# Diabetic Retinopathy: Identification and Classification using Different Kernel on Support Vector Machine

Ahmad Zoebad Foeady, Dian Candra Rini Novitasari and Ahmad Hanif Asyhar
*UIN Sunan Ampel Surabaya, Jln.A. Yani 117, Surabaya, Indonesia*

Keywords: SVM Classifier, GLCM, Diabetic Retinopathy, Polynomial, Gaussian, Kernel.

Abstract: Diabetic Retinopathy (DR) is one complication of diabetes that characterized by high glucose levels in the eyes that ultimately lead to blindness. To minimize the occurrence of blindness from DR, required diagnosis on the eye to possible for early treatment. In this paper, identified and classified DR using Gray Level Co-occurrence Matrix (GLCM) as feature extraction and Multiclass SVM with different kernel functions. The purpose of this study is to provide a breakthrough for patients in diagnosing the severity of the DR. The components identified in DR images include blood vessels, microaneurysms, and hemorrhages with contrast, energy, correlation, and homogeneity as feature extraction data on the GLCM method. The feature data will be classified using the Multiclass SVM method with 4 different kernel functions such as quadratic, linear, gaussian, and polynomial. The feature data will be classified using the Multiclass SVM method with 4 different kernel functions. Identification and classification of the DR image have an accuracy from each of quadratic, linear, Gaussian, and polynomial kernels functions are 72.72%, 22.72%, 63.64%, and 90.91%. From that accuracy, it has seen polynomial kernel function is more suitable for DR classification.

## 1 INTRODUCTION

Diabetic Retinopathy (DR) is one of the many complications caused by diabetes mellitus. It caused by the hormone insulin that can't be produced effectively causing blood sugar levels in the pancreas is not balanced and make the concentration of glucose in the blood increases (Gori et al., 2017). Diabetes is often a problem that has long faced by some people in the world due to having a great chance in causing death. In patients with diabetes for more than 10 years will arise a variety of complications as a side effect of diabetes is one of them is DR. DR occurs because there is an increase in glucose concentration in the eye nerve. high glucose levels will cause leakage and swelling due to blockage of blood vessels in the eye nerve. As a result, there are several signs to recognize as DR, such as microaneurysms, hemorrhages, hard exudates, cotton wool spots, and venous loops (Sopharak et al., 2008). These components are used to identification of DR epidemics. Under certain conditions in patients with DR, nerve of the eye experiences abnormalities as it grows on the surface of the retina. It difficult to treat that conditions because can approach blindness (Aravind et al., 2013).

Yau et al. (2012) estimated that the number of diabetics in the world around 34.6% or more precisely about 93 billion people and about 10.2% of the world's people suffer from DR. From the results obtained by the World Health Organization (WHO), about 5% of cases of blindness in the world caused by DR. Based on that high prevalence rate, it necessary then further treatment is needed for DR cases to be reduced or be prevented. However, treatment is needed for the identification of the DR to know the severity and that treatment can more effective. In DR there are several levels to measure its severity. In DR there are several levels to measure its severity, such as normal, non-proliferative DR (NPDR), and proliferative DR (PDR). Non-proliferative DR itself consists of 3 levels of severity that is mild, moderate, and sever (Sopharak et al., 2008).

On the identification of DR can be done in several ways, one of them by using color fundus image. To find color fundus image data, can be found or obtained at the nearest eye specialist hospital for the classification process. For identification, the obtained image is processed to obtain images of microaneurysms and hemorrhages contained in the blood vessel (BV). To simplify identification, it



Foeady, A., Novitasari, D. and Asyhar, A.
Diabetic Retinopathy: Identification and Classification using Different Kernel on Support Vector Machine.
DOI: 10.5220/0008517400720079
In *Proceedings of the International Conference on Mathematics and Islam (ICMIs 2018)*, pages 72-79
ISBN: 978-989-758-407-7
Copyright © 2020 by SCITEPRESS – Science and Technology Publications, Lda. All rights reserved

necessary to detect that BV because in BV have microaneurysms and hemorrhages (Yun et al., 2008).

