

Radiomics in CMR

Extracting More Information from Cardiac Images

Esmeralda Ruiz Pujadas

06-05-2022

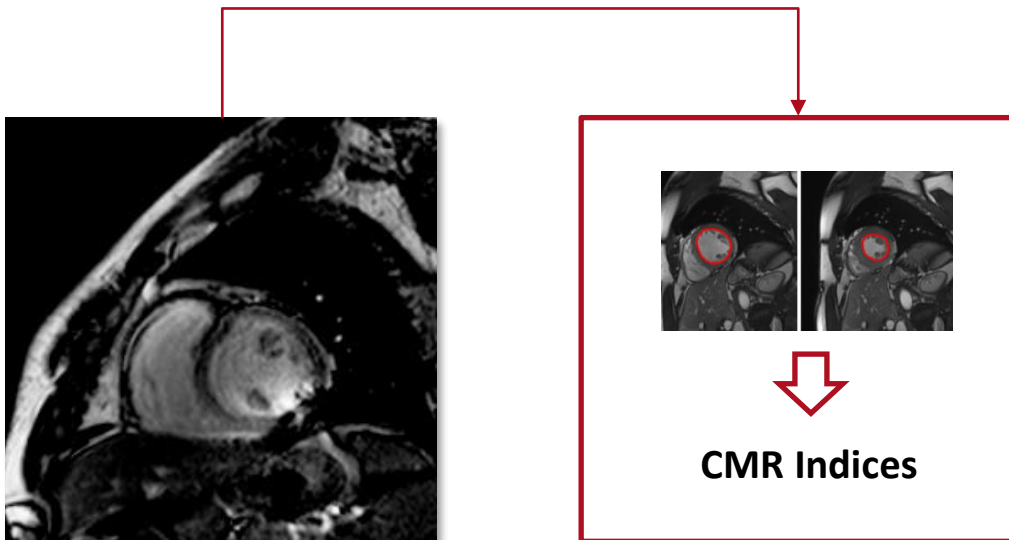


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BARCELONA



1 - Radiomics in CMR: Motivations

Conventional CMR Indices



**Standard CMR indices
do not capture:**

Advanced morphological
quantification

Advanced quantification of
cardiac remodeling

Changes in
cardiac tissues

CMR radiomics

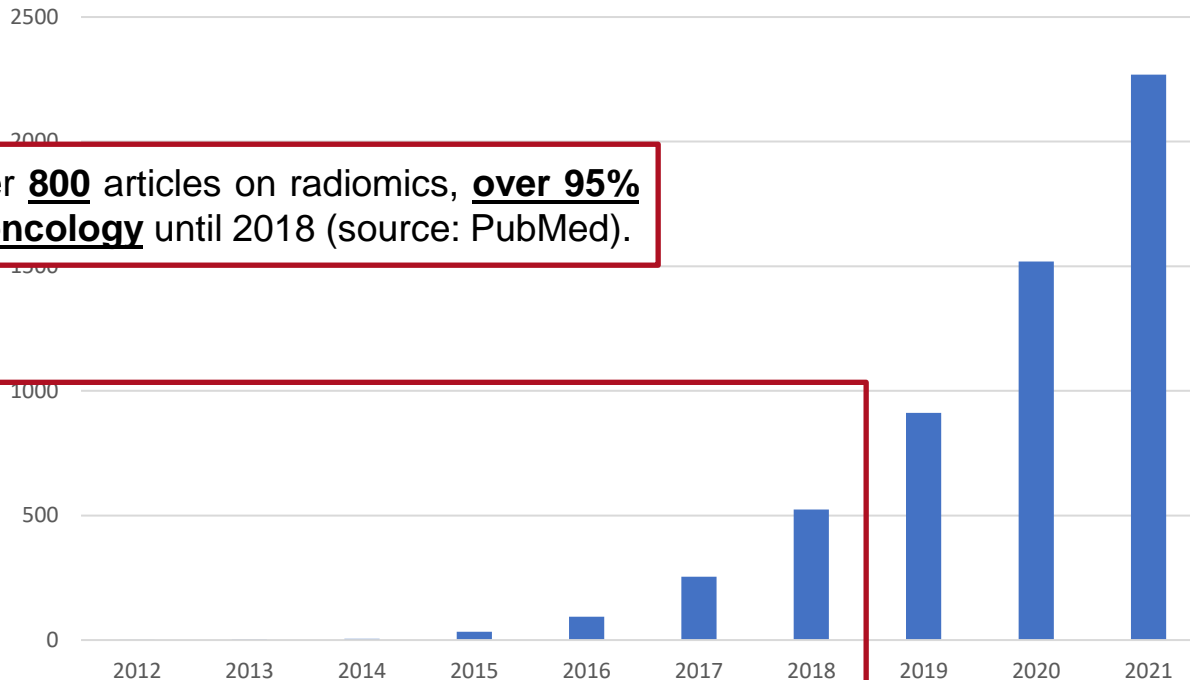
Traditional indices. Myocardial mass, ejection fraction, ED volume, ES volume, stroke volume and the corresponding values indexed to body surface area, height or weight, strain and strain-rates in three directions (radial, circumferential and longitudinal).

Radiomic markers. Size radiomics: Diameters, elongations, surface areas, surface to volume ratios. Shape radiomics: Sphericity, axes, compactness, flatness, eccentricity. Boundary radiomics: Sharpness, regularity, smoothness, etc. Intensity radiomics: Mean, standard deviation, skewness, intensity range, entropy, uniformity. Textural radiomics: Homogeneity, localised contrast, tissue complexity, structure repeatability, total energy, fractal dimension, structure continuity/connectivity, tissue coarseness, directionality, etc.

Radiomic transforms. Wavelets transform: identifies patterns in different spatial frequencies; Fourier: extracts information on periodicity (coarseness/fineness) and directionality of textures; Laplacian: Highlights discontinuities and fine tissue changes (e.g. trabeculae); Logarithmic: increases dynamic ranges of dark regions (e.g., trabeculae); Exponential: Enhances detail in high-value regions; Histogram of gradients: Encodes the spatial arrangement of gradients in the image.

