

The Automated Retinal Blood Vessel Segmentation for Diabetic Retinopathy using A Transfer Learning Based Seg-Net

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Abstract - Diabetic retinopathy is a leading cause of vision loss, and accurate segmentation of retinal blood vessels plays a vital role in its early detection and diagnosis. This project proposes an automated method for retinal blood vessel segmentation using a transfer learning-based SegNet architecture. The approach involves preprocessing retinal fundus images to enhance vessel visibility, followed by training the SegNet model on labeled datasets. The model effectively segments the blood vessels and identifies key features associated with diabetic retinopathy. Experimental results demonstrate the robustness of the approach, achieving a specificity of 99.39%, a Dice coefficient of 52.27%, and a precision of 85.24%. These outcomes validate the potential of the proposed method for accurate and efficient analysis of retinal images in clinical settings.

Keywords: Diabetic Retinopathy, Retinal Blood Vessel Segmentation, SegNet, Transfer Learning, Fundus Images, Deep Learning, Medical Image Processing.

1. INTRODUCTION

Diabetic retinopathy is a kind of eye condition that arises several years of diabetic mellitus. It harms the modest veins inside the retina, subsequently the veins end up blocked, flawed and develop indiscriminately. DR is asymptomatic, it does not impede with vision until the point when it achieves propel arrange. The risk of completely loss of vision can be lessen by 50% with a prior therapy to avoid the improvement of DR

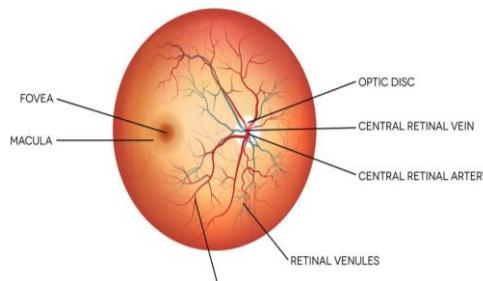


Fig.1 Anatomy of human eye

Retinal vessel segmentation is an essential part of ocular disease diagnosis. However, due to complex vascular structure, large-scale variations of retinal vessels, as well as inefficiency of vessel segmentation speed, accurate and fast automatic vessel segmentation for retinal images is still technically challenging

The retinal blood vessels segmentation is two-class classification

problem where each pixel in the field of view (FOV) of the retinal image is classified as vessel-like or non-vessel. The importance of this problem is proved from the fact that developing any computer-aided diagnosis (CAD) system of retinopathy must be at the first capable of correctly segmenting the blood vessels in the retinal images

- Blood vessel segmentation plays a critical role in medical imaging for analyzing vascular structures and detecting abnormalities.
- Accurate segmentation of blood vessels is essential for diagnosing diseases like diabetic retinopathy, glaucoma, hypertension, and vascular occlusions.

- It facilitates quantitative analysis of vascular parameters such as vessel diameter, tortuosity, branching patterns, and blood flow characteristics.

