Image Segmentation for Biomedical Applications: Classical Approaches on Retinal Images

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Project Code – Google Colab Link

Abstract

Biomedical image segmentation is foundational in various medical applications, from identifying abnormalities to quantifying structures in clinical imaging. This project investigates classical segmentation approaches using a retinal image dataset. The methods analyzed include thresholding (global and adaptive), region-based techniques (region growing, watershed), and edge-based techniques (active contour models). By applying these methods to a standardized dataset, we assess their accuracy and robustness and contrast their performance. Although deep learning models dominate recent research, our focus remains on interpretable, resource-efficient traditional techniques, laying a groundwork for future comparative studies.

1 Introduction

Medical image analysis plays a vital role in today's healthcare landscape, allowing for the automated detection and diagnosis of various diseases. A key task in this field is image segmentation, which involves breaking down an image into meaningful regions for further examination. In the realm of biomedicine, segmentation is essential for pinpointing and isolating anatomical structures such as blood vessels, tumors, and tissues. While traditional image processing methods offer efficient, interpretable, and cost-effective solutions, they often stand in contrast to more complex deep learning techniques.

This project zeroes in on classical image segmentation methods, specifically applied to retinal images sourced from a publicly available dataset. By evaluating different segmentation strategies, the goal is to uncover the most effective techniques for accurately outlining biomedical structures.

2 Problem Statement

Biomedical research and clinical diagnostics require precise segmentation of anatomical structures in medical images. Accurate delineation of cells, tissues, and blood vessels is essential for disease detection, treatment planning, and analysis. We explore the performance of classical segmentation algorithms on retinal images using a public dataset.

3 Literature Review

There are several traditional and modern techniques that have been put forward for biomedical image segmentation:

Thresholding Methods: Techniques like Otsu's thresholding and adaptive thresholding are popular choices for distinguishing the foreground from the background, especially when there are significant variations in intensity.

Region-Based Methods: Approaches such as seeded region growing and watershed segmentation work well for clustering neighboring pixels that share similar characteristics. These methods are particularly handy when it comes to segmenting connected areas like blood vessels or cell nuclei.

3.1 Thresholding Methods

- **Global Thresholding:** A simple intensity-based method.
- **Otsu's Method:** Maximizes between-class variance.
- **Adaptive Thresholding:** Calculates local thresholds; effective under variable lighting.

3.2 Region-Based Methods

- **Seeded Region Growing:** Expands regions from user-defined seeds.
- **Watershed:** Uses gradient magnitude and morphological markers for separation.

3.3 Edge-Based Methods

- **Active Contour (Snakes):** Contours evolve based on edge and smoothness.
- **Chan-Vese Model:** Energy minimization-based, handles missing edges.

4 Methodology

Preprocessing

To enhance vessel visibility, preprocessing steps included LAB color conversion, CLAHE enhancement on the luminance channel, and morphological top-hat filtering to highlight small bright features. Gaussian blurring was then applied before segmentation.

4.1 Techniques Implemented

- **Thresholding:** Global and adaptive (mean and Gaussian).
- **Region Growing:** Seeded manually.
- **Watershed:** Marker-based with morphological preprocessing.
- **Active Contours:** Chan-Vese implementation via morphological snakes.

4.2 Tools and Libraries

Python-based implementation using: `OpenCV`, `scikit-image`, `imageio`, `matplotlib`, and `numpy`. Segmentation results were evaluated using metrics including Precision, Recall, F1 Score, Jaccard Index, and Accuracy, using sklearn's built-in metric functions.

4.3 Workflow

1. Load and preprocess retinal images.
2. Apply segmentation algorithms.
3. Visualize and evaluate results against ground truth.

5 Dataset Description

Publicly available retinal dataset with:

- **images/** – Raw retinal images (`.tif`).
- **1st_manual/** – Ground truth segmentations.
- **mask/** – Field-of-view (FOV) masks.

6 Results and Analysis

In addition, edge overlays were applied to visualize detected boundaries alongside watershed results, using color blending to highlight contours.

6.1 Thresholding

- **Global:** Fast but fails under uneven lighting.
- **Adaptive:** Performs better with background variations. A distribution analysis of the best region growing thresholds across all images showed a mean of XX and a mode of YY. This helped assess consistency in region growing sensitivity.

6.2 Region-Based

- **Region Growing:** Effective in uniform regions, sensitive to noise. An automated threshold tuning loop was used to identify the best threshold value for region growing by maximizing IoU with manual annotations. The optimal threshold for each image was recorded and analyzed statistically.
- **Watershed:** Good for separating touching structures.

