



# INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X

Impact factor: 4.295

(Volume 4, Issue 1)

Available online at [www.ijariit.com](http://www.ijariit.com)

## A Survey on Retinal Red Lesion Detection Techniques for Diabetic Retinopathy Screening

Shameena P P  
[shamzz89@gmail.com](mailto:shamzz89@gmail.com)  
Department of ECE, KTU  
University

Jamsheera. K  
[jemseerakallingal@gmail.com](mailto:jemseerakallingal@gmail.com)  
Department of ECE University

Ayisha Shamna. K K  
[ayishamna@gmail.com](mailto:ayishamna@gmail.com)  
Department of ECE, KTU  
University

### ABSTRACT

*Diabetic retinopathy (DR) is a sight-threatening condition occurring in persons with diabetes, which causes progressive damage to the retina. People with diabetes mellitus need annual screening to check for the development of diabetic retinopathy (DR). The early detection and diagnosis of DR are vital for saving the vision of diabetic persons. The early signs of DR which appear on the surface of the retina are the dark lesions such as microaneurysms (MAs) and hemorrhages (HEMs). The shape and count of these features are used to indicate the severity level of diabetic retinopathy. A computer-aided diagnosis system can help to reduce the burden on the ophthalmologist and rapidly identify the most severe cases. So in this paper, a survey of different red lesion detection techniques and automated analysis are discussed.*

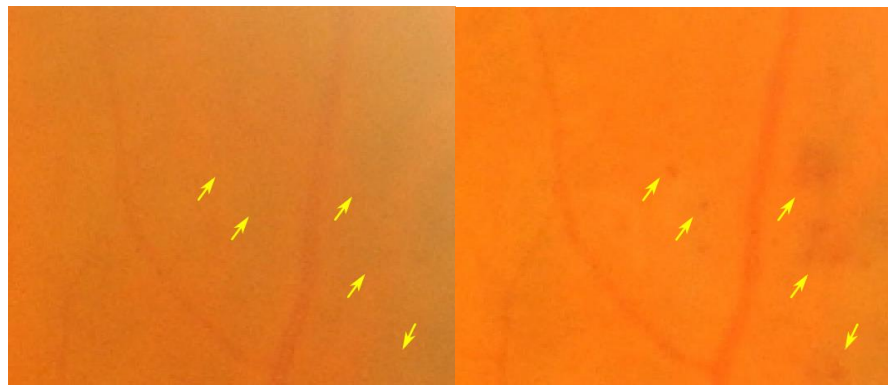
**Keywords:** *Diabetic Retinopathy, Microaneurysm, Hemorrhages, Circular Hough Transform, Dynamic Shape Features, Automatic Detection.*

### 1. INTRODUCTION

Diabetic Retinopathy is a complication of diabetes mellitus, which progressively damages retinal blood vessels and may result in vision loss and even blindness if not diagnosed and treated adequately. A regular eye examination is necessary for timely detection and treatment of DR at an early stage. The current eye care practice for screening DR involves examination of multiple field fundus images for pathognomonic abnormalities by a trained expert. Depending on the observed retinal abnormalities at the time of the examination, diabetic patients are either scheduled for a follow-up examination or referred to an ophthalmologist for further diagnostic evaluation and possibly treatment. This screening procedure is subjective time consuming and puts a considerable demand on diabetic eye care resources.

Microaneurysms are small circular red spots with diameter 10 to 100  $\mu\text{m}$  which are the first sign of DR. It is tiny swelling appears in the retinal capillaries as a small, round, red spot located in the inner nuclear layer of the retina.

Moreover, in addition to examining how far the disease has progressed at the time of examination, the goal of regular DR screening is also to identify patients with a high risk of progression. DR is a progressive disease that results in retinal changes such as the appearance (and the disappearance) of associated lesions such as microaneurysms and haemorrhages (see figure 1) showing longitudinal retinal change locations (yellow arrows) due to early-stage DR lesions. Diabetic retinopathy can be classified as proliferative diabetic retinopathy and nonproliferative diabetic retinopathy [4]. NPDR occurs when the blood vessels get damaged inside the retina and leak extra fluid and small amounts of blood onto the retina. With this condition, retina becomes wet and swollen.



(a) Baseline Image

(b) Followup Image

**Figure.1. A Pair of Spatially Aligned Fundus Image Patches**

Three subclasses of NPDR are

- Mild
- Moderate
- Severe

A. Mild NPDR

Presence of at least one microaneurysm with or without the retinal haemorrhages.

