3D MRI Segmentation for Congenital Heart Disease

Mohammad Imrul "Jubair"

Research Area

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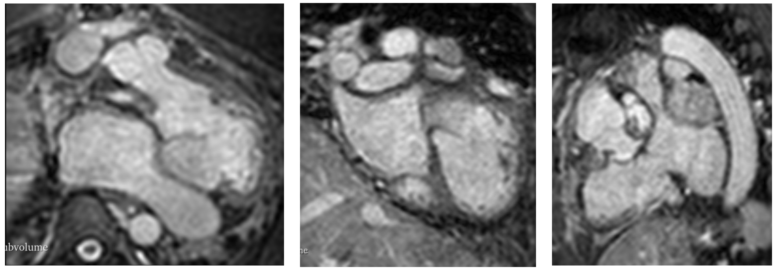

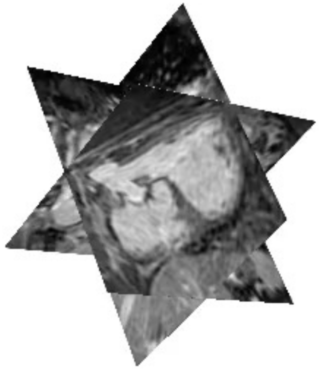

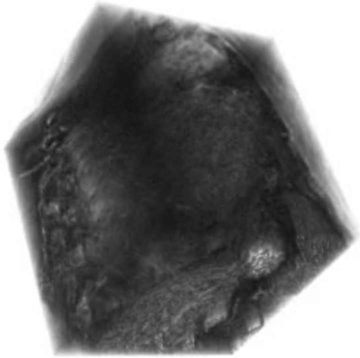

- Magnetic Resonance Imaging. MF and RW
    - Scanner ▸ Series of 2D ▸ 3D Vol reconstruction
    - Angle view ▸ Organs and Tissues ▸ Diagnoses and treatment plans.

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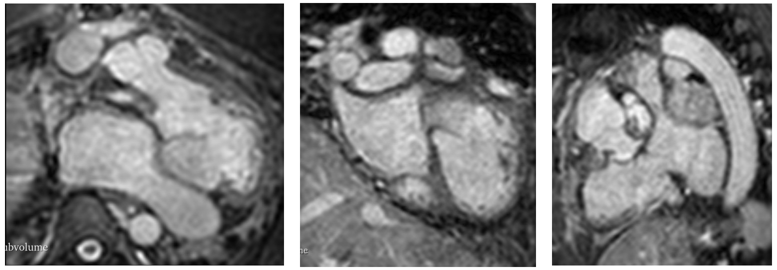
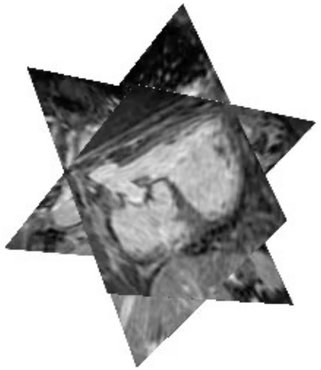
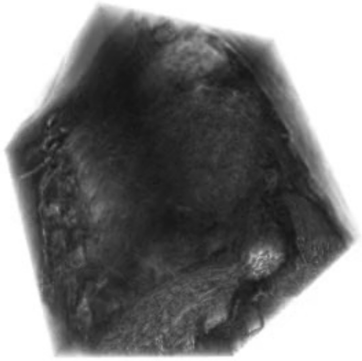
3D MRI Segmentation for Congenital Heart Disease







- Difficulties ▸ Examine individual 2D slices
  - Mentally picture of heart’s 3D anatomy
  - Coarse 3D blood pool ▸ Lack of precision
  - Obscured by surrounding structures

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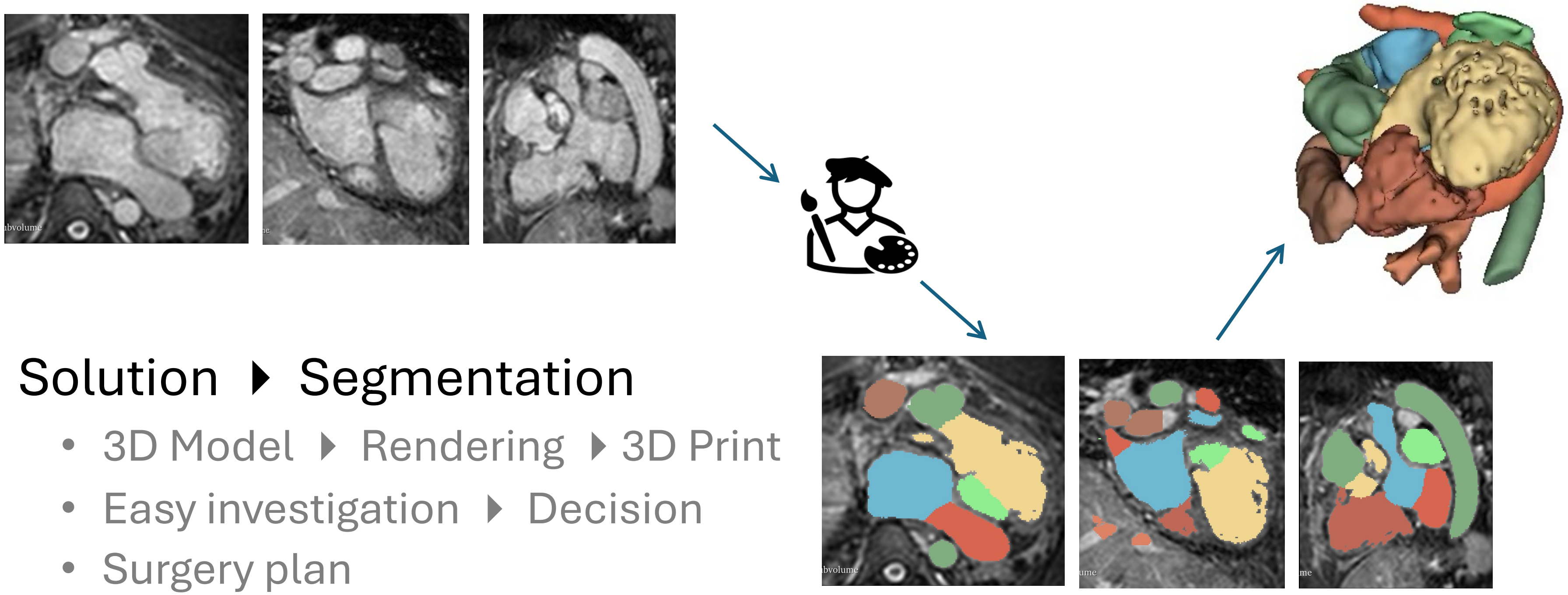
3D MRI Segmentation for Congenital Heart Disease



- Solution ⏵ Segmentation
  - 3D Model ⏵ Rendering ⏵ 3D Print
  - Easy investigation ⏵ Decision
  - Surgery plan

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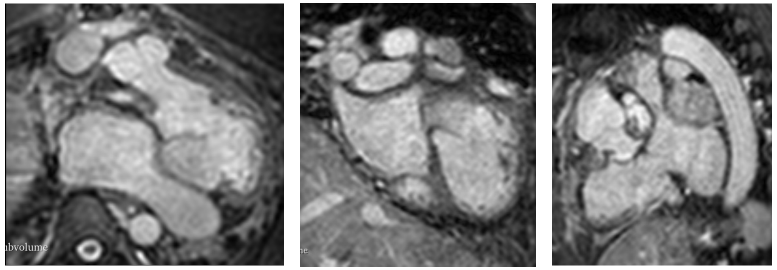
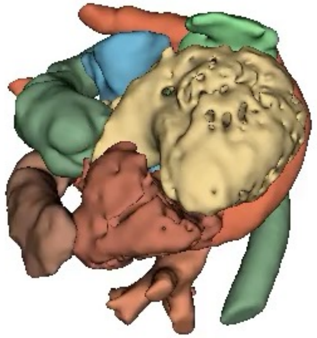
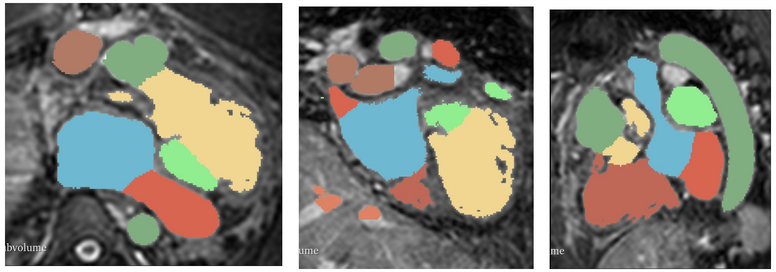
3D MRI Segmentation for Congenital Heart Disease







- Difficulties ▸ Manual
  - Expertise
  - Time

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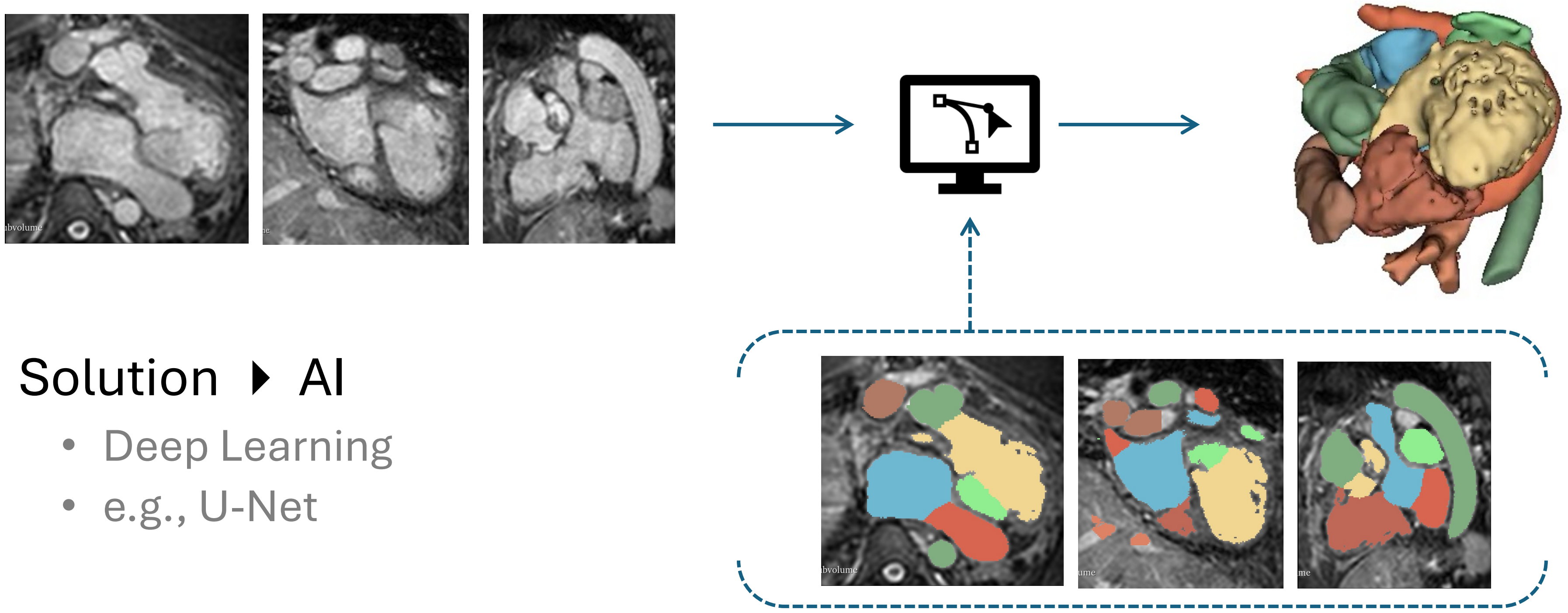
3D MRI Segmentation for Congenital Heart Disease



- Solution ▶ AI
  - Deep Learning
  - e.g., U-Net

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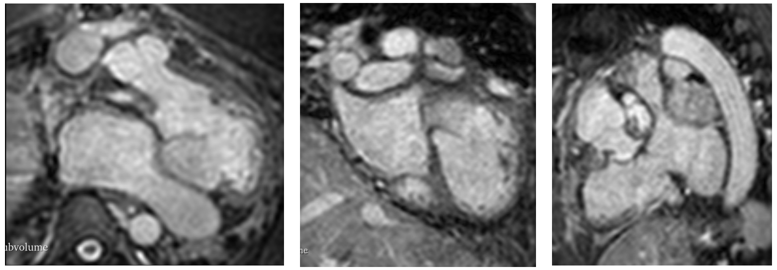
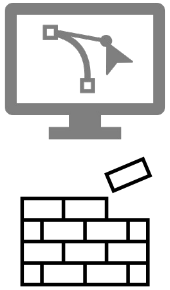
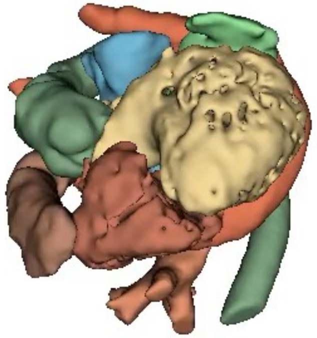
3D MRI Segmentation for Congenital Heart Disease







