



KU Leuven
Group Biomedical Sciences
Department Cardiovascular Sciences
Research Unit Hypertension and Cardiovascular Epidemiology



Artificial intelligence in cardiac imaging

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Academic career at KU Leuven, Belgium

BSc/MSc Biomedical Sciences (2009-2014)

↳ **PhD in Cardiovascular Medicine (2014-2019)**

↳ **Full-time postdoc researcher (2019- ...)**



**“Europe’s Most Innovative University since 2016”
(Reuters top 100)**





Our research pillars

Healthy → CV risk factors → subclinical CV damage → symptomatic CVD

Machine Learning



Ability to learn without being explicitly programmed



Understand CVD pathogenesis

Biomarkers for CV risk stratification and early disease detection

Disease prophylaxis / therapy

AI in cardiac imaging

- **Introduction to AI**
- AI applications in cardiac imaging
- Challenges

Artificial intelligence (AI)

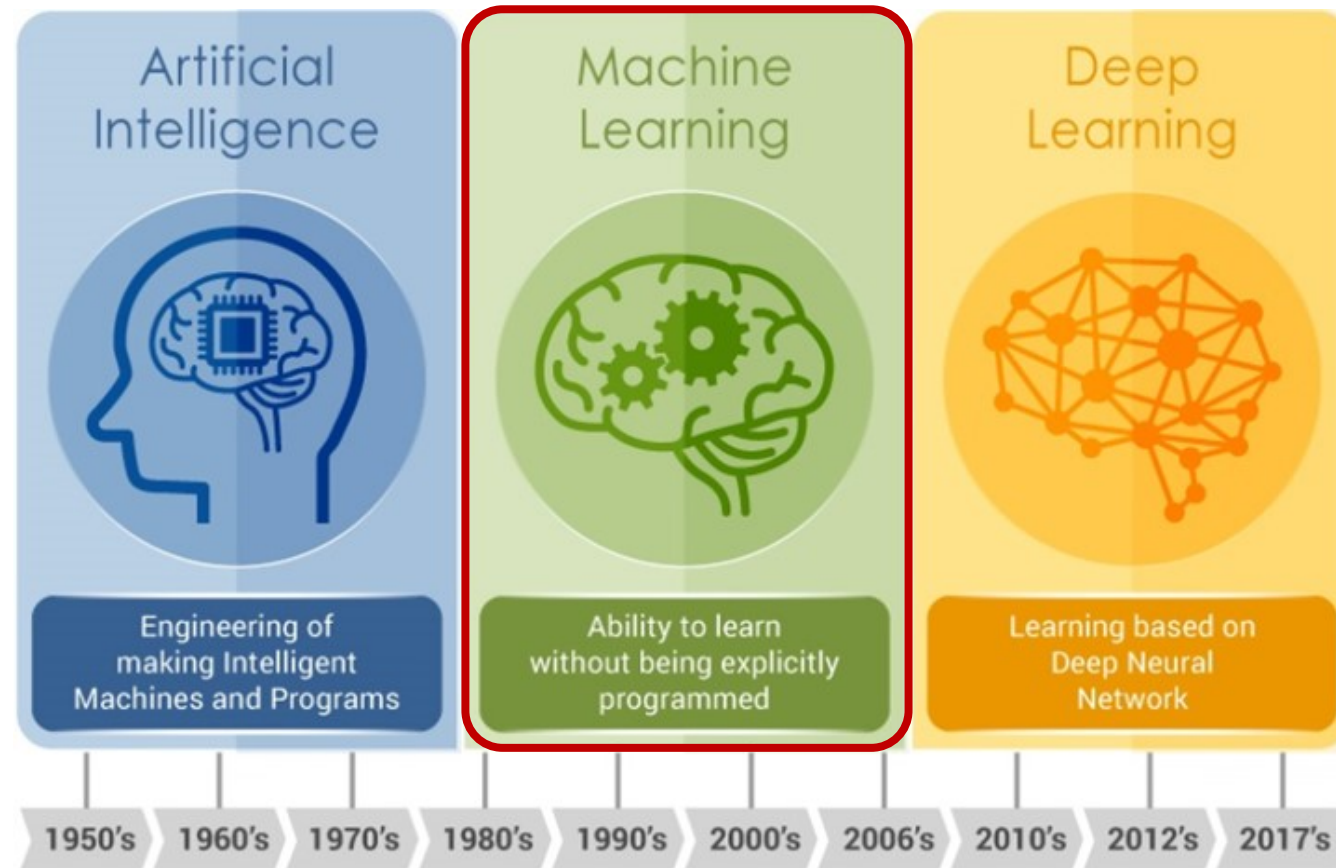
“The non-human ability to deal with cognitive complexity”¹



