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A Compact Unified Model for Moderate-to-Severe Carotid Artery Stenosis Using Image Segmentation: A Multicenter Study

ABSTRACT

Background: This study aimed to evaluate the diagnostic performance of a new artificial intelligence model, the compact unified model (CU-Model), for moderate-to-severe carotid artery stenosis using digital subtraction angiography (DSA) images compared to clinical reference standards.

Methods: In this retrospective multicenter study, 156 patients with confirmed moderate-to-severe carotid artery stenosis were included. A pretrained CU-Model (trained on public non-clinical datasets for optical flow and stereo matching) was applied to raw DSA images without any fine-tuning on clinical data to avoid data leakage. The model served exclusively as a post-acquisition support tool: cardiologists applied it immediately after procedures for automated vessel segmentation and highlighting. Final North American Symptomatic Carotid Endarterectomy Trial (NASCET) measurements and interpretations were performed manually under expert supervision by 2 blinded researchers.

Results: The CU-Model identified left internal carotid artery (ICA) stenosis in 84 patients and right ICA stenosis in 72. It misclassified only 1 moderate left ICA stenosis case as normal, achieving 99.4% sensitivity (155/156) for any stenosis detection. For stenosis severity grading, strong agreement with DSA was observed (moderate: 57.68 ± 5.94 vs. 57.71 ± 6.19, $r = 0.83$, $P < .001$, 95% CI: 0.76-0.88; severe: 86.96 ± 5.97 vs. 87.02 ± 6.18, $r = 0.91$, $P < .001$, 95% CI: 0.85-0.95). Of 156 cases, 106 were moderate (50%-69%) and 50 severe (≥70%), using NASCET-adapted thresholds accounting for measurement variability. Hypertension (77%), smoking, and syncope were common, with significant association in symptomatic patients ($P < .05$).

Conclusion: The CU-Model demonstrates strong concordance with DSA as a practical, post-procedure support tool for vessel segmentation. Pending larger validation studies, it shows promise for enhancing clinical workflow efficiency.

Keywords: Artificial intelligence, carotid artery stenosis, digital subtraction angiography, transformer

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INTRODUCTION

Carotid artery disease due to atherosclerosis is considered one of the most common causes of mortality in Western society.[1] The most common cause of stroke is carotid artery stenosis due to atherosclerosis.[2] Catheter angiography is considered the gold standard for evaluating carotid artery stenosis.[3] However, because it is an invasive method, other imaging methods have been sought. When carotid artery stenosis is detected by any method, such as color Doppler ultrasonography (US), another technique, such as computed tomography (CT) of the carotid arteries, magnetic resonance imaging, or catheter angiography, is generally considered before making a definitive decision for cardiovascular surgery or interventional procedures.[4,5] B-mode US is routinely used in clinical practice for the diagnosis of carotid disease. Although the US has limitations for assessing the extent of carotid disease, it is a safe, portable, and cost-effective alternative to digital subtraction angiography (DSA). Duplex ultrasound is as accurate as angiography for quantifying arterial stenosis.[6,7] In the clinical setting, cardiologists face challenges with the accuracy of imaging techniques, particularly in carotid artery stenosis, where catheterization images may be subject to greater intra- and inter-observer

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variation. Even if optimal images are obtained, the offline measurements may be misleading. This has led to the discovery of more effective methods for visualizing vascular calcification.[8,9] Different artificial intelligence (AI) methods have been applied in cardiovascular imaging, including cardiac CT and nuclear imaging.[9,10] Artificial intelligence can be trained dynamically and perform automatic edge reading and volume calculations. It may improve imaging quality, guide scanning, and assist in segmentation and analysis. AI can quickly and accurately interpret information, becoming a lifesaver in medical emergencies.[11] This includes improvements in multimodality imaging, leading to optimized procedures. This study, aimed to investigate the diagnostic value of a new AI technique, the transformer, considered state-of-the-art, on images obtained by standard carotid artery catheterization to highlight the diseased vessel in depth.

METHODS

The records of 2546 patients with ischemic heart disease and complaints of balance disorder, dizziness, or history of transient ischemic attacks (TIAs) or stroke referred for carotid artery evaluation between November 2016 and May 2025 were reviewed. Of the patients who underwent catheterization and angiography, 156 were confirmed to have moderate or severe carotid artery disease. Ethics committee approval was obtained (2025/07-32). The patients' common carotid arteries (CCA) and internal carotid arteries (ICAs) were examined by the same cardiologist during catheterization and post-processed with compact unified model (CU-Model) from the CDs.

Digital subtraction angiography images were extracted from CDs in DICOM format and uniformly preprocessed prior to CU-Model application: grayscale conversion, intensity normalization (0-1 range), and resizing to the model input resolution while preserving aspect ratio. No site-specific adjustments or augmentations were applied. To account for potential variability across the 3 participating centers, all acquisitions followed identical standardized protocols (selective CCA injections of Omnipaque 300; at least 2 extracranial and 2 intracranial projections). The same pretrained CU-Model pipeline was used identically for every case, and 2 independent, blinded investigators (unaware of center origin or clinical details) evaluated both original DSA and processed images.