- Manual Segmentation Pipeline
  - Handcrafting
    - Fine tuning ▸ *"Grad Student Descent!!!"*
  - Barrier for non-DL experts

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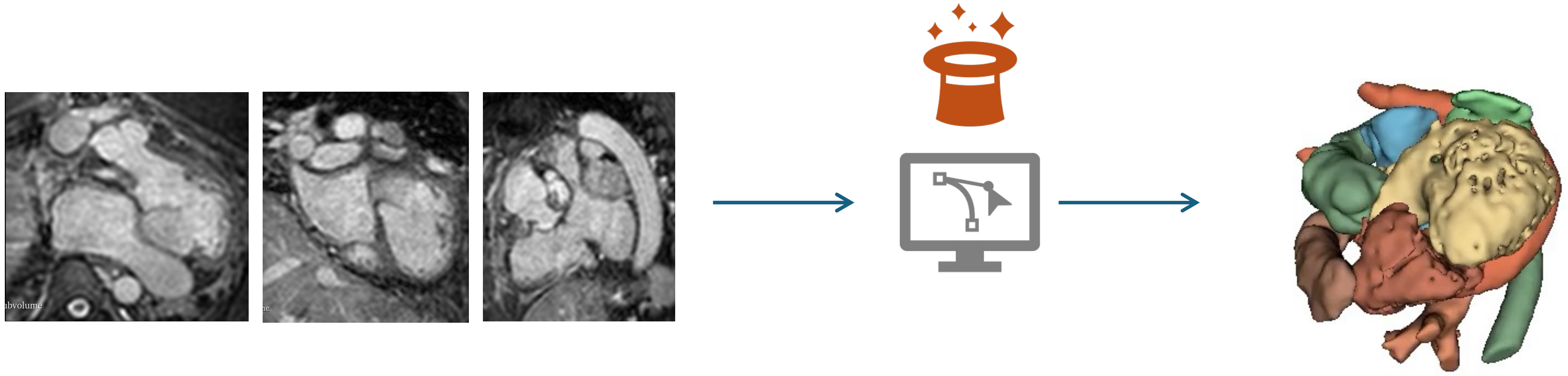
3D MRI Segmentation for Congenital Heart Disease



- End-to-End Segmentation Frameworks
  - Raw input ⟶ 🎁 ⟶ Segmentation
    - Out of the box solution
  - Easy-to-use ▸ Training, inferencing, etc.

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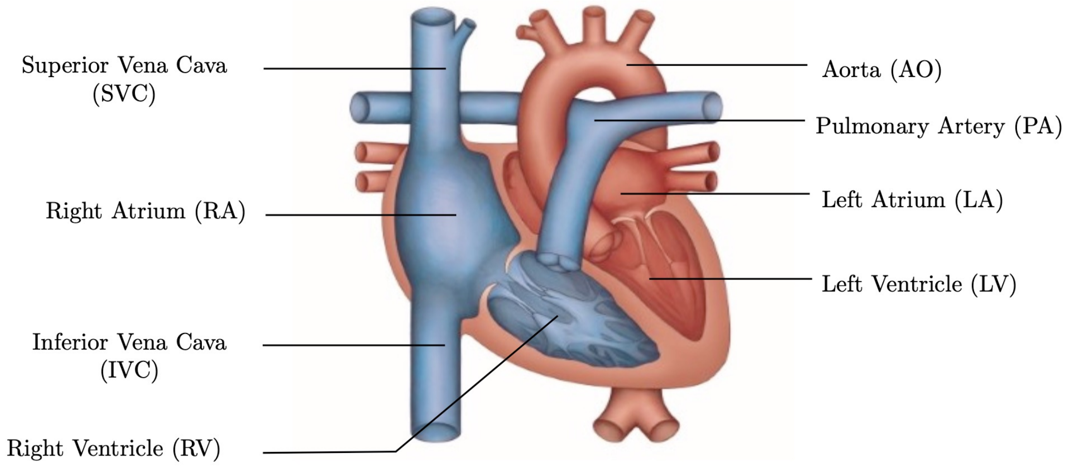
3D MRI Segmentation for Congenital Heart Disease

- Structures
- Connections
- Locations



Research Area

3D MRI Segmentation for Congenital Heart Disease

- Structures
  Missing, Duplicate, Change
- Connections
  Unnatural
- Locations
  Abnormal

Can arise in simultaneously!

Research Area

3D MRI Segmentation for Congenital Heart Disease

Leading cause of **birth defect** related **Deaths**

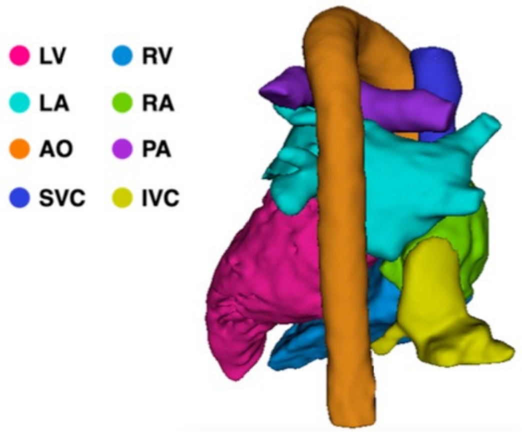
Affects **~1%** of births in the USA

~25% are critical CHD ‣ **Surgery** or interventions necessary

Research Area

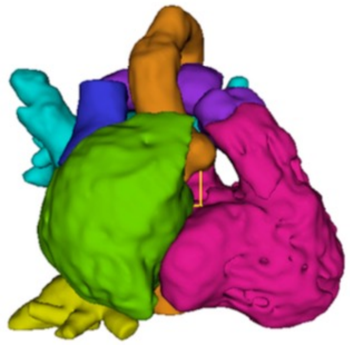
3D MRI Segmentation for Congenital Heart Disease

- CHD Examples –



(a) Normal heart

(b) CHD Example 1: two SVCs



(c) CHD Example 2: single Ventricle

Research Area

3D MRI Segmentation for Congenital Heart Disease

- Whole Heart ▸ AO, LV, PA, RA, SVC, IVC, LA, RV
- Using End-to-end Segmentation Frameworks

Research Area | Question

"How well do existing end-to-end segmentation frameworks perform?"

Study ▶ Experiment ▶ Analyze

Research Area | Why difficult?

3D MRI Segmentation for Congenital Heart Disease

- High Anatomical Variability.
  - Difficult ‣ anatomical prior
  - Overfit
  - Generalization problem

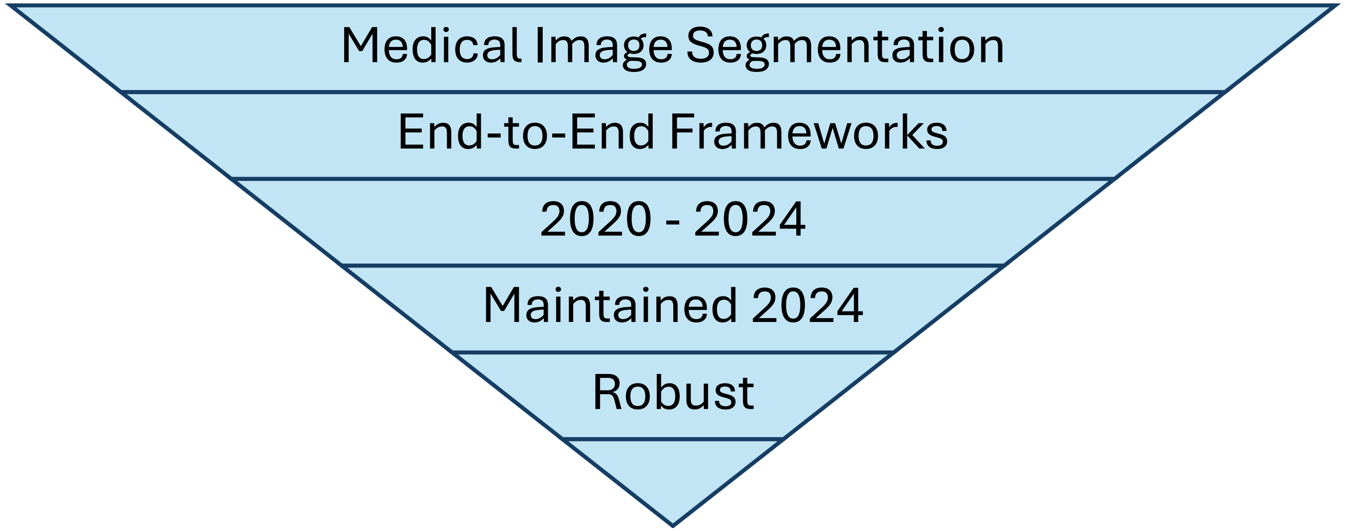
- Image Appearance.
  - Normal: Heart parts can be identified ‣ global context
  - CHD: Not possible

Research Area | Why difficult?

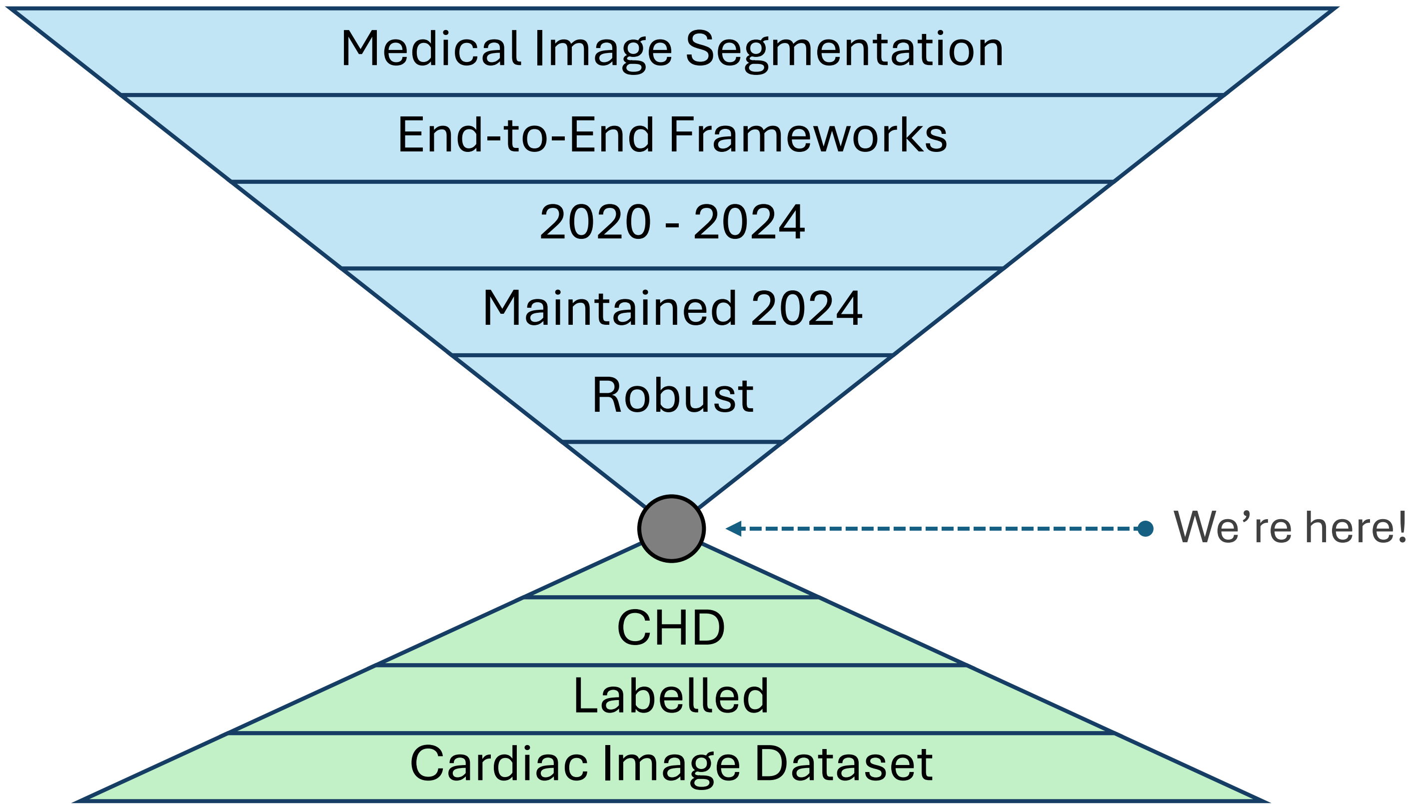
3D MRI Segmentation for Congenital Heart Disease

