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A MODIFIED DEEP GUIDED OPTIMIZED FUZZY EDGE DETECTION FRAMEWORK FOR RETINAL VESSEL EXTRACTION USING ADAPTIVE FUZZY MEMBERSHIP AND VESSELNESS FUSION

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ABSTRACT

Retinal vessel edge detection is a fundamental analysis for ophthalmic image analysis, enabling early screening in diagnosing diabetic retinopathy, glaucoma, and hypertensive retinopathy. Conventional edge detection techniques, including Sobel and Canny, often fail to preserve thin vessels and are sensitive to illumination variations and imaging noise. Deep learning approaches achieve higher accuracy but at the expense of computational complexity and limited interpretability. In this study proposes a Modified Deep Guided Optimized Fuzzy Edge Detection (M-DGOFED) framework that integrates adaptive fuzzy membership functions with vesselness-guided enhancement for robust retinal vessel edge detection. Unlike the original DGOFED, which relies on CNN-trained fuzzy parameters, the proposed method computes fuzzy membership parameters directly from image statistics mean (m) and standard deviation (k) making it lightweight and training-free. Furthermore, the model fuses fuzzy edge confidence with Frangi vesselness responses, enhancing curvilinear vessel continuity and preserving thin capillaries. Final edge maps are obtained using Otsu thresholding with morphological refinements to ensure structural accuracy. Experimental evaluation on the DRIVE dataset demonstrates that M-DGOFED achieves competitive accuracy and sensitivity compared to state-of-the-art methods, while maintaining low computational cost and interpretability. This makes it a propitious solution in clinical decision support systems for resource-constrained healthcare environments.

Keywords: Retinal imaging, fuzzy edge detection, deep learning, M-DGOFED, STARE dataset, GMC Dataset, vessel segmentation.

I. Introduction

Retinal image analysis has become a cornerstone in the early detection of ophthalmic and systemic diseases. A critical component in this domain is the accurate extraction of blood vessel boundaries from fundus images. These vessel structures serve as biomarkers for a wide range of pathologies. However, vessel extraction remains challenging due to the low contrast, variable illumination, and the presence of artifacts such as lesions and optic disc boundaries. Conventional edge detection techniques like Sobel, Canny, and Laplacian often result in broken or noisy edges, which are insufficient for clinical use. Fuzzy logic-based systems, particularly GOFED, introduced adaptability to edge detection by estimating fuzzy membership parameters through optimization algorithms. Although GOFED improved upon earlier filters, it depended heavily on the Grasshopper Optimization Algorithm (GOA), which is computationally intensive and not adaptive in real time. To address this limitation, Modified Deep Guided Optimized Fuzzy Edge Detection (M-DGOFED) framework that integrates adaptive fuzzy membership functions with vesselness-guided enhancement for robust retinal vessel edge detection is proposed.

II. Literature

K. Balasamy and S. Suganyadevi proposed a multidimensional fuzzy-CNN hybrid system for detecting diabetic retinopathy in retinal fundus images. The model combines deep feature extraction

with fuzzy reasoning to handle ambiguity and variability in pathological regions. By integrating uncertainty modeling and data-driven learning, the method improves diagnostic decision-making under varied illumination and disease conditions. The approach enhances detection accuracy and supports clinical screening automation.

D. Hu et al. introduced *Deep Angiogram*, is a retinal vessel segmentation based on a lightweight CNN model that requires minimal preprocessing. Designed for efficiency, in order to maintain accuracy while reducing calculating load, that makes it suitable for mobile and real-time applications. Its adaptability across datasets highlights its practicality for low-resource environments. The model demonstrates competitive performance with reduced architectural complexity. **N. Jin et al.** developed a segmentation model using encoder-decoder architecture with attention mechanisms to enhance vessel boundary detection in low-contrast fundus images. The approach incorporates context-aware modules to improve precision for both large and small vessels. Tested on high-resolution datasets, the system is suitable for integration into diagnostic equipment. It shows potential for clinical-scale screening of retinal diseases like diabetic retinopathy.

