

# Capturing cardiac anatomy and function with AI models

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**SCMR**

*Society for Cardiovascular  
Magnetic Resonance*



**EACVI**

European Association of  
Cardiovascular Imaging

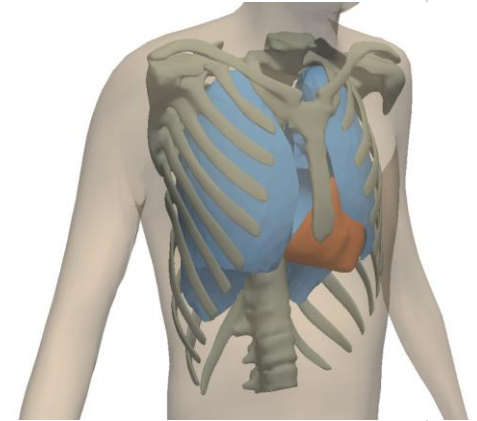
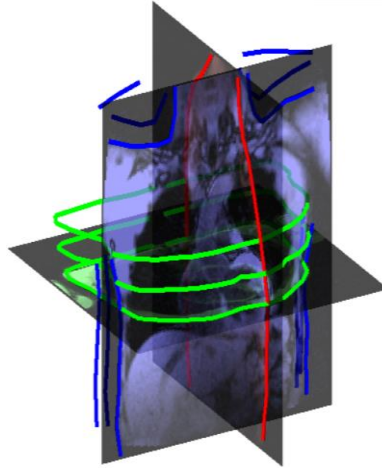
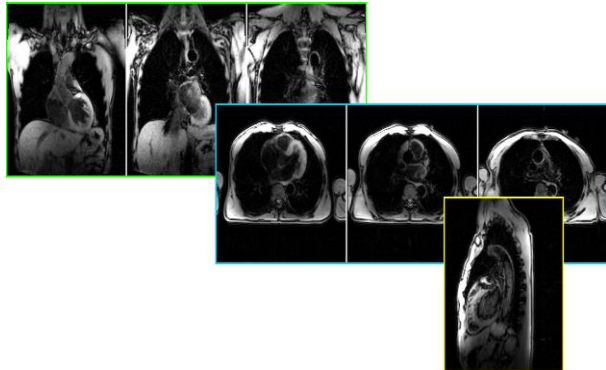
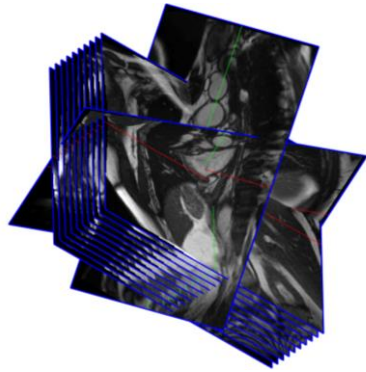
 European Society of Cardiology

