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# Novel Approach for Automated Diagnosis of Diabetic Retinopathy

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#### Abstract

Automated and early diagnosis of diabetic retinopathy is a crucial need. Diabetic retinopathy (DR) is the major cause of blindness among people. DR is a progressive disease classified according to the presence of various clinical abnormalities. It doesn't have any visible symptoms till the disease is at late stage. Therefore, it necessary to detect DR at early stage and to ensure proper treatment. For early detection of DR, different automated diagnosis systems have been designed. A number of studies have investigated DR and this paper presents novel approach for automated diagnosis of DR which is implemented with the help of contour detection algorithm in OpenCV and Raspberry Pi used as hardware.

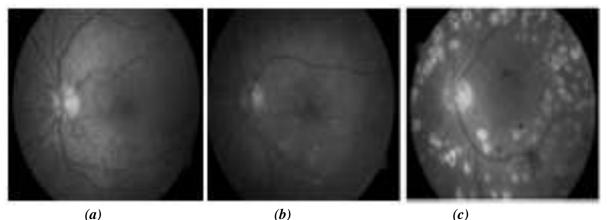
**Keywords:** Retina, retinopathy, blood vessels, diabetes, biomedical imaging, Euler number, computer aided diagnosis, medical image processing, feature extraction, eye, contour detection

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# **INTRODUCTION**

Diabetic retinopathy (DR) is a complication of diabetes, which can lead to blindness. It occurs due to damage of the retinal blood vessels. These damaged retinal vessels will leak blood and fluid on the retina forming abnormalities such as micro aneurysms, hemorrhages, hard exudates, cotton wool spots or venous loops [1].

Diabetic retinopathy can be classified in different stages such as non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). It depends on the presence of PDR and NPDR on the retina, the phases of DR can be identified. A normal retina does not have NPDR and PDR as shown in Figure 1(a). Figure 1(b) shows the primary phase of disease, NPDR phase. In this phase, the disease can advance from mild, moderate to severe phase. Figure 1(c) shows the advanced phase of NPDR, PDR phase. In this phase the fluids for the nourishment which are sent by the retina triggers the surface of the clear, vitreous gel that fills the inside of the eye. If they leak blood, severe vision loss and even blindness can result. Figure 1(c) is the image of retina in PDR stage [1].



(b) (c) Fig. 1: Retinal Fundus Images of (a) Normal, (b) NPDR. (c) PDR.

The diabetic retinopathy disease can be diagnosed by examining the retina for its characteristic features. So, it is necessary that diabetic patients must be screened at regular intervals. Computer assisted diagnosis can help eve care specialists in the analysis of large number of patients in less time. One such instance is Thailand diabetic project which shows that numbers of ophthalmologists have to work with almost ten thousand diabetic patients using direct ophthalmoscopy [2]. But, ophthalmologists were able to examine 75% of the patients and 31% of the examined patient were affected by diabetic retinopathy. Therefore, automatic retinal image analysis is very essential to help ophthalmologists in diagnosis detection and of diabetic retinopathy.

The primary signs of diabetic retinopathy are exudates, which appear as bright lesions with the random yellowish deposits of varying size, shape and location in retinal images. Exudates increases and become intense as time passes in a diabetic patient and can also cause blindness if not treated.

# PREVIOUS METHODS FOR AUTOMATED DIAGNOSIS

In recent years many researchers have proposed various algorithms which are useful for automated diagnosis of diabetic retinopathy. These methods extract features such as exudates with the help of intensity based algorithms [3], fuzzy clustering method [4], statistical features and intensity based features [5] which require accurate detection and elimination of optical disk which otherwise leads to detection of optical disk as exudates and increases the number of false positives.

The automated diagnosis algorithm by Sreng and Takada requires the elimination of optical disk before applying any exudates detection algorithm [3]. For detection of optical, the was image equalized histogram using equalization and then Blob boundary measurement is used for optical disk detection and morphological reconstruction is done to mask the optical disk. For exudates detection, intensity based algorithm maximum entropy thresholding is used. The drawback of intensity based detection is that it is unable to detect exudates, hence increases the false negatives. This method had 89% of accuracy. The automated diagnosis algorithm by Princye and Vijayakumari is based on fuzzy clustering method; in this method also optical disk is detected using circular Hough transform (CHT) and then it is masked [4]. After the masking of optical disk, exudates are detected using fuzzy clustering means (FCM) method. FCM method detects exudates by first predicting the possible clusters of exudates, though initial predictions are wrong but it detects exudates in iterative steps with certain degree of accuracy.

The method used for retinal feature extraction by Jestinv and Anitha extracts statistical features such as mean, standard deviation, variance. entropy, contrast. energy. homogeneity and diseased based textural features area, minimum intensity and mean intensity [5]. So, this method is unable to extract shape based information. Extraction of shape based information helps to increase the accuracy of the algorithm as observed while implementing the proposed method as explained later in this paper.

