Automatic Detection of Microaneurysms in Retinal Fundus Images

Mahdi Islam, Musarrat Tabassum
Erasmus + Erasmus Mundus Joint Master Degree in Medical Imaging and Applications (MAIA)
Universite De Bourgogne, Le Creusot, France.

Abstract

Diabetic Retinopathy (DR) is an eye condition that can cause vision loss and blindness in people with diabetes by damaging and destroying the blood vessels in the retina. Early symptoms may include Microaneurysms (MAs) so early and accurate detection is important for diagnosis and grading of diabetic retinopathy. In this paper, a new method for the automatic detection of MAs in eye fundus images is proposed. The proposed method consists of four main steps: preprocessing, candidate extraction, feature extraction and classification. A total of 27 characteristic features which contain local features and profile features are extracted for KNN classifier to distinguish true MAs from spurious candidates.. The experimental result demonstrates the efficiency and effectiveness of the proposed method, and it has the potential to be used to diagnose DR clinically.

1. Introduction

Diabetic retinopathy (DR) is one of the main complications caused by diabetes. It is reported that DR has been the leading cause of new cases of blindness among adults between 20 and 60 years old[1]. In general, DR can be classified into two types: non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). It is a time-consuming work for an ophthalmologist to diagnose a diabetic patient manually, and it is also prone to error. Hence, automatic analysis of diabetic patients' retina is urgent needed for ophthalmologists to screen larger populations of patients.

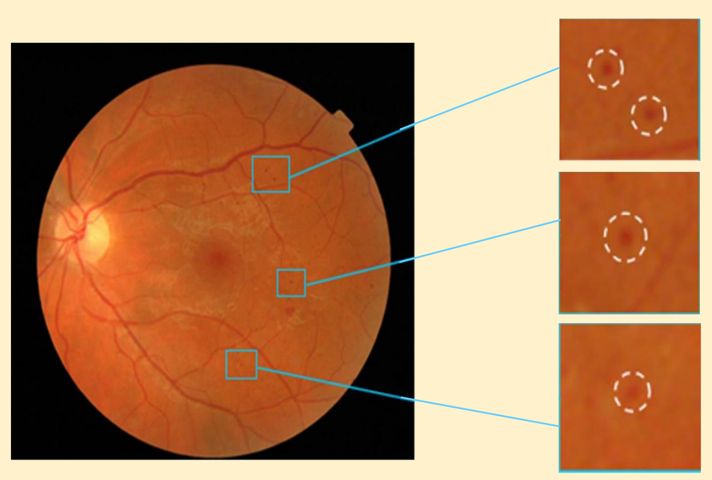

Fig 1: An example of a fundus image with several MAs.

In DR, microaneurysms (MAs) are the important lesions and appear as small and round shape dots near tiny blood vessels in fundus image which are present at the earliest stage of DR and remain in the development. In this paper, a novel MA detection has been proposed with three important contributions; (1) A different candidate extraction is used. The candidates are extracted based on not only the peak detection but also the region area and shape features. (2) A more robust preprocessing method is applied. The normalization of illumination and contrast limited adaptive histogram equalization (CLAHE) enhancement methods have been proposed to apply in the preprocessing step to enhance the input image (3) In the feature extraction step, other important features are extracted.

2. Proposed method

2.1.Overview

In the proposed method, the inverted green channel of fundus images is used as main input. The green channel provides the best MA-background contrast. The binary region of interest (ROI) mask is also considered. The flowchart of the proposed method presented in this paper is illustrated below in Fig 2.

