Techniques for Exudate Detection for Diabetic Retinopathy

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***Abstract*- Diabetic Retinopathy (DR) is an eye disease caused by diabetic complications that have early signs of a disease containing microaneurysms and exudates. Diabetic retinopathy for a long time can cause vision loss (blindness). So automatic detection is needed. Therefore we conduct research for the detection of exudates based on segmentation using the STARE and DIARETDB1 datasets. The exudate appears yellowish and glowing in the background of the retina with irregular size and shape. The use of several segmentation methods can be done in exudate detection. The method used is the adaptive threshold method, multi-threshold otsu, top-hat and bottom hat, and fuzzy c-means performance. The average performance results of several methods used in segmenting for each image in the STARE dataset are otsu multi threshold 87.1%, adaptive threshold of 89.9%, top-hat and bottom hat 87.7% and fuzzy c-means 95.4%. and in the DIARETDB1 dataset, otsu multi threshold is 89%, adaptive threshold is 88.2%, top-hat and bottom hat 92.9% and fuzzy c-means 90.6%. These results indicate that the proposed method can provide good exudate segmentation results.**

Keywords – diabetic retinopathy, segmentation, detection, exudate, adaptive thresholding, Otsu multi thresholding, top-hat and bottom hat, fuzzy c-means

I. INTRODUCTION

The retina is a thin membrane located at the back of the eye. Diabetic retinopathy is damage to the retina that occurs in people with diabetes mellitus. Diabetic retinopathy will cause vision to decrease gradually until a long time the patient will experience blindness [1]. Diabetes is characterized by the appearance of several disorders. Abnormalities that occur in the retina one of them is described by exudate [3]. Exudate detection is one of the main signs of diabetic retinopathy. Exudate is caused by leakage and dilation of blood vessels around the retina. In humans, exudate is a clear liquid that comes out of a vein and into the surrounding tissue. This liquid has a yellowish color with various sizes and shapes [2].

To find out diabetic retinopathy, that is by automatic detection [4]. The initial step to find out the exudate is to first erase the optical disk. because the optical disk is considered as noise, because the optical disk has a brightness level that is almost the same as the exudate. This is important for analysis of retinal images in diagnosis as one of the main features for extracting the structure of the anatomy of the retina [5].

In detecting segmentation of the exudate of the retina, we propose techniques such as Adaptive Thresholding, Otsu Multi Thresholding, Bottom hat and top hat and Fuzzy c-means. In this case we compare several methods using the STARE dataset and DIAREDB1 to get a good method.

II. RELATED WORK

Different methods have been developed to detect exudates, for example Monzurul Islam et al in subsequent studies [1] Exudates detected using the SURF function to diagnose diabetic retinopathy with an accuracy of 94.4%. A similar study was also conducted by A.Sopharak, et al.[6] with automatic exudate detection using fuzzy c-means clustering with an accuracy value of 85.6%.

Exudate detection accuracy values were further investigated by A. Benzamin [7] using the Lifting Wavelet Transform (LWT) and Support Vector Engine (SVM) methods with high accuracy. Although it produces high accuracy, this method still has shortcomings as it still requires a good and precise quality of exudate detection. Shortcomings in subsequent studies using the Multiscale Morphology method. Obtain a high enough but not relevant accuracy between a number of pixels that lack contrast.

Subsequent research [8] used the Histogram Analysis method on retinal fundus images. An algorithm is used to localize the optical disk and detect exudates from the image. This algorithm uses histogram information. Generates an accuracy of 99%, 90%, and 89% for DRIVE, DIARETDB1 and local datasets respectively.

The next exudate detection methods are Mean Shift and Adaptive Thresholding showing better performance than other systems. Its performance by eliminating the optical disk first then applying the Mean Shift to the retinal fundus image to segment the exudate. Measured in two datasets namely DIARETDB0 and DIARETDB1 by obtaining an average accuracy of 93.34% [9].

III. METHODS

We used images from the STARE (Structured Analysis of The Retina) dataset and DIARETDB1 dataset. This research uses 4 segmentation techniques in conducting exudate detection. Steps of performing an exudate detection are present in the form of a flowchart in Figure 1.

A. Pre-processing

The Pre-processing step is conversion of green color component G of fundus RGB image. In addition to converting, there are several methods used such as CLAHE,Illumination Correction and Morphological Operation

- *Contrast-limited adaptive histogram equalization* (CLAHE) manually increases image contrast. The high contrast of fundus images is very important because, in addition to high intensity, contrast is another feature that is useful in detecting exudates.
- Illumination Correction, lighting usually occurs unevenly in retinal images due to variations in the shape of the retinal tissue and eyeball. To suppress this non-uniform illumination, improvements in lighting need to be applied[10]. To improve this image enhancement, a large spatial median filter (90 a. 90) is applied to the image input. The blurry image is subtracted from the original to get a good image.
- Morphological operations play an important role in digital image processing. The principle of morphological operations is to extract image components that are useful in representing and describing forms such as boundary extract from a region. In morphological operations such as dilation, erosion, opening and closing.

