Improving Microaneurysm Detection from Non-dilated Diabetic Retinopathy Retinal Images using Feature Optimization

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Abstract: Diabetic retinopathy usually not presents symptoms in an early stage until it goes in a severe stage. An early stage of diabetic retinopathy is associated with the presence of microaneurysms (MAs). The occurrence of blindness can be reduced significantly if MAs are detected. This paper presented an approach to improve automatic MAs detection using feature optimization. Candidate MAs are detected using mathematic morphological. Original 20 features are present. To verify the relevance of all original features, feature optimization process is performed. The optimal feature set is searched by machine learning approach, like naïve Bayes and support vector machine classifier. Hand-drawn ground-truth images from expert ophthalmologists are used to measure the performance evaluation. The results showed that the proposed optimal feature set could significantly improve MA detection.

Keywords: Diabetic retinopathy; Microaneurysms; Machine learning approach; Feature optimization

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1. Introduction

One of the leading cause of blindness is diabetic retinopathy (DR). A rising number of diabetes patients are undiagnosed. The blindness could happen if the presence of disease is not detected in time. Around 7% of patients with diabetes will have developed retinopathy after a duration of 10 years and rising to 90% after 25 years [1] – [3]. At risk of blindness will be 25 times with people with untreated diabetes and 2% of diabetic patients will become blind. Most patients with diabetes are not aware of DR. Early detection of DR is very important. A continuous eye screening is needed to prevent the risk of blindness. The screening process is cost-effective due to a large amount of patience. A number of trained clinician/ophthalmologists are needed to analyse the lesions that are indicative of DR. An automated MA detection could help to screen the patients with diabetes more efficiently and reduce the workload of the ophthalmologist. As the first sign of non-proliferative diabetic retinopathy (NPDR), MAs are the aneurysm in the side of the blood vessel caused by an impairing of the vessel wall. They present as small round isolated dark red dots. Due to the similarity to the blood vessels, MA is some time missing detected. Fig. 1 shows a normal retinal image and NPDR retinal images with some lesions as exudates and MAs.

MA detection within fluorescein angiograms is exploiting [4], Cree et al. [5] and Frame et al. [6]. Niemeijer et al. [7] combines a detection system with kNN classifier with works by Spencer et al. [4] and Frame et al. [6]. Color feature is added into original feature set (area, perimeter, aspect-ratio, circularity, intensity, and mean-intensity). In Walter et al. [8], MA detection in color image is proposed. The candidate MAs are detected by means of the diameter closing. The 15 features are extracted including binary, gray-level and color features. The kernel method, Gaussian classifier, and KNN are used. Some author works on region growing segmentation techniques [9], [10]. Usher et al. [10] used an artificial neural network to classified MA from 4 features, size, shape, hue and intensity. Dupas et al. [11] applied a diameter-closing and black top hat on green channel image. Zhang et al. [12] extracted 31 features based on shape, color and intensity. The multi-scale correlation coefficients (MSCF) and feature classification are used to detect MA. Zohra and Mohamed [13] and Wen-Hua [14] proposed a SVM technique on diabetic retinopathy identifying. Akram et al. [15] proposed 15 features based on physical (gray level, color and shape) and statistical. A combination of the Gaussian mixture model (GMM), SVM and an extension of multimodel mediod are applied to classified MA region. Srivastava et al [16] proposed MAs and H (hemorrhages) detection from the presence of blood vessels. The original image were divided in to sub-image with a difference grid sizes and Frangi filter is used. The maximum value of the response image is used as a feature. The SVM is used as a classifier. Habib et al. [17] proposed a Tree Ensemble classifier to detect MAs. A set of 70 features were used. With a large number of features, the Predictor Importance are calculated for feature analysis. They found that some features were less important than the others. However, feature selection method was left for future work. Bo Wu et al. [18] proposed MAs detection using KNN classifier. Peak detection and region growing were used to detect candidate MAs. A total of 27 features were extracted. The results were compared with Naïve Bayes and Adaboost classifier. Akram et al. [19] proposed a hybrid

classification, m-Mediods based modeling and Gaussian Mixture Model. All types of NPDR lesions were grading and grade the diabetic retinopathy. The 16 features were used.