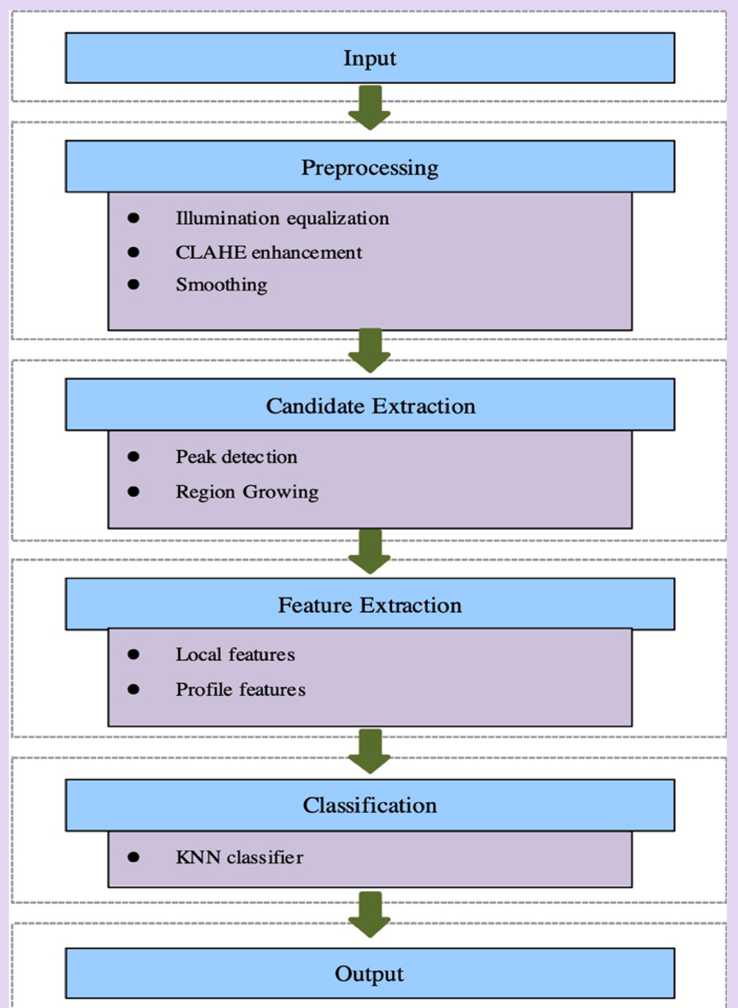

Fig 2: Flowchart of the proposed method.

2.2.Image Preprocessing

Retinal fundus images are often nonuniform illumination, poor contrast and noise images. To reduce these drawbacks and make a suitable image for MA candidate extraction and feature extraction, three preprocessing steps are applied as follows in the Fig 3.

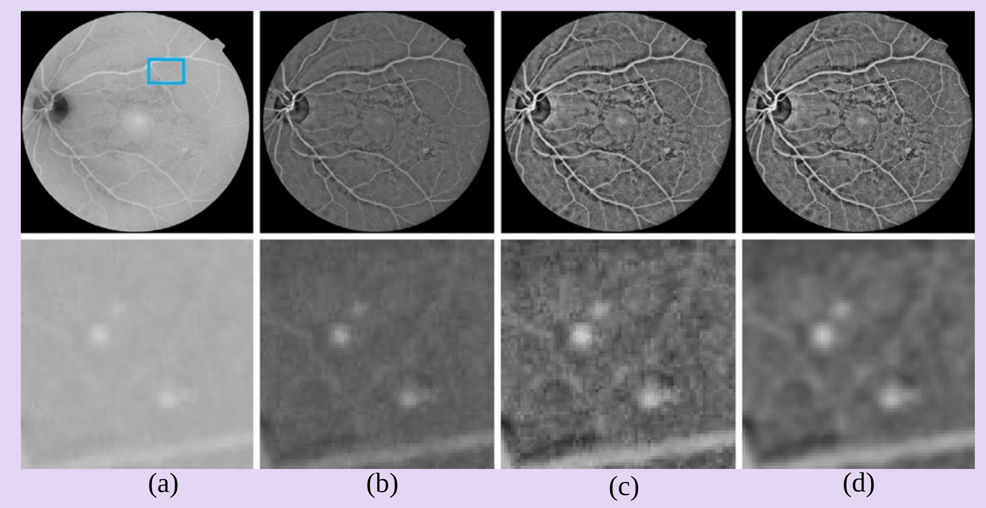

Fig 3. The illustration of preprocessing steps.

- Fig3(a) Original inverted green channel image
- Fig3(b)The **illumination equalization** method is used to correct shade. $\boldsymbol{I_{ie} = I - I_{bg} + u}$.
- Fig3(c)**Contrast limited adaptive histogram equalization enhancement** CLAHE is applied to enhance the contrast to make the MAs look more visible
- Fig3(d)The resulting image after the step of smoothing by applying a Gaussian filter to reduce the effect of noise.

