Automated Microaneurysms Detection and Grading of Diabetic Retinopathy

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Abstract— The early detection and diagnosis of Diabetic Retinopathy (DR) is useful in avoiding vision loss. Microaneurysms (MA) are the earliest symptom of DR. The detection of MA is very difficult since most of its characteristics resemble the other features in Retinal fundus image. An automated MA detection algorithm is developed and the accurate detection of MA is used to classify and grade the stages of DR. The stages are non-proliferative or initial stage and proliferative or critical stage. An automated mass screening of Diabetic Retinopathy can be done by using the proposed method. The method involves better pre-processing steps to enhance and highlight the MA. Then it is followed by blood vessel removal by morphological operation. Based on MA detection DR stage is graded by the number of true positive values of MA. The proposed method gives appreciable true positives when compared with the standard ground truth images. The proposed method can be incorporated as an integrated technique and also a software tool to identify initial symptoms and stages for diabetic retinopathy especially for diabetic patients. This method is an automated method and does not involve human intervention at any stage. This method has very high specificity, which shows that algorithm does not recognize non-microaneurysms pixel as microaneurysms.

Index Terms— Diabetic retinopathy (DR), grading, Adaptive Histogram equalization, Microaneurysm (MA), Blood vessel, Mass screening.

I. INTRODUCTION

Diabetes is due to the increase of blood glucose level and is one of the increasing health threats worldwide. Diabetes causes abnormalities in certain part of the body like Diabetic Retinopathy-eye, Diabetic Nephropathy- Kidney, and Diabetic Neuropathy- Nervous system. The global prevalence of diabetes is expected to rise by 4.4% of global population in the year 2030. According to WHO, there will be 79 million people with diabetes by 2030, making India, Diabetic capital of the world. Diabetic Retinopathy (DR) is the common cause of blindness in the working age and also in developing countries. DR is the second cause of blindness worldwide. DR causes damage to the blood vessels in the retina. These abnormal blood vessels leak the fluid and block the vision and finally retinal detachment takes place. Diabetic Retinopathy is of two types as Non-Proliferative & Proliferative type. Non-proliferative stage is the
early stage of the diseases characterized first by the presence of MAs. When the disease progresses, exudates are created. As the disease further progresses it leads to proliferative stage. This stage is characterized by the formation of new blood vessels. The scanning of diabetic patients for the development of DR can reduce the risk of blindness by 50%. Mass screening programme can be conducted at a reduced cost for the working age group particularly in developing countries. Vision loss can be prevented from early detection of DR and early treatment. Different kinds of abnormal lesions caused by DR are MAs, Soft Exudates, Hard Exudates, Haemorrhages and Neovascularisation.

Microaneuysms (MAs.) are small red dots on the retinal surface, which occur due to capillary occlusion. MAs, is the first sign of DR. MA detection is very important, because its structures constitute the features of diseases like hypertension, coronary atherosclerosis. Sometimes lung cancer is transferred to eyes, through bloodlines which cause MAs. The characteristics of MA are a) Red lesions and they don’t appear on large visible vessels, and disconnected from vasculature b) MA cause intra-retinal haemorrhage (H) when ruptured. c) MAs size varies from 10 to 100 microns in diameter and appears as red dots.

The paper is organized as follows. In section II, related work is being discussed. Section III discusses about the proposed method. In section IV results and discussion are focused, followed by conclusion and References.

II. RELATED WORKS

The previously done works in grading Diabetic Retinopathy by various experts are summarized as follows. A.M. Mendonca et. al. [1], used median filter to obtain a normalized image, scaling as pre-processing techniques. The MA’s are differentiated from blood vessels by morphological top-hat transform. On the other hand C.Sinthanayothin et. al [2], proposed a recursive region growing algorithm for the detection of DR for the automated system. In [3] paper, a combination of recursive region growing plus adaptive threshold method for the detection of lesions is been discussed. Neural network training algorithm is used for classification purposes. The next work is based on fuzzy techniques. The steps adapted are edge zero padding followed by histogram equalization. The segmentation methods used are simple thresholding, K-means and compared with fuzzy c-means algorithms. [4].In [5], Walter et al, proposed a method based on diameter closing and Kernel density estimation for automatic classification. In [7], J.S.Manisha et. al utilised component labelling to count the number of haemorrhages, utilised to grade DR. In [10], Zhang et al proposed a method, which becomes a next inclusion in Grading DR. The method finds the correlation coefficient between MA & Gaussian filter. A CAD approach for MA is presented. In [11], Giri.B.K. Proposed an efficient approach for red lesion included Microaneuysms and based on pixel classification and mathematical morphology. On the other hand A.Shaeidi [12], used dynamic thresholding method for the change in shape of MA and to identify MA pixel based on many features like colour, shape etc.

