Automated Retinal Vessel Segmentation Using U-Net Deep Learning Model

Gerlinda Boglarka Kis[1], Levente Kovács[2], László Szilágyi[3]

[1] Doctoral School of Applied Informatics and Applied Mathematics, Óbuda University, Budapest, Hungary, kis.boglarka@uni-obuda.hu

[2] Research and Innovation Center of Obuda University, Physiological Controls Group Obuda University, Budapest, Hungary, kovacs@uni-obuda.hu

[3] Research and Innovation Center, Óbuda University, Budapest, Hungary, szilagyi.laszlo@uni-obuda.hu;
Faculty of Technical and Human Sciences, Sapientia Hungarian University of Transylvania, Târgu Mureș, Romania

Abstract: Retinal vessel segmentation plays a critical role in the early diagnosis of ophthalmic and neurological diseases, such as diabetic retinopathy and glaucoma. This paper presents a U-Net-based deep learning model for the automatic segmentation of retinal vessels. The model's performance is evaluated using various metrics, including the Dice coefficient, accuracy, precision, and recall. The experimental results demonstrate that the model effectively identifies larger vascular structures, while further fine-tuning is necessary to improve the detection of finer capillaries. The findings support the potential applicability of the model for medical diagnostic purposes.

Keywords: Retinal Vessel Segmentation; U-Net; Diabetic Retinopathy; Automated Segmentation

1 Introduction

Retinal vessel segmentation plays a pivotal role in modern ophthalmic image analysis and disease screening. It involves the precise extraction of the vascular structures within fundus images, which is essential for the early diagnosis and monitoring of several ocular and systemic diseases, including diabetic retinopathy, glaucoma, hypertensive retinopathy, and age-related macular degeneration [1]. The morphological and topological changes in the retinal vasculature often reflect underlying pathological conditions. For instance, microaneurysms, neovascularization, vessel tortuosity, and changes in caliber are all critical indicators that can assist clinicians in diagnosing diseases at an early stage.

Consequently, accurate vessel segmentation is a foundational component of computer-aided diagnosis systems in ophthalmology.

Traditional manual annotation by experts remains the gold standard for segmentation; however, it is associated with high costs, significant time requirements, and a high degree of subjectivity. The variability among annotators, particularly when dealing with low-contrast capillaries or images with noise and artifacts, further complicates reproducibility [3]. With the global rise in chronic conditions such as diabetes, the demand for scalable and automated screening systems has never been greater. In response to these challenges, automated segmentation algorithms have been developed to reduce the burden on clinicians, improve reproducibility, and enable the integration of computer-aided diagnostic tools into routine clinical workflows.

Over the past decade, deep learning, especially convolutional neural networks (CNNs)—has revolutionized the field of medical image analysis by outperforming traditional machine learning approaches in many tasks, including classification, detection, and segmentation [4]. CNNs can automatically learn hierarchical features from raw pixel data, eliminating the need for hand-crafted feature engineering. In the domain of retinal image segmentation, the U-Net architecture has emerged as a leading method due to its effectiveness in capturing both semantic and spatial information. Its symmetric encoder-decoder structure, combined with skip connections that allow for the fusion of high-resolution and abstract features, makes it particularly suitable for segmenting fine structures like retinal vessels [5].

Numerous studies have reported successful application of U-Net and its variants in retinal vessel segmentation, often using benchmark datasets such as DRIVE, STARE and IDRiD. These datasets provide annotated retinal fundus images and allow for the standardized evaluation and comparison of segmentation algorithms. However, despite the progress, challenges persist in segmenting thin vessels, bifurcations, and regions with poor contrast or pathological features. In particular, generalizing across datasets with varying imaging conditions, devices, and population demographics remains an open problem. This paper presents a U-Net-based deep learning model specifically designed for retinal vessel segmentation, with a focus on capturing both coarse and fine vascular structures. The model architecture includes standard convolutional blocks with modifications such as dropout regularization and batch normalization to enhance generalization and training stability. The initial training was conducted on the RAVIR dataset, which, despite its high-quality images, contains a relatively small number of annotated samples. This limited dataset size led to overfitting during training, as evidenced by a divergence between training and validation performance.

