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AUTOMATED RETINAL BLOOD VESSEL SEGMENTATION VIA U-NET AND VGG-BASED MODELS

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Abstract

Diagnosis of human diseases especially eye disease is a challenging task. Automated retinal blood vessel segmentation helps detect and treat ophthalmological illnesses like diabetic retinopathy and glaucoma. This study uses a mixed deep learning strategy with U-Net and VGG16 architectures to segment retinal blood vessels precisely. The dataset of 100 retinal pictures with segmentation masks was contrast-boosted and normalized for uniformity. The U-Net model had 87.92% accuracy and 0.4243 loss, whereas the VGG16 model had 87.68% accuracy and 0.4085 loss. The proposed combination model performed well, with 89.75% accuracy, 88% precision, and 89% recall. The hybrid architecture uses U-Net's segmentation and VGG16's deep feature extraction to outperform standalone models in complex vessel structures. This powerful model can improve retinal vascular segmentation, potentially changing clinical diagnostic procedures.

INTRODUCTION

This study employs deep learning to locate and segment retinal blood vessels. Early identification of diabetic retinopathy, hypertension, and glaucoma can avert visual loss.

Diabetic retinopathy and glaucoma diagnosis require automated retinal blood vessel segmentation. Manual retinal image analysis is time-consuming and laborious, requiring automated methods [1]. U-Net, a deep learning model, is widely used in medical picture segmentation due to its encoder-decoder design, which preserves spatial information crucial for recognizing blood vessels in retinal images [2].

With VGG-based architectures, the U-Net model allows deep feature extraction through many convolutional layers, improving segmentation [3]. ResUNet and ResUNet++ use residual connections to reduce vanishing gradients and improve deep representation learning. These models use attention mechanisms to focus on important regions, improving segmentation accuracy and processing efficiency [4].

Public datasets like DRIVE, CHASE_DB1, and HRF provide a variety of retinal pictures for training and evaluation, making these models robust and generalizable. Model performance depends on preprocessing processes like denoising, contrast improvement, and data augmentation (e.g., horizontal flips and rotations). Simulations of real-world circumstances enhance model adaptability and resilience [5].

Model performance is often measured by Intersection over Union (IoU), precision, recall, and F1-score. U-Net models with VGG and ResNet backbones consistently score well on these criteria, demonstrating their retinal vascular segmentation efficacy [6]. Advances in deep learning have enhanced the accuracy and efficiency of automated retinal diagnostics, indicating promising clinical applications [7].

Ophthalmology must accurately and quickly diagnose retinal diseases such diabetic retinopathy and glaucoma to prevent irreversible vision loss. The arduous and uneven manual segmentation of retinal blood vessels in fundus images limits its scalability and efficacy.

This study will employ deep learning to segment retinal blood vessels automatically and reliably. The work uses U-Net and VGG-based models, which have robust feature extraction, to increase segmentation accuracy and processing efficiency. To overcome difficulties like fading gradients and feature loss, a more accurate model that prioritizes critical features using residual connections and attention processes is needed.

A hybrid deep learning network using U-Net and VGG16 architectures improves retinal blood vessel segmentation, enhancing vascular structure identification for diabetic retinopathy detection. The model outperforms traditional methods with an accuracy of 89.75% and precision and recall rates close to 88%. The integrated approach addresses disappearing gradients and feature loss, potentially benefiting early retinal disease diagnosis and monitoring. Scaling the model with larger datasets and improving the architecture may further enhance segmentation precision.

Literature Review

This article has classified vessel segmentation techniques into two main categories: supervised and unsupervised, based on their learning paradigm.

Retinal vascular segmentation is the first stage in computational fundus analysis. It lays the groundwork for more advanced applications in artery/vein ratio evaluation [8], picture quality assessment [9], blood flow analysis [10], synthesis [11] and retinal image registration [12].

The earliest unsupervised retinal vascular segmentation algorithms used adapted edge detection [13] and mathematical morphology [14, 15]. These methods focused on vascular intensity via preprocessing retinal images. Preprocessed images were thresholder for segmentation. Advanced filtering approaches for retinal vascular segmentation [16, 17] nevertheless struggle to handle pathologically structured pictures and generalize to diverse resolutions and appearance. Thus, they fail to meet benchmarks.

