International Journal of Advanced Technology and Innovative Research

ISSN 2348–2370
Vol.01,Issue.01,
January-2009,
Pages:10-16

www.semargroup.org

The Ensemble-Based System for Microaneurysm Detection and Diabetic Retinopathy Grading

HIMANEE[1], KARTHIK[2]

[1]M.Tech, Dept of ECE, NREC, Hyderabad, AP-India, Email: nvhimanee417@gmail.com,
[2]M.Tech, Dept of ECE, NREC, Hyderabad, AP-India.

Abstract: Reliable in the digital fundus images are the micro aneurysm detection is still an open issue in medical image processing an ensemble-based framework to improve micro aneurysm detection it is well-known approach of considering the output of multiple classifiers to the combination of internal components of preprocessing methods and candidate extractors. We have evaluated our approach for micro aneurysm detection in this algorithm is currently ranked as first, and also on two other databases. Since micro aneurysm detection is decisive in the diabetic retinopathy (DR) we are also tested the proposed method for this task on the publicly available Messidor database, where a promising AUC 0.90±0.01 is achieved in a "DR/non-DR"-type classification based on the presence or absence of the micro aneurysms.

Keywords: Diabetic Retinopathy (DR) Grading, Ensemble Based Systems, Fundus Image Processing, Micro Aneurysm (MA) Detection.

I. INTRODUCTION

Diabetic retinopathy (DR) is a serious eye disease that originates from diabetes mellitus and is the most common cause of blindness it can prevent patients to become affected from this condition or at least the progression of DR can be screening of patients suffering from diabetes is slow and resource demanding. Therefore, much effort has been made to establish reliable computer aided screening systems based on color fundus images [2]. The promising results reported by Fleming et al. [3] and Jelinek et al. [4] indicate that automatic DR screening systems are getting closer to be used in clinical settings. A key feature to recognize DR is to detect micro aneurysms (MAs) in the fundus of the eye. The importance of handling but 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 [4], [4]. In this paper, we propose a MA detector that provides remarkable results from both aspects. One way to ensure high reliability and raise accuracy in a detector is to be considering it can be ensembles which have been proven to be efficient in the usual ensemble techniques aim to combine class labels or real values that cannot be adopted and it can be provides the spatial coordinates as centers of potential MA candidates will be use of well-known ensemble techniques would require a classification which can be misleading since different algorithms extract MAs with different approaches and the MA centers may not be overcome, we gather close MA candidates of the individual detectors and apply a voting scheme on them.

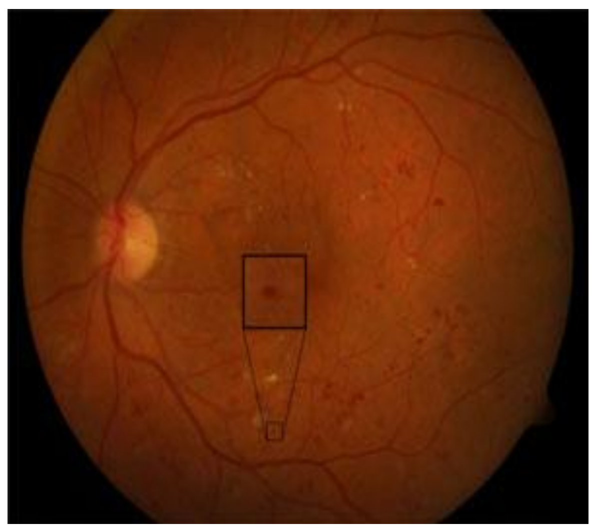

Fig.1. Sample digital fundus image with a MA.

In [6], Niemeijer et al. showed that the fusion of the results of the several MA detectors leads to an increased average sensitivity measured at seven predefined false positive rates. In this paper, we propose a framework to build MA detector ensembles based on the combination of the internal components of the detectors not only on their output as in [6]. Some of our earlier research on combining MA detectors did not provide reassuring results [7]. To increase the accuracy of such ensembles, we must identify the weak points of the first difficulty originates from the shape characteristics of this appearance as a small circular dark spots on the surface of the retina (see Fig. 1), which can be hard to distinguish from fragments of the vascular system or from certain MA detectors tackle this problem in first; the green channel of the fundus image is extracted and preprocessed to enhance MA like characteristics. Then, in a coarse level step (which will be referred as candidate extraction in the rest of this paper), all MA-like objects are detected in the image. Finally, a fine level algorithm (usually a supervised classifier) removes the potentially false detections based on some assumptions about MAs. Our former investigations showed that the low sensitivity of MA detectors originates from the candidate extractor part [8]. However, we could increase the sensitivity by applying proper preprocessing methods before this technique causes a slight increment in the positives, but it can be decreased by classification or voting.

