Retinal Blood Vessel Segmentation

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Abstract

This project presents a U-Net–based deep learning approach for retinal blood vessel segmentation. Focal Tversky Loss was used to handle class imbalance and improve detection of thin vessels. The proposed model achieved high Dice, IoU, and AUC values, demonstrating accurate segmentation and good generalization, making it suitable for medical image analysis applications.

1. Introduction

Retinal blood vessel segmentation is a crucial task in medical image analysis, as it plays an important role in the early diagnosis and monitoring of several ocular and systemic diseases such as diabetic retinopathy, hypertension, and cardiovascular disorders. Manual segmentation of blood vessels from retinal fundus images is time-consuming, subjective, and highly dependent on the expertise of clinicians, which highlights the need for automated and reliable segmentation techniques.

With the advancement of deep learning, convolutional neural networks (CNNs) have shown remarkable performance in medical image segmentation tasks. Among these architectures, U-Net has become one of the most widely used models due to its ability to capture both global contextual information and fine-grained details, making it especially suitable for biomedical images with limited training data.

In this project, an automated deep learning-based approach is proposed for segmenting retinal blood vessels from fundus images using the Retina Blood Vessel Segmentation dataset. The implemented pipeline includes data loading, preprocessing, model training, and evaluation. Preprocessing steps were applied to enhance vessel visibility and improve model performance, with special focus on handling class imbalance between vessel and background pixels. A U-Net-based architecture was employed and trained using appropriate loss functions and evaluation metrics to accurately delineate blood vessels.

The objective of this project is to develop and evaluate an effective segmentation model that can accurately extract retinal blood vessels and demonstrate the applicability of deep learning techniques in medical image analysis.[1].

2. Dataset Description

The Retina Blood Vessel Segmentation dataset is used in this project to support automated retinal blood vessel extraction for medical image analysis. Accurate vessel segmentation is essential for diagnosing and monitoring retinal diseases such as diabetic retinopathy.

The dataset contains 100 retinal fundus images, each with a corresponding binary ground truth mask where vessel pixels are labeled as 1 and background pixels as 0. The dataset is divided into 80 images for training and 20 images for testing. The images show variations in vessel width, branching patterns, and contrast, reflecting real-world retinal imaging conditions.

This dataset enables the development and evaluation of deep learning-based segmentation models using standard performance metrics .[3].

3. Image Processing and Preprocessing

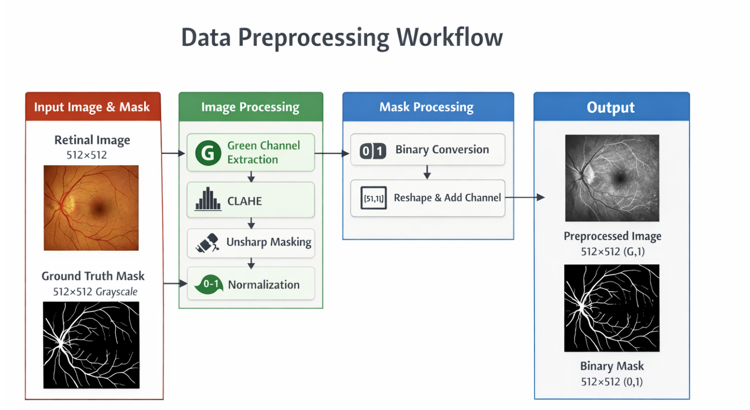


Fig. 1. Processing Workflow.

In this project, several image processing techniques were applied to enhance retinal blood vessels and improve segmentation performance. Initially, the retinal fundus images were converted from BGR to RGB color space. The green channel was then extracted, as it provides the highest contrast between blood vessels and the background in retinal images.2

To further enhance vessel visibility, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to the green channel in order to improve local contrast and reduce illumination variations. After that, an unsharp masking technique was used by combining the enhanced image with a blurred version to sharpen vessel edges and highlight fine vascular structures.

The processed images were subsequently normalized to the range [0, 1] to ensure numerical stability during model training. A channel dimension was added to match the input requirements of the segmentation model.

For the ground truth masks, binary preprocessing was applied by converting all non-zero pixel values to 1, representing vessel regions, while background pixels were set to 0. The mask dimensions were also expanded to maintain consistency with the model input format.

