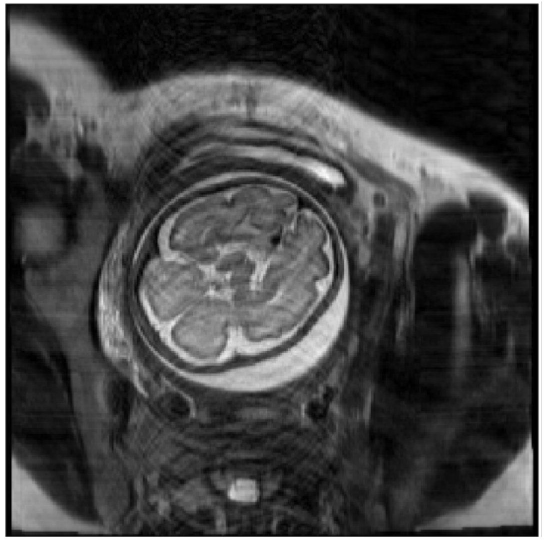
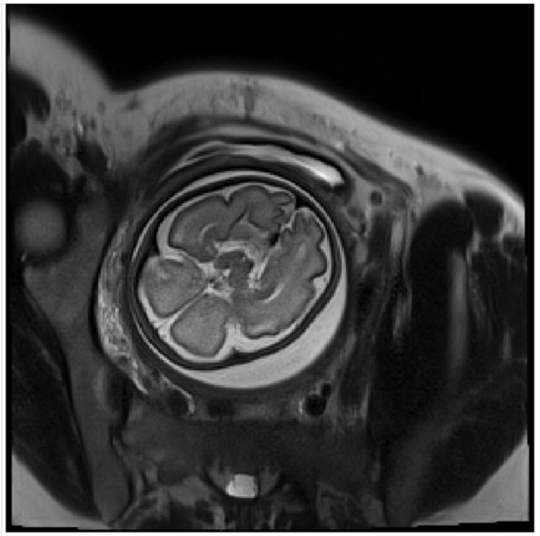
A Machine Learning Approach for Mitigating Artifacts in Fetal Imaging due to an Under-sampled HASTE Sequence



$\boxed{\xrightarrow{\phi}}$



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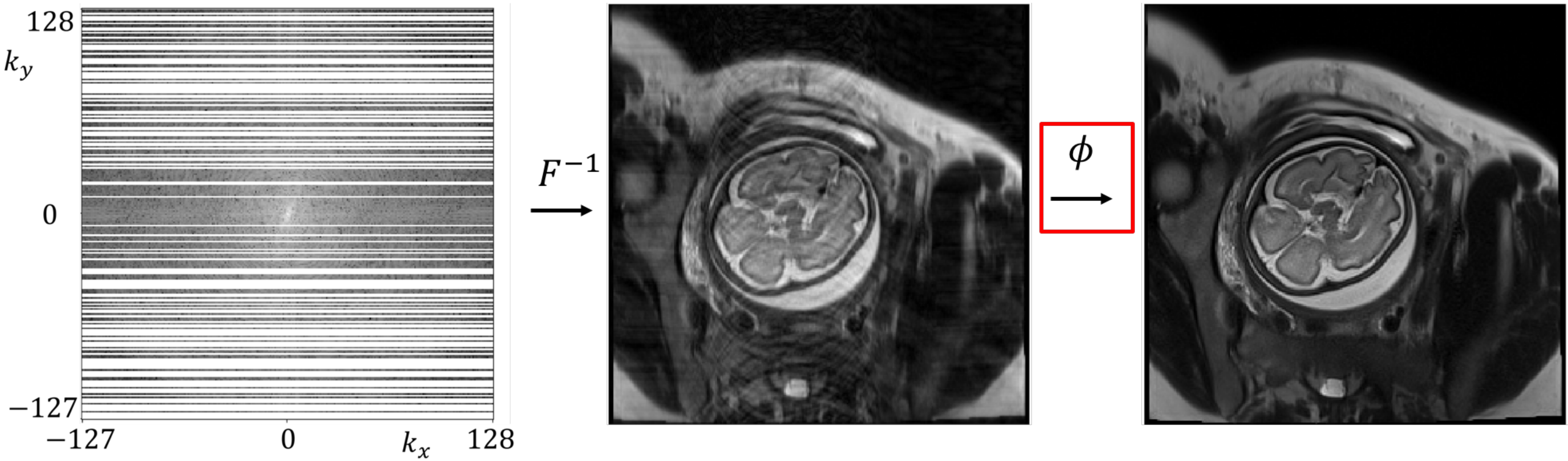
Declaration of Financial Interests or Relationships

Presenter Name: Sayeri Lala

I have no financial interests or relationships to disclose with regard to the subject matter of this presentation.

Image Reconstruction Problem

Goal: Learn ϕ



Undersampling k-space improves T2 contrast by shortening echo train length.

