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An automated detection of glaucoma using histogram features

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Abstract

• **Glaucoma is a chronic and progressive optic neurodegenerative disease leading to vision deterioration and in most cases produce increased pressure within the eye. This is due to the backup of fluid in the eye; it causes damage to the optic nerve. Hence, early detection diagnosis and treatment of an eye help to prevent the loss of vision. In this paper, a novel method is proposed for the early detection of glaucoma using a combination of magnitude and phase features from the digital fundus images. Local binary patterns (LBP) and Daugman´s algorithm are used to perform the feature set extraction. The histogram features are computed for both the magnitude and phase components. The Euclidean distance between the feature vectors are analyzed to predict glaucoma. The performance of the proposed method is compared with the higher order spectra (HOS) features in terms of sensitivity, specificity, classification accuracy and execution time. The proposed system results 95.45% output for sensitivity, specificity and classification. Also, the execution time for the proposed method takes lesser time than the existing method which is based on HOS features. Hence, the proposed system is accurate, reliable and robust than the existing approach to predict the glaucoma features.**

• **KEYWORDS:** Daugman's algorithm; Euclidean distance; glaucoma; higher order spectra; histogram features; local binary patterns

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INTRODUCTION

Glaucoma describes a collection of ocular disorders with multi-factorial etiology combined by a clinically featured intraocular pressure (IOP) related optic neuropathy. This can permanently damage vision in the injured human eye and it leads to blindness if left untreated. Visualization loss is caused by damage to the optic nerve, which carries image details collected from the light receptors in the brain. It is estimated that more than four millions in America have affected by Glaucoma and nearly half of them are unaware that they are affected by these disease [1]. Premature recognition and prevention is the only way to prevent the total loss of eye vision. Many techniques have been developed for the detection of the glaucoma diseases. The recognition of optical disk (OD) is an important issue for the computation for most of the diagnostic indexes like glaucoma. The OD is the position where ganglion cell axons leave the eye to form the optic nerve. Most of the research, assumes that the center of an iris is closer to the center of an image, they fix a range of radius based on the size of an image.

The optic disc of an eye image is automatically detected based on the region of interest (ROI). As the position of the optic disk is an important process to diagnose the glaucoma disease. Then, the ROI is processed for image enhancement and feature extraction before performing the classification process. Because, the segmentation process needs prior information about discriminant image features. The accurate edge detection helps the segmentation steps to yield an accurate decision to detect the medical diseases like glaucoma. There are enormously large number of edge detection filters are existing, each considered to be susceptible to certain types of edges [2]. Mishra *et al* [3] proposed an active contour method to find the cup to disc ratio (CDR) from the color fundus images to determine the medicinal process of glaucoma. Glaucoma was evaluated by monitoring IOP, visual field and the optic disc appearance. This approach was applied on 25 color fundus images, which were obtained from optic disk organization to test the detection of glaucoma images. in the proposed method, the ROI is automatically extracted. It reduces the time to detect the disease in an efficient manner.

In this paper, local binary patterns (LBP) and Daugman's algorithm are proposed as a preprocessing step prior to the computation of histogram features. In existing approaches, ROI is extracted based on some CDR measures. In this paper, we are only using the features to detect the disease. Hence, it is not necessary to cumpute the CDR measure. The LBP is a non parametric and computationally easy descriptor of local texture patterns. It is an image operator that transforms an image into an array or image of integer labels. These labels or statistics, forms a histogram features for further image analysis. The LBP illustration is less susceptible to changes in explanation, because it is invariant to monotonic grayscale transformation. The Daugman operator depends on the fact that the illumination difference between the outside and inside of pixels in iris edge circle. It is impossible to determine the Daugman operator for all the circle of human eye image.

The rest of the paper is organized as follows. Section II involves the detailed description about the proposed method. Section III presents the performance analysis. Section IV presents a discussion about the previous research which is relevant to the detection of glaucoma disease, edge detection techniques and histogram features This paper concludes in section V.

