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An Efficient Refining Of Cbir through Supervised Learning Approach

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ABSTRACT
CBIR(Content Based Image Retrieval) technique has its own importance in medical field to store, manage, and retrieve data images based on user query. Here we propose a framework based on design and development of a multi-tier Content-Based Image Retrieval system for MRI brain images utilizing a reference database that contains both normal and tumor brain images under the category which it falls(i.e. normal, benign or malignant tumor) ,with their identity number, which are mostly difficult to classify and discriminate. The features of the image are extracted using gray level co-occurrence matrix (GLCM) technique and a subset of features is selected using Differential Evolution Feature Selection (DEFS) technique. The selected features are sent through the classifier (SVM). Searching is done by means of matching the image features such as texture, shape, or different combinations of them. SVM (Support Vector machine) classifier followed by KNN (K-nearest neighbor) for CBIR using texture and shape feature.This CBIR system enables both multi-image query and slide-level image retrieval in order to protect semantic consistency among the retrieved images. The performance of the system is tested on the dataset by several MRI brain images of various categories, and the features of the image in the dataset matching more accurately of the features of query images are listed as retrieved images with their identification number for better accuracy.

Keywords-CBIR,MRI brain images,GLCM,DEFS,SVM,KNN.

I. INTRODUCTION

An image retrieval system is a computer system for browsing, search and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding datasuch as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Manual image annotation is time-consuming, laborious and expensive; to address this, there has been a large amount of research done on automatic image annotation. Additionally, the increase in social web applications and the semantic web have inspired the development of several web-based image annotation tools.

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the retrieval problem, that is, the problem of searching for digital images in large databases."Content-based" means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image metadata itself. CBIR is desirable because most web based image search engines rely purely on and this produces a lot of garbage in the results Also having humans manually enter keywords for images in a large database can be inefficient, expensive and may not capture every keyword that describes the image Thus a system that can filter images based on their content would provide better indexing and return more accurate results.

Image search is a specialized data search used to find images. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query. The similarity used for search criteria could be meta tags, color distribution in images, region/shape attributes, etc

II. PROPOSED METHOD

We propose a robust retrieval using a supervised classifier which concentrates on extracted features. Gray level co-occurrence matrix algorithm is implemented to extract the texture features from images. The feature selection is done on the extracted features to select best features out of it to train the SVM classifier.

The classification is performed on the dataset and it is classified into three categories such as normal, benign and malignant. To locate the abnormality and to reduce the training time of SVM classifier we insert clustering mechanism. The query image is classified by the classifier to a particular class and the relevant images are retrieved from the database.

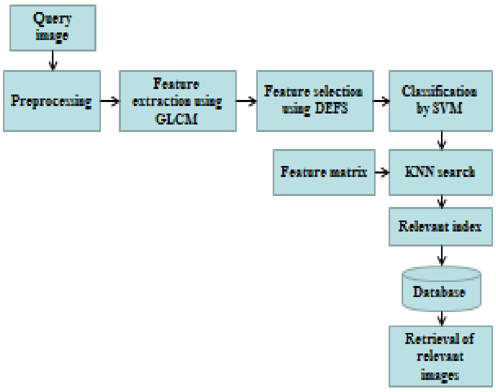

Fig.2.1 overall architecture

2.1 MEDIAN FILTERING

We have seen that smoothing (low pass) filters reduce noise. However, the underlying assumption is that the neighboring pixels represent additional samples of the same value as the reference pixel, i.e. they represent the same feature. At edges, this is clearly not true, and blurring of features results.In the median filtering operation, the pixel values in the neighborhood window are ranked according to intensity, and the middle value (the median) becomes the output value for the pixel under evaluation.Median filtering does not shift boundaries, as can happen with conventional smoothing filters. Since the median is less sensitive than the mean to extreme values (outliers), those extreme values are more effectively removed. Median filtering preserves the edges.

2.2 FEATURE EXTRACTION

Transforming the input data into the set of features is called *feature extraction*. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector). The features provide the characteristics of the input type to the classifier by considering the description of the relevant properties of the image into a feature space. If the features extracted are carefully chosen, it is expected that they will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction can be used in the area of image processing which involves using algorithms to detect and isolate various desired portions or shapes (features) of a digitized image or video stream. Another important feature processing stage is feature selection. This section has given an overview of many possible features that can be used, and feature set that encodes a diverse variety of types of information is used in order to enhance discrimination between normal and abnormal areas.

