AI for Rapid CMR: Parametric Mapping

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EACVI
May 5, 2022

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Declaration of Financial Interests or Relationships

Speaker Name: Nicole Seiberlich

I have the following financial interest or relationship to disclose with regard to the subject matter of this presentation:

Company Name: Siemens

Type of Relationship: Research Support, Royalties for MRF

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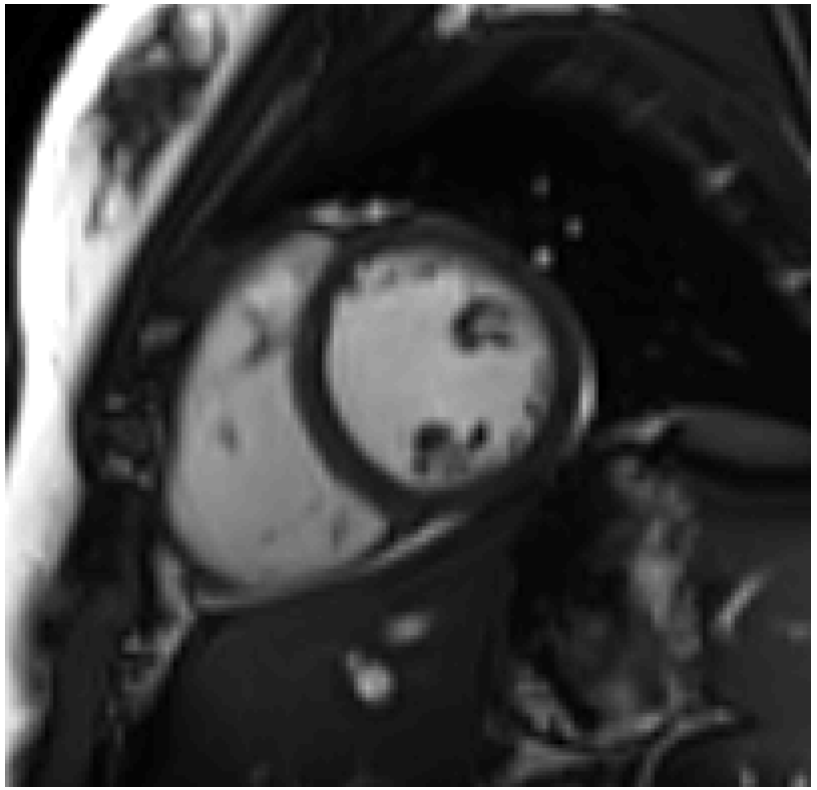
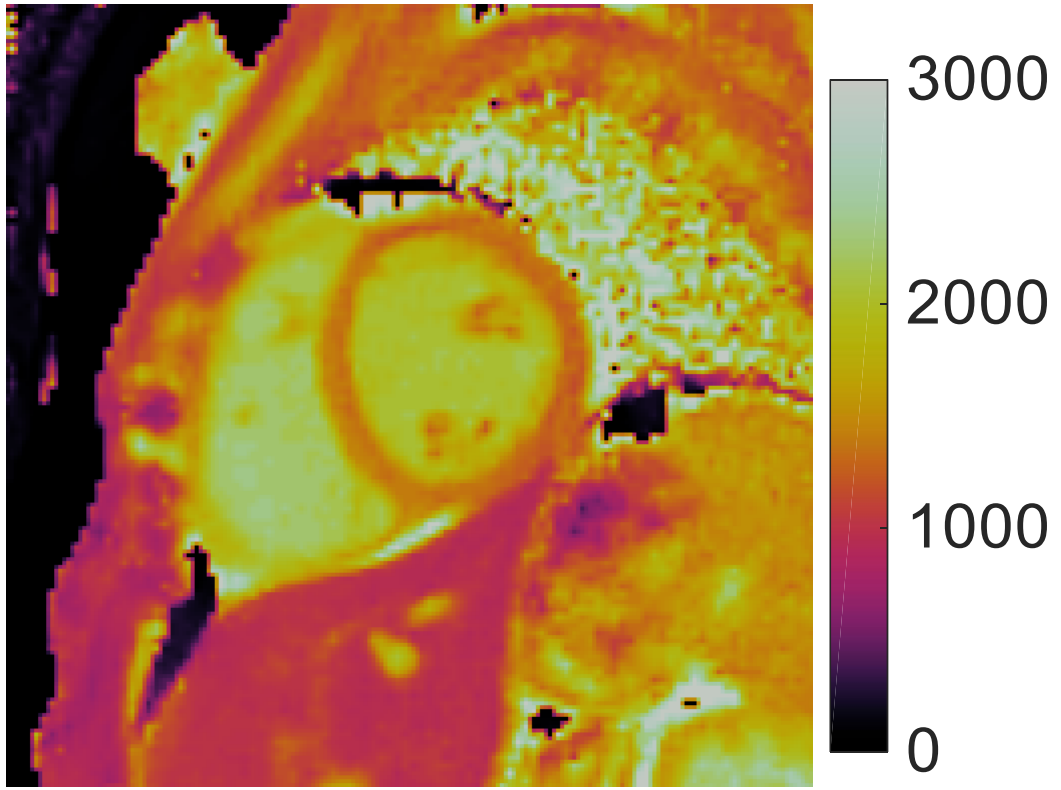
Qualitative Imaging vs. Quantitative Mapping

Balanced SSFP



T_1 Map



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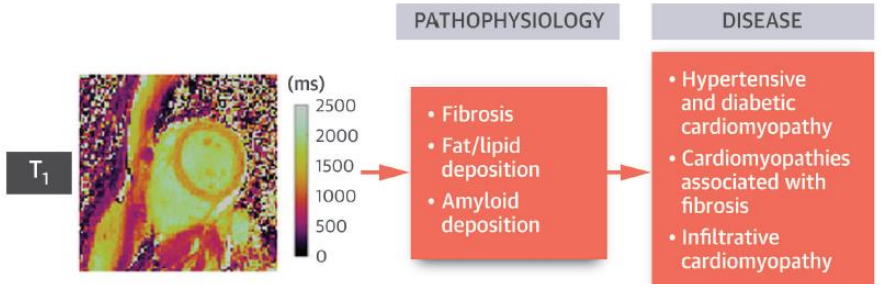
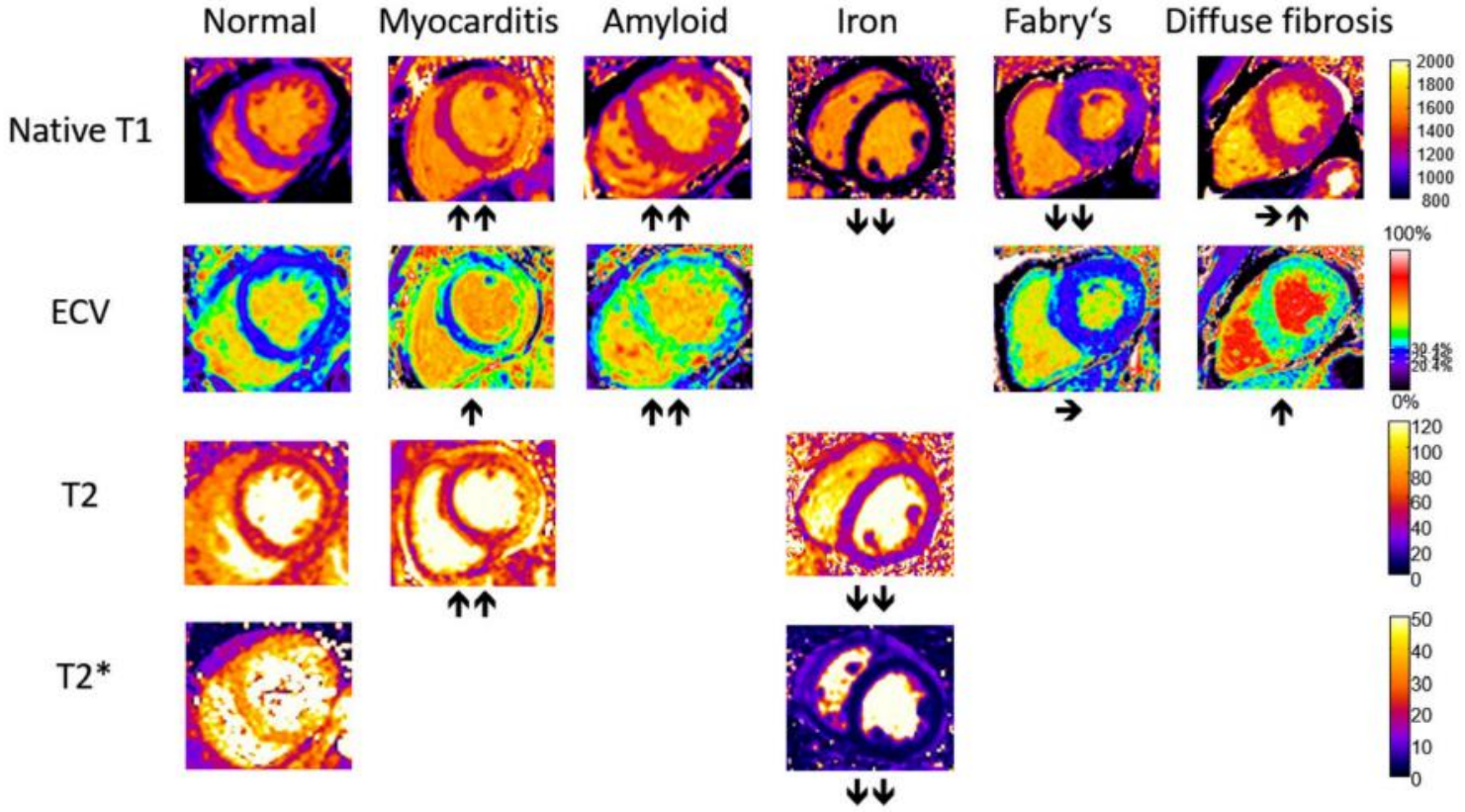
Different Tissue Properties → Different Pathologies





1. Liu et al. J Am Coll Cardiol Img (2018) 11:1837–53.
2. Messroghli et al. Journal of Cardiovascular Magnetic Resonance (2017) 19:75.

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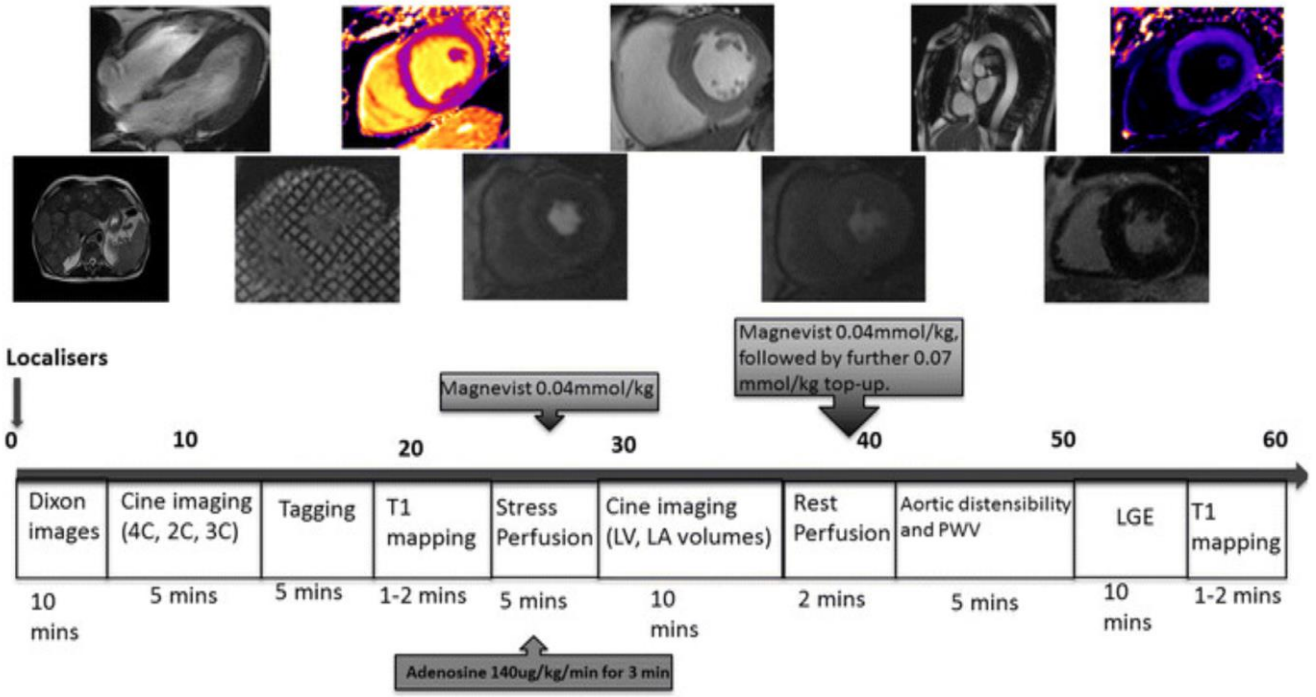
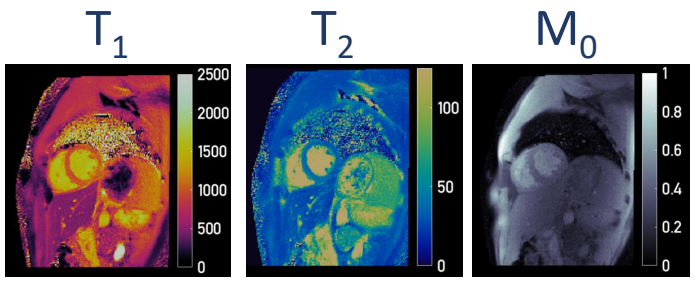
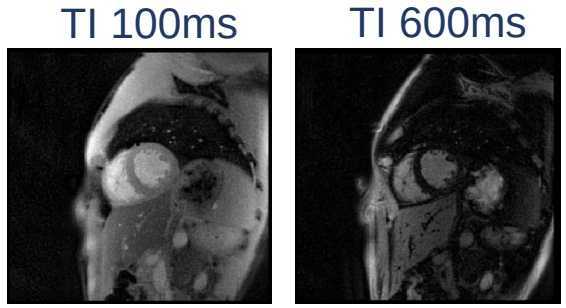
Parametric Mapping = Rapid CMR?

