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Detecting Central Serous Retinopathy from Optical Coherence Tomography (OCT) Images using Segmentation Techniques

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ABSTRACT:

The tiny tissues that make up the retina are responsible for absorbing light and converting it into visual recognition in the brain. These people may experience vision loss and blindness as a result of damage to this vital organ. Thus, early diagnosis of the disease may prevent total blindness and, in certain situations, allow vision to return to normal. Therefore, timely and precise CSR detection prevents serious macular damage and is a foundation for detecting other retinal diseases. The OCT pictures have been used to identify CSR, but developing a system that is both accurate and computationally economical is still a difficult task. This research designs a framework for precise and automatically segmenting CSR from denoised OCT images using the Level set segmentation technique. It helps to identify the central serous retinopathy from the OCT images. The recommended system is assessed using the method of the healthy macula and central serous retinopathy OCT images. The proposed system provides an assessment based on the Dice Coefficient (DC), Jaccard Index(JC), and HD(Hausdorff Distance). The outcome of this Level-set segmentation technique compared with the Graph-based segmentation approach. Among these two techniques Level set segmentation produces better results in terms of DC, JC, and HD.

Keywords: Biomedical Imaging, Central Serous Retinopathy(CSR), Optical Coherence Tomography (OCT), Noise Removal, Image Segmentation

1. INTRODUCTION

OCT is a high-resolution, non-invasive imaging method that allows biological sample properties to be visualized (Xing Wei et al., 2023). According to Yukihiro Aoyama et al., 2021 visual deficits are the result of a serous retinal detachment in the macular area, with the fovea, which is linked to chorioretinal disorders such as CSR. According to Donghuan Lu et al. 2019, OCT pictures can be used to detect changes related to the disease that occur beneath the surface of the retina, such as edoema, or the buildup of fluid that can cause vision distortion and be a sign of problems with the retina's vasculature. Figure 1 displays an OCT image of the individual without any signs of CSR or any other retinal syndrome, while Figure 2 displays the OCT image of the subject who has CSR. The choroid, fovea thickness, serous retinal detachment, and Inner Limiting Membrane (ILM) showed differences between OCT pictures of healthy subjects and those with CSR.

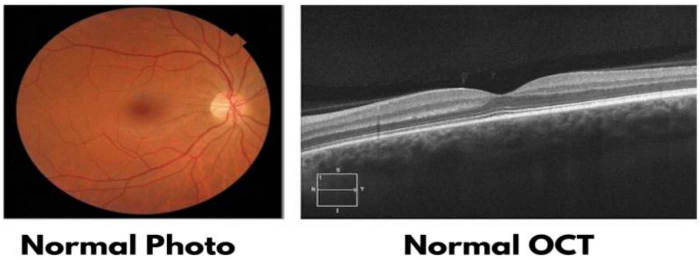

Fig 1: OCT Image of Normal Retina

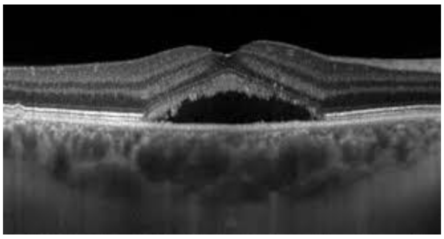

Fig 2: OCT Image with affected Retina by CSR

Section III has covered a thorough and in-depth explanation of the suggested framework for separating CSR from OCT pictures. The assessment and comparison of the segmentation scheme for CSR detection are covered in Section IV. In Chapter V, the conclusion and future directions have been covered.

2. LITERATURE REVIEW

The DL-based CSR detection method put forth by Syed Ale Hassan et al. in 2024 makes use of fundus image and OCT. Before categorization, these input photos are manually enhanced. Then, using both datasets, DarkNet and DenseNet networks are trained. Additionally, pre-trained DenseNet and DarkNet classifiers are adjusted based on requirements. Lastly, assessment parameters are used to compare the two networks' performances on their respective datasets. The experimental findings show that the suggested model is appropriate for use in clinical settings and is effective for CSR identification with the OCT dataset.

A DL system model was developed by Jeewoo Yoon et al., 2020, to diagnose CSC and differentiate between chronic and acute CSC using spectral domain OCT (SD-OCT) images.

