Fundus Image Classification Using Two Dimensional Linear Discriminant Analysis and Support Vector Machine

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Abstract— *It is constructed in this study a classification system of diabetic retinopathy fundus image. The system consists of two phases: training and testing. Each stage consists of preprocessing, segmentation, feature extraction and classification. The tested image comes from the MESSIDOR dataset which has a total of 100 images. The number of classes to be classified consists of four classes with each class consists of 25 images. The classes are normal, mild, moderate and severe of Diabetic retinopathy. In this study, the level of preprocessing uses grayscales green channel, Wavelet Haar, Gaussian filter and Contrast Limited Adaptive Histogram Equalization. The level of segmentation uses masking as a process of doing the subtracting operation of between the original image and the masking image. The purpose of the masking is to split between the object and the background. The feature extraction uses Two Dimensional Linear Discriminant Analysis (2DLDA). The classification uses Support Vector Machine (SVM). The test results of some scenarios show that the highest percentage of accuration of the system is up to 90%.*

***Keywords*— *Diabetic Retinopathy, Two Dimensional Linear Discriminant Analysis, Support Vector Machine, Fundus Image, MESSIDOR*.**

I. INTRODUCTION

Diabetic Retinopathy (DR) is a disease of the eye as a result of complications of Diabetes Mellitus (DM). The Symptom of DR is a decrease in vision sharpness; moreover, it is a blindness. The percentage of patients with diabetes mellitus who suffered DR is quite high reaching around 40% to 50%. Normally, the symptom of DR only comes with patients who have been over than 10 years of experiencing DM. DR has been often easily detected for the patient with old age that the patient is unaware of the DM [1]. DR can cause abnormalities in the retina. The abnormality has five categories, namely [2]:

a. Microaneurism is a bulging of capillary wall especially in the area of veins shaped like a small red spot which is close to the veins.
b. Hemorrhages usually appear on the capillary wall and are visible from the spot of blood out of the veins which are dark red and is larger than microaneurism.
c. Hard exudates are lipid infiltration into the retina with yellowish and irregular shape. Soft exudates or often called cotton wool patches are a retinal ischemia with yellow and white spots.
d. Neovascularization is a new blood vessel in the tissue surface, irregularly shaped, winding and in groups.

The results of the medical diagnosis of fundus image show the level of DR disease being experienced. There are four classes of diagnostic results, namely: Class Normal, level 1 of DR, level 2 and of level 3 of DR. Here is the characteristic of the DR level obtained from the fundus image [2]:

a. Normal
   No Microaneurysm AND No Hemorrhages
b. Mild Diabetic Retinopathy
   Microaneurysm is between more than 0 to less than or equal to 5 AND No Hemorrhages
c. Moderate Diabetic Retinopathy
   Microaneurism is between more than 5 to less than 15 OR Hemorrhages is between more than 0 to less than 5 AND No Neovascularization
d. Severe Diabetic Retinopathy
   Microaneurysm is more than or equal to 15 OR Hemorrhages is more than 5 AND
   Neovascularization is equal to 1

II. RELATED WORKS

Several previous studies on automatic detection of DR has been done in [3] uses the green channel preprocessing, CLAHE and also uses exudate detection, vessel detection, and microaneurism detection. The test results obtained 81.61% of sensitivity, 99.99% of specificity, 99.98% of accuracy and 63.70% of precision.

The research [4] uses preprocessing, feature extraction and classification. The preprocessing uses the Color Space Conversion, Image Normalization, Adaptive

Median Filter, Adaptive Histogram Equalization. It is then further processed on Boundary Tracing using edge detection, Adaptive Threshold & Centroid, Optic Disk Localization and Vessel Extraction. The next process is by doing Image Segmentation, namely Class Segmentation and Class Boundary. The results of the study [4] show 97.1% of sensitivity, specificity 98.3%.

The following research is the automatic detection of diabetic retinopathy using feature extraction and classification of Support Vector Machine. This study discusses the feature extraction of Gray Level Co-occurrence Matrix (GLCM) and classification using Support Vector Machine method. The classification is divided into two classes, namely Normal and Diabetic Retinopathy. The imagery used is around 200. The research result shows that the system accuracy is reaching 93% [5]. In the study [6] use the same classification method which is an SVM. The difference lies in the preprocessing and the feature extraction used. In the study [6], the preprocessing being used are green channel, Contrast Limited Adaptive Histogram Equalization (CLAHE), filtering, Contrast Enhancement, Morphological Operation, Optic Disc Elimination. Statistical Feature is used for the Feature Extraction process. 92% of Sensitivity, 80% of Specificity, 90% of accuracy.

