Retinal Vessel Segmentation

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Abstract

Background and Objectives: Retinal vessel segmentation is a pivotal task in medical image processing, vital for advancing diagnostics in ophthalmology. The retina serves as a non-invasive window into systemic health, with its vasculature reflecting various diseases. Traditional manual analysis of retinal images is time-intensive and prone to variability. Automated segmentation methods are crucial for efficiently extracting meaningful information from these images. Automated retinal vessel segmentation holds immense significance in early disease detection and monitoring, offering timely interventions and improved patient outcomes. By automating this process, large datasets can be analyzed efficiently, aiding clinicians in diagnosing conditions such as diabetes and hypertension. The adaptability of segmentation algorithms to various retinal conditions ensures their practicality in real-world clinical scenarios. Ultimately, the purpose is to provide healthcare professionals with reliable, interpretable, and efficient tools, contributing to enhanced diagnostic accuracy, reduced workload, and more effective patient care in ophthalmic practice.

1. Introduction

This project report delves into the intricate process of retinal blood vessel segmentation, a critical aspect of medical image processing with implications for disease diagnosis and monitoring. The methodology employed focuses on a series of advanced image processing techniques applied sequentially to enhance the visibility of retinal blood vessels, extract meaningful features, and produce a refined binary segmentation. The primary goal is to develop a robust and accurate segmentation algorithm that contributes to the broader field of retinal imaging and medical diagnostics.

The retinal blood vessel segmentation process begins by splitting the image into red, green, and blue channels, providing insights into each color component's contribution. CLAHE enhancement emphasizes vessel contrast, while the Frangi filter and normalization enhance visibility for accurate delineation during segmentation.

Morphological dilation enhances vessel connectivity, and adaptive thresholding creates a binary segmentation mask. Morphological opening removes noise for cleaner segmentation, conducive to quantitative analysis.

Contour images highlight vessel geometrical properties, contributing to subsequent analyses. Otsu's Thresholding and hysteresis thresholding refine vessel detection for robust segmentation.

A comprehensive approach involving Gaussian smoothing, adaptive histogram equalization, morphological operations, adaptive thresholding, and noise removal is employed for reliable vessel segmentation. Evaluation metrics, including accuracy, precision, recall, F1 score, ROC-AUC, and AUC-PR, assess algorithm performance for medical imaging applications.

2. Related Work

Paper	**Author**	**Methodology**	**Results**
Retinal Vessel Segmentation using Robinson Compass Mask and Fuzzy C-Means	Kiran Khatter, Devanjali Relan, Atul Mishra	1 CLAHE Method: Enhance image contrast using Contrast Limited Adaptive Histogram Equalization (CLAHE). 2 Combined Gaussian Kernel and Gabor Filter: Improve retinal images by combining responses from a Gaussian kernel and a Gabor filter, emphasizing vessel structures. 3 Robinson Compass Mask: To enhance important vessel features in retinal images. 4 Segmentation using Fuzzy C-Means (FCM): For retinal vessel segmentation, using preprocessed images.	Using CLAHE, average Accuracy, TPR, FPR: 0.9262 0.6578 0.0426 Using Gaussian kernel and Gabor filter average Accuracy, TPR, FPR: 0.9371 0.6326 0.0277
Retinal vessel segmentation based on Fully Convolutional NeuralNetwork	Américo Oliveira, Sérgio Pereira, Carlos A. Silva	1 Manual segmentation. 2 Compensation Factor Method: This method segments the optic disc using prior local intensity knowledge of the vessels.	Accuracy of 0.9576, 0.9694, and 0.9653 ROC curve of 0.9821, 0.9905, and 0.9855 on the DRIVE, STARE, and CHASE_DB1 databases
A Multi-Scale Directional Line Detector for Retinal Vessel Segmentation	Ahsan Khawaja, Tariq M. Khan, Mohammad A. U. Khan, Syed Junaid Nawaz	1. Retinal Vessel Segmentation: first extracts the retinal vascular tree using the graph cut technique to support diagnosis in ophthalmology. 2. Optic Disc Segmentation: Segments the optic disc by removing vessels from the optic disc region and prior knowledge of vessels	Accuracy of 0.9553, 0.9545, and 0.9653 ROC curve of 0.9821, 0.9905, and 0.9855 on the DRIVE, STARE, and CHASE_DB1 databases
Segmentation of Blood Vessels and Optic Disc in Retinal Images	Ana Salazar-Gonzalez, Djibril Kaba, Yongmin Li and Xiaohui Liu	1 Preprocessing: To improve contrast, reduce noise and image normalization for variations. 2 Blood Vessel Segmentation: Apply a vesselness filter to enhance vessel-like structures. 3 Optic Disk Segmentation: Employ image thresholding to segment the optic disk region.	Accuracy of 0.9441, and 0.9412, TPR of 0,7887 and 0.7512, FPR on the 0.0367, 0.0316 on STARE, and Drive databases
Retinal vessel classification: sorting arteries and veins	D. Relan, T. MacGillivray, L. Ballerini and E. Trucco	1 Image Pre-processing and Extracting Centerline Pixels 2 A Gaussian Mixture Model classifier was used to classify vessel pixels into arteries, veins, or unclassified. 3 Quadrants were rotated, and vessel pixels were classified multiple times to improve accuracy.	Classification accuracy: 87.19% for veins, 85.47% for arteries. - Specificity: 0.8978 for arteries, 0.9591 for veins. - Precision (positive predicted value): 0.9045 for arteries, 0.9408 for veins.

