SCMR
Society for Cardiovascular Magnetic Resonance

EACVI
European Association of Cardiovascular Imaging
European Society of Cardiology

AI for CMR Reporting – Technique Talk III

AI-enabled Reporting for CMR Perfusion Datasets: Uncertainty Assessment and Artifact Detection

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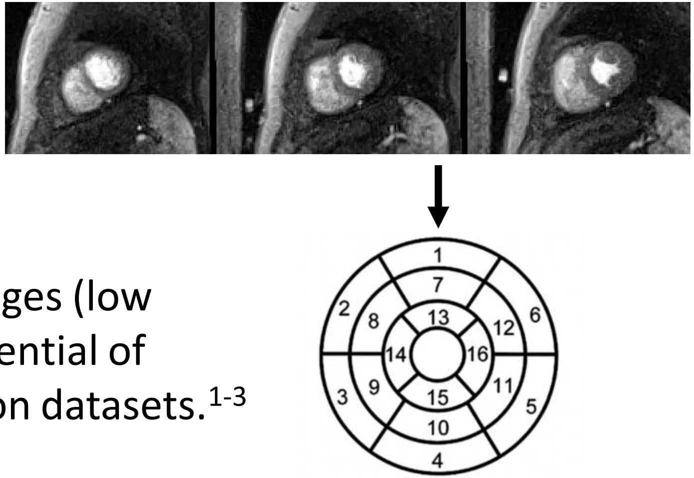
Declaration of Interest

- I do not have any conflicts to declare.

Background: **Reporting in Stress Perfusion** CMR

— Stress perfusion CMR → superior modality for detection of vasodilator-induced ischemia for assessment of both obstructive and non-obstructive ischemic heart disease.

— Manual reporting of CMR perfusion images involves reading through 180+ image (first pass of Gd) per study.



Absence/Presence of Enhancement
Persistence (severity) of Defects:
>5 frames? >10 frames?

— Despite the rapid contrast dynamics and image-quality challenges (low SNR and CNR vs. Cine), recent work has demonstrated the potential of AI/ML to enable rapid fully automatic analysis of CMR perfusion datasets.[1-3]

— On modern platforms, advanced non-rigid MoCo enables a faster workflow.[4]

1. Sandoval et al. Proc of ISMRM 2019;27:1230
2. Scannell et al. JMRI 2020;51(6):1689-1696
3. Xue et al. Radiology: AI 2020;2(6)
4. Xue et al. MICCAI 2009;741-9

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Focus: AI-enabled Reporting for CMR Perfusion Datasets

- Uncertainty Assessment for AI-based Segmentation of Stress Perfusion CMR Using Test-time Analysis

- Automated Detection of Motion-induced Dark Rim Artifacts in Stress Perfusion CMR Enabled by AI-based Segmentation

Focus: AI-enabled Reporting for CMR Perfusion Datasets

- Uncertainty Assessment for AI-based Segmentation of Stress Perfusion CMR Using Test-time Analysis
  - Improving robustness to variations in pulse sequence parameters
  - Enabling human-in-the-loop AI by detecting uncertain segmentation
  - Enabling retrospective analysis of old datasets acquired with subpar quality

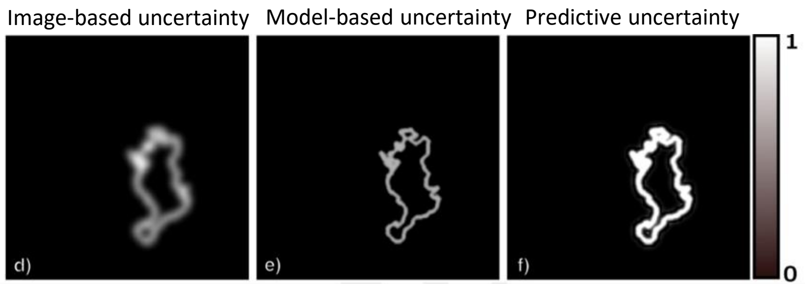
Joint work with PhD Student Dilek M. Yalcinkaya

Background

— **Segmentation of perfusion CMR datasets has been proposed using Deep Neural Networks (DNNs)[1,2,3]**

— Despite their impressive performance, however, DNNs may suffer from miscalibration where potential overconfidence may be implied on the segmentation results[4]

— Uncertainty assessment can offer improved interaction with the expert-user and provide insights to the "black box" nature of the DNNs



McCrindle et al., Radiology: AI

Objective

— Develop a test-time confidence measure for DNN-based segmentation in stress CMR

1. Sandoval et al. Proc of ISMRM 2019;27:1230
2. Scannell et al. JMRI 2020;51(6):1689-1696
3. Xue et al. Radiology: AI 2020;2(6)
4. Guo et al. ICML 2017;arXiv1706.04599

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Contributions

— **patch3D-UNet:** a patch-level UNet-based deep learning method using **spatially sliding 2D+time patches** to segment dynamic CMR perfusion images

— **segmentation uncertainty map** extraction and **localization** with **test-time analysis**

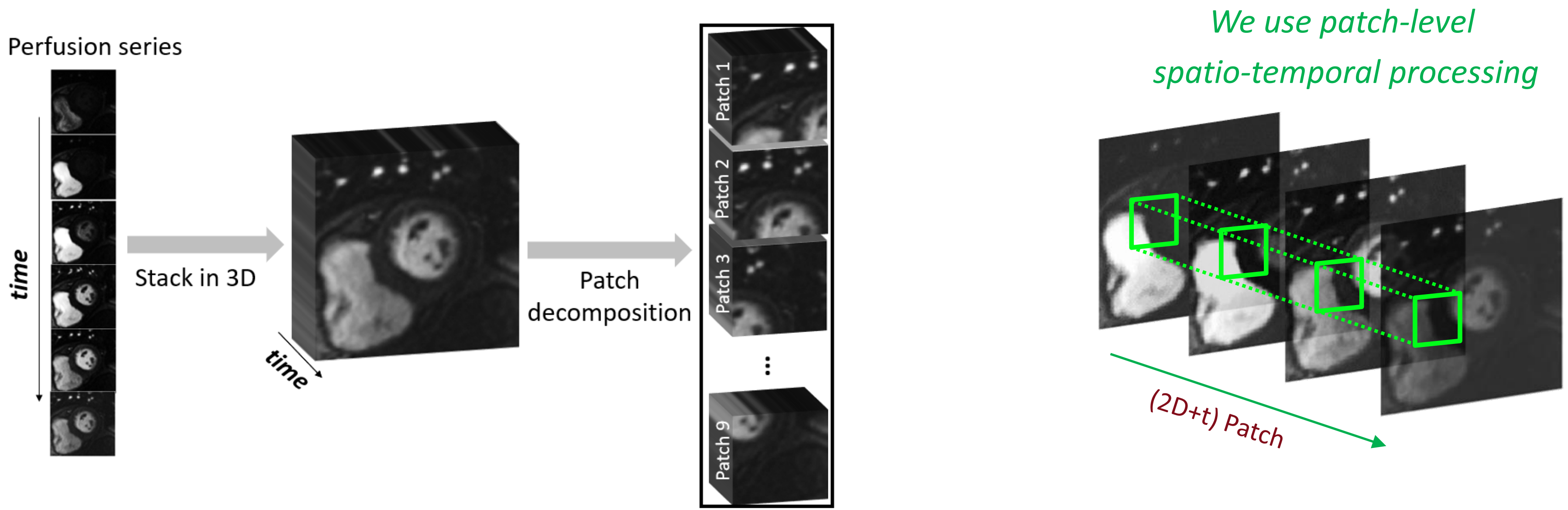
Datasets

— **test** on held-out data from **two institutions** obtained at **distinct field strengths and pulse sequences**

	Training/Validation	Test Set I	Test Set II
Institution	Medical Center #1	Medical Center #1	**Medical Center #2**
Field strength	3 T	**1.5 T**	3 T
Pulse sequence	**SR-prepared FLASH**	**SR-prepared EPI-GRE**	**SR-prepared bSSFP**
No. of patients	69	20	40
No. of females	62 (90%)	20 (100%)	10 (25%)
No. of rest scans	62	24	0
No. of stress scans	65	14	40
Age (years)	56.61±11.56	46.7±11.64	60.1±14.29
BMI (kg/m^2)	26.8±5.31	24.24±4.08	30.28±5.55
Suspected Obstructive CAD (%)	0%	0%	100%
Suspected INOCA (%)	100%	100%	0%
Normal Control (%)	12%	0%	0%

Methodology: Patch-level training

— The data processing pipeline for the proposed patch-level approach:



— Motion-corrected 2D+time perfusion image series is decomposed into patches using a spatial sliding window

* Yalcinkaya et al. IEEE Proc EMBC, Nov 2021

* Yalcinkaya et al. 2022, Under Review.