- Insufficient Training Data
  - Limited ⟵ Confidentiality, Laborious Task
  - A particular type ‣ unseen in training
    - but appears in test

Literature Selection



Literature Selection



Overview

- Datasets
- Methods
- Experimental Result
- Conclusion and Future Works

Datasets

- GCI-CHD [2023] and Image CHD [2020]
- CHLA-CHD [2020]
- CAP-CHD [2011]
- MM-WHS [2023]
- 20-HVSMR [2016]. and 48-HVSMR+ [2022]

Datasets | Comparisons

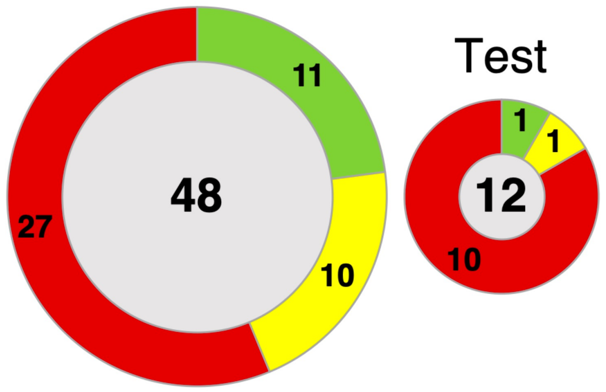
Dataset	CHD?	CHD Types	Patient Age	Heart Chambers								Modality	Subjects	Normalized?	Segment Type	Public?
				AO	LV	PA	RA	SVC	IVC	LA	RV					
GCI-CHD [Yao et al., 2023]	✓	14	1y - 21y	✓	✓	✓	✓	×	×	✓	✓	CT	68	No	Mask	×
Image CHD [Xu et al., 2020]	✓	16	1m - 40y	✓	✓	✓	✓	×	×	✓	✓	CT	110	No	Mask	✓
CHLA-CHD [Karimi-Bidhendi et al., 2020]	✓	8	2m - 18m	×	✓	×	×	×	×	×	✓	MRI	64	No	Mask	×
CAP-CHD [Fonseca et al., 2011]	✓	1	0m - 62y	×	✓	×	×	×	×	×	✓	MRI	422	No	Cotour + Landmark	×
MM-WHS [Wu and Zhuang, 2023]	Partially	NA	NA	✓	✓	✓	✓	×	×	✓	✓	MRI + CT	60 + 60	No	Mask	✓
20-HVSMR [Pace et al., 2022]	✓	25	1m - 55y	✓	✓	✓	✓	✓	✓	✓	✓	MRI	20	Custom	Mask	✓
48-HVSMR+ [Pace et al., 2022]	✓	33	1m - 55y	✓	✓	✓	✓	✓	✓	✓	✓	MRI	60	Custom	Mask	×

Datasets | Comparisons

Dataset	CHD?	CHD Types	Patient Age	Heart Chambers: AO	LV	PA	RA	SVC	IVC	LA	RV	Modality	Subjects	Normalized?	Segment Type	Public?
GCI-CHD [Yao et al., 2023]	✓	14	1y - 21y	✓	✓	✓	✓	×	×	✓	✓	CT	68	No	Mask	×
Image CHD [Xu et al., 2020]	✓	16	1m - 40y	✓	✓	✓	✓	×	×	✓	✓	CT	110	No	Mask	✓
CHLA-CHD [Karimi-Bidhendi et al., 2020]	✓	8	2m - 18m	×	✓	×	×	×	×	×	✓	MRI	64	No	Mask	×
CAP-CHD [Fonseca et al., 2011]	✓	1	0m - 62y	×	✓	×	×	×	×	×	✓	MRI	422	No	Cotour + Landmark	×
MM-WHS [Wu and Zhuang, 2023]	Partially	NA	NA	✓	✓	✓	✓	×	×	✓	✓	MRI + CT	60 + 60	No	Mask	✓
20-HVSMR [Pace et al., 2022]	✓	25	1m - 55y	✓	✓	✓	✓	✓	✓	✓	✓	MRI	20	Custom	Mask	✓
48-HVSMR+ [Pace et al., 2022]	✓	33	1m - 55y	✓	✓	✓	✓	✓	✓	✓	✓	MRI	60	Custom	Mask	×

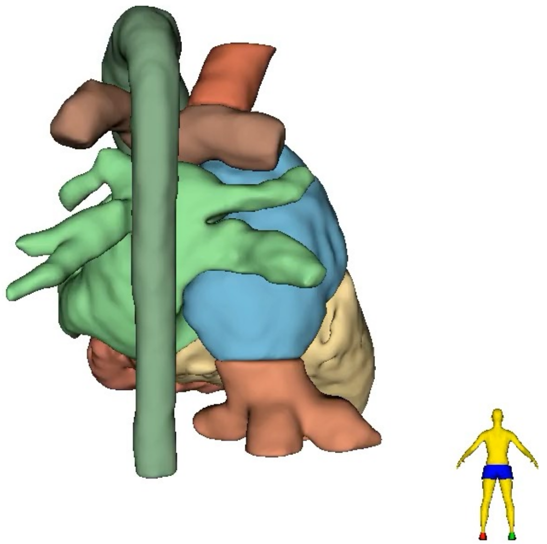
Datasets | 48-HVSMR+

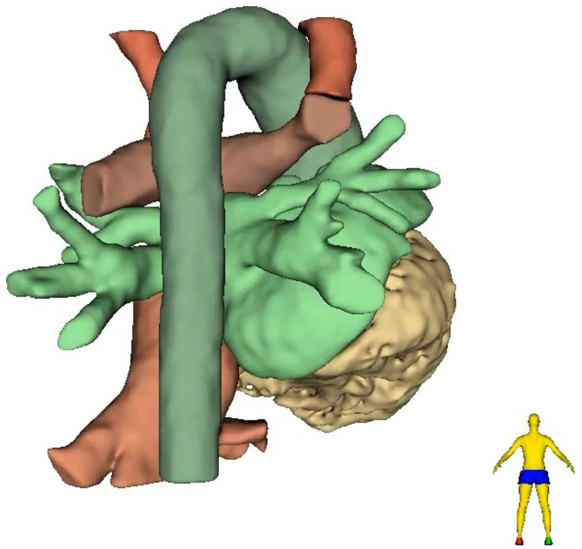
- Manually Segmented
- Normalized
- Types: **Mild**, **Moderate** and **Severe**
- Train: Test = 48:12
- 4-cross Validation
  - ~ Equal distribution ⟶ Mild, Moderate and Severe
- Case notes
  - Description



Datasets | 48-HVSMR+

- Examples –



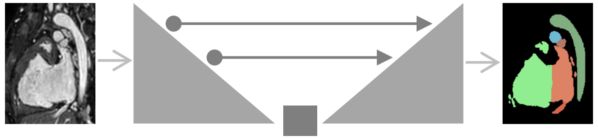


Methods

- nnU-Net [2020]
- TotalSegmentor [2023]
- Auto3dSeg [2023]
- UniverSeg [2023]
- MedSAM [2024]

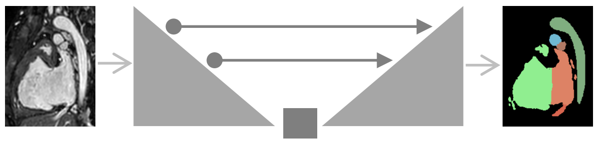
Methods | 3D U-Net

- Encoder
  - Conv layers ⟶ Max-pool
    - Spatial dimensions (↓) • Feature channels (↑)
    - Learn hierarchical representation
- Decoder
  - Trans conv ⟶ Conv
    - Feature maps (↑) • Feature channels (↓)
    - Learn reconstructing segments



Methods | 3D U-Net

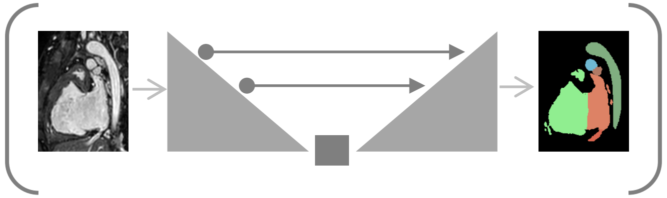
- Skip Connections ‣ Layer $_{\text{Encoder}} \longrightarrow$ Layer $_{\text{Decoder}}$
  - Feat. maps from earlier stage
- 3D Version ‣ 3D {conv, pooling, up-sampling}
- Too many variants
  - Manual Segmentation Pipeline



Methods | nnU-Net

- No New U-Net
  - Domain Knowledge ⟶ U-Net

Fixed
(No adaption needed)
LR?, Loss,? Optimizer?, Augmentation?



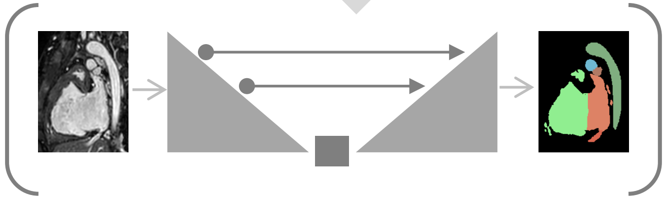
Methods | nnU-Net

- No New U-Net
  - Domain Knowledge ⟶ U-Net

Dataset fingerprints: voxel spacing, intensity distribution, modality, etc.

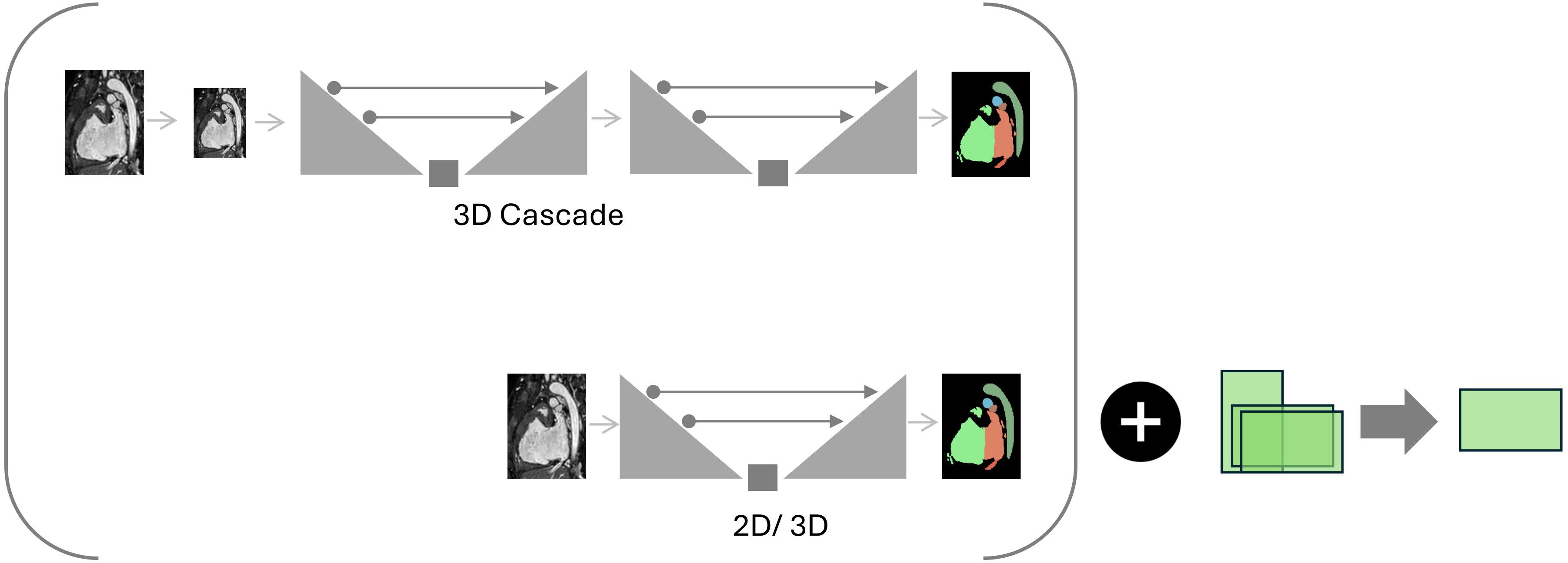
Rule-based
(Domain Knowledge ▸ Heuristic)
Batch size? Patch size? Architecture?

Fixed
(No adaption needed)
LR?, Loss,? Optimizer?, Augmentation?