Even though many methods have been proposed for MA detection, these methods are limited or work well only on dilated pupil retinal images where the qualities of images are good. Some methods used a feature set to classify MA but none of them has suitable feature selection/optimization. This might be because of large computational efforts. Some features may not influence the system accuracy. The limitation of computer specification and running time should be considered.

In our previous work, MA detection using naïve Bayes classifier is applied [20]. Here SVM classification is proposed. The rest of the paper is organized as follows. In Section 2, preprocessing process, candidate MAs extraction, feature optimization and MAs classification are proposed. In Section 3, the experimental result is reported. The discussion and conclusion are finally presented in Section 4.

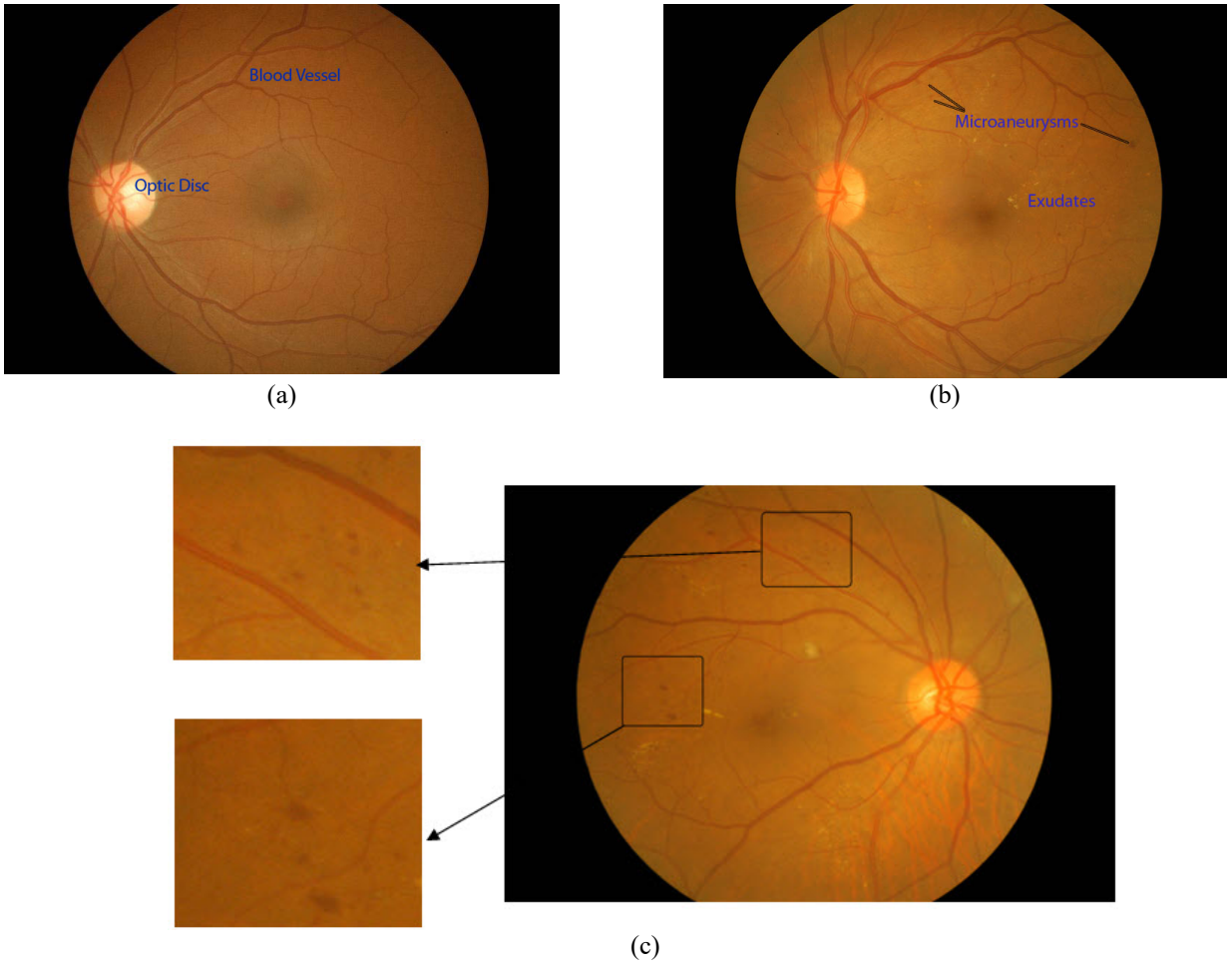


Fig. 1. Diabetic retinopathy image (a) normal retinal image, (b) NPDR retinal image and (c) cropped region contains MAs.

