ARAMIS LAB
BRAIN DATA SCIENCE

www.aramislab.fr

ninonburgos.com

ESIA
-
15 mai 2023

IA pour l'imagerie médicale :

de l'acquisition des images au pronostic

Ninon Burgos

Chargée de recherche CNRS & Chaire PR[AI]RIE

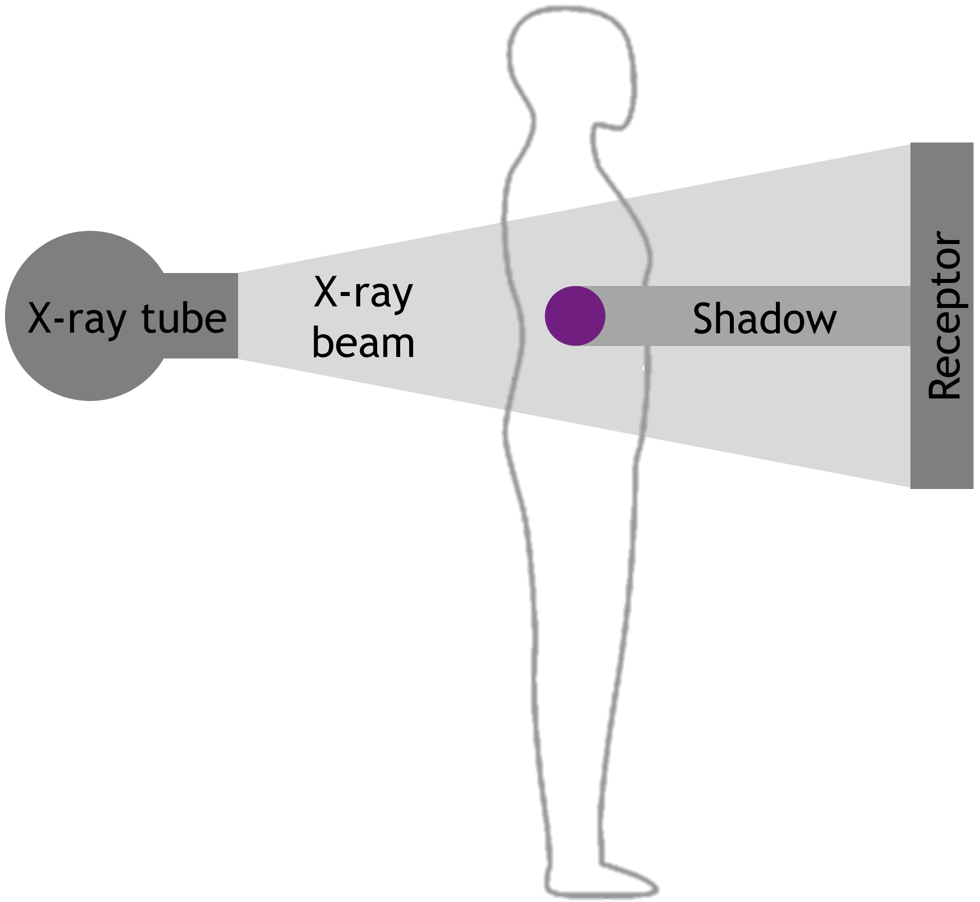
Institut du Cerveau, Paris

cnrs ICM Paris Brain Institute Inserm SORBONNE UNIVERSITÉ Inria PR[AI]RIE PaRis Artificial Intelligence Research InstitutE

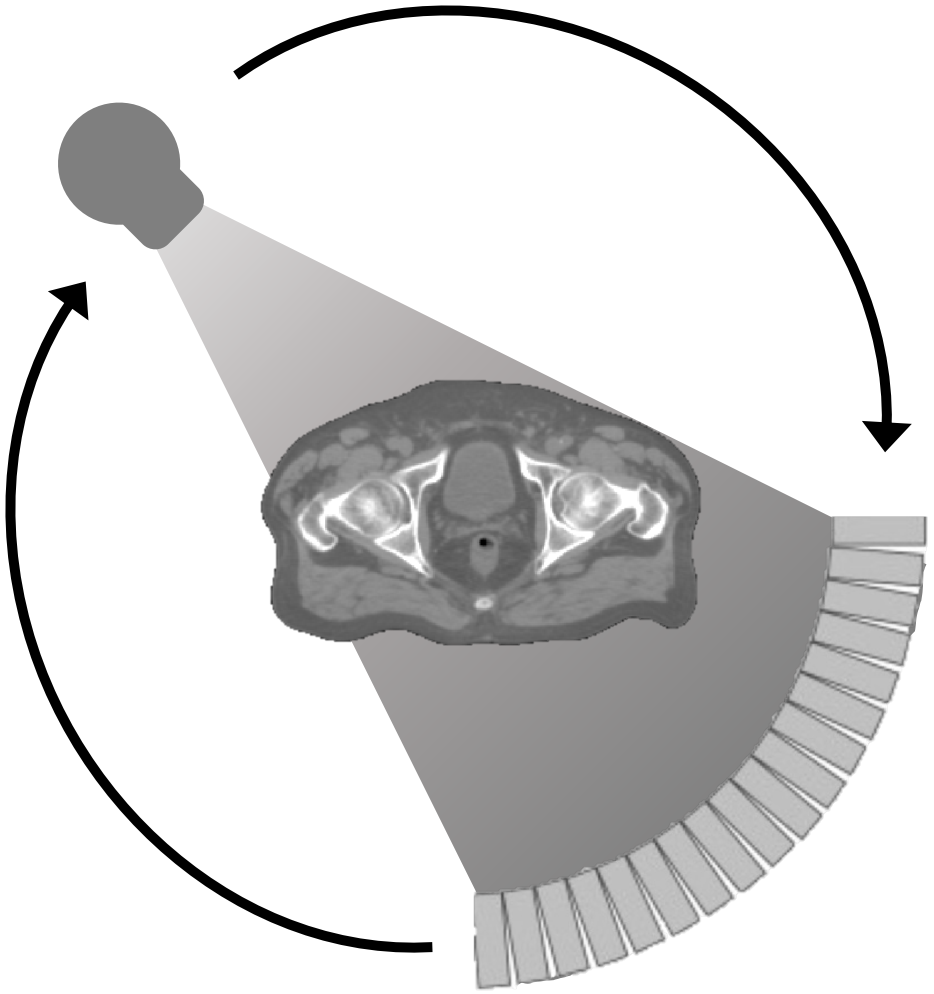
Medical imaging

X-ray computed tomography

X-ray image contrast



X-ray computed tomography (3D)



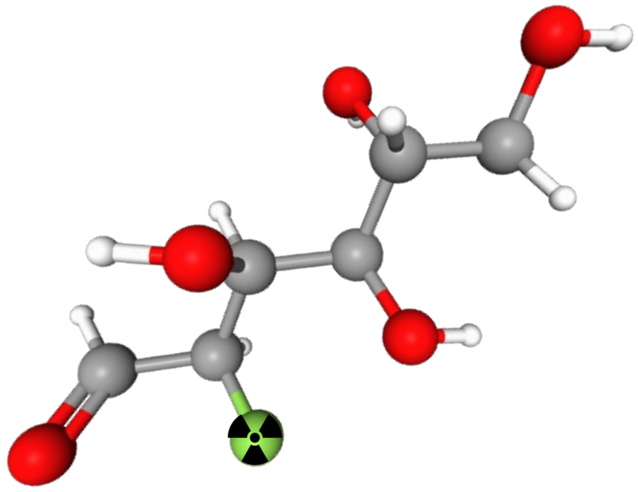
X-ray computed tomography

Hand X-Ray

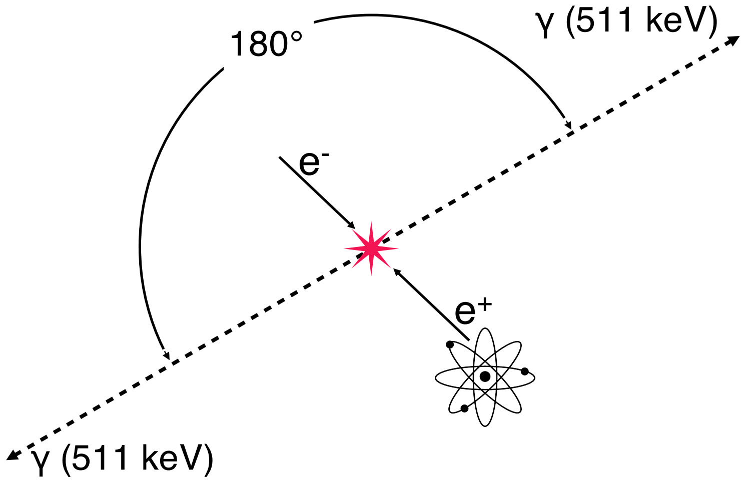
Abdomen CT

Case courtesy of Dr Mohammad A. ElBeialy (rID: 47341) and Dr René Pfleger (rID: 40922), Radiopaedia.org

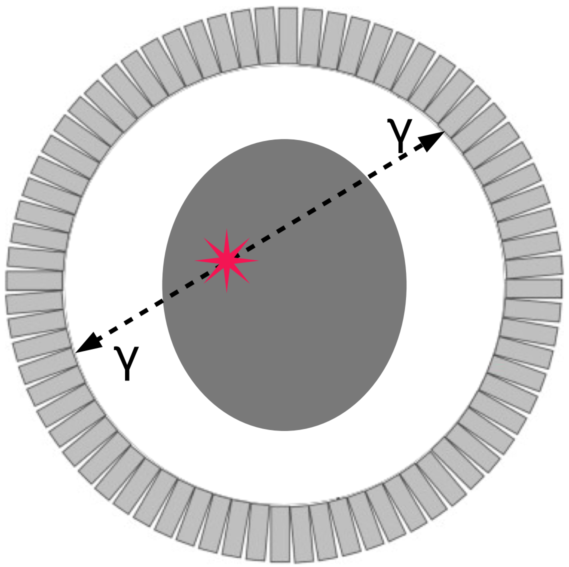
Positron emission tomography



Radiotracer
(molecule marked with a radioactive atom)

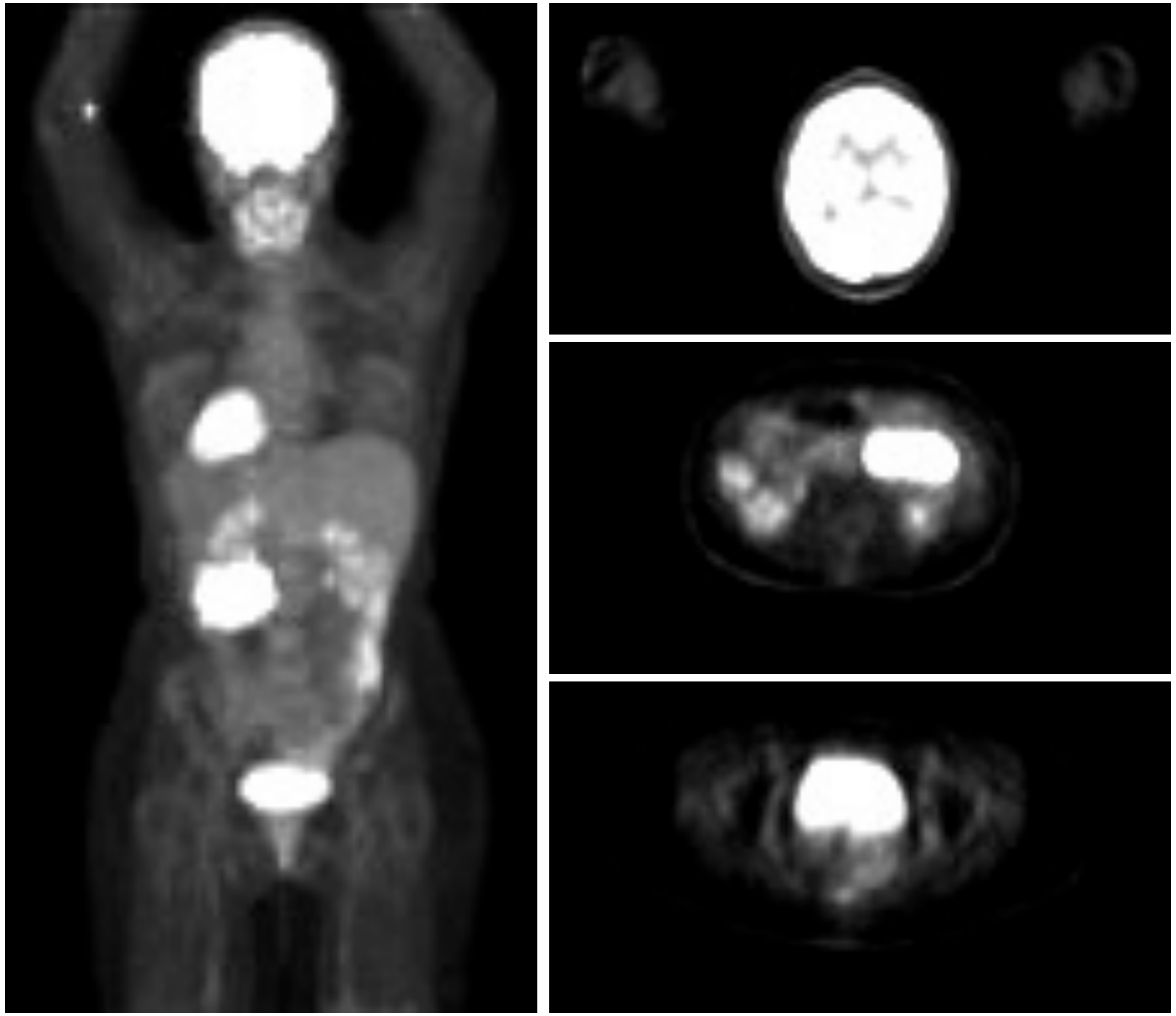


The radioactive atom emits positrons which, when they meet electrons, create pairs of photons.

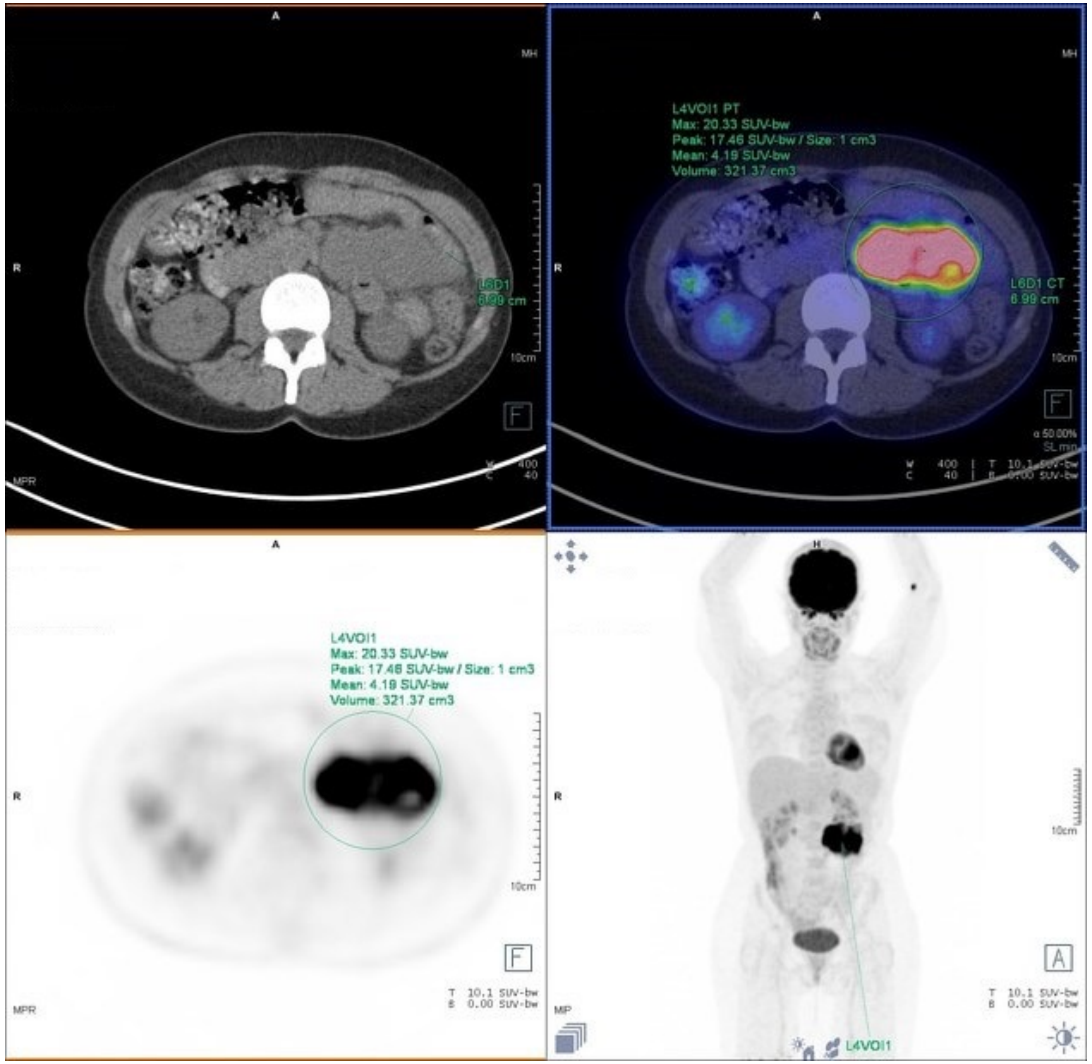


Photon pairs are counted when they reach the detectors simultaneously.

Positron emission tomography



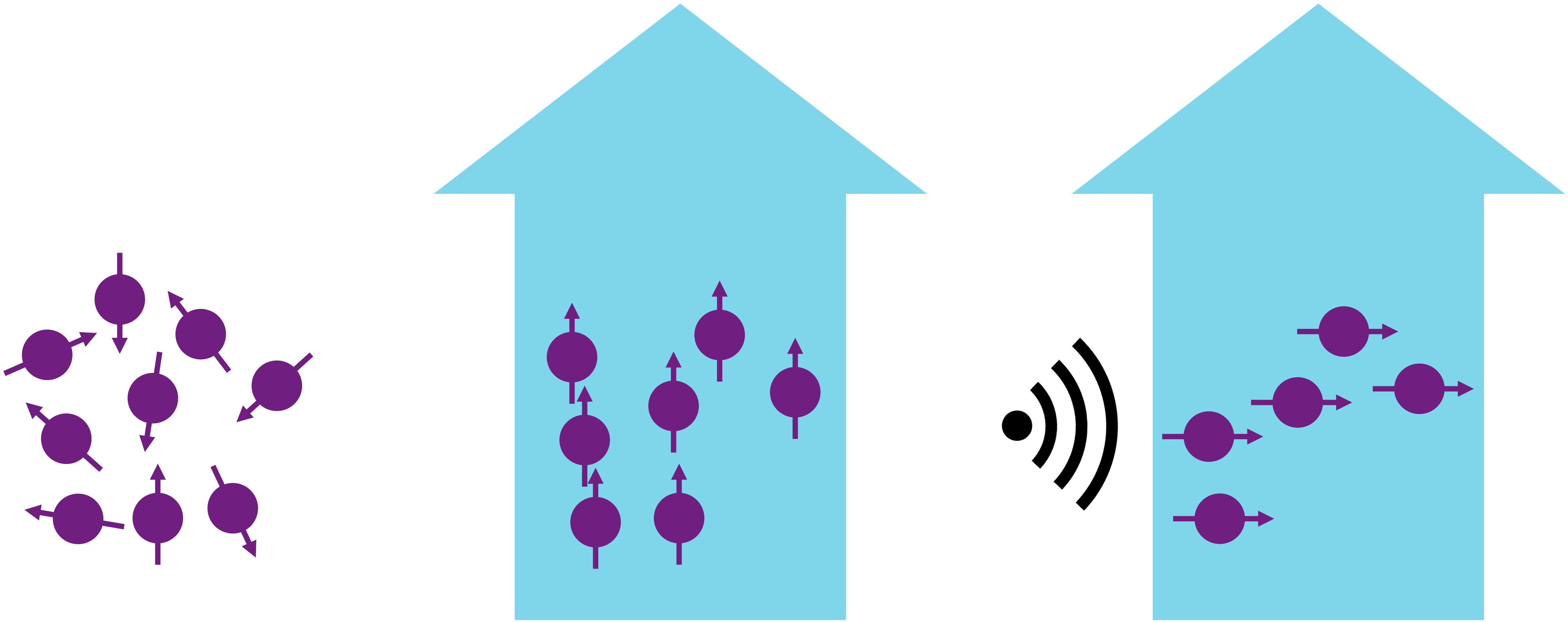
Whole-body PET



PET overlaid on CT

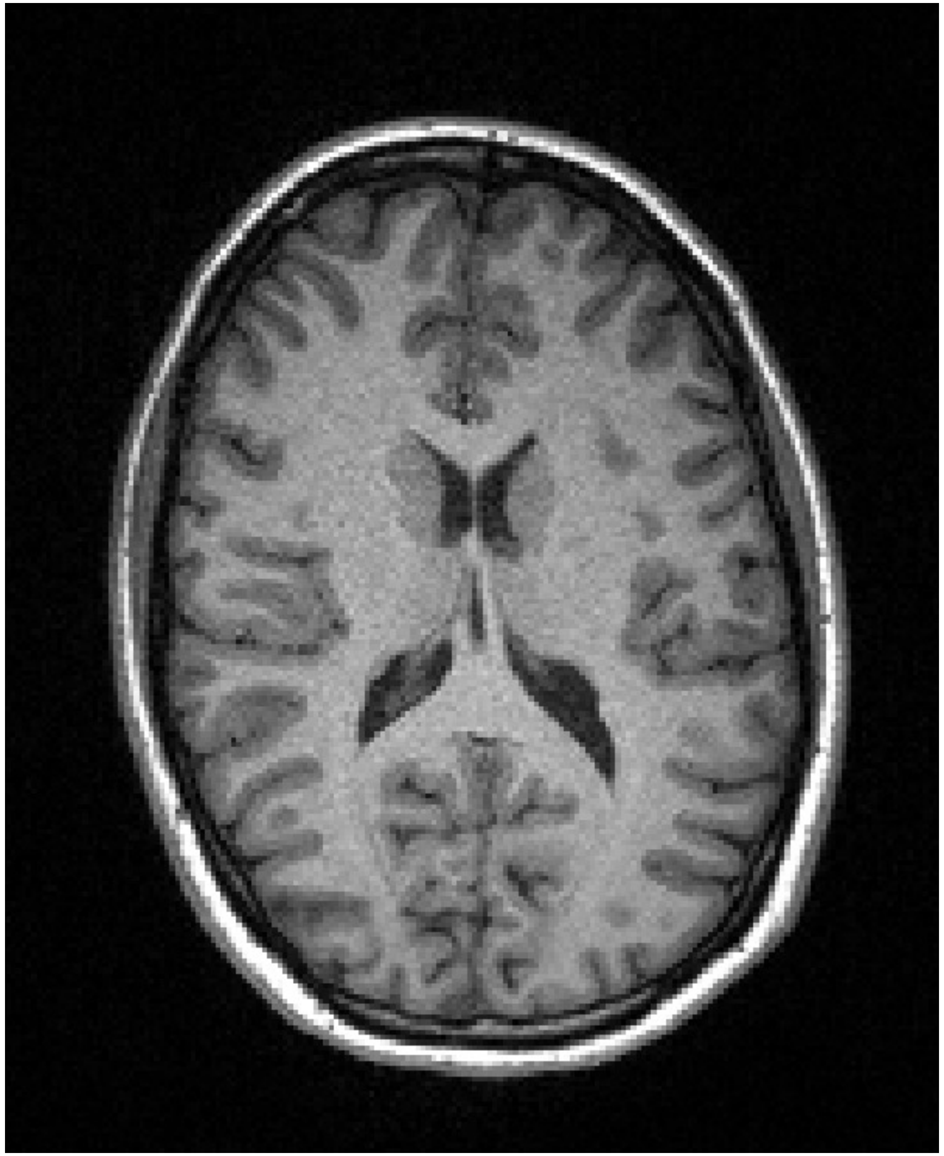
Case courtesy of Dr Bruno Di Muzio (rID: 65743), Radiopaedia.org

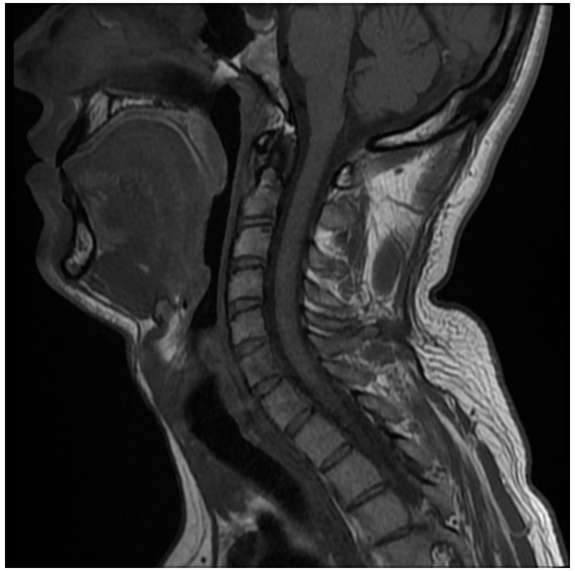
Magnetic resonance imaging



Protons in the body | Protons in the MRI scanner, aligned with the magnetic field | Protons subjected to the MRI magnetic field when a radio frequency pulse is applied

Magnetic resonance imaging



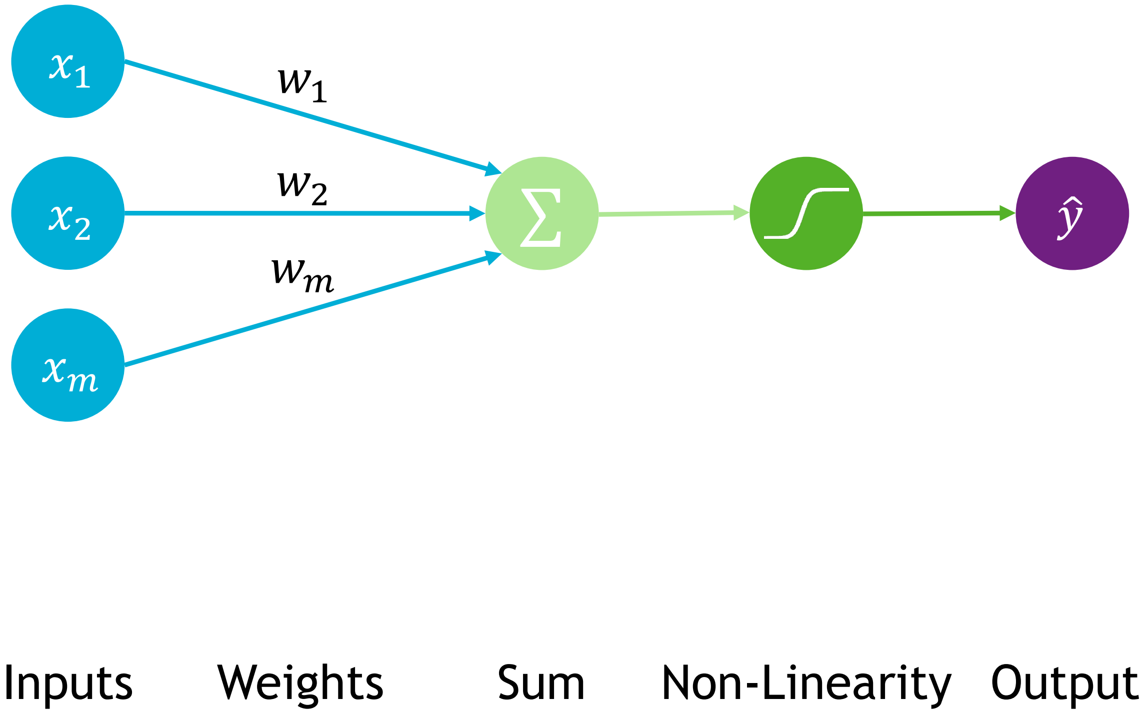


Case courtesy of Dr Mostafa El-Feky (rID: 79193), Dr Pierre Vlala (rID: 27366) and Dr Mohammad A. ElBeialy (rID: 52084), Radiopaedia.org

Neural networks

Perceptron

Forward propagation in a neuron



Output

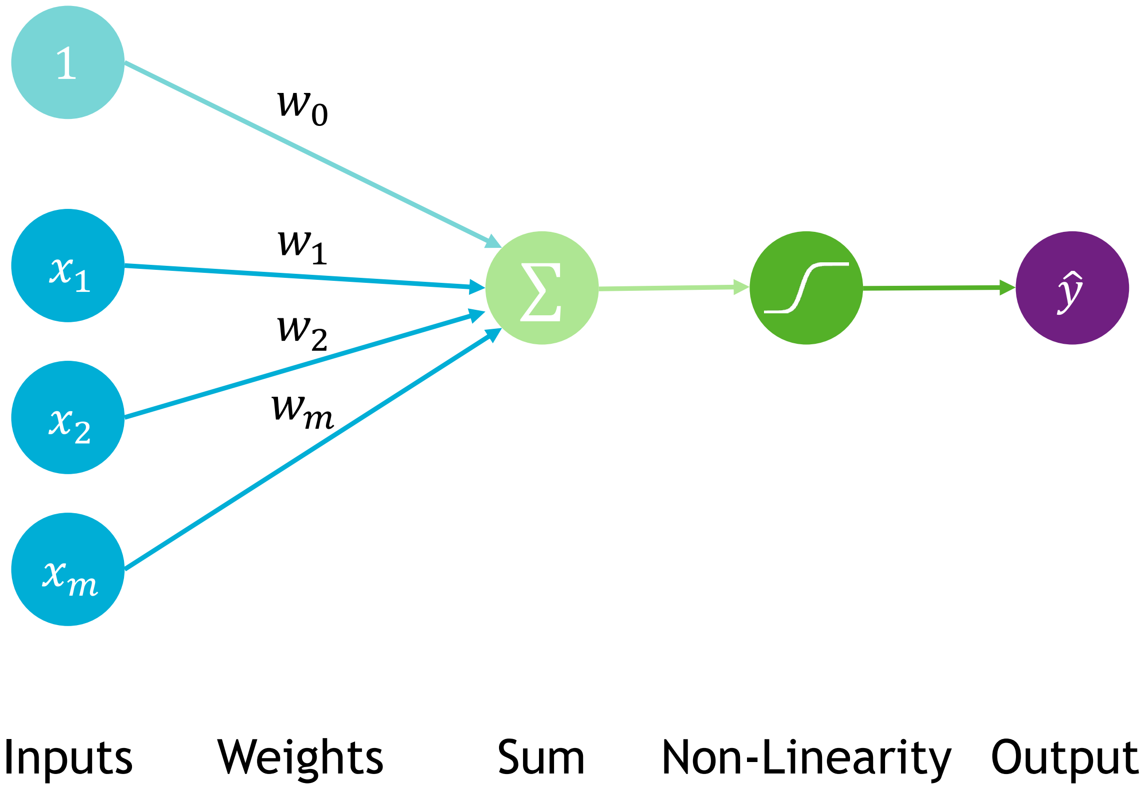
Linear combination of inputs

$$\hat{y} = h\left(\sum_{j=1}^{m} x_j w_j\right)$$

Non-linear activation function

Perceptron

Forward propagation in a neuron



Output

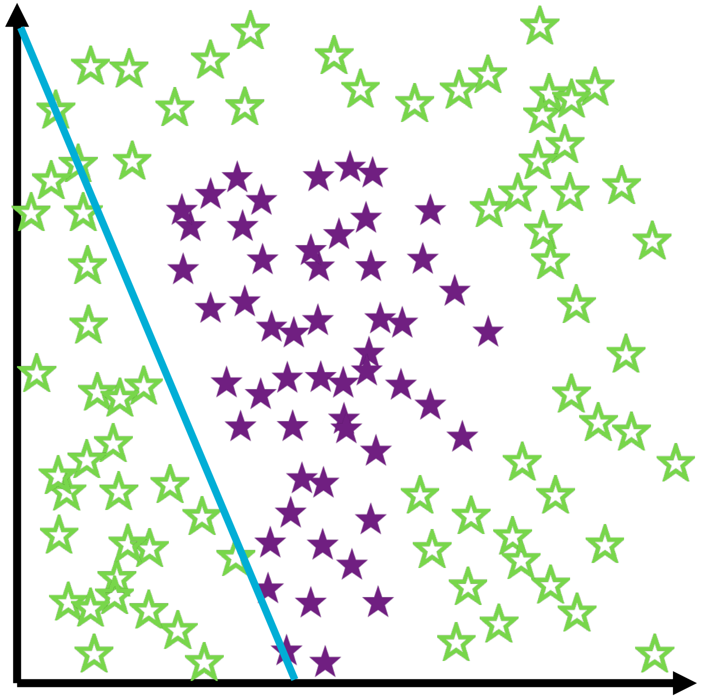
Bias

Linear combination of inputs

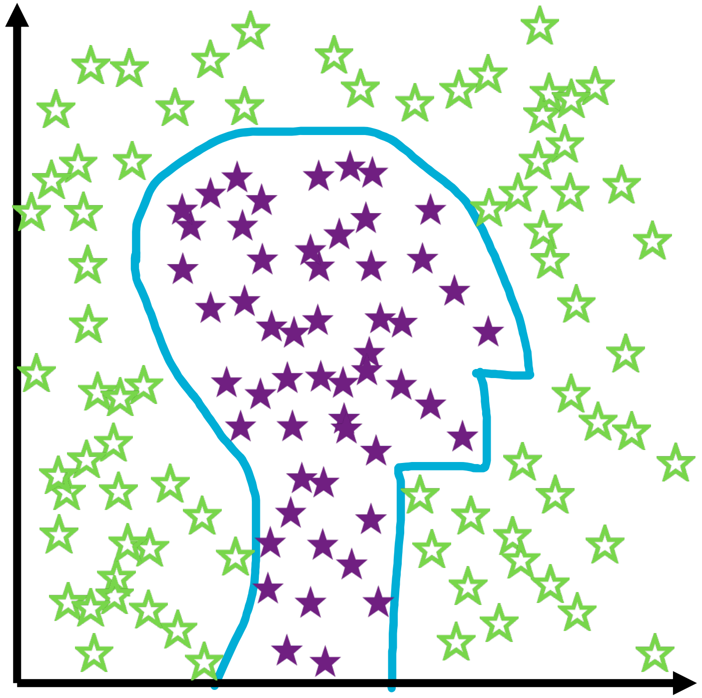
$$\hat{y} = h\left(w_0 + \sum_{j=1}^{m} x_j w_j\right)$$

Non-linear activation function

Importance of non-linear activation functions



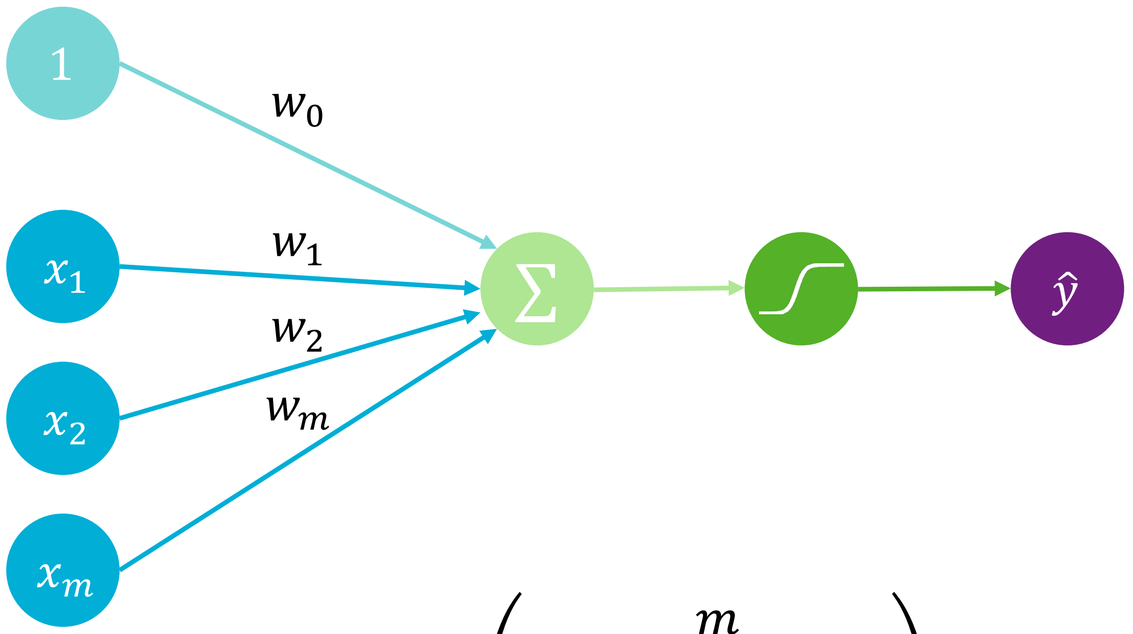
Linear activation functions
→ linear decisions



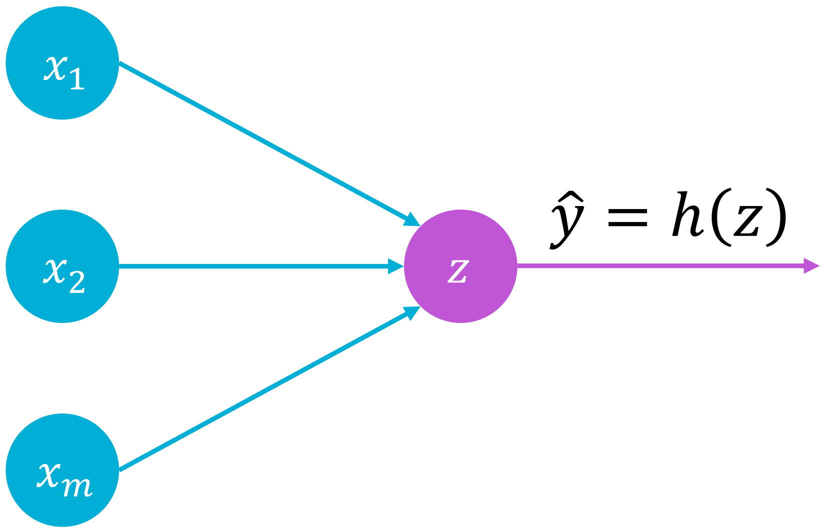
Non-linear activation functions
→ arbitrarily complex decisions