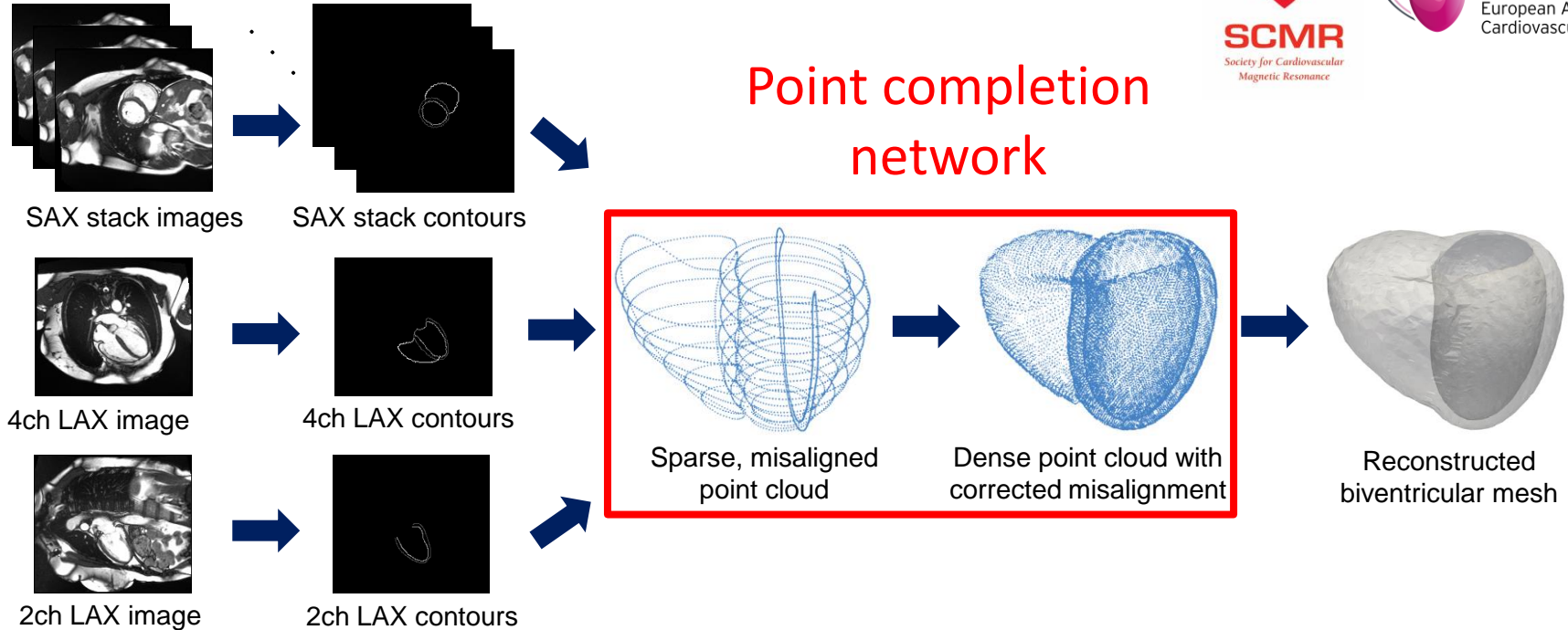
- **Founder and shareholder, AiSentia**
- **Group research partly funded by**
  - Perspectum
  - Philips
  - GE Healthcare
  - IBM

# Aims

- **Capturing healthy anatomy/function and variability**
  - 3D analysis
  - Includes electrophysiology and mechanics
  - Natural and pathological variability
- **Apply these models to clinical questions**
- **Mostly using CMR – UK Biobank**

# Methodology: building 3D representations from CMR scans





1 Segment SAX and LAX images

2 Convert contours to 3D point cloud

3 Point Completion Network

4 Meshing algorithm

# Reconstructions from UK Biobank

Apply Point Completion Network to cine MR images of the UK Biobank

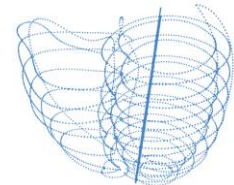
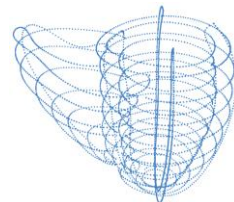
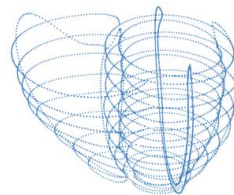
Left ventricular volumes of reconstructed meshes are **in line with established clinical reference** ranges and error estimates

**Table 2:** Comparison of UKB results with references values

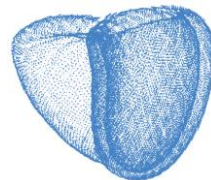
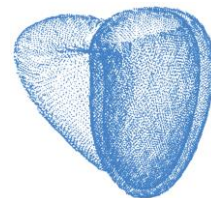
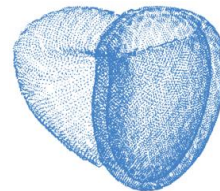
	Ours	Petersen et al. [18]
LV ED Volume (ml) <sup>1</sup>	112 ( $\pm 11$ )	124 ( $\pm 21$ )

<sup>1</sup> Values represent *mean* ( $\pm$  *SD*).

