

# Detection of Diabetic Retinopathy from Fundus Camera Images

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**Abstract**— Diabetic Retinopathy is the major cause of adult blindness. We can prevent loss of vision if the disease is identified in the early stage itself. Also early detection of the disease is essential for preventing the progress of the disease. Examination of retinal vessels is the first step towards detection of the disease. Moreover segmentation of retinal vasculature helps in the diagnosis of many diseases like Hypertension, Arteriosclerosis etc. This paper presents segmentation of retinal vasculature by Gabor wavelet feature based kernel classifier (Support Vector Machine) and its use for detection of early symptoms of Diabetic Retinopathy. Performance evaluation is conducted using publicly available database DRIVE with reference to the manually segmented images given in the database. The performance of the classifiers are evaluated in terms of accuracy, sensitivity, specificity.

**Keywords**— Retina, Diabetic Retinopathy, Gabor Wavelet, Support Vector Machine.

## I. INTRODUCTION

Digital Fundus Images help ophthalmologists a far in the diagnosis of diseases like glaucoma, diabetic retinopathy, hypertension, arteriosclerosis, cardiovascular diseases etc. Diabetic retinopathy results in retinal disorders like microaneurysms, hard exudates and intra-retinal microvascular abnormalities. DR can be easily detected at an early stage itself by a thorough analysis of vascular abnormalities. Manual segmentation of retinal vasculature is a tedious task. Automated retinal vessel segmentation methods become significant in this context.

Several competent methods exist for automatic segmentation of retinal vessel structure. Huiqi Li *et.al.* developed an algorithm to detect the blood vessels from colour fundus images [1]. By combining the methods of detection of center lines and morphological reconstruction the vessels are extracted by Ana Maria Mendonca *et.al.*[2]. Gaussian Intensity Distribution model of the blood vessels have been used for extraction of diabetic retinopathy features Divyanjali Sathyarthi *et.al.*[3]. The method achieved 90% success in diagnostic performance. R. Gadheri *et.al.* proposes a method based on the analysis of feature vectors extracted from a prototype image, to classify pixels as vessels or non-vessel using a multilayer feed forward neural network [4]. The performance of the classifier is evaluated by the area under the receiver operating characteristics curve and evaluates to 96.68%. Yong Yang *et.al.* propose a hybrid method for vessel extraction. This method used mathematical morphology and a fuzzy clustering algorithm followed by a

purification procedure. Experimental results reveal that their methodology is promising and effective [5].

Retinal vessel segmentation using preprocessed Gabor and Local Binary Pattern Classifier have been put forward by Shaharam[6]. Their work illustrates that use of preprocessing increases the accuracy of vessel extraction. The multi resolution property of Gabor wavelet is utilized for feature extraction. Gaussian Mixture model classifier is used for classification. Seyed Mohsen Zahibi *et.al.* [7] used colour image morphology and local binary pattern for vessel extraction. The proposed multiscale morphological algorithm enhances the vessels in both colour image and colour component images. Vijayakumari *et.al.*[9] developed a method for detecting exudates for the diagnosis of Diabetic Retinopathy.

In this work the retinal vasculature is extracted using Gabor Wavelet based features. Classification is performed using SVM Classifier. The performance of the classifier is evaluated using the parameters Sensitivity, Specificity, and Accuracy. The vasculature is analysed for variation in width, presence of microaneurysms, tortuosity and exudates in order to detect diabetic retinopathy.

## II. DIABETIC RETINOPATHY

Diabetic Retinopathy is the leading cause of blindness in adults around the world today. The international Diabetes Foundation reports that India has the largest share of this population. DR often strikes with few initial symptoms before invoking irreversible blindness. Surgical replacement of clouded vitreous with saline, laser photocoagulation to prevent clotting or closing off of damaged blood vessels and steroid injection are the most common methods to treat the disease once discovered. With regard to a limited medical staff, an automated system can significantly decrease the manual labour involved in diagnosing large quantities of retinal images.

Diabetic Retinopathy has four stages viz.

1. Mild Non-proliferative Retinopathy At this early stage thickness of blood vessels increases and microaneurysms may occur. Microaneurysms are small areas of balloon-like swellings in the tiny retinal vessels.

