COMP2047: Introduction to Image Processing

Segment the retina blood vessel

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Contents

1 Introduction

Retina vessel segmentation could be done with image processing. This report presents the designation and techniques used for filter-based retina vessel segmentation. Moreover, their advantages and limitations in comparison to other possible solutions and well-performed algorithms are discussed.

2 Design and Justification

The design proposed and the justification of choices for each technique used are presented in this section.

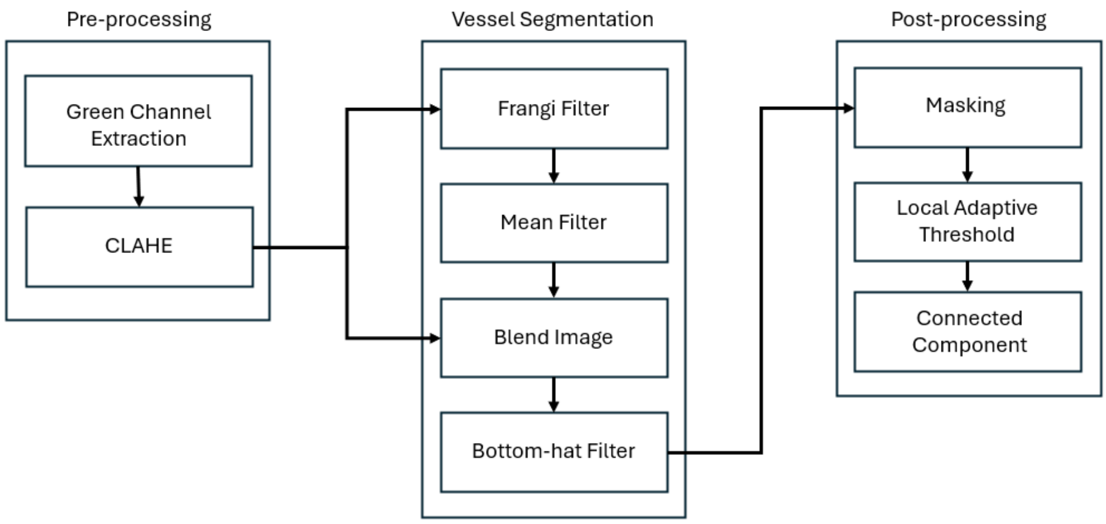

Figure 1: Flow of Retina Blood Vessel Segmentation

2.1 Pre-processing

Pre-processing of retina images includes two steps: Green Channel Extraction and CLAHE. The objective is to maximize the vessel segmentation in the further steps.

2.1.1 Green Channel Extraction

During the initial processing step, the green channel of the retina blood vessel image is extracted. Green channel shows a better vessel-background contrast compared to the blue and red channels. Specifically, studies have found that the green channel provides a higher signal-to-noise ratio and greater image contrast, making it particularly suitable for enhancing vessel structures in medical images (Ramos-Soto et al., 2021).

To verify the reliability of this approach, an experiment was done to compare the performance of each color channel. The results of this experiment are shown in Figure 2. This visual comparison helps to demonstrate the contrast and clarity of the vessel structures in the green channel and support this selection for further analysis and processing.