TABLE I
THE SUMMARY OF THE KEY DIFFERENCES OF THE PREPROCESSING METHODS

Algorithm	Aim	Method
Walter-Klein	contrast enhancement	gray level transformation
CLAHE	salient object enhancement	local histogram equalization
Vessel Removal	MA enhancement near vessels	vessel removal and inpainting
Illumination eq.	MA enhancement at the border of the ROI	vignette correction

In this paper, we propose an effective MA detector based on the combination of preprocessing methods and candidate extractors. We provide an ensemble creation framework to select the best exhaustive quantitative analysis is also given to prove the superiority of our approach over individual algorithms. We also investigate the grading performance of our method, which is proven to be competitive with other screening systems. The rest of the paper is organized as follows: Methods of Detection and Classification are presented in Sections II and III. Related work And Proposed Work is discussed in Section IV. In Section V, we summarized in the present experimental results. If finally, we draw the conclusions in Section VI.

II. METHODS OF DETECTION AND CLASSIFICATION

The micro aneurysm in digital fundus images is detected by creating an ensemble of preprocessing and candidate extraction methods. The preprocessing improves the contrast of the image or enhances salient objects present in the image. Another preprocessing method removes the vessels for better detection of micro aneurysm. Then micro aneurysm is detected in the preprocessed image by extracting the candidates. Candidate extraction is a process that aims to spot any objects in the image showing micro aneurysm-like characteristics. Individual micro aneurysm detectors consider different principles to extract micro aneurysm candidates.

To eliminate wrong detection of micro aneurysm candidates, the image is subjected to classification using Support Vector Machine Classifier. The support vector classification approach is a relatively recent development in statistical pattern recognition with earlier origins. In this approach, optimal classification of a separable two-class problem is achieved by maximizing the width of the empty area (margin) between the two classes. The margin width is defined as the distance between the discrimination hyper surface in n-dimensional feature space and the closest training patterns: these are called support vectors. The support vectors thus specify the discrimination function. The general flow diagram is shown in Fig 2.

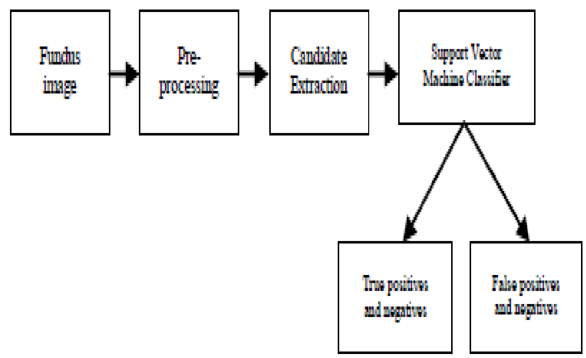

Fig.2. General Flow Diagram

2.1. Pre-Processing

Preprocessing is among the simplest and most appealing areas of digital image processing and is mainly composed for image filtering and enhancement. Basically, the idea behind enhancement techniques is to bring out detail to highlight certain features of a familiar example of enhancement is when the contrast of an image is increased the image is important to keep in mind that enhancement is a very subjective area of image processing. There is no general theory of an image is processed for the viewer is the ultimate judge of how well a particular method works.

A. Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE differs from ordinary adaptive histogram equalization in its contrast limiting as proposed. This feature can also be applied to global histogram is to contrast-limited histogram equalization (CLHE), which is rarely used in the contrast limiting procedure has to be applied for each neighborhood from which a transformation function is developed to prevent the overamplification of noise that adaptive histogram equalization can give rise to. The image is divided into Corner regions (CR), Border regions (BR) and Inner regions (IR) as shown in Fig.3.

