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(Medical) Image Quality Assessment Using Deep Learning

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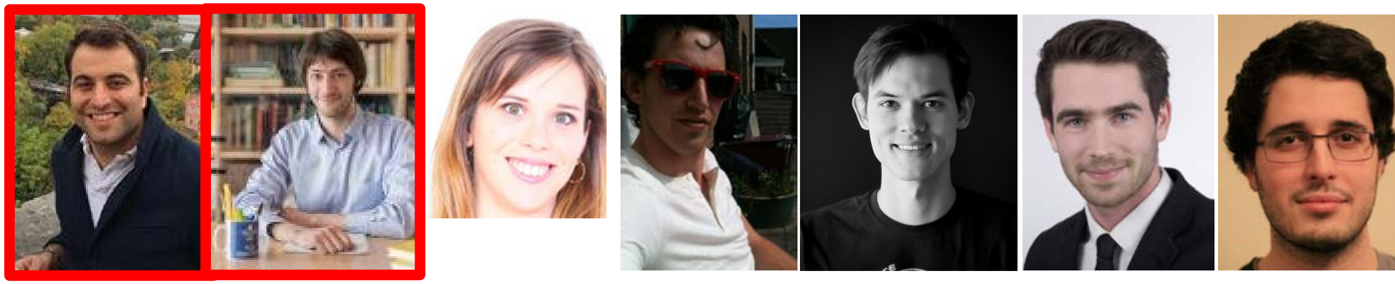
Acknowledgments – Upfront!



Ilkay Oksuz, King's | Giacomo Tarroni, Imperial | Esther Puyol Anton, King's | Bram Ruijsink, King's | Matthew Sinclair, Imperial | Aurelien Bustin, King's | Gastao Cruz, King's

Daniel Rueckert Imperial | Yike Guo, Imperal | Steffen Petersen, QMUL | Alison Noble, Oxford | Rene Botnar, King's | Claudia Prieto, King's | Andy King, King's | Julia Schnabel, King's | Reza Razavi, King's

References:

Oksuz et al., *Automatic Left Ventricular Outflow Tract Classification for Accurate Cardiac MR Planning, Proc. ISBI 2018;*

Oksuz et al.*, Accepted for MICCAI 2018.*

Oksuz et al., *Accepted for MLMR 2018.*

Tarroni et al.*, Learning-Based Quality Control for Cardiac MR Images. preprint arXiv:1803.09354*

UK Biobank Resource – Application #18545

Overview

- Part 1:
  - Image Quality Issues
  - Automatic Quality Assessment using DL/ML
- Part 2:
  - Image Artefact Correction using DL
- Application to cardiac MRI

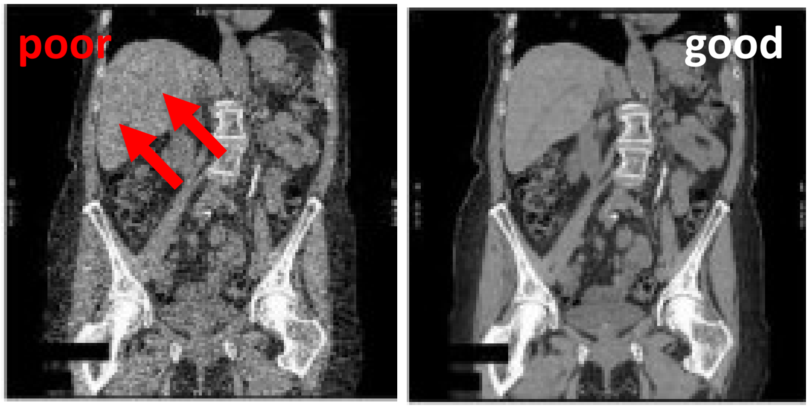
References:
Oksuz et al., *Automatic Left Ventricular Outflow Tract Classification for Accurate Cardiac MR Planning, Proc. ISBI 2018;*
Oksuz et al.*, Accepted for MICCAI 2018.*
Oksuz et al., *Accepted for MLMR 2018.*
Tarroni et al.*, Learning-Based Quality Control for Cardiac MR Images. preprint arXiv:1803.09354*

Quality of Medical Images

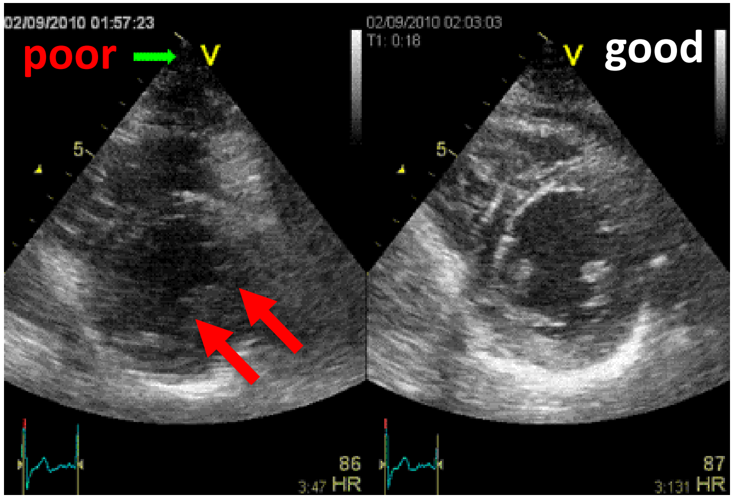
- Need for high-quality images for accurate diagnostics and prognostics
- Wide range of imaging artefacts:
  - Acquisition related: bias field, probe position, injection of contrast agent…
  - Reconstruction related: e.g. iterative methods, undersampling, …
  - Patient related: physiological motion (e.g. breathing, heart beat) and sudden motion (patient moving)

Quality of Medical Images

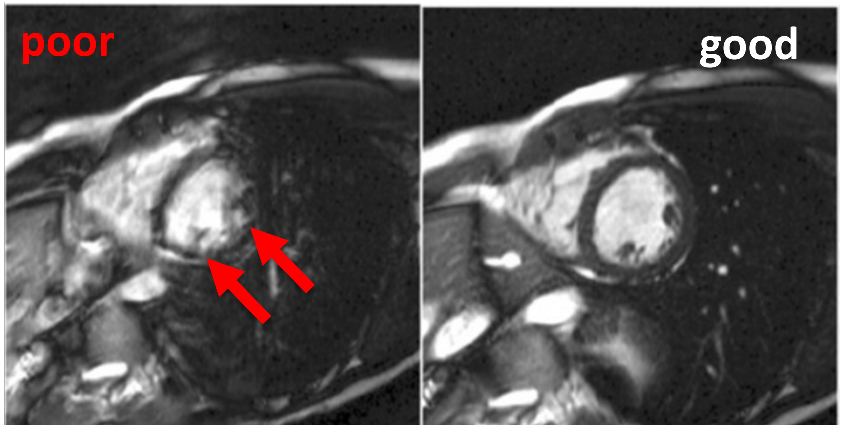
CT



Ultrasound



Cardiac MR



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Adopted from Ferreira et al., JCMR, 2013.

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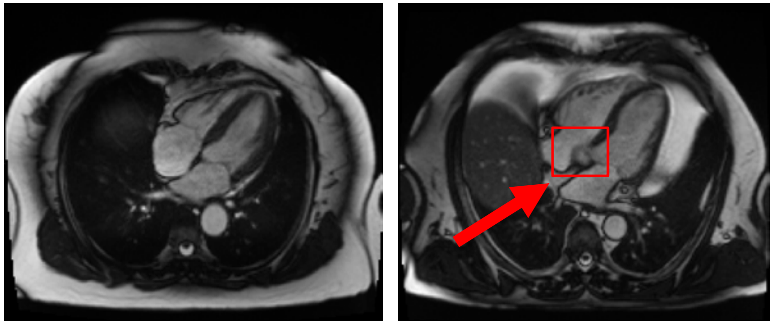
Cardiac MR quality assessment

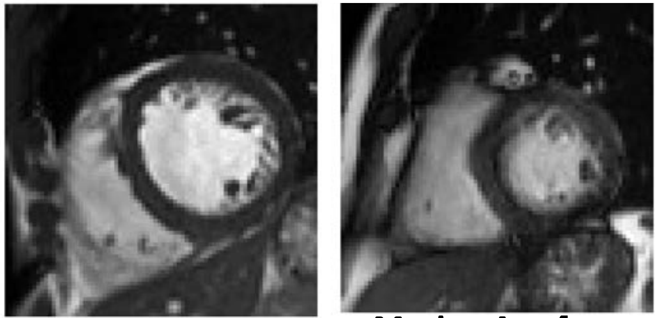
- CMR imaging requires operator to manually define a set of acquisition parameters
- QC is performed retrospectively by visual inspection by the same or a different operator
- Acquisition of large-scale studies
  - Visual inspection is becoming infeasible

Cardiac MR Quality Issues

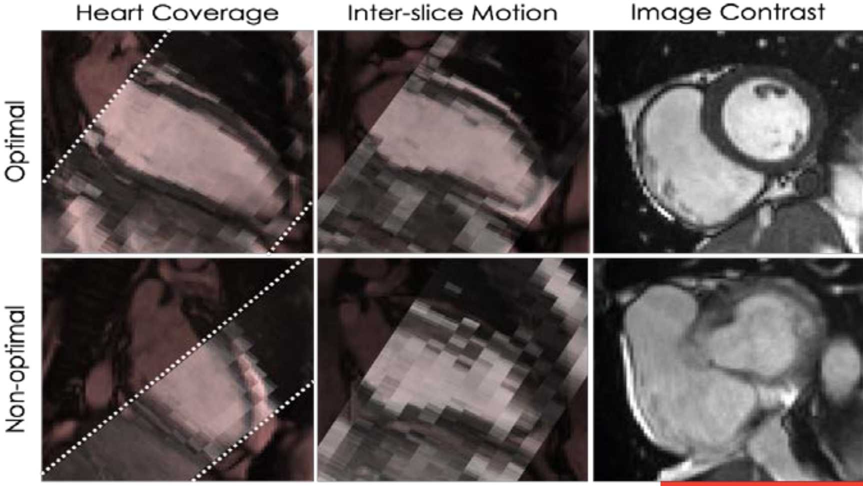
1. **<u>Off-axis (4ch</u>)***
   – Left Ventricular Outflow Tract
   – "5 chamber look"
2. **<u>Motion related issues (SAX)</u>**
   – Breathing
   – Mis-triggering
   – Arrhythmia
3. **<u>Other quality control issues</u>**
   – Heart coverage estimation
   – Inter-slice respiratory motion
   – Image contrast estimation
   – …



Good Planning Bad Planning

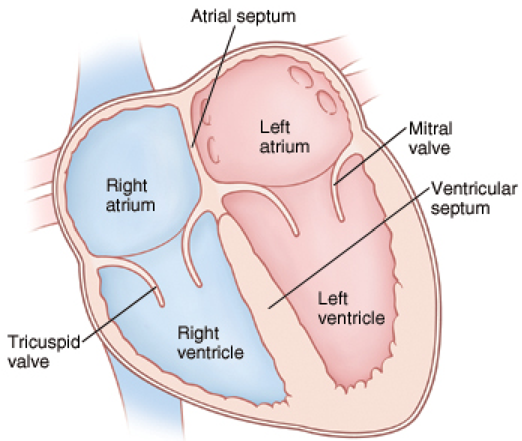


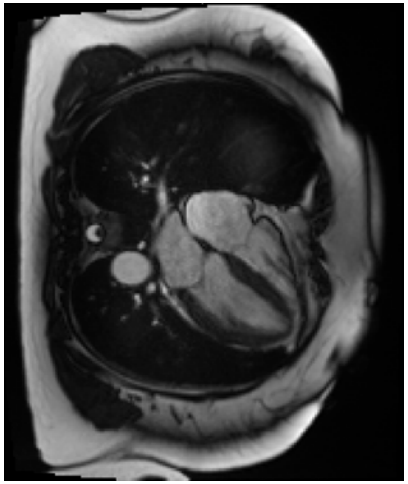
Good Quality Motion Artefact



4-Chamber Cine Cardiac MRI

- Good 4-chamber CMR image shows all chambers clearly.
- Right and left atrium analysis can be achieved with 4-chamber view.





