CDS6334

VISUAL INFORMATION PROCESSING

Individual Assignment

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Abstract

This report presents a comprehensive analysis of retinal vessel segmentation algorithms applied to fundus images. The task involved evaluating segmentation performance using two distinct datasets with metrics such as Error, Precision, Recall, and Intersection over Union (IoU). The first dataset achieved an Error of 0.2873, Precision of 0.7378, Recall of 0.7104, and IoU of 0.5597, demonstrating reliable segmentation. The second dataset, designed to test algorithm robustness, yielded an Error of 0.2881, Precision of 0.7354, Recall of 0.7227, and IoU of 0.5604. Key methodological differences between the two algorithms were analyzed to understand their impact on performance. This report also includes actionable suggestions for improvement based on observed limitations, offering insights into enhancing segmentation pipelines for diverse and challenging datasets.

Introduction

Retinal vessel segmentation from fundus images is a critical task in medical image analysis, facilitating the detection and monitoring of ocular and systemic diseases such as diabetic retinopathy and hypertension. The primary motivation for this task lies in its potential to support early diagnosis and treatment planning, significantly improving patient outcomes. Fundus imaging, widely used in ophthalmology, offers a non-invasive method to visualize the retinal vasculature. However, the complexity of vessel patterns and background noise introduces significant challenges to achieving accurate segmentation. This report evaluates two segmentation pipelines tailored for datasets of varying complexity, analyzing their performance and exploring their potential applications in medical diagnostics, including automated screening systems, disease progression monitoring, and integration into clinical workflows.

Description of Methods

Algorithm Overview

The Python script, `imageSegment.py for both add_dataset and Dataset images`, implement retinal vessel segmentation algorithms tailored for their distinct datasets. These scripts employ a structured pipeline of preprocessing, noise reduction, thresholding, and post-processing to produce binary masks that accurately delineate retinal vessels from the background. The segmentation process integrates advanced techniques like CLAHE for contrast enhancement, adaptive thresholding for vessel highlighting, and morphological operations for refining segmentation outputs. Each script is customized to its dataset, with parameter adjustments designed to handle unique challenges such as varying noise levels, lighting conditions, and vessel appearances.

Detailed Steps to Achieve Results

1. **Input Image Preprocessing**:
    - Input images are read in BGR format and converted to process the green channel, which provides the highest contrast for retinal vessels.
    - The preprocessing pipeline uses CLAHE (Contrast Limited Adaptive Histogram Equalization) to enhance local contrast, ensuring better visibility of fine details. For the initial dataset, `clipLimit=2` and `tileGridSize=(3, 3)` were applied, while the additional dataset required adjustments to `clipLimit=2.7` and `tileGridSize=(2, 2)` to handle its complexity.
2. **Noise Reduction through Median Filtering**:
    - A median filter with a kernel size of 1 is applied to smoothen the image and suppress noise, crucial for preserving vessel edges without distorting their structures.This step ensures minimal distortion of fine vessel details, which are crucial for accurate segmentation. Median filtering is especially effective for removing salt-and-pepper noise, which is common in medical images.

3. **Adaptive Thresholding with Mean-C Filtering**:
   - `The first dataset` sets the mean filter size to `18x18` with a threshold offset `C` of `-10`, enhancing vessel structures effectively in the simpler dataset by emphasizing high-contrast regions corresponding to vessels. In `the second dataset`, the mean filter size remains unchanged at `18x18`, but the threshold offset `C` is adjusted to `-8` to address more challenging vessel appearances and reduce false negatives. This smaller offset increases sensitivity to faint vessels in noisier images while maintaining effective segmentation.
4. **Morphological Operations for Refinement**:
   - Morphological closing followed by opening is applied to eliminate small gaps and artifacts in the segmented vessels. A kernel of size 1 was consistently used to maintain computational efficiency and precision.The choice of a small kernel ensures that fine vessel structures are preserved while achieving noise reduction.
5. **Contour Detection and Mask Creation**:
   - In both scripts, contours are detected using `cv2.findContours`, and the largest contour is selected to generate the binary mask. The mask is refined using a `5x5` kernel (`np.ones((5, 5), np.uint8)`) for morphological closing and opening to smooth the edges and ensure vessel connectivity. This approach prioritizes the most prominent vessel regions, reducing false positives caused by smaller artifacts.
6. **Post-Processing with Smoothing**:
   - Gaussian smoothing with slight adjustments between datasets reduces abrupt transitions in the segmentation output, producing cleaner masks. For the initial dataset, a standard Gaussian blur was applied with a kernel size of (5, 5) and a sigma value of 1 to achieve a balance between noise reduction and detail preservation. For the additional dataset, Gaussian smoothing is applied with the same kernel size `(5, 5)` but a sigma value of `0`. In this case, OpenCV automatically calculates the sigma based on the kernel size, effectively adapting to the image characteristics. This adjustment addresses the higher noise levels in the additional dataset, enhancing vessel connectivity.

7. **Final Binarization**:
    ○ The post-processed image is binarized, ensuring that the output mask contains only two values: 0 for the background and 1 for the vessels. Thresholding is performed at 128, providing a consistent separation between vessels and non-vessel regions.This step standardizes the output, making it compatible with downstream evaluation metrics.

The Differences Between Scripts

The main distinctions lie in parameter settings to accommodate dataset variability:

- CLAHE parameters were intensified in the second script to adapt to higher image complexity.
- The threshold offset C was adjusted to better delineate vessels in challenging scenarios, enhancing Recall with a slight impact on Precision.
- While both scripts follow a similar pipeline, the second script for add_dataset incorporates parameter adjustments to handle increased dataset complexity. These refinements ensure enhanced adaptability and robustness against more challenging backgrounds and vessel appearances.

