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A Web-Based Platform for Automated Diabetic Retinopathy Screening

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Abstract

Diabetic patients are encouraged to undergo frequent retinal examination because of diabetic retinopathy (DR): the most common cause of blindness in working population. As this population is generally too large for healthcare systems, exam reviewing must be optimized. Therefore, a web-based application is proposed. It features user interfaces for healthcare professionals, including ophthalmologists, and an automated DR detection module (by means of image processing and diverse computational intelligence techniques) that allows to relieve their work load. Overall automated system performance reaches 91.9% and 65.2% in terms of sensitivity and specificity, respectively.

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Keywords: Diabetic retinopathy; Digital image processing; Pattern recognition; *k*NN; Fuzzy c-means (FCM); Neural networks; Extended-minima transform; Web-based platform

1. Introduction

Diabetic retinopathy (DR) affects working population[1], blinding about 25,000 patients with diabetes annually in the United States (U.S.) alone[2]. Although early detection and laser treatment of DR have proved effectiveness in preventing visual loss[3,4], many diabetic patients are not treated in time because of inadequacies of the currently available screening programs[5,6]. This applies, for example, to almost 50% of the 18 million patients with diabetes in the U.S. who do not undergo any form of regular documented dilated eye exam[7–10].

The main goal of this paper is to develop a classifier that allows to discriminate among patients with and without presence of DR by means of an automated digital eye fundus images processing[11,12]. As a local application at its dawn, the project demands: collection and preparation of a dataset for the occasion; identification of state of the art

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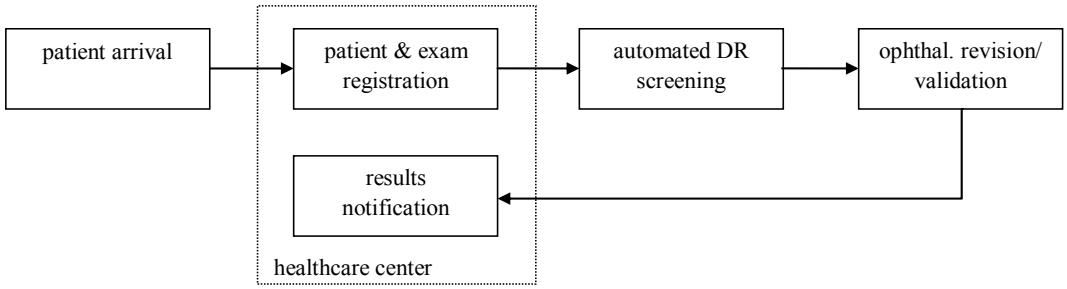

Fig. 1: Web-based platform workflow. Dashed box indicates actions that take place in the healthcare center, while the rest of them can be remote.

techniques and methodology to the particular problem; and development of effectiveness indicators of the system which allows drawing useful conclusions for feasibility assessment. Additionally, a web-based user interface is fully developed in order to satisfy eye fundus exams uploading, automated screening and further remote manual diagnosis and referring by ophthalmologists.

Our research has been conducted independently in four major themes that converge to DR detection. These are: blood vessel localization, optic disc (OD) localization, bright lesions detection, and red lesions detection. For blood vessel localization, evaluation of existing methods[13], Quadtrees and post-filtration of edges[14], Gabor wavelet transform responses with Gaussian mixtures classifier[15] and combination of shock filter and Binarization[16] have been performed. OD localization has been proposed by combination a Hausdorff-based template matching technique[17], simulated annealing optimization techniques[18], fitting a single point-distribution-model[19], matching the expected directional pattern of the retinal blood vessels[20] and prediction of the distance to the object of interest at any given location based on a set of features measured at that location, using a *k*NN regressor[21]. Bright lesions have been found by means of morphological reconstruction techniques[22], using *k*NN and linear discriminant classifiers[23], fuzzy morphology for lesion enhancement[24], fuzzy c-means (FCM) segmentation, classified using a multilayer neural network (NN) classifier[25] and contextual information incorporation[26]. For red lesions detection, region-of-interest and matched-filter use[27], enhancement of small round features[28], scale and orientation selective Gabor filter banks usage[29], set of features and a *k*NN classifier usage[30] and optimally adjusted morphological operators[31], have been surveyed.

