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A COMPARATIVE EVALUATION OF FEATURES FOR MEDICAL IMAGE MODALITY CLASSIFICATION

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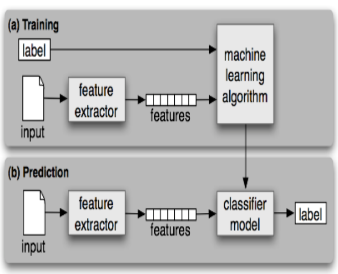
Graphical abstract



Abstract

Medical images are increasing at an alarming rate. This increasing number of images affects the interpreting capacity of radiologists. In order to reduce the burden of radiologists, automatic categorization of medical images based on modality is the need of the hour. Because image modality is an important and fundamental image characteristic. The important factor in the automatic medical image categorization based on modality are the features used for categorization purpose, because nice treatment on these subtleties can lead to good results. Many descriptors have been proposed in the literature for medical image categorization. It is unclear which descriptor encodes the content information efficiently. The descriptors that are calculated from these medical images should be descriptive, distinctive and robust to various transformations. The stability of these descriptors are evaluated under various transformations and are then analyzed for their discriminatory ability for the task of classification. In this study the criteria of transformations, repeatability, matching and classification accuracy on the basis of precision recall is used to evaluate the performance of these descriptors. The experimental results illustrates that among global descriptors local features patches histogram and among local descriptors SIFT encodes the content information quite efficiently.

Keywords: Modality classification; features; local; global; evaluation.

Abstrak

Imej perubatan semakin meningkat pada kadar yang membimbangkan. Ini Semakin imej memberi kesan keupayaan mentafsir daripada pakar radiologi. Dalam usaha untuk mengurangkan beban ahli radiologi, pengkategorian automatik imej perubatan modaliti adalah penting saat ini kerana modaliti imej merupakan satu ciri imej penting dan asas. Faktor penting dalam pengkategorian imej perubatan automatik berdasarkan modaliti adalah ciri-ciri yang digunakan untuk tujuan pengkategorian kerana rawatan yang bagus pada kehalusan ini boleh membawa kepada keputusan yang baik. Banyak deskriptor telah dicadangkan daripada rujukan pengkategorian imej perubatan. Ia adalah tidak jelas yang penghurai mengekod maklumat kandungan cekap. Deskriptor yang dikira daripada imej perubatan harus deskriptif, tersendiri dan mantap untuk pelbagai transformasi. Kestabilan deskriptor ini dinilai di bawah pelbagai transformasi dan kemudiannya dianalisis untuk keupayaan diskriminasi mereka untuk tugas klasifikasi. Dalam kajian ini kriteria transformasi, kebolehulangan, padanan dan klasifikasi ketepatan atas dasar ingat ketepatan digunakan untuk menilai prestasi deskriptor ini. Keputusan eksperimen menunjukkan bahawa di kalangan deskriptor global ciri-ciri tempatan patch histogram dan antara huraian tempatan menapis mengekod maklumat kandungan agak cekap.

1.0 INTRODUCTION

Radiology is a branch of medicine that uses imaging technology to diagnose and treat diseases. Diagnostic radiology refers to the use of various imaging modalities for the diagnosis of various diseases. The commonly used imaging modalities are radiography, magnetic resonance imaging (MRI), computed tomography (CT), nuclear imaging techniques, mammography, positron emission tomography (PET), and ultrasound. The radiological imaging including various imaging modalities is increasing at an alarming rate and for interpreting these various imaging modalities, workload on radiologists also increases as well. This increase in number and the complexity of these images affects the interpreting capacity of the radiologists. In order to reduce the burden of radiologists machine learning provides efficient ways to automate the analysis and diagnosis for medical images. So there is a need of effective management of these images.

Till now certain medical image management systems have been incorporated, such as Picture Archiving and Communications System (PACS) and Digital Imaging and Communication in Medicine (DICOM). However these systems don't aid automatic image analysis and categorization. As a result of which, these huge amount of images are categorized and analyzed manually which is a cumbersome task. Manual categorization is subjective, repetitive and requires a highly trained expert. In addition to this, manual categorization is not always reliable because of human subjectivity, tiredness and variable image quality, which will lead to the miss categorization [1].

Categorization of medical images is defined as the classification of the images into a predefined order[2]. In order to create an intelligent navigation and visualization tools, automatic classification of medical images as per their modality, pathology and anatomy is an important factor to achieve the aforementioned goals. It also plays an important role in diagnostics and research.

The most important factors for efficient medical image categorization are features of these images[3].A large amount of research has been carried out on the medical image categorization in the last decade [4-12]. In this study we are going to look at the features that have been used for medical image categorization and their pros and cons that effect the categorization because the various properties of these features will finally effect the categorization process. Figure 1 shows the organization of this categorization process.

