Medical Image Retrieval System for Diagnosis of Brain Tumor Based on Classification and Content Similarity

Megha. P. Arakeri, G. Ram Mohana Reddy
Department of Information Technology
National Institute of Technology Karnataka (NITK), Surathkal, Mangalore, India-575025.
Email: meghalakshman@gmail.com, profgmreddy@gmail.com

***Abstract*—Accurate diagnosis is important for successful treatment of brain tumor. Content based medical image retrieval (CBMIR) can assist the radiologist in diagnosis of brain tumor by retrieving similar images from medical image database. Magnetic resonance imaging (MRI) is the most commonly used modality for imaging brain tumors. During image acquisition there can be misalignment of magnetic resonance (MR) image slices due to movement of patient and also the low level features extracted from MR image may not correspond with the high level semantics of brain tumor. These problems create a semantic gap and limit the application of automated image analysis tools on MR images. In order to address these problems, this paper proposes a two-level hierarchical CBMIR system which first classifies the query image of brain tumor as benign or malign and then searches for the most similar images within the identified class. Separate set of rotation invariant shape and texture features are used to discriminate between brain tumors at each level. Experiments have been conducted on medical image database consisting of 820 brain MR images. The proposed approach gives promising retrieval results by improving precision, recall and retrieval time.**

I. Introduction

Images of various patients obtained for diagnosis are maintained by the hospitals in the medical image database known as Picture Archiving and Communication System (PACS) [1]. Medical image retrieval is a very demanding application since it is expected to provide the physician a decision support for diagnosis by retrieving relevant cases. Today, most of the PACS in hospitals adopt text based retrieval of images which uses patient id, name or disease type. But, text based retrieval is laborious and subjective [2]. Whereas given a query image, CBMIR retrieves images from the database by extracting visual contents of the image like color, shape and texture. Hence in the recent years, the research is towards how to effectively integrate CBMIR into PACS to improve diagnosis decision of the radiologist.

MRI in particular has emerged as an effective imaging modality most frequently used to evaluate brain tumors [3]. Brain tumor can be cured without much risk if it is diagnosed in early stages. When the physician is doubtful about his diagnosis of brain tumor, he can query the CBMIR system to retrieve similar cases from the medical database [4]. This helps him to perform diagnosis in a faster and non invasive way. Discrimination between benign (non-cancerous) and malign (cancerous) is required for optimal patient management.

There have been quite a number of papers in the recent years addressing the content based image retrieval (CBIR) in medical applications. CBMIR system first segments the region of interest on the query image to extract its visual features [5]. Color has got limited expressive power in MR image retrieval as these images are in gray scale. The most vital features in medical images are shape and texture. Traina et al. [6] presents a content based system where shape information of the brain regions are extracted to retrieve similar images from the database. The system was not able to retrieve similar images in all the cases as it is based on global features which consider information of entire image. In medical radiology, the clinically useful information consists of variations in the highly localized region of the image. Tsang et al. [7] used both local and global texture descriptors for tissue identification on computed tomography (CT) images and also experimented with several similarity measures such as Euclidian distance, Minkowski distance and Jeffrey divergence. He achieved highest precision of 91.57% with local features and Jeffrey divergence similarity measure. The method suggests improvements as it is based on imperfect segmentation where tissues were delineated by radiologists. Yun et al. [8] presented brain image database building approach using registration, rotation and scale normalization for effective CBIR.

Region based shape descriptors such as region moments are sensitive to noise and shape variations. Wan Ahmad et al. [9] showed that the most robust contour based shape descriptor is Fourier descriptor (FD). It obtains the shape information of the region by applying Fourier transform on region contour points. Compared to the existing rotation invariant texture descriptors like contourlet transform [10], Gabor wavelet [11] and co-occurrence matrix [12], local binary pattern (LBP) [13] is the most simple and effective texture descriptor. But, LBP fails in presence of noise and flat areas. Li-xin et al. [14] filled the semantic gap between visual data and richness of human semantics by incorporating relevance feedback into CBIR system. But, the relevance feedback consumes lot of time to fine tune system parameters. Hence, in order to overcome the limitations of the existing systems, this paper proposes effective and efficient CBMIR system based on classification and content similarity. The proposed system reduces retrieval

