teknik for eksudat deteksion

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Techniques For Exudate Detection on Diabetic Retinopathy

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Abstract

Diabetic Retinopathy (DR) is an eye disease caused by long-term diabetes that can cause vision loss (blindness). Microaneurisma and exudate are the earliest signs of this disease. Exudates appear yellowish and glowing in irregular size and shape on the background of the retina. We therefore conducted a study using the STARE and DIARETDB1 datasets to detect exudates based on segmentation. ***Use of multiple segmentation methods to make a comparison in the detection of exudates. Adaptive thresholding, Otsu multi thresholding, top-hat and bottom hat, and fuzzy c-means are the method used. The performance of the proposed segmentation method was tested using calculation accuracy to compare the output image with the image of ground truth. The average performance results of several methods used to segment each image on the STARE dataset are 88.62% adaptive threshold, 89.15% multi-threshold, 86.32% top-hat and bottom-hat, and 95.47% fuzzy c-means. And in the DIARETDB1 dataset is adaptive threshold 88.28%, multi-threshold Otsu 89.05 top-hat and bottom-hat 97.54% and fuzzy c-means 92.50%.. These results indicate that the proposed method can provide good results in the segmentation of exudates.***

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

I. INTRODUCTION

Retina is an eye retina disorder that adversely affects a person's vision. Diabetic retinopathy is a condition that occurs in people with diabetes that causes progressive damage to the retina, a sensitive layer of light behind the eyes. Diabetes is characterized by abnormalities or abnormalities such as exudates and retinal vessels [1]. An important step to automatically detect a retinal disease can be taken by detection [2]. The cause of diabetes is characterized by two characteristics in the retinal blood vessels through optical disks and exudates. Disc optical detection is a very important step in analyzing retinal images in a diagnosis as one of the main features of retinal anatomical structures [3]. Exudate is one of the main signs of diabetic retinopathy, which is primarily a cause of blindness. The initial screening process can prevent this blindness. Exudate is a symptom that can cause diabetic retinopathy. exudates can be characterized by the appearance of yellowish fundal images of various sizes and shapes [2].

Some of the symptoms that cause diabetic retinopathy are described as exfoliations in the form of capillary leakage and dilution of blood vessels around the retina[4]. Exudates can be fluid like pus or clear fluid in humans. When an injury occurs, the skin opens, leaves the blood vessel and enters the surrounding tissue. This fluid consists of blood cells of serum, fibrin and white[5].

We propose techniques such as Adaptive Thresholding, Otsu Multi Thresholding, Bottom hat and top hat and Fuzzy c-means to achieve better results in detecting segmentation exudates on the retina.

II. RELATED WORKS

Different methods have been developed to detect exudates, for example Diana T.S, et al. [2] Using the space color reference approach to exudate detection, the accuracy value obtained is 95.54%. Ravitej et al are also proposing automatic detection of exudates [4] The DIARETDB1 dataset and Messidor results obtained 92.13% and 90%accuracy in each dataset with adaptive anistropic diffusion and thresholding techniques. 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%.

A also studied the exudate detector as one of the early characteristics of diabetic retinopathy (DR). Benzamin [7] Use the Lifting Wavelet Transform (LWT) and Support Vector Machine (SVM) method. Getting high accuracy, but this method's confusion still requires good quality exudate detection. and detect exudates appropriately. The next researcher used the Multiscale Morphology method. Get a fairly high accuracy value. Although it is irrelevant among a number of pixel intensities that lack contrast. Research Next [8] use retinal image histogram analysis. Automatic algorithms are used to locate optical disks and detect exudates from background retinal images. Algorithm uses information from the histogram. For exudate detection, accurate levels are 99%, 90%, and 89% for DRIVES, DIARETDB1 and local datasets respectively. The results obtained from the study of exudate detection using Mean Shift and Adaptive Thresholding showed better performance than other systems. By first eliminating the optical disk by applying Mean Shift to the retinal image to segment the exudate. Measured in two datasets, DIARETDB0 and DIARETDB1, with an average accuracy of 93.34% [9].