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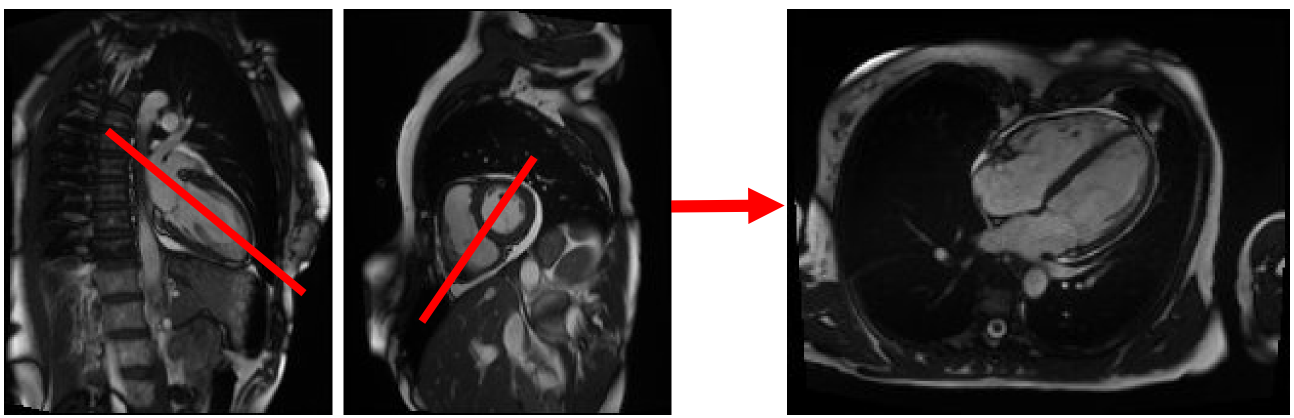
4-Chamber view planning

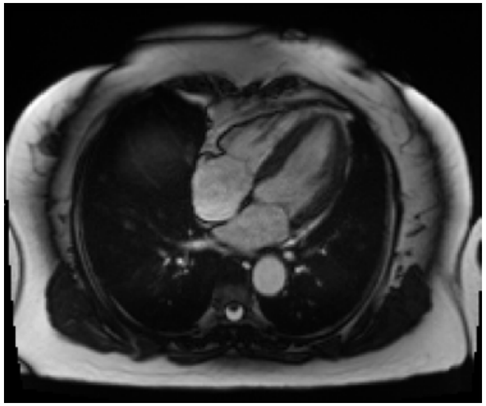
- 4C view is planned using 2-chamber and SAX images
- An appropriate angle is defined on SAX



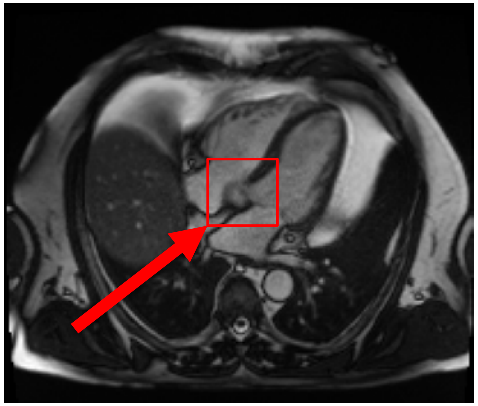
2-chamber view   Short axis view   4-chamber view

Left Ventricular Outflow Tract (LVOT)

- Wrong cardiac planning leads to off-axis acquisitions
- Presence of Left Ventricular Outflow Tract (LVOT) – “5 chamber look”
- Poses challenges right/left atrial analysis
- Automatic LVOT detection can help automatic cardiac planning

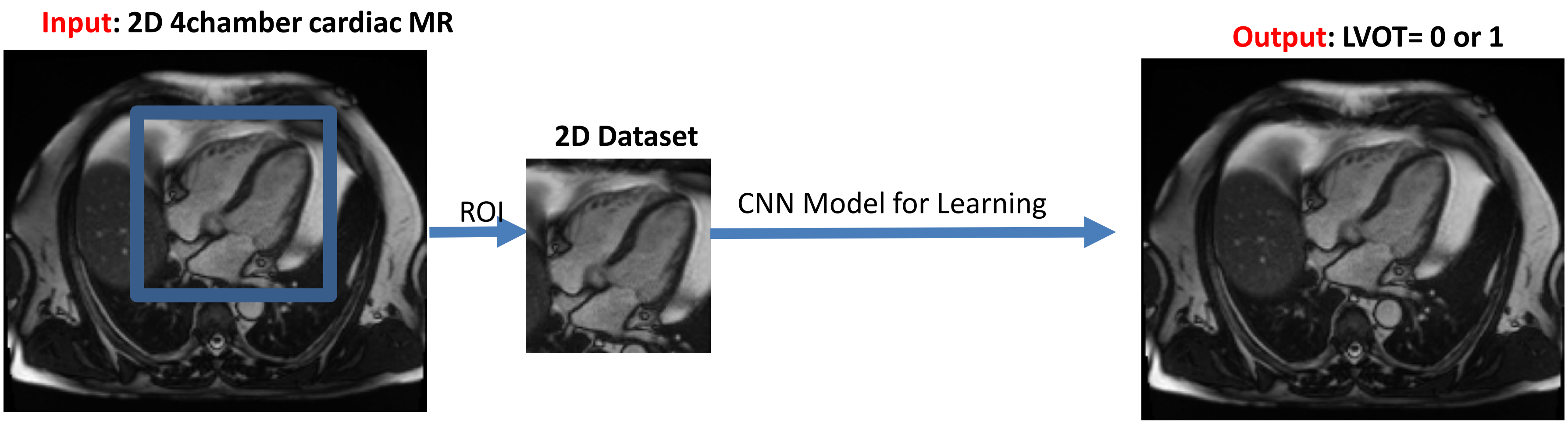


Good Planning



Poor Planning

Method*



1. Contrast Normalization
2. Region of Interest Extraction
3. Training a CNN Model

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Oksuz et al., *Automatic Left Ventricular Outflow Tract Classification for Accurate Cardiac MR Planning, Proc. ISBI 2018;*

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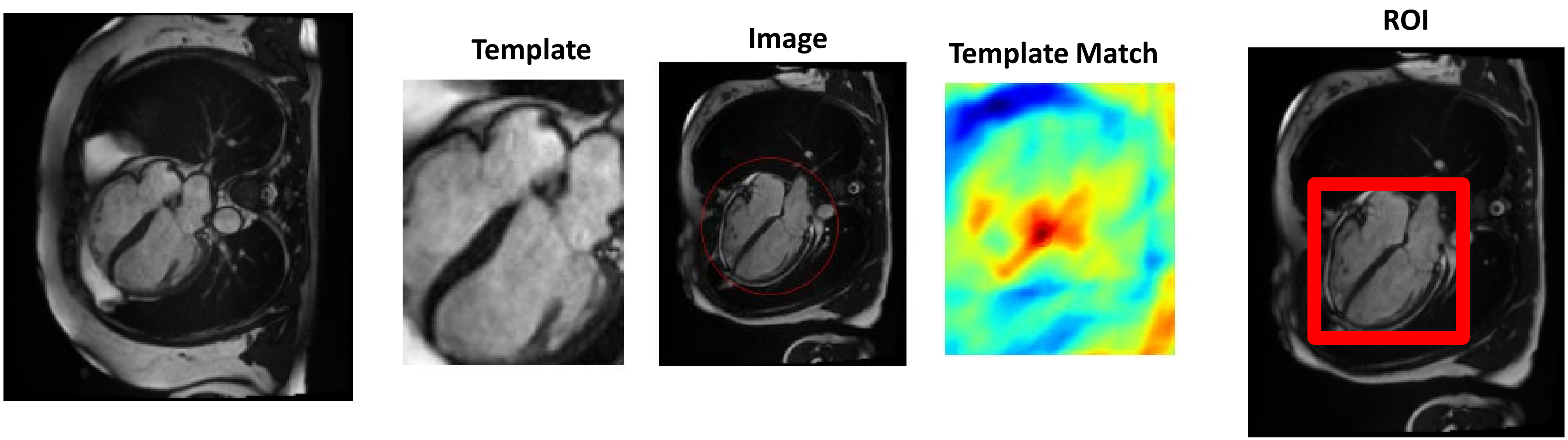
ROI Extraction-Template Matching

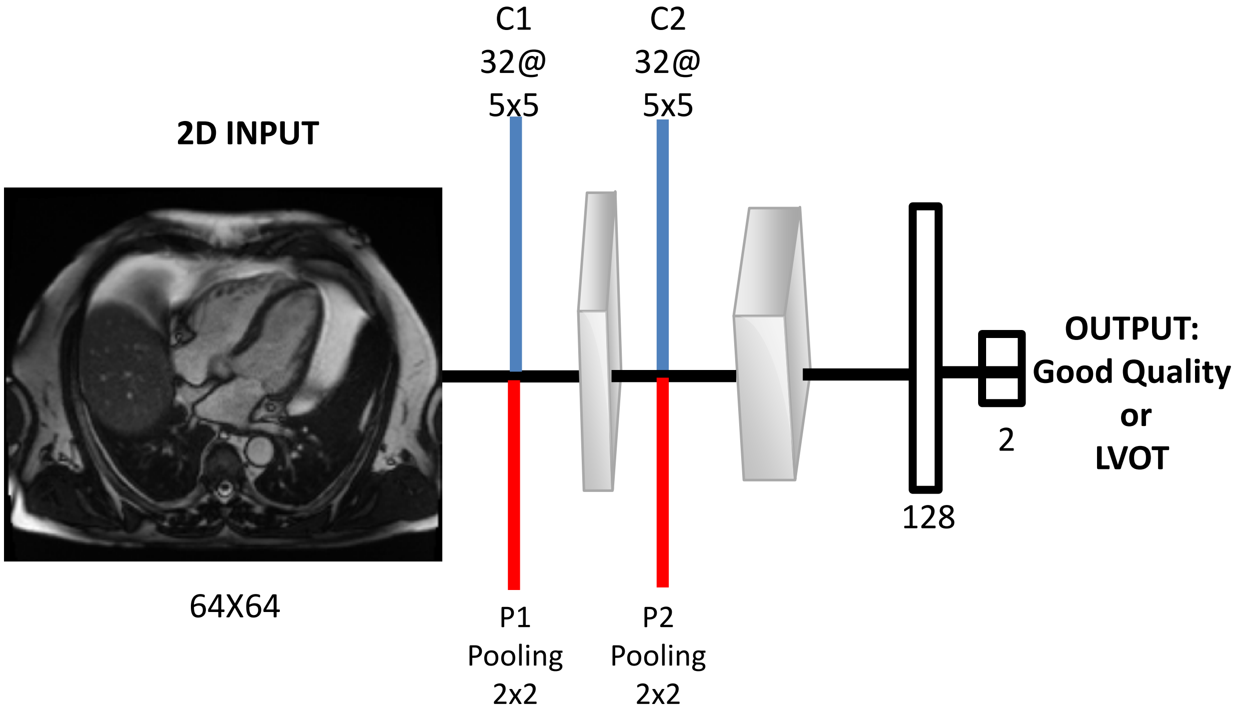
- Use a separate dataset to generate templates
- Normalized cross-correlation for template matching



