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Classifiers to Identify Normality/Abnormality on MRI Images based on CBIR

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Abstract—*This work presents a model to support medical diagnosis through the classification of abnormality/normality in medical brain images. Our system is based on retrieving images and classifying images by extracting local image features using GLCM to extract texture features from arbitrary shaped regions which is use FCC separated from an image after segmentation to increase the system effectiveness. In preprocessing step we have to using median filter as and then segmentation on region based. CBIR system is to speed up retrieval and similarity computation with the help of KNN classifier, the database images are segmented and the extracted regions are clustered according to their feature vectors. Increase the retrieval accuracy of our system, we combine the region based features extracted from image regions, which are using FCC on shape based and GLCM on texture based features. We find that proposed system is better than the other existing system. The test results are robustness performance with respect to precision, recall, sensitivity and accuracy.*

Keywords*: CBIR, Preprocessing, FCC, GLCM, KNN classifier.*

1. INTRODUCTION

MRI images plays an important role to decide treatment strategy especially for brain injuries, which can be avoided by early diagnosis and correspond treatment Moreover it is difficult to radiologist make a diagnostic when he is tired or there are injuries which need a lot of time to make a decision, it will be very helpful if exists a tool for decision's support to avoid the problems above, works likes try to resolves some problems on the classification of MR images processing[8].

This paper is organized in 4 sections. In Section 2 we present the proposed approach. Section 3 describes about the Test results, Section 4 describes some possible extensions and future works.

2. PROPOSED METHOD

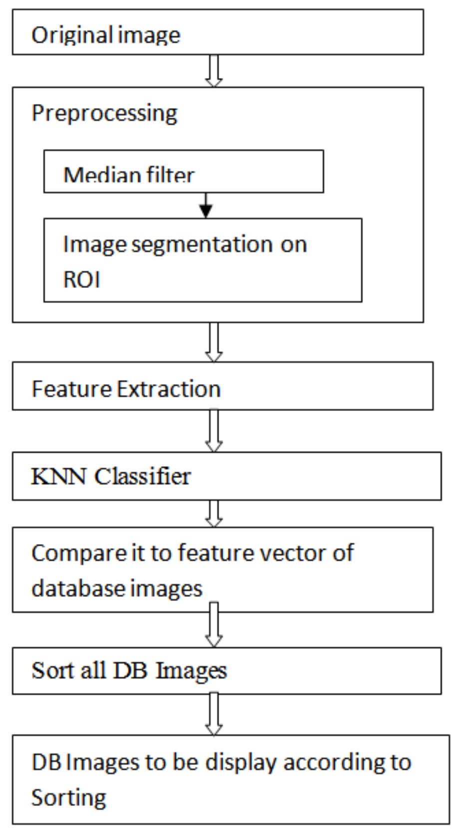


Fig. 1: Proposed method

A. Segmentation

Segmentation is of two types on the basis of discontinuity and similarity.

Similarity based segmentation is done by region based which again categorized into:
1) Those which merge pixels,
2) Those which split the image into regions,
3) Those which both split-and-merge in an iterative search scheme.

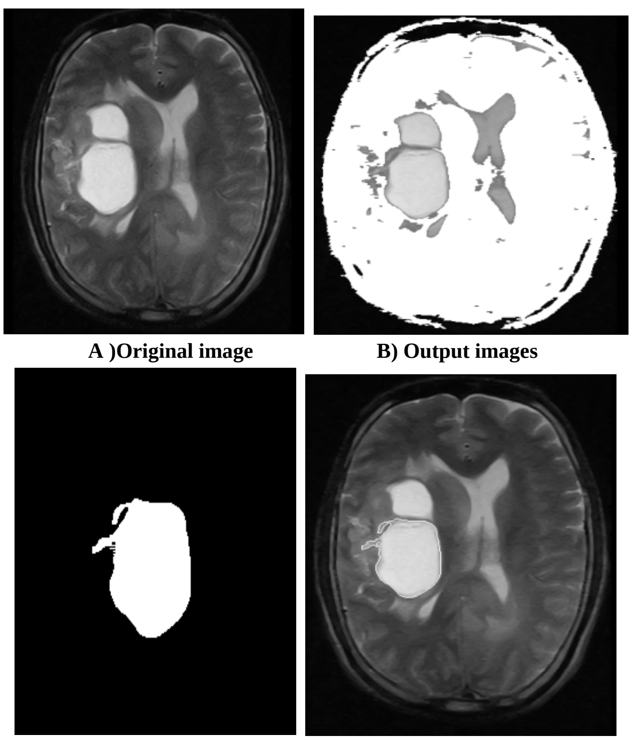
Algorithm for Region Growing

1. We select a threshold parameter to detect tumor and use it to partition the regions into pure black and white.

2. Use different labels to identify different objects in images.

3. Use region growing area to connect parts that should have belong to the same region in MRI images. This is called as "connected component analyses".