¹ Gottfredson L, *SciAm.* 1998

Machine learning: the AI most used in medicine

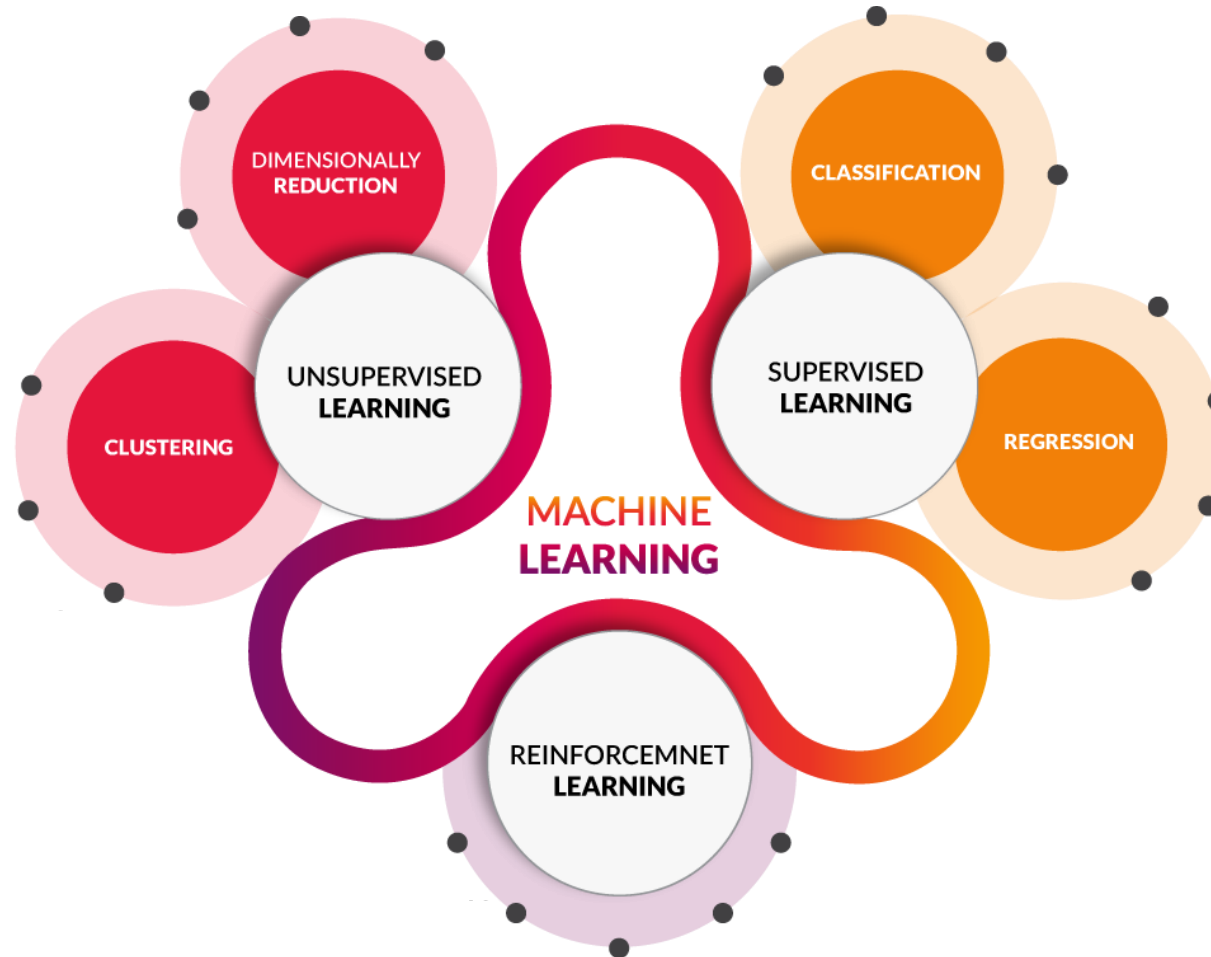
~~Rule-based systems~~



Learn by example

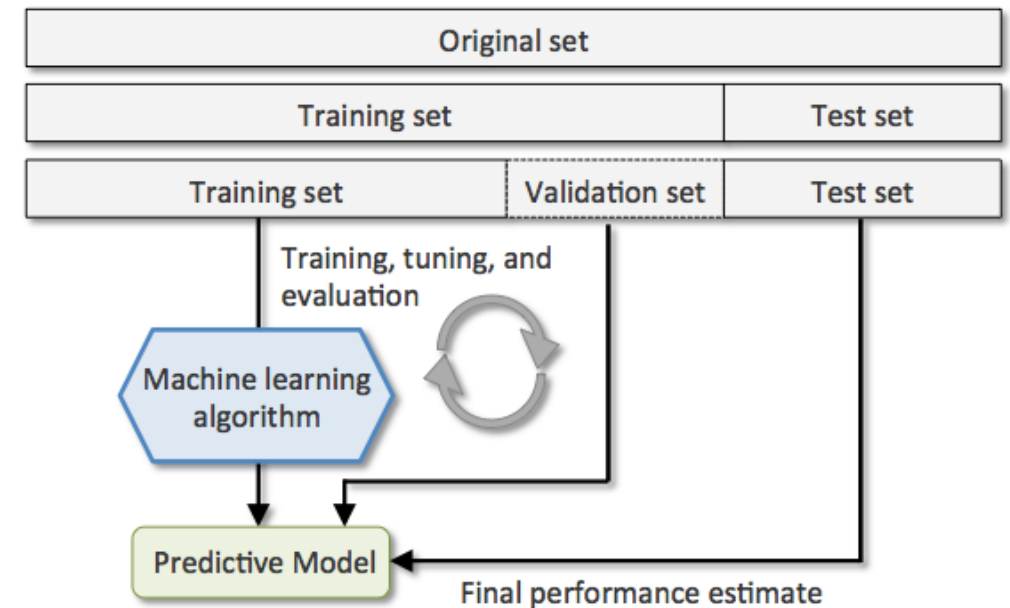
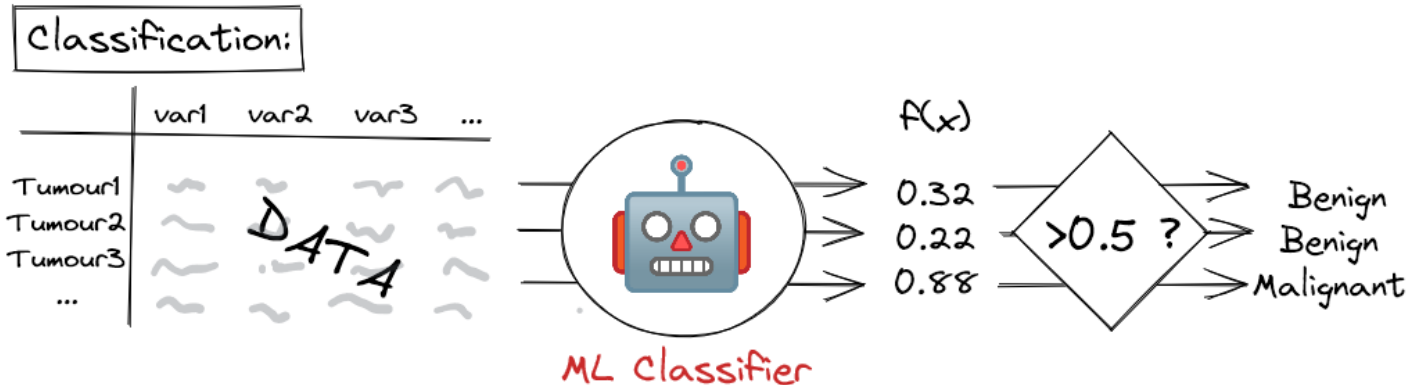
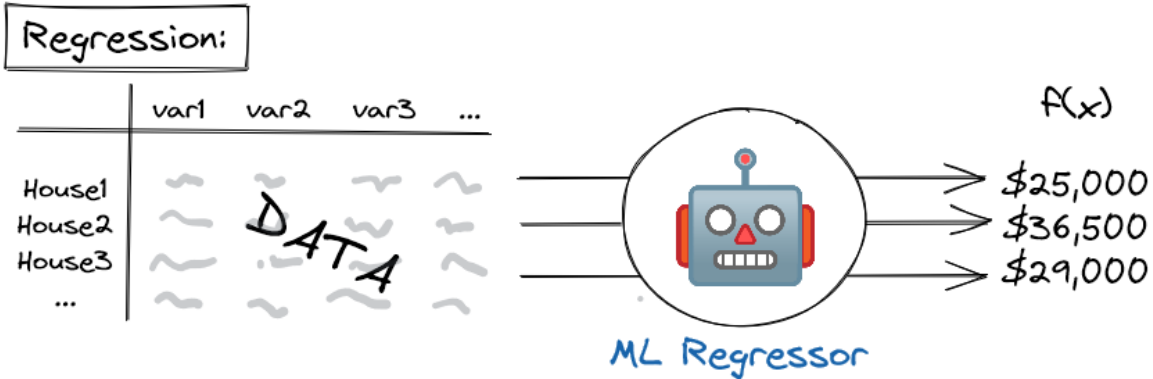
ML approaches

K-means clustering
K-nearest neighbours
Hierarchical clustering
Principle Component Analysis
...



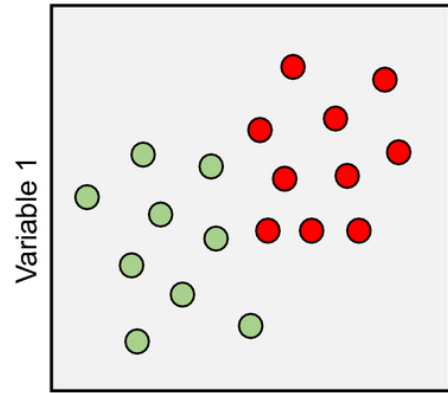
XgBoost
Random Forest
Support Vector Machines
Linear methods
...

Supervised ML: Regression or classification

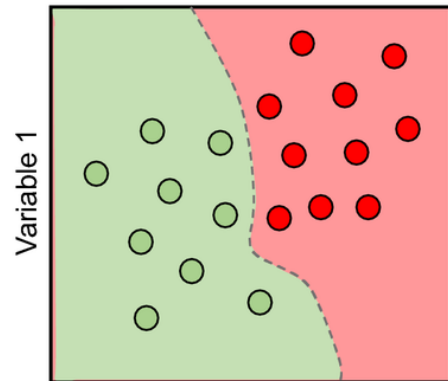


Unsupervised ML: discover patterns / subsets

b) Supervised learning

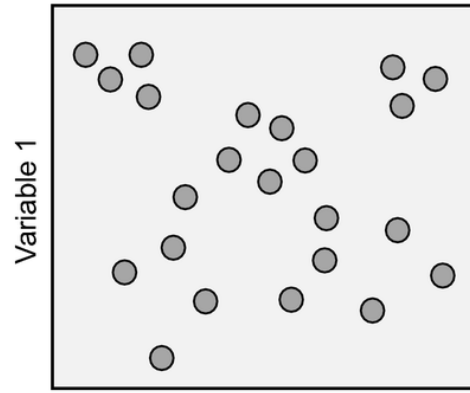


Variable 2

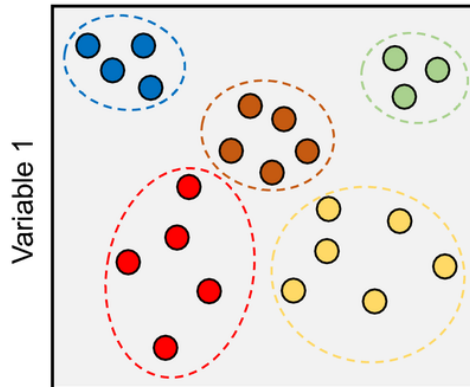


Variable 2

a) Unsupervised learning



Variable 2



Variable 2

➔ Input data and # clusters ~ prior knowledge, supervised ML and metrics

➔ Validation by characterization

AI in cardiac imaging

- Introduction to AI
- **AI applications in cardiac imaging**
- Challenges

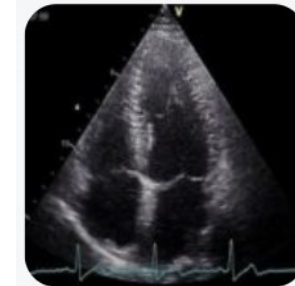
Why do we need AI in cardiology?

- **Automation**

e.g. echocardiographic imaging and post-processing
↔ €€€, time-consuming, injuries!

- **Reduce clinical complexity:** Interpret ever complex data
e.g. wearables, -omics, ..

