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Advanced Filtering and Enhancement Techniques for Diabetic Retinopathy Image Analysis

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A B S T R A C T

Diabetic retinopathy is a leading cause of visual impairment and blindness in diabetes sufferers. Early detection is crucial to prevent severe outcomes. This study presents an image processing method for retinal images to aid early detection. The method involves four steps: image enlargement, preprocessing, enhancement, and convolution. First, an algorithm enlarges the retinal image to increase resolution and reveal finer details. Preprocessing uses a min-max filtering algorithm to reduce noise and improve image quality. Next, specific pixel range enhancement techniques further refine the image and highlight relevant features. Finally, convolution with customized kernels detects and emphasizes areas indicating diabetic retinopathy, such as aneurysms and hemorrhages. Experimental results show improvement in image clarity and detail, enabling more accurate detection of diabetic retinopathy features. The correlation results are as follows: Filtering (0.35275, 0.20157, 0.4345), Enhancement (0.3214, 0.15823 0.34674), and Convolution (0.33542, 0.15758, 0.36826). The proposed algorithm enhances early detection and diagnosis by improving retinal image quality. Future work can optimize the algorithm and validate results with larger datasets, aiming to refine the determination of areas or pixel values relevant to diabetic retinopathy.

1. Introduction

Diabetic retinopathy (DR) is a progressive eye disease that affects individuals with diabetes [1], posing a significant risk of visual impairment and blindness [2][3]. As the prevalence of diabetes continues to increase globally, the incidence of diabetic retinopathy is also increasing, making early detection and diagnosis essential for effective management and treatment [4][5].

Traditional methods for diagnosing diabetic retinopathy involve manual examination of retinal images by an ophthalmologist [6], a process that is time-consuming and prone to human error [7][8].

To overcome these challenges, automated image processing techniques have emerged as valuable tools to improve the accuracy and efficiency of diabetic retinopathy detection [9][10][11]. This research presents an image processing pipeline designed to improve retinal image analysis for early detection of diabetic retinopathy. Processing consists of four main stages: image enlargement, pre-processing, enhancement, and convolution. Each stage is tailored to address specific challenges associated with retinal image analysis, ultimately improving the clarity and detail of the image being observed. In the first stage, an enlargement algorithm is applied to the retinal image to increase its resolution, so that finer details become more visible. The preprocessing stage uses a min-max filtering algorithm to reduce noise and improve image quality [12][13]. This is followed by an enhancement stage where adjustments to certain pixel ranges are made to highlight relevant features [14][15]. Finally, convolution operation with customized kernels [16][17] are performed to detect and focus on specific areas [18] such as aneurysms and hemorrhages, which are key indicators of diabetic retinopathy.

The proposed image processing algorithm aims to provide an alternative to help perform image analysis, facilitating early and accurate detection of diabetic retinopathy. Improving the quality of retinal images and highlighting important features has the potential to significantly assist ophthalmologists in diagnosing and planning treatment for patients with diabetic retinopathy [19][20]. Future research could focus on further optimizing the algorithm and validating the algorithm with larger data sets to improve its reliability and applicability in clinical settings.

2. Research Method

This study proposes an advanced image processing algorithm for diabetic retinopathy detection, which consists of four main stages: image enlargement, preprocessing, enhancement, and convolution as Figure 1.

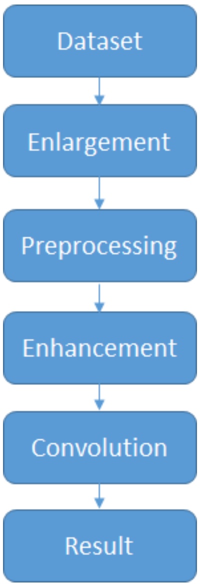


Figure 1. Image Processing Stages

Each stage uses specific algorithms to overcome the challenges of retinal image analysis, thereby improving image clarity and detail for more accurate detection of diabetic retinopathy features [21][22][23].