2. Methods

In this work, a hundred of non-dilated retinal images from the Eye Care Center, Thammasat University hospital, Thailand and St Thomas' Hospital, UK are studied. A Kowa'snon-mydriatic 7 camera is used.

The paper is organized as follows: Section 2.1 described an overview of preprocessing step.

Section 2.2 explains the optic disc, exudates and vessel elimination. Section 2.3 explains the feature extraction. Section 2.4, feature optimization and classification using the naïve Bayes and SVM classifier are presented. Section 3 reported the results and performance comparison of our proposed system. The last section, a discussion and conclusion is described. Fig. 2. shows process diagram of our proposed method.

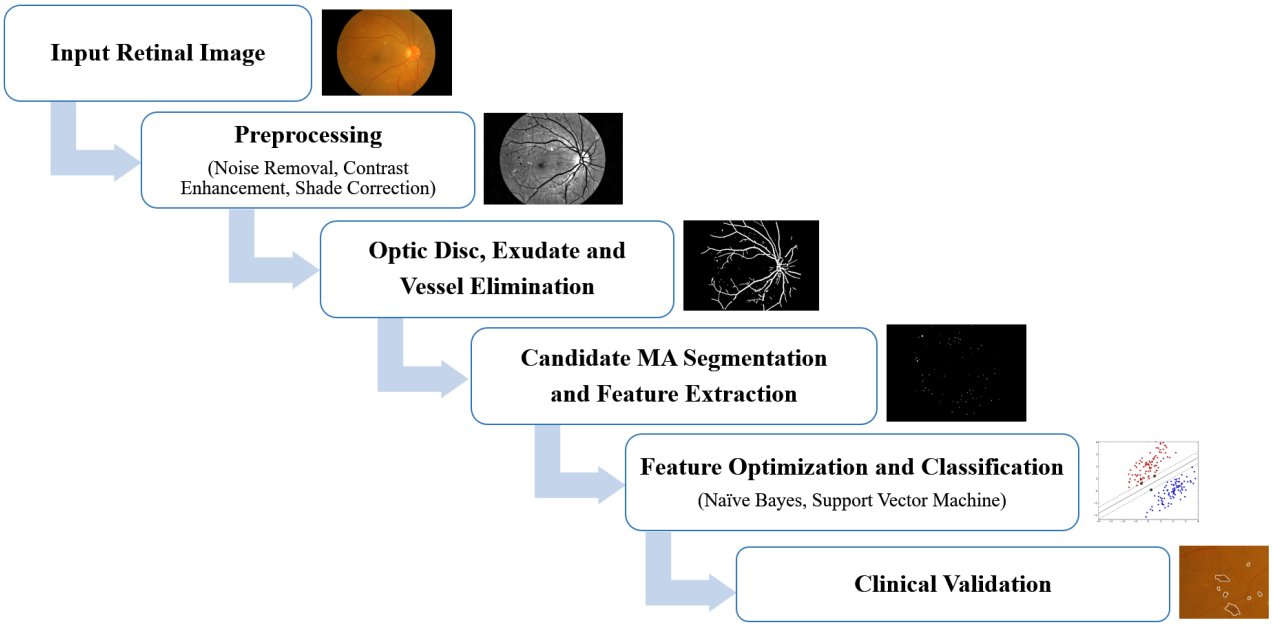


Fig. 2. A process diagram improvement of Microaneurysm detection.

2.1 Preprocessing

Several steps of preprocessing are applied in order to improve the poor quality image. Noise removal, low contrast enhancement and non-uniform illumination correction are applied. The original images are in RGB color space. To remove noise, median filtering is applied on a green plane in which MA has the highest contrast with the background. Contrast Limited Adaptive Histogram Equalization (CLAHE) and Morphological filter are applied for contrast enhancement. After CLAHE is applied, Morphological filter is performed. The CLAHE image is added to the top hat filtered image (subtracts the morphological opening of the image from the image), and then subtract the bottom hat filtered image (subtracts the image from the morphological closing of the image). Shade correction algorithm is then applied to remove slow background variation by subtracting the image with a median filter. The result improves the visibility of MA.