CR	BR	BR	CR
BR	IR	IR	BR
BR	IR	IR	BR
CR	BR	BR	CR

Fig.3. Splitting the image into regions

After calculating the histogram of each region, based on the desired limit of contrast expansion, a clip limit β for clipping histograms is obtained as follows

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}\left(s_{max} - 1\right)\right) \quad (1)$$

where M is the number of pixels, N is the number of grayscales, α is the clip factor and smax is the maximum possible slope. Each histogram is redistributed in such a way its height does not go beyond the clip limit. The cumulative distribution functions (CDF) of the resultant contrast limited histograms are determined for gray scale mapping as shown below

$$f_{i,j}(n) = \frac{N-1}{M} \cdot \sum_{k=0}^{n} h_{i,j}(k);\ n = 1,2,3 \ldots . N-1 \quad (2)$$

Pixels in the inner region are bilinear interpolated (IR), pixels in the boundary region(BR) are linearly interpolated, and pixels near corners (CR) are transformed with the transformation function of the corner tile

B. Shade Correction

The non-uniform illumination in the image has to be corrected if the micro aneurysm in these areas has to be detected correctly. The non-uniform illumination is corrected by shade correction. The shade correction is done by subtracting settings as

$$IscadeCorrected = ICLAHE - Ibackgorund\ Estimate \quad (3)$$

The background estimation is done by using a polynomial fitting algorithm. Pixels in the inner region are bilinear interpolated (IR), pixels in the boundary region (BR) are linearly interpolated, and pixels near corners (CR) are transformed with the transformation function of the corner tile. The non-uniform illumination in the image has to be corrected if the micro aneurysm in these areas has to be detected correctly. The non-uniform illumination is corrected by shade correction. The shade correction is done by estimating the background and subtracting it from the preprocessed image as shown below.

$$IsadeCorrected = ICLAHE - IbackgorundEstimate \quad (4)$$

The background estimation is done by using a polynomial fitting algorithm.

III. RELATED WORK

The proposed work can be reliable for micro aneurysm detection in digital fundus images used in medical image processing. They propose an ensemble-based framework to improve the well known approach of considering the output of multiple classifiers; they propose a combination of internal components of methods and candidate extractors. They have evaluated their approach for micro aneurysm detection in an online competition, where his algorithm is currently if the ranked as it is first, and also on two other databases. Since, micro aneurysm detection is decisive in diabetic retinopathy (DR) grading, they also tested the proposed method for this task on the publicly available Messidor database, where a promising AUC 0.09 (=, -) 0.01 is achieved in a “DR/non DR” type based on the presence or absence of the micro aneurysms. The grading results presented in this paper we can proper screening system should be expected to increase the performance. Retinopathy is a progressive disease and is broadly classify into two Non proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). A sign of PDR is the appearance of new blood vessels in the fundus area and inside optic disc known as the study of blood vessel is very important for detection of this paper, they present a method for vessel detection which can be used for detection of the paper presents a new method for vessel segmentation using a multilayered in this method is tested using two publicly available retinal image databases and an experimental result shows the significance of proposed work. Fig, 4 shows the complete flow diagram of proposed work.

The accurate and timely detection of vascular abnormalities can help in prevention of vision loss cause due to diabetic retinopathy. Using the method for accurate vessel segmentation which can be used for detection of neovascularization. The blood vessels are enhanced using two dimensional wavelets and a new multilayered thresholding technique is used for vessel segmentation. Abnormal blood vessels are detected using a sliding window technique. It presents a new supervised method for blood vessel detection in digital retinal images. He uses a neural network (NN) scheme for pixel classification and computes a 7-D vector composed of gray-level and moment invariants based features for pixel representation. He evaluated it on the publicly available DRIVE and STARE is widely used for this images where the vascular structure has been precisely marked by the performance on both sets of test images is better than other existing solutions in this method will be proves especially accurate for vessel detection in STARE images. Its application to this database (even when the NN was trained on the DRIVE database) outperforms all analyzed by the segmentation approaches it is more effectiveness and robustness with different image conditions with its simplicity and fast implementation and then segmentation proposal and it is suitable for retinal image computer analyses such as automated screening for early diabetic retinopathy detection.

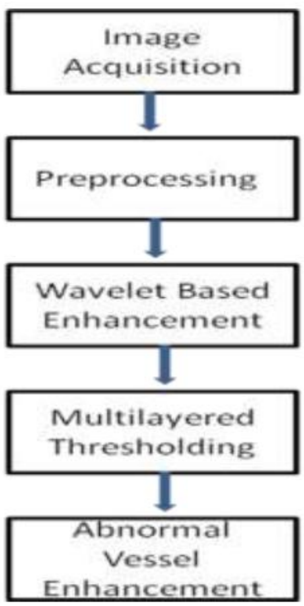

Fig.4. Flow diagram of proposed work

IV. PROPOSED WORK

In this paper, we propose an effective MA detector based on the combination of preprocessing methods and candidate extractors. We provide an ensemble creation framework to select the best combination. Fig. 5 shows the proposed plan of work and methodology. If we can be involved in the various steps that can be provide Preprocessing, Candidate Extractors, and Ensemble Creation.