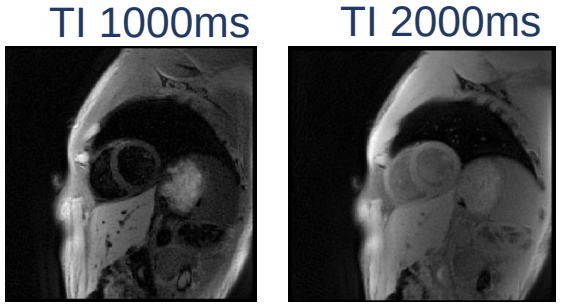
Instead of



We could







Htike ZZ, Yates T, Brady EM, Webb D, Gray LJ, Swarbrick D, McCann GP, et al. Cardiovasc Diabetol. 2016 Jul 21;15(1):102.

Shorten CMR scan time

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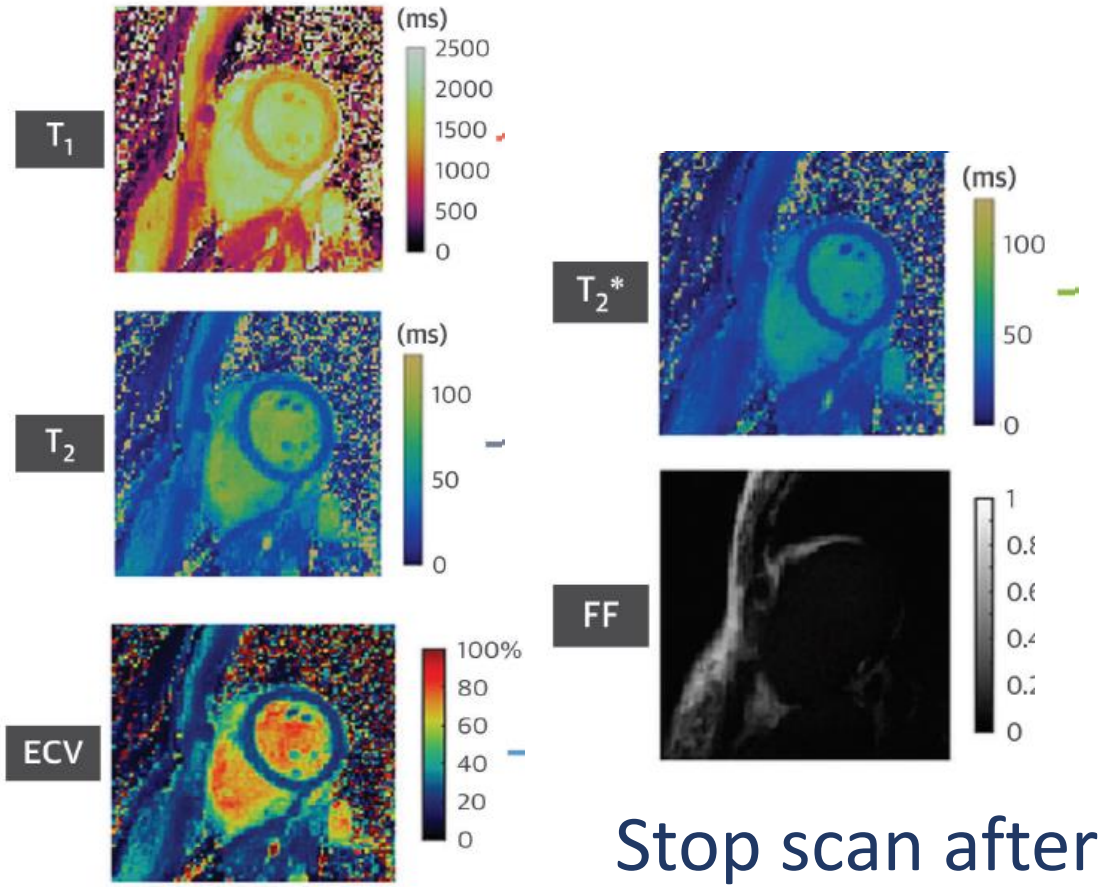
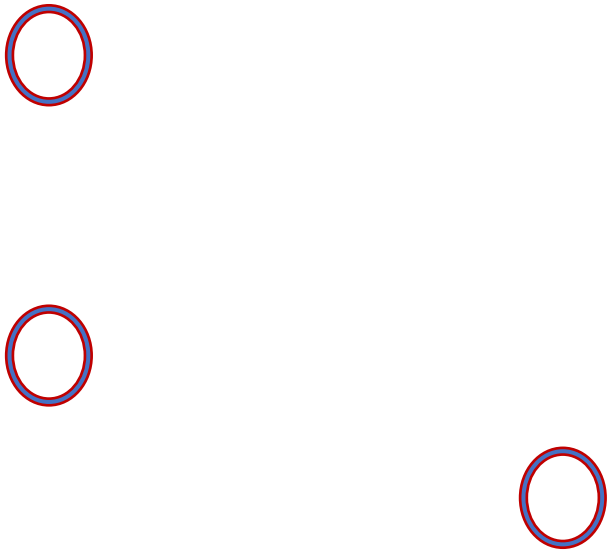
Parametric Mapping = Rapid CMR?

Instead of



We could



Stop scan after sufficient info has been collected

Reduce burden on physician readers

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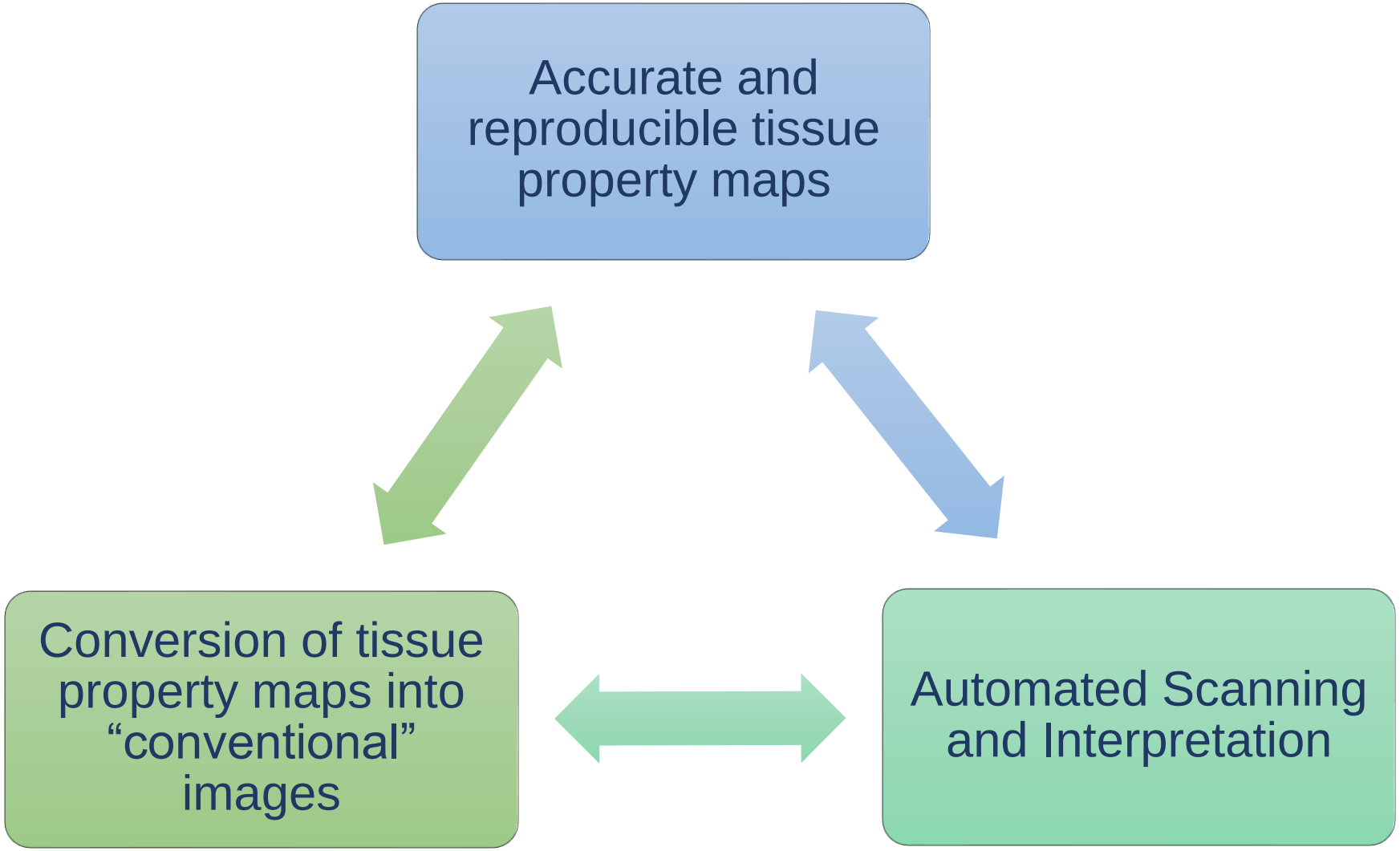
Role of Artificial Intelligence in CMR Mapping