Overall DR detection systems has also been evaluated before. One of the main articles[8] performed tasks including discarding images with insufficient image quality[10]. Results were a sensitivity of 0.84 and a specificity of 0.64. Other authors obtained sensitivity and specificity of 0.839 and 0.727, respectively[9]. In a similar way we expect to achieve better results by selecting state of the art techniques and adapting them for each of the major detection stages[15,21,25,31].

2. Materials and Methods

As has been said, our main goal is to develop a system for automated DR detection. The input of the system is a digital image corresponding to a retinal exam. All images were clinically validated as appropriate for DR diagnosis. DR presence results from any of two type of abnormalities presence: bright lesions or red lesions. Therefore, both types of lesions should be searched for in the studied patient image. Besides specific methods to perform such search, morphological landmarks of any retina (OD and blood vessels) need to be located as well, because of their graphical structure reliance when looking for abnormalities.

Fig. 1 shows a simplified diagram of our web-based platform with DR detection approach, including manual and automated steps.

Selected detection approaches in “automated DR screening” step need completeness of one another. For bright lesions detection, OD must be located. For OD localization, blood vessels must be segmented. Now, for red lesions detection, pixels of the image corresponding to bright lesions, blood vessels and OD need to be discarded in order to analyze the background of the retina for additional abnormalities.

2.1. Materials

A dataset of 550 images for training and testing purposes, disaggregated in Table 1, was obtained from eye fundus exams from a DR screening program of the Peñalolén Health Reference Center (CRS, for its acronym in Spanish). These images were acquired using a Canon CR DGi nonmydriatic retinal camera (EOS 30D). JPEG image compression was applied. Images were resized to 701×468 pixels because of state of the art experiences. Images are non-stereoscopic pictures of 45°, ones with macular field and another ones with disc/nasal field[32]. The system was implemented using MATLAB software.

Medical experts were ophthalmologists from the University of Chile and from the CRS. They labeled images into lesion and non-lesion, as well as OD and fovea centers locations. For this matter, a specially designed off-line graphical user interface (GUI) was designed. For bright lesions detection, a pixel-level precision detection is not critical. Therefore, a post-segmentation method is used to validate the training and testing databases; a 550 images set (previously segmented using the section listed algorithms) was handed to medical specialists, in addition to the ad-hoc GUI.

Training and testing sets are specified in Table 1, because they differ according to expert labeling. Red lesions detection does not need a training set.

2.2. Blood Vessel Localization

Retinal blood vessels segmentation from the rest of the image's components is mandatory in order to detect DR-related abnormalities. It is strictly necessary for OD localization and for red lesions detection. In this work, methods are not fully developed and therefore not deeply explained. This is because, as it is an intermediate step in DR detection, available open source scripts for implementation have been used. The implemented method[15] produces segmentations by classifying each image pixel as vessel or nonvessel, based on the pixel's feature vector. Feature vectors are composed of the pixel's intensity and two-dimensional Gabor wavelet transform responses taken at multiple scales. The Gabor wavelet is capable of tuning to specific frequencies, thus allowing noise filtering and vessel enhancement in a single step. A Bayesian classifier with class-conditional probability density functions (likelihoods) described as Gaussian mixtures is used, yielding a fast classification, while being able to model complex decision surfaces. The probability distributions are estimated based on a training set of labeled pixels obtained from manual segmentations. Blood vessel localization stage is almost fully based on mentioned authors' work.