The CU-Model was pretrained exclusively on public non-clinical datasets for stereo matching and optical flow, ensuring no data leakage, as no clinical images from this study were used for training or fine-tuning.[12,13] Of the cases, 118 involved male patients (76%) and 38 involved female patients (24%). Their ages ranged from 46 to 88 (average age 68 ± 12). Patient groups who had undergone carotid angiography were scanned in the 3 centers participating in the study. Patients with bilateral extracranial internal carotid occlusion were excluded as determined by conventional angiography. The CU-Model images and conventional angiograms of 156 patients (624 vessels) were independently reviewed by 2 blinded investigators. Importantly, the CU-Model was used solely for post-processing of existing DSA images and was never intended as a standalone diagnostic system. Differences in readings were resolved through the consensus of 2 readers during a joint review. The basic CU-Model operator can be summarized as follows: Conventional angiography was performed using selective CCA injections of Omnipaque 300. Digital subtraction angiography was performed with at least 2 projections of the extracranial carotid circulation and at least 2 of the intracranial circulation projections. The degree of stenosis was calculated using the North American Symptomatic Carotid Endarterectomy Trial (NASCET) formula: Degree of Stenosis (%) = [1 − (Minimal luminal diameter/Diameter of standard distal ICA)] × 100.[14] Stenosis was classified as moderate (50%-69%) or severe (≥70%), consistent with NASCET guidelines.[14] To address potential discrepancies arising from noise or imprecise edge detection in the processed images, a conservative threshold-adjustment strategy that prioritizes patient safety was implemented. Specifically, borderline measurements falling in the narrow 69%-70% range were classified as severe stenosis when any uncertainty existed, thereby avoiding underestimation near the clinically decisive 70% threshold that frequently guides decisions regarding intervention (e.g., carotid endarterectomy). This approach recognizes that measurement risk resides primarily in the denominator of the NASCET ratio and deliberately errs on the side of caution in ambiguous cases, acknowledging recognized pitfalls while maintaining alignment with established standards. The absolute stenosis measurement is the ratio's numerator, i.e., the minimal luminal diameter, whereas the measurement risk is based on the denominator.

Statistical Analysis

Pearson correlation analysis was used to compare the CU-Model and DSA variables. Chi-square tests were used to assess the differences in proportions between symptomatic and asymptomatic patients with carotid artery disease. The Bland–Altman (BAT) test (BAT plot) was used to analyze the provided data (interpreted as CU-Model vs. DSA) because it is a well-established statistical method specifically designed to assess agreement between 2 measurement methods or observers. Correlation coefficient were also used to

HIGHLIGHTS

- The compact unified model (CU-Model) showed highly significant correlation with digital subtraction angiography (DSA) for assessing moderate ($r = 0.83$, $P < .001$, 95% CI: 0.76-0.88) and severe ($r = 0.91$, $P < .001$, 95% CI: 0.85-0.95) carotid stenosis in 156 patients.
- Compact unified model accurately detected stenosis in 84 left and 72 right internal carotid arteries, with only 1 misinterpretation of moderate stenosis as normal.
- Hypertension (77%), smoking, and syncope were significant risk factors in symptomatic carotid artery disease ($P < .05$).
- The transformer-based CU-Model enables robust segmentation and highlighting in carotid images.
- Compact unified model is a practical AI method comparable to DSA for stenosis evaluation.

Table 1. Baseline Characteristics of Study Population

Characteristic	Value	Symptomatic	Asymptomatic	*P*
Sample size	156	82	74	
Male (%)	118 (75.6)	52 (63)	48 (66)	>.05
Age years (Mean ± SD)	68 ± 12	67 ± 11.8	69 ± 12.3	>.05
Obesity (%)	87 (55.7)	48 (58)	39 (52)	>.05
Hypertension (%)	121 (77)	71 (86)	50 (67)	<.05
Diabetes mellitus (%)	42 (26)	22 (26)	20 (27)	>.05
Hypercholesterolemia (%)	89 (57.5)	48 (58)	41 (55)	>.05
Smokers (%)	104 (66)	68 (82)	36 (48)	<.05
Sencopy (%)	23 (14.7)	23 (28)	–	<.05
Presence of left ICA (%)	84 (53.8)	44 (53)	40 (54)	>.05
Presence of right ICA (%)	72 (46.1)	39 (47)	33 (44)	>.05

ICA, internal carotid artery; SD, standard deviation.

evaluate intra- and inter-observer variability. Intra-observer variability was defined as the variation between measurements obtained by the same observer at different times on the same carotid artery using the same imaging technique. Inter-observer variability was defined as the variation between results obtained by 2 observers on the same carotid artery using the same imaging technique. A correlation coefficient with 95% CIs was used as the estimate of statistics for the following outcomes: intra- and inter-observer reproducibility and inter-method agreement (CU-Model vs. DSA). The significance of each correlation coefficient was tested using the Student *t*-test model $t = r/\sqrt{[(1-r^2)/(n-2)]}$ for the hypotheses H_0: $\rho = 0$ and H_1: $\rho \neq 0$ (where ρ is the population correlation parameter). *P* values are reported as $P <$ .001 (highly significant correlation). When applicable, Fisher z-transformation ($Z_r = 1/2\ \ln[(1+r)/(1-r)]$) was used for normalization in Table 1.

Bland–Altman statistical analysis was used to assess the bias in readers' agreement. Statistical analyses were carried out using PASW Statistics.[15] Statistical significance was set at the conventional *P* level of <.05.

