# DETECTION OF EXUDATES IN DIABETIC RETINOPATHY

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*Abstract*— **Diabetic Retinopathy (DR) is an eye abnormality in which the human retina will get affected and is becoming one of the leading cause of preventable blindness. In the world, it is found that nearly 4.8% of blindness is caused due to DR. Preliminary symptoms include the formation of microaneurysms, exudates and hemorrhages. Early detection of DR can save the vision of diabetes patients and manual diagnosis takes time and effort for confirmation. In this paper, a Computer-aided Automated Diagnosis (CAD) is developed to solve this problem. The proposed approach uses edge-based segmentation method for segmenting the optic disc and blood vessels more accurately than region-based methods, followed by extraction of most probable exudates regions, feature extraction and the classifier stage to detect the presence of exudates. This system achieved sensitivity 82.61%, specificity 92.31% and moreover an accuracy of 87.75% for DIARETDB dataset.**

***Keywords— Blindness, CAD, Diabetic Retinopathy, edge-based segmentation, exudates, NPDR, PDR***

## I. INTRODUCTION

The world has 425 million diabetes patients where 82 million are from SEA (South-East Asian) region. This data has been extrapolated to 2045 and found to be at 151 million. 72 million diabetes cases have been reported in 2017 in India and this constitutes to 8.7% of the total Indian population. Among these many patients are undetected for preventable blindness [1]. People having diabetes for more than 20 years will be affected by Diabetic Retinopathy (DR). This DR may lead to blindness in people with age ranging from 20 to 64 years.

DR is an eye disorder which is caused when the blood vessels in the retina gets damaged which may lead to bleeding or leaking of blood fluids and result in blocking of vision. Non-proliferative diabetic retinopathy (NPDR) is the initial phase in which the formation of Microaneurysms (MA), Hemorrhages (HM), Exudates (Exd), and Neovascularization takes place. Among these the microaneurysms and hemorrhage are categorized as the mild NPDR, the formation of exudates as moderate NPDR and the formation of neovascularization will be considered as the severe stage. If left untreated the disease will progress to the PDR, the advanced stage where vision loss starts to occur.

Small swellings will be formed within the retina's blood vessels in the initial stage and they are called microaneurysms. The discharge of blood from the ruptured blood vessels is called hemorrhage. The second stage is the formation of Exudates or Cotton Wool Spots (CWS). These are formed due to the leakage of fluids such as serum, fibrin, white blood cells and lipids from the blood vessels. The microaneurysms and hemorrhages are called as dark lesions as they are red in color and the exudates are called as bright lesions as they are yellowish white in color. Both these lesions have different properties such as brightness, shape and size [2]. Screening of each patient manually is time consuming as there are very less ophthalmologists in India and it is necessary to detect DR at its earlier stage to prevent vision loss. Therefore, an automated system has to be developed that can assist the ophthalmologists in the detection of DR. This paper limits to detecting one of the NPDR lesions, that is, the exudates.

The main contribution of our work is to efficiently segment the optic disc and blood vessels to decrease the false positives and false negatives. In this paper, we propose an edge-based segmentation significantly at the pixel level thereby aiding to increase the classifier's accuracy. This paper includes other techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Bi-linear interpolation, Morphological operators, Canny edge detector and Gabor filter with Gaussian kernel. The reason on which this set of methods were chosen are explained in their respective sections.

The rest of the paper is organized as follows, section II gives an insight on the earlier work done by various researchers, section III has detailed explanation for the pre-processing and segmentation of optic disc and blood vessels using edge-based segmentation algorithm, section IV explains the method for detection of possible exudates regions using Gabor filter and the contents of the feature set, section V explains about the classifier, section VI discusses the result obtained and is followed by conclusions.

