

# Detection of Red Lesions and Hard Exudates in Color Fundus Images

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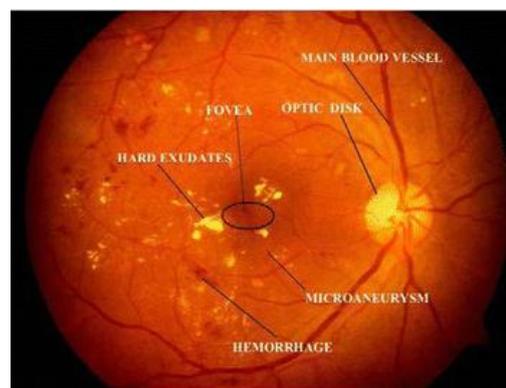
**Abstract:** Diabetic Retinopathy is the damage caused to the blood vessels in retina due to diabetes. The severe case of diabetic retinopathy leads to vision loss. It is important to diagnose diabetic retinopathy in earlier stage. In this work automatic methods for detection of various lesions of diabetic retinopathy from color fundus images are explained. The retinal structures which include blood vessels, optic disc and fovea are also detected. The prominent lesions present in an abnormal color fundus image include the brighter lesion such as hard exudates and darker lesions such as microaneurysms and haemorrhages. The severity of the disease based on location of the hard exudates in the retina is also explained. Hard exudates are detected by a supervised learning technique on normal color fundus images. The global features of normal color fundus image are captured using a feature extraction technique. Based on this feature the images are classified to be normal or abnormal. The classification of abnormal image as moderate or severe is done by considering the rough rotational symmetry of the macula of a normal color fundus image. The presence of red lesions is detected based on its appearance on the color fundus image. A moat operator is used for the red lesion detection. The algorithms were tested on a small dataset. Hard exudates are detected with an accuracy of 95% and classified with an accuracy of 96%. Red lesions are detected with an accuracy of 90%.

**Keywords:** Color fundus image, Diabetic retinopathy, hard exudates, haemorrhages, microaneurysms, retinal structures

## 1. Introduction

The diabetic retinopathy [1] is a disease occurring in persons suffering from diabetes. The disease leads to progressive damage of retina and eventually in vision loss. Thus the detection of diabetic retinopathy in its earlier stage is very significant. Any damage to the tiny blood vessels of the retina results in diabetic retinopathy. This also leads to leakage of blood and other fluids resulting in swelling of retinal tissue. Manual detection of diabetic retinopathy lesions by an ophthalmologist is difficult as it requires more time to analysis the color fundus images. Thus automated screening techniques for lesion detection have great significance in saving cost and time. The automatic disease detection system can highly reduce effort of ophthalmologist to limit the immediate attention to the severe cases. Diabetic retinopathy can be automatically detected by examining the different lesions present in the color fundus images. The different lesions that may be present in an affected retina are microaneurysms, haemorrhages, hard exudates etc. Figure. 1 shows the color fundus image with different retinal structures and lesions labeled on it. Microaneurysms [2] are the red dots seen in the layers of retina which represent out pouching of the retinal capillaries and are the first sign of diabetic retinopathy. Haemorrhages are present in severe case of the disease with bleeding into the deep layer of the retina. Hard exudates are minute, yellow, and well defined deposits of lipo-protein

[3].The hard exudates are detected by a supervised learning technique on normal images. The severity of diabetic retinopathy depends on the proximity of hard exudates to the



**Figure1:** Color fundus image with retinal structures and lesions labeled

macula. If the hard exudates are present outside macula the disease is moderate and severe if it is present inside the macula. The methods presented in [4] and [5] are limited to the detection of hard exudates only. In this paper, both hard exudates and red lesions of diabetic retinopathy are detected and the severity of the disease is also analyzed. The paper is

organized as follows: Section 2 is the detection of the retinal structures. Section 3 explains the detection of red lesions. Section 4 describes the hard exudates detection. Section 5 includes the result and section 6 is the result.

