Biomedical Image Segmentation for Retinal Images

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This project aims to improve an automatic image segmentation system applied to retinal images. Various preprocessing, segmentation, and post-processing techniques are tested to enhance segmentation accuracy. The project evaluates the effectiveness of each approach using the Jaccard Index (IoU) as the performance metric.

1 Introduction

This report explores biomedical image segmentation techniques applied to retinal images with the objective of improving upon a baseline system provided by Professor Fernando. The baseline system utilized a threshold-based segmentation method involving preprocessing steps like Gaussian smoothing, illumination compensation, and contrast enhancement, followed by thresholding and small-object removal to isolate retinal structures. Our goal is to enhance this system to maximize the Jaccard score (IoU).

2 Results

2.1 Performance Comparison

Table 1 summarizes the performance of each technique applied to improve the baseline results, represented by the Jaccard (IoU) metric.

Table 1: Performance (IoU) of Segmentation Techniques

Technique	Description	IoU
Baseline	Threshold-Based Segmentation	0.340 ± 0.036
Method 1	Illumination Compensation with Median Filter and stronger denoising	0.544 ± 0.065
Method 2	Removal of Small Objects	0.544 ± 0.063
Method 3	Higher Blurring and CLAHE	0.561 ± 0.058
Method 4	Enhanced Contrast with Adaptive Masking	0.568 ± 0.057
Method 5	Refined Masking with Adjusted Thresholding	0.571 ± 0.056
Method 6	Moderate Blurring with Enhanced Illumination	0.554 ± 0.062
Method 7	Vessel Enhancement with Frangi Filter	0.578 ± 0.056
Method 8	Frangi Filter with Enhanced Post-Processing	0.577 ± 0.056

2.2 Technique Descriptions

In order to describe the procedures, we will call the names of the functions when necessary. Also, only the changes with respect to any former method are commented.

2.2.1 Baseline: Illumination Compensation through Gaussian Filter with Otsu

Pre-processing: We converted to grayscale and applied Gaussian blur (getting_retina_mask). We corrected illumination with a Gaussian filter (illumination_compensation) and enhanced contrast with histogram equalization (contrast_enhancement). **Segmentation:** We used Otsu's thresholding (th_based_segmentation) within the retina mask [1]. **Post-processing:** We removed small objects (remove_small_objects). This method achieved an IoU of 0.340.

2.2.2 Technique #1: Illumination Compensation with Median Filter and Stronger Denoising

Pre-processing: We used a larger sigma in the Gaussian filter (getting_retina_mask) for better denoising and replaced the Gaussian filter with a median filter (illumination_compensation) and a large kernel to keep only the illumination patterns. These changes improved vessel visibility, increasing the IoU to 0.541.

2.2.3 Technique #2: Improvement of Technique #1 through Removal of Small Objects

Post-processing: We refined the final step by removing smaller noise (remove_small_objects), preserving small vessels that were eliminated in Technique #1. This led to a slight IoU improvement to 0.544.

2.2.4 Technique #3: Higher Blurring, Stronger Illumination Removal, and CLAHE

Pre-processing: We increased the Gaussian blur sigma (getting_retina_mask) for better smoothing, applied a double median filter (illumination_compensation) for even stronger illumination removal, and used CLAHE (contrast_enhancement) for local contrast enhancement to find even the smallest vessels. These adjustments improved the IoU to 0.561.

2.2.5 Technique #4: Enhanced Contrast with Adaptive Masking

Post-processing: We removed larger structures due to noise introduced by CLAHE, as the drawback of CLAHE is that it also enhances local noise. This led to better isolation of retinal structures and an IoU of 0.568.

2.2.6 Technique #5: Refined Masking with Adjusted Thresholding

Pre-processing: We applied a slightly reduced threshold (99% of Otsu value) in getting_retina_mask to increase the area of the retinal region mask, and used a smaller median filter (illumination_compensation) to enhance local contrast. This improved the IoU to 0.571.

2.2.7 Technique #6: Moderate Blurring with Enhanced Illumination Removal

Pre-processing: We used moderate Gaussian blur (sigma = 9) in getting_retina_mask and a larger median filter (sigma = 15) in illumination_compensation to further reduce the effect of light and noise in the retinal segmentation. This method resulted in an IoU of 0.554, slightly less effective than Techniques #4 and #5.

2.2.8 Technique #7: Vessel Enhancement with Frangi Filter

Segmentation: We applied the Frangi filter (th_based_segmentation) to enhance vessel tubular structures and adapted thresholds [2, 3]. **Post-processing:** We introduced morphological dilation and removed small objects to reduce noise. This technique achieved an IoU of 0.578.

