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Using Deep Learning to Accelerate Magnetic Resonance Imaging (MRI)

Itthi Chatnuntawech

Nanoinformatics and Artificial Intelligence Research Team

National Nanotechnology Center (NANOTEC)

July 19, 2022

Outline

- Magnetic Resonance Imaging (MRI)
- MR Image Acquisition and Reconstruction
  - Imaging parameters
  - Reconstruction from accelerated scans
- Deep Learning for Accelerated MRI
  - Supervised learning
  - Experimental Results
- Recent Advances

Magnetic Resonance Imaging

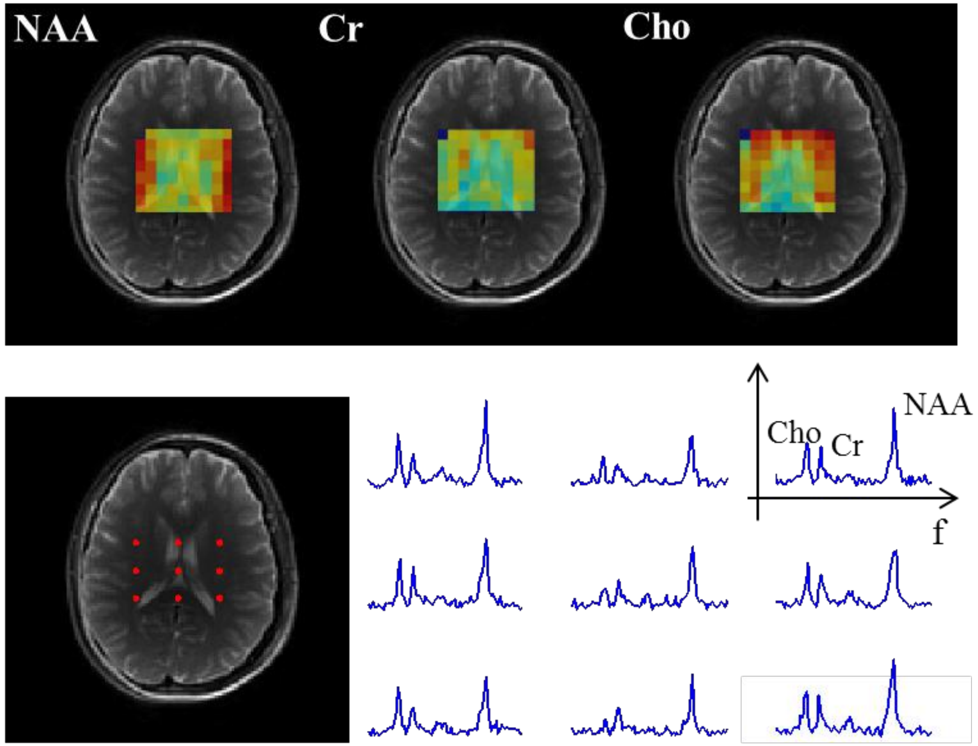
- Magnetic Resonance Imaging (MRI)
  - Non-invasive imaging modality without ionizing radiation

The Beckman Institute, University of Illinois

Magnetic Resonance Imaging

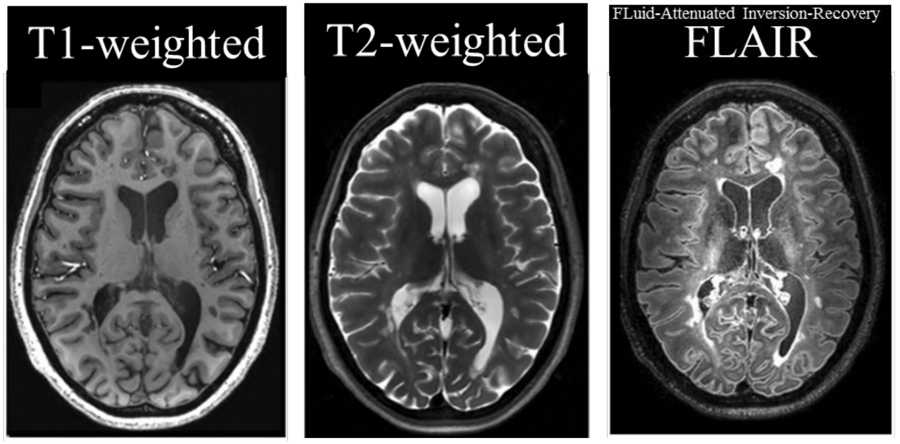
- Magnetic Resonance Imaging (MRI)
  - Non-invasive imaging modality
    - Anatomy
    - Physiology

Magnetic Resonance Spectroscopic Imaging (MRSI)



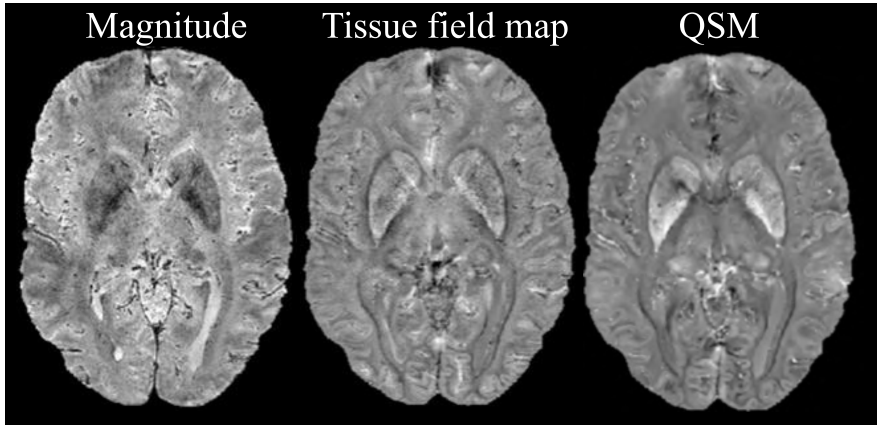
Chatnuntawech I et al. MRM (2014)

Multi-Contrast MRI



De Graaf WL et al. Eur Radiol (2013)

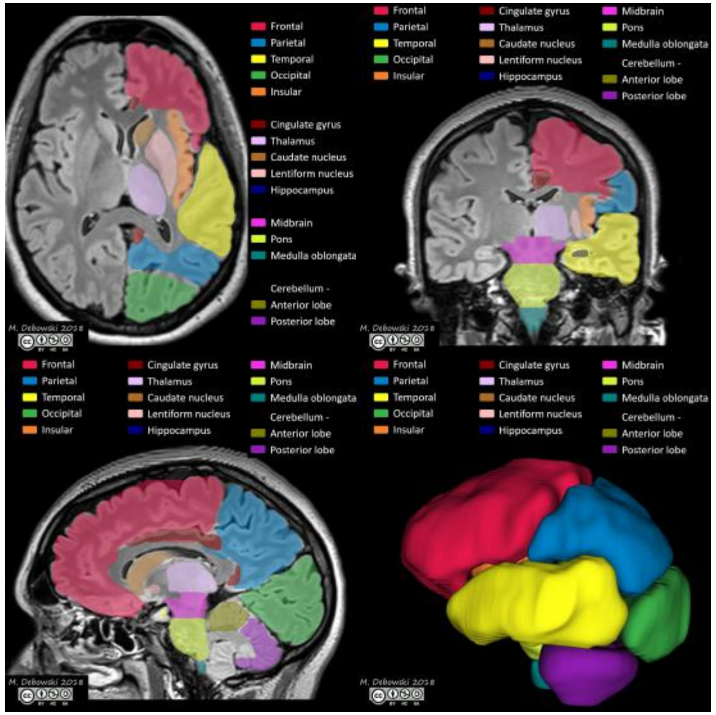
Quantitative Susceptibility Mapping (QSM)



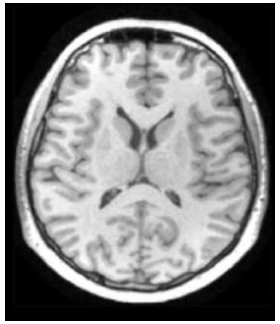
Chatnuntawech I et al. NMR in Biomedicine (2016)

Data acquisition

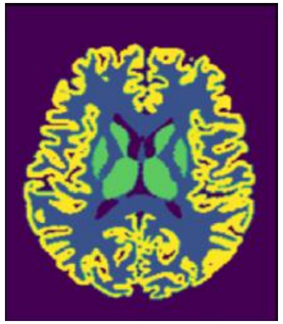
Data reconstruction, enhancement and analysis



Case courtesy of Dr Maciej Debowski, Radiopaedia.org, rID: 61691



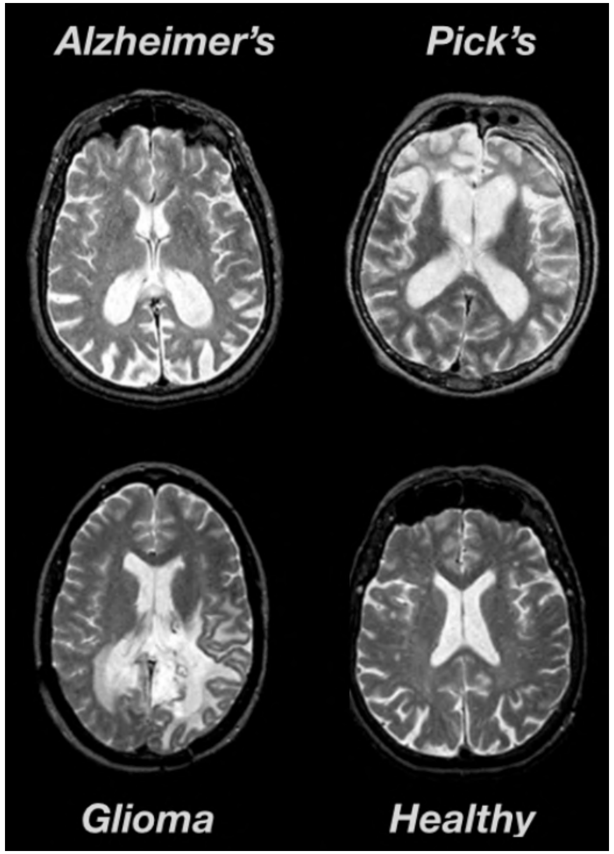
Reconstruction



Segmentation

Cho J et al. ISMRM (2021)

Diagnosis and monitoring



med.harvard.edu/AANLIB

Magnetic Resonance Imaging

The Beckman Institute, University of Illinois

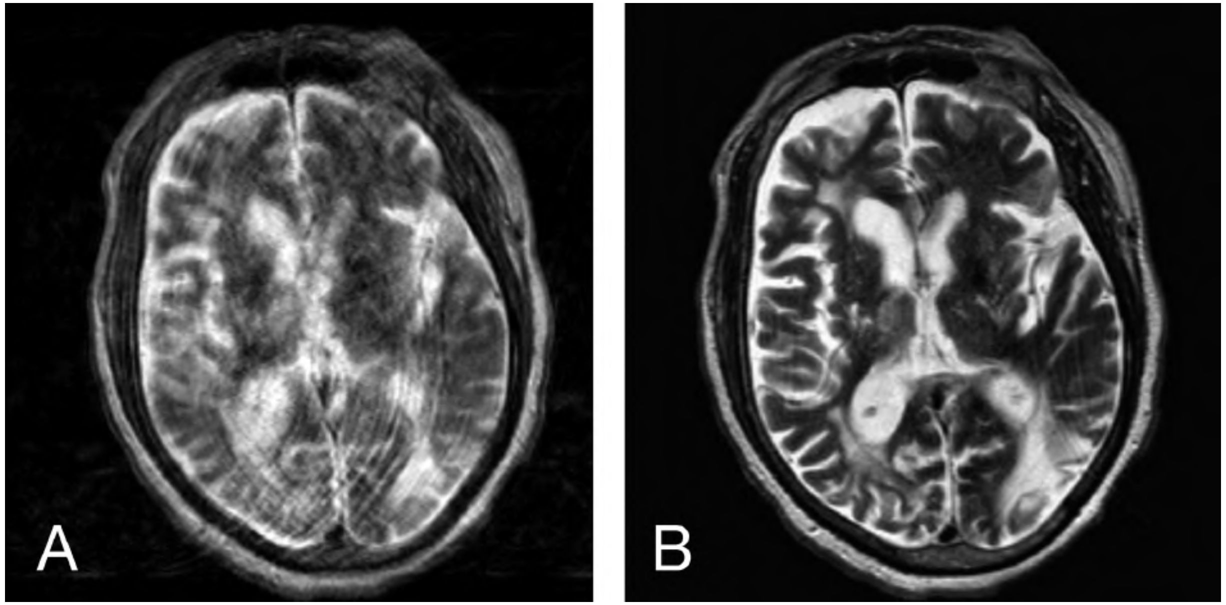
https://youtu.be/hvXoHU9Cexk

"Depending on the machine and the sequence used, it can easily reach aircraft volume levels…The main source of these sounds is the gradient coils we mentioned earlier whose magnetic field overlays the fixed magnetic field of the superconducting magnets. These additional magnetic fields are necessary to precisely localize the MRI signal. For this to work, the gradient coils have to constantly be switched on and off very rapidly, at a very high current of up to 800 amperes a second. The result is that the coils and the plastic structures in which they're embedded bend. Depending on the frequency at which the gradient magnetic fields are switched on and off, there can be different vibration and resonance phenomena. That's what's knocking."

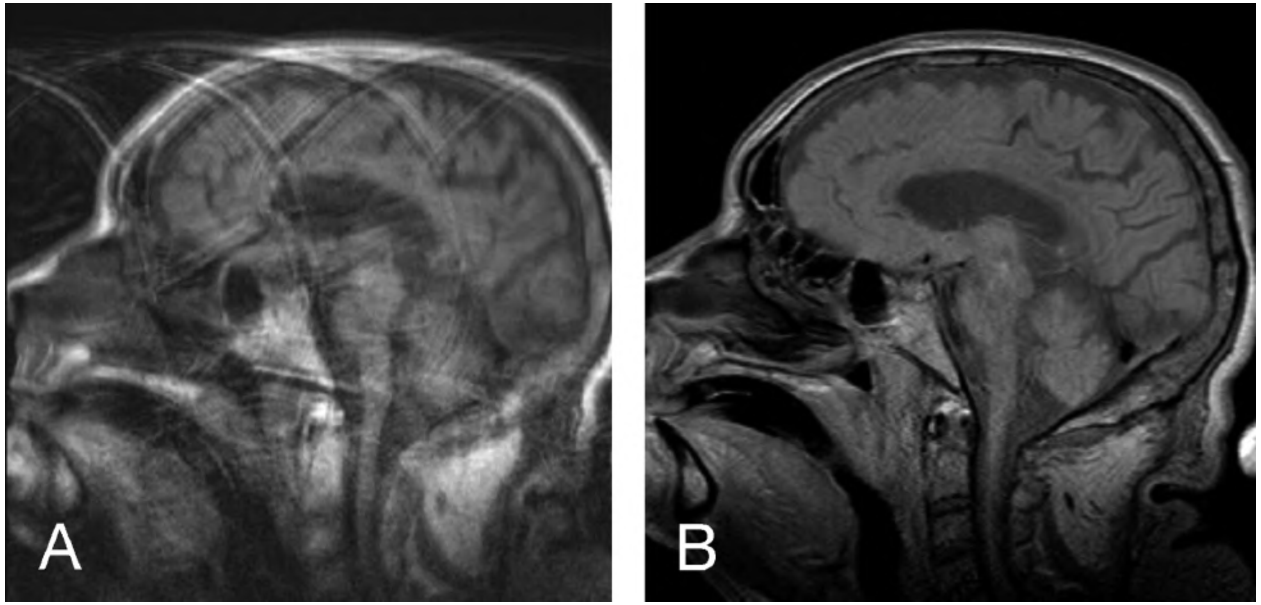
https://www.siemens-healthineers.com/perspectives/mso-whats-that-knocking

Magnetic Resonance Imaging

Motion corrected image



Motion corrected image



Barnwell, J. D., J. K. Smith, and M. Castillo. "Utility of navigator-prospective acquisition correction technique (PACE) for reducing motion in brain MR imaging studies." American journal of neuroradiology 28.4 (2007): 790-791.

Magnetic Resonance Imaging

Ma, Dan, et al. "Music-based magnetic resonance fingerprinting to improve patient comfort during MRI examinations." Magnetic resonance in medicine 75.6 (2016): 2303-2314.

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  - Imaging parameters
  - Reconstruction from accelerated scans
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  - Supervised learning
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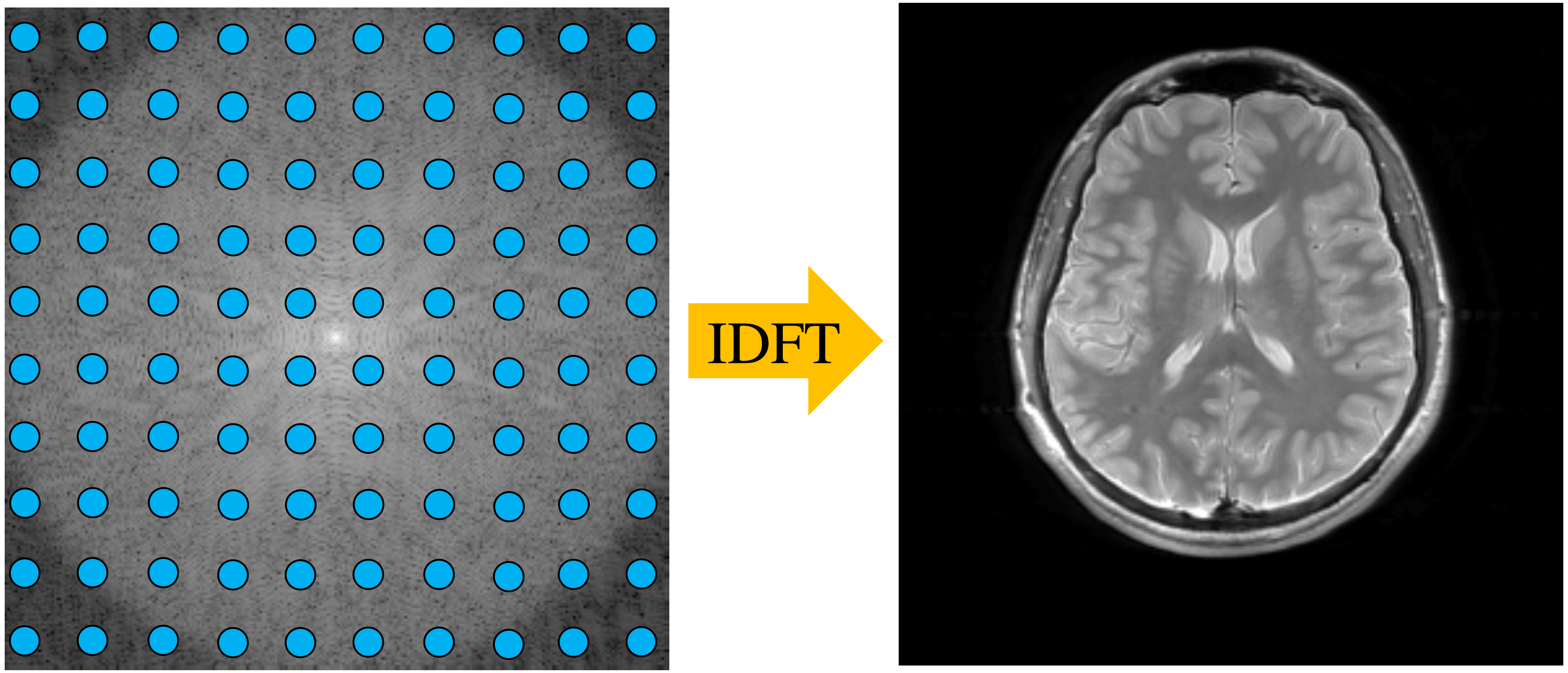
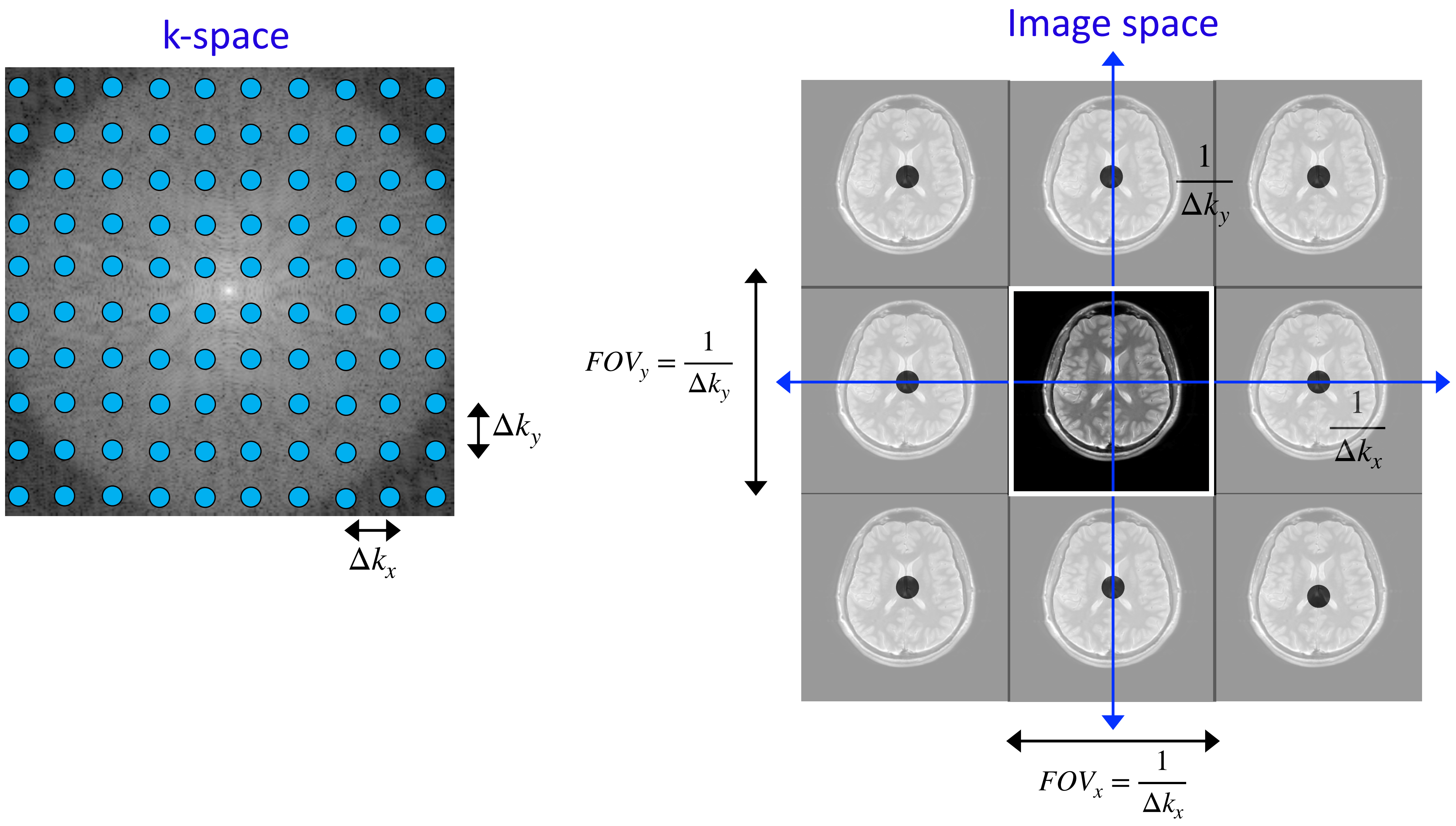
MR Image Acquisition and Reconstruction

