "Pattern Recognition and Image processing", Marcel Dekker, New York, USA, 2002.

[5] Chun-Ming et al," MRI Brain Image Classification by Artificial Neural Network trained via ABP ", International Journal of Research and Reviews in Soft and Intelligent Computing (IJRRSIC) Vol 2, No. 1, 2012.

[6]Gonzalez R. C., et.al., " Digital Image Processing ", Prentice Hall, USA, Second Edition , 2002.

[7] Jayashri J., et al, " Feature Extraction And Texture Classification In MRI ", Int. Con. , Vol. 2, Dec., 2010.

[8] Noor E. A., et al, " Comparative Study Of Adaptive Network-Based Fuzzy Inference System, K-Nearest Neighbors And Fuzzy c-means For Brain Abnormalities Segmentation", Int. J. of Computers, Issue 4, Vol. 5, 2011.

[9] Sahar J., et al, " A Robust Brain MRI Classification With GLCM Features", Int. J. of Computer Applications, Vol. 37, No. 12, Jan. 2012.

[10]Shafaf I., et al, " MRI Brain Abnormalities Segmentation Using K-Nearest Neighbors (K-NN)", Int. J. on Computer Science and Engineering, Vol. 3, No. 2 , Feb. 2011.

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