

A Survey on Content Based Image Retrieval Using Different Techniques

A. Anbarasa Pandian¹, Dr.R.Balasubramanian²,

Research Scholar, Department of Computer Science & Engineering Manonmaniam Sundaranar University, Tirunelveli, India¹

Professor, Department of Computer Science & Engineering Manonmaniam Sundaranar University, Tirunelveli, India²

Abstract—Content-based image retrieval (CBIR) is the problem of searching for digital image features such as color, texture and shape in large databases. Literature survey is the most important application of computer vision techniques to the image retrieval for gaining much more information about specific areas of a subject. In this paper a survey on content based image retrieval using various techniques is presented. In order to improve the retrieval accuracy of content based image retrieval systems focus on reducing the semantic gap between the visual features and richness of human semantics. Recent research area publications are covered in the survey of various different aspects of the research areas. The Techniques, image dataset, advantages and disadvantages of the several approaches in content based image retrieval are discussed. Finally, some other related issues and retrieval performance metrics are also discussed.

Index Terms— Content based image retrieval (CBIR), Texture, Color, Shape, retrieval accuracy .

I. INTRODUCTION

In the advance development of the Internet, and recent technologies of the availability of image capturing devices such as digital cameras, image scanners, the size of the digital image collection are increasing rapidly. Efficient image searching, browsing and retrieval from various application areas, including medical fields, building, fashion, crime prevention, publishing, medicine, remote sensing and architecture, etc. There are two types of schema : text-based and content-based.. There are two disadvantages with this approach. The first approach is the manual annotation for the level of human labour is required. The second approach is the inaccuracy of annotation because the subjectivity of human perception [1,2]

II. IMAGE RETRIEVAL SYSTEM

In 1990s, Content based image retrieval is a very interesting and active research area. The commercial and research has been built in many image retrieval systems. Figure 1 shows the block diagram of an image retrieval systems. The image retrieval system has supported one or more of the following options [13]

Search by example
Search by sketch
Random browsing
Search by text (including key word or speech) navigation with image categories.

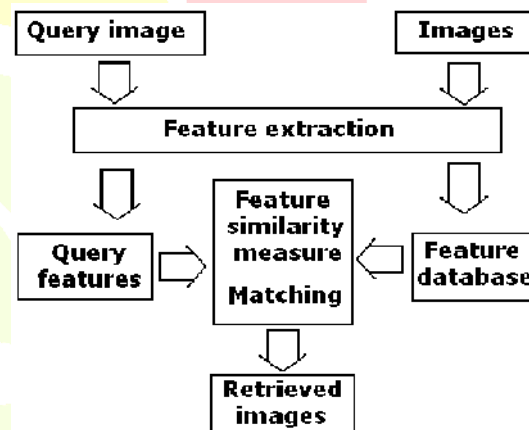


Fig.1 Image retrieval process

III. FEATURE EXTRACTION

The feature extraction is used in content based image retrieval like texture, color and shape.

A. Texture

Texture is a visual pattern with properties of homogeneity that do not result from the presence of only single color or intensity. Textures are represented by texels which are then placed into a number of sets. Motivated by the psychological studies in human visual perception of texture, Tamura have representation of image texture from a different angle. There are six visual image texture properties were *coarseness*, *contrast*, *directionality*, *linelikeness*, *regularity*, and *roughness*. The texture representation and the co-occurrence matrix representation is that all the texture properties in Tamura representation [3, 4, 5, 6].

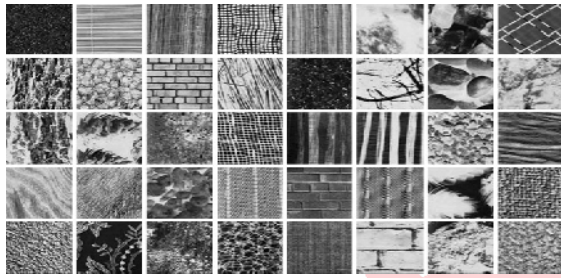


Fig.2 Texture feature extraction of Brodatz dataset

B. Color

The most important feature of an image content is a color. The image scaling, translation and rotation are widely used in the image retrieval. There are some of the color feature techniques are color moment, color histogram and histogram of gradients. It is independent of image size, orientation and relatively robust to background complication. Color perception and color spaces can be found and studied [7, 8, 9, 10].



