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Automatic Quality Assessment of Cardiac MRI

smartheart

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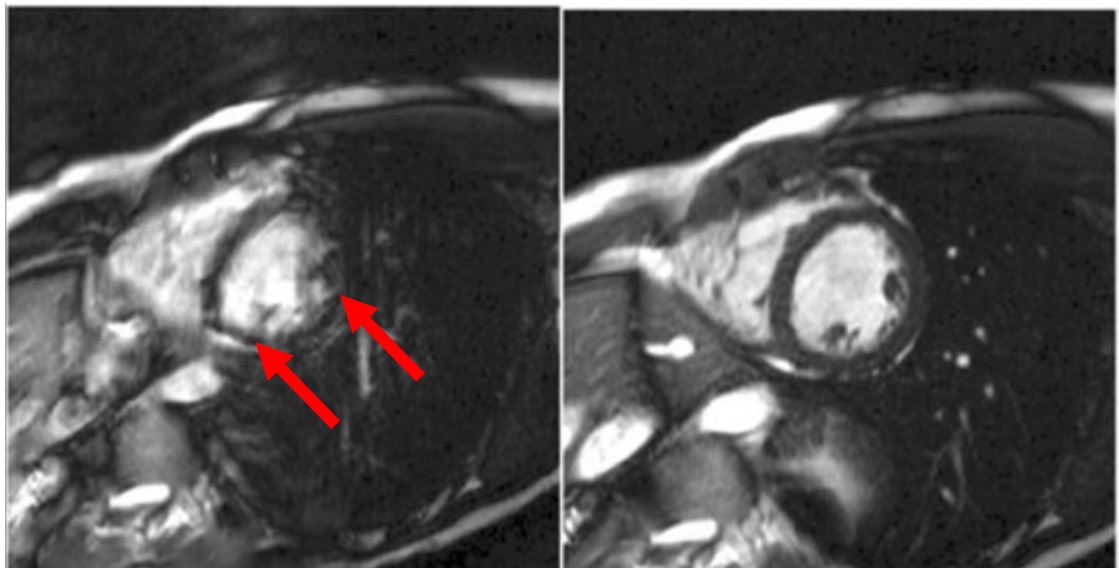
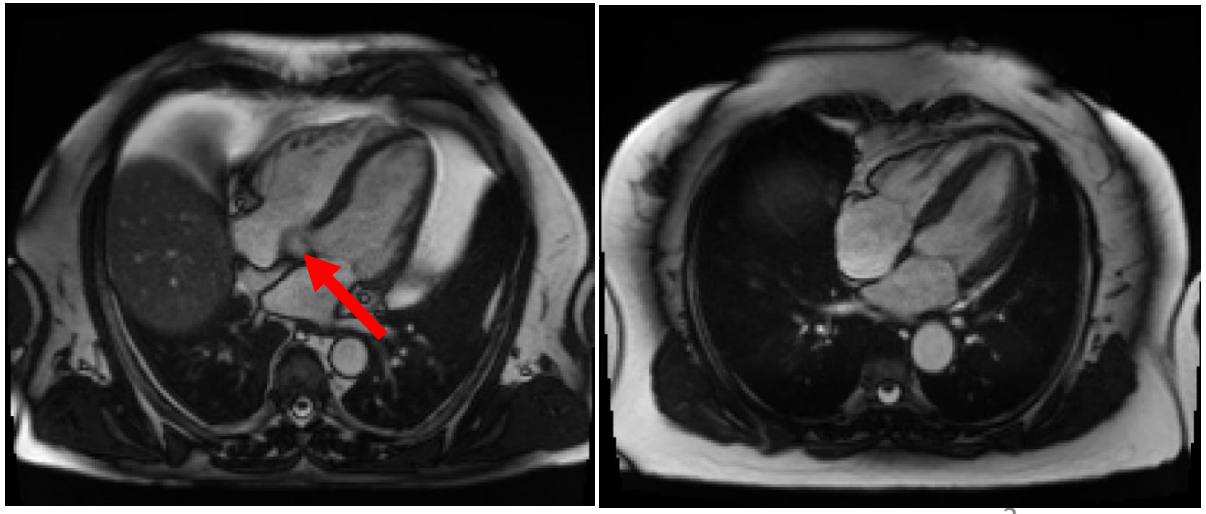
http://kclmmag.org

Cardiac MRI Quality Issues

- Need for high quality images
- Wide range of artefacts
- Manual labeling tedious for large datasets
- Need for automatic quality assessment tools
- Automatic cardiac MR planning



Adopted from Ferreira et al., JCMR, 2013.

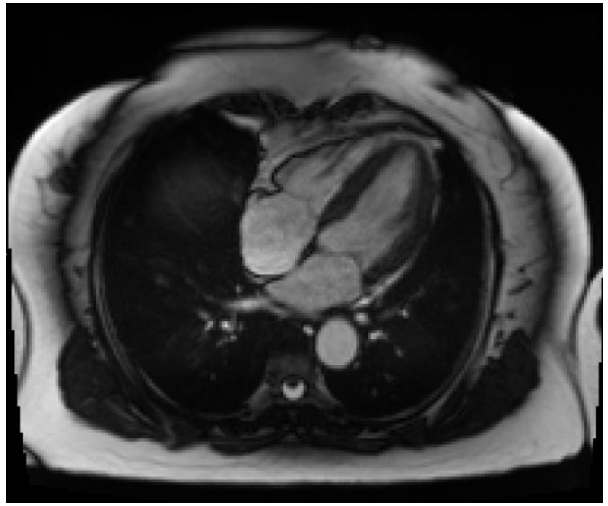


Cardiac MR Quality issues

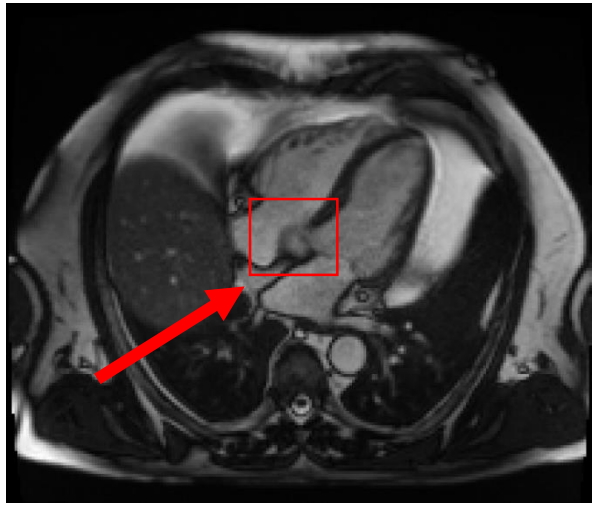
1. **Off-axis (4ch)***
   - Left Ventricular Outflow Tract
   - 5 chamber look

