OPTIMAL REGION SIZE FOR AN EFFICIENT MEDICAL IMAGE RETRIEVAL

Dr. Ch. Raja*

* Associate Professor, Department of Electronics and Communications Engineering, MGIT, Hyderabad.

Abstract:

Medical Image Retrieval is an emerging area in research community from past four decades for providing a better healthcare decision making system. Extracting similar looking anatomical images from huge databases based on the features extracted from the images is known as Content Based Medical Image Retrieval (CBMIR). Though lot of work already done in this domain, researches are still trying for the new approaches to still improve the retrieval performance in terms of precision, recall and time of retrieval. Efficient retrieval of medical images better done with local features computed regionally over globally determined features. In this paper we presented a comparison analysis of retrieval performance of X-Ray images by computing the heterogeneous features for whole image and dividing the image into 16, 64 and 256 symmetrical regions. The features computed are (i) Intensity features using block pixel count, (ii) Texture attributes using Discrete Wavelet Transform (DWT) coefficients and (iii) Eigen values by computing Singular Value Decomposition (SVD) coefficients. Experimentation is done IRMA 2008 X-Ray image dataset. SVD based Eigen values and block pixel count features computed from smaller regions increased the MAP where as DWT energy computed over entire image shown good MAP compared to region wise features.

Keywords: RBMIR, SVD, DWT, Intensity features

I. Introduction:

The medical related health professional use and store visual information in the form of X-rays, ultrasound and other scanned images for diagnosis and monitoring purposes. There are strict rules on confidentiality of such information. The images are kept with the patients' health records which are, in the main, manual files, stored by unique identifier (NI number). Visual information, provided it is rendered anonymous, may be used for research and teaching purposes. Much of the research effort related to images is undertaken in the medical physics area. Aspects of concern include effective image processing (e.g. boundary/feature detection) systems which aid the practitioner in detecting and diagnosing lesions and tumours and tracking progress/growth.

Without burdening a physician unduly, what can be accomplished by a computer is the primary goal of Content Based Medical Image Retrieval. Texture contains important information about the structural arrangements of their surfaces and their relationships to the surrounding environment. Small area of patches with little gray variation is called tone [1]. Medical images produced by various imaging modalities characterised in different ways based on their content distribution such as X-Ray images are best analyzed with textural attributes compared to tomographic or endoscopic images. Various characteristics of medical images and the ways to build a medical imaging database is presented in [2]. The intension of CBMIR in medical domain is to improve the performance of healthcare and medical decision making systems and finally need to be included into PACS. Importance of CBMIR in achieving Picture Archiving and Communication Systems (PACS) was discussed in [3]. Paper [4] explored gaps and short comings of CBIR for medical images and suggested to make the system much realistic. Four state of art CBIR approaches - Cervigram Finder, SPIRS, IRMA, SPIRS-IRMA were taken into consideration. CBIR applications towards medical domain explored in [5], reviewed on state of art techniques, discussed on challenges, opportunities and speculations for future research.

Paper [6] listed out color, texture and shape features of images to use in cbir. The logical image representation in image databases systems is based on different image data models. An image objects may be either an entire image or some other meaningful portion (consisting of a union of one or more disjoint regions) of an image. The logical image description includes: meta, semantic, color, texture, shape, and spatial attributes. Color attributes could be represented as a histogram of intensity of the pixel colors. A histogram refinement technique is also used by partitioning histogram bins based on the spatial coherence of pixels.

The ability to retrieve medical images on the basis of texture similarity seems very useful. A variety of techniques has been used for measuring texture similarity; the best-established rely on comparing values of what are known as second-order statistics calculated from query and stored images. Essentially, these calculate the relative brightness of selected pairs of pixels from each image. From these it is possible to calculate measures of image texture such as the energy, degree of contrast, coarseness, directionality and regularity, or periodicity, directionality and randomness. Alternative methods of texture analysis for retrieval include the use of Gabor filters and fractals. A recent extension of the technique is the texture thesaurus, which retrieves textured regions in images on the basis of similarity to automatically-derived code words representing important classes of texture within the collection.

