Applied Medical Informatics
Original Research Vol. 36, No. 1 /2015, pp: 13-22

Screening Diabetic Retinopathy in Developing Countries using Retinal Images

D. SIVA SUNDHARA RAJA[1,*], S. VASUKI[2]

[1] Department of Electronics & Communication, SACS MAVMM Engineering College, Madurai 625301, India.
[2] Department of Electronics & Communication, Velammal College of Engineering & Technology, Madurai 625009, India.
E-mail (*): ssrrvs@gmail.com

* Author to whom correspondence should be addressed; Tel.: +91-98651 30941

Received: 16 December 2014 /Accepted: 17 March 2015 / Published online: 31 March 2015

Abstract
In developing countries, diabetic retinopathy (DR) is the leading cause of blindness in diabetic patients due to intraocular hypertension or high glucose level. Its detection in an earlier stage is essential to prevent vision loss in type 2 diabetic patients. In this paper, the computer aided automatic screening system for diabetic retinopathy is proposed. DR can be diagnosed by detecting the abnormal lesions such as hemorrhages in retinal images and analyzing its relationship with the fovea region. The proposed method consists of the following stages, namely: retinal image enhancement and classification, hemorrhages detection and segmentation, fovea localization and Diabetic Retinopathy classification. The multi directional local histogram equalization is used to enhance the retinal image for better classification rate. The Gabor transform and Support vector machine (SVM) classifier is used for retinal image classifications. The proposed method is tested on publicly available HRFand DIARETDB1datasets. The sensitivity and specificity of hemorrhages detection are 94.76% and 99.85%, respectively. Thus, the severity of Diabetic Retinopathy in Type 2 diabetic patients can be easily identified by detecting fovea region and hemorrhage lesions and analyzing the relation between them to prevent vision loss in diabetic patients.

Keywords: Diabetic Retinopathy (DR); Hemorrhages; Diagnosis system; Fovea

Introduction

Diabetic retinopathy (DR) is the leading ophthalmologic cause of blindness among people of working age in developing countries [1]. The main cause of DR is abrupt blood glucose level increasing in diabetic patients. It will damage the retinal blood vessels permanently which causes leakage of the lipids around it. These lipids cause lesions in the retina such as exudates, hemorrhages and Microaneurysms and macular edema and finally lead to retinal detachment [2]. Even though, DR is not a curable complication, it can be prevented in earlier stages to prevent vision loss in diabetic patients. Hence, diabetic patients require frequent eye–fundus screening. Due to the large population of developing countries, it is not possible to screen the diabetic patient's eye in frequent manner by the ophthalmologist at the eye care center. It will also increase the work capacity/efficiency in this endeavor/situation. Hence, the computer aided automatic screening of retinal fundus of diabetic patients is required in such a scenario.

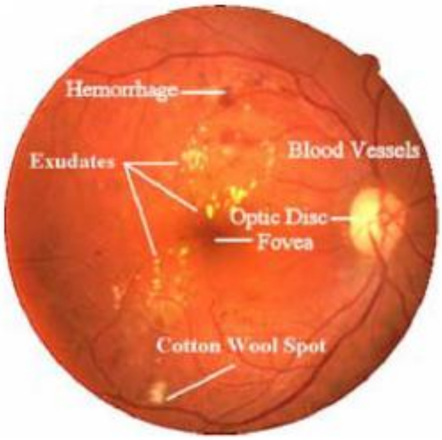


Figure 1. Retinal image showing various lesions

Related Works

Saikat et al. [1] have used the Contrast Limited Adaptive Histogram Equalization technique for the enhancement of retinal images. The proposed approach simultaneously addresses the intensity saturation and noise amplification issues that are commonly encountered in enhancement algorithms. Selvathi et al. [2] used Gray Level Co-occurrence Matrix (GLCM) and Support vector machine classifier for the classification of retinal images. The authors achieved 93% of classification accuracy rate.

