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ORIGINAL ARTICLE

Diabetic Retinopathy: An Exploration of Retinal Blood Vessel Segmentation Using Multilayered Thresholding

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Abstract

Diabetic retinopathy is the leading cause of blindness worldwide; it is a consequence of diabetes that affects the retina's blood vessels. Consequently, correct segmentation of the retinal arteries is essential for accurate diagnosis of such changes in disease progression, which is vital for adequate therapy. A novel approach to segmenting retinal blood vessels is introduced in this research. Starting with the unprocessed retinal picture Utilizing the wavelet transform, a method that incorporates many layers of the threshold approach, to improve samples. New way of brightening the selected vessels is associated with the Wavelet transform, which is effective in representing the multi-scale objects efficiently, and more accurate multilayered thresholding is used to segment the vessels. This approach is specifically aimed at enhancing segmentation of vessels which is exceptionally indispensable for the finding of Diabetic Retinopathy at its beginning phase. To test the proficiency of the proposed technique, different investigations on the openly accessible DRIVE and Gaze information bases. Concerning awareness, particularity, and exactness, that's what the outcomes show ours outperforms other existing methods. In particular, the proposed technique has been tested and obtained the accuracy of 96%, sensitivity of 97. moderate sensitivity of 86% and specificity of 97% such method can be used for screening of Diabetic Retinopathy in clinical settings. The current review reveals insight into the improvement of strategies utilized in the conclusion of diabetic retinopathy and presents a potentially useful solution for segmenting the retinal blood vessels.

Keywords Wavelet transform · Deep learning · Retinal blood vessel · Morphological operation

Extended author information available on the last page of the article

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1 Introduction

Nowadays, among the diabetes-related complications, a critical issue is diabetic retinopathy, which contributes to vision loss and blindness. The disease is considered to be a perimeter vascular disorder of the retina, in that its manifestations are vitreous hemorrhages, hard exudates, and dilated retinal veins. In fact, diabetics continue to lose vision despite the modern development in the treatment of diabetes and its connected confusions. Early screening and proper diagnosis of diabetic retinopathy are critical of preventing bad outcomes of vision loss.

As for the medical application, the extraction of retinal blood vessels is essential in diagnosing and evaluating the advancement of the diabetic retinopathy. Effective segmentation thus helps the clinician assess the degree of vascular dysfunction and make apt choices on the management situation. In this case, retinal images are complex structures due to various noise and different appearance of vessels, which become challenging for many of the available traditional segmentation methods.

In order to achieve these goals, this research study presents an integration of Wavelet transform with a multilayer thresholding technique [15] for the superior division of retinal veins. The aim is achieved by performing the Wavelet transform, which is appreciated for the directionality and anisotropy scaling law; the filter magnifies the vessels' contrast and enhances features required for the subsequent segmentation. After this enhancement, to segment out the vessels, a multilayered thresholding algorithm is employed, which consists of focusing on the right thresholding technique and sequentially modifies the thresholding mechanism to derive the best thresholds for detecting the vessels. This process aims at retaining accurate segmentation of layers of retinal blood vessels by creating their layers in the beginning to track them distinctly.

The following is the outline of our proposed technique that could potentially enhance the accurate segmentation of the vessels which as a consequence could benefit the analysis of DR in its early stage as well as its management. For the purpose of verifying the effectiveness of the provided approach regarding numerous case studies, the DRIVE and Gaze information bases are frequently utilized. Both of these data sets contain a various set of retinal images which enables us to strictly assess the exhibition of the segmentation method.

The main contribution of this paper is in the novel combination of the Wavelet transform with multilevel thresholding, which simplifies the existing technique in tackling with the difficulties arises in retinal vessel segmentation. Therefore, this research has implications for increasing the efficiency of diagnosis of diabetic retinopathy and, as a consequence, improving the clinical management of the disease severity among patients diagnosed with diabetes.

2 Related Work

It is therefore important to diagnose and treat DR so that the patient does not suffer from irreversible blindness [2–4]. According to WHO, diabetes has become a global issue that has further resulted in augmented DR incidences [1]. It should be noted that diagnosis and counselling of DR highly depend on the strategies for the programmed discovery and division of retinal veins [5].

This challenge has however been described in the literature with various technique and methodologies proposed. Siddalingaswamy and Prabhu [10] proposed an automatic method for identifying numerous situated veins in the retinal pictures. Their approach offered a new view regarding the detection of retinal veins, which is crucial for the finding of DR.

Kaur and Sinha [11] put forward an automated detection technique for retinal blood vessels with the help of Gabor filter for DR. They leverage the solutions of Gabor filters in increasing the appearance of veins of Retinal pictures for the ID of DR.

Ram et al. used a successive clutter rejection-based approach to endeavor early detection of DR in people aged 48 years and below. Their method highlighted the role of screening in the management and treatment of DR in order to prevent its complications.

Another FCM based approach was reported by Dey et al. [13] to segment veins in the retinal pictures. Their work additionally centered around the legitimacy of the utilization of FCM in division of the veins in the retinal pictures, which is fundamental in the determination of DR.