2.2.1 Features

In image processing the concept of feature is used to denote a piece of informationwhich is relevant for solving the computational task related to a certain application. More specifically, features can refer to the result of a general neighborhood operation (feature extractor or feature detector) applied to the image.Specific structures in the image itself, ranging from simple structures such as points or edges to more complex structures such as objects. Other examples of features are related to motion in image sequences, to shapes defined in terms of curves or boundaries between different image regions, or to properties of such a region. The feature concept is very general and the choice of features in a particular computer vision system may be highly dependent on the specific problem at hand.

2.2.2 Choice Of Features

A specific image feature, defined in terms of a specific structure in the image data, can often be represented in different ways. For example, an edge can be represented as a Boolean variable in each image point that describes whether an edge is present at that point. Alternatively, we can instead use a representation which provides a certainty measure instead of a Boolean statement of the edge's existence and combine this with information about the orientation of the edge. Similarly, the color of a specific region can either be represented in terms of the average color (three scalars) or a color histogram (three functions).When a computer vision system or computer vision algorithm is designed the choice of feature representation can be a critical issue. In some cases, a higher level of detail in the description of a feature may be necessary for solving the problem, but this comes at the cost of having to deal with more data and more demanding processing. In this project mathematical features are used to classify the images.

2.2.3 Texture

An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image.

2.2.4 Texture Feature Extraction Using GLCM.

A co-occurrence matrix is a two-dimensional array, **P**, in which both the rows and the columns represent a set of
possible image values where $\mathbf{n_{ij}}$ is the number of occurrences of the pixel values **(i,j)** lying at distance **d** in the image.A GLCM **Pd**[i,j] of dimension **n× n** where n is the number of gray levels in the image.is defined by first specifying a displacement vector **d**=(dx,dy) and counting all pairs of pixels separated by **d** having gray levels i and j.
From the co-occurrence matrix obtained, we have to extract the 12 different statistical features.

1. Contrast
2. Correlation
3. Cluster prominence
4. Cluster shade
5. Dissimilarity
6. Energy
7. Entropy
8. Homogeneity
9. Maximum probability
10. Sum of squares

Contrast:

Contrast is a measureof the local variations present in an image.

$$C(k,n) = \sum_i \sum_j (i-j)^k P_d[i,j]^n$$

If there is a large amount of variation in an image the **P[i,j]**'s will be concentrated away from the main diagonal and contrast will be high (*typically k=2, n=1*).

Homogeneity

A homogeneous image will result in a *co-occurrence matrix* with a combination of high and low P[i,j]'s.

$$C_h = \sum_i \sum_j \frac{P_d[i,j]}{1+|i-j|}$$

Where the ***range of gray levels*** is small the **P[i,j]** will tend to be clustered around the main diagonal.

Entropy:

Entropy is a measure of information content. It measures the randomness of intensity distribution.

$$C_e = -\sum_i \sum_j P_d[i,j] \ln P_d[i,j]$$

Correlation:

Correlation is a measure of image linearity.

$$C_c = \frac{\sum_i \sum_j [ijP_d[i,j]] - \mu_i \mu_j}{\sigma_i \sigma_j}$$

Where,

$$\mu_i = \sum i P_d[i,j], \qquad \sigma_i^2 = \sum i^2 P_d[i,j] - \mu_i^2$$

Energy:

After the convolution with the specified kernel, the *texture energy measure (TEM)* is computed by summing the absolute values in a local neighborhood:

$$L_e = \sum_{i=1}^{m} \sum_{j=1}^{n} |C(i,j)|$$

If ***n*** kernels are applied, the result is an ***n***-dimensional feature vector at each pixel of the image being analyzed.

Maximum Probability:

This is simply the largest entry in the matrix, and corresponds to the strongest response. This could

$$C_m = \max_{i,j} P_d[i,j]$$

be the maximum in any of the matrices or the maximum overall.