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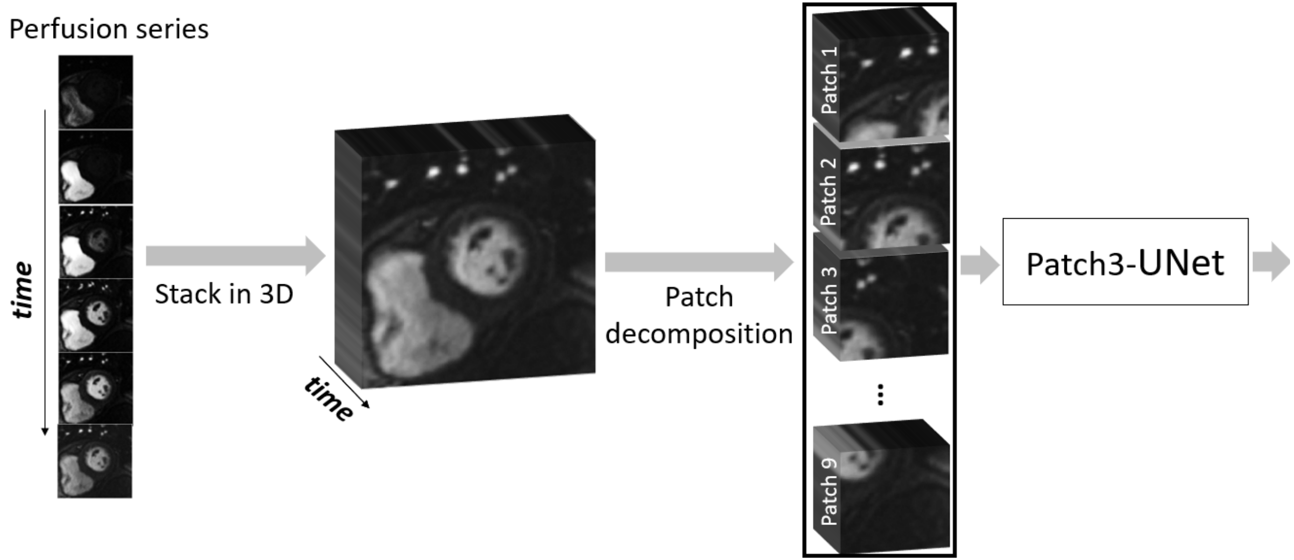
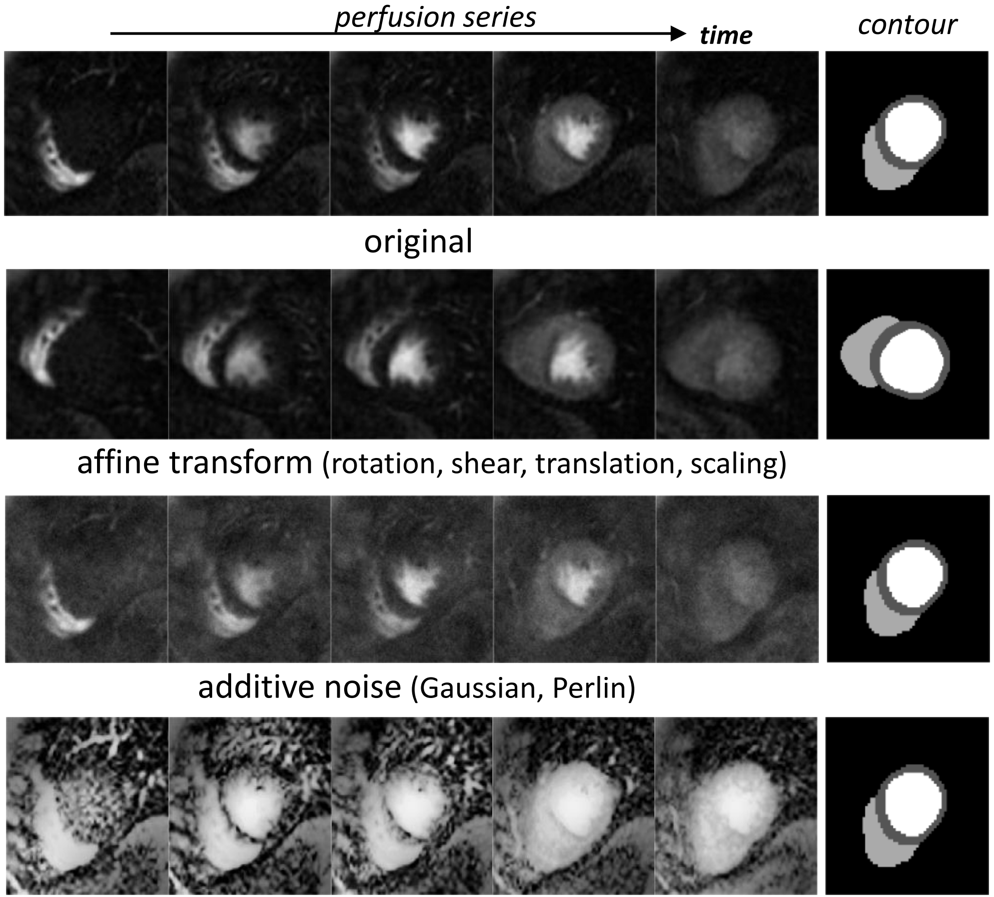


— Motion-corrected 2D+time perfusion image series is decomposed into patches using a spatial sliding window
— Patch3D-UNet detects the myocardial pixels within each patch by processing the dynamic patches
— The segmented patches are combined to yield the result

* Yalcinkaya et al. IEEE Proc EMBC, Nov 2021
* Yalcinkaya et al. 2022, Under Review.