B. Adaptive Thresholding

Segmentation is part of the process of image processing. The pre-processing process in the object recognition system in the image during the image segmentation process. As for the image segmentation process itself there are several algorithms, including: Point Detection, Line Detection, and Side Detection algorithms (based on Robert Operators and Sobel Operators). The threshold is divided into two, namely local thresholds and global thresholds. Local thresholding is also used as a dynamic threshold or adaptive thresholding [11].

$$G(x,y) = \begin{cases} 0 jika f(x,y) \geq T(x,y) \\ 1 jika f(x,y) \leq T(x,y) \end{cases} \quad (1)$$

Where G (x, y) is the result of Adaptive Threshold and f (x, y) and T (x, y) represent the conditions for image enhancement and threshold functions.

C. Otsu Multi Thresholding

Thresholding is the most common method used in image segmentation. Thresholding can be used to form a binary image from a grayscale image. During the thresholding process, an image pixel is marked as a foreground pixel if its value exceeds a threshold value and is marked as a background if the value is lower than the threshold value [12]. One area is less than the threshold value and the other is more than the threshold value [13]. At this stage, the image that has undergone the process of being a binary image is now being processed to get a value from the Otsu threshold. Otsu Multi Thresholding is used to detect the desired image area by selecting the appropriate threshold value. The threshold level is a normalized intensity value that lies in the range [0, 1]. It was chosen to minimize intra-class variance of black and white pixels[12].

The technique developed in Otsu is a technique based on differences in class. The technique is used to determine the gray intensity value, namely: { 1, 2,. L). At that level, the probability of an image occurring is given by[14]:

$$p_a = \frac{na}{N}, \; p_{a \geq 0}, \; \sum_{a=1}^{L} p_a = 1, \quad (2)$$

When the histogram is divided into two classes (objects and backgrounds), the weights between the two classes are expressed by:

$$W_1(th) = \sum_{a}^{th} p_a \text{ dan } W_2(th) = \sum_{a=th+1}^{L} p_a \quad (3)$$

Means level of gray scales calculated by class:

$$\mu_a = \sum_{a=1}^{th} \frac{ap_a}{W_1(th)}, \mu_b = \sum_{a=th+1}^{th} \frac{ap_a}{W_2(th)} \quad (4)$$

If μ_T is the mean intensity for the entire image, then:

$$W_1\mu_a + W_2\mu_b = \mu_T, \text{ dan } W_1 + W_2 = 1 \quad (5)$$

After the values are calculated, automatic variation between classes σ_c^2 can be calculated as follows:

$$\sigma_c^2 = \sigma_a + \sigma_b \,, \tag{6}$$

where

$$\sigma_a = W_1(\mu_a - \mu_T)^2 \text{ dan } \sigma_b = W_2(\mu_b - \mu_T)^2 \tag{7}$$

D. Top Hat and Bottom Hat

White top-hat transformation is a morphological operation designed to extract bright parts of an image. Opening Morphology is component of erosion and dilation Dark areas of the image will absorb the bright parts of the image. Conversely, if the image is subtracted from the original, the peak intensity will be increased and the exudate can be better differentiated

Top hat transformation is the difference between input image (grayscale image) and image after an opening operation. This operation is given by Eq

$$TopHat(f) = f - (f \circ B) \tag{8}$$

Where the symbol (o) represents the gray morphology of the opening operation given by the equation

$$f \circ B = (f \ominus B) \oplus B \tag{9}$$

Bottom hat transformation is the difference between images after the closing operation and the input image (grayscale image).