- **Accurate risk / diagnosis / prognosis / management**
e.g. cardiovascular disease predicted from routine clinical data²



AI echocardiogram reports fully automated from a GE Vivid E95

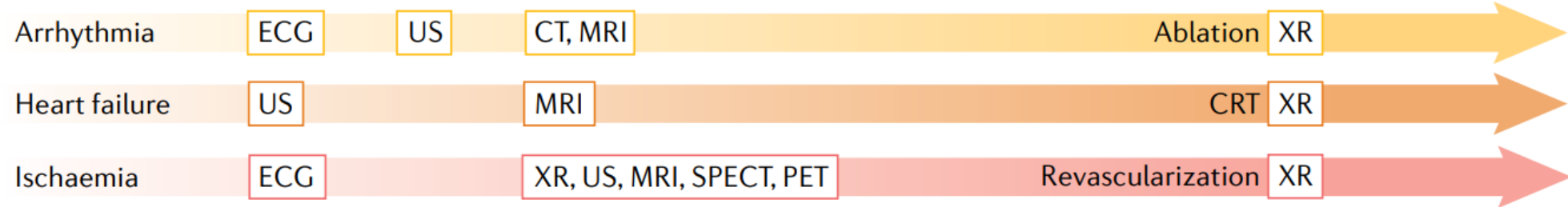
By Us2.ai / 26 May, 2023 / Comments Off



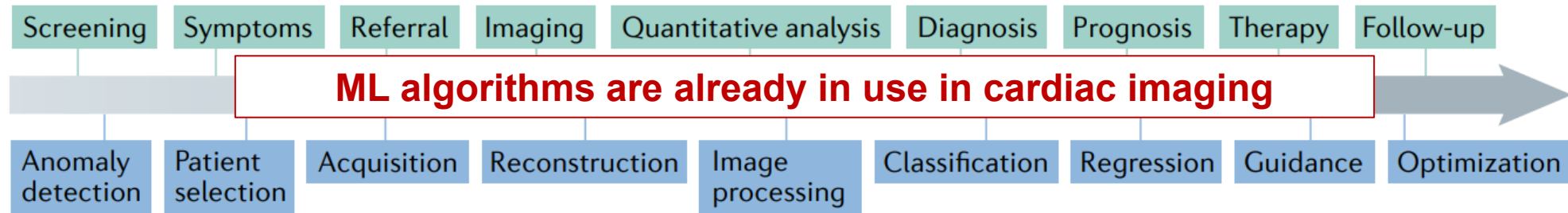
¹ For instance, see EchoGO, us2.ai and others

² Sabovčik F, EHJ Cardiovasc Imaging. 2020

Clinical workflows



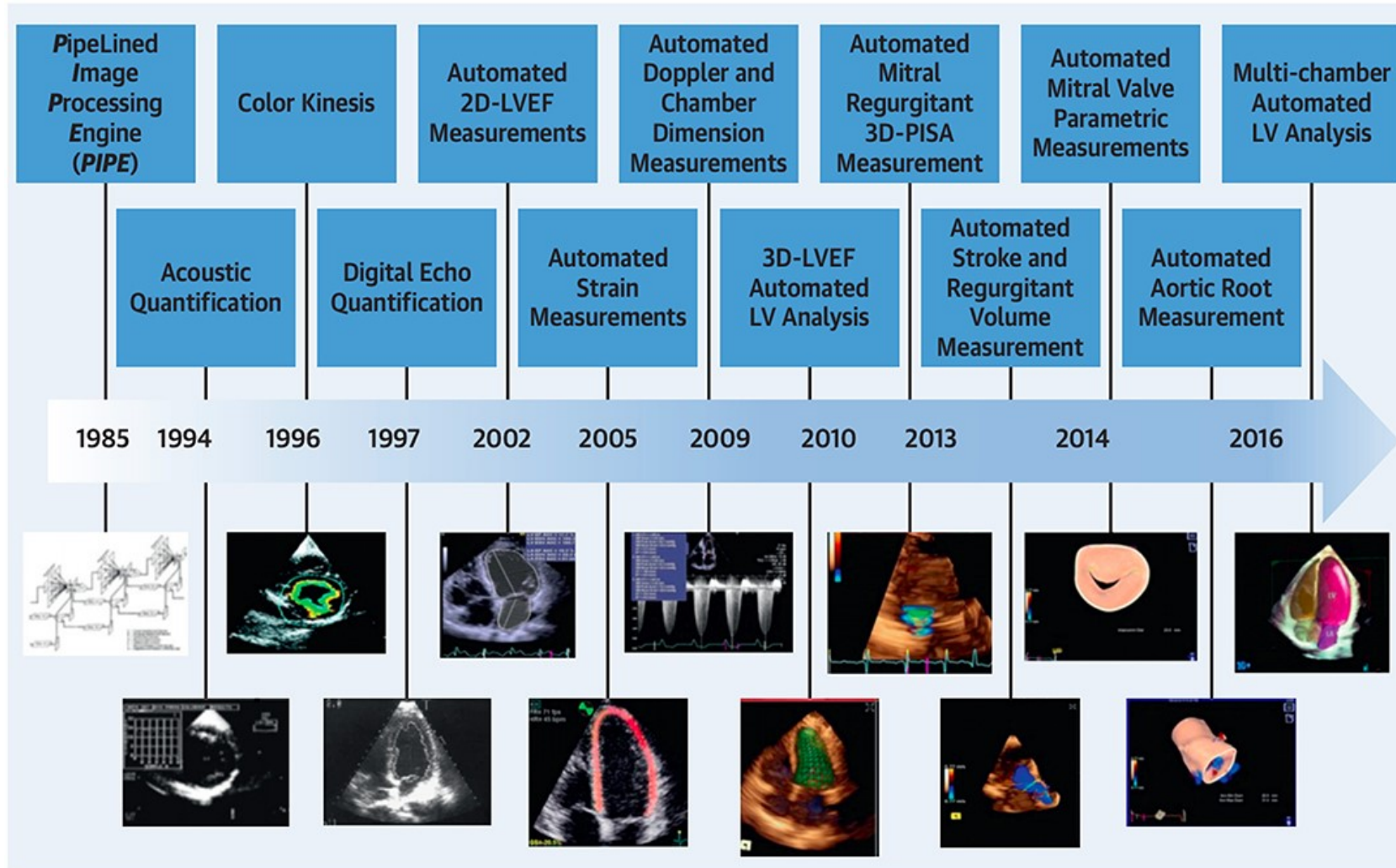
AI-supported decision-making



AI-based algorithms

Fig. 1 | **Clinical workflow, AI-based algorithms and AI-supported decision-making.** A patient's pathway through the clinical workflow often includes the acquisition of a number of cardiovascular images with the use of various imaging modalities. Artificial intelligence (AI) can contribute to many of the required steps to acquire, reconstruct and process these images to achieve AI-supported decision-making. CRT, cardiac resynchronization therapy; ECG, electrocardiogram; SPECT, single-photon emission CT; US, ultrasonography, XR, radiography.

AI powered cardiac imaging



AI powered cardiac imaging

	Aim of study	AI algorithm or commercial technique	Detail method/software	Diagnostic Efficiency ^a	Reference
Section recognition/ image acquisition	Automatic classification of cardiac views	AI algorithm	CNN	ACC = 98.3%	Ultrasound Med Biol, 2019 [19]
		AI algorithm	CNN	ACC = 97.8%	NPJ Digital Med, 2018 [12]
Segmentation	Left ventricular segmentation (provide accuracy improvement of the endocardial boundary recognition)	AI algorithm	Ant colony optimization	N/A	Biomed Mater Eng, 2014 [13]
		AI algorithm	Radial active contour method Snake	N/A	Comput Methods Programs Biomed, 2014 [20]
		AI algorithm	Iterative 3-D cross-correlation algorithm	N/A	Ultrasound Med Biol, 2014 [21]
		AI algorithm	Ant colony optimization	N/A	Biomed Mater Eng, 2014 [13]
	Right ventricular segmentation	AI algorithm	Sparse matrix transform/ wall thickness constraint feature	Dice = 90.8% (epicardial boundary), 87.3% (endocardial boundary)	Phys Med Biol, 2013 [22]
	Atrial and multi-chamber heart segmentation	AI algorithm	Active shape model/ fusion-imaging technology	Mean dice = 83.3% ~ 91.3% (LV)	Ultrasound Med Biol, 2015; IEEE Trans Ultrason Ferroelectr Freq Control, 2015 [23, 24]
LV assessment	Assessment of left heart function	Commercial technique	HeartModel (Philips)	$r = 0.87 \sim 0.96 / r = 0.98$	JACC: Cardiovascular Imaging, 2016; J Am Soc Echocardiogr, 2017 [25, 26]
		Commercial technique	AutoLV (TomTec Imaging system)	ICC = 1.0	J Am Coll Cardiol, 2015 [27]
		Commercial technique	AutoEF (BayLabs)	$r = 0.95$	Circ Cardiovasc Imaging, 2019 [28]
		AI algorithm	3D CNN	AUC = 0.92	J Am Soc Echocardiogr, 2020 [29]
		AI algorithm	PWC-Net	ACC = 97% ~ 98%	JACC Cardiovasc Imaging, 2021 [30]
		AI algorithm	Neural network	Intraclass correlation = 0.86 – 0.95 (AI and physician), 0.84 (novice using AI and physician)	Circ Cardiovasc Imaging, 2021 [31]

