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MACULAR EDEMA CLASSIFICATION USING SELF-ORGANIZING MAP AND GENERALIZED LEARNING VECTOR QUANTIZATION

Rizal Adi Saputra, Yuwanda Purnamasari Pasrun, and Amalia Nurani Basyarah

Department of Informatics, Faculty of Information Technology, Institut Teknologi Sepuluh Nopember, Kampus ITS Sukolilo, Surabaya, 60111, Indonesia

E-mail: rizal.adi.saputra13@mhs.if.its.ac.id

Abstract

Macular edema is a kind of human sight disease as a result of advanced stage of diabetic retinopathy. It affects the central vision of patients and in severe cases lead to blindness. However, it is still difficult to diagnose the grade of macular edema quickly and accurately even by the medical doctor's skill. This paper proposes a new method to classify fundus images of diabetics by combining Self-Organizing Maps (SOM) and Generalized Vector Quantization (GLVQ) that will produce optimal weight in grading macular edema disease class. The proposed method consists of two learning phases. In the first phase, SOM is used to obtain the optimal weight based on dataset and random weight input. The second phase, GLVQ is used as main method to train data based on optimal weight gained from SOM. Final weights from GLVQ are used in fundus image classification. Experimental result shows that the proposed method is good for classification, with accuracy, sensitivity, and specificity at 80%, 100%, and 60%, respectively.

Keywords: *Fundus Image, GLVQ, Macular Edema, SOM*

Abstrak

Edema makula adalah jenis gangguan penglihatan sebagai akibat dari diabetik retinopati stadium lanjut. Penyakit ini mempengaruhi pusat penglihatan pasien dan dalam kasus yang parah dapat menyebabkan kebutaan. Namun, diagnosis tingkatan penyakit edema makula secara cepat dan akurat masih sulit, meskipun dilakukan oleh dokter. Makalah ini mengusulkan sebuah metode baru klasifikasi citra fundus penderita diabetes dengan menggabungkan Self-Organizing Maps (SOM) dan Generalized Vector Quantization (GLVQ) untuk menghasilkan bobot optimaldalam klasifikasi kelas penyakit edema makula. Metode yang diusulkan terdiri dari dua tahap proses pelatihan. Pada tahap pertama, SOM digunakan untuk mendapatkan bobot optimal berdasarkan dataset dan masukan bobot secara random. Tahap kedua, GLVQ digunakan sebagai metode utama untuk melatih data berdasarkan bobot optimal yang diperoleh dari SOM. Bobot akhir dari GLVQ akan digunakan dalam klasifikasi citra fundus. Hasil pengujian menunjukkan hasil klasifikasi yang baik, dengan akurasi, sensitivitas, dan spesifisitas masing-masing 80%, 100%, dan 60%.

Kata Kunci: *Citra Fundus, GLVQ, Makula Edema, SOM*

1. Introduction

Fundus examination is widely used in detection of diseases whose symptoms related to human eyes. Digital fundus images can provide information on pathological changes caused by eye's abnormality and systemic diseases. Common diseases that can be identified from the changing of pathologies of the human eye are Diabetic Retinopathy (DR), Macular Edema (ME) and Glaucoma [1].

Macular Edema (ME) is a common eye disease, an advance stage of diabetic retinopathy (DR) caused by the increasing amount of insulin in blood. It is one of the leading cause of blindness in industrialized countries [2]. ME is a progressive disease but early detection and diagnosis of ME can save vision loss. Skills of a medical doctor are necessary to measure diabetic macular edema grade, but within a short time, it is still difficult to diagnose the condition of many examinees accurately. Therefore, a quick and reliable diagnosis method is needed. Methods to diagnose diabetic macular edema have been proposed by some recent research. [3] used a detailed feature set and Gaussian mixtures model based classifier, new hybrid classifier. [4] used bayesian decision rule to classify ME grade.

Optimal weight is important in classification phase, because of its representation of data sample from each class. Optimal weight can be obtained from learning phase or input by user. The learning method with high accuracy have been proposed by some recent research using different data. [5] developed LVQ2.1 and made GLVQ algorithm to recognize chinese character and yields the accuracy of 100%. GLVQ along with last mean square used by [6] to generate confidence maps for each feature point in facial feature detection and has accuracy of 99.1%. SOM and LVQ combined to classify fundus image in glaucoma disease classification by [7] with 69.7% of accuracy. [8] also proposed combination of SOM method with LVQ 3 to diagnose fault on motor based on its sound and the result was 100% for its accuracy.