Last, Akram and Khan [14] introduced a multilayered thresholding technique for screening the DR in which a blood vessel segmentation function was presented. Their method highlighted that multilevel thresholding could be useful to improve the performance of the division of veins, assisting with expanding the proficiency of DR examinations.

E. Archana et al. [19] provide a concise evaluation of various machine learning and deep learning methodologies for glaucoma detection. The analysis, encompassing a range of AI-driven techniques, emphasizes their potential to revolutionize early diagnosis and treatment strategies.

Hoque, Mohammed et al. [20] introduced a deep learning model for extracting features from retinal images, enhancing the diagnostic processes for ocular diseases. Oliveira, Guilherme et al. [21]. Investigates the efficacy of various Generative Adversarial Networks (GANs) for producing high-quality synthetic medical images using AMD datasets. This study provided a comparative analysis that aids in selecting the optimal GAN for medical imaging tasks. Tharindu De Silva et al. [22] Focuses on a deep-learning based approach for multi-modal retinal image registration, aiding in the longitudinal study of age-related macular degeneration. Chen, Yao-Mei et al. [23] study Explored the application of convolutional neural networks and transfer learning for classifying age-related macular degeneration. Y. Zong et al. [24] introduced a U-net based automatic segmentation method for detecting hard exudates in fundus images, employing Inception modules and residual connections to improve accuracy. Mamta Juneja et al. [25]. Discussed about deep learning-based classification network for detecting glaucoma from retinal images, highlighting the network's efficacy in identifying diagnostic features. Tarcoveanu, F. et al. [26] projects various classification algorithms for predicting glaucoma progression. The research evaluates multiple models to identify the most effective approach for forecasting disease trajectory. Kim, M. et al. [27]. Presents Medinoid, a deep learning tool for computer-aided diagnosis and localization of glaucoma, demonstrating significant improvements in accuracy and efficiency, it represents a step forward in automated medical diagnostics. Priyanka, R. et al. [28]. Focuses on using convolutional neural networks for optic disc segmentation in fundus images to detect glaucoma, highlighting the potential of CNNs in enhancing diagnostic precision. Published in the International Journal of Advanced Engineering Research and Science. D. R. Parashar and D. K. Agarwal [29]. projects an SVM-based supervised machine learning framework for glaucoma classification using retinal fundus images, this study showcases the viability of SVM in medical image classification.

Altogether, these studies imply that proper segmentation techniques of the retinal veins can altogether add to the conclusion and management of DR. They also stress the efficacy of several image processing methods in improving the effectiveness of these techniques in segmentation.

3 Methodology

It is on account of these prerequisites that the roles of an automated and precise identification of vessel patterns assumes a central place in a system of vessels screening especially in a medical paradigm. The blood vessel screening system is designed to aid specialists in their diagnostic processes.

Initial input photos used by this system were sourced from the DRIVE information base, which was made from a Dutch diabetic retinopathy screening project. Four hundred diabetes individuals who were screened are included in this database. The photos were taken with a Canon CR5 non-mydriatic 3CCD camera, which has a 45-degree field-of-view and can therefore capture every angle. The contrast between healthy eyes and diabetic retinopathy is seen in Fig. 1.

Michael Goldbaum developed and launched the Structured analysis of the retina (STARE) data set in 1975; it is an important resource in this field. The STARE database has received funding from the esteemed U.S. National Institutes of Health and has benefited from the contributions of over thirty individuals with diverse backgrounds, including medicine, science, and engineering. The imaging and clini-