2.2 Candidate MA detection

To prevent high false positive or wrongly detected pixels, bright/yellowish lesions such as optic disc and exudates are removed. The dark/red object such as blood vessels has to be removed too, since they appear in a same reddish color as MAs and MAs are not occurring on vessels.

The entropy method and compactness property are used to detect the optic disc. From our previous work, the series of mathematical morphology techniques are applied to detect exudates and vessels [20], [21]. The MA regions are obtained by differentiating the coarse candidate MA image with optic disc, exudates and vessel removed image. Fig. 3 (a) – Fig.3 (d) show the original RGB image, shade corrected image, vessel detected result with MAs candidate and MAs candidate, respectively.

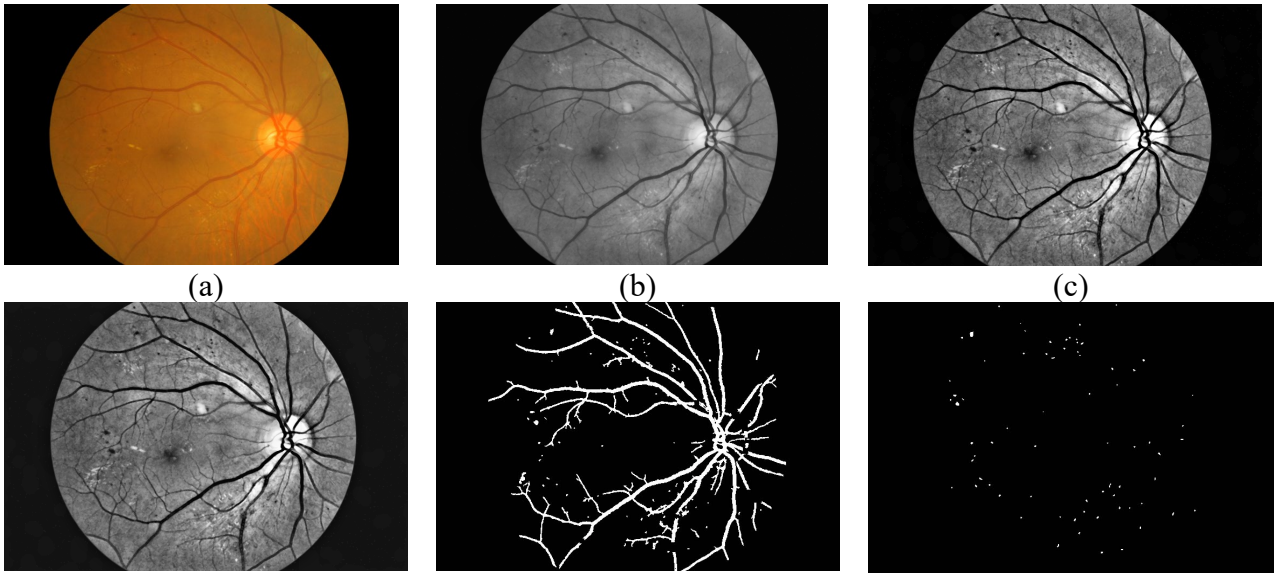


Fig. 3. The result of preprocessing and MA candidate detected (a) Original RGB image, (b) CLAHE image, (c) Morphological filter image, (d) Shade corrected image, (e) vessel detected with MAs candidate region, and (f) MAs candidate regions.

2.3 Feature Extraction

The 20 candidate features are extracted according to the MA characteristic and used as initial input to the classifier. Mathematic morphological method [20] are applied. In our previous work, these features are extracted for exudates (lipid leaks from a retinal blood vessel) detection. We aim to use the same feature set in order to integrate all works with the same feature extraction method to complete the overall diabetic retinopathy detection system in the future. The features can be grouped based on their property as listed in Table 1.

2.4 Feature Optimization and Classification

Feature optimization and classification are integrated. The data are separated into training and testing sets. All features are scaling to standardize the range between 0 and 1. There are many optimization techniques used in feature selection step [23]. In this paper, high-performance classification techniques are applied, namely Naive Bayes (NB) and support vector machine (SVM). To verify the performance of the optimal feature set, two feature optimization methods and classifiers are proposed: 1) sequential backward selection with NB classifier and 2) sequential forward selection with SVM classifier. Finally, the informative subset of features can be obtained effectively.

