CHAPTER 4

EXUDATES DETECTION METHODOLOGIES

4.1 INTRODUCTION

The detection of exudates is our major goal in this thesis. For this, the pre-requisite stage is the detection of the optic disk. Once the optic disk has been found, certain algorithms can be used to detect the presence of exudates. Some of the methods used were Feature extraction, Template Matching, MDD classifier and enhanced MDD classifier etc. These methods were used for the exudates detection and the performance was evaluated.

4.2 FEATURE EXTRACTION METHOD

Here, in this method the concept used was that in normal retinal images, the optic disk was the brightest part and next to it the exudates. So, once after detecting the optic disk, the centre point was determined for the extraction of various features in the image. Then the optic disk was removed from the image, thus the image had exudates as the next brightest region. Here again, Binary Imaging method (Nicholas et al 1989) as like the optic disk detection was applied and a proper threshold value was set and the exudates were easily identified from the test image. The input optic disk extracted image is shown in Figure 4.1 and the output is shown in Figure 4.2.
4.3 TEMPLATE MATCHING METHOD

The concept behind this method was that, a normal and healthy retinal image was taken and it is kept as the reference to isolate the abnormalities in the test image. This reference image acts as the template. Both the reference image and test images were converted from RGB to GRAY levels and then pixel by pixel both the images were compared. During comparison, the additional object present in the test image gets isolated and they were clearly visible in the output. If the test image is normal, then while
comparing it gets cancelled as there is no difference of pixel value between the two, whereas in the test image with exudates, the optic disk got cancelled and only exudates were separated in the output.

The basic requirement of this method was that, the normal and healthy retinal image act as reference image (Figure 4.3) and the test images (Figure 4.4) must be taken in the same orientation as the reference with same lighting, angle, etc. It should be taken in the same manner as that of the reference. Then only this algorithm will work well or else it would produce a wrong result. Hence this basic need must be satisfied to work with this method. The result of this method is shown in Figure 4.5.

Figure 4.3 Reference Image

Figure 4.4 Test Image
4.4 MDD (MINIMUM DISTANCE DISCRIMINANT) CLASSIFIER METHOD

Color information has been shown to be effective for lesions detection under certain conditions. On the basis of color information, the presence of lesions can be preliminarily detected by using MDD (Minimum Distance Discriminant) classifier based on statistical pattern recognition techniques.

If the background color of a good quality retinal image was sufficiently uniform, then a simple and effective method to separate hard lesions from such background can be easily applied by selecting a proper threshold. However, the limitation of these thresholding techniques was that they typically work well only for the trained images, but once an unknown image comes along, they may not be able to accurately detect the exudates. This was because, the processing steps require different threshold parameters for different types of retinal images and need user’s intervention on a case by case basis. As a result, these thresholding based algorithms were not scalable for analyzing large number of retinal images. This MDD (Minimum Distance
Discriminant) classifier has used a simple but effective method, based on statistical classification to identify lesions in retinal images (Wang et al 2000).

Objects in an image usually can be described in terms of some features $f_1, f_2 \ldots f_k$ such as color, size, shape, texture and other more complex characteristics. These features, $f_1, f_2 \ldots f_k$ form a k-dimensional feature space, $F$. Ideally, a space ‘$F$’ has to be found such that different objects map to different, non-intersecting clusters in this feature space. If this condition was satisfied, different objects were easily identified and classified into corresponding classes by certain rules. Assume ‘N’ different objects have to be identified in an image. Let $C_i (f_{i1}, f_{i2}, \ldots f_{ik})$ denote the center of class ‘$i$’ in the k-dimensional feature space ‘$F$’, where $i=1,2,\ldots N$. Let $X(x_1, x_2, \ldots x_k)$ be the unknown object’s feature measurement values in $F$. Let $D_i (X)$, $i=1, 2 \ldots N$, be the discriminant function that was used to determine whether $X$ should be classified as belonging to class ‘$i$’. Given a specified pixel $x$ with feature vector $X$, pixel $x$ was classified as belonging to class ‘$i$’ if $D_i (X)$ is maximum among all $D_j (X)$, where $j=1, 2, \ldots N$ and ‘$j$’ not equal to ‘$i$’.