EARLY DETECTION OF GLAUCOMA IN RETINAL IMAGING

Glaucoma is a group of disease that kills retinal ganglion cells. High IOP is the strongest known risk factor for glaucoma but it is neither necessary nor sufficient to induce the neuropathy. To efficiently detect the glaucoma images, the proposed method is introduced. The proposed novel method for early detection of glaucoma from the fundus retinal images are described in the following sections. It includes ROI selection, Gabor filtering, LBP steps to extract the features, and Daugman's algorithm. Each topic is described in the further sections in detail. Figure 1 illustrates the architecture for the detection of glaucoma in retinal images.

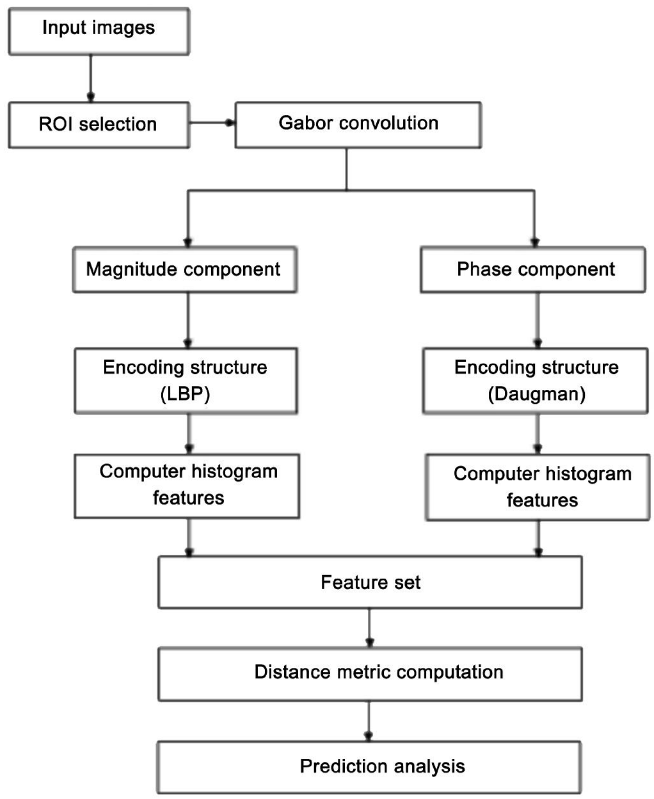

Figure 1 Architecture for the detection of glaucoma in retinal images.

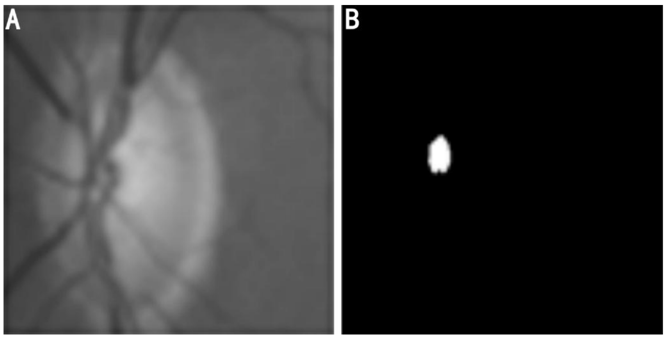

Figure 2 ROI selection A: ROI of input glaucoma image; B: BW image.

Region of Interest Selection ROI is a selected region within the image identified for a particular purpose of analysis. In this proposed method, the OD is detected by finding the ROI of the input glaucoma image. In order to estimate the ROI, the mathematical morphology like dilation, erosion is performed. The small holes in the image get filled and the object boundary is smoothened after the performance of the morphological functions. Figure 2 shows the ROI of an input glaucoma image and their corresponding BW image.