These processing steps directly implemented in the code help improve thin blood vessels, reduce noise, and prepare the data in a suitable form for accurate segmentation of the retinal blood vessels.3

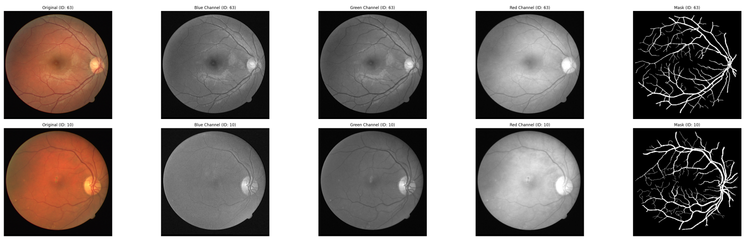


Fig. 2. Enhanced green channel of a retinal fundus image showing blood vessels.

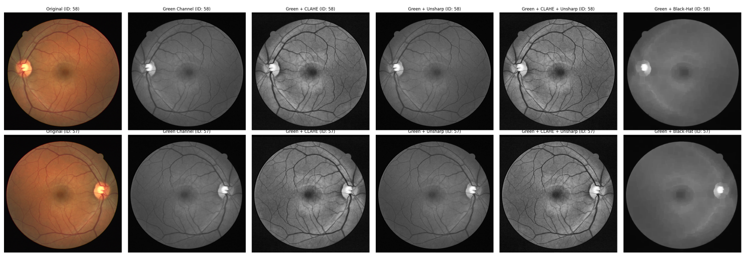


Fig. 3. Visualization of Retinal Image Preprocessing Techniques.

4. Data Generator and Data Preparation

In this work, a data generator was implemented to efficiently load and preprocess retinal images and their corresponding ground truth masks during training. Since the images are high resolution (512×512), loading the entire dataset into memory at once is not memory efficient. Therefore, the generator feeds the model with data in batches.

For each batch, the generator reads the input images and their corresponding segmentation masks, applies the required preprocessing steps, and then yields them to the model. These preprocessing steps include resizing the images to a fixed input size, converting them to single-channel (green channel), and normalizing pixel intensity values to a suitable range for neural network training.

The generator ensures that each input image is always correctly aligned with its corresponding mask, which is critical for segmentation tasks. This approach allows the model to be trained efficiently while maintaining low memory usage and stable training performance.

5. Model Architecture

In this project, a U-Net based deep learning architecture was employed for retinal blood vessel segmentation. U-Net is a fully convolutional network specifically designed for biomedical image segmentation tasks, where precise localization of fine structures such as blood vessels is required.

The network consists of three main parts: an encoder, a bottleneck, and a decoder. The encoder path is responsible for extracting hierarchical features from the input retinal images through a series of convolutional layers followed by max-pooling operations. Each encoder block contains two convolutional layers with ReLU activation functions, allowing the model to learn increasingly complex feature representations at different spatial resolutions.

At the deepest level of the network, a bottleneck block with a higher number of convolutional filters is used to capture rich semantic information from the input image. This stage represents the most abstract representation of the retinal structures.

The decoder path performs up-sampling operations to gradually restore the spatial resolution of the feature maps. After each up-sampling step, skip connections are applied by concatenating the corresponding feature maps from the encoder path. These skip connections play a crucial role in preserving spatial details that may be lost during down-sampling, which is especially important for accurately segmenting thin and elongated blood vessels.

The final output layer consists of a 1×1 convolution followed by a sigmoid activation function, producing a binary segmentation mask where each pixel represents the probability of belonging to a blood vessel. The input and output images have the same spatial dimensions, enabling pixel-wise classification.

Overall, the U-Net architecture provides an effective balance between global contextual understanding and precise localization, making it well-suited for retinal blood vessel segmentation tasks.6

6. Training Process

The training process was conducted using the prepared retinal image dataset and the implemented data generator. The model was trained in a supervised manner, where each input image was paired with its corresponding ground truth vessel mask.