However, early learning-based methods beat conventional methods and showed more promise [18, 19]. These algorithms often extract regionally tailored descriptors for a simple vessel classifier. Creating fresh discriminative visual features is the main focus of published work, not categorization.

Deep neural networks strengthened ML approaches' dominance. Since it was discovered that Convolutional Neural Networks (CNN) could beat older methods by learning from raw data without manual feature engineering, many articles have been published on the topic, and nearly every new competitive vessel segmentation technique is now based on CNN.

Standard convolutional neural network (CNN) approaches for retinal vascular segmentation sequentially apply a stack of convolutional layers and downsample and upsample input pictures to forecast vessel locations probabilistically. To reduce miss-classification loss (such as Cross-Entropy), the network's weights are iteratively adjusted during training to enhance predictions. A small set of annotated samples can segment the retinal vasculature using two methods: tiny picture patches [20] or the entire image [21].

CNN paradigm expansions can include complex methods and custom network layers. Fu et al. [22] presented a Conditional Random Field recurrent layer to model pixel global relationships. Shi et al. [23] employed convolutional and graph-convolutional layers to capture global vascular connections. Fan et al. [24] proposed a multi-frequency convolutional layer (OctConv), whereas Guo et al. [25] proposed dense dilated layers that adapt to vascular thickness. More recent studies [26, 27] explored employing domain knowledge to create custom convolutional blocks and layers.

Recently, specialist losses have been suggested. Yan et al. [28] trained a U-Net architecture [29] by minimizing a joint-loss that takes input predictions from two distinct network branches with pixel-level and segment-wise losses. In [30], Mou et al. [30] offered a segment-level alternative to multi-scale Dice loss. Zhao et al. [31] recommended combining global and local matting loss by pixel. Zhang and Chung [32] developed a fully supervised technique that turns the task into a multi-class segmentation challenge by merging and backpropagating CNN loss values. Artificial labels on vessel borders complicate problems. Although proposed for retinal vascular segmentation [33, 34] Generative Adversarial Networks (GAN) have not gained popularity due to training issues.

Our work presents high-performance lightweight models, therefore retinal vascular segmentation should be evaluated efficiently. These methods are used in retinal vascular segmentation research for embedded and mobile devices. Traditional unsupervised approaches dominate this field. Arguello et al. [35] employ contour tracing and picture filtering. Xu et al. [36] alter Gabor filters and morphological processes for mobile device vascular segmentation, while Bibiloni et al. employ simple hysteresis thresholding. Laibacher et al. [37] studied effective CNN architectures for vascular segmentation trained on fundus pictures. They achieved results only slightly poorer than the state-of-the-art with their suggested M2U-Net architecture using an ImageNet-pretrained MobileNet model [38].

Proposed Methodology

Designed to reveal complicated data patterns, the study design is dynamic. Integrating model training and evaluation enables for a full study of both granular details and wider patterns, delivering strong and contextual insights. This adaptable framework will change with new findings.