The physical threshold for extracting OD includes the removal of the blood vessels in the retinal images. The dilation and erosion of X and Y is defined as $X \ominus Y= \{ i \in S \mid Y_i \subseteq X \}$ (1)

Erosion is performed to contrast the boundary of an image. The result obtained in this process is a smooth image without any blood vessels. Usually, an image pixel value is given as '1' and the background pixel value is given as '0'. Among the pixel values, the minimum pixel value is set as a threshold to extract the boundary of an OD.

Gabor Convolution Gabor filter for edge detection depends on the frequency and orientation representation of the particular image. In this proposed approach, the 2D Gabor filter is applied on the glaucoma images. It is a Gaussian kernel function, which is regulated by a sinusoidal plane wave. In this work, this filter is used to extract the edges of an OD. This 2D Gabor filter composed of a complex exponential at a specified frequency. Due to the complex exponential of the filter, it has both the real and imaginary parts of an image. The 2D Gabor filter expresses as follows:

$$f(m,n,\omega,\theta,\sigma_m,\sigma_n)=\frac{1}{2\pi\sigma_m,\sigma_n}\{\frac{-1}{2}[(\frac{m}{\sigma_m})^2+(\frac{n}{\sigma_n})^2]+j\omega(m cos\theta+n sin\theta)\} \quad (2)$$

Where σ denotes the spatial spread, ω denotes the frequency and θ denotes the orientation. The magnitude (real) and phase component (imaginary) features extraction are described in the following sections.

Local Binary Patterns The LBP is a non-parametric operator that describes the local spatial structure of an image. At a specified pixel position (x_p, y_p), it is defined as an ordered sequence of binary comparisons of pixel intensities between the pixel which is placed at the center and the surrounding pixel. The resulted LBP code can be expressed as follows: $LBP(x_p, y_p) = \sum_{j=0}^{7} c\,(k_j - k_p)2^{j}$ (3)

Where k_p corresponds to the gray scale of the centered pixel (x_p, y_p), to the gray values of the 8 surrounding pixels; the function c(x) is defined as: $c(x)=\begin{cases} 1 & if\, x \geqslant 0 \\ 0 & if\, x < 0 \end{cases}$ (4)

Steps for Local Binary Patterns Reature Vector 1) Divide the given image into 8× 8 cells; 2) For each pixel in a cell, compare the pixel to each of its 8 neighbors. The circle goes on clockwise or counter-clockwise; 3) If the center pixel value>neighbor pixel value, write 1; 4) Else, write 0; 5) It results in 8 digit binary number; 6) A binary number is converted into decimal; 7) Normalize the histogram; 8) Concatenate histogram of all the cells. It results feature vector. Figure 3 shows the circular operations of LBP and Figure 4 describes the LBP operator.

Daugman´s Algorithm The Daugman's algorithm depends on the integral differential operator to the calculation of the iris and the pupil contour. It is estimated based on the following equation:

$$\max_{(g,a_o,b_o)} \left| G_\sigma(g) \times \frac{\partial}{\partial r_{g,a_o,b_o}} \oint \frac{I(a,b)}{2\pi r} ds \right| \quad (5)$$

Here are the radius and center of the coarse circle, $G_\sigma(g)$ denotes the Gaussian function, $I\ (a,b)$ is the original iris image. If any of the pixels in the circle has a value higher than a predefined threshold value, then mark it as "objects" or it may be a "background" pixels. After that, the histograms are constructed to extract the feature vectors. The combined feature sets are extracted based upon the Euclidean distance between the features to detect the glaucoma image.

Figure 5 describes the step by step procedure to obtain the histogram feature vectors. The image is divided into 8 ×8 cells. For each step the histogram is computed to analyze the histogram features.