***Oksuz et al.**, Automatic Left Ventricular Outflow Tract Classification for Accurate Cardiac MR Planning, Proc. ISBI 2018;*

CNN model

- Similar to Lenet* Model
- 2 convolutional layers
- 2 Max Pooling Layers
- Dropout 0.5 after each layer
- ReLU activation



ReLU: Rectified Linear Unit to generate activation maps

* **LeCun et al.,** ***Proceedings IEEE, 1998***

Oksuz et al., *Automatic Left Ventricular Outflow Tract Classification for Accurate Cardiac MR Planning, Proc. ISBI 2018;*

Implementation Details

- Data augmentation
  - Rotations: angle between 0 and 90 degrees
  - Translations: horizontal and vertical shifts 0.1 width and height
  - Triple the total data
- Adadelta Optimizer
  - momentum=0.90 learning rate=0.0001
- Binary cross entropy loss
- Zero mean Gaussian initialization
- 100 epochs

Oksuz et al., *Automatic Left Ventricular Outflow Tract Classification for Accurate Cardiac MR Planning, Proc. ISBI 2018;*

Dataset and methods of comparison

- 123 Good Quality Images and 123 LVOT Images from UK Biobank*   *** Petersen et al., *JCMR*, 2016**
- 5 temporal frames of each sequence, 615 images for each class
- Stratified 10-fold cross validation
- Data augmentation: rotation, translation, additional temporal frames to increase amount of training data

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Oksuz et al., *Automatic Left Ventricular Outflow Tract Classification for Accurate Cardiac MR Planning, Proc. ISBI 2018;*

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Dataset and methods of comparison

- State-of-the-art classification methods for comparison using same input data:
  - K-nearest neighbors
  - Linear SVM
  - Decision Tree
  - Random Forests
  - Adaboost
  - Naïve Bayesian
  - Quadratic Discriminant Analysis

Oksuz et al., *Automatic Left Ventricular Outflow Tract Classification for Accurate Cardiac MR Planning, Proc. ISBI 2018;*

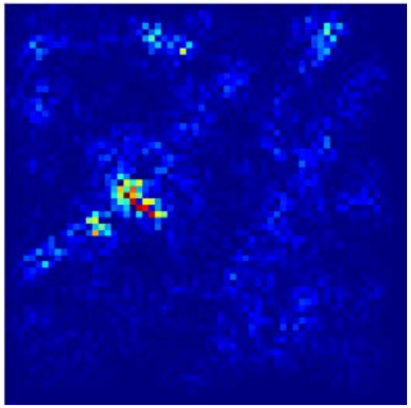
Experimental Results

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

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

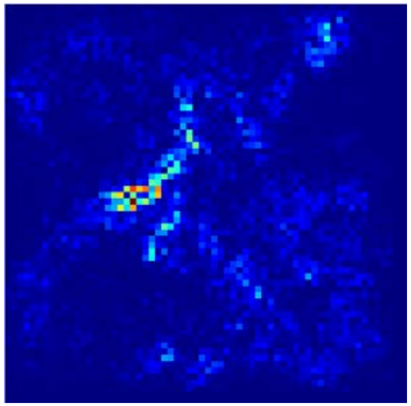
$$\text{Precision} = \frac{TP}{TP + FP} \qquad \text{Recall} = \frac{TP}{TP + FN}$$

LVOT



LVOT attention map*

Good Quality Image



Good Quality Attention Map*

*** Zhou et al., *CVPR*, 2016**

Oksuz et al., *Automatic Left Ventricular Outflow Tract Classification for Accurate Cardiac MR Planning, Proc. ISBI 2018;*

Cardiac MR Quality Issues

1. **Off-axis (4ch)***
   – Left Ventricular Outflow Tract
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   – Breathing
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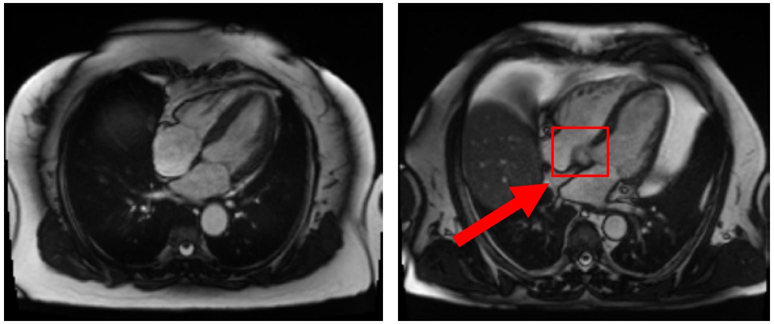
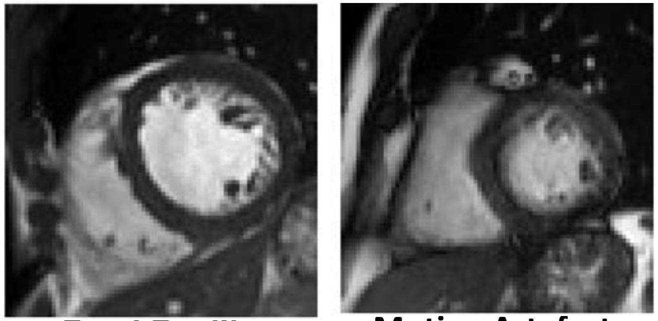
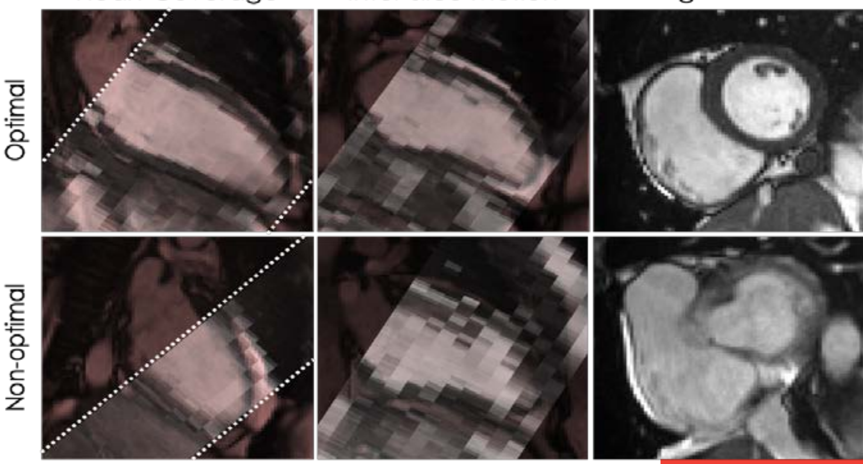
   – …







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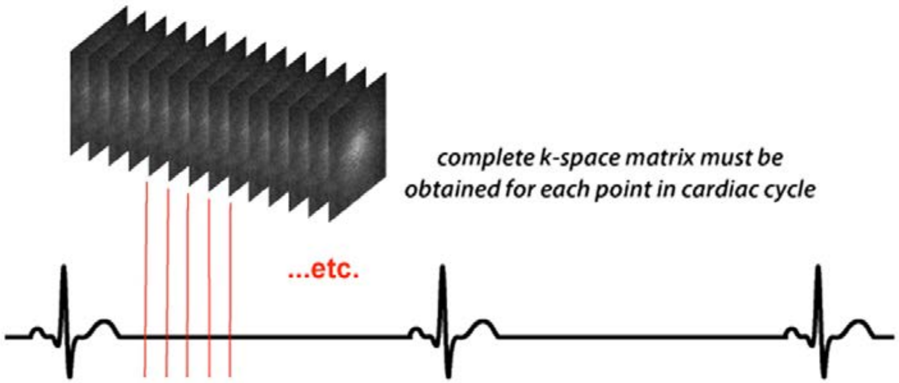
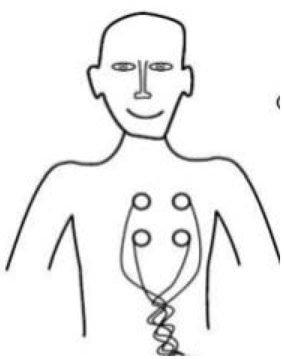
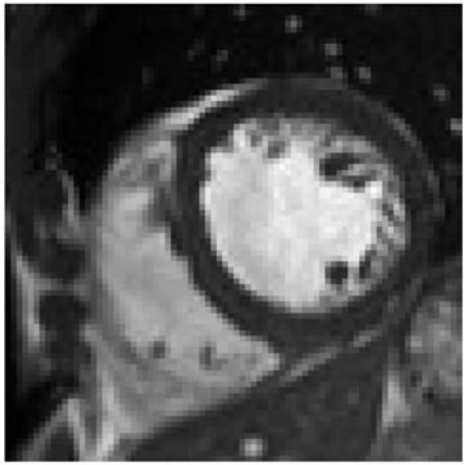
Cardiac MRI Acquisition





Good Quality



Good Quality

Motion Artefact

Motion Artefact

Dataset

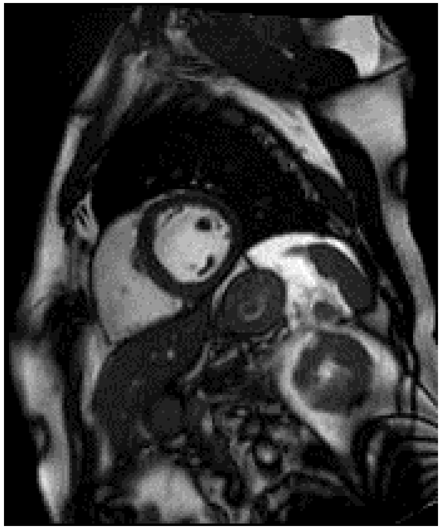
- 105 subjects with motion artefacts:
  - Breathing, mis-triggering, arrhythmia
- 53 for mis-triggering, 23 for breathing, 24 arrhythmia, 4 mixed
- 105 artefact Images versus 3360 good-quality Images
- Class imbalance!

