Content-based Image Retrieval System for Medical Domain Using Spatial Color and Texture Histograms

Cristian Gabriel Mihai, Alina Doringa, Liana Stanescu, Dumitru Dan Burdescu, Cosmin Stoica Spahiu
Faculty of Automation, Computers and Electronics
University of Craiova
Craiova, Romania
{mihai_gabriel, stanescu, burdescu, stoica.cosmin}@software.ucv.ro
alinadoringa@hotmail.com

***Abstract*—Indexing and retrieving are two important tasks for color image databases. These tasks are possible when using the histogram as an efficient technique for content-based image retrieval domain. In this paper, a content-based image retrieval system that can be used in the medical domain is presented. The system is using an original combination of two types of histograms: a spatial color histogram and a texture histogram based on the Local Binary Pattern descriptor. Both histograms are computed in the HVC color space. The computation of the binary code associated to a Local Binary Pattern descriptor is made in an original manner using the NBS distance instead of using a simple difference between colors' components.**

Keywords- spatial color histogram; annular color histogram; content based image retrieval.

I. INTRODUCTION

Color histograms have two main advantages: easy computation and a broad applicability for a wide range of images. The main drawback is that histograms capture only global color distributions of the images and there is a lack of information about the spatial relationship among image's colors. It is highly possible that two images with similar color histograms to have a very different spatial appearance causing false positives. Because the content of images is indexed in a limited way using only color histograms it was decided that it would be an advantage to take into account the spatial information [10]. This combination has led to effective techniques for content-based image retrieval tasks based on the new spatial color histogram. It was used for our system an efficient spatial color histogram called the annular histogram [10] which is based on a density map. The experimental results have proven that this histogram outperforms the traditional color histogram and the color coherent vector [11].

Because color measurements are sensitive to varying illumination conditions texture measures can be used in many real-world applications, including for example, outdoor scene image analysis. Texture characteristics gives additional information compared to color or shape measurements of the objects. It is considered to be important in many image analysis and computer vision tasks. We have used the local binary pattern (LBP) [13] to obtain a texture histogram of patterns. LBP is one of the most used texture descriptors in medical image analysis and it has recently proven useful in describing medical images [17][18][19]. It has a low computational complexity and a low sensitivity to changes in illumination.

This descriptor is used for texture classification [13][21], face recognition [20][22][24], fingerprint identification [23], etc.

The HVC (Hue-Value-Chroma) color space [5] has been used because it represents colors along human perceptual dimensions [6]. HVC is a representation of the IE 1976 (L*a*b*) under the cylinder coordinate system. The components of a color in the HVC space are defined as:

$$H = \arctan\left(\frac{b^*}{a^*}\right), V = L^*, \ C = \sqrt{{a^*}^2 + {b^*}^2}\ . \quad (1)$$

The distance between two pixels in this space is computed using the NBS distance [4]. Colors with the NBS color distance below 3.0 are perceived to be almost the same color by human beings. Given a pair of colors A = (H1; V1; C1) and B = (H2; V2; C2), the NBS color distance is defined as follows [4]:

$$E_{NBS}(A,B) = 1{,}2 * \sqrt{2C_1C_2\left\{1-\cos\left(\frac{2\pi}{100}\Delta H\right)\right\} + (\Delta C)^2 + (4\Delta V)^2}\ . \quad (2)$$

where:

$$\Delta H = |H_1 - H_2|, \Delta V = |V_1 - V_2|, \Delta C = |C_1 - C_2|. \quad (3)$$

The correspondence between the human color perception and the NBS color distance is shown in the following table:

TABLE I. CORRESPONDENCE BETWEEN HUMAN COLOR PERCEPTION AND NBS COLOR DISTANCE

NBS Value	Human Perception of Color
0 ~ 1.5	almost the same
1.5 ~ 3.0	slightly different
3.0 ~ 6.0	remarkably different
6.0 ~ 12.0	very different
12 ~	different

The paper is organized as follows: related work is discussed in Section 2. In Section 3, some details about the

 ISBN: 978-1-61208-129-8

spatial color histograms and local binary patterns are presented. Section 4 provides a description of the modules included in the system architecture. In Section 5, the experimental results are discussed. Section 6 presents the conclusion of the paper.

