Comparative Analysis of Image Segmentation Techniques for OCT Imaging: Evaluating Performance Using MSE and PSNR Metrics

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***Abstract*—Image segmentation is an essential step in picture processing, involving the division of a photo into smaller segments for extra efficient evaluation. Various strategies, such as thresholding, Edge detection, clustering, graph cut segmentation, watershed segmentation, and flood fill, had been explored for this reason. Among these, clustering-based totally segmentation has established especially effective for separating images in OCT pictures. Additionally, preprocessing methods just like the Wiener filter out are hired to reduce speckle noise. Evaluation of segmentation strategies includes calculating metrics like MSE (Mean square Error) and PSNR (Peak signal-to-noise ratio) to assess segmented photo pleasant. Techniques like thresholding, edge detection (utilizing algorithms consisting of Sobel, Canny, Prewitt and Robert's), clustering, graph reduce segmentation, Watershed segmentation and flood fill are compared primarily based on these metrics. This article evaluations these segmentation strategies and their overall performance, emphasizing the importance of choosing the right technique primarily based at the particular necessities of the photo processing venture.**

***Index Terms*—Clustering; Edge detection; Image segmentation; Region-based; Threshold, graph cut segmentation and flood fill.**

I. INTRODUCTION

Retinal [1] Optical Coherence Tomography (OCT) imaging has revolutionized the prognosis and remedy tracking of numerous ocular sicknesses inclusive of glaucoma, macular degeneration, and diabetic retinopathy. The excessive-resolution photographs furnished by way of OCT permit for designated visualization of retinal layers, facilitating early detection and unique tracking of pathological modifications. However, the translation of OCT pictures frequently necessitates the segmentation of retinal layers to extract meaningful records, a technique crucial for correct diagnosis and treatment planning.

Segmentation, in the context of picture analysis, refers to the partitioning of a picture into a couple of areas or items based totally on certain criteria. Various segmentation strategies have been advanced and carried out to OCT photographs, every with its strengths and obstacles. This analysis objectives to discover and examine the efficacy of various segmentation techniques on retinal OCT pictures, specializing in thresholding, part-primarily based techniques (such as Sobel, Canny, Prewitt and Robert's), and clustering-primarily based segmentation techniques.

[2] The integration of saliency-driven lively contour models and advanced picture preprocessing strategies has appreciably more suitable the accuracy and efficiency of retinal vessel segmentation. Saliency detection allows in highlighting outstanding areas, guiding active contours to attention on vessel boundaries with more precision. Combined with preprocessing steps which include evaluation enhancement, noise elimination, and normalization, the technique enables advanced function extraction and [3] segmentation performance. Particularly in clinical imaging, inclusive of retinal scans, accurate vessel segmentation is essential for diagnosing situations like diabetic retinopathy and glaucoma. This

hybrid methodology not simplest complements visual readability but also helps computerized evaluation and sturdy medical choice-making systems.

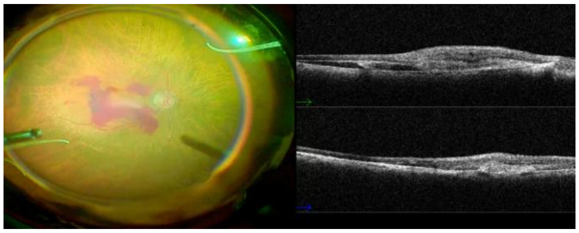


Figure 1: Retinal Oct Image

[4] Medical image segmentation algorithms play an important position in pc-aided analysis through allowing particular analysis of anatomical systems and abnormalities. Among numerous medical imaging modalities, retinal image segmentation is crucial for the early detection and tracking of illnesses which includes diabetic retinopathy, glaucoma, and hypertensive retinopathy. Retinal pix, typically acquired thru fundus pictures, require correct segmentation of blood vessels, optic disc, and macula for powerful diagnosis. Various segmentation strategies, along with thresholding, vicinity-based methods, clustering, and deep learning-based fashions, have been advanced to enhance the accuracy and reliability of retinal evaluation. To support these algorithms, photo preprocessing techniques along with grayscale conversion, contrast enhancement, noise removal, and normalization are carried out to improve picture fine and function visibility. These preprocessing steps help lessen computational complexity and enhance segmentation performance. Overall, the mixing of robust photograph preprocessing with advanced segmentation [5] methods substantially contribute to accurate, green, and automated analysis of retinal scientific pictures.

II. LITERATURE REVIEW

[6] The Segment Anything Model (SAM) has emerged as a powerful tool in image segmentation, garnering attention for its prompt-based interface and broad applicability. Despite its success in various domains, its application to retinal OCT (Optical Coherence Tomography) imaging remains largely unexplored. To address this gap, we present a comprehensive evaluation of SAM and its adapted variants using a large-scale public OCT dataset from the RETOUCH challenge. Our analysis spans multiple retinal diseases, fluid types, and imaging devices, benchmarking SAM against leading retinal fluid segmentation techniques. Results demonstrate that the adapted SAM performs well in OCT segmentation, showing strong potential, although it occasionally underperforms compared to specialized methods. These findings underline SAM's flexibility and its promise as a valuable tool for retinal OCT analysis, offering new directions for research and clinical implementation.

[7] In addition, we propose a novel convolutional neural network architecture tailored for medical segmentation tasks where the output mask represents a reduced-dimensional projection of the input. This model selectively reconstructs encoded features in specific spatial dimensions using innovative projective skip-connections within a UNet-style framework. Evaluated on retinal OCT tasks such as geographic atrophy and vessel segmentation, our method surpasses current state-of-the-art models, effectively bridging the gap between image classification and dimensional segmentation.

[8] Automated retinal layer segmentation in OCT images combines hybrid edge detection and thresholding techniques to accurately identify and separate the various retinal layers. Edge detection algorithms highlight the boundaries between different tissue layers by detecting intensity changes in the OCT scans. Thresholding methods then classify pixels based on intensity values, distinguishing retinal layers from background and noise. By integrating both approaches, the system enhances boundary detection precision and reduces errors caused by image artifacts or low contrast. This hybrid method improves the segmentation's accuracy and robustness, enabling reliable measurement of retinal thickness and assisting in diagnosing and monitoring ocular diseases.

