AI-enabled cardiac imaging quality control

Julia A. Schnabel, King's College London, *Helmholtz Munich, Technical University of Munich*

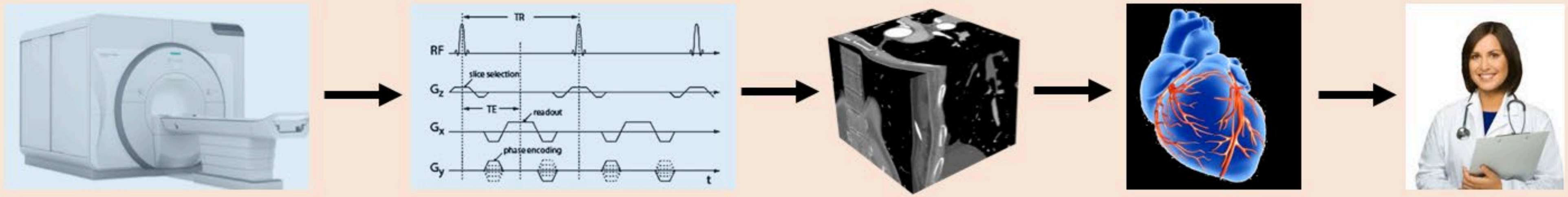
Ilkay Oksuz, Ines Machado, Andy King

James Clough, Devran Ugurlu, Esther Puyol-Antón, Bram Ruijsnik,
Claudia Prieto, Daniel Rueckert, Rene Botnar

AI-enabled imaging

We typically fall into one of the following categories:

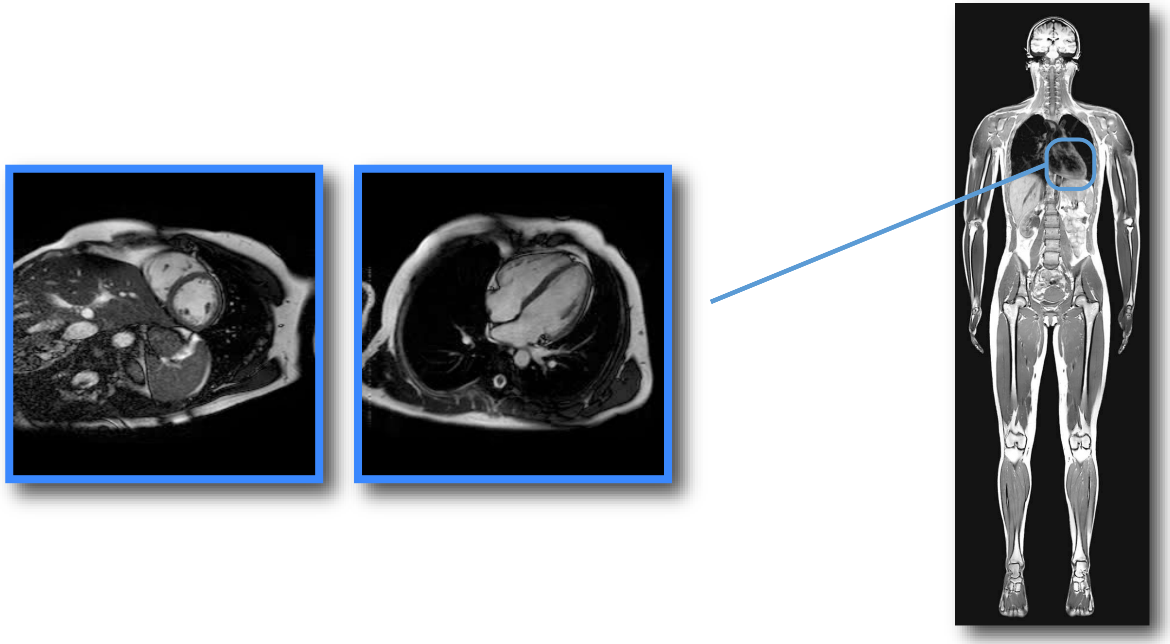
- **Image acquisition** – generate raw data using an imaging sensor
- **Image reconstruction** – transform the raw sensor data into an image for viewing
- **Image "post-processing"** – image filtering, segmentation, registration, …
- **Image analysis** – model construction, detection and classification
- **Image interpretation** – by clinicians

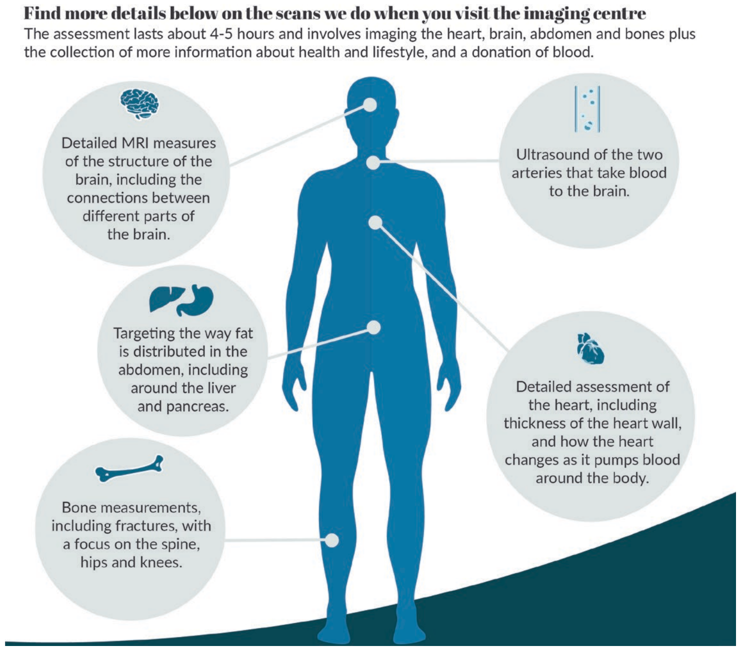


- **AI-enabled imaging** - apply AI within and increasingly across each of these groups

In a perfect world, we have (near)perfect imaging

- In 2014, **UK Biobank** invited back **100,000 original volunteers** for brain, **heart** and body imaging.
  - Scanned across dedicated centres across the UK
  - Tight quality control and scan consistency





In the real (clinical) world, not so much…

- Image quality is dependent on:
  - **underlying MR physics**:
    - ie trade-off between the signal-to-noise, spatio-temporal resolution, scan time,…
  - **patient physiology and movements**:
    - beating heart, cardiovascular disease patterns, (in)consistent breath-holds, movement in scanner

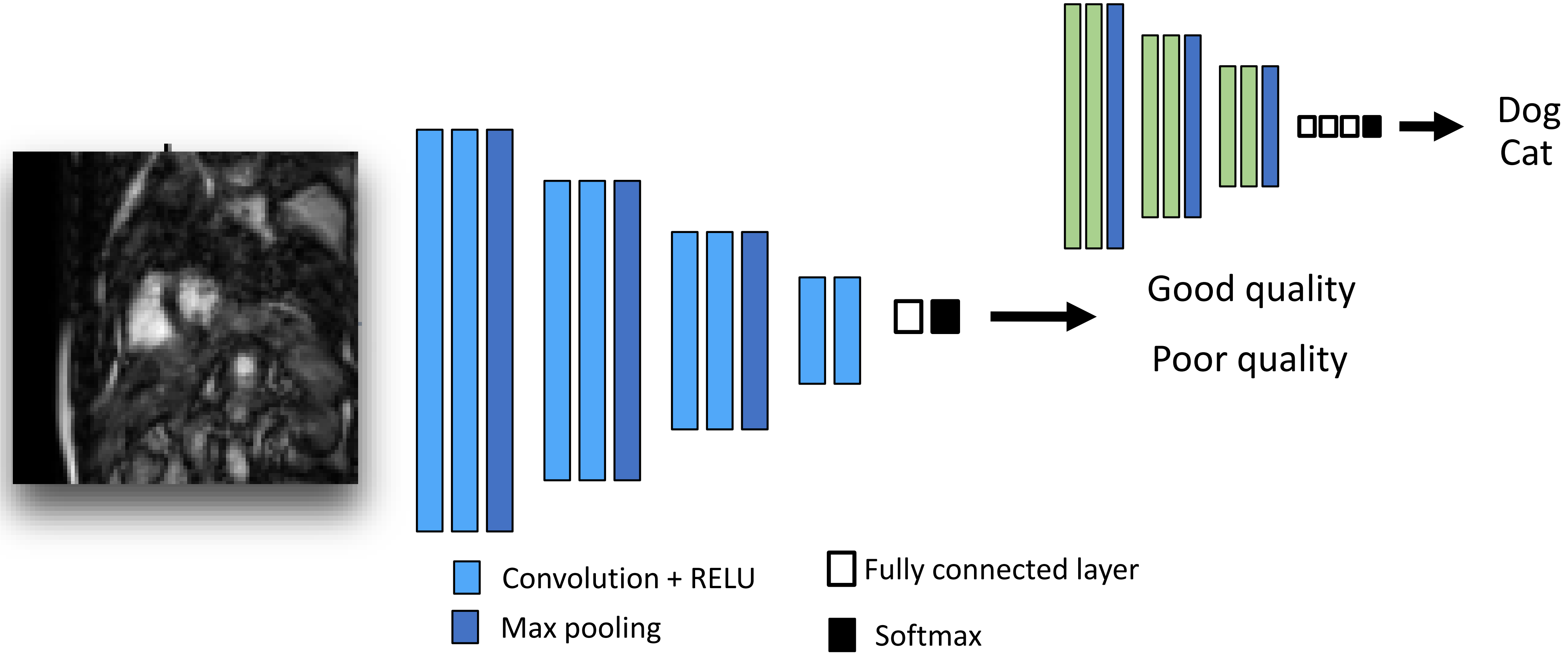
- Poor quality images:
  - **discarded**, or annotations are negatively impacted, misleading diagnosis
  - **patient recall** - affecting hospital workflow and timely diagnosis