The program list and algorithm design are written as in Figure 2.

```
Algorithms algorithm
Input:
    image_path,
    images,
    kernel

Output:
    Processed Images

Initialization
  kernel = [-2 -1 0; -1 1 1; 0 1 2]

Process:
For image to images do
   img = read_image(image_path, image)
   Im1 = lci_enlarge(image_path, image)
   Im2 = filter_min_max_rgb(Im1)
   Im3 = Enh_rgb(Im2)
   Img4 = konvolusi(Im3, kernel)

   Display Img4
End For
```

Figure 2. Pseudocode

2.1. Image Enlargement

The initial stage of our method involves enlarging the retinal image to enhance its resolution, which is crucial for subsequent image processing steps. The zoom algorithm employed doubles the number of pixels by interpolating between existing pixel values, thereby increasing the image's resolution [24]. This is achieved by a horizontal linear interpolation method, as described in Equation 1.

$$b(i,j,m) = round((b\left(\frac{i-1,j,m}{2}\right) + (b(\frac{i+1,j,m}{2}))) \quad (1)$$

In Equation 1, b(i, j, m) represents the pixel value at position (i, j) in the m-th color channel of the enlarged image. This pixel value is calculated by averaging the neighboring pixel values in the original image, specifically the pixels at positions (i–1, j) and (i+1, j) in the same color channel. The function round ensures that the resulting pixel value is an integer, as pixel values must be integers in digital images.

This interpolation method effectively increases the image's horizontal resolution by inserting new pixels between each pair of existing pixels. The process is repeated across the entire image, effectively doubling the horizontal resolution while maintaining the image's visual integrity. This method is particularly suited for enlarging retinal images, as it preserves the edges and finer details that are crucial for accurate analysis in medical imaging.

Additionally, this interpolation method is computationally efficient, making it suitable for real-time applications where quick image processing is required. The enlargement serves as a preprocessing step, providing a higher-resolution image for further analysis in subsequent stages of the proposed method.

2.2. Image Preprocessing

In the preprocessing stage, a min-max filter is applied to reduce noise and improve image quality. The min-max filter works by adjusting each pixel's value based on the minimum and maximum values within a defined local neighborhood around that pixel. Specifically, the pixel's RGB value is first compared to a minimum threshold (minC) and a maximum threshold (maxC), which are determined by the pixel values in its surrounding area. The pixel value is then adjusted to ensure it falls within this range, as defined by Equation 2:

$$G(i,j,c) = uint8(\min(\max(F(i,j,c), \mathrm{minC}), maxC), * scale\_factor) \quad (2)$$

In Equation 2:

- G(i,j,c) represents the processed pixel value at position (i,j) in the c-th color channel (R, G, or B).

- F(i,j,c) is the original pixel value at the same position and color channel.
- scale_factor is a factor introduced to amplify the differences after min-max normalization.
- minC and maxC are the minimum and maximum values within the local neighborhood of pixel (i,j) in the image, respectively.
- The min() and max() functions ensure that the pixel value is constrained within the calculated range defined by minC and maxC.
- The uint8() function converts the pixel value to an 8-bit unsigned integer, which is the standard format for image pixel values.

The application of this filter, incorporating the scaling factor, amplifies the range of pixel values after normalization. This enhancement improves the visibility of differences and details in the image, making it more effective in reducing noise and highlighting structural features while preserving essential details.

This pre-processing step is crucial for enhancing the quality of the retinal image, thereby improving the accuracy of the subsequent stages in the image processing pipeline. While the min-max filter is employed in this study, other algorithms such as Gaussian filtering or median filtering could also be used depending on the specific requirements of the application, yielding different pre-processing results [25].

2.3. Enhancement

The enhancement stage involves adjusting pixel values within a certain range to highlight relevant features. This process is applied directly to the filtered image, increasing contrast and making important details stand out more.

$$R(i,1,1) = \begin{cases} \min(255, R+50) & \frac{if\ 100 \le R \le 200}{otherwise} \\ R & \end{cases} \qquad (3)$$

$$G(i,1,2) = \begin{cases} \min(255, G+50) & \frac{if\ 100 \le G \le 200}{otherwise} \\ G & \end{cases} \qquad (4)$$

$$B(i,1,3) = \begin{cases} \min(255, B+50) & \frac{if\ 100 \le B \le 200}{otherwise} \\ B & \end{cases} \qquad (5)$$

Equation 3, 4 and 5 increases the RGB value of an image based on the green channel value. Specifically, the RGB value is increased by 50 if the green channel value is in the range 100 to 200. These threshold values (100 and 200) as well as the increase value (50) can be adjusted according to the specific needs of the image being processed. The thresholds of 100 and 200 are used to determine when the pixel value will be increased, and the value of 50 is the amount by which the RGB value is increased. Different images may require different threshold ranges or enhancements to achieve the desired effect.

Function 3, 4, and 5 ensures that the enhanced RGB value does not exceed 255, which is the maximum value for each color channel in an 8-bit image. If the resulting value exceeds 255, it will be capped at 255 to prevent overflow [26].