PERFORMANCE ANALYSIS

This section describes the results obtained from the experimentation of the proposed method for the early detection of glaucoma from retinal images. The performance is evaluated based on the following metrics: sensitivity, specificity, time consumption and Receiver Operating Characteristics (ROC) classification. During the training

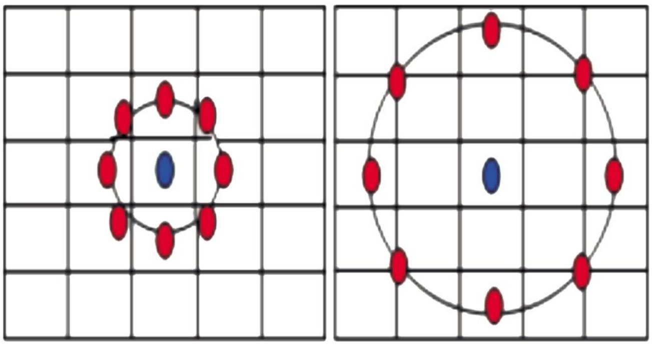

Figure 3 The Circular (8,1) and (8,2) neighborhoods of LBP.

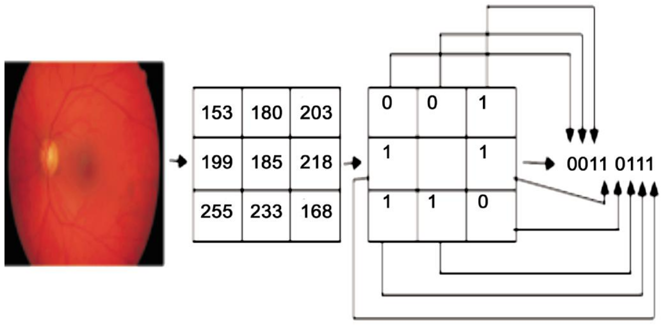

Figure 4 LBP operator and their conversions LBP operator: Equivalent decimal number for the given binary number is 37.

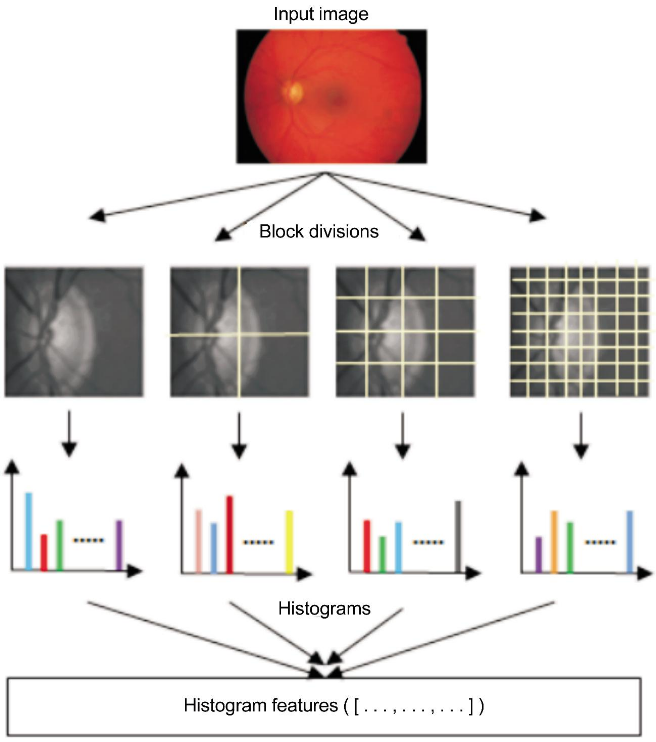

Figure 5 Steps to obtain the histogram features.

phase, 80 samples are taken and for testing phase 44 samples are taken. The same accuracy can be obtained even the system is implemented under more number of samples.

The input image is loaded and the optic disc is extracted (*i.e.* ROI) from the input image. The image filtered based on Gabor filtering method is shown in Figure 6. The magnitude and phase features are retrieved using LBP and Daugman's algorithm is shown in Figures 7, 8.

