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The Communal System for Early Detection Microaneurysm and Diabetic Retinopathy Grading Through Color Fundus Images

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Abstract

Reliable microaneurysm detection in digital fundus images is still an open issue in medical image processing. We propose an ensemble-based framework to improve microaneurysm detection. Unlike the well-known approach of considering the output of multiple classifiers, we propose a combination of internal components of microaneurysm detectors, namely preprocessing methods and candidate extractors. Since microaneurysm detection is decisivein diabetic retinopathy grading, we also tested the proposed method for this task on the publicly available Messidor database.

I. INTRODUCTION

DIABETIC retinopathy (DR) is a serious eye disease that originates from diabetes mellitus and is the most common cause of blindness in the developed countries. Early treatment can prevent patients to become affected from this condition or at least the progression of DR can be slowed down. Thus, mass screening of patients suffering from diabetes is highly desired, but manual grading is slow and resource demanding. Therefore, several efforts have been made to establish reliable computer-aided screening systems based on color fundus images. The promising results reported by Fleming et al. and Jelinek et al. indicate that automatic DR screening systems are getting closer to be used in clinical settings.

A key feature to recognize DR is to detect microaneurysms (MAs) in the fundus of the eye. The importance of handling MAs are two-fold. First, they are normally the earliest signs of DR, hence their timely and precise detection is essential. On the other hand, the grading performance of computer-aided DR screening systems highly depends on MA detection. In this paper, we propose a microaneurysm detector which provides remarkable results from both aspects.

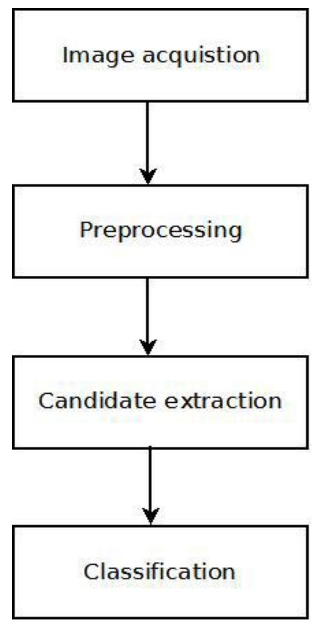


Figure 2: Stages of microaneurysm detection.

Color fundus images are used by ophthalmologists to study eye diseases like diabetic retinopathy. Figure 1 shows a typical retinal image labeled with various feature components of Diabetic Retinopathy. Microaneurysms are small secular pouches caused by local distension of capillary walls and appear as small red dots. This may also lead to big blood clots called hemorrhages. Hard exudates are yellow lipid deposits which appear as bright yellow lesions. The bright circular region from where the blood vessels emanate is called the optic disk. The fovea defines the center of the retina, and is the region of highest visual acuity. Thespatial distribution of exudates and microaneurysms and hemorrhages, especially in relation to the fovea can be used to determine the severity of diabetic retinopathy.They appear as small circular dark spots on the surface of the retina (see Figure 1), which canbe hard to distinguish from fragments of the vascular system or from certain eye features.

In this paper, we propose an effective microaneurysm detector based on the combination of preprocessing methods and candidate extractors. We provide an ensemble creation framework to select the best combination. An exhaustive quantitative analysis is also given to prove the superiority of our approach over individual algorithms. We also investigatethe grading performance of our method, which is proven to be competitive with other screening systems.

The rest of the paper is organized as follows: the selected preprocessing methods and candidate extractors are presented in section II and III, respectively. The details of the proposed

Fig. 1. Sample digital fundus image with a microaneurysm.

ensemble creation framework is discussed in section IV. We present our evaluation methodology in section V. In section VI, we summarize our experimental results. A detailed discussion is given in section VII to address several issues. Finally, we draw conclusions in section VIII.

II. PREPROCESSING METHODS

In this section, we present the selected preprocessing methods, which we consider to be applied before executing MA candidate extraction. The selection of the preprocessing method and candidate extractor components for this framework is a challenging task. Comparison of preprocessing methods dedicated to microaneurysm detection has not been published yet.

