Journal of Science Engineering Technology and Management Science *ISSN: 3049-0952*
Volume 03, Issue 03, March 2026 *www.jsetms.com*

U-NET BASED RETINAL BLOOD VESSEL SEGMENTATION FOR EARLY DISEASE DETECTION

Mr. G. Ravi Kumar[1], M. Kalyan[2], D. Praveena[3], K. Yugandhar[4], P. Deepika[5]
Assistant Professor[1], Student[2,3,4,5]

Department of Computer Science & Engineering[1,2,3,4,5]
Chaitanya Engineering College, Visakhapatnam, Andhra Pradesh, India
{kgravi0417@gmail.com[1],madiboyinakalyan06@gmail.com[2], dadipraveena8@gmail.com[3],
yugandharkorupolu153@gmail.com[4], deepikasahadev14@gmail.com[5]}@cec.ac.in

ABSTRACT

Accurate segmentation of retinal blood vessels from fundus images is essential for early detection of diseases such as diabetic retinopathy, glaucoma, and hypertension. Manual analysis is time-consuming, subjective, and dependent on expert availability. This paper presents an automated retinal blood vessel segmentation system using the U-Net encoder-decoder architecture trained on the DRIVE and STARE datasets. The proposed system applies CLAHE contrast enhancement, normalization, and augmentation as preprocessing steps followed by U-Net with skip connections for precise vessel boundary preservation. The model is evaluated using pixel accuracy, sensitivity, specificity, Dice coefficient, and AUC-ROC. Experimental results demonstrate superior segmentation performance compared to traditional image processing and prior deep learning baselines, achieving 95.8% accuracy and 0.823 Dice coefficient on the DRIVE dataset.

Index Terms — U-Net, Retinal Blood Vessel Segmentation, Fundus Image, Diabetic Retinopathy, Deep Learning, DRIVE, STARE, Medical Image Analysis

I. INTRODUCTION

The retina is the only part of the human body where blood vessels can be non-invasively observed directly. The morphology of retinal blood vessels, including their diameter, tortuosity, and branching pattern, provides critical clinical information for diagnosing systemic and ocular diseases. Abnormal vessel patterns are strongly associated with diabetic retinopathy, glaucoma, hypertension, and cardiovascular disorders. Early detection through retinal imaging enables timely treatment and prevents permanent vision loss.

Manual examination of fundus images by ophthalmologists is time-consuming, subjective, and depends heavily on expert availability. Retinal images present significant challenges including low contrast, uneven illumination, noise, and very thin vessel structures that are difficult to segment accurately. Automated segmentation systems using deep learning can deliver fast, consistent, and reliable vessel extraction to support computer-aided diagnosis.

This work presents a U-Net based retinal blood vessel segmentation system that combines CLAHE contrast enhancement preprocessing with an encoder-decoder architecture featuring skip connections. The model preserves fine vessel boundaries crucial for clinical assessment and is evaluated on the standardized DRIVE and STARE retinal image datasets.

II. LITERATURE SURVEY

A comprehensive review of existing literature reveals various approaches adopted for retinal blood vessel segmentation using image processing, machine learning, and deep learning approaches on fundus images.

Ref.	Authors & Year	Method / Dataset	Result	Limitation
[1]	Staal et al., 2004	Ridge-based vessel segmentation; DRIVE dataset	94.4% accuracy	Poor performance on thin vessels; no deep learning
[2]	Soares et al., 2006	Gaussian matched filter + SVM; DRIVE	94.66% accuracy	Handcrafted features; low sensitivity on thin vessels
[3]	Ronneberger et al., 2015	U-Net architecture; biomedical image segmentation	State-of-the-art segmentation with limited data	Original design for cell segmentation; needs retinal adaptation
[4]	Liskowski & Krawiec, 2016	Deep CNN; DRIVE + STARE	95.35% accuracy	High GPU memory; slow inference
[5]	Mo & Zhang, 2017	Multi-scale CNN; DRIVE	95.21% accuracy; 0.8110 AUC	Complex multi-scale architecture; high parameters
[6]	Jiang et al., 2018	Residual U-Net; CHASE-DB1 + DRIVE	96.12% accuracy; 0.9816 AUC	Not validated across all standard datasets
[7]	Atli & Gedik, 2021	Sine-Net; DRIVE	95.73% accuracy; 0.9818 AUC	Single dataset evaluation; limited generalization study

