Deep Learning Models for Image Reconstruction in MRF and QSM

AIM2.T2 Quantification Models in MRI
AIM General Meeting, 15-16/10/2020

Cristiana Fiscone, Marco Barbieri, Nico Curti, Claudia Testa, Caterina Tonon, Daniel Remondini

cristiana.fiscone2@unibo.it

IRCCS Istituto delle Scienze Neurologiche di Bologna (ISBN)
DIBINEM – Biomedical and Neuromotor Sciences Department, University of Bologna
DIFA - Physics and Astronomy Department, University of Bologna
DIMES – Experimental, Diagnostic and Specialty Medicine Department, University of Bologna
INFN Sezione di Bologna

Quantification Models in MRI:

1. Magnetic Resonance Fingerprinting – MRF
2. **Quantitative Susceptibility Mapping – QSM**
3. **Super Resolution on MR images**

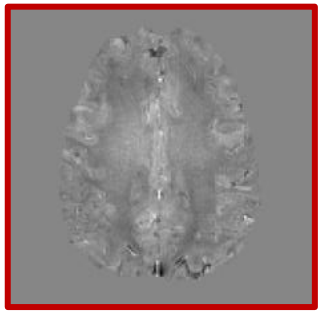
2. Quantitative Susceptibility Mapping - QSM

Advanced MRI Technique

Biomarkers

Ill-posed Problem

Solving the Inversion Problem: Standard Methods

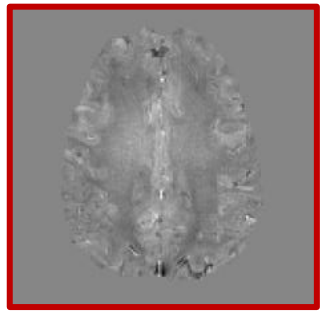


Phase map
MR Measurements

$$\chi(k) = \frac{\Delta B(k)}{B_0 \cdot D(k)}$$

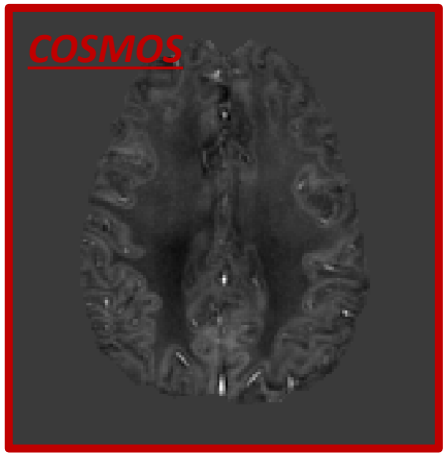
2. Quantitative Susceptibility Mapping - QSM

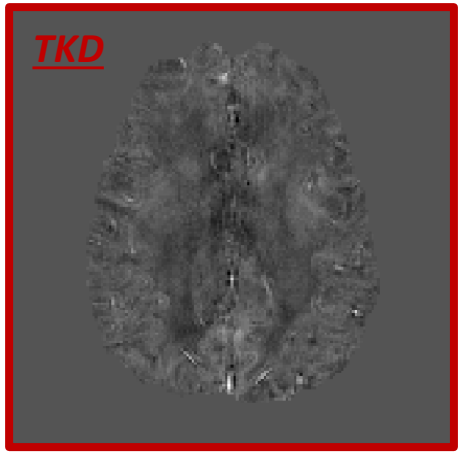
Advanced MRI Technique
Biomarkers
Ill-posed Problem
Solving the Inversion Problem: Standard Methods



Phase map
MR Measurements

$$\chi(k) = \frac{\Delta B(k)}{B_0 \cdot D(k)}$$





- **Multiple head-orientation approach**

COSMOS (Calculation of Susceptibility through Multiple Orientation Sampling)

- (-) Long acquisition time
- (-) Uncofortable for the patient
- (+) Accurate and precise reconstruction

- **Single head-orientation approach**

- TKD (Thresholded K-space Division)
- iLSQR (initial Least-SQuaRes)

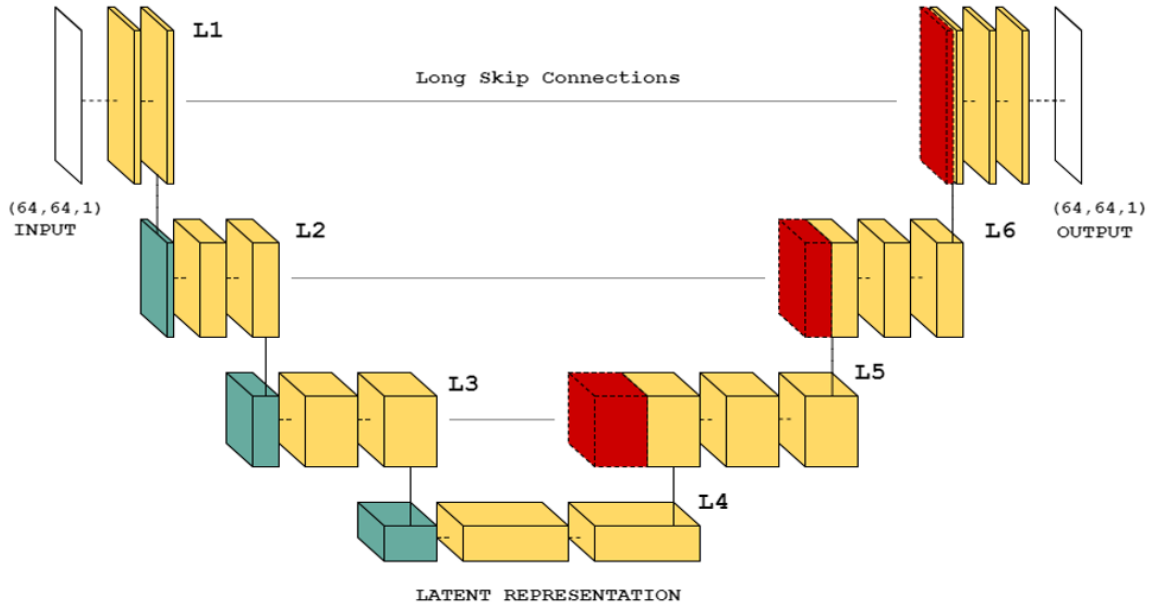
- (+) Short acquisition time
- (-) Numerical strategies (k-space cutoff, iterative methods)
- (-) Noisy reconstruction

2. Quantitative Susceptibility Mapping - QSM

Solving the Inversion Problem: Deep Learning Approach

- Convolutional Neural Network (CNN) to reconstruct precise susceptibility map
- Supervised Learning: COSMOS as gold standard

- **AIMs**:
  - Comparison with standard methods (TKD, iLSQR)
  - Trained model application to UK Biobank



1. Single-subject dataset (QSM Challenge 2016)

2. New measurements in Nottingham (SPMIC Sir Peter Mansfield Imaging Centre, University of Nottingham, UK) (Achieva 3T, Philips)

