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Enhancing Retinal Image Morphological Blood Vessel Segmentation: A Modified Reduced Optimal Devotion-Based Gaussian Filter Approach

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Abstract:
Retinal blood vessel segmentation is a crucial task in ophthalmology, cardiology, and neurology for disease diagnosis, pre-surgical analysis, and condition monitoring. However, factors such as image noise, inconsistent lighting, and the presence of other retinal features complicate the segmentation process. This paper proposes a Modified optimal devotion-based Gaussian Filter (MGF) for blood vessel (BV) image segmentations, utilizing an adaptive thresholding approach. The research evaluates the Gaussian filter's performance for blood vessel extraction, with the deviation ranging from 1.35 to 1.5. The proposed method employs the Iterative Self-Organizing Data Analysis Technique (ISODATA) for computing global image thresholds and approach utilized the principal curvature approach for BV extraction. Qualitative and quantitative evaluations are performed on three optical images with different illuminations and unique features. The results demonstrate that the proposed lower deviation value of 1.35 offers improved brightness and edge detection compared to the existing value of 1.45. Quantitative evaluation using True Positive Rate (TPR), False Positive Rate (FPR), and Accuracy (AC) metrics further confirms the superiority of the proposed method. The lower deviation value of 1.35 consistently outperforms the existing value in terms of accuracy and exhibits smaller FPR rates. This research highlights the potential of the modified optimal devotion-based Gaussian filter for enhancing blood vessel segmentation in retinal image. These enhanced images were then subjected to morphological processing on reduced-gradient masks. The method demonstrated maximum accuracy of 94.97% when tested on ground truth images.
Keywords: Retinal Images, Blood Vessels, Segmentation, CLAHE, Gaussian Filter, Thresholding,

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I. INTRODUCTION

Optical imaging technology is employed to detect and segment blood vessels (BV) in retinal images, a process widely used for pre-surgical analysis, particularly for diabetic retinopathy Arun T et al [1]. This crucial task in retinal health processing is essential for disease diagnosis and condition monitoring in ophthalmology, cardiology, and neurology, because it involves the assessment of vascular networks. Enhancing image quality is vital for improving the accuracy of blood vessel segmentation in retinal fundus images [1]. Several factors complicate the vessel segmentation process, including image noise, inconsistent lighting, and the presence of other retinal features such as the optic disc and exudates. To address these issues and enhance blood vessel visibility, sophisticated image processing methods such as adaptive histogram equalization and contrast enhancement are frequently utilized. Additionally, artificial intelligence techniques, particularly deep learning models, have demonstrated significant potential for automating and enhancing the precision of blood vessel segmentation in retinal imagery.

Blood vessel segmentation in retinal images by Maison et al [2] is crucial for disease diagnosis, pre-surgical analysis, multidisciplinary applications, condition monitoring, image quality enhancement, customization, research opportunities, non-invasive assessment, early detection, and quantitative analysis. Techniques like CLAHE improve visibility of blood vessels, while CLAHE can be fine-tuned for specific datasets and algorithms. It also offers non-invasive assessment, early detection, and precise measurements of vessel characteristics, supporting objective assessment and comparison.

Various techniques have been proposed to enhance blood vessel visibility and facilitate segmentation. CLAHE is an effective method for improving retinal fundus images prior to blood vessel segmentation. Its ability to enhance contrast while minimizing noise amplification makes it a popular choice in preprocessing workflows. However, optimal results are achieved when CLAHE is fine-tuned for specific datasets and segmentation algorithms, and combined with other complementary techniques. This paper utilizes the adaptive contrast enhancement method using CLAHE. As an initial case study, the effects of different bin sizes in CLAHE enhancement are examined, and the optimal bin size for BV extraction is determined.

In field of retinal blood vessel segmentation, Gaussian filters (MGF) have gained widespread adoption due to their capacity to enhance vessel structures across various orientations and scales. Numerous research efforts have incorporated MGF into their BV segmentation methodologies. These investigations have showcased the efficacy of Gaussian filters in accentuating vessel-like structures while mitigating background noise. The multi-scale and multi-orientation characteristics of Gaussian filters render them particularly suitable for identifying vessels of different widths and directions within retinal images. Nevertheless, the efficacy of methods based on MGF can be influenced by parameter selection, necessitating meticulous adjustment to achieve optimal outcomes across diverse datasets and imaging conditions.