Sparse,  
misaligned  
input point cloud



Dense  
output  
point cloud



Output  
mesh



# Predicting Major Adverse Cardiac Events post MI



## PRINCIPAL COMPONENT ANALYSIS (PCA)

ES Shape - Septal view - MEAN

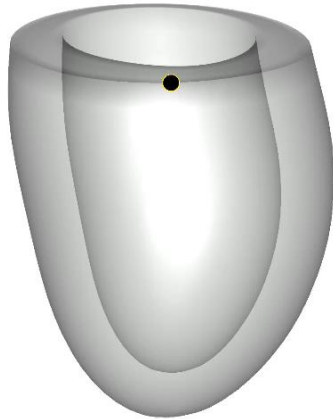


J. Corral Acero et al. "Understanding and Improving Risk Assessment after Infarction: AI-Enabled Study of 3D Left Ventricular Patterns". *JACC Cardiovasc Imaging* 2021

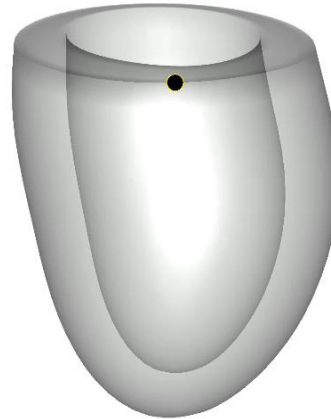
# ES Shape risk-related patterns

## End-Systolic Shape

Interpretability of the ES shape descriptors found prognostic. This is not contraction but the evolution from representative MACE shape features (red) to No MACE ones (blue). Septal view.



**ES1** ~ Global Impairment (ESV)



**ES5** ~ Anterior Impairment







**ES6** ~ Impaired Thickening

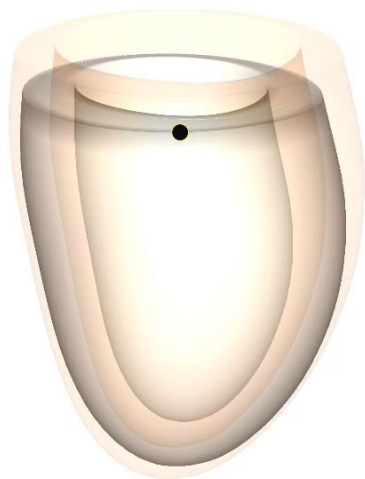


# 3D Contraction risk-related patterns

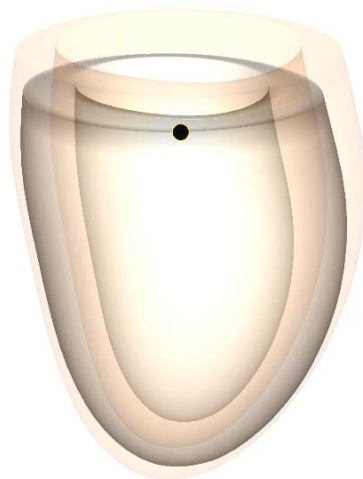
## Contraction

Interpretability of the 3D contraction descriptors found prognostic. Contractions are applied on the mean ED shape and visualized as resulting ES shapes. This does not illustrate contraction over time but the evolution from the resulting representative MACE shape features (red) to No MACE ones (blue). Septal view.

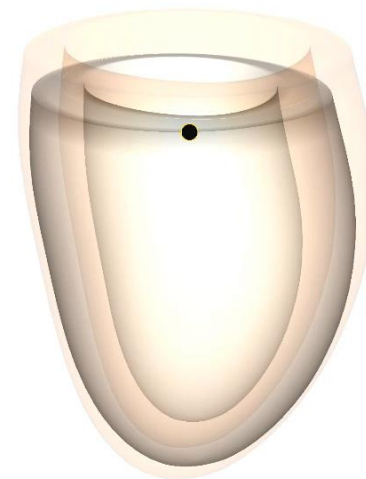
	MACE
	No MACE
	Mean ED Shape
	RV mass center