III. METHODS

We used images from the STARE (Structured Analysis of The Retina) dataset and images in the DIARETDB1 dataset in this study. This study uses 4 techniques of segmentation to detect exudates. The exudate detection steps are shown in the form of a flow diagram in Figure 1.

A. *Pre-processing*

The step in the pre-processing that is done is to convert the green G component from the RGB fundus image. In addition to converting RGB images to green channels, several methods are used, including clahe, illumination correction, and morphological operations.

- *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].

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

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. The resulting image is a threshold using the threshold level chosen automatically. The threshold level is the normalized intensity value which lies in the range [0, 1]. Chosen to minimize intra-class variance from 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] :

$$P_i = \frac{n_i}{N}, \quad P_{i\geq 0}, \quad \sum_1^L P_i = 1 \tag{2}$$

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

$$w_1 = \sum_1^t P_i \tag{3}$$

$$w_2 = \sum_{i=t+1}^L P_i \tag{4}$$

The average number of gray scales indicates that L is both calculated by class:

$$m_1 = \sum_{i=1}^t i.P_i \;\; /w_1 \tag{5}$$

$$m_2 = \sum_{i=1}^t i.P_i \;\; /w_2 \tag{6}$$

The two class variants are represented by formulas:

$$\sigma_1^2 = \sum_{i=1}^t (1-m_1)^2 . \frac{P_i}{w_1} \tag{7}$$

$$\sigma_2^2 = \sum_{i=t+1}^t (1-m_2)^2 . \frac{P_i}{w_2} \tag{8}$$

The total variant can be stated by:

$$\sigma^2 = \sigma_w^2 + \sigma_B^2 \tag{9}$$

where:

$$\sigma_w^2 = w_1\sigma_1^2 + w_2\sigma_2^2 \tag{10}$$

$$\sigma_B^2 = w_1 w_2 (m_2 - m_1)^2 \tag{11}$$

D. Bottom Hat & Top Hat

White top-hat transformation is a morphological operator designed to extract bright areas from pictures. Because the opening operator is erosion followed by dilation, the darker areas on the open image will press the lighter. If this dark negative image is subtracted from the original, the peak intensity will be increased and the exudate can be distinguished better than the image background.

Transformation of the top hat is the difference between the input image (grayscale image) and the image after an opening operation. This operation is done by Eq

$$TopHat(f) = f - (f \circ B) \quad (12)$$

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

$$f \circ B = (f \ominus B) \oplus B \quad (13)$$

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

E. Fuzzy C-Means

The Fuzzy C-Means algorithm is an overlapping grouping algorithm where each point can be owned by two or more groups with different membership levels. The Fuzzy C-means algorithm was mainly used to produce exudate extraction and disk optics. Further techniques are needed to be applied so that the disk is detected and separated from the exudate[15][16]. How to determine the Fuzzy C-Means algorithm is the following:

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

$$\begin{bmatrix} X_{11} & X_{11} & \cdots & X_{1j} \\ X_{11} & X_{11} & & X_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ X_{k1} & X_{k2} & & X_{kj} \end{bmatrix} \quad (15)$$

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).

$$\begin{bmatrix} U_{11} & U_{11} & \cdots & U_{1i} \\ U_{11} & U_{11} & & U_{2i} \\ \vdots & \vdots & \ddots & \vdots \\ U_{k1} & U_{k2} & & U_{ki} \end{bmatrix} \quad (16)$$

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

$$V_{ij} = \frac{\sum_{k=1}^{n} (\mu_{ik})^{w} . x_{kj}}{\sum_{k=1}^{n} (\mu_{ik})^{w}} \quad (17)$$

