# Joint CS-MRI Reconstruction and Segmentation with a Unified Deep Network

CS 732 Advanced Machine Learning

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# INTRODUCTION

- Magnetic resonance imaging (MRI) is an important technique for visualizing human tissue.
- Automatic MR image segmentation is essential because it allows for finer localization of focus.
- Accelerating imaging speed while maintaining high imaging quality is key for MRI.

# CS-MRI

- Compressed sensing (CS) theory, which shows the possibility of recovering signals with sub-Nyquist sampling rates, has been introduced to the field of MRI to accelerate imaging.
- Sub-Nyquist sampling: recovering signals by samples.
- In 2017, the US Food and Drug Administration (FDA) approved CS-MRI techniques for use by two major MRI vendors: Siemens and GE.

# MOTIVATION

- Current segmentation algorithms for MRI assume a “clean” (i.e., fully-sampled) image as input and do not take CS-MRI scenarios into consideration.
- CS-MRI reconstruction methods do not consider their output’s potential downstream segmentation.
- The anticipated increase in the number of CS-reconstructed MRI for clinical application will call for automatic segmentation algorithms optimized for this type of data.

# MRI Segmentation

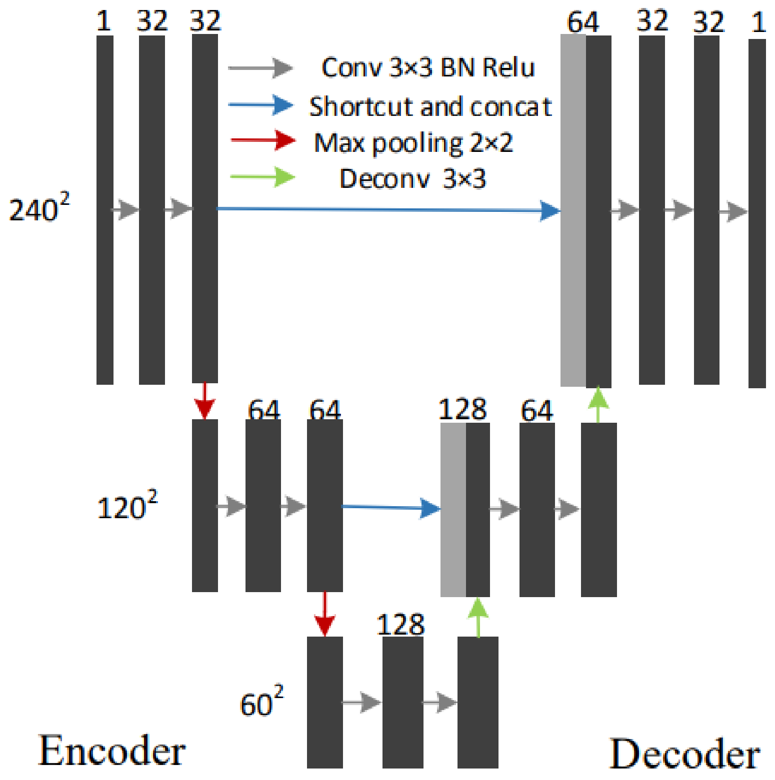
- Atlas-based segmentation with registration
- Machine learning models with hand-crafted features
- Deep learning models
- HOWEVER, these MRI segmentation models do not take the input quality into consideration, but assume full measurements.