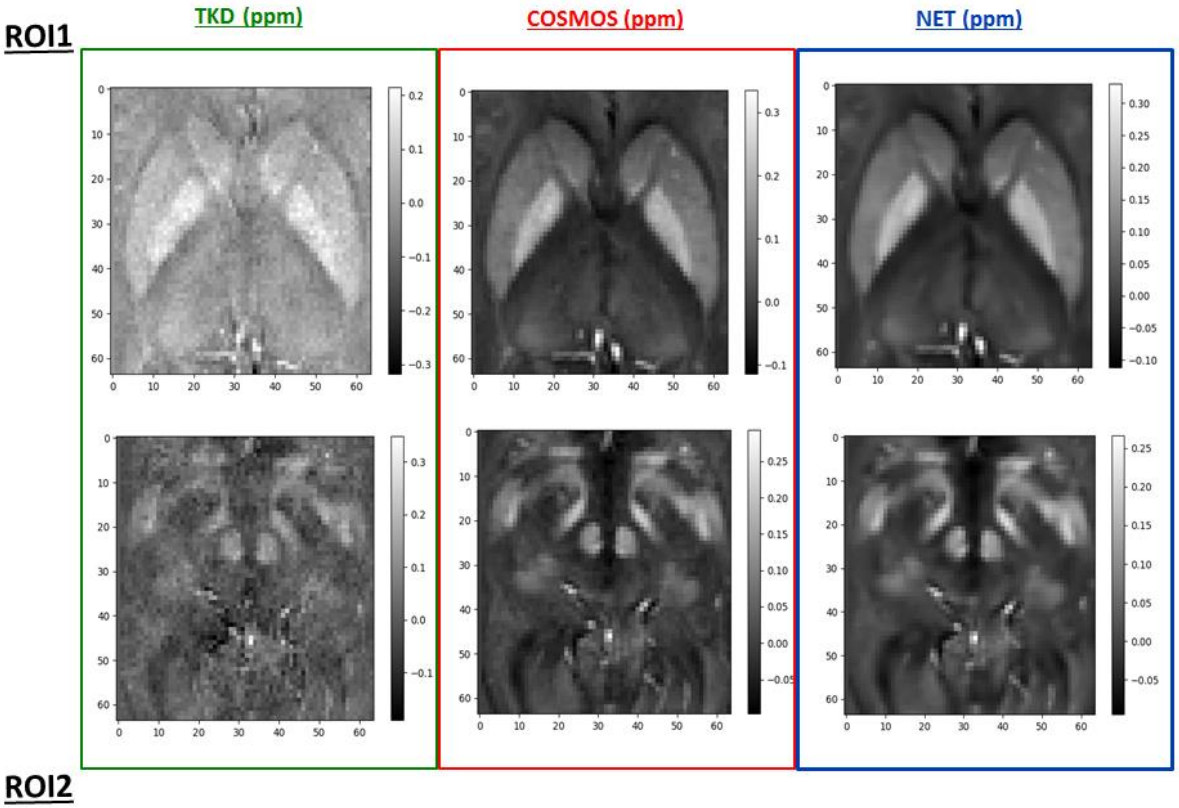
3. Application on data from - Ospedale Bellaria, Bologna (Skyra 3T, Siemens)

2. Quantitative Susceptibility Mapping - QSM

Single-subject dataset (QSM Challenge 2016)

12 head orientation
Supervised learning: COSMOS as label
2D and 3D patches as input data

Original model implementation



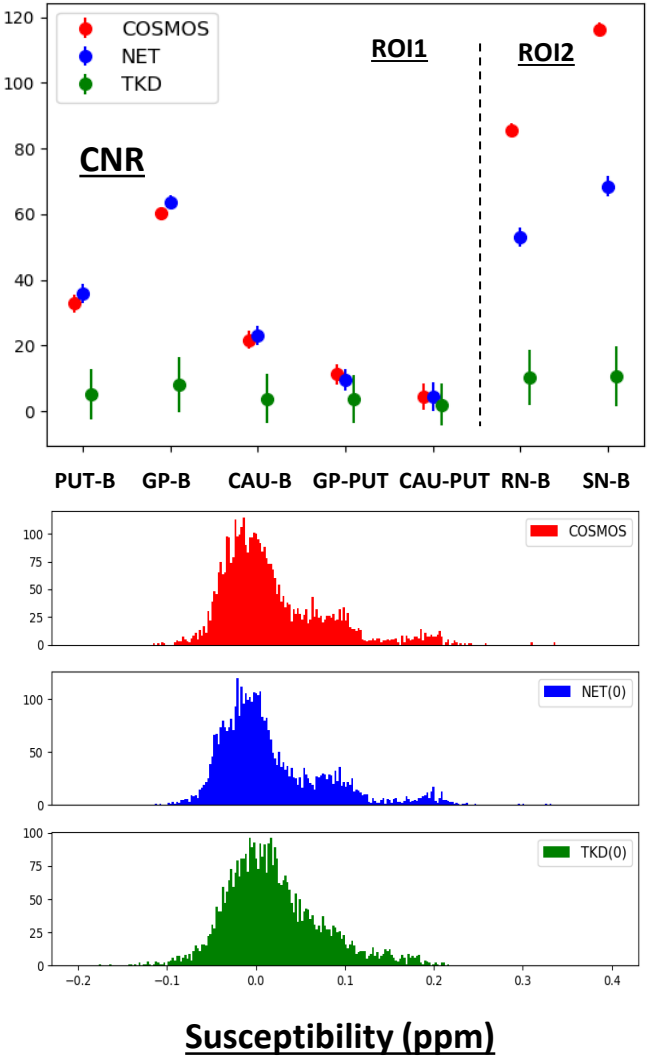
Globus Pallidus - GP
CAUdate - CAU
PUTamen – PUT
Red Nucleus - RN
Substantia Nigra - SN

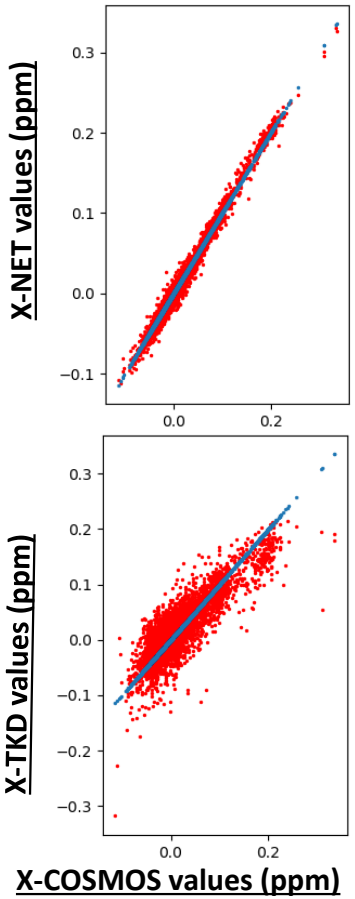
- Similarity parameters, CNR in specific ROIs
- Better performance than standard methods

