ARAMIS LAB
BRAIN DATA SCIENCE

www.aramislab.fr

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AI4Health School 2021

Practical session DL4MI

Medical image synthesis with deep learning

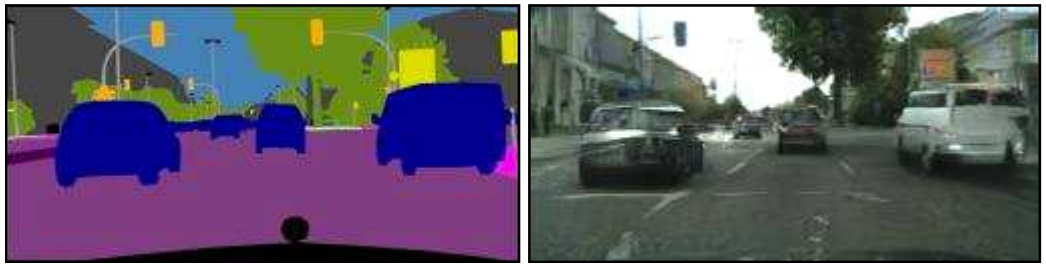
Principle and applications

Ninon Burgos, with Simona Bottani, Mauricio Diaz Melo, Johann Faouzi and Elina Thibeau-Sutre

Aramis Lab, Paris Brain Institute, France

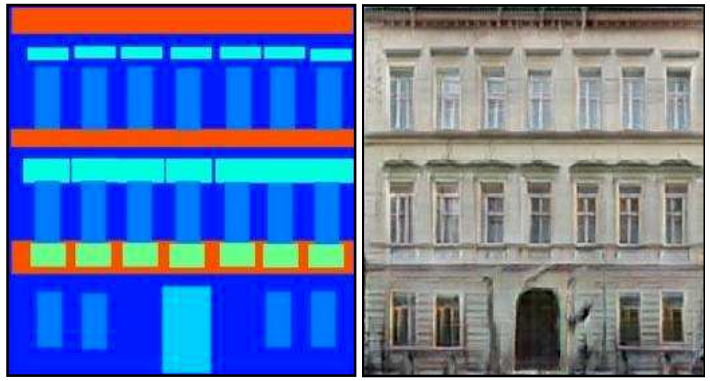
Image-to-image translation

Labels to Street Scene



input output

Labels to Facade



input output

BW to Color

input output

Aerial to Map

input output

Day to Night

input output

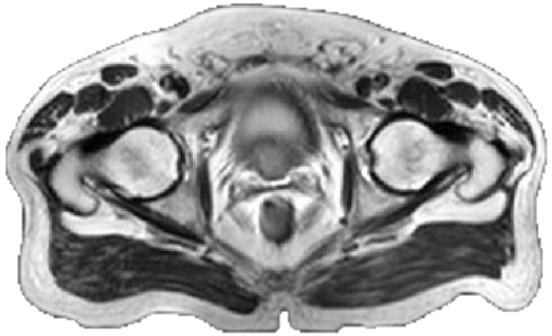
Edges to Photo

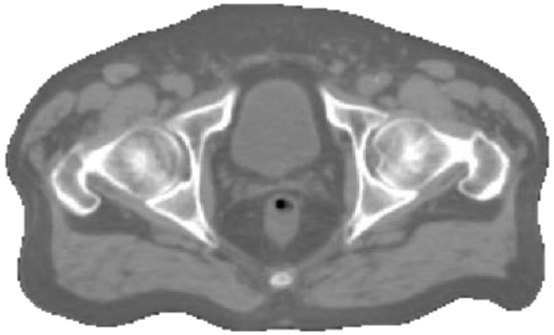
input output

Isola et al., CVPR, 2017

Medical image-to-image translation

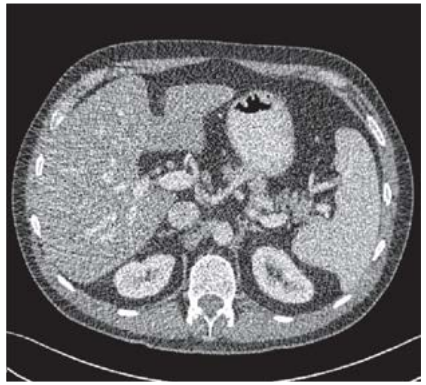
MRI

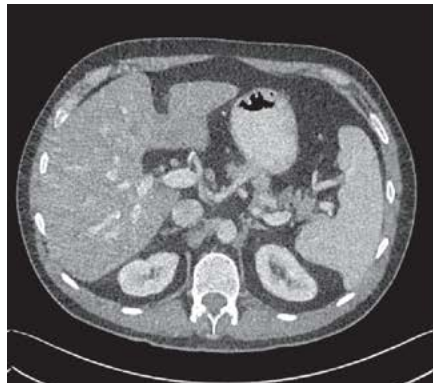




Pseudo CT

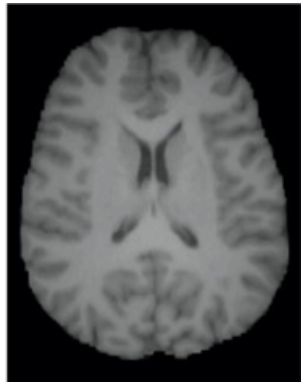
Low dose CT

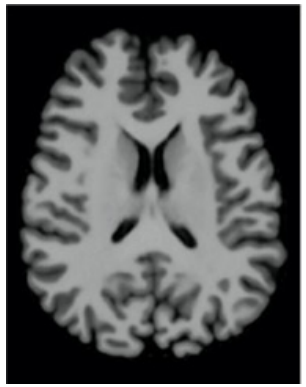




Pseudo high dose CT

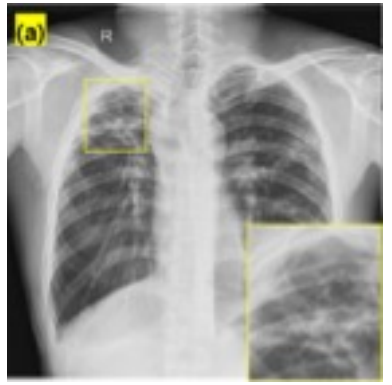
3T MRI

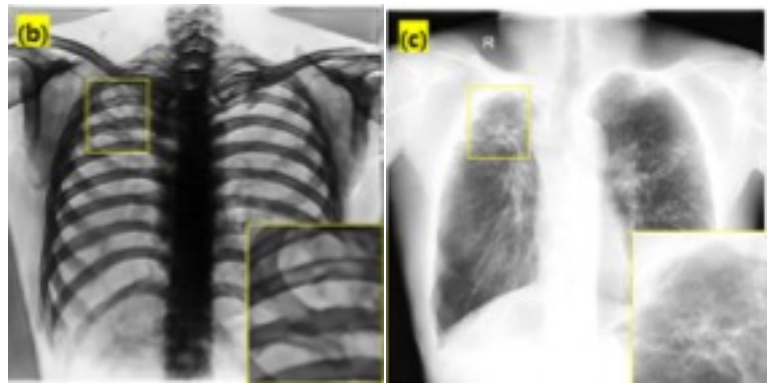




Pseudo 7T MRI

Single-energy X-ray





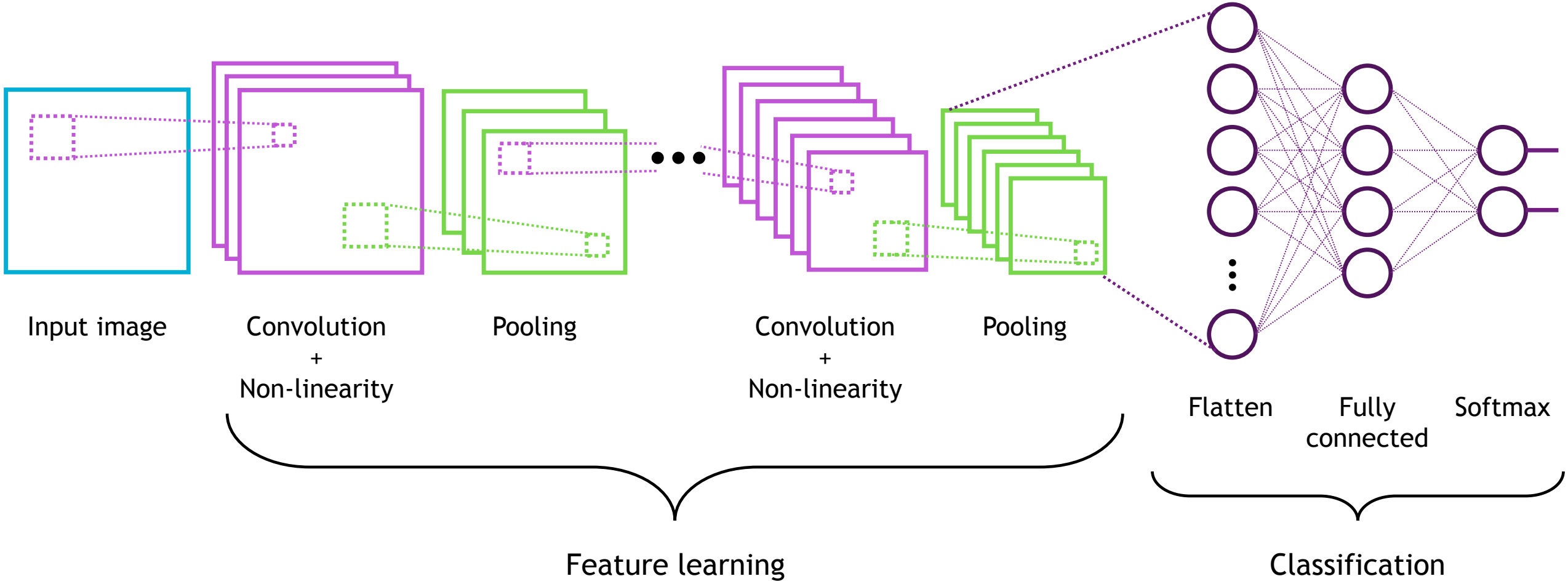
Pseudo bone and soft-tissue images

Burgos et al., PMB, 2017; Yang et al., IEEE TMI, 2018; Qu et al., MedIA, 2020; Lee et al., PMB, 2019

Generative Deep Learning

Convolutional neural networks

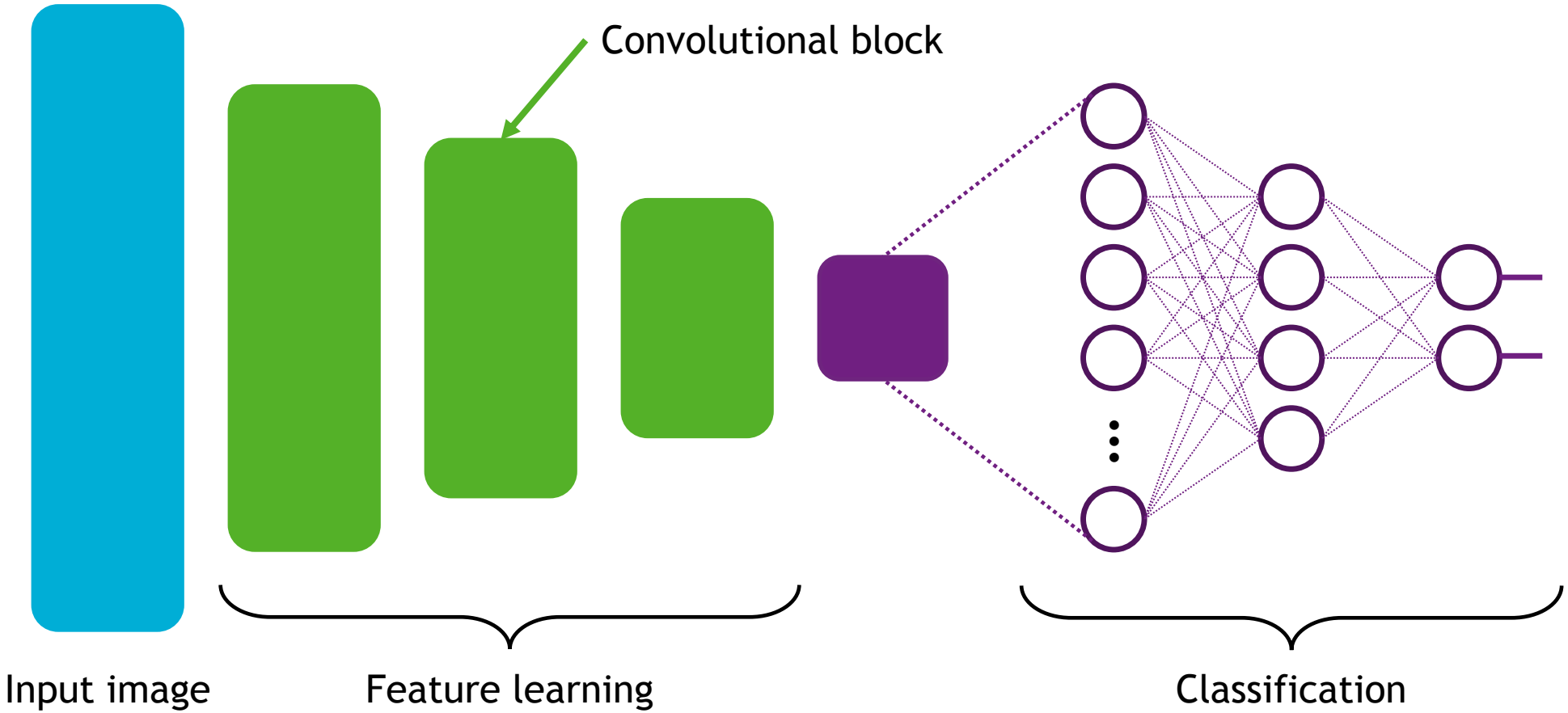
CNNs for classification



MIT Introduction to Deep Learning (introtodeeplearning.com)