Perceptron

Simplified notation



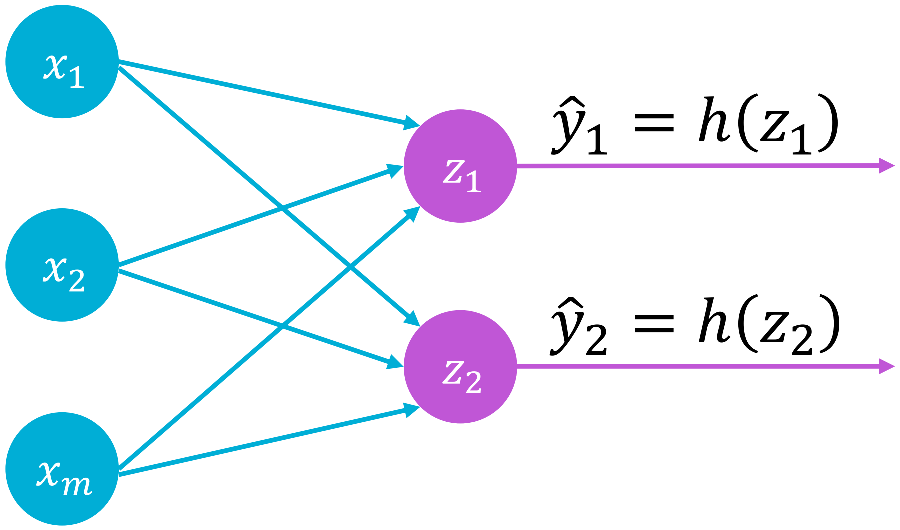
$$\hat{y} = h\left(w_0 + \sum_{j=1}^{m} x_j w_j\right)$$



$$z = w_0 + \sum_{j=1}^{m} x_j w_j$$

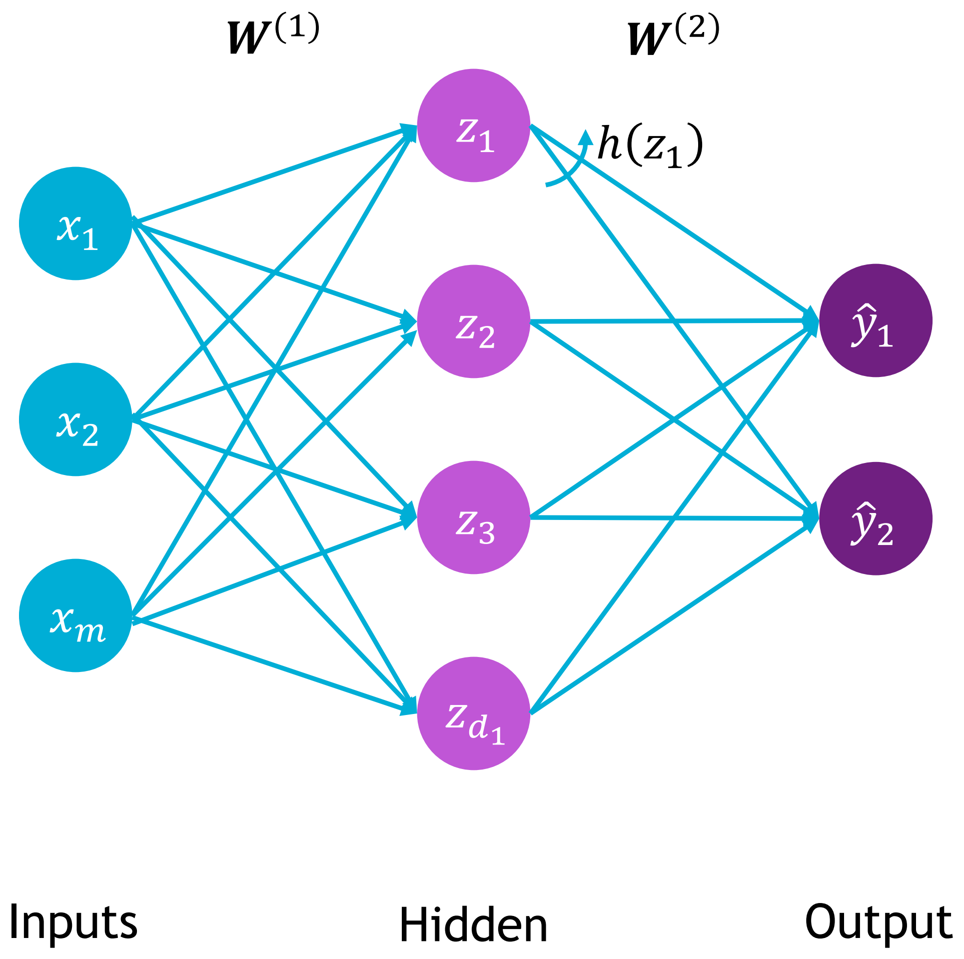
Multi output perceptron

Multi output neural network with dense layers



$$z_i = w_{0,i} + \sum_{j=1}^{m} x_j w_{j,i}$$

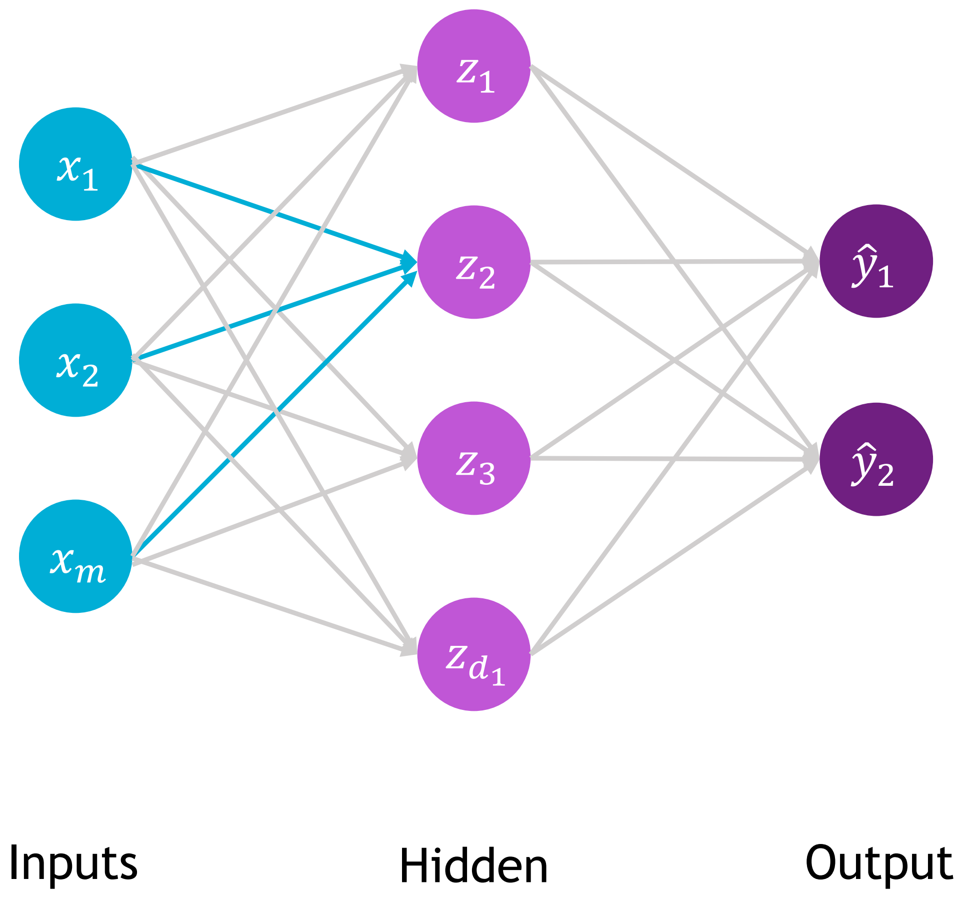
Single layer neural network



$$z_i = w_{0,i}^{(1)} + \sum_{j=1}^{m} x_j w_{j,i}^{(1)}$$

$$\hat{y}_i = h\left(w_{0,i}^{(2)} + \sum_{j=1}^{d_1} z_j w_{j,i}^{(2)} \right)$$

Single layer neural network

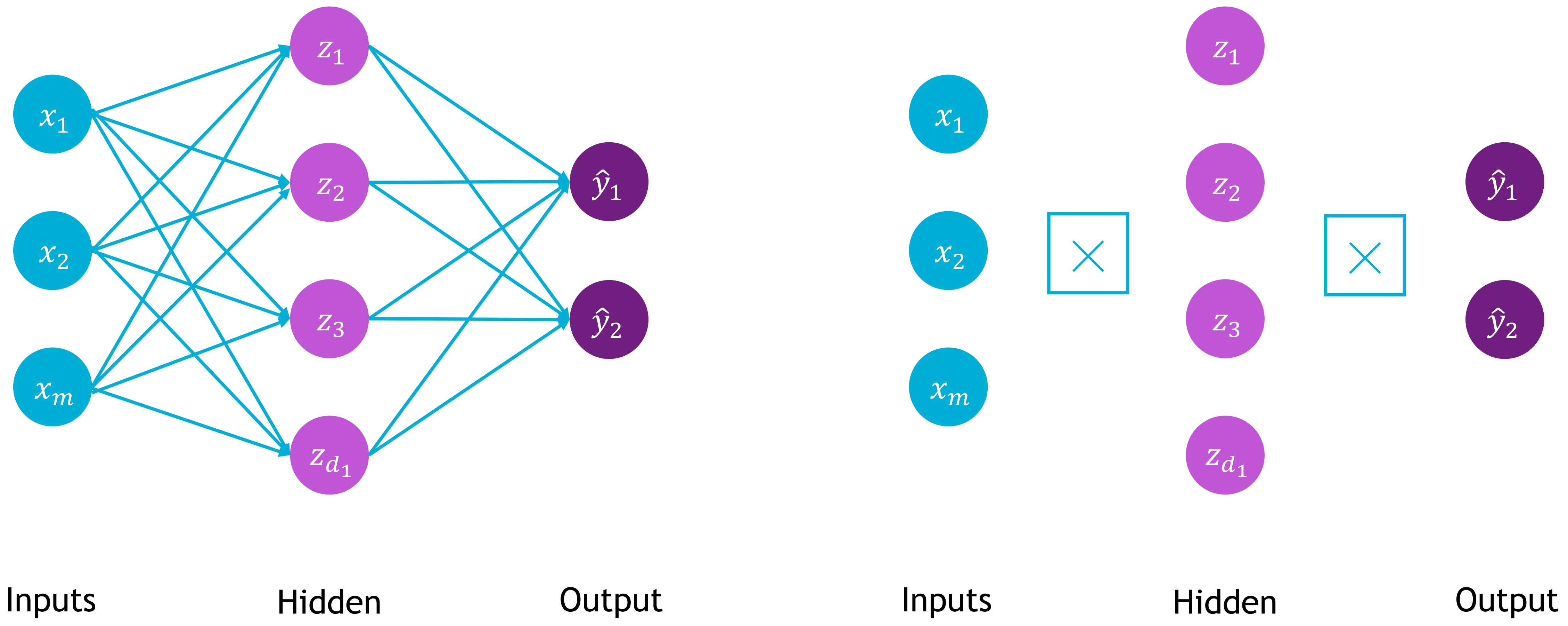


$$z_2 = w_{0,2}^{(1)} + \sum_{j=1}^{m} x_j w_{j,2}^{(1)} \text{x}$$

$$= w_{0,2}^{(1)} + x_1 w_{1,2}^{(1)} + x_2 w_{2,2}^{(1)} + x_m w_{m,2}^{(1)}$$

Single layer neural network

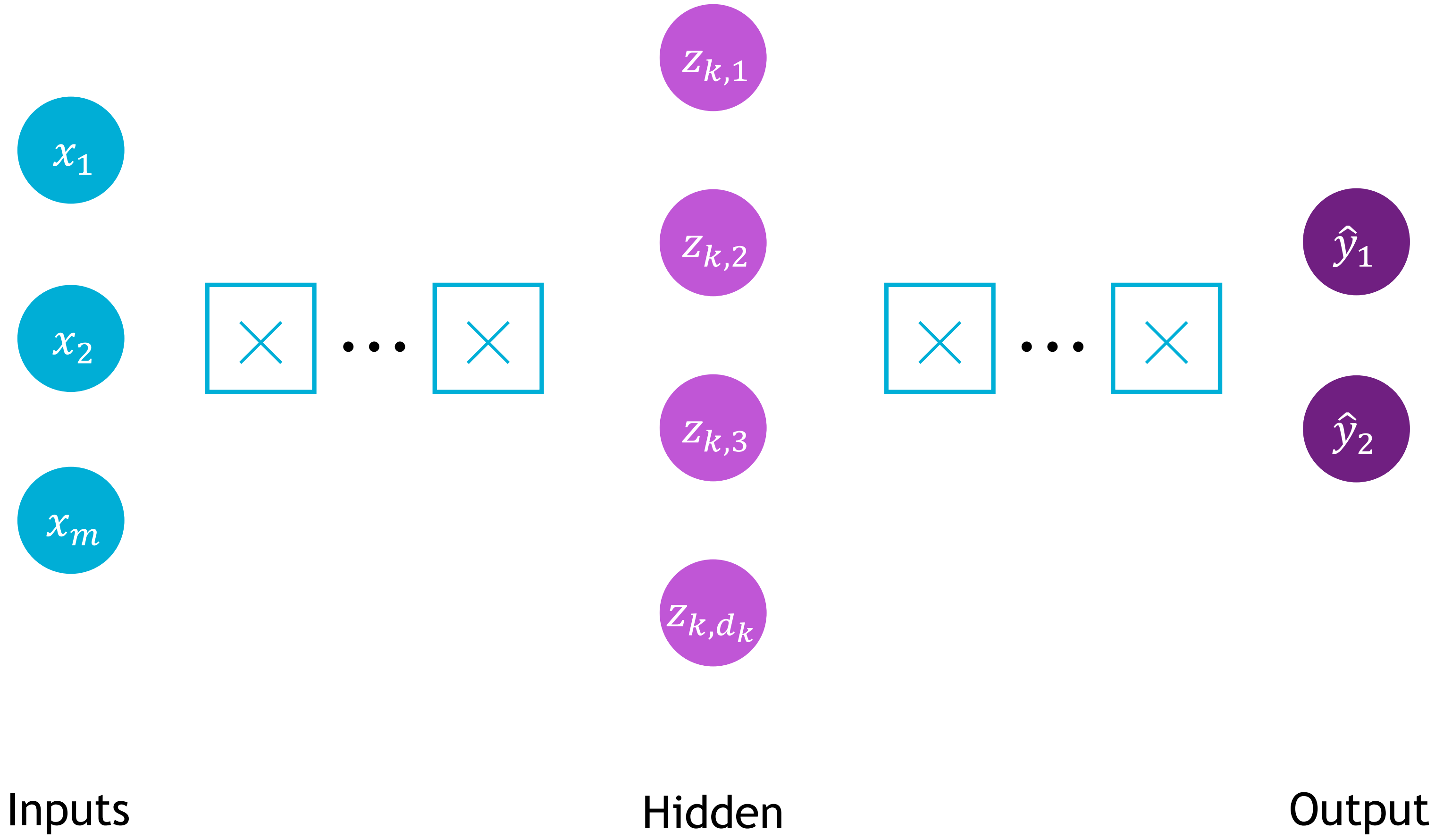
Simplified notation



MIT Introduction to Deep Learning (introtodeeplearning.com)

Deep neural network

Stacking layers

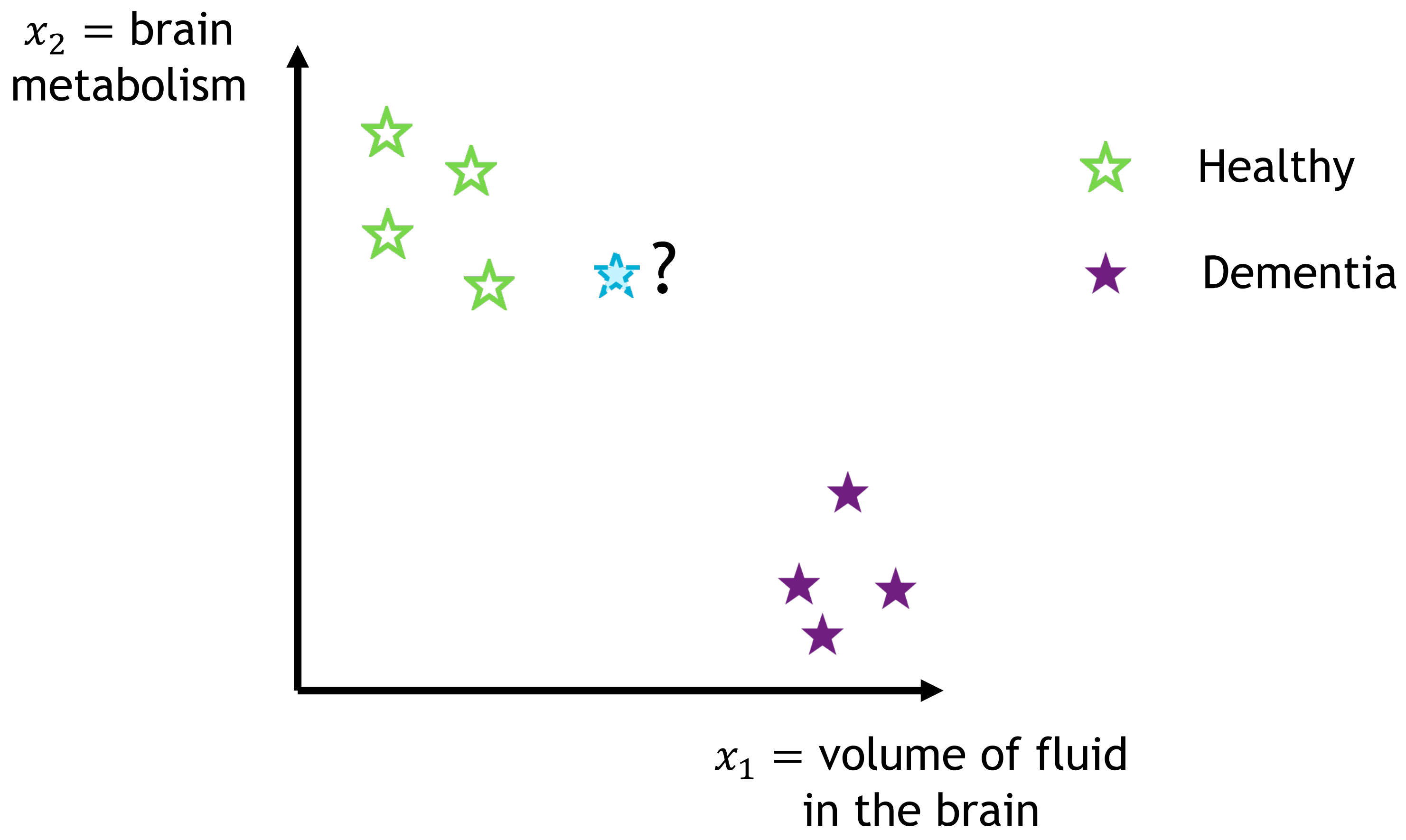


MIT Introduction to Deep Learning (introtodeeplearning.com)

Applying neural networks

Diagnosis of dementia based on imaging biomarkers

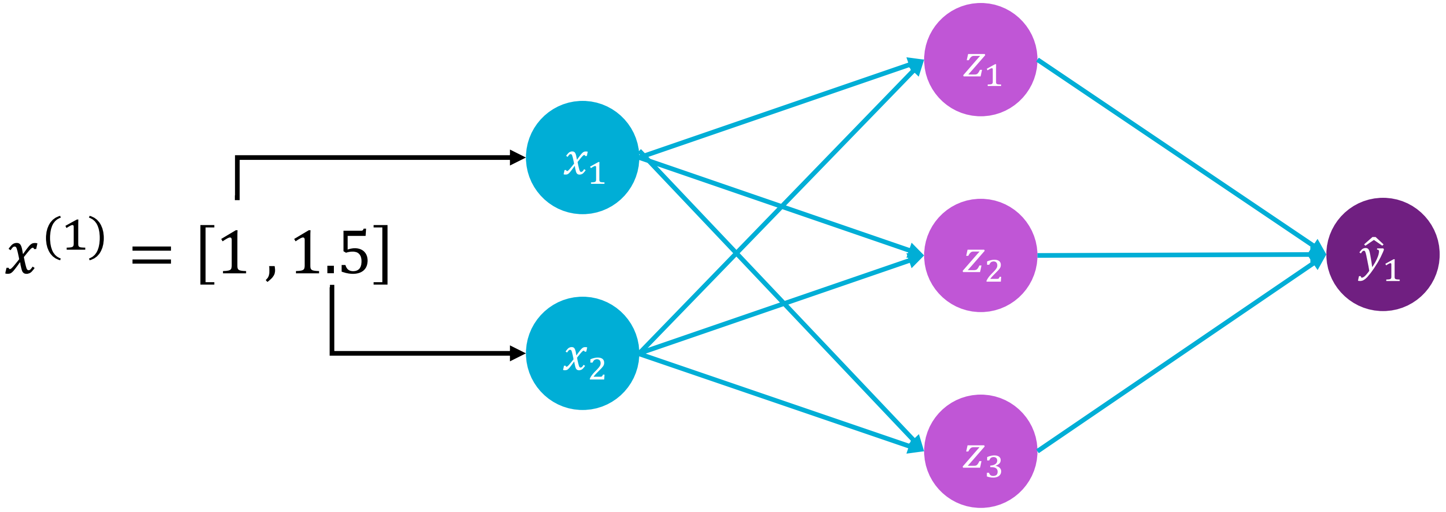
Is this subject healthy?



Applying neural networks

Diagnosis of dementia based on imaging biomarkers

Is this subject healthy?



Predicted: 0.1
Actual: 1

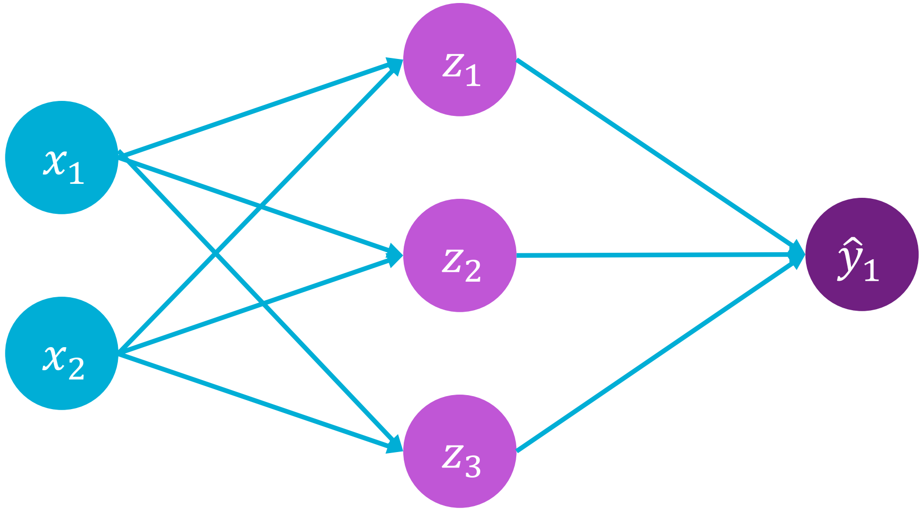
Loss: $l\big(\underbrace{f\big(x^{(i)}; \boldsymbol{W}\big)}_{\text{Predicted}}, \underbrace{y^{(i)}}_{\text{Actual}}\big)$

Applying neural networks

Diagnosis of dementia based on imaging biomarkers

Is this subject healthy?

$$\boldsymbol{X} = \begin{bmatrix} 1 & 1.5 \\ 3.5 & 1.2 \\ 5 & 0.9 \\ \vdots & \vdots \end{bmatrix}$$



$$f(x) \quad \begin{bmatrix} 0.1 \\ 0.4 \\ 0.6 \\ \vdots \end{bmatrix} \qquad y \quad \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \end{bmatrix}$$

Cost function: $$J(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n} l\big(\underbrace{f(x^{(i)};\boldsymbol{W})}_{\text{Predicted}}, \underbrace{y^{(i)}}_{\text{Actual}}\big)$$

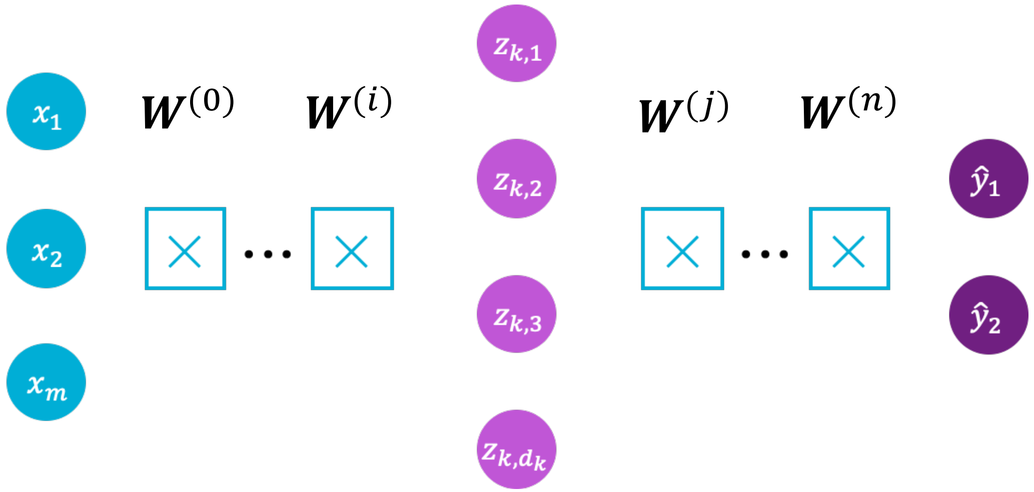
MIT Introduction to Deep Learning (introtodeeplearning.com)

Loss optimisation

- **Find the network weights that achieve the lowest loss**

$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}}\, J(\boldsymbol{W}) = \underset{\boldsymbol{W}}{\operatorname{argmin}} \frac{1}{n}\sum_{i=1}^{n} l\left(f\left(x^{(i)};\boldsymbol{W}\right), y^{(i)}\right)$$

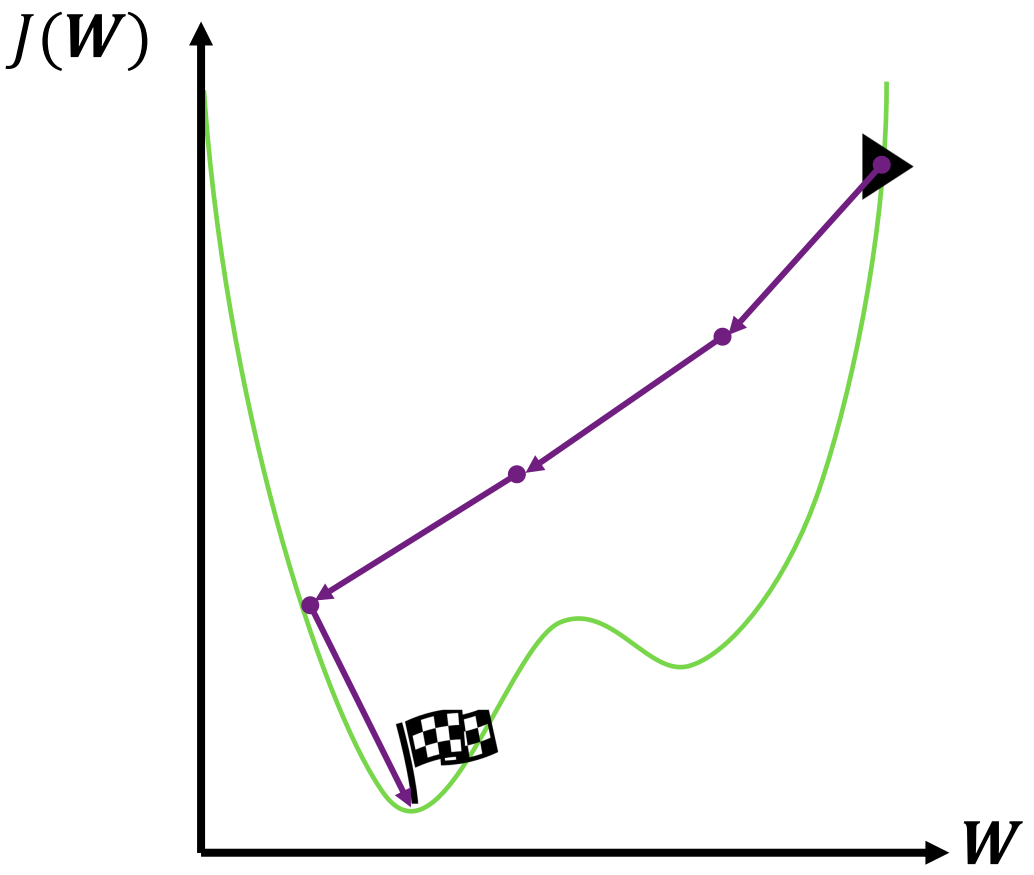
$$\boldsymbol{W} = \left\{\boldsymbol{W}^{(0)}, \boldsymbol{W}^{(1)}, \dots\right\}$$



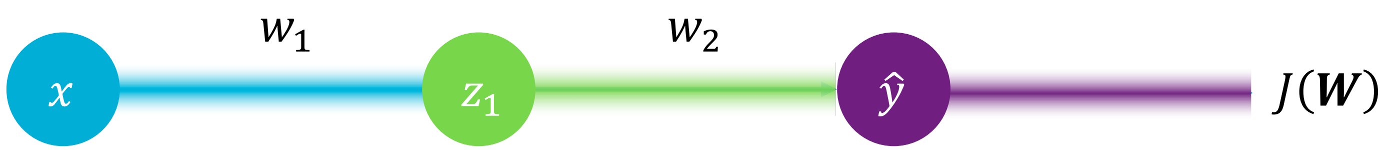
Gradient descent

Algorithm

1. Initialise weights randomly $\sim\mathcal{N}(0, \sigma^2)$
2. Loop until convergence
   a. Compute gradient $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
   b. Update weights $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
3. Return weights



Computing gradients: backpropagation



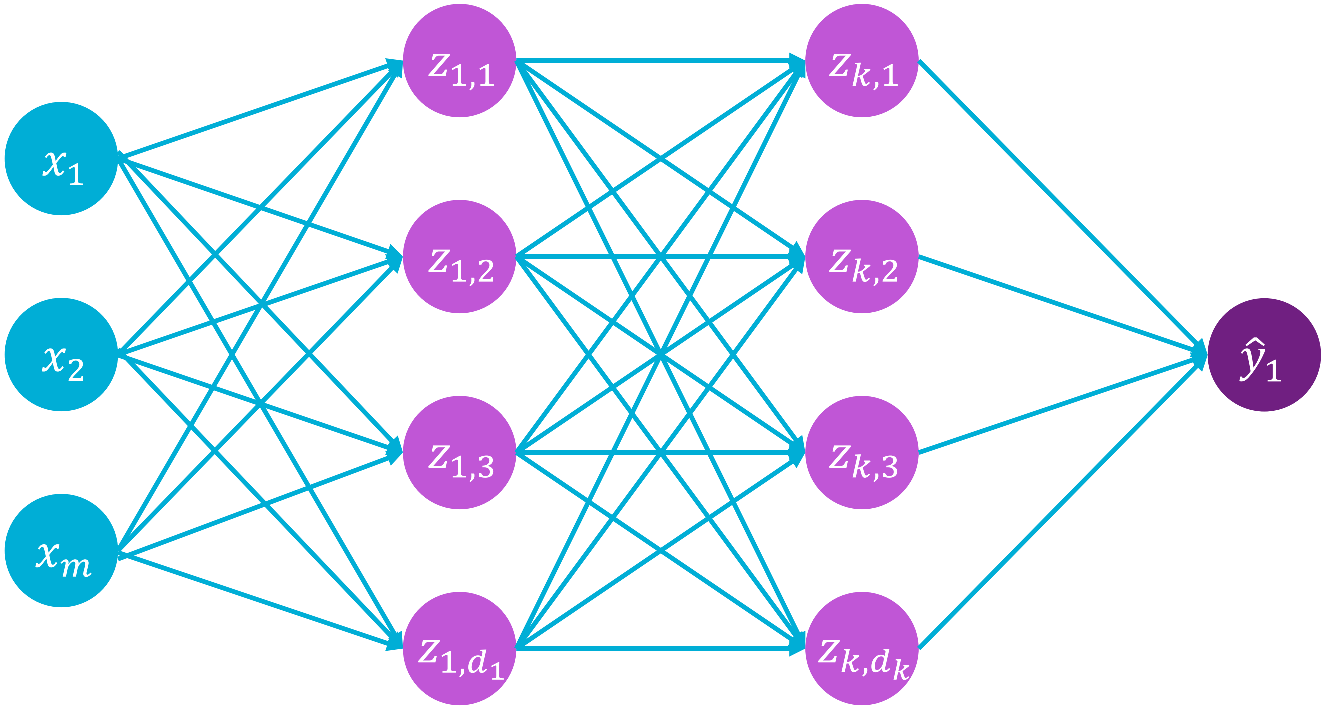
$$\frac{\partial J(\boldsymbol{W})}{\partial w_2} = \frac{\partial J(\boldsymbol{W})}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial w_2}$$

$$\frac{\partial J(\boldsymbol{W})}{\partial w_1} = \frac{\partial J(\boldsymbol{W})}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial w_1} = \frac{\partial J(\boldsymbol{W})}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z_1} \times \frac{\partial z_1}{\partial w_1}$$

Applying neural networks

Diagnosis of dementia based on imaging biomarkers

Is this subject healthy?