A. Preprocessing (P)

In this we present the selected that we can consider to be applied before executing MA candidate selection of the preprocessing method and the candidate extractor components for this framework is a challenging task. Preprocessing method need to be highly select algorithms that can be used before any candidate extractor and do not change the characteristics of the original images. Thus we have to select the method which are well known in medical image processing and preserve image characteristics. Color fund soften show important lighting variations, poor contrast and noise. In order to reduce these imperfections and generate images more suitable for extracting the pixel features demanded in the classification step, a preprocessing comprising the following steps is applied.

- Vessel central light reflux removal,
- Background homogenization,
- Vessel enhancement.

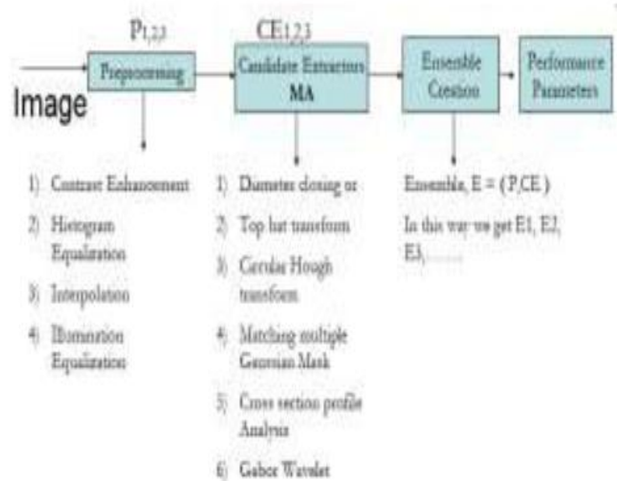

Fig.5. Proposed plan of work and design methodology

1. Vessel Central Light Reflux Removal

The retinal blood vessel have lower reflectance when compared to other retinal surfaces, they appear darker than the cross-sectional grey-level profile of vessel can be approximated by a Gaussian shaped curve (inner vessel pixels are darker than the outermost ones), some blood vessels include a light streak (known as a light reflex) which runs down the central length of the blood vessel. To remove this bright strip, the green plane of the image is filtered by applying a morphological opening using a three-pixel diameter disc, defined in a square grid by using this structuring element. Disc diameter was fixed to the possible minimum value to reduce the risk of merging close vessel. I gamma denotes the resultant image for future references.

2. Background Homogenization

Fundus image often contains background intensity variation due to non uniform illumination. Consequently, background pixels may have different intensity for the same image and although their grey-levels are usually higher than those of vessel pixels and the intensity values of some background pixels is comparable to that of brighter vessel pixels. So with the purpose of removing these variations, a shade corrected image is accomplished from this image is the result of a filtering operation as it can be described in below:

1. Firstly, a 3×3 mean filter is applied to smooth occasionally salt and noise smoothing is performed by convolving the resultant image with a Gaussian kernel of dimensions m×m = 9×9, mean μ = 0 and variance σ^2 = 1.8^2.
2. Secondly, a background image IB, is produced by applying a 69×69 mean filter. When this is applied to pixels in the FOV near the border, the results are strongly biased by the external dark region. To overcome this problem, out of the FOV grey-levels are replaced by average grey-levels in the remaining pixels in the square. Then the difference between I gamma and IB is calculated for every pixel.

$$D(x, y) = I \text{ gamma} - IB(x, y) \quad (5)$$

3. Finally, a shade-corrected image Isc is obtained by transforming linearly RD values into integers covering the whole range of possible grey-levels ([0-255], referred to 8-bit images). The shade-correction algorithm is used to reduce background intensity variations and enhance contrast in relation to the original green channel image.
4. Besides the background intensity variations in images, intensities can reveal significant variations between images due to different illumination conditions in the acquisition process. In order to reduce this influence, a homogenized image IH is produced as follows- The Histogram of Isc is displaced toward the middle of the grey scale by modify pixel intensities according to the following grey level global transformation function.