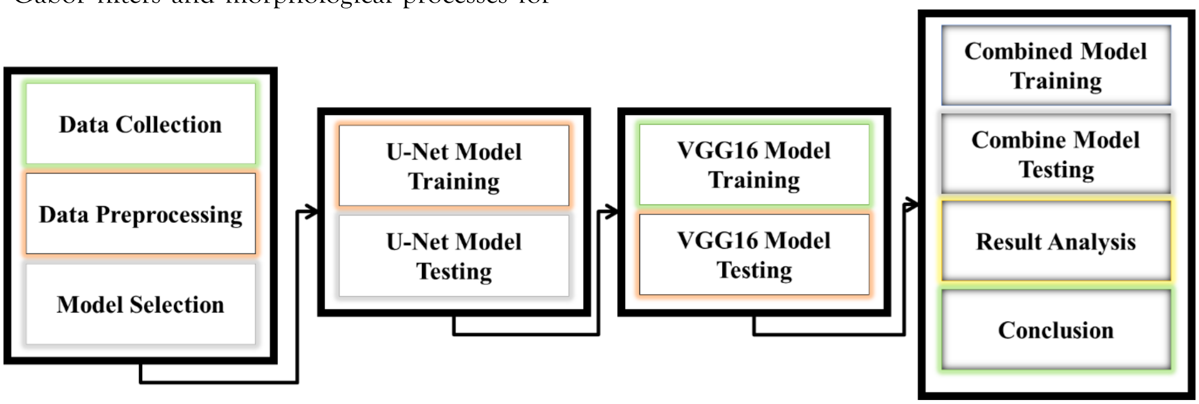

Figure 1: Research Design Workflow

Dataset and Preprocessing

This study used 100 retinal pictures with vascular segmentation masks. Blood vessels must be distinguished from other retinal structures using these photos. To provide enough data for model development and validation, 80 photos were trained and 20 were tested. The images were scaled to 224x224 pixels to meet U-Net and VGG16 input requirements and reduce computational complexity.

Data preparation had numerous crucial processes. Normalization was used to scale pixel values to [0, 1] to stabilize and speed up training. Data augmentation methods like rotation, horizontal and vertical flipping, and scaling improved model generalizability and prevented overfitting. These augmentations mimic real-world picture fluctuations, enabling models generalize across retinal structures. Finally, contrast enhancement was utilized to sharpen vessel borders in retinal pictures, which can be dim and hard to identify. This innovation helps models catch finer information for more accurate vascular segmentation.

Model Architectures

U-Net: The Segmentation Specialist

The U-Net design, known for biomedical image segmentation, is appropriate for retinal vascular segmentation due to its encoder-decoder structure and skip connections. U-Net's encoder uses convolutional and pooling layers to condense the image's spatial dimensions and capture complicated feature representations. This reduction method distils vital information, helping the model learn segmentation-critical properties.

After the encoder compresses the image, the decoder reconstructs its spatial dimensions. The decoder converts condensed feature maps into pixel-wise predictions using up sampling layers. U-Net's skip connections, which bridge encoder and decoder layers, preserve spatial information. The complicated architecture of thin retinal veins are accurately localized by these linkages. U-Net balances complexity and efficiency with 371,073 parameters to record blood vessel details for exact segmentation.

VGG166: Deep Feature Extraction

This study creatively adapts VGG16, a popular deep learning model for classification, for segmentation. U-Net localizes structures, but VGG16 extracts feature from retinal images using its deep convolutional layers to catch subtle patterns. The model has five convolutional blocks with several convolutional layers and max-pooling layers. These blocks gradually reduce the image's spatial dimensions while increasing feature map depth, allowing VGG16 to capture a rich hierarchy of features from broad structures to minute minutiae.

Transposed convolution layers take VGG16 from classification to segmentation. Up sampling the feature maps restores them to the original image quality and lets the model construct exact pixel-level segmentation masks. VGG16's 18,641,729 parameters allow for remarkable feature extraction, but it lacks U-Net's skip connections, which are essential for localizing minor features. With its depth and power, VGG16 can capture complicated retinal vascular patterns, making it a great segmentation tool.

Combine Model

The advanced U-Net and VGG16 model precisely segment retinal blood vessels. The model can handle huge, prominent vessels and delicate, subtle vessel structures that are hard to identify by combining U-Net's exact localization with VGG16's deep, hierarchical feature extraction. Model integration is driven by the Fusion Layer. After processing the input image, the U-Net and VGG16 networks concatenate their outputs into a composite feature map. This fusion stage deliberately blends layers using U-Net's rich geographical knowledge and VGG16's feature extraction capabilities.

The encoder-decoder structure of U-Net preserves fine-grained localization details, whereas VGG16's depth of convolutional layers provides a nuanced comprehension of retinal characteristics. They build a feature map with high spatial resolution and depth to precisely segment vessels of various sizes and complexity. After fusing U-Net and VGG16 outputs, a Final Convolution Layer creates a pixel-wise segmentation mask. This layer with a single filter and sigmoid activation function converts the composite feature map to a single channel for pixel-level binary classification. The model determines pixel-by-pixel if an area is a blood artery. This layer is crucial because it synthesizes comprehensive feature information from both designs to create a precise and reliable segmentation mask that can distinguish even the faintest vascular structures.