- No generalization changing subject
- Further training

2. Quantitative Susceptibility Mapping - QSM

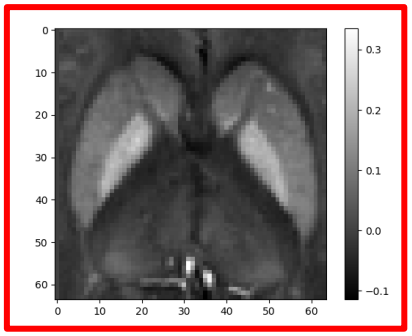
Single-subject dataset (QSM Challenge 2016)



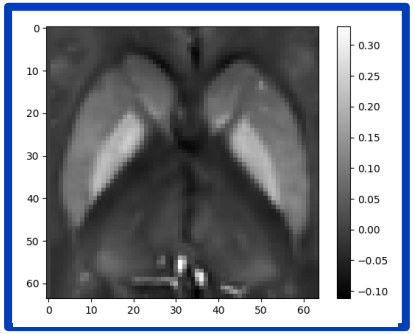


Globus Pallidus - GP
CAUdate - CAU
PUTamen – PUT
Red Nucleus - RN
Substantia Nigra - SN

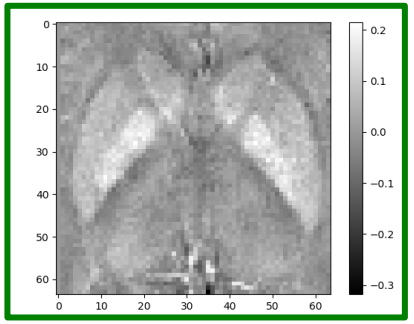
COSMOS (ppm)



NET (ppm)



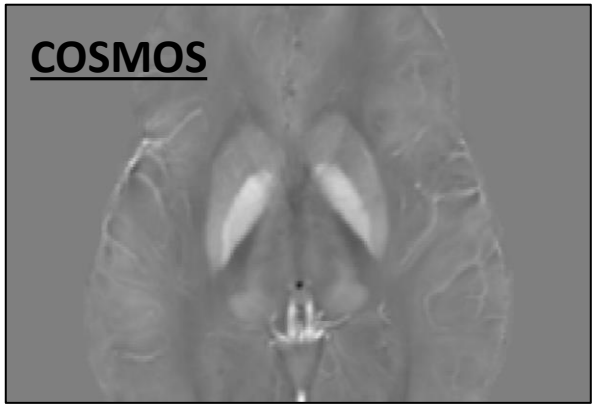
TKD (ppm)



2. Quantitative Susceptibility Mapping - QSM

New measurements in Nottingham (SPMIC Sir Peter Mansfield Imaging Centre, University of Nottingham, UK) (Achieva 3T, Philips)

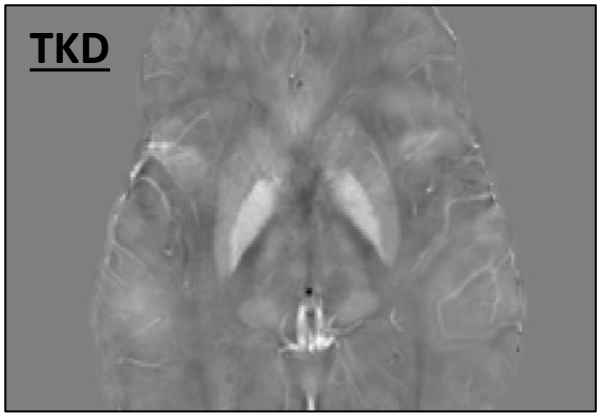
5 subjects (4 training, 1 test), 5 head orientations each
Supervised learning: COSMOS as label

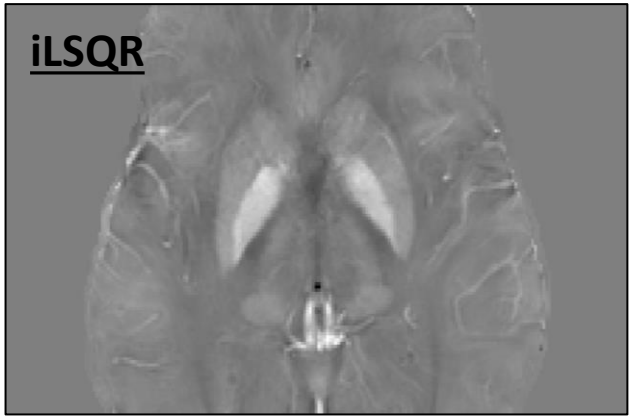


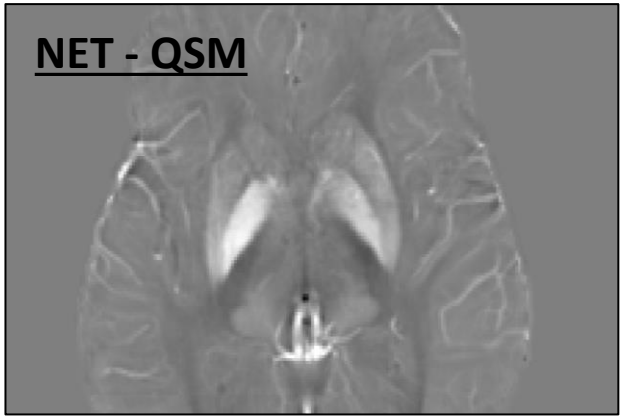
- New experiments (2D and 3D)
- Similarity parameters and CNR
- Blur factor

Promising results
Better performance than standard methods

Generalization skill (subject)







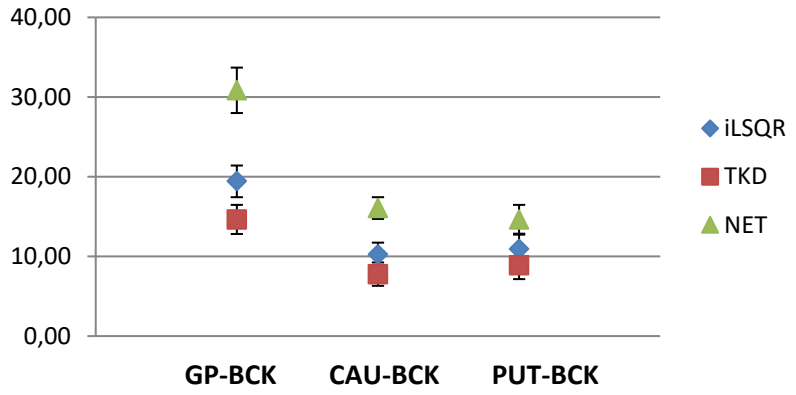
2. Quantitative Susceptibility Mapping - QSM