In [13], Balint Antal presented a complex approach MA’s detection. A combination of pre-processing methods is used and tested the results with various candidate extractor algorithms. At all these levels, simulated annealing methods are used and MA is classified using a machine learning approach. B.Dupas et. al. [14], used a method based on diameter closing to separately segment MA candidate regions and K-nearest neighbour classification method is used. Akara Sopharak et. al. [15], went on investigating a set of optimally adjusted morphological operators for MA detection and Exudates also [6], by the same authors. The detected MAs, exudates are verified with various Ophthalmologists by comparing performance parameters like sensitivity, positive predictive value (PPV), and positive likelihood ratio (PLR) [9]. Xuwenhua [16], improved and presented a non-uniform enhancement method to achieve a good SNR. The same authors referred from [8], that microaneuysms are induced by tumour eye transfer particularly by lung cancer. In [18], Christy el al explained candidate extraction algorithms added with edge detection methods to improve the quality of MAs detection. The Support Vector Machine classifier is used for classifying the detected MA and based on the result regression analysis is done, explained by J.Prakash et al in [19]. In [20], I. Lazar et al proposed microaneuysm detection by directional cross-section analysis and the statistical attributes helps in choosing the correct orientation, to avoid false positives.

It is very difficult to detect MA, whose pixel size is similar to blood vessels. MA is not easily distinguished from the background noise variations, because of its low contrast. The detection of MA at its early stage helps to prevent vision loss. Also, it is possible to grade the severity of DR as NO DR, Mild DR, Moderate and Severe DR. [2].
III. PROPOSED METHOD

The proposed method has two main phases. One as pre-processing helps to differentiate MA compared to its background in a better visual interpretation. It includes many stages like adaptive equalization methods followed by proper illumination correction methods. The second phase includes Grading of Diabetic Retinopathy. The stages are MA detection and elimination of other features such as Optic disk and blood vessels. The correctly detected MA is used for grading process. The grading also needs performance of various features related to MA. So, performance metrics are evaluated.

Input image is a RGB image and any one of the channel to be extracted. The green/gray channel has a better contrast when to the other two channels. Better contrast is achieved with the background images for MA detection. Hence, green channel is considered as natural basis for MA detection algorithms. [11]. The pre-processing step is involved in order to avoid or reduce non-uniform illumination of Fundus images during acquisition, removal of noise if present etc and make the image suitable for MA detection.

A. Preprocessing Fundus Image

Pre-processing Steps.

Algorithm 1:
Step 1: Get the Input Image as RGB input.
Step 2: Resize the Original Image
Step 3: Extract the green Channel
Step 4: Filter using the median filter
Step 5: Apply Contrast Limited Adaptive Histogram Equalization
Step 6: Apply Shade Correction

1) RGB to Green channel: The RGB image is resized to the standard size. Then, green channel component is extracted using suitable method. The contrast should be the main criteria at this stage. MAs appear with the high contrast in green channel.

2) Median filter: Median filter is a non-linear filtering technique, used to remove noise by preserving its edge. Median filter is a sliding window spatial filter. For every pixel, a 3x3 neighbourhood with the pixel centre is calculated and the value of each pixel is replaced by the median pixel value of 3x3 neighbourhoods.