[9] [1]The method of multi-scale edge detection and segmentation of retinal layers in OCT images using wavelet transform involves analyzing images at multiple resolutions to accurately identify retinal layer boundaries. Wavelet transform decomposes the image into different frequency components, helping to highlight fine details like edges at various scales. By detecting edges across multiple levels, this approach enhances the accuracy of identifying subtle layer transitions in the retina. Segmentation then isolates these layers, supporting precise retinal analysis. This

technique is particularly effective in medical imaging, as it improves layer detection even in noisy or low-contrast regions, aiding in the diagnosis of eye diseases.

[10] Automated retinal layer segmentation in OCT images using edge enhancement and region growing is a technique designed to accurately identify and separate the distinct layers of the retina. Edge enhancement improves the visibility of layer boundaries by sharpening transitions between different retinal structures. Once these edges are highlighted, the region growing method is applied, which starts from seed points and expands outward by grouping neighboring pixels with similar intensity or texture. This combination allows for more precise boundary detection and segmentation, even in low-contrast or noisy images. It improves diagnostic accuracy and supports early detection of retinal diseases such as macular degeneration or diabetic retinopathy.

[11] The segmentation of retinal layers in OCT (Optical Coherence Tomography) images using morphological and edge-based methods involves identifying and isolating different retinal layers for medical analysis. Morphological techniques apply shape-based operations like dilation, erosion, and opening to enhance structures and remove noise. Edge-based methods detect boundaries between layers by identifying rapid intensity changes in the image. Combining these two methods improves accuracy and preserves structural integrity. This hybrid approach helps in diagnosing eye diseases such as glaucoma, diabetic retinopathy, and macular degeneration by providing clear layer separation, which is essential for assessing retinal thickness and changes in layer morphology.

[12] Retinal OCT image segmentation using anisotropic diffusion and edge detection is a technique that enhances and segments different layers of the retina for medical analysis. Anisotropic diffusion is applied first to smooth the image while preserving important edges, reducing noise without blurring significant structures. This improves the visibility of retinal layer boundaries. Next, edge detection methods such as the Sobel or Canny operators are used to identify the sharp transitions between retinal layers. Combining these two techniques allows for accurate segmentation of the retina's anatomical structures, which is critical for diagnosing and monitoring diseases like glaucoma or diabetic retinopathy.

Existing method:

K-means segmentation is like sorting candy into different jars. Imagine you have a bunch of colorful candies, and you want to group them by their colors. K-means helps you do that. You pick how many groups you want (let's say three jars), and the candies get sorted based on their colors into those jars. It's used for pictures too. Instead of candies, it sorts pixels by their colors, so you can separate objects in an image. However, sometimes it might mix up similar colors or need help to figure out how many groups to use.

Segmentation plays a pivotal role in various fields, from image processing to data analysis. Among the multitude of segmentation techniques, K-means segmentation stands out as a popular and effective method. Its analogy to sorting candies into different jars makes it intuitively understandable. This article delves into the intricacies of K-means segmentation, elucidating its principles, applications, challenges, and potential solutions.

III. PROPOSED METHOD

The proposed method for image segmentation leverages a combination of clustering-based techniques and preprocessing methods to enhance the accuracy and efficiency of segmenting images, particularly in OCT (Optical Coherence Tomography) images. Initially, preprocessing methods like the Wiener filter are applied to reduce speckle noise, improving the quality of the input images.

Next, the image is segmented using clustering algorithms, which have demonstrated effectiveness in separating images in OCT scans. These clustering techniques partition the image into smaller, more homogeneous segments, facilitating subsequent analysis. Additionally, edge detection algorithms such as Sobel, Canny, Prewitt and Robert's are employed to enhance the delineation of object boundaries, further refining the segmentation results.

To evaluate the performance of various segmentation techniques, metrics like MSE (mean square error) and PSNR (peak signal-to-noise ratio) are calculated, providing quantitative measures of segmented image quality. Techniques including thresholding, edge detection, clustering, graph cut segmentation, and flood fill are compared based on these metrics.

This proposed method emphasizes the importance of selecting appropriate segmentation techniques tailored to the specific requirements of the image processing task, ensuring optimal results in terms of accuracy, efficiency, and image quality. By integrating preprocessing, clustering, and evaluation techniques, this method offers a comprehensive approach to image segmentation in OCT images.

Image segmentation stands as a pivotal step in image processing, involving the partitioning of an image into smaller, meaningful segments. This process is crucial for efficient tasks such as object recognition and image compression. Several techniques have been explored for image segmentation, including thresholding, edge-based methods (such as Sobel, Canny, Prewitt and Robert's), clustering-based approaches, graph cut segmentation, watershed segmentation and flood fill. Among these, clustering-based segmentation has proven particularly effective for segmenting OCT images. To mitigate speckle noise during preprocessing, the Wiener filter approach is employed. Evaluation of segmentation quality involves calculating metrics like Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) across the various techniques. This comprehensive analysis aids in determining the most suitable method for a given application, ensuring optimal image segmentation outcomes.

