Comparison of Different Supervisied Classifiers in Detection of Microaneurysms

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Abstract*—**Diabetes is a rapidly increasing illness around the world. It can further cause diabetic rethinopathy(DR). If not treated properly it can make a person blind. Therefore a early detection system for (DR) is required which can be done by detecting abnormalities in eye known as microaneurysms. The main objective of this paper is to find out how different supervised classifiers responds to our morphological operation algorithm of detection of microaneurysms. The performances of the classifiers are examined by the images obtained from database DIARETDB1 which also gives ground truths. ***(Abstract)

Keywords-*diabetic retinopathy, microaneurysms, mathematical morphology, preprocessing, supervised classifiers*

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I. INTRODUCTION

Diabetes mellitus, commonly known as diabetes, can be defined as a exponential increase of blood glucose. It is one of the fastest increasing health threats worldwide. If the illness is not treated properly and as early as possible, it can lead to other health hazards such as diabetic retinopathy, diabetic nefropathy, diabetic neuropathy.

The diabetic rethinopathy(DR) is a caused by diabetes, which can lead to problems in the retina, and in the worst case, blindness. The DR at first starts as small alternation in the retinal capillary. The first detectable deformity are microaneurysms (MAs) which are local inflation of the retinal capillary and which when fracture cause intra-retinal haemorrhage (H). Microaneurysms are normaly of 10 to 100 microns in diameter, and looks like red dots. Therefore, early detection of diabetes can be performed by monitoring the MAs.

The severity of DR is estimated with the help of microaneurysms (MA), haemorrhages and exudates. The detection of MA is difficult beacuase of the similarity of their pixels with that of blood vessels. The low contrast of MA makes it very hard to distinguish from noise/background variations. Their detection can be used to grade the DR stage into four stages: no DR, mild DR, moderate DR, and severe DR.

In this paper, a publicly available diabetic retinopathy database, DIARETDB1, is used to verify the result. It contains the ground truth collected from several experts and a strict evaluation protocol.

II. RELATED WORK

[17] Different methods for MA detection have been researched before. T. Spencer et al. [7], M.J. Cree et al. [8] and A. Frame et al. [9] gives a morphology idea to segment MA with fluorescent angiograms. To detect candidate MA for classification J.H. Hipwell et al. [10] used Gaussian matched filters. Back propagation neural network was used by Gardner et al. [11]. Recursive region growing segmentation was given by C. Sinthanayothin et al. for detecting MA [12]. Diameter closing and kernel density estimation was used by T. Walter et al. [14].

In this paper, we come up with a technique which can be used to extract different candidate regions. Blood vessels, exudates and microaneurysms can be detected very precisely with the help of different morphological operations if applied appropriately.

III. PROPOSED METHOD

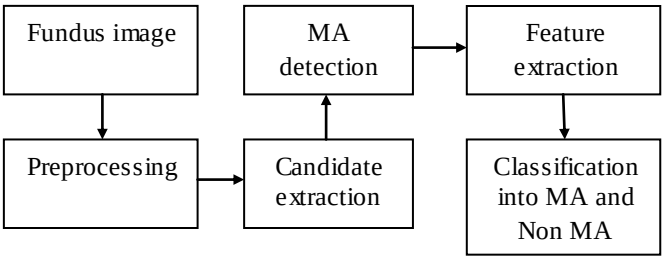

Fig 2: Block diagram of detection & classification of MA

A. *Materials*

Fundus images can be obtained by various means most easily by fundus cameras or using readily available online databases. In our work we have taken a dataset of 25 images from diaretdb1 or both training and testing purposes. Out of 25 images 20 are used for training and 5 are used for testing. The diaretdb1 database also has ground truths images where all the lesions are marked by an ophthalmologist based on the type of lesions (exudates/ microaneurysms). An image without any MA is taken as normal and the image which contains MA is considered not normal.

B. *Pre-Processing*

The image preprocessing is done in most of the medical image processes. The image resolution of the dataset diaretdb1 is 1500 x 1152. The input image is rescaled to a standard size of 576 x 768 while preserving the original aspect ratio. The green channel image is taken from the original image for our work. It is done because the blue channel image has a very

low contrast whereas the red channel image has a very high saturation value. Later for detection of MAs contrast enhancement is applied to the green channel to further enhance the MAs. The MAs appear as small black dots in the green channel image. Applying contrast enhancement further enhances their features.

C. Classification into MA and Non MA

It is done with the help of classifiers. Features are extracted from the candidate areas and with the help of that candidate regions are classifiers.