# Compressed Sensing MRI

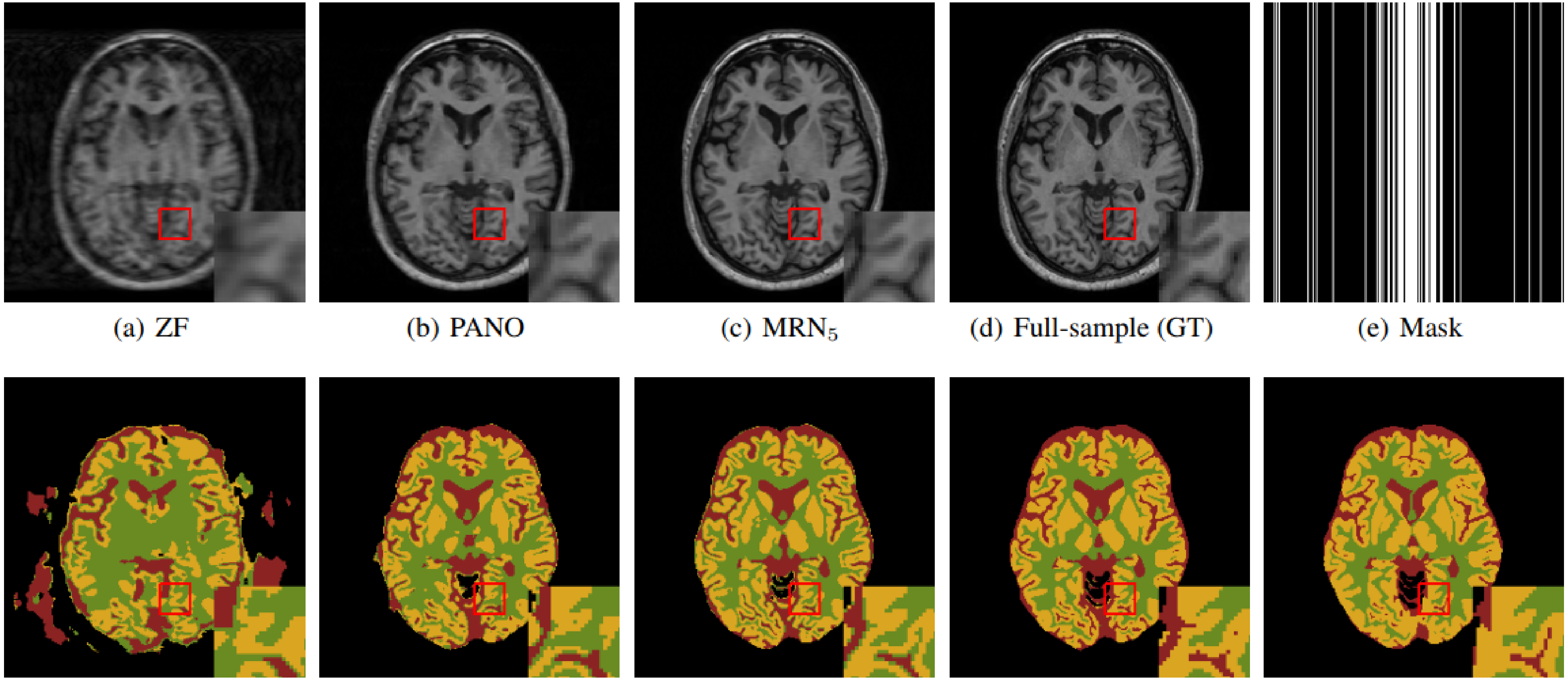
- Deep neural networks have been introduced to CS-MRI. Researchers have directly applied convolutional neural networks (CNN) to learn a direct mapping from the zero-filled MRI to the true MRI.
- Zero filling: Processing of MRI requires the input data to be in a matrix. If the acquired *k*-space data does not complete the matrix, it is customary to fill the missing cells with zeroes.
- Data fidelity terms have been incorporated into the deep neural network to add more guidance. These deep learning based CS-MRI models have achieved higher reconstruction quality and faster reconstruction speed.

# MRI segmentation network (MSN)

- Inspired by the state-of-the-art medical image segmentation model U-Net.



