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EMPIRICAL EVALUATION OF LBP AND ITS DERIVATES FOR ABNORMALITY DETECTION IN MAMMOGRAM IMAGES

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Abstract

Digital image processing techniques are useful in abnormality detection in mammogram images. Recently, texture based image segmentation of mammogram images has become popular due to its better precision and accuracy. Local Binary Pattern has been a recently proposed texture descriptor which attracted the research community rigorously towards texture based analysis of digital images. Many texture descriptors have been developed as variants of Local Binary Pattern, because of its success. In this work, the performance of Local Binary Pattern descriptor and its variants namely Local Ternary pattern, Extended Local Ternary Pattern, Local Texture Pattern and Local Line Binary Pattern are evaluated for mammogram image segmentation using a supervised KNN algorithm. Performance metrics such as accuracy, error rate, sensitivity, specificity, Under Estimation Fraction and Over Estimation Fraction are used for comparison purpose. The results show that Local Binary Pattern outperforms other descriptors in terms of abnormality detection in mammogram images.

Keywords:

Mammogram Image Segmentation, Texture Segmentation, Local Binary Pattern, Local Ternary Pattern, Extended Local Ternary Pattern, Local Texture Pattern and Local Line Binary Pattern

1. INTRODUCTION

Texture is one of the most important image attributes to identify, characterize and distinguish regions with different patterns. Texture plays a vital role in satellite imaging, medical diagnosis, content based image retrieval and many other applications. Because of its success rate in image classification, recognition and segmentation, many texture descriptors have been proposed. The Local Binary Pattern descriptor proposed by Ojala et al. [21] is a simple and powerful method for analyzing textures. Medical Texture Local Binary Pattern was proposed by Nezamoddin N. Kachouie and Paul Fieguth [12] for TRUS prostate segmentation. In Completed Local Binary Pattern which was proposed by Zhenhua Guo et al. [28], centre pixel value is combined with other components sign and magnitude to extract the image local gray level and used for image classification. Bayesian Local Binary Pattern was proposed by Chu He et al. [5] in which local labelling procedure is modelled as a probability and optimization process. Local Directional Pattern (LDP) proposed by Taskeed Jabid et al. [22] is another variant of Local Binary Pattern and tested for face recognition. Some other variants of Local Binary Pattern like Derivate based Local Binary Pattern, Dominant Local Binary Pattern and Centre-Symmetric Local Binary Pattern have been proposed and their performance has been studied in various papers.

Advanced Local Binary Pattern was proposed by Shu Liao et al. [18]. Different approaches were presented for local and global description. Faisal Ahmed [7] proposed Compound LBP (CLBP) which exploits 2P bits to encode a local neighborhood of P neighbors and magnitude of centre and neighborhood pixels. Shu Liao proposed Elongated LBP (ELBP) [17]. This descriptor was evaluated by conducting facial expression experiments. For object detection, Non-Redundant Local Binary Pattern was proposed by Nguyen,Duc Thanh [13]. This descriptor was used to reflect the relative contrast between the background and foreground. Shen and Haihong [16] proposed Adaptive Local Binary Pattern. This method selects the most suitable patterns according to its tasks and experiments were conducted on 3D face databases. For video detection, Markov chain local binary pattern (MCLBP) was proposed by Wu and Weixin [25]. Partition Local Binary Pattern was proposed and tested by Wang et al. [23]. Yun-Hong Wang [3] proposed Statistical Local Binary Pattern for face recognition.

Breast cancer is the most common disease among women and second cause of cancer death. Mammography is used for breast cancer diagnosis. Manual interpretation of a mammogram is very difficult due to the following reasons: (i) the abnormal masses mix with normal tissues in the breast (ii) the size of the significant details is very small in most of the cases (iii) the mammogram image of different patients has different dynamics of intensity and (iv) the presence of weak contrast. Hence many image processing techniques have been developed for automated detection of abnormality.

