Detection of Diabetic Exudates from Color Retinal Image

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Abstract:
Diabetic retinopathy is one of the major complications of diabetes; it causes bleeding of the retinal blood vessel. In late stages this bleeding progress and led to vision loss. There are several signs of diabetic retinopathy, includes bright lesions as exudates and dark lesions as Micro aneurysms and hemorrhages. In this paper, we concentrate on detecting retinal bright lesions, which occur due to the buildup of lipidic accumulate within the retina, it appears as bright-yellow in color fundus image. First, high performance preprocessing is applied, not only for de-noising and normalization but also to detect artifacts and reflection that could mislead exudate’s detection. Then, candidate exudates segmentation using morphological operations is applied. Finally, eight features information are proposed for exudate segmentation, extracted from the color intensity, size and gradient magnitude of the image, which is then used into a random forest classifier for pixel-level validation. This algorithm has been tested and trained using89 fundus images from e-ophtha-ex databases, achieving 79% sensitivity and area under curve 0.94.

Keywords: Color fundus image, Retinal exudates, Diabetes, Morphological operation, Random forest.

I. INTRODUCTION:
All types of diabetic eye cause severe vision loss and blindness. Diabetic retinopathy is the most common among them all, it affects blood vessel in the light-sensitive tissue at the retina. It’s usually the reason behind vision loss among people with diabetes and also a reason behind vision impairment and blindness among working-age adults. The patients with diabetic retinopathy are generally asymptomatic in the more advantage stages of the disease. Diabetic retinopathy (DR) common signs are Microaneurysms, small hemorrhages, cotton spots, and exudates. As a result of the difference in the appearance of these lesions, different techniques have been designed to detect each type of these lesions separately in the Diabetic Retinopathy detection system. The paper is focused on the detection of hard and soft exudates. [1] Exudate occurs due to the flow of serum protein and lipids through abnormal vessels due to the breakdown of the blood barrier of the retina. Appear as a white/yellow bright spot of variable shape and size [2]. The optic disk appears as a bright, circular or oval-shaped anatomical structure, it has similar color and bright as exudates, so for accurate detection of exudate id done by eliminating optic disk from the fundus image. Also, Blood vessels and other dark lesions in the retina cause false detection of exudates so these dark lesions must be removed during preprocessing the image. There are varies methodologies were developed for detection of different bright lesions (exudates). Wisaeng et al. [3] proposed a method for exudate detection using morphological operations, after normalizing the image, contrast enhancement and optic disk localization; a coarse segmentation of exudates using mean shift algorithms in retinal images then fine morphological operations is applied to only detect the most contrasted and similar size exudate pixel.

Figure (1):fundus image showing the anatomical structure of the eye and the different type of diabetic lesion (from Wikipedia).
Welfer et al. [4] present a method for detecting exudates from color fundus image based on mathematical morphological techniques Using L channel of the LUV color space. The only disadvantage of this approach is the low specificity value and the increase in the misclassification proportion of the images that do not contain exudates.

Zhang et al. (5) proposed an algorithm for exudate detection. This algorithm is processes images containing high availability in term of definition and quality and presence of artifacts. Morphological operations are applied for preprocessing and removing image artifacts. And random forest classifier is used to distinguish the data. Some algorithms are proposed for optic disk elimination and segmentation using morphological operations.

Walter et al. (6) proposed a method based on pixel brightness. First applying some morphological operation to detect the optic disk then for optic disk contour apply classical watershed transformation in the red channel of RGB color spacing.

Also, Welfer et al. (7) proposed a two-stage algorithm for optic disk center detection and segmentation using morphological operations.

D. Marin at al. [8] proposed a method using pattern recognition to detect exudate. A feature-based and supervised classifier was applied on 1058 fundus image corresponded to 529 patient 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 onits numerical representation, the obtained map of probabilities is the threshold to consider those regions of great probability as the lesion.

Kar et al. [9] proposed a method for the detection of dark and bright lesions. Both log filter response and matched filter response are applied for pre-processing, and fuzzy c mean kernel is applied for optic disk extraction. First dark lesion (hemorrhages and Microaneurysms) curvelet wavelet is applied for lesion extraction.

For dark 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.

Other algorithms used traditional image processing algorithms for preprocessing as Kaur et.al [10], used dynamic thresholding for exudate segmentation. First high pass filter issued for image processing and contrast enhancement then blood vessels are extracted by applying multi-scale matched filter with the first derivation of the Gaussian filter. For optic disk detection canny edge-based algorithms and circular Hough transform is applied.

Then feature vector is extracted and applied to a supervised classifier. Franklin at al. [11] used artificial neural network for exudate detection; the color information and the high grey level variation is used for detecting exudates, then the candidate region is classified by applying significant feature as size, texture, color, and shape to achieve the best class classification.