2. **Motion related artefacts (SAX)$**
   - Breathing
   - Mis-triggering
   - Arrhythmia

3. **Heart not fully covered**
   - Missing apex
   - Missing basal slice

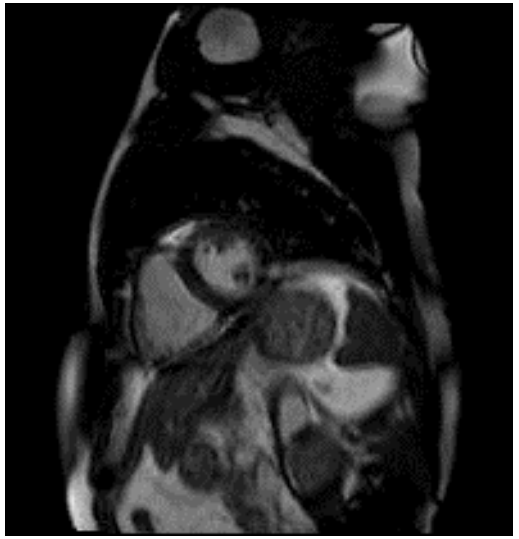


Good Planning



Bad Planning

Good Quality



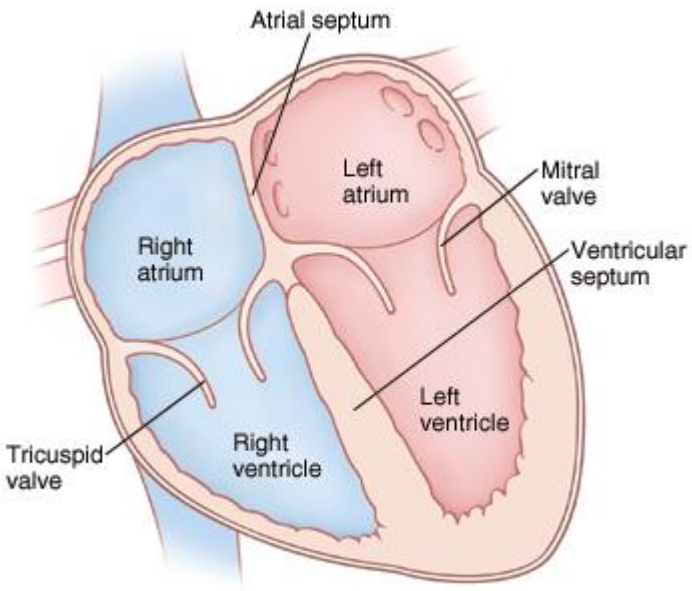
Motion Artefact

*** Oksuz et al., ISBI 2018**

$Oksuz et al., under review

4-Chamber cine Cardiac MRI

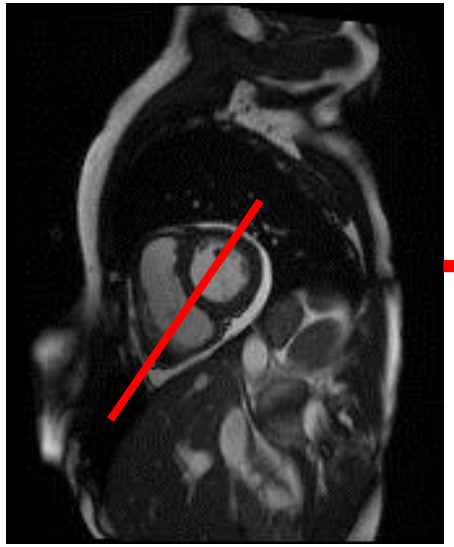
- Good 4-chamber CMR image shows all chambers clearly.
- Right and left atrium analysis can be achieved with 4-chamber view.



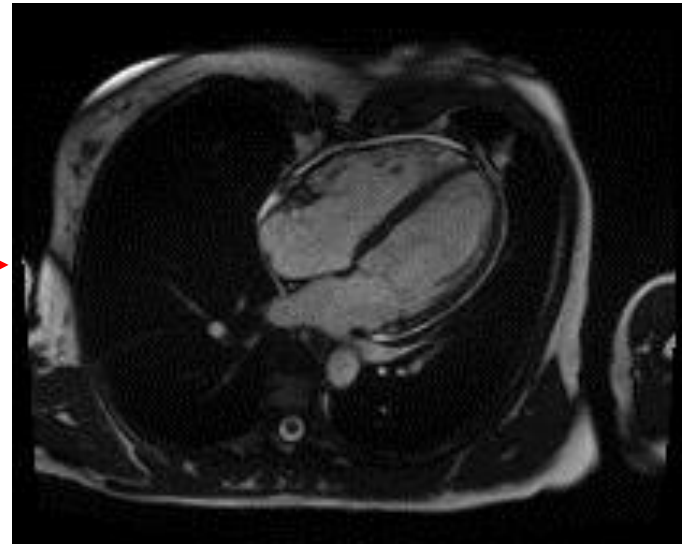
4-Chamber view planning

- Planned using 2-chamber and short axis images
- An appropriate angle is necessary

