

A Novel Approach for Classification of Diabetic Retinopathy by Detection of Exudates and Microaneurysms using Efficient Retinal Blood Vessel Segmentation

S.Rohini and V.Raghavendra Rajan

Abstract— DR is a serious eye disease which causes blindness to the Diabetic patients. Early detection is help to avoid such Seriousness of the diseases. When the small blood vessels have a high level of glucose in the retina, the vision will be blurred and can cause blindness eventually, which is known as DR. Regular screening is essential to detect the early stages of DR for timely treatment and to avoid further deterioration of vision Vascular pattern of human retina helps the ophthalmologists in automated screening and diagnosis of diabetic retinopathy. In this article, I have presented a method for vascular pattern enhancement and segmentation using length filtering and CCA algorithm and the detection of abnormalities in retina such as Microaneurysm(MA) and exudates using image processing techniques like Modified Candidate Extractor Algorithm and K means algorithm and then finally the automatic detection and grading of Diabetic Retinopathy (DR) is done. The method is evaluated and tested using publicly available retinal databases and we further compare our method with already proposed techniques.

Key Words: Microaneurysm, Exudates, Ensemble, Optic Disk, Diabetic Retinopathy.

INTRODUCTION

Diabetic Retinopathy (DR) is one of the most important cause of visual loss in the world, Diabetic retinopathy is the result of microvascular changes in retina and is the principal cause of impaired vision of diabetic patients. The vast majority of patients who develop DR have no symptoms until the very late stages. Because the rate of progression may be rapid, and therapy can be beneficial for both symptom amelioration and reduction in the rate of disease progression It is important to screen patients with diabetes regularly for the development of retinal disease.

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S.Rohini is with Department of Electrical & electronics Engineering Department, Oxford Engineering College, TamilNadu , India. srohinishelvaraj@gmail.com

V.aghavendra Rajan is with Department of Electrical & electronics Engineering Department, Oxford Engineering College, TamilNadu , India.

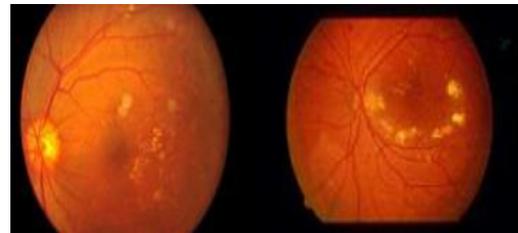
This project aims to detect the abnormalities in the retina such as the structure of Microaneurysms (MA), exudates and also an efficient retinal blood vessel segmentation using image processing techniques In some patient with diabetic retinopathy, blood vessels may swell and leak fluid . In other, new abnormal blood vessels grow on the surface of the retina that is why blood vessel segmentation is an important part of automated diabetic retinopathy screening system. A tool which can be used to assist in the diagnosis of diabetic retinopathy should automatically detect all retinal image features such as optic disk, fovea and blood vessel and all abnormalities in retinal image such as microaneurysms hard exudates and soft exudates, hemorrhages, and edema. Illumination equalization is needed to enhance the image quality as the acquired color retinal images are normally of different qualities.

Inspection of blood vessels provides the information regarding pathological changes caused by ocular diseases including diabetes, hypertension, stroke and arteriosclerosis . Patients with diabetes are more likely to have eye diseases . The hand mapping of retinal vasculature is a time consuming process that entails training and skill. Automated segmentation provides consistency and reduces the time required by a physician or a skilled technician for manual labeling .Retinal vessel segmentation may be used for automatic generation of retinal maps for the treatment of age-related macular degeneration. In this paper, I present segmentation using digital retinal images. I have used length filtering and CCA algorithms to remove false edges and for efficiency.

This process is achieved by the fundus images using morphological processing techniques to extract features such as blood vessels, MAs and exudates. Then the area is calculated of each extracted feature. Depending on the area of each feature and the number of MA and exudates the severity of the disease is classified. Then finally knowing the severity of the disease corresponding treatment measures can be analyzed. It will surely help to reduce the risk and increase efficiency for ophthalmologists.