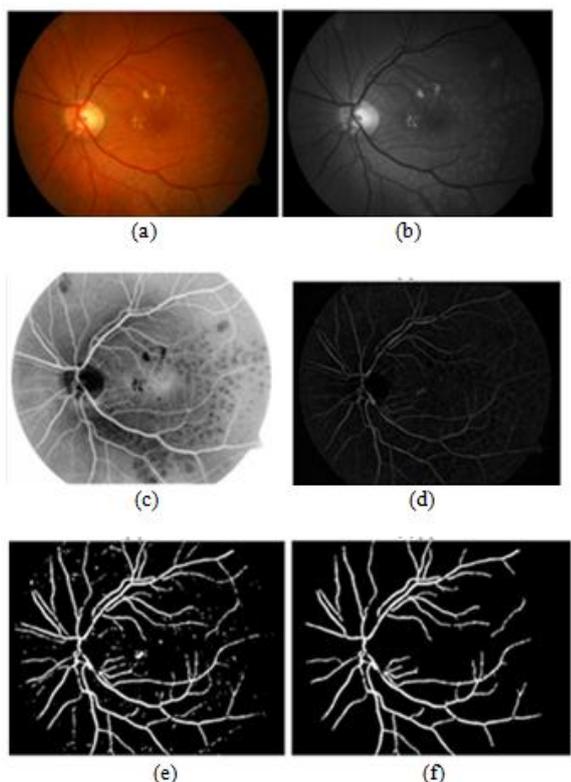
## 2. Detection of Retinal Structures

### 2.1 Blood Vessel

Morphological image processing [2], [6] is used to determine the retinal blood vessels from the color fundus image. The blood vessels are most visible in the green channel. The different steps involved in the detection of blood vessels [2] are:

- Step 1 The green channel of the color fundus image is extracted.
- Step 2 The intensity levels of the image are inverted and adaptive equalization is performed which improves the contrast of the image.
- Step 3 Top hat transform is performed on the resulting image using non flat structuring element 'ball' of radius and height eight.
- Step 4 Gaussian filter of size 10 and standard deviation 3.28 is applied on the image.
- Step 5 The Image is converted to binary image applying suitable threshold value.
- Step 6 Median filtering is performed to remove the noise.

Figure. 2 shows the results of different stages of Blood vessel segmentation.



**Figure 2:** Different stages of blood vessel segmentation

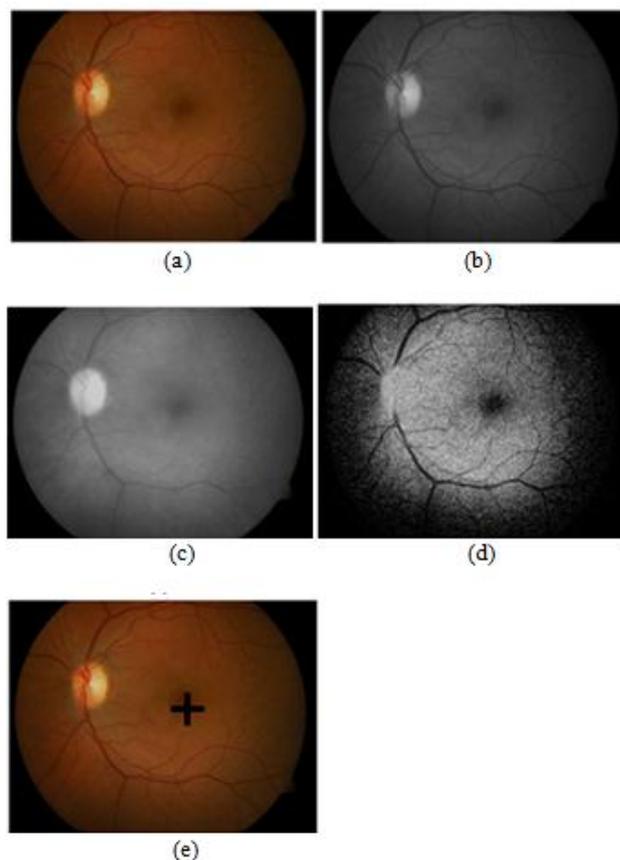
- (a) Input color fundus image (b) Green channel
- (c) Adaptive equalized complemented image
- (d) Top hat transform (e) Binary image
- (f) Blood vessel segmented