Qaisar et al. [3] has used multi-scale discrete shearlet transformation to improve the contrast of the retinal images. This methodology preserved the edges in the images during contrast improvement. The quality analysis parameter such as Peak signal to noise ratio (PSNR) is achieved about 23.49db by this method. Hillol et al. [4] proposed pixel level image fusion technique to classify the normal and abnormal retinal images. The mask is created with region of interest. A classification rate of 81.17% is achieved by this method.

Tirupati et al. [5] used Discrete Wavelet Transform (DWT) and Singular Value Decomposition to enhance the retinal images. The retinal image is decomposed into four frequency sub band images and Singular Value Decomposition applied on Low-Low sub band Image, which determines the intensity information. Bae et al. [6] proposed a hybrid methodology for detection and segmentation of hemorrhages in the retinal fundus images. Contrast-limited adaptive histogram equalization (CLAHE) is used to differentiate the hemorrhages from the background. The sensitivity rate of about 85% is achieved in this methodology. Shivaram et al. [7] have used morphological operators such as erosion and dilation to detect and segment the hemorrhages in the retinal images. The sensitivity and specificity rate was 89.49% and 99.89% respectively. Acharya et al. [8] used morphological image processing to detect various lesions. The authors achieved 82% sensitivity and 86% specificity for the detection of hemorrhages candidates in the retinal fundus images. Wang et al. [9] has detected and segmented exudates and hemorrhages using minimum distance discriminant classifier algorithm. This method did not differentiate exudates from hemorrhages accurately. The proposed detection algorithm has achieved average sensitivity of 100% and average specificity of 70%.

Material and Method

To evaluate the performance of Diabetic Retinopathy, the publicly available databases HRF and DIARETDB1 were being used. Each database consists of several sets of retinal images under normal and abnormal pathologies. Many researchers have made use of these databases to investigate their lesion segmentation methodologies since these data sets are public and also provide ground truth data sets which are manually segmented images reported by experts.

Dataset

HRF Dataset[14] was used for retinal image classification.It includes 15 images of healthy persons,15 images of patients with diabetic retinopathy and 15 images of glaucomatous patients. Each retinal image was taken with a Canon CR-1 fundus camera with a field of view of 45° and different acquisition setting.

DIARETDB1 Dataset [15]was used for the detection and segmentation of hemorrhages and its performance analysis for DR classifications. 89 colour fundus images of which 84 contain at least mild non-proliferative signs of the diabetic retinopathy, and 5 are considered as normal which do not contain any signs of the diabetic retinopathy.

Diagnosis System for Diabetic Retinopathy

The diagnosis system for DR consists of retinal image classification system, fovea localization, hemorrhage lesion detection and segmentation. The number of hemorrhage lesion pixels on fovea region is analyzed and DR is classified as mild, moderate or severe. Systematic flow diagram of the proposed DR Diagnosis System is depicted in Figure 2. The retinal image classification system classifies the retinal image into either normal or abnormal using SVM Classifier as depicted in Figure 3. The fovea and hemorrhages are segmented further in classified abnormal image.