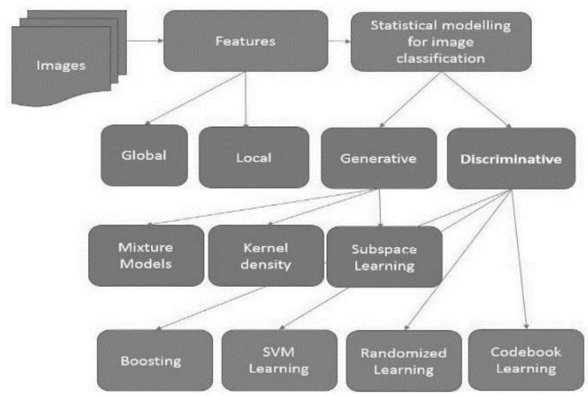


Figure 1 Organization of the categorization process

2.0 RELATED WORK

The categorization of the medical images starts with the extraction of the suitable features that represents the image correctly. The features that have been used so far for medical image categorization can be broadly classified into two categories [13], which are global and local.

2.1 Global Image Features

The global features are the image descriptors that are computed over the entire image. These features include colour, texture and shape. The colour has been found inapplicable in medical imaging domain because of their grey level representation. On the other hand, texture image descriptors have been widely used for classification purposes especially in medical image categorization [2]. The research [14] has shown that visual content of medical images is best described using texture and shape. Various global texture features have been used for medical image categorization. The taxonomy of the texture descriptors has been adapted from [15] and is shown in Figure 2.

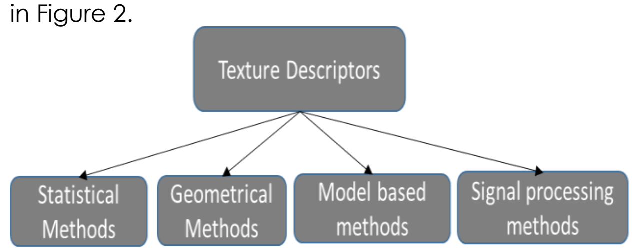


Figure 2. Taxonomy of texture descriptors adapted from [15]

2.1.1 Statistical Methods

Statistical methods captures the spatial distribution of grey levels of an image. One of the examples of the statistical analysis is capturing the probability of co-occurrences of different grey values in different directions and distances. Grey level co-occurrence matrix [16] is the most popular statistical method for image categorization based on texture. In medical image categorization GLCM descriptor has been used by various studies [17-21].

The grey level co-occurrence matrix proposed by Haralick [16] contains the entries in the form of the probability of finding a pixel with grey level *i* at a distance *d* and angle *θ* from a pixel with grey level *j:* This statement can be written formally as *P (i,j:d, θ)*. Each pixel is connected to the 8 nearest neighbours except the edge pixels. Therefore four GLCM'S are required to describe the texture content in the horizontal (P_H=0⁰), vertical (P_V =90⁰), right diagonal (P_{RD} =45⁰) and left diagonal (P_{LD} =135⁰) as shown Figure 3.

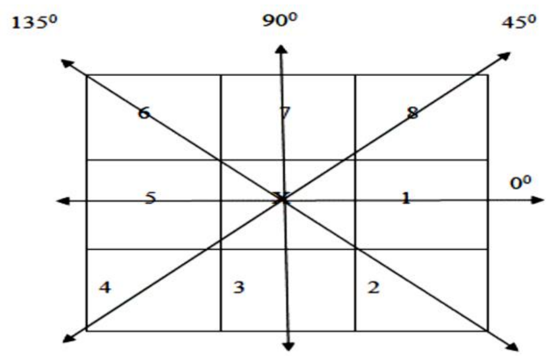


Figure 3 GLCM matrix

A number of features can be extracted using the co-occurrence matrices for texture subtlety as stated in [16].Some of the features that have been used for classification are defined by equations that follow, where *μ*; *σ*are the mean and the standard deviations of the row and column sums of the matrix respectively:

Energy

The Energy returns the sum of squared elements in the GLCM as follows:

$$\sum_{i,j=0}^{N-1} (P_{ij})^2 \tag{1}$$

Contrast

The contrast returns the intensity contrast between a pixel and its neighbour over the whole image as follows:

$$\sum_{i,j=0}^{N-1} P_{ij}\,(i-j)^2 \tag{2}$$

Correlation

The correlation returns a value how a pixel is correlated to its neighbour as follows:

$$\sum_{i,j=0}^{N-1} P_{ij}\ \frac{(i-\mu)\,(j-\mu)}{\sigma^2} \tag{3}$$

Homogeneity

The homogeneity returns a value that measures the closenessof the distribution of elements in the GLCM to the GLCMdiagonal as follows:

$$\sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \tag{4}$$

Where $P_{i,j}$= element *I, j* of the normalized symmetrical GLCM.

N = no of grey level in the image,*μ*= is the mean calculated over the whole image and σ^2 = is the variance of the intensities of all reference pixels.

In medical image categorization, grey level co-occurrence matrix has been used extensively in the literature. As stated in [17], the authors used 11 GLCM features to define the texture content of the images for classification of ultrasonography images. Similarly in [18], authors used 13 Haralick features calculated over four orientations and in addition to this they calculated average matrix of all four directions. In [19], the authors used just two features, i.e. contrast and entropy for classification of abdominal medical images. So in the context of medical image classification GLCM features have been used quite often, but there are some drawbacks of using GLCM and Haralick features [22], [23]. These features are computationally intensive and are not able to describe all the textures. Therefore in medical imaging classification it will affect the efficient classification.

