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ANALYSIS OF VARIOUS IMAGE SEGMENTATION TECHNIQUES ON RETINAL OCT IMAGES

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Abstract:
One of the most crucial steps in image processing is image segmentation. An image is segmented when it is divided into smaller sections, called segments. Because analysing the entire image would be inefficient for tasks like object recognition or image reduction, these are the areas where it is most useful. The process of separating an image's components for additional processing is known as image segmentation. Several image segmentation strategies were examined in this paper, such as the threshold approach, edge-based method, and clustering-based method. Clustering-based segmentation is the most successful segmentation technique for separating pictures in OCT images. The wiener filter method is employed during preprocessing to lessen speckle noise. Determine the mean square error (MSE) and peak signal to noise ratio (PSNR) for the segmented image quality in relation to threshold, edge-based (Sobel, Canny, Roberts), and clustering-based segmentation approaches.

Keywords— Clustering, Edge detection, Image segmentation, Region-based, Threshold

1. Introduction

New technologies are constantly developing in the area of image processing, particularly in the segmentation arena. This paper provides a brief overview of some of the most widely used segmentation techniques, including edge detection, clustering, thresholding, and model-based approaches, outlining both their benefits and downsides. A few of the methods work well with photos that are noisy. In this sense, thresholding is the most straightforward segmentation technique, whereas Markov Random Field (MRF) offers the best image noise cancellation methodology. One of the core functions of image processing is image segmentation, which divides an image into meaningful areas or segments according to predetermined standards such texture, colour, intensity, or spatial coherence. It is essential to many applications, including as computer vision, remote sensing, medical imaging, and object recognition.

A multitude of segmentation approaches have been presented in the literature due to the growing complexity of picture data and the growing need for precise and effective segmentation methods. This study of the literature offers a thorough analysis of the segmentation strategies now in use, emphasising their benefits, drawbacks, advantages, and methods [1]. Image segmentation technology is widely applied in face recognition, pedestrian detection, medical image processing, and other fields. Presently available methods for segmenting images include segmentation based on clustering, segmentation based on edge detection, segmentation based on weakly-supervised learning in CNN, and more. In this work, various picture segmentation methods are analysed, summarised, and their benefits and drawbacks are compared. Using the combination of these techniques, we finally forecast the direction of image segmentation development [2].

A macula tear or break is known as a macular hole. It impairs older people's central vision and is situated in the centre of the retina. Macular hole diagnosis can be made accurately by optical coherence tomography (OCT). While there are algorithms in place to identify retinal layers and cysts, a reliable method for accurately diagnosing macular holes is still lacking. Therefore, we suggest an automated technique for the precise identification of macular holes. Six steps make up the suggested system. Preprocessing the OCT picture is the initial step, followed by Nerve Fibre Layer (NFL) detection. After processing the identified NFL layer, the depth feature is extracted. Next, our suggested system finds the macular hole in OCT images. OCT images of the retinal hole and healthy macula are used to assess the suggested system.

In addition, the suggested approach is contrasted with alternative machine learning algorithms [3]. It is frequently possible to extract regions from an image that are texturally distinct from their surroundings by 1) executing a local operation at each place in the image, 2) averaging the outcomes, and 3) thresholding. If there are too many sections with varying textures, this method normally won't work since the average of one kind of region could blend in with the average of a combination of two adjacent types. The coarseness of the texture determines how much averaging should be done. Although an automatic method of determining this quantity was explored, the outcomes did not meet the quality standards of a predetermined high degree of averaging. To sum up, region extraction by averaging and thresholding is a basic method in computer vision and image processing that provides a straightforward yet efficient way to divide images into discrete areas according to intensity levels. In spite of its simplicity, this approach has shown to be adaptable and useful in a variety of contexts, and research is still being done to improve its scalability, resilience, and performance. Researchers and practitioners can effectively and efficiently handle a wide range of image analysis tasks by grasping the fundamentals, approaches, and applications of region extraction by averaging and thresholding [4]. This work presents a new colour image segmentation technique based on Rough-set theory and utilising the histon notion. The term "histon" refers to an encrustation of a histogram in which the elements are all the pixels that can be categorised as potentially belonging to the same segment. The histogram correlates with the lower approximation and the histon correlates with the upper approximation, according to rough-set theory [5]. The application of a simple algorithm for identifying the size and shape of tumours in brain magnetic resonance imaging is the subject of this paper. An unchecked growth of tissues in any part of the body is called a tumour.

There are various forms of tumours, each with unique characteristics and approaches to therapy. Because of their nature in the restricted area of the cerebral cavity, brain tumours are known to be intrinsically dangerous and potentially fatal (space produced inside the skull). The majority of research conducted in affluent nations indicates that a significant number of brain tumour deaths were caused by incorrect diagnosis. A comprehensive image of the brain is often obtained from an intracranial CT scan or MRI. This image is visually examined by the physician for detection & diagnosis of brain tumour. However, this method of detection resists the accurate determination of stage & size of tumour.