The color features were taken as the feature space, ‘$F$’. The color fundus retinal image consists of three planes-red, green and blue, each plane with 256 levels of intensity denoted as (R, G, and B). Color can be also represented by $\theta$, $\varphi$, and $L$ in the spherical co-ordinates. The relation between the two color spaces were expressed as:

$$L = (R^2 + G^2 + B^2)^{1/2}$$  \hspace{1cm} (4.1)

$$\theta = \arctan (G/R)$$ \hspace{1cm} (4.2)

$$\varphi = \arccos (B/L)$$ \hspace{1cm} (4.3)
‘L’ denotes the exposure or brightness of an image, whereas \( \theta \) and \( \phi \) emphasize the differences or changes of colors. When ‘L’ was held constant, ‘\( \theta \)’ and ‘\( \phi \)’ describe the chromaticity in an iso illuminant surface. Since our focus was to differentiate between yellowish lesions and other darker objects in the color retinal images, both the brightness of the image as well as the changes of color information were to be included. Hence, L, \( \theta \), \( \phi \) were selected as the feature space, \( (f_L, f\theta, f\phi) \). An appropriate discriminant function was derived. Let \( P(C_i /X) \) be the posterior probability and denotes the probability of measurement vector X belonging to event i(class i).

\[
P(C_i /X) = \frac{P(C_i)P(X/ C_i)}{P(X)}
\]  

(4.4)

\( P(C_i) \) is the priori probability of class i in the image to be classified. \( P(X/ C_i) \) is the conditional probability of X given class \( C_i \).

The Discriminant factor can be defined as a posterior probability

\[
D_i (X) = \frac{P(X/ C_i)}{P(X) C_i} = \frac{P(C_i)P(X/ C_i)}{P(X)}
\]  

(4.5)

Since \( P(X) \) is independent of any class, it will not affect the discriminating power of \( D_i (X) \), so it can be ignored / discarded. \( P (X/C_i) \) can be approximated to normal distribution

\[
P (X/C_i) = \frac{1}{|\Sigma_i|^{1/2} \sqrt{2\pi}} \exp \left( -\frac{(X - C_i)^T \Sigma_i^{-1} (X - C_i)}{2} \right)
\]  

(4.6)

Assume that the covariance matrix

\[
D_i (X) = - (X - C_i)^T (X - C_i)
\]  

(4.7)

\( \Sigma_i \) (i=1,2,...,N)is almost identity for all classes and that \( P(C_i) \) is almost equally likely for i=1,2,3,...,N. Taking logarithm on equation (4.5) and ignoring the negative sign

\[
D_i (X) = (X - C_i)^T (X - C_i)
\]  
is called the Minimum Distance Discriminant (MDD)
Applying \( D_l(X) \) as defined above to the problem of detecting presence of exudates in retinal images, only two classes-yellow patches (lesions) and dark reddish background were detected. The feature centers of lesions and background, \( C_{\text{lesion}}(f_L, f_0, f_\phi) \) and \( C_{\text{bkgnd}}(f_L, f_0, f_\phi) \), can be obtained and trained by selecting small windows inside exudates patches and background regions respectively in a set of typical sample images.

The means of exudates and background were then computed and stored as feature centers for the two classes respectively. For each pixel \( X (x_L, x_0, x_\phi) \) from the retinal image, the discriminant \( D_{\text{lesion}} \) and \( D_{\text{bkgnd}}(X) \) were calculated. If \( D_{\text{lesion}}(X) \) is less than \( D_{\text{bkgnd}}(X) \), then pixel \( X \) was classified as lesion otherwise it was classified as background. In this way, exudates or other yellowish lesions could be quickly detected. This simple and fast algorithm was able to achieve good accuracy in the detection of exudates in color fundus images. The training image for exudates and for the background is shown in Figures 4.6 and 4.7.