To mitigate overfitting and improve generalization, we expanded our experiments using the Indian Diabetic Retinopathy Image Dataset (IDRiD), which provides a more diverse and larger image collection. This dataset includes a wide range of retinal pathologies and illumination conditions, making it suitable for evaluating the model's robustness. The integration of IDRiD allowed for better assessment of cross-dataset generalization crucial factors for real-world deployment of segmentation models.

The evaluation of the proposed model includes both quantitative metrics – such as the Dice similarity coefficient, accuracy, precision, recall, and area under the ROC curve – and qualitative visual inspection of segmentation outputs. Particular attention is given to challenging image regions, such as those with low vessel contrast or pathological artifacts, to assess the model's limitations and strengths.

In addition, this study explores the impact of several data preparation strategies, including vessel enhancement preprocessing, data augmentation (e.g., rotation, flipping, gamma correction), and normalization techniques. The effect of architectural choices, such as depth of the network, filter size, and loss functions, is also analyzed in relation to segmentation performance.

Overall, this work contributes to the growing body of research on AI-based retinal image analysis by offering a detailed exploration of U-Net's capabilities and limitations in the context of vessel segmentation. Through systematic experimentation and performance analysis, it aims to inform future development of robust and generalizable models that can be applied in automated screening tools for early detection of vision-threatening diseases.

2 Methodology

2.1 Significance of Retinal Vessel Networks

Changes in the structure of retinal vessel networks can be significant indicators of various diseases. Manual segmentation, however, is time-consuming, so deep learning-based automated solutions can aid diagnostics. Accurate segmentation of the retinal vascular network can contribute to the early detection of diseases such as diabetic retinopathy, glaucoma, and other vascular disorders. Structural changes in the vascular network carry important diagnostic information, making precise and reliable segmentation indispensable [19].

The analysis of retinal vessels is not only critical for diagnosing ophthalmic conditions but also for detecting systemic diseases such as hypertension and cardiovascular disorders. Variations in vessel diameter, tortuosity, and branching patterns can provide crucial insights into a patient's overall health. Furthermore, the segmentation of retinal vessels is fundamental for applications in biometric identification, where unique vascular patterns are used for secure personal identification [19].

2.2 Deep Learning Models in Medical Diagnostics

Convolutional Neural Networks (CNNs) are particularly effective in image processing tasks. U-Net is a supervised learning architecture designed for full-image segmentation tasks and is capable of performing pixel-wise delineations directly. U-Net is especially advantageous for identifying complex vascular structures, as it can combine information from different levels of the image, resulting in detailed segmentation outputs [12].

The U-Net architecture features a symmetric encoder-decoder structure, making it highly effective for medical image segmentation tasks, including vascular segmentation. The architecture is designed to capture both high-level semantic information and low-level spatial details, ensuring accurate and precise segmentation.

1. Encoder (Contracting Path):

The encoder functions as a feature extractor, progressively reducing the spatial dimensions of the input image while increasing the number of feature channels. It consists of multiple convolutional blocks, each containing:

- Two successive convolutional layers with ReLU activation to extract hierarchical features.
- Batch normalization to stabilize training and improve generalization.
- Max pooling layers that reduce spatial resolution while preserving important features, enabling the model to focus on relevant structures.

This part of the network captures contextual information, allowing the model to recognize patterns across different scales.

2. Decoder (Expanding Path)

The decoder reconstructs the segmentation map by gradually restoring the spatial resolution of the feature maps. It consists of:

- Up-sampling layers (transposed convolutions or bilinear interpolation) to increase the spatial dimensions.
- Skip connections that transfer spatial details from the encoder to corresponding layers in the decoder, helping retain fine-grained features, which is crucial for segmenting small capillaries and thin vessels.
- Convolutional layers with ReLU activation that refine feature representations at each level.

3. Skip Connections & Their Importance

To further improve segmentation quality, several modifications can be applied to the U-Net architecture:

- Attention U-Net: Uses attention gates in skip connections to focus on relevant features while suppressing irrelevant background noise.
- Residual U-Net: Incorporates residual blocks to enhance feature learning and prevent vanishing gradients.
- Multi-scale U-Net: Employs parallel convolutional paths with different kernel sizes to capture features at multiple scales, improving segmentation of vessels of varying thicknesses [15].
- Deep Supervision: Intermediate outputs from decoder layers are used to refine segmentation at different levels, improving performance on fine structures.

