Automatic Detection of Microaneurysms and Classification of Diabetic Retinopathy Images using SVM Technique

C.Aravind
PG Scholar
Dept. of EIE,
Kongu Engineering College.

M.PonniBala
Assistant Professor (SRG),
Dept. of EIE,
Kongu Engineering College.

S. Vijayachitra, Ph.D
Professor
Dept. of EIE,
Kongu Engineering College.

ABSTRACT
At present, Diabetic Retinopathy was considered as the main cause of blindness for diabetic patients. The Diabetic Retinopathy can be identified at an earlier stage by detecting the microaneurysms in the retina of the patients. For this purpose, opthalmologists will regularly supervise the retinal images obtained using the color fundus camera. During this regular supervision the ophthalmologists should spend more amount of time and energy. The space required to store the normal and abnormal retinal images will also increases. A new method for detecting the microaneurysms from the color fundus retinal image based on feature classification was proposed in this project, to reduce the ophthalmologists' time and energy for verifying the retinal images. The microaneurysms are detected from the color fundus image by applying the preprocessing techniques inorder to remove the optic disk and similar blood vessels using morphological operations. The preprocessed image was then used for feature extraction and these features were used for classification purpose. The classifier used is Support Vector Machine which improves sensitivity, specificity and gives an average accuracy of 90%.

General Terms
Medical Image processing, Automatic detection.

Keywords
Diabetic Retinopathy (DR), Microaneurysms, Morphology, Support Vector Machine.

1. INTRODUCTION
The most common diabetic eye disease and a leading cause of blindness in adults is the Diabetic Retinopathy (DR) [1], [5]. The changes in the blood vessels of the retina cause this abnormality. For some patients in addition to diabetic retinopathy, blood vessels may swell and leak fluid [2]. For other patients, abnormal new blood vessels grow on the surface of the retina. The retina is the light-sensitive tissue at the back of the eye. A healthy retina is necessary for good vision [6]. At the initial stage of Diabetic Retinopathy, there will be some changes in the vision and it can be noticed. But over time, diabetic retinopathy can get worse and cause vision loss [11]. Diabetic retinopathy usually affects both eyes. The World Health Organization (WHO) has estimated that diabetic retinopathy is responsible for 4.8% of the 37 million cases of blindness throughout the world. In [1], Akara Sopharak *et al.* investigate a set of optimally adjusted morphological operators to detect microaneurysms from non-dilated pupil and low contrast retinal images. For this purpose, the preprocessing of retinal image was performed using mathematical morphology and a shade corrected algorithm was employed for vessel detection. Thresholding and exudate reconstruction were employed for exudate removal. The extended minima transform and local thresholding were applied to the preprocessed image for microaneurysms detection. Finally, these detected microaneurysms were compared with the groundtruth of the specialists. The sensitivity and specificity are rated as 81.66% and 99.99% respectively. In [2], Alan D Fleming *et al.* showed how image contrast normalization can improve the ability to differentiate microaneurysms and other dots on the retinal images. The watershed transform was applied to obtain better contrast normalization. Dots within the blood vessels are handled using local vessel detection technique. Prior to this, preprocessing was done with candidate region growing, candidate evaluation techniques. Watershed retinal region growing was also employed. The k-NN classifier was used for the classification of images based on the features. The sensitivity and specificity are given as 85.4% and 83.1% respectively.

In [4], Meindert Niemeijer *et al.* provided novel red lesion detection based on a hybrid approach with two contributions. One was the new candidate detection system based on pixel classification. Using this, vasculature and red lesions are separated from the background. The second was the detection of a number of features to classify the severity of the disease. Mathematical morphology was used for preprocessing of the image. The k-nearest neighbor classifier was used for classification purpose. The proposed was reported to have a sensitivity of 100% and a specificity of 87% during the detection of red lesions. In [6], Usman Akram M *et al* extracts all possible candidate MA regions. A feature vector was formulated based on certain properties for classifying as MAs and Non-MAs. Candidate region extraction was performed to improve the contrast of dark regions using mathematical morphology, contrast normalization and filter banks. The feature vector comprises of shape based features, gray level features, color features and statistical features. A hybrid classifier combining Gaussian Mixture Model (GMM) and Support Vector Machine (SVM) was used to improve the accuracy of the classification. In [15], Chih-Wei Hsu *et al* compared the methods of the multiclass SVM and provided the decomposition implementations for two such "all-together" methods. Then their performance was compared with three methods based on binary classifications: "one - against-all," "one-against-one," and DAGSVM. The experiments indicate that the "one-against-one" and DAG methods were more suitable for practical use than the other methods.