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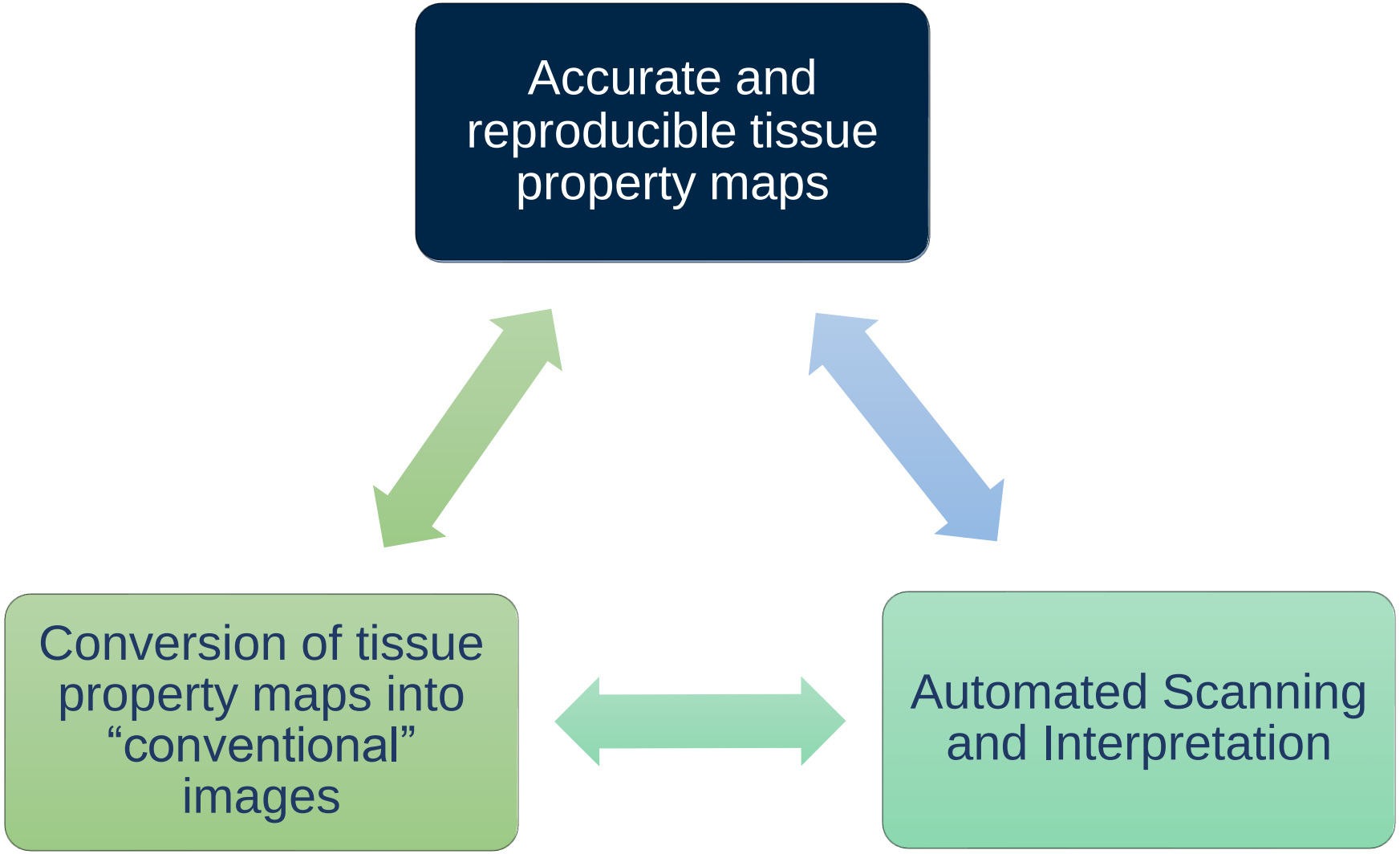
Role of Artificial Intelligence in CMR Mapping



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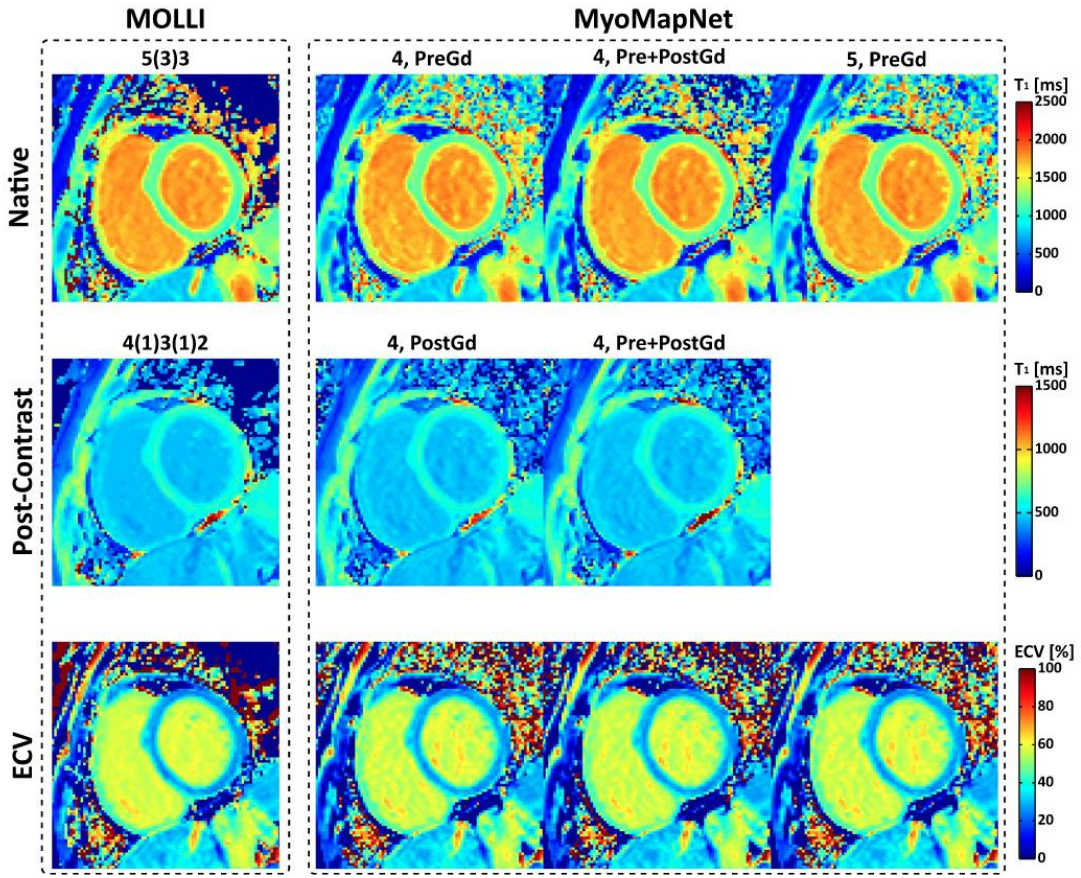
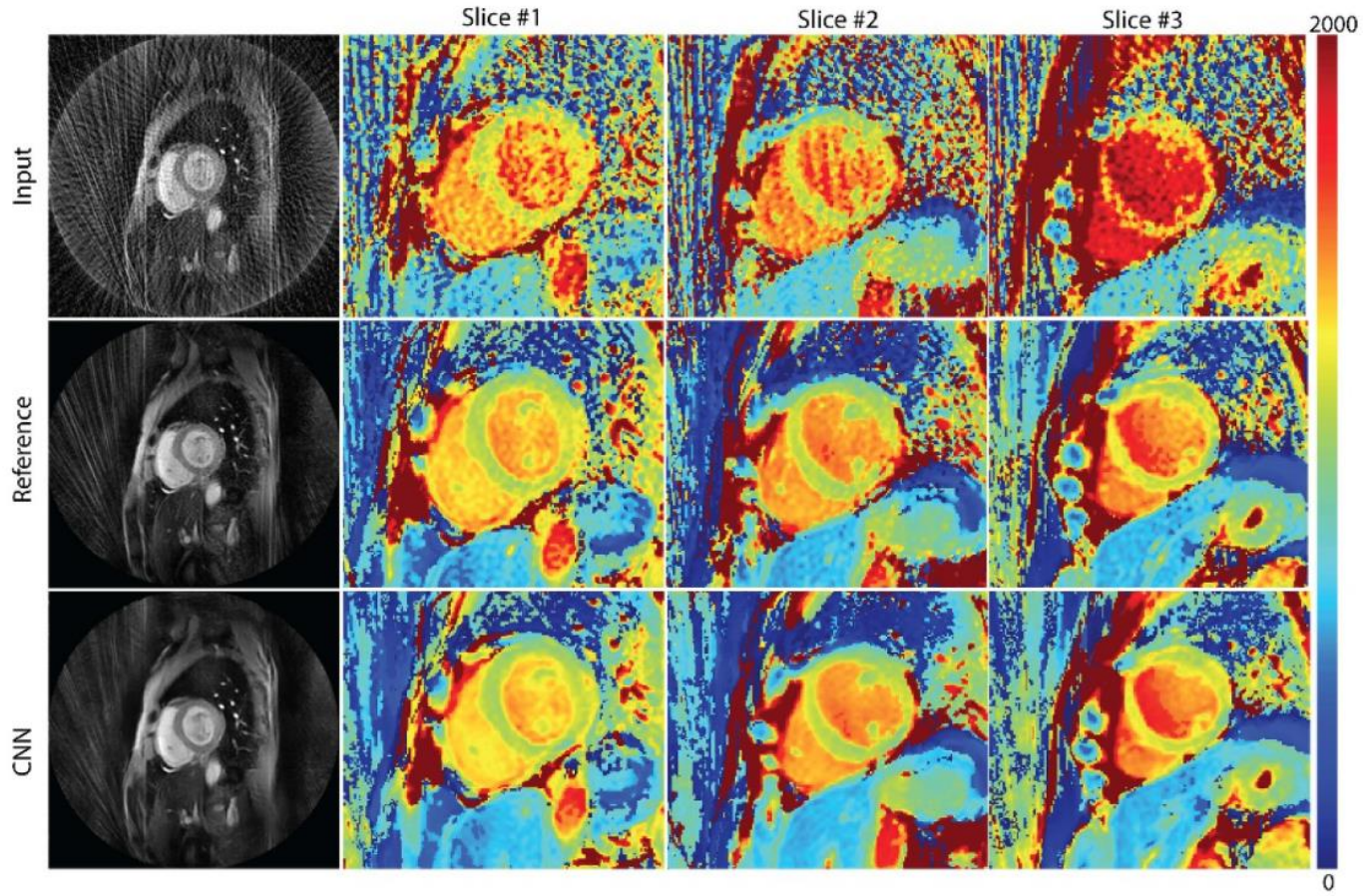
AI to accelerate T_1 mapping



Guo R, et al. Accelerated cardiac T_1 mapping in four heartbeats with inline MyoMapNet: a deep learning-based T_1 estimation approach. J Cardiovasc Magn Reson. 2022 Jan 6;24(1):6.



Nezafat M, et al. Deep convolution neural networks based artifact suppression in under-sampled radial acquisitions of myocardial T_1 mapping images. Phys Med Biol. 2020 Nov 24;65(22):225024.