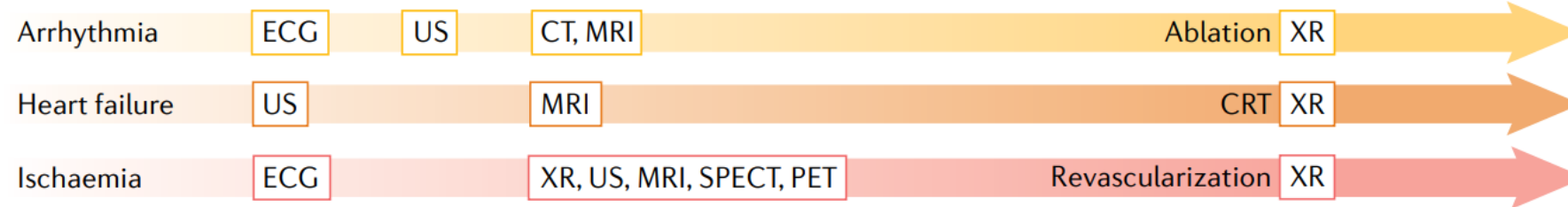
Cardiac disease diagnosis	Valvular heart disease	Commercial technique	Proximal isovelocity surface area (PISA)	Intraclass correlation coefficients = 0.96	Circ Cardiovasc Imaging, 2013; J Am Soc Echocardiogr, 2012 [32, 33]
		Commercial technique	Real-time 3D volume color-flow Doppler (RT-VCFD)	$r = 0.93$	Int J Cardiovasc Imaging, 2015 [34]
		Commercial technique	Mitral Valve Navigator (Philips)	N/A	Echocardiography, 2016 [35]
		Commercial technique	Anatomical Intelligence in ultrasound (AIUS)	ACC = 89%	J Am Soc Echocardiogr, 2016 [36]
		AI algorithm	Anatomical affine optical flow	Intra- and interobserver variability = 0.85 and 0.65	Int J Cardiovasc Imaging, 2019 [37]
		AI algorithm	2D/3D CNN	Sensitivity (Recall) = 67%, PPV = 74% ~ 77%	Nat Commun, 2021 [38]
	Cardiomyopathy	Commercial technique	Myocardial strain analysis	N/A	Circ J, 2019 [39]
		AI algorithm	Associative memory classifier	AUC = 89.2%	Circ Cardiovasc Imaging, 2016 [40]
		AI algorithm	Support Vector Machine	AUC = 77.8%	AMIA Annu Symp Proc, 2014 [41]
	Coronary atherosclerotic heart disease	AI algorithm	discrete wavelet transform and texture feature analysis	AUC = 90% ~ 99%	JACC Cardiovasc Imaging, 2019 [42]
		Commercial technique	EchoPAC PC (GE)	$r = 0.67 \sim 0.99$	Echocardiography, 2015 [43]
		AI algorithm	A specialised software for MCE quantification	Sensitivity = 77% Specificity = 94%	Ultrasound Med Biol, 2017 [15]
		AI algorithm	Texture analysis	Highest accuracy = 79%	IEEE, 2016 [44]
	Intracardiac masses	AI algorithm	Feed-forward neural network	Accuracy = 91%	Comput Med Imaging Graph, 2006 [45]
		AI algorithm	Gray level co-occurrence matrix-based features/ ANN (Classification)	Mean sensitivity = 0.955 Specificity = 0.970	J Ultrasound Med, 2014 [46]

AI in cardiac imaging

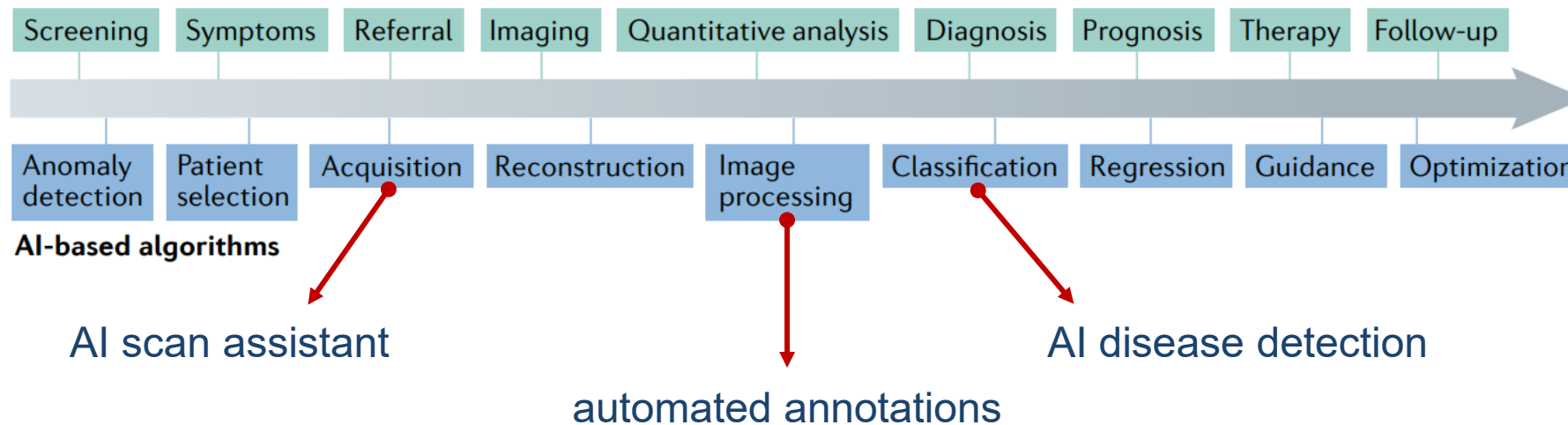
- Introduction to AI
- AI applications in cardiac imaging:
 - **Automation for workflow optimization**
 - Integrative profiling for CV disease prediction / diagnosis / prognosis
- Challenges