Fig.3 Color feature extraction of corel dataset

C. Shape

There are two types of shape representation are regionally based and boundary based representation. Shape can be represented as the outer boundary of the shape and the entire shape region [11]. The shape of an image that can be a particular region that is being sought out. The Shape filter technique is used to identify the shapes of an image. There are some of the shape feature technique are Scale invariant fourier transform, Zernike moments and harris interest point. The Shape of an object can be represented by the outline or contour [12].

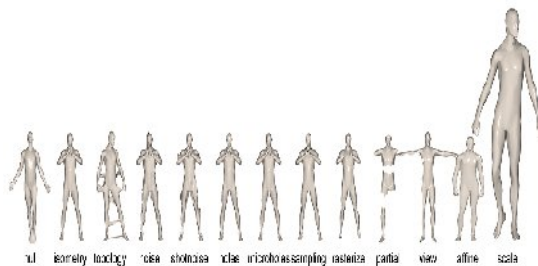


Fig.4 Shape feature extraction of SHREC '10 dataset

APPLICATIONS

- Art galleries
- Museums
- Archaeology
- Textile industry
- Medical imaging
- Criminal investigations
- Military
- Retail catalogs
- Face finding
- Remote sensing systems

IV. LITERATURE SURVEY

Xianwang et al, [14] have developed a novel framework for low level feature and high level feature. To tackle the issues in leveraging low-level features (eg. Color) and high-level features (attributes) of clothing. To improve search quality by using re-ranking approach exploiting clothing attributes, including the type of clothing, sleeves, patterns, etc. The attributes have better robustness to clothing variations, and carry semantic meanings as high-level image representations.

Theo et al, [15] has been proposed from color invariant edges which shape invariant features are computed. Color and shape invariant method are combined into a unified high-dimensional invariant feature set for the discriminatory object search.

Lingyang et al, [16] are retrieving the near duplicate images with large area of duplicates region, since the spatial structure of the near duplicate images could be described by the COP consistency.

Gaurav et al, [17] a reasonably accurate and fast color segmentation technique that leverages the strengths of region-based and edge-based segmentation. Also, a new parametric relevance feedback algorithm is explicitly utilizes information about non relevant examples.

Guo-Dong et al, [18] a content based image retrieval for the constrained similarity measure. The constrained similarity measure takes consideration for the perceptual similarity between images and improves the retrieval performance.

Issam El-Naqa et al, [19] a learning machine-based framework for modelling human perceptual similarity for content-based image retrieval. They are evaluated for retrieval of clinical mammograms containing clustered microcalcifications.

Hao et al, [20] have shown that Online Multiple Kernel Similarity (OMKS) significantly surpasses the state-of-the-art linear and nonlinear metric learning techniques for image similarity search.

Qianni et al, [21] a strategy for multifeature-based retrieval of history images database. The multifeature fusion model is a suitable model for feature combination based on multiple query images that are associated with the keyword in concern.

Hatice et al, [22] a weighting scheme inspired by IR theory, retrieval performance of the CBIR system is better than the traditional image-level retrieval. Its retrieval accuracy for all seven subtypes. There are two challenging diseases are interreading and intrareading semantic variations. Both intraslide semantic variations, and intersubtype are visual similarities.

Dimitris et al, [23] a scheme involves block-based low level feature are extracted from images to form higher level clustering of the feature space. An expectation-maximization algorithm is clustering of the feature space that uses an iterative approach to automatically determine the number of clusters.

Md Mahmudur et al, [24] the probabilistic outputs of a multiclass support vector machine (SVM) classifier. SVM classifier is used for prediction of the query and database images are exploited. The image category information is utilized directly to filter out irrelevant images and adjust the feature weights in a linear combination of similarity matching.