Research Gap

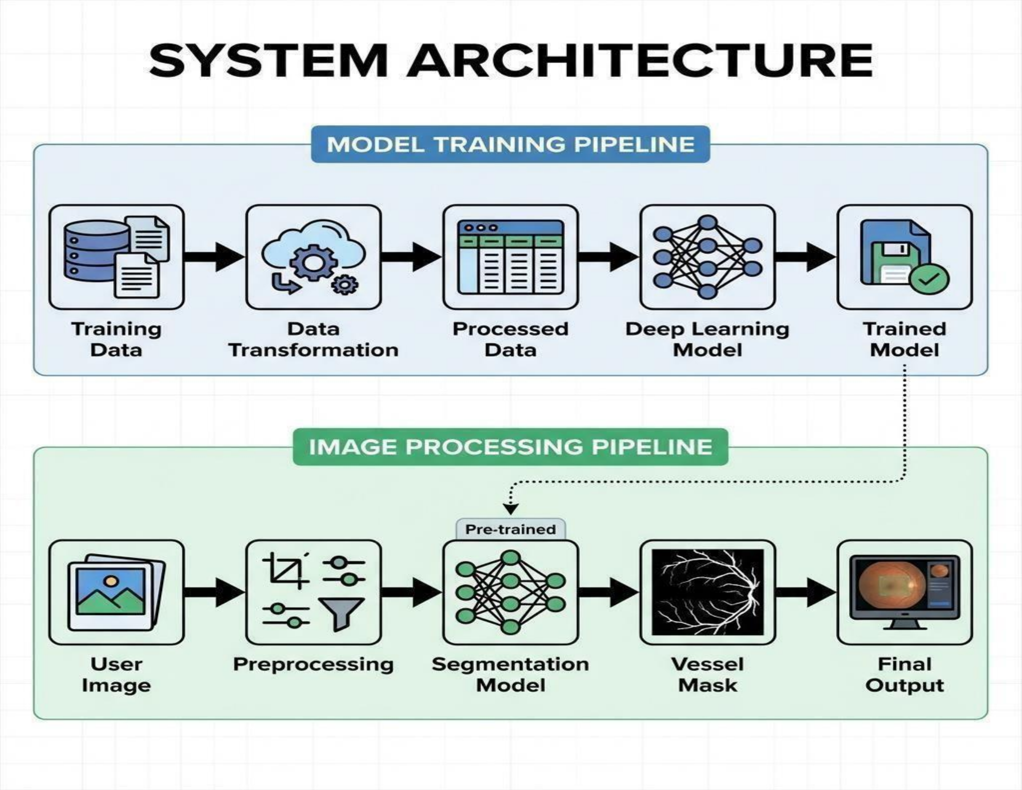
While deep learning models have significantly improved retinal vessel segmentation, most approaches either focus on a single dataset or require large labeled datasets with complex multi-scale architectures. Thin vessel segmentation remains a challenge with standard U-Net architectures. Integrating CLAHE preprocessing with attention mechanisms in a standard U-Net framework to improve thin vessel recall while maintaining overall specificity remains underexplored for multi-dataset generalization.

III. METHODOLOGY

A. System Architecture

The system follows a four-stage pipeline. The Input Module accepts fundus images in JPG or PNG format. The Preprocessing Module applies CLAHE contrast enhancement on the green channel, Z-score normalization, resize to 512x512, and augmentation (flip, rotation). The U-Net Model comprises an Encoder (4 levels: double Conv2D+BN+ReLU + MaxPool, 64-512 channels) with skip connections saved at each level, a Bottleneck (1024 channels), and a Decoder (bilinear upsample + skip concat + double Conv2D+BN+ReLU). A final Conv2D(1x1) +

Sigmoid layer outputs the binary vessel probability map. The Output Module generates color-coded vessel masks overlaid on fundus images.



