Complex Texture Features for Glaucomatous Image classification System using Fundus Images

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Abstract— *In this paper, an efficient approach for glaucomatous image classification system using fundus images is proposed. The main aim of this study is to detect glaucoma accurately in order to reduce the visual loss and impairment. The proposed system uses two important texture features; Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) in an efficient manner. These texture features are extracted not only from the fundus image but also the optical density image obtained from the fundus image. Before extracting features, region of interest is obtained from the Green channel of the fundus image as it has high contrast than other two colour components. Support Vector Machine (SVM) classifier is used for the classification of fundus image into normal or abnormal based on the extracted features. Results show that the proposed system provides promising results with 100% sensitivity and 99% specificity.*

Keywords— *Glaucoma, fundus image, optical density, GLCM, LBP, SVM classifier.*

I. INTRODUCTION

Blindness is the lack of visual perception due to neurological or physiological factors. The major causes of blindness are glaucoma, cataract, age-related macular degeneration, and corneal opacity. Among them, glaucoma is one of the irreversible blindness. An extensive literature survey has been done and some of them are outlined here. An approach to detect glaucoma using Cup to Disc Ratio (CDR) and ISNT rule is discussed in [1]. At first, Region Of Interest (ROI) is extracted and CDR is measured by segmenting optic disc and cup region. The blood vessels in the optic disc area are tracked using hessian based vessel enhancement technique to compute ISNT ratio. Then, SVM classifier is used for classification.

Deep convolutional neural network based glaucoma detection is discussed in [2]. It consists of six layers; four convolutional layers and two fully connected layers. Overlapping-pooling layers and response-normalization layers are adopted to reduce the overfitting problem. A review of various automated techniques for glaucoma diagnosis is discussed in [3] including active contour model, super pixel clustering, vessel bend, simple linear iterative clustering, and pallor information.

Four different features such as CDR, horizontal to vertical CDR, cup to disc area ratio and rim to disc area ratio are used for glaucoma diagnosis in [4]. Optic disc segmentation is done with geodesic active contour model and cup segmentation is based on pallor appearance in the optic disc region. Finally, naïve Bayes, K- nearest neighbour and SVM classifiers are used for classification. Image based features along with segmentation based features are used for glaucoma diagnosis in [5]. Illumination correction is done before extracting features. Optic disc region is detected using Hough transform and template matching is used for ROI extraction. Finally, SVM classifier is adopted for classification.

Texture and higher order spectral features are employed in [6] for glaucoma detection. Histogram equalization is applied to enhance the contrast before feature extraction. Texture features are extracted using GLCM. Random forest, SVM, and sequential minimal optimization algorithms are used for classification. Optic disc segmentation using morphological operations and hybrid level-set methodology for glaucoma diagnosis is described in [7]. Optic disc is segmented with the help of SVM classifier to detect blood vessels and bending points on the circum linear vessels.

Glaucoma is detected by using cup to-disc area ratio and vertical cup-to-disc ratio. The segmentation of optic disc is done by LBP in [8]. LBP are obtained from the red channel of the fundus image after improve the quality of the image by histogram equalization. Finally, the artifacts are removed by morphological operations and filtering the LBP output. CDR and ISNT features are used for the diagnosis of glaucoma in [9]. It uses various morphological operations for optic disc and cup segmentation and also for blood vessel extraction.

The assessment of glaucoma using optic disc and optic cup segmentation from monocular color retinal images is presented in [10]. In multidimensional feature space, the information of local image is integrated around each point of interest for OD segmentation. For cup segmentation, the region of support concept is used to detect vessel bends. Then, the right scale is

selected automatically for examination. An approach to detect multiple applicant regions of optic disc from fundus image using optic disc localization and segmentation technique is presented [11]. The hybrid features are extracted based on blood vessels and intensity to every applicant region which are finally fed to the classifier stage using SVM classifier.

The diagnosis of glaucoma using empirical wavelet transform and correntropy features are extracted using fundus image is described in [12]. The image is decomposed using empirical wavelet transform for obtaining different frequency bands. Then, correntropy features are extracted and are given as input to the classifier. Least squares SVM classifier is employed for classification purpose. Haralick texture features based glaucoma detection using digital fundus image is presented in [13]. Thirteen Haralick features are extracted using the computed GLCM. Finally, these extracted features are fed to the K-Nearest Neighbour classifier.