Cluster Shade:

SHADE=$\sum_{i=0}^{2G-2}(i-2\mu)^3 \, \mathrm{H_s}(\mathrm{i}|\Delta\mathrm{x},\Delta\mathrm{y})$

Where, μ=$\frac{1}{2}\sum_{i=0}^{2G-2} i \, \mathrm{H_s}(\mathrm{i}|\Delta\mathrm{x},\Delta\mathrm{y})$

Local Homogeneity, Inverse Difference Moment (IDM) :

$IDM = \sum_{\mathrm{i}=0}^{\mathrm{G}-1}\sum_{\mathrm{j}=0}^{\mathrm{G}-1}\frac{1}{1+(i-j)^2}P(i,j)$IDM is also influenced by the homogeneity of the image. Because of the weighting factor IDM will get small contributions from inhomogeneous areas. The result is a low IDM value for inhomogeneous images, and a relatively higher value for homogeneous images.

Sum of Squares, Variance:

VARIANCE=$\sum_{\mathrm{i}=0}^{\mathrm{G}-1}\sum_{\mathrm{j}=0}^{\mathrm{G}-1}(\mathrm{i}-\mu)^2\mathrm{P}(\mathrm{i},\mathrm{j})$

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

Cluster Prominenc

$$\mathrm{PROM} = \sum_{\mathrm{i}=0}^{\mathrm{G}-1}\sum_{\mathrm{j}=0}^{\mathrm{G}-1}\{\mathrm{i}+\mathrm{j}-\mu_\mathrm{x}-\mu_\mathrm{y}\}^4 \times \mathrm{P}(\mathrm{i},\mathrm{j})$$

Dissimilarity:

$$\sum_{\mathrm{i,j}=1}^{\mathrm{G}} \mathrm{c_{ij}}|\mathrm{i}-\mathrm{j}|$$

Autocorrelation:

Other statistical approaches include an autocorrelation function, which has been used for analyzing the regularity and coarseness of texture by Kaizer. This function evaluates the linear spatial relationships between primitives. The set of autocorrelation coefficients shown below are used as texture features:

C(p,q) = $\frac{\boldsymbol{MN}}{(\boldsymbol{M-p})(\boldsymbol{N-q})}\frac{\sum_{i=1}^{M-p}\sum_{j=1}^{N-q}f(i,j)(i+p,j+q)}{\sum_{i=1}^{M}\sum_{j=1}^{N}f^2(i,j)}$

Where, *p*, *q* is the positional difference in the *i*, *j* direction, and *M*, *N* are image dimension.

2.2.5 Shape Feature

- Lines
- Circles/ellipses
- Arbitrary shapes (generalized Hough transform)

2.2.6 Moment Invariants

Moments are “projections” of the image function into a polynomial basis.Invariants are functional defined on the image space such that

I(f) = I(D(f)) for all admissible *D*

I(f₁), I(f₂) “different enough“ for different *f₁, f₂*

2.2.7 Moment Invariant Features

Traditionally, moment invariants are computed based on the information provided by both the shape boundary and its interior region. The moments used to construct the moment invariants are defined in the continuous but for practical implementation they are computed in the discrete form. Given a function f(x,y), these regular moments are defined by:

$\mathrm{M_{pq}} = \int\int \mathrm{x^p y^q}\, \mathrm{f(x,y)dxdy}$ where $\mathrm{M_{pq}}$ is the two-dimensional moment of the function *f(x,y)*. The order of the moment is (p + q) where p and q are both natural numbers. For implementation in digital from this becomes:

$$\mathrm{M_{pq}} = \int\int \mathrm{x^p y^q}\, \mathrm{f(x,y)}$$

To normalize for translation in the image plane, the image centroids are used to define the central moments.

