DGOFED: DEEP LEARNING GUIDED OPTIMIZED FUZZY EDGE DETECTION FOR RETINAL FUNDUS IMAGES

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ABSTRACT:
Retinal vessel edge detection is essential in computer-aided diagnosis of vision-threatening diseases such as diabetic retinopathy, glaucoma, and hypertensive retinopathy. Traditional edge detectors, while computationally fast, often fail in complex retinal environments with variable illumination and vessel widths. This paper presents DGOFED, a Deep Learning-Guided Optimized Fuzzy Edge Detection method that integrates adaptive fuzzy logic with a Convolutional Neural Network (CNN) for estimating fuzzy membership parameters. DGOFED uses a CNN to dynamically learn fuzzy parameter values for each patch. A combination of gradient magnitude features and Gaussian fuzzy membership functions produce a continuous edge confidence map, followed by Otsu thresholding and vessel-specific post-processing. Experiments on the STARE and GMC datasets demonstrate that DGOFED achieves higher edge accuracy, particularly in preserving capillaries and suppressing background noise. The model’s hybrid nature bridges interpretability and deep learning, offering real-time edge maps with superior diagnostic clarity.
Key words : Retinal imaging, fuzzy edge detection, deep learning, DGOFED, STARE dataset, GMC Dataset,vessel segmentation.

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, DGOFED—a hybrid edge detection system that integrates fuzzy logic with a CNN-based optimizer to dynamically learn the fuzzy parameters for local patches, enabling real-time and accurate retinal vessel edge detection is proposed.

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*, a lightweight CNN-based model for retinal vessel segmentation requiring minimal preprocessing. Designed for efficiency, it maintains accuracy while reducing computational load, making 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. improved the U-Net architecture for retinal vessel segmentation by enhancing 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.** introduced a multi-resolution contextual network enhanced with adversarial learning for accurate retinal vessel segmentation. The framework 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 multi-scale 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 segmentation of retinal vessels 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.

PROPOSED METHODOLOGY

The accurate detection of retinal vessel edges plays a critical role in the early diagnosis of a wide range of ocular and systemic diseases, such as 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 Deep Learning-Guided Optimized Fuzzy Edge Detection (DGOFED) framework is proposed as a robust hybrid system that synergizes the adaptability of fuzzy logic with the learning capability of deep neural networks.

DGOFED aims to overcome the key drawbacks of its predecessor, GOFED, which used a Grasshopper Optimization Algorithm to tune fuzzy membership parameters. While GOFED demonstrated good accuracy, its optimization phase was computationally expensive, stochastic, and not inherently adaptive to local image contexts. In contrast, DGOFED introduces a Deep Learning Optimization Module (DLOM) based on Convolutional Neural Networks (CNNs), which learns to predict fuzzy membership parameters in a non-iterative, feed-forward manner. This allows the system to respond dynamically to the local structural patterns present in retinal fundus images.

The overall DGOFED pipeline involves four major phases: (1) preprocessing of retinal images to enhance contrast and suppress noise, (2) extraction of directional gradients to highlight potential edge features, (3) prediction of fuzzy membership function parameters using the DLOM, and (4) computation of edge confidence values through a Type-2 fuzzy inference system. The final edge map is obtained using Otsu's thresholding, resulting in a binary image that delineates vascular boundaries.

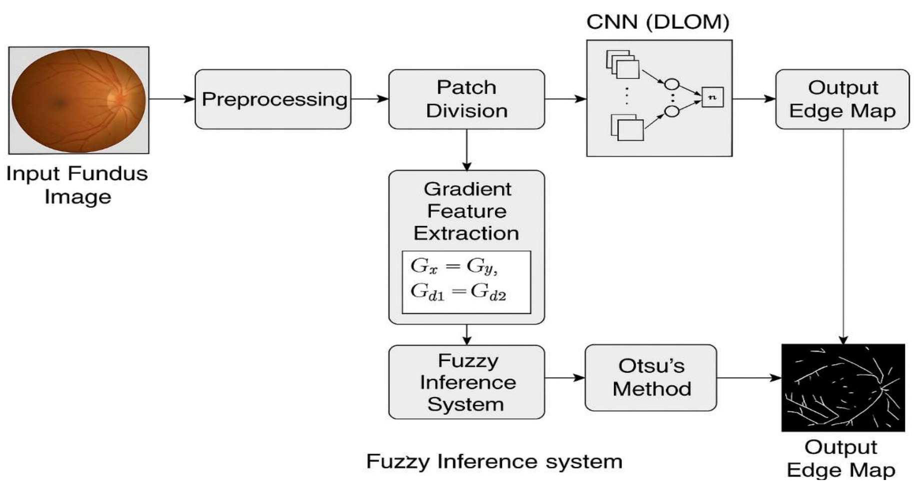

Fig. 1. Block diagram of the DGOFED pipeline.