## II. PREVIOUS WORK

M. Usman Akram et al. [2] has considered the color, shape, size, intensity, statistical features and texture as their features for detection of exudates. M A. Rao et al. in [3] has considered the shape, color, size, contrast, correlation, energy, homogeneity and entropy as their features to extract the clinical features. T.Ruba and K.Ramalakshmi [4] has proposed a method of identifying the exudates at the first stage using features like contrast, inverse different Moment, maximum probability, homogeneity, cluster shade, auto correlation, energy, entropy, correlation, sum of squares. For the exudates detected images the blood vessels were removed using morphological closing operation and optic disc was segmented using the level select operator. A.Narang et al. [5] used Lifting Wavelet Transform (LFT) for enhancing the image for proper detection and use SVM classifier to classify the detected

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regions. K.Narasimhan et al. [6] performed the optic disc and blood vessel segmentation by morphological methods and region growing algorithm for detection of exudates and feature extraction. Two classifiers namely Bayesian classifier and SVM classifier was used and found that SVM to be working better than the other. AkaraSopharak et al. [7] used Naïve Bayes classifier (NB) for exudates classification and Support Vector Machine (SVM) for feature selection. A systematic review [13] of the developed algorithms for processing maculopathy is done using fundus fluorescein angiogram (FFA) images of patients suffering from diabetic maculopathy in which also exudates can be detected.

## III. PREPROCESSING

The main issue of concern here is to highlight the region of interest (ROI) and filter the regions that may interfere in exudates detection so as to reduce false detections.

### *A. Background seperation and noise removal*

The initial step is to remove the background. Multiple background removal techniques such as mean and variance based methods and Column Wise Neighborhood Operation (CWNO) method can be used to get the desired results. In this approach, it is done by evaluating intensity spikes in all the pixels of the image and the pixels with similar spikes are then stored into the memory (all the location of pixels is continuous). A mask is created by binarizing the image and filling the full retina as shown in Fig 3.1(b). The regions that don't fall under this mask will be deleted from the original image. Thus, the region of interest is reduced, and the processing time is saved.

The salt and pepper noise is removed from the image using 2-D median filtering with 31X31 as its mask size. The image is then converted into the HSI (Hue Saturation Intensity) plane where the intensity plane becomes free of noise [10]. Background intensity variations is due to non-uniform illumination is rectified by enhancing the contrast using CLAHE, this limits over amplification of the pixel's intensity value in the ROI, shown in Fig 3.1(c).

Bi-linear interpolation technique enhances the efficiency without causing any significant change in the quality of the output image. The small background color holes are covered using morphological dilation operator and the resulting distortion effects is compensated by a morphological erosion operation immediately after the dilation, both process collectively called as the morphological closing operation, given in equation (1) and (2), shown in Fig 3.1(d). This results in smoothing the image, suppressing the blood vessels and enhancing the bright lesions [2].

$$\Phi_1(\xi,\psi)=\xi_1^{(B1)}(\,\phi(\xi,\psi)) \quad (1)$$

$$\Phi_2(\xi,\psi)=\xi_2^{(B1)}(\,\Phi_1(\xi,\psi)) \quad (2)$$

Where, $\xi_1$ and $\xi_2$ represent the morphological dilation and erosion operators respectively, B1 is the structuring size with 'disk' as its structuring element, $\phi(\xi,\psi)$ is the interpolated image.

### *B. Segmentation of Optic Disc*

The optic disk must be segmented out from the image as it shares certain features like intensity, size and luminosity with the exudates. If not removed, it will result in false detection.

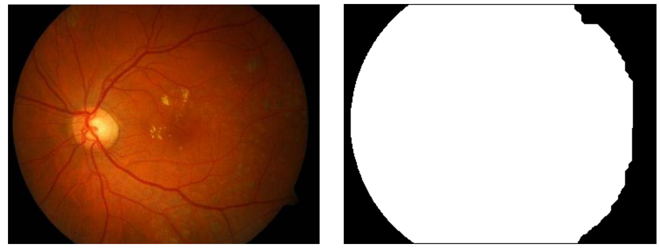


Fig 3.1(a): RGB Fig 3.1(b): Mask

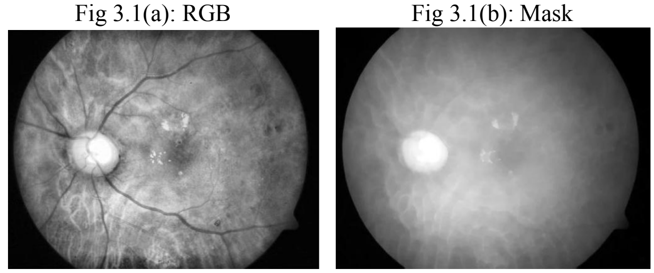
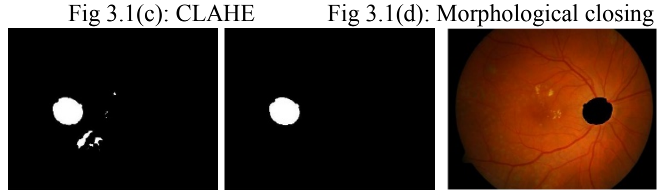


