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COMPLETED LBP BASED TEXTURE ANALYSIS IN MAMMOGRAM

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Abstract-Breast cancer is a frequent cancer diseases and it is the leading cause of cancer death among women in most of the occidental countries. Mammography is one among the key tool to identify the location and size of tumor in the breast. Texture analysis plays an important role in detecting the disease patterns in mammogram and to identify the masses as normal or abnormal. The local binary pattern descriptor provides an illumination invariant and rotation invariant approach for the texture analysis. However the LBP consider only the sign parameters. So it may lose some textural information. This can be overcome by considering the sign, magnitude and centre gray level values. Here a new approach for the Texture analysis in mammogram using completed LBP is presented. Although different methods have been proposed most of them suffer from large number of false positives. In contrast this method uses textural properties to reduce the number of false positives.

Keywords*: Breast cancer, Mammogram, Texture analysis, Texture feature extraction, CLBP*

I. INTRODUCTION

Breast cancer is a major cause of cancer related death among women, aged between 15-54 in most of the occidental countries [1]. It is estimated that between one in eight and one in twelve women will develop breast cancer during their lifetime [2].Mammography is used for the early prognosis of breast cancer. Mammography is a reliable technique for the X-Ray examination of breast. It is a very safe procedure which make use of low doses of radiation to produce high quality X-Rays. This allows the visualization of breast tissue and can identify the size and location of tumor cells [3]. Although the breast cancer has very high incidence the causes of breast cancer is still unknown.

Texture feature extraction plays an important role in detecting the disease pattern in breast from the mammogram image. Texture is a commonly used feature which can be used for the analysis and interpretation of images. Texture contains the information about tonal variation. Texture is one of the important characteristics that can be used for identifying the region of interest and classifying those regions [4]. A large number of techniques have been introduced for the texture feature extraction. Texture analysis involves the procedure to identify the spatial variation within the image by extracting information.

II. RELATED WORKS

A Mohd. Khuzil, R Besar, Zaki, NN Ahmad developed an automated system for the analysis of digital mammograms [5]. Image processing techniques will be applied to enhance images which is then followed by segmentation of the region of interest and texture feature extraction from a particular ROI. The extracted textural features are used to classify the ROI as mass or non-mass.Jia-Lin Chen and Amlan Kundu developed a rotation and gray scale transform invariant texture recognition scheme using the combination of quadrature mirror filter (QMF) bank and hidden Markov model [6]. The QMF is used to decompose the image into sequence of sub bands. This sequence of sub bands can be then modeled by as HMM.

T. Ojala, M. Pietikainen, and T. T. Maenpaa, proposed Local binary pattern approach rotation invariant texture classification [7]. The LBP is an efficient operator which has achieved accurate texture classification. In LBP approach , it compares the neighborhood of each pixel with the center pixel value and the center pixel value will be taken as threshold value(1 is assigned to higher or equal gray levels and 0 to the lower ones).

S. Liao, Max W. K. Law, and Albert C. S. Chung proposed a novel approach to extract image features for texture classification [8]. It comprises of two sets of features: dominant local binary patterns (DLBP) in a texture image and the supplementary features which can be extracted by using the circularly symmetric Gabor filter responses. The DLBP can be used to extract the descriptive textural information while the Gabor filter response for providing the global textural information to DLBP.

Marko Heikkila, Matti Pietikainen, Cordelia Schmid. introduced a new texture feature called center-symmetric local binary pattern (CS-LBP) which is an advanced version of the local binary pattern (LBP) operator [9]. In CS-LBP it compares the centre symmetric pairs of pixel rather than comparing each pixel with the center pixel. Here the strengths of the

SIFT and LBP are combined. The resulting descriptor is called the CS-LBP descriptor. Texture feature extraction methods can be classified into four categories: structural, statistical, model and transform-based [10]. The structural approaches texture is analyzed as consisting of many textural elements called Texels which are arranged according to particular placement rules [11]. In statistical approach, it involves the computation of local feature at each point in the image which can further be used for analyzing the spatial distribution of gray level values.

III. METHODOLOGY

Textural features are widely used for discriminating texture classes in mammography which can further be used for the breast cancer detection. In mammography texture and its gray level spatial information plays an important role in detecting the masses. The Completed Local Binary Pattern method combines the characteristics of structural and statistical texture analysis, describing the texture with its micro-primitives and their statistical placement rules.

A. Image Enhancement by Morphological operators.
Mammogram image has been taken from MIAS database. Most of the mammogram images are difficult to interpret. This can be overcome by performing Image Enhancement. Image enhancement is a pre-processing stage which will make the image more suitable for further analysis. This involves image sharpening, increasing the contrast of the image, and denoising. Here the image enhancement is performed with the aid of morphological operators. Morphological operations performed are Dilation, Erosion, Top-Hat transform, Bottom-Hat transform. The Top-Hat transform is used to obtain detailed information of an image and after applying the Top–Hat transform the brightest part of the image become highlighted. The Bottom Hat transform highlight the black spot in a white background. The contrast high image can be obtained by subtracting the Bottom-Hat image from original and Top-Hat image. Then the complement of contrast high image is taken to enhance the resultant image. This is followed by Region of Interest selection from the enhanced image.