MATHEMATICAL FORMULATION:

The DGOFED framework is composed of the following stages: preprocessing, patch extraction, fuzzy edge estimation, CNN-guided fuzzy parameter tuning, and binarization. Preprocessing includes CLAHE-based contrast enhancement and green channel extraction. Gradient features are extracted using Sobel filters in four directions. The fuzzy edge confidence is calculated using Gaussian membership functions where the mean (m) and spread (σ) are adaptively predicted using a trained CNN.Each patch of size 32×32 is processed to predict fuzzy parameters using a lightweight CNN comprising two convolutional layers and a dense regressor. The output fuzzy map is a pixel-wise likelihood of edge membership. Finally, Otsu thresholding converts the fuzzy confidence into a binary edge map. Morphological post-processing refines the edges, removing noise and enhancing connectivity.

The DGOFED model combines classical image processing with fuzzy inference and deep learning to perform edge detection in retinal fundus images. This section presents a rigorous mathematical description of each stage of the model, highlighting the relationships between image features, fuzzy membership functions, and the final edge decision.

GRADIENT-BASED EDGE REPRESENTATION :

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Let the input image be defined as I(x,y), where x and y denote pixel coordinates. The **gradient magnitudes** are computed using discrete Sobel operators along the primary directions:

$$G_x = I * K_x, \quad G_y = I * K_y$$

Where Kx and Ky are the horizontal and vertical Sobel kernels, respectively. The diagonal gradients are obtained similarly:

$$G_{d1} = I * K_{d1}, \quad G_{d2} = I * K_{d2}$$

The **overall gradient magnitude** at a pixel is given by:

$$G_{mag}(x,y) = \sqrt{G_x^2(x,y) + G_y^2(x,y)}$$

These directional gradients form the input variables for the fuzzy inference system.

FUZZY MEMBERSHIP FUNCTIONS:

Each directional gradient $G_i \in \{G_x, G_y, G_{d1}, G_{d2}\}$ is passed through a **Gaussian Type-2 membership function**:

$$\mu_{Gi}(g) = e^{\frac{-(g - m_i)^2}{2\sigma_i^2}}$$

Where:

- g is the gradient value at a pixel.
- m_i, σ_i: fuzzy membership parameters (mean and spread) predicted by the CNN.

The membership grade $\mu \in [0,1]$ represents the **confidence** that the input belongs to a high-edge region in the given direction.

FUZZY RULE EVALUATION:

Let us define a set of fuzzy rules in the Mamdani format:

IF G_x is High AND G_y is Medium THEN Edge is Strong

The **firing strength** of each rule is computed as the **T-norm (min or product)** of the corresponding memberships:

$$\alpha_j = \min\left(\mu_{Gx}^{(j)}, \mu_{Gy}^{(j)} \ldots\right)$$

The rule outputs are aggregated using fuzzy union (max operator). In Type-2 fuzzy logic, this produces an **interval-valued output**, which must be reduced.

Type-Reduction and Defuzzification

The interval-valued output of the inference system is **type-reduced** using the **Karnik-Mendel algorithm**, which computes the centroid of the Type-2 fuzzy set. This produces a crisp value $E(x,y) \in [0,1]$ in [0, 1] representing the **edge confidence** at location (x,y):

$$E(x,y) = \text{Centroid}[\tilde{F}_{Edge}(x,y)]$$

This process is repeated for all pixels in the image, generating an edge confidence map:

$$E = \{E(x,y) \mid \forall (x,y) \in I\}$$

CNN Output and Integration

The CNN component (DLOM) processes each image patch $P_k \subset I$, and predicts parameters $\hat{m}_k, \hat{\sigma}_k$. These are used to compute the membership grades for all pixels within P_k. The final edge confidence at each pixel is then:

$$E_k(x,y) = f_{fuzzy}(G_{x,y}; \hat{m}_k; \hat{\sigma}_k)$$

This allows DGOFED to perform **adaptive edge detection** using learned parameters from the CNN while maintaining fuzzy interpretability.

Binarization with Otsu's Thresholding

Once the edge confidence map E is obtained, the final task is to convert it into a binary edge map. This is achieved through **Otsu's thresholding**, a non-parametric method that determines the threshold value that maximizes the between-class variance in the image histogram.

Mathematical Background

Let the image histogram be divided into two classes at a threshold T:

- C1: pixels $\leq$ T
- C2: pixels $>$ T

Let:

- ω1(T) and ω2(T): probabilities (weights) of the two classes
- μ1(T) and μ2(T): means of the classes

The between-class variance $\sigma_b^2(T)$ is defined as:

$$\sigma_b^2(T) = \omega 1(T)\omega 2(T)[\mu 1(T) - \mu 2(T)]^2$$

The optimal threshold T* is selected as:

$$T^* = arg \max_T \sigma_b^2(T)$$

Application to Edge Confidence Map

Otsu's method is applied directly to the normalized edge confidence map E. Pixels with confidence greater than T* are classified as **edge pixels**, and the rest as **non-edge**:

$$\text{EdgeMap}(x,y) = \begin{cases} 1, & \text{if } E(x,y) > T^* \\ 0, & \text{otherwise} \end{cases}$$

This binarization step finalizes the vessel edge map and ensures that the output is usable for downstream tasks such as vessel tracking, classification, or pathology localization.