5. Calculate the objective value (Pn) :

$$P_n = \sum_{k=1}^{n} \sum_{i=1}^{c} (\mu_{ik})^{w} (d_{ik})^{2} \quad (18)$$

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

$$\mu_{ik} = \left[\sum_{j=1}^{C} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(w-1)} \right]^{-1} \quad (19)$$

$$d_{ik} = d(x_k - v_i) = \left[\sum_{j=1}^{m} (x_{kj} - v_{ij}) \right]^{1/2} \quad (20)$$

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

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.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (21)$$

Table 1. Results of Exudate Detection in Dataset STARE

No	Image	Accuracy (%)			
		Otsu Multi Threshold	Adaptive Threshold	Bottom Hat and Top Hat	Fuzzy C-Means
1	Im0001	86.43	77.11	93.1	93.78
2	Im0009	95.9	98.66	88.81	97.98
3	Im0016	87.08	97.7	52.27	99.30
4	Im0050	88.69	71.95	80.44	99.77
5	Im0057	91.19	91.23	85.75	98.80
6	Im0058	83.53	94.11	92.36	98.17
7	Im0070	84.83	92.2	89.31	93.47
8	Im0096	84.83	89.69	85.49	98.72
9	Im0122	90.39	84.59	88.24	95.88
10	Im0124	76.54	88.93	82.68	95.72
11	Im0125	89.94	92.72	91.83	98.88
12	Im0126	83.85	89	89.61	92.38
13	Im0135	96.51	98.62	91.92	98.54
14	Im0140	89.64	90.81	86.3	95.03
15	Im0141	90.88	90.06	84.45	96.69
16	Im0157	97.06	86.32	96.53	98.46
17	Im0186	74.81	93.77	87.99	96.00
18	Im0224	71.13	87.55	88.95	98.94
19	Im0225	83.95	91.8	81.32	99.16
20	Im0247	87.17	92	89.14	96.43
	Average	**86.68**	**89.94**	**86.32**	**95.47**

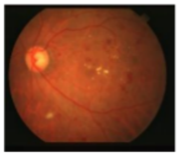
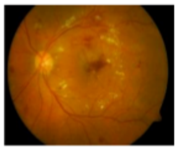
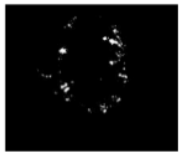
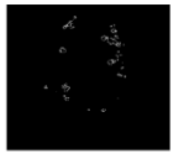
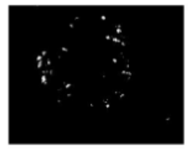
Table 1 summarizes the exudate detection results from the results of other methods. Obviously seen in table 1 above, the method used has a pretty good performance. The research image was obtained from a different source between the STARE and DIARETDB1 datasets. In table 1 we examine 20 retinal images of the STARE dataset to detect exudates using 4 methods that have been done. The success rate of exudate detection resulted in a respective accuracy of 86.68% multi-threshold Otsu, 89.94% adaptive threshold, bottom hat & top hat 86.32% and finally fuzzy c-mean 97.11%. Table 1. The results of the STARE data set comparison show that with the fuzzy k-means technique the highest accuracy value is 95.47% and the lowest accuracy value is 86.32% with the bottom hat and top hat technique.