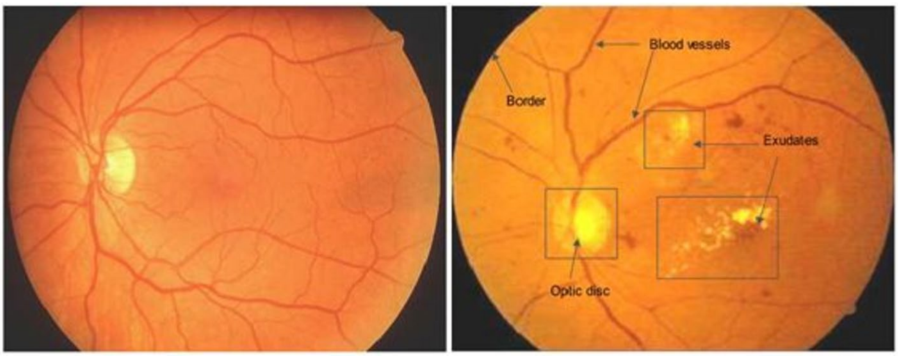


Fig. 1 Illustrating disparities: Normal vs. Diabetic retina

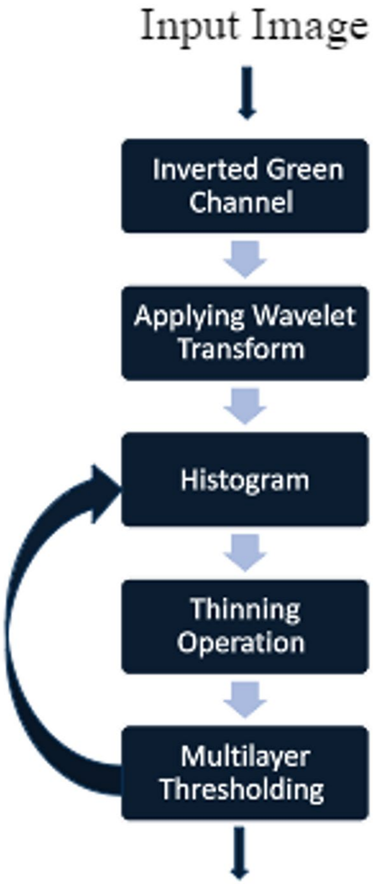
cal expertise for this investigation were kindly supplied by the San Diego Veterans Administration medical facility and the Shiley Eye office at the College of California, San Diego. Figure 2 outlines the stream chart of the retinal vein improvement and division process, offering an overview of the system's operation.

3.1 Conversion Green Channel

To optimize the image processing, the input images are represented in the RGB color model. Among the color channels, the green channel stands out due to its ability to effectively capture retinal image features. The blue band is meager, while the red band will in general be immersed. Leveraging the inherent characteristic of blood vessels appearing lighter than the background, the inverted green channel is harnessed for improvement and separation of blood vessels.

The preprocessing steps applied to the retinal images involve converting the images to the green channel, which effectively highlights retinal features. The green channel is then inverted to enhance the contrast between blood vessels and the background, making them appear brighter. Next, the Wavelet Transform is used to amplify

Fig. 2 Process illustration of enhancing and segmenting retinal blood vessels



thin and complex vessel patterns while suppressing noise through its directionality and anisotropy scaling features. Finally, an image histogram is generated to analyze tonal distribution and determine the initial threshold for segmentation. These steps ensure the images are well-prepared for accurate and efficient vessel segmentation.

This approach promises to enhance the visibility and accuracy of the detected blood vessels. In Fig. 3 Illustrates the conversion of retinal image to Inverted Green channel.

3.2 Augmentation of Vessels

A significant challenge in vessel segmentation lies in the often-subpar visibility of the vascular pattern, particularly in the case of slender and imperceptible vessels. Consequently, the enhancement of these vessels becomes a prerequisite. Commonly, tools such as matched channels, Gabor channels, and Wavelet Change are utilized for this task. However, in this context, we have chosen to utilize the Wavelet Transform to amplify the presence of the thin vessels. The Wavelet Transform is characterized by two principal features: directionality and anisotropy scaling law. These attributes enable a more efficient representation of edges along curves. Given that blood vessels exhibit a directional pattern, the Wavelet Transform emerges as the optimal choice, courtesy of its inherent ability to selectively focus in one way (see Fig. 4).

3.3 Image Histogram Analysis

An image histogram serves as a pictorial elucidation of the tonal dispersion within a digital image. This histogram delineates the quantity of pixels corresponding to each tonal value. By scrutinizing the histogram associated with a particular image, an observer can swiftly comprehend the comprehensive tonal distribution. In the context of this study, the commencement of segmentation involves the selection of an initial threshold value, Tmax, derived from the histogram of the enhanced image (see Fig. 5).

