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Classification Using K Nearest Neighbor for Brain Image Retrieval

P.A.Charde, S.D.Lokhande

Abstract— We propose the algorithm for the retrieval of the most visually similar images to a given query image from a database of medical images by content. In this algorithm we take shape feature extraction by canny Edge detection and texture feature extraction by using Gabor filter. Gabor filter is best feature extraction method for texture. And on the basis of these feature, medical images are classified using KNN method. The retrieval performance of the proposed system is tested using large medical image database of about 500 computed tomography images of brain. The retrieval performance and retrieval complexity are measured and evaluated.

Index Terms—Canny Edge Detection, Gabor Filter, K Nearest neighbour classifier, Medical images, Precision, Recall, Accuracy.

1 Introduction

Image Retrieval has been active research area over the last 25 years, but first review articles on access methods in Image database appeared in the early 80s. This section gives an Introduction to CBIR systems [1, 2, 3] and the features used in these systems. The basic idea behind content-based image retrieval is that, when building an image database, or retrieving an image from the database, we first extract features from images, the features can be color, shape, texture etc. These features are stored in the database for future use. When given a query image, we similarly extract its features, and match these vectors with those already in the database, if the distance between two feature vectors is small enough then we consider the corresponding image in the database match the query. Retrieval results are ranked according to similarity index and group of similar target images are presented to users.

In most of the image retrieval systems, a query is specified by an image to be matched. We refer to this as an overall search, as similarity is based on the overall properties of images. By contrast, there are also partial search querying systems that retrieve based on a particular region in an image.

Content based medical image retrieval system has been found useful in medical applications and the medical domain, as one of the principal application domains for content based technologies.

Shape is the fundamental visual features in content based image retrieval .Edge information can be used to feed-in various applications seeking the shapes, size, or edge locations of particular objects. In all edge detection algorithms, the main objective is to locate the edge (intensity transitions) from the scene neither with prior information nor with human interpretation.

Some popular algorithms include Sobel, Roberts, Prewitt, Laplace, LOG, and Canny Algorithm [9]. These edge detection operators share almost the same concept which is to find the singularities and locate them accurately.

P.A.Charde is currently pursuing masters degree program in Electronics Engineering (Digital System) in University of Pune, India,
E-mail: prachiti.charde@gmail.com.
S.D.Lokhande is currently working as a Principal in Sinhgad College of Engineering in University of Pune, India.E-mail: sdlokhande.scoee@sinhgad.edu

The gradient intensity changes rapidly in the edge and the maximal intensity change along a particular orientation produces a peak or a zero-crossing. Hence, the first derivative and the second derivative of the gradient of every pixel in an image are used to find edges in the image.

Canny method has proven to be superior over many of the available edge detection algorithms and thus was chosen mostly for real time implementation and testing. Canny edge detection algorithm was introduced in 1986. It is considered as the modern "standard" in the sense that the validity of all other algorithms is often checked against it.

Texture is the key component of human visual perception. Everyone can recognize texture, but it is more difficult to define. Texture is an important but difficult to describe feature in an image. Many techniques have been developed for measuring texture similarity. Most technique compares second order statistics of query and stored images. These method calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity [7, 8]. Alternative methods of texture analysis for image retrieval include the use of Gabor filters [5] have shown the image retrieval using Gabor features outperforms that using pyramid-structured wavelet transform features, tree structured wavelet transform features and multi-resolution simultaneous autoregressive model features.

This paper describes the medical image retrieval system using shape feature extraction by canny edge detection and texture feature extraction by Gabor Filter. These features are used for training and classification using K nearest neighbor classifier. Algorithm performance has been measured by the Precision and Recall measures.

2 Proposed Method

The proposed method has training and classification phases. In training phase, from a given set of training images the shape and texture features are extracted and used to train the