Process Flowchart

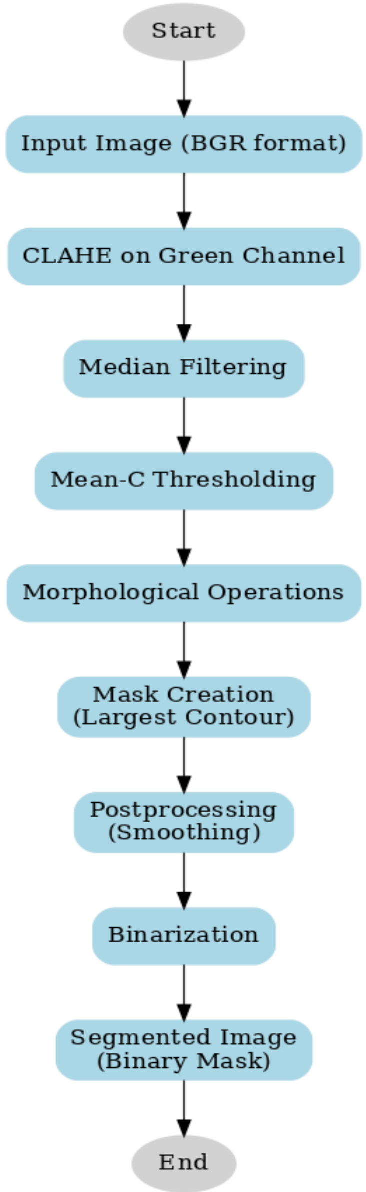

Figure 1.0 Flowchart

The process flowchart outlines the steps for retinal vessel segmentation from input images. The process begins with loading the input image in BGR format, followed by extracting the green channel, which contains the most vascular information. Contrast enhancement is performed using CLAHE (Contrast Limited Adaptive Histogram Equalization). The enhanced image undergoes noise reduction via median filtering and is subsequently processed with a Mean-C thresholding technique to segment vessels. Morphological operations, including closing and opening, refine the segmentation, ensuring continuity and removing artifacts. The largest contour is identified to create a mask representing the region of interest, which is further smoothed to reduce noise. Finally, binarization converts the processed image into a binary mask where pixels are classified as either vessels or background, yielding the final segmented image.

Results & Analysis

Overall Evaluation Results

Dataset	Error	Precision	Recall	IoU
Dataset	0.2873	0.7378	0.7104	0.5597
Add_Dataset	0.2881	0.7354	0.7227	0.5604

- **Error**: Both datasets achieved comparable error rates, with a slight increase in the second dataset, indicating robust performance despite increased complexity.
- **Precision and Recall**: The second dataset exhibited improved Recall but marginally lower Precision, suggesting better detection of vessels at the cost of slightly increased false positives.
- **IoU**: The IoU metric, reflecting overall segmentation quality, showed minor improvement for the second dataset.

Dataset Evaluation & Analysis

Segmentation Performance Metrics (Box Plot)

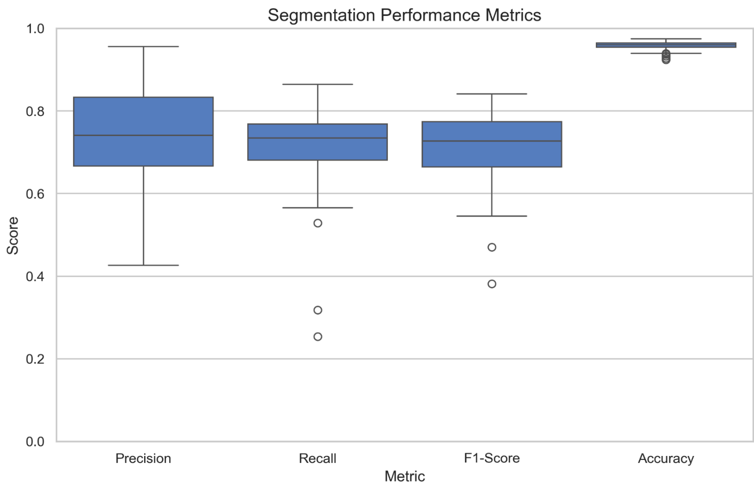

Figure 2.0 Metrics Summary(Dataset)

This box plot provides a summary of the segmentation performance metrics across the entire first dataset. The metrics displayed are **Precision**, **Recall**, **F1-Score**, and **Accuracy**.

- **Precision**: Measures how many of the predicted vessels are actual vessels.
- **Recall**: Indicates how many of the actual vessels were correctly predicted.
- **F1-Score**: Represents the harmonic mean of Precision and Recall, balancing false positives and false negatives.
- **Accuracy**: Measures the overall correctness of predictions (true positives and true negatives out of all pixels).

Observations:

- The **Precision** has a wider range compared to other metrics, indicating more variability in the model's ability to correctly identify true vessels.
- **Recall** and **F1-Score** are more consistent, suggesting the model performs well across most images in identifying true vessels.
- Outliers in Precision, Recall, and F1-Score indicate images where the model struggled due to potential noise, complex backgrounds, or poor vessel visibility.
- The **Accuracy** is consistently high, showing that the model handles the overall task well.

Insights:

The box plot highlights the need to investigate outliers in Precision and Recall. These could be associated with specific images or challenging conditions in the dataset.

Per-Image Metrics (Scatter Plot)

