Detection of Lesions and Classification of Diabetic Retinopathy Using Fundus Images

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***Abstract*— Diabetes retinopathy is a retinal disease that is affected by diabetes on the eyes. The main risk of the disease can lead to blindness. Detection the disease at early stage can rescue the patients from loss of vision. The major purpose of this paper is to automatically detect as well as to classify the severity of diabetic retinopathy. At first, the lesions on the retina especially blood vessels, exudates and microaneurysms are extracted. Features such as area, perimeter and count from these lesions are used to classify the stages of the disease by applying artificial neural network (ANN). We used 214 fundus images from DIARECTDB1 and local databases. We found that the system can give the classification accuracy of 96% and it supports a great help to ophthalmologists.**

Keywords—diabetic retinopathy; neural network; blood vessels; exudates; microaneurysms

I. INTRODUCTION

Medical image diagnosis plays a major role of research for healthcare purposes. Diabetic retinopathy (DR) is a diabetes complication that affects eyes. It can be occurred because enough rate of insulin in the body is not secreted properly by the pancreas [1]. If a person has diabetes for 20 years or more, he or she has the more probability to suffer diabetic retinopathy [2]. DR usually shows no symptoms or vision problems at early stage of the disease. However, it can lead blindness eventually. The earliest clinical sign of DR is the detection of microaneurysms (MAs). They are formed due to the leakage of blood from capillary. MAs are small, red dots and spread on the superficial retinal layers. When the walls of MAs get ruptured, hemorrhages (HMs) occur. The small HMs similar to MAs are called dot and blot HMs. Splinter hemorrhages that occur in the more superficial nerve fiber layer are called flame-shaped hemorrhages. The more leakage from damaged capillaries can cause exudates (EXs). They are usually yellow in color and irregular-shaped on the retina. The EXs differ from MAs and HMs from brightness. MAs and HMs are dark lesions and EXs are bright [3]. The more serious DR shows one of the symptoms of venous beading (VB), neovascularization and intra-retinal micro-vascular abnormalities (IRMA). These are abnormalities of the blood vessels that supply the retina of the eye.

During the year 1990 to 2010, DR became the fifth most common reasons for visual deterioration and blindness. In 2010, over one-third of estimated 285 million people worldwide suffering diabetes had symptoms of DR. The Forth National Health Examination Survey in Thailand reported that 7.7% of females and 6.0% of males had the prevalence of DM. To treat DM and its complications, a high budget is applied in Thailand [4]. Blindness, the main risk of DR, can be saved by early detection and treatment. DR can be detected during a dilated eyes exam by an ophthalmologist or optometrist, normally lead to time, cost and effort consuming. The automated detection of DR can help ophthalmologist by advantaging fast, reliable and accurate detection. Therefore, medical image analysis becomes one of the important areas of research for diabetic retinopathy.

Many researchers in the literature investigated classification of DR using the retinal images. Saifuddin & Vijayalakshmi [5] introduced a novel method to locate exudates and classify color eye fundus images. They performed detection of exudates from regions using mathematical morphology and classified exudates and non-exudates by engaging multilayer perceptron (MLP) classifier. They reported 100% accuracy for the tested dataset. Nayak & Bhat [6] introduced a method that used morphological processing and texture analysis. They extracted hard exudates, blood vessels and find area, perimeter and contrast. Then, they classified normal, NPDR and PDR using the artificial neural network (ANN) and demonstrated classification accuracy 93%. Sargunar & Sukanesh, [7] detected exudates and blood vessels using morphological techniques. Their proposed method classified the DR severity based on area, perimeter and hurst coefficient. Their method's accuracy was measured as 85%. Mahendran, Dhanasekaran & Narmadha [8] focused on an automated method to detect exudates applying morphological processing and calculated the gray level matric of the extracted exudate. Their classification is done using Probabilistic Neural Network (PNN) classifier. However they didn't report accuracy of the system. Shahin et al. [9] surveyed a system to detect the blood vessels, exudates, microaneurysms and calculate the area of these extracted lesions. Moreover they find the entropy and homogeneity to classify by applying artificial neural network (ANN) and achieved accuracy over 92 %.