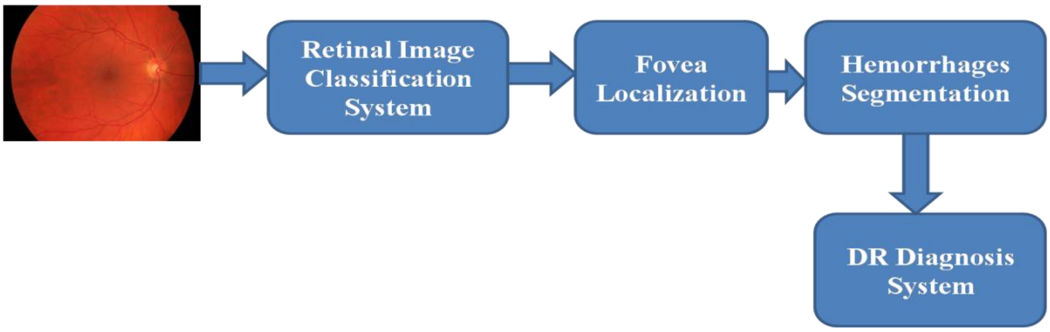


Figure 2. Systematic flow diagram of the proposed DR diagnosis system

The retinal image enhancement and Classification system consists of directional local histogram equalization, Multi Resolution Gabor Transform, feature extraction and SVM Classifier. This proposed system classifies the retinal fundus images in to either normal or abnormal retinal images for further diabetic retinopathy diagnosis system. The detailed flow of proposed retinal image classification system is depicted in Figure 3.

Directional Local Histogram Equalization (DLHE)

Multi directional local histogram equalization technique [10] is used in this research to enhance the retinal fundus image for classification. This technique detects and enhances the edges pixels based on their orientations in all eight directions. Contrast limited Adaptive histogram Equalization [1] detected some edge orientation pixels during its enhancement process. However, this information was partially discarded during contrast enhancement.

The directional local histogram equalization technique is represented and explained in the following equation and steps.

$$\pounds = \pounds_x$$

$$\pounds_x = \{\pounds_0, \pounds_{45}, \pounds_{90}, \pounds_{135}, \pounds_{180}, \pounds_{225}, \pounds_{270}, \pounds_{315}\} \qquad (1)$$

