Diagnosis System for Diabetic Retinopathy and Glaucoma Screening to Prevent Vision Loss

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Abstract

Aim: Diabetic retinopathy (DR) and glaucoma are two most common retinal disorders that are major causes of blindness in diabetic patients. DR caused in retinal images due to the damage in retinal blood vessels, which leads to the formation of hemorrhages spread over the entire region of retina. Glaucoma is caused due to hypertension in diabetic patients. Both DR and glaucoma affects the vision loss in diabetic patients. Hence, a computer aided development of diagnosis system for Diabetic retinopathy and Glaucoma screening is proposed in this paper to prevent vision loss. *Method*: The diagnosis system of DR consists of two stages namely detection and segmentation of fovea and hemorrhages. The diagnosis system of glaucoma screening consists of three stages namely blood vessel segmentation, Extraction of optic disc (OD) and optic cup (OC) region and determination of rim area between OD and OC. *Results*: The specificity and accuracy for hemorrhages detection is found to be 98.47% and 98.09% respectively. The accuracy for OD detection is found to be 99.3%. This outperforms state-of-the-art methods. *Conclusion*: In this paper, the diagnosis system is developed to classify the DR and glaucoma screening in to mild, moderate and severe respectively.

Keywords: Diabetic Retinopathy (DR); Glaucoma; Hemorrhages; Diagnosis; Fovea.

Introduction

Nowadays diabetic retinopathy, glaucoma, hypertension and macular degeneration have become the most common causes of visual impairment and blindness. Earlier diagnosis and appropriate medical advice for treatment of these diseases avoids visual loss. The foresaid diseases can be identified with the help of direct and regular ophthalmologic examinations of the risk population. The number of ophthalmologists required for evaluation by direct examination becomes a limiting factor due to ageing, population growth, physical inactivity and obesity which contributes to increase the risk of vision loss.

However, in large-scale screening scenario, these manual assessments are not precise, mostly in developing countries due to the insufficiency of trained experts and scarce modern imaging equipments. Hence, an automatic diagnosing system which automatically identifies the characteristics of these pathological disorders may be of great advantage for the disease identification. Diabetic retinopathy and Glaucoma is one of the common causes of blindness with

about 79 million in the world likely to be affected with glaucoma and DR by the year 2020 [1]. It is the primary cause for blindness and the detection of DR and glaucoma is essential in preventing visual loss.

Ophthalmologists are using retinal images to diagnose severity of DR and glaucoma screening. Figure 1 shows a retinal image labeled with various feature components of DR and glaucoma. Micro aneurysms appear as small red dots, and may lead to hemorrhage(s); while the hard exudates appear as bright yellow lesions. The spatial distribution of exudates and microaneurysm and hemorrhages, especially in relation to the fovea is generally used to determine the severity of DR. In this paper, the hemorrhages and its relation with fovea region is diagnosed for diabetic retinopathy.
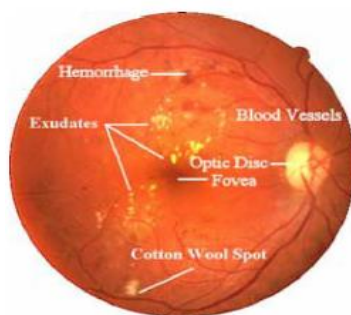
Figure 1. Retinal Image

Due to the high pressure in blood vessels in retina, the blood is leaked from blood vessels in to the retina. If the blood leaking appears as small red lesions, it is called as hemorrhages. It is primary symptoms for diabetic retinopathy in diabetic patients. If the pressure level is increased, it will affect the optic disc and optic cup region which leads to glaucoma.

Xu et al. [2] has used modified deformable model glaucoma diagnosis by extracting optic disc features such as shape and size. This method discussed various classifiers suited for the glaucoma disease detection and diagnosis.

Bae et al. [3] has proposed a hybrid method using template matching algorithm for the detection of hemorrhages in retinal images. They have achieved a sensitivity of 85% at 4.0 false positives per image. Zhang et al. [4] has proposed background estimation and vessel exclusion based algorithm for hemorrhages detection. Vessel exclusion is used to remove non-hemorrhage pixels which clearly show the hemorrhage lesions. Köse et al. [5] has used inverse segmentation method to segment hemorrhages lesions from other lesions in retinal images. This proposed work has been tested on different data sets and achieved 95% in detection of the optic disc (OD), and 90% in segmentation of the DR. Hatanaka et al. [6] has proposed gamma correction estimation algorithm for the detection of hemorrhages. False positives were removed by using rule-based method and 3 Mahalanobis distance classifiers. The sensitivity and specificity for the detection of abnormal cases were 80% and 80%, respectively. Esmaeili et al. [7] has used Curvelet transform for the detection and segmentation of hemorrhages. The extracted reddish lesions are used for detecting diabetic retinopathy. Sinthanayothin et al [8] has used recursive region growing segmentation algorithms for the detection of hemorrhages and microaneurysms (HMA). The algorithm achieved a sensitivity of 77.5% and specificity of 88.7% for detection of HMA.