Hayit et al, [25] the medical image retrieval for GMM-KL framework as a localized statistical framework. The similarity image matching measure for GMM-KL framework combines a continuous and probabilistic and region-based image representation scheme.

Jorma et al, [26] the self-organizing CBIR system named PicSOM and shown that MPEG-7-defined content descriptors can be successfully used. To implement relevance feedback, the PicSOM system is based on using SOMs from the user of the system.

Zhong et al, [27] a novel method for the feature subspace extraction. The progressive learning capability is the new feedback approach. This approach is based on a Bayesian classifier and treats positive and negative feedback examples with different strategies. They have proposed a new relevance feedback approach by integrating a feature subspace extraction process into a Bayesian feedback process in content-based image retrieval.

Lining et al, [28] a geometric optimum experimental design (GOED) a novel active learning method to select multiple representative samples in the database. The main problem in GOED can be small-sized training data. The Kernel Hilbert space has the geometric structure of unlabeled samples and to enhance the retrieval performance.

Erchan et al, [29] a multiscale texture descriptors, namely, the circular covariance histogram and the rotation-invariant

point triplets. The proposed approach is the best retrieval performance.

Igor et al, [30] to represent the information contained in the original images for geometrical constraints of the trace transform that can be optimized. The dimensionality reduction in terms of the mean and kurtosis value pairs of frequency coefficients has demonstrated. The results have a very robust set of features in terms of precision

Mina et al, [31] a medical decision support system. The medical decision making system has been designed with normal and finding two certain abnormalities. The techniques used to find images with tumor and image of multiple sclerosis are the gray level co-occurrence matrices (GLCM). The supervised learning method like principal component analysis (PCA), and support vector machine (SVM) which help in classifying the normal images, and abnormal images.

Yang et al, [32] have a generalized brain state in a box (gBSB) based hybrid neural network. Using Hybrid neural network can store and retrieve large-scale patterns combining the pattern decomposition concept and pattern sequence storage and retrieval.

Esther et al, [33] to retrieve brain image using soft computing technique. The shape features are extracted using 2-D Zernike moment. The soft computing technique of Extreme Learning Machine is used with different distance metric measures like Euclidean, Quasi Euclidean, City Block, Hamming distance. The Fuzzy Expectation Maximization Algorithm is used to remove the non-brain portion of the MRI Brain image.

Rajalakshmi et al, [34] a relevance feedback method using a diverse density algorithm is used to improve the performance of content-based medical image Retrieval. The texture features are extracted based on Haralick features, Zernike moments, histogram intensity features and run-length features. The hybrid approach of branch and bound algorithm and artificial bee colony algorithm using brain tumor images.

Ahmed et al, [35] the efficacy of different types of features such as texture, shape and intensity for segmentation of Posterior-Fossa tumor. The four different techniques like PCA, boosting, KLD and entropy metrics demonstrate the efficacy of 249 real MRI of ten pediatric patients.

Murala et al, [36] a new image retrieval algorithm for local mesh pattern using biomedical image retrieval. The significant improvement for retrieval performance LBP with gabor transform and domain methods.

Manjunath, et al, [37] an image retrieval method using gabor texture feature. To measure the similarity of image. The retrieval performance of the texture is useful for region based retrieval.