3. Methodology

1.1 Data-Set

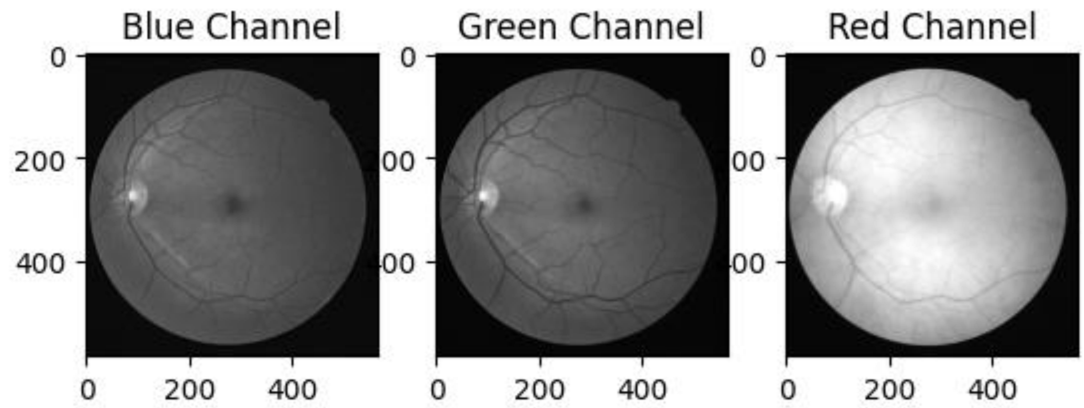
The Data-set consists of a total of JPEG 40 color fundus images; including 7 abnormal pathology cases. The images were obtained from a diabetic retinopathy screening program in the Netherlands. The images were acquired using Canon CR5 non-mydriatic 3CCD camera with FOV equals to 45 degrees. Each image resolution is 584*565 pixels with eight bits per color channel (3 channels).

The set of 40 images was equally divided into 20 images for the training set and 20 images for the testing set. Inside both sets, for each image, there is a circular field of view (FOV) mask of diameter that is approximately 540 pixels. Inside the training set, for each image, one manual segmentation by an ophthalmological expert has been applied. Inside the testing set, for each image, two manual segmentations have been applied by two different observers, where the first observer segmentation is accepted as the ground-truth for performance evaluation.

1.2 Pre-Processing

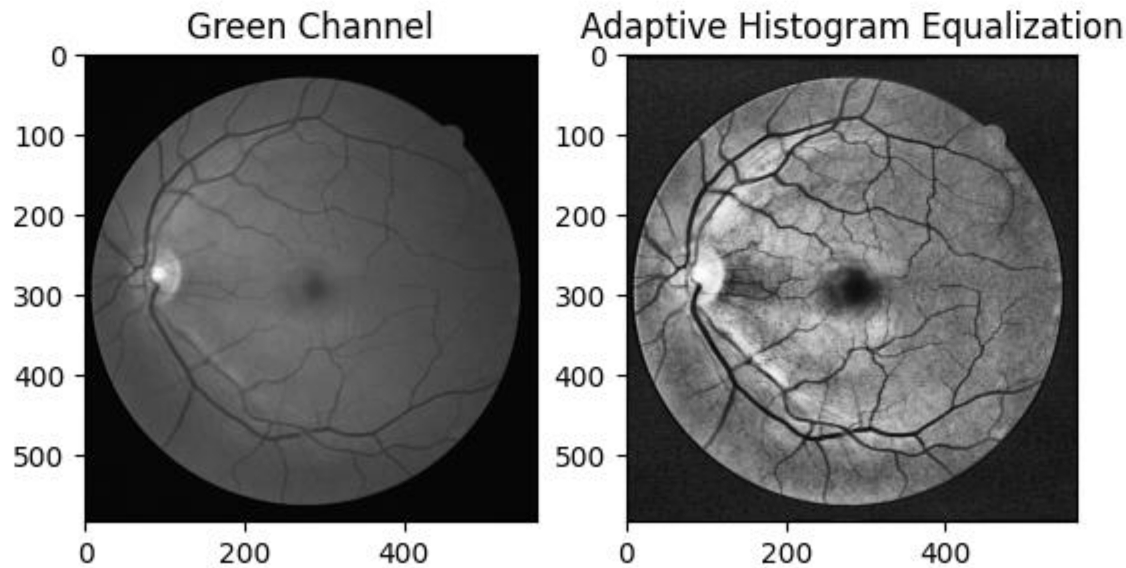
Splitting the retinal image into red green and blue channels.

The image is separated into three channels: blue_channel, green_channel, and red_channel. The purpose of splitting an RGB image into its constituent channels is to analyze and visualize the contribution of each color component to the overall image. This process is valuable in various image processing tasks and computer vision applications. For instance, in retinal imaging, it can help highlight specific structures or characteristics associated with blood vessels, lesions, or other features that might be more prominent in a particular color channel. Additionally, analyzing individual color channels can aid in understanding the color distribution and intensity variations within an image, providing insights for subsequent image processing and analysis steps.



