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An Efficient MATLAB App. for the grading of Diabetic Retinopathy Using Color Fundus Images

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ABSTRACT

Exudates, that appears as bright yellow or white lesions in color fundus images, is an important symptom of Diabetic Retinopathy. In this paper, an efficient image based method for the automatic detection of exudates, is presented and validated. To identify the exudates, the proposed approach performs a hierarchical correlation clustering on the input retinal images. Ten different features, based on dynamic shape, colour, contrast and brightness, are extracted for each patient segment. Based on the values of the feature vectors, each patient segment is categorized as mild, moderate and severe using random forest (RF) Classifier. The proposed MATLAB app. is validated on per-image basis using four different publicly available databanks. While interpreting the obtained result, it is inferred that the developed system achieves an area under Receiver Operating Curve(ROC) of 0.87 and the average computational time of 6.38s is achieved. This approach outperforms the other state of art approaches and may play an efficient clinical role in the detection of Diabetic Retinopathy.

Index Terms: Color fundus images, Diabetic Retinopathy, Exudates, lesions, Random Forest Classifier.

1. INTRODUCTION

DR is one of the complication of diabetes, which causes impairment of sight by damaging the blood vessels in the retina. It is the common cause of vision loss [1]. Many studies show that one out of three persons with diabetes have the signs of DR[2] and 10 out of 100 DR patients should be referred to a doctor (Dr.) since their complications are very severe [3][4]. On a survey by World Health Organization (WHO), it is reported that in 2025, nearly 300 million people will suffer with diabetes and will requires a consistent fundus examination annually [5],[6][7].

In order to extend the quality of patient's life, there is a need of an efficient automatic computational system that assists the ophthalmologist to grade the disease and reduce their burden. As the number of specialist is limited, the analysis of retinal images is really a very challenging task for the image processing community [8].

DR causes several kinds of lesions in the retina. The most common visible type of lesion and the very first sign of retinopathy is the exudates. These appears as yellow-white patches with varying shapes and size. The blood vessels in the retina get damaged and leaks fats and protein-based particles called as Exudates [9].

Some other lesions of DR are hemorrhages, microaneurysms and cotton wool spot. Anatomical features like Optic Disc, fovea, macula and blood vessels are also used to recognize DR [10].Typical color retinal image having various lesions and anatomical features are shown in Fig. 1

In this work, the detection of exudates is mainly concentrated because exudates are the prime cause of macular edema, which leads to severe vision loss and detecting DR by screening large number of patients is very expensive and time consuming.

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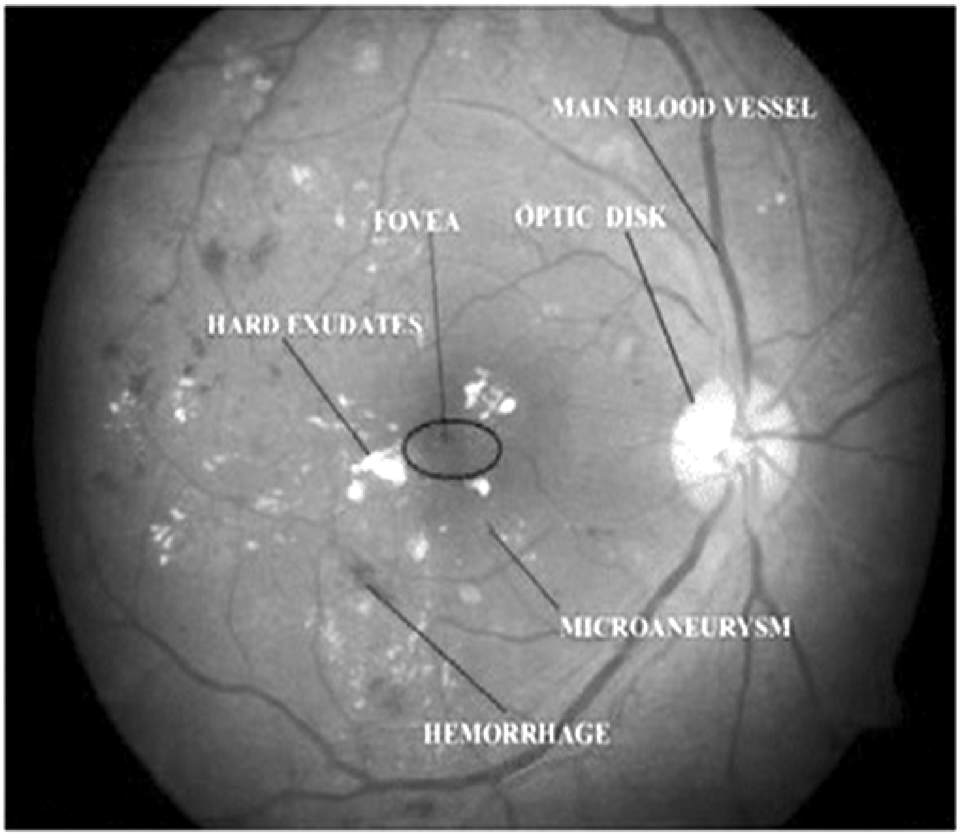

Figure 1: Color fundus image with exudates, microaneurysm, hemorrhages, fovea and optic disc.