2. Moderate Non-proliferative Retinopathy – As the disease progresses some blood vessels that nourish the retina are blocked.
3. Severe Non-proliferative Retinopathy - many more blood vessels are blocked, depriving several areas of the retina with their blood supply. These areas of the retina send signals to the body to grow new blood vessels for nourishment.
4. Proliferative Retinopathy – At this advanced stage the signal sent by the retina for nourishment trigger the growth of new blood vessels. These new blood vessels are abnormal and fragile. They grow along the retina and along the surface of the clear, vitreous gel that fills the inside of the eye. By themselves these blood vessels do not cause symptoms of vision loss. However, they have thin, fragile walls. If they leak blood severe vision loss and even blindness can result.

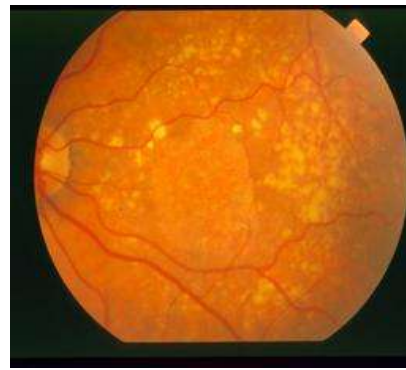


Fig.4 Fundus camera image with exudates.

The above figures represent various symptoms of DR.

### III. METHODOLOGY

#### A. Gabor Wavelet

Gabor Wavelet is the best choice for detection of directional features. Neurophysical studies suggest that the receptive fields of the simple cells of primary visual cortex can be easily modelled by Gabor Wavelet. A Gabor Wavelet is a sinusoidal wave modulated by a two dimensional Gaussian Envelope. Each wavelet has a certain wavelength and orientation. That is a 2D Gabor Wavelet kernel is the convolution of two orthogonal one dimensional components – a sinusoidal wave and a Gaussian envelope. The Gaussian function is

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{x^2}{2\sigma^2}\right) \quad (1)$$

$$\text{and } \omega(x) = G(x) e^{j\omega x} \quad (2)$$

where  $j = \sqrt{-1}$  and  $\omega$  is the frequency of the wavelet. The convolution of 1D components reduces the computational complexity from  $O(pn^2)$  to  $O(2np)$  for an  $n \times n$  kernel and an image with  $p$  pixels. The basic frequency and scales has to be selected so as to match the blood vessels filtering out from an environment of undesirable high frequency noise and low frequency background variations. The Gabor wavelet response with maximum modulus over all angles

ie,  $M_\Psi(b,a) = \max_\theta |T_\Psi(b,\theta,a)|$  is used to detect vessels in any orientation. The scale value  $a$  is chosen so as to span all possible widths of vessels. In order to ensure an equivalent weight during distance calculation normalization is applied after feature generation.

#### B. Kernel Classifiers

Support Vector Machine, Relevance Vector Machine, and Principle Component Analysis are examples of kernel classifiers. Support Vector Machine with Radial Basis Function kernel is used in this method for segmentation as it gives accurate and robust results even when the input data is non-monotone and non-linearly separable. SVM is a

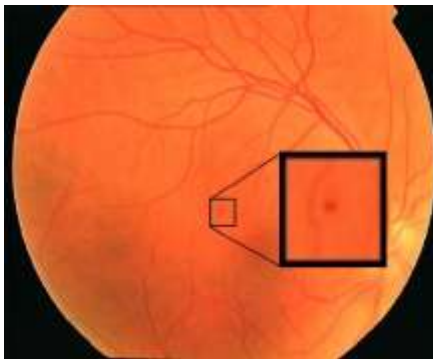


Fig.1 Digital fundus image with microaneurisms.

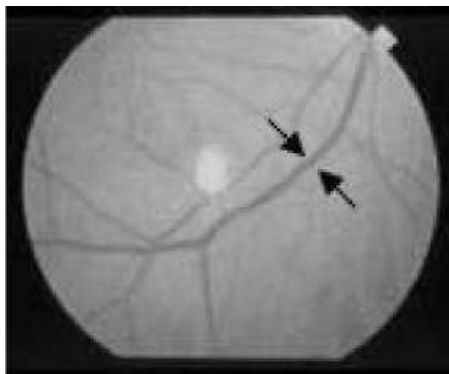


Fig.2 An eye with increased thickness of blood vessels.