978-1-4673-2272-0/12/$31.00 ©2012 IEEE

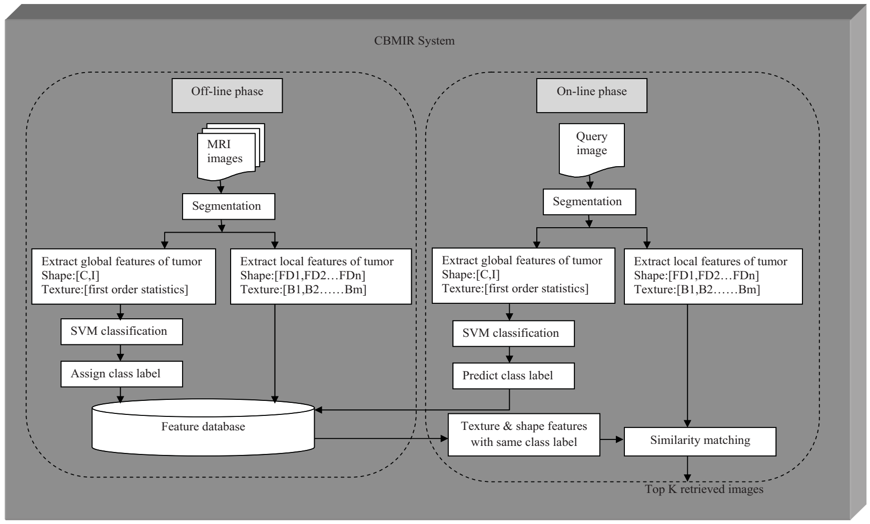

Fig. 1. Block diagram of the proposed CBMIR system

time as well as retrieves most relevant images from the database.

The paper is organized as follows. Details of the proposed system are given in Section II. Section III presents the experimental results and performance evaluation of the proposed retrieval system. Finally, in section IV some concluding remarks are given.

II. Proposed Methodology

The block diagram of the proposed CBMIR system is shown in Fig. 1. It consists of two phases: database building (off-line) phase and query processing (on-line) phase.

In the off-line phase, MR images are automatically segmented using our previously proposed modified fuzzy c-means clustering technique [15] to extract brain tumor from MR image. Tumors can be well discriminated by their shape and texture characteristics. Hence rotation invariant global shape features such as circularity (C) and irregularity (I) and texture features based on first order statistics are extracted from the tumor region on MR image in the first level of CBMIR. These features are fed to the trained support vector machine (SVM) classifier to assign label to the image sample as benign or malign. In the next level, local shape features such as wavelet based fourier descriptors (FD1, FD2,...FDn) and texture features such as local binary patterns (B1, B2,...Bm) are extracted from the brain tumor for discrimination between tumors within the class. The class label along with local features are stored in the feature database.

Similarly, in the online phase, the class label of the query image is identified using SVM classifier based on rotation invariant global shape and texture features of tumor. Using this label, the similarity comparison is restricted to images with similar class labels in the database. This derives reduced search space from the feature database. Then, the local shape and texture features of the query image are compared with the reduced feature database using Euclidian and Chi-square distance respectively to retrieve K most similar images from the database.

A. Global Feature Extraction

The following features are extracted from the brain tumor region to assign class label to the tumor as benign or malign.

1) Shape Features: Benign tumors are more circular whereas malign are more irregular in shape. Circularity and irregularity of tumor are measured as:

$$Circularity(C) = \frac{4\pi A}{P^2}. \tag{1}$$

Where, P and A are tumor perimeter and area respectively.

$$Irregularity(I) = \frac{1}{N}\sum_{i=1}^{360} d_i, \tag{2}$$

$$d_i = \sqrt{(X_i - X_c)^2 + (Y_i - Y_c)^2}. \tag{3}$$

Where, (X_i, Y_i) are boundary points and (X_c, Y_c) is the region centroid. These features are rotation invariant.

2) Texture Features: Tissues exhibit consistent and homogeneous texture. Therefore in this work, texture features of the tumor are represented using first order statistics such as average gray level, standard deviation, entropy, coefficient of variation, skewness and kurtosis obtained from the histogram of the brain tumor image [16].

B. Local Feature Extraction

The following features are extracted from the tumor region to find the similarity within the identified class of the query image.