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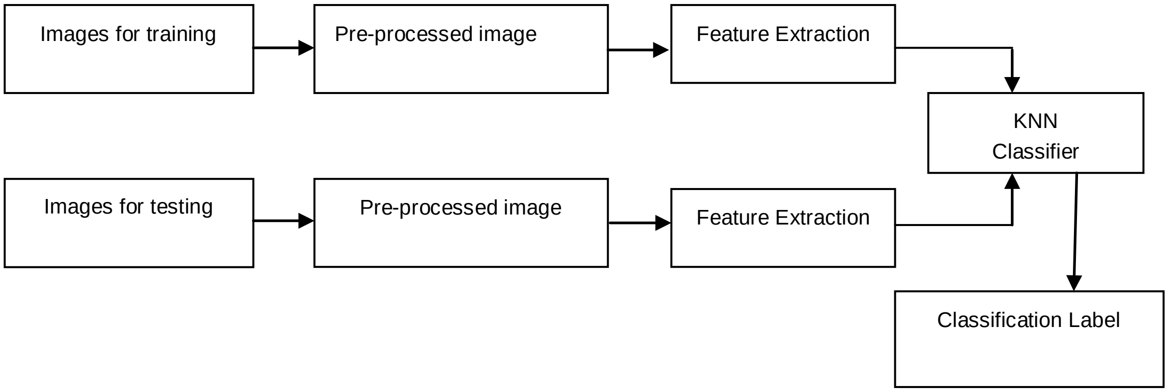

Fig 1: A Block diagram of the proposed method using KNN

system using the K-nearest neighbor classifier. In classification phase a given test ct of brain image pre-processed and then texture features are extracted for classification. These features are queried to K-nearest neighbor classifier to label an unknown image. The block diagram of the proposed method is given in Figure 1.

2.1 Pre-processing

Pre-processing includes conversion of Input image into gray scale image and noise removal. In this work median filter used for de-noising.

In median filtering, the neighbouring pixels are ranked according to brightness (intensity) and the median value ones the new value becomes the new value for the central pixel. A median filter offers three advantages

1. No reduction in contrast across steps since output values available consists only those presents in the neighborhood.
2. Median filtering does not shift boundaries.
3. The median is, in a sense a more robust average that the mean, as it is not affected by outliers.

2.2 Feature Extraction

The purpose of feature extraction is to reduce the original data set by measuring certain properties of features that distinguish on input pattern from another.These extracted features used for preparation of Training data. These features are saved into feature library.

2.2.1 Shape Feature

Algorithm: For detecting edges using Canny Edge Detection Algorithm

Step 1: Smoothing: Smooth the image with a two dimensional Gaussian. In most cases the computation of a two dimensional Gaussian is costly, so it is approximated by two one dimensional Gaussians.

Step 2: Finding Gradients: Take the gradient of the image this shows changes in intensity, which indicates the presence of edges. This actually gives two results, the gradient in the x direction and the gradient in the y direction.

Step 3: Non-maximal suppression: Edges will occur at points where the gradient is at a maximum. The magnitude and direction of the gradient is computed at each pixel.

Step 4: Edge Threshold: The method of threshold used by the Canny Edge Detector is referred to as "hysteresis". It makes use of both a high threshold and a low threshold.

Step 5: Thinning: Using interpolation to find the pixels where the norms of gradient are local maximum.

The following Fig 2 depicts the results after applying Canny Edge Detection Algorithm.

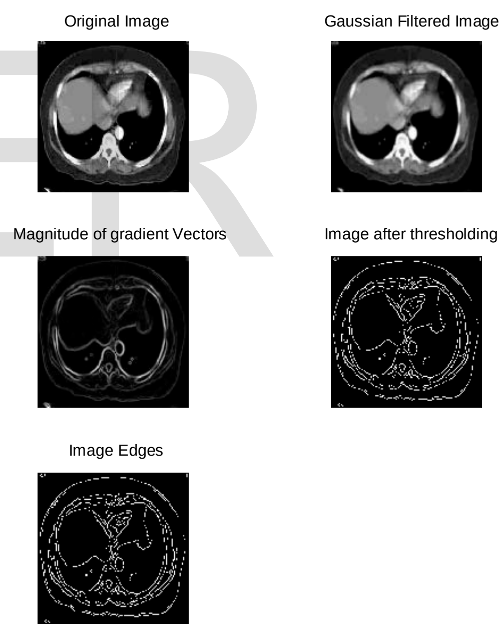

Fig. 2: A Result after applying Canny Edge Detection

2.2.2 Texture Feature

Gabor filter [5] is one of the most popular signal processing based approach for texture extraction. Basically, Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and specific direction. It acts as a local band pass filter with certain optimal joint localization properties in both the spatial domain and the frequency domain. An image is filtered with a set of Gabor filters with different preferred orientations and spatial frequencies and the features, which are obtained from a feature vector, is used further. Texture features are found by calculating the mean and variation of the Gabor filtered image.