B. Moderate NPDR

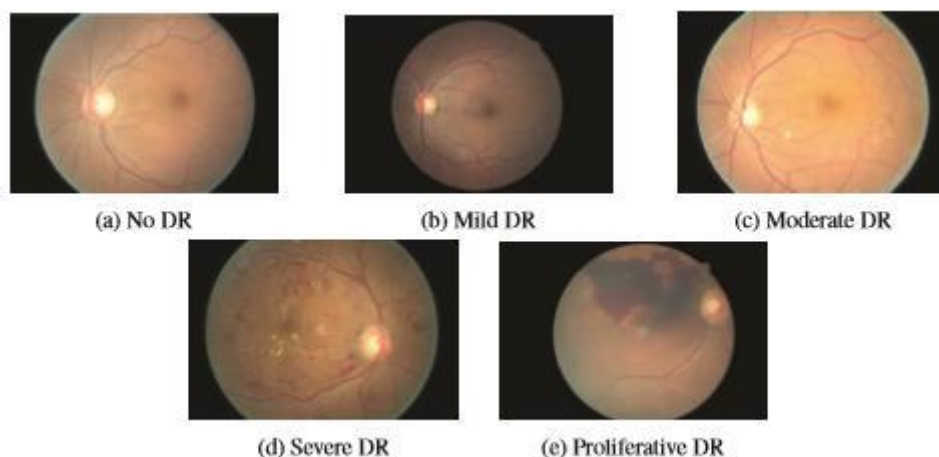
Presence of Numerous microaneurysms and retinal haemorrhages.

C. Severe NPDR

Numerous haemorrhages and microaneurysms in four quadrants of the retina.

PDR is an advanced stage of diabetic retinopathy. Growth of new abnormal blood vessels in different regions of the retina may lead to total blindness [5].

Figure 3 shows different stages of diabetic retinopathy based on increasing severity [6]. The research focuses on the analysis of different red lesion detection techniques used in available automatic telemedicine systems for computer-aided screening and grading of DR.



**Figure.3. Stages of Diabetic Retinopathy (DR)**

## **2. RELATED WORKS**

Diabetic retinopathy screening is a popular research vicinity and a number of researcher's awareness on and contributes toward the development of having a look at on this area. Computerized detection strategies for diabetic retinopathy screening had been proposed so that you can address the guide screening troubles. The intention of computerized techniques for screening is to perceive the desires of referral for further treatment. Different methods have been proposed and used for detecting the red lesions in order to produce an efficient and reliable detection system.

### **A. Threshold Based Method**

Vijay M Mane et al [7] proposed a method for combined MA and HE detection consists in identifying all dark colored structures in the image, mainly through a thresholding and removing the vessels from the resulting set of candidates using matched filtering. Unfortunately, the major limitation to this approach is that most of the false positives at the vessel segmentation step are actually lesions. These lesions are removed along with the detected vessels and cannot retrieve in subsequent processing.

### **B. Mathematical Morphology Based Method**

Sopharak et al [8] proposed a set of optimally adjusted morphological operators for exudate detection. In preprocessing stage the RGB space of the original image is transformed to HSI space and a contrast limited adaptive histogram equalization (CLAHE) is applied. Then a morphological operator such as a closing operator and a local variation operator is used to eliminate the vessels and to detect exudates respectively.

### **C. Circular Hough Transform**

Amiri et al [9] present an automated method for detecting microaneurysms in the retinal angiographic images by using image processing techniques. In the presented method, retinal images are preprocessed to fade or remove the pseudo-images. Then the central points of microaneurysms are identified by circular Hough transform. Then by using the region growing technique, the total areas of pixels associated with these lesions are identified. Hough transform is a kind of Brute Force method. Its computational complexity and large memory requirement lead to slowness in performance.

### **D. Curvelet Transform**

Syed Ayaz et al [10] proposed an automated microaneurysm detection system based on curvelet transform. Blood vessels are removed and a local entropy thresholding technique is used to select the microaneurysm candidates. Image background is estimated using statistical features. The results are allowed to identify the microaneurysm candidates which are also present in the image foreground. A collection of three set of features, namely color based, hessian matrix based and curvelet coefficients based are fed to a rule-based classifier to divide the candidate as microaneurysms and non microaneurysms.

### **E. Dynamic Shape Features**

Lama Seoud et al [3] proposed a method for the detection of both MAs and HEs that does not require prior vessel segmentation. A supervised classification scheme is considered to discriminate between lesions and other structures like vessel segments and background noise. After image pre-processing, candidate regions are identified. Features are extracted and used to classify each candidate. The major contribution is a new set of shape features that do not require precise segmentation of the candidates. Every regional minimum is considered as a candidate. Since the boundaries of the minima do not necessarily correspond to the edges of the structures of interest, propose to extract shape features through the process of morphological image flooding.

### **F. Convolutional Neural Network**

Harry Pratt et al [6] introduce a deep learning based CNN method to diagnosing DR from digital fundus images. A network with CNN architecture and data augmentation is developed to identify the intricate features involved in the classification task. A high-end graphics processor unit (GPU) is used to train the network.

