

# Early Stage Detection of Diabetic Retinopathy Using an Optimal Feature Set

S.D. Shirbahadurkar<sup>1</sup>, Vijay M. Mane<sup>2</sup>(✉), and D.V. Jadhav<sup>3</sup>

<sup>1</sup> Department of E&TC Engineering, Zeal COER, Pune, India

<sup>2</sup> Vishwakarma Institute of Technology, Pune, India

vijay.mane@vit.edu

<sup>3</sup> Department of Electronics Engineering, Government Polytechnic,  
Ambad, India

**Abstract.** Diabetic Retinopathy (DR) is the most common source of blindness in the current population worldwide. The development of an automated system will assist ophthalmologists. DR is a worsening disease, hence early detection is important for diagnosis and proper treatment to prevent blindness. Microaneurysms (MAs) are the first signs of DR; hence their accurate detection is necessary for early stage detection of DR. This paper proposes a three stage system to detect all MAs in the retinal fundus image. First stage extracts all possible candidates using morphological operations and Gabor filter. Feature vector using statistical, gray scale and wavelet features for each candidate is formed in second stage. In the last stage, classification of these candidates as MAs and non MAs is performed using a multilayered feed forward neural network (FFNN) classifier and support vector machine (SVM) classifier. The main objective of the proposed work is to propose a list of important and optimal features for MA detection using the most common features used in the literature. The experiments have been performed on the database DIARETDB1 to evaluate the proposed system. The evaluation parameters accuracy, sensitivity and specificity are obtained as 92%, 79%, 90% and 95%, 76%, 92% respectively for FFNN and SVM classifiers.

**Keywords:** Diabetic Retinopathy · Microaneurysms · Classifier · Neural network classifier · Gabor filter

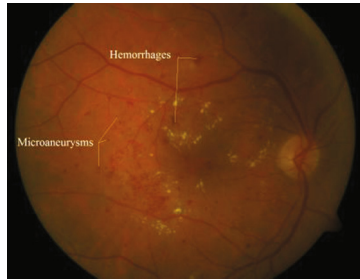
## 1 Introduction

Diabetes is a chronic disease and found in a large number of working populations in most of the developed and developing countries. Diabetes develops when the body does not create sufficient quantity of insulin or fails to process it properly. This increases glucose level in the body which causes damage to almost all organs of the body [1]. The most common damage due to diabetes causes in feet and visual system. The damage to the retina because of diabetes is called diabetic retinopathy (DR).

DR results because of damage to the retinal blood vessels. The blood vessels of the eyes become blocked or swollen due to which they leak the blood into the retina. DR causes damage to the retina without showing any indications at the early stage [2].

Treatment at the later stage is complicated and almost impossible. Hence the before time detection of DR is important to avoid failure of the vision in the patients.

The non-proliferative DR (NPDR) occurs due to blood vessels leak the blood in the retina. Proliferative DR (PDR) is the next stage to NPDR; this causes blindness in the patient. Microaneurysms (MAs) are the before time symptom of DR, which are formed by small swellings near tiny blood vessels. Hemorrhages, hard exudates, and soft exudates are other signs of NPDR. A number of lesions present in the retina decide the stage of NPDR as mild, moderate or severe. The retinal fundus image with signs of DR is shown in Fig. 1.



**Fig. 1.** Retinal fundus image showing early stage signs of DR

For the detection and treatment of DR, regular examination of the retina of the patient is necessary before it affects the sight of the patient. Manual detection is costly, time-consuming and resource demanding. Hence, there is a need to develop an automated system for early stage detection of DR. The system must be sensitive to distinguish images of without DR from images with DR [3].

MAs occur at the end of tiny blood vessels due to swelling of the vessel walls. They are round shaped red color dots of different sizes ranging from 10 to 125  $\mu\text{m}$ . MA detection is a difficult process since they are of the same colour as of blood vessels and variable in sizes. Automatic detection of MAs will lesser the cost as well as difficulties faced in manual detection.

This paper presents a system for automatic detection of MAs for early stage detection of DR. In the proposed system, the image is preprocessed for the removal of noise, shade correction and removal of blood vessels. The main contribution of the proposed system is to show the accuracy of the detection mainly depends on the set of features extracted for the classification. A set of features are proposed for the extracted candidate MAs. The support vector machine and neural network classifiers are used for final classification into MAs and non-MAs. The rest of the paper is organized as, Sect. 2 presents the related work, Sect. 3 elaborates the proposed methodology, Sect. 4 presents the results obtained and Sect. 5 concludes the paper.