2-chamber view



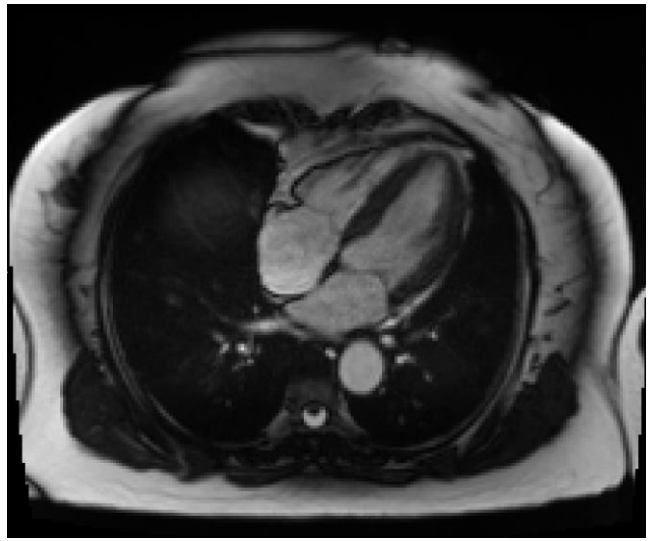
Short axis view



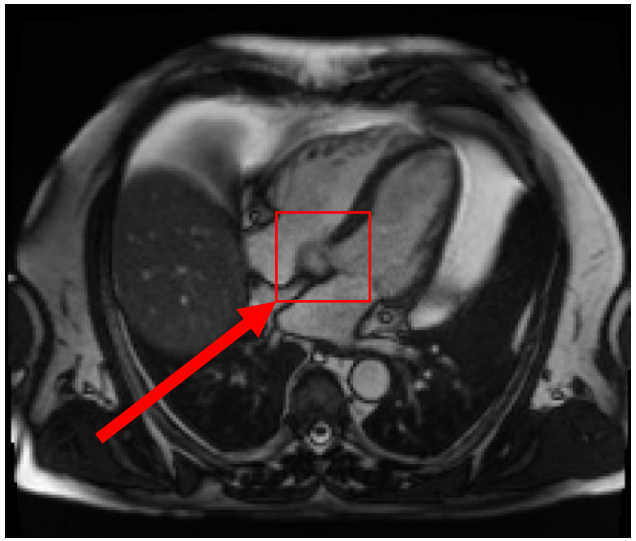
4-chamber view

Left Ventricular Outflow Tract (LVOT)

- Wrong cardiac planning leads to off-axis acquisitions
- Presence of Left Ventricular Outflow Tract (LVOT)
- Challenges RA and LA analysis
- Automatic LVOT detection can help automatic cardiac planning



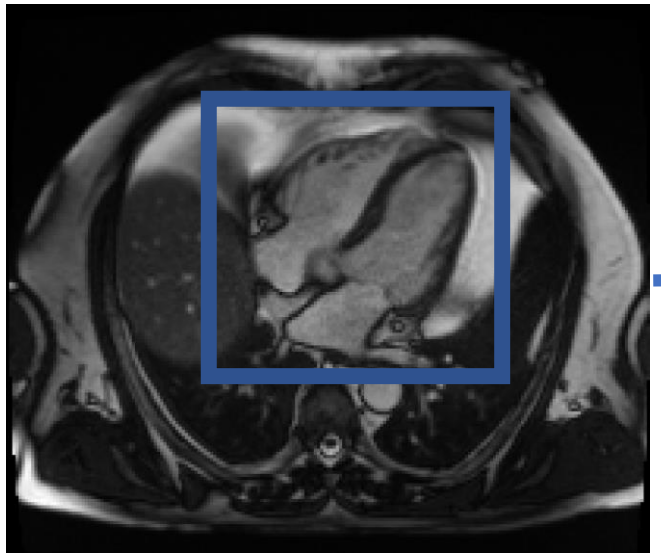
Good Planning



Bad Planning

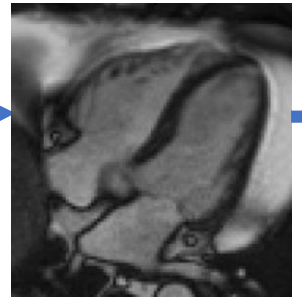
Method

Input: 2D 4chamber cardiac MR



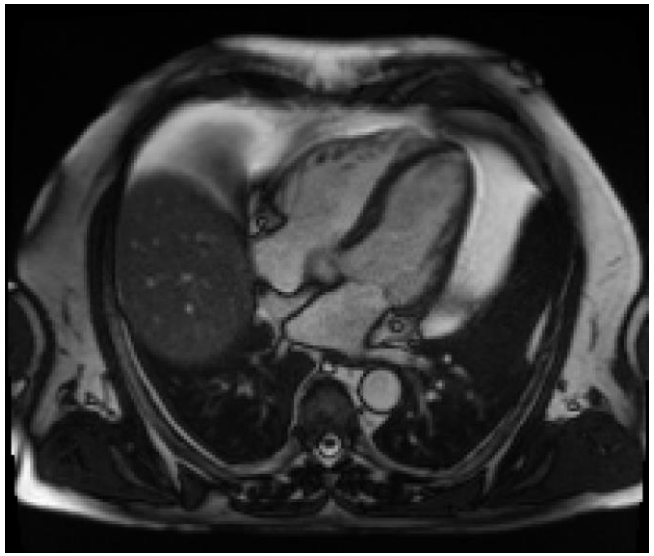
ROI

2D Dataset



CNN Model for Learning

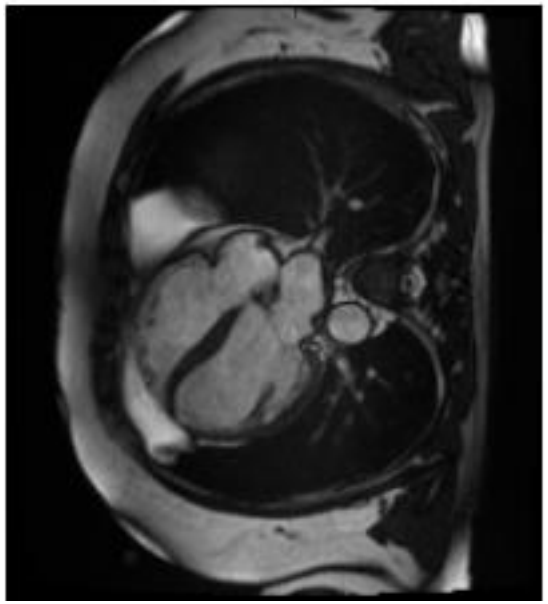
Output: LVOT= 0 or 1



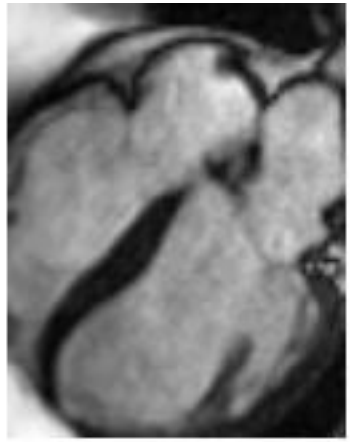
1. Contrast Normalization
2. Region of Interest Extraction
3. Training a CNN Model