The rest of the paper is organized as follows: the retinal abnormalities, the preprocessing and feature extraction steps used are provided in sections 2 and 3 respectively. In section 4 the details about the SVM classifier are given. The results of the classifier are discussed in section 5. The final conclusion and the acknowledgement are provided in sections 6 and 7 respectively.

2. RETINAL ABNORMALITIES

The common abnormalities found in the human retina are stated below as

2.1 Microaneurysms

A small swelling that forms on the side of tiny blood vessels [4]. These small swellings may break and allow blood to leak into nearby tissue. People with diabetes may get microaneurysms (MAs) in the retina of the eye [9]. The earliest visibility of diabetic retinopathy is the microaneurysms [4].

2.2 Haemorrhages

Retinal hemorrhage is a disorder of the eye in which bleeding occurs into the retina [6]. Retinal hemorrhages that take place outside of the macula if left undetected for many years, and may sometimes only be picked up when the eye is examined in detail by ophthalmoscopy or fundus photography. However, some retinal hemorrhages can cause severe impairment of vision [9].

2.3 Exudates

As Diabetic Retinopathy progresses, a fluid rich in protein and cellular elements that oozes out of blood vessels due to inflammation and is deposited in nearby tissues [1]. Exudates are manifested as spatially random yellowish or whitish patches of varying sizes, shapes and locations [5]. These are the visible sign of DR and a major cause of visual loss in Non-Proliferative forms of DR [12].
The various abnormalities found in retinal image is shown in Fig 1.

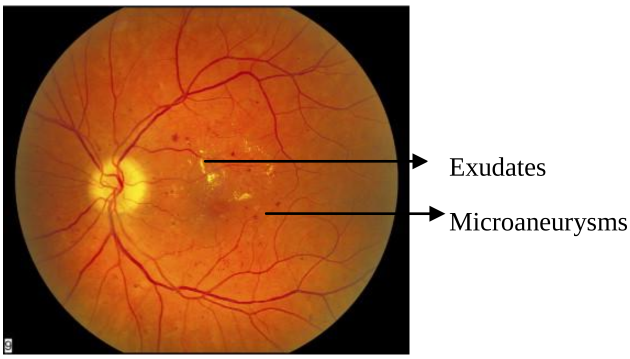


Fig 1: Abnormal Retinal Image

3. PROPOSED METHOD

The main objective of this project work is to detect the early stage of DR using the features extracted from the preprocessed image [3]. The image obtained from the database is subjected to the preprocessing steps such as green channel extraction, contrast enhancement, median filtering and histogram equalization [5]. After preprocessing, the image is morphologically operated by a disk shaped structuring element [1]. Connected component analysis method is used for the removal of optic disk [10]. This image is then utilized for feature extraction. The features like microaneurysms area, homogeneity and texture properties are extracted [6], [7]. The appropriate features for classification are selected. Support Vector Machine technique is used for classifying the input images as normal and DR based image as well as detecting the earlier stage of DR using the extracted features [9].

3.1 Image Acquisition

The proposed methodology is given in fig-1. In this method, a dataset of manually labeled images is taken. This dataset consists of 105 images taken from a screening program for DR in Lotus Eye Care Hospital, Coimbatore. The images were acquired using Cannon non-mydriatic ZEISS camera. Each image is 24 bit per pixel at a resolution of 774x893 in JPEG format. Of the 105 images in the dataset, 95 are of patients with abnormal (contains microaneurysms) and the rest of the images are normal.