$$g_{output} = \begin{cases} 0, if\ g < 0 \\ 255, if\ g > 255 \\ g, oherwise \end{cases} \quad (6)$$

Where, $g = g_{Input} + 128 - g_{Input\_max}$

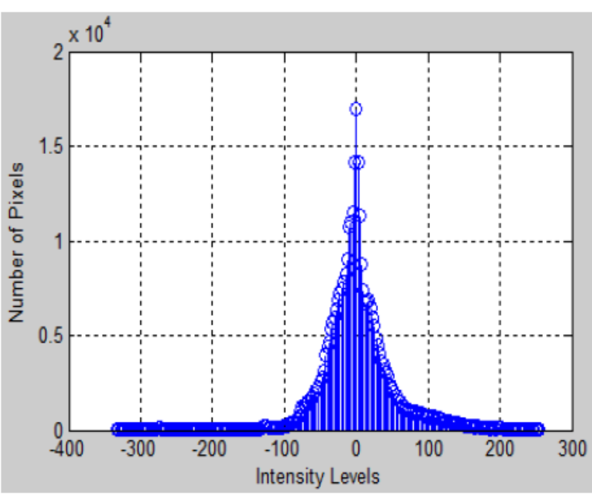

Fig.6. Histogram of Isc

In this images are within the different illumination conditions is it will be standardize their intensity around this value.

3. Vessel Enhancement

The final preprocessing step consists of generating a new vessel enhanced image Ive. Vessel enhancement is performed by estimating the complementary image of the homogenized image IH, and applying the morphological Top-Hat transformation

$$I_{VE} = I_H^C - \gamma(I_{HVE}^C) \quad (7)$$

where γ is a morphological opening operation using a disc of eight pixels in radius. Thus, bright retinal structures are removed (i.e. optic disc, possible presence of exudates) structures remaining after the opening operation become enhanced (i.e. blood vessels, fovea, and possible presence of MA).

V. RESULTS

If we can present our experimental results for both MA detection and DR grading.

A. MA Detection

In Table II, we exhibit the preprocessing method, candidate extractor pairs included in the selected ensembles for the three datasets, respectively the table show the preprocessing methods, while the columns label

TABLE II

PREPROCESSING METHOD, CANDIDATE EXTRACTOR PAIRS SELECTED AS MEMBERS OF THE ENSEMBLE FOR THE THREE DATASET. R, D, M DENOTES WHETHER THE PAIR IS IT CAN BE SELECTED FOR THE ROC.

	Walter	Spencer	Hough	Lazar	Zhang
Walter-Klein		M			R
CLAHE	R, D	M		R	D
Vessel Removal	D			R, D, M	R, D
Illumination eq.				R, M	
No preprocessing	R		M	R, D	R

the candidate extractor algorithms listed it contains the ranked quantitative results of the participants at the ROC competition, with the proposed ensemble (DRSCREEN) highlighted as the current leader. The performance of the ensemble is also shown in Fig. 7 in terms of a FROC curve. As we can see from Table III, the proposed ensemble earned both a higher CPM score and a higher partial AUC than the individual algorithms. The FROC curves of the ensemble for the DiaretDB1 v2.1and for the Moor fields database is shown in Figs. 8 and 9, 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.

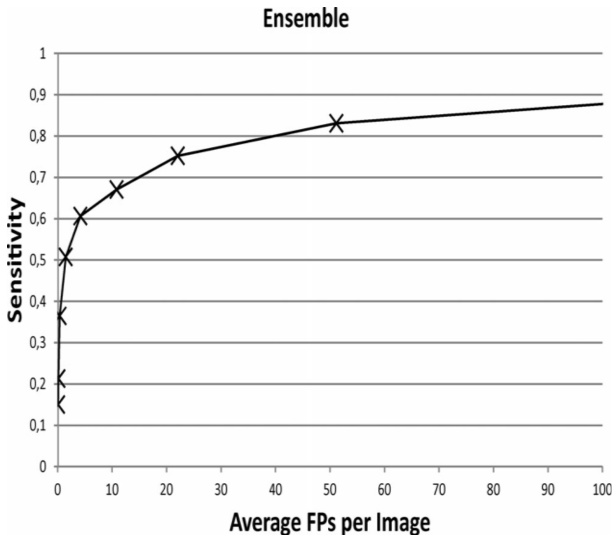

Fig.7. FROC curve of the ensemble on the ROC dataset.