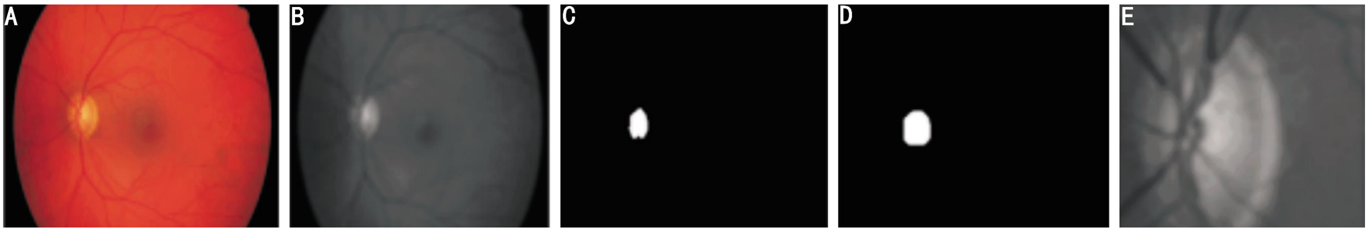

Figure 6 ROI extraction process A: Input glaucoma image; B: Filtered image; C: BW image; D: Optic disk; E: ROI.

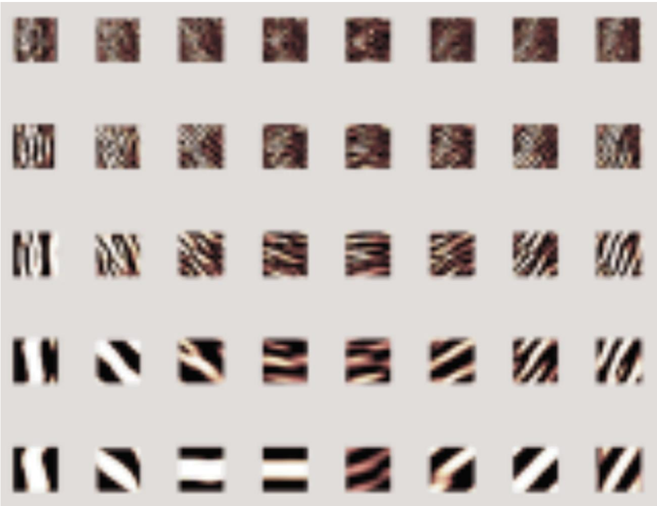

Figure 7 Magnitude features (LBP encoding structure).

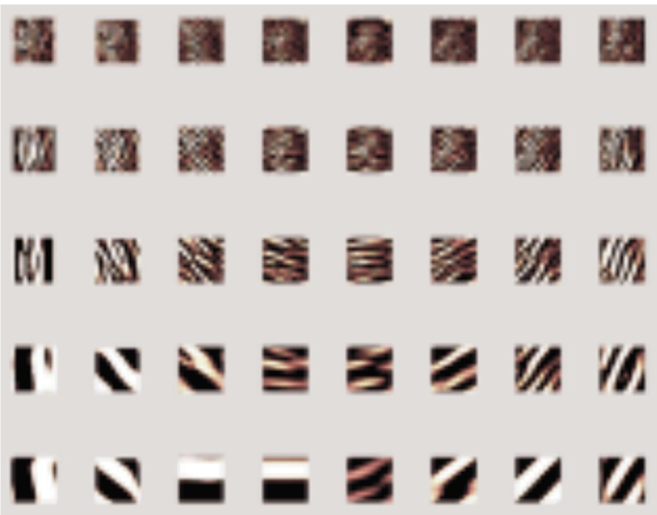

Figure 8 Phase features (Daugman encoding structure).

Sensitivity (Recall Rate) and Specificity The sensitivity of a test is defined as the proportion of people with disease who will have a positive result. Sensitivity deals with the study of uncertainty in the output of a system can be allocated to different sources of uncertainty in its inputs. It is used to test the robustness of the results of a proposed system in the presence of uncertainty. Whereas, specificity measures the proportion of negatives which are correctly identified (not having any condition). The specificity of a test is the proportion of people without the disease who will have a negative result.