2.2.9 Technique #8: Frangi Filter with Enhanced Post-Processing

Post-processing: We applied additional morphological closing and dilation after Frangi enhancement to fill gaps and enhance vessel continuity. The IoU remained similar at 0.577, indicating a practical upper-bound.

3 Discussion

After evaluating 9 different approaches, it is clear that each methodology has its advantages and disadvantages. There is always a tradeoff between keeping small vessels, and thus, some noise; or keeping only the large vessels and, at the same time, removing all small components, including vessels. None of these approaches efficiently segments the images perfectly, but there is still a significant improvement from the baseline output to the best one. The results were improved from a Jaccard Score of 0.340 to 0.578 [4, 5].

3.1 Unsuccessful Approaches

Incorporating a Canny edge detector in the preprocessing pipeline was attempted. Despite producing clear edges after adaptive histogram equalization and Gaussian smoothing, filling the spaces between edges was challenging. Incomplete edge closures led to unintended background filling during morphological operations, making edge detection unsuitable for segmentation when structures are not fully connected. Consequently, this method was discarded.

Another approach that was considered was to use registration to segment images. In other words, we could have used the best individual output mask from Technique #7 and, through the usage of SimpleElastix, performed a non-linear registration with respect to the other images [6]. However, as some retinal images include vessels even on the corners, that task would have been extremely difficult. Therefore, we discarded it.

Dividing the retina image into three color components and processing each separately is counterproductive because the vessels' prominence is reduced in some channels. Thus, this option was ruled out.

3.2 Conclusion

This study significantly improved retinal vessel segmentation, increasing the IoU score from 0.340 to 0.578. Techniques like Gaussian blurring and CLAHE enhanced contrast, while median filtering reduced noise and preserved edges. The Frangi filter, optimized for tubular structures, achieved the highest IoU scores when combined with morphological post-processing. Combining vessel-specific filters, adaptive contrast enhancement, and morphological operations proved most effective. Future work could explore deep learning approaches or further optimize filtering parameters to enhance performance.

References

[1] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62–66, 1979.

[2] A. F. Frangi, W. J. Niessen, K. L. Vincken, and M. A. Viergever, "Multiscale vessel enhancement filtering," in *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, 1998, pp. 130–137.

[3] W. Fu, K. Breininger, T. Würfl, N. Ravikumar, R. Schaffert, and A. Maier, "Frangi-net: A neural network approach to vessel segmentation," *Journal Name*, 2022.

[4] J. Almotiri, K. Elleithy, and A. Elleithy, "Retinal vessels segmentation techniques and algorithms: A survey," *Journal Name*, 2020.

[5] A. Khandouzi, A. Ariafar, Z. Mashayekhpour, M. Pazira, and Y. Baleghi, "Retinal vessel segmentation, a review of classic and deep methods," *Journal Name*, 2021.

[6] K. Marstal et al., "Simpleelastix: A user-friendly, multi-lingual library for medical image registration," 2016. [Online]. Available: https://simpleelastix.readthedocs.io/

Annex: Graphical Summary of the Work

This annex presents a sequence of images illustrating the evolution of the retinal image through our segmentation pipeline, highlighting the effect and contribution of each proposed technique.