Before classification, the image processing through the preprocessing stage such as green channel extraction, histogram equalization, contrast enhancement, filtering, and binarization. Preprocessing aims to process the image so that information can be obtained in accordance with the components to be taken. After that, the image will be taken statistical data through feature extraction process. In this research, the extraction of features using Gray Level Co-occurrence Matrix (GLCM) because of feature extraction based on texture analysis and it suitable for DR identification (Minajagi & Mashal, 2015). Feature extraction is obtained by statistical data to be classified according to the specified target. GLCM is particularly suitable in extracting DR images because it can decrease the positive false value of the confusion matrix and it can increase the accurate value (Maule et al., 2016).

Classification is performed after feature extraction process. The classification process using the multiclass SVM method with normal, NPDR, and PDR classes. NPDR classes data being mild, moderate, and severe. The SVM method was chosen because that classification method gives good results with a fast process than other classification methods (Herrera et al., 2013). SVM method has a function that used to transform data for input in classification, this function is called kernel function. There are several types of kernel functions present in SVM, such as polynomial, quadratic, gaussian, and linear (Anthony, Greg & Tshilidzi, 2007).

In a study conducted by Dian Candra R. N. has succeeded in classifying DR using decomposition wavelet method as feature extraction and ANMBP method as its classification method (Novitasari, 2016). Further research was conducted by Maule et al. (2016). Maule et al. (2016) extract the DR data feature using GLCM method and Backpropagation as the classification method with accuracy was 76.6% and the accuracy have been increased due to GLCM method. Using the same classification method and using DR data from DIARETDB1, Hashim & Hashim (2014) resulted accuracy occurred about 71.94%. Based on the previous research, GLCM method was chosen as feature extraction and SVM method as classification and it can obtain optimal accuracy and the purpose of this study is to assist the medical check to determine the severity of the DR easily and can perform treatment effectively.

# 2 LITERATURE REVIEW

## 2.1 Diabetes Mellitus

Diabetes mellitus is a long-term illness because it can provide both physical and psychological changes. Many factors that make a person infected with diabetes include external factors and internal factors. Heredity is one of a factor to infected with this disease and for external factors are usually influenced by the lifestyle of an individual (Kosti & Kanakari, 2012). Although diabetes mellitus is one of 4 most deadly diseases, but the disease is not infectious. Diabetes mellitus caused by high blood glucose levels because the pancreas in the body cannot produce enough of the hormone insulin (Li et al., 2015).

## 2.2 Diabetic Retinopathy

Diabetic retinopathy is a complication of diabetes that attacks the eyes because glucose levels in the nerves of the eye increases, causing blood vessels in eyes that are sensitive to damaged light. Damaged blood vessels cause the DR patient in vision problem and DR is the main cause of blindness in adults (Neuwirth, 1988). DR is divided into 2 categories, such as NPDR and PDR. NPDR is a DR in the presence of microaneurysms, hemorrhages, hard exudates, cotton wool spots, or venous loops in the retina of the eye. PDR is characterized by the presence of new abnormal blood vaselin optic disk, that condition called neovascularization (Vishali Gupta, Amod Gupta, M. R. Dogra, 2013).

## 2.3 Microaneurysms

Microaneurysms is an early sign of DR infection caused by elevated glucose levels in eyes that cause blood clots in blood vessel. Microaneurysms are marked with small red dots located on the edge of the eye nerve. Microaneurysms have 1/12 size of optical disk diameter is about 25-100 micron (Vishali Gupta, Amod Gupta, M. R. Dogra, 2013; Hsu et al., 2005).

## 2.4 Hemorrhages

Diabetes mellitus can attack blood vessel more fragile and easily damaged and that can be exposed to minor injuries will give a large impact injury. Diabetes makes the blood sugar levels rise can cause injury to the wound, it called hemorrhages. Bleeding can also arise due to damaged microaneurysms so that virgin can flow out of the eye nerve (Vishali Gupta, Amod

Gupta, M. R. Dogra, 2013; Cunha-Vaz & Bernardes, 2005).

## 2.5 Color Fundus Image

Fundus image is an image with the spatial resolution that has enhanced the brightness and contrast, it can identify any information from that image. The eye image has a small brightness level, since the required fundus image can be identified (Hubbard, 2009).

## 2.6 Gray Level Co-occurrence Matrix

Gray Level Co-occurrence Matrix (GLCM) is a feature extraction method of grayscale images. GLCM is very often used as a texture extraction of images because GLCM takes into intensity and brightness of the image, that texture can be clearly recognized. The matrix generated by GLCM is a matrix whose rows and columns are same and can be called square matrix (Öztürk & Akdemir, 2018). In the GLCM method there are 4 different offsets. That offset can be used as follows {[0 1] for 0$^o$, [-1 1] for 45$^o$, [-1 0] for 90$^o$, and [-1 -1] for 135$^o$}. GLCM offsets direction can be seen in figure 1.