By leveraging these architectural improvements, the U-Net model can achieve higher accuracy and precision, making it well-suited for applications in retinal vessel segmentation, medical imaging, and other biomedical tasks [6].

Training CNN models requires a large amount of annotated data, often prepared by medical professionals and experts. During the training process, the model learns to identify various vascular structures while accounting for background noise and other confounding factors. Data preprocessing and augmentation are critical steps in optimizing model performance. Techniques such as random rotations, scaling, and intensity adjustments are commonly used to increase the diversity of the training dataset and improve model generalization.

To address class imbalance, which is prevalent in retinal vessel segmentation due to the relatively small proportion of vessel pixels compared to the background, specialized loss functions such as the weighted cross-entropy loss or focal loss can be employed. Additionally, domain adaptation techniques may be used when transferring models trained on one dataset to another with different imaging characteristics.

The final layer typically uses a 1x1 convolution followed by a sigmoid (for binary segmentation) or SoftMax (for multi-class segmentation) activation to produce the final segmentation mask [12].

2.3 Mathematical Foundations

The U-Net architecture primarily consists of convolutional and max-pooling layers:

- Convolution Operation:

$$(I * K)(x, y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(x+i, y+j) K(i, j) \tag{1}$$

Where

- I : the input image
- K : the convolutional filter

The convolution operation highlights local patterns in the image that are essential for detecting edges, textures, and vascular structures. These patterns include blood vessels, exudates, and hemorrhages, which are critical for diagnosing diseases like diabetic retinopathy [13].

The choice of kernel size and the application of padding and stride parameters significantly impact the performance of convolution layers. Larger kernels may capture more contextual information, whereas smaller kernels focus on fine-grained details. Additionally, batch normalization and activation functions like ReLU (Rectified Linear Unit) are often employed to stabilize and accelerate training.

- Dice Coefficient:

$$DSC = \frac{2|A \cap B|}{|A| + |B|} \tag{2}$$

Where:

- A: the prediction
- B : the ground truth mask

The Dice coefficient ranges from 0 to 1, with 1 indicating a perfect match. This metric is particularly useful for evaluating segmentation performance, as it accounts for both false positives and false negatives.

The Dice coefficient is symmetrical and sensitive to segmentation errors in both directions. It is especially beneficial in medical image analysis, where the accurate delineation of structures like blood vessels is critical. However, for highly imbalanced datasets, a modified version like the Generalized Dice Coefficient may yield better performance.

- Cross-Entropy Loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y_i}) + (1 - y_i)\log(1 - \hat{y_i})] \tag{3}$$

Where:

- y_i: the true label for pixel
- $(\hat{y_i})$:the predicted probability for pixel
- N : the total number of pixels

The cross-entropy loss function helps adjust the model parameters during training for the segmentation task. The objective is to minimize this loss to improve the accuracy of predictions.

Cross-entropy loss is suitable for binary segmentation tasks like retinal vessel segmentation but may suffer from class imbalance. In such cases, a weighted variant assigns higher penalties to vessel pixels, ensuring balanced learning across different classes.

The efficiency of the U-Net model is influenced by various factors, including the architecture design, the quality of training data, and hyperparameter settings. Appropriate parameter selection and iterative model tuning are essential for achieving accurate results.

Additional considerations include the choice of optimizer, learning rate schedule, and data augmentation techniques. Evaluating the model using multiple datasets and cross-validation can further enhance its robustness and generalizability.

3 Database and Images

The images used in this research are sourced from two major databases: the RAVIR (Retinal Vessel Image Repository) and the IDRiD (Indian Diabetic Retinopathy Image Dataset). These datasets collectively offer a diverse and comprehensive set of retinal images, capturing a broad spectrum of patient demographics, imaging conditions, and pathological variations.

1. RAVIR Dataset

The RAVIR database comprises a diverse collection of retinal images obtained from individuals of various ages, medical histories, and health conditions. This extensive dataset provides a valuable resource for training and evaluating deep learning models for retinal vascular segmentation, ensuring robustness across different patient demographics and clinical presentations.