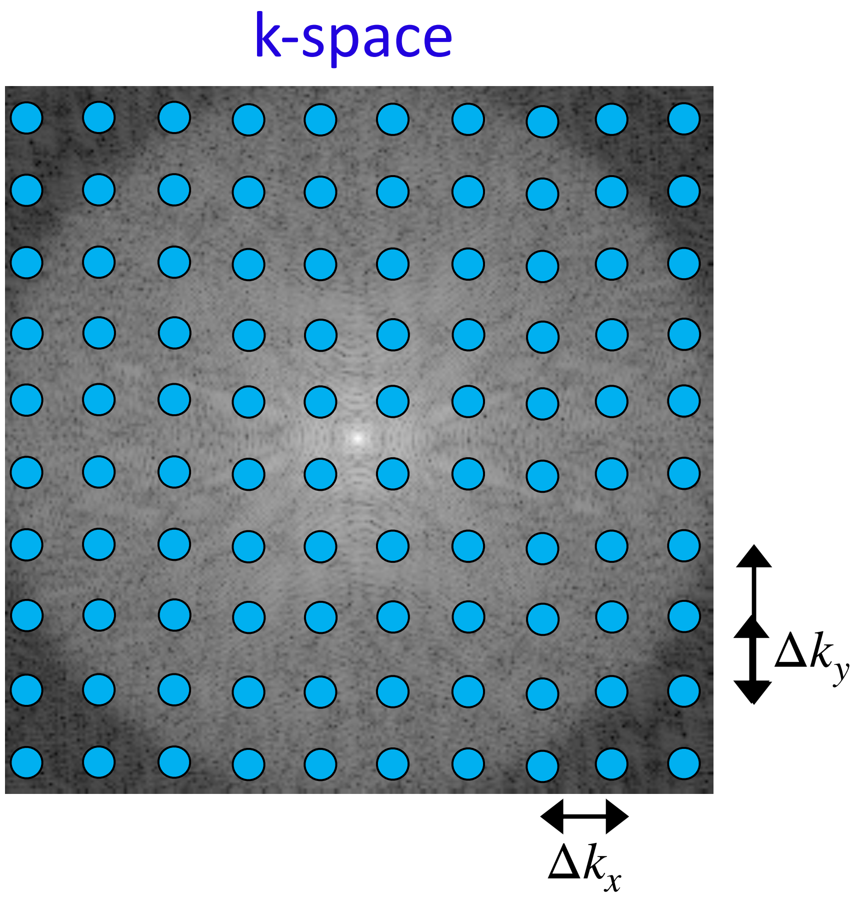
- Raw data are collected in the Fourier domain (k-space)
  - The acquired data are the discrete Fourier transform (DFT) samples of the object being imaged
  - Using the conventional 2DFT acquisition, each line of k-space is acquired one after the other (one per repetition time (TR) of the readout sequence)
- If the sampling rate is high enough ("Nyquist"), the image can be reconstructed by applying the inverse DFT to the k-space data

k-space

Image space




k-space
Δk_y
Δk_x
Image space
$\frac{1}{\Delta k_y}$
$FOV_y = \frac{1}{\Delta k_y}$
$\frac{1}{\Delta k_x}$
$FOV_x = \frac{1}{\Delta k_x}$


k-space
Δk_y
Δk_x

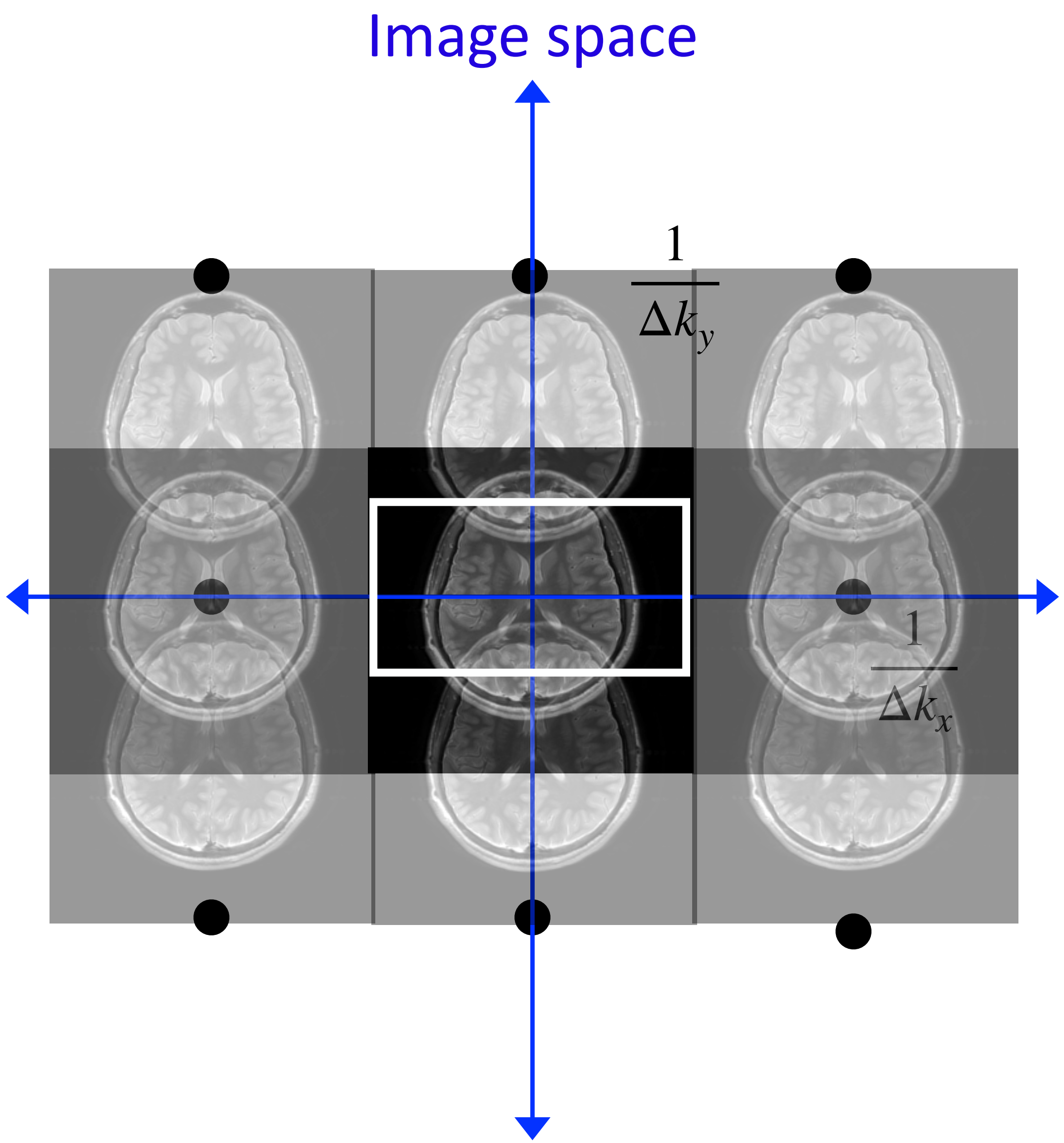
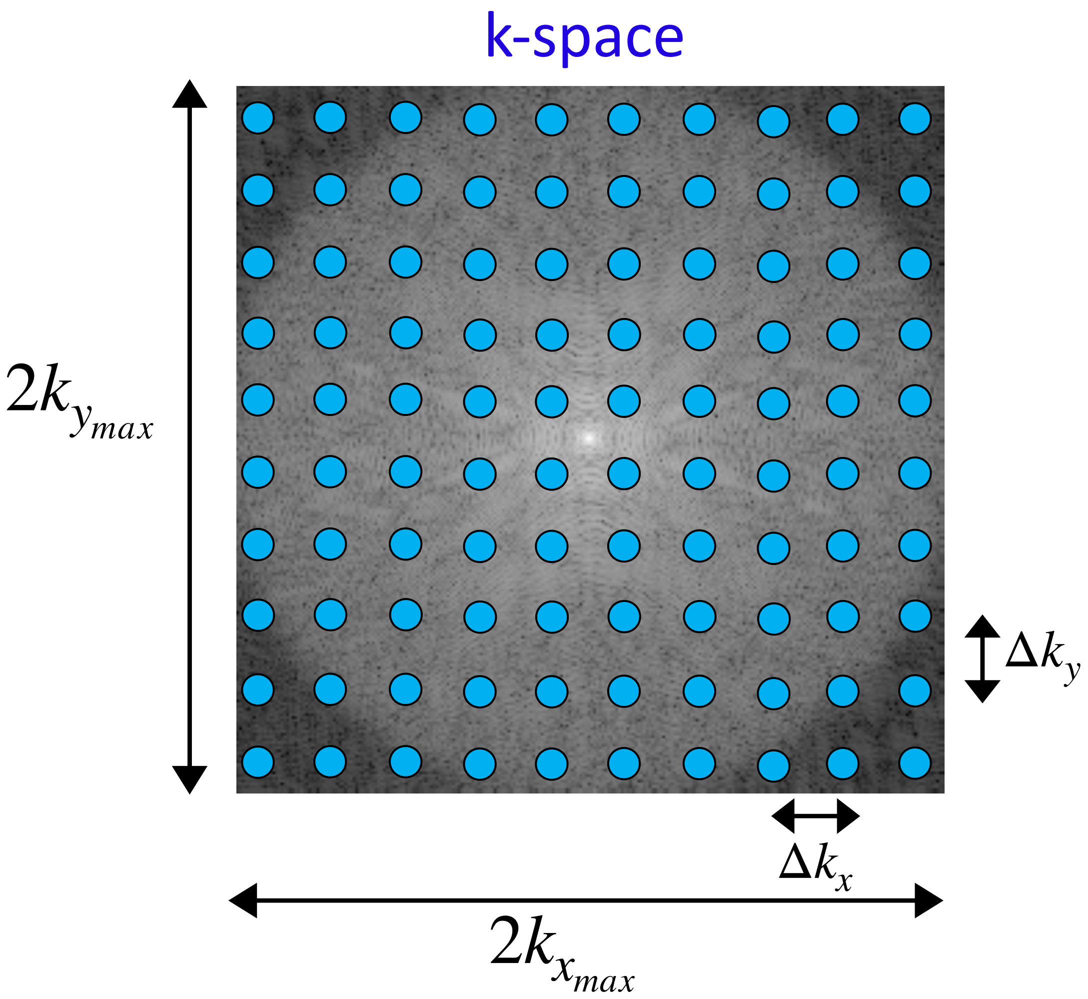
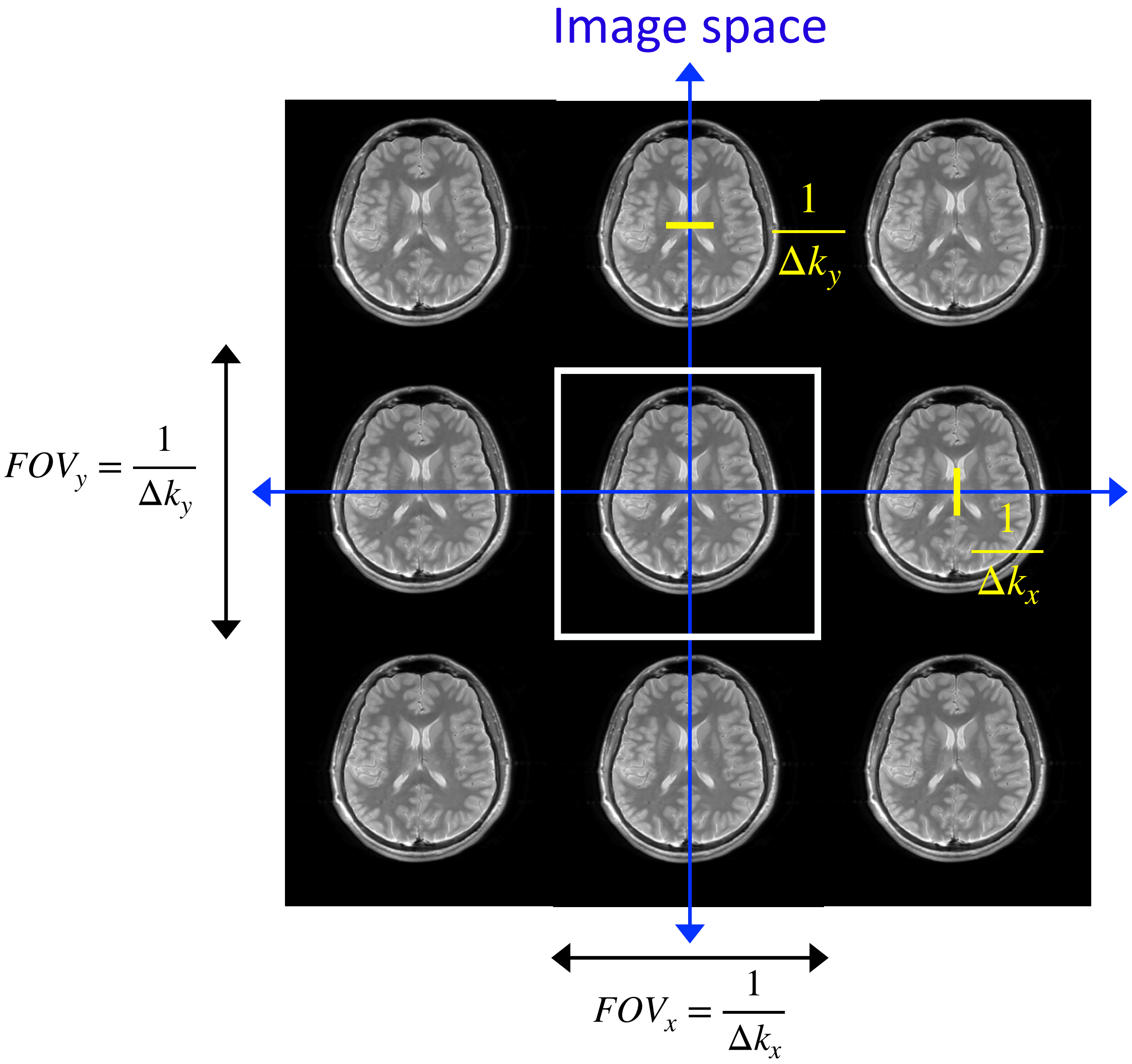


Image space
$\frac{1}{\Delta k_y}$
$\frac{1}{\Delta k_x}$



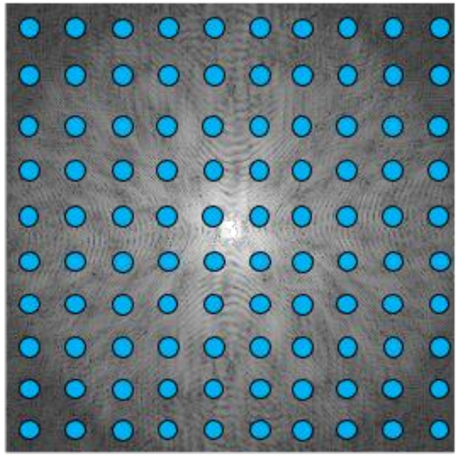


Pixel size

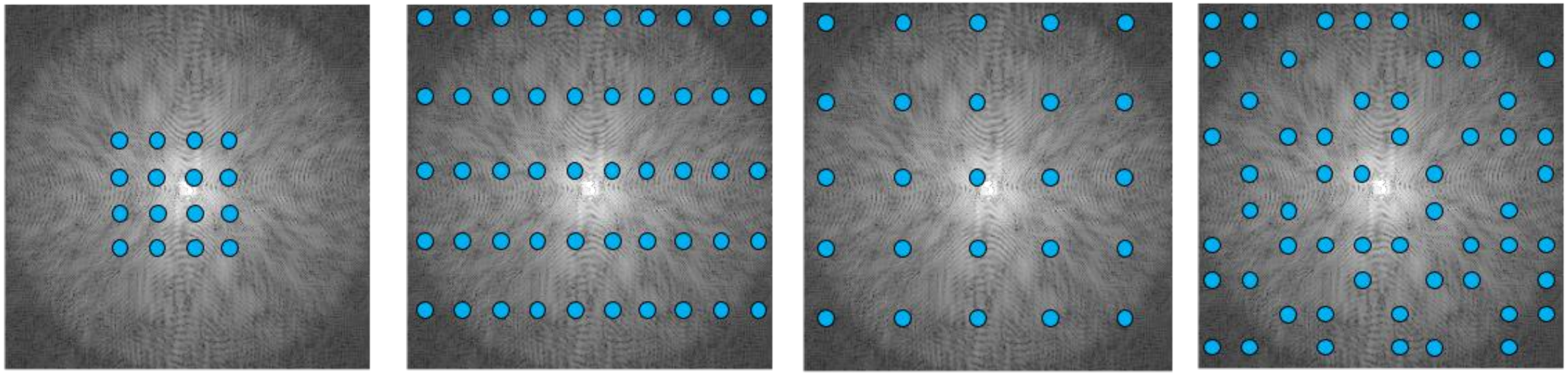
$$\Delta x \approx \frac{1}{2k_{x_{max}}} \qquad \Delta y \approx \frac{1}{2k_{y_{max}}}$$

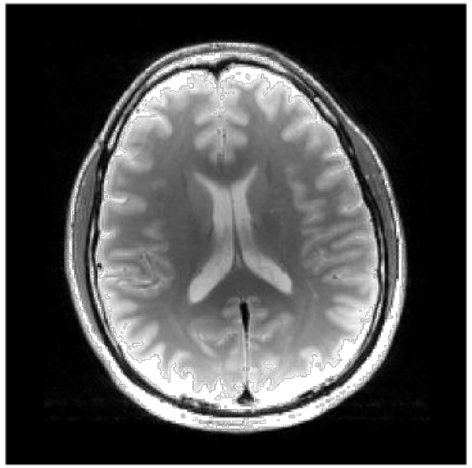
Accelerated MRI – Collect fewer k-space samples

Fully sampled acquisition

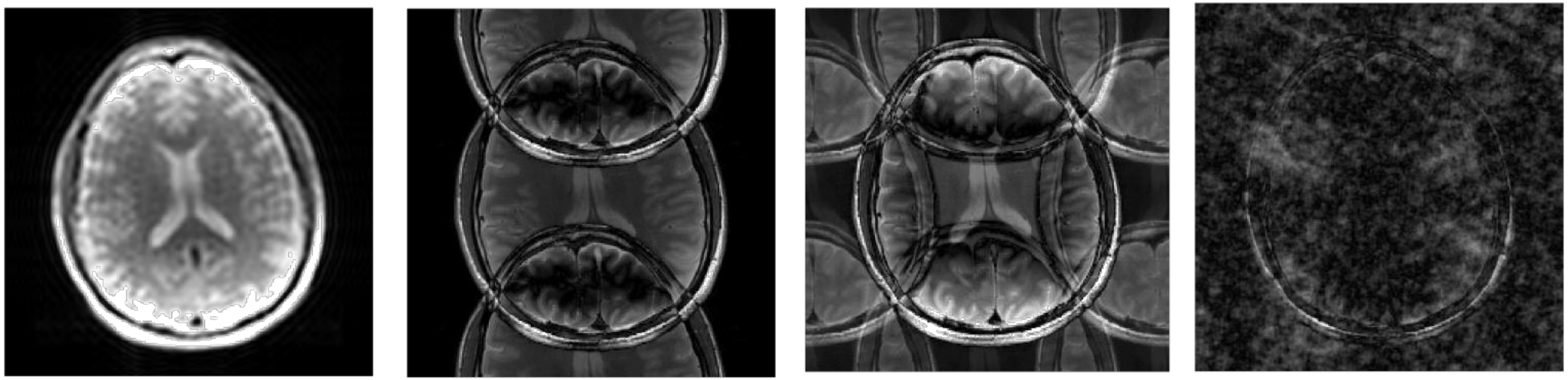


Accelerated acquisition





Direct application of 2D inverse Fourier transform to the acquired data



blurry

Artifact (one direction)

Artifact (two directions)

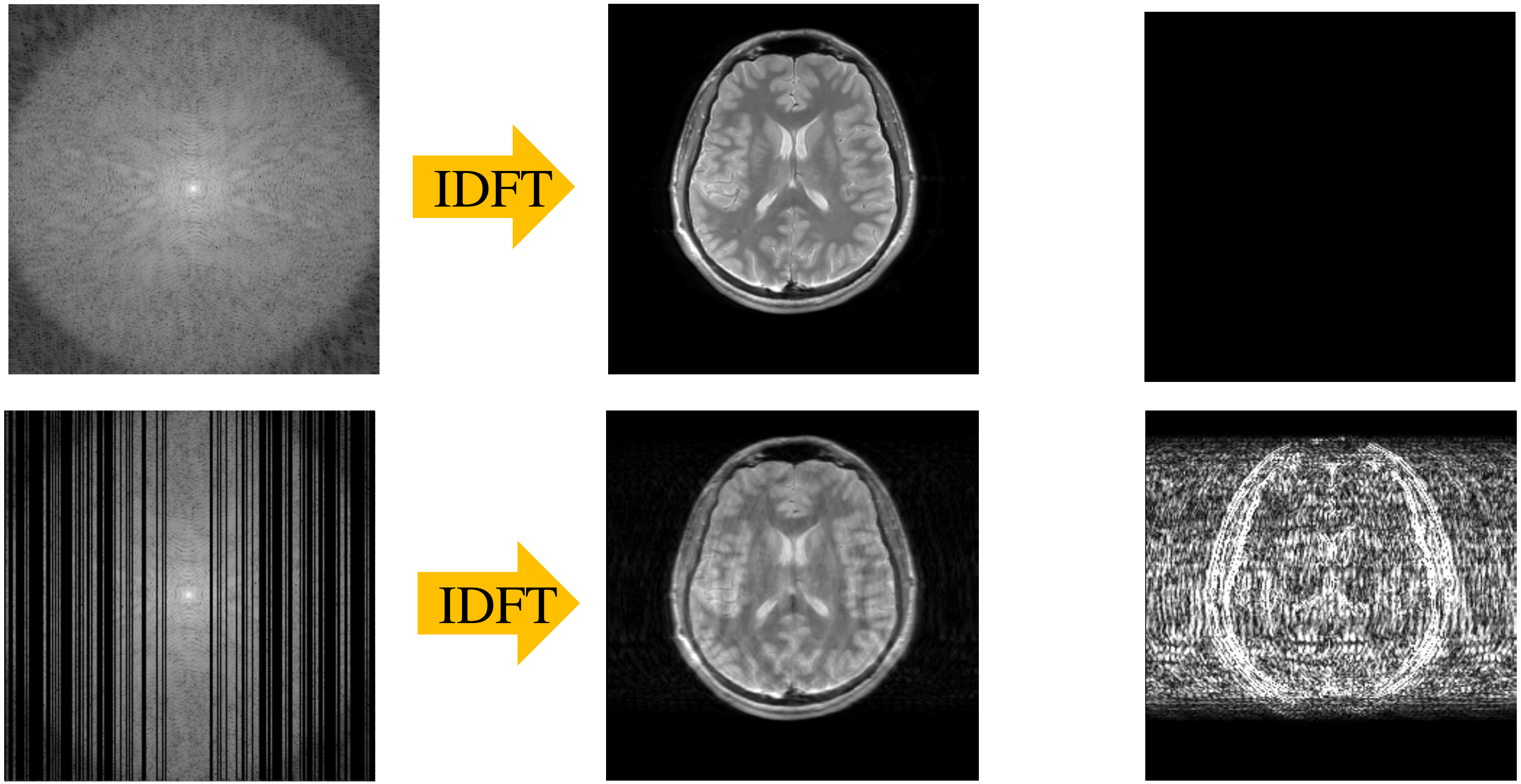
Noise-like artifact

MR Image Reconstruction from Accelerated Scans

k-space

Image space

Error image (scaled 10x)
with respect to fully sampled data



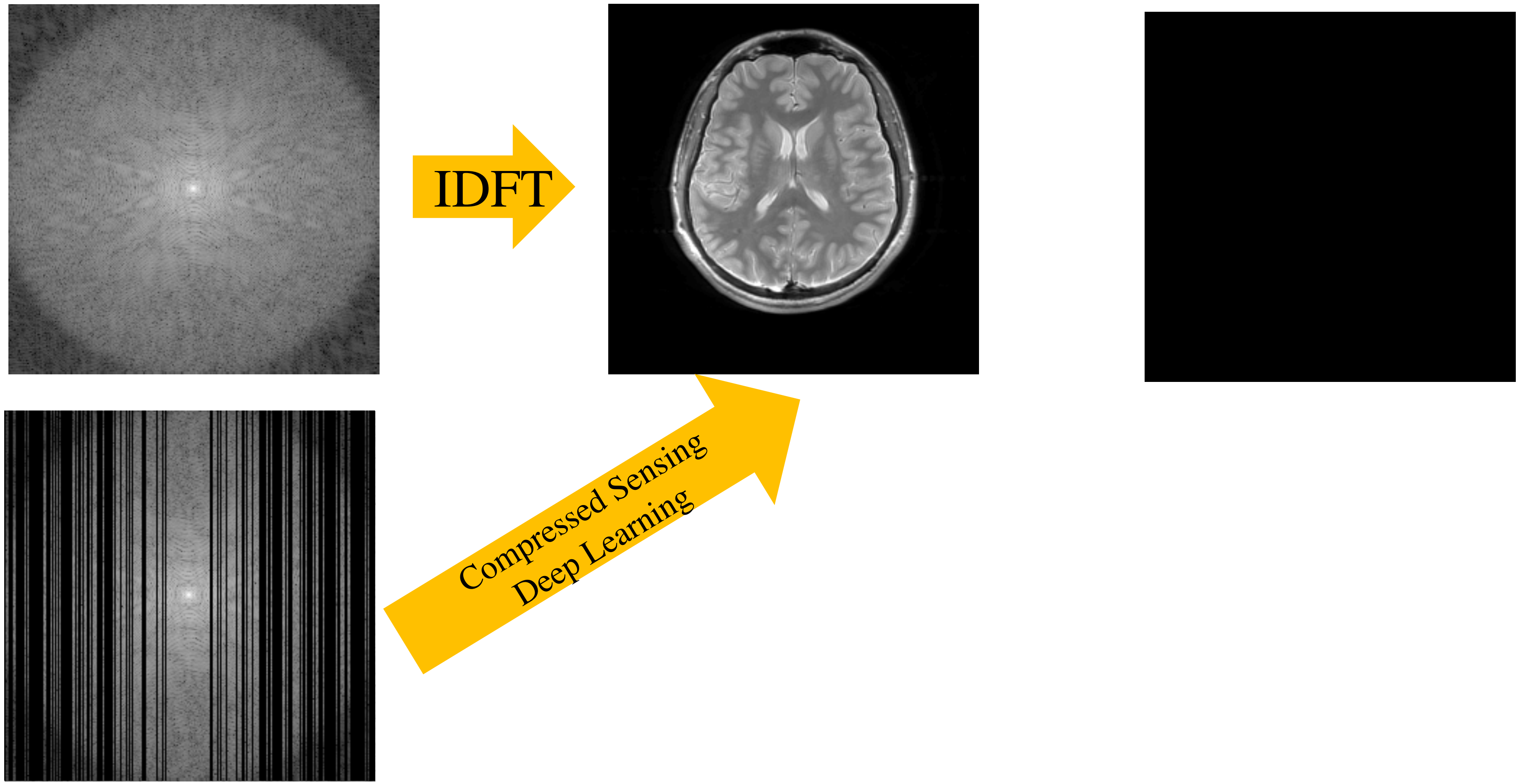
Acquire only half of the data
Reduction factor = 2