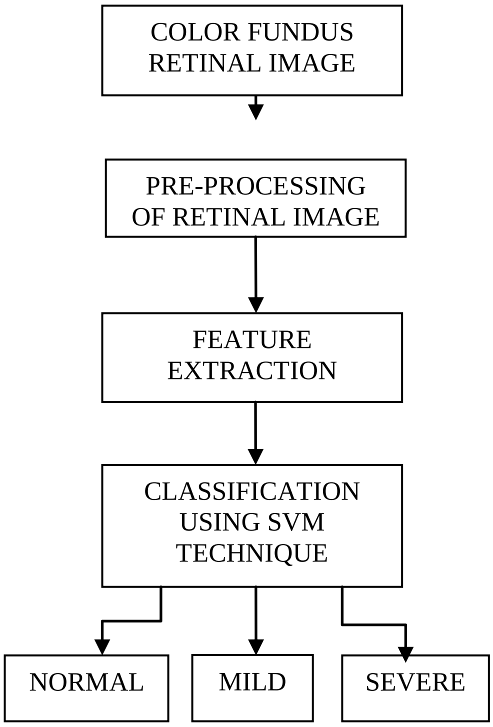


Fig 2: Proposed methodology

3.2 Preprocessing

Pre-processing is the initial step in all the case of image related diagnosis system and it helps in accurate feature extraction. In case of Diabetic Retinopathy, the retinal images in the dataset are often noisy and poorly illuminated because of unknown noise and camera settings. Also the color of retina has wide variation from patient to patient. Thus to remove noise and undesired region the images are subjected to preprocessing steps, which include green channel extraction, histogram equalization and contrast enhancement.

3.2.1 Green Channel Extraction

In the green channel of color images, MAs appear as dark patterns, small, isolated and of circular shape. The green channel is the most contrasted one, that the red channel is saturated and that the blue channel does not contain any information [3]. Green light is less absorbed by the fundus layers than the blue part of the spectrum, but more than red light, which penetrates deeper into the layers of the inner eye and which is mainly reflected in the choroid. The red light is less absorbed by the pigments of the inner eye, and it dominates the reflected spectrum. This is the reason why the color fundus images appear reddish. Because of the lower absorption coefficients for red light, structures containing pigments are less contrasted than it is the case for green light. This does not mean that there cannot be any useful information in the red and blue channel. It just means that blood containing elements (as MA or vessels) in the retinal layer are best represented and have highest contrast in the green channel [5].

3.2.2 Histogram Equalization

Histogram equalization is defined as the process of adjusting intensity values of the image [3]. Here contrast-limited adaptive histogram equalization (CLAHE) is performed. Unlike histogram equalization, it operates on small data regions (tiles) rather than the entire image. Each tile's contrast is enhanced so that the histogram of each output region approximately matches the specified histogram (uniform distribution by default). The contrast enhancement can be limited in order to avoid the amplification of noise which might be present in the image [1].

3.2.3 Filtering

The necessity of filtering the histogram equalized image is to suppress the background pixels along the microaneurysm pixels. Here a 3x3 median filter is used to remove the poor illuminated pixels [3].

3.2.4 Contrast Enhancement

It is essential to distinguish the MAs from the blood vessels and background of the image [2]. For this purpose, Contrast enhancement step is used in the preprocessing to enhance the contrast of the microaneurysms. This process facilitates the image for further processing.

3.2.5 Morphological Operation

The contrast enhanced image is then converted to binary image by applying proper thresholding value. This binary image is subjected to morphological operations i.e. opening and closing [1]. Closing operation is defined as dilation and opening as erosion. Dilation is an operation that grows or thickens objects in a binary image. Erosion shrinks or thins the objects in the binary image [3]. Structuring element is defined as the shape (dimension) that controls the process of thickening and thinning [5]. As the optic disk and microaneurysms are circular in shape, a disk shape structuring element is used in this project.

3.2.6 Optic Disk Elimination

The optic disk occupies more area of the retinal image and it should be removed for facilitating the microaneurysms detection. Thus the connected component analysis method is used for the elimination of optic disk [10].
The various preprocessing steps are shown in fig-2.