Workflow optimization and education

Clinical workflows



AI-supported decision-making



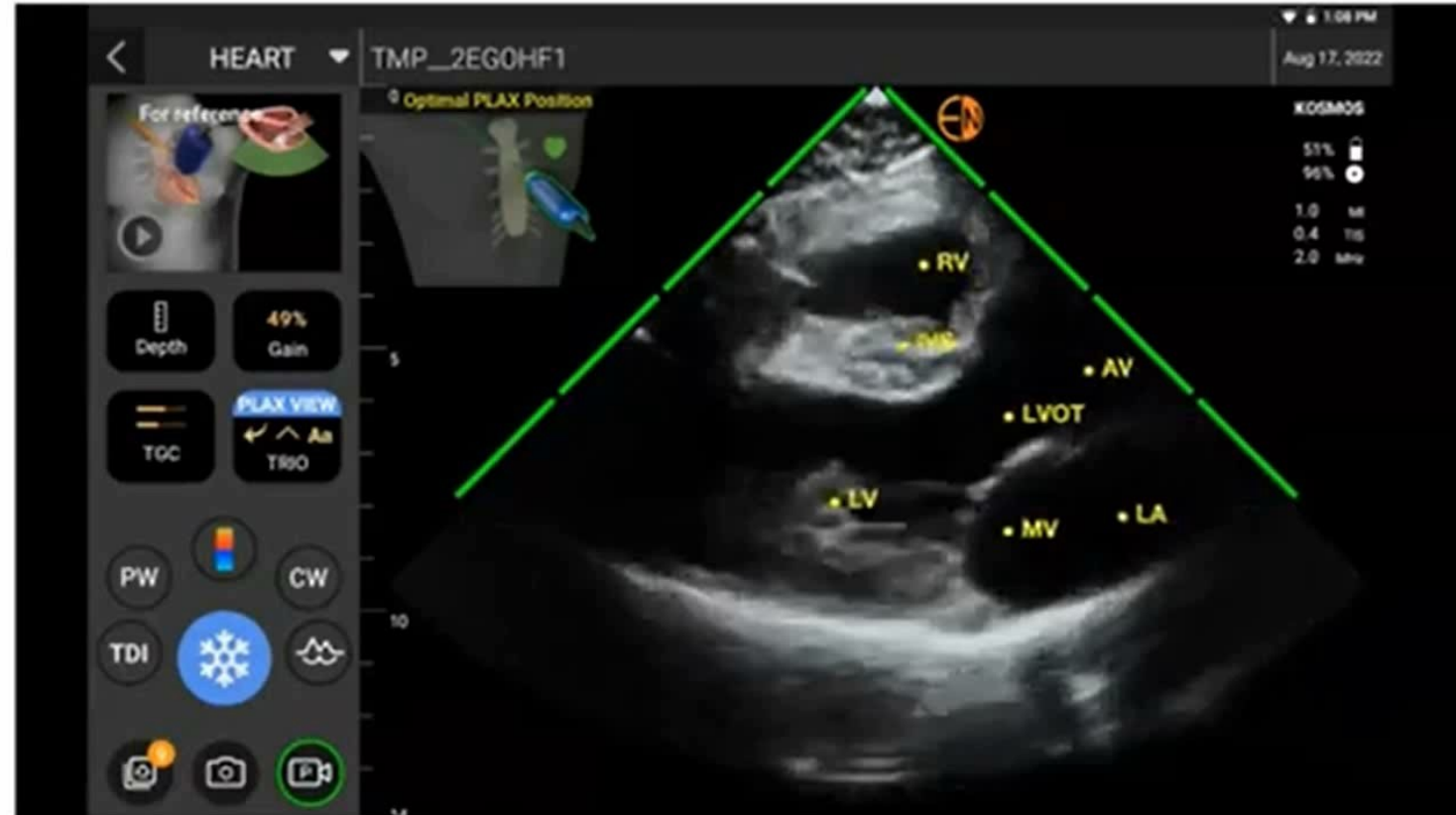
AI scan assistant

TRIO

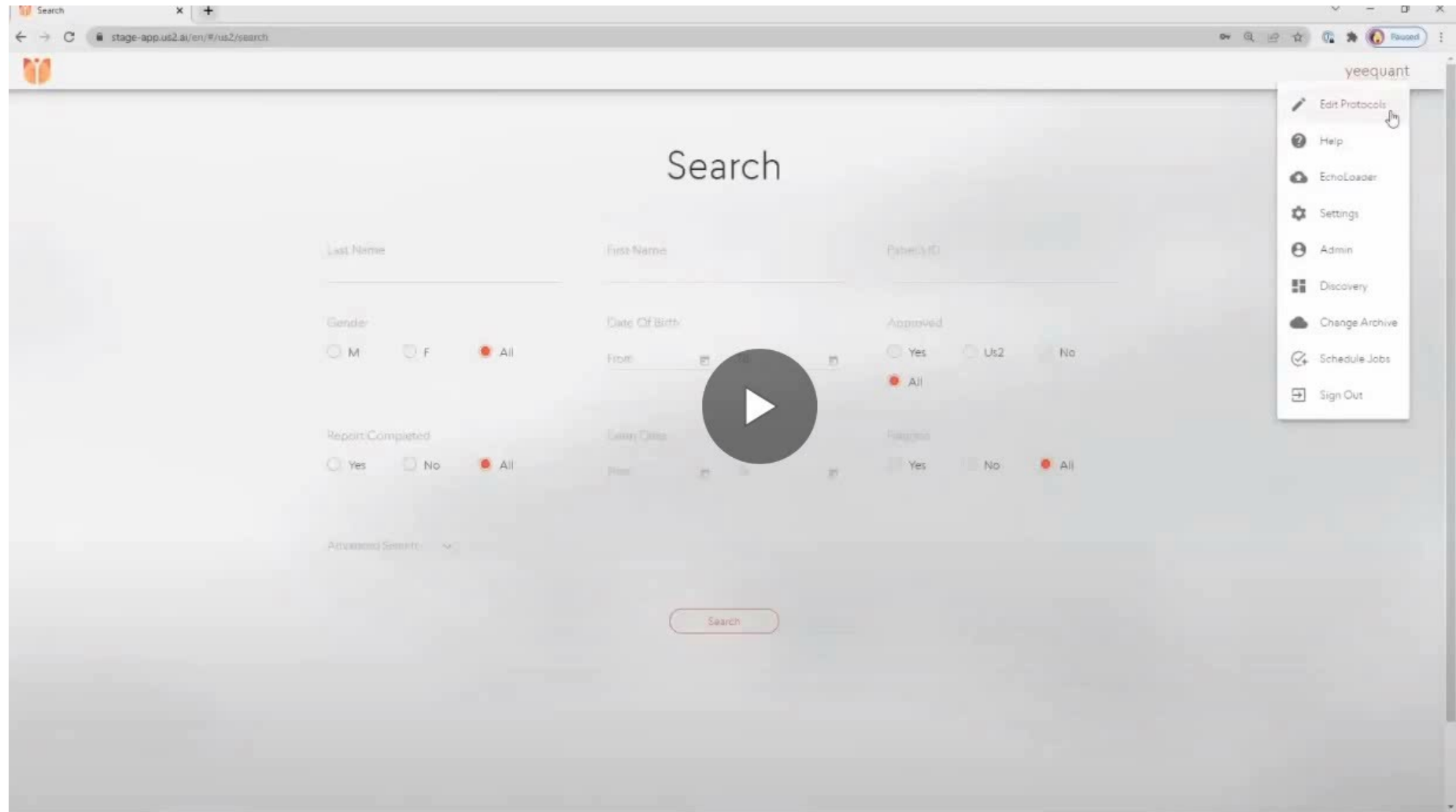
Automated grading, guiding, and labeling

Our AI TRIO helps scanners move quickly from novice to expert. Our anatomical detection techniques offer real time guidance for probe positioning in cardiac and FAST examinations. The highlighted bar system shows when you are in the optimal plane for measurement purposes or for assessing anatomical structures

- True scanning guidance in real-time
- Fast & accurate identification of cardiac structures
- Real-time grading of image quality
- Drive repeatability and reproducibility of key clinical measurements
- Accelerates user learning curves and improve confidence
- Provides data to support evidence based decision making



Fully automated echocardiogram interpretation and reporting



AI disease detection from echocardiography

✓ Heart failure (HF)
HF with reduced ejection fraction | HF with mildly reduced ejection fraction
| HF with preserved ejection fraction

✓ Pulmonary hypertension & right heart failure


✓ Hypertrophic cardiomyopathy

✓ Cardiac amyloidosis

✓ Valvular disease
Aortic stenosis | Mitral regurgitation
| Tricuspid regurgitation

✓ Ischemic heart disease (regional wall motion abnormalities)

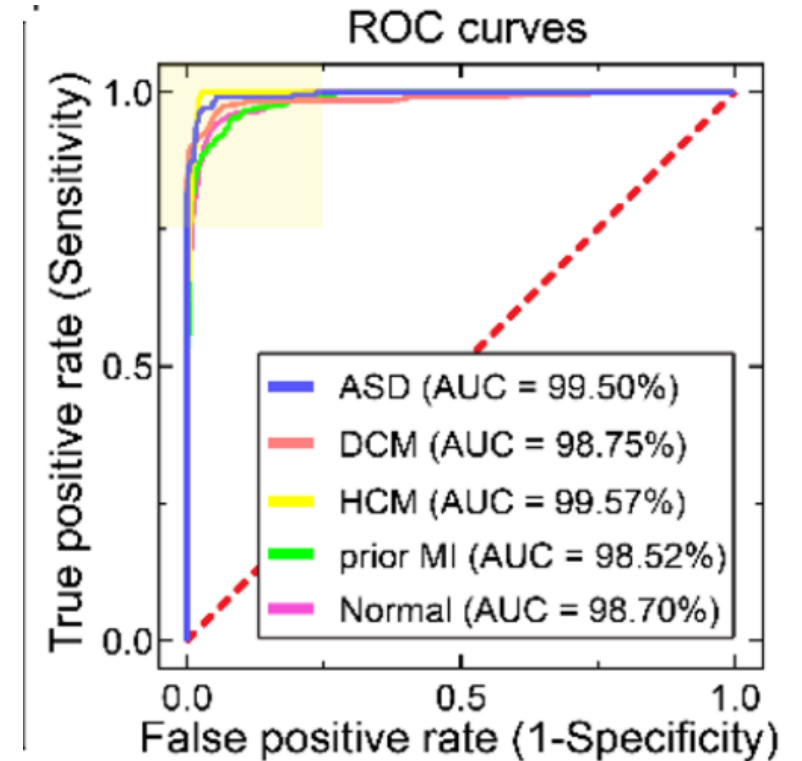
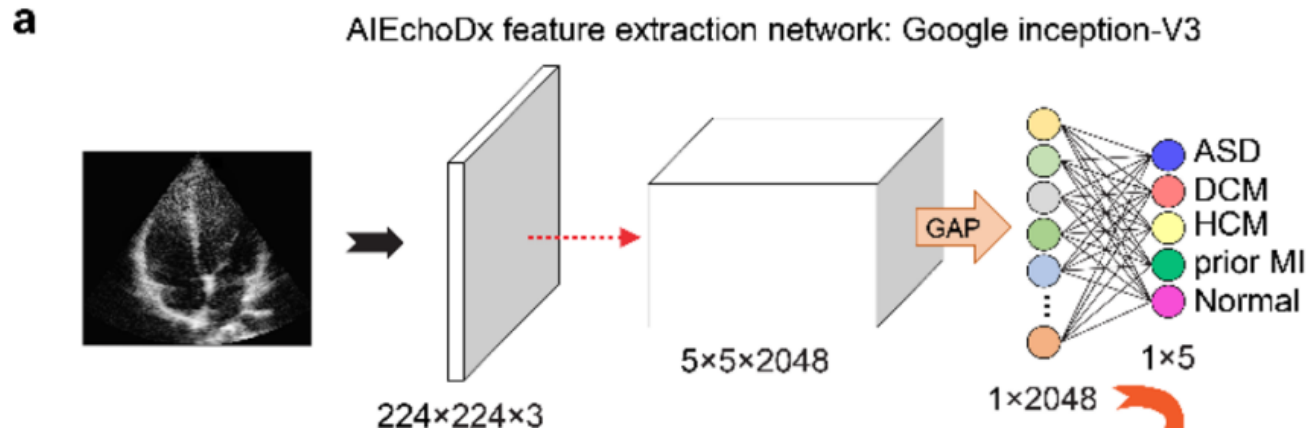
Us2.ai software facilitates the possible detection of multiple disease conditions. All clinical conditions are suggested based on international guidelines.



