Carotid Artery Plaque Analysis Using Deep Neural Networks for Improved Detection and Classification

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MSc.in Data Analytics

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Carotid Artery Plaque Analysis Using Deep Neural Networks for Improved Detection and Classification

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Abstract

Carotid artery one of the major blood vessels that carries oxygenated blood to the brain and that buildup of plaque in the artery can lead to serious cardiovascular disease including atherosclerosis, stroke or rupture of the arteries and all of these conditions being life-threatening. Plaque clogging the flow of oxygen to the brain causes strokes. High-penetration ultrasound scanners are commonly used to identify problems such as plaque buildup in the carotid artery, but those devices are costly. In other cases, general practitioners simply don't have access to low-cost, low-depth ultrasound scanners and available devices tend not to provide sufficient sensitivity for plaque identification or measurement. The authors explore whether AI methods can be used to derive the same diagnostic information from low-depth ultrasound images as can be obtained with high-penetration scanners. Specifically, characteristics from the images were extracted using CNN models including U-Net, which also segmented the carotid artery and plaque sections. We used Roboflow to improve segmentation accuracy for artery and plaque detection. Additionally, SRCNN and Real-ESRGAN were used to enhance low-penetration ultrasound images. Ultimately, Linear Regression was employed to successfully determine measurements from these low-res images.

1 Introduction

With the growing burden of cardiovascular diseases, including stroke and atherosclerosis, innovative diagnostic tools that can provide precise and timely information about clinical status are increasingly needed. Such high-resolution ultrasound scanners capable of detecting plaque buildup in carotid arteries are critical, but go for exorbitant prices and remain out of reach for numerous healthcare practitioners. Family doctors often use low-price and shallow ultrasound device, unable for solid analysis due to a poor resolution and sensitivity. This study explores how Artificial Intelligence (AI) can be used to overcome these challenges through the reconstruction of low-depth ultrasound images and extraction of clinically relevant features. To prove that inexpensive ultrasound machines can produce sound diagnostic results equivalent to expensive ones when combined with significant computer science methods such as U-Net for segmentation and Real-ESRGAN for image upscaling, just like the studies presented in this one.

1.1 Motivation

One of the main arteries responsible for providing oxygen to the brain is the carotid artery. Now, if cholesterol plaque blocks the inside of this artery and thereby prevents its passage then serious cardiovascular diseases like atherosclerosis, stroke or arteriosclerosis also stat causing potential harm to people that they never thought possible before. The one thing all these conditions share in common: they're deadly. Blockage of the carotid artery's circulation leads to strokes.Currently, there are no cheap low-penetration ultrasound scanners other than high-penetration devices. And although the latter are used to identify problems such as plaque buildup in the carotid artery and elsewhere, these are relatively expensive instruments.General practitioners do not have access to low-cost, low-penetration ultrasound scanners in some cases. And the higher penetration devices which are available to them tend not to be sensitive enough for plaque detection and measurement.The authors investigate whether AI methods can be used to get the same diagnostic information as is obtained by high-penetration scanners from low-depth ones. In particular, the characteristics extracted from the images using CNN models include U-Net, which also provides segmentation for the carotid artery and its present sections. Being able to detect plaque in the carotid arteries early can help reduce death rates and improve patient outcomes.However, the high cost and limited availability of ultrasound scans with technologies of higher penetration in resource-constrained health care settings present a serious challenge to accurate diagnosis.

A great many general practitioners are in a situation where they only have low-cost ultrasound devices that do not give the necessary resolution for accurate detection and measurement of arterial plaques. This makes it not only difficult to diagnose the patient effectively and in a timely manner, but also leads to delayed treatment which puts the patient at risk. It is essential to bridge this gap: cheap systems must produce valid diagnostic output.

AI has the potential to make a major contribution to advanced medical diagnostics, and this area of research is influenced by the vision of democratizing healthcare so as indeed deliver higher-quality acuity within these under-resourced areas both in low-resource settings. Such rapid AI-imaging-based decisions can lead to much reduced long-term disabilities, effectively a low-cost intervention. This research aims to demonstrate the possibilities of AI enhanced imaging.

1.2 Research Objective

We conducted this research mainly to test and validate AI methods for enhancing the diagnostic value of low-depth ultrasound images in carotid artery analysis. Directives organized around models and methods used by subject are as follows.

1.2.1 Objective One

- There are those who can't make contact without appearance from original low-resolution scan image quality upscaled ones using like PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) metrics, look instead.

- By increasing picture resolution it brings greater detail into view thus demonstrates up-scaled images holding the potential for maintaining diagnostic quality. This is necessary to complete the gap between amateur cheap scanners and professional high-speed models.

1.2.2 Objective Two

Use CNN-based models for segmentation of carotid artery features.

- Through the research on the degree of accuracy in carotid artery wall and plaque total segmentation achieved by U-Net contrasted number training epochs (100 v 200) tests showed.
- Focusing on its capacity to detect above-mentioned, YOLOv8 is a plaque detection and categorization tool.

1.2.3 Objective Three

Evaluate predictions statistically and measure arterial characteristics.

- Using high-depth measurements as a benchmark, Linear Regression was employed to predict arterial wall thickness and plaque dimensions from low-depth ultrasound images.
- Statistical assessments such as paired T-tests-cement that measurements made using low-resolution and upscaled pictures are reliable in clinical practice.
- Investigate whether upscaled image gives added diagnostic value by narrowing the error margin for measurements of familiar features.

1.2.4 Objective Four

Deal with difficulties and suggest future improvements.

- Point up constraints such segmentation errors and short datasets, then provide strong data augmentation methods based on synthetic data generation and Roboflow.
- Suggest architectural changes to CNN models using loss functions and ideal layers to improve feature segmentation accuracy and lower false positives.
- Promote the creation of automated measurement extraction tools to lower hand-off mistakes and increase repeatability in diagnostic procedures.

2 Related Work

Recent improvements in Artificial Intelligence (AI) have had a major result on medical imaging, allowing diagnostic solutions in a cost-effective and healthful manner. Carotid arteries being vital components for human imaging due to plaque buildup non-invasively is a common challenge since traditional imaging methods offer only low-quality inadequate depth as-is-Ultrasound images of carotid arteries (Azzopardi, Hicks and Camilleri 2017; R. Zhou et al. 2019). Here we present a summary of the relevant methodologies in feature segmentation, image upscaling, and measurement of features, along with their limitations and how they fit this study. To aid clarity, we provide summarizing tables within the respective subsections with regard to approaches.

