

Highlights

Objective: Design an automated algorithm for highly accurate plaque segmentation on non-contrast computed tomography (CT) data for clinical purposes.

Challenges:

- ▶ Detecting small, subtle plaque structures
- ▶ Overcoming the limitations of low spatial resolution
- ▶ Coronary arteries are hardly visible due to lack of contrast

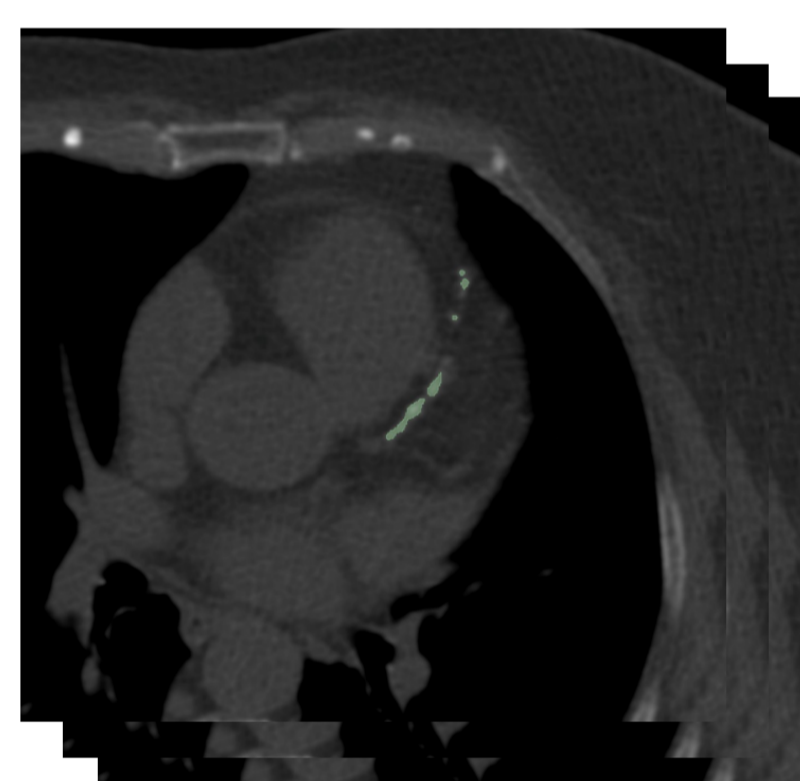
Contribution:

- ▶ Developed an automated approach for plaque segmentation.
- ▶ Compared 2D and 3D models in terms of accuracy for plaque volume and Agatston scoring.
- ▶ Demonstrated the feasibility of scalable, automated CACS in clinical settings

Agatston Score

The Agatston score quantifies coronary artery calcification, aiding in the assessment of cardiovascular disease risk. It combines the area of calcified plaques with a density factor, where higher Hounsfield Unit (HU) ranges contribute more to the score.