ROI Extraction-Template Matching

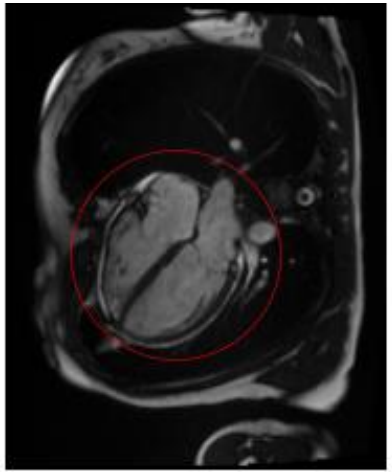
- Use a separate dataset to generate templates
- Normalize cross correlation for template matching



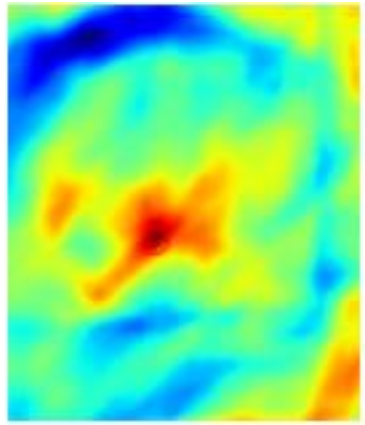
Template



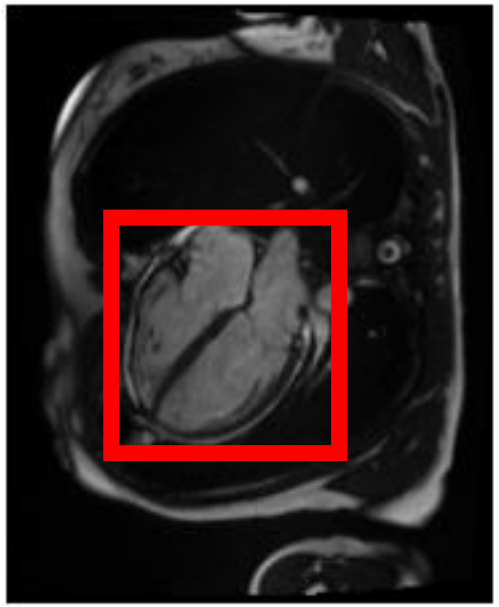
Image



Template Match

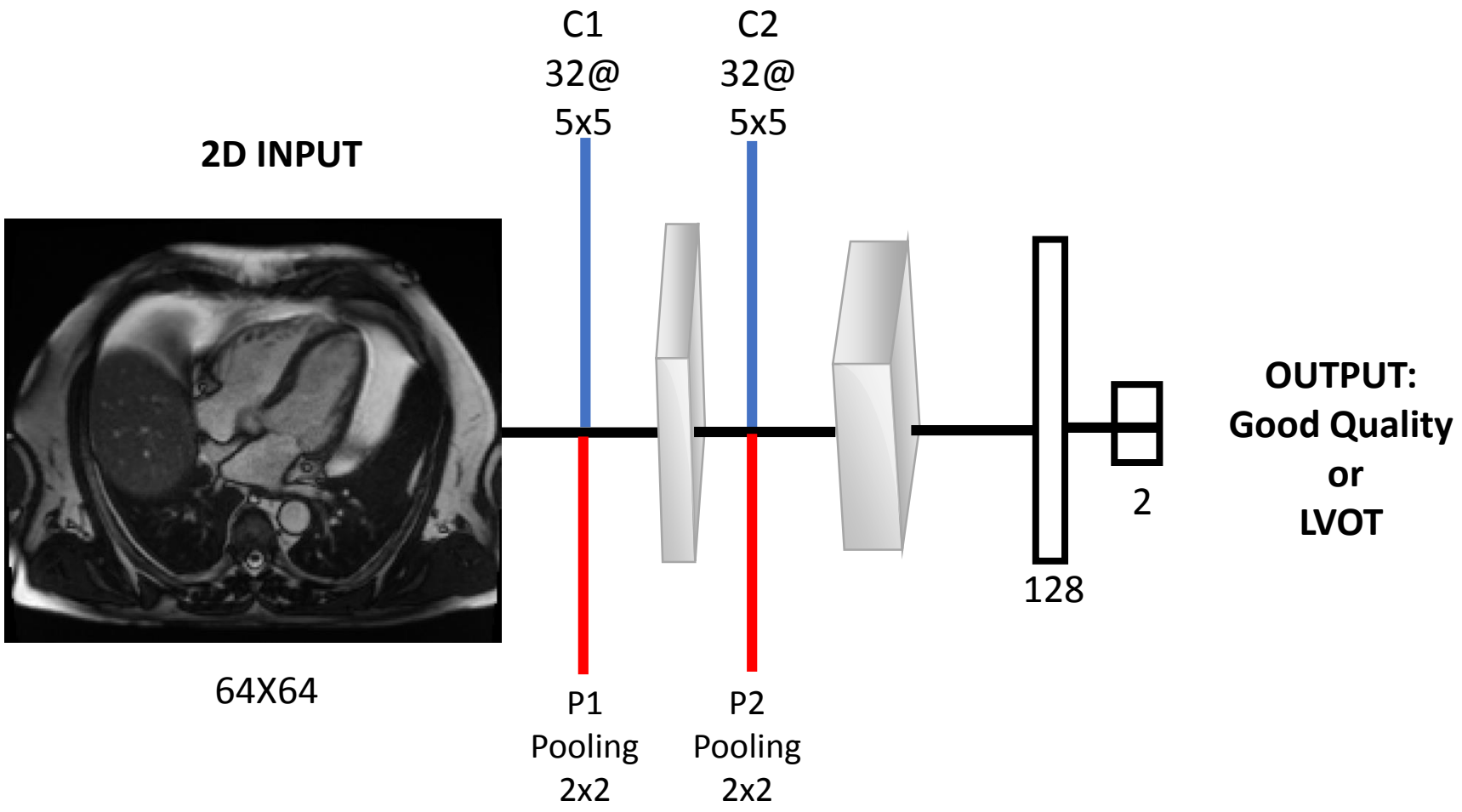


ROI



CNN MODEL

- Similar to Lenet* Model
- 2 Convolutional Layers
- 2 Max Pooling Layers
- Dropout 0.5 after each layer
- ReLU Activation