The co-ordinates of the centre of gravity of the image are calculated using equation and are given by:

$$\bar{\mathrm{x}} = \frac{\mathrm{M_{10}}}{\mathrm{M_{00}}}\ \bar{\mathrm{y}} = \frac{\mathrm{M_{01}}}{\mathrm{M_{00}}}$$

The central moments can then be defined in their discrete representation as

$$\mu_{\mathrm{pq}} = \sum_\mathrm{x}\sum_\mathrm{y}(\mathrm{x}-\bar{\mathrm{x}})^\mathrm{p}(\mathrm{y}-\bar{\mathrm{y}})^\mathrm{q}$$

The moments are further normalized for the effects of change of scale using the following formula:

$$\eta_{\mathrm{pq}} = {\mu_{\mathrm{pq}}}\Big/{\mu_{00}^{\gamma}}$$

Where the normalization factor: $\gamma = \left(\frac{\mathrm{p+q}}{2}\right)+1$

From the normalized central moments a set of seven values can be calculated and are defined by

$\square_1 = \mu_{20}+\mu_{02}$

$\square_2 = (\mu_{20}-\mu_{02})^2+4\mu_{11}^2$

$\square_3 = (\mu_{30}-3\mu_{12})^2+(3\mu_{21}-\mu_{03})^2$

$\square_4 = (\mu_{30}+\mu_{12})^2+(\mu_{21}+\mu_{03})^2$

$$\square_5 = (\mu_{30}-3\mu_{12})(\mu_{30}+\mu_{12})((\mu_{30}+\mu_{12})^2 - 3(\mu_{21}+\mu_{12})^2 + (3\mu_{21} - \mu_{03})(\mu_{21}+\mu_{03})(3\mu_{30}+\mu_{12})^2 - (\mu_{21}-\mu_{03})^2$$

$$\square_6 = (\mu_{20}-\mu_{02})((\mu_{30}+\mu_{12})^2-(\mu_{21}+\mu_{03})^2 + 4\mu_{11}(\mu_{30}+\mu_{12})(\mu_{21}+\mu_{03}))$$

$$\square_7 = (3\mu_{21}-\mu_{02})(\mu_{30}+\mu_{12})((\mu_{30}+\mu_{12})^2 - 3(\mu_{21}+\mu_{03})^2) - (\mu_{30} - 3\mu_{12})(\mu_{12} + \mu_{21})(3(\mu_{30}+\mu_{12})^2 - (\mu_{21}+\mu_{03})^2)$$

These seven invariant moments $\square_\mathrm{I}\, 1 \le \mathrm{I} \le 7$, set out by Hu, were additionally shown to be independent of rotation. However they are computed over the shape boundary and its interior region.

2.3 FEATURE SELECTION

2.3.1 Feature Selection Using DEFS

Feature selection is essentially a task to remove irrelevant and/or redundant features. A motivation for feature selection is to overcome the curse of dimensionality. The proposed DEFS highly reduces the computational cost while at the same time proves to present a powerful performance. DEFS was introduced to solve problems with real values. After preprocessing stage data it is passed to DEFS method. It prepares a subset with the best parameters. In DE, the parameters of the search space are encoded in the form of strings called chromosomes. A collection of such strings is called a population denoted by *P*. It is a collection of NP number of *d*-dimensional parameter vectors xi,G= [$x1,i,G$, $x2,i,G$, . . . , xD,i,G] , i = 1,2, . . . ,NP for each generation G. The value of D represents the number of real parameters on which optimization or fitness function depends. The value of NP does not change during the minimization process. The initial vector population is chosen randomly which represents different points in the search space and should cover the entire parameter space. An objective or a fitness function is associated with each string that represents the degree of goodness of the string.

Differential evolution generates new parameter vectors by adding the weighted difference between two population vectors to a third vector. This operation is called mutation. The mutated vector's parameters are then mixed with the parameters of another predetermined vector, the target vector, to yield the so-called trial vector. Parameter mixing is often referred to as "crossover". If the trial vector yields a lower cost function value than the target vector, the trial vector replaces the target vector in the following generation. This last operation is called selection. The process of selection, crossover and mutation continues for a fixed number of generations or till a termination condition is satisfied.