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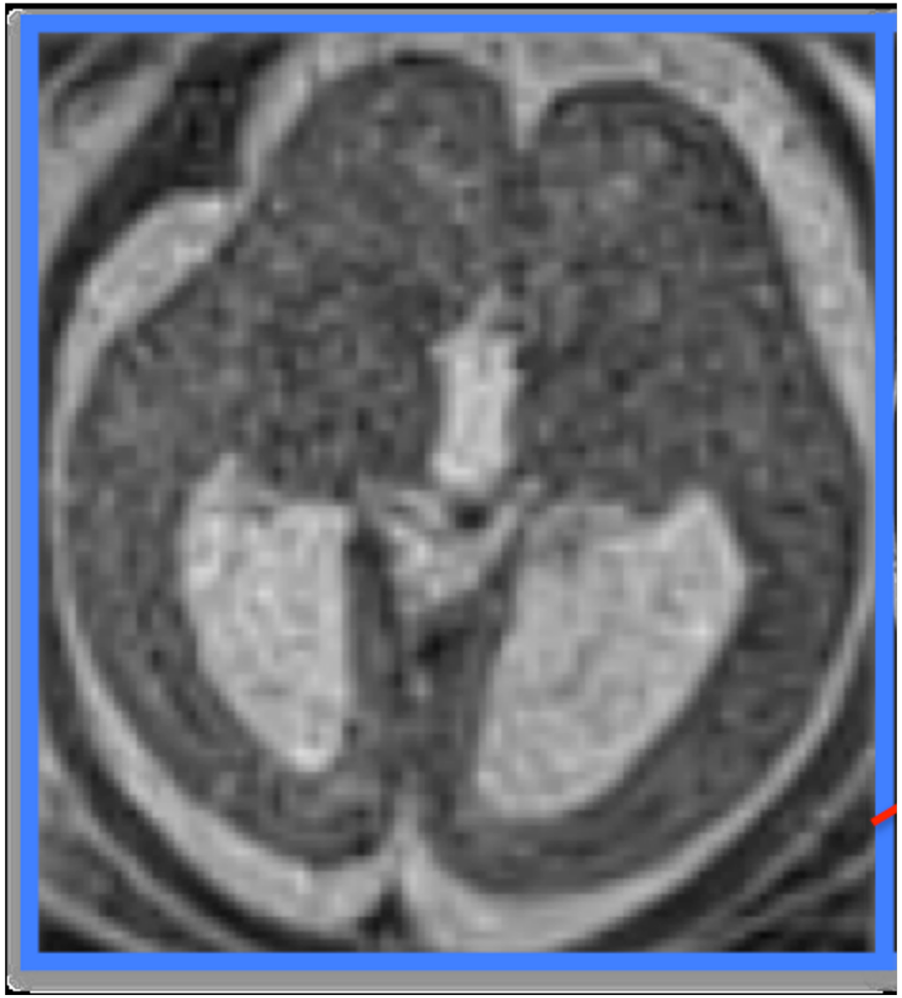
HASTE – Single Shot



TSE – Multi Shot

Voxel resolution	$1.2x1.2x3\ mm^3$	$0.4x0.4x2.5\ mm^3$

Image Reconstruction Algorithms

Naïve Zero-Filled

$$m_{zf} = F^{-1}y$$

Compressed Sensing

$$m_{CS} = \underset{m}{argmin}\, \|F_u m - y\|_2^2 + \alpha\|\psi m\|_1$$

m is the reconstructed image

y are the measured Fourier space samples

F^{-1} is the inverse Fourier transform operator

F_u is the Fourier undersampling operator

α captures the tradeoff between data consistency and regularization

ψ is a non-linear operator transforming from pixel to sparse domain

Lustig, Michael, David Donoho, and John M. Pauly. "Sparse MRI: The application of compressed sensing for rapid MR imaging."

Schlemper, Jo, et al. "A deep cascade of convolutional neural networks for MR image reconstruction."

Image Reconstruction Algorithms

Deep Learning

$$m_{dl} = f(m_{zf} | \theta)$$

$$L(\theta) = \sum_{(m_{zf}, m) \in training\ set} \min_{\theta} \| m - m_{dl}(\theta) \|_2^2$$

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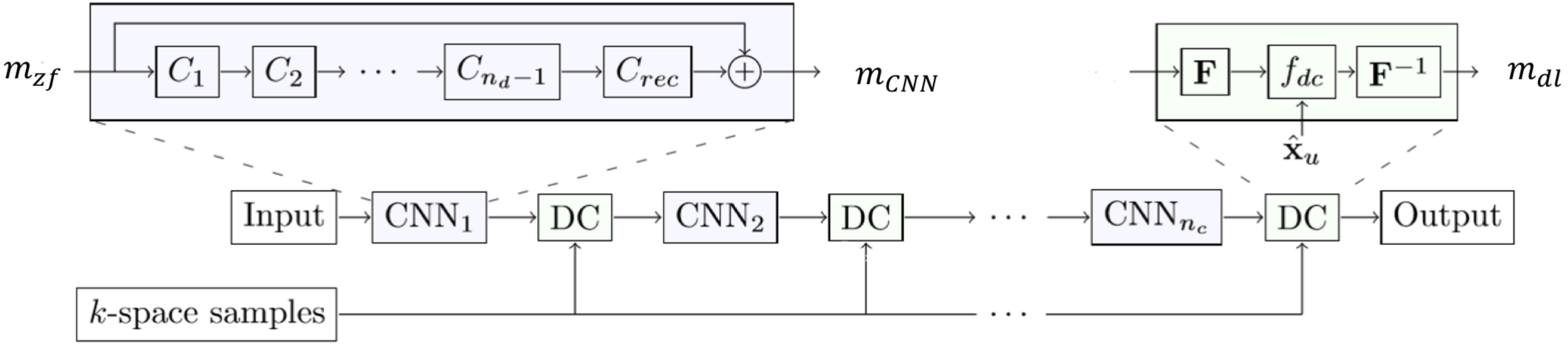
Deep Learning Image Reconstruction Architecture: Cascade of CNNs



Schlemper, Jo, et al. "A deep cascade of convolutional neural networks for MR image reconstruction."

