CHAPTER 6
DETECTION OF DIABETIC MACULOPATHY FROM RETINAL IMAGES

6.1 BACKGROUND

Two main mechanisms account for loss of vision arising as a consequence of diabetic retinopathy: Macular edema and proliferative retinopathy. Macular edema is the accumulation of fluid called exudate in macula. This is the main cause of vision loss and its rising prevalence is predicted. The retina is the inner and most important layer of the eye. It is composed of several important anatomical structures which can indicate various diseases. Cardiovascular disease such as stroke and myocardial infarction can be identified from retinal blood vessels. Diabetic Retinopathy is the retinal complication commonly associated with diabetes. It is a major cause of blindness in both middle and advanced age groups.

Exudates are one among the primary signs of Diabetic Retinopathy [79]. They are yellow-white lesions with relatively distinct margins. They are lipids and proteins that deposit and leak from damaged blood vessels located in the retina. Detection of Exudates by ophthalmologists is a laborious process considering the enormous time they have to spend in manual analysis and diagnosis. Manual detection requires use of chemical dilation material which takes time and has negative side effects on the patients. Hence automatic screening techniques for exudates are preferred.

6.2 STEPS INVOLVED FOR THE ANALYSIS

6.2.1 Imaging and Image Acquisition

This study was performed on 60 Indian subjects whose age ranged from 50 - 85 years. The details of the data collection, inclusion and exclusion criterion were described in Chapter-3, section-3.2.1. Fifty images were selected for this analysis based on the severity of the disease. The digital image of the affected eye was acquired using a digital fundus camera in combination with Visupac image management software system. The
acquired digital fundus images (CARL ZEISS FF 450 plus) were of size 640 \times 480 and stored on the local hard drive of a computer system for further analysis.

6.2.1.1 Algorithm for Detection of Diabetic Maculopathy

The steps involved in the development of the Diabetic Maculopathy system are presented below:

Step 1: Get the input image

Step 2: Obtain the Green component of the image (G) from the original RGB image

Step 3: Apply median filter and contrast limited adaptive histogram equalization to the green component of the image

Step 4: Apply Top-Hat transform to the image G and add the result with the image G. Let the output image be T1

Step 5: Apply Bottom-Hat transform to the image G

Step 6: Subtract the result with the image T1

Step 7: Macula, which is the darkest region of an image is detected

Step 8: End the process

The flow chart for diabetic maculopathy is shown in Figure 6.1. The input retinal image has been acquired from the Diabetic Patients. The input image is in RGB color space. The green component alone has been extracted from the input image since it contains vast information on the darkest region. It is then applied to the median filter for removing the noise. The image is enhanced through use of the Contrast Limited Adaptive Histogram Equalization. The histogram equalized image is then subjected to the Top-Hat Transform. The input image and the green component of the image are shown in Figure 6.2 and Figure 6.3.

6.2.1.2 Contrast Enhancement

The Colour fundus images often display significant lighting variations, poor contrast and noise. A preprocessing comprising the following is applied
for reducing these [94] and for generating images highly suitable for extracting the pixel features in the classification process. 1) RGB to HSI conversion 2) Median Filtering 3) Contrast Limited Adaptive Histogram Equalization (CLAHE).

(1). RGB to HSI Conversion

The input retinal images in RGB Colour space are converted to HSI colour space. The noises in the images are due to the uneven distribution of the Intensity (I) component [95].

(2). Median Filtering

In order to distribute the intensity throughout the image uniformly, the I-component of HSI colour space is extracted and filtered out through a $3 \times 3$ median filter.

(3). Contrast Limited Adaptive Histogram Equalization (CLAHE)

The Contrast Limited Adaptive Histogram Equalization is applied on the filtered I-component of the [96]. Figure 6.4 and Figure 6.5 shows the green component output and CLAHE output. The histogram equalized I component is combined with HS component and transformed back to the original RGB colour space.
Figure 6.1. Flow diagram for the proposed diabetic maculopathy detection system

Figure 6.2. Sample retinal Fundus image used in this analysis.
Figure 6.3. Green component of an input retinal image

Figure 6.4. Histogram of the Green component

Figure 6.5. CLAHE-green component
6.2.1.3 Morphological Operation

In this section, the basic operations of dilation, erosion, opening and closing to gray-scale images are discussed, which is used to detect the white and black regions in the image. Diabetic Maculopathy is a white region which is detected by the above operations. Assume that \(f(x, y)\) is a gray-scale image and \(b(x, y)\) is a Structuring Element (SE) and both functions are discrete. Similar to binary morphology [96], the structuring elements are used to examine a given image for specific properties. SE belongs to one of two categories.

None flat (continuous variation of intensity rarely used) and flat. The origin of SE must be specified. Unless mentioned otherwise, SEs is flat, symmetrical, of unit height, with the origin at the center.

