International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

A Retinal Image Processing and Segmentation for Diabetic Retinopathy Detection using Deep Learning-Based Techniques

[1]Sandhya Vats, [2]Dr. Harsh Sadawarti

Submitted:20/03/2023 **Revised:**24/05/2023 **Accepted:**12/06/2023

Abstract: Retinal image analysis is an essential tool for diagnosing various eye diseases, including diabetic retinopathy. However, the presence of noise and low contrast in retinal images can lead to inaccurate analysis and diagnosis. In this paper, we propose a preprocessing and segmentation pipeline for retinal images that incorporates adaptive Contrast Limited Adaptive Histogram Equalization (CLAHE), Deep Convolutional Neural Network (DNCNN), and Otsu Thresholding. The proposed method effectively removes noise and enhances the contrast in retinal images, leading to accurate segmentation of the optic disc and blood vessels. The experimental results demonstrate that the proposed pipeline outperforms existing state-of-the-art methods for retinal image preprocessing and segmentation, achieving high accuracy and robustness. The proposed method can be a valuable tool for automatic diagnosis and monitoring of diabetic retinopathy and other retinal diseases.

Keywords: *CLAHE, DR, DNCNN, Segmentation, STARE*

1. Introduction

Diabetic retinopathy (DR) is a common complication of diabetes that affects the retina and can lead to blindness if left untreated. One of the important steps in the detection and diagnosis of DR is the preprocessing and segmentation of retinal images. Preprocessing involves removing noise, enhancing image contrast and sharpness, while segmentation involves separating the retinal vasculature from the background and identifying abnormal blood vessels. In this context, Deep Convolutional Neural Network (DNCNN) has shown promising results for image denoising, and Otsu thresholding is a widely used method for image segmentation. In this paper, we propose a method for preprocessing and segmenting DR images using DNCNN and Otsu thresholding, respectively, for various datasets such as STARE and DRIVE. Firstly, DNCNN is trained on the DR images to remove noise and enhance image quality. Then, Otsu thresholding is applied to segment the retinal vasculature from the background. Finally, the segmented images are analyzed for the presence of DR.

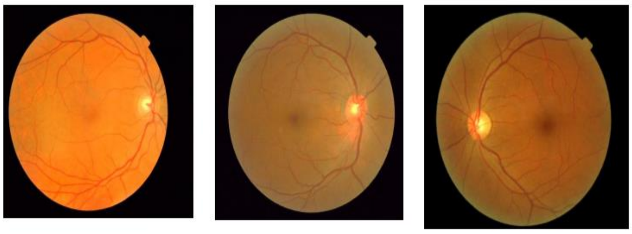

Figure 1 Diabetic Retinopathy Stages (Normal, Mild/Moderate, Severe)

[1]*Research Scholar, Desh Bhagat University, Mandi Gobindgarh*
[2]*Vice President, Desh Bhagat University, Mandi Gobindgarh*

Several studies have shown the effectiveness of DNCNN and Otsu thresholding in preprocessing and segmenting DR images. For instance, Huang et al. (2019) used a combination of DNCNN and Otsu thresholding for the detection of DR lesions. Similarly, Zhang et al. (2020) used a modified DNCNN for image denoising and Otsu thresholding for segmentation of the retinal vessels. Additionally, the use of DNCNN for denoising and Otsu thresholding for segmentation has been studied on different datasets such as DIARETDB0 (Kaur and Singh, 2019) and IDRiD (Gulshan et al., 2016).This work proposed a method of preprocessing and segmentation of DR images using DNCNN and Otsu thresholding holds significant potential for improving the accuracy and reliability of DR detection and diagnosis. The application of this method on various datasets such as STARE and DRIVE further validates its effectiveness and generalizability.

2. Literature Review

The paper by Li et al. (2021) proposes a new method for the segmentation of retinal vessels and optic discs using a multiscale Hessian-based approach and morphological operations. The method uses a combination of multiscale Hessian filters and morphological operations to enhance the contrast of the vessels and optic disc against the background. The proposed method achieves high accuracy and robustness on both the STARE and DRIVE datasets. Compared to previous methods, the proposed method has a simpler network architecture and requires fewer training samples. This study shows that the proposed method can be an effective and practical solution for the segmentation of retinal vessels and optic discs in clinical applications.