To detect glaucoma using moment and wavelet features to prevent vision loss is discussed in [14]. Three wavelets; Daubechies, symlets and Bi-orthogonal are used to extract features. Fifteen moment features are also computed from the combination of sub-bands. The extracted features are applied to classifier such as SVM and KNN for classification. An approach for detection of glaucoma using GLCM feature and logistic regression classifier from ocular thermal images is discussed in [15]. Using linear transformation, the images are transformed from RGB to YIQ image. Four features are extracted in GLCM technique such as Energy, Homogeneity, contrast, and correlation. Then they are used to train a logistic regression classifier for diagnose glaucoma.

In this paper, an efficient glaucomatous image classification system based on complex statistical features is proposed. The rest of the paper is organized as follows: Section 2 gives the methods and materials used in this study. Section 3 illustrates the results obtained from the proposed system and conclusion is given in the last section.

II.   SYSTEM DESIGN

The success of any pattern recognition system relies on the appropriate design of two computational modules: feature extraction and classification. These two modules are discussed in the following subsections in detail.

2.1   Feature extraction

Figure 1 depicts the various computational blocks of the proposed feature extraction module. The proposed system uses GLCM and LBP technique as feature extraction technique. The proposed features are extracted for the Region Of Interest (ROI) only. ROI is selected using intensity value of pixels, whereas an approximate region of size 360x360 pixels is cropped automatically around the identified brightest intensity pixels. Commonly, the optic disc has bright characteristics features and high contrast in the Green channel of the retinal fundus image. As green channel provides better contrast than the other two planes, it is only taken into account for ROI identification and the proposed features are extracted for the same.
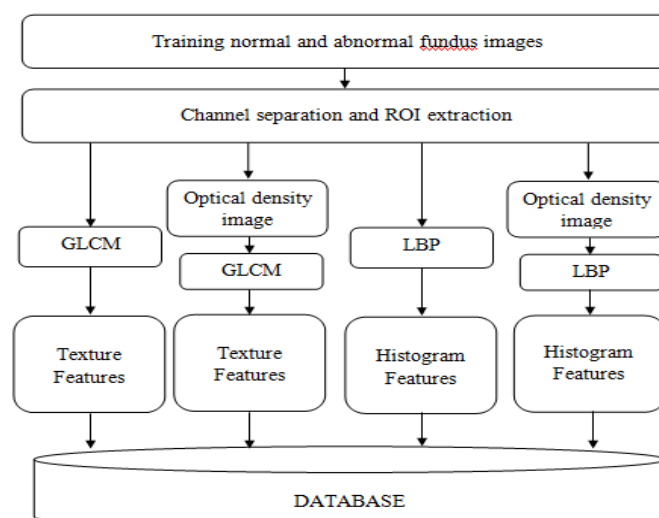

FIGURE 1: FEATURE EXTRACTION MODULE OF THE PROPOSED GLAUCOMATOUS IMAGE CLASSIFICATION SYSTEM

2.1.1 Gray Level Co-occurrence Matrix

GLCM is the basis for texture features [16]. This matrix is square with dimension N_g, where N_g is the number of gray levels in the image. Element [i,j] of the matrix is generated by counting the number of times a pixel with value i is adjacent to a pixel with value j and then dividing the entire matrix by the total number of such comparisons made. Each entry is therefore considered to be the probability that a pixel with value i will be found adjacent to a pixel of value j.

$$G = \begin{bmatrix} p(1,1) & p(1,2) & ... & p(1,N_{g)}) \\ p(2,1) & p(2,2) & ... & p(2,N_g) \\ . & . & ... & . \\ . & . & ... & . \\ p(N_g,1) & p(N_g,2) & ... & p(N_g,N_g) \end{bmatrix} \qquad (1)$$