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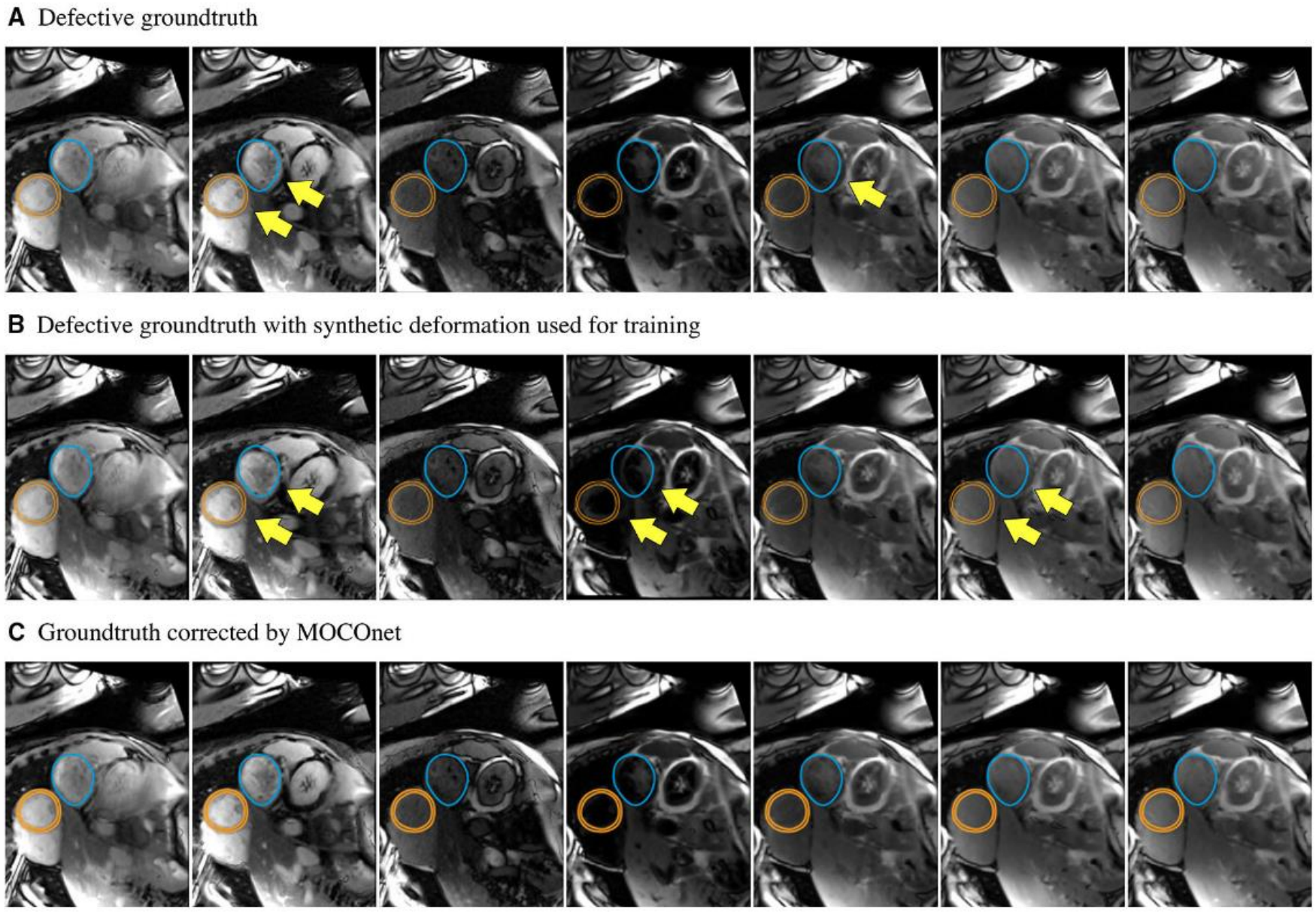
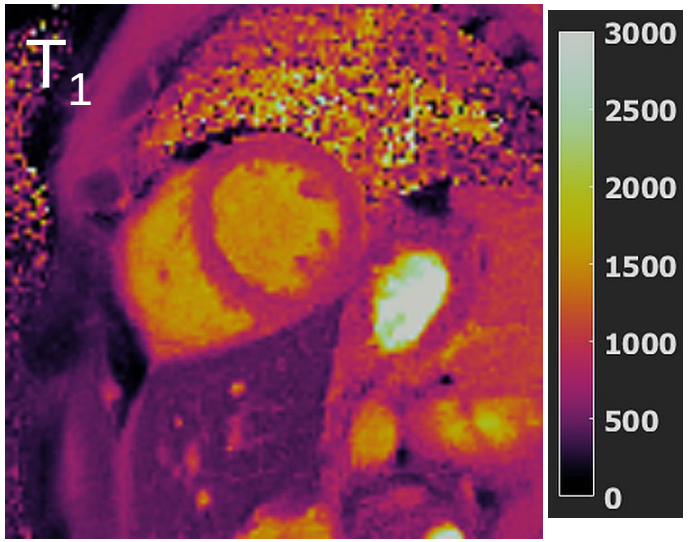
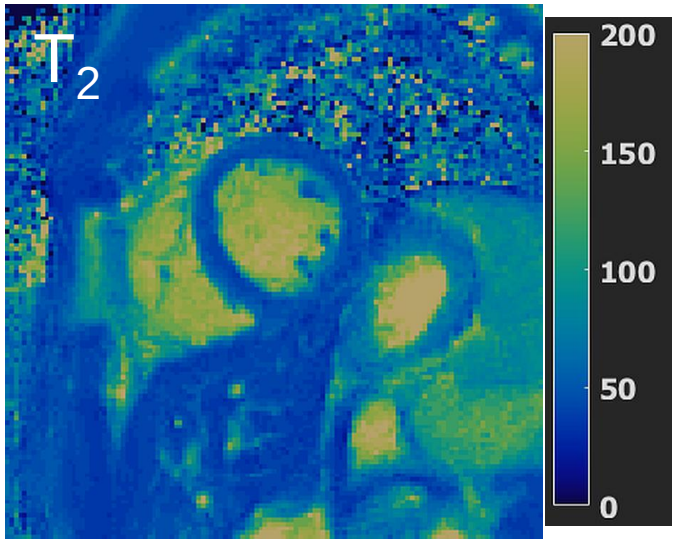
AI-facilitated motion correction for improved T_1 mapping

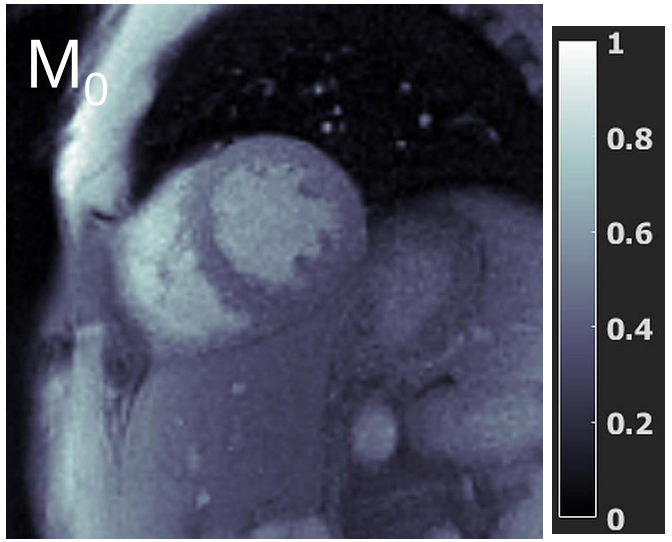


Gonzales RA, et al. MOCOnet: Robust Motion Correction of Cardiovascular Magnetic Resonance T1 Mapping Using Convolutional Neural Networks. Front Cardiovasc Med. 2021 Nov 23;8:768245.

AI for multi-parametric approaches







Hamilton JI, et al. Deep learning reconstruction for cardiac magnetic resonance fingerprinting T_1 and T_2 mapping. Magn Reson Med. 2021 Apr;85(4):2127-2135.

Shao J, et al. Fast and accurate calculation of myocardial T_1 and T_2 values using deep learning Bloch equation simulations (DeepBLESS). Magn Reson Med. 2020 Nov;84(5):2831-2845.

Chen Y, et al. Deep learning within *a priori* temporal feature spaces for large-scale dynamic MR image reconstruction: Application to 5-D cardiac MR Multitasking. Med Image Comput Comput Assist Interv. 2019 Oct;11765:495-504.

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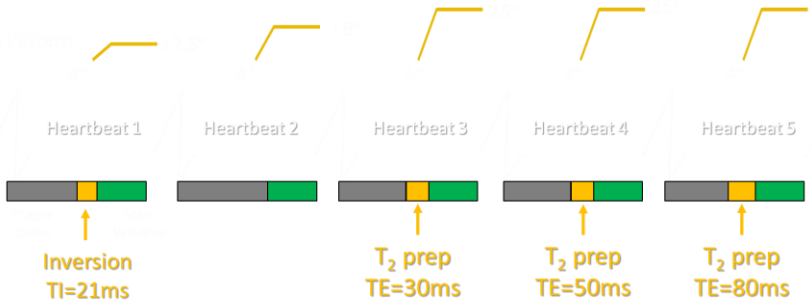
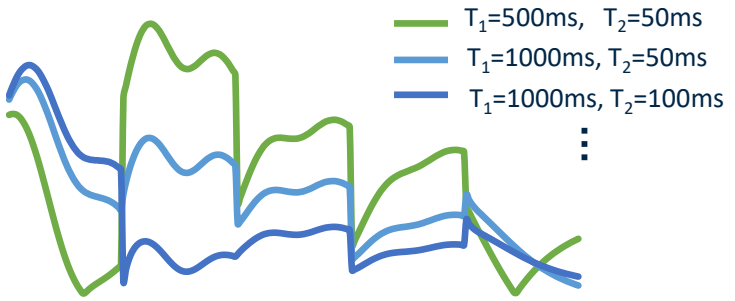
Cardiac Magnetic Resonance Fingerprinting[1,2]

Time-Varying Pulse Sequence



Bloch equation simulation
(including cardiac rhythm from ECG)

MRF Dictionary

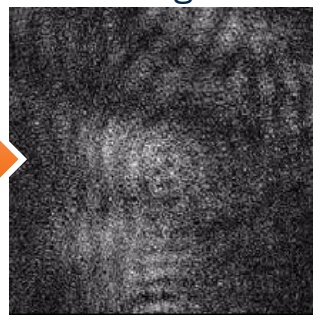


Highly Undersampled Non-Cartesian Acquisition

k-space

Golden angle spiral (R=48)

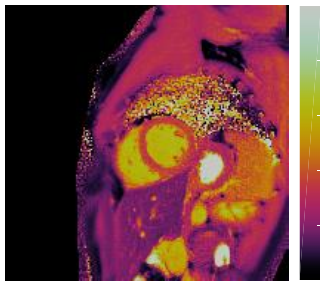
image



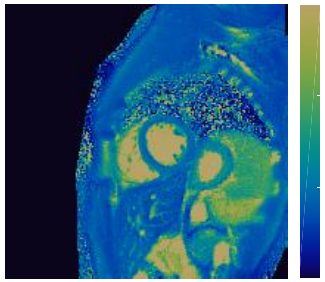
Pattern Matching

Quantitative Maps

T_1



T_2



[1] Ma D, et al. *Nature* 2013;495(7440):187-192.
[2] Hamilton J, et al. *MRM* 2017; 77(4):1446-1458.

Courtesy of Jesse Hamilton

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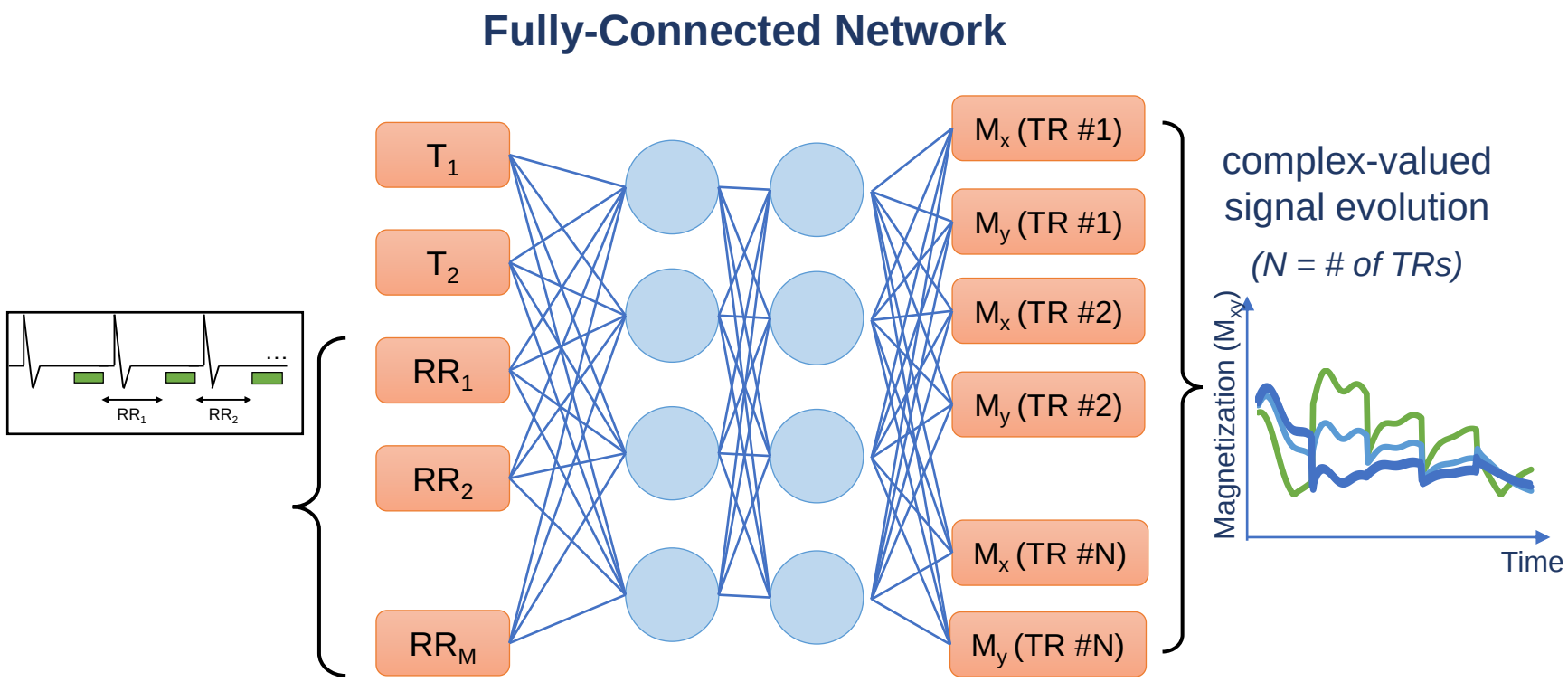
Fingerprint Generator Network[1]



Time needed to simulate ~30,000 fingerprints:

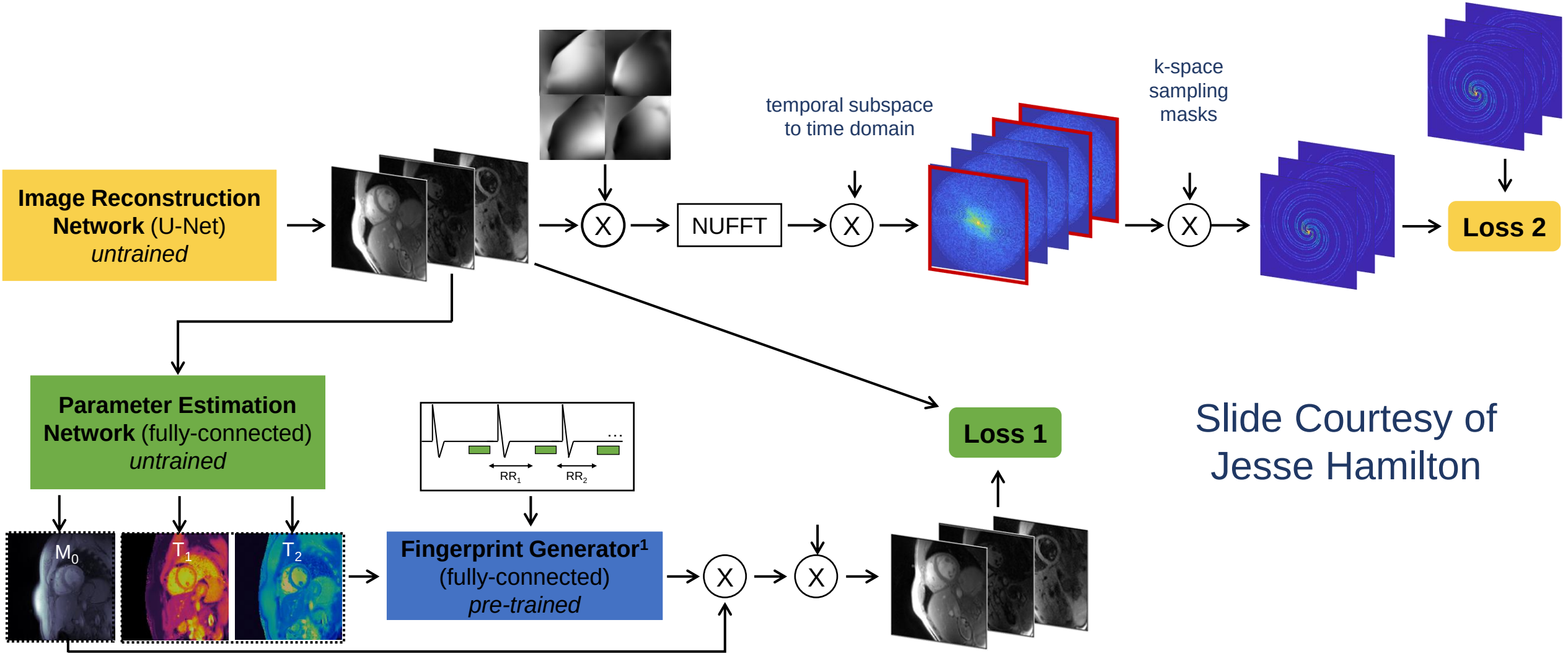
5 min
Bloch equation simulation
Compiled MATLAB Mex
12 parallel cores

30 ms
Neural network
Tensorflow / Keras
GPU

Slide Courtesy of Jesse Hamilton

1. Hamilton JI, Seiberlich N. **Machine Learning for Rapid Magnetic Resonance Fingerprinting Tissue Property Quantification**. Proc IEEE. 2020;108(1):69-85.

Self-Supervised Training of cMRF Deep Image Prior



Slide Courtesy of Jesse Hamilton

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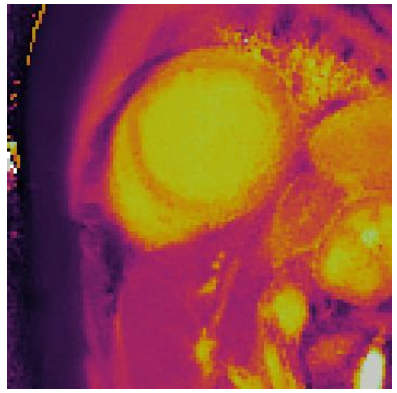
Cardiomyopathy Patient Example: Reduced Motion Artifacts

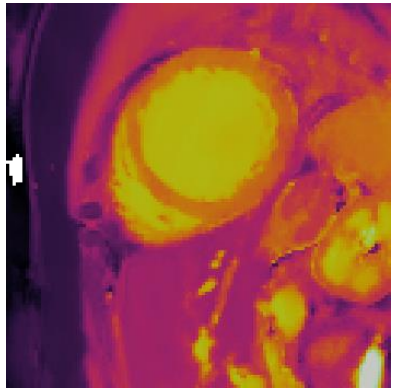
MRF
15HB Breathhold
250ms Acquisition Window
Low-Rank Reconstruction

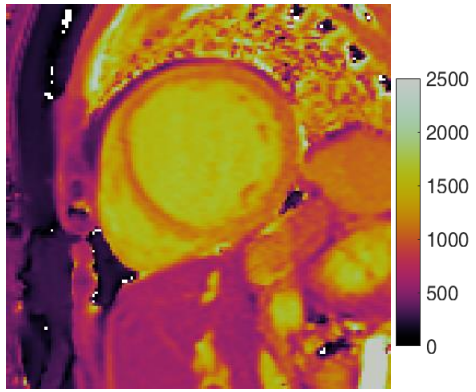
MRF
5HB Breathhold
150ms Acquisition Window
Deep Image Prior

Conventional Mapping

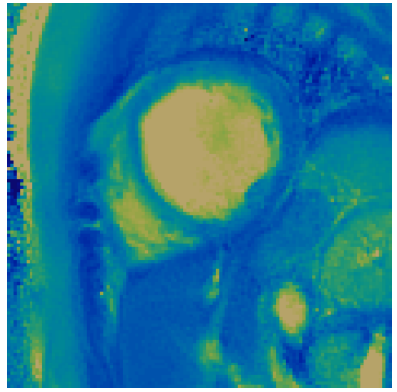
T_1

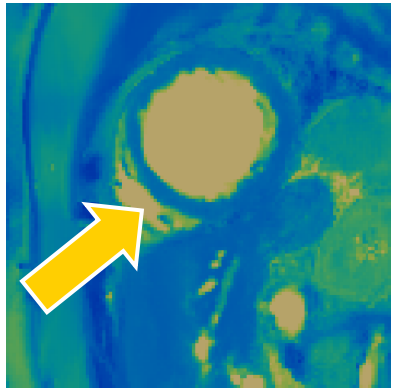


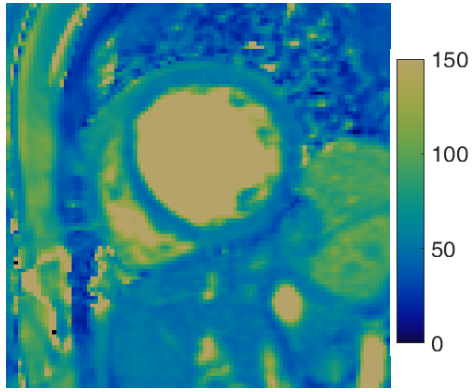




T_2







AI leads to
shorter scan
and
better maps!

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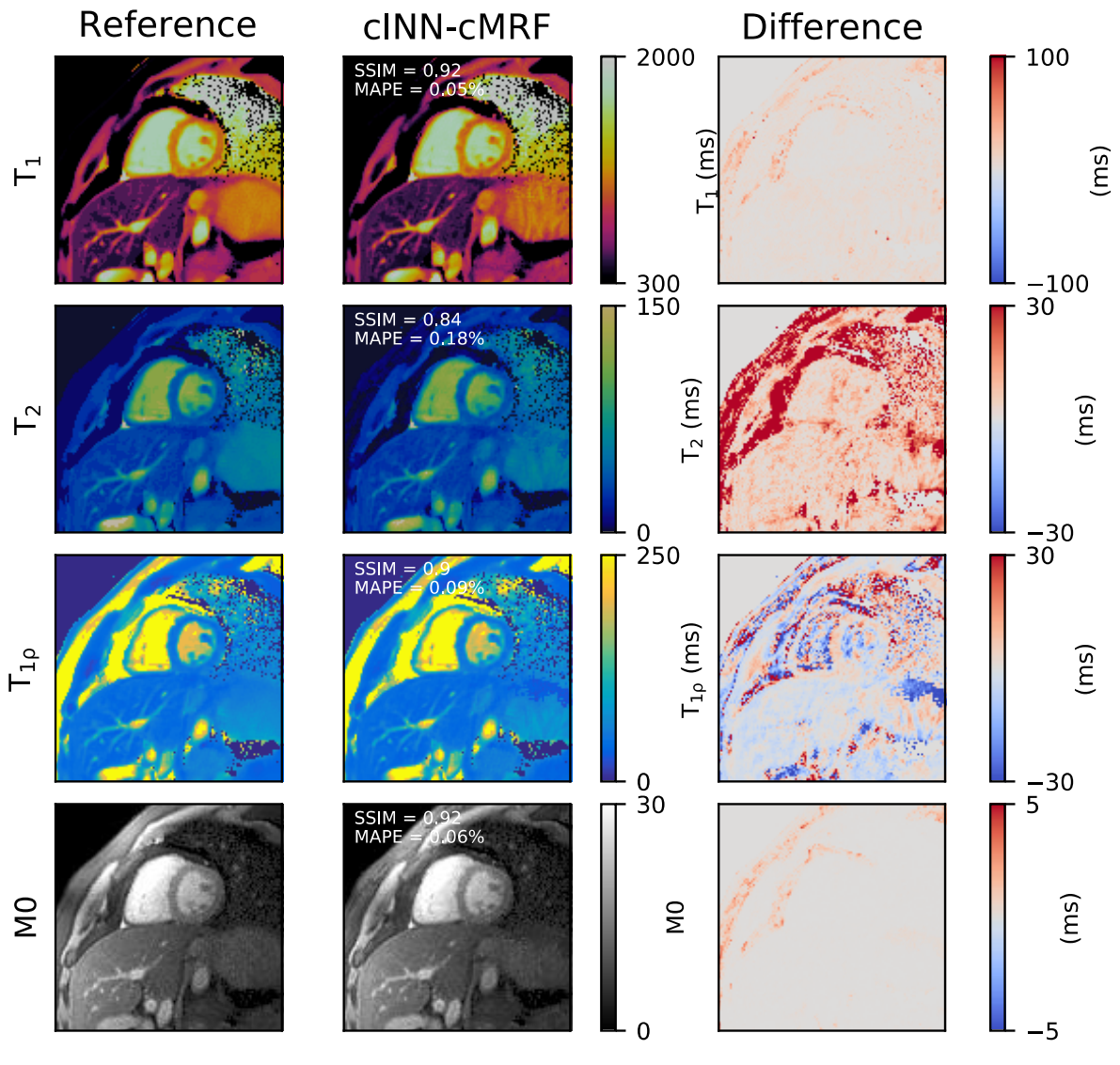
Conditional Invertible Neural Network for Cardiac MRF

Thomas J. Fletcher, Carlos Velasco, Gastão Cruz, Alina Schneider, René M. Botnar and Claudia Prieto, ISMRM 2022