1) Wavelet Based Fourier Descriptors: Fourier descriptors describe the local shape of brain tumor. FDs are spectral descriptors derived from fourier transform of shape signature. In this work, wavelet based fourier descriptor (WFD) are used as local shape features because they are more effective compared to other variants of fourier descriptors [17]. The algorithm for computing WFD is as follows:

Step-1: Extract the boundary points of the brain tumor using canny edge detector [18].

$$B(n) = \{(x(n), y(n)), n = 0, 1, .., L-1\} \tag{4}$$

Step-2: Obtain the shape signature of the boundary using centroid distance.

$$S(n) = [(x(n)-x_c)^2 + (y(n)-y_c)^2]^{\frac{1}{2}} \tag{5}$$

$$x_c = \frac{1}{L}\sum_{n=0}^{L-1} x(n), y_c = \frac{1}{L}\sum_{n=0}^{L-1} y(n) \tag{6}$$

Step-3: Normalize shape signature by sampling K boundary points using equal arc length (P/K).

$$n = n + \frac{P}{K} \tag{7}$$

$$U(t) = S(n), t = 0, 1, ..K-1 \tag{8}$$

Where, P is boundary perimeter.

Step-4:Apply wavelet transform on U(t) using following equation.

$$C_a(b) = \frac{1}{\sqrt{|a|}}\int_R U(t)\varphi(\frac{t-b}{a})dt \tag{9}$$

Where, $C_a(b)$ are wavelet coefficient at scale a and position b.

Step-5: Apply discrete fourier transform (DFT) on wavelet coefficients.

$$a_n = \frac{1}{N}\sum_{b=0}^{N-1} C_a(b) exp(-j2\pi b/N) \tag{10}$$

The Fourier coefficients, a_n are called FD of the shape denoted as $[FD_1, FD_2, ..FD_{N-1}]$. These are made rotation invariant by ignoring phase information. The area (A) of the tumor is also calculated to find match within tumors of similar size.

2) Local Binary Patterns: LBP is a gray scale invariant operator that characterizes the local texture of the image [19]. Hence it is considered as a suitable operator in texture analysis of MR images. It labels each pixel with a binary code by thresholding relative gray values of its circularly symmetric neighbors which is given as:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p, s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{11}$$

Where, g_c and g_p 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 $R = 1$. The rotation invariant LBP is given as:

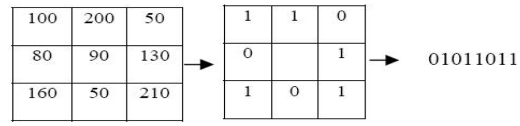

Fig. 2. LBP code computation.

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c), U(LBP_{P,R}) \leq 2 \\ P+1, \text{otherwise} \end{cases} \tag{12}$$

Where,

$$U(LBP_{P,R}) = |s(g_p - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \tag{13}$$

According to (12), if the number of bit transitions in LBP is at most 2 then it is considered as uniform else as non uniform code. After the LBP codification of the image, a histogram with P+2 bins is built to represent image texture. In the histogram, P+1 bins contain uniform patterns and all non uniform patterns are put in one single bin.

The drawback of $LBP_{P,R}^{riu2}$ is, it is unsuitable for analyzing flat areas on image where all gray values of neighbor pixels are nearly same and also it cannot describe the image texture completely as all non uniform patterns are put in one bin. In this work, the flat area problem is solved by modifying (12) as:

$$LBP_{P,R}^{riu2mod} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c + \alpha), U(LBP_{P,R}) \leq 2 \\ P+1, \text{otherwise} \end{cases} \tag{14}$$

Where, α is a small constant which changes the difference in pixel values without affecting the result. In this work, α was given a value of 2 keeping the discriminative ability of LBP unaffected. This change makes the LBP operator work effectively even in flat areas of image. To effectively describe the image texture, non uniform patterns are assigned to the bins of uniform patterns based on the similarity measure [20] which is given as:

$$D_{ROR}^{min}(LBP_{P,R}) = min\{D_{ROR}(LBP_{P,R}, LBP_{P,R}^{uniform}), all LBP_{P,R}^{uniform}\} \tag{15}$$

Where,

$$D_{ROR}(X,Y) = min\{\phi(ROR(X,i),Y), i = 0..P-1\} \tag{16}$$

$$\phi(P,Q) = \sum_{i=0}^{P-1} |P_i - Q_i| \tag{17}$$

$ROR(X,i)$ is a circular bitwise right shift i times the P-bit number X.