Shahbeig et al. [9] has used principle-component-analysis for the detection of optic disc in glaucoma screening. Dehghani et al [10] proposed new method for localizing optic disc. The optic disc of four retinal images in DRIVE dataset was used to extract the histograms of each color component. Then, the average of histograms was calculated for each color as template for localizing the center of optic disc. The success rate was 100, 91.36, and 98.9%, for DRIVE, STARE and a local database, respectively. Foracchia et al [11] proposed a geometrical parametric model, where two of the model parameters are the coordinates of the OD center. The estimated values provide the coordinates of the center of OD. The OD position was correctly identified in 79 out of 81 images (98%). The component analysis method [12] identifies the cup area more exactly compared to manual threshold analysis method. The image obtained by morphological processing is then converted into binary image. The accurate optic cup is acquired only from the binary image.

The area of optic cup can be calculated by finding the number of white pixels in the obtained binary image.

Obviously, all the previous research works for hemorrhage lesion, optic disc and optic cup detection were based only on gray level information and they failed to provide optimum lesion detection. In this paper, we mainly focus not only in detection alone, but also go beyond in diagnosing, which provides a much higher level of accuracy in detection of the hemorrhages to analyze the severity of Diabetic Retinopathy leading to vision loss. The proposed diagnosis system is clearly shown in Figure 2.
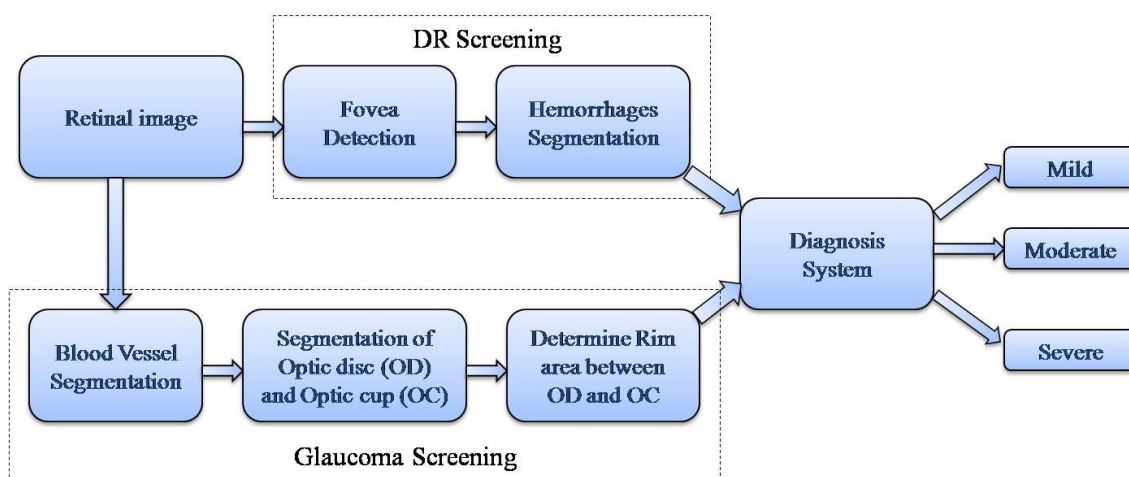

Figure 2. The Proposed DR and Glaucoma Diagnosis System

Material and Method

To evaluate the performance of Diabetic Retinopathy and glaucoma screening, two publicly available databases, DRIVE and STARE used in this paper. Each database consists of a large number of retinal images under normal and abnormal pathologies.

Dataset

The DRIVE database consists of a large set of retinal images which includes both normal and abnormal images. Each retinal image was taken with a Canon CR5 non-mydriatic 3 CCD camera with a 45° field-of view (FOV). Each image has 1500×1150 pixels as image size with 24-bit color. Of the 128 images used in our dataset, 90 images are abnormal (contain pathologies such as exudates, cotton wool spots, microaneurysms and hemorrhages) and the rest of the images being normal. We have also used another dataset STARE, which comprises 20 retinal fundus color images captured with a TopCon TRV-50 fundus camera at 35° FOV. The images were digitalized to 700×605 pixels.