As stated in the literature review, we found that [5], [7] and [8] extracted features from only exudate and classified only normal or DR. In [6], they didn't take into account microaneurysms and so the mild stage of the DR may be wrongly detected with normal. Our proposed method is similar with [9] in extracting three lesions and the use of classifier but

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feature extraction is different. Moreover they roughly classified two stages of DR normal and abnormal.

In our proposed method, three lesions of eye including blood vessels, exudates and microaneurysms are detected using morphological operations and histogram matching. Feature extraction are performed to get three main criteria (i) area, perimeter of blood vessels (ii) area, perimeter and counts of the exudates and (iii) counts of the microaneurysms. By using these criteria, classification is carried out by the use of artificial neural network (ANN). The retina images from Standard Diabetic Retinopathy Database (DIARECTDB1) and local database are used as inputs of our proposed work.

II. METHODOLOGY

The methodology of our proposed system is conducted based on the following steps as illustrated in Fig.1.

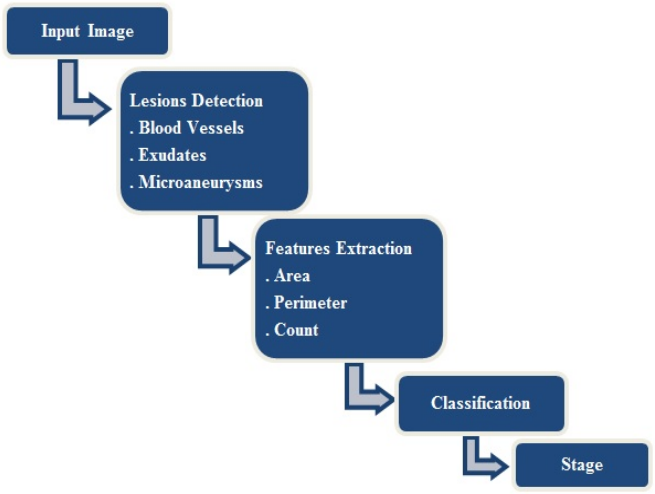

Fig. 1. Proposed Methodology

A. Input Image

In our methodology, we collect color fundus images from Standard Diabetic Retinopathy Database (DIARECTDB1) [10] and local databases. The images are initially kept to a standard size 640 x 480 before detecting lesions. Image pre-processing such as removing noises, smoothing and converting to gray scale are performed in each stage because each needs different pre-processing requirements.

B. Lesions Detection

According to medical term, a lesion means any abnormal changes of tissue or organ as a result of the disease.

i. Detection of Blood Vessels

The blood vessels spread most of area on the retina and have lower reflectance compared to other retinal surface. The green channel can give the higher contrast than red and blue. For this reason, the input fundus image is turned to green channel. Complement function helps to invert the green channel image.

$$C(i) = 255\text{-}A(i) \quad (1)$$

Where $A(i)$ is the input pixel values of the original image and $C(i)$ is the output pixel values are given by complement function.

The inverted image is improved in contrast applying contrast-limited adaptive histogram equalization (CLAHE). After that, optic disk (OD) must be eliminated in order to detect the vessels clearly. OD is simply removed by morphological opening method with ball shaped structuring element of size 8. Opening is the dilation followed by the erosion using structuring element (SE).

$$R \circ S = (R \ominus S) \oplus S \quad (2)$$

Where, R is the retina image that is improved by CLAHE, S is the structuring element, $\ominus$ denotes erosion and $\oplus$ denotes dilation respectively. Then subtracting of the opening image from the original adaptive-histogram image is performed. The noise is reduced by the median filter.

After removing the OD, we need to remove the background in order to left only vessels. The background image can be obtained by applying opening again but with the disk-shaped structuring element of size 15. Then we subtracted the filtering image from background to get only blood vessels. Then the image intensity is adjusted and performed binarization [9]. Fig.2. illustrates the processes in the detection of blood vessels.

