Automatic measurement of left atrial appendage and pulmonary-vein diameter in atrial fibrillation patients using artificial intelligence

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COI Disclosure

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Introduction

- An understanding of left atrial (LA) anatomy and pulmonary vein (PV) diameter is important for the effectiveness and safety of atrial fibrillation (AF)-related procedures.
- However, labor-intensive measurements are required to obtain this information.

- We propose an artificial intelligence algorithm for the automated measurement of PV based on computed tomography (CT).

Eur J Radiol. 2009 Jul;71(1):61-8.

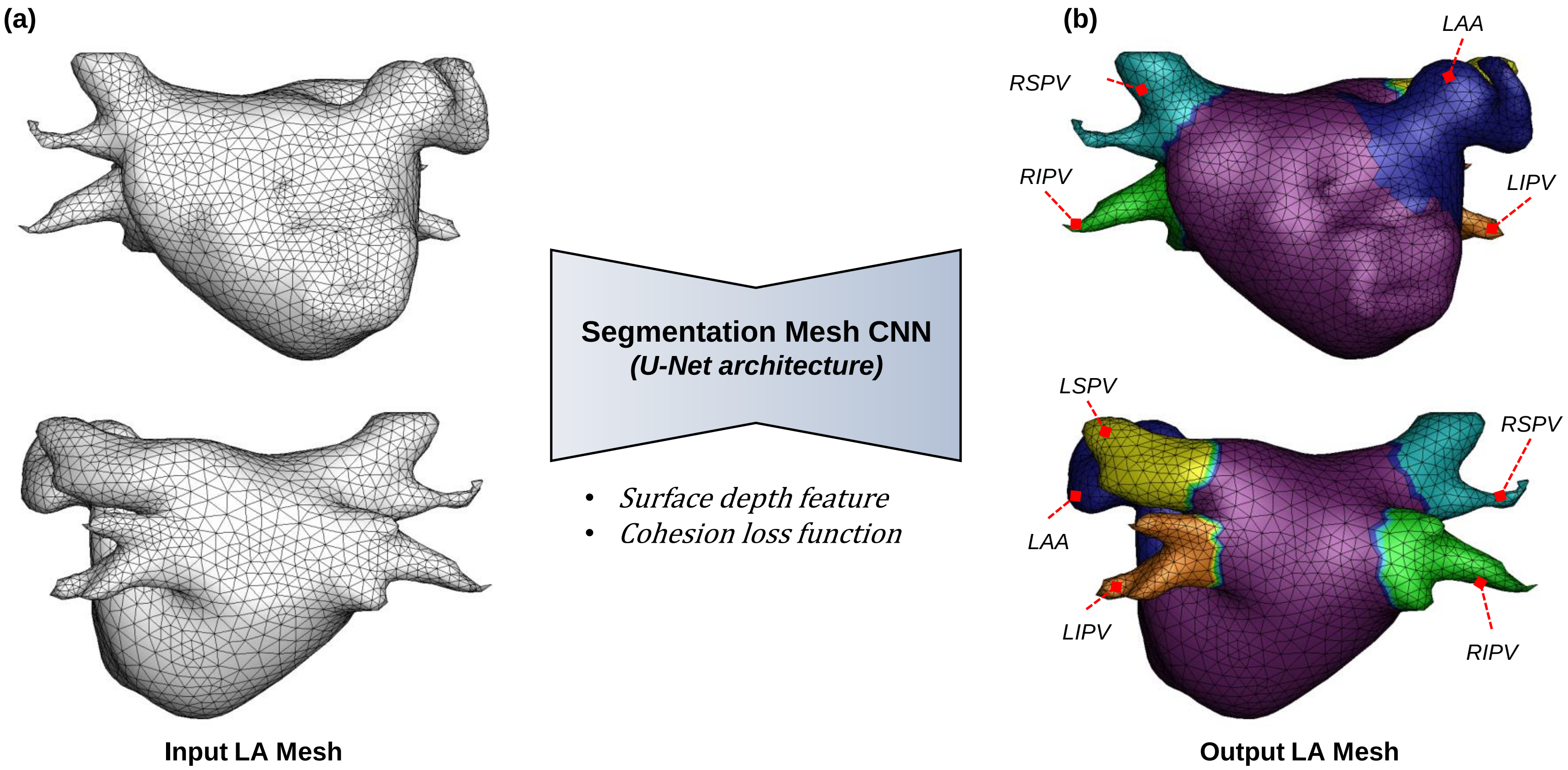
Methods

- We implemented a mesh-based convolutional neural network for the surface segmentation of four PVs and the LA appendage (LAA) in a 3D LA surface mesh.