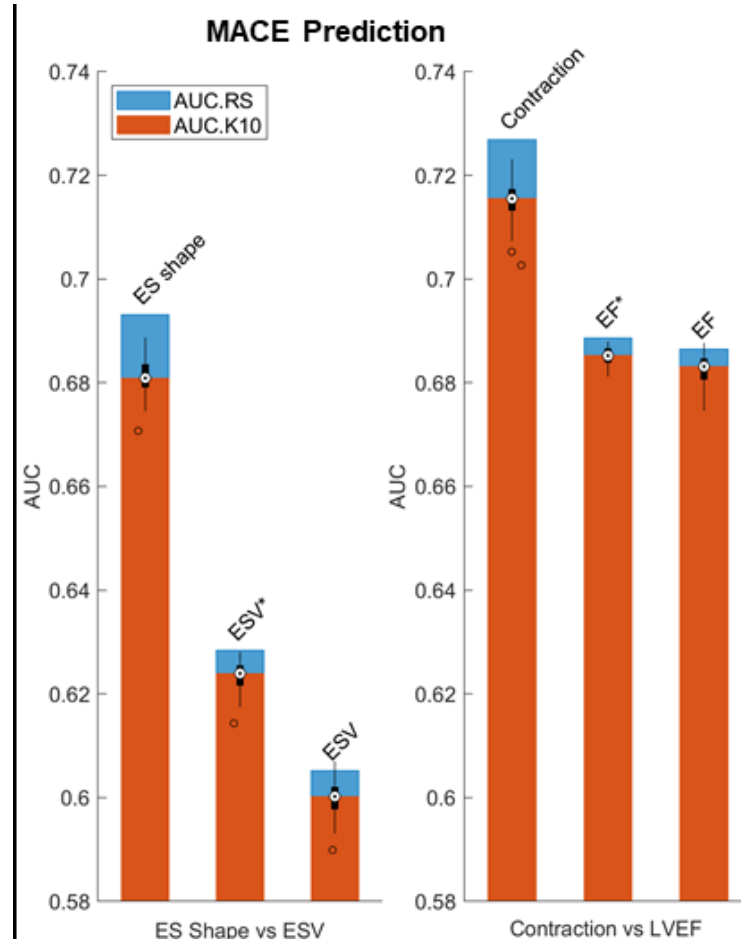
**C3** ~ Global Impairment  
(LVEF)



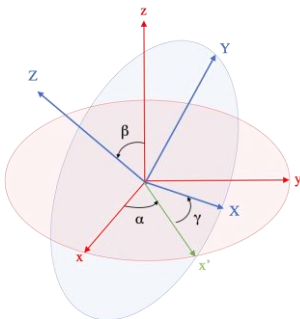
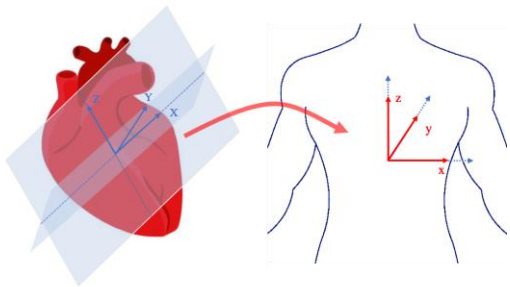
**C5** ~ Anterior Impairment