AI-enabled (cardiac) image quality control

- **Image quality assessment**:
  - Establish whether patient needs to be rescanned
  - Establish/curate training databases
- **Image restoration:**
  - Avoid patients having to be rescanned
  - Improve further downstream tasks (segmentation, classification…)
- ***Imaging acceleration*** *(very briefly – but see our poster):*
  - *Stop imaging when image quality is “good enough”*
  - *Allow more time for dedicated scans*

Image quality assessment

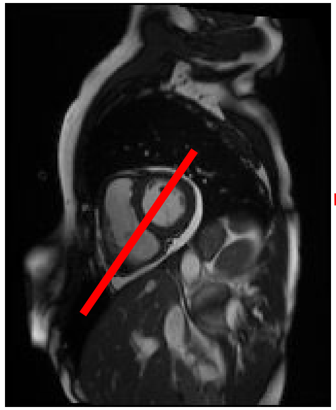
Classify images into good/bad quality:



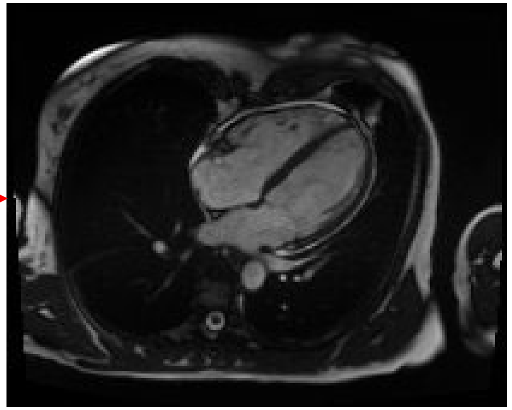
Incorrect scan planning

- Planning based on 2-chamber and SAX images
  - Appropriate angle needs to be placed on SAX,
  - Need to exclude the aorta

2-chamber view

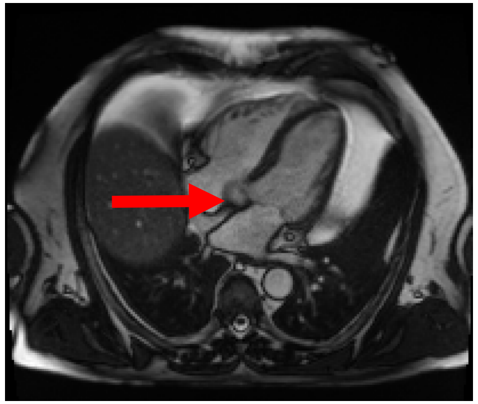


Short axis view



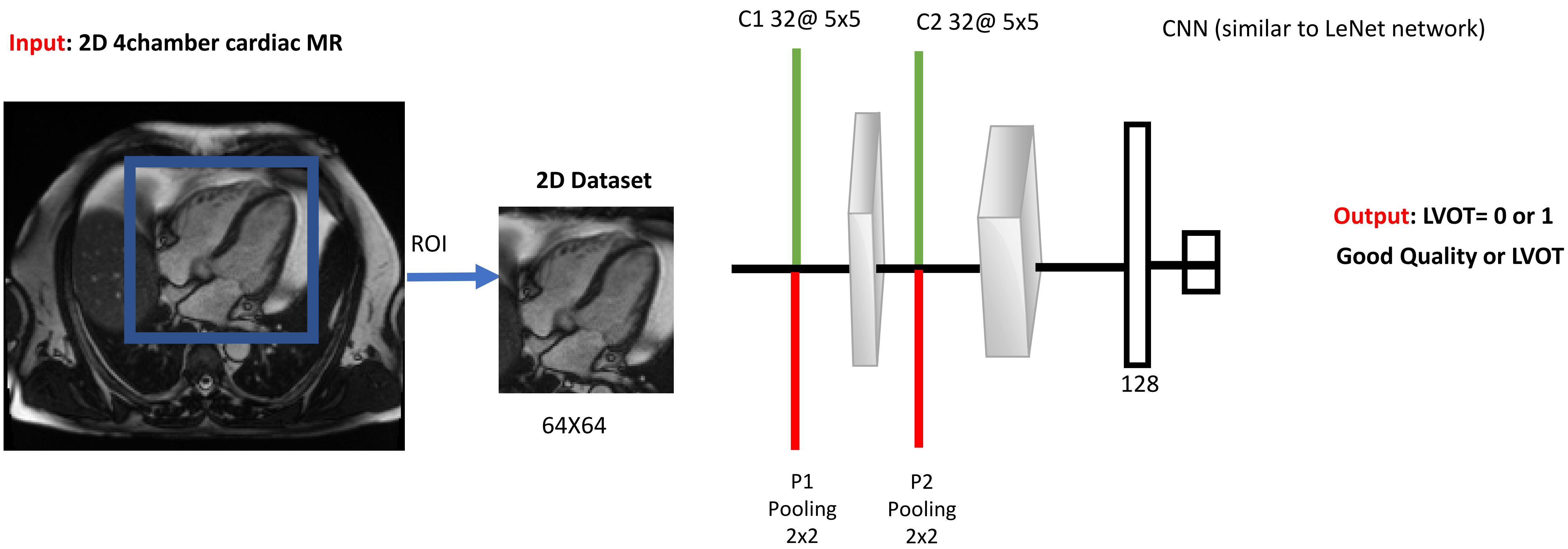
4-chamber view

- If done incorrectly, this results in:
  - Off-axis images
  - Presence of Left Ventricular Outflow Tract (**LVOT**) – “5 chamber look”
  - Difficulties in atrial analysis



Oksuz et al., Proc. ISBI 2018

Incorrect scan planning

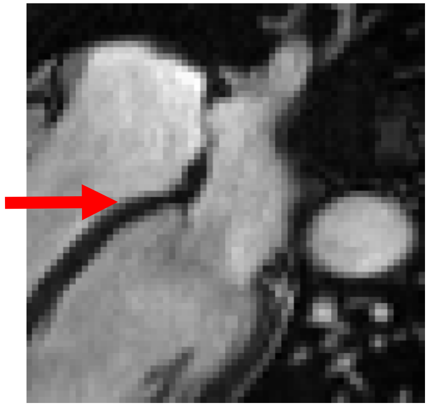


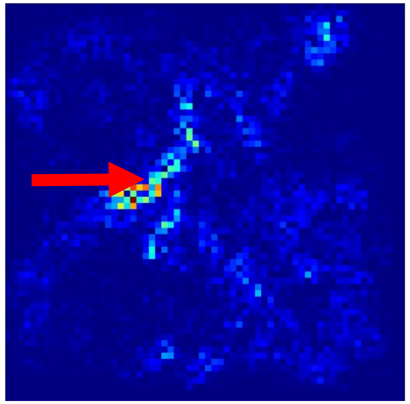
Oksuz et al., Proc. ISBI 2018

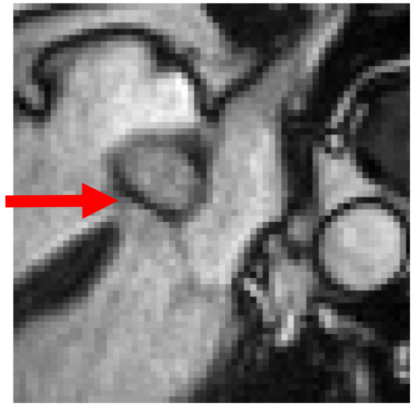
Incorrect scan planning

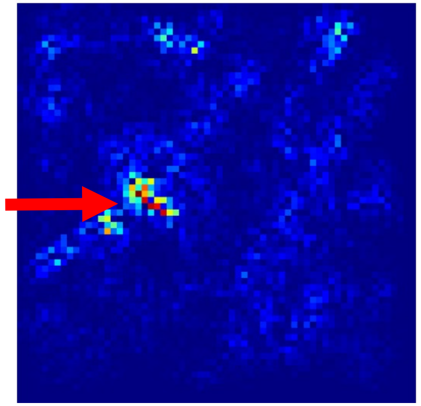
- 123 Good Quality Images and 123 LVOT Images from UK Biobank, plus data augmentation