2.4.1 Sequential backward selection with Naive Bayes Classifier

The Naive Bayes classifier [24], [25] is based on Bayes's theorem. The maximum a posteriori (MAP) is computed to estimate the most probable hypothesis. The features $\mathbf{x} = (x_1, \ldots, x_n)$ is classified to a class y when class y has the highest posterior probability over the others.

$$\hat{y} = \underset{y}{\operatorname{argmax}}\, P(y|\mathrm{x}) \tag{1}$$

Table 1
Feature extraction.

Intensity-based feature	
1	The intensity value of pixel in shade corrected image (I_{sc}).
2	The intensity value of pixel in green band image after preprocessing (I_g).
3	The mean intensity of the candidate MA pixel on shade corrected image.
4	The mean intensity of the candidate MA pixel on green band image.
Color-based feature	
5	The hue value
6	The saturation value
7	The red value
Size-based and Shape-based feature	
8	The area (total number of pixels) of the candidate MA.
9	The perimeter (boundary) of the candidate MA.
10	The eccentricity (ratio of the distance of ellipse) of the candidate MA.
11	The circularity of the candidate MA.
12	The ratio of the major axis length and minor length of the candidate MA.
Texture-based feature	
13	The standard deviation of pixels in shade corrected image.
14	The standard deviation of pixels in green band image after preprocessing.
15	Difference of Gaussian with standard deviation of 0.5 and 1
16	Difference of Gaussian with standard deviation of 1 and 2
17	Difference of Gaussian with standard deviation of 2 and 4
18	Difference of Gaussian with standard deviation of 4 and 8
19	Difference of Gaussian with standard deviation of 8 and 16
20	Difference of Gaussian with standard deviation of 16 and 32

All features are used as initial input to train the classifier. The performance is evaluated on the test set. Then the feature is sequentially removed and the performance is evaluated again. The outline of the sequential backward selection with naive Bayes classifier shows as follows:

Inputs:

Training set with correct class labels.

Initialize:

1. Extracted features $f = [1,2,\ldots,n]$, $n=18$
2. Train the NB classifier with all features
3. Compute accuracy of the test set
4. Sequentially remove one feature from f
5. Train the NB classifier with update feature f
6. Repeat step 3-5 for all the training iterations.
7. Compare the performance to the accuracy of the classifier without deleted feature
    a. if the performance improved, permanent delete feature and repeat the process
    b. else stop the selection

Outputs:

Feature selected by NB (f_{NB})

2.5 Sequential forward selection using Support Vector Machines

Support vector machine is a one of efficient machine learning technique. It works well on the classification problem. The data are mapped into an *n*-dimensional feature space. Then a hyperplane is constructed to different two classes. The right hyperplane is identified by maximizing the margin or distance between nearest data point and hyperplane.

We implementation the SVM using libSVM's [26]. The ν-SVM with the radial basis function kernel is used. Two parameters are considered, ν (the tolerance for misclassified training examples) and γ (the width of the radial basis function). A grid search on ν and γ is performed to obtain the best cross-validation accuracy. A coarse grid is used first, then a finer grid search is conducted. The best parameter ν and γ are then used to train the whole training set. All features are added back in order to ensure that none of any important features are loss.

The outline of the sequential forward selection with SVM classifier shows as follows:

Inputs:

Training set with correct class labels.

Initialize:

1. The best feature set selected from NB classifier (f_{NB})
2. Initialize parameter ν and γ
3. Train the SVM classifier
4. Compute accuracy on test set
5. Perform grid search to find the optimal parameter ν and γ in which gives the highest accuracy
6. Sequentially add feature back into the classifier
7. Train the SVM classifier with update feature f
8. Repeat step 4-7
9. Selected the optimal feature set in which gives the best performance

Outputs:

The optimal parameter ν and γ and optimal feature set selected by SVMs

3. Results

We used totally 50 retinal images for the training set. A testing set comprises of 25 retinal images with DR signs and 25 normal retinal images. The number of MA pixel and non-MA pixels are selected equally for training. Our work is pixel-based classification, so the numbers of pixels are large enough to verify the system. The sample size of training and testing datasets are shown in Table 2. We evaluate the system performance with the ophthalmologists' hand-drawn ground-truth images. Two expert ophthalmologists will both agree on a ground-truth image. The binary ground-truth images are then compared with the detected MAs to evaluate the performance of the classifier.