Table. 1 Different technique, dataset, advantage and disadvantage

S.No	Title	Author	Year	Dataset	No of Images	Method	Advantage	Disadvantage
1	Remote Sensing Image Retrieval with Global Morphological Texture Descriptors	Erchan Aptoula	May 2014	Land cover	2100 images	Mathematical Morphological	Execution time is lower	Description of irrelevant content
2	Trace Transform Based Method for color image domain identification	Igor et al,	April 2014	Corel , Geoeeye	1000 images, 1003 images	DITEC	Efficient, Robust, Accuracy	Recall and F-score measure have not been compared
3	Geometric Optimum experimental Design for Collaborative Image Retrieval	Lining et al,	February 2014	Small Scale Image	3139 images	GOED & CiR	Effective, to Achieve better performance	To difficult in small sized training data
4	Personal Clothing retrieval on Photo Collections by color attributes	Xianwang et al,	December 2013	Clothing database, Consumer photos	12823 images, 26324 images	Bags of visual words	It Improves retrieval efficiency and Robust	It has a Scalability Issue
5	Robust Spatial Consistency Graph Model for Partial Duplicate Image retrieval	Lingyang et al,	December 2013	Web Images	1 Million images	COP- Combined Orientation Position	Efficient, Robust, Effective and Increases speed	It is a Poor PR performance in over domination
6	Relevance feedback in CBIR Bayesian framework, feature subspaces and progressive learning	Zhong et al,	August 2013	Corel database	10000 images	PCA- principal component analysis	It is speed, reduces the memory and improve the retrieval accuracy	One positive example for each iteration
7	Histology Image retrieval in optimized Multifeature space image	Quianni et al,	January 2013	Histology database	20,000 images	Multiobjective learning method	More precise results, fusion model for each keyword	Direct linear multifeature retrieval did not bring significant improvement
8	Online Multiple Kernel Similarity Learning for visual search	Hao et al,	January 2012	Indoor database	15620 images	OMKS- Multiple Similarity Online Kernel	It is more flexible and efficient	Learning similarity function for ranked image
9	A learning based similarity fusion & filtering approach for biomedical image retrieval using SVM classification & relevance feedback	Md Mahmudur et al,	July 2011	Biomedical images	5000 images	Similarity fusion approach	It is Efficient and effective	Linear search time without filtering is twice
10	CBIR system for human brain magnetic resonance image indexing	Mina et al,	October 2010	Human brain dataset	120 images	GLCM, PCA, SVM	It is easy to operate, non invasive, & inexpensive It is accurate & robust	There is an increase in image database, it requires fresh trainage each time

11	PicToSeek: combining color and shape invariant features for image retrieval	Theo et al,	January 2010	World scenes	500 images	Color & Shape invariant	It is high accuracy & robust	It is poor discriminative power
12	A pattern similarity scheme for medical image retrieval	Dimitris et al,	July 2009	Radiographs	10000 images	PANDA- PATterns for Next generation Database systems framework	Its Efficient & Effective	Yet not capable of coping with large image retrieval task
13	Content-Based Image Retrieval Using Multiresolution Color and Texture Features	Chun et al,	October 2008	Corel ,VisTex, MPEG-7 Common color dataset (CCD), Corel_MR, VisTex_MR and MPEG-7 CCD_MR	990 RGB, 1200 RGB and 5420 color images	Color- Color autocorrelogram, Texture- BDIP and BVLC	It gives higher retrieval accuracy than conventional methods	The retrieval rank is much higher in color autocorrelogram
14	Medical image categorization & retrieval for PACS using GMM-KL framework	Hayit et al,	March 2007	Radiological	1501 images	GMM-KL- gaussian mixture modelling- Kullback Leibler	It is Efficient retrieval performance	A dominant characteristic of image is poor contrast
15	Generalized Manifold Ranking Based Image Retrieval	Jingrui et al,	October 2006	Corel database	5000 images	GMRBIR method	It gives higher precision	Feature selection is a large problem
16	Texture Image Retrieval Using New Rotated Complex Wavelet Filters	Kokare et al,	December 2005	D1-Brodatz Texture database and D2- MIT VisTex database	D1- 1856 images D2- 640 images	Dual-tree rotated complex wavelet filter (DT-RCWF) and dual-tree complex wavelet transform (DT-CWT) method	Retrieval accuracy is more and less computational complexity	To obtain rotation, translation, and scale invariance
17	A Similarity learning approach to CBIR: Application of Mammography	Issam El-Naqa, et al,	October 2004	Medical image	76 images	SVM regression, GRNN regression	It is faster speed & retrieval accuracy	Reduction in computation time high in two network
18	Relevance Feedback Based Image Retrieval Interface Incorporating Region and Feature Saliency Patterns as Visualizable Image Similarity Criteria	Stejic et al,	October 2003	Vistex-60, VisTex-167, Brodatz-208, Corel-1000-A and Corel-1000-B database	2500 images	RFSP- Region and Feature Saliency Pattern method	It improves retrieval performance	Relevance Feedback Based Image Retrieval Interface Incorporating Region and Feature Saliency Patterns as Visualizable Image Similarity Criteria
19	Learning Similarity measure for natural image retrieval with relevance feedback	Guo-Dong et al,	July 2002	Natural image	10,009 images	Constrained similarity measure	It is used for usefulness & effectiveness	The boundary is complex