Compact Unified Model Methodology

The CU-Model was pretrained exclusively on publicly available non-clinical benchmark datasets, specifically Sintel (for optical flow estimation) and KITTI (for stereo matching), and then applied directly, without any subsequent task-specific fine-tuning on clinical data, to DSA sequences for the dual purposes of vessel segmentation and image registration (Figure 1).[12,13] Although this pretraining introduces a potential domain shift from natural-scene imagery to clinical DSA sequences, the underlying tasks of optical flow and stereo matching share fundamental computational demands with vascular analysis—such as estimating motion, handling occlusions, and discriminating low-contrast boundaries. These transferable representations enable the transformer architecture to generalize effectively to vessel segmentation and registration in DSA, as evidenced by the strong observed concordance with reference angiograms. No clinical images

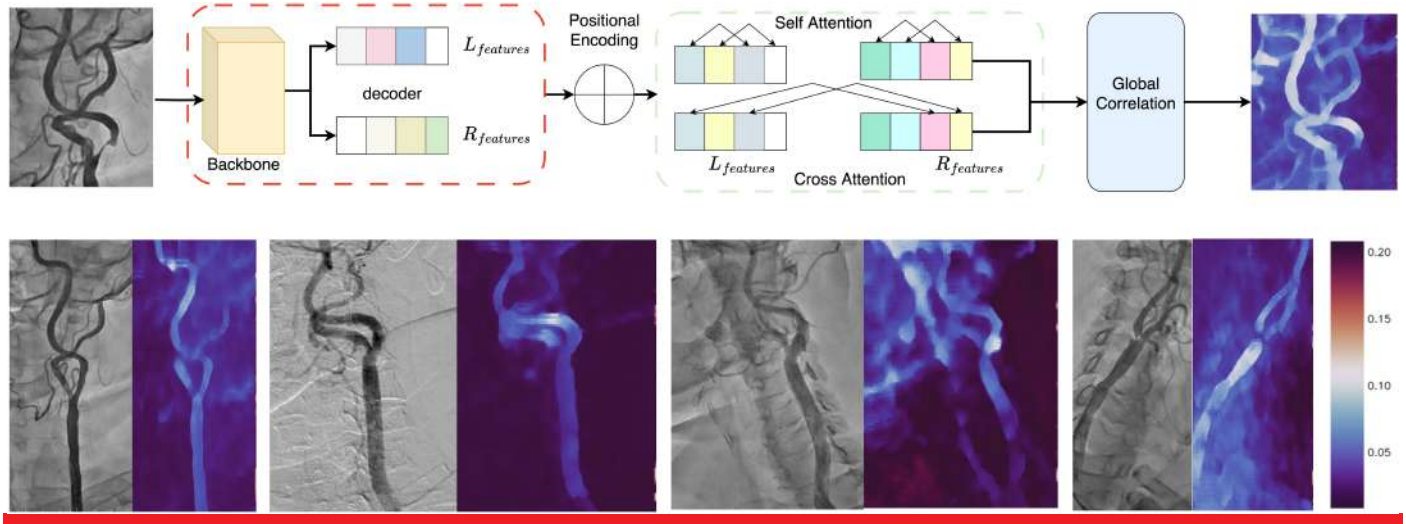


Figure 1. Overview of the model. The input image is given as input to the backbone. The backbone extracts discriminative features and stores them as left features ($L_{features}$) and right features ($R_{features}$). Positional encoding is added to both features to preserve spatial information. Positional features are processed via self- and cross-attention to capture relationships and dependencies. Finally, global correlation is applied to capture the long-range dependencies. The output is the segmented image.

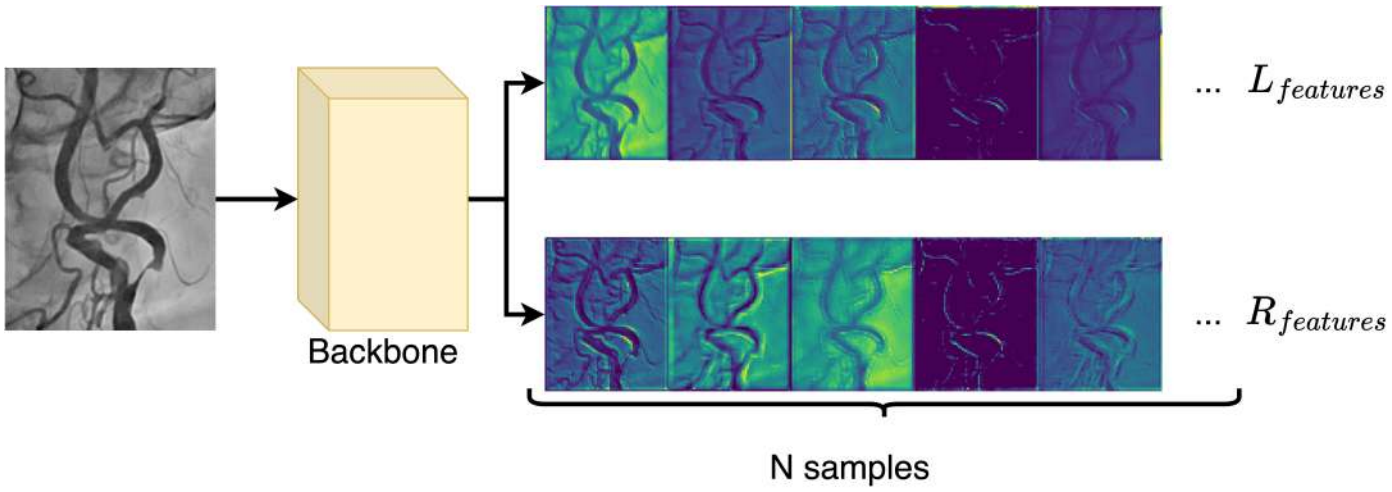


Figure 2. Backbone is responsible for creating hierarchical feature extraction. Starting from a single sample, it generates multiple diverse versions that vary in texture, color, and resolution. This process enables the model to learn and generalize effectively from the augmented samples. Even if the input image contains artifacts, they do not significantly affect the outcome.

