Smartphone-Based Decision Support System for Elimination of Pathology-Free Images in Diabetic Retinopathy Screening

João Costa, Inês Sousa, and Filipe Soares(✉)

Fraunhofer AICOS, Rua Alfredo Allen 455, 4200-135 Porto, Portugal
{joao.costa,ines.sousa,filipe.soares}@fraunhofer.pt

Abstract. Diabetic Retinopathy is a Diabetes complication and the leading cause of blindness in the United States. Early detection can be accomplished by analysis of images of the retina, generally obtained by expensive fundus cameras. Recent developments allow the use of mobile ophthalmoscopes that can be adapted to smartphones to acquire these images, but the low computational power of smartphones limits the use of Computer-Aided Diagnosis systems. In this paper, an approach for automatic retinal image analysis on a smartphone is proposed, with emphasis on high sensitivity and fast computation. A set of 1200 images from the Messidor database were analyzed for extraction of features related to vessel segmentation, presence of exudates and microaneurysms. SVM and k-NN classifier models were trained with these features, resulting in a sensitivity of 87% and a specificity of 66%. An analysis of the computational performance validates the feasibility of using this approach on quad-core smartphones.

Keywords: Diabetic Retinopathy · Decision support system · Vessel segmentation · Microaneurysms · Exudates · Image processing

1 Introduction

Diabetic Retinopathy is a complication of diabetes caused by general physiological deregulation, and eventually may lead to blindness. The asymptomatic nature of the disease progression and the very large diabetic population make the implementation of extensive screening programs particularly challenging. Notwithstanding, the high effectiveness of treatment in the initial stages contributes to the great clinical value of early detection and motivate the need to improve the cost-effectiveness of screening programs.

The current gold standard for diagnosis is the acquisition of images of the retina by a retinal camera and subsequent analysis by a clinical expert. However, two challenges arise from this approach: retinal cameras are relatively expensive for wide deployment in various screening sites and are not easily transported among different screening locations; in addition, the large screening population poses a significant burden on healthcare systems, due to the necessity of manual image analysis by a scarce number of experts.

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In order to tackle the first challenge, handheld systems for acquisition of retinal images, integrating smartphone imaging capabilities with the optical principles of retinal cameras have been proposed in the literature [1,2], taking advantage of the significant image quality currently afforded by the smartphone cameras. Favourable comparisons between the image quality of these approaches to commercial retinal cameras validate their clinical potential [3].

The use of smartphone cameras as opportunistic sensors, besides significantly reducing the cost for retinal image acquisition, also allows to exploit the considerable computing power of these devices to perform automatic analysis of the acquired retinal images.

Extensive research work has been developed for the automatic detection of Diabetic Retinopathy in images acquired by traditional retinal cameras, but few address the constraints of running the proposed methods in mobile hardware. This paper describes a Decision Support System for automatic classification of retinal images according to the presence of Diabetic Retinopathy, with emphasis on fast computation and high sensitivity in detecting pathological cases, for use in mobile devices.

2 Methods

A total of 1200 images from the publicly available Messidor database [4] are used. The images were acquired by a Topcon TRC NW6 retinograph with a 45° field of view and saved in 8-bit color depth uncompressed TIFF format, with a resolution of 2240×1488 pixels, 1440×960 pixels and 2304×1536 pixels.

The ground truth for this database considers four different Retinopathy grades: R0 (no Retinopathy signs) and R1, R2 and R3, in ascending order of severity. Since our goal is to exclude images without signs of Diabetic Retinopathy, all images with grade above R0 were considered as presenting this pathology - from the 1200 images, 654 present Diabetic Retinopathy and 546 do not.

Classification uses three specific retinal structures detected by image analysis methods: retinal vessels, microaneurysms and exudates. The proposed methods are implemented in C++, using the OpenCV library.

From the original input image, the green channel of the RGB color space is often used for the main processing steps. The reason for this decision is the superior contrast of this channel, in opposition to the significant oversaturation of the red channel and undersaturation of the blue channel.

2.1 Vessel Segmentation

A significant increase in the area of vessels is indicative of late stage Diabetic Retinopathy, where neo-vascularization often occurs.

The first step of this method removes the background variations of the retina, by subtracting the original green channel image by its median filtered version. Grayscale morphological operations are then used to evidentiate the vessels: a top hat transform will subtract the image with a morphological opened version of itself. The result is thresholded and small connected components are removed in order to obtain the final vessel segmentation.

2.2 Microaneurysm Lesions

Microaneurysms appear as small red dots in the retinal images and are the earliest sign of Diabetic Retinopathy. Microaneurysms present specific characteristics in retinal images that are suitable for detection: small size, circular shape and hypointensity in relation to the background. These features can be leveraged by image processing methods to evidentiate these structures.

An approach similar to the one proposed by Zhang et al. [5] was employed to extract microaneurysm regions from the image. An inverted 2D Gaussian kernel is used to perform template matching in the original green channel image. This kernel emulates the distribution of intensities of a microaneurysm in a retinal image and is modeled by the Eq. (1).

$$F(x, y) = -e^{-\left(\frac{x^2}{2\sigma_x^2} + \frac{y^2}{2\sigma_y^2}\right)} \tag{1}$$

In order to account for different microaneurysm sizes, different σ values are used for the kernel. The result of the template matching is thresholded and each connected component will constitute a detected microaneurysm. Since the vessels are the regions of frequent false positives, the vessel mask is used to exclude those erroneous detections (see Fig. 1).