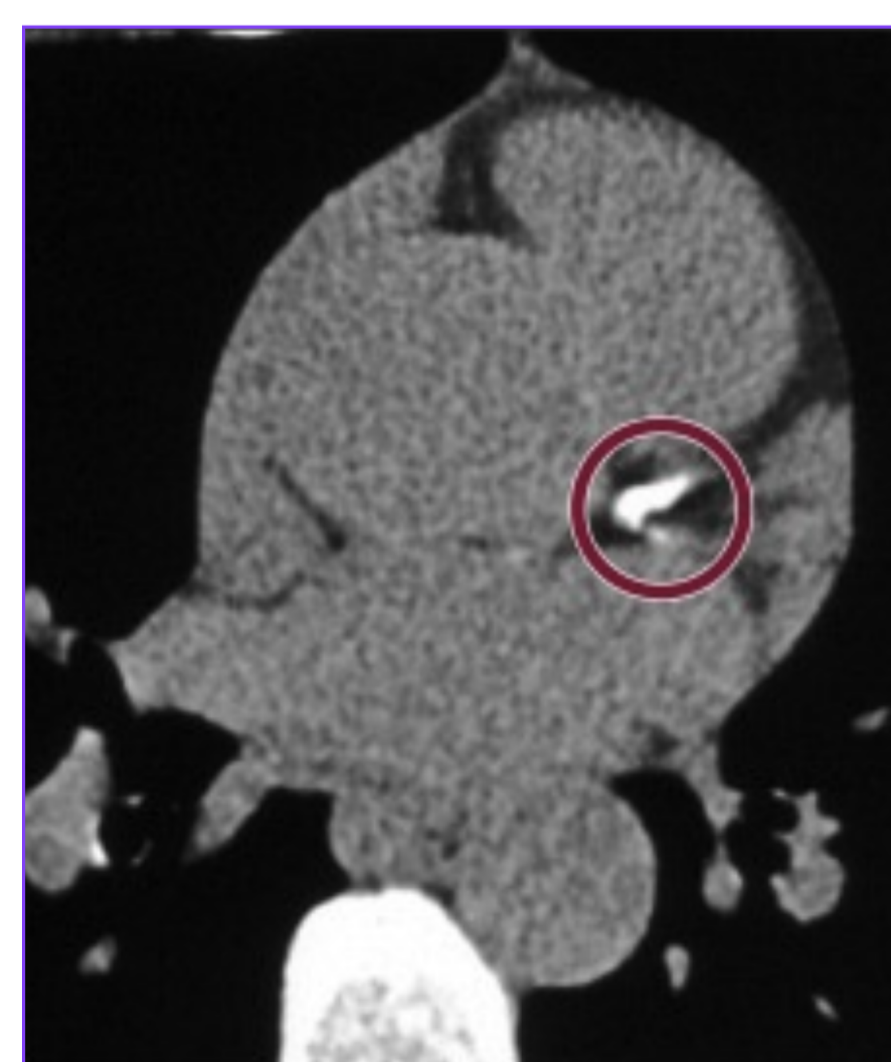
$$Agatston\ Score = \sum_{slices} Area \times Density\ Factor$$



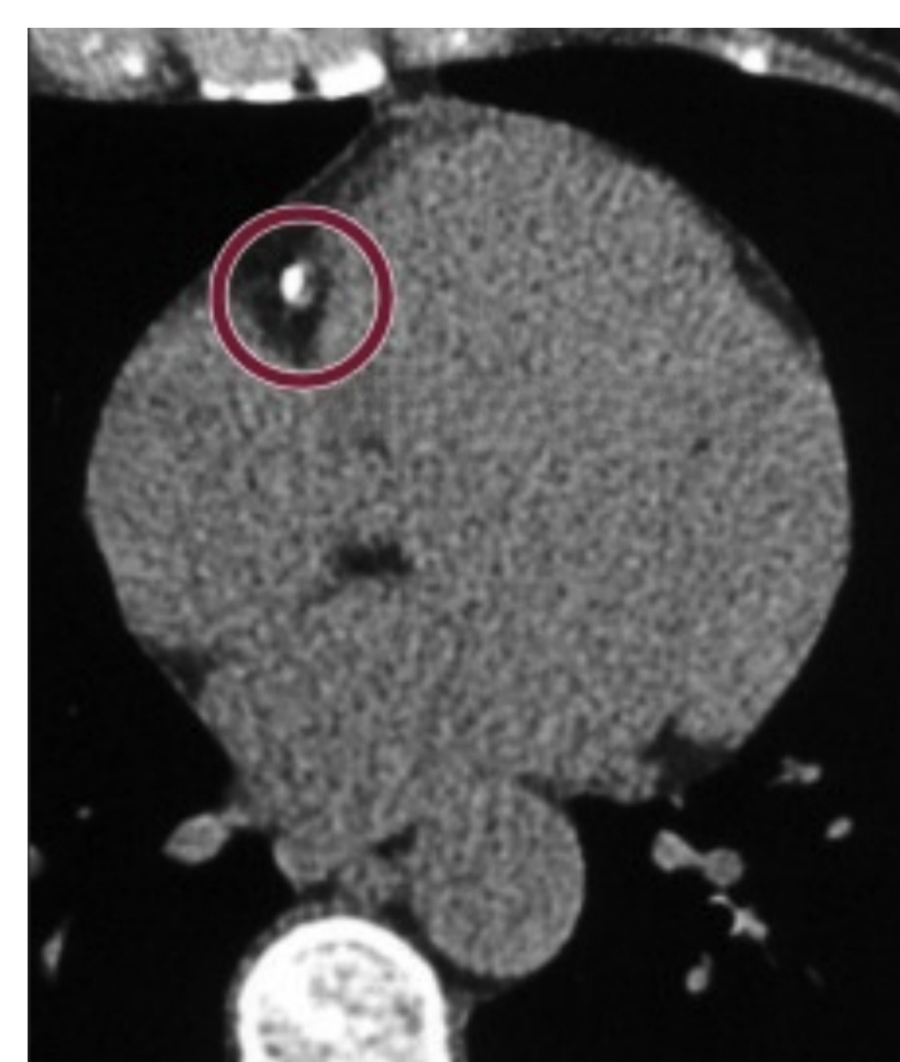
Density in Hounsfield units [HU]:

- ▶ 1: 130-199 HU
- ▶ 2: 200-299 HU
- ▶ 3: 300-399 HU
- ▶ 4: 400 HU ≤

Coronary calcium scan score	Plaque visual	Amount of plaque	Risk Level	Treatment recommendation
0		None	Low	No treatment
1-10		Minimal	Low	Lifestyle change
11-100		Small	Moderate	Lifestyle changes and medication
101-400		Moderate	Moderate to high	Lifestyle changes, medication, and further testing
Over 400		Extensive	High	Immediate testing and treatment



Area = 15mm², Peak HU = 450
Lesion score = 15 × 4 = 60



Area = 8mm², Peak HU = 290
Lesion score = 8 × 2 = 16

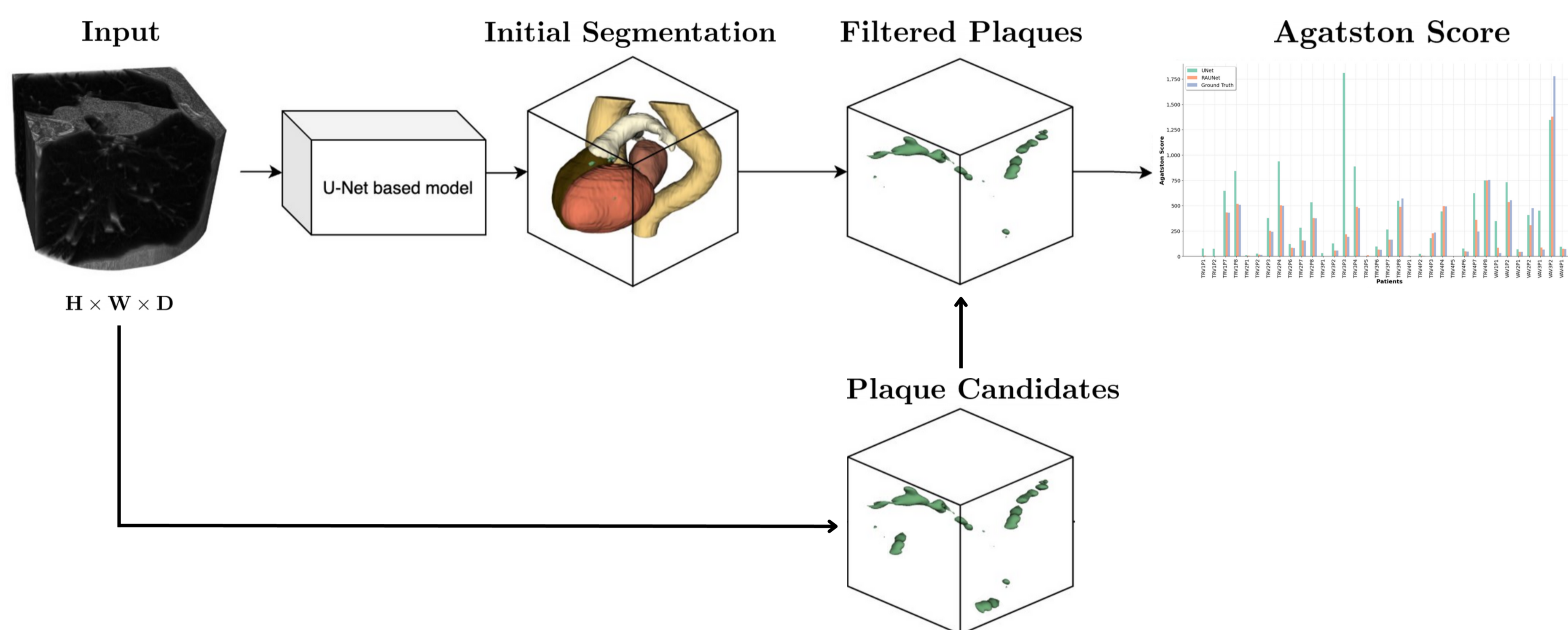
Method Diagram

▶ **Dataset:** 32 training and 40 test anonymized non-contrast cardiac computed tomography scans.