To avoid that, this project uses computer aided method for segmentation (detection) of brain tumour based on the combination of two algorithms. This method allows the segmentation of tumour tissue with accuracy and reproducibility comparable to manual segmentation. In addition, it also reduces the time for analysis. At the end of the process the tumour is extracted from the MR image and its exact position and the shape also determined. The stage of the tumour is displayed based on the amount of area calculated from the cluster. In biomedical applications, the clustering approach is commonly employed, especially for aberrant magnetic resonance imaging (MRI) scans that may indicate brain tumours.

In terms of segmentation efficiency, fuzzy clustering utilising the fuzzy C-means (FCM) method turned out to be better than the other clustering techniques. However, the FCM algorithm's main flaw is the enormous amount of computing time needed for convergence. By altering the cluster centre and membership value updating criterion, the FCM algorithm's computational efficiency is raised. This research investigates the use of the modified FCM algorithm for the detection of MR brain tumours. The segmentation method makes use of an extensive feature vector space. The modified FCM and the regular FCM are compared with respect to convergence rate and segmentation efficiency.

Based on performance measures, the improved FCM algorithm performs better according to experimental results [6].

2. Proposed Method

Block Diagram and Implementation

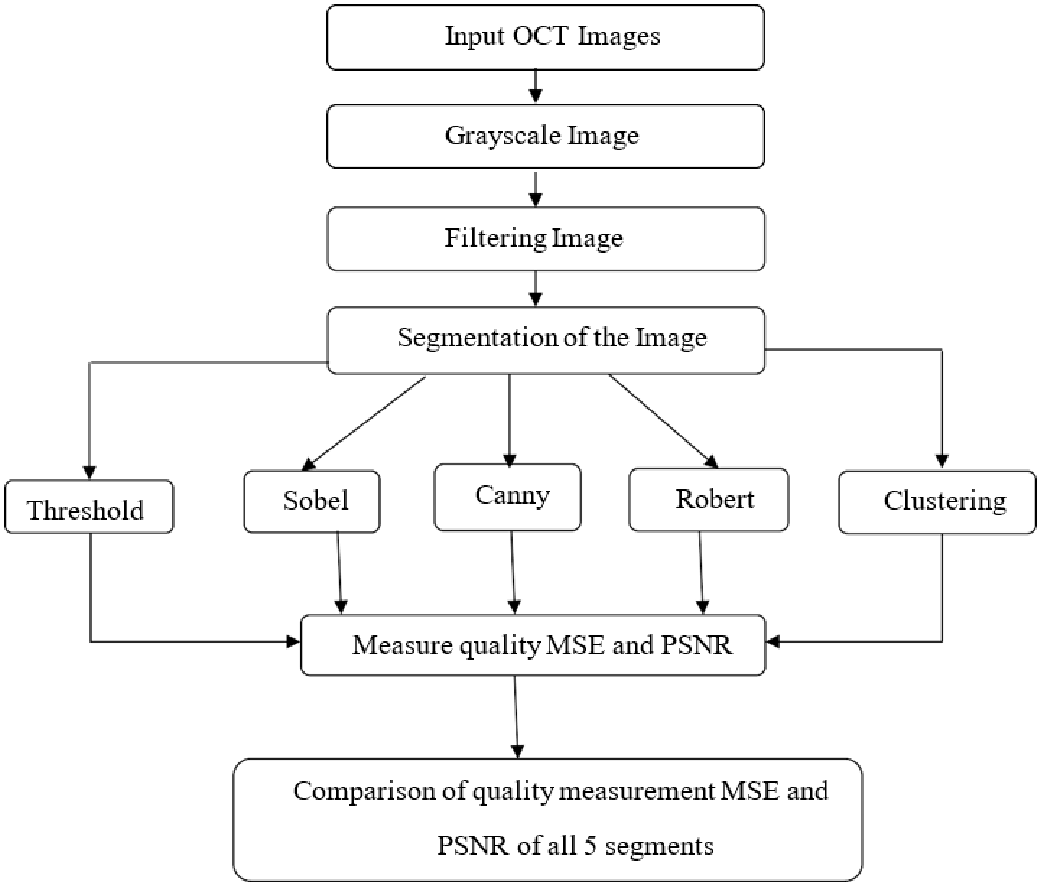


Figure.1. Architecture / Block Diagram

2.1 Input Oct Images

We are giving an input retinal Optical Coherence Tomography image and in the second step it converts into grayscale image.

2.2 Grayscale Image

A grayscale image is a type of digital image in which each pixel is represented by a single value indicating the intensity of light at that particular location. Unlike color images, which use multiple channels to represent different color components, grayscale images have only one channel, typically ranging from black to white. Wiener filtering is a signal processing technique employed for the restoration and enhancement of images by reducing noise and improving overall quality. Named after the mathematician Norbert Wiener, this filtering method is particularly effective in scenarios where the characteristics of the noise are known or can be estimated. In the context of grayscale images, Wiener filtering is applied to address issues such as blur and noise. The primary goal is to reconstruct a high-quality image from a degraded or noisy version. The Wiener filter operates in the frequency domain, where the power spectral density of the image and the noise are considered.