**C16** ~ Basal Impairment

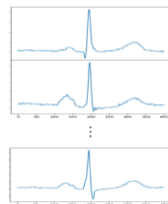


# Capturing ECG patterns

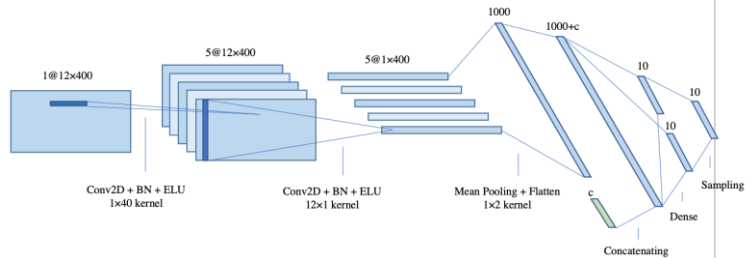


- Encoder

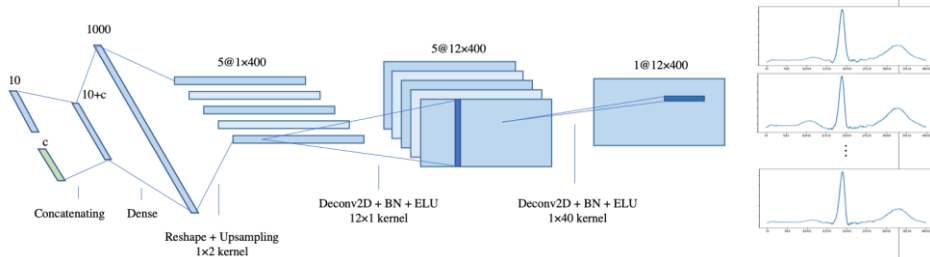
12 leads



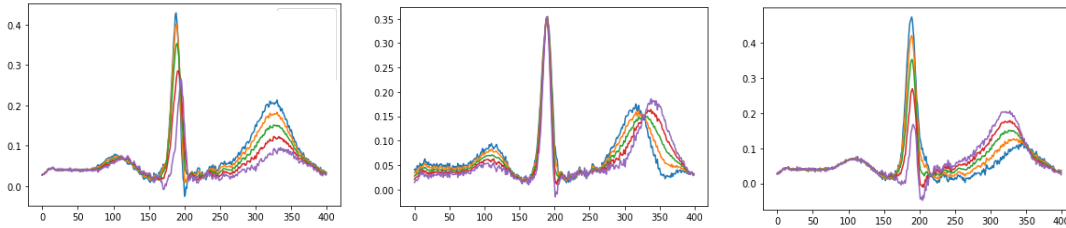
## Conditional VAE



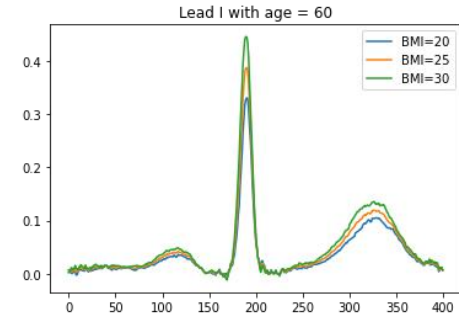
- Decoder



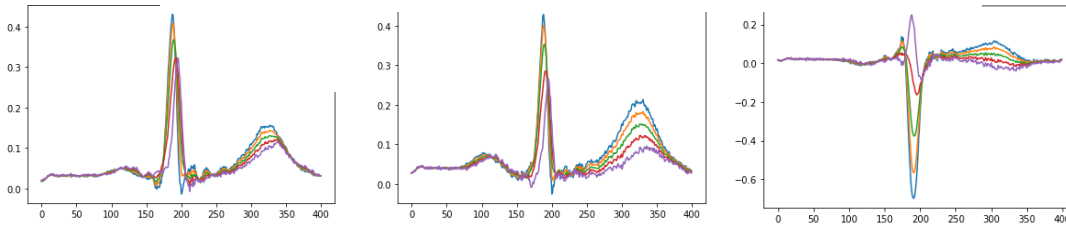
## Variation of different modes in single lead



