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Neural network based detection of hard exudates in retinal images

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ABSTRACT

Diabetic retinopathy (DR) is an important cause of visual impairment in developed countries. Automatic recognition of DR lesions in fundus images can contribute to the diagnosis of the disease. The aim of this study is to automatically detect one of these lesions, hard exudates (EXs), in order to help ophthalmologists in the diagnosis and follow-up of the disease. We propose an algorithm which includes a neural network (NN) classifier for this task. Three NN classifiers were investigated: multilayer perceptron (MLP), radial basis function (RBF) and support vector machine (SVM). Our database was composed of 117 images with variable colour, brightness, and quality. 50 of them (from DR patients) were used to train the NN classifiers and 67 (40 from DR patients and 27 from healthy retinas) to test the method. Using a lesion-based criterion, we achieved a mean sensitivity (SE_l) of 88.14% and a mean positive predictive value (PPV_l) of 80.72% for MLP. With RBF we obtained $SE_l = 88.49\%$ and $PPV_l = 77.41\%$, while we reached $SE_l = 87.61\%$ and $PPV_l = 83.51\%$ using SVM. With an image-based criterion, a mean sensitivity (SE_i) of 100%, a mean specificity (SP_i) of 92.59% and a mean accuracy (AC_i) of 97.01% were obtained with MLP. Using RBF we achieved $SE_i = 100\%$, $SP_i = 81.48\%$ and $AC_i = 92.54\%$. With SVM the image-based results were $SE_i = 100\%$, $SP_i = 77.78\%$ and $AC_i = 91.04\%$.

1. Introduction

Diabetic retinopathy (DR) is a visual complication of diabetes, which has become the most common cause of visual impairment among people of working age in industrialized countries [1]. Laser photocoagulation can slow down the progression of DR if detected in its early stages. However, this is not an easy task because DR patients perceive no symptoms until visual loss develops. This happens in the later stages of the disease, when treatment is less effective. To ensure that treatment is received on time, diabetic patients need to undergo a yearly eye fundus examination [2]. Including digital photographs of the retina in the screening protocol is a sensitive and specific means for detecting early clinical signs of retinopathy in at-risk populations [3]. As demonstrated in [4], manual and automated analysis of digital retinal images reach satisfactory results in the detection of DR and diabetic macular oedema. Moreover, their inclusion in the exam protocol showed a high performance in the detection of patients who need further ophthalmological assessment [4].

The growing incidence of diabetes increases the number of images that need to be reviewed by physicians. In addition, the high cost of examinations and the lack of specialists prevent many patients from receiving effective treatment. Computer

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aided detection of retinal lesions associated with DR offers many potential benefits. In a screening setting, it allows the examination of a large number of images in less time and more objectively than current observer-driven techniques [5]. In a clinical setting, it can be an important diagnostic aid and can reduce the workload of trained graders and, therefore, reduce costs [5].

DR signs include red lesions, such as microaneurysms (MAs), intraretinal microvascular abnormalities (IRMAs) and haemorrhages (HEs), and bright lesions like hard exudates (EXs) and soft exudates or cotton–wool spots (CWs). Other bright lesions that can appear in fundus images are drusen, which are associated with age related macular degeneration (AMD) [6]. Sometimes they appear similar to exudates and may confound automatic systems. The small laser scars caused by panretinal photocoagulation also appear as bright areas in retinal images belonging to DR patients that have received this treatment. Therefore, their presence is an additional difficulty for bright lesion detection. Retinal exudates can represent the only visible sign of DR in some patients [6]. Moreover, it is important to distinguish among lesion types as they have different diagnostic importance and management implications [6]. This paper focuses on EXs detection and their differentiation from other bright areas in our images, specifically CWs and the optic disk (OD). As EXs are among common early clinical signs of DR [7], their detection would be an important contribution to the screening tasks and could serve as a first step towards a complete monitoring and grading of the disease. EXs are lipid and lipoprotein deposits, white, yellowish or waxy, that appear as compact patches with well-defined borders in retinal images.

