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Automatic Detection of Diabetic Retinopathy Eye Fundus Images Using Matlab

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Abstract - Diabetic Retinopathy (DR) is one of the causes of diabetes mellitus and is an important cause of visual disability and blindness. Screening of diabetic retinopathy is essential for both early detection and early treatment. Currently, the ophthalmologists use a non-mydriatic fundus camera to capture retinal images. Based on the fundus images, the ophthalmologists diagnose manually, which is time-consuming and prone to errors. The objectives of this project are to study image processing techniques, particularly on fundus images for diabetic retinopathy screening, to develop an automatic screening and classification system for diabetic retinopathy using fundus images in order to detect diabetic retinopathy at an early stage, and finally, to propose use of new eye fundus images, expert diagnosis image processing techniques, machine learning classifiers, and also App Designer as the Graphical User Interface (GUI) environment for early detection of the signs of diabetic retinopathy. An accurate retinal screening, therefore, is required to assist the retinal screeners to classify the retinal images effectively. Highly efficient and accurate image processing techniques must thus be used in order to produce an effective screening of diabetic retinopathy. It is envisaged that the proposed decision support system for clinical screening would greatly contribute to and assist the management and the detection of diabetic retinopathy.

Kata Kunci: *Detection, Diabetic Retinopathy, Classification, Images;*

1. INTRODUCTION

Diabetic Retinopathy (DR) is the main causes of diabetes mellitus complication. High levels of sugar in the blood (glucose) are caused by the inability of the pancreas to produce insulin and this can lead to retinopathy and blindness [1]**,** small changes in retinal capillaries appear as diabetic retinopathy. The earliest sign of diabetic retinopathy is microaneurysms, which is categorized as mild non-proliferative diabetic retinopathy [2]**.** The cause of microaneurysms (MAs) is an abnormal condition of the sugar levels in the blood vessels. [3] revealed that the prevalence in Indonesian residents aged move than 30 years who live in urban and rural Yogyakarta with Diabetic Retinopathy (DR) and Vision-Threatening Diabetic Retinopathy (VTDR) is 43.1% and 26.3%. It is also reported that there are about 25 people with DR, and 1 in 12 people with Vision-Threatening Diabetic Retinopathy (VTDR), namely bilateral blind. **[4]** The cause of the retinal blood vessels to swell and discharge blood because of complications from diabetes. The loss of vision results from not being detected early and various types of lesions on the retina will appear. [5] revealed that there are 463 million people diagnosed with diabetes worldwide. It is also estimated that in 2045, the number of people with diabetes will increase to 700 million**.** Generally, there are two types of diabetic retinopathy, namely non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). Figure 1.1 shows the diabetic retinopathy signs, includes microaneurysms, hemorrhages, exudates, cotton- wool spots, and neovascularization.

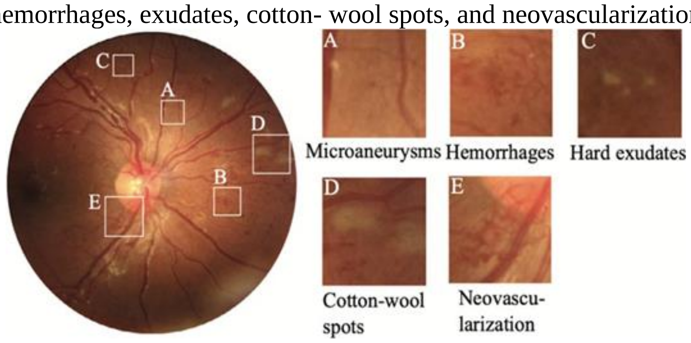

Figure 1: Typical retinal lesions characteristic of diabetic retinopathy **[6]**

The damage caused by diabetic retinopathy can be prevented if the regular diagnosis is carried out at an early and appropriate stage. Currently, based on the fundus images captured, ophthalmologists will manually diagnose all patients, which are time consuming and prone to error. **[7]** claimed that systematic screening for diabetic retinopathy has been identified as a way to save costs as a health care resource. Automatic retinal image analysis is emerging as an important screening tool for early detection of diabetic retinopathy, which can reduce the workload associated with manual examinations and save time and costs. Therefore, a development of automated tool to help in the detection and evaluation of diabetic retinopathy lesions using an algorithmic method to detect and classify the pathology of diabetic retinopathy is vital.