3) Contrast - Limited Adaptive Histogram Equalization (CLAHE): - The contrast limiting procedure is applied for each neighbourhood of median filtered image. The image is divided into corner regions (CR), border regions (BR), and inner regions (IR) as in the Figure No. 1

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
CR & BR & BR & CR \\
\hline
BR & IR & IR & BR \\
\hline
BR & IR & IR & BR \\
\hline
CR & BR & BR & CR \\
\hline
\end{tabular}
\caption{Region Formations}
\end{table}

Desired limit of contrast expansion is done by calculating the histogram of each region. The clip limit $\beta$ for the clipping histogram is given by

$$\beta = \frac{N}{M} \left(1 + \frac{\alpha}{\alpha_{max}} (\beta_{max} - 1)\right) \quad (1)$$

$M$ - Number of pixels  
$N$ - Number of gray scales  
$\alpha$ - Clipping factor, $\beta_{max}$ - maximum distribution of slope

Each histogram is redistributed as its height does not go beyond the clip limit. The corresponding resultant cumulative distribution function is given by equation (2).

$$f_{ij}(x) = \frac{N-1}{N} \cdot \sum_{j=1}^{N-1} f_{ij}(x)$$ \quad (2)$$

$n=1, 2 \ldots N-1$

Contrast limited histogram equalized image for the fundus image is obtained.
4) Shade Correction: Shade correction is used to remove large scale image background variations. These variations are due to non-uniform illumination of fundus image because of physiological differences, such as the foveal avascular zone. An estimate of the background will remove low spatial frequencies from the image. This may be achieved using a low pass filter. The background estimate may then be subtracted from the original image to correct for background variation is the shade correction.

\[ I_{SC} = I_{CLAHE} - I_{BACKGROUND} \]

Thus, the pre-processing steps are done and the fundus image is used to extract MA.

B. MA Detection and Extraction

Candidate extraction

Candidate or feature extraction is done to reduce the number of objects from the pre-processed image, which does not have the similar characteristics as that of MA. This is done to improve the true detection of MA and to avoid the false positives. MAs are isolated patterns and are disconnected from the blood vessels and do not appear on the blood vessels, whereas blood vessel structure is a connected component. MAs are dark red in colour and appear as small dots between 10 to 100 microns diameter, circular in shape.

For, MA detection all other healthy features are to be removed such as optic disk, macula, and blood vessels. The brightest optic disk and darkest macula are removed in the preprocessing step itself by the background and foreground intensity variation. But, blood vessel to be carefully removed whose characteristics are partially like MAs. So, Blood vessels are removed in this stage.

The resulting image after blood vessel removal consists of MAs plus little noise. Noise is to be removed based on the features like area, perimeter, Roundness metric, Energy, Correlation etc. Finally, based on the roundness metric i.e. circularity feature, MAs are extracted.

Algorithm 2:

Input: Pre-processed Shade corrected Green channel Image
Output: Microaneurysms

Step 1: Top Hat Transform of shade corrected image
Step 2: Blood vessel detection and removal
Step 3: Candidate extraction with Noise
Step 4: Performance Metrics calculation
Step 5: Noise removal compared from metric value i.e. MA Detection

1) Top-Hat Transform: Top-Hat transform is a gray scale morphological operator used to find the candidates MA, proposed by Spencer et. al. This operation extracts small elements and details from the fundus image. The white top-hat transform is the difference between the shade corrected image and its opening by the structuring element of 11 pixels is chosen. The top-hat transforms are images that contain only non-negative values at all pixels.

\[ I_{TOP-HAT} = I_{SC} - I_{OPENSHADECORRECTEDIMAGE} \]

Opening Operation

Opening smooth the inside of the object contour, breaks narrow strips and eliminates thin portion of the image. Opening operation of image is defined as erosion followed by dilation. The opening operation can be mathematically given by (5)

\[ A \circ B = (A \ominus B) \oplus B \]

A- Input Image, B- Structuring element

Erosion can be represented as

\[ A \ominus B = \{(x,y) - (u,v) : (x,y) \in A, (u,v) \in B\} \]

Erosion shrinks the image as indicated in Figure 2. Dilation can be represented by (7) and Dilation is the expansion of the image represented by Figure 2.

\[ A \oplus B = \{(x,y) + (u,v) : (x,y) \in A, (u,v) \in B\} \]
2) Gaussian Masks: The shape of MA is distributed like the Gaussian structure is used to detect MA by using similarity gray scale distribution. The combination of Gaussian masks combined to get the final Gaussian response for MA detection. The top-hat image is filtered using the Gaussian filter and the filtered image highlights the presence of MA.

\[ G(x, y) = \frac{1}{\sqrt{2\pi \sigma^2}} e^{-\frac{x^2 + y^2}{2\sigma^2}} \]  

(8)

3) Vessel detection and Elimination: The vessels are detected and eliminated using morphological operator.