2.3 Filtering

The Wiener filtering process involves a balance between enhancing the image details and suppressing the noise. It takes into account the trade-off between signal enhancement and noise amplification. By utilizing knowledge about the statistical properties of the image and the noise, Wiener filtering adapts its parameters to optimize the restoration process. The Wiener filter is mathematically expressed as a convolution in the frequency domain, where the filter's transfer function is defined based on the estimated signal-to-noise ratio. This transfer function acts as a spatial filter that is applied to the frequency components of the degraded image. In practical applications, Wiener filtering finds use in various fields, including medical imaging, astronomy, and remote sensing. It is employed to improve the clarity and fidelity of grayscale images, ensuring that important details are preserved while minimizing the impact of unwanted noise.

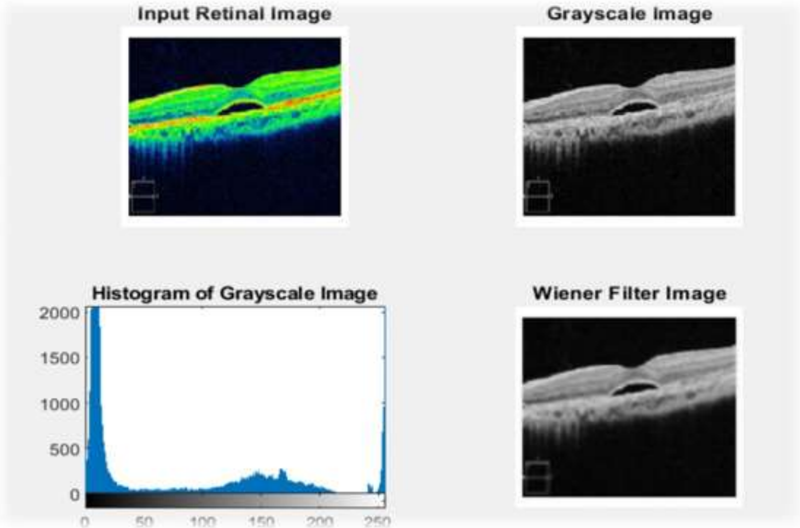


Figure.2. a) Input image b) Grayscale image c) Histogram of grayscale image d) Weiner Filter

2.4 Segmentation Techniques

There are many commonly used image segmentation algorithms as follows.

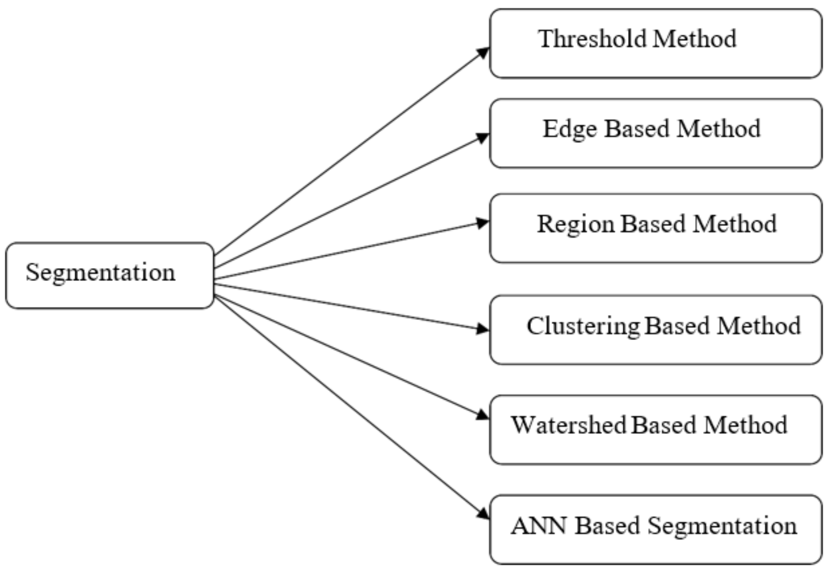


Figure.3. Segmentation Techniques

2.4.1 Threshold method

Focus on peak values as it examines the histogram of the image to locate associated pixels. This is probably the most straightforward but efficient technique for finding the important objects in an image. Each pixel in a photograph is separated into groups based on its intensity by comparing it to a threshold value. The threshold method proves to be useful when it is anticipated that the image's subject would be more intense than its background and other undesirable components. On a fundamental stage, the threshold value T is treated as a stable. That method, however, might be useless given how much noise the image contain.

i) Simple Thresholding

This method converts the pixel in an image to either black or white. A pixel is replaced with black when its intensity (Ii , j) at position (I , j) is less than the threshold (T), and with white when it is larger. This thresholding technique uses binary logic.

ii) Global Thresholding

Bimodal images are those that have a histogram with two distinct peaks and a valley in the middle. At the valley point, a threshold T is chosen. The pixels of the given image, f(x , y), are then assessed against the threshold. If the pixel's values are more than or equal to the threshold value, it receives a value of 1. If not, the output threshold picture g is created with a value of 0. (x, y). When using the threshold approach, one can

$$G(x, y) = \begin{cases} 1 & \text{if } f(x, y) >= T \\ 0 & \text{otherwise} \end{cases}$$

Equation: 1

Algorithm for choosing a thresholding value is given as follows:

1. Choose an initial threshold T=T0, Where T0 is the mean of the two peaks or the mean pixel value.
2. Calculate the mean value of the pixel below the threshold (µ1) and the mean value of the pixel above this threshold (µ2).
3. Compare a new threshold as T1= µ1 + µ2 /2
4. Repeat steps 2 and 3 until there is no change I T.

iii) Adaptive Thresholding

Adaptive algorithm is also known as the dynamic thresholding algorithm. During dynamic thresholding, the image is divided into several overlapping sub-images. The local thresholds are found and the histograms of all the sub-images are generated. Following that, the threshold value is determined by extrapolating the results from the sub images.