Because of good performance from the result of previous research, this paper proposes a new method combining SOM and GLVQ to train image. This combination is hoped to handle fundus image classification to diagnose macular edema and make good classification.

2. Methods

This paper proposes learning phase to classify macular edema disease class based on fundus image includes preprocessing and feature extraction process as shown in Figure 1.

Dataset

Fundus image dataset as shown in Figure 2 were downloaded from Messidor digital retinal images database [9]. There are 40 images segmented from different labeled fundus image sized 256 x 256. Fundus image is divided into two labels, class one and class two. Since hard exudates have been used to grade the risk of macular edema, data is labeled based on the size of apparent hard exudates. Data is labeled as class one, if the size of hard exudates is big enough to be seen and labeled as class two, if the size of hard exudates is small or hard to be seen.

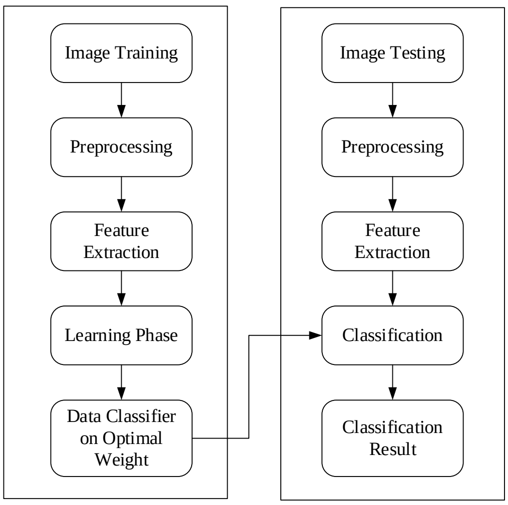

Figure 1. The Proposed Methodology

Preprocessing

Image preprocessing was used to remove part of image that was not used in classification phase, focused on exudates part. There are four steps in preprocessing phase. Those are closing grayscale, invert, and thresholding.

Closing [3,10] was used to fill contour of exudates in fundus image. Exudates in fundus image were composed by bright lesion which have variety of size. For big or medium size lesion, the gap or interspace between spot of lesion are small and often have no space at all. But for small size of lesion that consisted of tiny spots of lesion, the distance between spot is bigger, tend to spread and not just assembled in one area. The holes created between spots of lesion can make exudates becomes too small to be recognized. Thus, it needed to be smoothed. By using closing, holes between adjacent spot of lesion could be filled and make contour of exudates became more apparent.

Closing itself consisted of process of dilation followed by erosion. The closing of set A as image input by structuring element B, denoted $A \bullet B$ defined as the following equation(1).

$$\boldsymbol{A} \cdot \boldsymbol{B} = (\boldsymbol{A} \oplus \boldsymbol{B}) \ominus \boldsymbol{B} \quad (1)$$

After applying closing method, Green channel grayscale was used because red channel of the fundus image mostly on diabetic retinopathy was oversaturated, especially in the central region and the optic nerve. While blue channel could be low saturation in result (under saturated) and there is a lot of noise [1]. Therefore, green channel was used for processing the image because this channel is the only channel that has right composition of saturation. Green channel is obtained by taking original green pixel $I_{greenchannel}$ value from original RGB image.

In order to make the vessels brighter than the background, green channel of the image $I_{greenchannel}$ was inverted (see equation(2)) [11]. Pixel result of invert operation is obtained from maximum pixel $I_{maximum}(i,j)$ of $I_{greenchannel}$ minus each of pixel

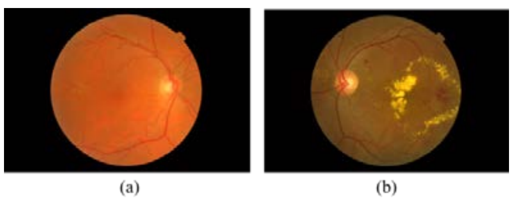

Figure 2. Image From Messidor Database (a) class 1 (b) class 2

$I_{greenchannel}(i, j)$.

$$\boldsymbol{I_{invcrted}(i,j) = I_{maximum}(i,j) - I_{greenchannel}(i,j)} \quad (2)$$