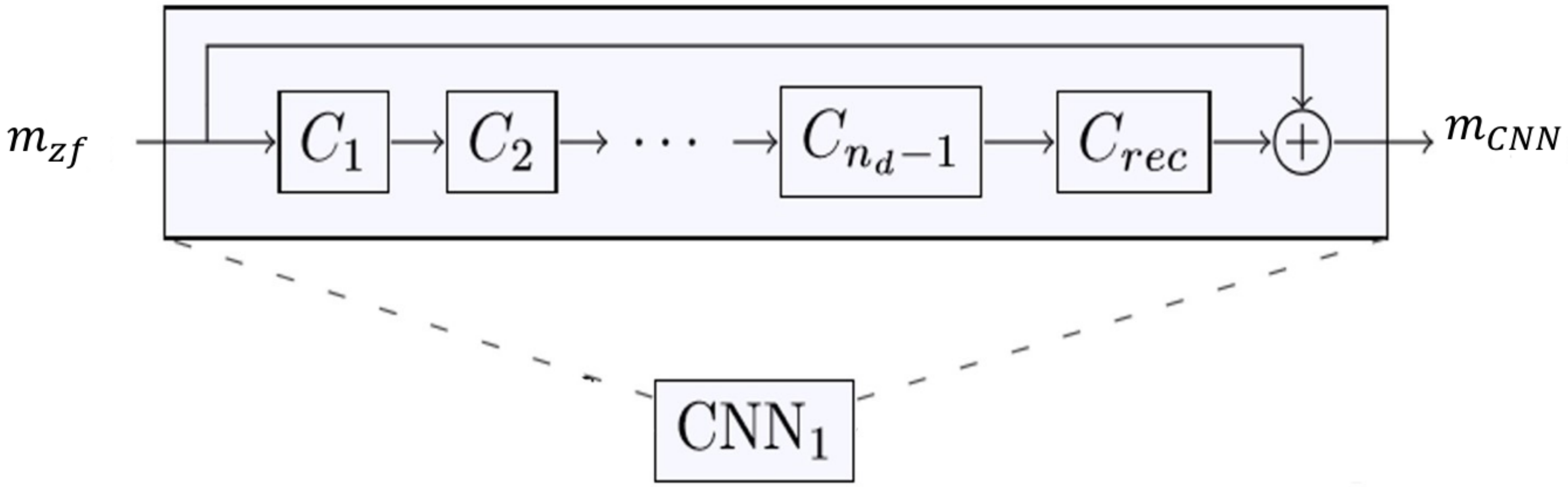
Deep Learning Image Reconstruction Architecture: CNN Module

Parameters for each convolutional layer C_i

- Each is followed by ReLu
- Kernel size: 3 x 3
- Number of filters: 64

Parameters for convolutional layer C_{rec}

- Kernel size: 3 x 3
- Number of filters: 2



Schlemper, Jo, et al. "A deep cascade of convolutional neural networks for MR image reconstruction."

Evaluation Method: Architecture and Training Parameters

- Network: $n_c = 5, n_d = 5$
- Batch size: 10
- Network weights: He initialization
- Adam optimizer: $\alpha = 10^{-4}, \beta_1 = 0.9, \beta_2 = 0.999$
- Weight decay: $l_2 = 10^{-7}$

Dataset

- 10 scans from fetal imaging[1]
  - Training dataset: 7 patients' data, ~3000 images
  - Test dataset: 3 patients' data, ~1000 images
- Parameters for MRI
  - Magnitude images from vendor reconstructions of Fourier data using GRAPPA=2 HASTE and partial Fourier
  - Image size: 256 x 256

[1]Obtained from Boston Children's Hospital in collaboration with Dr. Ellen Grant, Director of Fetal-Neonatal Neuroimaging and Development Science Center

Dataset Creation via Retrospective Undersampling

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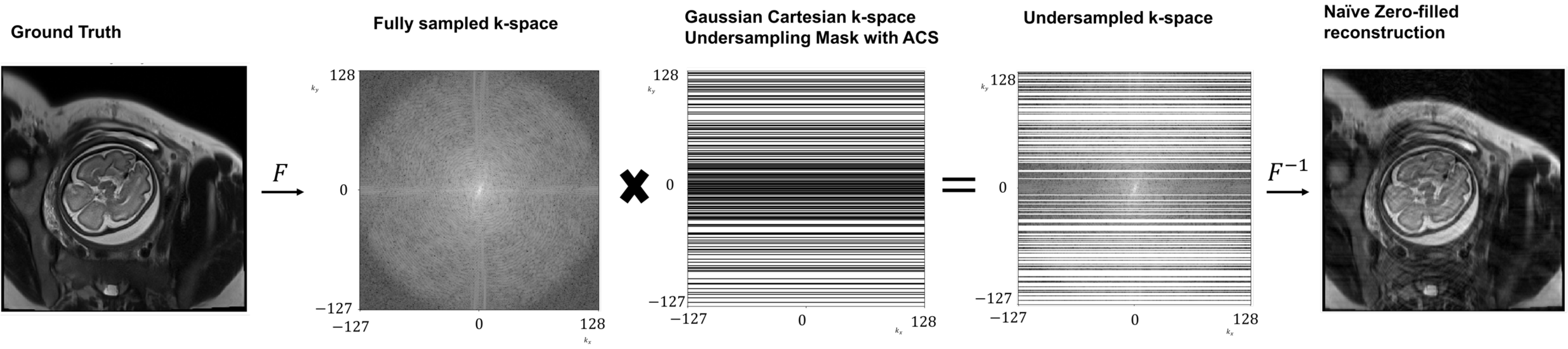