▶ **Segmentation Method:** UNet-based architectures with Dice Cross-Entropy Loss.

▶ **Methods for Assessing Segmentation Results:**

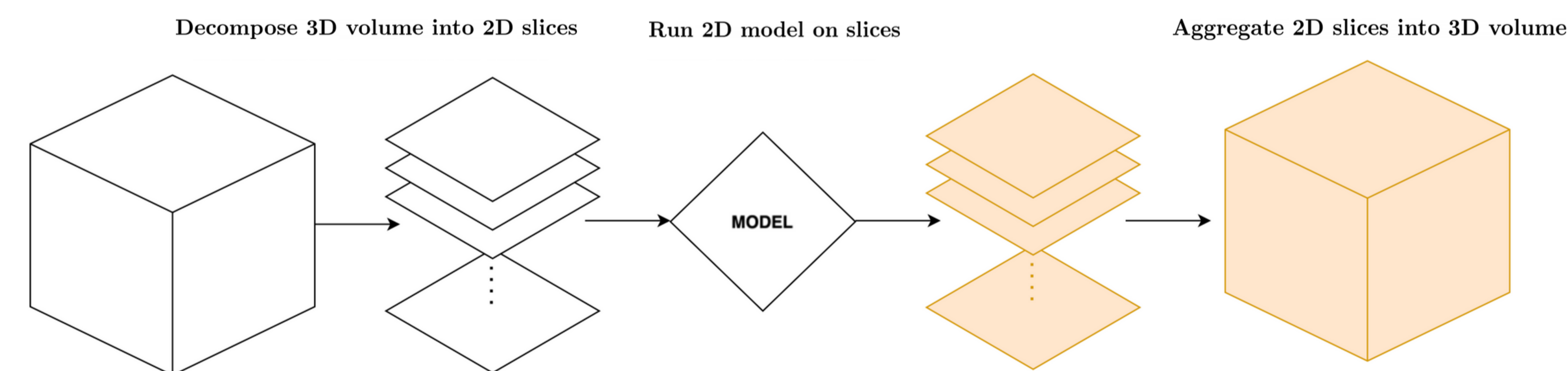
1. Apply thresholding (HU ≥ 130) to identify calcified regions as plaque candidates. → **Plaque Candidates**
2. Perform initial segmentation of plaques along with other anatomical regions such as the aorta, pulmonary artery, and heart chambers. → **Initial Segmentation**
3. Filter **Plaque Candidates** based on overlap with plaques in **Initial Segmentation**. → **Filtered Plaques**
4. Calculate clinically relevant metrics using **Filtered Plaques** and corresponding Hounsfield Units from the **Input** image. → **Agatston Score**



