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A Novel Approach for Diabetic Retinopthy Classification

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ABSTRACT
Sustainable Diabetic Mellitus may lead to several complications towards patients. One of the complications is diabetic retinopathy. Diabetic retinopathy is the type of complication towards the retinal and interferes with patient's sight. Medical examination toward patients with diabetic retinopathy is observed directly through retinal images using fundus camera. Diabetic retinopathy is classified into four classes based on severity, which are: normal, non-proliferative diabetic retinopathy (NPDR), proliferative diabetic retinopathy (PDR), and macular edema (ME). The aim of this research is to develop a method which can be used to classify the level of severity of diabetic retinopathy based on patient's retinal images. Seven texture features were extracted from retinal images using gray level co-occurence matrix three dimensional method (3D-GLCM). These features are maximum probability, correlation, contrast, energy, homogeneity, and entropy; subsequently trained using Levenberg-Marquardt Backpropagation Neural Network (LMBP). This study used 600 data of patient's retinal images, consist of 450 data retinal images for training and 150 data retinal images for testing. Based on the result of this test, the method can classify the severity of diabetic retinopathy with sensitivity of 97.37%, specificity of 75% and accuracy of 91.67%

Keywords – diabetic retinopathy, 3D-GLCM, Levenberg-Marquardt, neural network

I. INTRODUCTION

Diabetic retinopathy (DR) is one of the Diabetic Mellitus complications and if not be treated immediately will lead to permanent blindness. The symptoms shown by patients with DR are microneurism, hemorrhages, hard exudates, soft exudates and neovascularis. At some intensity, these symptoms can be used as stages of DR severity. These stages generally divided into three stages namely non-proliferative diabetic retinopathy (NPDR), proliferative diabetic retinopathy (PDR), and macular edema (ME) [1].

Medical examination by opthamologist towards patients with DR is directly observed through retinal images that was obtained using fundus camera. Thus the more patients to be diagnosed the more time will be needed. Therefore, to overcome this lacking, the digital images processing system based on machine learning is needed moreover a system that can be used to classify the retinal images promptly and accurately into DR stages. This will assist optamologists to determine suitable medical treatment for patiens.

The problem that often occurs in anomaly detection using digital images is difficulty in separating between area which is abnormal and area which is non normal. The normal area that has similar feature with abormal if be computed as a feature of an anomaly image can diminish the uniqueness of an anomaly [2]. This can also happen in the study of DR where there are certain areas in retinal images that should be eliminated because it can reduce the uniqueness of DR images. Study in [3] stated that optic disc (OD) constitutes an area in normal retinal images that contains similar features with DR images such as DR images that contain exudates symptom. Several studies that conducted OD elimination before detecting exudate symptoms indicated higher accuracy than classification without OD elimination [4]. Build upon this analysis, OD should not to be computed because it can influence the accuracy of classification.

Based on background above, the purpose of this study is to develop a method that can be used to classify stages of diabetic retinopathy using 3D-GLCM method that taken from [5] with levenberg-marquardt backpropagation neural network (LMBP).

This study expected to give information to the researcher as the continuity of classification stages of diabetic retinopathy.

II. LITERAURE REVIEW

The study of detecting DR symptoms was conducted by [6], which study about recognized hemorrhage symptoms using template matching.

The result of this study shows sensitivity of system 85%. Similar study was also conducted by [7] about classification of hard exudates symptoms on DR images using RBF method. The accuracy of this study is 88.1%.

David, et al [4] conducted comparisons of DR classification using LVQ and backpropagation classifier. The result is backpropagation can classify with better accuracy 93.3% than LVQ which is 90.3%. Similar study was also conducted [9] in classifying DR symptoms on DR images using feature extraction method along with classification algorithm Learning Vector Quantization (LVQ). DR symptoms that were classified namely microneurisme, exudates and hemorrhage. The performances of this study produce sensitivity of 93.33% and specificity of 90%.

Study about classifying DR stages was also conducted in [8] using histogram features and multi layer perceptron (MLP) classifier. The proposed approach in this study is calculating the area of exudates and blood vessel area henceforth being trained to MLP.

Acharya, et al [9] conducted a study using support vector machine (SVM) to classify stages of DR. In their study, preprocessing conducted by converting RGB to grayscale form and applying adaptive histogram equalization subsequently. After preprocessing, retinal images of DR cropped manually to separate retinal region from its background. The next step is to extract features using Gray Level Co-occurance (GLCM) method as inputs to SVM classifier. The result of this study shows that system is capable in classifying DR with 85% of accuracy.

Chen, et al [5] in their research using 3D-GLCM to extract features from iris images with system accuracy up to 99.65%. In this study, researcher utilized 3D-GLCM to extract features from DR images then classified using ANN Backpropagation.

III. THE PROPOSED METHOD

The proposed method divided into six steps, which are explained in detail in the next subsections. The overall scheme of the method developed in this work is depicted in Fig. 1.