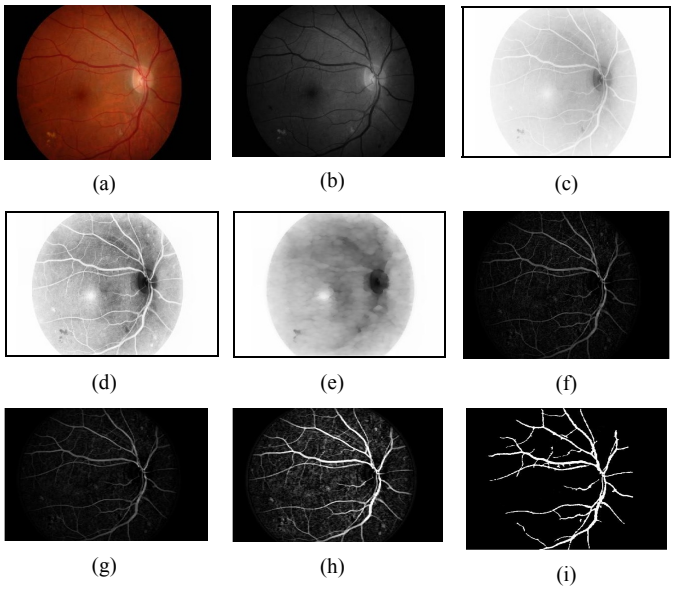

Fig.2. Processes in Detection of Blood Vessels (a) Original Fundus Image (b) Green Channeled Image (c) Complement Image (d) CLAHE Image (e) Opening Image (f) OD Eliminated Image (g) Median Filtering Image (h) Adjusted Image (i) Extracted Blood Vessel Image

ii. Detection of Exudates

Exudates have different shapes, sized and usually bright or yellow in color. Moreover, they have the highest contrast compared to other parts on the retina. But they are similar to the contrast of the optic disc (OD) and wrongly detect.

Therefore, OD should be removed first. There are different ways to remove the OD.

We don't use opening for removing OD like the detection of blood vessels because opening makes blur exudates. In this step we use histogram matching method similar to [11]. Firstly, the four different retina images are removed noise and converted to gray scale. The ODs in these images are manually cropped into size 80 x 80 and then create a template. The input retina image is firstly pre-processed with an average filter of the size 6 x 6 pixels and then converted to gray scale. Window 80 x 80 pixels is moving thorough the retina image and compare its histogram to the template histogram. The similarity of two histograms is calculated by applying the correlation function. If the histogram is the same, OD is detected and localized the center of OD. Then the OD is eliminated by filling with a 90 x 90 rectangular. The OD removed image is used to detect exudates. It is turned into green channel and enhanced applying Contrast Limited Adaptive Histogram Equalization (CLAHE).

After that we use thresholding with the value 70% of the maximum gray level to detect only exudates. The step by step processes for the detection of exudates are shown in Fig.3.