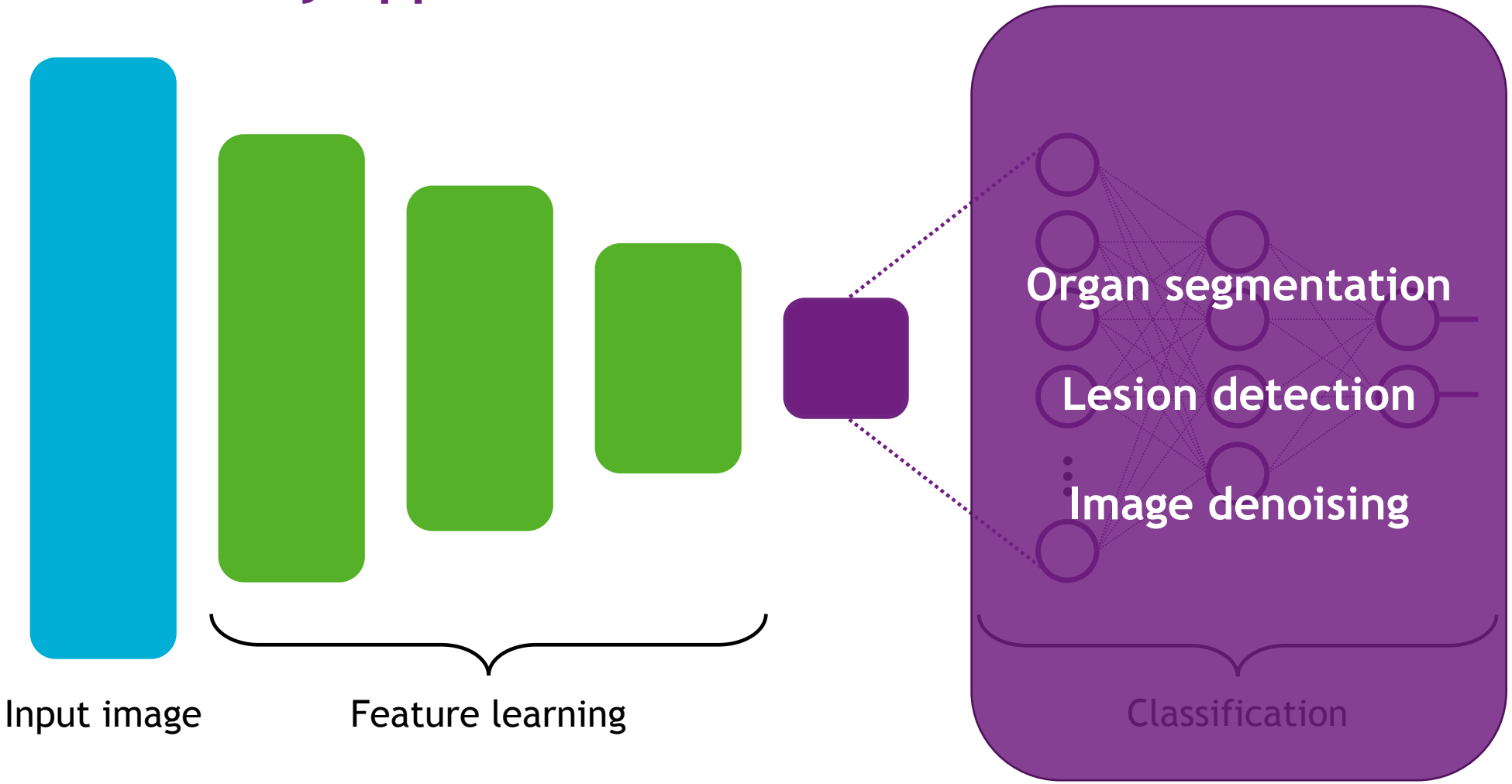
Convolutional neural networks

CNNs for classification



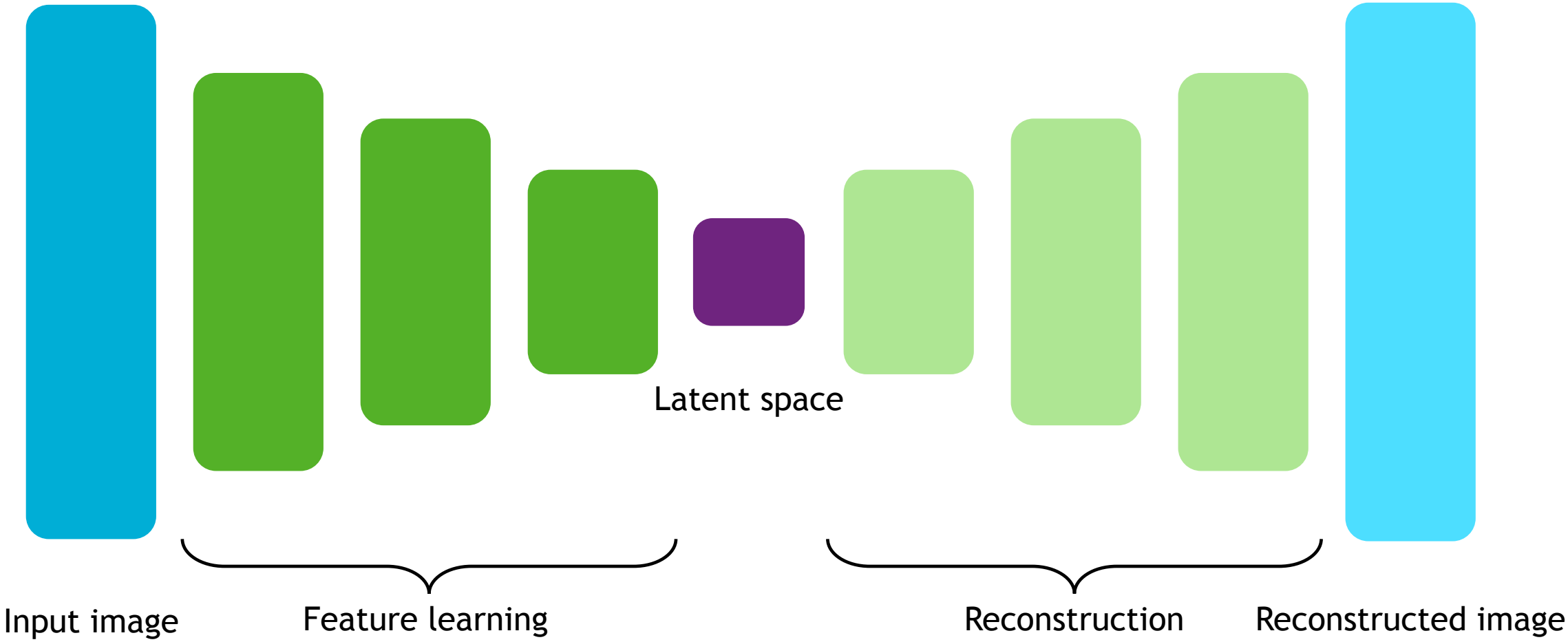
Convolutional neural networks

CNNs for many applications



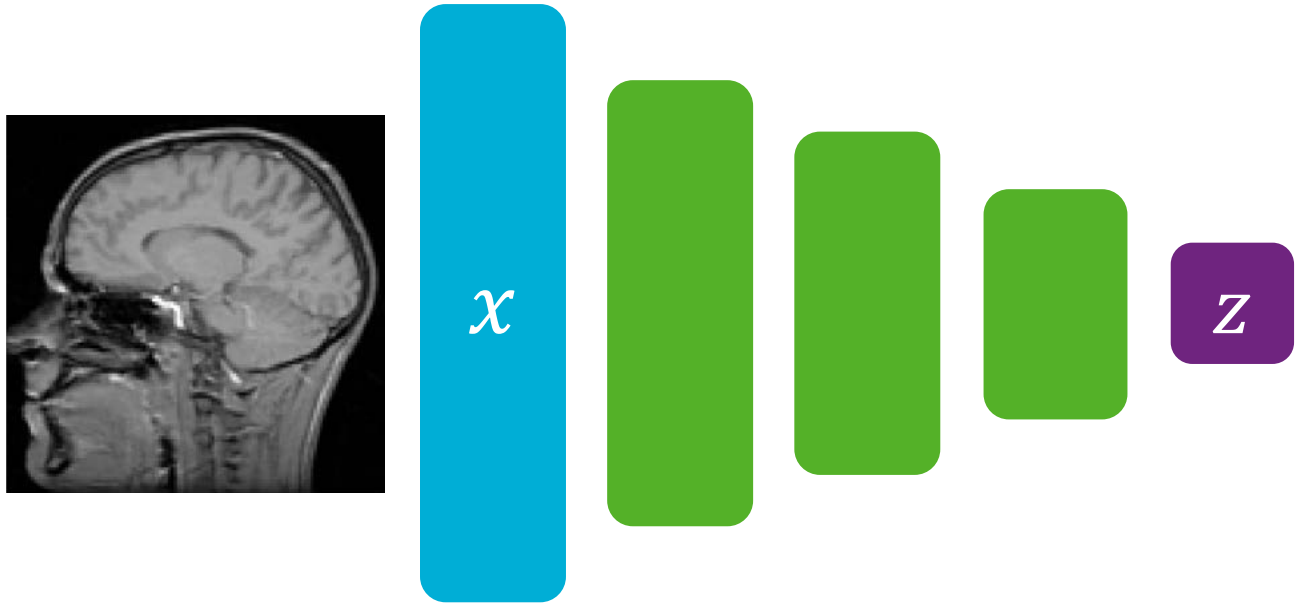
Convolutional neural networks

CNNs for image generation



Autoencoders

Encoder

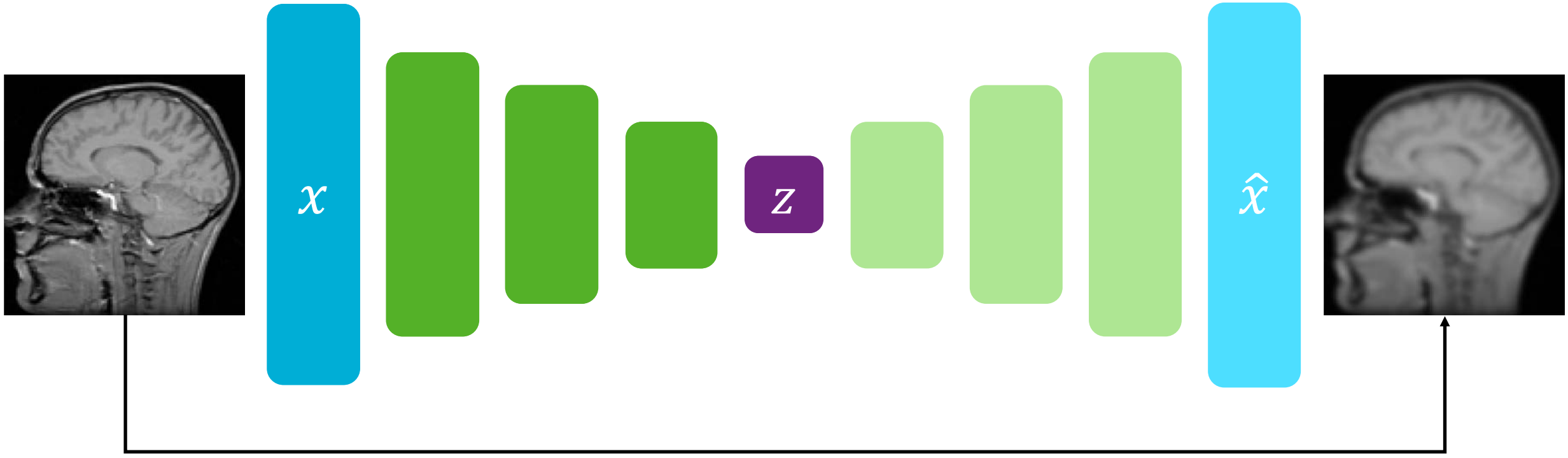


Input image
=
observed data

Latent space
=
low dimensional representation
of the observed data

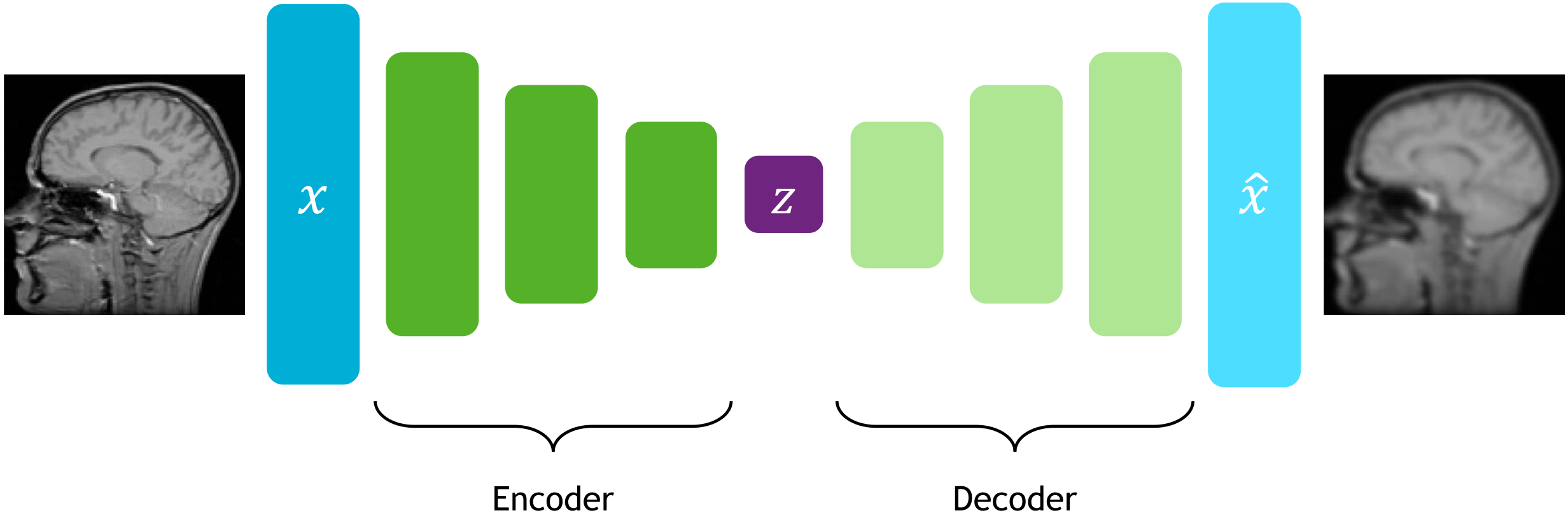
Autoencoders