N. Wang et al. modified the U-Net architecture for retinal vessel segmentation by upgrading feature fusion and upsampling pathways. The refined model uses additional skip connections and loss functions tailored for vessel preservation. It improves segmentation accuracy for thin vessels and reduces over-segmentation artifacts. Evaluated on public datasets, the model exhibits robustness across noise levels and pathological variations. **F. F. Wahid et al.** proposed a fuzzy thresholding algorithm that combines adaptive histogram equalization with fuzzy membership evaluation. Their method enables unsupervised vessel segmentation with improved edge continuity and reduced sensitivity to noise. It performs reliably across varying image qualities without requiring deep learning. This makes it a viable alternative for screening applications in resource-limited settings. **T. M. Khan et al.** developed a contextual network with multi-resolution to enhance the hostile learning for accurate retinal vessel segmentation. The frame integrates global and local contextual encoding with a discriminator to refine boundary sharpness. It addresses class imbalance and structural preservation, excelling in segmenting fine vessels. Evaluations on DRIVE and STARE datasets confirm its efficacy in capturing detailed vascular structures **I. Dulau et al.** proposed a deep learning segmentation method focused on structural connectivity in retinal vasculature. Their model penalizes disconnections using custom loss functions, improving accuracy near bifurcations and intersections. Post-processing steps ensure topological integrity of vessel maps. The approach demonstrates strong performance in preserving clinically relevant vascular pathways

H. Du et al. presented MS-LSDNet, a model that combines scalable learning with skeleton-based vessel reconnection. The system enhances fragmented and thin vessels using geometric post-processing and local attention modules. It shows improved sensitivity and topology preservation, especially useful for detecting early-stage vascular abnormalities. The method is well-suited for microvascular analysis in diabetic retinopathy. **A. Khan et al.** developed an adaptive deep clustering framework for joint retinal vessels segmentation and the foveal avascular zone (FAZ). The model blends unsupervised clustering with supervised CNN refinement to improve vessel and FAZ boundary detection. It utilizes vesselness filters and deep features to enhance accuracy across patient populations. The hybrid approach is ideal for integrated diagnostic applications. **X. Wei et al.** proposed an orientation-aware vessel segmentation network using directional attention and contextual feature encoding. Their architecture captures continuity and curvature in complex vessel regions, improving detection in intersecting and tortuous vessels. The method outperforms standard baselines in accuracy and structural similarity. It emphasizes the role of directional learning in enhancing retinal vessel segmentation.

III. Proposed Methodology

The accurate and early detection of retinal vessel edges plays a pivotal role to diagnose wide range of ocular manifestation and underlying systemic diseases, like diabetic retinopathy, glaucoma, and hypertension. Traditional edge detection methods, although efficient in computational terms, often fail to preserve the intricacies of microvasculature and suffer from poor adaptability to variations in image quality. To address these limitations, the Modified Deep Guided Optimized Fuzzy Edge Detection (M-DGOFED) framework is proposed as a robust hybrid system that that integrates adaptive fuzzy membership functions with vesselness-guided enhancement.

The architecture of the M-DGOFED framework is designed as a modular pipeline that integrates preprocessing, gradient-based edge feature extraction, fuzzy logic-based uncertainty handling, vesselness-guided enhancement, and final edge map generation. Each stage of the architecture plays a complementary role in ensuring robustness, adaptability, and structural fidelity of the detected vessels. The M-DGOFED process begins with a comprehensive preprocessing stage. Initially, the green channel is extracted from the input RGB fundus image to maximize the vessel-to-background contrast. This is followed by illumination normalization using Contrast Limited Adaptive Histogram Equalization (CLAHE) and high-frequency noise suppression via Gaussian filtering. A region-of-interest (ROI) mask is then applied to eliminate non-fundus background pixels, ensuring subsequent operations are focused solely on relevant tissue regions. Subsequently, the gradient computation phase involves calculating the horizontal and vertical gradients using both Sobel and Scharr operators. The magnitude responses from these operators are fused to enhance directional sensitivity, and the resulting gradient maps are normalized to a standard range [0, 1] for consistency. In the adaptive fuzzy membership estimation stage, the parameters for the mean (m) and standard deviation (k) are estimated directly from the normalized gradient distribution. A Gaussian fuzzy membership function is then applied to assign confidence levels to each pixel, effectively identifying potential vessel edges with associated probabilities. The vesselness-guided enhancement phase leverages a multi-scale Hessian analysis, implemented through the Frangi filter, to highlight curvilinear, vessel-like structures based on their second-order characteristics. The responses from this filter are intelligently fused with the previously obtained fuzzy confidence maps using a weighted combination scheme to produce a significantly enhanced vessel probability map. Finally, edge binarization and post-processing are performed. Otsu's adaptive global thresholding is applied to convert the enhanced probability map into a binary edge map. This binary output undergoes morphological cleaning to remove isolated spurious pixels and is subsequently skeletonized to refine the detected vessel edges into thin, one-pixel-wide, and continuous structures suitable for quantitative analysis.