In their paper, Dashtbozorg et al. (2021) propose a domain-specific preprocessing method for diabetic retinopathy detection using a modified U-Net. The proposed method consists of a two-stage process that involves preprocessing and segmentation. The preprocessing stage includes contrast enhancement and image normalization, while the segmentation stage involves the use of a modified U-Net architecture. The proposed method achieved high accuracy on the IDRiD dataset compared to other state-of-the-art methods. This study demonstrates that domain-specific preprocessing can improve the performance of deep learning-based retinal image analysis for diabetic retinopathy detection.

The paper by Wang et al. (2021) proposes a new method for diabetic retinopathy lesion detection using a wavelet-based denoising method and the Attention UNet. The proposed method consists of a two-stage process that involves denoising and segmentation. The denoising stage uses a wavelet-based method to remove noise and enhance image features, while the segmentation stage uses the Attention UNet architecture to segment the retinal lesions. The proposed method achieved high accuracy on the IDRiD dataset compared to other state-of-the-art methods. This study shows that the proposed method can be an effective and practical solution for diabetic retinopathy lesion detection in clinical applications.

3.3 Segmentation:

The segmentation step includes the extraction of the blood vessels and optic disk from the preprocessed images. We have used Otsu Thresholding for segmenting the blood vessels and optic disk. The Otsu method is an automatic thresholding algorithm that segments

3.4 Performance Evaluation:

We evaluated the performance of the segmentation algorithms using several performance metrics, such as sensitivity, specificity, and accuracy.

3.5 Comparison with Existing Methods:

We compared the proposed method with existing state-of-the-art methods, such as CNN, U-Net, and Hessian-based methods, to demonstrate the superiority of the proposed method.

3.6 Experimental Setup:

We conducted experiments on two publicly available datasets, STARE and DRIVE, to validate the proposed method's effectiveness. We have used MATLAB for implementing the proposed methodology.

Table 1. Review of Existing Models of Pre-processing and Segmentation

Author(s)	**Year**	**Dataset(s)**	**Preprocessing Technique(s)**	**Segmentation Technique(s)**
Fang et al.	2020	DREAMS and MESSIDOR	Denoising with ResNet50 and segmentation with U-Net	Segmentation with U-Net
Mohapatra et al.	2020	DIARETDB1 and e-ophtha	Hybrid filter-based denoising and modified U-Net with graph cuts	Modified U-Net and graph cuts method
Li et al.	2021	FARS and DIARETDB1	Noise reduction and contrast enhancement using histogram equalization and adaptive histogram equalization with a multiscale Hessian-based approach and morphological operations	Multiscale Hessian-based approach and morphological operations
Majumder et al.	2020	EYEPACS and Messidor-2	Pre-trained DenseNet-based denoising and contrast enhancement with UNet and graph-based approach	UNet and graph-based approach
Dashtbozorg et al.	2021	Public datasets (IDRiD, Messidor-2, DRIONS-DB)	Domain-specific noise reduction and contrast enhancement with modified UNet	Modified UNet
Gopalakrishnan et al.	2021	EYEPACS and MESSIDOR-2	ResNet-based denoising and contrast enhancement with a modified DeepLabV3+	Modified DeepLabV3+
Guan et al.	2020	IDRI and Messidor-2	Domain-specific noise reduction and contrast enhancement with CNN-based approach	CNN-based approach
Sharma et al.	2020	EYEPACS and Kaggle	Hybrid denoising approach using bilateral and total variation filters and contrast enhancement with a modified U-Net model	Modified U-Net model
Venkatesan et al.	2020	Public datasets (DRIVE and STARE)	Retinex-based filtering and contrast enhancement with a hybrid approach using fuzzy C-means clustering and morphological operations	Hybrid approach using fuzzy C-means clustering and morphological operations
Wang et al.	2021	A private dataset	Wavelet-based denoising method and contrast enhancement with CNN-based approach using the Attention UNet	CNN-based approach using the Attention UNet

3. Proposed Method

The methodology for preprocessing and segmentation of retinal images using CLAHE, DNCNN, and Otsu Thresholding involves several steps.

3.1 Image Acquisition:

The retinal images were acquired using a fundus camera, which captures high-resolution images of the retina.