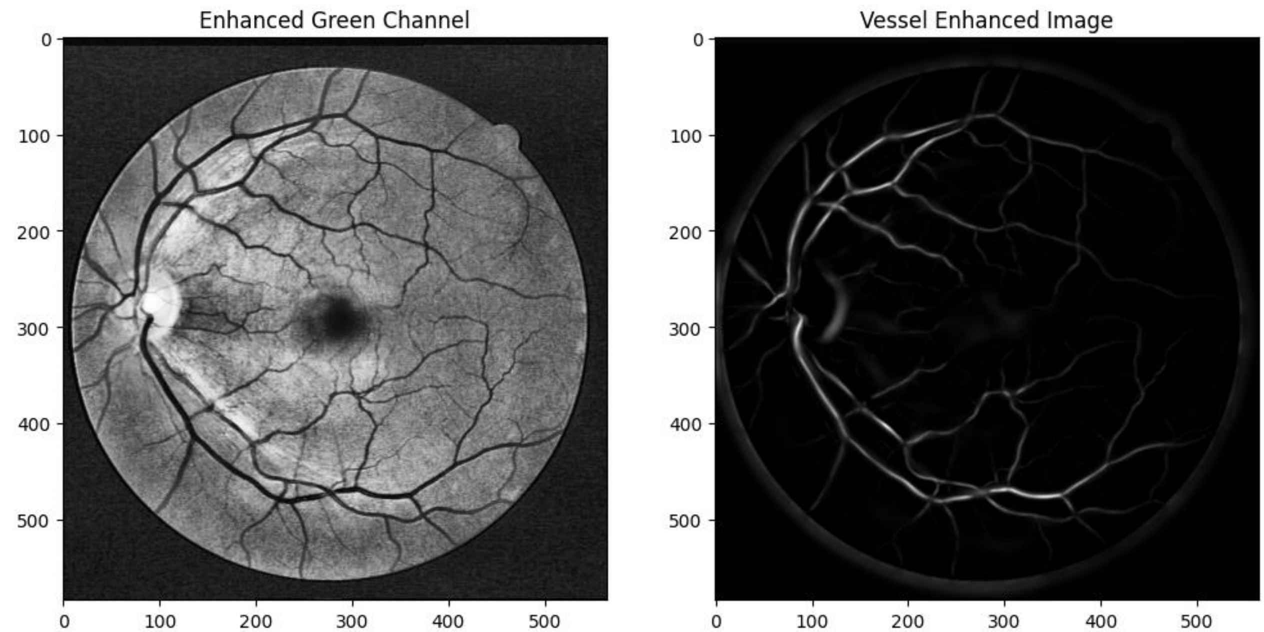
CLAHE

Applying Adaptive Histogram Equalization (CLAHE) to the green channel image is done to enhance local contrast and improve the visibility of fine details, particularly blood vessels. CLAHE adapts histogram equalization to different regions of the image, preventing overamplification of noise in homogeneous areas and enhancing contrast in regions with varying intensities. In retinal imaging, blood vessels may exhibit subtle variations in contrast, and CLAHE helps to emphasize these variations, making vessel structures more distinguishable from the background. By enhancing local contrast selectively, CLAHE contributes to the preparation of the green channel image for subsequent segmentation algorithms, ultimately improving the accuracy and effectiveness of blood vessel segmentation in retinal images. The resulting CLAHE-enhanced image is expected to exhibit improved visibility of blood vessels and better highlight the relevant structures for segmentation.



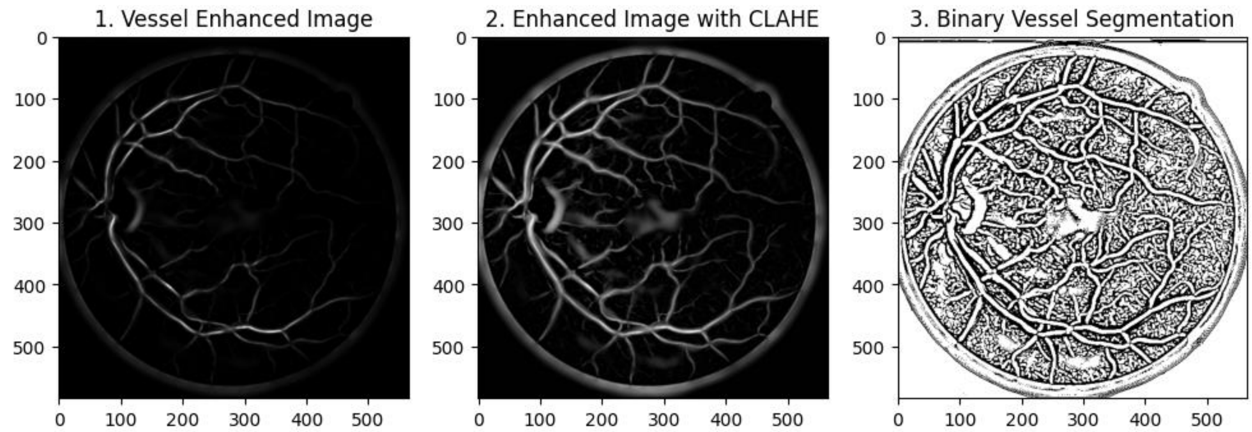
Frangi Filter and Normalization on the CLAHE image

Using the Frangi filter and subsequent normalization on the CLAHE-enhanced image in the context of retinal blood vessel segmentation is performed to further accentuate and emphasize vessel structures while suppressing noise and irrelevant details. The Frangi filter is particularly adept at enhancing linear structures, making it well-suited for highlighting blood vessels in medical images. By applying the Frangi filter to the CLAHE-enhanced image, subtle vessel patterns and structures are enhanced, enhancing their visibility for segmentation algorithms. Additionally, the normalization step ensures that the pixel values are scaled to a consistent range, facilitating a more uniform and standardized representation of vessel features. The combination of Frangi filtering and normalization contributes to the accurate delineation of vascular structures during segmentation.