Dataset

Arrhythmia

Breathing

Mis-triggering

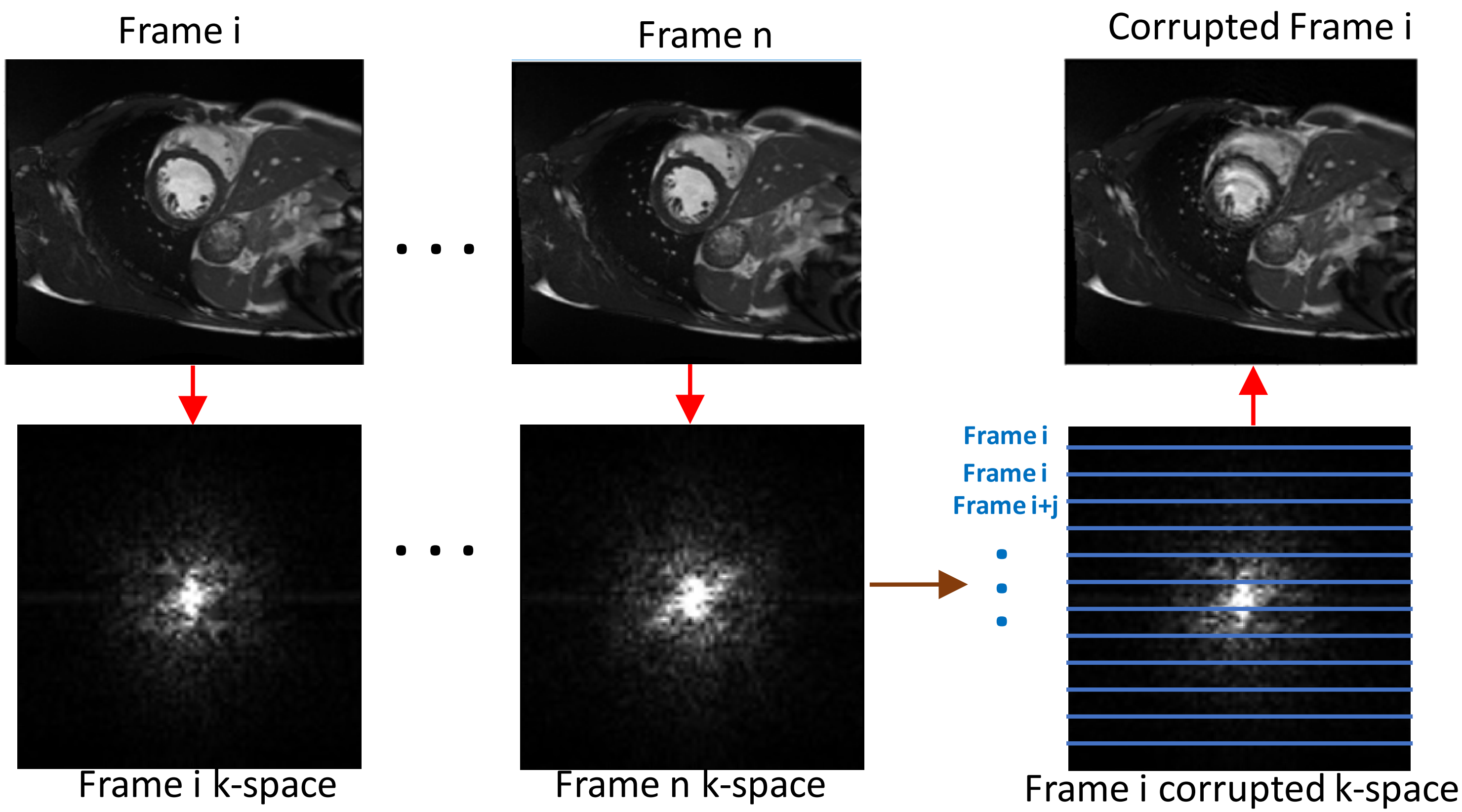


Good Quality

Data imbalance-TODOs

1. **Can You Collect More Data?**
   – Difficult task in many medical imaging applications
2. **Try Resampling Your Dataset**
   – You can add copies of instances from the under-represented class called over-sampling (or more formally sampling with replacement) or
   – Delete some data from the over-represented class.
   – Not the best strategy to make use of your data to the fullest.
3. **Try to Generate Synthetic Samples**
   – Generate synthetic examples that best represent the original data from the under-represented class.

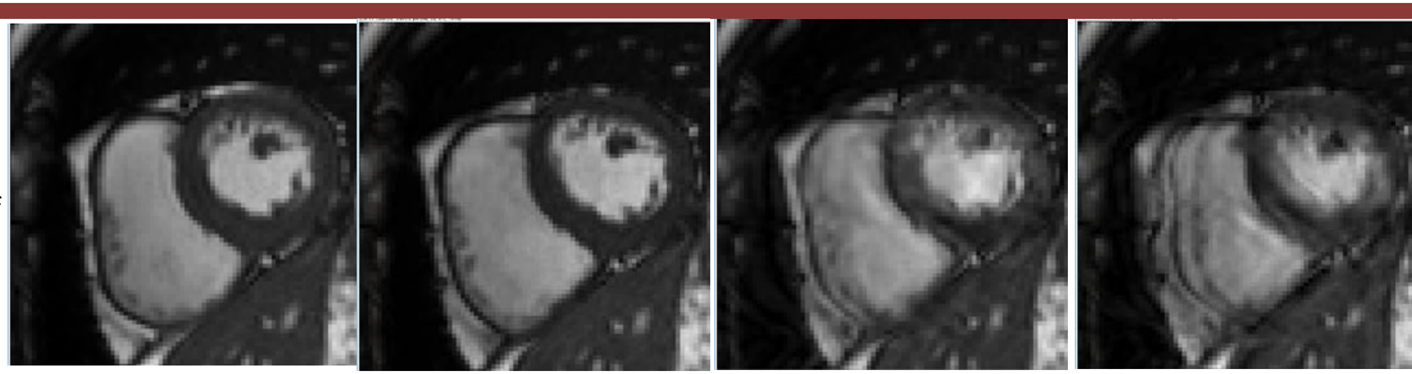
K-space corruption*



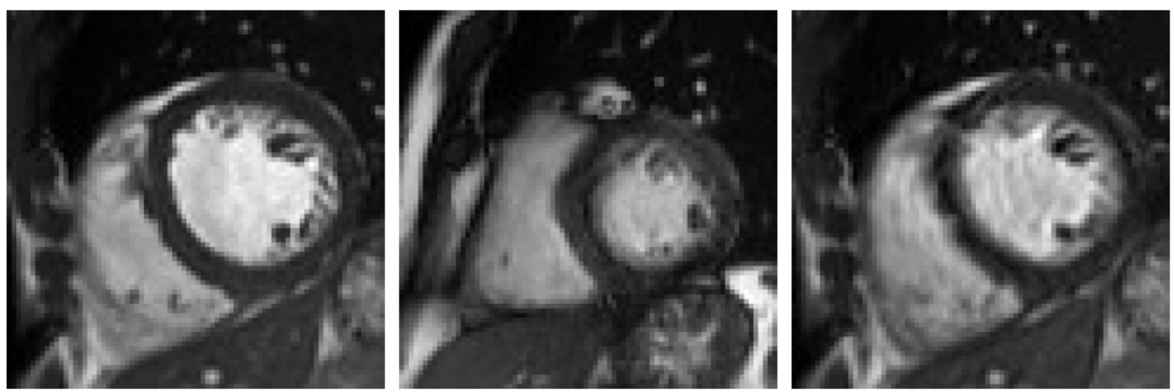
***Oksuz et al.**, Accepted for MICCAI 2018.*

Synthetic Images

Different corruption levels of k-space

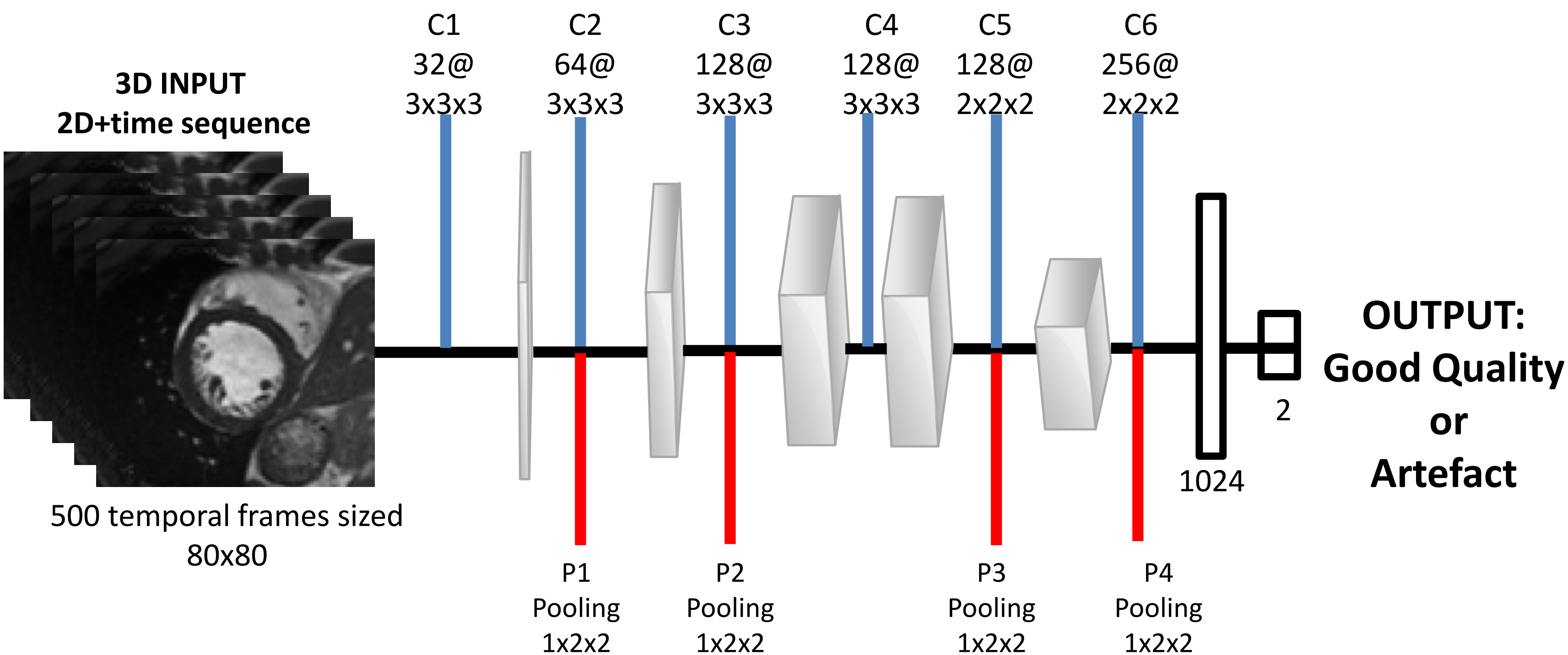


HIGH QUALITY → **LOW QUALITY**



Good Quality | **Motion Artefact** | **K-space corrupted image**

“3D” (2D+time) CNN MODEL



Experimental Results

$$\text{Precision} = \frac{TP}{TP + FP} \qquad \text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

$$\text{F1 score} = \frac{2 * (\text{Recall} * \text{Precision})}{\text{Recall} + \text{Precision}}$$