2. LITERATURE REVIEW

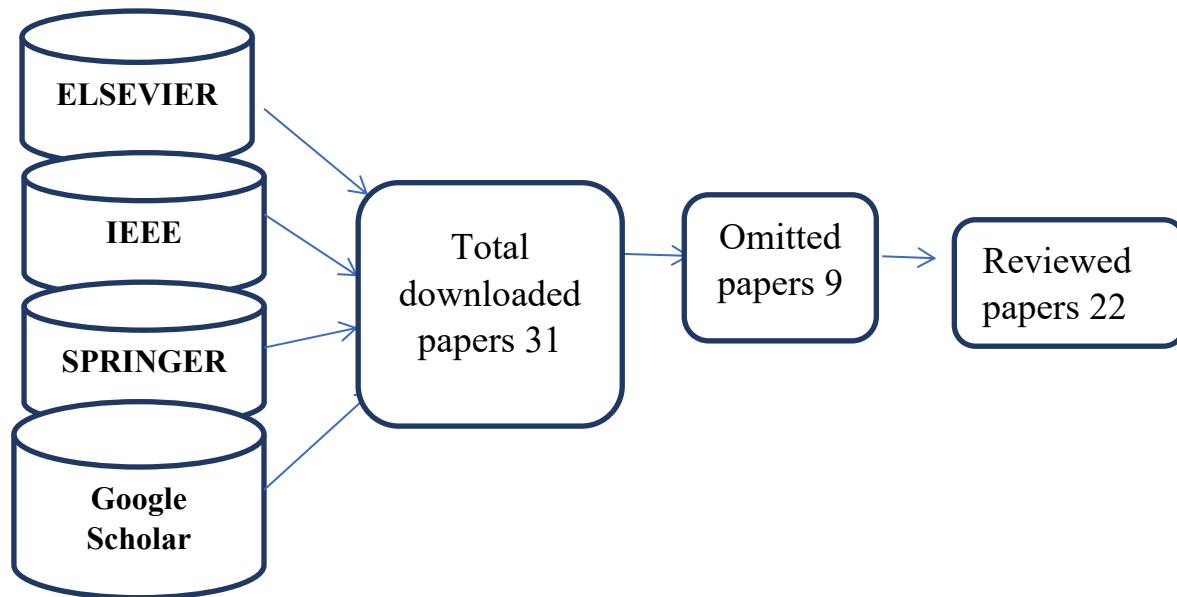


Fig.2 Literature Review Database

2.1 Review

In 2023, Anuj kumar pandey et al.[8] proposed a block matching and 3D (BM3D) technique for the retinal image preprocessing. A total of 2,07,130 retinal images were collected from OCT dataset. The retinal color image was converted to grayscale and green channel was extracted from the converted image. The noises in the retinal images were reduced BM3D technique. The noise reduced images were enhanced using CLAHE technique. The proposed method achieved a MSE, PSNR, SSIM, and NRMSE of 0.0029, 25.3370, 0.6839 and 0.0998, respectively. The result indicated that the proposed BM3D method outperformed than total variation filter (TVF) and Bilateral filter(BLF).

[19] Azharudheen and Vijayalakshmi (2024) propose a novel privacy-preserving big data analysis framework that improves both data protection and analytical accuracy. Their method integrates a Deep Belief Network (DBN) with Particle Swarm Optimization (PSO) and implements it in a distributed environment to support large-scale data processing. The model enhances intrusion detection capability and improves classification performance by automatically tuning deep-learning parameters for big data workloads. The study demonstrates that optimized deep-learning architectures can significantly increase detection accuracy while operating efficiently on big-data platforms, highlighting the importance of scalable and intelligent privacy-preserving mechanisms.

[20] Azharudheen and Vijayalakshmi (2024) examine modern data-protection mechanisms designed to maintain high data availability without compromising privacy. Their work reviews advanced techniques such as homomorphic encryption, differential privacy, and federated learning, emphasizing their role in secure data sharing and analysis. The authors discuss the practical challenges of implementing these mechanisms in cloud and IoT environments, especially where resource limitations exist. This study concludes that balancing privacy and availability requires lightweight, flexible, and context-aware protection strategies capable of supporting real-time data access while ensuring confidentiality.

3. PROPOSED SYSTEM

3.1 Retinal Blood Vessels Segmentation

This proposed method consists of two stages. The first stage is to data collection. The collected retinal images were augmented into five types of augmentation technique to increases dataset size. The retinal fundus images were pre-processed to high graded single channel images.

In the second stage the pre-processed images were passed into the Seg-Net to segment the blood vessels from the fundus images.