Many attempts to detect these lesions can be found in the literature. Some works [8,9] used the high luminosity of EXs to separate them from the background by thresholding. In [8] a global threshold was used for the detection of EXs after image enhancement. The wide variability among images made the method dependent on user intervention to select the adequate threshold for each case. A similar approach was used in [9], where a combination of global and local thresholds was applied to segment EXs. This method, however, needed a previous definition of a region of interest by an operator. Edge detectors, combined with other techniques, were applied in [10–14]. A two-stage method was applied in [10]. First, the borders of candidate EXs and HEs were detected. Then, colour, shape and location properties were used to separate both types of lesions. Other authors [11,12] also used edge detection in combination with different techniques to detect bright lesions. In [12] authors also created a model of the retina to automatically identify the presence of lesions in the macular region. Edge and brightness information was combined in [13] to identify EXs and the severity of DR. In [14] the borders of EXs were extracted using a mathematical morphology based method. However, these studies [8–14] did not explicitly address the differentiation among lesion types.

Some works [15,16] focused on the study of the ability of Bayesian classifiers to detect retinal lesions. The intensity of a set of pixels was used to train the classifier in [15]. On the contrary, the training set in [16] was created by extracting several features from image regions. A statistical classifier was also used in a previous work by our group, where Fisher's linear discriminant analysis was part of a method to segment EXs [17]. The classification rule was automatically adapted to each image. The distinction between CWs and EXs was faced in [16,17], but not in [15].

A method for detecting EXs and CWs, and separate them from drusen was proposed in [6]. A *k*NN classifier was used in a first stage to detect candidate bright lesions. Linear discriminant analysis was subsequently used to differentiate among lesion types. Neural network (NN) based classifiers have also been used [18–20]. A multilayer perceptron (MLP) was used in [18] to determine the presence of bright lesions in image regions of size 20×20 pixels. In [19] candidate bright regions were segmented using Fuzzy *C*-means clustering. A support vector machine (SVM) was used afterwards to determine if a segmented region is an EX or another type of bright region. A similar approach was used in [20], where MLP and SVM NNs were analysed and compared.

In this study, we examined and compared the ability of three different types of NNs to detect EXs in retinal images: MLPs, radial basis function (RBF) networks and SVMs. We developed an automatic method that was suitable for the great variability of images that ophthalmologists could find in their daily practice. Therefore, it could be used as a clinical aid in the diagnosis and monitoring of DR.

2. Image database

A total of 117 images with variable colour, brightness, and quality were used in this study. All the images were provided by the Instituto de Oftalmobiología Aplicada (IOBA) of the University of Valladolid, Spain. 31 of these images were captured using a TopCon TRC-NW6S non-mydriatic retinal camera at a field-of-view (FOV) of 45°. The remaining 86 images were captured with a TopCon TRC-50IX mydriatic retinal camera at 50° FOV. Due to the wider FOV, the images taken with the TopCon TRC-50IX cover more retinal area and the image details appear bigger. On the other hand, images captured with the TopCon TRC-NW6S showed, generally, better quality and contrast. Image resolution was 576×768 pixels in 24 bit JPEG format. An experienced ophthalmologist manually marked all EXs in the images. These annotations have been considered as the reference standard to compare our results with.

Images came from a clinical set of 106 diabetic patients who were referred to the ophthalmologist for further examination. Therefore, our database contained two images (right and left eye) from 11 patients and the remaining 95 images belonged to different subjects. 90 of these images belonged to patients who suffered from mild to moderate non-proliferative DR, according to an expert. In the remaining 27 images the ophthalmologist did not mark any EXs. The images from DR patients also contained CWs (in 19 images) and HEs (in 87 images). However, drusen were not present in any of the images.

The 117 images were divided into a training set and a test set in a pseudo-random manner:

- The training set contained 50 images from DR patients, with the only restriction that two images from the same patient could not be included in this set. In this way, the ability of the