2.1 Early Models and Approaches

Methods developed in the early years like Hough Transform (HT) and SRCNN (Mittal et al. 2022) were characterized by using feature detection and image enhancement as primary approaches. Ultrasound boundary detection and segmentation—the Hough Transform especially was suitable for line detection in ultrasound boundary detection and segmentation , such as the boundaries of the carotid artery (Golemati et al. 2007; Matsakou et al. 2011).Even so, the utility in isolation was limited due to its inability to resolve complex shapes — such as plaques. As one of the first deep learning-based super-resolution methods, SRCNN was successful at enhancing images but remained unable to maintain the informative details needed for medical imaging applications (Mittal et al. 2022).

Table 1: Approach/Model, Key Features/Innovations, and Performance Metrics

Approach/Model	**Key Features/Innovations**	**Performance Metrics**
Hough Transform (HT)	Linear feature detection, suitable for longitudinal views	Struggled with irregular shapes
SRCNN	Basic image clarity improvement, early super-resolution	Low PSNR, poor detail retention

2.2 Feature Segmentation

It is crucial to segment the features of the carotid artery, as it plays an important role in the diagnosis of cardiovascular diseases. Hough Transform and other traditional techniques used are good for linear segmentation but are not accurate with respect to plaques and other such features (Golemati et al. 2007).Convolution Neural Networks (CNNs) (U-Net, 2015) implemented a new encoder-decoder architecture that has the advantage of learning spatial hierarchies for segmentation at different scales and making possible accurate segmentation of arterial walls and plaques (R. Zhou et al. 2019). The last feature that finely tuned these capabilities, was that YOLOv8 also detected and classified plaques in the form of bounding boxes (Redmon et al. 2016).

To overcome the challenge of small datasets, we relied on Roboflow for data augmentation, which resulted in multiple datasets that were diverse and augmented, which helps in training the model better. The Roboflow first full-scale segmentation datasets we created were critical to the enabling U-Net, YOLOv8 and other segmentation models to generalize more smoothly from simulated to reals (Bai et al. 2023).

Table 2: Approach/Model, Key Features/Innovations, and Performance Metrics

Approach/Model	**Key Features/Innovations**	**Performance Metrics**
U-Net	Encoder-decoder architecture, high segmentation accuracy	Captures fine spatial details
YOLOv8	Object detection with bounding boxes	Accurate plaque classification
Roboflow	Dataset augmentation and pre-processing	Enhanced model generalization

2.3 Image Upscaling

The resolution for accurate diagnosis is often absent in low depth ultrasound images. Frameworks such as SRCNN that pioneered convolution-based image enhancement for simple super-resolution still struggled with maximizing the information required for diagnostic value (Mittal et al. 2022). Since then, the Enhanced Super-Resolution GAN (ESRGAN) and its modernized version, Real-ESRGAN, become powerful tools for synthesising high-quality enlarged images (Wu and Ma 2020; Mekapothula, Pullagura and Potharlanka 2023).

In order to obtain sharper images with more high-frequency details, Real-ESRGAN uses residual-in-residual dense blocks. While the upscaling process greatly improved visual clarity, the resulting images contained artifacts, that led to false positives in segmentations. Real-ESRGAN with x4 scaling was used in this study as this was the optimal setting between preventing artifacts and increasing the resolution.

Table 3: Approach/Model, Key Features/Innovations, and Performance Metrics

Approach/Model	**Key Features/Innovations**	**Performance Metrics**
SRCNN	Basic super-resolution	Low PSNR, poor diagnostic clarity
ESRGAN	High-fidelity upscaling	Moderate PSNR and SSIM
Real-ESRGAN	Advanced dense blocks for sharper images	High PSNR, SSIM (optimal at x4)

2.4 Feature Measurements

Measurements of arterial characteristics – wall thickness, dimensions of plaque sizes, – are vital to carotid artery diagnostics. These metrics were extracted manually, which were extremely high in labor but low in quality of consistency and high in labor (exposing the manual nature to human error)(Dhupia et al. 2020). To automate this process, regression models (especially linear regression) have been applied to ensure consistent and scalable solutions.

Linear regression models were trained on high-resolution images, able to correctly predict depth on low-depth images, including upscaled versions. Statistical validation of the equivalence of measurements between high-depth and low-depth scans was performed using paired T-tests, with acceptance of clinical reliability (Kumar et al. 2019).

Table 4: Approach/Model, Key Features/Innovations, and Performance Metrics

Approach/Model	**Key Features/Innovations**	**Performance Metrics**
Linear Regression	Automated measurement prediction	Consistent results across datasets
Paired T-Tests	Statistical validation of measurement equivalence	No significant difference between high-depth and low-depth measurements

The below image Figure 1 is an example of how the U-Net architecture shows that workflow for medical image segmentation. Complication: Input images from modalities like MRI, CT, X-ray, and ultrasound may require different stages of pre-processing (e.g.

normalization, filtering) in order to achieve quality preprocessing. At the center of the workflow is a U-Net model with an encoder-decoder structure and skip connections that allow for pixel level segmentation with high-level and fine-grain features. 3D U-Net has variants and other similar models that let you use this architecture for volumetric data. Some post-processing (like morphological operations) might help clean up the segmentation mask defined by U-Net but in the most cases U-Net outputs quite good defined objects without post-processing steps. It returns a segmentation mask, which is critical for detecting tumors and segmenting organs.

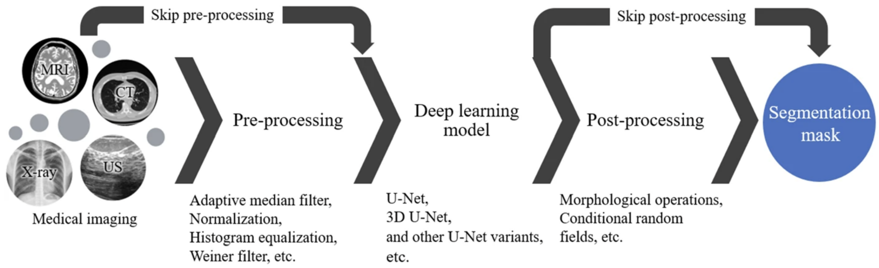


Figure 1: Medical Image Segmentation Workflow Using U-Net Architecture

2.5 Summary

In contrast, this study builds on insights from earlier methodologies but takes pains to overcome the shortcomings. A great pipeline for low-depth ultrasound images analysis was established by combining Roboflow for data augmentation (Bai et al. 2023), Real-ESRGAN for image up-scaling (Mekapothula, Pullagura and Potharlanka 2023) and state-of-the-art CNN models such as U-net (R. Zhou et al. 2019) and YOLOv8 (Redmon et al. 2016). Such developments allowed for accurate segmentation and dimensions of various features of the carotid artery, further closing the distance between low-cost imaging technologies and advanced diagnostic devices.