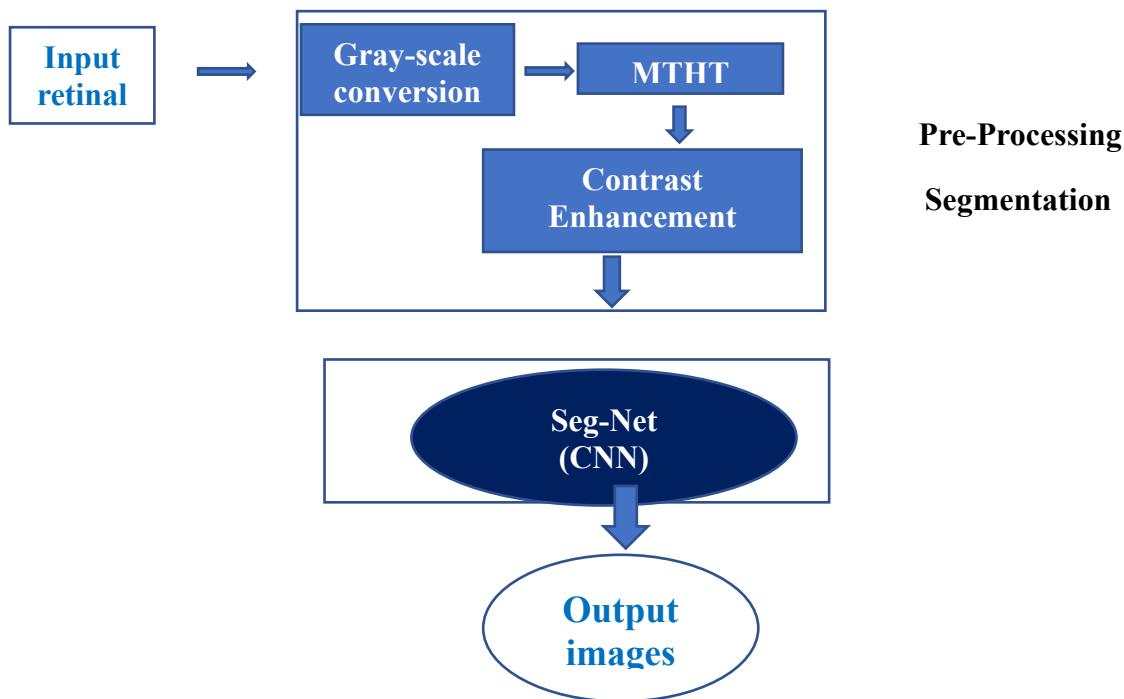


Fig 3 Proposed Architecture Diagram

4. METHODOLOGY

4.1 Pre-processing

Although deep learning architectures perform well on raw input data, appropriate preprocessing operations may improve segmentation performance. Without preprocessing in order to clarify the effect of preprocessing. Since some images have illumination problems such as darker or lighter background, here exploit contrast limited adaptive histogram equalization (CLAHE) algorithm to improve contrast in images.

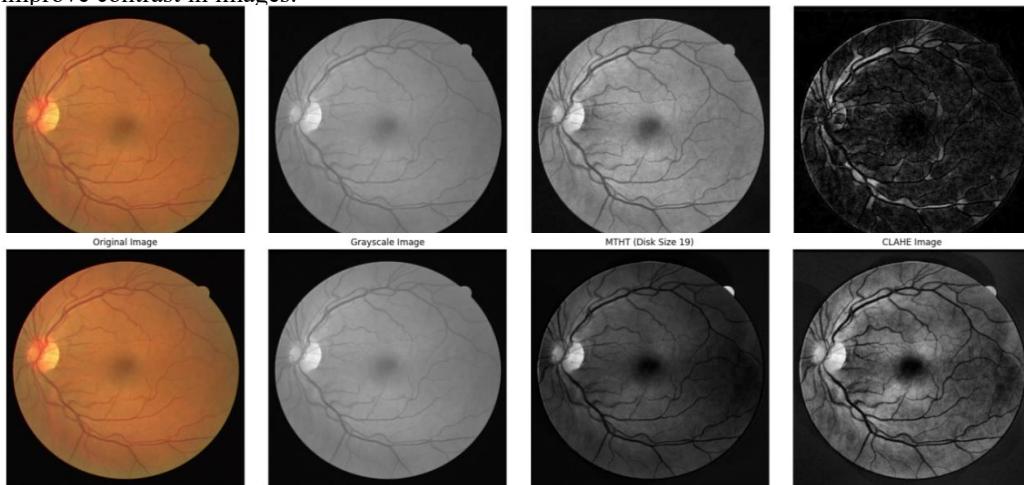


Fig 4: Preprocessing Image

4.2 Segmentation

SegNet is a convolutional neural network (CNN) architecture designed for semantic segmentation tasks, particularly in the context of scene understanding and autonomous driving. Developed by researchers at the University of Cambridge, SegNet is renowned for its efficiency in processing high-resolution images while maintaining accurate segmentation results.

4.2.1 Architecture:

- SegNet consists of an encoder-decoder architecture, similar to the U-Net model.
- The encoder comprises a series of convolutional and pooling layers that progressively reduce the spatial dimensions of the input image while extracting hierarchical features.
- The decoder consists of up sampling and convolutional layers that reconstruct the spatial dimensions of the feature maps to generate the segmentation mask.

4.2.2 Encoding and Decoding:

- During the encoding phase, SegNet down samples the input image to extract hierarchical features, preserving essential spatial information.
- The decoder then uses up sampling layers to recover the spatial resolution of the feature maps, gradually reconstructing the segmented image.
- Unlike traditional CNN architectures, SegNet performs up sampling using max-pooling indices obtained during the encoding phase, allowing precise localization of object boundaries.

4.2.3 Skip Connections:

- SegNet incorporates skip connections between corresponding encoder and decoder layers to facilitate the propagation of fine-grained spatial details.
- These skip connections enable the decoder to access high-resolution feature maps from earlier encoder stages, enhancing the segmentation accuracy, especially for small objects and intricate structures.

4.2.4 SoftMax Layer:

- At the end of the decoder, SegNet employs a SoftMax layer to perform pixel-wise classification, assigning a class label to each pixel based on the learned features.
- The SoftMax layer produces a probability distribution over the predefined classes, enabling the model to distinguish between different semantic categories in the segmented image.