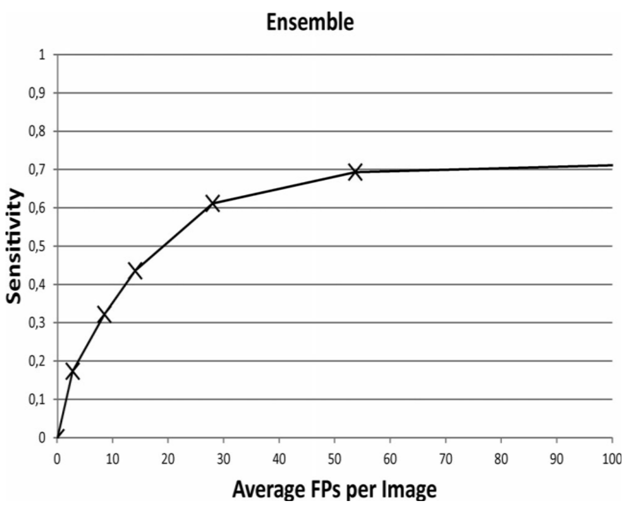

Fig.8. FROC curve is based on the DiaretDB2.1 and the dataset can be ensemble.

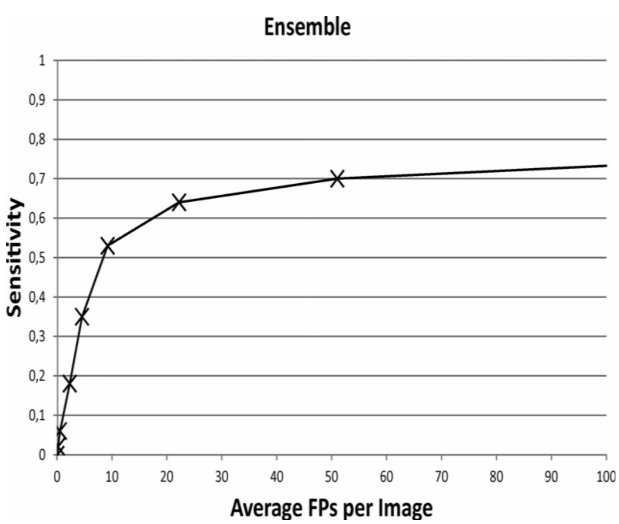

Fig.9. FROC curve of the ensemble on the Moor fields dataset.

TABLE III
QUANTITATIVE RESULTS OF THE ROC COMPETITION. FOR EACH PARTICIPATING TEAM, THE COMPETITION PERFORMANCE METRIC AND THE PARTIAL AUC ARE PRESENTED

Team	CPM	AUC
DRSCREEN	**0.434**	**0.551**
Niemeijer et al.	0.395	0.469
LaTIM	0.381	0.489
ISMV	0.375	0.435
OKmedical II	0.369	0.465
OKmedical	0.357	0.430
Lazar et al.	0.355	0.449
GIB	0.322	0.399
Fujita	0.310	0.378
IRIA	0.264	0.368
Waikato	0.206	0.273

TABLE IV
RESULTS ON THE MESSIDOR DATASET. FOR EACH THRESHOLD, SENSITIVITY, SPECIFICITY, ACCURACY AND THE PERCENTAGE OF CORRECTLY RECOGNIZED CASES FOR EACH GRADE ARE PRESENTED

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
R0	0.00	0.01	0.03	0.14	0.51	0.88	0.98
R1	1.00	1.00	1.00	0.97	0.92	0.60	0.18
R2	1.00	1.00	1.00	1.00	0.96	0.72	0.29
R3	1.00	1.00	1.00	1.00	0.98	0.92	0.42

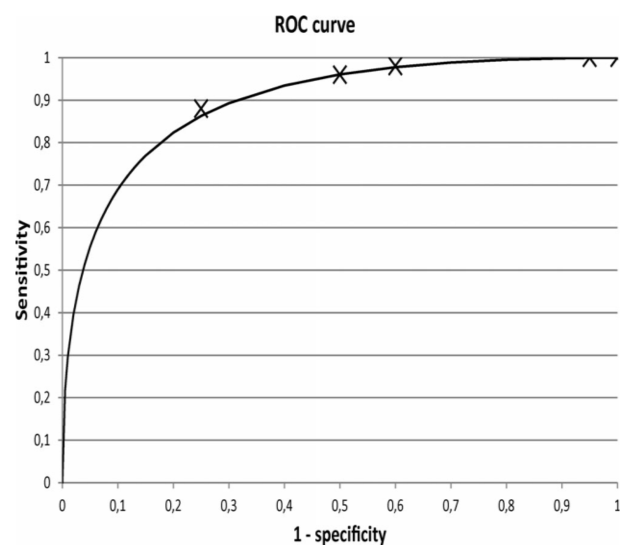

Fig.10. ROC curve of the ensemble on the Messidor dataset.