Training autoencoders

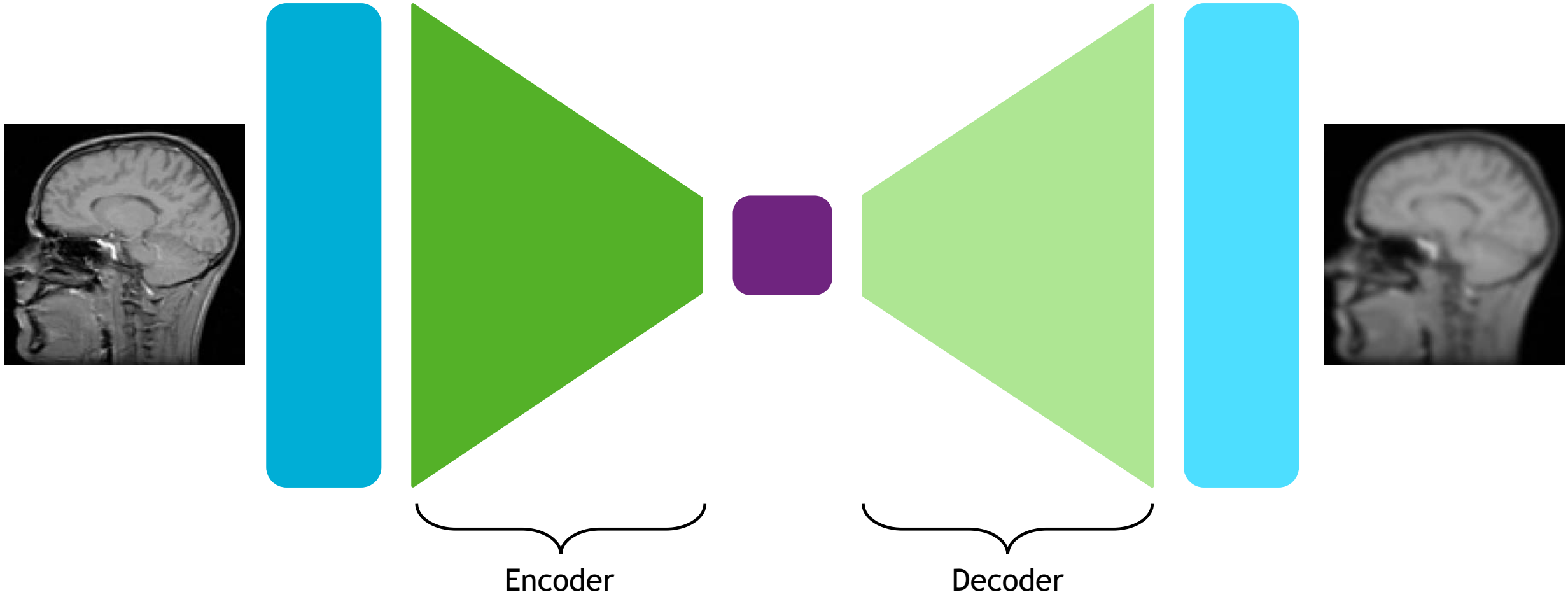


$$\mathcal{L}(x, \hat{x}) = \|x - \hat{x}\|^2$$

Autoencoders



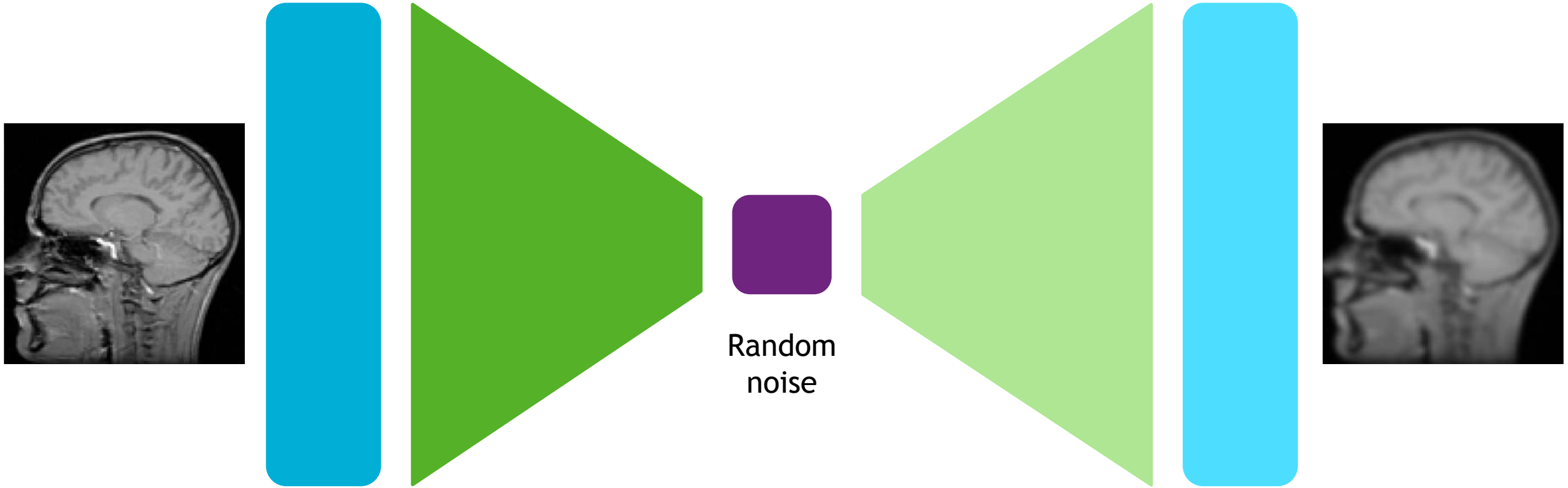
Autoencoders



MIT Introduction to Deep Learning (introtodeeplearning.com)

Generative adversarial networks

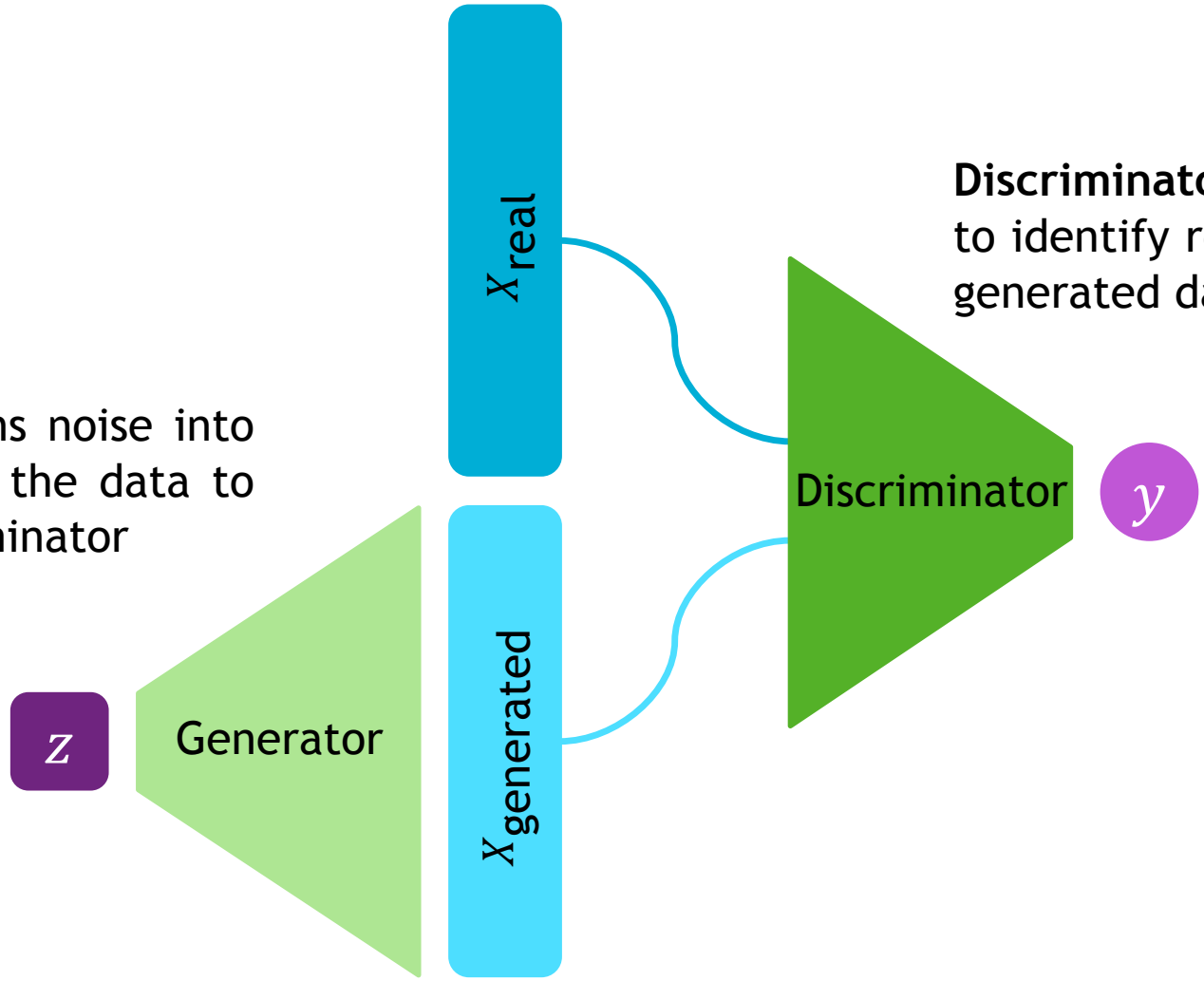
Generating images from scratch



Generative adversarial networks

Competing networks

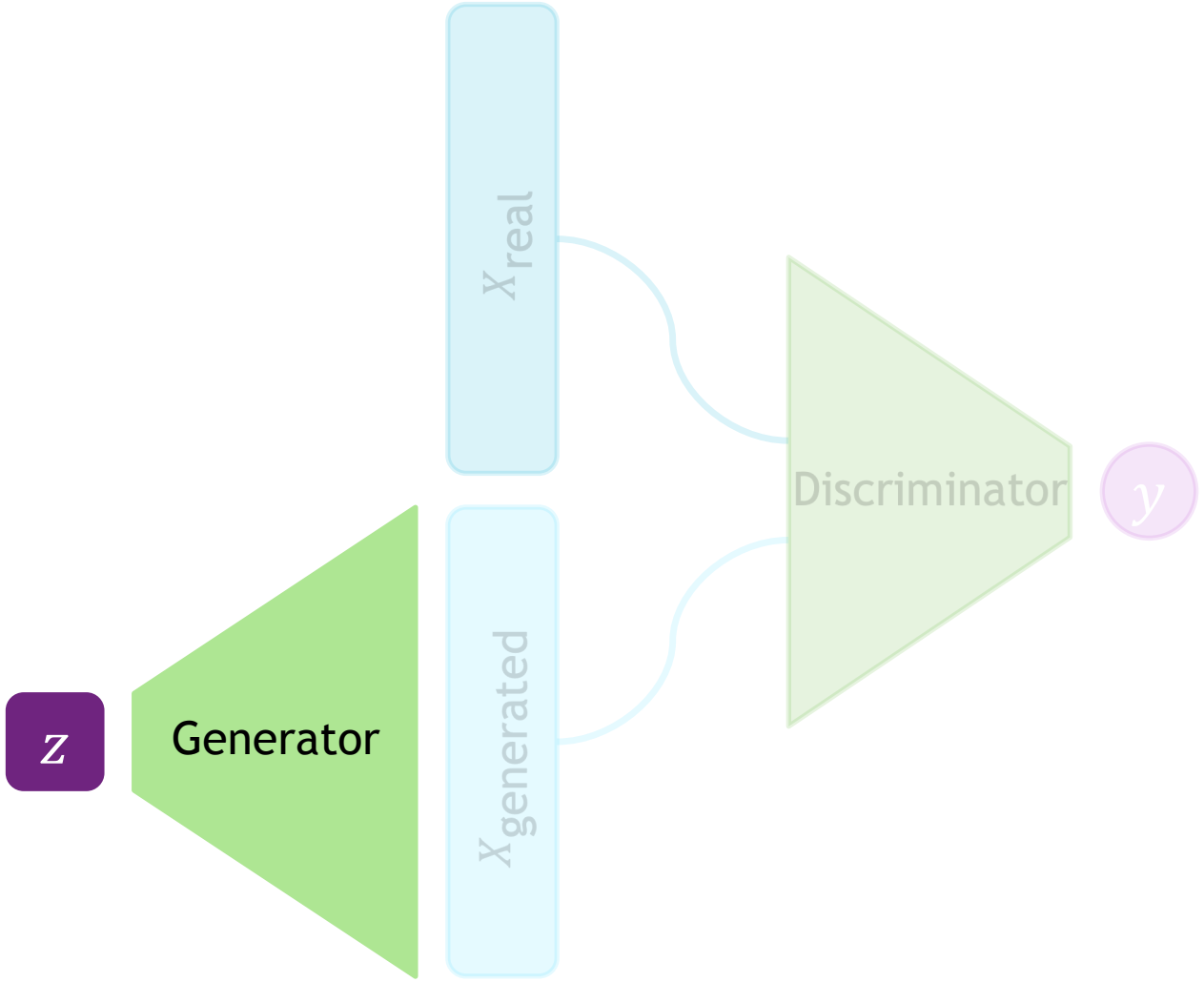
Generator: turns noise into an imitation of the data to trick the discriminator