3 Methodology

In this section,a systematic approach is provided as the methodology adapted in this study to perform a content based analysis on low depth carotid artery ultrasound images using AI techniques. This includes processes from data collection to pre-processing, model designing to evaluation, with the inclusion of many visuals to depict the workflow as clearly as possible.

3.1 Data Gathering

To ensure ethical conduct of the study, we used publicly available repositories for image data to simulate both low-cost and high-cost ultrasound scanners. The dataset contained publicly available images, representing high and low-depth ultrasound scans.

In order to reproduce low-penetration conditions, high-resolution images were artificially down scaled.Such data also meant that the study could evaluate and compare AI-enhanced images with low-depth and high-resolution ground truth images. The wide range of resolutions in the dataset made the training and testing of models sufficiently diverse so the AI pipeline is generalizable enough for actual usage scenarios.

3.2 Data Preparation

Pre-processing of data was a general need to standardize the dataset and make it to be a proper data for analysis. The following approach was done:

- **Image Pre-processing:** All images were processed at a specific size with normalization on all pixel levels. As a result, this step was necessary for it to sync with AI Models.
- **Data Augmentation:** In this approach we pumped the dataset through a series of algorithms via using the Roboflow so we use flip, rotate,Add noise and then Roboflow was responsible to increase our dataset. This increases the range of imaging conditions, improving the generalizability of the models.
- **Annotation:** Segmentation tasks for marking of arterial walls and plaques led to the generation of ground truth labels. They were useful for training segmentation models.
- **Simulation of Low-Depth Images:** Low-penetration ultrasound scans, which are customarily performed, were emulated by down scaling high-resolution images. Both the simulated images and original high-depth images were employed to assess the performance of the AI pipeline.
- **Data Splitting:** To validate the model without over fitting, the dataset was split into 3 separate parts training-70 percent, validation-20 percent, testing-10 percent).

3.3 Training the Model

A fine-tuning of the models was required during the training process in order to maximize their performance for each individual task:

- **Segmentation Training:** U-Net and YOLOv8 that were trained with the annotated data for the 100 and 200 epochs. For U-Net performance measurement, we employed the loading sample and obtaining the Dice coefficient values after segmentation, and for YOLOv8, we manually checked the bounding box predictions.

  Patch-based approaches, such as U-Net, were trained with upscaled images leading to increased false positives, particularly in plaque segmentation.
- **Upscaling Training:** IReal-ESRGAN was trained on x2, x4, and x8 upscaling factors. In others, the x4 scaling never failed to improve image clarity while avoiding excessive artifacts.
- **Measurement Training:** Linear regression models were fitted to low-depth images coupled with manually obtained measurements including the arterial thickness and plaque measurements. Image-based ground truth with high-depth images.

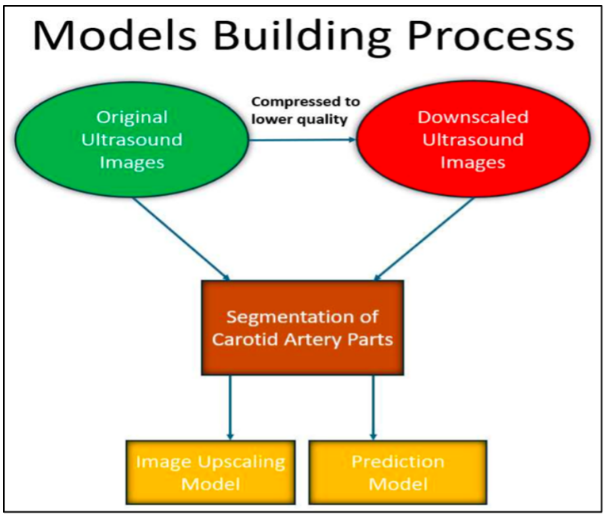


Figure 2: Model Development Process For The Project

Figure 3 shows how original and down scaled images are prepared for segmentation and analysis. Over here one can see how the images flow from raw images to the segmentation step and how they were essentially used for up-scaling and prediction models.

4 Design Specification

The AI pipeline was built to solve three main problems: feature segmentation, image up-scaling and prediction of measurement. Each component was customized to fulfill the aims of this study

4.1 Image Up-scaling:

- **Real-ESRGAN:** The main model used for upscaling was Real-ESRGAN, which upscaled low resolutions of images with low depths. Three scaling factors (x2, x4, x8) were experimented with; and again x4 yielded best results in terms of object clarity with minimal artifacts.

- **SRCNN:** Was used as baseline comparison but was inadequate for medical image use since it does not retain small detail for diagnosis.

4.2 Feature Segmentation:

- **U-Net:** As the anchor model for segmentation, the U-net's encoder-decoder architecture allowed for accurate segmentation of arterial walls and plaques. Images were downscaled for training and upscaled for testing to see how they ensure performance at different resolutions.

- **YOLOv8:** Using this model, plaques are also detected and arterial features are localized with bounding boxes. It was more helpful to U-Net pixel-level segmentation due to the insights at the object level.

4.3 Measurement Prediction:

This means that if you have deep images, you can use them to obtain arterial measurements (e.g.wall thickness, plaque sizes setting up a regression model to predict these metrics from low-depth images. To test the accuracy, these predictions were validated with high-depth measurements.

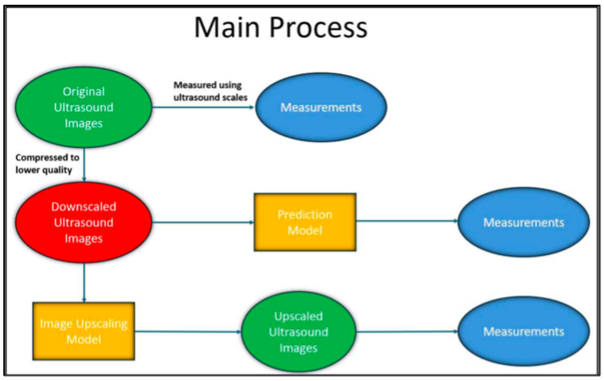


Figure 3: Project Workflow Overview

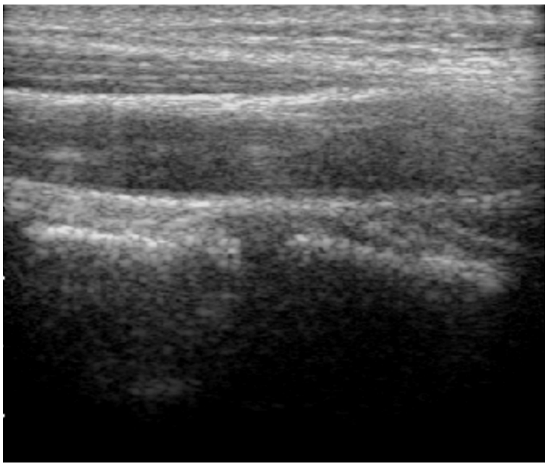
As shown in Figure 3 how the different components of the pipeline—segmentation, up-scaling, and prediction—work together. It gives a clear picture of the general flow of images through the pipeline up to the measurements

