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Automated Detection and Counting of Hard Exudates for Diabetic Retinopathy by using Watershed and Double Top-Bottom Hat Filtering Algorithm

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***Abstract*— Diabetic Retinopathy (DR) is one of diabetes complications that affects our eyes. Hard Exudate (HE) are known to be the early signs of DR that potentially lead to blindness. Detection of DR automatically is a complicated job since the size of HE is very small. Besides, our community nowadays lack awareness on diabetic where they do not know that diabetes can affect eyes and lead to blindness if regular check-up is not performed. Hence, automated detection of HE known as Eye Retinal Imaging System (EyRis) was created to focus on detecting the HE based on fundus image. The purpose of this system development is for early detection of the symptoms based on retina images captured using fundus camera. Through the captured retina image, we can clearly detect the symptoms that lead to DR. In this study, proposed Watershed segmentation method for detecting HE in fundus images. Top-Hat and Bottom-Hat were use as enhancement technique to improve the quality of the image. This method was tested on 15 retinal images from the Universiti Sains Malaysia Hospital (HUSM) at three different stages: Normal, NPDR, and PDR. Ten of these images have abnormalities, while the rest are normal retinal images. The evaluation of the segmentation images would be compared by Sensitivity, F-score and accuracy based on medical expert's hand drawn ground truth. The results achieve accuracy 0.96 percent with 0.99 percent sensitivity for retinal images.**

***Keywords*— Diabetes; diabetic retinopathy; image segmentation; hard exudates; fundus images.**

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I. Introduction

Diabetes is a chronic disease that is popular in our society every year. It often causes many complications such as kidney failure, heart disease and may eventually lead to eye complication. Therefore, the complication on eye occurs when the glucose level in the blood vessel in the retina uncontrolled. These complications will lead eyes become blurred and turn into blindness which call as Diabetic Retinopathy (DR). DR is a retinal damage that caused by diabetes complications which leading to blindness [1]. DR was classified into two major types, Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [2]. NPDR are divided into Mild, Moderate, and Severe stages. This complication is occurring because the excess amount of glucose in blood vessel that led to abnormal features such as hard exudates, cotton wool spots, micro aneurysms, and hemorrhages [3]. DR can result to a detached retina in some situations. These problems can occur when the scar tissue drags the retina out from the back of the eye. Moreover, this disease was the most common cause of blindness and impairment of vision towards females compared to males with a prevalent blindness in aged 50 years and older [4]. World Health Organization (WHO) also estimated that 422 million people worldwide have diabetes. This group are most of the patient from low- and middle-income countries which suffer with the environment and social factor such as obesity, lack of exercise etc. [5]. According to the WHO, Malaysia will have 2.48 million diabetes in 2030, up from 0.94 million. In addition, by 2025, seven million Malaysian people are expected to develop diabetes, an alarming trend that would result in a 31.3 percent prevalence of diabetes among adults aged 18 and above [6].

Surprisingly, Datuk Seri Dr Dzulkefly Ahmad, Minister of Health, declared in 2019 that 3.6 million Malaysians already have diabetes. This indicates that Malaysia has seen the greatest growth in diabetes sufferers in Asia [7]. This is because Malaysia currently is lack of eye specialist or known as ophthalmologist particularly in government [8]. Hence, the patient needs to wait for a long time for a regular check-up and treatment since the cases are increasing every year [9]. In addition, we also have many diabetic patients from a low and middle income which living in rural areas without facilities and sufficient specialists. [10] Next, the diagnosis of DR usually depends on the observation of specialist which the procedure can be costly and time consuming even for an expert [11]. Therefore, automated detection and counting system was developed to detect a extrac of DR based on fundus images known as Eye Retinal Imaging System (EYRIS).