### 2.2 Fovea

Fovea is located at the center of retina. Fovea is the center of the macula. Macula is a dark structure located roughly at the

center of the retina. Fovea is detected based on its appearance in the retinal image. The different steps in detecting fovea [7] are:

- Step 1 Generate the intensity image  $I_i$  and red channel image  $I_r$  of the input color fundus image.
- Step 2 Apply contrast enhancement to both images to obtain  $I_a$  and  $I_b$  respectively.
- Step 3 Calculate  $I_s = I_a - (I_b)^c$
- Step 4 Binarize by applying a global threshold.



**Figure 3:** stages of fovea detection

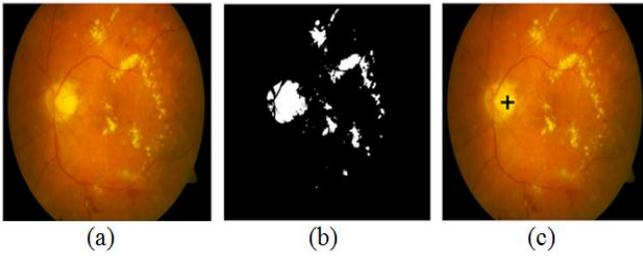
- (a) Input color fundus image (b) Intensity channel ( $I_a$ )
- (c) Red channel ( $I_b$ ) (d)  $I_s = I_a - (I_b)^c$
- (e) Fovea detected (denoted by '+')

### 2.3 Optic disc

Optic disc is the brightest retinal structure. This feature of optic disc makes the detection easier. But certain lesions such as hard exudates also have brightness similar to optic disc. The optic disc is most visible in green channel of the image. The different steps in optic disc detection [7], [8] are:

- Step 1 The green channel of the color fundus image is extracted.
- Step 2 Convert the image to binary image by applying a high threshold value.
- Step 3 Find the segment with maximum area on the binary image which will be the one corresponding to optic disc.

Figure. 4 shows the outputs of optic disc detection.



**Figure 4:** stages of Optic disc detection

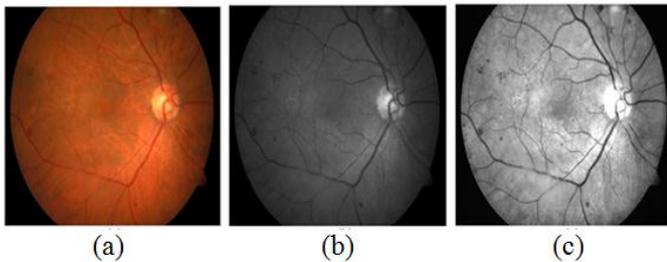
- (a) Input color fundus image (b) Binary image  
(c) Optic disc detected (marked as '+')

### 3. Detection of Red Lesions

The red lesions of diabetic retinopathy include microaneurysms and haemorrhages. To enhance the presence of red lesion in a color fundus image first a pre-processing is performed. Then the red lesions are detected using a moat operator.

#### 3.1 Pre-processing

For detecting red lesions, mostly, the green channel of the color fundus image is used as it shows the best contrast between the background and red lesions. But other than red lesions there is chance of presence of brighter lesions such as hard exudates. Thus the contrast between the bright lesions and background should be least for the accurate detection of the red lesions. The red channel is brighter and has a wider range of gray-level values. Thus in red channel there is less contrast between bright lesions and the background. Hence, by mixing the intensity information of both green and red channels of the same fundus image is used for detecting the red lesions. To acquire this histogram matching is used in which the histogram of the green component of the image is modified with the histogram of the red component of the same retinal image to obtain a new image having the advantages of both red and green channels. Figure. 5 show the pre-processed image.