Therefore, there is an need of an automated computational system that accurately assess the severity of the Diabetic Retinopathy and this becomes the aim of this proposed system.

The Organization of the paper is as follows. Section II describes the overview of state of art approach. The details of the proposed method are discussed in section III. Section IV reports the methodology of performance evaluation and the experimental results. Finally the main points are summarized and the conclusion is given in section V.

2. OVERVIEW OF STATE OF ART

Several techniques have been proposed for the automatic detection of other symptoms in fundus images with DR, but only few methods have been done to detect and grade the severity of the disease by detecting exudates.

In [11], Alireza Osareh et al developed a method for automatic identification of exudates. The color retinal images were preprocessed and it is segmented using FCM clustering algorithm. The feature vectors were calculated and classified using multi-layer neural network. The classification performance for this stage was only 96% sensitivity and 94.6% specificity.

The bright lesions like exudates, cotton wool spots and drusen were distinguished by Niemeijer et al in [12]. The clusters are formed based on the probability map. Based on the probability, the clusters were classified as exudates, cotton wool spots or drusen. Sensitivities and specificities were used as the performance parameter.

Sinthanayothin et al in [13] proposed the automatic detection of DR using Recursive Region Growing techniques. The authors reported 88.5% of sensitivity and 99.7% of specificity as their performance on a dataset of 21 abnormal and 9 normal fundus images.

In [14], Akara sopharak et al conducted a series of experiments for exudates classification using Naive Bayes (NB) and Support Vector Machine (SVM) classifiers. They compared the obtained result with nearest neighbor (NN) classifier and proved that Naive Bayes (NB) and SVM classifier produces better result than the NN classifier.

Lama seoud et al in [15] detected the presence of Hard exudates and microaneurysms in color fundus images using dynamic shape features. The author achieved a FROC score of 0.420 on the Retinopathy Online Challenge Database and area under ROC curve of 0.889 on the publicly available Messidor database.

3. PROPOSED METHODOLOGY

The aim of this approach is to introduce a novel efficient methodology for the grading of Diabetic Retinopathy by detecting exudates. The schematic overflow of the proposed method is shown in figure 2 for the better understanding.

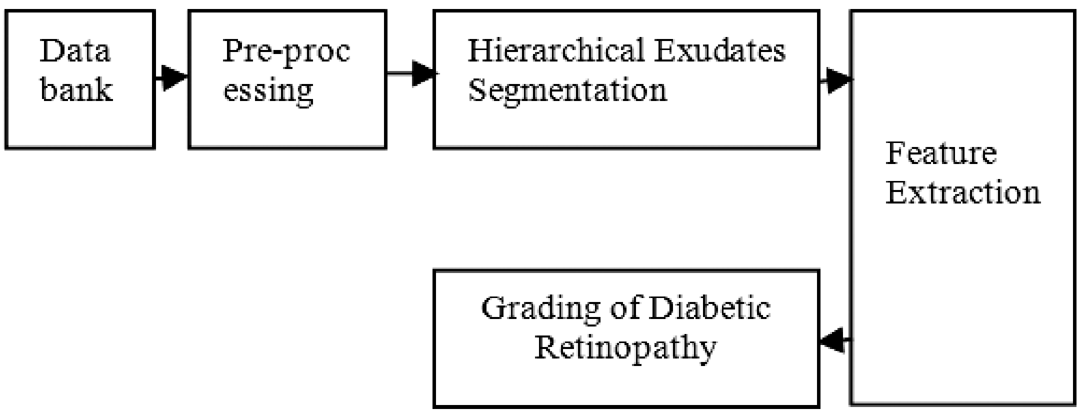

Figure 2: Schematic overflow of the proposed method.

3.1. Databank

To achieve an efficient grading of the disease, the primary thing is to obtain an effective database. The color fundus images required for simulation are collected from four different publicly available databank- diaretdb1, Messidor, Erlangen and STARE.

3.1.1. Diaretdb1 Databank

This databank consists of 60 images for testing and 28 images for training along with the manual segmentations of exudates. This databank is publicly available in PNG format [16].