from this study were used for training or fine-tuning, thereby ensuring complete absence of data leakage and positioning the model strictly as a post-acquisition support tool. The resulting segmentations exhibit markedly crisper delineation of vascular contours, thereby enabling dependable quantification of stenosis severity in accordance with NASCET methodology.[14-18] The overall architecture comprises 3 purposefully integrated modules, each contributing to the practical clinical evaluation of carotid artery stenosis:

Backbone

The backbone generates multi-scale hierarchical representations of vascular anatomy. These representations capture the relational geometry among carotid artery branches and enhance boundary discrimination, which is critical for achieving the exacting precision demanded by NASCET stenosis grading (Figure 2).[19]

Positional Encoding

This component translates the inferred vascular hierarchy into explicit relative spatial coordinates across the DSA image series. Consequently, focal narrowings within individual carotid segments can be precisely localized and distinguished (Figure 3).[20]

Attention Mechanism and Global Correlation

Through its attention operations, the model selectively emphasizes pertinent vascular elements while effectively attenuating irrelevant background signals and low-contrast noise; simultaneously, it facilitates robust alignment across frames for registration. These capabilities underpin consistent percentage-stenosis assessments, even under difficult imaging conditions (correlation coefficients $r = 0.83$-0.91, $P < .001$; Table 2).[21-28]

RESULTS

A total of 156 patients were included to assess the severity of carotid artery stenosis as measured by the CU-Model (the proposed AI model) compared to angiographically determined carotid artery stenosis. Digital subtraction angiography detected 156 carotid artery stenoses (84 left ICA, 72

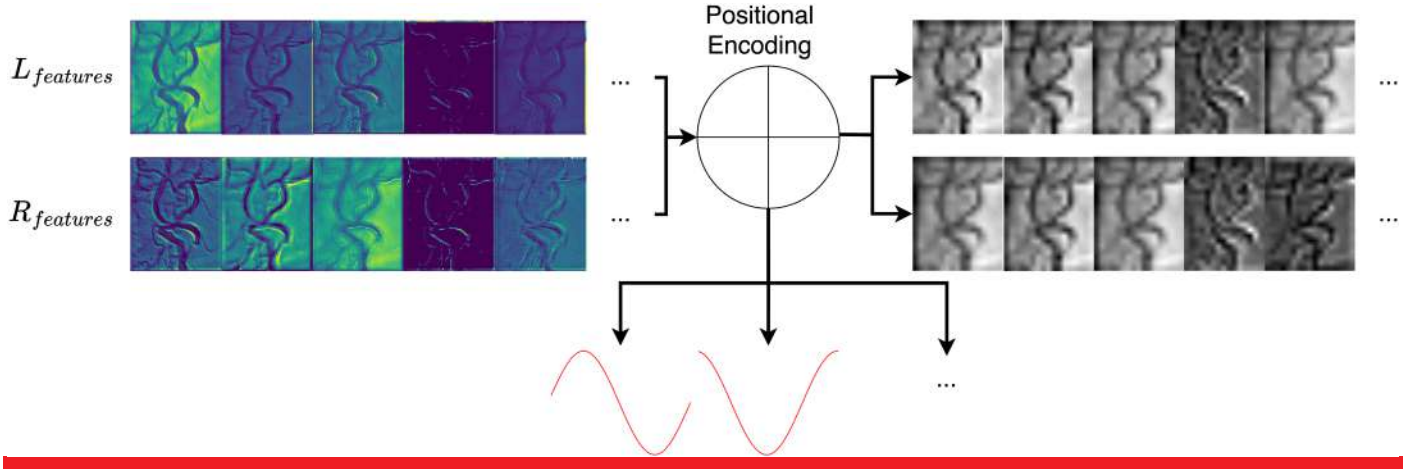


Figure 3. The effect of adding sinusoidal positions to the backbone outputs. As observed, the output images became smoother and more visually discernible. Different types of sinusoidal waves were applied to each output, and the resulting diverse, smooth samples were used for training.

Table 2. CU-Model and DSA Results

	CU-Model	DSA	*r*
Moderate stenosis (n = 106)	57.68 ± 5.94	57.71 ± 6.19	0.83
Severe stenosis (n = 50)	86.96 ± 5.97	87.02 ± 6.18	0.91

CU-Model, compact unified model; DSA, digital substraction angiography.

right ICA). The demographic characteristics of the study population are summarized in Table 1. The mean age at the time of the scan was 68 ± 12 years. Of the participants, 118 (75.6%) participants were male, and 84 patients were diagnosed with left ICA stenosis. Severe carotid artery stenosis was detected in all patients with a history of syncope. The Pearson chi-square test showed that hypertension, smoking, and syncope were significant risk factors in patients with symptomatic carotid artery disease ($P < .05$). Table 2 shows the results of the relationship between the CU-Model and DSA. As shown in the Results section, the CU-Model demonstrated excellent concordance with DSA (detailed numerical values and BAT plots in Figures 6-7).