2.3.Candidate Extraction

Here the main objective is to reduce the number of objects which are not similar to MAs. Preliminary candidates are extracted using peak detection. Since MAs appear as bright structures so the local maximum pixels can be considered as MA candidate. Using peak detection and applying different line detector profiles fake MA candidates were removed.

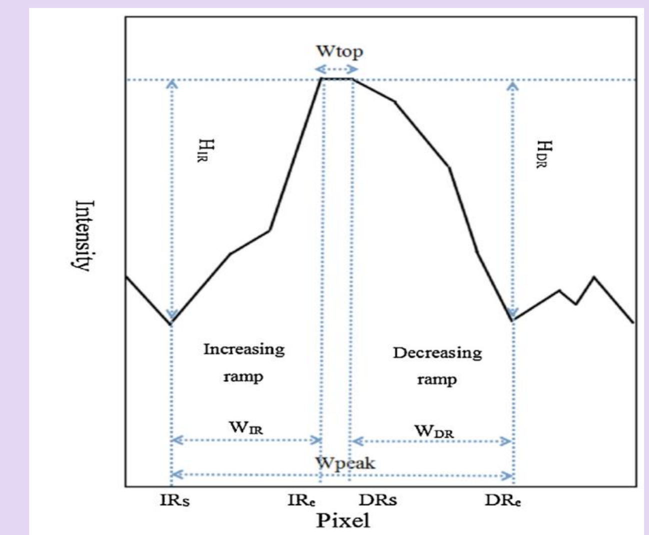

Fig 4. The intensity distribution of a profile and the definitions of the peak.

- Region growing is used to grow MA candidate pixel back to original pathology shape at candidate extraction step.
- An adaptive threshold t based on the dynamic transformation is used to determine the threshold value t of the growing MAs to solve the problem of MAs variable intensity and size can be calculated for region growing as follows: $t = i_{seed} - \beta * d_{seed}$

2.4.Feature Extraction

Profile features are derived from profile analysis whereas local features are added for classification by investigating MA and its surroundings.

2.4.1.Local Features

- Hessian Matrix based features: Hessian matrix in 2D images is taken by second partial derivative from image's pixel and given as: $H(x) = \begin{bmatrix} Dxx & Dxy \\ Dxy & Dyy \end{bmatrix}$

Finding the eigenvalues of the matrix λ_1 and λ_2, the MA probability map is established;

$$PM(x,y;\sigma) = \begin{cases} 0 & \lambda_1>0 \| \lambda_2>0 \\ \frac{2}{\pi}\arctan\left(\frac{|\lambda_2|+|\lambda_1|}{|\lambda_2|-|\lambda_1|}\right) & \lambda_1 \neq \lambda_2 \\ 1 & \lambda_1=\lambda_2 < 0 \end{cases}$$

A total of 6 features are extracted.

- Shape and Intensity features: For extracting intensity and shape features, a sub-ROI is considered. For candidate region 11 shape and intensity features are extracted.

2.4.1.2.Profile Features

Previous study[3] used a total of seven profile features during the classification. In this paper three new features are introduced based on the peak and intensity distribution curve of each profile.

4) The mean height of the peak
5) The start of increasing ramp height
6) The end of the decreasing ramp height

3. Results

Classification

At the stage of feature extraction, each MA candidate is characterized by a vector in a 27-D feature set.

$$F=\{f_1, f_2, f_3, \ldots\ldots\ldots\ldots f_{27}\}.$$

Different ranges and values of different features fi are normalized by zero mean and unit variance by applying:

$$\bar{f_i} = \frac{f_i - \mu_i}{\sigma_i}$$

To select suitable classifier for the feature set, three supervised classifier are selected as the underlying classifiers: K-Nearest Neighbor (KNN), Naïve Bayes (NB) and AdaBoost.

Database

The proposed method has been tested on two public available database: e-Optha, and Retinopathy Online Challenge (ROC) database.

