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Diabetic Exudate Detection in Color Retinal Images

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Abstract

Diabetic retinopathy is a vascular complication of long-term diabetes. It causes damage to the small blood vessels positioned in the retina. These damaged blood vessels affect the macula and lead to vision loss. Exudates are one of the early signs of diabetic retinopathy disease in the retinal image, which occurs due to the built-up of lipidic accumulation within the retina. In this paper, an image processing method is presented for diabetic exudates detection. First, high performance pre-processing is applied not only for de-noising and normalization but also to remove artefacts and reflection that could mislead exudates detection. Then, morphological operations are applied for the final candidate segmentation. Eight region features are extracted from the exudate region then a random forest classifier is applied to differentiate between exudates and non-exudates region. The proposed method is evaluated using e_ophtha_EX dataset, achieving 79.6% sensitivity and 77% positive predicted value.

Keywords: Exudates, Diabetes, Machine Learning, Image Processing Techniques, Retinal Images.

1. Introduction

The retina is a spherical anatomical structure on the inner side of the eye. It is responsible for receiving the light that is focusing by the lens and converts the light into signal then this signal is sent back to the brain. The dark round spot located at the center of the retina called macula and the center of the macula called fovea, which is responsible for sharp vision. Optic disk including the optic cup is the bright oval batch, where the optic nerve fibers leave the entry of the major arteries and veins. The special structure of the retina restricts the possible appearances of distortions due to different diseases. Mainly, the most frequent lesions appear in the retinal image as patches of blood or fat. Diseases affecting the blood vessel system cause similar vascular distortions here than in any area of the body but are easier and better seen if examined by an experienced professional [1].

Diabetic retinopathy is one of the diseases that affect the retina. It is a consequence of diabetes. It damages the retinal blood vessels. These damaged blood vessels affect the macula [2]. Fluid can leak to the macula. The macula is the part of the retina responsible for clear central vision. The leaking fluid causes swell in the macula, lead to blurred vision. In an attempt to enhance blood circulation in the retina, new blood vessels may form on its surface. These fragile, abnormal blood vessels can cause blood leakage into the back of the eye and cause vision loss. The patients with diabetic retinopathy are often asymptomatic in the advantage level of the disease. However, the patient at the initial stage may experience symptoms that include spots or floaters, blurred vision, fluctuating vision, impairment color vision, and dark or empty area in vision. Signs of diabetic retinopathy include Microaneurysms (MA), hard/soft exudates, hemorrhages, neovascularization, and macular edema [3]. In this paper, we will concentrate on detecting diabetic exudates, which appear as bright yellow in color retinal images. Figure 1 shows a color fundus image with the main structural elements of the eye and some lesions. There are varies image processing techniques applied for exudates detection.

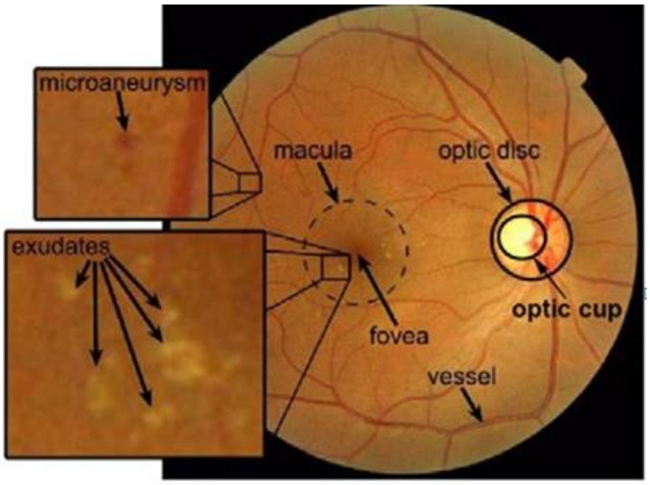


Fig.1 Different types of lesion and anatomical structures in retinal images.