Sample Reconstruction, R=2

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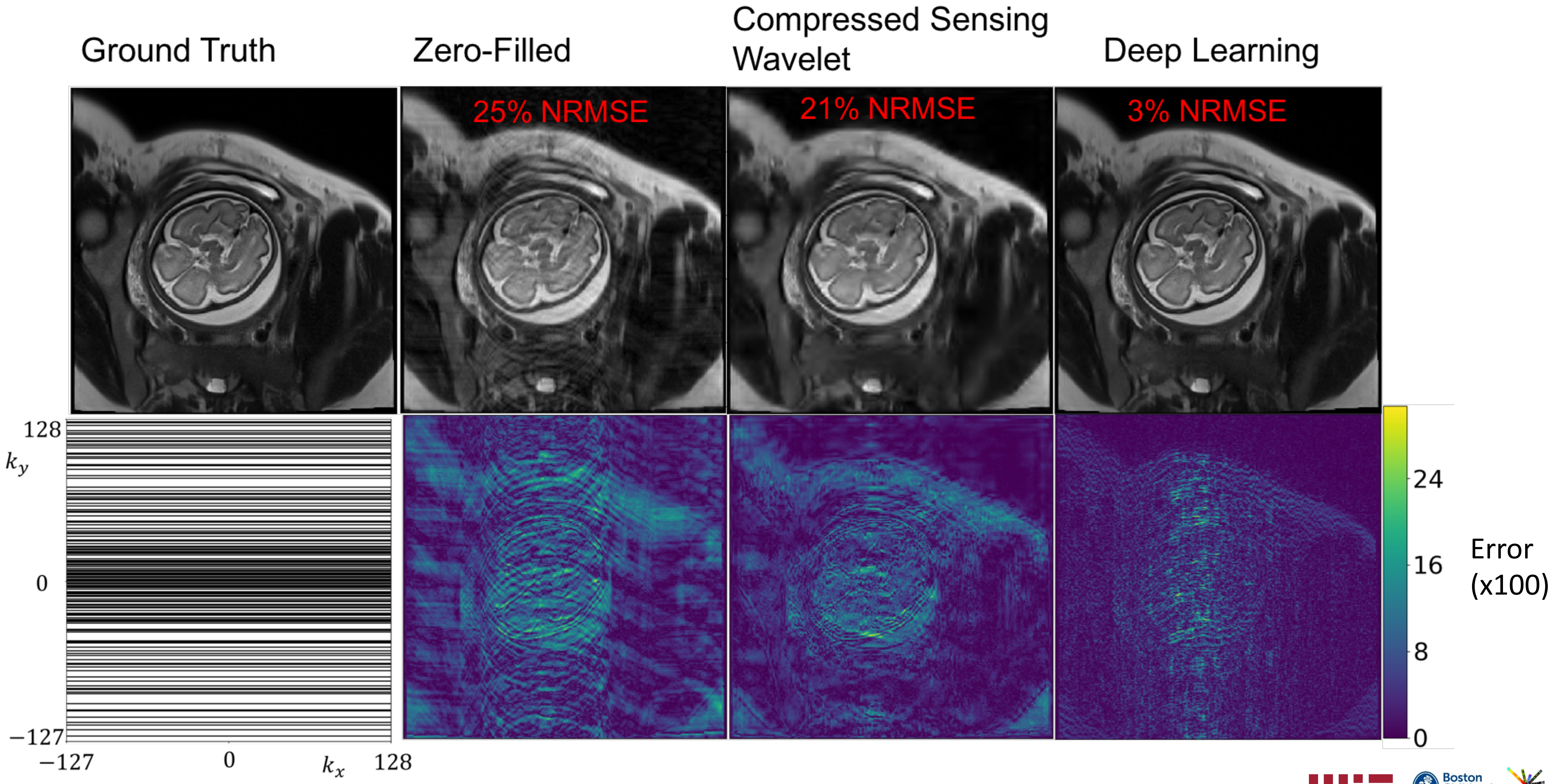
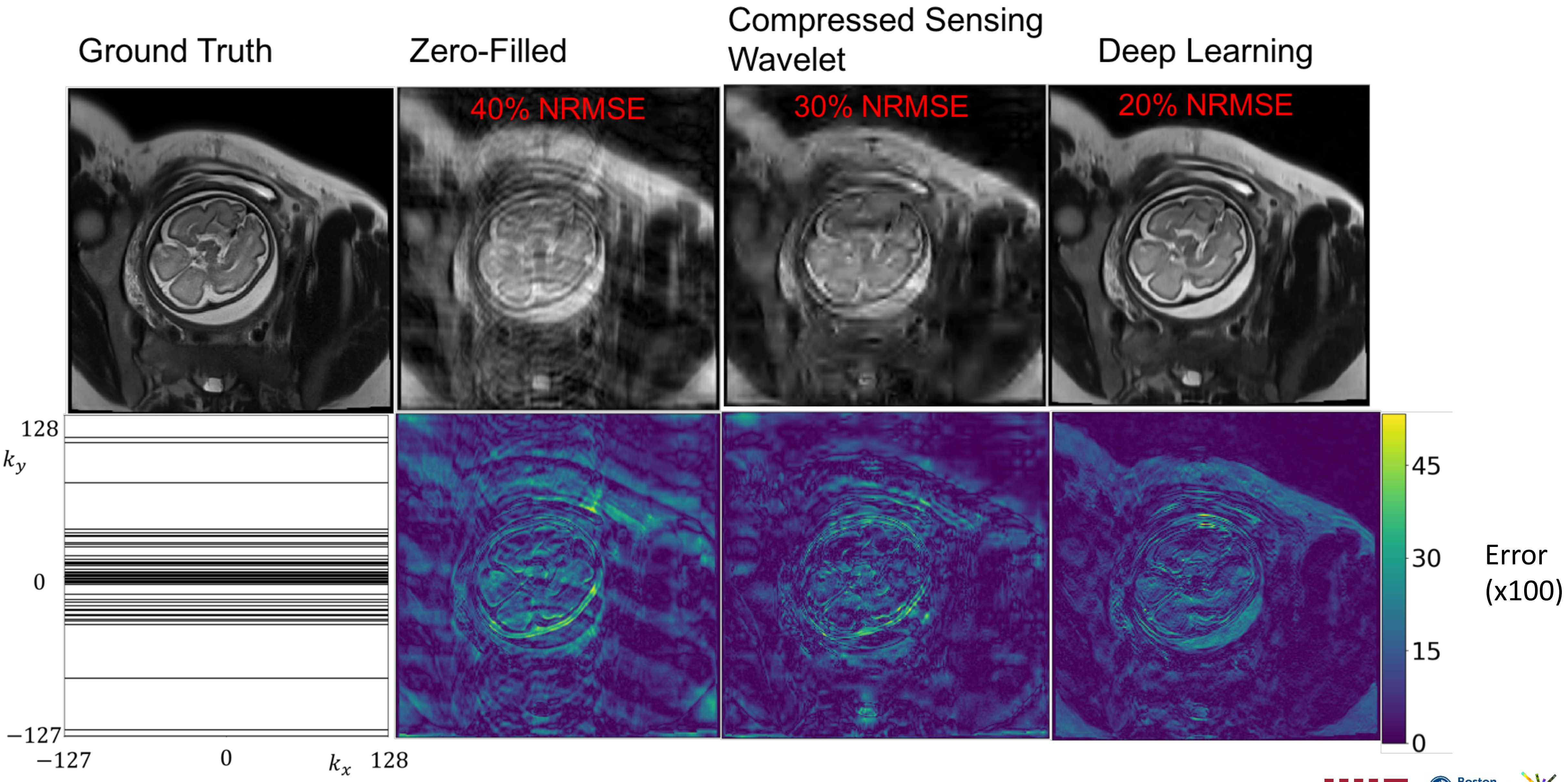