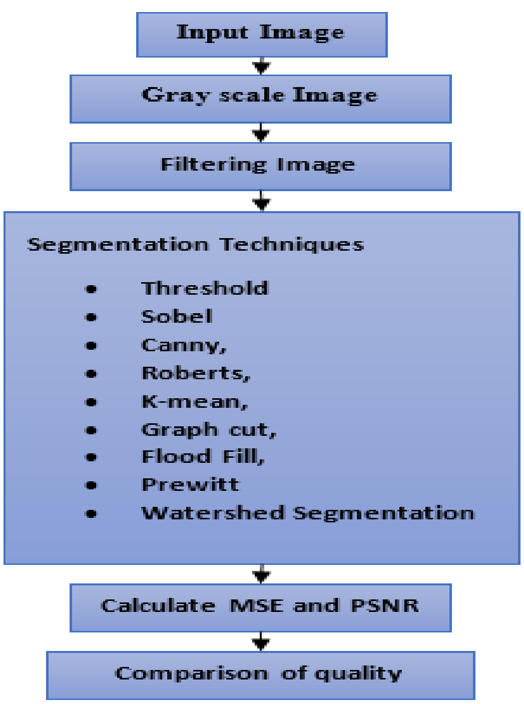


Figure 2: Block Diagram

Gray Conversion:

A grayscale image represents light intensity at each pixel using a single brightness value, unlike color images which use three channels (RGB). Each pixel in a grayscale image typically ranges from 0 (black) to 255 (white), with varying shades of gray in between.

Key features include:

- Single Channel: Easier and faster to process than color images.
- Efficient Storage: Requires less memory, useful in large-scale applications.
- Simplified Processing: Ideal for tasks like edge detection and filtering.
- Better Focus on Texture & Shape: Common in medical and scientific imaging.
- Conversion: Done by averaging RGB values with or without custom weights.

Wiener Filter:

The Wiener filters out, named after Norbert Wiener, is a famous technique in picture processing for noise discount and picture recovery. It uses signal processing and statistical estimation ideas to beautify noisy images whilst maintaining key details. The filter out assumes the degraded picture effects from a convolution with a factor spread feature (PSF) accompanied by using additive noise, permitting effective reconstruction of the authentic photo.

$$y\,(x,y)\ = h\,(x,y)\ * x\,(x,y)\ + n\,(x,y)$$

Where:

- $y\,(x, y)$ represents the degraded image,
- $x\,(x, y)$ represents the original, noise-free image,
- $h\,(x, y)$ represents the PSF or the degradation function,
- Denotes the convolution operation,
- $n\,(x, y)$ represents the additive noise.

The Wiener filter goals to estimate the unique photograph from a degraded version by means of minimizing the imply square blunders (MSE). It works within the frequency area, the use of the Fourier remodel to procedure the degraded picture and point spread characteristic (PSF).

$$H(u,v) =| F(u,v) | 2 + Sn(u,v)G(u,v) \cdot| F(u,v) | 2$$

Where:

- H (u, v) is the frequency response of the Wiener filter,
- G (u, v) is the Fourier transform of the degraded image,

- F (u, v) is the Fourier transform of the original image,
- Sn (u, v) is the power spectral density (PSD) of the noise.

The Wiener filter reduces noise by using suppressing frequency components with excessive noise-to-signal ratios at the same time as maintaining crucial photo details. It calls for estimates of the point unfold feature (PSF) and noise energy spectral density (PSD), often derived from the degraded image or previous know-how. Accurate parameter estimation is prime to its performance.

While powerful, the filter out assumes linear degradation and Gaussian noise, which won't usually follow. Inaccurate estimates can result in artifacts or blurring in the restored photograph.

1) Adaptive thresholding:

Adaptive Thresholding is a picture processing approach used to phase items from backgrounds under choppy lights conditions. Unlike worldwide thresholding that makes use of an unmarried fee, adaptive thresholding computes thresholds regionally based totally on pixel neighborhoods, permitting more accurate binarization.

$$T(x,y) = \mu(x,y) - C$$

Where:

- T (x, y): threshold at pixel (x, y)
- μ (x, y)): mean intensity of the neighborhood around (x, y).
- C: a constant to fine-tune thresholding

This approach improves object detection under varying illumination, widely used in document scanning, medical imaging, and vision systems.

2) Sobel Edge Detection

Sobel Edge Detection is a simple and effective image processing method used to detect edges—areas with significant intensity change. It uses two 3×3 convolution kernels to estimate gradients in the horizontal and vertical directions.

$$G = (Gx2 + Gy2) \quad \dots\dots\dots\dots (1)$$

Where Gx and Gy are the horizontal and vertical gradient approximations, respectively.

Edge Detection uses a threshold on gradient significance to perceive edge pixels—people with values above the brink. The Sobel operator successfully detects edges in each horizontal and vertical directions, making it suitable for numerous orientations. However, it's far sensitive to noise, so preprocessing like smoothing is often carried out. Proper threshold tuning enhances detection accuracy.

$$gradient\_magnitude = sqrt((gradient\_x)^\wedge 2 + (gradient\_y)^\wedge 2)$$

- Gradient_x represents the rate of change in pixel intensity along the horizontal direction.
- gradient_y represents the rate of change along the vertical direction.

3) Canny Edge Detection

Canny Edge Detection is a widely used technique for detecting edges in images, known for its accuracy and noise reduction. The process involves:

1. Gaussian Smoothing: Reduces image noise by applying a Gaussian blur.
2. Gradient Calculation: Uses Sobel kernels to find intensity gradients and directions.
3. Non-maximum Suppression: Thins edges by keeping only local maxima along gradient directions.
4. Edge Tracking by Hysteresis: Connects weak edges to strong edges, discarding isolated noise.

The result is a binary image highlighting clear edges, useful in object detection, segmentation, and feature extraction.

$$Gradient\ magnitude = \sqrt{G_x^2 + G_y^2}$$

$$Gradient\ Direction: 2tan2(G_x\ , G_y)$$

- G_x: Gradient (intensity change) in the horizontal direction.
- G_y: Gradient (intensity change) in the vertical direction.

4) Robert Edge Detection:

Robert's Cross is a simple and fast edge detection method used in image processing. It detects edges by measuring rapid intensity changes using two 2×2 convolution kernels.

Steps:

1. Grayscale Conversion – Convert the image to grayscale to focus on intensity changes.
2. Convolution – Apply two kernels to approximate horizontal (G_x) and vertical (G_y) gradients.
3. Edge Magnitude – Compute the edge strength using:

$$magnitude = \sqrt{(G_x)^2 + (G_y)^2}$$

$$Direction = \arctan\left(\frac{G_x}{G_y}\right)$$

- Gx: Gradient (change in intensity) in the horizontal or x-direction.
- Gy: Gradient in the vertical or y-direction.