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It is envisaged that this screening tool can help patients minimize their finances without having to spend a lot of money and producing a fast and precise results of the diagnosis. **[8]** screening ophthalmic for diabetic retinopathy changes can decrease morbidity due to diabetic retinopathy and suggest maintaining the levels of HbA1c below 7.5 %, which will minimize the risk of diabetic retinopathy progressing and developing. **[9]** Diabetic Retinopathy may lead to worse problems, including vision loss, without continual supervision by a professional ophthalmologist. With the growing number of Diabetes Mellitus patients in Indonesia, the need for ophthalmologists to diagnose and treat Diabetic Retinopathy patients is increasing.**[10]** There are approximately 1184 individuals (82.5%) with type 2 diabetes and 1138 (79.3%) have complete data with gradually retinal images among them in Jogjakarta with community based. As mention **[11]** the number of diabetic retinopathy sufferers in Indonesia is expected to rise by 6.9 % in 2025, which may result in ongoing monthly or periodic costs while the patient is being treated. To avoid vision loss, not many patients can afford to see a doctor prevent vision loss. With **[12]** Systematic screening with the telemedicine system for diabetic retinopathy has improved patient coverage and cost-effectiveness, although several factors still impede screening adoption in Asia-Pacific regions with lower middle incomes currently.

2. RESEARCH METHODOLOGY

2.1. Introduction

System Development Life Cycle (SDLC) Waterfall is used as the methodology to develop this project. The methodology is divided into four main phases.

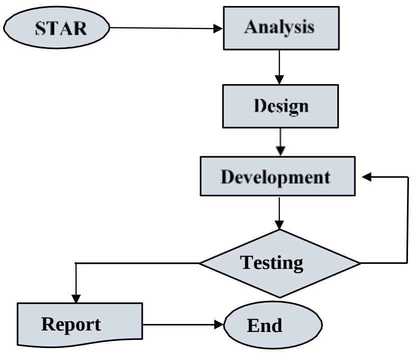

Figure 2: Research Methodology [13]

2.2. Data Sets

The data set consists of 200 images color fundus images. The High quality and detail are provided from the original images, which are 2144 x 1424 in JPEG format. These were shot using a digital fundus camera from NONMYD 7. The NONMYD 7 digital fundus camera is one of the tools used by the screening team and expert from the Department of RUMAH SAKIT PROVINSI NTB, which was involved in diagnosing and classifying the fundus images into two retinopathy stages: No Diabetic Retinopathy and Diabetic Retinopathy.

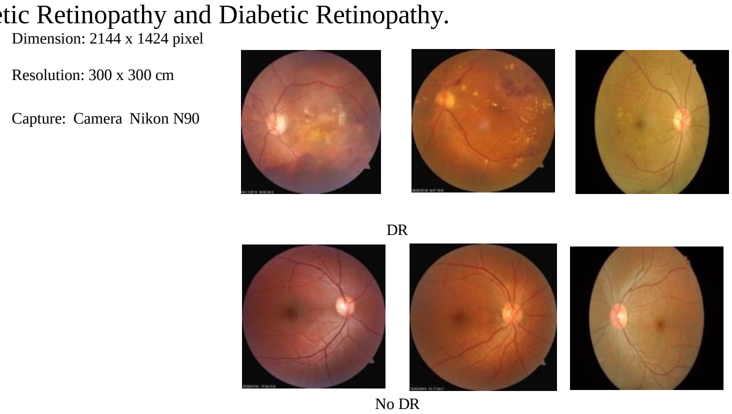

Figure 3. Example of images in the dataset expert

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2.3. Analysis

An analysis is carried out by studying the screening process for diabetic retinopathy and extensive literature of image processing techniques and machine learning classifiers. In addition, data is collected from the Department of Ophthalmology and Screening, RUMAH SAKIT UMUM PROVINSI NTB and from the public databases are collected and used to compare between the diagnosis generated by the system and the manual diagnosis.