2.1.2 Geometrical Methods

In geometrical method of analyzing texture, texture is analyzed by texture elements or primitives [2]. The most commonly used texture elements are Textons [24]. The term Texton was first coined by [24] for describing the human textural perception. The concept of Textons was vague until [25] provided the mathematical formulation in terms of co-occurrence filter responses of linear oriented Gaussian derivative filters. Texture is characterized by a set of orientation and spatial frequency filter bank. In the context of medical image categorization Textons have been used in the literature [26-29].In [26], the authors compared seven filter banks to characterize the texture of the dermoscopic images. The filter banks that have been used are those of Leung and Malik (LM) [25],Root Filter Set, Maximum Response Filters (MR8) [30]. The authors used 39 filters to detect average intensity, edges, spots, waves, meshes and ripples of dermoscopic structures. In [28],authors used patch representation by extracting the small sized patches from each image. These patches are then clustered using an unsupervised algorithm to build the Texton codebook. In [29], the authors used auto correlation Gabor feature filter responses on the images to build the Texton code book to classify images from two complementary gastroenterology imaging scenarios (chromo-endoscopy and narrow-and imaging)broadly into three different groups: normal, precancerous, and cancerous. But it is found in the literature [31] that there are limitations of Textons, i.e. it is difficult to define Textons and these Textons are sensitive to noise, scale and rotation. In medical image categorization these are the important factors to take into consideration, because the sensitiveness to noise, scale and rotation will ultimately effect the classification and diagnosis.

2.1.3 Model Based Methods

In model based methods texture is described and synthesized by the construction of image models. The variables from these models encapsulates the perceived qualities of texture [32].The most used model based texture method is Local Binary Pattern descriptor [33].

The concept of the Local Binary Pattern has been formulated on the assumption that a texture has two locally complementary aspects, i.e. a pattern and its grey scale contrast [33], [34]. The LBP operator works in 3x3pixel image by thresh holding the pixels values by center pixel value, which are then multiplied by powers of two and then summed to obtain a label for center pixel [34]. The $LBP_{P,R}$ operator is defined as follows:

$$LBP_{P,R} = \sum_{P=0}^{P-1} s(gp - gc)^{2p} \quad (5)$$

Where s is the thresh holding step, gp is the grey level value of sampling point and *g, c* is the grey level value of an arbitrary pixel as shown in Figure 4.In medical image categorization Local Binary Patterns have shown good results [8], [10], [20], [35-37] as compared to above mentioned statistical and geometrical texture features. In [8], authors used block based Local Binary Pattern for image description. In [10], authors stated that Local Binary Pattern describes only global texture information. So in order to capture the local information that is robust to occlusion overlapping sub images and then each sub image was further divided into non overlapping square image block. The Local Binary Pattern distribution has been calculated as a histogram having 59 bins over sub-images and final histogram was generated by combining the local histograms of sub-images. In [35], the authors used the Center Symmetric Local Binary Pattern proposed by [38], which uses a modified scheme of comparing neighboring pixels of the original LBP to simplify the computation as shown in Figure 5.

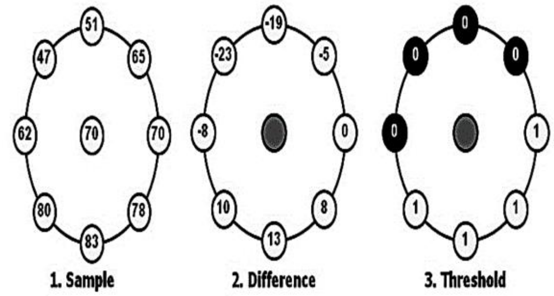


Figure 4. Illustration of local binary pattern adapted from [33]

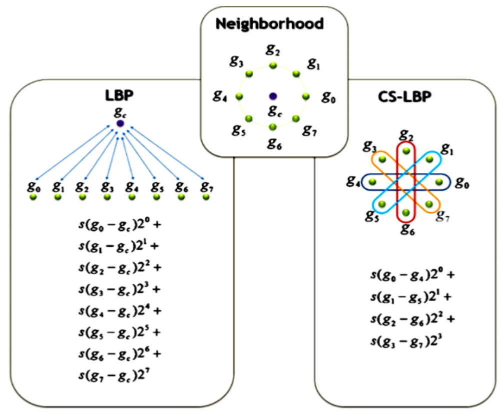


Figure 5. Illustration of LBP and CS-LBP features for a neighbourhood of 8 pixels adapted from [35].

Centre symmetric-Local Binary Pattern compares the centre symmetric pair of pixels against a centre pixel, instead of comparing each pixel with the centre pixel. In [37], authors used three stages of feature extraction for calculating Centre Symmetric Local Binary Patterns. In first stage each image has been divided into 25 sub images, after that Gabor transform has been applied to extract shape and directional information and in the last step CS-LBP are extracted from the filtered images .But it has been found in the literature [35], even LBP is widely used as a texture descriptor, it produces long histograms, which is computationally intensive.

To overcome this problem the authors proposed in [38] a new LBP descriptor known as CS-LBP but this descriptor has also some shortcomings, likethese descriptors discard the low frequency information of a region, which is quite important in case of computer aided diagnosis and are the essential components to retain during image compression process because during image compression most of the times high frequency components are discarded and low frequency component are retained. So in order to have good efficient CAD systems and good compression these lowfrequency components need to be retained.