Thresholding [12] is the last step in preprocessing phase. This method changed the $I_{inverted}$ into a binary image $I_{threshold}$ to differentiate exudate area and background of the image. Then the two levels were assigned to pixels that were below or above the specified threshold value T as defined in equation(3).

$$\boldsymbol{I_{threshold}(i,j) = \begin{cases} 1 \; if \; I_{inverted}(i,j) \geq T \\ 0 \; if \; I_{inverted}(i,j) < T \end{cases}} \quad (3)$$

Using T=127 as value threshold. Rated T held an important role in the flotation process. The quality of the binary image is highly dependent on the value of T used. Images that have been preprocessed are shown in Figure 3 as binary image.

Feature Extraction

Total of feature obtained from preprocessing was 65536 features consisting of pixel 0 and 1. The number of features was really large and could make computation became complex. In order to prevent the complexity, then feature extraction method was used to get features containing exact characteristic of the image.
Integral projection [12] was used to extract the feature of fundus binary image by enumera-ting the feature from horizontal *h(j)* and feature from vertical *h(i)* using equation(4) and equation (5). After enumerating, feature was placed in one row as feature identity for each data. Ilustration of integral projection is shown at Figure 4.

$$\boldsymbol{h(j) = \sum_{i=1}^{N\,row} I_{threshold}(i,j)} \quad (4)$$

$$\boldsymbol{h(i) = \sum_{i=1}^{N\,columnd} I_{threshold}(i,j)} \quad (5)$$

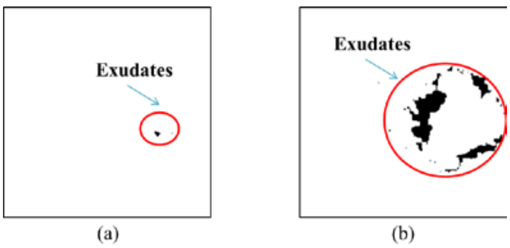

Figure 3. Threshold image (a) Class 1 and (b) Class 2

Learning Phase

Learning phase is used to adjust weights and biases of data based on characteristic of feature in each class. There are two processes in learning phase. First, finding input weight by SOM and then the result from SOM is used in GLVQ as input weight that would be learned with training data.

Self-Organizing Maps

Self-Organizing Maps is a clustering and data visualization technique based on neural network viewpoint [13]. Input dataset in this phase used feature from feature extraction result (integral projection). Self-Organizing Maps obtain the optimal weight based on input dataset and random weight input. The distance between each input data in dataset and random weight is computed to find out the minimal distance value. Resultant data that has minimal value would be updated.

In SOM Algorithm [14], firstly define initial weight (w_{ij}) randomly from each class, learning parameter such as learning rate (α) and maximum epoch. For each data (x_i) compute distance of neuron j (D_j) using equation(6).

$$\boldsymbol{D_j = \sum_{i=1} (W_{ij} - X_i)^2} \quad (6)$$

x_i is input and w_{ij} is weight consisting of feature image from integral projection operation, with i = 1,….,N where N is dimension of data. The next step is finding index of neuron distance (D_j) which have minimum value. D_j with minimum value then will updated using equation(7).

$$\boldsymbol{w_{ij}(new) = w_{ij}(old) + \alpha(x_i - w_{ij}(old))} \quad (7)$$

with $w_{ij}(new)$ is new weight and $w_{ij}(old)$ is previous weight that yet been updated. The next

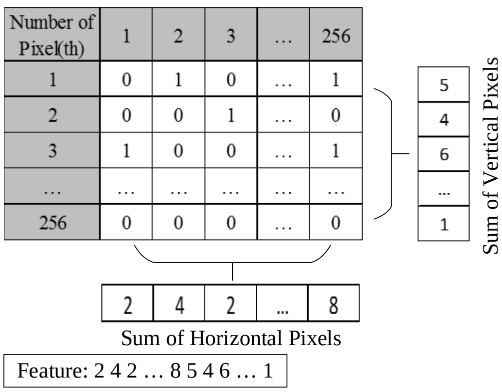

Figure 4. Integral projection illustration

step is updating learning rate value α. As long as the maximum number of iterations has not been reached, previous step from computing distance (D_j) until updating learning rate value α will be done continuously.