(1). Erosion

The erosion of \(f\) by a flat structuring element \(b\) at any location \((x, y)\) is defined as the minimum value of the image in the region coincident with \(b\) when the origin of \(b\) is at \((x, y)\). Therefore, the erosion at \((x, y)\) of an image \(f\) by a structuring element \(b\) is given by Equation 6.1:

\[
(f_b)(x,y) = \min_{t,s} \{f(x+s, y+t)\}
\]  

(6.1)

Where, similar to the correlation, \(x\) and \(y\) are incremented through all values required so that the origin of \(b\) visits every pixel in \(f\). That is, to find the erosion of \(f\) by \(b\), the origin of the structuring element is placed at every pixel location in the image. The erosion is the minimum value of \(f\) from all values of \(f\) in the region of \(f\) coincident with \(b\). Since gray-scale erosion with a flat SE computes the min intensity value of \(f\) in every neighbourhood, the eroded gray scale image should be darker (bright features are reduced, dark features are thickened and background is darker).

(2). Opening and Closing

The dilation of \(f\) by a flat structuring element \(b\) at any location \((x, y)\) is defined as the maximum value of the image in the window outlined by \(b\) when the origin of \(b\) is at \((x, y)\).
That is Equation 6.2:

\[
[fb](x\Theta y) = \max_{(x-s, y-t)} \{ f(x-s, y-t) \}
\]  

(6.2)

The explanation is similar to the one for erosion except for using maximum instead of minimum and that the structuring element is reflected about the origin. Since gray-scale dilation with a flat SE computes the min intensity value of \( f \) in every neighbourhood, the dilated gray scale image should be brighter. (Darker features are reduced, bright features are thickened and background is brighter).

(3). Opening and Closing

Same as for binary images, the opening of the image \( f \) by structuring element \( b \) is defined as the erosion of \( f \) by \( b \) followed by a dilation of the result with \( b \) Equation 6.3:

\[
f \Theta b = (f \Theta b) \oplus b
\]  

(6.3)

Similarly, the closing of \( f \) by \( b \) is Equation 6.4

\[
f \Theta b = (f \Theta b) \Theta b
\]  

(6.4)

Opening: The intensity of all bright features decreased, depending on the sizes of features compared to the SE. Unlike the erosion, opening has negligible effect on the dark features and the effect on the background is negligible.

Closing: Dark features are attenuated and the background is unaffected.

(4). Top-Hat and Bottom Hat Transform

Combining image subtraction with opening and closing, results in top-hat and bottom-hat transformations. Top-hat transform is an operation that extracts small elements and details from given images. The top-hat transform is defined as the difference between the input image and its opening by some structuring element. Top-hat transform can also be used to correct uneven illumination when the background is dark.
Top-hat = Original image-opened image. The Bottom-hat transform is defined as the difference between the input image and its closing by some structuring element.

Bottom-hat = Original image-closed image.

One principal application of these transforms is that of removing objects from an image using an SE in the opening and objects from an image by using an SE in the opening and closing that does not fit the objects to be removed. The difference then yields an image with only the removed objects. The top-hat is used for light objects on a dark background and the bottom-hat for dark objects on a light background. An important use of top-hat transformation is correcting the effects of non-uniform illumination.

6.2.2 Feature Extraction

From Table 6.1, sensitivity, specificity parameters are chosen as a measurement of accuracy and are calculated using the following Equation 6.5 to 6.7:

\[
\text{Sensitivity} = \frac{TP}{(TP + FP)} \quad (6.5)
\]

\[
\text{Specificity} = \frac{TN}{(TN + FP)} \quad (6.6)
\]

\[
\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FN + FP)} \quad (6.7)
\]

Table 6.2 shows the performance analysis of different images. The sensitivity, specificity, accuracy values were calculated and an average accuracy of 94.67% is obtained.

6.2.3 Classification Using Support Vector Machine (SVM)

The standard SVM is a binary classifier which has found widespread use in pattern recognition problems such as image and audio recognition, handwriting recognition, medicine, science, finance and so on. The support vector machine or SVM framework is currently the most popular approach for “off-the-shelf” supervised learning.

There are three properties that make SVMs attractive. SVMs construct a maximum margin separator-a decision boundary with the largest possible distance to example points [97]. This helps them generalize well.
SVMs create a linear separating hyper plane, but they have the ability to embed the data into a higher-dimensional space, using the so-called kernel trick. Often, data that are not linearly separable in the original input space are easily separable in the higher dimensional space.

The high-dimensional linear separator is actually nonlinear in the original space. This means the hypothesis space is greatly expanded over methods that use strictly linear representations. SVMs are a non parametric method—they retain training examples and potentially need to store them all. On the other hand, in practice they often end up retaining only a small fraction of the number of examples, sometimes as few as a small constant time the number of dimensions. Thus SVMs combine the advantages of non parametric and parametric models: They have the flexibility to represent complex functions, but they are resistant to over fitting. The input points are mapped to a high dimensional feature space, where a separating hyperplane can be found. The algorithm is chosen in such a way as to maximize the distance from the closest patterns, a quantity which is called the margin. SVMs are learning systems designed to automatically trade-off accuracy and complexity by minimizing an upper bound on the generalization error. In a variety of classification problems, SVMs have shown a performance which can reduce training and testing errors, thereby obtaining higher recognition accuracy [98]. SVMs can be applied to very high dimensional data without changing their formulation.