Table 3 presents the results of a compact, unified model for intra-observer variability in patients with moderate-to-severe carotid artery stenosis. Intra-observer variability between CU-Model-1 and CU-Model-2 in the assessment of the severity of carotid artery stenosis (57.46 ± 7.19 and 57.61 ± 6.76 for moderate, $r = 0.86$, $P < .001$, 95% CI: 0.80-0.90; 86.96 ± 5.97 and 87.12 ± 4.33 for severe, $r = 0.93$, $P < .001$, 95% CI: 0.88-0.96). The correlations were highly significant ($r = 0.86$ and $r = 0.93$, $P < .001$). Table 4 presents the results of a compact, unified model for inter-observer variability in patients with carotid artery stenosis. Inter-observer variability between CU-Model-1 and CU-Model-2 in the assessment of the severity of carotid artery stenosis (57.46 ± 7.23 and 57.93 ± 6.53 for moderate, $r = 0.91$, $P < .001$, 95% CI: 0.87-0.94; 86.96 ± 5.97, and 88.54 ± 6.46 for severe, $r = 0.90$, $P < .001$, 95% CI: 0.83-0.94), respectively. The correlations were highly significant ($r = 0.91$ and $r = 0.90$, $P < .001$). The linear correlation coefficient for inter-observer variability in patients with moderate-to-severe or severe carotid artery stenosis is shown in Figure 4. The Pearson correlation coefficient regression line in patients with severe carotid stenosis is presented in Figure 5. Figure 6 illustrates the difference between CU-Model and DSA, as assessed by the BAT plot test, in patients with severe carotid artery disease. Based

Table 3. CU-Model Results for Intra-Observer Variability in Patients with Carotis Artery Stenosis

	CU-Model-1	CU-Model-2	*r*
Moderate stenosis (n = 106)	57.46 ± 7.19	57.61 ± 6.76	0.86
Severe stenosis (n = 50)	86.96 ± 4.37	87.12 ± 4.33	0.93

CU-Model, compact unified model; CU-Model-1 (%), compact unified model (reader 1); CU-Model-2 (%), compact unified model (reader 1 different time).

Table 4. CU-Model Results for Inter-Observer Variability in Patients with Carotis Artery Stenosis

	CU-Model-1	CU-Model-2	*r*
Moderate stenosis (n = 106)	57.46 ± 7.23	57.93 ± 6.53	0.91
Severe stenosis (n = 50)	84.41 ± 8.27	81.88 ± 7.92	0.89

CU-Model, compact unified model; CU-Model-1 (%), compact unified model (reader 1); CU-Model-2 (%), compact unified model (reader 1 different time).

on the BAT statistical analysis of the measurements for severe carotid artery stenosis, there was good agreement with no significant bias, making them sufficiently reliable for CU-Model comparisons in clinical practice. The minimal mean difference (0.08 as specified and narrow) 95% limits of agreement (−5.28% to 5.44%) indicate that differences are clinically acceptable for stenosis percentages in the 70%-99% range. Figure 7 illustrates the differences between the CU-Model and DSA in patients with moderate carotid artery stenosis (BAT plot test). These results demonstrate strong agreement between the CU-Model and DSA. The model may therefore serve as a reliable post-processing aid in clinical practice when used together with expert cardiologist review, although larger prospective studies are needed before widespread adoption.

DISCUSSION

Imaging plays a critical role in evaluating carotid artery calcification and stenosis, with trade-offs between invasive gold standards like catheter angiography and non-invasive alternatives. Building on this, recent advancements have increasingly favored non-invasive modalities, with a notable shift from focusing solely on stenosis severity to assessing plaque

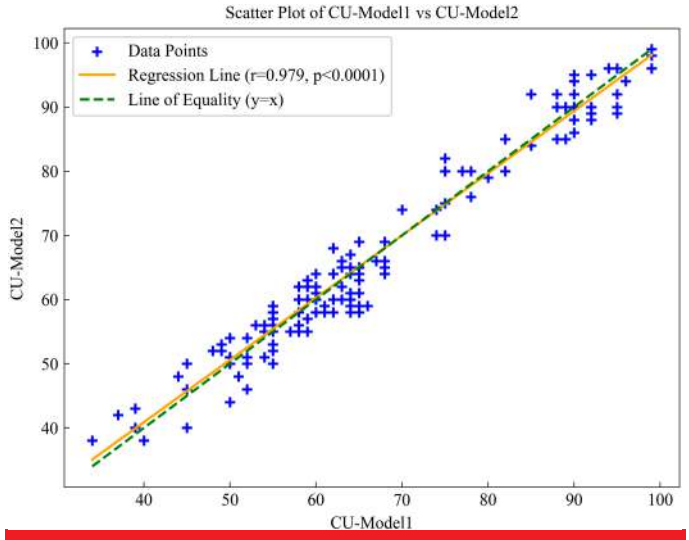


Figure 4. Linear correlation coefficient for inter-observer variability in patients with moderate-to-severe carotid artery stenosis (CU-Model-1 vs. CU-Model-2), where CU-Model-1 is compact unified model (reader 1) and CU-Model-2 is compact unified model (reader 2). CU-Model, compact unified model.