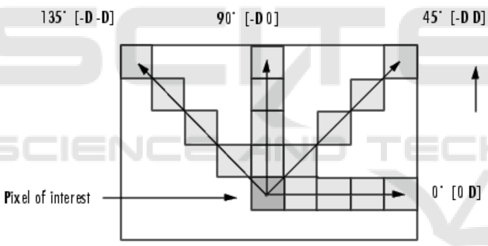



Figure 1: GLCM offsets direction.

For each offset for feature extraction also give a different result (Pathak & Barooah, 2013). The feature extraction data generated by GLCM are contrast, homogeneity, entropy, energy, and correlation. Let$f(x,\ y)$ represent images of size $Nx$and $Ny$ that have pixels with L levels and r is the direction vector of spatial offset. $p(i,j)$ is a GLCM function and defined by the number of pixels $(j)$ occurring at offset r to pixel $(i)$and where the offset r can be an angle or distance, $i \in 1,2,..,L$ and $j \in 1,2,..,L$. GLCM function can be seen in equation (1).

$$p(i,j) = \{(x_1,y_1),(x_2,y_2)\}. \qquad (1)$$

### 2.6.1 Contrast

Contrast is the ratio of the brightness intensity between pixel of that image. That result of the image is good if that have a high brightness intensity(A, Suresh & Shunmuganathan, 2012). Contrast can be obtained with equation (2).

$$Contrast = \sum_{i}^{L}\sum_{j}^{L}|i-j|^2 p(i,j), \qquad (2)$$

where $p(i,j)$ is matriks co-occurrence, $i \in 1,2,..,L$ and $j \in 1,2,..,L$.

### 2.6.2 Homogeneity

Homogeneity is a value from the level of uniformity at the local gray level. Homogeneity is can be called Inverse Difference Moment (IDM). Homogeneity is inversely proportional to the value of contrast and high contrast value have low homogeneity (Mohanaiah et al., 2013). The homogeneity equation can be seen in equation (3).

$$Homogeneity = \sum_{i=1}^{L}\sum_{j=1}^{L}\frac{p(i,j)^2}{1+(i-j)^2}. \qquad (3)$$

### 2.6.3 Entropy

Entropy can be used to search for information on images and the results obtained based on the amount of missing information present in the image (Mohanaiah et al., 2013). The entropy equation can be seen in equation (4).

$$Entropy = \sum_{i=1}^{L}\sum_{j=1}^{L}p(i,j)(-\ln p(i,j)). \qquad (4)$$

### 2.6.4 Energy

Energy is the uniformity of co-occurrence matrix. This energy can also be called Angular Second Moment (ASM) (Mohanaiah et al., 2013). The energy equation can be seen in equation (5).

$$Energy = \sum_{i=1}^{L}\sum_{j=1}^{L}p(i,j)^2. \qquad (5)$$

#### 2.6.5 Correlation

Correlations are used to measure the degree of interconnectedness or dependency between pixels and other pixels (Mohanaiah et al., 2013). The correlation equation can be seen in equation (6).

$$Correlation = \sum_{i=1}^{L}\sum_{j=1}^{L}\frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j}, \quad (6)$$

where

$$\mu_i = \sum_i i \sum_j p(i,j) \quad (7)$$

$$\mu_j = \sum_j j \sum_i p(i,j) \quad (8)$$

$$\sigma_i = \sum_i (i-\mu_i)^2 \sum_j p(i,j) \quad (9)$$

$$\sigma_j = \sum_j (j-\mu_j)^2 \sum_i p(i,j) \quad (10)$$

### 2.7 Support Vector Machine

Support Vector Machine (SVM) is a classification method that find the best hyperplane and the results obtained optimal classification. The hyperplane is the dividing line between the first class with the other class. The SVM method can specify two types of data sets, such as linear and non-linear data. Based on the target classification result, SVM is divided into Binary Classification and Multiclass Classification (Ahuja & Yadav, 2012). SVM also have a kernel to transformation that input data and it can be used in the Lagrange equation in the SVM process. There are 4 kinds of kernels in SVM and MATLAB, such as linear, quadratic, polynomial, and Gaussian. For kernel equation can be shown on equation11, 12, 13, and 14.