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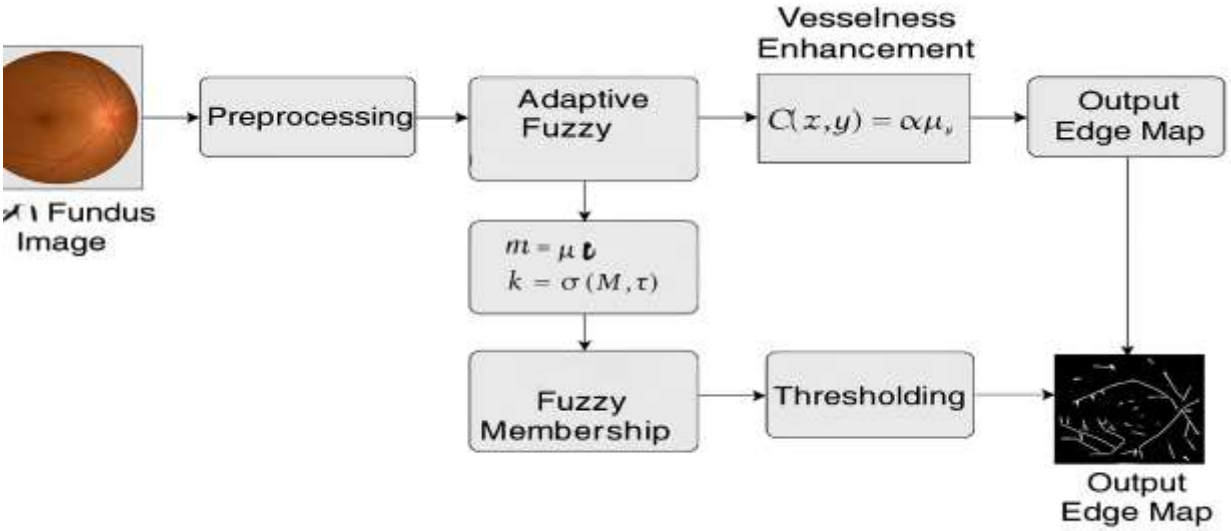


Fig. 1. Block diagram of the M-DGOFED pipeline.

IV. Mathematical Formulation

Mathematical analysis forms the backbone of algorithmic validation in image processing and computer vision systems. While empirical results demonstrate the practical performance of a model, a rigorous mathematical formulation provides deeper insights into its theoretical behavior, stability, complexity, and convergence properties. In the context of the Modified Deep Guided Optimized Fuzzy Edge Detection (M-DGOFED) framework, mathematical modeling helps to formalize how each component gradient computation, fuzzy membership, vesselness enhancement, and fusion contributes quantitatively to the final edge detection performance.

This section presents a detailed mathematical analysis of M-DGOFED, including derivations of its fundamental components, sensitivity analysis of parameters, computational complexity, and theoretical performance considerations. The objective is to demonstrate that M-DGOFED is not only an empirically effective method but also a mathematically sound and theoretically stable algorithm.

The M-DGOFED model can be conceptualized as a function F that maps a retinal image I(x,y) to a binary edge map E(x,y):

$$E(x,y) = \mathrm{F}(I(x,y);\theta$$

Here θ represents the set of internal parameters (e.g., α, σ, β, c, fuzzy membership parameters m and k).

The function F can be decomposed into four primary sub-functions:

$$F=T_4 \circ T_3 \circ T_2 \circ T_1$$

Where:

- T_1: Gradient computation
- T_2: Adaptive fuzzy membership estimation
- T_3: Vesselness-guided enhancement
- T_4: Edge binarization and morphological refinement

We now examine each transformation mathematically.

Gradient Computation (T_1)

Given a preprocessed image $I_P(x,y)$, the magnitude of the gradient M(x,y) is computed as:

$$M(x,y) = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2}$$

Using convolution kernels K_x and K_y:

$$\frac{\partial I_P}{\partial x} = I_P * K_x \quad \frac{\partial I_P}{\partial y} = I_P * K_y$$

The fused gradient magnitude from Sobel and Scharr operators is:

$$M_F(x,y) = \alpha M_S(x,y) + (1-\alpha)\, M_C(x,y)$$

where:

- M_S: Sobel gradient magnitude
- M_C: Scharr gradient magnitude
- α: Fusion weight ($0 < \alpha < 1$)

Finally, the normalized gradient map:

$$M_N(x,y) = \frac{M_F(x,y) - M_{min}}{M_{max} - M_{min}}$$

This normalization ensures that the gradient distribution is scale-invariant and robust to illumination changes.