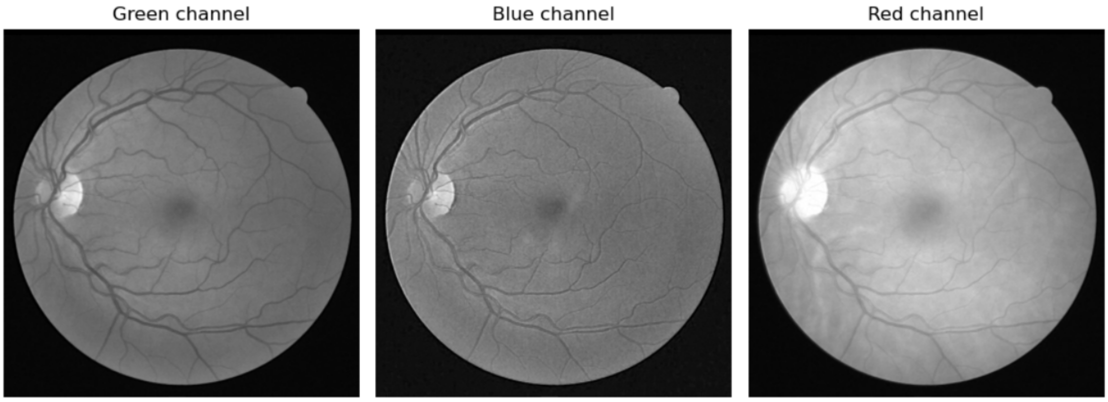

Figure 2: Result of each Colour Channel of Image

2.1.2 CLAHE (Contrast Limited Adaptive Histogram Equalization)

Next, to enhance the contrast of the green channel image, the contrast-limited adaptive histogram equalization (CLAHE) technique introduced by the built-in function of the openCV is employed ("Histogram Equalization", 2016). The result presented by Ramlugun et al. (2012) shows that applying CLAHE could obtain a higher accuracy of vessel segmentation. Compared to global histogram equalization, adaptive histogram equalization adapts its enhancement strategy to smaller local regions within the image, thereby preserving more detailed information. CLAHE is proven to have a higher visibility to the retina vessels compared to histogram equalization (HE) and adaptive histogram equalization (AHE) (Lestari, Luthfi, et al., 2019).

The images are divided into smaller block tiles by a grid size of 20 X 20 and each block tile performs the histogram equalization independently and achieves localized contrast enhancement. However, this approach may amplify noise within the block tiles. To prevent over-amplification, the contrast limit needs to be set to control the maximum amount of contrast enhancement applied to each tile. In this proposed method, the contrast limit is set to 3.5 which provides a balance between enhancing vessel structures and depressing noise. The result of applying the CLAHE filter to the green channel image is shown in Figure 3. It shows how the contrast enhancement technique effectively enhances the visibility of vessel structures while preserving important details within the image.

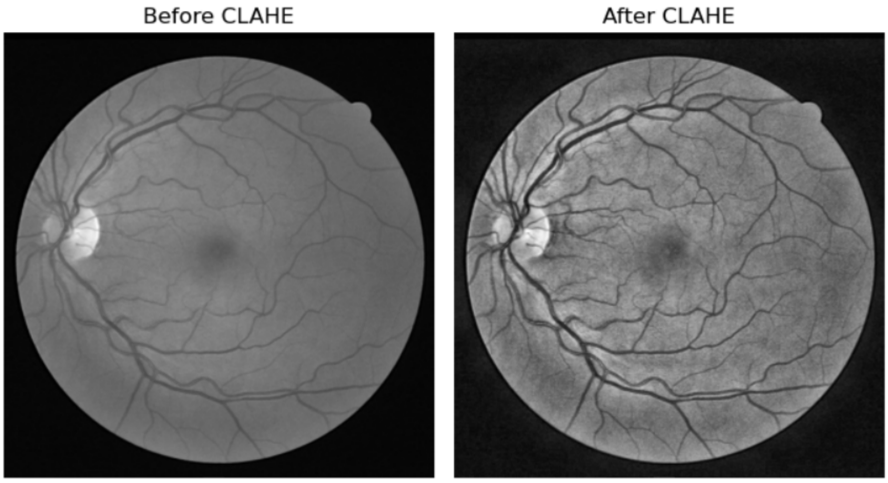

Figure 3: Result before and after CLAHE

2.2 Vessels Segmentation

The vessel segmentation process introduces two main filters: Frangi and Bottom-Hat Transformation incorporated with mean filter and image blending.