Table 2
Microaneurysm and non-Microaneurysm sample size

Dataset	MA sample points (pixels)	Non-MA sample points (pixels)
Training set	5,273	5,273
Testing set	3,982	5,638,018
Overall	8,255	5,643,291

To measure the performance of the proposed system, sensitivity, specificity, precision and accuracy are computed. These quantities values are computed using Eq. (2) through Eq. (5).

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{5}$$

where TP (True Positive) is a number of MA pixels that are correctly classified, FP (False Positive) is a number of non-MA pixels that wrongly classified as MA, TN (True Negative is a number of non-MA pixels that are correctly classified, and FN (False Negative) is a number of MA pixels that are wrongly classified.

The detail test results of the SVM classifier with parameter values are listed in Table 3. A performance of each classifier without feature optimization and the classifier with feature optimization are compared in Table 4. The execution time of each feature set is also shown in Table 5.

Table 3
SVM feature optimization and classification performance with parameter values.

Features	SE(%)	SP(%)	PR(%)	Accuracy(%)
10 Optimal feature set from NB (γ=0.004, ν=0.999)	84.82	97.99	90.01	90.99
11 features (γ=0.004, ν=0.999)	84.81	97.89	87.01	92.99
12 features (γ=0.004, ν=0.995)	**90.82**	**98.19**	**92.02**	**96.99**
13 features (γ=0.002, ν=0.98)	89.20	99.36	89.35	95.99
14 features (γ=0.002, ν=0.9)	88.10	99.99	90.14	95.98
15 features (γ=0.004, ν=0.98)	88.06	99.98	87.94	94.99
16 features (γ=0.002, ν=0.98)	89.01	99.70	87.70	93.99
17 features (γ=0.004, ν=0.98)	87.82	99.81	86.19	93.00
18 features (γ=0.002, ν=0.98)	83.82	99.99	86.01	91.99
19 features (γ=0.002, ν=0.97)	83.00	98.00	86.01	91.00
20 features (γ=0.002, ν=0.92)	82.82	99.70	85.01	90.99

SE= sensitivity, SP = specificity, PR = precision

Table 4
Performance comparison for MA detection

Method	Sensitivity(%)	Specificity(%)	Precision(%)	Accuracy(%)
All features with NB classifier	83.28	97.10	81.57	85.32
All features with SVM classifier	85.82	97.89	88.01	89.11
Feature optimization with NB classifier	84.82	98.21	89.01	92.56
Feature optimization with SVM classifier	90.82	98.19	92.02	96.99

Table 5
Number of features and execution time comparison

Method	No. Of features	Execution time (s.)
All features with NB classifier	20	15
All features with SVM classifier	20	25
Optimal feature set from NB classifier	10	8
Optimal feature set from SVM classifier	12	10

The final feature vector is formed by the 12 features out of 20 features. The best performance obtains from SVM classifier with $\nu = 0.004$ and $\gamma = 0.995$. The optimal feature set from Naïve Bayes classifier and SVM classifier is shown in Fig. 4.

Table 4 shows a comparison of the accuracy of all 20 features and the optimal feature from NB classifier and SVM classifier. The accuracy of the final optimal feature set from NB classifier is increased by 7.24% (from 85.32% to 92.56%). The accuracy of the final optimal feature set from SVM classifier is increased by 7.88% (from 89.11% to 96.99%). The execution time is also compared. The optimal feature set shortens execution time of 25 s. to 10 s. Thus, we believe that the optimal feature set could improve the performance of classifiers.

Optimal feature set from Support Vector Machine classifier ***(12 out of 20 features)***

Optimal feature set from Naive Bayes classifier ***(10 out of 20 features)***

Intensity-based feature

The intensity value of pixel in shade corrected image (I_{sc}).

The mean intensity of the candidate MA pixel on shade corrected image.

Color-based feature

The hue value

Size-based and Shape-based feature

The area (total number of pixels) of the candidate MA.

The perimeter (boundary) of the candidate MA.

The eccentricity (ratio of the distance of ellipse) of the candidate MA.

The circularity of the candidate MA.