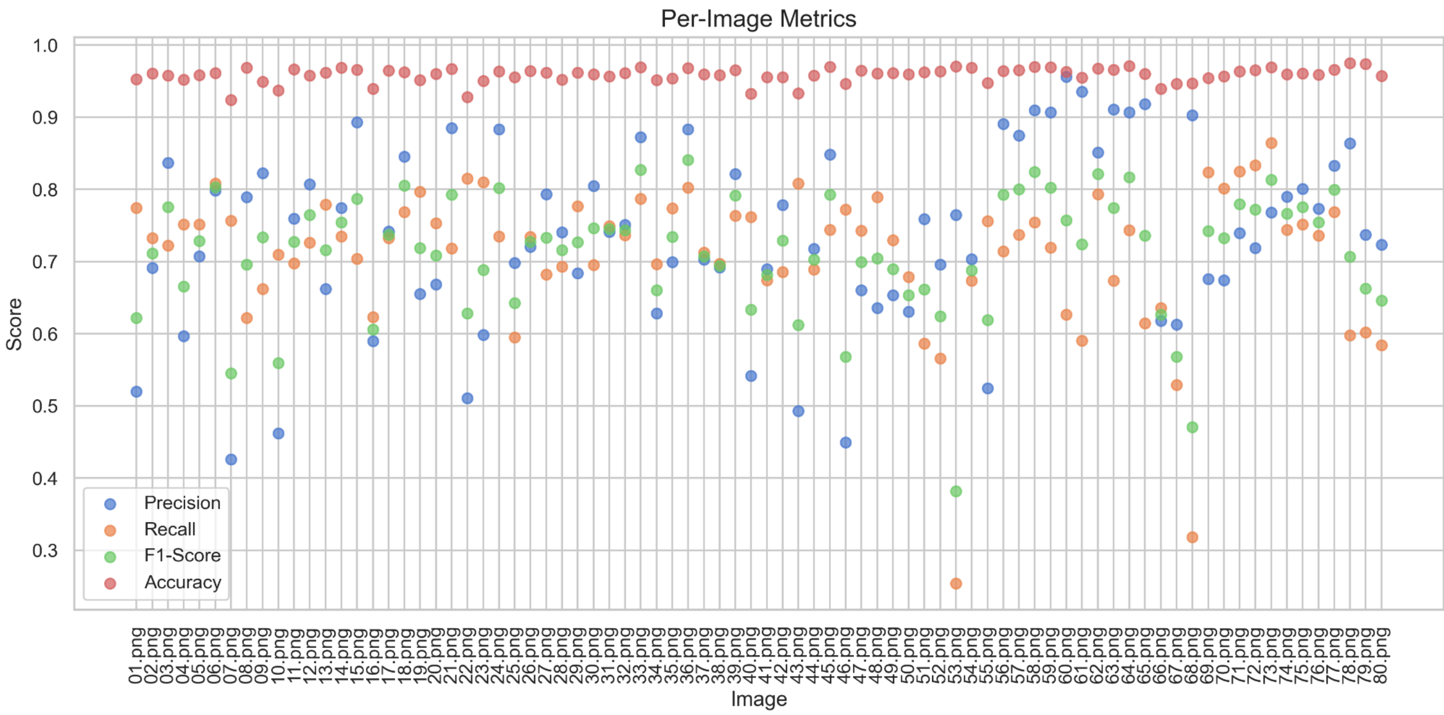

Figure 3.0 Metrics (Scatter Plot)(Dataset)

This scatter plot visualizes individual image metrics across the dataset. Each point represents the score for a specific metric (**Precision**, **Recall**, **F1-Score**, or **Accuracy**) for a single image.

Observations:

- The **Accuracy** is consistently high across most images, with minimal variation.
- **Precision** and **Recall** vary significantly across images, with some images having lower scores. This suggests differences in the complexity of vessel structures or noise levels in the dataset.
- **F1-Score** tends to follow trends in Precision and Recall since it is derived from both metrics.
- Clusters of points near the upper limit (1.0) suggest that the model performed very well on many images.

Insights:

This visualization makes it easier to identify specific images with poor performance. These images may be used for further error analysis to improve the model.

Best and Worst Image Analysis

Best IoU, (Image 36)

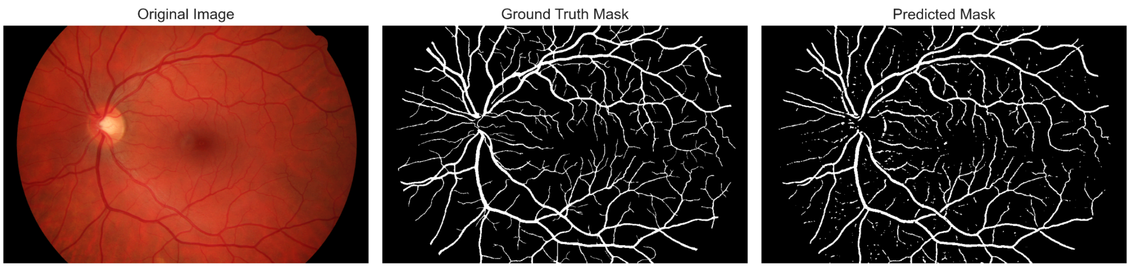

Figure 4.0 Best IoU Segment Comparison

Precision	Recall	F1-Score	IoU	Error
0.883	0.802	0.841	0.726 (Highest IoU)	0.159

Analysis:

- **High IoU** indicates strong overlap between the predicted mask and the ground truth, meaning most vessels were accurately captured.
- Balanced Precision and Recall contributed to the high F1-Score and IoU.

Factors:

- High-quality image with minimal noise.
- Preprocessing and model effectively enhanced and segmented the vessel structures.

Worst IoU, Recall and Error, (Image 53)

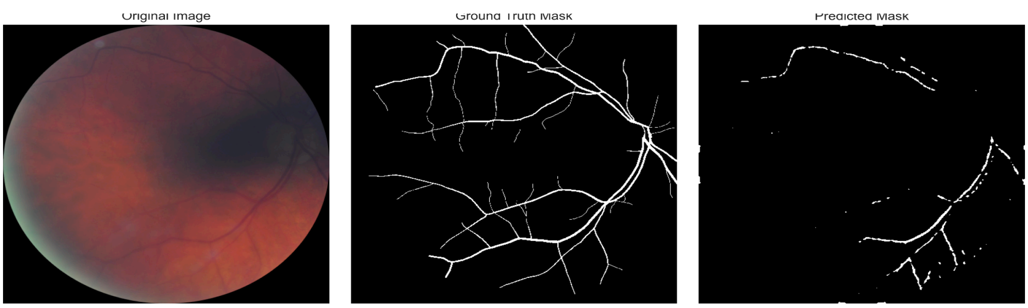

Figure 4.1 Worst IoU, Recall and Error Segment Comparison

Precision	Recall	F1-Score	IoU	Error
0.765	0.254	0.382	0.236	0.618

Analysis:

- **Low Recall** (0.254) indicates that a large portion of actual vessels was missed, which significantly contributed to the poor IoU.
- **Minimal IoU** reflects the model's struggle to create an overlap between the predicted mask and the ground truth mask.
- **High Error** (0.618) highlights an imbalance between false positives and false negatives, leading to missed vessels and misclassified background regions.
- While Precision was relatively higher, suggesting that detected vessels were mostly accurate, the combined failure to identify most vessels and manage segmentation alignment resulted in poor overall performance.