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

Dataset and methods of comparison

- 123 Good Quality Image and 123 LVOT Images from UK Biobank*
- 5 temporal frames of each sequence, 615 images for each class
- Stratified 10-fold cross validation
- State of the art classification methods for comparison:
  - K-nearest neighbors
  - Linear SVM
  - Decision Tree
  - Random Forests
  - Adaboost
  - Naïve Bayesian
  - Quadratic Discriminant Analysis

*** Petersen et al., *JCMR,* 2016**

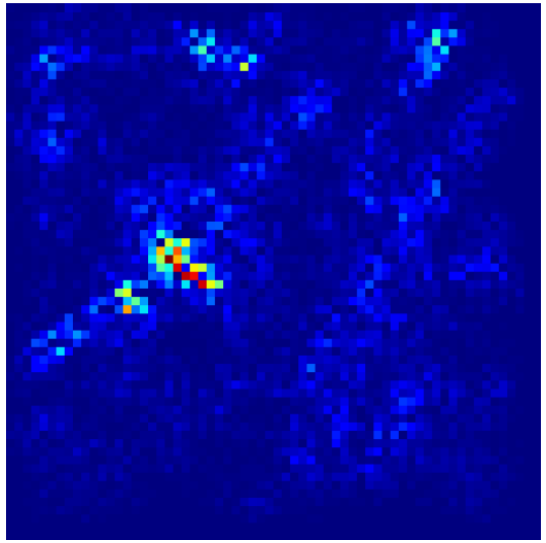
Experimental Results

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

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

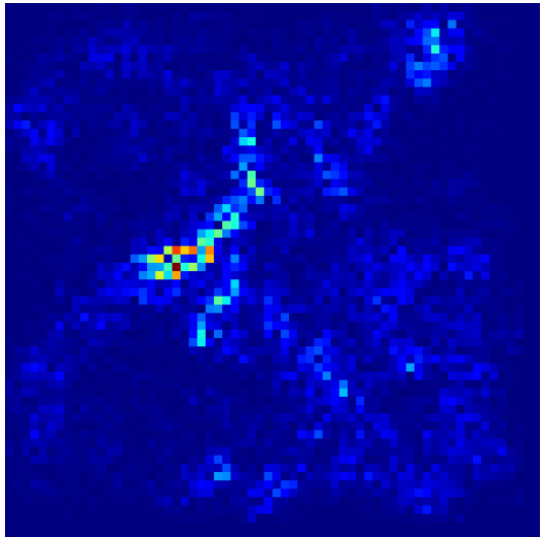
$$\text{Precision} = \frac{TP}{TP + FP} \qquad \text{Recall} = \frac{TP}{TP + FN}$$

LVOT



LVOT attention map*

Good Quality Image



Good Quality Attention Map*

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

Cardiac MR Quality issues

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   - 5 chamber look

2. **<u>Motion related issues (SAX)</u>$**
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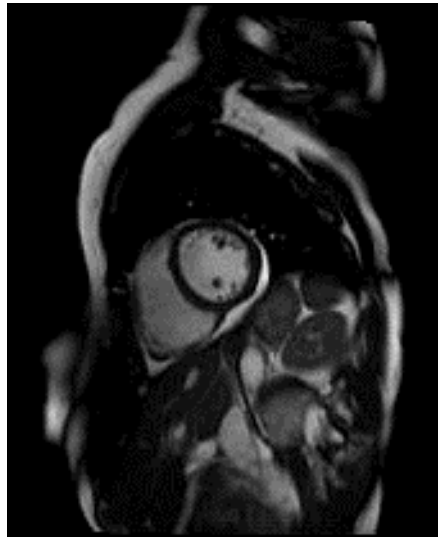
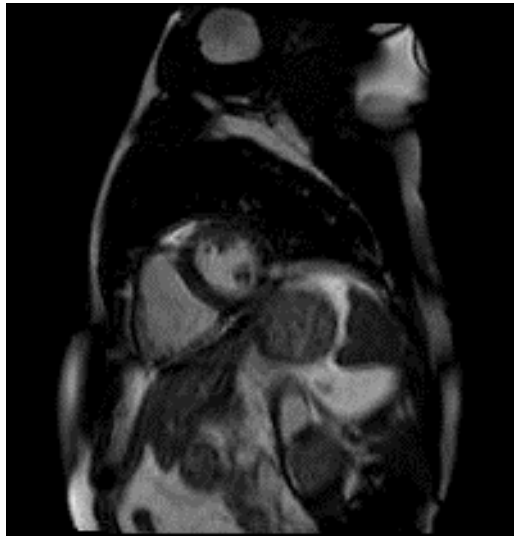