2.2.1 Frangi Filter

Frangi filter is a Hessian-based Frangi vesselness filter that is widely applied in enhancing vasculature in optoacoustic images due to its effectiveness and simple implementation in identifying blood vessels (Longo et al., 2020). This filter operates by evaluating the similarity of image regions to vessel structures through the computation of eigenvalues derived from the Hessian matrix ("skimage.filters", n.d.). Nugroho et al. (2017) underscore its utility in this domain, emphasizing the Frangi filter's proficiency and ability to detect vessels with continuous edges.

The proposed method used the frangi filter introduced by the skimage library ("skimage.filters", n.d.). Specific parameters are also passed to the function to optimize the Frangi filter's performance. By setting sigmas to (0.5, 1.4, 1.5), the filter operates at multiple scales, enabling it to capture vessels of varying widths. Additionally, 1 scale step between the sigmas is used to ensure a comprehensive examination of the image at different resolutions with a choice of a beta value of 1 as the Frangi correction constant enables fine-tuning of the filter's sensitivity to deviations from blob-like structures.

2.2.2 Mean Filter

After applying the Frangi filter, additive noise exists in the background of the vessel image as shown in the left image in Figure 4. Hence, a mean filter is used to smooth the image and further reduce false edges. The mean filter is a symmetric filter that will replace the pixel value of the image with the mean value of itself and its neighbours. The kernel size of the mean filter used is 3 X 3 with a sigma value of

0. The background noise is significantly reduced after applying the mean filter as shown in the right image of Figure 4.

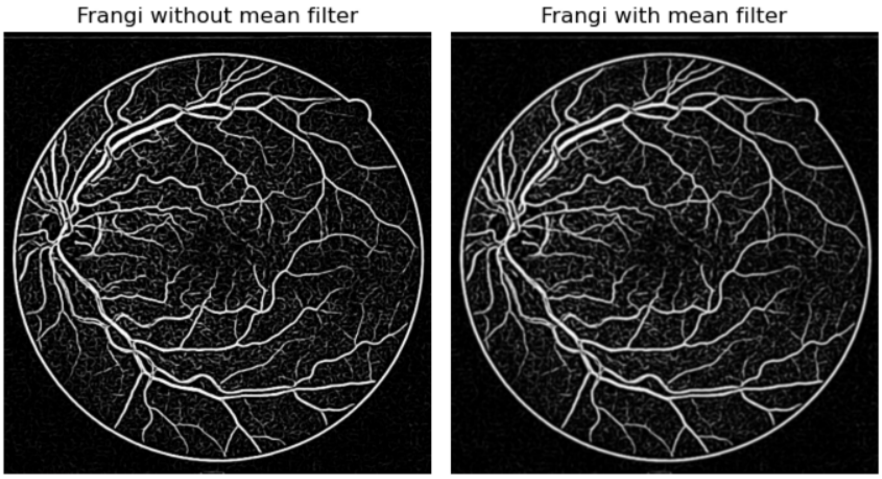

Figure 4: Result of Applied Frangi Filter and Mean Filter

2.2.3 Blending of Image

The filtered is then blended with the previously equalized image to enhance the vessel structures for further segmentation with the introduction of `addWeighted()`, a built-in function of openCV library ("Image Blending with OpenCV's addWeighted Function", 2023). Both images are blended with different weights of 1 for the equalized image and -0.41 for the Frangi and Mean image. A negative value is used to invert the image colour to darken the existence of vessels. By combining the information from both the equalized and Frangi-filtered images, the proposed method achieves more robust and accurate segmentation results and provide a better visibility of retinal blood vessels. The comparison before and after blending the image with the Frangi filtered image is shown in Figure 4.