Their approach produced very good findings when separating acute from chronic instances, and it worked well when diagnosing CSC. Therefore, algorithms of automated DL systems may be able to assist in the diagnosis of CSC without the need for human expertise.

Vascular shadows, vitreous artifacts, and noise interference can seriously misidentify or detect targets when utilizing the conventional Canny operator for retinal segmentation. An enhanced Canny operator for the automatic segmentation of retinal borders was proposed by Jian Liu et al. in 2022. By modifying the convolution kernel and adding a multi-point boundary search step based on the original technique, the enhanced methodology resolves the issues with the conventional Canny operator. As a first border detection approach, this strategy can be applied either independently or in conjunction

An automated technique for concurrently segmenting fluid and layers in 3-D OCT retinal images of patients with CSR is described. Dehui Xiang et al. 2018 propose multiscale bright and dark layer recognition filters to improve contrast between adjacent layers. The presence of serous fluid or pigment epithelial detachment-induced fluid frequently results in significant morphological alterations as well as decreased contrast between neighboring layers. Additionally, 24 attributes are made with RF (Random Forest) classifiers in mind. The trained RF classifiers are then used to generate 8 coarse surfaces. Ultimately, the smoothed image and the layer formation finding answers are used to build a hypergraph. Despite the low contrast and highly distorted layers in OCT images containing fluids, a customized live wire approach is suggested to precisely identify surfaces among retinal layers. On 48 spectral domain OCT pictures with CSR, the suggested approach was assessed. The testing findings demonstrated that, in terms of layers and fluid segmentation, the suggested method performed better than the most advanced techniques.

Awais Khan et al.'s 2023 proposal uses OCT pictures to automatically detect and classify retinal disorders using DL. Age-related macular degeneration, CSR, branch retinal vein occlusion, and diabetic macular edoema are among the illnesses. The suggested approach consists of four major steps: first, the pre-trained models are adjusted based on the dataset's characteristics, and then the features are extracted using transfer learning. Ant colony optimization is used to refine the retrieved features and choose the best ones. For final classification, the best features are sent to SVM(Support Vector Machine) and k-nearest neighbor algorithms. The achieved accuracy is 97.4% in the absence of ACO. Additionally, the suggested approach performs at the cutting edge and exceeds previous methods in terms of accuracy.

3. PROPOSED MODEL

Detecting CSR from OCT images involves a series of image processing steps to accurately segment and identify affected areas. Initially, the raw OCT images are subjected to noise removal to enhance image quality. This is achieved using the EAC-NLM filter, which effectively reduces noise while preserving important edge information crucial for subsequent segmentation. The denoised images are then processed using two distinct segmentation techniques: Graph-based segmentation and Level-set segmentation. The performance of these methods is assessed using three metrics: DC, JC, and HD.

Graph-based segmentation

In the Graph-based segmentation technique, the image is treated as a graph where each pixel is a node connected to its neighbors by weighted edges. The segmentation is achieved by partitioning the graph into regions that minimize the cut cost while maximizing internal homogeneity. A popular optimization technique for image processing and computer vision issues is called graph-cutting. Graph cut approaches became one of the crucial methods for segmenting the retinal layers when they were applied to picture segmentation (Zhijun Gao et al., 2017). Graph-based segmentation treats the image as a graph, where each pixel represents a node, and edges between nodes are assigned weights based on the similarity or dissimilarity of their pixel values. The goal is to partition the graph into segments that correspond to meaningful regions in the image.

Graph Construction: Represent the image as a graph G=(V, E), where V is the group of vertices (pixels) and E is the set of edges involving adjacent vertices. Each edge e∈E has a weight w(e) that reflects the similarity between the connected pixels. For example, the weight can be defined as the difference in intensity values:

$$w(e_{ij}) = |I(i) - I(j)| - - - - - - - - -(1)$$

where $I(i)$ and $I(j)$ are the intensity values of pixels i and j.
Edge Weight Calculation: Calculate the weights for all edges in the graph. Lower weights indicate higher similarity between pixels, while higher weights indicate dissimilarity.
Graph Partitioning: Apply a graph partitioning algorithm to divide the graph into segments. One common method is the normalized cut, which aims to partition the graph such that the similarity within segments is maximized while the similarity between segments is minimized. The normalized cut criterion can be defined as:

$$NCut(A, B) = \frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)} - - - - - - - - -(2)$$

where:

- $cut(A, B)$ denotes the total value of the weights of edges that have one endpoint in segment A and the other in segment B.
- $assoc(A, V)$ is the amount of the weights of edges that have at least one endpoint in segment A (similarly for B).