From an image processing stand point the automatic detection of the MAs and exudates present various challenges. Their color and size is the same as the vessels. They have a variable size and often they are so small that can be easily confused with the images noise or vice versa. Even expert ophthalmologists do not always agree whether a red lesion is a MA or small dot Exudates.

A method for detecting MA and Exudates in retinal fundus images without using contrast medium is also proposed. The aim of the present project is to develop methods for detecting MAs in no contrast images of the retinal fundus. A MA and Exudates is one of the early signs of the onset of DR. It appears as a point lesion darker than the surrounding regions in retinal fundus images.



(c) (d)

Fig.1.1. (a)Healthy image (b)Mild DR (c)Moderate DR (d)Severe DR

The Input retinal fundus image database is received from hospital . The retinal image which is taken from Non-Mydriatic camera at 45° field of view (FOV) which has DRIVE & STARE databases. The Image size is 768 × 584 pixels, 8 bits per pixel with color mode, where the retina is illuminated by white light and examined in full color.

I. STEPS INVOLVED IN PREPROCESSING AND CANDIDATE EXTRACTION

A. WALTER KLEIN CONTRAST ENHANCEMENT:

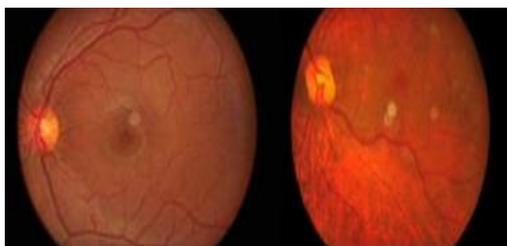
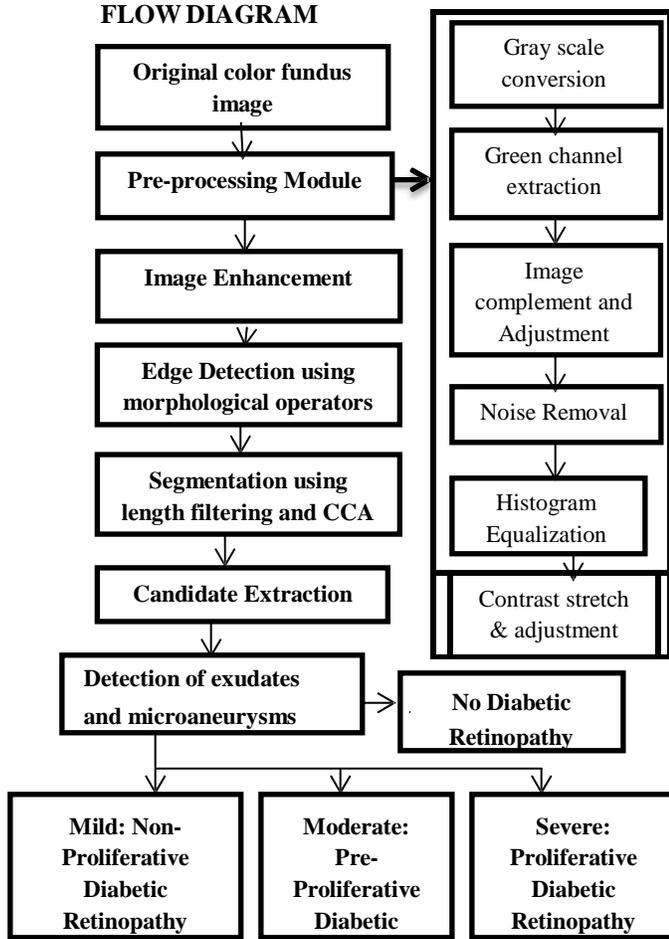
This preprocessing method aims to enhance the contrast of fundus images by applying a gray level transformation using the operator(f')

- Assigning the walter preprocessing operation in the variable.
- Computing the mean of the intensity values of original image and assigning into the variable (μ).
- Assign constant(r)=2
- Finding the smallest and the largest elements in the array and assigning it into the minimum and maximum intensity levels of the original and enhanced image. Where, f_{min} - minimum intensity level of the original image. f_{max} - maximum intensity level of the original image. f'_{min} - minimum intensity level of the enhanced image. f'_{max} - maximum intensity level of the enhanced image.