Methods	Accuracy	Precision	Recall
K-Nearest Neighbours	0.613	0.604	0.602
Linear SVM	0.732	0.741	0.736
Decision Tree	0.651	0.626	0.619
Random Forests	0.598	0.613	0.610
Adaboost	0.718	0.729	0.727
Naive Bayesian	0.653	0.625	0.637
Discriminant Analysis	0.669	0.684	0.643
CNN w.o Augmentation	0.801	0.811	0.781
CNN	0.826	0.828	0.821


Good Quality Image


Good Quality Attention Map


LVOT


LVOT attention map*

Oksuz et al., Proc. ISBI 2018

Image restoration

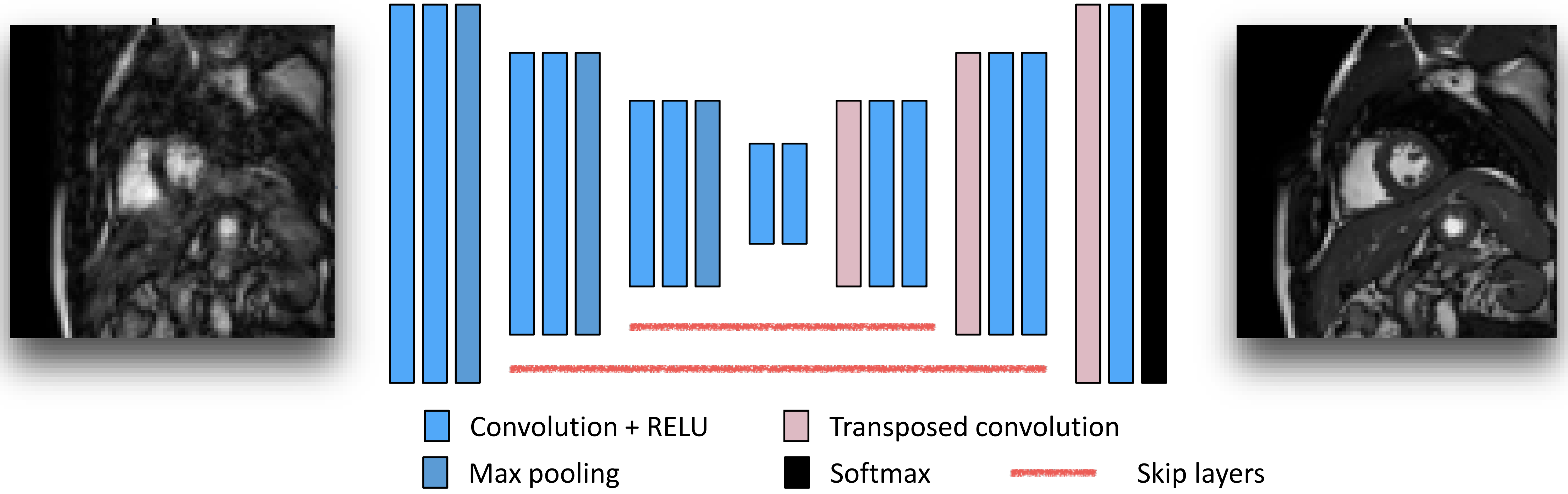
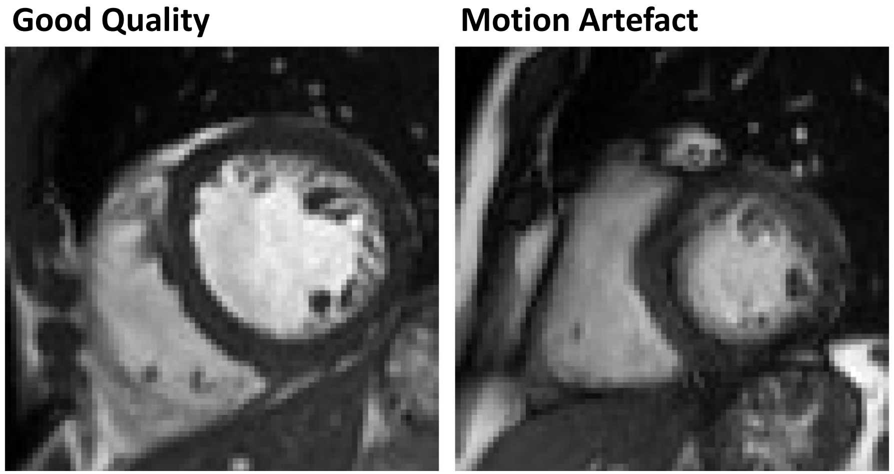


Image restoration of specific artefacts

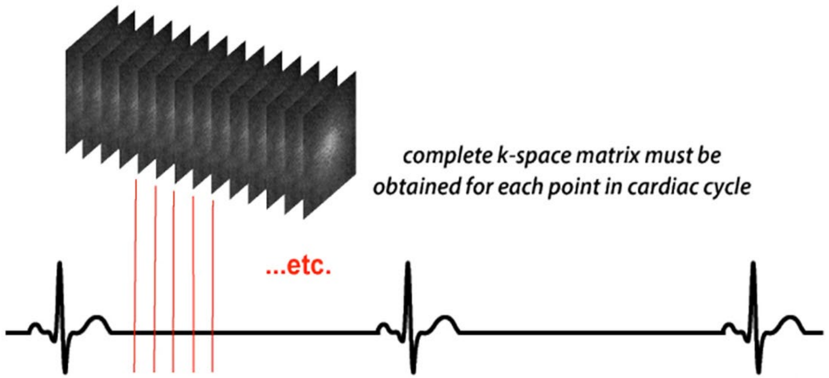
- Requires some understanding of the **underlying imaging physics and acquisition**