5 Implementation

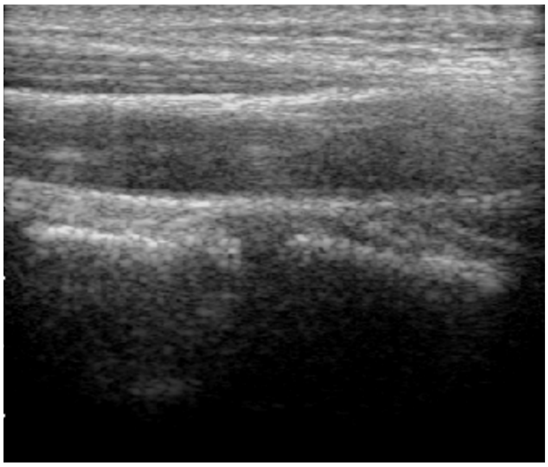
This study established a comprehensive AI instantiation to process carotid artery ultrasound images by overcoming the challenges associated with low-depth imaging. This mechanism handles image refinement, segmentation and measurement prediction, holding valid results for diagnostic tasks.

5.1 Data Collection and Simulation

This dataset contains ultrasound images of carotid arteries collected in different conditions. Low-penetration conditions were simulated by down-scaling high-resolution images typical for low-cost ultrasound scanners. The synthetic examples of images at varying low depth served as a controlled dataset to evaluate the performance of image enhancement and segmentation algorithms in this domain.



(a) A high-resolution ultrasound image of the carotid artery



(b) A low-resolution image of the same carotid artery

Figure 4: A low and High -resolution image of the same carotid artery.

5.2 Image Up-scaling Pipeline

Real ESRGAN—state of the art deep learning model was applied to up-sample depth ultrasound images to a higher resolution. I had previously tried other up-scaling (definitely up-sampled images) models but this one provided much better image quality. Its pipeline included several sophisticated components intended to maintain diagnostic information:

5.2.1 Residual in Residual Dense Block (RRDB) Network:

Residual in Residual Dense Block (RRDB) Network: The Real ESRGAN uses RRDB as backbone to extract features efficiently without losing high-frequency details relevant to diagnosis.

5.2.2 Pixel Unshuffling and Grid-Based Flow Warping:

These pre-processing and manipulation techniques lent precision over the transformation coupled with enhancing clarity.

5.2.3 Patch-Based Processing

Allowed processing of big images without degrading the output quality.

Images were up-scaled by three channels, x2, x4 and x8, describing different image settings and degrees of enhancement. Out of these, x4 scaling always provided the best overall result, striking the most appropriate balance of optimal resolution and minimal artifacts.

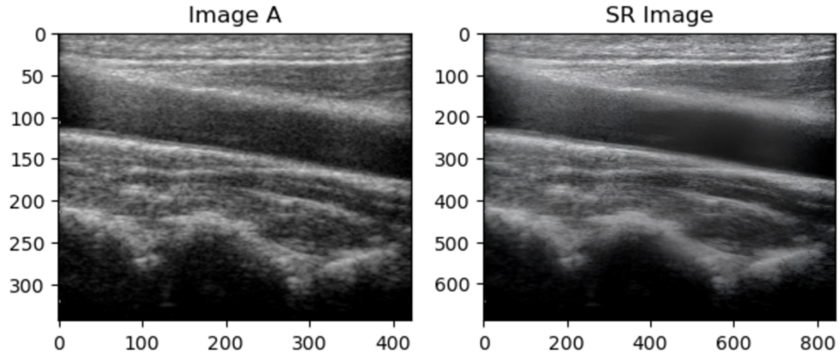


Figure 5: x2 Super-Resolution Using Real ESRGAN

Here, Figure 5 we compare the original low-resolution ultrasound image with its SR counterpart (shown on the right) applying the x2 scaling factor from Real ESRGAN. SR image showing a conspicuous improvement in A. resolution; B. the arterial border and C. finer textures. These enhancements are essential in for correct diagnostic interpretation and demonstrate the effectiveness of Real ESRGAN in improving low-depth ultrasound images whilst preserving diagnostic features.

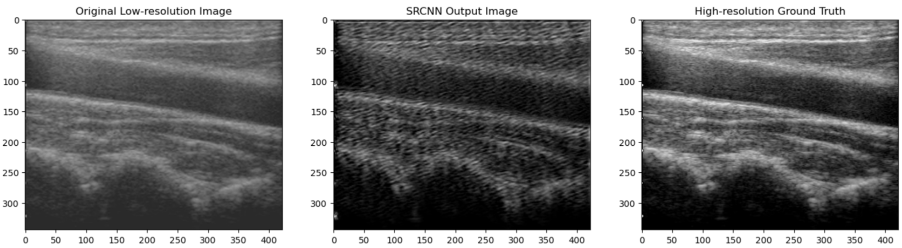


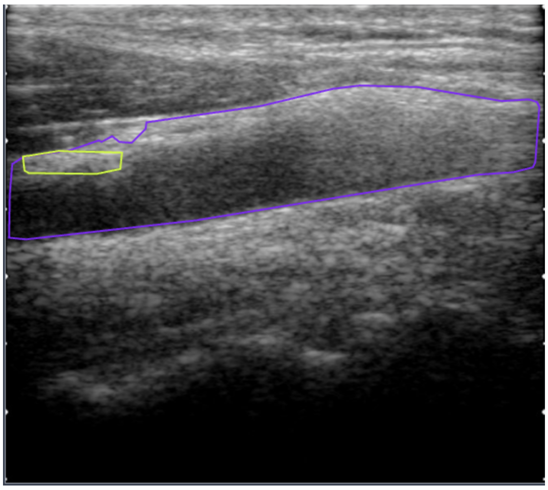
Figure 6: SRCNN in Super-Resolution Compared to Ground Truth

Figure 6 shows three variations of the same image side by side, including the original low-resolution ultrasound image, the SRCNN output after completing upscaling, and the high-resolution ground truth. The original low-resolution image lost a lot of detail and is blurry as can be seen. We can observe a minor improvement in resolution on the SRCNN-upscaled image, however this upscaling does not dominate the clarity nor diagnostic details needed for proper analysis of the specimen. As a comparison, the high-res ground truth acts as the reference, demonstrating the best resolution and details which are absolutely essential in clinical diagnosis. Analyzing the results, it becomes evident that although the traditional method (SRCNN) has its merits, Real ESRGAN exhibits a clear edge, revealing the necessity for advanced models when it comes to diagnostic-quality super-resolution in medical imaging.