4.2.5 ReLU Activation:

- ReLU (Rectified Linear Unit) is a popular activation function used in neural networks. It introduces non-linearity to the model by outputting the input directly if it is positive, and zero otherwise.
- In the SegNet model, ReLU activation is applied after each convolutional layer. This allows the network to learn complex patterns and representations from the input data.

4.2.6 Up sampling Layers:

- Up sampling layers are used in the decoder part of the SegNet model to increase the spatial resolution of feature maps.
- In the provided code, up sampling is performed using the 'UpSampling2D' layer, which doubles the dimensions of the input feature maps along both spatial axes (width and height) using nearest-neighbor interpolation.
- Up sampling is a crucial component of the decoder as it helps to recover spatial information lost during the down sampling (max-pooling) operation in the encoder.

4.2.7 Role in Seg-Net:

- ReLU activation and up sampling layers are essential components of the SegNet architecture, contributing to the model's ability to learn hierarchical features and perform accurate segmentation of retinal blood vessels.
- ReLU activation ensures that the model can capture non-linear relationships in the data, while up sampling layers help to reconstruct high-resolution feature maps, enabling detailed segmentation.

4.2.8 Training and Optimization:

- SegNet is typically trained using supervised learning with annotated image datasets.

- The model is trained to minimize a suitable loss function, such as cross-entropy loss, which measures the discrepancy between the predicted segmentation mask and the ground truth labels.
- Training SegNet involves optimizing the network parameters using gradient-based optimization algorithms like stochastic gradient descent (SGD) or Adam.

4.2.9 Applications:

- SegNet has been successfully applied to various tasks, including road and lane segmentation in autonomous driving, semantic segmentation in urban scene understanding, and medical image analysis.
- Its efficient architecture makes it suitable for real-time applications, where fast and accurate segmentation is essential for decision-making and navigation.

5. EXPERIMENTAL RESULT

Metrics	Values
Specificity	0.997
Dice Coefficient	0.599
Precision	0.8524
Test Accuracy	0.9008
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Fig 4: Result