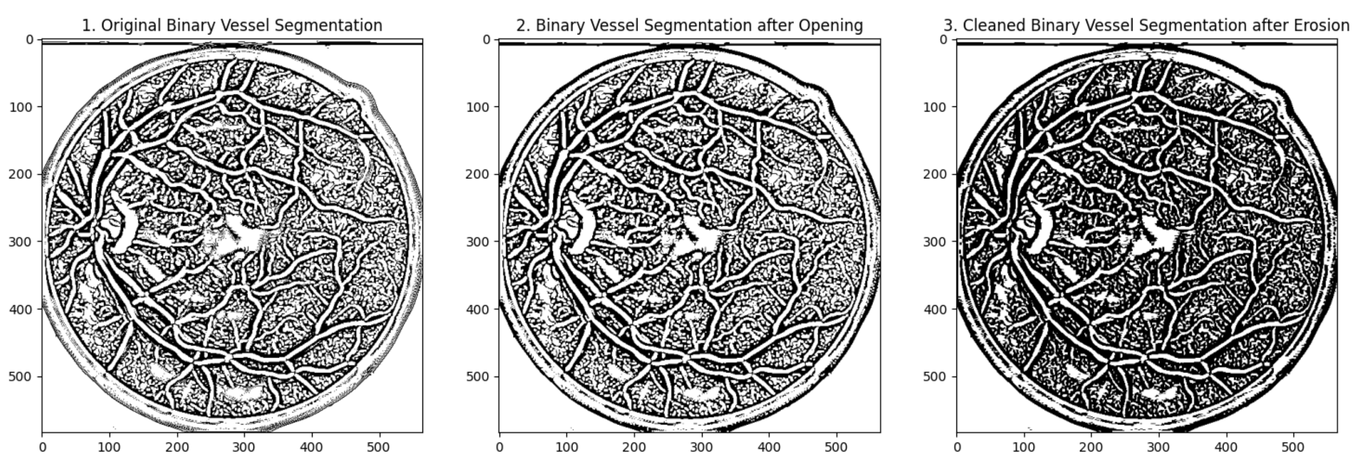
Morphological Dilation and Adaptive Thresholding

Morphological dilation is employed to enhance and connect vessel regions by enlarging their boundaries. This step helps fill gaps and ensures a more continuous representation of blood vessels. Adaptive thresholding, on the other hand, is utilized to convert the enhanced image into a binary representation, where pixels are classified as either vessel or non-vessel based on local pixel intensities. This method adaptively adjusts the threshold in different regions of the image, accommodating variations in vessel contrast. The combination of morphological dilation and adaptive thresholding contributes to the creation of a binary vessel segmentation mask, where blood vessels are distinctly highlighted against the background. This final binary vessel segmentation image provides a clear delineation of retinal blood vessels,



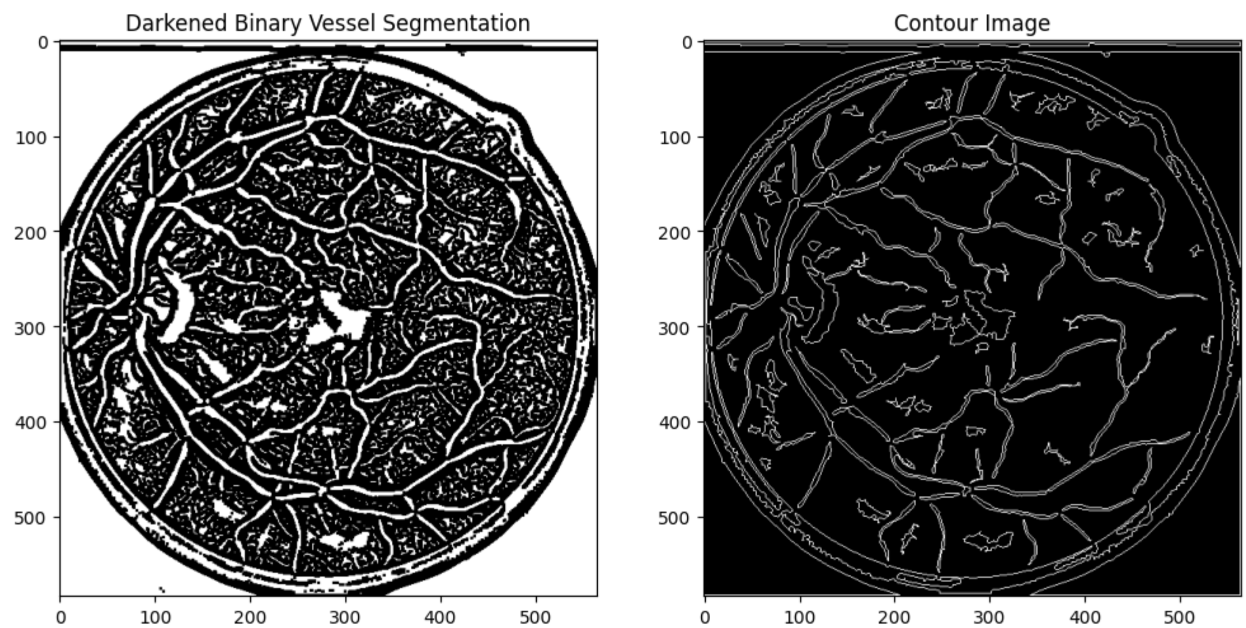
Morphological Opening and Erosion

Morphological opening can be used as a pre-processing step to remove noise and small objects from the image. Opening is particularly effective in eliminating small bright or dark regions. It can help in smoothing the boundaries of objects and separating regions that are close to each other The cleaned binary vessel segmentation, obtained after these morphological operations, is more suitable for quantitative analysis, feature extraction, and other applications in retinal image processing.