1.1 Research Problems

Designing MGF-based BV segmentation methods faces several challenges, including parametric optimization, computational complexity, low-contrast regions, noise sensitivity, varying vessel widths, non-uniform illumination, pathological conditions, false positives, integration with other techniques, dataset variability, edge cases, and balancing sensitivity and specificity. These issues can be addressed by combining MGF with other image enhancement techniques, machine learning algorithms, or exploring alternative approaches, such as deep learning, for more robust and adaptive blood vessel segmentation. An, adaptive approaches may be necessary to overcome these limitations.

The various challenges of MGF-based BV segmentation design are illustrated in Fig. 1. Despite their effectiveness, Gaussian filters may struggle to accurately segment vessels in areas of low contrast or in the presence of pathological abnormalities. To address these limitations, researchers have explored combining Gaussian filters with contrast enhancement techniques such as CLAHE algorithms or morphological operations. This is expected to improve the effectiveness of the Gaussian filters for different BV retinal images.

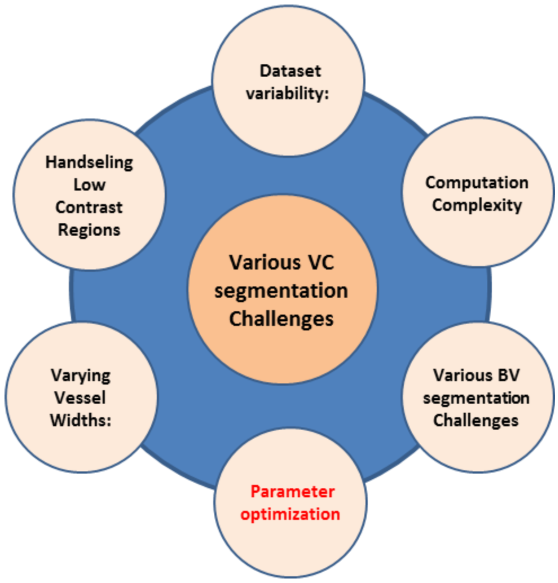


Fig 1 Challenges of BV segmentation approaches using MGF

II.Literature Review

Extensive research has been conducted to improve BV segmentation of retinal optical images. The major classifications are based on filtering, embankment, and segmentation approaches, as illustrated in Fig. 2. Gaussian filters have been widely used in retinal blood vessel segmentation owing to their ability to enhance vessel structures at different orientations and scales.

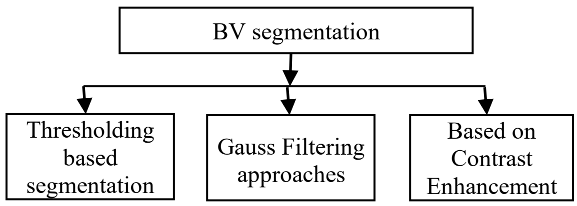


Figure 2 Classification of BV segmentation methods

This section has reviewed some of most relevant research works in these fields.

A. Gaussian Filter Approaches

Several studies have employed Gaussian filters as a part of their segmentation approach. Oliveira et al. (2016) proposed combining Gaussian Wavelet filters with matched filters and Frangi's filters to enhance retinal images before segmentation. Fraz et al. (2012) utilizes Gaussian filter responses as part of a feature vector for a supervised segmentation method using bagged and boosted decision trees. This approach encodes information for handling both healthy and pathological retinal images. Interestingly, although MGF are commonly used, some studies have explored alternative or complementary techniques. Li et al. (2011) proposes a multi scale vessel extraction scheme using matched filters at three scales, which enhances vessels while suppressing noise. Shukla et al. (2020) introduces a novel fractional filter designed with a weighted fractional derivative and an exponential weight factor, achieving high accuracy on standard datasets. In many studies, Gaussian filters have proven effective for blood vessel segmentation in retinal images, and are often used in combination with other techniques to improve accuracy. However, researchers continue to explore innovative approaches to address the challenges of vessel segmentation, such as varying vessel widths and the presence of noise in retinal images.