Good Quality

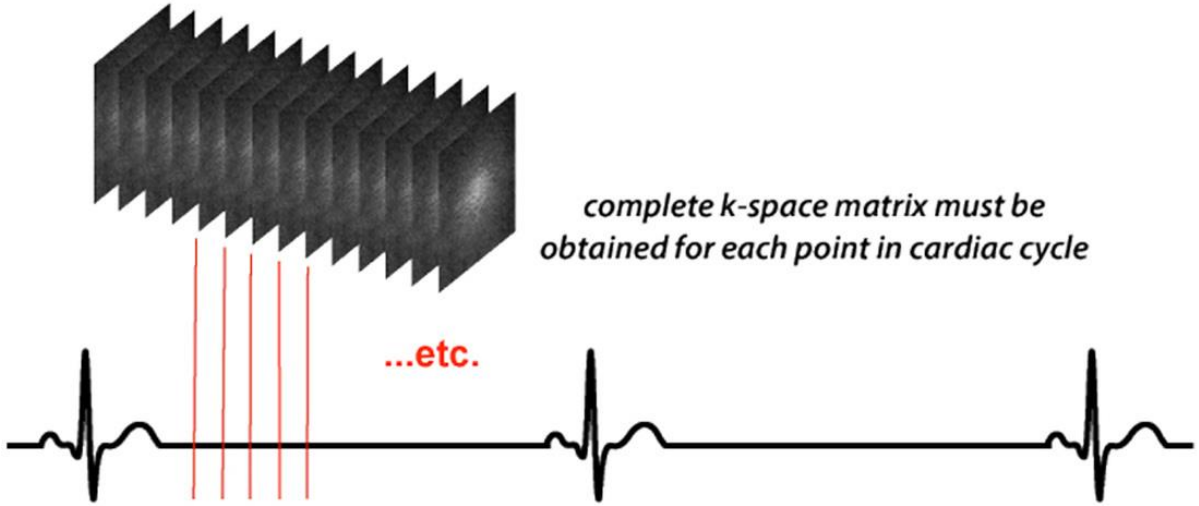


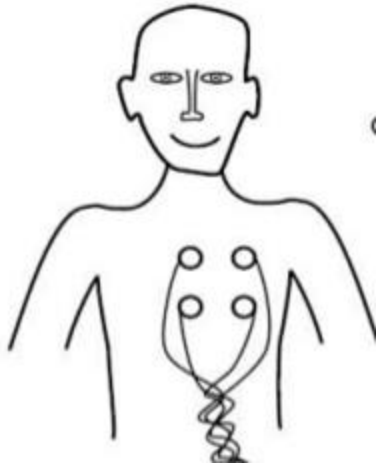
Motion Artefact

*** Oksuz et al., ISBI 2018**

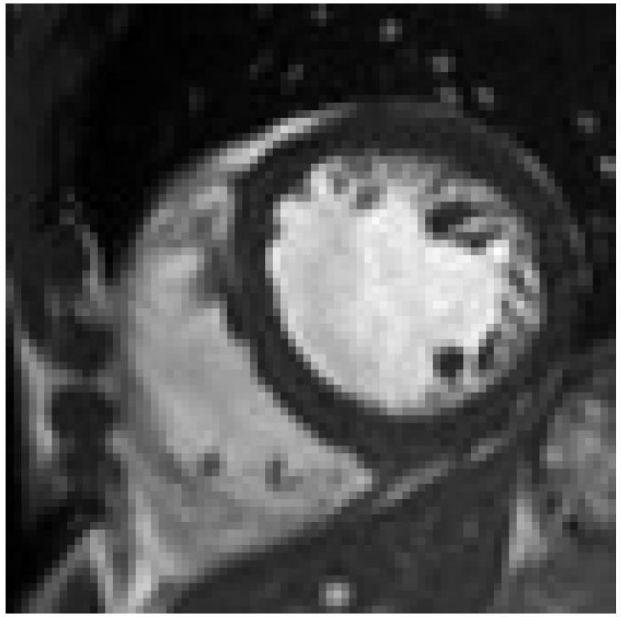
$Oksuz et al., under review

Cardiac MRI Acquisition

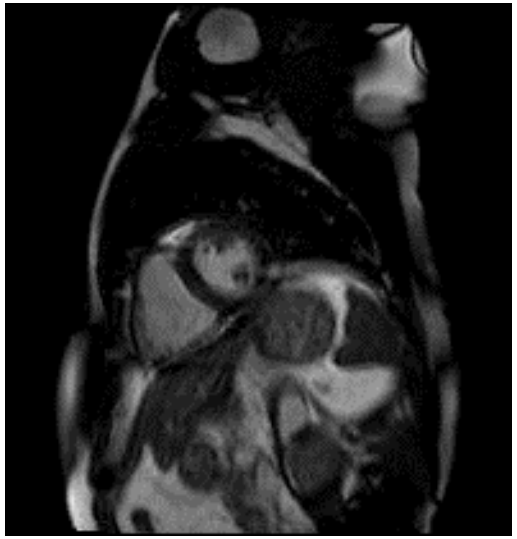




Good Quality



Good Quality

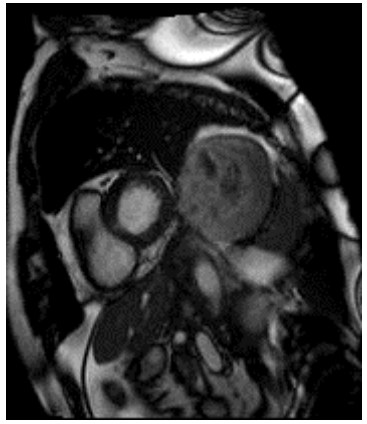


Motion Artefact

Motion Artefact

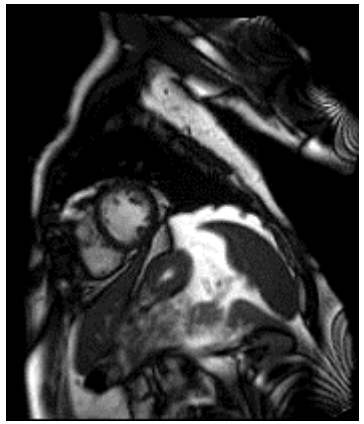
Dataset

- ***105 subject*** with motion artefacts (Breathing, Mis-triggering, Arrhythmia)
- 53 for Mis-triggering, 23 for Breathing, 24 Arrhythmia, 4 mixed
- **105 Artefact Images, 3360 Good quality Images**
- ***DATA IMBALANCE!!!***