- We trained the model with the **LA mesh of 210** AF patients' CT scan and validated the accuracy of surface segmentation and PV diameter with **independent 158 samples**.

- Our algorithm includes two originative methods of surface depth feature and cohesion loss function to improve the performance.

Surface segmentation using meshCNN



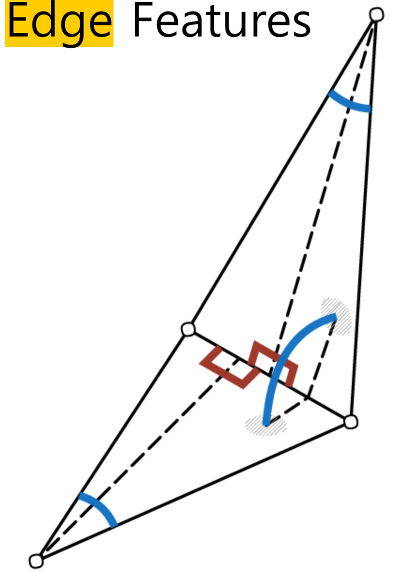
Left atrium surface segmentation procedure using meshCNN architecture.

(a) Enter the LA surface mesh.

(b) The meshCNN model generates region labels for each vertex.

Surface depth feature

Input Edge Features



- Conventional geometric feature in meshCNN

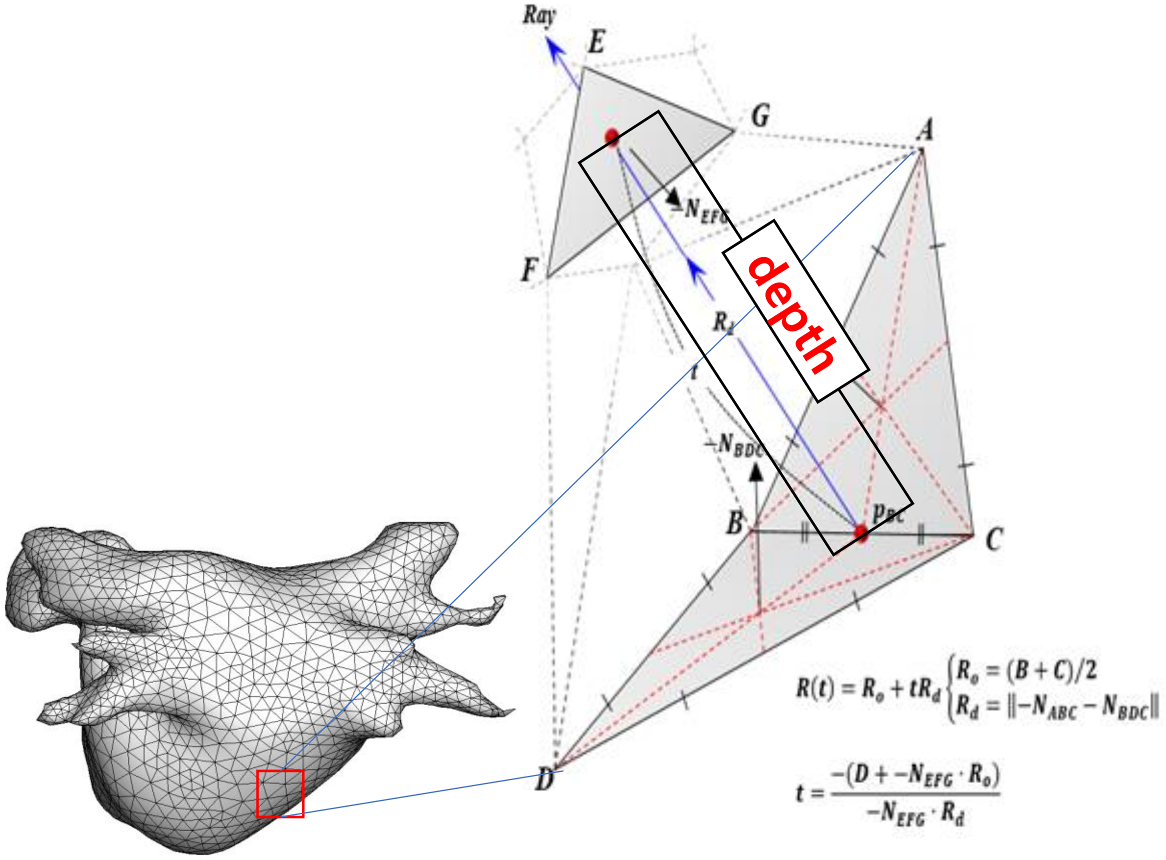
  Relative Geometric Features

  ➔ Invariant to *similarity* transformations

  5-dimensional vector

  - dihedral angle
  - two inner angles
  - two edge-length ratios.