B. Review of Image Enhancement for BV segmentation

Image enhancement plays a crucial role in improving the accuracy of blood-vessel segmentation in retinal fundus images. Several techniques have been proposed to enhance the visibility of blood vessels and to facilitate segmentation. One approach involves the use of multiple enhancement methods in combination. For instance, Tang and Yu (2020) described four types of green channel image enhancements: adaptive histogram equalization, morphological processing, Gaussian matched filtering, and Hessian matrix filtering. These enhanced images are then used as input features for a BP neural network to segment the blood vessels (Tang & Yu, 2020). Similarly, Roychowdhury et al. (2015) employed tophat reconstruction of a negative green plane image to generate a vessel-enhanced image, which serves as the basis for their iterative segmentation algorithm. Some methods have focused on specific enhancement techniques. Santos et al. (2020) utilizes contrast limited adaptive histogram equalization (CLAHE) for contrast improvement and the Wiener filter for noise reduction. These parameters were optimized using a multilayer artificial neural network to achieve improved blood vessel segmentation (Santos et al., 2020). In a different approach, Li et al. (2023) proposes a two-stage image enhancement method that combines the benefits of convolutional neural networks and traditional image enhancement techniques. In conclusion, image enhancement is a critical step in blood vessel segmentation, and various methods have shown promising results. The combination of multiple enhancement techniques, along with the integration of machine-learning approaches, appears to improve segmentation accuracy. Future research may focus on developing more sophisticated enhancement methods or optimizing existing techniques for specific types of retinal images.

C. CLAHE Based BV Methods

Contrast-limited adaptive histogram equalization (CLAHE) is widely used to enhance retinal fundus images to improve blood vessel segmentation accuracy. Several studies have demonstrated its effectiveness in preprocessing retinal images before applying various segmentation techniques.

CLAHE has been successfully combined with other preprocessing methods to enhance the image quality. Santos et al. (2020) used CLAHE along with the Wiener filter for noise reduction, achieving high accuracy (0.9505) and specificity (0.9696) in blood vessel segmentation (Santos et al., 2020). Similarly, Memari et al. (2017) employed CLAHE in conjunction with morphological operations and the retinex approach for inhomogeneity correction, resulting in impressive accuracy across multiple datasets (0.972 for DRIVE, 0.951 for STARE, and 0.948 for CHASE_DB1) (Memari et al., 2017). Shubhangi Y. Chaware et al..have provided a three-stage method to evaluate the effect of segmenting retinal BV’s. To create an image with segments of the vasculature, the method starts with a processing module and continues with double threshold and morphology image reconstruction approaches. The publicly accessible DRIVE database of the proposed method is verified using a publicly accessible DRIVE database. Sensitivity scores of 0.911 and 0.921 were obtained, outperforming those of the other approaches. Beaudelaire Saha Tchinda et al have suggested a novel approach to blood vessel separation in retinal images.

TABLE 1 COMPARISON OF THE LITERATURE SUMMARY TABLE

Author	Methodologies	Performance Parameter
Oliveira et al [3]	As a component of their categorization strategy, Gaussian filters	Suggested enhancing retinal pictures prior to classification by combining Frangi's filter and Gaussian Wavelet filtering with matching filters.
Fraz et al [4]	Approach that makes use of boosted and bagged choice trees	It's interesting to note that while MGF is frequently utilized, some research has looked into complimentary or alternative methods.
Shukla et al [6]	Vascular segmentation, including an environment of noise in ocular	In order to increase accuracy, Gaussian filters are frequently used