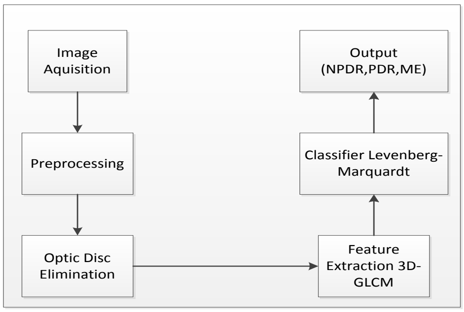

Fig 1. The proposed method

A. Data Acquisition

In this research, the images used were collected from MESSIDOR database (http://messidor.crihan.fr). It has been established to falicitate the computer aided diagnosis of DR. 1,200 eye fundus color images of the posterior pole for the database were acquired by 3 ophthalmologic departments using a color video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinograph with a 45°FOVand were stored in sizes of either 1,440*960, or 2,240*1,488, or 2,304*1,536 pixels with 8 bits per color plane. 800 images were acquired with pupil dilation (one drop of Tropicamide at 0.5%) and 400 without dilation (http://messidor.crihan.fr).

B. Preprocessing

Preprocessing was performed to remove the non-uniform background which may be due to non-uniform illumination or variation in the pigment color of eye. Contrast stretching operation was performed to solve this problem [10] before applying median filter process. This technique adjusts the local variation in contrast by increasing the contrast in lower contrast area and lowering the contrast in high contrast area.

These preprocessing technics are explained briefly in the following sections:

Contrast Stretching

The contrast of an image is the distribution of dark and light pixels. Gray image with low contrast will be seen too dark, too light, or too gray. In the stretch contrast, each pixel in the image transformed using the following functions:

$$B(i, j) = \frac{A(i, j) - c}{(d - c)}(L - 1) \qquad (1)$$

B (i, j) and A (i, j) respectively represent the transformed pixel before and after. c and d are minimum and maximum value of an input image meanwhile L is maximum value of grayscale image.

Filter Median

The median filter is an excellent in reducing salt and pepper noise and often used to improve retinal image quality, especially in diabetic retinopathy [11] [12]. Median filter works by changing the value of a pixel in the original image (center) with a median value of the the original image pixel based on a neighborhood (window) formulated as follows:

$$f(x, y) = \underset{(s,t) \in S_{x,y}}{\text{median}} \{g(s, t)\} \qquad (2)$$

C. Optic Disc Elimination

The he optic nerve head or optic disk (OD) is one of the important anatomical features that are usually visible in a fundus image of the retina. The OD represents the location of entrance of the blood vessels and the optic nerve into the retina. In fundus images, the OD usually appears as a bright region, white or yellow in color In the commonly used macula-centered format for fundus images, the OD is located toward the left-hand or right-hand side of the image and is an approximately circular area that is about one sixth the width of the image in diameter, is brighter than the surrounding area, and appears as the convergent area of the blood vessel network. In an image of the retina, all of the properties mentioned above (shape, color, size, and convergence) contribute to the identification of the OD. Identification of the OD is an important step in the detection and analysis of the anatomical structures and pathological features in the retina [13]. In order to eliminate OD, this paper used thresholding, dilation, invert and image multiplication. The steps work as follows :

a) Thresholding

Thresholding is the process of changing the degree of gray image into a binary image in order to differentiate the area towrds object and background. For the purpose of OD segmentation, this study used thresholding method with T = 203, as shown in equation:

$$g(x,y) = \begin{cases} 1 & if \quad f(x,y) > T \\ 0 & if \quad f(x,y) \le T \end{cases} \tag{3}$$

b) Dilation

Dilation is a morphological operation which state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image. An essential part of the dilation operations is the structuring element (SE) used to probe the input image. A structuring element is a matrix consisting of only 0s and 1s that can have any arbitrary shape and size.

c) Invert

$$D(A,B) = A \oplus B = \{x : B_x \cap A \ne \varnothing\} \tag{4}$$

Invert is the process of mapping pixels value of an image in which the value of black pixels (0) will be converted to white pixel (255) and vice versa.

d) Image Multiplication

Multiplication of two images is done by following equation :

C(x,y)=A(x,y)*B(x,y) (5)

Where C is output image, A and B is input image.

D. Features Extraction

Since the 2D-GLCM is unable to fully represent the texture features of the space domain images, this study used an improved of GLCM, called 3D-GLCM, which is expanded from the original 2DGLCM and thus can strengthen and demonstrate the texture features of the space [5].

Six features extracted from 3D-GLCM in this study are : (i) maximum probability, (ii) entropy, (iii) energy, (iv) correlation, (v) contrast, and (vi) homogeneity as used in [14].

All features computed as follows:

a. MaxProbability= $\max(p_{(i,j)})$ (6)

b. Entropy.