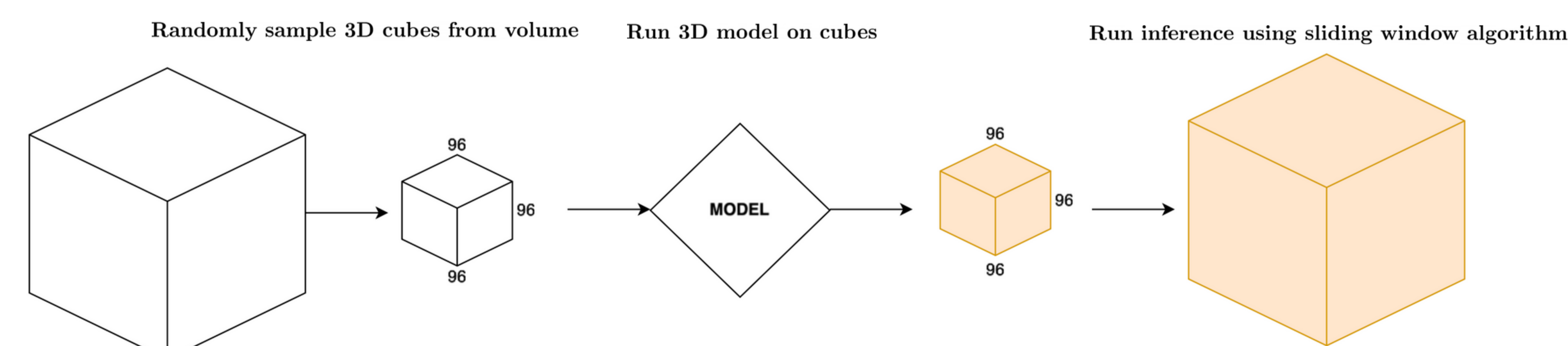
Approaches

This study assessed various UNet-based models—standard UNet, RaUNet with attention layers, and transformer-based UNETR—in both 2D and 3D configurations for plaque segmentation on non-contrast cardiac CT. Testing these models provided insights into their effectiveness in capturing anatomical details under challenging imaging conditions.