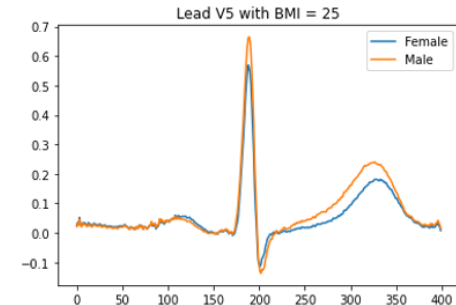
## BMI on Lead 1



## Effect of single mode on multiple leads

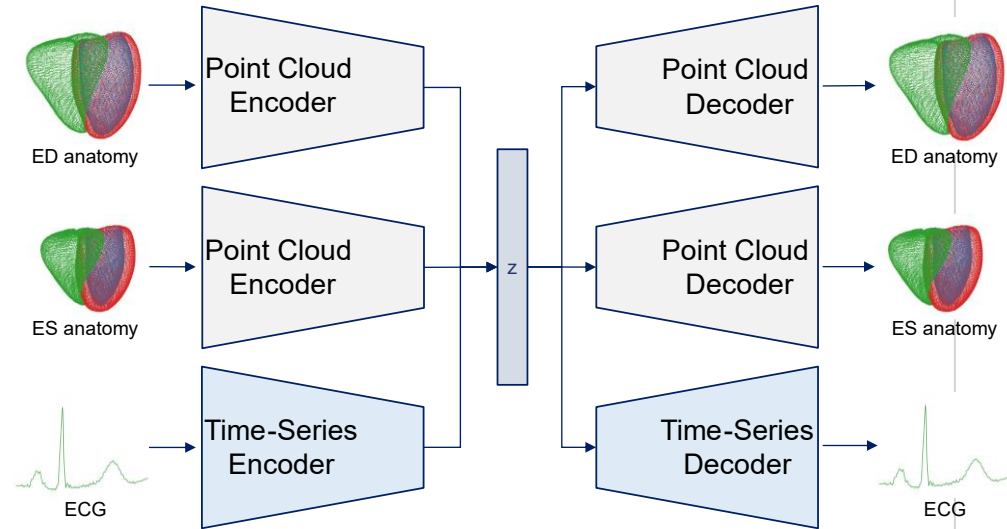


## Gender on Lead V5

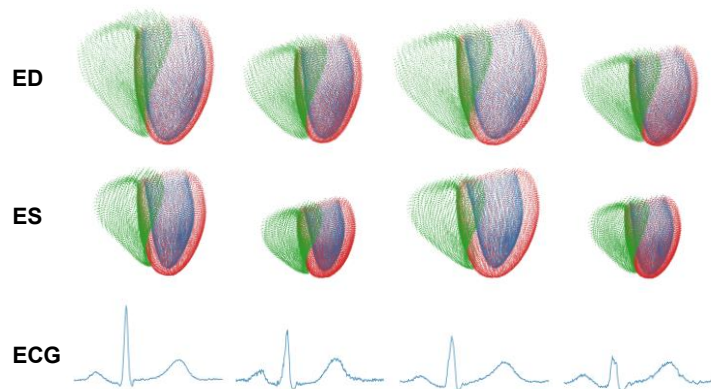


# Capturing multimodal ECG/anatomy patterns

- Three different **branches** tailored to each **modality**
- All branches **share latent space**
- **Anatomy branches** based on **point cloud-based deep learning**
- **ECG branch**: combination of **convolutional, pooling, and fully connected** layers



# Experiments - Generative Ability



**Table 4.** Clinical metrics of ED and ES anatomy point clouds.

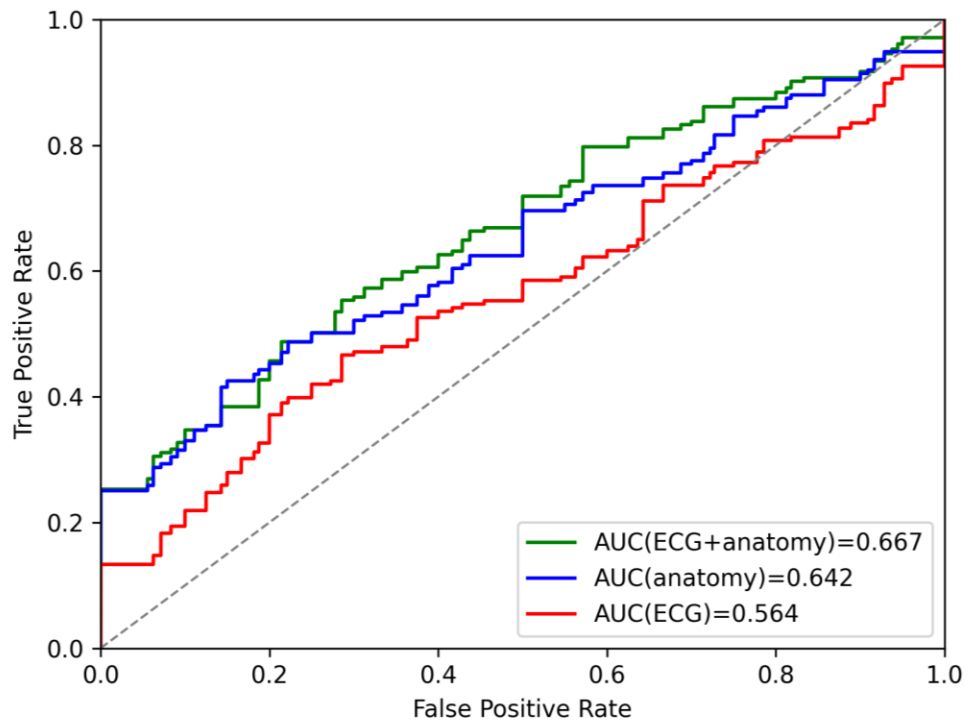
Phase	Clinical Metric	Gold Standard	Ours
ED	LV volume (ml)	141 ( $\pm 30$ )	139 ( $\pm 31$ )
	RV volume (ml)	170 ( $\pm 34$ )	176 ( $\pm 37$ )
ES	LV volume (ml)	59 ( $\pm 15$ )	58 ( $\pm 16$ )
	RV volume (ml)	78 ( $\pm 20$ )	80 ( $\pm 24$ )
ED/ES	LV mass (g)	102 ( $\pm 28$ )	99 ( $\pm 29$ )