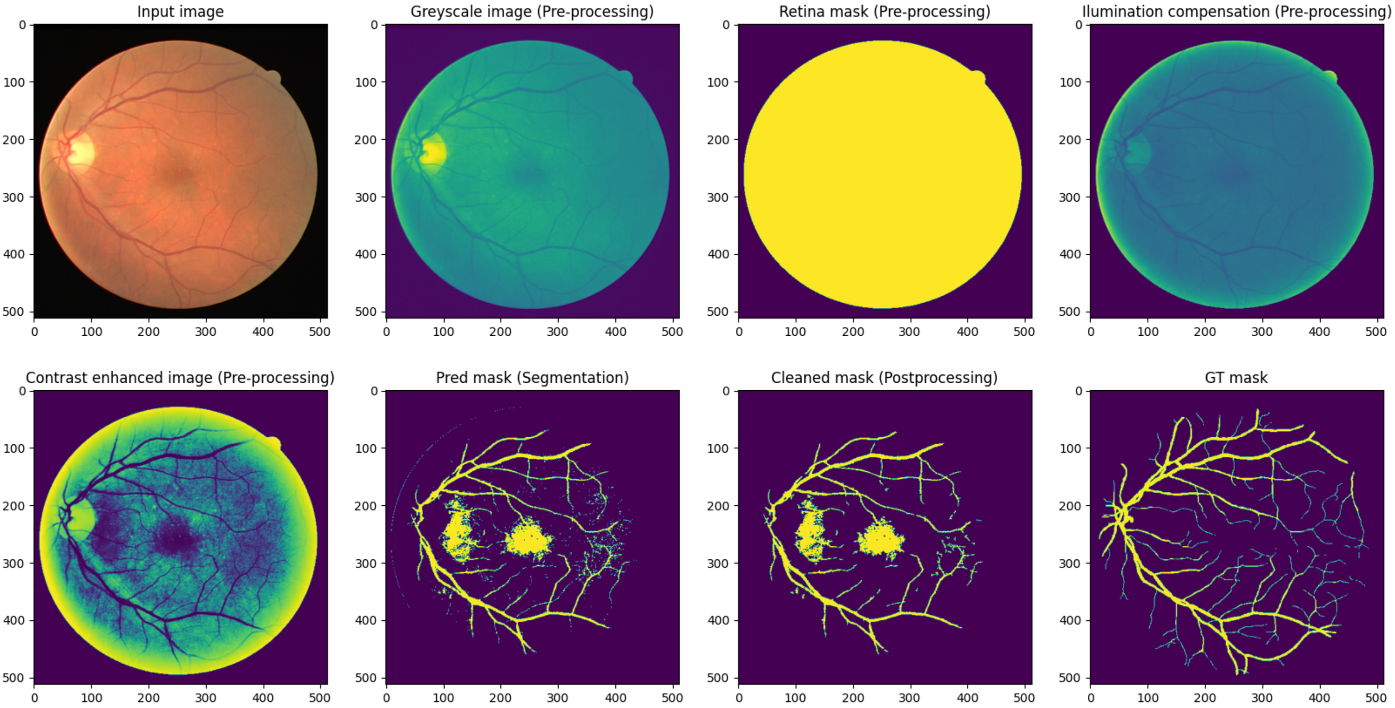

Figure 1: Output after each step using Baseline

Technique #1

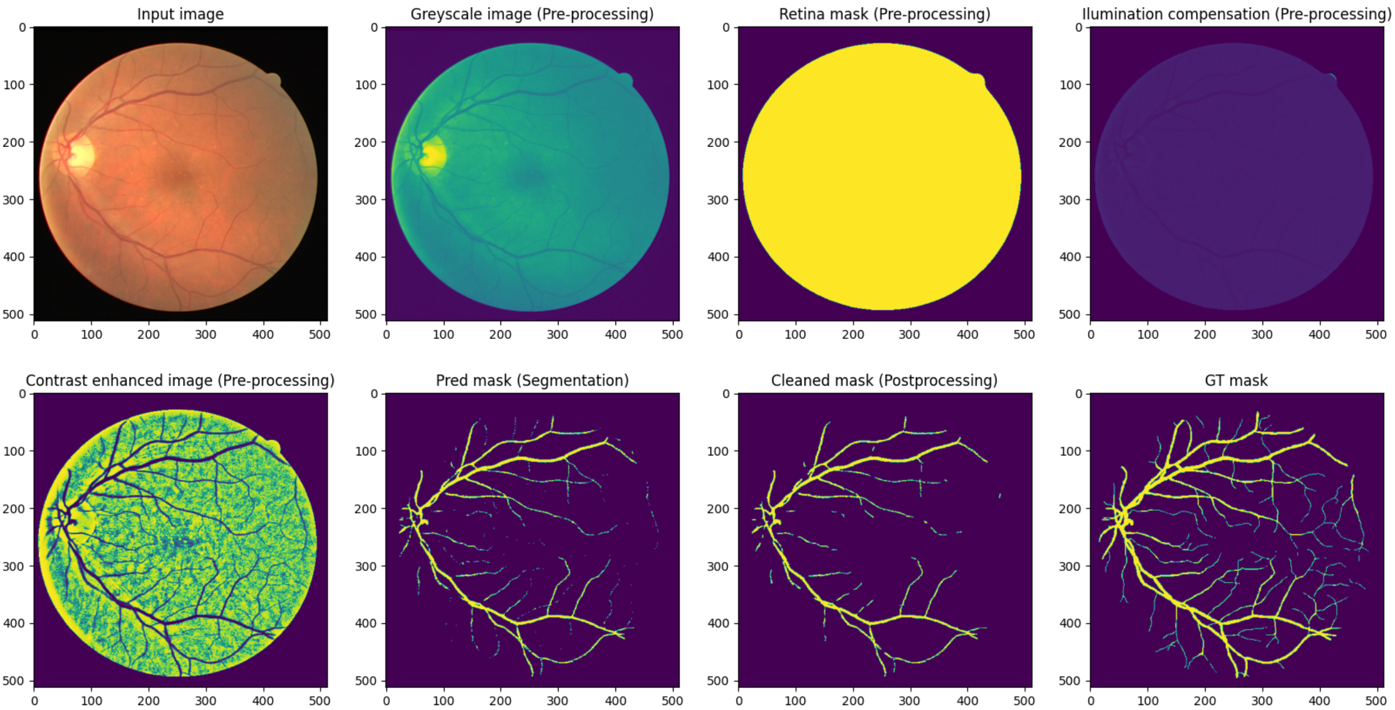