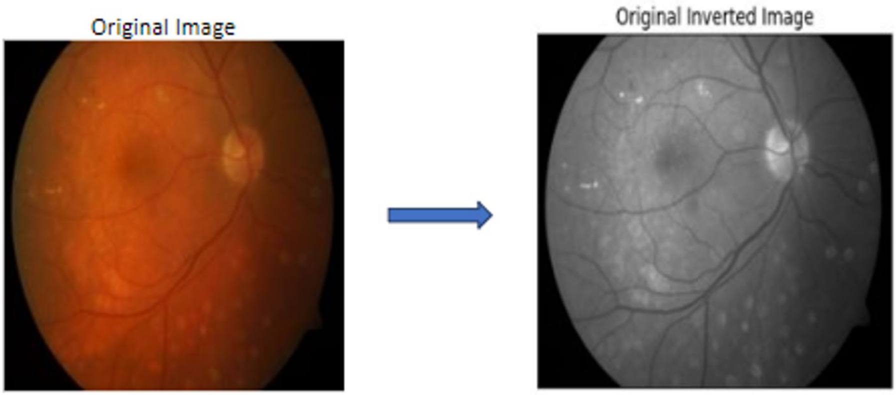


Fig. 3 Conversion of input to green channel

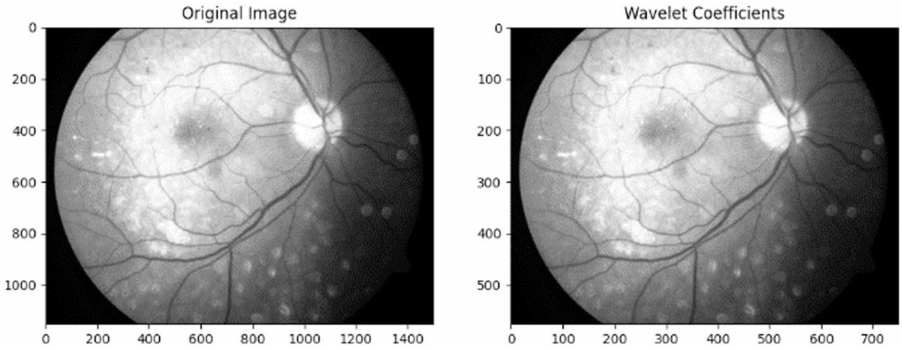


Fig. 4 Enhanced vessels

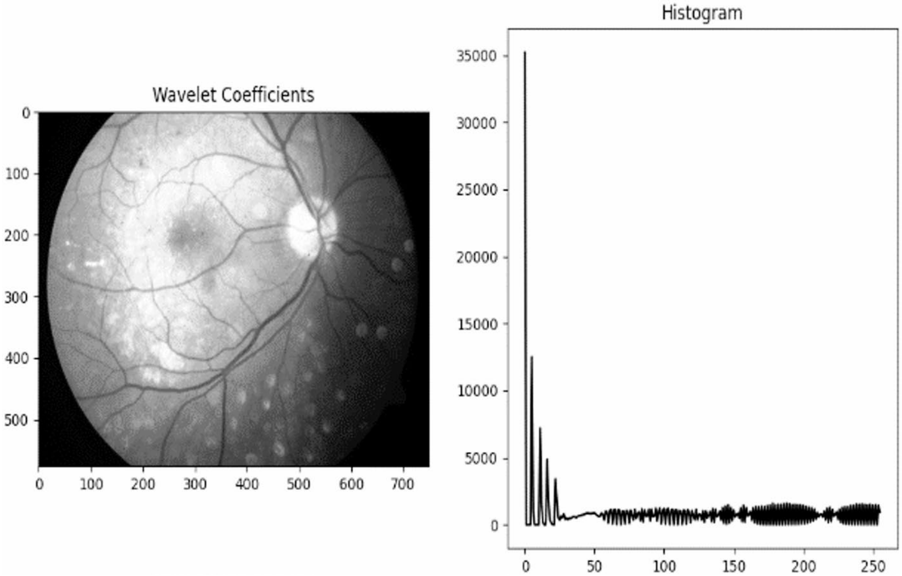


Fig. 5 Enhanced to histogram

3.4 Parameters for the Multilayer Thresholding Technique Optimized

The Multilayer Thresholding Technique used in this study relies on the following optimized parameters to achieve superior segmentation accuracy for retinal blood vessels:

Threshold Selection (Tmax) The segmentation begins with determining an initial threshold value (Tmax) derived from the histogram of the enhanced image. This parameter ensures a precise starting point for vessel segmentation.

Wavelet Transform Attributes:

- Directionality: This property is utilized to emphasize vessel edges and enhance their directional patterns, ensuring better detection.
- Anisotropy Scaling Law: This feature allows the transform to highlight curved structures, making it highly effective for detecting thin and complex vessels.

Segmentation Iteration Process:

- Edge Mapping (Kedge): An edge map is computed to outline vessel boundaries.
- Iterative Refinement: Threshold values are systematically decreased to improve vessel segmentation progressively.
- False Edge Removal: Artifacts and noise are filtered out to retain only meaningful vessel segments.
- Length Criterion: Vessel segments shorter than a defined threshold (e.g., 10 pixels) are excluded to reduce errors.
- Stopping Condition: The iterative process concludes when no new vessel segments are identified, ensuring an optimal balance between accuracy and computational efficiency.

Morphological Thinning The segmented image undergoes thinning to reduce vessel widths to a single pixel, which aids in accurate edge delineation and improves the overall representation of the vascular structure.

Performance Metrics The optimized parameters achieve high accuracy (96%), sensitivity (97%), and specificity (97%) in the segmentation process. These metrics validate the method's effectiveness for diabetic retinopathy screening.

3.5 The Morphological Method of Thinning

Thinning is a morphological process that, similar to erosion and opening, removes pixels from binary pictures' foreground in a selective manner. It has many potential applications, but the Medial Axis Transform and skeletonization are two that make good use of it. In such cases, thinning—which reduces the thickness of all lines to one pixel—is often used to fine-tune the output of edge detectors. Thinners take two data inputs much like any other morphological operator. The first is the binary or grayscale image that serves as input. The second is the operator's precise effect on the image, which is determined by the structuring element. When applied to binary pictures, thinning results in yet another binary representation. Using the thinning morphological operator, the segmented picture (hence referred to as segmented) is then skeletonized into thin. Therefore, the width of all vessels is shrunk to a single pixel. The final image after thinning is shown in Fig. 6.