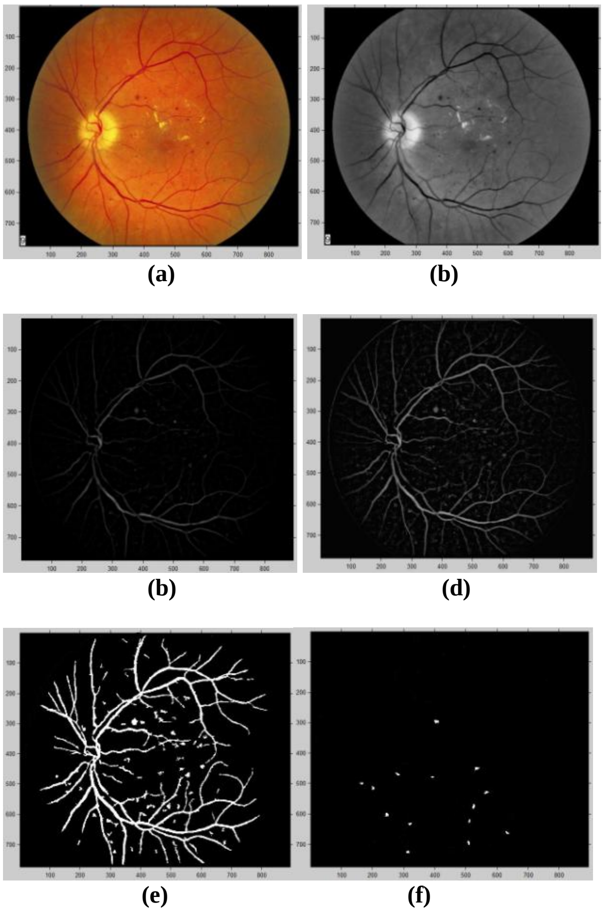


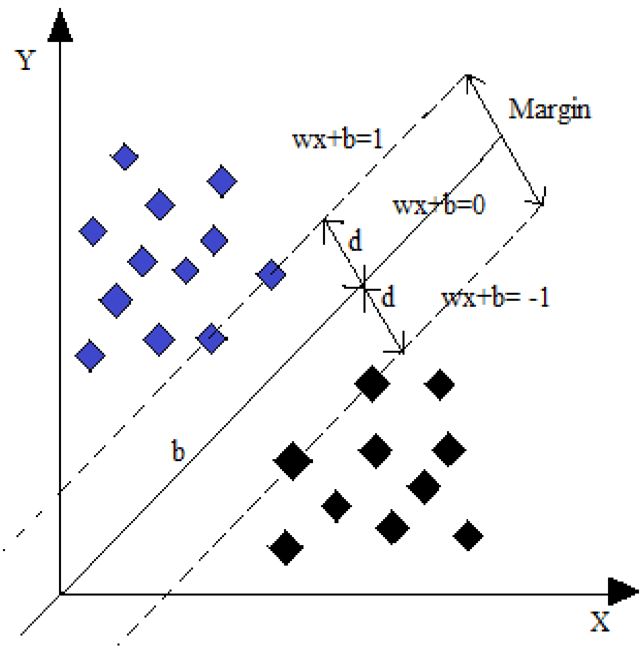
Fig 3: (a) RGB image with MAs, (b) Green channel of microaneurysm image (c) Filtered microaneurysm image (d) Histogram equalized image (e) Image with MAs and blood vessels (f) Image with MAs.