The development phases of EYRIS system are presented in this paper. The image segmentation algorithms employed in EYRIS might be a useful in early detection method to diagnose DR. All the processes in EYRIS were carried out using the MATLAB Software. Green channel was used to improve the quality of retina image. Next, double top-hat and bottom-hat were used to enhance the visibility of hard exudates. Following that, Watershed was done to remove the uneven background and separate the various shapes of hard exudates. Afterwards, object counting is done get number of segmented areas. Counting objects is important for medical diagnosis and biological study. Counting cell is one of the most fundamental tasks in health test, food quality control, agricultural analysis, and so on.[11]. As a result, performance evaluation score has been performed to assess the quality of segmentation by comparing the detection result with medical expert's hand drawn ground truth images. Diabetic Retinopathy (DR) is a medical disease that affects the eyes when blood sugar levels rise. Hard exudate (HE) is one of the early symptoms of DR that can lead to blindness [12]. Because HE is so tiny, detecting DR automatically is a difficult task. Early stages of HE might be difficult to diagnose since the characteristics themselves cannot be seen clearly [13]. [14] proposed image detection of hard exudates and removal of the optic disc using K-means and Genetic Algorithm (GA). The exudates and optic disc are separated using K-means. After that, GA were used to segment hard exudates. GA is utilized to achieve the most accurate optimization result for exudate segmentation. This algorithm achieved 94% accuracy which has improved with the existing approaches [14].

S. Long et al. [15] focuses on detection of exudates using dynamic threshold and fuzzy C-means clustering (FCM). Following that, support vector machine (SVM) was used for automatic hard exudates classification. In this work, SVM used 10-fold for trained and cross validate data. FCM clustering was utilized initially to determine the local dynamic threshold of each sub image. The exudates and non-exudates areas were then separated using SVM classifiers. The result achieved sensitivity, specificity, accuracy of 97.5%, 97.8% and 97.7% [15]. Study in [16] also proposed new method using curvelets transform to detect Microaneurysms (MAs). MA are selected using a local thresholding approach throughout the procedure. This study's findings will enable the researcher to detect preliminary MA. The suggested method was evaluated using the Retina Online Challenge database and obtained a sensitivity of 48.21% with 65 false positives per image [16].

Furthermore, Bae et al. [17] investigate the detection method based on region growing segmentation. The paper processed the retina images with hue saturation value brightness adjustment and Contrast-Limited Adaptive Histograms Equalization (CLAHE). Following that, region growth rebuilt the form of the hemorrhages. This method allowing them to compute the size of the hemorrhages. As a result, this study achieves a sensitivity of 85% with a false positive rate of 4.0 per image [17]. In addition, P. Wang et al. [18] proposed a mathematical morphology, Curvature Scale Space (CSS) for detection and SVM for classification. This method was applied to gain a better accuracy and robustness. The experiment result obtained sensitivity 91.53% and specificity 91.64% [18].

Sopharak et al. [19] and Harini R et at. [20] performed feature extraction and categorization on retinal images using fuzzy C-means. This study proposes a technique for detecting diabetic retinopathy using Fuzzy C-means (FCM) clustering and morphological image processing. This method achieve sensitivity, specificity, accuracy 87.28%, 99.24 and 99.11% when compare with ophthalmologist ground truth [19]. Harini R et at. [20] includes image reduction, contract enhancement with CLAHE, and classification with SVM. This study achieves an accuracy of 96.67% sensitivity of 100% and specificity of 95.83%. Moreover, analysis from [21] proposed a clustering approach for exudates detection in screening diabetic retinopathy. This study proposes a technique for detecting exudates in low contrast retinal images using K-means clustering and morphological image processing. The results of this investigation demonstrate that the technique successfully identifies exudates with a sensitivity of 87.28%, specificity 99.24% and accuracy 99.11% [21]. Furthermore, detected optic disc in retinal pictures using a combination of marked controller watershed segmentation and mathematical morphology. The results indicated that the suggested technique has an optic disc performance of around 99.33% accuracy [22].

In addition to cell segmentation, [23] shows cell counting by detecting cell centroids using distance mapping. the preprocess was done by using CLAHE to enhance the image. Next, the cell is separated from background using global thresholding. The binary images distance transform is next computed, which turns the binary image into a distance map giving the distance of each cell pixel from its nearest background pixel. The template image is built from the distance transform of a circular disc to do template matching. The cell centroids are identified using a distance map. To get the count, the matrix was separated by region and counted. The result show accuracy of 92 percent for cell counting even at very high 60 percent probability. [24] also proposed using an Artificial Neural Network (ANN) and the Hough transform to count blood cells in urine sediments. The feedforward backpropagation method was utilized in this study to distinguish between background and blood cell segments. The image with the Hue Saturation Value (HSV) was utilized to train the neural network method. The blood cells were counted using the circular Hough transform, with an average percentage of inaccuracy ranging from 5.28 to 8.35 percent.

