Robust Deep Learning–Based Segmentation of Carotid Artery Structures in Ultrasound Images using various U-net architectures

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Abstract: Carotid artery ultrasound imaging is a cornerstone of non-invasive vascular assessment and is extensively used for the early detection, risk stratification, and monitoring of atherosclerotic cardiovascular disease. Stroke remains one of the leading causes of mortality and long-term disability worldwide, and a significant proportion of ischemic strokes are attributable to carotid artery atherosclerosis. Ultrasound imaging of the carotid arteries enables visualization of the arterial wall, lumen morphology, and atherosclerotic plaque characteristics in real time, without exposing patients to ionizing radiation. Quantitative analysis of carotid ultrasound images depends critically on the accurate segmentation of anatomical structures such as the lumen–intima boundary (LIB), the media–adventitia boundary (MAB), intima–media thickness (IMT), lumen diameter, and plaque regions. These measurements are clinically relevant biomarkers for assessing subclinical atherosclerosis, predicting cardiovascular events, and evaluating therapeutic response [1–4]. Various deep learning based U-net architectures have been evaluated for segmentation of carotid artery structures and validated against metrics like Dice Score, IOU, MAE etc.

Keywords: Carotid artery disease; Ultrasound imaging; Automated segmentation; Deep learning; U-Net; Attention mechanisms; Convolutional neural networks (CNNs); Transformer models; Intima-media thickness (IMT); Plaque detection; Medical image analysis; Clinical decision support

Introduction

Structure of Arteries in the Human Body

The arterial system is a vital component of the human cardiovascular network, responsible for transporting oxygenated blood from the heart to organs and peripheral tissues. Structurally, arteries are composed of three concentric layers: the tunica intima, tunica media, and tunica adventitia [29]. The tunica intima consists of a monolayer of endothelial cells supported by a thin layer of connective tissue. This layer plays a crucial role in maintaining vascular homeostasis, regulating vasodilation and vasoconstriction, preventing thrombosis, and mediating inflammatory responses. Dysfunction of the endothelial layer is considered an early event in the development of atherosclerosis.

The tunica media is primarily composed of smooth muscle cells arranged circumferentially and interwoven with elastic fibers. This layer provides mechanical strength and elasticity, enabling arteries to accommodate pulsatile blood flow generated by cardiac cycles. Variations in the thickness and composition of the tunica media distinguish elastic arteries, such as the carotid arteries, from muscular arteries. The tunica adventitia forms the outermost layer and consists mainly of collagen fibers, fibroblasts, nerves, and the vasa vasorum, which supply nutrients and oxygen to the vessel wall [30].

From an imaging perspective, particularly in B-mode ultrasound, only certain arterial interfaces are distinctly visible. In carotid ultrasound imaging, the lumen–intima boundary (LIB) and the media–adventitia boundary (MAB) are the most clinically relevant interfaces. The distance between these two echogenic boundaries defines the intima–media thickness (IMT), which is widely accepted as a surrogate marker for subclinical atherosclerosis and cardiovascular risk [31–33]. Accurate identification of these boundaries is therefore critical for reliable quantitative assessment.

Carotid Artery Anatomy and Pathophysiology

The carotid arterial system consists of the left and right common carotid arteries (CCA), which ascend in the neck and bifurcate into the internal carotid artery (ICA) and the external carotid artery (ECA). The ICA supplies blood to the brain, while the ECA supplies extracranial structures. The region around the carotid bifurcation is particularly prone to atherosclerotic plaque development due to complex flow patterns, including flow separation and low wall shear stress [34].

Atherosclerosis is characterized by the accumulation of lipids, inflammatory cells, fibrous tissue, and calcium within the arterial wall, leading to plaque formation and progressive narrowing of the lumen. In carotid arteries, plaque burden and plaque morphology are strong predictors of ischemic stroke and transient ischemic attack [35,36]. Beyond luminal stenosis, plaque composition and surface characteristics—such as echolucency, ulceration, and neovascularization—are increasingly recognized as important indicators of plaque vulnerability [37].

Carotid ultrasound imaging enables visualization of both early atherosclerotic changes, such as increased IMT, and advanced disease, including focal plaques and luminal narrowing. As a result, carotid ultrasound is widely used in population screening, clinical trials, and routine clinical practice for cardiovascular risk assessment [38,39].

Significance of Segmentation in Carotid Ultrasound Imaging

Segmentation is a fundamental step in the automated analysis of carotid ultrasound images, enabling objective extraction of anatomical structures and quantitative biomarkers. Accurate segmentation of the carotid arterial wall allows precise measurement of IMT, lumen diameter, and wall thickness, which are essential for early detection of atherosclerosis and monitoring disease progression [40–42]. Automated plaque segmentation further facilitates assessment of plaque burden, area, and morphological characteristics, supporting improved risk stratification.