## 2 Related Work

Quelleg et al. [4] proposed a general framework for automated detection of lesions in the fundus image. The feature space was obtained from reference images presenting target lesions using factor analysis. Giancardo et al. [5] used Radon transform to identify lesions using minimum preprocessing and without previous knowledge of retinal morphological features. Antal et al. [6] presented a multi-level ensemble-based approach, where ensemble was formed by a specific group of various preprocessing schemes and candidate extraction schemes. An optimal feature set was used to classify the MAs. Sopharak et al. [7, 8] performed preprocessing, candidate detection using the extended-minima transform, and a Bayesian classification to perform the pixel-level MA detection. Ram et al. [9] presented a two stage classification methodology to detect MAs. The candidate MA lesions were detected using thresholding. The separation of MAs from blood vessels was done using first classifier. The second classifier was applied for final detection of MAs. Haloi et al. [10] detected MAs in color images using deep neural networks. Sinthanayothin et al. [11] detected both MAs and hemorrhages from the fundus images. They enhanced the red lesions using a moat operator. The final set of candidate lesions were extracted after removal of blood vessels. A distinctive method was introduced by Lazar et al. [12, 13] using an unsupervised classification method. The uniqueness of this technique is to distinguish between vessels and MAs by using a 1D scan line at different directions for each pixel. They formed a probability map for each pixel and then by using simple thresholding the final set of candidate's were formed for classification. Akram et al. [14] proposed a system using Gabor filter banks to extract candidate regions. A hybrid classifier combining Gaussian mixture model, SVM and extension of multimodal medioder based modeling approach was used for classification. The study shows that MA detection is a difficult task since they are small in size and are of color same as that of blood vessels. This paper presents an approach to overcome limitations of previous methods by combining different stages. The main objective of the proposed system is to propose a list of important and optimal features for accurate detection of MAs.

## 3 Proposed Methodology

This paper presents a three stage system for automatic MA detection. The stages of the proposed system includes - extracting the candidate MAs, to form the feature vector for each candidate MA and finally classify them as true MAs or non MAs. The block diagram of the proposed system is as shown in the Fig. 2.

### A. Candidate Region Extraction

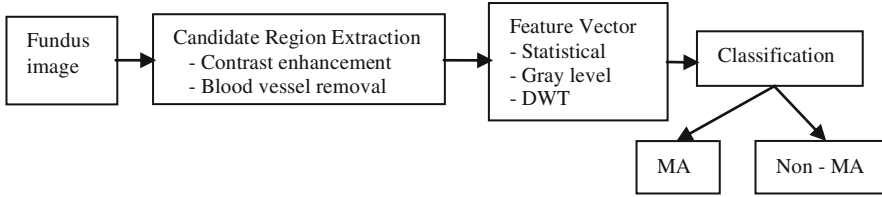
Pre-processing of the fundus images is required to improve the quality of an input retinal fundus image. Morphological operations such as opening and closing are performed to enhance the MAs in retinal fundus image using Eqs. (1) and (2) respectively, where,  $f$  is input image and  $b$  is structuring element. Morphological opening operation

is erosion followed by dilation. Morphological closing operation is dilation followed by erosion.

$$f \circ b = (f \ominus b) \oplus b \quad (1)$$

$$f \bullet b = (f \oplus b) \ominus b \quad (2)$$

The green plane of the input color fundus image is selected for further processing. The adaptive histogram equalization is performed to remove noise and brightness variations in the fundus image. The morphological opening is used to smooth the optical disk. Figure 3 shows the outputs of the preprocessing steps.



**Fig. 2.** Block diagram of the proposed system

The Gabor filter is applied to the preprocessed image for blood vessel enhancement. The normalized Gabor filter response is obtained by spanning theta from  $0^\circ$  to  $360^\circ$  at the step of  $45^\circ$ . Gabor filter is characterized by Gaussian kernel function. This interprets different types of shapes based on values of parameters. A 2-D Gabor filter function in the spatial domain is given in Eq. (3), where,  $f$  is spatial frequency,  $\theta$  is orientation angle,  $\gamma$  is aspect ratio and  $\eta$  is wavelength.

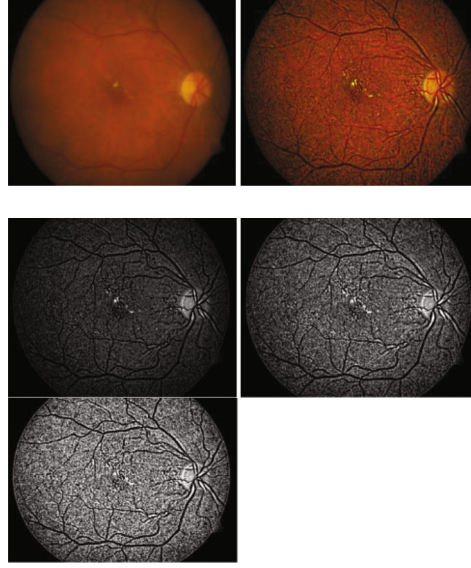
$$(x, y) = \frac{f^2}{\pi\gamma\eta} e^{-\left(\frac{f^2}{\gamma^2}x'^2 + \frac{f^2}{\eta^2}y'^2\right)} e^{j2\pi fx'} \quad (3)$$