Sample Reconstruction, R=6



Results

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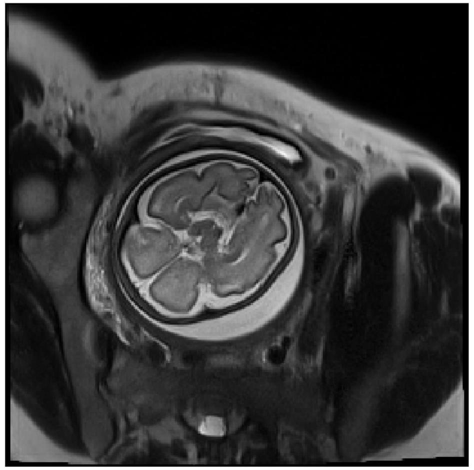
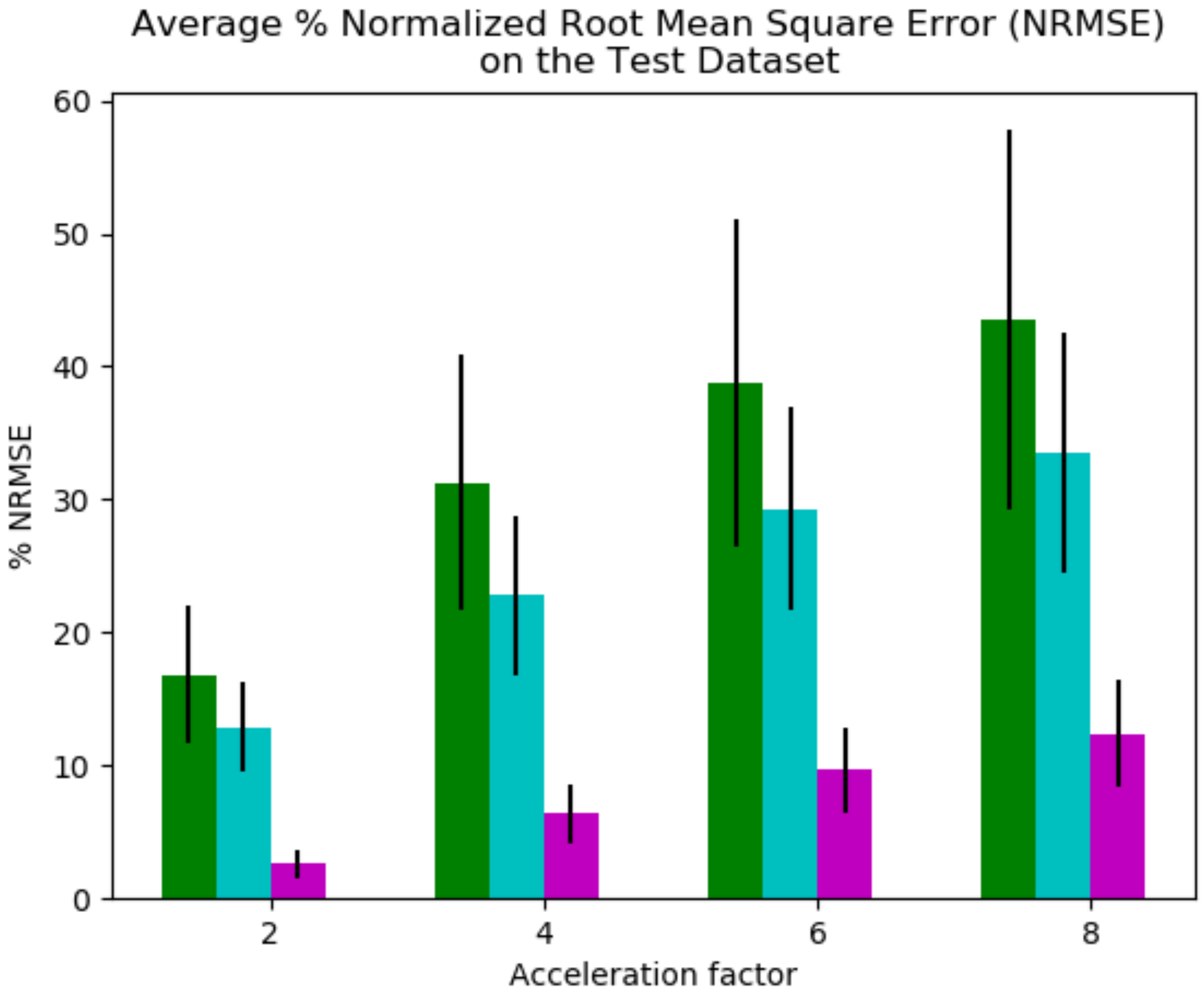
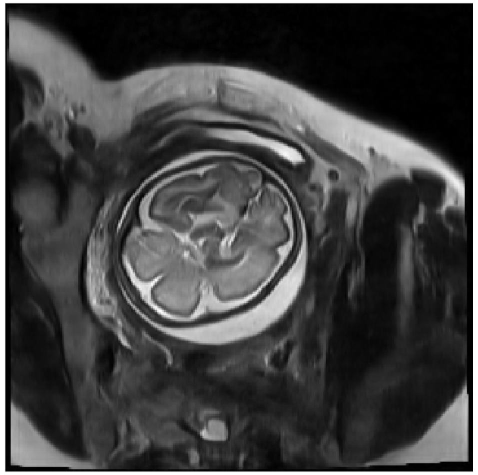
R=2





