HEMORRHAGE SEGMENTATION ON RETINAL IMAGES FOR EARLY DETECTION OF DIABETIC RETINOPATHY

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ABSTRACT

Diabetes mellitus is a chronic disorder that can lead to serious complications, including diabetic retinopathy, which affects the eyes and can potentially lead to blindness. Rapid identification of diabetic retinopathy is crucial to facilitate quicker and more efficient treatment for patients. This study aims to segment hemorrhages in retinal images using the Laplacian of Gaussian (LoG) approach in conjunction with threshold-based segmentation and analysis of region properties, including eccentricity. The LoG approach is utilized for its ability to detect edges, features, and abrupt variations in image intensity, thereby optimally highlighting the bleeding lesion area. With accurate segmentation, it is hoped that early detection and monitoring of diabetic retinopathy can be improved. This research uses the IDRiD, DR_2000, and DIARETDB1 datasets, recommending the use of IDRiD and DIARETDB1 for optimal results. Through this methodology, it is expected to make a significant contribution to reducing the risk of blindness in diabetes patients.

Keywords: *Diabetic retinopathy, Segmentation, Hemorrhage, Laplacian of Gaussian, Image processing*

1. INTRODUCTION

Diabetes Mellitus, more commonly known as diabetes, is a chronic condition that affects millions of individuals throughout the world. Diabetes mellitus is a chronic illness characterized by the pancreas' inability to produce adequate insulin or the existence of insulin resistance. Diabetes mellitus increases the risk of many disorders, including stroke, heart disease, renal failure, neuropathy, and even diabetic retinopathy [1], [2]. Diabetic retinopathy, an eye condition that can compromise vision, is a common consequence among diabetes patients [3], [4].

A person suffering from diabetic retinopathy may experience impaired vision, difficulties seeing in the dark, and sudden loss of eyesight. Diabetic retinopathy develops when high blood sugar levels persist for an extended period of time, causing damage to the tiny blood vessels in the retina [5], [6]. This condition is defined by changes in the retinal blood vessels, such as leakage and occlusion, which can result in the creation of aberrant blood vessels. These aberrant arteries can cause bleeding in the retina, potentially leading to blindness [7].

Diabetic retinopathy cannot be diagnosed immediately by human eye examination since the symptoms arise in the retinal nerves. Images from a fundus camera can reveal signs of this condition, but the interpretation process takes a long time and can be harmful to the patient [8]. Diabetes patients can benefit from the early identification of diabetic retinopathy [9]. There are two forms of diabetic retinopathy, each with three phases. There are two types, Non Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy. NPDR is the initial stage of diabetic retinopathy and can advance to more significant phases such as mild NPDR, moderate NPDR, and severe NPDR [10], [11]. NPDR has distinct disease features such as microaneurysms, hemorrhages, soft exudates, and hard exudates. Meanwhile, PDR becomes problematic when minute blood vessels form and cover the surface of the retina without causing any symptoms. Proliferative Diabetic Retinopathy (PDR) may cause vitreous hemorrhage (HE), neovascularization, and retinal detachment [12], [13]. Further study into the management and therapy of this condition is critical to avoid significant effects that might compromise vision [14].

This research develops an automated approach for bleeding segmentation in fundus retinal images, which is highly valuable for the early diagnosis of diabetic retinopathy. The focus of this work includes the development of effective problem-solving methods for image segmentation by utilizing image processing techniques. The dataset used in this study comprises images from various sources, allowing for model testing across different conditions and image qualities. The testing process was conducted to evaluate the accuracy and reliability of the model in detecting bleeding. The results of this research indicate that the proposed automated approach can enhance early detection capabilities, potentially improving treatment outcomes for diabetes patients.

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2. RESEARCH METHODOLOGY

2.1 Research Flowchart

The method used in this research involves preparing materials for segmentation, consisting of seven steps: first process resizing the image, next process converting RGB to grayscale, applying top-hat, bottom-hat, Laplacian of Gaussian (LoG), thresholding, and region properties analysis. The method flow used in this research is illustrated in Figure 1.

The Figure 1 is a flowchart created for this research that explains the flow of the segmentation process in retinal pictures to detect hemorrhage. The process starts with loading the input retinal picture. The next process image is scaled to guarantee consistency in further processing. Next step, convert to grayscale. The color image is transformed to grayscale to make analysis and processing easier. The Top-Hat filter is used in the following step of the study to improve contrast and accentuate light details against a darker background. The bottom-hat filter is used to highlight dark elements against a light background. The following step Laplacian of a Gaussian (LoG) filter: In this part, the LoG filter is used to detect edges and major intensity changes in the image, making it easier to locate key structures. The following phase uses global thresholding to identify the area containing the target object from the background. The following stage in this study employs region features, which are used to evaluate and filter out areas that indicate hemorrhage areas, eccentricity is important for finding specific sites of bleeding.

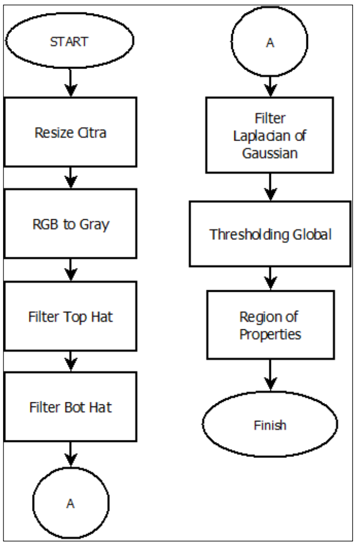

Figure 1. Proposed Method

Figure 2. Resize image

2.2 Resize Image

This technique involves a picture with a resolution of 1500x1152 pixels. When utilizing a normal dataset, the study duration is prolonged; however, using an image with a resolution of 729x552 pixels expedites the process compared to the default setting [15]. Figure 2 depicts the original image following the resizing procedure. Decreased image pixel count allows for faster image segmentation while maintaining acceptable picture quality.