$$f' = \begin{cases} \frac{1}{2}(f'_{max}-f'_{min})(f-f_{min})^r + f'_{min}, f \leq \mu \\ \frac{1}{2}(\mu-f_{min})^r \\ \frac{-1}{2}(f'_{max}-f'_{min})(f-f_{max})^r + f'_{max}, f \geq \mu \\ (\mu-f_{max})^r \end{cases}$$

Implementing the formula. μ is the mean value of the original grayscale image. Performing the reshape operation for the f_{im} and assign it into the variable Finally displayed the walter Klein contrast enhanced image.

FLOW DIAGRAM



(a) (b)

B. CLAHE (CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALISATION):

Assign the CLAHE operation into the variable. Performing the adaptive histogram equalization to the original image(used to enhance the contrast of the image). Displaying the CLAHE image.

II. EDGE DETECTION USING MORPHOLOGICAL OPERATIONS AND SEGMENTATION

Medical images like retinal images edge detection is an important work for object recognition and noise and edge belong to the scope of high frequency. In real world applications, medical images contain object and object shadows and noise. Therefore, they may be difficult to distinguish the exact edge from noise. Mathematical morphology can be used to process and analyze the images. It provides an alternative approach to image processing based on shape concept from set theory not on traditional mathematical modeling and analysis. In the mathematical morphology theory, images are treated as sets, and morphological transformations which derived from addition and subtraction are defined to extract features in images. In this paper, a novel mathematical morphology edge detection algorithm is proposed to detect medical image edge. It is a better method for edge information detecting and noise filtering than differential operation, which is sensitive to noise. The purpose of detecting sharp changes in image brightness is to capture changes in properties of the retina. Discontinuities in image brightness are likely to discontinuities in depth, discontinuities in surface orientation, changes in material properties and variations in scene illumination. The result of applying an edge detector to an image may lead to a set of connected curves that indicate the boundaries of objects, the boundaries of surface markings as well as curves that correspond to discontinuities in surface orientation. Thus, applying an edge detection algorithm to an image may significantly reduce the amount of data to be processed therefore while preserving the important structural properties of an image. Dilation, erosion, opening, closing are the basic mathematical morphological operators.

Dilation is defined as the maximum value in the window. Hence the image after dilation will be brighter or increased in intensity. It also expands the image and mainly used to fill the spaces.

Erosion is just opposite to dilation. It is defined as the minimum value in the window. The image after dilation will be darker than the original image .It shrinks or thins the image.

Opening and closing both parameters are formed by using dilation and erosion. In opening, firstly image

will be eroded and then it will be followed by dilation. In closing, first step will be dilation and then result of this is followed by erosion. Opening is generally smoothens the contour of an image, breaks narrow gaps, eliminates holes, and fills gaps in the contours. Morphological tophat is implemented by first applying the opening operator to the original image, then subtracting the result from the original image.

All above operators perform their tasks by using structuring elements, which is a matrix of 0's and 1's with various sizes and shapes.

III. IMAGE SEGMENTATION

In order to find the vascular abnormalities, it is very important to extract vascular patterns accurately. The vessel varies in terms of structure, shape and size so it is difficult to extract them. Thin blood vessels or capillaries are less visible than the normal blood vessels and require enhancement before extraction. Mostly matched filters (MFs) are used for blood vessel enhancement but the drawback is that MFs not only enhance blood vessels edges but also enhance bright lesions. The goal of segmentation is to simplify and/or change the representation of an image into more meaningful and easier to analyze and is typically used to locate objects and boundaries (lines, curves, etc.) in images. First assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (edge detection). The image obtained after the edge detection operation contains pixels which are not classified as vessel. In order to produce a clean and complete vessel network these misclassified pixels are removed using length filtering. , the concept of CCA is used where connected components pixels which are identified above a specific threshold and labeled using eight connected neighborhood and are considered as a single object. The thresholding equation relates to standard deviation of gray levels; therefore, the large range of gray levels may cause that considering a single threshold for the entire image lead to loss of some parts of thin vessels. In order to deal with this problem, performing a kind of adaptive CCA, meaning that we consider images in separate tiles and apply CCA and length filtering to each tile, individually. By this means, there is no large range of gray levels in each block, and a proper threshold can be chosen which separates the false edges from vessel edges efficiently. After applying CCA, the components having length less than a specific threshold will be eliminated. As in length filtering and CCA is used to remove small vessel like structure that are not part of the vascular tree. Individual objects that resemble vessel like structure but are not part

