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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 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 random forest classifier is applied to differentiate between exudates and non-exudates region. The proposed method is evaluated using e\_ophtha\_EX dataset, achieving 80% 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 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 oval bright 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, haemorrhage's, neovascularization, and macular edema [3]. In this paper, we will concentrate on detecting diabetic exudates which appear as bright yellow in color fundus images. Figure 1 shows a color fundus image with the main structural elements of the eye and some lesions.

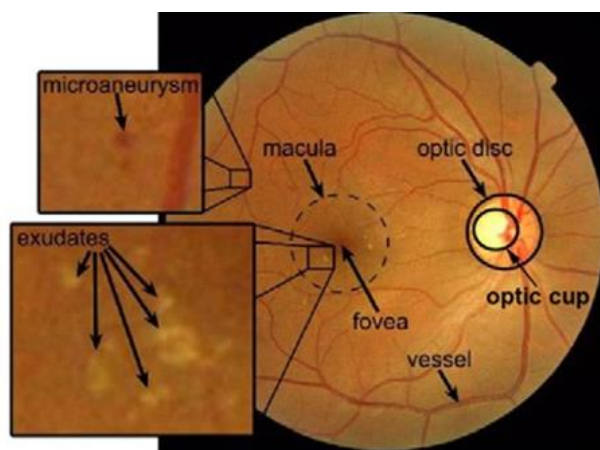


Fig.1 Different types of lesion and anatomical structures in retinal images.

There are various image processing techniques applied for exudates detection. 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 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 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 bright lesions. Both log filter response and matched filter response are applied for pre-processing. For optic disk extraction fuzzy c mean kernel is applied. For dark lesion extracted (haemorrhage'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 et al. [11] a feature-based and supervised classifier was applied on 1058 fundus images corresponding to 529 patients with diabetes. Each patient had two macular centered retinal images, one of each eye. First feature extraction by applying a group of mathematical descriptions 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 depending on its numerical representation. The obtained map of probabilities is then thresholded to consider those regions of great probability as the lesion.

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

## 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 89 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 1140 × 960 and 2048 × 1360 & captured with 45° field of view. Figure 2 shows a sample of the e\_ophtha\_EX dataset.

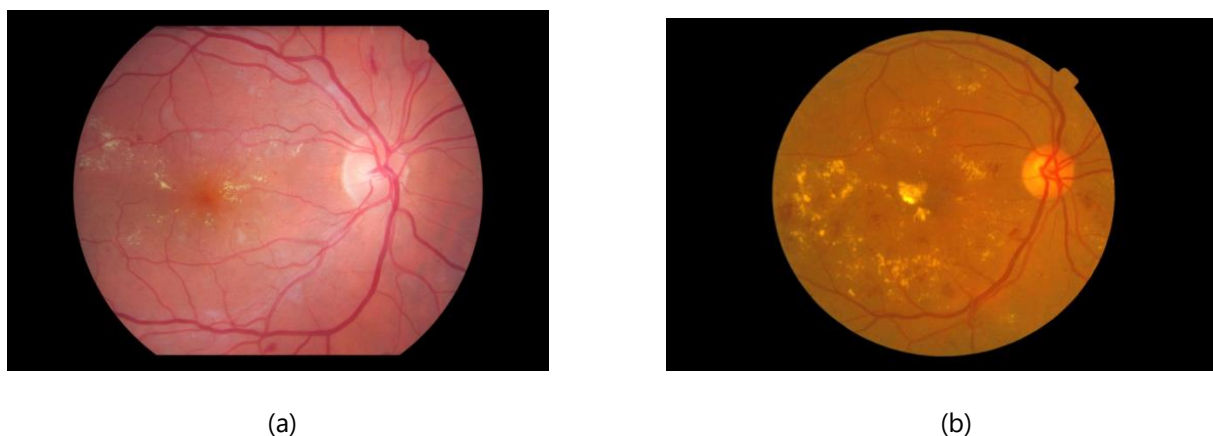


Fig.2 Sample of e\_ophtha\_EX dataset.