For a given image I(x, y) with size PxQ, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x,y)=\sum_{x}\sum_{y} I(x-s,y-t)\psi^{*}_{mn}(s,t) \quad (1)$$

where s and t are filter mask size variables and * *mn* Ψis the complex conjugate of Ψmn which is a class of self-similar functions generated from dilation and rotation of the following mother wavelet:

$$\psi(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma^2}+\frac{y^2}{\sigma^2}\right)\right].\exp(j2\pi Wx) \quad (2)$$

Where W is the modulation frequency. The self similar Gabor wavelets are obtained through the generating function.

$$\tilde{x}=a^{-m}(x\cos\theta+y\sin\theta) \quad (3)$$

$$\tilde{y}=a^{-m}(-x\sin\theta+y\cos\theta) \quad (4)$$

where a>1 andθ = nΠ/N. The variables in the above equation are defined as follows:

$$a=(U_h/U_l)^{\frac{1}{M-1}} \quad (5)$$

$$W_{mn}=a^{m}U_l \quad (6)$$

$$\sigma_{xmn}=\frac{(a+1)\sqrt{2\ln 2}}{2\pi a^{m}(a-1)U_l} \quad (7)$$

$$\sigma_{ymn}=\frac{1}{2\pi\tan\left(\frac{\pi}{2N}\right)\sqrt{\frac{U_h{}^2}{2\ln 2}-\left(\frac{1}{2\pi\sigma_{xmn}}\right)^2}} \quad (8)$$

In our implementation, we used the following constants:
Ul = 0.05, Uh = 0.4, s and t range from 0 to 60. After applying Gabor filters on the image with different orientation and at different scale, we obtain an array of magnitudes:

$$E(m.n)=\sum_{x}\sum_{y}\left|G_{mn}(x,y)\right| \quad (9)$$

$$m=0,1.....,M-1; n=0,1.....,N-1$$

These magnitudes represent the energy content at different scale and orientation of the image. Texture feature are found by calculating the mean μ_{mn} and standard deviation σ_{mn} of the energy magnitude.

$$\mu_{mn}=\frac{E(m,n)}{P\times Q} \quad (10)$$

$$\sigma_{mn}=\frac{\sqrt{\sum_{x}\sum_{y}\left(\left|G_{mn}(x,y)\right|-\mu_{mn}\right)^2}}{P\times Q} \quad (11)$$

A feature vector f which represents the texture is created using μ_{mn} and σ_{mn} as the feature components. In our implementation we have used 4 scales and 6 orientations and the feature vector is given by f = (μ00, σ00, μ01, σ01… μ35, σ35). An example of a filter bank generated is shown in the figure 3.

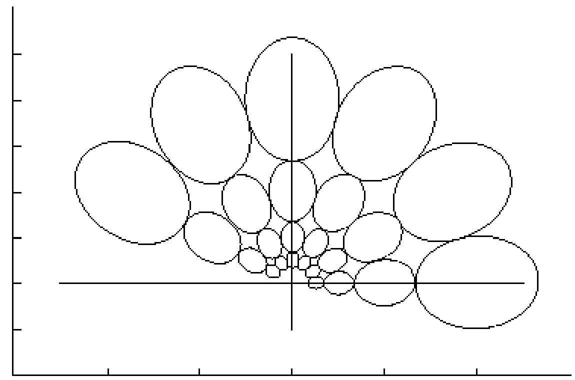

Fig.3: Filter Response of A Gabor Filter Bank with 4 Scale and 6 Orientation

2.3 Classification

K-Nearest Neighbour classification technique [4] is the simplest technique conceptually and computationally that provides good classification accuracy. The K-NN algorithm is based on a distance function and a voting function in k-Nearest Neighbours, the metric employed is the Euclidean distance. The K-NN has higher accuracy and stability for MRI data than other common statistical classifiers, but has a slow running time. Yet, the issues of poor run time performance is not such a problem these days with the computational power that is available [6]

The k-nearest neighbour classifier is a conventional non-parametric supervised classifier that is said to yield good performance for optimal values of k. Like most guided learning algorithms, K-NN algorithm consists of a training phase and a testing phase. In the training phase, data points are given in a n-dimensional space. These training data points have labels associated with them that designate their class.