5) Prewitt

Prewitt edge detection helps highlight edges in an image by computing intensity changes using two basic filters (kernels) and then calculating how strong and in what direction those changes occur. It is simple, fast, and works well for basic edge detection tasks.

1. Grayscale Conversion – Convert image to grayscale.
2. Convolution – Apply Prewitt kernels to detect horizontal and vertical gradients.
3. Gradient Magnitude – Calculate edge strength using:

$$magnitude = \sqrt{(G_x)^2 + (G_y)^2}$$

- Gx: intensity changes along the horizontal axis
- Gy: intensity changes along the vertical axis

6) K-Means Segmentation

K-means segmentation divides an image into K clusters based on pixel similarity (usually intensity or color). It works by:

1. Initializing K random cluster centroids.
2. Assigning each pixel to the nearest centroid using Euclidean distance.
3. Updating centroids as the mean of assigned pixels.
4. Repeating steps 2–3 until centroids stabilize.

The result is a segmented image where pixels in the same cluster share similar features. It's fast and effective, but sensitive to initial centroids and requires pre-defining K.

7) Graph cut:

The optimization problem in graph cut segmentation is formulated using an energy function, which captures both the data term and the smoothness term:

$$E(S) = \sum_{p \in V} D_p(S_p) + \lambda \sum_{(p,q) \in E} V_{pq}(S_p, S_q)$$

This energy function is used in graph cut segmentation to separate an image into meaningful regions (like foreground and background):

- $D_p(S_p)$ Data term – how well pixel p fits its assigned label Sp (e.g., foreground/background).
- $V_{pq}(S_p, S_q)$ Smoothness term – penalizes differences between neighboring pixels p and q to maintain region consistency.
- λ balances between data accuracy and smoothness.

The segmentation is achieved by minimizing this energy function using the min-cut/max-flow algorithm, which efficiently partitions the image graph into regions with minimal energy.

8) Flood Fill:

Flood fill is a region-filling algorithm that starts from a seed point and fills all connected pixels matching a target condition with a new color. It's commonly used in image editing and games.

- Recursive method: Simple to implement but may cause stack overflow in large areas.
- Iterative method: Uses a stack or queue to avoid recursion and is more memory-efficient.

9) Watershed Segmentation:

Watershed segmentation treats a grayscale image as a topographic map and segments regions by "flooding" from minima. It identifies catchment basins and watershed lines (boundaries).

- In MATLAB, gradient images are used to guide the segmentation.
- Marker-based watershed helps prevent over-segmentation by defining known regions.
- Commonly used in biomedical imaging and object separation tasks.

Peak Signal-to-Noise Ratio (PSNR) is a common metric in MATLAB for measuring the quality of a compressed or reconstructed image compared to its original. It quantifies the ratio between the maximum possible pixel value and the level of noise or distortion introduced during processing. Calculated using the Mean Squared Error (MSE), PSNR indicates how closely the output image matches the original. Higher PSNR values reflect better image quality with minimal loss, while lower values suggest significant degradation. PSNR is widely used in image compression, restoration, and denoising applications to evaluate and compare the effectiveness of different image processing techniques.

$$MSE = \frac{1}{mn} \sum_{j=1}^{n-1} |I(i,j) - K(i,j)|^2$$

where $m \times n$ is the image size, I and K are two monochrome images, one of which is a noisy approximation of the other. PSNR is represented as

$$PSNR = 20log_{10}(\frac{MAX_1}{\sqrt{MSE}})$$

where $MAXI$ is the maximum pixel value of the image.

IV. RESULTS

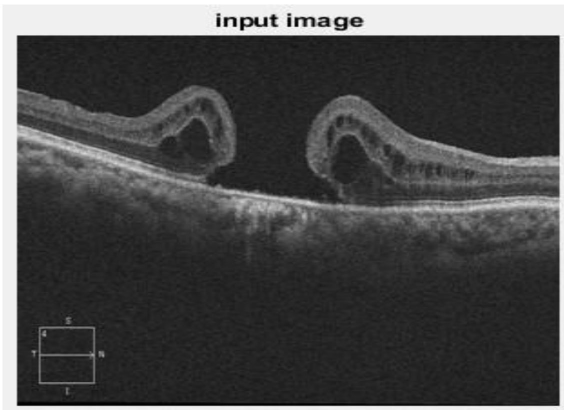


Figure 3: Input Image

This figure 3 displays the original retinal OCT image selected by the user and resized to 299×299 pixels. This pre-processed image serves as the initial input for subsequent segmentation and classification procedures in glaucoma detection. The resizing helps standardize input dimensions for consistent analysis.

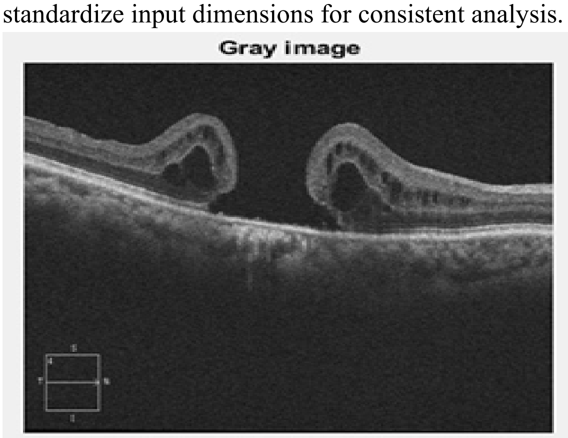


Figure 4: Gray image

Figure 4 indicates RGB input image is converted to grayscale to simplify further processing. Grayscale conversion reduces computational complexity while preserving essential structural information required for edge detection and segmentation.