**Figure 5:** Preprocessing of color fundus image

- (a) Input color fundus image  
(b) Green channel image  
(c) Pre-processed image

#### 3.2 Discrete Fourier Transform and High Pass Filtering

Consider the image,  $g(x,y)$  in the spatial domain. Convert it to the frequency domain by finding the discrete fourier transform [9] of the image. The fourier transform of an image of size  $N \times N$  is given by:

$$G(u, v) = \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} g(x, y) e^{-j2\pi \left( \frac{ux+vy}{N} \right)} \quad (1)$$

The edges and sudden changes in contrast in greyscale image contribute to the high frequency components in its fourier transform. Thus by applying a high frequency filter in

the frequency domain image sharpening can be achieved. This attenuates the low frequency components without attenuating the high frequency information.

The Fourier Transform  $G(u,v)$  of the image and the filter spectrum  $H(u, v)$  are related by the equation given below:

$$I(u, v) = H(u, v)G(u, v) \quad (2)$$

An inverted Gaussian high pass filter is used in this work. The equation of a Gaussian high pass filter  $H(u, v)$  is given by:

$$H(u, v) = 1 - e^{-\frac{u^2+v^2}{2\sigma^2}} \quad (3)$$

Where ' $\sigma$ ' is the standard deviation.

The image with sharpened edge is transformed back to spatial domain by finding the inverse fourier transform. The inverse Fourier transform is given by:

$$i(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} I(u, v) e^{j2\pi \left( \frac{ux+vy}{N} \right)} \quad (4)$$

The image  $i(x,y)$  has both real and imaginary parts. The real part is expressed as:

$$Re(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} I(u, v) \cos \left[ 2\pi \left( \frac{ux + uy}{N} \right) \right] \quad (5)$$

The imaginary part is expressed as:

$$Im(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} I(u, v) \sin \left[ 2\pi \left( \frac{ux + vy}{N} \right) \right] \quad (6)$$

#### 3.3 Moat Operation

To sharpen the edges of the red lesions, a moat operator is applied. The expression for the moat operator is given by:

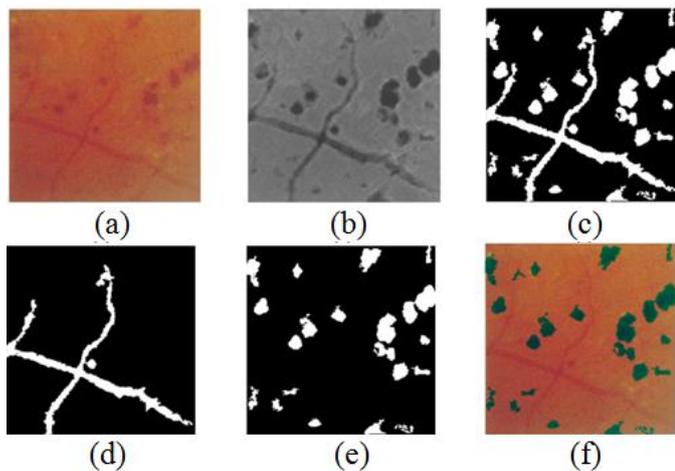
$$G_n(x, y) = g(x, y) - \sqrt{Re^2 + Im^2} \quad (7)$$

The moat operator increases the contrast between the background and the red lesions which makes the segmentation of the red lesions easier. Since blood vessels also have similar color of red lesions the application of moat operator will enhance the presence of both red lesions and blood vessels. Thus complementing and binarizing of the resulting image will have both red lesions and blood vessels. The blood vessels are detected by the method explained in section 2.1 and are removed to obtain the image containing only red lesions. These red lesions are masked over the original color fundus image. The results of red lesion detection are shown Figure. 6.