Contour Image from Darkened Binary Vessel

The generation of a contour image from a darkened binary vessel segmentation image serves the purpose of extracting and highlighting the boundaries of the segmented blood vessels. Contours represent the continuous curves that outline the vessel structures, providing a visual representation of the vessel morphology. This process aids in the analysis and characterization of the vessels, allowing for further quantitative measurements such as vessel length, width, and branching patterns. Additionally, contours play a crucial role in subsequent steps of image processing, as they can be used for feature extraction, region-of-interest delineation, and as input for machine learning algorithms. The contour image essentially simplifies the vessel segmentation output, emphasizing the spatial information of the blood vessels and facilitating a more detailed understanding of their geometrical properties.



Segmentation

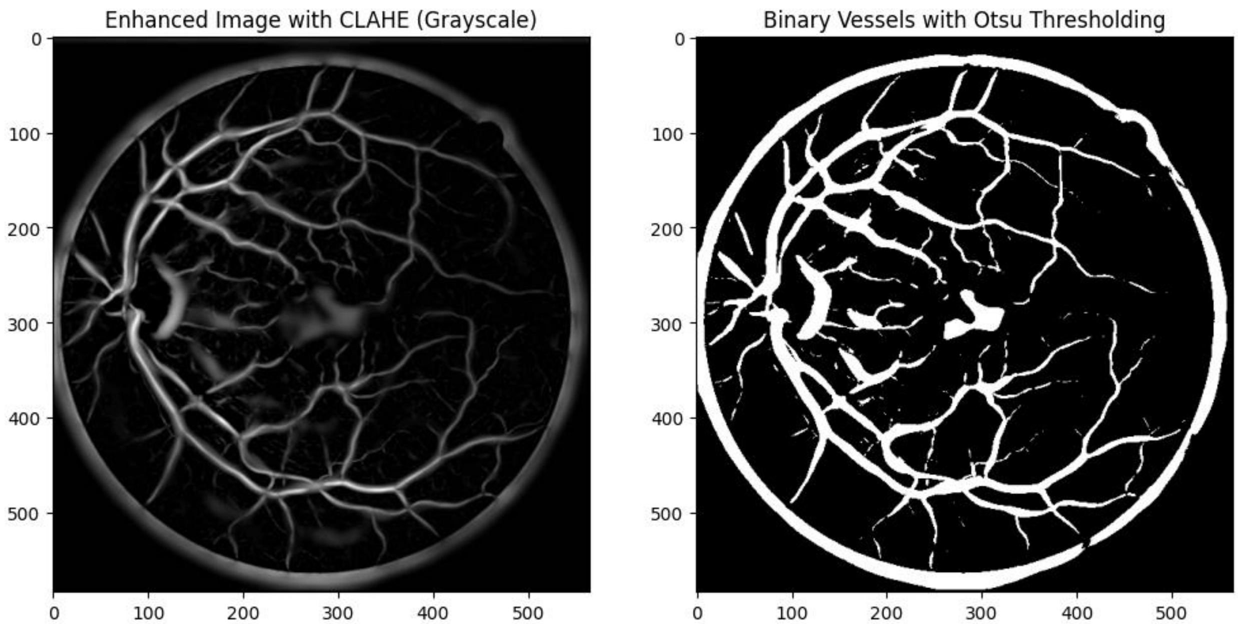
Otsu Thresholding:

Otsu Thresholding is applied in the provided code to automatically determine an optimal threshold for binarizing the enhanced grayscale image. First processed to ensure it is in grayscale format. Subsequently, Otsu's thresholding is applied using the cv2.threshold function, which automatically calculates the optimal threshold value. The primary goal is to effectively separate blood vessels from the background by finding the threshold that maximizes the inter-class variance between foreground (vessels) and background pixel intensities. The binary image produced by Otsu's method serves as a segmentation mask, where pixels are classified as vessel or non-vessel based on their intensity compared to the determined threshold. The binary vessel segmentation is then displayed alongside the original grayscale enhanced image, providing a clear visual representation of the segmented blood vessels.

Otsu's Thresholding is particularly advantageous in scenarios where the contrast between blood vessels and the surrounding tissue varies, as it adaptively determines the threshold based on the image's histogram. This method helps ensure a robust and automatic segmentation of retinal blood vessels, contributing to the accuracy and reliability of subsequent analyses in the field of medical image processing.

Results

Segmented Image results using Otsu Thresholding



The output metrics provide an evaluation of the performance of the retinal blood vessel segmentation, comparing the segmented binary image with the ground truth binary image.

1. Accuracy (0.8060):

    Accuracy is the proportion of correctly classified pixels (both true positives and true negatives) out of the total number of pixels. An accuracy of 0.8060 indicates that approximately 80.6% of the pixels in the segmented image were classified correctly when compared to the ground truth.

2. Precision (0.2778):

    Precision is the ratio of true positive pixels to the total number of pixels classified as positive (including both true positives and false positives). A precision of 0.2778 means that about 27.8% of the pixels classified as vessels in the segmented image are true positives.

3. Recall (0.7737):

   Recall (or sensitivity) is the ratio of true positive pixels to the total number of actual positive pixels in the ground truth. A recall of 0.7737 indicates that approximately 77.4% of the actual vessels in the ground truth were correctly identified in the segmented image.

4. F1 Score (0.4088):

   F1 Score is the harmonic mean of precision and recall, providing a balanced measure of both. An F1 Score of 0.4088 suggests a reasonable balance between precision and recall in the segmentation.