II. RELATED WORK

Many research efforts have been made in the last decades to overcome the problems associated with color histograms. For content-based image retrieval systems it is more important the result of an approximate matching of two histograms than exact matching of images. Approximate matching is more useful since the interest is to retrieve similar images, rather than images identical with the sample image.

The solution proposed by Stricker and Dimai [2] divided an image into five fixed overlapping blocks. From each block the first three color moments were extracted and these were used to form a features vector of the image. Huang, et al. [3] proposed the correlogram to take into account the local color spatial correlation as well as the global distribution of this spatial correlation. In [10][12], the spatial color histograms are described for the content based image retrieval task.

A typical example of histogram-based image retrieval system is the FINDIT system developed by M.J. Swain and his colleagues [1]. The HVC color space was adopted for this system and for each image it was created a two-dimensional H-C histogram. It was used the histogram intersection to measure the similarity between a pair of images. In [4], a histogram-based image retrieval method was implemented. This method is similar to the one used in FINDIT system. The H and C-axes of the HVC color space were used, and the two axes were equally subdivided into 8 intervals, resulting in histograms of 64 bins.

Another example of a texture-based image retrieval system is the UCSB system developed by Manjunath et al. [16]. The system adopted the Gabor wavelet model to compute feature vectors of texture patterns and used the weighted L1 distance between a pair of feature vectors to measure the image similarity.

Ojala et al. [13] proposed an effective local binary pattern (LBP) method for texture analysis. They have developed powerful extensions to their approach including rotation invariance and multi resolution analysis [14]. The approach is theoretically very simple and binds together the properties of statistical and structural texture analysis. LBP and its extensions have performed very well in various comparative studies and have been applied successfully in several real-world texture analysis problems [15]. In [25], the HVC color space is used for pixels classification. The described method is based on statistical characteristics and it is used for the recognition of the airline coupons. In [27], the LBP are used to describe images of brain magnetic resonance (MR) volumes. When a query image is given the system retrieves relevant slices. LBP are used in [28] for representing salient micro-patterns in mammographic mass detection and to train a support vector machine (SVM) with the aim of distinguishing between the true recognized masses and the ones which actually are normal parenchyma.

In [30], an indexing and retrieval scheme is presented that uses the spatial color distribution. The indexing technique is based on the Gaussian Mixture modeling of the histogram of weights provided by the bilateral filtering scheme. In this way the proposed technique considers not only the global distribution of the color pixels comprising the image but also takes into account their spatial arrangement. In [8], the spatial histograms are used for region based tracking. In this context, these histograms are named *spatiograms*, which are histograms augmented with spatial means and covariances to capture a richer description of the target. In [9], it is used a medical image retrieval system that is very similar with our approach. This system is based on multiple features: color features - exploited by cumulative histograms, texture features - extracted by using gray level co-occurrence matrix (GLCM) and shape features - represented by a histogram of edge’s directions. This system extract the primitive feature of a query image and then compares it with existing features of the images from the database using a similarity measure. This similarity measure is evaluated using Euclidean distance. The experiments are made on a set containing 1000 images, covering MRI images, X-Ray images, Patology images. Retrieval Accuracy and Precision are used as performance measures. For evaluating the retrieval operation this system is using four retrieval modes: a retrieval mode based on a color histogram, a retrieval mode based on GLCM, a retrieval mode based on shape and a retrieval mode based on a combination of a color histogram and GLCM. The experimental results have shown the following results for the four retrieval modes (in the same order as before): (% Recall Accuracy : 66.1 ; % Precision: 55.3), (% Recall Accuracy : 68.4 ; % Precision: 62.6), (% Recall Accuracy : 65.12 ; % Precision: 58.3), (% Recall Accuracy : 72.3 ; % Precision: 65.4). It can be seen that using a combination of color and texture it was obtained the best retrieval result.

III. SPATIAL COLOR HISTOGRAM AND LOCAL BINARY PATTERN

A spatial color histogram is based on two main concepts: the distribution density and the density map. The distribution density can have three types: annular, angular and hybrid. The density map is obtained after performing the following algorithm:

- Calculate the centroid and the radius of each subset of pixels having the same color - considered as a geometric subset of the 2-D plan.
- Partition the enveloping disk either in annular, angular or sector (combination of annular and angular) regions.
- Count the number of pixels in each region and form a vector called the density map of a color.
- Arrange the density maps of all colors in a matrix where the density map of a color represents a matrix row; the matrix obtained is called either annular,

angular or hybrid depending on which partition was adopted.