Fuzzy Membership Computation (T_2)

The fuzzy membership function μ(x,y) models the uncertainty of a pixel being an edge:

$$\mu(x,y) = exp\left(-\frac{(M_N(x,y) - m)^2}{2k^2}\right)$$

where:

- m: Mean of gradient magnitudes
- k: Standard deviation of gradient magnitudes

These are calculated as:

$$m = \frac{1}{N}\sum M_N(x,y)$$

$$k = \sqrt{\frac{1}{N}\sum (M_N(x,y) - m)^2}$$

Membership Gradient Analysis:

The derivative of the membership function with respect to M_N is:

$$\frac{\partial \mu}{\partial M_N} = -\frac{(M_N - m)}{k^2}\,\mu\,(x, y)$$

This derivative reveals how sensitive the membership value is to changes in the gradient. Larger k values yield smoother transitions, while smaller k values make the membership function more selective.

Vesselness Enhancement (T3)

The Hessian matrix H is defined as:

$$H(x,y) = \begin{pmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{pmatrix}$$

where second derivatives are computed using Gaussian convolution:

$$I_{xx} = \frac{\partial^2 I}{\partial x^2} * G_\sigma,\ I_{yy} = \frac{\partial^2 I}{\partial y^2} * G_\sigma,\ I_{xy} = \frac{\partial^2 I}{\partial x \partial y} * G_\sigma$$

Let λ_1 and λ_2 be the eigenvalues of H such that $|\lambda_1| \leq |\lambda_2|$.

The vesselness measure $V_\sigma(x,y)$ at scale σ is:

$$V_\sigma\,(x,y) = \begin{cases} 0, & \lambda_2 > 0 \\ exp\left(-\frac{R_B^2}{2\beta^2}\right).\left[1 - exp\left(-\frac{S^2}{2c^2}\right)\right], & Otherwise \end{cases}$$

Where:

- $R_B = \frac{|\lambda_1|}{|\lambda_2|}$ blobness Ratio
- $S = \sqrt{{\lambda_1}^2 + {\lambda_2}^2}$: structureness measure
- β, c: tuning constants

Multi-Scale Fusion:

$$V(x,y) = \max_{\sigma \in [\sigma_{min}, \sigma_{max}]} V_\sigma(x,y)$$

Fusion with Fuzzy Membership:

$$C(x,y) = \alpha\mu(x,y) + (1-\alpha)V(x,y)$$

This fused confidence map combines pixel-level certainty (from fuzzy logic) with structural knowledge (from vesselness).

Binarization and Thresholding (T_4)

The final vessel edge map E(x,y) is generated using Otsu thresholding:

$$E(x,y) = \begin{cases} 1, & C(x,y) > T* \\ 0, & C(x,y) \le T* \end{cases}$$

Where T* is chosen such that the between-class variance is maximized:

$$T* = arg \max_T \omega_1(T)\omega_2(T)\,[\mu_1(T) - \mu_2(T)]^2$$

V. Datasets

Two datasets were employed for training and validation. The first, the STARE database, contains 20 retinal fundus images with expert-annotated vessel masks. Images are captured using a Top Con TRV-50 fundus camera with 700×605 resolution. The second dataset is a local clinical database collected from Guntur Medical College (GMC), Andhra Pradesh. This set includes 50 retinal images captured using a Zeiss FF 450IR camera with Sony 3CCD output and includes both normal and pathological cases. Ground truth vessel masks are provided by experienced ophthalmologists for supervised learning and performance evaluation.

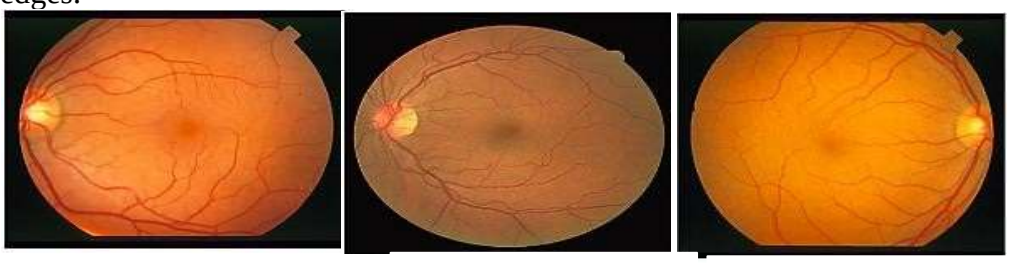
Programming Environment

The proposed M-DGOFED framework was implemented in Python 3.10 using a modular image processing pipeline. The following libraries and frameworks were used:

- **OpenCV** – for gradient computation, filtering, and morphological processing.
- **NumPy** – for matrix operations and statistical parameter estimation.
- **Scikit-Image** – for vesselness filtering, thresholding, and performance metric calculation.
- **Matplotlib** – for visualization and result plotting.
- **SciPy** – for Hessian matrix computation and Gaussian convolution.