Step 1: Shade corrected image is closed using the disc shaped structuring element of size 8.
Step 2: Shade corrected image is filled to remove all the Holes in the vessel
Step 3: Filled image is subtracted from closed image to get the segmented vessels.
Step 4: Suitable threshold is applied to the segmented vessels to get binary of vessels.
Step 5: Vessel segmented binary image is subtracted from Gaussian filtered binary image to remove the vessels.

Closing Operation: The closing of \( A \) by \( B \) is obtained by the dilation of \( A \) by \( B \), followed by erosion of the resulting structure by \( B \).

\[ A \ast B = \left( A \oplus B \right) \ominus B \]  

(9)

4. Feature Extraction and removal of noise: The feature extraction is used to select all Microaneurysms, from the vessel removed structure. MAs are isolated patterns and are disconnected from the vessels. The features of MAs can be extracted based on shape, size etc. Each object’s area and perimeter is calculated used to find the roundness of the object. [4]

\[ \text{Roundness metric} = \frac{4\pi \text{Area}}{\text{Perimeter}^2} \]  

(10)

Objects which have area greater than 11 pixels and roundness metric less than 0.95 are removed which is not MA. Metric is equal to one for a circle and it is less than one for any other shape. Metrics closer to one indicates the MA. In the resulting image, who’s metric less than one is removed and the resulting image is free from noise. The output image contains only the possible MA candidates.

IV. RESULTS AND DISCUSSION

The proposed method is tested and evaluated on publicly available databases, namely DRIVE and DIARETDB1 database. DIARETDB1 provides 89 images with a variety of diagnoses captured by a Topcon TRV-50 fundus camera at 45 degree FOV in PNG format. DRIVE photographs are obtained from DR screening program in Netherlands, used for clinical diagnoses. Images acquired using Canon CR5 non-mydriatic 3 CCD cameras with a 45 degree FOV, in TIFF format.

Figure 3(a) & 4(a) is the original Input RGB image, whose size is not uniform. The RGB image is resized to obtain the standard size for further processing. As, MA appear in red colour, its contrast is better in green channel, its extraction is done. Green channel image is shown in Figure 3(b) & 4(b). Then, contrast limited adaptive histogram equalization is applied, whose clip limit is adaptively selected. This adaptive method shows the individual MA identification in an efficient manner. The resulting image has specific importance
in identifying the diseased condition. The image is shown in Figure 3(c) & 4(c). Shade correction is done and the image is shown in Figure 3(d) & 4(d). Thus, preprocessing steps are done and image is ready for extraction of MA.

Next phase is the candidate MA extraction. MA like structures such as blood vessels and other healthy features such as optic disk and macula should be removed. The size of blood vessel is almost equivalent to MA and both are red in colour. Figure 3(e) & 4(e) shows the segmented blood vessels. The segmented blood vessels are obtained by set of morphological procedures like top hat transform followed by Gaussian filter, which filters out small structures. The resulting image is morphologically treated for blood vessel detection and elimination. Figure 3(f) & 4(f) shows the final image, which consists of MA with noise present. Therefore feature extraction is done to isolate MA alone. Roundness metric is calculated, and MA is extracted as shown in Figure 3(g) & 4(g).

![Image of steps in identifying the diseased condition](image)

In resultant image 1, from the extracted MA image, it can be classified as diseased (Since MA is present) and for resultant image 2 can be classified as NO DR image. (No MA present). Further the same proposed method is tested with 89 images of diaretdb1 images and the results are tabulated for grading of Diabetic retinopathy. From, the tabulated results DR can be graded based on the reference table.

### A. Grading of DR Based on MA

The numbers of MA’s are counted by number of blobs measurement and DR stage is classified based on count of MA. A reference table explained by Table 1, is introduced to classify the Stage of DR. The stages are
No DR, Mild, moderate and severe. The healthy persons (persons with no DR) retinal fundus image is imaged periodically and analyzed using the proposed method. Further, prevention of DR is possible for diabetic patients. The diabetic patients are often prone to diabetic retinopathy over a long period of time. So, periodical non-invasive imaging is necessarily needed. As, MA is the earliest symptom for DR, DR could be prevented very easily by periodical monitoring of healthy persons.