MR Image Reconstruction from Accelerated Scans

k-space

Image space

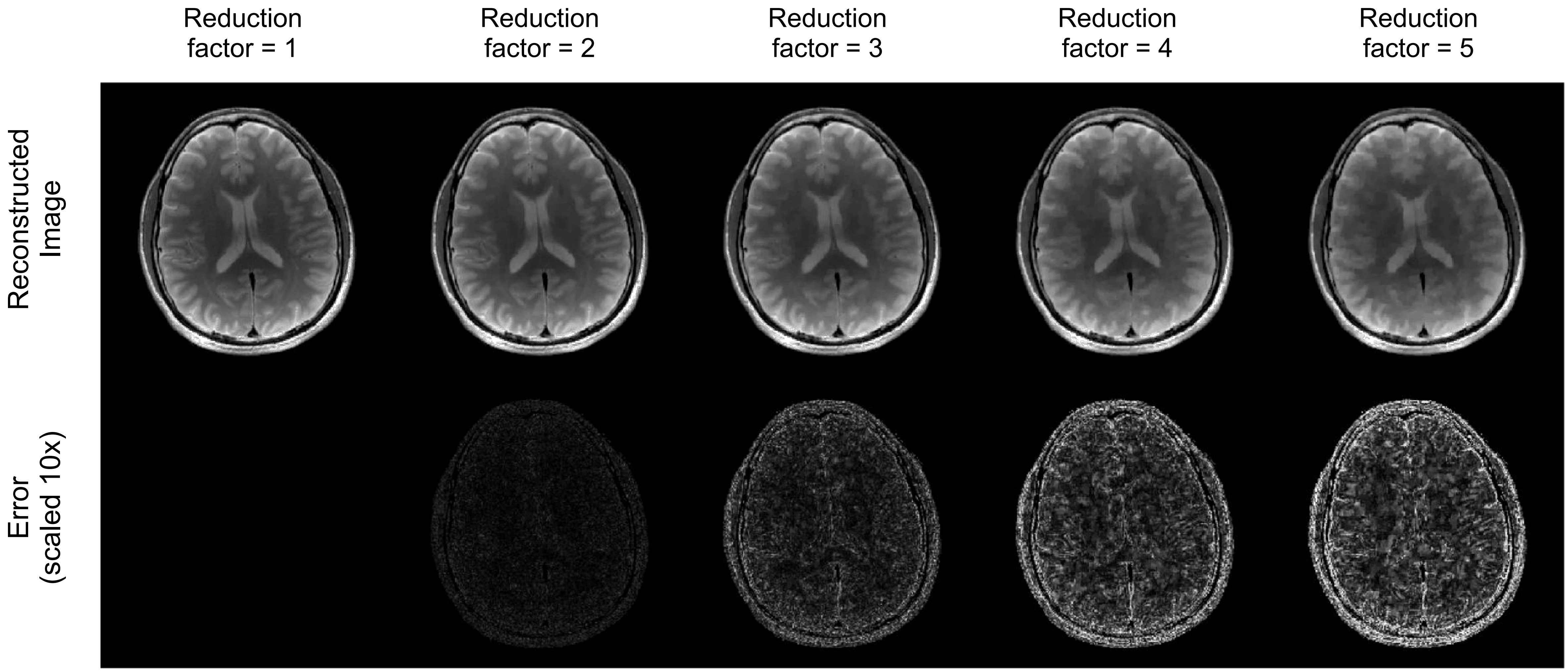
Error image (scaled 10x)
with respect to fully sampled data



Acquire only half of the data
Reduction factor = 2

Compressed Sensing

$$\hat{x} = \arg\min_x \frac{1}{2}\|MFx - y\|_2^2 + \lambda\|Gx\|_1$$



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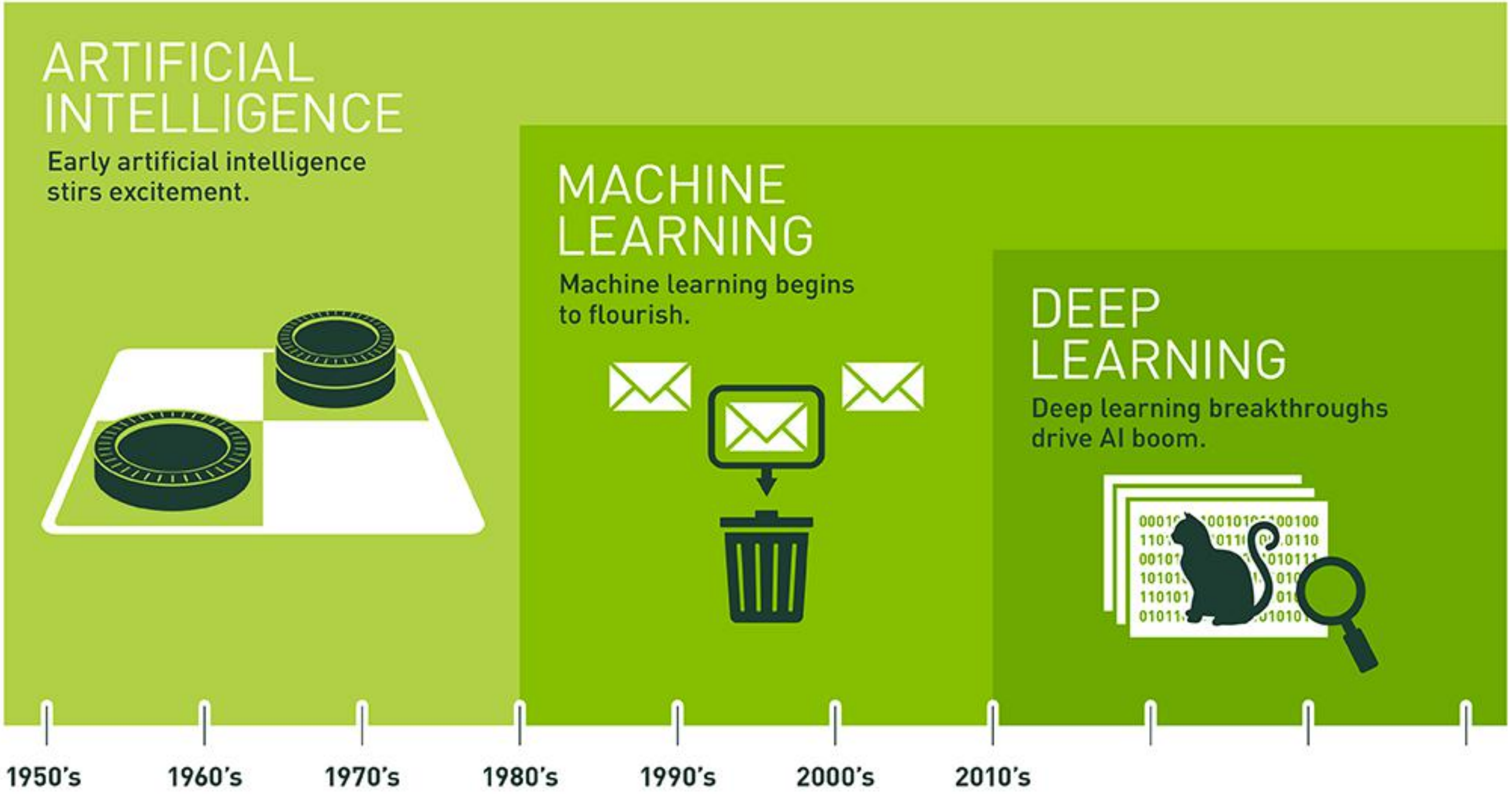
Slides: https://bit.ly/3NyCtCn

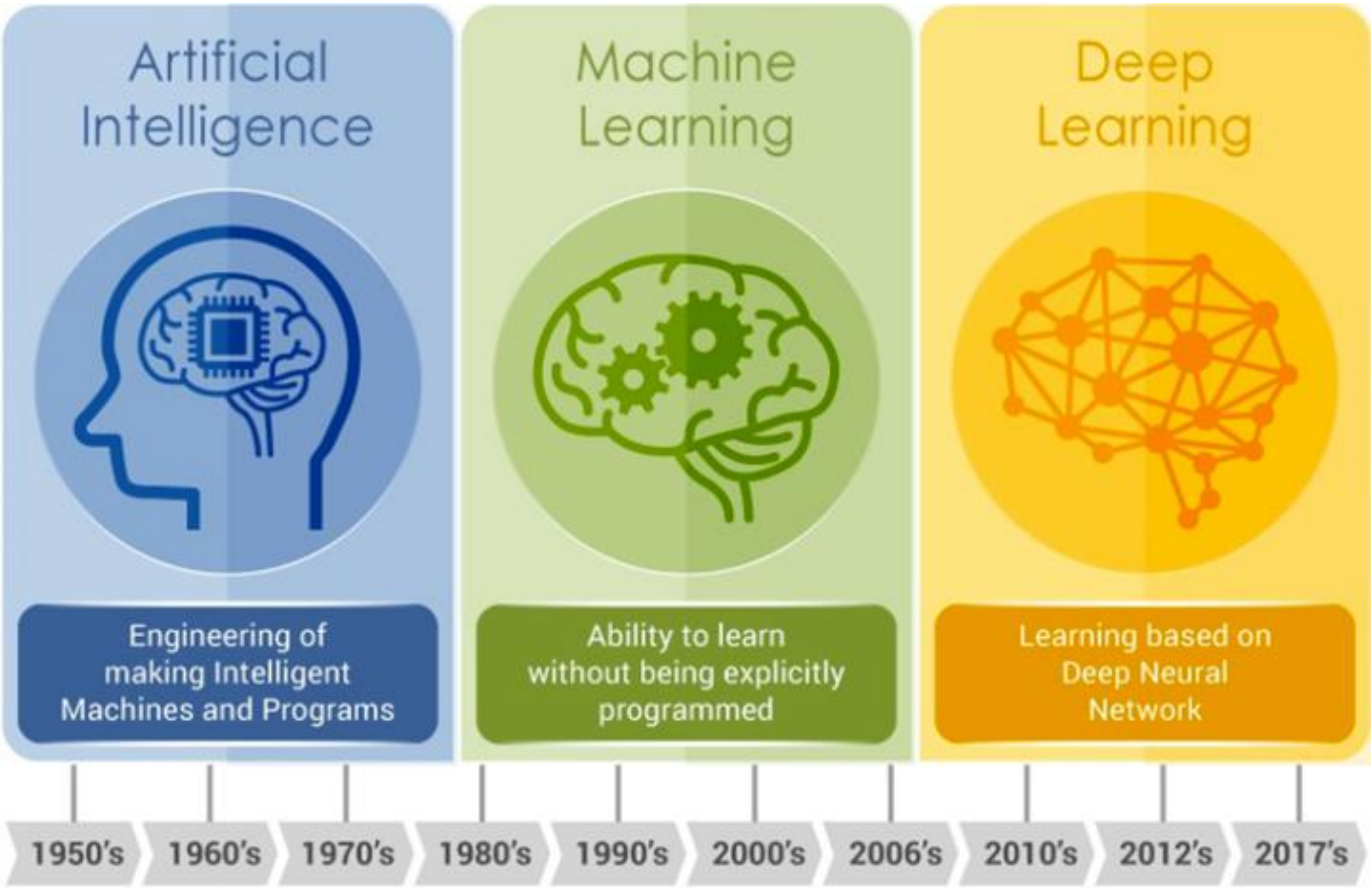
Deep Learning



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

NVIDIA

Deep Learning

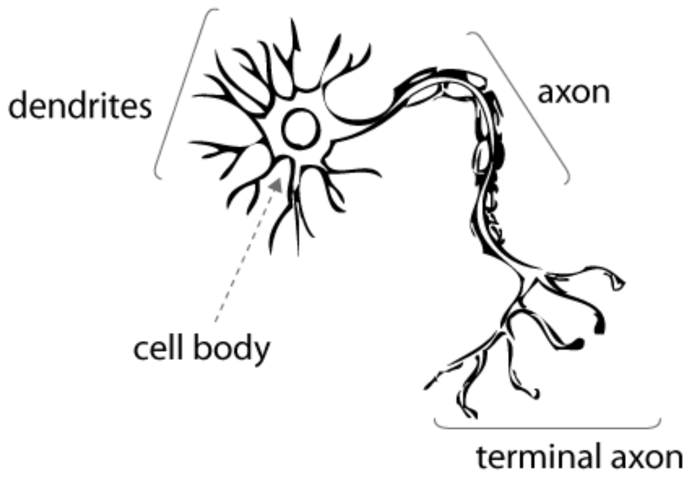


Embedded Vision

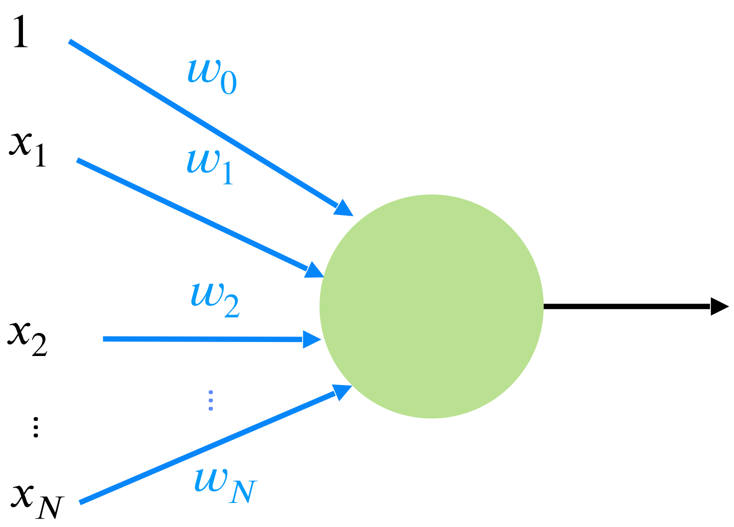
Deep Learning

- Deep learning is a subfield of machine learning that stems from artificial neural networks (ANN)

Single neuron

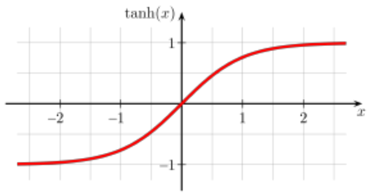


Artificial neuron



$$y = a\left(\sum_{n=1}^{N} x_n w_n + w_0\right)$$

non-linear function (activation)

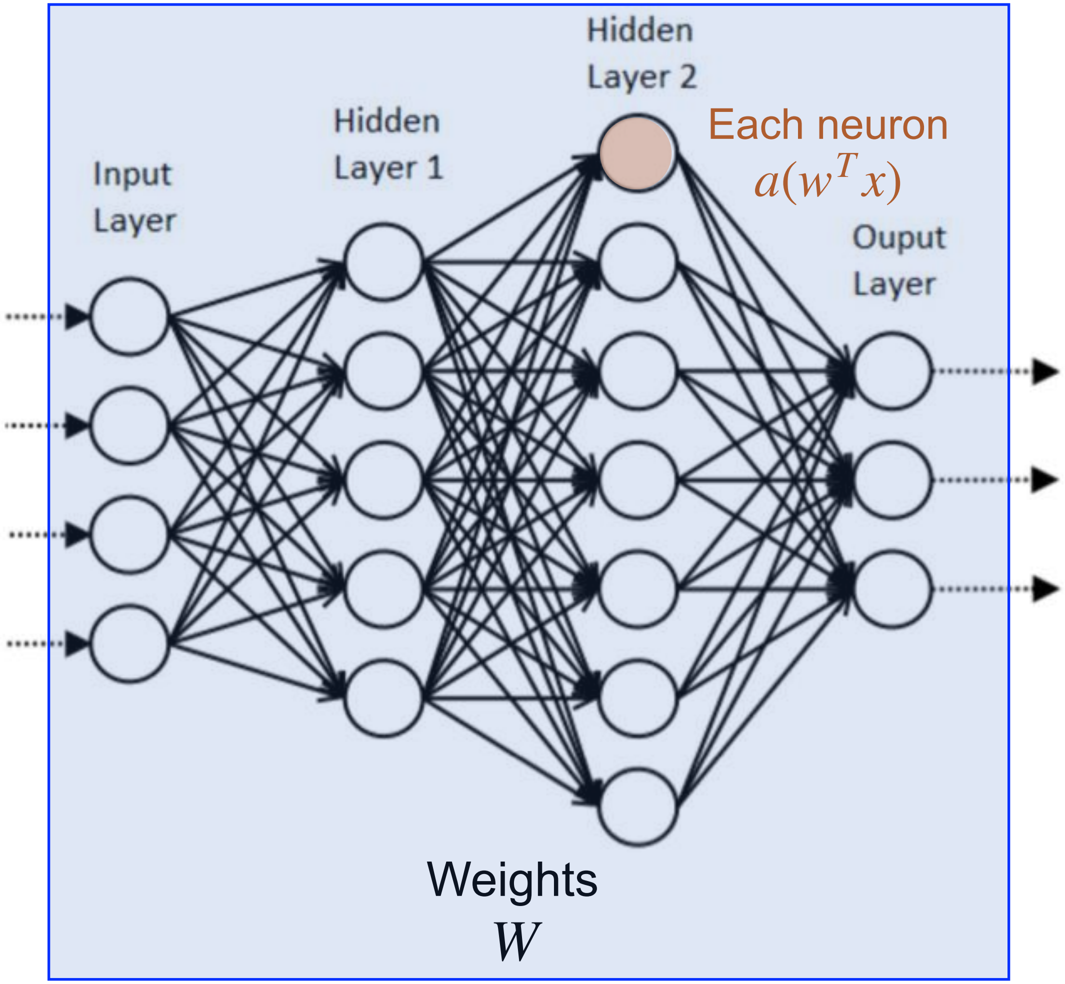


https://medium.com/@ivanliljeqvist/the-essence-of-artificial-neural-networks-5de300c995d6

Deep Learning

- An artificial neural network with many hidden layers is called a deep artificial neural network (ANN)

Input
x



Output
y

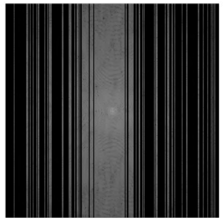
$$y = f_W(x)$$

A function that can change behavior depending on the current values of W

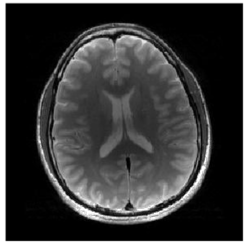
Deep Learning

- We can use a deep artificial neural network to approximate any functions by modifying its weight
  - MRI reconstruction function

k-space data



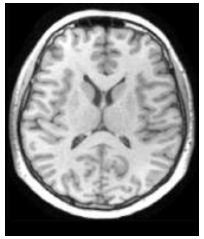
$f_{recon,W}$



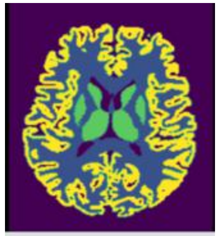
Reconstructed image

  - MRI segmentation function

Image-space data



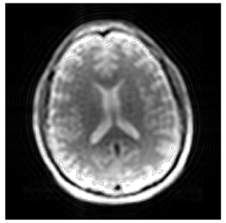
$f_{segment,W}$



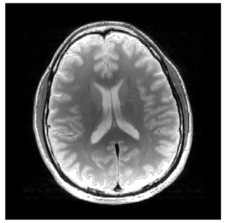
Segmentation map

  - MRI super-resolution function

Low-resolution image-space data



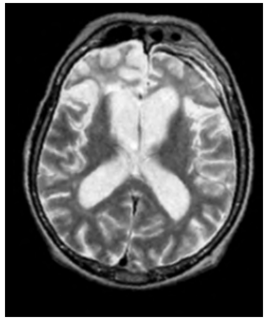
$f_{sr,W}$



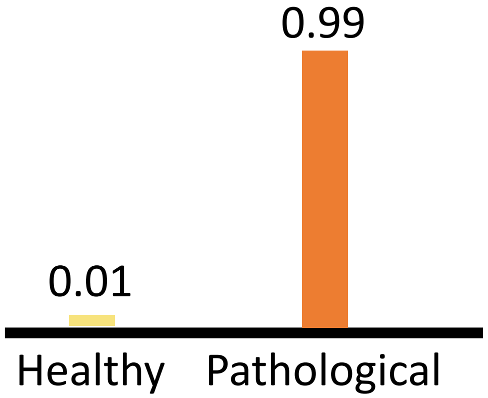
High-resolution image-space data

Deep Learning

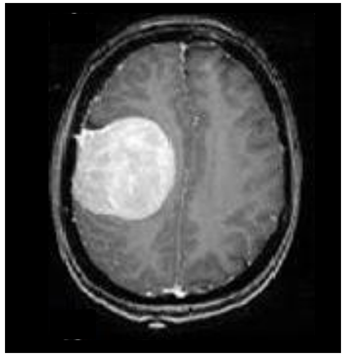
- We can use a deep artificial neural network to approximate any functions by modifying its weight
  - MR image classification function



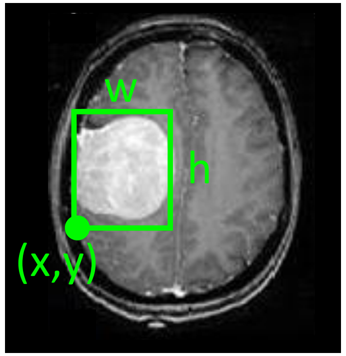
$f_{classif,W}$



  - Detection function

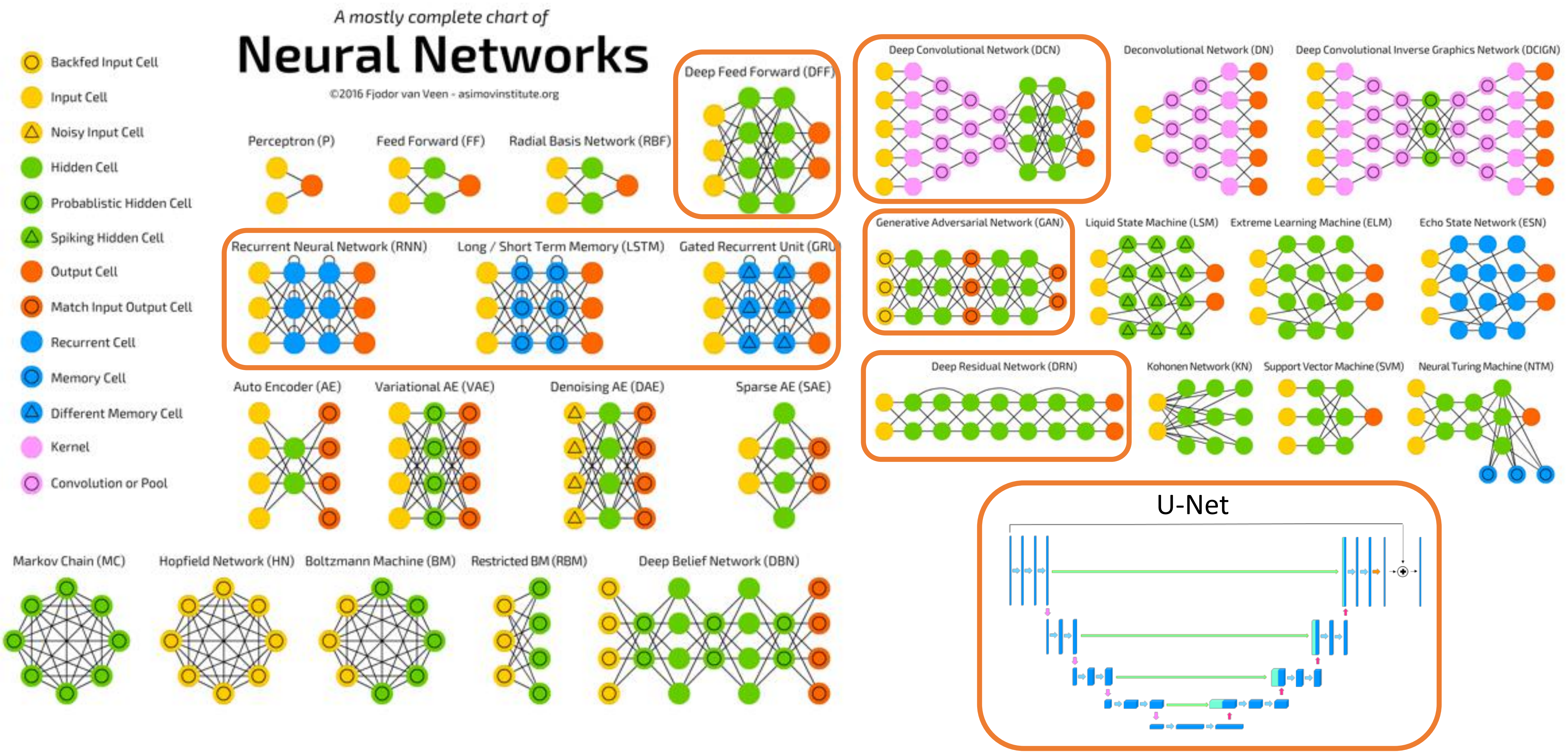


$f_{detection,W}$



class: tumor

Alam, Sadia, et al. "An efficient image processing technique for brain tumor detection from MRI images." 2019 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE). IEEE, 2019.