8 Us2.ai :: Ultrasound Anyone Anywhere

US2.AI

AI disease detection from echocardiography

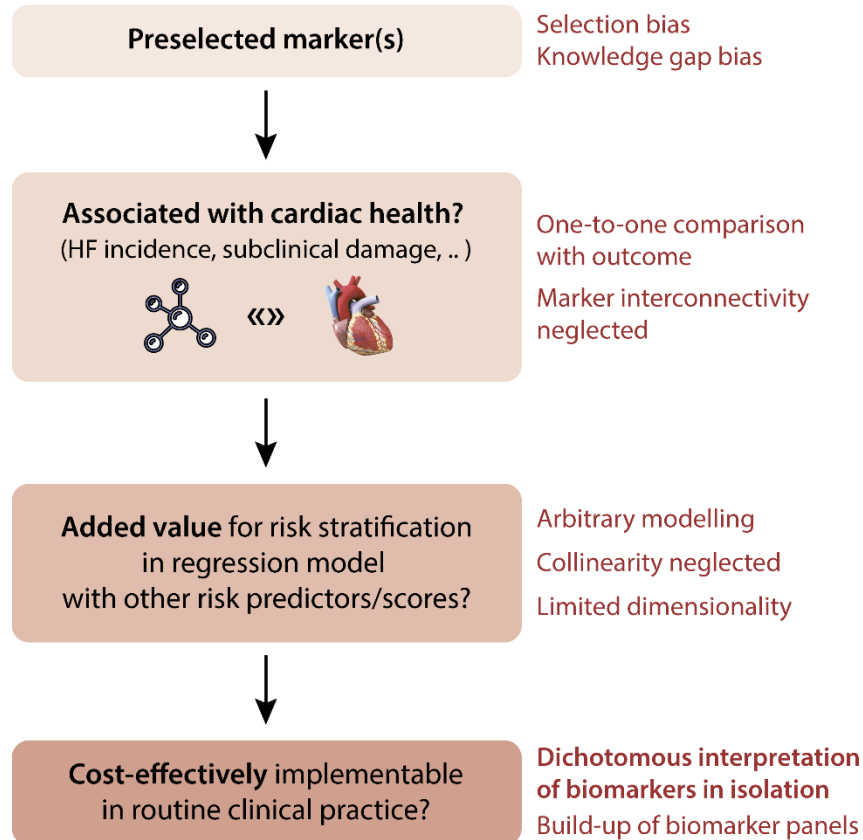


AI in cardiac imaging

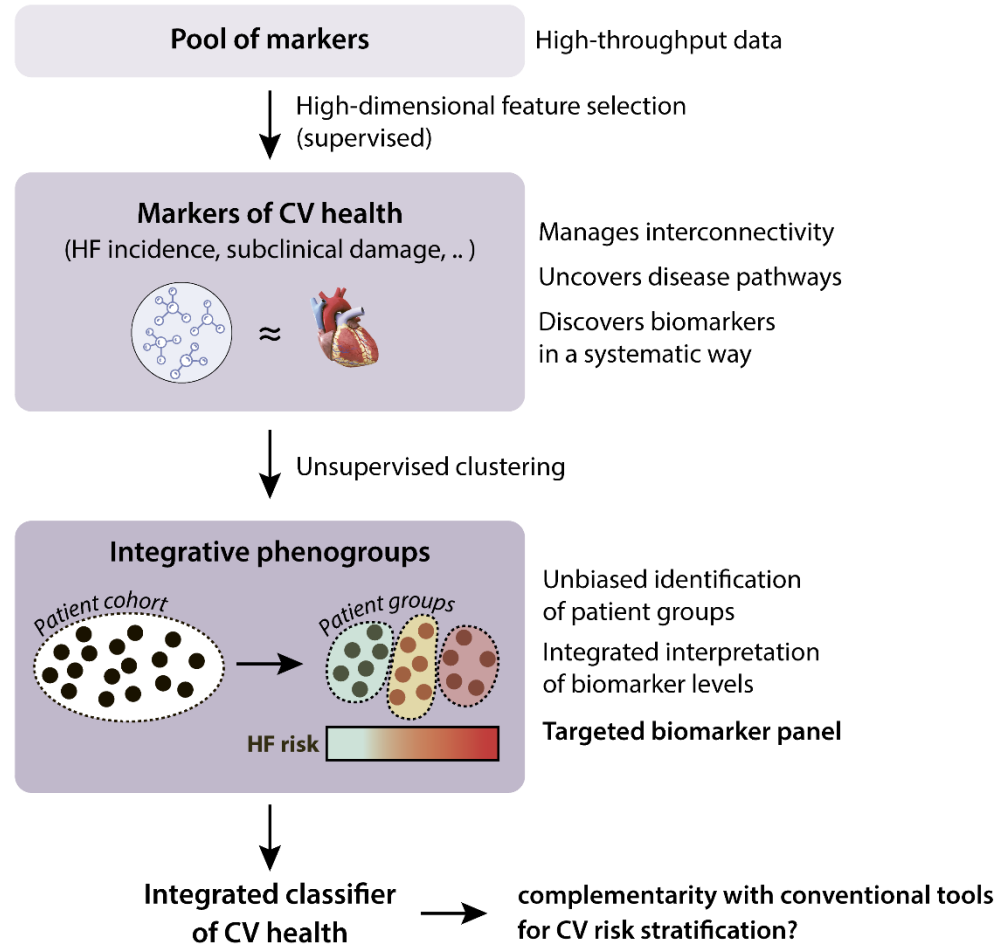
- Introduction to AI
- AI applications in cardiac imaging:
 - Automation for workflow optimization
 - **Integrative profiling** for CV disease prediction / diagnosis / prognosis
- Challenges

Integrative profiling of cardiac health

A. "One-by-one" validation of biomarker



B. Pipeline for integrative profiling of CV risk





CVD risk stratification based on routine clinical data

Patients with CV risk factors: Whom to refer to cardiac imaging?



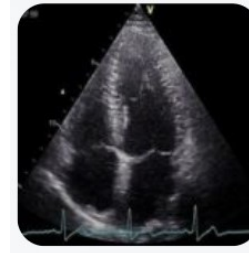
n=1407

(FLEMENGHO study)



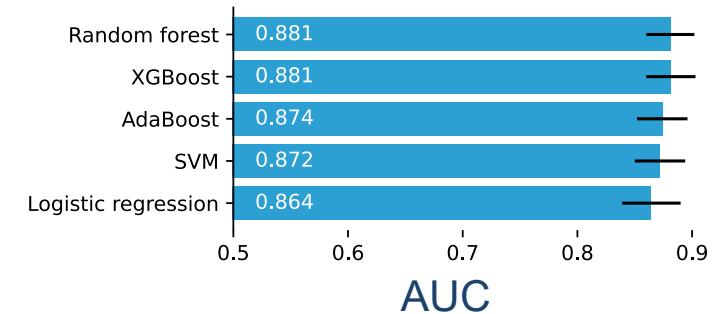
Routine clinical data
(BP, ECG, biochemistry)
67 features

Supervised ML



LV hypertrophy
LV diastolic dysfunction

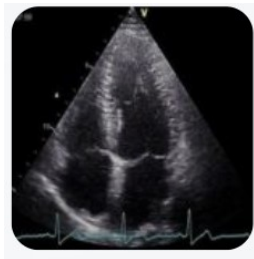
Early LV diastolic dysfunction





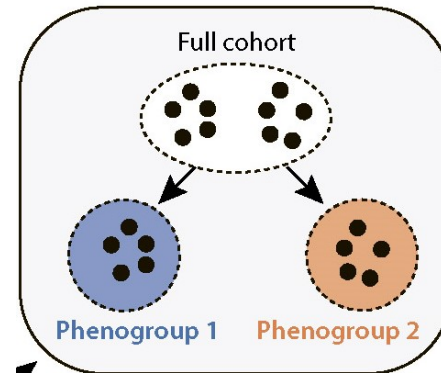
CVD risk stratification based on imaging data

How to interpret imaging data integratively
and does it help predict future CV events?