20	An image retrieval system with automatic query modification	Gaurav et al,	June 2002	Corel database	2200 images	iPURE- Perceptual and User friendly Retrieval	It is very accurate & fast color segmentation	iPURE system does not give good at relevant example
----	---	---------------	-----------	----------------	-------------	---	---	---

V. PERFORMANCE EVALUATION

$$\text{Error rate} = 100 - \text{Accuracy} \tag{4}$$

To measure the performance based on time for finding the correct images in content based image retrieval system is performed [37].

F. F-score

F-score is a measure of a test's accuracy [38].

A. Time

Time is always important to do a process in the minimum amount of time.

$$F\text{-Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{5}$$

B. Precision

Precision is defined as the number of relevant retrieved images to the total number of retrieved images. It is expressed as percentage [38].

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images in retrieved}} \tag{1}$$

C. Recall

Recall is used to measure the number of relevant images retrieved to the number of relevant images in the database for the considered query, measures the ability of a model to retrieve all relevant images. It is expressed as percentage [38].

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in database}} \tag{2}$$

D. Accuracy

Accuracy is the measurement system, which measure the degree of closeness of measurement between the original value and the extracted value [38].

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \tag{3}$$

Where, TP – True Positive (equivalent with hit)

FN – False Negative

TN – True Negative

E. Error Rate

Error rate is used to compare an estimate value to an exact value [38].

VI. CONCLUSION

In past years, content-based image retrieval (CBIR) has been focused on research in image processing, low-level feature extraction, etc. CBIR systems should provide the semantic gap between low level feature and semantic retrieval. The method, advantages and disadvantages of the several approaches in content based image retrieval are discussed. Some other related issues and retrieval performance metrics are also discussed. In future, Humans aim to use the higher level feature in everyday life. The low level feature image is automatically extracted from the current computer vision techniques. In a general setting, the low-level features do not have a direct link to the high-level concepts. Some off-line and on-line processing need for semantic gap. The supervised learning, unsupervised learning, or the combination of the two is achieved in off-line processing. Neural network, genetic algorithms, fuzzy logic and clustering are such learning tools needed [39, 40, 41, 42].

REFERENCES

- [1] Eakins J., M.Graham, "Content-based image retrieval, Technical Report", University of Northumbria at Newcastle, 1999.
- [2] Sethi. I.K, LL.Coman, "Mining Association rules between low level image feature and high level concepts", proceeding of the SPIE Data Mining and Knowledge Discovery, vol. III, 2001, pp. 279-290.
- [3] Anbarasa Pandian .A, B.Gayathri Devi, R.Balasubramainian, "Performance Analysis On Texture Based Image Retrieval Using LBP, LTP, LDP and LTRP" Proceedings of National conference on Recent Trends in Advanced Computing, September 2013
- [4] Baicy .C, R.Balasubramainian, A.Anbarasa Pandian "Performance Analysis On Texture Based Image Retrieval Using Perceptual Model and MOGG", International Journal of Engineering Research & Technology (IJERT), volume. 3, issue. 03, March 2014.
- [5] Shapiro, Linda, George Stockman, "Computer Vision" Upper Saddle River, NJ: Prentice Hall, 2001.
- [6] Tamura .H, S. Mori, and T. Yamawaki, Texture features corresponding to visual perception, *IEEE Trans. On Sys., Man. and Cyb.* SMC-8(6), 1978.
- [7] Vittorio Castelli, Lawrence D. Bergman, "Image Databases: Search and Retrieval of Digital Imagery", 2004.
- [8] McCamy .C.S., H. Marcus, and J. G. Davidson, A color-rendition chart, *Journal of Applied Photographic Engineering* 2(3), 1976.
- [9] Miyahara .M, Mathematical transform of (r,g,b) color data to munsell (h,s,v) color data, *SPIE Visual Commun. Image Process.* 1001, 1988.