Existing Works on Radiomics

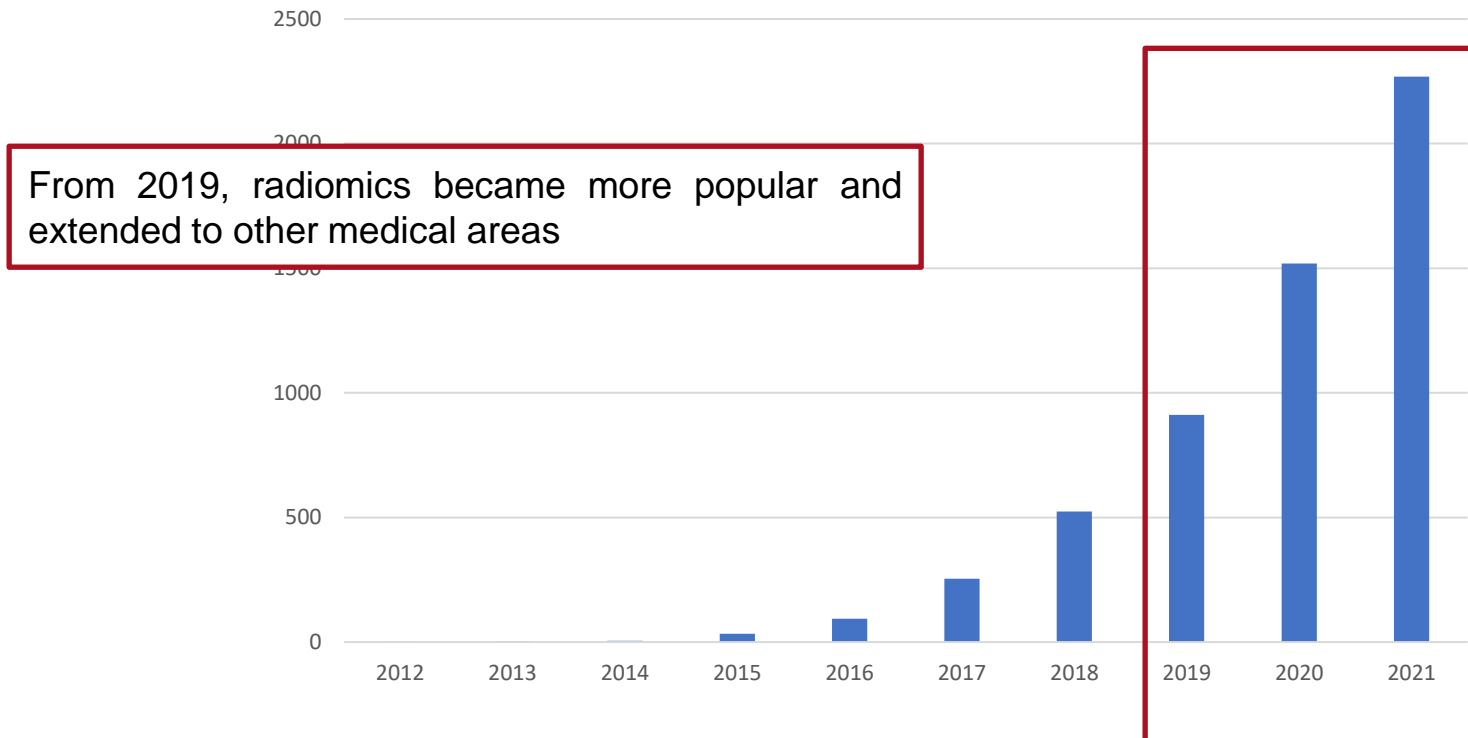
Radiomics publications per year



There are over **800** articles on radiomics, **over 95%** dedicated to **oncology** until 2018 (source: PubMed).

Existing Works on Radiomics

Radiomics publications per year

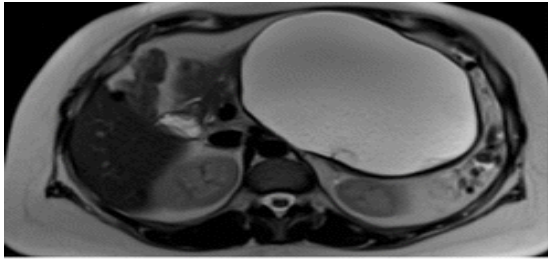


Radiomics in Oncology

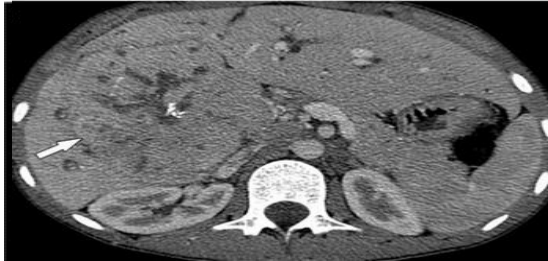
Diagnosis

Treatment Planning

Prognostication



Uniform high signal intensity. No lesion is shown



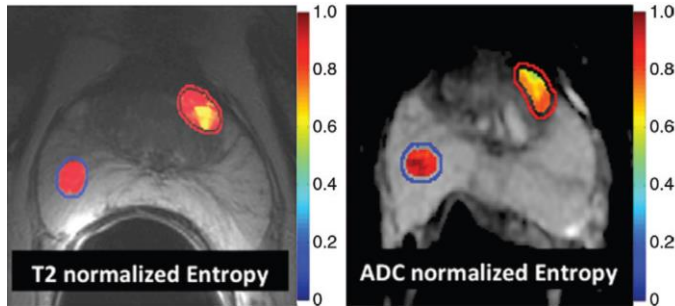
Shows the heterogeneity of a malignant tumor

Radiomics in Oncology

Diagnosis

Treatment Planning

Prognostication



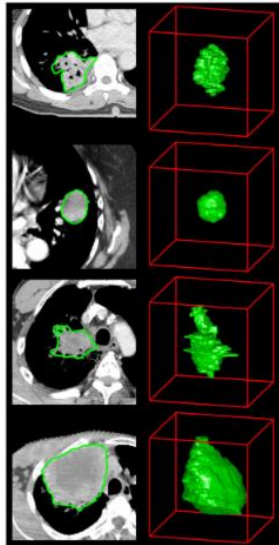
Heatmap shows tumour aggressiveness

Radiomics in Oncology

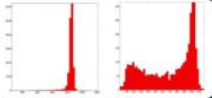
Diagnosis

Treatment Planning

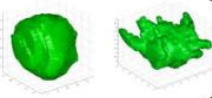
Prognostication



1. Tumor intensity
(m=15)



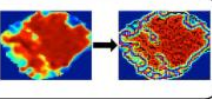
2. Tumor shape
(m=12)



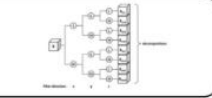
3. Tumor texture
(m=44)



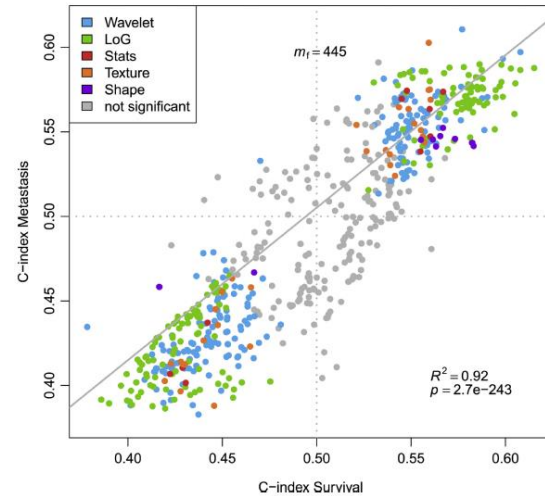
A. LoG filter
(m=180)