Our proposed system results 95.45% output for sensitivity and specificity, which is shown in Figure 8. Sensitivity and specificity are estimated based on the following equation:

$$Sensitivity = \frac{Number\ of\ true\ positives}{Number\ of\ true\ postives+number\ of\ false\ negatives} \quad (6)$$

$$Specificty = \frac{Number\ of\ true\ negatives}{Number\ of\ true\ negatives+number\ of\ false\ positives} \quad (7)$$

The accuracy is calculated based on the following equation:

$$Accuracy = \frac{Number\ of\ true\ positive+number\ of\ true\ negative}{TOTAL} \quad (8)$$

Total=number of true positive+number of false positive+ number of false negative+number of true negative (9), where, true positive is the number of images that are correctly identified, false positive is the number of images that are incorrectly identified, true negative is the number of images that are correctly rejected, and false negative is the number of images that are incorrectly rejected.

Real time images were obtained from Aravind Eye Hospital, Madurai, India. Stereophotograph-derived information from glaucomatous eyes coincides with visual performance and is predictive of visual field damage. Images are considered to be normal when there are no structural changes on the optic nerve head over a period of time. So ground truth images based on the progressive structural optic nerve damage from stereophotography provided by ophthalmologists were taken as the gold standard for this work. Histogram features are related with the structural changes that occur in the optic disc and cup. The proposed method using histogram features was tested on the real time data set of retinal images that has 22 normal and 22 glaucomatous (total of 44) images and compared with the ground truth images.

Table 1 shows the usual standard to compute the sensitivity and specificity calculation. It is estimated that the true positive is 21, false positive is 1, false negative is 1 and true negative is 21. The total test positives value is 22, total test negatives value is 22 and the total population is 44.

Figure 9 shows the performance analysis for the existing and our proposed system to detect the glaucoma images. The proposed system uses both the magnitude and phase features. The combination of magnitude and phase features for the detection of glaucoma disease results in better performance than they are applied as individually in the magnitude and higher order spectra (HOS) features. It provides 95.45% for sensitivity, specificity and accuracy for the detection of glaucoma disease in the retinal images. Whereas, the existing methods like magnitude features and HOS features results 90.91% and 77.2727%, which is shown in Table 2 [4]. It is

Table 1 Sensitivity and specificity calculation

Parameters	Glaucoma disease present	Glaucoma disease absent	Total
Test positive	True positive: 21	False positive: 1	Total test positive: 22
Test negative	False negative: 1	True negative: 21	Total test negative: 22
Total	Total diseased: 22 Sensitivity=21/(21+1) =95.45	Total normal: 22 Specificity=21/(1+21) =95.45	Total population: 44

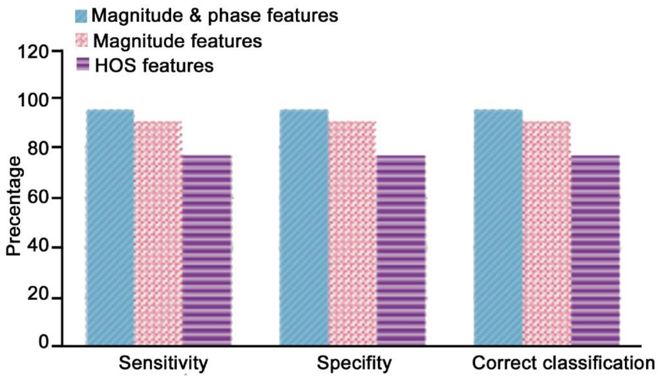

Figure 9 Performance analysis between magnitude & phase features (proposed), magnitude features and HOS features (existing) [4].

Table 2 Comaprison of sensitivity, specificity and correct classification %

Algorithm	Sensitivity	Specificity	Correct classification
HOS features	77.2727	77.2727	77.2727
Magnitude features	90.91	90.91	90.91
Magnitude & phase features (proposed)	95.45	95.45	95.45

Table 3 Time analysis

No.	Algorithm	Time (s)
1	HOS features	1.4143
2	Magnitude features	0.5243
3	Magnitude & phase features (proposed)	0.2488

obviously proved that the proposed system performing well to detect the glaucoma disease than the existing method.