2D



3D

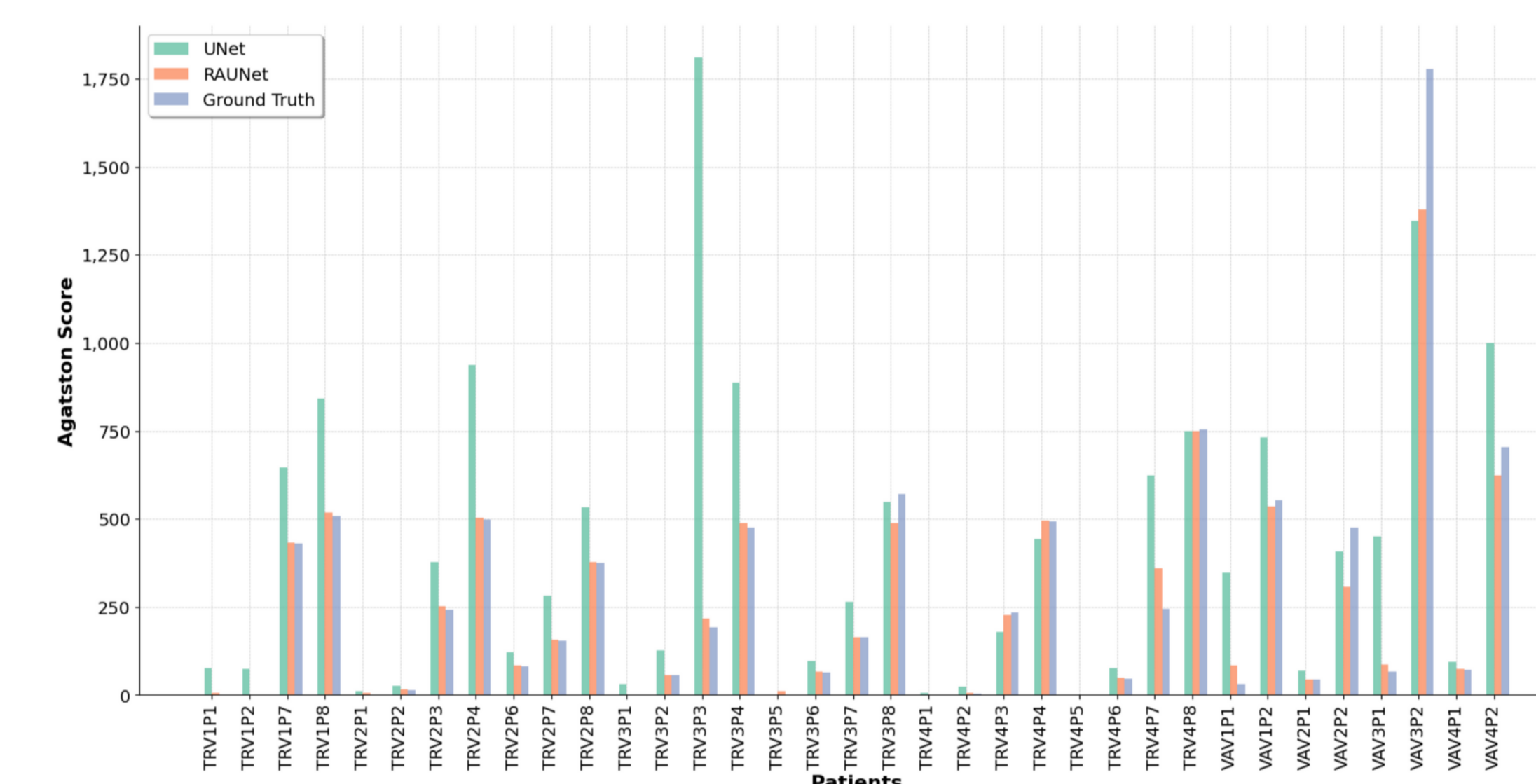


Quantitative Results

Segmentation results obtained by 2D and 3D architectures. The approaches were evaluated according to Dice score and absolute errors (mean ± standard deviation) in measured Agatston Score and Plaque Volume.