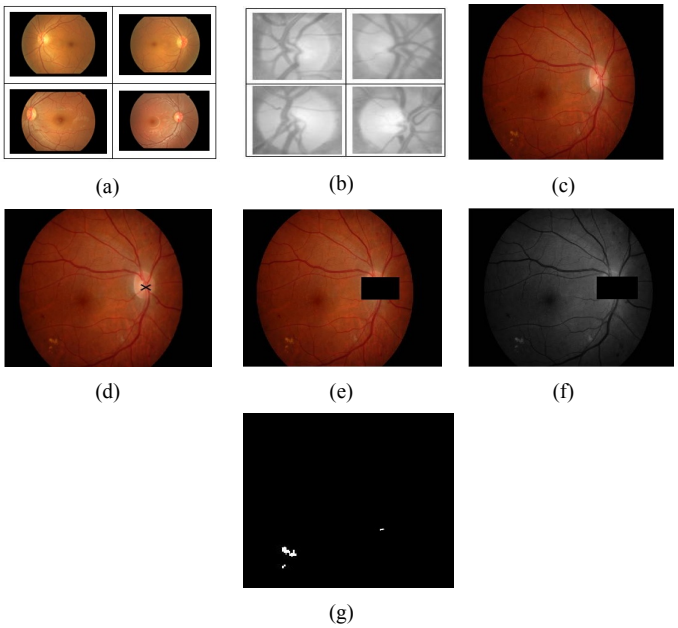

Fig.3. Processes in Detection of Exudates (a) Four Retina Images (b) Four ODs for Template (c) Input Retina Image (d) OD Detected Image (e) Eliminated OD Image (f) Green Channel OD Eliminated Image (g) Extracted Exudate

iii. Detection of Blood Microaneurysms

Microaneurysms (MAs) are small areas with balloon-like swelling in the retina's blood vessels and each has a diameter of $\lambda < 125\mu m$ approximately. Similar to previous stages, the green channel image is used to detect MAs. Then the intensity of green channel image is inversed. To adjust the contrast of the image, adaptive histogram equalization is applied. Subsequently, the Canny edge detection method is used to detect a wide range of edges in images. It is a multi-step algorithm that detects sedges with noise suppressed at the same time. The Canny method finds edges using edge function that calculates the gradient using the derivative of a Gaussian filter.

$$BW = edge(I,'Canny',threshold) \quad (3)$$

Where *BW* is the output image of the Canny method, *I* is the input image and *threshold* is a two-element vector in which the first element is the low threshold, and the second element is the high threshold. We use 0.2 for the high value and uses *threshold**0.4 for the low threshold. Then filling the holes with a disc-shaped structuring element size 6 is performed to detect appeared lesions.

Subtraction of the edge detected image from the filled image helps to get the image without boundary. Then the extracted vessel image obtained from the blood vessel detection stage is subtracted from no-boundary image [9]. After that, the spots that are greater than MAs are removed and MAs are detected. The processes in the detection of MAs are illustrated in Fig.4.

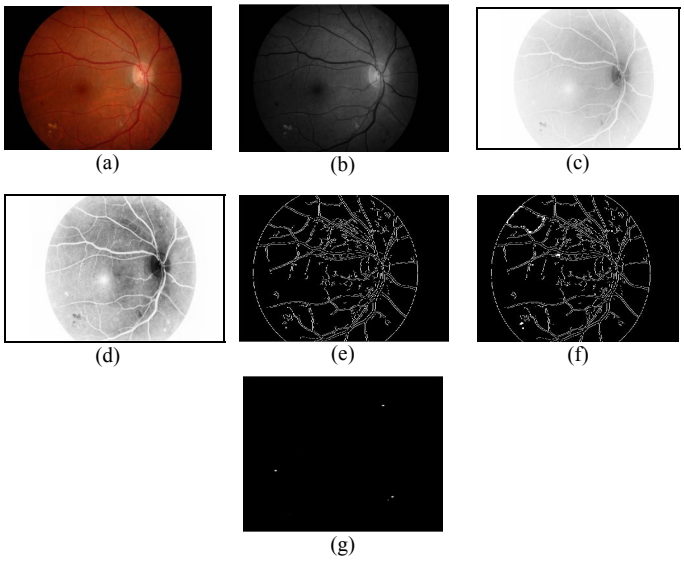

Fig.4. Processes in Detection of Microaneurysms (a) Original Fundus Image (b) Green Channel Image (c) Reversed Image (d) CLAHE Image (e) Edge Detected Image (f) Holes Filled Image (g) Extracted Microaneurysms

C. Features Extraction

This is an important stage for classification of diabetic retinopathy. Diabetic retinopathy has two main classes: non proliferative (NPDR) and proliferative (PDR). The NPDR is divided into three stages: mild, moderate and server. The clinical guidelines of grading of DR from the center of health are shown in Table I. [12]. In our proposed system, we define four classes namely R1 for normal, R2 for mild NDPR, R3 for moderate and R4 for severe NPDR and PDR.