2.4.2 Edge based method

Edge detection, a vital first step in understanding visual features, is the procedure of locate edges in an image. It is believed that edges contain significant information and pertinent characteristics. It preserves and concentrates only on the essential structural components of an image. Edge- based segmentation algorithms search for edges in a picture by spotting variations in texture, contrast, saturation, brightness, and other elements. The Sobel operator, the Canny operator, the Robert's variable, etc. are some examples of basic edge detection operators used in these techniques. These operators support the detection of edge discontinuities, which supports the detection of edge borders. Our goal is to at least partially segment the input image using this technique, combining all restricted edges into a new binary image.

2.4.3 Region based method

The method separates the image into different mechanism with related features in region-based segmentation approaches to create segments. These mechanisms are really a set of pixels, to put it simply. Region- based image segmentation methods start by probing the input image for some seed places, which could be smaller pieces or visibly larger chunks. Next, either extra pixel is additional to the seed points or the seed points are more downsized or reduced to lesser segments and combined with other smaller seed points. The subsequent process is therefore based on two key methods.

- Region Growing
- Region Splitting and Merging

2.4.4 Clustering based method

Contrary to user-defined traits, classifications, or groups, unsupervised algorithms are those employed in clustering. Clustering techniques can be used to extract from the data the fundamental, concealed data as of the perspective of structures, clusters, and groups that are normally unidentified from a heuristic approach. Using "clustering-based methods", the image is separated into "clusters" or detached set of pixels with connected characteristics. Due to the fundamental properties of facts clustering, which favour clusters with similar objects over clusters with dissimilar objects, the data components are separated into "clusters". Few of the most capable clustering algorithms, such as "k-means" and "fuzzy c-means" algorithm, are heavily included into the "clustering-based "systems.

- k-means clustering

- Fuzzy C Means

2.4.5 Watershed based method

A ridge method known as "watershed" upholds the notion of topological interpretation. Additionally, it is a regional approach. We contrast several aspects of a photograph with an analogous hilly and valley landscape. The angle and height of the indicated topography are clearly quantified by the grey value of the relevant pixels, also referred to as the gradient magnitude. On the basis of this common 3D representation of Earth landscape, the watershed transform separates an image into region known as "catchment basins." Every pixel whose greatest fall in grey values ends at a local minimum constitutes a catchment basin.

2.4.6 Artificial neural network-based segmentation method

Image recognition is a term that is widely used to describe the technique of employing neural networks for image segmentation. Artificial intelligence (AI) is used to routinely method and recognize visual elements such as objects, faces, text, handwritten text, etc. An image can be seen as a raster or as a collection of vectors, depending on the technique used. The “vector” or “raster” is divided into simple parts to show the distinct objective elements and features that make up an image. Computer vision systems may reasonably investigate these creations by picking the main parts of them. After that, the data is organized utilizing feature extraction and categorization methods.

Edge detection is a fundamental image processing technique used to identify boundaries within an image. Among the various methods available, Sobel, Canny, and Prewitt are prominent edge detection algorithms. The Sobel operator, named after its inventor Irwin Sobel, is a simple and computationally efficient method for detecting edges in an image. It operates by convolving the image with a pair of 3x3 kernels, one for horizontal changes and the other for vertical changes. The gradients obtained from these convolutions highlight areas of rapid intensity changes, indicating potential edges.

The Canny edge detection algorithm, developed by John Canny, is a more sophisticated approach that involves multiple steps. It begins with smoothing the image to reduce noise, followed by calculating gradients to find the intensity changes. Non-maximum suppression is then applied to thin the edges, and finally, edge tracking by hysteresis is used to connect the weak edges and discard the insignificant ones. The Canny algorithm is known for its ability to produce accurate and well-connected edges. The Prewitt operator, similar to the Sobel operator, is designed to detect edges based on gradient information. It also employs 3x3 convolution kernels for horizontal and vertical changes.

The Prewitt method is straightforward and computationally efficient, making it suitable for real-time applications where computational resources are limited. While these edge detection methods share the common goal of identifying abrupt changes in intensity, they differ in their approach and complexity. Sobel and Prewitt are relatively simple and easy to implement, making them suitable for real-time applications with limited computational resources. On the other hand, Canny, with its multi-stage process, offers more advanced edge detection capabilities and is widely used when high accuracy is required, such as in computer vision and image processing applications.