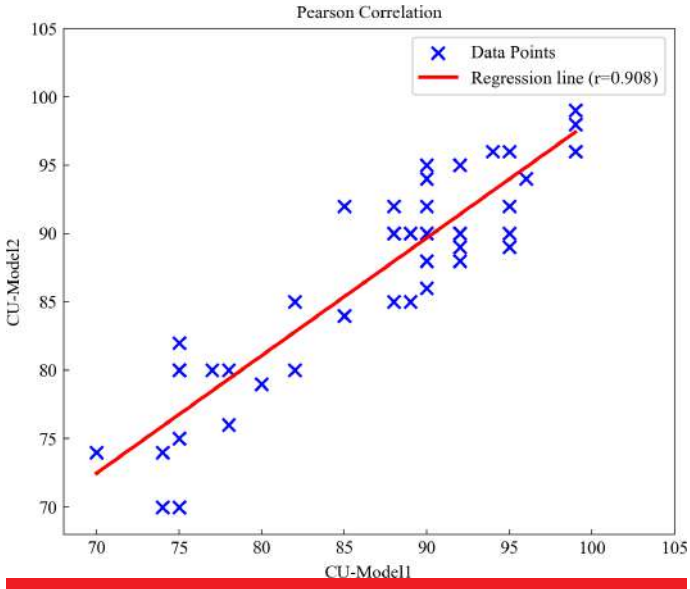


Figure 5. Pearson correlation coefficient regression line in patients with severe carotid stenosis. CU-Model, compact unified model.

composition and vulnerability, which better predict stroke risk. For instance, guidelines recommend incorporating high-rich necrotic cores and neovascularization into risk stratification, even for plaques with moderate stenosis, and recent perspectives suggest rethinking endarterectomy in near-occlusive severe cases to optimize outcomes.[29] Hypertension was the most common risk factor (77%, $P = .009$), with symptomatic patients more likely to have it than asymptomatic ones.[30-32] Smoking was also significantly associated with symptomatic disease, while syncope occurred in 14.7% of cases, all with severe stenosis ($P < .05$). No significant associations were found for diabetes (26% prevalence) or obesity, possibly due to controlled cases or small sample size. Larger studies are needed to confirm these clinical risk factors. Cigarette smoke promotes plaque build-up via oxidative stress and inflammation.[34] Syncope was present in 14.7% of patients with carotid artery stenosis, and severe carotid artery stenosis was detected in all patients. Nno association was found between ICA stenosis and cerebrovascular symptoms ($P > .05$). Hypercholesterolemia is a significant risk factor for carotid artery disease. In this study, although hypercholesterolemia was more prevalent in patients with cerebrovascular symptoms (58% vs. 55%), the difference was not significant. Inter- and intra-observer variability showed excellent agreement (Tables 3-4, Figure 6-7). From a clinical perspective, the narrow limits of agreement coupled with minimal bias underscore a dependable consistency between the CU-Model and DSA. The strong correlations ($r \geq 0.83$) and excellent intraclass correlation coefficient (ICC = 0.90) indicate that the CU-Model may serve as a reliable adjunct tool for stenosis evaluation when integrated into the post-processing workflow alongside expert cardiologist review. While differences remain unlikely to substantially alter treatment choices in most cases—such as recommending carotid endarterectomy for ≥70% stenosis or medical management for moderate stenosis—the model should not be regarded as a fully interchangeable replacement for conventional DSA. Rather, it shows promise as a complementary aid that can enhance workflow efficiency pending validation in larger, prospective studies.

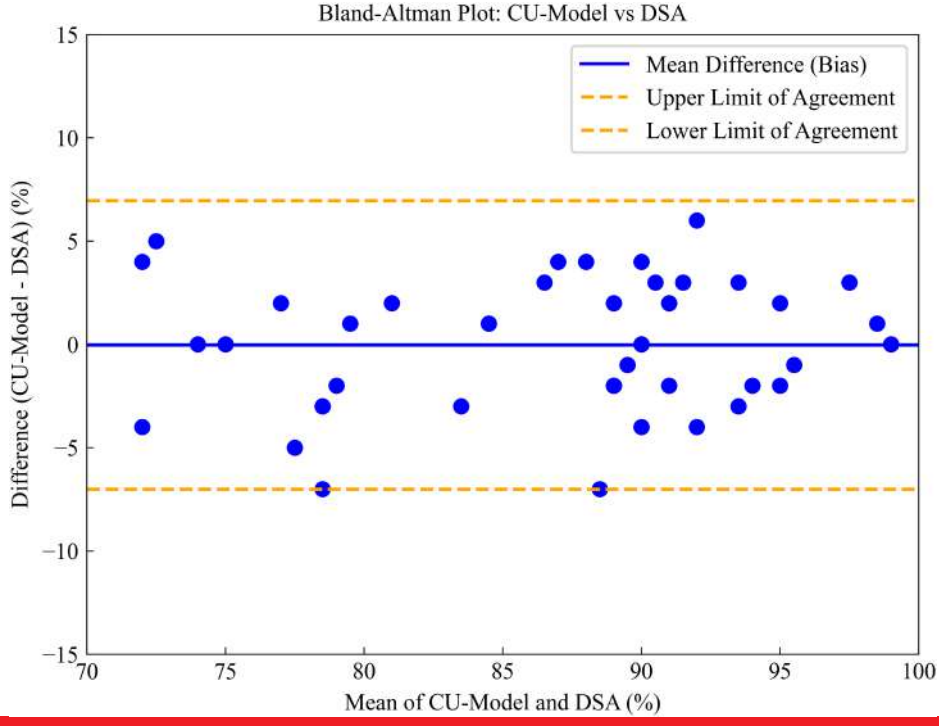


Figure 6. Difference between CU-Model and DSA (BAT plot test) in patients with severe carotid artery stenosis. BAT, Bland–Altman; CU-Model, compact unified model; DSA, digital subtraction angiography.