The GLCM is normalized so that the sum of its elements is equal to 1. Each element (i,j) in the normalized GLCM is the joint probability occurrence of pixel pairs with a defined spatial relationship having gray level values i and j in the image. Let us consider p is the normalized GLCM of the input texture image. Contrast is a measure of the intensity contrast between a pixel and its neighbor over the whole image and given by the equation (2) and the measure of how correlated a pixel is to its neighbor over the whole image is given by the equation (3).

$$\text{Contrast} = \sum_{i,j}|i-j|^2 p(i,j)^2 \qquad (2)$$

$$\text{Correlation} = \sum_{i,j}\frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i\sigma_j} \qquad (3)$$

The energy is the sum squared element in the normalized GLCM and given by the equation (4) and the homogeneity in equation (5) is a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\text{Energy} = \sum_{i,j} p(i,j)^2 \qquad (4)$$

$$\text{Homogenity} = \sum_{i,j}\frac{p(i,j)}{1+|i-j|} \qquad (5)$$

2.1.2 Local Binary pattern

LBP operator utilizes a binary representation of texture units localized in image neighbourhoods, which also represents the shape of image. This operator works with the eight neighbours of a pixel, using the value of the center pixel as a threshold. If a neighbor pixel has a higher or equal gray value than the center pixel than one is assigned to that pixel, else it gets a zero. Then assigned ones among eight neighbors of a pixel are multiplied by powers of two in clockwise or counter clock wise direction and then summed to obtain a pattern for the center [17]. LBP is a simple and efficient gray scale invariant texture analysis, which integrates the statistical and structural texture features of the ROI image.LBP features are computed by using the following eqn.

$$LBP(X_c,Y_c) = \sum_{n=0}^{7} 2^n S(i_n - i_c) \qquad (6)$$

where i_c indicates the value of central pixel is, i_n represents the value of N neighborhood pixels. LBP feature is computed for the whole input fundus image and from the obtained patterns, histogram is formed. From the histogram, the following statistical measures are computed.

The computation of histogram features are as follows: Let us consider an image I, the probability of occurrence of a particular gray level l is defined by

$$p(l) = \frac{N(l)}{T}$$

(7)

where T is the total number of pixels in the stego image, $N(l)$ is the number of occurrence of gray level l. After computing the probability expression, statistical features such as mean, standard deviation, variance, skewness, and kurtosis are calculated and used as histogram features for the particular stego image. Table 1 shows the types of histogram features and their corresponding definition.

TABLE 1
TYPES OF HISTOGRAM FEATURES ANALYZED FOR CLASSIFICATION

Types of features	Information captured	Computation
Mean	Brightness	$\bar{l} = \sum_{l=0}^{L-1} l p(l)$
Standard deviation	Contrast	$\sigma_l = \sqrt{\sum_{l=0}^{L-1} (l - \bar{l})^2 p(l)}$
Variance	Dispersion around their mean	$\sigma_l^2 = \sum_{l=0}^{L-1} (l - \bar{l})^2 p(l)$
Skewness	Asymmetry about the mean	$S = \frac{1}{\sigma_l^3} \sqrt{\sum_{l=0}^{L-1} (l - \bar{l})^3 p(l)}$
Kurtosis	Measure of peakedness	$K = \sum_{l=0}^{L-1} \frac{(l - \bar{l})^4}{\sigma_l^4}$
Where L is the total number of gray levels (256).		

2.1.3 Optical Density Image

The Optical Density (OD) image is computed from the ROI. It is defined by

$$OD_{ij} = \log\left(\frac{I_{ij}}{I_o}\right)$$

(8)

where I_o is the average intensity and I_{ij} is the intensity at each pixel. From the OD image, GLCM and LBP features are computed for the OD image as well and all are combined to form the database.