Figure 2: Output after each step using Technique 1

Technique #2

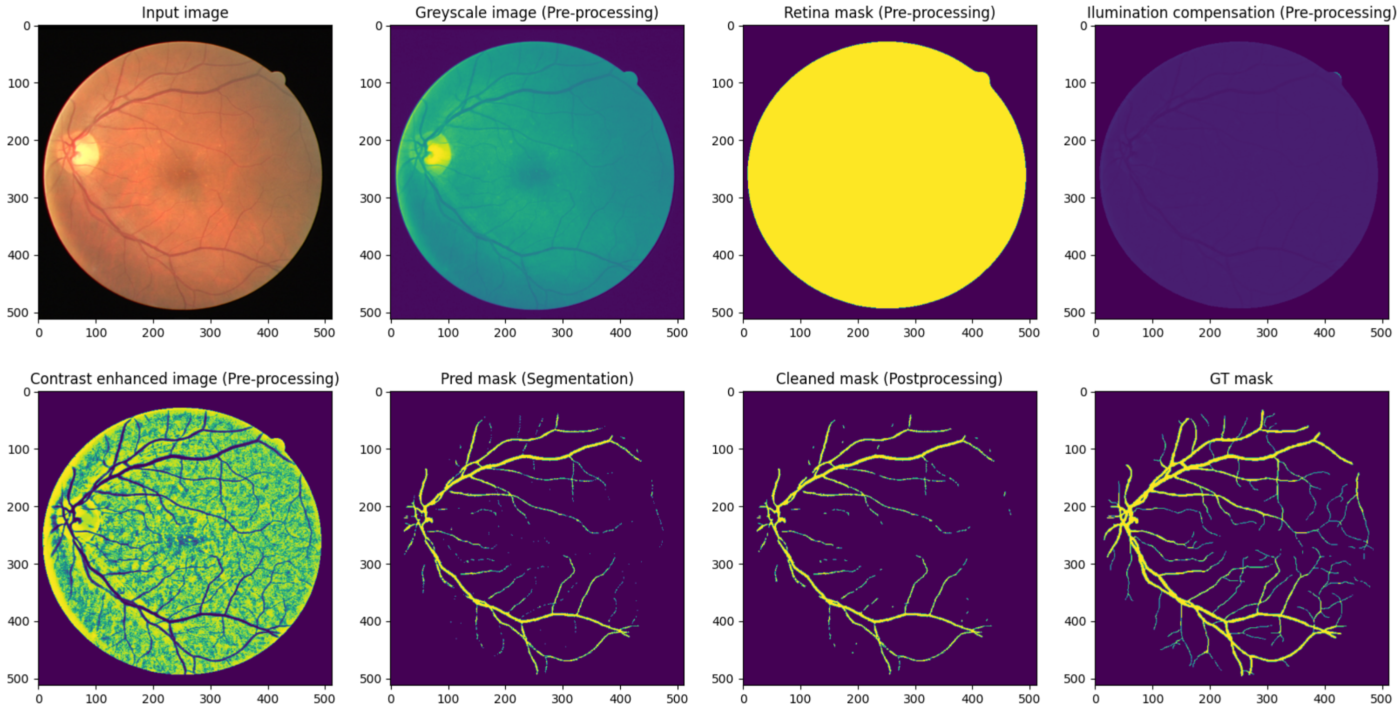

Figure 3: Output after each step using Technique 2

Technique #3