R=8



Results

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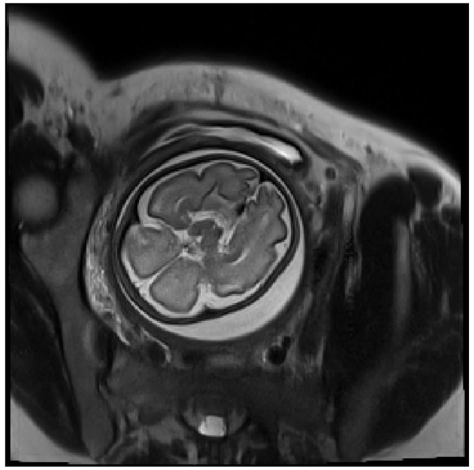
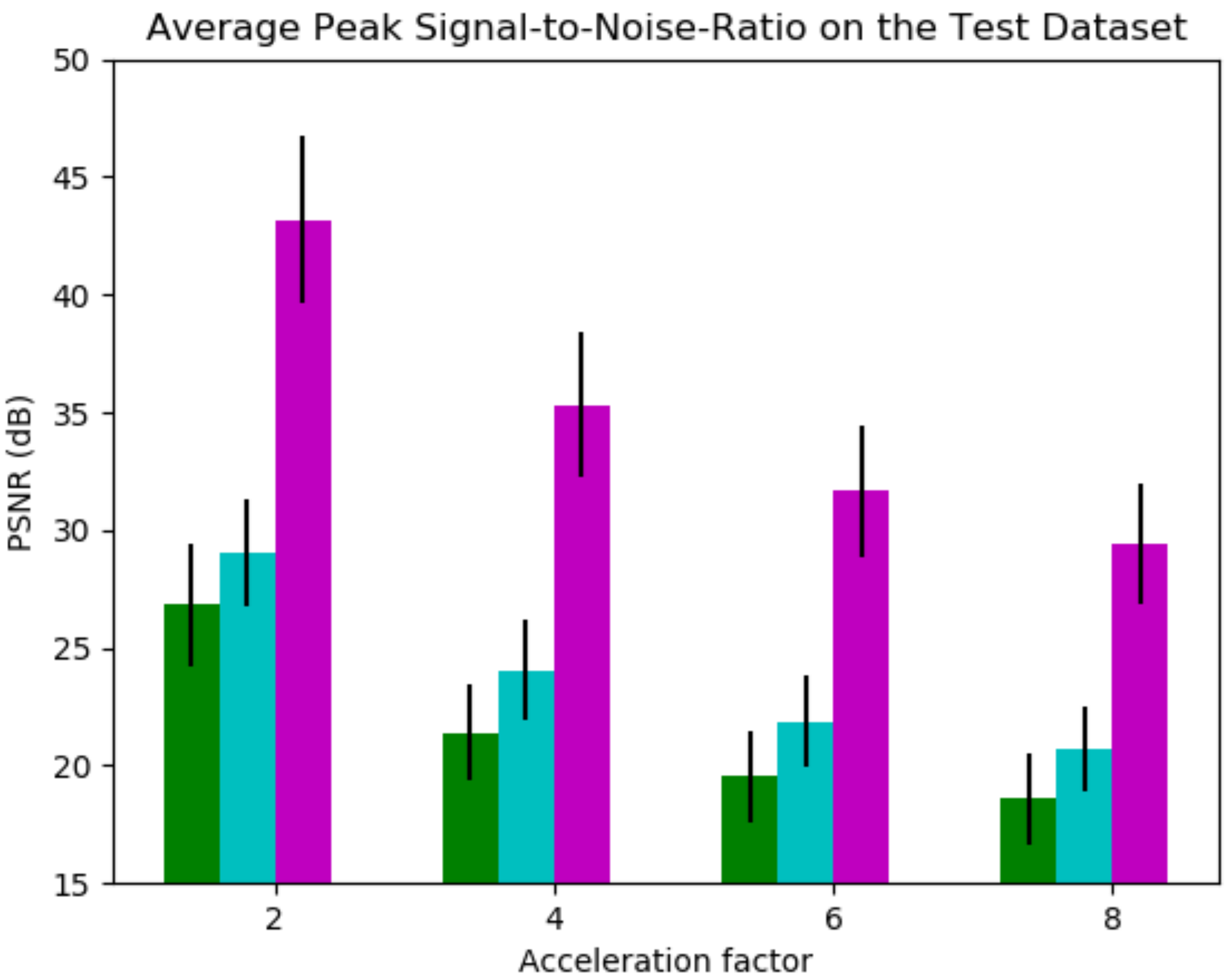
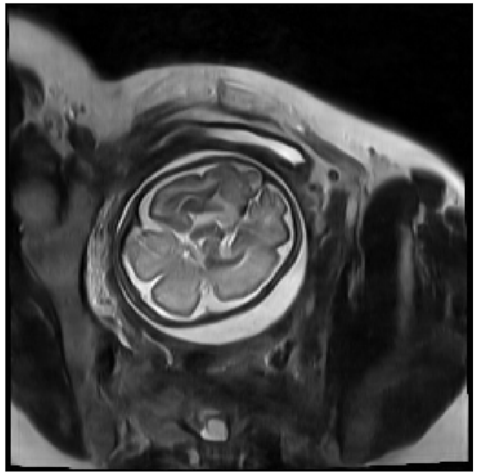
R=2