where x represents eight equal orientations around the center pixel

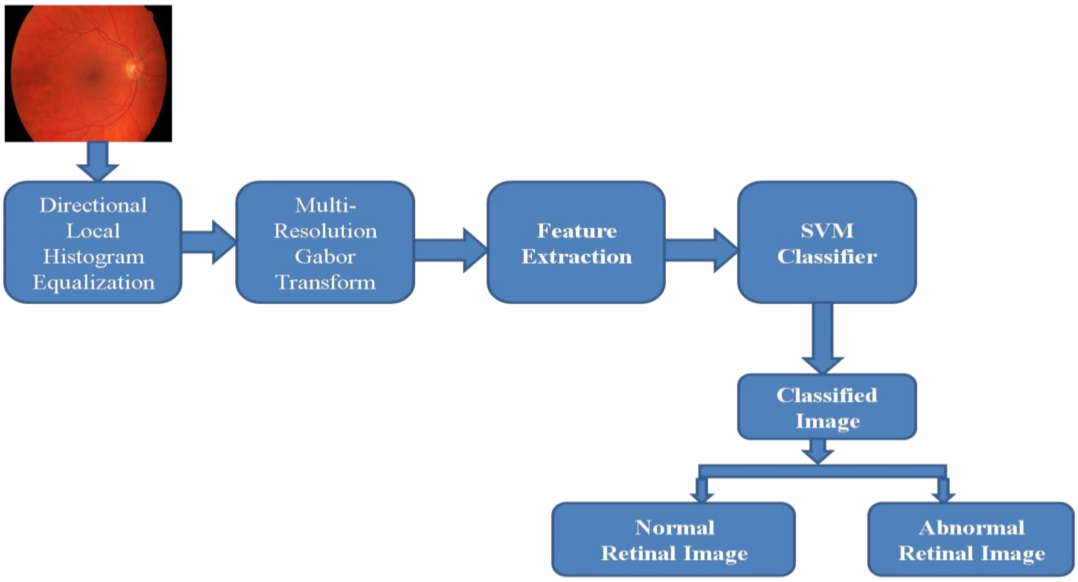


Figure 3. Proposed retinal image classification system

Steps

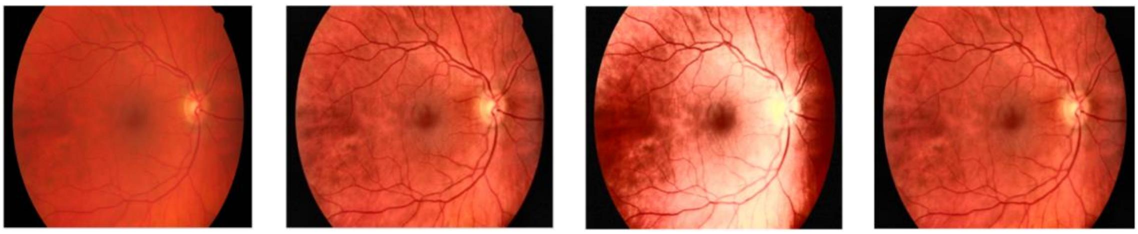
1) To find the value of $\pounds_{45}$, consider the eight neighboring pixels by keeping $\pounds_{45}$ as center pixel.
2) Adaptive local histogram equalization (ALHE) is computed for these 3×3 pixels by keeping $\pounds_{45}$ as center pixel.
3) Determine the remaining directional values using the same procedure.
4) Finally, apply the ALHE technique to all eight surrounding pixels in order to find the enhanced pixel.

Figure 4(a) shows the normal retinal image, Figure 4(b) shows the retinal image after enhancement by DLHE (proposed) method, Figure 4(c) shows the enhanced retinal image by histogram equalization and Figure 4(d) shows the enhanced retinal image by contrast limited adaptive histogram equalization. Figure 5(a) shows the abnormal retinal image, Figure 5(b) shows the retinal image enhanced by DLHE (proposed) method, Figure 5(c) shows the enhanced retinal image by histogram equalization and Figure 5(d) shows the enhanced retinal image by contrast limited adaptive histogram equalization.

The performance of the proposed retinal image enhancement is analyzed using the evaluation parameter PSNR as stated in equation 2.

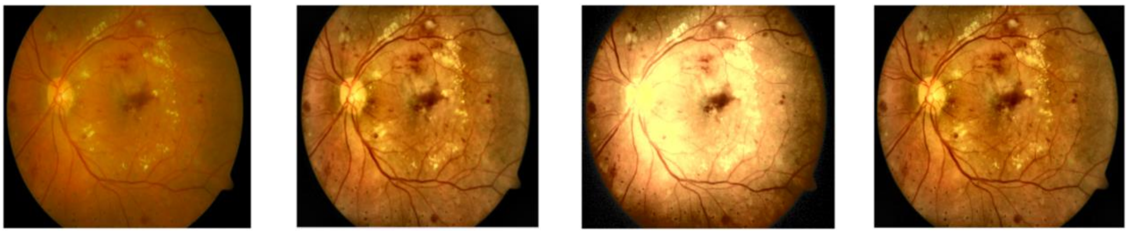
$$PSNR = 200 \times \log_{10}(MAX_f/\sqrt{MSE}) \qquad (2)$$

where PSNR = Peak signal to noise ratio; MAX_f = higher grey level value 255, MSE = mean square error between the test retinal image and enhanced retinal image.



(a) (b) (c) (d)

Figure 4. **(a)** Normal Retinal Image; Retinal image enhancement using; **(b)**proposed method; **(c)** histogram equalization; **(d)**contrast limited adaptive histogram equalization



(a) (b) (c) (d)

Figure 5. (a) Abnormal Retinal Image; Retinal image enhancement using; **(b)** proposed method; **(c)** histogram equalization; **(d)** contrast limited adaptive histogram equalization

Multi-Scale Multi-Orientation Gabor Transform

Gabor transform represents the frequency properties of retinal image which is used to classify the retinal images as either normal or abnormal retinal images. It can be constructed using different scales (f) and orientations (theta).Specifically, the proposed Gabor transform is constructed using 5 different scales(2,4,6,8,10) and 4 orientations(0 pi/4 pi/3 pi/2). The multi scale and multi orientation Gabor filter is convolved with retinal image to decompose them for image classifications.