of the vessel are removed. This algorithm that segments the retinal blood vessels in very short time with very high accuracy is presented. The false edges are removed by morphological reconstruction, while preserving thin vessels. The application of CCA and length filtering helped to remove the remaining false edges more accurately. Most of the thin and small vessels are detected by the usage of level dependent threshold in CCA. The various assessments prove that the proposed method segments the retinal blood vessels with an accuracy of more than 97% .

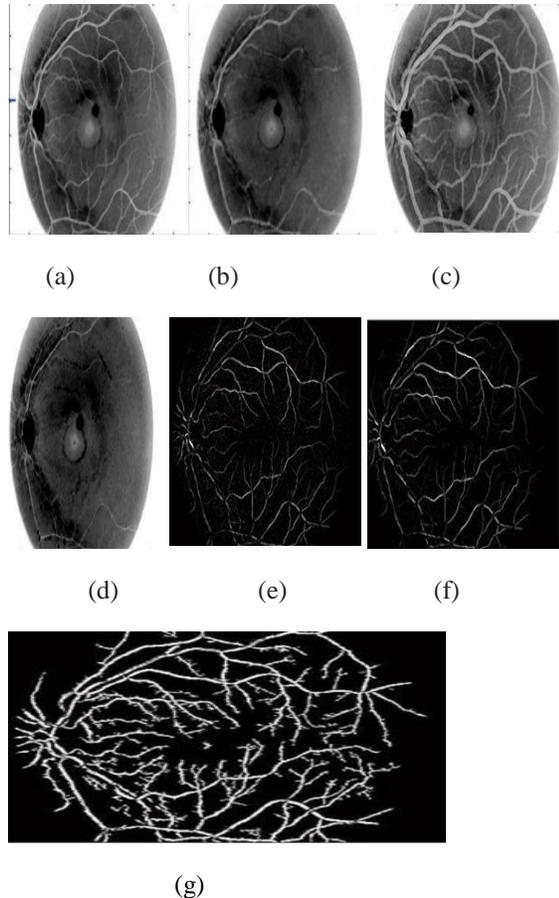


Fig 1.2 (a)Open (b)Close (c) Dilate (d)erode (e) Edge Detected (f)Reconstructed Images (g)Segmented Image

IV. STEPS FOLLOWED IN MULTILEVEL MA DETECTION

A. VESSEL REMOVAL METHOD:

To detect MA appearing near vessel and enhance it. Assign the vessel removal operation into the variable Performing the inpainting algorithm for conversion of image to double precision type. Displaying the vessel removed image.

B. ILLUMINATION EQUALISATION:

Assign the illumination equalisation operation into the variable (f)

- Assigning the desired intensity value. Converting the elements of original into uint8 and then compute the mean of the intensity values and then assign into the variable local average intensity.

- Subtract the local intensity value from the desired intensity value.

- $f = f + \mu d - \mu l$ where f , f are the original and the new pixel intensity values, respectively, μd is the desired average intensity, and μl is the local average intensity. MAs appearing on the border of the retina are enhanced by this step.

C. CANDIDATE EXTRACTORS

The approach proposes a mathematical morphology based one, which recommends contrast enhancement and shade correction as preprocessing steps. Candidate extraction is then accomplished by grayscale diameter closing. This method aims to find all sufficiently small dark patterns on the green channel.

Finally, a double threshold is applied. `medfilt2` performs median filtering of the matrix in 2D. Shade corrected image= `medfilt image - original image`. Creating disk shaped structuring element operation.