K-NN algorithm comprises of following stages:

1. Determine a suitable distance metric.
2. In the training phase: Stores all the training data set P in pairs (according to the selected features) P = (y_i; c_i), i = 1. Where, y_i is a training pattern in the training data set, c_i is its corresponding class and n is the amount of training patterns.
3. During the test phase: Computes the Distances between the new feature vector and all the stored features (training data).
4. The k nearest neighbours are chosen and asked to vote for the class of the new example. The correct classification given in the test phase is used to assess the correctness of the algorithm. If this is not satisfactory, the k value can be tuned until a reasonable level of correctness is achieved.

3 Experimental Result

This section depicts the retrieval effectiveness of the proposed

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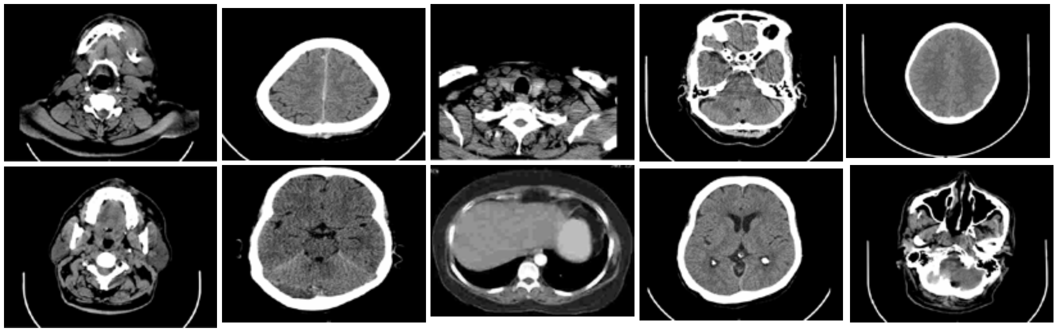

Fig. 4: Representative image of each class

system. The medical image retrieval system was implemented using MATLAB version 7.13.0.564 with Pentium–IV processor on Windows platform. Retrieval performance in terms of Precision and Recall of proposed system was tested by conducting experiments on database consists of 500 medical images of CT scan of brain. These images are finely defined into 10 categories as shown in figure 4.Most images are grey level images converted from the DICOM format into BMP. Ten images from the database collection representing various anatomical regions were chosen as the query images for evaluation of the system. Precision (P) is used to represent the retrieval accuracy which is the percentage of similar images retrieved with respect to the number of retrieved images and Recall(R) is the percentage of relevant images among all possible relevant images. Precision and Recall is defined as:

$$P = \frac{number\ of\ relevant\ images\ retrieved}{total\ number\ of\ images\ retrieved} \quad (12)$$

$$R = \frac{number\ of\ relevant\ images\ retrieved}{total\ number\ of\ relevant\ image\ in\ database} \quad (13)$$

By the above equation we can conclude that precision and Recall measures the retrieval accuracy. It is calculated as the average of 10 queries. Table 1 shows Retrieval Performance of Canny Edge Detection, Gabor Filter and Combining both Method obtained by varying the values of n1. Fig 5(a), 5(b), 6(a) and6 (b) gives the screen shot of the retrieval of a sample query image using Combined Method and Gabor Filter. Fig.7 shows Average Precision and Recall graph of Canny Edge, GF and combining both method.

Classification rate is defined as the percentage of images classified to i. Table 1 shows theretrieval performance using average precision and recall values for 10 randomly selected queries. Table 2 shows that a comparision of classification using KNN for different value of k. Table 3 shows that images of each class in testing set are almost classified to its true class or its four most adjacent classes. The average of classification rate of the KNN classifier is 52.30%.

We apply this classifier to automatically classify images in our brain image database.. In the process of retrieval, the images in database, whose class label are in the scope of [*i*-3, *i*+3], are selected to compare with the query image which is supposed to have been classified into *i*-th class. Applying this