Methods | nnU-Net

- Cross validation ‣ Ensemble
  - 2D • 3D • 3D Cascade



Methods | nnU-Net

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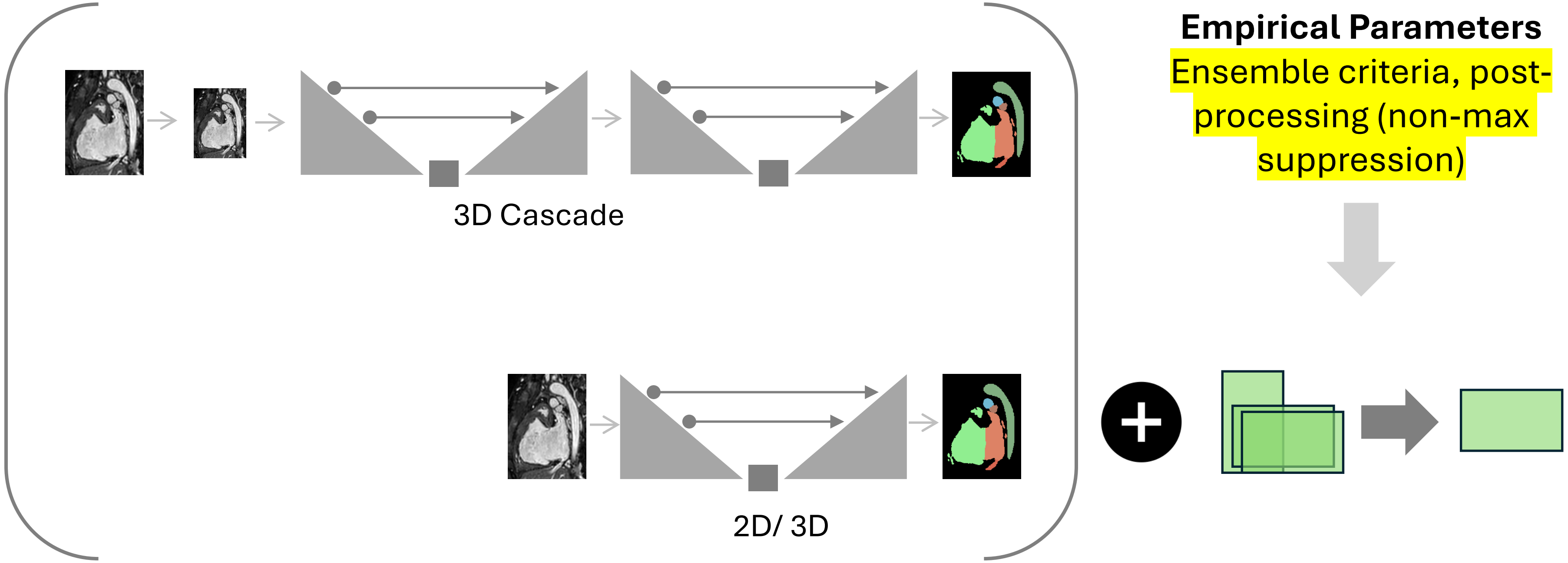
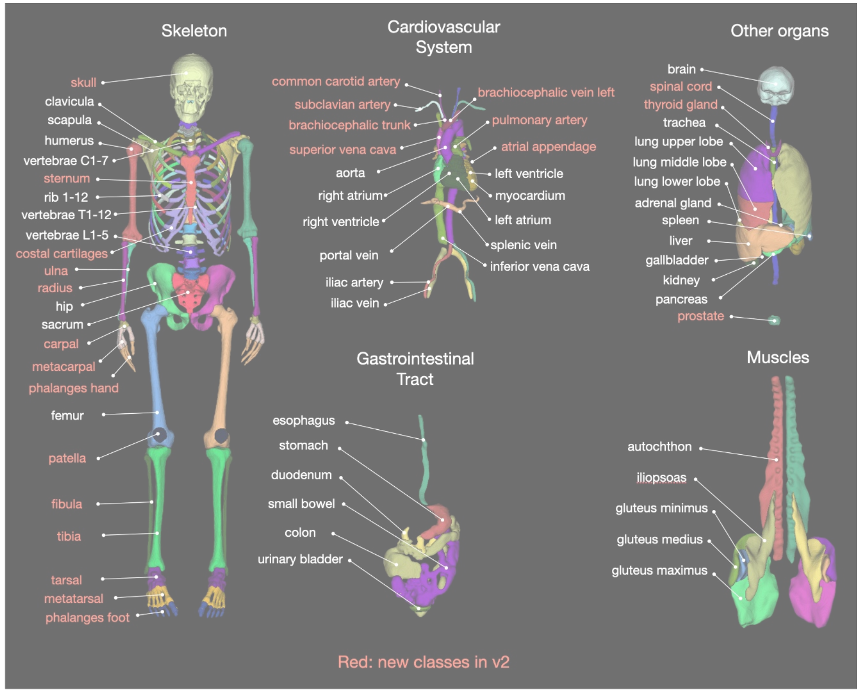
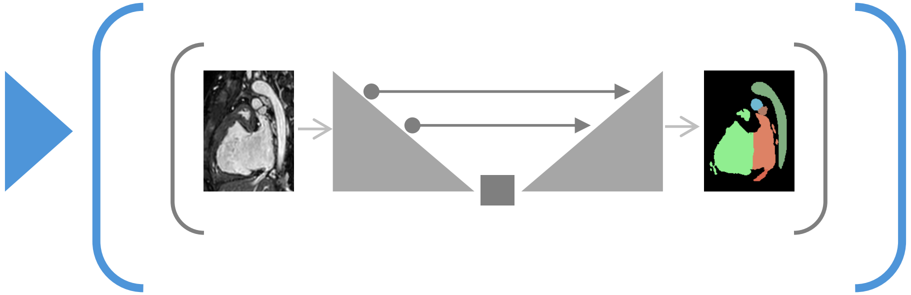


Methods | TotalSegmentor



- Leverage nnU-Net
- Whole Human Anatomy
- https://totalsegmentator.com/

Trained on large-scale
medical images



Methods | Auto3dSeg

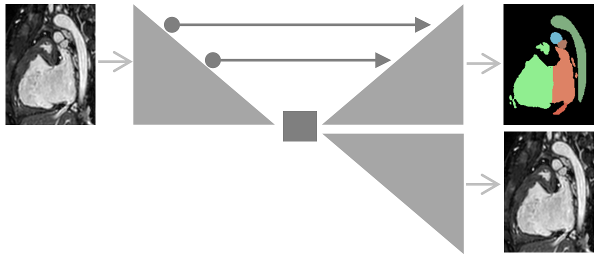
Data Analysis
(Domain Knowledge)
Global information: intensity, data size, and spacing