Huo et al. [8] proposed a spiculation-sensitive pattern recognition technique to measure the degree of speculation of a lesion present in the mammogram image and classified as malignant or benign masses. They obtained higher classification accuracy comparing with a spiculation rating of an experienced radiologist. Sameti et al. [15] developed a segmentation algorithm using fuzzy sets to partition the mammogram image data. Starnatakis et al. [19] proposed a method to select a set of features such as mean, variance, standard deviation, skewness of intensity etc. to discriminate lesions and normal region. Kai Hu et al. [9] proposed adaptive thresholding segmentation method to detect calcification. Edge feature vectors were used by Zhang Shengjun [27] to obtain complete micro calcification in mammograms. Chengdan Pei et al. [4] applied marker controlled watershed method for breast region segmentation.

Texture property exists in mammogram image is identified as the main attribute for abnormality diagnosis. A set of three texture descriptors Sum Histogram, the Gray Level Co-Occurrence Matrix (GLCM) and Local Binary Pattern were used for breast tissue segmentation [2]. Kegelmeyer et al. [10] detected spiculated masses using local edge orientation and Laws texture features. In their algorithm, a statistical classifier is used to label each pixel with its probability of being located on an abnormality region. But it is not applicable for detecting non-spiculated masses. Comer et al. [6] and Li et al. [11] used Markov random fields to classify a mammogram image into different regions based on texture feature. Sahiner et al. [14] proposed a three stage segmentation method to detect spiculated and nonspiculated masses. The result indicated that combining texture features with morphological features was an effective approach for automated characterization of masses present in the mammogram.

The objective of this work is to analyze the role of Local Binary Pattern based texture descriptors in the process of distinguishing lesions and healthy tissues in mammogram images. The descriptors considered for this work are (i) Local Binary Pattern (LBP) proposed by Tan ojala et al. [21], (ii) Local Ternary Pattern (LTP^T) proposed by Tan and Triggs [26], (iii) Extended Local Ternary Pattern (ELTP) proposed by Wen-Hung Liao [24], (iv) Local Line Binary Pattern (LLBP) proposed by Amnart Petpon and Sanun Srisuk [1], (v) Local Texture Pattern (LTP^S) proposed by Suruliandi and Ramar [20]. LBP is a popular technique used for image characterization and classification. LBP was introduced as grayscale and rotation invariant operator. LBP has been widely applied in various applications due to its high discriminative power. LTP^T was introduced as three valued code descriptor with user specified threshold to provide noise resistance. The power of LTP^T was proved by face recognition experiments. ELTP, the modified version of LTP^T was proposed with difference in calculating the threshold value. In LLBP, instead of considering the circular neighborhood, the pixels in vertical and horizontal directions are considered. The line length along the directions plays a vital role in this method. LTP^S was introduced as a grayscale, rotational invariant descriptor. In LTP^S, the centre pixel is compared with neighborhood pixel and the result is thresholded to ternary value which results in more number of distinct patterns. In this paper, using LBP and its variant texture descriptors, abnormalities in mammogram images are detected through segmentation process. Supervised K-nearest neighbor (KNN) algorithm is employed for that purpose. The data from Mammography Image Analysis Society (MIAS) [29], an organization of UK research groups is used for the experiment and reported in this work.

The rest of the paper is organized as follows. Section 2 describes texture descriptors and segmentation methodology. Section 3 reports experimental results and Discussion. Section 4 concludes this work.

2. TEXTURE DESCRIPTORS

For mammogram image analysis, textural features are calculated in two phases. In the first phase, local description of a small region is computed and a pattern label is assigned to that region. In the second phase, global description about the entire region is computed using the occurrence frequency of local patterns and they are collected in a histogram with fixed number of bins. The histogram characterizes the global textural features of the mammogram image. In this paper, local description is computed using five texture descriptors LBP, LTP^T. ELTP, LLBP and LTP^S. The procedure for global description is common for all texture descriptors.