Table 1: Summary of analysis phase

Source of Images	**Department of Ophthalmology and Screening, RUMAH SAKIT UMUM PROVINSI NTB**
No. of fundus images	8000 eye fundus images
No. of images from expert ground truth	200 images (100 DR eye fundus images and 100 No DR images)
Expert diagnosis	Dr. I Gede Supartha, Sp.M

2.4 Design

The proposed application design uses the App Designer (GUI) system-MATLAB because it is easy to use and to visualize and offers many GUI components. Fundus images taken from fundus cameras are the most important data for this research study. Fundus images of diabetic patients are taken for screening by experienced medical staff.

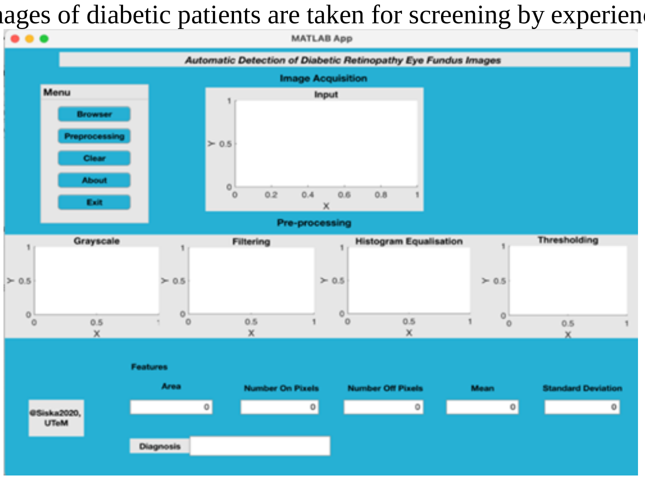

Figure 4: The design used for detection of diabetic retinopathy system

2.4 Development

In this process, the system development is using MATLAB, implementing the image preprocessing techniques combination and classification. The system will provide automatic diagnosis result from the fundus image input. There are 5 stages for the implementation of the image to be processed, from the red, green, blue (RGB) input is converted to greyscale with the scale value changed to 0 to 1 and the image is reduced by changing the dimensional resolution to 64x64 pixels.

2.5 Testing

For this research project, manual diabetic retinopathy diagnosis, carried by an experienced paramedic, is then compare to the results of the automated system in order to test and improve the sensitivity and specificity of the proposed grading methods. The sensitivity and specificity are calculated to test the capability of the proposed system and its potential as a quality assurance in retinal screening. Accuracy is also be calculated as a feature of the screening's quality assurance.

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3. RESULT AND DISCUSSION

This chapter presents the experimental results from automatic detection of diabetic retinopathy eye fundus images. The experiment will be described in this chapter with the following result. The system starts with input images. For pre-processing of fundus images, there are four techniques, which are grayscale, filtering, histogram equalization, and thresholding used in diabetic retinopathy systems. The feature extracted are number on pixel, number off pixel, mean, standard deviation, and area. Finally, for classification stage, images are classified using Support Vector Machine (SVM) and K-nearest Neighbors (KNN) classifiers.

3.1 Feature Extraction

After performing the pre-processing techniques, feature extraction takes place in order to obtain the features from the given images. Within the modelling for the classification and screening of diabetic retinopathy, five features, including the area of on pixels, on pixel, off pixel, the mean, and the standard deviation, also the total area are extracted for the purpose of diabetic retinopathy detection. The five values have been chosen as they are basic features and suitable for the pre-processed candidate image. These values for both normal and diabetic retinopathy images are used in order to create a model for training.