Figure 1 presents an example of annular distribution density vector (4, 11, 9, 5) computed by counting the number of points (starting with the center region) in each region:

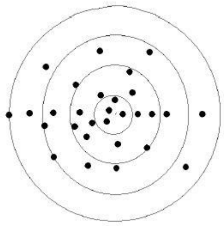

Figure 1. Annular distribution density.

In [10], five techniques for computing color histograms in the HVC color space were evaluated: the traditional histogram, color coherent vector (CCV) [11], the three types of histograms mentioned above: annular, angular, and hybrid. Features vectors were generated for each of the histograms mentioned above having the dimension equal to 2048. The color space was then quantized by making a uniform partition in each color dimension. Histogram types and the parameters used for quantification are listed in Figure 2. The experimental results have shown the following performance (in this order): annular, angular, hybrid, color coherent vector, and traditional histogram. The improvement of the spatial color histograms over the traditional one are: 36.49 % (annular), 30.41 % (angular), 26.71 % (hybrid). The improvement of the spatial color histograms over CCV are: 22.39 % (annular), 16.93 % (angular) and 13.61 % (hybrid).

Dim.	*Ann.*	*Ang.*	*Hyb.*	*Trad.*	*(CCV)*
H	8	8	8	32	16
V	4	4	4	8	8
C	4	4	4	8	8
r	16	1	4	1	1
θ	1	16	4	1	1
Total	2048	2048	2048	2048	2048

Figure 2. Histogram types and the parameters used for quantification where r, θ are polar coordinates.

LBP is one of the most used texture descriptors in medical image analysis being very useful in describing medical images. In Figure 3 it is shown how to calculate the LBP and the contrast for a pixel having 8 neighbor pixels.

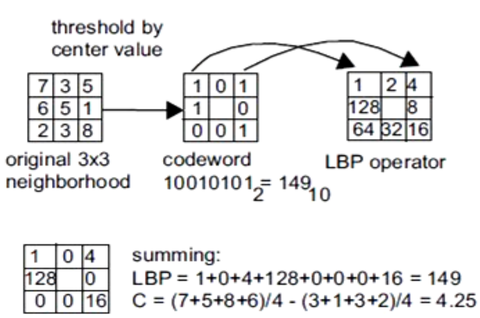

Figure 3. Computation of LBP and local contrast features.

A binary code is produced for each pixel in an image, by thresholding its neighborhood (8 pixels) with the value of the center pixel. The average of the gray levels below the value of the center pixel is subtracted from that of the gray levels above (or equal to) the center pixel. A histogram is constructed to collect up the occurrences of different binary patterns representing different types of curved edges, spots, flat areas, etc.

The original 8-bit version of the LBP operator considers only the eight nearest neighbors of each pixel. For this version there are 256 local patterns, 36 of them being rotation invariant.

The definition of the LBP has been extended to arbitrary circular neighborhoods of the pixel to achieve multi-scale analysis and rotation invariance. In Figure 4 it is presented the circularity idea behind the multi resolution approach.

The circular neighborhood definition allows obtaining a rotation invariant descriptor, but in some problems the anisotropic structural information is an important information source. To exploit this anisotropic structural information, an elliptical neighborhood definition has been used [28] for a face recognition system. This variant to the standard LBP has been named elliptical binary pattern (EBP).

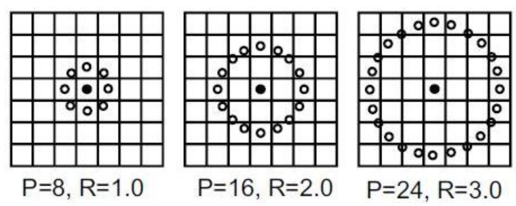

Figure 4. Circular neighborhood of pixel in multi resolution LBP.

Another variant has been proposed by [29] to solve the problem of the sensitivity to noise in near-uniform image regions. This method, called local ternary patterns (LTP), proposed a 3-valued coding that includes a threshold around zero for the evaluation of the local gray-scale difference.

The distance between two LBP histograms (histograms of patterns) can be evaluated using:

Chi square distance:

$$\chi^2(S,M) = \sum_{b=1}^{B} \frac{(S_b - M_b)^2}{S_b + M_b}. \quad (4)$$

Histograms intersection:

$$H(S,M) = \sum_{b=1}^{B} \min(S_b, M_b). \quad (5)$$

with a significantly smaller computational overhead.