The Gabor Kernel is defined as,

$$G(X,Y,theta,f)=exp([-1/2\{(x' / s x')^2 + (y' /s y')^2\}]) * Cos(2 *pi*f* x') \quad (3)$$

where, x' and y' are defined as

$$x' =x * Cos (theta) +y*Sin (theta)$$
$$y' =y * Cos (theta)-x*Sin (theta)$$

The Gabor transformed image (G) contains both real and Imaginary Part. For further analysis, the magnitude part of the Gabor transformed output is required. The Magnitude of the Gabor transformed image is determined as:

$$G_m =Root [Re[G(z)^2]+ Im[G(z)^2]] \quad (4)$$

In this research, 5 scales and 4 orientations on a geometric grid were considered. For each scale, 4 orientation images are obtained, hence totally 20 orientation images are finally determined for a single retinal image. The final Gabor transformed image(G_m) is chosen as the transform scale and orientation which gives the maximum average response at each location in 20 orientation images.

Feature Extraction

The features are extracted from Gabor transformed image (G_m) in order to classify the retinal images in to normal or abnormal. The feature vector is composed of mean, smoothness, entropy, contrast, homogeneity and kurtosis. These features are extracted from Gabor transformed image (G_m).These extracted features are trained using SVM classifier.

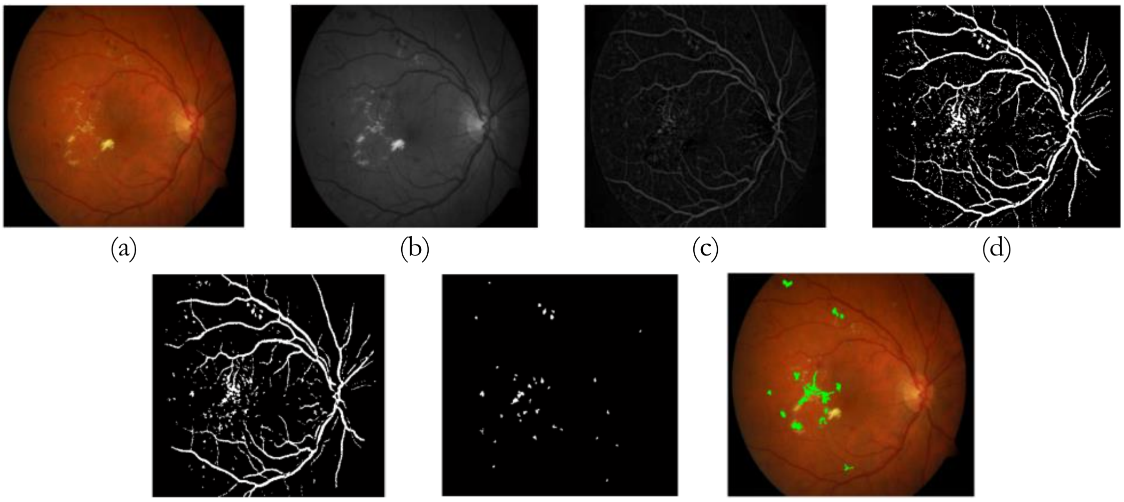
SVM Classifier

The extracted features are used in training of Support Vector Machine (SVM) classifier in training mode. After the training is completed, the same features are extracted from input retinal image and classified by SVM classifier using the trained feature patterns for retinal image classifications.

Fovea and Hemorrhages Detection

The fovea is the middle of the macula, whose detection plays a vital role in analyzing the severity of DR, which can be analyzed with the relationship between fovea region and hemorrhage lesions [11]. Initially, the LAB color transform is applied over the retinal image to enhance the fovea region. Since the fovea is the darkest black region in the retinal image, all the pixels below the threshold value, i.e. 60, (using histogram count) are detected as fovea region pixels by applying morphological operations using a disc shaped structuring element of radius 3 pixels.