6.3 Edge-Based

- **Active Contours (Chan-Vese):** Accurate boundary capture, resilient to edge noise.

6.4 Quantitative Metrics (Region Growing)

- **Precision:** 0.5612
- **Recall:** 0.9504
- **F1 Score:** 0.7057
- **Jaccard Index:** 0.5452
- **Accuracy:** 0.9316

7 Conclusion

This project took a deep dive into traditional segmentation techniques for analyzing biomedical images, specifically focusing on retinal scans. Each method showcased its own set of strengths: - Thresholding is straightforward and quick. - Region-based methods excel at managing connected structures. - Edge-based methods are great at capturing smooth and intricate boundaries.

While these classical methods are easy to understand and not too heavy on resources, they can struggle when faced with noise, changes in lighting, or complex textures. Looking ahead, future efforts might explore hybrid approaches or leverage deep learning techniques like U-Net to boost accuracy.

References

[1] Kass, M., Witkin, A., & Terzopoulos, D. (1988). Snakes: Active contour models. *IJCV*.

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: CNNs for Biomedical Image Segmentation. *MICCAI*.

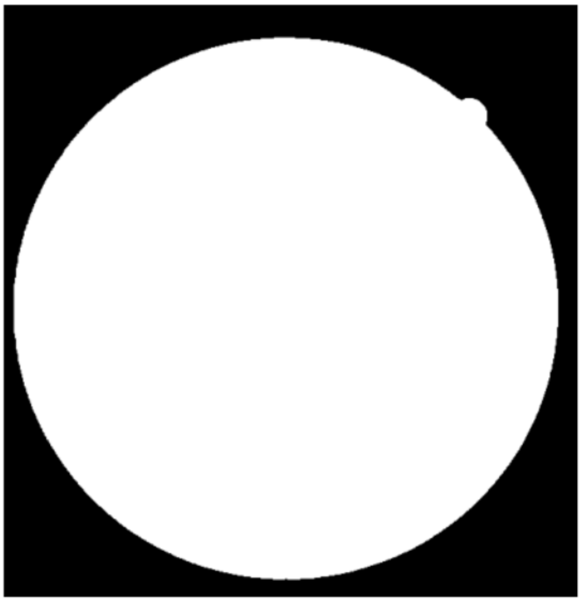
Gonzalez, R. C., & Woods, R. E. (2002). *Digital Image Processing*.