MIT Introduction to Deep Learning (introtodeeplearning.com)

Convolutional neural networks

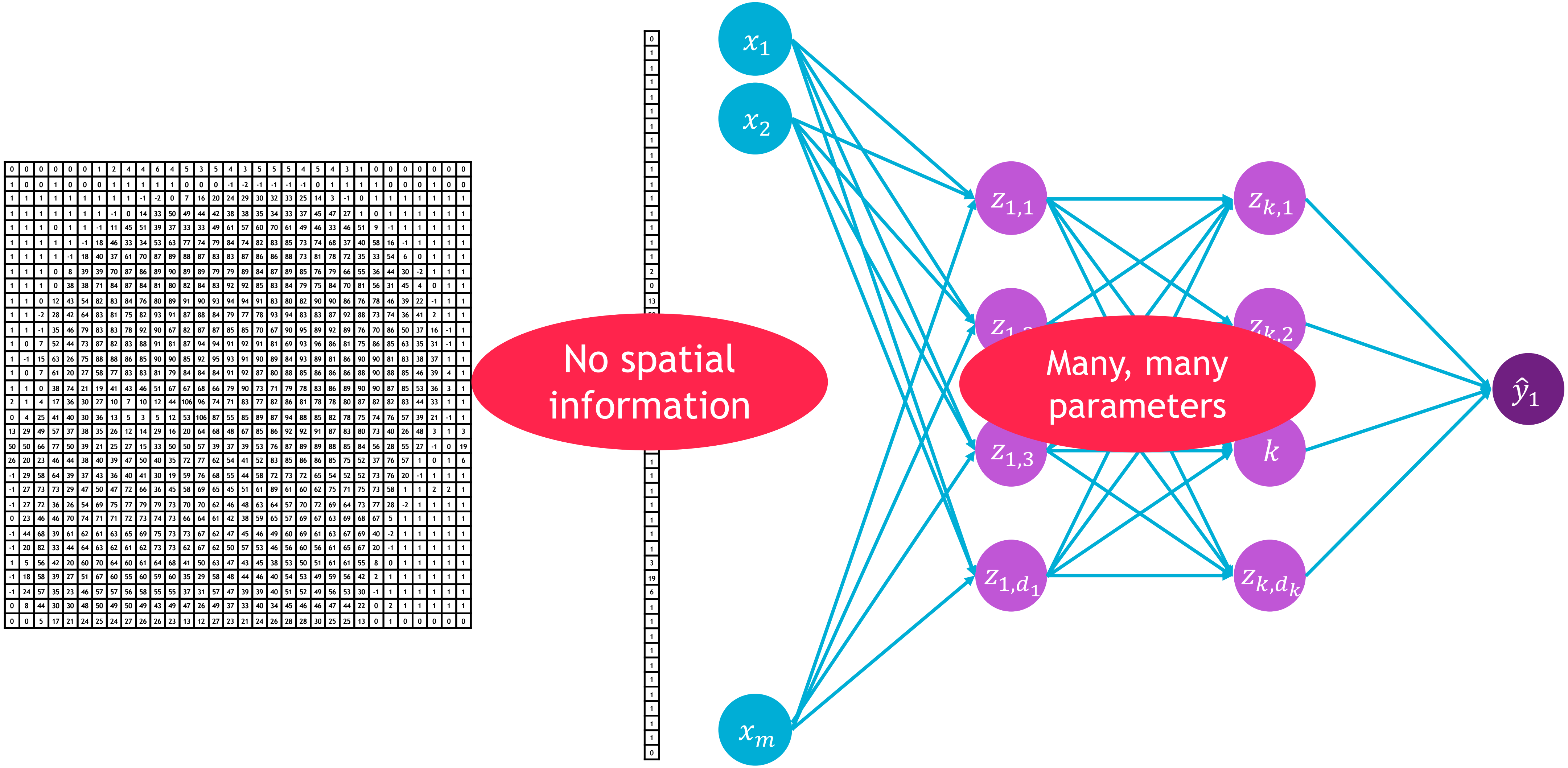
Using an image as input of a neural network

Image = matrix of numbers

0	0	0	0	0	0	1	2	4	4	6	4	5	3	5	4	3	5	5	5	4	5	4	3	1	0	0	0	0	0	0	0
1	0	0	1	0	0	0	1	1	1	1	1	0	0	0	-1	-2	-1	-1	-1	-1	0	1	1	1	1	0	0	0	1	0	0
1	1	1	1	1	1	1	1	1	-1	-2	0	7	16	20	24	29	30	32	33	25	14	3	-1	0	1	1	1	1	1	1	1
1	1	1	1	1	1	1	-1	0	14	33	50	49	44	42	38	38	35	34	33	37	45	47	27	1	0	1	1	1	1	1	1
1	1	1	0	1	1	-1	11	45	51	39	37	33	33	49	61	57	60	70	61	49	46	33	46	51	9	-1	1	1	1	1	1
1	1	1	1	1	-1	18	46	33	34	53	63	77	74	79	84	74	82	83	85	73	74	68	37	40	58	16	-1	1	1	1	1
1	1	1	1	-1	18	40	37	61	70	87	89	88	87	83	83	87	86	86	88	73	81	78	72	35	33	54	6	0	1	1	1
1	1	1	0	8	39	39	70	87	86	89	90	89	89	79	79	89	84	87	89	85	76	79	66	55	36	44	30	-2	1	1	1
1	1	1	0	38	38	71	84	87	84	81	80	82	84	83	92	92	85	83	84	79	75	84	70	81	56	31	45	4	0	1	1
1	1	0	12	43	54	82	83	84	76	80	89	91	90	93	94	94	91	83	80	82	90	90	86	76	78	46	39	22	-1	1	1
1	1	-2	28	42	64	83	81	75	82	93	91	87	88	84	79	77	78	93	94	83	83	87	92	88	73	74	36	41	2	1	1
1	1	-1	35	46	79	83	83	78	92	90	67	82	87	87	85	85	70	67	90	95	89	92	89	76	70	86	50	37	16	-1	1
1	0	7	52	44	73	87	82	83	88	91	81	87	94	94	91	92	91	81	69	93	96	86	81	75	86	85	63	35	31	-1	1
1	-1	15	63	26	75	88	88	86	85	90	90	85	92	95	93	91	90	89	84	93	89	81	86	90	90	81	83	38	37	1	1
1	0	7	61	20	27	58	77	83	83	81	79	84	84	84	91	92	87	80	88	85	86	86	86	88	90	88	85	46	39	4	1
1	1	0	38	74	21	19	41	43	46	51	67	67	68	66	79	90	73	71	79	78	83	86	89	90	90	87	85	53	36	3	1
2	1	4	17	36	30	27	10	7	10	12	44	106	96	74	71	83	77	82	86	81	78	78	80	87	82	82	83	44	33	1	1
0	4	25	41	40	30	36	13	5	3	5	12	53	106	87	55	85	89	87	94	88	85	82	78	75	74	76	57	39	21	-1	1
13	29	49	57	37	38	35	26	12	14	29	16	20	64	68	48	67	85	86	92	92	91	87	83	80	73	40	26	48	3	1	3
50	50	66	77	50	39	21	25	27	15	33	50	50	57	39	37	39	53	76	87	89	89	88	85	84	56	28	55	27	-1	0	19
26	20	23	46	44	38	40	39	47	50	40	35	72	77	62	54	41	52	83	85	86	86	85	75	52	37	76	57	1	0	1	6
-1	29	58	64	39	37	43	36	40	41	30	19	59	76	68	55	44	58	72	73	72	65	54	52	52	73	76	20	-1	1	1	1
-1	27	73	73	29	47	50	47	72	66	36	45	58	69	65	45	51	61	89	61	60	62	75	71	75	73	58	1	1	2	2	1
-1	27	72	36	26	54	69	75	77	79	79	73	70	70	62	46	48	63	64	57	70	72	69	64	73	77	28	-2	1	1	1	1
0	23	46	46	70	74	71	71	72	73	74	73	66	64	61	42	38	59	65	57	69	67	63	69	68	67	5	1	1	1	1	1
-1	44	68	39	61	62	61	63	65	69	75	73	73	67	62	47	45	46	49	60	69	61	63	67	69	40	-2	1	1	1	1	1
-1	20	82	33	44	64	63	62	61	62	73	73	62	67	62	50	57	53	46	56	60	56	61	65	67	20	-1	1	1	1	1	1
1	5	56	42	20	60	70	64	60	61	64	68	41	50	63	47	43	45	38	53	50	51	61	61	55	8	0	1	1	1	1	1
-1	18	58	39	27	51	67	60	55	60	59	60	35	29	58	48	44	46	40	54	53	49	59	56	42	2	1	1	1	1	1	1
-1	24	57	35	23	46	57	57	56	58	55	55	37	31	57	47	39	39	40	51	52	49	56	53	30	-1	1	1	1	1	1	1
0	8	44	30	30	48	50	49	50	49	43	49	47	26	49	37	33	40	34	45	46	46	47	44	22	0	2	1	1	1	1	1
0	0	5	17	21	24	25	24	27	26	26	23	13	12	27	23	21	24	26	28	28	30	25	25	13	0	1	0	0	0	0	0

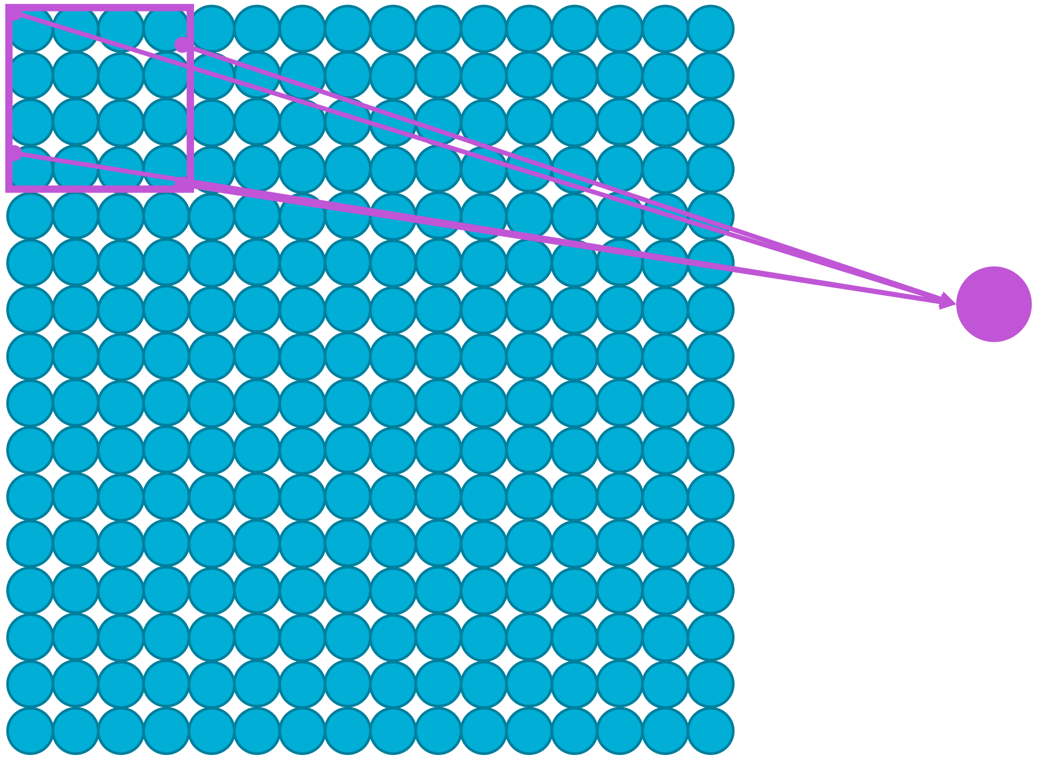
Using an image as input of a neural network

Fully connected neural network



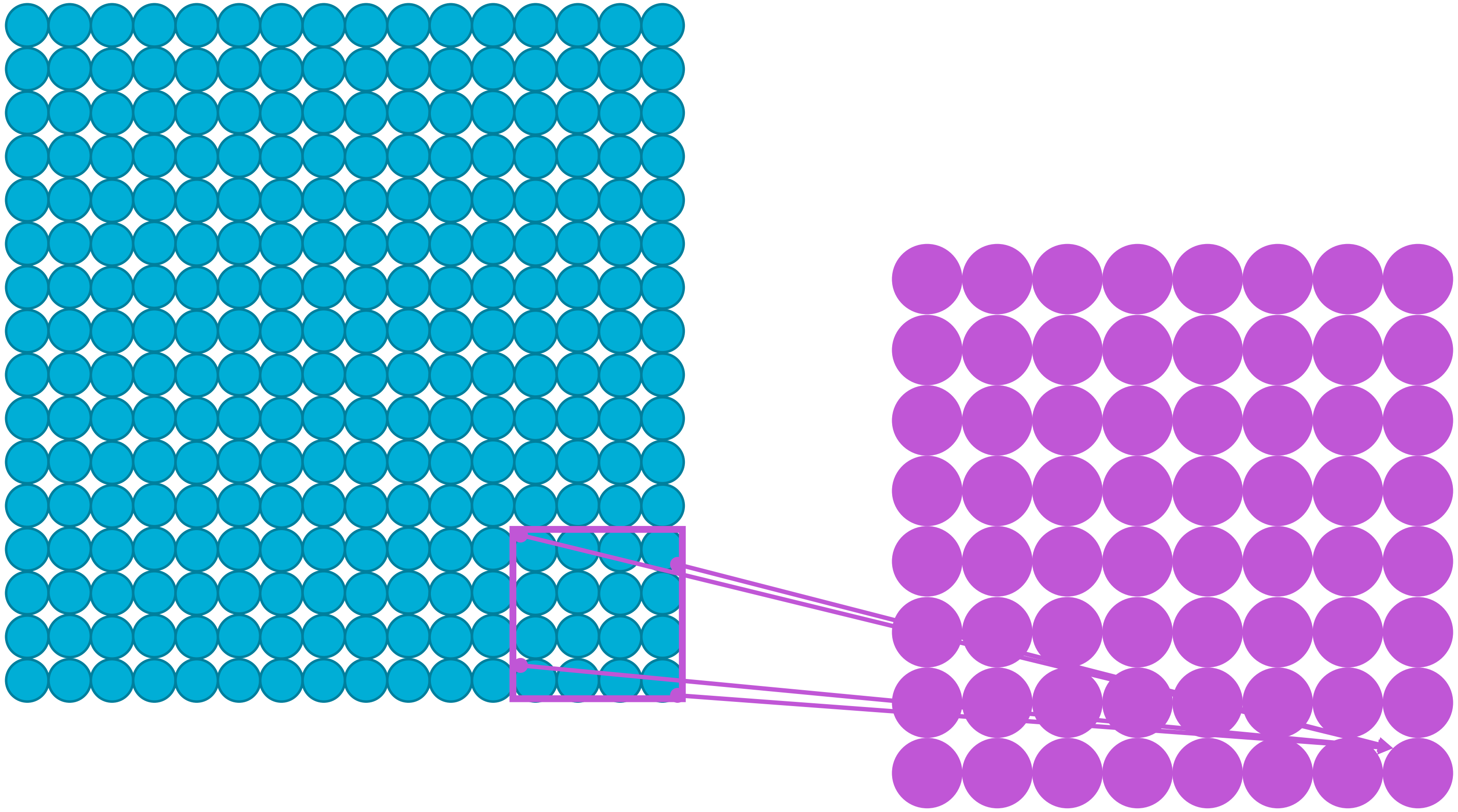
Using an image as input of a neural network

Using spatial features



Idea: connect patches of input to neurons in hidden layer

Using spatial features



- Slide patch window across input image
- Weight pixels inside the patch
- Apply weighted summation

→ Convolution

The convolution operation

- Slide the filter over the input image
- Element-wise multiply
- Add the outputs

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Image

$\otimes$

1	0	1
0	1	0
1	0	1

Filter

The convolution operation

- Slide the filter over the input image
- Element-wise multiply
- Add the outputs

$$
\begin{aligned}
& 1\times1 + 1\times0 + 1\times1 \\
& + 0\times0 + 1\times1 + 1\times0 \\
& + 0\times1 + 0\times0 + 1\times1 \\
& = 4
\end{aligned}
$$

$$
\begin{bmatrix}
1_{\times1} & 1_{\times0} & 1_{\times1} & 0 & 0 \\
0_{\times0} & 1_{\times1} & 1_{\times0} & 1 & 0 \\
0_{\times1} & 0_{\times0} & 1_{\times1} & 1 & 1 \\
0 & 0 & 1 & 1 & 0 \\
0 & 1 & 1 & 0 & 0
\end{bmatrix}
\otimes
\begin{bmatrix}
1 & 0 & 1 \\
0 & 1 & 0 \\
1 & 0 & 1
\end{bmatrix}
=
\begin{bmatrix}
4 & & \\
 & & \\
 & &
\end{bmatrix}
$$

Image Filter Feature map

MIT Introduction to Deep Learning (introtodeeplearning.com)

Using an image as input of a neural network

The convolution operation

- Slide the filter over the input image
- Element-wise multiply
- Add the outputs

$$
\begin{aligned}
&1\times1 + 1\times0 + 0\times1 \\
&+ 1\times0 + 1\times1 + 1\times0 \\
&+ 0\times1 + 1\times0 + 1\times1 \\
&= 3
\end{aligned}
$$

1	$1_{\times1}$	$1_{\times0}$	$0_{\times1}$	0
0	$1_{\times0}$	$1_{\times1}$	$1_{\times0}$	0
0	$0_{\times1}$	$1_{\times0}$	$1_{\times1}$	1
0	0	1	1	0
0	1	1	0	0

Image

$\otimes$

1	0	1
0	1	0
1	0	1

Filter

$=$

4	3	

Feature map

MIT Introduction to Deep Learning (introtodeeplearning.com)

The convolution operation

- Slide the filter over the input image
- Element-wise multiply
- Add the outputs

$$
\begin{aligned}
&1\times 1 + 1\times 0 + 1\times 1 \\
&+ 1\times 0 + 1\times 1 + 0\times 0 \\
&+ 1\times 1 + 0\times 0 + 0\times 1 \\
&= 4
\end{aligned}
$$

$$
\begin{bmatrix}1&1&1&0&0\\0&1&1&1&0\\0&0&1_{\times1}&1_{\times0}&1_{\times1}\\0&0&1_{\times0}&1_{\times1}&0_{\times0}\\0&1&1_{\times1}&0_{\times0}&0_{\times1}\end{bmatrix} \otimes \begin{bmatrix}1&0&1\\0&1&0\\1&0&1\end{bmatrix} = \begin{bmatrix}4&3&4\\2&4&3\\2&3&4\end{bmatrix}
$$

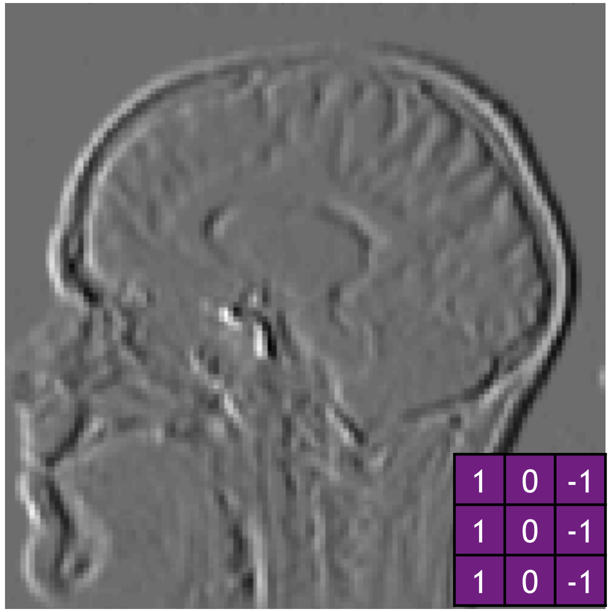
Image | Filter | Feature map

MIT Introduction to Deep Learning (introtodeeplearning.com)

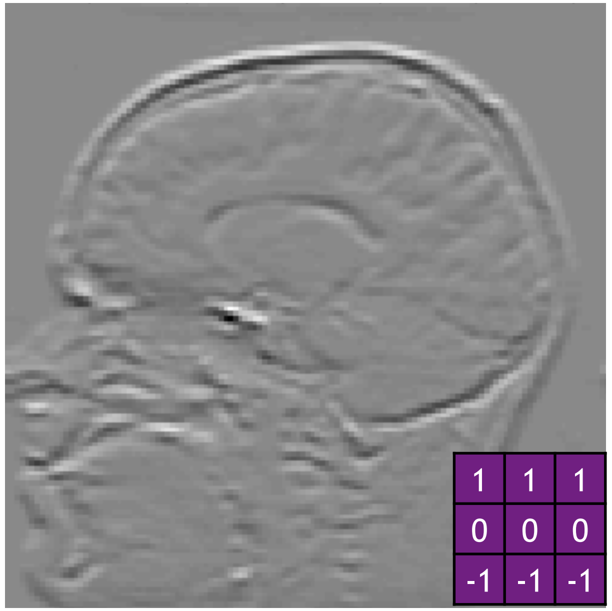
Using an image as input of a neural network

Different filters = different feature maps

Original image



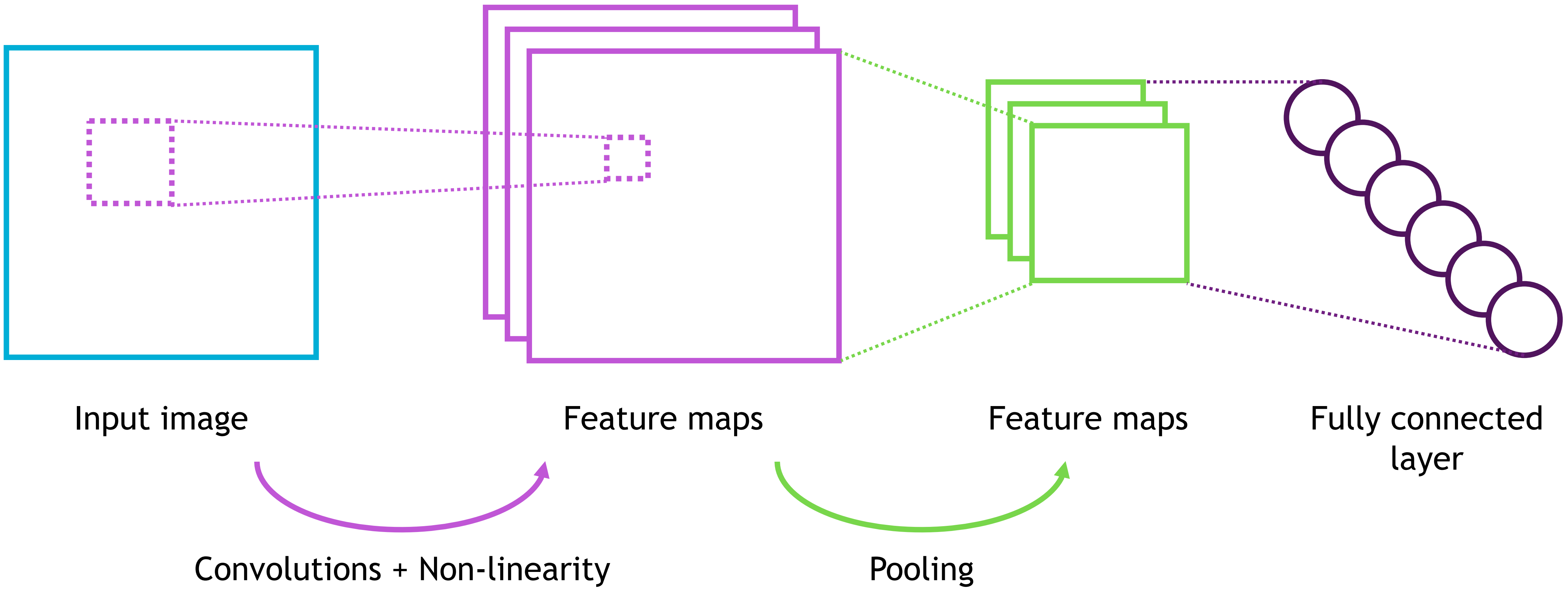
Vertical edge detection



Horizontal edge detection

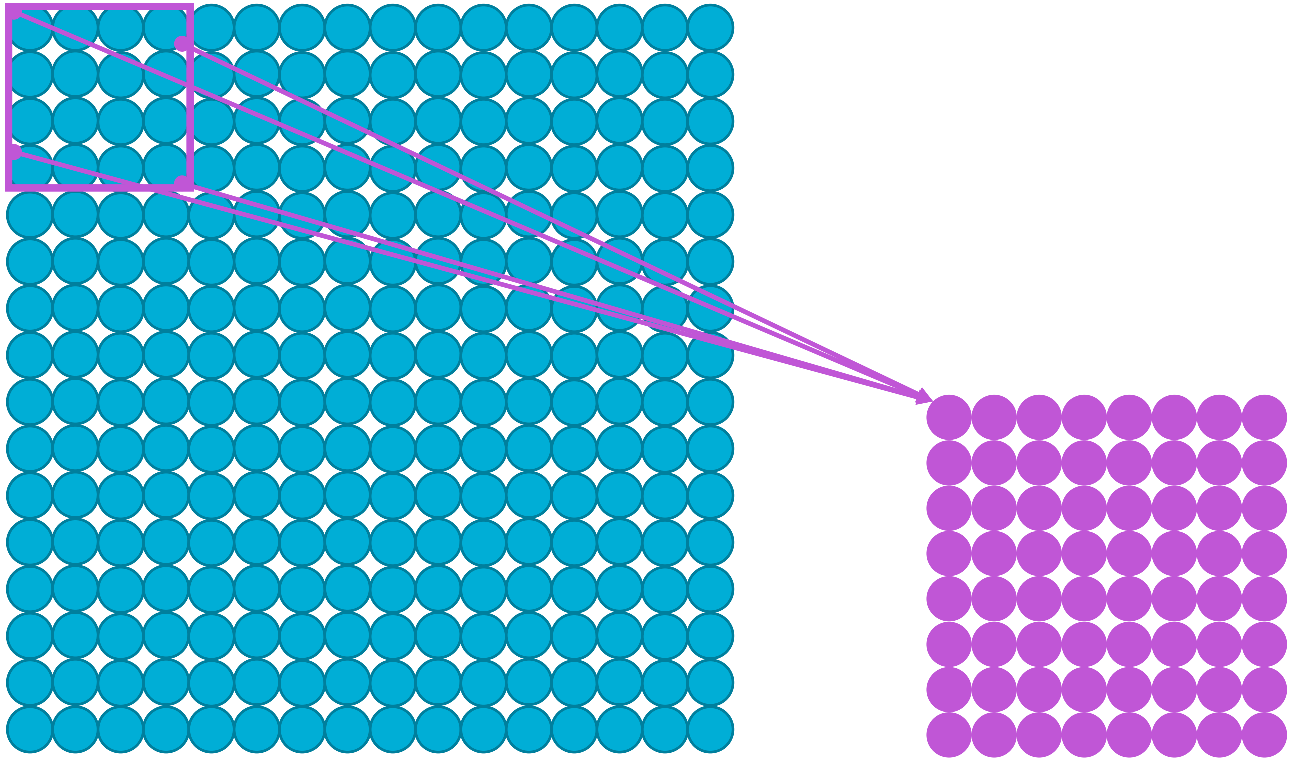
Convolutional neural networks

CNNs for classification

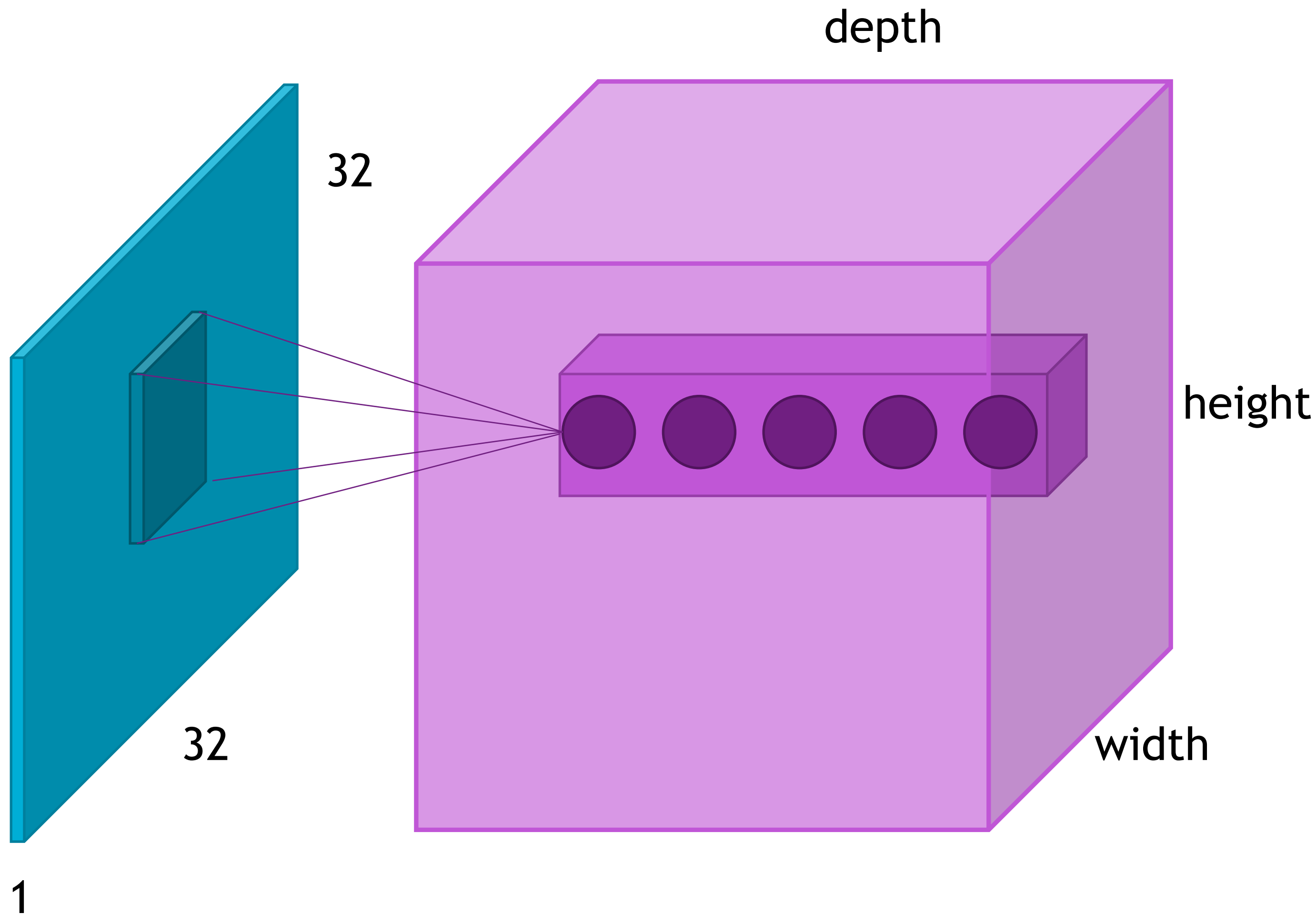


MIT Introduction to Deep Learning (introtodeeplearning.com)

Convolutional layer



Spatial arrangement of output volume



Layer Dimensions:

$h \times w \times d$

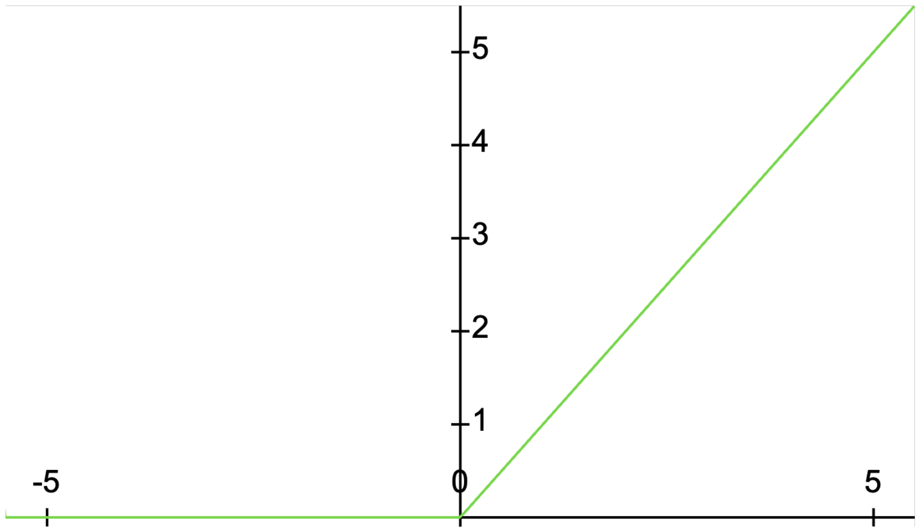
h & w = spatial dimensions

d = number of filters

Convolutional neural networks

Introducing non-linearity

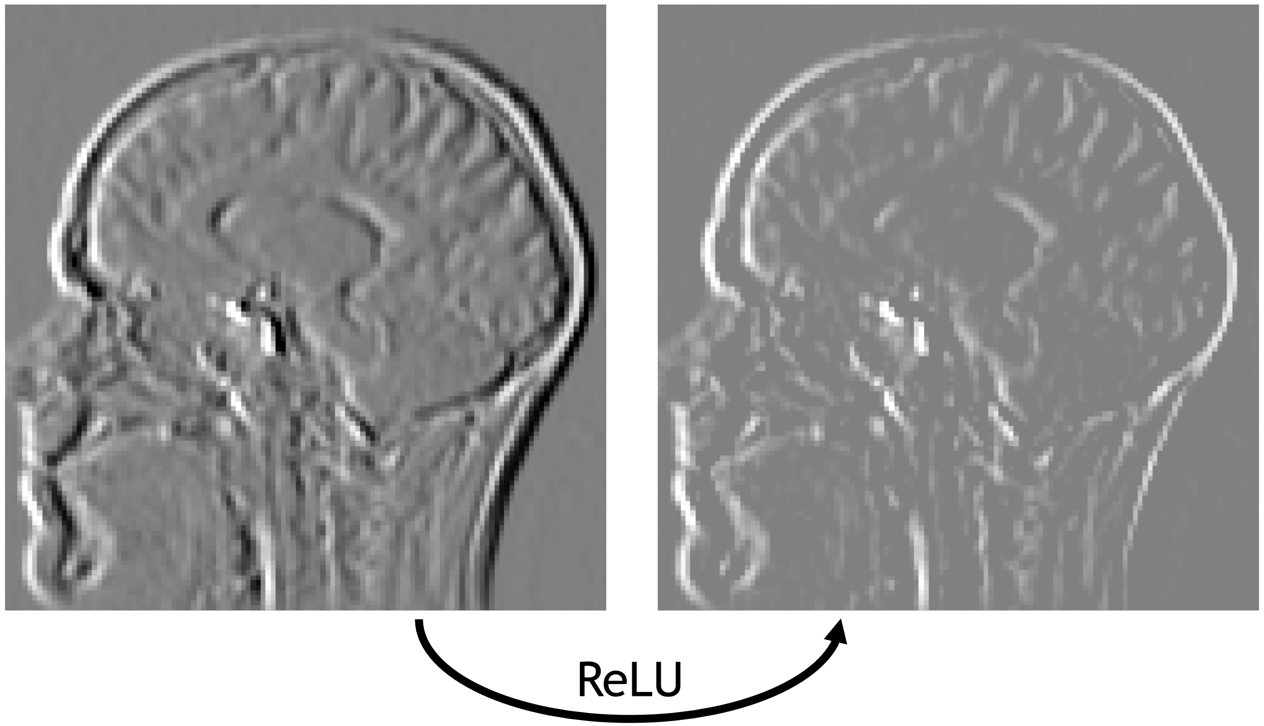
Rectified linear unit (ReLU)



$$h(z) = \max(0, z)$$

Input feature map

Rectified feature map



Black: negative values - White: positive values

MIT Introduction to Deep Learning (introtodeeplearning.com)

Pooling

- **Reduce dimensionality while preserving spatial invariance**

Input feature map

1	1	8	3
4	7	1	9
5	3	1	4
2	3	6	0

Max pooling with
2×2 filter and stride 2
→

Pooled feature map

7	9
5	6

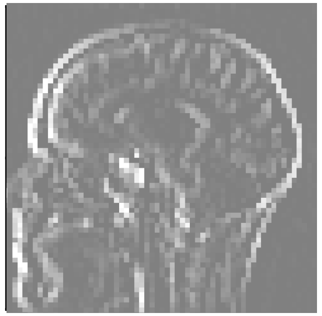
Pooling

- **Reduce dimensionality while preserving spatial invariance**

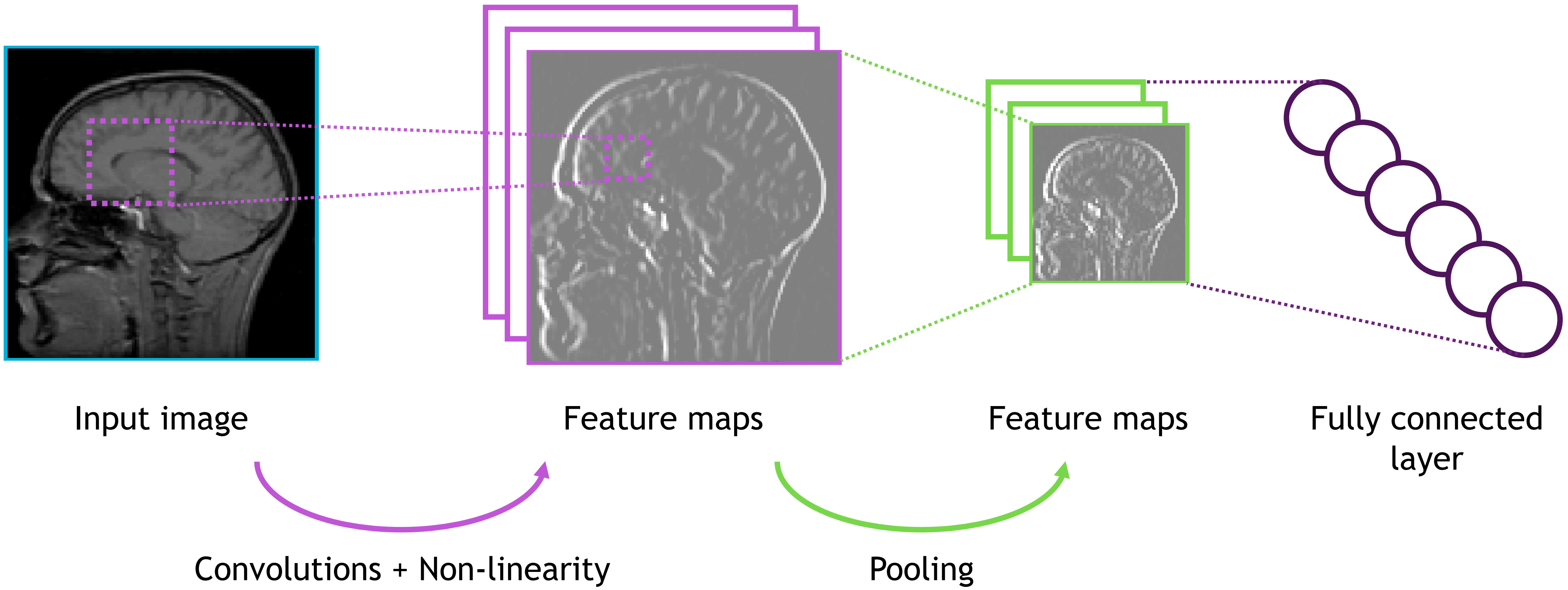
Input feature map

Max pooling with
2×2 filter and stride 2

Pooled feature map

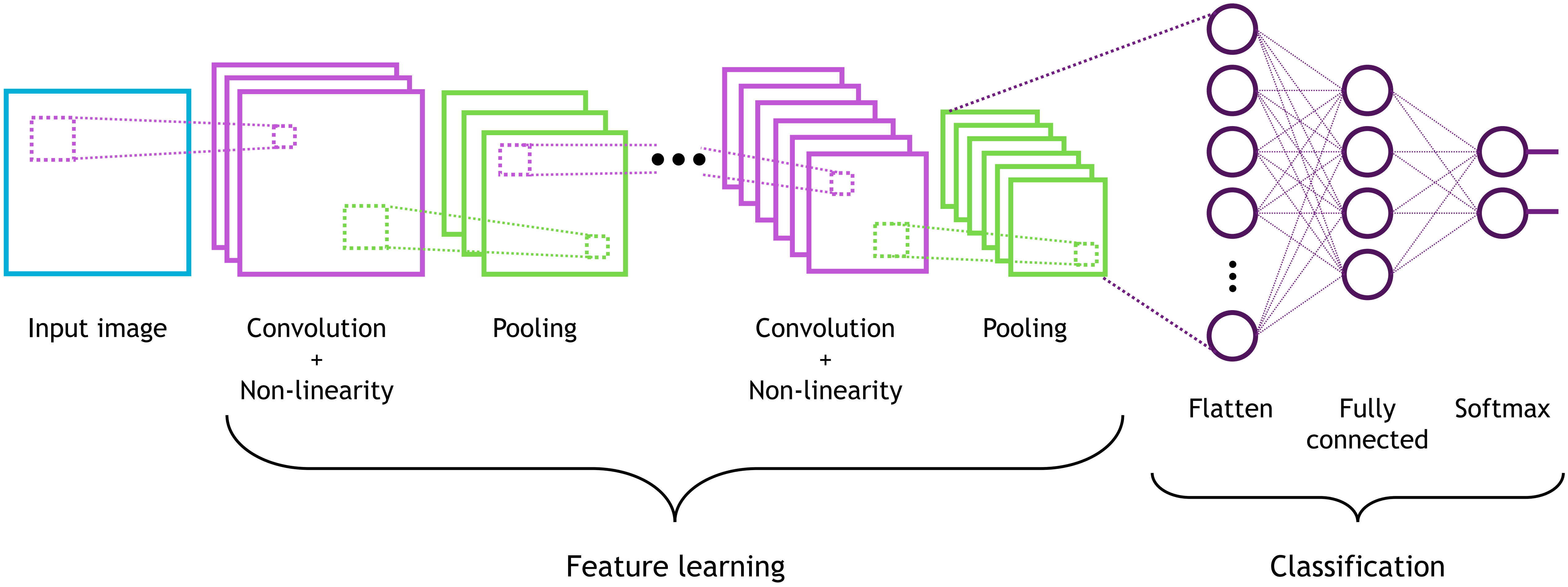


CNNs for classification



Convolutional neural networks

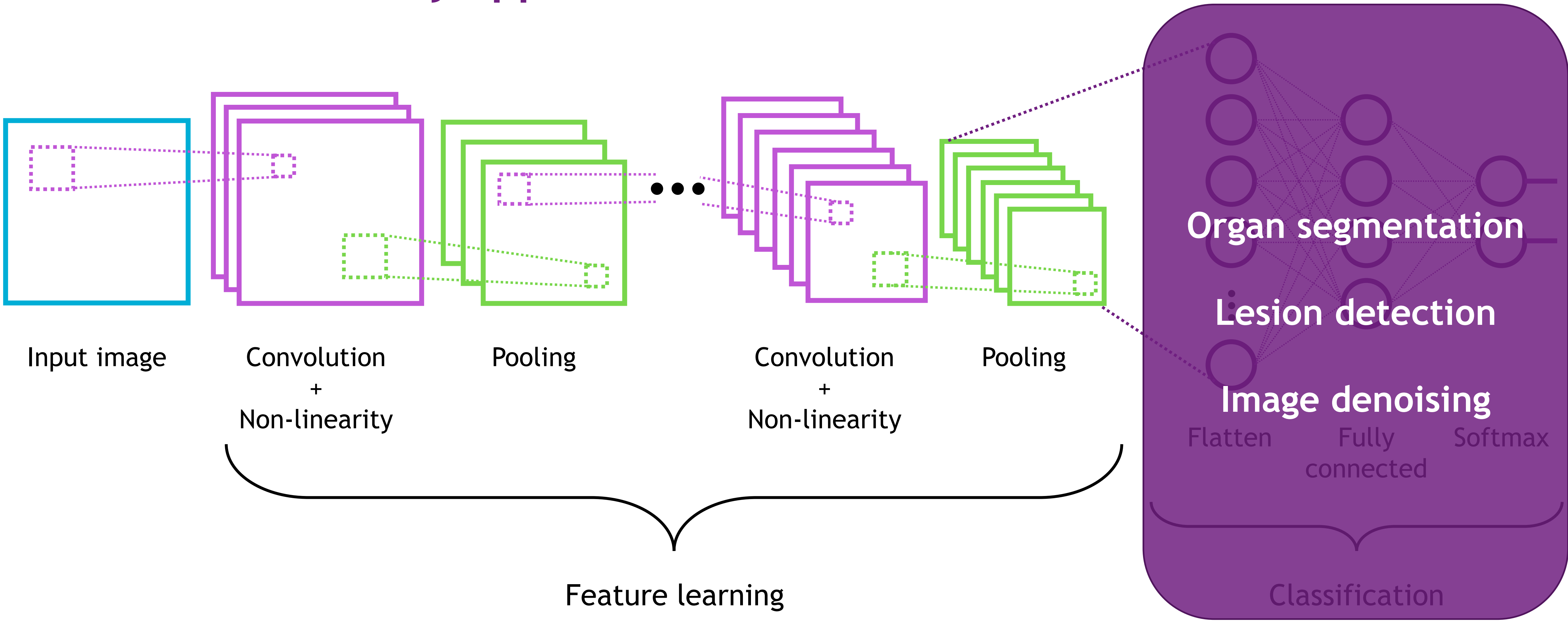
CNNs for classification



MIT Introduction to Deep Learning (introtodeeplearning.com)