Segmentation: Use the partitioned graph to label the image pixels, resulting in segments that represent different regions in the image.
By using these steps, the graph-based segmentation technique effectively partitions the image into distinct regions based on pixel similarity, facilitating the identification of meaningful structures in the image.

Level Set Segmentation

On the other hand, the Level set segmentation technique evolves contours iteratively to detect the boundaries of the CSR regions by solving partial differential equations. This approach allows for flexible handling of complex shapes and topologies. It is crucial to segment retinal OCT pictures to diagnose, stage, and monitor ophthalmological disorders. Automatic segmentation techniques can still take more minutes to segment a 3D retinal scan, even though they are usually significantly faster than manual segmentation (Yihao Liu et al., 2018). This can be prohibitive for normal clinical applications.

Level set segmentation is an iterative method used to detect and evolve contours within an image to accurately capture object boundaries. The procedure can be summarized as follows:
Initialization: Define an initial contour, often represented by a zero level set of a higher-dimensional method, known as the level set function ϕ(x,y). Typically, ϕ is declared as a signed distance method, where ϕ=0 represents the initial contour, ϕ>0 represents the outside of the contour, and ϕ<0 denotes the inside.
Level Set Evolution: Evolve the contour over time using a partial differential equation (PDE). The evolution is governed by the level set expression:

$$\frac{\partial\emptyset}{\partial t} + F\,|\nabla\emptyset| = 0 - - - - - - - - -(3)$$

where $\frac{\partial\emptyset}{\partial t}$ is the temporal change of the level set method, $|\nabla\emptyset|$ is the gradient magnitude, and F is a speed function that determines the evolution's direction and speed.

Speed Function Definition: Define the speed function F based on image characteristics. Common choices include:

Edge-Based: F is designed to slow down near object boundaries, often incorporating image gradient.

$$F = g(|\nabla I|) = \frac{1}{1 + |\nabla I|^2} - - - - - - - - -(4)$$

here I is the image intensity and g is an edge-stopping function.

Region-Based: F is defined based on region statistics, such as mean intensity inside and outside the contour.

Contour Update: Iteratively update the level set function ϕ\phiϕ using the level set equation until the contour converges to the object boundary. The iteration continues until the change in ϕ\phiϕ is below a predefined threshold.

Final Segmentation: The zero level set (ϕ=0) at convergence indicates the final segmented contour, delineating the object boundary.

By using this procedure, level set segmentation dynamically and accurately captures complex object boundaries, accommodating changes in topology such as merging and splitting of contours. This makes it a powerful tool for segmenting objects in medical imaging and other applications.

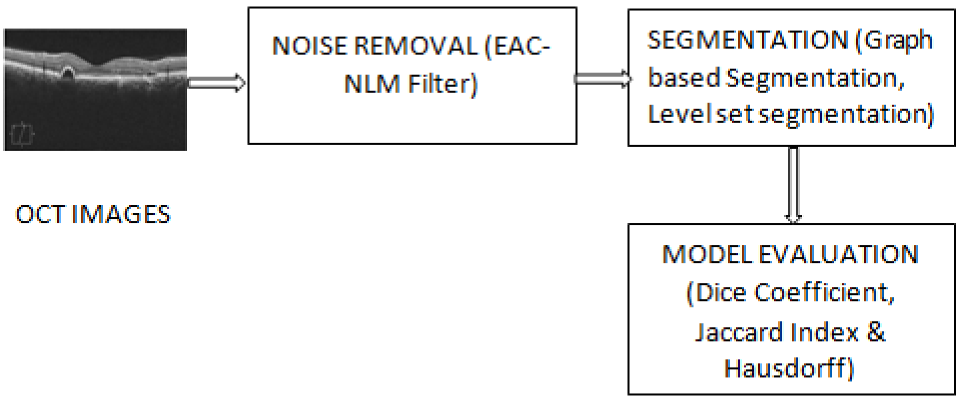

Fig 3: Block Diagram of Proposed System

The workflow for detecting CSR from OCT images begins with acquiring the OCT images, which are specialized medical images used to visualize the layers of the retina in detail. These images often contain noise, which can interfere with the accuracy of subsequent image analysis. To address this, the first step involves noise removal using the EAC-NLM filter. This advanced filtering technique effectively reduces noise while preserving important edge information, ensuring that the structural details necessary for accurate segmentation are maintained.