+ surface depth

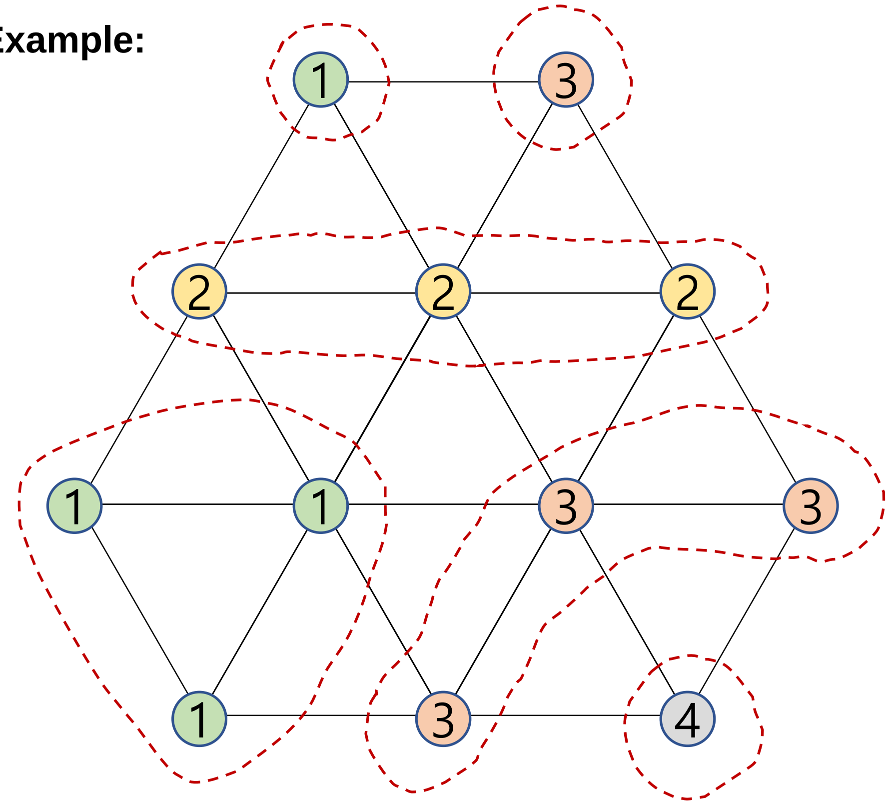


Loss function

$$Loss = WCE\ loss + cohesion\ loss$$

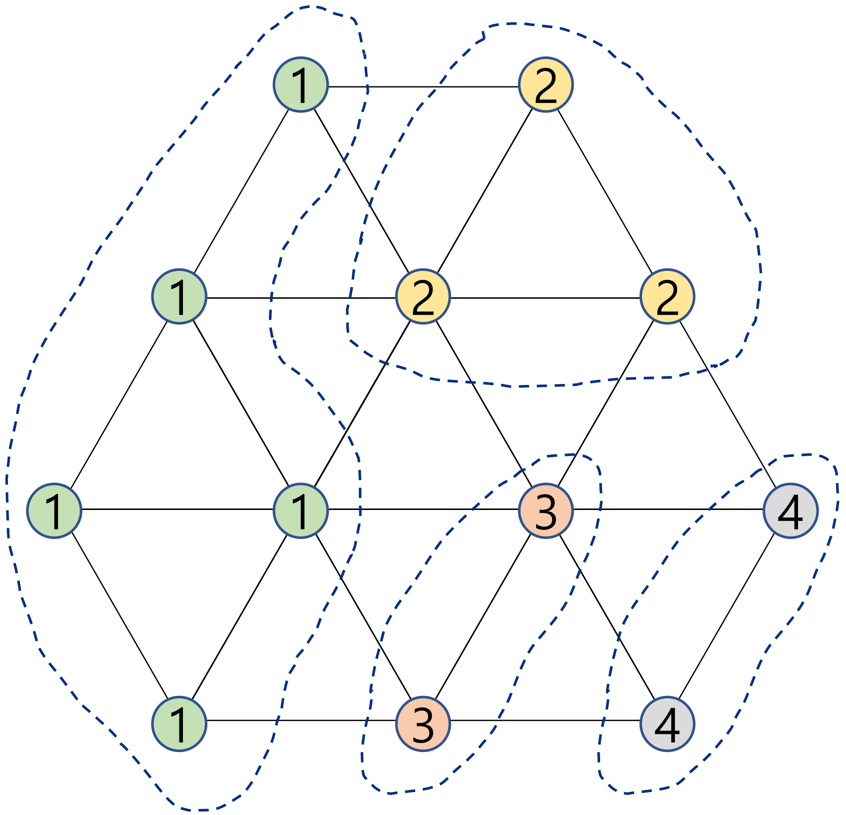
$$cohesion\ loss = |N_{class} - number\ of\ cluster|$$