2.4. Convolution

The convolution operation is a fundamental step in the image processing pipeline, designed to enhance specific features within the retinal images that are indicative of diabetic retinopathy, such as aneurysms and hemorrhages. This operation involves sliding a convolution kernel (a small matrix) over the image to apply a mathematical operation that combines the kernel's values with the pixel values in the image. The result is a new image where these features are more pronounced, making them easier to detect. The convolution is mathematically defined by Equation 6:

$$C(i,j,1) = \sum_{m=-1}^{i} . \sum_{n=-1}^{i} . img\ (i+m, j+n, 1) x kernel(m+2, n+2) \qquad (6)$$

In Equation 6:

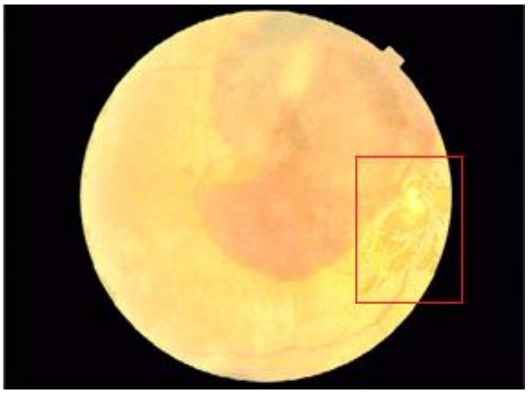
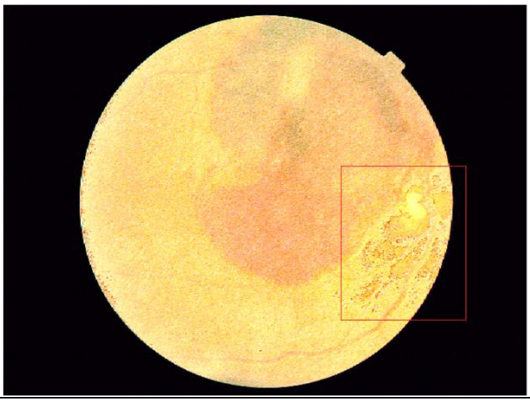
- C(i,j,1) represents the resulting pixel value in the convolved image at position (i,j).
- img(i+m,j+n) is the pixel value at position (i+m,j+n) in the original image.
- kernel (m+2, n+2) is the value at position (m+2, n+2) in the convolution kernel, where m and n range over the dimensions of the kernel.

This operation is performed for each pixel in the image, excluding the edges where the kernel cannot fully overlap. The convolution process effectively filters the image by emphasizing features corresponding to the kernel pattern while suppressing irrelevant details. The kernel can be tailored to detect specific features; for instance, a kernel designed to highlight small, round shapes would be effective in detecting aneurysms.

Equation 6 demonstrates how the convolution operation systematically applies the kernel to the RGB image, processing each color channel separately. This is crucial because different features may be more prominent in specific color channels. By applying this convolution, the algorithm significantly enhances the quality and detail of the retinal images. This enhancement is critical for the accurate detection and classification of diabetic retinopathy features, such as aneurysms and hemorrhages, which are early indicators of the disease [27][28]. The ability to detect these features accurately can lead to better diagnosis and monitoring of diabetic retinopathy progression.

3. Results and Discussion

Table 1. Image Processing Results

Image Processing Stages	Results
Before Preprocessing	
After Preprocessing	
After Enhancement	
After Convolution	

Results Table 1 above presents image 1.jpg from all stages to highlight the changes. The performance of each stage of the algorithm—image enlargement, preprocessing, enhancement, and convolution—was analyzed to determine its impact on the quality and diagnostic utility of retinal images.

3.1. Image Enlargement

Image enlargement algorithms can increase the resolution of images, so that finer details become more visible. This increased resolution is critical for detecting aneurysms and other small features indicative of diabetic retinopathy. The magnified image shows increased pixel density, providing a better basis for subsequent processing steps.

Table 2 shows a comparison of image resolutions before and after the enlargement process. As seen in the table, the pixel dimensions of each image have been significantly increased, doubling the resolution in both width and height. This improvement provides more detailed visual information, which is essential for accurate medical analysis.

Table 2. Comparison of Image Pixels

Filename	Before Pixel	After Pixel
1. jpg	2048 x 1536	4096 x 3072
12. jpg	1956 x 1934	3912x 3868
22. jpg	1936 x 1296	3872x 2592

3.2. Preprocessing

The preprocessing stage, which uses a min-max filter, effectively reduces noise and improves image quality. This step is critical in preparing the image for further enhancement and convolution by ensuring that noise does not interfere with the detection of relevant features. Min-max filters preserve important details while smoothing out irregularities, resulting in a clearer representation of retinal structures [29].