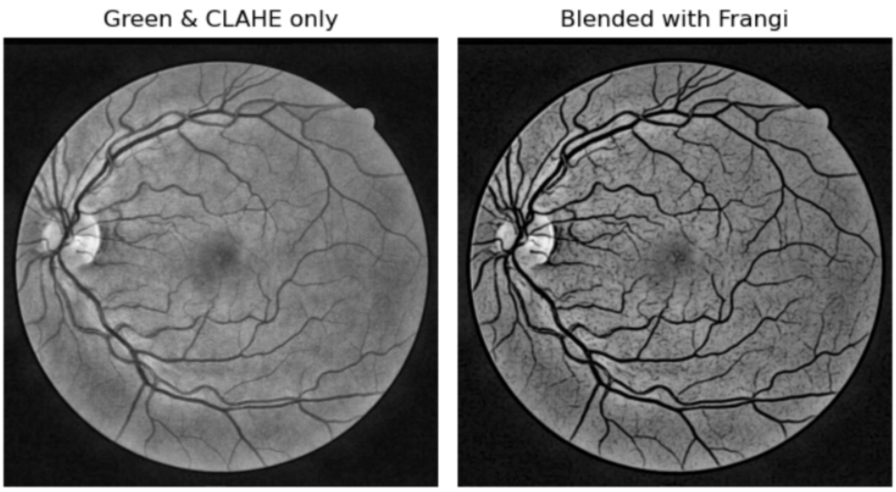

Figure 5: Result of Blended Image

2.2.4 Bottom-Hat Transformation

In morphological image processing, fundamental operations known as top-hat (white top-hat) and bottom-hat (black top-hat) are used to highlight specific features within an image. These operations are complements to each other, with the top-hat operation emphasizing bright structures against a dark background, while the bottom-hat operation focuses on enhancing dark structures against a light background (Thapar & Garg, 2012). Bottom-hat operation involves subtracting the input image from the result of morphological closing applied to the input image resulting in an isolation of the darker structures. In the proposed method, the blood vessels appear darker than their surroundings. Hence, the bottom-hat morphological operator is used to enhance the contrast and visibility of these vessels with a disc kernel of size 13 X 13. Figure 6 illustrates the outcomes of both the top-hat and bottom-hat operations. Moreover, the use of blended images with Frangi instead of only equalized images is more significant in highlighting the retina vessels.

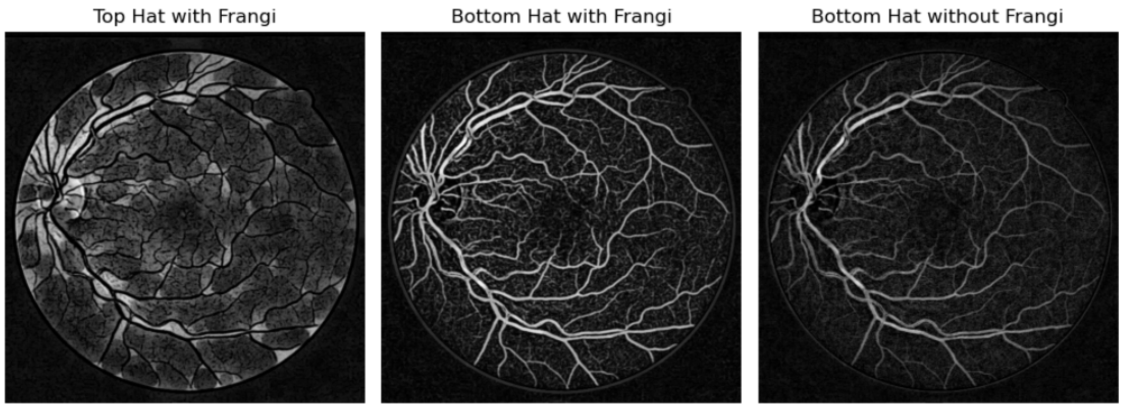

Figure 6: Result of Top-Hat and Bottom-Hat Filters

2.3 Post-processing

The post-processing includes three methods: masking, local adaptive thresholding and removing background noise using connected components.

2.3.1 Masking

Mask image allows definition of Region of Interest (ROI). In the proposed method, masking on the bottom-hat image highlights the area of the retina where vessels are expected to be present. Through masking, the accuracy and quality of segmentation results are enhanced by focusing the algorithm's attention on the ROI.