A summary on the key differences of the algorithms is given in Table.

A. *Walter-Klein contrast enhancement*

This preprocessing method aims to enhance the contrast of fundus images by applying a gray level transformation using the following operator:

$$f' = \begin{cases} \dfrac{\frac{1}{2}\left(f'_{max} - f'_{min}\right)}{\left(\mu - f_{min}\right)^r} \cdot \left(f - f_{min}\right)^r + f'_{min}, & f \leq \mu, \\ \dfrac{-\frac{1}{2}\left(f'_{max} - f'_{min}\right)}{\left(\mu - f_{max}\right)^r} \cdot \left(f - f_{max}\right)^r + f'_{max}, & f \geq \mu, \end{cases}$$

where $\{f_{min}, \ldots, f_{max}\}$, $\{f'_{min}, \ldots, f'_{max}\}$ are the intensity levels of the original and the enhanced image, respectively, μ is the mean value of the original grayscale image and $r \in \mathbb{R}$ is a transition parameter.

B. *Contrast limited adaptive histogram equalization*

Contrast limited adaptive histogram equalization (CLAHE)is a popular technique in biomedical image processing, since

Algorithm	Aim	Method
Walter-Klein	**contrast enhancement**	**gray level transformation**
CLAHE	**local histogram equalization**	**local histogram equalization**
Vessel Removal	**MA enhancement near vessels**	**vessel removal and inpainting**

it is very effective in making the usually interesting salient parts more visible. The image is split into disjoint regions, and in each region local histogram equalization is applied. Then, the boundaries between the regions are eliminated with a bilinear interpolation.

C. *Vessel removal and extrapolation*

This preprocessing algorithm is proposed in. It aims to enhance the contrast on fundus images by applying a gray level transformation.

III. MICROANEURYSM CANDIDATE EXTRACTORS

Candidate extraction is an effort to reduce the number of objects in an image for further analysis by excluding regions which do not have similar characteristics to microaneurysms. Individual approaches define their own measurement for similarity to extract MA candidates. In this section, we provide a brief overview of the selected candidate extractors, as the current state-of-the-art literature recommendations.

A. Walter et al.

The approach proposed in is a mathematical morphology based one, which recommends contrast enhancement and shade correction as preprocessing steps.

B. Spencer et al.

This approach is one of the most popular candidate extractors, originally proposed by Spencer and Frame. The algorithm uses shade correction as preprocessing.

c. *Lazar et al.*

Pixel-wise cross-section profiles with multiple orientations are used to construct a multi-directional height map. This map assigns a set of height values that describe the distinction of the pixel from its surroundings in a particular direction.

Algorithm	Method	Sensitivity	FP / I
Walter	Diameter closing	36%	154.42
Spencer	top-hat transformation	12%	20.3
Lazar	cross-section profile analysis	48%	73.94

IV. METHODOLOGY

We have evaluated the proposed approach for both MA detection and DR grading. In this section, we present the evaluation methodology we used in each case.

A. MA detection

We have evaluated the MA detection capabilities of the proposed method in the ROC competition for MA detectors, as well as on a publicly available and a private database. In this section, we provide a brief overview on these databases and on the methodology we used for the evaluation of MA detection performance of the proposed approach.

*1) Retinopathy Online Challenge (ROC):*ROC is aworldwide competition dedicated to measure the accuracy of microaneurysm detectors. The ROC database consists of 50 training and 50 test images with different resolutions (768 ×576, 1058 × 1061 and 1389 × 1383), 45◦ FOV and JPEG compression. The average number of MAs for the training and test sets are 6.72 and 6.86, respectively. There are 13 and 10 images of the training and test sets, where no MAs aremarked by the experts.

