Advanced Retinal Vessel Segmentation: Combining AGD-GIF, CRGCN, and Improved Mask R-CNN-PO

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Abstract.

Accurate segmentation of retinal blood vessels plays a vital role in medical image analysis for the diagnosis and management of eye diseases, as most health conditions affect the retinal vascular network. Despite progress made in recent decades, issues such as complex textures, vessel discontinuities, and unidentified areas remain unresolved, particularly in segmenting fine veins and handling low-contrast images. This method integrates three advanced techniques for retinal vessel segmentation. Initially, it applies Adaptive Gradient Domain Guided Image Filtering (AGD-GIF) for preprocessing. Subsequently, it utilizes an efficient feature extraction method called the proposed Cascading Residual Graph Convolutional Network (CRGCN). Finally, segmentation is performed using an enhanced Mask Region-Based Convolutional Neural Network with a Parrot Optimizer (Improved Mask R-CNN-PO), ensuring precision and reliability in detecting retinal vessels from medical images. When tested on the CHASE_DB1 datasets, the proposed model achieves specificity of 99.53%, accuracy of 99.65%, and an AUC of 99%. Additionally, it attains an accuracy of 99.63% and F1 scores of 99.59%.

Keywords. Adaptive Gradient Domain Guided Image Filtering, Biomedical Image Analysis, Cascading Residual Graph Convolutional Network, Improved Mask Region-Based Convolutional Neural Network with Parrot Optimizer, Retinal Vessel Segmentation.

1. INTRODUCTION

The onset of the disease is closely linked to unusual alterations in retinal characteristics, as the retina is the only terminal vessel observable in a living human body. Diabetic retinopathy is associated with abnormalities in the retinal microvascular diameter [1]. Vascular density of the outer macular area was positively correlated with vasospasm, glaucoma, visual field defects, arterial reflex zone widening, and blood vessel constriction. Arteriovenous sclerosis and hypertension are connected by the cross-compression of arteries and veins in the retina. Precise segmentation and morphological analysis of retinal blood vessels are crucial for diagnosis, treatment, monitoring, and prevention of numerous diseases, particularly chronic conditions [2-3].The retina, a critical light-sensitive layer, significantly affects central and peripheral vision in humans. It is sustained by an intricate network of retinal blood vessels, essential for maintaining the visual system's integrity [4]. Alterations to these vessel structures can indicate various major health issues affecting the eyes and cardiovascular system. These changes have been linked to conditions such as diabetic retinopathy (DR), macular edema (ME), glaucoma, cataracts, malignancies, and hypertension [5-6]. Competing automated retinal vascular segmentation (RVS) techniques have emerged, offering improved diagnostic accuracy for eye diseases and facilitating early diagnosis and treatment [7].

The approach utilizes Adaptive Gradient Domain-Guided Image Filtering (AGD-GIF) to preprocess retinal images, effectively minimizing noise and improving vessel visibility, which aids in more precise segmentation. The research implements a Cascading Residual Graph Convolutional Network (CRGCN) for feature extraction, ensuring complex retinal structures are accurately represented through hierarchical learning from multiple levels of abstraction. The technique incorporates the enhanced Mask R-CNN with the Parrot Optimizer (Improved Mask R-CNN-PO), fine-tuning network parameters and enhancing the model's ability to generalize across various retinal image datasets.

2. Literature Survey

Sun et al. (2023) [8] have introduced a technique for segmenting retinal blood vessels using a U-net structure-based series of deformable convolution and attention mechanisms (SDAU-Net).Potential increases in computer complexity and cost are the proposed method's drawbacks. In 2022, Muzammil et al. [9] have demonstrated an unsupervised technique for vessel segmentation from retinal pictures. The disadvantages of the proposed approach are its computational complexity and dataset constraints. Li et al. (2024) [10] have presented a retinal vessel segmentation model.The suggested method's disadvantage is that it takes longer and requires more computing. Guo (2022) [11] have presented a cascade semantic guided network (CSGNet) to enhance retinal vascular segmentation for ocular disease early identification.

2.1. Problem Statement

Current methods face difficulties in achieving high vessel segmentation accuracy due to image preprocessing challenges, limited feature extraction capabilities, and substantial computational requirements. To tackle these problems, the proposed solution incorporates three key components: an adaptive gradient domain-guided image filtering technique to enhance the preprocessing phase, a Cascading Residual Graph Convolutional Network for improved feature extraction, and the Parrot Optimizer to refine the segmentation process.