Factors:

The poor performance in IoU, Recall, and Error can be attributed to the following combined factors:

- Low contrast between vessels and the background, making vessel boundaries difficult to discern.
- Noise or artifacts in the image interfering with the vessel detection process.
- Ineffective preprocessing steps, such as CLAHE or thresholding, which failed to enhance vessel visibility and improve contrast sufficiently.
- Segmentation algorithm's inability to handle noisy backgrounds effectively, contributing to both false positives and false negatives.

Best Combined Performance ,Lowest Error, Best Recall , (Image 73)

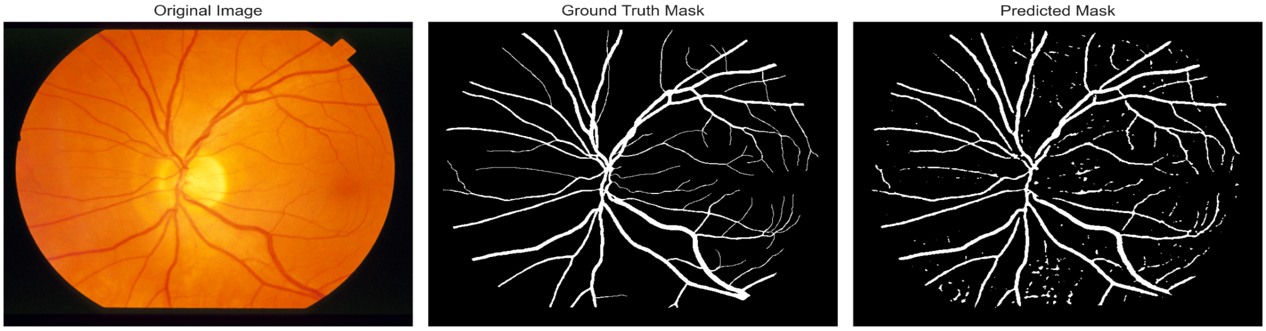

Figure 4.2 Best Combined Performance Segment Comparison

Precision	Recall	F1-Score	IoU	Error
0.768	0.864	0.813	0.685	0.187

Analysis:

Best Combined Performance:

- **Scores**: Precision: 0.768, Recall: 0.864, F1-Score: 0.813, IoU: 0.685, Error: 0.187.
- Balanced high scores across all metrics, with a low Error rate.
- The model captured most vessels while maintaining minimal false positives and false negatives, achieving consistency in segmentation quality.

Lowest Error:

- **Scores**: Error: 0.187 (lowest).
- Low Error indicates minimal misclassifications, reflecting the model's accurate differentiation between vessels and the background.
- High Precision and Recall (0.768 and 0.864, respectively) ensured a balanced segmentation performance with few errors.

Best Recall:

- **Scores**: Recall: 0.864 (highest Recall).
- High Recall highlights the model's effectiveness in capturing the majority of actual vessels, with a strong balance between false positives and false negatives.
- Strong F1-Score (0.813) and IoU (0.685) further validate the effectiveness of both Precision and Recall in achieving high-quality segmentation.

Factors:

The strong performance across Best Combined Performance, Lowest Error, and Best Recall can be attributed to:

- Clear vessel structures with well-defined intensity differences from the background, providing optimal conditions for accurate segmentation.

- Low noise levels in the images, minimizing distractions and aiding in precise vessel detection.
- Effective preprocessing techniques, such as CLAHE and thresholding, which enhanced vessel boundaries while reducing artifacts.
- Balanced preprocessing pipeline that neither over-segmented nor under-segmented, ensuring accurate vessel delineation and robust segmentation.
- Strong contrast between vessels and the background, enabling the model to maintain high Precision and Recall simultaneously.

Best Precision, (Image 60)

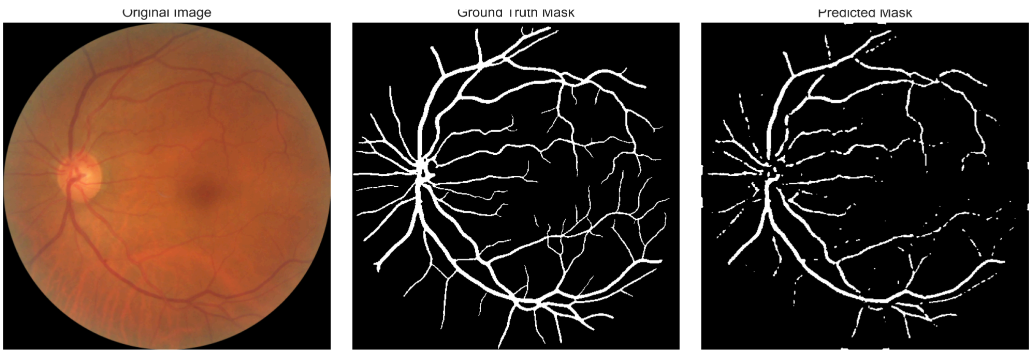

Figure 4.3 Best Precision Segment Comparison

Precision	Recall	F1-Score	IoU	Error
0.956	0.627	0.757	0.609	0.243

Analysis:

- **High Precision** indicates that most of the predicted vessels were correct, with minimal false positives.
- The slightly lower Recall suggests that some actual vessels were missed, leading to a moderate F1-Score and IoU.

Factors:

- Likely a high-contrast image with clear vessel boundaries.
- Minimal noise or artifacts in the background.

- Effective preprocessing enhanced the vessel structures, leading to accurate predictions.