Convolutional neural networks

CNNs for many applications

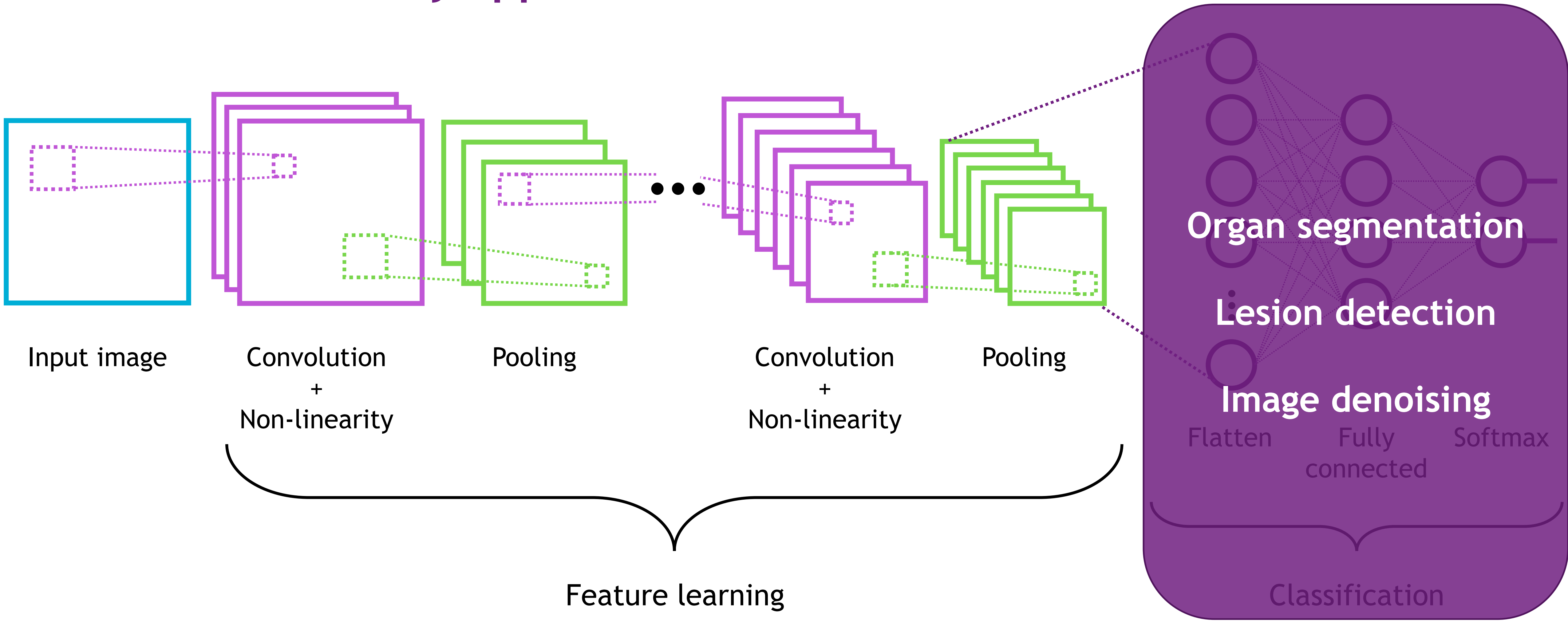


MIT Introduction to Deep Learning (introtodeeplearning.com)

Deep Learning for Image Synthesis & Segmentation

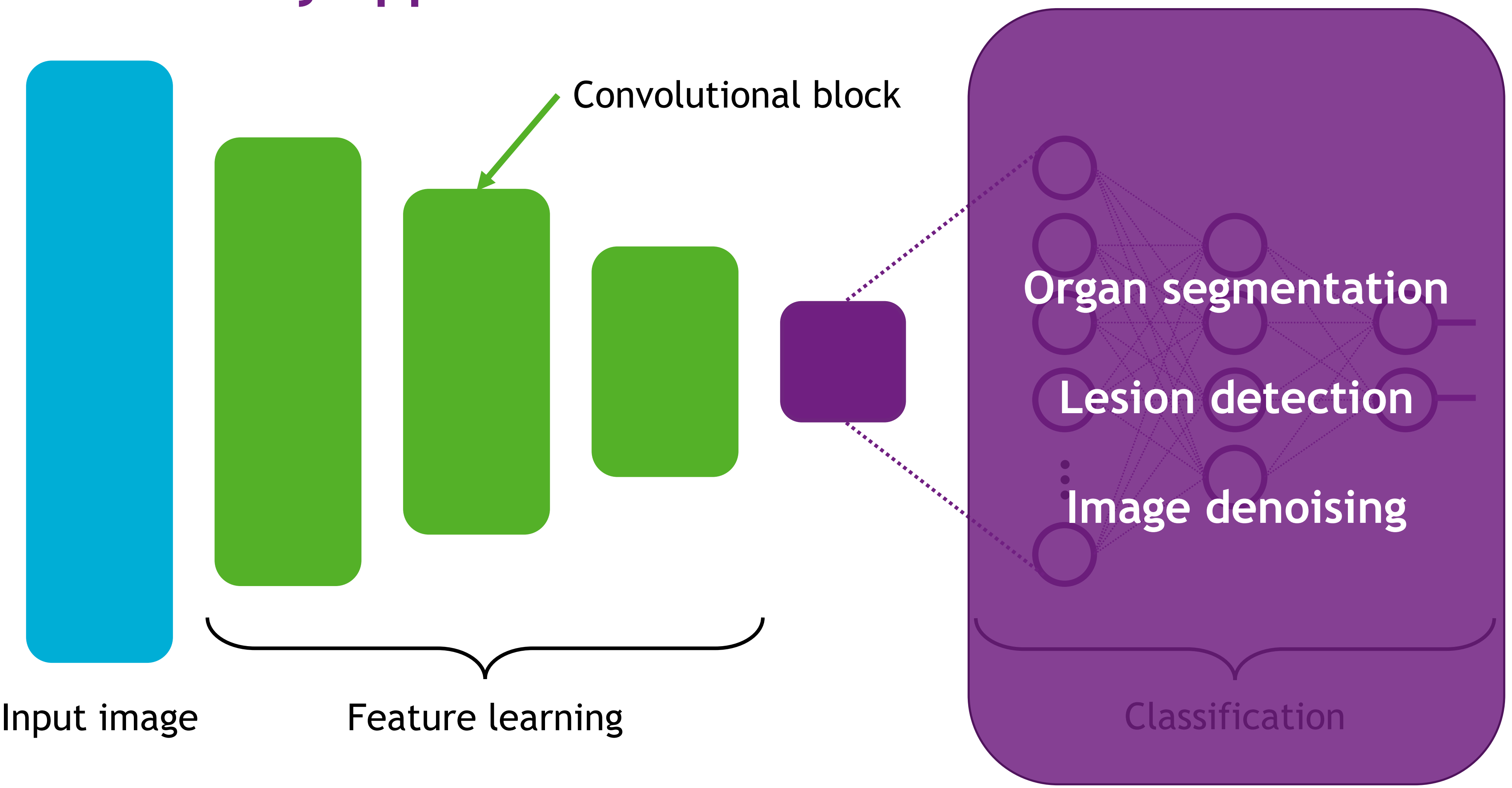
Convolutional neural networks

CNNs for many applications



MIT Introduction to Deep Learning (introtodeeplearning.com)

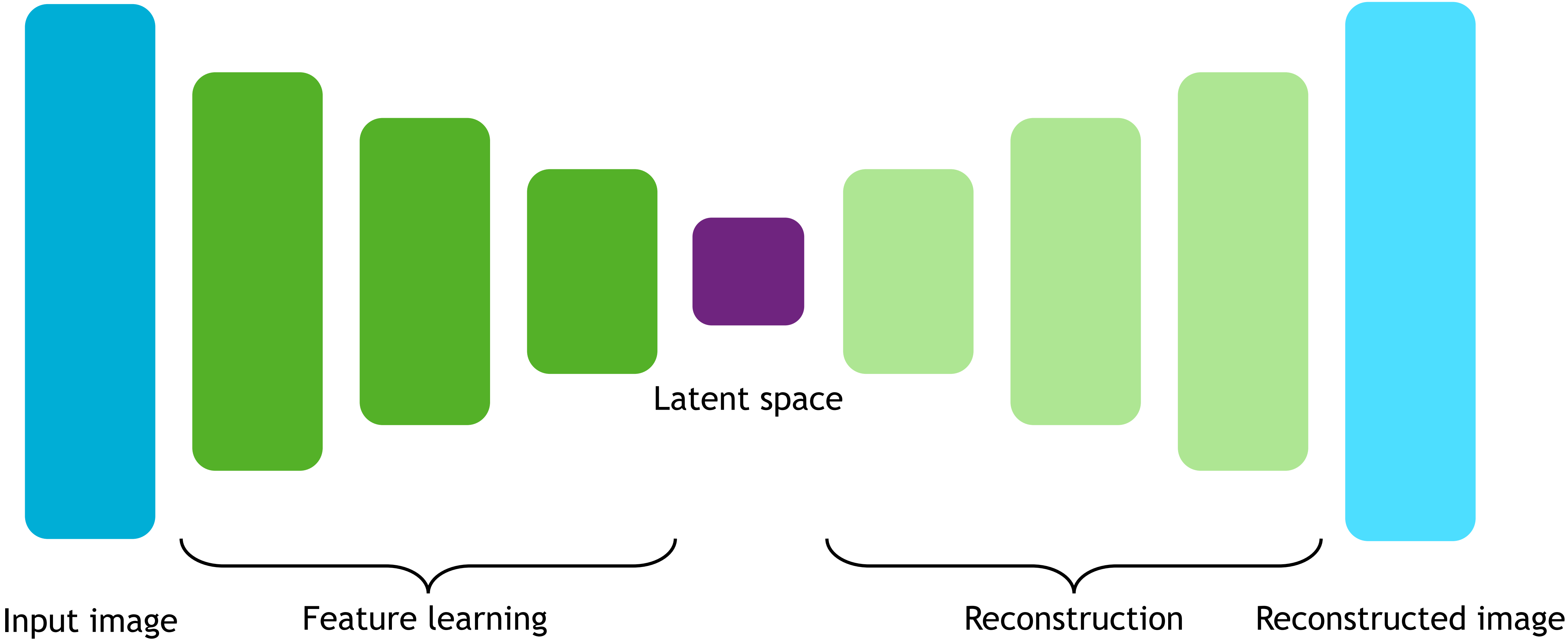
CNNs for many applications



MIT Introduction to Deep Learning (introtodeeplearning.com)

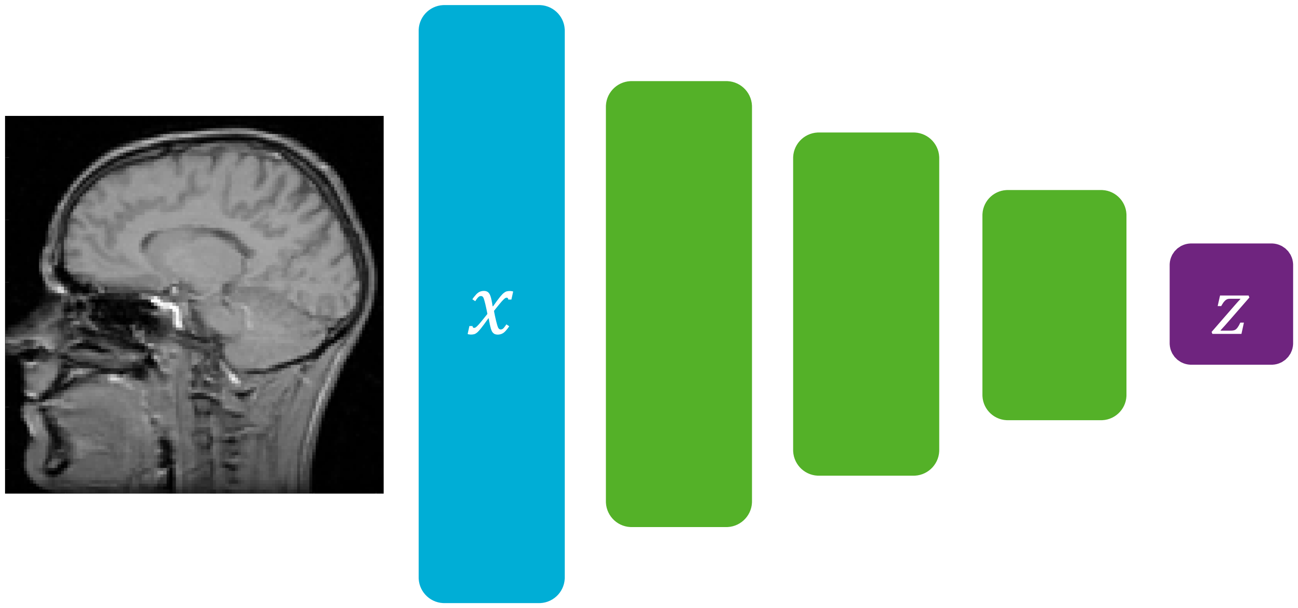
Convolutional neural networks

CNNs for image generation



Autoencoders

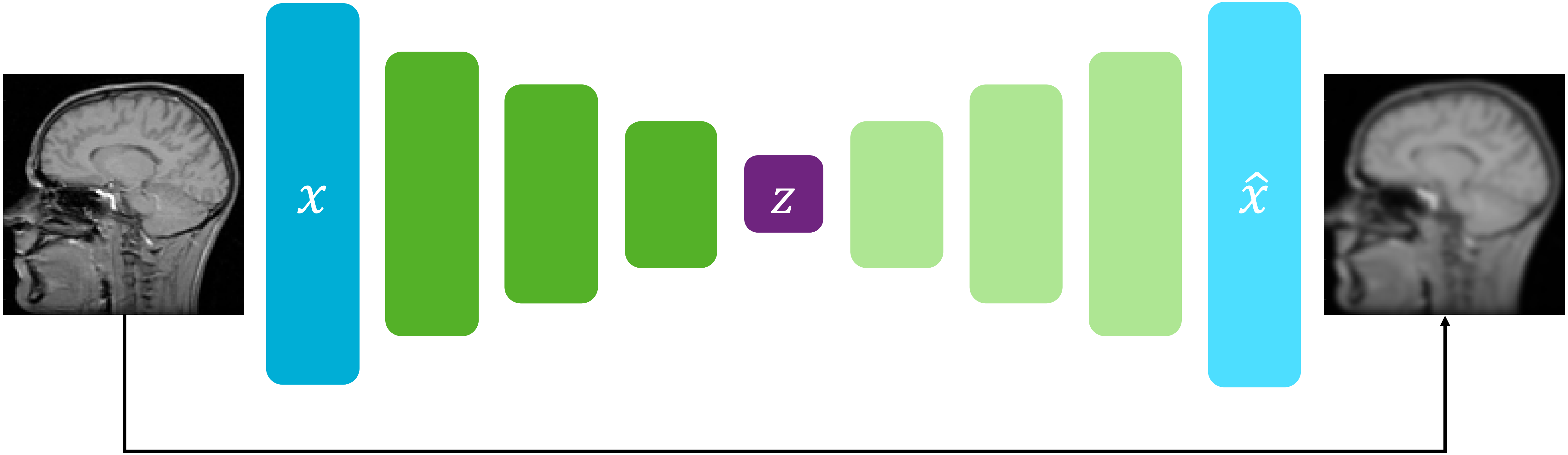
Encoder



Input image
=
observed data

Latent space
=
low dimensional representation of the observed data

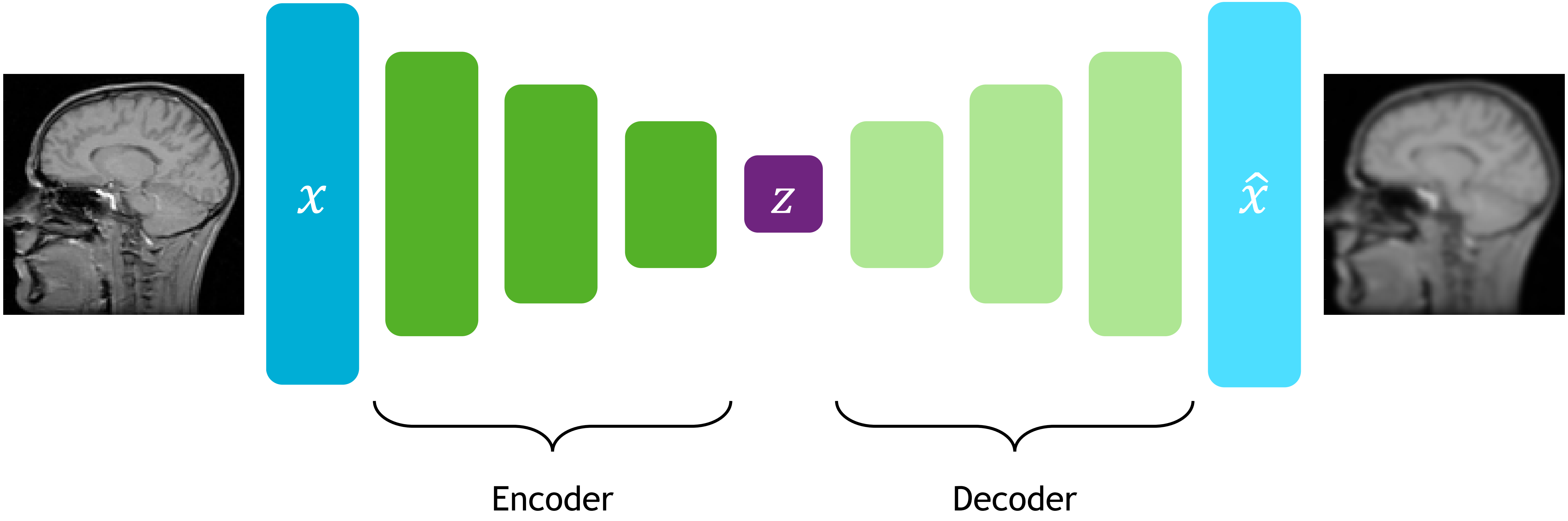
Training autoencoders



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

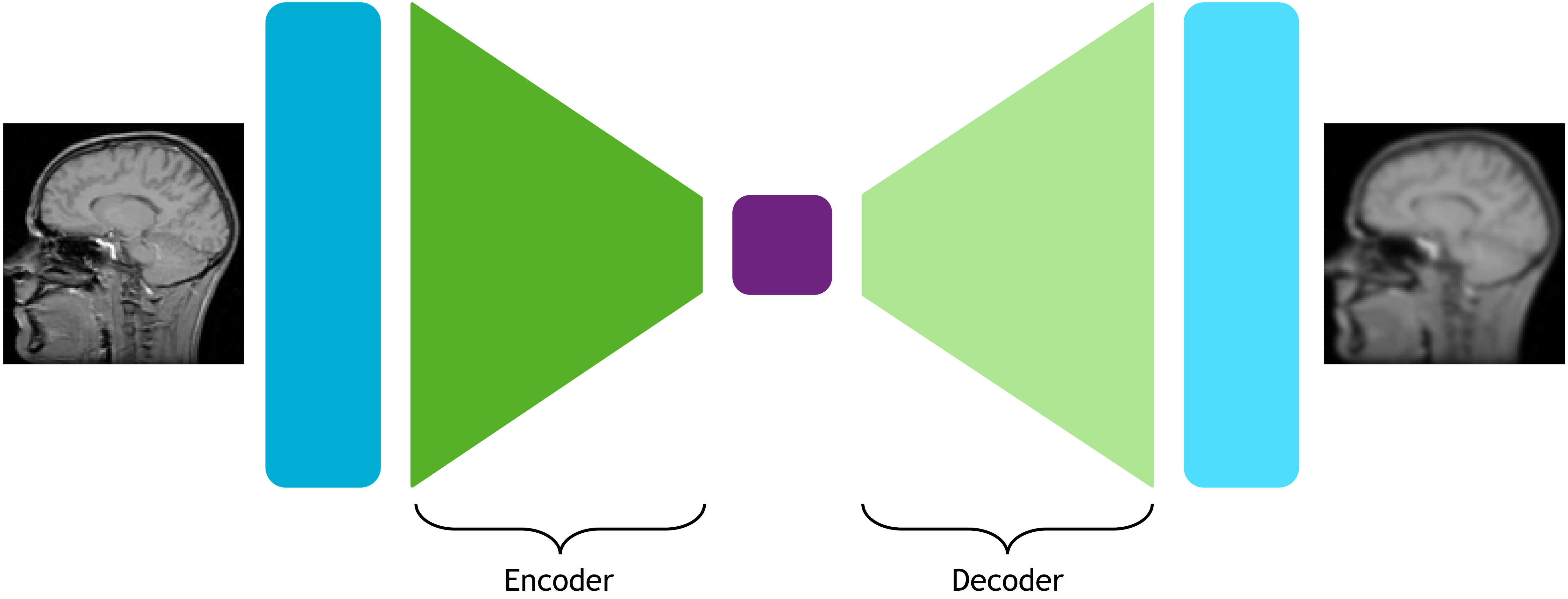
MIT Introduction to Deep Learning (introtodeeplearning.com)

Autoencoders



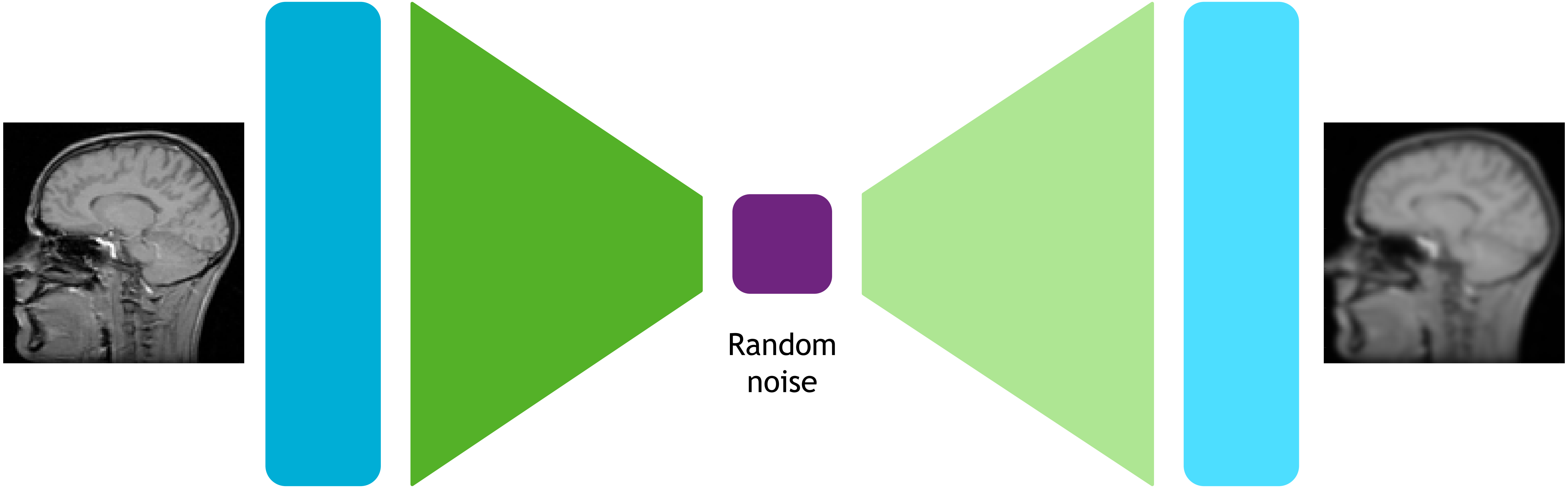
MIT Introduction to Deep Learning (introtodeeplearning.com)

Autoencoders



Generative adversarial networks

Generating images from scratch

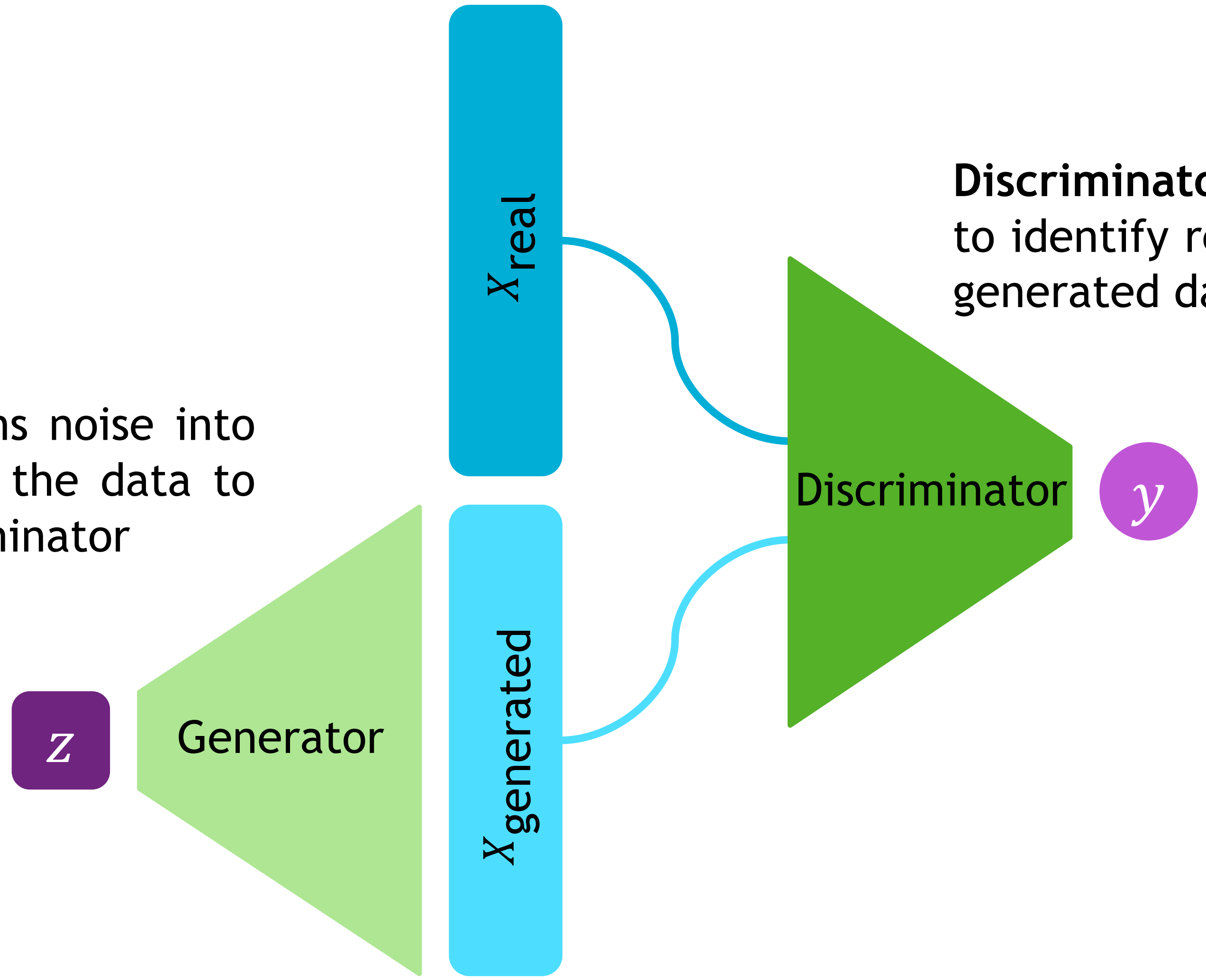


Generative adversarial networks

Competing networks

Discriminator: tries to identify real from generated data

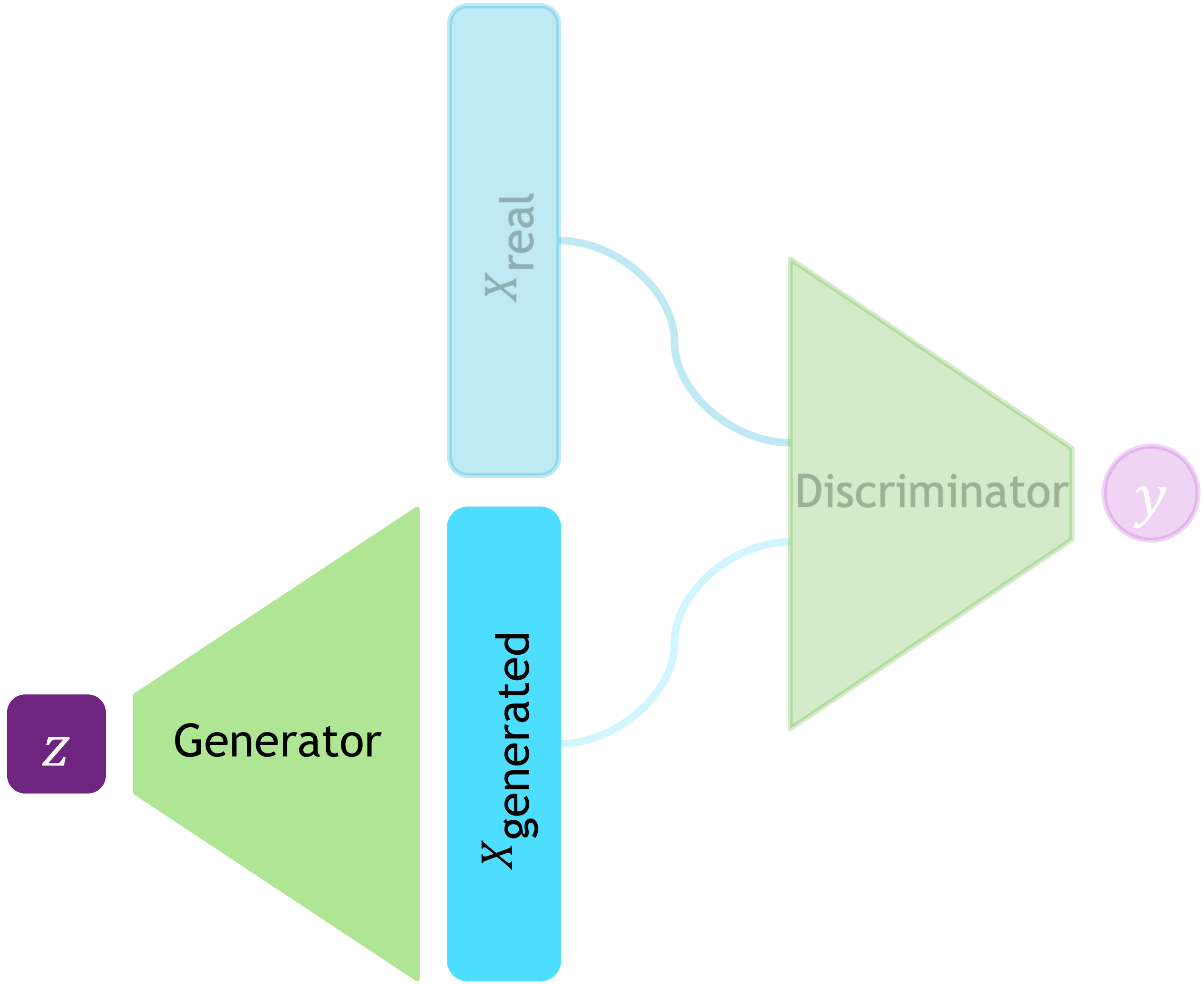
Generator: turns noise into an imitation of the data to trick the discriminator



MIT Introduction to Deep Learning (introtodeeplearning.com)

Generative adversarial networks

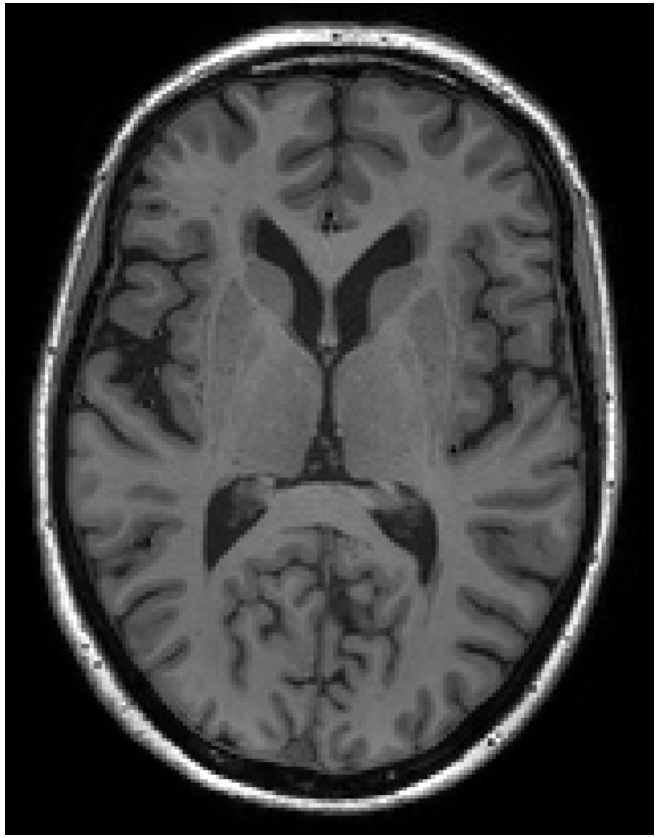
Generating new images



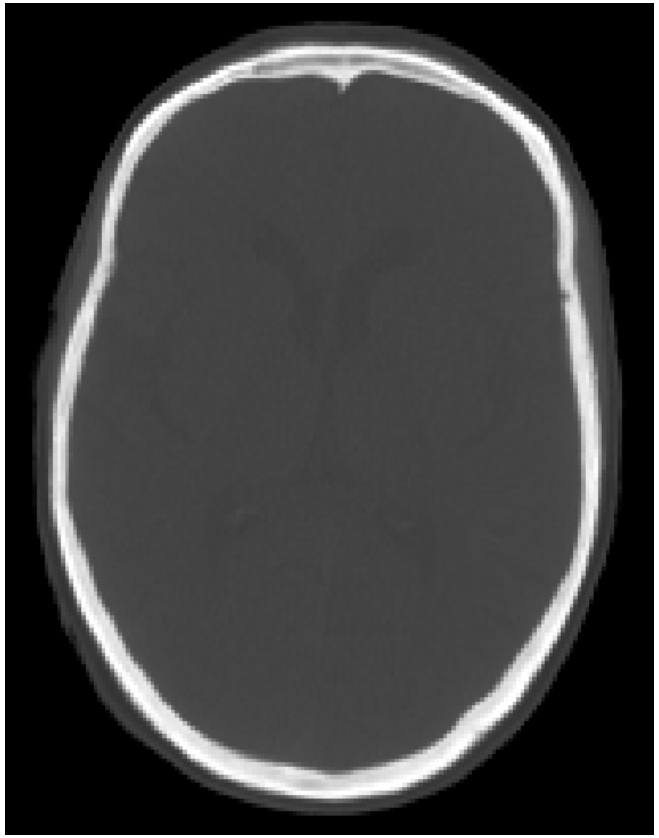
MIT Introduction to Deep Learning (introtodeeplearning.com)