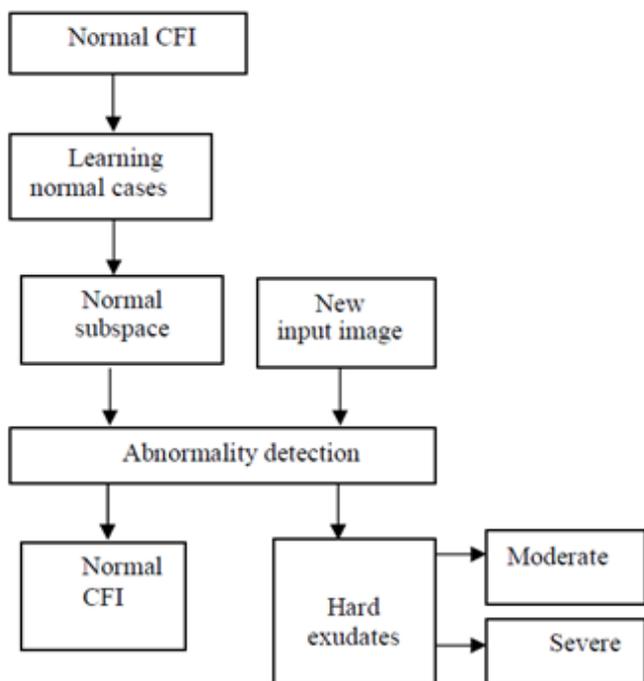
### 4. Detection and Classification of Hard exudates

Hard exudates appear as bright structures with well defined edges and variable shapes. The block diagram showing the different stages of hard exudates detection and classification of the disease is shown in Figure. 7. First a decision module validates the presence or absence of hard exudates in a color fundus image. Once the existence of hard exudates is confirmed next a second module assesses the macular region to

measure the risk of the disease. Thus, a two-stage methodology for both detection and assessment of the disease is proposed. A supervised learning technique is used for detecting the hard exudates. The global characteristics of the normal color fundus image are analyzed and are used to discriminate it from abnormal images. The rotational symmetric feature of the macula of a normal image is used to access the severity of the disease.



**Figure 6:** Different stages of red lesion detection  
 (a) Input color fundus image  
 (b) Image after applying moat operator  
 (c) Binary image  
 (d) Blood vessel segmented  
 (e) Red lesions detected  
 (f) Red lesions overlaid onto original image



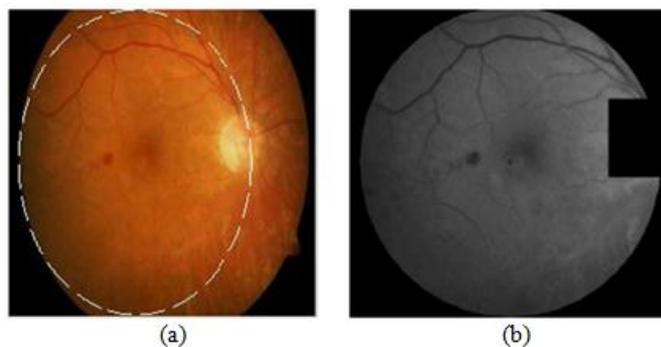
**Figure 7:** Block diagram for detection and classification of hard exudates

#### 4.1 Detection of Hard Exudates

A circular region of interest with fovea as the center is cropped from the RGB image. Motion patterns are generated and studied to detect the hard exudates. Different steps in the detection of hard exudates are explained next.

#### 4.1.1 Region of Interest

Since the severity of disease is found by analyzing the location of hard exudates with respect to the macula, the images used for hard exudates detection usually focus around the macular region. Thus a circular region with macula as the center is cropped and optic disk is masked by a black rectangular mask. The green channel of resulting image forms the input for all subsequent processing. Figure.8 (a) shows the region of interest. The fovea and optic disc are detected by the methods explained in section 2.2 and 2.3 are masked as shown in Figure. 8 (b).