Discriminator: tries to identify real from generated data

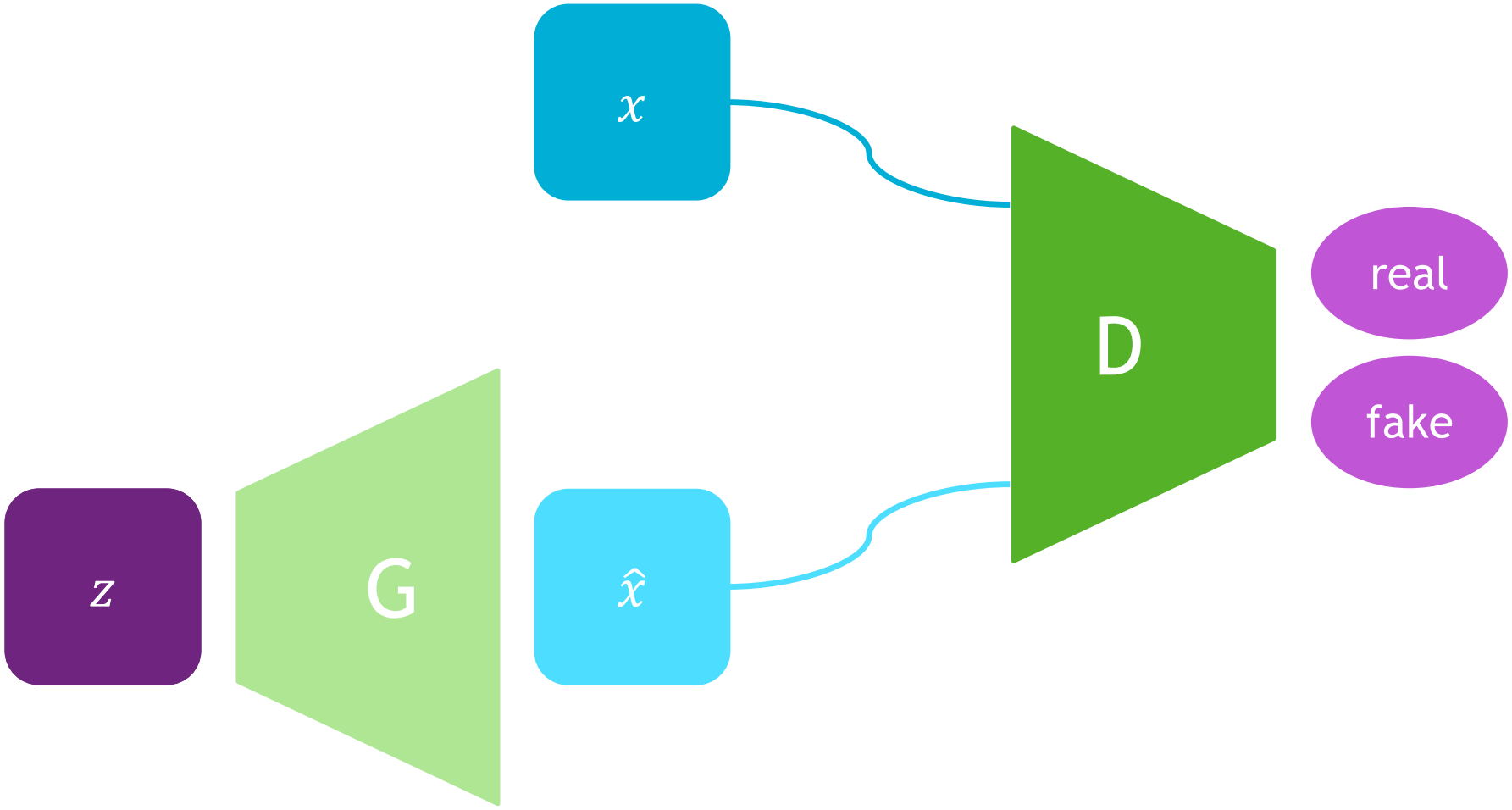
Generative adversarial networks

Generating new images



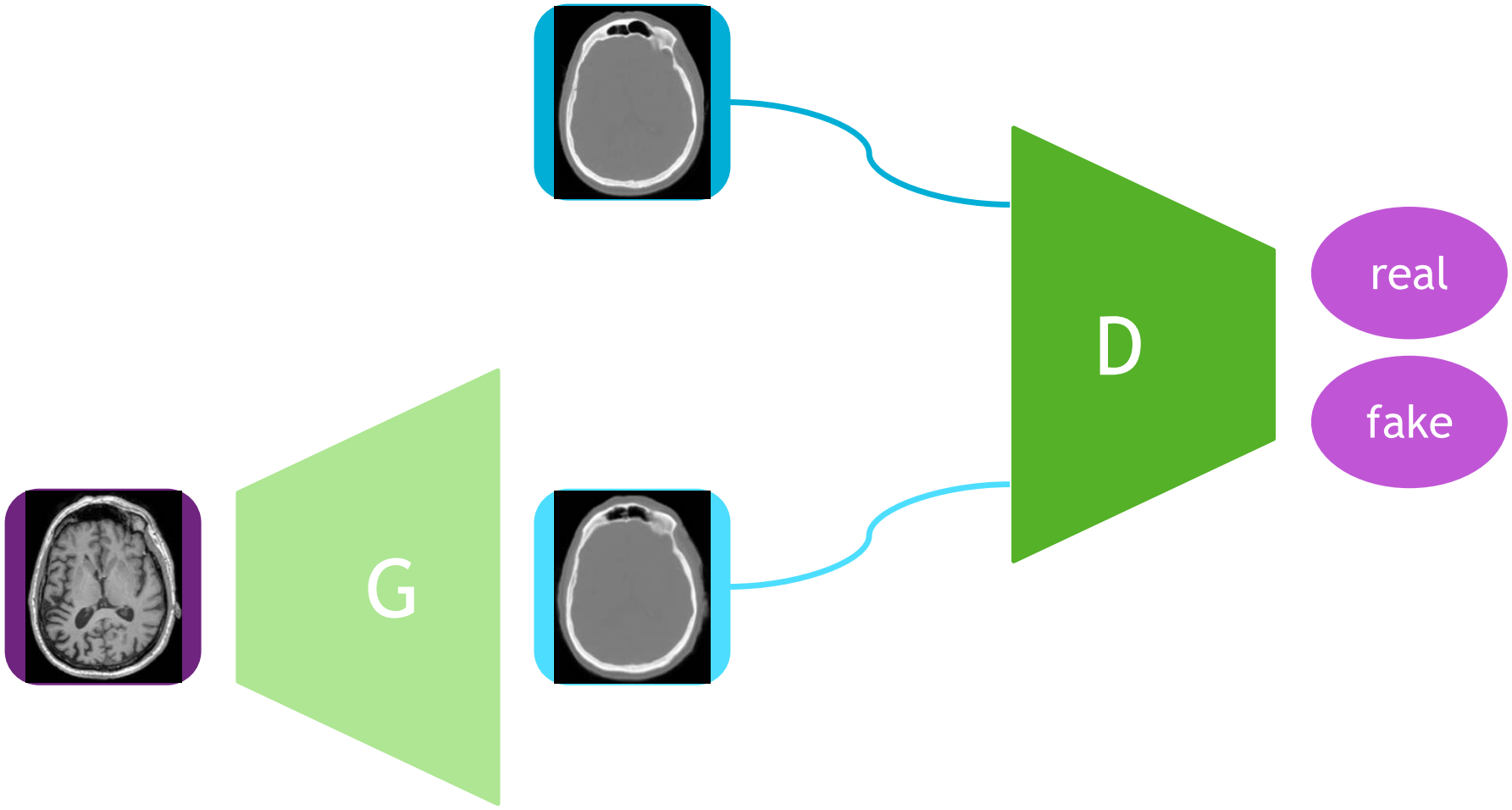
Generative adversarial networks

Image translation with conditional GANs



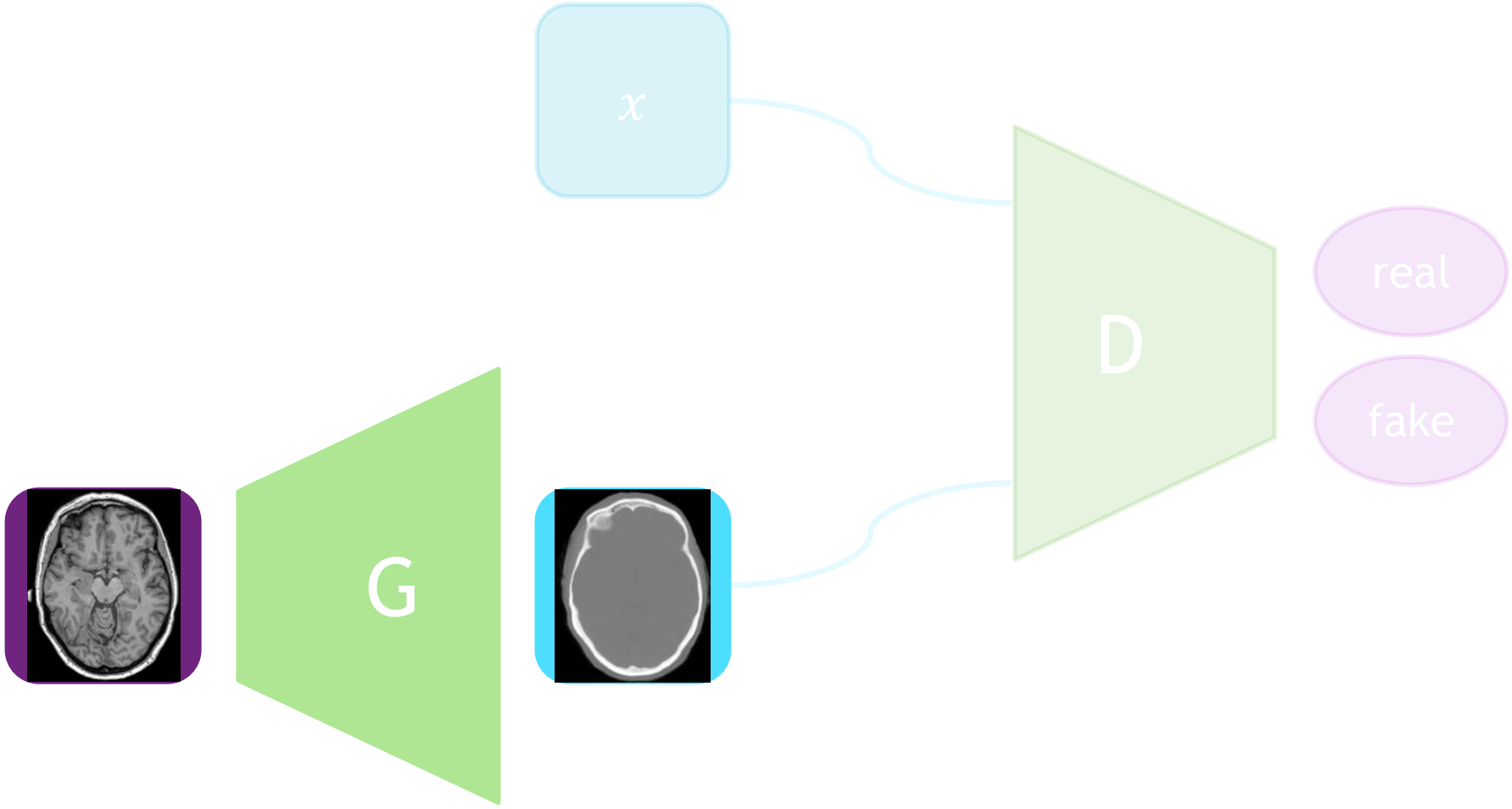
Generative adversarial networks

Image translation with conditional GANs



Generative adversarial networks

Image translation with conditional GANs



Generative adversarial networks

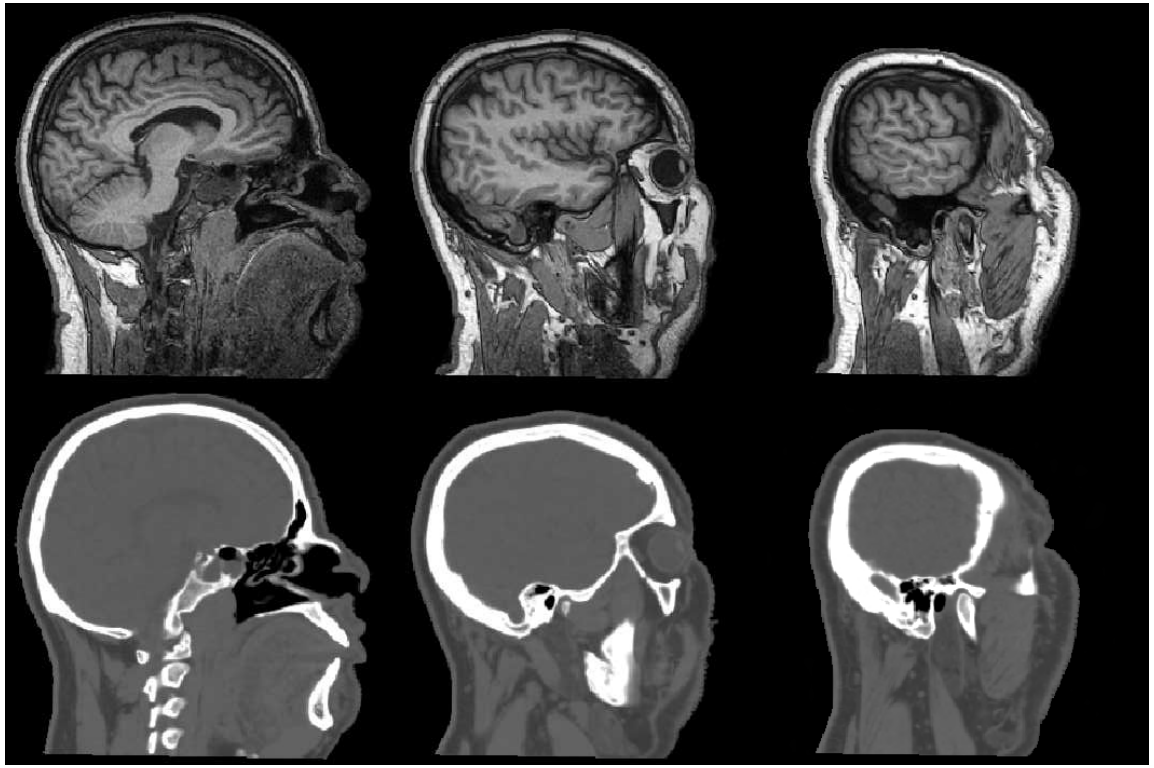
Dealing with unpaired data

Paired data

Unpaired data

MR

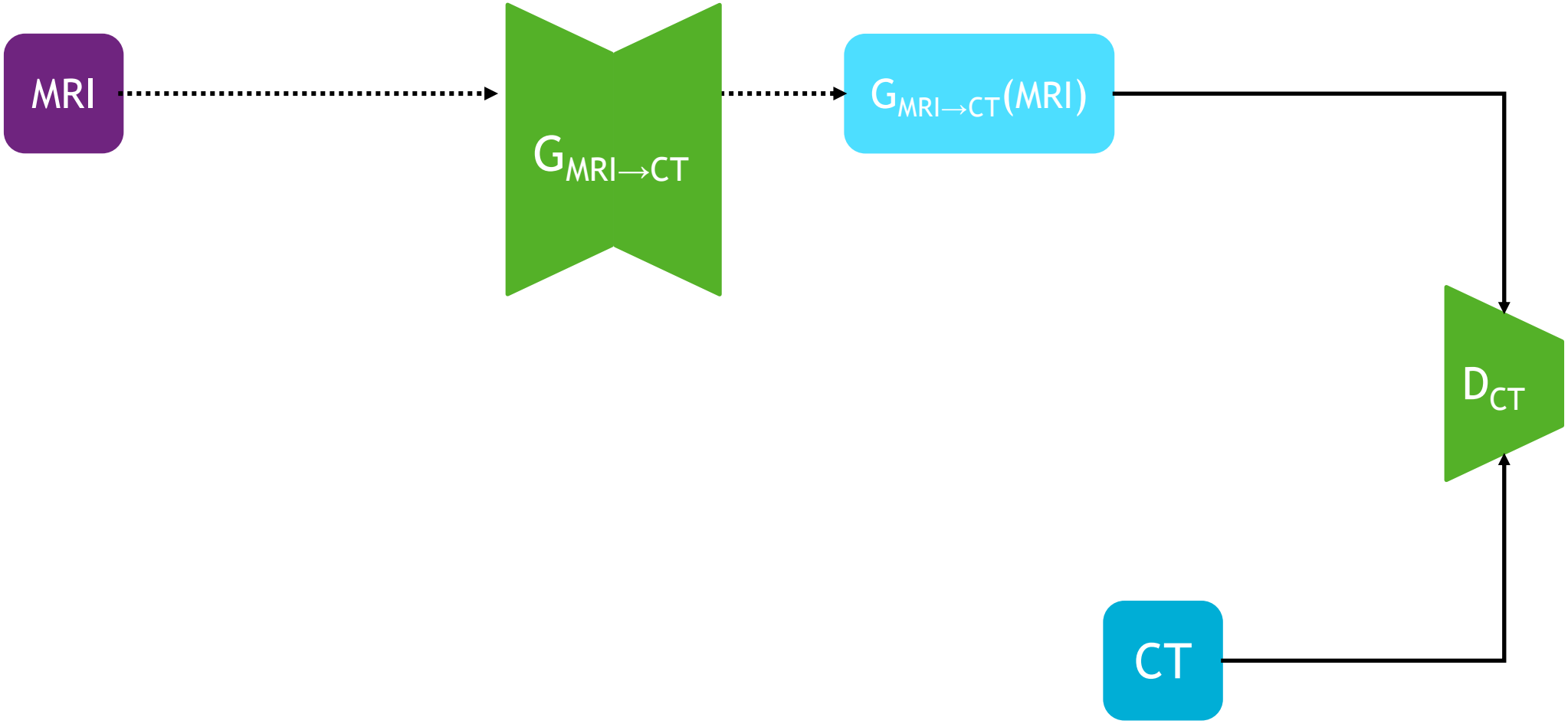
CT



Wolterink et al., SASHIMI, 2017

Generative adversarial networks

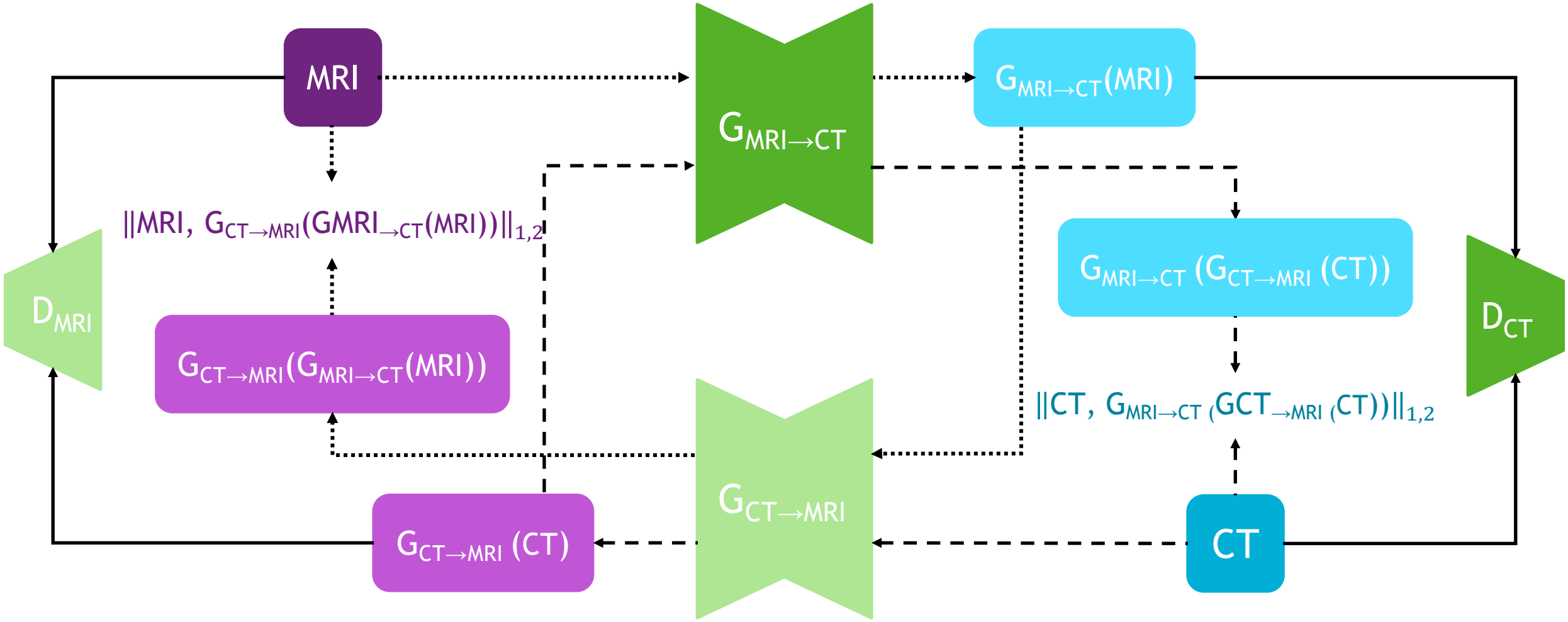
GANs



Isola et al., Image-to-Image Translation with Conditional Adversarial Networks, CVPR 2017