C. Classification

The extracted global shape and texture features of the tumor are fed to the SVM classifier for predicting the class of tumor on MR image. SVM is based on statistical learning theory and structural risk minimization principle. It is an unsupervised

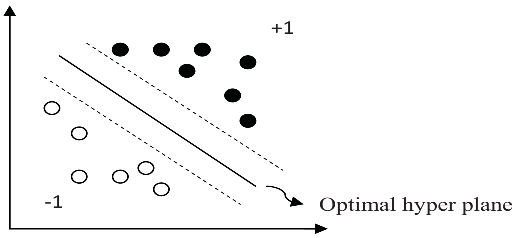

Fig. 3. SVM classification.

binary classifier which separates the given data by finding an optimal hyperplane as shown in Fig. 3. If the training data set is (x_i, y_i), i=1, 2, .., N and $y_i \in$ -1, +1, the optimal hyper plane function for non linear classification is given as:

$$f(x) = sign(\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b) \tag{18}$$

where α is the Lagrange multiplier, b is bias and $K(x, x_i)$ is the kernel function. In this work, radial basis function is chosen as the kernel function which is represented as:

$$K(x, y) = exp\left(\frac{\|x - y\|^2}{2\sigma^2}\right) \tag{19}$$

D. Similarity Matching

The shape similarity between the query image (x) and images stored in the database (y) is computed using Euclidian distance:

$$DS(x, y) = \sqrt{(A^x - A^y)^2 + (\sum_{i=0}^{N-1} (FD_i^{(x)} - FD_i^{(y)})^2)} \tag{20}$$

Where, A and FD represent area and Fourier descriptors of the tumor respectively.

The LBP occurrence histogram of the query image is compared with texture features stored in the database using Chi-square distance [21].

$$DT(x, y) = \chi^2(x, y) = \sum_{k=1}^{K} \frac{[B_x(k) - B_y(k)]^2}{[B_x(k) + B_y(k)]} \tag{21}$$

Where, $B_x(k)$ and $B_y(k)$ are k^{th} LBP histogram bin of image x and y respectively. The similarity measures are normalized and fused to form a single similarity measure as given by:

$$D(x, y) = DS(x, y) + DT(x, y) \tag{22}$$

In order to retrieve K most relevant images from the database, the calculated distances are sorted in ascending order and corresponding images are retrieved.

III. Experimental Results

The proposed method is implemented using MATLAB. All the experiments were performed on a personal computer with 3GHz Pentium processor and 3GB of memory running under Windows XP operating system. The experimental results were evaluated with the help of the experienced radiologist.

A. Data set

The image database was built with 820 MR images of brain tumor (benign:420, malign:400). The images for the experiments were collected from Kidwai Memorial Institute of Oncology, Bangalore, Shirdi Sai Cancer Hospital, Manipal and also from Harward Medical School [22]. All images were of size 640×480.

B. Retrieval Results

In order to test the robustness of the proposed CBMIR system with respect to rotation, some of the original images were rotated by $10^o, 15^o, 20^o$ and 25^o in clock wise and anti clockwise directions using bicubic interpolation. Table I shows the average similarity scores between the original images and the rotated images when they are represented with rotation invariant shape and texture features discussed in section II. Rotations change the texture and shape patterns of tumors. But as shown in Table I, the rotation invariant shape and texture features extracted in this work help in capturing the similar pathology even in rotated images.

TABLE I
Average similarity scores between the original and rotated MR images.

Rotation angle	Similarity score
-10^o	0.00
-15^o	0.00
-20^o	0.01
-25^o	0.00
10^o	0.00
15^o	0.00
20^o	0.01
25^o	0.01

The graphical user interface (GUI) for the CBIR system along with retrieval results for a given query image is shown in Fig. 4.