Where R -radius($R=7$) Performing morphological closing operation on the shaded image with the `strel`. The morphological close operation is a dilation followed by erosion, using the same structuring element for both operations. `Infill` fills the holes in the shade corrected image. Subtracting holes filled image by the morphological closed image and assign into the variable (`vess`) Computes a global threshold (`level`) and assign into the variable `alp`. `thres=max()` returns an array (`thres`) the same size as the variables (`alp`) with the largest elements taken from `alp`. Product the subtracted image and the `thres`. And assign into the variables

D. ENSEMBLE CREATION

In this framework, an ensemble E is a set of preprocessing method, candidate extractor or shortly PP, CE pairs. The meaning of a preprocessing method, candidate extractor pair is that first preprocessing method is applied to the input image That is, such a pair will extract a set of candidates HE from the original image. If an ensemble E contains more preprocessing method, candidate extractor pairs, their outputs are fused in the following way: for each candidate c , all such candidates of the other participants are collected, whose Euclidean

distance d is smaller than a predefined constant $r \in \mathbb{R}$ from c . Let I_c denote that the set of these points collected for a candidate c . Then, the centroid calculated from I_c is put into HE . Ensemble creation is a process where all ensembles E from an ensemble pool E is evaluated and the best performing one $E_{best} \in E$ regarding an evaluation function on a training set is selected.

To evaluate an ensemble E , its output candidate set HE must be compared to the ground truth in the following

way. if for a $c \in HE$ there exists a point in the ground

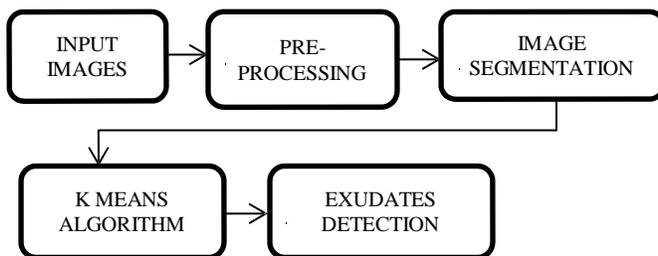
truth, whose Euclidean distance d from c is smaller than a predefined constant $r \in \mathbb{R}$, then c is considered as a true positive. Otherwise, c is false positive, while each ground truth point is a false negative that does not have a close candidate from HE . The selection of the optimal ensemble E_{best} would require each possible preprocessing method, candidate extractor ensembles to be evaluated.

However, currently $M = N = 5$ preprocessing methods and candidate extractors in this experiments is considered. That is, 25 preprocessing method, candidate extractor pairs with 225 numbers of possible combinations to form the ensemble. It would be very resource demanding to evaluate such a large number of combinations, so simulated annealing is used as a search algorithm to find the final ensemble, which is proven to be effective in such large search spaces. This ensemble E_{best} then can be used to detect MAs on unknown images. The final ensemble is applied in real detection in the same way as in the training phase. Namely, the final MAs are detected by the fusion of the MA candidates of the individual pairs building up the ensemble E_{best} . Similarly, for every detected MA, a confidence value as described earlier. Thus, for the final decision on the presence of MAs, the output MA set needs to be thresholded according to the assigned confidence values.

V EXUDATES DETECTION AND LOCATION

Exudates are lipid leakages from blood vessels which are visible signs of an early stage of retinal abnormality in DR. It appears as bright lesion in retinopathy images and have sharp edges and high contrast with the background.

FLOWCHART & METHODOLOGY FOR EXUDATE DETECTION



A. Retinal color normalization

One of the main obstacles for detection of retinal exudates is the wide variability in the color of retinal image from different patients. These variations are strongly correlated to skin pigmentation and iris color. Thus, the color of exudates in some region of an image may appear dimmer than the background color of other regions. As a result, the exudates can wrongly be classified as the background. In fact, without some type of

color normalization the larger variation in the natural retinal pigmentation across the patient dataset can hinder discrimination of the relatively small variations between the different lesion types. The two methods are histogram equalization and histogram specification. Histogram specification is found to be most appropriate for the restoration of the retinal image. Therefore, a retinal image is selected as a reference and applied the described histogram specification technique to modify the values of each image in the dataset such that its frequency histogram matched the reference image distribution. The histogram specification technique was independently applied to each individual RGB channel to match the shapes of three specific histograms of the reference image. The color normalization process improves the clustering ability of the different lesion types and removes the variation due to the retinal pigmentation differences between individuals.