Methodology: Effect of several data augmentation techniques



original

Segmentation-variant augmentation

affine transform (rotation, shear, translation, scaling)

Segmentation-invariant augmentation
(proposed aug.)

additive noise (Gaussian, Perlin)

intensity modulation and contrast enhancement

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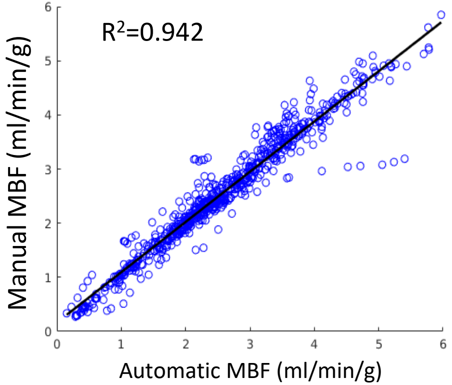
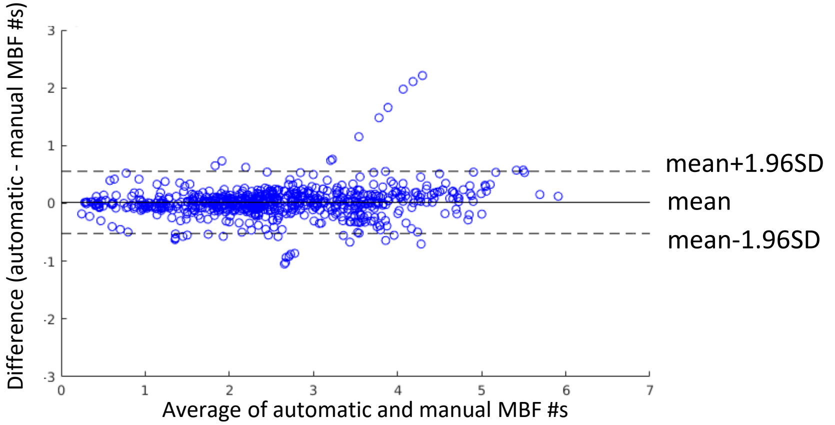
Results: Conventional vs. Proposed Data Augmentation

— Machine-generated MBF quantification for conventional and proposed augmentation at 3 T

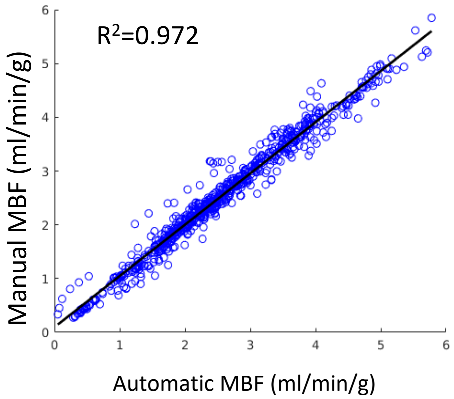
— **Better correlation and agreement with the proposed augmentation**

