

AI for cardiomyopathy discovery

From Images to Mechanisms

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Declaration of Interest

- I have no conflicts to declare

Overview

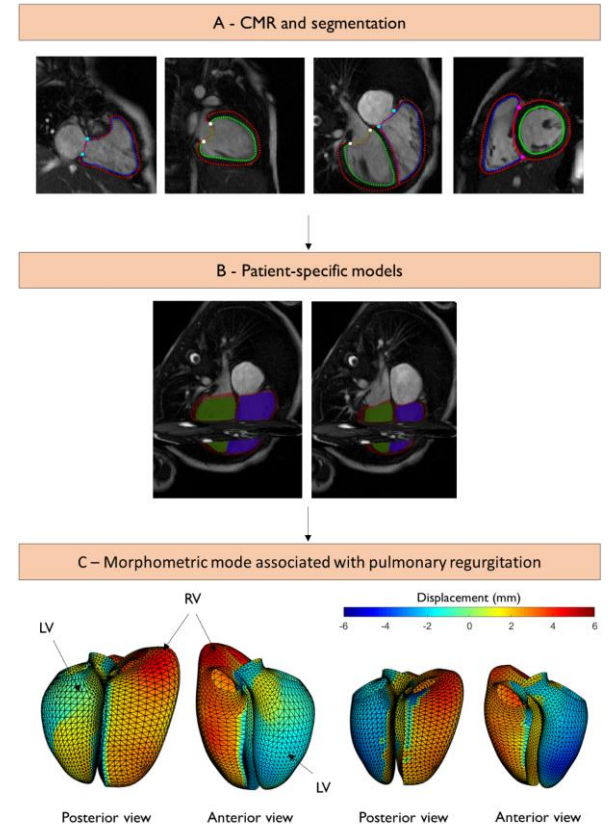
- **Tetralogy of Fallot: From shape to outcomes**
- **4DFlow: From flow to remodelling**
- **CRT: From CMR to Echo**
- **Digital twins: From strain to stress**

Tetralogy of Fallot

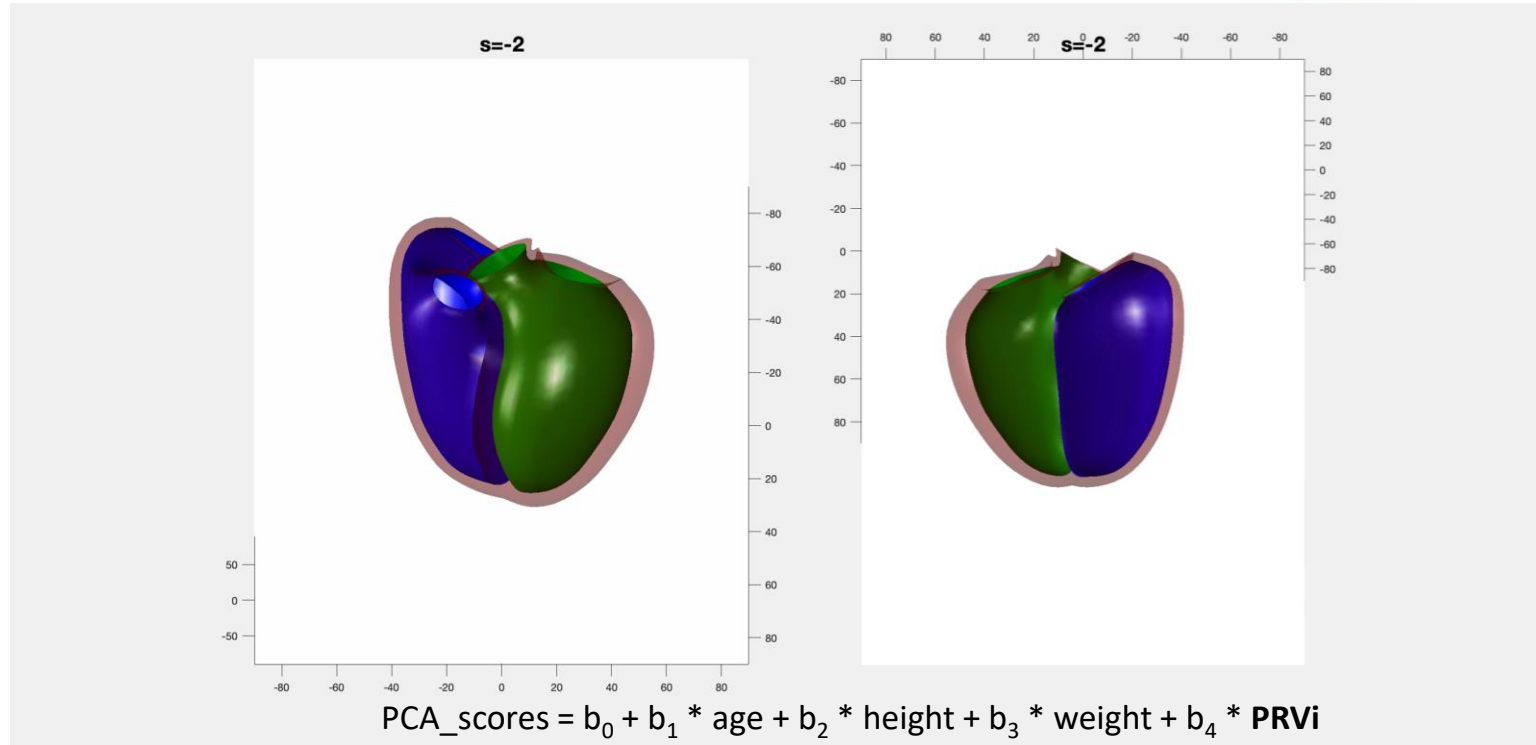
- RVLV statistical shape atlas of adult TOF**