2.5 Best Method to USE

K-means clustering is a popular unsupervised machine learning algorithm used for image segmentation, a crucial task in computer vision and image processing. Image segmentation involves partitioning an image into distinct regions or segments based on certain characteristics. K-means clustering is particularly effective in this context as it helps group pixels with similar features, thereby facilitating the identification of meaningful structures within an image.

In the context of image segmentation, K-means clustering treats each pixel as a data point in a multi-dimensional space, where the dimensions represent the pixel's color values. The algorithm aims to partition the pixels into K clusters, with each cluster having a centroid that represents the mean color of the pixels in that cluster. The iterative nature of K-means involves assigning pixels to the cluster whose centroid is closest and updating the centroids based on the assigned pixels. This process continues until convergence, where the centroids stabilize, indicating the final segmentation. One of the advantages of using K-means clustering for image segmentation is its simplicity and efficiency.

The algorithm is computationally less expensive compared to some other segmentation techniques. However, its effectiveness is influenced by factors such as the choice of the number of clusters (K) and the initialization of centroids. In the context of image segmentation, K-means clustering can be applied to various color spaces, such as RGB (Red, Green, Blue) or HSV (Hue, Saturation, Value), depending on the characteristics of the image and the segmentation requirements. The resulting segmented image consists of regions with similar color characteristics, effectively highlighting distinct objects or structures within the original image. Despite its simplicity and efficiency, K-means clustering may face challenges when applied to images with complex structures, varying illumination, or gradients.

Additionally, it may struggle with segmenting images containing objects with similar colors but different textures. In conclusion, K-means clustering serves as a valuable tool for image segmentation by grouping pixels based on their color values. Its simplicity and efficiency make it a popular choice for various applications in computer vision, although careful consideration of parameters and potential limitations is necessary for optimal results, especially in complex image scenarios.

2.5.1 Advantages of Clustering Method:

- **Simplicity:** K-Means clustering is a straightforward and easy-to-understand algorithm, making it accessible to both researchers and clinicians without extensive machine learning expertise. It is an attractive choice for those seeking a simple yet effective segmentation method.
- **Efficiency:** K-Means is computationally efficient, making it suitable for real- time or near-real-time applications, such as in a clinical setting where quick decisions are crucial. It can handle large datasets with relatively low computational resources.
- **Interpretability:** The segmentation process in K-Means is highly interpretable. Each cluster represents a distinct segment or region in the image, allowing clinicians to visually inspect and understand the segmentation results. This transparency is valuable for clinical decision-making.
- **Flexibility:** K-Means allows for flexibility in the number of clusters. By adjusting the number of clusters, it can adapt to different retinal imaging modalities and anatomical variations, providing versatility in its application.
- **Potential for Semi-Supervised Learning:** K-Means can be combined with expert annotations to improve segmentation accuracy. In a semi-supervised setting, manual corrections or additional annotations can be integrated into the clustering process, enhancing the segmentation quality.

2.5.2 Applications of Clustering Method:

- **Image Segmentation:** K-Means clustering is widely used for image segmentation across various domains, including medical imaging (e.g., retinal OCT image segmentation), object recognition, and satellite image analysis. It helps partition images into meaningful regions or segments based on pixel intensity or color similarity.
- **Customer Segmentation**: In marketing and e-commerce, K-Means clustering is applied to group customers with similar purchasing behaviours, preferences, or demographics. This information can be used to tailor marketing strategies, recommend products, and enhance customer satisfaction.
- **Document Classification**: K-Means clustering can be employed for document clustering and topic modelling. It can group similar documents together, aiding in content organization, information retrieval, and content recommendation systems.
- **Anomaly Detection:** K-Means clustering can identify anomalies or outliers in datasets by labelling data points that do not belong to any cluster as anomalies. This is valuable in fraud detection, network security, and quality control.Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) are two widely used metrics in image processing and compression to evaluate the quality of reconstructed or compressed images. MSE, or Mean Squared Error, is a mathematical measure that quantifies the average squared difference between corresponding pixel values in the original and reconstructed images.

It is calculated by taking the average of the squared differences between each pixel's intensity in the original and reconstructed images. MSE provides a quantitative measure of the overall distortion or error in the reconstructed image, with higher MSE values indicating greater distortion. PSNR, or Peak Signal-to-Noise Ratio, is a metric that assesses the quality of an image by comparing the peak signal strength to the noise level. It is expressed in decibels (dB) and is calculated using the logarithm of the ratio of the maximum possible pixel value squared to the MSE. A higher PSNR value indicates a smaller amount of distortion in the reconstructed image, suggesting better image quality.

Both PSNR and MSE are inversely related to image quality, meaning lower values represent higher distortion or lower quality, while higher values indicate better fidelity to the original image. However, it's essential to note that these metrics have limitations and may not always correlate perfectly with human perception of image quality. While they provide quantitative measures, they might not capture certain aspects of visual quality that are important to human observers. Therefore, these metrics are often used in conjunction with other evaluation methods to provide a more comprehensive assessment of image quality in various applications, such as image compression, video coding, and image restoration.