2.2 Classification

The classification module of the proposed glaucomatous image classification system using GLCM, LBP and their OD features is shown in Figure 2.
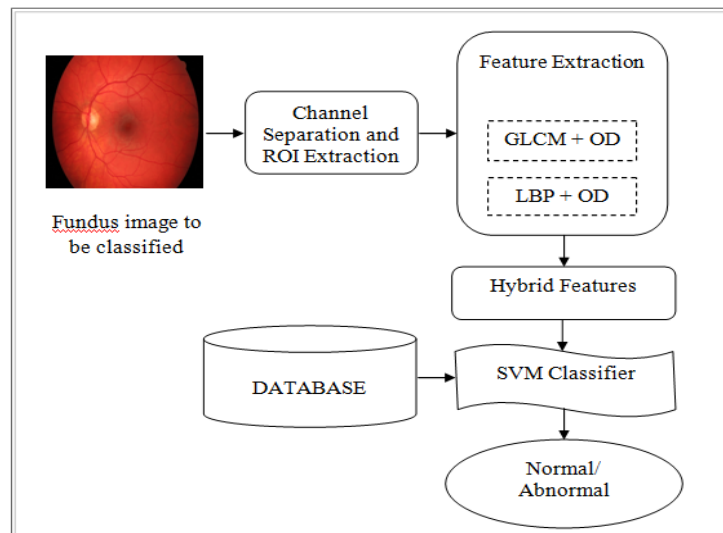
FIGURE 2: CLASSIFICATION MODULE OF THE PROPOSED GLAUCOMATOUS IMAGE CLASSIFICATION SYSTEM

The classification task is the final stage of the proposed glaucomatous image classification system where the given fundus image is diagnosed into one of the predefined class; normal or abnormal. Most of the classification system often operates in two phases: The training phase is where the relationship between certain features and outcomes is determined and optimized. This is often a long and computationally intensive process. The classification phase is when the training data is put to use to classify an object. This is usually much quicker. Supervised model of binary SVM classifier is employed in this proposed method for its generalization and discriminative learning approaches. In this study, the binary SVM classifier uses Radial Basis Function (RBF) kernel for better classification. The reason is that the RBF-SVM is suitable if the number of features is very low. The linear mapping does not improve the performance if the number of features is very low and it is a time consuming process to map the data.

III.   RESULTS AND DISCUSSIONS

The performance of the proposed glaucomatous image classification system is evaluated on 200 fundus images: 100 images for normal case and 100 images for glaucomatous cases. It is obtained by auto focus fundus camera with a resolution of 1504x1000 pixels in the RGB mode. Figure 3 shows sample fundus images. The performance of the proposed approach for the classification of fundus image into normal or glaucomatous image is measured by classification accuracy, confusion matrix and Receiver Operating Characteristics (ROC) curve.
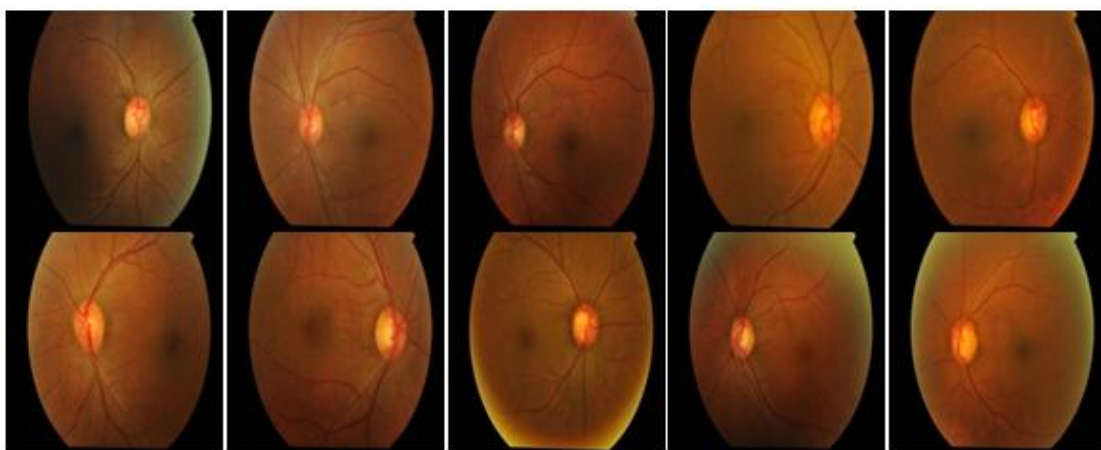