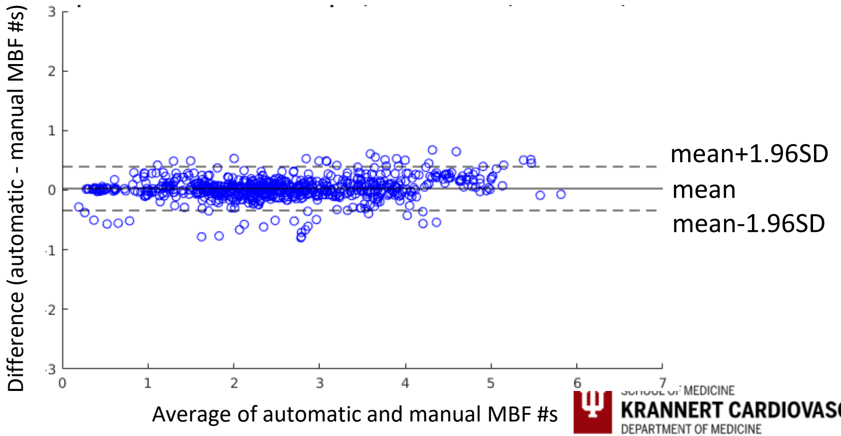
conventional augmentation



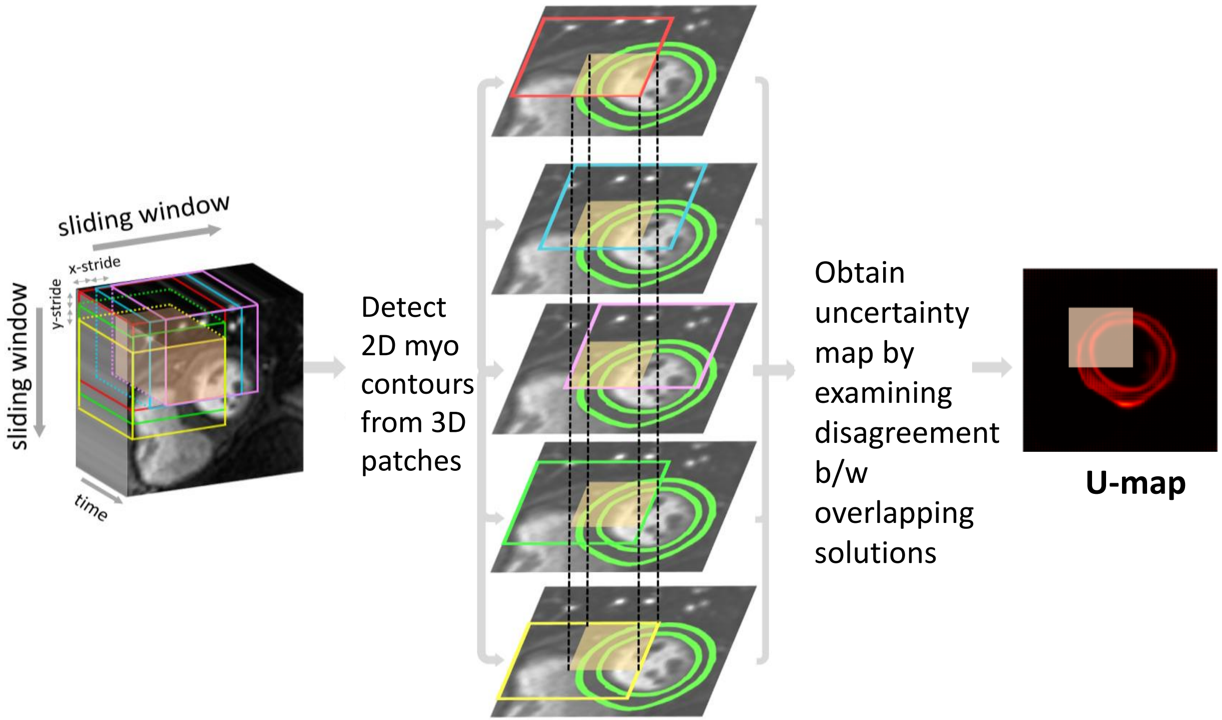


proposed augmentation





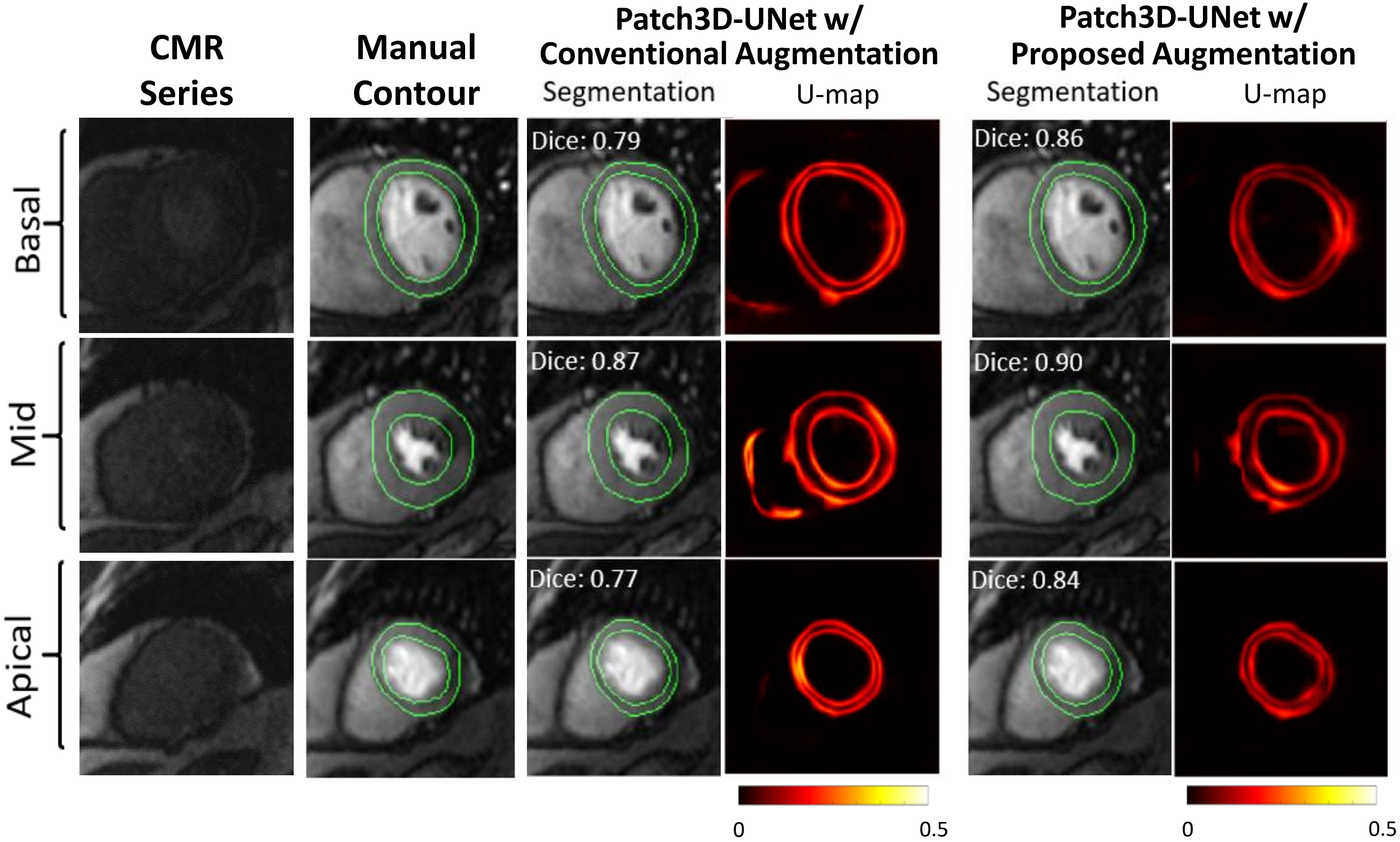
Method: Uncertainty mapping using test-time patch sliding



— During test time, multiple patches are extracted from the perfusion series
— Multiple inferences with slight differences in the location of the ROI (i.e., orange volume)
— Next, these solutions are incorporated to create the U-map

* Yalcinkaya et al. IEEE Proc EMBC 2021; 4078-84

Results: A patient with single-vessel CAD (training: FLASH; test: SSFP)



— Evaluated the effect of different data augmentation settings on the level of uncertainty

— Proposed augmentation led to reduced uncertainty

* Yalcinkaya et al. IEEE Proc EMBC 2021; 4078-84

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Results: Cumulative uncertainty in 3 T test set (n=40)

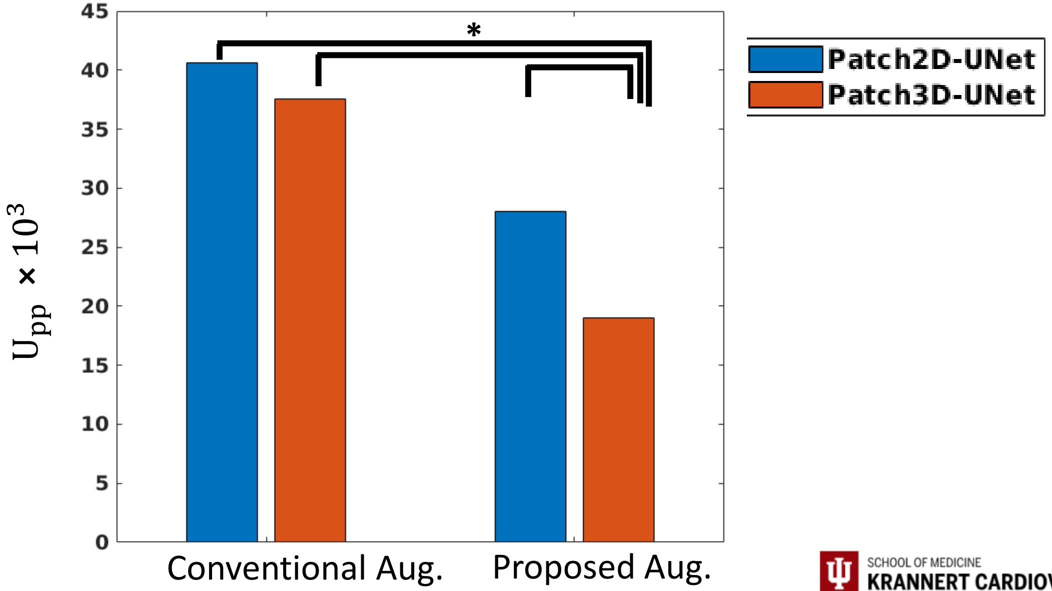
— Define uncertainty as the **per-pixel energy in the U–map**: $\mathrm{U_{pp}} = \dfrac{\|\text{U-map}\|_2^2}{\sum_x \mathrm{S(x)}}$

Energy in the U–map

no. of pixels in segmentation $\mathrm{S(x)}$

— **Baseline model Patch2D-UNet:** Patch-level network trained with 2D patches

— Uncertainty reduced in 3D vs. 2D and proposed vs. conventional augmentation:



* Yalcinkaya et al. 2022, Under Review.

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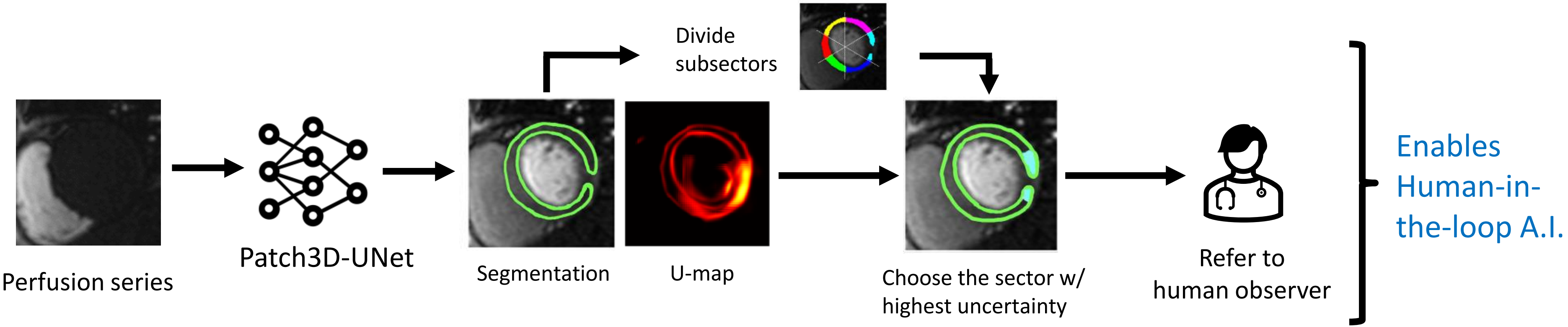
Uncertainty Quantification & Localizations Enables Human-in-the-loop A.I.



