Content based Image Retrieval System for Diagnosis of Brain Tumor

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Abstract— Accurate diagnosis is important for treatment of any disease. Content based medical image retrieval (CBMIR) can assist radiologist in diagnosis by retrieving similar images from medical image database. Here we proposed CBMIR for brain tumor. Magnetic Resonance imaging is most commonly used for imaging the brain tumor. During the image acquisition there can be misalignment of MR images due to movement of patient and also low level semantics from MR image may not corresponds with high level semantics of brain tumor, for this two level CBMIR system used, which first classifies (using SVM and ANN) query image of brain tumor as cancerous and non-cancerous tumor using global feature (circularity, irregularity and texture feature) and then search for most similar images with identified class using local feature. This experiment has been performed on 94 brain MR images and result of classification is compare with precision rate, accuracy and recall rate.

Key words: CBMIR, Brain MRI, Global Feature, LBP, ANN, SVM

I. INTRODUCTION

An image contains rich information for extraction and processing purposes. Medical image is important in medicine as it can provide important information for diagnosis, monitoring treatment responses and disease management of patients with faster speed. Nowadays, volumes of digital images in softcopy format have extremely increased. According to the Diagnosis Imaging Department of the University Hospital of Geneva Medical Centre, they serve hundreds of patients in need of medical imaging and other radiology procedures every day [1].Hospitals are maintain image of patient which contain diagnosis in medical image database known as Picture Archiving and communication System (PACS) [1]. Content based medical image Retrieval is becoming an important field with advancement in imaging and Multimedia technique, which is the automatic retrieval of images from a database and assist the radiologist in diagnosis by retrieving the relevant cases. Now a days most of the PACS in hospitals use Text based image retrieval which use keywords as descriptor to index an image, but it often cause an ambiguity in performance. And it is also very subjective and laborious task. Where CBMIR use visual content such as color, texture and shape to represent images, because content of image is much richer than set of keywords.

Many researchers have done work on CBMIR and contribute in this field. Megha P. at al [2] used CBMIR on brain MR images with two level hierarchical approach which used shape and texture feature to classify the query image as benign and malign using SVM and retrieve the most similar image using ED and get 97.95% classification accuracy. N Rajasekhar at al. [3] classify MRI Brain tumor images as normal and abnormal images which used different texture feature extraction technique and classify them using SVM, k-NN and HMM classifier and get 93.08% accuracy using SVM. Abraham Varghese at al [4] used local binary pattern (LBP) and MOD-LBP and moment feature which retrieve similar slice of T1 weighted images from T2 weighted images and vice-versa and get 93.6% accuracy using MOD-LBP.

Abderrahim Khatabi at al.[5] used method based on image characteristic such as visual feature of shape using angular redial transform (ART) which is robust to the noise and classify image as tumor or non-tumor image using SVM classifier and retrieve the most similar image using k-NN and get 98.45% accuracy.

II. PROPOSED METHODOLOGY

Our proposed work presents a complete CBMIR system. There is main two part of this system one is to offline part to create a databased and other is online part which we used to retrieve the similar image.

In the off-line phase, MR images are automatically segmented using k-means clustering technique to extract brain tumor from MR image. Tumors can be well discriminated by their shape and texture characteristics. These features are fed into SVM and ANN classifier and assign label to the image as cancerous or non-cancerous tumor. In second stage local feature such as Local Binary Pattern (LBP) is extracted are extracted from the brain tumor for discrimination between tumors within the class.

Similarly, in the online phase, the class label of the query image is identified using ANN classifier based on rotation invariant global shape and texture features of tumor. Using this label, the similarity comparison is only to images with similar class labels in the database. This reduced search time from the database. Then, the features of the query image are compared with database using Euclidian distance and retrieved most similar K images.