II. RELATED WORK

Texture classification and discrimination based on the energies of image subbands using DCT, wavelet and spatial partitioning [7]. Images decomposed into blocks and wavelet coefficients are computed for each block and the query features compared with these features for fast retrieval of similar images from large databases [8]. High Resolution (HRCT) image retrieval based on locally selected pathology based regions (PBR) and global features that include shape, texture and gray level attributes. Texture features include energy, entropy, homogeneity, contrast, correlation and cluster tendency, computed from a GLCM matrix. Mean and standard deviation of PBR region, local histogram computation and shape attributes including longer axis, shorter axis, orientation and shape complexity measurement using Fourier descriptors and moments discussed in [9]. Retrieval using Customized Queries approach (CQA) is used in which query features compared with a class features and then compared with the image features of that particular class presented in [10]. IRMA database category classification using cross-correlation function and Euclidean distance presented in [11].

Two level image retrieval processes was implemented in [12] where group categorization is done by wavelet decomposition and the actual retrieval process is performed within that group. In [13] images are represented as signatures based on the distribution of wavelet transform and weighted signature distances computed between query and database images and an adapted wavelet database is proposed. Experimentation using image features including intensity, texture and shape presented in [14] and their suitability for various image datasets comprising outdoor, indoor, medical, aerial images is discussed by stating which particular feature set suits well for a particular group of images. Rather generating features, a signature is built for each image based on its wavelet transform in [15], these signatures characterize the wavelet coefficients distributed in each subband after decomposition and distance measure compare these signatures. Weights can also be included in the subbands. By using partial coefficients of 16 x 16, 32x32, 64x64 and 128x128 sized images are computed by four different transformations (DCT, Walsh, Haar and Hartley) and analyzed the image classification in [16], [17].

III. METHODOLOGY:

In this paper we presented the comparison analysis of an X-Ray image retrieval system performance. Ten different classes of X-Ray images (200 each class) of IRMA 2008 database is used in experimentation. 50 % of each class that is 100 images were used as queries and analyzed the performance at 100% average retrieval rate. At first these images resized to 128 x 128. Image attributes computed are (i). Intensity distributions block pixel count, (ii). Textural attributes using Discrete Wavelet Transform and (iii). Large Eigen values Singular Value Decomposition. These attributes were calculated globally for whole image. The attributes also computed locally by partitioning the image into 256 regions of 8 x 8 in size, 64 regions of 16 x 16 and 16 regions of 32 x 32 sized.

The retrieval performance is analyzed in terms of class wise average precision (AP) and Mean Average Precision (MAP) for the entire data set with three features computed in four different block sizes. The proposed retrieval system is shown in Fig.1.