— Patch3-UNet outputs the myocardial contours **and** U-map

— Patch3-UNet highly uncertain in the inferolateral wall (resulting in non-contiguous segmentation)

— Segmentation is split into subsegments

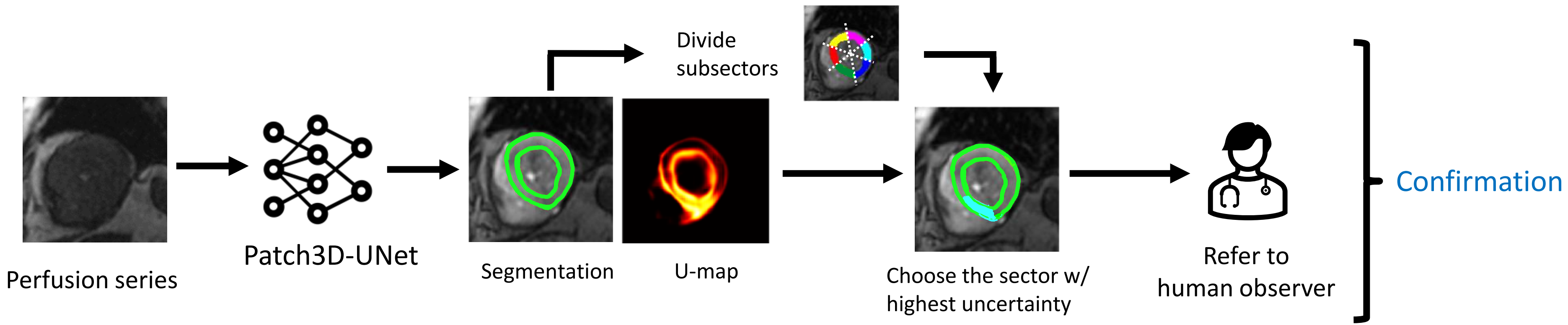
— Uncertainty is localized

— The U-map can be used to alert the end-user to correct/exclude this subsector

* Yalcinkaya et al. IEEE Proc EMBC 2021; 4078-84
* Yalcinkaya et al. 2022, Submitted.

Uncertainty Quantification & Localizations Enables Human-in-the-loop A.I.

Another Challenging Case:



* Yalcinkaya et al. IEEE Proc EMBC 2021; 4078-84

* Yalcinkaya et al. 2022, Submitted.

Enabling retrospective analysis of old datasets acquired with subpar quality

— Applying ML-based automatic analysis to old datasets which have 10+ years of f/u data has the potential to lead to new insights w/o the need for often-prohibitive costs of a prospective study w/ modern seqs.

— **15-year old dataset** acquired at 1.5T using a GRE-EPI sequence w/ no ground truth (training: 3T SR-FLASH)

* Yalcinkaya *et al.* Unpublished

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— U-map detects acquisition error (#1; basal)

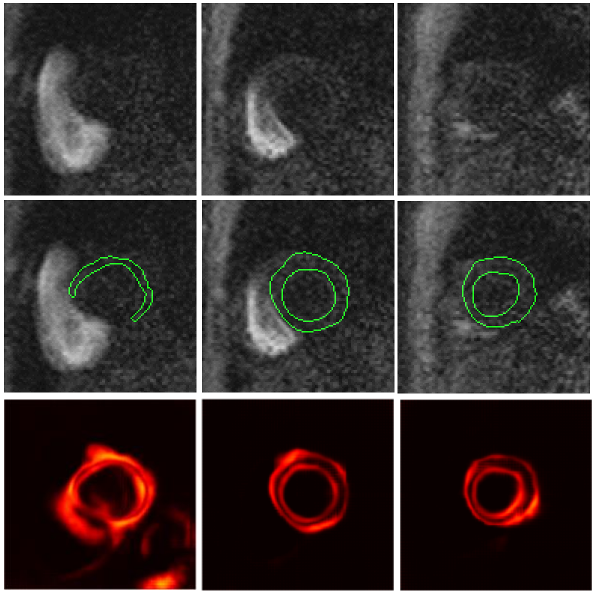
Example #1

basal | mid | apical

perfusion Image series

machine segmentation (Patch3-Unet)

U-map



U_{pp} = 196.5 | **U_{pp}** = 20.1 | **U_{pp}** = 22.5

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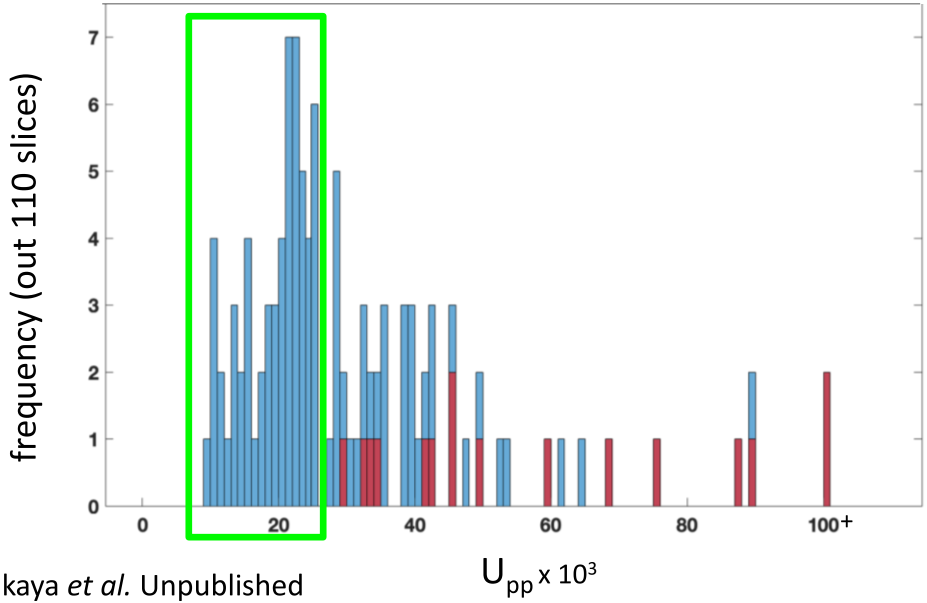
— **15-year old dataset** acquired at 1.5T using a GRE-EPI sequence w/ no ground truth (training: 3T SR-FLASH)

— Distribution of normalized U values across 110 slices

Red bars show the distribution of inaccurate segmentations using visual inspection after machine analysis



→ **55% of analyzed slices are clustered in a “low-uncertainty group”** and did not include any segmentation errors upon visual inspection.

* Yalcinkaya *et al.* Unpublished

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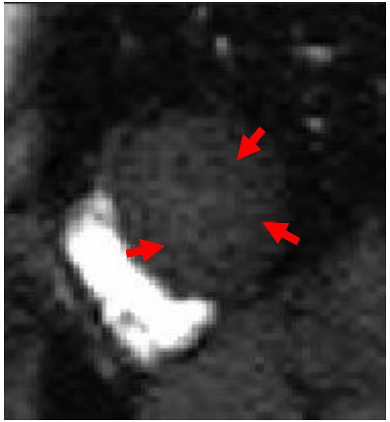
Joint work with PhD Student Hazar B. Unal

The Dark Rim Artifact (DRA)

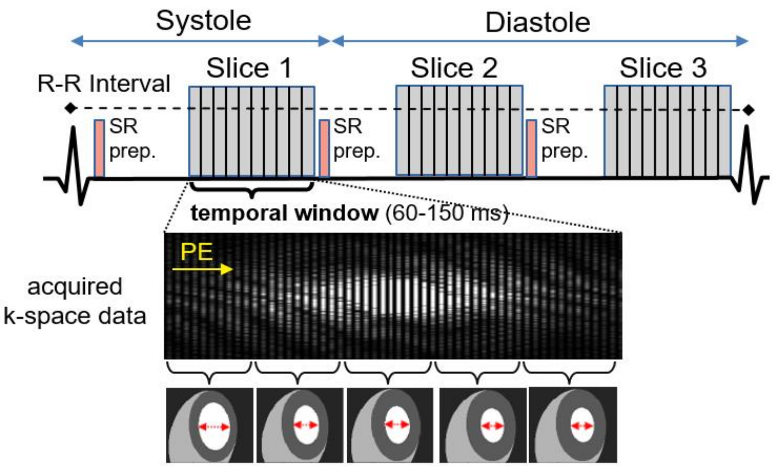
— Dark Rim Artifact (DRA) is an important challenge in CMR perfusion studies with Cartesian sampling.