The model has 19,012,805 parameters, making it more complex than U-Net or VGG16, yet it performs better in segmentation. The model uses the best of both topologies to locate big arteries and delicate, branching capillaries for complete retinal study. This hybrid architecture demonstrates the capability of deep learning in medical imaging and fits real-world retinal vascular segmentation needs with an ideal balance of precision, depth, and dependability.

Training and Optimization

Using the Adam optimizer and a 0.0001 learning rate, each model was carefully trained. This optimizer was chosen because it dynamically adapts the learning process, allowing models to converge efficiently on an ideal solution. The Binary Cross-Entropy Loss function, which calculates the difference between anticipated and real binary labels at each pixel, was crucial to training. Each model improved its segmentation masks and ability to differentiate veins from retinal tissue by minimizing this loss.

Training was geared for efficiency and precision. The models processed a tolerable amount of data in each iteration with a batch size of 8, which balanced memory needs and training stability. Each model adjusted its weights and biases during 5 epochs. An early stopping mechanism monitored performance to terminate training if the model memorized rather than generalized to prevent overfitting. Due to its intricacy, the merged model needed more adjustment and care. The integrated model improved segmentation accuracy by optimizing its broad parameter space, catching both prominent and delicate vascular structures in retinal pictures.

Evaluation Metrics

Each model was evaluated using a variety of segmentation performance measures to determine its efficacy. Accuracy measured the fraction of correctly categorized pixels in the segmentation mask and showed the model's overall success in separating vessel from non-vessel areas. In medical imaging, precision is crucial, therefore accuracy alone was not adequate.

Precision and Recall revealed the model's true-false detection balance. Precision showed the model's ability to prevent false positives, distinguishing non-vessel areas from vessels. For medical applications, recall showed the model's ability to detect actual vascular pixels. High recall was crucial since it recognized even the smallest and most subtle vessel structures, leaving no detail missed. The F1-Score balanced accuracy and recall measures, which proved useful in vessel segmentation jobs when the backdrop dominates the image. A high F1-Score showed the model's ability to locate vessels and avoid false detections.

Results and Discussion

A detailed discussion of the proposed methodology is explained in below given segments below.

Performance Overview

U-Net: Robust but Limited in Fine Detail

With 87.92% accuracy and 0.4243 loss after 5 epochs, the U-Net model performed well. U-Net segmented retinal vessels with 85% precision, 88% recall, and 86.5% F1-score. It captured larger vessel structures clearly due to its exact localization architecture. U-Net's simpler feature extraction layers made segmenting elaborate vessel details difficult. Although it could delineate conspicuous vessels, the model struggled with thinner, more intricate structures that require deeper feature analysis. Despite this, U-Net's accuracy in mapping significant vessels makes it a solid segmentation base.