Generative adversarial networks

Image translation

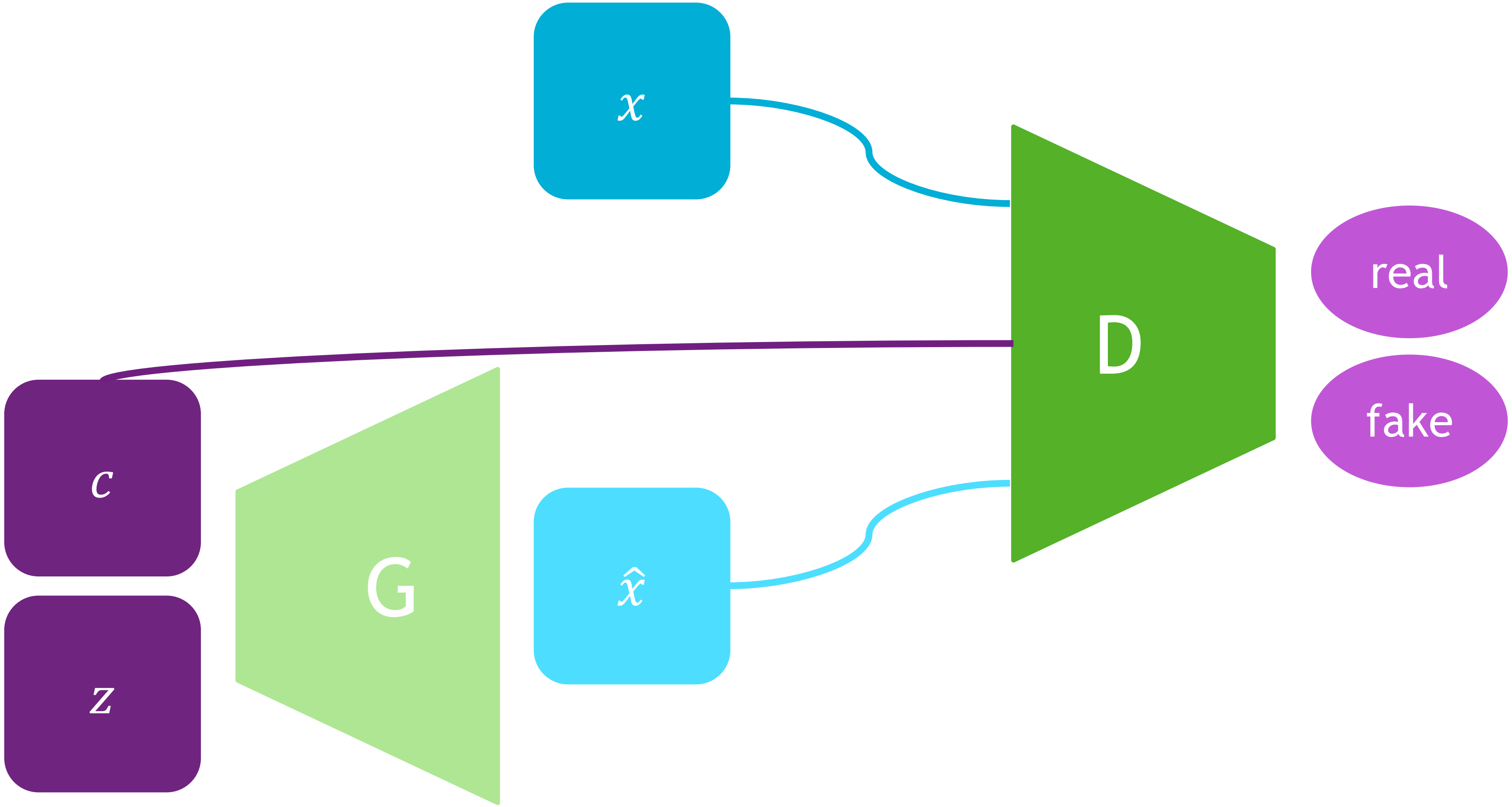


MRI



CT

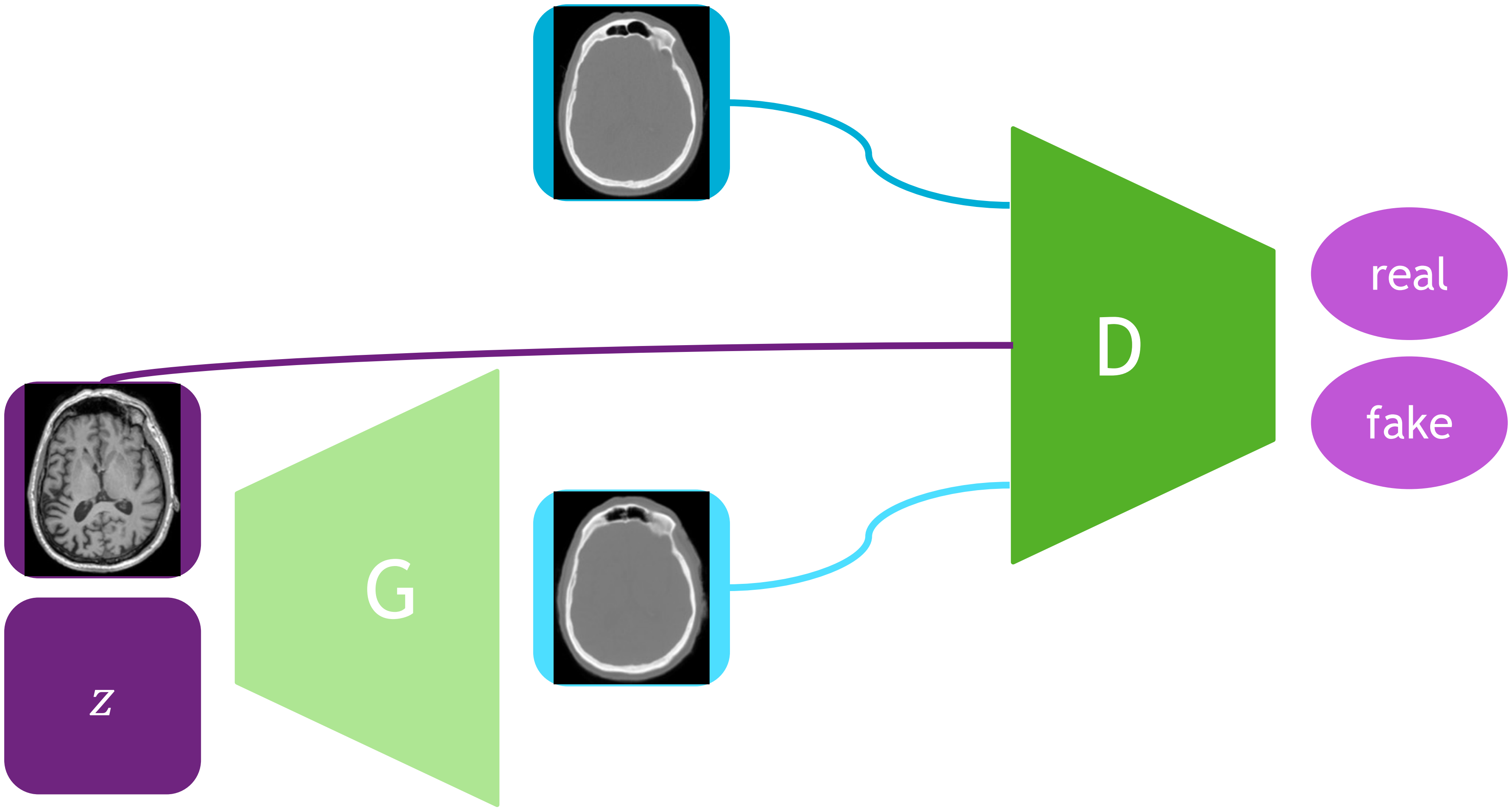
Image translation with conditional GANs



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

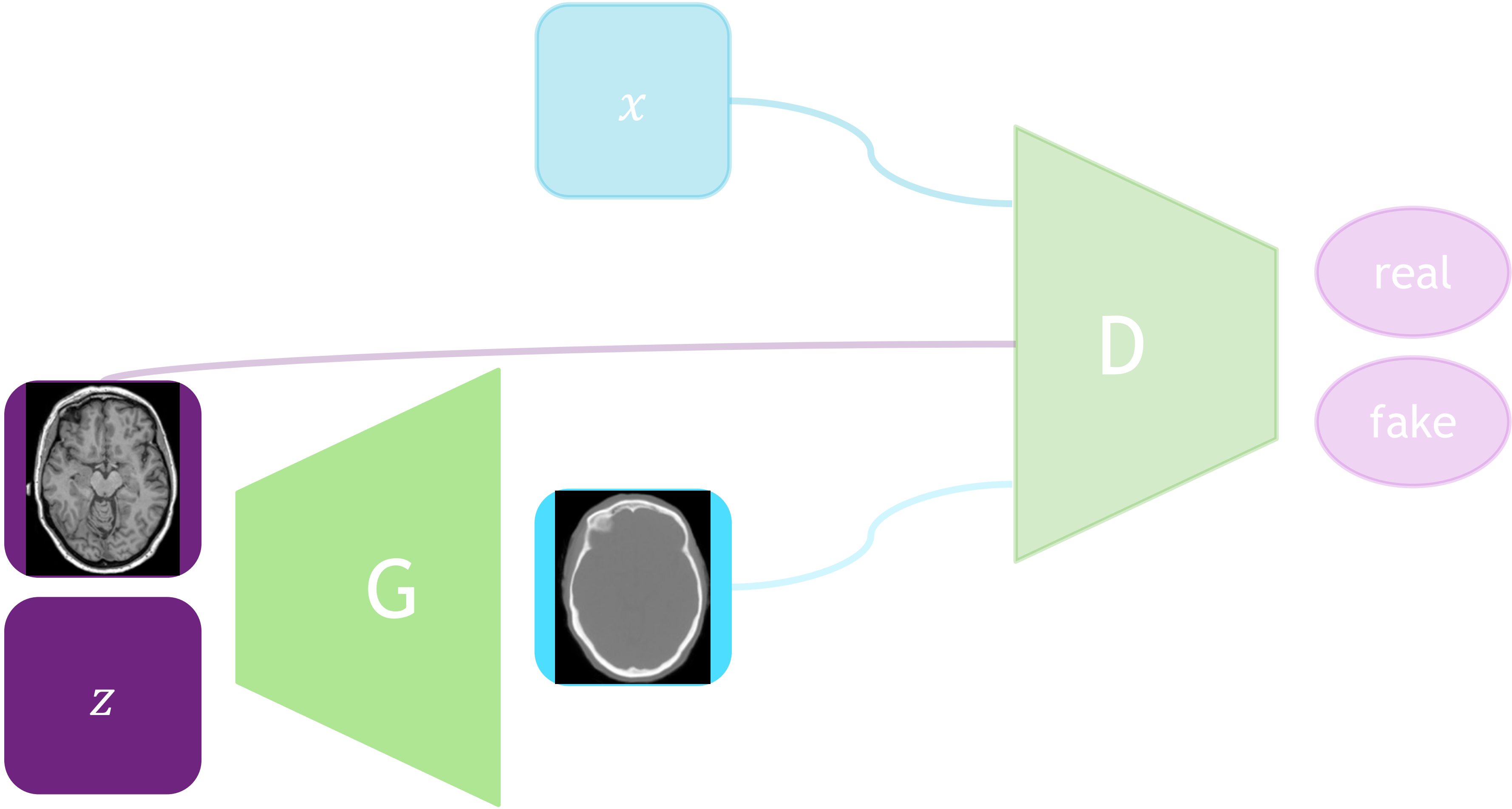
Generative adversarial networks

Image translation with conditional GANs



Generative adversarial networks

Image translation with conditional GANs



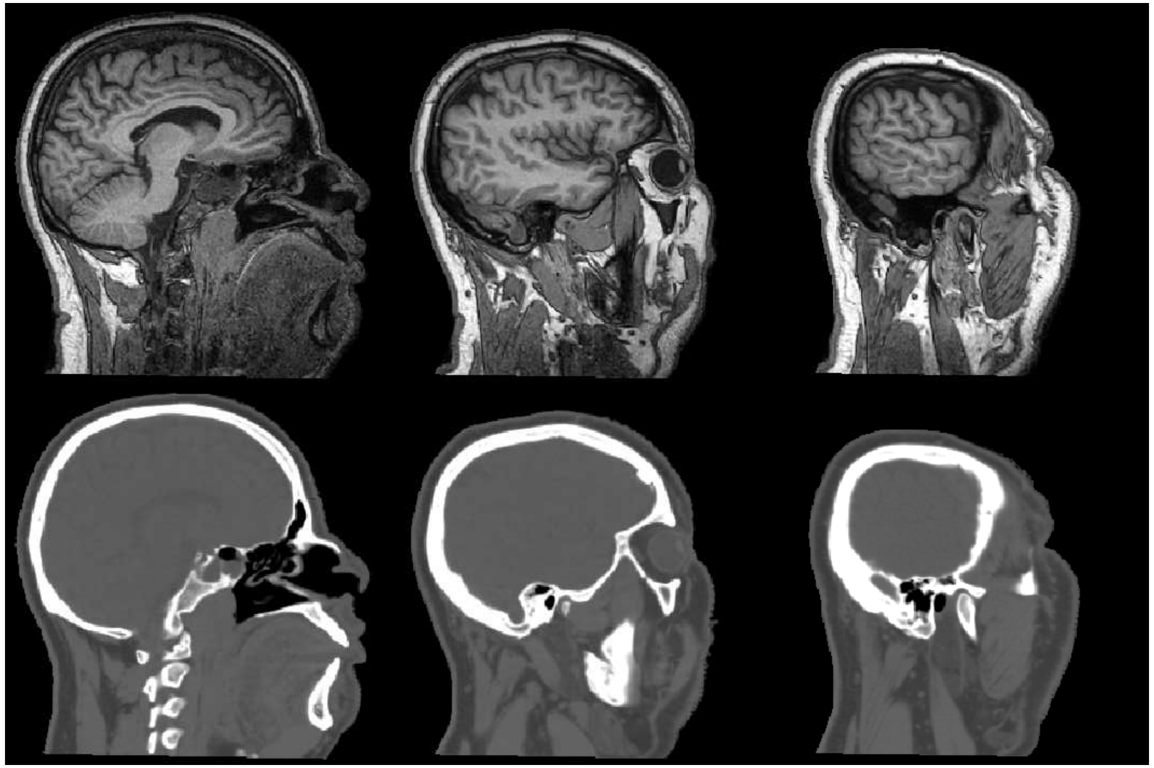
Generative adversarial networks

Image translation from paired or unpaired data

Paired data

MR

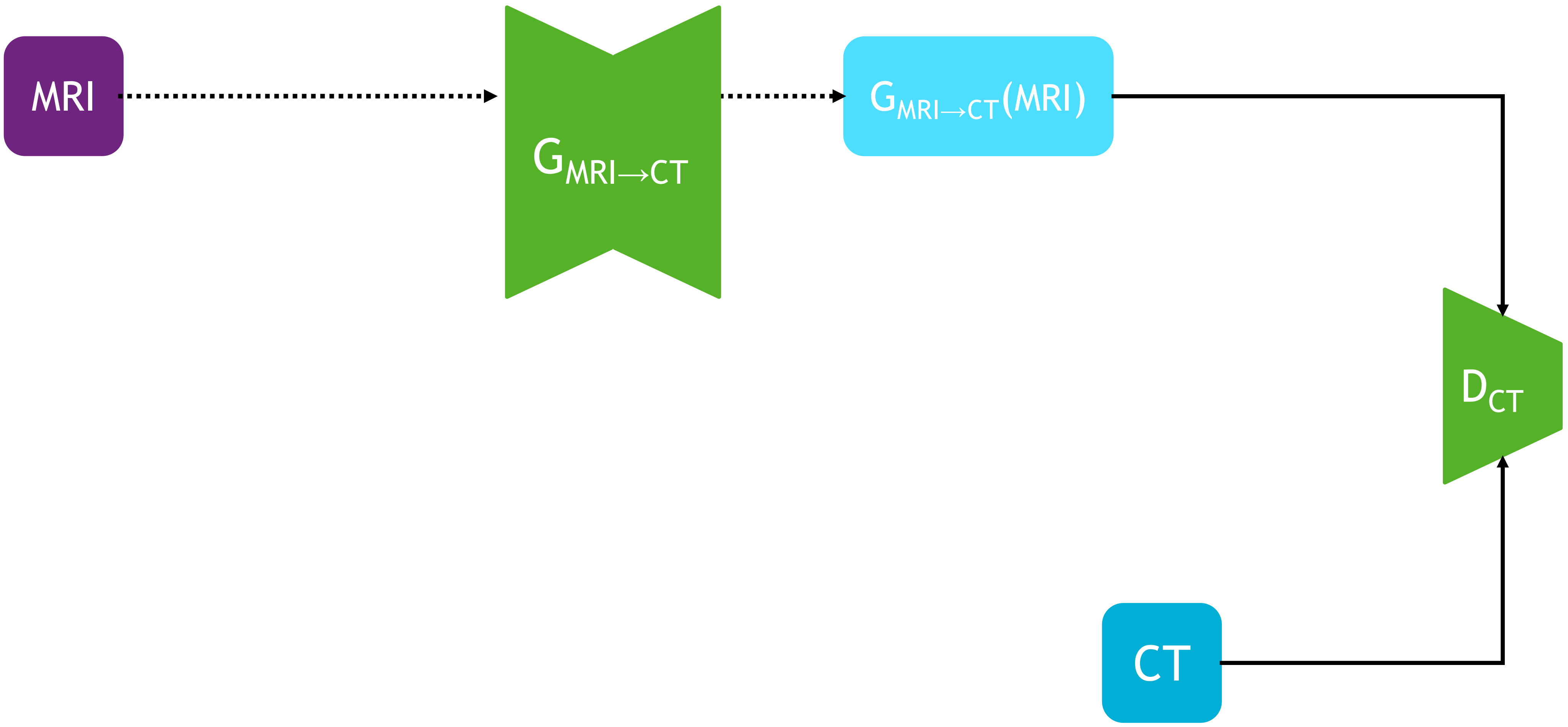
CT



Unpaired data

Wolterink et al., SASHIMI, 2017

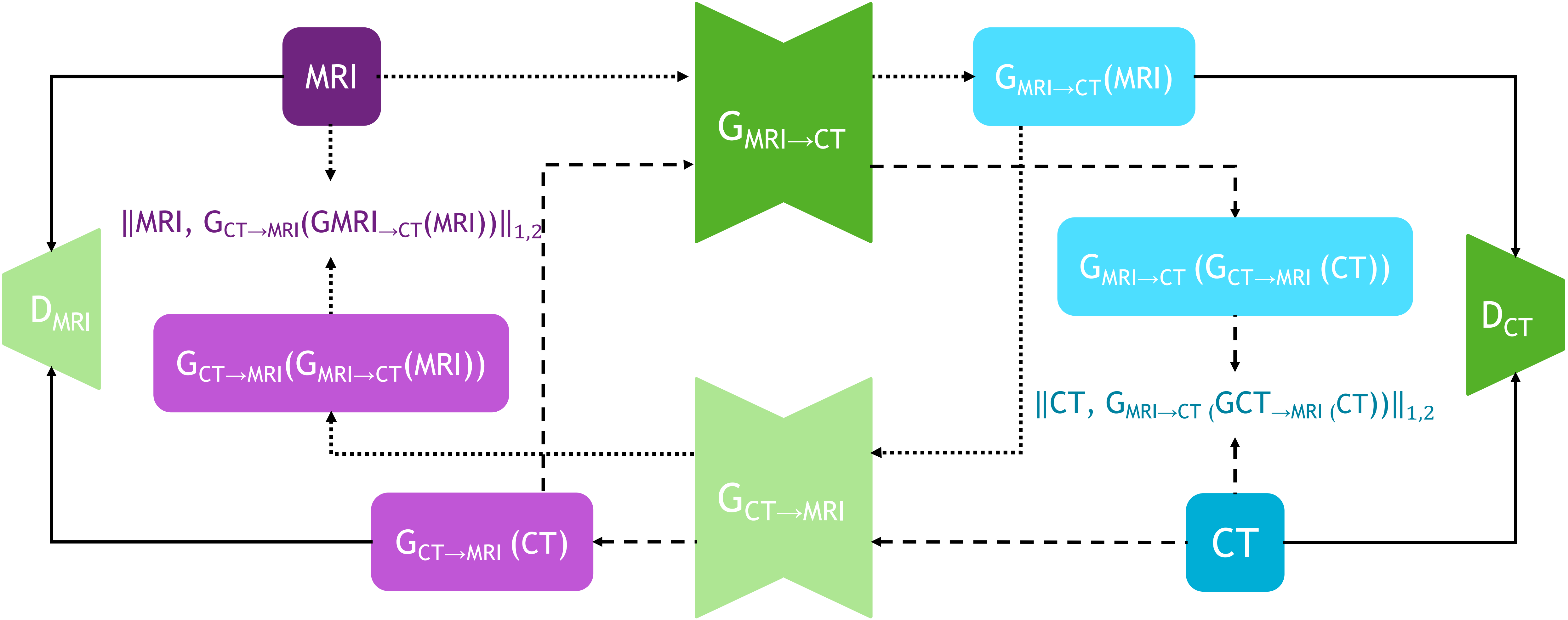
Image translation with conditional GANs



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

Generative adversarial networks

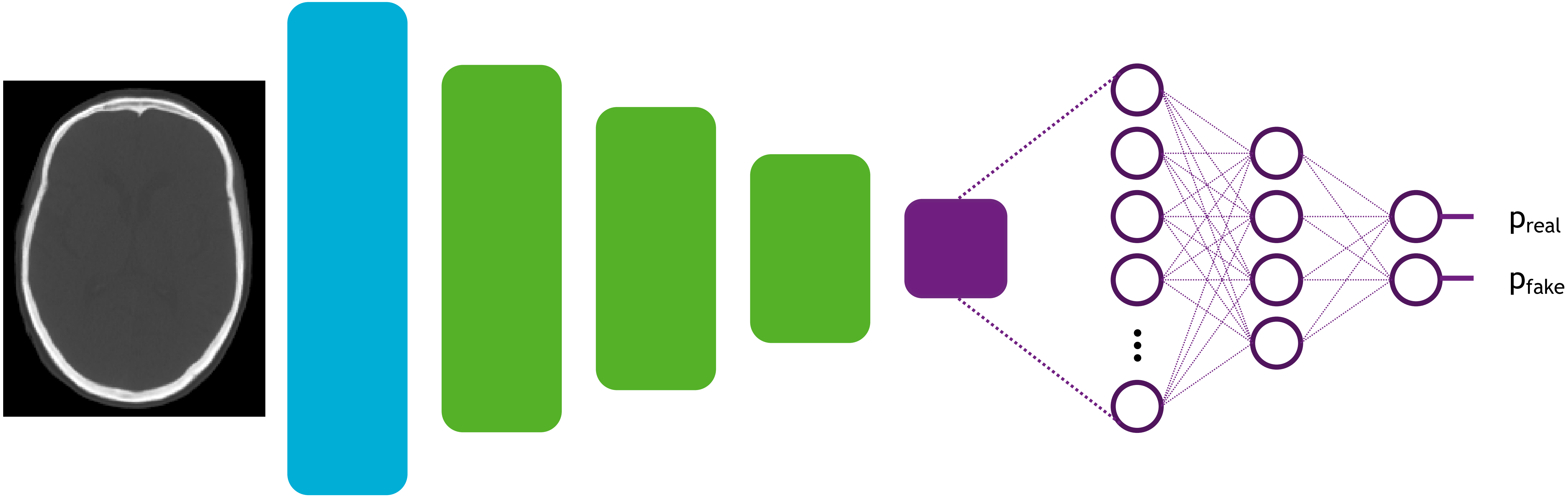
Image translation with cycle GANs



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

Generative adversarial networks

Structure of the discriminator



Generative adversarial networks

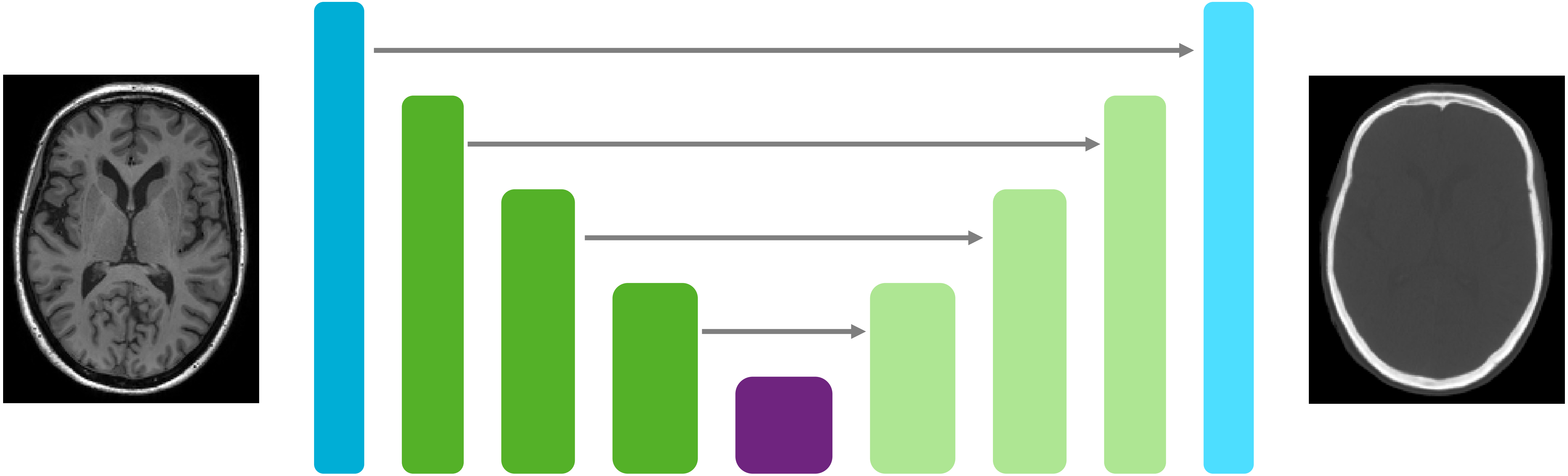
Structure of the generator:

- encoder-decoder

Generative adversarial networks

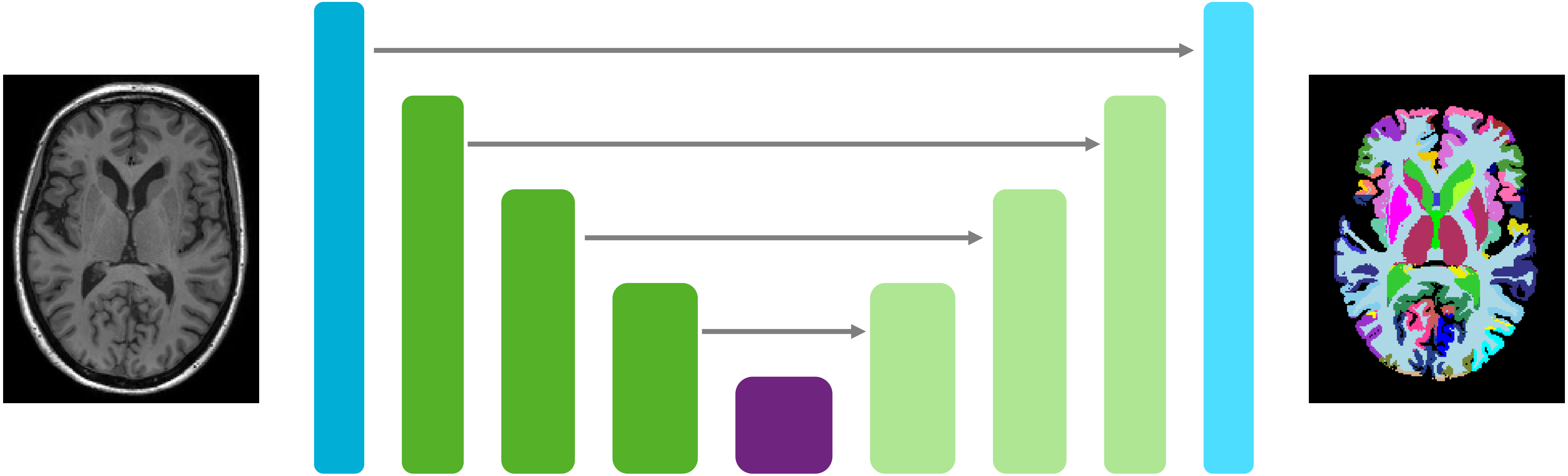
Structure of the generator:

- U-Net



Ronneberger et al., MICCAI, 2015 (**61570** citations on 10/05/2023)

Convolutional Networks for Biomedical Image Segmentation

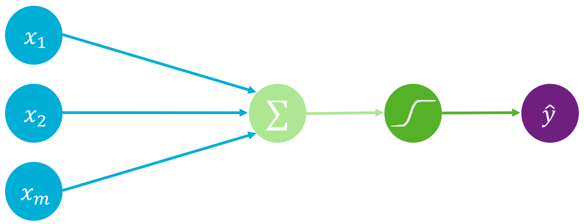


Ronneberger et al., MICCAI, 2015 (**61570** citations on 10/05/2023)

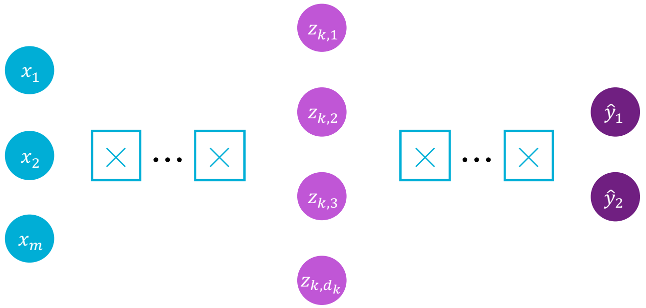
Summary

Neural Networks

- Perceptron = structural building block

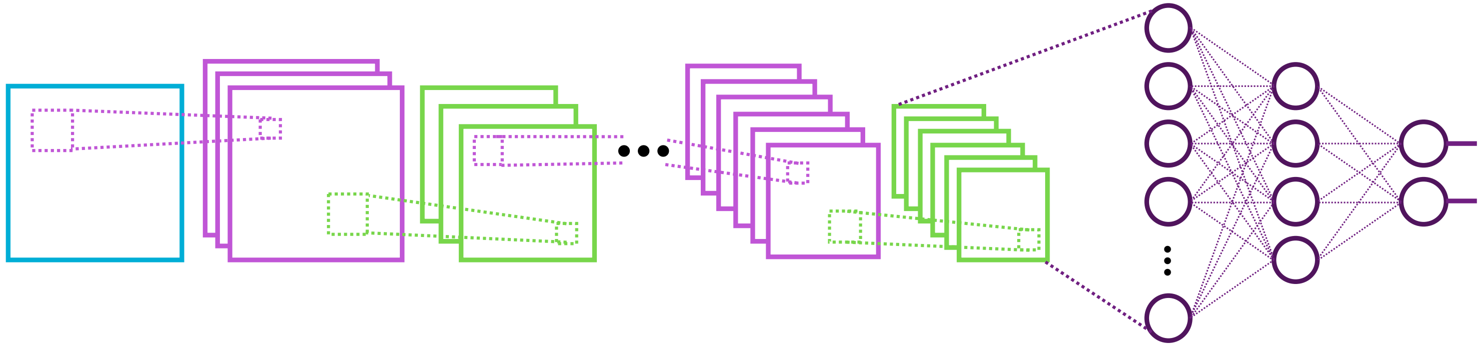


- Stacking perceptrons to form neural networks



CNNs

- Convolutions for feature extraction
- Convolution → non-linearity → pooling
- Stacking layers



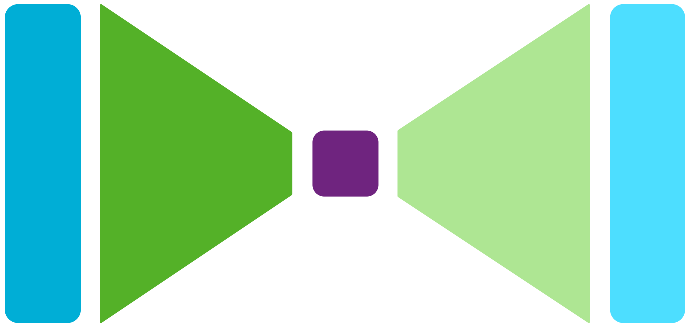
Applications

- Classification
- Segmentation
- Synthesis

Summary

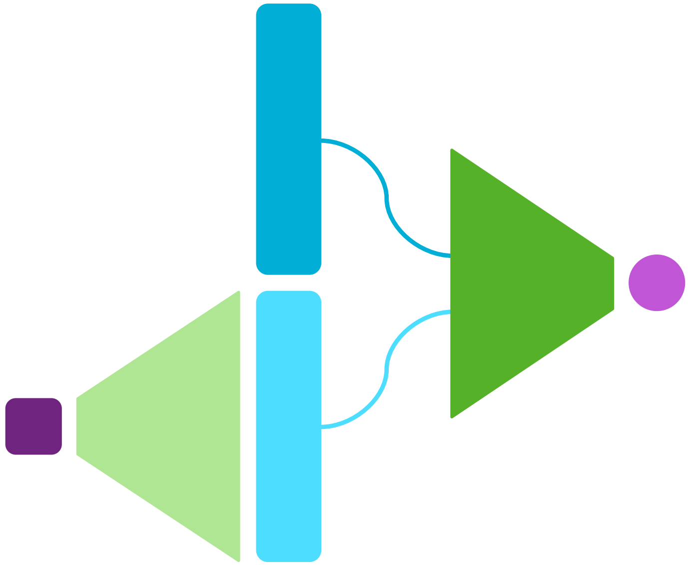
Autoencoders

- Learn low dimensional latent space

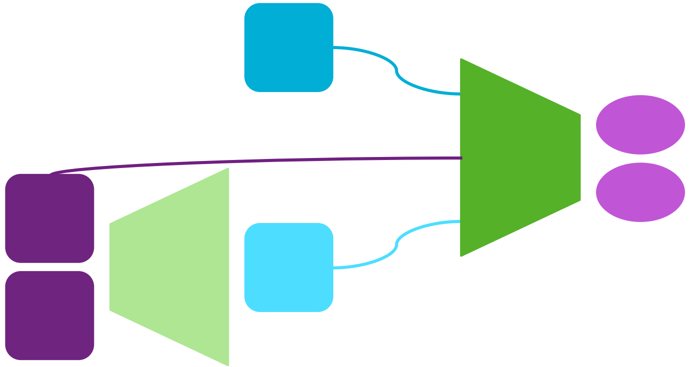


GANs

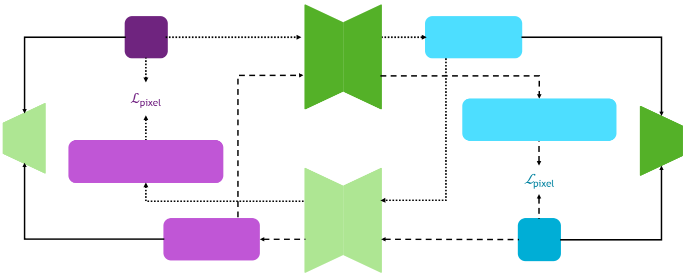
- Competing generator and discriminator networks