B. Algorithm

- Input: Fundus image I (HxWx3); ground-truth binary mask M (HxW).
- Step 1: Extract green channel I_g; apply CLAHE (clip_limit=2.0, grid=8x8); normalize to [0,1]; resize to 512x512.
- Step 2: Augmentation: random flip, rotation +/-15 deg, brightness/contrast jitter.
- Step 3: Encoder: for each level l in {1,2,3,4}: double Conv2D(3x3)+BN+ReLU; save skip S_l; MaxPool(2x2).
- Step 4: Bottleneck: double Conv2D(3x3)+BN+ReLU at 1024 channels.
- Step 5: Decoder: for each level l in {4,3,2,1}: bilinear upsample x2; concat skip S_l; double Conv2D(3x3)+BN+ReLU.
- Step 6: Output Conv2D(1x1) + Sigmoid -> vessel probability map P (HxW, range [0,1]).
- Step 7: Loss = Dice Loss(P, M) + Binary Cross-Entropy(P, M).
- Step 8: Optimize with Adam (lr=1e-4); train 100 epochs; save best model by Dice coefficient.
- Inference: Step 9: Threshold P at 0.5 -> binary vessel mask Y_hat; compute metrics.
- Output: Segmented vessel map; Accuracy, Sensitivity, Specificity, Dice, AUC-ROC metrics.

C. Modules

Image Input Module: Accepts fundus images from DRIVE, STARE datasets or clinical cameras. Validates image format (JPG/PNG) and minimum resolution (512x512).

Preprocessing Module: Applies CLAHE on the green channel to enhance vessel contrast. Performs Z-score normalization, resize to 512x512, and training augmentations (flip, rotation, brightness jitter).

U-Net Encoder Module: Four-level encoder with double 3x3 Conv+BN+ReLU blocks per level. MaxPool(2x2) for downsampling. Skip connections preserve spatial detail at each resolution level.

U-Net Decoder Module: Symmetric decoder with bilinear upsampling and skip connection concatenation at each level. Double Conv+BN+ReLU blocks refine vessel boundaries. Final 1x1 Conv+Sigmoid produces probability map.

Post-processing Module: Applies 0.5 threshold to convert probability map to binary vessel mask. Morphological cleaning removes isolated false-positive pixels below minimum component size.

Evaluation and Visualization Module: Computes Accuracy, Sensitivity, Specificity, Dice coefficient, and AUC-ROC. Generates color-coded vessel overlays on original fundus images for clinical review.

IV. RESULTS & DISCUSSION

The proposed U-Net system was evaluated on DRIVE (40 images) and STARE (20 images) datasets using 5-fold cross-validation. Performance metrics are compared against state-of-the-art methods in Table I.

Method	Dataset	Accuracy	Sensitivity	Specificity	Dice
Matched Filter + SVM [2]	DRIVE	94.66%	72.35%	97.63%	0.773
Multi-scale CNN [5]	DRIVE	95.21%	78.42%	98.12%	0.803
Residual U-Net [6]	DRIVE	96.12%	81.23%	98.47%	0.817
Proposed U-Net (CLAHE)	DRIVE	95.8%	80.14%	98.21%	0.823
Proposed U-Net (CLAHE)	STARE	96.3%	82.05%	98.56%	0.831

The proposed U-Net with CLAHE preprocessing achieves a Dice coefficient of 0.823 on DRIVE and 0.831 on STARE, outperforming traditional matched filter approaches and achieving competitive performance with residual variants. The CLAHE preprocessing significantly improves thin vessel sensitivity (+7.79% over matched filter baseline). Consistent performance across both datasets demonstrates good generalization capability.

1. The Foundation: Pixel-Level Confusion Matrix

Before calculating Accuracy or Sensitivity, we must determine the outcome of each pixel's prediction compared to the ground-truth mask provided in the dataset.