SegResNet
DiNTS
Swin UNETR

Algorithm Bundle

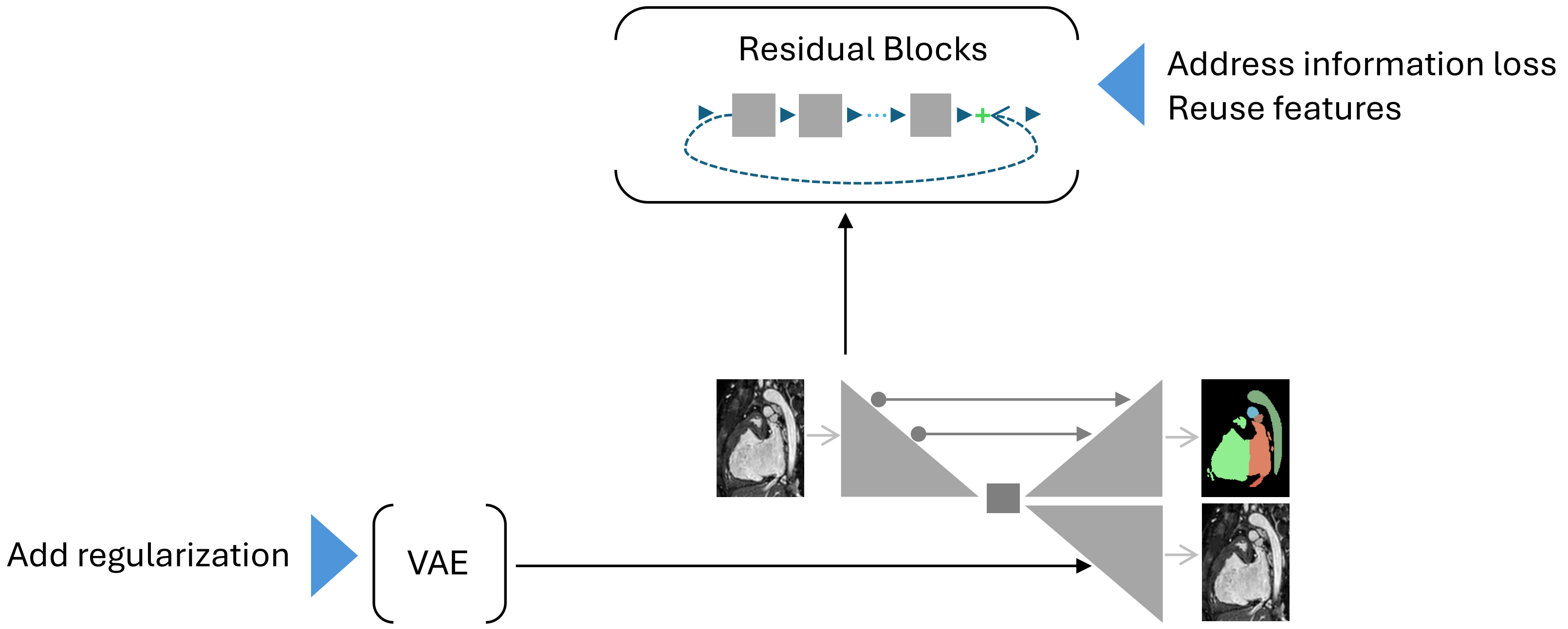
Methods | Auto3dSeg | SegResNet

- Like U-Net
  - Encoder • Decoder • Skip connections



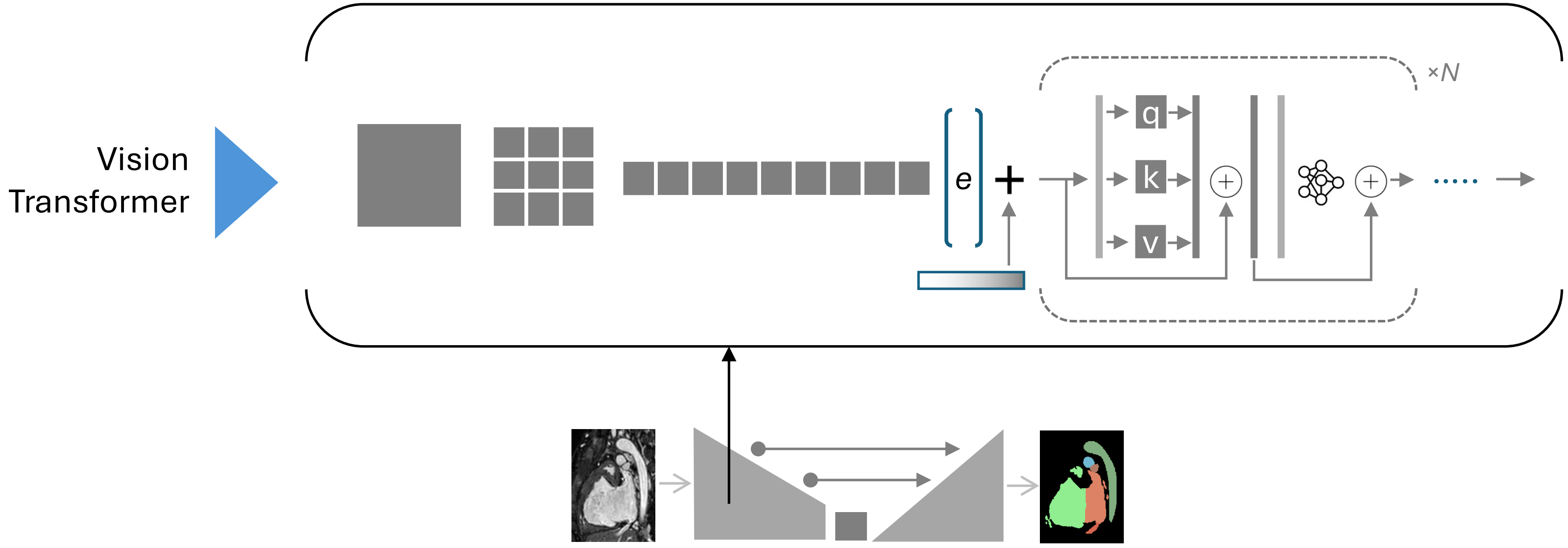
Methods | Auto3dSeg | SegResNet

- Residual Block
- VAE



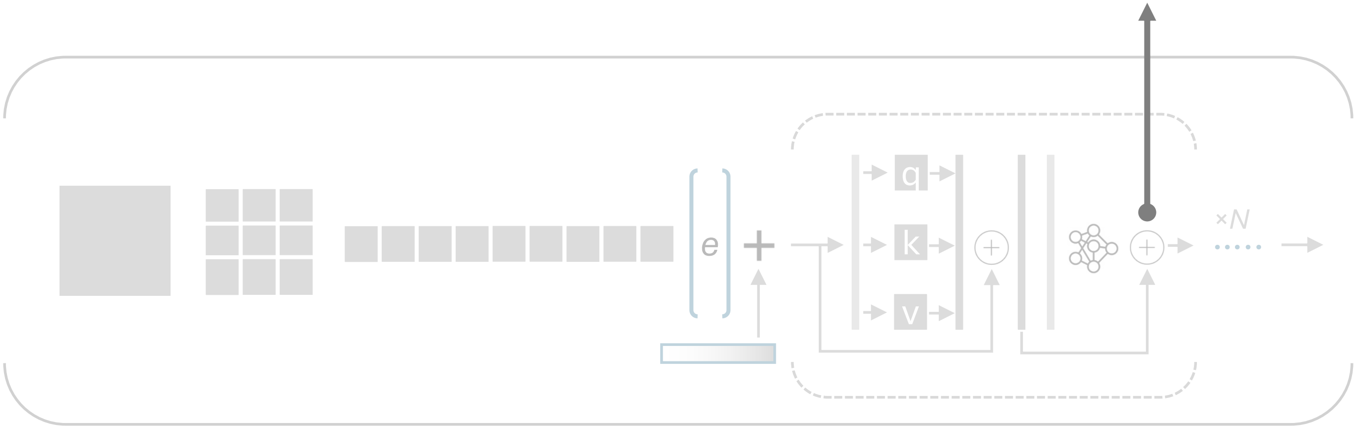
Methods | Auto3dSeg | Swin UNETR

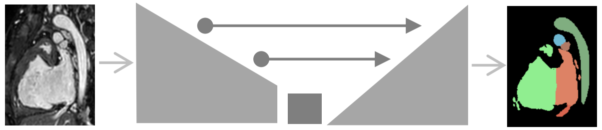
- UNETR
  - Encoder



Methods | Auto3dSeg | Swin UNETR

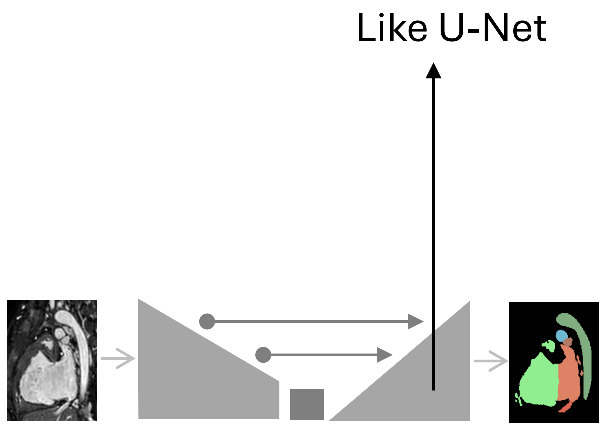
- UNETR
  - Skip connection





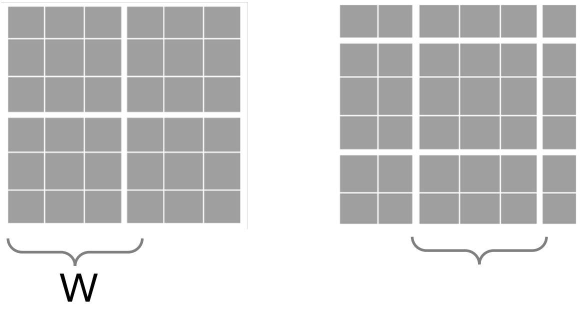
Methods | Auto3dSeg | Swin UNETR

- UNETR
  - Decoder

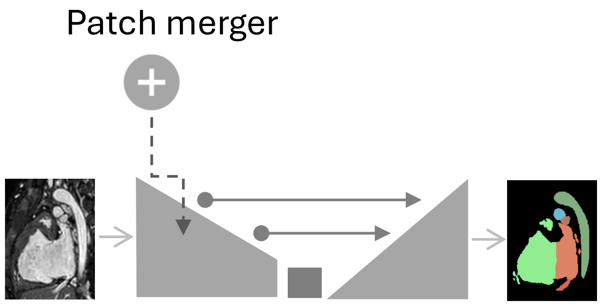


Methods | Auto3dSeg | Swin UNETR

- Swin-UNETR
  - Swin Transformer (Shifter window-based patch) + UNETR

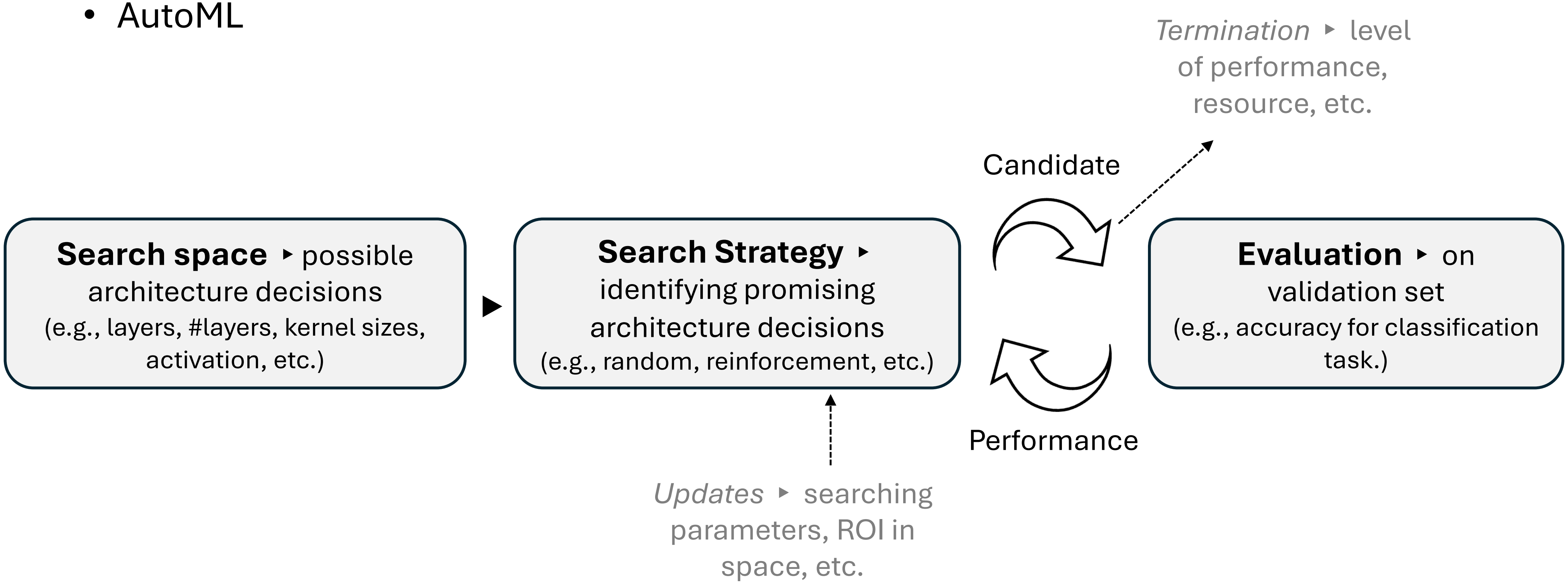


Obtain Local
Information



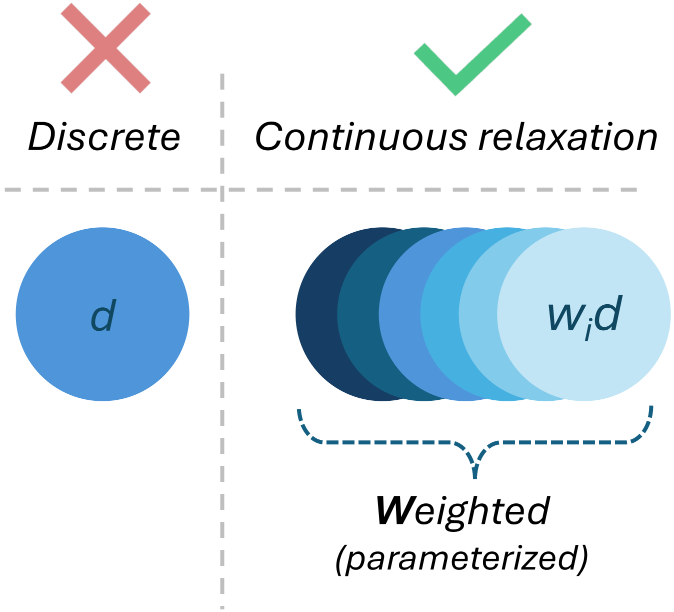
Methods | Auto3dSeg | DiNTS

- Neural Architecture Search (NAS)
  - AutoML



Methods | Auto3dSeg | DiNTS

- Differential Neural Architecture Search (DNAS)



Differentiable
Optimize ***(W)*** ▸ SGD

Search space ▸ possible architecture decisions (e.g., layers, #layers, kernel sizes, activation, etc.)

▶

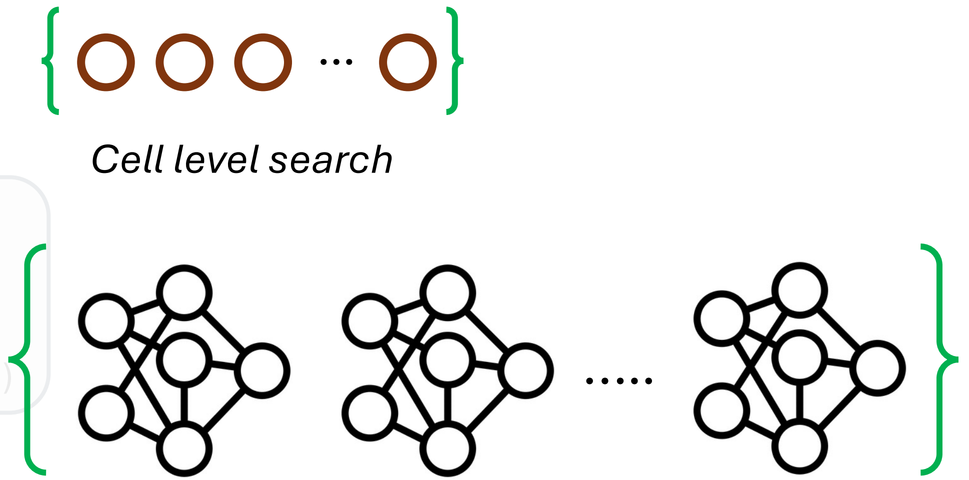
Search Strategy ▸ identifying promising architecture decisions (e.g., random, reinforcement, etc.)

Methods | Auto3dSeg | DiNTS

- Differential Neural Architecture Search (DNAS)
- Hierarchical Search (HS)
- DiNTS ▸ DNAS + HS

Search space ▸ possible architecture decisions
(e.g., layers, #layers, kernel sizes, activation, etc.)

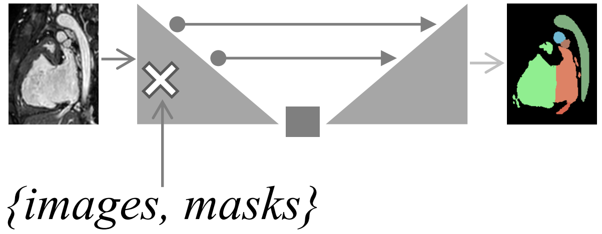
Search Strategy ▸ identifying promising architecture decisions
(e.g., random, reinforcement, etc.)