B. DR Grading

In Table IV, we provide the sensitivity, specificity and accuracy measures of our detector corresponding to different ROC curves of the detector can be seen in Fig.10. The empirical area under curve (AUC) is 0.875, while the AUC for the fitted curve is 0.90 ± 0.01. Table IV also contains the percentage of the correctly recognized cases for each class.

VI. CONCLUSION

In this paper, we have proposed an ensemble-based MA detector that 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 approach is modular and it can be 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 the Messidor database. We have achieved a 0.90 ± 0.01 AUC value, which is competitive with the previously reported results on the grading results presented in this paper are already the proper screening system should be contain and which is expected to increase the performance.

VII. REFERENCES

[1] Balint Antal, Student Member, IEEE, and Andras Hajdu, Member, IEEE, “The Ensemble-Based System for Micro aneurysm Detection and Diabetic Retinopathy Grading”, IEEE Transactions On Biomedical Engineering, Vol. 59, No. 6, June 2002.

[2] M. Abramoff, M. Niemeijer, M. Suttorp-Schulten, M. A. Viergever, S. R. Russel, and B. van Ginneken, “Evaluation of a system for automatic detection of diabetic retinopathy from color fundus photographs in a large population of patients with diabetes,” Diabetes Care, vol. 31, pp. 193–198, 2008.

[3] A. D. Fleming, K. A. Goatman, S. Philip, G. J. Prescott, P. F. Sharp, and J. A. Olson, “Automated grading for diabetic retinopathy: A large-scale audit using arbitration by clinical experts,” Br. J. Ophthalmol., vol. 94, no. 12, pp. 1606–1610, 2006.

[4] H. J. Jelinek, M. J. Cree, D. Worsley, A. Luckie, and P. Nixon, “An automated micro aneurysm detector as a tool for identification of diabetic retinopathy in rural optometric practice,” Clin. Exp. Optom., vol. 89, no. 5, pp. 299–305, 2006.

[5] M. Abramoff, J. Reinhardt, S. Russell, J. Folk, V. Mahajan, M. Niemeijer, and G. Quellec, “Automated early detection of diabetic retinopathy,” Ophthalmology, vol. 117, no. 6, pp. 1147–1154, 2006.

[6] M. Niemeijer, M. Loog, M. D. Abramoff, M. A. Viergever, M. Prokop, and B. van Ginneken, “On combining computer-aided detection systems,” IEEE Trans. Med. Imag., vol. 30, no. 2, pp. 215–223, Feb. 2001.

[7] B. Antal, I. Lazar, A. Hajdu, Z. Torok, A. Csutak, and T. Peto, “A multilevel ensemble-based system for detecting micro aneurysms in fundus images,” in Proc. 4th IEEE Int. Workshop Soft Comput. Appl., 2000, pp. 137–142.

[8] B. Antal and A. Hajdu, “Improving micro aneurysm detection using an optimally selected subset of candidate extractors and preprocessing methods,” Pattern Recog., vol. 45, no. 1, pp. 264–270, 2002.

[9] A. A. A. Youssif, A. Z. Ghalwash, and A. S. Ghoneim, “Comparative study of contrast enhancement and illumination equalization methods for retinal vasculature segmentation,” in Proc. Cairo Int. Biomed. Eng. Conf., 2006, pp. 21–24.

[10] T. Walter and J. Klein, “Automatic detection of micro aneurysm in color fundus images of the human retina by means of the bounding box closing,” Lecture Notes in Computer Science, vol. 2526. Berlin, Germany: Springer-Verlag, 2002, pp. 210–220.

[11] K. Zuiderveld, “Contrast limited adaptive histogram equalization,” Graphics Gems, vol. 4, pp. 474–485, 1994.

[12] S. Ravishankar, A. Jain, and A. Mittal, “Automated feature extraction for early detection of diabetic retinopathy in fundus images,” in Proc. IEEE Conf. Comput. Vision Pattern Recog. 2009, pp. 210–217.