Worst Precision, (Image 07)

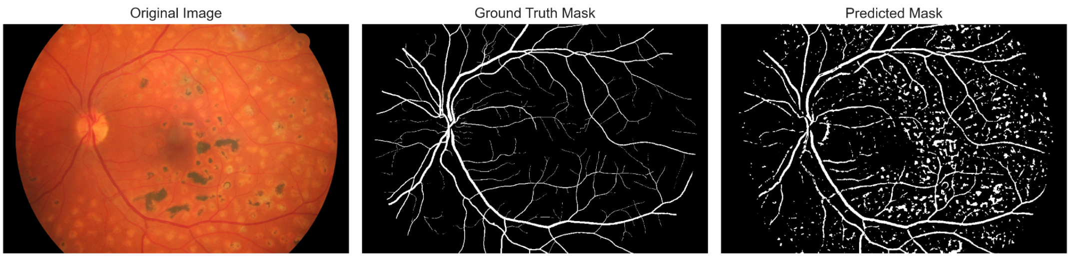

Figure 4.4 Worst Precision Segment Comparison

Precision	Recall	F1-Score	IoU	Error
0.426	0.757	0.545	0.375	0.455

- **Analysis**:
  - **Low Precision** indicates a significant number of false positives, meaning the model incorrectly predicted background regions as vessels.
  - Higher Recall suggests that the model captured a large portion of the actual vessels but at the cost of accuracy.
- **Factors**:
  - Potential issues with preprocessing leading to over-segmentation.
  - Noisy or complex background affecting the thresholding process.

Pixel Intensity Distribution (Histogram)

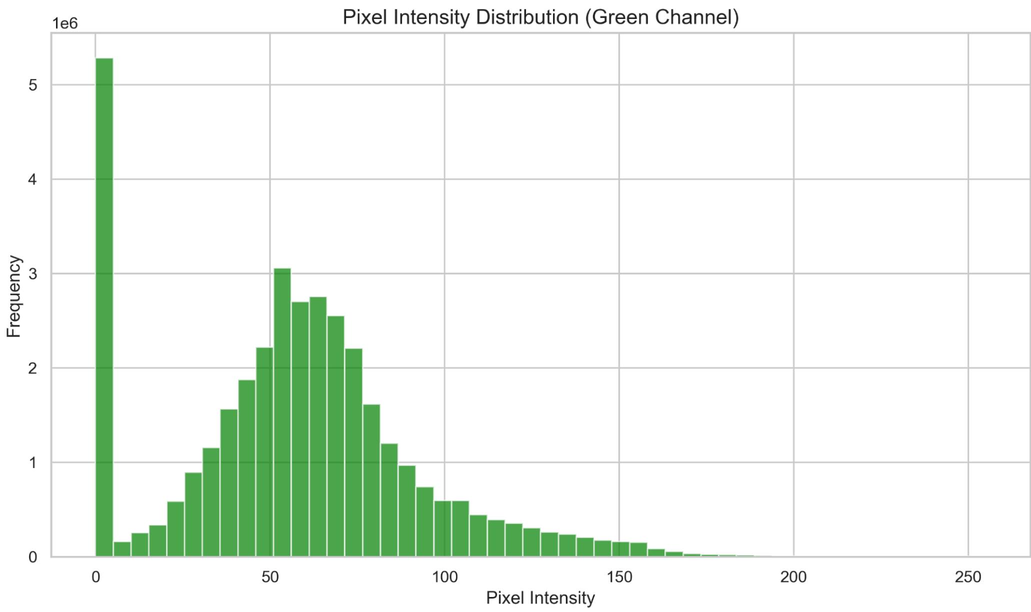

Figure 5.0 Pixel Intensity Distribution

This histogram shows the distribution of pixel intensities in the green channel of the dataset images. The green channel is often used for retinal vessel segmentation as it typically contains the most contrast between vessels and background.

Observations:

- Most pixel intensities are concentrated in the lower range (0-100), indicating that the images are relatively dark.
- A sharp peak near the lowest intensity values suggests the presence of background pixels.
- A gradual decline in the frequency of higher intensity values represents the vessels and other bright regions in the images.

Insights:

The pixel intensity distribution emphasizes the importance of preprocessing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance vessel visibility in darker regions. Proper preprocessing helps improve the model's performance.

Add_Dataset Evaluation & Analysis

Segmentation Performance Metrics (Box Plot)

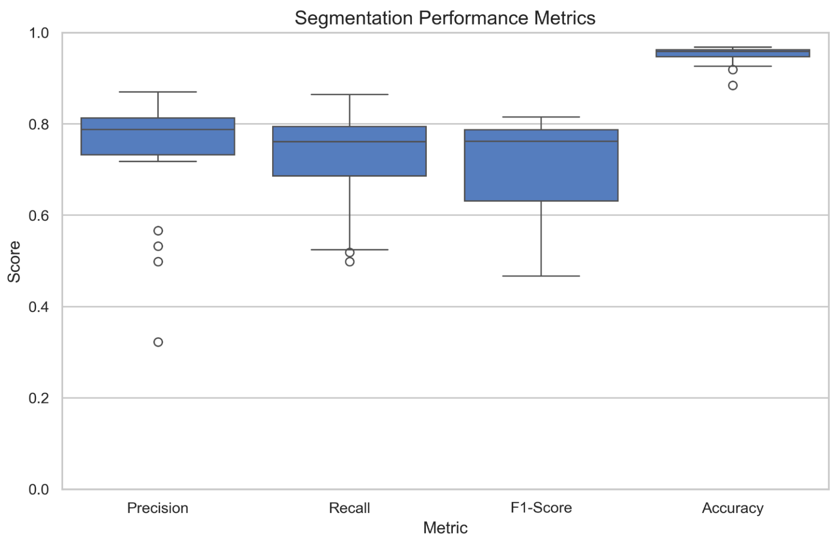

Figure 6.0 Segmentation Performance Metrics(Add_Dataset)

This box plot summarizes the performance metrics (Precision, Recall, F1-Score, and Accuracy) across all images in the **add_dataset**.

Observations:

- The **Precision** shows a moderate spread with some outliers, indicating variability in how well the model avoids false positives across images.
- The **Recall** has a wider range, suggesting that the model's ability to capture actual vessels varies significantly.
- **F1-Score** follows the trends of Precision and Recall, highlighting the need for balance between the two metrics.
- **Accuracy** remains consistently high across the dataset, showing that the model performs well overall.

Insights:

- Variability in Precision and Recall may be due to differences in vessel visibility or noise levels across the images.