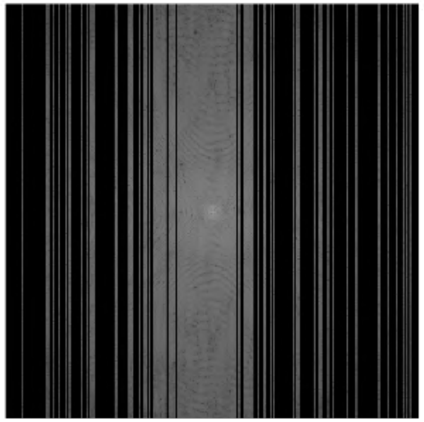


The Mostly Complete Chart of Neural Networks by the team at the [Asimov Institute]

Deep Learning for MR Image Reconstruction

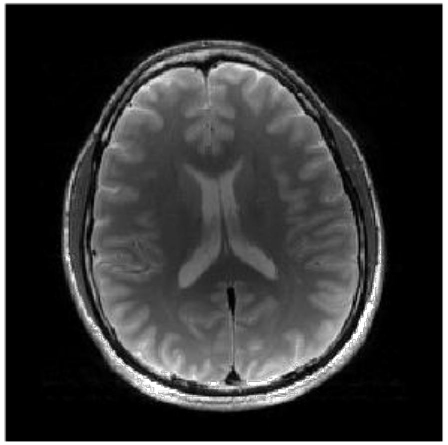
Underlying Process

g_{recon}



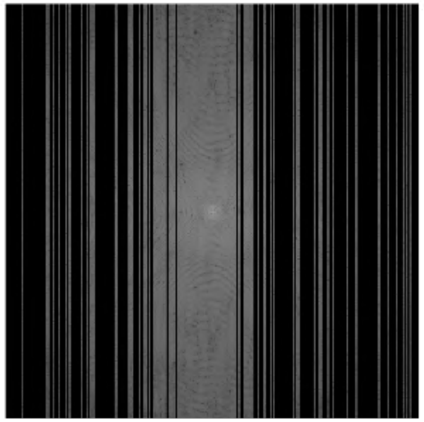
An *unknown* highly complicated function that includes (but not limited to)

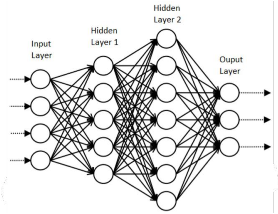
- Inverse Fourier transform
- Artifact removal
- Magnetic field map correction



Deep Learning

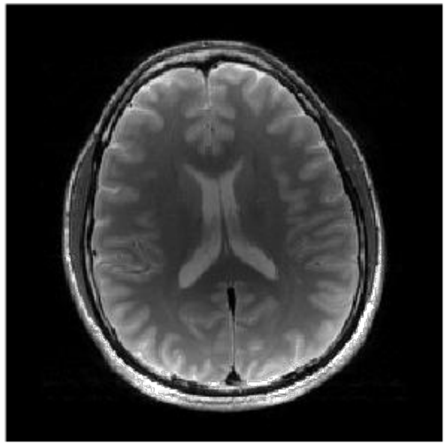
f_W





With model training, we could obtain

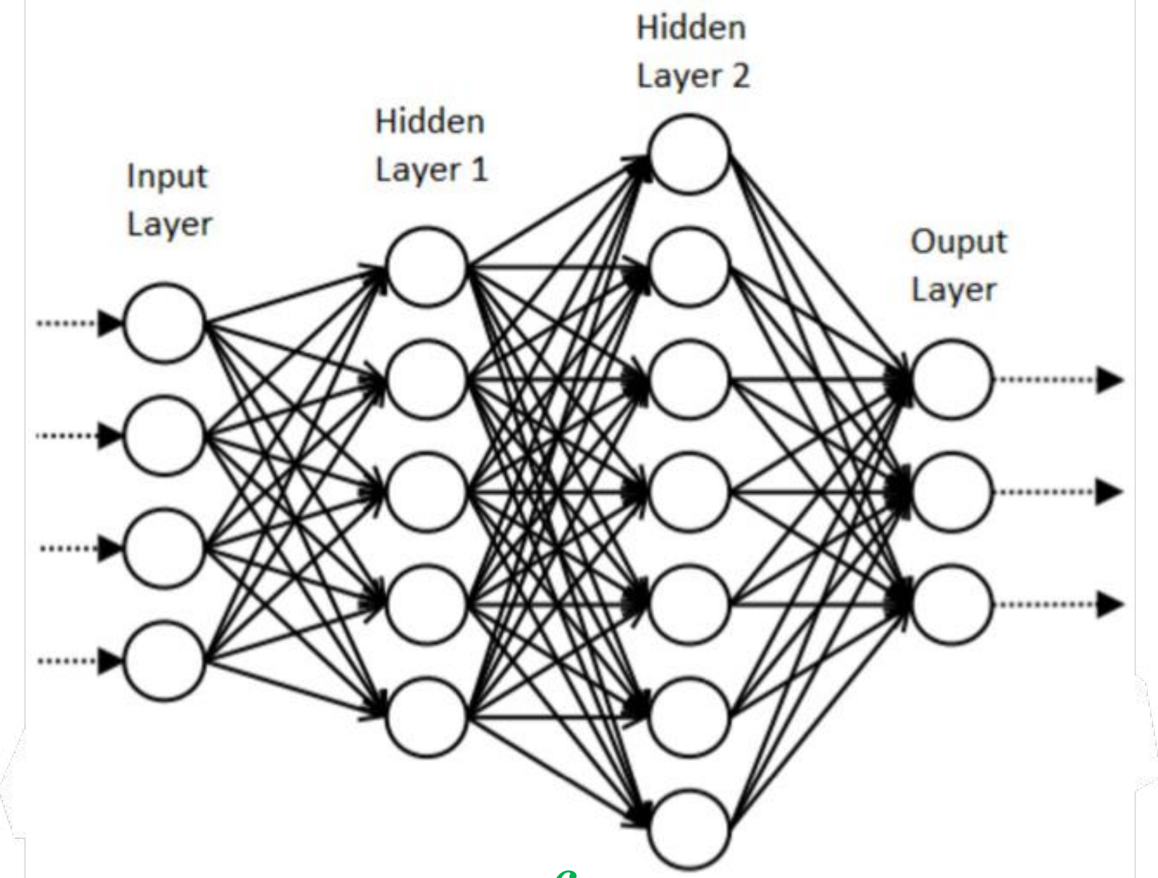
$f_W \approx g_{recon}$



Keyword: weight initialization

Supervised Model Training

Step 1: Create a neural network with some initial weight f_{W_0}



f_{W_0}

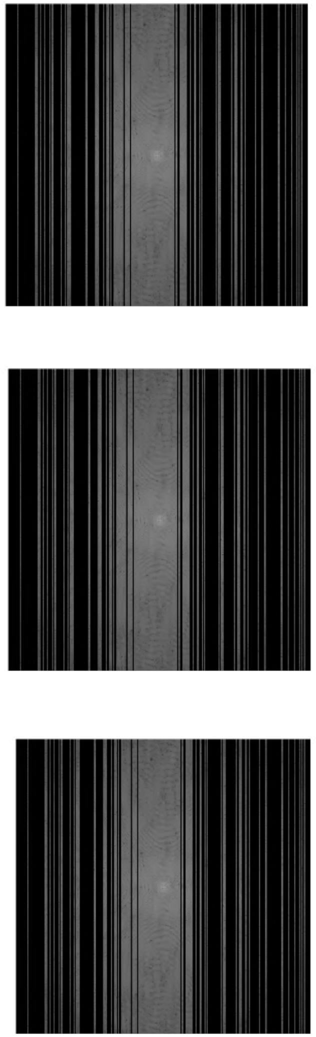
Supervised Model Training

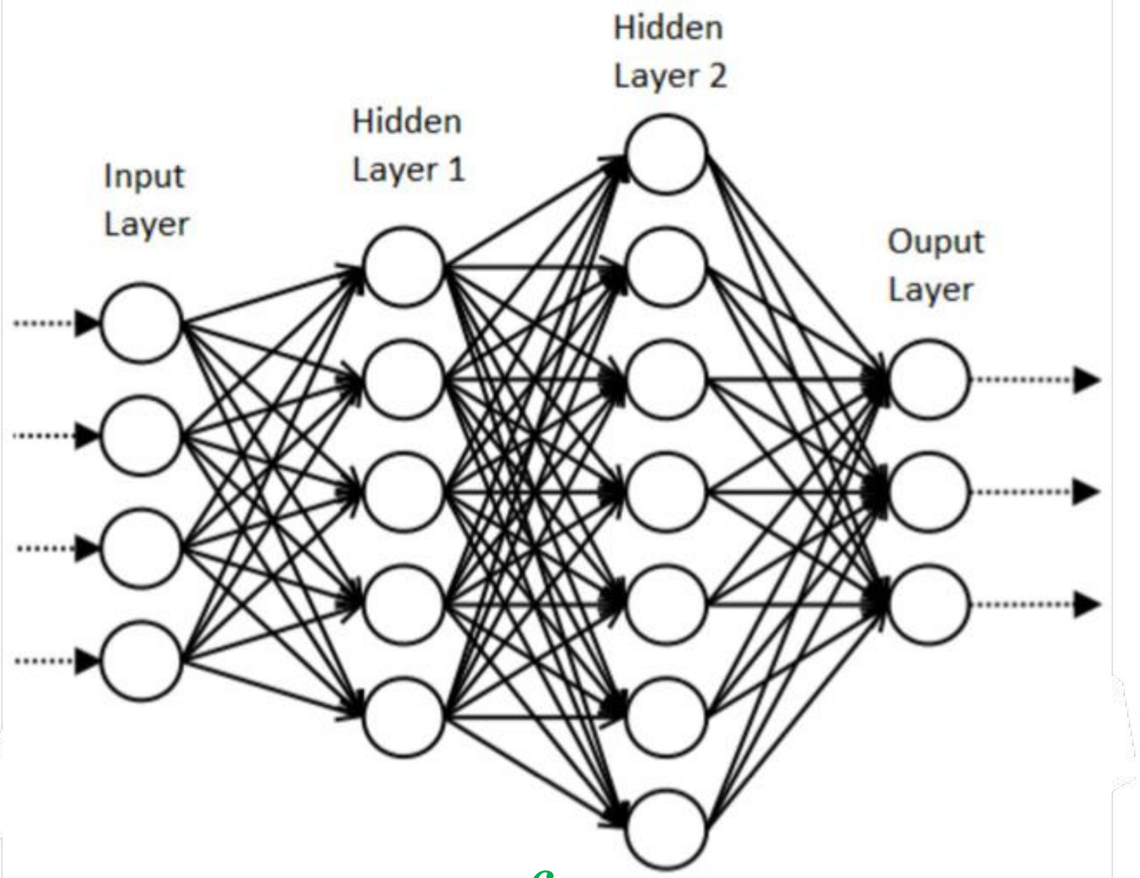
Keywords: dataset preparation, target, labels, ground truth, true, input-output pairs

Step 2: Prepare a dataset which is a collection of input-output pairs

Prepared input

x

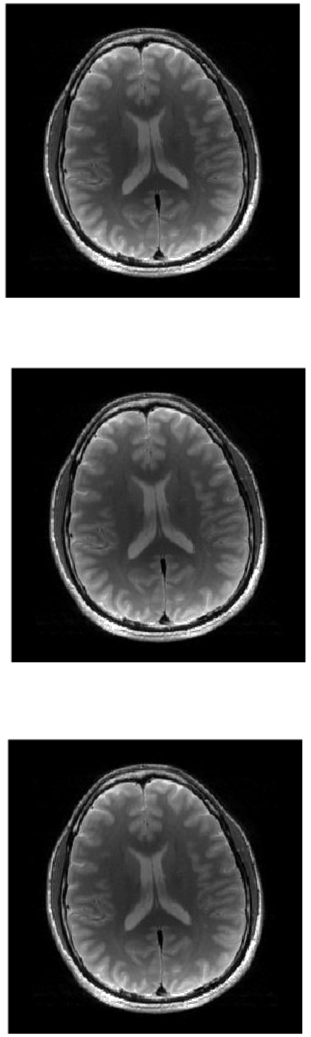




f_{W_0}

Prepared output

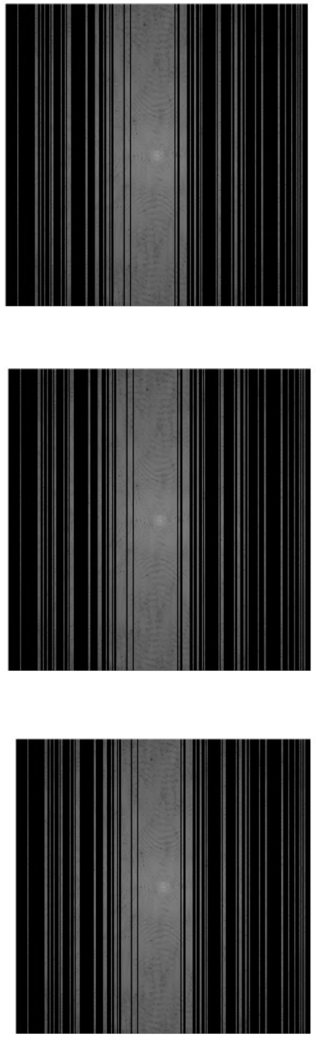
y



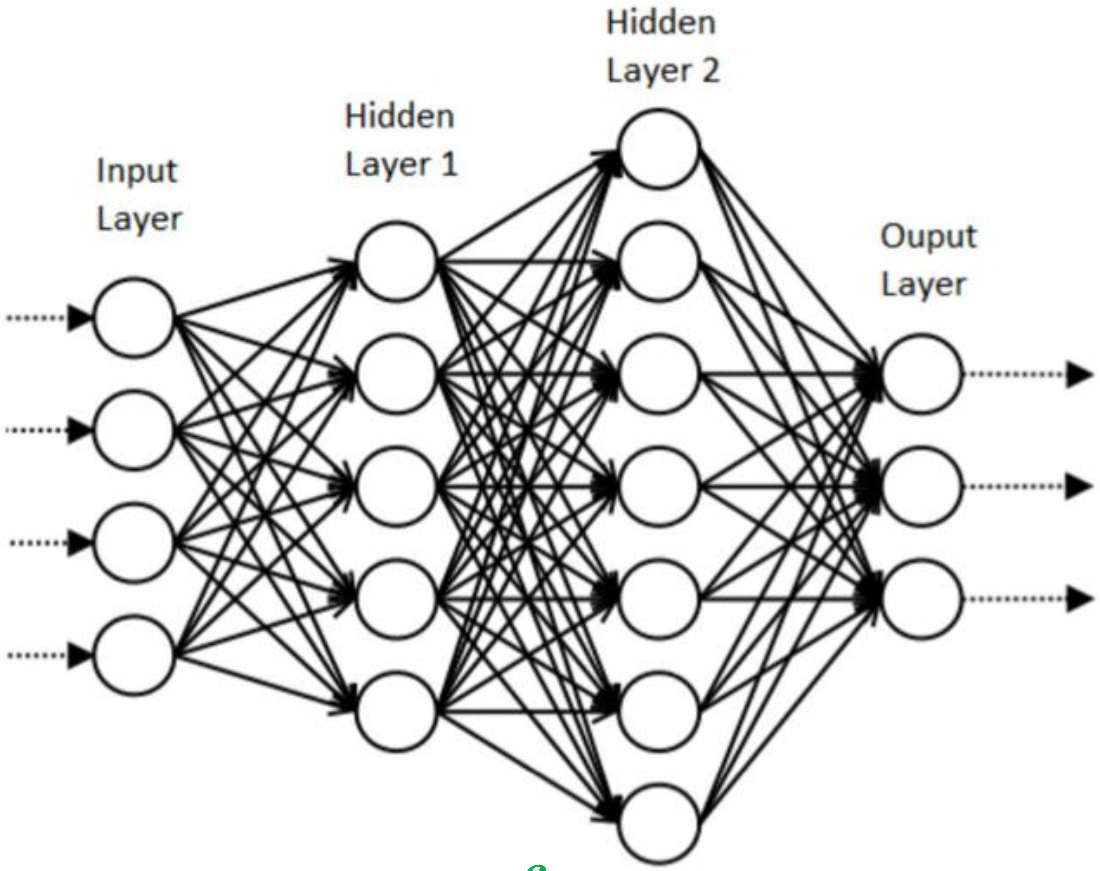
Supervised Model Training

Prepared input

x



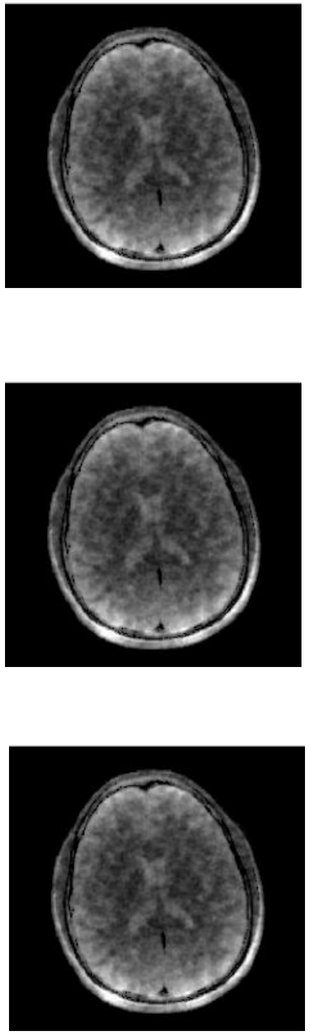
Step 3: Pass the prepared input to the network



f_{W_0}

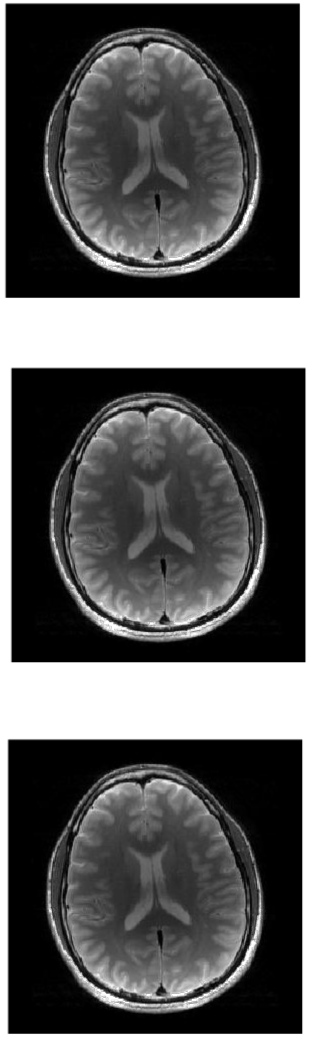
Estimated output

$\hat{y} = f(x)$



Prepared output

y

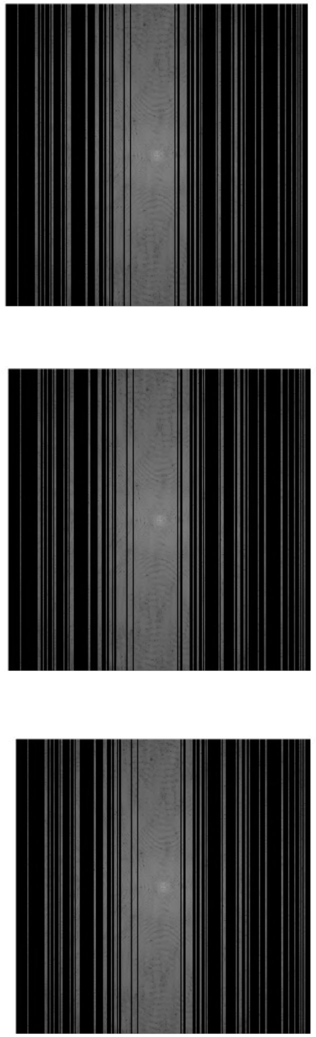


Keywords: loss function, backpropagation

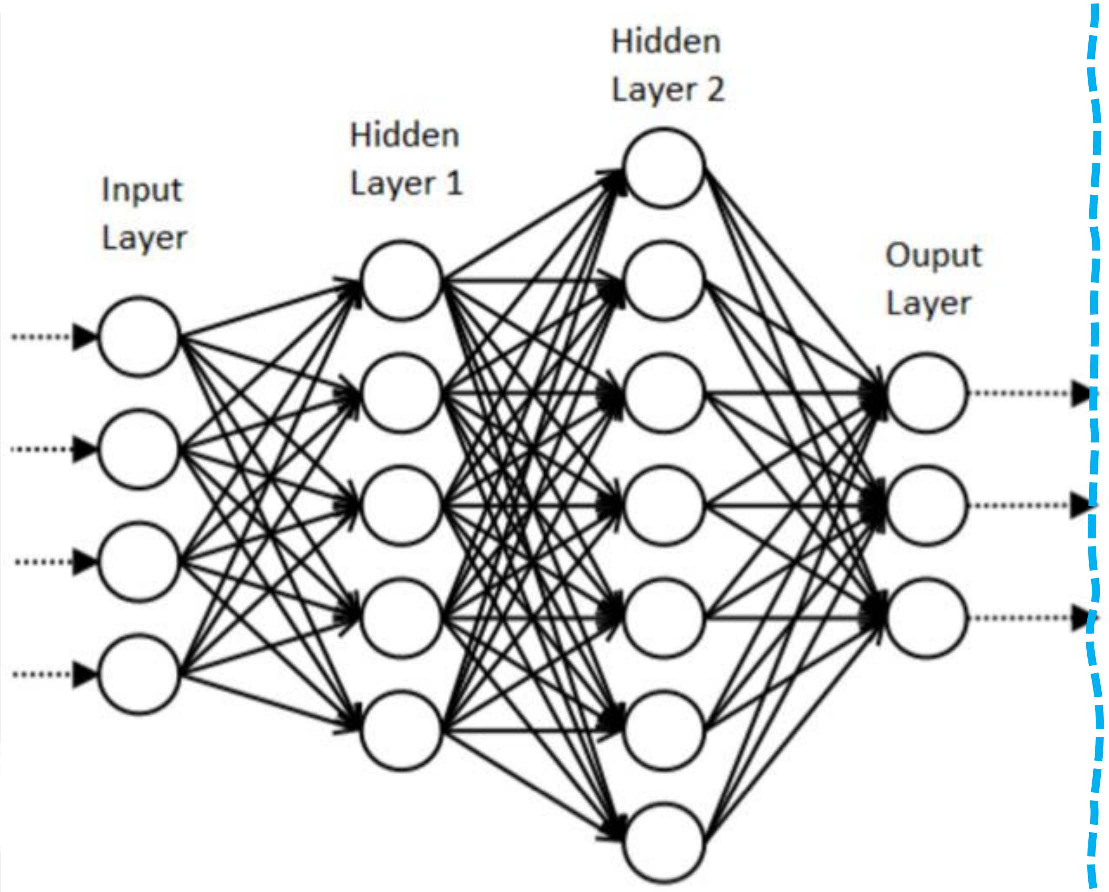
Supervised Model Training

Prepared input

x



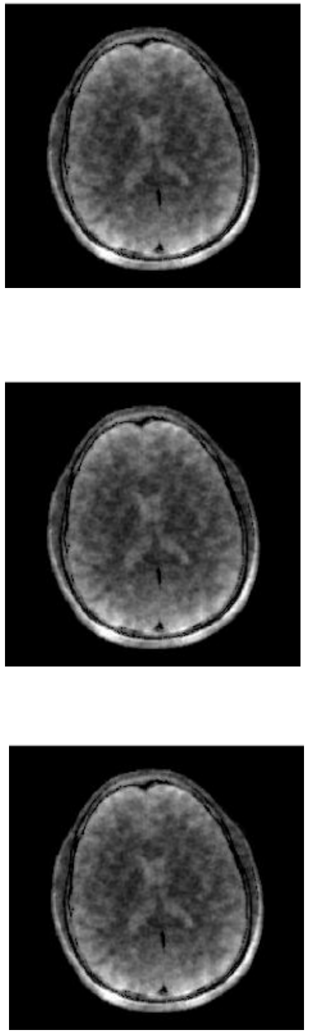
Step 4: Compare $\hat{y}$ to y and modify the weights of the neural network to make $\hat{y}$ approach y using the backpropagation algorithm



