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A Review on Exudates Detection in the Diagnosis of Diabetic Retinopathy

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Abstract:
Diabetic retinopathy is a complication of diabetes that is caused by changes in the blood vessels of the retina. Diabetic retinopathy is a major cause of blindness. Earliest signs of diabetic retinopathy are damage to blood vessels in the eye and then the formation of lesions in the retina. This paper presents an automated method for the detection of exudates in retinal images with high accuracy. First, the image is converted to HSI model. After pre processing possible regions containing exudates using gray scale morphology are identified. Then descriptors for each candidate pixel to classify them are extracted. Using Naive-Bayes classifier, Diabetic retinopathy is classified.

***Key words** : Diabetic Retinopathy, Retinal image, Exudates, Morphology, Pre processing*

1.Introduction

Diabetes is a group of metabolic diseases in which a person has high blood sugar, either because the body does not produce enough insulin, or because cells do not respond to the insulin that is produced. Diabetic retinopathy is the damage to the retina caused by complications of diabetes, which can eventually lead to blindness.

The risk of the disease increases with age and therefore, middle aged and older diabetic patients are prone to Diabetic Retinopathy. Diabetic retinopathy affects up to 80% of all patients who have diabetes for 10 years or more. 90% of these new cases could be reduced if there is proper treatment and monitoring of the eyes.

Early diagnosis of DR and treatment can prevent blindness, and therefore, systematic screening (by specialists) of diabetic patients is a cost-effective health care practice. However, due to the large number of people that require screening, an automated and accurate screening tool is a useful adjunct in diabetes clinics.

1.1.Diabetic Retinopathy Has Four Major Stages

Mild Non proliferative Retinopathy**:** At this earliest stage, micro aneurysms occur. They are small areas of balloon-like swelling in the retina's tiny blood vessels.

Moderate Non proliferative Retinopathy**:** As the disease progresses, some blood vessels that nourish the retina are blocked.

1.2.Severe Non proliferative Retinopathy

Many more blood vessels are blocked, depriving several areas of the retina with their blood supply. These areas of the retina send signals to the body to grow new blood vessels for nourishment.

1.3.Proliferative Retinopathy

At this advanced stage, the signals sent by the retina for nourishment trigger the growth of new blood vessels. These new blood vessels are abnormal and fragile. They grow along the retina and along 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.

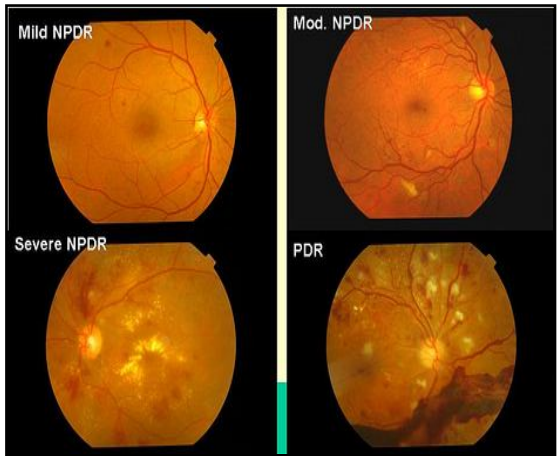

Figure 1: Stages Of Diabetic Retinopathy

Exudates occur when lipid or fat leaks from blood vessels or aneurysms. Exudates are of two types namely hard exudates and soft exudates. Hard exudates are small, yellow or white waxy glistening patches with discrete margins. In the case of severe hypertensive retinopathy cotton wool exudates or soft exudates are present.

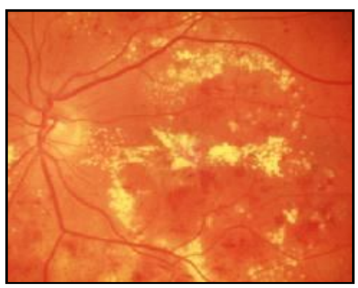

Figure 2: Exudates

2.Previous Work

Many techniques have been employed to the exudate detection. Gardner et al. proposed an automatic detection of diabetic retinopathy using an artificial neural network. The exudates are identified from grey level images [2].

Sinthanayothin et al. reported the result of an automated detection of diabetic retinopathy on digital fundus images by Recursive Region Growing Segmentation (RRGS) algorithm where the performance was measured on 10×10 patches rather on the whole image[3].

Usher et al. detected the candidate exudates region by using a combination of RRGS and adaptive intensity thresholding. The candidate regions were extracted and used as input to a neural network. Poor quality images affected the separation result of bright and dark lesions using thresholding and exudate feature extraction using RRGS algorithm [4].

Zheng et al. detected exudates using thresholding and a region growing algorithm. The fundus photographs were taken with a non-mydriatic fundus camera and were then scanned by a flat-bed scanner [5].