2.1.4 Signal Processing Methods

In signal processing methods, texture is characterized by applying filters on an image. In these methods both spatial domain and frequency domain filters can be used.

In spatial domain filtering, image is manipulated or changed in space in order to enhance it for a given application. The techniques used for spatial domain filtering are smoothing, unsharp masking and Laplacians.

While as in frequency domain filtering, image is transformed to its frequency representation by modifying the spectral transform of an image. The techniques used for frequency domain filtering are Fourier transform, Wavelet transform.

The commonly signal processing methods to characterize texture are based on Wavelets and Gabor filters. Multiresolution analysis is the most employed method for characterizing medical images because of its capability to capture high time frequency resolutions. The wavelet transform methods are the classic examples of multiresolution analysis. The wavelet transform [39], [40] starts with a basis function called as mother wavelet and decomposes a signal into components of different frequency scales.

The most employed wavelet transform in medical image processing [41] is discrete wavelet transform. The discrete wavelet transform is a linear transformation that separates the image data into different frequency components. DWT is computed by applying a cascade of filters over an image followed by sub sampling of ↓2 [42] as shown in Figure 6.In this figure L and H denotes the low pass and high pass filters respectively, ↓2 denotes the sub sampling and *a1, d1*arethe wavelet coefficients.

On the other hand Gabor features are constructed from response of Gabor filters, which are defined in spatial domain as a Gaussian kernel function [43], which are modulated by a sinusoidal plane wave as shown in equation 6 as follows:

$$\psi(x,y) = e^{-x^2+y^2 \div 2\sigma^2 e^{j2\pi\mu_0 2x}} \quad (6)$$

$$x = x cos\theta + y sin\theta \quad (7)$$

$$y = -x sin\theta + y cos\theta \quad (8)$$

In the equation 7 and 8, θ is the rotational angle of the Gaussian major axis.

In medical image categorization, wavelets have been used in addition with Gabor filters [44] for classifying magnetic resonance tumor images. In this study two main features of frequency and space are captured. Frequency component has been used for measuring the texture of the tumor area and discrete wavelet transform has been used to remove the noise from high frequency components and each image is convolved with several Gabor wavelets with 8 orientations and two frequency ranges, high frequencies and low frequencies. As stated in [45], one of the major drawback of these Gaborwavelet based features is that it is computationally expensive in terms of feature extraction cost.

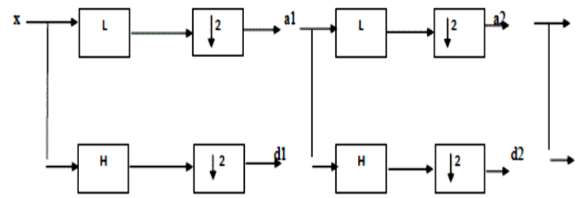


Figure 6. Illustration of Discrete wavelet transform adapted from [42]

2.2 Local Features

Local features are the image patterns that differs from its neighbourhood that is immediate to it [46]. The change occurs in the pixels with respect to its immediate neighbours because of change of an image property or several properties simultaneously. These features can be points, edges or image patches.

Local features are considered important because of many reasons. Firstly for instance edge detected in aerial images often correspond to roads, blob detection can be used to detect impurities in some inspection task, therefore these local features may have specific semantic interpretation in the limited context of a certain application. Secondly a set of local features can be used as an efficient image representation that allows to recognize objects in images without segmenting them [46].

In the context of medical image categorization the local features that have been used so far are Harris corner detector [47]. The authors used corner pixels for classification of normal and abnormal mammogram images. Another prominent local feature that has been used for medical image categorization is Scale invariant Feature Transform (SIFT) [48]. SIFT has been used in various studies for the classification of medical images asin [49, 50].

Local binary patterns (LBP) have been also used as local features for medical image categorization. In[51] authors used block based Local Binary Pattern for image description and in [52], authors stated that Local Binary Pattern describes only global texture information. So in order to capture the local information that is robust to occlusion and clutter, in this study authors divided the image into 4x4 non overlapping sub images and then each sub-image was further divided into non overlapping square image block. The Local Binary Pattern distribution has been calculated as a histogram having 59 bins over sub-images and final histogram was generated by combining the local histograms of sub-images. Even LBP is widely used as a texture descriptor, it produces long histograms.

To overcome this problem the authors proposed in [38] a new LBP descriptor known as CS-LBP but this descriptor has also some shortcomings, like these descriptors discard the low frequency information of a region, which is quite important in case of computer aided diagnosis and are the essential components to retain during image compression process because during image compression most of the times high frequency components are discarded and low frequency component are retained. So in order to have good efficient CAD systems and good compression these low frequency components need to be retained.