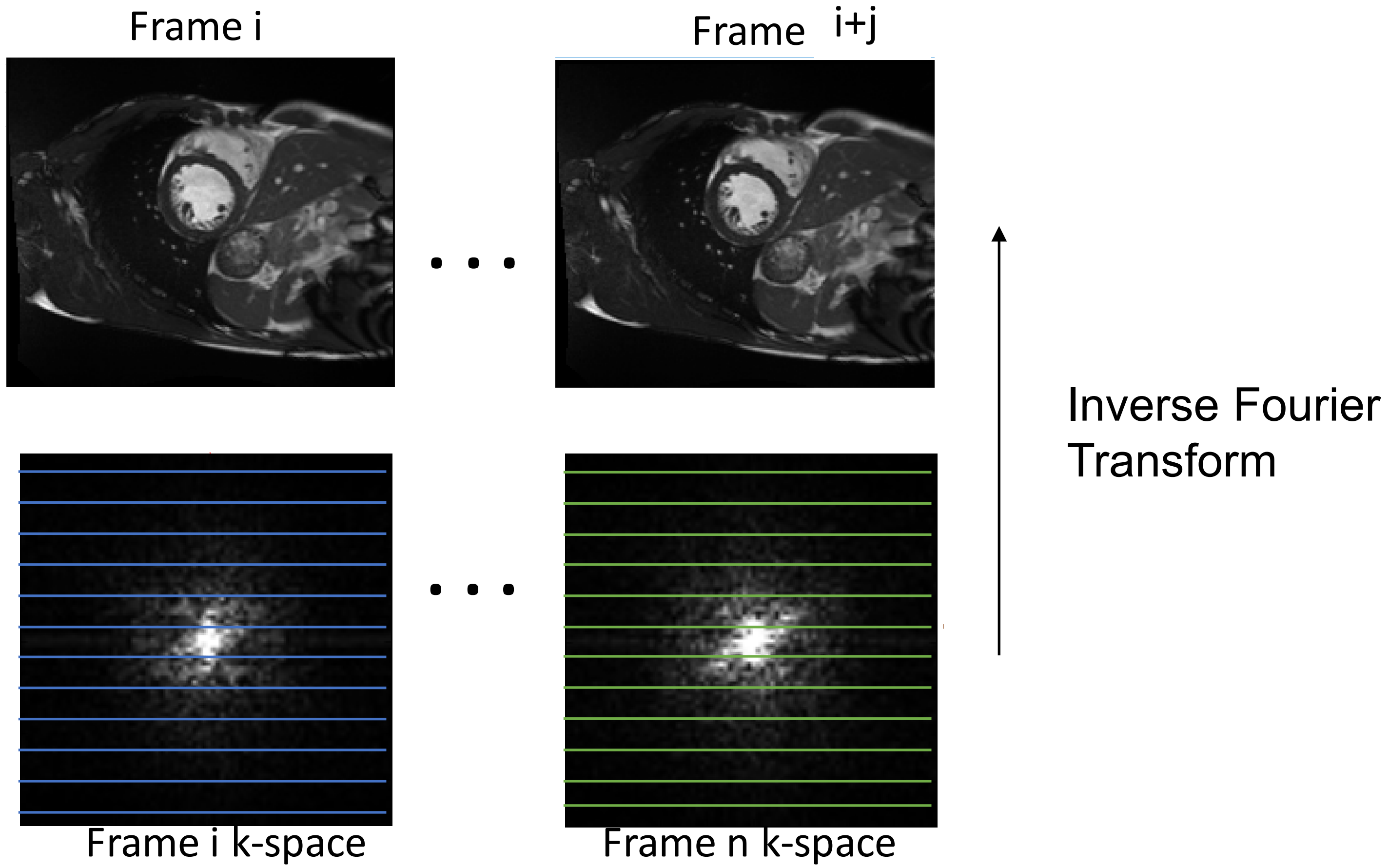


Oksuz et al. MedIA 2019

Image restoration of specific artefacts

ECG mistriggering

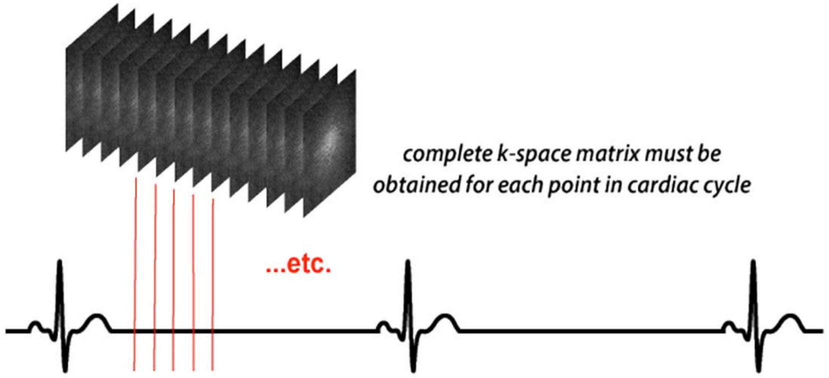


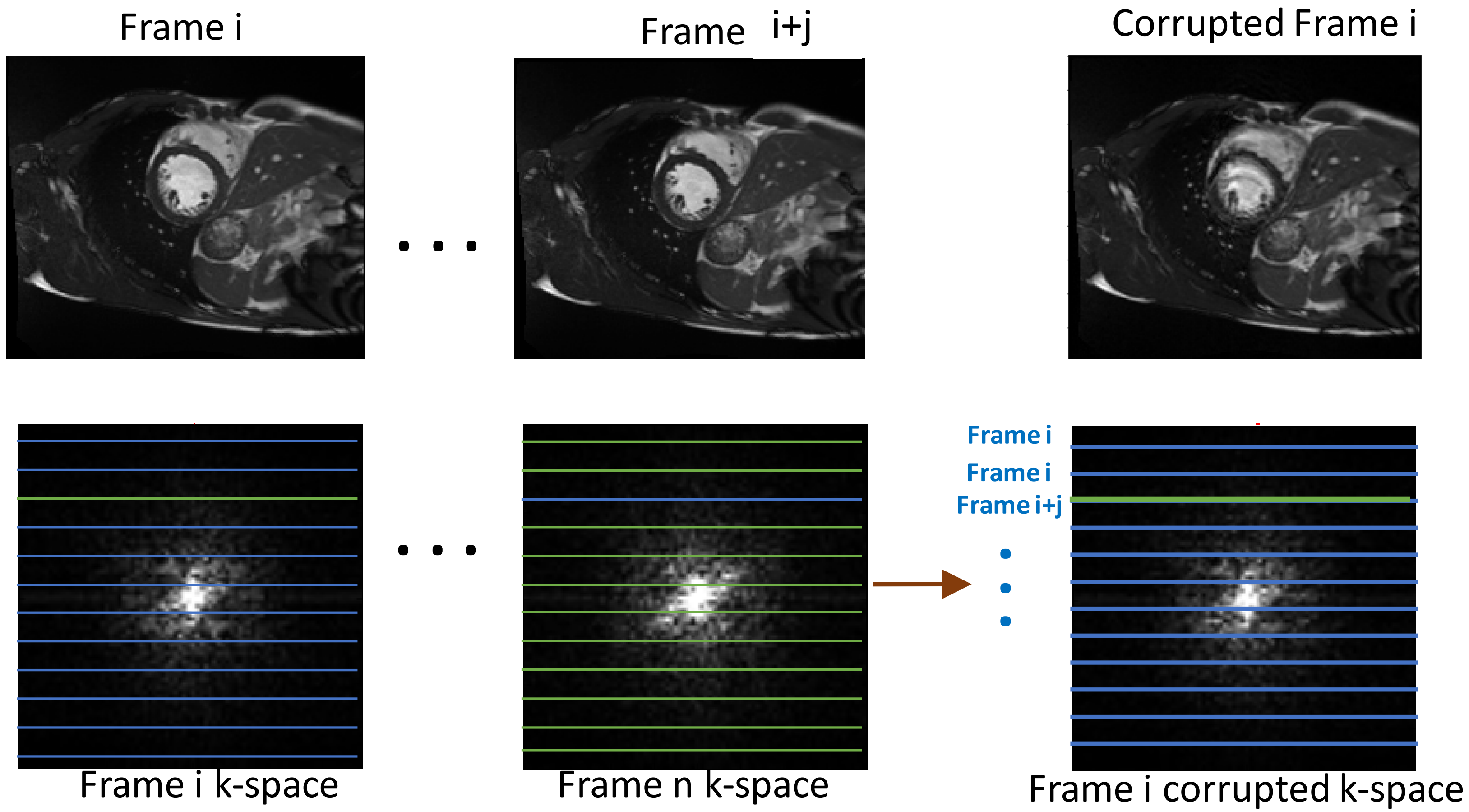


Oksuz et al. MedIA 2019

Image restoration of specific artefacts

ECG mistriggering



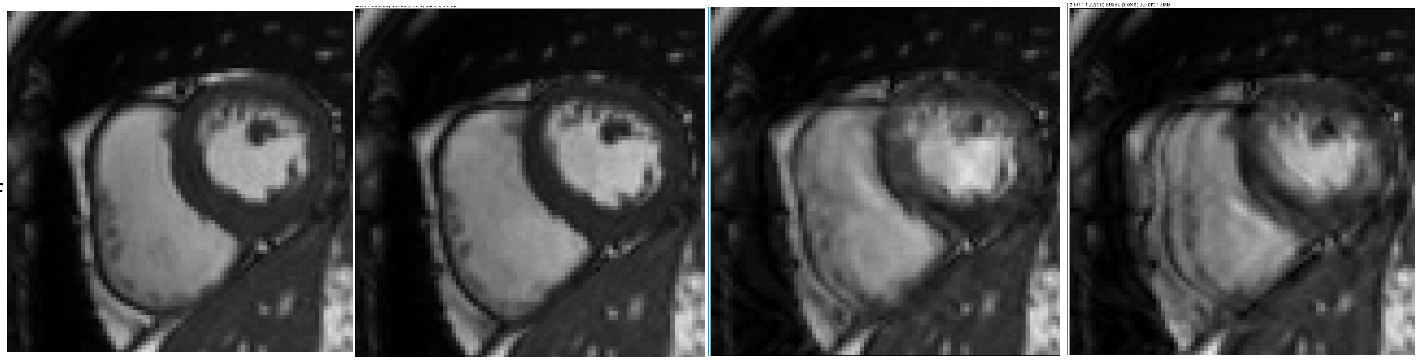


Oksuz et al. MedIA 2019

Physics-based data augmentation

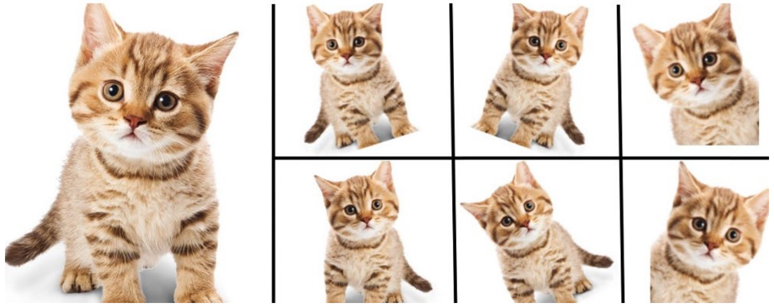
- We can simulate these artefacts in good quality images from UKBB to mimic clinical reality:

Different corruption levels of k-space



HIGH QUALITY → **LOW QUALITY**

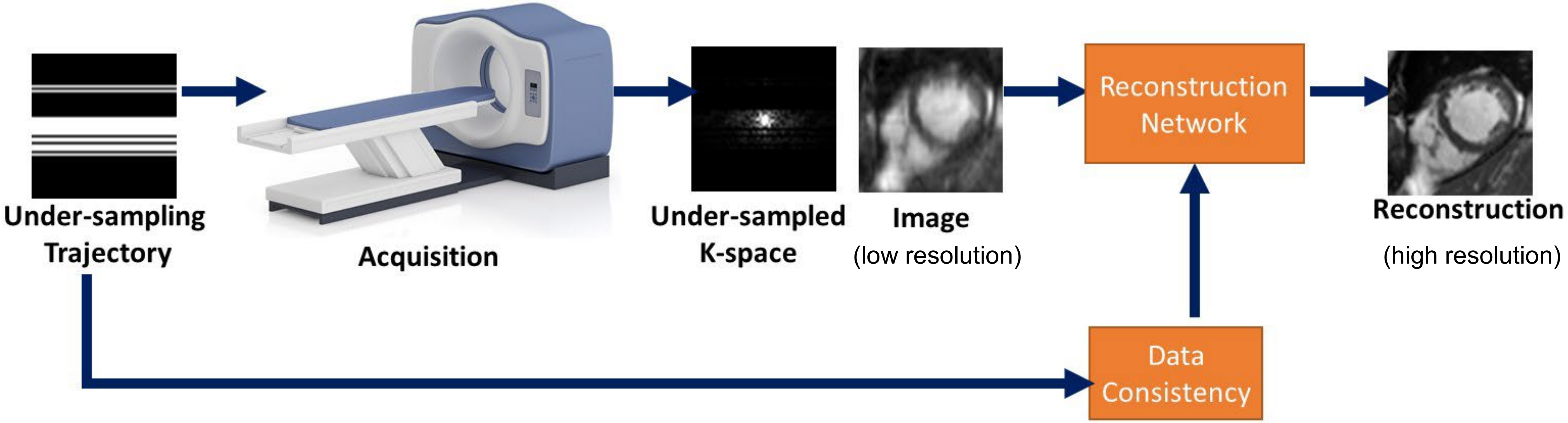
- This is a form of realistic data augmentation



Oksuz et al. MedIA 2019

Image restoration of specific artefacts

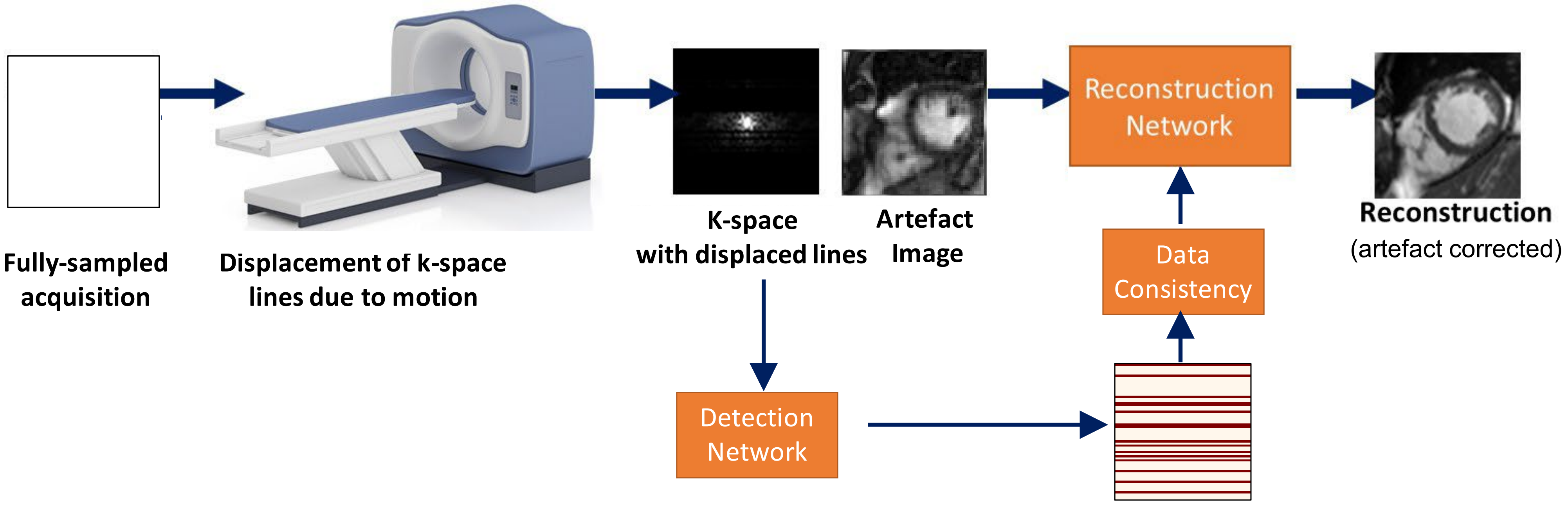
- For accelerated imaging, a reconstruction network can be trained on undersampled raw (k-space) data:



Oksuz et al. MedIA 2019

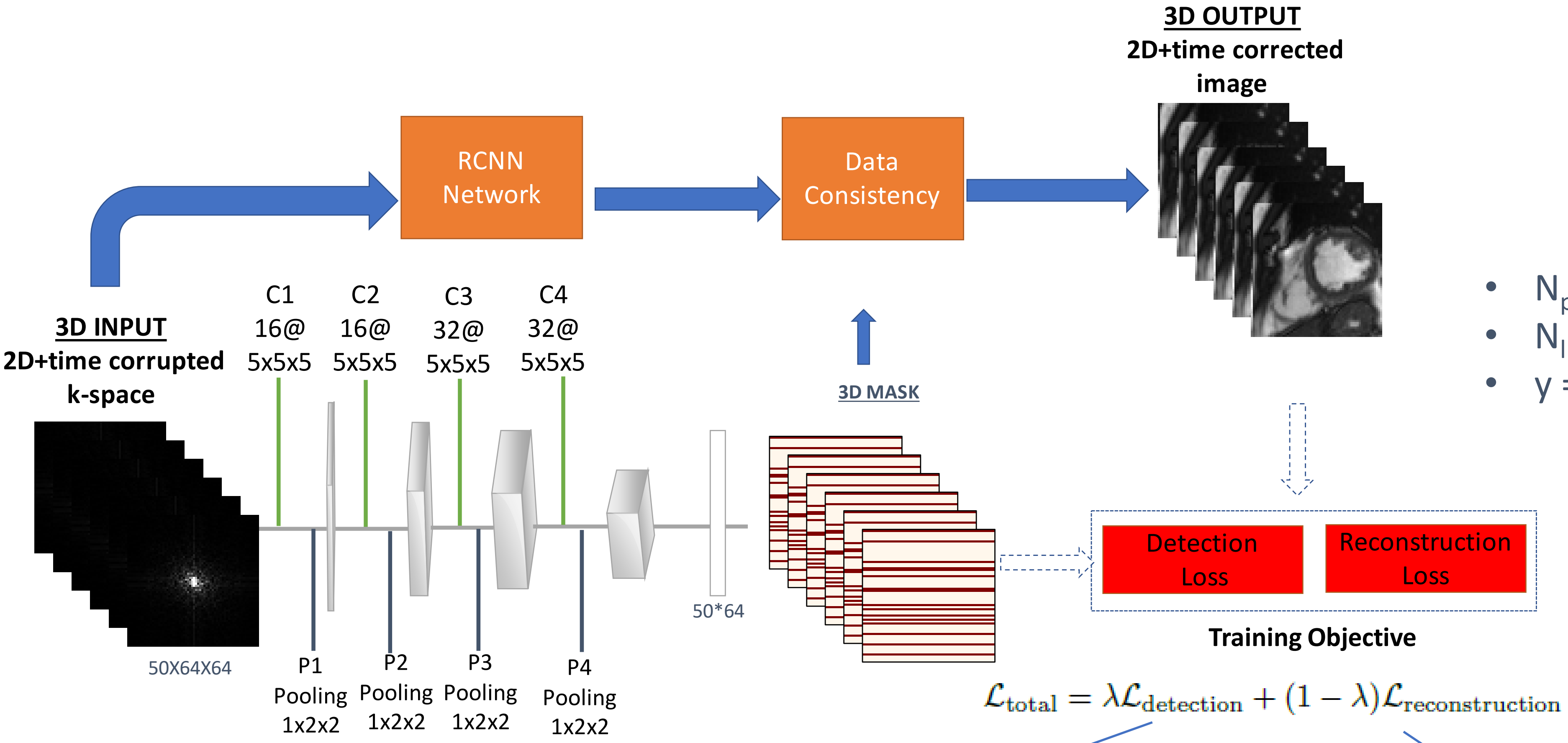
Image restoration of specific artefacts

- We can transform this into an artefact correction network:



Oksuz et al. MedIA 2019

Image restoration of specific artefacts



- N_p = # Pixels
- N_l = # K-space lines
- y = Binary Indicator

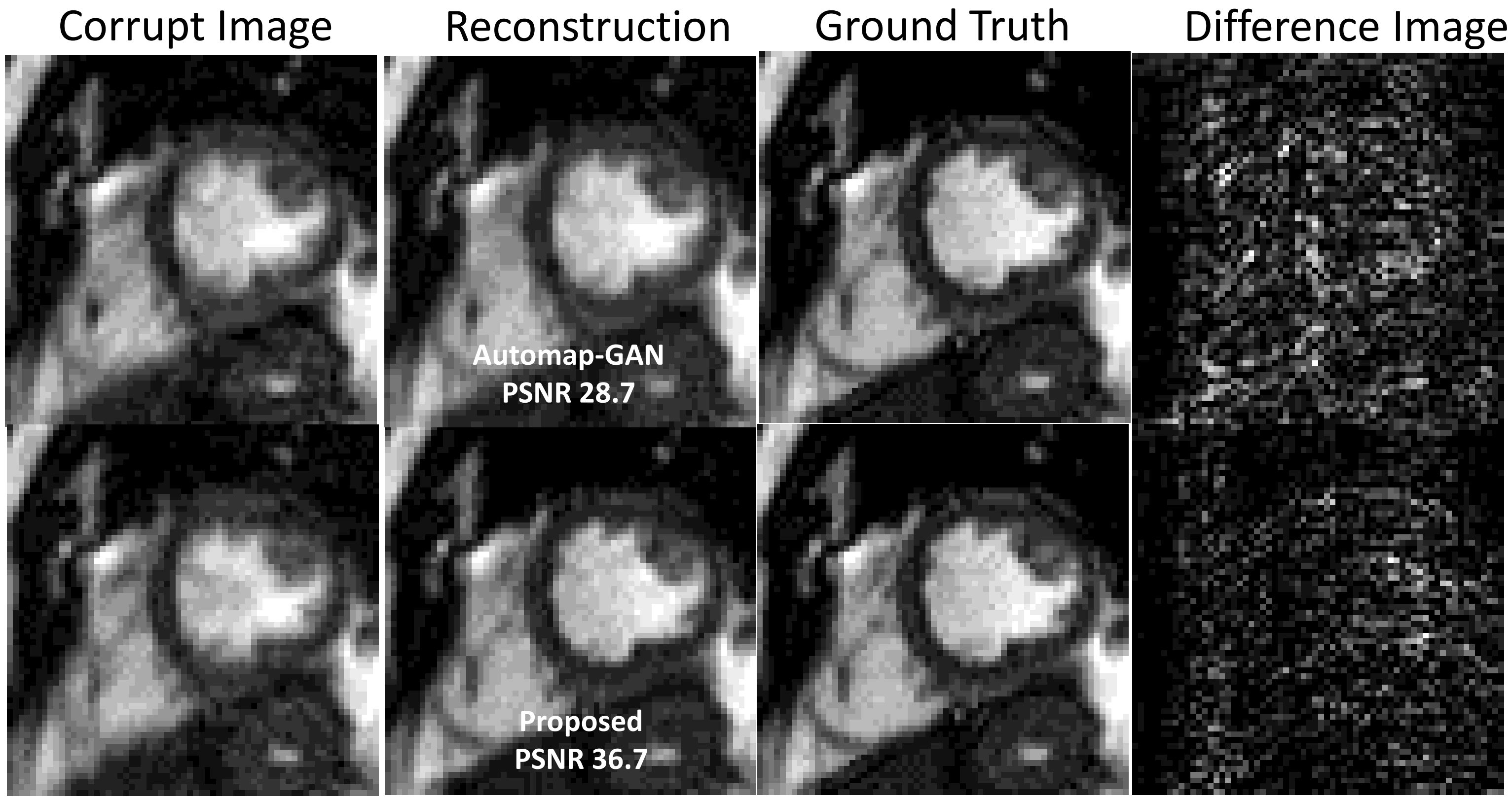
$$\mathcal{L}_{\text{total}} = \lambda \mathcal{L}_{\text{detection}} + (1-\lambda)\mathcal{L}_{\text{reconstruction}}$$

$$\mathcal{L}_{\text{detection}}(pr, y) = \frac{1}{N_l} - (y \log(pr) + (1-y)\log(1-pr))$$

$$\mathcal{L}_{\text{reconstruction}} = \frac{1}{N_p}\sum_{p=0}^{N_p}(I_x(p) - I_y(p))^2$$

Oksuz et al. MICCAI 2019

Corrupt k-space line detection

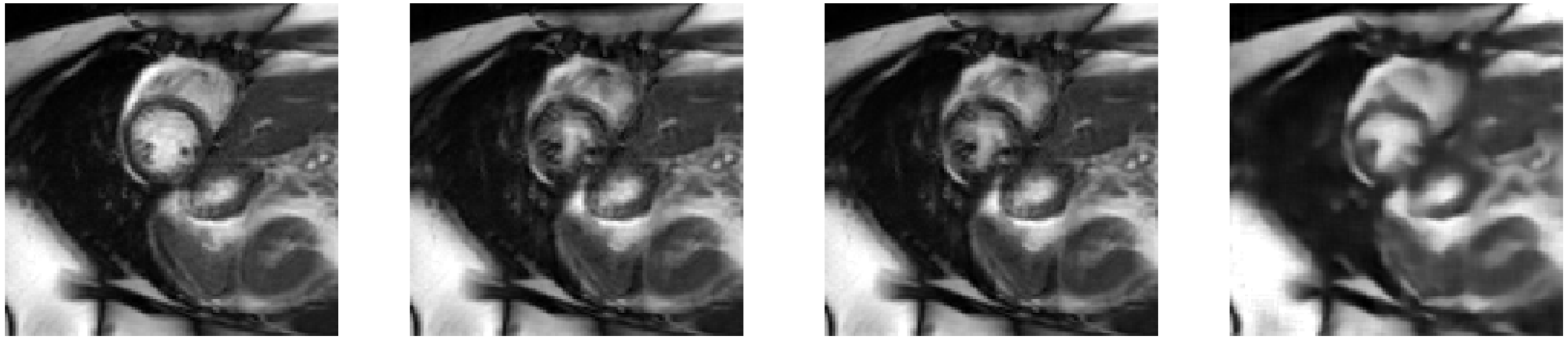


Methods	Corrupted PSNR	Corrupted RMSE	Corrupted SSIM
Baseline	26.3	0.068	0.821
DNCNN	30.8	0.049	0.845
Win5	32.2	0.041	0.853
Automap-GAN	34.8	0.028	0.878
Proposed-separate	34.7	0.026	0.879
Proposed-end to end	**37.1**	**0.023**	**0.890**
Proposed-known Mask	38.9	0.019	0.901

Methods	Uncorrupted PSNR	Uncorrupted RMSE	Uncorrupted SSIM
Baseline	-	-	-
DNCNN	36.7	0.005	0.905
Win5	37.2	0.004	0.913
Automap-GAN	38.7	0.003	0.927
Proposed-separate	39.3	0.003	0.947
Proposed-end to end	**40.8**	**0.002**	**0.972**
Proposed-known Mask	-	-	-

Oksuz et al. MedIA 2019

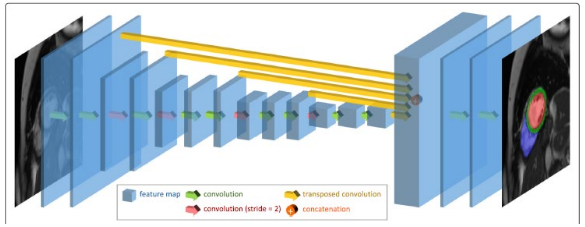
Can artefact removal help segmentation*?