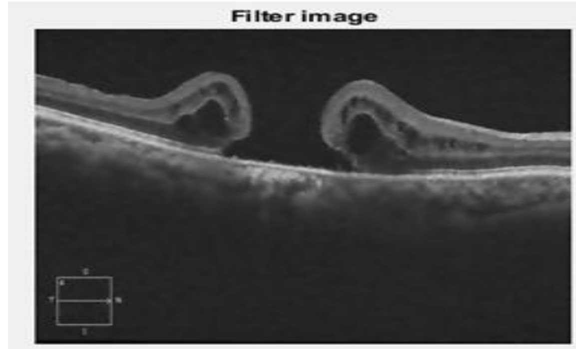


Figure 5: Filter image

Figure 5 indicates grayscale image undergoes noise reduction using a Wiener filter with a 5×5 neighborhood. This step enhances image clarity and prepares it for effective thresholding and edge detection by minimizing unwanted noise artifacts.

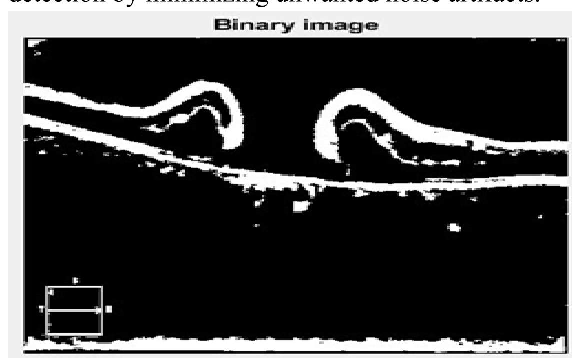


Figure 6: Binary image

Figure 6 indicates Adaptive thresholding is applied to the filtered image to create a binary image. This process distinguishes foreground structures from the background, forming a crucial step in object isolation for further segmentation.

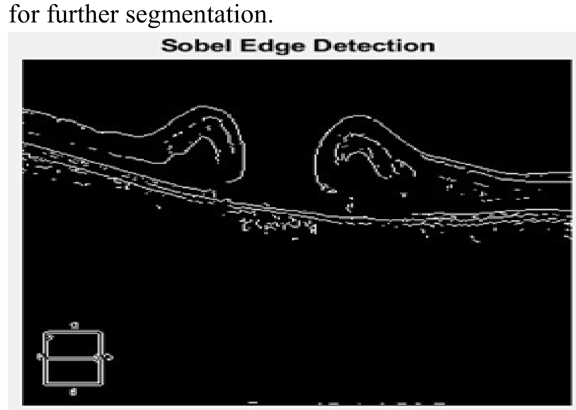


Figure 7: Sobel Edge detector

Figure 7 indicates Sobel operator is used to detect edges in the filtered retinal image. This technique emphasizes vertical and horizontal boundaries, aiding in the detection of anatomical features within the retina.

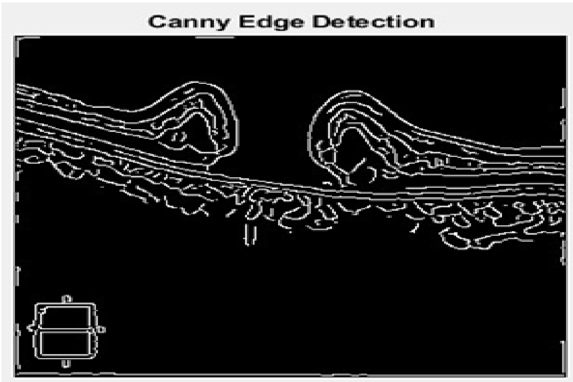


Figure 8: Canny edge detector

Figure 8 indicates The Canny edge detector identifies sharp intensity changes with high accuracy and low error rates. It is effective in extracting fine retinal structures, offering precise boundary detection in the OCT image.

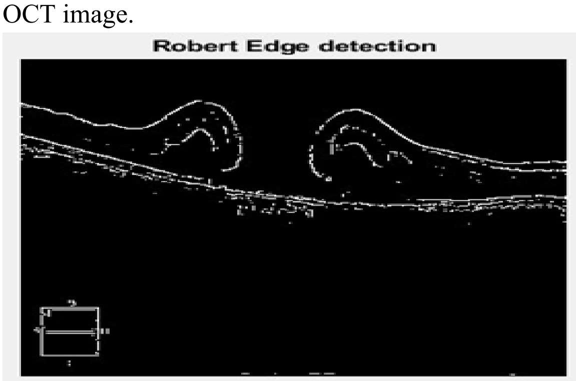


Figure 9: Robert edge detector

Figure 9 indicates The Roberts edge detection method highlights diagonal edges. This figure showcases fine boundary details, offering an alternative approach to traditional edge detectors by focusing on rapid intensity transitions.

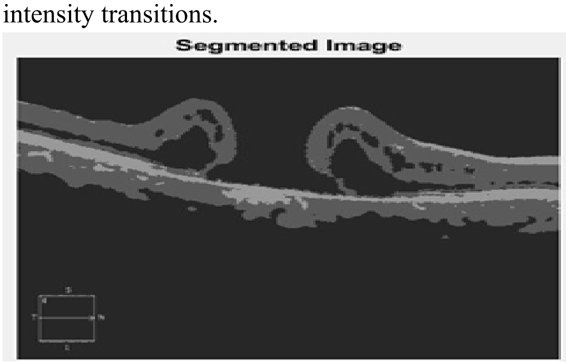


Figure 10: K-mean segmentation

Figure 10 indicates K-means clustering is applied to the filtered image, segmenting it into three distinct regions. This unsupervised segmentation technique groups pixels based on intensity similarity, facilitating layer differentiation within the retina.