Generative adversarial networks

Cycle GANs

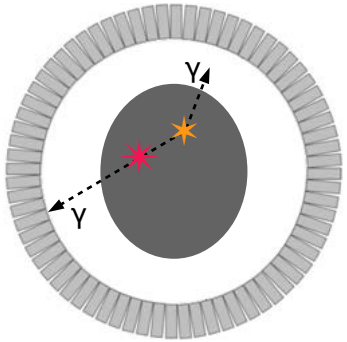


Zhu et al., Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, ICCV 2017

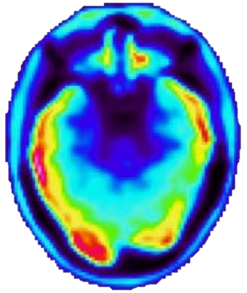
Application examples

Image synthesis

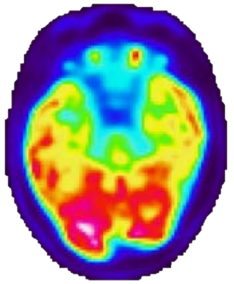
Attenuation correction for PET/MR scanners



Attenuation



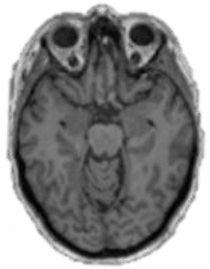
PET without attenuation correction



PET with attenuation correction

Solution

- Synthesise CT from MR images

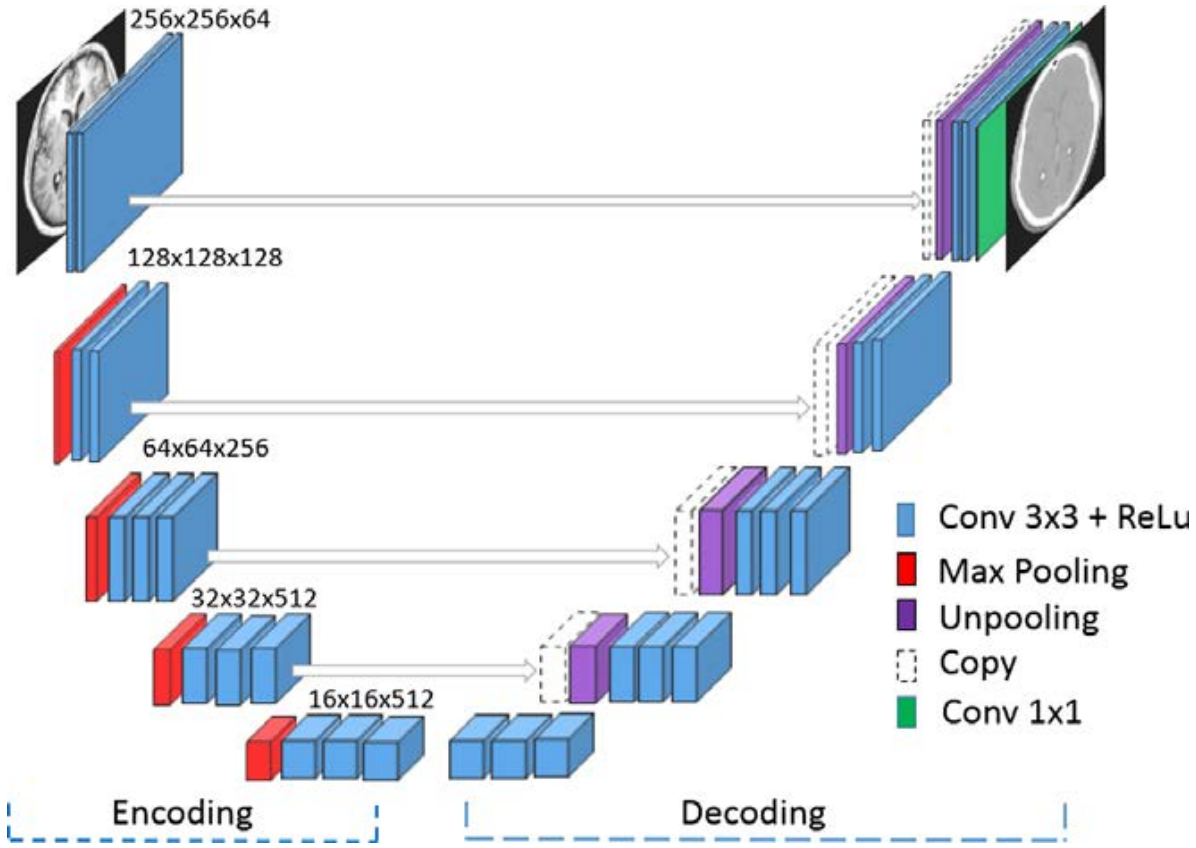


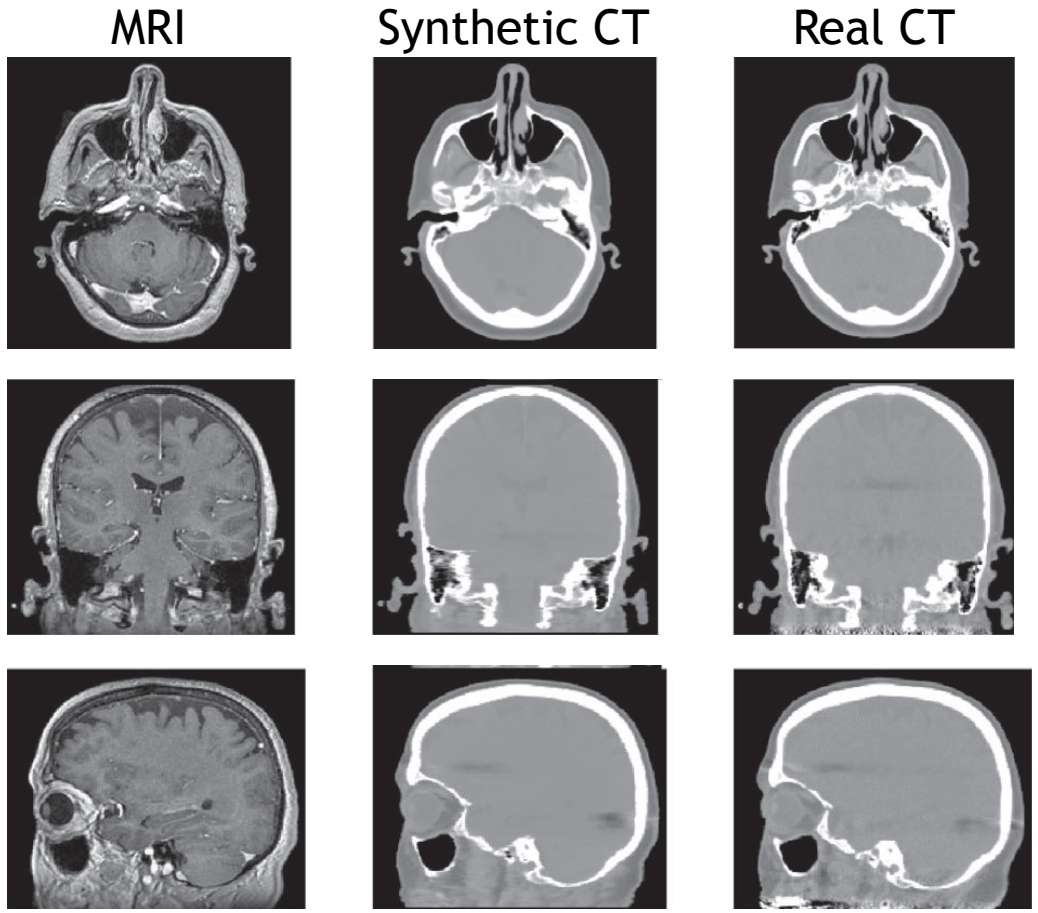
MRI

CT

Image synthesis

MR-based synthetic CT generation using a deep CNN method

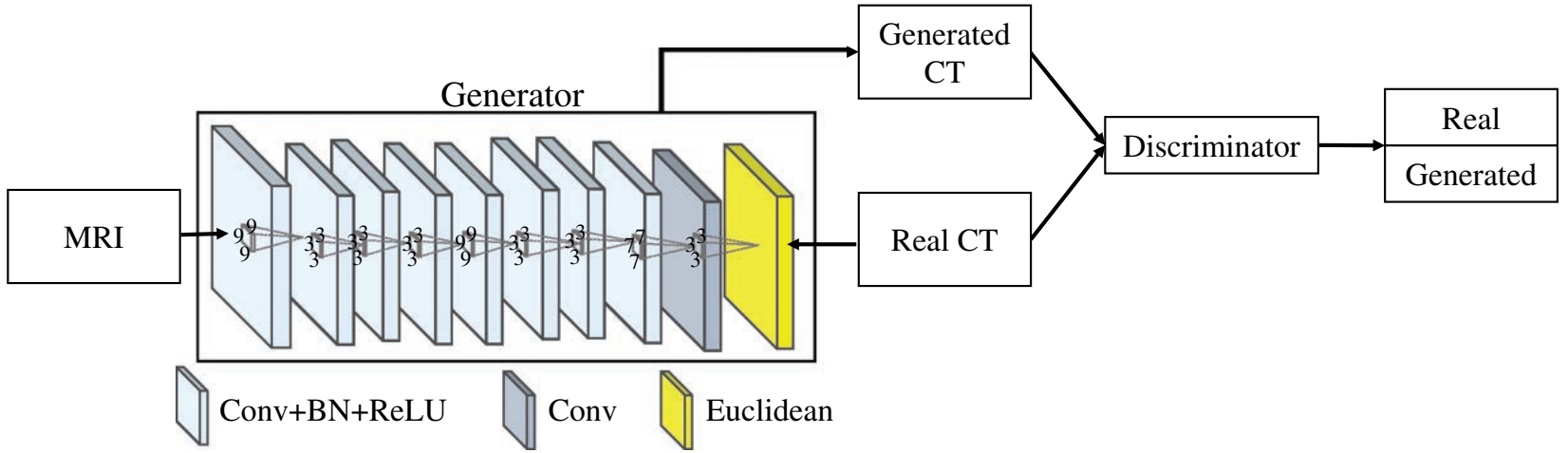


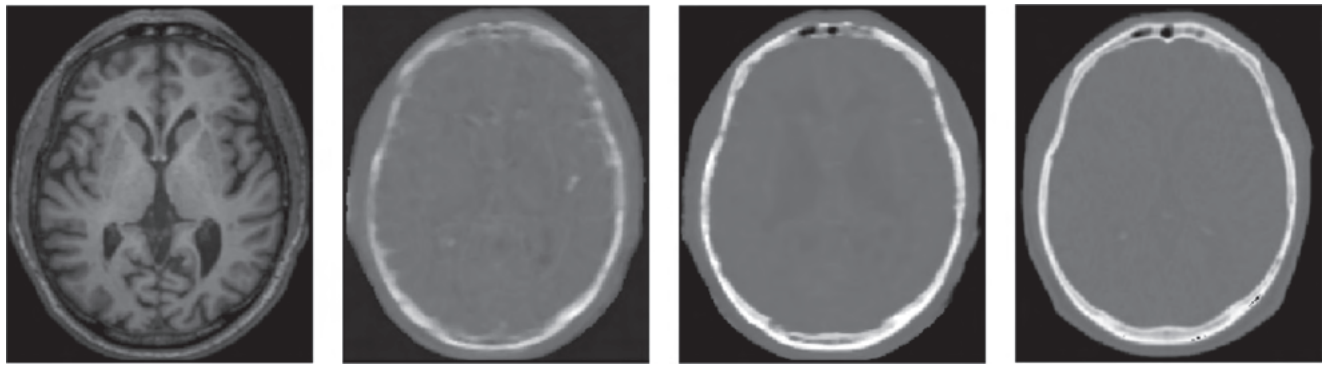


Han, Medical Physics, 2017

Image synthesis

Medical Image Synthesis with Context-Aware GANs





Nie et al., MICCAI, 2017

Image synthesis

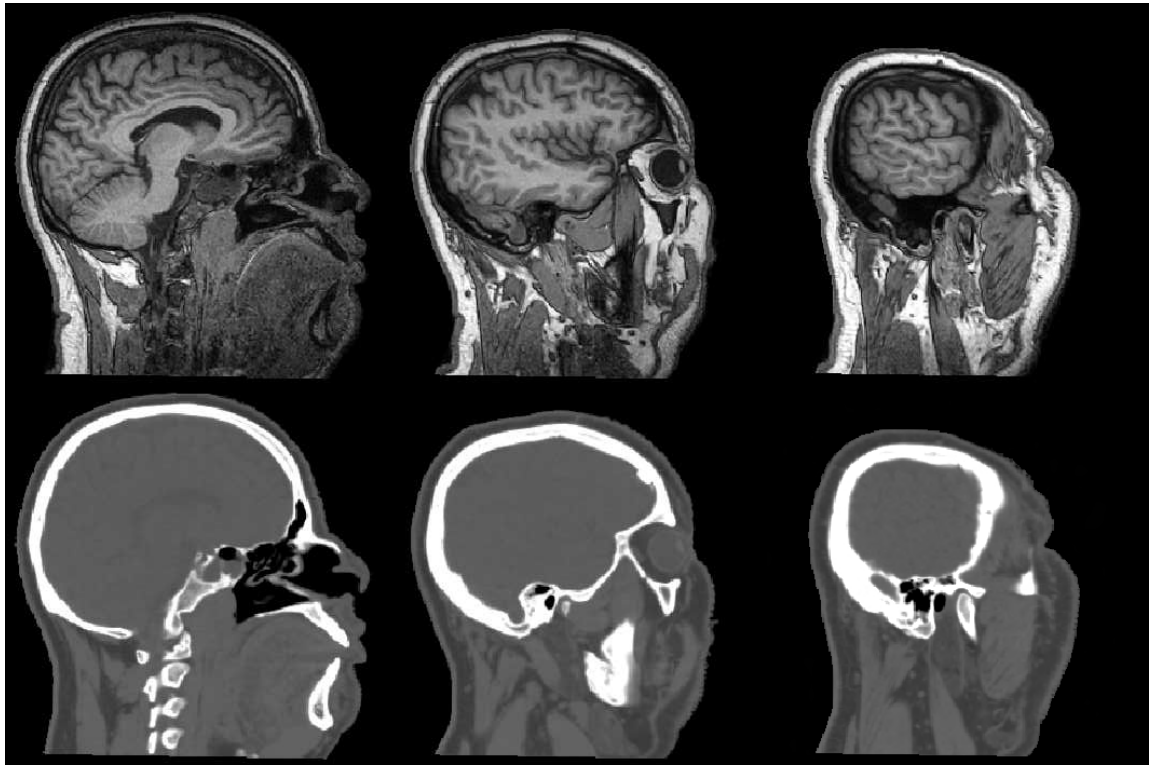
Deep MR to CT Synthesis using Unpaired Data