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 model is implemented using Python with the following major libraries:

- **OpenCV** and **NumPy** for image processing
- **Tensor Flow/Keras** for building and training the CNN
- **scikit-image** for applying Otsu’s thresholding
- **Matplotlib** for visualization and ROC curve generation

GPU acceleration is used when training the CNN but is not strictly required during inference, as the DLOM is lightweight.

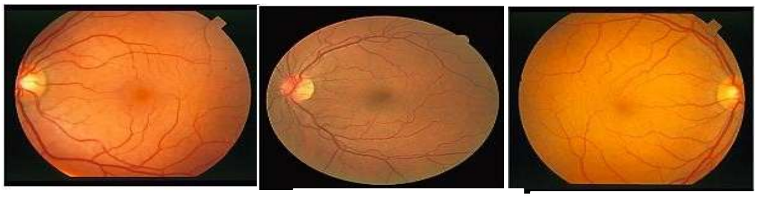
The CNN (DLOM) is trained using the following configuration:

- **Optimizer**: Adam
- **Loss Function**: Mean Squared Error (MSE)
- **Epochs**: 100–200 (early stopping used)
- **Batch Size**: 64
- **Validation Split**: 20%

Data augmentation (e.g., flipping, rotation, brightness jitter) is applied to enhance generalization across image styles and scanners.

EXPERIMENTAL RESULTS:

Qualitative outputs show that DGOFED preserves both large and fine vessels, with minimal false edges. The CNN-based fuzzy estimation adapts to local vessel contrast and suppresses background noise effectively.



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

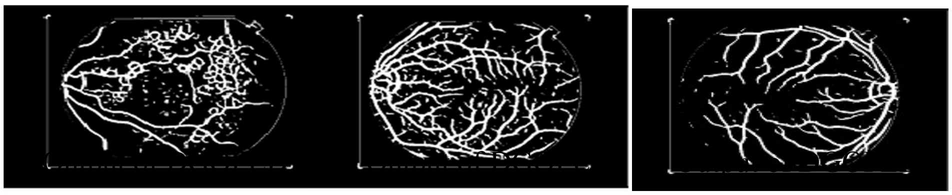
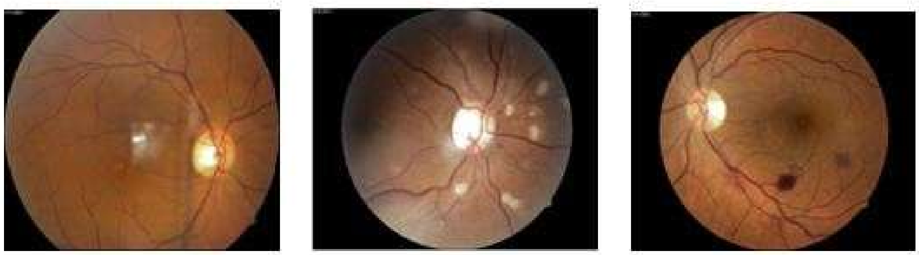
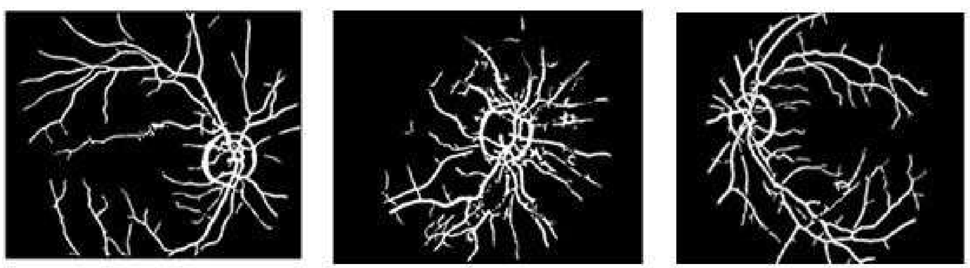


Fig. 2 Outputs of STARE database



Fundus image of Patient-1 Fundus image of Patient-2 Fundus image of Patient-3



Output of DGOFED Output of DGOFED Output of 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 **DGOFED**	STARE DATABASE	0.7704	0.9795	0.9853
		GMC DATABASE	0.7672	0.9781	0.9800

The Table 1 shows the comparison of vessel detection strategies on STARE images and local database GMC Database performed by 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. DGOFED technique method proposed in the thesis gives SN (sensitivity) of 0.7704, SP (specificity) of 0.9795, Acc (accuracy) of 0.9853for STARE Database and SN (sensitivity) of 0.7672, SP (specificity) of 0.9781, Acc (accuracy) of 0.9800 for GMC database.

CONCLUSION:

This paper presents DGOFED, a novel edge detection framework that integrates fuzzy logic with a deep learning-based optimizer for retinal image analysis. The model balances interpretability and accuracy, achieving superior results in vessel boundary extraction. The system is adaptable, computationally efficient, and suitable for real-time implementation in teleophthalmology platforms. Future work includes extending DGOFED to multi-modal datasets and incorporating supervised CNN training using full-resolution vessel maps.

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