2.3 RGB to Gray

The initial fundus retina image is a 24-bit true color RGB image including three color channels: red, green, and blue. Pixel intensities for each channel possess an 8-bit depth, ranging from 0 to 255. Equation 1 demonstrates the formula that produces a grayscale image with uniformly balanced color intensities throughout the three color channels. Green light provokes a heightened sensitivity in the human eye compared to red or blue light. Consequently, an often utilized method is the brightness formula; equation 1 represents the conversion from RGB to grayscale.

$$(R + G + B)/3 \tag{1}$$

The formula R+G+B/3, represented as Gray=0.2989×Red+0.5870×Green+0.1140×Blue, signifies the calculation of grayscale value from the RGB color model. The color intensity levels of the individual channels in the RGB image are denoted by Red, Green, and Blue. The value of gray denotes the resultant intensity in grayscale. This method preserves substantial information from the image while facilitating analysis and processing. The result is presented in Figure 3.

The transition from RGB to grayscale is a crucial phase in digital picture analysis. At this stage, a color image comprising three channels (red, green, and blue) is transformed into a grayscale image with a single channel. The objective is to streamline picture processing, diminish computing complexity, and highlight significant characteristics while minimizing extraneous color information.In a grayscale image, each pixel denotes a light intensity ranging from black (0) to white (255), representing the cumulative contribution of all color channels. This conversion enables additional analysis, including the implementation of filters, edge detection, and segmentation, as illustrated in the image where retinal structures are more distinctly visible and contrast is adjusted to highlight critical locations such as blood arteries and lesions.

2.4 Filter Top-hat

The completion of this stage involves employing a top hat filter on the initial fundus retina image, which is a 24-bit truecolor RGB image including three color channels, red channel, green channel, and blue channel. Each channel pixel intensities are represented using 8 bits, permitting values from 0 to 255. Employing a Top-hat filter enhances image quality by highlighting subtle characteristics often overlooked by conventional image processing methods. This filter can be employed in several applications, including medical image processing. The result is a grayscale image that precisely depicts uniform color intensities throughout the three color channels. Equation 2 illustrates the formula for top hat filtering.

$$Top - hat(f) = (f) - (f \circ \mathrm{g}) \tag{2}$$

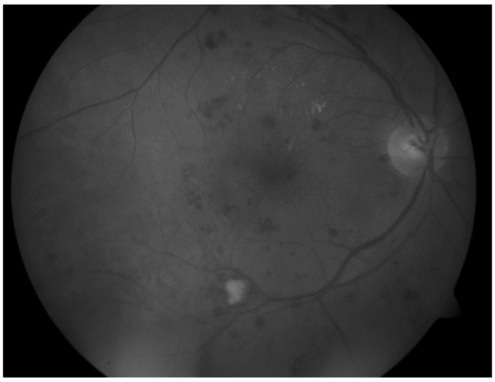

Figure 3. Grayscale Fundus Retina Image

The Top-hat modification is utilized to identify features or objects with increased brightness in fundus retina pictures, including areas affected by hemorrhage [16]. In this scenario, the Top-hat filter is employed alongside the Bot-hat filter. A top hat filter accentuates visual features that are more luminous than the surrounding background. This phase entails mitigating the impact of dilatation erosion (expansion) on the original image.

2.5 Bot-Hat Filtering

Subsequently, the Bot-hat filter is implemented, wherein Bot-hat (f) denotes the outcome of the Bot-hat transformation applied to the picture (f). The Bot-hat alteration enhances the visibility of things against a luminous background. The product of the functions f and g, which signifies the kernel or filter, indicates the structural elements in the Bot-hat transformation. This filter assists in detecting objects or features with lower intensities, including regions impacted by bleeding. The subtraction of the original image (f) from the product of the multiplication with the structural element (g) amplifies the distinction of boundaries or contrast between the salient objects (hemorrhage zones) and the picture backdrop [16]. This filter facilitates the comprehension of regions potentially impacted by bleeding in fundus retinal imaging.

$$Bot - hat(f) = (f \bullet \mathrm{g}) - (f) \tag{3}$$

The Bot-hat modification is utilized to identify features or entities with diminished intensities in fundus retina pictures, potentially including areas affected by bleeding. The bot hat filter is utilized to enhance visual features that are less pronounced than the surrounding background. At this stage, the method entails reducing the effects of dilatation, erosion, and closure processes applied to the original image. The tophat and bothat filter methods are now integrated to enhance image segmentation results. Figure 4 depicts an example of the integration of the tophat and bothat filtering techniques.

The Figure 4 depicts the application of combining tophat and bothat filters. This combination aims to improve local contrast, thereby highlighting the lighter and darker features of the background. This phase is especially significant in medical imaging and microscopy. Another application of integrating both Tophat and bot hat filters is to augment Edge Detection by accentuating the contrast between luminous and shadowy areas in the image. This facilitates the identification of the contours and shapes of objects. The objective of integrating these two filters is to reduce noise. The Top-hat filter removes small luminous artifacts in dim images, and the bottom-hat filter removes small obscure artifacts in brilliant images. Employing both methods simultaneously facilitates the elimination of unwanted artifacts from the image.