Table 1 Characteristics of the 88 rTOF participants

Variables	N = 88
Age at CMR scan (y)	16 (11.8, 24.3)
Sex (F/M)	35/53
Height (cm)	160 (149.8, 168)
Weight (kg)	58.3 ± 25.4
PRF (%)	36.9 ± 14.4
PRV _i (ml/m ²)	23.7 (14.2, 33.3)
Age at primary repair (y)	0.8 (0.25, 1.6)
Time after primary repair (y)	15.7 (10.9, 21)



Tetralogy of Fallot

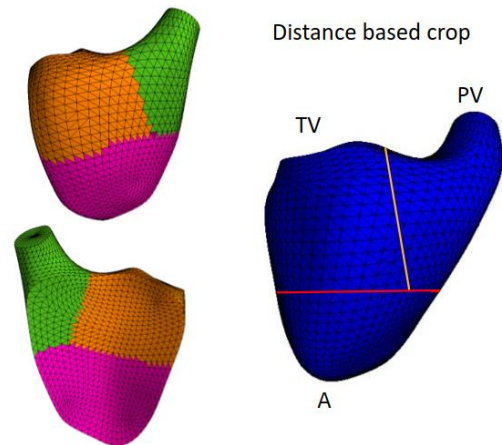


Tetralogy of Fallot

- German Competence Network for Congenital Heart Defects
- Median follow up 10 years: death, arrhythmia, arrest.

Table 1: Patient demographics.

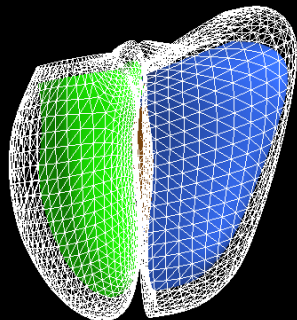
	All patients (n=192)	Adverse outcomes (n=16)	No adv. outcome (n=176)
Gender [F (%)]	77 (40)	(5) 31	72 (41)
Height [cm]	163.3±14.7	164.2 ±12.3	163.2 ±14.9
Weight [kg]	57.0±18.9	55.0±18.4	57.2±19.0
BSA [m²]	1.59±0.3	1.57 ±0.3	1.6 ±0.3
Median age at BE [years](IQR)	15 (6.3)	16.5 (9.3)	15 (6)