E. Fuzzy C-Means

Fuzzy C-Means are groupings piled up, where each point can be owned by two or more groups with various levels of partnership. Grouping using Fuzzy C-means has been used to produce extraction of exudate and optic disc. Optical disc needed in the application to be removed and removed from the exudate Further techniques are needed to be applied so that the disk is detected and separated from the exudate[15][16]. Here's how to determine Fuzzy C-Means algorithm is the following:

1. X matrix which is the data to be clustered.

$$\begin{bmatrix} X_{11} & X_{11} & \cdots & X_{1j} \\ X_{11} & X_{11} & & X_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ X_{k1} & X_{k2} & & X_{kj} \end{bmatrix} \tag{10}$$

2. The number of clusters to be formed ($n > c \geq 2$), weighting ($w > 1$).

3. Form the initial partition matrix U (degree of membership in the cluster).

$$\begin{bmatrix} U_{11} & U_{11} & \cdots & U_{1i} \\ U_{11} & U_{11} & & U_{2i} \\ \vdots & \vdots & \ddots & \vdots \\ U_{k1} & U_{k2} & & U_{ki} \end{bmatrix} \tag{11}$$

4. Calculate the center of the cluster (V) for each cluster:

$$V_{ij} = \frac{\sum_{k=1}^{n}(\mu_{ik})^{w}.x_{kj}}{\sum_{k=1}^{n}(\mu_{ik})^{w}} \tag{12}$$

5. Calculate the objective value (Pn) :

$$P_n = \sum_{k=1}^{n}\sum_{i=1}^{c}(\mu_{ik})^{w}(d_{ik})^2 \tag{13}$$

6. Improve the degree of membership of each data in each cluster (fix the partition matrix)

$$\mu_{ik} = \left[\sum_{j=1}^{C}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/(w-1)}\right]^{-1} \tag{14}$$

$$d_{ik} = d(x_k - v_i) = \left[\sum_{j=1}^{m}(x_{kj} - v_{ij})\right]^{1/2} \tag{15}$$

7. Stop iteration if the center of cluster V does not change. The alternative termination criterion is if the change in error value is less than | Pn - Pn-1 | <ε.

8. If the iteration stops, it is determined the cluster of each data. Clusters are selected based on the largest partition matrix value.

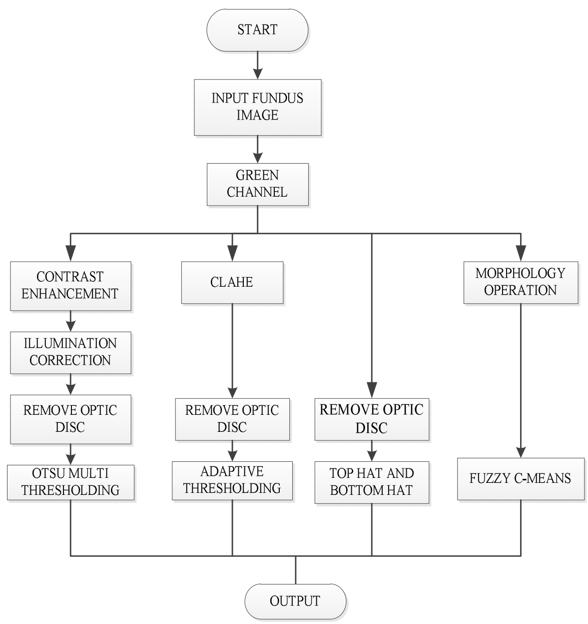


Figure 1. Stages Exudate Detection method

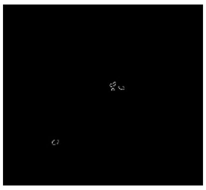
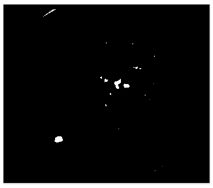
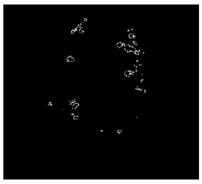
In Figure 1 shows the framework of several methods used. All methods use the green channel extraction process at an early stage. The Multi Thresholding method includes the Contrast Enhancement, Illumination correction, and remove optical disk stages. In the Adaptive Thresholding method includes the CLAHE stage and remove optical disk. In the Fuzzy C-Means method through the morphology operation stage. Morphology methods include Remove Optical disks and Top Hat and Bottom Hat.

IV. RESULT

In measuring performance using confusion matrix, there are 4 (four) terms as a representation of the classification process results. The four terms are True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). True Negative (TN) is the number of negative data correctly detected. False Positive (FP) is negative data but it is detected as positive data. True Positive (TP) is correctly detected positive data. False Negative (FN) is the opposite of True Positive, so the data is positive, but detected as negative data.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{21}$$

Table 1. Results of Exudate Detection in Dataset STARE and DIARETDB1

No	Dataset	Image	Accuracy (%)			
			Otsu Multi Threshold	Adaptive Threshold	Top Hat and Bottom Hat	Fuzzy C-Means
1	STARE					
2	DIARETDB1					

In table 1. Shows the final image of exudate detection and exudate segmentation of the STARE and DIARETDB1 dataset using each method. Various methods of erasing the optic disk. This was done so that the object was not detected when exudate segmentation was performed.
The table above summarizes the final image results from exudate detection using each of these methods. Obviously seen in table 1 above, the method used has a pretty good performance. The research image was obtained from a different source between the STARE and DIARETDB1 datasets. In table 1, we examine 20 retinal images of the STARE and DIARETDB1 dataset to detect exudates using 4 methods that have been done.