### 2.2 Exudate detection

For better detection of exudates first, we need to enhance the image by removing any artefacts that mislead exudate detection. First, removing bright artefacts as the optic disk because it appears similar to the exudate in color and contest. Second, remove the dark lesion like small Microaneurysms and blood vessels. After enhancing the image and remove any artefacts. Morphological operations are applied for final segmentation. Then random forest classifier is used to calculate the accuracy of this proposed algorithm.

#### 2.2.1 Bright artefacts removal

First, enhance the image by applying a median filter as it helps to smooth the image and to reduce the amount of intensity ( $I_{med}$ ). For optic disk removal, a binary mask is obtained by extracting the red channel of the RGB color band then apply thresholding value. The result will be an image without optic disk. The binary image is then subtracted from the image green channel, and the result will be a masked optic disk ( $I_{mask}$ ). Morphological reconstruction ( $R_{I_{mask}}$ ) is applied by using the masked optic disk image as the marker and the enhanced image as the mask. The result will be an image without optic disk ( $I^*$ ), which is mathematically expressed as equation (1). Figure 3 shows the steps for the removal of the bright artefacts.

$$I^* = R_{I_{mask}} I_{med} \quad (1)$$

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 4.

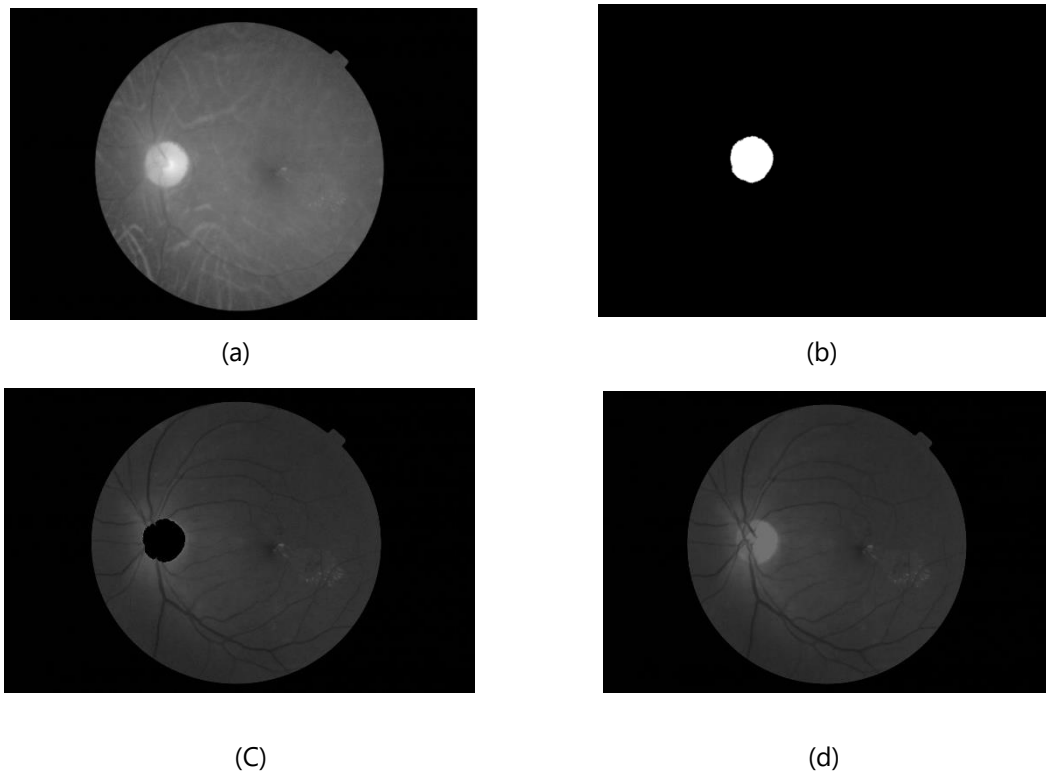


Fig.3 (a) Extracted red channel, (b) Binary image of the optic disk, (c) Masked optic disk, (d) Image  $I^*$ , obtained after applying morphological reconstruction.