— DRA mimics true perfusion defect; confounds both qualitative and quantitative analyses.

— Clinically important to detect DRA in CMR image series for accurate diagnosis of subendocardial ischemia.

Background



— The two main causes for DRA:

1) Gibbs ringing (k-space truncation[1])

2) **Cardiac motion**[2]

— Previous studies mainly focused on *removing* DRA:

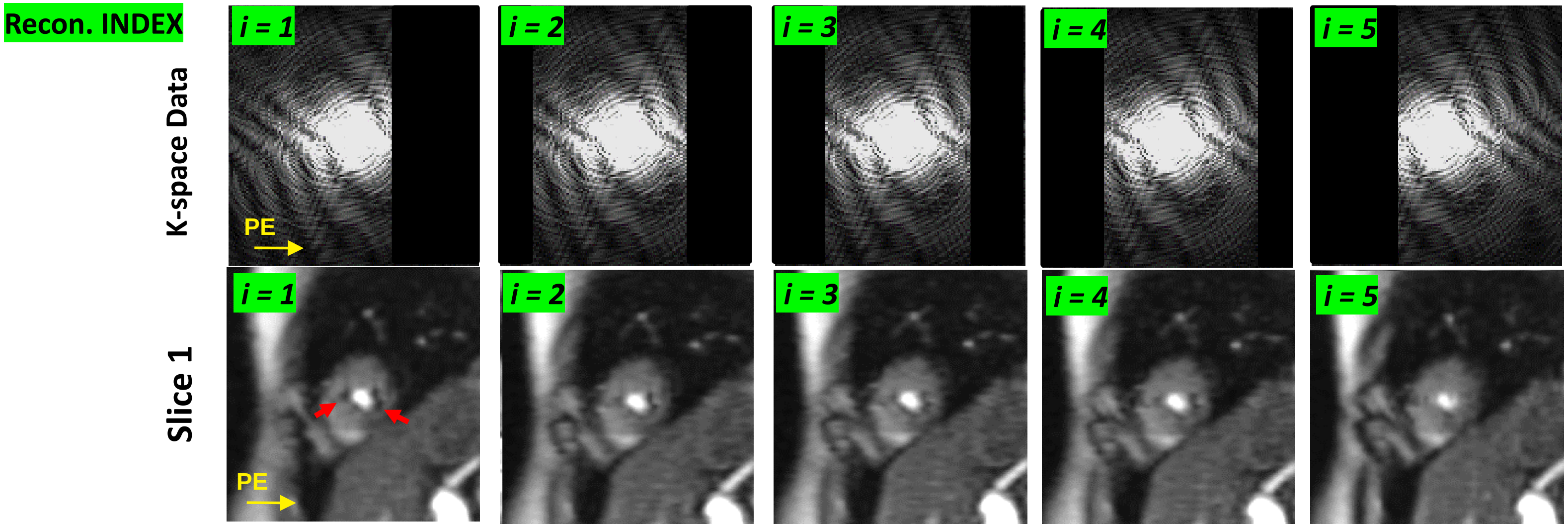
- with post-processing[3-5]
- with optimized acquisition including non-Cartesian trajectories[6-8]

— The only study[9] done so far on *detecting* DRA is not automatic.

— Key idea: if a subendo defect "changes" by a ≈25 ms change in acq. temporal window → DRA

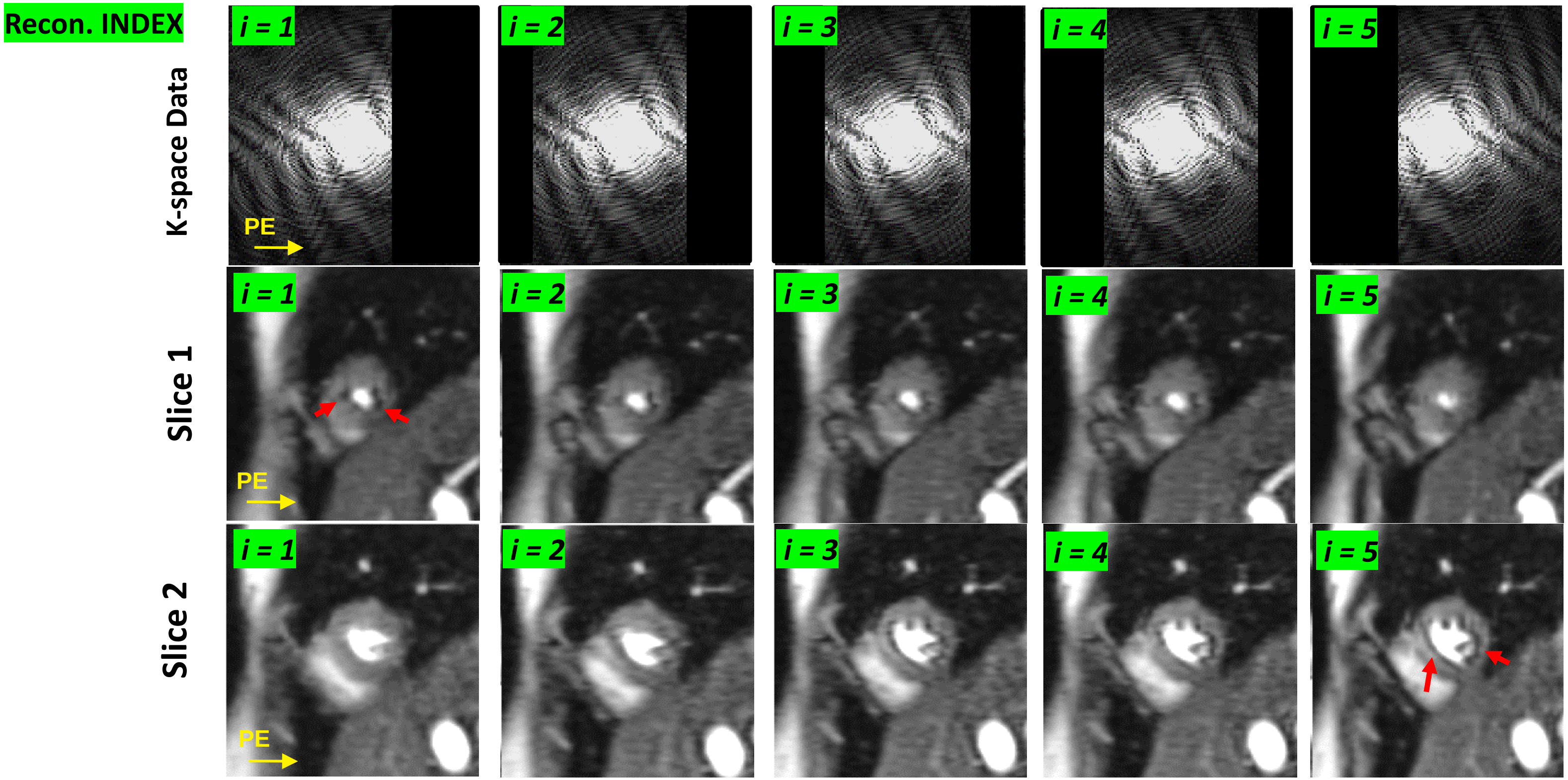
1. Di Bella et al: MRM 2005
2. Storey et al: MRM 2002
3. Ferreira et al: JCMR 2009
4. Kellner et al: MRM 2016
5. Lee et al: MRM 2021
6. Salerno et al: MRM 2013
7. Sharif et al: MRM 2014
8. Zhou et al: JMRI 2017
9. Ta et al: JCMR 2018