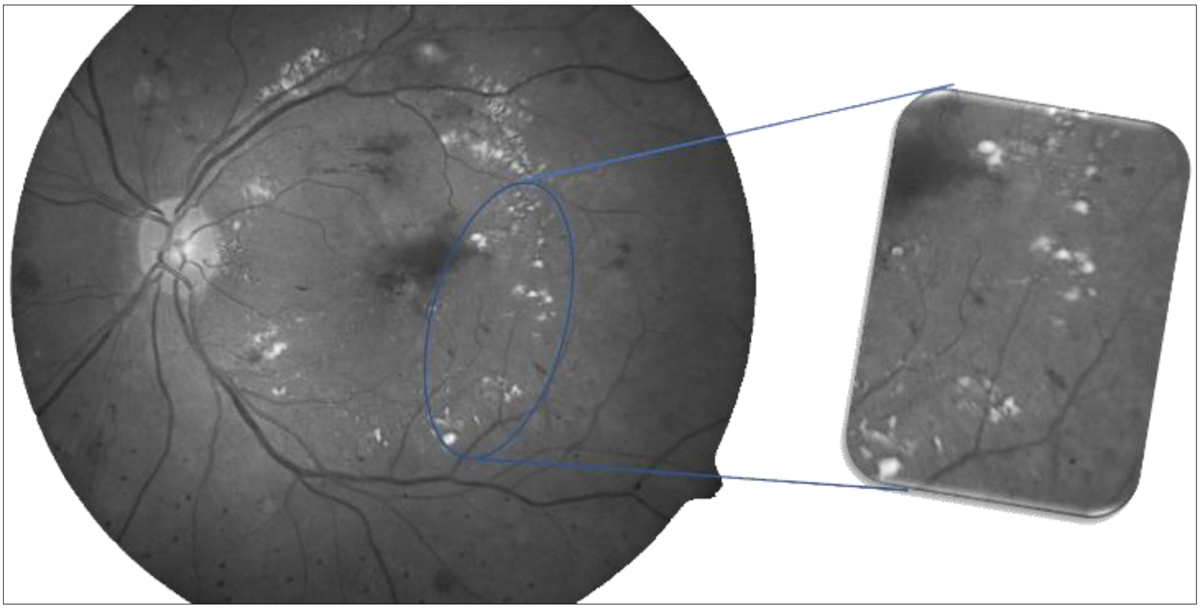

Figure 4. Fundus Retina Image with Top-Hat and Bot-Hat Filters

2.6 Laplacian Of Gaussian

LoG filter is a derivative utilized to identify regions in a picture that experience abrupt variations, such as edges. Nonetheless, this laplacian filter may exhibit sensitivity to noise interference. The preliminary procedure prior to edge detection involves applying a Gaussian filter to smooth the image. The Laplacian of Gaussian technique is denoted by (x, y) , incorporating the laplacian operator ∇^2 and the second partial derivatives of the variables x and y. The part $\frac{\partial^2 f(x.y)}{\partial x^2}$ measures the rate of change of the rate of change of the function f with respect to x , while the part $\frac{\partial^2 f(x.y)}{\partial y^2}$ measures the rate of change of the rate of change of the function f with respect to y. The laplacian operator is the sum of these two second derivatives, reflecting the total change in the rate of change of the function f with respect to both of its variables[11]. Therefore, $L(x, y)$ is the laplacian of the function $f(x.y)$ and can be used to identify rapid changes or edges in images [17]. Overall, this formula reflects the laplacian of Gaussian value at a point in the image and highlights areas around edge details. In the methodology of hemorrhage segmentation in fundus retina, the application of LoG can assist in extracting relevant edge features for identifying areas that may be affected by hemorrhage.

$$L(x, y) = \nabla^2 f(x, y) = \frac{\partial^2 f(x.y)}{\partial x^2} + \frac{\partial^2 f(x.y)}{\partial y^2} \quad (4)$$

This formula represents the value of the LoG at a certain place in the image and emphasizes the region surrounding edge details. The second derivative of the Gaussian function is typically known as the LoG function or the Mexican hat function, owing to its similarity to the form of a Mexican hat. Figure 5 is the result of image processing using the LoG filter.

The Figure 5 presents a retinal image that has undergone processing with a Laplacian of Gaussian filter. LoG methodology is an image processing method that integrates Gaussian blur with the Laplacian operator. This technique is utilized to delineate the boundaries of several retinal regions, including Microaneurysm (MA) and hemorrhage (HA) blood vessels, by the identification of edges and characteristics in hemorrhage images. The logarithmic filter is essential for noise reduction and is particularly important in medical imaging for concealing signals that necessitate study. Furthermore, the logarithmic filter is advantageous for improving the contrast of tiny characteristics such as MA and HA.

2.7 Thresholding

In the following segmentation phase, the digital image denoted by f (x,y) may undergo thresholding using a threshold value T, which is established based on particular attributes, including the average gray level values of adjacent pixels surrounding (x,y) in the context of hemorrhage segmentation in the fundus retina [18]. The result segmented image, referred to as g(x,y), can be articulated as follows.