Figure 2. Accuracy Results of Exudate Detection in Stare dataset

in figure 2. The detection success rate obtained by each method is 87.1% in the multi-threshold otsu method, 89.9% in the adaptive threshold method, 87.7% in the top-hat and bottom hat methods and finally in the fuzzy method c - means 95.4%.

The graph above is the result of a STARE dataset comparison showing that with the fuzzy k-means technique the highest accuracy value is 95.4% and the lowest accuracy value is 87.1% with multi-threshold otsu.

Table 2. Results of Exudate Detection in Dataset DIARETDB1

No	Image	Accuracy (%)							
		Otsu Multi Threshold		**Adaptive Threshold**		**Bottom Hat and Top Hat**		**Fuzzy C-Means**	
		Hard exudates	Soft exudates	Hard exudates	Soft exudates	Hard exudates	Soft exudates	Hard exudates	Soft exudates
1	Image001	99.3	99	96.1	96	99.1	99	99.2	98.5
2	Image002	99.6	99.2	99.7	99.7	99.3	99.2	98.3	96.8
3	Image003	62.9	62.9	96.7	96.7	87.8	87.8	94.6	93.9
4	Image004	91.9	88.7	98.3	98	97	96	69.7	90.2
5	Image005	87.3	77.6	77.1	66.5	82.7	70.4	94.9	89.4
6	Image006	75.2	73.8	74.6	74.2	95.4	95.2	98.4	96.9
7	Image007	99.1	99.2	92.3	92.1	98.2	97.5	78.6	64.2
8	Image008	96.3	95.5	77.3	76.2	96.4	96.3	72.4	96.3
9	Image009	99.1	98.4	95.5	95.3	99.6	99.2	95.1	92.4
10	Image010	92.9	92.4	84.4	83.9	99.2	99.1	81.9	72.8
11	Image011	96.9	96.1	90	89.6	91.1	91	98.3	97
12	Image012	90.8	90.4	92	91.6	94.7	94.6	99.4	98.5
13	Image013	92.8	88.2	93.8	91.7	91.7	91.8	96.2	86.1
14	Image014	97.1	95.1	90.1	88.1	94.3	89.8	88.9	71.3
15	Image015	96.1	93.9	82.8	80.6	92.1	89.2	89.4	69.8
16	Image016	93.2	88	96.7	94.3	94	90.4	84.3	91.4
17	Image017	98.3	98.3	88.3	88	86.6	86.6	97.8	94.4
18	Image018	98.8	98.1	93.6	93.2	87	86.4	84.2	81.4
19	Image019	93	87.7	71.1	63.9	84.7	76.4	96.9	91.1
20	Image020	89.2	88.3	74.5	70.7	88.8	88.5	95.1	92.2
Average		**92.4**	**90.5**	**88.2**	**86.5**	**92.9**	**91.2**	**90.6**	**88.2**

in table 2. accuracy results from the DIARETDB1 dataset with two expected results, namely hard exudates and soft exudates. of each method performed there is the highest accuracy value of the tophat and bottom hat methods with an accuracy value of 92.9% for hard exudates and 91.2% for soft exudates. and the lowest accuracy value is owned by the adaptive threshold method with a value of 88.2% for hard exudates and 86.5% for soft exudates.

Table 3. Accuracy avarege results of exudate detection for STARE and DIARETDB1 dataset

No	Dataset	Image	Accuracy (%)			
			Otsu Multi Threshold	Adaptive Threshold	Top Hat and Bottom Hat	Fuzzy C-Means
1	STARE		87.1	89.9	87.7	95.47
2	DIARETDB1	Hard Exudates	92.4	88.2	92.9	90.6
		Soft Exudates	90.5	86.5	91.2	88.2

Table 3 summarizes the results of exudate detection based on the STARE and DIARETDB1 data sets using several techniques. In the STARE dataset it has high accuracy results for detecting exudates found in the fuzzy c-means method with an accuracy value of 95.4% and in the DIARETDB1 dataset using the top hat and bottom hat methods which have high accuracy values with a value of 92.9% for hard exudates and 91.2% for soft exudates. This method displays the results of almost the same segmentation of exudate.