6.3 RESULTS

Figure 6.6 shows the detection of diabetic maculopathy in a single GUI window. Macula is the center part of the retina [95]. It is also the darkest part in the retinal image. This region is localized using morphological operation.
Table 6.1
Alternative diagnostic test (classifier) results with respect to the ground-truth outcome

<table>
<thead>
<tr>
<th>Diagnostic tool (classifier) result</th>
<th>Ground-truth result (Ophthalmologists’ hand-drawn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>Positive (present)</td>
</tr>
<tr>
<td>Negative</td>
<td>False (present)</td>
</tr>
</tbody>
</table>

Table 6.2
Performance Analysis

<table>
<thead>
<tr>
<th>IMAGESAMPLES</th>
<th>SENSITIVITY</th>
<th>SPECIFICITY</th>
<th>ACCURACY</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.7778</td>
<td>0.9734</td>
<td>0.9577</td>
</tr>
<tr>
<td>2</td>
<td>0.7665</td>
<td>0.9793</td>
<td>0.9474</td>
</tr>
<tr>
<td>3</td>
<td>0.7225</td>
<td>0.9711</td>
<td>0.9649</td>
</tr>
<tr>
<td>4</td>
<td>0.7032</td>
<td>0.9855</td>
<td>0.9479</td>
</tr>
<tr>
<td>5</td>
<td>0.6815</td>
<td>0.9872</td>
<td>0.9459</td>
</tr>
<tr>
<td>6</td>
<td>0.6296</td>
<td>0.9893</td>
<td>0.9585</td>
</tr>
<tr>
<td>7</td>
<td>0.6780</td>
<td>0.9861</td>
<td>0.9453</td>
</tr>
<tr>
<td>8</td>
<td>0.5704</td>
<td>0.9917</td>
<td>0.9688</td>
</tr>
<tr>
<td>9</td>
<td>0.6530</td>
<td>0.9882</td>
<td>0.9489</td>
</tr>
<tr>
<td>10</td>
<td>0.6967</td>
<td>0.9846</td>
<td>0.9502</td>
</tr>
</tbody>
</table>
Figure 6.6. Detection of macular edema
Diabetic Maculopathy, is a severe stage of diabetic retinopathy [99]. This study is focused to detect the severity of the disease which is called maculopathy. The low contrast digital image is enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE). The color fundus images are subjected to pre-processing followed by edge detection using morphological operations. The overall sensitivity, specificity and accuracy is obtained as 70.42, 98.43 and 94.67% respectively. Also the detection of diabetic maculopathy, which is the severe stage of diabetic retinopathy, is obtained using morphological operation.

This system is very useful in detecting the severe as well as early stage of diabetic retinopathy. The SVM classifier gives the accuracy of 94.67%.

6.4 DISCUSSION

The fundamental concept behind the proposed system was to extract exudate or macular edema which is at the center of the retina. The maculopathy is detected by applying morphological operators. The input image is converted to green component image from the original RGB image. A 3x3 median filter is applied to remove the noise. Since most of the retinal images show lightning variations, Contrast limited Adaptive Histogram Equalization (CLAHE) is used to reduce these imperfections. Basic morphological operations of dilation, erosion opening and closing are used to detect the white and black regions in the gray scale image. The top Hat and Bottom Hat Transform is applied to remove the unwanted regions from the disease affected image. Top Hat Transform is used to extract the light objects from the dark back ground and the Bottom Hat Transform is used to extract the dark objects from the light back ground. Finally by subtracting both the images macular edema is detected. The proposed CAD system based on SVM classifier is a fast tool for the detection of macular edema. The SVM classifier achieves a high level of accuracy in the classification of Macular edema. The findings of Osareh et al [77] also confirm that the SVM classifier achieves a high level of diagnostic accuracy in DR classification over others. Table 6.2 shows the predicted values of sensitivity, specificity and accuracy as 70.42%, 98.43% and 94.67%.
6.5 CONCLUSION

Diabetic Maculopathy, is a severe stage of Diabetic Retinopathy [99]. This study is focused to detect the severity of the disease which is called Maculopathy. Enhancement of the low contrast digital image is done using Contrast Limited Adaptive Histogram Equalization (CLAHE). The color fundus images are subjected to pre-processing followed by edge detection using morphological operations. The overall sensitivity, specificity and accuracy is obtained as 70.42, 98.43 and 94.67% respectively. Also the detection of Diabetic Maculopathy, which is the severe stage of Diabetic Retinopathy, is obtained using morphological operation. The SVM Classifier gives the accuracy of 94.67%.