The hemorrhages are formed in the retinal image due to the retinal blood vessels damage or blockage in retinal blood vessels as reddish abnormal lesions. The hemorrhages in the retinal images are detected and segmented by a three stage process:1) each retinal image is preprocessed such as separation of RGB retinal image in to three channels, namely, red, green and blue color sub channels. The green color channel shown in Figure 6(b) provides the best hemorrhages background contrast and hence provides an accurate detection of hemorrhages. The red sub channel provides the lower contrast for hemorrhages and the blue sub channel offers poor contrast for hemorrhages in the retinal images; 2) 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; 3) morphological operations such as opening is performed on histogram equalized image with disc structuring element of radius 15 pixels.



(a) (b) (c) (d) (e) (f) (g)

Figure 6. (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

Finally, the histogram equalized image is absolutely subtracted from morphological opened image to get I_{top} (Figure 6(c)). All the pixels greater than the threshold value of 30 are segmented to separate the reddish lesions in retinal image. Then, morphological opening with disc shaped structuring element of radius 2 pixels is applied on the thresholded image (Figure 6(d)) to extract hemorrhages lesions boundary region with blobs (Figure 6(e)). Then it is morphologically processed (using eccentricity property) to remove blobs (Figure 6(f)). The final hemorrhages detected and segmented image is shown in Figure 6(g).

Severity Classification of DR

In order to help diabetic patients get a proper and timely treatment, the severity analysis of DR becomes very useful in developing countries where there is a lack of ophthalmologists or physicians. The severity of DR can be categorized into mild, moderate and severe. The relation between fovea region and hemorrhages count is explained as follows [11] (Table 1).

Moderate DR causes starting of blindness and Severe DR leads to blindness.

Table 1. Constraints for DR classification

Classifications of DR	Conditions for DR Analysis
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

Statistical Parameters used is Evaluation of the Methods

The parameters considered for evaluation of proposed method are Sensitivity (Se), and Specificity (Sp).'Se' denotes the ratio of well classified hemorrhages and 'Sp' is the ratio of well classified non-hemorrhage lesions. The performance parameters are as follows:

Sensitivity [Se = TP / (TP + FN)] (5)

Specificity [Sp = TN / (TN + FP)] (6)

where TP = true positive, TN = true negative, FP = false positive, and FN = false negative.

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 proposed algorithm was implemented using MATLAB R2010.

Results and Discussion

Evaluation Details of Retinal Image Enhancement and Classifications

The proposed retinal fundus image classification system using multi scale –multi orientation Gabor transform and SVM classifier achieved 100% of average classification rate on both normal and abnormal retinal images. The proposed classification rate is compared with different state of arts and indicated in Table 2. The performance evaluation of proposed retinal contrast enhancement is stated in Table 3.

Table 2. Retinal image Classification rate

Methodology	Classification Rate (%)
Gabor and SVM (Proposed)	100
GLCM and SVM [2]	93
Image fusion [4]	81.17

Table 3. Performance evaluation of Enhancement

Methodology	Peak Signal to Noise Ratio (dB)
Gabor and SVM based Enhancement(Proposed)	51.45
Histogram Equalization [1]	26.21
Contrast limited Adaptive histogram Equalization [1]	50.22
Multi scale discrete shearlet transform [3]	23.49

Evaluation Details of Hemorrhages Detection

After segmenting the fovea region from the retinal image, the segmentation of hemorrhages lesion is done. The performance of our proposed technique is analyzed which was exclusively designed to prevent vision loss in diabetic patients at earlier stage.