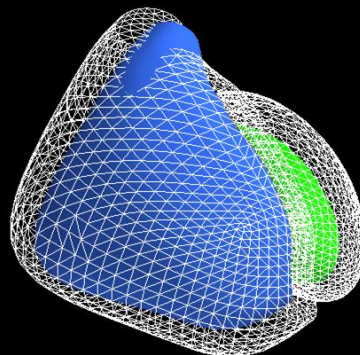
Tetralogy of Fallot

Adverse
Outcome

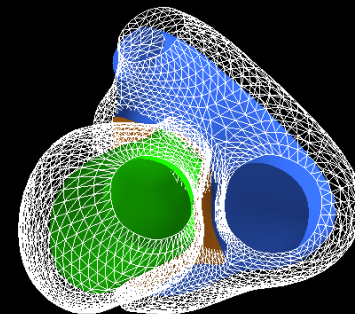
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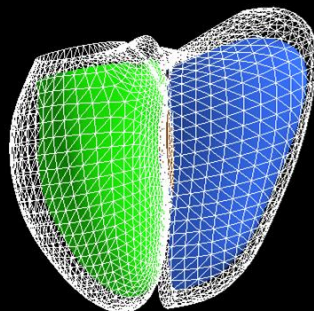
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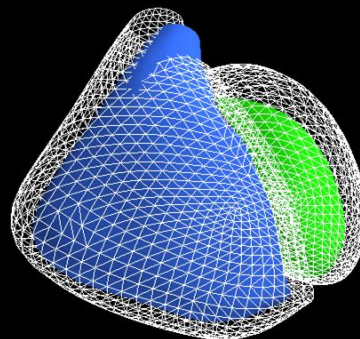
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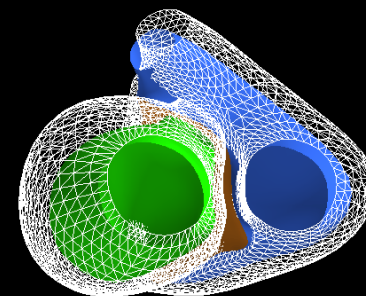
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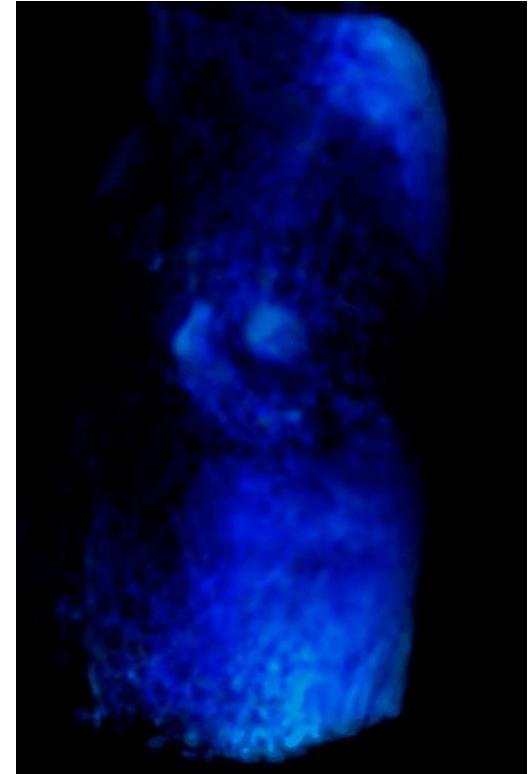
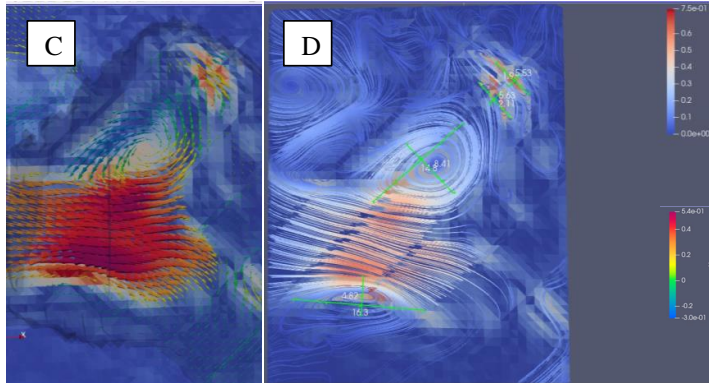
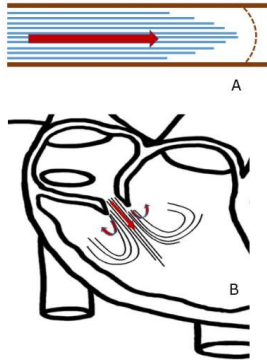
Pulmonary
regurgitation

Mira et al. In review.