3.1.2. Messidor Databank

Messidor databank is one of the widely used dataset in the research work. It consists of 546 normal images, 654 abnormal images which are captured with a field of view (FOV) of 45^0 [17].

3.1.3. Erlangen Databank

This databank comprises of 15 normal and 30 affected images which are acquired with a field of view (FOV) of 60^0 and are publicly available as JPEG file format [18].

3.1.4. STARE Databank

This databank of 81 color fundus images were captured by TRV-50 camera with a 45^0 field of view. Out of 81 images, 50 images are abnormal images and 31 are healthy images[10].

3.2. Image Pre-processing

Generally, the color fundus images are pre-processed to overcome the problem of non-uniform illumination, poor contrast and noise. In this approach, the images are first preprocessed by illumination equalization and then the noise is removed by progressive median filter.

3.2.1. Illumination Equalization

Because of the non-uniformity of the imaging system and vignette effect, the illumination in color fundus image is non-uniform. To overcome this non-uniformity, illumination equalization is applied [19, 20, 21]. The color fundus images are read as RGB images in MATLAB. Since the green channel contains more information about the exudates, the G-channel is separated from the RGB image. Then the illumination equalization is applied to this extracted G-channel.

Each pixel in the G-channel is adjusted using the following equation as

$$G_{eq}(x, y) = G(x, y) + \mu - G_w(x, y) \tag{1}$$

where $G_{eq}(x, y)$ = Illumination Equalized Image, $G(x, y)$ = Green channel extracted from the RGB image. μ = desired mean intensity and $G_w(x, y)$ = average intensity value of the pixels within a running window of size 40×40.

3.2.2. Progressive Switching Median filter

Once the non-uniform illuminations are overcome, then the next step is to remove the noise present in the image. Hence the equalized G-channel is passed through a progressive switching median (PSM) filter [22]. This filter helps to remove both the impulse noise and salt and pepper noise simultaneously. Finally, the filtered G-channel is combined with the red and blue channel and converted as RGB image.

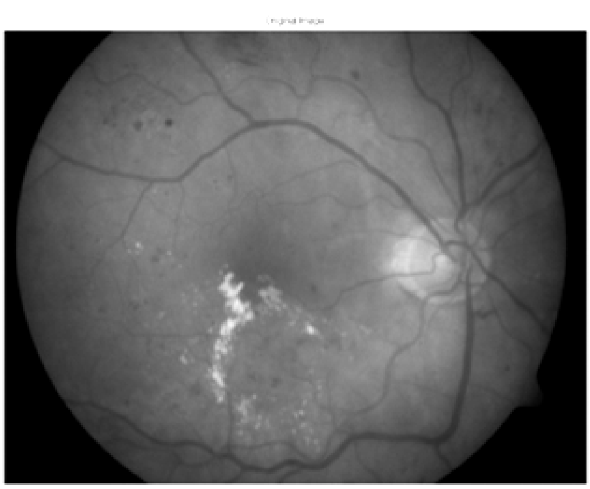

Figure 3: Input Color fundus image

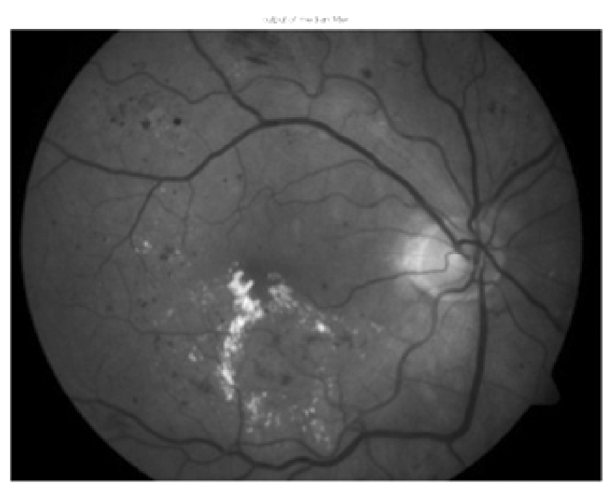

Figure 4: Output of PSM filter.

3.3. Hierarchical Exudates Segmentation

Hierarchical Exudates segmentation divides a color retinal image into homogenous regions based on particular features like color, shape or size. The output of this segmentation algorithm is not a single partition of exudates but rather a hierarchy of region that captures different partitions.

There are two different approaches for performing hierarchical exudates segmentation. One is Bottom-up approach and the other method is Top-down approach. In this proposed work, the top-down approach is applied since it helps to solve the problem of linear programming that occurs during segmentation.