Diagnosis System for Diabetic Retinopathy

The diagnosis system for DR consists of fovea region detection, hemorrhage lesion detection and segmentation. The presence of hemorrhage lesion on fovea region is analyzed and DR is classified in to mild, moderate and severe.

Fovea Region Detection

Fovea is the middle region of the macula in the retina. After the elimination of blood vessels from retinal fundus image, then fovea region is segmented. The fovea region detection plays a key

function in the analysis of DR, determining the relationship between fovea region and exudates. For detecting the fovea region, the fundus image has to be transformed into 'Lab' Color model. This relationship is explained as,

$$L^* = 226\left[k\left(\frac{y}{b}\right) - 16\right] \tag{1}$$

$$a^* = 300\left[k\left(\frac{x}{a}\right) - k\left(\frac{y}{b}\right)\right] \tag{2}$$

$$b^* = 100\left[k\left(\frac{x}{a}\right) - k\left(\frac{z}{c}\right)\right] \tag{3}$$

where, *a, b* and *c* are the tristimulus values of the reference white point. *L* channel image is used as an input image. After this transformation is complete, the contrast of the retinal fundus image is further enhanced using contrast limited adaptive histogram equalization over the transformed image. Fovea is the darkest black region in the retina image, hence, the pixel values below the threshold value, i.e. 60, are identified as fovea region pixel by using morphological operations with a structuring element (disc shaped) having a radius of 3. All these dark pixels are labeled and from among those dark pixels, the largest value of the darker region is denoted as fovea region. Then the estimation of the centroid point (x, y) of the fovea region is done. A circle with a radius of 60 pixels is drawn from the fovea centroid to indicate the fovea region in the retinal image as shown in Figure 3.
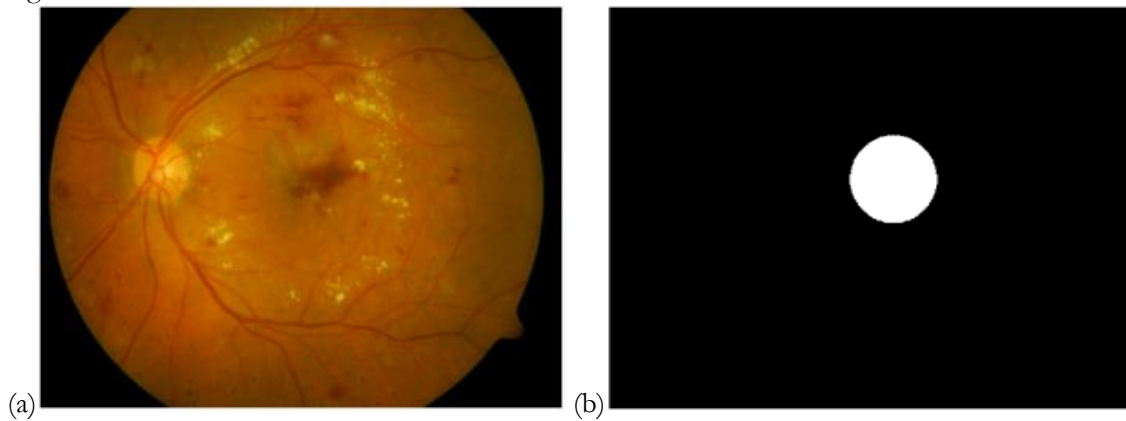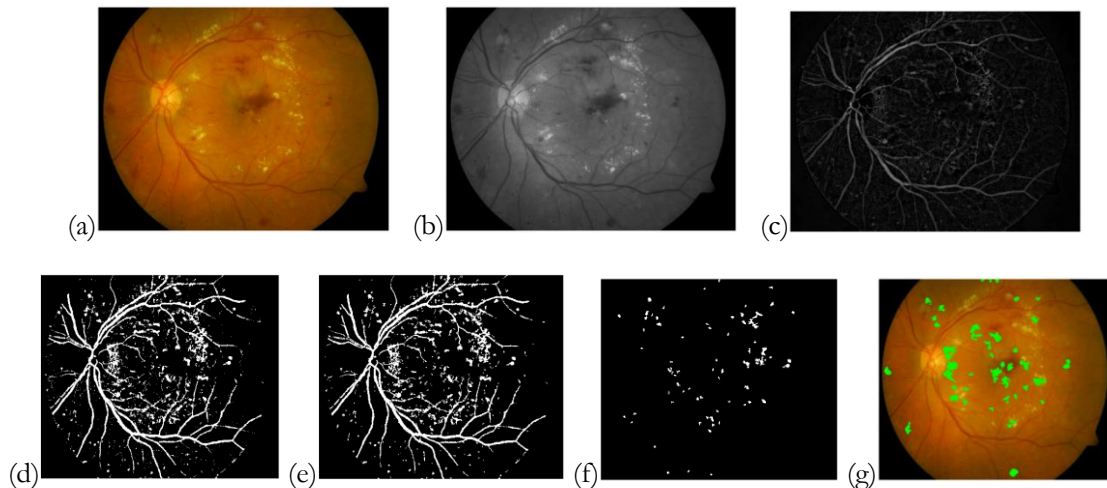