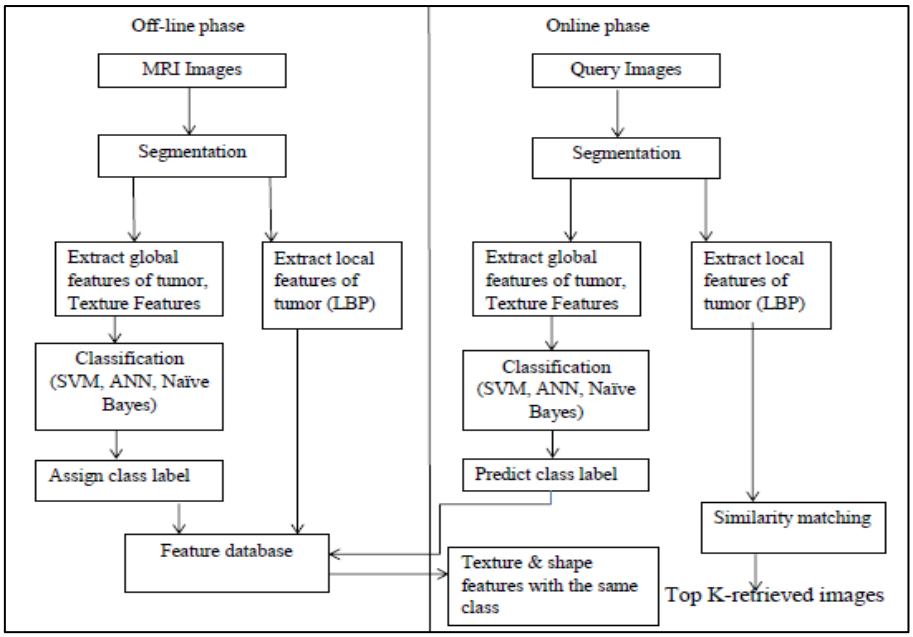


Fig. 1: Proposed Diagram for CBMIR)

III. FEATURE EXTRACTION

A. Global Feature Extraction

Non-Cancerous tumor are more circular whereas cancerous are more irregular in shape so circularity and irregularity is main feature we extract from the tumor.

1) Shape Feature

Circularity and Irregularity of Tumor is measure as:

Circularity (C) = $4\pi A/P^2$

Where, P is perimeter of tumor and A is area of tumor.

Irregularity (I) = $1/N \sum_{i=1}^{360} d_i$,

$$d_i=\sqrt{(xi - xc)^2 + (yi - yc)^2} \quad (1)$$

Where, (x_i, y_i) are boundary points and (x_c, y_c) is the region centroid. These features are rotation invariant.

2) Texture Feature

Tissue exhibit consistent and homogeneous texture. In this texture of the tumor are represented using first order statistics. So we can find following texture feature from tumor.

a) Skewness

Skewness is a measure of the asymmetry of the data around the sample mean. If skewness is negative, the data are spread out more to the left of the mean than to the right

The skewness of a distribution is defined as

$$s=\frac{E(x-\mu)^3}{\sigma^3} \quad (2)$$

b) Kurtosis

It is measure sharpness of the peak of a frequency distribution curve. It is same as skewness

$$k=\frac{E(x-\mu)^4}{\sigma^4} \quad (3)$$

c) Entropy

Entropy is a statistical measure of randomness or complexity that can be used to characterize the texture of the input image. Entropy is defined as

$$e = -sum(p.* log2(p)) \quad (4)$$

d) Standard Deviation

It is measure variation of pixel value from its mean.

$$S=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(Ai - \mu)^2} \quad , \mu \text{ is mean of } Ai \quad (5)$$

a) Coefficient of Variance

The coefficient of variation is a measure of spread that describes the amount of variability relative to the mean. And it is defined as

CV = Standard deviation / Mean

From this we have got 9 dimensional feature vector using different global features techniques. We have computed this feature from the segmented tumor of brain MRI image. And then we have fed this extracted feature vector into three classifier namely SVM, ANN

B. Local Feature Extraction

The Local Binary Pattern (LBP) [12] operator is a gray invariant texture primitive, derived from a general definition of texture in a local neighborhood. Due to its discriminative power and computational simplicity, the LBP operator has become a highly popular approach in various computer vision applications, including visual inspection, image retrieval, remote sensing, biomedical image analysis, biometrics, motion analysis, environment modeling, and outdoor scene analysis, etc. LBP is formed by comparing gray value of center pixel (g_c) with that of P neighborhood pixels in the local neighborhood.

$$\text{LBP} = \sum_{i=0}^{p-1} s(g_i - g_c)2^i \,, \quad \begin{matrix} s(x) = 1, & x \geq 0 \\ 0, & x < 0 \end{matrix} \tag{6}$$

Where, g_c and g_i are the gray value of the center pixel and neighbor pixel respectively. P is the total number of neighbors located in a radius R. LBP code computation is shown in Fig.2 with P = 8 and R = 1.

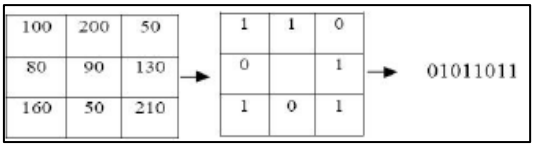


Fig. 2: LBP Code Computation

IV. CLASSIFICATION TECHNIQUES

Classification or Recognition process is for decision making, like this query image fit in which class or looks like. It means, in the phase of classification characters are identified and assign labeling. Performance of the classification depends on good feature extraction and selection. Various classification techniques are available and they all are ultimately based on image processing and artificial intelligence.

A. Support Vector Machine

Support Vector Machine is a binary classifier [13], it finds the separation line which maximizes the distance between two classes. It is based on statistical learning theory and quadratic programming optimization. The linear SVM classifier can be represented as

$$p(x) = \sum \alpha_i x_i \, x + b \tag{7}$$

Here "x_i" represents support vectors, whereas "α_i" and "b" are calculated by solving the quadratic equation.

