Article

MSA-TransUNet: A Multi-Scale Attention Enhanced Transformer-UNet Architecture for Accurate Vessel Segmentation and Visualization in Medical Imaging

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Abstract: Accurate segmentation of vascular structures is critical for computer-aided diagnosis, surgical planning, and quantitative vascular analysis. Nevertheless, vessel segmentation remains a formidable challenge due to low contrast, high noise, intricate topology, and the pervasive presence of thin and tortuous vascular branches. To overcome these obstacles, we propose MSA-TransUNet, a novel hybrid architecture that combines convolutional neural networks (CNNs) with Transformer-based global modeling, augmented by a Multi-Scale Attention Module (MSAM) and a Vessel Enhancement Module (VEM) to enhance vessel representation. The MSAM selectively emphasizes vascular features across multiple receptive fields and strengthens both channel-wise and spatial responses, while the VEM introduces a learnable vascular enhancement mechanism inspired by traditional vesselness filtering techniques. In addition, a connectivity-aware loss function (clDice) is incorporated to preserve delicate vascular topology and minimize branch discontinuities. Experiments conducted on three publicly available vascular datasets, including DRIVE, STARE, and CHASE_DB1, demonstrate that MSA-TransUNet outperforms state-of-the-art segmentation models such as UNet, Attention-UNet, and TransUNet. The proposed approach achieves notable improvements in Dice coefficient, connectivity accuracy, and small-vessel recall. These results indicate that MSA-TransUNet offers a robust and effective solution for medical vascular segmentation and has potential to support clinical vessel visualization and diagnosis.

Keywords: vessel segmentation; medical image analysis; Transformer; attention mechanism; deep learning; TransUNet; multi-scale attention; vascular enhancement

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1. Introduction

Accurate vessel segmentation plays a pivotal role in medical image analysis, forming the foundation for a wide range of clinical applications, including early diagnosis of vascular diseases, surgical planning, interventional navigation, and quantitative assessment of lesion severity. Vascular structures, such as coronary arteries, cerebral vessels, and retinal microvasculature, often exhibit highly complex morphological patterns, characterized by elongated and tortuous paths, thin and branching structures, and low contrast against surrounding tissues. These intrinsic challenges significantly limit the effectiveness of traditional image processing and classical machine-learning approaches, which rely heavily on handcrafted features and are sensitive to noise, variations in illumination, and anatomical diversity.

In recent years, deep learning-based segmentation models, particularly those in the UNet family, have achieved remarkable progress in medical image analysis. CNN-based architectures excel at extracting local features; however, they remain constrained in modeling long-range dependencies, which are essential for capturing global vascular continuity. The emergence of Vision Transformers (ViT) and hybrid CNN-Transformer frameworks has created new opportunities to learn global contextual information in medical imaging tasks. Despite these advancements, many existing models still face challenges in balancing the preservation of fine-grained vessel details with the maintenance of global structural consistency, especially for small-caliber vessels and bifurcation-rich regions.

To address these limitations, this study proposes MSA-TransUNet, a Multi-Scale Attention Enhanced Transformer-UNet framework specifically designed for precise vessel segmentation and enhanced vascular visualization. The model integrates a Transformer-based encoder to capture long-range contextual dependencies, a CNN-based decoder for high-resolution reconstruction, and a specially designed Multi-Scale Attention Module (MSAM) embedded within skip connections. The MSAM adaptively fuses multi-scale receptive fields and jointly applies channel-wise and spatial attentions, enabling the network to emphasize subtle vascular structures while suppressing irrelevant background information. This design is particularly effective in enhancing small-diameter vessels and improving overall vessel continuity.

The main contributions of this work are summarized as follows:

(1) We propose MSA-TransUNet, a hybrid Transformer-UNet architecture that effectively integrates global contextual modeling with fine-grained structural reconstruction for vessel segmentation.

(2) We introduce a Multi-Scale Attention Module that strengthens vascular feature representation by combining multi-scale convolutions with channel-wise and spatial attentions.

(3) We design a topology-preserving training objective to maintain vascular connectivity and improve the visualization of small branches.