### **G. Scale Space Based Method**

Ivo soares et al [11] proposed a scale space based method for the microaneurysm detection. The method performs a segmentation of the retinal vasculature. Then defines a global set of microaneurysm candidates using coarser and finer scales. Finer scales are used for analysis. The numbers of false microaneurysm candidates are reduced by using a set of gaussian shaped matched filters.

### **H. Hybrid approach**

M Usman Akram et al [12] proposed a system consisting of a novel hybrid classifier for the detection of retinal lesions. In pre-processing the systems eliminates the background pixels and extract the blood vessels. Gabor filter bank is used to extract the candidate lesion detection phases that have any type of lesion. A feature set based on shape, intensity, and statistics is formulated and classified using a hybrid classifier which is a combination of m- Medoids and Gaussian Mixture model.

### **I. Intensity and Shape Features based Method**

Kedir M. Adal [13] proposed a system consisting of a novel hybrid classifier for the detection of retinal changes. This is a robust and flexible approach for automated detection of longitudinal retinal changes due to small red lesions by exploiting normalized fundus images that significantly reduce illumination variations and improve the contrast of small retinal features. To detect spatio-temporal retinal changes, the absolute difference between the extremes of the multiscale blobness responses of fundus images

from two time-points is used as a simple and effective blobness measure. DR related changes are then identified based on several intensity and shape features by a support vector machine classifier.

**J. Gaussian Filtering, Top-Hat Transformation**

Walter et al. [14] introduced an algorithm for MA candidate extraction. It starts with image enhancement and green channel normalization, followed by candidate detection with diameter closing and an automatic thresholding scheme. Finally, the classification of the candidates was performed based on kernel density estimation.

**K. Morphological Operators, Matched Filtering**

Among the most widely applied candidate extractor methods are by Spencer et al. [89] and Frame et al. [90]. Here, shade correction was applied by subtracting a median filtered background from the green channel image. Candidate extraction was accomplished by morphological top-hat transformations using twelve structuring elements. Finally, a contrast enhancement operator was applied followed by the binarization of the resulting image.

**L. Morphological Operators, Matched Filtering**

Lazar and Hajdu [96] proposed a method using pixel intensity profiles. After smoothing the green channel with a Gaussian filter, the image was analyzed along lines at several directions. Based on intensity peaks, adaptive thresholding was applied to binarize the image and the final components were filtered based on their sizes.

**4. DISCUSSION**

Three measures are used to compare the performance of automated detection of red lesions. Sensitivity, specificity, and accuracy.

- **Sensitivity:** Probability of a positive test given that the patient has disease

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{1}$$

- **Specificity:** Probability of a negative test given that the patient has no disease

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{2}$$

**Table.1. Comparison Results of Methods for Red Lesion Detection**

Author	Methods	Dataset	Performance Measure
Vijay M Mane [7]	Thresholding Filtering	DIARET DB1	Sensitivity - 96.42% Specificity - 100% Accuracy – 96.62%
Sophara k [8]	Morphologica l operators	ROC database	Sensitivity - 80% Specificity- 99.5%
Amiri [9]	Circular hough transform	OWN database	Accuracy - 88.5%
Syed Ayaz [10]	Local thresholding Curvelet transform	ROC database	Sensitivity - 48.21%
Lama Seoud [3]	Dynamic shape features	ROC database	Sensitivity - 93.3% Specificity – 93.3%
Harry Pratt [6]	Convolutional neural network	Kaggle dataset	Sensitivity - 95% Accuracy - 75%
Ivo soares [11]	Coarser and finer scales	ROC database	Sensitivity - 47%

Author	Methods	Dataset	Performance Measure
M Usman Akram [12]	Multilayered thresholding Gabor filtering	ROC database	Sensitivity - 97.83% Specificity - 98.36% Accuracy - 98.12%
Kedir M. Adal [13]	Intensity and shape features based method	A regular DR Screening program at the Rotterdam Eye Hospital.	Sensitivity - 80%
Walter et al. [14]	Gaussian filtering, top-hat transformation	Non-public dataset	Sensitivity- 88.5%
Spencer et al. [15]	Morphological operators, matched filtering	Non-public dataset	Sensitivity- 82.4% Specificity- 85.6%
Lazar and Hajdu [16]	Directional cross-section profiles	Non-public dataset; ROC	NA

#### 4. CONCLUSION

This review presents a detailed survey of methods and results used for the automatic detection of Diabetic Retinopathy stages. The process of analyzing retinal images involves series of steps. Image acquisition, Image pre-processing, Candidate feature extraction and Classification. All these steps include various techniques or algorithms. Some existing methods are compared to give a complete view of the field.

Most of them use a threshold based method to segment the image and blood vessels are removed. Intensity features are formulated to classify the images. Unfortunately, the major limitation to this approach is that most of the false positives at the vessel segmentation step are actually lesions. These lesions are removed along with the detected vessels and cannot retrieve in subsequent processing.