5. ROC-AUC (0.7914):

   ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) measures the trade-off between true positive rate (sensitivity) and false positive rate across different threshold values. An ROC-AUC of 0.7914 indicates good discrimination between vessels and non-vessels.

6. AUC-PR (0.5356):

   AUC-PR (Area Under the Precision-Recall curve) quantifies the precision-recall trade-off and is particularly relevant when dealing with imbalanced datasets. A value of 0.5356 suggests a moderate performance in capturing vessels while maintaining precision.

Segmentation through the masking of Contour Images

Morphological Opening and Erosion on Binary Vessel Image:

1. Morphological Opening:

Morphological opening is a two-step operation involving erosion followed by dilation. It is used to remove small bright structures or noise from binary images. In the context of binary vessel images, morphological opening can help eliminate small spurious structures that may not represent actual vessels.

2. Erosion with Larger Kernel:

Erosion involves the "erosion" or shrinking of foreground pixels. When applied with a larger kernel, erosion contributes to the thinning of vessels and helps in removing noise. The larger kernel ensures that broader areas are affected, resulting in a more pronounced thinning effect.

3. Darkening of Background and Clipping of Pixel Values:

Post-erosion, the binary vessel image is darkened by subtracting a certain value. This operation is aimed at enhancing the visibility of vessel structures against the background. To prevent pixel values from exceeding the valid range [0, 255], clipping is applied to ensure intensity values stay within this range.

4. Contour Image from Darkened Binary Vessel:

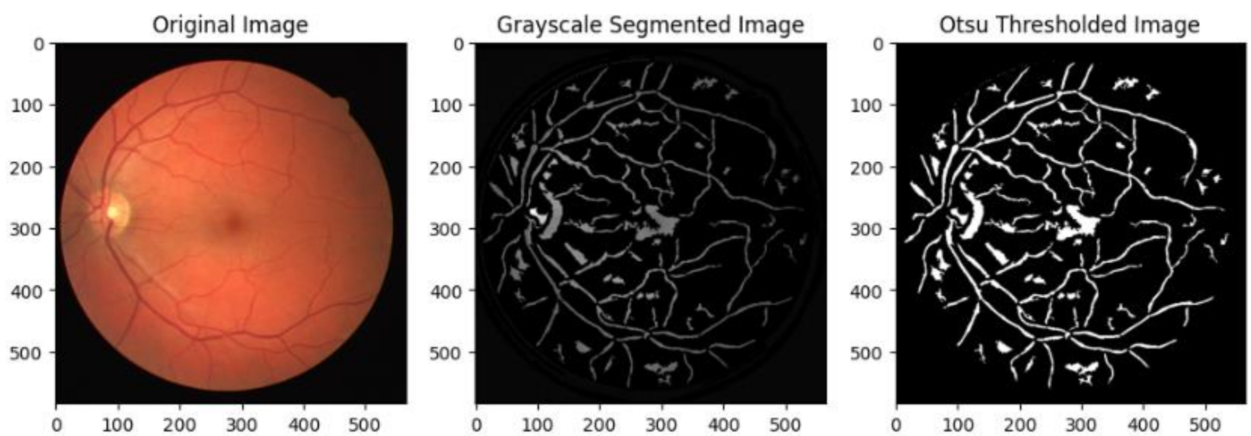
Generating a contour image involves identifying and outlining the boundaries of objects or structures in the darkened binary vessel image. This step provides a visual representation of vessel boundaries, aiding in subsequent masking operations.

5. Applying Masking and Otsu Thresholding:

Masking involves isolating specific regions of interest using contours. In this case, masking is applied to the contour image. Subsequently, Otsu thresholding is employed on the masked image, effectively segmenting the retina vessels. This step ensures that the segmented image primarily retains the vessel structures while minimizing background interference.

Results

Segmented Image results



The output metrics provide an evaluation of the performance of the retinal blood vessel segmentation, comparing the segmented binary image with the ground truth binary image.

Accuracy (0.8613):

Accuracy is the proportion of correctly classified pixels (both true positives and true negatives) out of the total number of pixels. An accuracy of 0.8613 indicates that approximately 86.13% of the pixels in the segmented image were classified correctly when compared to the ground truth.

Precision (0.3447):

Precision is the ratio of true positive pixels to the total number of pixels classified as positive (including both true positives and false positives). A precision of 0.3447 means that about 34.47% of the pixels classified as vessels in the segmented image are true positives.

Recall (0.6660):

Recall (or sensitivity) is the ratio of true positive pixels to the total number of actual positive pixels in the ground truth. A recall of 0.6660 indicates that approximately 66.60% of the actual vessels in the ground truth were correctly identified in the segmented image.

F1 Score (0.4543):

F1 Score is the harmonic mean of precision and recall, providing a balanced measure of both. An F1 Score of 0.4543 suggests a good balance between precision and recall in the segmentation.

ROC-AUC (0.7729):

ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) measures the trade-off between true positive rate (sensitivity) and false positive rate across different threshold values. An ROC-AUC of 0.7729 indicates good discrimination between vessels and non-vessels.