Iteration 1 f_{W_1}

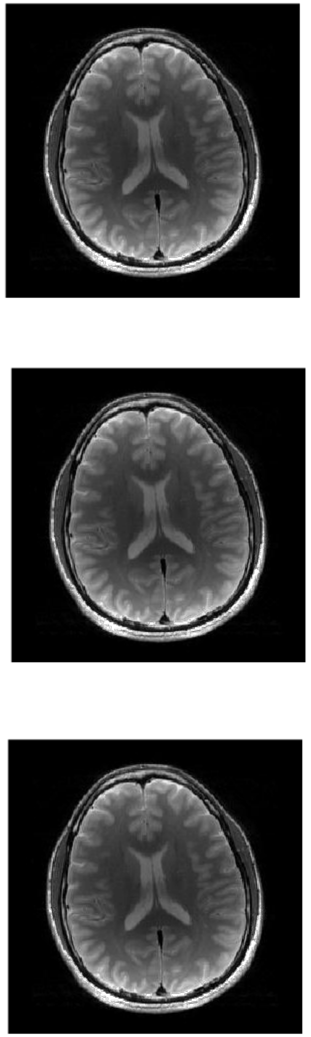
Estimated output

$\hat{y} = f(x)$



Prepared output

y



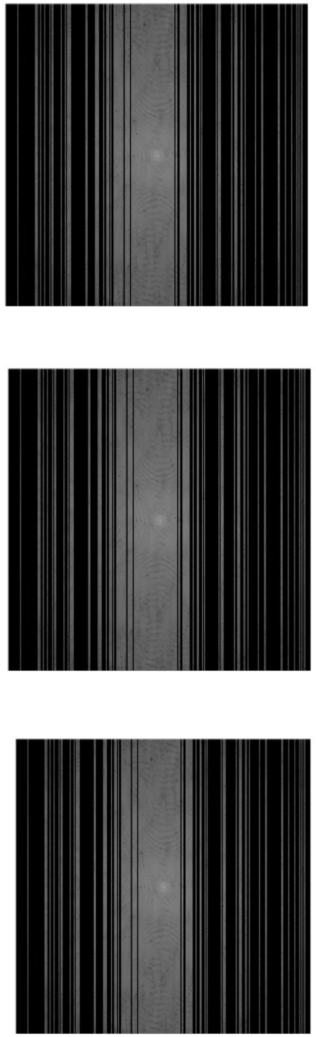
Keywords: loss function, backpropagation

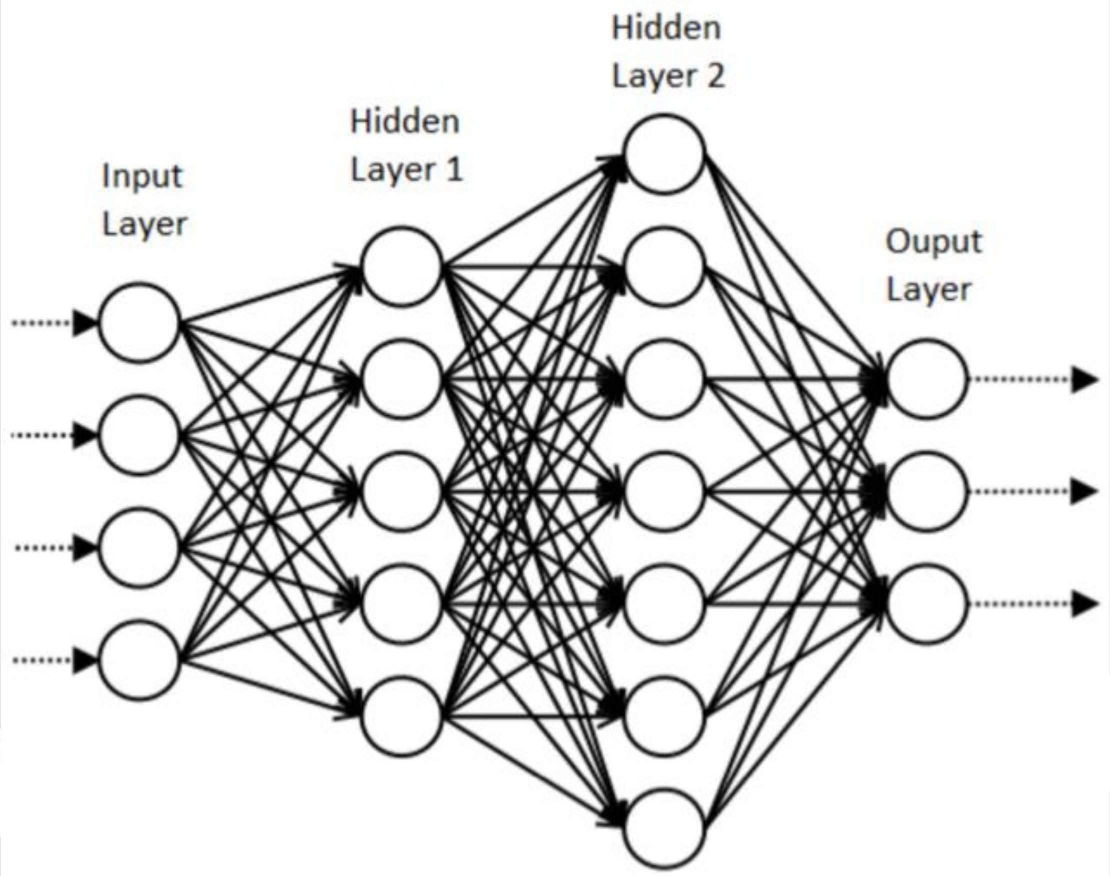
Supervised Model Training

Repeat steps 3 and 4 to continuously improve the weights of the neural network

Prepared input

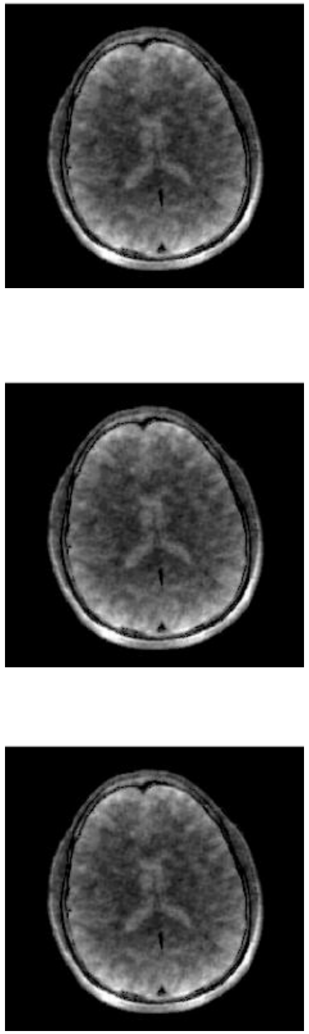
x





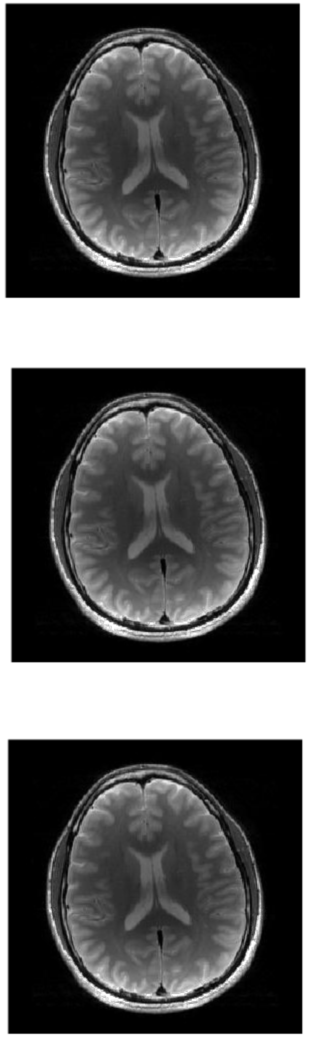
Estimated output

$\hat{y} = f(x)$



Prepared output

y



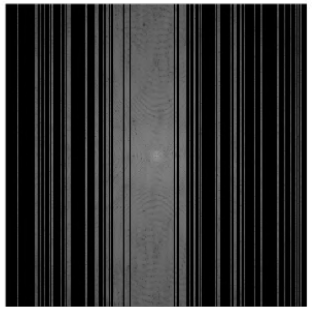
Iteration 2 f_{W_2}

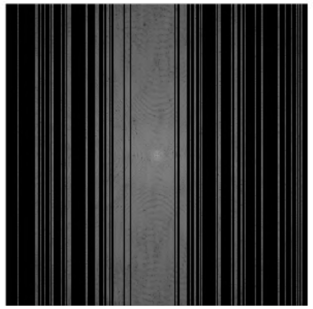
Keywords: loss function, backpropagation

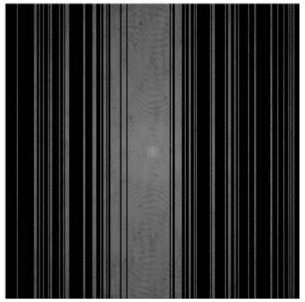
Supervised Model Training

Prepared input

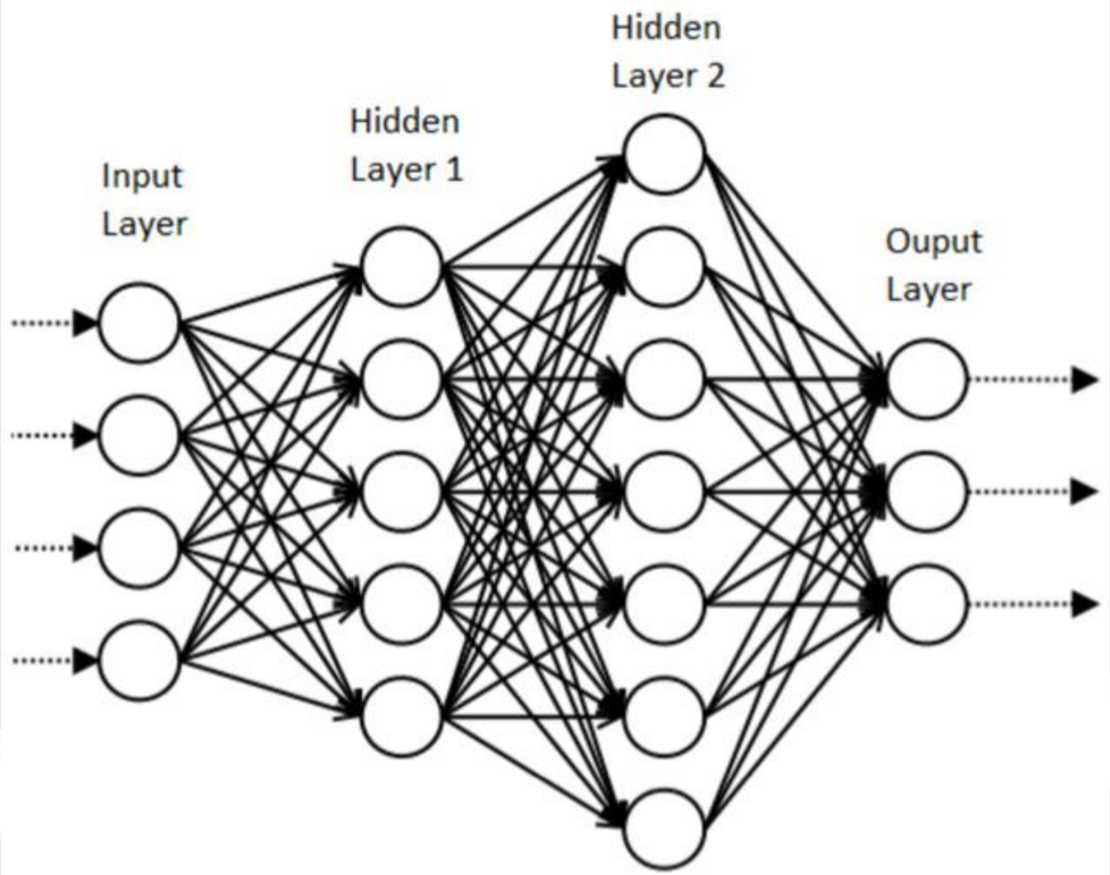
x







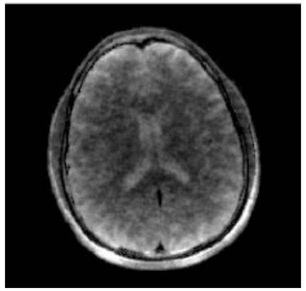
Repeat steps 3 and 4 to continuously improve the weights of the neural network

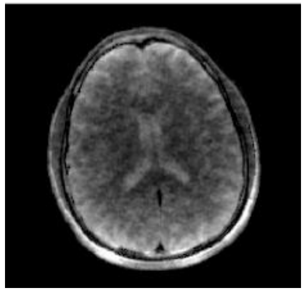


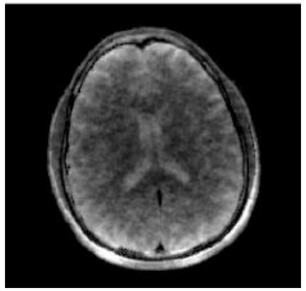
Iteration 20 $f_{W_{20}}$

Estimated output

$\hat{y} = f(x)$

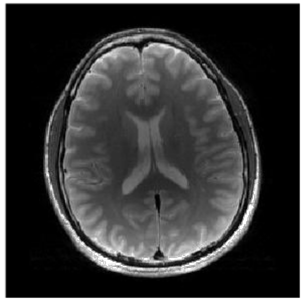


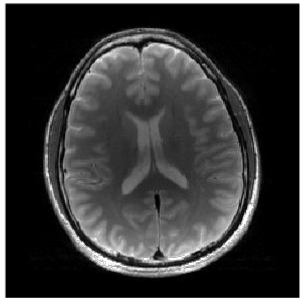


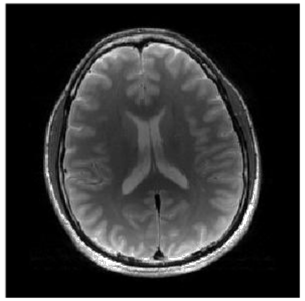


Prepared output

y







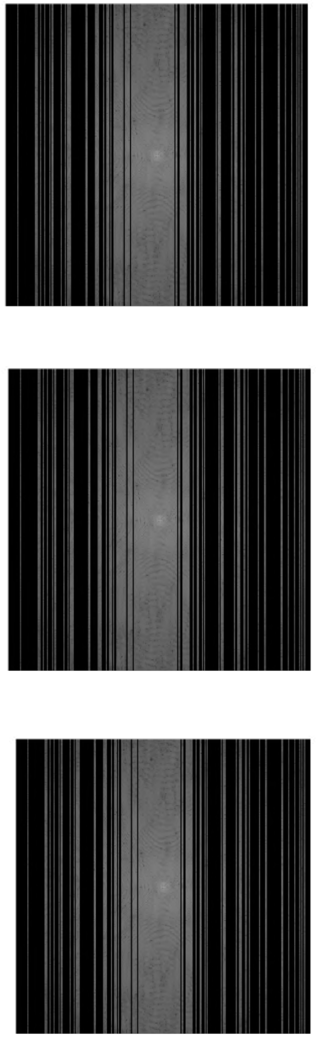
Keywords: loss function, backpropagation

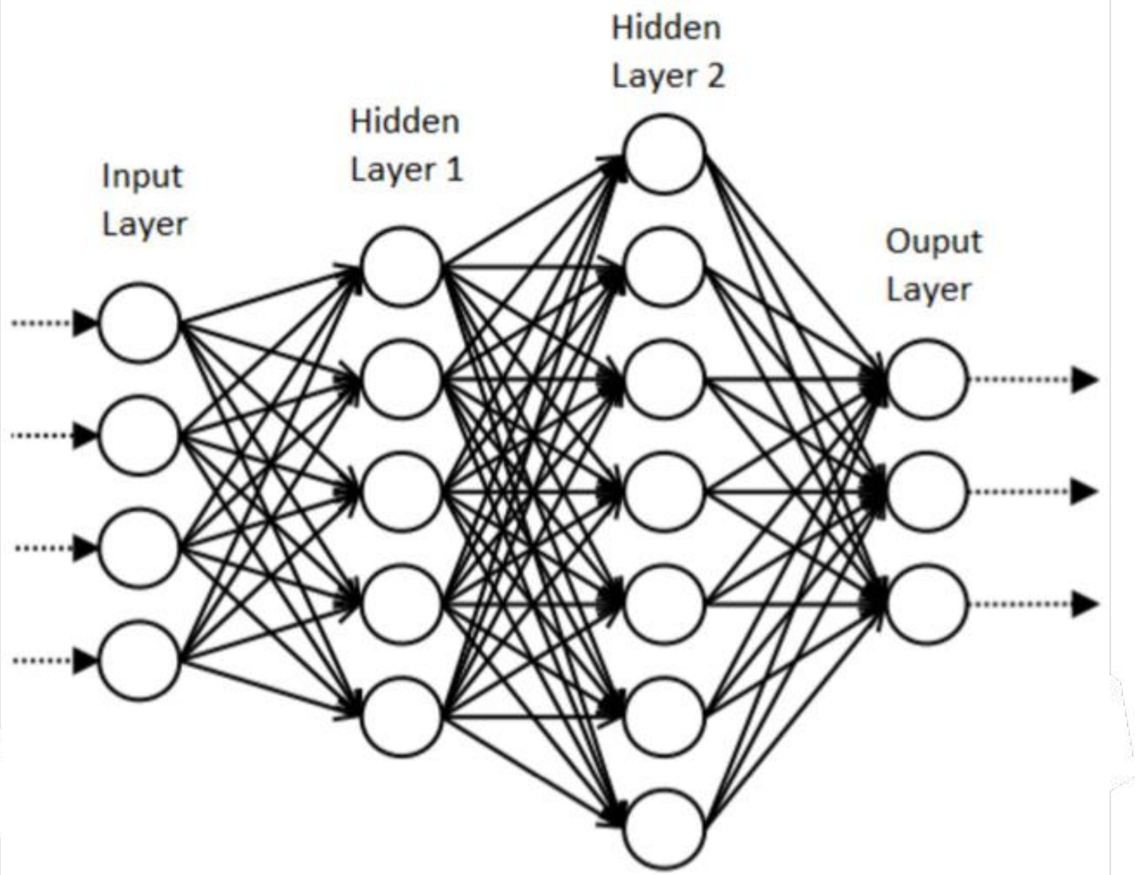
Supervised Model Training

Repeat steps 3 and 4 to continuously improve the weights of the neural network

Prepared input

x

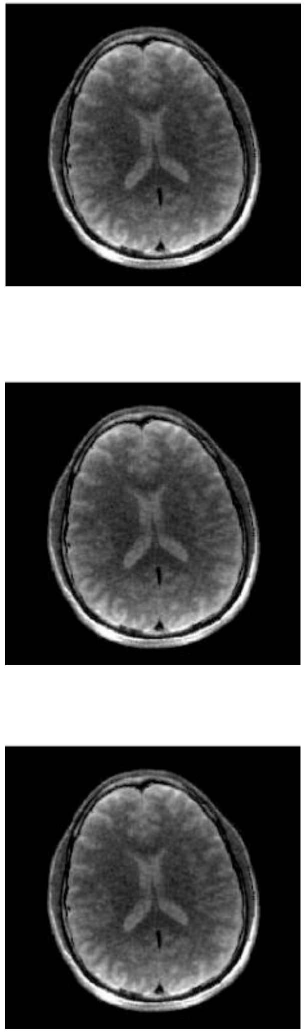




Iteration 30 $f_{W_{30}}$

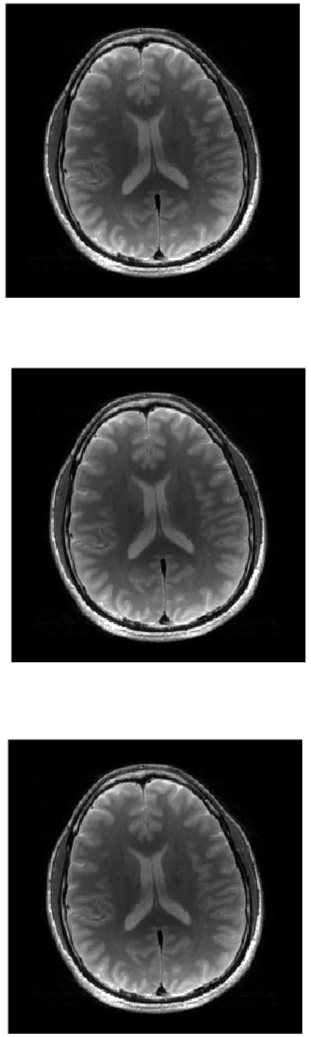
Estimated output

$\hat{y} = f(x)$



Prepared output

y

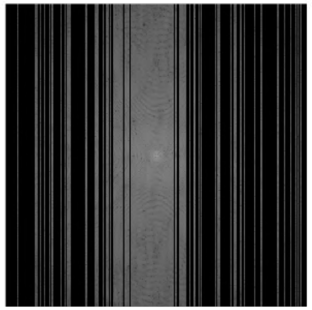


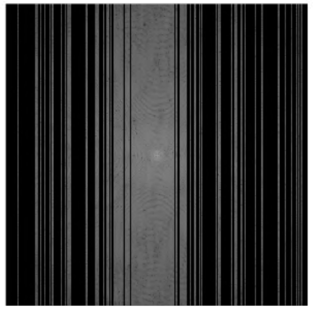
Keywords: loss function, backpropagation