Conditional GANs

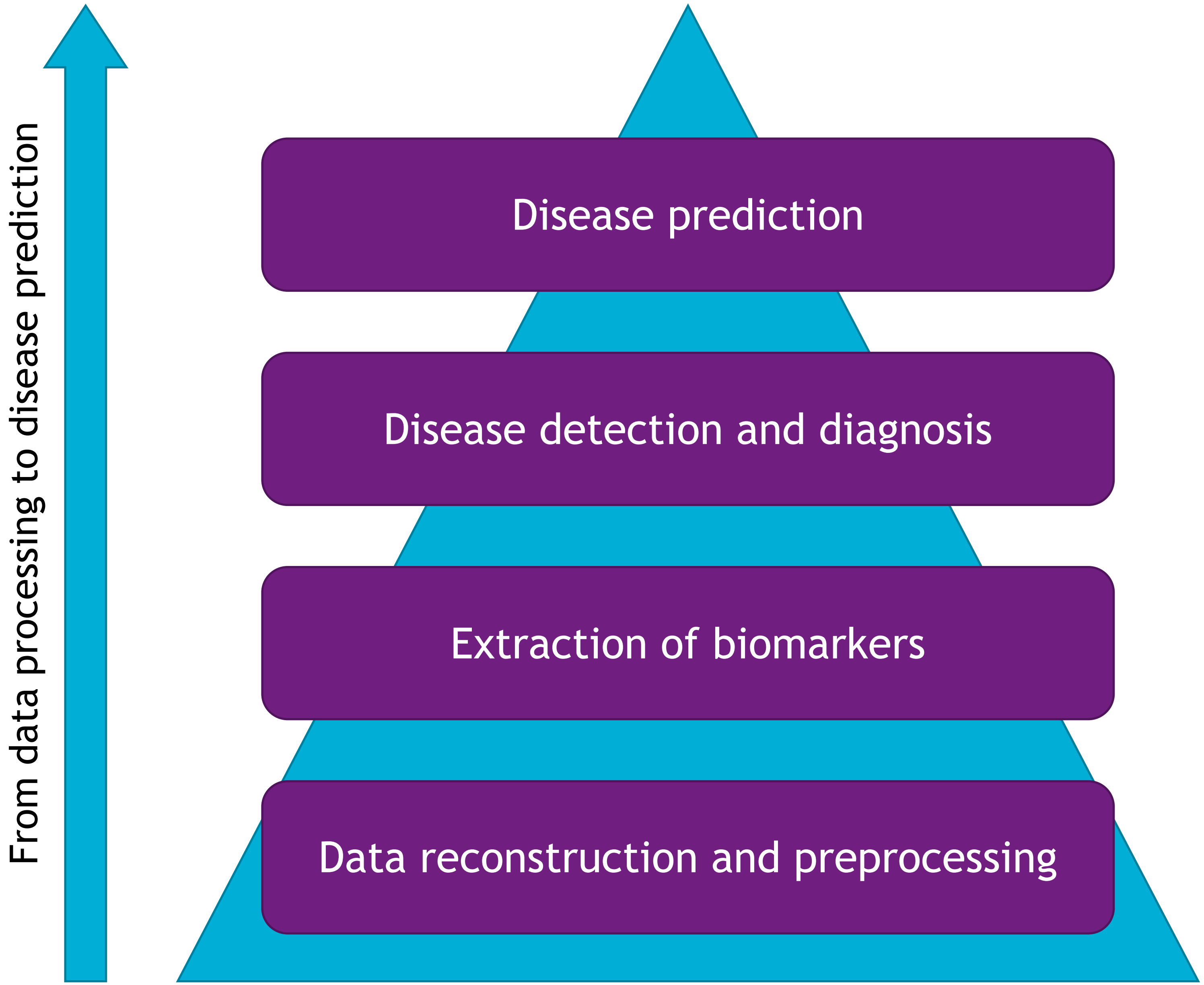


Cycle GANs



Deep Learning for Medical Imaging

Deep learning for medical imaging



Deep learning for medical imaging

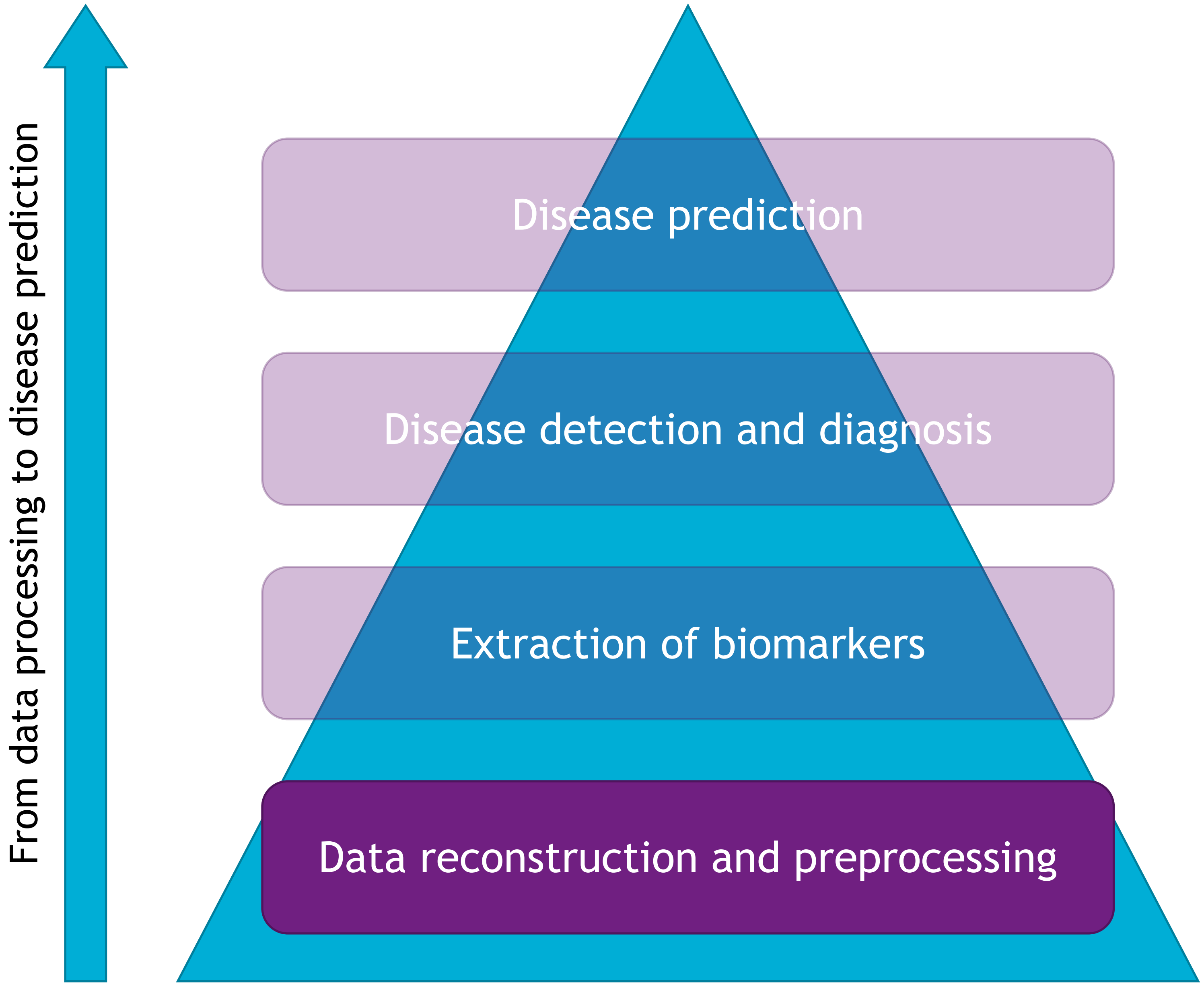
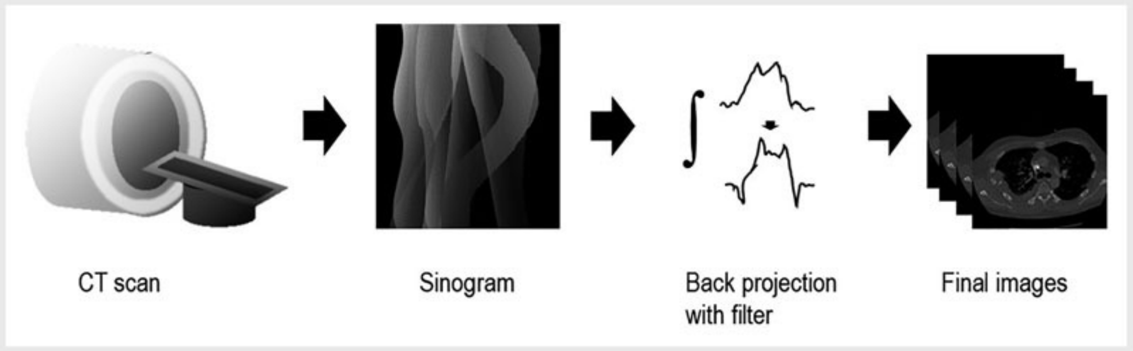


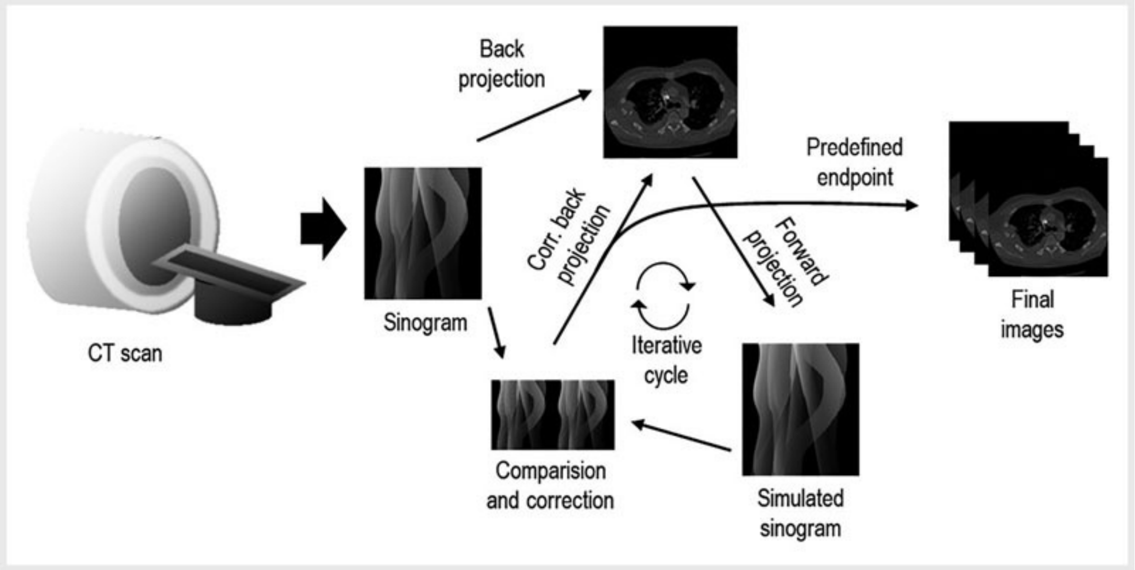
Image reconstruction

Historical techniques

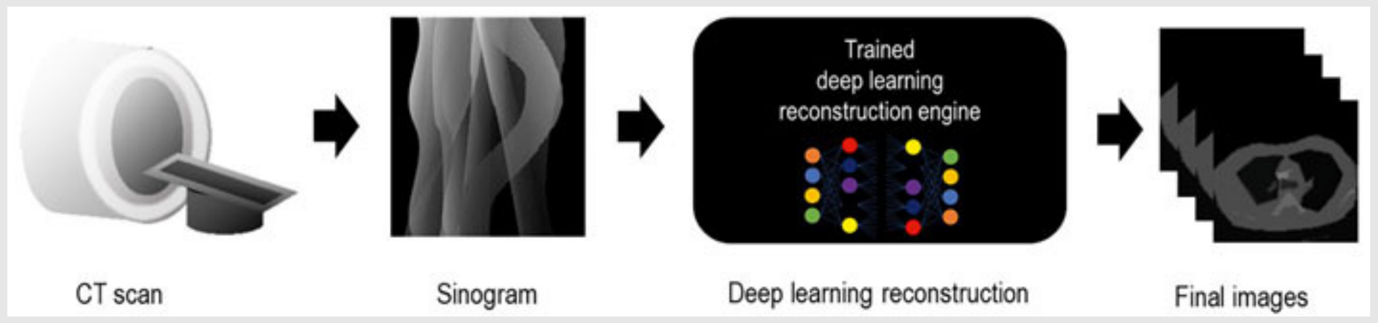
Analytical reconstruction



Iterative reconstruction

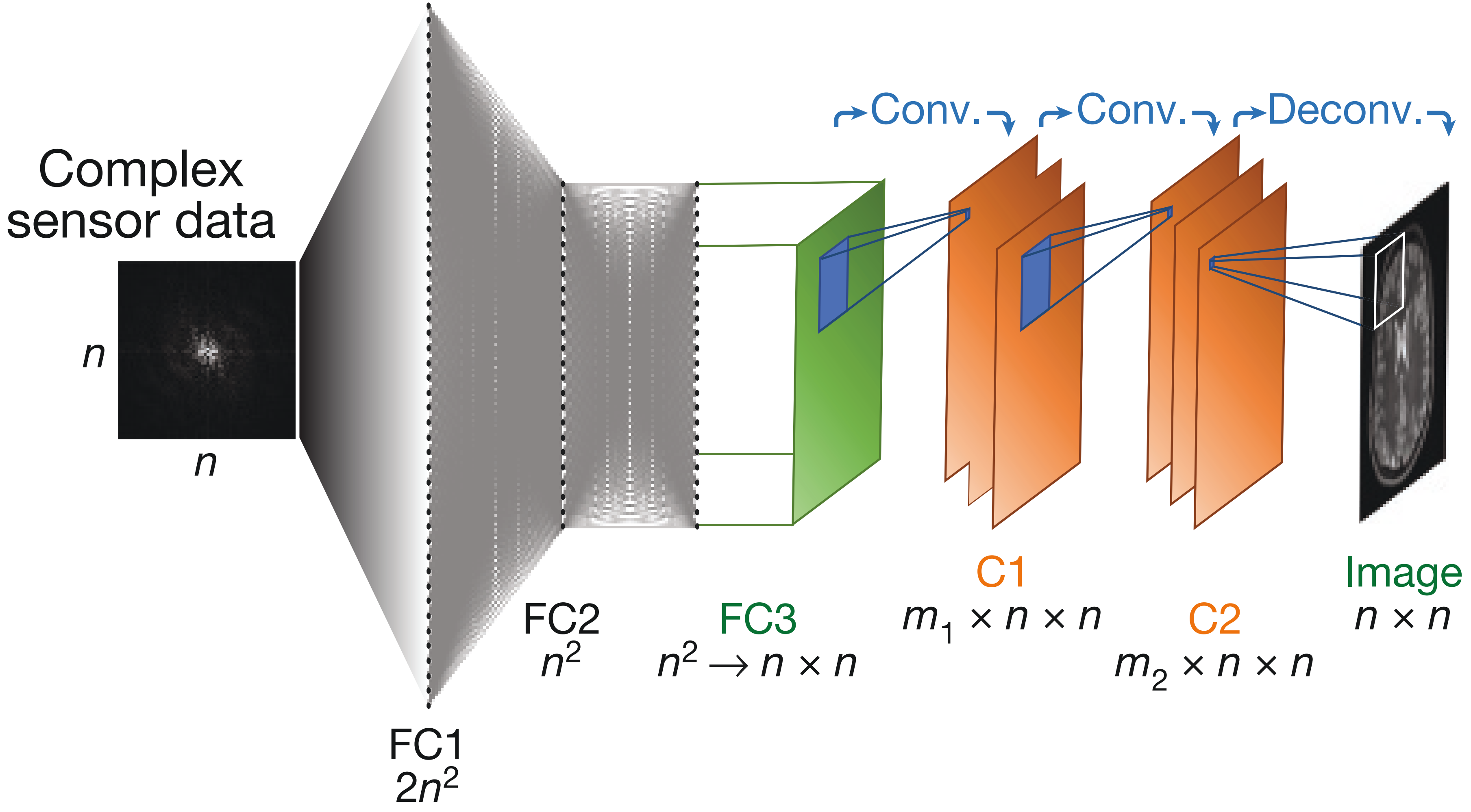


Deep learning



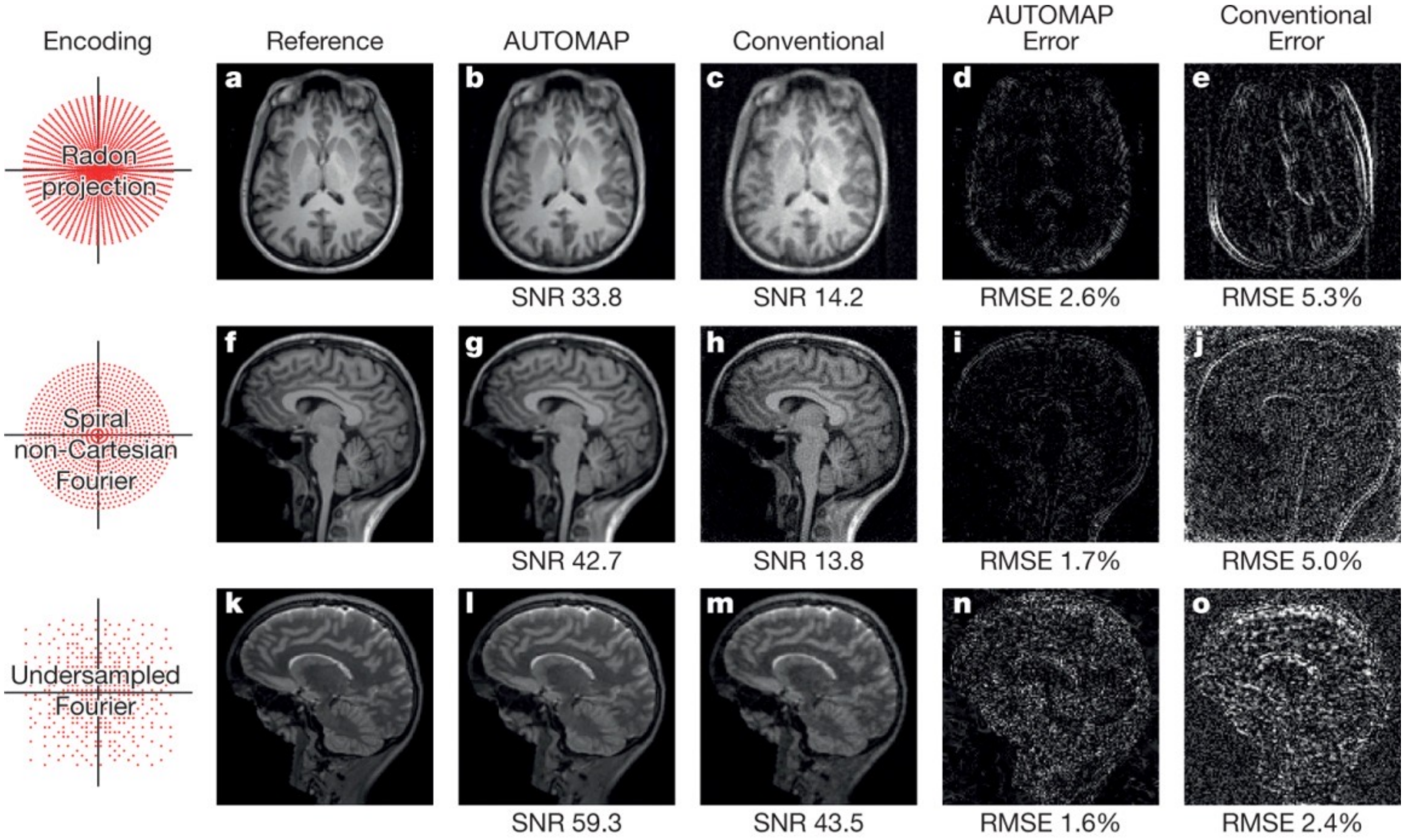
Arndt et al., Fortschr Röntgenstr, 2021

Image reconstruction by domain-transform manifold learning



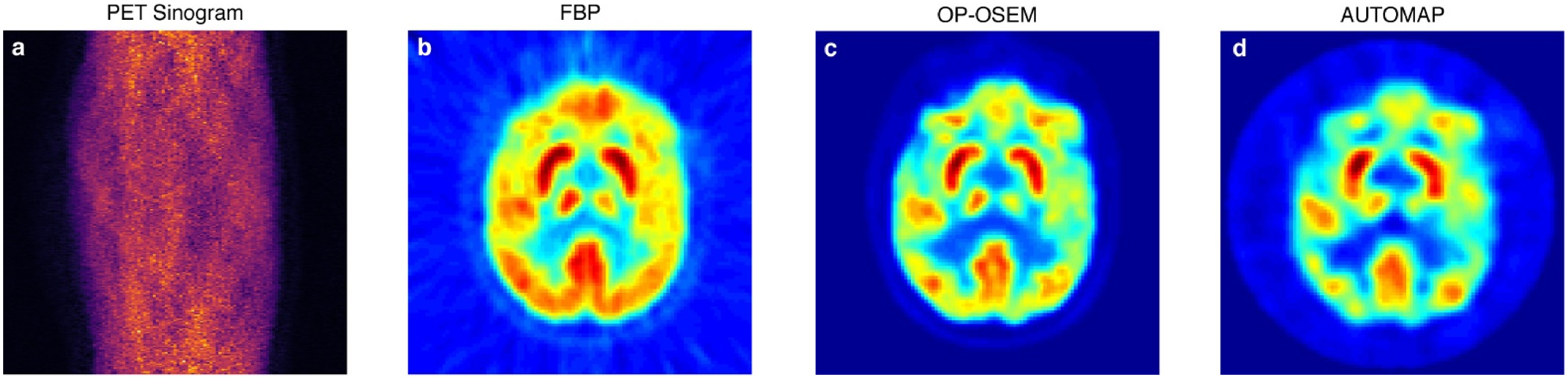
Zhu et al., Nature, 2018

Image reconstruction by domain-transform manifold learning



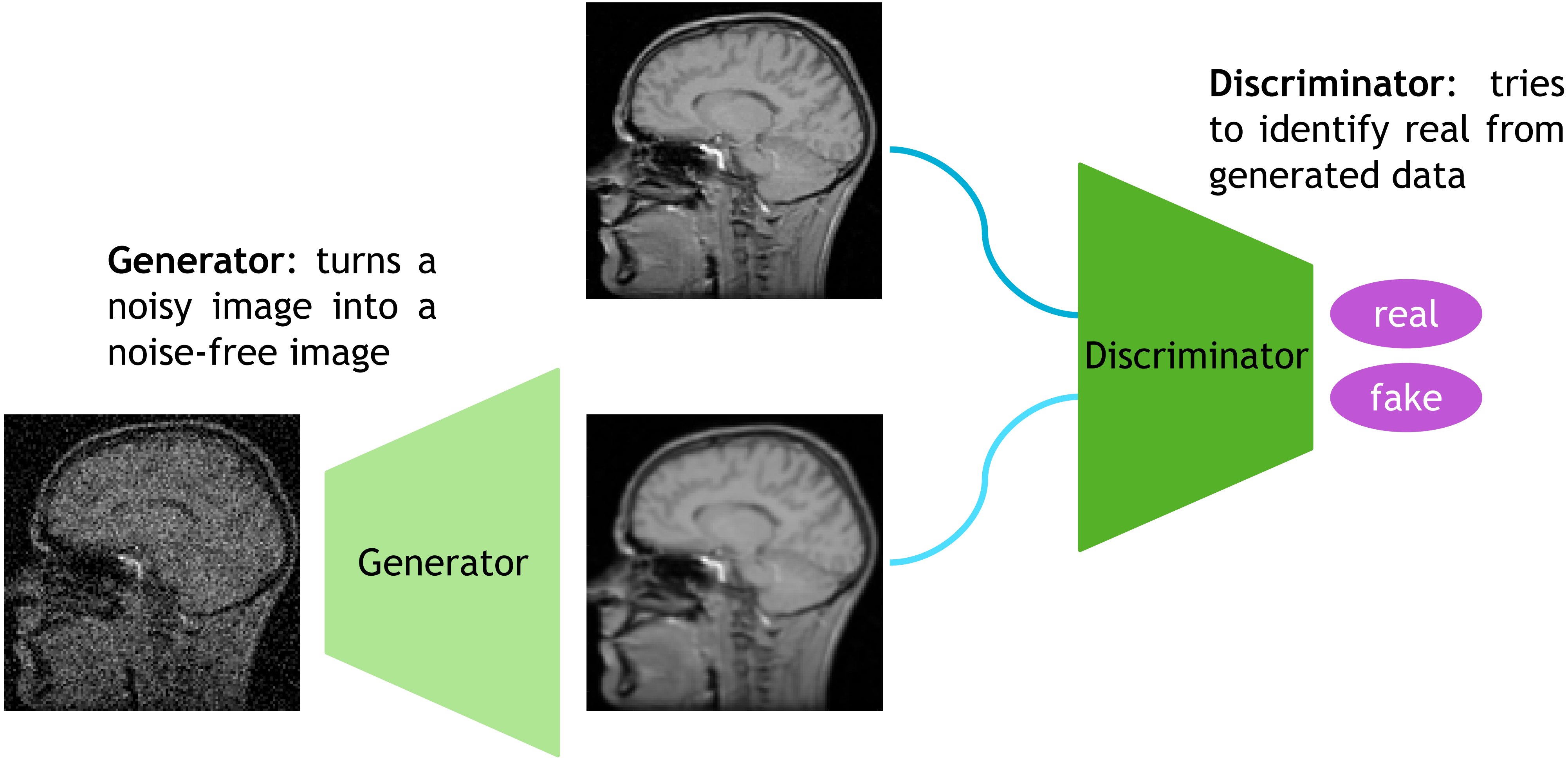
Zhu et al., Nature, 2018

Image reconstruction by domain-transform manifold learning



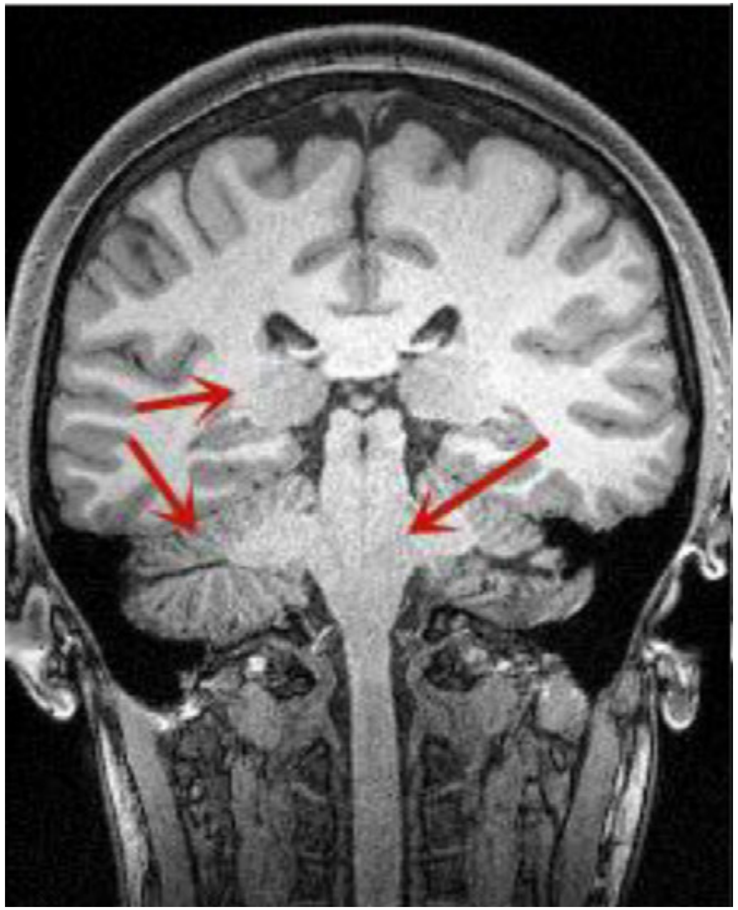
Zhu et al., Nature, 2018

Image denoising using a cGAN

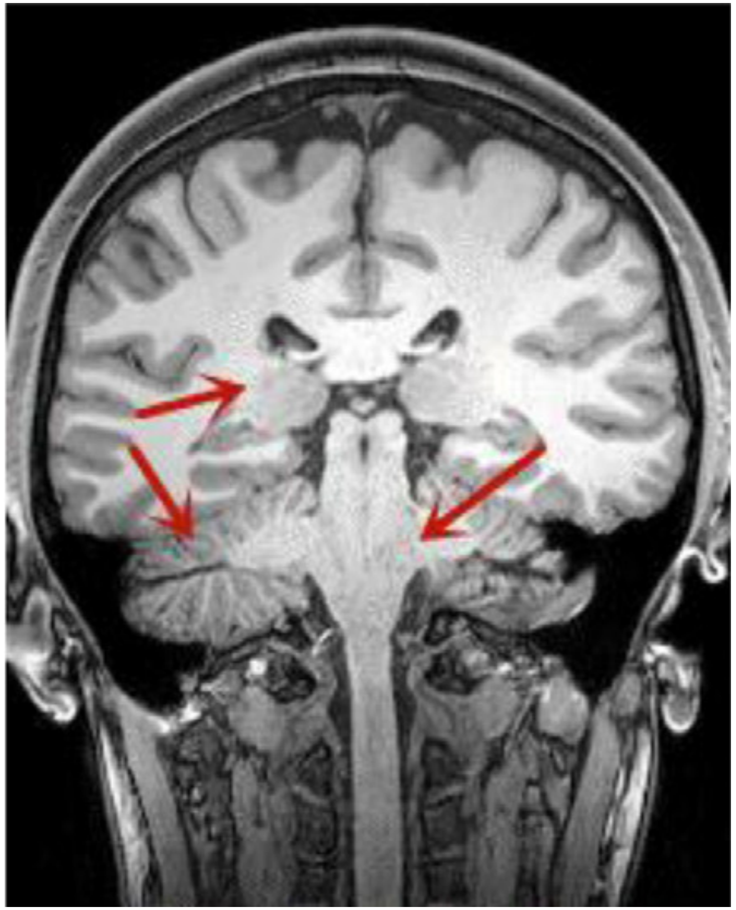


Signal enhancement

Image denoising using a cGAN



Original noisy MRI



Denoised MRI

Ran et al., Medical Image Analysis, 2019

Signal enhancement

Image denoising using a cGAN

Full dose CT

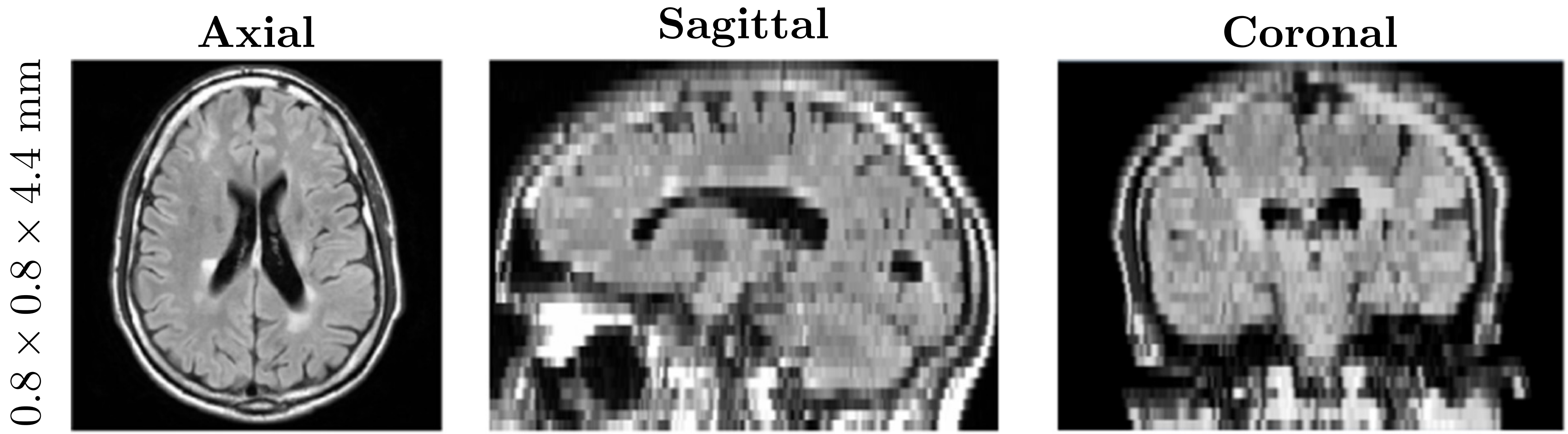
Low dose CT

Low dose CT
after denoising

Yang et al., IEEE Transactions on Medical Imaging, 2018

Signal enhancement

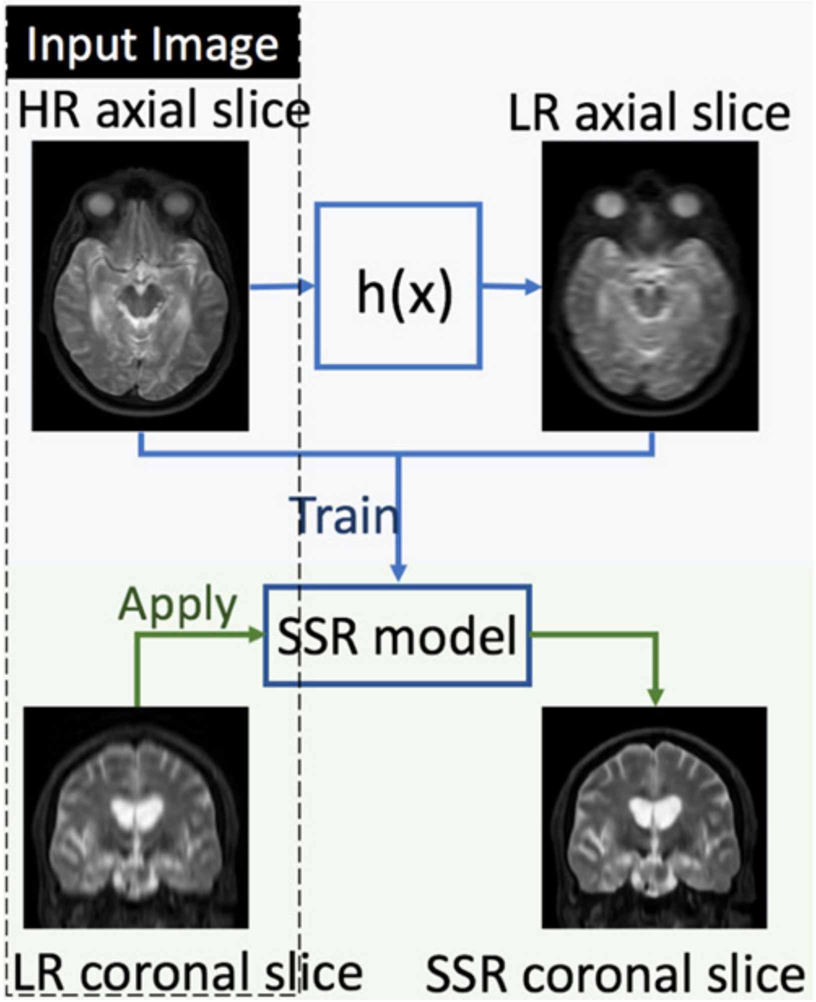
Example of 2D brain MRI

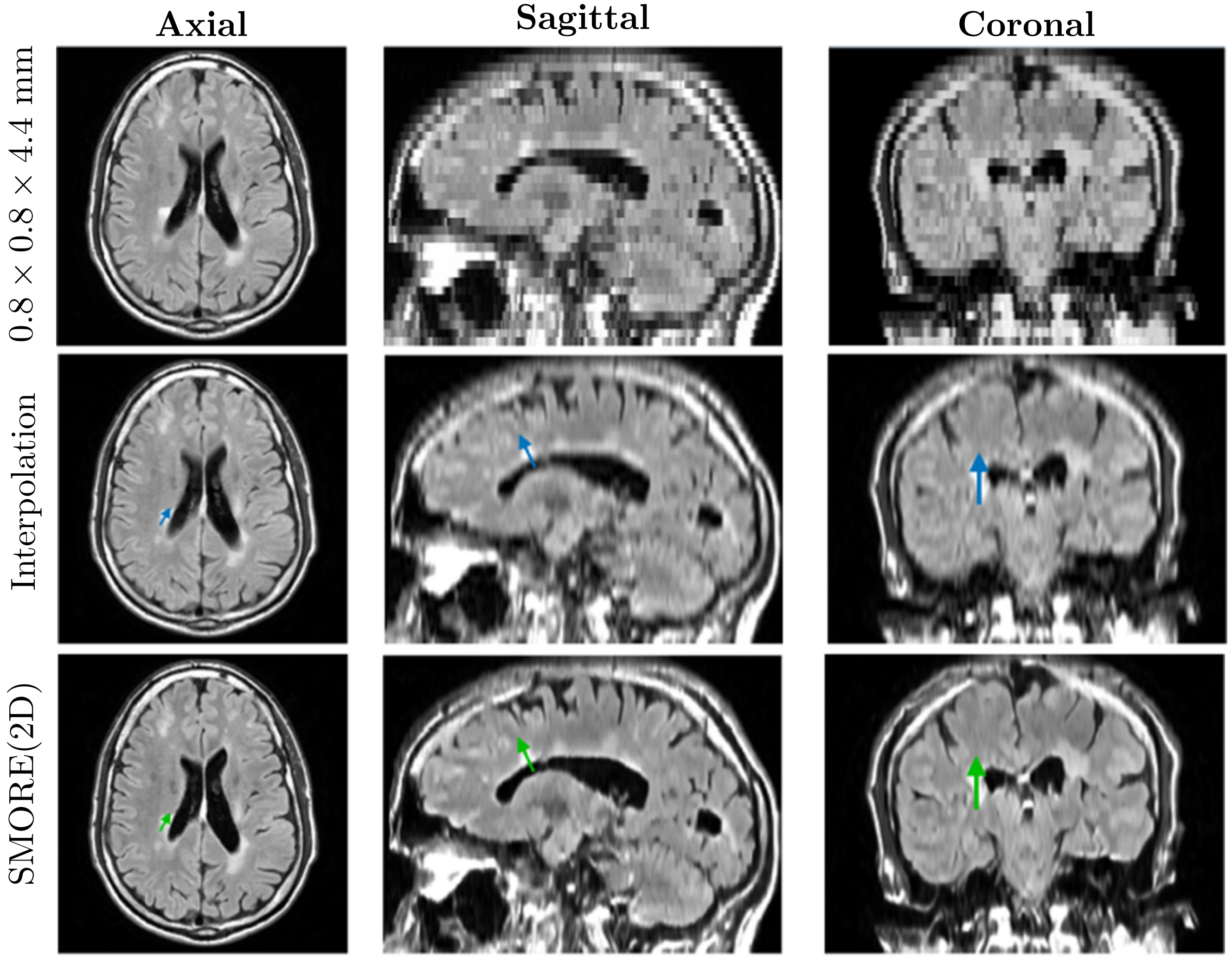


Zhao et al., Magnetic Resonance Imaging, 2019

Image super-resolution

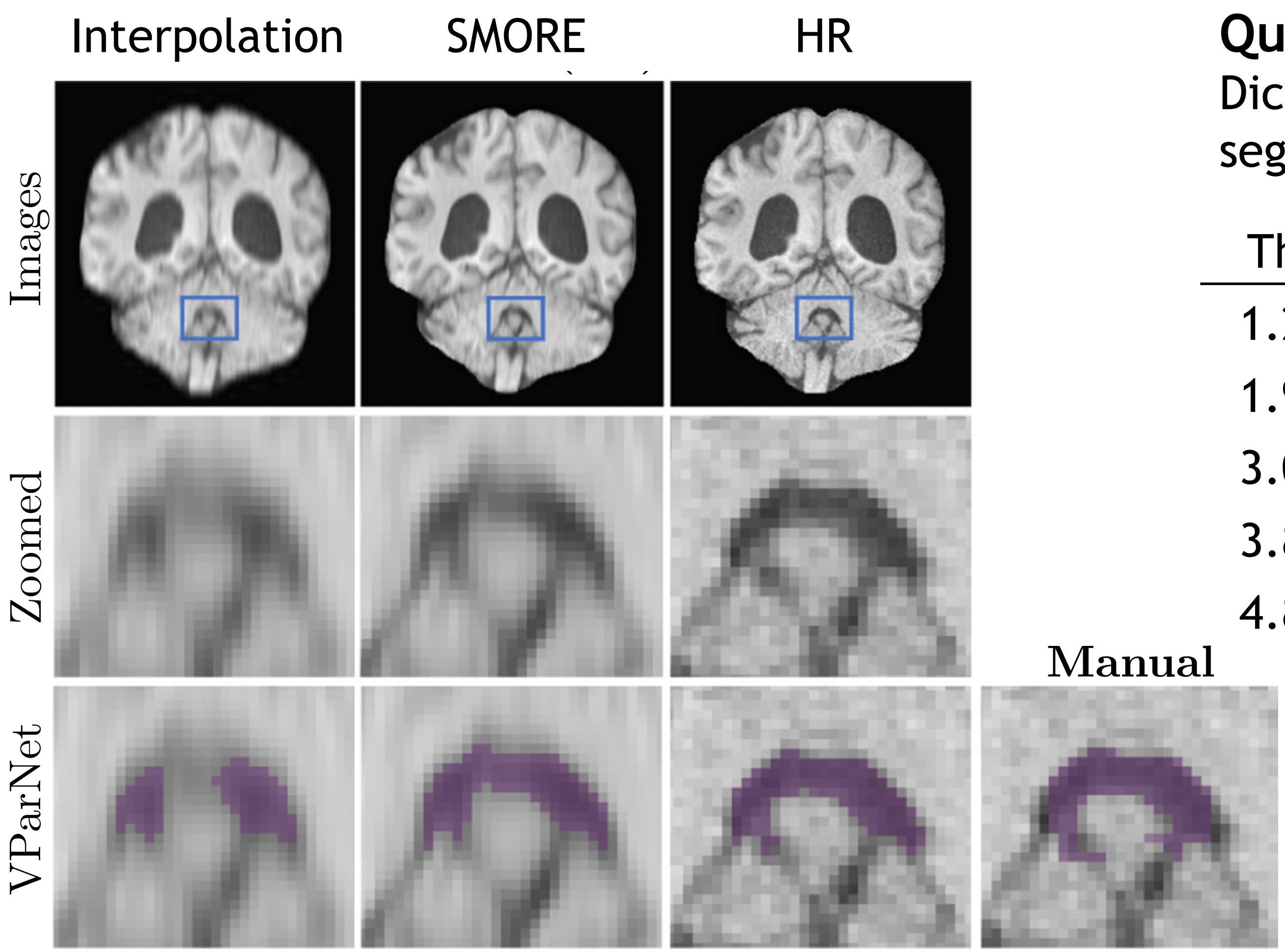
Image super-resolution, a self-supervised approach