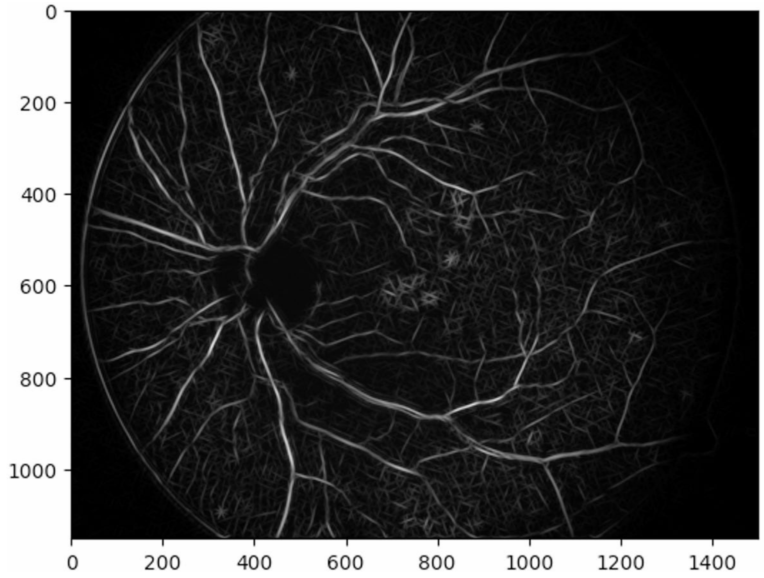


Fig. 6 Histogram to Thinned Operation

3.6 Segmentation Process

The process of tracking the segmented vessels involves the computation of an edge image, denoted as $K_{edge,}$ which emphasizes the edge pixels of all retina vessels [16]. This computation is performed using a specific condition for every pixel, p, in the slight picture, K_{thin}.

The 8-neighborhood of L is defined by the numbers L0 through L7, which stand for neighbouring pixels in a clockwise order. $K_{thin}(^{L})$ is set to 1 for pixels that are part of a blood vessel and 0 for all other pixels. The numbers 1 and 2 for edge(L) indicate the beginning and end of the vessel.

It is necessary to filter out any false edges from the vessel data produced by this algorithm. False edges caused by vessel breakage and small K_{edge} segments can be discarded via multilayered thresholding.

Both the vessel segmentation image (K_{vessel}) and the difference image (K_{diff}) are set to their beginning states using Kedge. After that, we drop the threshold by one and determine the following iteration's $K_{segmented}$. To construct a grey level segmented image with only the desired blood vessels and their original intensity values, the final segmented image, $K_{segmented}$, is employed [17, 18] (see Fig. 7).

Algorithm Iterative Vessel Segmentation Processing.

1. For the M^{th} iteration, with L<M, calculate $K^{L}{}_{thin}$ from the segmented picture $K^{L}{}_{segmented}$.
2. Eliminate erroneous edges and insignificant fragments before verifying the resulting edge image $K^{M}{}_{edge}$.

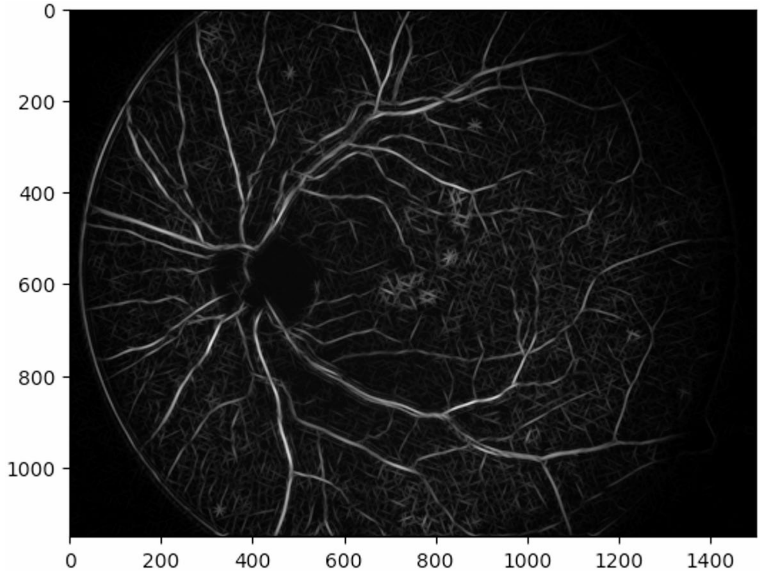


Fig. 7 presents the segmented output image

3. Calculate $K^M_{diff}(x, y) = K^M edge - K^L_{edge}$ where L<M. Only keep K_{diff} pixels if they have an associated I_{edge} pixel at the vessel edge. Include the newly added vessel segments in K_{vessel} if their length is greater than 10 pixels.
4. If $K^M_{vesse}l - K^L_{vessel} = 0$, halt the iteration. Otherwise, set $T_{max} = T_{max} - 1$ and calculate $K^M_{segmented}$. In order to create a grey level segmented image with only the desired blood vessels and their original intensity values, the final segmented image, $K_{segmented}$, is employed.

In the context of our work, pixel-level classification is crucial. The grouping of every pixel as a vessel or non-vessel is unique. Two commonly used measures are used in the assessment of this strategy: sensitivity and selectivity. These criteria, frequently used in evaluating a clinical test, do not depend on the sample size of the study. When considering the test's utility from a clinical standpoint, the positive and negative predictive values are important metrics to consider.