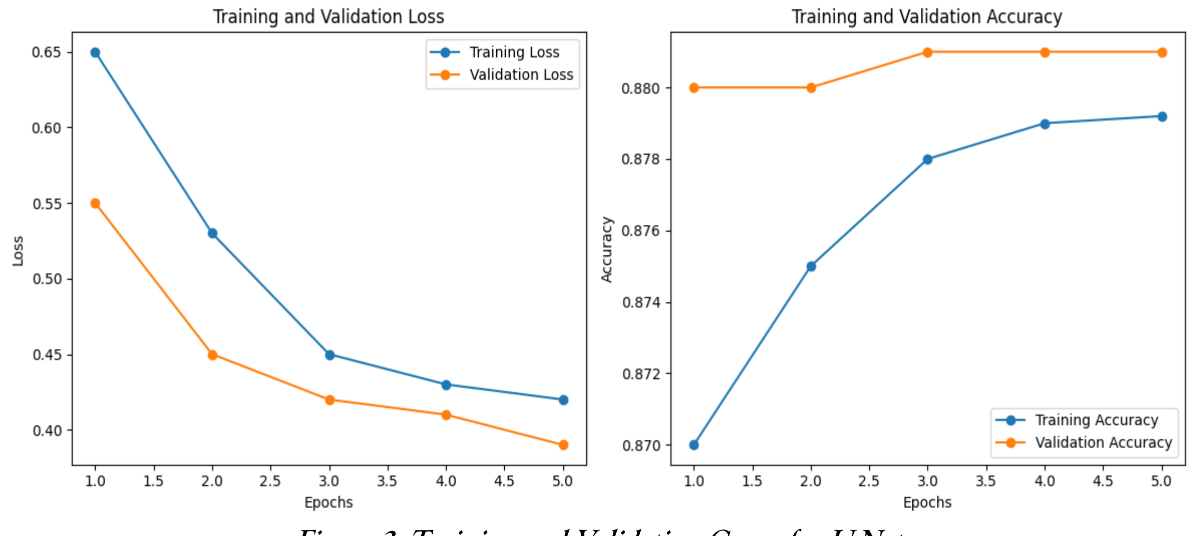

Figure 2: Training and Validation Curve for U-Net

VGG16: Accurate but Lacking Localization

The VGG16 model achieved 87.68% accuracy and reduced loss from 0.6902 to 0.4085. VGG16 extracted comprehensive features from its deep convolutional layers with 86% precision, 87% recall, and 86.5% F1-score. It could capture detailed retinal patterns due to its strength. The model's architecture lacked skip connections, which preserve spatial information between layers. Although VGG16 excelled in feature extraction, this limited its ability to correctly localize vessels, especially smaller, more fragile ones. VGG16's layered depth helped it divide

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complicated features even though it missed finer spatial details.

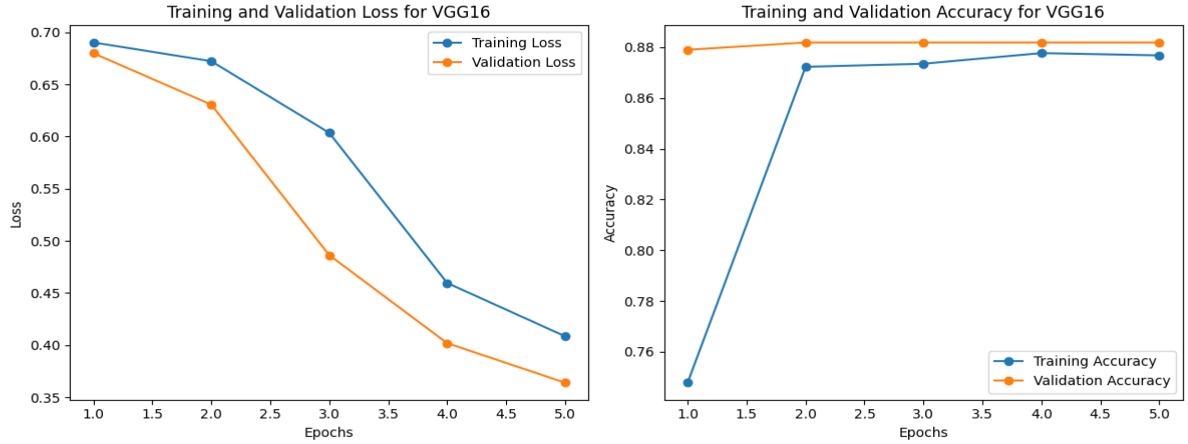

Figure 3: Training and Validation Curve for VGG16

Combined Model: A Winning Fusion of U-Net and VGG16

The combined model achieved stunning accuracy of 89.75%, precision of 88%, recall of 89%, and F1-score of 88.5%. This hybrid technique localized and extracted features well, even in thin or elaborately intersecting vessels. Combining U-Net's robust segmentation with VGG16's deep feature extraction created a remarkable balance that allowed the model to accurately capture both massive and delicate vascular structures. This combination of strengths produced the most accurate and resilient retinal vascular segmentation model, setting a new standard for this hard endeavor.