4. The region with the same label generates one segment[11].



A)Original image **B) Output images**

C) Tumor image **D) Segmented image**

Fig. 2: A is Original image A& B is output image on ROI segmentation

B. Feature Extraction

Feature is to be extracted on the basis of shape, texture.

Shape- New improved Freeman Chain Code (FCC) is used to represent the segmented regions in addition to the shape features. The chain code based features allow us to efficiently represent all the closed contours. Chain codes are used to represent a boundary by a connected sequence of straight-line segments of specified length and direction. Usually this representation is based on 4- or 8- connectivity of the segments. The chain code of a boundary depends on the starting point.

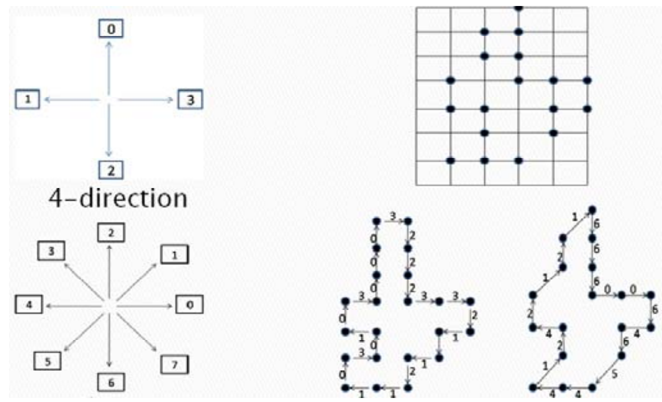


Fig. 3: FCC

Additionally the FCC based representation has important property of translational and rotational invariance during comparison [6].

Fig. 4: Boundary of tumor image

The FCC correlation matrix is used to find the correspondence and similarity for each region in the image. The correlation coefficients thus become the feature for assessment of similarity of MR Images in this work.

Texture- Gray-level co-occurrence matrix (GLCM) is the statistical method of examining the textures that considers the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The gray co matrix function in MATLAB creates a gray-level co occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value *i* occurs in a specific spatial relationship to a pixel with the value *j*. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels.

Each element (*i*, *j*) in the resultant GLCM is simply the sum of the number of times that the pixel with value *I* occurred in the specified spatial relationship to a pixel with value *j* in the input image [9].

(i)CONTRAST

Contrast is defined as the separation between the darkest and brightest area.

$$Contrast = \sum_{i,j=0}^{n-1} P_{i,j}\ (i-j)^2$$

(ii)CORRELATION

Correlation is computed into what is known as the correlation coefficient, which ranges between -1 and +1.

$$Correlation = \sum_{i,j=0}^{n-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$$

(iii)HOMOGENITY

Homogeneity is defined as the quality or state of being homogeneous.

$$Homogenity = \sum_{i,j=0}^{n-1} \frac{P_{ij}}{1+(i-j)^2}$$

(iv) ENTROP

Entropy is a measure of the uncertainty in a random variable

$$Entropy = \sum_{i,j=0}^{N-1} -ln(P_{ij})P_{ij}$$

Table 1: Texture based on 10 images in database

	Contrast	Correlation	Entropy	Homogeneity
1	0.0060	0.9019	0.9332	0.9970
2	0.0113	0.8642	0.9054	0.9943
3	0.0098	0.8717	0.9138	0.9951
4	0.0180	0.8412	0.8689	0.9910
5	0.0099	0.8563	0.9216	0.9951
6	0.0088	0.8313	0.9393	0.9956
7	0.0089	0.8090	0.9448	0.9956
8	0.0111	0.8366	0.9210	0.9944
9	0.0088	0.8618	0.9276	0.9956
10	0.0134	0.8612	0.8906	0.9933

C. Classification

Classification (generalization) using an instance-based classifier can be a simple matter of locating the nearest neighbor in instance space and labeling the unknown instance with the same class label as that of the located (known) neighbor. This approach is often referred to as a nearest neighbor classifier. The downside of this simple approach is the lack of robustness that characterizes the resulting classifiers. The high degree of local sensitivity makes nearest neighbor classifiers highly susceptible to noise in the training data.

More robust models can be achieved by locating k, where k > 1, neighbors and letting the majority vote decide the outcome of the class labeling. A higher value of k results in a smoother, less locally sensitive, function. The nearest neighbor classifier can be regarded as a special case of the more general k-nearest neighbors classifier, hereafter referred to as a KNN classifier. The drawback of increasing the value of k is of course that as k approaches n, where n is the size of the instance base, the performance of the classifier will approach that of the most straightforward statistical baseline, the assumption that all unknown instances belong to the class most frequently represented in the training data.