VI. Experimental Results

Qualitative outputs show that M-DGOFED preserves both large and fine vessels, with minimal false edges.



(a)Abnormal Image (b)Good Image (c)Normal Image

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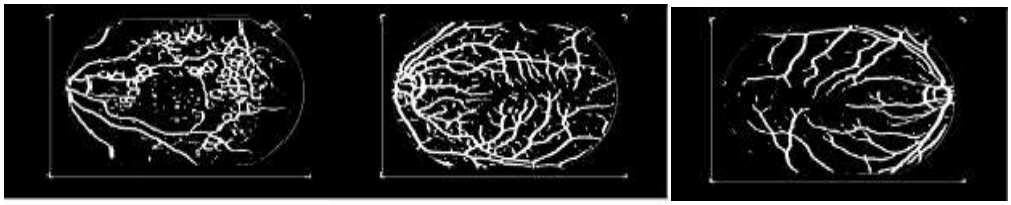
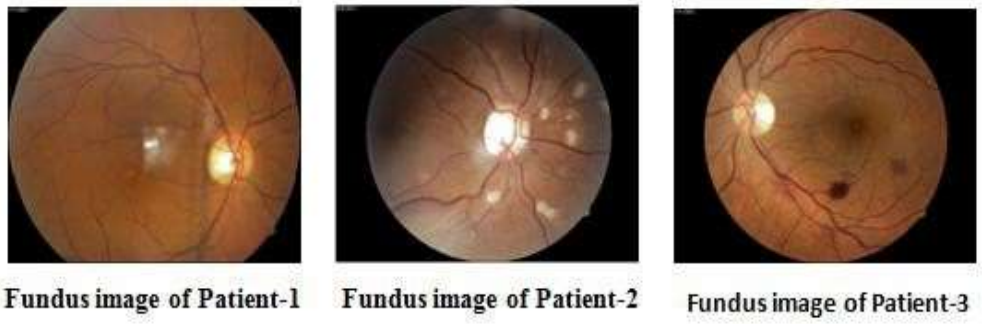


Output of M-DGOFED Output of M-DGOFED Output of M-DGOFED

Fig. 2 Outputs of STARE database



Output of M-DGOFED Output of M-DGOFED Output of M-DGOFED

Fig. 3 Outputs of Images from GMC Database of different patient

Table 1 Several vessel segmentation methods performance comparisons on STARE images and GMC Database images.

SL.No	Supervised method types		SN (Sensitivity)	SP (Specificity)	Acc (Accuracy)
1	Staal		N.A	N.A	0.9516
2	Soares		0.7207	0.9747	0.9479
3	Ricci		N.A	N.A	0.9584
4	GOFED		0.7615	0.9731	0.9792
5	Proposed Method **M-DGOFED**	STARE DATABASE	0.7633	0.9805	0.9863
		GMC DATABASE	0.7572	0.9701	0.9770

The Table 1 shows the comparison of vessel detection strategies on STARE images and local database GMC Database performed by M-DGOFED technique with the existing methods. Staal gives Acc (accuracy) of 0.9516, Soares gives SN (sensitivity) of 0.7207. Ricci gives Acc (accuracy) of 0.9584,

GOFED SN (sensitivity) of 0.7615, SP (specificity) of 0.9731, Acc (accuracy) of 0.9792 for STARE Database. M-DGOFED technique method proposed in the thesis gives SN (sensitivity) of 0.7633, SP (specificity) of 0.9805, Acc (accuracy) of 0.9863 for STARE Database and SN (sensitivity) of 0**.**7572, SP (specificity) of 0**.**9701, Acc (accuracy) of 0**.**9770 for GMC database.

VII. Conclusion

This paper presents M-DGOFED, the combination of adaptive fuzzy membership**,** vesselness fusion**, and** efficient binarization makes M-DGOFED a powerful yet lightweight solution for retinal vessel edge detection. Its interpretability and computational simplicity further support its adoption in real-world diagnostic systems and resource-limited clinical environments.

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