# **PROPOSED METHOD**

This paper proposes novel approach for detection of exudates. It uses shape and size detection algorithm for detection of exudates which reduces false negatives and avoids detection of optical disk. It also gives information about number of exudates and the size of exudates so the ophthalmologist can get information about spread of disease and stage of diabetic retinopathy.

The proposed algorithm was applied and evaluated on two retinal image databases namely STARE database and DRIVE database. Retinal images in DRIVE database acquired from diabetic retinopathy are screening program, for the purposes of diagnoses. Images were acquired using Canon CR5 non-mydriatic 3 CCD cameras with a 45 deg FOV, in TIFF format. STARE was mainly used for STARE project. This database is dedicated for automated diagnosis and medical research, as it contains retinal images having different retinal diseases. The images captured by a TopConTRV-50 fundus camera with 35 degree field of view.



In the proposed method as shown in Figure 2, the RGB input image is first converted to grayscale and then preprocessed by image processing methods such as blurring, edge detection, filtering and thresholding. The binary image is obtained after the preprocessing which is used to detect exudates with the help of contour detection algorithm.

## **RGB to Gray Image**

Color image is converted into gray scale image using suitable command in OpenCV. The optic disk appears brighter than its background.

# Blurring

Blurring, also called smoothening, is a simple and frequently used image processing operation. This operation smoothens the image using the normalized box filter having kernel (K) as shown in Eq. (1). Kernel has certain height and width. It can be observed from Eq. (1) that each output pixel is the mean of its kernel neighbors.

$$K = \frac{1}{kernel \ width * kernel \ height} \begin{bmatrix} 1 \ 1 \ 1 \ \dots \ 1 \\ 1 \ 1 \ \dots \ 1 \\ \dots \\ 1 \ 1 \ \dots \ 1 \\ 1 \ 1 \ \dots \ 1 \end{bmatrix}$$
(1)

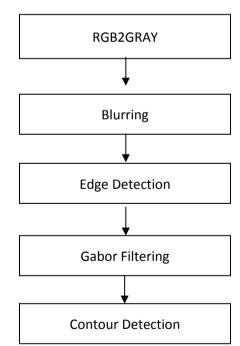


Fig. 2: Block Diagram of Proposed Method.

# **Edge Detection**

Canny edge detection algorithm is used in this method for detection of edges such as blood vessels and exudates. Also known as the optimal detector, Canny edge detection algorithm aims to satisfy three main criteria:

- Low error rate: Almost zero false detection.
- Good localization: Retaining the original positions of the detected edges.
- Minimal response: Only one detector response per edge.

Canny edge detection uses the algorithm as shown in Figure 3 for detection of edges [6]. Gaussian filter is first applied to remove the noise and suppress the false detection of edges. This process smoothen the image. Intensity gradient is calculated from the filtered image to get the edge direction. The detected edge may point in different directions: therefore four filters are used in Canny algorithm for detection of edges in all the direction in the filtered image. The value returned by edge detection operator for the first derivative is given as the horizontal direction  $(G_x)$  and the vertical direction  $(G_y)$ . From this the edge gradient and direction can be determined using Eqs. (2) and (3). The edge direction angle is calculated from Eq. (3) and rounded off to one of four angles representing vertical, horizontal and the two diagonals.

$$G = \sqrt{G_x^2 + G_y^2} \tag{2}$$

$$\theta = \tan^{-1} \frac{G_y}{G_x} \tag{3}$$

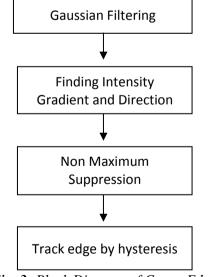


Fig. 3: Block Diagram of Canny Edge Detection.

The edge extracted after this processes is still quite blurred. Thus, non maximum suppression is applied; it is an edge thinning algorithm. According to Canny edge detection criteria, one detector response per edge is necessary. Thus non-maximum suppression is used to fulfill these criteria. This algorithm measures the change in intensity of a pixel as compared to its neighboring pixels and preserves the pixel with maximum change and suppresses the other neighboring pixels to 0.

After the above discussed image processing algorithms, the high pixels are detected accurately. However, there will be some weak image pixels that can either be extracted from the noise or variations in color variations. The algorithm to determine, to which case does the weak edge belongs to is that, usually the weak edge pixel caused from true edges will be connected to the strong edge pixel. To track the connection of edge, an algorithm is applied which checks the weak edge pixel and its 8connected neighborhood pixels. If there is one strong edge pixel then that weak edge point can be identified as one that should be preserved. This technique is called edge tracking by hysteresis.