Figure 3. (a) Retinal Image, (b) Fovea Identified Image

Hemorrhages Detection

Hemorrhages are reddish lesions in the retinal fundus image which can be caused by the damage of retinal blood vessel or because of the blockage in retinal blood vessels. We address the problem of detecting red-lesions in three stages. First, each image is pre-processed; next, candidate objects that may represent red-lesions are extracted. Initially, the retinal RGB image is separated into three channels, namely, red, green and blue color channels. The green color channel provides the best hemorrhages background contrast of the RGB-representation, while the red channel offers the low contrast and the blue channel provides poor dynamic range for hemorrhages. Thus, hemorrhages are denoted better in the green channel(Fig.4b) due to high contrast.

The pixel with maximum intensity value is first chosen and then every pixel of the image is now subtracted from the maximum intensity value to obtain G_n. The adaptive histogram equalization is performed over G_n to get G_{hist} image. Then, the morphological opening is performed on G_{hist} image with disk structuring element 15. The histogram equalized image is now subtracted from morphological opened image to get I_{top} (Fig. 4c).The pixels with values greater than the threshold value of 30 are segmented to separate the reddish lesions in retinal image (Fig. 4d).The morphological opening with disc shaped structuring element 2 is applied on the thresholded image to extract hemorrhages lesions boundary region with blobs (Fig. 4e). The blobs are filtered by applying morphological properties such as eccentricity (Fig. 4f).The processing flow for hemorrhage lesion detection and segmentation are shown in Figure 4.

Figure 4. Hemorrhages Segmentation Process. (a) Retinal image, (b) Green channel image, (c) Results of I_{top}, (d) Thresholded image, (e) Extraction of hemorrhages boundary region with blobs, (f) Morphologically processed Image, (g) Hemorrhages identified image

Diagnosis of Diabetic Retinopathy

The diagnosing of DR is very useful for proper timely treatment of diabetic patients to prevent vision loss. The severity of diabetic retinopathy is categorized into mild, moderate, and severe. For early detection of DR, there is a relation between fovea region and hemorrhages count. If more number of hemorrhages (more than 10% of fovea area) is formed in and around the fovea region, then it leads to Severe DR which causes blindness. If the hemorrhages cover 5 to 10% of the fovea region, then it leads to Moderate DR which causes starting of blindness. If hemorrhages counts less than 5% of the fovea area, then it leads to Mild DR. Severity estimation of DR is shown in Table 1.

Table 1. Stipulations for DR Classification

DR Classification	Conditions for DR diagnosis
Severe DR	Hemorrhages covered more than 10% of Fovea Area
Moderate DR	Hemorrhages covered between 5% and 10% of Fovea Area
Mild DR	Hemorrhages covered less than 5% of Fovea Area

Diagnosis System for Glaucoma Screening

The proposed methodology consists of the following procedure for the screening process of glaucoma.
1. Blood Vessel Segmentation
2. Optic Disc Segmentation
3. Optic Cup Segmentation
4. Diagnosis of glaucoma severity
5. Performance Analysis