**Figure 8:** (a) Region of interest (b) Optic disc masked

#### 4.1.2 Generation of Motion Patterns

There is much information about a scene in its smear pattern and is thus used to represent an image [10]. A smear pattern is generated by inducing motion in a single image. Sequences of rotated images are generated by inducing motion in given image. The rotated images are combined by using a function to combine the intensities at each pixel location to give a motion pattern [11]. Here a motion pattern is generated for the green channel of the region of interest with optic disc masked. A motion pattern  $I_{MP}$  for region of interest (I) is given by:

$$I_{MP}(r) = f(G_N(I(r))) \quad (8)$$

Where 'r' represents the pixel location,  $G_N$  is a transformation representing the induced motion which is assumed to be rigid. Here, 'N' rotated images are generated and are combined using a function 'f' to coalesce the intensities at each pixel location. Here,  $G_N(I)$  is expressed as follows:

$$G_N(I) = \{R_{\theta_n}(I)\} \quad (9)$$

Here for detecting the hard exudates the choice of 'f' should satisfy the condition that it should enhance the presence of hard exudates by increasing the content of the smear caused due to it in the motion pattern. Accordingly the function maximum is used to combine the rotated images. The function maximum is given by:

$$I_{MP}^{max} = \max_{n=\{0, \dots, (N-1)\}} R_{\theta_n}(I(r)) \quad (10)$$

Where ' $I_{MP}^{max}$ ' is the motion pattern of the rotated image combined using maximum as the function. Motion patterns of normal image and image with hard exudates are shown in figure 9(a) and (b) respectively.

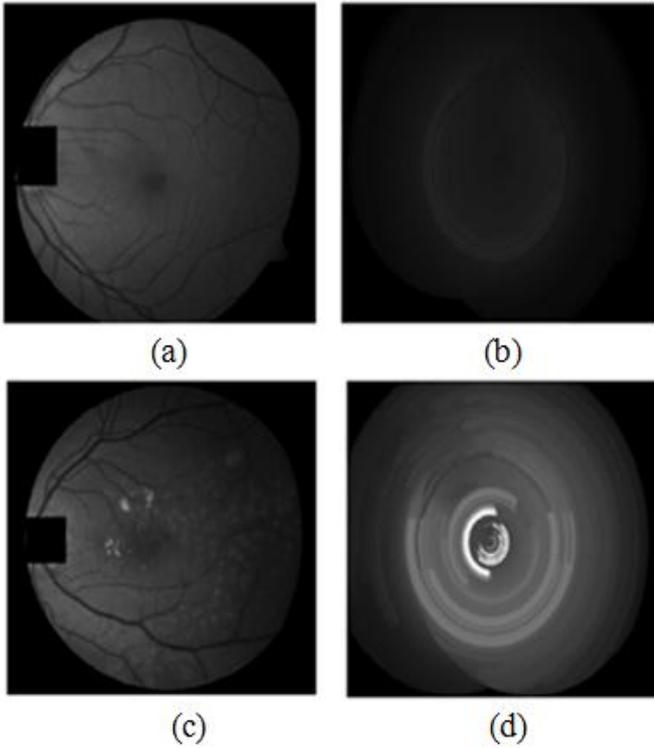


Figure 9: Motion pattern of the images

- (a) Green channel image and the motion pattern of normal image
- (b) Green channel image and the motion pattern of abnormal image with hard exudates

The difference between the motion patterns of normal image and abnormal image with hard exudates can be clearly seen in fig. 9. The motion pattern of normal image does not have any white patches whereas the motion pattern of the abnormal image has white patches on it.

#### 4.1.3 Feature Selection

To effectively describe the motion pattern, a descriptor formed from the Radon space is used. The Radon transform of is the integral of a function  $f(x,y)$  along a line oriented at angle ' $\alpha$ ' and distance ' $r$ ' from the origin. The image is projected to get a vector response for each angle. By combining the responses for different orientations the desired feature vector is obtained. The extent of hard exudates present in the image is extended in the motion pattern and is reflected in the projection based feature vector. Thus for an abnormal image the feature vector will have many peaks due intensity of hard exudates whereas for a normal image the feature vector will have comparatively uniform values which result in a compact normal subspace. The feature vector thus obtained is used to learn the subspace of normal images.