FIGURE 3: FUNDUS IMAGE DATABASE

The proposed glaucomatous image classification system is a pattern recognition system. As the classification system requires training images for normal and abnormal category, the whole dataset is divided into two parts by equally splitting it. The splitting is done by random selection. Among the two parts, one part is used for SVM training and another is used for testing. This step is repeated for 10 times and the averaged output is shown. The confusion matrix shown in Figure 4 is obtained by using the GLCM and its OD features. The number of training and testing images in each category is 50 fundus images.
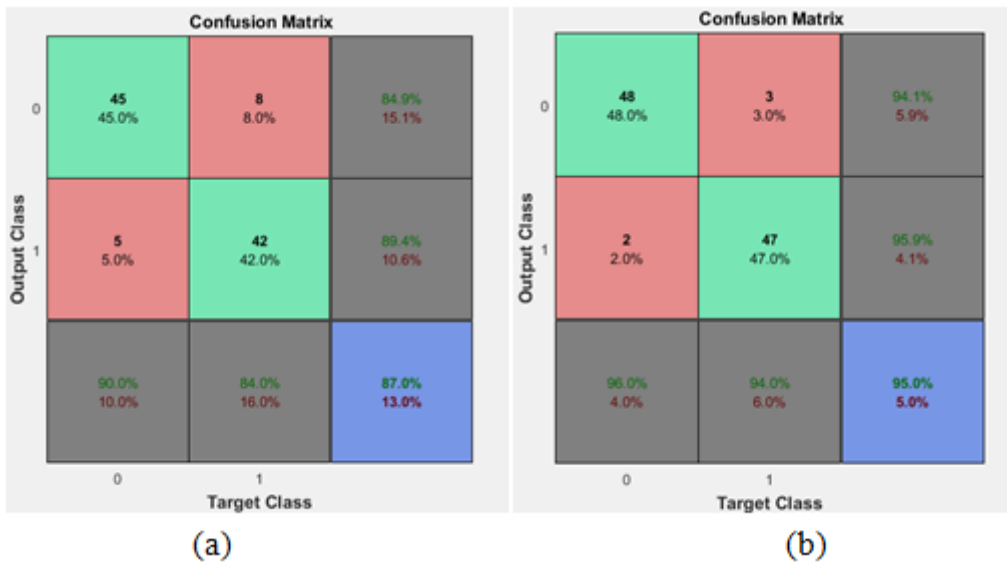
FIGURE 4: CONFUSION MATRIX OF THE PROPOSED GLAUCOMATOUS IMAGE CLASSIFICATION SYSTEM