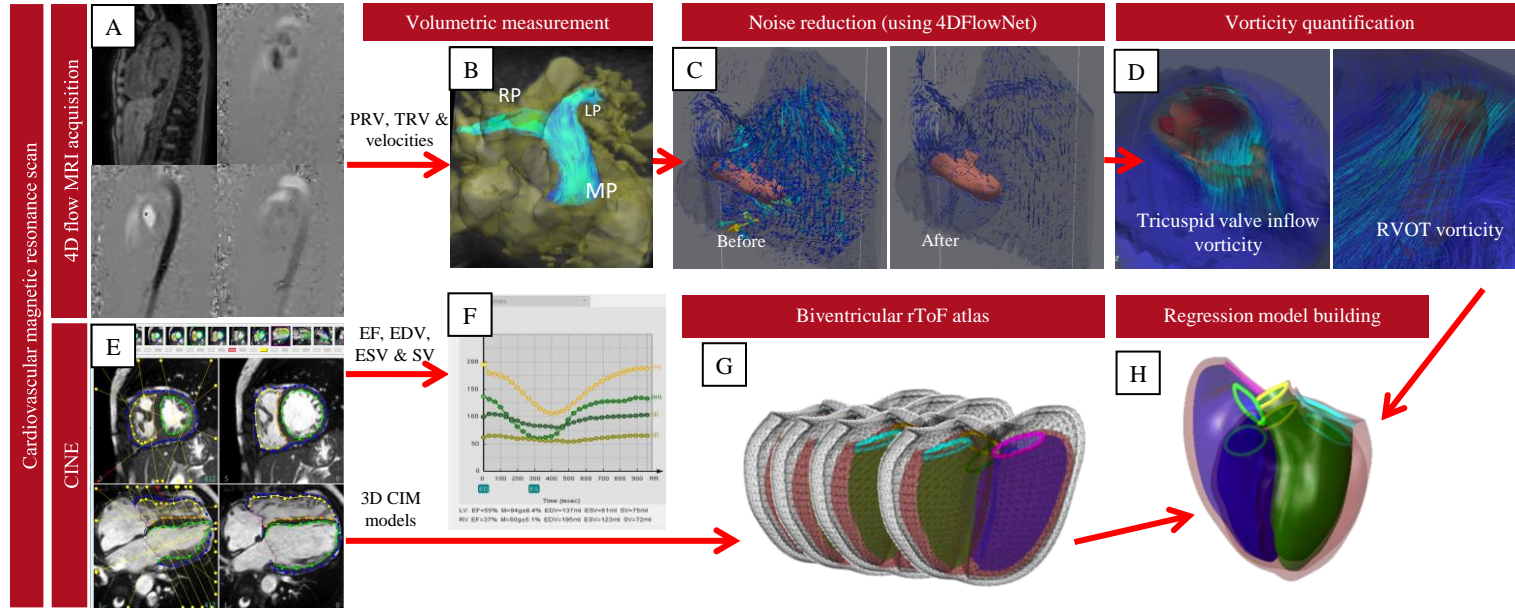
4DFlow

- Vorticity has been associated with function
- 4DFlowNet enables noise reduction
- Associations with shape

$$\omega(x,t) = \nabla \times v(x,t)$$



4DFlow



Aims:

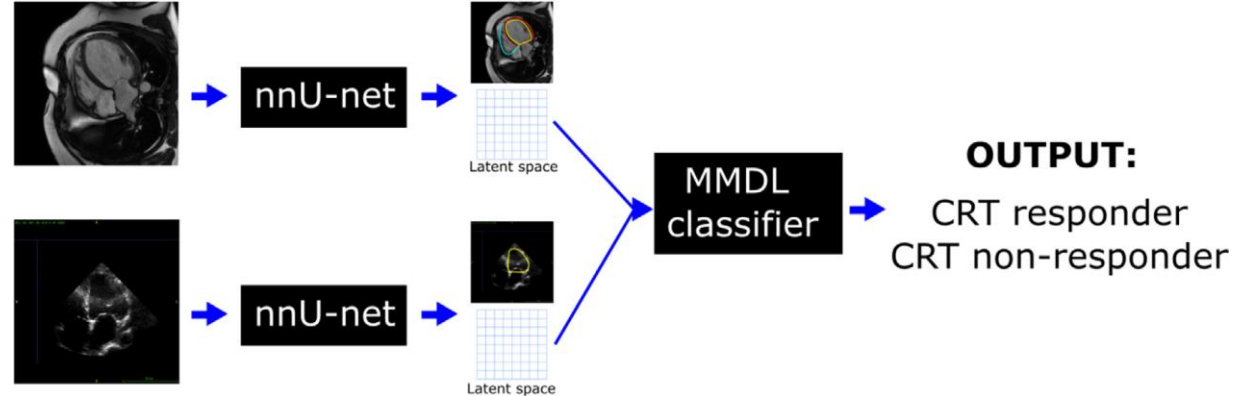
First multimodal deep learning method for CRT response prediction.

The model has the ability to predict CRT response using only echocardiography data but at the same time taking advantage of the implicit relationship between CMR and echocardiography.

Database:

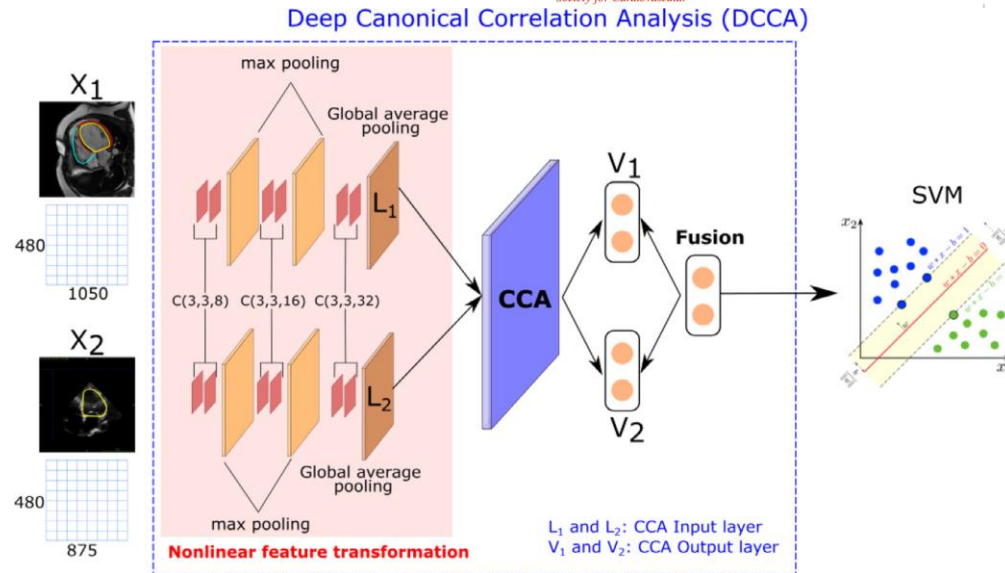
50 paired CMR and echo CRT patients from Guys and St Thomas' NHS Foundation Trust

Proposed framework:



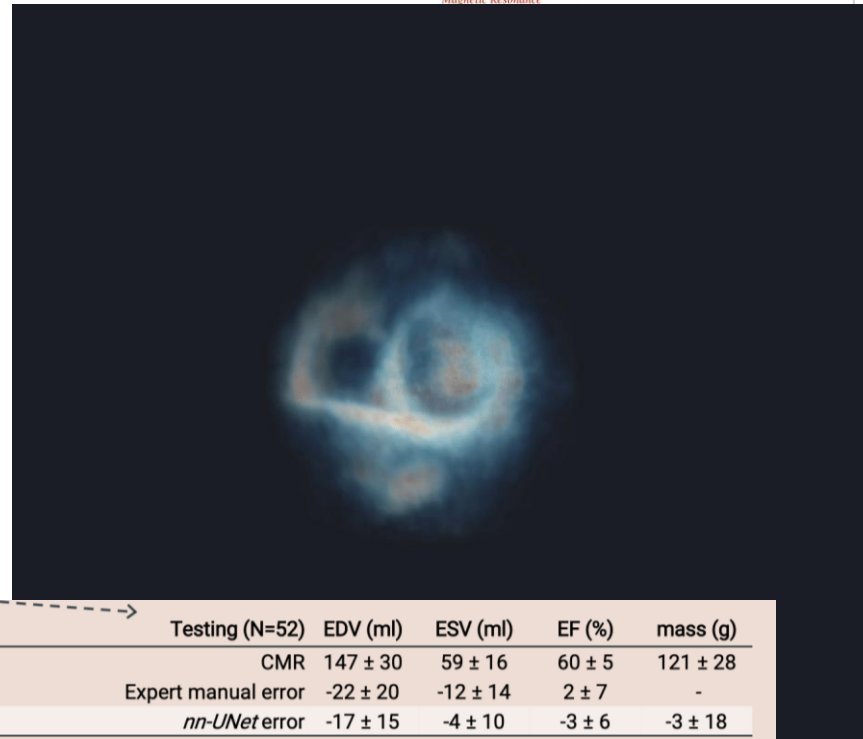
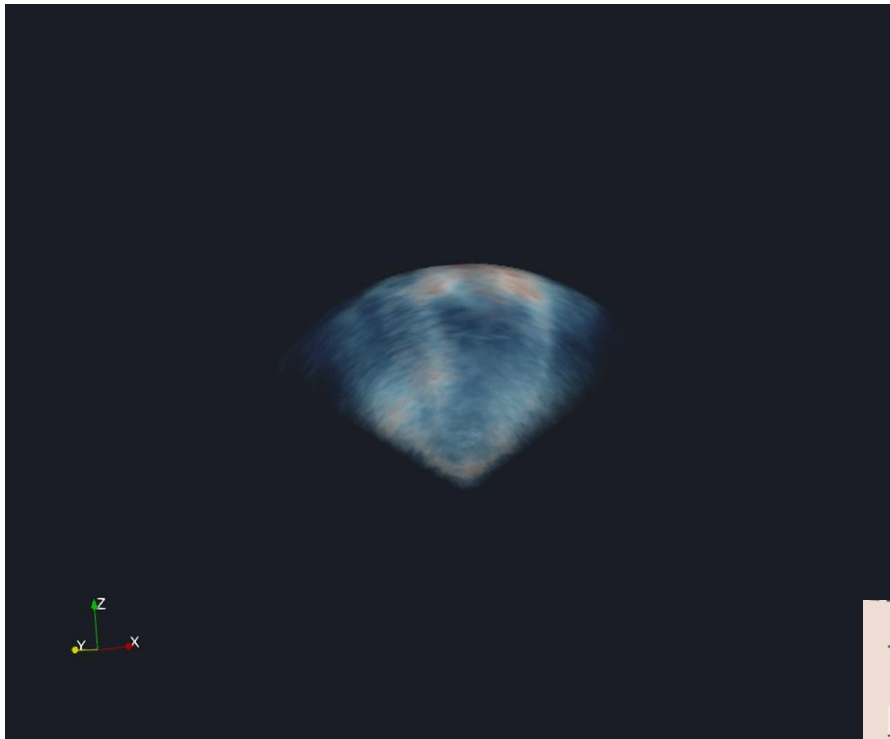
From CMR to Echo

- **Nonlinear feature transformation: View-specific feature extraction**
- **CCA layer: Jointly learn parameters for both views**
- **Feature fusion: Combines the outputs of the CCA layer**
- **SVM classifier: binary classifier to distinguish between CRT responders and CRT non-responders.**