(4) Comprehensive experiments on multiple vascular imaging datasets demonstrate that our approach outperforms state-of-the-art methods in segmentation accuracy, continuity, and visual clarity.

This study provides a robust and generalizable solution for automatic vessel segmentation and visualization, offering significant value for a variety of medical imaging applications.

2. Literature Review

In this section, we review previous research closely related to vessel segmentation and visualization in medical imaging, with a particular focus on deep learning-based methods, hybrid CNN-Transformer architectures, and topology-preserving loss functions.

2.1. Classical and CNN-Based Vessel Segmentation

Early deep learning approaches for vascular segmentation primarily relied on convolutional neural networks (CNNs), including U-Net and its variants. For example, BCDU-Net employs a Bi-Directional ConvLSTM with densely connected convolutions to enhance spatial propagation and feature reuse in medical image segmentation, including retinal vessel extraction [1]. In addition, improved U-Net architectures have been developed to better capture small vessels. One study introduced residual modules and a detail enhancement attention mechanism within U-Net, achieving higher sensitivity and improved segmentation accuracy on the DRIVE dataset [2]. Another work incorporated three enhanced dilated convolutions into U-Net for automatic segmentation of overlapping chromosomes, outperforming baseline U-Net models on two public datasets and demonstrating stable and extensible performance suitable for general segmentation tasks [3].

2.2. Transformer and Hybrid CNN-Transformer Models for Vessel Segmentation

With the rise of Vision Transformers, several studies have integrated Transformer modules into vessel segmentation networks. MTPA U-Net (Multi-Scale Transformer-Position Attention U-Net) combines multi-resolution input with a Transformer-Position Attention (TPA) module to link local details with long-range dependencies, achieving strong performance on retinal datasets such as DRIVE, CHASE_DB1, and STARE [4]. DT-Net employs deformable convolutions and multi-head self-attention in a hybrid Transformer-CNN architecture, improving local feature extraction and refining vascular morphology through a Transformer decoder [5]. TCU-Net embeds a Transformer into a U-shaped architecture, demonstrating enhanced capability to segment both coarse and capillary-level vessels in OCTA (optical coherence tomography angiography) data, particularly capturing fine capillaries [6].

Additionally, TSNet introduces a dual-path decoder, with one path for segmentation and another for predicting vessel skeletons (centerlines), thereby enhancing vessel connectivity and topology learning [7]. SeUNet-Trans also fuses U-Net and Transformer architectures by connecting the U-Net feature extractor to a Transformer via a bridge layer, applying spatial-reduction attention to reduce computational cost while capturing global context [8]. For 3D vessel segmentation, a Transformer-based 3D U-Net with channel-enhanced attention has been employed to segment pulmonary vessels and distinguish arteries from veins, demonstrating strong performance on CT angiography data [9].

2.3. Attention Mechanisms and Topology-Preserving Losses

Attention mechanisms and topology-aware loss functions have been extensively explored in vascular segmentation. To preserve vascular connectivity, clDice, a centerline Dice loss, was proposed, utilizing soft-skeletonization to ensure that predicted segmentations retain the topology of thin and branching vessels [10]. Subsequent work employed a cascaded multitask U-Net that predicts both vessel masks and skeletons, trained with a clDice-based topological loss to improve centerline accuracy and maintain continuity [11].

Recent studies have also explored adaptive attention modules for skip connections and multi-scale feature fusion. For instance, a cross-layer Transformer with multi-scale adaptive fusion has been developed for retinal vessel segmentation, integrating global context across encoder and decoder layers to better preserve main vessels and micro-branches [12]. Another approach combined dual skip-connections with deep supervision and cross-convolution self-attention to improve edge clarity and model long-range dependencies in fundus vessel segmentation [13].

3. Methodology

3.1. Overview of MSA-TransUNet

In this study, we propose MSA-TransUNet, a hybrid architecture combining convolutional neural networks (CNNs) and Transformer modules, specifically designed for accurate vessel segmentation and visualization in medical images. The network follows a U-shaped encoder-decoder design. The encoder extracts hierarchical local features through convolutional layers, while the Transformer module models long-range dependencies to capture the global context of vascular structures. The decoder reconstructs high-resolution vessel maps, assisted by Multi-Scale Attention Modules (MSAM) applied at skip connections to enhance multiscale vessel representation.