IV. CANDIDATE EXTRACTION

i. Blood Vessel Extraction

[19] The blood vessel extraction is done by a morphological operations. First a closing operation is done using two different sizes of structuring element on the green channel image. A closing operation is defined by the process of dilation and erosion. The process of dilation in a green channel image opens the brighter areas and closes small dark areas. The erosion process shrinks back the dilated objects back to their original size and shape. The dark area closed by dilation do not get effected by erosion. As we know the vessels on a green channel fundus image is dark and the background is bright, therefore the darker vessel gets closed by closing operation. The resultes obtained by the closing operation by the two different sizes of structuring element is subtracted and it gives the blood vessel in green channel. For all the morphological operations we use a disk shaped structuring element. The size of the radius of the structuring element disk is fixed at 6 (S2) and 2 (S1). The larger radius disk closes all the vessels including the main vessels. The image is thresholded using Otsu's method and then it is median filtered to get a binary image of the blood vessels.

i. Exudate Detection

[19] Exudates are bright lesions in DR image. It has sharp edges and high contrast. To detect the exudates we do a boundary A morphological thinning operation is performed on the binary image. The resulting image is median filtered by 2 x 2 filter to remove the specs of noise. Result is shown in Fig 1. detection using different morphological operations. The dilation is performed on the normal green channel image at two dissimilar sizes, S3 and S4. Both the structuring elements are larger than S2 which was used for vessel extraction. Therefore after dilation operation at S3 and S4 the blood vessels do not appear in the result. Since exudates are bright and have sharp edges, it responds to dilations operation. After subtracting the results of dilation at S3 and S4, it gives the exudates.

The resulting image is thresholded with Otsu's method. Hard exudates give closed boundaries in the thresholded result. The thresholded image filled by filling operation. Morphological filling operation on the binary image thus gives us the candidate exudate patches. Fig 2 is the result.

ii. Detection of Microaneurysms

[17] MAs looks like small dark red dots on the surface of the retina. MA is defined in medical area as[5], [6], a red, circule pattern with a diameter less than 125 µm. The aim of our paper is to find the MA with the help of its diameter, red pixels which are isolated and connected and has a constant intensity value. The MA pixels at external boundary have a higher value in green channel. The extended-minima transform is applied to the contrast enhanced preprocessed image. Extended-minima transform is a thresholding process. The h-minima transform suppresses all the minima in the intensity image whose depth is less than or equal to a predefined threshold [17]. The output binary image with the white pixels represent the regional minima in the original image. The selection of threshold is very important where the higher threshold value will lower the number of candidate area and a lower threshold value will raise the number of candidate area [17].

The result is shown in Fig. 3(b). A change in threshold value causes either surplus-segment or under-segment the MA. The earlier exudates and vessel tree are removed from the thresholded image [17]. The candidates of size larger than 17 pixels are removed and the left over candidates are taken as MAs. The result is shown in Fig. 3 (c). After testing and trying it is found out that the optimum value of $\alpha 2$ is 0.35.

V. POST PROCESSING

a. Feature Extraction

[18] The MA candidate area has properties like color, size and shape. MAs are dark red colored circles. To automatically separate MA from non-MAs features are extracted so that the classifier can use it. The features are divided into these groups:

- Shape based
- Gray level
- Color
- Statistical

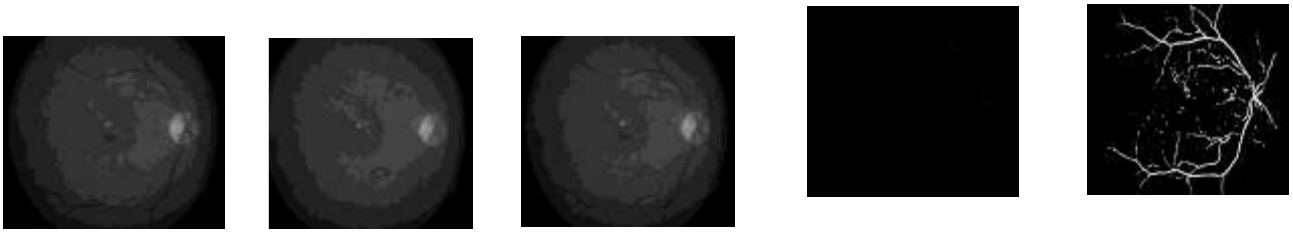

Figure 1: (a) Green Channel image, (b),(c) Closing operation (d) result after subtraction of closing, (e) After thresholding

Features are extracted from all possible candidate area which looks like MA area. The candidate features which are used in our paper:

i. Eccentricity
ii. Area
iii. Aspect ratio
iv. Compactness
v. Perimeter
vi. Mean & standard deviation of green channel candidate area.
vii. Mean & standard deviation of lesion area in contrast enhanced photograph.
viii. Mean of HSV
ix. Standard deviation of HSV
x. Entropy
xi. Third moment

b. Classification using classifier

In our paper we are using four classifiers to separate the MAs from the falsely detected non MA lesions. The classifiers used here are:

1. Support Vector Machine (SVM)
2. Naive Bayes classifier
3. Nearest neighbour classifiers
4. Linear discriminant analysis

VI. RESULTS

In our paper we are comparing different supervised classifiers with the help of classifier performance parameters. We are using Support Vector Machine (SVM), Nearest Neighbor, Linear discriminant Anlaysis and Naive Bayes classifiers for our experiment. The training dataset consist of features 250 segments which are obtained from the 20 training images. 5 images are taken for the testing purpose. Features are extracted for each segment from these testing images are used to evaluate the performance of the classifiers. The performance of proposed system is measured using sensitivity and specificity as figure of merit. They are defined by the equations:

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

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

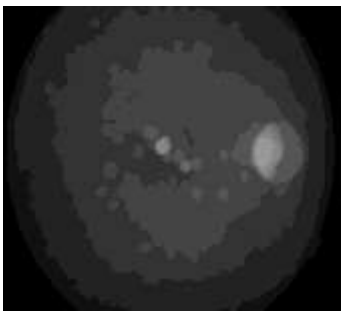

fig 2(a):Dilation with S3

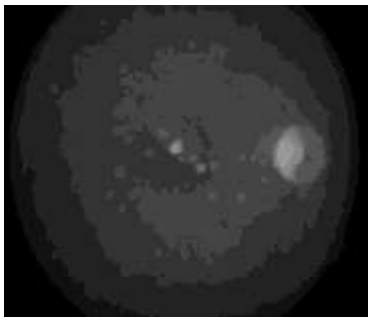

fig 2(b):Dilation with S4

fig 2(c):subtracted image

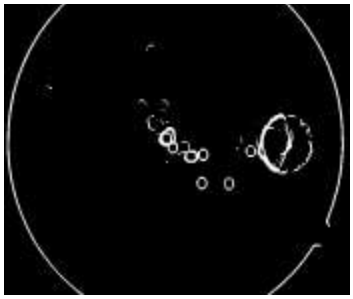

fig 2(c):Thresholded image

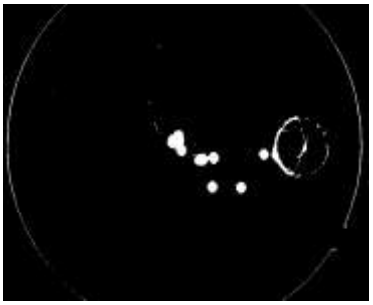

fig 2(c):filled image

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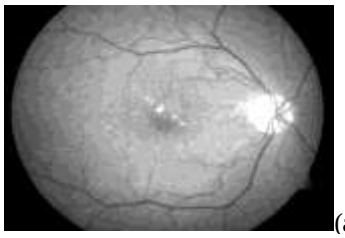
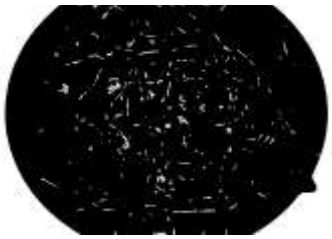

(a)

(b)

(c)

Figure 3: (a) contrast enhance green channel, (b) Extended-minima transform, (c) Detected microaneurysms

Where
TP (True Positive): MA area correctly detected by the classifier.
FP (False Positive): Non-MA area falsely detected as MA regions.
TN (True Negative): Non-MA area correctly detected
FN (False Negative): MA area falsely detected as non-MA.

After running the classifiers with the training and 5 different testing set we get the following result for each type of classifier.

TABLE I. SENSITIVITY AND SPECIFICITY(PERCENTAGE)

Naive Bayes									
Image 1		*Image 1*		*Image 3*		*Image 4*		*Image 5*	
Sens	*Sens*	*Sens*	*Spec*	*sens*	*Spec*	*Sens*	*Spec*	*Sens*	*Spec*
71.4	60	33.3	33.3	66.7	33.3	73.7	50	60	50

SVM									
Image 1		*Image 1*		*Image 3*		*Image 4*		*Image 5*	
Sens	*Sens*	*Sens*	*Spec*	*sens*	*Spec*	*Sens*	*Spec*	*Sens*	*Spec*
85.75	60	33.3	0	0	0	33.3	10	33.3	0

Nearest Neighbour									
Image 1		*Image 1*		*Image 3*		*Image 4*		*Image 5*	
Sens	*Sens*	*Sens*	*Spec*	*sens*	*Spec*	*Sens*	*Spec*	*Sens*	*Spec*
85.75	60	100	33.3	100	70	84.3	60	100	80

Linear discriminant analysis									
Image 1		*Image 1*		*Image 3*		*Image 4*		*Image 5*	
Sens	*Sens*	*Sens*	*Spec*	*sens*	*Spec*	*Sens*	*Spec*	*Sens*	*Spec*
85.75	30	33.3	33.3	66.7	30	50	33.3	33.3	30

TABLE II. AVERAGE SENSITIVITY AND SPECIFICITY(PERCENTAGE)

Sl No	*Classifier name*	*Sensitivity*	*Specificity*
1	Support Vector Machine (SVM)	37.07%	14%
2	Nearest Neighbour	94.41%	60.66%
3	Linear Discriminent Anlaysis	53.81%	31.32%
4	Naive Bayes classifiers	61.05%	45.32%

VII. CONCLUSIONS

From our result we can conclude that the Nearest neighbor classifier works better than the rest of the classifiers. In the morphological detection process of MAs, some of the MAs are missing therefore some other techniques should be used in that step of the paper.

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