Zhao et al., Magnetic Resonance Imaging, 2019

Image super-resolution, a self-supervised approach



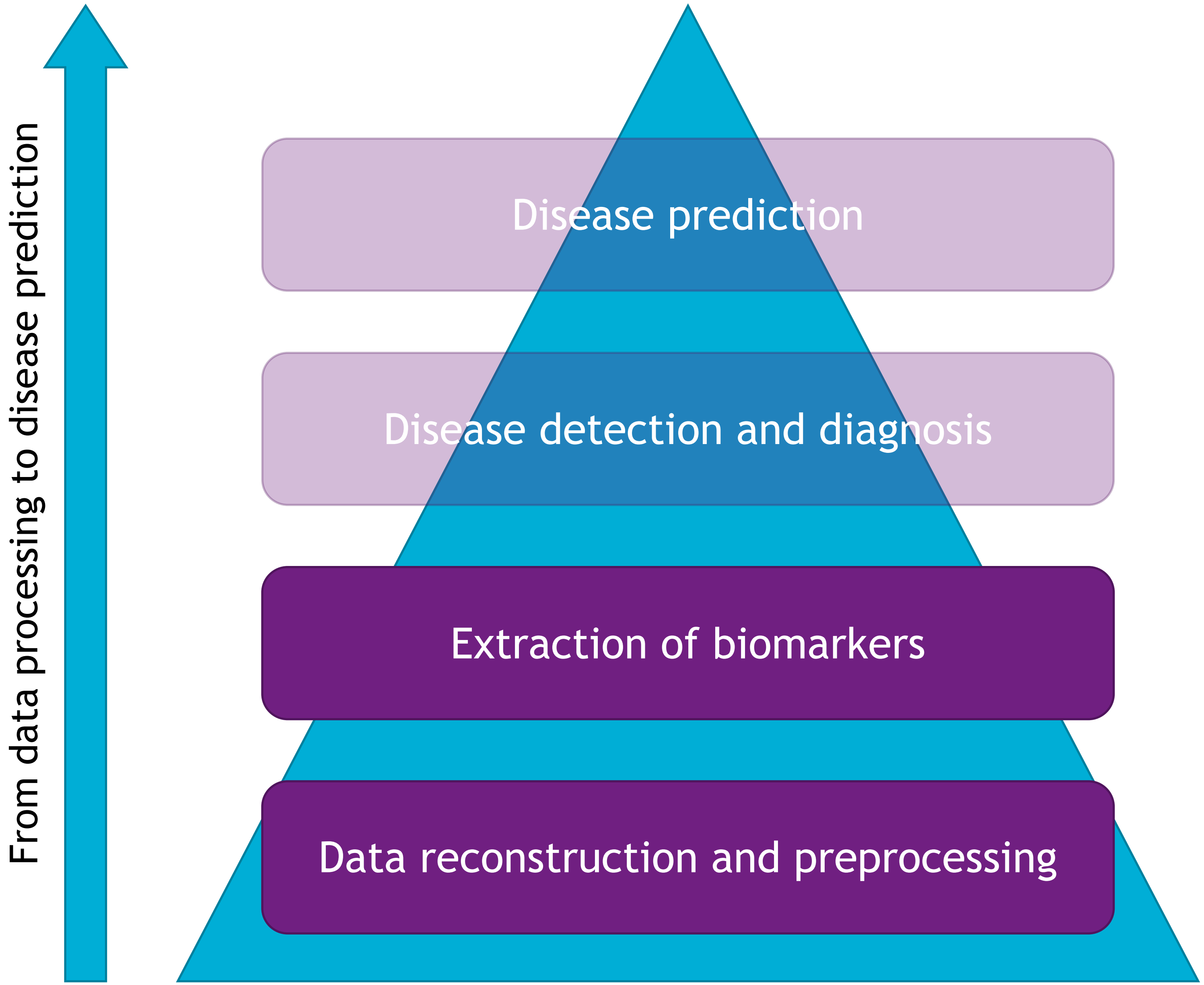
Quantitative results

Dice score (overlap between manual and automatic segmentations)

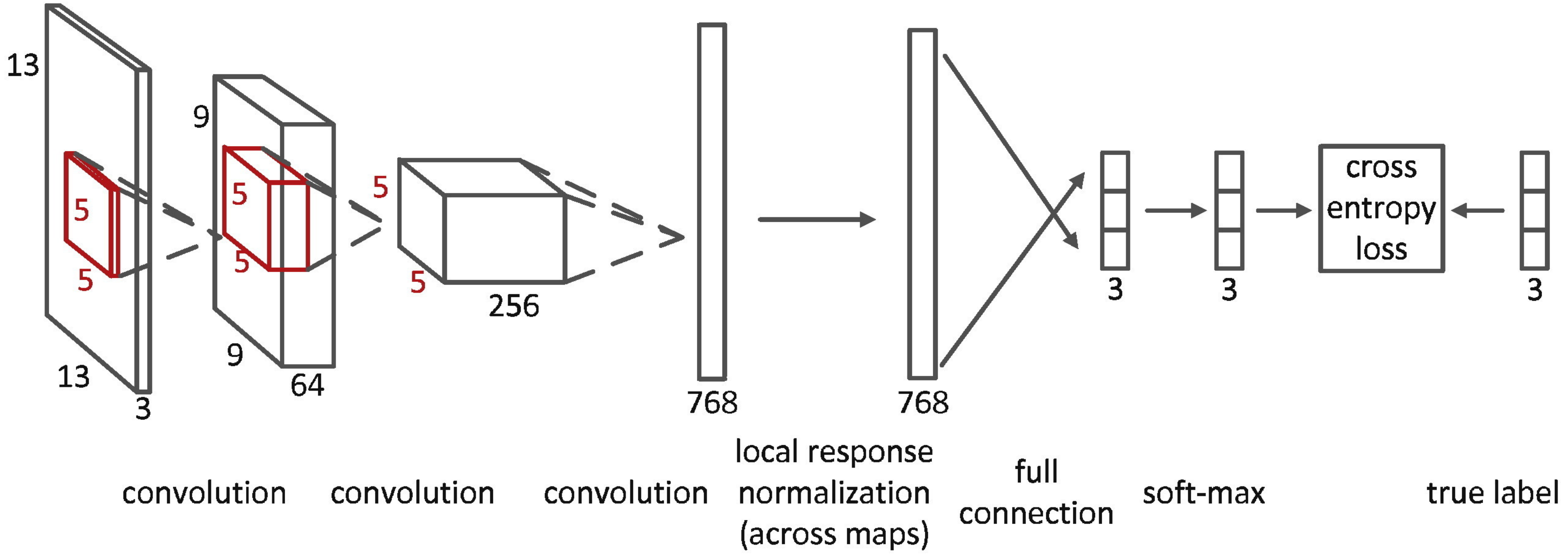
Thickness	Interpolation	SMORE	HR (0.9 mm)
1.205 mm	0.969	0.9696	0.9699
1.928 mm	0.9665	0.9690	
3.0125 mm	0.9602	0.9675	
3.856 mm	0.9524	0.9632	
4.82 mm	0.9408	0.9607	

Zhao et al., Magnetic Resonance Imaging, 2019

Deep learning for medical imaging



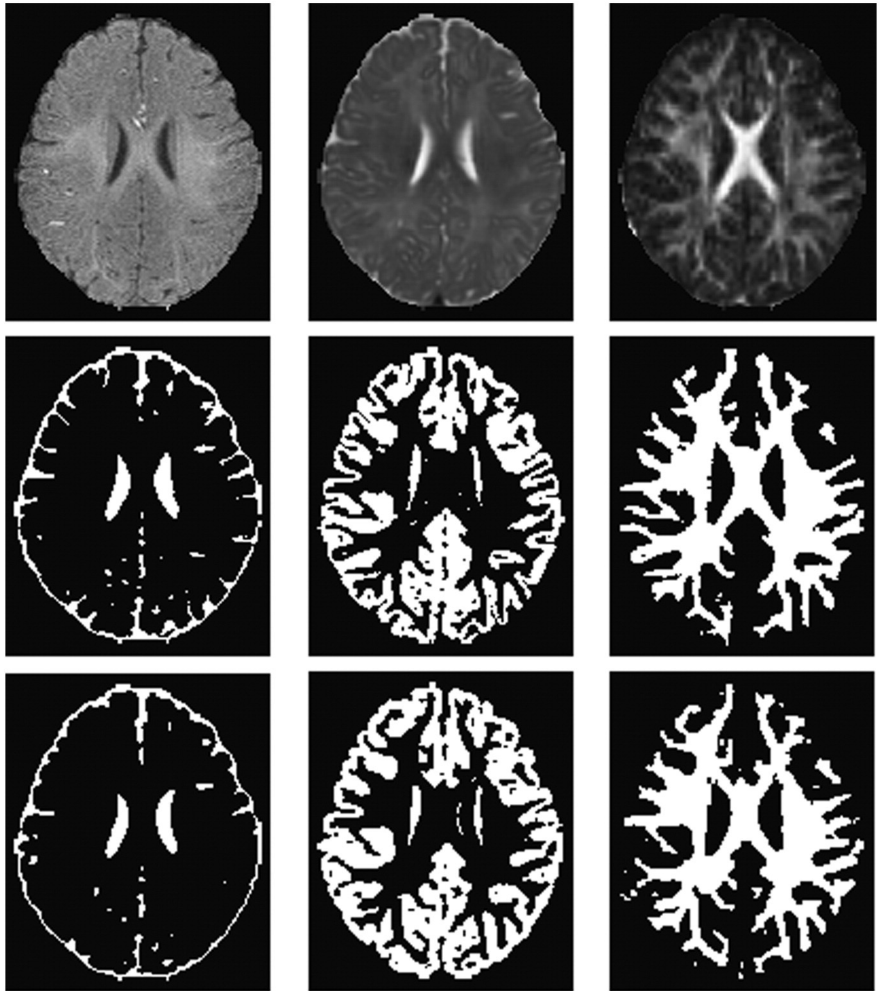
Segmentation with a sliding-window CNN



Zhang et al., NeuroImage, 2015

Segmentation of anatomical structures

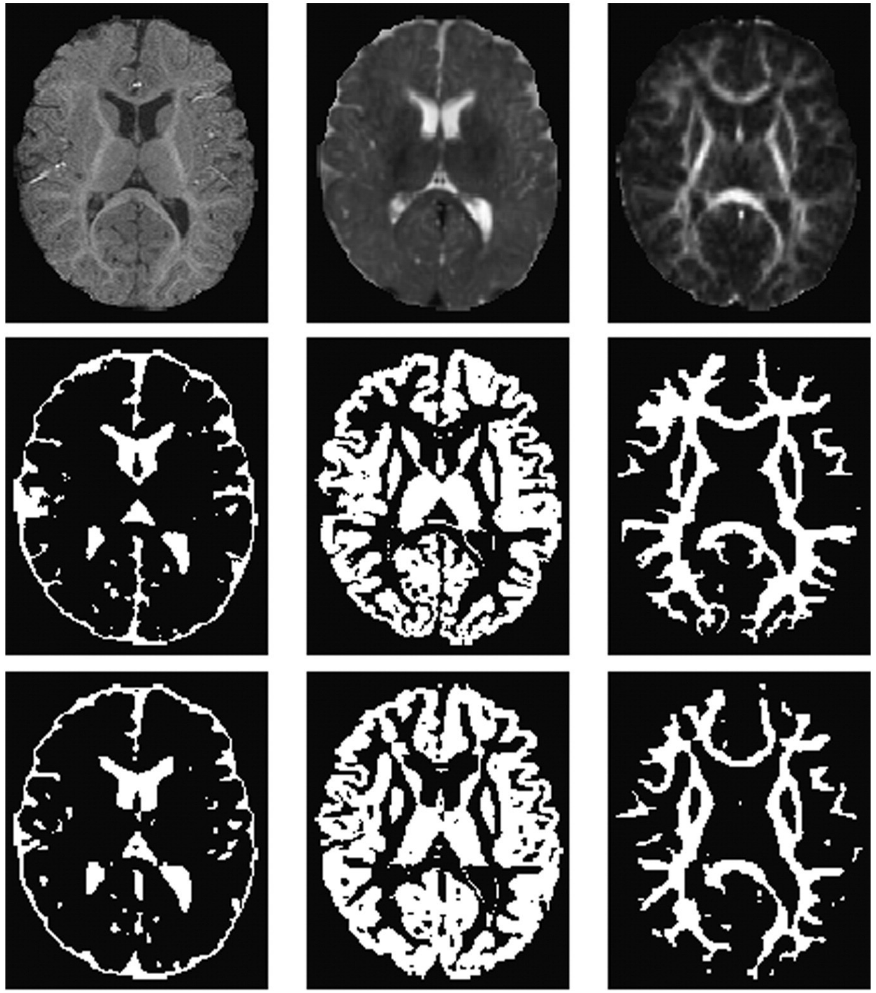
Segmentation with a CNN



Input images
(T1w, T2w, FA)

Manual segmentations
(CSF, GM, WM)

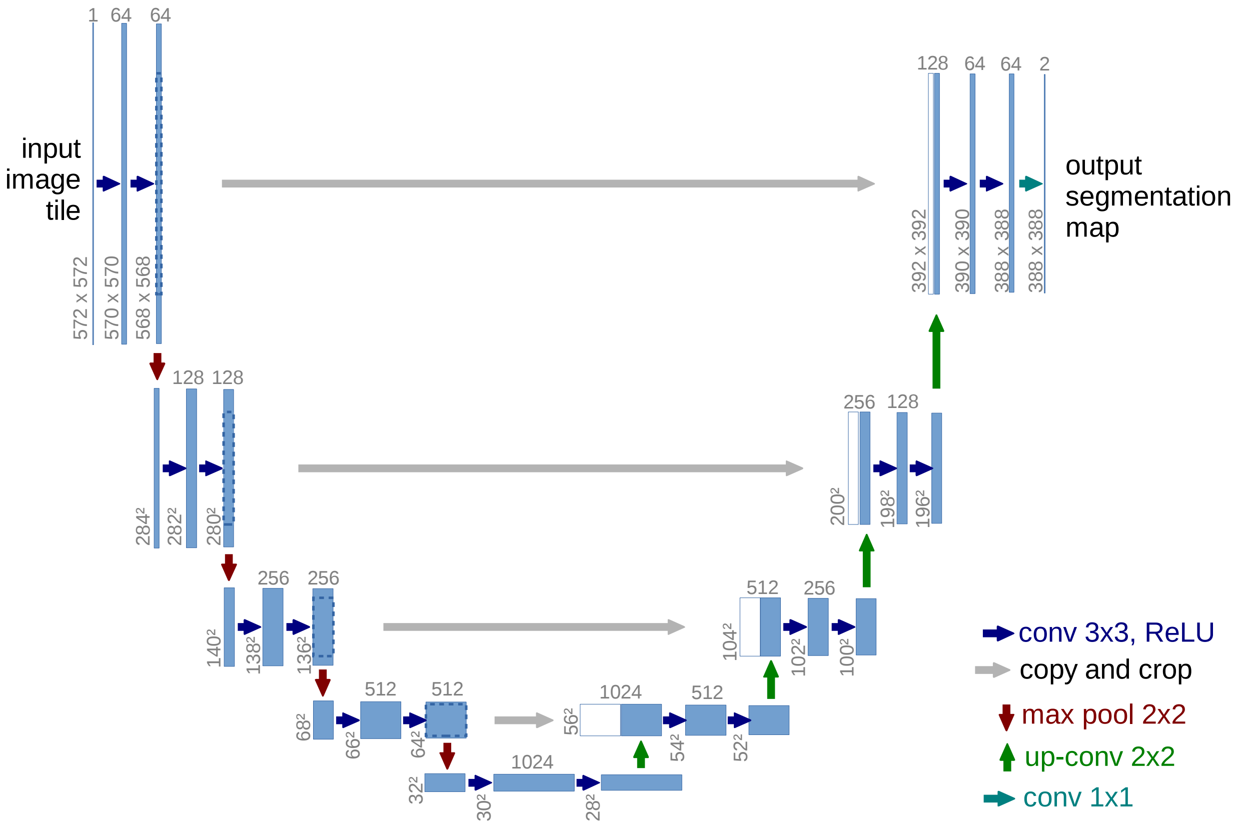
CNN segmentations
(CSF, GM, WM)



Zhang et al., NeuroImage, 2015

Segmentation of anatomical structures

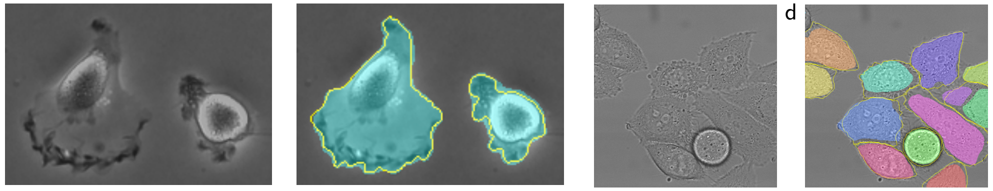
Segmentation with a U-Net



Results on the ISBI cell tracking challenge

“PhC-U373” data set

“DIC-HeLa” data set



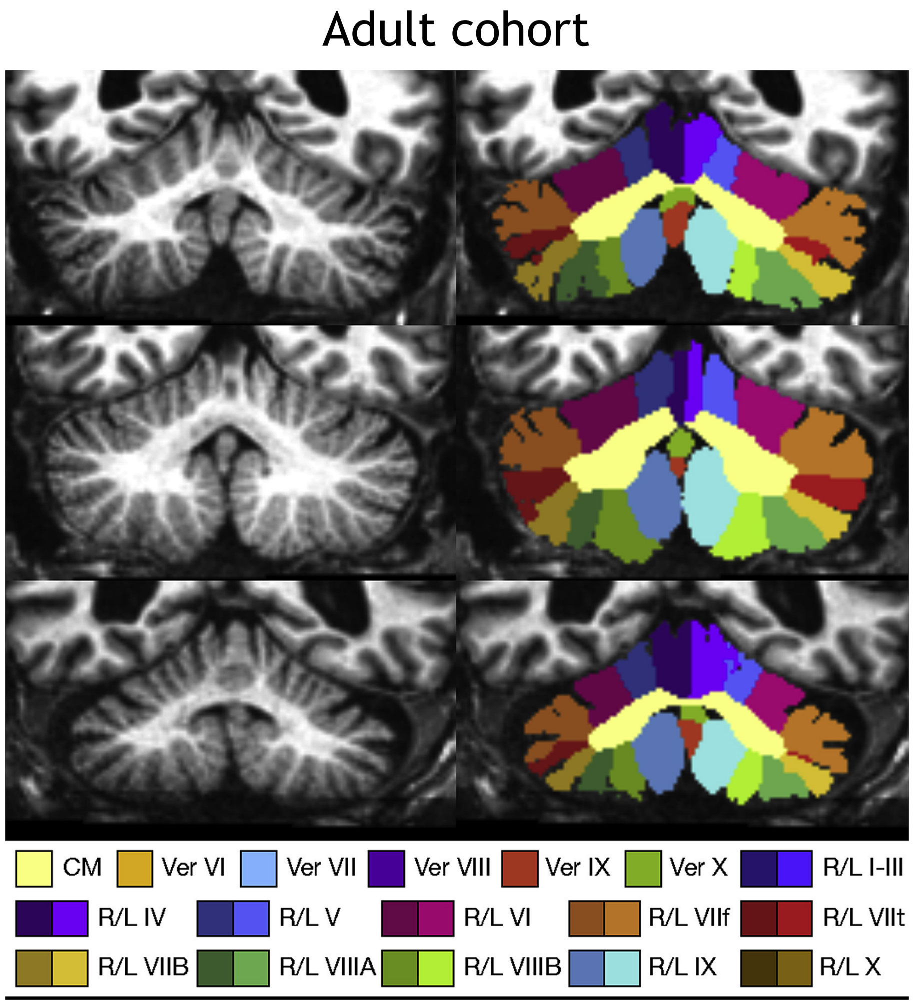
Segmentation results (IOU “intersection over union”)

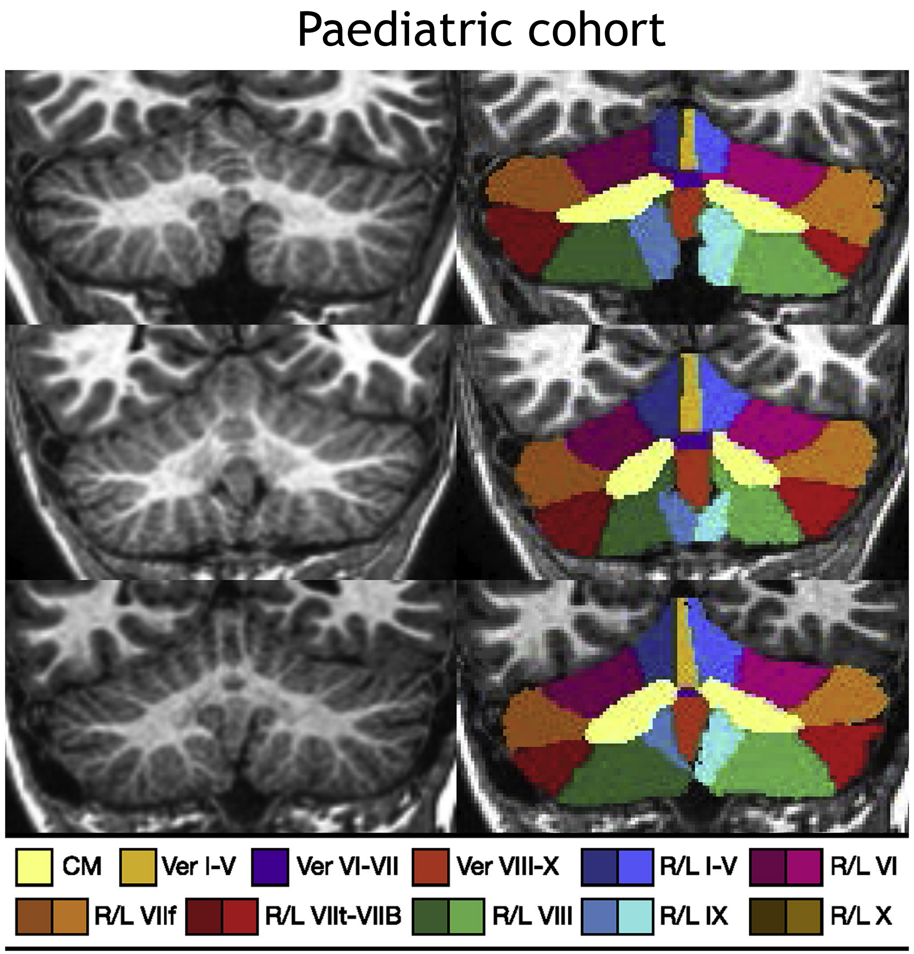
Name	PhC-U373	DIC-HeLa
IMCB-SG (2014)	0.2669	0.2935
KTH-SE (2014)	0.7953	0.4607
HOUS-US (2014)	0.5323	-
second-best 2015	0.83	0.46
u-net (2015)	**0.9203**	**0.7756**

Ronneberger et al., MICCAI, 2015 (**61570** citations on 10/05/2023)

Segmentation of anatomical structures

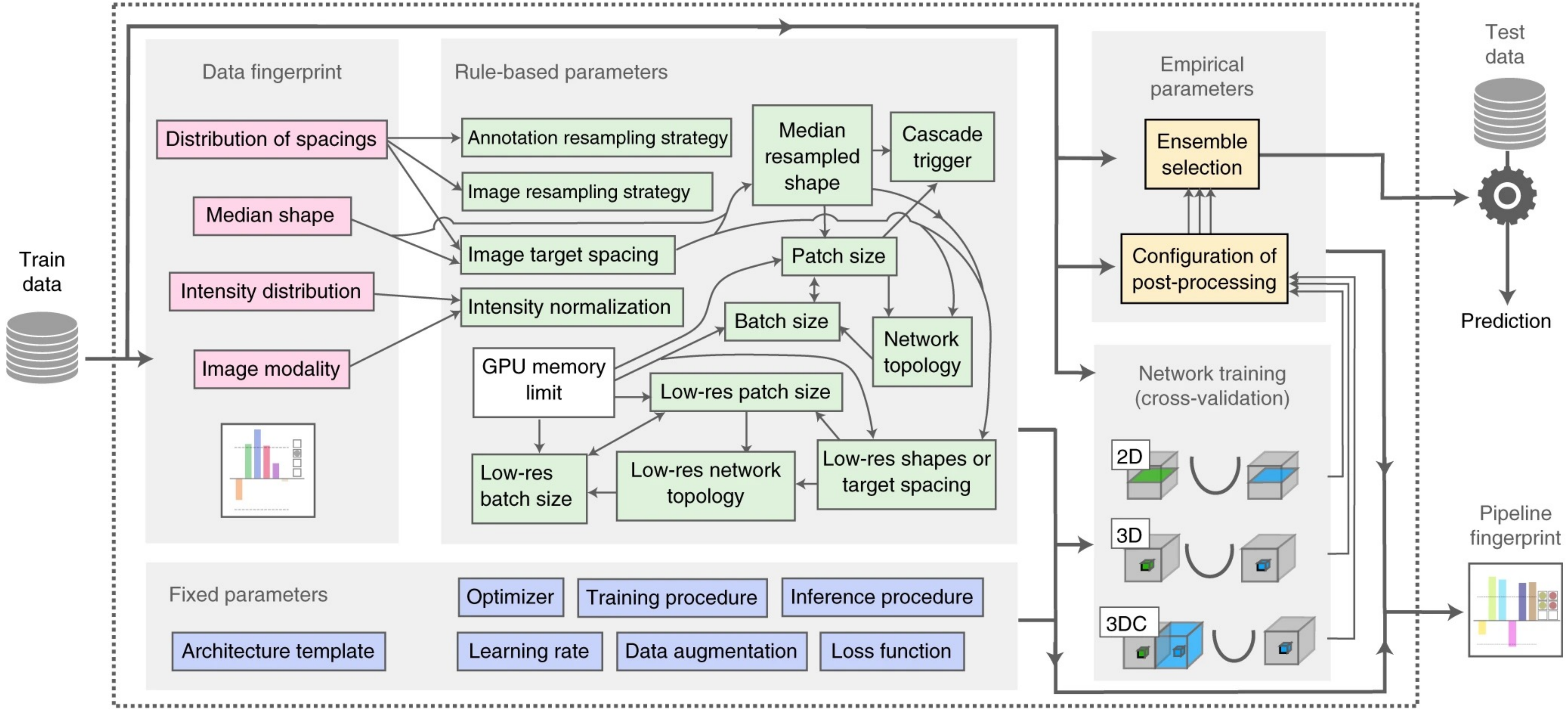
Segmentation with a U-Net





Han et al., NeuroImage, 2020

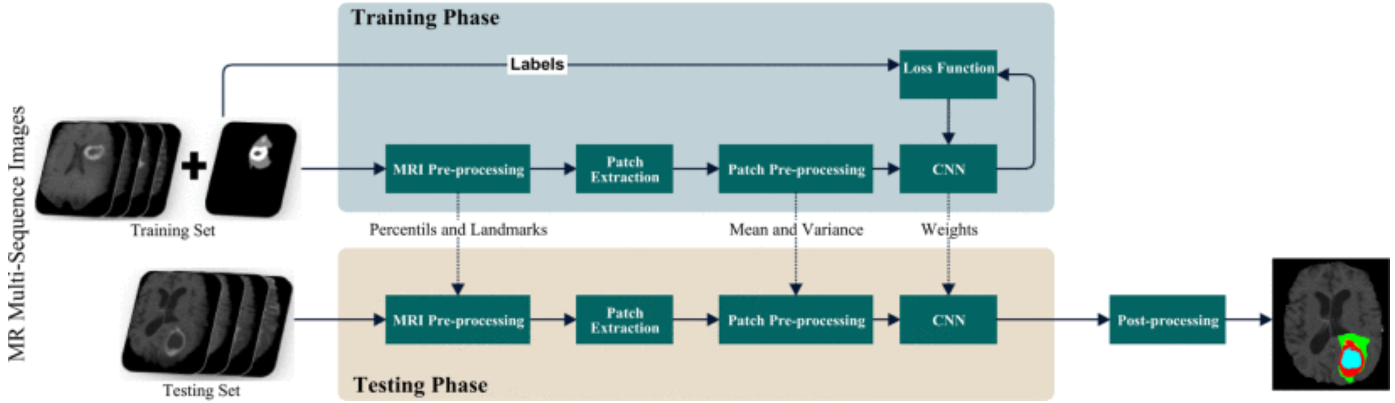
nnU-Net (‘*no new net*’)

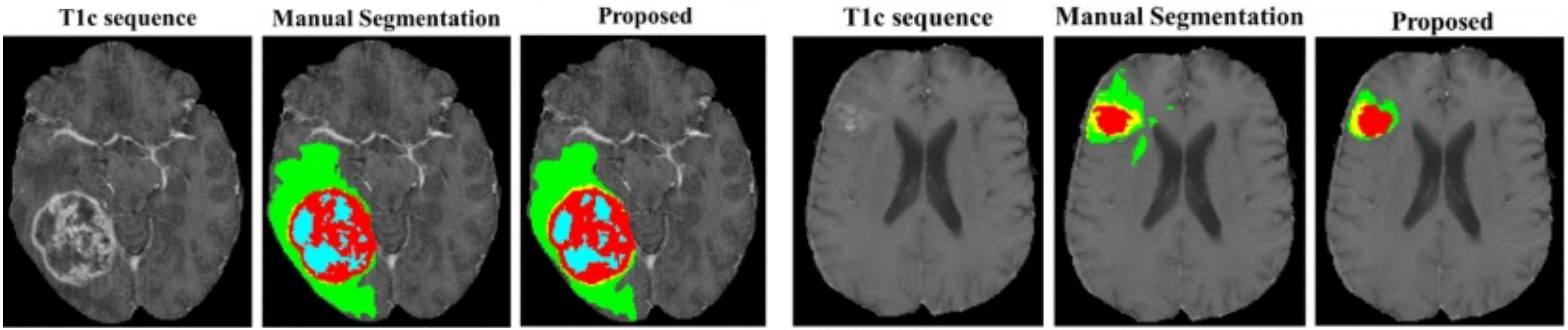


Isensee et al., Nature Methods, 2021

Segmentation of lesions

Segmentation with a sliding-window CNN

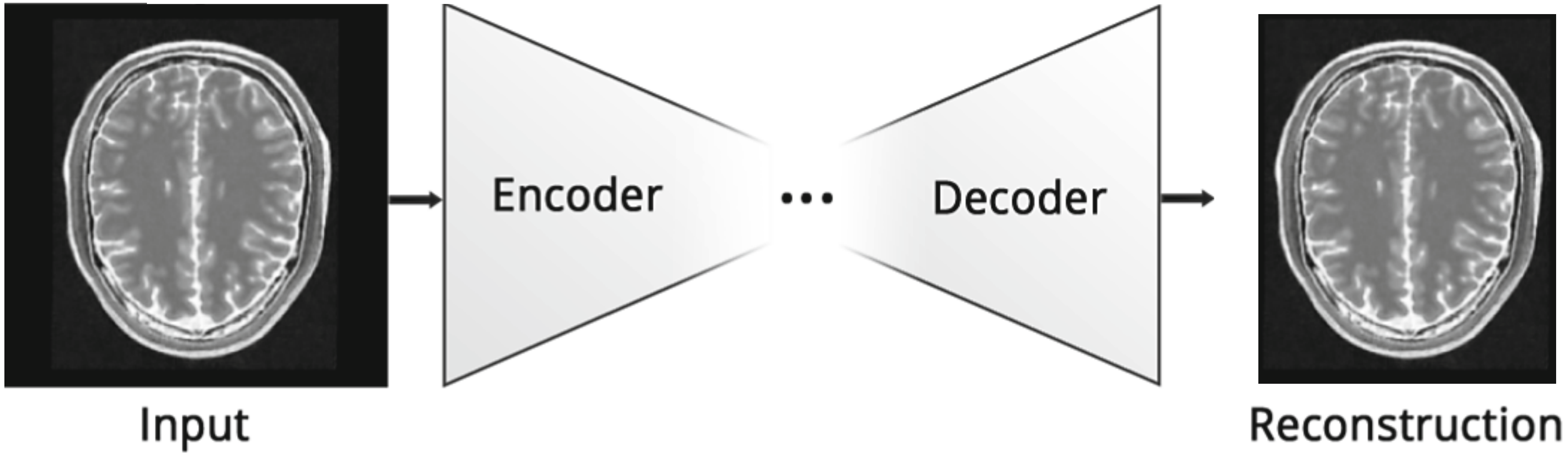




Pereira et al., IEEE TMI, 2016

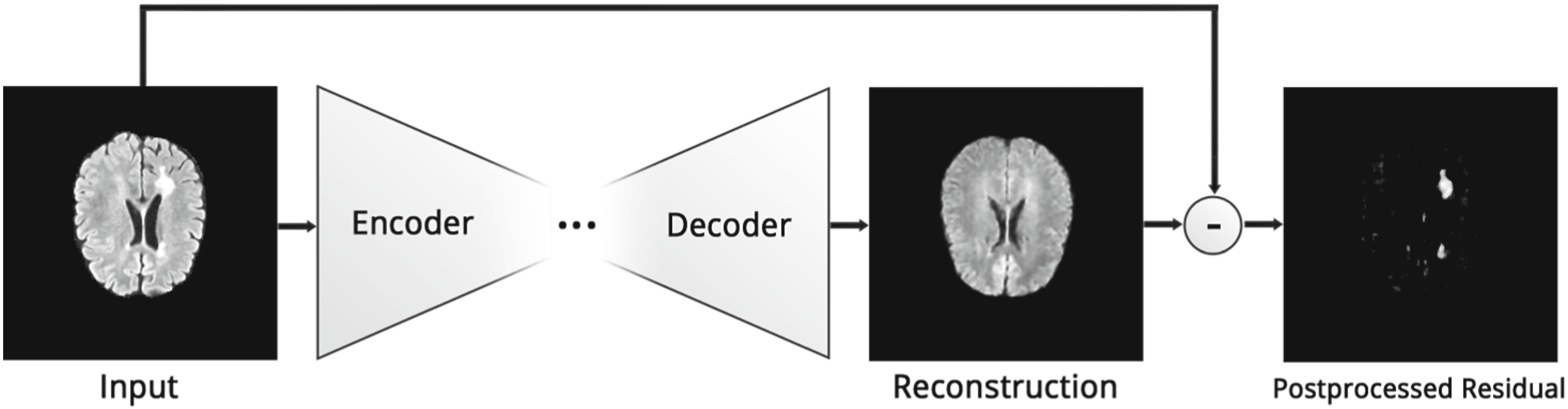
Segmentation of lesions

Unsupervised anomaly segmentation in brain MR images



Baur et al., MICCAI Brainlesion Workshop, 2019

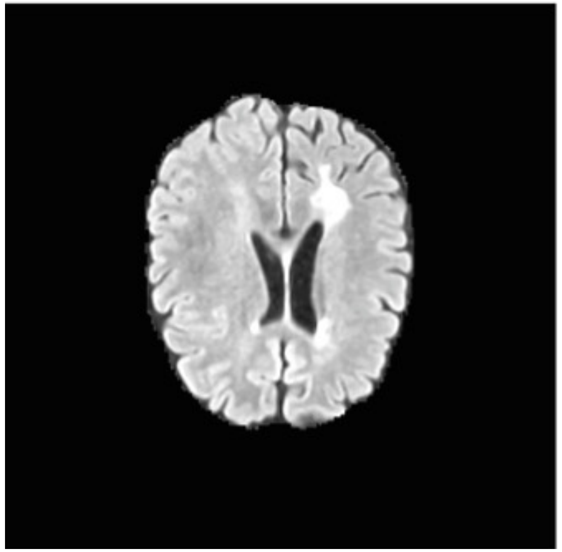
Unsupervised anomaly segmentation in brain MR images