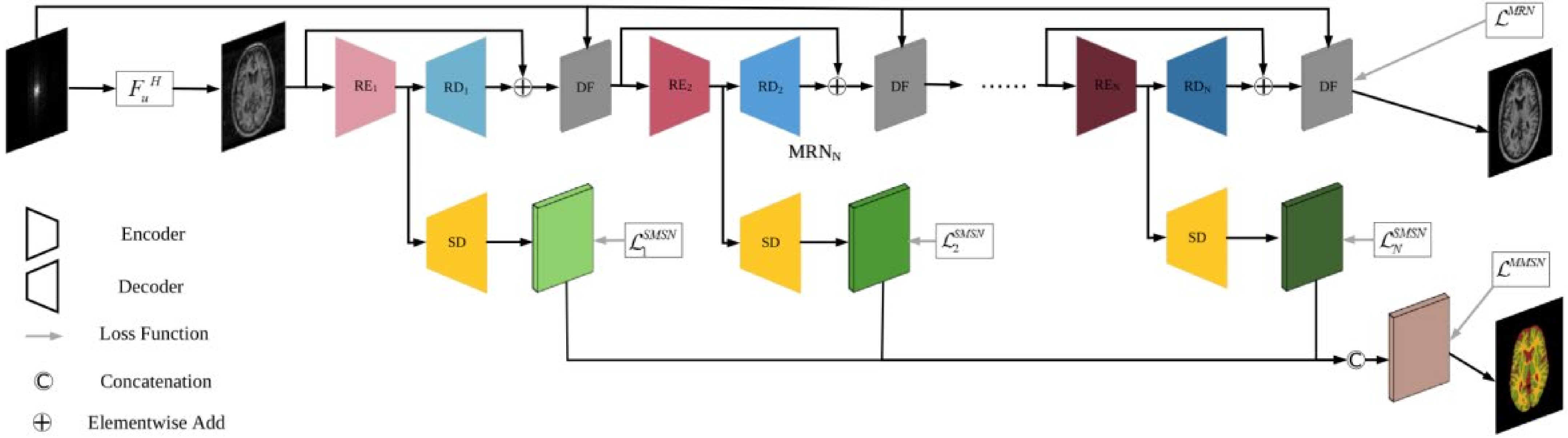
# MRI reconstruction network (MRN)



(a) ZF (b) PANO (c) $MRN_5$ (d) Full-sample (GT) (e) Mask

(f) ZF Seg (g) PANO Seg (h) $MRN_5$ Seg (i) Full-sample Seg (j) Manual Seg

# MRI reconstruction network (MRN)




RE: each of the encoder components of each MRN
RD: each of the decoder components of each MRN
DF: data fidelity unit
SD: single decoder component of the MSN
SE: single encoder component of the MSN

# Loss function

$$\mathcal{L}^{\text{MRN}} = \frac{1}{L}\sum_{i=1}^{L}\left\|x_i^{fs} - x_i\right\|_2^2,$$

$$\mathcal{L}^{\text{MSN}} = -\sum_{i=1}^{L}\sum_{j=1}^{N}\sum_{c=1}^{C} t_{ijc}^{gt}\ln t_{ijc},$$

$$\mathcal{L}^{\text{SegNetMRI}} = \mathcal{L}^{\text{MRN}} + \lambda\mathcal{L}^{\text{OMSN}}.$$ OMSN: overall MSN loss

$$\mathcal{L}^{\text{OMSN}} = \frac{1}{N+1}\left(\mathcal{L}^{\text{MMSN}} + \sum_{i=1}^{N}\mathcal{L}_i^{\text{SMSN}}\right),$$