2.3. Optic Disc Localization

OD, together with the vasculature and the fovea, is one of the most important anatomical landmarks present in retinal exams. Locating it serves as spatial reference, but is also helpful because of its color similarity with bright lesions and the confusion this could lead to in an automated system; thus its masking importance. A fast detection of the OD (with extension to fovea) is selected to develop this stage[21]. This approach makes few assumptions about this structure's default localization; it defines the task as a regression problem: the distance at a given location to the object of interest is predicted based on a set of features measured at that location, using a *k*NN regressor. Features combine cues measured directly in the image with cues derived from previous segmentation of the retinal vasculature.

Table 1: Total of 550 images distribution into normal-abnormal and train-test according to the stage; each train/test set has a total of 275 images (note that red lesions stage does not need a training set)

	Bright lesions		Red lesions	Overall DR	
	Train	Test	Test	Train	Test
Normal	206	206	181	173	164
Abnormal	69	69	94	102	111

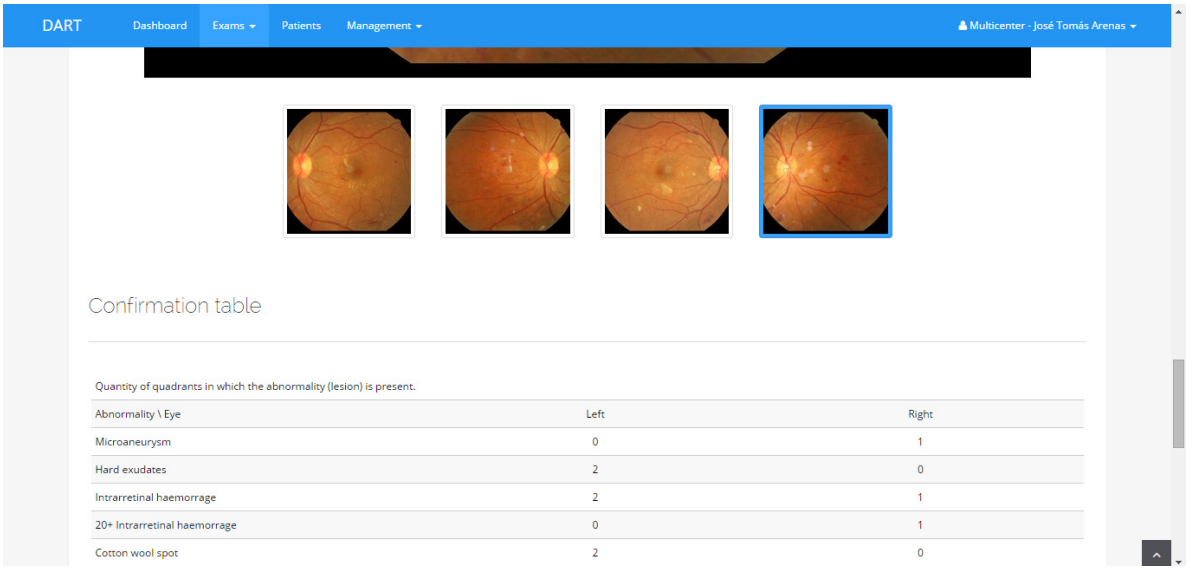

Fig. 2: Web-based platform screen. This specific shot shows all the images present in a specific exam displayed to the user and part of the lesion counter table.

A distance prediction is made for a limited number of image locations and the point with the lowest predicted distance to the OD is selected as the OD center. This section's manually labeled images are distributed as in Table 1.

2.4. Bright Lesions Detection

Bright lesions and, specifically, exudates are one of the most important detectable retinal lesions. An automated method for screening purposes was selected and fully developed. This method is mostly inspired by a computational-based approach structure[25] with some changes and customization. It aims to investigate the effectiveness of computational intelligence toward automatic detection and identification of exudate pathologies. Starting with a color normalization and contrast-enhancement preprocessing steps, the retinal images are segmented based on a combination of color representation in Luv color space and an efficient coarse to fine segmentation using FCM clustering. To classify these regions into exudates and nonexudates, a NN classifier is investigated. This section's dataset is described in Table 1.