Walter et al. [4] applied morphological operation for blood vessel removal. Then, for exudate region extraction, the calculation of the local standard deviation and thresholding is used. Also, Sopharak et al. [5] applied morphological reconstruction for exudates detection using non-dilated retinal images. Zhang et al. [6] proposed an algorithm for exudate detection. This algorithm is processes images containing high availability in terms of definition and quality and presence of artefacts. Morphological operations are applied for pre-processing and removing image artefacts; then, a random forest classifier is used to distinguish the data.

Other methodologies, as Pereira et al. [7] applied the colony optimization to detect regions of exudates using the analysis of the connected components. Giancardo et al. [8] depend on the set of features like the color feature and use it to train the classifier using the automatic exudate segmentation and wavelet decomposition. Sánchez et al. [9] depend on the contextual information to improve candidate exudate detection. This method achieves a significant gain in the classifier accuracy value of the pathology. Kar et al. [10] proposed a method for the detection of dark and bight lesions. Both log filter response and matched filter response are applied for pre-processing. For optic disk extraction, a fuzzy c mean kernel is applied. For dark lesion extracted (hemorrhage's and Microaneurysms) curvelet wavelet is applied. For bright lesion detection (exudates) a band-pass filter is first applied to enhance exudate detection. Then, the candidate extracted using Gaussian filtering and matched filter response.

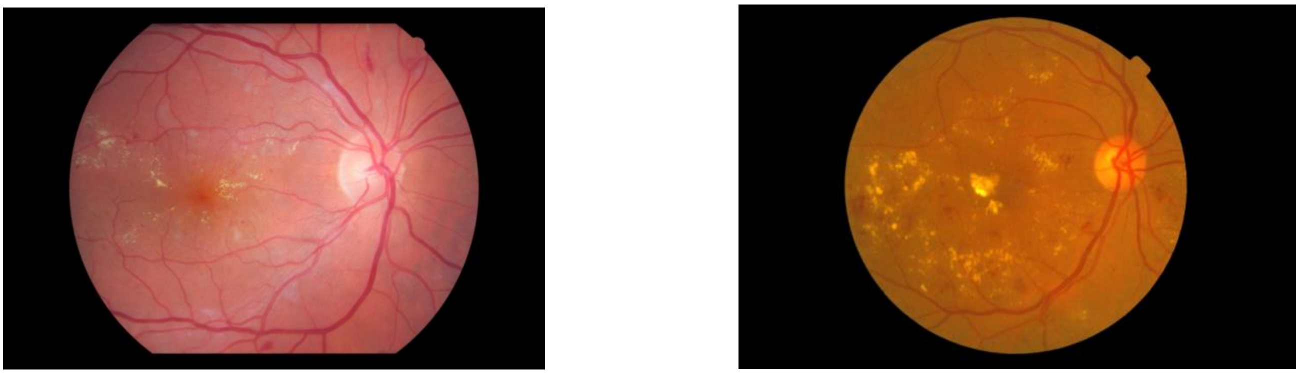
Another methodology used pattern recognition algorithms as D. Marin at al. [11], a feature-based and supervised classifier, was applied on 1058 fundus image corresponded to 529 patients with diabetic. Each patient had two macular centered retinal images, one of each eye. First, feature extraction by applying a group of mathematical description that allows differentiating the exudate and non-exudate. For classification, regularized local regression is applied to determine the probability of each region to be exudate depend on its numerical representation. The obtained map of probabilities is then threshold to consider those regions of great probability as the lesion.

The purpose of this paper is to effectively present image processing method for detecting diabetic retinal exudates using color fundus image in a clinical context. This paper is organized as follows: Section (2), present the material used in this work and the proposed image processing technique. Also, present the extracted feature information and random forest classifier. Section (3), showing the result of the exudate detection process. Section (4), conclusion.

2. Proposed method

2.1 Material

In this study, the e_ophtha_EX dataset is used for evaluating the exudates detection method [12]. Dataset obtained from OPHDIAT Tele-medical network for screening diabetic retinopathy. This dataset contains 82 color fundus images, 47 images with exudates, and 35 normal images. The image of this dataset contains different quality, contrast, color, and illumination. Different image sizes are presented in this dataset; captured with 45° field of view; as shown in Figure 2.