	pictures and different vessel diameters.	alongside other methods for BV separation in retinal imaging.
Tang & Yu et al [7]	One strategy entails combining many BV performance improvement techniques.	Picture enhancements: Hessian matrix filtration, Gaussian matched filtering, morphology processing, and adaptive histogram equalization
Roychowdhury et al. [8]	Techniques have concentrated on iterative BVsegmentation approach of improvement.	Accuracy and perceptual quality of segmentation are measured.
Santos et al. [9]	Uses the Wiener filter to reduce noise contrasting limited adaptive histogram equalizing (CLAHE) to improve contrasts.	A multilayered artificial neural network (ANN) was used to tune parameters in order to improve blood vessel identification.
Memari et al [1]2	Used the retinex technique for inhomogeneity restoration in combination with morphological procedures and CLAHE, yielding remarkable accuracy across several datasets.	0.972 for DRIVE, 0.951 for STARE, and 0.948 for CHASE_DB1
Shubhangi Y. Chaware et al. 13]	A publicly available DRIVE database is used to validate the suggested method's DRIVE dataset.	Sensitive scores of 0.911 & 0.921 were achieved, which were superior to the other methods.
Beaudelaire Saha Tchinda et al [14]	This method is based on conventional edge identification filtering and artificial neural networks.	The DRIVE, CHASE, & STARE databases are publicly accessible.
K.Geethalakshmi et al [16]	Proposed morphological BV separation using principal curvature method	Have used the DRIVE dataset and compared the Accuracy and specificity
Proposed	Proposed BV segmentation using modified deviation based Gaussian Filter with optimal masking. (MDGFM)	Achieved the higher maximum accuracy is the goal

Artificial neural networks and traditional edge recognition filtering serve as the foundation for this technique. First, a feature vector is extracted using edge-detection filtering. An artificially intelligent neural network was trained using the obtained features to determine whether each pixel was a blood artery. The freely available DRIVE, CHASE, and STARE datasets, which include retinal pictures commonly used for this purpose, were used to assess the developed method.

Verma, Prem Kumari et al have proposed as deep learning (DL) have become so popular, new techniques for image segmentation utilizing DL and ML models, each, have been developed. A comprehensive review of this latest research is provided, covering the variety of innovative efforts in conceptual and segmenting instances such as convolutional pixel-labeling relationships, encoder-decoder structures, multiple scales and pyramid-based approaches, recurrent systems, eye movement models, and productive algorithms in competitive environments.

III.Optical retinal image data

The limitations of existing methods include the following challenges.

- Several existing OD detection methods employ histogram-based techniques. Histogram Equalization (HE) or contrast-limited adaptive HE (CLAHE) to preprocess the images. However, these methods suffer from the major problem of color shifting owing to brightness variations. Thus, the efficiency of these methods degrades slightly in the presence of image noise.
- Existing clustering-based methods are effective only for healthy retinal images. Therefore, it is necessary to improve efficiency of the probabilistic nature of the fuzzy clustering methods.
- Morphology-based segmentation is common for optical disc identification; however, every method uses a mask of varying size (from 1 to 5). Therefore, it is necessary to compare and analyze the performance of various mask sizes for optical disc location.

- Blood vessels in the optical disc regions may cause poor segmentation efficiency. Therefore, many methods have been used to remove them before segmentation. However, most of these methods are computationally complex or inefficient.
- Efficient threshold selection is a major problem. Many automatic thresholding methods may not perform well for different types of retinal image. Since position of the optical disc varies in the retinal images

IV. Proposed BV Segmentation Methodology

In this study, a modified optimal devotion-based Gaussian filter was proposed for BV image segmentation. The adaptive thresholding-based approach was used for BV segmentation. The deviation is ranged from1.35 to 1.5 and the Gaussian filter is evaluated for the performance of BV extractions.

The suggested technique exhibited exceptional effectiveness in precisely identifying blood vessels in retinal images. The tests revealed a notable enhancement in segmentation precision when compared to conventional methods. Additionally, the use of an adaptive thresholding approach enables more effective management of fluctuations in vessel intensity and thickness across various areas of the retina.

4.1 MGF Smoothening

The paper proposed using the modified reduced deviation based Gaussian filter (MGF) defined as;

$$g(x, y) = \exp\left(-\frac{\mathrm{X}.^2 + \mathrm{Y}.^2}{2\sigma^2}\right) \quad (1)$$

The modified filter is capable of improving the features of the BV images and preserves the edges much better and thus is expected to improve the segmentation accuracy.