2.3.2 Local Adaptive Threshold

Threshold is a fundamental image processing technique used to enhance the characteristics of an image and segment or separate regions of interest from the background in an image based on pixel intensity values. The proposed method applies the adaptive threshold method to the masked image. Adaptive thresholding allows local thresholding to adapt to different lighting based on smaller regions. The adaptive threshold used is the built-in function of the OpenCV library ("Image Thresholding", n.d.). The threshold value is calculated with the mean value of neighbour area of size 257 X 257 increased by 39 making it less likely for a pixel to be classified as foreground even if its intensity is significantly higher than the local mean. The mean filtering is chosen instead of Gaussian to prevent the preservation of false edges. Compared to the normal binary threshold which has a constant threshold value for all images, the adaptive threshold preserved more correct edges and has a higher adaptability by calculating the threshold value according to different situations of different images. Although the Otsu threshold calculates the global optimal threshold value automatically according to the image, the adaptive threshold shows better thresholding in separating vessels from the background. The comparison is shown in Figure 7.

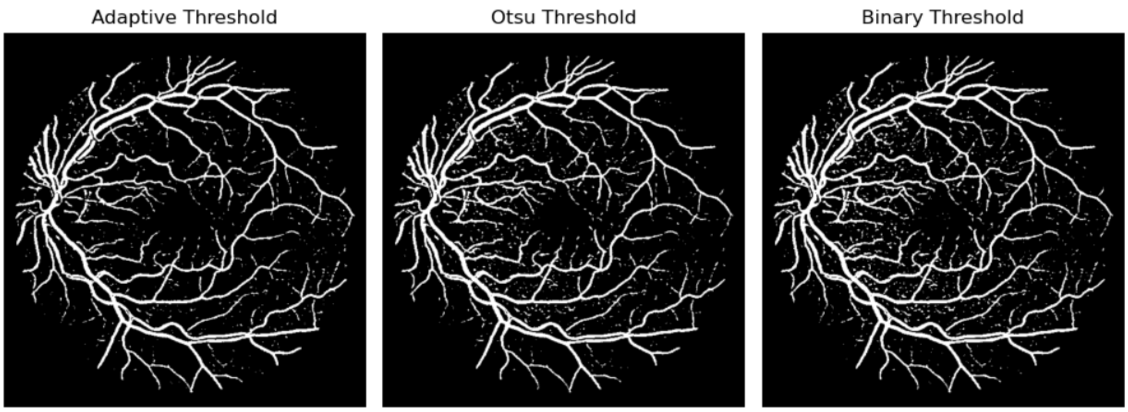

Figure 7: Result of Different Threshold Method

2.3.3 Connected Component

The connected component analysis is a powerful approach for noise removal of binary images. The proposed method applies connected component analysis to the thresholded image to remove unwanted background noise ("Python OpenCV – Connected Component Labeling and Analysis", 2023). It applies two passes over the image which uses 4-neighbours and a threshold T=48 to the number of pixels in the component. The first pass of the image will scan from top-left to bottom-right and determine if they belong to the same connected component then assign labels (foreground or background) to each pixel based on its top and left given labels. If the neighboring pixels have the same label, the current pixel is assigned with that label. If not, the current pixel is assigned a new label. This process continues until all pixels in the image have been labeled. Then, the second pass will consider and merge each equivalent pair of labels to resolve the inconsistencies. After the labeling, the pixels assigned as background will be removed from the image and show only blood vessels. The result is shown in Figure 8.