V. CONCLUSION

From each exudate detection method in diabetic retinopathy images, the fuzzy c-means technique is the best technique for detecting exudates in the STARE dataset and the top hat and bottom hat techniques are the best techniques for detecting exudates in the DIARETDB1 dataset. Overall the method or technique used to detect exudates in the retinal diabetic retinopathy image is quite good. Exudate detection for each test image varies. This is because the images tested on the system have a fairly wide range of quality, both in contrast and sharpness. This system can help the ophthalmologist to see the symptoms of exudate, but management decisions will then remain in the hands of the optometrist.

VI. REFFRENCE

[1] M. Islam, A. V. Dinh, and K. A. Wahid, “Automated Diabetic Retinopathy Detection Using Bag of Words Approach,” *J. Biomed. Sci. Eng.*, vol. 10, no. 05, pp. 86–96, 2017.

[2] D. Tri, S. Madenda, and R. R, “An Approach to Exudates Detection using Color Reference Segmentation in Retinal Fundus Image,” *Int. J. Comput. Appl.*, vol. 146, no. 2, pp. 25–29, 2016.

[3] H. S. Alghamdi, H. L. Tang, S. A. Waheeb, and T. Peto, “Automatic Optic Disc Abnormality Detection in Fundus Images: A Deep Learning Approach,” in *Proceedings of the Ophthalmic Medical Image Analysis International Workshop*, 2016, pp. 17–24.

[4] S. Joshi and P. T. Karule, “Biomedicine & Pharmacotherapy A review on exudates detection methods for diabetic retinopathy,” *Biomed. Pharmacother.*, vol. 97, no. October 2017, pp. 1454–1460, 2018.

[5] B. J. J, S. Divakaran, S. Abraham, G. Meera, and G. Umashankar, “Detection and classification of exudates in retinal image using image processing techniques,” *J. Chem. Pharm. Sci.*, vol. 8, no. 3, pp. 541–546, 2015.

[6] A. Sopharak, B. Uyyanonvara, and S. Barman, “Automatic Exudate Detection from Non-dilated Diabetic Retinopathy Retinal Images Using Fuzzy C-means Clustering,” *Sensors*, vol. 9, pp. 2148–2161, 2009.

[7] A. Benzamin and C. Chakraborty, “Detection of Hard Exudates in Retinal Fundus Images Using Deep Learning,” in *2018 IEEE International Conference on System, Computation, Automation and Networking (ICSCA)*, 2018, pp. 1–5.

[8] K. Y. Win and S. Choomchuay, “Automated Detection of Exudates Using Histogram Analysis for Digital Retinal Images,” in *2016 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, 2016, pp. 1–6.

[9] A. Elbalaoui and M. Fakir, “Computer Methods in Biomechanics and Biomedical Engineering : Imaging & Visualization Exudates detection in fundus images using mean- shift segmentation and adaptive thresholding,” *Comput. Methods Biomech. Biomed. Eng. Imaging Vis.*, vol. 1163, pp. 1–9, 2018.

[10] B. Harangi and A. Hajdu, “Automatic exudate detection by fusing multiple active contours and regionwise classi fi cation,” *Comput. Biol. Med.*, vol. 54, pp. 156–171, 2014.

[11] M. Zubair, “Automated Segmentation of Hard Exudates Using Dynamic Thresholding to Detect Diabetic Retinopathy in Retinal Photographs,” *J. Multimed. Process. Technol.*, vol. 7, no. 3, pp. 109–116, 2016.

[12] S. Hazra *et al.*, “Exudates Detection of Retinal Images using Otsu ’ s Thresholding and Kirsch ’ s Templates,” *Int. J. Comput. Sci. Netw.*, vol. 5, no. 4, pp. 615–621, 2016.

[13] A. H. Setianingrum, A. S. Rini, N. Hakiem, and A. Radiology, “Image Segmentation Using the Otsu Method in Dental X-Rays,” in *2017 Second International Conference on Informatics and Computing (ICIC)*, 2017, pp. 1–6.

[14] D. T. Hidayat, Isnan, and M. A. Fauzi, “Optimum Multilevel Thresholding Hybrid GA-PSO by Algorithm,” *J. Comput. Sci. Inf.*, vol. 6, no. 1, pp. 1–5, 2013.

[15] A. Roy, D. Dutta, P. Bhattacharya, and S. Choudhury, “Filter and Fuzzy C Means Based Feature Extraction and Classification of Diabetic Retinopathy using Support Vector Machines,” in *2017 International Conference on Communication and Signal Processing (ICCSP)*, 2017, pp. 1844–1848.

[16] P. H. Princye, “Detection Of Exudates and Feature Extraction Of Retinal Images Using Fuzzy Clustering Method,” in *Third International Conference on Computational Intelligence and Information Technology (CIIT 2013)*, 2009, pp. 388–394.