2.1 LOCAL BINARY PATTERN (LBP)

The LBP descriptor is a powerful and simple method used for texture analysis. The LBP texture descriptor is introduced as a complementary measure for local image contrast. This descriptor considers a local neighborhood of size 3 × 3 with centre pixel value as the threshold. The LBP code for a neighborhood is calculated by multiplying the thresholded values with weights given to the corresponding pixel positions and summing up the result as shown in Eq.(1).

$$LBP = \sum_{n=0}^{7} s(I_n - I_c)2^n \tag{1}$$

$$s(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases} \tag{2}$$

where, I_c is the gray level value of centre pixel and I_n is the gray level value of neighborhood pixels. Fig.1 shows an example for computing LBP value for a 3 × 3 region.

55	25	40
75	35	30
60	35	20

(a)

1	0	1
1		0
1	1	0

(b)

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(c)

$1\times2^0 + 0\times2^1 +$
$1\times2^2 + 0\times2^3 +$
$0\times2^4 + 1\times2^5 +$
$1\times2^6 + 1\times2^7 = 229$

(d)

Fig.1. LBP computation: (a). Sample 3 × 3 neighborhood, (b). Thresholded Value, (c). Weight assigned to pixel positions, (d). LBP sum value

In this method, the minimum LBP value will be 0 when all the thresholded value is 0 and maximum LBP value will be 255 when all the thresholded value is 1. Hence, a histogram of 256 bins is required to represent the occurrence frequency of local texture patterns over the entire image.

2.2 LOCAL TERNARY PATTERN (LTP^T)

The LTP^T descriptor is the extension of LBP in which the thresholded binary code is replaced by ternary code. A specific range of gray levels around the centre pixel I_c are quantized to 0, gray levels above this range are quantized to +1 and below this range are quantized to –1. The LTP^T is calculated similar to LBP where $s(x)$ is computed using the Eq.(3).

$$s(x) = \begin{cases} 1 & if\ I_n \geq I_c + t \\ 0 & if\ I_n - I_c < t \\ -1 & if\ I_n \leq I_c - t \end{cases} \tag{3}$$

where, I_c and I_n represent the intensity of centre pixel and neighborhood pixels respectively. 't' is a predefined threshold value which plays an important role to measure the closeness of neighborhood pixel with centre pixel of 3 × 3 local region. This method will generate the histogram with 6551 bins. In order to achieve the dimensionality reduction, the LTP^T is divided into positive and negative halves. The positive half is called as upper LBP pattern which considers +1 values and other values are replaced by zeros. The negative half is called as lower LBP pattern which considers –1 values and other values are replaced by zeros. The –1 values in lower LBP pattern are converted as +1 values. The two separate channels of LBP descriptors form two separate histograms which can be concatenated to characterize the global description of the entire image.

2.3 EXTENDED LOCAL TERNARY PATTERN (ELTP)

The process for converting a local region into ELTP representation is very similar to LBP where $s(x)$ is computed using Eq.(4).

$$s(x) = \begin{cases} 1 & if\ I_n - I_c > t \\ 0 & if\ |I_n - I_c| \le t \\ -1 & if\ I_n - I_c < -t \end{cases} \tag{4}$$

where, I_c is the intensity of the centre pixel, and I_n is the intensity of the neighboring pixel. Instead of defining a constant threshold t, the threshold value is calculated based on the local statistics of the region. Eq.(5) is used to compute t,

$$t = \{\alpha \times \sigma\} \tag{5}$$

where, σ is the standard deviation of the local patch, α is a scaling factor ranges from 0 to 1.

2.4 LOCAL LINE BINARY PATTERN (LLBP)

The basic idea of LLBP is similar to the LBP but the difference is that its neighborhood shape is a vertical and horizontal line with N pixel length. The lower weight values are assigned to adjacent pixels and higher weight values are distributed to pixels which are far away from centre pixel.