Example:



- N_{class} = 4
- Number of cluster = 6

Cohesion loss = 2



- N_{class} = 4
- Number of cluster = 4
- **Cohesion loss = 0**

How does it work?

Hanocka et al.

Mesh Convolution

Normal of triangle

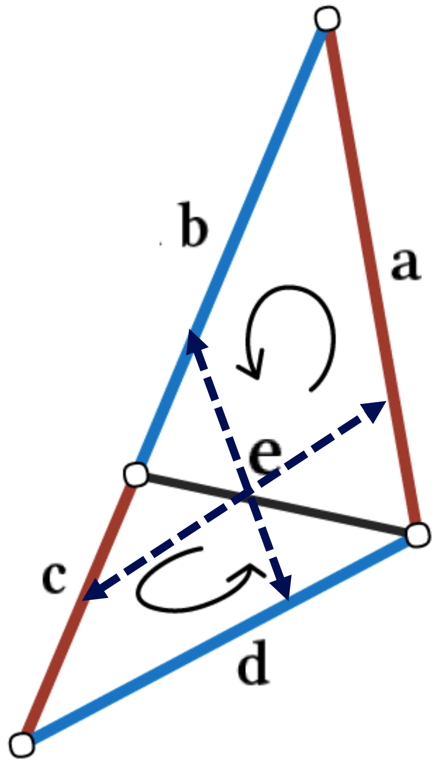
➔ Consistent ordering in each face

Two *valid* orderings

➔ (a, b, c, d) or (c, d, a, b)

Solve: build symmetric features

➔ {e: (a+c, |a-c|, b+d, |b-d|)}



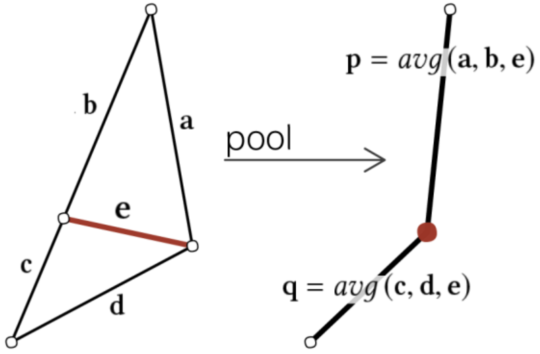
How does it work?

Hanocka et al.