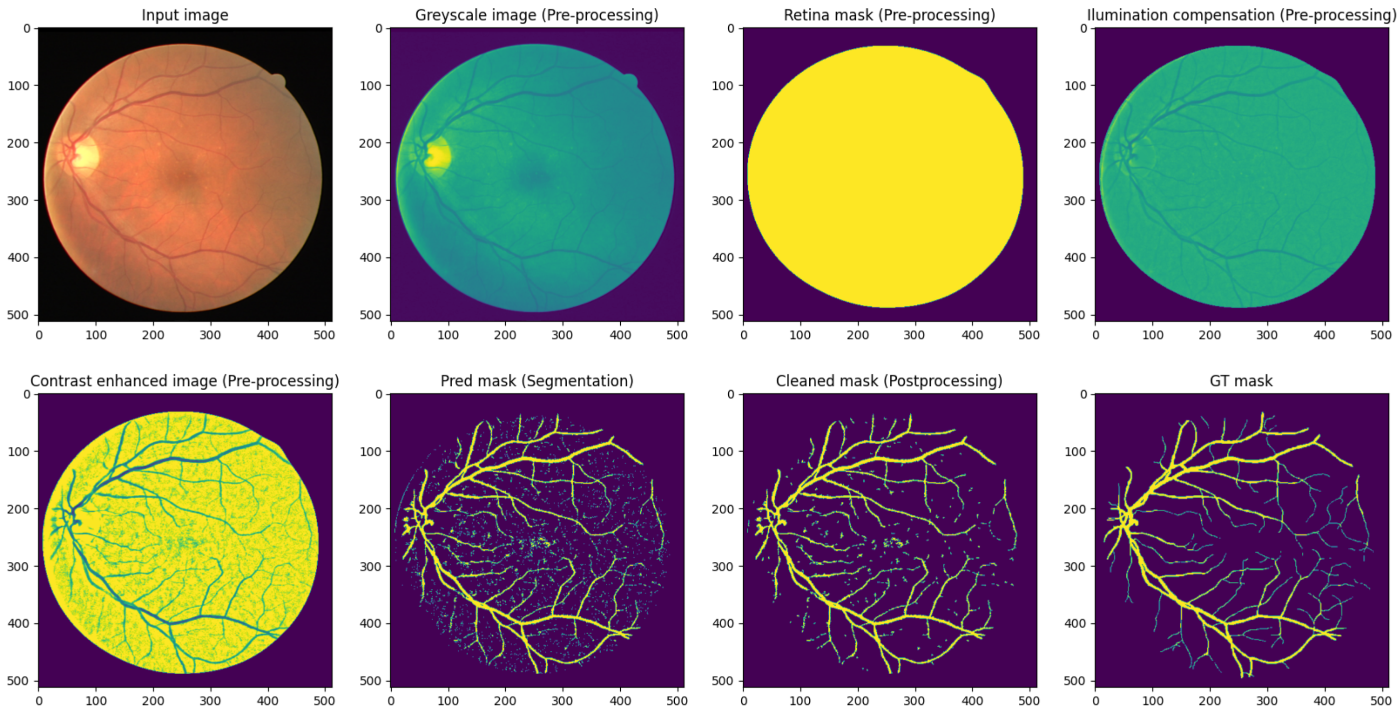

Figure 4: Output after each step using Technique 3

Technique #4

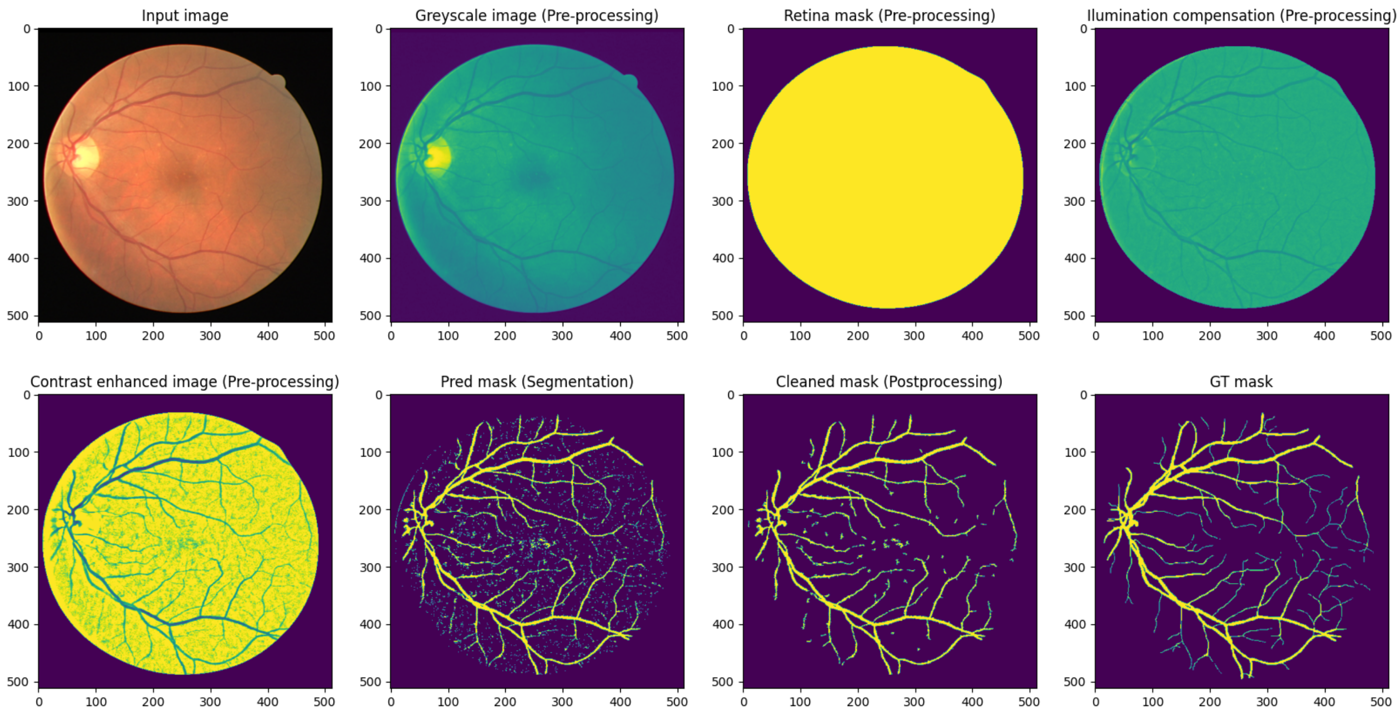