Hough transform is used to find features of any shape in an image. Regular curves such as lines, circles, and ellipses can be detected using this method. Circular Hough transform is used to find circles in imperfect image inputs. But its computational complexity and large memory requirement lead to slowness in performance.

Dynamic shape features have proven to be robust features, highly capable of discriminating between lesions and vessel segments. The concept of DSFs could be exploited in other applications, particularly when the objects to be detected do not show clear boundaries and are difficult to segment precisely.

#### 5. REFERENCE

- [1] S. S. Rahim, C. Jayne, V. Palade and J. Shuttleworth, "Automatic detection of microaneurysms in color fundus images for diabetic retinopathy screening," *Neural Computing and Applications*, pp. 1–16, 2015.
- [2] M. U. Akram, S. Khalid, A. Tariq, S. A. Khan and F. Azam, "Detection and classification of retinal lesions for grading of diabetic retinopathy," *Computers in biology and medicine*, vol. 45, pp. 161– 171, 2014.
- [3] L. Seoud, T. Hurtut, J. Chelbi, F. Cheriet and J. P. Langlois, "Red lesion detection using dynamic shape features for diabetic retinopathy screening," *IEEE transactions on medical imaging*, vol. 35, no. 4, pp. 1116–1126, 2016.
- [4] M. R. K. Mookiah, U. R. Acharya, C. K. Chua, C. M. Lim, E. Ng and A. Laude, "Computer-aided diagnosis of diabetic retinopathy: A review," *Computers in biology and medicine*, vol. 43, no. 12, pp. 2136– 2155, 2013.
- [5] O. Faust, R. Acharya, E. Y.-K. Ng, K.-H. Ng and J. S. Suri, "Algorithms for the automated detection of diabetic retinopathy using digital fundus images: a review," *Journal of medical systems*, vol. 36, no. 1, pp. 145–157, 2012.
- [6] H. Pratt, F. Coenen, D. M. Broadbent, S. P. Harding, and Y. Zheng, "Convolutional neural networks for diabetic retinopathy," *Procedia Computer Science*, vol. 90, pp. 200–205, 2016.
- [7] V. M. Mane, R. B. Kawadiwale, and D. Jadhav, "Detection of red lesions in diabetic retinopathy affected fundus images," in *Advance Computing Conference (IACC), 2015 IEEE International. IEEE, 2015*, pp. 56–60.

- [8] A. Sopharak, B. Uyyanonvara, S. Barman and T. H. Williamson, "Automatic detection of diabetic retinopathy exudates from nondilated retinal images using mathematical morphology methods," *Computerized medical imaging and graphics*, vol. 32, no. 8, pp. 720–727, 2008.
- [9] S. A. Amiri, H. Hassanpour, M. Shahiri and R. Ghaderi, "Detection of microaneurysms in retinal angiography images using the circular Hough transform," *Journal of Advances in Computer Research*, vol. 3, no. 1, pp. 1–12, 2012.
- [10] S. A. A. Shah, A. Laude, I. Faye and T. B. Tang, "Automated microaneurysm detection in diabetic retinopathy using curvelet transform," *Journal of biomedical optics*, vol. 21, no. 10, pp. 101 404–101 404, 2016.
- [11] I. Soares, M. Castelo-Branco, and A. M. Pinheiro, "Microaneurysms detection using a novel neighborhood analysis," 2014.
- [12] Akram, M. Usman, Shehzad Khalid, Anam Tariq, Shoab A. Khan, and Farooque Azam. "Detection and classification of retinal lesions for grading of diabetic retinopathy". *Computers in biology and medicine* 45 (2014). 161-171.
- [13] Kedir M. Adal\_, Peter G. van Etten, Jose P. Martinez, Kenneth W. Rouwen, Koenraad A. Vermeer, Member, IEEE And Lucas J. van Vliet, Member, and IEEE. "An Automated System for the Detection and Classification of Retinal Changes Due to Red Lesions in Longitudinal Fundus Images", *IEEE Transactions on Biomedical Engineering*, 2017
- [14] Walter, TMassin, PErginay, AOrdonez, RJeulin, CKlein, J-C "Automatic detection of microaneurysms in color fundus images", *Med Image Anal* 11 (6) (2007) 555–66
- [15] Spencer, TOlson, JAMcHardy, KCSharp, PFForrester, JV "An image-processing strategy for the segmentation and quantification of microaneurysms in fluorescein angiograms of the ocular fundus", *Comput Biomed Res* 29 (4) (1996) 284–302.
- [16] Lazar, IHajdu, "A Retinal microaneurysm detection through local rotating cross section profile analysis", *IEEE Trans Med Imaging* 32 (2) (2013) 400–7.