Network level search

Methods | UniverSeg

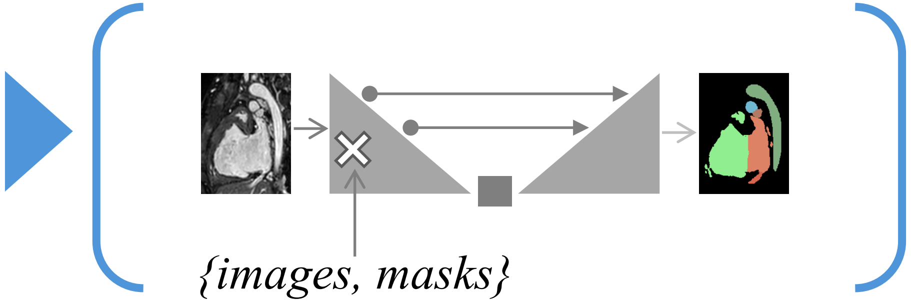
- Unseen Data
  - Test **Query** (input image) and **Support** set {images, masks}



Methods | UniverSeg

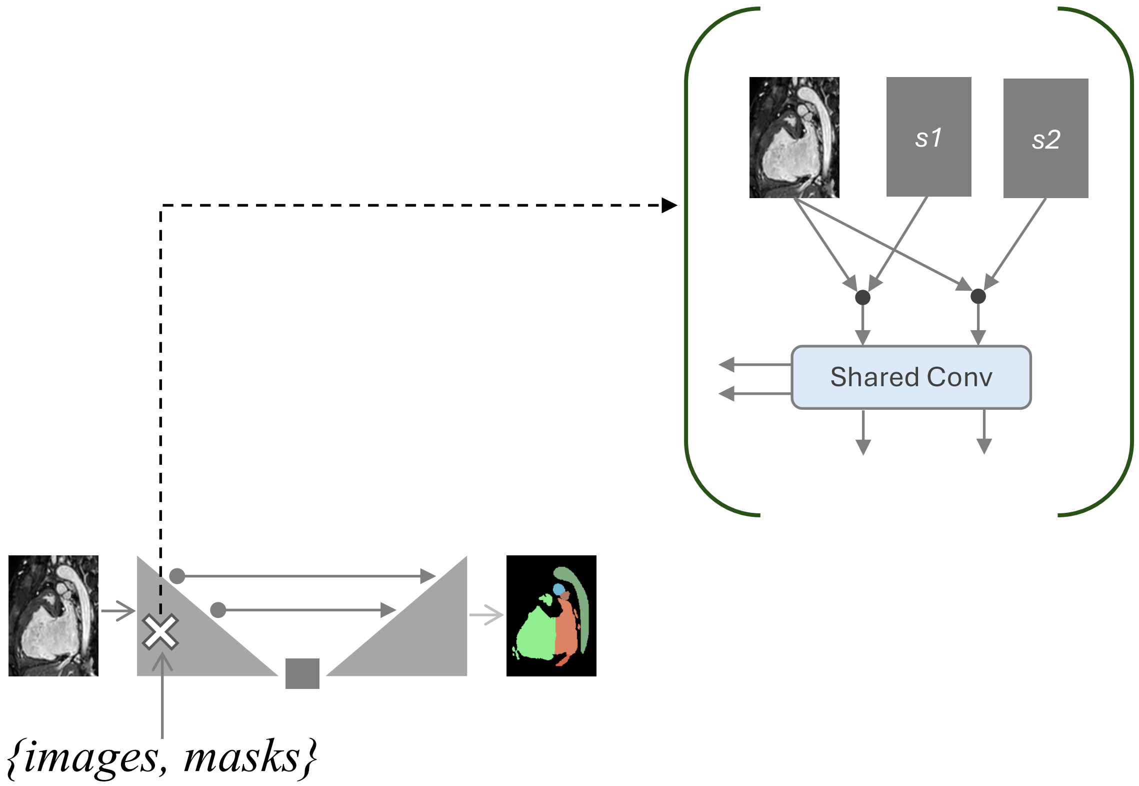
- Unseen Data
  - Test **Query** (input image) and **Support** set {images, masks}
  - No additional training

Trained on large-scale medical images



Methods | UniverSeg

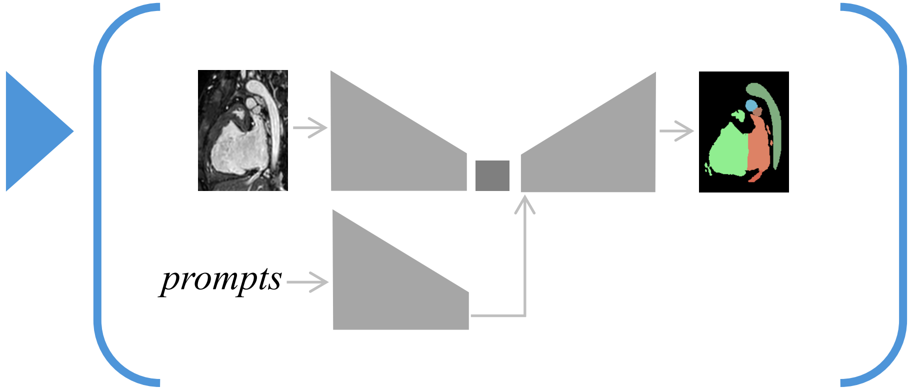
- Unseen Data
  - *CrossBlock*
    - Cross-convolution
    - Query and Support interacts



Methods | MedSAM

- SAM inspired
  - Prompt ▸ Bounding box, points.
- Transformer based
  - Image encoder • Prompt encoder
  - Mask decoder

Trained on large-scale
medical images



Methods | Comparisons

Frameworks	Slicer Plugin?	Input				Trained on Own Dataset?	Multi-label?	Trainable on Custom Dataset?	Tuning possoble?	Tested on CHD Dataset?
		Prompt?	3D?	MRI?	Any size?					
nnU-Net [Isensee et al., 2020]	×	×	✓	✓	✓	×	✓	✓	✓	×
TotalSegmentor [Wasserthal et al., 2023]	✓	×	✓	×	✓	✓	✓	×	×	×
Auto3DSeg [MONAI Medical Open Network for AI, 2023]	✓	×	✓	✓	✓	×	✓	✓	✓	×
UniverSeg [Butoi et al., 2023]	×	×	×	✓	×	✓	×	×	×	×
MedSAM [Ma et al., 2024]	✓	✓	✓	✓	✓	✓	✓	✓	✓	×

Methods | Comparisons

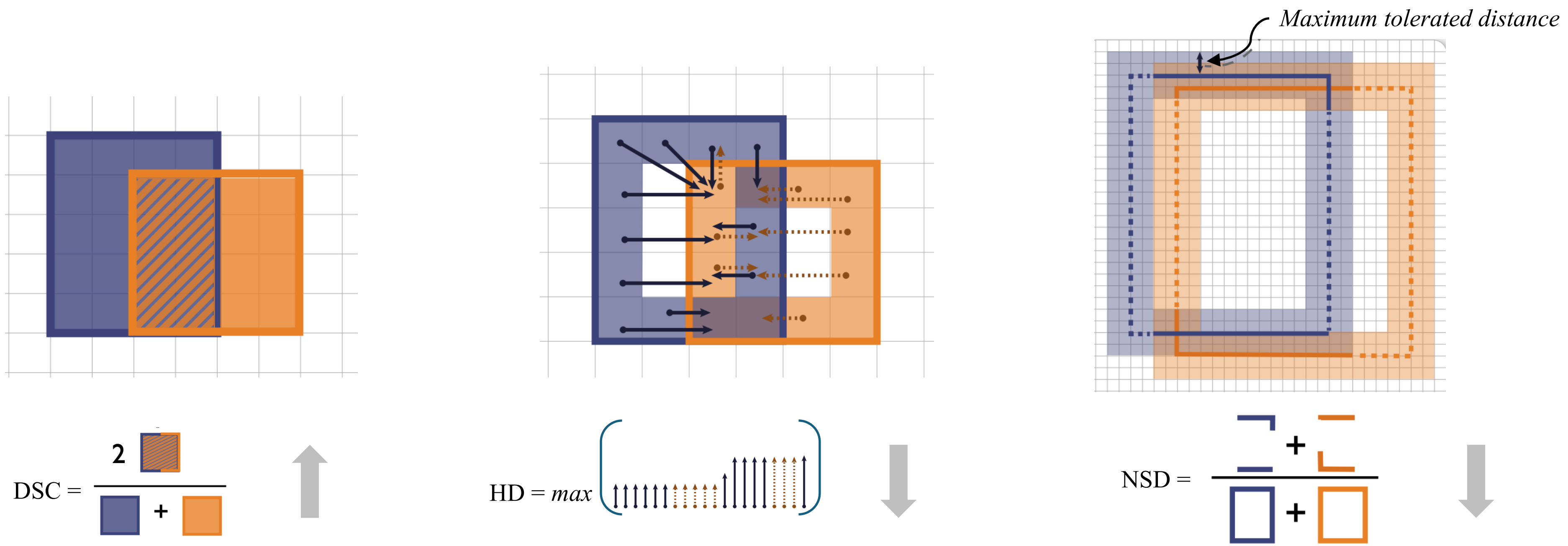
Frameworks	Slicer Plugin?	Input				Trained on Own Dataset?	Multi-label?	Trainable on Custom Dataset?	Tuning possoble?	Tested on CHD Dataset?
		Prompt?	3D?	MRI?	Any size?					
nnU-Net [Isensee et al., 2020]	×	×	✓	✓	✓	×	✓	✓	✓	×
TotalSegmentor [Wasserthal et al., 2023]	✓	×	✓	×	✓	✓	✓	×	×	×
Auto3DSeg [MONAI Medical Open Network for AI, 2023]	✓	×	✓	✓	✓	×	✓	✓	✓	×
UniverSeg [Butoi et al., 2023]	×	×	×	✓	×	✓	×	×	×	×
MedSAM [Ma et al., 2024]	✓	✓	✓	✓	✓	✓	✓	✓	✓	×

Methods | Comparisons

Frameworks	Slicer Plugin?	Input				Trained on Own Dataset?	Multi-label?	Trainable on Custom Dataset?	Tuning possoble?	Tested on CHD Dataset?
		Prompt?	3D?	MRI?	Any size?					
nnU-Net [Isensee et al., 2020]	×	×	✓	✓	✓	×	✓	✓	✓	×
Auto3DSeg [MONAI Medical Open Network for AI, 2023]	✓	×	✓	✓	✓	×	✓	✓	✓	×

Evaluation Metric

- Dice Score ▸ Overlapping of two.
- Hausdorff Distance ▸ Max distance between two boundaries.
- Normalized Surface Distance ▸ One's boundaries within other's range.



Results | Setup

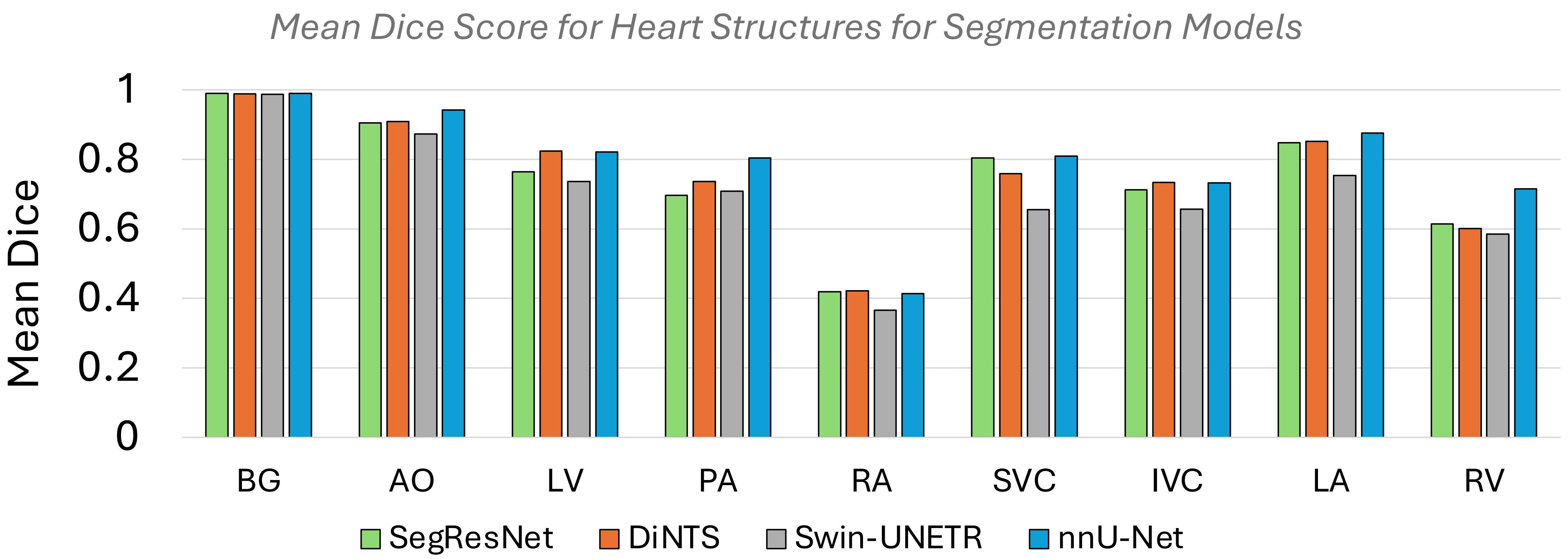
- Linux Server - A100 GPU 40GB
- For nnU-Net
    - Nomenclature ‣ files and directory
    - Optional splitting file
- For Auto3dSeg
    - Directory and list (with optional splitting)
- No 48-HVSMR+ Normalization
- Default settings + Epochs 1K
- Results shown –
    - **nnU-Net** {3D U-Net} and **Auto3dSeg** {SegResNet, DiNTS, Swin UNETR}
    - For Sever Cases