$$LLBP_h(N,c) = \sum_{n=1}^{c-1} s(h_n - h_c).2^{(c-n-1)} + \sum_{n=c+1}^{N} s(h_n - h_c).2^{(n-c+1)} \tag{6}$$

$$LLBP_v(N,c) = \sum_{n=1}^{c-1} s(v_n - v_c).2^{(c-n-1)} + \sum_{n=c+1}^{N} s(v_n - v_c).2^{(n-c+1)} \tag{7}$$

$$LLBP_m = \sqrt{LLBP_h^2 + LLBP_v^2} \tag{8}$$

The LLBP on horizontal direction, vertical direction, and its magnitude is defined in Eqs.(6-8).The computation of $s(x)$ value is similar to that of LBP method. N is the length of the line expressed in pixel, $c = \left[\frac{n}{2}\right]$ represents the position of the pixel on the horizontal line (h_c) and on the vertical line (v_c), h_n represents pixel along the horizontal line and v_n represents the pixel along the vertical line. An example for computing LLBP value is shown in Fig.2.

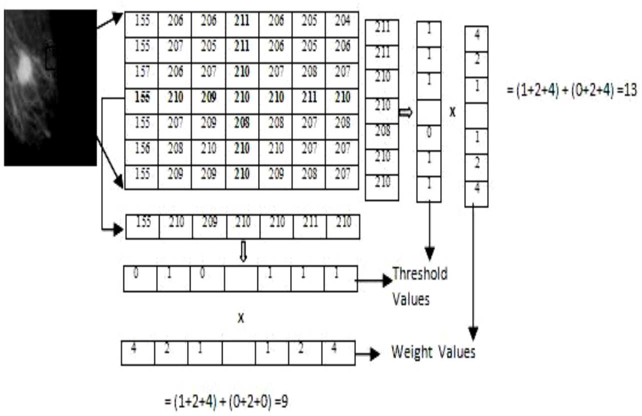

Fig.2. Calculation of LLBP values in vertical and horizontal direction for line length 7

2.5 LOCAL TEXTURE PATTERN (LTPS)

This descriptor is designed as a gray scale and a rotational invariant texture measure on a local neighborhood to operate on ternary pattern. In this method, the number of transitions or discontinuities in the circular form of patterns in a local region is detected. If the transitions follow a rhythmic pattern, the pattern is considered as uniform local texture pattern and a unique label is assigned to that pattern. All other non uniform patterns are assigned a single label. The uniform local texture patterns correspond to the micro textural primitive. The occurrence frequency of LTP is termed as 'LTP Spectrum' and the LTP spectrum is used as a global image descriptor. In LTP method, the pattern unit P, between I_c and its neighbor I_i (i = 1, 2,…,8) is defined as,

$$P(I_i, I_c) = \begin{cases} 0 & if\ I_i < (I_c - \Delta g) \\ 1 & if\ (I_c - \Delta g) \le I_i \le (I_c + \Delta g) \\ 9 & if\ I_i > (I_c + \Delta g) \end{cases} \quad i = 1,2,\ldots 8 \tag{9}$$

where, Δg is a small positive value which helps to detect the uniform patterns. The values 0,1 and 9 are selected to make the pattern labelling process easier. Fig.3 shows a 3 × 3 local region, corresponding P values and its pattern string. The pattern string can be formed from the pattern unit matrix by combining all the P values, starting from any position.

1	0	0
1		9
9	9	9

(a)

213	200	203
207	210	225
220	215	218

(b)

00999911

(c)

Fig.3. Computation of LTP^S (a). 3 × 3 local region, (b). Pattern unit matrix for Δg = 4, (c). Pattern String

To find whether a pattern is uniform or not, a uniformity measure U based on spatial transition (0/1, 1/0, 1/9, 9/1, 0/9, 9/0) is defined as,

$$U = s(P(I_8, I_c), P(I_1, I_c)) + \sum_{i=2}^{8} s(P(I_i, I_c), P(I_{i-1}, I_c)) \tag{10}$$

where, $$s(X,Y) = \begin{cases} 1 & if\ |X - Y| > 0 \\ 0 & otherwise \end{cases} \tag{11}$$

The patterns with at most U value of 3 are designated as 'Uniform Local Texture Patterns' (ULTP) and other patterns are designated as non uniform patterns. The rotational, gray scale, shift invariant LTP^T descriptor is defined as,

$$LTP^s = \begin{cases} \sum_{i-1}^{8} P(I_i, I_c) & if\ U \le 3 & for\ Uniform\ pattern \\ 73 & otherwise & for\ non\ Uniform\ pattern \end{cases} \tag{12}$$

The total number of LTP labels in the range 0-73 is 46. There are some holes in the pattern range. Hence, patterns are relabelled from 1 to 46 by using a lookup table.