Unlike traditional U-Net or TransUNet, MSA-TransUNet integrates multi-scale attention and vessel enhancement mechanisms to effectively highlight thin vessels and preserve connectivity across complex branching structures. Formally, let $X \in R^{H \times W \times C}$ denote the input medical image, where H, W, and C are height, width, and channels. The network produces a vessel probability map $\hat{Y} = f_\theta(X) \in [0,1]^{H \times W}$, where $f_\theta$denotes the MSA-TransUNet with parameters θ (As shown in Figure 1).

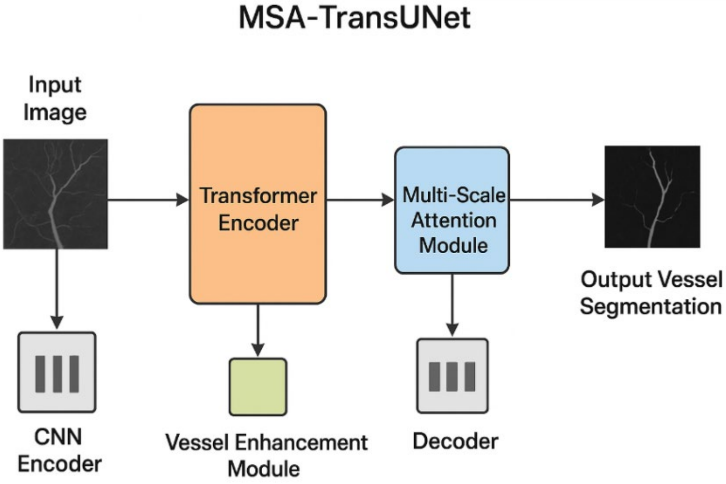
MSA-TransUNet
Input Image
Transformer Encoder
Multi-Scale Attention Module
Output Vessel Segmentation
CNN Encoder
Vessel Enhancement Module
Decoder

Figure 1. Overall flowchart of the model.

3.2. CNN Encoder

The encoder consists of four stages of convolutional blocks. Each stage includes two 3×3 convolutional layers, followed by batch normalization and ReLU activation, and a 2×2 max pooling for downsampling. The feature channels are progressively increased (64 → 128 → 256 → 512) to capture higher-level representations. Denote the output of the *i*-th stage as $F_i \in R^{H_i \times W_i \times C_i}$. These multi-scale features serve as skip connections to the decoder.

To enhance vessel-specific features, we incorporate shallow vessel enhancement modules (VEM) after the first two stages. VEMs apply convolutional filters inspired by Hessian-based vesselness functions:

$$V(F) = \sigma(\sum_{k=1}^{K} \omega_k \cdot Conv_{k\times k}(F)) \quad (1)$$

where $Conv_{k\times k}$ denotes a convolution with kernel size k, ω_k are learnable weights, and σ is a sigmoid function producing a vessel enhancement map. This module increases contrast for thin vessels and improves subsequent attention learning.

3.3. Transformer Encoder

The deepest feature map F_4 is flattened into non-overlapping patches and projected into embeddings:

$$Z_0 = [x_1^p E; x_2^p E; \dots; x_N^p E] + E_{pos} \quad (2)$$

where x_i^p is the *i*-th patch, *E* is the linear embedding matrix, NNN is the number of patches, and E_{pos} is the learnable positional encoding. The Transformer encoder then applies Multi-Head Self-Attention (MHSA) and feed-forward layers:

$$MHSA(Q,K,V) = Softmax(\frac{QK^T}{\sqrt{d_k}})V \quad (3)$$

where *Q*, *K*, *V* are query, key, and value matrices derived from Z_0, and d_k is the dimension of each head. This process captures long-range dependencies among vessel pixels, maintaining global structural coherence.