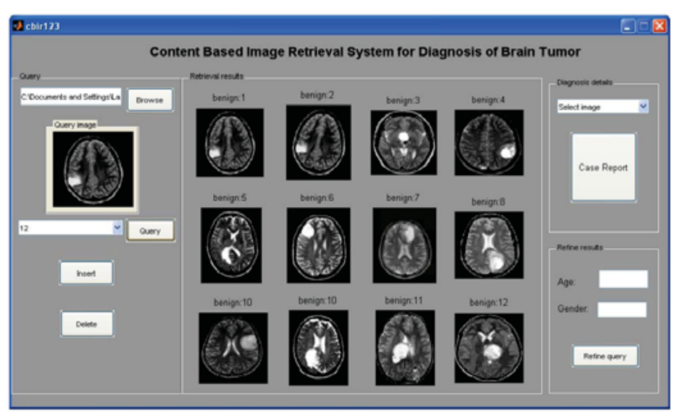

Fig. 4. GUI for content based image retrieval of brain tumor.

It can be seen that the system retrieves benign tumor images in response to query image which is also benign. With the help of GUI, user can select a query image and the number of images to be retrieved from the database. The retrieved images are ranked by degree of similarity to the query feature vector. The top 12 most similar images are retrieved and displayed along with the patient data in response to query image. Also the retrieval results can be refined for detailed analysis based on the age and gender of the patient. The physician can then study the characteristics of the retrieved tumors and also refer diagnosis report to know the tumor type, severity and prescribed treatment of the corresponding cases. All these parameters assist the radiologist in making case based reasoning in the diagnosis of brain tumor.

C. Performance Analysis

The performance of the proposed system is evaluated by measuring retrieval accuracy and efficiency. For the brain tumor classification, SVM classifier was trained and tested by feeding global shape and texture features of 576 and 244 tumors respectively. The classification performance was measured with confusion matrix, sensitivity, specificity and accuracy as given below:

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \tag{23}$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{24}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{25}$$

TABLE II
CONFUSION MATRIX OF CLASSIFICATION

Tumor Type	Malign	Benign
Malign	TP(132)	FN(2)
Benign	FP(3)	TN(107)

Where, TP (true positive), FN (false negative), TN (true negative) and FP (false positive) measure classification rate of benign and malign tumors. The SVM classification results in classification accuracy of 97.95% (sensitivity:98.50%, specificity:97.27%).

$LBP_{P,R}^{riu2mod}$operator was tested with different values of (P,R). The computing speeds of (8,1),(16,2),(24,3) are 0.0824sec, 1.53241sec, 3.7563sec respectively. The larger the value of (P,R), the larger the computation time of feature extraction. But their retrieval accuracy are 94%, 97% and 91% respectively. Therefore we choose (P,R)=(16,2) as it is acceptable to have more powerful texture descriptor with a slight increase of the computational cost. The comparison of modified rotation invariant operator $LBP_{P,R}^{riu2mod}$ with the other LBP operators such as $LBP_{P,R}^{riu2}$, $LBP_{P,R}^{ri}$ [19] is shown in Table III. It can be observed that the proposed operator performs better compared to other operators. The CBMIR system's retrieval effectiveness is measured with precision and recall metrics as follows:

$$Precision = \frac{\text{No.of relevant images retrieved}}{\text{No.of images retrieved}} \times 100 \tag{26}$$

TABLE III
COMPARISON OF LBP OPERATORS

Operator	No.of Bins	Retrieval time	Retrieval precision
$LBP_{P,R}^{ri}$	65536	167 sec	91%
$LBP_{P,R}^{riu2}$	18	100 sec	93%
$LBP_{P,R}^{riu2mod}$	17	92 sec	97%

$$Recall = \frac{\text{No.of relevant images retrieved}}{\text{No.of relevant images in the database}} \times 100 \tag{27}$$

Fig. 5 shows the comparison of shape based retrieval, texture based retrieval and proposed method in terms of precision and recall graph. It is seen that proposed method achieves

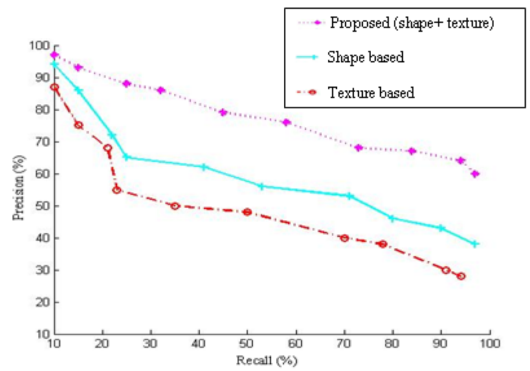

Fig. 5. Performance comparison of different features.

highest retrieval precision of 97% and recall of 95.78% as a combination of more robust shape and texture features are employed in the proposed system. Also, the proposed system has good retrieval speed of 192.250sec. If the exhaustive search is performed without classification, then the system requires 338.506sec to retrieve relevant images. Hence, the proposed system can retrieve most similar pathology bearing images in response to query image in less amount of time and hence provides faster diagnosis of brain tumor to the radiologist.