Values represent mean ( $\pm$  standard deviation) in all cases.

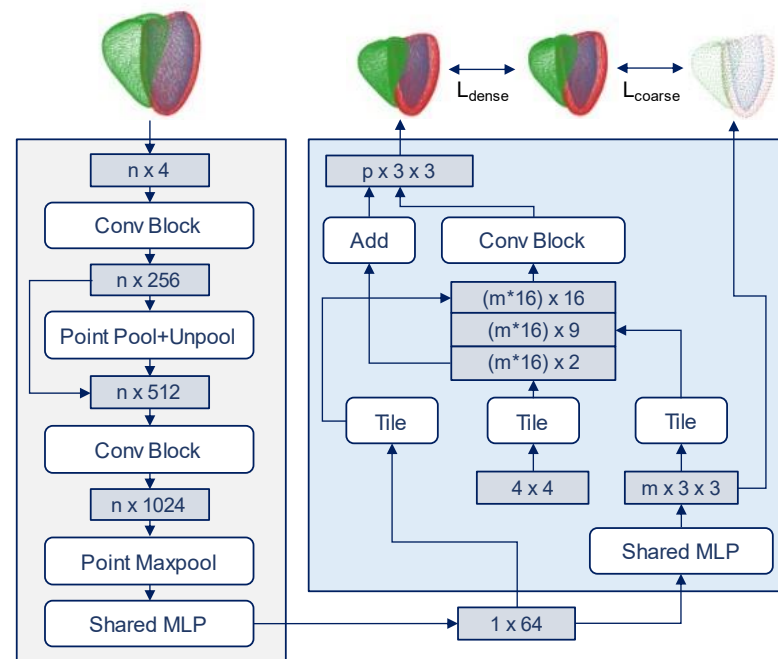
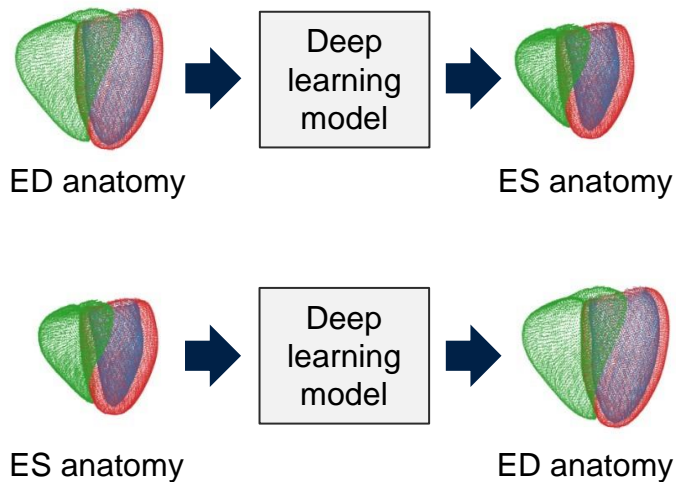
- Method generates **realistic** and **diverse** bitemporal **anatomies** and **ECGs**