$$\text{Linear} = K(x,y) = x.y \quad (11)$$

$$\text{Polynomial} = K(x,y) = (x.y+c)^d \quad (12)$$

$$\text{Gaussian} = K(x,y) = exp\left(\frac{-||x-y||^2}{2.\sigma^2}\right) \quad (13)$$

$$\text{Quadratic} = K(x,y) = \frac{1}{\sqrt{||x-y||^2 + C^2}} \quad (14)$$

#### 2.7.1 Binary Classification

SVM binary classification that class will be set to only 2 classes and the hyperplane will be split up clearly into two parts that match the target classification. SVM occurs the data close to hyperplane called support vector data. That research used binary classifications such as fingerprint recognition, data matching that have yes or no results, and more (Ahuja & Yadav, 2012).

#### 2.7.2 Multiclass Classification

Basically, SVM is created with binary classification. However, since many cases classify more than 2 classes, SVM must upgrade to allow for the classification of more than 2 classes called multiclass SVM. In multiclass SVM is divided into 2 different classification models. Indirect classification is one of the SVM multiclass models. In indirect classification, the way to do is to divide the 2 classes which are then taken one class and classified again into 2 classes. The second is direct classification which directly divides into many required classes (Ahuja & Yadav, 2012).

## 3 RESEARCH METHOD

This research is categorized as quantitative study. Based on its function, this research serves to help to accelerate in introducing DR process, so that the treatment can be done optimally without any diagnostic errors.

Color fundus image data of diabetic retinopathy is obtained from DIARETDB and it is validated by an ophthalmologist in Dr. Soetomo Hospital Indonesia. The data which is used in the classification is divided into training and testing. The Ratio of data that used in training and testing is 60%:40%; 70%:30%; 80%:20%. The diagram of the DR classification process can be shown in the flowchart in figure 2.

The steps of the DR identification and classification process include pre-processing, feature extraction, and SVM Classifier. Pre-processing is useful to process the images and the images can be used for the feature extraction process by using GLCM which result is to the input of SVM classification.

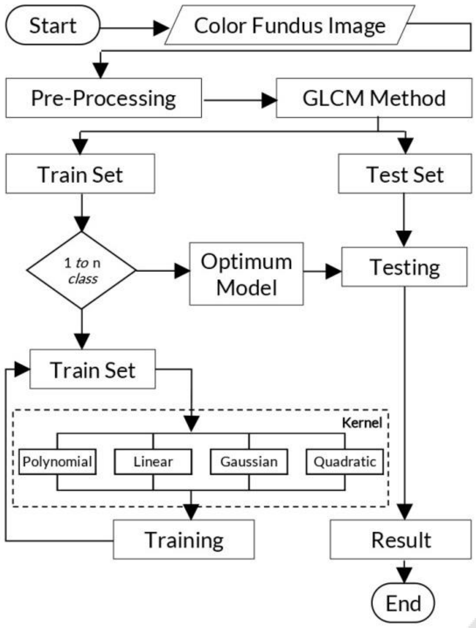



Figure 2: flowchart for DR identification.

In primary data, the color fundus image can't be directly identified by the DR component. And for the statistical data from the feature extraction must also go through a process called pre-processing. The maximum results can be obtained with high accuracy. The steps which are taken during the pre-processing stage are green channel extraction, histogram equalization, optical disk elimination, filtering, and contrast enhancement. Form of image grayscale that contains clearly images of blood vessel, microaneurysms, and hemorrhages is obtained from the results of pre-processing. Therefore, after this process, it will proceed to the feature extraction process.

The feature extraction process uses the GLCM method. This method extracts features of grayscale images in the form of the statistical data required for classification. In GLCM, the data taken is contrast, correlation, homogeneity, and energy using the default offset of {[0 1] for $0^o$, [-1 1] for $45^o$, [-1 0] for $90^o$, and [-1 -1] for $135^o$}. The researcher takes only contrast, correlation, homogeneity, and energy as the data because MATLAB can only extract the 4 characteristics above. This data will be used as input matrix for classification by using SVM method.