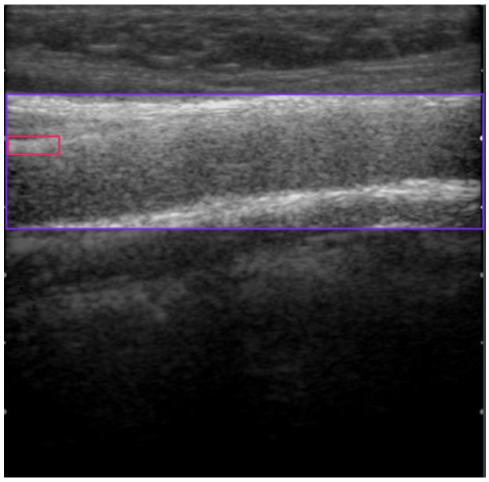
5.3 Segmentation of Arterial Components

CNN models trained for the segmentation of arterial components, Roboflow used for data pre processing and data augmentation. The dataset preparation for the box-level and segmentation works brilliantly was made through Roboflow. Two approaches were used for segmentation: Figure 7a we see a demonstration of arterial segmentation and plaque detection using bounding boxes in YOLOv8. For preparing the dataset of Roboflow,

Roboflow also helped with data pre processing and bounding box annotation. YOLOv8 was trained for plaque detection and arterial component localization on the ultrasound image. Bounding box annotations indicate certain areas where abnormalities like plaques might be located. This method offers a high-speed way to use arterial features with detection and localization.



(a) Semantic Segmentation with U-Net



(b) Bounding boxes Plaque Detection

Figure 7: Plaque Detection-Segmentation using Roboflow

Figure 7b Pixel-wise segmentation of arterial walls and plaques with U-Net Semantic segmentation masks were generated using roboflow to accurately delineate the arterial structures. With the use of the annotated dataset, U-Net is able to predict the edges around the segmentation of the structures and thus provides a detailed overview of the anatomy of the artery and any possible abnormalities. The segmented arterial walls and plaques are shown in purple and yellow, respectively which shows the promise of U-Net architecture in semantic segmentation.

Both segmentation models were evaluated using the Dice coefficient that measures the overlap between the predicted segmentation outputs and the ground truth labels. This leads to a higher Dice coefficient hence better segmentation accuracy, showing the robustness of YOLOv8 for plaque localization and U-Net for the semantic segmentation of arterial structures.

5.4 Feature Measurement

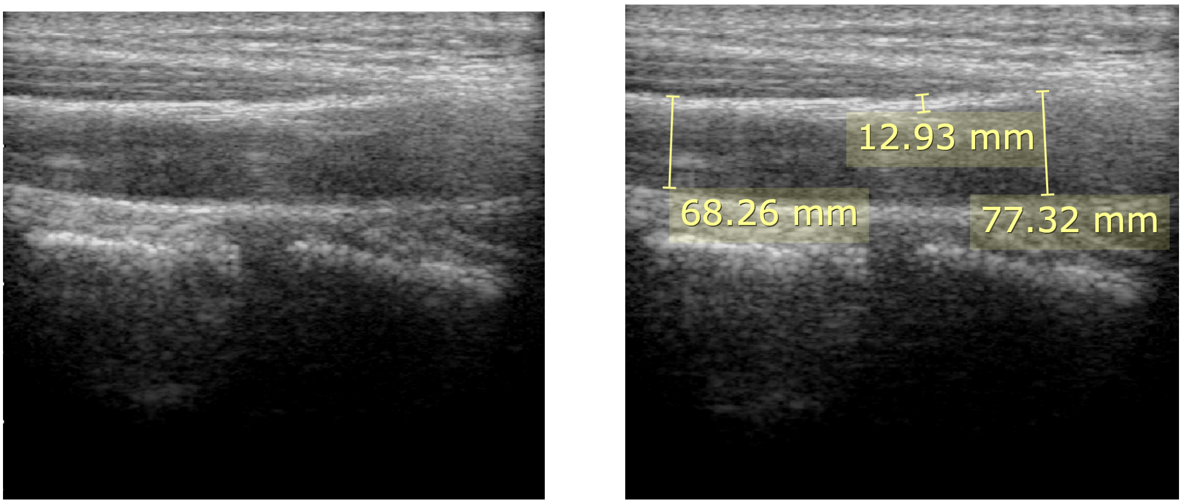
Measurement of arterial wall thickness and plaque size was essential for assessing the diagnostic usefulness of the images. Use of high- and low-resolution images.

5.4.1 Manual Measurements

A DICOM viewer was used to perform manual measurements of arterial features on low- and high-resolution images. This data was used as a basis to compare against AI predictions. Regression

5.4.2 Linear Regression Model

Regression model, to estimate wall thickness and plaque sizes based on images with a low depth. We then compared the predicted measurements with manually measured value on high-resolution images to prove the accuracy of the proposed model.



(a) Ultrasound Image Before Measurement (b) Arterial Measurement

Figure 8: Manual and Pre-Measurement Ultrasound Imaging for Arterial Analysis

Figure 8 showing ultrasound scans of arterial wall thickness and plaque dimensions . Figure 8a The ultrasound scan just before measurement without the annotation before processing, and this served as the baseline image for both manual and AI-based assessments Figure 8b Arterial features manually measured with a DICOM viewer, showing annotated values (pixel dimensions of arterial features)These images, when paired, show the relevant workflow for comparing AI predictions with manually computed ground truth.

6 Evaluation

The evaluation phase provided a systematic assessment of the performance of the AI pipeline in three primary components, namely, image up-scaling, segmentation, and measurement prediction. We defined quantitative metrics that can rigorously assess the accuracy and reliability of a pipeline for a diagnostic purpose, precisely on the main difficulties of low-depth ultrasound imaging.