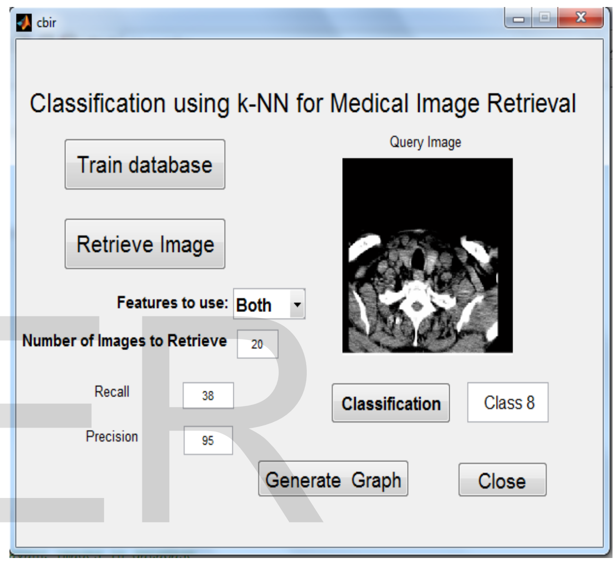

Fig. 5(a): GUI of proposed system using Combined Feature

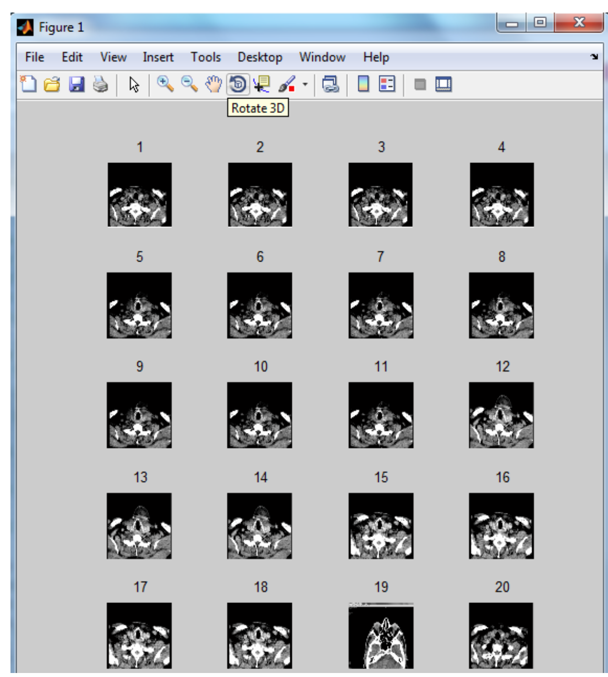

Fig.5 (b): Retrieved images for the query image using combined feature in fig. 5(a) classifier in our system can prevent retrieving images which are not similar to the query image on anatomical structure and content from the database.