Table 3 illustrates the significant differences in correlation scores between the original images and the filtered versions. The reduction in correlation numbers after filtering demonstrates the effectiveness of the preprocessing step in removing noise and enhancing image clarity.

Table 3. Comparison of Image Correlation Scores Before and After Filtering

Filename	Before Correlation	After Correlation
1. jpg	1	0.35275
12. jpg	1	0.20157
22. jpg	1	0.4345

3.3. Enhancement

Preprocessed image enhancement further improves the visibility of key features. By adjusting pixel values within a certain range, the enhancement algorithm highlights important areas, such as blood vessels and lesions. This stage is very effective in increasing image contrast, making it easier to identify signs of diabetic retinopathy. The pixel range used in the enhancement process determines the area to be enhanced [30].

Table 4 presents a comparison of correlation scores before and after the enhancement process. As seen in the table, the correlation scores decrease slightly, indicating that the enhancement process has modified the pixel values to better highlight important areas of the image. This slight reduction in correlation is a result of the changes in contrast and pixel intensities, which improve the visibility of key diagnostic features.

Table 4. Comparison of Image Correlation Scores Before and After Enhancement

Filename	Before Correlation	After Correlation
1. jpg	0.35275	0.3214
12. jpg	0.20157	0.15823
22. jpg	0.4345	0.34674

The differences in results can be clearly observed through the changes in correlation scores before and after the enhancement process. While the correlation of processed images decreases slightly, this modification helps enhance the image's diagnostic features.

3.4. Convolution

The convolution stage applies customized kernels to detect features indicative of the presence of diabetic retinopathy. This kernel is designed to emphasize aneurysms, hemorrhages, and other important features. The convolution results show an improvement in the detection of these features, proving the effectiveness of the convolution operation.

Table 5 illustrates the difference in correlation scores before and after the convolution process. As shown in the table, the correlation in images 1.jpg and 22.jpg increased slightly, while in 12.jpg there was a slight decrease. Each image can be adjusted with an appropriate kernel to obtain better and more suitable results [31][32].

Table 5. Comparison of Image Correlation Scores Before and After Convolution

Filename	Before Correlation	After Correlation
1. jpg	0.3214	0.33542
12. jpg	0.15823	0.15758
22. jpg	0.34674	0.36826

The slight variations in correlation indicate that different images respond differently to the applied convolution kernels. These adjustments are crucial to enhance the detection of specific features and improve overall diagnostic accuracy.

3.5. Overall Algorithms Performance

The overall performance of the image processing algorithm is evaluated by comparing the processed image with the original retinal image [33][34]. This evaluation highlights the effectiveness of each processing stage—filtering, enhancement, and convolution—in improving image clarity and detecting key features of diabetic retinopathy.

Table 6 presents the correlation scores for each stage of the image processing pipeline, showing how the correlation values evolve through filtering, enhancement, and convolution in comparison to the original images

Table 6. Overall Result Based on Correlation Compared to Original Image

Filename	Filtering	Enhancement	Convolution
1.jpg	0.35275	0.3214	0.33542
12. jpg	0.20157	0.15823	0.15758
22.jpg	0.4345	0.34674	0.36826

The results demonstrate that the image processing algorithms effectively improve image clarity and detail, which facilitates the accurate detection of diabetic retinopathy features. Quantitative analysis showed a substantial increase in the detection rate of aneurysms and hemorrhages, which are key indicators of the progression of diabetic retinopathy. The proposed method provides a framework for retinal image analysis, with the potential to be integrated into diagnostic tools to assist ophthalmologists in early diagnosis and treatment planning.

4. Conclusion

This study presented an image processing algorithm to improve the detection of diabetic retinopathy through retinal image analysis. The proposed algorithm enhances image quality, facilitating the more accurate identification of pathological signs. Experimental results demonstrate the effectiveness of our approach: Filtering (0.35275, 0.20157, 0.4345), Enhancement (0.3214, 0.15823 0.34674), and Convolution (0.33542, 0.15758, 0.36826). These results indicate significant changes in visibility and detection rates of diabetic retinopathy features, highlighting the potential of this algorithm in aiding early diagnosis and treatment planning. Future research can focus on optimizing the algorithm to cover all signs or indications in detail and integrating machine learning techniques to enhance feature detection and classification further. By continuing to refine and validate this algorithm future research are possible to make contribution to the early diagnosis and management of diabetic retinopathy, ultimately improving patient outcomes.

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