Time Consumption The time taken to extract the histogram feature vectors is analyzed. The HOS features take more time to extract the feature vectors. The comparison time consumption among the existing and proposed method are tabulated in Table 3.

Receiver Operating Characteristics ROC is formed by plotting the fraction of true positives out of the total actual positives (TPR) *vs* the fraction of the false positives out of the total actual negatives (FPR) at different thresholds. Whereas, TRP is the true positive rate and FPR is the false positive rate. The result of the proposed system shows the perfect ROC curve shown in Figure 10.

The proposed method results above 95% results for classification, hence the system performance is stable to detect the glaucoma disease. Also, the time taken for detection also takes lesser time. Hence it is well suited for clinical applications.

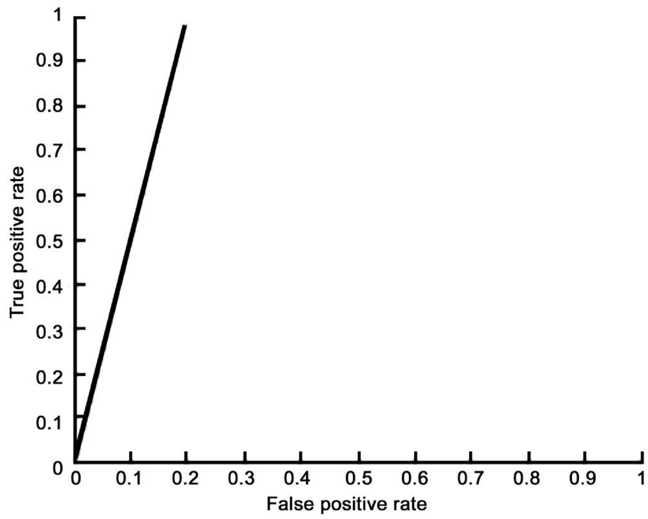

Figure 10 Proposed system ROC classification (95.45%).

DISCUSSION

Detection of glaucoma visual field loss and estimation of subsequent field evolution are among the major aspects of glaucoma management. For most patients, glaucoma is a slowly progressive disease that may be present for years without producing symptoms. However, even in asymptomatic patients, damage can occur in the form of optic disc changes and loss of retinal ganglion cells (RGC). These anatomical changes are believed to precede the functional changes in glaucoma as detected by standard perimetry. Although finding pathological changes in the optic disc and retina is critical to glaucoma diagnosis and monitoring, visualizing these changes is technically challenging and has largely been a matter of subjective assessment. In recent years, there are many researches have been carried out in the field of glaucoma detecion. Some of the existing paper related to the detection of glaucoma detection is discussed in the following sections.

Rajendra Acharya *et al* [4] proposed an approach for glaucoma detection based on the combination of texture and HOS features commencing digital fundus images. Some of the techniques are used to perform supervised classification. They are support vector machine, sequential minimal optimization, and naive Bayesian and random-forest classifiers. The proposed system considers both the phase and magnitude component to compute the feature set. Krishnan and Faust [5] proposed a system for the automated identification of normal and glaucoma classes. This system was based on HOS, trace transforms (TT) and discrete wavelet transform (DWT) features. The extracted features were fed into a Support Vector Machine classifier to select the best kernel for automated decision making. Mookiah *et al* [6] proposed a glaucoma diagnosis system. This method was discussed about the automated identification of normal and glaucoma classes using HOS and DWT features. Later the extracted features were fed into the support rector machine (SVM) classifier with linear, polynomial and radial basis function (RBF) to choose the best kernel function. In this work, SVM classifier with kernel function of polynomial order 2 was used to identify the glaucoma and normal images. Also an integrated index called glaucoma risk inalex (GRI) was used to diagnose the unknown class using a single feature. These schemes only utilizes the texture and HOS features. Instead, our proposed scheme takes both the phase and magnitude with the HOS features, which provide better results [4,5,6].