Colour normalization and local contrast enhancement followed by fuzzy C-means clustering and neural networks were used by Osareh et al. [6].The system works well only on colour space but in the case of non-uniform illumination the detection accuracy is low.

Much work has been performed for exudate detection based on variety of techniques. Most techniques mentioned earlier worked on dilated pupils in which the exudates and other retinal features are clearly visible. Based on experimental work reported in previous work, good quality images with larger fields are required. The retinal image of the patient must be clear enough to show retinal detail.

3.Methodology

In this work, RGB image is converted to HSI image[1]. Then intensity image is median filtered to remove the noise. Adaptive histogram equalization is applied for contrast enhancement. Then the image is thresholded to get binary image which detects optic disc. After this step, local variation operator is applied, resultant image is thresholded and dilated to detect exudates. Then using the Naive Bayes classifier, Diabetic Retinopathy is classified into mild, moderate and severe conditions [16].

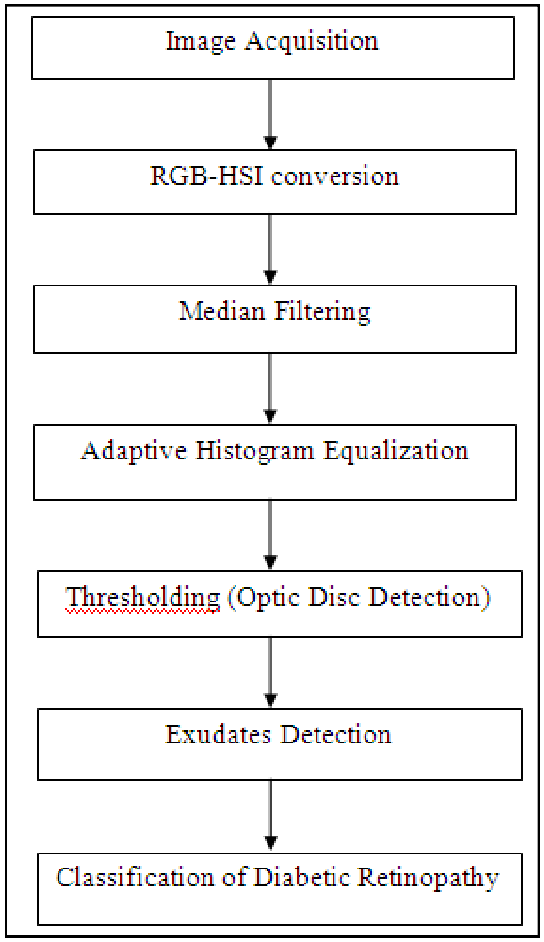

Figure 3: Block Diagram of procedure

3.1.Steps

3.1.1.<u>Image Acquisition</u>

Retinal images are collected from DIARETDB0, DIARETDB1 database which is freely available. Dimensions of images are 1201x901 pixels [16]. Images are also collected from hospital.

3.1.2.<u>RGB to HSI Conversion</u>

First, we convert RGB color space image to HSI space beginning with normalizing RGB values:

r=R/(R+G+B), g=G/(R+G+B), b=B/(R+G+B)

Each normalized H, S and I components are then obtained by,

$h=\cos^{-1}\left\{\frac{0.5[(r-g)+(r-b)]}{[(r-g)2+(r-b)(g-b)]^{1/2}}\right\}$, h $\epsilon[0,\prod]$ for $b\leq g$

$h=2\prod-\cos^{-1}\{\frac{0.5[(r-g)+(r-b)]}{[(r-g)2+(r-b)(g-b)]^{1/2}}\}$,

h $\epsilon[\prod,2\prod]$ for b>g

s=1-3*min(r,g,b), s ϵ [0,1]

i=(R+G+B)/(3*255), i ϵ [0,1]

For convenience, h, s and i values are converted in the ranges of [0,360], [0,100], [0,255] respectively, by:

H=h$\times 180/\prod$, S=s×100, I=i×255

3.1.3.Median Filtering

The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing. Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value.

Adaptive Histogram Equalization (AHE): Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast of an image and bringing out more detail.

However, AHE has a tendency to over amplify noise in relatively homogeneous regions of an image.

3.1.4.Thresholding

Segmentation divides an image into its constituent regions or objects. Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images. This approach assumes that the image is divided in two main classes: the background and the foreground.

The detection of the optic disc in the human retina is a very important task. It is indispensable for approach to detection of exudates, because the optic disc has similar attributes in terms of brightness, colour and contrast, and we shall make use of these characteristics for the detection of exudates. Image is binarized by thresholding so that optic disc is detected.

3.1.5. Exudates Detection

Exudates are of two types namely hard exudates and soft exudates. Hard exudates are small, yellow or white waxy glistening patches with discrete margins. When hard exudates encroach on the macula vision is affected. In the case of severe hypertensive retinopathy cotton wool exudates or soft exudates are present. Exudates are primary signs of diabetic retinopathy and occur when lipid or fat leaks from blood vessels or aneurysms.