B. Artificial Neural Network

The concept of ANN [14] is derived from the working of biological neurons in the brain. It is having the capability to learn automatically from the examples. Generally it gives good performance with noisy data. It can also learn large databases efficiently. It can also be implemented to run in parallel. Due to all these characteristics ANN is a well-known classifier. Here we used Multilayer perceptron and Backpropagation feed forward neural network in this domain

C. Naive Bayes classifier

Naive Bayes classifiers are linear classifiers that are known for being simple yet very efficient. The probabilistic model of naive Bayes classifiers is based on Bayes' theorem, and the adjective naive comes from the assumption that the features in a dataset are mutually independent.

It assume that the presence of the particular feature in the class is unrelated to presence of any other feature, it calculate posterior probability,

$$p(c/x) = \frac{p\left(\frac{x}{c}\right)p(c)}{p(x)} \tag{8}$$

Where, p(c) is prior probability of any class, p(x/c) is likelihood which is probability of predictor given class, p(x) is prior probability of predictor

V. RESULT ANALYSIS

A. Data Set

The image database was built with 94 MR images of brain tumor (non-cancerous:28, cancerous: 66). All images for experiment were collected from Radiology Department, Civil Hospital, Ahmedabad and all images are of the size 256x256.

B. Results

We have Extracted 9 dimensional feature vector for all 94 images using Global feature extraction techniques and fed it to the two different classifier SVM and ANN. Result of compression is as shown in TABLE 1 and performance of the system is measured with help of classification rate, precision and recall.

Classifier	Accuracy	Precision	Recall Rate
SVM	85.11%	83.96%	79.11%
ANN	93.62%	93.21%	91.34%
Naïve Bayes	76.60%	73.13%	76.13%

Table 1: Result of Classification

So, we have classified query image using ANN and Retrieved most similar images using LBP Feature and ED and get following result.

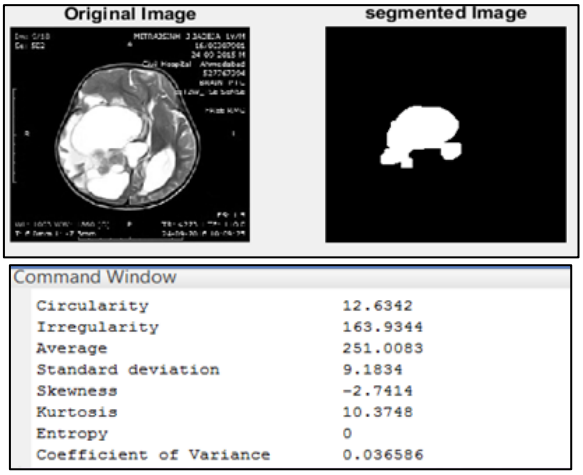
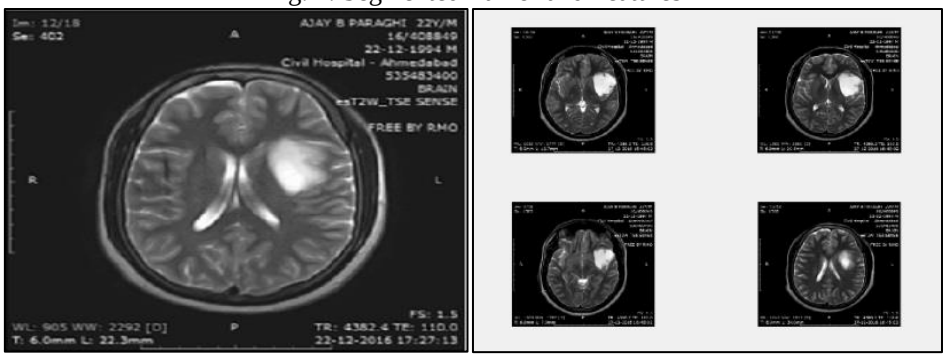


Fig. 2: Segmented Tumor and Features



Selected Image has Cancer

Fig. 3: Output of Test image and Retrieved Images

VI. CONCLUSION

Several application of content based image retrieval but use of CBIR for medical image is one of the important applications. CBIR can assist the radiologist in diagnosis of brain tumor by retrieving similar images from medical image database. To get more accurate retrieving system main task is to generate good database of images from visual feature of images.

We have extracted the features using Combination of Global Feature Extraction from Cancerous and Non-Cancerous MR Images and create the database and then fed these features to three different classifiers namely SVM, ANN and Naïve Bayes classifier for Classification of tumor in two classes. Then we have measured the accuracies of different classifiers and we have got highest accuracies 93.62% using ANN. Secondly we extract Local feature of query image and retrieved most similar four images by measuring the ED within the identified class.

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