B. Wavelet filter
(m=384)



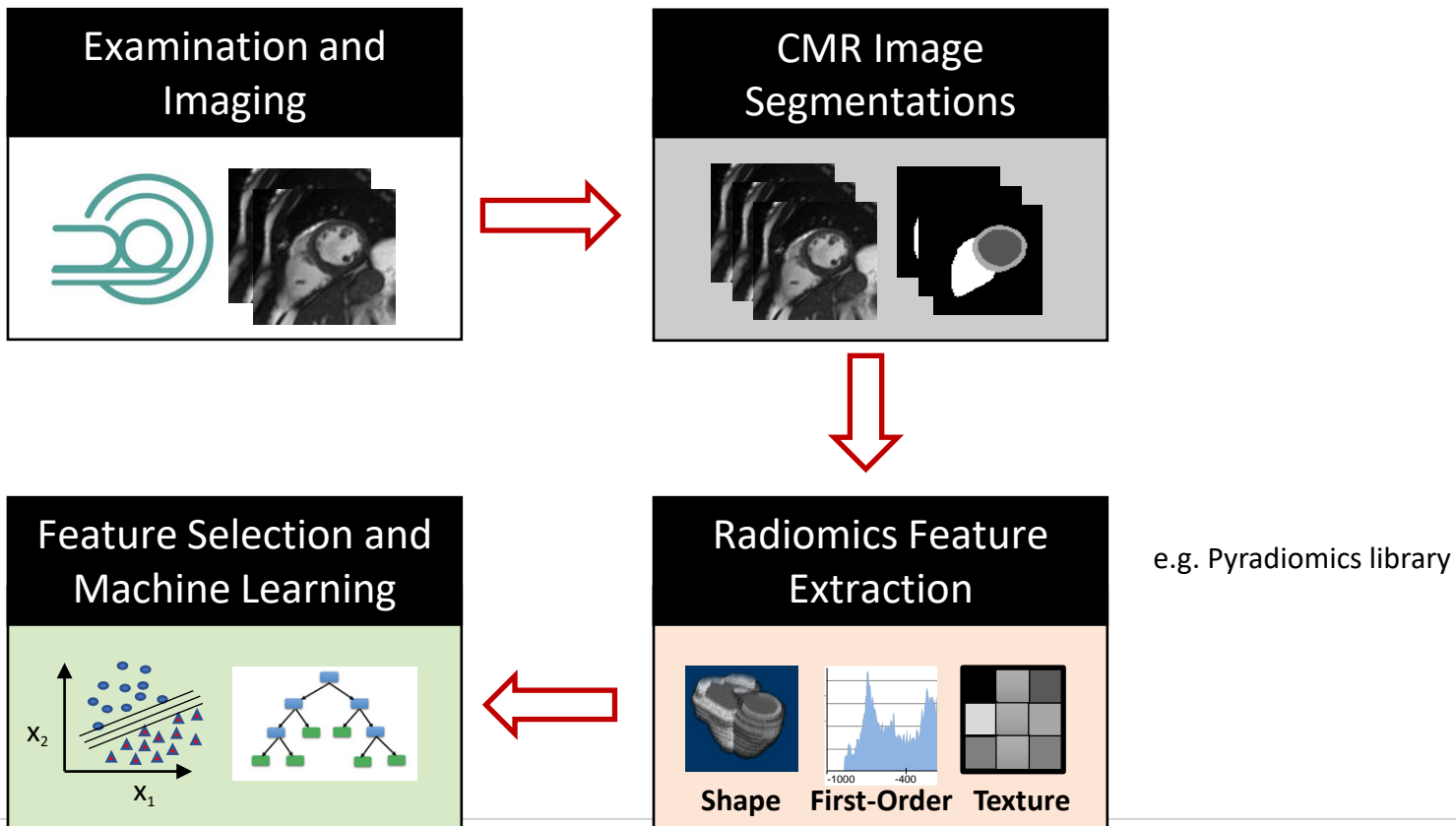
Metastasis
prediction



(T.P Coroller et al., Radiother Oncol. 2015)

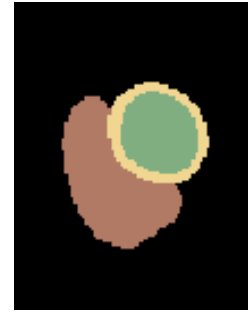
2 - Radiomics in CMR: Methods

Workflow of Radiomics

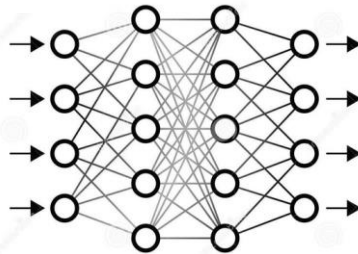
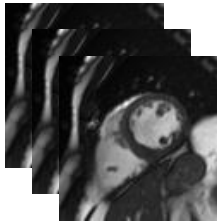