MMSN: loss for the merged prediction

SMSN: loss for each sub-MSN decoder prediction

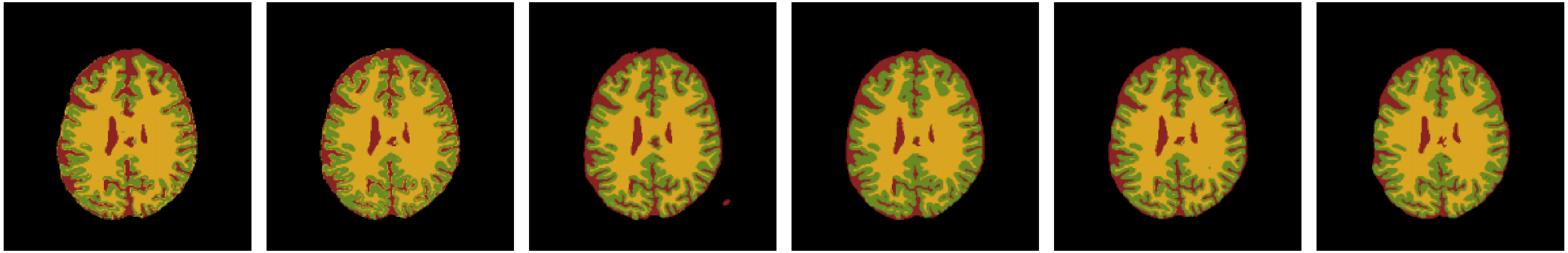
# Experiments

- Implement all deep models on TensorFlow for the Python environment.
- Apply Xavier initialization for pre-training MRN and MSN. MSN is pre-trained for 60, 000 iterations using 64×64 fully-sampled MRI patches randomly cropped (16 patches in a batch) and MRN is pre-trained for 30, 000 iterations using the entire training image (4 images in a batch).
- Finetune the SegNetMRI model for 8, 000 further iterations using entire images (4 images in a batch). ADAM is chosen as optimizer.
- Select the initial learning rate to be 0.0005, the first-order momentum to be 0.9 and the second momentum to be 0.999.

# Data

- MRBrainS datasets from the Grand Challenge on MR Brain Image Segmentation (MRBrainS) Workshop.
- The datasets are acquired using 3T MRI scans. Five datasets are provided containing T1-1mm, T1, T1-IR and T2-FLAIR imaging modalities already registered and with manual segmentations. Use the T1 MRI data of the size $240 \times 240$ throughout the paper. We use four datasets for training (total 192 slices) and one dataset for testing (total 48 slices).

# Results



(a) GBRWT+MSN (b) MRN$_5$+MSN (c) [Liu *et al.*, 2017] (d) SegNetMRI$_5$ (e) FS+MSN (f) GroundTruth

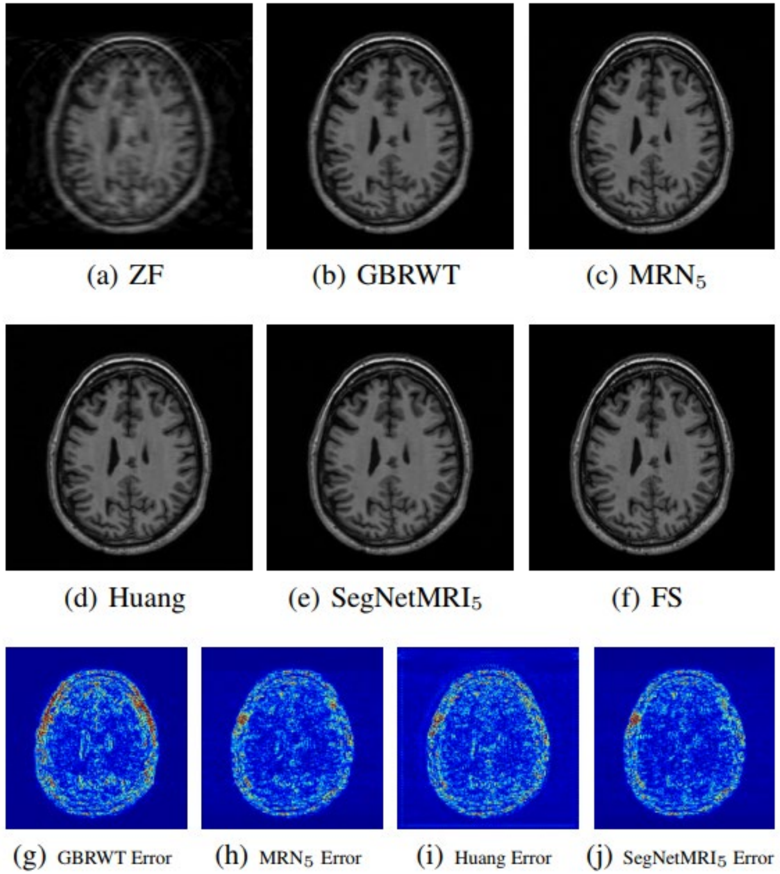
The proposed SegNetMRI5 model provides better segmentation and approximates the ideal FS+MSN most closely, both of which are not perfect compared with the human labeling.