![Figure 4.6 Training Image for Exudates](image.png)
The various stages and the final result of MDD classifier are shown in Figures 4.8 to Figure 4.11

Figure 4.8 Input Image with Optic Disk Circled
Figure 4.9 Optic Disk Extracted Image

Figure 4.10 Image Converted to Spherical Coordinates

Figure 4.11 Output Image with Exudates marked as black
4.5 ENHANCED MDD (MINIMUM DISTANCE DISCRIMINANT) CLASSIFIER

This image works on the RGB co-ordinates rather than spherical co-ordinates (Wang et al 2000). In the Minimum Distance Discriminant (MDD) Classifier method, the centre of class was found using a training set and hence remains fixed. But this may cause a problem because of the difference in image illumination and their average intensity. So a method was employed such that the centre of class (C_{yell} and C_{bgnd}) varies dynamically depending on the image.

From the previous optic disk detection method, the position of the optic disk was known for the image. Using this knowledge, a group of pixels that surrounds the optic disk and the mean of these pixels form the C_{bgnd} was selected. The optic disk usually has the same color and intensity as that of exudates. So the pixels that belong to the OD were used for calculation for C_{yell}. They are given by

\[
C_{yell} = \frac{1}{m} \sum_{i=1}^{m} Y_i \quad (4.8)
\]

\[
C_{bgnd} = \frac{1}{n} \sum_{i=1}^{n} B_i \quad (4.9)
\]

where m & n were number of pixels in yellowish and background region respectively, that were used to calculate these centers. ‘Yi’ and ‘Bi’ were the vectors of the 3 color features in the different region of optic disk and background.

The method attempts to detect exudates by using the two important features of exudates, its color and its sharp edges. It was carried out in the following steps:

- Detection of Optic Disk.
- Detection of yellowish objects in the image.
- Detection of objects in the image with sharp edges.
- Combination of the previous steps to detect yellowish objects with sharp edges.

### 4.5.1 Detection of Optic Disk

Principal Component Analysis between clusters and propagation through radii were used to detect the optic disk. The area enclosing the Optic Disk was traced out (Figure 4.12) and removed from the retinal image. The extracted image shows the optic disk in black color (Figure 4.13) and the enhanced image is shown in Figure 4.14.

![Figure 4.12 Input Image with Optic Disk Circled](image1)

![Figure 4.13 Optic Disk Extracted Image](image2)
4.5.2 Detection of yellowish objects

The detection of yellowish objects was carried out performing color segmentation, based on statistical classification method (Clara et al 2004). It is based on the fact that if a group of features can be defined, so that the objects in an image map to non intersecting classes in feature space, then we can easily identify different objects classifying them into corresponding classes. Two classes, yellowish objects and background were defined which were characterized using only three color features (R, G, and B).

Using Baye’s theory the Minimum Distance Discriminant (MDD) is found as,

\[ D_i(x) = -(x-C_i)^T(x-C_i) \]  \hspace{1cm} (4.10)

where \( i = 1 \ldots N \), \( N \) is the number of classes, here \( N=2 \).

So, for each pixel \( X (x_R, x_G, x_B) \) the distances \( D_{\text{yell}}(X) \) and \( D_{\text{bgnd}}(X) \) were calculated. If \( D_{\text{yell}}(X) \) is less than \( D_{\text{bgnd}}(X) \), then the pixel \( X \) was classified as yellowish lesion, otherwise it was classified as background.
Next an adjustment for non-uniformity of illumination was performed because of lighting variation, decreasing color saturation, skin pigmentation etc… the color of lesions in some regions of an image may appear dimmer than the background color that was located in another region and would be wrongly classified. A new color image which was obtained by performing an operation of channels (N1, N2, N3) of the NTSC color space,

\[ N1' = 1.5N1 - N2 - N3 \]  

(4.11)

Then the image obtained (N1, N2, and N3) was converted into the RGB color space again. Both contrasting attributes of lesions and overall color saturation were improved in image, making optic disk and exudates to appear with the same color independent of their location. Minimum Distance Discriminant (MDD) was applied to all the pixels and the exudates were identified. While converting the NTSC image to RGB, the color map was normalized. Hence in mathematical computation, RGB, the contrast improved image’s value had to be multiplied by 255 since both the centre of class were obtained from the original RGB image where maximum intensity value was represented by 255. Along with exudates, other lesions like drusens, artifacts, optic disk were also identified. The detected yellowish objects are shown in Figure 4.15.