Results | Mean Dice

- Mean Dice Score –
  - For 8 segment (AO, LV, PA, RA, SVC, IVC, LA, RV)
  - All patients

Model	Mean Dice
SegResNet	0.7202
DiNTS	0.7296
Swin-UNETR	0.6668
nnU-Net	0.7642

Results | Mean Dice



Results | nnU-Net configs

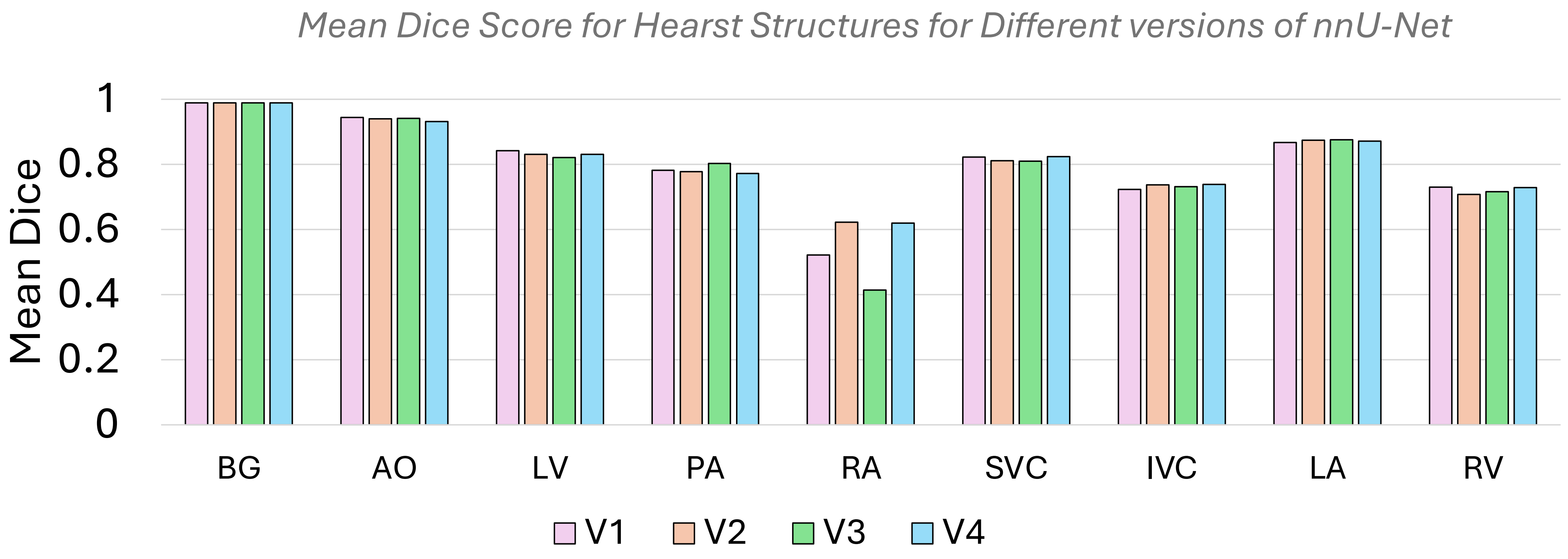
- Different nnU-Net configurations –
- Why?
  - Finding suitable setup for CHD
    - Helpful for domain scientists

Results | nnU-Net configs | Mean Dice

- Different nnU-Net configurations –
  - Splitting • Normalization • Augmentation • Epochs

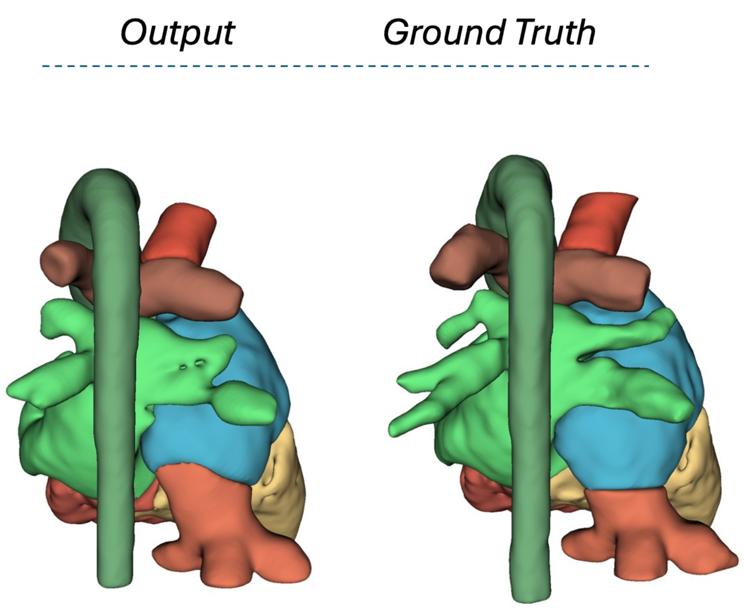
Version	Split	Normalization	Augmentation	Epochs	Mean Dice
V1	48-HVSMR+	48-HVSMR+	nnU-Net's Level-5	2K	0.7789
V2	48-HVSMR+	48-HVSMR+	nnU-Net's default	2K	0.7877
V3	48-HVSMR+	nnU-Net's default	nnU-Net's default	1K	0.7755
V4	Random	nnU-Net's default	nnU-Net's default	1K	0.7898