One of the main stages of this step, the segmentation, operates in its fine phase through FCM assigning any remaining unclassified pixels (pixels from ambiguous regions) to the closest cluster based on a weighted similarity measure between the pixels in the image and each of classes (C, e.g., exudates and nonexudates) cluster based on FCM clustering centers[33]. Local extrema of this objective function are indicative of an optimal clustering of the image. The function is defined as

$$J_{FCM}(U, v; X) = \sum_{k=1}^{n} \sum_{i=1}^{C} (\mu_{ik})^m \|x_k - v_i\|^2, \qquad 1 \leq m < \infty \tag{1}$$

where μ_{ik} is the fuzzy membership value of a pixel k to class i and $X = x_1, \ldots, x_n$ is a finite dataset in $\mathbb{R}^d$. $\{v = v_1, \ldots, v_c\}$ is a set of class centers, where $v_i \in \mathbb{R}^d, 1 \leq i \leq C$, represents a d-dimensional ith class center, and is regarded as a prototype. The objective function (1) is minimized when high membership values are assigned to pixels whose values are close to the centroid for its particular class, and low membership values are assigned when the pixel data are far from the centroid. Taking the first derivatives of (1) with respect to μ_{ik} and v_i, and setting them to zero yields necessary conditions for minimizing the objective function. The parameter m is a weighting exponent that satisfies $m > 1$ and controls the degree of fuzziness in the resulting membership functions. As m increases, the membership functions become increasingly fuzzy.

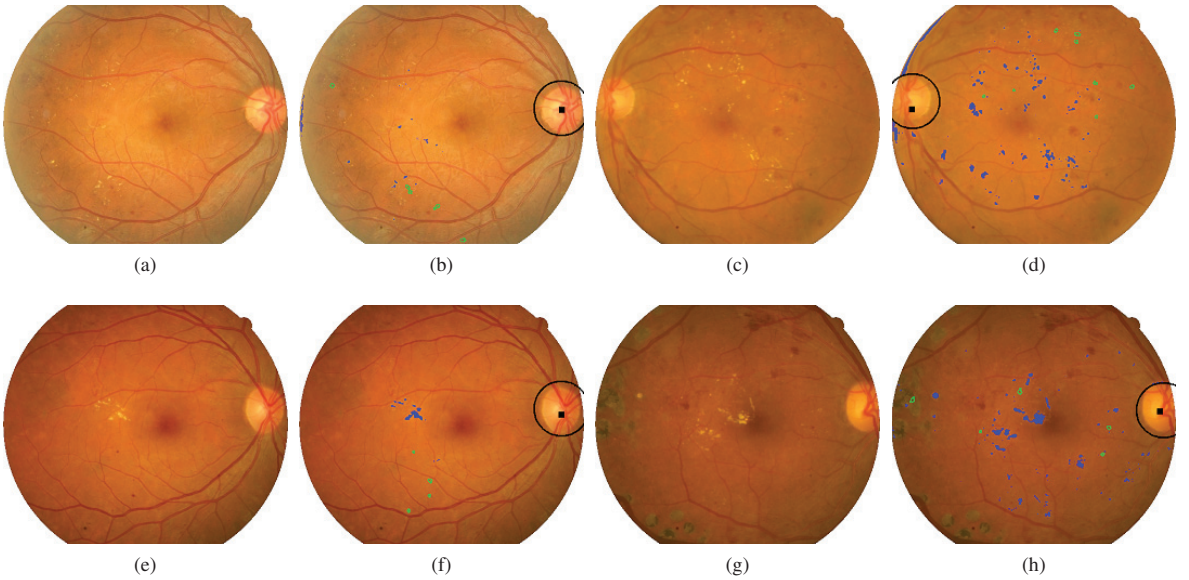

Fig. 3: DR detection graphic results. First column shows original images and second column shows: OD localization (square) and actual position (circular object); bright lesions detection (blue); red lesions detection (green).