Blood Vessel Segmentation

In order to segment fovea region from retinal image, the blood vessels should be eliminated from retinal image. The blood vessels are eliminated as follows: The Green channel (Fig. 6b) is extracted from retinal RGB image and morphological closing operation is applied over green channel with disk shaped structuring element 10 (Fig. 7a). The absolute difference image (Fig. 7b) is constructed by subtracting morphologically processed image from RGB retinal fundus image. The

cumulative histogram is taken on absolute difference image. It removes all objects or pixels in the absolute difference image whose value fewer than 50 and produced vessel eliminated retinal image.
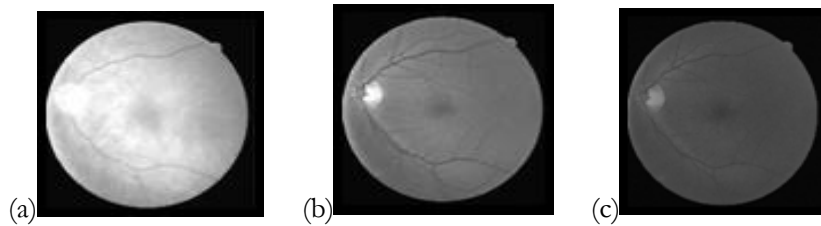

Figure 5. Retinal Image

(a)   (b)   (c)

Figure 6. Illustration of Sub Bands of Retinal Fundus Image. (a) R-Sub band, (b) G-sub band, (c) B-sub band
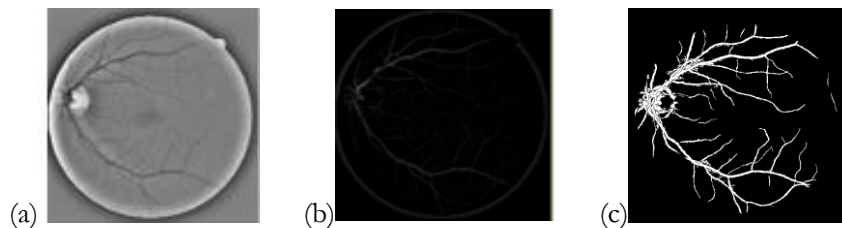

(a)   (b)   (c)

Figure 7. (a) Morphologically Processed Image, (b) Absolute Difference Image, (c) Vessel Segmented Image

Optic Disc Segmentation

The optic disc (OD) which is the bright intensity region in the retinal image is segmented from the retinal image using semi-automatic threshold method. This threshold can be adjusted or set by ophthalmologist by comparing the region marked as optic disc using the proposed algorithm with the optic disc segmented region as viewed by ophthalmologist. The OD is more contrasted in Red (R) band image and hence, R band is used in the segmentation process. Before segmenting the optic disc from the retinal image, the blood vessels should be eliminated from the retinal image. The elimination of blood vessels includes the following steps:

Step1. The Green channel (high contrast of retinal blood vessels) is extracted from retinal RGB image.

Step2. Apply morphological closing operation on green channel with disk shaped structuring element 10(Fig.8c and d).

Step3. The absolute difference image is constructed by subtracting morphologically processed image from RGB retinal fundus image.

Step4. The cumulative histogram is calculated on absolute difference image which removes all objects or pixels from the absolute difference image with value less than 50, thus producing vessel eliminated retinal image which clearly shows the optic disc region.

Step5. The morphologically processed retinal image is converted into binary image(Fig.8e) in which white pixels are close to the edge of the optic disc, thereby detecting the boundary of the

optic disc. The boundary of OD is more accurately determined only when the contrast disc is present in the image.

Optic Cup Segmentation

The segmentation of optic cup (OC) is significantly more difficult than that of OD due to high density of vascular architecture traversing the cup boundary. The optic cup segmentation localizes the optic cup in an efficient way, even if the image is of very low contrast.

Step1: The Green component is extracted from the original fundus image.

Step2: Apply morphological operations like opening and closing to obtain the area of optic cup accurately. The open operation removes all tiny stray bright spots present in the image. The close operation fills the gap in the optic cup, thereby, smoothening its boundary.

Step3: Employ component analysis method [12] to identify the cup area more exactly than manual threshold analysis method.

Step4: The image obtained by morphological processing is then converted into binary image.