Table 2: Description of feature extraction

Feature	Description
Area of on pixels	Area the actual number of pixels in the region. Number of grey levels on the black and white images, where white pixels on are all pixels above a thresholding of 100 pixels.
On	On value white of pixels
Off	Off value black on pixels
Mean	Mean value of on pixels
Standard deviation	Standard deviation of on pixels

3.2 Classification

In the classification phase, various machine learning classifiers can be trained in order to classify the images into their respective classes using the features extracted after the image pre-processing stage. The proposed classifiers are to Support Vector Machine (SVM) and K-nearest Neighbors (KNN), where the extraction of features is essentially embedded in the stage of classification.

3.2.1 K-nearest Neighbors (KNN)

The 200 ground truth expert data were processed using the K-nearest Neighbors (KNN). classification model to produce a prediction in the form of confusion matrix. The confusion matrix consists of 4 points (true positive (1,1), false negative (1,2), false positive (2,1) and true negative (2,2). These results show that there are 56 true positive data, 91 true negative data, 44 false negative data and 9 false positive data. The data that was processed using the classification model obtained a percentage of 56% calculation sensitivity, 45% specificity and 73% accuracy.

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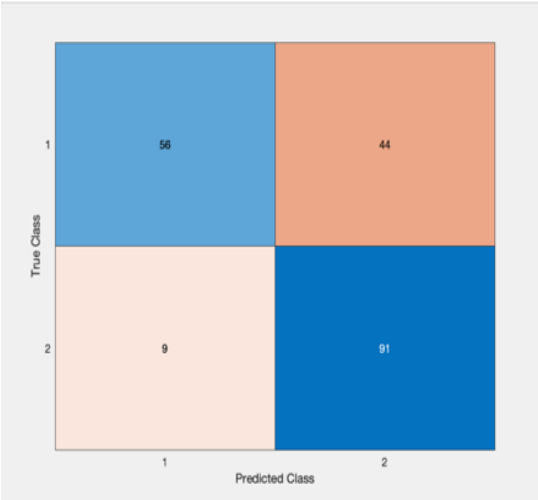