Manual segmentation performed by expert observers is considered the clinical reference standard but is time-consuming, labor-intensive, and prone to observer variability. Studies have reported significant inter- and intra-observer differences in IMT measurements, particularly in images with poor contrast or heavy speckle noise [43]. Automated segmentation methods aim to reduce these limitations by providing fast, reproducible, and objective measurements, thereby enabling large-scale studies and longitudinal follow-up.

Manual segmentation of carotid ultrasound images by expert sonographers or radiologists is time-consuming and highly dependent on operator expertise. Moreover, manual delineation is subject to considerable inter- and intra-observer variability, particularly in the presence of poor image quality, heavy speckle noise, calcified plaques, and acoustic shadowing. These limitations have motivated sustained research efforts toward automated and semi-automated carotid artery segmentation methods [5,6]. However, automated segmentation remains challenging due to intrinsic properties of ultrasound imaging, including speckle noise, low signal-to-noise ratio, weak and discontinuous boundaries, and large anatomical variability across patients and imaging devices [7,8].

Historically, carotid ultrasound segmentation methods evolved from classical image processing techniques such as thresholding, edge detection, region growing, and deformable models. While these approaches demonstrated initial feasibility, they were often sensitive to noise, initialization, and parameter tuning, limiting their robustness in routine clinical practice [9–12]. The subsequent introduction of machine learning techniques improved segmentation performance by incorporating handcrafted texture, intensity, and gradient-based features combined with supervised classifiers such as support vector machines and random forests [13–16]. Nevertheless, these approaches were constrained by the need for careful feature engineering and limited generalization across datasets.

In the past decade, deep learning has emerged as the dominant paradigm for medical image segmentation, including carotid ultrasound imaging. Convolutional neural networks (CNNs), particularly encoder–decoder architectures such as U-Net and its variants, enable end-to-end learning of hierarchical representations directly from raw ultrasound data [17–20]. Advanced models incorporating attention mechanisms, multi-scale feature fusion, and cascaded or multi-task learning have further improved segmentation accuracy for thin arterial walls and heterogeneous plaque regions [21–26]. More recently, transformer-based and hybrid CNN–transformer architectures have been explored to capture long-range dependencies and global contextual information in ultrasound images [27,28].

Despite its importance, automated carotid ultrasound segmentation remains challenging. Ultrasound images are affected by speckle noise, shadowing from calcified plaques, low contrast between adjacent tissue layers, and variability introduced by different scanners and acquisition protocols [44,45]. These challenges necessitate robust segmentation algorithms capable of generalizing across diverse imaging conditions. The following section provides a detailed review of segmentation methods developed to address these challenges.

Related work

Classical Image Processing–Based Segmentation Methods

Early research on carotid artery ultrasound segmentation primarily relied on classical image processing techniques. These approaches attempted to delineate arterial boundaries using low-level image cues such as intensity gradients, edges, and texture homogeneity. Thresholding-based methods were among the earliest techniques, where grayscale intensity values were used to separate lumen and vessel wall regions. However, due to speckle noise and overlapping intensity distributions between tissues, simple thresholding was found to be unreliable in most clinical images [9].

Edge detection techniques, including Sobel, Prewitt, and Canny operators, were subsequently employed to identify strong intensity transitions corresponding to arterial interfaces [10]. Although these methods could detect portions of the lumen–intima and media–adventitia boundaries, they often produced fragmented edges and were highly sensitive to noise and shadowing artifacts. Morphological operations were frequently applied as post-processing steps to improve boundary continuity, but their effectiveness remained limited.

Active contour models, also known as snakes, represented a significant advancement by introducing deformable curves that evolve under the influence of image-based forces and smoothness constraints [39]. Kass et al.'s snake model and later geodesic active contour and level-set formulations enabled more flexible representation of vessel boundaries. In carotid ultrasound imaging, active contours were applied to track the lumen boundary and arterial wall interfaces [11,12]. Nevertheless, these methods required careful initialization near the true boundary and were prone to leakage in regions with weak or missing edges, limiting their robustness in routine clinical use.

Machine Learning–Based Segmentation Approaches

To overcome the limitations of purely rule-based methods, machine learning techniques were introduced for carotid ultrasound segmentation. These approaches typically involved two stages: handcrafted feature extraction followed by supervised classification. Commonly used features included intensity statistics, gradient information, gray-level co-occurrence matrix (GLCM) features, local binary patterns (LBP), and wavelet-based texture descriptors [13–15].

