

# Red Lesion Detection Using Extreme Learning Machine for Diabetic Retinopathy Screening

K.Selvalakshmi and S.Karthikeyan

**Abstract-** Diabetic retinopathy (DR) is damage to the retina of human eye which is caused by the complication of increase in blood glucose level which can eventually leads to blindness. The longer the patient has diabetes the higher the chance of developing diabetic retinopathy. DR is the deterioration of retinal blood vessel. This project, a novel method for automatic detection of both microaneurysms and hemorrhages in color fundus images is described and validated. The main contribution is a new set of shape features, called Dynamic Shape Features, that do not require precise segmentation of the regions to be classified. These features represent the evolution of the shape during image flooding and allow discriminating between lesions and vessel segments. Extreme learning machine (ELM) is used to improve segmentation accuracy. MATLAB tool used to evaluate a performance of proposed system.

**Index Terms**—Extreme learning machine (ELM), Diabetic retinopathy (DR), Image processing

## 1. INTRODUCTION:

DIABETIC retinopathy (DR) is a complication of diabetes that can lead to impairment of vision and even blindness. It is the most common cause of blindness in the working-age population. One out of three diabetic person presents signs of DR and one out of ten suffers from its most severe and vision-threatening forms. DR can be managed using available treatments, which are effective if diagnosed early. Since DR is asymptomatic until late in the disease process, regular eye fundus examination is necessary to monitor any changes in the retina. With the increasing prevalence of diabetes and the aging population, it is expected that, in 2025, 333 millions diabetic patients worldwide will require retinal examination each year. Considering the limited number of ophthalmologists, there is an urgent need for automation in the screening process in order to cover the large diabetic population while reducing the clinical burden on retina specialists.

Automation can be achieved at two levels: first, in detecting cases with DR, and, second, in grading these cases. Indeed, the identification of the severity level, through DR grading, allows more appropriate and

consistent referral to treatment centers. Our research focuses on the development of an automatic telemedicine system for computer-aided screening and grading of DR. Since computer analysis cannot replace the clinician, the system aims at identifying fundus images with suspected lesions and at sorting them by severity. Such an automatic system can help to reduce the specialist's burden and examination time, with the additional advantages of objectivity and reproducibility. Moreover, it can help to rapidly identify the most severe cases and to focus clinical resources on the cases that need more urgent and specific attention.

A difference of a single pixel can have a significant impact on the circularity measure, for example, especially for small candidate lesions. Our major contribution is a new set of shape features that do not require precise segmentation of the candidates. We consider every regional minimum as a candidate. Since the boundaries of the minima do not necessarily correspond to the edges of the structures of interest, we propose to extract shape features through the process of morphological image flooding. The general idea behind this approach lies in the physical phenomenon of blood leaking from (as opposed to blood flowing in) the vessels.

In the case of a lesion, the local minimum represents the focal point from which the blood is leaking gradually, in a more or less isotropic manner, depending on whether the lesion is an MA or an HE. This can be represented as nested layers of progressively higher intensities: as the intensity threshold increases, each evolving layer encompasses those found previously. The difference with a vessel segment is that the layers evolve more anisotropically in the latter case, following the vessel's orientation, and, at some intensity threshold, start merging with other vessel segments. This novel set of features, called Dynamic Shape Features (DSF), was briefly introduced in a preliminary study. For classification Extreme Learning Machine (ELM) has been used.

## 2. LITERATURE SURVEY:

[1] Red lesion detection using dynamic shape features for diabetic retinopathy screening:

The author lama seoud proposes a method for automatic detection of retinal lesions. DSF, that do not require precise segmentation of the regions to be classified and allow discriminating between lesions and vessel segments. But this method is failed for larger variation in intensity.

[2] Retinal vessel segmentation by improved matched filtering:

The author Jan Odstcilik proposes a method for segmenting retinal vessels which is based on matched filtering (MF) in combination with minimum error thresholding technique. The main disadvantage is that it has the computational complexity.

[3] A comparison of computer based classification methods applied to the detection of microaneurysms in ophthalmic fluoresceinangiograms:

The author Allan J. Framea, Peter E. Undrill proposes an automated method for segmented 'candidate' object. Applied three classification methods and compared their accuracy using receiver operator characteristic (ROC) analysis. Finally the computational time was more for ROC analysis.

[4] A multiple-instance learning framework for diabetic retinopathy screening:

The author Gwenole Quéllec proposes framework was applied to diabetic retinopathy screening in 2-D retinal image datasets. A novel multiple-instance learning framework, for automated image classification, is presented in this paper. But feature generation requires manual segmentation.

[5] Retinal microaneurysm detection through local rotating cross-section profile analysis:

The author Istvan Lazar realizes MA detection through the Peak detection. It is applied on each profile, and a set of attributes regarding the size, height, and shape of the peak are calculated subsequently. It takes higher execution time.

[6] An Adaptive Threshold Based Algorithm for Detection of Red Lesions of Diabetic Retinopathy in a Fundus Image:

The author Shaunak Ganguly Proposed an algorithm for detection of Red Lesions present in a fundus image of an eye. The proposed method will estimate the upper threshold and the lower threshold of the red lesions for the given fundus image individually based on local image information. Threshold basis is not suitable at all times.