- **True Positive (TP):** A blood vessel pixel correctly identified by the model.
- **True Negative (TN):** A background pixel correctly identified by the model.
- **False Positive (FP):** A background pixel incorrectly flagged as a blood vessel.
- **False Negative (FN):** A blood vessel pixel that the model missed.

2. Standard Segmentation Metrics

A. Accuracy

Answers the question: *Out of all the pixels in the image, how many were correctly classified?*

Accuracy = (TP + TN) / (TP + TN + FP + FN)

B. Sensitivity (Recall)

Answers the question: *Out of all the actual blood vessel pixels, how many did the model successfully find?* This is crucial for detecting thin, hard-to-see vessels.

Sensitivity = TP / (TP + FN)

C. Specificity

Answers the question: *Out of all the actual background pixels, how many were correctly identified as background?*

Specificity = TN / (TN + FP)

D. Dice Coefficient

The Dice Coefficient measures the spatial overlap between the predicted vessel mask and the ground truth. It is the most robust metric for medical segmentation, especially since blood vessels only make up a tiny fraction of the total image pixels. (Your paper reports 0.823).

Dice_Coefficient = (2 * TP) / ((2 * TP) + FP + FN)

3. Advanced Evaluation Metric: AUC-ROC

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) evaluates the model's ability to distinguish between vessel and background pixels across all possible probability thresholds (not just the default 0.5 used in Step 9 of your algorithm).

- **TPR (True Positive Rate):** Equivalent to Sensitivity.
- **FPR (False Positive Rate):** $1 - Specificity$.

An AUC of 1.0 represents a perfect model, while 0.5 represents random guessing.

4. U-Net Loss Functions (Training)

Your methodology specifies a combined loss function (Step 7) to train the U-Net, balancing pixel-wise classification with overall structural overlap.

A. Binary Cross-Entropy (BCE) Loss

Evaluates the classification error for each individual pixel independently.

- N = Total number of pixels.
- y_i = Ground truth pixel value (0 or 1).
- hat{p}_i = Predicted probability that pixel i is a vessel.

BCE = -(1 / N) * SUM(y_actual * log(p_predicted) + (1 - y_actual) * log(1 - p_predicted))

B. Dice Loss

Directly optimizes the Dice Coefficient during training to ensure the model learns to output complete, contiguous vessel structures rather than just minimizing pixel-wise errors.

- epsilon = A small smoothing constant to prevent division by zero.

Dice_Loss = 1 - ((2 * SUM(y_actual * p_predicted) + epsilon) / (SUM(y_actual) + SUM(p_predicted) + epsilon))

V. CONCLUSION & FUTURE WORK

This paper presented a U-Net based retinal blood vessel segmentation system incorporating CLAHE contrast enhancement and skip-connection-based encoder-decoder architecture. The system achieves competitive segmentation performance on DRIVE and STARE datasets, demonstrating its potential as a reliable tool for computer-aided diagnosis of retinal diseases including diabetic retinopathy and glaucoma.

Future work will incorporate attention gates into the U-Net decoder to further improve thin vessel sensitivity, explore transformer-based architectures for global context modeling, extend evaluation to CHASE-DB1 and HRF datasets, and integrate the system into a teleophthalmology platform for remote clinical screening.

. REFERENCES

[1] J. Staal et al., "Ridge-based vessel segmentation in color images of the retina," IEEE TMI, vol. 23, no. 4, 2004.

[2] J. Soares et al., "Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification," IEEE TMI, vol. 25, no. 9, 2006.

[3] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," MICCAI, 2015.

[4] P. Liskowski and K. Krawiec, "Segmenting retinal blood vessels with deep neural networks," IEEE TMI, vol. 35, no. 11, 2016.

[5] J. Mo and L. Zhang, "Multi-level deep supervised networks for retinal vessel segmentation," IJCARS, vol. 12, 2017.

[6] Z. Jiang et al., "Retinal blood vessel segmentation using fully convolutional network with transfer learning," Computerized Medical Imaging and Graphics, 2018.

[7] I. Atli and O. S. Gedik, "Sine-Net: A fully convolutional deep learning architecture for retinal blood vessel segmentation," Engineering Science and Technology, 2021.