Methods	Accuracy	Precision	Recall	F1-score
K-Nearest Neighbours	0.952	0.074	0.268	0.116
Linear SVM	0.968	0.721	0.385	0.502
Decision Tree	0.951	0.250	0.385	0.303
Random Forests	0.958	0.320	0.315	0.317
Adaboost	0.960	0.230	0.567	0.327
Naive Bayesian	0.801	0.527	0.183	0.111
Variance of Laplacian	0.958	0.113	0.161	0.133
NIQE *	0.958	0.210	0.248	0.227
CNN with no augmentation	0.968	0.700	0.466	0.560
CNN with translational augmentation	0.974	0.750	0.600	0.667
CNN with k-space augmentation	0.977	0.779	0.642	0.704
CNN with k-space+translational augmentation	0.982	0.809	0.652	0.722

** Mittal et al.,Naturalness Image Quality Evaluator. IEEE Signal Processing Letters, 2013*

Cardiac MR Quality Issues

1. **Off-axis (4ch)***
   – Left Ventricular Outflow Tract
   – "5 chamber look"
2. **Motion related issues (SAX)**
   – Breathing
   – Mis-triggering
   – Arrhythmia
3. **Other quality control issues**
   – Heart coverage estimation
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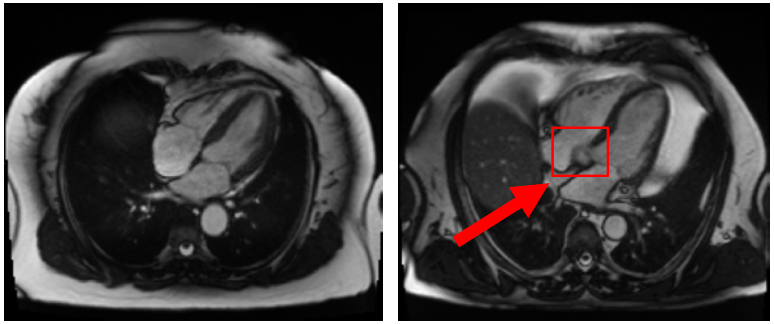
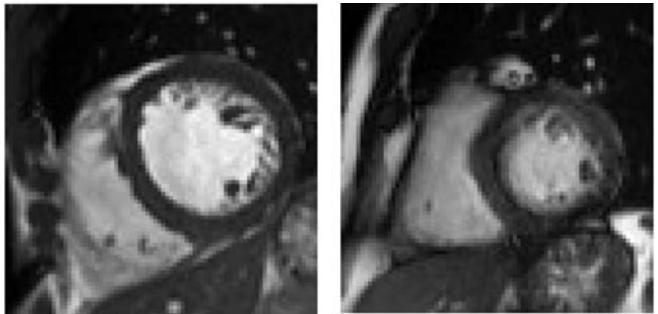
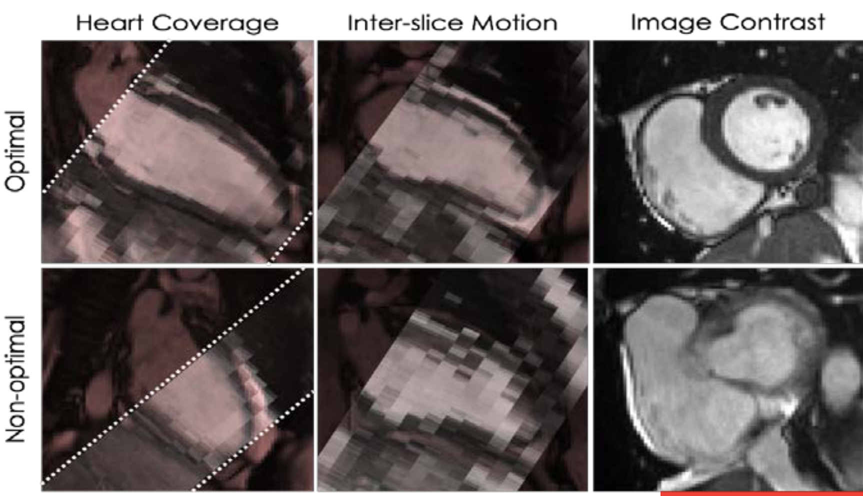
   – …

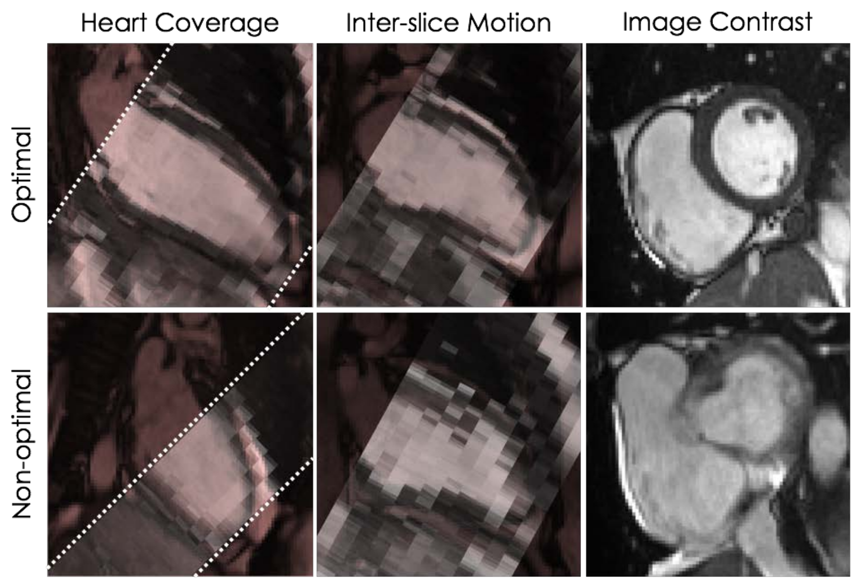

Good Planning   Bad Planning


Good Quality   Motion Artefact



Automated Quality Control*

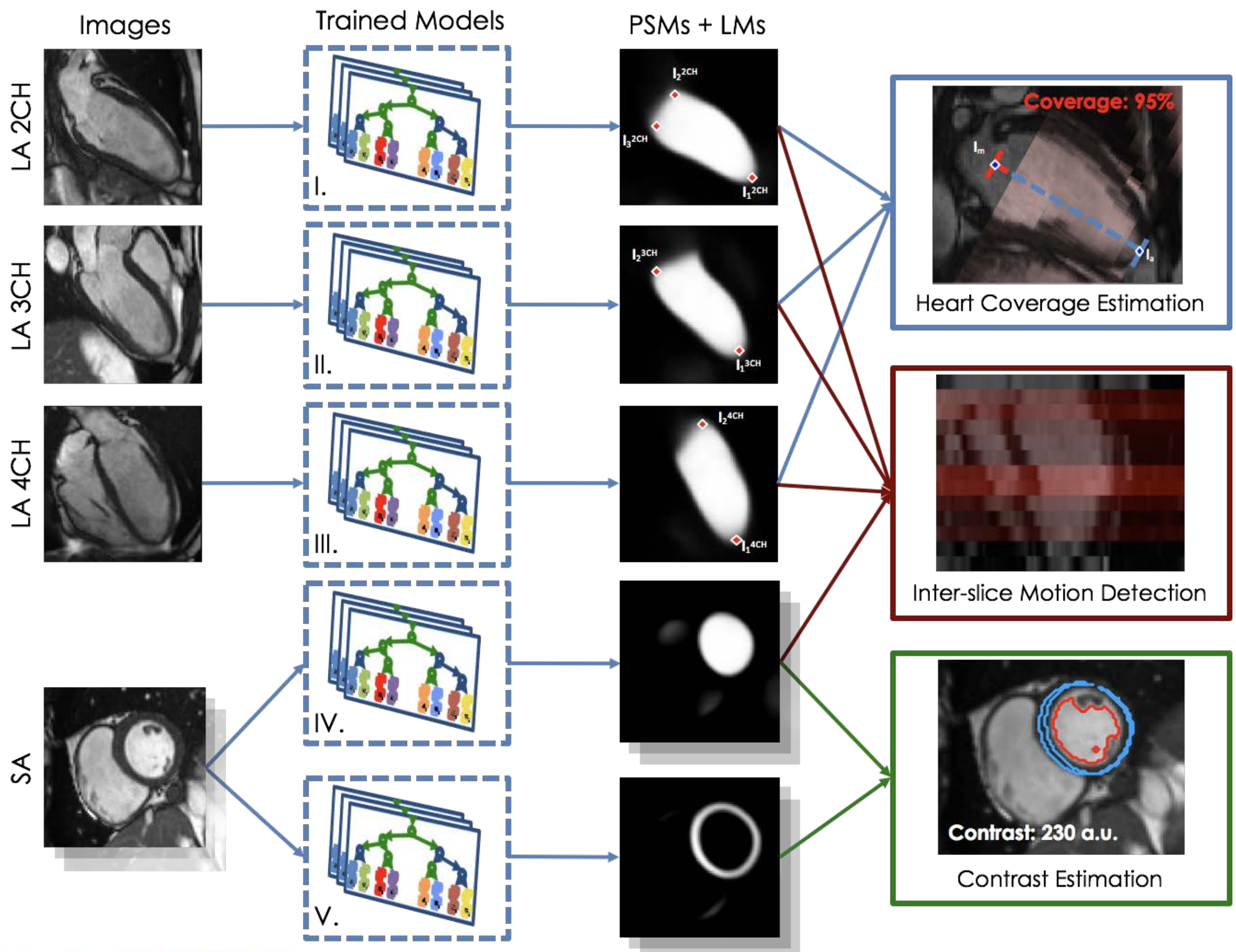
- Learning-based fully-automated quality control pipeline for cardiac MRI
- Tested on up to 3000 cases from the UK Biobank