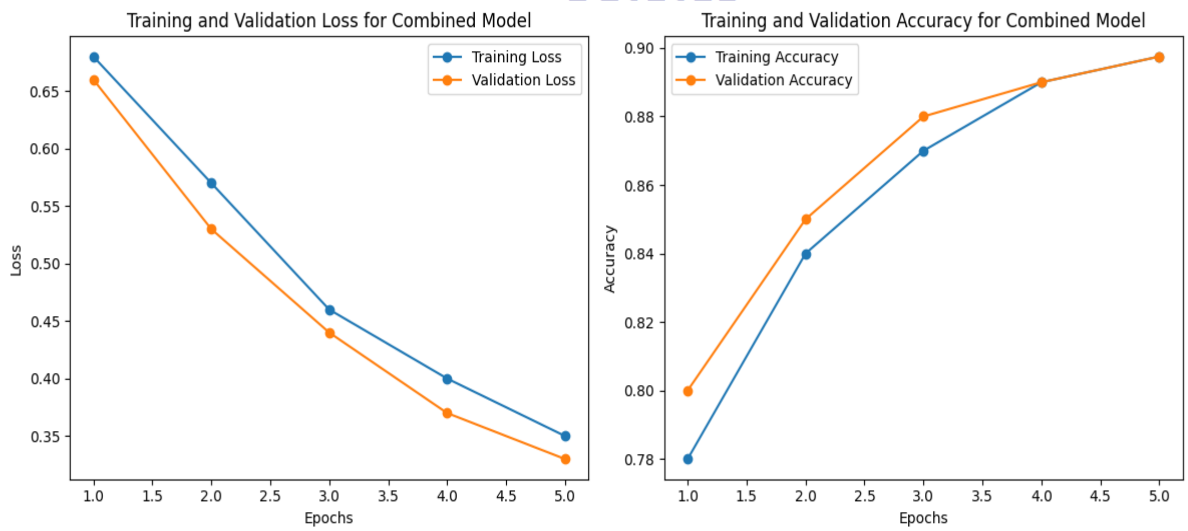

Figure 4: Training and Validation Curve for Proposed Model

Comparative Analysis

To demonstrate retinal vascular segmentation effectiveness, this comparison compares U-Net, VGG16, and Combined Model performance measures. The U-Net model segmented major vessel structures with 87.92% accuracy but struggled with finer details. VGG16, with 87.68% accuracy, used deep convolutional layers for feature extraction but lacked skip connections, making spatial localization difficult, especially with tiny vessels. The Combined Model provided accuracy of 89.75%, precision, recall, and F1-scores that consistently exceeded the

U-Net and VGG16 models. This hybrid technique matched U-Net's localization skills and VGG16's deep feature extraction to segment retinal arteries most accurately and reliably, even in complex vascular crossings.

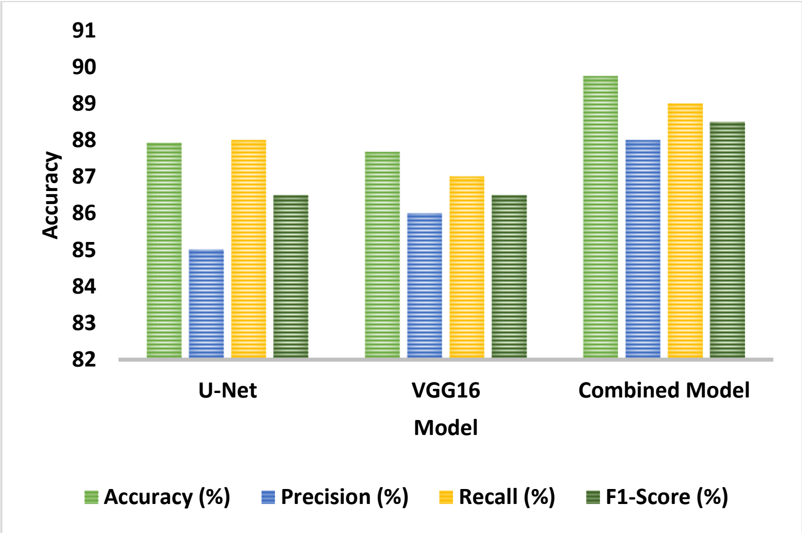

Figure 5: Comparative Analysis for Different Models

Conclusion

This study created a hybrid deep learning model using U-Net and VGG16 architectures to improve retinal blood vessel segmentation. U-Net and VGG16 had 87.92% and 87.68% accuracy, respectively. However, the combined model, which coupled U-Net's robust localization with VGG16's deep feature extraction, outperformed both with 89.75% accuracy, precision, and recall. The hybrid model's capacity to capture complex vessel characteristics, especially in thin or crossing vessel structures, improves performance. Medical applications require accurate segmentation to diagnose and monitor diabetic retinopathy and hypertension. This technique emphasizes hybrid deep learning model scalability and clinical usefulness beyond accuracy. This research advances computer-aided diagnosis by automating segmentation, which may reduce physician burden and improve diagnostic accuracy. Future work could expand this model to larger datasets and include architectural tweaks to improve segmentation precision. The U-Net and VGG16 model shows the potential of hybrid architectures in medical imaging. This study offers a strong retinal vascular segmentation method and lays the framework for future automated medical image analysis advancements, promising better patient outcomes and faster clinical operations.