Figure 5: Output after each step using Technique 4

Technique #5

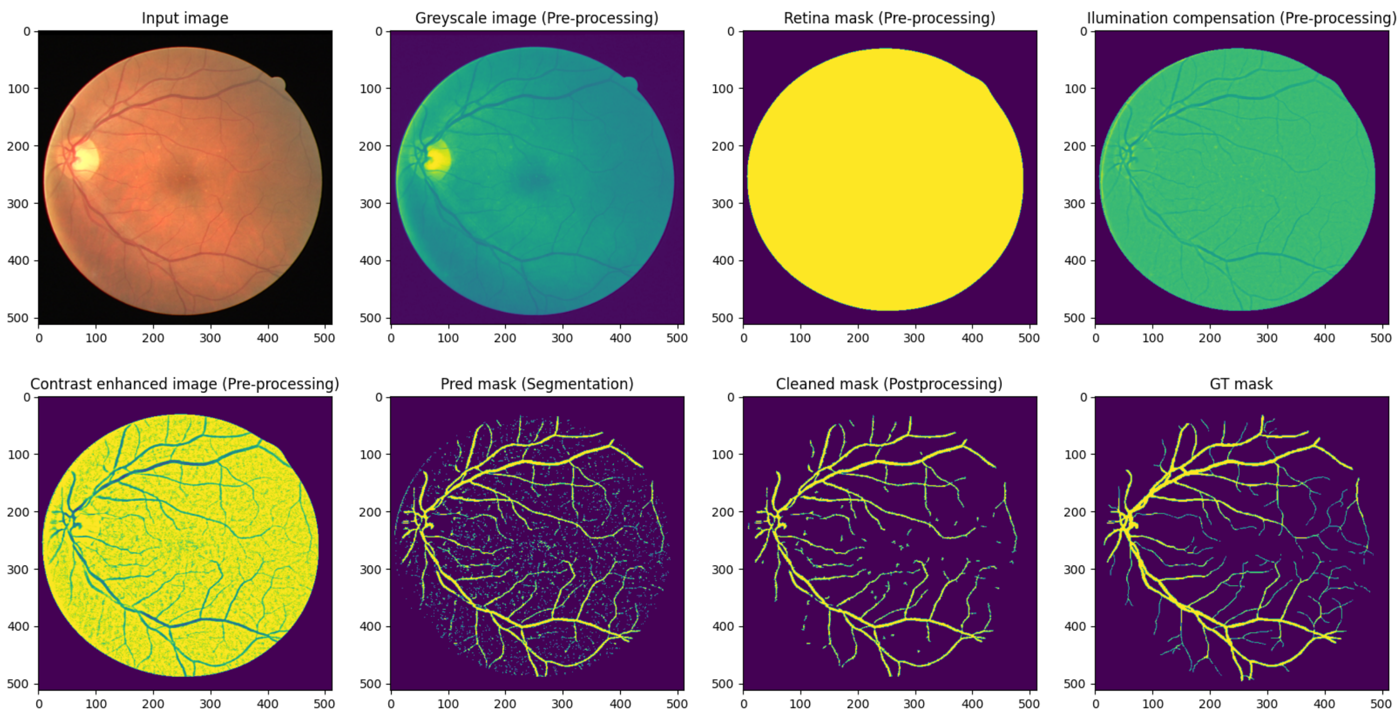

Figure 6: Output after each step using Technique 5