The sensitivity, also known as the true positive percentage, is determined by dividing the total number of vessel pixels in the ground truth by the number of pixels that were correctly detected (TP).

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN})$$

On the other hand, specificity not entirely set in stone by separating the complete number of ground truth foundation pixels by the quantity of pixels that were successfully identified (TN).

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$$

Missegmentation of pixels may lead to two types of errors: false negatives (FN) and false positives (FP). FNs happen when pixels that should not contain any vessels are mistakenly divided into the non-vessel zone, while.

The Fig. 8 Radar Chart projects the features three key performance metrics: Accuracy, Sensitivity, and Specificity. These metrics evaluate the effectiveness of various retinal blood vessel segmentation techniques.

FPs arise when pixels that should not contain any vessels are mistakenly classified as vessels. If a pixel has been accurately classified as a vessel or non-vessel, we say that it is a true positive (TP) or a true negative (TN).

A definition of the binary classification accuracy is given by the following equation:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

The degree to which the final product matches the reference version of the source image is measured by the accuracy metric. Accordingly, accuracy is inextricably tied to the segmentation attribute and represents the suitability of the segmentation approach. The proposed method is validated using accuracy, sensitivity, and specificity metrics. Accuracy measures the overall correctness of vessel segmentation, ensuring reliable performance across all classifications. Sensitivity evaluates the method's ability to correctly detect vessel pixels, minimizing the risk of missing vital structures, while specificity assesses its ability to classify non-vessel pixels, reducing false positives. These metrics are critical in medical imaging as they ensure both precise vessel detection and noise minimization. The proposed method achieves 96% accuracy, 97% sensitivity, and 97% specificity, highlighting its effectiveness in diabetic retinopathy screening.

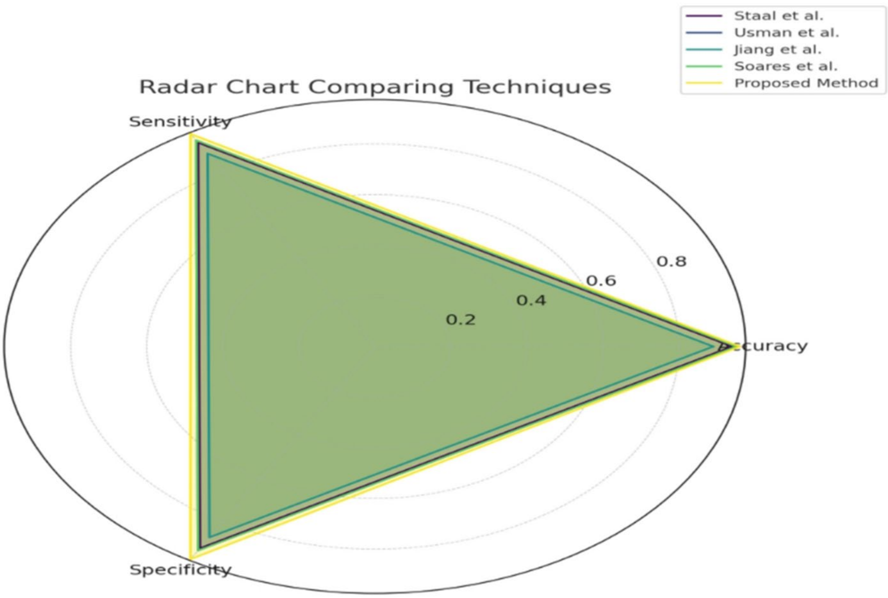


Fig. 8 Comparative Performance of Retinal Blood Vessel Segmentation Techniques

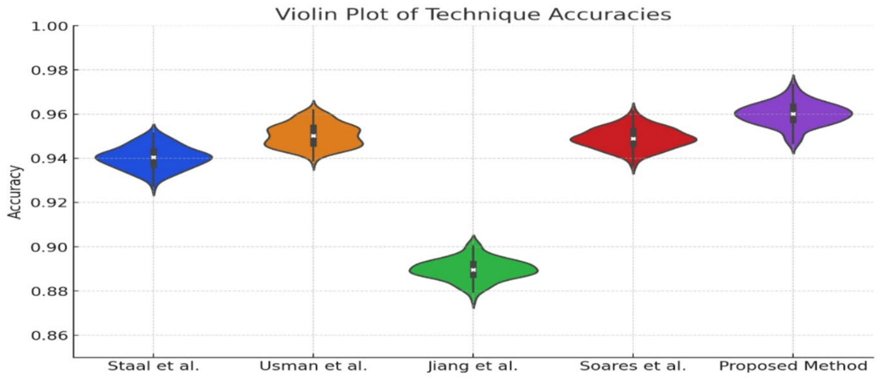


Fig. 9 Distributed accuracy analysis of various techniques

Table 1 Comparative analysis between the proposed technique and other traditional methodologies