3. Proposed Methodology

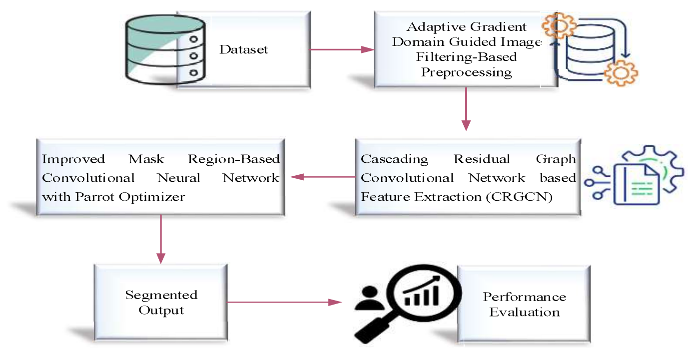

Figure.3.16. Illustration of the proposed method

Figure 3.1 illustrates a workflow of retinal vessel segmentation. The process begins with a dataset that undergoes image pre-processing through adaptive gradient domain-guided image filtering (AGD-GIF). This pre-processing step helps improve the performance of the cascading residual graph convolutional network (CRGCN) by extracting better features. The CRGCN effectively reconstructs fine spatial and structural patterns of the retinal vessels. The features are finally forwarded to an optimized Parrot optimizer based on an improved Mask Region Convolutional Neural Network (Improved Mask R-CNN-PO). The CHASE_DB1 dataset, which was gathered from multiethnic schools as part of the Child Heart and Health Study in England (CHASE), is used in the suggested strategy. The pre-processing step receives the data inputs.

For the input data, the pre-processing approach is applied. For image enhancement, the Adaptive Gradient Domain Guided Image Filtering approach (AGD-GIF) is employed [12]. The feature extraction process takes place after pre-processing. Retinal vessel learning characteristics are the only features that CRGCN-based feature extraction efficiently targets. Using the hierarchical structure of GCNs, this technique learns intricate spatial connections between the image's pixels and regions of interest. As the data moves through the stages, the connections that stay in the network keep features from previous layers, allowing for a higher level of feature extraction [13].

After feature extraction, segmentation takes place. To find features in input images, it makes use of residual networks, a region proposal network, and a feature pyramid network. Popular and open-source, Mask R-CNN offers precise segmentation and localization abilities for tasks involving object detection. By better suiting the physical characteristics of retinal vasculature and lesions for segmenting retinal vascular features, a flexible convolutional network improves detection accuracy [14]. Due to its charming appearance, close bond with its owner, and ease of training, the Pyrrhura Molinae is a favoured species of parrot among pet owners. The four distinct behavioral traits and breeding endeavours of Pyrrhura molinae include foraging, remaining, communication, and dread of strangers [15]

4. Result and Discussion

4.1 Dataset Description

The Child Heart and Health Study in England (CHASE), which gathered pictures from multiethnic schools, includes the CHASE_DB1 dataset. A handheld Nidek NM-200-D fundus camera with a 30° field of view was used to take the retinal images of the students' two eyes, which make up this dataset.

4.2. Comparison of performance with existing methods

In this section, the effectiveness of the presented approach is compared with other existing approaches. The proposed method has been compared with existing methods such as SDAU-Net [8], MUVS [9], AttMSFCU-Net [10], and CSGNet [11].