The further research is the detection of diabetic retinopathy using machine learning. The class is divided into two (2), namely Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). The methods used include Probabilistic Neural Network (PNN), Bayesian Classification and Support Vector Machine. The imagery used for training are 100 images, and 250 images of testing. The valid percentages are 89.6% for PNN, 94.4% for Bayesian, 97.6% for SVM [7].

In [8], CLAHE, median filtering and image catenation on four tiles are method for preprocessing. In the study [9], the preprocessing used are the green channel, CLAHE, mathematical morphology, optical disks detection and removal and max tree algorithms. Classification used SVM. The trial results show 96.9% of sensitivity, 100% of Specificity.

In [10] the preprocessing method used applies Green Channel, Filtering, Image Enhancement, morphological Operation, Hard exudates Segmentation, feature extraction. The classification uses Adaptive Neuro Fuzzy Inference System (ANFIS) and Extreme Learning Machine (ELM).

The research [11] is a review of methods for DR Classification. This research include preprocessing, feature extraction method such as optic disc, flovea vessel blood and abnormal feature extraction. It can classify 5 class i.e normal, Mild NPDR, Moderate, Severe and Proliferative Retinopathy.

Diagnosis of DR based on feature extraction is the next research. This research implementing Neuro Fuzzy for feature extraction[12]. In reference to [13], the research uses Fuzzy C Means segmentation. In the process of preprocessing, there is a change of pilot image to binary image which is then performed a labeling on the objects and the holes. The next process is the boundary detection and classification using FCM.In [14] , the research proposed system for detecting DR. The system consist of preprocessing, morphological operation, feature extraction and SVM Classifier.

The research [15] using several methods i.e preprocessing used compressed image 640x480 pixel using bi-cubic interpolation, detection of optic disc, blood vessels, white lesions, red lesions. The test produces 80% and 50% for sensitivity and spesificity.

In [16] , the research is used convolutional Neural Network for detecting DR. The next research focus is to [17] discuss the stages of retinopathy detection using preprocessing, feature extraction and classification. Preprocessing uses image enhancement, edge detection, morphological operations, thinning to only 1 pixel, scanning window analysis (SWA). Overal accuracy of proposed method is 92.72%

III. METHODOLOGY

This study consists of two parts: training and testing. Each section consists of four stages: preprocessing, segmentation, feature extraction and classification. The research methodology that was created is shown in Figure 1.

3.1 Preprocessing

Preprocessing aims to improve the quality of the image by manipulating the parameters of the image. In this study, the preprocessing process consists of the grayscale green channel, Gaussian filter, Contrast Limited Adaptive Histogram Equalization (CLAHE).

3.2 Segmentation

Segmentation uses masking as a way to separate between the retinal image with the background. The masking is applied by subtracting the original image after the preprocessing with the image masking. The Image as a result of masking is shown in Figure 2.

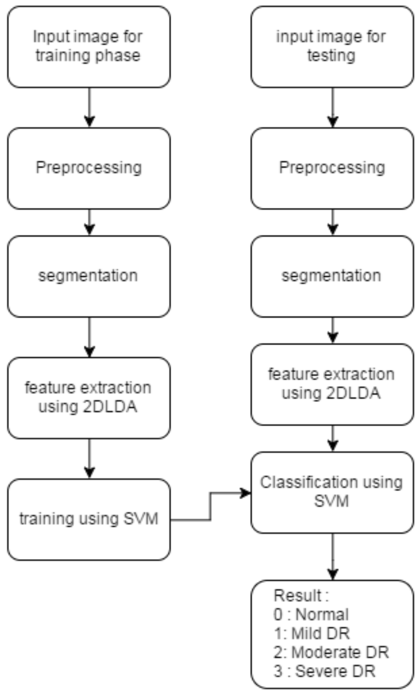
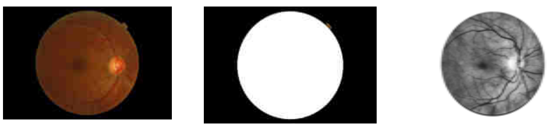


Fig.1 : Retinopathy Research Methodology



(a) (b) (c)

Fig.2 : (a) before the image preprocessing, (b) the image masking, (c) the image as a result of masking

3.3 Feature Extraction

Feature extraction is a retrieval characteristic of an object image which is a unique value differentiator as to compare with another object. The feature extraction is applied to checking the Cartesian coordinates, namely horizontal, vertical, diagonal right and left diagonal.