(a) (b)

Fig.2 Sample of e_ophtha_EX dataset.

2.2 Exudate detection

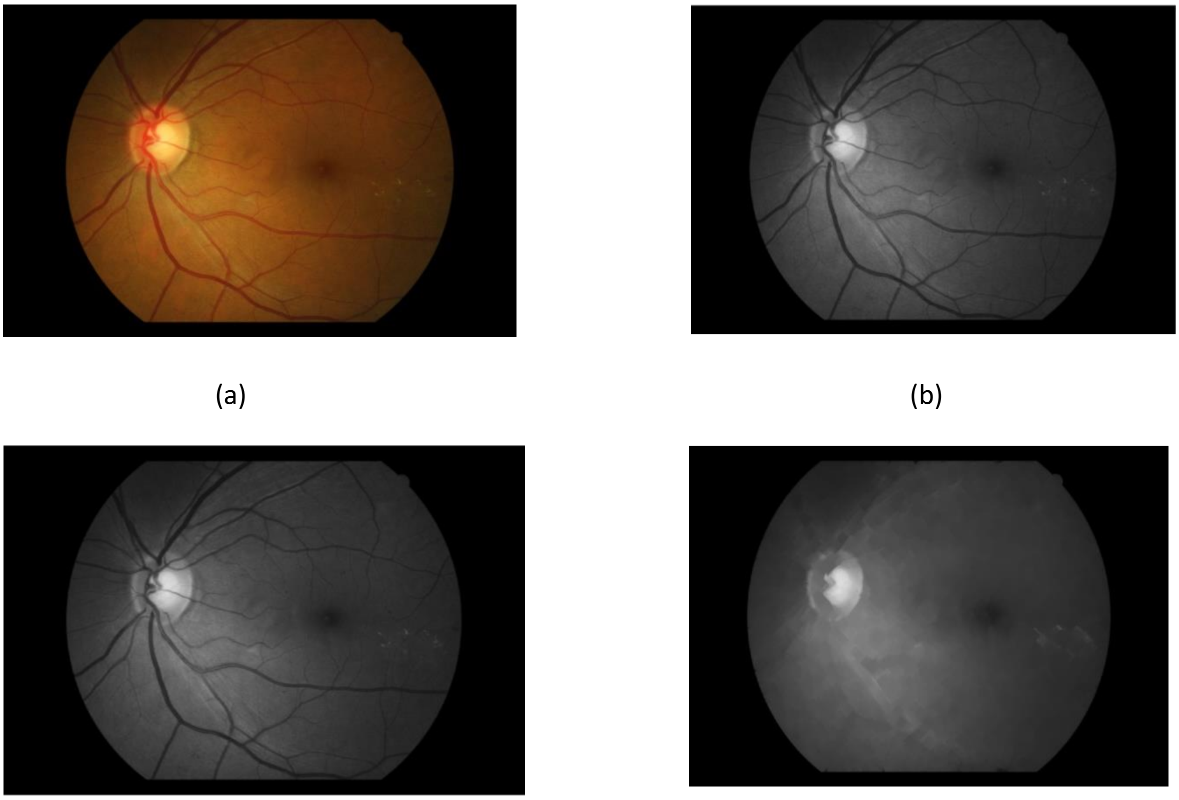
Exudate looks like white/yellow dots in the retina. Some times its size as small as the MA, and at late phases of the disease, its size similar to OD size. For better detection of exudates; the image is enhanced by removing any artefacts that mislead exudate detection. First, remove the dark lesion like small Microaneurysms and blood vessels. Second, removing bright artefacts as the optic disk; as it appears similar to the exudate in color and contest. After enhancing the image and remove any artefacts; Morphological operations are applied for final segmentation. Then random forest classifier is used to calculate the performance of the proposed algorithm.