The ratio of the major axis length and minor length of the candidate MA.

Texture-based feature

The standard deviation of pixels in shade corrected image.

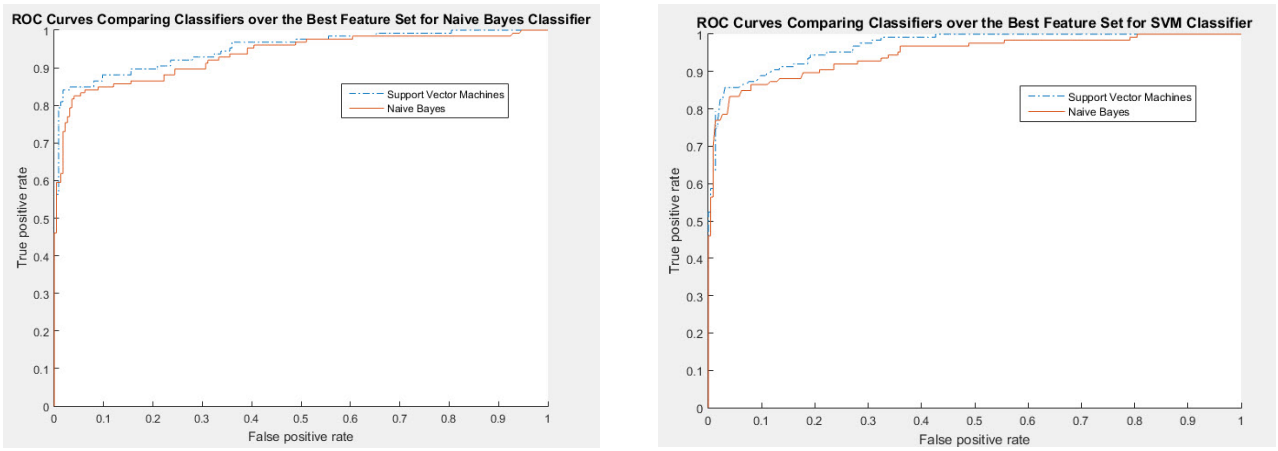
Difference of Gaussian with standard deviation of 4 and 8

Difference of Gaussian with standard deviation of 2 and 4

Difference of Gaussian with standard deviation of 16 and 32

Fig. 4. Optimal feature set from Naïve bayes classifier and SVM classifier.

Fig.5 shows the performance of the proposed MA detection on the Retinopathy Online Challenge (ROC) curve. The efficiency of the best feature obtained from naïve Bayes and SVM classifier is compared. The SVM classifier shows an improvement over the naïve Bayes.



(a) (b)

Fig. 5. ROC curve of the purposed method (a) the result of using the best feature set for naïve Bayes classifier (b) the result of using the best feature set for SVM classifier.

4. Discussion and conclusion

This paper presented an MA detection system on a non-dilated retinal image. The 20 features based on MA properties (intensity, color, size, shape and texture) are extracted. The feature optimization and classification are investigated. A naïve Bayes classifier and SVM classifier are considering for the optimal feature set selection. The final optimal feature set from SVM classifier reduces the feature vector space from 20 combinations to 12 combinations. The size based and shape based feature have an impact in accomplishing high accuracy. The optimal feature set shows the higher accuracy rate and lowers the execution time. The best sensitivity and specificity are 90.82% and 98.19%. The execution time is also acceptable for the ophthalmologist. The results show that our proposed system could be used for early detection of MA.

Fig. 6 displays the comparison of MA detection from naive Bayes classifier and SVM classifier. The SVM classifier could trace MAs boundaries more precisely. The problem of the SVM classifier is its sensitive on turning parameters ν and γ to maximize the performance and overfitting may occur if the number of the training set is small while the number of features is large. We overcome the risk of overfitting by select the optimal feature set. Less incorrectly detects of a faint blood vessel and choroidal blood vessels are presented.

Our proposed system can use in a prescreening step of eye screening as a prior diagnosis tool for ophthalmologists, likewise a decision support system. Patients still need to be referred to ophthalmologists for further diagnosis if only one suspicious MA is detected. Automatic MAs detection could reduce the cost-effective in screening step. It can increase the opportunity of passing patients to the treatment step faster.