Assessment of classification Performance

The free response ROC (FROC) is used to evaluate the classification performance hence to get the correct localization of the MAs for true positive detection.

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

The final score of a method is calculated as the average sensitivity at seven false positive rates (1/8, ¼, ½, 1, 2, 4 and 8 false positive rates per image).

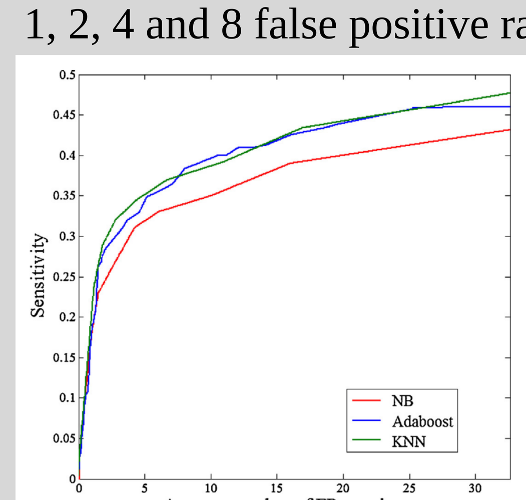

Fig 5: The FROC curves of classification results by applying the KNN, NB and AdaBoost classifiers to ROC database

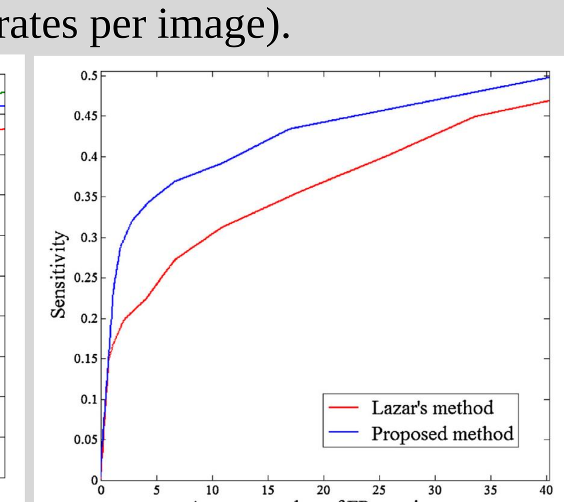

Fig 6: The FROC curves of proposed method and Lazar's method

	1/8	1/4	1/2	1	2	4	8
Previous Study[3]	0.037	0.055	0.103	0.162	0.196	0.223	0.285
Proposed Method	0.037	0.056	0.103	0.206	0.295	0.339	0.376

Table 1: Sensitivities at Predefined False Positive Per Image rate for the Proposed Method and The Lazar's Method in the ROC Database.

The evaluation results show that the KNN (k=14) has the best performance. Though AdaBoost classifier has also the similar performance and both outperform NB but the proposed method is compared with a previous study and thus KNN is chosen as the suitable classifier for proper comparison. Table 1 shows the sensitivities at seven false positive rates. The proposed method achieves a overall score of 0.202 which is better than Previous Study[3]

4. Discussion

The Proposed method has been evaluated on two public databases for automatic detection of MAs in fundus image. Different Image processing technique have been applied to prepare the images for candidate extraction and feature extraction. For classification eventually, KNN classifier is selected for classification and the proposed method is compared with one of the Previous study. In summary a fully automated and efficient methodology is proposed for detection of MA. The future work may include the detection of other lesions like Hemorrhages, Exudates and so on to make the proposed method more robust and efficient.

5. Reference

1. Walter, T., Massin, P., Erginay, A., et al., 2007. Automatic detection of microaneurysms in color fundus images. Med. Image Anal. 11 (6), 555–566.
2. Istvan, L.,Andras,H., 2013. Retinal microaneurysm detection through local rotating cross-section profile analysis. IEEE Trans. Med. Imaging 32 (2), 400–407.
3. Bo Wu,Weifang Zhu,Fei Shi,Shuxia Zhu, Xinjian Chen,Automatic detection of microaneurysms in retinal fundus images, Computerized Medical Imaging and Graphics,Volume 55, 2017, Pages106 112,ISSN0895-6111, https://doi.org/10.1016/j.compmedimag.2016.08.001