- Outliers indicate challenging images where the model struggled with segmentation accuracy.

Per-Image Metrics (Scatter Plot)

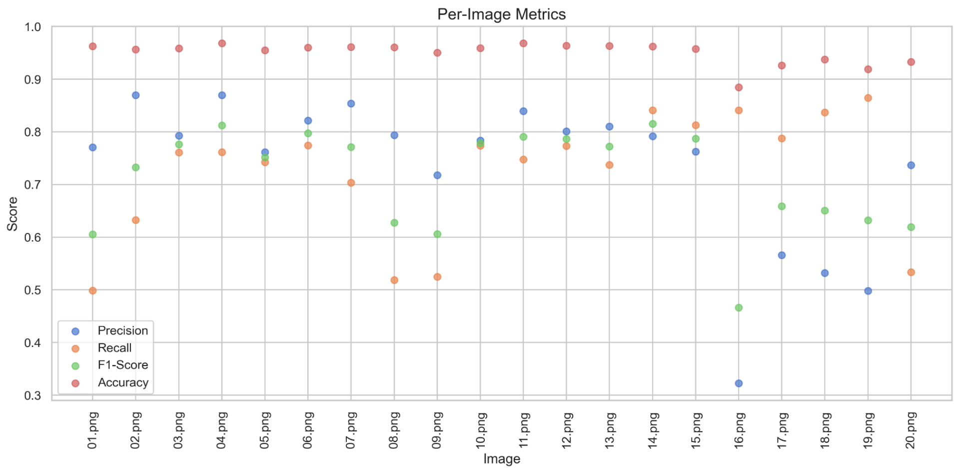

Figure 7.0 Per-Image Metrics(Add_Dataset)

This scatter plot shows the performance of individual images in the **add_dataset** for four metrics: Precision, Recall, F1-Score, and Accuracy.

- Each dot represents a metric's value for a specific image.
- Metrics are color-coded for easier comparison (e.g., Precision in blue, Recall in orange).

Observations:

- **Accuracy** is consistently high across most images, with minimal variability.
- **Precision** and **Recall** show significant variability, with some images achieving near-perfect scores while others perform poorly.
- Images with lower Precision or Recall suggest challenges like noise, poor contrast, or overlapping pixel intensities between vessels and the background.

Insights:

- Images with high Precision and Recall are likely to have clear vessel structures and low noise.

- Poorly performing images may require improved preprocessing or additional training data to enhance segmentation performance.

Best and Worst Image Analysis

Best Combined (All Aspects) , Lowest Error , Best IoU (Image 14)

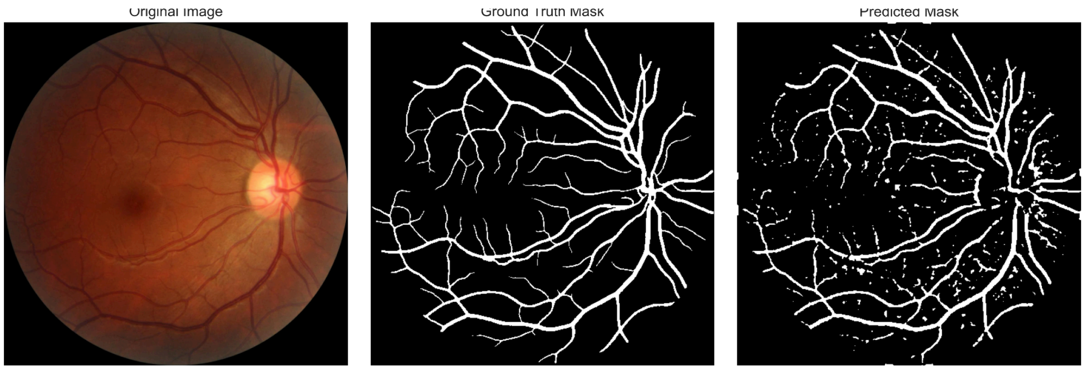

Figure 8.0 Best Combined Performance Segment Comparison(Add_Dataset)

Precision	Recall	F1-Score	IoU	Error
0.792	0.841	0.816	0.689	0.184

Analysis:

- Represents the best overall performance across all metrics, showcasing balanced segmentation.
- High Precision and Recall indicate accurate vessel detection with minimal false positives and negatives.
- High IoU reflects significant overlap between the predicted and ground truth masks.
- Low Error suggests effective distinction between vessels and background, contributing to robust segmentation.

Factors:

- The image likely featured high vessel clarity with minimal noise or artifacts.
- Preprocessing steps (e.g., CLAHE and thresholding) effectively enhanced vessel boundaries.

- Consistent vessel structures provided an ideal scenario for segmentation accuracy.

Worst Precision, Worst IoU, and Worst Error (Image 16)

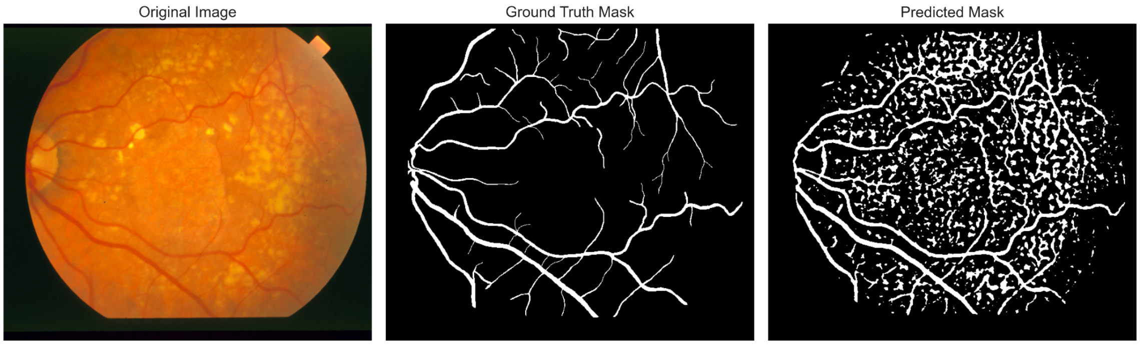

Figure 8.1 Worst Precision,WorstIoU & Worst Error Segment Comparison(Add_Dataset)

Precision	Recall	F1-Score	IoU	Error
0.323	0.841	0.467	0.304	0.533

Analysis:

- Poor Precision reflects a high rate of false positives, with significant over-segmentation.
- Low IoU indicates minimal overlap between the predicted mask and the ground truth, revealing poor segmentation accuracy.
- High Error highlights difficulties in correctly distinguishing vessels from the background.