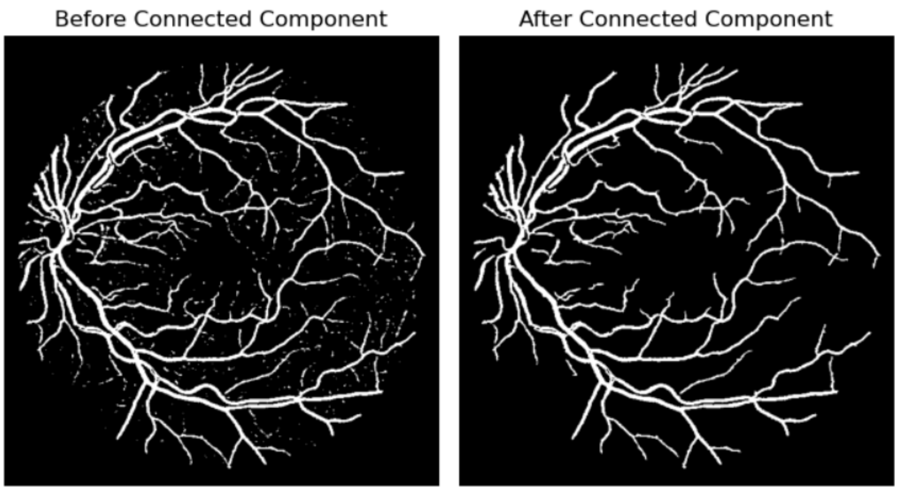

Figure 8: Result of Connected Component

3 How to Run the Program

To run the program, open the document `IIP.ipynb` in Jupyter Notebook. Firstly, run the first cell to import all required libraries and image paths. If the image path is not the path written, please change it to the required path. Running the last cell will show the segmentation of all 20 images from the dataset with the result of average P, N and T. All 20 segmented images will be printed with each P, N, T and its image number as the title. The cells in between show each step for segmentation and the comparison with other solutions. To run the cells in between, the previous cells need to be run in advance according to their sequence. By changing the number of `i` variable in the second cell, the image to be segmented can be changed.

4 Result

The proposed method obtains a result of an average accuracy with 94.84% while the highest is 96.70% and the lowest is 93.59%. The average percentage of blood vessel pixels (sensitivity) and background pixels that are being correctly classified (specificity) is 72.93% and 98.07% respectively.

5 Discussion

This section discusses the advantages and disadvantages of the proposed method including comparisons to other well-performed filter-based algorithms. The table 1 below shows the result of comparison to other algorithms.

No.	Algorithm Proposed	P (%)	N (%)	T (%)
A1	Ramlugun et al. (2012)	64.13	97.67	93.11
A2	Nugroho et al (2017)	72.13	96.65	94.50
A3	**Proposed Method**	**72.93**	**98.07**	**94.84**
A4	Ramos-Soto et al. (2021)	75.78	98.60	96.67

Table 1: Comparison With Other Algorithms

5.1 Advantages

5.1.1 Adaptive Thresholding

Every dataset has a different contrast and visibility. Hence, the proposed method uses adaptive thresholding techniques that allow localized adjustment of threshold values based on the image content. This enables better segmentation results compared to global and non-adaptive thresholding. Subsequently, compared to A1 algorithm that uses double-sided thresholding, proposed method with adaptive thresholding is able to calculate the threshold value dynamically for each pixel neighborhood. Proposed method provides better local adaptation, noise robustness, details preservation and minimum manual tuning in the thresholding process. This enhanced flexibility and performance in handling diverse image conditions, making them well-suited for a wide range of image segmentation tasks compared to traditional double-sided thresholding methods.

5.1.2 Noise Reduction and Edge Preserving

Compared to A1 and A2 algorithms, proposed method is better in reducing noise and false edges in the background as shown in Figure 9. To reduce noise and enhance the contrast of blood vessels against the background, different filters are used for noise reduction. Mean filter, morphological bottom-hat operation and connected component analysis are used for various types of noise removal in proposed method. The segmentation result of proposed method shows a better reduction of retina disk and unwanted noise further preserving more details of vessels compared to the other two.