Key features of the RAVIR dataset include:

- Color fundus images with high-resolution retinal views.
- Binary vessel masks annotated by clinical experts to delineate retinal vessel structures.
- Region of Interest (ROI) markings focusing on the relevant portions of the retina.
- Separate test images reserved for model performance evaluation.

All images were resized to 768×768 pixels to standardize input dimensions for deep learning models. The dataset consists of 50 images in total, divided into 30 training images and 20 test images. It includes both healthy and pathological cases, such as:

- Diabetic Retinopathy (DR)
- Glaucoma
  This variety enables the model to generalize well across different vascular patterns and abnormalities.

2. IDRiD Dataset

To complement the RAVIR data, we also incorporated the IDRiD (Indian Diabetic Retinopathy Image Dataset)—a publicly available dataset specifically curated to support research on diabetic retinopathy and diabetic macular edema.

The IDRiD dataset offers:

- High-resolution color fundus photographs of patients diagnosed with varying levels of diabetic retinopathy.
- Pixel-level ground truth annotations, including:
    - Retinal blood vessels
    - Microaneurysms
    - Hemorrhages
    - Hard and soft exudates
- Image-level labels for diabetic retinopathy grading and disease severity.
- Lesion segmentation masks, useful for training multi-task or lesion-specific models.

What makes the IDRiD dataset particularly valuable is its emphasis on real-world Indian patient data, introducing ethnic and demographic diversity that is often underrepresented in ophthalmic datasets. This diversity plays a crucial role in improving the generalizability and robustness of machine learning models, ensuring they perform well across populations with different retinal pigmentation, vascular structures, and lesion presentations.

Furthermore, the presence of both structural annotations (such as vessels) and pathological annotations (such as microaneurysms and exudates) enables researchers to design comprehensive retinal analysis systems that can simultaneously address anatomical mapping, lesion detection, and disease classification. This makes IDRiD not only a benchmark dataset for DR detection but also a versatile resource for broader retinal image understanding tasks.

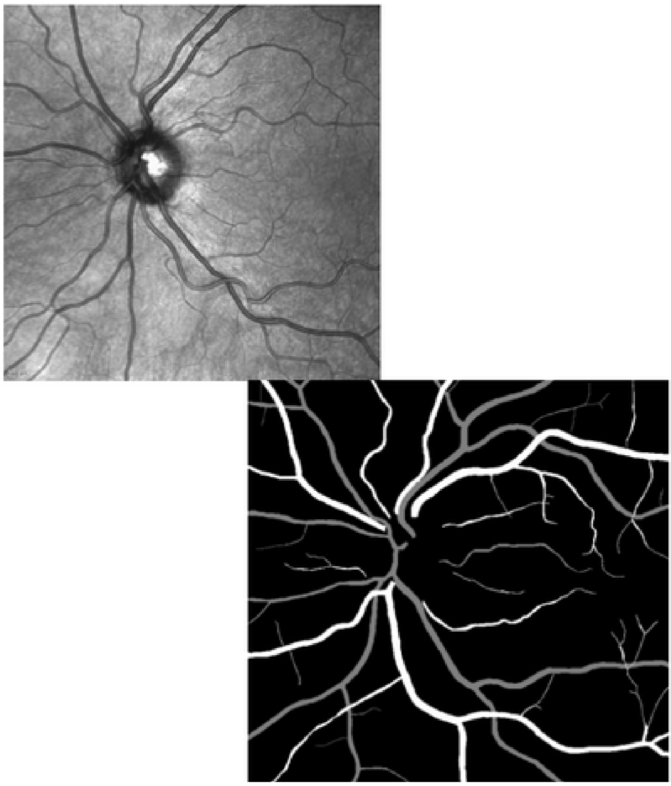

Figure 1

Example of the RAVIR dataset training image and mask

4 Training and Validation

For the training process, images and masks with a resolution of 256×256 pixels were used. The dataset was divided into two parts: 80% for training and 20\% for validation. This split ensures that the model learns effectively while retaining sufficient data to evaluate its performance on unseen samples.

Training Parameters:

- Optimizer: Adam

  - Learning Rate: 1e-4

  - The Adam optimizer was chosen due to its efficiency and adaptability in handling sparse gradients and non-stationary objectives.