According the clinical criteria, we can know that R1 can be classified by checking the existence of lesions especially MAs and EXs. For R2, we need to detect and classify the count of MAs only. However, for R3 we need to detect not only MAs but also exudates. Sometimes R3 has only MAs with more

numbers or only exudate or sometimes both. Therefore we extract MAs and EXs counts. For R4, there are one more criteria for abnormalities of blood vessels. R4 may have one or two or all of these facts: more numbers of MAs, more number EXs and blood vessels abnormalities.

To meet all the criteria mentioned above, we extracted the features such as (i) the microneurysms counts, (ii) the area, perimeter and counts of the exudate and (iii) the area and perimeter of blood vessels. However we don't find the area, perimeter and count for all lesions. We limit the extraction of features based on the clinical criteria, so it can save the execution time.

$$Count = max\ (max(\ l(ROI)));\qquad (4)$$

Where *l(ROI)* is the labeling the region of interest and max is the function of finding maximum value.

TABLE I. CLINICAL CRITERIA FOR DR GRADING [12]

Level	Clinical Criteria
Normal	No abnormalities
Mild NPDR	Microaneurysms only
Moderate NDPR	Microaneurysms and one or more of exudates but less than the definition of sever
Severe NPDR	One of the following: 1. Microaneurysms and exudates in all four quadrants as fovea is a center of four quadrants, 2. Intra retinal micro vascular abnormalities in one or more quadrants 3. Venous beading in at least two quadrants
PDR	Any of the following: 1. New vessels elsewhere 2. New vessels on the (optic) disc 3. Neovascularisation

$$Area = \sum(weights(:),[],'double')/8;\qquad (5)$$

Where *weights(:)* is all elements of the set that results from nonlinear neighborhood operation on ROI.

$$Perimeter = \sum (T_{edges}, L_{edges,} B_{edges}\ , R_{edges})\qquad (6)$$

Where T_{edges}, $L_{edges,}$ B_{edges} , R_{edges} are the top, left, bottom and right edge of the ROI respectively.

E. Classification

After detecting the features, the extracted features are applied to artificial neural network (ANN) for staging disease severity. ANN is a computer system for the simulation of a network based on the human nervous system. It is composed of simple, highly interconnected processing elements in the form of layers as shown in Fig.5.

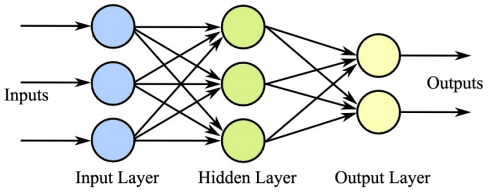

Fig.5. Artificial Neural Network (ANN) Classifier

In our proposed method, we use pattern recognition networks for classification. They are feed forward artificial neural networks that can be trained to classify inputs according to target classes.

III. EXPERIMENTAL RESULTS

The retinal images for our proposed method are achieved 134 images from DIARECTDB1 and 80 images from local datasets. We examined those 214 retinal images in order to classify the severity level of diabetic retinopathy. The six features namely blood vessel area, blood vessels perimeter, exudates area, exudates perimeter and microneurysms counts from 80 images already classified by the ophthalmologist are used for training the neural network. Training images are divided into four classes such as 20 for normal (R1), 20 for mild (R2), 20 for moderate (R3) and 20 for severe (R4) respectively. Then the network is trained according to the diagram shown in Fig.6.