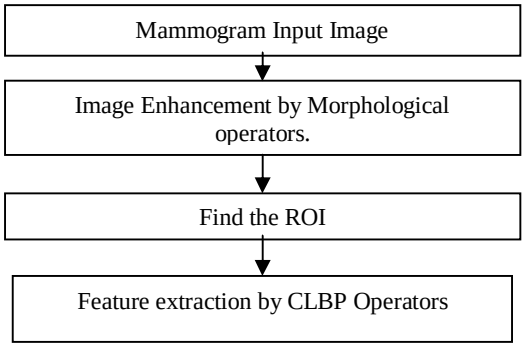


Figure 1: Block diagram for Feature Extraction using CLBP

B. Texture Feature Extraction by CLBP Operator
In Completed Local Binary Pattern, a local region can be represented as its centre gray level and the local difference sign magnitude transform (LDSMT). The LDSMT which in turns decomposed into sign and magnitude components. The Completed LBP includes CLBP_C, CLBP_S, CLBP_M Operators. CLBP_C is used to code the centre gray level after global thresholding. CLBP_S and CLBP_M are used to code the sign and magnitude components respectively. Then the three code maps are combined to form CLBP feature map and the CLBP histogram.

The CLBP_S operator can be given by

$$CLBP_{S_{P,R}} = \sum_{p-0}^{P-1} S(g_p - g_c)2^P \quad (1)$$

Where $S(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$, and g_c is the gray value of the center pixel, g_p is the value of its neighbors, P is the number of involved neighbors.

The CLBP_M operator can be defined by

$$CLBP_{M_{P,R}} = \sum_{p=0}^{P-1} t(m_p, c)2^P \quad (2)$$

Where $t(x,c) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$, and c is the threshold value, here it is set as m_p which is the mean value for the whole image. The CLBP_C can be defined by

$$CLBP_{C_{P,R}} = t(g_c, C_l) \quad (3)$$

C_l is the threshold here it is set as average gray level of the image [12].

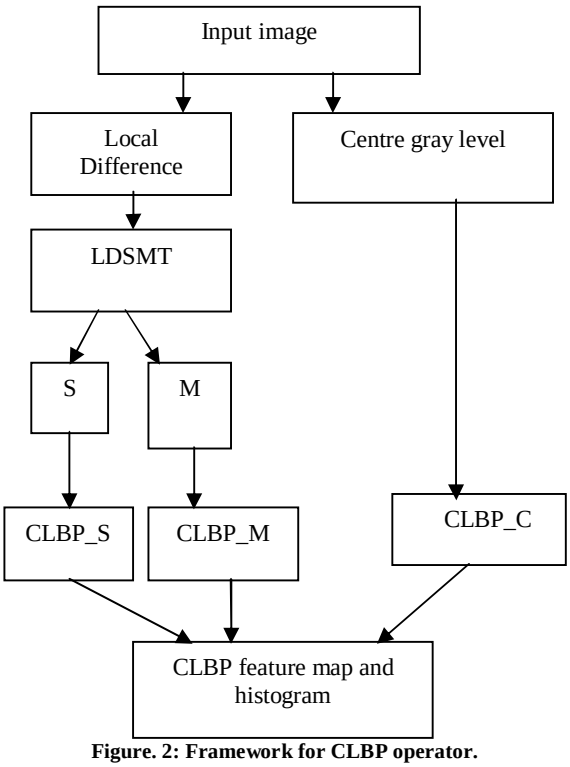


Figure. 2: Framework for CLBP operator.

IV. RESULTS AND DISCUSSIONS.

Here the texture feature extraction using the Completed Local Binary Pattern is performed in the mammogram image taken from MIAS database. Then the Image enhancement technique using morphological operators has to be done because the mammogram images are difficult to interpret. So that ROI can be selected more precisely from the enhanced image.

Following are the steps involved in the image enhancement.
1. Read the input image and perform the basic morphological operations like dilation and erosion. 2. Apply Top-hat transform in order to highlight the brightest part of the image.
3. Apply Bottom-hat transform to emphasize the gaps between the objects of the input image.
4. The contrast high image can be obtained by subtracting the Bottom Hat Image from original and Top Hat Image.
5. Enhanced Image is obtained by complementing contrast high image.

This is followed by region of interest from the enhanced image. Then the feature extraction can be done for that particular ROI using CLBP Operator. The results are shown in figure 3-9.

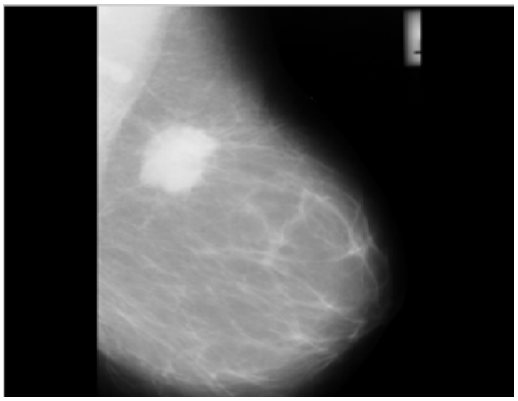


Figure 3: Original cancerous image.