Factors:

- Poor contrast between vessels and the background led to false positives.
- Noise or artifacts in the image disrupted the segmentation process.
- Preprocessing steps failed to enhance vessel visibility effectively, leading to suboptimal thresholding results.

Best Precision, (Image 04)

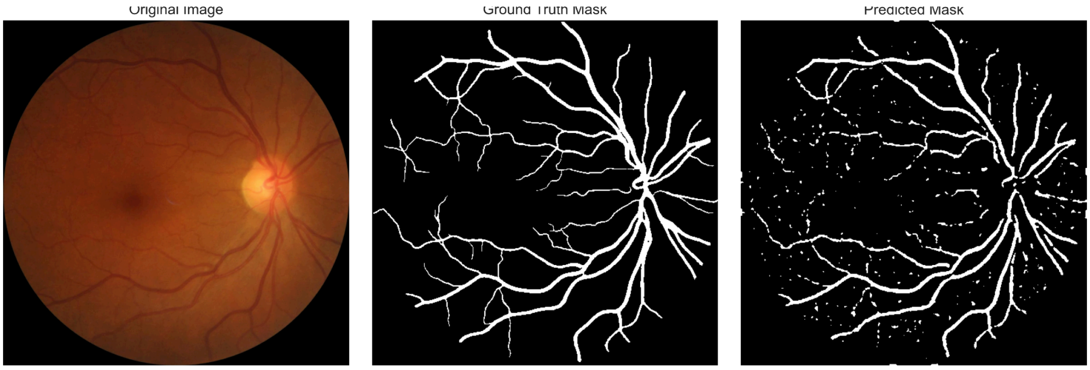

Figure 8.2 Best Precision Segment Comparison(Add_Dataset)

Precision	Recall	F1-Score	IoU	Error
0.870	0.761	0.812	0.684	0.188

Analysis:

- High Precision demonstrates minimal false positives, indicating that detected vessels were highly accurate.
- Balanced F1-Score and IoU reflect effective segmentation.

Factors:

- Clear vessel boundaries and consistent intensity differences from the background.
- Preprocessing steps successfully reduced noise and enhanced vessel clarity.

Best Recall, (Image 19

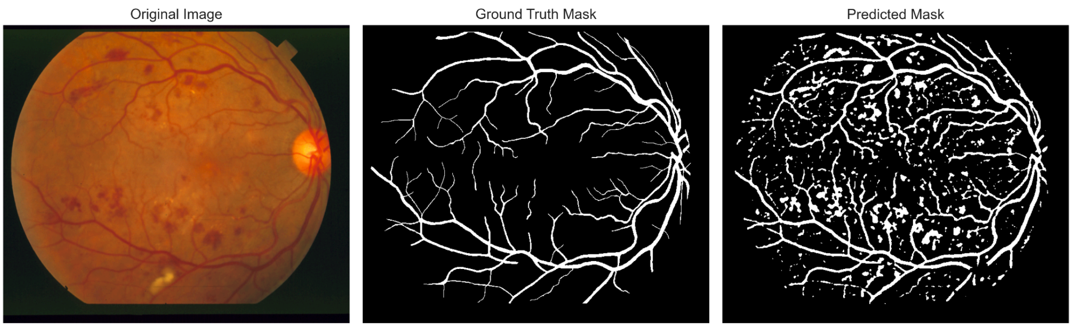

Figure 8.3 Best Recall Segment Comparison(Add_Dataset)

Precision	Recall	F1-Score	IoU	Error
0.498	0.865	0.632	0.462	0.368

Analysis:

- High Recall indicates effective vessel detection, with minimal missed vessels.
- Balanced F1-Score and IoU suggest that the segmentation model captured most vessel structures accurately.

Factors:

- Clear vessel structures and high contrast from the background.
- Preprocessing steps maintained vessel integrity while minimizing false negatives.

Worst Recall, (Image 01)

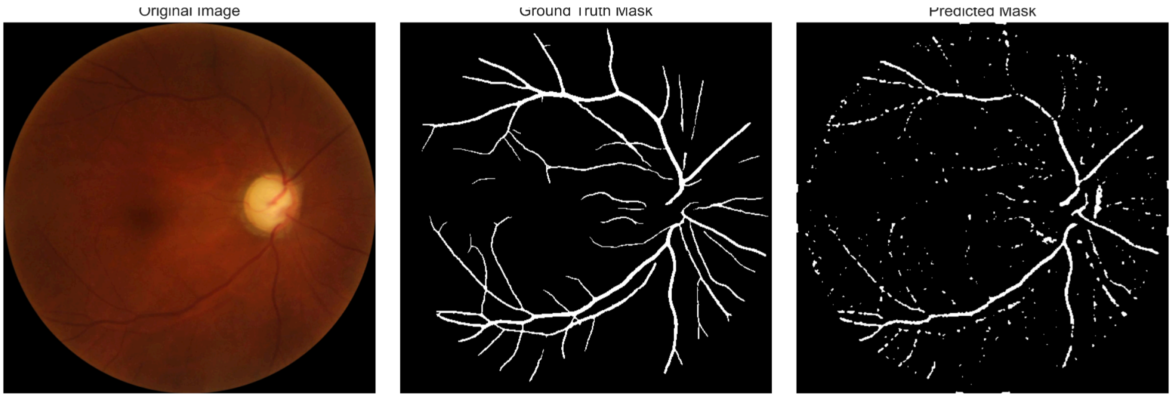

Figure 8.4 Worst Recall Segment Comparison(Add_Dataset)

Precision	Recall	F1-Score	IoU	Error
0.770	0.499	0.605	0.434	0.395

Analysis:

- Low Recall highlights the model's failure to detect a significant portion of vessels.
- Despite relatively high Precision, the low F1-Score and IoU reflect poor segmentation accuracy.