Fig 3.1(c): CLAHE Fig 3.1(d): Morphological closing



(a) (b) (c)

Fig 3.2: (a) Thresholded image. (b) Optic disc extracted image. (c) Optic disc segmented from RGB image.

In this work, an edge-based segmentation algorithm is performed, which is more suitable in marking the edges sharply [9]. Moreover, processing the image pixel by pixel will result in better segmentation as compared to that of the region-based segmentation where the edges are not marked very sharply and has a possibility of over segmentation of the ROI or under segmentation of the unwanted region and thus result in low accuracy, sensitivity and specificity [10].

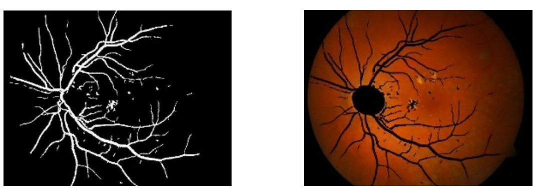
Here, the image is binarized by setting a threshold value for the intensity. Apart from the optic disk other regions will also be highlighted, shown in Fig 3.2(a). But optic disk will be having the biggest area when compared with other highlighted regions. So, the perimeter for all the regions is marked with the help of canny edge detector. The addresses of the marked edges are stored in a cell and these regions are subjected to binary fill so as to obtain a separate solid fill of each region. Then the cell array having maximum number of pixel addresses corresponds to maximum area. The addresses stored in this cell array with maximum size are taken one by one and the location of the pixel given by the address will be marked as black in the original RGB image, shown in Fig 3.2(c). By this way, the optic disc can be removed from the RGB image. In this method, canny edge detector is chosen apart from sobel and prewitt because it initially removes the speckle noise, normalizes the image locally, gets the gradient of the image to highlight the regions with high spatial derivatives, suppresses the non-maximum pixels and mark the edges based on the hysteresis which is used to reduce the gradient array [9].

### *C. Segmentation of Blood Vessels*

Blood vessels are the thin long elongated structures that are seen in the image. All the blood vessels emerge from the center of the optic disk and should be removed as some part of them may interfere in exudates detection. Thus, removing this will avoid spurious and false detection of exudates in the retinal image. The blood vessels are extracted by morphological operations and an edge-based segmentation algorithm is used to remove these blood vessels from the original RGB image.

Initially, the green channel is extracted from the input RGB image. This image is then complemented and CLAHE is performed to enhance the contrast. Morphological erosion operation is performed followed by morphological dilation process and (called morphological opening), both having 'disk' as its structuring element.

This enhances the dark regions and thus helps in blood vessel identification [2]. Further, median filtering with a mask of size $31X31$ is performed on the green channel image to remove the speckle noise and morphological opening with disk as its structuring element and bigger in size than that used before.



(a) (b)

Fig 3.3: (a) Blood Vessels extracted. (b) Blood vessels segmented from RGB image

The median filtered image is subtracted with later image and is converted to a binary image with a suitable threshold given by Otsu thresholding algorithm, shown in Fig 3.3(a).

The canny edge detector algorithm is then applied to mark the perimeter, fill the regions and calculate the area of individual regions. The regions that are less than the threshold area is removed, and the rest of the regions are highlighted. These pixel addresses will be copied in an array and the corresponding pixel locations in the original RGB image will be marked as black, shown in Fig 3.3(b).

Thus, the resulting image at this stage will be free from blood vessel and optic disk and is left with the lesions that has to be detected.