Application on data from Ospedale Bellaria, Bologna (Skyra 3T, Siemens)

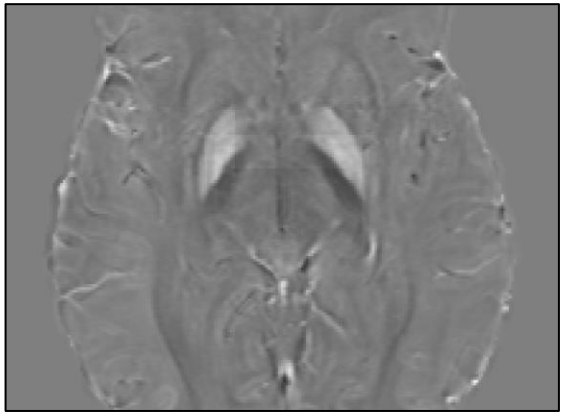
→ Generalization skill changing the aquisition system

Globus Pallidus - GP
CAUdate - CAU
PUTamen - PUT

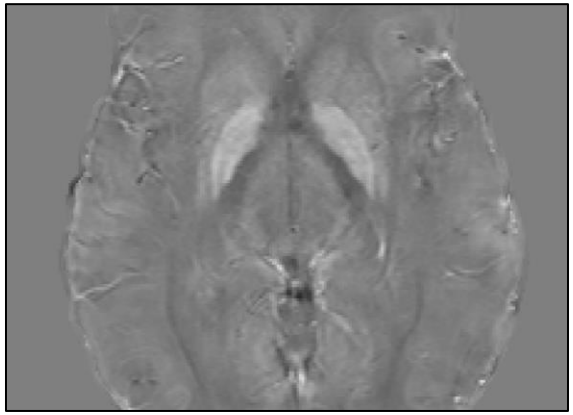
	GP-BCK	ε	CAU-BCK	ε	PUT-BCK	ε
iLSQR	19,43	1,98	10,24	1,49	10,93	1,92
TKD	14,64	1,83	7,77	1,46	8,90	1,75
NET-QSM	30,85	2,86	16,08	1,36	14,62	1,86



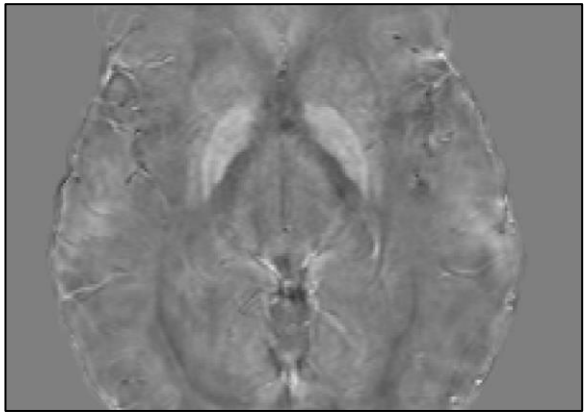
NET - QSM



iLSQR



TKD



2. Quantitative Susceptibility Mapping - QSM

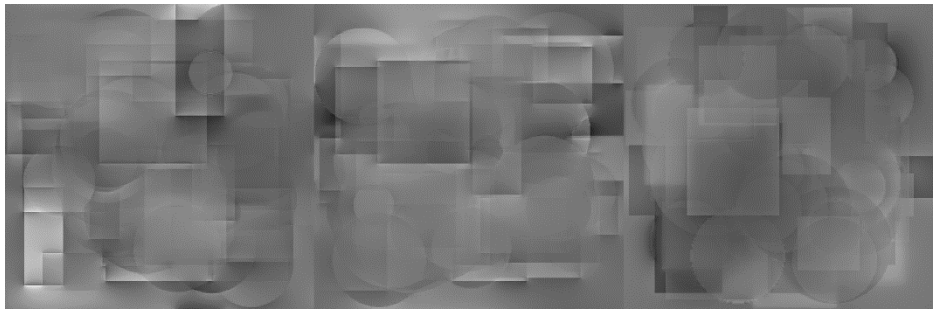
Future work

- Different performance
- New experiments (whole brain, specific ROIs)
  - Model architecture
  - Label data: synthetic patches
- Texture analysis and explain ability
- Application on UK Biobank

$$\chi(k) \cdot D(k) = \frac{\Delta B(k)}{B_0}$$

SIMULATED SUSCEPTIBILITY MAP $\chi(r)$

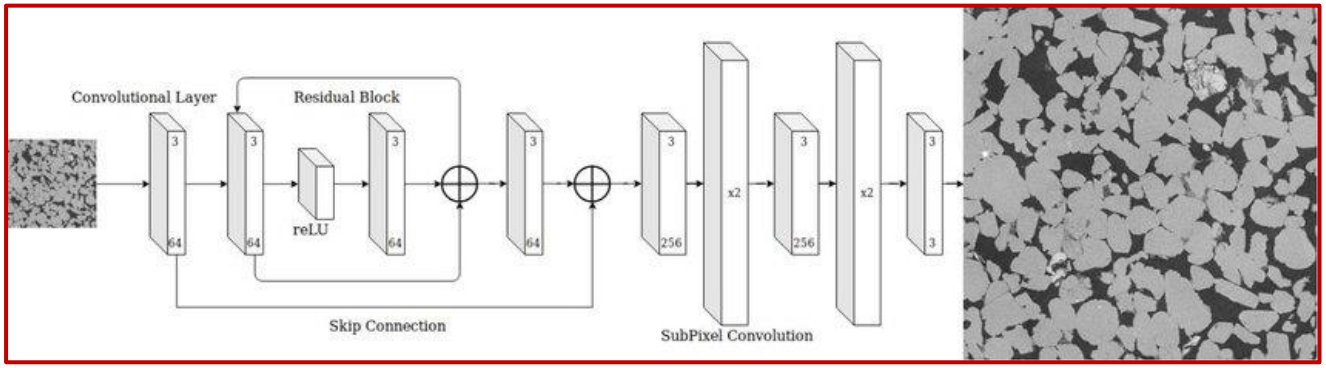
EVALUATED FIELD PERTURBATION MAP $\Delta B(r)/B_0$



3. Super Resolution on MR Images

- EDSR (2x), WDSR (4x): model already trained on non medical images

- **AIMs**:
  - Test the models on biomedical images (2D processing)
  - Comparison with standard methods (bicubic upsampling)