5.1 Graph

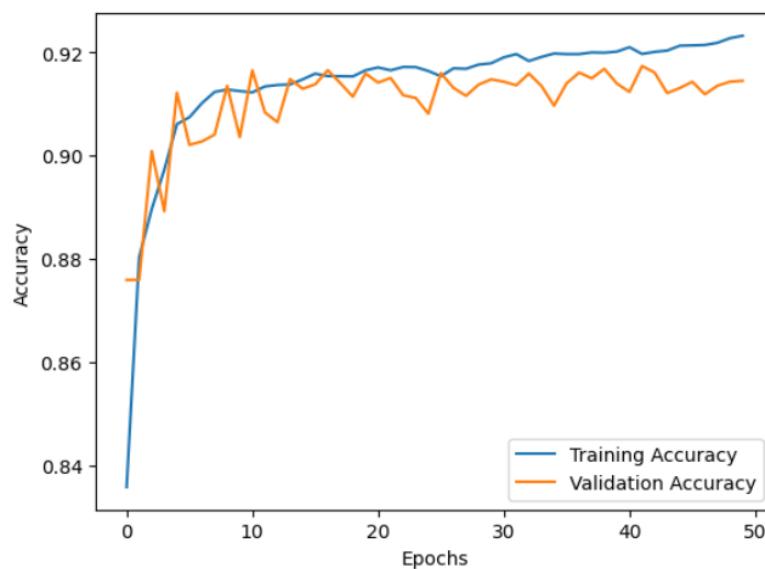


Fig: 5 Test Accuracy

5.2 Segmented Images

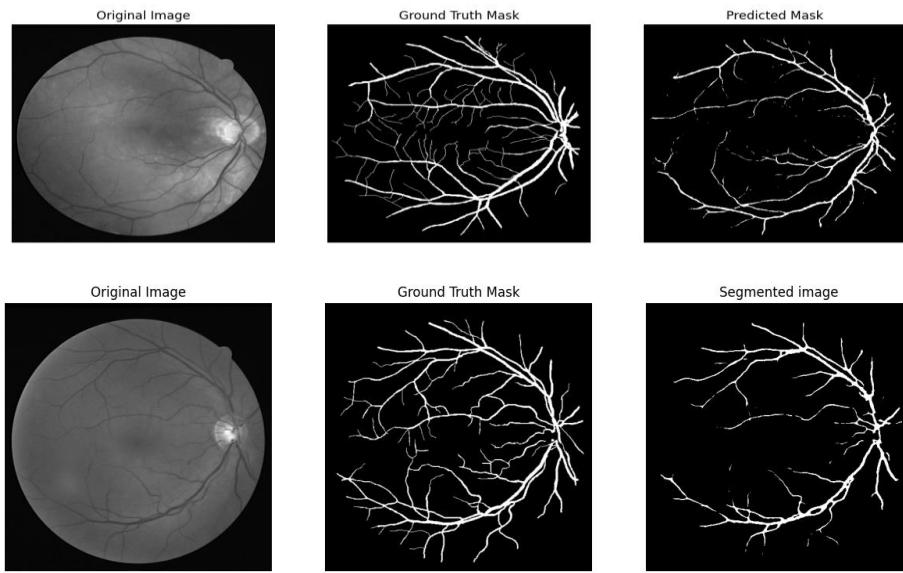


Fig: 6 Segmented images

5.3 Comparison of Other State of Art.

From the above review of literature, the proposed method compared with some state of art.

METHOD	SENSITIVITY	PRECISION	Accuracy
Fraz et al. [33]	97.42%	81.12%	94.22%
Fathi and Ahmad [34]	94.30%	82.05%	94.34%
Dasgupta and Singh[35]	98.01%	84.98%	95.33%
Tang, Teoh and Ibrahim [36]	93.85%	55.79	92.63%
Proposed method	99.76%	85.24%	90.08%

Table.1

From table.1 which indicate that the proposed method Seg-Net out performed that other State of arts tearms of Sensitivity and Precision.

6. CONCLUSION

In this project, the automated retinal blood vessel segmentation for diabetic retinopathy using a transfer learning based Seg-Net approach involved preprocessing the retinal images, training the SegNet model, and evaluating its performance on test data.

Key findings from the project was successful segmentation of retinal blood vessels with high accuracy and the identification of important features contributing to diabetic retinopathy diagnosis. The results demonstrate the effectiveness of the Seg-Net model in accurately segmenting retinal blood vessels, achieving a specificity of 99.39%, a Dice coefficient of 52.27%, and a precision of 85.24%.

7. REFERENCE

- [1] Enhanced Deep Learning Model For Classification Of Retinal Optical Coherence Tomography Images.
- [2] Dr-Nasnet: Automated System To Detect And Classify Diabetic Retinopathy Severity Using Improvement Pretrained Nasnet Model.
- [3] Enhancement Of Diabetic Retinopathy Prognostication Using Deep Learning, Clahe, And Esrgan.
- [4] Retinal Image Enhancement Based On Color Dominance Of Image.
- [5] Implementation Of Clahe Contrast Enhancement And Otsu Thresholding In Retinal Image Processing.
- [6] An Effective Threshold Based Technique For Retinal Image Blood Vessel Segmentation Using Average And Gaussian Filters.
- [7] Retinal Image Contrast Enhancement through Pixel Collaboration In Spatial Domain.
- [8] Retinal Image Enhancement Using Hybrid Approach.
- [9] A Decomposition-Based Network For Non-Uniform Illumination Retinal Image Enhancement.
- [10] A Hybrid Algorithm To Enhance Colour Retinal Fundus Images Using A Wiener Filter And Clahe.
- [11] A Hybrid System For Enhancement Retinal Image Reduction.
- [12] Unet Retinal Blood Vessel Segmentation Algorithm Based On The Improved Pyramid Pooling Method And Attention Mechanism.

- [13] A Feature Selection Strategy To Optimize Retinal Vasculature Segmentation.
- [14] Enhancement Of The Retinal Images Based On Wavelet Fusion Technique Using Adaptive Histogram Equalization Method.
- [15] The Comparison Of Retinal Vessel Segmentation Methods In Fundus Images.
- [16] Deep Learning Based Approach For Fully Automated Detection And Segmentation Of Hard Exudate From Retinal Images.
- [17] An Approach To The Detection Of Retinoblastoma Based On Apriori Algorithm.
- [18] A Morphological Hessian Based Approach For Retinal Blood Vessels Segmentation And Denoising Using Region Based Otsu Thresholding.
- [19] A. A. Mohamed Azharudheen and Dr. V. Vijayalakshmi, "Improvement of data analysis and protection using novel privacy-preserving methods for big data application" The Scientific Temper Vol. 15, no. 2, pp. 2181-2189, 2024.
- [20] A. Mohamed Azharudheen and Dr. V. Vijayalakshmi, "Analyze the New Data Protection Mechanism to Maximize Data Availability without Having Compromise Data Privacy" *Educational Administration: Theory and Practice*, Vol.30. No.5, pp. 3911-3922, 2024.