$$x' = x \cos \theta + y \sin \theta$$

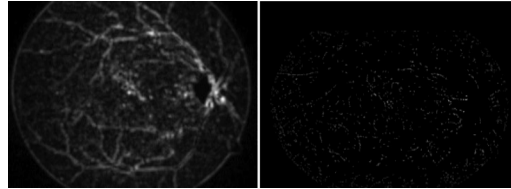
$$y' = -x \sin \theta + y \cos \theta$$

The Gabor filter in Eq. (3) is simplified version of general 2-D function derived from 1D Gabor elementary function [15].

The accurate segmentation of blood vessels is important to decrease the occurrence of false MAs and to improve the overall accuracy of the system. The blood vessels are removed by applying a suitable threshold to present all possible candidate regions. The normalized Gabor filter output and all extracted candidates after blood vessel pixels removal is shown in Fig. 4.



**Fig. 3.** Pre-processing results (a) Original image (b) Enhanced MAs using morphological operations (c) Green plane (d) Optic disk smoothing (e) Contrast enhanced image (color figure online).



**Fig. 4.** (a) Normalized Gabor filter output (b) Extracted candidates.

## B. Feature Vector Formation

The extracted candidate MAs includes both lesion and non lesion regions. To classify lesions accurately, a proper selection of the features of the regions is very important. A list of features for each candidate lesion is proposed. A feature vector is generated for each extracted candidate MA region to distinguish between MAs and Non-MAs. For an automatic system, selection of optimal features decides the effectiveness of the system. The accurate selection of feature set is very important for the automatic MA detection system. Total twenty eight features are proposed. The feature vector for all candidates is formed using statistical, Gray level Co-occurrence Matrix (GLCM) and wavelet features. Statistical features give shape and area related information of each candidate region. GLCM features are used for extracting information related to intensity of the candidate regions. For the wavelet features, first level DWT transform for 2D images are applied to obtain coefficient matrices for approximation,

horizontal details, vertical details and diagonal details sub-bands. Approximation coefficients contain significant information in image while other coefficients contain detailed information. For accurate classification absolute features must be extracted to obtain difference between objects, hence approximation coefficients are used to extract wavelet based features. The set of proposed optimal features are as follows:

1. Area: Entire amount of pixels present in candidate region.
2. Aspect ratio: Ratio of width of bounding box to height of bounding box of candidate region.
3. Perimeter: The distance around the boundary of the candidate region.
4. Eccentricity: Ratio of the distance between foci of the ellipse and length of its major axis.
5. Mean intensity: The mean of all the intensity values in candidate region.
6. Major axis length: Length of the major axis of the ellipse in pixels.
7. Minor axis length: Length of minor axis of ellipse in pixels.
8. Compactness:  $C = P^2/A$  where  $P$  and  $A$  are perimeter and area of candidate region.
9. Equivalent diameter: Diameter of the circle which has same area as the candidate region.
10. Roundness:  $r = 4\pi A/P^2$  where  $A$  and  $P$  are area and perimeter.
11. Skewness: A measure of asymmetry of the data around the sample mean.
12. Orientation: The angle involving x axis and main axis of ellipse.
13. Convex hull: The number of vertex of polygon that contains the region.
14. Convex area: Area of the polygon that contains the candidate region.
15. Euler number: The number of objects minus holes in the region.
16. Mean gradient magnitude of pixels in the candidate region.
17. Mean of all the pixel values in the candidate region.
18. Standard deviation for pixels in the candidate region.
19. Contrast: The contrast in the intensity of pixel and its neighbor over candidate region.
20. Correlation: Measure of how correlated is a pixel to its neighborhood over region.
21. Energy: Sum of squared elements of GLCM for candidate region image.
22. Homogeneity: The nearness of the division of elements of GLCM to its diagonal.
23. Entropy: The entropy of grayscale image of candidate regions.
24. Wavelet energy: Sum of squares of all the elements in coefficient matrices.

$$Energy_{wave} = \sum_{i=1}^m \sum_{j=1}^n C_{a(i,j)}^2$$

25. Wavelet entropy: This feature is used to characterize the randomness texture of the image

$$Entropy_{wave} = \sum_{i=1}^m \sum_{j=1}^n C_{a(i,j)} \log C_{a(i,j)}$$

26. Wavelet homogeneity: To compute the closeness of the distribution of wavelet coefficients.  $Homogeneity_{wave} = \sum_{i=1}^m \sum_{j=1}^n \frac{C_{a(i,j)}}{1+|i-j|}$