Step5: The area of optic cup is finally computed by estimating the number of white pixels present in the binary image.
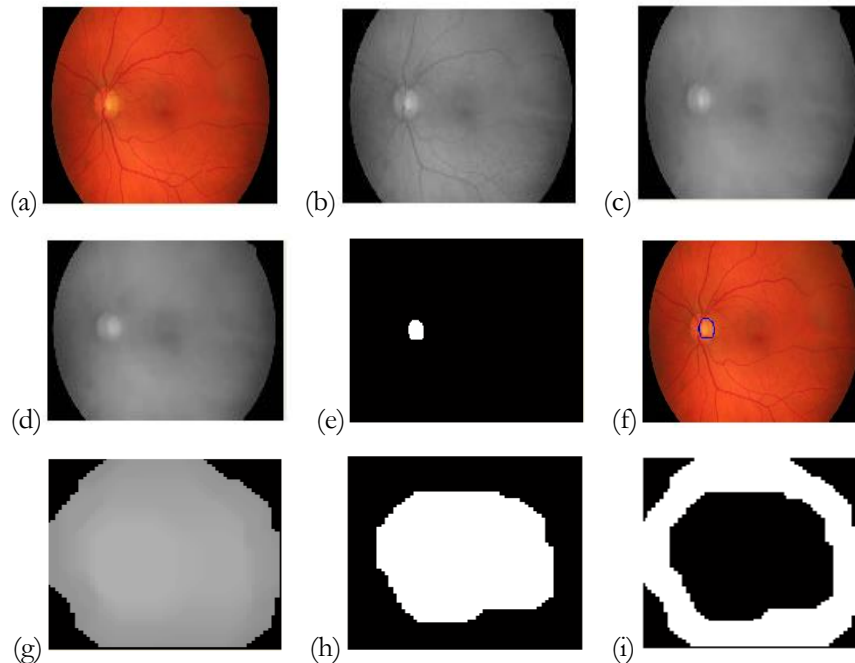
Figure 8. Glaucoma Screening Process. (a) Retinal image, (b) Intensity image, (c) Morphologically closed image, (d) Morphologically opened image, (e) Binary image, (f) OD detected image, (g) OD segmented image, (h) OC segmented image, (i) Segmented rim region

Diagnosis of Glaucoma Severity

To analyze the Glaucoma severity, different characteristics of image features are extracted by a process named 'glaucoma feature extraction'. After OD and OC are segmented, the local binary pattern (LBP) features[13] are extracted from these segmented regions. For training mode, initially, LBP features are extracted from normal, mild, moderate and severe glaucoma retinal images. These extracted features are used in training of Support Vector Machine (SVM) classifier in training mode. After the training is complete, the LBP features are extracted from input retinal image and classified by SVM classifier using the trained feature patterns. We integrate the result of SVM classifier with Cup-to-Disc Ratio (CDR) results for the classification of glaucoma severity. If CDR lies within 0.3 and SVM classification result is 1, then the image is classified as normal, meaning no symptoms for glaucoma. If CDR value lies between 0.3 and 0.5 and SVM classification result is 2, then the image is classified as moderate, which indicates initial symptoms for glaucoma. If CDR lies

above 0.5 and SVM classification result is 2, then the image is classified as severe, resulting in severe symptoms for glaucoma which needs immediate surgery to avoid blindness.

Results and Discussion

Evaluation Details of Hemorrhages Detection

The performance of DR system is analyzed for the proposed hemorrhages detection method with their corresponding ground truth images. The ground truth retinal images used for our experimentation were obtained from the publicly available database.

The performance of hemorrhages segmentation is analyzed with the following parameters,

- Specificity [$Sp = T_{neg} / (T_{neg} + F_{pos})$]
- Accuracy [$Acc = (T_{pos} + T_{neg}) / (T_{pos} + F_{neg} + T_{neg} + F_{pos})$]

where, T_{pos} is True positive, T_{neg} is True negative, F_{pos} is False positive and F_{neg} is False negative. The above quality parameters are evaluated and listed in Table 2. True Positive denotes the correctly identified hemorrhage pixels, False Positive indicates the wrongly identified hemorrhage pixels; True Negative and False Negative refers to the correctly identified background pixels and wrongly identified background pixels, respectively.

The entire algorithm was processed using MATLAB R2008b and results were accomplished for fovea region and hemorrhage detections. The MATLAB coding uses an average run time of 10seconds/image to run on a 2.4 GHz Intel Pentium Core2 duo machine with 4GB internal RAM.

The computed values for the hemorrhage detection and its comparison with other state of arts [4-8] are summarized in Table 2 and also graphically illustrated in Figure 9. The performance parameters Specificity (Sp) define the ratio of well classified hemorrhages and non-hemorrhages lesions, respectively.Accuracy (Acc) is the number of total well classified pixels that is about 98.09%.