Figure 5: Confusion matrix expert ground truth

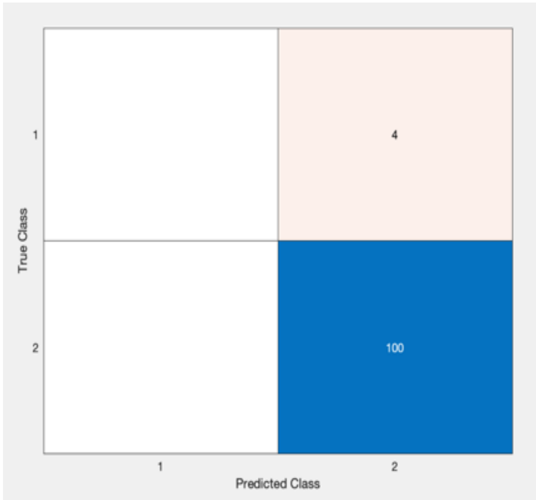

Figure 6: Confusion matrix Diaretdb0 dataset

Table 3: The summary of result from dataset

Dataset	Performance evaluation	
RUMAH SAKIT UMUM PROVINSI NTB (Expert ground truth)	Sensitivity	$\frac{TP}{TP+FN} = \frac{56}{56+44} = 0{,}56 \text{ x } 100 = 56\%$
	Specificity	$\frac{TN}{TN+FP} = \frac{e1}{e1+e} = 0.45 \text{ x } 100 = 45\%$
	Accuracy	$\frac{TP+TN}{TP+FP+FN+TN} = \frac{56+e1}{56+e+44+e1}$ $= \frac{147}{200} = 0.73 \text{ x } 100\% = 73\ \%$
Diaretdb0	Sensitivity	$\frac{TP}{TP+FN} = \frac{0}{0+4} = 0\ \%$
	Specificity	$\frac{TN}{TN+FP} = \frac{100}{100+0} = 1\%$
	Accuracy	$\frac{TP+TN}{TP+FP+FN+TN} = \frac{0+100}{0+100+0+4}$ $= \frac{100}{104} = 0.96 \text{ x } 100\% = 96\%$
	Sensitivity	$\frac{TP}{TP+FN} = \frac{76}{76+24} = 0{,}76 \text{ x} 100 = 76\%$

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Messidor	Specificity	$\frac{TN}{TN+FP} = \frac{e6}{e6+4} = 0.96 \text{ x } 100= 96\%$
	Accuracy	$\frac{TP+TN}{TP+FP+FN+TN} = \frac{76+e6}{76+24+4+e6}$ $= \frac{172}{200} = 0.86 \text{ x } 100\% = 86\%$

For each test conducted, the number of true positions (TP), true positive (TP), false true (FT) and false negative (FN) were measured and compared to the results of other datasets. Sensitivity (SN) is correctly defined on true positives based on these findings specificity (SP) is determined for each test on incorrect false identification from true negatives. Accuracy is measured as the proportion of real outcomes among the total number of cases tested in the uncertainty matrix (both true positive and true negative).

3.2.2 Support Vector Machine (SVM)

The 200-ground truth expert data were processed using the Support Vector Machine (SVM) classification model to produce a prediction in the form of confusion matrix. The confusion matrix consists of 4 points (true positive (1,1), false negative (1,2), false positive (2,1) and true negative (2,2). These results show that there are 54 true positive data, 46 false negative data, 50 false positive data and 50 true negative data. The data that was processed using the classification model obtained a percentage of 54% calculation sensitivity, 50% specificity and 52% accuracy. Figure 3.3 shows confusion matrix of ground data expert by classification Support Vector Machine.

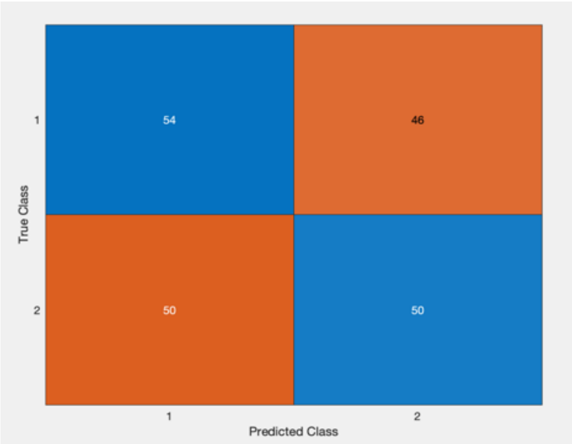

Figure 7: Confution matrix Diaretdb0 dataset

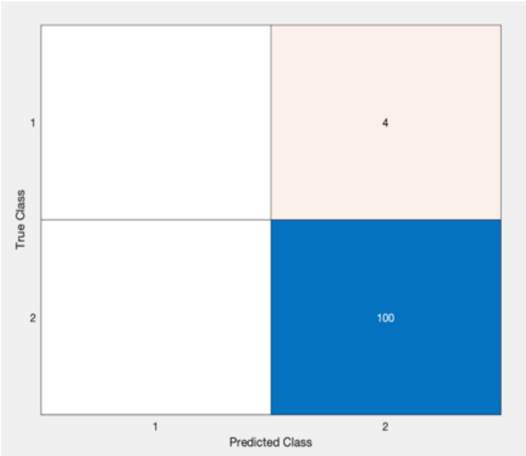

Figure 8: Confution matrix Messidor dataset

Table 4: The summary of result from dataset

Dataset	Performance evaluation	
Expert ground truth	Sensitivity	$\frac{TP}{TP+FN} = \frac{54}{54+46} = 0.54 \text{ x}100= 54\ \%$
	Specificity	$\frac{TN}{TN+FP} = \frac{50}{50+50} = 0.5 \text{ x } 100 = 50\%$