(a) Original Image (b) Corrupted Image (c) WIN5 (d) Proposed

*** Peng et al., *arXiv, 2017***

(e) Original Mask (f) Corrupted Mask (g) WIN5 Mask (h) Proposed Mask

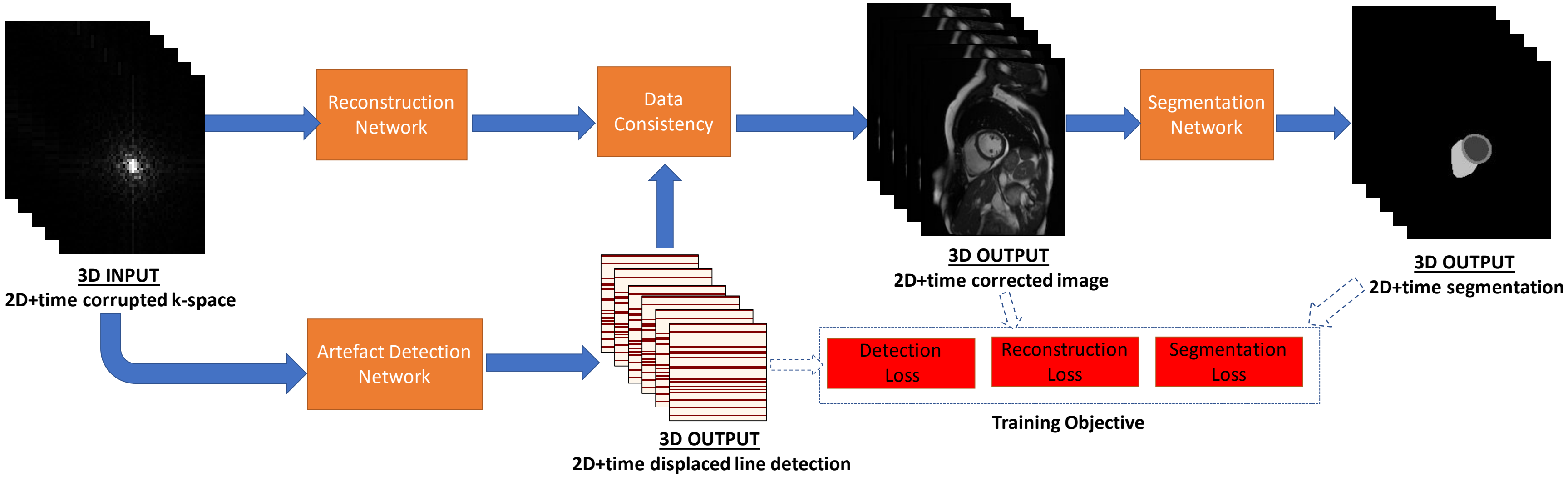


** Bai et al., JCMR, 2018*

Oksuz et al. MIDL 2019

Improving further downstream tasks:

- We can perform end-to-end training:

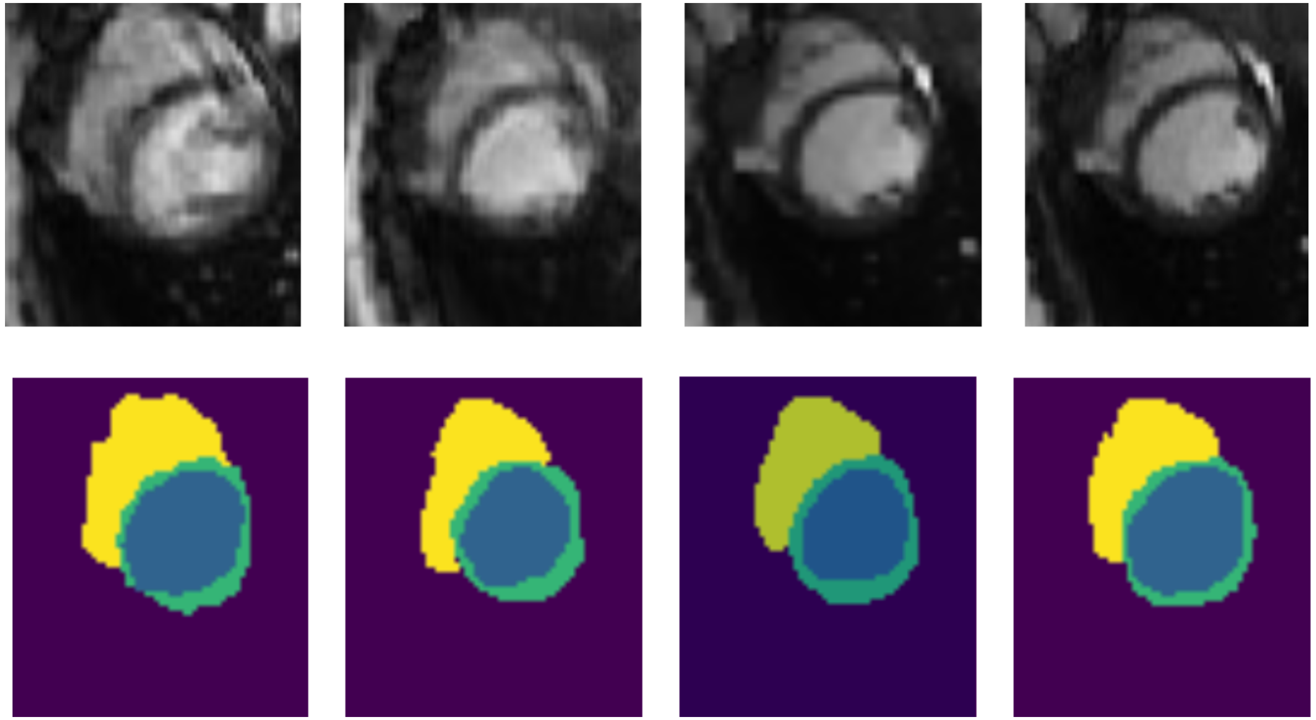


Oksuz et al. IEEE TMI 2020

Improving further downstream tasks

- Reconstruction and segmentation using:
  - **Deliberate ECG mistriggering** during acquisition
  - **Good-quality acquisition** of same volunteer without mistriggering

Artefact image with **deliberate mistriggering** and resulting segmentation	Motion reconstruction followed by segmentation	Joint motion reconstruction and segmentation	**Corresponding good-quality image** and resulting segmentation



Oksuz et al. IEEE TMI 2020

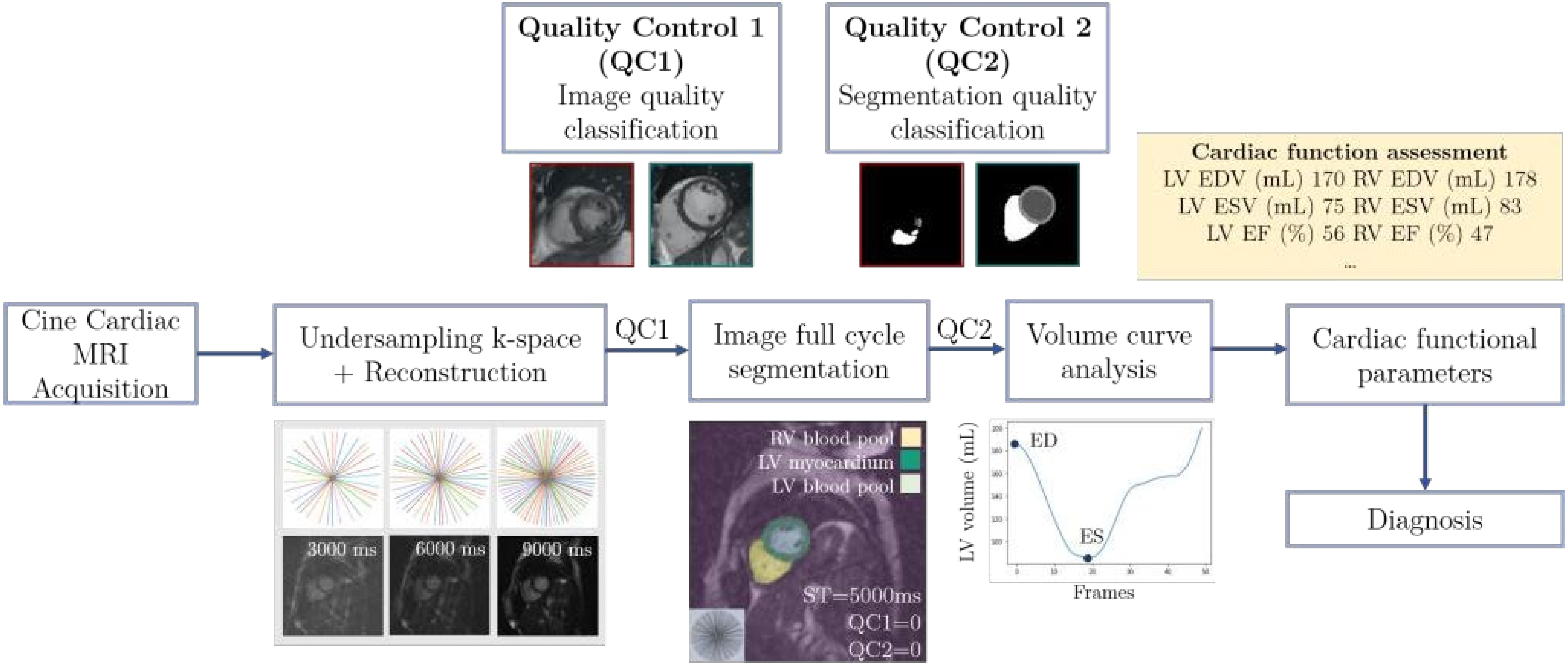
Towards quality-aware AI enabled imaging