B. Contrast enhancement

The retinal images taken at standard examinations are sometimes poorly contrasted and contain artifacts. The retinal image contrast is decreased as the distance of a pixel from the center of the image increased. Moreover, non-uniformity of illumination raises the intensity levels in some regions of an image, while other regions farther away from the optic disc may suffer from a reduction of brightness. Thus, the exudates or similar lesions in such regions are not distinguishable from the background color near the disc. The retinal image quality has a great impact on the features of retinal lesions, especially exudates. Local contrast enhancement is applied to a transformation of the values inside small windows in the image in a way that all values are distributed around the mean and show all possible intensities.

The size of window M should be chosen to be large enough to contain a statistically representative distribution of the local variations of pixels. On the other hand, it must be small enough to not be influenced by the gradual variation of the contrast between the retinal image center and the periphery. The local contrast enhancement depends on the mean and variance of the intensity values within the considered local region. The exponential function produces significant enhancement when the contrast is low (σ_w is small), while it provides less enhancement if the contrast is already high (σ_w is large).

C. Color space selection

The first task in image processing is to choose an appropriate representation using a color space definition. There are several different color spaces in the literature and each has its own advantages. Indeed, there is no color space that better than the others and suitable for all kinds of images.

To select the most appropriate color space, a quantitative analysis is conducted and utilize the evaluation function value $J = \text{trace}(S_b/S_w)$ as a measure of color space efficiency.

This function estimates the class separate of exudates and non-exudates pixels classes in different color space and was measured using within-class and between class scatter matrices. The within-class scatter matrix (Sw) indicates the distribution of sample points around their respective mean vectors and (Sb) represents the scatter of samples around the mean vector of class mixture.

In fact the numerator of function J represents the overall color difference of exudates and non-exudates sample points, while the denominator denotes the variations of the color distribution for these two classes. A higher value of J shows that the classes are more separated, while the numbers within each class are closer to each other.

D. Optic localization

Optic Disc (OD) localization is indispensable in this automatic exudates detection approach, since it illustrates similar attributes to the exudates in terms of color, brightness and contrast. By detecting it from the exudates classification process can be removed. To locate OD in this study, two techniques are combining Morphological Reconstruction (MR) and Otsu algorithms are presented. The implementation steps of using a MR methods and Otsu algorithm to detect the OD boundary.

E. K means Algorithm

K-means Algorithm is used in this project to localize the Exudates. The general syntax of kmeans algorithm is given below,

Syntax

```

IDX=                                kmeans(X,k)
[IDX,C]=                             kmeans(X,k)
[IDX,C,sumd]=                         kmeans(X,k)
[IDX,C,sumd,D]=                       kmeans(X,k)
[...] = kmeans(...param1, val1, param2, val2, ...)
    
```

Description $IDX = kmeans(X,k)$ partitions the points in the n-by-p data matrix X into k clusters. This iterative partitioning minimizes the sum, over all clusters, of the within-cluster sums of point-to-cluster-centroid distances. Rows of X correspond to points, columns correspond to variables. K means returns an n-by-1 vector IDX containing the cluster indices of each point. By default, k means uses squared Euclidean distances.

- $[IDX,C] = kmeans(X,k)$ returns the k cluster centroid locations in the k-by-p matrix C.
- $[IDX,C,sumd] = kmeans(X,k)$ returns the within-cluster sums of point-to centroid distances in the 1-by-k vector sumd.
- $[IDX,C,sumd,D] = kmeans(X,k)$ returns distances from each point to every centroid in the n-by-k matrix D.

F. Conversion to gray-scale image

The OD is the exit point of retinal nerve fibers from the eye and exit point for retinal vascular.

It solves this problem and the result is much smoother image, which is depicted. In this step, gray-scale

closing operator (\odot) applied to the intensity or lightness channel (CI). $OD = \phi(B1)(CI)$

Where, B1 is the morphological structuring element. This stage, a flat disc shaped structuring element with a fixed radius of eight is used. It is evident that this approach produces a more homogeneous region while preserving the OD edges.