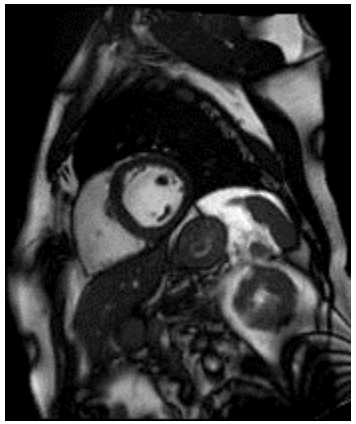


Arrhythmia

Breathing



Mis-triggering

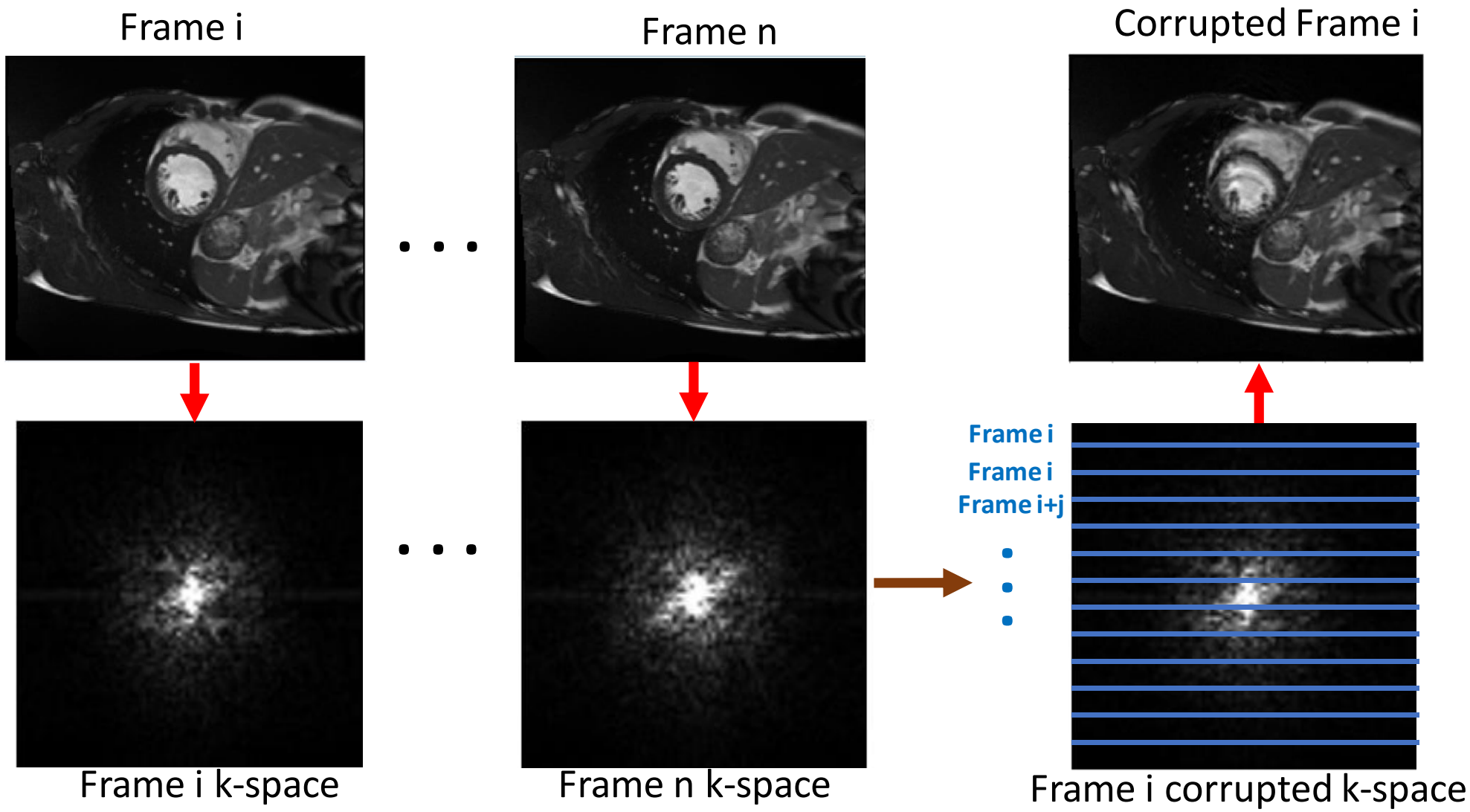


Good Quality

Data Imbalance-TODOs

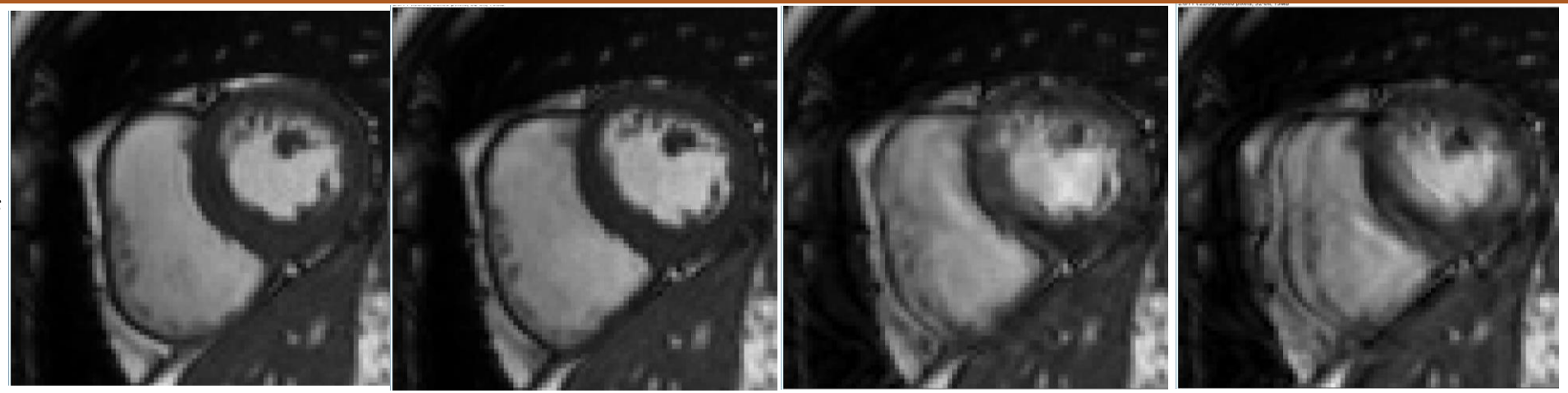
1. **Can You Collect More Data?**
   - Difficult task in many medical imaging applications
2. **Try Resampling Your Dataset**
   - You can add copies of instances from the under-represented
   - Delete some data from the over-represented class.
   - It is not the best strategy to make use of your data 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