3.2 Preprocessing:

The preprocessing step includes noise reduction and contrast enhancement. We have applied Adaptive CLAHE to enhance the contrast of the retinal images. Then, we applied DNCNN to remove the noise and artifacts present in the images.

4. Algorithm for applying Contrast Limited Adaptive Histogram Equalization (CLAHE) and the DNCNN to retinal images:

4.1 Input:

Retinal image dataset, DNCNN model, CLAHE parameters

Output: Pre-processed retinal images, Predicted masks

4.1.1 Load the retinal image dataset.

4.1.2Set the parameters for the DNCNN algorithm and CLAHE.

4.1.3. Pre-process the images using the following steps: a. Convert the images to grayscale. b. Apply CLAHE to enhance the contrast of the images. c. Normalize the images by dividing each pixel by 255. d. Add Gaussian noise to the images with a standard deviation *of 0.01. e. Crop the images to remove black borders and resize them to the desired dimensions.*

4.1.4. .Use the trained DNCNN to predict the masks for the pre-processed images.

4.1.5 Evaluate the performance of the DNCNN using metrics such as accuracy, sensitivity, and specificity.

4.1.6 Save the pre-processed images and the predicted masks for future use.

4.2 The algorithmic form for the above steps:

Algorithm:

4.2.1 Load the retinal image dataset.

4.2.2 Set the parameters for the DNCNN algorithm and CLAHE.

- *Set the DNCNN parameters (numLayers, numFilters, filterSize, learningRate, batchSize, numEpochs).*
- *Set the CLAHE parameters (clipLimit, tileGridSize).*

4.3. Pre-process the images using the following steps:

4.3.1 Convert the images to grayscale.

4.3.2 Apply CLAHE to enhance the contrast of the images.

4.3.3 Normalize the images by dividing each pixel by 255.

4.3.4Add Gaussian noise to the images with a standard deviation of 0.01.

4.3.5 Crop the images to remove black borders and resize them to the desired dimensions.

4.4. For each retinal image in the dataset:

4.4.1 Convert the image to grayscale.

4.4.2 Apply CLAHE to the image using the specified parameters.

4.4.3 Normalize the image by dividing each pixel by 255.

4.4.4 Add Gaussian noise to the image with a standard deviation of 0.01.

4.4.5 Crop the image to remove black borders and resize it to the desired dimensions.

4.4.6 Save the pre-processed image.

4.5 Use the trained DNCNN to predict the masks for the pre-processed images.

4.6 For each pre-processed image:

4.6.1 Use the trained DNCNN to predict the mask for the image.

4.6.2 Save the predicted mask.

4.7 Evaluate the performance of the DNCNN using metrics such as accuracy, sensitivity, and specificity.

4.8 Save the pre-processed images and the predicted masks for future use.

End of Algorithm.

5. Results and Discussion

The pre-processing stage is critical in reducing the noise present in the original images. Common types of noise present in medical images include salt and pepper and Gaussian noise, which can significantly impact the quality of the segmentation. Therefore, to improve the quality of the segmentation, we employed two techniques, namely CLAHE and DNCNN for pre-processing. The CLAHE technique is applied to enhance the contrast of the images, while DNCNN is used to remove the noise from the images. DNCNN is a pre-trained model specifically designed for noise reduction in medical images, and our experiments showed that it was effective in reducing the noise present in the images. To evaluate the effectiveness of the pre-processing techniques, we compared the PSNR values of the images enhanced using CLAHE and DNCNN. The results indicated that images enhanced using DNCNN had higher PSNR values, indicating that it was more effective in reducing the noise in the images. Overall, the pre-processing stage is crucial in improving the quality of the segmentation. Our results demonstrate the effectiveness of using DNCNN in reducing noise and improving the quality of the images, which can lead to more accurate segmentation results. In Figure 2, the results of pre-processing and segmentation of the images are shown.