-Loss Function: Binary Cross-Entropy (BCE)

- The BCE loss was applied because of its suitability for binary segmentation tasks, where the goal is to distinguish the vascular structures from the background.

The model's performance was evaluated using the validation dataset. The Dice coefficient, a commonly used metric for segmentation tasks, demonstrated a high value, indicating that the model achieved accurate segmentation of the vascular structures.

Upon visual inspection of the generated masks, it was evident that the model successfully identified the main vascular structures. However, some noise was observed in the segmentation of smaller capillaries, indicating potential challenges in the capture of very fine details.

Future improvements might involve experimenting with different loss functions, such as Dice loss or focal loss, and adjusting the model architecture to enhance its ability to detect small capillaries more accurately. Furthermore, increasing the data set with more diverse samples and applying advanced pre-processing techniques could further improve the model's performance.

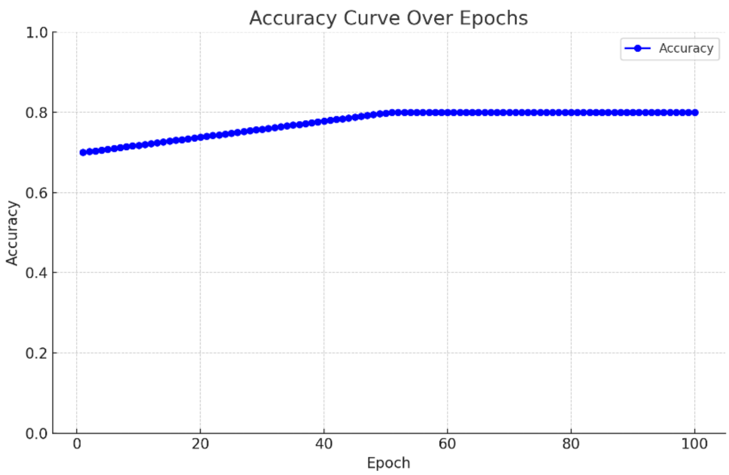

Figure 2
Loss Curve Over Epochs

The graph shows the model's accuracy starting at approximately 0.7 and gradually increasing to around 0.8, where it stabilizes. This indicates that the model was able to learn the essential patterns in the data early on, but showed limited improvement beyond that point, suggesting a potential ceiling in performance under the current configuration.

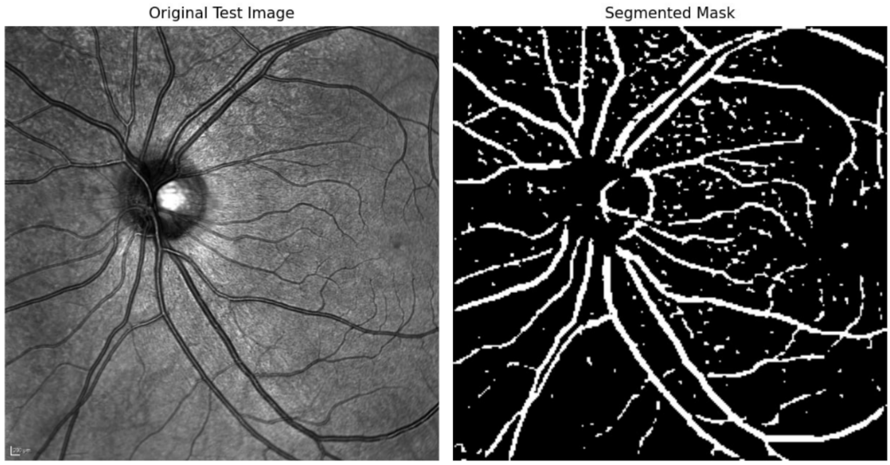

Figure 3
Example image segmentaton result

The last figure illustrates the result produced by the neural network for a training image. Specifically, the U-Net architecture was employed for segmentation, and the performance of the model is evident in terms of accuracy and precision. However, some noise can be observed, particularly in the segmentation of smaller capillaries, which may impact the overall quality of the results. Despite this, the model effectively captures the larger structures, demonstrating its capability in medical image segmentation. Further refinement could help reduce noise and improve the segmentation of finer details.