3. Results and Discussion

3.1 Training Data

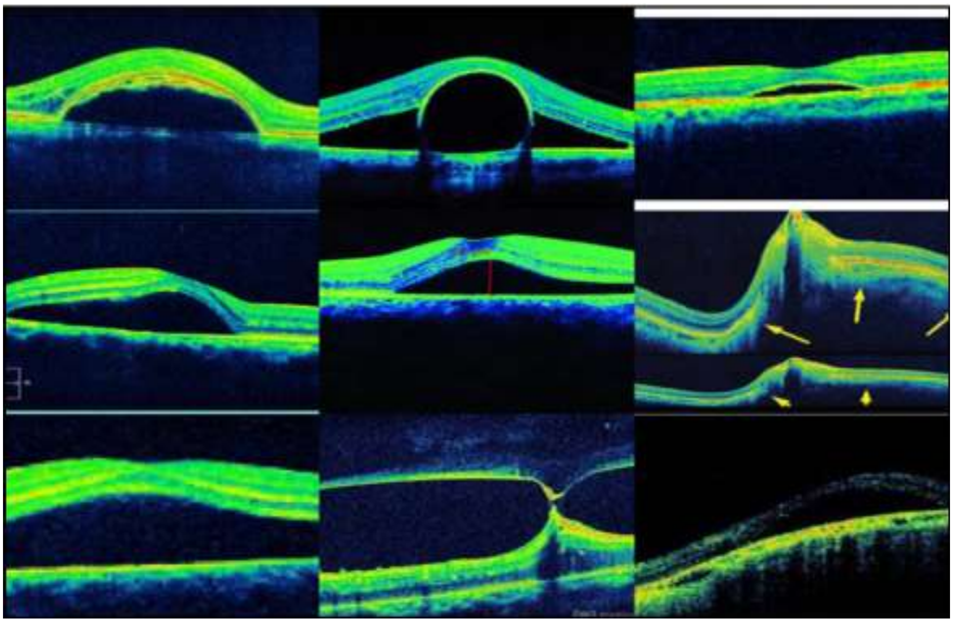


Figure.4. X-Linked Retinoschisis (XLRS)

3.2 Testing Image

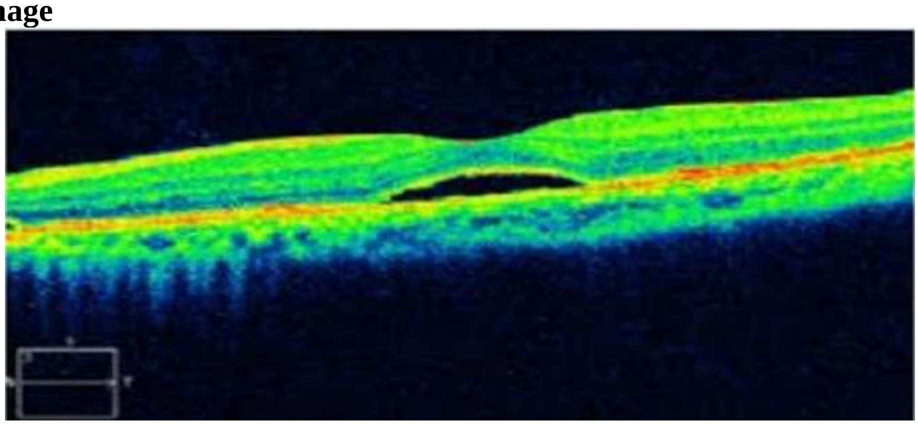


Figure.5. Macular Degeneration, OCT scan- Stock image-C024/0949

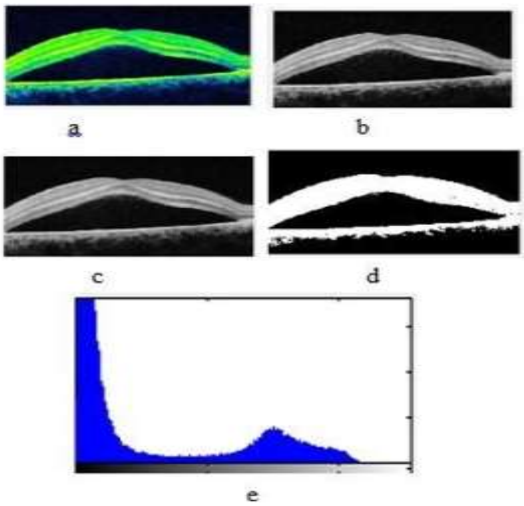


Figure.6. Threshold Segmentation a) Original image b) Grayscale image c) Wiener filter d) Binary image e) Histogram of Grayscale image

We have employed Sobel, Canny, and Robert's to detect edges in this technique, which is one of the simplest. displays edge-based segmentation for an OCT image.

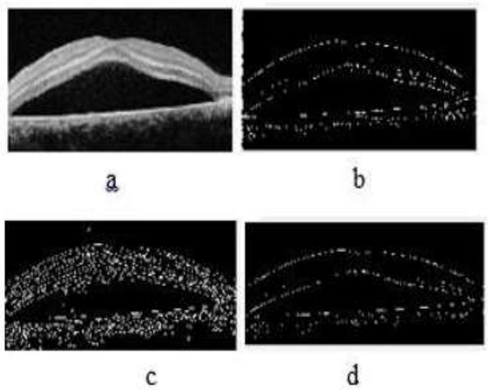


Figure.7. a) Grayscale b) Sobel c) Canny d) Robert K in this case denotes the use of an algorithm. When compared to the Threshold approach and the Edge based method, there are more missing pixels in the clustering.