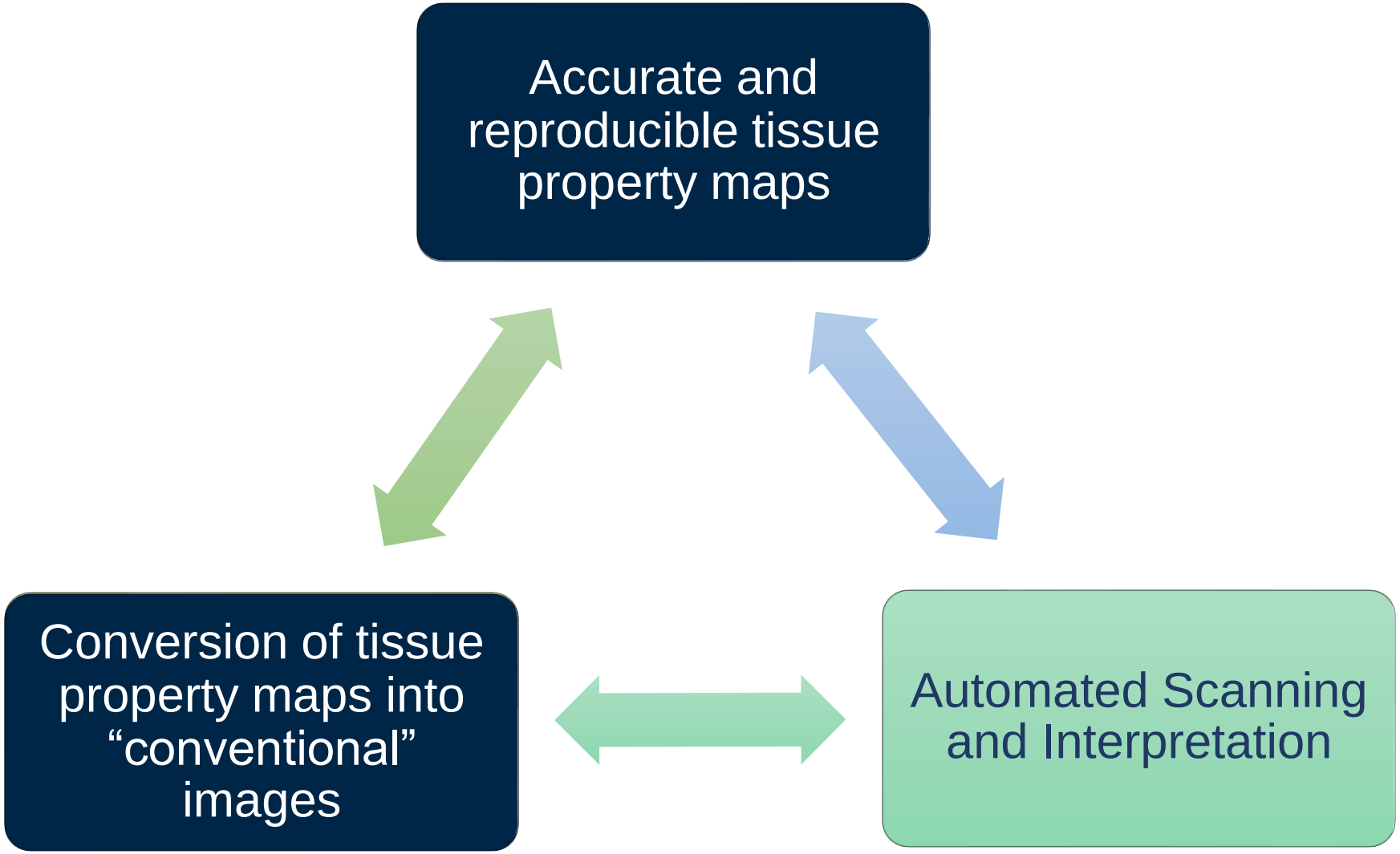
KING'S College LONDON

cINN-cMRF provides accurate predictions for parameter maps in 3.2 seconds without the need of additional dictionary generation

- Simulated test data evaluated on the cINN-cMRF achieves excellent agreement with ground truth (EPG and pattern matching based) maps
- SSIM > 0.84 and low relative errors for myocardium
- Further work will investigate the inclusion of a latent space in the network, improvements to simulated data and tuning of the network for *in-vivo* data



Role of Artificial Intelligence in CMR Mapping



Synthetic MRI for Multiple Contrasts

T_1 and PD weighted

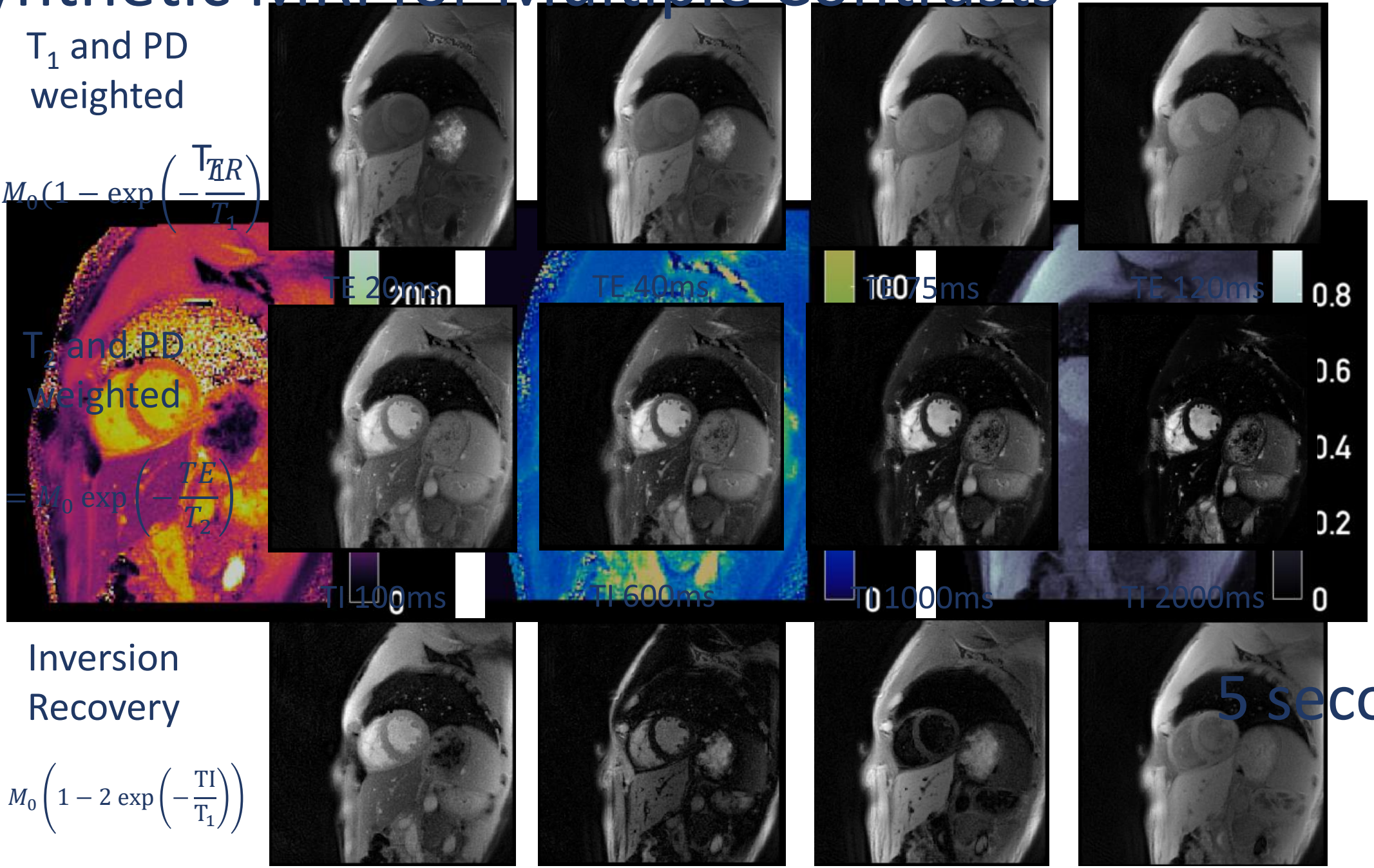
$$S = M_0\left(1 - \exp\left(-\frac{TR}{T_1}\right)\right)$$

T_2 and PD weighted

$$S = M_0 \exp\left(-\frac{TE}{T_2}\right)$$

Inversion Recovery

$$S = M_0\left(1 - 2\exp\left(-\frac{TI}{T_1}\right)\right)$$



5 seconds!

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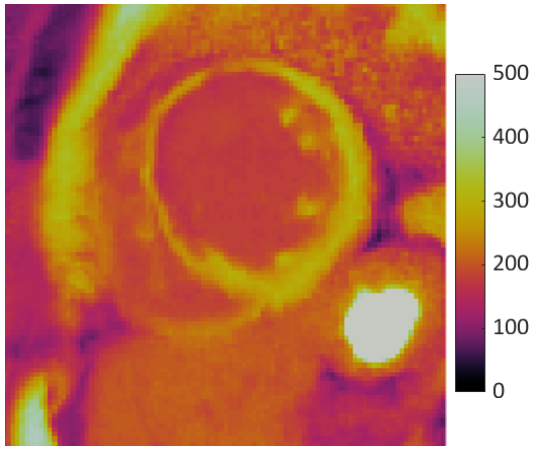
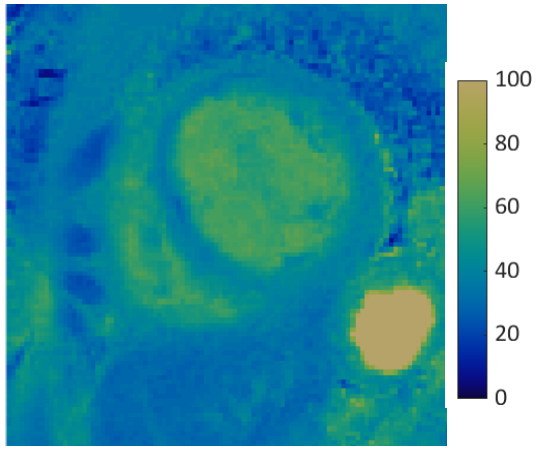
Patient with Ischemic Cardiomyopathy

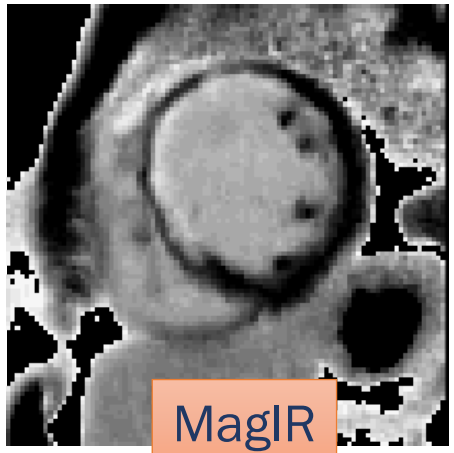
MRF Post-Contrast T_1

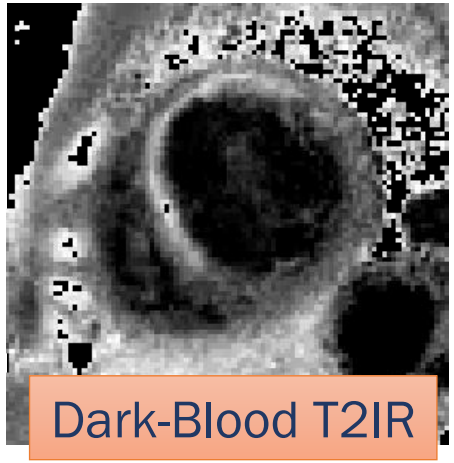


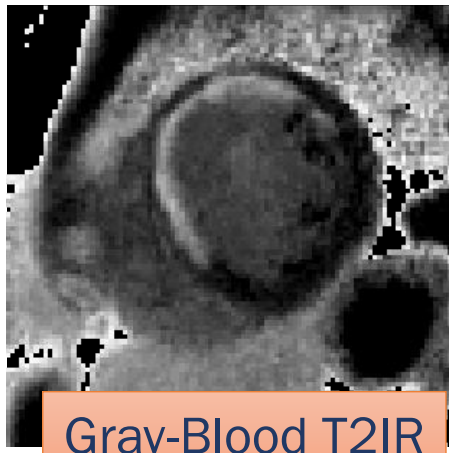
MRF Post-Contrast T_2

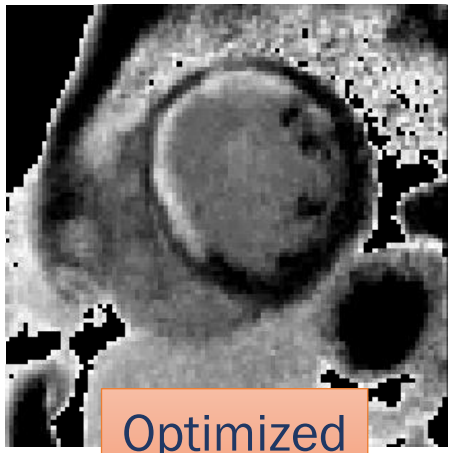


Synthetic Multicontrast LGE

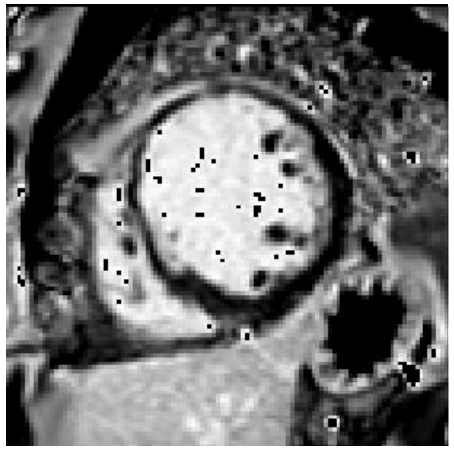








Conventional LGE



Not yet informed by AI but…..