Following noise removal, the denoised OCT images are subjected to segmentation to identify and delineate regions affected by CSR. Two segmentation techniques are employed: Graph-based segmentation and Level-set segmentation. In the Graph-based segmentation method, the image is represented as a graph where each pixel is a node connected by weighted edges based on pixel similarity. This technique partitions the graph to maximize internal homogeneity and minimize the cut cost between different segments. Conversely, the Level set segmentation method evolves contours iteratively using partial differential equations to accurately capture object boundaries within the image

The final step in the workflow is model evaluation, where the performance of both segmentation techniques is assessed using three metrics: DC, JC, and HD. These metrics provide quantitative measures of the segmentation accuracy, comparing the identified regions against ground truth data. The results indicate that the Level-set segmentation technique generally produces better outcomes in terms of DC, JC, and HD, highlighting its effectiveness in accurately identifying CSR regions in OCT images. This workflow demonstrates a comprehensive approach to improving the detection and analysis of retinal conditions using advanced image processing techniques.

4. RESULTS AND DISCUSSION

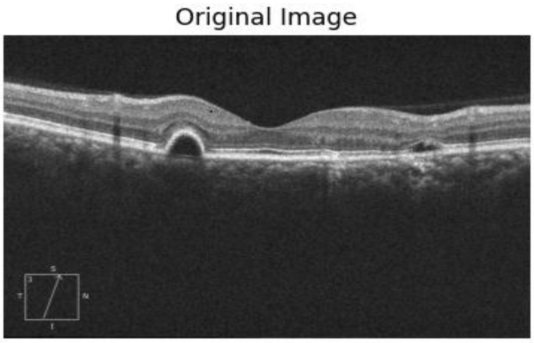

Fig. 4. Original Retinal OCT image

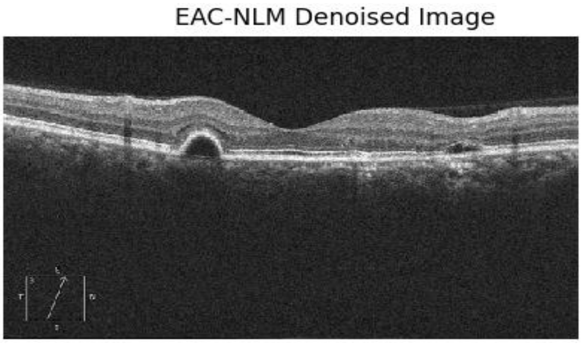

Fig. 5. Denoised Image

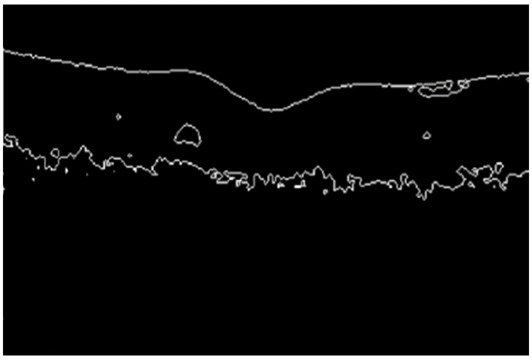

Fig. 6 Segmented using Level set Segmentation

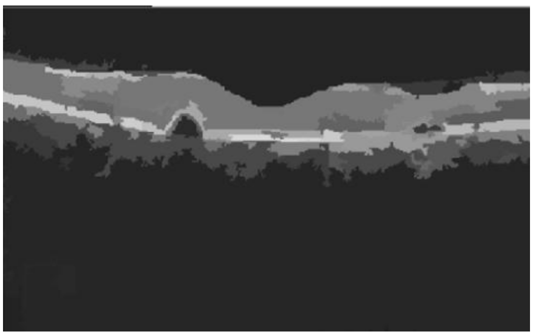

Fig.7 Segmented using Graph-based Segmentation:

Fig. 6 and Fig. 7 show the segmented images. The outcomes of these segmentation techniques are then compared based on their performance metrics. It was observed that Level set segmentation consistently produced better results in terms of DC, JC, and HD, indicating more precise and reliable identification of CSR regions in OCT images compared to the Graph-based approach.