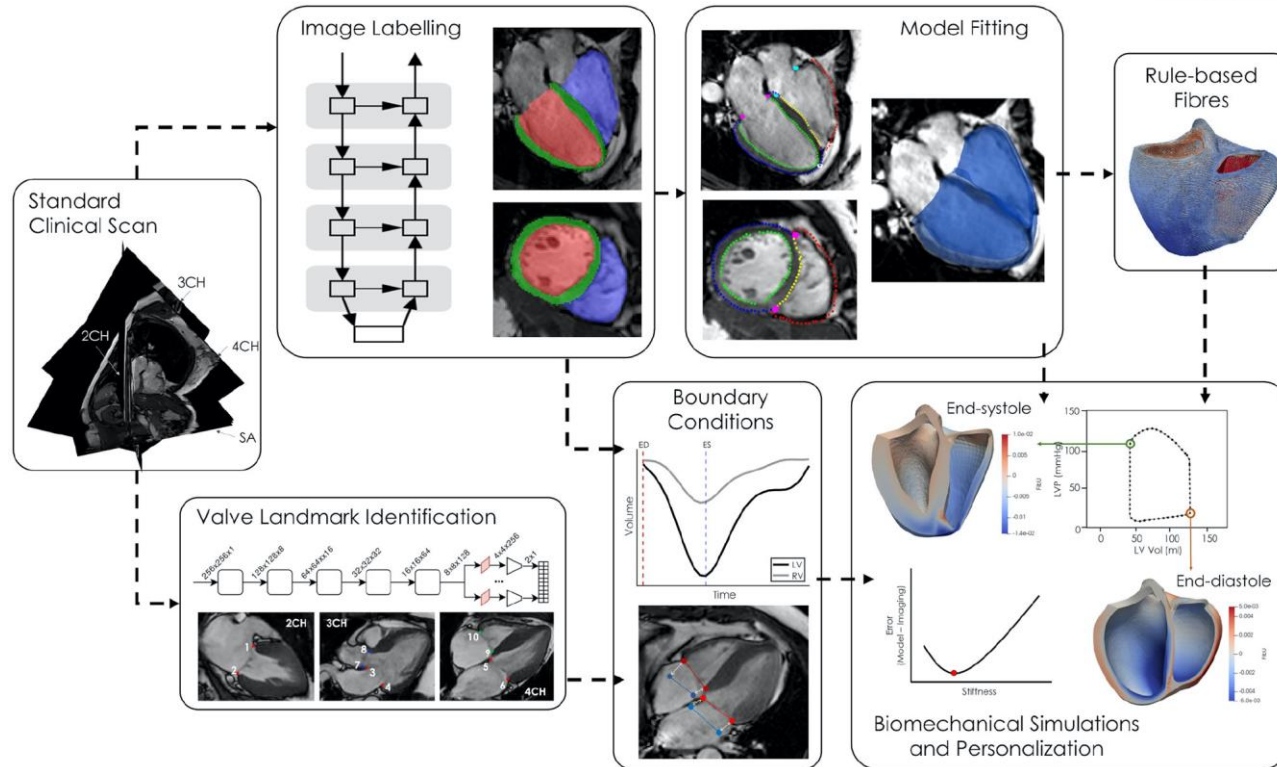
	CMR			Echocardiography		
	BACC(%)	SEN(%)	SPE(%)	BACC(%)	SEN(%)	SPE(%)
	<i>1. Multimodal deep learning approach</i>					
MMDL	81.19*	86.21	76.19	77.38*	83.33	71.43
	<i>2. Baseline approach (echocardiography-trained)</i>					
VGG _{Echo}	-	-	-	70.26	75.00	65.52

From CMR to Echo



	Testing (N=52)	EDV (ml)	ESV (ml)	EF (%)	mass (g)
	CMR	147 ± 30	59 ± 16	60 ± 5	121 ± 28
	Expert manual error	-22 ± 20	-12 ± 14	2 ± 7	-
	<i>nn-UNet</i> error	-17 ± 15	-4 ± 10	-3 ± 6	-3 ± 18
	Expert manual scan-rescan error	16 ± 10	9 ± 7	4 ± 4	-
	<i>nn-UNet</i> scan-rescan error	8 ± 6	4 ± 4	3 ± 2	9 ± 7

Digital Twins



Summary

- **Adverse vs adaptive remodelling shape signatures**
- **Flow features of remodelling**
- **Multimodal leveraging of depth for width**
- **Biophysical parameter estimation**