3. Super Resolution on MR Images

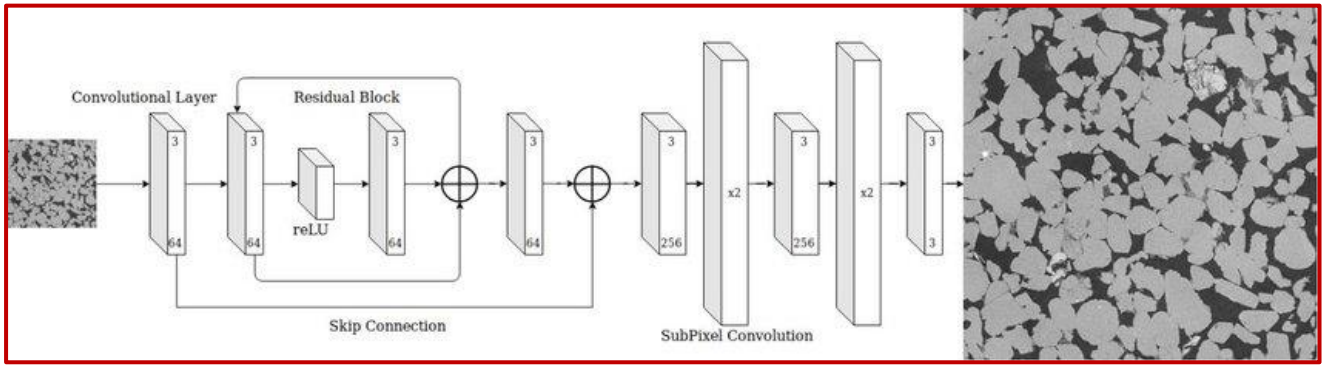
- EDSR (2x), WDSR (4x): model already trained on non medical images
- **AIMs**:
  - Test the models on biomedical images (2D processing)
  - Comparison with standard methods (bicubic upsampling)
- CamCan Dataset (~600 subjs, T1w maps) → significant statistical sample

High resolution images (HR) → Low resolution images (bicubic interpolation + Gaussian filter *)

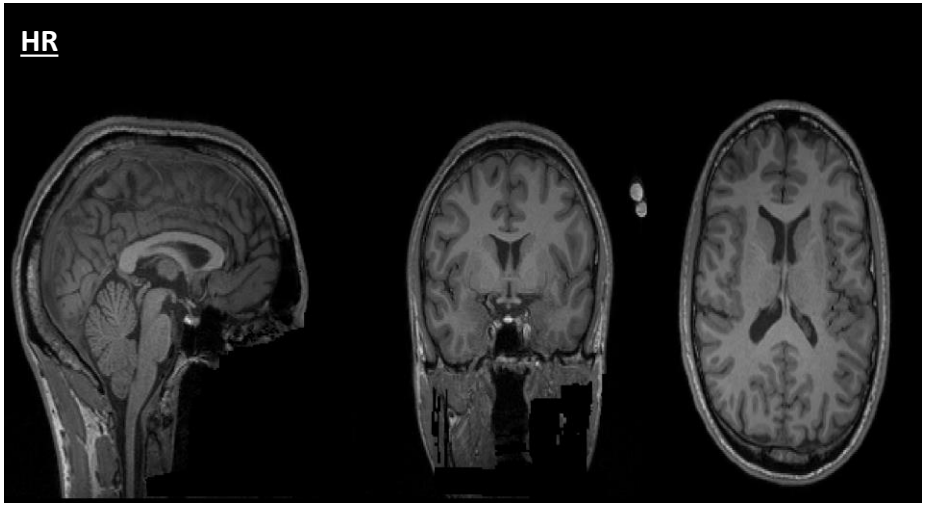
→ Upsampling: Bicubic interpolation

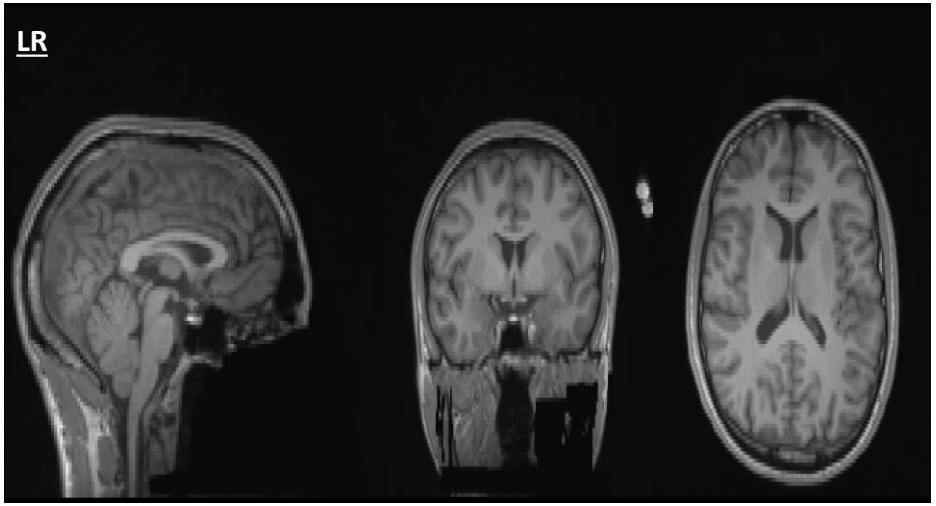
→ Upsampling: Super resolution

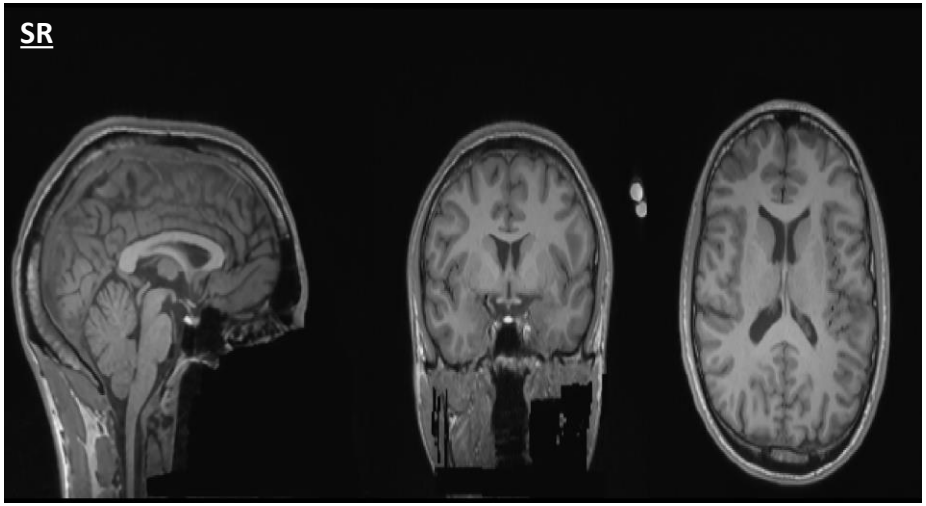
** Gaussian filter application before the dowsampling to simulate low-resolution acquisition*