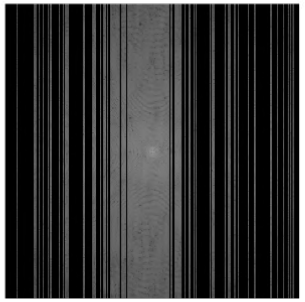
Supervised Model Training

Prepared input

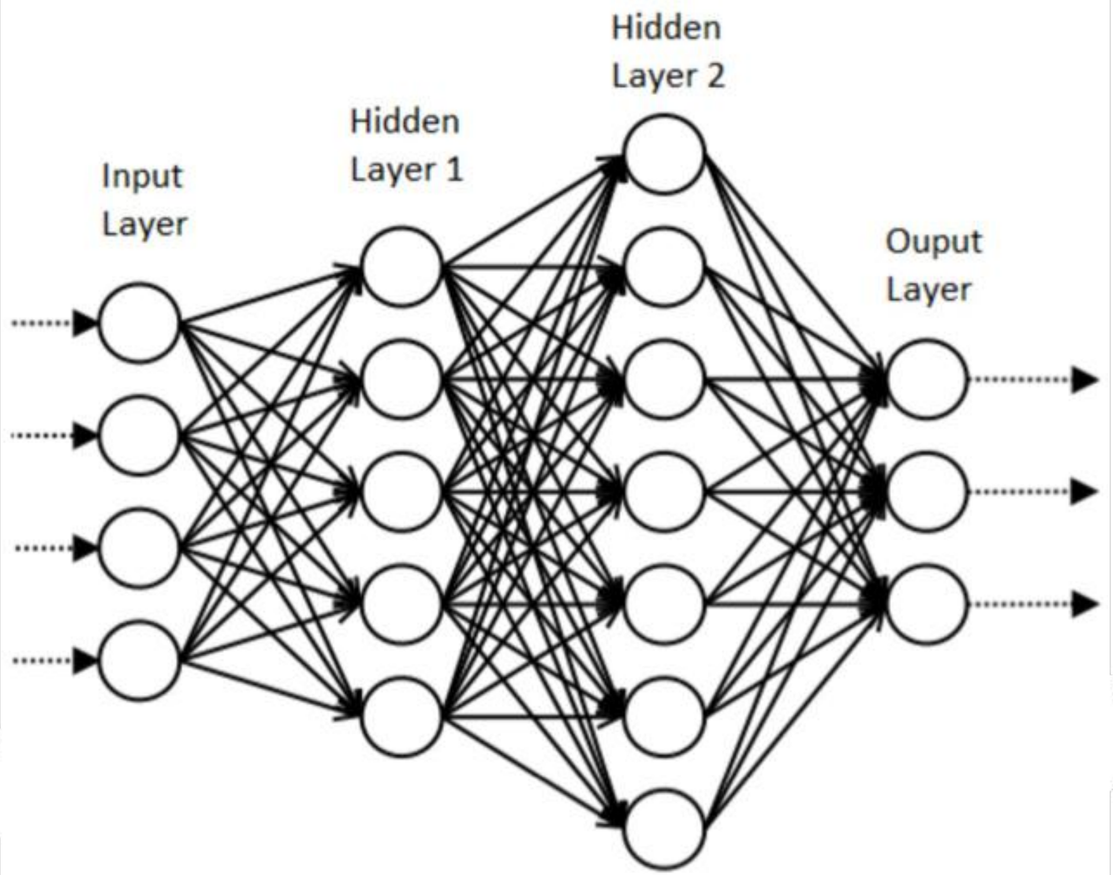
x







Repeat steps 3 and 4 to continuously improve the weights of the neural network



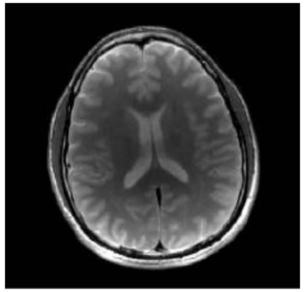
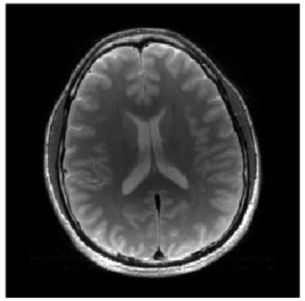
Iteration 100 $f_{W_{100}}$

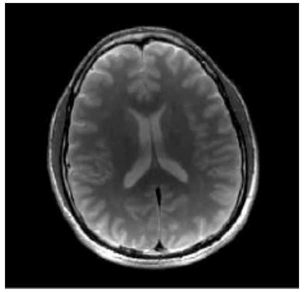
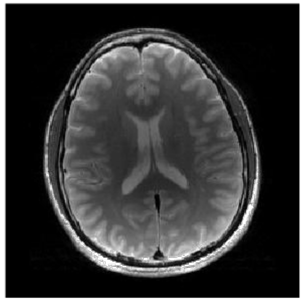
Estimated output

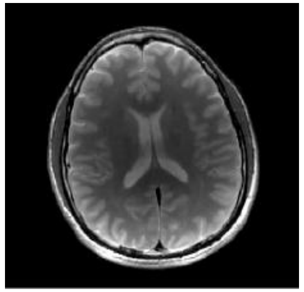
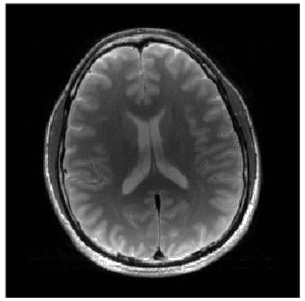
$\hat{y} = f(x)$

Prepared output

y

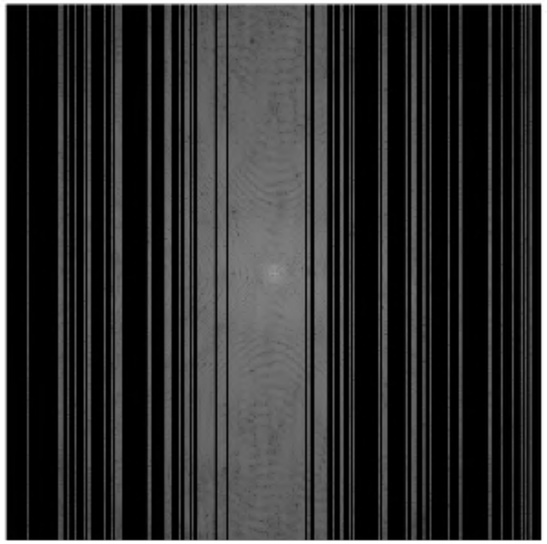
 $\approx$ 

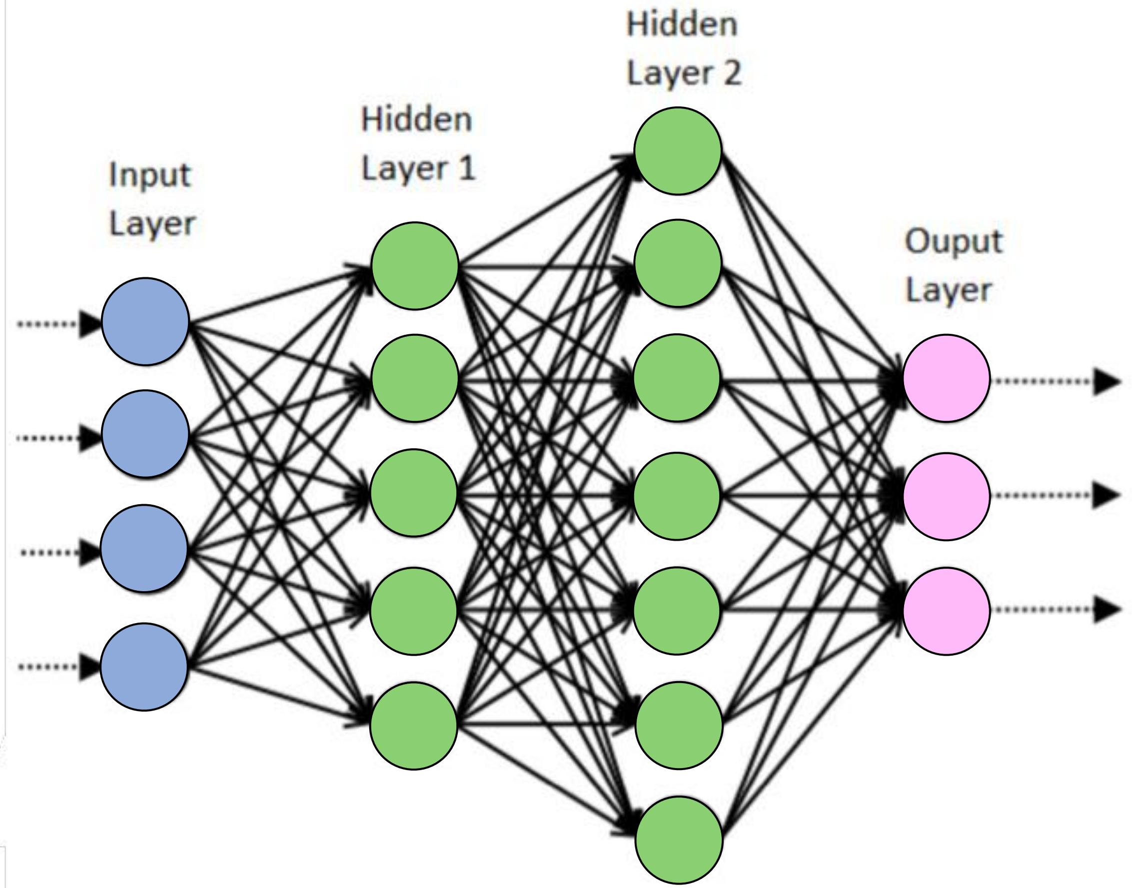
 $\approx$ 

 $\approx$ 

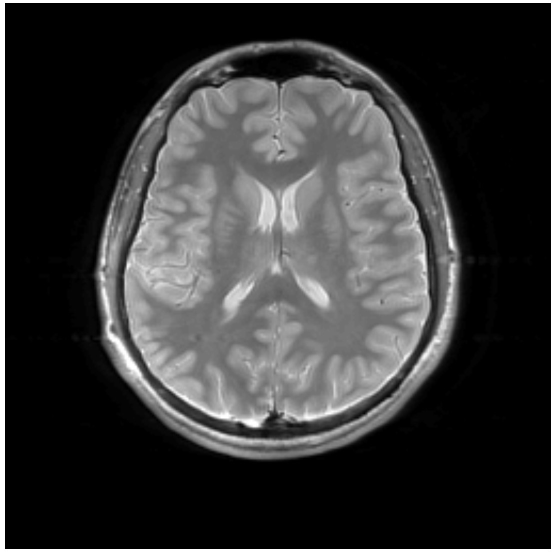
Test the Trained Model

Acquired undersampled k-space data that you wish to reconstruct





Reconstructed image



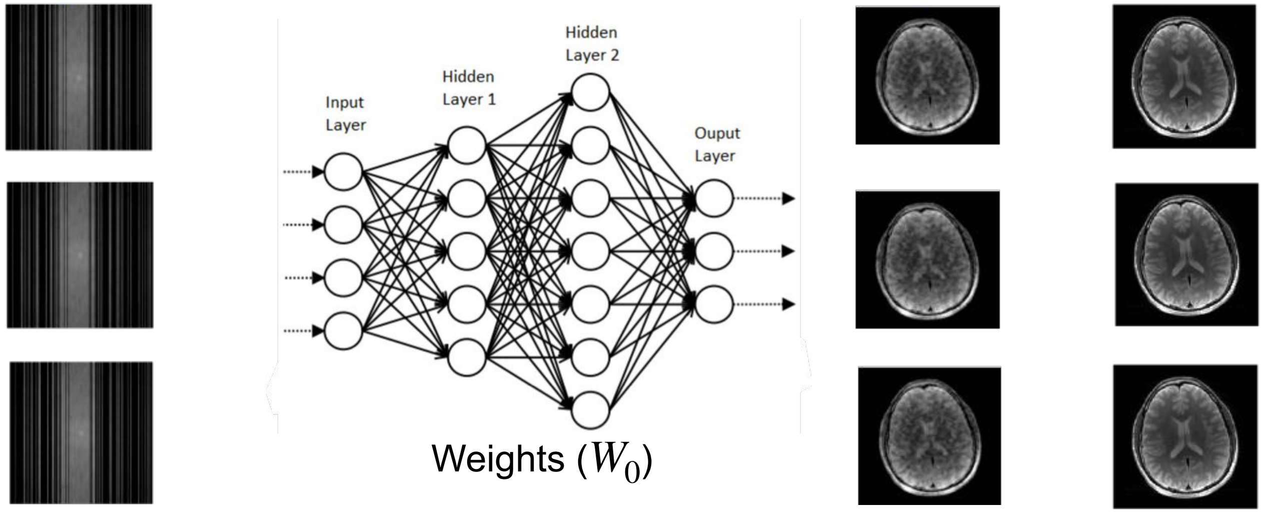
Trained model

f_{W^*}

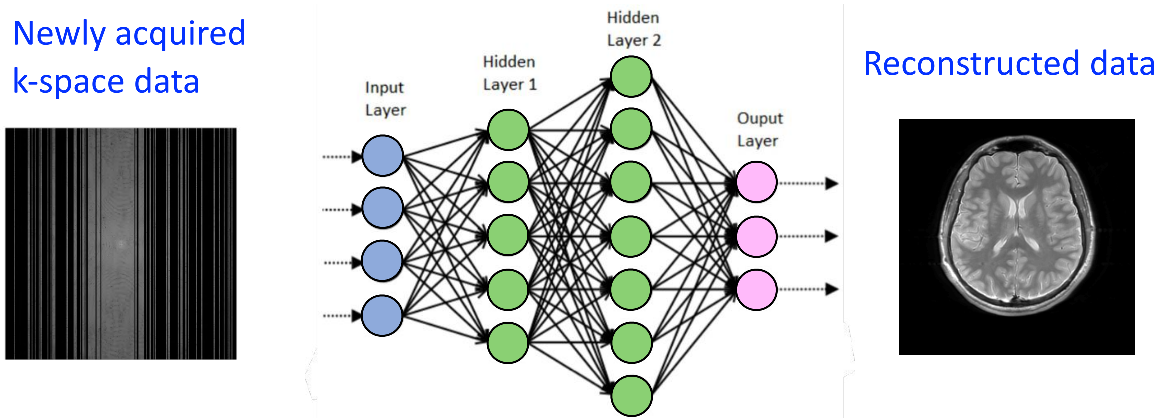
Keywords: training/validation/test data, overfitting, regularization, early stopping, data augmentation

Accelerated MRI Using Deep Learning

- Training phase: Optimize the weights of a deep neural network

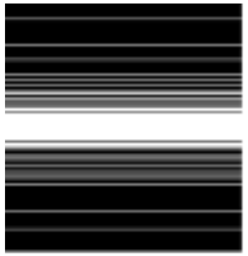


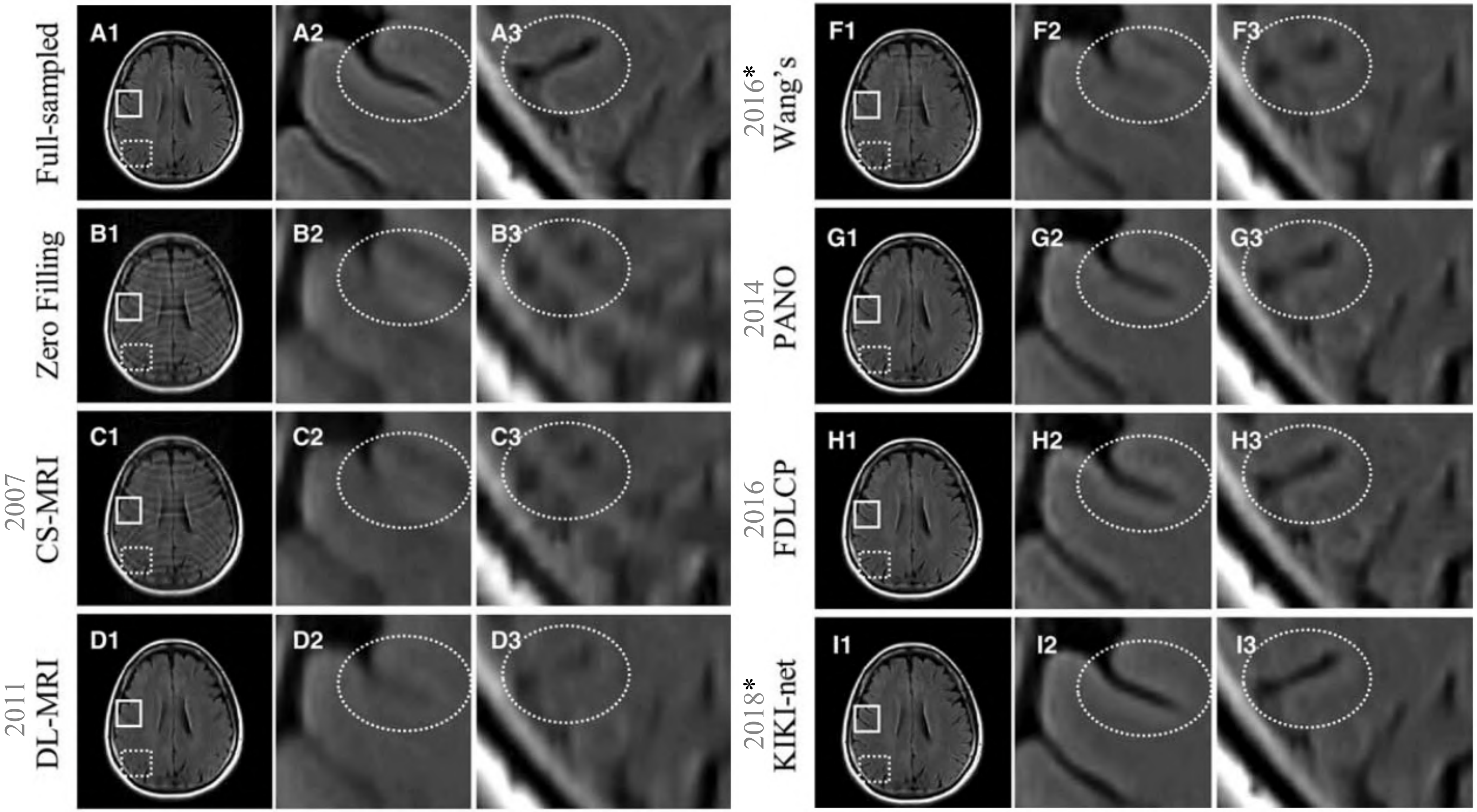
- Test phase: Reconstruct new data using the trained deep neural network



Cross-domain CNNs for Reconstructing Undersampled MRI

T_2-FLAIR
(R=4)

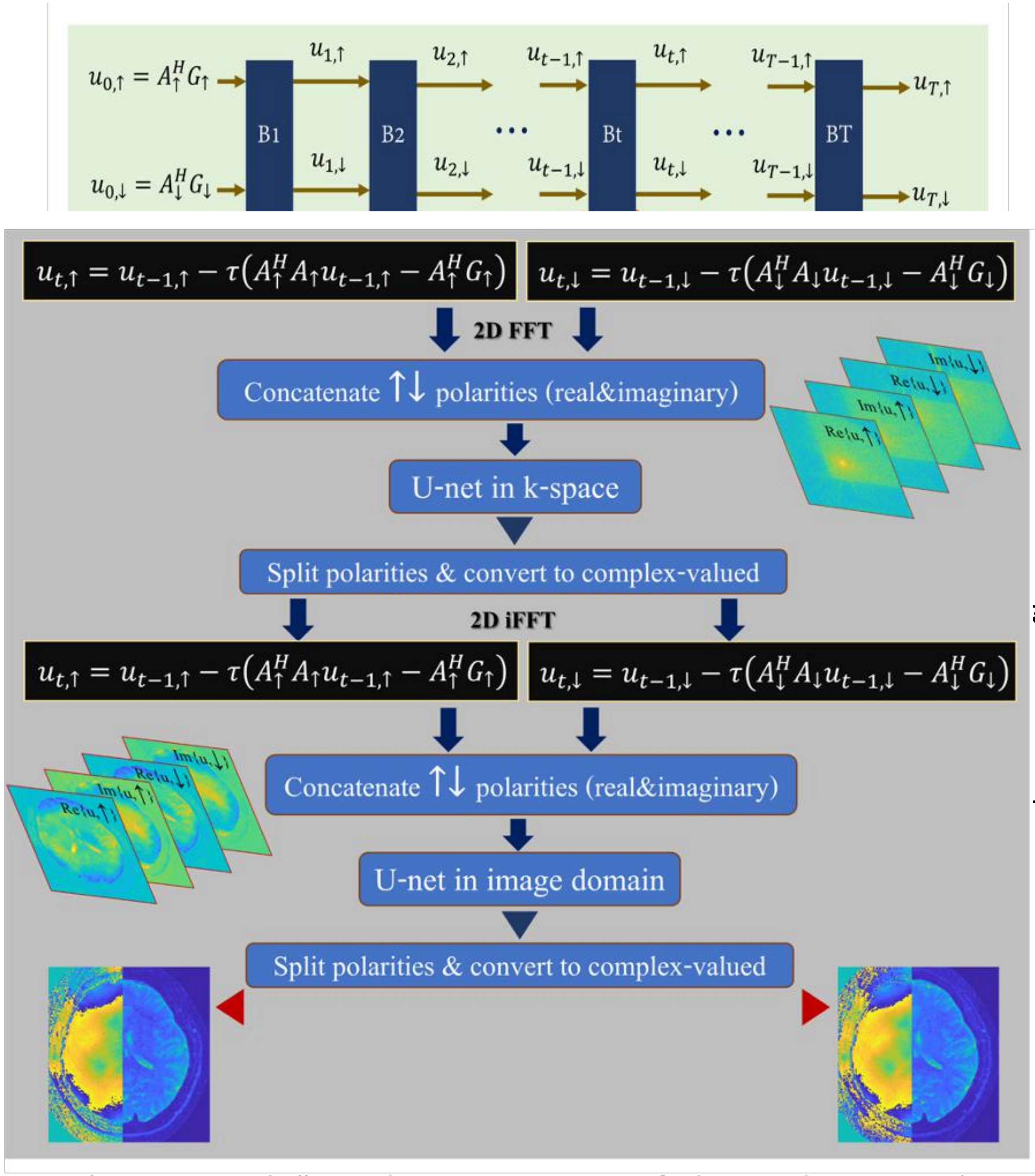




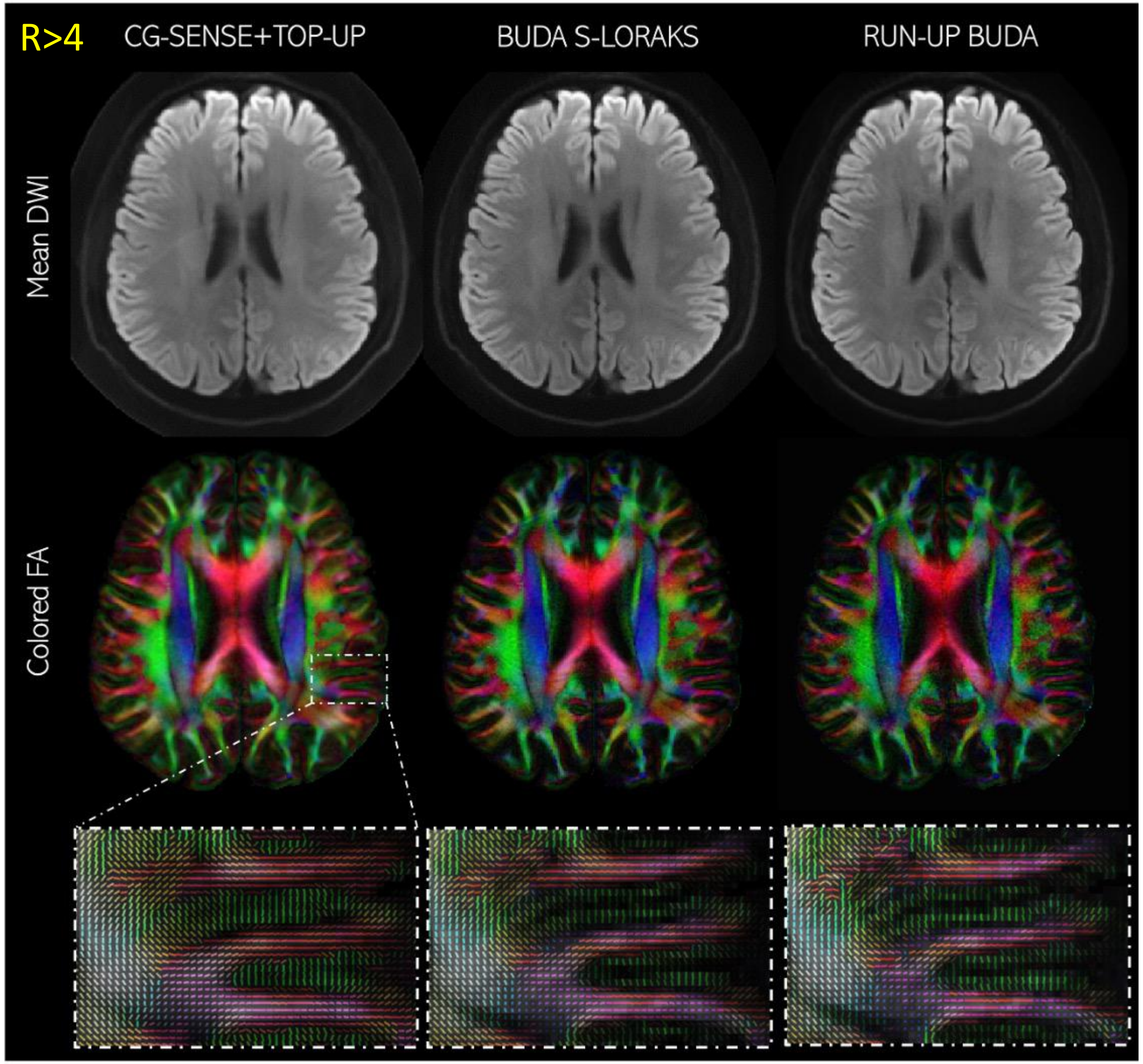
Eo, Taejoon, et al. "KIKI-net: cross-domain convolutional neural networks for reconstructing undersampled magnetic resonance images." Magnetic resonance in medicine 80.5 (2018): 2188-2201.