Another extension to the original operator is the definition of so called uniform patterns. This extension was inspired by the fact that some binary patterns occur more commonly in texture images than others. A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is traversed circularly. For example, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) and 01010010 (6 transitions) are not. For (8, R) neighborhood there are 58 uniform patters from the total of 256 patterns.

IV. THE SYSTEM ARCHITECTURE

The system architecture is presented in Figure 5 and contains four main modules:

- Annular histogram Module: is used to compute the annular histogram and the distribution density vector. As described above for this type of histogram the HSV space dimensions were split: H- 8 bins, V- 4 bins and C - 4 bins obtaining in this way a histogram of 8x4x4 = 128 bins. In the first step this module computes the histogram using the information extracted from the specified image. After this process completes for each histogram bin, it is computed the distribution density vector having a dimension of 16. These vectors are concatenated obtaining a single density vector having a dimension of 128×16 = 2048 that is stored in the database.

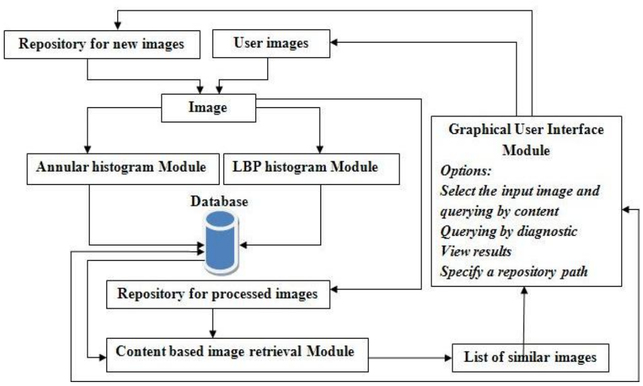

Figure 5. System architecture.

- LBP histogram Module – this module computes a histogram of rotational invariant local binary patterns. For our system we have used a histogram of patterns having 37 bins (36 bins for the rotation invariants and one bin for the rest of the patterns) and an original method for computing the pattern code: the NBS distance is calculated between the color components of the center pixel and the color components of a neighbor pixel; if the distance is greater that 3 (remarkably different colors) then we have 1, otherwise we have 0. In this way it is obtained the binary representation of the pattern and later the number associated with the pattern using a transformation from base 2 in base 10. The histogram of patterns is normalized and after that its content is stored in the database.
- Content based image retrieval Module: this module computes a distance D having two components :
  - D1 – the Euclidian distance between the density vector of the analyzed image and a density vector corresponding to an image already processed
  - D2 - a distance equal with 1 – HI, where *HI* is the histogram intersection between the histogram of patterns of the analyzed image and the histogram of patterns corresponding to an image already processed. The value of D is obtained as:

$$D = \sqrt{D_1{}^2 + D_2{}^2} \quad (6) \quad \text{where } D2 = 1 - HI \qquad (6)$$

- Graphical User Interface Module: is used by the user to retrieve the images that are similar with the specified input image, to specify a repository path, to retrieve the images from the database that have a diagnostic similar with the specified one – the diagnostic is specified as a text and after pressing a button a select statement is made on the database in tables *Images* and *Diagnostics* and all images having that diagnostic are returned; this option can be used to detect the total number of relevant images from the database when knowing the diagnostic of an input image.

For each input image it is returned a list of similar images having the value of the distance D smaller than a threshold value which is configurable.

V. EXPERIMENTAL RESULTS

The system has been tested using a set of 2000 images belonging to the digestive tract and they were obtained during the patients' diagnosis process. The training set contained 1800 images and the testing set 200 images. Each image from the training set has in the database information about the associated diagnostic. This information is used to detect the number of relevant images from the database having the same diagnostic. The performance and the efficiency of the information retrieval operation are measured with two parameters: recall and precision. The recall parameter measures the ability of the system to find relevant information in the database and it is defined as: the number of retrieved images that are also relevant / the total number of relevant images from the database. The precision parameter measures the accuracy of the retrieval operation and it is defined as: the number of retrieved images that are also relevant / the total number of retrieved images. For each image from the testing set it is calculated a (precision, recall) pair of values. The precision is computed easily by identifying the relevant images from the returned list and computing the value as described above. For recall we need also to detect the total number of relevant images existing in the database. This number is calculated by making the following assumption: the diagnostic associated with the input image is known. As the diagnostic is known, the option "querying the database by diagnostic" can be used. This option is in the Graphical User Interface module. In this way it is obtained the list of all images having the specified diagnostic. After this value is obtained the precision value is computed. At the end of this process 200 pairs (precision,