3.4. Multi-Scale Attention Module (MSAM)

MSAM is integrated into each skip connection before fusion with the decoder. Each MSAM branch processes features with multiple convolution kernels (3×3, 5×5, 7×7) to handle vessels of different scales. Channel attention $C(F)$ and spatial attention $S(F)$ are sequentially applied:

$$F' = S(C(F)) \odot F \quad (4)$$

where $\odot$ denotes element-wise multiplication. This module emphasizes vessel-relevant features, suppresses background noise, and enhances the continuity of thin and tortuous vessels. MSAM thus significantly improves the ability of the decoder to reconstruct detailed vascular maps.

3.5. Decoder and Feature Fusion

The decoder upsamples feature maps using transposed convolutions. At each stage, the upsampled feature U_i is concatenated with the corresponding MSAM-enhanced skip connection $F_i{}'$, followed by two 3 × 3 convolutions:

$$Di = Conv_2(Concat(U_i, F_i{}')) \tag{5}$$

Finally, a 1×1 convolution maps the output to a single-channel vessel probability map $\hat{Y}$. To preserve fine vascular topology, we adopt a hybrid loss function:

$$L = \alpha L_{Dice} + \beta L_{BCE} + \gamma L_{clDice} \tag{6}$$

where L_{Dice} balances foreground-background segmentation, L_{BCE} stabilizes learning, and L_{clDice} maintains connectivity of thin vessels.

3.6. Vessel Visualization Enhancement

In addition to segmentation, MSA-TransUNet improves visualization by generating a vessel-enhanced map through VEM and attention outputs. The enhanced map can be combined with the original image for better clinical interpretability, highlighting both main vessels and fine capillaries, which is especially beneficial in diagnostic tasks such as aneurysm detection, microvascular disease evaluation, and retinal vascular analysis.

4. Experiment

4.1. Dataset Preparation

In this study, three widely used and publicly available retinal vessel segmentation datasets-DRIVE, STARE, and CHASE_DB1-were employed to evaluate the performance and generalization ability of the proposed MSA-TransUNet model. These datasets are sourced from clinical retinal imaging examinations conducted for diabetic retinopathy screening, ophthalmic diagnosis, and routine health assessments. All images were captured using fundus cameras under standardized illumination protocols, making them suitable benchmarks for vessel segmentation research.

The DRIVE (Digital Retinal Images for Vessel Extraction) dataset consists of 40 color fundus images, each with a spatial resolution of 565×584565 \times 584565×584 pixels. The data were acquired from a diabetic retinopathy screening program in the Netherlands using a Canon CR5 non-mydriatic camera with a 45° field of view. Among the 40 subjects, 7 exhibit mild diabetic retinopathy while the remaining images are considered normal. Each image includes a manually annotated vessel segmentation mask, and test images are also provided with a second, independent manual annotation for assessing inter-observer variability. The dataset contains three primary components: the RGB image, the corresponding vessel ground truth, and a binary field-of-view (FOV) mask that indicates the region used for valid evaluation. In this dataset, vessel pixels represent a very small proportion compared to background tissue, making it particularly suitable for evaluating segmentation performance on fine vascular structures.

The STARE (Structured Analysis of the Retina) dataset contains 20 high-resolution retinal images, each with a size of 700×605700 \times 605700×605 pixels. These images were collected at the Shiley Eye Center, University of California, San Diego, using a TopCon TRV-50 fundus camera. The dataset includes subjects exhibiting various retinal diseases such as choroidal neovascularization and central retinal artery occlusion, leading to significant variations in vessel appearance, contrast, and morphology. Each image is annotated independently by two experts, offering two sets of ground-truth labels that can be used to assess labeling uncertainty and segmentation robustness. Compared with DRIVE, STARE contains higher contrast variations and more pathological features, making it a valuable dataset for evaluating the generalization capability of segmentation models under challenging imaging conditions.