*deep learning based methods

88x faster recon time



colors represent fiber tract orientations

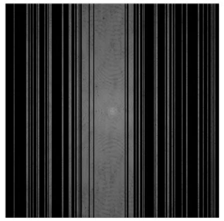


Yarach, Uten et al. “Rapid reconstruction of Blip up-down circular EPI (BUDA-cEPI) for distortion-free dMRI using an Unrolled Network with U-Net as Priors.” Proceedings of the 30th Scientific Meeting of ISMRM. Online Conference. 2022.

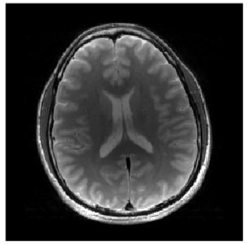
Deep Learning

- We can use a deep artificial neural network to approximate any functions by modifying its weight
  - MRI reconstruction function

k-space data



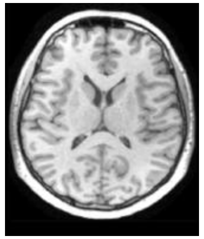
$f_{recon,W}$



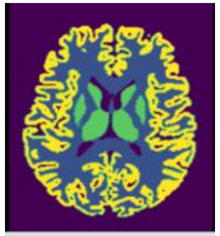
Reconstructed image

  - MRI segmentation function

Image-space data



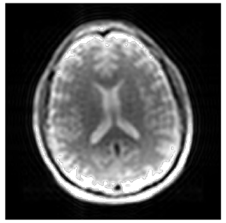
$f_{segment,W}$



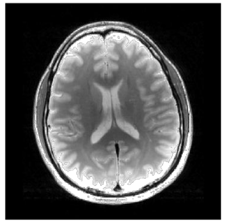
Segmentation map

  - MRI super-resolution function

Low-resolution image-space data



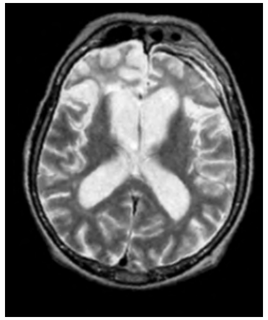
$f_{sr,W}$



High-resolution image-space data

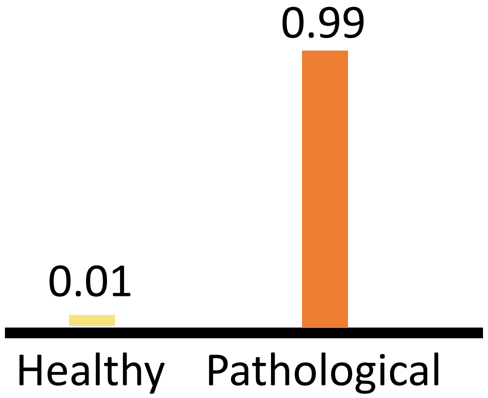
Deep Learning

- We can use a deep artificial neural network to approximate any functions by modifying its weight
  - MR image classification function

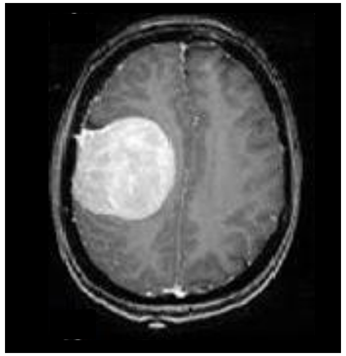


Doesn’t require hand-crafted features

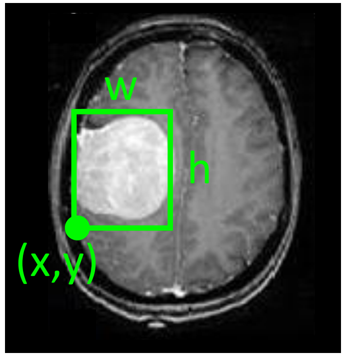
$$f_{classif,W}$$



  - Detection function



$$f_{detection,W}$$



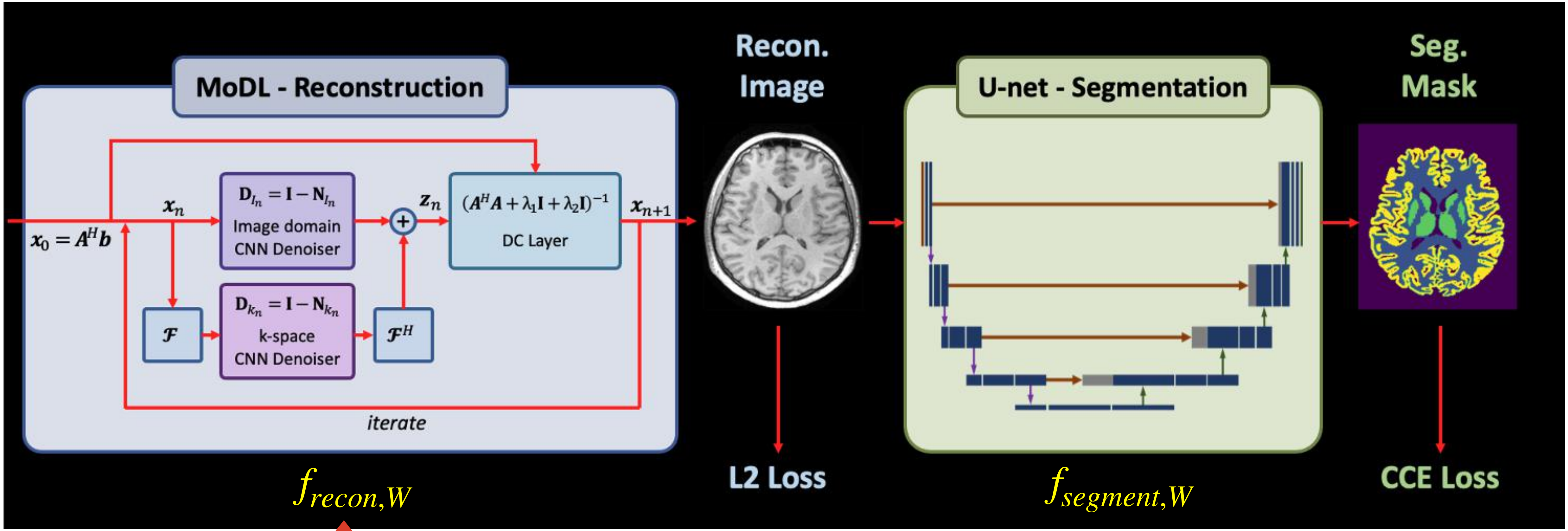
class: tumor

Alam, Sadia, et al. "An efficient image processing technique for brain tumor detection from MRI images." 2019 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE). IEEE, 2019.

Outline

- Magnetic Resonance Imaging (MRI)
- MR Image Acquisition and Reconstruction
    - Imaging parameters
    - Reconstruction from accelerated scans
- Deep Learning for Accelerated MRI
    - Supervised learning
    - Experimental Results
- Recent Advances

Joint Reconstruction and Segmentation



Unrolled $\min_x \frac{1}{2}\|Ax - y\|_2^2 + \lambda_1\|N_k(x)\|_2^2 + \lambda_2\|N_i(x)\|_2^2$

Cho, Jaejin, et al. "Wave-encoded model-based deep learning with joint reconstruction and segmentation." Proceedings of the 29th Scientific Meeting of ISMRM. Online Conference. 2021.

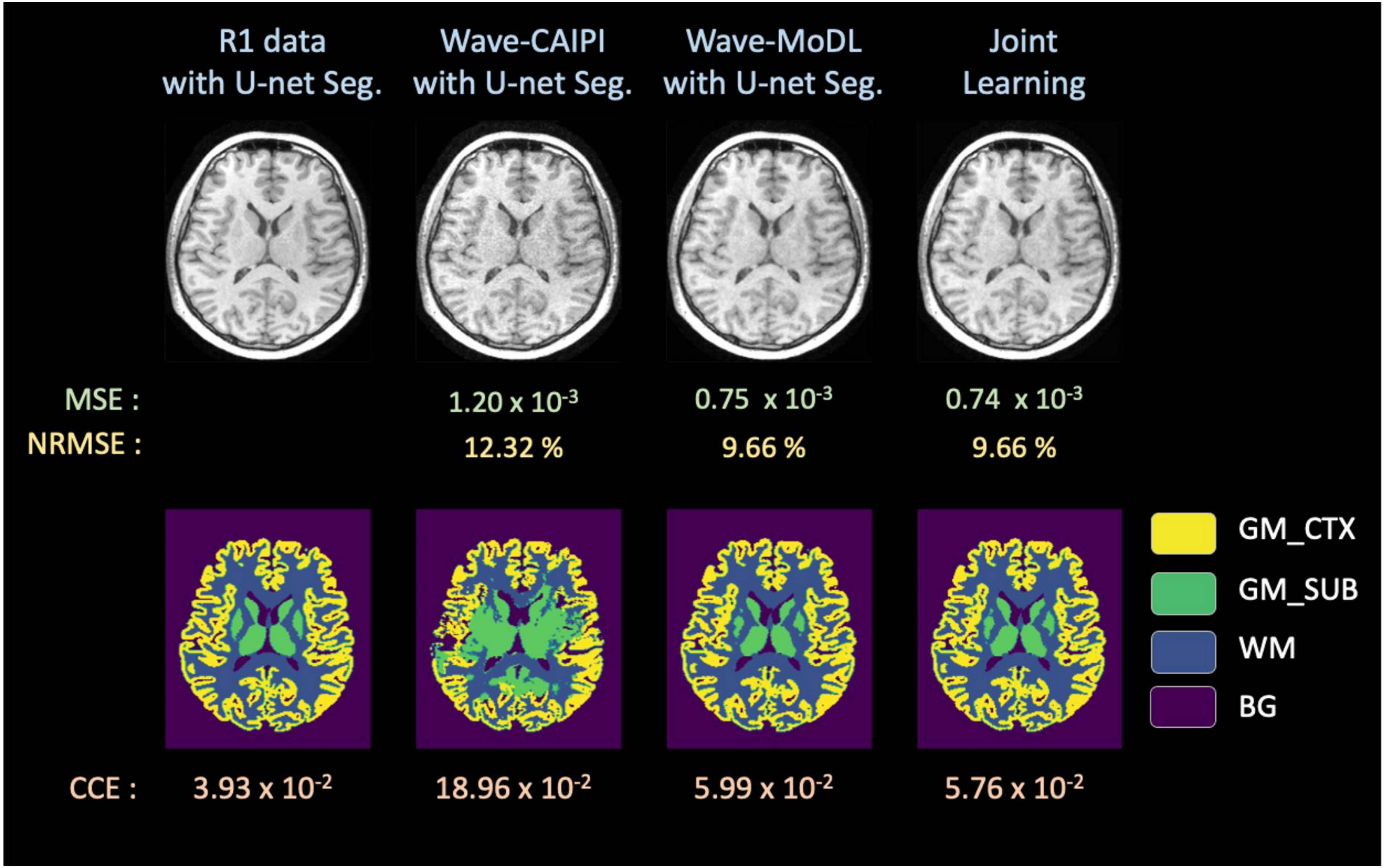
Ground truth image → U-Net seg.

CS recon → U-Net seg.

Unrolled DL recon → U-Net seg.

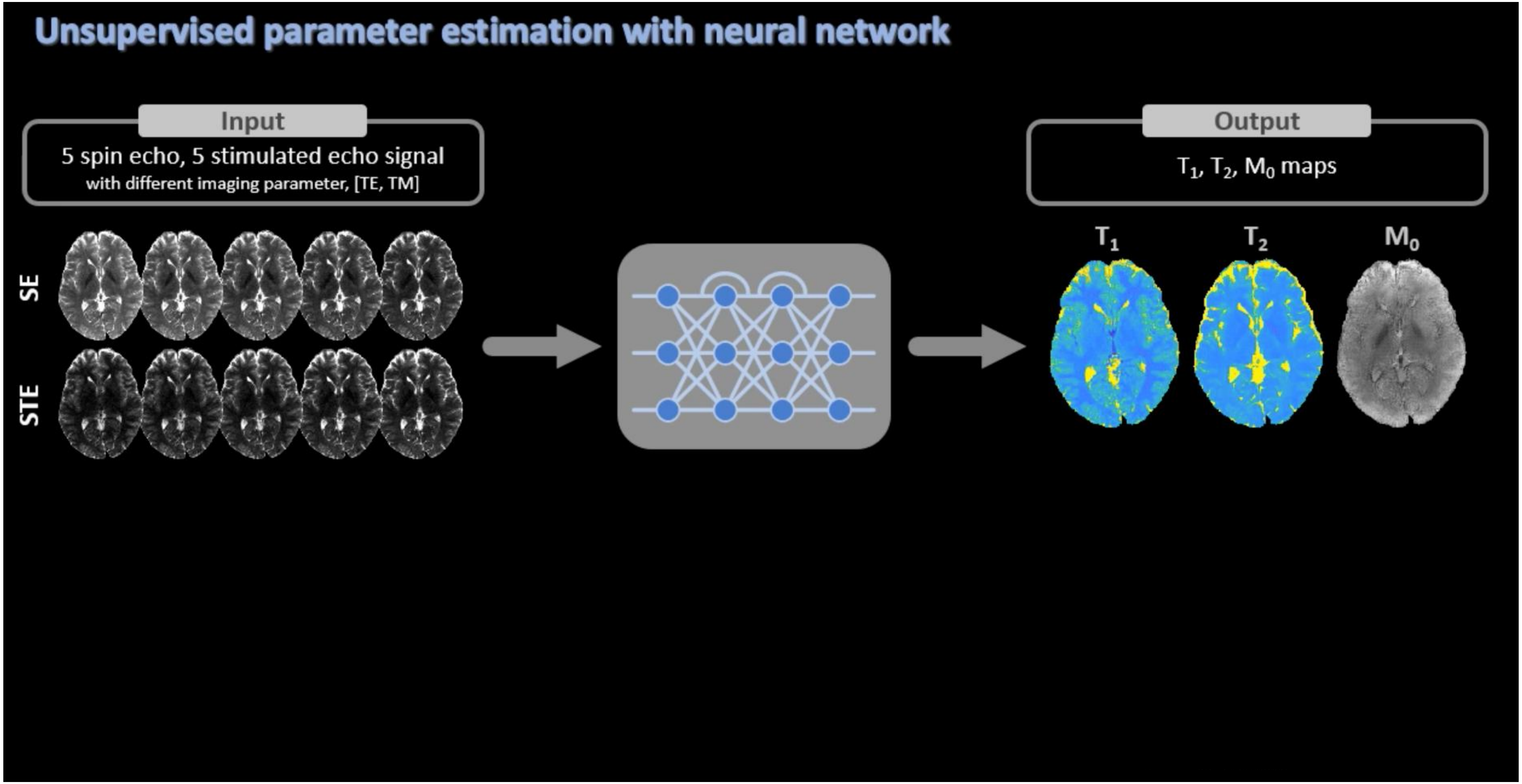
Unrolled DL recon + U-Net seg.

- R_y x R_z = 3 x 3
- 12-channel data
- 64 subjects
    - 70% training data
    - 15% validation data
    - 15% test data



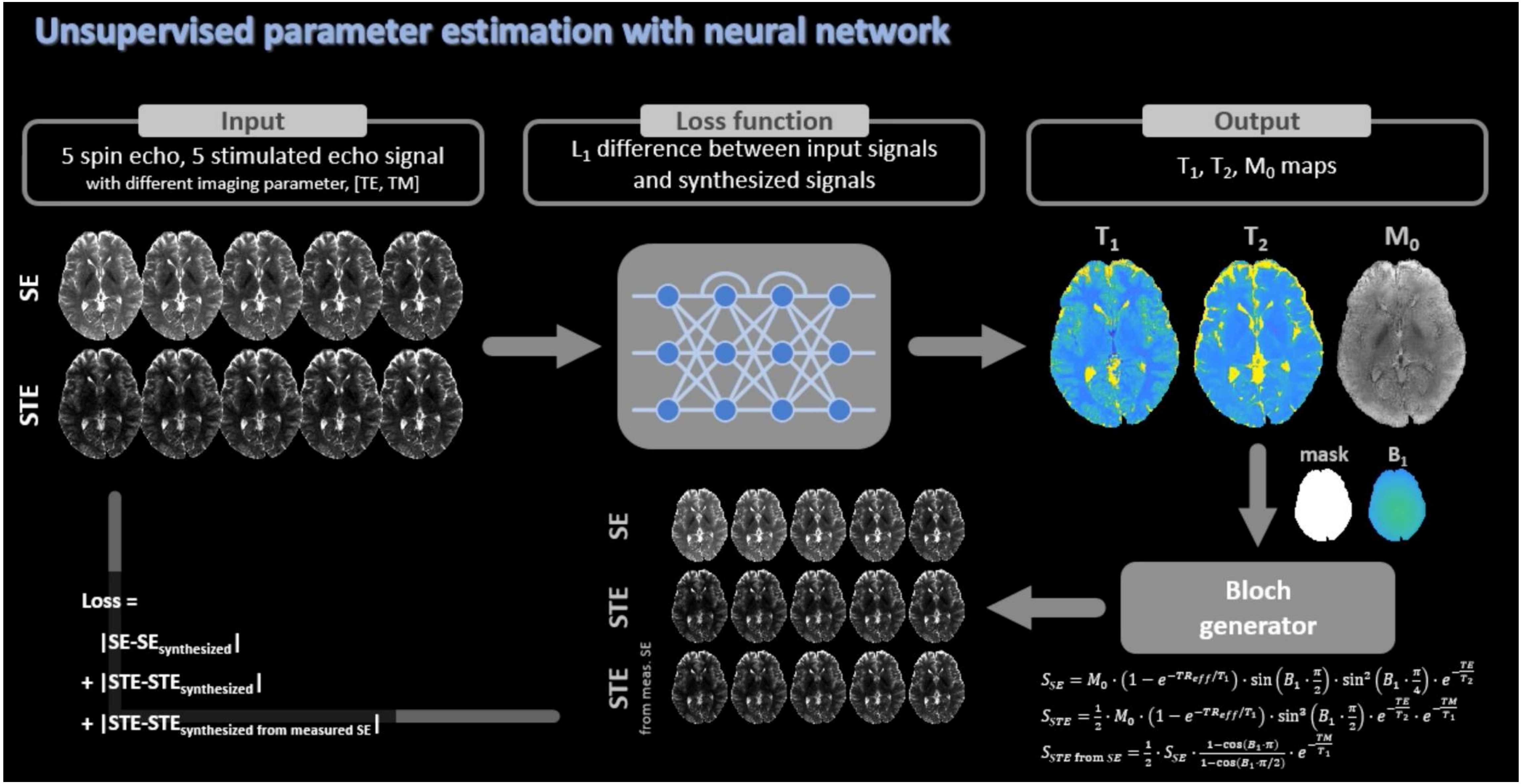
Cho, Jaejin, et al. "Wave-encoded model-based deep learning with joint reconstruction and segmentation." Proceedings of the 29th Scientific Meeting of ISMRM. Online Conference. 2021.

Quantitative Imaging



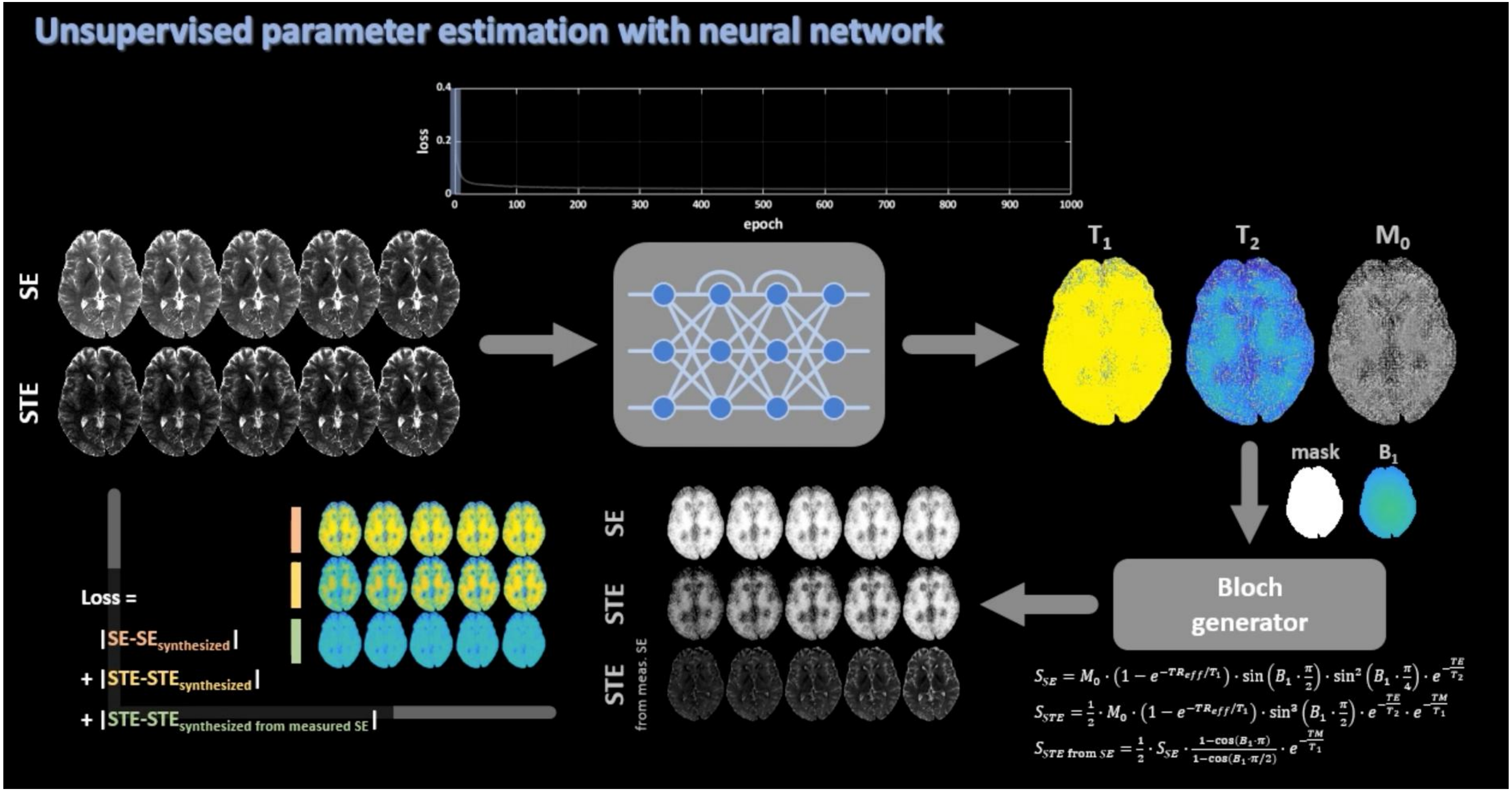
So, Seohee, Kim, Byungjai, Park HW, Bilgic, Berkin. “BUDA-STEAM: A rapid parameter estimation method for T1, T2, M0, B0 and B1 using three-90° pulse sequence” Proceedings of the 29th Scientific Meeting of ISMRM. Online Conference. 2021.

Quantitative Imaging



So, Seohee, Kim, Byungjai, Park HW, Bilgic, Berkin. "BUDA-STEAM: A rapid parameter estimation method for T1, T2, M0, B0 and B1 using three-90° pulse sequence" Proceedings of the 29th Scientific Meeting of ISMRM. Online Conference. 2021.