CMR Image Segmentation

- Manual segmentation using a commercial software

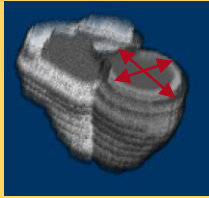


- Automatic segmentation with deep learning techniques



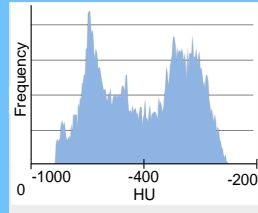
Radiomics Feature Extraction

Shape



Geometrical properties such as volume, diameter, minor/major axis and sphericity

First-Order

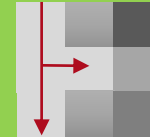


Histogram-based features

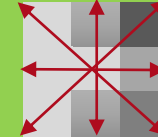
Texture



NGTDM



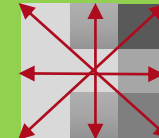
GLRM



GLCM



GLSZM

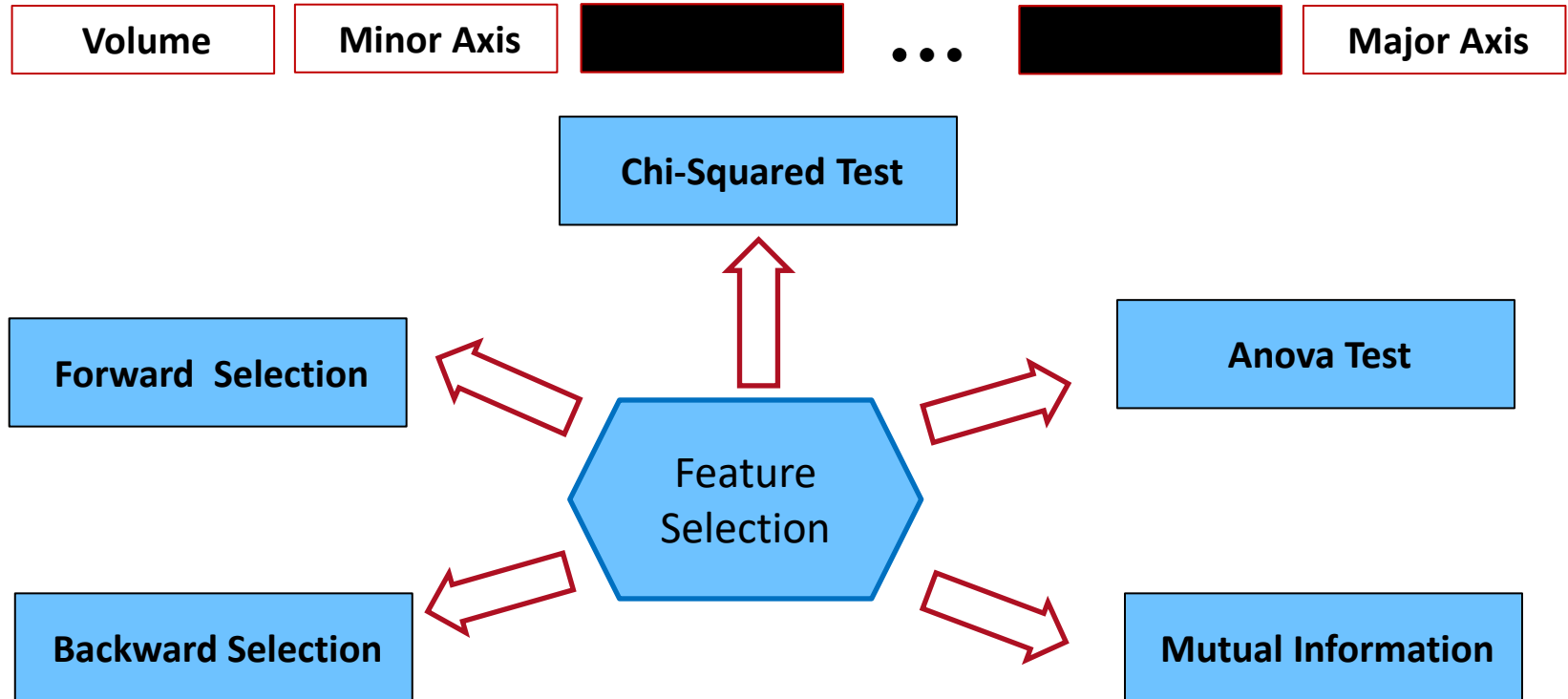


GLDM

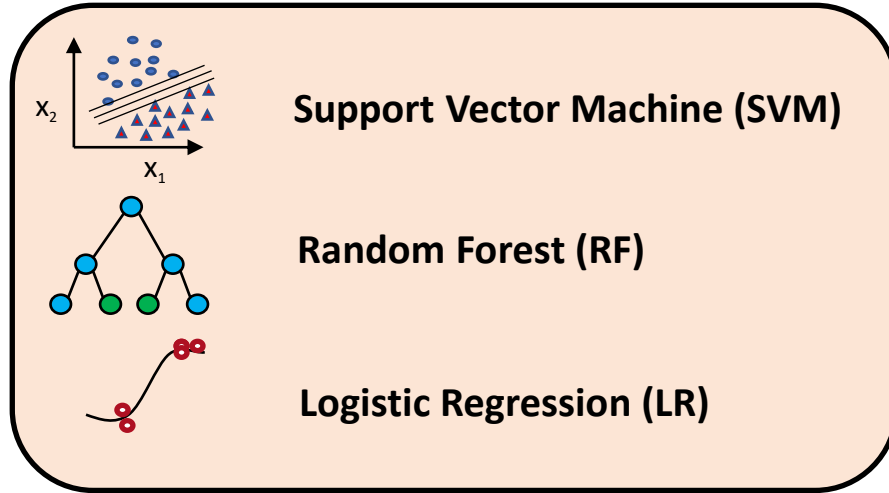
Spatial distribution of the intensity levels

Feature Selection

- Reduce the number of input variables



Machine Learning



**Hyper-parameter
optimization**



**Training tuned
algorithms**



Model selection

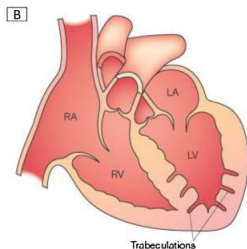
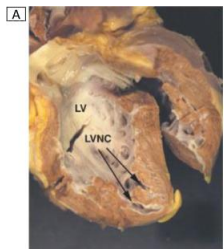
Examples of CMR radiomics applications

Study 1: Diagnosis

Radiomics-Based Classification of Left Ventricular Non-compaction, Hypertrophic Cardiomyopathy, and Dilated Cardiomyopathy in Cardiovascular Magnetic Resonance

Cristian Izquierdo^{1*}, Guillem Casas^{2,3,4,5}, Carlos Martin-Isla¹, Victor M. Campello¹, Andrea Guala^{3,4}, Polyxeni Gkontra¹, Jose F. Rodríguez-Palomares^{2,3,4,5} and Karim Lekadir¹

¹ Artificial Intelligence in Medicine Lab (BCN-AIM), Departament de Matemàtiques i Informàtica, Universitat de Barcelona, Barcelona, Spain, ² Department of Cardiology, Hospital Universitari Vall d'Hebron, Barcelona, Spain, ³ Vall d'Hebron Institut de Recerca (VHIR), Barcelona, Spain, ⁴ CIBER-CV, Instituto de Salud Carlos III, Madrid, Spain, ⁵ Departament de Medicina,



U. Ikeda et al., "Isolated left ventricular non-compaction cardiomyopathy in adults" J. Cardiology, 65(2) 2015.

Sample size: 118

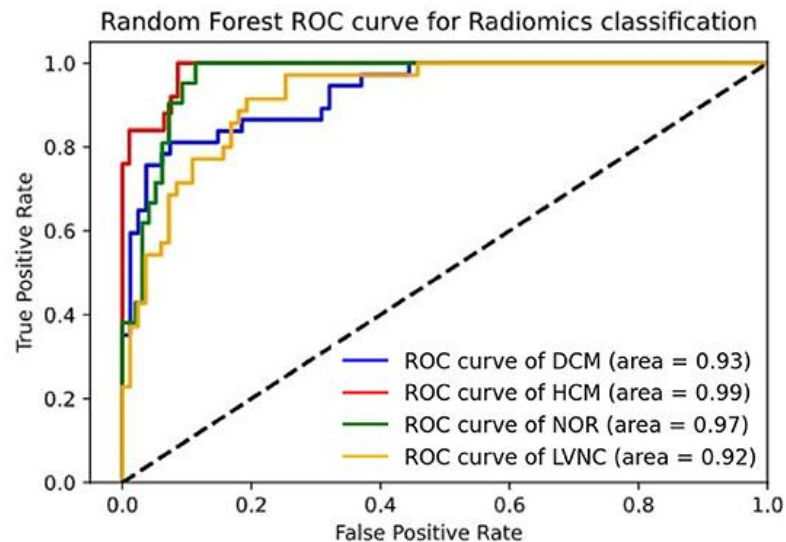
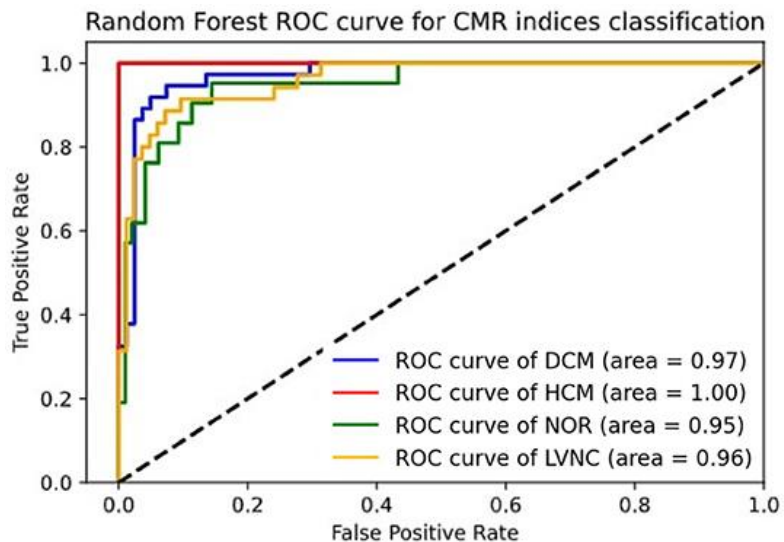
Datasets:



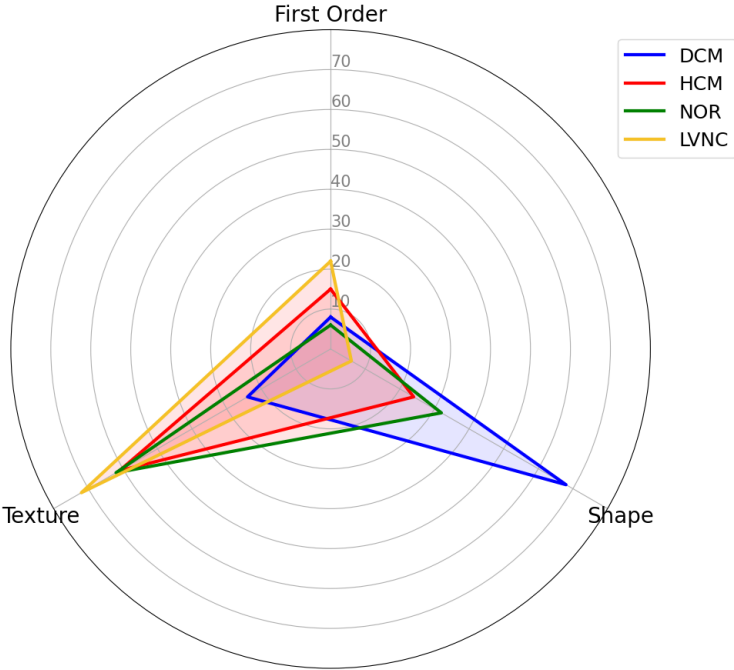
Diseases:

- Left Ventricular Non-compaction (LVNC) - 35 cases
- Hypertrophic Cardiomyopathy (HCM) - 25 cases
- Dilated Cardiomyopathy (DCM) - 37 cases

Study 1: Results



Study 1: Results



Study 2: Diagnosis



Prediction of incident cardiovascular events using machine learning and CMR radiomics

Esmeralda Ruiz Pujadas*¹, Zahra Raisi-Estabragh*^{2,3}, Liliana Szabo*^{2,3}, Celeste McCracken⁴, Cristian Izquierdo Morcillo¹, Víctor M. Campello¹, Carlos Martín-Isla¹, Angelica M. Atehortua¹, Hajnalka Vago⁵, Bela Merkely⁵, Pal Maurovich-Horvat⁶, Nicholas C. Harvey^{7,8}, Stefan Neubauer⁴, Steffen E. Petersen^{1,2,3,9,10}, Karim Lekadir^{1,1}

¹ Departament de Matemàtiques i Informàtica, Universitat de Barcelona, Artificial Intelligence in Medicine Lab (BCN-AIM), Barcelona, Spain

² William Harvey Research Institute, NIHR Barts Biomedical Research Centre, Queen Mary University of London, Charterhouse Square, London, EC1M 6BQ, UK

Sample size: 32115

Datasets:



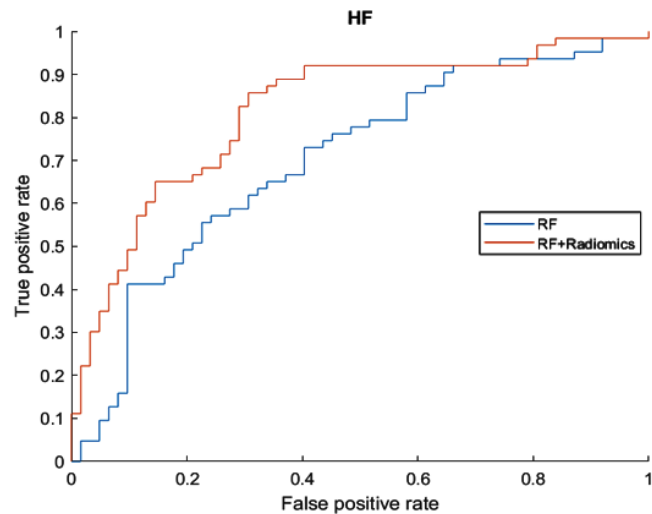
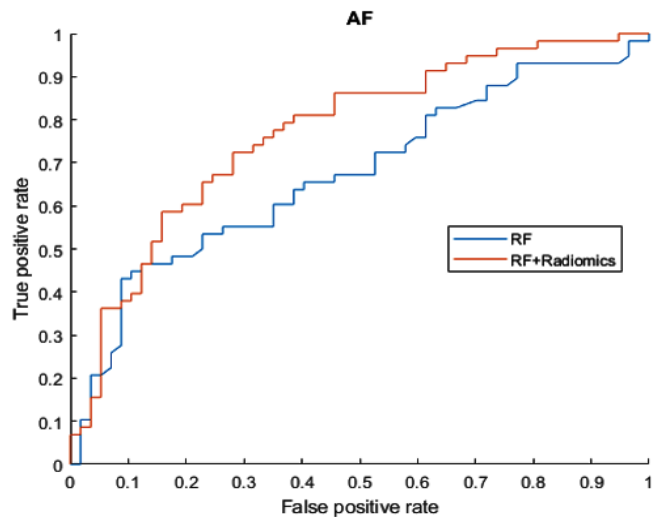
Diseases:

- **Atrial Fibrillation (AF) – 193 cases**
- **Heart Failure (HF) – 209 cases**

Method for classification:

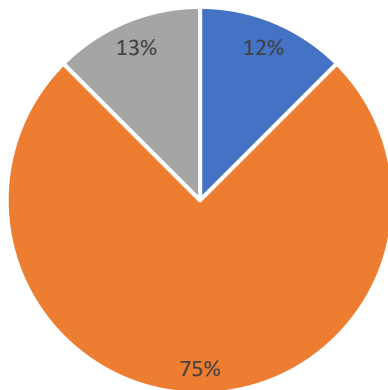
SVM

Study 2: ROC Curves



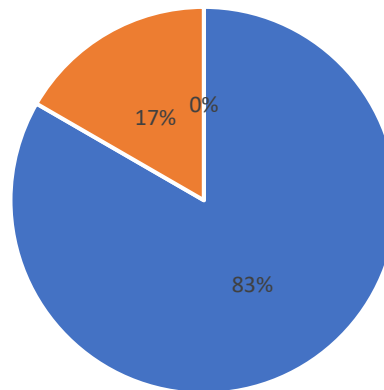
Study 2: Feature Distribution

Features for AF in Rads+RF



■ Shape ■ Texture ■ First-Order

Features for HF in Rads+RF



■ Shape ■ Texture ■ First-Order

CMR radiomics applications: Knowledge extraction

Study 3: Radiomics of Risk Factors

Radiomics Signatures of Cardiovascular Risk Factors in Cardiac MRI: Results From the UK Biobank

Irem Cetin^{1*}, Zahra Raisi-Estabragh^{2,3}, Steffen E. Petersen^{2,3}, Sandy Napel⁴, Stefan K. Piechnik⁵, Stefan Neubauer⁵, Miguel A. Gonzalez Ballester^{1,6}, Oscar Camara¹ and Karim Lekadir^{7*}

¹ BCN MedTech, Department of Information and Communication Technologies, Universitat Pompeu Fabra, Barcelona, Spain,

² William Harvey Research Institute, NIHR Barts Biomedical Research Centre, Queen Mary University of London, London, United Kingdom, ³ Barts Heart Centre, St. Bartholomew's Hospital, Barts Health NHS Trust, London, United Kingdom,

⁴ Department of Radiology, Stanford University, Stanford, CA, United States, ⁵ Division of Cardiovascular Medicine, Radcliffe Department of Medicine, University of Oxford, Oxford, United Kingdom, ⁶ Catalan Institution for Research and Advanced Studies (ICREA), Barcelona, Spain, ⁷ Departament de Matemàtiques i Informàtica, Universitat de Barcelona, Artificial Intelligence in Medicine Lab (BCN-AIM), Barcelona, Spain

Sample size: 32115

Datasets: **biobank**^{uk}

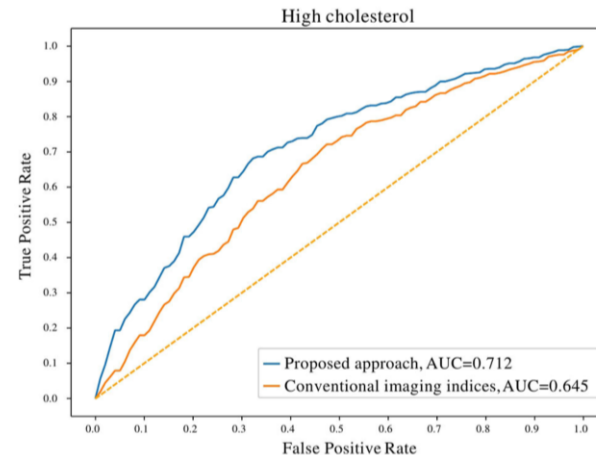
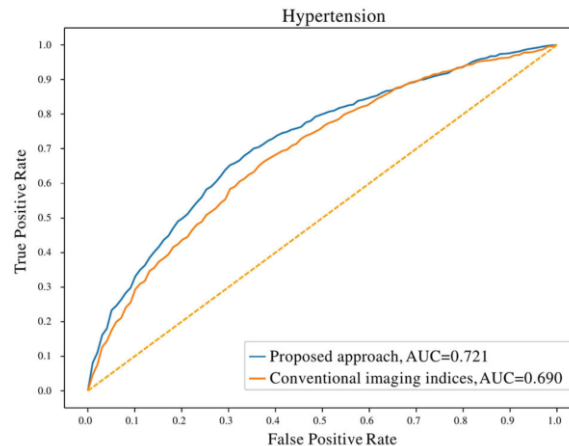
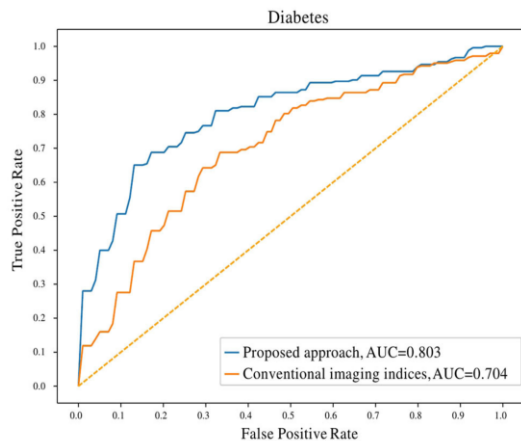
Diseases:

- Diabetes (N=243)
- Hypertension (N= 1934)
- High cholesterol (N= 779)

Machine Learning methods:

1. SVM
2. LR
3. RF

Study 3: Results



Radiomics challenges: Image variability across scans

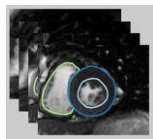
Study 4: Repeatability of CMR Radiomics

Repeatability of Cardiac Magnetic Resonance Radiomics: A Multi-Centre Multi-Vendor Test-Retest Study

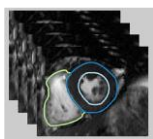
Zahra Raisi-Estabragh^{1,2}, Polyxeni Gkontra³, Akshay Jaggi³, Jackie Cooper¹, João Augusto^{2,4}, Anish N. Bhuvu^{2,4}, Rhodri H. Davies^{2,4}, Charlotte H. Manisty^{2,4}, James C. Moon^{2,4}, Patricia B. Munroe¹, Nicholas C. Harvey^{5,6}, Karim Lekadir³ and Steffen E. Petersen^{1,2*}

¹ NIHR Barts Biomedical Research Centre, William Harvey Research Institute, Queen Mary University of London, London, United Kingdom, ² Barts Heart Centre, St Bartholomew's Hospital, Barts Health NHS Trust, London, United Kingdom, ³ Departament de Matemàtiques i Informàtica, Universitat de Barcelona, Barcelona, Spain, ⁴ Institute of Cardiovascular Science, University College London, London, United Kingdom, ⁵ MRC Lifecourse Epidemiology Unit, University of Southampton, Southampton, United Kingdom, ⁶ NIHR Southampton Biomedical Research Centre, University of Southampton and University Hospital Southampton NHS Foundation Trust, Southampton, United Kingdom

Test



Retest



Sample size: 110 subjects

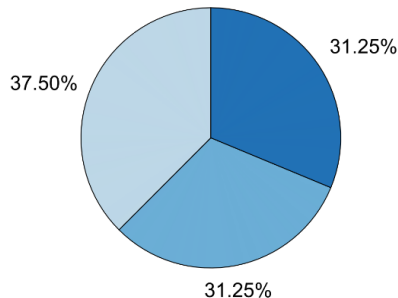
Dataset: “VOLUME” resource of 5 UK research centres