4.2Segmentation Methodology

In this research the optical image segmentation is proposed to implement as compilation of adaptive global threshold and morphological reconstruction. The technique of mathematical morphology is used to identify the essential components that define the limits, contours, and shape of an image. Based on their forms, these methods are helpful for identifying, altering, and managing visual characteristics. An image's surrounding pixels are identified and defined using a matrix called a Structuring element (SE). The pixels that are deemed adjacent are determined by the origin point of the SE.The following set theory equation can be used to mathematically depict the erosion process

$$(A\,\theta\,B)(x, y) = min\{A(x + x', y + y') - SE\,(x', y')|(x', y') \in DSE \quad (2)$$

Also the image opening is given as a combination of erosion followed by di-lotion as;

$$(A\,\theta\,B)(x, y) = max\{A(x + x', y + y') - SE\,(x', y')|(x', y') \in DSE \quad ()$$

The combination of erosion and dilation may leads to the morphological opening figure.

4.2.1 ISODATA (Iterative Self-Organizing Data Analysis Technique)

It is an iterative method for computing global image thresholds involves the following steps:

1. Iteratively set the threshold T using a rough estimate of the average image intensity via ISODATA function.
2. Divide the image across two groups: G1 (pixels via intensities above T) as well as G2 (pixels using intensities less than T).
3. Determine the mean intensities (µ1 and µ2) for G1 and G2.
4. Let L is the shape parameter, q is correlation factor of L; Calculate a threshold T between two class groups $\boldsymbol{G_1(\mu_1, p_1)}$ and$\boldsymbol{G_2(\mu_2, p_2)}$:

$$T = \frac{\mu_1\mu_2}{q}\sqrt{\frac{log(R)}{L(\mu_1{}^2 - \mu_2{}^2)}} (2)$$

Where R is defined as$\boldsymbol{p_1/p_2}\left(\frac{\mu_2}{\mu_1}\right)^{2L}$.

Calculatethe new threshold$\boldsymbol{T_{new}}$;

$$T_{new} = (\mu1 + \mu2) / 2 (3)$$

5. Steps 2-4 should be repeated until the threshold value converges, meaning that the difference between T and T_{new} is less than a tolerance.

This technique successfully separates foreground and background pixels by iteratively fine-tuning the threshold. Images with bimodal intensity distributions benefit greatly from it.

V. Proposed BV Extraction System

This paper focuses to use the morphological masking and principal curvature based BV segmentation method. The efficiency of the segmentation is enhanced using the modified deviation parameter based MGF smoothening for BV extraction from optical images.Thus, paper proposes to improve the K means clustering efficiency by using the wavelet based cluster fusion.

To implement this in practice:

1. Use image processing libraries
2. To read and process the image.
3. Implement the iterative algorithm as described above.

4. Apply the final threshold to create a binary image.
5. Consider post-processing steps like morphological operations to refine the segmentation results.

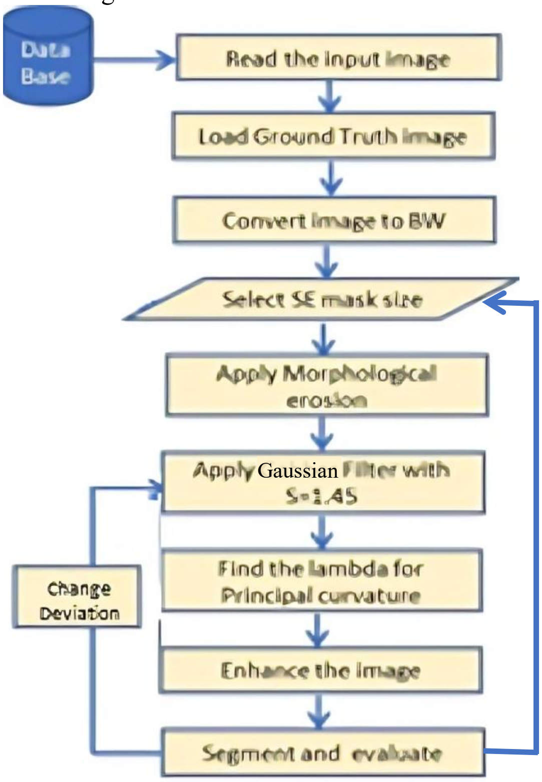


Figure 3 Proposed Flow chart

Proposed BV Segmentation Algorithm
The sequential algorithm to further clarify the proposed modified deviation Gaussian Filter and masking (MDGFM) Algorithm 1 is given in Algorithm:.