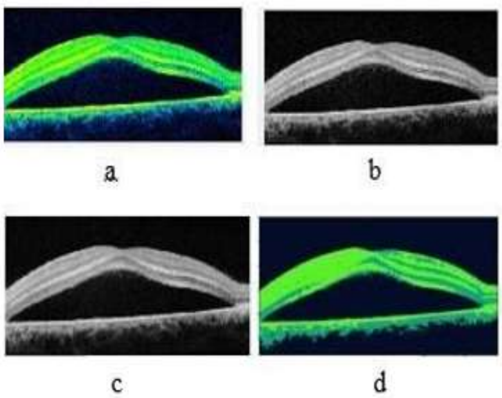
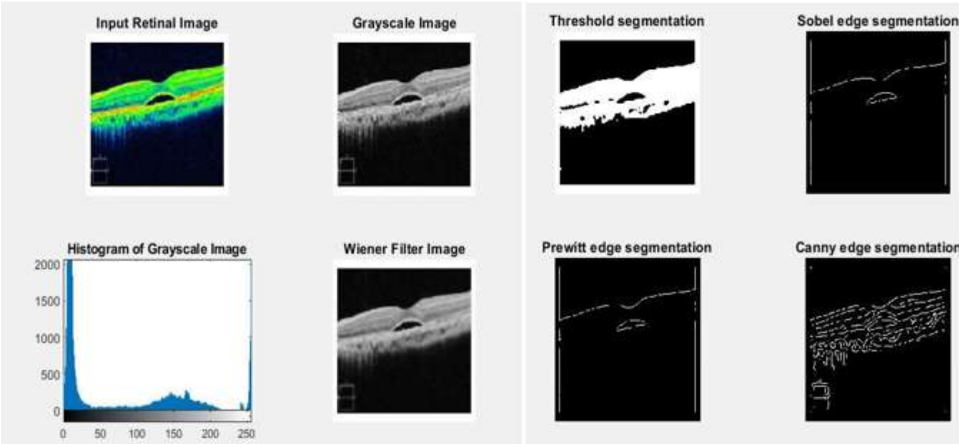
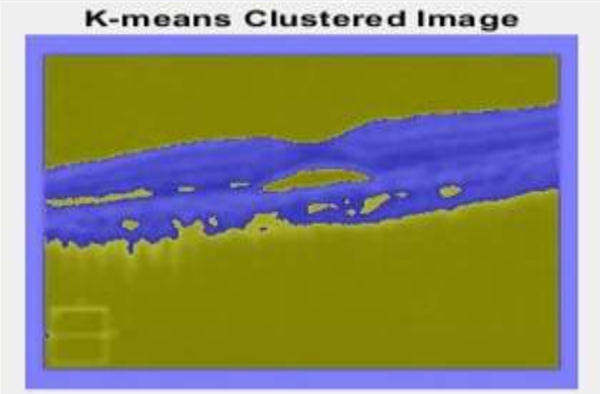


Figure.8. displays the clustering segmentation for the OCT image

The aforementioned comparisons in Tables 1 and 2 for picture segmentation show the qualitative outcome metrics when compared to other methodologies. When the PSNR and MSE values are both high, the segmentation technique yields respectable results. MSE calculates the difference between the segmented image and the source image, sometimes referred to as the filtering image; the lower the value of MSE, the more effective the segmentation. Equation gives a numerical illustration of MSE (1). The PSNR ratio calculates the background noise level in relation to the image's maximum value. In the equation, PSNR is stated in terms of MSE (2). After e xa mining the PSNR and MSE of all the tactics taken into account, it is evident that the k- means approach yields the best suited results. because K- means segmentation is more accurate than threshold and edge- based approaches, both of which have lower PSNR and MSE values. The k- means method produces the best results for OCT image segmentation.