II. Material and Method

This study was carried out in accordance with Rapid Application Development (RAD). RAD is a technique that focuses on efficiently creating applications through regular implementation and constant feedback. This research is divided into six phases: analysis and quick design, construction, demonstration, refinement, testing, and implementation. As shown in Fig. 1, all phases were carried out successively.

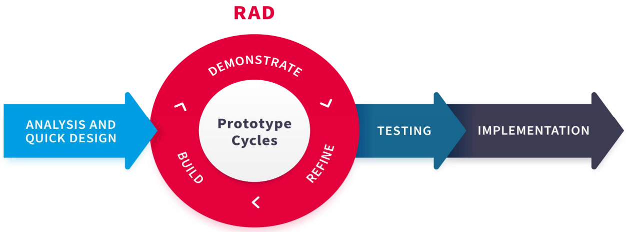

Fig. 1 Rapid Application Development (RAD) phases.

During the initial phase, fundus image data was received from Hospital Universiti Sains Malaysia (HUSM). The requirements were gathered to find the optimal solution and set the aim for the EYRIS system. Following that, a fast design of system architecture was created to see the structure and features of the system requirements in greater depth. The construction process begins by assembling all the necessary components, and the system's programming is developed in MATLAB software. The flowchart of the proposed method is shown in Fig. 2. In the following, the proposed algorithm is explained.

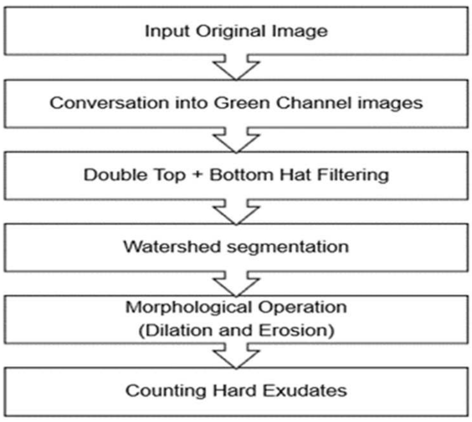

Fig. 2 Flowchart of the proposed method

A. *Image Processing Algorithm*

Step 1: The original retinal images are used as input.
Step 2: The colored input image is converted to a green channel image.
Step 3: On these green channel images, double top-bottom hat filtering is applied.
Step 4: Watershed segmentation is done to this preprocess image.
Step 5: Using morphological techniques to removes small pixels on object boundaries.
Step 6: Counting hard exudates is applied by MATLAB functions.

1) Input Image: 15 retinal images of patients with three types of stages, Normal, Non-Proliferative Diabetic Retinopathy (NPDR), and Proliferative Diabetic Retinopathy (PDR) are used as input image. This image was taken with a 45-degree field of vision using fundus camera from Hospital University Sains Malaysia (HUSM). The images were saved in JPEG format (.jpg) files with the lowest compression rates.

2) Conversation into green channel images: The input images are turned into green channel images for preprocessing. This is accomplished using an in-built MATLAB function. The purpose behind this is to make it easier to handle the image. In general, a color image is represented by three matrices, although only the green color is defined by the matrices.

3) Preprocessing of the Image: Hard exudates are hard white or yellowish color with varied sizes, forms, and locations that can only be identified using fundus camera. It is typically seen near leaking capillaries in the retina. Furthermore, fundus images are usually recorded in low contrast. The images in the green channel were preprocessed with double top hat and bottom hat filtering [25]. The visuals get clearer as a result, and the abnormalities in the retina image become more visible [26]. The flow is explained in Fig. 3.

4) Segmentation using Watershed: Image segmentation algorithms generally based on one of the two basic properties of intensity values, discontinuity and similarity [27]. Watershed-based segmentation is a technique in which the entire image is separated into discrete nonoverlapping sections using the watershed concept. Watershed is often conducted using flooding simulation processing, with the entire image overlaid over a grayscale image.