Algorithm 1:MDGFM BV segmentation
1. Load Images → In_{img} , *and* GT_{img}
2. Generate Mask →gray to binary image conversion with level=20/100
3. Select SE size ← $(S1, S2\ or\ S3)$diamond shape
4. Erode mask as ($SE\ \ominus$ se)
5. Change Deviation σ *between* $1.35 - 1.45$ and kernel size k as (1-3)
6. Apply Gaussian Filteras$g(x, y) = \exp\left(-\frac{X.^2+Y.^2}{2\sigma^2}\right)$
7. Determine λ for principal curvature
8. CLAHE Enhancement →
9. Select theISODATA threefold T_{new}
10. Enhance contrastvia CLAHE$g = g_{min} - \left(\frac{1}{\alpha}\right) * \ln[1 - P(f)]$ (4)
11. Evaluate performance Accuracy, specificity
12. Loop and change the mask SE and σ repeat 3-11
end Algorithm

VI. Results and Discussions

This research paper has presented the optimal Gaussian filter tuning methodology for improving the accuracy of the BV segmentation. This section has presented the qualitative and quantitative evaluation of the proposed modified results for BV segmentation.The evaluation is performed for the three optical images as illustrated in the Fig. 3. These optical retinal images are of different illuminations and of left and right eyes. Thus due to unique features are selected randomly for the evaluation.

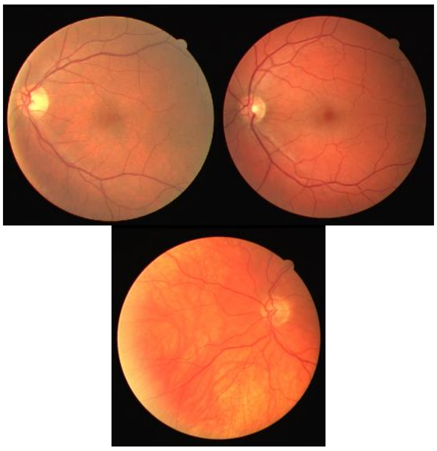
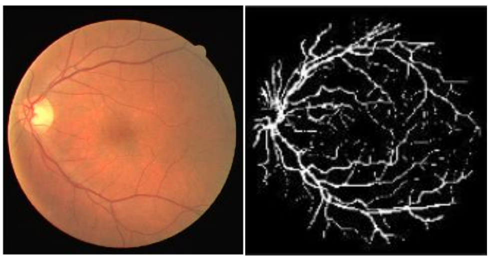
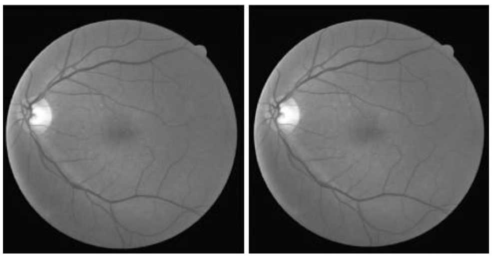


Fig. 3 Input images used a) image 1 b) image 2 c) image 3

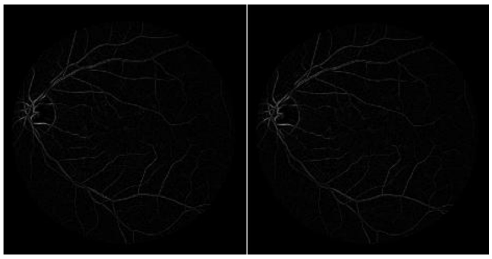
Experiment 1: Experiment has represented the qualitative comparisons of the various stages of segmentation process for the two case of Gaussian filter for $\sigma = 1.45$ *and the* 1.35respectively in the each column of the Fig. 4. The results in the Fig.4 displaying a series of processed retinal images. The top row (a) shows the original retinal image which is a full-color retinal image of the left eye, representing theBV in red colors. The following rows show a comparison of results for steps in a BV segmentation algorithm. The row two (b) shows the results after applying a Gaussian-based filter (MGF), reducing noise and enhancing the blood vessels.