In future work, a larger data set should be tested. An integrate exudates and the MA detection system should be performed. More accuracy of the system leads to less number of blind patients. The system aims to assist ophthalmologists in screening patients with suspected/monitoring the diabetic retinopathy faster and more accurate.

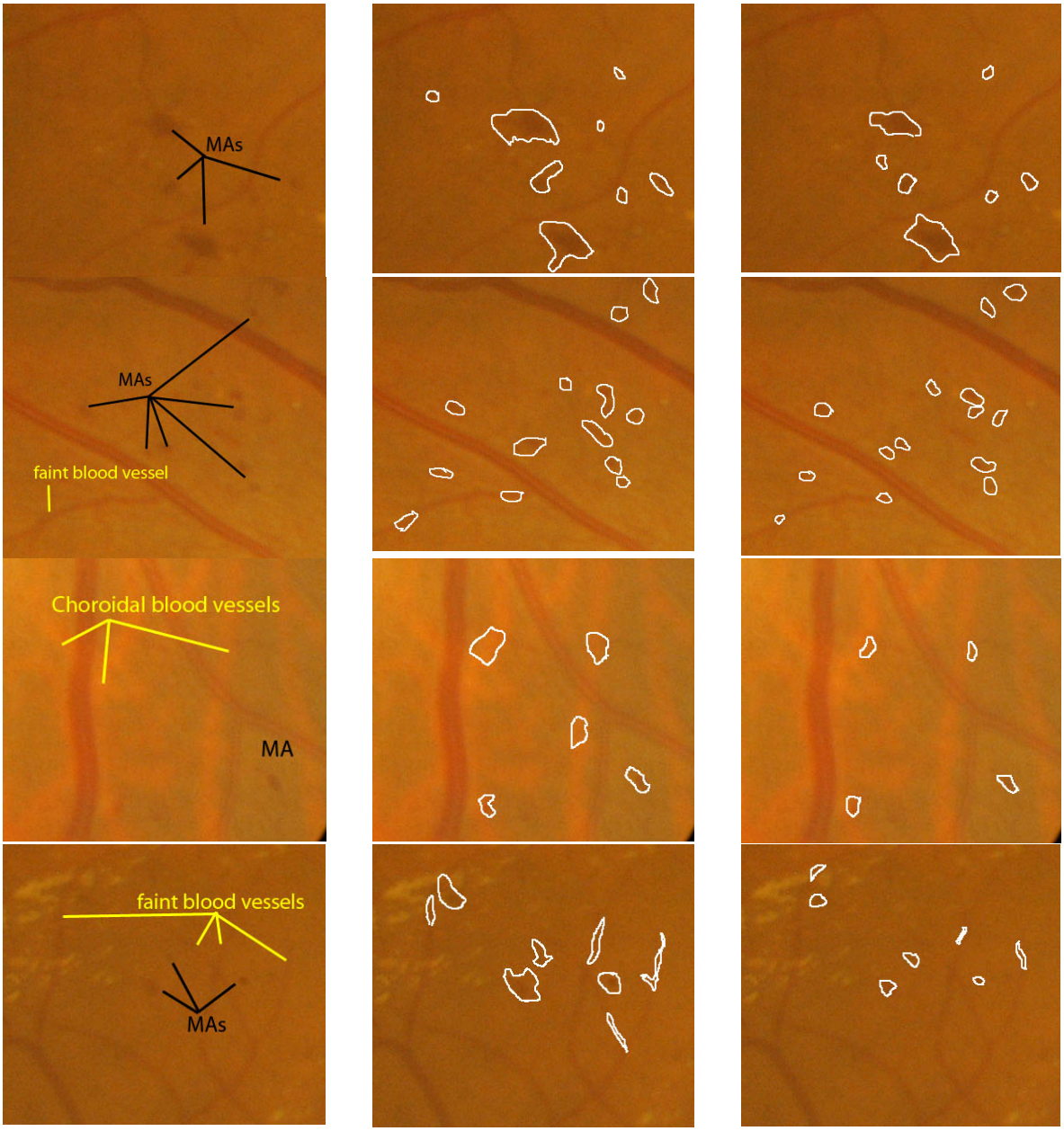


Fig. 6. Comparison of microaneurysm detection results. (a) Original image, (b) Result from Naïve Bayes classifier and (c) Result from SVM classifier

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