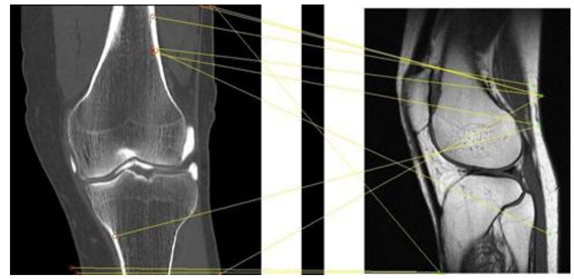
3.0 PERFORMANCE EVALUATION OF GLOBAL AND LOCAL FEATURE DESCRIPTORS

The performance of various global and local features have been evaluated on two data sets, one that has been acquired from the Department of Health and Human Services, Montgomery County, Maryland. The data set contains 138 X-rays,80 of them are normal and 58 X-rays are abnormal with manifestations of tuberculosis and second CLEF2012 data set [53]. This data set contains 18 image modalities. Among 18modalities we considered just 4 modalities with 938 images for evaluation of features. The modalities we used are X-ray, CT, MR and Ultrasound. Among 938 images, 70% of the images from each modality are selected for the training data and the remainder of 30% for the test data. In this study we follow the work of [54] for evaluation of performance of local image features i.e. repeatability and matching score. Where repeatability depicts the persistence of the features and matching score depicts the match-ability of features. The repeatability for a pair of images is computed as the ratio between the numbers of region to region correspondences. Regions in given pair of images are deemed to correspond, if the overlap error, defined as the error in the image area covered by the regions, is sufficiently small:

$$1-\frac{R_{\mu_a}\cap R_{(H^T\mu_b H)}}{(R_{\mu_a}\cup R_{H^T\mu_b H})} < \epsilon_0 , \qquad (9)$$

Where R_μ represents the elliptic region defined by $x^T\mu x = 1$. H is the homography relating the two images. The union of the regions is represented by $(R_{\mu_a} \cup R_{H^T\mu_b H})$ and the intersection is represented by $R_{\mu_a} \cap R_{(H^T\mu_b H)}$. The second criterion that we used for evaluating features is the matching score which is computed between the reference image and other image in a given image set. The matching score is computed as follows:

a) Find features in common area



$\{R_a : a \in A\}$ $\{R_b : b \in B\}$

b) Computing the descriptor distance:
$\{d_a : a \in A\}$ $\{d_b : b \in B\}$

$$d_{ab} = ||d_a - d_b||2. \qquad (10)$$

c) Computing the descriptor matches:

$$M_d^* = \min_{M\ bipartite} \sum_{(a,b)\in M} d_{ab}. \qquad (11)$$

The repeatability score and matching score for our dataset are shown in Figure 7 and Figure 8 . These comparative observations depicts that Harris laplace and SIFT obtains the highest repeatability score.

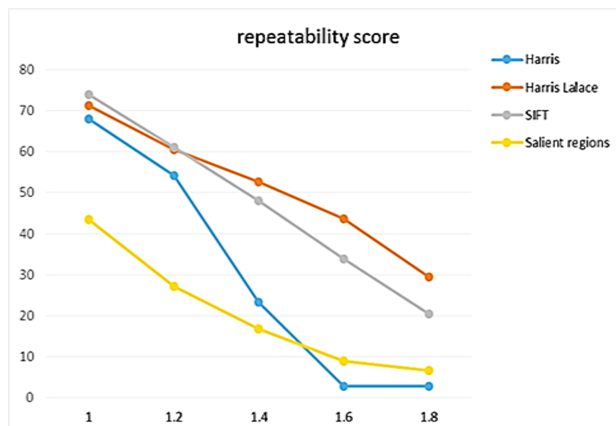


Figure 7. Repeatability score

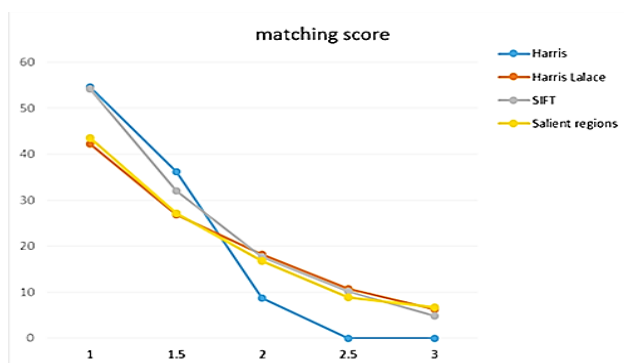


Figure 8. Matching score

For evaluation the images are subjected to five different transformations or distortions i.e. illumination, rotation and scale, blurring, and JPEG compression shown in Figure 9. The experiments have been evaluated on features on individual basis i.e. individual features have been taken into consideration for classification and the evaluation results are shown in the Table 1.

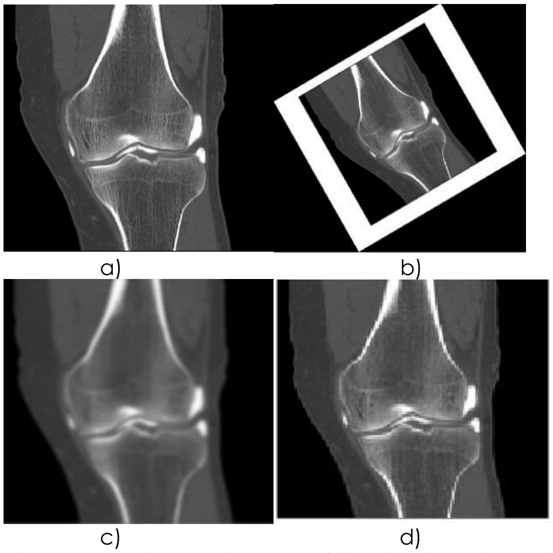


Figure 9 Transformed images a) illumination b) rotation and scale c) blurring and d) compression

Table 1 Evaluation results of local features for medical image categorization

Feature descriptor	Accuracy
Harris corner	68.4%
Harris Laplace	70.3%
SIFT	76.3
Salient regions	72.5

After evaluating local image feature, we evaluated the global features on the evaluation criteria of precision, recall and accuracy, which is shown in Table 2.