27. Wavelet correlation: Correlation calculates the gray level correlation of elements in coefficient matrices, where,  $\mu_i, \mu_j$  and  $\sigma_i, \sigma_j$  are mean and standard deviation respectively.  $Correlation_{wave} = \frac{(1-\mu_i)(1-\mu_j)C_{a(i,j)}}{\sigma_i\sigma_j}$
28. Wavelet contrast: Contrast measures local intensity level variation in wavelet decomposed image.  $Contrast_{wave} = \sum_{i=1}^m \sum_{j=1}^n (i-j)^2 C_{a(i,j)}$

A feature vector is formed for each extracted candidate MA using above twenty-eight features.

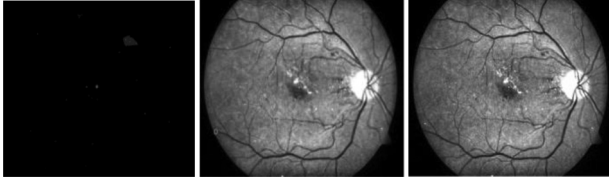
### C. Classification

The feature vector formed for the entire candidate MAs were used for classification. A multi layered feed forward neural network and a support vector machine (SVM) classifiers are used for final classification. A multilayer feed-forward artificial neural network relates of input data to an appropriate output. The error signals are used to calculate the updated weights. The error in the output layer is feed back to previous layer, and weights of these layers are updated. The Levenberg- Marquardt (LM) algorithm for weights updating have been implemented for classification. Levenberg-Marquardt neural network (LMNN) algorithm executes a combined training while updating weights, the algorithm shifts to the steepest descent algorithm. This makes the quadratic approximation using the proper training data. Then it converges to the Gauss Newton algorithm to speeds up the convergence.

Support vectors are the data points that are positioned near to the decision surface (a hyper-plane). In SVM input A is mapped to output C, where a  $\epsilon A$  is some object and  $c \in C$  is a class label. Training set  $(a1, c1), \dots, (am, cm)$  is formed by features of all the candidate MAs. Testing set is formed by features of candidates in test input fundus image. All the candidates were individually classified as MAs or Non MAs.

## 4 Results and Analysis

The experimental evaluation of the proposed system has been performed on publically available digital fundus image database DIARETDB1 [16]. These images were recorded in Kuopio university hospital, Finland. The database contains 89 color fundus images with 84 images having some mild NPDR signs as MAs of DR and 5 images are normal without DR. These images were recorded with a  $50^\circ$  field-of-view with unfamiliar camera situation. The total 1304 lesions are present in the 89 images. The database is also provided the groundtruth, the locations of the MAs in the retinal fundus image. For the experimentation purpose we used 652 lesions for training and remained 652 lesions are tested using these two classifiers. The performance measures accuracy, sensitivity, and specificity were used to find efficiency of the system. The sensitivity defines the correctly classifying the MA lesions; the specificity is the number to correctly classifying non MA lesions. The true results are the accuracy. True positive TP is defined as correctly classified lesions and false negative FN denotes the incorrectly rejected lesions. The true negative - TN, is the correctly rejected lesions. The incorrectly detected lesion is the false positive- FP. MAs detected using both the classifiers



**Fig. 5.** (a) Ground truth, detected MAs using (b) LMNN (c) SVM

**Table 1.** Performance measures for two classifiers

Classifier	SVM	LMNN
Factors		
TP	168	182
TN	384	397
FP	52	38
FN	48	35
Precision	.76	.82
Recall	.77	.83
Sensitivity	.77	.83
Specificity	.88	.91
Accuracy	.84	.88

are shown in Fig. 5. Table 1 shows the performance measures for SVM classifier and Levenberg- Marquardt neural network (LMNN) classifier.

The significance of the result is measured by precision. The total number of accurately significant results returned by classifier is a measure called recall. Table 1 shows low false positive rate with high precision values, whereas low false negative rate indicated by high recall values. High values for both the precision and recall show that the classifier yields accurate results.

## 5 Conclusion

For an automated detection of MAs from retinal fundus image a three stage system is implemented. All possible MAs were extracted and feature vectors of all the candidates along with class labels are given as input to the classifier for training. Classification performance for two classifiers, multilayered feed forward neural network classifier and support vector machine classifier is compared. The proposed system gives better results for detection of individual MAs. The main contribution of the proposed system is the use of an optimal feature set for accurate detection and classification of MAs. In future, the system can be improved for automated screening and to reduce false positive ratios. Also the DR stages can be found using number of lesions present in the retinal fundus image.



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