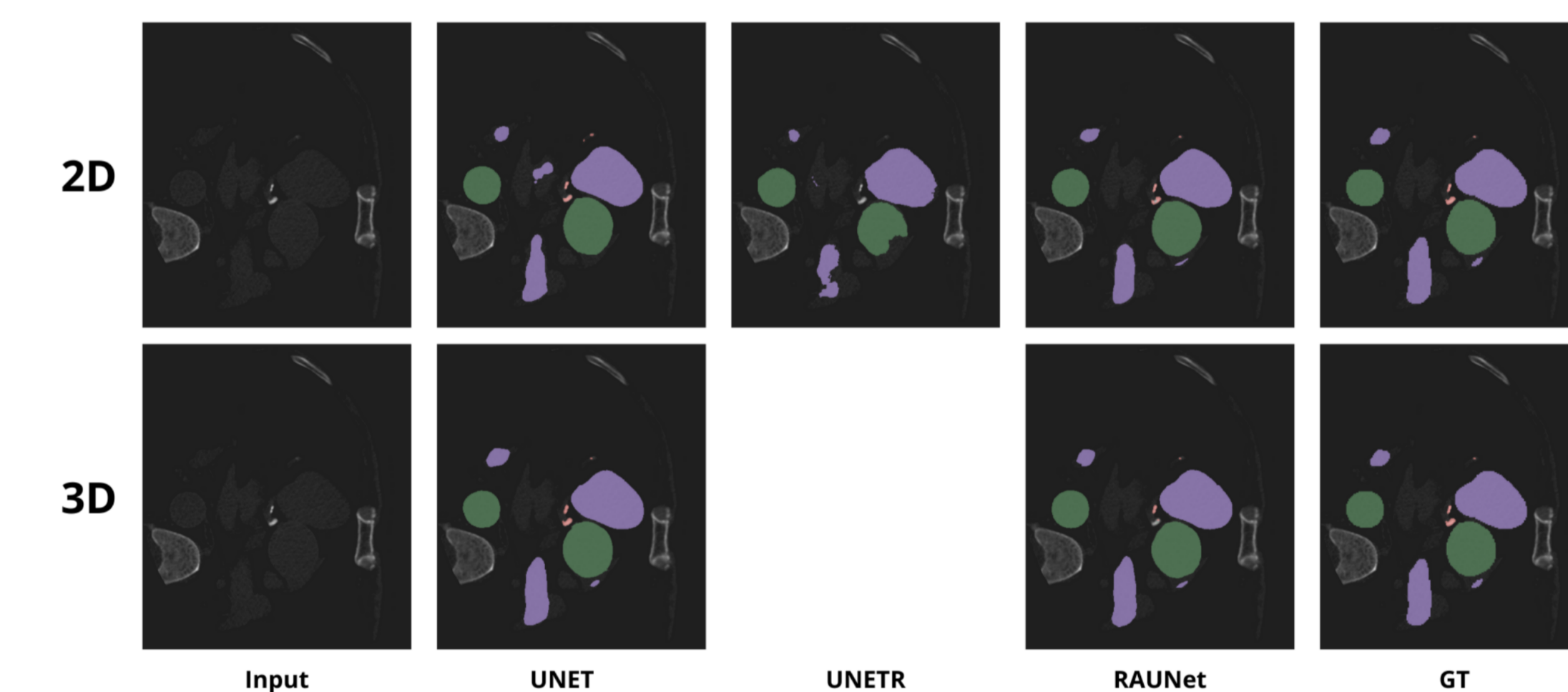
Input Dim.	Model	Dice (↑)	Agatston (↓)	Plaque (↓)
2D	UNet	0.51	166.98 ± 248.76	158.65 ± 201.59
	UNeTR	0.41	229.38 ± 319.95	200.78 ± 280.89
	RAUNet	0.56	21.04 ± 52.95	22.74 ± 48.88
3D	UNet	0.84	45.49 ± 60.46	40.69 ± 59.69
	RAUNet	0.87	52.14 ± 120.36	54.44 ± 127.02

By comparing the predicted Agatston Scores with the actual scores, we could assess not only the accuracy of the predictions, but also their practical relevance in a clinical context. This ensured that the model output was meaningful accurate and meaningful for medical diagnosis and treatment planning.



Qualitative Results

Segmentation results comparison for different models. Orange label represents plaques, purple represents anatomical structures, such as the right atrium of the heart, the left atrium, the myocardium, the left ventricle, and the right ventricle and color green represents aorta.



Training model to also segment other anatomical structures helped improve model reasoning by enabling it to identify regions where plaques are unlikely to be located.

Conclusion

- ▶ Take advantage of clinically relevant metrics to ensure meaningful clinical impact.
- ▶ Large inter-slice distances pose significant challenges for capturing small objects.
- ▶ 2D models effectively mitigate noise, enhancing clarity in object representation.
- ▶ 3D models run the risk of overfitting