A local variation operator was then applied to the previous result to get a standard deviation image which shows the main characterization of the closely distributed cluster of exudates.

The resulting image is thresholded to get rid of all regions with low local variation. To ensure that all the neighboring pixels of the thresholded results are also included in the candidate region, a binary dilation operator was also applied. Resulting image will detect the exudates.

3.2.5. Classification of Diabetic Retinopathy

Based on the number of exudates, True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) values are calculated. Sensitivity and specificity are determined. By considering all these values, Naive Bayes classifier and Support vector machine classifier classifies Diabetic Retinopathy into mild, moderate and severe conditions.

Sensitivity=TP/ (TP+FN)

Specificity=FN/ (FN+TP).

3.3.6. Algorithm

- Read the image.
- Convert RGB image to HSI image.

- Apply median filtering on intensity image to reduce noise.
- For contrast enhancement, adaptive histogram equalization is applied.
- 5. Resulting image is binarized by thresholding.
- Morphological reconstruction by dilation.
- Local variation operator is applied.
- Again thresholding is applied.
- Dilation is applied which detects the exudates.

4.result

4.1.RGB to HSI Conversion:

RGB image is converted to HSI model in which intensity component can be separated from other components

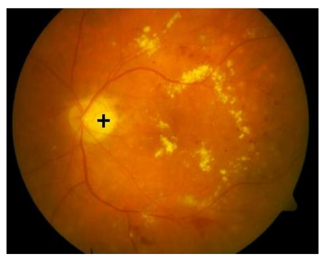

Figure 4 (a): Original Image(RGB)

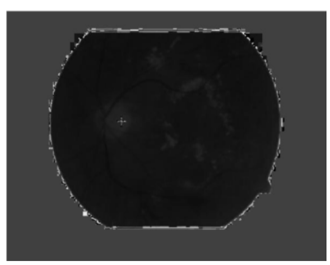

Figure 4(b): Hue Image

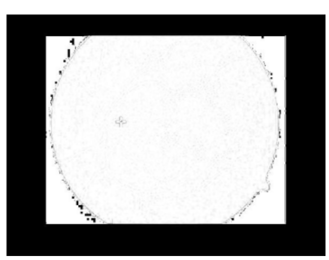

Figure 4(c): Saturation Image

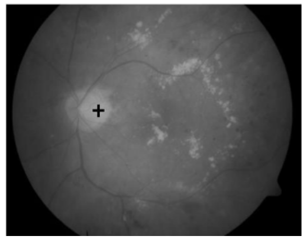

Figure 4(d): Intensity Image

4.2.Median Filtering

Intensity image is median filtered to remove noise

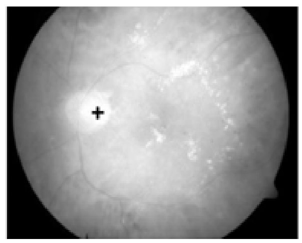

Figure 5: Median Filtered Image

4.3.Adaptive Histogram Equalization (AHE)

Adaptive histogram is applied to median filtered image

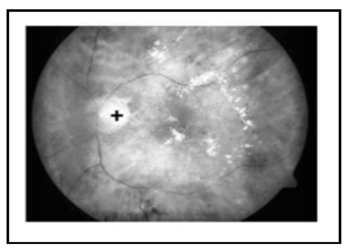

Figure 6: AHE

4.3.Thresholding

Thresholding is applied to histogram equalized image. Optic disc is detected.

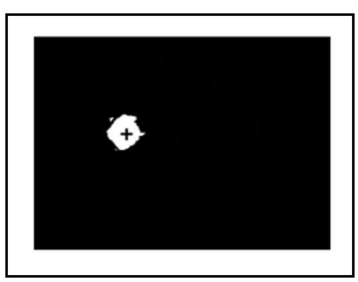

Figure 7: Optic disc

4.4.Exudate Detection

Local variation operator is applied to histogram equalized image. Thresholding followed by dilation detects the exudates.

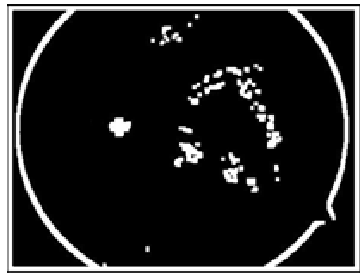

Figure 8: Exudates

5.Conclusion

There are different methods available for the exudates detection in the diagnosis of diabetic retinopathy but Naive Bayes classifier is efficient compared to other system. This technique is very fast and requires lower computing power. It also has high performance.

Future work can be done in the classification of exudates into hard and soft. Based on threshold value exudates are classified.

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