Table 2. Performance Comparison of Hemorrhages Detection

Methodology	Sp
Proposed	98.47
Zhang et al. (2011) [4]	81.6
Kose et al. (2012) [5]	98.3
Hatanaka et al. (2008) [6]	80.0
Esmaeili et al. (2010) [7]	87.0
Sinthanayothin et al. (2002) [8]	88.7
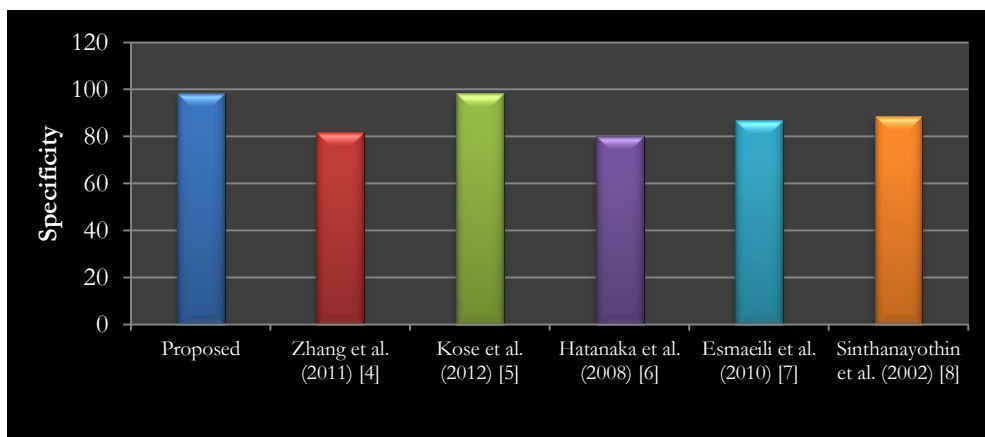
Figure 9. Graphical Plot for Performance Comparison of Hemorrhages Detection

Evaluation details of Glaucoma Screening

The proposed optic disc and cup segmentation algorithm have been applied for a set of images available in DRIVE and STARE database and the segmentation results were compared with their respective ground truth images given by specialized ophthalmologists for performance evaluation.

The performance of optic disc segmentation is analyzed with the same parameters used in hemorrhage segmentation. In Table 3, the accuracy in detection of optic disc is compared with other techniques [9-11].

A number of glaucoma risk factors are considered for glaucoma screening such as Cup to Disc Ratio (CDR), Optic band top, optic band bottom, optic band left and optic band right. All of these factors, CDR has been widely used parameter to classify the glaucoma screening. Although different ophthalmologists have different opinions on the usefulness of these factors, CDR is well accepted and commonly used. A larger CDR indicates a higher risk of glaucoma.

The CDR is computed as the ratio of the optic cup diameter (OCD) to optic disc diameter (ODD) clinically. Accurate segmentations of optic disc and optic cup are essential for CDR measurement in glaucoma screening. These CDR values were obtained from expert ophthalmologists for a set of images containing normal, moderate and severe glaucoma. These CDR values are utilized for the proposed classification technique, whose value indicates the severity of glaucoma disease in retinal images. If the computed CDR lies less than or equal to 0.2, then it is concluded as normal retinal images. If the computed CDR lies between 0.3 and 0.4, then it is concluded as moderate glaucoma cases. If the computed CDR lies greater than or equal to 0.5, then it is concluded as severe glaucoma cases.

Table 5 illustrates the glaucoma severity classification. The performance of classification result for glaucoma screening is analyzed for several cases such as normal, moderate and severe. For evaluation purpose, 15 images from DRIVE and 15 images from STARE database is used. The proposed algorithm classifies the retinal images at an average classification rate of 100% and 93.3%, respectively as shown in Table 4.

Table 3. Performance Comparison of OD Segmentation

| Methods	Accuracy (%)
Proposed Method	99.30
Shahbeig et al. [9]	97.53
Dehghani et al. [10]	91.36
Foracchia et al. [11]	98.0
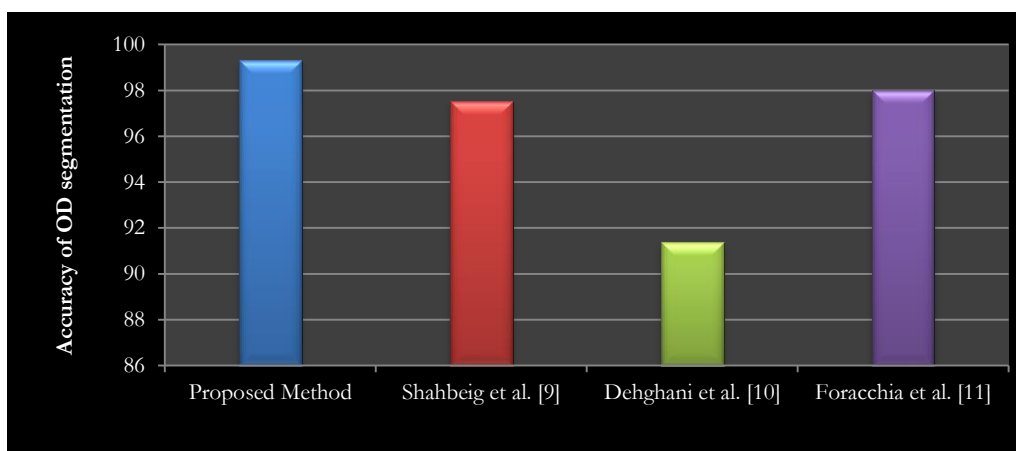
Figure 10. Graphical Plot for Comparison of Accuracy in OD Segmentation