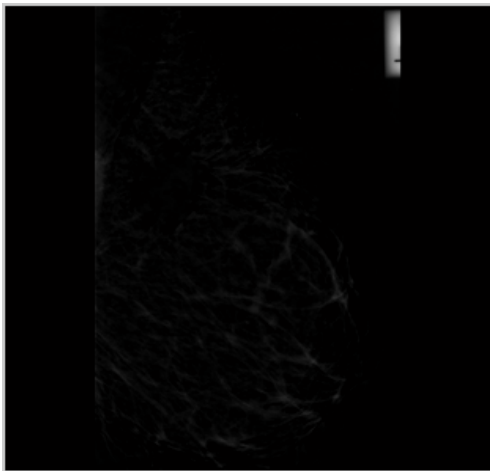


Figure 4: Top –Hat Image

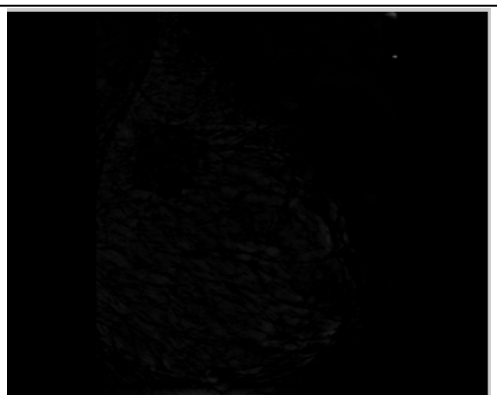


Figure 5: Bottom –Hat Image

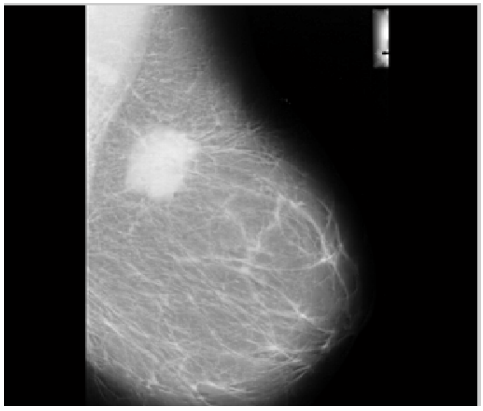


Figure 6: Contrast High Image

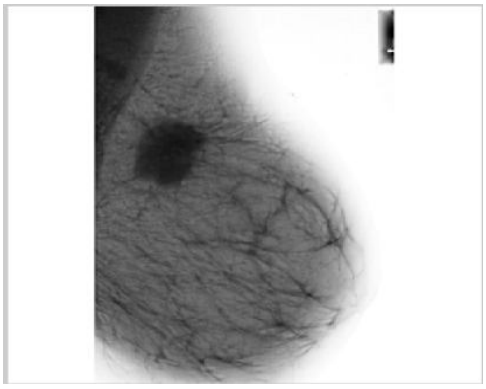
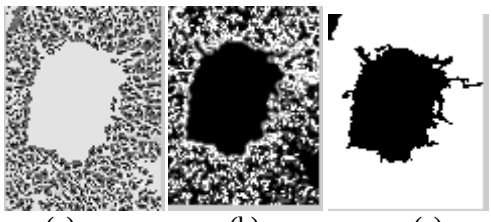


Figure 7: Enhanced Image



(a) (b) (c)

Figure 8: (a).CLBP_S,(b).CLBP_M,(c).CLBP_C Images

The figure 9 shows the CLBP histogram for the selected ROI. The CLBP histogram shows the occurrence of pixel at different intensity level of image. As the number of bins in the histogram increases the feature information and entropy will become increases [13].Thus less sparse the number of bins in the histogram means it contain more textural

feature information. Here the image is in gray level. So the histogram value will change from 0 to 255. So there are256 bins in the histogram.

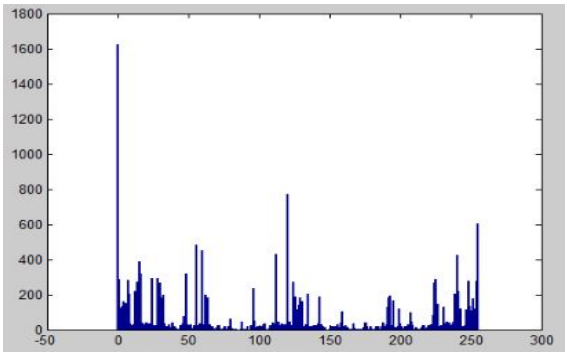


Figure 9: CLBP Histogram

V. CONCLUSION AND FUTURE WORKS

The completed Local Binary Pattern is an effective tool for extracting large number of texture features so it plays an important role in false positive reduction at different ROI image sizes. The most important property of the CLBP operator in real world applications is its tolerance against illumination changes and computational simplicity. This work will be extended further for the classification of mammograms as normal or abnormal based on the texture features. There are so many techniques available for the classification such as artificial neural network, SVM. In that SVM is the better tool for discriminating the real masses and non real masses.

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