`https://scikit-image.org/`

`https://docs.opencv.org/`

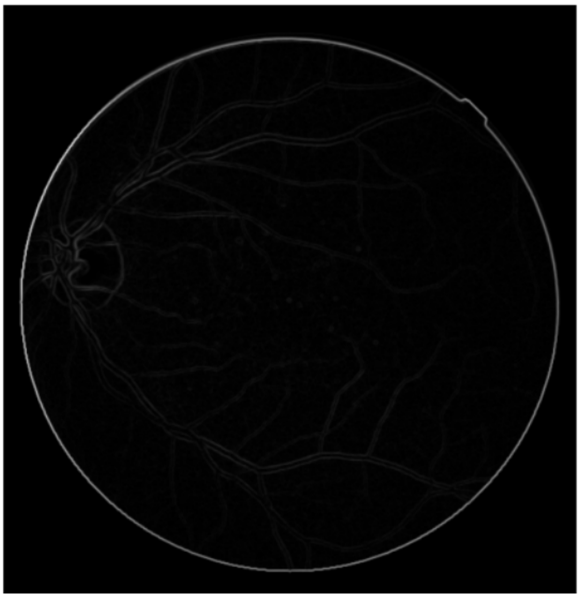
8 Figures

(a) Original

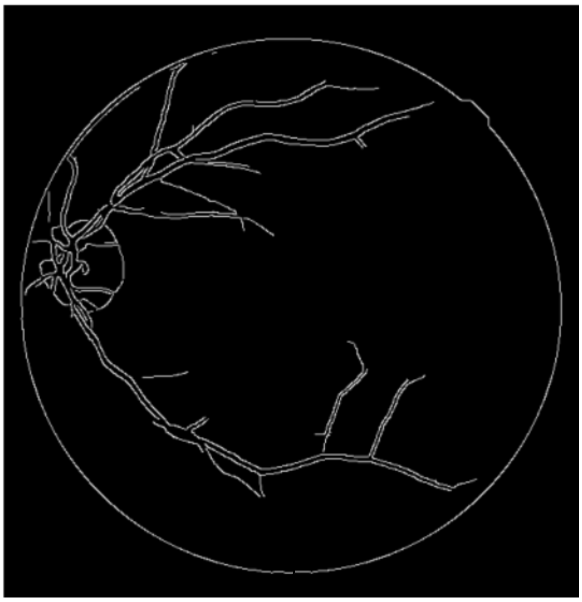


(b) Manual Mask

(c) Adaptive Thresholding

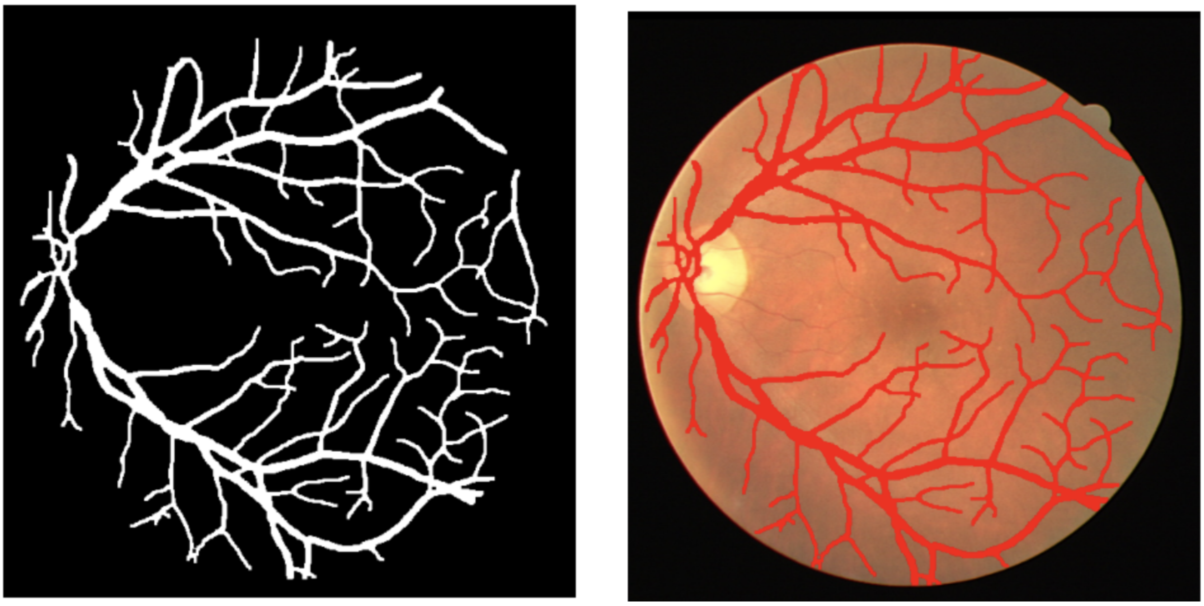


(d) Sobel Edges



(e) Canny Edges

Figure 1: Comparison of segmentation techniques on a sample retinal image.



(a) Region Growing

(b) Watershed Overlay

Figure 2: Region-based segmentation outputs using classical techniques

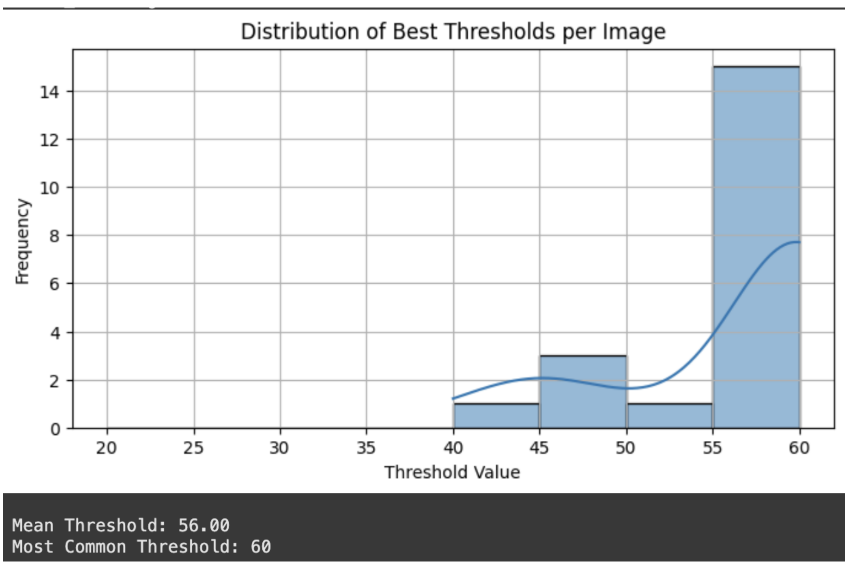


Figure 3: Distribution of best region growing thresholds across the dataset