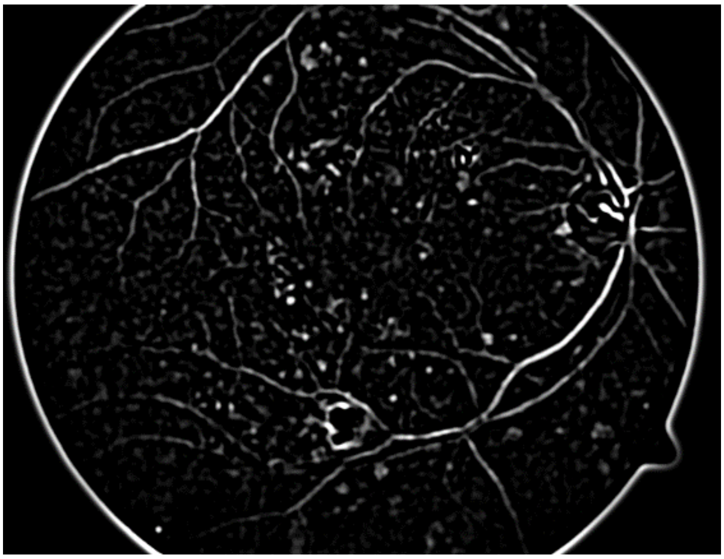

Figure 5. Fundus Retina Image with Laplacian of Gaussian Filter.

$$g(x,y) = \begin{cases} 1\ jika\ f\ (x,y) \geq T \\ 0\ jika\ f\ (x,y) \leq T \end{cases} \quad (5)$$

Where f is the outcome and g is the ultimate result of segmentation, where the value 0 represents the black area to be segmented. If f ≥1, the region is the white area that needs to be separated, or not. Using this method, the picture $g(x,y)$, becomes the final segmentation result, where the value 0 represents the black area to be segmented and the value 1 indicates the white area to be segmented. Figure 6 shows the outcome of the image using thresholding.

The Figure 6 depicts the application of thresholding for segmentation, which enhances the visibility of bleeding features. Utilizing thresholding enhances the precision of diagnosis. The region obtained through thresholding can be further examined to quantify the dimensions, morphology, and quantity of hemorrhages, which serve as crucial markers in the diagnosis of diabetic retinopathy.

2.8 Region Properties

Eccentricity is used to extract additional information from each generated region after going through preprocessing stages such as employing the LoG filter and global thresholding segmentation to isolate bleeding spots. Eccentricity is a measurable quantity for each region in the resulting binary segmented image. Eccentricity can be defined in geometry as the distance between an ellipse (a visual representation of a region) and a circle [19]. The eccentricity (E) equation can be calculated using the lengths of the major semi-axis (a) and minor semi-axis (b), as discussed in Chapter 2 on eccentricity. An eccentricity around zero indicates a circular form, whereas a value near one indicates a significantly elongated elliptical shape. Using this approach on fundus retina images, the authors can acquire measurements, shapes, and locations suspected of hemorrhage. The result is the average intensity value for the image's region or item. Figure 7 is the image result using region properties using eccentricity.

Eccentricity, in the context of regional features in image analysis, quantifies the form of an item or region in relation to its similarity to an ellipse. Eccentricity varies from 0 to 1, wherein: A value of 0 signifies that the region is a perfect circle. Values approaching 1 signify that the region is more elongated or elliptical, with the length of the major axis significantly exceeding that of the minor axis. Figure 7 illustrates multiple locations (white areas) against a dark backdrop. Examining the eccentricity of each region will yield insights into the morphology of each object or cluster within the image. Objects exhibiting high eccentricity are typically oval in shape.

3. RESULTS AND DISCUSSIONS

3.1 Result

This research demonstrates that the Laplacian of Gaussian (LoG) method effectively categorizes hemorrhages in retinal images, which are significant indicators of Diabetic Retinopathy (DR). The LoG method allows for the precise identification of areas affected by hemorrhages, thus facilitating the early detection of this disease.