Paired data

Unpaired data

MR

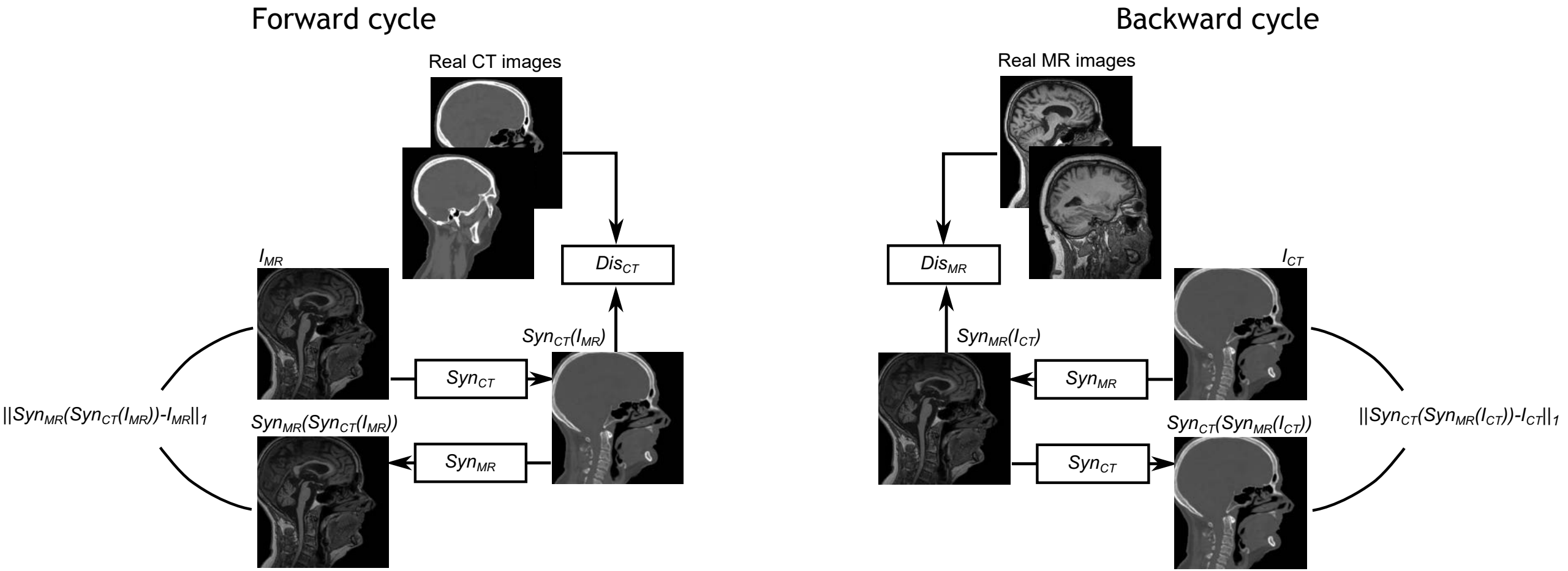
CT



Wolterink et al., SASHIMI, 2017

Image synthesis

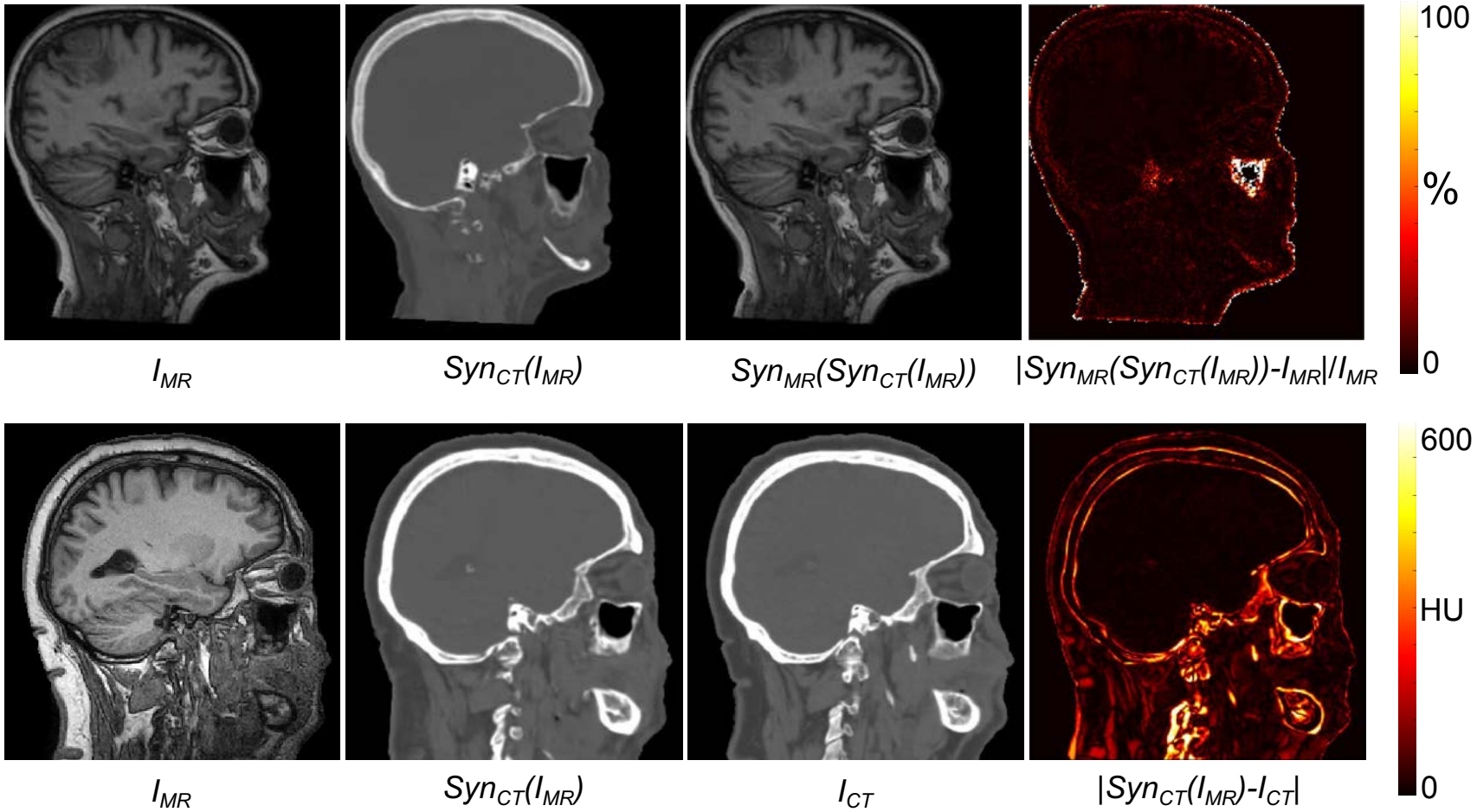
Deep MR to CT Synthesis using Unpaired Data



Wolterink et al., SASHIMI, 2017

Image synthesis

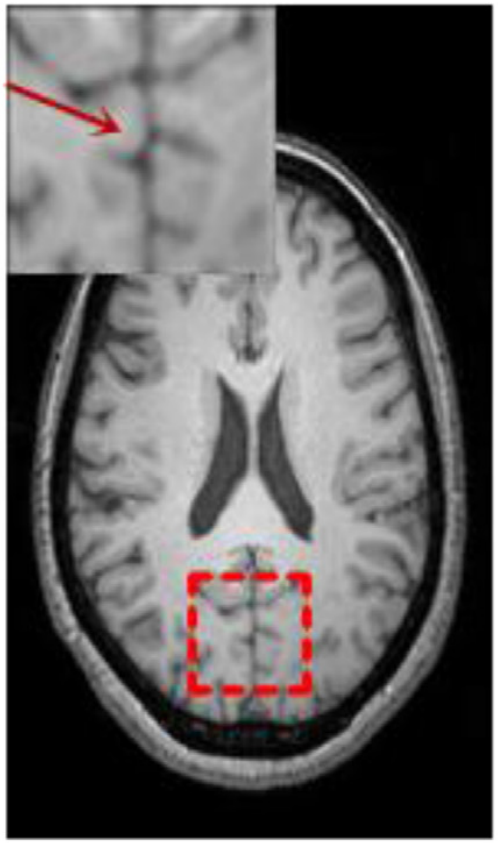
Deep MR to CT Synthesis using Unpaired Data



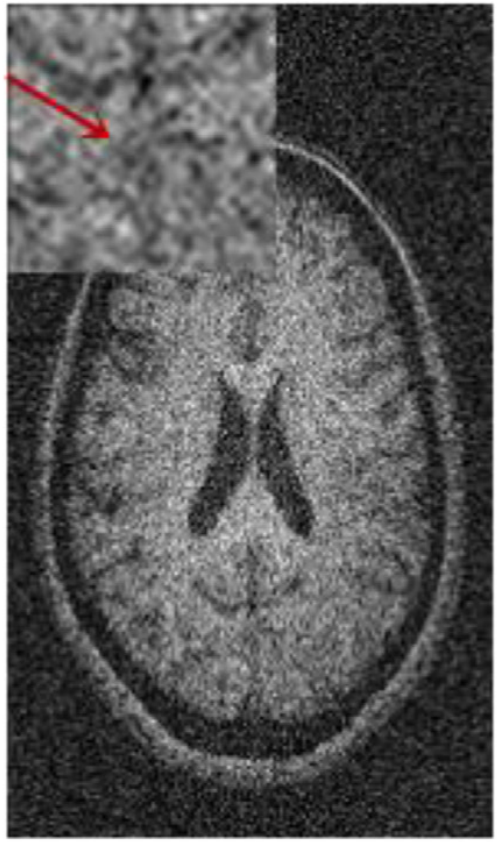
Wolterink et al., SASHIMI, 2017

Image denoising

Magnetic resonance imaging (MRI)



Noise-free MRI



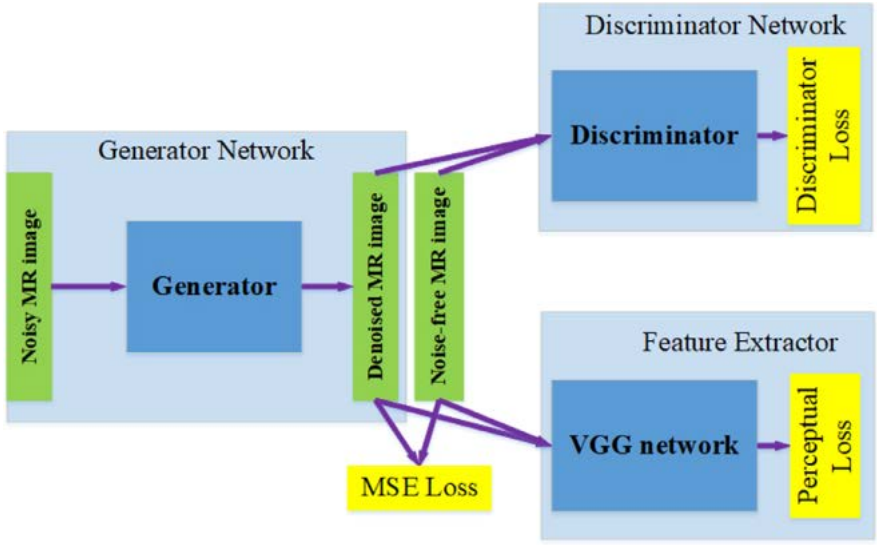
Noisy MRI

Ran et al., Medical Image Analysis, 2019

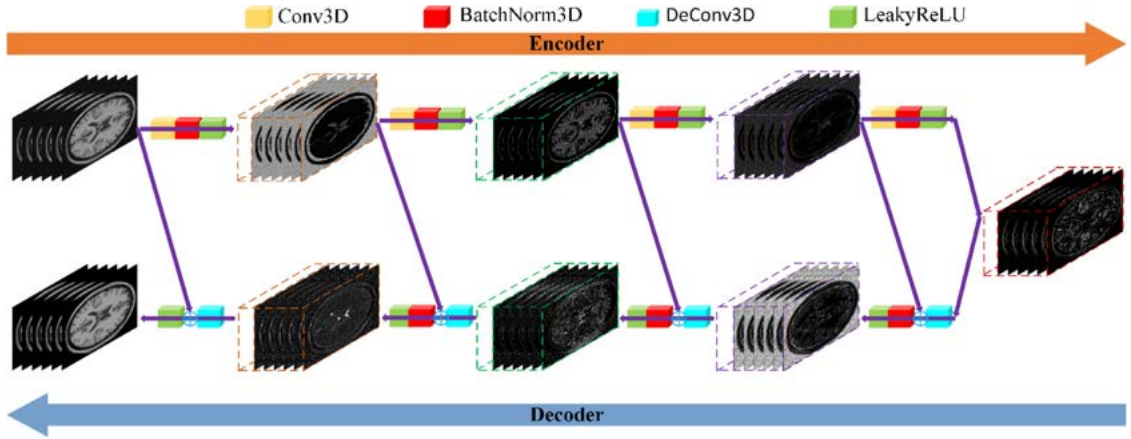
Image denoising

Denoising of 3D MRI using a residual encoder-decoder Wasserstein GAN

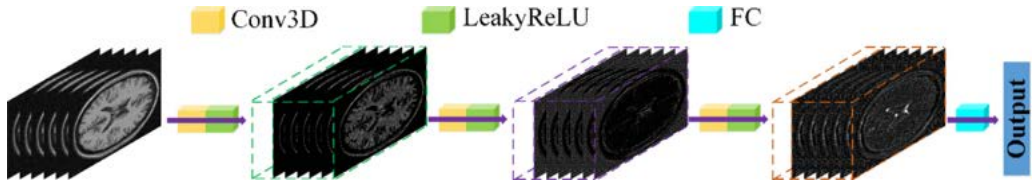
Overall architecture



Generator



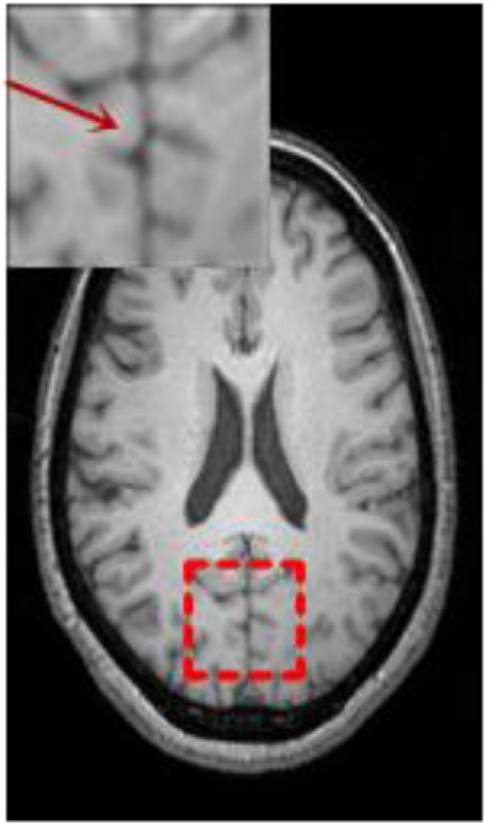
Discriminator



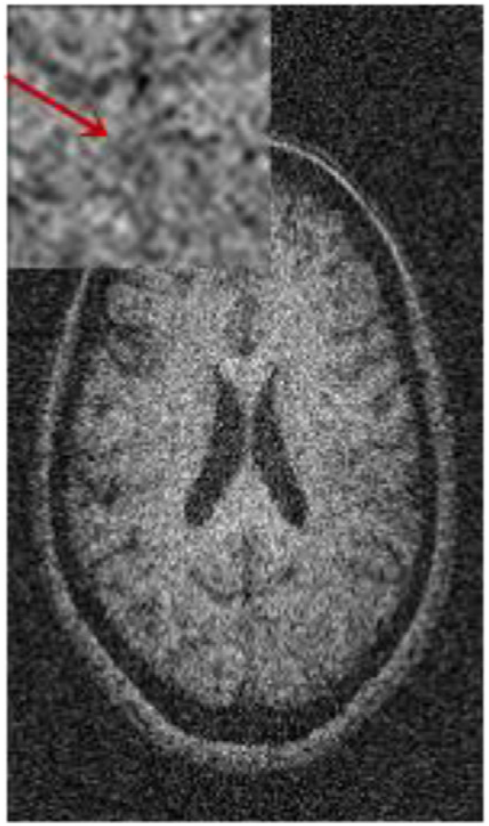
Ran et al., Medical Image Analysis, 2019