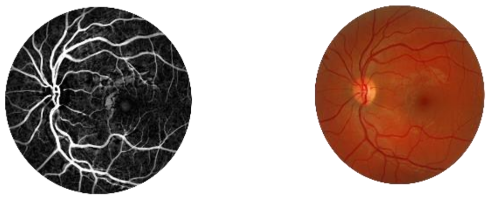
Furthermore, the feature extraction results are used as input from the SVM classifier. In this case, the Multiclass SVM is used for more than two classification classes, so the regular SVM cannot be used. There have a training and testing in classification process which each process has slightly different steps. In the training process, it will be used data that has been prepared. Then, the data will be transformed with kernel. Those are polynomial, gaussian, linear, quadratic. The kernel is used in conformity with feature extraction data. The transformed data will be classified on the SVM multiclass, so that the optimum hyperplane is divided into 3 classification classes. The optimum model is then simulated with the test feature matrix from the feature extraction result. The simulation result is the result of the classification which is then compared with the actual test data.

# 4 RESULT AND DISCUSSION

The process to identify and classify the DR consists of pre-processing which aims to process images to obtain appropriate information, GLCM which is to obtain feature extraction matrices used in classification inputs, and Multiclass SVM as a means of classifying DR with normal classes, NPDR, and PDR.

Before doing the classification process, a pre-processing process is needed to eliminate unnecessary information. So, it can produce more accurate calcification data. In pre-processing, the researcher conducts green channel extraction, histogram equalization, optical disk removes, filtering, and contrast enhancement process as the final image of pre-processing to be a grayscale image. The transformation that occurs in the pre-processing process can be shown in figure 3.

In Figure 3(a) is a fundus image that will be used as input data. Fundus images will pass pre-processing steps that include green channel extraction, histogram equalization, optical disk remove, filtering, and contrast enhancement. The results of pre-processing can be seen in Figure 3(b). After obtaining the final image, it proceeds to the next process by taking of statistical features on the picture or commonly known as the feature extraction stage. At this feature extraction stage, the researcher uses GLCM method which takes texture analysis in the form of contrast, correlation, energy, entropy, and homogeneity. However, this paper statistics takes only contrast, correlation, energy, and homogeneity. At this stage, the data is taken using the degree of neighborliness $0^o$, $45^o$, $90^o$, and $135^o$. In Table 1, there is a feature extraction sample with 3 data as an example with all available degree of buffering.



(a) (b)

Figure 3: (a) color fundus image, (b) pre-processing result.

Table 1: Sample of extraction feature data.

| Degree | Homo-geneity | Contrast | Energy | Correlation |
|---|---|---|---|---|
| 0° | 0.26365 | 0.90901 | 0.58194 | 0.93756 |
| | 0.23801 | 0.92797 | 0.59734 | 0.94336 |
| | 0.24239 | 0.90892 | 0.59127 | 0.94239 |
| 45° | 0.40921 | 0.85893 | 0.56370 | 0.92059 |
| | 0.37720 | 0.88605 | 0.58147 | 0.92699 |
| | 0.37199 | 0.86048 | 0.57366 | 0.92505 |
| 90° | 0.27090 | 0.90649 | 0.58400 | 0.93874 |
| | 0.23146 | 0.92999 | 0.59799 | 0.94301 |
| | 0.22589 | 0.91517 | 0.59265 | 0.94347 |
| 135° | 0.44639 | 0.84611 | 0.56299 | 0.91938 |
| | 0.38232 | 0.88450 | 0.58190 | 0.92668 |
| | 0.37240 | 0.86033 | 0.57519 | 0.92699 |

Table 2: Result of Classification 60% training data and 40% testing data.

| Kernel | Degree | Ac |
|---|---|---|
| Polynomial | 0° | 90.91% |
| | 45° | 63.63% |
| | 90° | 59.09% |
| | 135° | 77.27% |
| Gaussian | 0° | 63.64% |
| | 45° | 68.18% |
| | 90° | 59.09% |
| | 135° | 63.63% |
| Linear | 0° | 22.72% |
| | 45° | 27.27% |
| | 90° | 27.27% |
| | 135° | 27.27% |
| Quadratic | 0° | 72.72% |
| | 45° | 54.54% |
| | 90° | 68.18% |
| | 135° | 63.64% |

Table 3: Result of Classification 70% training data and 30% testing data.