B. DR grading

We have also evaluated our ensemble-based approach to see its grading performance to recognize DR. For this aim, we determined the image-level classification rate of the ensemble on the Messidor1 dataset containing 1200 images. That is, the presence of any MA means that the image contains signs of DR, while the absence of MAs indicates a healthy case. In other words, a pure yes/no decision of the system has been tested.

	Walter	Spencer	Lazar
Walter-Klein		M	
CLAHE	R, D		R
Vessel Removal	D		R, D, M

V. RESULTS

In this section, we present our experimental results for both MA detection and DR grading.

A.MA detection

In Table above, we exhibit the ⟨preprocessing method, candidate extractor⟩pairs included in the selected ensembles for the three datasets, respectively. The rows of the table show the preprocessing methods from section II, while the columns label the candidate extractor algorithms.

Table belowshows the performance of the ensemble is also shown in Figure 3 in terms of a FROC curve.

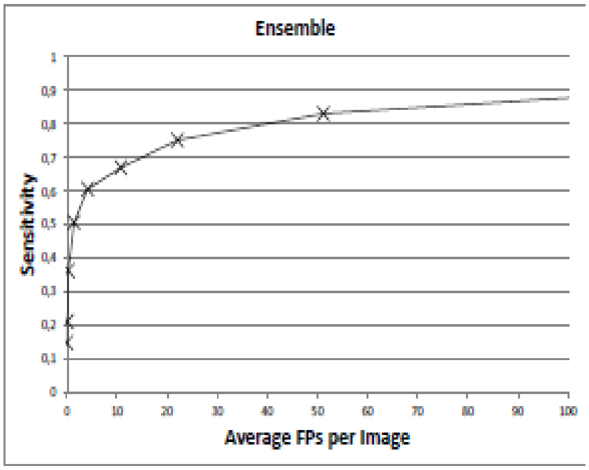


Fig. 2. FROC curve of the ensemble on the ROC dataset.

The FROC curves of the ensemble for the DiaretDB1 v2.1 and for the Moorfields database is shown in Figures 4 and 5, respectively. To the best of our knowledge, no corresponding quantitative results have been published for these databases yet. Thus, we disclose the results of the ensemble-based method only.

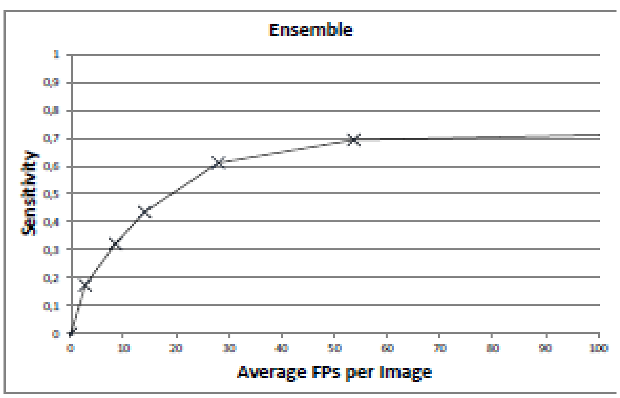


Fig. 3. FROC curve of the ensemble on the DiaretDB2.1 dataset.

Threshold	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Sensitivity	1	1	1	0.99	0.96	0.76	0.31
Specificity	0	0.01	0.03	0.14	0.51	0.88	0.98
Accuracy	0.53	0.54	0.55	0.59	0.75	0.82	0.62

A. DR grading

In Table above, we provide the sensitivity, specificity andaccuracy measures of our detector corresponding to different threshold values, respectively. The fitted ROC curve of the detector can be seen in Figure 6. The empirical area under curve (AUC) is 0.875, while the AUC for the fitted curve is 0*:*90 ± 0*:*01. Table V also contains the percentage of the correctly recognized cases for each class.