3.3 Input Test Data





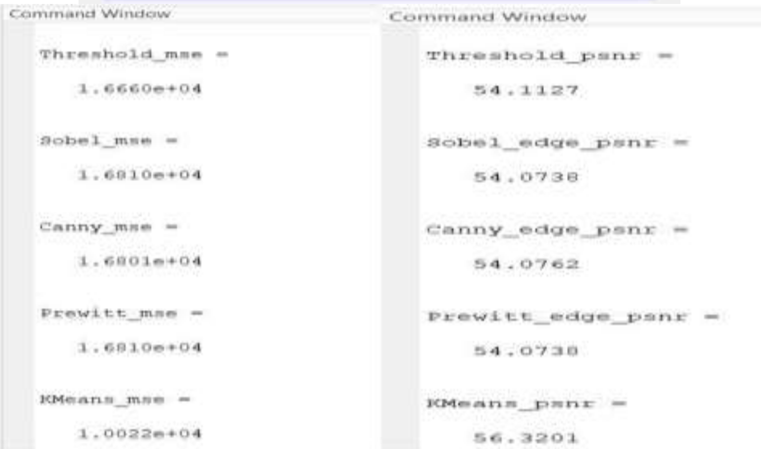
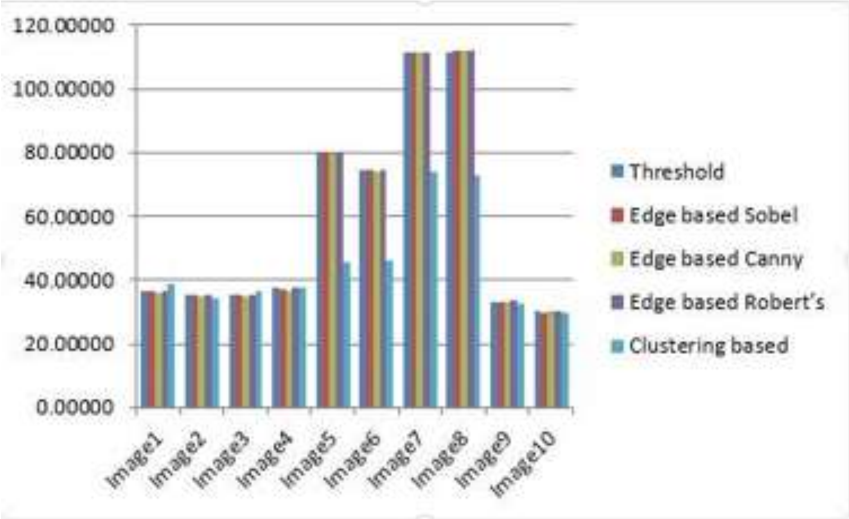


Table 1: MSE Value of Segmented Images

Input Images	Threshold	Edge Based			Clustering based
		Sobel	Canny	Robert's	
Image1	36.34478	36.34758	35.90287	36.32202	38.45937
Image2	35.41763	35.21695	34.71428	35.38762	34.05055
Image3	35.36239	35.21382	34.91701	35.24541	36.18660
Image4	37.41585	37.13707	36.69281	37.44882	37.56159

Image5	80.19056	80.43612	79.37778	80.28223	45.31770
Image6	74.57108	74.28950	73.69823	74.38707	46.29470
Image7	111.18076	111.35405	111.53150	111.39521	73.81819
Image8	111.52163	111.66537	111.89172	111.69552	72.79627
Image9	33.17331	33.20894	32.83196	33.37810	32.70422
Image10	30.14928	29.93522	30.26177	30.11239	29.42549
Total	**585.32727**	**584.80462**	**581.81993**	**585.65439**	**446.61468**
Average	**58.53273**	**58.48046**	**58.18199**	**58.56544**	**44.66147**



4. Conclusion

The four basic analytical algorithms are the main topic of discussion in this work. The comparison analysis demonstrates that for OCT picture segmentation, the k means segmentation methodology performs better than alternative methods. When compared to the threshold, Sobel, Canny, and Robert's approaches, the K-means strategy yields the highest PSNR and the lowest MSE value. The results of the experiment demonstrate that the "k-means segmentation method" increases classification accuracy while simultaneously lowering the difficulty of segmenting OCT images. The clustering methodology employed in intensity-based clustering approaches, particularly the k-means clustering method, provides the best segmentation because there would be minimal changes in intensity in the OCT picture.

Consequently, clustering will turn into a very simple, easy-to-perform technique that is easy to categories. Because an OCT image will have less intensity variations, the k-means clustering method works very well for segmenting OCT images, comparing the "features" of aberrant and normal clinical images, and assessing the application of the results. We can determine that the optimal segmentation method for OCT pictures is k-means based on the previously listed characteristics. We'll evaluate OCT image segmentation performance in the future utilizing a range of segmentation techniques.

Reference

[1] R. Yogamangalam, B. Karthikeyan , "Segmentation Techniques Comparison in Image Processing", International Journal of Engineering and Technology (IJET), Vol 5 No 1 Feb-Mar 2013.

[2] Song Yuheng , Yan Hao," Image Segmentation Algorithms Overview",

[3] M. Anand and Dr. C. Jayakumari ,"Study of Retina Image Segmentation Algorithms from Optical Coherence Tomography (OCT) Images", Jour of Adv Research in Dynamical & Control Systems, Vol. 9, No. 4, 2017.

[4] M. Anand and Dr. C. Jayakumari ,"Automated Detection of Macular Hole in Optical Coherence Tomography Images using Depth-Check Algorithm", International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-9 Issue-1, October 2019.

[5] Davis L S, Rosenfeld A, Weszka J S. Region extraction by averaging and thresholding[J]. IEEE Transactions on Systems, Man, and Cybernetics, 1975 (3): 383-388.

[6] K. M. Hassan, M. R. Islam, T. Tanaka, and M. K. I. Molla, "Epileptic seizure detection from EEG signals using multiband features with Feedforward neural network," Cyberworlds 2019, Kyoto, Japan (in press).