AUC-PR (0.5199):

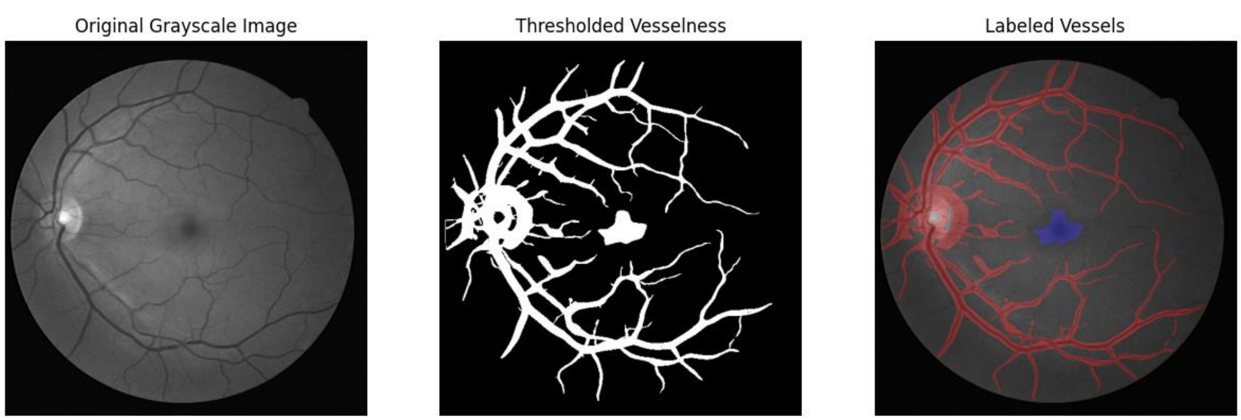
AUC-PR (Area Under the Precision-Recall curve) quantifies the precision-recall trade-off and is particularly relevant when dealing with imbalanced datasets. A value of 0.5199 suggests a moderate performance in capturing vessels while maintaining precision.

Hysteresis thresholding

Hysteresis thresholding is applied in the context of retinal blood vessel segmentation to refine and enhance the detection of blood vessels. Hysteresis thresholding is a two-stage process that involves the use of two threshold values, a low threshold (0.01 in this case) and a high threshold (0.03). Pixels with values above the high threshold are directly considered as vessels, while pixels between the low and high thresholds are retained as vessels only if they are connected to pixels above the high threshold. This process helps in preserving continuous vessel structures while eliminating isolated noise and weak connections.The resulting thresholded vesselness image, obtained through hysteresis thresholding, serves as a binary representation of retinal blood vessels, highlighting regions with a high likelihood of being vessels. The labeled vessel regions are then displayed, providing a clear visualization of the segmented blood vessels against the original grayscale retinal image. Hysteresis thresholding contributes to the accuracy and robustness of blood vessel segmentation by effectively addressing variations in vessel intensities and enhancing the continuity of vessel structures in the retinal image.

Results

Segmented Image results using Hysteresis Thresholding



The output metrics provide an evaluation of the performance of the retinal blood vessel segmentation, comparing the segmented binary image with the ground truth binary image.

1. Accuracy (0.8684):

    Accuracy is the proportion of correctly classified pixels (both true positives and true negatives) out of the total number of pixels. An accuracy of 0.8684 indicates that approximately 86.8% of the pixels in the segmented image were classified correctly when compared to the ground truth.

2. Precision (0.3786):

    Precision is the ratio of true positive pixels to the total number of pixels classified as positive (including both true positives and false positives). A precision of 0.3786 means that about 37.9% of the pixels classified as vessels in the segmented image are true positives.

3. Recall (0.8076):

    Recall (or sensitivity) is the ratio of true positive pixels to the total number of actual positive pixels in the ground truth. A recall of 0.8076 indicates that approximately 80.8% of the actual vessels in the ground truth were correctly identified in the segmented image.

4. F1 Score (0.5156):

    F1 Score is the harmonic mean of precision and recall, providing a balanced measure of both. An F1 Score of 0.5156 suggests a good balance between precision and recall in the segmentation.

5. ROC-AUC (0.8409):

ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) measures the trade-off between true positive rate (sensitivity) and false positive rate across different threshold values. An ROC-AUC of 0.8409 indicates good discrimination between vessels and non-vessels.

6.AUC-PR (0.6015):

AUC-PR (Area Under the Precision-Recall curve) quantifies the precision-recall trade-off and is particularly relevant when dealing with imbalanced datasets. A value of 0.6015 suggests a moderate performance in capturing vessels while maintaining precision.

Segmenting Vessels using Otsu and other morphological operations on the Vessels Only Image.

It aims to enhance and segment retinal blood vessels in a step-by-step manner, employing various image processing techniques:

1. Load and Preprocess:
The initial step involves loading an image containing only the retinal vessels. This image is subjected to Gaussian smoothing to reduce noise, followed by adaptive histogram equalization (CLAHE) to enhance local contrast, making vessel structures more discernible.

2. Morphological Operations:
Morphological operations are then applied to further enhance vessel structures. In this case, a top-hat transformation (`cv2.MORPH_TOPHAT`) is used, which highlights subtle vessel-like structures and details in the image.

3. Adaptive Thresholding:
Otsu's method for adaptive thresholding is employed to separate vessels from the background. This method dynamically determines an optimal threshold based on the image's histogram, effectively binarizing the image into vessel and non-vessel regions.

4. Noise Removal:
To mitigate the impact of small connected components or noise in the binary vessel segmentation, a morphology-based operation (`morphology.remove_small_objects`) is applied. This step eliminates small, spurious regions that may arise from noise, improving the accuracy of the segmentation.