The Adam optimizer was used for training with a learning rate of 1e-4, as it provides stable convergence and adaptive learning rate adjustment. The model

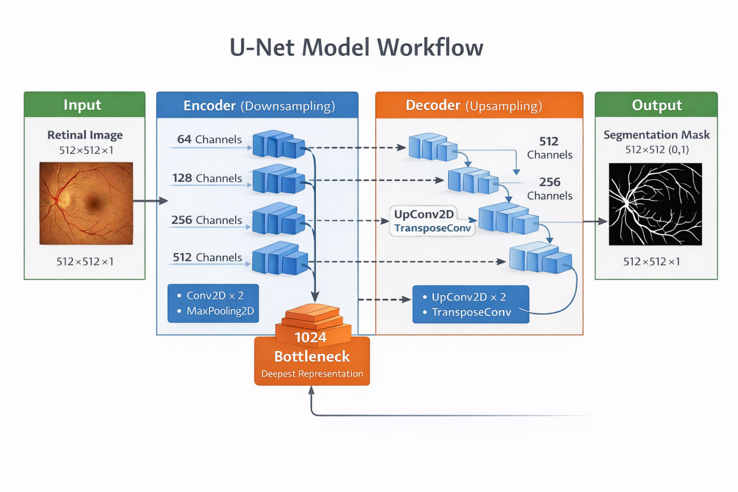


Fig. 4. Model Workflow.

was trained for 100 epochs to ensure sufficient learning and convergence of the segmentation network.

To address the class imbalance between retinal blood vessels and background pixels, Focal Tversky Loss was employed as the loss function. This loss function emphasizes hard-to-segment pixels and reduces false negatives, which is particularly important for accurately detecting thin blood vessels.

During training, Dice coefficient, Intersection over Union (IoU), and accuracy were used as evaluation metrics. These metrics provide a more reliable assessment of segmentation performance compared to accuracy alone.

Validation data was used alongside training data to monitor the model's performance and prevent overfitting. ModelCheckpoint was applied to save the best-performing model based on the validation Dice coefficient. In addition, ReduceLROnPlateau was used to dynamically reduce the learning rate when the validation performance stopped improving, which helped enhance model convergence and stability.

Overall, this training strategy ensured efficient learning, improved generalization, and robust segmentation performance.

7. Results and Evaluation

The performance of the proposed U-Net model for retinal blood vessel segmentation was evaluated using quantitative metrics, training and validation curves, classification measures, and visual analysis. The evaluation was conducted on the validation and test datasets to assess the model's segmentation accuracy and generalization capability.

The final training and validation results demonstrate stable convergence and strong performance. The model achieved a training accuracy of 96.44 and a validation accuracy of 96.98, indicating consistent learning behavior. The Dice coefficient reached 0.8658 for training and 0.8842 for validation, reflecting a high overlap between the predicted vessel masks and the ground truth annotations. Similarly, the Intersection over Union (IoU) achieved values of 0.7636 and 0.7926 for training and validation, respectively. The validation loss (0.1711) was slightly lower than the training loss (0.1888), suggesting good generalization and no significant overfitting.

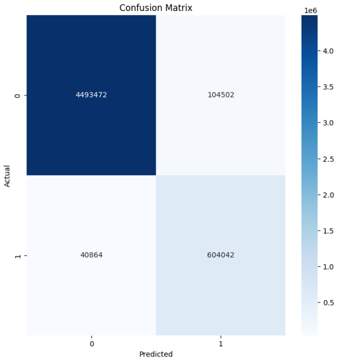
Further evaluation using classification metrics confirmed the robustness of the model. The model achieved a precision of 0.8525, a recall of 0.9366, and an F1-score of 0.8926. The high recall value indicates that the model successfully detected most retinal blood vessel pixels, which is particularly important in medical image segmentation tasks where missing vessel structures can negatively affect diagnosis. The Area Under the ROC Curve (AUC) reached 0.9853, demonstrating excellent discrimination capability between vessel and background pixels.

Training history analysis further supports these findings. The accuracy curves show rapid improvement during the early epochs followed by stable convergence, while the loss curves exhibit a consistent decrease for both training and validation sets. The Dice coefficient and IoU curves steadily increase over epochs and converge to high values, with close alignment between training and validation curves. This behavior confirms stable training dynamics and effective model convergence without overfitting.

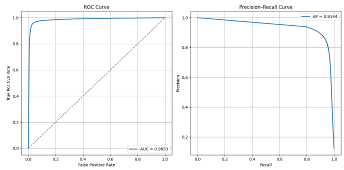
Additional analysis using ROC and Precision–Recall curves further validates the model's performance. The ROC curve shows a high true positive rate at low false positive rates, with an AUC of 0.9853. The Precision–Recall curve achieved an Average Precision (AP) score of 0.9144, indicating a strong balance between precision and recall despite the inherent class imbalance between vessel and background pixels.

Qualitative evaluation was performed by visually comparing the predicted segmentation masks with the corresponding ground truth masks. The visual results demonstrate that the model accurately segments both major and thin retinal blood vessels with clear boundaries and minimal noise, further confirming the effectiveness of the proposed approach.