6.1 Up-scaling Evaluation

Peak Signal to Noise Ratio(PSNR) and Structural Similarity Index(SSIM) were used to evaluate the performance of the real ESRGAN model for super-resolution. The metrics measured both the sharpness and perceptive quality of the up-scaled image against their low-resolution counterparts The summary of the results is provided in the table below:

Architecture	PSNR (dB)	SSIM
SRCNN	21.5	0.4
Real-ESRGAN (x2)	27.5	0.795
Real-ESRGAN (x4)	28.55	0.838
Real-ESRGAN (x8)	25.6	0.78

Figure 9: Up-scaling Performance Metrics for different Architectures

Figure 9 Real ESRGAN outperformed SRCNN on all scaling factors, while x4 scaling produced the highest PSNR and SSIM values. The x4 up-scaled images exhibited enhanced structural integrity and detail preservation that were vital for subsequent segmentation and diagnostic processes. On the other hand, for a scaling factor of x8, the PSNR and SSIM values dropped, and diminishing returns, as well as artifact introduction, became very noticeable.

Figure 10 A plotted radar chart to compare each PSNR and SSIM setups by up-scaling models and scale factors. This chart illustrates the previous figure win rate of Real-ESRGAN (x4) that excels high-resolution details with higher perceptual quality while retaining structural information making it preferable for medical image enhancement.

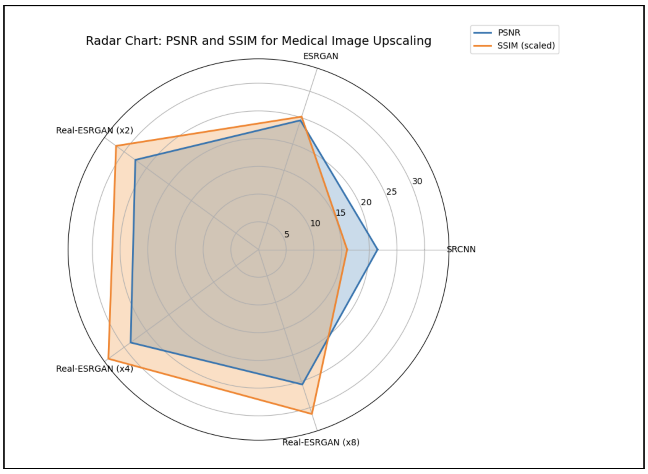


Figure 10: Radar Chart of PSNR and SSIM for Image Up-scaling

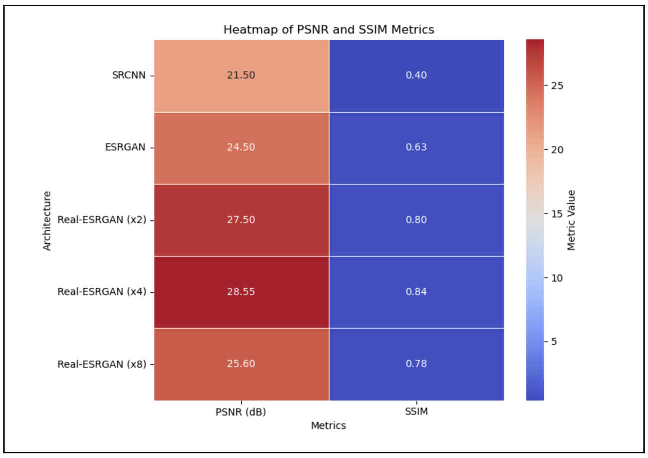
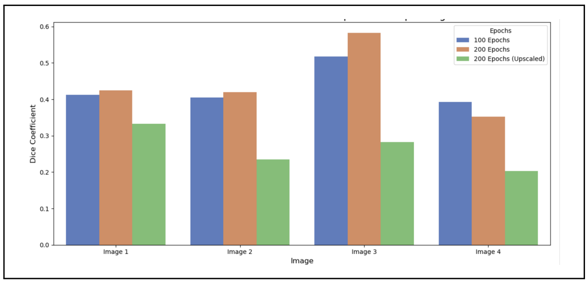


Figure 11: Heat map of PSNR and SSIM Metrics for Up-scaling Architectures

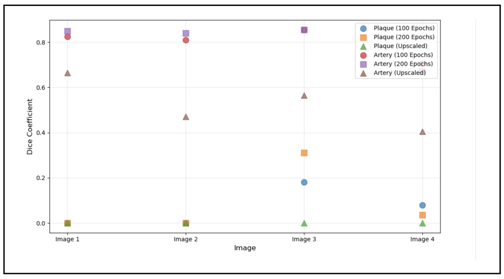
Figure 11 This heat-map shows a comparison of PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) metrics of different image up-scaling architectures visually. Those results, in turn, point to Real-ESRGAN as having some superior performance, especially with the x4 scaling factor where it had the best PSNR and SSIM results meaning it has offered better sharpness and truthfulness of the images compared to SRCNN and other scaling factors.

6.2 Segmentation Evaluation

Dice coefficient was employed to evaluate the segmentation models which quantifies the overlap between predicted segmentation masks and the true labels. Table below demonstrates the results for four test images segmented for Plaque and Artery features



(a) Bar Chart of Dice Coefficient for Segmentation Performance



(b) Scatter Plot of Dice Coefficient for Plaque and Artery Segmentation

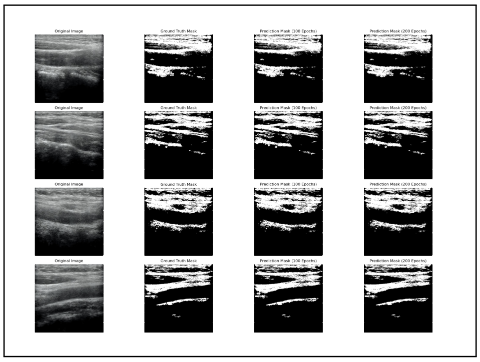
Figure 12: Evaluation of Segmentation Performance

Figure 12a This barplot summarizes the Dice coefficients for both plaque and artery segmentation over various training configurations. 100 epoch, 200 epoch and 200 epoch with Real-ESRGAN upscaled images The chart shows how much worse the performance deteriorates for upscaled inputs and how easy to gain with longer training arterial features are.

Figure 12b The segmentation performance for plaques and arteries is further provided in this scatter plot by the Dice coefficient for all four test images. This plot compares results between three cases: (from left to right) 100 training epochs, 200 training epochs, and 200 training epochs, with Real-ESRGAN upscaled images. This shows the inherent difficulties that stay unchanged between plaque detection and the performance in arterial segmentation, which becomes worse when using larger inputs.