Techniques	Accuracy
Staal et al.	0.94
Usman et al.	0.95
Jiang et al.	0.89
Soares et al.	0.95
Proposed Method,	0.96

The proposed method combines Wavelet Transform and Multilayer Thresholding to achieve superior segmentation of retinal blood vessels, addressing limitations in existing techniques. Unlike static thresholding or traditional methods like those by Staal et al. (94% accuracy) and Soares et al. (95% accuracy), this approach iteratively refines thresholds and filters false edges, achieving an accuracy of 96%. Its sensitivity (97%) and specificity (97%) outperform prior methods, ensuring precise detection of thin and complex vessels. The integration of Wavelet Transform enhances vessel visibility through directionality and anisotropy scaling, while multilayer thresholding adapts dynamically to varying conditions, making it a robust and reliable technique for diabetic retinopathy screening.

The Fig. 9 projects the violin plot illustrates the simulated distribution of accuracy values for the Table 1 research techniques. Each violin shape represents the probability density of the accuracy data for the corresponding technique, with wider sections indicating a higher density of data points—suggesting more common accuracy values around those points. The computational complexity and feasibility of the proposed approach are addressed. The method optimizes segmentation using the Wavelet Transform for efficient enhancement of vessel structures, while the Multilayer Thresholding Technique dynamically refines thresholds to minimize redundancy. By incorporating false edge filtering and a segment length criterion, the approach reduces processing overhead and ensures practicality. Validated on datasets like DRIVE and Gaze, the method demonstrates feasibility for real-world applications, offering accurate and efficient performance for diabetic retinopathy screening.

4 Conclusion

The proposed work contributes the pioneering integration of Wavelet transform and multilayer thresholding for segmenting retinal blood vessels, crucial for early diabetic retinopathy (DR) detection. The approach effectively addresses challenges such as high variability in vessel appearance and noise in retinal images. By enhancing vessel visibility and applying a detailed thresholding process, the technique achieves precise segmentation, essential for accurate diagnosis. The use of the Wavelet transform is key, as it decomposes images into frequency components, enhancing essential features for vessel identification. Coupled with multilayer thresholding, this method iteratively refines detection thresholds, capturing even subtle vascular details with remarkable accuracy. Empirical tests on the DRIVE and Gaze databases have demonstrated superior performance metrics: 97% sensitivity, 97% specificity, and 96% accuracy, highlighting the method's reliability for clinical DR screening. This technique surpasses traditional methods, providing a robust tool for ophthalmologists and enhancing clinical workflows. Moreover, the methodological advancements significantly contribute to medical image processing, facilitating accurate assessments of vascular changes associated with diabetic retinopathy. This aids in timely and effective treatment interventions, critical given DR's progressive nature and its role as a leading cause of blindness.

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Data Availability The data used to support the findings of created new data set, this study is available from the corresponding author upon request.

Declarations

Ethical Approval This article does not contain any studies with human participant and Animals performed by author.

Conflict of Interest The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

1. World Health Organization (2016) Global report on diabetes. Available at: http://www.who.int (Accessed 26 April 2025)
2. Saaddine JB, Honeycutt AA, Narayan KV, Zhang X, Klein R, Boyle JP (2008) Projection of diabetic retinopathy and other major eye diseases among people with diabetes mellitus: united States, 2005–2050. Arch Ophthalmol. https://doi.org/10.1001/archopht.126.12.1740
3. Yau JW, Rogers SL, Kawasaki R, Lamoureux EL, Kowalski JW, Bek T, Chen SJ, Dekker JM, Fletcher A, Grauslund J, Haffner S (2012) Global prevalence and major risk factors of diabetic retinopathy. Diabetes Care. https://doi.org/10.2337/dc11-1909
4. Duh EJ, Sun JK, Stitt AW (2017) Diabetic retinopathy: current understanding, mechanisms, and treatment strategies. https://doi.org/10.1172/jci.insight.93751