Banerjee et al. [12] used the normalized cut and mean shift algorithm for detecting exudates. First, pre-process the image by applies bottom hat operations on the red channel of the RGB color space and then the optic disk is eliminated by applying an active contour model. After the exudate segmentation, canny edge detection was used to show the detected boundaries.

Giancardo et al. [13] used assets of feature-based for exudate detection. The proposed algorithm acquired from classification of a single feature vector generates from every image. This information feature vector used three types of analysis: exudate probability map, color analysis, and wavelet analysis.

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. The paper is organized as follows: Section (II), present the dataset used in this work and proposed methodology. Section (III), present the feature information and apply random forest classifier. Section (IV), the result of the exudate segmentation process and conclusion

II. MATERIAL AND METHOD

A) Material

In this study, the e_ophtha_EX database is used for evaluating the exudates detection method. 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 x960 and 2048 x1360 & captured with 45° field of view. Due to different image resolution and for accurate detection of exudates, the field of view width that first proposed by Zhang et al (2014) is used. The field of view is useful to detect the main anatomical structure size without lead to resize the image. One of the reasons that this technique is effective that the anatomical structure as optic disk and blood vessel size is different from one patient to another so the exact segmentation of the anatomical structure still a problem. Also can’t depend on the optic disk and the fovea distance for image normalization because accurate detection of OD and fovea location is not easy, also in some image of e_ophtha_EX dataset the optic disk is missing, so we depend on the value of the FOV diameter. As a result of variable image size, all fundus image used is captured with the same FOV.

B) Exudate detection

Exudates are found to be in the highest contrast in the green channel of the RGB color space, compared to the red channel which is too saturated and the blue channel is the darker than the other two channels, so the green channel for preprocessing. A group of morphological operation is applied for exudate detection including morphological closing, normalization, reconstruction, and morphological top-hat. Nine features were extracted from the exudate region. This feature is then used to train the classifier to distinguish between exudates and non-exudates. The flow chart of the proposed algorithm is shown in fig (2)
B.1) Preprocessing
Preprocessing is important not only for removing image noise and enhance the non-uniform illumination but also remove the anatomical structure that acts as distractors in the detection of retinal exudates as, bright regions as the optic disk, blood vessels, dark lesions.

For fundus image enhancement green channel is used as it contains high contrast and reasonable information about different lesions and anatomical structure of the retinal image. Image enhanced($I_{H}$) is obtained by applying a median filter to the green channel, then apply morphological top hat the result will be image with bright region only then morphological bottom hat(top hat by closing) the result will be image contain dark region then subtracting, the result will be the enhanced image eq.(1)

$$I_{H}=I_G + (\gamma_{TH})I_G - (\emptyset_{TH})I_G$$

(1)

B.2) Optic disk detection and segmentation:
Detection of the optic disk is an important step as to distinguish it from another abnormal lesion as hard exudates because sometimes information related to optic disk & hard exudates may be the same in machine learning systems, the optic disk and exudates share similar color features as they both appear white or yellow coloring. The optic disk is best to appear in the red channel of the color band. From the red channel apply thresholding value to segment only the optic disk, the result will be a binary image with only the optic disk, subtract the resulted binary image from the green image, the result will be masked optic disk $I_3$ and then apply morphological reconstruction. The result will be an image without optic disk $I_3$, figure (3).

$$I_3 = R_{TH}I_2$$

(2)
B.3) Vessel mask: For obtaining the main vessel structure, adaptive histogram equalization is applied to the green channel of the image as the blood vessels don’t have high contrast in comparing with the surrounding background in this channel. Then apply average filter and take the different, then automatically obtain the thresholding value, finally apply area opening for removing small pixels, as shown in figure (4). The vessel segmentation helps to detect the optic disk location.

B.4) Blood vessel segmentation
Image in-painted method is used by applying morphological closing. Morphological closing removes most of the dark artifacts in the retinal image. Apply morphological closing with ‘diamond’ structure element. The size of the structure element depends on the blood vessel diameter which equals d1. The removed blood vessels are shown in figure (5)

\[ I_4 = \varphi_R^G(I_3) \] ..................................................... (3)

B.5) Candidate exudates segmentation:
For any other bright structure appear around the optic disk, a small mean filter with size 3\times3 is applied. Then for candidate extraction apply morphological top-hat using disk shape structure element followed by thresholding. As shown in figure (6)

\[ I_5 = (\gamma_{TH}) I_5 \] .....................................................(4).
III. CLASSIFICATION OF EXUDATES:

Random forest is an ensemble learning technique 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 advantage is that it is effectively deal with large database and effectively estimation of the missing data. For further exudates segmentation regions and differentiate between exudates and other types of lesions or other bright artifacts, some features were extracted from each region and used as an input of random forest.