[7] Red Lesion Detection in Retinal Fundus Images Using Frangi-based Filters:

The author Ruchir Srivastava Proposed a method to detect red lesions. Filters based on Frangi filters are used for the first time for this task. Due to the usage of filters it adds more complexity.

[8] Automated Detection of Red Lesions in the Presence of Blood Vessels in Retinal Fundus Images using Morphological Operations:

The author Navkiran Kaur focuses an automated haemorrhage detection system is done by applying the morphological operations and SVM classifier. Processing time was more compared to other methods.

[9] Locating the Optic Nerve in a Retinal Image Using the Fuzzy Convergence of the Blood Vessels

The author Adam Hoover\_ and Michael Goldbaum presents a novel algorithm we call fuzzy convergence to determine the origination of the blood vessel network.

## 3. EXISTING METHOD:

1. Red Lesion Detection Using Dynamic Shape Features for Diabetic Retinopathy Screening.

The development of an automatic telemedicine system for diabetic retinopathy depends on reliable detection of retinal lesions in fundus images. The main contribution is a new set of shape features, called Dynamic Shape Features, that do not require precise segmentation of the regions to be classified. These features represent the evolution of the shape during image flooding and allow to discriminate between lesions and vessel segments.

First, spatial calibration is applied to support different image resolutions. Second, the input image is preprocessed via smoothing and normalization. Third, the optic disc (OD) is automatically detected, to discard this area from the lesion detection. Fourth, candidate regions corresponding to potential lesions, based on their intensity and contrast. Fifth, the DSF together with color features are extracted for each candidate. Sixth,

candidates are classified according to their probability of being actual red lesions. But this method is failed for larger variation in intensity.

## 2. Random Transform-based Classification on Retina Images

The creation of an automatic diabetic retinopathy screening system using retina cameras is currently receiving considerable interest in the medical imaging community. In this work, we propose a method to identify the lesions without any previous knowledge of the retina morphological features and with minimal image preprocessing. The performance is particularly good at low false positive ratios, which makes it an ideal candidate for diabetic retinopathy screening systems.

This algorithm seems particularly well suited as a component of DR screening applications. In the near future, we will test the algorithm performance in this context and we will couple it with other techniques to determine if combining approaches improve its sensitivity to subtle MAs.

## 4. PROPOSED METHOD:

The proposed method takes as input a color fundus image together with the binary mask of its region of interest (ROI). The ROI is the circular area surrounded by a black background. It outputs a probability color map for red lesion detection. The method comprises six steps.

### A. Image Preprocessing:

The illumination of the retina is often non uniform, leading to local luminosity and contrast variation. Lesions may be hardly visible in areas of poor contrast and/or low brightness. Preprocessing steps are required to address these issues.

#### 1. Illumination Equalization:

To overcome the vignetting effect, the illumination equalization method is used. A large mean filter is applied to each color component of the original image  $I$  in order to estimate its illumination. Then, the resulting color image is subtracted from the original one to correct for potential shade variations.

#### 2) Denoising:

A small mean filter is applied to each color channel of the resulting image in order to attenuate the noise

resulting from the acquisition and compression steps without smoothing the lesions.

#### 3) Adaptive Contrast Equalization:

Areas with low standard deviation indicate either low contrast or smooth background. To enhance low contrast areas, we sharpen the details in these specific regions.

#### 4) Color Normalization:

Color normalization is necessary in order to obtain images with a standardized color range.

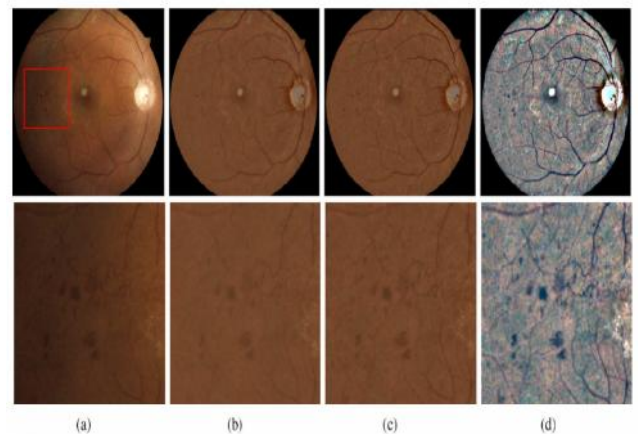


Fig.1. a). Original image; (b) illumination equalization; (c) adaptive contrast equalization; (d) color normalization.

### C. Optic Disc Removal:

The OD is a significant source of false positives in red lesion detection therefore its removal is a necessary step. The radius and position of the matched filter that minimizes the convolution are selected as the OD's final radius and center position.

### D. Candidate Extraction:

Since blood vessels and dark lesions have the highest contrast in the green channel, the latter is extracted from the preprocessed image. In addition, all candidates whose distance to the OD's center is smaller than the OD's radius are removed from the set of candidates and not considered any further.