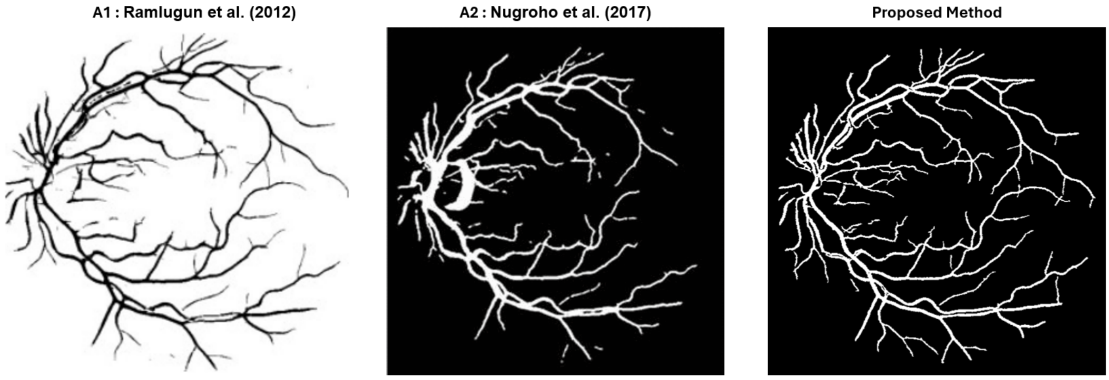

Figure 9: Comparison with A1 and A2 algorithm

5.1.3 Relatively Better Segmentation Result

The proposed method achieved a higher accuracy, sensitivity and specificity compared to referenced A1 and A2 algorithms. A significant difference in accuracy can be observed in Figure 9 and data supported in Table 1. All A1, A2 and proposed method apply extraction of green channel and CLAHE while A2 and proposed methods apply Frangi filtering. However, they are applied in different sequences and different segmentation implementations with thresholding techniques. A1 uses only one filter for vessels enhancing and a global thresholding while the proposed method uses several filters for segmentation with adaptive thresholding. The complexity in the case of segmentation and thresholding techniques further results in a different accuracy. A1 algorithm used a single filter may have limitations in adapting to different situations while proposed method uses different segmentation mtechniques to adapt to different contrast and visibility in maximizing the sensitivity and specificity of the datasets.

5.1.4 Simple Implementation

The proposed method stands out for its simplicity in implementation when compared to other algorithms listed in Table 1. By making use of built-in filters and functions available in OpenCV and skimage libraries, the code becomes more straightforward to comprehend. This simplicity not only facilitates faster development but also enhances the readability of the codebase.

5.2 Disadvantages

5.2.1 Computational Complexity

The proposed method involves multiple preprocessing and segmentation steps, including contrast enhancement, Frangi filtering, and morphological operations, which can result in increased computational complexity, especially for large-scale datasets.

5.2.2 Parameter Sensitivity

The performance of the method may be sensitive to the selection of parameters such as Frangi filter scales, morphological structuring elements, and constant value of adaptive thresholding. Tuning these parameters for optimal results may require manual intervention and it may not be the optimal solution for every dataset. Proposed method uses built-in function that limits the modification of code and parameters for adaptation compared to A4 algorithm which proposed an own-optimized top-hat that obtained a higher flexibility in changing parameters to adapt to different situations.

5.2.3 Loss of Fine Details

By comparison, the separation of segmentation process for thick and thin vessels in the A4 algorithm referenced above shows a higher accuracy and correctness for both vessels and background classification than the proposed method (Figure 10). The proposed method did not separate the thick and thin vessels for segmentation but only enhanced the visibility of thin vessels using Frangi filter and image blending. The vessels are then segmented together using morphological bottom-hat regardless of their thickness.