## IV. DETECTION OF EXUDATES

Exudates are one of the preliminary stages of DR and occur in different shapes and sizes on the surface of the retina. They are generally bright lesions, so morphological closing operation should be performed on the optic disk and blood vessel segmented RGB image so as to preserve these bright lesions. An adaptive contrast enhancement technique should be performed on this image to make the detection of bright lesions easy. This technique is specified by equation (3). Where the ϕw is called sigmoid window for a window given by equation (4). ϕfmax, ϕfmin, *mw* and *σw* are maximum, minimum, mean and variance of intensity values of the smooth green channel image.

$$\gamma = 255\frac{[\phi w(\phi f) - \phi w(\phi f min)]}{[\phi w(\phi f max) - \phi w(\phi f min)]} \qquad (3)$$

$$\phi w(\phi f) = [1+\exp^{\left(\frac{mw - f}{\sigma w}\right)}] \qquad (4)$$

*mw* and *σw* are the mean and variance of intensity values within the window [11].

### *A. Gabor Filter*

Gabor filter is used for exudates detection based on the texture analysis. In addition, its invariance to rotation, scale, transition and robustness against noise due to illumination changes makes it more suitable for lesion detection. A Gaussian kernel is used in Gabor filter which makes it suitable for lesion detection by tuning its parameters. Gabor filter expression is given in equation (5).

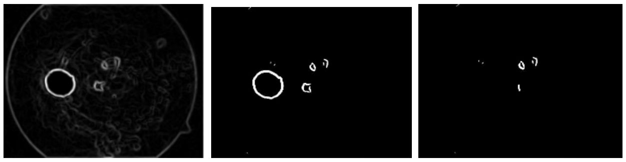
$$G(x,y,\sigma,\Omega,\theta,r) = \frac{1}{\sqrt{\pi r \sigma}} e^{-\frac{1}{2}\left[\left(\frac{d_1}{\sigma}\right)^2+\left(\frac{d_2}{\sigma}\right)^2\right]^2} (d1(\cos\Omega + i\sin\Omega)) \qquad (5)$$

σ – standard deviation of Gaussian
Ω – spatial frequency
θ – orientation of the filter
r – aspect ratio
$d_1 = x\cos\Omega + y\sin\Omega$
$d_2 = -x\sin\Omega + y\cos\Omega$ [3].

The contrast enhanced image g is convolved with Gabor filter G to generate Gabor filter response for selected values of θ and σ, as given in equation (6). Here the Gabor filter is centered at (s,t).

$$\gamma(\sigma,\theta,\Omega)=\sum_x \sum_y g(x,y)G(s-x,t-y,\sigma,\Omega,\theta,r) \qquad (6)$$

Generally, the σ values are 2, 5 and 7 for exudates, and the θ varies from 0° to 180° in step of 45°. The maximum image $M_\gamma(\theta,\Omega)$ out the Gabor filter responses is chosen, Fig 4.1 (a). A suitable threshold is given to the maximized image to highlight the possible regions of exudates, Fig 4.1 (b). Binary SVM classifier is then used to determine the exudates (Fig 4.1 (c)) and non-exudates regions.



(a) (b) (c)

Fig 4.1: (a) Maximized Gabor response. (b) Thresholded image. (c) Possible regions of exudate

### *B. CLASSIFIER*

NPDR lesions will appear in different intensity, shape, size and color. A feature set is formed which directly or indirectly explains about the clinical data of the possible exudate regions. This set consists of features consisting of area, perimeter, mean intensity, compactness, mean intensity of bottom hat and top hat filter responses, hue, saturation and intensity channels, and standard deviation. This feature set is the input to the automated system for differentiating the exudates and non-exudates regions. Exudate classification is performed using SVM classifier. In SVM classifier the data set for the features need to be non-redundant to reduce dimensionality and execution time. The particle swarm optimization can also be used to reduce the set up and build time by performing parameter optimization in SVM [12]. The latter is not followed as better accuracy can be achieved by the following. RBF kernel is used in SVM classifier to get the best 'C' and best 'gamma' values for the hyper-plane [2].

The data set being quite big, sparse and the features are dependent on each other, the Naïve Bayes classifier does not seem to be th right choice. The performance of neural network also will be poor as the data is sparse. Decision tree method for classification will work well only if the classes are unbiased. Using the features and the classifier output, the position of exudates and its properties are detected in the digitalized image.