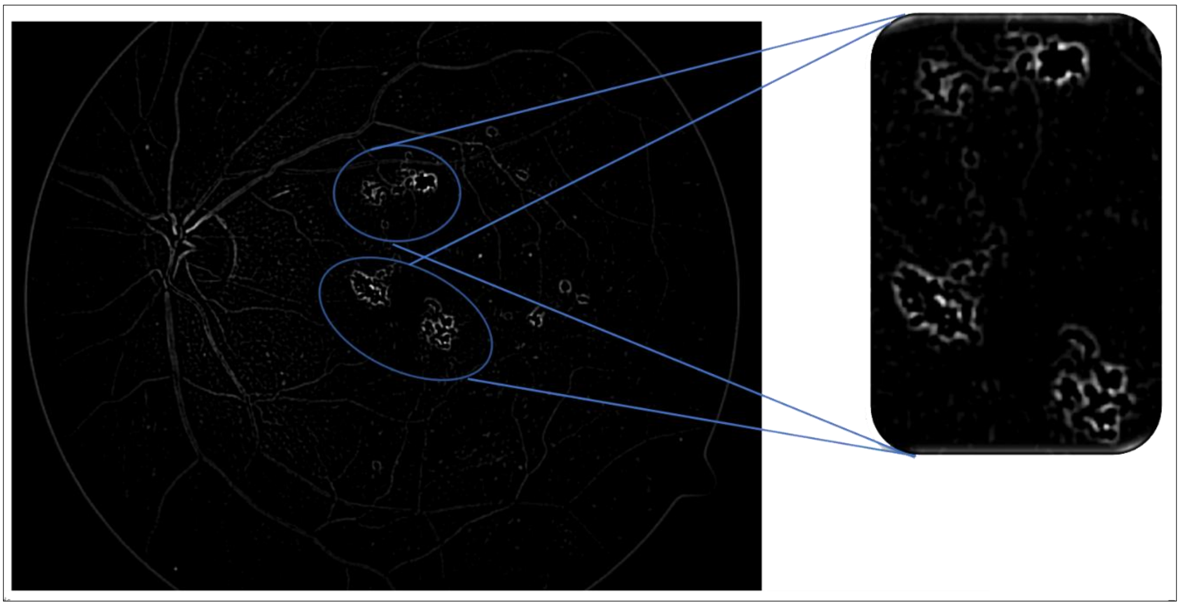

Figure 6. Retina Image with Thresholding Segmentation

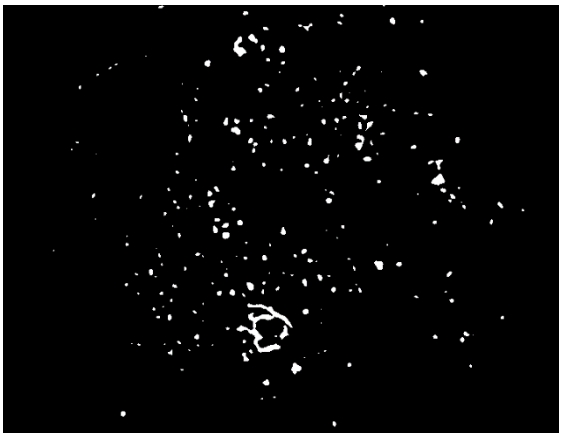

Figure 7. Fundus Retina Image with Region Properties (Eccentricity)

This work utilizes three primary datasets: IDRiD, DR_2000, and DIARETDB1, during the results phase to ensure the generalizability and reliability of the proposed technique. Each dataset contains 20 retinal images that explicitly show the presence of hemorrhage in the fundus retinal images. The segmentation results indicate that the LoG approach reliably identifies hemorrhage areas across all three datasets with a high level of precision. LoG demonstrates enhanced sensitivity in detecting intensity fluctuations characteristic of hemorrhage areas while effectively distinguishing these areas from adjacent retinal structures. Figure 8 shows the results of image processing using the IDRiD dataset. Figure 9 depicts retinal image processing with the DR_2000 dataset, while Figure 10 illustrates retinal image processing using the DIARETDB1 dataset and 20 images of hemorrhage.

3.2 Discussions

This study utilizes a variety of images from the three datasets to evaluate the performance of LoG segmentation under varying lighting and contrast settings, reflecting the discrepancies found in real clinical photographs [11].