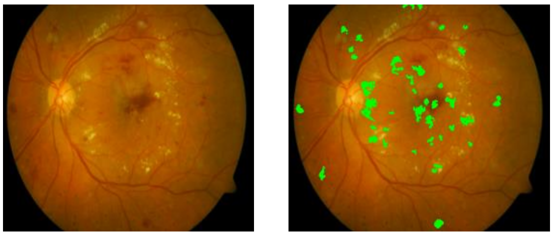
The proposed fovea region detection algorithm is applied over a set fundus images available from publicly available database. These images exhibit lesions or abnormalities caused by hyper tension, damaged blood vessels, etc. The Fovea detection method calculates the fovea pixels count in the retina and the proposed hemorrhages detection method gives an estimation of the hemorrhages pixels present in the retina.

The computed values for the hemorrhage detection are summarized in Table 4 and the corresponding hemorrhages lesion identified images are illustrated in Figure 7.

Table 4. Results on DR classifications

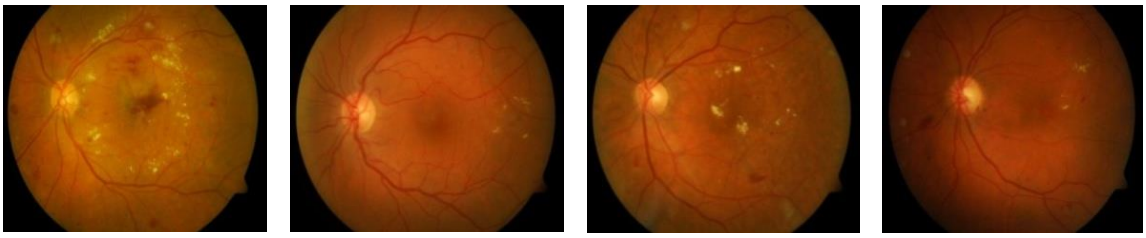
Image	No. of Fovea Pixels	Total No. of Hemorrhages in Retina	Total no. of Hemorrhages in Fovea	DR Classification Results
1	12187	11761	2290	Severe DR
2	12187	512	0	No DR
3	12187	2523	1393	Severe DR
4	12187	4463	342	Mild DR
5	12187	7020	1370	Severe DR

*the result of 5 abnormal retinal images in DIARETDB1 database is shown for example



(a) (b)

Figure 7.(a) Retinal images showing severe DR; **(b)** Detected and segmented hemorrhages



(a) (b) (c) (d)

Figure 8. Classification of Diabetic Retinopathy: **(a)** Mild DR.**(b)** No DR.**(c)** Severe DR.**(e)**Moderate DR

The reason for Diabetic Retinopathy severity detection and further diagnosis is to help ophthalmologists and physicians for effective clinical treatment in developing countries by reducing the time for executing the treatment and further diagnosis. It is also found that, hemorrhages lesion detection achieves 94.76% Se, and 99.85% Sp for a set of retinal images available in public database DIARETDB1.

The severity analysis of DR for various test images is shown in Figure 8. This proposed technique for DR diagnosis assists to reduce the manual work time and reduces the risk of committing classification errors. This also facilitates further clinical treatment, diagnosis, and an earlier treatment to prevent vision loss. Thus, this discussion helps in the classification of DR severity on retinal images.

The proposed work is also being compared with existing Hemorrhages detection and segmentation algorithms and shows better results in terms of Sensitivity and Specificity. The compared results are tabulated in Table 5. Finally, it is validated that the proposed method performs well in detecting hemorrhages in retinal images.

Table 5. Performance comparison of Hemorrhages Detection

Methodology [ref]	Se (%)	Sp (%)
Proposed method	94.76	99.85
Bae et al. [6]	85.0	n.a.
Köse et al. [12]	93.2	98.3
Zhang et al. [13]	91.3	81.6

n.a. = indicates that this information was not available

Conclusions

The proposed scheme described in this paper mainly helps the ophthalmologists to diagnose the severity of DR into mild, moderate and severe. The abnormality lesions hemorrhages are detected and analyzing the relation between these lesions and fovea region, the severity of DR is diagnosed. The proposed system classifies the retinal images into normal and abnormal images and achieved 95% classification rate on both dataset.The proposed method also achieved 94.76% sensitivity and 99.85% specificity for hemorrhages detection. All of these results are evaluated with ground truth images obtained from expert ophthalmologists. By evaluating the hemorrhages and fovea region, the severity of Diabetic Retinopathy can be easily identified to prevent vision loss in the diabetic patients.