Key Idea: Multiple reconstructions of each frame



* Unal et al. IEEE EMBC 2021; PMID: 34892125

Key Idea: Multiple reconstructions of each frame from partially-masked k-space



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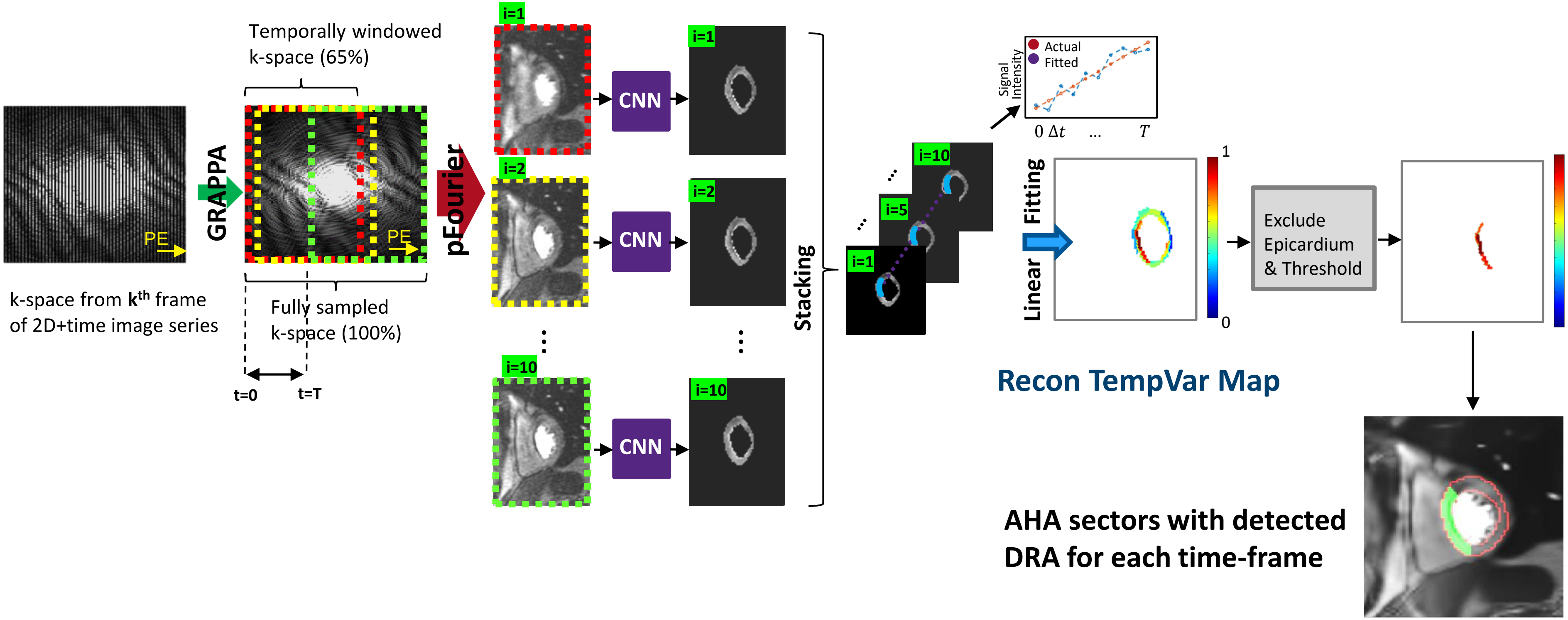
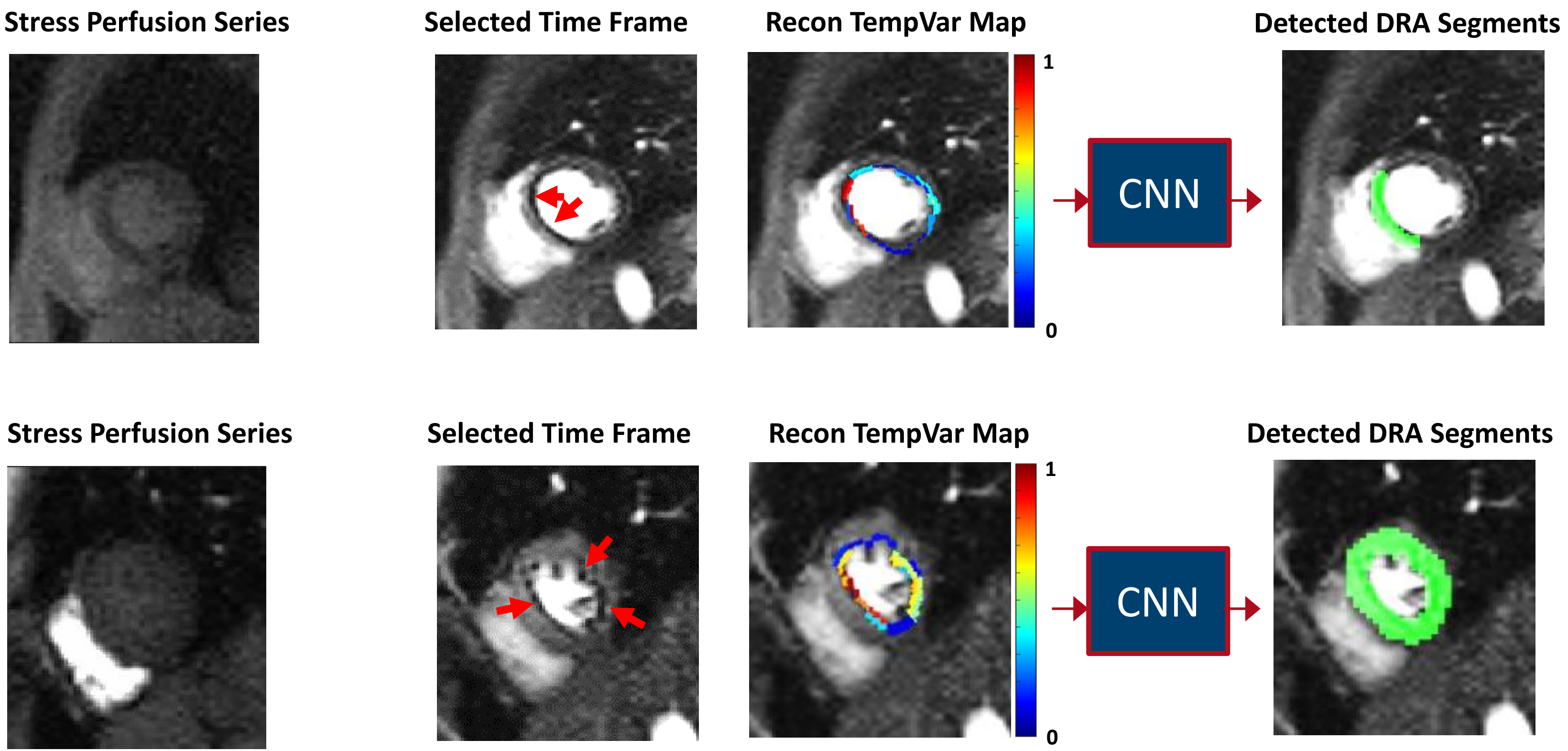
Key Idea:

Leveraging ML-based segmentation to automatically generate **Recon Temporal Variability** maps



* Unal et al. 2022, In Preparation.