3. MAMMOGRAM IMAGE SEGMENTATION

The aim of Mammogram segmentation is to partition the image into regions that are similar in texture. The distinct regions present in the mammogram images are normal breast region, background film region and abnormal region. The pre processing involves enhancing the image and removing the irrelevant and unwanted area in the background of the mammogram image. There are various types of noises present in mammogram images. Hence, high intensity noises such as labels, scanning artifacts, tape artifacts and other shadows presenting in the images are replaced with black pixels. The micro calcifications in a sufficiently dense mass may not be readily visible because of low contrast. In order to increase the contrast, Contrast limited adaptive histogram equalization (CLAHE) method is used in this work. The segmentation procedure is outlined in the Fig.4.

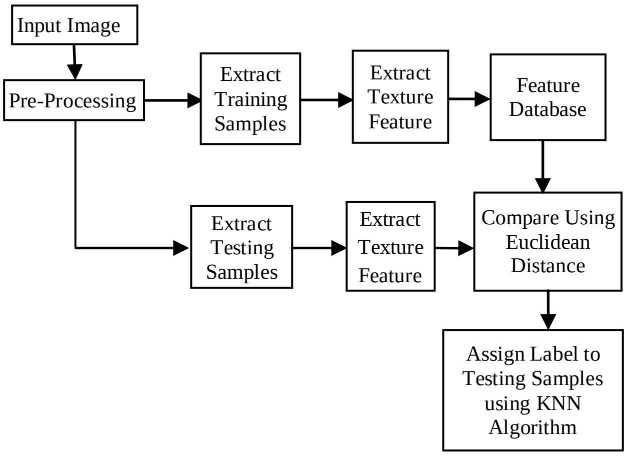

Fig.4. Segmentation procedure

KNN classifier is applied for classifying the pixel. Training samples are taken from the pre-processed input image and texture feature histogram is calculated for each training sample. They are stored along with their classes in the feature database as training set. To classify every pixel in the input image, a $n \times n$ block centered at that pixel is considered as testing sample. The texture feature histogram for every testing block is compared with training data available in feature database and assigned a class label of closer feature set. The Euclidean distance measure is used for comparison. The lower the value means higher the possibilities that the two image textures are from same primitives.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1 EXPERIMENTAL SETUP

The mammogram images used in the experiments are taken from the Mammographic Image Analysis Society (MIAS). Three classes present in the mammogram images are background region, normal tissue region and abnormal region. The background region represents the mammography film. Three types of samples are taken from various images (mdb004, mdb008, mdb009, mdb141, mdb271, mdb023). One sample is taken from each class of regions and used for training. Samples for normal tissue region are taken from mdb004, mdb008 and mdb009. Samples for background region are taken from mdb004, mdb141 and mdb271. Samples for abnormal region are extracted from mdb141, mdb271 and mdb023. We consider three different cases of mammogram images to test the efficiency of texture descriptors. They are (i) Normal mammogram (mdb272) which is comprised of Fatty-Fibro Glandular tissue without any abnormalities (ii) Mammogram with abnormal region (mdb028). This image comprises predominantly fatty tissues. (iii) Fatty-Fibro Glandular Tissue with abnormalities (mdb265). This image comprised predominantly Fatty Fibro- Glandular tissues with abnormalities. Comparing with mdb028, the abnormality volume is higher in mdb265.