List of abbreviations

DR = Diabetic Retinopathy
SVM = Support vector machine
PSNR = Peak signal to noise ratio
DWT = Discrete Wavelet Transform
Se = Sensitivity
Sp = Specificity
FOV = Field-of-view
CCD = Charge Coupled Devices

Conflict of Interest

The authors declare that they have no conflict of interest.

Acknowledgements

The authors would like to thank their friends and colleagues for their constant help and support throughout this research work and to obtain the results.

References

1. Saikat Kumar Shome, Siva Ram Krishna Vadali. Enhancement of Diabetic Retinopathy Imagery using Contrast Limited Adaptive Histogram Equalization. International Journal of Computer Science and Information Technologies 2011;2(6):2694-9.
2. Selvathi D, Prakash NB, NeethiBalagopal. Automated detection of diabetic retinopathy for early diagnosis using feature extraction and support vector machine. International Journal of Emerging Technology and Advanced Engineering 2012;2:103-8.
3. Qaisar Abbas, Amjad Farooq, Thahir Abbas, Emre Celebi, Irene Fondon Garcia, Jimenez

Carmona. Features Preserving Contrast Improvement for retinal vascular Images. International Journal of Innovative Computing, Information and Control 2013;9:3731-9.
4. Hillol Das, AshimSaha, Suman Deb,GautamNath. An automated approach to differentiate a normal eye from a defective eye. International Journal of Computer Applications 2013;79:10-4.
5. Tirupati G, Subba Rao B. A Novel Technique for Fundus Image Contrast Enhancement. International Journal of Bio-Medical Informatics and e-Health 2014;2:1-6.
6. Bae JP, Kim KG, Kang HC, Jeong CB, Park KH, Hwang JM. A Study on Hemorrhage Detection Using Hybrid Method in Fundus Image, J Digital Imaging 2011;24:394-404.
7. Shivaram JM, Patil R, Aravind HS. Automated detection and quantification of hemorrhages in diabetic retinopathy images using image arithmetic and mathematical morphology methods. Int J Recent Trends Eng 2009;6:174-6.
8. Acharya UR, Lim CM, Ng EYK, Chee C, Tamura T. Computer-based detection of diabetes retinopathy stages using digital fundus images. InstMechEngProc2009;14:545-53.
9. Wang H, Hsu H, Goh K, Lee M. An effective approach to detect lesions in retinal images. In: IEEE Conf Comput Vis Pattern Recogn Proc 2000;24:181-7.
10. Ping-Han Lee, Szu-Wei Wu, Yi-Ping Hung. Illumination Compensation using Oriented local histogram equalization and its application to face recognition. IEEE Transactions on Image Processing 2012;21:1123-9.
11. Siva Sundhara Raja D, Vasuki S.Diagnosis System for Diabetic Retinopathy and Glaucoma Screening to Prevent Vision Loss. Applied Medical Informatics 2014;34:10-21.
12. Köse C, Şevik U, Ikibaş C, Erdöl H. Simple methods for segmentation and measurement of diabetic retinopathy lesions in retinal fundus images. Computer Methods Programs Biomed 2012;107:274-93.
13. Zhang D, Li X, Shang X, Yi Y, Wang Y. Robust hemorrhage detection in diabetic retinopathy image. First Asian Conference on Pattern Recognition (ACPR'2011). Proc. Beijing; 2011:209-13.
14. HRF database [online] [Accessed 2014 November]. Available from: https://www5.cs.fau.de/research/data/fundus-images/
15. DIARETDB1 database[online] [Accessed 2014 November]. Available from: http://www.it.lut.fi/project/imageret/diaretdb1/