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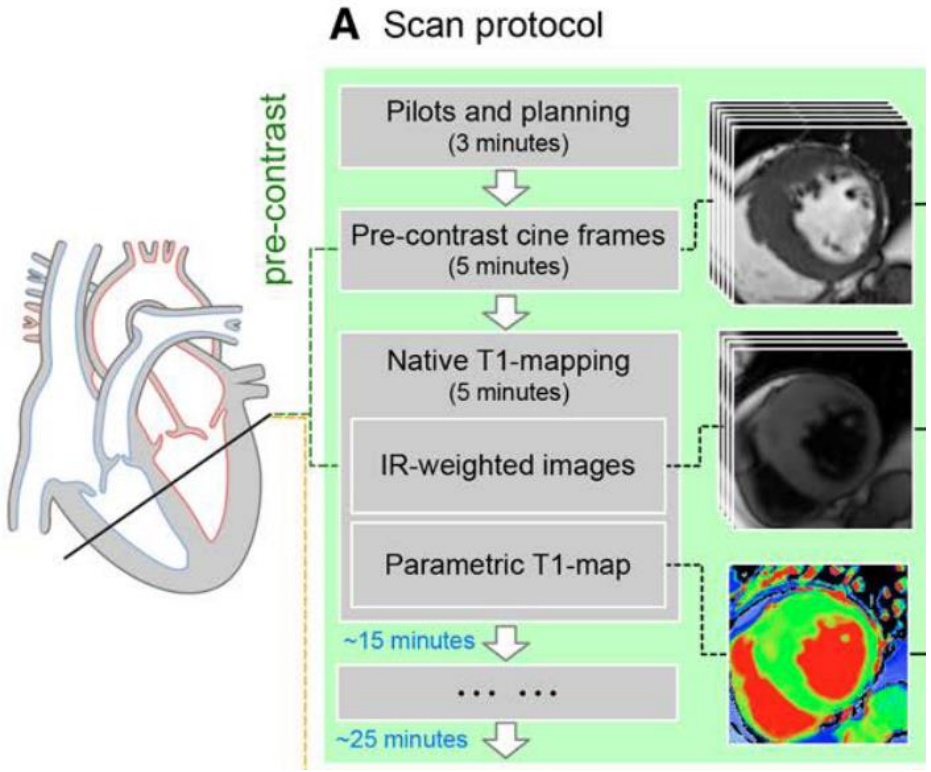
Contrast-Free Enhancement via Deep Learning?



Next Step →
Move to comprehensive synthetic imaging via Parametric Mapping + AI

Zhang Q, et al. Toward Replacing Late Gadolinium Enhancement With Artificial Intelligence Virtual Native Enhancement for Gadolinium-Free Cardiovascular Magnetic Resonance Tissue Characterization in Hypertrophic Cardiomyopathy. *Circulation*. 2021;144(8):589-599.

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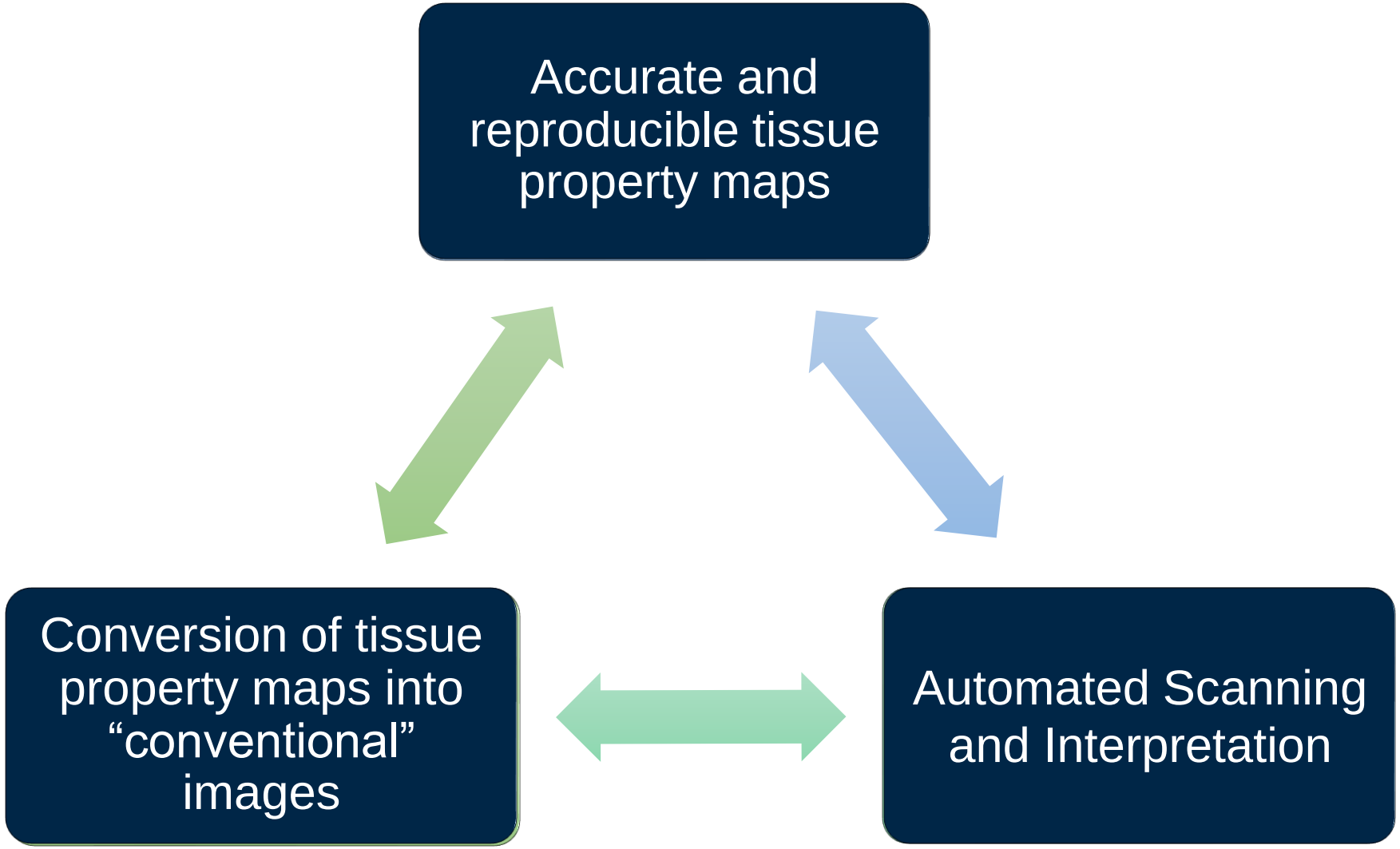
Role of Artificial Intelligence



Automated analysis of T_1 maps

Fahmy AS et al. J Cardiovasc Magn Reson. 2019 Jan 14;21(1):7.

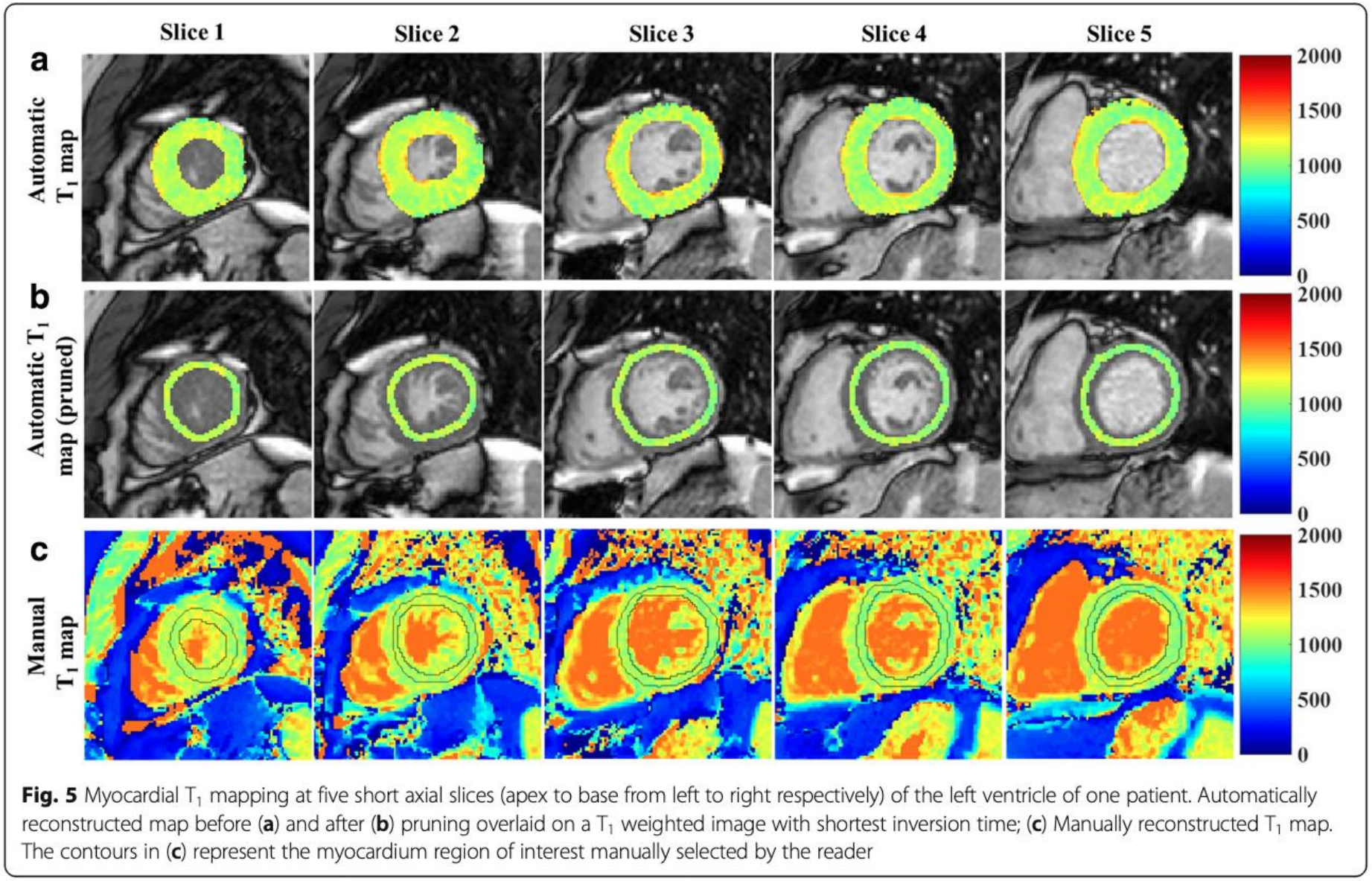


Fig. 5 Myocardial T_1 mapping at five short axial slices (apex to base from left to right respectively) of the left ventricle of one patient. Automatically reconstructed map before (**a**) and after (**b**) pruning overlaid on a T_1 weighted image with shortest inversion time; (**c**) Manually reconstructed T_1 map. The contours in (**c**) represent the myocardium region of interest manually selected by the reader

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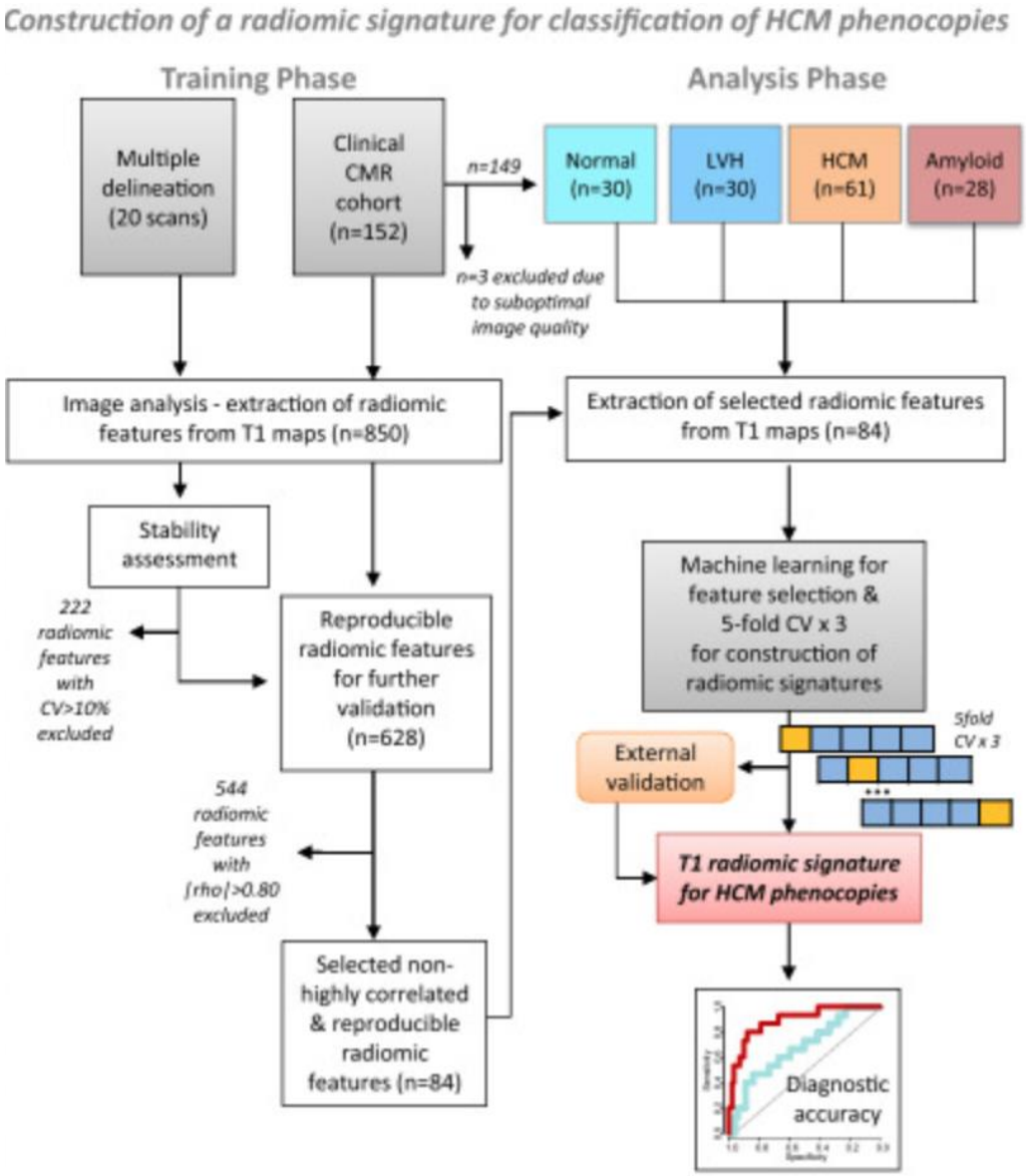
Automated diagnosis using quantitative mapping and AI