Technique #6

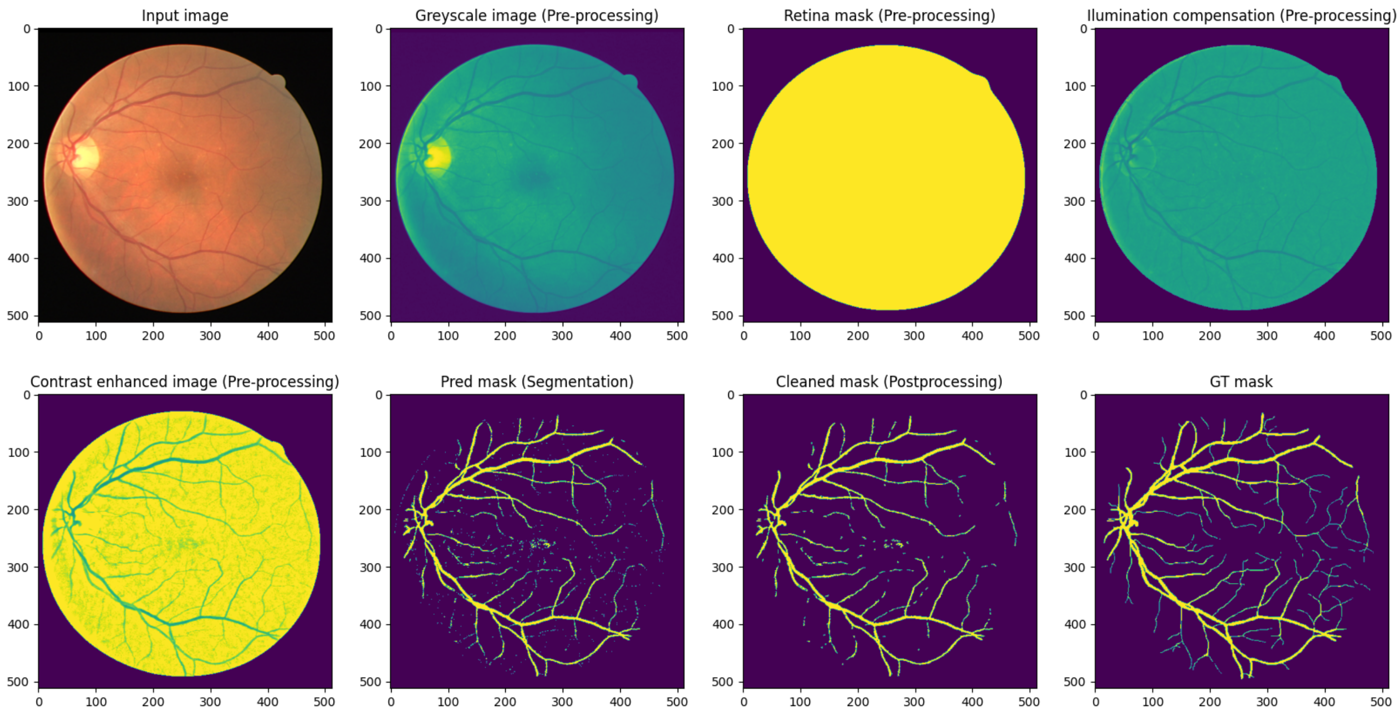

Figure 7: Output after each step using Technique 6

Technique #7

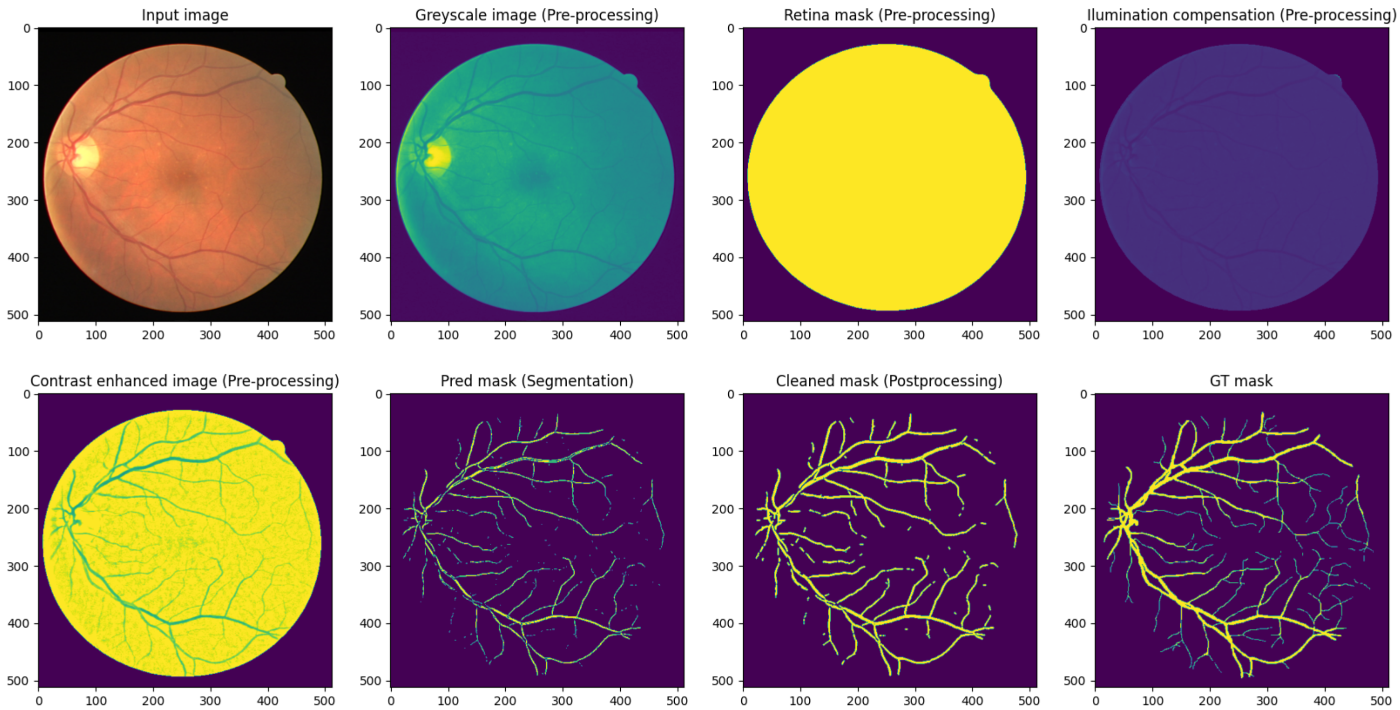