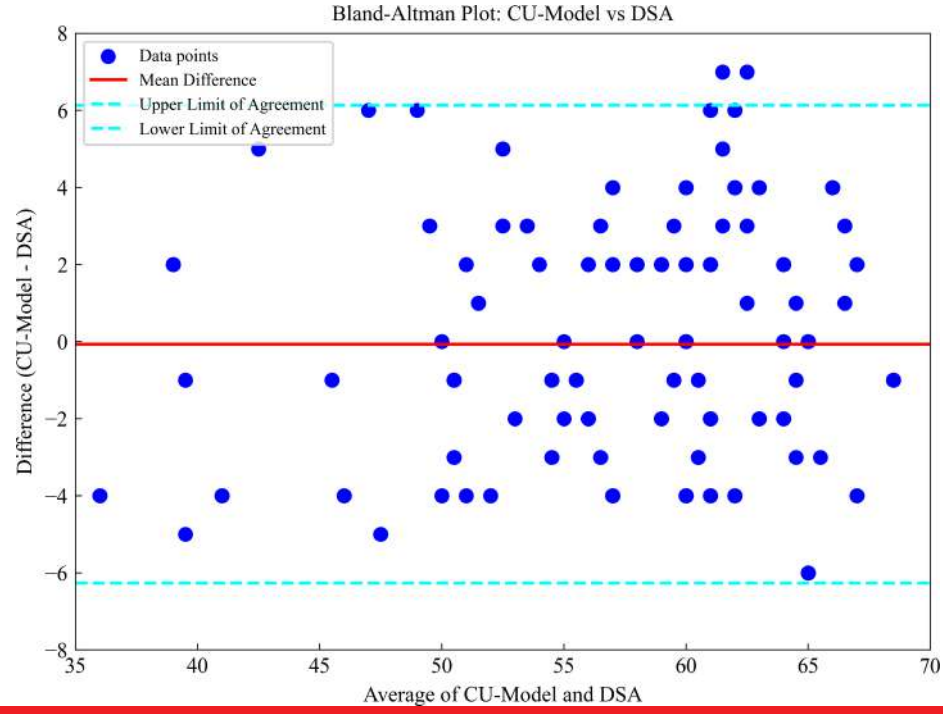


Figure 7. Difference between CU-Model and DSA (BAT plot test) in patients with moderate carotid artery stenosis. BAT, Bland–Altman; CU-Model, compact unified model; DSA, digital subtraction angiography.

Figure 6 shows clinically, the narrow 95% limits of agreement (−5.28% to 5.44%) and minimal bias (0.08) indicate good concordance, suggesting that CU-Model measurements are sufficiently interchangeable with DSA for informing interventions in severe stenosis (≥70%), such as endarterectomy in symptomatic patients, without substantial risk of altering clinical decisions. Figure 7 illustrates the disparities between the CU-Model and DSA among patients exhibiting moderate carotid artery stenosis, as assessed via a BAT plot in this pilot study. The analysis indicates a modest negative bias in mean differences (−0.07), suggesting that the CU-Model generally yields marginally lower measurements compared to DSA. With 95% limits of agreement spanning −6.24 to 6.10 (calculated as mean ± 1.96 × SD), the majority of variations are expected to reside within this interval under conditions of strong methodological concordance, and the visualization overall points to a solid level of alignment between the approaches. From a clinical perspective, this narrow interval (−6.24% to 6.10%) coupled with the minimal bias underscores a dependable consistency, indicating that the CU-Model may facilitate precise risk evaluation for moderate stenosis cases (50%-69%) and thereby assist in conservative treatment strategies while obviating the need for supplementary diagnostic scans. A more comprehensive statistical evaluation of the agreement between the 2 methods (CU-Model and DSA) was performed using the complete dataset of 106 paired measurements. A 95% limit of agreement (LoA) indicates that 95% of differences fall within about ±6.2 units, suggesting reasonable agreement for most clinical or practical purposes, assuming the measurements are in comparable units. The systematic bias for the paired *t*-test is not significantly different (t = -0.21, $P = .83$) from zero ($P \geq .05$), so there is no evidence of systematic bias. If differences increased with measurement magnitude, differences were regressed on averages using a linear model to account for proportionality bias (slope = 0.05, $P = .28$, $R^2 = 0.01$). The slope is not significant ($P \geq .05$), and R^2 is very low, indicating no trend differences are consistent across the range of averages (no need for adjustments like log transformation). Intraclass correlation coefficient was 0.90 (using a 2-way mixed effects model for absolute agreement). This is considered excellent agreement (typically, ICC ≥ 0.75 is good; ≥0.90 is excellent). Confirming that the methods are highly concordant. Since there is no significant proportionality bias, no adjustments to the LoA are required. Clinically, these strong correlations ($r \geq 0.83$) and excellent ICC of 0.90, combined with narrow BAT limits of agreement, mean the CU-Model and DSA measurements are interchangeable for decision-making: differences are unlikely to alter treatment choices such as recommending carotid endarterectomy (≥70% threshold) or opting for medical management in moderate stenosis cases.

Digital subtraction angiography remains the go-to method for accurate diagnosis. Still, it's not without its drawbacks—like risks from ionizing radiation, problems with contrast materials, and neurological complications that occur in 0.1%-4.9% of procedures.[31-36] That's why they are often preferred as non-invasive options, such as ultrasound. However, these can yield variable results because they focus on the reduction in cross-sectional area rather than the vessel's actual diameter. Additionally, when using NASCET guidelines manually, there's a tendency to overestimate the degree of stenosis, which might result in unnecessary treatments. In clinical practice, one of the most challenging decisions regarding carotid artery revascularization is whether to treat a carotid artery near occlusion. In addition to periprocedural

complications, TIA, ipsilateral ischemic stroke, retinal TIA, and other postoperative neurologic complications have been reported in previous studies in these patients.[28]Therefore, it is clear that new models are needed to identify calcified, ulcerated, and potentially occlusive carotid lesions at risk. AI enables opportunistic screening via routine dental imaging. A meta-analysis of AI studies on panoramic radiographs and cone-beam CT demonstrated good sensitivity and specificity for detecting carotid calcifications.