Edge Pooling: edge collapse

Delete edge with smallest feature activations

- → Aggregate features (average pooling)
- → Update topology



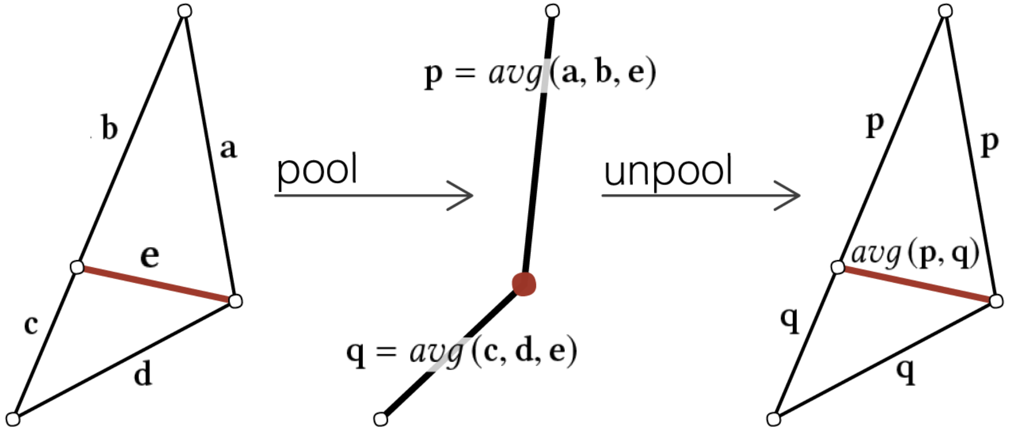
Average pooling aggregation

- → 5 edges to 2 edges
- → Average per-channel

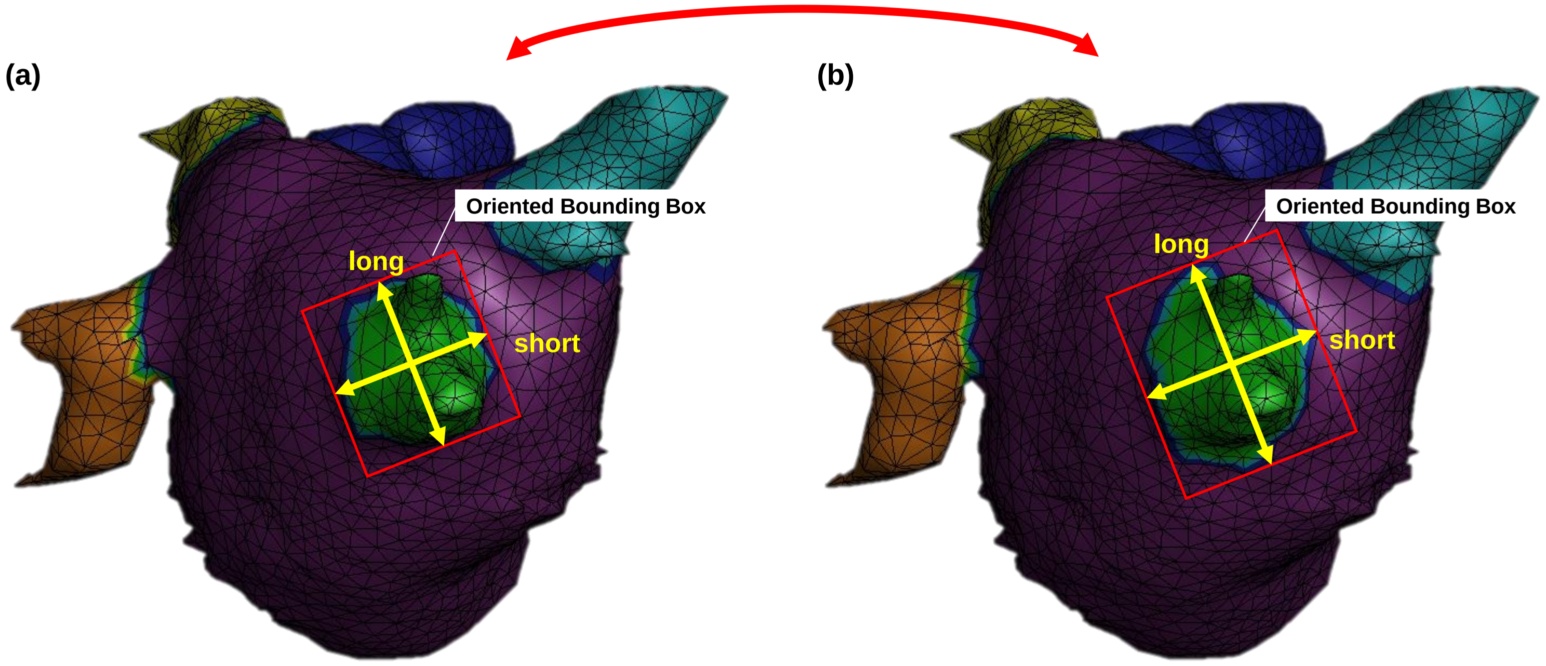
Edge Unpooling

Partial Inverse of Pooling

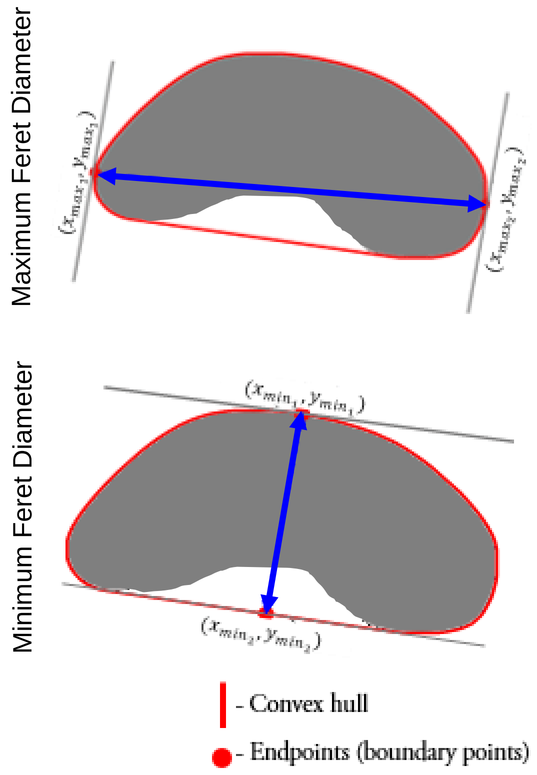
- → Restores upsampled topology (reversible)
- → Unpooled features weighted combination of pooled features