 ISBN: 978-1-61208-129-8

recall) of values were obtained and used to calculate a mean precision and a mean recall. Similar with the approach described in [9] we have made an evaluation of three retrieval modes: one retrieval mode based on an annular histogram, one retrieval mode based on a LBP histogram and a retrieval mode based on a combination between an annular histogram and an LBP histogram. Using the approach described above we have obtained 3 pairs of mean values for precision and recall corresponding to the three retrieval modes (in the same order as above): (% Recall: 61.3; % Precision: 54.7), (% Recall : 64.5 ; % Precision: 59.6), (% Recall : 76.1 ; % Precision: 70.1). It can be seen that using a combination of an annular histogram and a LBP histogram it was obtained the best retrieval result.

Below, the results obtained using the following query image having the ulcer diagnostic are presented.

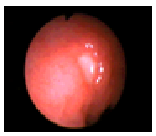

Figure 6. Query image.

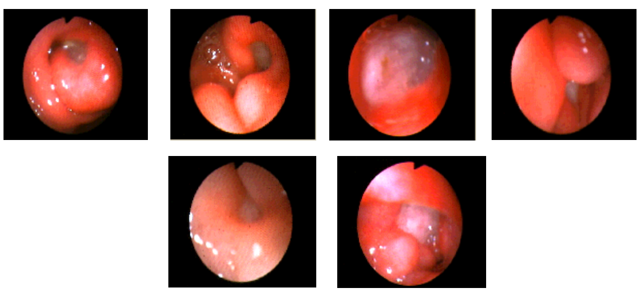

Figure 7. The similar images belonging to stomach and duodenum ulcers that were retrieved by the system.

VI. CONCLUSION

In this paper, a system for content based image retrieval that can be used in the medical domain was described.

An element of originality of this system is the usage of the combination of two histograms: annular histogram and LBP histogram for content based image retrieval.

The binary code associated to each LBP descriptor is computed using an original method based on NBS distance. This method is much better than computing simple difference between colors' components.

The limitations of the color histogram were improved by taking into account the spatial relationship between pixels.

The system was tested only on a limited dataset containing 2000 medical images, but in the future a larger dataset will be used and more experiments will be made. The experiments refer both for retrieval quality and speed.

Further extensions of the system will include shape information and the extraction of other texture-related features (Gabor and Tamura based). It should be also made comparative performance studies between this system and other existing systems (like the system described in [9]) and to include relevance feedback which is commonly used in image retrieval.

REFERENCES

[1] M. J. Swain, "Interactive indexing into image databases," in SPIE Proceedings, vol. 1908, 1993.

[2] M. Stricker and A. Dimai, "Color indexing with weak spatial constraints," in SPIE Proceedings, vol. 2670, 1996, pp. 29-40.

[3] J. Huang, S. Kumar, et al., "Image indexing using color correlograms", in Proceedings of CVPR'97, 1997, pp. 762-768.

[4] Y. Gong, "Advancing Content-based Image Retrieval By Exploiting Image Color and Region Features", Multimedia Systems, vol. 7, 1999, pp. 449-457

[5] The Japanese Society of Chromatology, The Handbook of Chromatology. University of Tokyo, 1980.

[6] M. Miyahara and Y. Yoshida, "Mathematical transform of (r,g,b) color data to munsell (h,v,c) color data," in SPIE Proceedings in Visual Communication and Image Processing, vol. 1001, 1988.

[7] M. J. Swain and D. H. Ballard. "Color indexing", International Journal of Computer Vision, vol. 7(1), 1991, pp.11–32.

[8] S.T. Birchfield and S. Rangarajan, "Spatial histograms for region-based tracking", ETRI Journal, vol.29(5), 2007, pp.697-699.

[9] B. Jyothi, Y. Madhavee Latha, and V.S.K. Reddy, "Medical Image Retrieval using Multiple Features", Advances in Computational Sciences and Technology, vol. 3 (3), 2010, pp. 387–396.