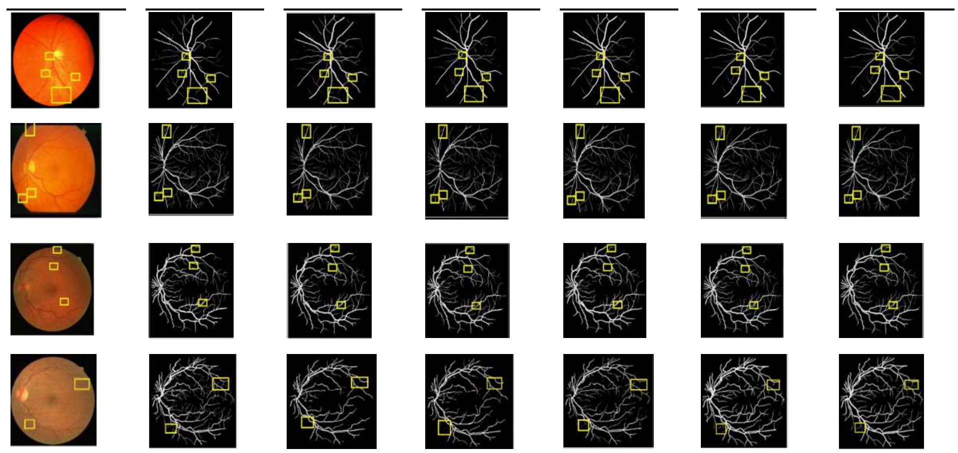

Table.4.1. Comparison of Improved Mask R-CNN-PO and Prior Methods on CHASE_DB1

Table 4.1 shows the comparison of the segmentation outcomes on the CHASE_DB1 dataset between the improved Mask R-CNN-PO and other earlier techniques.

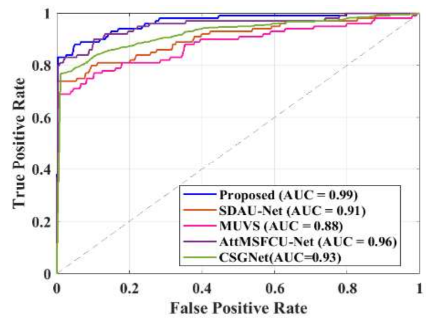

Figure.4.1. ROC curves of proposed and comparative methods

Figure 4.1 presents the ROC curves of different methods for retinal vessel segmentation. The proposed method yields the best AUC score of 0.99, outperforming SDAU-Net with an AUC of 0.91, MUVS with an AUC of 0.88, AttMSFCU-Net with an AUC of 0.96, and CSGNet with an AUC of 0.93. An increased AUC means improved sensitivity and specificity of the given or tested diagnostic method. The dotted diagonal line in the illustration means chance or no discrimination at all (AUC of 0.5). As for the benchmark methods, the proposed method yields better results, and accuracies are quite high.

Table 4.2 shows the comparison of the segmentation performance metrics of various methods on the dataset CHASE_DB1: precision, F1-score, recall, and specificity. The suggested improved Mask R-CNN-PO is best compared to prior methods. Hence, all previously developed methods are surpassed while the best is achieved in every metric by it; that includes 99.65% accuracy, 99.63% precision, 99.59% F1-score, 99.58% recall, and 99.53% specificity.

Techniques	Accuracy	Precision	F1-Score	Recall	Specificity	Accuracy
SDAU-Net [8]	90.54	90.59	89.73	90.43	90.86	90.54
MUVS [9]	85.73	80.36	82.55	84.92	84.40	85.73
AttMSFCU-Net [10]	72.33	70.46	72.27	70.47	75.49	72.33
CSGNet [11]	73.55	71.23	69.76	65.64	66.39	73.55
Proposed Improved Mask R-CNN-PO	99.65	99.63	99.59	99.58	99.53	99.65

Table. 4.2 Performance Comparison of Retinal Vessel Segmentation Techniques

On all of the performance metrics, the existing methods, SDAU-Net, MUVS, AttMSFCU-Net, and CSGNet, significantly low exhibit performance. However, SDAU-Net comes closest with an accuracy of 90.54%. Thus, the effectiveness of the proposed approach is highly superior.

Techniques	Error rate	Computational Time (s)
SDAU-Net [8]	1.67	1.43
MUVS [9]	1.89	1.65
AttMSFCU-Net [10]	1.45	1.38
CSGNet [11]	1.33	1.12
Proposed Improved Mask R-CNN-PO	0.01	0.02

Table.4.3. Comparison of Error Rate and Computational Time

Table 4.3 shows the comparison of error rate and computational time for segmentation techniques on the CHASE_DB1 dataset. The proposed improved Mask R-CNN with Parrot Optimizer, improved Mask R-CNN-PO, has the lowest error rate at 0.01 and the fastest computational time at 0.02 seconds.