| Kernel | Degree | Ac |
|---|---|---|
| Polynomial | 0° | 88.89% |
| | 45° | 44.44% |
| | 90° | 66.67% |
| | 135° | 55.56% |
| Gaussian | 0° | 55.56% |
| | 45° | 66.67% |
| | 90° | 61.11% |
| | 135° | 55.56% |
| Linear | 0° | 55.56% |
| | 45° | 61.11% |
| | 90° | 61.11% |
| | 135° | 66.67% |
| Quadratic | 0° | 66.67% |
| | 45° | 66.67% |
| | 90° | 66.67% |
| | 135° | 61.11% |

The extraction feature data used as input for classification. In the classification process, there is a process of training and testing. In this study, the ratio of training data and testing data used were 60%:40%; 70%:30%; 80%:20%. The results of classification will show the accuracy (Ac), which is obtained by using the method of recognition rate. The results of classification on each ratio of data sharing can be shown on table 2, table 3 and table 4.

Based on table 2, it showed that the maximum results are obtained in the polynomial kernel with statistical data obtained from GLCM at 0° degree. In the polynomial kernel, there is a very high accuracy value, this is caused by the characteristics of feature extraction data in the form of polynomial data. So, it has a high accuracy of 90.91%when doing SVM classification by using polynomial kernel. That result is the best result from this research.

Based on table 3, it showed that best accuracy result is 88.89% on polynomial kernel. From the result the data is not because of that characteristic of feature extraction data not representative that classify. Based on table 4, that have decrease accuracy. The best accuracy is 80% that caused by the lack of data and doesn't have perfectly representative the data.

The best result in this research is on 60% training data, 40% testing data, polynomial kernel, and 0° degree with 90.91% accuracy.

Table 4: Result of Classification 80% data training and 20% testing data.

| Kernel | Degree | Ac |
|---|---|---|
| Polynomial | 0° | 80% |
| | 45° | 60% |
| | 90° | 60% |
| | 135° | 60% |
| Gaussian | 0° | 50% |
| | 45° | 60% |
| | 90° | 50% |
| | 135° | 60% |
| Linear | 0° | 70% |
| | 45° | 70% |
| | 90° | 70% |
| | 135° | 70% |
| Quadratic | 0° | 60% |
| | 45° | 50% |
| | 90° | 50% |
| | 135° | 50% |

## 5 CONCLUSIONS

From the results above, it can be concluded that kernel polynomial is the best kernel for data DR, because it states 90.91% accuracy from the process of each image in classification. The results of research concluded that the data used DR is the type of data polynomial due to the match with the polynomial kernel.

## REFERENCES

Ahuja, Y., & Yadav, S. K., 2012. Multiclass Classification and Support Vector Machine. *Global Journal of Computer Science and Technology Interdisciplinary*, *12*(11), 15–19. Retrieved from https://globaljournals.org/GJCST_Volume12/2-Multiclass-Classification-and.pdf, accessed on November 1, 2018).

Anthony, G., Greg, H., & Tshilidzi, M., 2007). Classification of images using Support Vector Machines. Retrieved from *https://arxiv.org/ftp/arxiv/papers/0709/0709.3967.pdf*, accessed on November 1, 2018.

Aravind, C., PonniBala, M., & Vijayachitra, S., 2013. Automatic Detection of Microaneurysms and Classification of Diabetic Retinopathy Images using SVM Technique. *International Journal of Computer Applications (0975-8889). International Conference on Innovations in Intelligent Instrumentation, Optimization and Signal Processing* (*ICIIIOSP*), 18–22.

Cunha-Vaz, J., & Bernardes, R., 2005. Nonproliferative retinopathy in diabetes type 2. Initial stages and characterization of phenotypes. *Progress in Retinal and Eye Research 24,* 355–377. https://doi.org/10.1016/j.preteyeres.2004.07.004.

Gori, N., Kadakia, H., Kashid, V., & Hatode, P., 2017. Detection and Analysis of Microanuerysm in Diabetic Retinopathy using Fundus Image Processing. *International Journal of Advance Research, Ideas and Innovations in Technology* (*IJARIIT*), 3(2), 907–911.

Gupta, V., Gupta, A., Dogra, M. R., Singh, R., 2013. *Diabetic Retinopathy Atlas 1st Edition*. New York: MC Graw Hill Medical.

Hashim, M. F. & Hashim, S. Z. M., 2014. Diabetic retinopathy lesion detection using region-based approach. *2014 8th Malaysian Software Engineering Conference, MySEC,* 306–310. https://doi.org/10.1109/MySec.2014.6986034.