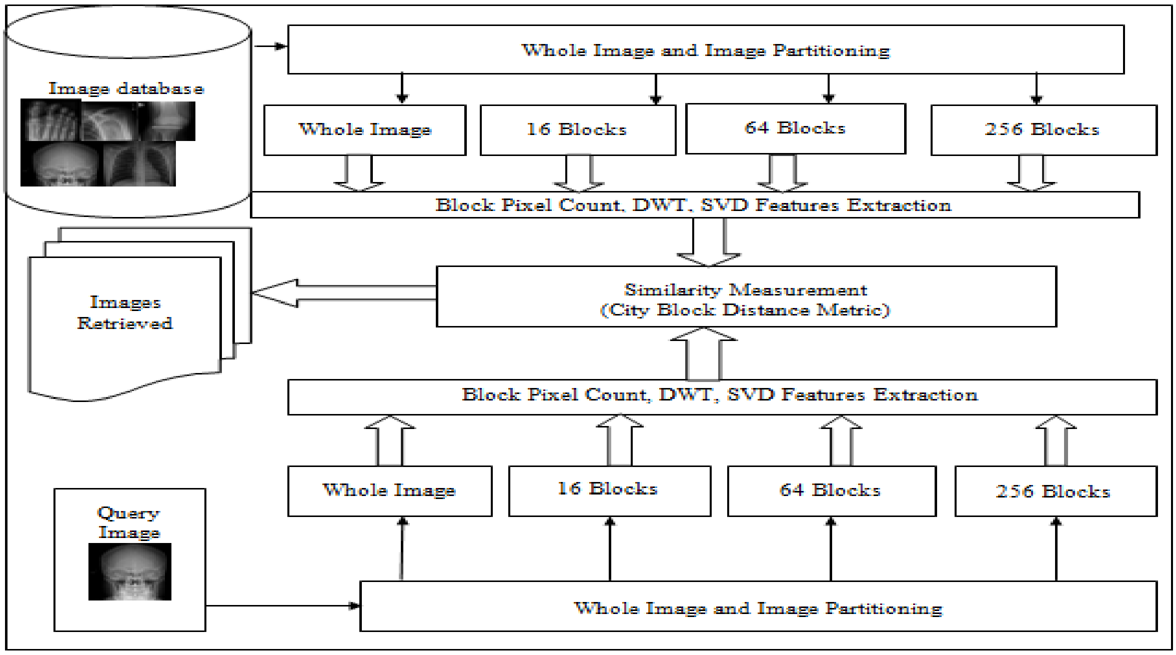

Fig.1. Proposed Retrieval System

3. a. Feature Extraction

For computation of intensity based features, the pixel intensities got summed up for the whole image and the chosen block size as shown in eq.1. These sum of pixel values computed from query image and database images checked with city block distance similarity and the images of the database that shown least distance retrieved by the system.

$$[F_k] = \sum_{i=1}^{m}\sum_{j=1}^{n} f(i,j) \;\; for\; k = 1{:}R \qquad (1)$$

F_k is the feature computed at K^{th} block.

f (i, j) indicates the block of the image with i rows and j columns.

R indicates number of blocks, the image got partitioned.

m and n indicate size of block that changes with respect to the value of R.

Texture is another important property of images. Various texture representations have been investigated in pattern recognition and computer vision. Basically, texture representation methods can be classified into two categories: structural and statistical. Structural methods, including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules. They tend to be most effective when applied to textures that are very regular. Spectral approaches involve the sub-band decomposition of images into different channels, and the analysis of spatial frequency content in each of these sub-bands in order to extract texture features. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura feature, Wolds decomposition, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and wavelet transform, characterize texture by the statistical distribution of the image intensity. Discrete Wavelet Transform (DWT) coefficients computed over various regions are used as textural features. The DWT (Discrete Wavelet Transform) separates an image into a lower resolution approximation image (LL) as well as horizontal (HL), vertical (LH) and diagonal (HH) detail components. The process can then be repeated to computes multiple "scale" wavelet decomposition, as in the 2 scale wavelet transform shown below in Figure 2. The first step is to resize the image size into 128 X 128 in a matrix format. Then the pyramid wavelet transform is applied to get the sub bands of the image. To find the energy measures of the image Daubechies filter is applied. The decomposition is applied and can able to get the low frequency contents in the LL sub band and other frequencies in LH, HL and HH bands separately. Once the wavelet coefficients of an image are available, features are computed from each sub-band. One of the many advantages over the wavelet transform is that that it is believed to more accurately model as compared to the DFT or DCT.

Singular value decomposition (SVD) can be looked at from three mutually compatible points of view. On the one hand, we can see it as a method for transforming correlated variables into a set of uncorrelated ones that better expose the various relationships among the original data items. At the same time, SVD is a method for identifying and ordering the dimensions along which data points exhibit the most variation. This ties in to the third way of viewing SVD, which is that once we have identified where the most variation is, it's possible to find the best approximation of the original data points using fewer dimensions. Hence, SVD can be seen as a method for data reduction. Singular value decomposition takes a rectangular matrix of gene expression data (defined as A, where A is a *n* x *p* matrix) in which the *n* rows represents the genes, and the *p* columns represents the experimental conditions. As given in eq.2, The SVD theorem states

$$A_{nxp} = U_{nxn} S_{nxp} V_{pxp}^T \tag{2}$$

$U^T U = I_{nxn}$ *and* $V^T V = I_{pxp}$ i.e. U and V are orthogonal.

Where the columns of U are the left singular vectors gene coefficient vectors, S the same dimensions as *A* has singular values and is diagonal mode amplitudes and V^T has rows that are the right singular vectors expression level vectors. The SVD represents an expansion of the original data in a coordinate system where the covariance matrix is diagonal. Calculating the SVD consists of finding the Eigen values and eigenvectors of AA^T and A^TA. The eigenvectors of A^TA make up the columns of *V* the eigenvectors of AA^T make up the columns of *U*. Also, the singular values in S are square roots of Eigen values from AA^T or A^TA. The singular values are the diagonal entries of the *S* matrix and are arranged in descending order. The singular values are always real numbers. If the matrix *A* is a real matrix, then *U* and *V* are also real.