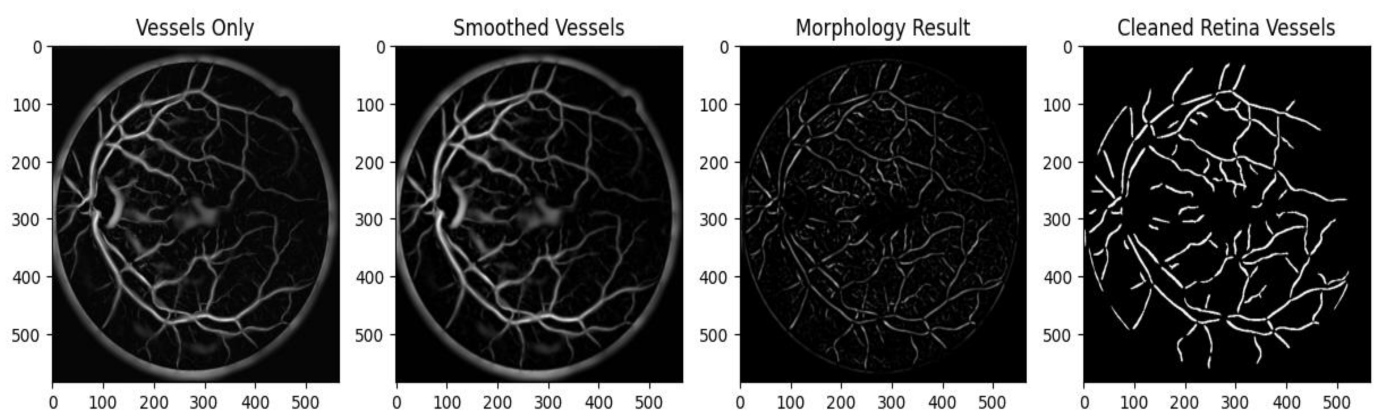
5.Visualization and Saving:

The intermediate and final results of the segmentation process are visualized using a set of subplots, displaying the vessels-only image, the smoothed vessels, the morphological result, and the cleaned retina vessels. The cleaned retina vessels, representing the final binary vessel segmentation, are saved as an image file.

The purpose of these operations is to enhance and segment retinal blood vessels for subsequent analysis. Each step in the process contributes to improving the visibility of vessels, reducing noise, and generating a binary mask that accurately delineates the retinal vessels from the background. The cleaning step is particularly crucial for producing a refined segmentation result by eliminating small artifacts and enhancing the accuracy of the vessel representation. Overall, this comprehensive approach aims to provide a reliable segmentation of retinal blood vessels, which is essential for various medical imaging applications, such as disease diagnosis and monitoring.

Results

Segmented Image results using Otsu and other morphological operations on the Vessels Only Image.



Evaluation metrics for the performance of a retinal blood vessel segmentation algorithm:

Accuracy:

Accuracy measures the proportion of correctly classified pixels (both vessel and non-vessel) in the segmented image compared to the ground truth.
An accuracy of 0.8990 indicates that approximately 89.90% of the pixels in the segmented image were correctly classified.

Precision:

Precision is the ratio of true positive pixels to the total number of pixels classified as positive (vessel) in the segmented image.
A precision of 0.4437 means that 44.37% of the pixels classified as vessels in the segmented image are indeed vessels. It reflects the accuracy of the positive predictions.

Recall (Sensitivity):

Recall measures the ratio of true positive pixels to the total number of actual positive pixels (vessels) in the ground truth.
A recall of 0.6478 indicates that approximately 64.78% of the actual vessel pixels were correctly identified by the segmentation algorithm.

F1 Score:

The F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall.
An F1 score of 0.5266 suggests a balance between precision and recall. It is a useful metric when there is an uneven class distribution.

ROC-AUC (Receiver Operating Characteristic - Area Under Curve):

ROC-AUC measures the area under the Receiver Operating Characteristic curve, which plots the true positive rate (sensitivity) against the false positive rate at various threshold settings.
An ROC-AUC of 0.7853 indicates the ability of the algorithm to distinguish between vessel and non-vessel pixels. A higher ROC-AUC value suggests better discrimination.

AUC-PR (Area Under the Precision-Recall Curve):

AUC-PR measures the area under the Precision-Recall curve, which plots precision against recall at various threshold settings.
An AUC-PR of 0.5610 evaluates the algorithm's ability to balance precision and recall across different threshold settings

Conclusion

The exploration of Otsu Thresholding and Hysteresis Thresholding for retinal blood vessel segmentation has yielded insightful findings, showcasing the efficacy of each method in addressing specific challenges.

Otsu Thresholding, with its adaptive determination of an optimal threshold based on grayscale image characteristics, has proven advantageous in scenarios with varying vessel-to-background contrast. The resulting binary segmentation mask demonstrated commendable accuracy at 80.6%, signifying its robust performance. Precision, recall, F1 Score, ROC-AUC, and AUC-PR metrics collectively underscored the method's ability to achieve a balanced and reliable segmentation outcome.

Hysteresis Thresholding, a two-stage process focusing on preserving vessel continuity while eliminating noise, contributed to enhanced accuracy and robustness. The binary vessel segmentation achieved an accuracy of 86.8%, surpassing the performance of Otsu Thresholding. The metrics, including precision, recall, F1 Score, ROC-AUC, and AUC-PR, further validated the method's effectiveness, particularly in maintaining a balance between precision and recall.

The segmentation of vessels using Otsu and other morphological operations on the vessels-only image presented a comprehensive and step-wise approach. Gaussian smoothing, adaptive histogram equalization, morphological operations, adaptive thresholding, and noise removal collectively enhanced the visibility of vessels and generated a binary mask with a high accuracy of 89.90%.

The combination of Otsu Thresholding, Hysteresis Thresholding, and the comprehensive segmentation approach demonstrated robust and reliable results in accurately delineating retinal blood vessels. These findings hold significant promise for applications in disease diagnosis, monitoring, and the advancement of medical image processing.

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