The above criteria's are computed as follows:

Precision = TP / TP + FP (12)

Recall = TP / TP + FN (13)

Accuracy = TP + TN / TP + TN + FP + FN (14)

Where TP is the true positive, FP is the false positive, TN is true negative and FN is false negative.

Table 2 Evaluation results of global features for medical image categorization

Feature Detector	Accuracy
Local feature patches histogram	75.1 %
Gabor Histogram	55.4 %
MPEG-7 Edge histogram descriptor	44.3 %
Tamura texture	66.8 %
GLCM	57.7 %
Global texture feature	32.5 %
32x32 image patches	73.6 %

After evaluating features individually we performed the fusion of various descriptors and it is quite evident from the results that the fusion of descriptors yields the best results as shown in Table 3.

Table 3 Comparative evaluation results of combined features for medical image categorization

Combined features	Accuracy
GLCM+ canny edge descriptor	70.45%
LBP+EHD +CED	71.2%
BOVW(SIFT + local image patches)	79.2%

The evaluation criteria used in evaluating fused descriptors is same as used for global features and the results of fused descriptors are shown in Figure 10.

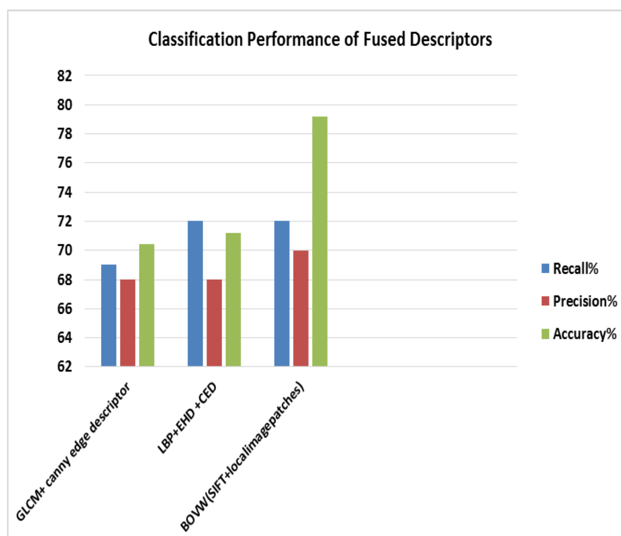


Figure 10 Classification Performance of Fused Descriptors

After evaluating the features mentioned in Table 1, Table 2 and Table 3, it is evident from the results that among global features and local features, local feature patches histogram and SIFT and Harris Laplace performs well in terms of classification accuracy. But when these features are fused together, the classification accuracy increase, which means that even if these images are distorted or transformed these fused features encodes the content information efficiently.

4.0 CONCLUSION

In this study we evaluated various features on the basis of their applicability either local or global for medical image categorization. The features have been evaluated in the context of medical image categorization on the basis of modalities. Four modalities are taken into consideration and different feature schemes have been applied on these images for categorization purpose. It is evident from the above results that fused image descriptors whether local or global with bag of visual words representation performs quite better than individual descriptors. Our future work will emphasize on automatic detection of various anatomical objects from these modalities to develop an automatic medical image categorization system.

References

[1] R. Mar´ee, P. Geurts, and L. Wehenkel. 2007. Random Subwindows And Extremely Randomized Trees For Image Classification In Cell Biology. *BMC Cell Biology*. 8: S2.

[2] M. O. Gueld, D. Keysers, T. Deselaers, M. Leisten, H. Schubert, H. Ney, et al. 2004. Comparison Of Global Features For Categorization Of Medical Images. *Medical Imaging 2004*. 211-222.

[3] M. Awedh. 2015. Medical Image Classification Using Multi—Vocabulary.

[4] A. T. Pinhas and H. K. Greenspan. 2004. A Continuous And Probabilistic Framework For Medical Image Representation And Categorization. Medical Imaging. 230-238.

[5] J. Goldberger, S. Gordon, and H. Greenspan. 2006. Unsupervised image-set clustering using an information theoretic framework. Image Processing, IEEE Transactions 15: 449-458.

[6] H. Greenspan and A. T. Pinhas. 2007. Medical Image Categorization And Retrieval For PACS Using The GMM-KL Framework. Information Technology in Biomedicine, IEEE Transactions. 11: 190-202.

[7] A. Mueen, R. Zainuddin, and M. S. Baba. 2008. Automatic Multilevel Medicalimage Annotation And Retrieval," *Journal Of Digital Imaging*. 21: 290-295.

[8] A. Mojsilovic and J. Gomes. 2002. Semantic Based Categorization, Browsing And Retrieval In Medical Image Databases. In Image Processing. Proceedings. *2002 International Conference*. III-145-III-148.