The performance of the proposed CBMIR method was compared with the following existing methods as shown in Fig. 6:

- E1: Retrieval using multiple features (Emmanuel et al. [23]).
- E2: Retrieval based on classification (Dube et al. [24]).
- E3: Retrieval based on machine learning and clustering (Rahman et al. [25]).

Emmanuel et al. [23] extracted multiple features to characterize the tumor completely. But large number of features leads to 'curse of dimensionality' problem. Dube et al. [24] retrieved brain tumors based on classification. They achieved accuracy of only 87% as the system could not match the images of sub classes. In order to enhance similarity learning, Rahman et al. [25] combined classification with clustering. But the same feature set was used both for classification and for retrieval after classification. Thus the system could not achieve higher performance in retrieving most similar images. Our proposed method for CBMIR fills the semantic gap by learning the similarity hierarchically with different set of features to represent tumor at each level. Thus, it achieves good precision and recall rates as compared to other CBMIR methods.

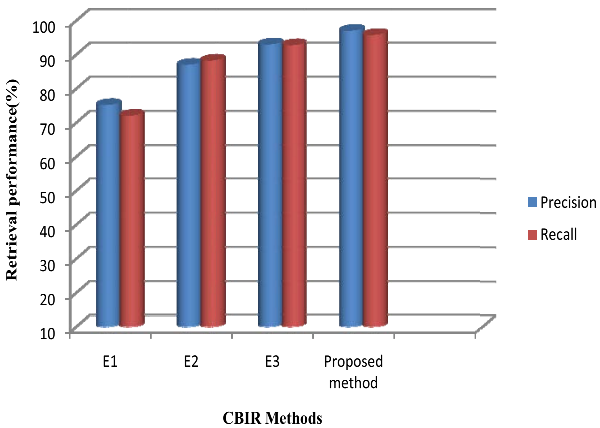

Fig. 6. Performance comparison of CBMIR systems.

IV. Conclusion

In this paper, we proposed a novel approach to medical image retrieval by integrating classification and content similarity. The separate set of rotation invariant texture and shape features used in this system diminish the semantic gap and database search time. Hence, the proposed CBMIR system is able to retrieve similar pathology bearing brain tumor MR images in less amount of time in response to query image. The proposed system can be used as a diagnostic aid to assist the radiologist by case based reasoning in situations when he is not confident about his diagnostic decision.

References

[1] H. Muller, N. Michoux, D. Bandon, and A. Geissbuhler, A review of content-based image retrieval systems in medical applications-clinical benefits and future directions, *International Journal of Medical Informatics*, vol. 73, pp. 1–23, 2004.

[2] P. Agarwal, H. K. Sardana, and G. Jindal, Content based medical image retrieval:Theory,gaps and future directions, *International Journal on Graphics, Vision and Image Processing* , vol. 9, no. 2, pp.27–37, 2009.

[3] D. A. Sanghvi, Recent advances in imaging of brain tumors, *Indian Journal of Cancer*, vol. 46, no. 2, pp. 82–87, 2009.

[4] G. Quellec, M. Lambard, G. Cazuguel, C. Roux, and B. Cochener, Case retrieval in medical databases by fusing heterogeneous information, *IEEE Transactions on Medical Imaging*, vol. 30, no. 1, pp. 108–118, 2011.

[5] Y. Shao-zhen and Y. Xian-dong, Medical image retrieval based on extraction of region of interest, *International Conference on Bioinformatics and Biomedical Engineering*, IEEE, pp. 1–4, 2010.

[6] A. J. M. Traina, A. G. R. Balan, L. M. Bortolotti and C. Jr. Traina , Content based image retrieval using approximate shape of objects, *IEEE symposium on computer Based Medical Systems*, pp. 91–96, 2004.