- Aim: to accelerate the scanning process while ensuring sufficient image quality
- Data: 270 subjects from UK biobank (200 healthy, 70 with cardiomyopathy)
- Perform **retrospective radial undersampling, followed by:**
  - Quality check 1: assess **reconstruction quality**
  - Quality check 2: assess **segmentation quality**
  - Clinical function assessment via **volume curve analysis**

- **Unified framework to reduce scanning time from 12sec to 4sec per slice within 5% error**

Machado et al. MICCAI 2021 STACOM workshop

Towards quality-aware AI enabled imaging

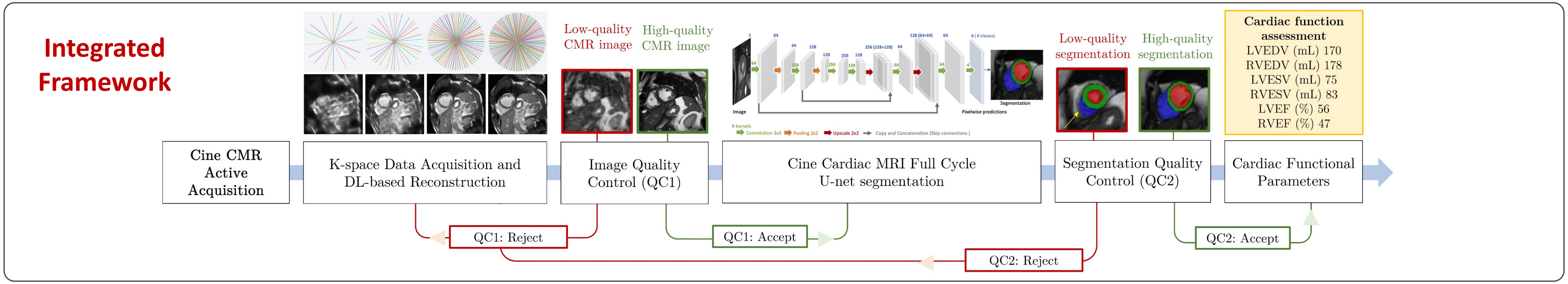


Machado et al. MICCAI 2021 STACOM workshop

More on Ines Machado’s poster!

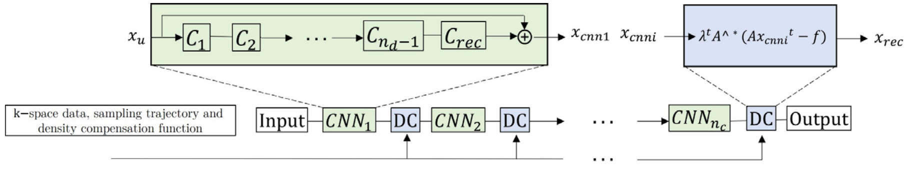
A Deep Learning-based Integrated Framework for Quality-aware Undersampled Cine Cardiac MRI Reconstruction and Analysis

Inês P. Machado, Esther Puyol-Antón, Kerstin Hammernik, Gastão Cruz, Devran Ugurlu, Ihsane Olakorede, Ilkay Oksuz, Bram Ruijsink, Miguel Castelo-Branco, Alistair A. Young, Claudia Prieto, Julia A. Schnabel and Andrew P. King



A. Reconstruction

As k-space profiles are acquired, images are continually reconstructed using the Deep Cascade of Convolutional Neural Networks (DCCNN) [1,2].

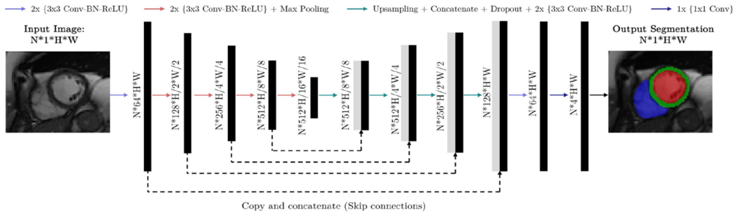


B. Image and Segmentation QC

1) Resnet classification network
2) Image-segmentation pairs
3) DSC per class
4) Data: 30,000 samples (100 subjects * 10 slices * 2 time frames * 15 undersampling factors)

C. Full-cycle segmentation

U-net based architecture for automatic segmentation of LV and RV from all SAX slices and all frames throughout the cardiac cycle [3].

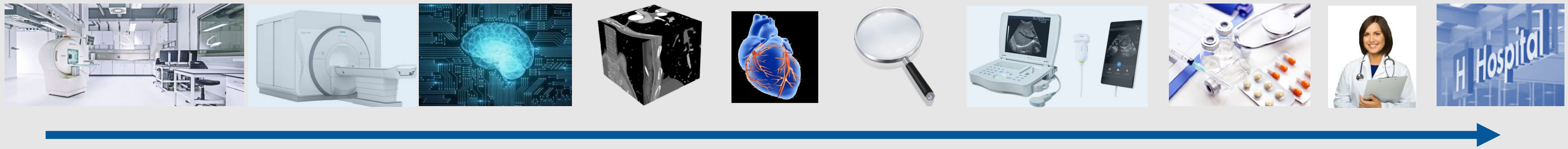


Machado et al. Submitted for journal publication.

[1] J. Schlemper, J. Caballero, J. V. Hajnal, A. N. Price, and D. Rueckert, “A deep cascade of convolutional neural networks for dynamic MR image reconstruction,” IEEE transactions on Medical Imaging, vol. 37, no. 2, pp. 491–503, 2017.
[2] K. Hammernik, T. Klatzer, E. Kobler, M. P. Recht, D. K. Sodickson, T. Pock, and F. Knoll, “Learning a variational network for reconstruction of accelerated MRI data,” Magnetic resonance in medicine, vol. 79, no. 6, pp. 3055–3071, 2018.
[3] C. Chen, W. Bai, R. H. Davies, A. N. Bhuva, C. H. Manisty, J. B. Augusto, J. C. Moon, N. Aung, A. M. Lee, M. M. Sanghvi, K. Fung, J. M. Paiva, S. E. Petersen, E. Lukaschuk, S. K. Piechnik, S. Neubauer, and D. Rueckert, “Improving the generalizability of convolutional neural network-based segmentation on CMR images,” Frontiers in cardiovascular medicine, vol. 7, p. 105, 2020.

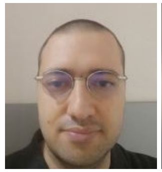
Conclusions

- **AI-enabled image quality control is unlocking the full potential of cardiac MRI** – from accelerated, quality-controlled acquisition to interpretation
- Can operate along the **entire imaging pipeline**, at time of scanning or end-to-end
- Can improve **clinical workflow** and **downstream analysis**



smartheart

Thank you – any questions?



KING'S College LONDON

Imperial College London

Queen Mary University of London

UNIVERSITY OF OXFORD

UKRI Engineering and Physical Sciences Research Council

biobank uk

TUM

KING'S College LONDON