#### Filtering

Gabor filtering is a linear filtering method which is used to enhance the edges detected from canny edge detection. Gabor filtering implements one or multiple convolutions of an input image with a two-dimensional Gabor function, Eq. (4).

$$g(x', y', \lambda, \Theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) * \cos\left(2\pi \frac{x'}{\lambda} + \psi\right)$$
(4)  
Where,

 $x' = x\cos\Theta + y\sin\Theta$ 

 $y' = -xsin\Theta + ycos\Theta$ 

## **Binary Thresholding**

Binary thresholding converts the grayscale image to binary by thresholding. The output binary image i.e. B/W has values of 1 for all pixels in the input image with luminance greater than certain level and 0 for all other luminance. Proper value of threshold is chosen for training and fixed in accordance with accuracy.

#### **Contour Detection**

The contours are a useful tool for shape analysis and object detection and recognition. Contours are detected accurately if the image is in binary form. So before finding contours, threshold or canny edge detection is applied.

For extraction of features of image such as area, perimeter, bounding rectangle etc. of the contours can be found in OpenCV. On the basis of this, features exudates can be detected and diagnosis can be performed.

## RESULTS

The performance of this method is calculated by measuring the accuracy. The performance of the method was evaluated quantitatively by sensitivity ( $\sigma$ ) using Eq. (5) and specificity ( $\rho$ ) using Eq. (6) which are chosen as the measurement of accuracy using Eq. (7) of the algorithms. The statistical results are shown in Tables 1 and 2.

$$\sigma = \frac{TP*100}{TP+FN} \tag{5}$$

$$\rho = \frac{TN*100}{TN+FP} \tag{6}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
(7)

| Image | ТР | FN | FP | TN  | σ     | Р     | Accuracy |
|-------|----|----|----|-----|-------|-------|----------|
| DR_1  | 20 | 1  | 1  | 127 | 95.24 | 99.22 | 98.66    |
| DR_2  | 12 | 1  | 0  | 145 | 92.31 | 100   | 99.37    |
| DR_3  | 7  | 2  | 0  | 72  | 77.78 | 100   | 97.53    |
| DR_4  | 19 | 2  | 0  | 205 | 90.48 | 100   | 99.12    |
| DR_5  | 18 | 1  | 2  | 98  | 94.74 | 98    | 97.48    |
| DR_6  | 29 | 3  | 3  | 152 | 90.63 | 98.06 | 96.79    |
| DR_7  | 46 | 5  | 2  | 313 | 90.2  | 99.37 | 98.09    |
| DR_8  | 49 | 2  | 1  | 172 | 96.08 | 99.42 | 98.66    |

 Table 1: Exudates Detection Results.



| DR_9  | 55 | 3 | 1 | 204 | 94.83 | 99.51 | 98.48 |
|-------|----|---|---|-----|-------|-------|-------|
| DR_10 | 34 | 3 | 1 | 372 | 91.89 | 99.73 | 99.02 |
| DR_11 | 38 | 0 | 2 | 73  | 100   | 97.33 | 98.23 |
| DR_12 | 48 | 3 | 2 | 57  | 94.12 | 96.61 | 95.45 |
| DR_13 | 32 | 2 | 1 | 41  | 94.12 | 97.62 | 96.05 |
| DR_14 | 23 | 2 | 1 | 94  | 92    | 98.95 | 97.5  |
| DR_15 | 90 | 7 | 0 | 338 | 92.78 | 100   | 98.39 |

TP=True Positive, TN=True Negative, FP=False Positive, FN=False Negative, Accuracy is from 100%.

| Table 2: | Percentage | of Exudates. |
|----------|------------|--------------|
|----------|------------|--------------|

| Image | % Exudates |
|-------|------------|
| DR_1  | 13.42      |
| DR_2  | 7.59       |
| DR_3  | 8.64       |
| DR_4  | 8.41       |
| DR_5  | 15.13      |
| DR_6  | 15.51      |
| DR_7  | 12.57      |
| DR_8  | 21.88      |
| DR_9  | 20.91      |
| DR_10 | 8.29       |
| DR_11 | 33.63      |
| DR_12 | 43.64      |
| DR_13 | 42.11      |
| DR_14 | 19.17      |
| DR_15 | 20.69      |

The percentage of exudates in retina is calculated using:

% exudates =  $\frac{\text{Total no of exudates} \times 100}{\text{number of connected areas}}$  (8)

# CONCLUSION

The proposed method uses shape based algorithm instead of intensity based algorithm for detection of exudates. So, the optical disk does not interfere with exudates. As a result there is no need of optical disk detection and elimination algorithm, therefore processing time is saved and most importantly accuracy of exudates detection increases.

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# **Cite this Article**

Chachan Manmohan S, Savani Vijay G. Novel Approach for Automated Diagnosis of Diabetic Retinopathy. *Journal of Electronic Design and Technology*. 2016; 7(1): 9–13p.