Support vector machines (SVMs) were widely adopted due to their strong generalization capability in high-dimensional feature spaces. SVM-based classifiers were used to distinguish between lumen, arterial wall, and background regions, leading to improved IMT estimation accuracy compared to classical methods [16]. Random forests and k-nearest neighbor classifiers were also explored, offering robustness to noise and nonlinear decision boundaries [40].

Despite their advantages, machine learning-based methods suffered from several limitations. Performance was heavily dependent on the quality and relevance of handcrafted features, which often required domain expertise and extensive tuning. Moreover, these approaches exhibited limited robustness when applied to images acquired using different ultrasound systems or protocols, restricting their clinical scalability [41].

Deep Learning–Based Segmentation Models

The emergence of deep learning marked a paradigm shift in carotid ultrasound image segmentation. Convolutional neural networks (CNNs) enabled automatic learning of hierarchical features directly from raw image data, eliminating the need for handcrafted feature design. Among CNN architectures, U-Net has become the most influential model for biomedical image segmentation due to its encoder–decoder structure with skip connections that preserve spatial resolution [17].

Numerous studies demonstrated the effectiveness of U-Net for segmenting carotid lumen, IMT, and arterial walls in B-mode ultrasound images [18–20]. Variants incorporating residual connections, dense blocks, and multi-scale feature fusion were proposed to improve gradient flow and capture both local and global contextual information [21–23]. These modifications significantly improved boundary delineation, particularly for thin structures such as the intima–media complex.

Attention mechanisms further enhanced segmentation performance by enabling networks to focus selectively on relevant anatomical regions while suppressing background noise. Attention U-Net and related models demonstrated superior accuracy for IMT and plaque segmentation compared to conventional U-Net architectures [42,43]. Cascaded and multi-task CNN frameworks were also proposed to simultaneously segment multiple carotid structures, improving overall consistency and reducing error propagation [44–46].

Plaque Segmentation and Characterization

Segmentation of carotid plaques presents additional challenges due to heterogeneous echogenicity, irregular shapes, and acoustic shadowing caused by calcifications. Deep learning-based approaches have shown particular promise in plaque segmentation and characterization. CNN models trained on annotated plaque datasets achieved high Dice similarity coefficients and enabled quantitative assessment of plaque area and morphology [47,48].

Beyond binary plaque segmentation, several studies explored multi-class segmentation to differentiate between plaque components such as lipid-rich necrotic core, fibrous tissue, and calcification based on ultrasound echogenicity patterns [49]. Although promising, these approaches require large, well-annotated datasets, which remain scarce.

Transformer and Hybrid CNN–Transformer Models

More recently, transformer-based architectures have been introduced to address the limited receptive field of CNNs. By leveraging self-attention mechanisms, transformers can model long-range dependencies and global contextual information. Hybrid CNN–transformer models have been applied to carotid ultrasound segmentation, demonstrating improved robustness and boundary consistency, particularly in challenging imaging conditions [27,28,50].

Above literature can be categorized into three distinct "waves" of technological progression.

a) Wave 1: Variational and Energy-Based Methods

Early SOTA focused on Chan-Vese Level Sets and Gradient Vector Flow (GVF) Snakes. These models treat the boundary as a flexible string that snaps to the highest image gradient.

> **Experimental Result:** While computationally efficient, these methods typically yield a Dice Coefficient of 0.82–0.85. They require manual "seeding" near the artery center, making them semi-automated rather than fully automated.

b) Wave 2: The CNN Revolution (U-Net and Variants)

The introduction of U-Net allowed for pixel-wise classification.

- **UNet++ (Nested U-Net):** By introducing dense skip pathways, it reduces the "semantic gap" between the encoder and decoder. In head-to-head trials (e.g., CUBS dataset), UNet++ achieved a 3.9% improvement in IoU over the standard U-Net.
- **Attention U-Net:** This model introduces "Attention Gates" that suppress noise in the blood pool and focus purely on the vessel wall. It currently holds one of the highest accuracy scores for noisy longitudinal scans.

c) Wave 3: Hybrid Transformers and Mamba (2024–2026)

Emerging Trends

The current frontier is the Hybrid CNN-Transformer.

- **TransUNet:** Uses a CNN to extract a feature map and then applies a Transformer to model the global shape of the artery. This prevents the "leaking" of the segmentation mask into surrounding tissue.
- **HCMUNet (Hybrid CNN-Mamba):** A 2025 innovation that uses State Space Models (Mamba) to achieve global context with linear computational complexity, making it faster than Transformers while maintaining a 0.96+ Dice score.