Based on the experimental results, the threshold values and other parameters used in various descriptors are selected. The centre pixel is considered as the threshold value for LBP and LLBP descriptors. In LTP^T descriptor, user specified threshold‘t’ is used. In our experiment, the threshold value is set to 5. In ELTP descriptor, the threshold parameter is‘t’ and its value is derived from local statistics of the pattern. The value for α is set to 0.3. In LTPS descriptor, Δg is set to 4. KNN algorithm with Euclidean distance measure is used for segmentation where k is set to 3. The testing block centred on each pixel is set to 32×32 in all experiments. Experimentally the best window size is identified as 32×32. In this work, ground truth (GT) images are generated based on the x, y coordinate and radius values provided by MIAS to compare with output images obtained by applying various texture descriptors. Fig.5 shows the input images (mdb272, mdb028 and mdb265) used in our experiments, pre processed images and segmented output using LBP descriptor.

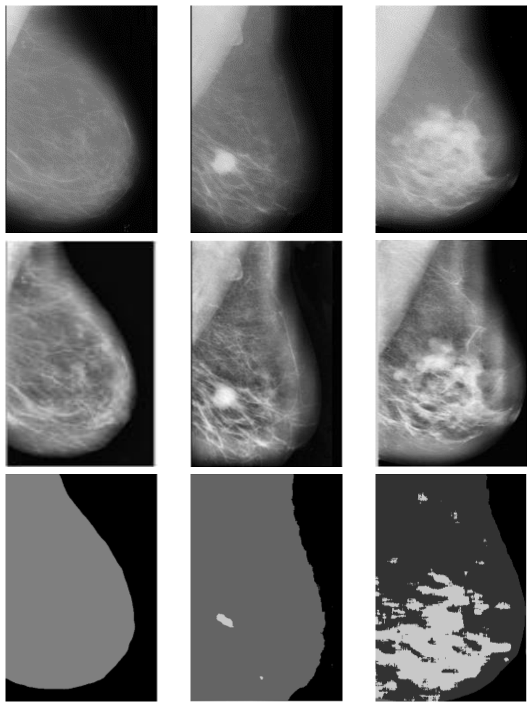

Fig.5. Input images (mdb272, mdb028 and mdb265), Pre-processed Images and segmented output using LBP descriptor

4.2 ACCURACY ESTIMATION

The quantitative measures such as Accuracy, Error Rate, Sensitivity, Specificity, Under Estimation Fraction and Over Estimation Fraction are derived to describe the accuracy of the texture models for mammogram image segmentation. Random pixels are selected from Normal Breast Region, Background Region and Abnormal Breast Region. The pixels extracted by the segmentation process using texture models, which matches Ground Truth image (GT) is denoted as true positive (TP). Pixels shown in the GT but wrongly classified are defined as true negative (TN). Pixels not shown in the GT and not identified in the segmented region are defined as false negative (FN) classifications. The pixels not in the GT, but in the mask are defined as false positive (FP) pixels. By using these parameters, the measures are computed using the formula as shown in the Table.1.

Table.1. Formula for Common Measures

Accuracy	(TN+TP)/(TN+TP+FP+FN)
Error rate	(FP+FN)/(FP+FN+TP+TN)
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)
Under estimation fraction (UEF)	FN /(TN+FN)
Over estimation fraction (OEF)	FP/ (TN+FN)

Table.2. Values of performance metrics for various texture descriptors using mdb272 image

Texture Descriptor	Region	Accuracy	Error Rate	Sensitivity	Specificity	UEF	OEF
LBP	NR	0.98	0.02	0.96	1.00	0.03	0.00
	BR	0.98	0.02	1.00	0.96	0.00	0.04
	AVG	**0.98**	**0.02**	**0.98**	**0.98**	**0.01**	**0.02**
LTP^T	NR	0.84	0.16	0.68	1.00	0.24	0.00
	BR	0.84	0.16	1.00	0.68	0.00	0.47
	AVG	**0.84**	**0.16**	**0.84**	**0.84**	**0.12**	**0.23**
ELTP	NR	0.98	0.02	1.00	0.96	0.00	0.04
	BR	0.98	0.02	0.96	1.00	0.03	0.00
	AVG	**0.98**	**0.02**	**0.98**	**0.98**	**0.01**	**0.02**
LLBP	NR	0.74	0.26	1.00	0.48	0.00	1.08
	BR	0.74	0.26	0.48	1.00	0.34	0.00
	AVG	**0.74**	**0.26**	**0.74**	**0.74**	**0.17**	**0.54**
LTP^S	NR	0.98	0.02	1.00	0.96	0.00	0.04
	BR	0.98	0.02	0.96	1.00	0.03	0.00
	AVG	**0.98**	**0.02**	**0.98**	**0.98**	**0.01**	**0.02**