2.5. Red Lesions Detection

Microaneurysms are the first clinical sign of DR. The number of microaneurysms is clinically used by ophthalmologists to indicate the severity of the disease. Early microaneurysm and red lesions detection can help reduce the incidence of blindness. An approach that investigates a set of optimally adjusted morphological operators used for red lesions detection on non-dilated pupil and low-contrast retinal images is selected and implemented[31], making some changes in order to adapt it to an image-based approach. The system has three main steps. The preprocessing step includes histogram normalization, noise removal and contrast enhancement. Candidate retinal features which may cause a false detection, i.e., exudates and vessels (plus OD) are extracted in the second step. And the last step is red lesions detection by using a set of optimally adjusted mathematical morphology. In this section, only the test set is required, discarding any training phase, as shown in Table 1.

2.6. Architecture

In order to enable user access to the technology for the users, a web interface is developed. This interface consists in a platform where healthcare professionals login with their user identification and password and can manage their workload, interacting with each other and with the automated image screening module. We have found that this is a suitable dynamic way for the patient to gain access to proper DR screening coverage and for the professionals to optimize their intervention.

The general workflow is the following. Previous to healthcare professionals' use of the system, an administrator must create the respective center and its users on the platform. Then, as patients are coming to get their exams taken, medical technicians enlist them whith all their personal information and their eye fundus exam, including digital retina images. Then, these exams are uploaded to the platform's remote server. This is when the automated system comes into play by processing each of the images with the methods already described and comes up with a result. According to this result, the exams go back to the users. Then, ophthalmologists go into the platform and can put more attention to the patients that need care instead of the ones that have been discarded, as they have all been already processed by the automated module. In this user-driven step, exams are manually checked and patients can be diagnosed and

referred according to the state of their exam. Fig. 2 shows one of the several screens where the user interacts with patient's and exam's records; in this case when ophthalmologist reviews an exam and its digital images.

3. Results

All image processing methods were applied in our database and therefore are not easily comparable to universal published databases. For this purpose, 550 images had been labeled in terms of OD (and fovea) center location, pixels corresponding to bright lesions, and classified in terms of presence of red lesions. They have been divided in halves for training and testing (See Table 1).

System overall results are estimated in 91.89% specificity and 65.24% sensitivity for DR detection at an image level. Examples on abnormal images are shown in Fig. 3. The whole procedure takes, on average, 9.6 minutes for processing each image using straightforward MATLAB implementation for tests. Retinal images are tested on an Intel Core i5 2.53 GHz with 6 GB memory.

On the other hand, the proposed web platform is fully operational and provides an intuitive tool which healthcare centers use without major issues. Suggestions have been made in terms of data of the medical record that goes with the exam, action buttons display and easier ways to grade DR according to observed situation. In general terms, further filtering of normal cases is expected once the technology is fully accepted and validated, so ophthalmologists can ignore these, concentrating and increasing analysis of patients in need.

4. Conclusion

As main conclusion, our system outperforms state of the art systems. A proof of these phrase are the following results: 100% precision in OD localization in the 275 testing images; identification of 85.5% of bright lesions images, i.e., sensitivity, while recognizing 50% of images without bright lesions, i.e., specificity (87.4% sensitivity and 79.1% specificity at a pixel level) in the same 275 samples; and, 77.7% sensitivity and 81.2% specificity in red lesions detection in the testing images. Vasculature localization performance is measured by the rest of the steps result. Overall system performance reaches 91.89% and 65.24% in terms of sensitivity and specificity, respectively.

A patient and exams system as a whole is also provided. This allows an integrated application as a solution for healthcare system and, specifically, for healthcare professionals. It provides an optimization tool that has the automated DR detection system as an intermediate module.

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