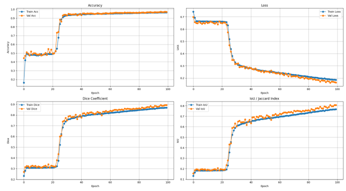
Overall, the obtained results demonstrate that the implemented U-Net model, combined with Focal Tversky Loss and an effective training strategy, provides accurate and robust retinal blood vessel segmentation, making it suitable for medical image analysis applications.



(a) Confusion Matrix



(b) ROC and PR Curve



(c) acc curve , dio , iou , loss

Fig. 5. Different stages of retinal blood vessel segmentation.

Table 1. Training and Validation Performance

Metric	**Training**	**Validation**
Accuracy	0.9649	0.9713
Loss	0.1862	0.1646
Dice Coefficient	0.8679	0.8929
IoU	0.7669	0.8066

Table 2. Evaluation Metrics on Test Dataset

Metric	**Value**
Precision	0.8525
Recall	0.9366
F1-score	0.8926
AUC	0.9853

8. Conclusion

This project presented a U-Net–based deep learning approach for retinal blood vessel segmentation. The model was trained using appropriate preprocessing and Focal Tversky Loss to handle class imbalance and improve the detection of thin vessels.

The proposed model achieved strong segmentation performance, as reflected by high Dice coefficient, IoU, and AUC values. Training and validation results showed stable convergence and good generalization without overfitting. Visual inspection further confirmed accurate segmentation of both major and fine retinal blood vessels.

Overall, the results demonstrate that the implemented approach is effective for retinal blood vessel segmentation and suitable for medical image analysis applications. Future work may focus on data augmentation and more advanced architectures to further enhance performance.

REFERENCES

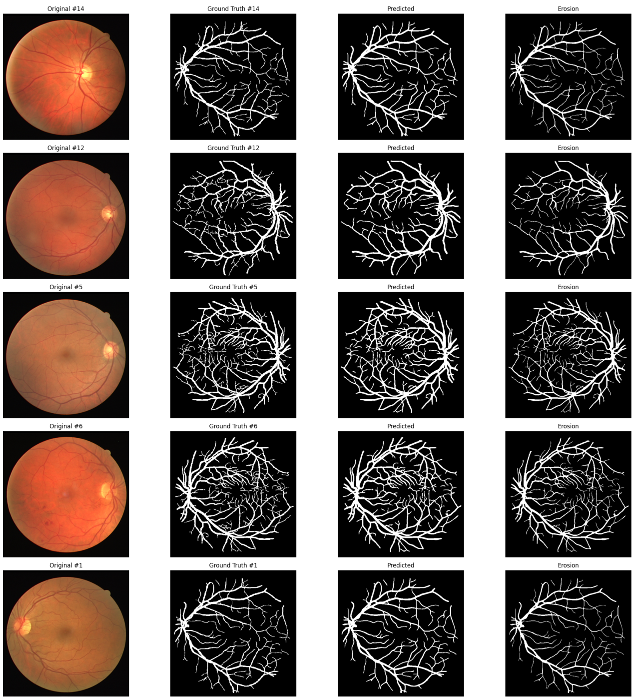


Fig. 6. Comparison of original retinal images, ground truth vessel masks, predicted segmentation, and erosion post-processing results.

1. R. Ren et al., “An improved U-Net based retinal vessel image segmentation,” *Journal of Biomedical Engineering and Medical Imaging*, 2022. Available: https://www.sciencedirect.com/science/article/pii/S2405844022024756 :contentReference[oaicite:0]index=0
2. C. Guo, M. Szemenyei, Y. Yi, W. Wang, B. Chen, and C. Fan, “SA-UNet: Spatial Attention U-Net for Retinal Vessel Segmentation,” *arXiv preprint arXiv:2004.03696*, 2020. Available: https://arxiv.org/pdf/2004.03696 :contentReference[oaicite:1]index=1
3. A. Wagih, “Retina Blood Vessel Segmentation Dataset,” *Kaggle*, 2020. Available: https://www.kaggle.com/datasets/abdallahwagih/retina-blood-vessel
4. R. Wael, “Retina-Blood-Vessel-Segmentation,” *GitHub Repository*, 2025. Available: https://github.com/Reemwael720/Retina-Blood-Vessel-Segmentation