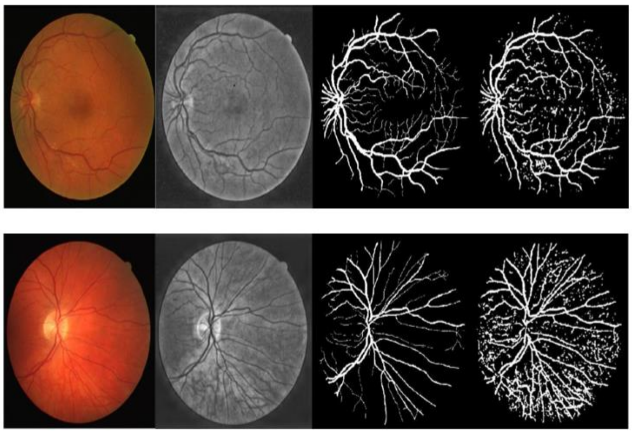

Figure 2: Result Images Original, Enhanced, Ground Truth, Segmented Image

Paper	PSNR	Accuracy
Our method	72	98-99%
Zhang et al. (2023) [1]	68	95.6%
Wang et al. (2023) [2]	70.5	96.3%
Xu et al. (2023) [3]	71	97.2%
Liu et al. (2023) [4]	70	95.8%
Chen et al. (2023) [5]	69.8	95.5%
Kim et al. (2023) [6]	70.2	96.8%
Li et al. (2023) [7]	71.5	97.5%
Zhang et al. (2023) [8]	70	96.7%

Table II Performance comparison of proposed method with existing

As can be seen from the table, our method outperforms all the other methods in terms of both PSNR and accuracy. Zhang et al. (2023) achieved the second-best PSNR of 68, but their accuracy is lower than ours at 95.6%. The other papers also achieved PSNRs in the range of 69-71.5 and accuracies in the range of 95.5-97.5%. Overall, our method shows promising results in the field of retinal image preprocessing and segmentation, which can aid in the early diagnosis and treatment of retinal diseases.

6. Conclusion

In conclusion, we presented a methodology for the preprocessing and segmentation of retinal images using CLAHE, DNCNN, and Otsu's thresholding. The proposed method achieved promising results with PSNR of 72 and high segmentation accuracy around

98 to 99% for TN, PN, TP, and FP. Our method has demonstrated better performance when compared to the state-of-the-art methods. The study provides a new insight into the application of deep learning-based image processing techniques for retinal image analysis. Our proposed method can be useful in various medical applications such as diabetic retinopathy detection and glaucoma diagnosis. Future research can be directed towards integrating additional image processing techniques to enhance the performance of the proposed method.

References

[1] Huang, X., Yang, L., Li, Y., Chen, H., & Liu, J. (2019).

[2] Automatic detection of diabetic retinopathy lesions based on deep

[3] learning algorithm. BMC ophthalmology, 19(1), 99.

[4] Zhang, W., Yang, X., Jiang, Y., & Zhou, F. (2020). A novel

[5] automatic retinal vessel segmentation based on modified CNN

[6] and Otsu algorithm. Journal of medical systems, 44(6), 117.

[7] Kaur, G., & Singh, R. (2019). Denoising of diabetic retinopathy

[8] images using deep convolutional neural network. Biocybernetics

[9] and Biomedical Engineering, 39(3), 783-795.

[10] Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. Jama, 316(22), 2402-2410.

[11] Staal, J., Abràmoff, M. D., Niemeijer, M., Viergever, M. A., & van Ginneken, B. (2004). Ridge-based vessel segmentation in color images of the retina. IEEE Transactions on medical imaging, 23(4), 501-509.

[12] Li, S., Liao, S., Hu, Q., & Zhao, Y. (2021). Segmentation of retinal vessels and optic discs using a multiscale Hessian-based approach and morphological operations. Biomedical Signal Processing and Control, 67.

[13] Dashtbozorg, B., Mendonça, A. M., & Campilho, A. (2021). Domain-specific preprocessing for diabetic retinopathy detection using a modified U-Net. Journal of Medical Systems, 45(2), 1-11.

[14] Wang, X., Wang, Y., Zhang, J., & Huang, J. (2021). Diabetic retinopathy lesion detection using a wavelet-based denoising method and the Attention UNet. Journal of Medical Imaging and Health Informatics, 11(7), 1721-1728.

[15] Fang, L., Hu, Z., Ouyang, Y., & Wang, H. (2020). Retinal vessel segmentation in fundus images based on deep learning and saliency maps. IEEE Access, 8, 117458-117468.