2.2.1 Dark artefacts removal

The green channel is the best channel to use, as the green channel gives the maximum contrast between candidate exudate and the neighbored regions. After converting to the green channel, the median filter is utilized to remove noise. Then, morphological closing φ_n^B with a size equal to the blood vessel diameter is used to remove retinal vessels and any other dark artifacts. The effect of this operation is to preserve foreground region that has a similar shape to the structural element or completely contain the structure element while eliminating all other areas of the foreground pixel, as mathematically represented in equation (1).

$$I_1 = \varphi_n^B I^* \quad (1)$$

Where I^* is the enhanced image after median filter, and I_1 is the result of the retinal image after blood vessel removal, as shown in figure 3



(a) (b)

(c) (d)

Fig.3 (a) Main image (b) Extracted green channel (c) After median filter (d) Image I_1

2.2.2 Bright artefacts removal

For optic disk removal; the red channel is used to obtain the optic disk mask, as the red channel is the best channel containing information about OD more than the green and the blue channel, as shown in figure 4.

After getting the OD the mask (Binary image I_{mask}); morphological reconstruction is applied using image I_1, as marker image, as mathematically represented in equation (2).

$$I_2 = R_{I_{mask}} I_1 \quad (2)$$

Some image of this dataset contains reflection around its borders. This reflection is removed by applying the mean filter to the blue channel of the RGB color band. The result will be the binary image of these reflections, as shown in figure 5.

2.2.3 Candidate exudate extraction

For the final stage, morphological top-hat (γ_{TH}) is utilized with the octagon structure element with a size equal to half the size of the vessel diameter for final exudate extraction; as mathematically represented in equation 3 The top-hat transform is defined as the difference between the original image and its opening (extract small element details from the given image). The opening of an image is the collection of foreground parts of an image that fit a particular structuring element. The octagon shape is chosen as a structural element for contrast enhancement of candidate exudate in the retinal images. The octagon shape structure element is selected due to the irregular roundish shapes of the candidate exudate.