- **Comparable clinical metrics** between generated and test dataset **anatomies**

# Classification based on latent space: mono vs multimodal



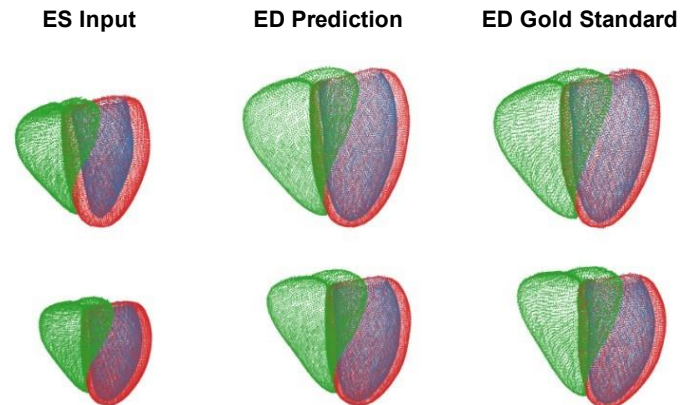
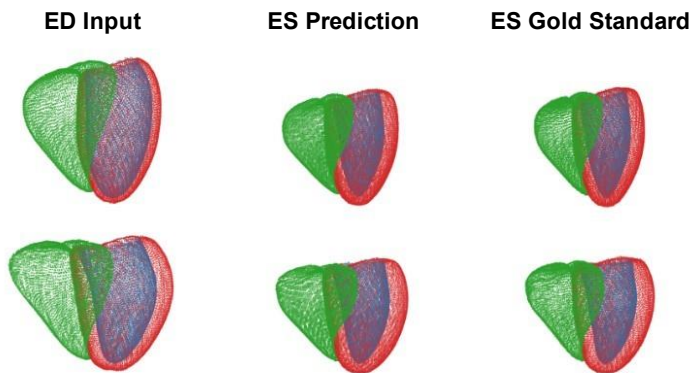
# Capturing mechanical function



**Point cloud autoencoder**

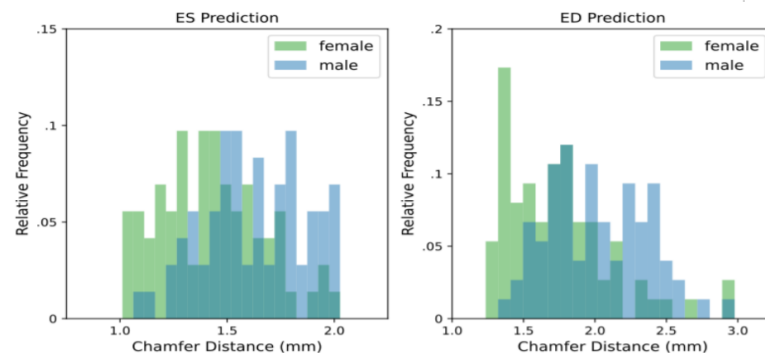


# Prediction results



Clinical Metric	Gold Standard	ES Prediction	ED Prediction
LV EF (%)	59 ( $\pm 7$ )	60 ( $\pm 6$ )	59 ( $\pm 6$ )
LV SV (ml)	83 ( $\pm 19$ )	83 ( $\pm 20$ )	80 ( $\pm 16$ )
RV EF (%)	62 ( $\pm 21$ )	62 ( $\pm 19$ )	60 ( $\pm 19$ )
RV SV (ml)	93 ( $\pm 25$ )	94 ( $\pm 19$ )	92 ( $\pm 26$ )

Values represent mean ( $\pm$  standard deviation).



# Conclusions

- Generative models can capture natural variability in anatomy and function
- Multimodal models are feasible and show improved performance
- Models capture differences between subpopulations
- Strong synergy with physics-based models

# Acknowledgments



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