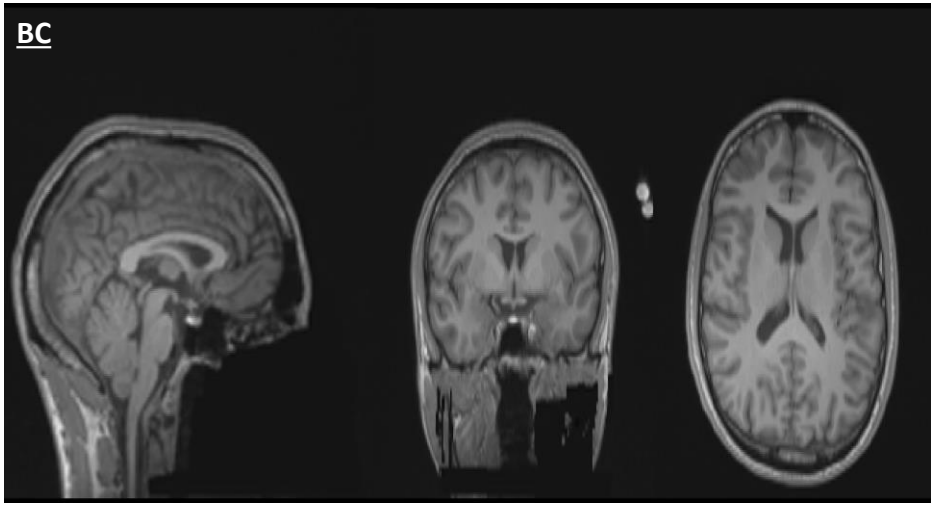


T1w map from CAMCAN database, subj 110033



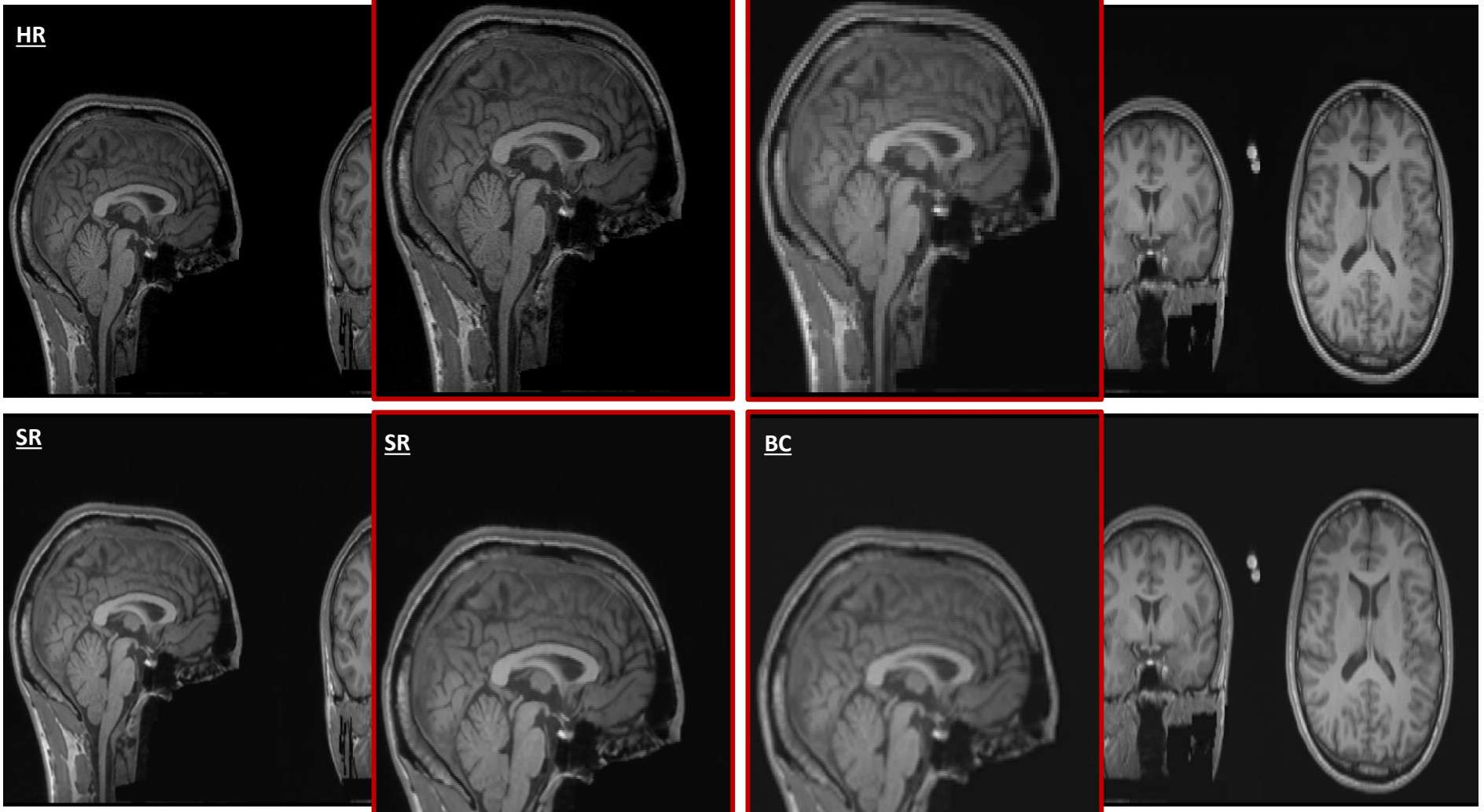






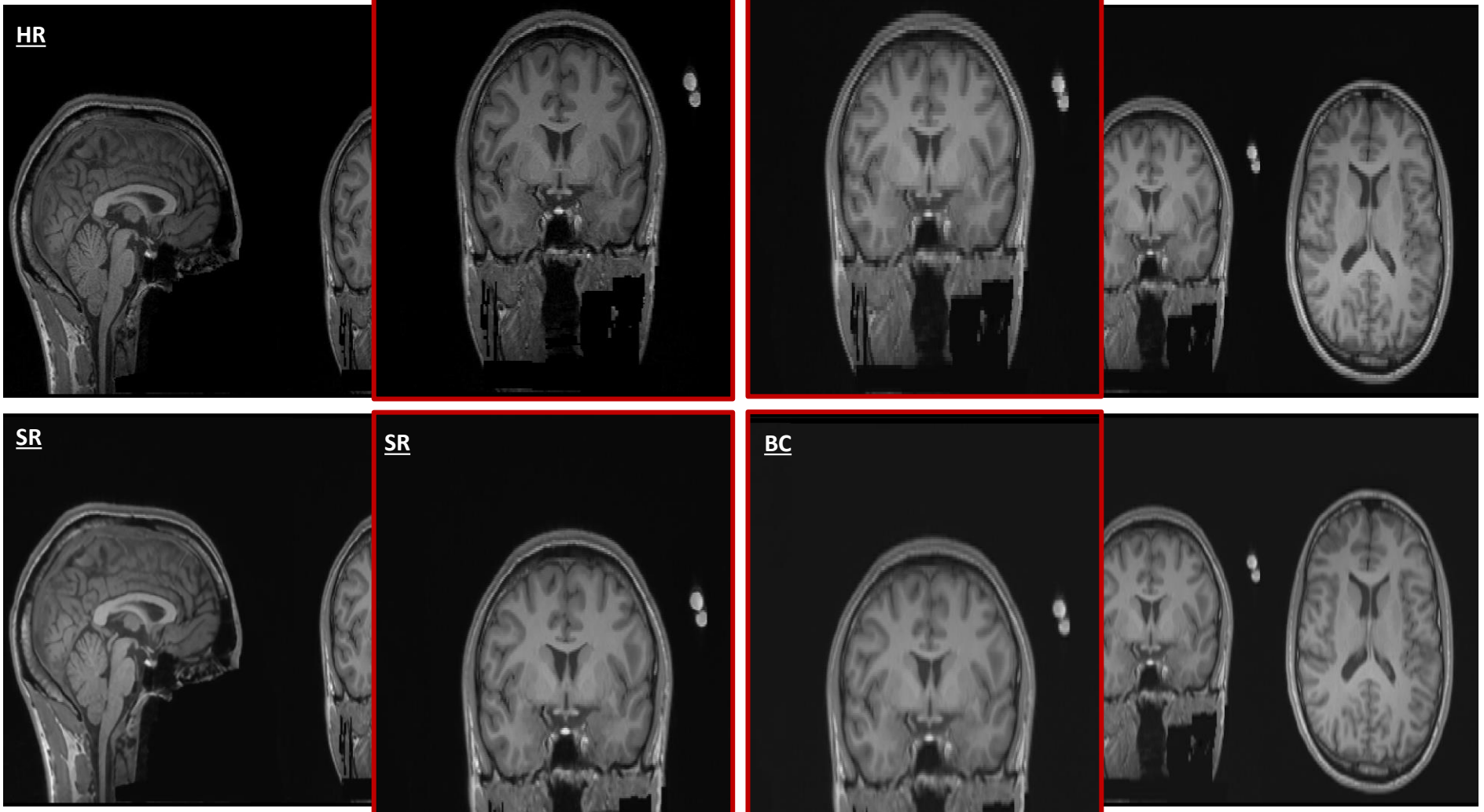
****downsampling 2D, sagittal slices**

T1w map from CAMCAN database,



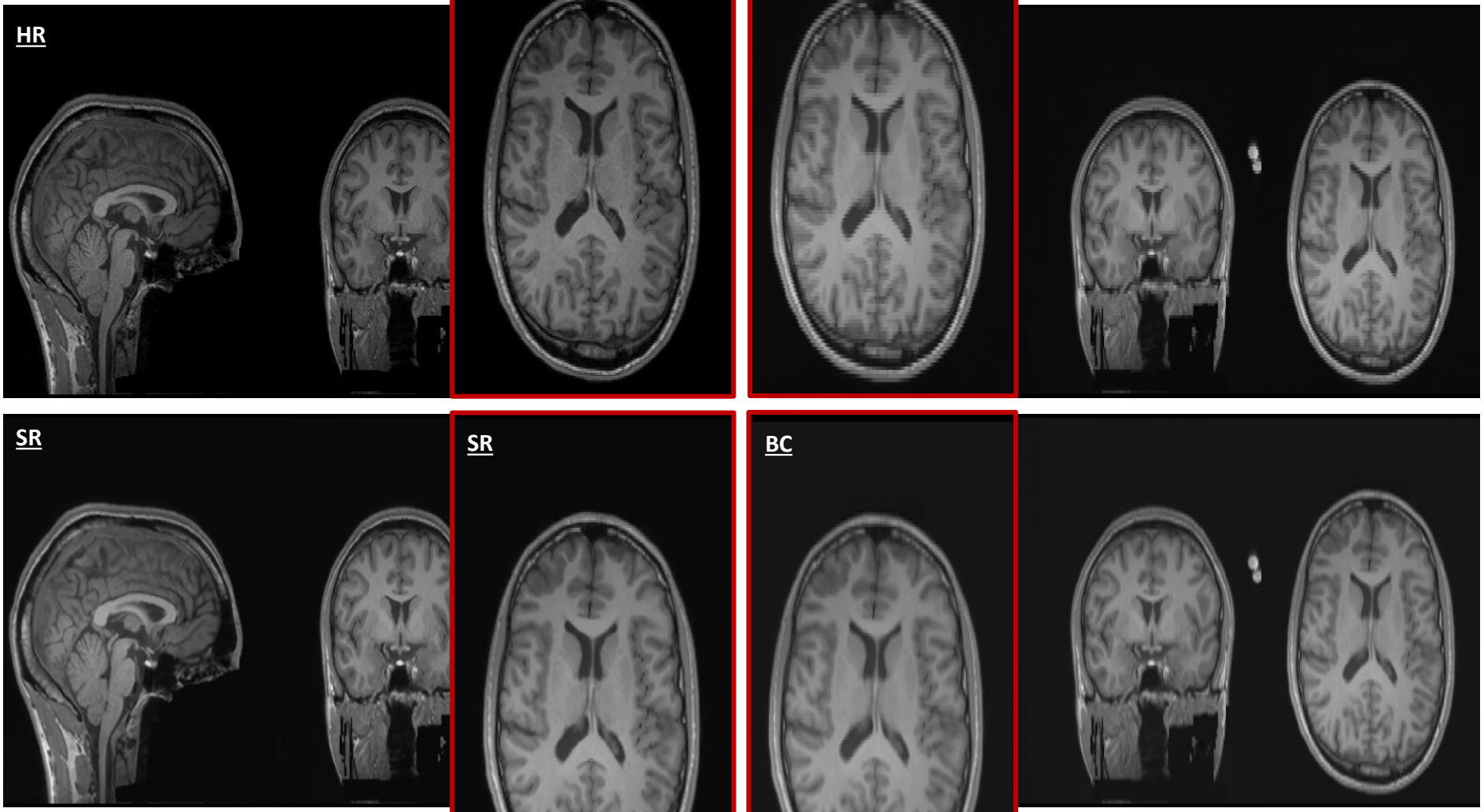
**downsampling 2D, sagittal slices

T1w map from CAMCAN database,