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Diaretdb0	Accuracy	$\frac{TP+TN}{TP+FP+FN+TN} = \frac{54+50}{54+50+46+50}$ $= \frac{104}{200} = 0.52 \times 100\% = 52\%$
	Sensitivity	$\frac{TP}{TP+FN} = \frac{0}{0+4} = 0 \times 100 = 0\ \%$
	Specificity	$\frac{TN}{TN+FP} = \frac{100}{100+0} = 1 \times 100 = 100\%$
	Accuracy	$\frac{TP+TN}{TP+FP+FN+TN} = \frac{0+100}{0+0+4+100}$ $= \frac{100}{104} = 0.96 \times 100\% = 96\%$
Messidor	Sensitivity	$\frac{TP}{TP+FN} = \frac{7e}{7e+21} = 0.79 \times 100 = 79\ \%$
	Specificity	$\frac{TN}{TN+FP} = \frac{31}{31+6e} = 0.31 \times 100 = 31\%$
	Accuracy	$\frac{TP+TN}{TP+FP+FN+TN} = \frac{7e+31}{7e+6e+21+31}$ $= \frac{110}{200} = 0.55 \times 100\% = 55\%$

3.2.3 Model Classification WEKA

WEKA software also is used to classify the feature extracted. Several classifiers are selected from the machine learning Waikato Environment for Knowledge Analysis (WEKA) in order to generate variety of analysis results performance of the proposed system.

Table 5: Summary dataset

Algorithm (Total instances:200, expert)	Correctly Classified Instances % (value)	Incorrectly Classified Instances % (Value)	Time Taken (seconds)	Kappa Statistic	Mean absolute error	Root mean squared error	Relative absolute error (%)	Root relative squared error (%)
Naïve Bayes	57.5 %	42.5 %	0	0.15	0.4319	0.5729	86.374 %	114.5874 %
SMO	56 %	44 %	0.01	0.12	0.44	0.6633	88 %	132.665 %
IBK	83 %	17 %	0	0.66	0.1739	0.411	34.7826 %	82.2071 %
Trees.J48	57%	43 %	0	0.14	0.4569	0.4938	91.3896 %	98.7579 %

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Algorithm (Total instances:200, expert)	Correctly Classified Instances % (Value)	Incorrectly Classified Instances % (Value)	Time Taken (seconds)	Kappa Statistic	Mean absolute error	Root mean squared error	Relative absolute error (%)	Root relative squared error (%)
Naïve Bayes	65%	35%	0.01	0.3	0.4193	0.4691	83.8621 %	93.8223 %
SMO	71%	29%	0.05	0.42	0.29	0.5385	58 %	107.7033 %
IBK	88.5%	11.5 %	0	0.77	0.1192	0.3373	23.8462 %	67.4586 %
Trees.J48	88.5 %	11.5 %	0.03	0.77	0.1541	0.3114	30.8285 %	62.2795 %

Algorithm (Total instances:200, expert)	Correctly Classified Instances % (value)	Incorrectly Classified Instances % (Value)	Time Taken (seconds)	Kappa Statistic	Mean absolute error	Root mean squared error	Relative absolute error (%)	Root relative squared error (%)
Naïve Bayes	96.1538 %	3.8462 %	0	0	0.1266	0.2347	152.393 %	96.1538 %
SMO	96.1538 %	3.8462 %	0.01	0	0.0385	0.1961	46.2921 %	96.1538 %
IBK	97.1154 %	2.8846 %	0	0.7132	0.0388	0.169	46.6455 %	97.1154 %
Trees.J48	96.1538 %	3.8462 %	0	0	0.0742	0.1936	89.2798	96.1538

In conclusion, between the two classification models used, the K-nearest Neighbors (KNN) classification is more superior based on the accuracy value (73% expert ground truth dataset, 96% Diaretdb0 and 86% Messidor) compared to the Support Vector Machine (SVM) (50% expert ground truth, 96% Diaretdb0, and 55% Messidor). Therefore, the K-nearest Neighbors (KNN) model is used for system app designers. Meanwhile, the WEKA classification model was created to be compared with the proposed system.