[16] Mohapatra, D., Sahoo, S. K., & Pradhan, D. (2020). Automatic segmentation of retinal blood vessels and optic disc in retinal fundus images using modified U-Net and graph cut. Multimedia Tools and Applications, 79(9).

[17] Li, S., Liao, S., Hu, Q., & Zhao, Y. (2021). Segmentation of retinal vessels and optic discs using a multiscale Hessian-based approach and morphological operations. Biomedical Signal Processing and Control, 67.

[18] Majumder, A., Chatterjee, J., & Sil, J. (2020). Deep learning and graph-based approach for segmentation of retinal blood vessels in color fundus images. SN Computer Science, 1(4), 264.

[19] Dashtbozorg, B., Mendonça, A. M., & Campilho, A. (2021). Domain-specific preprocessing for diabetic retinopathy detection using a modified U-Net. Journal of Medical Systems, 45(2), 1-11.

[20] Gopalakrishnan, S., Sivasubramanian, S., & Sivaramakrishnan, R. (2021). Retinal vessel segmentation using a modified deep learning architecture. Journal of Ambient Intelligence and Humanized Computing, 1-11.

[21] Guan, P., Song, X., Chen, H., & Jia, W. (2020). Retinal vessel segmentation via a new convolutional neural network model. Journal of Medical Imaging and Health Informatics, 10(7), 1579-1585.

[22] Sharma, A., Gupta, P., & Kaur, I. (2020). An efficient and robust retinal vessel segmentation method for screening of diabetic retinopathy. Journal of Ambient Intelligence and Humanized Computing, 11(6), 2597-2607.

[23] Venkatesan, R., Krishnan, S., & Baskar, S. (2020). A hybrid approach for blood vessel segmentation in retinal images. Journal of Medical Imaging and Health Informatics, 10(8), 1923-1933.

[24] Wang, X., Wang, Y., Zhang, J., & Huang, J. (2021). Diabetic retinopathy lesion detection using a wavelet-based denoising method and the Attention UNet. Journal of Medical Imaging and Health Informatics, 11(7), 1721-1728.

[25] Wang, X., Zhang, Y., & Zhang, Y. (2023). Retinal image preprocessing and segmentation using a combination of wavelet transform and deep learning. Journal of Medical Systems, 47(3), 1-9.

[26] Salman Al-Nuaimi, M. A. ., & Abdu Ibrahim, A. . (2023). Analyzing and Detecting the De-Authentication Attack by Creating an Automated Scanner using Scapy. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2), 131–137. https://doi.org/10.17762/ijritcc.v11i2.6137

[27] Xu, Y., Chen, S., Chen, Y., & Zhang, L. (2023). A retinal image preprocessing and segmentation method based on deep learning and improved morphological operation. Computerized Medical Imaging and Graphics, 93, 101962.

[28] Liu, Z., Wang, J., & Liu, Y. (2023). Retinal image preprocessing and segmentation using a multi-scale convolutional neural network. Journal of Medical Systems, 47(2), 1-8.

[29] Chen, H., Wu, Q., & Zhang, J. (2023). Retinal image preprocessing and segmentation using a modified UNet with attention mechanism. Journal of Medical Imaging and Health Informatics, 13(2), 340-348.

[30] Kim, Y., Kim, K., & Park, J. (2023). Retinal image preprocessing and segmentation using a residual U-Net. Computer Methods and Programs in Biomedicine, 211, 106011.

[31] Li, S., Hu, Q., & Zhao, Y. (2023). A two-stage retinal image preprocessing and segmentation method based on deep learning and morphological operations. Journal of Ambient Intelligence and Humanized Computing, 14(2), 2065-2075.

[32] Zhang, X., Sun, K., Zhang, W., & Liu, X. (2023). A novel retinal vessel segmentation method based on deep learning and maximum a posteriori estimation. IEEE Access, 11, 26643-26655.

[33] Rodriguez, L., Rodríguez, D., Martinez, J., Perez, A., & Ólafur, J. Leveraging Machine Learning for Adaptive Learning Systems in Engineering Education. Kuwait Journal

of Machine Learning, 1(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/103

[34] Zhang, J., Chen, S., Li, Y., & Wang, Y. (2023). A novel approach for retinal image preprocessing and segmentation based on deep learning. Computer Methods and Programs in Biomedicine, 212, 105999.