Table.3. Values of performance metrics for various texture descriptors using mdb028 image

Texture Descriptor	Region	Accuracy	Error Rate	Sensitivity	Specificity	UEF	OEF
LBP	NR	0.90	0.09	0.95	0.85	0.06	0.15
	BR	0.94	0.05	0.86	0.98	0.05	0.01
	AR	0.96	0.03	0.83	0.98	0.03	0.01
	AVG	**0.93**	**0.06**	**0.90**	**0.95**	**0.05**	**0.05**
LTP^T	NR	0.72	0.27	0.50	1.00	0.00	0.37
	BR	0.76	0.23	1.00	0.66	0.50	0.00
	AR	0.90	0.09	0.83	0.92	0.08	0.03
	AVG	**0.80**	**0.19**	**0.70**	**0.85**	**0.19**	**0.13**
ELTP	NR	0.89	0.10	0.90	0.88	0.11	0.11
	BR	0.94	0.05	0.95	0.94	0.01	0.05
	AR	0.94	0.05	0.75	0.98	0.04	0.01
	AVG	**0.93**	**0.06**	**0.89**	**0.94**	**0.05**	**0.05**
LLBP	NR	0.71	0.28	0.64	0.80	0.34	0.16
	BR	0.88	0.11	1.00	0.83	0.00	0.20
	AR	0.83	0.16	0.41	0.90	0.10	0.09
	AVG	**0.80**	**0.19**	**0.71**	**0.85**	**0.14**	**0.14**
LTP^S	NR	0.63	0.36	0.35	0.97	0.01	0.44
	BR	0.66	0.33	0.00	0.94	0.04	0.31
	AR	0.37	0.62	0.91	0.27	2.47	0.05
	AVG	**0.55**	**0.44**	**0.33**	**0.66**	**0.33**	**0.33**

Table.4. Values of performance metrics for various texture descriptors using mdb265 image

Texture Descriptor	Region	Accuracy	Error Rate	Sensitivity	Specificity	UEF	OEF
LBP	NR	0.96	0.04	0.90	1.00	0.06	0.00
	BR	0.84	0.16	0.85	0.83	0.10	0.17
	AR	0.84	0.16	0.60	0.90	0.10	0.10
	AVG	**0.88**	**0.12**	**0.82**	**0.91**	**0.09**	**0.09**
LTP^T	NR	0.68	0.32	0.90	0.53	0.11	0.77
	BR	0.74	0.26	0.45	0.93	0.28	0.05
	AR	0.90	0.10	0.60	0.97	0.09	0.02
	AVG	**0.77**	**0.22**	**0.66**	**0.83**	**0.17**	**0.17**
ELTP	NR	0.48	0.52	0.05	0.76	0.45	0.16
	BR	0.70	0.30	0.55	0.80	0.27	0.18
	AR	0.50	0.50	0.50	0.50	0.20	0.80
	AVG	**0.56**	**0.44**	**0.34**	**0.67**	**0.33**	**0.33**
LLBP	NR	0.42	0.58	0.05	0.66	0.48	0.25
	BR	0.24	0.76	0.00	0.40	0.62	0.56
	AR	0.78	0.22	1.00	0.72	0.00	0.37
	AVG	**0.48**	**0.52**	**0.22**	**0.61**	**0.39**	**0.39**
LTP^S	NR	0.06	0.94	0.10	0.03	0.94	1.52
	BR	0.24	0.76	0.00	0.40	0.62	0.56
	AR	0.82	0.18	0.10	1.00	0.18	0.00
	AVG	**0.37**	**0.62**	**0.06**	**0.53**	**0.47**	**0.47**

The values obtained for normal image (mdb272), abnormal images (mdb028 and mdb265) are shown in the Table.2, Table.3 and Table.4 respectively. NR, BR, AR represents a normal breast region, background region, abnormal breast region respectively. In Table.2, AR is not available, since the image is a normal image.