Table 4. Classification Accuracy Evaluation of Proposed Method

Database	Diagnosis System	Classification Rate (%)
DRIVE	Glaucoma	100
STARE	Glaucoma	93.3

The classification of DR and Glaucoma have been evaluated and their classification rates are graphically compared in Figure 11.
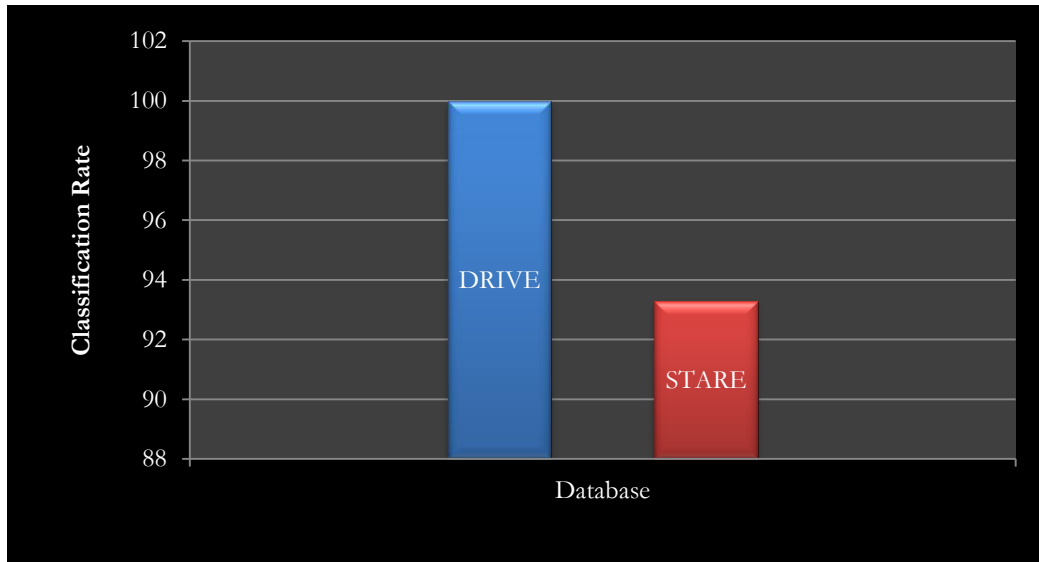
Figure 11. Graphical illustration of Classification Rate of Glaucoma

Conclusions

In this paper, we have diagnosed Diabetic Retinopathy and Glaucoma screening to prevent vision loss in diabetic patients. This proposed method can help the ophthalmologists to detect hemorrhages and fovea region in DR screening process. It also helps the ophthalmologists to diagnose the glaucoma by detecting and segmenting the optic disc and optic cup region. The proposed diagnosis system classifies DR and glaucoma screening in to mild, moderate and severe respectively. The result shows that, the proposed methodology used is well suited for the early diagnosis of the Diabetic Retinopathy and glaucoma.

List of abbreviations

Diabetic Retinopathy (DR)
Optic Disc (OD)
Optic Cup (OC)
Hemorrhages and Microaneurysms (HMA)
Sensitivity (Se)
Specificity (Sp)
Accuracy (Acc)
True Positive (TP)
False Positive (FP)
True Negative (TN)

False Negative (FN)
Field-of-view (FOV)
Charge Coupled Device (CCD)
Local binary pattern(LBP)
Support vector machine(SVM)
Cup-to-Disc Ratio (CDR)
Optic cup diameter (OCD)
Optic disc diameter (ODD)

Conflict of Interest

The authors declare that they have no conflict of interest.

Acknowledgments

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