3.3.1 Two-Dimensional Linear Discriminant Analysis (2DLDA)

2DLDA is the enhanced method of LDA. Firstly LDA 2D matrix is transformed into the form of a one-dimensional vector image, whereas in 2DLDA or it is called a direct image projection technique, the matrix 2D image does not need to be transformed into the form of vector image but its image matrix distribution can be formed directly by using the original image matrix.

$\{A_1,\ldots,A_n\}$ is the n image matrix, whereas A_i $(i=1,\ldots,k)$ is the r x c image. M_i $(i=1,\ldots,k)$ is the average training image of the class from the i and M which is the average of all the training data. ℓ_1 x ℓ_2 is the dimensional space of $L \otimes R$, whereas $\otimes$ is to show the tensor product, L covers $\{u_1,\ldots,u_{\ell_1}\}$ and R covers $\{v_1,\ldots,v_{\ell_2}\}$, and thus it is defined with two matrixes $L = [u_1,\ldots,u_{\ell_1}]$ and $R = [v_1,\ldots,v_{\ell_2}]$ [18].

Feature extraction method is for finding the L and R, so that the original image space - A_i is converted into low-dimensional image space as $B_i=L^T A_i R$.. Low dimensional space is obtained by a linear transformation of L and R, the distance between classes in D_b and the distance of class in D_w are defined as follows:

$$Db = \sum_{i=1}^{k} n_i \left\| L^T (M_i - M) R \right\|_F^2 \qquad (1)$$

$$Dw = \sum_{i=1}^{k} \sum_{x \in \Pi_i} \left\| L^T (X - M_i) R \right\|_F^2 \qquad (2)$$

Whereas $\| \quad \|_F$ is *Frobenius norm*.

Reviewing that $\|A\|_F^2$ = P trace $(A^T A)$ = trace (AA^T) is for matrix A and thus the equation of (3) and (4) can be represented more.

$$D_b = trace\,(\sum_{i=1}^{k} n_i L^T (M_i - M) RR^T (M_i - M)^T L) \qquad (3)$$

$$D_w = trace\,(\sum_{i=1}^{k} \sum_{x \in \Pi_i} L^T (X - M_i) RR^T (X - M_i)^T L). \qquad (4)$$

Similarly, LDA, 2DLDA method is to find the matrix L and R, so that the class structure of the original space remains in the projection room, so the benchmark (criterion) can be defined as:

$$J_1(L,R) = max\ \frac{D_b}{D_W}. \qquad (5)$$

It is clear that the equation (5) consists of a matrix transformation of L and R. Optimal transformation matrix of L and R can be obtained by maximizing D_b and minimize D_w. However, it is very difficult to calculate the optimal of L and R simultaneously. Two optimization functions can be defined to obtain L and R. For a definite R, L can be obtained by completing an optimization function as follows:

$$J_2(L) = max\ trace\,((L^T S_W^R L)^{-1} (L^T S_b^R L)) \qquad (6)$$

Where:

$$S_b^R = \sum_{i=1}^{k} n_i (M_i - M) RR^T (M_i - M)^T \qquad (7)$$

$$S_W^R = \sum_{i=1}^{k} \sum_{x \in \Pi_i} (X - M_i) RR^T (X - M_i)^T, \qquad (8)$$

Noting that the matrix size of S_W^R and S_b^R are r x r which are smaller that the size of S_W^R and S_b^R in classical *LDA*.

For a defitnite L, R can be obtained by completing an optimization function as follows:

$J_3(R) = \max \operatorname{trace} ((R^T S_W^L R)^{-1} (R^T S_b^L R)),$ (9)

Where:

$$S_b^L = \sum_{i=1}^{k} n_i (M_i - M)^T LL^T (M_i - M) \quad (10)$$

And,

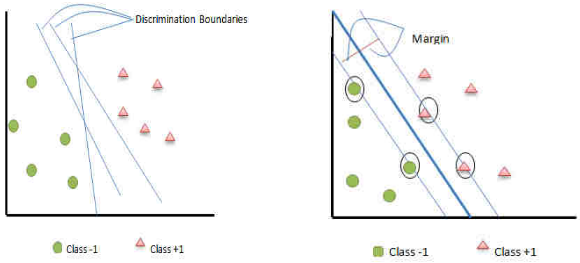
$$S_W^L = \sum_{i=1}^{k} \sum_{x \in \Pi_i} (X - M_i)^T LL^T (X - M_i). \quad (11)$$

3.4 Classification Using SVM

SVM concepts can be explained simply as an attempt to find the best *hyperplane* which serves as a separator of two classes in the input space. Hyperplane in a d-dimensional vector space is the affine subspace dimension of d-1 which divides the vector space into two parts where each corresponds to the different classes.