![Figure 4.15 Detection of Yellow Objects from the Image](image-url)
4.5.3 Detection of objects with sharp edges

There are various algorithms to find the edges of an image like sobel, canny etc. In this, sobel operator was used to find the sharp edges. A binary image with edges was shown white. This image contains the edges of optic disk, blood vessels, exudates and also the image boundary. So this cannot be independently used to determine the exudates. Hence this method has to be combined with earlier methods for the detection of exudates. The sharp objects obtained are shown in Figure 4.16.

![Figure 4.16 Detection of Sharp Objects from the Image](image)

4.5.4 Combination of the two previous images

To detect only exudates and to remove all the false detections in the previous stages, the two images obtained using Minimum Distance Discriminant (MDD) and edge detecting method were combined through a Boolean operation, feature based AND. In feature based AND, ON pixels in one binary image were used to select objects in another image. The image with objects having sharp edges was used to select objects in the image with yellowish elements, because in the last one the lesions were detected completely, apart from contours. Thus, the lesions obtained were
characterized by two desired features-yellowish color and sharp edge. The boundary of the exudates is shown in Figure 4.17.

Figure 4.17 Output Image Giving Boundary of Exudates

The comparison between the existing and the proposed methods are shown in table 1.

Table 4.1 Comparative table for exudates detection

<table>
<thead>
<tr>
<th>Method</th>
<th>Optic disk</th>
<th>Exudates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>sensitivity</td>
<td>specificity</td>
</tr>
<tr>
<td>Hough transform (normal)</td>
<td>60%</td>
<td>84%</td>
</tr>
<tr>
<td>Watershed transformation</td>
<td>96.7%</td>
<td>-</td>
</tr>
<tr>
<td>Fuzzy C means clustering</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Multiscale morphological process</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Lab color morphology</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Fuzzy C means clustering and</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Method</td>
<td>Support vector machine</td>
<td>Neural networks</td>
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<tr>
<td>--------------------------------------------</td>
<td>------------------------</td>
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</tr>
<tr>
<td>Support vector machine</td>
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<tr>
<td>Neural networks</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Hough transform</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Statistical classification</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Mahalanobis classifier</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Geometrical parametric model</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Pyramidal decomposition</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Artificial neural network</td>
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<td>-</td>
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<tr>
<td>PCA with active shape model</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Morphological processing and artificial neural network</td>
<td>-</td>
<td>-</td>
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<tr>
<td>Multilayer perceptron</td>
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<td>-</td>
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<tr>
<td>Machine learning</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Role of domain knowledge</td>
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<td>-</td>
</tr>
<tr>
<td>Ellipse fitting and wavelet transform</td>
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<td>-</td>
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<tr>
<td>Dynamic thresholding</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Proposed method (propagation through radii)</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
The exudates detection through the proposed method gives an accuracy of 100% in comparison with the existing methods.

4.6 CONCLUSIONS

The exudates were extracted by feature extraction, template matching, MDD classifier and enhanced MDD classifier methods. The extraction of exudates, by first detecting the optic disk through the propagation through radii method gives a better performance while calculating the PSNR ratio. The feature extraction again needs the proper thresholding values. The basic requirement in template matching is that both normal and abnormal images are needed. The orientation, angle, lighting of both reference and the abnormal image should be same otherwise it would give wrong identification of the presence of exudates.

Minimum Distance Discriminant (MDD) classifier is based on statistical recognition technique and this gives better result compared to feature extraction and template matching. But this works on spherical coordinates and the center are found using a training set and hence remain fixed. This may cause problems and so it is employed such that the centre of class varies dynamically, depending on the image. Enhanced Minimum Distance Discriminant (MDD) classifier uses RGB values of the image and the abnormality is characterized by the features, yellowish color and sharp edges. The next chapter discusses another method for exudates detection through the extraction of blood vessel.