3.3 Diabetic Retinopathy Preprcessing for the Proposed System

The preprocessing method for detection of diabetic retinopathy that has been carried out in this research, namely grayscale, filtering, histogram equalization, and thresholding.

a. Grayscale

At this stage, the input image in the form of RGB with pixel values in the image consisting of three colour values which give red, green and blue components from colour pixels 0-255 (0b00000000-0b11111111, '0b' means the following number is in binary format), with a total of 256 grayscale levels. The colour RGB has a 3D matrix, while grayscale only has 2D.

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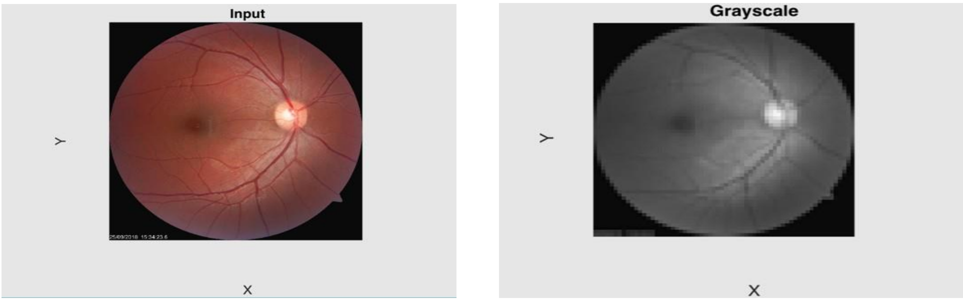


Figure 9: Convert RGB to Grayscale

b. Filtering

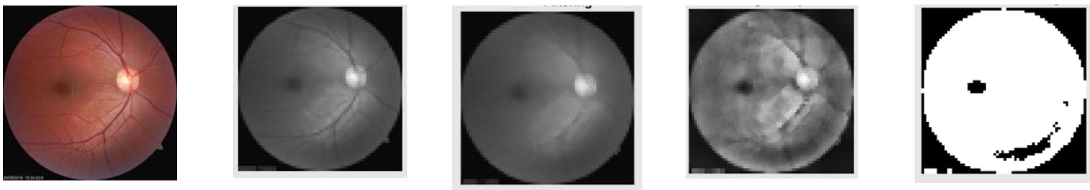
After preprocessing the grayscale with standard resize to make it easier to calculate the output image in the form of a 2-dimensional matrix. Then, the image will be filtered using the median filter 2 to remove noise from the previous image because it can disturb the quality of the image.

c. Histogram Equalization

To increase the contrast or quality in eye fundus images, histogram equalization is carried out to obtain maximum results and equalization of the pixel intensity values of eye fundus images.

d. Thresholding

The final image preprocessing technique is converting the processed image to binary by thresholding. The black, white output binary image has a value of 1 (white) for all pixels in the input image with luminance greater than LEVEL and 0 (black) for all other pixels.



Original Image | Grayscale | Filtering | Histogram Equalisation | Thresholding

Figure 10: Preprocessing images

The interface of the application for automatic detection of diabetic retinopathy using the app designer. Figure 4.9 prevent the design interface use for detection diabetic retinopathy.