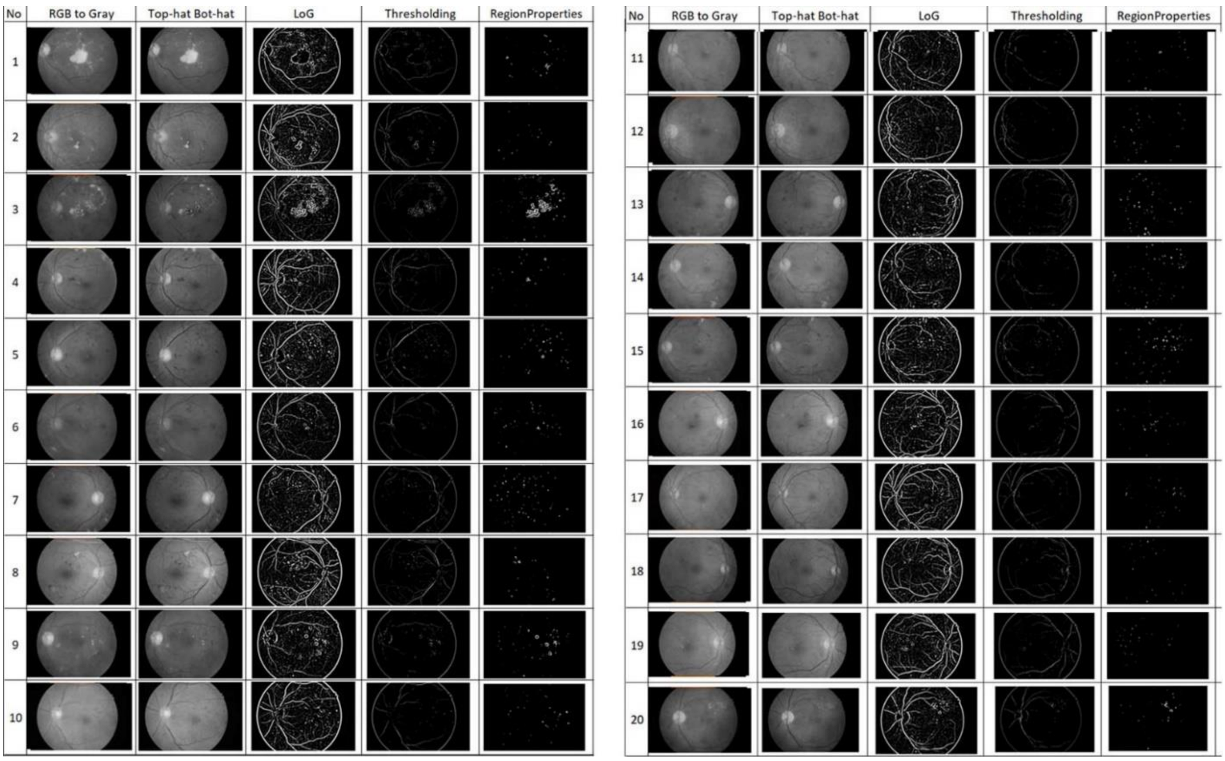

Figure 8. Processing process using idrid dataset

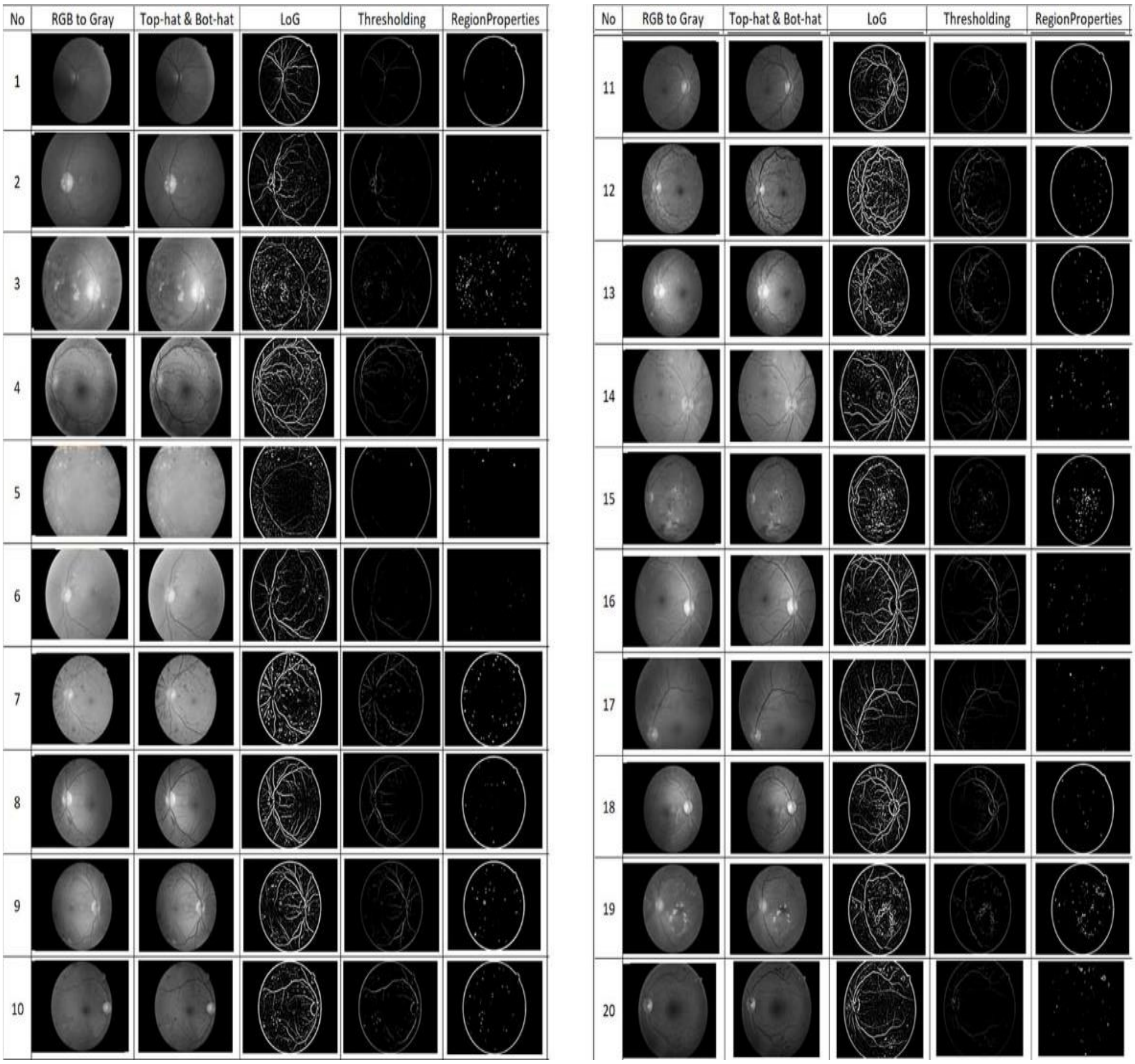

Figure 9. Processing Dataset DR_2000

The Figure 8 depicts the image processing phases of the IDRiD dataset for detecting hemorrhage and early identification of Diabetic Retinopathy (DR). This figure rows indicate one retinal fundus image from the IDRiD dataset, which had a total of 20 fundus photos evaluated.

The Figure 9 shows the results of processing retinal fundus pictures from the DR_2000 dataset to detect hemorrhage as an early sign of diabetic retinopathy (DR). Each row in the graphic depicts one retinal image from the DR_2000 dataset, for a total of 20 retinal images tested.

The Figure 10 depicts the image processing technique that uses the diaretdb1 dataset to find specific features in the retinal fundus picture. This procedure consists of numerous stages, including converting from RGB to grayscale, applying top-hat and bottom-hat filters, applying the Laplacian of Gaussian (LoG) filter, thresholding, and analyzing region attributes. Each level of processing seeks to improve the look of elements on the retina, such as blood vessels or lesions, to aid in the diagnosis of specific medical disorders.