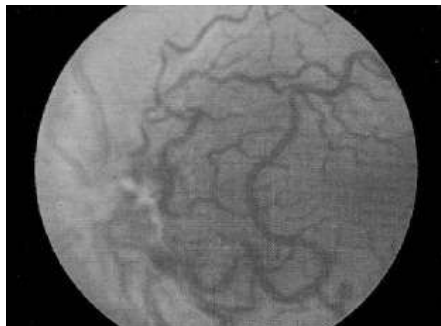


Fig.3 Grey level image with tortuosity of blood vessels.

supervised classifier. It constructs a maximum margin hyper plane in the feature space F. At the input space this represents a nonlinear decision boundary of the form

$$f(x) = \text{sgn} \left( \sum_{i=1}^k \alpha_i k(x, x_i) + b \right) \quad (3)$$

where  $x_i$  is the training example. The training examples can be separated by a hyper plane

$$f(x) = \omega^T x + b = 0 \quad (4)$$

Among the set of possible hyperplanes SVM find the one with largest separation between the two classes. Mathematically this is obtained by minimizing the cost function

$$J(\omega) = \omega^T \omega = \|\omega\|^2 \quad (5)$$

Kernel representation projects the data into a high dimensional feature space thereby increasing the computational power of the learning machine. The data that are nonlinearly separable uses kernel functions such as polynomial kernels, RBF and tan-sigmoid. Here RBF kernel is used for classifying pixels as vessel or nonvessel. The RBF used is

$$K(x, z) = \exp\left(-\frac{\|x-z\|^2}{\sigma^2}\right) \quad (6)$$

where  $\sigma$  is the standard deviation, a Gaussian kernel constant.

### C. Proposed Methodology

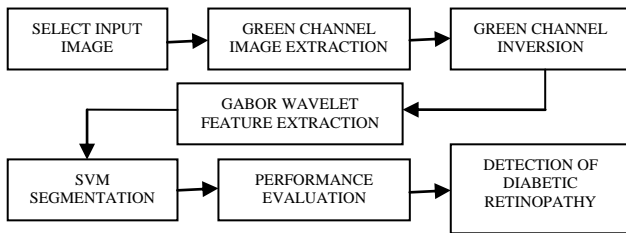


Fig.5. Proposed methodology.

The proposed method shown in figure5. consists of image selection, green channel extraction and inversion, feature extraction using Gabor wavelet, classification using SVM, performance evaluation of the classifier and detection of DR.

Coloured retinal images taken with digital fundus camera are available in DRIVE database. The ground truth images are also given in the database. The size of the image is 768 X 584 pixels.



Fig.6. An image from DRIVE database and the corresponding ground truth image.

An image from the database is selected and the red, green, and blue channel images are extracted. The green channel image shows the best vessel background contrast and minimum noise. Hence it is used for further processing. Inverted green channel image is used for wavelet feature generation. Inversion makes the vessels brighter than the background. The red, green and blue channel images are shown in figure7. and the inverted green channel image is shown in figure8.

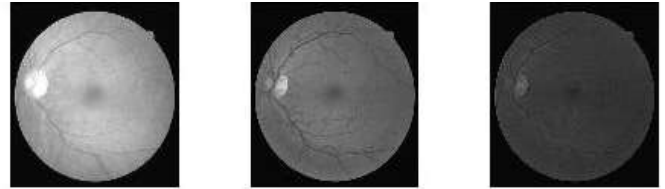


Fig.7. Red, green and blue channel images

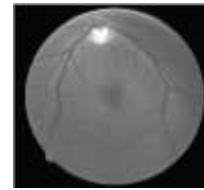


Fig.8. Inverted green channel image.

Gabor wavelet transform is used for feature extraction because of its directional property, image enhancement capability and noise filtering. Gabor wavelet transform coefficients are calculated for angles between  $0^\circ$  and  $170^\circ$ . Maximum modulus of the wavelet transform coefficient is taken as the feature to classify the pixels. Figure 9. Shows the Gabor wavelet response calculated for three different angles.



Fig 9. Gabor Wavelet Transform for three different values of  $\theta$

The pixels are classified into vessels or nonvessels using Gabor feature and SVM classifier. The performance of the classifier is evaluated using the parameters accuracy, sensitivity, and specificity. Accuracy represents the overall correctness of the classifier, sensitivity gives the accuracy among negative instances and specificity is a measure of accuracy among positive instances.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (8)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (9)$$

D. Detection of Diabetic Retinopathy

Diabetic Retinopathy is a serious eye disease originating from diabetes mellitus and the most common cause of blindness in the developed countries. Figure1. through figure4 are examples of retinal images showing various symptoms of diabetic retinopathy.