Antonopoulos AS, et al. Machine learning of native T1 mapping radiomics for classification of hypertrophic cardiomyopathy phenotypes. Sci Rep. 2021 Dec 8;11(1):23596.

What could AI do with more tissue properties, collected in a consistent fashion?



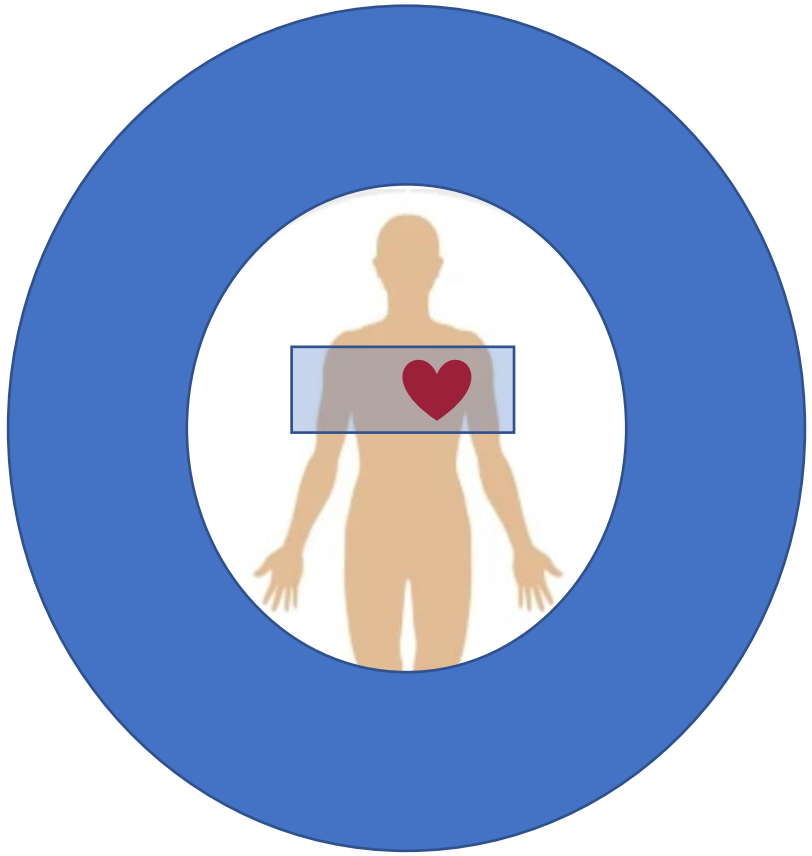
Role of AI and Parametric Mapping in Rapid CMR

Accurate and reproducible tissue property maps

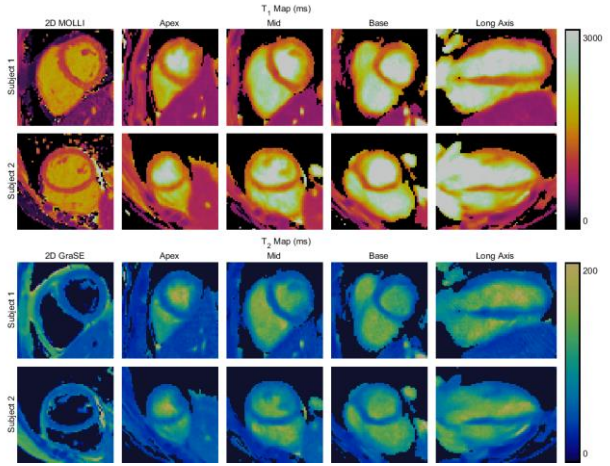
Conversion of tissue property maps into “conventional” images

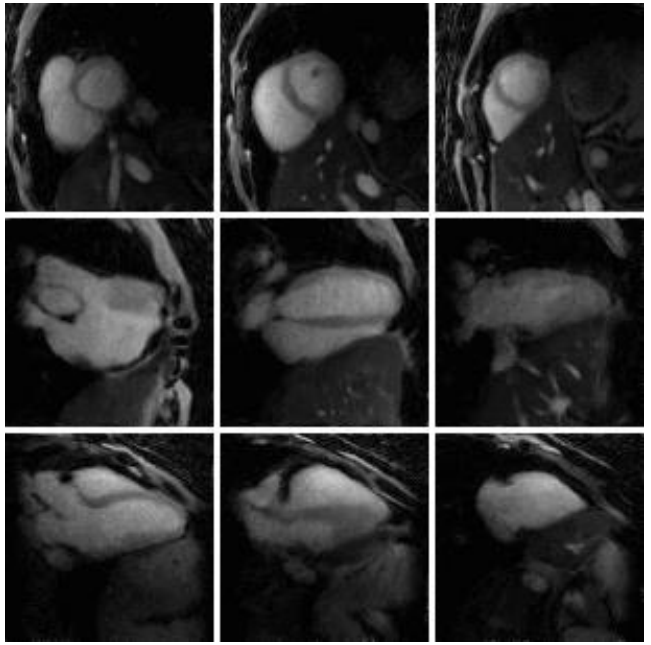
Automated Scanning and Interpretation

Smart CMR exam via AI-enabled parametric mapping



- Collect 3D free-running (no breathholding, gating, or contrast?) isotropic data to quantify multiple tissue properties





3D T1 & T2 maps and whole-heart CINE imaging (2mm isotropic) from a **single 3 minute scan**

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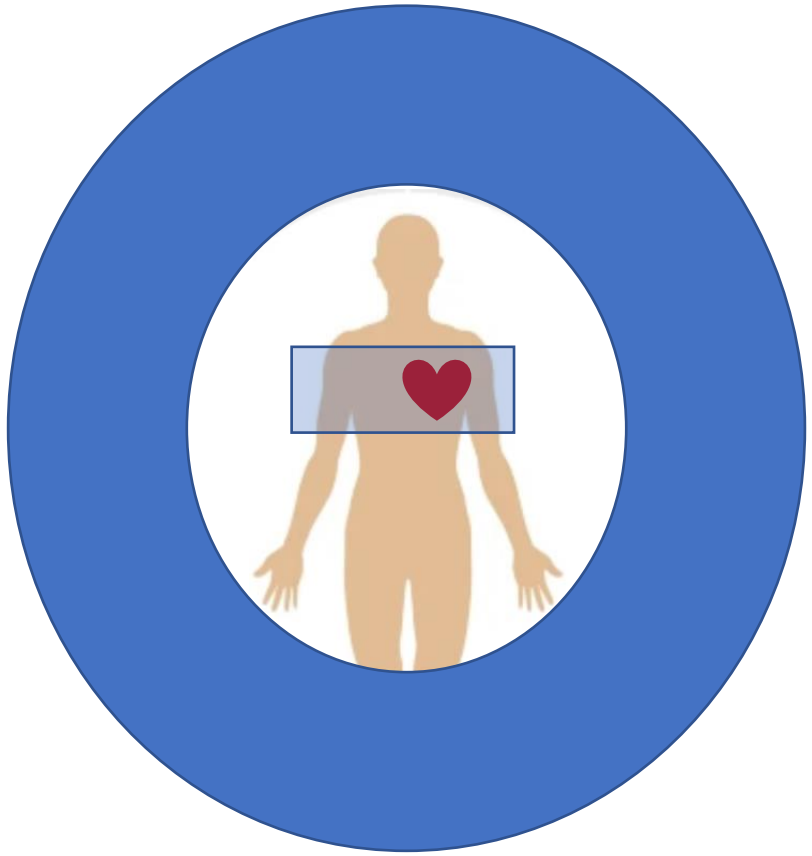
Smart CMR exam via AI-enabled parametric mapping



- Collect 3D free-running (no breathholding, gating, or contrast?) isotropic data to quantify multiple tissue properties
- Output standardized maps / synthetic images showing function and tissue characteristics
- Stop data collection once sufficient info is available according to AI physician assistant

Contijoch F, et al. Closed-loop control of k-space sampling via physiologic feedback for cine MRI. PLoS One. 2020 Dec 29;15(12):e0244286.

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Role of AI and Parametric Mapping in Rapid CMR

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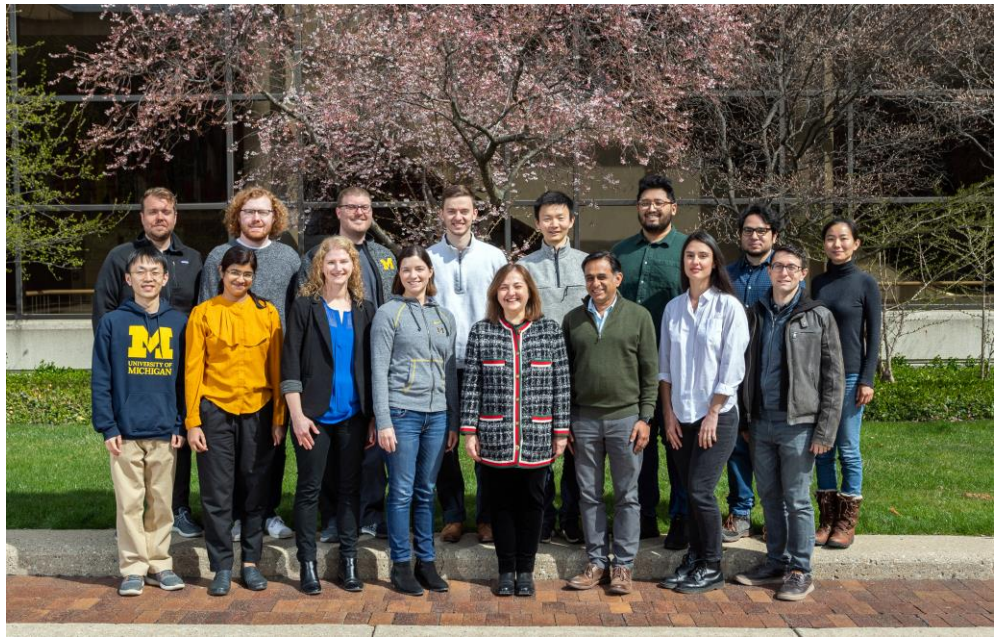
Acknowledgments

MIITT / Seiberlich Lab

- Vikas Gulani
- Hero Hussian
- Jesse Hamilton
- Yun Jiang
- Katherine Wright
- Rachel Liu
- Alex Fyrdahl
- Evan Cummings
- James Ahad
- Anupama Ramachandran
- Anna Lavrova



SeibLab

MIITT is HIRING at all levels!!!

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Research Funding/Support

NIH/NHLBI R01HL094557
NIH/NIDDK R01DK098503
NIH/NIBIB R01EB016728
NSF CAREER CBET 1553441
Siemens Healthineers

Thank you for slides!

- Jesse Hamilton
- Claudia Prieto

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