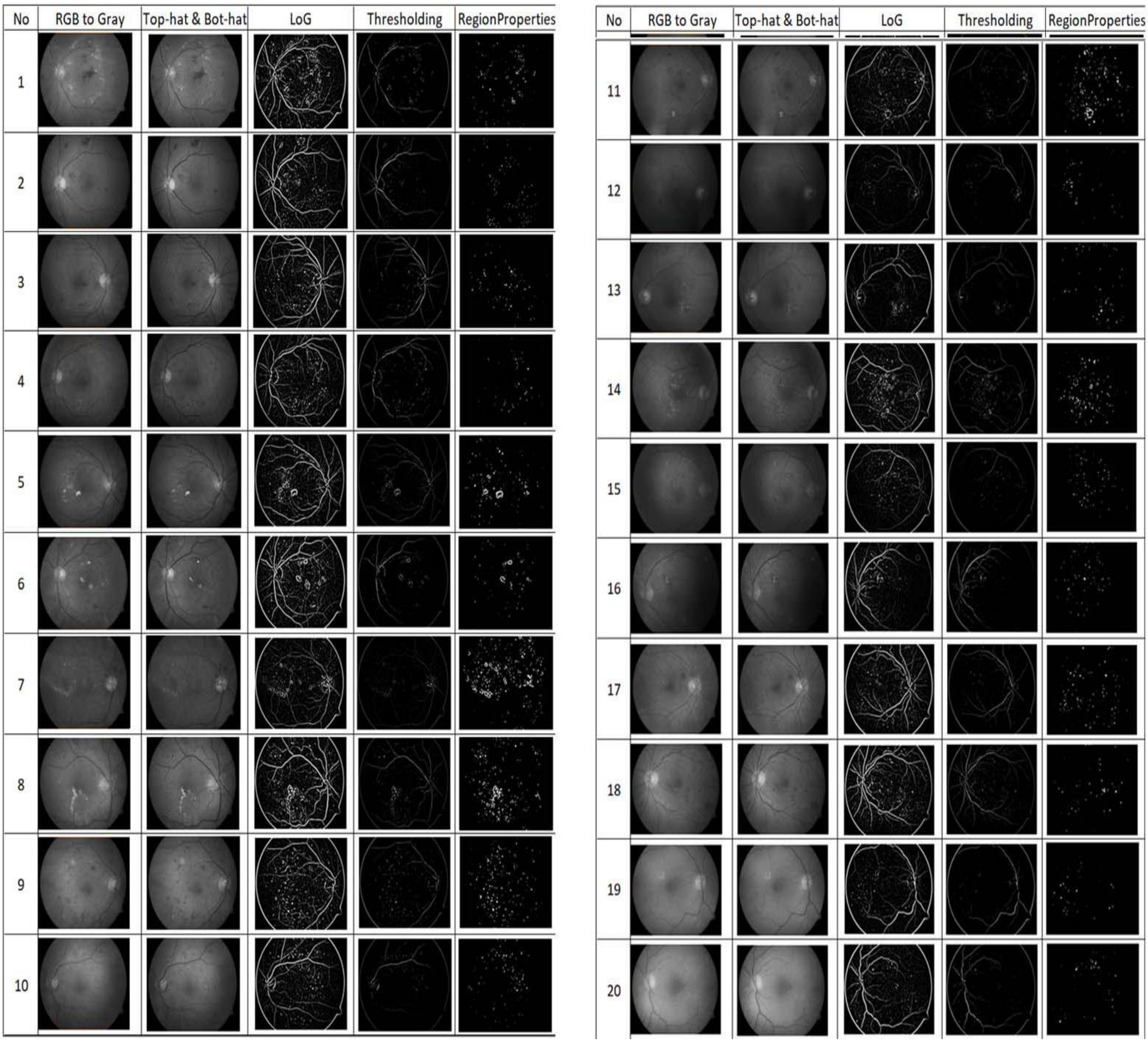

Figure 10. Processing Dataset Diaretdb1

3.2.1 Laplacian of Gaussian (LoG)

In the results and discussion stage, the filter process is implemented in the retinal fundus image processing in order to reduce noise in the retinal fundus image and minimize the level of detection errors in the hemorrhage area of the retinal fundus image [16]. Figure 11 shows the results of image processing using the LoG filter, resulting in a more distinct and detailed bleeding area, hence enabling precise segmentation of the HE area. This filter is more successful in emphasizing features with abrupt intensity variations and offers sensitivity to the scale of items in the image [17]. LoG is frequently employed in diverse image processing applications, including edge detection, image segmentation, and texture structure analysis in retinal images to accurately identify hemorrhage regions.

After applying the LoG filter, it has been observed that this filter effectively highlights the areas potentially containing hemorrhages in retinal images of patients with Diabetic Retinopathy. The results of using this filter reveal a significant improvement in the highlighting and segmentation of areas affected by hemorrhages as shown in Figure 11.