Feret diameter



Manual region labeling **AI-guided region labeling**

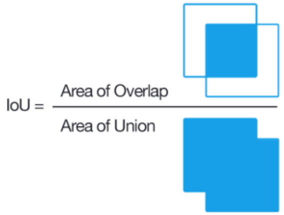


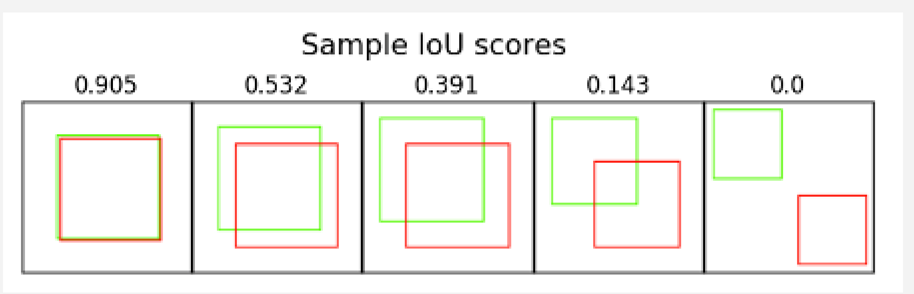
Accuracy evaluation of PV diameter measured with manual and automatic procedures.

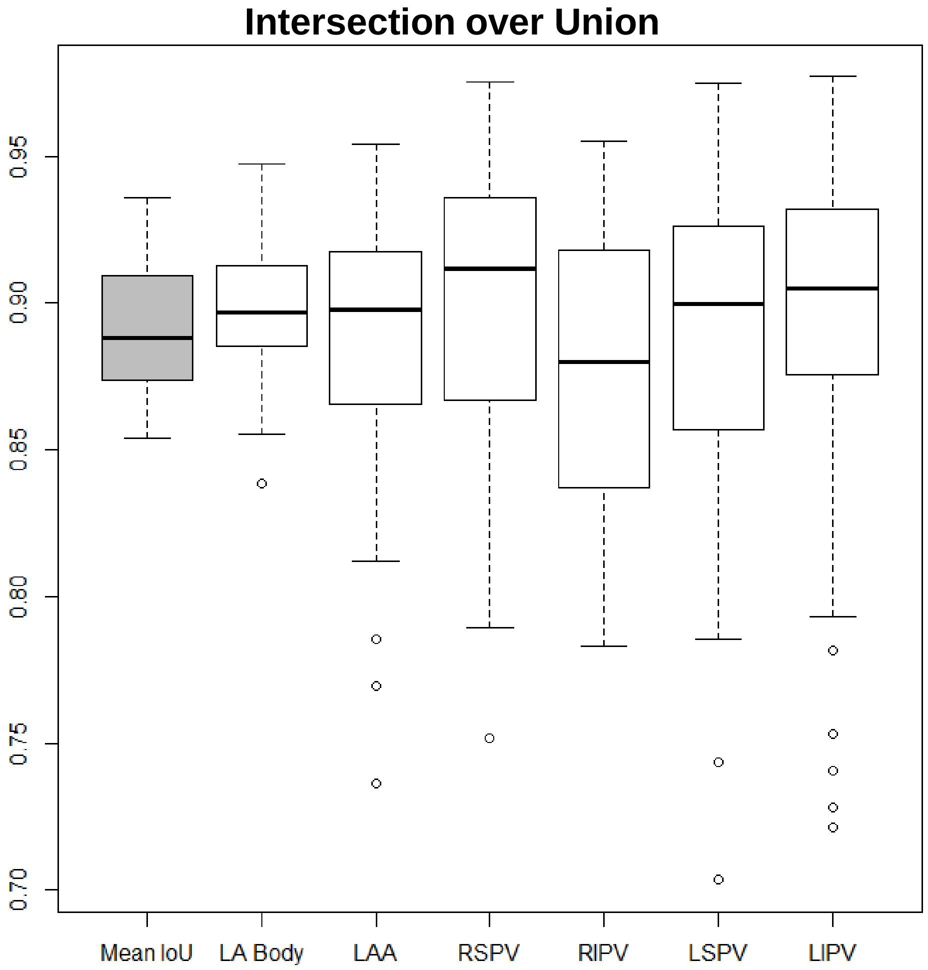
(a) PV diameters by manual region labeling.
(b) PV diameters by AI-guided region labeling.