# Results

| Methods | GM | | | WM | | | CSF | | |
|---|---|---|---|---|---|---|---|---|---|
| | DC | HD | AVD | DC | HD | AVD | DC | HD | AVD |
| GBRWT+MSN | 75.55 | 2.24 | 4.21 | 65.56 | 1.90 | 3.10 | 76.50 | 1.77 | 2.69 |
| $MRN_5$+MSN | 79.36 | 2.06 | 3.57 | 65.76 | 1.88 | 2.96 | 78.43 | 1.64 | 2.33 |
| [Liu *et al.*, 2017] | 83.41 | 1.81 | 2.96 | 78.05 | 1.24 | 1.61 | 77.81 | 1.76 | 2.58 |
| $SegNetMRI_5$ | **86.38** | **1.66** | **2.52** | **81.49** | **1.08** | **1.34** | **79.23** | **1.61** | **2.23** |
| FS+MSN | 87.36 | 1.60 | 2.33 | 85.94 | 1.00 | 1.14 | 81.01 | 1.61 | 2.18 |

- gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF)
- Dice Coefficient (DC), the 95th-percentile of the Hausdoff distance (HD) and the absolute volume difference (AVD)

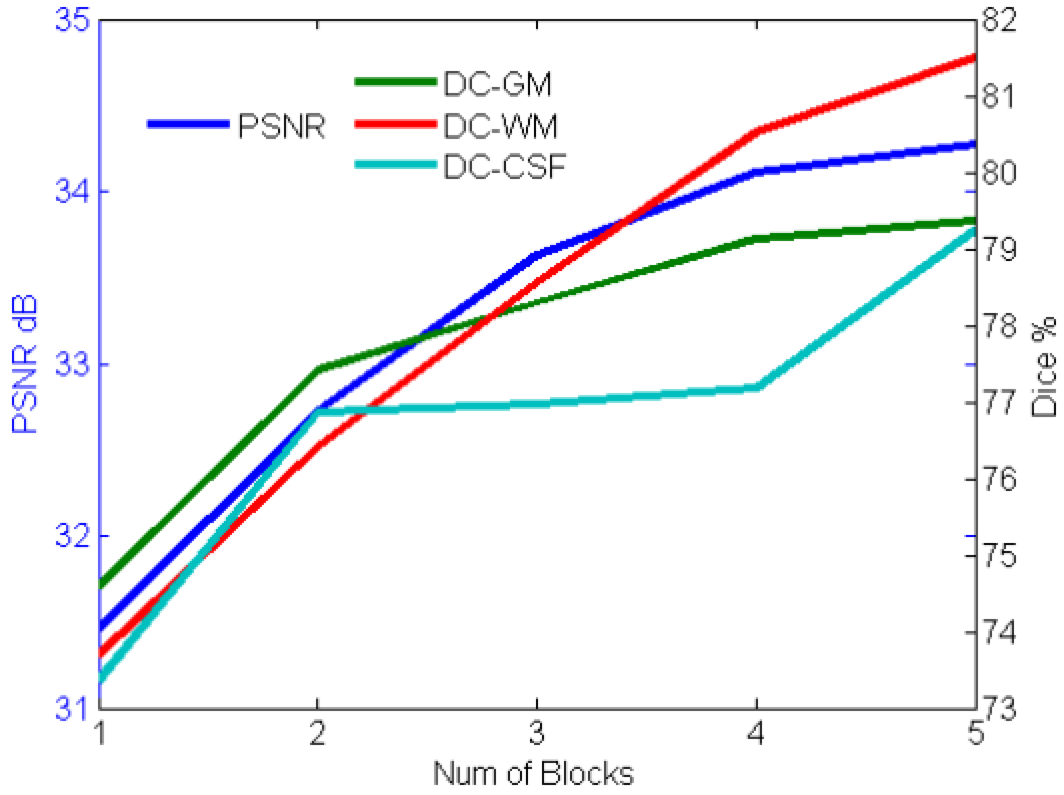
# Results




| | GBRWT | $MRN_5$ | [Liu *et al.*, 2017] | $SegNetMRI_5$ |
|---|---|---|---|---|
| PSNR | 31.80 | 33.94 | 33.47 | **34.27** |
| NMSE | 0.0584 | 0.0361 | 0.0388 | **0.0333** |

Averaged reconstruction performance measures using peak signal-to-noise ratio (PSNR) and the corresponding normalized mean squared error (NMSE) on all 37 test MRI.

# Results




The segmentation accuracy (in Dice Coefficient metric) as a function of blocks, N. The reconstruction quality (in PSNR metric) improves as the number of the blocks increases in the SegNetMRI model, but at the expense of longer training time.

THANK YOU