Herrera, L. J., Rojas, I., Pomares, H., Guillén, A., Valenzuela, O., & Banos, O., 2013. Classification of MRI Images for Alzheimer's Disease Detection. *2013 International Conference on Social Computing*, 846–851. https://doi.org/10.1109/SocialCom.2013.127

Hsu, W., Lee, M. L., Pallawala P. M. and Goh, S. S., 2005. Automated Microaneurysm Segmentation and Detection using Generalized Eigenvectors. *Applications of Computer Vision and the IEEE Workshop on Motion and Video Computing, IEEE Workshop on (WACV-MOTION)*, Breckenridge, Colorado, pp. 322-327. doi:10.1109/ACVMOT.2005.26.

Hubbard, L. D., 2009. Digital Color Fundus Image Quality : The Impact of Tonal Resolution. *The Journal of Ophthalmic Photography*, *31*(1), 15–20.

Kosti, M., & Kanakari, M. (2012). Education and diabetes mellitus. *Health Science Journal*, *6*(4), 654–662.

Li, S., Guo, S., He, F., Zhang, M., He, J., Yan, Y., Ding, Y., Zhang, J., Liu, J., Guo, H., Xu, S., & Ma, R., 2015. Prevalence of diabetes mellitus and impaired fasting glucose, associated with risk factors in Rural Kazakh adults in Xinjiang, China. *International Journal of Environmental Research and Public Health*, *12*(1), 554–565. https://doi.org/10.3390/ijerph120100554.

Maule, P., Shete, A., Wani, K., Dawange, A., & Shinde, J. V., 2016. GLCM feature extraction in Retinal Image. *International Journal of Advanced Research in Science Management and Technology* (*IJARSMT*) *2*(4), 1–8.

Minajagi, P., & Mashal, M., 2015. Automated Detection of Diabetic Retinopathy. *International Journal of Emerging Technology in Computer Science & Electronics* (IJETCSE) *14*(2), 621–626.

Mohanaiah, P., Sathyanarayana, P., & Gurukumar, L., 2013. Image Texture Feature Extraction Using GLCM Approach. *International Journal of Scientific & Research Publication*, *3*(5), 1–5. https://doi.org/10.1.1.414.96981.

Neuwirth, J., 1988. Diabetic retinopathy: what you should know. *Connecticut Medicine*, *52*(6), 361.

Novitasari, D. C. R., 2016. Sistem Diagnosis dan Deteksi Dini Pencegahan Kebutaan pada Pasien Diabet Berdasarkan Tingkat Stadium Diabetic Retinopathy. Unpublished. UIN Sunan Ampel, Surabaya.

Öztürk, Ş., & Akdemir, B., 2018. Application of Feature Extraction and Classification Methods for

Histopathological Image using GLCM, LBP, LBGLCM, GLRLM and SFTA. *Procedia Computer Science*, *132*, 40–46. https://doi.org/10.1016/j.procs. 2018.05.057.

Pathak, B., & Barooah, D., 2013. Texture analysis based on the gray-level co-occurence martix considering possible orientations. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, *2*(9), 4206–4212. Retrieved from http://www.ijareeie.com/ upload/2013/ september/7_-TEXTURE.pdf.

Sopharak, A., Uyyanonvara, B., Barman, S., & Williamson, T. H., 2008. Automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods. *Computerized Medical Imaging and Graphics*, *32*(8), 720–727. https://doi.org/10.1016/j.compmedimag. 2008.08.009

Suresh, A. & Shunmuganathan, K. L., 2012. An Efficient Texture Classification System Based on Gray Level Co- Occurrence Matrix. *International Journal of Computer Science and Information Technology & Security* (*IJCSITS*), **2**(4), 793–798.

Yau, J. W. Y., Rogers, S. L., Kawasaki, R., Lamoureux, E. L., Kowalski, J. W., Bek, T., … Wong, T. Y., 2012. Global Prevalence and Major Risk Factors of Diabetic Retinopathy. *Diabetes Care*, *35*(March), 556–564, https://doi.org/10.2337/dc11-1909.

Yun, W. L., Acharya, U. R., Venkatesh, Y. V., Chee, C., Min, L. C. & Ng, E. Y. K., 2008. Identification of different stages of diabetic retinopathy using retinal optical images. *Information Sciences*, *178*(1), 106–121. https://doi.org/10.1016/j.ins.2007.07.020.

SCIENCE AND TECHNOLOGY PUBLICATIONS