Results

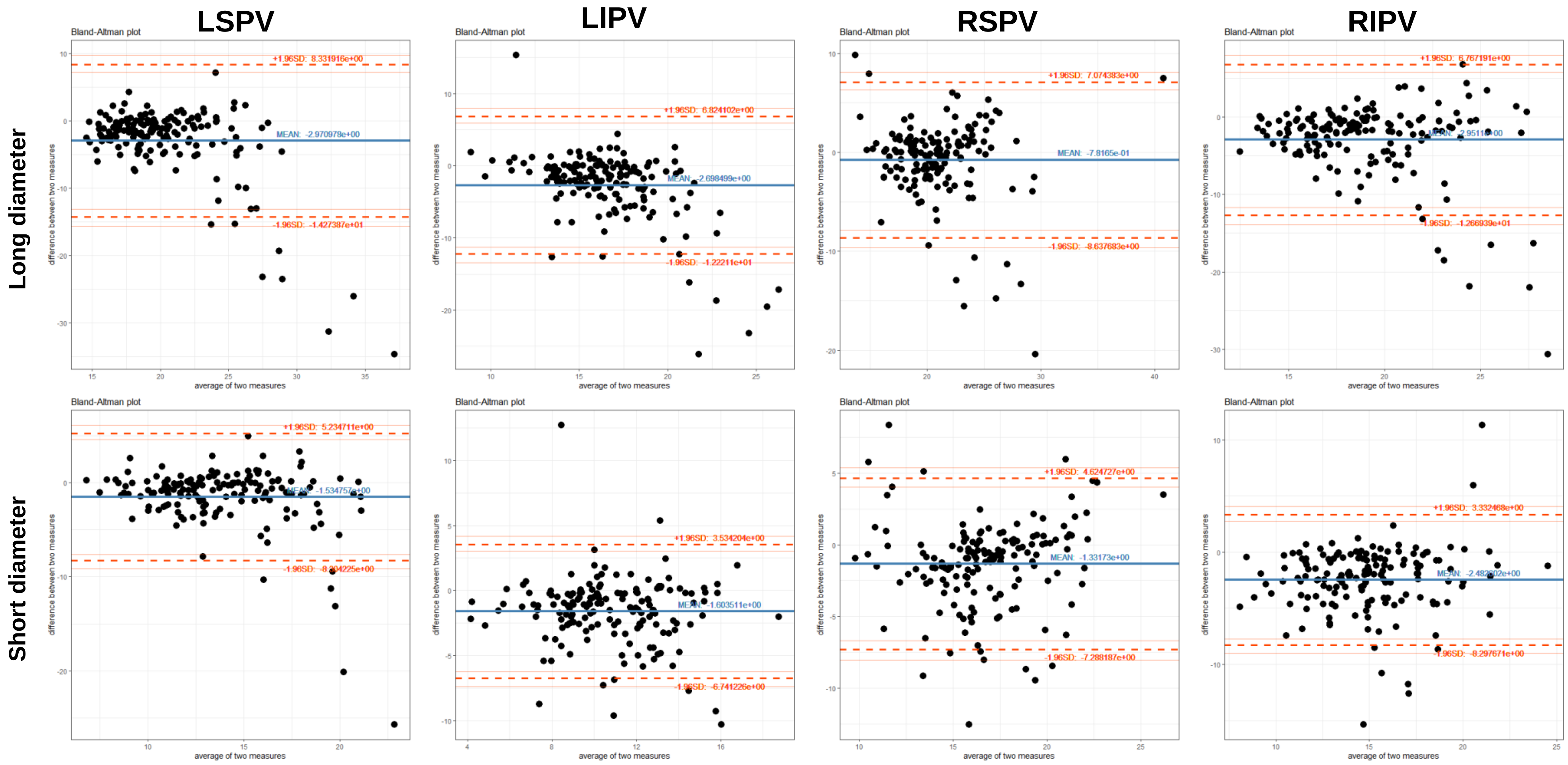
- We achieved an average Intersection over Union (IoU) of 83.4% and a regional IoU from 78.4 to 87.2 %.
- The surface depth feature improved the IoU by 31.7%.
- The cohesion loss function reduced the fragmentation rate of the surface label by 3.2%.