Image denoising

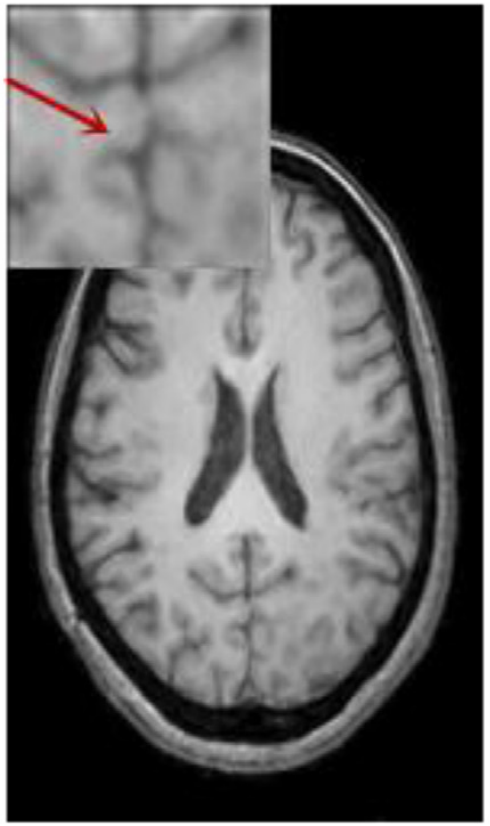
Denoising of 3D MRI using a residual encoder-decoder Wasserstein GAN



Noise-free MRI



Noisy MRI

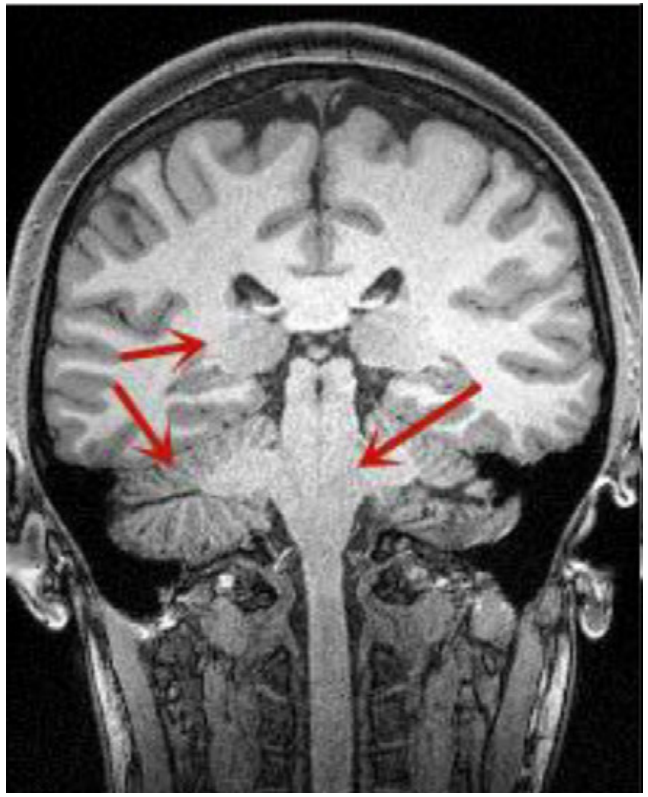


Denoised MRI

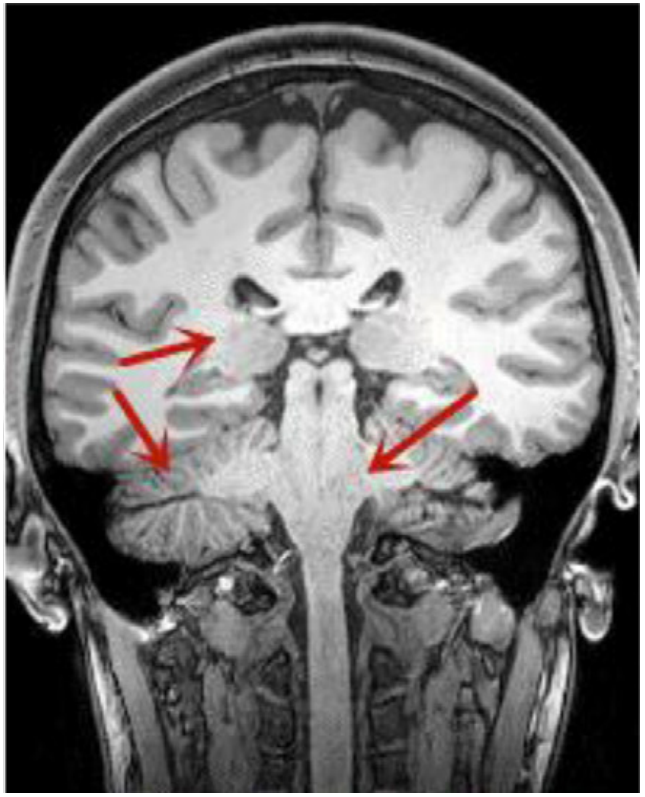
Ran et al., Medical Image Analysis, 2019

Image denoising

Denoising of 3D MRI using a residual encoder-decoder Wasserstein GAN



Original noisy MRI



Denoised MRI

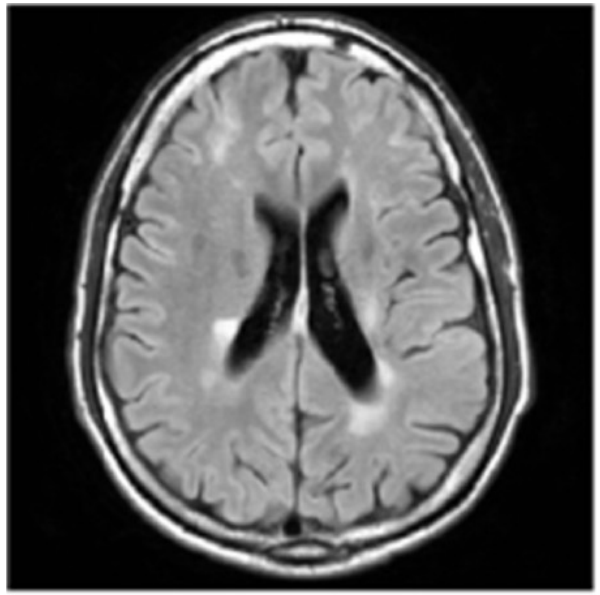
Ran et al., Medical Image Analysis, 2019