Figure 3 shows several patterns that are members of two classes: +1 and -1. Patterns belong to the class -1 is symbolized by the pink color (triangle), while the pattern on the class +1 is symbolized by the green color (circle). Problem of classification can be translated by figuring out a line (hyperplane) that separates between the two groups. Various alternatives of line separator (discrimination boundaries) are shown in Figure 3 (a).

Hyperplane as the best separator between the two classes can be found by measuring the margin of the hyperplane while looking for the maximum points. Margin is the distance between the hyperplane to the nearest pattern of each class. The closest pattern is called a support vector. The solid line in Figure 3 (b) shows the best hyperplane which is located right in the middle of the second grade while the red and yellow dots in black circle are the support vector. The attempts to locate this hyperplane are the core of the learning process on SVM [19],[20].



(a) (b)

Fig. 3 : SVM is trying to find the best hyperplane separating the two classes of -1 and +1

The data provided are denoted as $\vec{x}_i \in \Re^d$, while for each label is denoted with $y_i = \{+1, -1\}$ for $i = 1,2,3 \ldots l$ Where l is the number of the data. It is assumed that the second class of -1 and +1 can be separated completely by hyperplane with d dimension, which is defined as follows

$$\vec{w} \cdot \vec{x} + b = 0 \quad (12)$$

$\vec{w}$ pattern that includes class -1 (negative samples) can be formulated as a pattern that satisfies inequality

$$\vec{w} \cdot \vec{x} + b \le -1 \quad (13)$$

While $\vec{w}$ pattern including the classes +1 (positive samples) is

$$\vec{w} \cdot \vec{x} + b \ge +1 \quad (14)$$

To have the biggest margin is by maximizing the value of the distance between the hyperplane and the closest point namely $\frac{1}{\|\vec{w}\|}$. It can be formulated as a *Quadratic Programming* (QP) problem, which is by finding the minimum point of the equation that is finding the minimum point of the equation (15) with regard to constraint equation (16).

$$\min_{\vec{w}} \quad \tau(w) = \frac{1}{2} \|\vec{w}\|^2 , \quad (15)$$

$$y_i (\vec{x}_i \cdot \vec{w} + b) - 1 \ge 0, \quad \forall i \quad (16)$$

This problem can be solved with a variety of computational techniques, including *Lagrange Multiplier*.

$$L(\vec{w}, b, \alpha) = \frac{1}{2} \|\vec{w}\|^2 - \sum_{i=1}^{l} \alpha_i (y_i (\vec{x}_i \cdot \vec{w} + b) - 1)) \quad (17)$$

with $i = 1, 2, \ldots, l$.

αi are Lagrange multipliers, which is zero or positive (αi≥0). The optimal value from equation (17) can be calculated by minimizing the L and b, and maximize L to αi. With regard to the nature that at the point of optimal gradient L = 0, the equation (17) can be modified as the maximization of problem that only contains αi, as the below equation of (18).

$$\sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,i=1}^{l} \alpha_i \alpha_j y_i y_j \vec{x}_i \vec{x}_j , \quad (18)$$

Where:

$$\alpha_i \ge 0 (i = 1,2,\ldots,l) \quad \sum_{i=1}^{l} \alpha_i y_i = 0 \cdot \quad (19)$$

From the result of this calculation αi is obtained with its most positive value. Data were correlated with positive αi, it is then so called as a support vector.

IV. RESULT

The testing scenario is achieved by using a dataset of Messidor test. The number of images used are 100 images consisting from 25 normal, 25 mild DR, 25 moderate DR , and 25 severe DR. In addition to that there are some uses of varying of data training, data test and projections dimensional variations of rows and columns. Moreover the conduct of varying the data training sequence is to gain the highest percentage.

The test results of the MESSIDOR test with 2DLDA + SVM method is presented in Table 2. Previously, it had been conducted some trials with 2DLDA + kNN method for comparison.

Table.1: The test results of kNN Classification

∑ training data	∑ testing data	Acc.
40	20	68,33%
60	20	77,50%
80	20	80%

Table.2: The test results of SVM Classification

∑ training data	∑ testing data	Acc.
40	20	73,33%
60	20	80%
80	20	90%

The trial results show that the more the data trained, the better the accuracy. The percentage of accuracy with the more trained method of SVM is better with a 90% of maximum; compared with kNN method with its 80% of maximum.

V. CONCLUSION

There are two important variables that affect the success rate of introduction which are the sequence variations of training samples per class used and the number of training samples per class used. From the results of trials using kNN show the rate of optimal recognition accuracy is 80%, while the test results using methods SVM show the rate of optimal recognition accuracy is 90%

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