3. b. Similarity Measures:

There is more than one way to measure a distance. There are distances that are Euclidean and there are other distances based on similarity. Instead of exact matching, content-based image retrieval calculates visual similarities between a query image and images in a database. Accordingly, the retrieval result is not a single image but a list of images ranked by their similarities with the query image. Many similarity measures have been developed for image retrieval based on empirical estimates of the distribution of features in recent years. Different similarity/distance measures will affect retrieval performances of an image retrieval system significantly. In this *D* (*I*, *J*) as the distance between the query image *I* and the image *J* in the database and *fi* (*I*) as the number of pixels in bin *i* of *I.* The Euclidean distance is a commonly used measure of distance. The distance between two points is the length of the path connecting them. The Euclidean distance given in eq.3 is just the sum of the squared distances of two vectors of observation a_i and b_i.

$$d(i,j) = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2} \tag{3}$$

Normalization can be done by dividing the Euclidean distance by the maximum of all Euclidean distances. The normalized Euclidean distance is in the range of 0 to 1. 0 means the expression level of gene a and b are closely related, whereas 1 reflects most distant behavior. To normalize the Euclidean distance each distance was divided by the maximum of distance obtained for the whole matrix d (i, j) = d (i, j) / max (d (i, j)). The resulting normalized Euclidean distances are in range of 0 to 1.

3. c. Performance Metrics:

Retrieval performance is analyzed by computing the two performance measures precision and recall rate as given in eq.4 and eq.5 respectively.

$$Average\ Precision = \frac{No\ of\ relevant\ imagesretrieved\ for\ a\ class\ of\ images}{total\ number\ of\ images\ retrieved} \tag{4}$$

$$Recall = \frac{No.of\ relevant\ images\ retrieved}{Total\ Number\ of\ relevant\ images\ in\ the\ database} \tag{5}$$

IV. RESULTS AND DISCUSSIONS

This paper describes comparison analysis for X-Ray image retrieval by computing the (i) Intensity features using block pixel count, (ii) Texture attributes using Discrete Wavelet Transform (DWT) coefficients and (iii) Eigen values by computing Singular Value Decomposition (SVD) coefficients for whole image and dividing the image into 16, 64 and 256 symmetrical squared regions. Experimentation is done IRMA 2008 X-Ray image dataset. Class wise Average Precision (AP) and Mean Average Precision (MAP) at 100 % retrieval rate by computing sum of pixels over full image, 16 regions, 64 regions and 256 regions is shown in table 1. It is clearly understood that the feature computed in smaller regions result in better precision. Graphical interpretation of pixel sum result was shown in fig.3. Block pixel count computed over full image has no way good enough and when computed over regions, MAP improved a lot irrespective of block size i.e though the region size decreased from 32 x 32 to 16 x 16 and 8 x 8 the improvement in AP and MAP is very little.

Table I. SVD, Intensity Coefficients and DWT based AP and MAP

Class	SVD				Block Pixel Count				DWT			
No. of Regions	Full	R 16	R 64	R 256	Full	R 16	R 64	R 256	Full	R 16	R 64	R 256
Lungs	71.2	92	**96**	**96**	2	91.6	95.2	**96.4**	95.6	90.4	88	**96.8**
Abdomen	40	82	94.4	**95.2**	78.8	78.4	92.8	**95.6**	**96.4**	80.4	92.8	94.8
Spine	30	80	**86.4**	84.4	72.8	79.6	**84.8**	84	**81.2**	72.8	76.4	73.2
Skull	28.4	72.4	73.2	**77.2**	42.4	72.8	78.4	**79.6**	**79.2**	70	67.6	74.4
Foot	19.2	70.4	74	74.8	16.8	73.2	75.2	**76.4**	**76.8**	71.6	60.8	73.6
Breast	34.8	66	72.4	**74.8**	61.6	65.6	72	**75.2**	**76.4**	67.2	69.2	70.4
Knee	50.4	75.2	74.4	**76**	44	70.4	73.6	**74.8**	**76**	62.4	65.6	68.8
Hand	25.6	70.4	**71.6**	67.6	32.4	66.4	69.6	**70**	**66**	62.4	57.6	58.8
Shoulder	16	60.4	65.2	**67.6**	46.4	62	64.8	**66.4**	**67.2**	56	52	58
Elbow	23.2	44.8	54.8	**57.2**	32.8	44.4	54	**56.4**	**57.6**	44.8	52.4	52.8
%MAP	34.18	71.55	76.43	**77.24**	42.94	70.58	76.23	**77.7**	**77.4**	68	68.52	72.4