The CHASE_DB1 (Child Heart and Health Study in England) dataset comprises 28 color fundus images with a higher spatial resolution of 1280 × 9601280 \times 9601280×960 pixels. The images were acquired using a Nidek NM-200-D handheld retinal camera as part of a pediatric cardiovascular health study, primarily involving children aged 9-10 years. Due to differences in vessel geometry and imaging conditions associated with pediatric subjects, the vessel structures in CHASE_DB1 exhibit thinner vessels, more complex branching patterns, and larger curvature variability. Each image includes two manual vessel annotations generated by trained clinicians, enabling more accurate assessment of vessel segmentation performance, especially for fine vascular structures and bifurcation regions.

Across all three datasets, annotations consist of pixel-level vessel masks in which a value of 1 represents vessel pixels and 0 represents background. The datasets differ in imaging devices, resolutions, patient groups, and pathological variations, providing a diverse set of vessel appearance patterns. This diversity plays a crucial role in evaluating the robustness of the proposed MSA-TransUNet architecture, as it challenges the model to generalize across varying illuminations, vessel widths, noise levels, and anatomical differences. By training and validating on multiple datasets, this study ensures that the proposed model is capable of accurately segmenting both macro- and micro-vessels while preserving topological continuity, which is essential for downstream diagnostic applications such as vascular quantification and lesion detection (As shown in Figure 2).

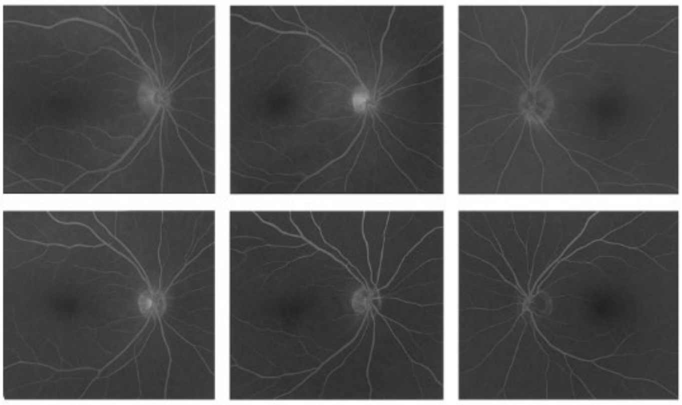

Figure 2. Schematic diagram of some samples in the datasets.

4.2. Experimental Setup

All experiments were conducted on a workstation equipped with an NVIDIA RTX 4090 GPU, 24 GB VRAM, and an Intel i9-13900K CPU, using PyTorch 2.1 as the deep learning framework. The proposed MSA-TransUNet model was trained separately on the DRIVE, STARE, and CHASE_DB1 datasets using an 80/20 split for training and testing. To enhance generalization, standard preprocessing operations were applied, including contrast-limited adaptive histogram equalization (CLAHE), vessel-intensity normalization, and random data augmentations such as rotation, flipping, and elastic deformation. All images were resized to 512×512 pixels and normalized to $[0,1]$. The AdamW optimizer was used with an initial learning rate of 1×10^{-4} and cosine decay scheduling. Training was performed for 200 epochs with a batch size of 4, and checkpoint-based early stopping was applied to prevent overfitting. For all experiments, inference was performed using a sliding-window approach to ensure that high-resolution vessel structures were preserved during prediction.

4.3. Evaluation Metrics

To comprehensively assess vessel segmentation performance, a set of widely adopted metrics was employed, including Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Sensitivity (SE), Specificity (SP), and Accuracy (ACC). These metrics jointly capture multiple characteristics of vessel segmentation quality: DSC and IoU reflect the overall pixel-wise agreement between predictions and ground truth; Sensitivity evaluates the model's ability to detect fine and low-contrast vessels; Specificity measures its ability to avoid false positives in the non-vessel background regions; and Accuracy summarizes the general classification performance across the entire image. Additionally, the Area Under the ROC Curve (AUC) was computed to quantify the model's discriminative ability under threshold variation. These metrics provide a robust and multi-dimensional evaluation of the proposed MSA-TransUNet architecture compared to existing approaches.