[9] G. Tian, H. Fu, and D. D. Feng. 2008. Automatic Medical Image Categorization And Annotation Using LBP and MPEG-7 Edge Histograms. *Information Technology and Applications in Biomedicine*. ITAB 2008. International Conference. 51-53.

[10] U. Avni, H. Greenspan, M. Sharon, E. Konen, and J. Goldberger. 2009. X-Ray Image Categorization And Retrieval Using Patch-Based Visualwords Representation. Biomedical Imaging: From Nano to Macro. ISBI'09. *IEEE International Symposium*. 350-353.

[11] S. H. Kim, J. H. Lee, B. Ko, and J. Y. Nam. 2010. X-Ray Image Classification Using Random Forests With Local Binary Patterns Machine Learning and Cybernetics (ICMLC), 2010 International Conference on, 2010, pp. 3190-3194.

[12] J. Wang, Y. Li, Y. Zhang, C. Wang, H. Xie, G. Chen, et al. 2011. Bag Of Features Based Medical Image Retrieval Via Multiple Assignment And Visual Words Weighting. IEEE *Transactions On Medical Imaging*. 30: 1996-2011.

[13] A. Mueen, M. S. Baha, and R. Zainuddin. 2007. Multilevel Feature Extraction and X-ray Image Classification. Journal of Applied Sciences, 1224-1229.

[14] F. Florea, H. M¨uller, A. Rogozan, A. Geissbuhler, and S. Darmoni. 2006. Medical Image Categorization With MedIC and MedGIFT. *Proc Med Inform Europe (MIE 2006)*. 3-11.

[15] O. A. Penatti, E. Valle, and R. d. S. Torres. 2012. Comparative Study Of Global Color And Texture Descriptors For Web Image Retrieval. *Journal of Visual Communication and Image Representation*. 23: 359-380.

[16] R. M. Haralick, K. Shanmugam, and I. H. Dinstein. 1973. Textural Features For Image Classification Systems. *Man and Cybernetics, IEEE Transactions*. 610-621.

[17] M. Roy. 2014. Classification of Ultrasonography Images of Human Fatty and Normal Livers using GLCM Textural Features.

[18] I. Kitanovski, K. Trojacanec, I. Dimitrovski, and S. Loskovska. 2012. Modality Classification Using Texture Features. *ICT Innovations 2011, ed: Springer*. 189-198.

[19] Y. Y. Gao, R. Fu, Y. Kuang, and Q. W. Lv. 2012. Classification and Retrieval of Abdominal Medical Image Based on Gray Level Concurrence Matrix. *Chinese Medical Equipment Journal*. 3: 006.

[20] M. R. Zare, A. Mueen, and W. C. Seng. 2014. Automatic Medical X-ray Image Classification using Annotation. Journal Of Digital Imaging. 27: 77-89.

[21] S. Jafarpour, Z. Sedghi, and M. C. Amirani. 2012. A Robust Brain MRI Classification with GLCM Features. *International Journal of Computer Applications*. 37.

[22] A. Shahbahrami, T. A. Pham, and K. Bertels. 2012. Parallel implementation of Gray Level Co-occurrence Matrices And Haralick Texture Features On Cell Architecture. *The Journal of Supercomputing*. 59: 1455-1477.

[23] D. Zhang, M. M. Islam, and G. Lu. 2012. A Review On Automatic Image Annotation Techniques. Pattern Recognition. 45: 346-362.

[24] B. Julesz. 1981. Textons, The Elements Of Texture Perception, And Their Interactions. *Nature*, 290: 91-97.

[25] T. Leung and J. Malik. 2001. Representing And Recognizing The Visual Appearance Of Materials Using Three-Dimensional Textons. *International Journal of Computer Vision*, 43: 29-44.

[26] M. Sadeghi, T. K. Lee, D. McLean, H. Lui, and M. S. Atkins. 2012. Global Pattern Analysis And Classification Of Dermoscopic Images Using Textons. *SPIE Medical Imaging*. 83144X-83144X-6.

[27] F. Riaz, M. Areia, F. B. Silva, M. Dinis-Ribeiro, P. P. Nunes, and M. Coimbra. 2011. Gabor Textons For Classification Of Gastroenterology Images. *Biomedical Imaging: From Nano to Macro, 2011 IEEE International Symposium*. 117-120.

[28] M. J. Gangeh, L. Sørensen, S. B. Shaker, M. S. Kamel, M. De Bruijne, and M. Loog. 2010. A Texton-Based Approach For The Classification Of Lung Parenchyma In CT Images. *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2010, ed: Springer*. 595-602.

[29] F. Riaz, F. B. Silva, M. D. Ribeiro, and M. T. Coimbra. 2012. Invariant Gabor Texture Descriptors For Classification Of Gastroenterology Images. *Biomedical Engineering, IEEE Transactions*. 59: 2893-2904.

[30] M. Varma and A. Zisserman. 2005. A Statistical Approach To Texture Classification From Single Images. *International Journal of Computer Vision*. 62: 61-81.

[31] Z. Guo, Z. Zhang, X. Li, Q. Li, and J. You. 2014. Texture Classification by Texton: Statistical versus Binary. *Plos One*. 9: e88073.