R=8



Results

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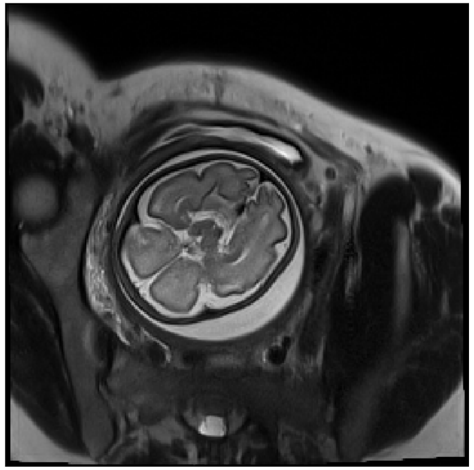
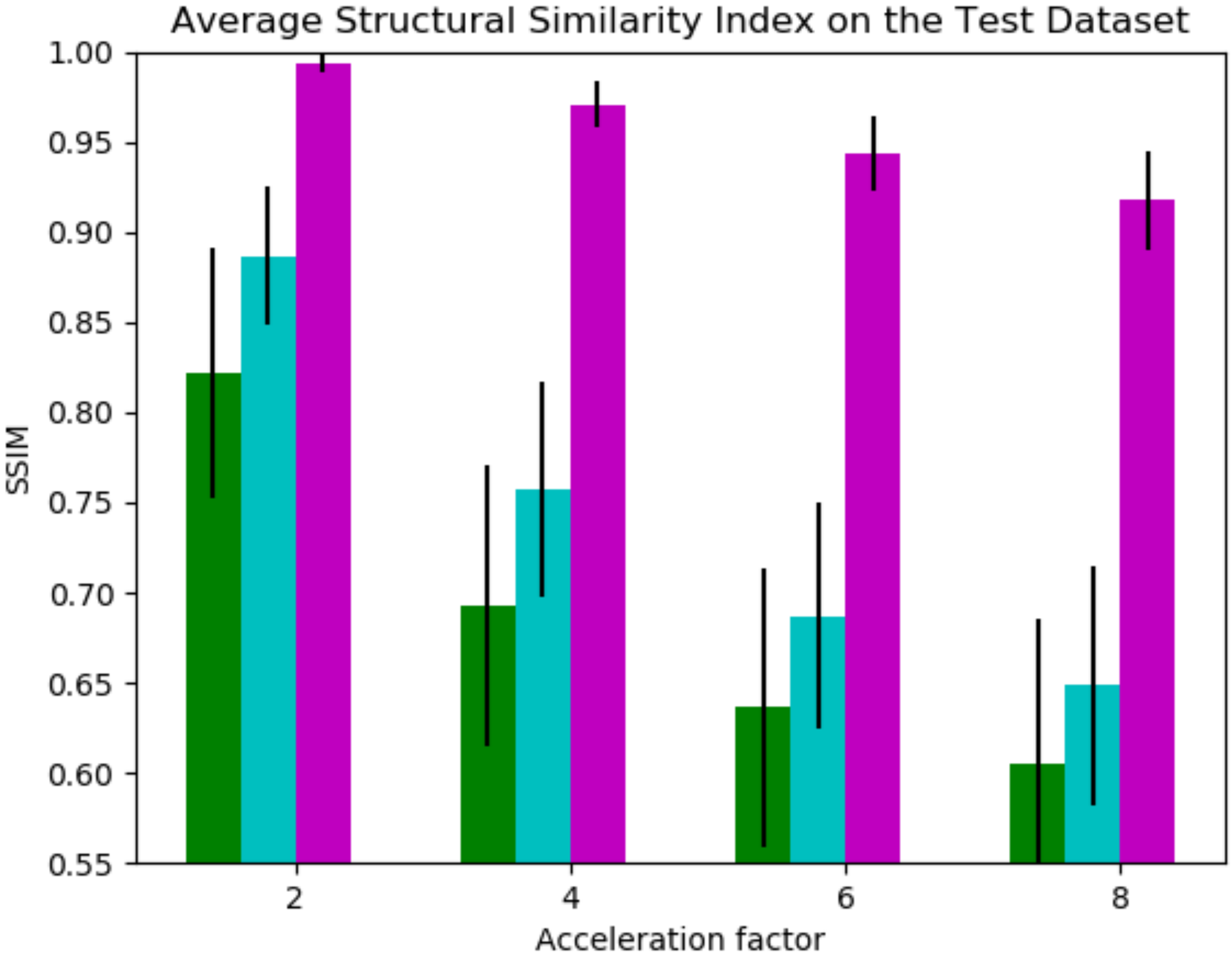
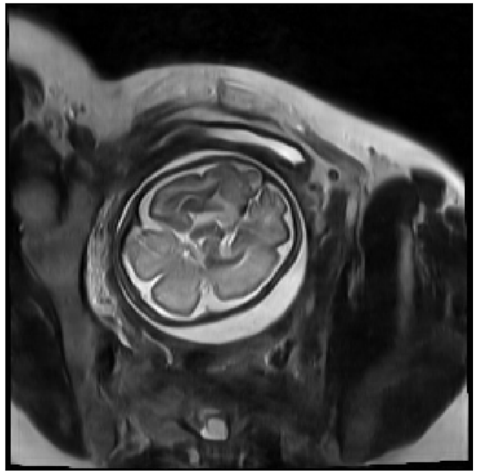
R=2