### E. Dynamic Shape Features:

Among the candidates, several regions correspond to non-lesions, such as vessel segments and remaining noise in the retinal background. To discriminate between these false positives and true lesions, an original set of features,

the DSFs, mainly based on shape information, is proposed.

D.ELM:

A new learning algorithm for Single Hidden Layer Feed-Forward Networks (SLFNs), called Extreme Learning Machine(ELM),has been proposed which helps in solving regression and classification problems.

It can also used to reach good solutions analytically, and its learning speed is extremely faster than other traditional methods.

Here, the input weights and biases are determined randomly and they are not updated during training iterations. The activation function like sine, gaussian, sigmoidal etc., can be chosen for hidden neuron layer and linear activation functions for the output neurons.

It is a Multi-class classification where number of output neurons will be automatically set equal to number of classes.

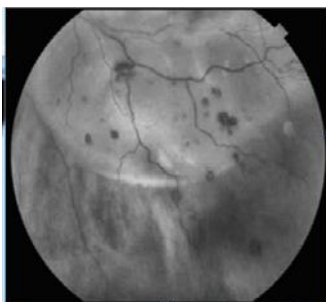
(For example, if there are 7 classes in all, there will have 7 output neurons; neuron 5 has the highest output means input belongs to 5-th class).

The output weights are obtained by using norm Least Squares (LS) and pseudo inverse of a linear system.

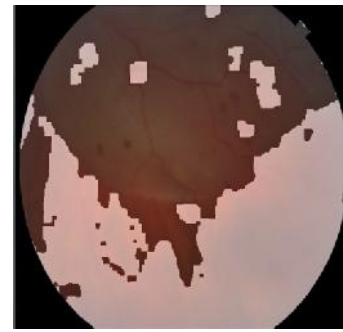
## 5. RESULTS AND DISCUSSION:



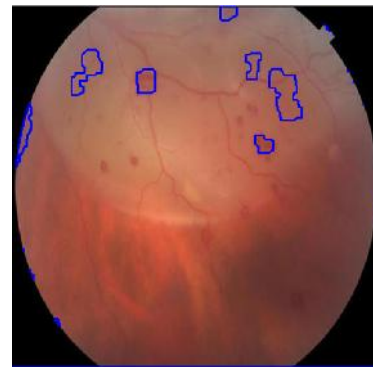
a). Input Image



b). Contrast Segmented Image



c). Equalisation Image



d). Lesion Detected Image

Fig. 2. Obtained Results

From Fig.2. the input image is a RGB image which contains the lesions. Then it will be viewed more contrast by equalization technique. The contrasted image is segmented to detect the lesion. The above method implemented in the red lesion using dynamic shape features and ELM which classifies the images without and with abnormalities. In this classification the images are separated as patches to detect the abnormality region of an image. Further work focusing on bright lesion detection based on neural network based classification.

K.Selvalakshmi (PG, Applied Electronics),

S.Karthikeyan (Assistant Professor)

PSNACET, Dindigul

selvamuthu094@gmail.com, skarthik@psnacet.in

## REFERENCES:

- [1] Lama Seoud, Thomas Hurtut, Jihed Chelbi, Farida Cheriet, and J. M. Pierre Langlois, "Red Lesion Detection Using Dynamic ShapeFeatures for Diabetic Retinopathy Screening" IEEE transactions on Medical imaging, Vol. 35, No. 4, PP.1116-1216, April 2016.
- [2] J. Odstrcilik *et al.*, "Retinal vessel segmentation by improved matched filtering: Evaluation on a new high-resolution fundus image database" *IET Image Process.*, vol. 7, no. 4, pp. 373–383, 2013
- [3] A. J. Frame *et al.*, "A comparison of computer based classification methods applied to the detection of microaneurysms in ophthalmic fluorescein angiograms," *Comput. Biol.Med.*, vol. 28, pp. 225–238, 1998.

- [4] G.Quellecet *al.*, “A multiple-instance learning framework for diabeticretinopathy screening,” *Med. Image Anal.*, vol. 16, no. 6, pp. 1228–40,2012.
- [5] I. Lazar and A. Hajdu, “Retinal microaneurysm detection through localrotating cross-section profile analysis,” *IEEE Trans. Med. Imag.*, vol.32, no. 2, pp. 400–7, Feb. 2013
- [6] Shaunak Ganguly and K shitijSrivastava,” An Adaptive Threshold Based Algorithm forDetection of Red Lesions of Diabetic Retinopathy in Fundus Image”*IEEE Trans.Med.Imag.*,vol.92,2014
- [7] RuchirSrivastava and Damon, W. K. Wong and LixinDuan,” Red LesionDetectionin Retinal Fundus Images Using Frangi-basedFilters”*Lancet*.vol.17,PP.178-89 ,2015
- [8] Navkiran Kauri, Jasmeen Kaur<sup>2</sup>, Mausumi Accharya<sup>3</sup> and Sheifali Gupta<sup>4</sup>,” Automated Detection of Red Lesions in thePresence ofBlood Vessels in Retinal FundusImages using Morphological Operations”, *IEEE International Conference on Power Electronics*,Vol.19,2016.