3.3 Feature Extraction

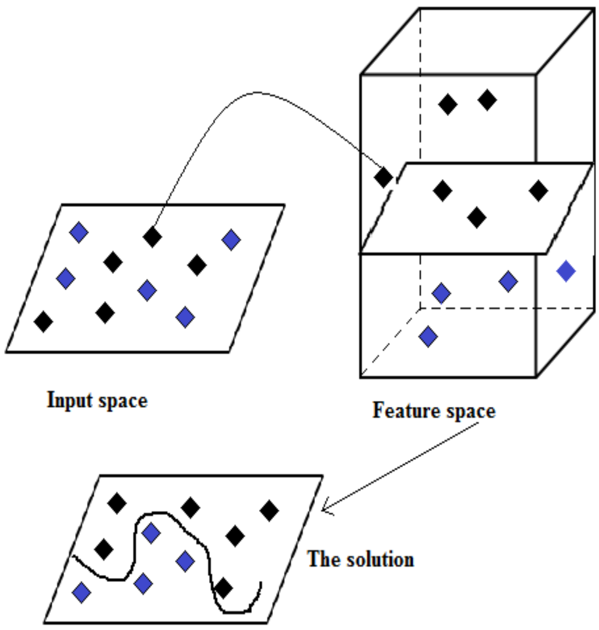
The preprocessed image after the removal of optic disk and blood vessels contains only microaneurysms. This image is used for feature extraction [6]. The statistical features extracted are microaneurysms area, entropy, correlation, energy, contrast, homogeneity, standard deviation, mean [5]. The extracted feature values will have different ranges of values. Thus it is necessary to normalize the values to an acceptable range. From these extracted features, effective features are selected for the SVM classification.

4. SVM Classifier

Support vector machine is a supervised learning process applied for analyzing the training data to find an optimal way to classify the diabetic retinopathy images into their respective classes namely Normal, Mild and Severe. SVM is a robust method used for data classification and regression. The SVM methods are described in detail by Vapnik [13]. SVM models constructs a hyperplane for separating the given data linearly into separate classes (Fig.3 a). Support vector machine method is used to distinguish between the various classes. The training data should be statistically sufficient. The classification parameters are formed according to the calculated features using the SVM algorithm. These classification parameters are used for classifying the images. The contents of the images are distinguished into various classes according to the designed SVM classifier. For nonlinear classification of the given data, SVM uses a non-linear *kernel function* to map the given data into a high dimensional feature space where the given data can be linearly classified and is shown in fig.4 (b). Kernel function K(x,y) represents the inner product $\langle \phi(x), \phi(y) \rangle$ in feature space.



(a) Linear classification



(b) Nonlinear classification

Fig 4: SVM Architecture

In this case, RBF kernel function is used as

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

Where x and x' are the training vectors, where σ is the parameter that controls the width of the Gaussian. The size of the input training vector is 70 x 6. The output can be one of the three categories namely normal, Mild and Severe.

5. EXPERIMENTAL RESULTS

The features like microaneurysms area, entropy, contrast, etc are obtained from the preprocessed image and are provided as input to the SVM classifier. The implementation of this technique is carried out using Matlab. The results of the classification procedures are given in the Table-1. The sensitivity, specificity and accuracy values are calculated using the formulas.

$$\text{Sensitivity}=\frac{TP}{TP+FN} \quad \text{-------} (1)$$

$$\text{Specificity}=\frac{TN}{TN+FP} \quad \text{------} (2)$$

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad \text{-----} (3)$$

Table 1. Results of the SVM classifier

Model	TP	TN	FP	FN
SVM	23	4	1	2

Table 2 shows the results of sensitivity, specificity and percentage of accuracy for the diabetic retinopathy images using SVM classifier.

Table 2: Results of sensitivity, specificity, accuracy

Model	Sensitivity	Specificity	Accuracy
SVM	92	80	90

6. CONCLUSION

The main aim of this work is to reduce the ophthalmologists work in screening the DR based on microaneurysms using SVM classifier. The retinal images are subjected to gray scale conversion, preprocessing and feature extraction steps. The SVM classifier classifies the images as Normal, Mild and Severe based on the extracted features as input. The sensitivity and specificity are 92% and 80% respectively. Thus this SVM technique has given a successful DR screening method which helps to detect the disease in early stage. Thus this SVM technique has given a successful DR screening method which helps to detect the disease in early stage.