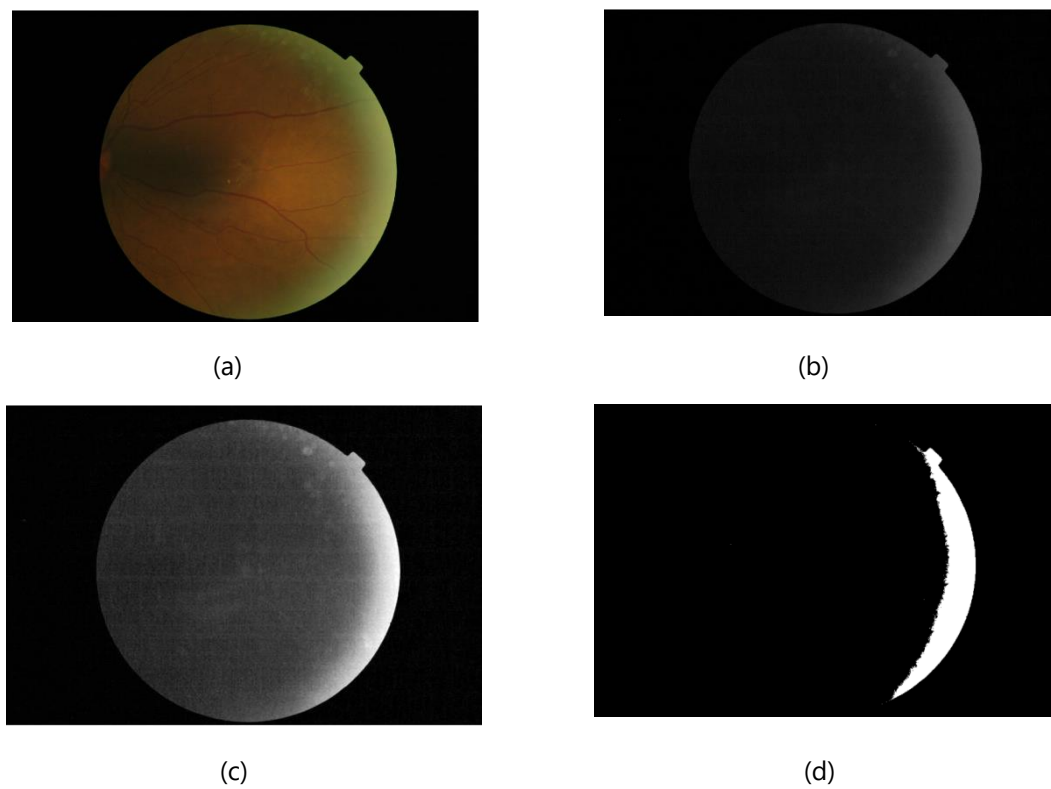


Fig.4 (a) The RGB image, (b) Extracted blue channel, (c) After applying a mean filter, (d) The mask image.

### 2.2.2 Dark artefacts removal

Some dark artefacts must be removed before exudates extraction. Dark artefacts include blood vessels and small Microaneurysms. To remove this artefacts morphological closing ( $\varphi_n^B$ ) is applied with a diamond shape with structure element size equal to the vessel diameter. The result of this operation will be an image without a blood vessel ( $I_1$ ), which is mathematically expressed as equation (2). Figure 5 shows the retinal image after dark structure removal.

$$I_1 = \varphi_n^B I^* \quad (2)$$

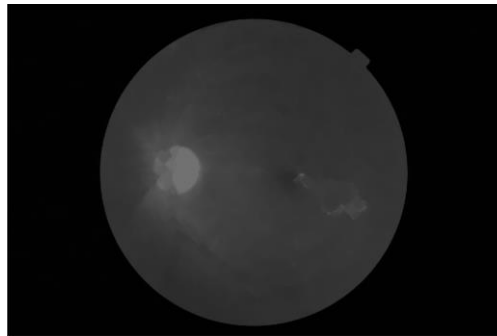


Fig.5 The retinal image after morphological closing ( $I_1$ ).