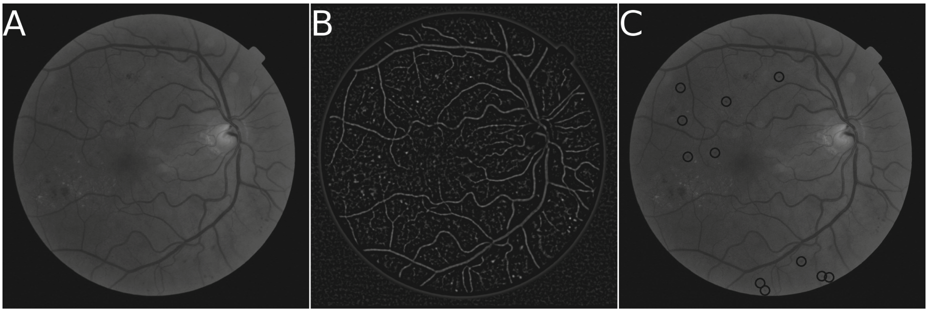

Fig. 1. Steps of the microaneurysm extractor: (A) Green channel image; (B) Result of correlation with inverted Gaussian kernel; (C) Candidates obtained by thresholding the correlation image (marked with black circles).

2.3 Segmentation of Exudate Lesions

Exudates are yellow structures that often appear in the retina as a result of the progression of Diabetic Retinopathy. Detection of these lesions is performed using morphological operations. The green channel of the retinal image is initially equalized using adaptive histogram equalization and a morphological closing operation is then applied. A local standard deviation filter is used in the resulting image - this filter will compute, for each pixel, the standard deviation of the pixel neighbourhood. The output of the filter is thresholded, and will constitute the exudates segmentation.

2.4 Classification

The area of detected vessels, the number of detected microaneurysms and the area of exudates are used as features for the decision support system. Both area values are normalized in respect to image resolution. Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) classifiers are used to classification models based on the aforementioned features. The SVM classifier uses a Radial Basis Function (RBF) kernel, with $\gamma = 1.0$ and $C = 0$. The k-NN classifier uses $k = 11$.

3 Results

The performance of the trained classifier models was evaluated using 10-fold cross validation, with sensitivity and specificity used as performance metrics. For the SVM model a sensitivity of 87% and a specificity of 66% is achieved and for the k-NN model the sensitivity is 83% and the specificity is 64%. The ROC curve for both classifiers is represented in Fig. 2. An AUC of 0.85 was registered for the SVM model and a AUC of 0.82 for the k-NN model.

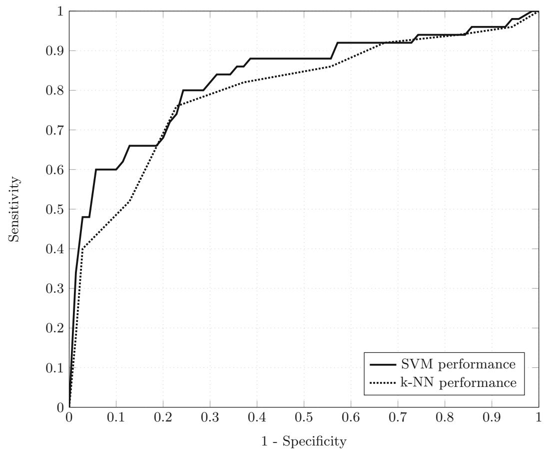

Fig. 2. Comparison of the ROC curves using SVM and k-NN classifiers.

To assess the feasibility of running the proposed methods on low power devices, the execution time of each stage was measured. The results are summarized in Table 1. All results were obtained for a smartphone with a Quad Core 2.5 GHz Snapdragon 801 CPU. The running time for the model based prediction is very low and for that reason was not considered.

Table 1. Average running time of the image processing methods.

Method	Running time (s)
Vessel segmentation	0.32 ± 0.07
Microaneurysm detection	3.02 ± 0.29
Exudates detection	3.46 ± 0.28

4 Discussion

Some studies [6,7] in the literature propose the automatic analysis of images from the Messidor database considering the four class ground truth for their results and therefore are not directly comparable. However, the work of Sánchez et al. [8] and Antal et al. [9] also uses this database with a two class prediction, considering a Diabetic Retinopathy present/absent classification.

Comparable results are obtained in these studies, in particular a sensitivity of 92% and a specificity of 50% are reported in [8], while in [10], a sensitivity of 96% and a specificity of 51% are disclosed.

Prasanna et al. [10] reports an average sensitivity of 86% and an AUC of 0.84 for pathology detection in images from the Messidor database, but these results are relative to only a portion of the database (400 out of the 1200 images) and it is not clear how the two classes were obtained from the original four class ground truth.

Execution time has been reported in [8], and for the several stages it is estimated to be under 3 min, for a desktop computer. In [11], the execution time is 31 s for an unrooted Galaxy S GT-I9000 device. Our results compare favorably with these, with a total average running time of under 7 s achieved on a smartphone. Experimentally, on a computer we found execution time to be 5 to 8 times inferior.

5 Conclusion

An approach for automatic exclusion of pathology-free cases by analyzing the retinal images, suitable for running in low-powered devices, is described in this paper. The execution time of the proposed methods is very low, which fits the use case of mobile applications. The classification results attest its competitiveness against other solutions with AUC of 0.85, specially considering the low number of features used.

In future work, we intend to validate the proposed method in images acquired using the smartphone and an optical adapter.

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