R=8



Conclusions

- Deep Learning reconstruction
  - performs significantly better than Compressed Sensing and Zero filled image reconstruction
  - suffers from higher residual error over high spatial frequency features with increased k-space undersampling
- Based on radiologist evaluation, deep learning recons. with < 5-6% NRMSE are high quality

Future work:

- Evaluate Deep Learning recon. on prospectively sampled data
- Extend the Deep Learning network to
  - Process Volumetric data

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BACKUP

Compressed Sensing Sparsifying Transforms

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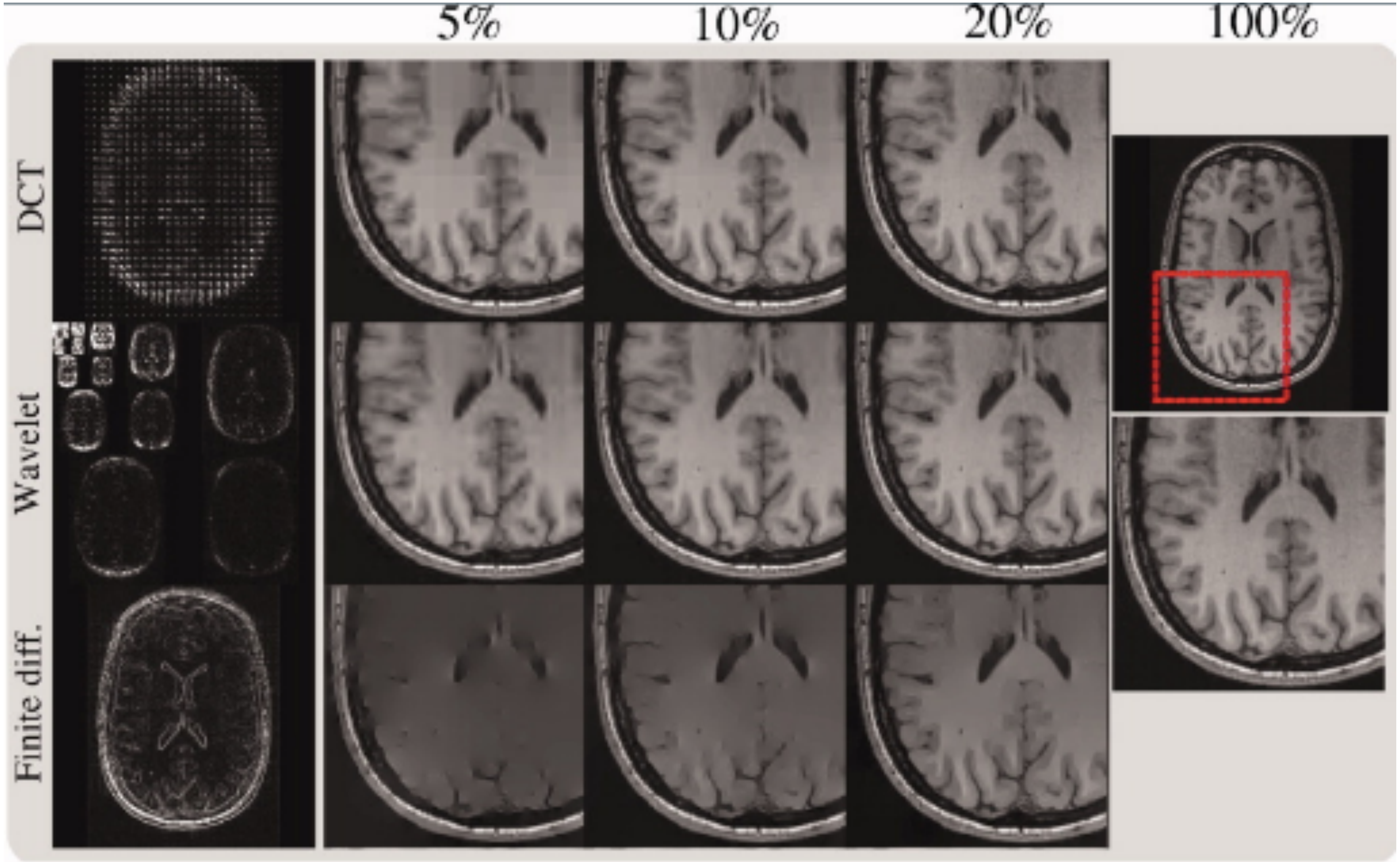

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