21 echocardiographic
/ BP features

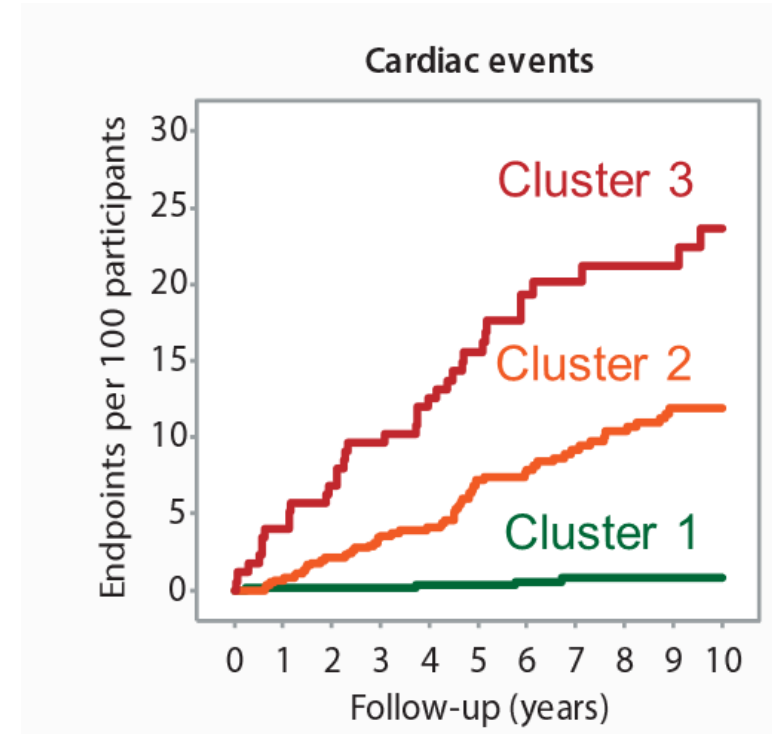
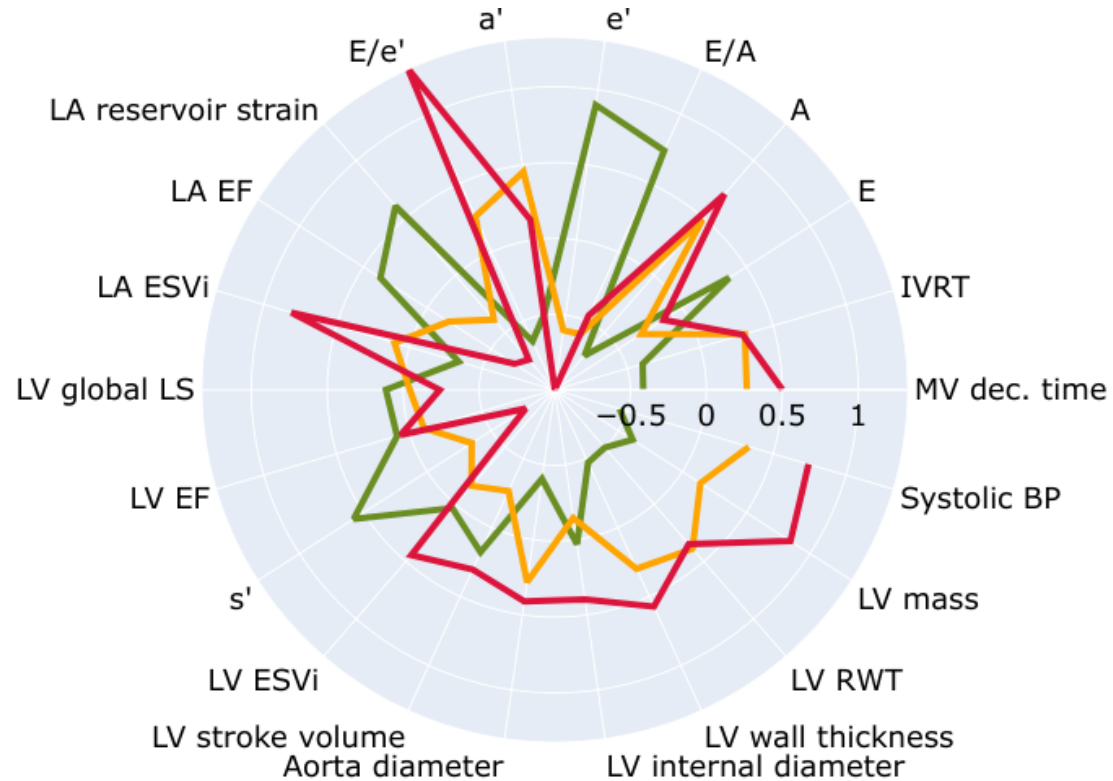
Unsupervised ML
(GMM)



predicting
CV events?



CVD risk stratification based on imaging data



Adjusted HR (95% CI)

Cluster 2 vs 1: 2.01 (1.86 - 3.50)

Cluster 3 vs 1: 1.84 (1.25 - 2.71)



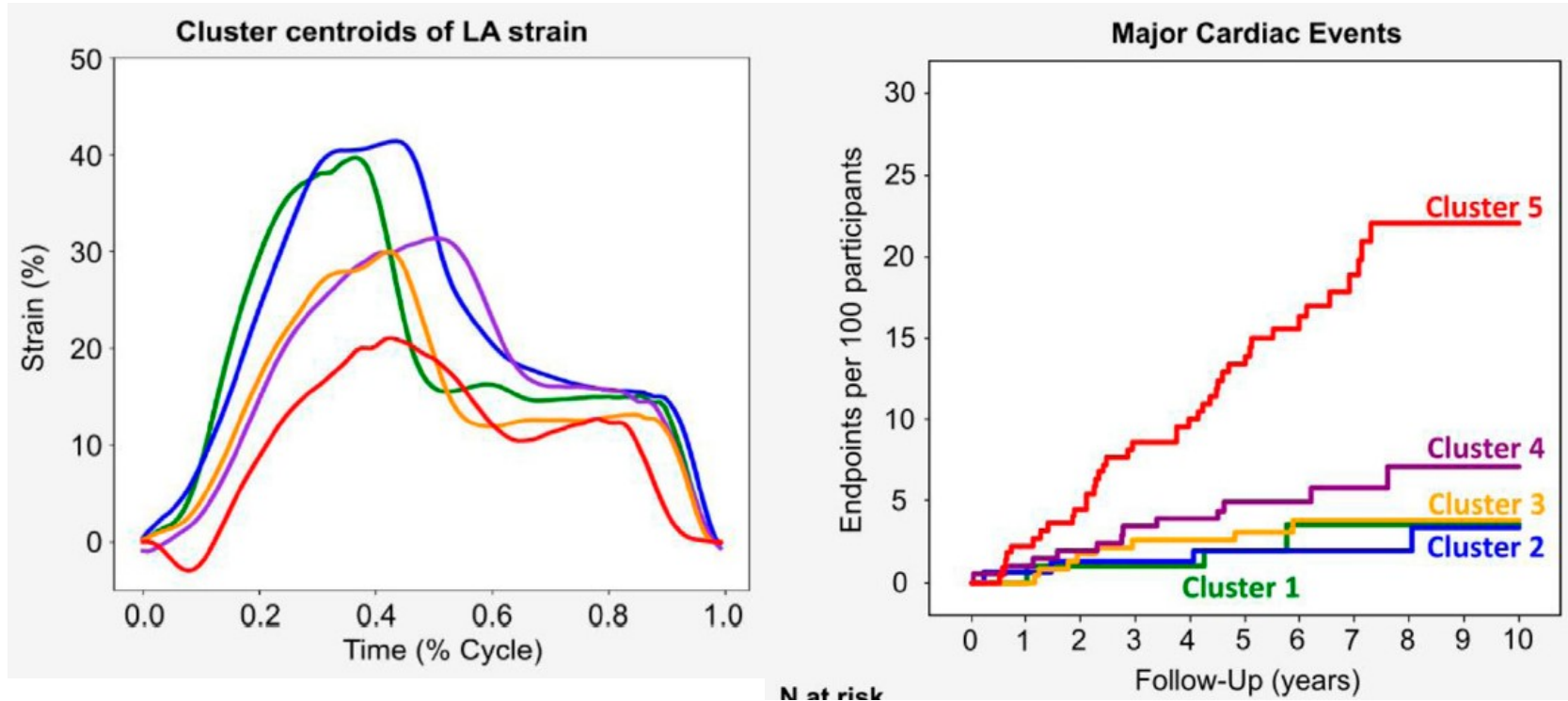
CVD risk stratification based on imaging data

~ Echo time series



n=1407

(FLEMENGHO)