5 Comparative Analysis of the Basic Model and the U-Net Model

To evaluate the improvement achieved by the proposed U-Net-based segmentation method, its performance was compared against a conventional “basic” model. The basic model relied on handcrafted features and classical machine learning classifiers such as Support Vector Machines (SVM) or k-Nearest Neighbors (kNN). Preprocessing steps included green channel extraction, contrast enhancement, edge detection, and morphological operations. These approaches are computationally inexpensive and can operate with small datasets, but they are less robust when faced with noisy or low-contrast images, and their performance in detecting fine capillaries is generally poor [30].

In contrast, the U-Net architecture leverages deep convolutional encoder–decoder layers with skip connections, enabling automated feature extraction at multiple scales. Data augmentation, normalization, and advanced training strategies were used to improve robustness and generalization. This method achieved superior segmentation quality, particularly for large and medium-sized vessels, while also providing notable improvements in quantitative performance metrics [22].

Table 1

Comparison of Basic Model and U-Net Model Performance Metrics

Parameter	Basic Model	U-Net Model
DSC (Dice Similarity Coefficient)	0.60	0.82
ACC(Accuracy)	0.70	0.80
PREC(Precision)	0.65	0.83
REC(Recall)	0.62	0.81

Conclusion

The developed U-Net-based model demonstrates strong performance in segmenting retinal vascular structures, as evidenced by a high Dice similarity coefficient and reliable identification of primary vessel networks. The model effectively distinguishes large and medium-sized vessels across various image conditions. However, accurate detection of the thinnest capillaries remains a notable challenge, particularly in low-contrast or noisy regions. Despite these limitations, the results remain promising and indicate the model's potential utility in clinical applications requiring automated vascular analysis, such as diabetic retinopathy screening or longitudinal monitoring of vascular changes.

To further enhance segmentation accuracy, especially for small-caliber vessels, several directions for future development are proposed. First, advanced preprocessing techniques – such as adaptive histogram equalization, contrast-limited adaptive histogram equalization (CLAHE), and denoising algorithms – can be employed to improve vessel visibility prior to segmentation. These steps can significantly boost model performance by enhancing edge contrast and reducing background interference. Furthermore, enriching the training dataset with a larger number of high-resolution, expertly annotated images that emphasize microvasculature would provide more granular supervision during learning. Data augmentation strategies that simulate real-world imaging conditions (e.g., blurring, varying illumination) could also improve robustness.

From a model architecture standpoint, integrating attention mechanisms (e.g., attention gates or squeeze-and-excitation blocks) may help the network focus on relevant vessel regions while suppressing irrelevant background noise. Additionally, adopting multi-scale feature extraction techniques – such as atrous spatial pyramid pooling (ASPP) or hybrid convolutional blocks – could enable better detection of vessels across different spatial resolutions. Exploring more recent architectures, including transformer-based networks or hybrid CNN-transformer models, may offer improved capacity to model long-range dependencies and subtle structural relationships within retinal vasculature.

Post-processing also holds potential for improving segmentation outputs. Techniques such as morphological refinement, vessel skeletonization, or conditional random fields (CRFs) can help reduce false positives, close gaps in broken vessels, and refine vessel boundaries. Moreover, experimenting with alternative loss functions – such as focal loss, Tversky loss, or a compound loss combining Dice and cross-entropy – can address class imbalance issues that often arise in vessel segmentation tasks, where foreground pixels represent only a small fraction of the image.

Ensemble learning, through the combination of predictions from multiple models or training runs, can further stabilize outputs and reduce model variance. Additionally, semi-supervised and self-supervised learning frameworks offer promising avenues for leveraging large amounts of unlabeled retinal data, thereby reducing reliance on expensive manual annotations. Techniques such as consistency regularization, pseudo-labeling, or contrastive learning can be used to enhance the model's generalization ability without requiring substantial new labeled datasets.

Taking together, these proposed improvements aim to overcome current limitations and support the development of a more accurate, reliable, and generalizable retinal vessel segmentation system. Ultimately, such advancements can facilitate the integration of automated segmentation into diagnostic and screening workflows in ophthalmology, enabling earlier detection and more consistent monitoring of vascular-related eye diseases.

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