- [10] Wang J, W.-J. Yang, and R. Acharya, Color clustering techniques for color-content based image retrieval from image databases, in *Proc. IEEE Conf. on Multimedia Computing and Systems, 1997*.
- [11] Rui Y, A. C. She, and T. S. Huang, Modified fourier descriptors for shape representation a practical approach, in *Proc. of First International Workshop on Image Databases and Multi Media Search, 1996*.
- [12] Yong Rui, Thomas S. Huang, Shih-fu Chang, "Image Retrieval: Current Techniques, Promising Directions And Open Issues", *Journal of Visual Communication and Image Representation, 1999*.
- [13] Chang .S.F, A. Eleftheriadis, and R. McClintock, Next-generation content representation, creation and searching for new media applications in education, *IEEE Proceedings, 1998*.
- [14] Xianwang .W, Z.Tong, R.T.Daniel and L. Qian, "Personal Clothing Retrieval on Photo Collections by Color and Attributes", *IEEE Transactions on multimedia, vol.15, No.8, December 2013*.
- [15] Theo .G, W.M.S.Arnold, "PicToSeek: Combinig color and shape invariant features for image retrieval", *IEEE Transactions on image processing, vol.9, no.1, January 2000*.
- [16] Lingyang .C, J.Shuqiang, W.Shuhui, Z.Yanyan and H.Qingming, "Robust Spatial Consistency Graph Model for Partial Duplicate Image Retrieval", *IEEE Transactions on multimedia, vol. 15, no.8, December 2013*.
- [17] Gaurav .A, T.V.Ashwin, G.Sugata, "An Image retrieval system with automatic query modification", *IEEE Transactions on multimedia, vol. 4, no.2, June 2002*.
- [18] Guo-Dong .G, K.J.Anil, M.Wei-Ying and Z.Hong-Jiang, "Learning Similarity Measure for natural image retrieval with relevance feedback" *IEEE Transactions on neural networks vol.13, no.4, July 2002*.
- [19] Issam El-Naqa .E, Y.Youngyi Yang, P.G.Nikolas, M.N.Robert and N.W.Miles, "A Similarity Learning approach to content based image retrieval: Application to digital mammography" *IEEE transactions on Medical imaging, vol.23, no.10, October 2004*.
- [20] Hao .X, C.H.H.Steven, J. Rong.Z. Peilin, "Online Multiple Kernel Similarity Learning for Visual Search" *IEEE Transactions on pattern analysis and machine intelligence, vol.1, no.1, January 2012*.
- [21] Qianni .Z and I.Ebroul, "Histology image retrieval in optimized multifeature spaces" *IEEE journal of biomedical and health informatics, vol.17, no.1, January 2013*.
- [22] Hatice .C.K. and N.G. Metin, "Content-Based Microscopic Image Retrieval System for Multi-Image Queries" *IEEE Transactions on information technology in biomedicine, vol.16, no.4, July 2012*.
- [23] Dimitris .K.I, P.Nikos Pelekis, E.K. Evangelos, K.Ioannis, K.Haralampos and T.Yannis, "A Pattern Similarity Scheme for Medical Image Retrieval" *IEEE Transactions on information technology in biomedicine, vol.13, no.4, July 2009*.
- [24] Md Mahmudur .R, K.A.Sameer, and R.T.George, "A Learning-Based Similarity Fusion and Filtering Approach for Biomedical Image Retrieval Using SVM Classification and Relevance Feedback", *IEEE Transactions on information technology in biomedicine, vol.15, no.4, July 2011*.
- [25] Hayit .G and T.P.Adi, "Medical Image Categorization and Retrieval for PACS Using the GMM-KL Framework", *IEEE Transactions on information technology in biomedicine, vol.11, no.2, March 2007*.