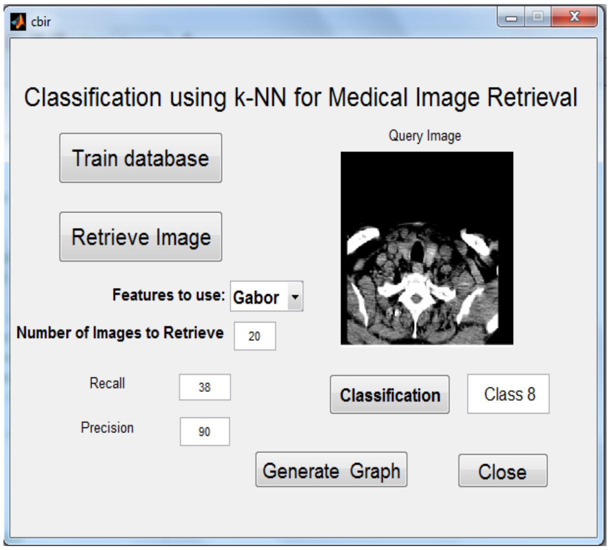

Fig. 6(a): GUI of proposed system using Gabor Feature

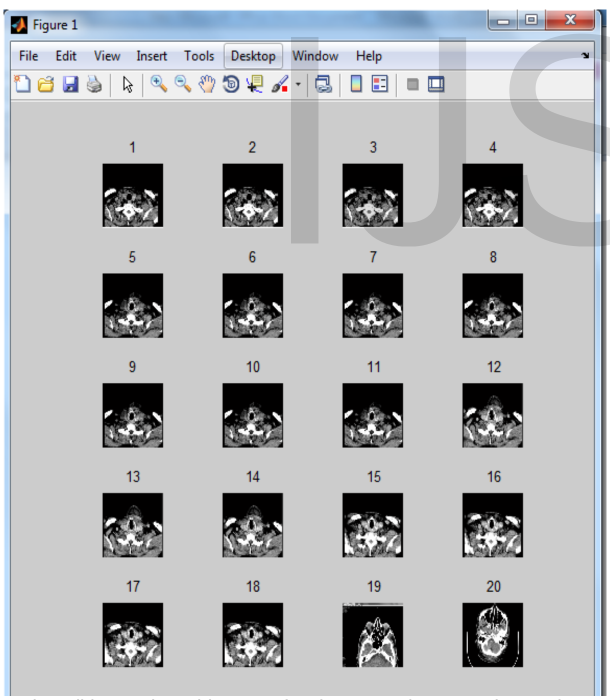

Fig.6 (b): Retrieved images for the query image using Gabor Feature in fig. 5(a)

Table1. Retrieval Performance of Canny Edge Detection, Gabor Filter and Combining both Method

Total number of re-trieved images	GF		CED		Combined Method	
	Average Precision	Average Recall	Average Precision	Average Recall	Average Precision	Average Recall
5	100	10.74	96	10.34	100	10.75
10	97	20.88	76	16.64	97	20.88
15	93.33	30.18	57.33	18.68	93.33	30.19
20	88.5	30.28	45.5	19.70	89	38.49
25	80.8	43.97	40	21.52	81.6	44.37
30	72	47.43	36.33	23.34	72	47.44
35	63.14	48.23	32.85	24.57	63.14	48.44
40	56.25	49.83	30.5	25.97	56.75	49.65
45	50.67	49.86	29.33	27.97	51.56	50.70
50	46.4	50.69	28	29.57	46.4	50.70

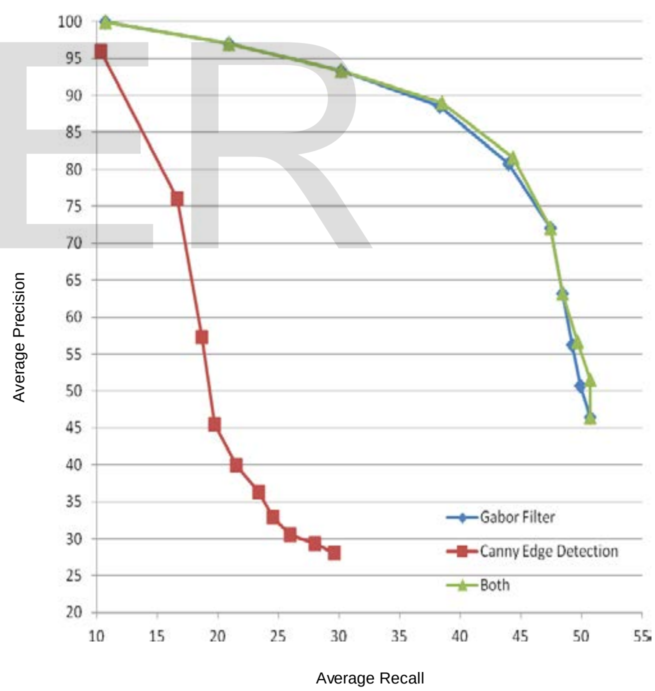

Fig.7: Average Precision and Recall graph of Canny Edge, GF and combining both method

Table 2: A comparision of Classification Using KNN for different values of k

	KNN		
	k=11	k=13	k=15
Average of Classification Rate (%)	96.363	95.38	93.33

Table 3: Detailed Result of Classification Using KNN

Predicted Class / True	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Total	Classification Accuracy (%)
Class 1	12		12		13		5			8	50	24
Class 2		23		11		14	1				49	46.94
Class 3			35	3		8				4	50	70
Class 4		16		25		6	3				50	50
Class 5			12		31					7	50	62
Class 6			26			15	7				48	31.25
Class 7			7				20			23	50	40
Class 8			4			11	4	30	1		50	60
Class 9		3		25			2		19		49	38.78
Class 10										30	30	100
Average (%)												**52.30**

CONCLUSION

In this paper, we proposed a method of medical image retrieval and classification based on Shape feature by Gabor feature and use this feature to do the image retrieval and classification. Results of experimentation show that the texture features mentioned in this paper can fully describe the content of image, and improve the recall and precision rate and classification accuracy on medical image retrieval. In the system implementation process, the features of images are stored in the image database uniformly. When users submit queries, the system retrieves all the images in database, and then returns the result

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