Generalized Learning Vector Quantization

Input dataset in this phase also used feature from feature extraction result (integral projection) with the weight $w_{ij}(new)$ was taken from SOM weight calculation. In GLVQ, reference vectors were updated based on steepest descent method in order to minimize the cost function. The cost function was determined so that the obtained learning rule could satisfy the convergence function [5].

In GLVQ we define initial weight ($w_{ij}(new)$ is optimal weight in SOM), learning parameter such as learning rate α, maximum epoch, ratio slope, and minimum learning rate. GLVQ compute two distances between input and weight. For input is equal to target class, compute the distance d_j as in equation(8).

$$\boldsymbol{d_j} = \sqrt{\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} (\boldsymbol{x_i} - \boldsymbol{w_{ij}})^{\boldsymbol{2}}} \tag{8}$$

Moreover, distance between input and other weight that is not its target d_k class, can be computed using equation(9)

$$\boldsymbol{d_k} = \sqrt{\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} (\boldsymbol{x_i} - \boldsymbol{w_{ik}})^{\boldsymbol{2}}} \tag{9}$$

From d_j and d_k which is the distance of x from w_1 (the correct weight of input) and w_2 (the other weight) respectively, the relative distance different, μ_x is computed, defined as the following equation(10).

$$\boldsymbol{\mu_x} = \frac{\boldsymbol{d_j} - \boldsymbol{d_k}}{\boldsymbol{d_j} + \boldsymbol{d_k}} \tag{10}$$

Updating weight are processed as long as epoch has not reached the maximum epoch yet. The weight that been updated is not only input's weight but also both of weight. The weights are updated using equation(11) and equation(12).

$$\boldsymbol{w_1}(\boldsymbol{new}) = \boldsymbol{w_1} + \boldsymbol{\alpha}\frac{\boldsymbol{df}}{\boldsymbol{du}}\frac{\boldsymbol{d_j}}{\boldsymbol{d_j} + \boldsymbol{d_k}} \tag{11}$$

$$\boldsymbol{w_2}(\boldsymbol{new}) = \boldsymbol{w_2} + \boldsymbol{\alpha}\frac{\boldsymbol{df}}{\boldsymbol{du}}\frac{\boldsymbol{d_j}}{\boldsymbol{d_j} + \boldsymbol{d_k}} \tag{12}$$

$\frac{df}{du}$ is a kind of gain factor for updating and its value depends on x. Learning rate value α is updated and all of step above are repeated until reach maximum epoch and minimum learning rate.

Classification

Fundus image were classified using distance calculation d based on data testing feature x and optimal weight feature w_{ij} from GLVQ result. Distance calculation is often used to determine similarity degree or dissimilarity degree of two vectors. Similarity level is a score and used to determine whether two vectors were similar or not [9].

The core of GLVQ neural network is calculating Euclidean distance. Distance between each input vectors and competitive layer neural nodes could be calculated, and the output node which was minimum distance designated as a winning node. Euclidean distance d calculated the differences between two as the following equation(13).

$$\boldsymbol{d} = \sqrt{\sum_{\boldsymbol{k=1}}^{\boldsymbol{n}} (\boldsymbol{x_k} - \boldsymbol{w}(\boldsymbol{new}))^{\boldsymbol{2}}} \tag{13}$$

with x_k is testing input and $w(new)$ is weight optimal from GLVQ training process.

3. Results and Analysis

Fundus image does not only contain bright focus in exudate area, but also optic disc. Optic disc area must be cropped before preprocessing because it has almost same intensity values as exudate of diabetic. If the area is not cut, it will affect the extraction of the image and characteristics of each grade. Cropping optic disc area used ImageJ application 1.47 version. Figure 5 and Figure 6 show preprocessing result from optic disc cropping until inversion.

This experiment used 40 preprocessed fundus images data, divided into two classes, class 1 and class 2. Each class has 20 images data which class 1 is be labeled as grade 1 and class 2 as grade 2. All data had been trained using SOM (Self-organizing Map) to produce ideal weights that would be used in further process, training using GLVQ. Some parameters used in this experiment are divided according to its method in SOM and GLVQ shown in Table 1 and Table 2.