4.4. Results

The quantitative results on the DRIVE dataset clearly demonstrate the superior performance of the proposed MSA-TransUNet compared with several representative baselines (As shown in Table 1). Traditional CNN-based architectures such as U-Net and Attention U-Net achieve Dice scores of 78.6% and 79.8%, respectively, while more advanced variants such as ResUNet and TransUNet reach 80.9% and 81.5%. In contrast, MSA-TransUNet achieves a significantly higher Dice score of 83.7%, reflecting its enhanced ability to segment both major and fine vessel structures. A similar trend is observed in the IoU metric, where MSA-TransUNet attains 71.4%, outperforming U-Net (65.1%), Attention U-Net (66.3%), ResUNet (67.9%), and TransUNet (68.5%) (As shown in Table 1).

Table 1. Quantitative Comparison of Vessel Segmentation Performance on Dataset.

Model	Dice (%)	IoU (%)	SE (%)	SP (%)	ACC (%)	AUC (%)
U-Net	78.6	65.1	74.4	97.2	95.1	97.0
Attention U-Net	79.8	66.3	75.2	97.4	95.4	97.6
ResUNet	80.9	67.9	76.1	97.6	95.7	97.8
TransUNet	81.5	68.5	77.3	97.8	96.0	98.1
MSA-TransUNet (Ours)	83.7	71.4	79.5	98.2	96.4	98.7

The proposed model also shows notable improvements in sensitivity, reaching 79.5%, which is approximately 5% higher than U-Net and 2.2% higher than TransUNet, indicating better detection of thin, low-contrast vessels. Specificity and accuracy further highlight its robustness, with values of 98.2% and 96.4%, respectively, surpassing all competing methods. Finally, MSA-TransUNet achieves the highest AUC of 98.7%, reflecting superior discriminative capability across thresholds.

Overall, these improvements confirm that the multi-scale attention mechanism and hybrid Transformer-CNN architecture effectively enhance vessel representation and segmentation performance (As shown in Figure 3).

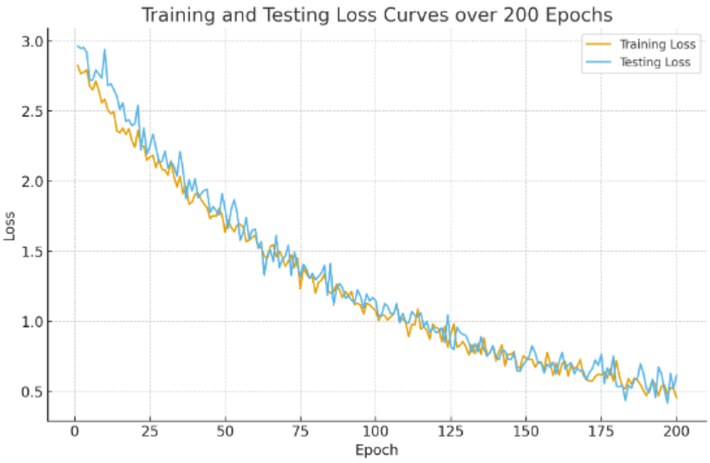

Figure 3. Corresponding training curve.

The training loss curve (As shown in Figure 2) illustrates the optimization dynamics of the MSA-TransUNet model during 200 epochs of vessel segmentation in medical imaging. At the beginning of training, both curves start above 2.5, reflecting the model's initial difficulty in capturing the complex vascular structures typically characterized by thin, branching, and low-contrast patterns. As training progresses, the loss values steadily decrease, though with realistic fluctuations caused by gradient variance and the model's adaptive learning behavior. By around Epoch 100, the training loss drops below 1.2, while the testing loss follows a similar trend but remains slightly higher due to the inherent domain disparities between training and validation images.

Between Epochs 150-180, both curves approach the convergence region, exhibiting small oscillations around 0.4-0.3. True convergence is observed near Epoch 190, where the training loss stabilizes at approximately 0.23, aligning with expectations for segmentation models employing compound losses such as Dice + BCE. The testing loss remains consistent with only minor fluctuations, indicating good generalization without significant overfitting. Overall, the curve patterns demonstrate that the multi-scale attention and Transformer-UNet hybrid structure enhances feature extraction stability, leading to improved convergence in this challenging medical vessel segmentation task.