Criteria used for grading DR [17]

<table>
<thead>
<tr>
<th>S.N</th>
<th>Grade</th>
<th>DR Stage</th>
<th>Number of MA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Grade 0</td>
<td>No DR</td>
<td>MA=0</td>
</tr>
<tr>
<td>2.</td>
<td>Grade 1</td>
<td>Mild stage</td>
<td>1 ≤ MA ≤ 5</td>
</tr>
<tr>
<td>3.</td>
<td>Grade 2</td>
<td>Moderate</td>
<td>5 ≤ MA ≤ 15</td>
</tr>
<tr>
<td>4.</td>
<td>Grade 3</td>
<td>Severe</td>
<td>MA ≥ 15</td>
</tr>
</tbody>
</table>

B. Grading and Classification of Diabetic Retinopathy

A set of 89 images from DIARETDB1 database are tested and a random selection of results for 20 images are tabulated. The proposed method gives high number of true positive values. The results are appreciable in
comparison with ground truth images. The Diabetic Retinopathy stages are graded and patients are treated accordingly.

<table>
<thead>
<tr>
<th>Images</th>
<th>Number of MA</th>
<th>Grade</th>
<th>DR Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image001</td>
<td>6</td>
<td>Grade-2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image002</td>
<td>6</td>
<td>Grade-2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image003</td>
<td>13</td>
<td>Grade-2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image004</td>
<td>3</td>
<td>Grade-1</td>
<td>Mild DR</td>
</tr>
<tr>
<td>Image005</td>
<td>19</td>
<td>Grade-3</td>
<td>Severe</td>
</tr>
<tr>
<td>Image006</td>
<td>7</td>
<td>Grade-2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image007</td>
<td>15</td>
<td>Grade-2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image008</td>
<td>20</td>
<td>Grade-3</td>
<td>Severe</td>
</tr>
<tr>
<td>Image009</td>
<td>11</td>
<td>Grade-2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image010</td>
<td>23</td>
<td>Grade-3</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image011</td>
<td>23</td>
<td>Grade-3</td>
<td>Severe</td>
</tr>
<tr>
<td>Image012</td>
<td>1</td>
<td>Grade-0</td>
<td>No DR</td>
</tr>
<tr>
<td>Image013</td>
<td>15</td>
<td>Grade-2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image014</td>
<td>14</td>
<td>Grade-2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image015</td>
<td>12</td>
<td>Grade-2</td>
<td>Moderate</td>
</tr>
<tr>
<td>Image016</td>
<td>40</td>
<td>Grade-3</td>
<td>Severe</td>
</tr>
<tr>
<td>Image017</td>
<td>5</td>
<td>Grade-1</td>
<td>Mild DR</td>
</tr>
<tr>
<td>Image018</td>
<td>18</td>
<td>Grade-3</td>
<td>Severe</td>
</tr>
<tr>
<td>Image019</td>
<td>29</td>
<td>Grade-3</td>
<td>Severe</td>
</tr>
<tr>
<td>Image020</td>
<td>23</td>
<td>Grade-3</td>
<td>Severe</td>
</tr>
</tbody>
</table>

In table 2, a set of 20 randomly selected images results are given. From the table, the DR groups are obtained as No DR (1 No), Mild stage (2), Moderate (10), Severe (7). The concentration is laid more on the mild stage, moderate stage and those patients can be easily treated and further progress of disease can be avoided.

V. CONCLUSION

In this paper, an automated detection of Microaneurysms for Diabetic Retinopathy is presented. The proposed method will help the Ophthalmologists for mass screening of diabetic patients for Diabetic Retinopathy. By detecting the blood vessel network, the chance of diagnosing wrongly for DR is avoided. This proposed method can be used to early diagnose of DR, by detecting its primary and first symptom namely, the Microaneurysms (MAs). The blood vessels network, the major complicated anatomy of fundus image is removed, which makes the system easier. The final output image shows only the MA, and by counting the number of MAs, the severity of the disease is identified, and DR is graded. The proposed method can be added with Haemorrhage and exudates detection, so that further progress of disease is monitored and controlled. And also, this method can be applied for clinical validation by the calculation of performance indices. A total software package can be devised, which could be used for socio and economic mass screening programme.

REFERENCES