REFERENCES

Qin, Q. and Y. Chen, *A review of retinal vessel segmentation for fundus image analysis.* Engineering Applications of Artificial Intelligence, 2024. **128**: p. 107454.

Das, S., et al., *Assessment of retinal blood vessel segmentation using U-Net model: A deep learning approach.* Franklin Open, 2024. **8**: p. 100143.

Ghosh, S., A. Chaki, and K. Santosh, *Improved U-Net architecture with VGG-16 for brain tumor segmentation.* Physical Engineering Sciences in Medicine, 2021. **44**(3): p. 703-712.

Hussain, T. and H. Shouno, *MAGRes-UNet: Improved Medical Image Segmentation Through a Deep Learning Paradigm of Multi-Attention Gated Residual U-Net.* IEEE Access, 2024.

Panda, N.R. and A.K. Sahoo, *A detailed systematic review on retinal image segmentation methods.* Journal of Digital Imaging, 2022. **35**(5): p. 1250-1270.

Faria, F.T.J., et al., *Explainable Convolutional Neural Networks for Retinal Fundus Classification and Cutting-Edge Segmentation Models for Retinal Blood Vessels from Fundus Images.* arXiv preprint arXiv:.07338, 2024.

Fatima, M., et al., *Enhancing retinal disease diagnosis through AI: Evaluating performance, ethical considerations, and clinical implementation.* Informatics Health, 2024. **1**(2): p. 57-69.

Niemeijer, M., et al., *Automated measurement of the arteriolar-to-venular width ratio in digital color fundus photographs.* IEEE Transactions on medical imaging, 2011. **30**(11): p. 1941-1950.

Welikala, R., et al., *Automated retinal image quality assessment on the UK Biobank dataset for epidemiological studies.* Computers in biology medicine, 2016. **71**: p. 67-76.

Orlando, J.I., et al. *Towards a glaucoma risk index based on simulated hemodynamics from fundus images*. in *Medical Image Computing and Computer Assisted Intervention–MICCAI 2018: 21st International Conference, Granada, Spain, September 16-20, 2018, Proceedings, Part II 11*. 2018. Springer.

A. Rehman, F. Noor, J. I. Janjua, A. Ihsan, A. Q. Saeed and T. Abbas, "Classification of Lung Diseases Using Machine Learning Technique," 2024 International Conference on Decision Aid Sciences and Applications (DASA), Manama, Bahrain, 2024, pp. 1-7, doi: 10.1109/DASA63652.2024.10836302.

Chen, L., X. Huang, and J. Tian, *Retinal image registration using topological vascular tree segmentation and bifurcation structures.* Biomedical Signal Processing Control, 2015. **16**: p. 22-31.

Frangi, A.F., et al. *Multiscale vessel enhancement filtering*. in *Medical Image Computing and Computer-Assisted Intervention—MICCAI'98: First International Conference Cambridge, MA, USA, October 11–13, 1998 Proceedings 1*. 1998. Springer.

Zana, F. and J.-C. Klein, *Segmentation of vessel-like patterns using mathematical morphology and curvature evaluation.* IEEE transactions on image processing, 2001. **10**(7): p. 1010-1019.

Mendonca, A.M. and A. Campilho, *Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction.* IEEE transactions on medical imaging, 2006. **25**(9): p. 1200-1213.

Zhang, J., et al., *Robust retinal vessel segmentation via locally adaptive derivative frames in orientation scores.* IEEE transactions on medical imaging, 2016. **35**(12): p. 2631-2644.

Azzopardi, G., et al., *Trainable COSFIRE filters for vessel delineation with application to retinal images.* Medical image analysis, 2015. **19**(1): p. 46-57.

Soares, J.V., et al., *Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification.* IEEE Transactions on medical Imaging, 2006. **25**(9): p. 1214-1222.