Issues potentially affecting short-axis image acquisition

***Tarroni et al.**, *Learning-Based Quality Control for Cardiac MR Images. preprint arXiv:1803.09354*

Automated Quality Control

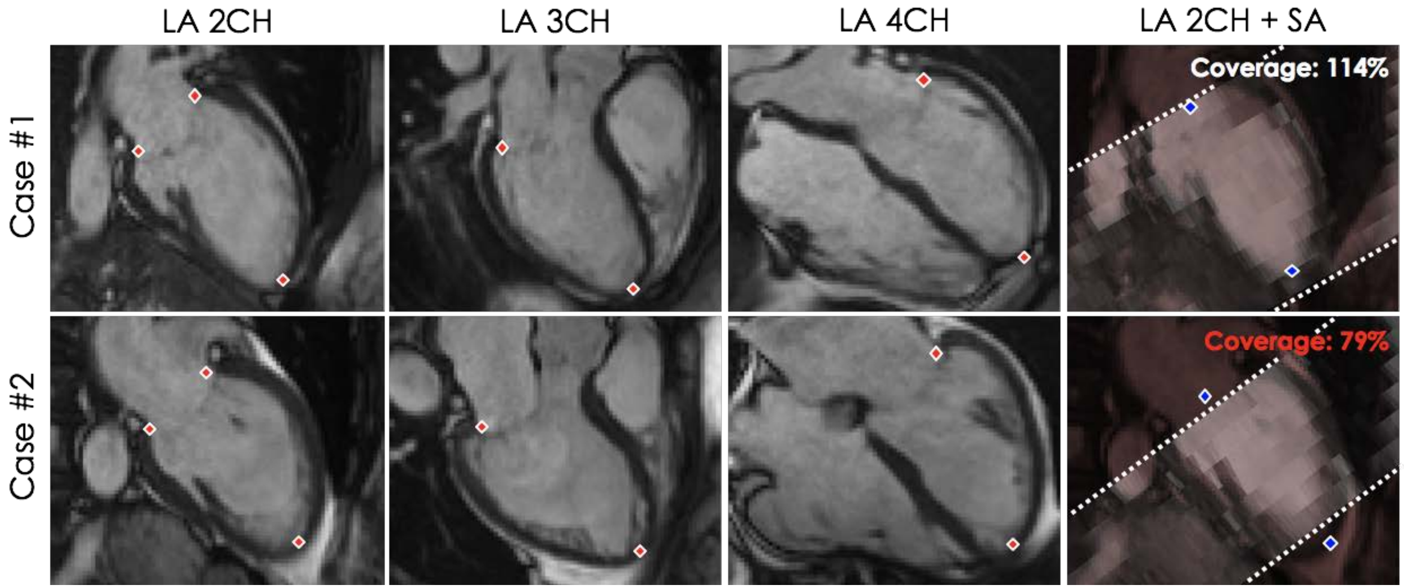


**Tarroni et al.*, *Learning-Based Quality Control for Cardiac MR Images. preprint arXiv:1803.09354*

Automated Quality Control

Heart Coverage Estimation

Tested on 3000 cases vs. visual assessment



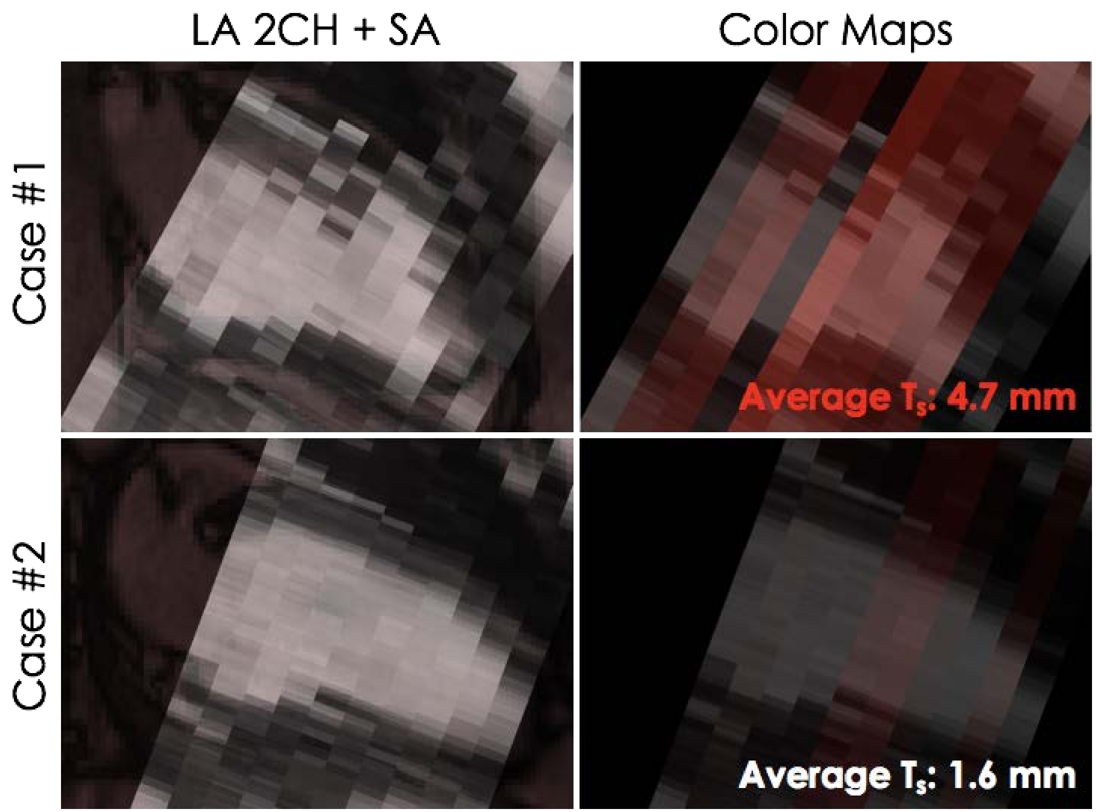
Binary classification test: Coverage < 90%

Sensitivity	Specificity
88%	99%

***Tarroni et al.**, *Learning-Based Quality Control for Cardiac MR Images. preprint arXiv:1803.09354*

Automated Quality Control

Inter-slice Respiratory Motion Detection: Tested on 1500 cases vs. visual assessment



Binary classification test

Mean translation magnitude < 3.4 mm

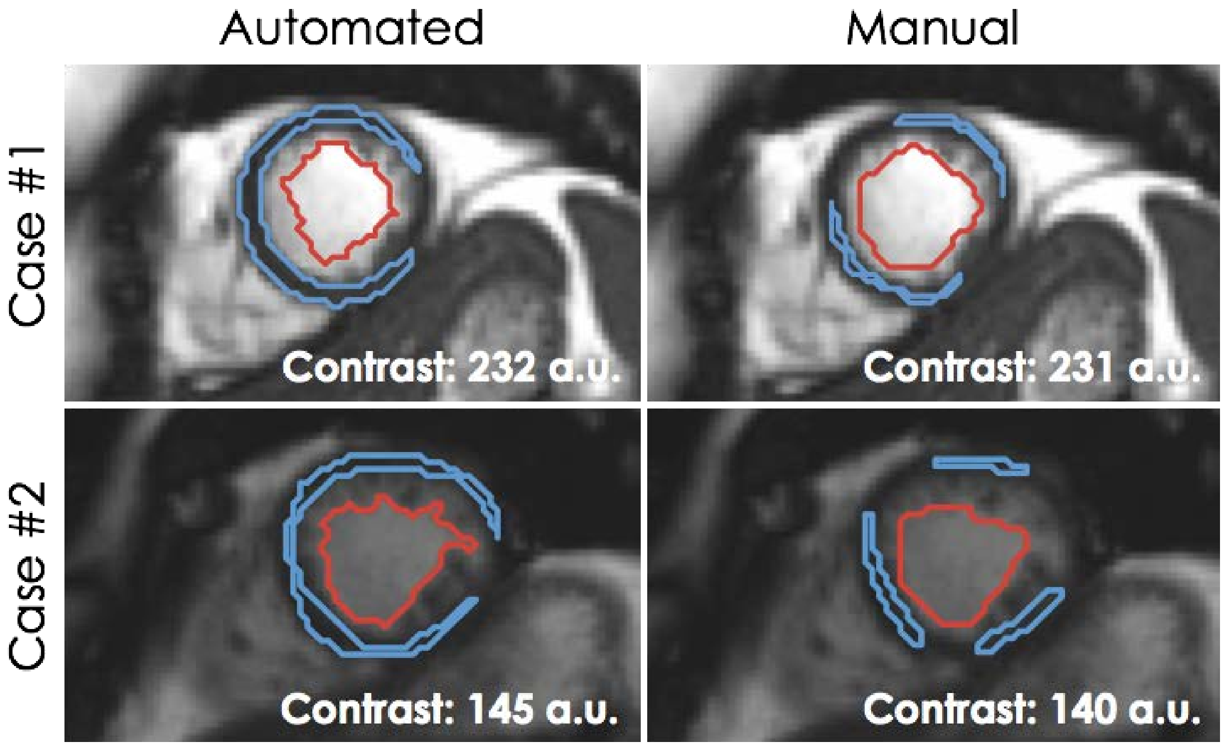
Sensitivity	Specificity
85%	95%

***Tarroni et al.**, *Learning-Based Quality Control for Cardiac MR Images. preprint arXiv:1803.09354*

Automated Quality Control

Cardiac Image Contrast Estimation:

Tested on 100 cases vs. manual contouring



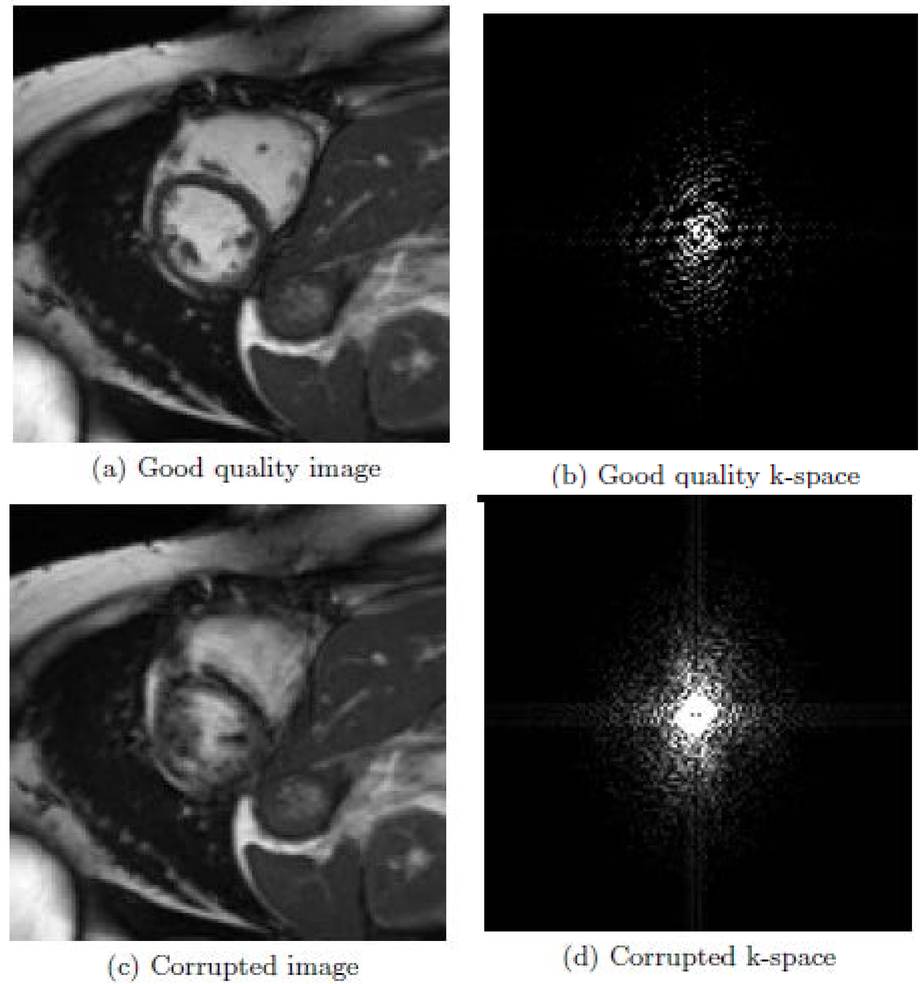
	Bland-Altman		Linear Regression		
R	**Bias**	**Std**	**a**	**b**	**Mean Value**
0.95	-0.6	12.1	0.96	7.8	190