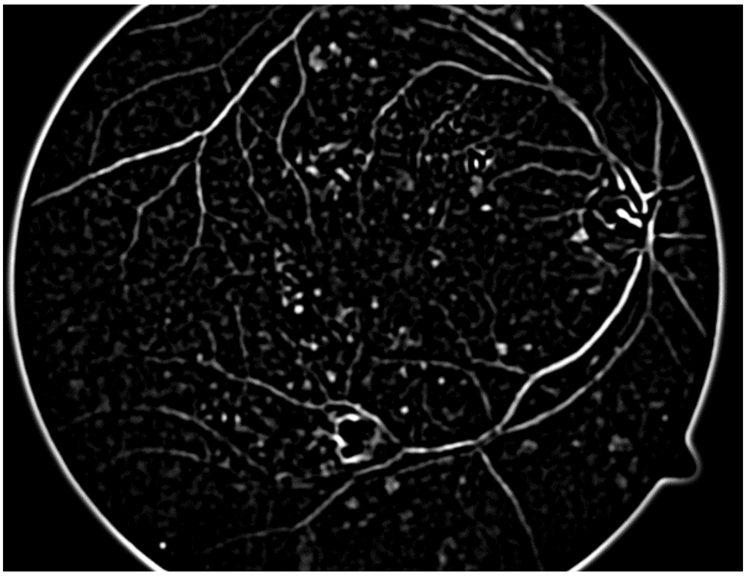

Figure 11.Processing Retina Image with filter Log

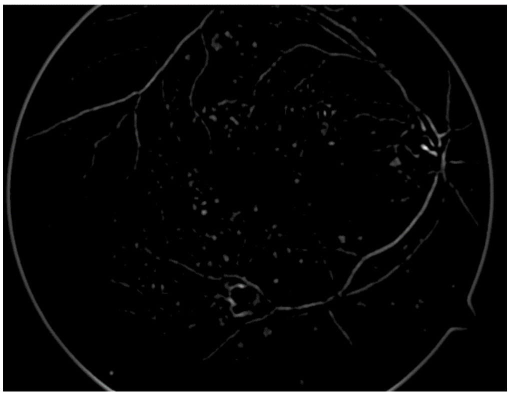

Figure 12. Processing Retina image fundus with Thresholding

3.2.2 Thresholding

The area affected by the hemorrhage is clearly delineated from the background of the retinal image during this process. By choosing multiple suitable threshold values, specifically T=0.2, T=0.3, T=0.4, T=0.5, T=0.6, and T=0.8, regions with color intensities indicative of hemorrhages can be precisely recognized. The segmentation results identify regions likely harboring hemorrhages automatically, offering explicit direction. The results of the segmentation are presented in Figure 12.

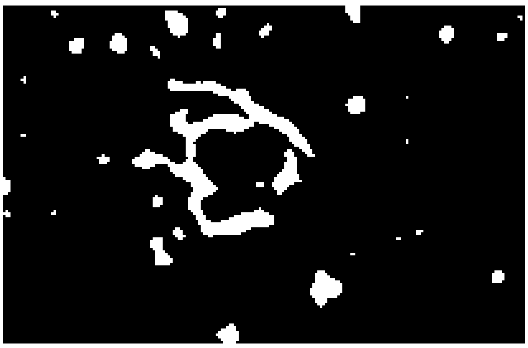

Figure 13. Processing retina fundus with eccentricity regionproperties.

The Figure 12 illustrates that thresholding in retinal fundus image analysis is a crucial technique for hemorrhage region detection. Utilizing the thresholding method, pixel intensity values in the image can be classified into two primary categories: hemorrhage regions and extraneous areas, such as blood vessels, which are deemed noise during the thresholding process, thereby enhancing the detection and monitoring of medical conditions. This technique offers an effective alternative for enhancing the accuracy of retinal fundus image-based diagnoses and can identify hemorrhage regions more distinctly.

3.2.3 Region Properties (Eccentricity)

This segmentation study employs region properties with eccentricity features in image analysis using the region properties approach, which is effective for analyzing shape-based object attributes in images. Eccentricity is a measure of an object's asymmetry. The application of eccentricity in this work facilitates the detection, segmentation, and characterization of objects in HE, particularly those with an elliptical or elongated shape. Eccentricity is commonly utilized to identify variations in items that are difficult to detect manually. The result is presented in Figure 13.

This study used a variety of eccentricity values, including 0.5, 0.7, 0.8, and 0.9, to extract the distinguishing aspects of hemorrhage, allowing for a more comprehensive approach to hemorrhage detection. This method is highly effective in isolating undesirable materials, such as hard exudates, in order to detect HE regions. The inclusion of eccentricity as a criterion in retinal image processing not only enhances HE detection precision, but it also makes it easier to differentiate between different lesion types, which is critical for more accurate evaluation and diagnosis of diabetic retinopathy.

4. CONCLUSION

LoG technique is demonstrated to be successful in segmenting hemorrhage lesions in retinal fundus pictures. This approach leverages LoG's capability to identify edges and evaluate texture, effectively delineating the pertinent hemorrhage lesion area. The findings indicate that LoG can consistently identify early indicators of Diabetic Retinopathy (DR) via hemorrhage segmentation, a crucial phase in the early diagnosis of the disease.

Analysis of three datasets revealed that DIARETDB1 and IDRiD are exemplary selections for Diabetic Retinopathy research, owing to their improved image quality, particularly in contrast and pixel sharpness, as compared to the DR_2000 dataset. The advantages render DIARETDB1 and IDRiD a superior reference for future study in the advancement of automated detection techniques for diabetic retinopathy. Consequently, it is advisable for future study to employ these datasets due to their superior consistency and representativeness in illustrating retinal diseases. This study significantly contributes to medical image analysis, particularly in developing an early detection system for Diabetic Retinopathy based on retinal fundus images. It is anticipated to serve as a reference for researchers and medical practitioners aiming to enhance the accuracy of DR diagnosis through advanced image processing techniques.

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