In contrast to the numerous publications on the automatic detection of aneurysms in DSA images and thrombus detection in CT images, research results on software-based analysis of DSA sequences from patients with carotid artery stenosis have been published sparingly, mostly in recent years.[38] Though perspectives on large language models suggest they could transform such diagnostic support.[39] Threshold-based algorithms help differentiate vascular wall calcification from contrast in the lumen, producing images similar to those in angiography. However, variability in threshold selection can affect vessel diameter measurements, underscoring the need for operator expertise, as in US.

The AI-based measurement relies on the quality and diversity of the dataset; however, limited external validation in many studies reduces the generalizability of the findings. Challenges with heavy calcification (blooming artifacts), irregular plaques, or low contrast can lead to over- or underestimation of the lumen. Automated measurement tools may differ from manual methods in handling perpendicular planes or minimal caliber (area-based vs. diameter-based), which can sometimes result in underestimation of severe stenosis. The transformer model may miss nuances of near-occlusion or tandem lesions without hybrid clinical input. Studies show high accuracy (e.g., 88%-94% for categories), but with variability across thresholds (better for <50% or 75%) and modalities. The CU-Model offers various post-processing techniques for 3D imaging of the carotid arteries. The model is an effective technique for distinguishing true vascular wall calcification from contrast material in the lumen. The analysis also showed excellent inter-method agreement in the evaluation of carotid disease. Findings have been reported in good to excellent agreement with the CU-Model and angiography.[38,39]

In routine clinical settings, the CU-Model could serve as an adjunct tool during the post-processing phase of DSA imaging, applied after initial image acquisition but before final interpretation. This hybrid workflow (raw DSA input to CU-Model enhancement to cardiologist review) ensures the model remains an adjunct rather than a replacement for clinical judgment. Trained cardiologists would input raw angiographic data into the model, which then automates vessel segmentation and stenosis quantification, potentially reducing analysis time in the study. This integration might occur in hybrid workflows, where the model's outputs are reviewed alongside manual assessments to inform decisions on interventions like endarterectomy, particularly in high-volume centers handling symptomatic cases. Together, these findings suggest that the CU-Model is a reliable and reproducible imaging model for evaluating carotid disease and shows preliminary promise in this retrospective cohort of 156 patients; larger prospective, multicenter studies with external validation are required before broader clinical implementation.[16]

By drawing on data from 3 independent medical centers involving 156 patients, the study partially mitigates potential institutional bias through exposure to diverse clinical protocols, equipment variations, and patient demographics, thereby enhancing preliminary generalizability within the studied Turkish population. Nonetheless, these correlations represent promising initial evidence, though limited by the study's scale and design (see Limitations below). Validation in larger prospective cohorts is essential. The AI tools like CU-Model reduce variability but depend on dataset quality. The findings show excellent inter-method agreement, supporting its use pending larger validation.[37-38]

Limitations of the Study

This study's primary limitations include its small sample size (n = 156), retrospective cohort design, and lack of external validation, which collectively limit its generalizability. A small study population may be a limitation. In this retrospective, cohort-designed study, the inclusion of severe stenosis cases undergoing atherectomy with bypass surgery introduces potential selection bias, as the cohort may overrepresent advanced disease from referral centers. While multicenter data from 3 sites partially mitigates institutional bias by incorporating diverse protocols and demographics, it does not fully address confounding factors inherent to retrospective data, such as recall bias or incomplete records. Moreover, the absence of prospective follow-up or external validation on independent cohorts restricts the applicability of the findings beyond this sample. Future high-quality research, including larger prospective multisite trials (e.g., n > 500) with blinded external validation datasets, is essential to confirm reliability, reproducibility, and broader generalizability. Further high-quality research is required to assess the reliability and reproducibility of the CU-Model for evaluating carotid disease. The NASCET adaptations may reduce comparability with strict standards, potentially shifting ~5% of cases near 70%. For instance, this approach could lead to a slight shift in classifications near the 70% cutoff, potentially reassigning 5% of cases from severe to moderate in real-world scenarios, as suggested by the BAT limits of agreement. Clinically, this might favor more conservative management strategies, such as opting for medical therapy over surgery in ambiguous cases, but it could also introduce inconsistencies when pooling data across trials. To enhance comparability, future research should align on standardized thresholds or report dual classifications, in future extensions.

CONCLUSION

A new AI architecture pretrained on public nonclinical datasets for stereo and optical flow tasks was proposed. The CU-Model could fit smoothly into cardiology practices, applied by cardiologists right after DSA capture to support stenosis assessment and cut down on interpretation time,

acting as a helpful aid under expert supervision. A growing body of research employs AI methodologies to assist in identifying carotid artery stenosis and complement physician diagnosis. While the results are encouraging, this retrospective study with only 156 patients demonstrates preliminary promise. Larger prospective, multicenter validation studies with external datasets are essential before routine clinical adoption.

Ethics Committee Approval: This study was approved by the Ethics Committee of Health Sciences University İzmir Tepecik Training and Research Hospital, Ethics Committee Decision Date: September 11, 2025; Ethics Committee Decision Number: 2025/07-32.

Informed Consent: Informed consent was not obtained from the patients as this was a retrospective study using existing medical records. The study was approved by the Ethics Committee (approval number: 2025/07-32), which waived the need for informed consent.

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