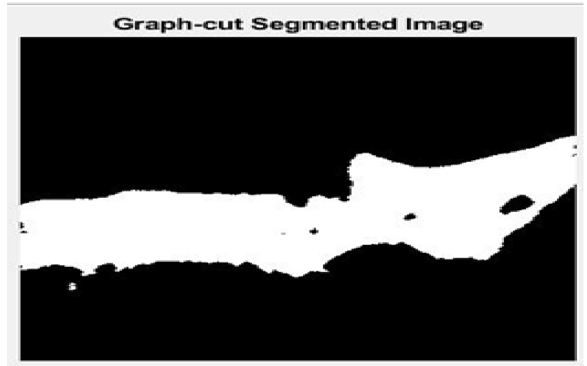


Figure 11: Graph-Cut Segmentation Image

Figure 11 indicates Graph-cut segmentation divides the image into object and background regions by minimizing energy functions. It offers precise boundary detection and is useful in highlighting pathological regions in retinal OCT scans.

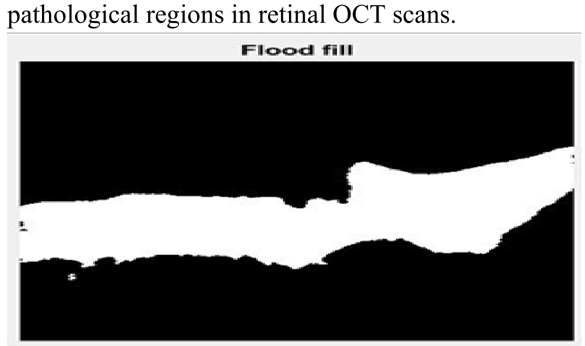


Figure 12: Flood Fill

Figure 12 indicates Holes within the segmented image (obtained from graph cut) are filled using morphological flood-fill operation. This step enhances completeness and continuity of segmented structures for more accurate analysis.

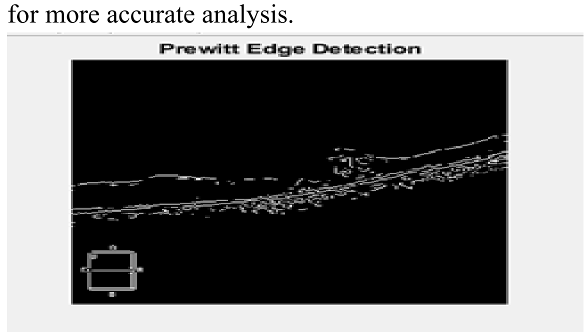


Figure 13: Prewitt Segmentation

Figure 13 indicates The Prewitt operator detects edges by evaluating horizontal and vertical gradients. This technique is used to extract structural outlines within the OCT image, contributing to the comparative evaluation of edge detection methods.

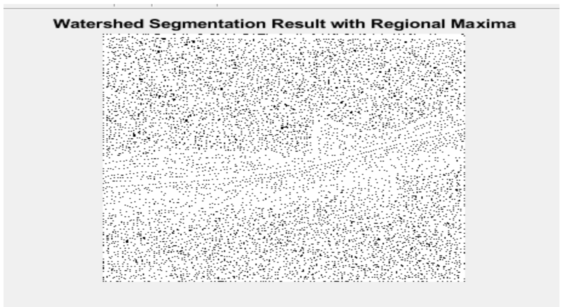


Figure 14: Watershed Segmentation

Figure 14 indicates Watershed segmentation uses gradient magnitude and regional maxima to delineate boundaries between objects. It is particularly effective in separating closely packed retinal layers or lesions by identifying intensity basins.

S. No	Adaptive Threshold	Sobel Edge	Canny Edge	Roberts Edge	K-means	Graph cut	Flood fill	Watershed	Prewitt
1	63.64	63.61	63.62	63.61	63.64	63.68	63.68	63.75	63.61
2	60.79	60.77	60.77	60.77	60.8	60.82	60.82	60.89	60.77
3	60.86	60.84	60.84	60.84	60.87	60.89	60.89	60.95	60.84
4	61.01	60.99	60.99	60.99	61.01	61.04	61.05	61.1	60.99
5	60.93	60.91	60.91	60.91	60.93	60.95	60.95	61.02	60.91
Average	61.446	61.424	61.426	61.424	61.45	61.476	61.478	61.542	61.424

Table 1: PSNR Comparison

The table 1compares nine edge detection and segmentation methods across five trials, showing PSNR percentages. Watershed achieves the highest average accuracy (61.54%), followed by Flood Fill (61.48%) and Graph Cut (61.48%). Adaptive Threshold, K-means, and Sobel Edge have similar, slightly lower averages around 61.4% and Comparison Graph also figure 15:

Adaptive Threshold	Sobel Edge	Canny Edge	Roberts Edge	K-means	Graph cut	Flood fill	Watershed Segmentation	Prewitt
1856.38	1868.7	1865.88	1869.04	1858.89	1840.78	1840.57	1811.94	1868.74
3582.46	3597.51	3593.23	3597.88	3575.1	3558.07	3555.88	3502.43	3597.52
3520.97	3540.12	3535.57	3540.76	3518.09	3499.5	3496.7	3450.91	3540.18
3407.23	3421.83	3416.77	3422.34	3400.83	3377.3	3375.5	3334.33	3421.85
3349.02	3358.98	3354.18	3359.03	3337.06	3320.25	3319.6	3262.89	3359.02
3143.212	3157.43	3153.13	3157.81	3137.99	3119.18	3117.65	3072.5	3157.46

Table 2: MSE Comparison

This table2 and figure 16: shows the Mean Squared Error (MSE) values for nine image processing methods across five trials. Lower MSE indicates better performance. Watershed Segmentation consistently has the lowest MSE average (3072.5), suggesting it produces the most accurate results. Graph Cut and Flood Fill also perform well with low MSE values, while methods like Sobel Edge, Canny Edge, and Prewitt have slightly higher MSE averages around 3150, indicating less accuracy.