2.4 CLASSIFICATION

2.4.1 Support Vector Machine

A support vector machine constructs a hyper plane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. Whereas the original problem may be stated in a finite dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mappings used by SVM schemes are designed to ensure that dot products may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function K(x,y) selected to suit the problem. The hyperplanes in the higher-dimensional space are defined as the set of points whose inner product with a vector in that space is constant. The vectors defining the hyperplanes can be chosen to be linear combinations with parameters $\alpha_i$of images of feature vectors that occur in the data base. With this choice of a hyperplane, the points xin the feature space that are mapped into the hyperplane are defined by the relation:

$$\sum_i \alpha_i K(x_i, x) = \text{constant}$$

Note that if $K(x,y)$becomes small as $y$grows farther away from x, each element in the sum measures the degree of closeness of the test point x to the corresponding data base point x_i. In this way, the sum of kernels above can be used to measure the relative nearness of each test point to the data points originating in one or the other of the sets to be discriminated. Note the fact that the set of points$x$ mapped into any hyperplane can be quite convoluted as a result, allowing much more complex discrimination between sets which are not convex at all in the original space. This classifier is sensitive to noisy data, prone to over fitting and thus bad generalization. Choice of kernel function and the parameters have to be set manually and can greatly impact the results.

The steps in SVM classsifiaction are,

(i).data setup: our dataset contains three classes, each N samples. The data is 2D plot original data for visual inspection**(ii).**SVM with linear kernel (-t 0). We want to find the best parameter value C using 2-fold cross validation (meaning use 1/2 data to train, the other 1/2 to test). **(iii).**After finding the best parameter value for C, we train the entire data again using this parameter value**(iv).**plot support vectors**(v).**plot decision area

2.4.2 Relevant Image Search by KNN within A Category

Place items in the class to which they are "closest". Must determine distance between an item and a class. Sorting the distances of number of close images within a particular class and the nearest neighbor indexes are computed.

III. SIMULATION RESULTS

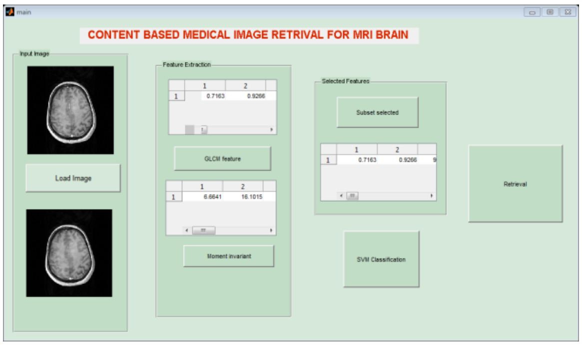

Fig.3.1 feature extraction and selection of query image.

The above image gives the features extraced from the
query image which is in the database. This is the first step of our process. The query image is given first and the features are extracted for the furthur process.Feature selection technique is then used to select a subset of features from the extarcted features.

Fig 3.2Result after classification

The classifier takes the features of the image and projects the category of the image by giving it to the classifier. This work is done by the SVM classifier.

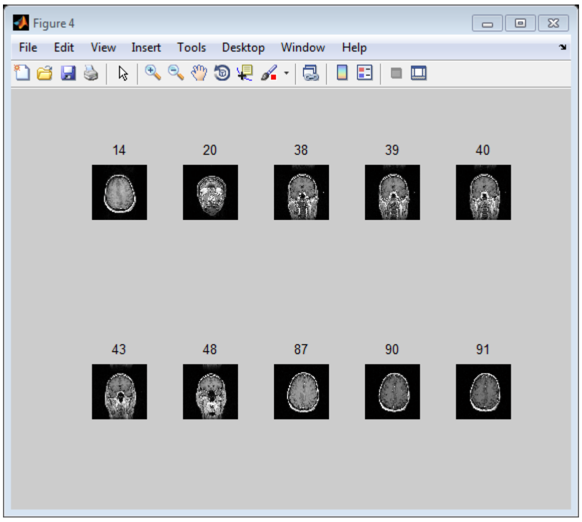

Fig3.3Retrieved images

The images are retrieved based on the features matching the query image. Thus the retrieved images are 90% accurate by using the K-NN search. After getting the relevant image ids from KNN search the corresponding database index will be computed by similarity feature matching. With the help of that database index values the relevant images are retrieved and displayed.

IV. CONCLUSION

Here we have presented a novel content based image retrieval algorithm. We have demonstrated that by using SVM (Support Vector machine) classifier followed by KNN (K-nearest neighbor) for CBIR using texture and shape feature. This is considerably better than the traditional image retrieval. Because of its poor efficiency due to the consideration of various modalities and inability to handle the challenging task in CBIR such as handling multi image queries, these are rectified by using SVM classifier followed by KNN. Here we yield a good performance by considering single modality (MRI) and multiple image query instead of single image.

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