The main features includes:

- Intensity: specifies the gray scale value of each pixel.
- Mean intensity of the green channel ($\mu_g$):
  \[
  \mu_g = \frac{\text{total number of pixel intensity of green channel}}{\text{total number of pixels}}
  \]  
  ......................................................(5)
- Mean saturation in HSV color space ($\mu_s$): it is hard to distinguish optical artifacts from normal exudates in any of the RGB channels. So we use the mean saturated value in HSV color space as the reflections are darker than the bright structure in this channel.
  \[
  \mu_s = \frac{\text{total number of hue pixel value in region}}{\text{number of pixel in region}}
  \]  
  ......................................................(6)
- Mean ‘v’ value of the HSV color space: it represents the color brightness in the candidate region
  \[
  \mu_v = \frac{\text{total value of the brightness pixel in region}}{\text{number of pixel in region}}
  \]  
  ......................................................(7)
- Mean gradient magnitude: represent gradient magnitude change in the intensity of the candidate region pixel. (Gradient magnitude only directional is not important)

\[ \mu_{\text{grad,mag}} = \frac{\sum \text{gradientimageintensitypixelinregion}}{\text{no.ofpixelsintheregion}} \]  

(8)

- Energy: represent the spectral density variation with frequency. It is the total intensity squares of all the green channel pixel value.

- Standard deviation: by applying a morphological opening to the image green channel as to keep the foreground regions that similar to the structure element, while discarding the foreground pixel region.

**IV. RESULT AND DISCUSSION**

E-optho-ex is dataset is used to test and train this algorithm. A 10-fold validation was employed to evaluate the random forest classifier. Each pixel represents the feature vector from the eight presented features, \( x_i \) represents the input feature vector sample positioned as following,

\[ x_i = (f_1, f_2, \ldots, f_8) \]  

(9)

Pixel by pixel evaluation is used to evaluate the proposed algorithm. The evaluation is performed by counting the pixels that are correctly classified. Some pixels for each image were chosen randomly to train the vector. However, this method was unsuitable for candidate exudates evaluation because the exudate contoured doesn’t match perfectly between the diagnoses obtained from different viewers. In the proposed study a hybrid validation approach is presented where small amounts overlap between the candidate exudate and ground truth is required. The exudate candidate connected component set \( \{D_1, D_2, \ldots, D_n\} \), and the exudate ground truth component \( \{G_1, G_2, \ldots, G_N\} \).

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

\[ \{D \cap G\} \text{such that } \{D_i \mid \frac{|D \cap G|}{|D_i|} > \delta \} \]  

(10)

\[ \{D \cap G\} \text{such that } \cup \{G_i \mid \frac{|D \cap G|}{|G_i|} > \delta \} \]  

(11)

\[ \delta = 0.2, \text{Where } \delta \text{ present a parameter range from } 0 \text{ to } 1 \text{. And } |\mid \text{ present the cardinal of a set (as proposed by zhang).} \]

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

\[ \{G_i \mid D_i \cap G = \emptyset \} \cup \{D_i \cap G_i \mid \frac{|D \cap G|}{|D_i|} > \delta \} \]  

(12)

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

\[ \{G_i \mid G_i \cap D = \emptyset \} \cup \{G_i \cap D \mid \frac{|G \cap D|}{|G_i|} \leq \delta \} \]  

(13)

The rest of the pixels are considered true negative.

To calculate Sensitivity (true positive rate): which is the probability between the result of the diagnoses is positive considering that the patient presents DR.

\[ \text{SN} = \frac{\text{TP}}{\text{TP+FN}} \]  

(14)

The area under curve (AUC): Represent how the model is able to differentiate between different classes, the higher the AUC better the algorithm is to differentiate between patient healthy patient and diabetic patients.

| Algorithms   | Area under curve | Sensitivity |
|--------------|------------------|-------------|
| Proposed method | 0.94          | 79 %        |
| Zhang        | 0.95             | 74%         |

**V. CONCLUSION:**

In the following paper exudate segmentation method is presented, by using morphological operation for preprocessing and random forest as a classifier to differentiate between exudate and non-exudates, 8 feature information’s were presented. This approach is tested and trained using 89 images of the e-optho-ex dataset. Achieve area under curve 0.94 and sensitivity 79%.
The proposed method not only detect exudates but successively segment and extract both optic disk and blood vessels from the retinal image. In future work, we intend to improve the algorithm for detecting other types of retinal lesion as Microaneurysms and hemorrhages.

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