Figure 8: Output after each step using Technique 7

Technique #8

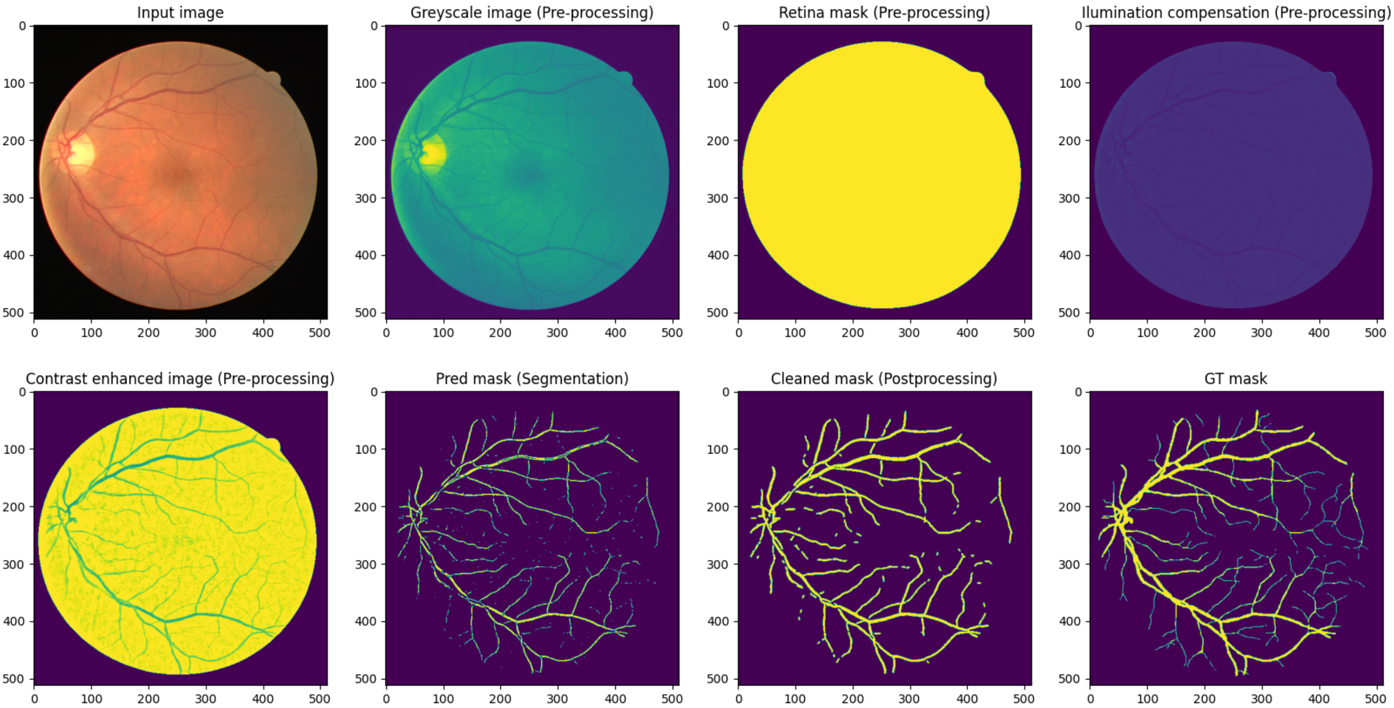

Figure 9: Output after each step using Technique 8