Synthetic Images

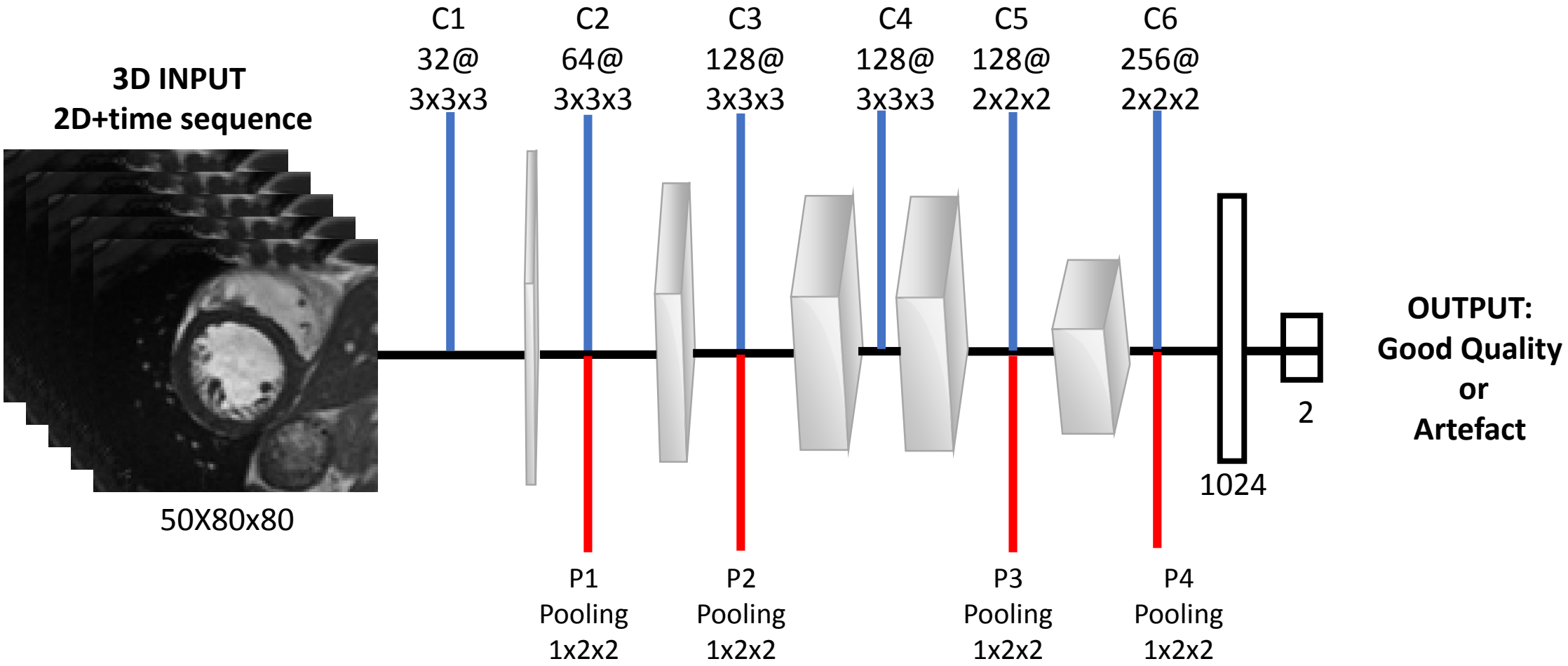
Different corruption levels of k-space



HIGH QUALITY → **LOW QUALITY**

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

3D CNN MODEL


3D INPUT
2D+time sequence
50X80x80
C1
32@
3x3x3
C2
64@
3x3x3
C3
128@
3x3x3
C4
128@
3x3x3
C5
128@
2x2x2
C6
256@
2x2x2
1024
2
OUTPUT:
Good Quality
or
Artefact
P1
Pooling
1x2x2
P2
Pooling
1x2x2
P3
Pooling
1x2x2
P4
Pooling
1x2x2

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

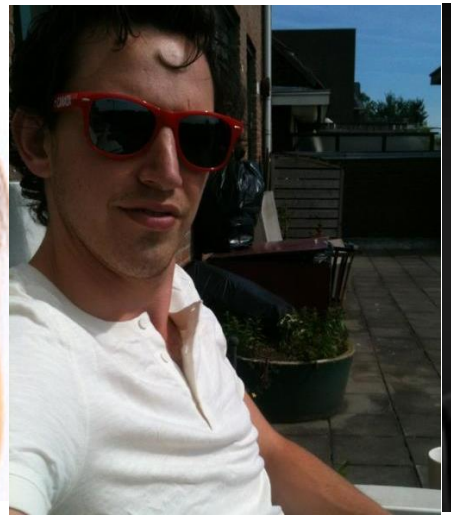
*** Mittal et al., *IEEE Signal Processing Letters*, 2013**

Conclusions and Future Work

- CNN-based techniques for identifying LVOT presence and motion artefacts
- K-space based corruption for data augmentation
- Neural network with high recall outperforming other state of the art techniques
- Implications for segmentation
- *Plan CMR view-planes automatically*
- *Validate on 100 000 CMR images*
- *Classify each type of artefact separately*
- *Address other CMR quality issues*

QUESTIONS ??

Esther Puyol Anton, KCL



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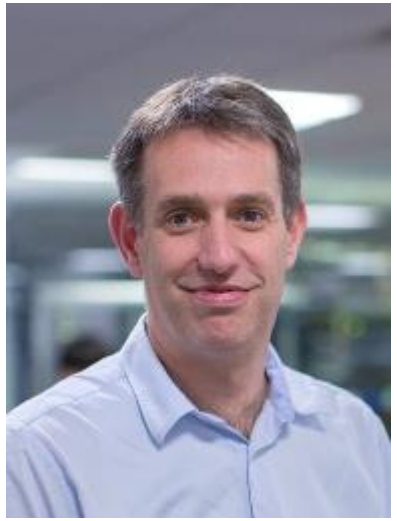

Daniel Rueckert, Imperial

Julia Schnabel, KCL

Andrew King, KCL