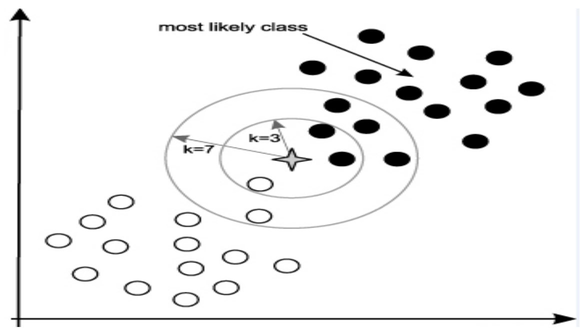
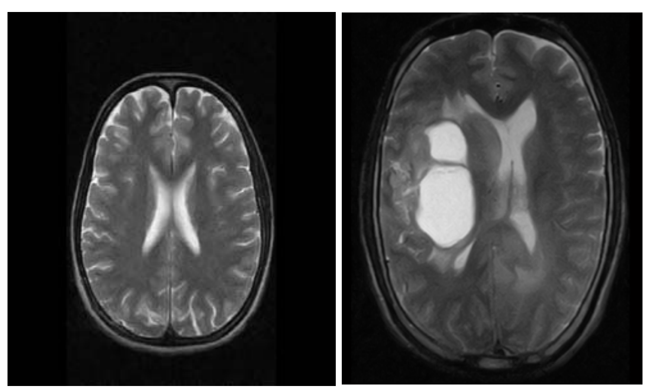


Fig. 5: KNN

3. DATABASE

The dataset consists of T2-weighted, 256×256 pixel MRI. The dataset consists of 400 images, which 315 are of abnormal MRI and 85 are of normal MRI.



(A) –Normal brain (B) - Tumor brain
Fig. 6: Shows samples images for abnormal and normal brain:

4. RESULT

We can see that using KNN classifier with 65 images in this 20 normal images and 45 abnormal images is obtained the highest classification rate (95.67%).

Table 2: We can see the confusion matrix using the SVM Classifier.

	NORMAL	ABNORMAL
NORMAL	19	1
ABNORMAL	2	43

Table 3: Comparison of images on the basis of average values of PRECISION, RECALL and F-MEASURE and ACCURACY value

	K=3	K=5	K=7
ACCURACY(%)	95.67	92.7	90.77
PRECISION	0.9048	0.8261	0.7917
RECALL	0.9550	0.9550	0.9550
F-MEASURE	0.9268	0.8837	0.8636
SENSITIVITY	0.9556	0.9111	0.8889

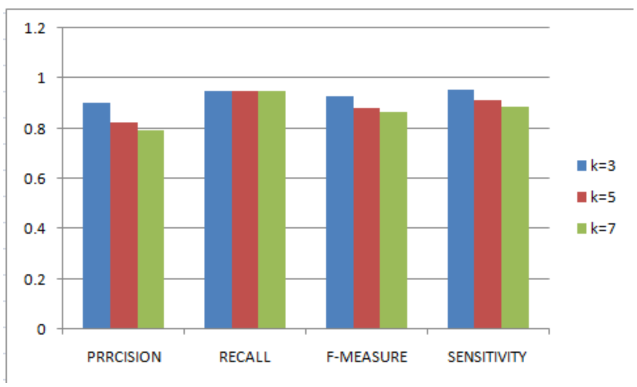


Fig. 7: Shows the plot of F-measure value of different images from the dataset

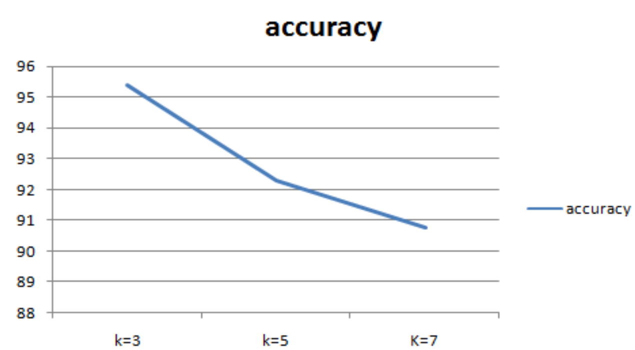


Fig. 8: Shows plot of Accuracy value of different images from the dataset

5. CONCLUSION

The goal of this research paper is to provide an effective means for organizing, searching, and indexing large collections of medical images. This requires intelligent systems that have the ability to recognize, capture, and understand the complex content of medical images. Content-based retrieval is a promising approach to achieve these tasks and has developed a number of techniques used in medical images. We used segmentation on region based is segment the brain image and FCC is to be used for shape and we used GLCM in texture representation. In this using evaluation parameter are precision and recall value and accuracy are to efficient retrieve images. Precision is the measure of accuracy of retrieval of our system. Higher value of precision is desired as it depicts the comparatively more accurate system.

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