Haogang *et al* [7] proposed an image registration algorithm. This algorithm is used to align the location of the optical coherence tomography (OCT) scan circles to the vessel features in the retina. The probabilistic modeling was optimized by an expectation-maximization algorithm. Muramatsu *et al* [8] formulated a computerized scheme for the detection of retinal nerve fiber layer defect (NFLD) on retinal fundus images. The images were transformed after the removal of major blood vessels. The curved paths of retinal nerves turned approximately straight on the basis of ellipses. Gabor filters were applied for improvement of NFLDs. Linear discriminant analysis and artificial neural network (ANN) was applied on the image features to calculate the likelihood of a true NFLD. Liu *et al* [9] proposed a method to detect the presence of normal macula and macula pathologies. A machine learning approach is based on global image descriptors which was formed form a multi-scale spatial pyramid. The LBP were capable of encoding texture and shape information in the retinal OCT images and their corresponding edge maps. In our system, the distance between the optic disc cup is not estimated. Because, in order to save the time, it doesn't consider the existing optic cup detection mechanisms. Instead of this, the proposed method involves the estimation of phase and magnitude feature extraction.

Pachiyappan *et al* [10] designed a system for the computerized diagnosis of diabetic retinopathy and glaucoma with the help of fundus and OCT images. Early detection of glaucoma was done by determining the retinal nerve fiber layer (RNFL) thickness from the OCT images. Xu *et al* [11] proposed a machine learning framework for glaucoma diagnosis. This method is based on sliding windows. The optic cup was automatically localized, which was the primary structural image cue for clinically identifying glaucoma. This localization depends on a set of sliding windows of different sizes to attain cup candidates in each disc image. Later, a histogram based feature was extracted from each sliding window. An ε-Support Vector Regression (SVR) model was designed, which was based on non-linear RBF kernels. RBF was used to rank each candidate and final decisions were made with a non-maximal suppression (NMS) method. Abramoff *et al* [12] reviewed a method for 2-D fundus imaging and 3-D OCT imaging. In our system, the gabor convolution filter result in frequency domain and it can be decomposed into magnitude and phase image based on the real and imaginary part. The gabor filters are very useful for the detection of texture directions. This is the main advantage of the gabor filters.

Sun *et al* [13] proposed a methodology for texture image classification. The LBP operator (LBP_ex) was developed for discriminative LBP selection and a directional Gaussian filter based LBP_ex descriptor was also proposed for texture image classification through two major steps. The first step was based on bank of directional Gaussian filters to retrieve the anisotropic information in the textural images. The second step was about combining the LBP_ex histograms, which was calculated from both original and filtered images to form feature vectors. It represents isotropic and anisotropic properties of the texture images to improve the classification accuracy. Bock *et al* [14] and Deepak *et al* [15] proposed an automated, global feature based approach to identify glaucoma from images. An image representation was devised to accentuate subtle indicators of the disease. Hence global image features can differentiate between normal and glaucoma cases. This method was demonstrated on a large image dataset. The classification performance on a dataset of 1186 color retinal images contained a mixture of normal, suspect and conformed cases of glaucoma [15]. Our proposed system is scalable and robust for any size of the dataset images.

CONCLUSION AND FUTURE WORK

In this paper, the early detection of glaucoma is done by estimating the histogram features. Here, ROI is extracted from the digital fundus images to localize the OD. Gabor filter is applied and it results better preprocessed input image. The histogram features are retrieved using LBP and Daugman's algorithm. The performance is evaluated based on sensitivity, specificity, time consumption and ROC classification. This proposed system results better classification than the existing classifications. The proposed system is well suited and scalable to detect the glaucoma features than the person consulting with the physician. It saves more time to detect the disease to take the preventive measures at earlier stage. The system can be used for clinical applications.

The following idea can be implanted in the future to enhance the proposed system. The future work is to analyze the new feature detection schemes and identify the best feature extraction algorithm to detect the glaucoma features.

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