Statistical Analysis:

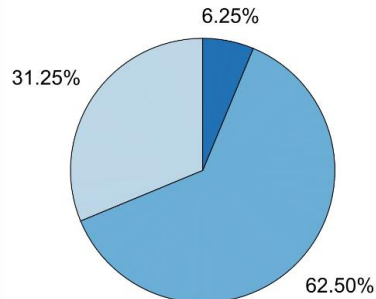
1. Intra-class correlation
2. Coefficient of variation (%)
3. Mean relative difference (%)

Study 4: Results

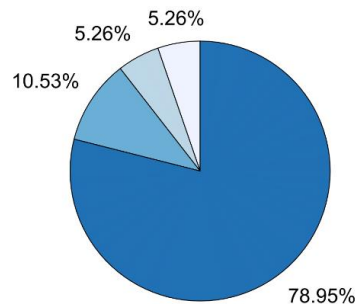
Shape radiomics
LV myocardium



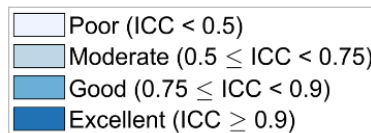
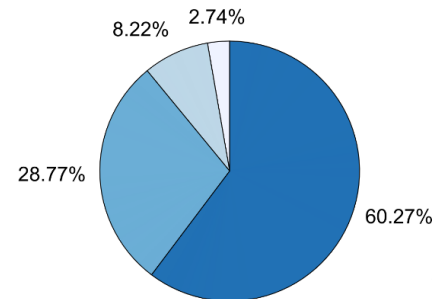
Shape radiomics
RV



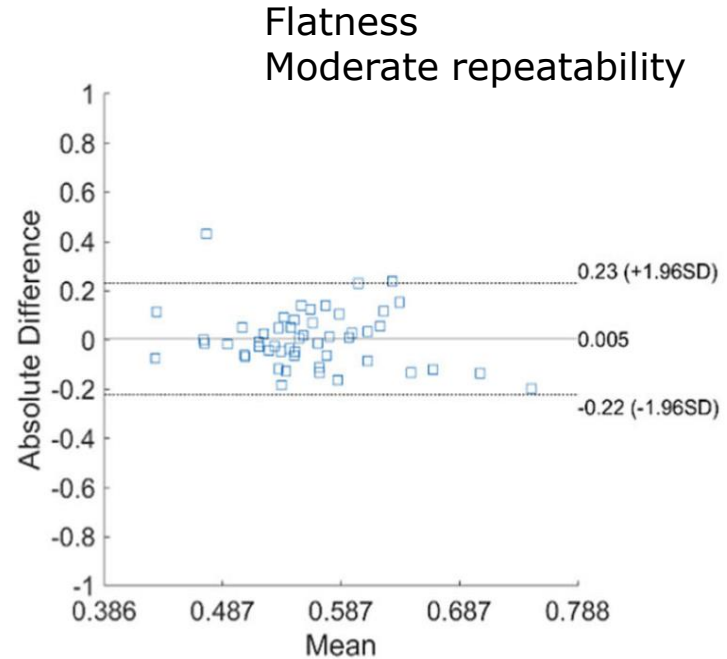
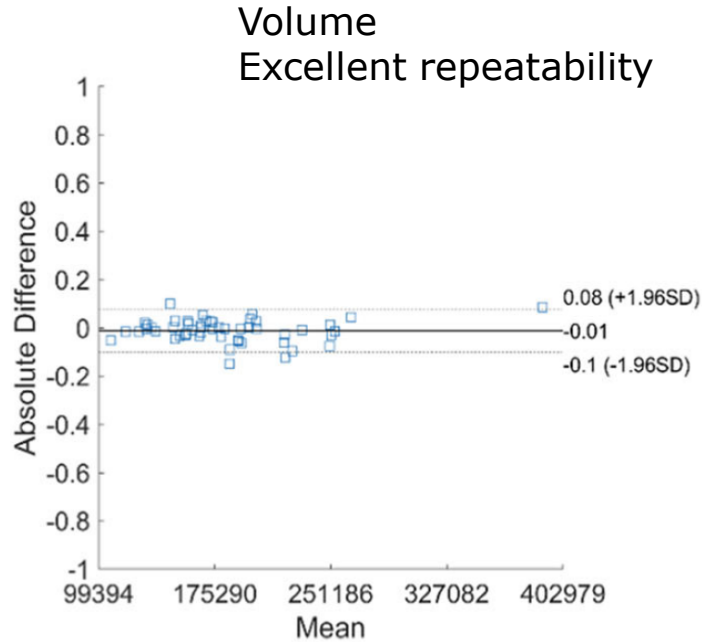
Intensity radiomics
LV myocardium



Texture radiomics
RV

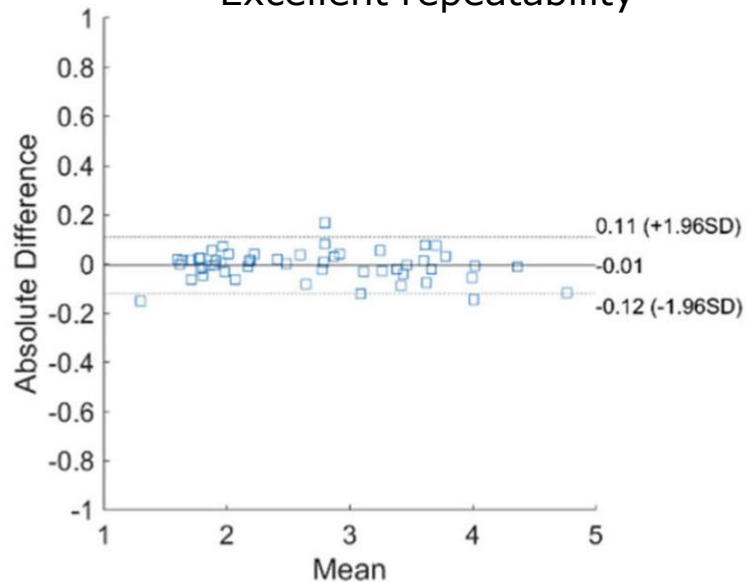


Study 4: Analysis of Shape Features

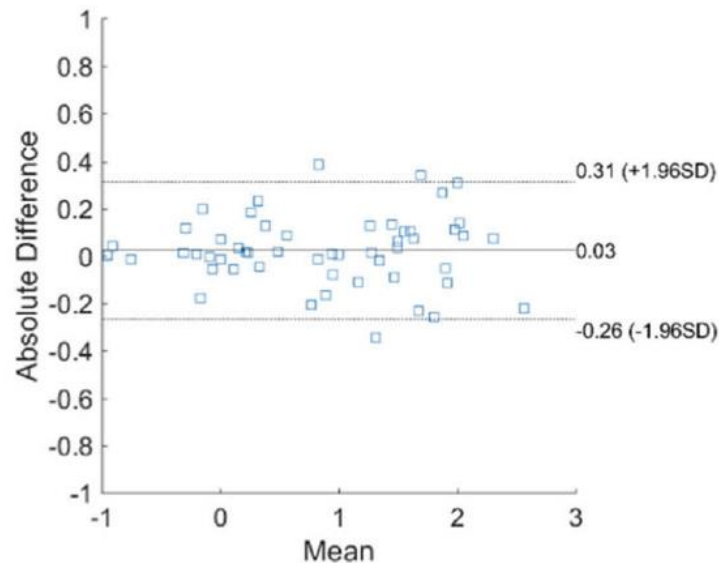


Study 4: Analysis of Intensity Features

Entropy
Excellent repeatability



Skewness
Good repeatability



Study 5: Radiomics Normalisation



Minimising multi-centre radiomics variability through image normalisation: A pilot study