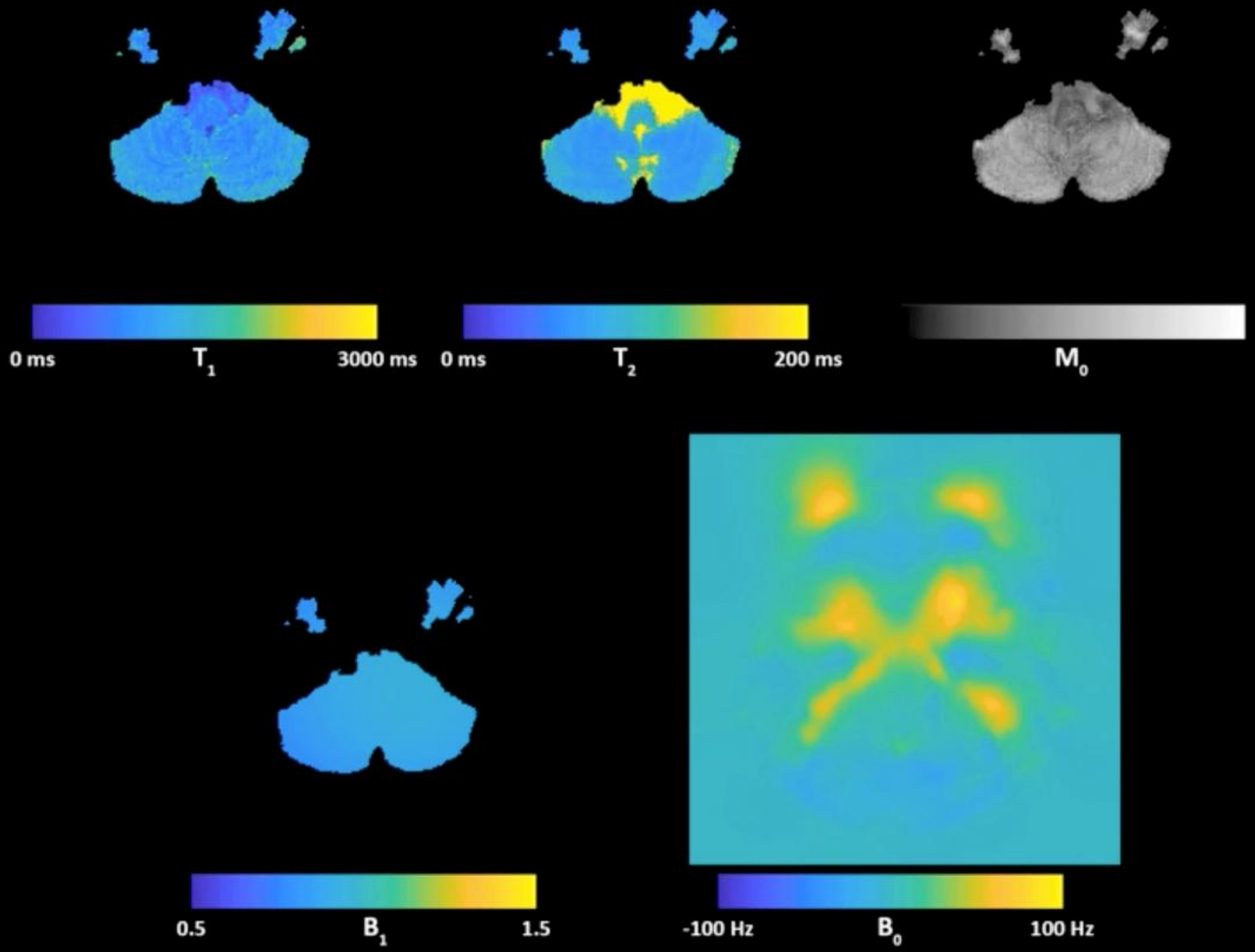
Quantitative Imaging



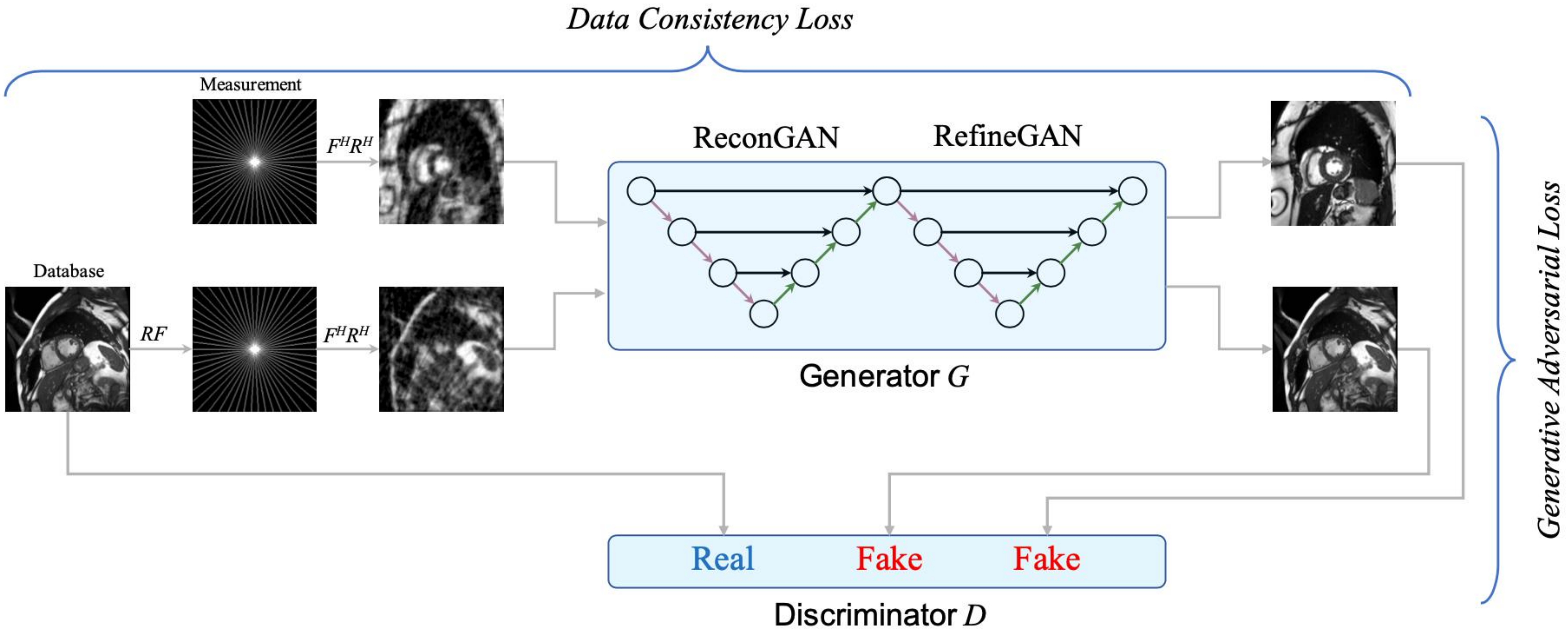
So, Seohee, Kim, Byungjai, Park HW, Bilgic, Berkin. “BUDA-STEAM: A rapid parameter estimation method for T1, T2, M0, B0 and B1 using three-90° pulse sequence” Proceedings of the 29th Scientific Meeting of ISMRM. Online Conference. 2021.

Whole brain experiment

Field-of-view	224mm × 224mm × 120mm
Resolution	1mm × 1mm × 5mm
TR	5 sec
[TE, TM]	[82ms, 1000ms], [90ms, 750ms], [100ms, 500ms], [110ms, 320ms], [120ms, 140ms]
# of measurements	5
# of shots	2 (BUDA)
In-plane acceleration	2
Partial Fourier	6/8
Multi-band	2 (CAIPIRINHA)
Total scan time	**50 sec**



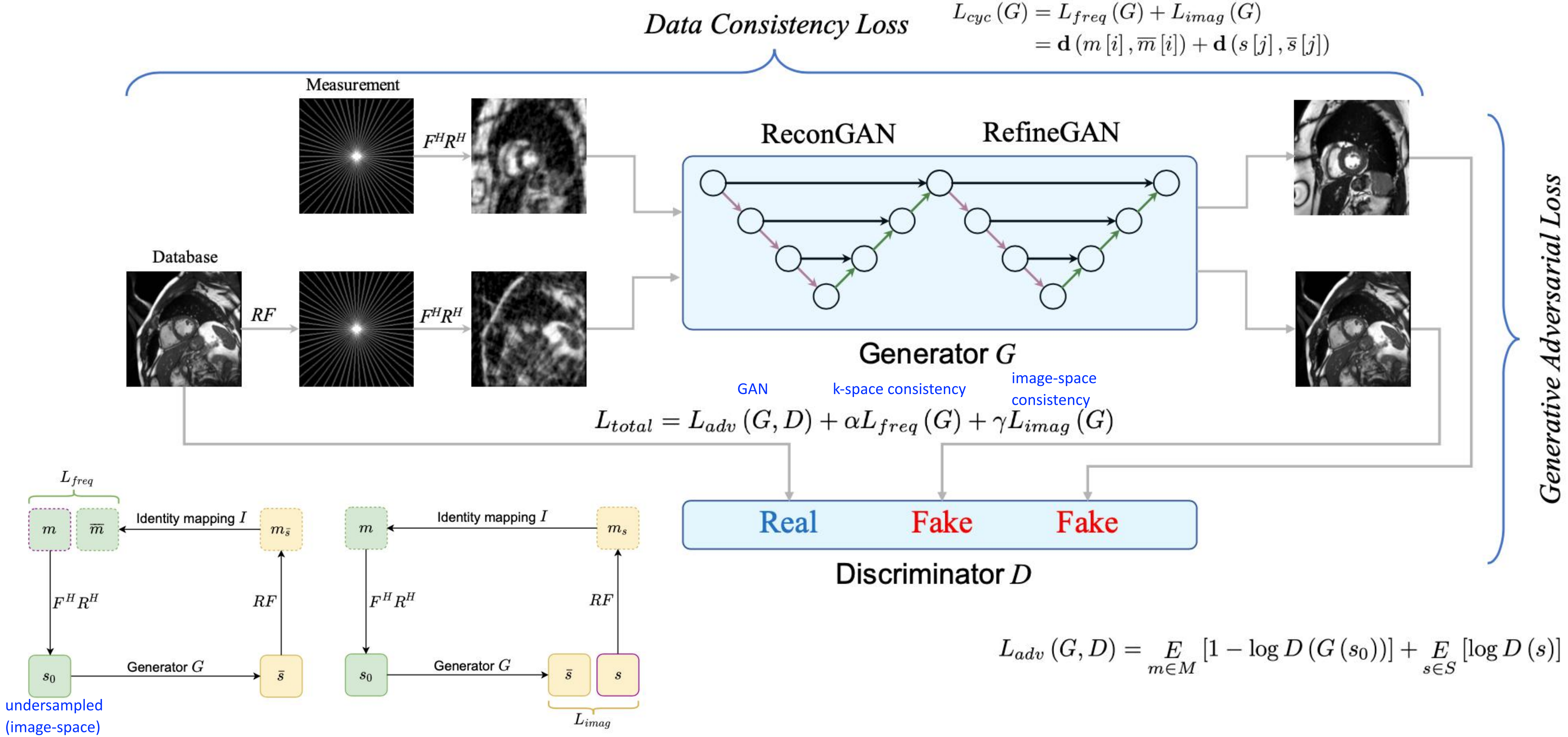
Generative Adversarial Network (GAN)



Quan, Tran Minh, Thanh Nguyen-Duc, and Won-Ki Jeong. "Compressed sensing MRI reconstruction using a generative adversarial network with a cyclic loss." IEEE transactions on medical imaging 37.6 (2018): 1488-1497.

Generative Adversarial Network (GAN)

$$L_{cyc}(G) = L_{freq}(G) + L_{imag}(G) = \mathbf{d}(m[i], \overline{m}[i]) + \mathbf{d}(s[j], \overline{s}[j])$$



$$L_{total} = L_{adv}(G, D) + \alpha L_{freq}(G) + \gamma L_{imag}(G)$$

$$L_{adv}(G, D) = \underset{m \in M}{E}\left[1 - \log D(G(s_0))\right] + \underset{s \in S}{E}\left[\log D(s)\right]$$

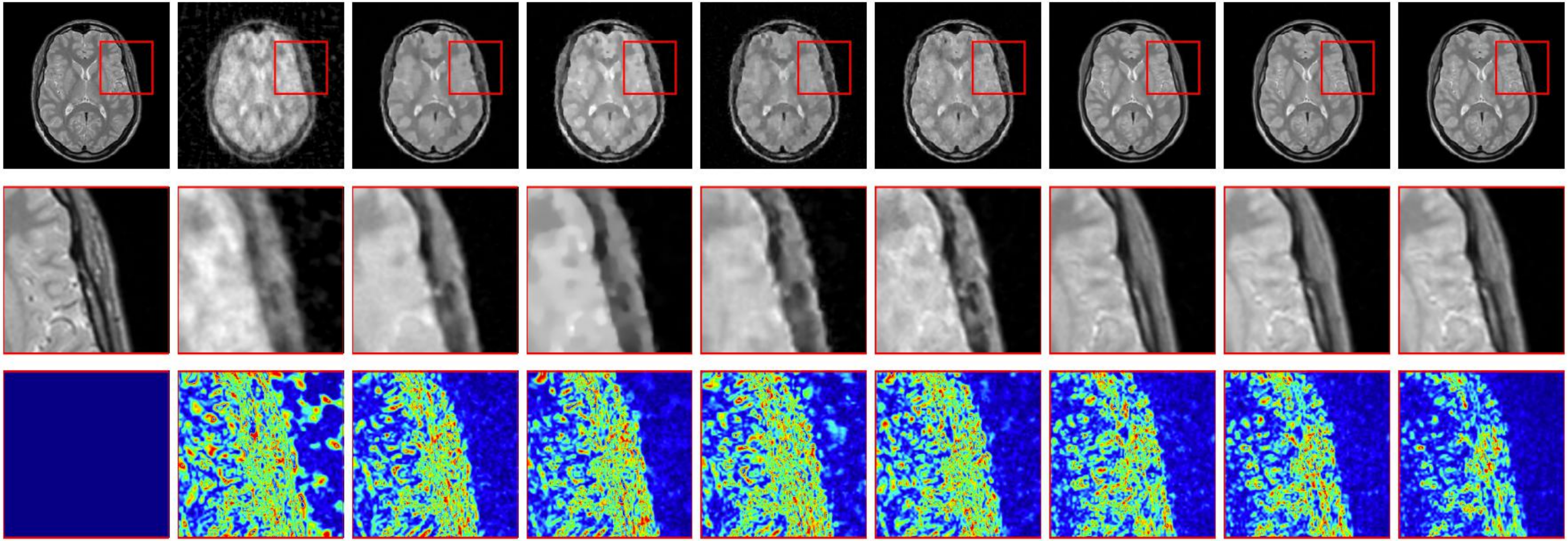
Quan, Tran Minh, Thanh Nguyen-Duc, and Won-Ki Jeong. "Compressed sensing MRI reconstruction using a generative adversarial network with a cyclic loss." IEEE transactions on medical imaging 37.6 (2018): 1488-1497.

Generative Adversarial Network (GAN)

R=10

256x256 pixels

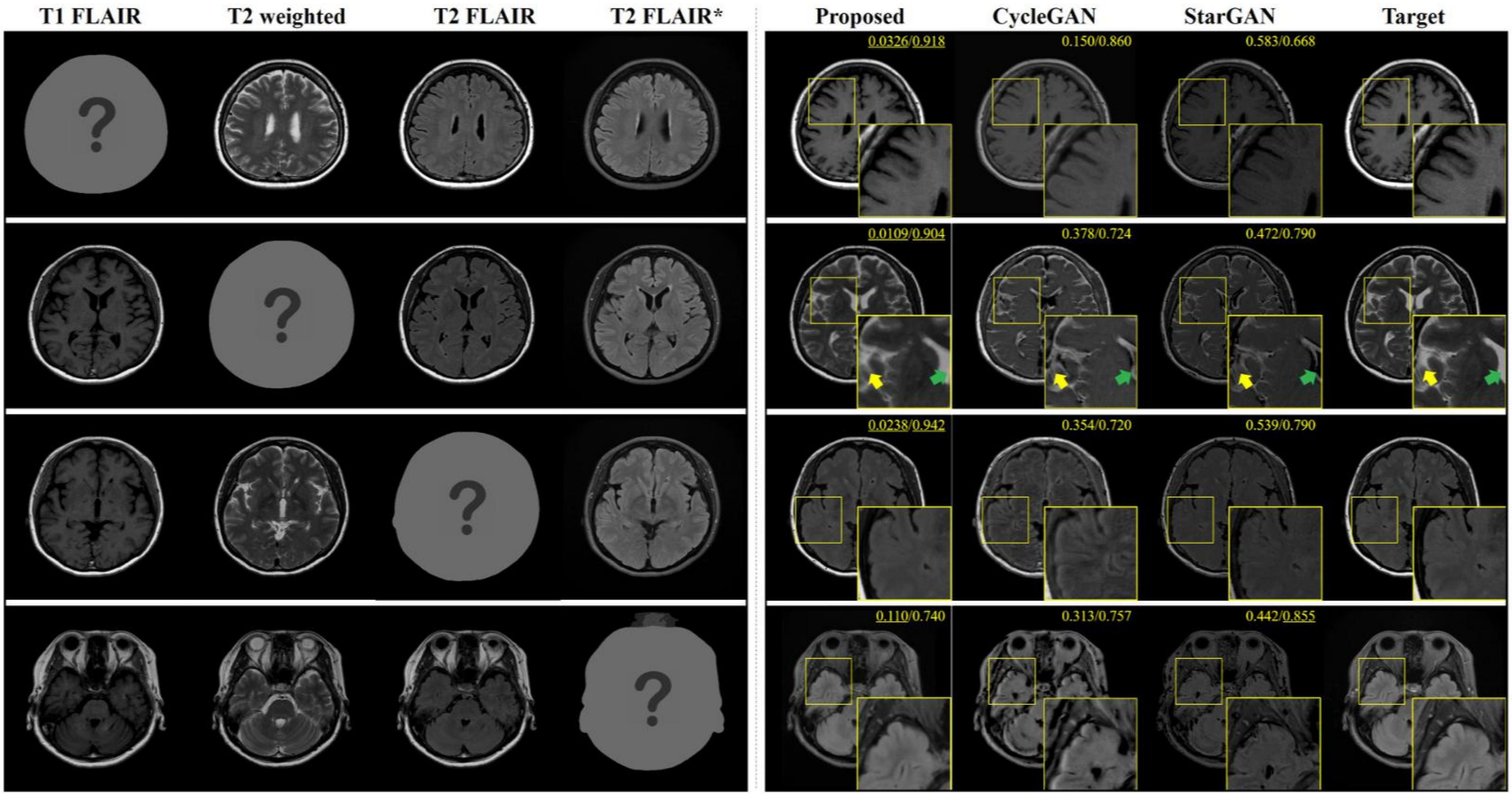
		2011-14	2016	2016	2017	2017	2018	2018
FullRecon	ZeroFilling	DLMRI	CSCMRI	DeepADMM	DeepCascade	SingleGAN	ReconGAN	RefineGAN



recon time (sec/slice)	604.25	8.57	0.32	0.22	0.06	0.06	0.11

Quan, Tran Minh, Thanh Nguyen-Duc, and Won-Ki Jeong. "Compressed sensing MRI reconstruction using a generative adversarial network with a cyclic loss." IEEE transactions on medical imaging 37.6 (2018): 1488-1497.

Collaborative GAN

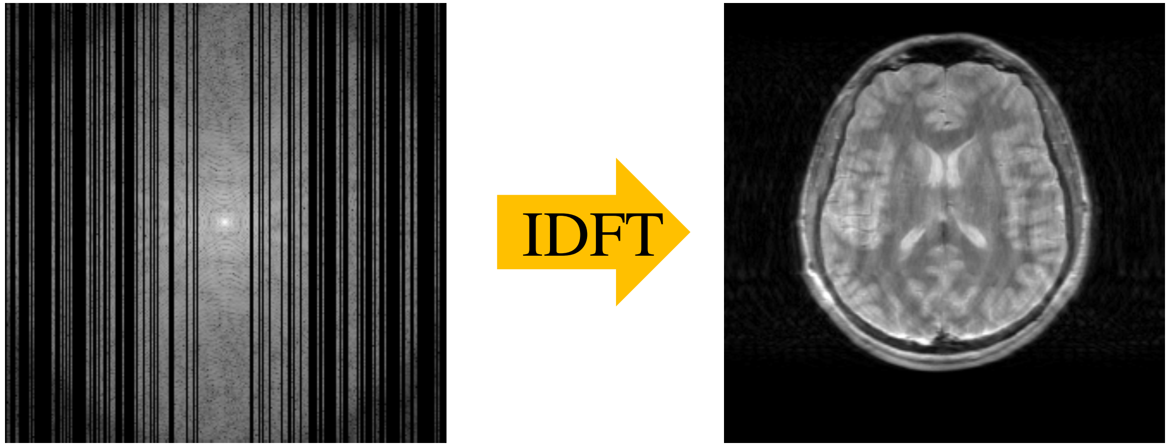


Lee, Dongwook, et al. "CollaGAN: Collaborative GAN for missing image data imputation." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019.

Summary

- Magnetic Resonance Imaging (MRI)
  - Data acquired in the Fourier transform domain (k-space)
    - If the sampling rate is high enough, the inverse DFT can be directly applied to recover the data
  - Data acquisition time can be reduced by collecting fewer k-space samples
    - Applying the inverse DFT to the undersampled k-space data leads to reconstruction with artifacts
      - Need more sophisticated approaches to reconstruct data: compressed sensing and deep learning

2x faster acquisition

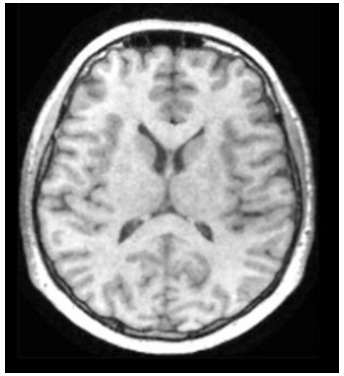


NANOTEC
a member of NSTDA

Summary

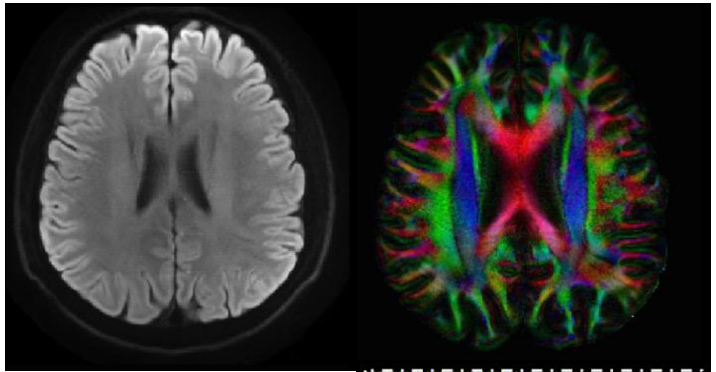
- ## Deep Learning for MRI
  - With lots of training data, supervised deep learning is an attractive approach for MR image reconstruction, analysis, quantification, and diagnosis
  - Other types of learning have recently gained in importance
- ## Current Challenges
  - Robustness
    - Uncontrollable factors
    - Adversarial attack
  - How to use data more efficiently
  - Explainable models

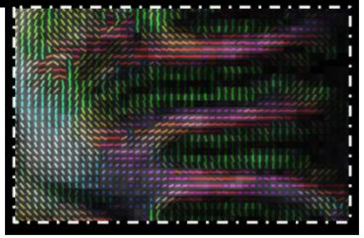
9x faster acquisition



Cho, Jaejin, et al. ISMRM (2021)

88x faster reconstruction





Yarach, Uten, et al. ISMRM (2022)

Acknowledgments

NANOTEC
a member of NSTDA

สวทช
NSTDA

MGH/HST Athinoula A. Martinos
Center for Biomedical Imaging
MASSACHUSETTS GENERAL HOSPITAL
Harvard-MIT Health Sciences & Technology

Massachusetts Institute of Technology

CHIANG MAI UNIVERSITY 1964
Faculty of Associated Medical Sciences

LELAND STANFORD JUNIOR UNIVERSITY
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RSL RADIOLOGICAL SCIENCES LABORATORY
STANFORD MEDICINE

Contact: itthi.cha@nanotec.or.th