TABLE 1
PARAMETERS IN SOM

Number of iteration	1000
Learning rate	0.001
Decrement of learning rate (dk)	0.01

TABLE 2
PARAMETERS IN GLVQ

Number of iteration	100
Minimum Learning	10^{-5}
Decrement of learning rate (dk)	10^{-3}

TABLE 3
TOTAL CONFUSION MATRIX FOR PROPOSED METHOD

	Class 1	Class 2
Class 1	TP = 20	FN= 0
Class 2	FP = 8	TN = 12

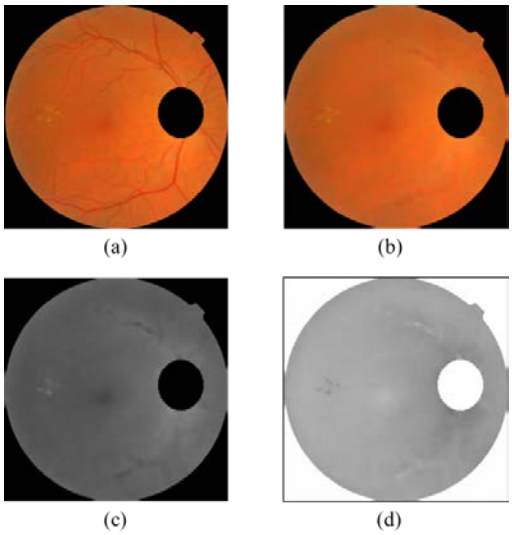

Figure 5. Preprocessing sample class 1 result (a) Optic disc Cropped, (b) Closing, (c) Green channel, (d) Invert

The detailed evaluation of proposed system was performed using different statistical evaluate-on parameters such as sensitivity (sen), specificity (spec), and accuracy (acc) to form *k*-fold. Those statistical evaluations can be computed using equation(14), equation(15), equation(16) respectively.

$$\boldsymbol{Sensitivity}(\%) = \frac{\boldsymbol{TP}}{\boldsymbol{TP} + \boldsymbol{FN}} \tag{14}$$

$$\boldsymbol{Specificity}(\%) = \frac{\boldsymbol{TN}}{\boldsymbol{FP} + \boldsymbol{TN}} \tag{15}$$

$$\boldsymbol{Accuracy}(\%) = \frac{\boldsymbol{TP} + \boldsymbol{TN}}{\boldsymbol{TP} + \boldsymbol{FP} + \boldsymbol{FN} + \boldsymbol{TN}} \tag{16}$$

TP is amount data testing from class 1 and classified correctly as grade 1, FN is amount data testing from class 1 and incorrectly classified as grade 2. TN represent amount of data testing from class 2 classified incorrectly as grade 1 and FP is amount data from class 2 and correctly classified as grade 2. The total confusion matrix for proposed method is shown in Table 3.

TABLE 4
COMPARISON OF CLASSIFICATION RESULT USING GLVQ AND LVQ

	GLVQ	LVQ
Accuracy (%)	80	65
Sensitivity(%)	100	100
Specificity(%)	60	30

TABLE 5
COMPARISON OF OUR PROPOSED METHOD WITH EXISTING TECHNIQUES FOR GRADING OF ME

Author	Sen (%)	Spec (%)	Acc (%)
Akram et al [3]	98.6	97.2	98.4
Lim et.al [15]	80.9	90.2	-
Deepak et.al [16]	95	90	-
Aquino et.al [17]	-	-	96.51
Proposed Method	100	60	80

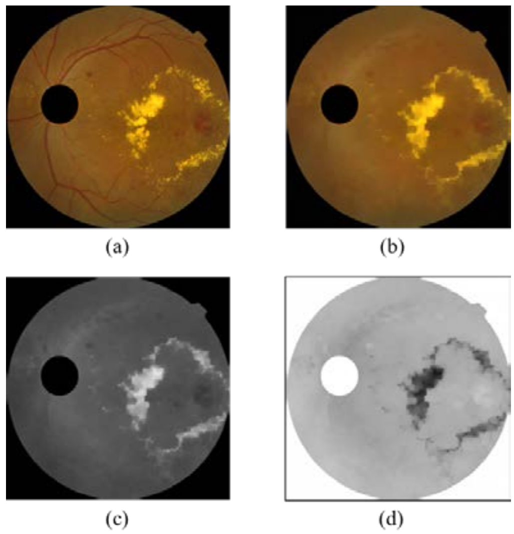

Figure 6. Preprocessing sample class 2 result (a) Optic disc Cropped, (b) Closing, (c) Green channel, (d) Invert

For training and testing requirement, data was split into 10 folds. In every 10-fold cross validation, data was divided into 16 training data and 4 testing data where each class had 8 data as training data and 2 data as testing data respectively. All the result gained from 10-fold cross validation were summed to obtain confusion matrix.