Image super-resolution

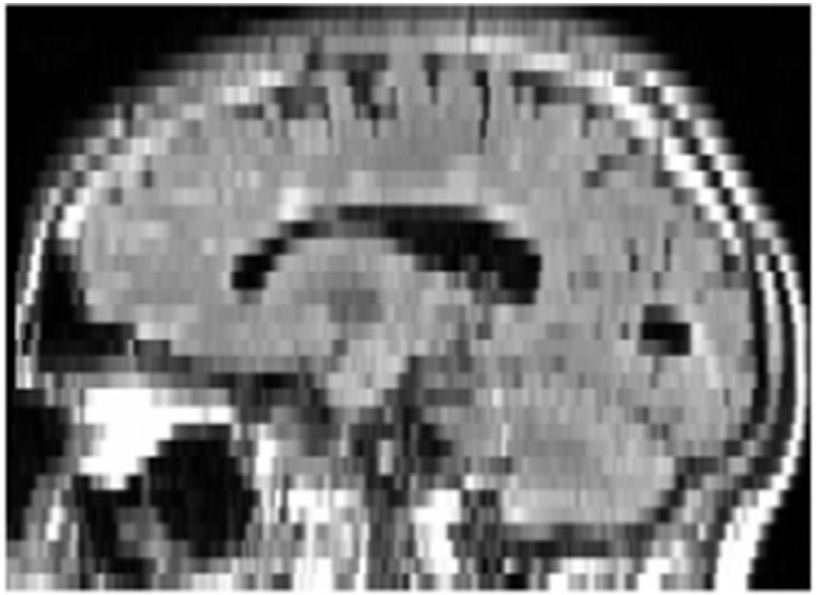
2D MRI

$0.8 \times 0.8 \times 4.4$ mm

Axial



Sagittal

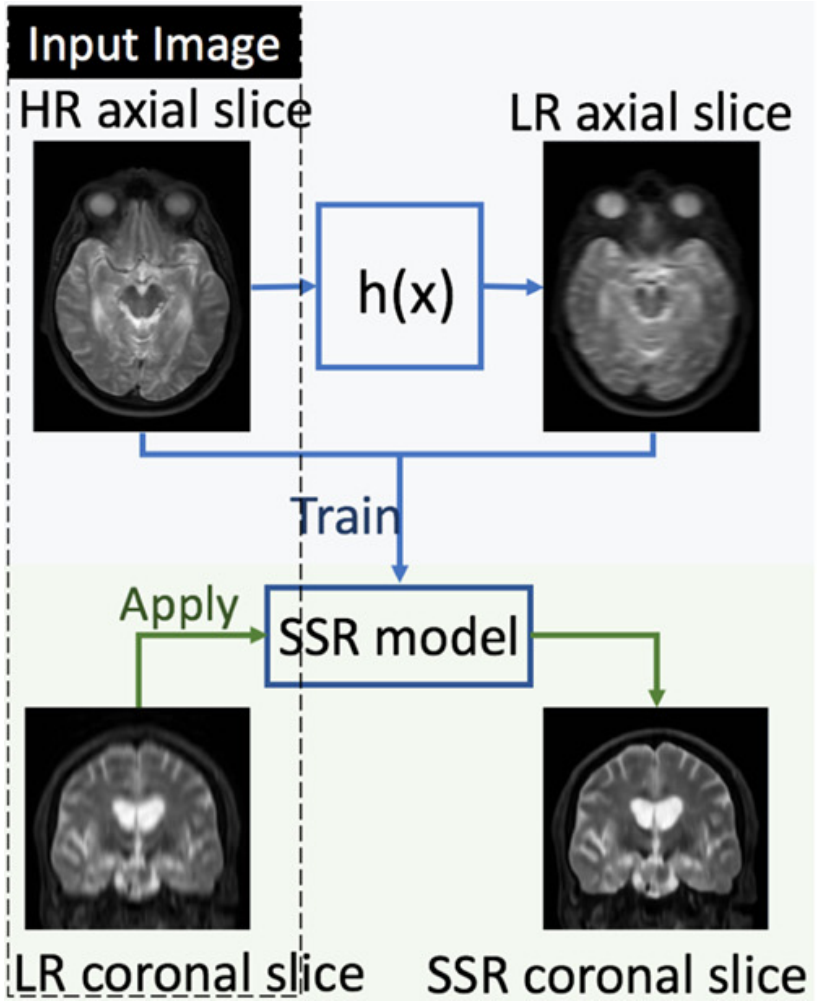


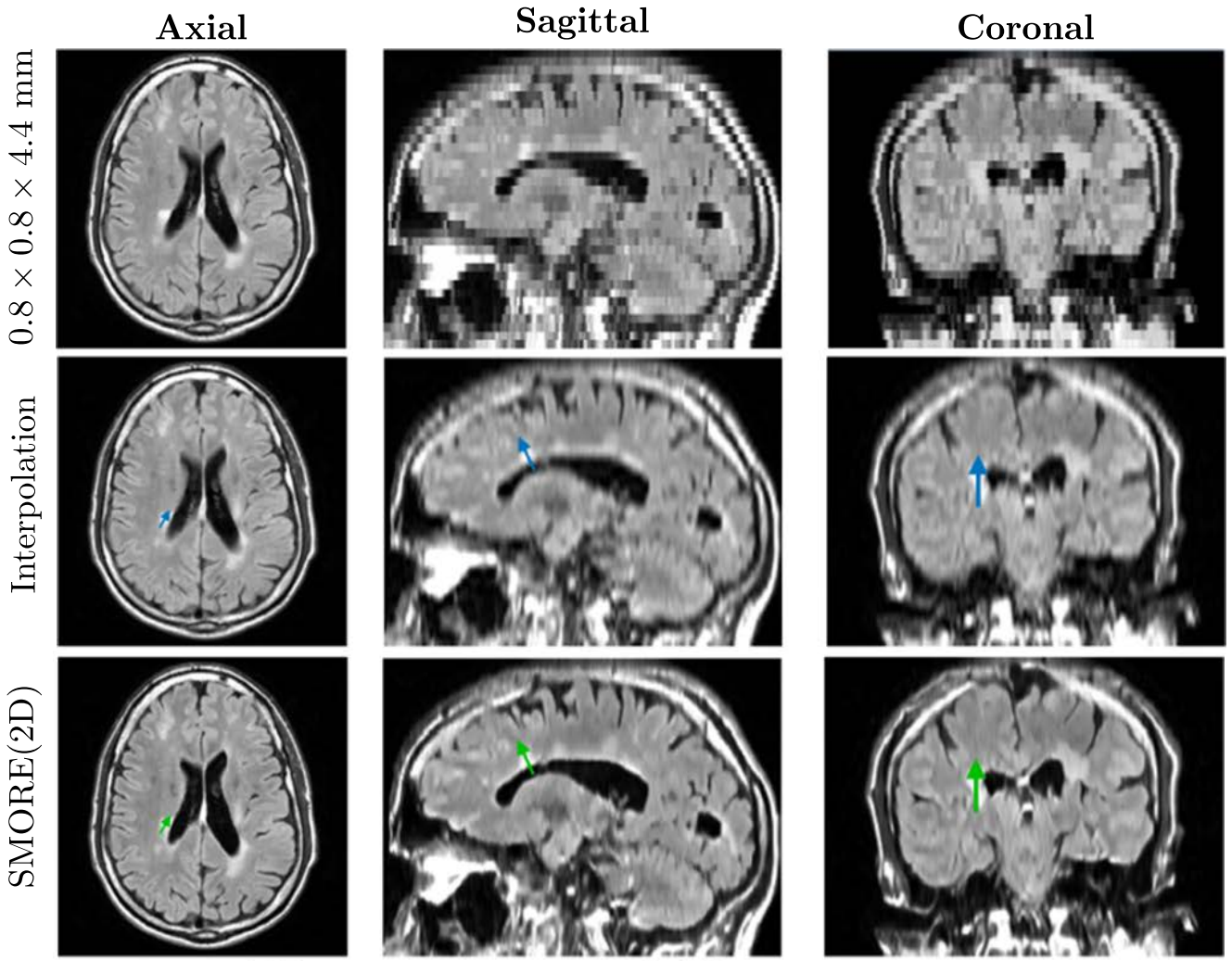
Coronal

Zhao et al., Magnetic Resonance Imaging, 2019

Image super-resolution

Self super-resolution for MRI

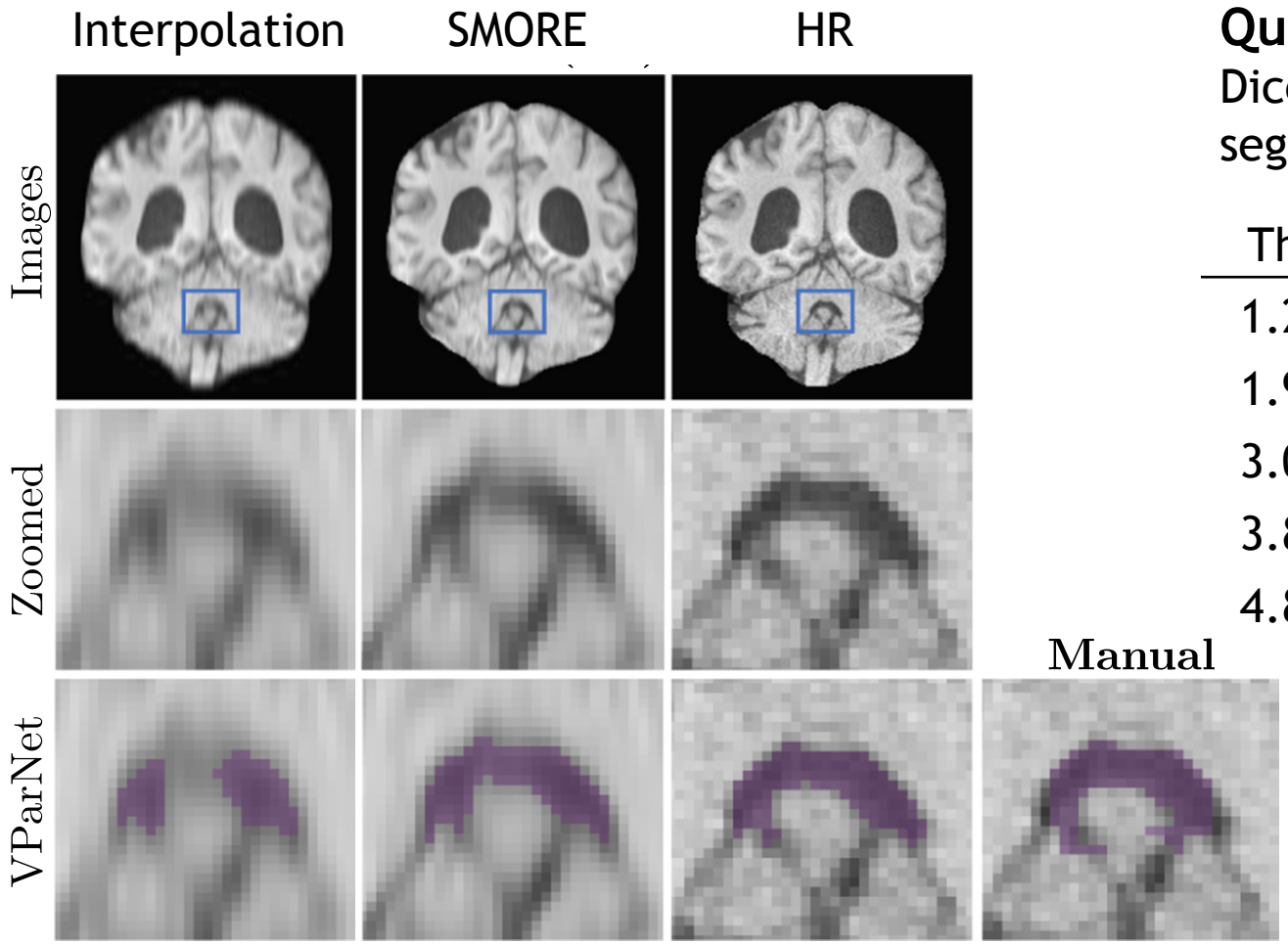




Zhao et al., Magnetic Resonance Imaging, 2019

Image super-resolution

Self super-resolution for MRI



Quantitative results

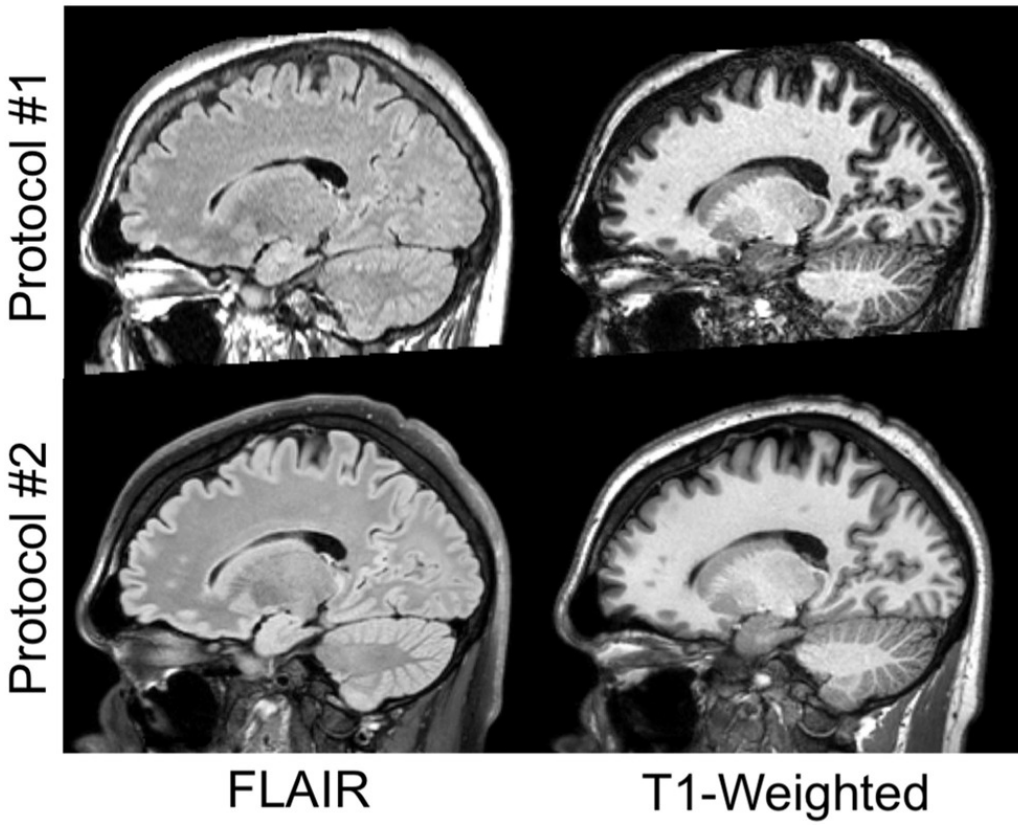
Dice score (overlap between manual and automatic segmentations)

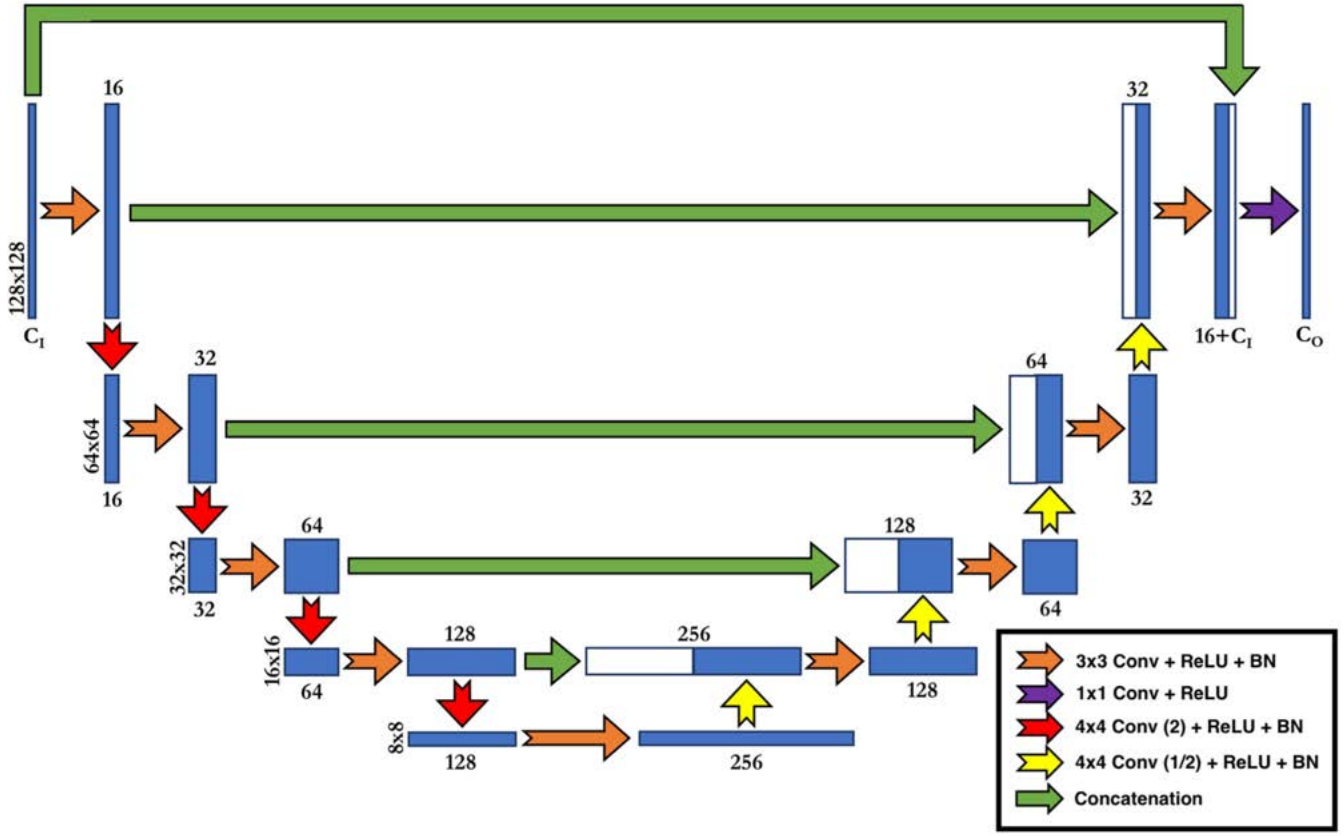
Thickness	Interpolation	SMORE	HR (0.9 mm)
1.205 mm	0.969	0.9696	0.9699
1.928 mm	0.9665	0.9690	
3.0125 mm	0.9602	0.9675	
3.856 mm	0.9524	0.9632	
4.82 mm	0.9408	0.9607	

Zhao et al., Magnetic Resonance Imaging, 2019

Image standardisation

DeepHarmony: A deep learning approach to contrast harmonization across scanner changes





Dewey et al., Magnetic Resonance Imaging, 2019

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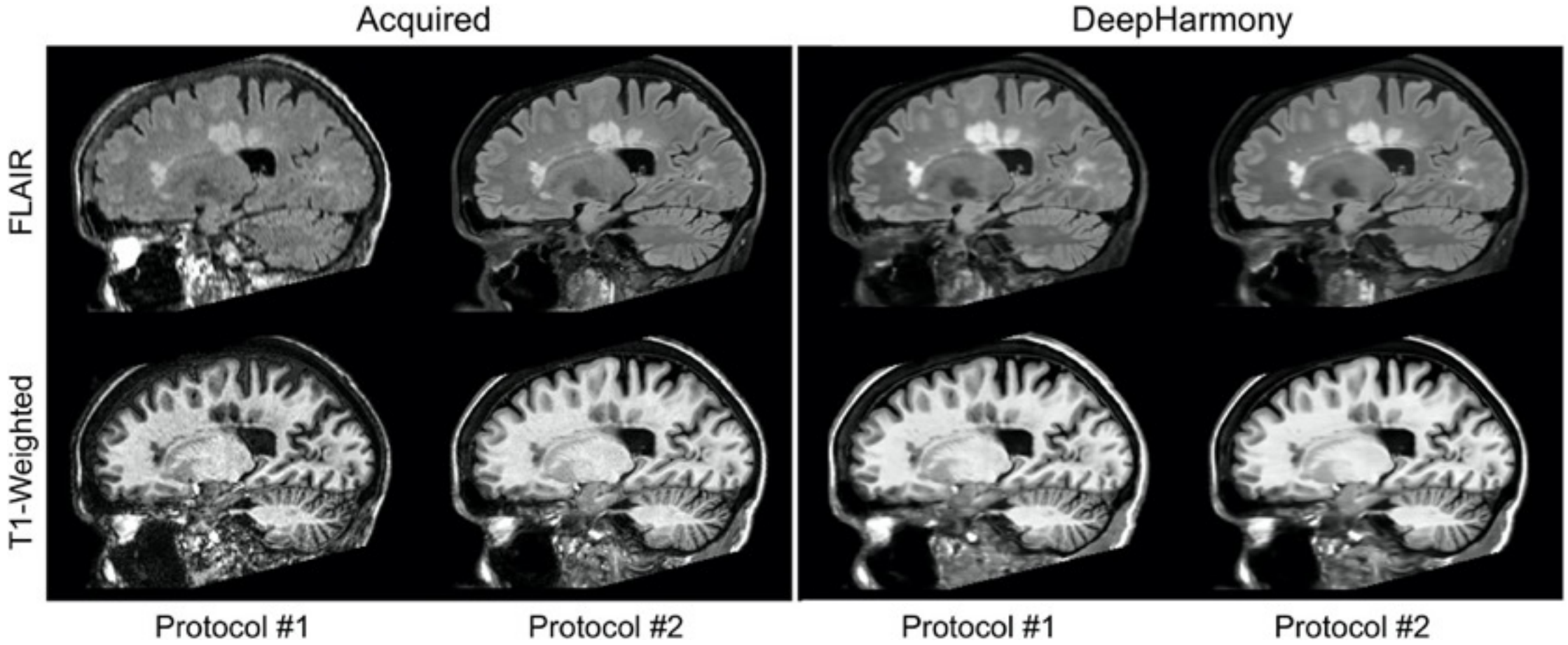

Dewey et al., Magnetic Resonance Imaging, 2019

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AI4Health School 2021

Practical session DL4MI

Medical image synthesis with deep learning

Principle and applications

https://aramislab.paris.inria.fr/workshops/DL4MI