***Tarroni et al.**, *Learning-Based Quality Control for Cardiac MR Images. preprint arXiv:1803.09354*

Part 2: Cardiac MR Artefact Correction

- **Problem Definition:**
- Motion artefact correction

- Denoising image space
- Denoising k-space
- **End-to-end→ (a to d)***


(a) Good quality image (b) Good quality k-space
(c) Corrupted image (d) Corrupted k-space

***Oksuz et al.**, Accepted for MLMR 2018.*

AUTOMAP

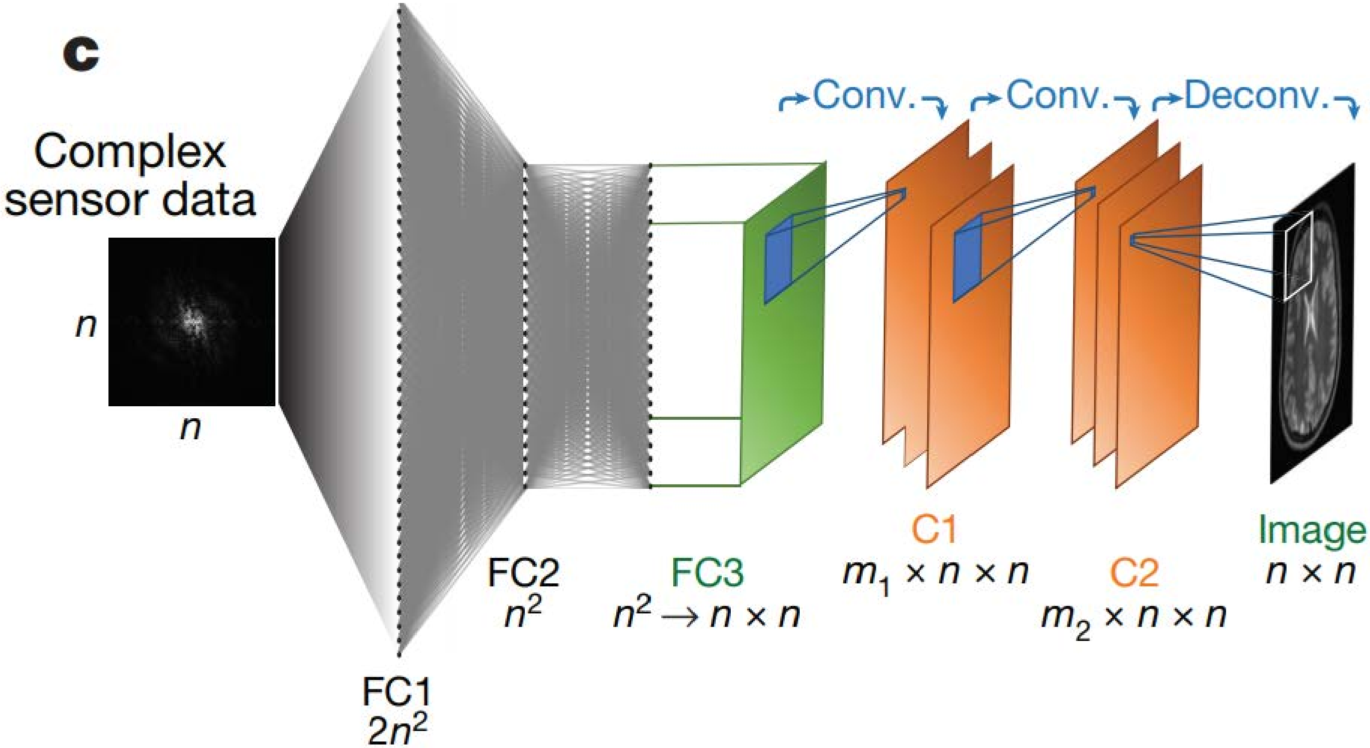
- Image reconstruction by domain transform manifold learning
- Developed for high quality image reconstruction from under-sampled k-space
- Insufficient image quality for corrupted k-space