### 2.2.3 Candidate exudate extraction

After enhance and normalize the image and remove any artefacts that mislead exudates detection. Apply morphological top-hat ( $\gamma_{TH}$ ) with disk shape with structure element size equal to half the radius of the maximum vessel width. The result will be ( $I_{final}$ ), as mathematical expressed in equation (3). Figure 6 represents the extracted exudates after applying the top-hat operation and the thresholding value, compared to the annotation image from the e\_optha\_EX dataset.

$$I_{final} = \gamma_{TH} I_1 \quad (3)$$



(a)

(b)

Fig.6 (a) The extracted exudates, (b) The annotation image.

### 2.2.4 Classification

Random forest is an ensemble learning technique [13] that classifies by 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. Numbers 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 gray scale 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 Discussions

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 7, represents a simple confusion matrix. There are two classes of data actual class and predicted class. Each pixel represents the feature vector from the eight presented features.

$X_i$ , represents the input feature vector sample, which is positioned as following,

$$x_i = (f_1, f_2, \dots, \dots, f_8). \tag{4}$$

Pixel by pixel evaluation is used to evaluate the proposed algorithm. The evaluation is performed by counting the pixels that are correctly classified. However, this method was unsuitable for candidate exudates evaluation because the exudate contoured doesn't match perfectly between the diagnoses obtained from different viewers. The exudate candidate connected component set  $\{D_1, D_2, \dots, \dots, D_N\}$ , and the exudate ground truth component  $\{G_1, G_2, \dots, \dots, G_M\}$ .

A pixel is considered a false positive if it belongs to,

$$\{D_i | D_i \cap G = \emptyset\} \cup \{D_i \cap \bar{G} | \frac{|D_i \cap G|}{|D_i|} \leq \delta\} \tag{5}$$

Also, every pixel considered to be false positive (FN) if belong to,

$$\{G_i | G_i \cap D = \emptyset\} \cup \{G_i \cap \bar{D} | \frac{|G_i \cap D|}{|G_i|} \leq \delta\} \tag{6}$$

A pixel is observed true positive (TP) if it belongs to the following set,

$$\{D \cap G\} \text{ such that } \{D_i | \frac{|D_i \cap G|}{|D_i|} > \delta\} \tag{7}$$

$$\{D \cap G\} \text{ such that } \cup \{G_i | \frac{|G_i \cap D|}{|G_i|} > \delta\} \tag{8}$$

The rest of the pixels are considered true negative.

$\delta = 0.2$ , Where  $\delta$  present a parameter range from 0 to 1. And  $|\cdot|$  present the cardinal of a set (as proposed by zhang).

To calculate Sensitivity (SN): which is the probability between the result of the diagnoses is positive considering that the patient presents DR, which is mathematically represented in equation (9)

$$SN = \frac{TP}{TP+FN} \tag{9}$$

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

Fig.7 The confusion matrix.

Positive predicted value (PPV): represent the probability that the patient has a disease given appositve 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 (10).

$$PPV = \frac{TP}{TP+FP} \quad (10)$$

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

Table (2) Overall performance compared to other algorithm.

Algorithms	Sensitivity	Positive predicted value
Proposed algorithm	80%	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 89 color retinal images from e\_ophtha\_EX dataset. Also, present a method for segmentation both blood vessel and optic disk. 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 80% sensitivity. In future work, we will try to present other image processing for detection of other types of retinal lesion.

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