Representative Results: Healthy Volunteers



* Unal et al. 2022, In Preparation.

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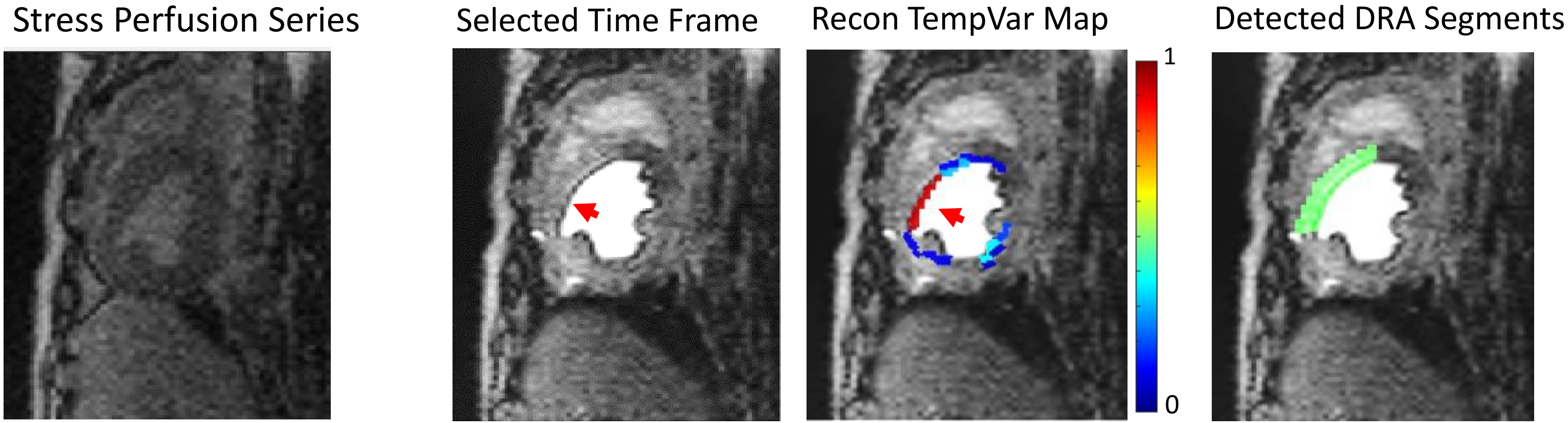
Example Results: Single-vessel obstructive CAD (animal)



— Adenosine-stress first pass perfusion in a canine with epicardial stenosis (90% LAD)

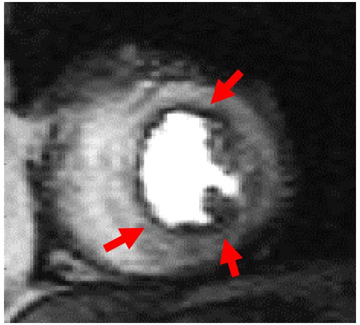
— Septal DRA detected accurately

* Unal et al. 2022, In Preparation.

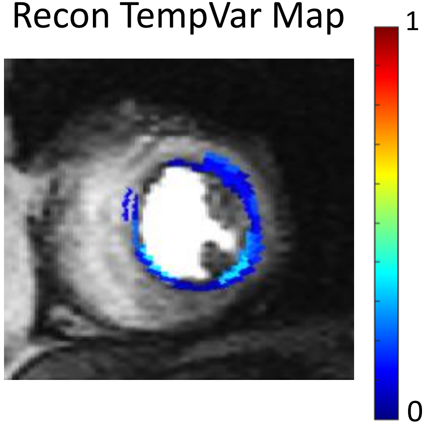
Example Results: Patients with Global Subendocardial Defect

Stress Perfusion Series

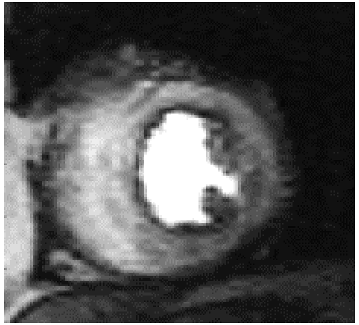
Selected Time Frame



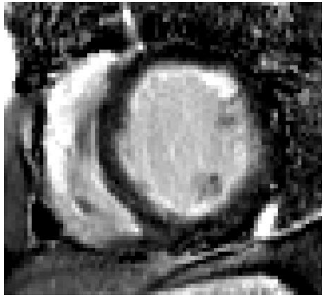
Recon TempVar Map



No DRA is detected



LGE



* Unal et al. 2022, In Preparation.

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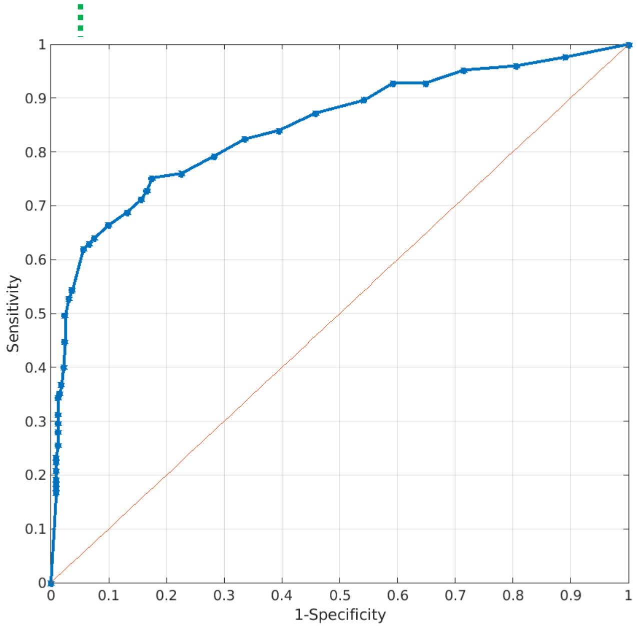
Overall Artifact-detection Performance (per segment)

- Determining the "optimal" TempVar threshold: trade off between sensitivity & specificity
- Preliminary results in n=26 subjects

  → aim is to minimize the likelihood of classifying a segment as DRA when it's a true defect



Specificity = 0.95

	AUC	95% CI	Sensitivity at 95% Specificity
per AHA segment	**0.83**	0.81 to 0.85	**62%**

→ Automatically **detecting >50% of true dark-rim image artifacts with near-perfect specificity**

* Unal et al. 2022, In Preparation.

Conclusions: **Uncertainty reporting** in ML-based analysis of perfusion CMR

— Uncertainty assessment may enable a more reliable integration of deep learning-based analysis of stress perfusion images into clinical CMR reporting practice.

— We presented a technique for mapping the uncertainty in ML-derived segmentations of CMR perfusion datasets using a test-time sliding-patch analysis approach.

— As expected, 3D (spatio-temporal) DNN architecture and ”advanced” data augmentation reduce uncertainty esp. when test/training data were acquired using different sequence.

— Our proposed U-map measure has practical value in interpreting the ML-derived segmentations specifically by enabling human-in-the-loop quality control of contours & assessing the generalizability to external datasets and/or datasets with subpar image quality.

Conclusions: ML-enabled **artifact detection in reporting** of perfusion CMR

— Currently, there does not exist any fully automatic approach for detecting dark-rim artifacts in CMR perfusion datasets.

— We have proposed a method that leverages ML-enabled automatic detection of the subendocardial contours to automatically detect DRAs.

— Our proof-of-concept study achieved AUC = 0.83 for per-segment DRA detection;
Enables detection of >50% of DRAs with near-perfect specificity.

— Future work involves testing on a larger patient dataset including true normal controls.

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Lab Members:

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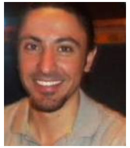

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