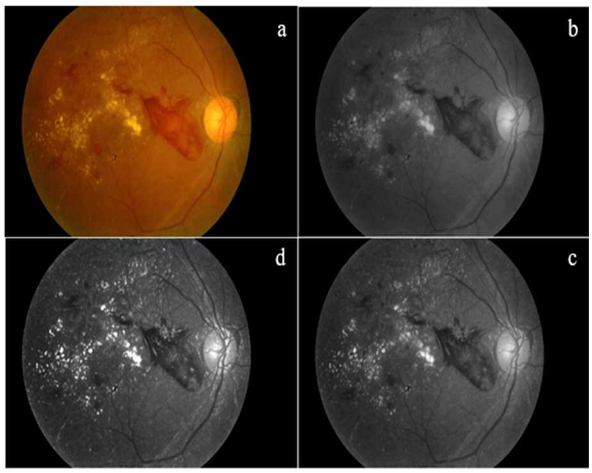

Fig. 3 (a) Original image, (b) Green Channel, (c) Single Top-Bottom-Hat, (d) Double Top-Bottom-Hat

During the Watershed process, the pixel intensities build a landscape with connected low intensity pixels known as local minima. The image with the highest index was chosen using a histogram of image data. Watershed with thresholding can be used to segment the HE since the object of interest appears brightest. To ensure that all bright items are chosen, a threshold (t) of 5 is employed. This extracted section contains hard exudates as well as OD, but the blood vessel and the empty retinal region have been removed as shown in Fig. 4.

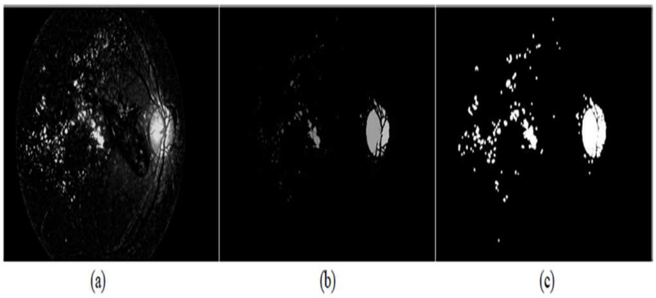

Fig. 4 (a) Filter image, (b) Watershed Segmentation, (c) Exudates extracted

5) Reduce pixels using morphological technique: A morphological process called dilation and erosion is used to add the pixels borders of an object and delete the smallest pixels on the object boundaries.

6) Counting hard exudates: In this step, a mask image is utilized to count hard exudates. This process involves such as binary erosion, dilation, opening, closing and reconstruction of the image. The process of counting hard exudates is performed based on the recognition of the size differentiation in pixels and color intensity present in each segmentation image.

B. Performance Evaluation

This study employed a Euclidean distance as a simple baseline for comparison. The nearest neighbor classifier simply classifies a test instance based on its proximity to the class of the nearby training. The parameters of this evaluation are measured by comparing the detection result to the medical expert's hand drawn ground truth. There are four types of measurements: True Positive (TP), which is the number of pixels that are successfully detected, False Positive (FP), which is the number of non-detect pixels that are incorrectly recognized as exudate pixels, False Negative (FN) is the number of exudates pixels that are not detected, while True Negative (TN) is the number of non-exudates pixels that are accurately classified as non-exudates pixels . The following equations are used to compute sensitivity, F-score, and accuracy as:

$$Sensitivity = \frac{TP}{TP + FN} \quad (1)$$

$$F - score = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \quad (2)$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (3)$$

C. Design and Development EYRIS

For this study, a standalone application was designed in MATLAB named Eye Retinal Imaging System (EYRIS) with the help of image processing technique like Watershed approach, Top hat, Bottom hat, etc. This system implements the requirements mentioned in the previous subsections.

III. Result and Discussion

This method was tested on 15 retinal images from Hospital Universiti Sains Malaysia (HUSM) at three different stages: Normal, NPDR, and PDR. Ten of these images have abnormalities, while the remainder are normal retinal images. Sensitivity, F-score, and accuracy are used in the performance analysis. The ratio TP/(TP+FN) is used to calculate sensitivity, where TP is the number of pixels that are described as hard exudates. FN is the number of pixels that are incorrectly identified as hard exudate pixels. Model accuracy on segmented images is measured using accuracy score. This score will compare the outcome to the hand-drawn ground truth of the medical expert. (Table 1, 2 and 3) displays the results of the performance score for all the images. Fig. 5 show the result of the detection process for hard exudates in retinal images.

The evaluation results displayed above are the outcomes of Sensitivity, F-Score, and Accuracy tests performed on ground truth images. According to the results of the experiment, only 5 of the 15 images include hard exudates, while the remaining 5 do not.