**downsampling 2D, sagittal slices

T1w map from CAMCAN database, subj 11



**downsampling 2D, sagittal slices

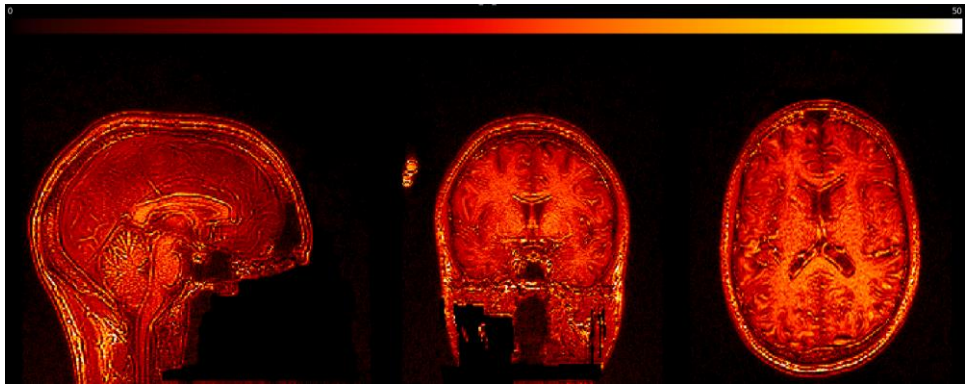
3. Super Resolution on MR Images

Brain extraction

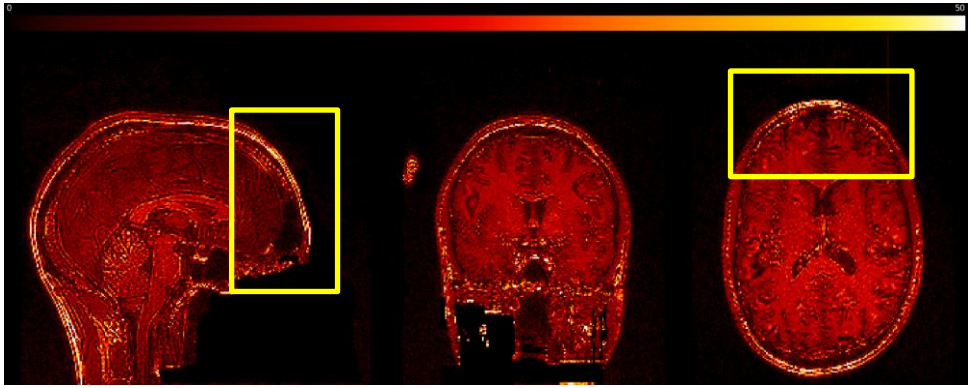
Similarity parameters: RMSE, pSNR, SSIM, HFEN