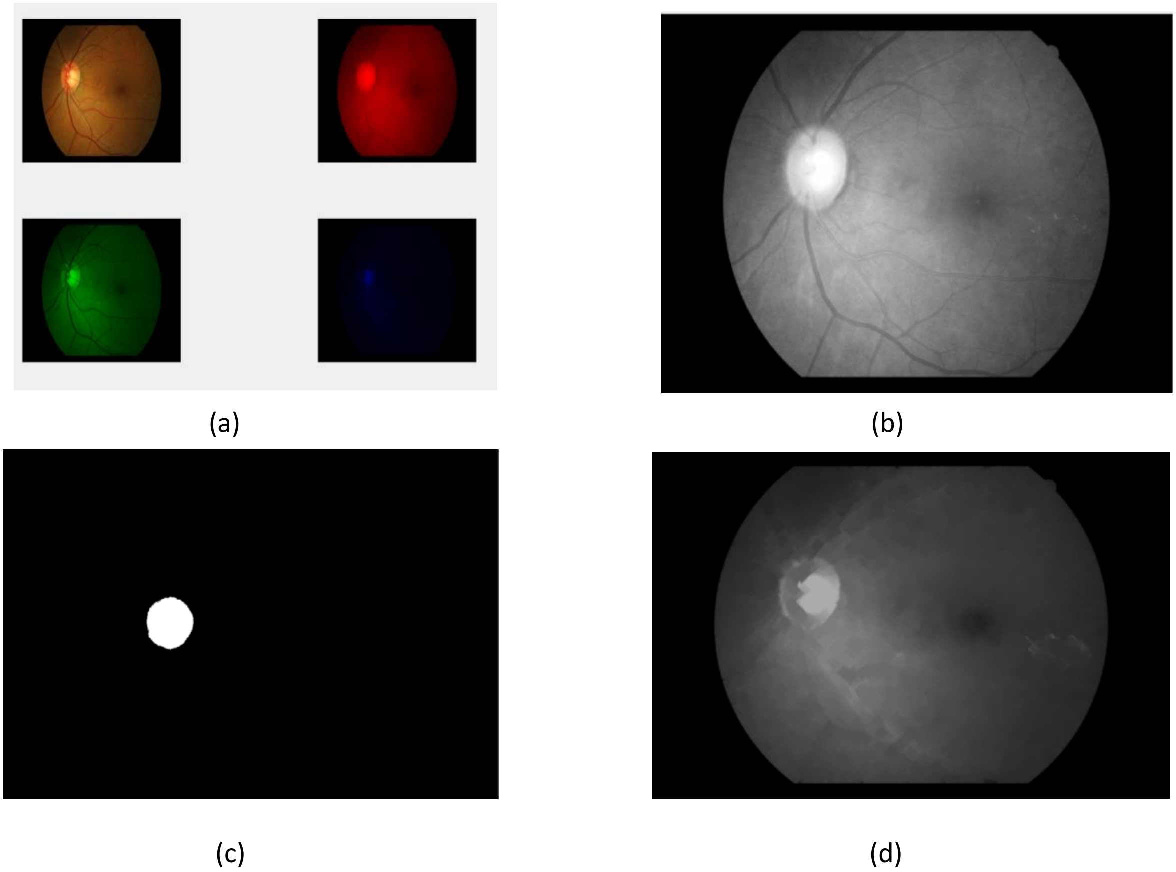


Fig.4 (a) Analyzed RGB channels, (b) Extracted red channel. (a) The optic disk mask, (b) Image (I_2).

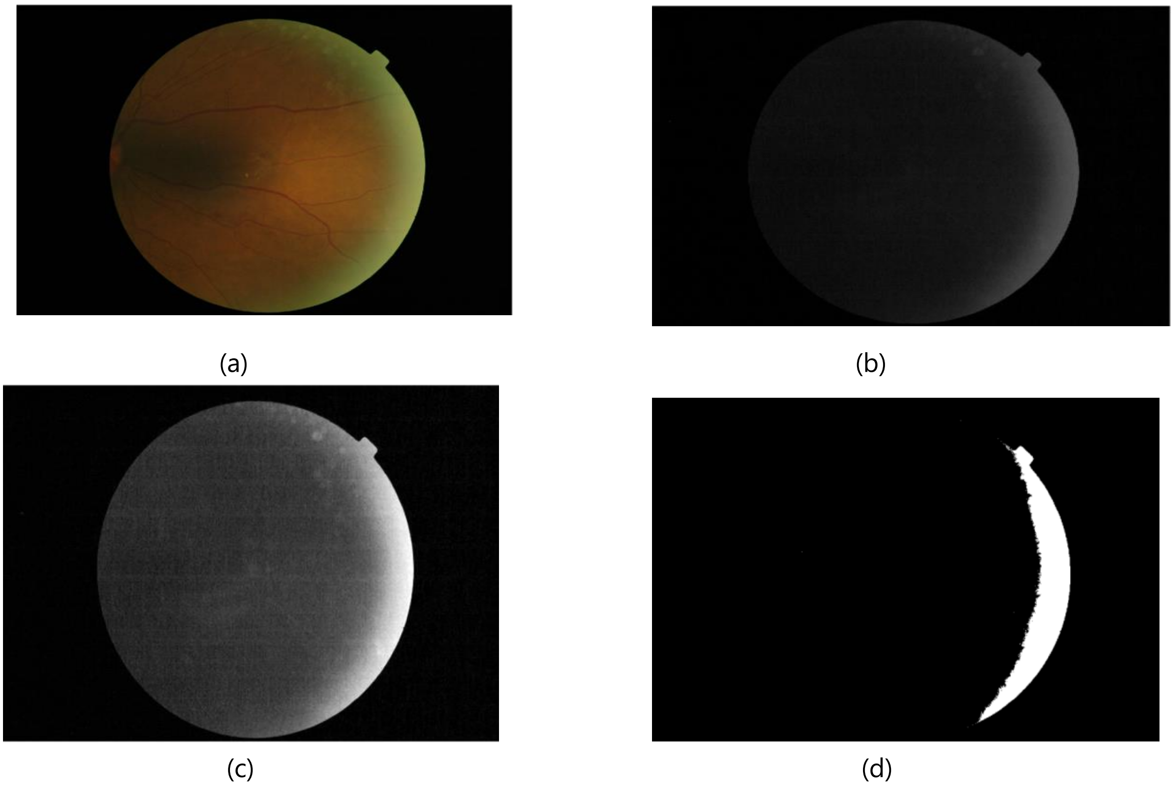


Fig.5 (a) The RGB image, (b) Extracted blue channel, (c) After applying a mean filter, (d) The mask image

$$I_{final}=\gamma_{TH}\ I_2 \tag{3}$$

Where I_2 is the image after morphological reconstruction, I_{final} is the final gray image after morphological reconstruction..