## V. RESULTS

In this paper, optic disc and blood vessels are segmented using the edge-based segmentation algorithm. This edge-based segmentation algorithm gives better results than any other region-based segmentation algorithm in which either over segmentation or under segmentation occurs and the edges may not be sharp and well defined which results in decreasing the classifier's accuracy. Gabor filter is then used for detection of exudates using texture analysis and the extracted clinical data from those regions are given to SVM classifier for detection of exudates. The performance of classifier is measured based on sensitivity, specificity, accuracy and AUC in the ROC curve, Fig 4.2.

$$sensitivity\,(sen) = \frac{TP}{TP + FN}$$

$$Specificity\,(spe) = \frac{TN}{TN + FP}$$

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

AUC in the ROC curve is the area covered by the curve on the x-axis (AUC).

| | method | Sen % | Spe % | Acc % | Auc % |
|---|---|---|---|---|---|
| T.Ruba et al. | Level select | 78.57 | 86.36 | 82 | - |
| L.Xu and S.Luo | SWT | 76 | 76 | 76 | - |
| L.Xu and S.Luo | GLCM | 84 | 56 | 70 | - |
| L.Xu and S.Luo | SWT+GLCM | 88 | 80 | 84 | - |
| A. sopharak et al. | Morphological process | 80 | 98 | - | - |
| Result obtained | Edge besed segmentation | 82.61 | 92.31 | 87.75 | 0.88 |

Table: 4.1 Results

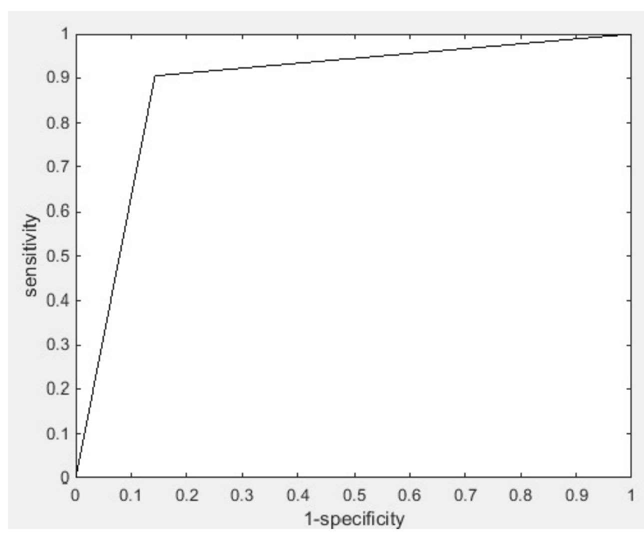



Fig 4.2: ROC curve

## VI. CONCLUSION

In this work, we explore methods towards the development of an automated CAD system for detecting and classifying exudates in DR. Previous works were mainly focused on segmenting the optic disc through region-based methods such as Hough transform, watershed transform, region growing methods, etc. In our work an edge-based segmentation algorithm is performed on the intensity channel of the retinal image and optic disc is removed pixel by pixel in the RGB image. Morphological operations are performed on this RGB image to extract the blood vessels from the green channel image and edge-based segmentation method is employed to segment this blood vessel from the retinal image. The purpose of using edge-based segmentation is that, it results in sharp edges and prevents both over-segmentation of ROI and under-segmentation of unwanted region. Gabor filter is used for detecting the possible exudate regions and SVM classifier is used for the detection of exudates. This method achieved a sensitivity of 82.61%, specificity 92.31%, accuracy 87.75% and AUC of 0.88. Thus, from the results it can be concluded that edge-based segmentation algorithm with Gabor filter gives better results than the region-based segmentation methods.

Each step explained in this paper had to deal with certain technical issues. For morphological operators the structuring element and size should be properly chosen with the help of samples chosen from the data set. Gabor filter with appropriate kernel and the parameters such as σ, θ and Ω must be chosen correctly. This step is time consuming. SVM classifier's hyperplane, best 'C' and best 'gamma' values must be chosen, and proper training set should be considered so as to cover all the possibilities in it.

In the future, the accuracy of the classifier can be increased by implementing the feature selection algorithm and optimizing the classifier's parameters.

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