Results | nnU-Net configs | Mean Dice

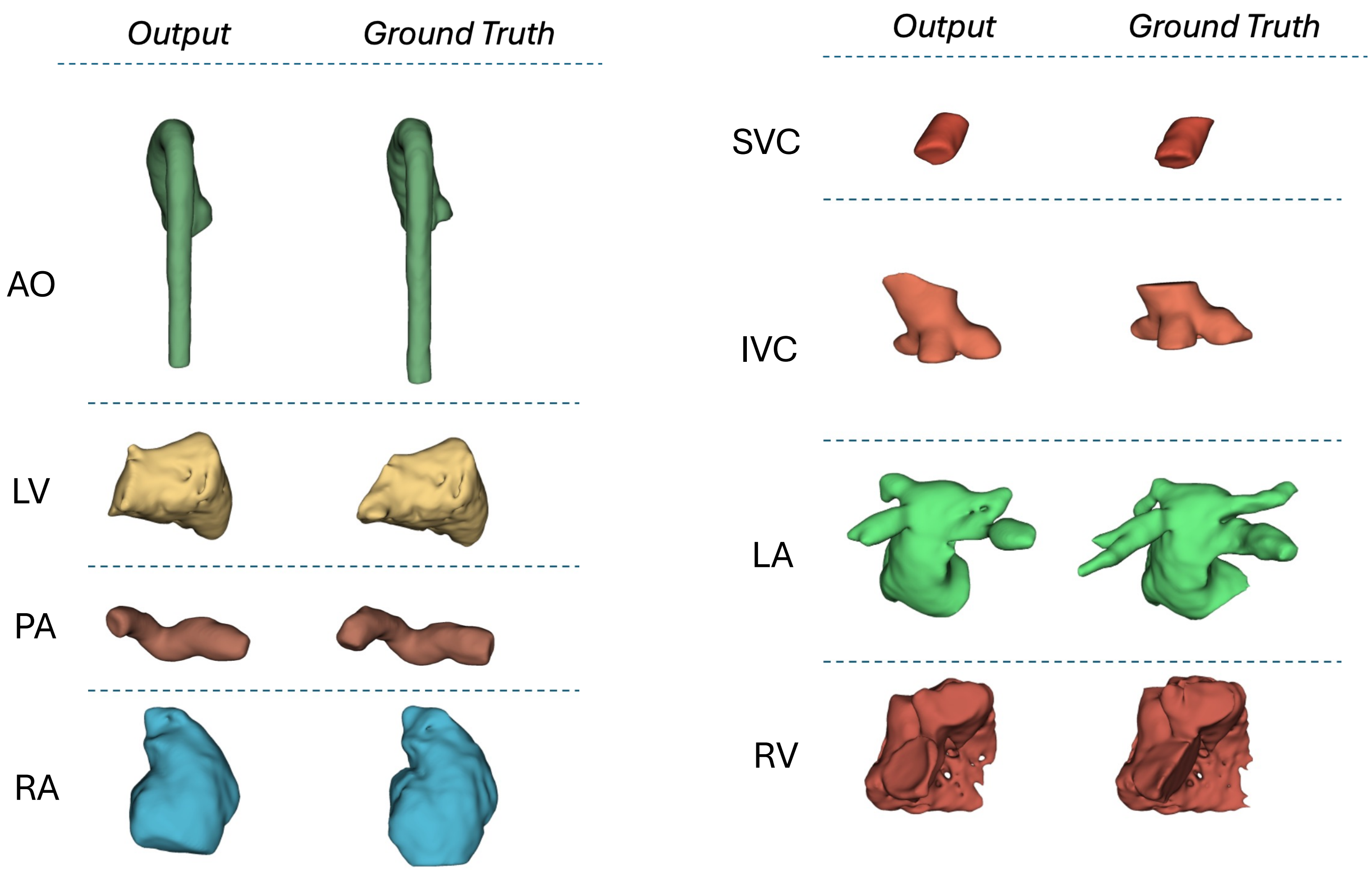


Results | Visualization

Severe Case – 1: Patient ID 007

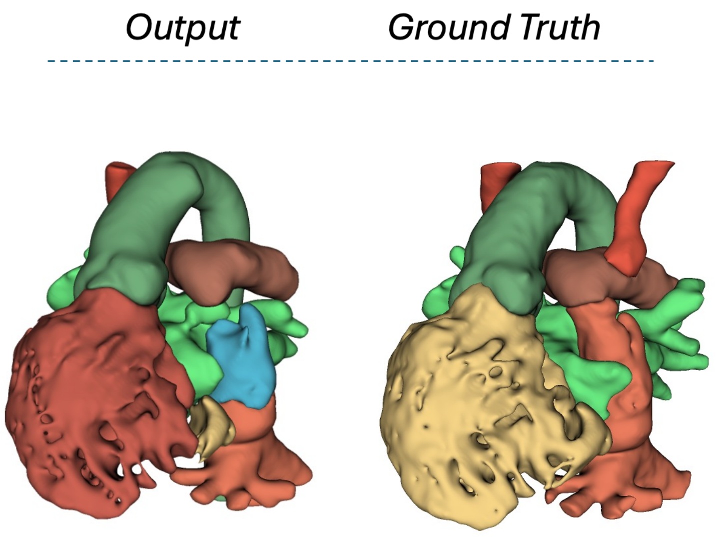


DSC = 0.9202

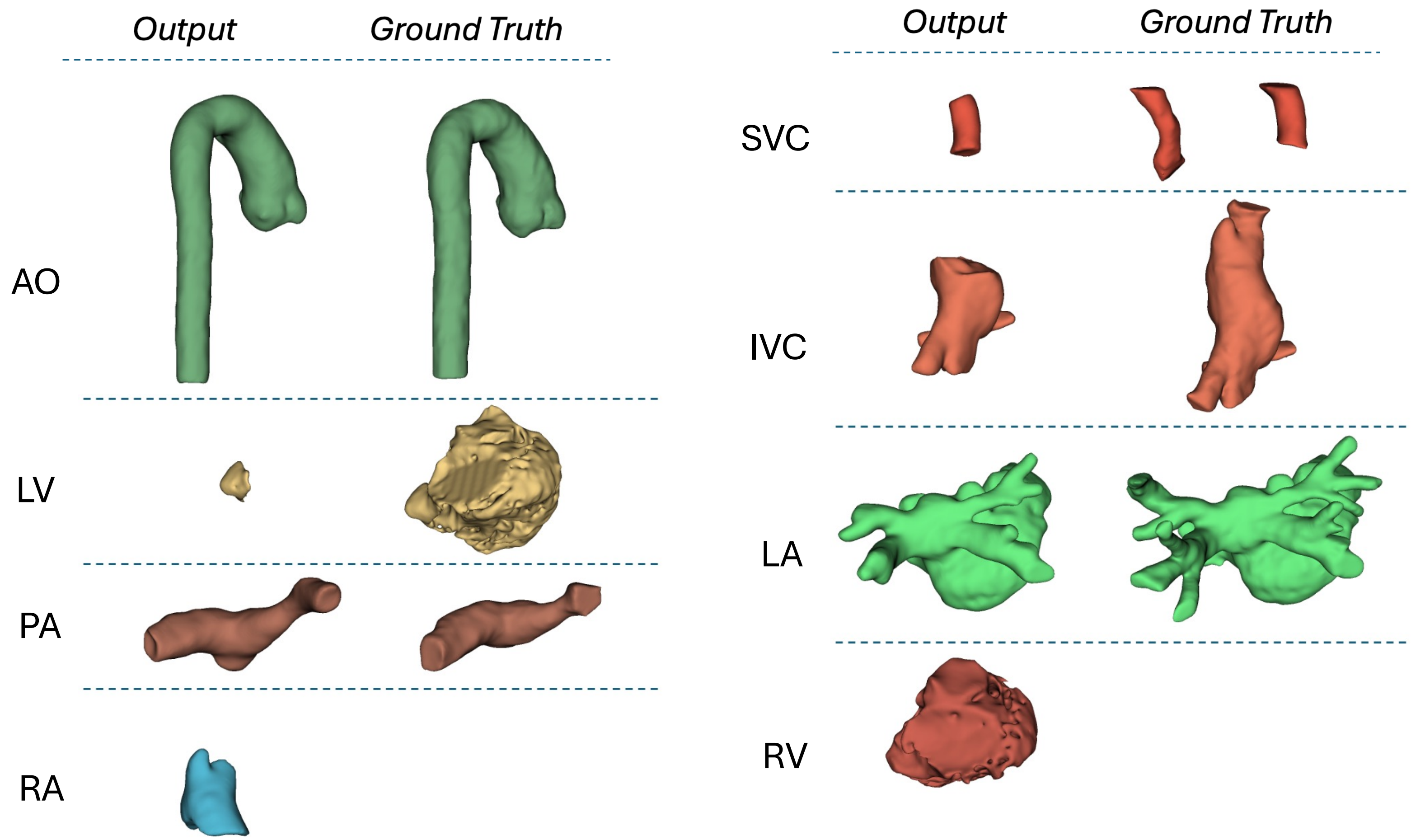


Results | Visualization

Severe Case – 2: Patient ID 010



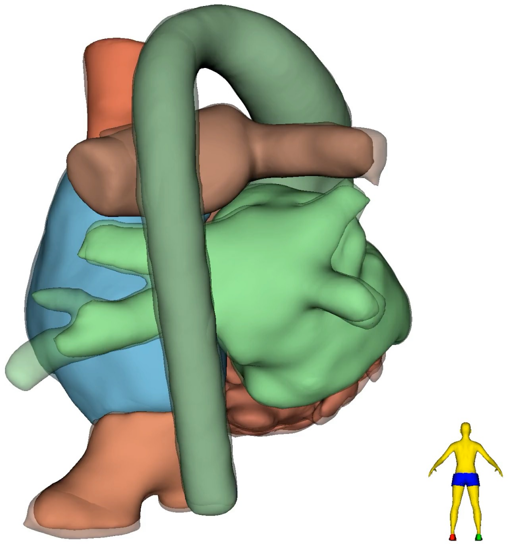
DSC = 0.4987



Results | Visualization

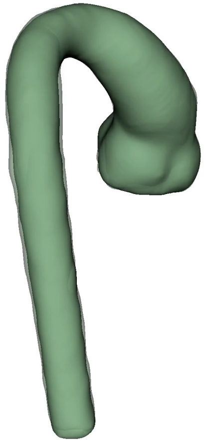
Severe Case – 3: Patient ID 005

Transparent ▸ GT | Solid ▸ Predicted

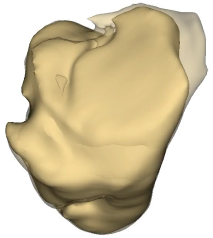


DSC = 0.9188

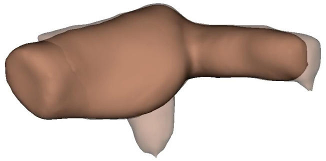
AO



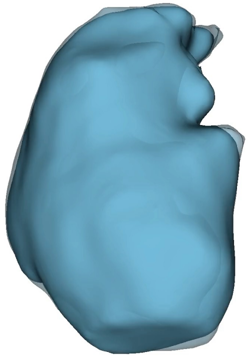
LV



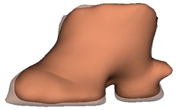
PA



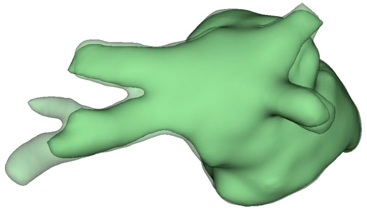
RA



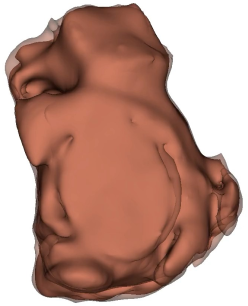
SVC



IVC



LA



RV

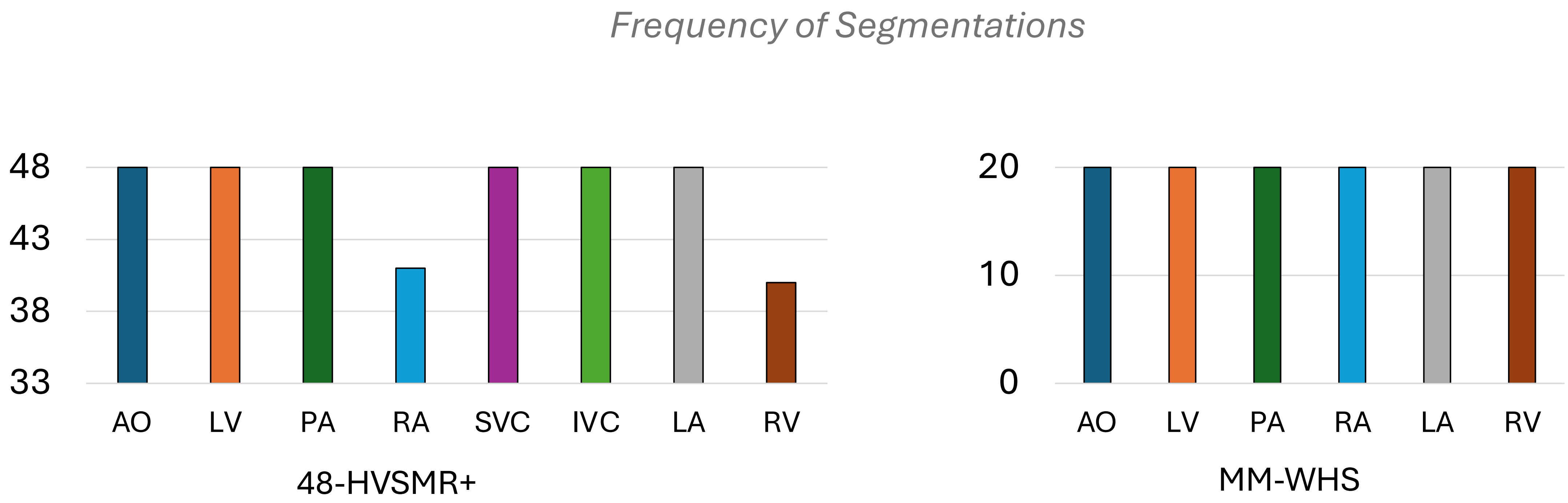
Findings

- Best Segmentation Framework? ▸ **nn-U-Net**
    - *Default settings*
    - *5-cross fold (random)*

- BG, AO, LA ▸ ☺
- RA, RV, IVC, SVC ▸ 😐
- RV, RA ▸ ☹

Findings

- Why RV and RA? ‣ lack of sample

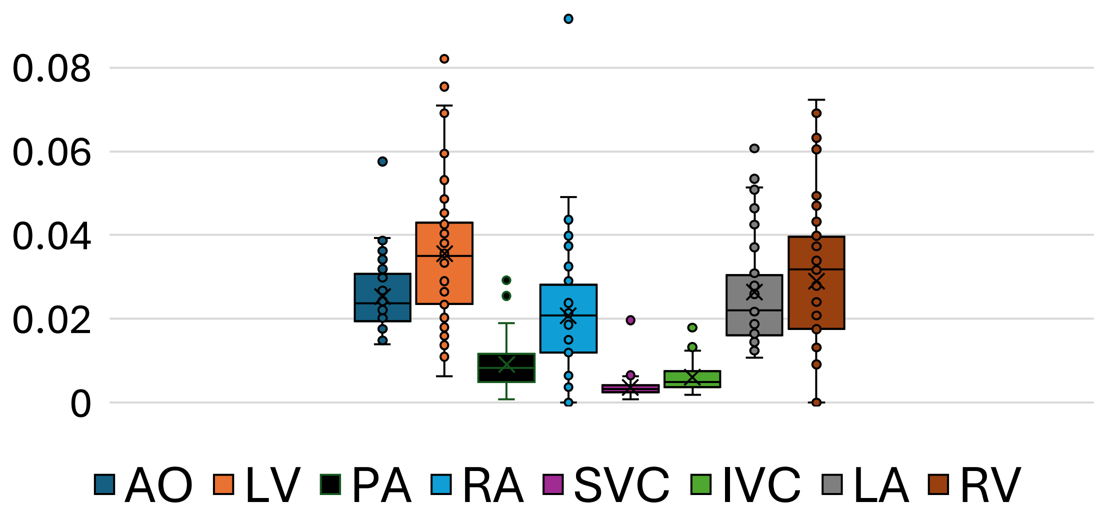


Findings

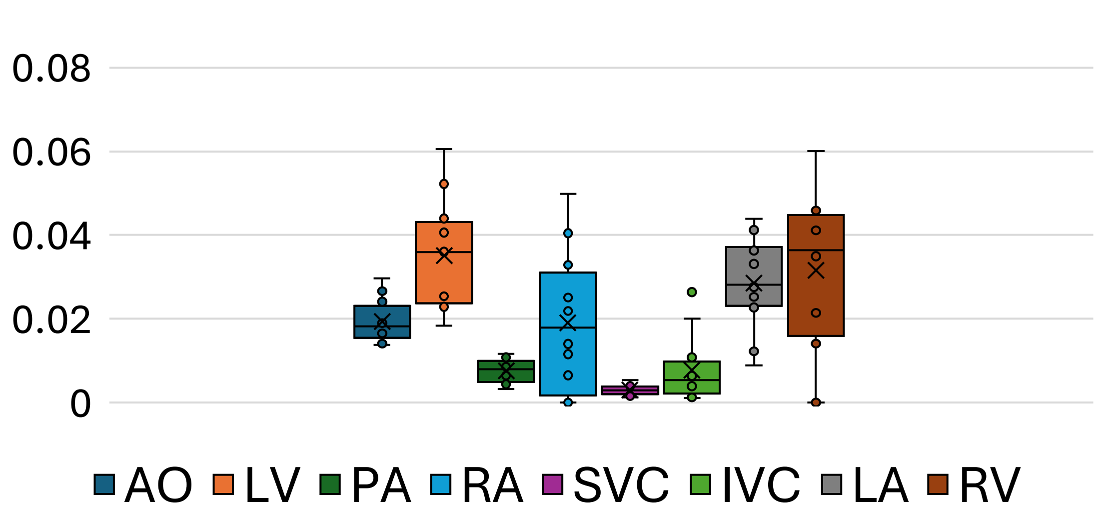
- Why RV and RA? ▸ high variability in size

Boxplot of Segment-to-Volume Ratio in 48-HVSMR+

Training Samples



Test Ground Truths



$$\text{Segment-to-Volume Ratio (} \blacksquare \text{) } = \frac{\text{Total number of } \blacksquare}{\text{Total number voxel}}$$

Future Work

- Final Goal
  - Beyond end-to-end segmentation frameworks
  - Performance only
- Manual Segmentation Pipeline ▸ still better

  - Pace et al. 2022 (DSC=0.85) > nnU-Net (DSC=0.79)

Future Work

- Plans
  - Experiment with other nnU-Net configs –
    - Different optimizers, loss functions, patch sizes, etc.
  - Augmentation –
    - Customized for anatomical variability
    - Delete segment ‣ inpainting background image
  - Denoising Diffusion Models –
    - MedSegDiff and MedSegDiff-v2
  - Text + Image –
    - 48-HVSMR+ contains case notes
    - Leverage CLIP (e.g., MedCLIP)

Conclusion

3D MRI Segmentation for Congenital Heart Disease

- Studied recent end-to-end segmentation frameworks
- Studied 3D MRI CHD datasets
- Experimented frameworks + datasets
- Analyze
- Future works

Questions?