7. ACKNOWLEDGEMENT

The authors are thankful to the Lotus Eye Care hospital, Coimbatore for providing the database of retinal images. We also extend our thanks to Dr. R.J.Madhusudanan, MBBS, DO, for his valuable guidance for carrying out this project work.

8. REFERENCES

[1] Akara Sopharak, Bunyarit Uyyanonvara, Sarah barman (2011) 'Automatic Microaneurysm Detection from Non-dilated Diabetic Retinopathy Retinal Images Using Mathematical Morphology Methods', IAENG International Journal of Computer Science, IJCS_38_3_15.

[2] Alan D Fleming, Sam Philip, Keith A Goatman, John A Olson, Peter F Sharp (2006) 'Automated microaneurysm detection using local contrast normalization and local vessel detection,' IEEE Trans. Med. Imag., vol. 25, no.9, pp. 1223–1232.

[3] Meindert Niemeijer, Bram van Ginneken, Marina S A Suttorp-Schulten, Michael D Abramoff (2005) 'Automatic detection of red lesions in digital color fundus photographs', IEEE Trans. Med. Imag., vol. 24, no. 5, pp.584–592.

[4] Simandjuntak R A, Suksmono A B, Mengko T L R, Sovani I (2005) 'Development of computer-aided diagnosis system for early diabetic retinopathy based on microaneurysms detection from retinal images', proceedings of the 7th International workshop on Enterprise networking and Computing in Health Care Industry, pp.364-367.

[5] Thomas Walter, Pascale Massin, Ali Erginary, Ricahrd Ordonez, Clotilde Jeulin, Jean-Claude Klein (2007) 'Automatic detection of microaneurysms in color fundus images' International Journal of Medical Image Analysis, pp.555-566.

[6] Usman Akram M, Shehzad Khalid, Shoab A Khan (2012) 'Identification and classification of microaneurysms for early detection of diabetic retinopathy', The Journal of the Pattern Recognition Society, pp.1-11

[7] Wong Li Yun, Rajendra Acharya, Venkatesh Y V, Carolie Chee, Lim Choo Min, E Y K Ng (2008) ' Identification of different stages of diabetic retinopathy using retinal optical images', International Journal of Information Sciences -178, pp.106-121.

[8] Jayanthi D, Devi N, SwarnaParvathi S (2010) 'Automatic diagnosis of retinal diseases from color retinal images', International Journal of Computer Science and Information Security, vol-7, No-1, pp .234-238.

[9] Priya R, Aruna P (2012) 'SVM and Neural Network based Diagnosis of Diabetic Retinopathy', International Journal of Computer Applications (0975 – 8887) Volume 41– No.1, pp. 6-12.

[10] QI Quan, ZHAO Qing-Zhan, DENG Hong-tao (2011) 'Location of Microaneurysms on Diabetic Retinopathy Images Based on Extraction of Connection Components', Proceedings of the International Conference on Compute and Management (CAMAN), pp.1-4.

[11] Neera Singh, Ramesh Chandra Tripathi (2010), 'Automated Early Detection of Diabetic Retinopathy Using Image Analysis Techniques', International Journal of Computer Applications (0975-8887), volume 8-No.2.

[12] Gonzalez and, R.C. and R.E. Woods, 2002. Digital image Processing. Prentice Hall Upper Saddle River, NJ.

[13] Vapnik. V, Statistical learning theory Wiley‖, New York, 1998.

[14]Akara Sopharak, Matthew Dailey N., Bunyarit Uyyanonvara, Sarah Barman, Williamson, Tom, Nwe, Khine Thet and Moe, Yin Aye (2010) 'Machine learning approach to automatic exudate detection in retinal images from diabetic patients', Journal of Modern Optics, 57(2):124-135.

[15] Chih-Wei Hsu and Chih-Jen Lin (2002) 'A Comparison of Methods for Multiclass Support Vector Machines', IEEE Transactions on Neural Networks, Vol. 13, No. 2, March 2002.

[16] Durgesh K.Srivastava and Lekha Bhambhu (2009), "Data Classification using Support Vector Machine", Journal of Theoretical and Applied Information Technology, Vol.12, No.1.