Factors:

- Low contrast between vessels and the background made detection challenging.
- Ineffective preprocessing steps led to under-segmentation and missed vessels.

Pixel Intensity Distribution (Histogram)

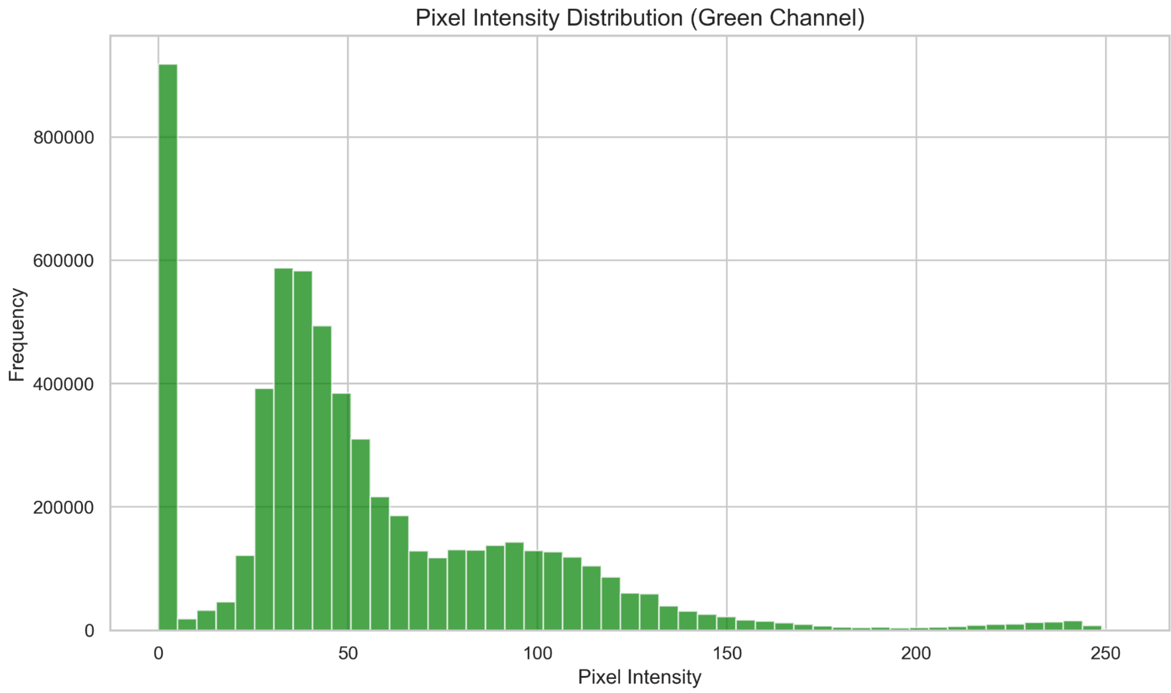

Figure 9.0 Pixel Intensity Distribution(Add_Dataset)

This histogram illustrates the distribution of pixel intensities (green channel) across all images in the **add_dataset**.

- Pixel intensity values range from 0 (darkest) to 255 (brightest).
- The frequency of each intensity value is plotted on the y-axis.

Observations:

- Most pixel intensities are concentrated in the lower range (0-100), indicating that the images are predominantly dark.
- The sharp peak near the lowest intensity values corresponds to the background pixels.
- A gradual decline in higher intensity values represents vessel and bright region pixels.

Insights:

- The distribution highlights the importance of preprocessing techniques like CLAHE to enhance vessel visibility in darker regions.

- Proper preprocessing helps mitigate the challenges posed by low-intensity distributions, improving segmentation accuracy.

Suggestions for Improvement

1. **Dynamic Parameter Adjustment Based on Input Characteristics**:
    - **Suggestion**: Implement an adaptive mechanism to modify CLAHE settings and thresholding parameters in real time, based on the histogram distribution of input images.
    - **Reason**: The CLAHE and thresholding parameters are static in the current implementation, which may not perform optimally across diverse images. Adapting parameters dynamically ensures that contrast enhancement and thresholding are tailored to each image, improving overall segmentation quality.
2. **Enhanced Morphological Operations**:
    - **Suggestion**: Introduce dynamic kernel sizing for morphological operations to better handle variations in vessel thickness.
    - **Reason**: The current fixed kernel size may not effectively address varying vessel widths. Dynamic kernels allow finer vessels to be preserved while refining broader structures, reducing segmentation errors.
3. **Optimized Contour Selection**:
    - **Suggestion**: Modify the contour detection step to account for vessel branching patterns by analyzing additional properties such as aspect ratios and contour connectivity.
    - **Reason**: The largest contour approach may overlook vessel branching patterns or misidentify non-vessel regions. Incorporating additional contour properties ensures more accurate identification of vessel regions.
4. **Improved Smoothing Techniques**:
    - **Suggestion**: Instead of standard Gaussian smoothing, experiment with bilateral filtering, which preserves edge sharpness while reducing noise.
    - **Reason**: Gaussian smoothing can blur fine vessel details. Bilateral filtering enhances vessel delineation without introducing artifacts, maintaining segmentation accuracy.

5. **Feedback Integration for False Positives**:
   - **Suggestion**: Develop a feedback mechanism to iteratively refine the mask by identifying and suppressing false positive regions based on statistical properties such as pixel intensity distribution or connectivity analysis.
   - **Reason**: The current implementation does not systematically address false positives. A feedback mechanism reduces these errors, improving Precision without affecting Recall.
6. **Evaluation of Edge Cases**:
   - **Suggestion**: Specifically target images with high background noise or irregular vessel patterns by introducing tailored preprocessing steps such as edge detection algorithms.
   - **Reason**: Challenging cases are inadequately addressed by the current pipeline. Specialized preprocessing helps focus on relevant features, improving robustness in outlier scenarios.

These suggestions are rooted in observed limitations within the current implementations and aim to enhance the adaptability and precision of the segmentation pipeline.