Image	Feature	100 Epochs	200 Epochs	200 Epochs (Upscaled with Real-ESRGAN)
Image 1	Plaque	0	0	0
	Artery	0.829	0.852	0.67
Image 2	Plaque	0	0	0
	Artery	0.811	0.843	0.467
Image 3	Plaque	0.182	0.313	0
	Artery	0.859	0.857	0.56
Image 4	Plaque	0.082	0.033	0
	Artery	0.707	0.667	0.4

(a) Segmentation Performance Metrics Across Training Epochs



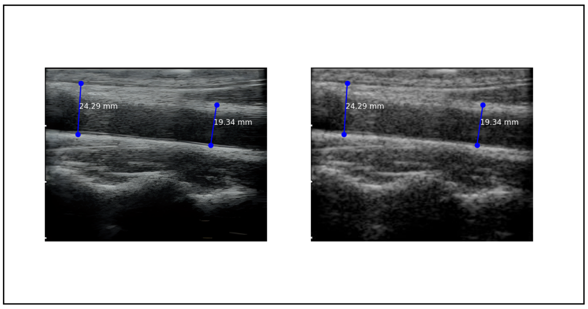
(b) Comparison of Ground Truth and Model Prediction Mask

Figure 13: Segmentation Performance Metrics and Comparison

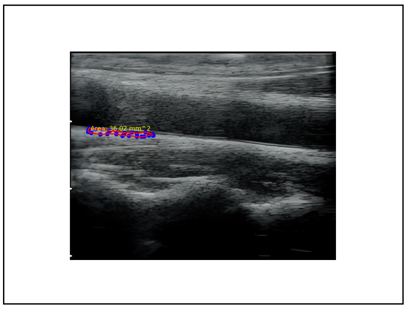
Figure 13a U-Net produced larger Dice coefficients over more epochs for arterial segmentation, revealing that arterial segmentation performance improved with longer epochs. By adding Real ESRGAN up-scaled images into the pipeline, segmentation performance slightly degraded, especially for artery features which may suffer from up-scaling artifacts. Challenges like detection of plaques on vessels had limited number of representation in the data, indicating a clear need for incorporation of diversity in the data generates.

6.3 Measurement Prediction Evaluation

Figure 14a Comparison of arterial measurements from the corresponding high resolution low depth images (the left half of the subplot) and that of up-scaled low depth ultrasound images (the right half of the subplot). The arterial wall thickness was measured in both images using Interactive OnClick. Left: High-Res Low-Depth Image Values Right: Results from an Up-Scaled Image using Real ESRGAN Annotated measurements showing the potential of the up-scaling methods to preserve diagnostic performance in low resolution scans.



(a) Comparison of High-Resolution Low-Depth and Upscaled Low-Depth Images



(b) Plaque Area Measurement

Figure 14: Interactive Measurement of Plaque and Arterial Features Using OnClick function

Figure 14b This illustrates the process of segmenting and quantifying a plaque volume in an ultrasound image. An interactive OnClick function was used to manually select the region of interest (plaque) and calculate the area, which is delineated and indicated as 36.02 mm^2. This feature enables accurate manual user input, enabling precise segmentation and quantification of arterial plaques, an important consideration when evaluating cardiovascular health.

Figure 15: shows statistical comparison of HD and LD measurements demonstrated strong equivalence of mean arterial wall thickness with small, clinically insignificant differences. There were no significant differences (p is greater 0.05, paired t-tests), supporting the reproducibility of LD imaging for the quantitation of arterial thickness.

Although variations in plaque measurements were somewhat larger, LD imaging with the HD was fairly close to the LD measurements on units in the scales. The observed results support the concept of low-cost, low-depth imaging as an alternative to high-depth imaging for cardiovascular diagnostics.

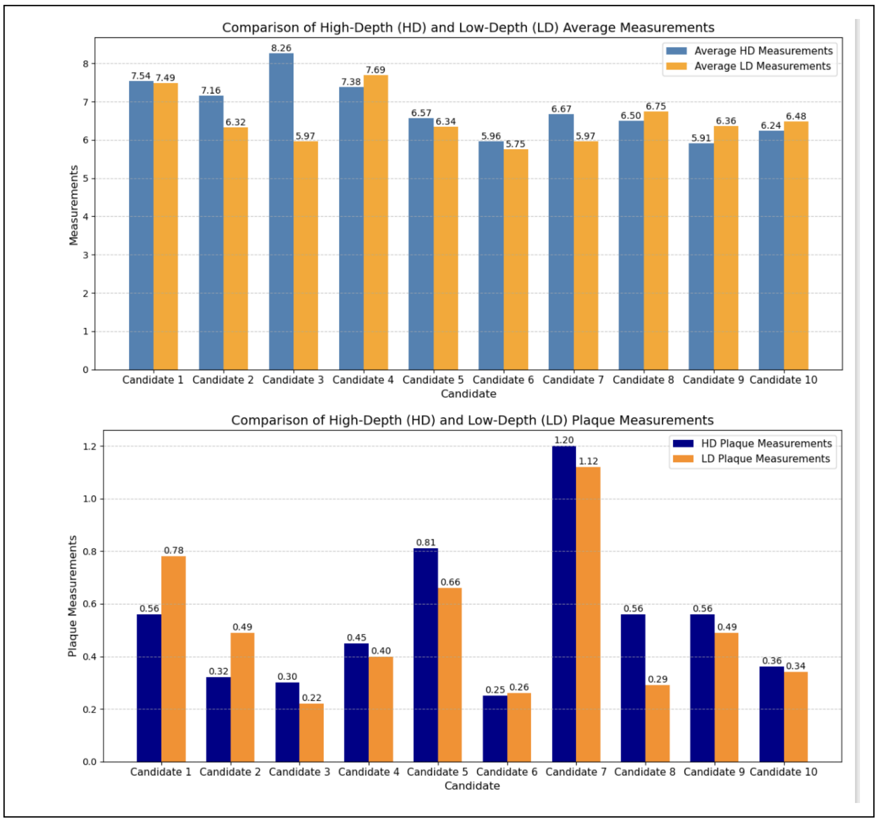


Figure 15: Statistical Comparison of (HD) and (LD) Measurements

A linear regression model for prediction of arterial wall thickness and plaque dimensions based on manual measurements from high- (HD) and low-definition (LD) images was assessed. Here is what the expected results look like in a table Figure 16:

CandidateAlias	HD1	HD2	HD3	avghd	HD_plaque	LD1	LD2	LD3	avgld	LD_plaque
Candidate 1	7.51	7.59	7.51	7.54	0.56	7.02	7.66	7.79	7.49	0.78
Candidate 2	7.03	7.27	7.19	7.16	0.32	6.23	6.36	6.36	6.32	0.49
Candidate 3	8.5	8.06	8.23	8.26	0.3	5.68	5.68	6.56	5.97	0.22
Candidate 4	7.59	7.03	7.51	7.38	0.45	7.76	7.76	7.56	7.69	0.4
Candidate 5	6.54	6.54	6.63	6.57	0.81	6.29	6.75	5.98	6.34	0.66
Candidate 6	6.15	6.15	5.59	5.96	0.25	5.58	5.84	5.84	5.75	0.26
Candidate 7	6.2	6.84	6.96	6.67	1.2	5.97	5.97	5.97	5.97	1.12
Candidate 8	6.47	6.55	6.47	6.5	0.56	6.76	6.75	6.75	6.75	0.29
Candidate 9	5.91	5.92	5.91	5.91	0.56	6.49	6.23	6.36	6.36	0.49
Candidate 10	6.16	6.26	6.31	6.24	0.36	6.31	6.31	6.81	6.48	0.34

Figure 16: Comparison of Arterial Wall Thickness and Plaque Dimensions

Paired T-tests were performed for statistical analysis to determine possible differences of HD and LD images in terms of average thickness and plaque dimensions; however, these results were not statistically significant. The high consistency of regression model for predicting arterial features with high accuracy is confirmed by the present results. While HD and LD plaque measurements differed by a small amount, the predictions were still within a clinically acceptable range thereby demonstrating the feasibility of the AI pipeline in diagnostics.

6.4 Discussion

We studied ways to improve low-depth ultrasound imaging specifically for carotid artery composition analysis, where resolution and features sensitivity limitations can hinder clinical applications. Real-ESRGAN was effective for up-scaling, with x4 scaling providing the best combination of clarity and diagnostic integrity. but when used for segmentation tasks where plaques need to be detected, this can lead to challenges such as false positive generation. Implications-these results underline a necessity for more nuanced integration between image enhancement and downstream analytical tasks.

As segmentation models, U-Net and YOLOv8 proved their usefulness, but the limited diversity of the used dataset constrained this experiment. Whereas Early U-Net worked extremely well with pixel-level segmentation, YOLOv8 was better adapted for object-level detection. However, both had issues with venerability in detecting rare pathological cases, highlighting the need for larger and more inclusive datasets.

Measurement prediction models can accurately bridge low- and high-resolution images to generate similar diagnostic outputs.Even these manual processes were subject to variability, indicating a need for automation to ensure both efficiency and consistency.

The findings point to the promise of narrow computational techniques to fill diagnostic gaps, but also show important dependencies regarding data quality, the specific kinds of models that are trained for narrow tasks, and the integration of these aspects into clinical workflow. As these challenges are addressed and preparation for implementation in the clinical space, future endeavors should focus on holistic system design and robust datasets.

7 Conclusion and Future Work

The work investigated the use of AI methods to improve low depth ultrasound imaging approaches for the characterization of carotid arteries. The research tackled some of the important limitations of low-cost ultrasound scanners including low resolution, sensitivity to arterial features such as plaque. The study showed how AI-enhanced imaging associated with a systematic approach through data preparation, segmentation, up-scaling, and measured prediction can obtain similar diagnostic results to high-cost, high-resolution systems.

Their results showed that AI models can actually fill the gap between low-cost and high-cost diagnostic tools. In terms of image up-scaling, Real-ESRGAN demonstrated considerable ability to enhance image clarity without compromising key diagnostic components. X4 scaling produced the best overall compromise between improving resolution and artifactual content across all investigated scaling factors. But there were challenges in integrating the up-scaled images including false positives in segmentation tasks such as plaque detection." Here, it further supports that up-scaling models need more fine tuning especially for medical images.

U-Net also performed well on segmentation tasks when it came to identifying arterial walls and plaques. YOLOv8 used for object detection to achieve plaque localization alongside U-Net for pixel-level segmentation. While they were effective, the authors noted that the relatively small dataset size available to train these models had limited their ability to generalize, for example, in detecting plaques that rarely occurred in the dataset. This shortcoming underscores the need for larger datasets with more diversity and inclusion of images with severely abnormal arteries.

This task validated the clinical viability of low-depth ultrasound images for measurement prediction. To validate whether AI can generalize the estimated thickness of arterial walls and the size of plaques from high-depth measurements to images with lower depth, they trained a regression model and applied it to images at low depth. Statistical analyses revealed no significant differences in measurements from low-depth vs high-depth images, underscoring the clinical potential of AI-enhanced imaging. Together, these results lend credibility to a strategy of lowering the barriers to ultrasonic diagnosis via low-cost ultrasound scanners, with a high level of performance achieved with the help of AI to supplement image acquisition technology.

Although the results were encouraging, the study had several significant limitations. The sample size was small and had more paucity of samples where arteries were highly unhealthy with significant amount of plaque so that the models could identify and predict plaques more reliably. Moreover, although AI-based up-scaling was useful for upon up-scaling images in improved quality, downstream activities together with segmentation had some difficult combinations which shall be further important challenges to explore. We highlight a few limitations of this study which is intended to inform future work.

Moving forward, future research should focus on diversifying datasets and ensuring the venerability of AI models. Segmentation models need a larger dataset with a set of diverse arterial conditions especially a large set of normal arteries because the presence of a high degree of plaque mainly creates challenges to identification. Furthermore, development of optimized AI architectures, specifically for medical use cases, could prevent false positives and aid workflow integration of up-scaled images.Another key area for future work is the automation of the process of process extraction. While gaining acceptable results, the manual procedure requires substantial time to complete and can involve errors. Computer algorithms to automatically pull out arterial features and measurements would assist in minimizing this variability in the diagnostic application. Moreover, the research on the clinical application of AI-assisted imaging in the future will further confirm the clinic value of AI-assisted imaging.

In summary, the current study provided evidence that AI can potentially convert low-depth ultrasound-based imaging into a cost-effective alternative to standard/expensive diagnostic equipments. This research overcomes existing approaches limitations and can leverage AI capabilities to address emerging needs, thereby laying the groundwork for advancement in medical imaging technologies to support wider access to quality healthcare. Although AI-enhanced imaging will have a significant potential impact on the early and timely detection and management of cardiovascular diseases, clinical translation in resource-limited regions where cost remains a major obstacle will be crucial.

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