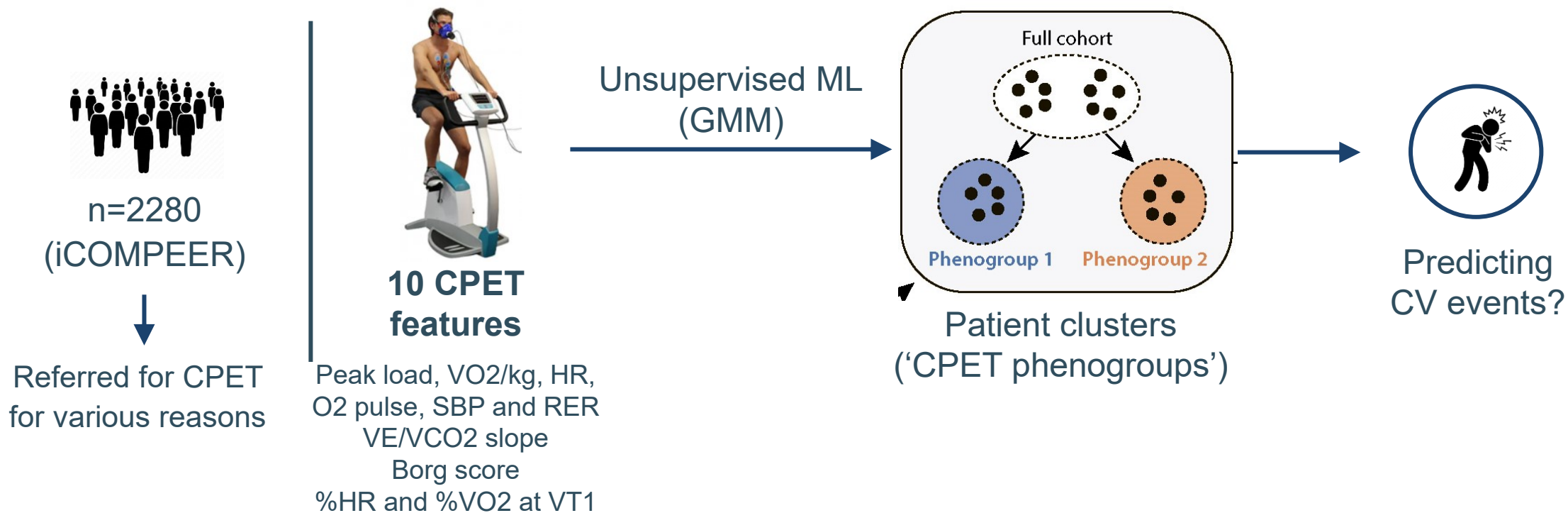


N at risk



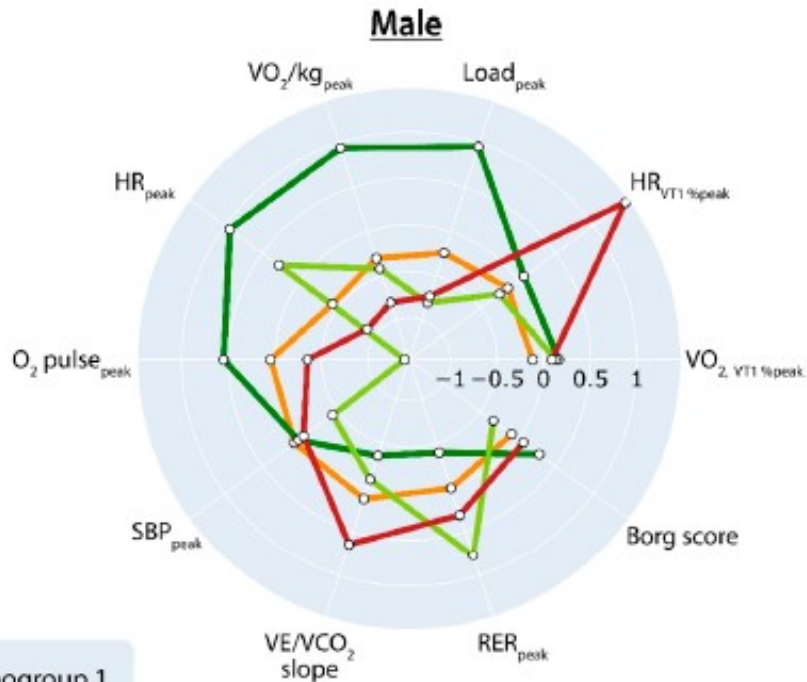
CVD risk stratification based on imaging data

How to interpret imaging data integratively and does it help predict future CV events?

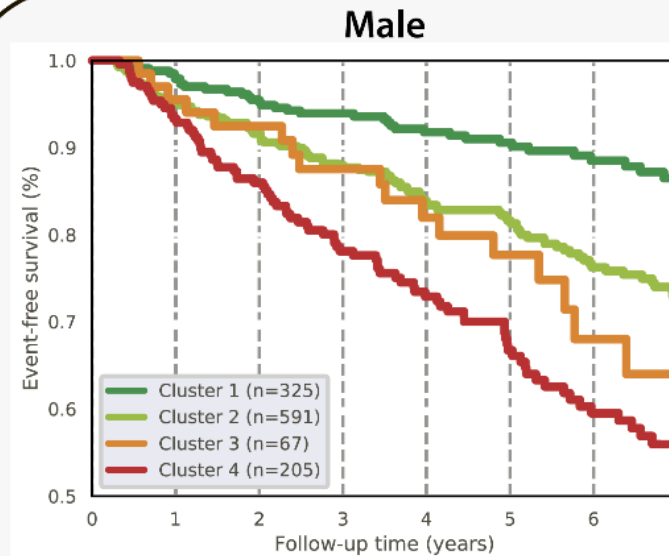




CVD risk stratification based on imaging data



Incidence of cardiovascular events

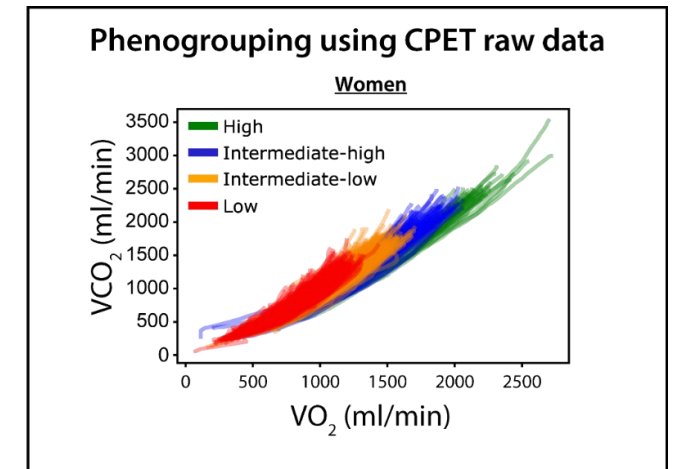


Adjusted HR (95% CI; P value) versus cluster 1

- Cluster 2 1.53 (0.90-2.60; $P=0.11$)
- Cluster 3 1.51 (1.00-2.27; $P=0.048$)
- Cluster 4 2.19 (1.31-3.66; $P=0.0028$)

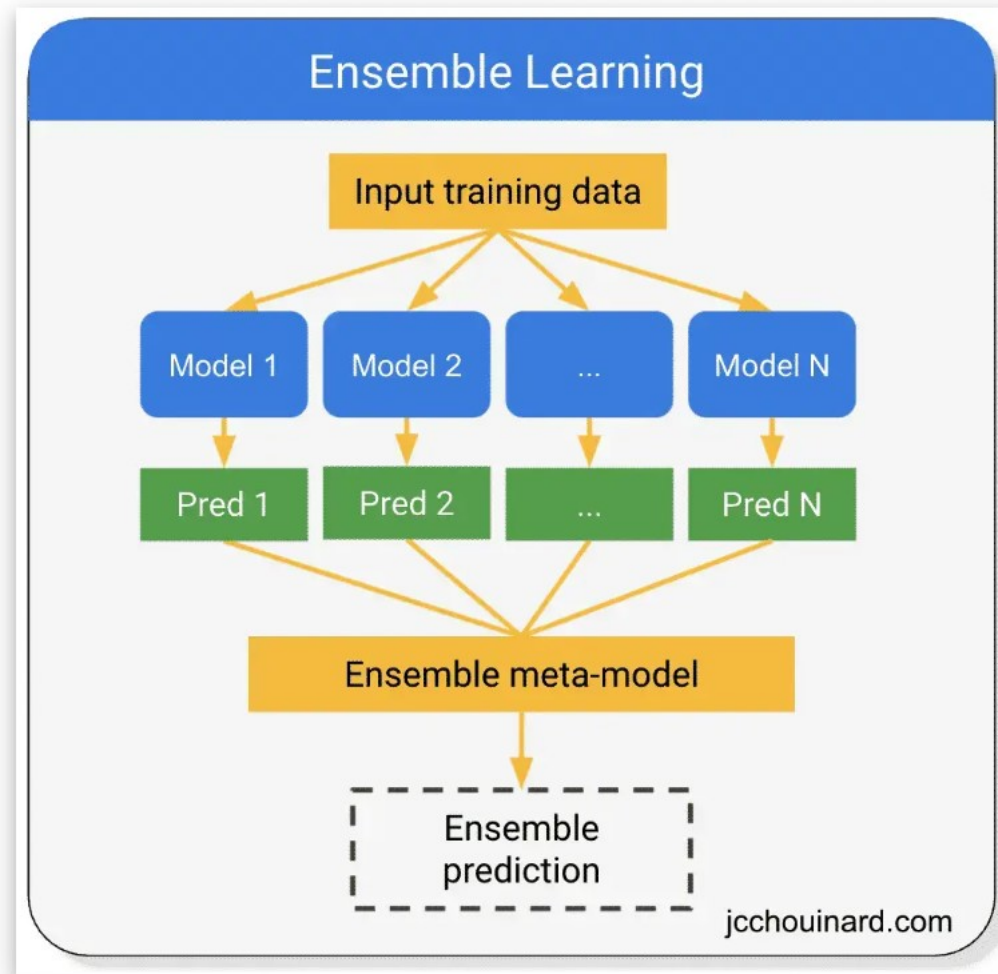
Integrative CPET evaluation for CV risk stratification

~ CPET time series



Imaging-based phenogroups may improve CV risk stratification

The future: ensemble models



AI in cardiac imaging

- Introduction to AI
- AI applications in CV imaging
- **Challenges**

Challenges for AI in CV medicine



Clinical autopilot



Interaction engineers / clinicians

→ bidirectional training

AI reporting and regulation

- engineer vs medical language
- methodology, QC, performance, ..
- Open code

Ethics

OPEN

Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension

Xiaoxuan Liu^{1,2,3,4,5}, Samantha Cruz Rivera^{5,6,7}, David Moher^{8,9}, Melanie J. Calvert^{10,4,5,6,7,10,11,12}, Alastair K. Denniston^{2,3,4,5,6,13} and The SPIRIT-AI and CONSORT-AI Working Group*

 Check for updates

Take-home messages

ESC on demand:

Artificial intelligence demystified

Can we trust artificial intelligence in cardiac imaging today?

Will AI replace cardiologists?

Clinical workflows

Arrhythmia

ECG

US

CT, MRI

Ablation XR

Heart failure

Ischaemia

AI-supported

Screening

Sy

w-up

Anomaly
detection

Patient
selection

Acquisition

Reconstruction

Image
processing

Classification

Regression

Guidance

Optimization

AI-based algorithms

- AI will stay and revolutionize medicine
 - ➔ To help, not to replace healthcare professionals
- AI already used in cardiac imaging, much more coming
- Clinical education on AI for appropriate application

Artificial Intelligence in Echocardiography: Workflow Efficiency & Patient Satisfaction

12:15 - 1:15PM EDT June 20th, 2021

CME & SDMS/CME Accredited Webinar



Jordan B. Strom
MD, MSc, FACC, FASE
Harvard Medical School
Boston, MA



Patricia A. Pellikka
MD, FACC, FAHA, FASE
Mayo Clinic
Rochester, MN



Partho Sengupta
MD, DM, FACC, FASE
WVU Heart & Vascular Institute
Morgantown, WV