#### 4.1.4 Abnormality Detection

A classification the boundary is fixed around the normal subspace. A new image to be tested is transformed to this normal subspace. If it lies inside the normal subspace boundary, the image is classified to be normal, else abnormal. A PCA DD (*principal component analysis data descriptor*) is used for classification [12],[13].

**PCA DD:** In a PCA classifier, a linear subspace is defined corresponding to the normal cases. The subspace is defined by the Eigen vectors corresponding to the covariance matrix of the training set. The feature vector for a new image is projected to this subspace and is reconstructed. Then based on a reconstruction error new case is classified to be normal.

Different steps in abnormality detection are:

- Step 1 Some normal images are selected for training and radon transform of these images are found.
- Step 2 The Eigen vector corresponding to the covariance matrix of images in training set is calculated.
- Step 3 The average of all the Eigen vectors of normal images in the training set are taken and stored as dataset.
- Step 4 The Eigen vector of the covariance matrix of the radon transform of each new image is calculated and projected to the dataset.
- Step 5 The difference in the data is found and if it's above a given threshold the image is said to be abnormal else normal.

#### 4.2 Classification of Hard Exudates

The circular ROI with macula as the center is the area of key interest as any hard exudates within this region indicates high risk of disease. The macula is a relatively darker structure compared to other regions in the fundus image. The macula also possesses a rough rotational symmetry. This symmetry information is used to find the risk of exhibiting the disease [11]. If the degree of symmetry is above a particular threshold, it shows that the abnormality is not inside the macula and thus the image is of moderate severity else the image shows high risk of disease.

A symmetry measure is given by the distance between second norms of the histograms of pair of diametrically opposite patches. The macula is divided into eight patches as illustrated in figure. 10. For each patch the histogram of 10 bins are computed. But for measuring the symmetry only the last five bins are used since intensity due to hard exudates is reflected in the higher bins of the histogram. The severity of the abnormal image is found by comparing the measure of symmetry this image to a threshold. Let  $S_{min}$  and  $S_{max}$  be the minimum and maximum symmetry values for normal images used in the training set for the detection of abnormal images. Now the severity of the given abnormal image is found by comparing the symmetry measure of this image against a threshold given by:

$$Severity(I_a) = \begin{cases} moderate, & \text{if } S(I_a) \leq T \\ severe, & \text{otherwise} \end{cases} \quad (11)$$

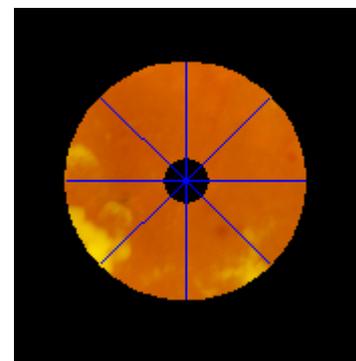


Figure 10: Illustration of using rotational symmetry of macula for describing severity of edema.

The threshold is selected as:

$$T = p(S_{max} - S_{min}) + S_{min} \quad (12)$$

Where 'p' is a value between 0 and 1.

## 5. Results

The algorithms were executed on MATLAB 2010. The algorithms were tested on a small dataset of 30 images. The results are shown in table 1.

**Table 1:** Results

Type of Lesion	Total No: of images tested	No: of normal images	No: of affected images
Red Lesions	30	19	11
Hard Exudates	30	16	14

## 6. Conclusion

Automatic methods for the detection of retinal structures such as blood vessels, fovea and optic disk in color fundus images are explained. The red lesions and hard exudates were also detected. The severity of the disease based on the location of hard exudates with respect to the fovea was also analyzed.

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