It is the randomness or the degree of disorder present in the image. The value of entropy is the largest when all elements of the co-occurrence matrix are the same

and small when elements are unequal:

$$\text{Entopy} = -\sum_{i=1}^{q}\sum_{j=1}^{q}\sum_{k=1}^{q} P_{i,y,k} \log_2 P_{i,j,k} \tag{7}$$

c. Energy

Energy is sometimes derived from the use of angular second moment. It is the sum of squared elements in the GLCM known as angular second moment. Basically, it is the measurement of the denseness or order in the image

$$\text{Energy} = \sum_{i=1}^{q}\sum_{j=1}^{q}\sum_{k=1}^{q} P_{i,j,k}^{2} \tag{8}$$

d. Correlation

$$\text{correlation} = \sum_{i=1}^{q}\sum_{j=1}^{q}\sum_{k=1}^{q} \frac{(i-m_r)(j-m_c)(k-m_o)}{\sigma_r\sigma_c\sigma_o} P_{i,j,k} \tag{9}$$

e. Contrast

The quantity contrast gives the measure of the amount of intensity variation in the image [15].:

$$\text{Contrast} = \sum_{i=1}^{q}\sum_{j=1}^{q}\sum_{k=1}^{q} \left[(i-j)^2 + (i-k)^2 + (j-k)^2\right] p_{i,j,k} \tag{10}$$

f. Homogeneity

Homogeneity measures how close the distribution of elements in the GLCM is to the diagonal of GLCM. Homogeneity weighs values by the inverse of the contrast weight, with weights decreasing exponentially away from the diagonal as shown in Eq.(11)

$$\text{Homogeneity} = \sum_{i=1}^{q}\sum_{j=1}^{q}\sum_{k=1}^{q} \frac{p_{i,j,k}}{1+\left[|i-j|+|i-k|+|j-k|\right]} \tag{11}$$

Subsequently extracted from 3D-GLCM, these features will be trained using LMBP neural network to obtain accuracy of classification.

E. Neural Network Classification

The LMBP neural network architecture had seven input neurons, one hidden layers with seven neurons each and one output neuron. The output neuron will classify four classes as‘0.0’ for Normal, ‘0.1’ for NPDR and‘0.2’ for PDR and '0.3' for ME. The network was trained with given set of training data and later tested with remaining testing samples. During the training phase, each output of the LMBP is a real value in the range 0.0–0.3, whereas the 'desired' output is 0.0, 0.1, 0.2, or 0.3. During the recall phase, the output signal is approximated to binary levels by comparing it with threshold the threshold. The mean square error of the LMBP was set to 0.0001.

IV. RESULTS AND DISCCUSION

This research used 600 images that divided into two groups namely: (a) training 450 images (b) testing 150 images. In order to measure the ability of LMBP classifer, these data afterwards were trained and tested. The results as shown in Table.1

Table 1. Results of LMBP Classifier

Classes	**training**	**testing**	**classification**		**(%)**
			correct	***incorrect***	
Normal	75	30	27	3	90.0
NPDR	150	30	27	3	90.0
PDR	150	45	42	3	93.3
ME	75	45	42	3	93.3

The results from Table 1 show that the classifier is able to identify their class up to 90%. This results were used to calculate the systems performance by calculating sensitivity, specificity, and accuracy [16]

$$Sensitivity = \frac{TP}{TP + FN} \qquad (12)$$

$$Specivicity = \frac{TN}{TN + FP} \qquad (13)$$

Tabel 2. Sensitivity, specificity, and accuracy

Sensitivity	***Specificity***	***Percentage of accuracy***
97.37%	75%	91.67%

Table 2 shows the result of sensitivity, specificity, accuracy for the four classes of eye images using neural network classifier. The sensitivity of the system is 97.37% and specificity is 75%, indicating that the result is clinically significant.

This research compared two methods namely method with OD elimination and without OD elimination and the result as shown in Table 3.

Table 3. Comparison of two emthods

Approach	**Feature extraction**	**Accuracy (%)**
OD elimination	3D-GLCM	91.67%
without OD elimination	3D-GLCM	72.18%

Table 3 shows that proposed approach produce accuracy of 91.67% higher than approach without OD elimination namely 72.18%. Therefore this method has increased the accuracy of 19.49%.

We also campared our method ability with other methods as shown in Table 4.

Table 4. Comparison with various approaches

Approaches	**Sensitivity**	**Specificity**	**Accuracy**
Nayak et. al	90%	80%	84%
Garcia et. al	Not reported	Not reported	88.1%
Fahrudin et. al	Not reported	90%	Not reported
Acharya et. al	Not reported	Not reported	85%
Proposed approach	97.37%	75%	91.67%

V. CONCLUSION

a) The proposed method is able to classify four classes images namely: normal, NPDR, PDR dan ME.
b) The result of this approach produced Sensitivity of 97.37%, Specificity of 75% and Accuracy of 91.67%.
c) The performance of proposed approach increased accuracy of 19.49% higher than approach without OD elimination

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