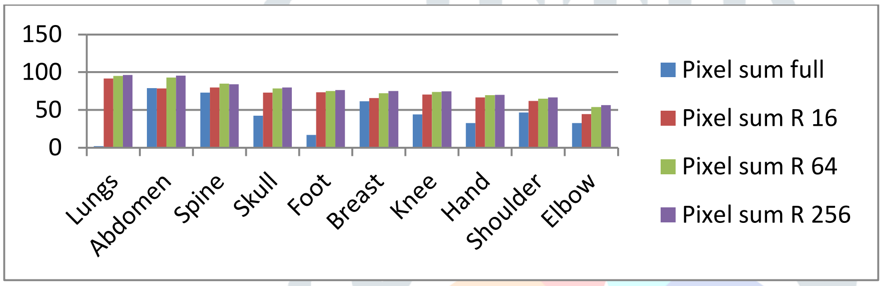

Fig 2: Graphical representation of pixel sum results

Performance analysis using DWT texture coefficients computed over full image and three different sized regions shown in table 1. Compared with region wise feature computation, DWT energy extracted from the LL band of entire image resulted in better AP and MAP scores for all the classes of organs. Graphical representation of DWT based retrieval is shown in fig.3

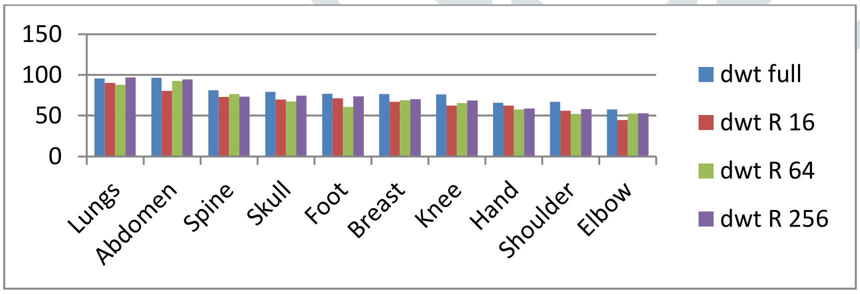

Fig 3: Graphical representation of DWT energy based results

Class wise Average Precision (AP) and MAP of image retrieval by computing large Eigen values using SVD coefficients given in table 1 and the graphical representation shown in fig.4. Here it is clearly understood that large Eigen values computed from smaller regions resulted in better AP and MAP scores compared to higher regions and full image extracted coefficients. Large Eigen values computed from whole image is no way good enough to retrieve the images.

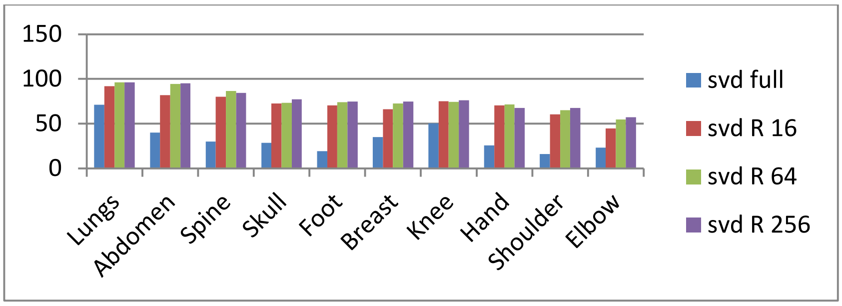

Fig 4: Graphical representation of large Eigen values from SVD coefficients based results

V CONCLUSIONS

At the outset we would like to conclude that ContentBased Medical Image Retrieval can be done in an efficient manner by extracting the optimal features from optimal region size that need to be chosen for feature extraction. Through experimentation on IRMA data set with three different features computed over four different sized regions of the image, intensity features and Eigen values resulted in a better retrieval when computed over smaller regions of the order of 8 x 8 pixel grid. Globally computed block pixel sum and Eigen values computed over entire image result in very minimum MAP scores and proven that local features extracted from image definitely improve the performance of retrieval. Textural features obtained by DWT energy retrieved the images with maximum precision for the whole image rather extracted from the regions. Hence with this work we would convey that computing features in optimal regions improved the MAP of the system a lot with reduced time requirements.