The optimal exudates segmentation is obtained as follows: In the first iteration, all the linear constraints are ignored and a solution is obtained.

The result of the first iteration where all the linear constraints are ignored is given by

$$x_{ij} = \begin{cases} 1; \ if \ \ wij > 0 \\ 0; \ if \ \ wij < 0 \end{cases} \tag{2}$$

If this solution defines a part of the graph, then it is considered as a optimal solution. Otherwise, there is a need to obtain new solution, by adding all the linear constraints that are not satisfied, in the next iteration. This process is continued until all the constraints are satisfied [23].

Let Ø be the optimal solution of the linear programming problem and it is given by

$$\mathrm{S}(\text{Ø}) = \sum_{0}^{i<j} wij \ \ \text{Ø}ij \tag{3}$$

where S(Ø) is the largest score among all the solutions.

3.4. Feature Extraction

To discriminate the exudate and the non-exudate region from the segmented image, ten different features based on dynamic shape [15], color, contrast and brightness are extracted.

These attributes are computed as follows.

i) Circularity (f_1)

The ratio of area of basin over its squared perimeter multiplied by 4π.

ii) Rectangularity (f_2)

The ratio of area of basin over the area of its bounding box.

iii) Solidity (f_3)

The ratio of area of basin over the area of exudates.

iv) Eccentricity (f_4)

$$f_4 = \sqrt{\frac{L^2 - W^2}{L^2}} \tag{4}$$

where W and L are the width and length of the bounding box.

v) Relative area (f_5)

The number of pixels in the basin area divided by total number of pixels in the region of interest (ROI).

vi) Elongation (f_6)

$$\mathrm{f}_6 = 1 - \frac{W}{L} \tag{5}$$

vii) Cluster Shade (f_7)

$$f_7 = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j)(i + j - \mu x - \mu y) \tag{6}$$

viii) Cluster Prominence (f_8)

$$f_8 = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j)\left(i + j - \mu_x - \mu_y\right)^4 \tag{7}$$

ix) Contrast (f_9)

$$f_9 = \sum_{n=0}^{G-1} n^2 \sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j) \tag{8}$$

x) Brightness(f_{10})

$$f_{10} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \log P(i,j) \tag{9}$$

These features are all combined and it is formed as a feature vector.

3.5. Grading of Diabetic Retinopathy

To grade the severity of the disease as mild, moderate and severe, Random Forest (RF) classifier [24] is used. The main reason for selecting this RF classifier is that it incorporates feature selection algorithm. Therefore it overcomes over fitting problem and suitable for non-linear high dimensional data classification.

Based on the extracted features, the RF classifier classifies the image as mild (if the patient is slightly affected), moderate (if the exudates is not present in the region of macula) and severe (if the exudates is present in the macula).

The RF implementation provided in [25] and the MATLAB interface provided in [26] are used. Finally, the MATLAB App. is generated by combining all the above step. The MATLAB App. generation provided in [27] is used.

4. RESULTS AND DISCUSSION

The proposed MATLAB App. has been tested with normal and abnormal images in the four different databanks like Diaetdb1, Messidor, Erlangen and STARE. Results are compared with the already existing methods. This App. is developed on a 2.8 GHz Intel Core i5 Personal computer with a 64-bit Operating Systems and RAM memory of 6 GB. The proposed algorithm takes a computational time of about 12 sec for each retinal image.

Sensitivity, specificity and area under receiving operating curve (AUC) are used to evaluate the performance of the method as follows:

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{10}$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FP})} \tag{11}$$

where TP, TN, FP and FN are true positive, true negative, false positive and false negatives respectively.

Table I depicts the overall sensitivity and specificity for the detection of exudates in four different databanks.

Table 1
Performance Measure of the Proposed Method.

Performance Parameter	*Diaretdb1*	*Messidor*	*Erlangen*	*STARE*
Sensitivity	95.36%	96.89%	97.1%	95.53%
Specificity	92.12%	93.75%	94.0%	91.25%

It is reported that a minimum standard sensitivity of 80% and specificity of 95% is to be achieved by any method.

The proposed method achieves an sensitivity of 96.3% and a specificity of 93.3%. The best performance was achieved in Messidor and Erlangen databanks with an AUC of 0.974.

5. CONCLUSION

Existing approaches for the screening of diabetic retinopathy are expensive, more time consuming and requires an expert ophthalmologists. An Efficient MATLAB App. for the grading of Diabetic Retinopathy was presented and validated on four different databanks. The performance of the proposed App. outperforms several existing approaches. For classification and grading of disease, RF classifier is used which itself have a feature selection algorithm. However, further development can be made by focusing on the detection of cotton wool spot and neo-vessels in the retina.

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