G. Binary segmentation

The examples above illustrate the used of gray scale reconstruction in OD analysis tasks. However, it is probably for binary segmentation that this operation is most useful. Therefore, a threshold is applied to binary segmentation and threshold image was then used as a mask. The resulting image is binarized by thresholding and the thresholded image is then used as a mask. All the pixels in the mask are inverted before they are overlaid on the original image to remove candidate bright regions. $OD_3(x) = R_{CI}(OD_2)$

H. Identification of OD

Typically, the OD can be seen brighter than the surrounding area. Despite its brightness, an accurate localization is not an easy task as some part are obscured by crossing blood vessels and in some case, such as the affected of bright the lesions. However, the shape of OD is round; therefore the OD region selection process needs to be made specific to the largest one among the regions and compactness whose shapes are circular. $OD_{seg} = \delta(M2)(OD_3)$

The selected result, OD5, is dilated with a binary dilation operator (δ) to ensure that all pixels in the OD area are covered. This step, a flat disc-shaped structuring element with a fixed radius of six (M2) is used. (M2). All OD area in original image is masked out using the previous output.

VI. DR GRADING

Ensemble-based approach is also evaluated for grading performance to recognize DR. For this aim, the image-level classification rate of the ensemble is determined if any MA means that the image contains signs of DR, while the absence of MAs indicates a healthy case. The Criteria used for grading the diabetic retinopathy is described in Table 1

TABLE I
 CRITERIA USED FOR GRADING DIABETIC RETINOPATHY

DR stages	
Grade 0 (no DR)	MA = 0 and E = 0
Grade 1 (mild)	$1 \leq MA \leq 5$ and $E = 1$ or 2
Grade 2 (moderate)	$5 < MA < 15$ or $0 < E \leq 5$
Grade 3 (severe)	$MA \geq 15$ or $E > 5$

MA = microaneurysm, E = Exudates

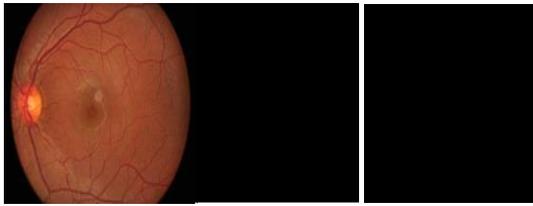


Fig (a) no DR

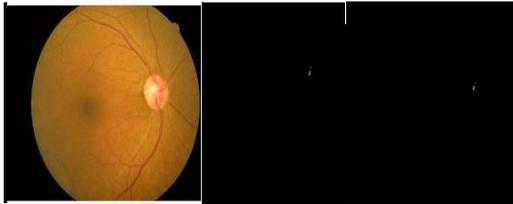


Fig (b) Mild



Fig (c) Moderate

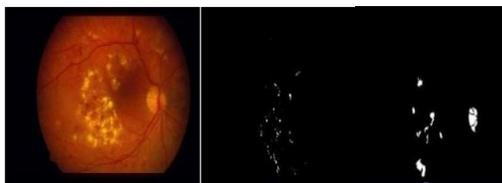


Fig (d) Severe

CONCLUSION

□ In this project, an efficient blood vessel segmentation and ensemble-based MA and Exudates detector is proposed that have proved its high efficiency. This novel framework relies on a set of preprocessing method, candidate extractor pairs, from which a search algorithm selects an optimal combination. Since this approach is modular, further improvements can be expected by adding more preprocessing methods and candidate extractors.

□ DR is a serious eye disease that originates from diabetes mellitus and is the most common cause of blindness in the developed countries. Early treatment can prevent patients to become affected from this condition or at least the progression of DR can be slowed down. Thus, mass screening of patients suffering from diabetes is highly desired, but manual grading is slow and resource demanding. Therefore, much effort has been made to establish reliable computer aided screening systems based on color funds images. An effective MA

detector based on the combination of preprocessing methods and candidate extractors is proposed in this work. An exhaustive quantitative analysis is also given to prove the superiority of our approach over individual algorithms. The grading performance of this method is also investigated, which is proven to be competitive with other screening systems.

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