- [26] Jorma .L, K.Markus, O.Erkki, "PisSOM – Self organizing image retrieval with MPEG-7 content descriptor", *IEEE Transaction in neural networks vol.13, no.4, July 2002*.
- [27] Zhong .S, Z.Hongjiang, L.Stan, and M.Shaoping, "Relevance feedback in content based image retrieval: Basesian Framework, features Subspaces and progressive learning", *IEEE Transactions on image processing, vol.12, no.8, August 2008*.
- [28] Lining .Z, W.Lipo, L.Weisi and Y.Shuicheng, "Geometric Optimum Experimental Design for Collaborative Image Retrieval", *IEEE Transactions on circuits and systems for video technology", vol.24, no.24, February 2014*.
- [29] Erchan .A, "Remote Sensing Image Retrieval With Global Morphological Texture Descriptors", *IEEE Transactions on geosciences and remote sensing, vol.52, no.5, May 2014*.
- [30] Igor .G.O, Q. Marco, F.Julián and S.Basilio, "Trace Transform Based Method for Color Image Domain Identification", *IEEE Transactions on multimedia, vol.16, no.3, April 2014*.
- [31] Mina .R.N and F.Emad, "A CBIR system for human brain magnetic resonance image indexing", *International journal of computer applications(0975-8887) vol. 7, no.14, October 2010*.
- [32] Yang, Liu, Rong Jin, Lily Mummert, Rahul Sukthankar, Adam Goode, Bin Zheng, Steven CH Hoi, and Mahadev Satyanarayanan. "A boosting framework for visuality preserving distance metric learning and its application to medical image retrieval." *Pattern Analysis and Machine Intelligence, IEEE Transactions on 32, no. 1: 30-44, January 2010*.
- [33] Esther, J., and M. Mohamed Sathik. "Retrieval of Brain Image Using Soft Computing Technique." *Intelligent Computing Applications (ICICA), 2014 International Conference on. IEEE, March 2014*.
- [34] Rajalakshmi, T., and R. I. Minu. "Improving relevance feedback for content based medical image retrieval." *Information Communication and Embedded Systems (ICICES), 2014 International Conference on. IEEE, February 2014*.
- [35] Ahmed, Shaheen, Khan M. Iftekaruddin, and Arastoo Vossough. "Efficacy of texture, shape, and intensity feature fusion for posterior-fossa tumor segmentation in MRI." *Information Technology in Biomedicine, IEEE Transactions on 15.2: 206-213, March 2011*.
- [36] Murala, Subrahmanyam, and Q. M. Wu. "Local mesh patterns versus local binary patterns: biomedical image indexing and retrieval." *Biomedical and Health Informatics, IEEE Journal of 18.3 (2014): 929-938*.
- [37] Manjunath, Bangalore S., and Wei-Ying Ma. "Texture features for browsing and retrieval of image data." *Pattern Analysis and Machine Intelligence, IEEE Transactions on 18.8 (1996): 837-842*.
- [38] https://en.wikipedia.org/wiki/Sensitivity_and_specificity
- [39] Ma .W.Y. and B.S. Manjunath, Texture features and learning similarity, in *Proc. IEEE Conf. on Computer Vision and Pattern Recognition, 1996*, pp. 425–430.
- [40] Manjunath B. S.and W.Y. Ma, Image indexing using a texture dictionary, in *Proceedings of SPIE Conference on Image Storage and Archiving System, Vol. 2606*.
- [41] Minka T.P. and R.W.Picard, Interactive learning using a "society of models," in *Proc. IEEE CVPR, 1996*, pp. 447–452.