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	72.71	63.37	96.14	96.01	98.48	98.55	99.25%	98.51%
2	Image002	87.89	87.06	99.72	99.72	99.88	99.88	98.31%	96.86%
3	Image003	95.64	95.45	96.79	96.79	99.21	99.21	94.67%	93.94%
4	Image004	99.43	98.86	98.39	98.05	99.33	99.63	95.10%	90.21%
5	Image005	53.27	21.12	77.17	66.55	92.7	91.01	94.69%	89.49%
6	Image006	88.63	85.92	74.68	74.21	96.73	96.73	98.46%	96.92%
7	Image007	97.57	95.13	92.31	92.15	96.31	96.32	76.66%	64.29%
8	Image008	98.5	97.71	77.37	76.22	95.95	96.07	98.17%	96.35%
9	Image009	96.61	94.58	95.5	95.35	99.36	99.31	94.68%	92.41%
10	Image010	91.14	90.24	84.45	83.97	98.59	98.67	74.15%	72.85%
11	Image011	99.47	95.92	90.06	89.61	99.48	99.64	98.33%	97.06%
12	Image012	98.8	98.07	92.06	91.67	99.46	99.48	99.29%	98.57%
13	Image013	95.28	91.07	93.86	91.74	98.04	99.07	92.27%	86.12%
14	Image014	71.01	45.97	90.1	88.15	96.88	95.67	83.59%	71.38%
15	Image015	80.62	65.89	82.8	80.64	95.06	93.57	82.08%	69.87%
16	Image016	94.43	89.2	96.7	94.34	95.87	95.49	95.60%	91.48%
17	Image017	98.82	94.88	88.34	88.02	99.6	99.8	97.13%	94.49%
18	Image018	98.14	98.14	93.61	93.25	97.71	97.61	86.50%	81.41%
19	Image019	78.62	57.73	71.1	63.99	92.86	89.61	95.59%	91.17%
20	Image020	89.41	87.19	74.51	70.78	99.31	99.35	95.57%	92.23%
Average		**89.05**	**82.67**	**88.28**	**86.56**	**97.54**	**97.23**	**92.50%**	**88.28%**

Table 2 is the same as table 1. But using the DIARETDB1 dataset. Obviously shown in the table above, the method used has a pretty good performance. The level of success in each method can be seen in table 2 with quite diverse values. In Table 2. the comparison results of the DIARETDB1 dataset are two comparative results, namely soft exudates and hard exudates. The highest accuracy value of hard exudates is 97, 54% uses top hat and bottom hat technique and the lowest accuracy value of hard exudates 88.28% uses adaptive threshold technique.

Table 3. Results of Exudate Detection And 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 3. Results of exudates detection and segmentation of STARE and DIARETDB1 datasets using each method. Various methods of reducing optical disks from grouped images produce exudates. Likewise, when removing blood vessels so they are not detected at the time of exudate detection. So the results are obtained as in table 3 above. The most similar exudates approach the original. While the other method has the disadvantage of still detecting optical disks, exudates are only partially detected and detected very little. In the DIARETDB1 dataset the method that displays the best results is the top hat and bottom hat method, which displays the results of the exudate segmentation closest to the original

V. CONCLUSION

From each exudate detection method in retina diabetic retinopathy images use fuzzy c-means best, because it has the best accuracy value. Overall the method or technique used to detect exudates in retinal diabetic retinopathy images is good enough. Detection of exudates for each test image varies. This is because the image tested on the system has quite a variety of quality ranges, both in contrast and sharpness. This system can help the ophthalmologist to see the symptoms of exudates, but the management decision will then remain in the hands of the ophthalmologist.

The results of the exudate segmentation accuracy process performance using several proposed methods:

1. Otsu Multi Threshold provides performance evaluation results with an average accuracy value of 86.68% on the STARE dataset and 89.05% in the DIARETDB1 dataset by comparing ground truth hard exudates and 82.67% by comparing ground truth soft exudates.
2. Adaptive Threshold provides performance evaluation results with an average value of 89.94% in the STARE dataset and 88.28% in the DIARETDB1 dataset by comparing ground truth hard exudates and 86.56% by comparing ground truth soft exudates.
3. Top Hat and Bottom Hat provide performance evaluation results with an average accuracy value of 86.32% in the STARE dataset and 97.54% in the DIARETDB1 dataset by comparing ground truth hard exudates and 97.23% by comparing ground truth soft exudates.
4. Fuzzy C-Means provides performance evaluation results with an average accuracy value of 95.47% on the STARE dataset and 92.50% on the DIARETDB1 dataset by comparing ground truth hard exudates and 88.28% by comparing ground truth soft exudates.

VI. REFFRENCE

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