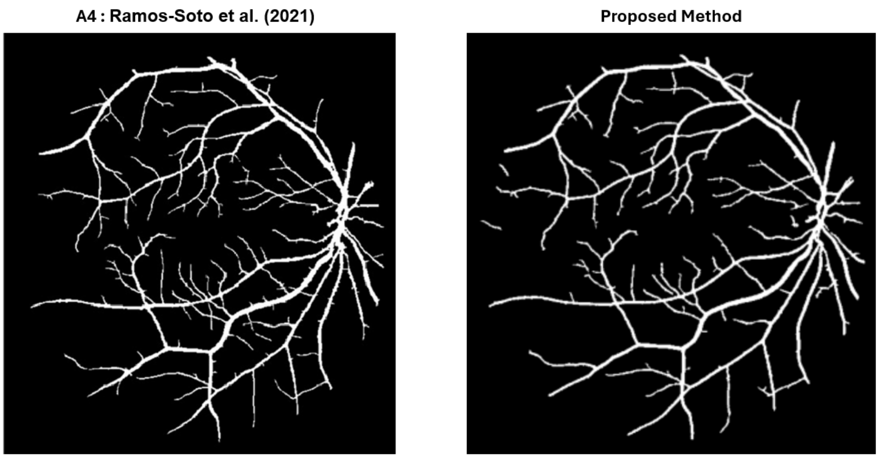

Figure 10: Comparison with A4 algorithm

Although there is a relatively high average accuracy of 94.84% of vessels detected, the average percentage of correctly identified blood vessel pixels is not too high at just 72.93%. This happens due to a significant loss of fine details especially for very thin vessels during the vessel segmentation process. The comparison of false detection and undetected thin vessels results are shown in Figure 11 where yellow colour shows the false background and green colour shows the false vessels detected.

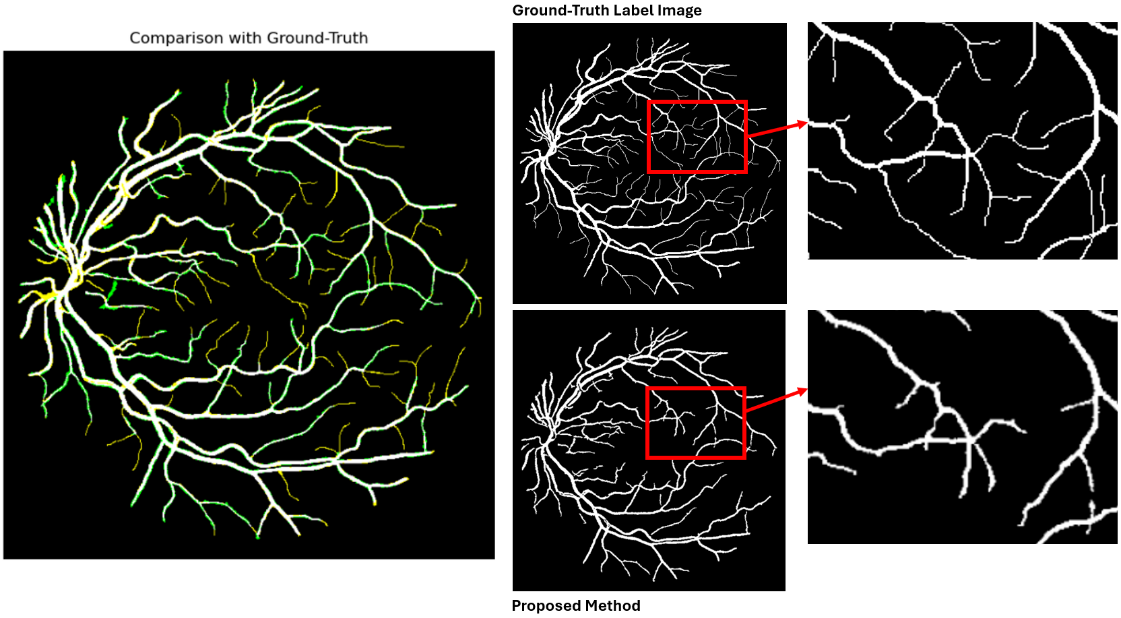

Figure 11: Comparison with Ground-Truth Label Image

6 Conclusion

In conclusion, this report has provided an insightful overview of filter-based retina vessel segmentation techniques used, detailing their designations and applications. By examining their advantages and limitations, alongside comparisons with alternative solutions and established algorithms, a comprehensive understanding is presented. In the future, machine learning could be applied to improve the accuracy of vessel segmentation.

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