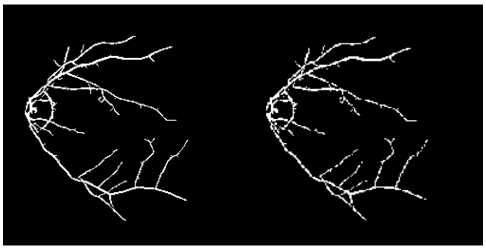
a) Original retinal imageand GT



b) MGF filtered results for $\sigma = 1.45$ and $\sigma = 1.35$

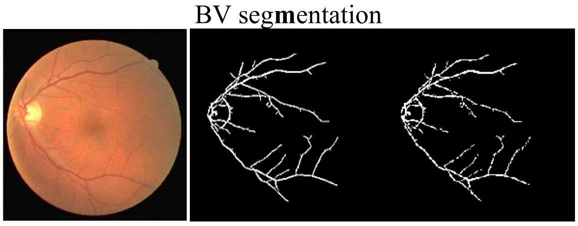


c) Results of principal curvature for $\sigma = 1.45$ and $\sigma = 1.35$

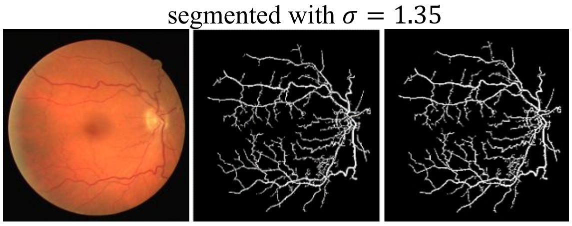


d) Segmented BV results for $\sigma = 1.45$ and $\sigma = 1.35$

Figure 4 results of principal curvature based MGFs BV segmentation



a) Image 1 b) segmented with $\sigma = 1.45$ c) segmented with $\sigma = 1.35$



a) Image 2 b) segmented with $\sigma = 1.45$ c) segmented with $\sigma = 1.35$

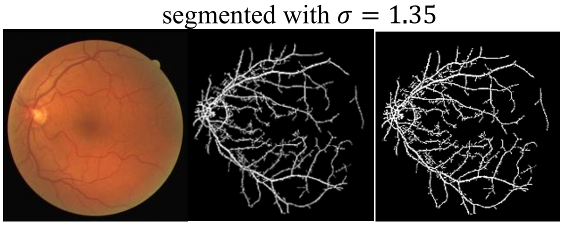


Figure 5 results of principal curvature based MGFs BV segmentation

It is to clearly note that for all results analysis the Ground truth (GT) is used as by K.Geethalakshmi et al.as mentioned in Figure 4 a). The Fig. 5 Results of the BV segmentatio0n for different images It can be clearly observed that the reduced values of σ=1.35 offers slight improvement in brightness of filtered image. This improvement is clearly reflected in next stage of results for the extraction of principal curvature results in the row 3 c). Fig 4 (c) presents the results after calculating the principal curvature of the filtered image, highlighting the vessel structure.

The Fig 4 (d) presents the segmented BV results clearly outlining their optical nerves by using the proposed σ=1.35. The entire sequence illustrates a process used in medical image analysis for tasks like retinal vascular disease diagnosis.

The proposed lowered parameters σ = 1.35 offered edge over the existing σ=1.45 consistently throughout the processing steps.The comparisons of the results for different images are illustrated in the Fig. 5 for the respective BV segmentation for two different deviations ranges.