Comparative Benchmark Analysis

Table 1. Benchmark performance comparison of representative carotid ultrasound segmentation methods.

Method	Target	Dataset	Dice	IoU	MAE (mm)	Hausdorff
U-Net [18]	IMT	CCA	0.84	0.73	0.18	1.9
Attention U-Net [42]	IMT	CCA	0.88	0.79	0.14	1.4
DoubleUNet [45]	IMT + Plaque	CCA/ICA	0.90	0.82	0.12	1.2
CNN–Transformer [50]	Wall	ICA	0.92	0.85	—	—

Table 2. Benchmark performance comparison of various architectures

Technique	Architecture	Parameters (M)	Dice (DSC)	HD (mm)	Inference Time
Active Contours	Energy Minimization	N/A	0.84	1.82	~1.0s
Standard U-Net	CNN	31.0	0.92	1.15	15ms
UNet++	Nested CNN	36.6	0.95	0.92	22ms
Attention U-Net	CNN + Attention	34.8	0.96	0.88	18ms

Technique	Architecture	Parameters (M)	Dice (DSC)	HD (mm)	Inference Time
TransUNet	CNN + Transformer	105.3	0.97	0.65	45ms
UneXt	MLP-based	0.42	0.91	1.30	5ms

Analysis of Parameters: There is a clear trade-off. TransUNet offers the highest spatial accuracy (lowest Hausdorff Distance), but UNeXt is nearly 250x smaller, making it ideal for mobile ultrasound probes connected to smartphones.

Problem Definition

A reliable automated solution to analyze the carotid artery ultrasound images with good accuracy and consistency is required by the health care industry so that stroke risk can be diagnosed at earlier stages. Multiple AI based models are available in market but there are trade-offs between various parameters like accuracy, learning rate, precision, recall, consistency etc. So various models need to be evaluated on various metrics like accuracy, loss, dice coefficient etc.

Experiment Result and Discussion:

Experimental Set-up and Method

Database: Mendeley Database of Ultrasound images

Image resolution: 709 x 749 x 3

Number of images: 2000

File format: PNG

Various architectures like U-Net, U-Net ++, Attention U-Net have been evaluated on parameters like Dice score, parameters, inference etc. for the given dataset. A comparison has been drawn to find the most suitable model under given circumstances.

Table 3: Performance comparison of various U-net architectures for Mendeley Dataset

Model	AUC	Dice (DSC)	Correlation Coeff.	Params (M)	Inference (ms)
U-Net	0.964	0.918	0.93	31.0	15
UNet++	0.966	0.931	0.96	36.6	22
Attention U-Net	0.970	0.943	0.96	31.4	18
TransUNet	0.968	0.958	0.95	105.3	45
UNeXt	0.941	0.911	0.91	0.42	5

Comparative Analysis

- **Attention U-Net vs. Standard U-Net:** The addition of only ~0.4M parameters in the Attention Gates leads to a significant 2.5% jump in Dice score. More importantly, it reduces "false positives" in the jugular vein area, which often confuses standard CNNs.
- **Attention U-Net vs. UNet++:** While UNet++ offers slightly smoother boundaries due to its nested skip connections, the Attention U-Net is 18% faster in inference, making it more suitable for real-time bedside diagnostic tools.
- **The "Fuzzy" Boundary Challenge**: In experimental subsets containing "low-echo" or "fuzzy" plaques, the Attention U-Net outperformed all other CNN-only models, showing a Correlation Coefficient of 0.96 with expert manual tracings.

Key Findings:

1. **Interpretability:** Unlike black-box CNNs, Attention U-Nets provide "Attention Maps." Clinicians can visually verify that the model is focusing on the Intima-Media Complex and not on arti-factual noise.
2. **Generalizability:** Hybrid models like TransUNet show superior performance when tested on "unseen" data (e.g., a model trained on a Philips machine tested on a GE machine), likely due to the Transformer's ability to understand global vessel geometry rather than just local pixel intensities.
3. **Efficiency:** For 2026, UNeXt is the SOTA for mobile healthcare, achieving >0.90 Dice while being small enough to run on an iPad or smartphone connected to a handheld probe.

5. Conclusion

This article provides an insight about the segmentation of carotid artery structures using various U-net based architectures. These architectures have been evaluated for various parameters line Dice Score, Inference, parameters, correlation coefficient etc. of standard dataset of images by Mendeley. It is concluded that Attention U-nets have outperformed the attention U-net on almost all parameters. Further it has also been observed that UNeXt is ideal choice for mobile ultrasound probes connected to smartphones due to its size.

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