Absolute intensity difference

HR - BC



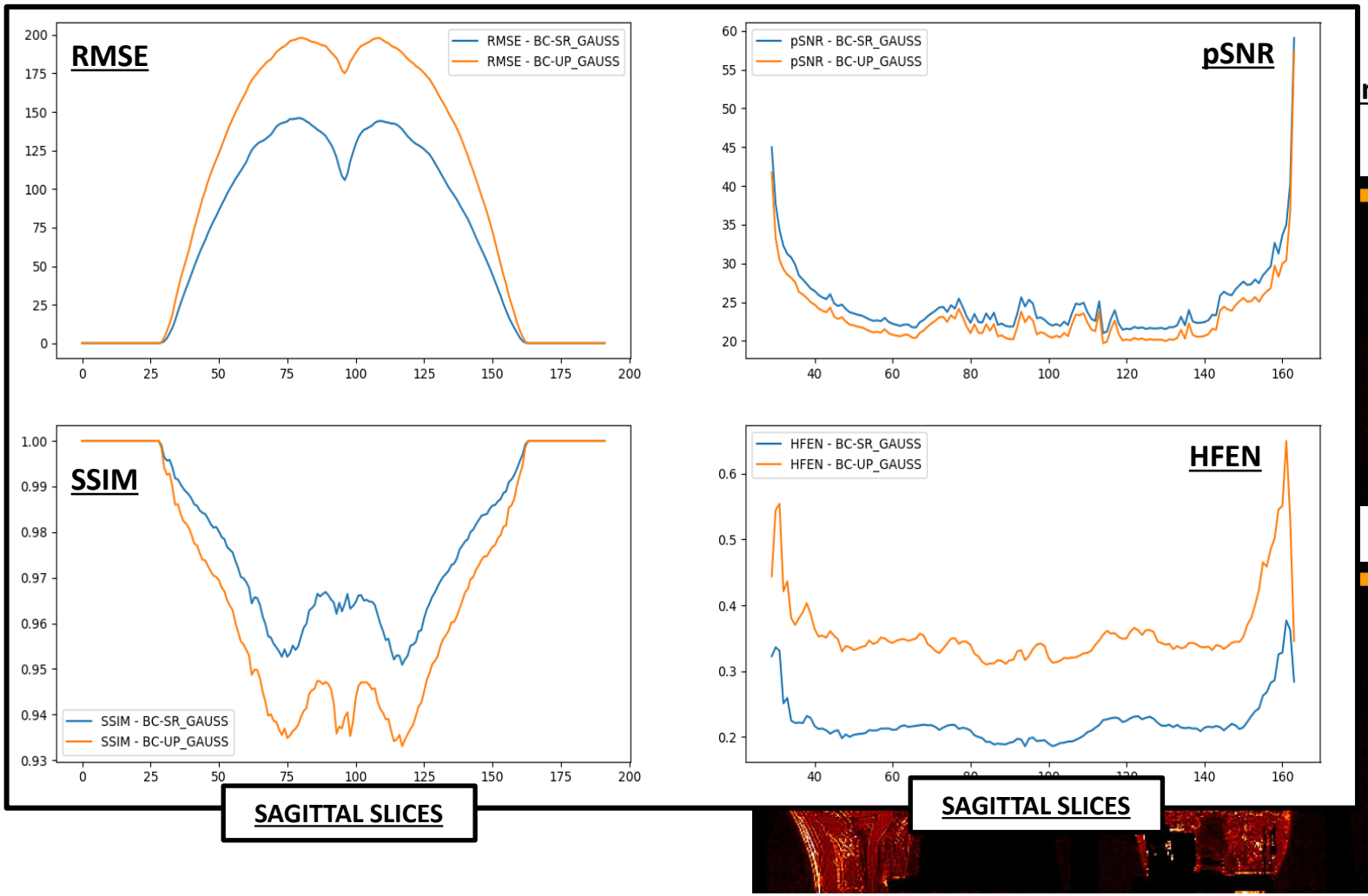
HR - SR



3. Super Resolution on MR Images

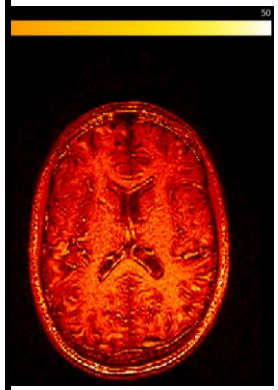
Brain extraction

Similarity parameters: RMSE, pSNR, SSIM, HFEN

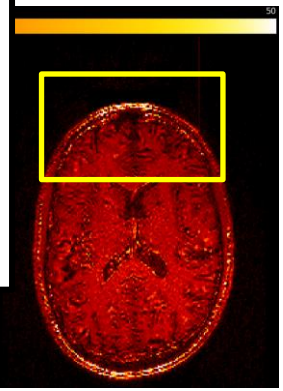


nsity difference

HR - BC



HR - SR



Thank you!