4.3 PERFORMANCE EVALUATION AND DISCUSSION

The overall performance for various texture descriptors is presented in the following Fig.6.

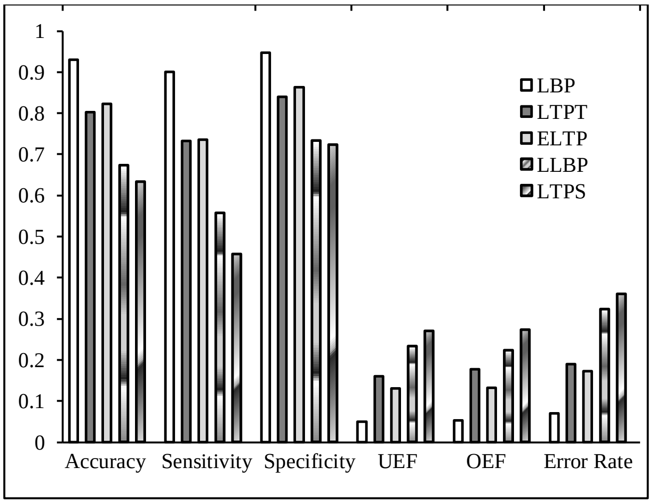

Fig.6. Overall Performance of Various Texture Descriptors

The challenging task in abnormality detection in mammogram images is identifying the correct feature for segmentation. The texture feature is the right choice for mammogram image segmentation. The overall average performance for various texture descriptors is computed and presented in the Fig.6. For a descriptor to be the best, it is expected that accuracy, sensitivity, selectivity values should be maximum and error rate, OEF and UEF should be minimum. From the overall results, it is found that LBP descriptor provides better accuracy while comparing with other descriptors. The overall accuracy rate for LBP is 93%. The overall sensitivity rate (90%) and selectivity rate (94.7%) are also high for LBP descriptors. Based on the values given in the Fig.6, it is observed that the performance of LBP is followed by ELTP, LTP^T, LLBP and LTP^S descriptors. In mdb028 image, the volume of abnormal region is small and clearly shown. But in image265, the abnormal region with mixed with fatty tissues and other normal regions. It reduces the performance of all descriptors.

5. CONCLUSION

Texture analysis is one of the promising areas in detecting abnormality in mammogram images, since texture structure place the predominant role in representing the regions of mammogram images. In this paper, we have analyzed the performance of five different texture descriptors LBP, LTP^T, ELTP, LLBP and LTP^S in detecting abnormality in mammogram images. For experimental analysis, three images from the mini MIAS database is considered. KNN based image segmentation is implemented. The overall performance of all texture descriptors are measured using the metrics accuracy, error rate, sensitivity, selectivity, UEF and OEF. The experimental results demonstrate that texture feature is the right choice for mammogram image analysis and LBP performs better comparing with other LBP variants for mammogram image segmentation. In LBP, the centre pixel is compared with neighbourhood pixels sign is used to represent the difference. While describing the relation between the centre pixel and neighbourhood pixel, fuzziness or uncertainty is not taken into account. Hence, a fuzzy based local texture description of the above methods may also be taken. The fuzzy based models for LBP and LTP^S have been already developed. The exploration of fuzziness for other models is still open problem. Most of the classification methods works with texture feature extraction techniques are conventional like KNN algorithms. Neural network approach can be combined with texture feature to improve the classification accuracy. Further research is going on to find an effective feature set for mammogram image segmentation to detect abnormality in challenging mammogram images. The abnormality shapes are also under consideration for mammogram image analysis.

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