[10] A. Rao, R. K. Srihari, and Z. Zhang, "Spatial Color Histograms for Content-Based Image Retrieval", Proceedings of the Eleventh IEEE International Conference on Tools with Artificial Intelligence, 1999, pp.183-186

[11] G. Pass and R. Zabih., "Histogram refinement for content-based image retrieval", IEEE Workshop on Applications of Computer Vision, 1996, pp. 96–102.

[12] A. Rao, R.K. Srihari, and Z. Zhang, "Geometric Histogram: A Distribution of Geometric Configurations of Color Subsets", Internet Imaging, vol. 3964, 2000, pp. 91-101.

[13] T. Ojala, M. Pietikainen, and D. Harwood, "A comparative study of texture measures with classification based on feature distributions. Pattern Recognition", vol. 29(1), 1996, pp. 51-59.

[14] T. Ojala, M. Pietikainen, and T. Maenpaa T, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24(7) , 2002, pp. 971–987.

[15] T. Maaenpaa and M. Pietikainen, "Texture analysis with local binary patterns". Proceedigs Handbook of Pattern Recognition and Vision, World Scientific, 3rd Edition, 2005, pp. 197–216.

[16] B. S. Manjunath and W. Y. Ma, "Texture features for browsing and retrieval of image data", IEEE Transactions on PAMI Special Issue on Digital Libraries, 1996.

[17] L. Nanni, A. Lumini, and S. Brahnam, "Local binary patterns variants as texture descriptors for medical image analysis", Artificial Intelligence in Medicine, vol. 49(2), 2010, pp.117-125.

[18] D. Unay and A. Ekin, "Intensity versus texture for medical image search and retrieval", Proceedings of the 5th IEEE international symposium on biomedical imaging: from nano to macro (ISBI 2008), 2008, pp. 241–244.

[19] O. X. Lladó, J. Freixenet, and J. Martí, "False positive reduction in mammographic mass detection using local binary patterns", Proceedings of the medical image computing and computer-assisted intervention (MICCAI 2007) Brisbane, 2007, pp. 286–293.

[20] S. Marcel, Y. Rodriguez, and G. Heusch, "On the recent use of local binary patterns for face authentication", International Journal of Image and Video Processing – Special Issue on Facial Image Processing, 2007.

[21] M. Pietikäinen, T. Ojala, and & Silvén O, "Approaches to texture-based classification, segmentation and surface inspection"

C.H. Chen, L.F. Pau, and P.S.P. Wang, (eds.), Handbook of Pattern Recognition & Computer Vision, 2nd ed., World Scientific, Singapore, 1999, pp.711-736.

[22] L. Nanni and A. Lumini, "RegionBoost learning for 2D + 3D based face recognition", Pattern Recognition Letters, vol. 28(15), 2007, pp.2063-2070.

[23] L. Nanni and A. Lumini, "Local binary patterns for a hybrid fingerprint matcher", Pattern Recognition vol. 11, 2008, pp. 346-3466.

[24] G. Zhang, X. Huang, S. Li, and Y. Wang, "Boosting local binary pattern-based face recognition", Lecture Notes in Computer Science, vol. 3338, Springer, 2004, pp. 180–187.

[25] Y. Heping, Z. Wang, and S. Guo, "String Extraction Based on Statistical Analysis Method in Color Space", Proceedings of GREC, 2005, pp. 173-181.

[26] D. Unay and A. Ekin, "Intensity versus texture for medical image search and retrieval", Proceedings of the 5th IEEE international symposium on biomedical imaging: from nano to macro (ISBI 2008), 2008, pp. 241–244.

[27] A. Oliver, X. Llado´, J. Freixenet, and J. Martı´, "False positive reduction in mammographic mass detection using local binary patterns", Proceedings of the medical image computing and computer-assisted intervention (MICCAI 2007), 2007, pp. 286–293.

[28] S. Liao and ACS. Chung, "Face recognition by using elongated local binary patterns with average maximum distance gradient magnitude", Asian conference on computer vision,2007,pp.672-679.

[29] X. Tan and B. Triggs, "Enhanced local texture feature sets for face recognition under difficult lighting conditions", Analysis and modelling of faces and gestures; 2007, pp.168-182.

[30] L. Maria and S. Bogdan, "Spatial Color Distribution Based Indexing andRetrieval Scheme," Advances in Soft Computing, vol.59, 2009, pp. 419-427.