The key to the early detection is to recognize microaneurisms (MAs) in the fundus image of the eye in time. Reliable detection of such lesions is still an open issue in medical image processing. Thus mass screening of diabetic patients is highly desired, but manual grading is slow and resource demanding. Therefore several efforts has been made to establish reliable computer-aided screening systems in this field. MA’s appear as small circular dark spots on the surface of the retina. Other symptoms of DR include increased thickness of blood vessels, tortuosity, presence of exudates or lesions. Growth of new branches of blood vessels is also an indication of DR. The salient feature in tortuous vessels are 's' and 'c' shapes. These features may have curvature of any radius and the frequency of occurrence depends on the curvature.



Figure10. Image showing 's' and 'c' patterns

These patterns may have curvature of any radius and the frequency of occurrence depends on the curvature. There are a large number of mathematical model for blood vessels. These models are based on the specific intensity profile of the blood vessels that is visible across the cross section. Gaussian Intensity Distribution model of blood vessel is:

$$\alpha = x \cos\theta - y \sin\theta - \mu \tag{10}$$

$$f(x, y) = t_{\max} - h_1 e^{-\alpha^2 / (2\sigma^2)} \tag{11}$$

where x and y map the image profile,  $\theta$  gives the orientation of the blood vessels in the image and  $\mu$  is the offset of Gaussian model,  $t_{\max}$  gives maximum intensity in a particular region under consideration,  $h_1$  is the height of the Gaussian and  $\sigma$  is the intensity spread. The parameters  $\sigma$  and  $h_1$  of the Gaussian profile are higher for blood vessels with diabetic retinopathy than for a normal healthy vasculature. The images are divided into small segments. Orientation of blood vessels are taken from  $0-\pi$  with the resolution of  $10^\circ$ . The  $\sigma$  and height values are calculated for the blood vessels. The vector

containing these parameters are trained, using the images bearing the same pathology. The iteration for training is performed till required accuracy is obtained.

Exudates are detected using an SVM classifier. Images from the DRIVE database are used for training and testing of the classifier. The higher contrast level of the exudates in the inverted image helped accurate detection of the exudates within a small execution time.

IV. RESULTS AND DISCUSSION

Figure 11. shows the retinal vasculature extracted using SVM Classifier. SVM Classifier is used to extract the vessels with four different values of kernel width.

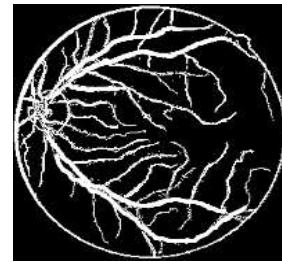


Figure11. Vessel extracted using SVM Classifier

Table.1. Performance measures of SVM for various Kernel widths

Kernel width	Sensitivity	Specificity	Accuracy
0.25	0.6667	0.9668	0.9369
0.5	0.6429	0.9667	0.9362
0.75	0.6552	0.9662	0.9356
1	0.6154	0.9625	0.9317

The sensitivity, specificity and accuracy of the classifier are evaluated for four kernel width values 0.25, 0.5, 0.75 and 1 with reference to the ground truth images given in the database. Table 1. shows the result of this evaluation.

Computational time and accuracy of extracting vessels with SVM Classifier and Kirsch’s edge detection method for normal and abnormal images are calculated and the results are tabulated in Table 2. Results show that the Kirsch’s method is faster than SVM Classifier but the accuracy is much better for SVM classifier.

Table.2. Comparison of SVM and Kirsch’s method

	Computational Time (Sec)	Accuracy Normal Image	Abnormal Image
SVM	78.7493	0.9369	0.9356
Kirsch’s method	56.1635	0.8907	0.8472



Table 3. Accuracy of the algorithm

Symptoms Considered	Accuracy(%)
Change in vessel width	78.32
Tortuosity of blood vessel	94.71
Presence of Exudates	98.83

## V. CONCLUSIONS

Evaluation and comparison of the performance parameters with the SVM Classifier shows that there is slight variation in accuracy for different values of kernel widths. Sensitivity, specificity and accuracy are found to be highest when kernel width is 0.25. Detection of Diabetic Retinopathy based on the symptoms increased vessel width, tortuosity and exudates is found to be more accurate than the detection methods mentioned in the references.

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