[7] W. Tsang and A. Corboy, K. Lee, D. Raicu, and J. Furst, Texture-based image retrieval for computerized tomography databases, *IEEE Symposium on Computer-Based Medical systems*, pp.1–5, 2005.

[8] K. Yun, Z. Tian, J. Zou, Y. Bai, and Q. You, Brain CT image database building for computer aided diagnosis using content based image retrieval, *Information Processing and Management*, vol. 47, no. 2, pp. 176–185, 2011.

[9] W. S. H. M. Wan Ahmad, and M. F. A. Fauzi, Comparision of different feature extraction techniques in content based image retrieval for CT brain images, *IEEE Workshop on multimedia Signal Processing*,pp. 503–508, 2008.

[10] J. Han and K. K. Ma, Rotation-invariant and scale-invariant gabor features for texture image retrieval, *Image and Vision computing*, vol. 25,pp. 1474–1481, 2007.

[11] K. S. Arun and H. P. Menon, Content based medical image retrieval by combining roation invariant contourlet features and fourier descriptors, *International Journal of Recent Trends in Engineering*, vol. 2, no. 2, pp. 35–39, 2009.

[12] B. G. Prasad and A. N. Krishna, Statistical texture feature-based retrieval and performance evaluation of CT brain images, *International Conference on electronics Computer Technology*, IEEE, pp. 289–293, 2011.

[13] L. Nanni, A. Lumini, and S. Brahnam, Local binary patterns variants as texture descriptors for medical image analysis, *Artificial intelligence in Medicine*, vol. 49, pp. 117–125, 2010.

[14] S. Li-xin, C. Rui-feng, and W. Qian, Image retrieval of calcification clusters in mammogram using feature fusion and relevance feedback, *International Forum on Strategic Technology*, IEEE, pp.15–18, 2010.

[15] M. P. Arakeri and G. R. M. Reddy, Efficient fuzzy clustering based approach to brain tumor segmentation on MR images, *Computational Intelligence and Information Technology, CCIS, Springer*, vol. 250, pp. 790-795, 2011.

[16] U. Akilandeswari, R. Nithya, and B. Santhi, Review on Feature Extraction Methods in Pattern Classification, *European Journal of Scientific Research*, vol. 71, no. 2, pp. 265-272, 2012.

[17] R. B. Yadav, N. K. Nishchal, A. K. Gupta, and V. K. Rastogi, Retrieval and classification of shape based objects using fourier, generic fourier and wavelet-fourier descriptor technique: A comparative study, *Optics and Lasers in Engineering*, vol. 45, no. 6, pp. 695-708, 2007.

[18] S. S. Kumar and R. Amutha, Edge detection of angiogram images using the classical image processing techniques, *IEEE International Conference On Advances In Engineering, Science And Management*, pp.55–60, 2012.

[19] T. Ojala, M. Pietikainen, and T. Maenpaa, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971-987, 2002.

[20] H. Zhou, R. Wang and C. Wang, A novel extended local binary pattern operator for texture analysis, *Information Sciences*, vol. 178, pp. 4314-4325, 2008.

[21] B. Jun, T. Kim and D. Kim, A compact local binary pattern using maximization of mutual information for face analysis, *Pattern recognition*, vol. 44, no. 3, pp. 532–543, 2011.

[22] The whole brain atlas, [Available]: http://www.med.harvard.edu/annlib/.

[23] M. Emmanuel, D. R. Ramesh Babu, G. P. Potdar, B. A. Sonkamble, and P. Game, Content based medical image retrieval, *International Conference on Information and Communication Technology in Electrical Sciences*, IEEE, pp. 712-717, 2007.

[24] S. Dube, S. El-Saden, T. F. Cloughesy, and U. Sinha, Content based image retrieval for MR image studies of brain tumors, *IEEE International conference on Engineering in Medicine and Biology*, pp. 3337–3340, 2006.

[25] Md. M. Rahman, P. Bhattacharya, and B. C. Desai, A framework for medical image retrieval using machine learning and statistical similarity matching techniques with relevance feedback, *IEEE Transaction on Information Technology in Biomedicine*, vol. 11, no. 1, pp. 58–69, 2007.