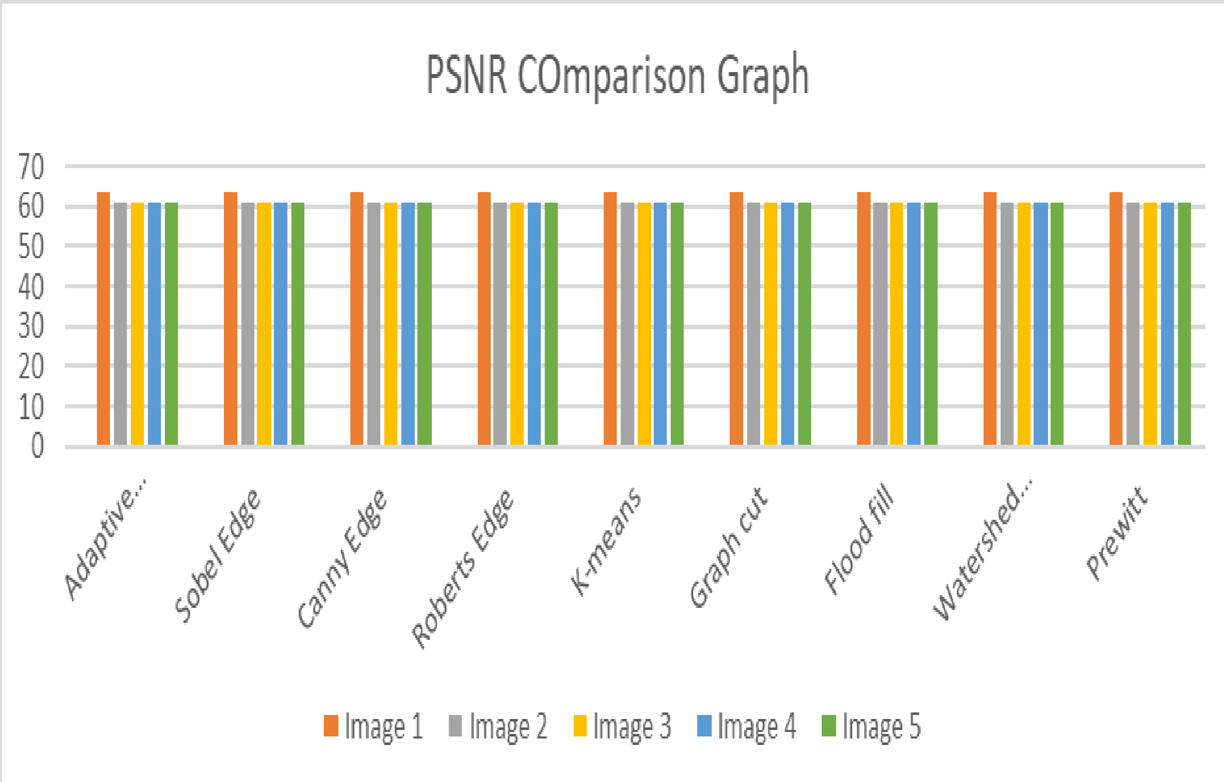


Figure 15: PSNR Comparison Graph

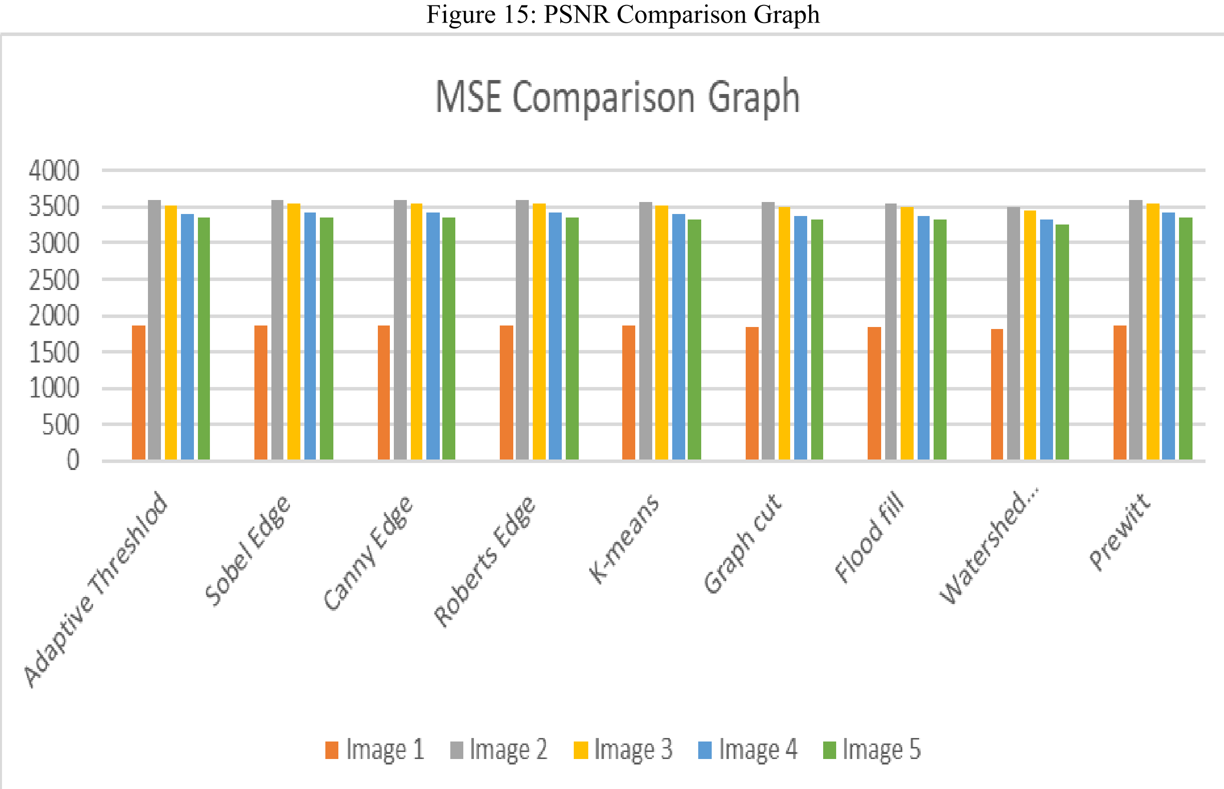
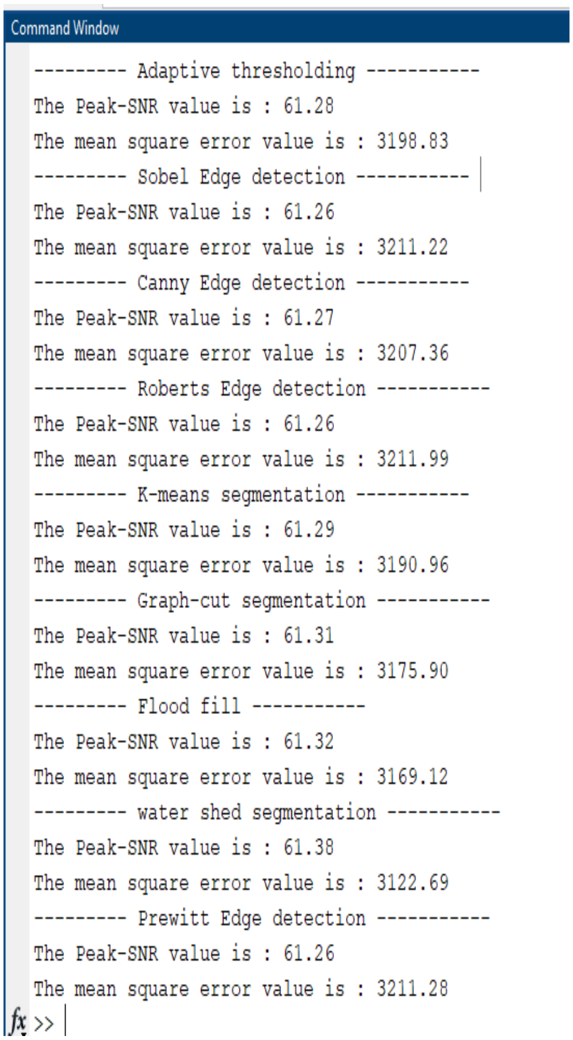