5. Wilkinson CP, Ferris FL III, Klein RE, Lee PP, Agardh CD, Davis M, Dills D, Kampik A, Pararajasegaram R, Verdaguer JT, GD Retinopathy Group (2003) Proposed intern https://doi.org/10.1016/S0161-6420(03)00475-5
6. National clinical diabetic Retinopathy and diabetic macular edema disease severity scales. Ophthalmol. https://doi.org/10.1016/S0161-6420(03)00475-5
7. Salz DA, Witkin AJ (2015) Imaging in diabetic retinopathy. Middle East Afr J Ophthalmol 22:145. https://doi.org/10.4103/0974-9233.151887
8. Fong DS, Aiello L, Gardner TW, King GL, Blankenship G, Cavallerano JD, Ferris FL, Klein R (2004) Retinopathy in diabetes. Diabetes Care 27(1):S84–S87. https://doi.org/10.2337/diacare.27.2007.s84
9. Harris Nwanyanwu K, Talwar N, Gardner TW, Wrobel JS, Herman WH, Stein JD (2013) Predicting development of proliferative diabetic retinopathy. Diabetes Care Jun 36(6):1562–1568. https://doi.org/10.2337/dc12-0790Epub 2012 Dec 28. PMID: 23275374; PMCID: PMC3661803
10. Siddalingaswamy PC, Prabhu KG (2010) Automatic detection of multiple oriented blood vessels in retinal images. JBISE 3:101–107. https://doi.org/10.4236/jbise.2010.31015
11. Kaur J, Sinha HP (2012) Automated detection of retinal blood vessels in diabetic retinopathy using Gabor filter. IJCSNS 12:109–116
12. Ram K, Joshi GD, Sivaswamy J (2011) A successive clutter-rejection-based approach for early detection of diabetic retinopathy. IEEE Trans Biomed Eng. 58(3):664– 73. https://doi.org/10.1109/TBME.2010.2096223. Epub 2010 Dec 3. PMID: 21134810
13. Dey N, Roy AB, Pal M, Das A (2012) FCM based blood vessel segmentation method for retinal images. IJCSNS 12(3):109–116. https://arxiv.org/abs/1209.1181
14. Akram MU, Khan SA (2013) Multilayered thresholding-based blood vessel segmentation for screening of diabetic retinopathy. Engineering with Computers 29:165–173. https://doi.org/10.1007/s00366-011-0253-7
15. Jiang X, Mojon D (2003) Adaptive local thresholding by verification based multithreshold probing with application to vessel detection in retinal images. IEEE Trans Pattern Anal Mach Intell 25:131–137. https://doi.org/10.1109/TPAMI.2003.1159954
16. Staal J, Abramoff MD, Niemeijer M, Viergever MA, van Ginneken B (2004) Ridge-based vessel segmentation in color images of the retina. IEEE Trans Med Imag 23:501–509. https://doi.org/10.1109/TMI.2004.825627
17. Soares JVB, Leandro JJG, Cesar RM, Jelinek HF, Cree MJ (2006) Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification. IEEE Trans Med Imag 25:1214–1222. https://doi.org/10.1109/tmi.2006.879967
18. Fraz MM, Basit A, Javed MY (2008) Evaluation of retinal vessel segmentation methodologies based on combination of vessel center lines and morphological processing. In: IEEE ICET08, pp.232–236. https://doi.org/10.1109/ICET.2008.4777506
19. Archana E, Geetha S, George GVS (2023) Short analysis of machine learning and deep learning techniques used for glaucoma detection. In: 5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, pp.968–975. https://doi.org/10.1109/ICSSIT55814.2023.10060909
20. Hoque M, Kipli K, Zulcaffle T, Al-Hababi S, Mat DAA, Sapawi R, Joseph A (2021) A deep learning approach for retinal image feature extraction. Pertanika J Sci Technol 29. https://doi.org/10.47836/pjst.29.4.17
21. Oliveira G, Rosa G, Pedronette D, Papa J, Kumar H, Passos Júnior L, Kumar D (2022) Which generative adversarial network yields high-quality synthetic medical images: investigation using AMD image datasets. https://doi.org/10.48550/arXiv.2203.13856
22. De Silva T, Chew EY, Hotaling N, Cukras CA (2021) Deep-learning based multi-modal retinal image registration for the longitudinal analysis of patients with age-related macular degeneration. Biomed Opt Express 12:619–636. https://doi.org/10.1364/BOE.408573
23. Chen YM, Huang WT, Ho WH, Tsai JT (2021) Classification of age-related macular degeneration using convolutional-neural-network-based transfer learning. BMC Bioinform 22. https://doi.org/10.1186/s12859-021-04001-1
24. Zong Y et al (2020) U-net based method for automatic hard exudates segmentation in fundus images using inception module and residual connection. IEEE Access 8:167225–167235. https://doi.org/10.1109/ACCESS.2020.3023273
25. Juneja M, Thakur S, Uniyal A, Wani A, Thakur N, Jindal P (2022) Deep learning-based classification network for glaucoma in retinal images. Comput Electr Eng 101:108009. https://doi.org/10.1016/j.compeleceng.2022.108009

26. Tarcoveanu F, Leon F, Curteanu S, Chiselita D, Bogdanici CM, Anton N (2022) Classification algorithms used in predicting glaucoma progression. Healthcare 10:1831. https://doi.org/10.3390/healthcare10101831
27. Kim M, Han JC, Hyun SH, Janssens O, Van Hoecke S, Kee C, De Neve W (2019) Medinoid: computer-aided diagnosis and localization of glaucoma using deep learning. Appl Sci 9:3064. https://doi.org/10.3390/app9153064
28. Priyanka R, Shoba SJG, Therese AB (2017) Segmentation of optic disc in fundus images using convolutional neural networks for detection of glaucoma. Int J Adv Eng Res Sci 4:170–179. https://doi.org/10.22161/ijaers.4.5.27
29. Parashar DR, Agarwal DK (2021) SVM based supervised machine learning framework for glaucoma classification using retinal fundus images. In: 10th IEEE Int Conf Commun Syst Netw Technol, Bhopal, India, 660–663. https://doi.org/10.1109/CSNT51715.2021.9509708

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