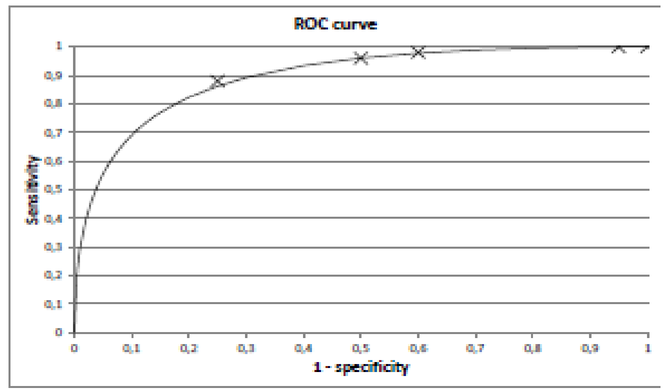
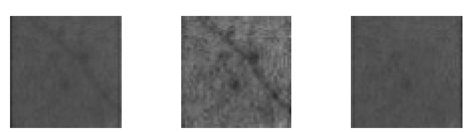


Fig. 5. ROC curve of the ensemble on the Messidor dataset.

VI. DISCUSSION

A strong point of the proposed method is that it performs well under difficult circumstances. Figure 7 shows an example image where the application of CLAHE made it easier to distinguish the MAs from their background. However, the use of the vessel removal and in painting preprocessing method caused the missing of a true MA, while the detection of the remaining MA is easier in the absence of thin retinal vessels. Thus, using different preprocessing methods with candidate extractors creates diversity among the members of the ensemble, which is desired for systems using multiple estimators.This diversity ensures the suppression of false detections, since diverse detectors tend to make different mistakes. Thus, the false detections are likely to receive lower confidence values in the voting procedure.



(a) Original (b) CLAHE (c) Vessel re-moval

Fig. 4. The effect of different preprocessing methods where MAs are hardto detect.

As for DR grading, our ensemble also performed well. It isalso important to see how the different classes (R0, R1, R2, R3) are recognized at different levels. As it can be desired, the severity of DR affects the performance of our detector. At each threshold level, where the sensitivity is less than 1.0, the more severe case recognized with higher probability.

The selection of the appropriate threshold is also an important issue for our detector to provide sufficient sensitivity and specificity rate. In, the authors suggest that sensitivity is more important for a screening system than specificity. In opposition, the British Diabetic Association (BDA) recommends 80% sensitivity and 95% specificity for DR screening. In Table V, we can see that the most accurate result is achieved with the threshold value 0.9. By applying the first idea, we might consider the results corresponding to the threshold value 0.8 as the best in our experiment, where 96% sensitivity and 51% specificity are achieved. That is, we recognized almost all of the cases where DR is present, and half of the healthy ones. The closest to the second recommendation is the performance achieved at the 0.9 level: 76% sensitivity and 88% specificity.

It is difficult to compare our method to other screening systems. First of all, to the best of our knowledge, no otherresults reported for the complete Messidor database. Other screening systems are tested on private images. Unfortunately, the proportion of non-DR/DR cases are varying in these experiments. Abramoff et al. reported 0.86 AUC on a population where 4.96% of the cases had at least minimum signs of DR. The databases on which Agurto et al. tested, 74.43% and 76.26% cases contained signs of DR and they achieved 0.81 and 0.89 AUCs, respectively. The closest to match the requirements of BDA is the system of Jelinek et al. with a 85% sensitivity and 90% specificity, where approximately 30% of patients had DR. Similar proportion (35.88%) of patients having DR are reported by Fleming et al.In their automatic screening system

VII. CONCLUSION

In this paper, we have proposed an ensemble-based microaneurysm detector which has proved its high efficiency in an open online challenge with its first position. Our novel framework relies on a set of ⟨preprocessing method, candidate extractor⟩pairs, from which a search algorithm selects an optimal combination. Since our approach is modular, we can expect further improvements by adding more preprocessing methods and candidate extractors. We have also evaluated the grading performance of this detector in the 1200 images of theMessidor database.We have achieved a $0{:}90\pm0{:}01$ AUC value, which is competitive with the previously reported results on other databases. The grading results presented in this paper are already promising. However, a proper screening system should contain other components, which is expected to increase the performance of this approach, as well.

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