*** Zhu et al., *Nature, 2018***

AUTOMAP

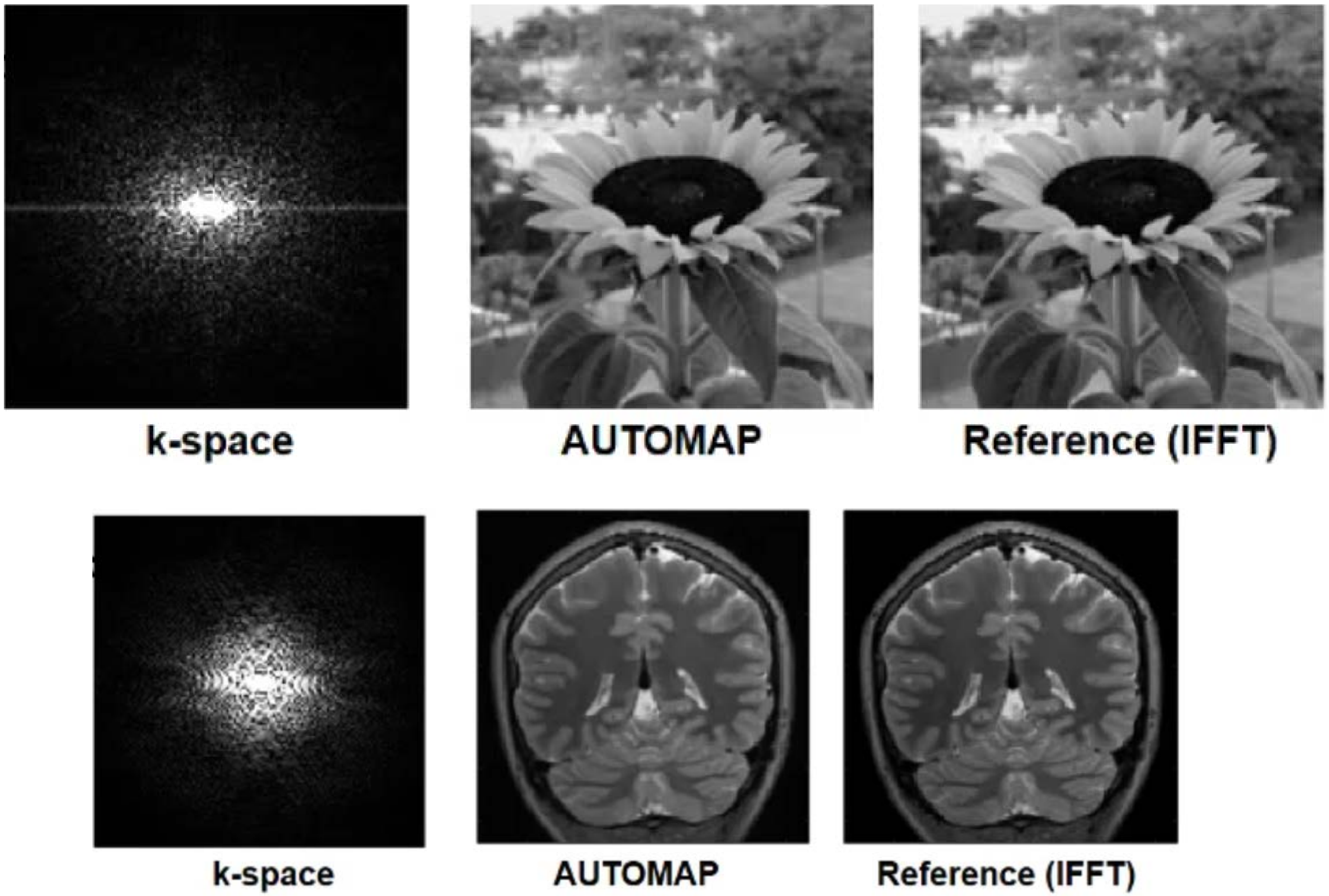
*** Zhu et al., *Nature, 2018***

- Learns image reconstruction

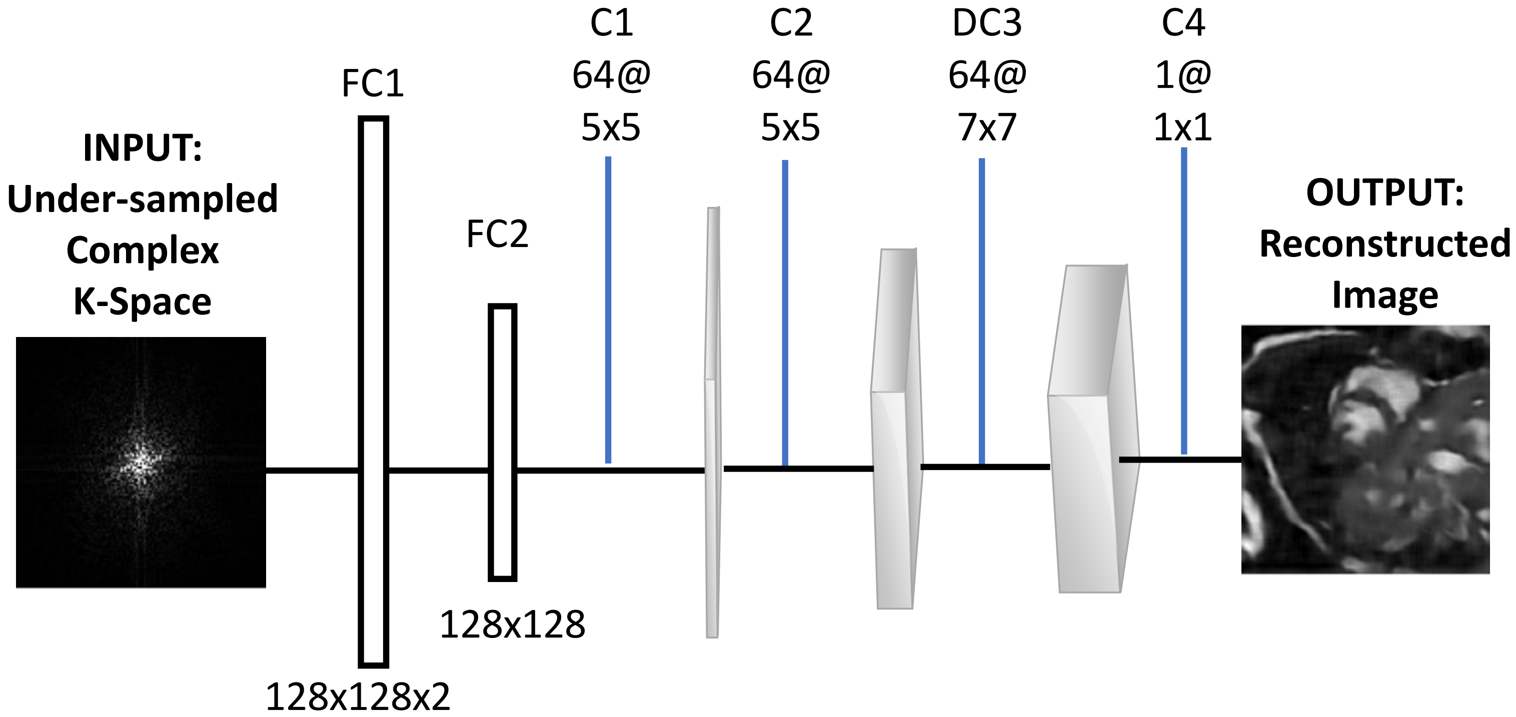


AUTOMAP

*** Zhu et al., *Nature, 2018***



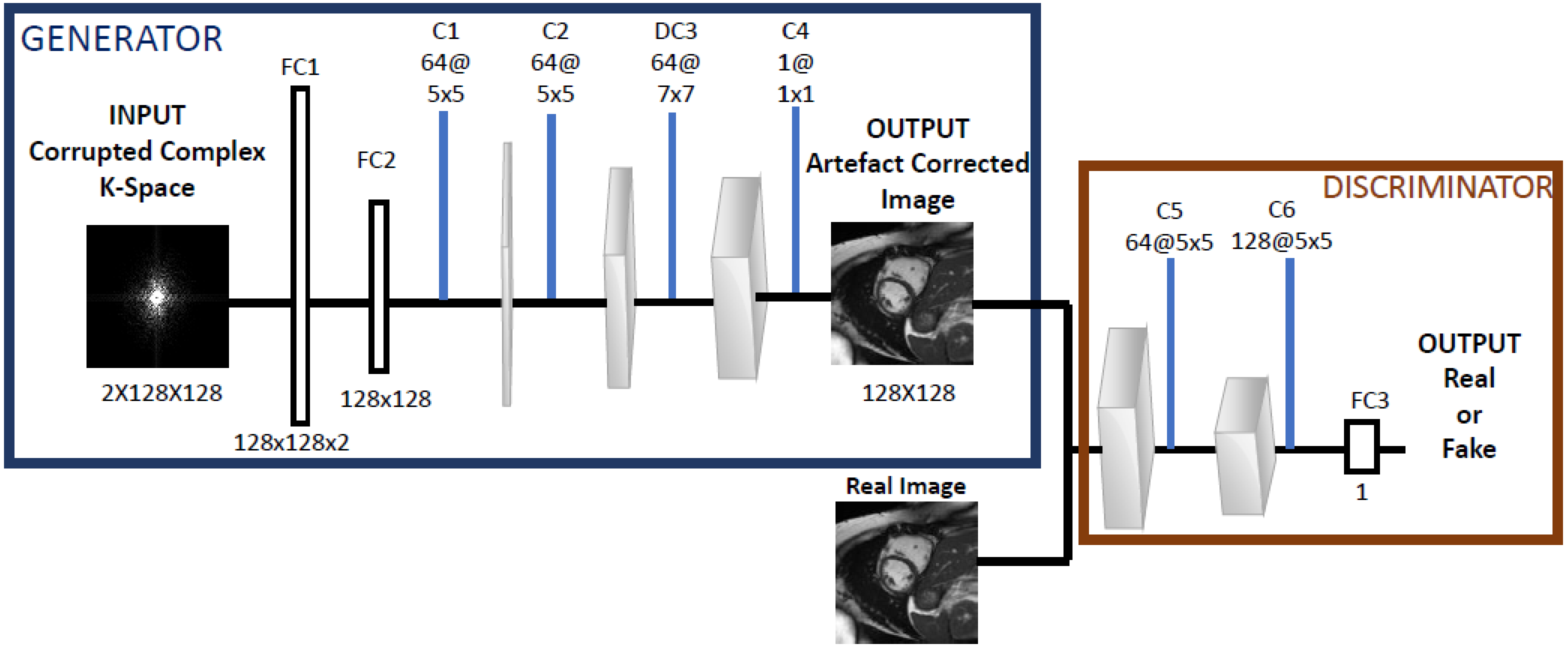
AUTOMAP – for CMR motion correction



***Oksuz et al.**, Accepted for MLMR 2018.*

AUTOMAP-GAN SETUP

- Adversarial setup for Motion Artefact Correction
  - Improved robustness and de-blurring of the image outputs



***Oksuz et al.**, Accepted for MLMR 2018.*

Experimental Results

- Dataset:
  - Synthetically generated corruptions
    - 75,000 2D images for training; 2,500 for testing

$$\mathrm{RMSE} = \sqrt{\frac{1}{N_x N_y} \sum_{x=0}^{N_x} \sum_{y=0}^{N_y} (r(x,}$$

$$\mathrm{PSNR} = 20 log_{10} \left(\frac{\sum_{x=0}^{N_x} \sum_{y=0}^{N_y} r(x,y)^2}{\sqrt{\sum_{x=0}^{N_x} \sum_{y=0}^{N_y} (r(x,y) - p(x,y))^2}} \right)$$

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Experimental Results

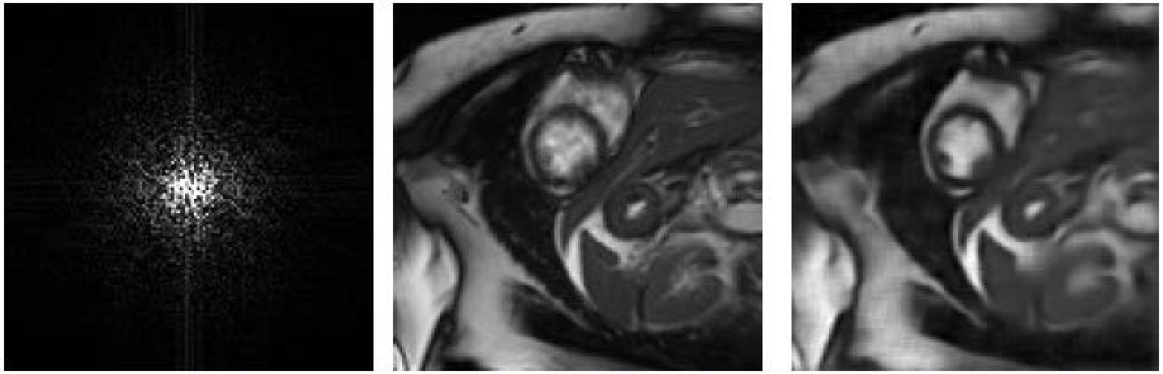
Methods	RMSE	PSNR	SSIM
Inverse Fourier Transform	0.045	27.8	**0.883**
Proposed-ImageNET	0.032	31.1	0.766
Automap-Cardiac	0.029	32.7	0.814
Proposed-Cardiac	**0.027**	**35.1**	0.850

***Oksuz et al.**, Accepted for MLMR 2018.*

Experimental Results

- Tested the network trained on the synthetic cases on in-vivo case with a mis-triggering artefact case
  - The motion corrupted image is corrected and now shows clear myocardial boundaries.

In-vivo example



(a) K-space (b) Motion corrupted image (c) Proposed

Conclusions

- Machine and deep learning techniques for identifying LVOT presence, motion artefacts and other image quality control issues in CMRI
  - K-space based corruption for data augmentation
  - Promise in outperforming other state-of-the-art techniques
  - Classification of each type of artefact separately or simultaneously
- Motion artefact correction in end-to-end setup based on AUTOMAP technique

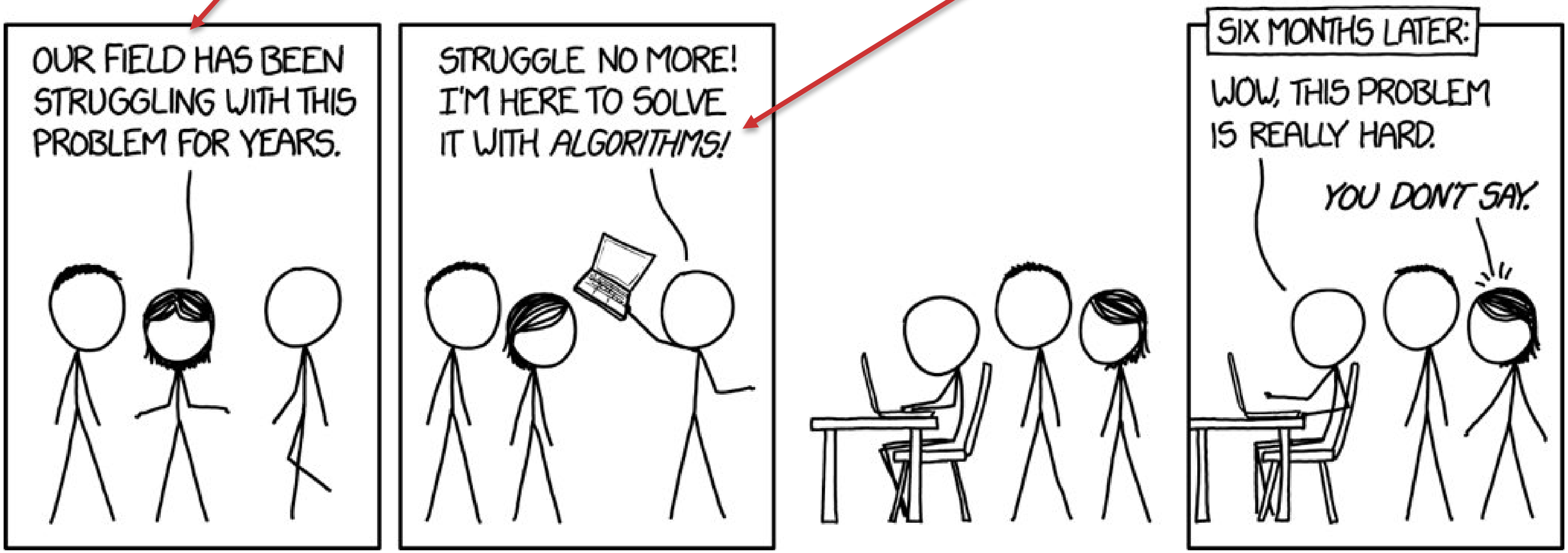
Future Work

- Classify each type of artefact separately
- Plan CMR view-planes automatically
- Correct for different types of artefacts
- Validate on 100,000 CMR images in UKBB
- Apply to own clinical data which will have much more severe image quality issues
- …

Outlook on Medical Imaging meets Deep Learning

"Our Field" = Medical Imaging

"Algorithms" = Deep Learning



Grazie!

MICCAI Satellite on Machine Learning for Medical Image Reconstruction (MLMIR)

MISS 2018 Medical Imaging Summer School

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