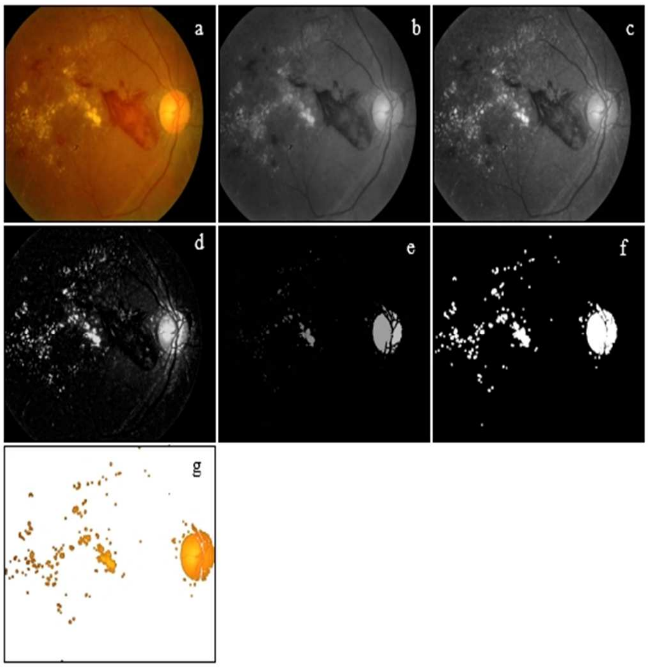

Fig. 5 The process of extracting hard exudates: (a) Original Image, (b) Green Channel, (c)Single Top-Bottom hat, (d) Double Top-Bottom hat, (e) Watershed Segmentation, (f) Hard Exudates Extraction, (g) Hard exudates detection.

TABLE I
Normal Retina Image

Image	Sensitivity (%)	F-score (%)	Accuracy (%)
Image 1	0.98	0.99	0.98
Image 2	0.99	0.99	0.99
Image 3	0.99	0.99	0.99
Image 4	0.98	0.99	0.98
Image 5	0.98	0.99	0.98

TABLE II
NON-PROLIFERATIVE DIABETIC RETINOPATHY (NPDR) RETINA IMAGE

Image	Sensitivity (%)	F-score (%)	Accuracy (%)
Image 1	0.99	0.99	0.98
Image 2	0.99	0.99	0.99
Image 3	0.99	0.99	0.99
Image 4	0.99	0.99	0.98
Image 5	0.99	0.99	0.98

TABLE III
PROLIFERATIVE DIABETIC RETINOPATHY (NPDR) RETINA IMAGE

Image	Sensitivity (%)	F-score (%)	Accuracy (%)
Image 1	0.97	0.97	0.94
Image 2	0.99	0.92	0.85
Image 3	0.99	0.97	0.94
Image 4	0.99	0.90	0.83
Image 5	0.99	0.99	0.99

This method achieves average sensitivity 0.99 percent, F-score, 0.98 percent, and accuracy of 0.96 percent per image in various ways. Table. 4 shows the results of the proposed system and those previously published in the literature.

TABLE IV
RESULT COMPARISON OF DIFFERENT DETECTION APPROACH

Reference	Methodology	Sensitivity (%)	Accuracy (%)
K. Gayathri Devi et al. [14]	Genetic Algorithm, K-means	93	94
S. Long et al [15]	Fuzzy C-means, Support Vector Machine	97.5	97.7
P. Wang et al. [18]	Support Vector Machine, Chain-like, Agent Genetic Algorithm	99.05	96.19
Our Method	Watershed Approach	99	96

IV. CONCLUSIONS

This paper describes an automated detection system for hard exudates that employs Watershed and a double Top-Bottom Hat Filtering approach. This technique was created to detect symptoms as early as possible using retina images captured with a fundus camera. The segmentation images' results will help the ophthalmologist in evaluating the symptoms that lead to diabetic retinopathy. The algorithm's performance is compared to ophthalmologist-drawn ground truth. Sensitivity, F-score, and accuracy are utilized to evaluate the quality of the segmentation in the performance measurement of exudates detection. This system is designed to assist ophthalmologists in the diabetic retinopathy screening procedure in detecting anomalies more quickly and effectively. This method has the potential to assist people suffering from diabetic retinopathy, particularly those who live in rural locations with no nearby access to medical care. However, this is not a final-result application. Instead, it can be used as a preliminary diagnosis tool or decision support system for the ophthalmologists. Human ophthalmologists are still required in situations where the detection results are not immediately apparent. Our future research will entail looking into various segmentation methods and detecting diabetic retinopathy features.

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