Figure 16: MSE Comparison Graph



```
Command Window
--------- Adaptive thresholding -----------
The Peak-SNR value is : 61.28
The mean square error value is : 3198.83
--------- Sobel Edge detection -----------
The Peak-SNR value is : 61.26
The mean square error value is : 3211.22
--------- Canny Edge detection -----------
The Peak-SNR value is : 61.27
The mean square error value is : 3207.36
--------- Roberts Edge detection -----------
The Peak-SNR value is : 61.26
The mean square error value is : 3211.99
--------- K-means segmentation -----------
The Peak-SNR value is : 61.29
The mean square error value is : 3190.96
--------- Graph-cut segmentation -----------
The Peak-SNR value is : 61.31
The mean square error value is : 3175.90
--------- Flood fill -----------
The Peak-SNR value is : 61.32
The mean square error value is : 3169.12
--------- water shed segmentation -----------
The Peak-SNR value is : 61.38
The mean square error value is : 3122.69
--------- Prewitt Edge detection -----------
The Peak-SNR value is : 61.26
The mean square error value is : 3211.28
fx >>
```

Figure 17: Classified Metrices

Figure 17: Displays the classified metrics in the Command Window, including PSNR and MSE values for evaluating segmentation accuracy.

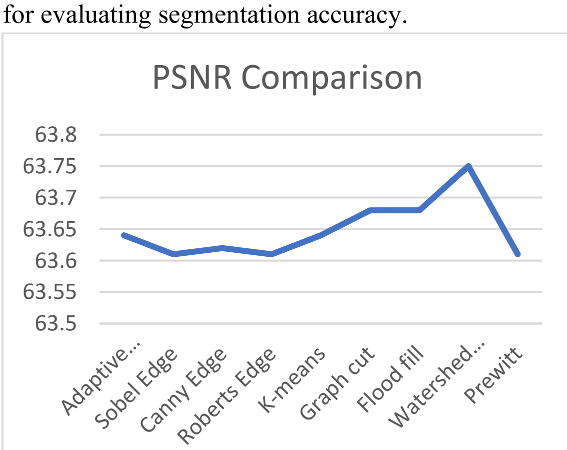


Figure 18: Image 1 PSNR Comparison Graph

Figure 18: The graph compares PSNR values of segmentation methods, showing Watershed achieves the highest image quality, followed by Flood Fill.

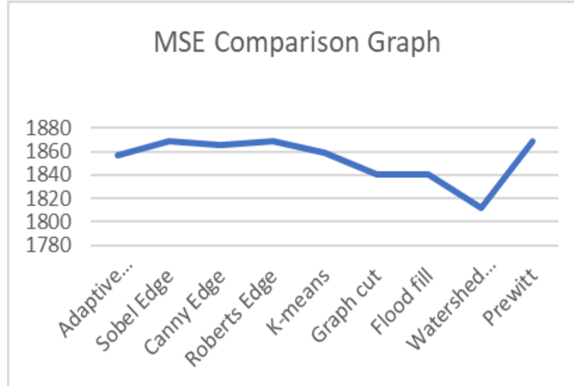


Figure 18: Image 1 MSE Comparison Graph

The MSE Comparison Graph shows Watershed Segmentation achieves the lowest error, indicating best performance. In contrast, Prewitt shows the highest MSE, meaning less accurate segmentation compared to other methods.

V. CONCLUSION

In conclusion, image segmentation is vital in image processing, especially for applications like medical imaging (e.g., OCT scans), where precision is crucial. It divides images into meaningful segments, enabling more effective analysis. Clustering-based methods have proven particularly effective for OCT image segmentation. Preprocessing techniques such as the Wiener filter help reduce speckle noise, improving segmentation accuracy. Performance evaluation using metrics like MSE and PSNR allows comparison of methods including thresholding, edge detection (Sobel, Canny, Prewitt, Roberts), clustering, graph cut, watershed, and flood fill. Understanding each method's strengths helps in selecting the most suitable approach for accurate and reliable image segmentation.

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