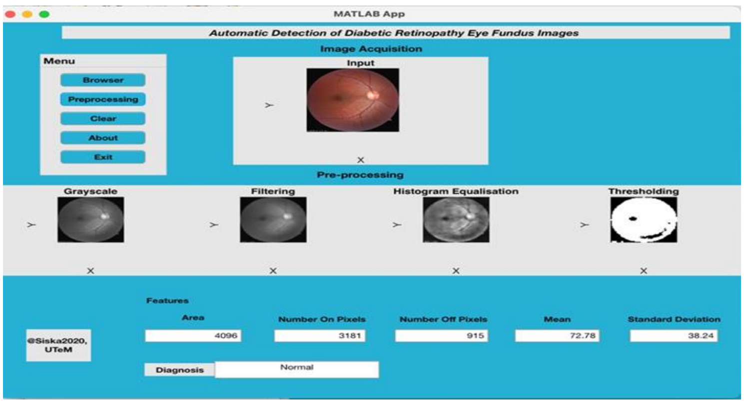


Figure 11: Design interface diabetic retinopathy

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3.4 Evaluation System

Based on expert data, the highest accuracy is IBK (83%) from the WEKA application followed by K-nearest Neighbors (KNN) from application (73%). Based on data from diaretdb0, the highest accuracy is Support Vector Machine (SVM and KNN (96%) of the application while IBK and Tress.J48 followed with accuracy of 88.5%. Based on data from messidor, the highest accuracy is IBK (97.1154 %) from WEKA followed by SMO, Naïve bayes, and Trees.j48 with 96.15%. From the proposed evaluation, the application perform better than WEKA on Diarethdb0 datasets. However, on Expert and Messidor datasets, WEKA application performs better accuracy.

Table 6: summary accuracy algorithm

Dataset	Algorithm	Accuracy
Expert	Naïve Bayes	57.5 %
	SMO	56 %
	IBK	83 %
	Trees.J48	57%
	KNN	73%
	SVM	52%
Diaretdb0	Naïve Bayes	65%
	SMO	71%
	IBK	88.5%
	Trees.J48	88.5 %
	KNN	96%
	SVM	96%
Messidor	Naïve Bayes	96.1538 %
	SMO	96.1538 %
	IBK	97.1154 %
	Trees.J48	96.1538 %
	KNN	86%
	SVM	55%

4. CONCLUSION

To answer the research question number one, one of processing techniques particularly on fundus images is **feature extraction.** After performing the pre-processing techniques, feature extraction takes place in order to obtain the features from the given images. Within the modelling for the classification and screening of diabetic retinopathy, five features, including the area of on pixels, on pixel, off pixel, the mean, and the standard deviation, also the total area are extracted for the purpose of diabetic retinopathy detection. There is some technique in terms of develop an automatic screening and classification system for diabetic retinopathy using fundus images in order to detect diabetic retinopathy at an early stage. This study decided to choose using the features extracted after the image pre-processing stage. The proposed classifiers are to Support **Vector Machine (SVM)** and **K-nearest Neighbors (KNN)**, where the extraction of features is essentially embedded in the stage of classification. Support Vector Machine (SVM) is classification models that are famously used currently. A supervised learning algorithm that can used make predictions, both predictions in case of regression and classification. In other hand, the machine learning K-nearest Neighbors (KNN) used to calculate the distance between different data points by classifying the data points. This study already finishes with the system evaluation system on the machine learning. **System evaluation** is done by comparing the accuracy of WEKA with the system created. Based on expert data, the highest accuracy is IBK (83%) from the WEKA application followed by K-nearest Neighbors (KNN) from application (73%). Based on data from diaretdb0, the highest accuracy is Support Vector Machine (SVM and KNN (96%)) of the application while IBK and Tress.J48 followed with accuracy of 88.5%. Based on data from messidor, the highest accuracy is IBK (97.1154 %) from WEKA followed by SMO, Naïve bayes, and Trees.j48 with 96.15%. From the proposed evaluation, the application perform better than WEKA on Diarethdb0 datasets. However, on Expert and Messidor datasets, WEKA application performs better accuracy.

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