Victor M. Campello^{1,*}, Carlos Martín-Isla¹, Cristian Izquierdo¹, Andrea Guala^{2,3}, José F. Rodríguez Palomares^{2,3,4}, David Viladés⁵, Martín L. Descalzo⁵, Mahir Karakas^{6,7}, Ersin Çavuş^{6,7}, Zahra Raisi-Estabragh^{8,9}, Steffen E. Petersen^{8,9,10,11}, Sergio Escalera^{1,12}, Santi Seguí¹, and Karim Lekadir¹

¹Artificial Intelligence in Medicine Lab (BCN-AIM), Barcelona, Spain

²Vall d'Hebron Institut de Recerca (VHIR), Barcelona, Spain

³CIBER-CV, Instituto de Salud Carlos III, Madrid, Spain

⁴Department of Cardiology, Hospital Universitari Vall d'Hebron, Barcelona, Spain

⁵Cardiac Imaging Unit, Cardiology Service, Hospital de la Santa Creu i Sant Pau, Universitat Autònoma de Barcelona, Barcelona, Spain

⁶Dept. of Cardiology, University Heart & Vascular Center Hamburg, Hamburg, Germany

⁷DZHK (German Center for Cardiovascular Research), Germany

Sample size: 218 subjects

Datasets:



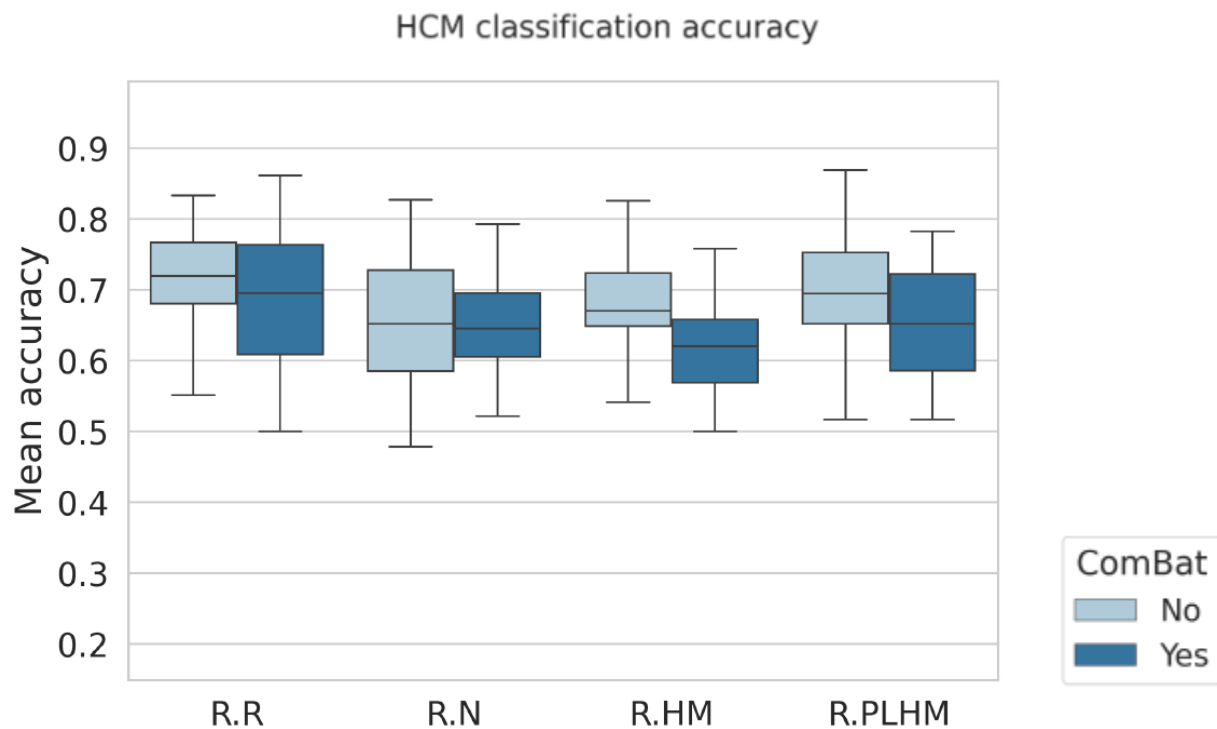
Diseases:

- Hypertrophic Cardiomyopathy (HCM) – 106 cases

Methods for normalisation:

1. Combat
2. Intensity rescaling (R)
3. Intensity normalisation (N)
4. Histogram normalisation (HN)
5. Piecewise normalisation (PHN)

Study 5: Results



Future of Radiomics in CMR: Opportunities & Challenges

Other Works in CMR Radiomics

Myocarditis

Cardiac MRI Texture Analysis of T1 and T2 Maps in Patients with Infarctlike Acute Myocarditis

Hypertrophic
Cardiomyopathy

Radiomic Analysis of Myocardial Native T₁ Imaging Discriminates Between Hypertensive Heart Disease and Hypertrophic Cardiomyopathy

Ischemic Heart
Disease

New Imaging Signatures of Cardiac Alterations in Ischaemic Heart Disease and Cerebrovascular Disease Using CMR Radiomics

Myocardial Infarction

Texture analysis of cardiac cine magnetic resonance imaging to detect nonviable segments in patients with chronic myocardial infarction



ALL

PROTEOMICS

IMAGING

OMICS

Homepage

User Workspace

Get Data

Run Tool / Visualizer

Help

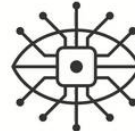
This is the 1.1 version of EC8H VRE



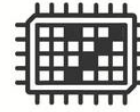
machine learning
toolbox



multi-omics
network analysis



radiomics
analysis



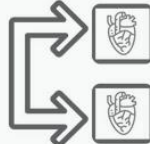
RNA-seq
analysis



SNP
filtering



biobb
MD setup



DICOM 2 NIFTI
converter



cardiac image
segmentation

DICOM to NIFTI file type converter



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BARCELONA



Stanford
University



Queen Mary
University of London



Vall d'Hebron
Hospital



Disclosure

- **No conflict to declare**