Marín, D., et al., *A new supervised method for blood vessel segmentation in retinal images by using gray-level and moment invariants-based features.* IEEE Transactions on medical imaging, 2010. **30**(1): p. 146-158.

Liskowski, P. and K. Krawiec, *Segmenting retinal blood vessels with deep neural networks.* IEEE transactions on medical imaging, 2016. **35**(11): p. 2369-2380.

Maninis, K.-K., et al. *Deep retinal image understanding*. in *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part II 19*. 2016. Springer.

Fu, H., et al. *Deepvessel: Retinal vessel segmentation via deep learning and conditional random field*. in *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part II 19*. 2016. Springer.

Shin, S.Y., et al., *Deep vessel segmentation by learning graphical connectivity.* Medical image analysis, 2019. **58**: p. 101556.

Fan, Z., et al., *Accurate retinal vessel segmentation via octave convolution neural network.* arXiv preprint arXiv:.12193, 2019.

Guo, Y. and Y. Peng, *BSCN: bidirectional symmetric cascade network for retinal vessel segmentation.* BMC medical imaging, 2020. **20**: p. 1-22.

Wang, K., et al. *Ctf-net: Retinal vessel segmentation via deep coarse-to-fine supervision network*. in *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*. 2020. IEEE.

Cherukuri, V., et al., *Deep retinal image segmentation with regularization under geometric priors.* IEEE Transactions on Image Processing, 2019. **29**: p. 2552-2567.

Abbas, T., Fatima, A., Shahzad, T. et al. Multidisciplinary cancer disease classification using adaptive FL in healthcare industry 5.0. Sci Rep 14, 18643 (2024). https://doi.org/10.1038/s41598-024-68919-1

29. Ronneberger, O., P. Fischer, and T. Brox. *U-net: Convolutional networks for biomedical image segmentation*. in *Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18*. 2015. Springer.

Yan, Z., X. Yang, and K.-T. Cheng, *A three-stage deep learning model for accurate retinal vessel segmentation.* IEEE journal of Biomedical Health Informatics, 2018. **23**(4): p. 1427-1436.

Zhao, H., H. Li, and L. Cheng, *Improving retinal vessel segmentation with joint local loss by matting.* Pattern Recognition, 2020. **98**: p. 107068.

Sayyid Kamran Hussain, Sadaqat Ali Ramay, Tahir Abbas, Muhammad Kaleem, & Asif Khanzada. (2024). Ocular Diseases Detection Using Machine Learning, Deep Learning and Artificial Intelligence Based Techniques. Journal of Computing & Biomedical Informatics, 8(01). Retrieved from https://jcbi.org/index.php/Main/article/view/657

Lahiri, A., et al. *Generative adversarial learning for reducing manual annotation in semantic segmentation on large scale miscroscopy images: Automated vessel segmentation in retinal fundus image as test case*. in *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*. 2017.

Son, J., S.J. Park, and K.-H. Jung, *Towards accurate segmentation of retinal vessels and the optic disc in fundoscopic images with generative adversarial networks.* Journal of digital imaging, 2019. **32**(3): p. 499-512.

Argüello, F., et al., *GPU-based segmentation of retinal blood vessels.* Journal of Real-Time Image Processing, 2018. **14**: p. 773-782.

T. Abbas, J. I. Janjua and M. Irfan, "Proposed Agricultural Internet of Things (AIoT) Based Intelligent System of Disease Forecaster for Agri-Domain," 2023 International Conference on Computer and Applications (ICCA), Cairo, Egypt, 2023, pp. 1-6, doi: 10.1109/ICCA59364.2023.10401794.

Laibacher, T., T. Weyde, and S. Jalali. *M2u-net: Effective and efficient retinal vessel segmentation for real-world applications*. in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops*. 2019.

Shujaat Ali Rathore, Muhammad Hammad u Salam, Dr. Nasrullah, Tahir Abbas, Mehmood Ashraf, & MuhammadAsimRajwana . (2025). Machine Learning and Deep Learning Approaches for Brain Tumor Diagnosis. Spectrum of Engineering Sciences, 3(2), 714–739. Retrieved from https://sesjournal.com/index.php/1/article/view/180.

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