2.2.4 Classification

Random forest is an ensemble learning technique [13] that classifies by a multitude of decision trees with training data and outputs the class with mean or mode of the individual tree class. One of the random forest advantages is that it is effectively deal with large database and effectively estimation of the missing data. The number of trees is set to 100. For further exudates segmentation regions and differentiate between exudates and other types of lesions or other bright artefacts, some features were extracted from each region and used as an input of random forest. Table 1 descript the main feature used.

Table (1) The feature vector information.

No.	feature	Description
1	Intensity	Specifies the grayscale value of each pixel.
2	Mean intensity of the green channel	Mean filter with size 3x3 is applied to the green channel image. This feature represents the total number of pixel intensity over the total number of pixels.
3	Mean saturation in HSV color space	Mean saturation value in the HSV color space using filter size 3x3. This feature is used as the reflections are darker than the bright structure in this channel.
4	Mean hue channel intensity in HSV color space	Mean hue is applied with filter size 3x3 in HSV color space. This feature represents the total value of the hue pixels over the number of pixels.
5	Mean 'v' value of the HSV color space	This feature represents the total value of the brightness region over the number of pixels using filter size 3x3.
6	Mean gradient magnitude	This feature represents gradient magnitude change in the intensity of the candidate region pixel using filter size 8x8.
7	Energy	Equal to the total intensity squares of all the green channel pixel value.
8	Standard deviation	It's a measure that is used to quantify the amount of variation or dispersion of a set of data values.

3. Results and Discussion

It is important to calculate the performance of the retinal image analysis technique by measuring the agreement level between the output and the annotation image, which is marked by ophthalmologist's experts. The four common measurements used to estimate the validation of segmentation methods of the retinal images are True positive (TP) which represent the value that is predicted as positive, and it's actual value is positive, True negative (TN) which represent the value that is predicted as negative and it's actual value is negative, False negative (FN) which represent the value that is predicted as negative and it's actual value is positive, false positive(FP) which represent the value that is predicted as positive, but it's actual value is negative. Figure 6, represents a simple confusion matrix. There are two classes of actual data class and predicted class. Each pixel represents the feature vector from the eight presented features.

		PREDICTED CLASS	
ACTUAL CLASS		Yes	No
	Yes	(TP)	(FN)
	No	(FP)	(TN)

Fig.6 The confusion matrix.

To measure the performance of the proposed algorithm, sensitivity and positive predicted value are calculated.

Sensitivity (SN): which is the probability between the results of the diagnosis is positive considering that the patient presents DR, which is mathematically represented in equation (4).

$$SN = \frac{TP}{TP+FN} \tag{4}$$

Positive predicted value (PPV): represent the probability that the patient has a disease given appositive test results. It is defined by the number of true positive divided by the sum of true positive and false positive, which is mathematically represented in equation (5).

$$PPV = \frac{TP}{TP+FP} \tag{5}$$

The result of the proposed algorithm compared to the result proposed by zhang is presented in table 2.

Table (2) Overall performance compared to another algorithm.

Algorithms	Sensitivity	Positive predicted value
Proposed algorithm	79.6%	77%
Zhang algorithm	74%	72%

4. Conclusion

The examination of retinal abnormality as exudates is essential for early detection of diabetic retinopathy. In this paper, an image processing algorithm is presented for exudate segmentation using 82 color retinal images from e_ophtha_EX dataset. Also, present a method for removing both blood vessel and optic disk from retinal images. Eight region feature information is extracted and used as the input for a random forest classifier to validate the performance of this approach and distinguish between the data. This proposed algorithm achieves 77% positive predicted value and 79.6% sensitivity. In future work, we will try to present other image processing for detection of different types of retinal lesions

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