[32] T. Ojala, M. Pietikainen, and T. Maenpaa. 2002. Multiresolution Gray-Scale And Rotation Invariant Texture Classification With Local Binary Patterns. *Pattern Analysis and Machine Intelligence, IEEE Transactions*. 24: 971-987.

[33] M. Tuceryan and A. K. Jain1998. Texture analysis. *The Handbook Of Pattern Recognition And Computer Vision*. 2: 207-248.

[34] M. Pietik¨ainen, A. Hadid, G. Zhao, and T. Ahonen2011. Local Binary Patterns For Still Images. *Computer Vision Using Local Binary Patterns, ed: Springer.* 13-47.

[35] B. C. Ko, S. H. Kim, and J.-Y. Nam. 2011. X-ray Image Classification Using Random Forests With Local Wavelet-Based CS-Local Binary Patterns. *Journal Of Digital Imaging*. 24: 1141-1151.

[36] J. D. Deng. 2009. Improving Feature Extraction For Automatic Medical Image Categorization. Image and Vision Computing New Zealand, 2009. IVCNZ'09. *24th International Conference*. 379-384.

[37] F. Ghofrani, M. Helfroush, H. Danyali, and K. Karimi. 2012. Medical X-ray Image Classification Using Gabor-Based CS-Local Binary Patterns*. Int Conf Electron Biomed Eng Appl (ICEBEA).* 8.

[38] M. Heikkil¨a, M. Pietik¨ainen, and C. Schmid. 2009. Description Of Interest Regions With Local Binary Patterns. *Pattern Recognition.*42: 425-436.

[39] C. K. Chui. 1992. An Introduction To Wavelets. 1: *Academic Press*.

[40] M. Vetterli and C. Herley. 1992. Wavelets And Filter Banks: Theory And Design. *Signal Processing, IEEE Transactions.* 40: 2207-2232.

[41] S. Lahmiri and M. Boukadoum. 2013. Hybrid Discrete Wavelet Transform And Gabor Filter Banks Processing For Features Extraction From Biomedical Images. *Journal of Medical Engineering 2013*.

[42] M. Kociołek, A. Materka, M. Strzelecki, and P. Szczypi´nski. 2001. Discrete Wavelet Transform-Derived Features For Digital Image Texture Analysis*. International Conference on Signals and Electronic Systems, Ł´od´z- Poland*. 99-104.

[43] J. K. Kamarainen, V. Kyrki, and H. Kalviainen. 2006. Invariance Properties Of Gabor Filter-Based Features-Overview And Applications. *Image Processing, IEEE Transactions* 15: 1088-1099.

[44] Y.-h. Liu, M. Muftah, T. Das, L. Bai, K. Robson, and D. Auer. 2012. Classification of MR Tumor Images Based On Gabor Wavelet Analysis*. Journal of Medical and Biological Engineering*, 32: 22-28.

[45] I. Buciu and A. Gacsadi. 2009. Gabor Wavelet Based Features For Medical Image Analysis And Classification. Applied Sciences in Biomedical and Communication Technologies, 2009. ISABEL 2009. *2nd International Symposium.* 1-4.

[46] T. Tuytelaars and K. Mikolajczyk. 2008. Local Invariant Feature Detectors: A Survey. Foundations and Trends. *Computer Graphics and Vision*. 3: 177-280.

[47] H. I. Kim, S. Shin, W. Wang, and S. I. Jeon. 2013. SVM-Based Harris Corner Detection For Breast Mammogram Image Normal/Abnormal Classification. *Proceedings of the 2013 Research in Adaptive and Convergent Systems*. 187-191.

[48] D. G. Lowe. 1999. Object Recognition From Local Scale-Invariant Features. Computer Vision. *The Proceedings Of The Seventh IEEE International Conference*. 1150-1157.

[49] I. Dimitrovski, D. Kocev, I. Kitanovski, S. Loskovska, and S. Dˇzeroski. 2014. Improved Medical Image Modality Classification Using A Combination Of Visual And Textual Features. Computerized Medical Imaging and Graphics.

[50] S. Manivannan, R. Wang, and E. Trucco. 2014. Inter-Cluster Features For Medical Image Classification. *Medical Image Computing and Computer- Assisted Intervention–MICCAI 2014, ed: Springer*. 345-352.

[51] G. Tian, H. Fu, and D. D. Feng. 2008. Automatic Medical Image Categorization And Annotation Using LBP and MPEG-7 edge histograms. *Information Technology and Applications in Biomedicine, 2008*. ITAB 2008. International Conference. 51-53.

[52] S.-H. Kim, J.-H. Lee, B. Ko, and J.-Y. Nam. 2010. X-ray Image Classification Using Random Forests With Local Binary Patterns. in *Machine Learning and Cybernetics (ICMLC), 2010 International Conference*. 3190-3194.

[53] H. Miller, J. Kalpathy-Cramer, I. Eggel, S. Bedrick and E. K. Charles Jr. W. 2010. Overview Of The CLEF 2010 Medical Image Retrieval Track. *The Working Notes of CLEF*.

[54] K. Mikolajczyk and C. Schmid. 2005. A Performance Evaluation Of Local Descriptors. Pattern Analysis and Machine Intelligence, IEEE Transactions. 27: 1615-1630.