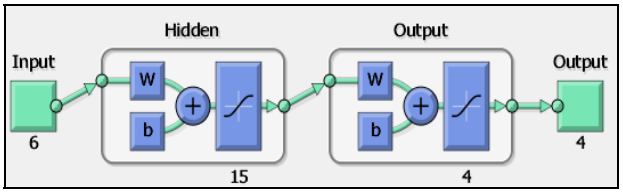

Fig.6. Training ANN Classifier

Firstly, a set of input vectors including the extracted feature values from training images is arranged as columns in a matrix. In this proposed method, the input data set consists of 80-element input vectors. Then arrange another set of target vectors. Each value in target vector corresponds to the classes of each trained image. Target vectors have 4 elements, representing four classes of DR and expressed in the form of one element as 1 and the others are 0. Then the input dataset is divided into 70% for training, 15% for validation and last 15% for testing. For hidden neurons, we repeat and test manually to get optimal performance and set it to 15. We used 4 output neurons, which is equal to the number of target vectors or disease classes. Then we train the neural network till getting the optimal performance. The performance of the classifier is evaluated confusion matrix or using contingency table. In this proposed method, the neural net classifier produces the confusion matrix of four classes of DR as shown in Table II.

TABLE II. CONFUSION MATRIX

Class	R1	R2	R3	R4
R1	20	0	0	0
R2	0	20	0	0
R3	0	0	18	2
R4	0	0	1	19

Using the prediction results, we evaluate four statistical measures of the performance such as sensitivity, fall-out, precision and accuracy for each class using the formulae [13] as shown in Table III.

TABLE III. FORMULE TO CALCULATE PERFORMANCE

Sensitivity	∑ True Positive / ∑ Condition Positive
Fall-out	∑ False Positive / ∑ Condition Negative
Precision	∑ True Positive / ∑ Test Outcome Positive
Accuracy	∑ True Positive + ∑ True Negative / ∑ Total Population

The results of the performance measurement for each class are listed in Table IV. We tested 130 retina images from DIARECTDB1 dataset and the accuracy of our proposed method for tested data is 96% and the processing time takes 28.064 seconds for computer having CPU 2.60GHz and RAM 8G.

TABLE IV. RESULTS OF PERFORMANCE MEASUREMENT

	R1	R2	R3	R4
Sensitivity	100%	100%	90%	95%
Fall Out	0%	0%	1%	3%
Precision	100%	100%	95%	90%
Accuracy	100%	100%	96%	96%

The fundus images that are wrongly classified are illustrated in Fig.7. The actual stage of Fig.7 (a) and (b) is R3 but our system wrongly classified them as R4. Fig.7. (c) is actually R4 because of it has intraretinal microvascular abnormalities but our system wrongly classified as R3. Fig.8. shows the comparison of accuracy of our method to the methods [6], [7] and [9] in the literature.

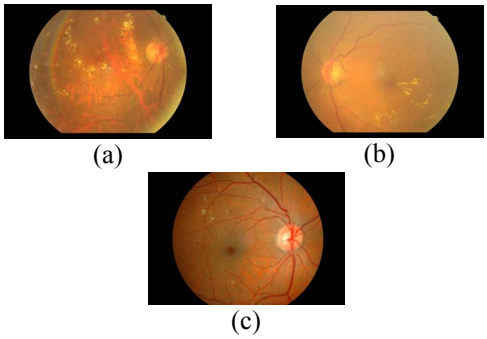

Fig.7. Wrongly Classified Fundus Images (a) and (b) Actual Class R3 but Predicted Class R4 (c) Actual Class R4 but Predicted Class R3

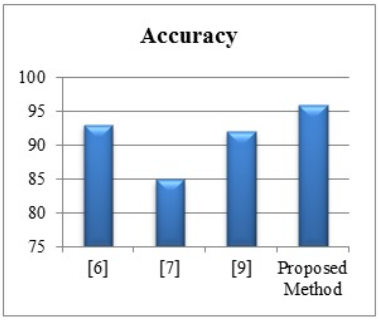

Fig.8. Comparison of Accuracy

IV. CONCLUSION

We propose a system for the objective of detecting and classification of DR. We used 214 fundus images from DIARECTDB1 and local databases. We detected there lesions namely blood vessels, exudates and microaneurysms from input images. And then extracted necessary features and classified using ANN classifier. The proposed method performed up to classification sensitivity of 95%, precision of 95% and accuracy 96% respectively. The execution time took about 28.064 seconds. As a future work, we can optimize the classifier performance with more images, extracting details features and using different classifier.

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