5. Conclusion

The proposed method uses advanced techniques integrated into preprocessing, feature extraction, and segmentation and provides a solid solution to the problem of retinal vessel segmentation. AGD-GIF demonstrates the ability to significantly enhance the image of the retina while minimizing noise interference and enhancing the visibility of the vessels. Feature extraction based on CRGCN performs significantly in accurately determining vessel structures. Finally, to improve cell segmentation, an improved Mask R-CNN-PO is employed, which provides better results for occluded images and varying image conditions. Thus, the improvement in terms of stability and accuracy qualifies it as a viable candidate for real-world applications, including computer-aided diagnosis and staging of treatments for retinal disorders.

6. References

[1] Y. Liu, J. Shen, L. Yang, G. Bian, and H. Yu, "ResDO-UNet: A deep residual network for accurate retinal vessel segmentation from fundus images," Biomed. Signal Process. Control, vol. 79, p. 104087, 2023.

[2] Y. Tan, K. F. Yang, S. X. Zhao, and Y. J. Li, "Retinal vessel segmentation with skeletal prior and contrastive loss," IEEE Trans. Med. Imaging, vol. 41, no. 9, pp. 2238–2251, Sep. 2022.

[3] Y. Tan, K. F. Yang, S. X. Zhao, J. Wang, L. Liu, and Y. J. Li, "Deep matched filtering for retinal vessel segmentation," Knowl. Base. Syst., vol. 283, p. 111185, 2024.

[4] Y. Liu, J. Shen, L. Yang, H. Yu, and G. Bian, "Wave-Net: A lightweight deep network for retinal vessel segmentation from fundus images," Comput. Biol. Med., vol. 152, p. 106341, Jan. 2023.

[5] D. E. Alvarado-Carrillo and O. S. Dalmau-Cedeño, "Width attention based convolutional neural network for retinal vessel segmentation," Expert Syst. Appl., vol. 209, p. 118313, 2022.

[6] F. Dong, D. Wu, C. Guo, S. Zhang, B. Yang, and X. Gong, "CRAUNet: A cascaded residual attention U-Net for retinal vessel segmentation," Comput. Biol. Med., vol. 147, p. 105651, Aug. 2022.

[7] T. M. Khan, S. S. Naqvi, A. Robles-Kelly, and I. Razzak, "Retinal vessel segmentation via a Multi-resolution Contextual Network and adversarial learning," Neural Netw., vol. 165, pp. 310–320, Aug. 2023.

[8] K. Sun, Y. Chen, Y. Chao, J. Geng, and Y. Chen, "A retinal vessel segmentation method based improved U-Net model," Biomed. Signal Process. Control, vol. 82, p. 104574, 2023.

[9] C. Li, Z. Li, F. Yu, and W. Liu, "An improved method for retinal vessel segmentation in U-Net," Multimedia Tools Appl., vol. •••, pp. 1–19, 2024.

[10] S. Guo, "CSGNet: Cascade semantic guided net for retinal vessel segmentation," Biomed. Signal Process. Control, vol. 78, p. 103930, 2022.

[11] L. Li, M. Lv, H. Ma, Z. Jia, X. Yang, and W. Yang, "X-ray Image Enhancement Based on Adaptive Gradient Domain Guided Image Filtering," Appl. Sci. (Basel), vol. 12, no. 20, p. 10453, 2022.

[12] M. Yan, Z. Cheng, C. Gao, J. Sun, F. Liu, F. Sun, et al., "Cascading residual graph convolutional network for multi-behavior recommendation," ACM Trans. Inf. Syst., vol. 42, no. 1, pp. 1–26, 2023.

[13] M. F. Lei, Y. B. Zhang, E. Deng, Y. Q. Ni, Y. Z. Xiao, Y. Zhang, et al., "Intelligent recognition of joints and fissures in tunnel faces using an improved mask region-based convolutional neural network algorithm," Comput. Aided Civ. Infrastruct. Eng., vol. 39, no. 8, pp. 1123–1142, 2024.

[14] J. Lian, G. Hui, L. Ma, T. Zhu, X. Wu, A. A. Heidari, et al., "Parrot optimizer: Algorithm and applications to medical problems," Comput. Biol. Med., vol. 172, p. 108064, Apr. 2024.

[15] J. Lian, G. Hui, L. Ma, T. Zhu, X. Wu, A. A. Heidari, et al., "Parrot optimizer: Algorithm and applications to medical problems," Comput. Biol. Med., vol. 172, p. 108064, Apr. 2024.