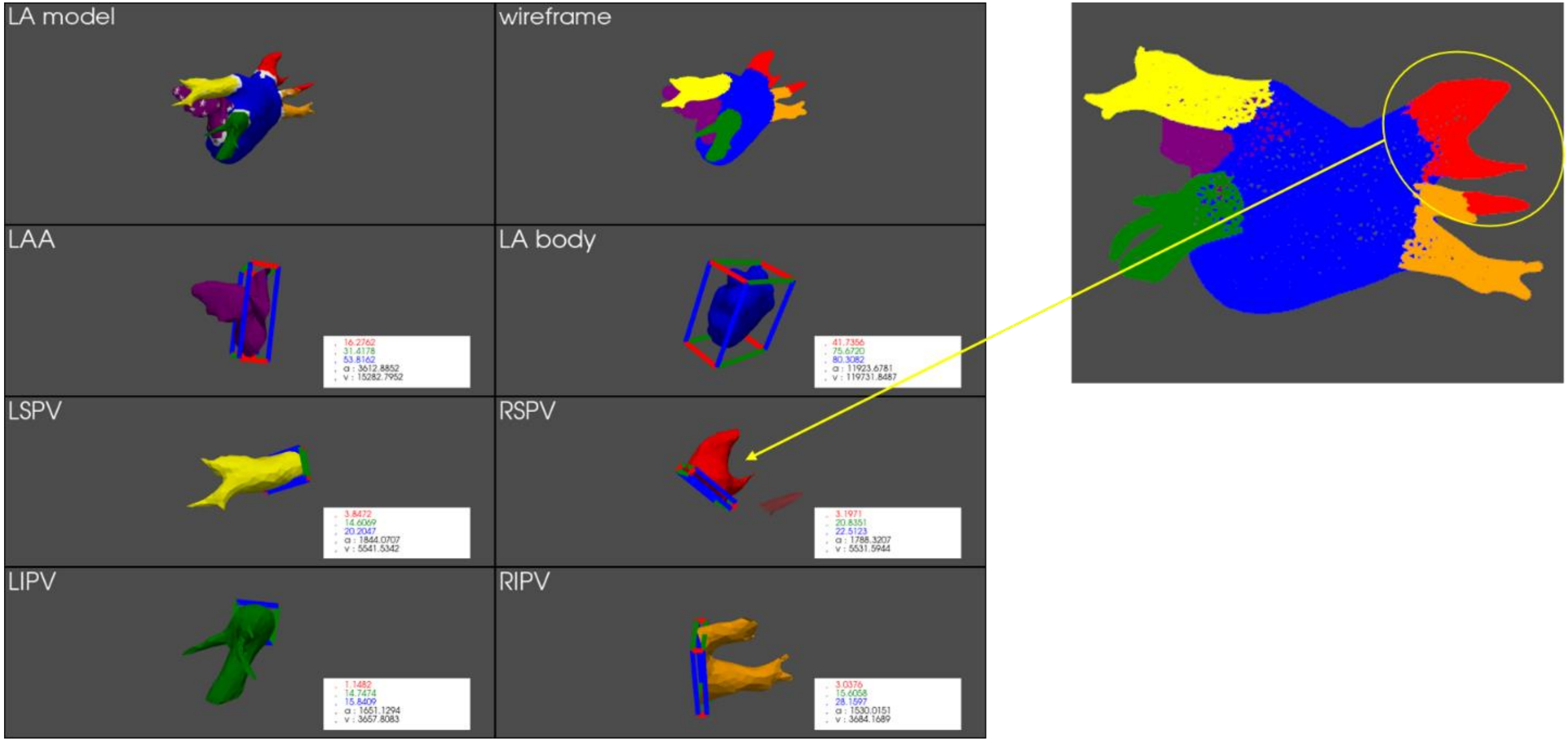




Bland-Altman plots



Visualization for monitoring (error detection)



Conclusions

- We proposed an AI-guided automated algorithm for surface segmentation and PV diameter measurement and validated it at both upper PVs and the eccentricity of the PV ostia.

- AI-based algorithms can be utilized to enhance the anatomical understanding of the LA and to streamline labor-intensive manual segmentation procedures for measuring the diameter of PV.

Thank you for your attention.

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