Experiment 2: Although in order to further represent the clarity and differences in the results of Fig 5, the quantitative evaluation of the three images are given in the Table 2

TABLE 2PERFORMANCE COMPARISON FOR BV SEGMENTATION FOR DIFFERTENT GF DEVATIONS

Images	Parameter	σ = 1.45	σ = 1.35
Image 1	TPR	0.7166	0.6945
	FPR	0.0324	0.0297
	AC	0.9489	0.9585
Image 2	TPR	0.0944	0.0930
	FPR	0.0724	0.0713
	AC	0.9457	0.9457
Image 5	TPR	0.2217	0.2182
	FPR	0.1086	0.1055
	AC	0.95.31	0.9535

The Table 2 showing a performance comparison of three images (Image 1, Image 2, Image 5) for the parameters TPR (True Positive Rate), FPR (False Positive Rate), and AC (Accuracy),The comparison is made under two conditions, signified by different standard deviations (σ): σ = 1.45 and σ = 1.35. The σ = 1.45 represented the existing BV segmentation system.

The columns display the calculated values of TPR, FPR, and AC for each image under both standard deviation conditions. The values themselves are numerical, representing the performance metrics. It can be concluded from the Table 2 that the proposed lowered σ = 1.35 out performs in terms of accuracy and also have smaller FPR rates.

TABLE 3STATE OF ART PERFORMANCE COMPARISONS

Methods	Accuracy (DRIVE)
Hesham Abdushkour et al [6] with Double threshold	95.1
Memari et al. (2017) [12]	95.1
Jyotiprava Dash et al 2017 [17]	95,55
Zafer Yavuz 2017 [18]	95.71
Proposed modified deviation Gaussian Filter with optimal masking	95.87

Table 3 presents a comparative analysis of the cutting-edge performance for a particular task, presumably related to BV segmentation, using the DRIVE dataset as a benchmark. The table evaluates the various methods based on their accuracy scores, which are presented as percentages ranging from 95.1% to 95.87%. The proposed modified deviation Gaussian Filter with the optimal masking\" technique achieved the highest accuracy of 95.87%.

This comparison indicates a highly competitive field with numerous approaches attaining exceptionally high accuracy levels. It is evident that the MDGFM method demonstrates a significant advantage over the existing techniques for the DRIVE dataset.The accuracy is mathematically defined as

$$AC = (TP + TN)/(TP + TN + FP + FN) \qquad (5)$$

Where TP, TN,FP, FN are true and falseprediction counts in each class.

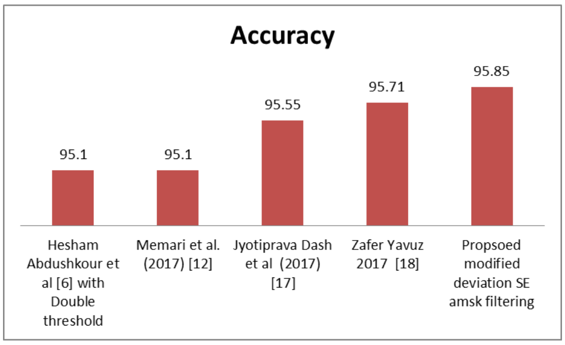


Figure 6 states of art methods comparisons.

Figure 6 displays a bar chart that illustrates the accuracy of different cutting-edge techniques. The newly introduced modified deviation mask filtering approach demonstrates superior performance, attaining an accuracy of 95.87%. In comparison, alternative methods such as Double threshold, Meimari et al, Hydropreva Dash et al, and Fater Yamur et al exhibit marginally lower accuracy rates"

VII.Conclusions and Scopes

Blood vessels (BV) in retinal images are frequently found and isolated using optical imaging technology in pre-operative analysis, especially for diabetic retinopathy. In order to improve the accuracy of BV extraction, this study recommended a reduced optimal Gaussian filter deviation and the use of a Gaussian filter using adjusted filtering deviations. A contrast enhancement method was used to enhance BV extraction through optical retinal images. In order to improve the accuracy of retinal disease diagnosis, the study sought to identify a suitable enhancement technique for BV extraction. The principal curvature method was applied in this procedure. A CLAHE based contrast improvement method was used to improve performance.

Then, using reduced-gradient masks, these improved images underwent morphological processing. The technique showed 95.87% accuracy when tested on lowered deviations.

Future research in blood vessel segmentation using principal curvature should enhance accuracy, incorporate machine learning, real-time processing, multi-modal imaging, patient-specific variations, validate methods, improve 3D reconstruction, automate vascular parameter analysis, and compensate for image quality variations.

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