REFERENCES

[1] Haralick, Robert M., Karthikeyan Shanmugam, and Its' Hak Dinstein. "Textural features for image classification." Systems, Man and Cybernetics, IEEE Transactions on 6 (1973): 610-621.
[2] Tagare, Hemant D., C. Carl Jaffe, and James Duncan. "Medical image databases." Journal of the American Medical Informatics Association 4.3 (1997): 184-198.
[3] Qi, Hairong, and Wesley E. Snyder. "Content-based image retrieval in picture archiving and communications systems." Journal of Digital Imaging 12, no. 1 (1999): 81-83.
[4] Antani, Sameer, L. Rodney Long, and George R. Thoma. "Bridging the gap: Enabling CBIR in medical applications." In Computer-Based Medical Systems, 2008. CBMS'08. 21st IEEE International Symposium on, pp. 4-6. IEEE, 2008.
[5] Akgül, Ceyhun Burak, Daniel L. Rubin, Sandy Napel, Christopher F. Beaulieu, Hayit Greenspan, and Burak Acar. "Content-based image retrieval in radiology: current status and future directions." Journal of Digital Imaging 24, no. 2 (2011): 208-222.
[6] Hussain, Chesti Altaff, D. Venkata Rao, and S. Aruna Mastani. "Low level feature extraction methods for Content Based Image Retrieval." In Electrical, Electronics, Signals, Communication and Optimization (EESCO), 2015 International Conference on, pp. 1-5. IEEE, 2015.
[7] Smith, John R., and Shih-Fu Chang. "Transform features for texture classification and discrimination in large image databases." Image Processing, 1994. Proceedings. ICIP-94., IEEE International Conference. Vol. 3. IEEE, 1994.
[8] Remias, Edward, et al. "Supporting content-based retrieval in large image database systems." Multimedia Database Management Systems. Springer US, 1997. 61-78.
[9] Shyu, Chi-Ren, C. E. Brodley, A. C. Kak, Akio Kosaka, A. Aisen, and L. Broderick. "Local versus global features for content-based image retrieval." In Content-Based Access of Image and Video Libraries, 1998. Proceedings. IEEE Workshop on, pp. 30-34. IEEE, 1998.
[10] Dy, Jennifer G., Carla E. Brodley, Avi Kak, Lynn S. Broderick, and Alex M. Aisen. "Unsupervised feature selection applied to content-based retrieval of lung images." IEEE transactions on pattern analysis and machine intelligence 25, no. 3 (2003): 373-378.
[11] Lehmann, Thomas M., Mark O. Güld, Thomas Deselaers, Daniel Keysers, Henning Schubert, Klaus Spitzer, Hermann Ney, and Berthold B. Wein. "Automatic categorization of medical images for content-based retrieval and data mining." Computerized Medical Imaging and Graphics 29, no. 2 (2005): 143-155.
[12] Wang, Qiang, Vasileios Megalooikonomou, and Despina Kontos. "A medical image retrieval framework." In 2005 IEEE Workshop on Machine Learning for Signal Processing, pp. 233-238. IEEE, 2005.
[13] Lamard, Mathieu, Guy Cazuguel, Gwénolé Quellec, Lynda Bekri, Christian Roux, and Béatrice Cochener. "Content based image retrieval based on wavelet transform coefficients distribution." In 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 4532-4535. IEEE, 2007.
[14] Deselaers, Thomas, Daniel Keysers, and Hermann Ney. "Features for image retrieval: an experimental comparison." Information Retrieval 11, no. 2 (2008): 77-107.

[15] Quellec, Gwénolé, Mathieu Lamard, Guy Cazuguel, Béatrice Cochener, and Christian Roux. "Wavelet optimization for content-based image retrieval in medical databases." Medical image analysis 14, no. 2 (2010): 227-241.

[16] Kekre, H. B., Tanuja K. Sarode, and Fauzia Ansari. "Performance evaluation of DCT, Walsh, Haar and Hartley transforms on whole images and partial coefficients in Image Classification." In Communication, Information & Computing Technology (ICCICT), 2012 International Conference on, pp. 1-6. IEEE, 2012.

[17] P. Nalini, Dr. B.L. Malleswari, " Modeling of X-Ray Image Retrieval System using Zone based Transform Techniques", International Journal of Inventive Engineering and Sciences (IJIES), ISSN: 2319–9598, 4, no 6, (2017), pp-13-17.

[18] Nalini, Mrs P., and B. L. Malleswari. "An Empirical Study and Comparative Analysis of Content Based Image Retrieval (CBIR) Techniques with Various Similarity Measures." EEECOS

[19]. Nalini, Mrs P., and B. L. Malleswari. "Performances of Different Color Representations in Image Retrieval and Classification: A Comparative Analysis." International Journal 12 (2016).