This experiment also compared proposed method with another classification method, LVQ, to observe which method would had better result to classify fundus image in ME classification. The result can be seen in Table 4 and Figure 7. Database used in this experiment, Messidor was also used in other experiments for grading Macular Edema. Table 5 shows result of other experiments.

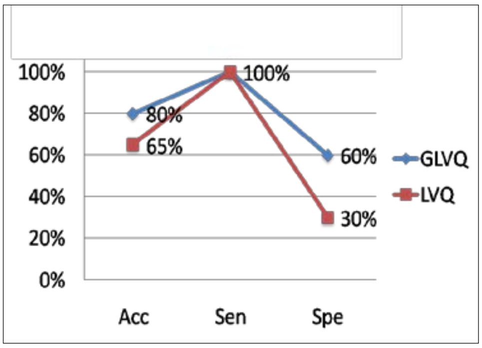

Figure 7. Comparison GLVQ and LVQ

There are two main stages in this experiment that focused in training process. SOM and GLVQ combined to train the data.

Training Using SOM

SOM (Self-organizing Map) as training process used feature data which was the sum of 512 features of each images from integral projection extraction to handle some of data which contained feature value 0. These feature values 0 will give bad influence in searching of ideal weights. In this process, some data were found having cluster which was not belong to its actual cluster.

Noted that from 20 data in class 1, 19 data were clustered correctly as grade 1 while 1 were clustered wrongly as grade 2. In class 2, from 20 of its data, 12 data were clustered correctly as grade 2 and the remaining 8 were clustered wrongly as grade 1. The reason of this incorrectly clustered data was because of similar feature of some data to class 1 so that some data were more inclined to class 1 than class 2.

Training Using GLVQ

In this experiment, total accuracy using proposed method is 80%. The sensitivity or accuracy of class 1 attained 100% where the specificity or accuracy of class 2 is 60%. The reason of specificity from this proposed method only reached 60% was because some data labeled as grade 2 from the expert did not indicate enough exudate to be labeled as grade 2, so instead of labeled as grade 2, those data were inclined and labeled as grade 1.

K-fold cross validation method was used in this experiment because amount of data in this experiment were not sufficient. Data retrieved from Messidor database actually has 1200 fundus image which 135 of them can used for ME classification. But only 40 of them were used as the rest of them have highly different quality as the result of bad acquisition like less exposure. Because of that, the resultant of preprocessing were not optimal and could not be used in this experiment.

This experiment also compared proposed method and other classification method like LVQ. From accuracy of the resultant in Figure 7, it can be seen that GLVQ has better accuracy which is 80% than LVQ which is only 65%. This indicates that GLVQ as the classifier is better used in this case, because in GLVQ weight updating process does not only use class from data which was classified. Instead of that, GLVQ also used weight from data which is close from correct class. In this case, 2 weights was used in learning process, so that its classification has better result.

Table 5 show performance of Messidor database used in various techniques for grading Macular Edema. Our proposed method has best result in sensitivity with 100% but doesn't have a better performance in specificity and accuracy than other methods. But this can't be compared directly to judge one classification method is better than others because all of those experiments have different method in preprocessing and feature extraction.

4. Conclusion

Diabetic macular edema is an advanced level of retinal abnormalities, which may be present in diabetes sufferers. This may cause total blindness if not detected and treated in right time. In this paper, we proposed a two-stage classification system consisted of SOM and GLVQ for diabetic macular edema diagnosis of fundus images. First stage, data that have been preprocessed is trained using SOM to gain ideal weight then used it to initialize weight in the next stage. GLVQ used in the next stage to train and classify fundus image either it's categorized as grade 1 or grade 2. The experimental result shows that proposed method have accuracy of 80% with sensitivity and specificity of 100% and 60% respectively. It proved that our proposed method is better than using LVQ which only have accuracy of 65%, sensitivity of 100% and specificity of 30%.

Future work can be done by adding another feature like distance of exudates from fovea in order to see the effectiveness of this method. Using another training method which is developed from GLVQ such as GRLVQ can be considered to be applied in future research.

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