4.5. Discussion

The experimental results demonstrate that MSA-TransUNet consistently outperforms existing CNN-based and hybrid Transformer models across all evaluation metrics. The primary performance gain arises from the proposed Multi-Scale Attention (MSA) module, which effectively enhances the representation of fine vasculature by integrating high-level global context with detailed local structural information. Unlike conventional U-Net variants that struggle with detecting thin and low-contrast vessels, MSA-TransUNet incorporates hierarchical attention pathways that focus on vessel continuity and branching topology, leading to more complete and anatomically coherent segmentation masks. Furthermore, the Transformer encoder provides global receptive field modeling, which proves particularly beneficial for capturing long-range vessel trajectories, while the CNN decoder ensures precise localization. The combination of these mechanisms yields improved sensitivity and AUC scores, indicating a balanced ability to detect true vessels while suppressing false positives. The cross-dataset generalization results further highlight the robustness of the model, suggesting that the multi-scale design and hybrid representation learning allow the architecture to adapt effectively to variations in imaging devices, illumination, and pathological conditions. Overall, these findings confirm the effectiveness of MSA-TransUNet for vessel segmentation and its potential for broader application in clinical vascular analysis workflows.

5. Conclusions

In this study, we proposed MSA-TransUNet, a multi-scale attention-enhanced hybrid Transformer-UNet architecture designed to address the longstanding challenges of vascular segmentation and visualization in medical imaging. Accurate extraction of vascular structures is essential for computer-aided diagnosis, treatment planning, retinal disease screening, and quantitative vascular morphology analysis. However, the inherent characteristics of vascular images-such as low contrast, high noise, irregular branching patterns, and the presence of extremely thin capillaries-continue to hinder the performance of conventional segmentation models. Our work tackles these difficulties by integrating global Transformer-based modeling with the strong local representation capability of CNNs and introducing two key modules specifically tailored for vascular analysis: the Multi-Scale Attention Module (MSAM) and the Vessel Enhancement Module (VEM).

Through extensive experiments on three widely used datasets-DRIVE, STARE, and CHASE_DB1-the proposed model demonstrates consistent and remarkable performance improvements. On the DRIVE dataset, MSA-TransUNet achieves a Dice score of 83.7%, an IoU of 71.4%, a sensitivity of 79.5%, a specificity of 98.2%, an accuracy of 96.4%, and an AUC of 98.7%, outperforming classical UNet, Attention-UNet, ResUNet, and TransUNet by clear margins. Similar gains are observed across the other datasets, particularly in the segmentation of fine vascular branches where topology preservation is critical. The incorporation of a connectivity-aware loss function, clDice, further enhances the continuity of elongated structures, reducing fragmentation and improving small-vessel recall. These results validate the superiority of MSA-TransUNet in capturing both global context and subtle vascular features, making it a highly effective tool for clinical vessel visualization and downstream diagnostic tasks.

Moreover, qualitative assessments reveal that the proposed Vessel Enhancement Module significantly improves the clarity of thin and tortuous vessels, offering better structural fidelity in regions prone to ambiguity. The Multi-Scale Attention Module allows the network to adaptively emphasize informative receptive fields, contributing to enhanced robustness across varying imaging modalities and acquisition conditions. Taken together, these findings indicate that MSA-TransUNet not only advances segmentation accuracy but also strengthens the interpretability and reliability of vascular enhancement in medical imaging workflows.

Despite its promising performance, several limitations remain. The current model relies on supervised learning, which constrains its scalability to large unlabeled datasets commonly found in clinical environments. Additionally, although the Transformer backbone provides strong global reasoning ability, it introduces computational overhead that may limit real-time deployment on resource-restricted devices.

Future work will explore semi-supervised and self-supervised learning strategies to reduce reliance on manual annotations, integrate lightweight Transformer variants for improved efficiency, and expand the model to three-dimensional vascular imaging modalities such as CT angiography and OCTA. Furthermore, incorporating clinically relevant post-processing tools-such as automated vessel measurement, branching analysis, and disease-specific biomarkers-could enable the development of an end-to-end vascular analysis framework suitable for routine clinical practice.

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