(A) GLCM FEATURES ALONE (B) GLCM + OD FEATURES

It is inferred from Figure 4 that five (5) abnormal images are misclassified as normal and among 50 normal images eight (8) images are misclassified while using the GLCM features. However, this misclassification is reduced by using the OD features along with GLCM features. Only 2 abnormal images are misclassified by combing OD features with GLCM features. The confusion matrix shown in Figure 5 is obtained by using the LBP and its OD features. The same training and testing images used in GLCM features analysis are employed for the analysis.
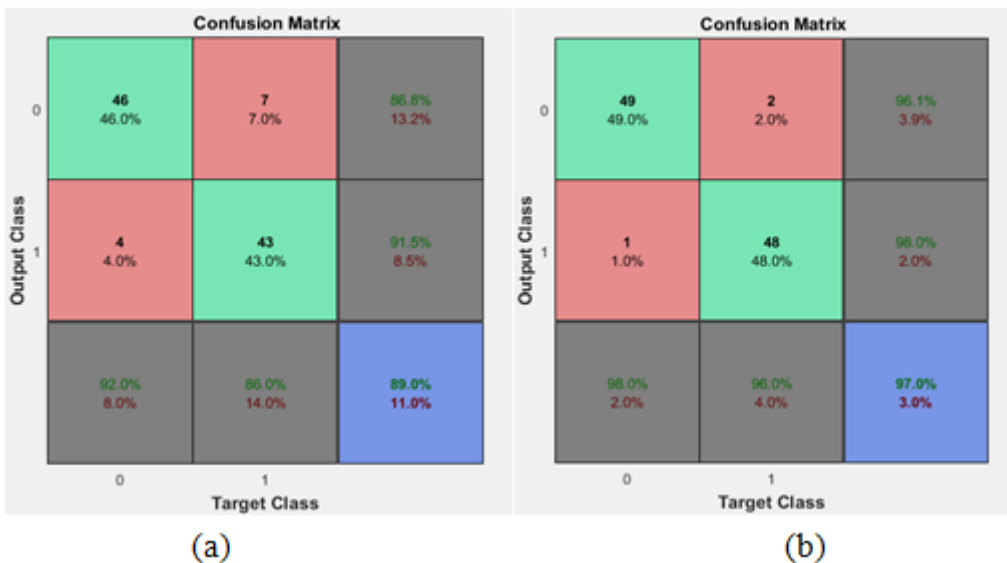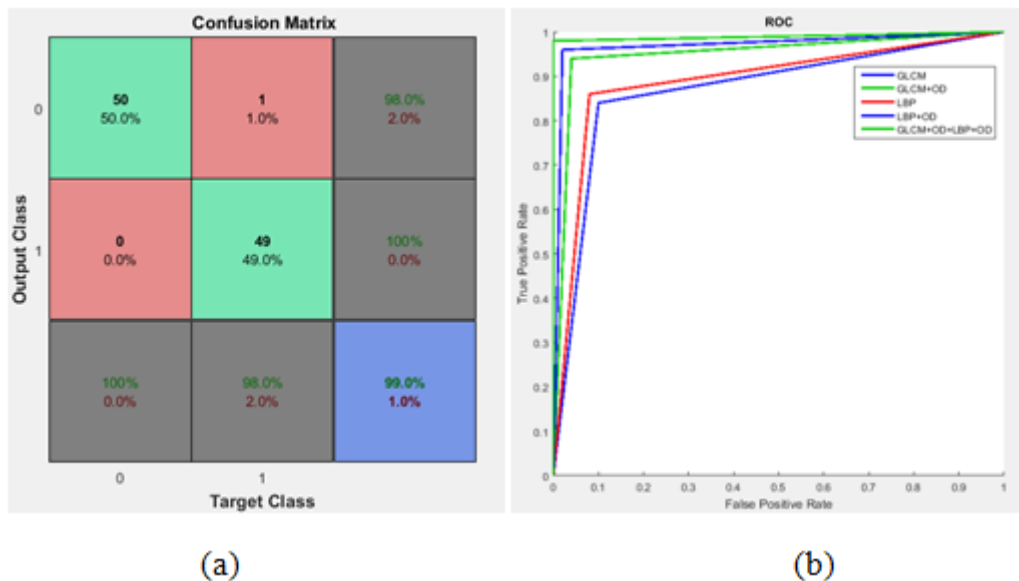

FIGURE 5: CONFUSION MATRIX OF THE PROPOSED GLAUCOMATOUS IMAGE CLASSIFICATION SYSTEM

(A) LBP FEATURES ALONE (B) LBP + OD FEATURES

It is inferred from Figure 5 that four (4) abnormal images are misclassified as normal and among 50 normal images seven (7) images are misclassified while using the LBP features. However, this misclassification is reduced by using the OD features along with LBP features. Only one (1) abnormal image is misclassified by combing OD features with LBP features. As the medical diagnosis system requires more accuracy, the proposed system uses a hybrid approach in the feature level. Both GLCM and LBP features are hybridized and trained with the SVM classifier. Figure 6 shows the confusion matrix and ROC plot of the classification system using hybrid features.

FIGURE 6: PERFORMANCE OF THE PROPOSED GLAUCOMATOUS IMAGE CLASSIFICATION SYSTEM

(A) CONFUSION MATRIX (B) ROC PLOT

IV.   CONCLUSION

An efficient fundus image classification system is presented in this paper. The proposed approach utilizes GLCM and LBP features extracted from the original image as well as from their optical density images. SVM classifier is designed for the classification of given fundus image into normal or glaucomatous image. The performance of GLCM, LBP and hybrid features are analyzed using the same set of training and testing fundus images. It is observed that the proposed system provides 99% classification accuracy while using the hybrid features. Also, it is observed that 100% sensitivity and 99% specificity is obtained by the proposed system.

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