PERFORMANCE METRICS

DC

The DC is a statistical measure used to gauge the similarity between two sets. It is normally employed in image segmentation tasks to evaluate the accuracy of a segmented image by comparing the overlap between the predicted segmentation and the initial segmentation. DC is defined as:

$$DC = \frac{2|A \cap B|}{\lceil A \rceil + |B|} - - - - - - - - (5)$$

where A denotes the group of pixels in the observed segmentation, B is the group of pixels in the initial segmentation, A∩B is the number of overlapping pixels between the two sets, and |A| and |B| are the number of pixels in each set, respectively. The DC ranges from 0 to 1, with 1 denoting perfect agreement among the two sets and 0 indicating no overlap.

JI

The JI is a metric used to measure the similarity and diversity of sample sets. In image segmentation, quantifies the accuracy of a segmented image by comparing the overlap between the observed segmentation and the initial segmentation. JI is defined as:

$$JI = \frac{|A \cap B|}{|A \cup B|} - - - - - - - - - - (6)$$

where A denotes the group of pixels in the observed segmentation, B is the group of pixels in the initial segmentation, A∩B is the number of overlapping pixels between the two sets, and A∪B is the total number of pixels in both sets combined. The Jaccard Index ranges from 0 to 1, with 1 representing perfect agreement and 0 representing no overlap among the two groups.

HD

The HD is a measure used to determine the extent of similarity between two sets of points, which is particularly useful in image processing for comparing segmented regions. It evaluates the utmost distance of a set to the adjacent point in the other group.

$$HD(A,B) = MAX \begin{Bmatrix} \sup_{a \complement A} \inf_{b \complement B} d(a,b), \sup_{b \complement a} \inf_{\complement A} d(b,a) \end{Bmatrix} - - - - - - - - (7)$$

where $d(a,b)$ indicates the distance among points a and b, sup denotes the, and nf indicates the infimum. In simpler terms, it measures the maximum of all the distances from a point in one group to the closest point in another group. This metric is particularly sensitive to the shape and boundary accuracy of segmented objects, making it valuable for evaluating segmentation algorithms.

Table 1 compares the performance of two segmentation techniques—Graph Cut Segmentation and Level Set Segmentation—using three evaluation metrics: DC, JI, and HD.

Table 1 Comparison of Segmentation Techniques Using DC, JI and HD Metrics

Segmentation Technique/Metrics	**DC**	**JI**	**HD**
Graph Cut Segmentation	0.1679	0.0917	374.0334
Level Set Segmentation	0.3700	0.2270	374.0120

Table 1 compares two segmentation techniques, Graph Cut Segmentation, and Level Set Segmentation, using metrics crucial for evaluating their performance in image analysis. Graph Cut Segmentation achieves a DC of 0.1679 and a JI of 0.0917, indicating moderate similarity between segmented regions, while Level Set Segmentation shows higher similarity with a DC of 0.3700 and JI of 0.2270. In terms of HD, both techniques perform similarly, with Graph Cut at 374.0334 and Level Set at 374.0120, suggesting comparable precision in capturing spatial discrepancies between segmentations. These metrics underscore Level Set Segmentation's superior overlap and Graph Cut Segmentation's marginally better spatial correspondence, providing insights into their applicability in tasks requiring precise delineation and analysis of image regions.

5. CONCLUSION

In conclusion, this study demonstrates that Level-set segmentation outperforms Graph-based segmentation for detecting CSR in OCT images. By utilizing the EAC-NLM filter for noise removal, the image quality is significantly enhanced, facilitating more accurate segmentation. When evaluating the two techniques, Level set segmentation yielded superior results in terms of DC, JC, and HD. These findings underscore the effectiveness of Level set segmentation in accurately delineating CSR regions, making it a more reliable method for clinical diagnostics and further research in retinal imaging.

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