Baur et al., MICCAI Brainlesion Workshop, 2019

Unsupervised anomaly segmentation in brain MR images

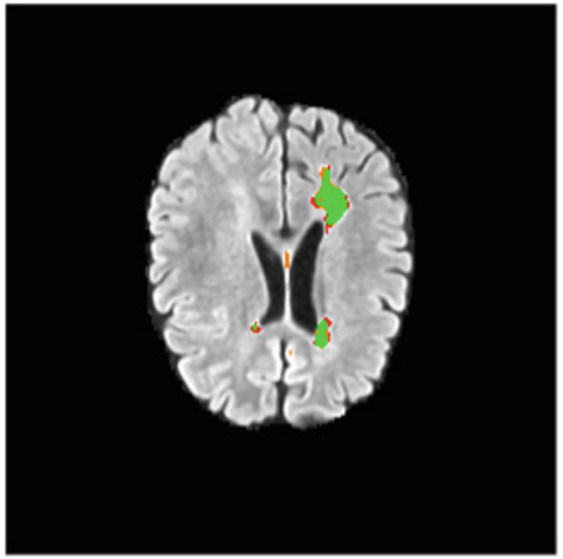
Input image



Ground-truth segmentation

Input - Reconstruction

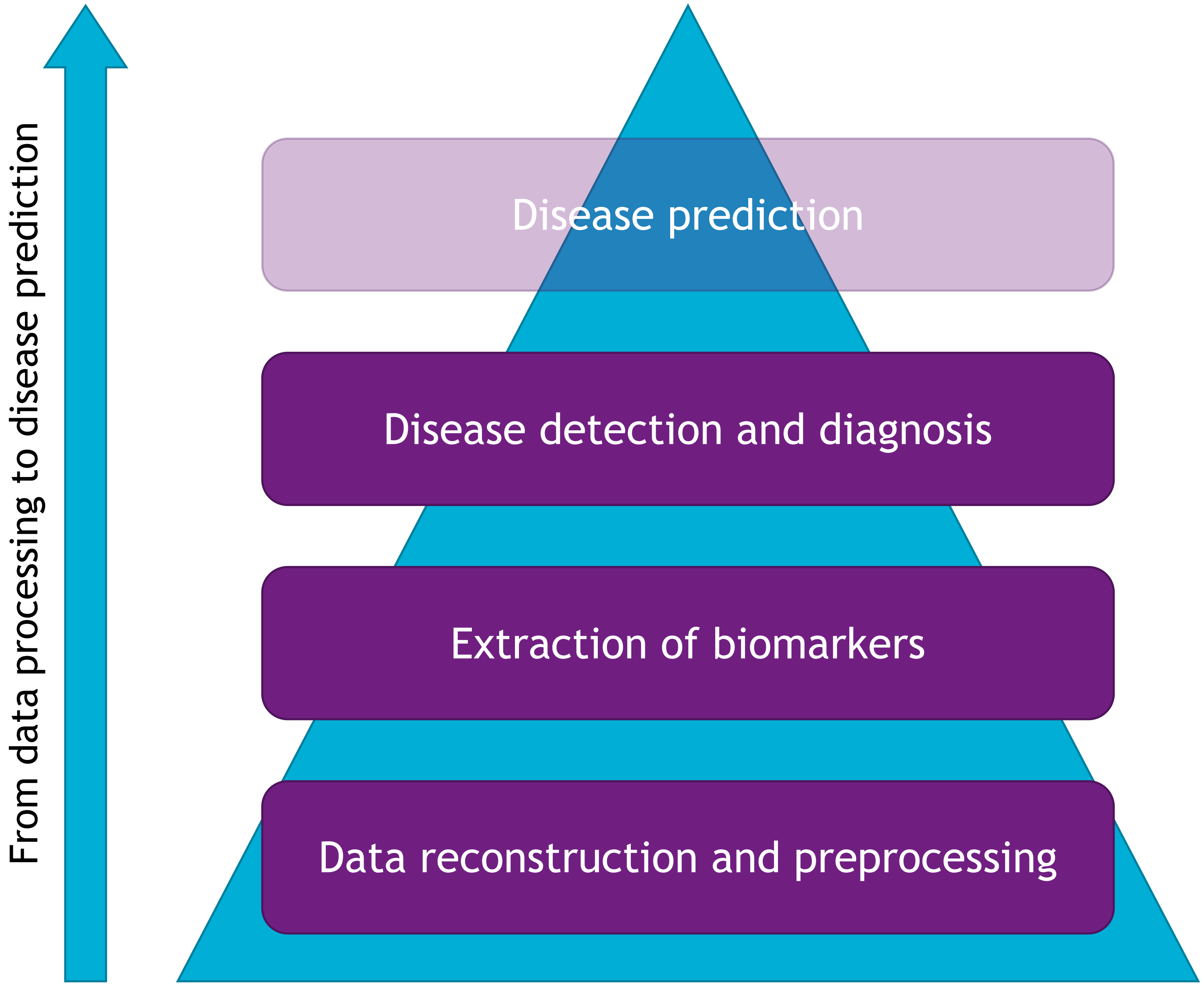
Resulting segmentation overlaid on input image



True Positives False Positives False Negatives

Baur et al., MICCAI Brainlesion Workshop, 2019

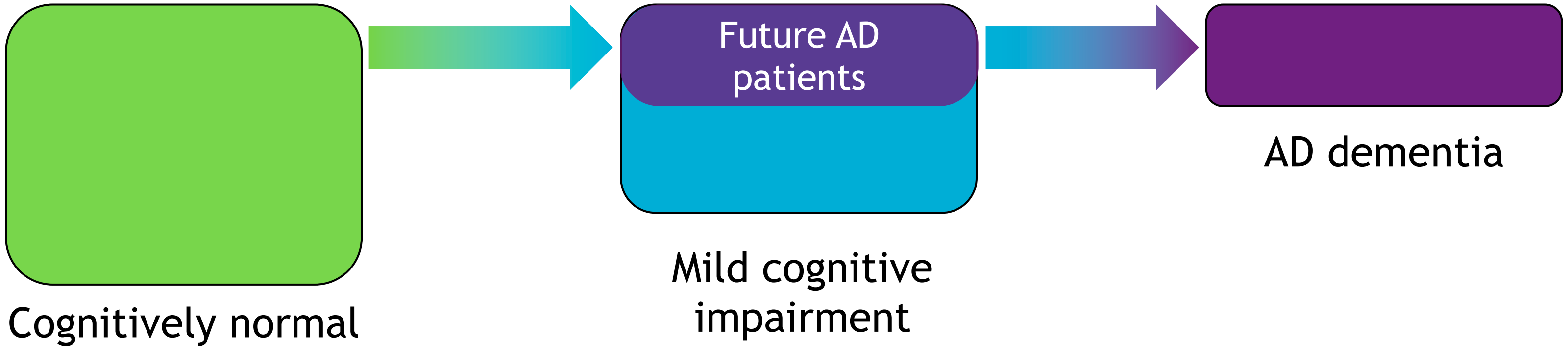
Deep learning for medical imaging



Parenthesis on Alzheimer's disease

What is Alzheimer's disease?

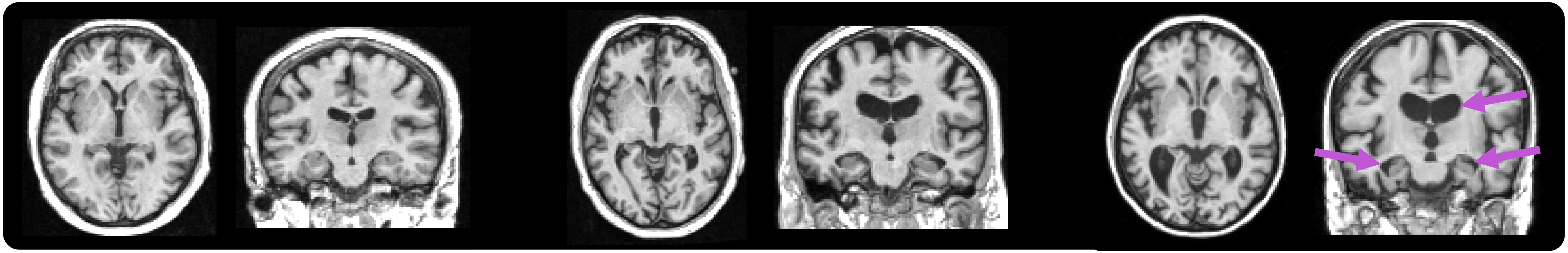
- Most common cause of dementia
- Disorder caused by abnormal brain changes
- Trigger decline in cognitive abilities, severe enough to impair daily life
- Affect behaviour, feelings and relationships
- Progressive disease



Imaging in Alzheimer's disease

- Structural magnetic resonance imaging (MRI) to detect atrophy

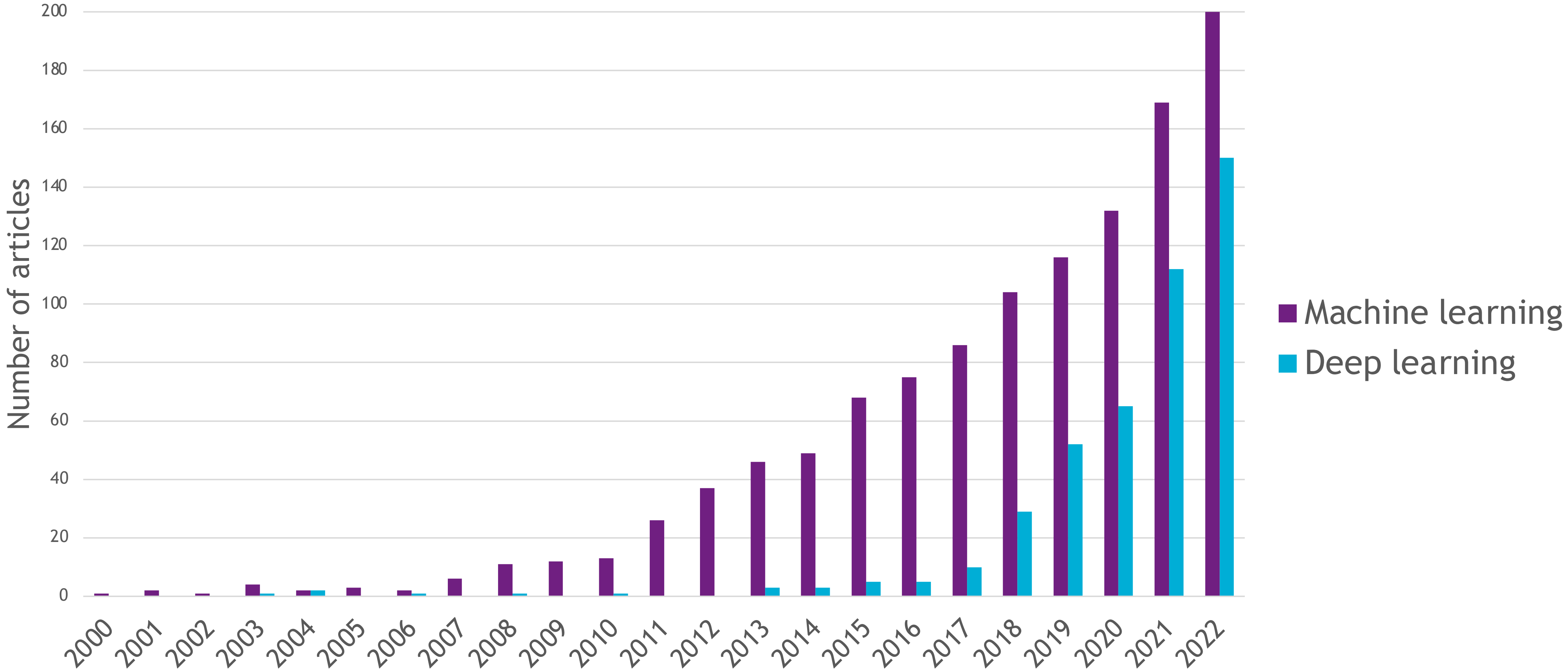
Cognitively normal | Mild cognitive impairment | Alzheimer's disease



Disease progression

ML/DL for dementia diagnosis & prognosis

- A very active field of research

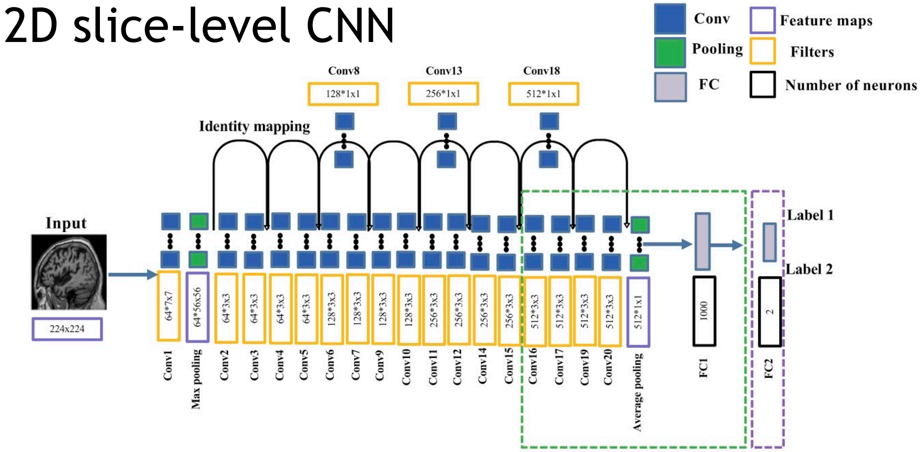


Classification of Alzheimer’s disease using CNNs

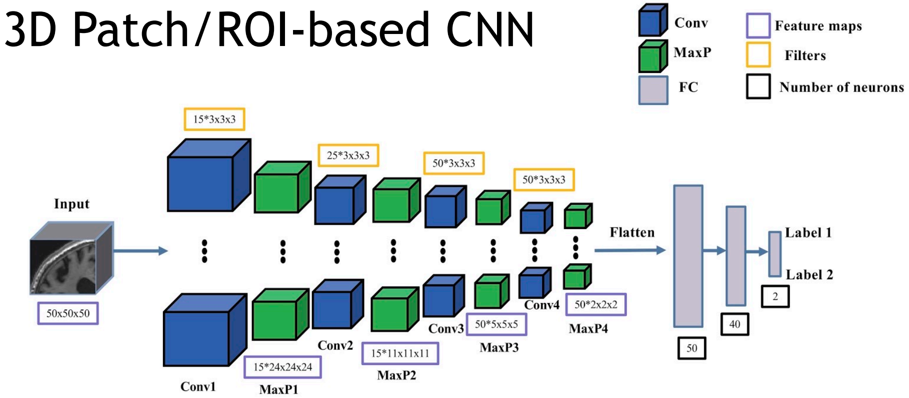
3D subject-level CNN

Bal. acc. (AD vs CN):
85%

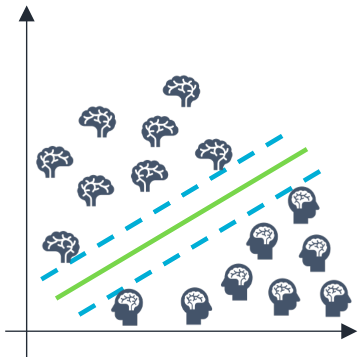
2D slice-level CNN



3D Patch/ROI-based CNN



SVM

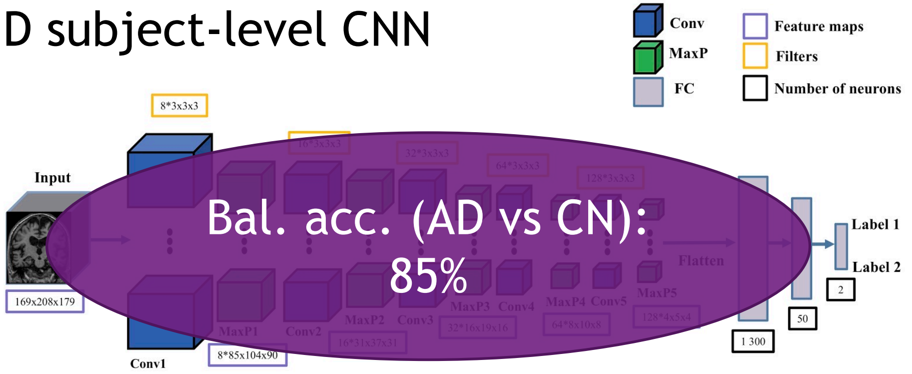


Wen, Thibeau-Sutre et al., Medical Image Analysis, 2020

Disease recognition

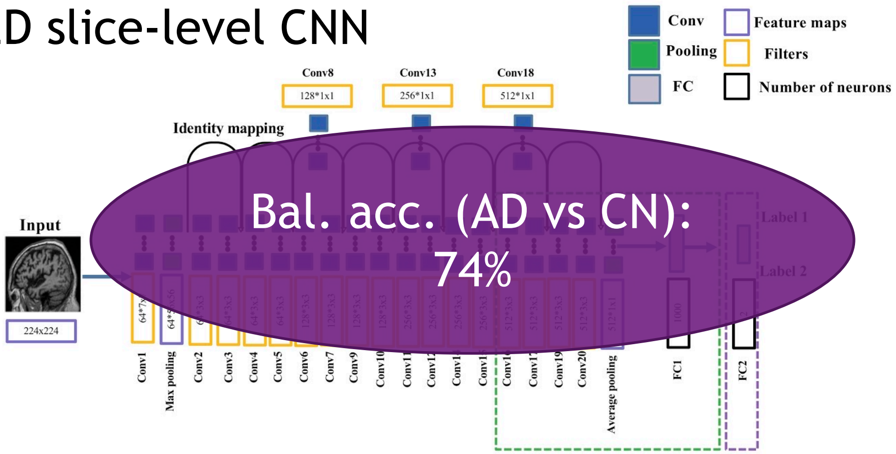
Classification of Alzheimer’s disease using CNNs

3D subject-level CNN



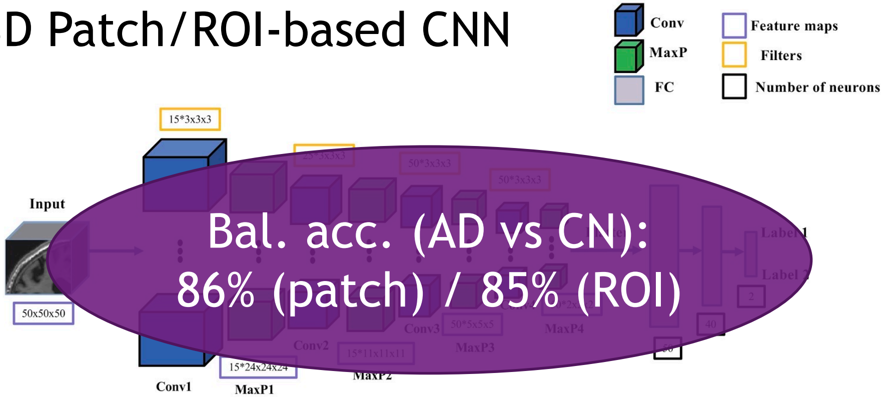
Bal. acc. (AD vs CN):
85%

2D slice-level CNN



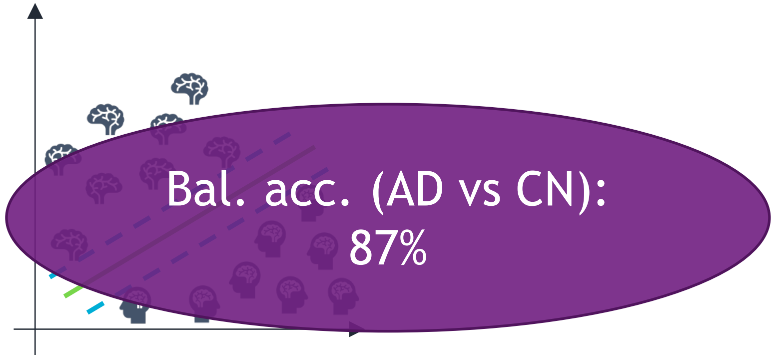
Bal. acc. (AD vs CN):
74%

3D Patch/ROI-based CNN



Bal. acc. (AD vs CN):
86% (patch) / 85% (ROI)

SVM

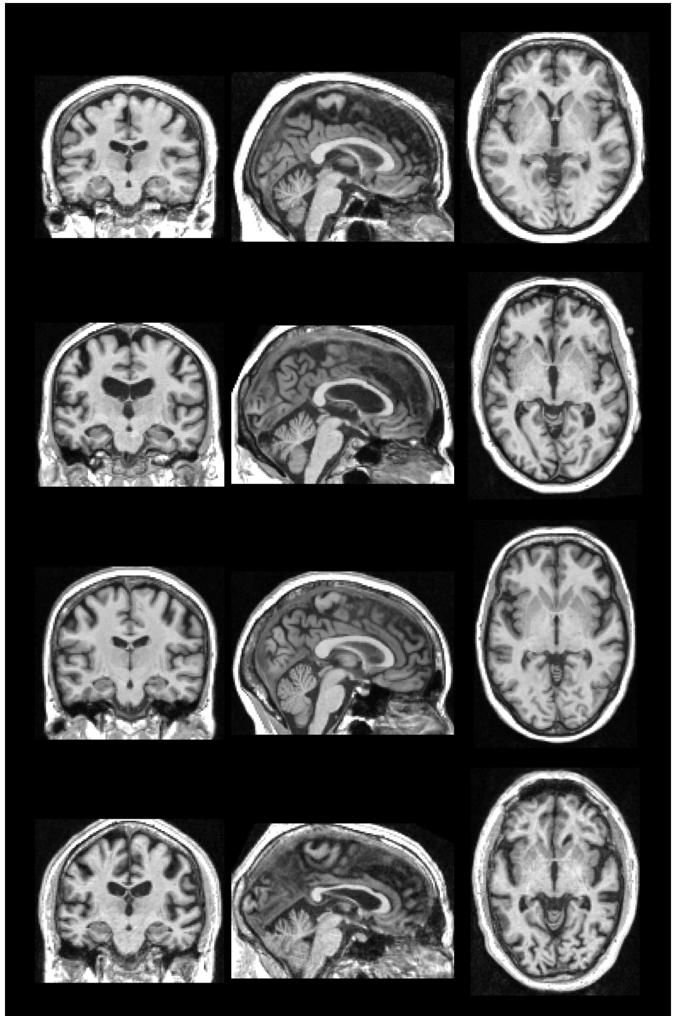


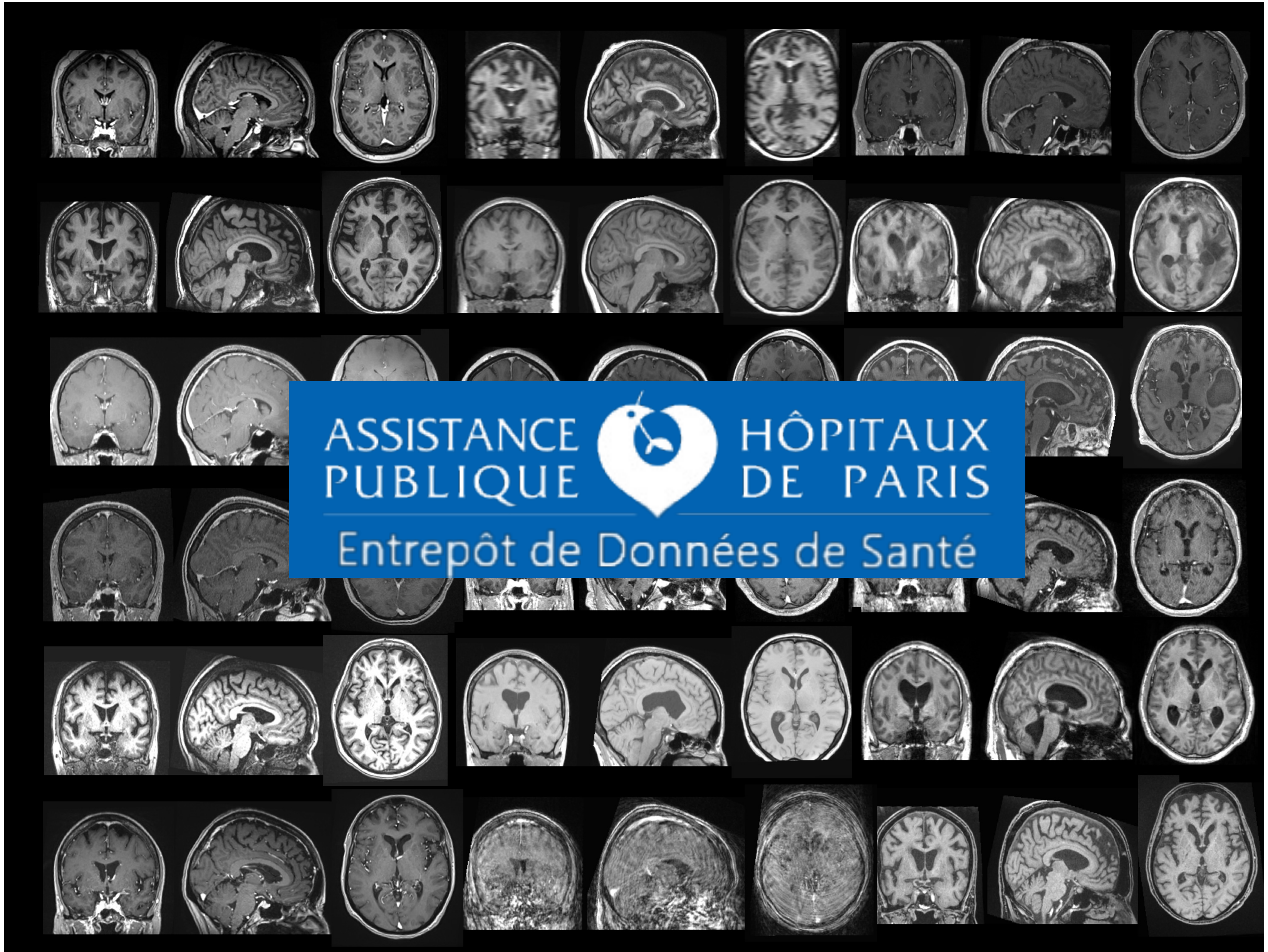
Bal. acc. (AD vs CN):
87%

Wen, Thibeau-Sutre et al., Medical Image Analysis, 2020

Disease recognition

ADNI
Alzheimer's Disease
Neuroimaging Initiative





Disease recognition

Computer-aided diagnosis of dementia in a clinical data warehouse

Data set	Task	Classification strategy	
		CNN	SVM
Clinical	D vs NDNL	63.2	61.9
	D vs NDL	67.5	64.6

Balanced accuracy (%)

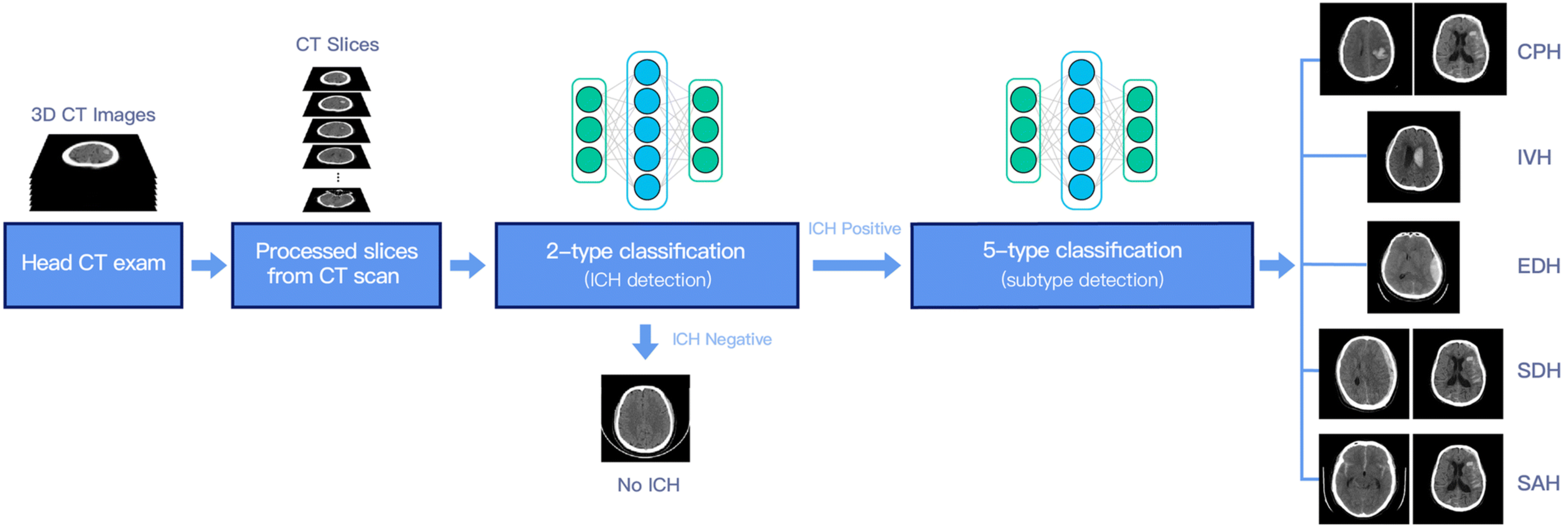
D: dementia,
NDNL: no dementia and no lesions,
NDL: no dementia with lesions

Balanced accuracy ~20 percent points lower than when training/testing on research data

Bottani et al., Under revision at Medical Image Analysis · hal-03656136

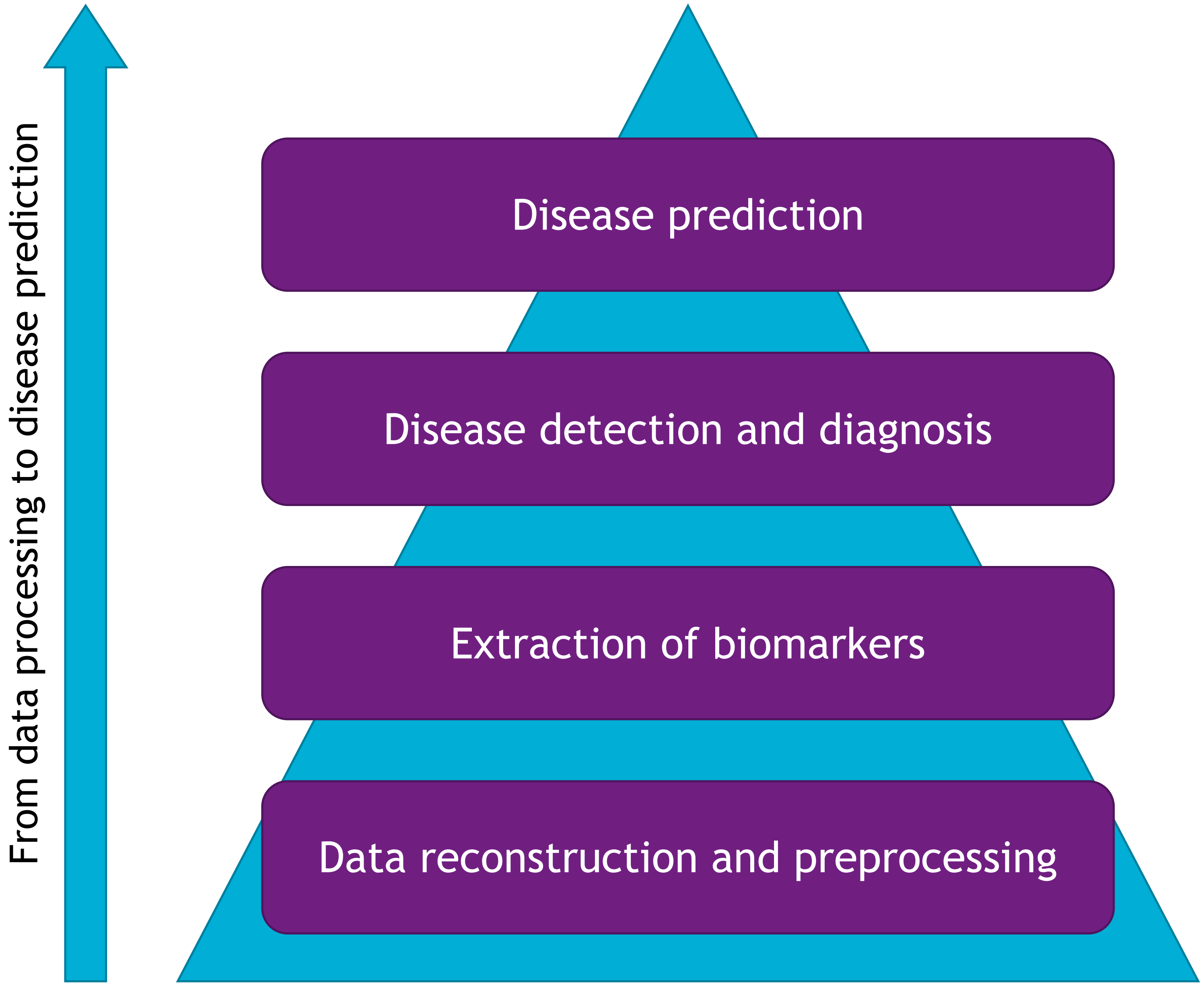
Identification of known disease subtypes

Identification and subtyping of intracranial haemorrhage (ICH)



Ye et al., European Radiology, 2019

Deep learning for medical imaging



Deep learning for the diagnosis and prognosis of AD

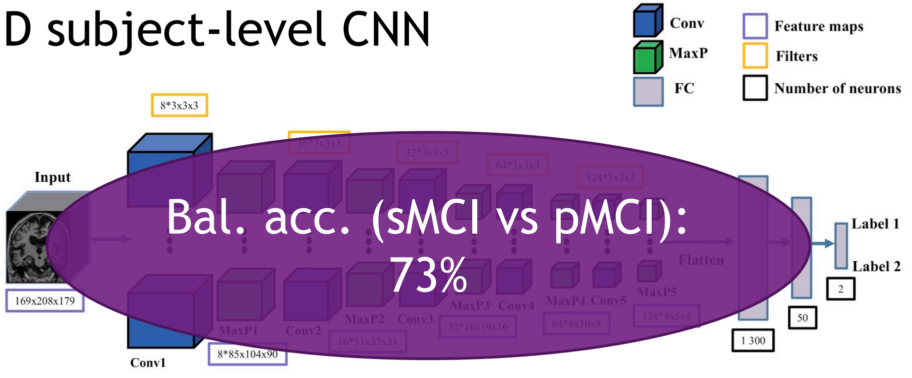
- 'Diagnostic' classification task
  - Differentiate cognitively normal (CN) subjects from patients with AD: CN vs AD
  - Not clinically relevant but useful when developing algorithms

- 'Predictive' classification task
  - Different patients with mild cognitive impairment (MCI) that will stay stable (sMCI) from the ones that will progress to AD dementia (pMCI): sMCI vs pMCI
  - Clinically relevant but more difficult

Fixed-time classification

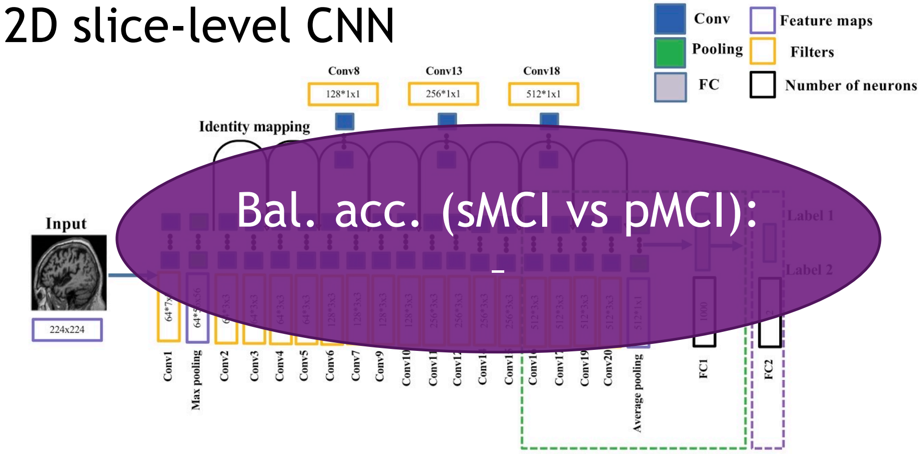
Classification of mild cognitive impairment using CNNs

3D subject-level CNN



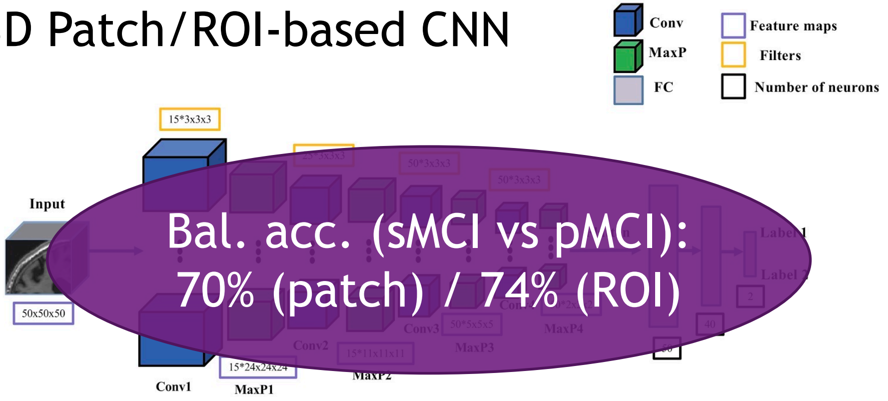
Bal. acc. (sMCI vs pMCI): 73%

2D slice-level CNN



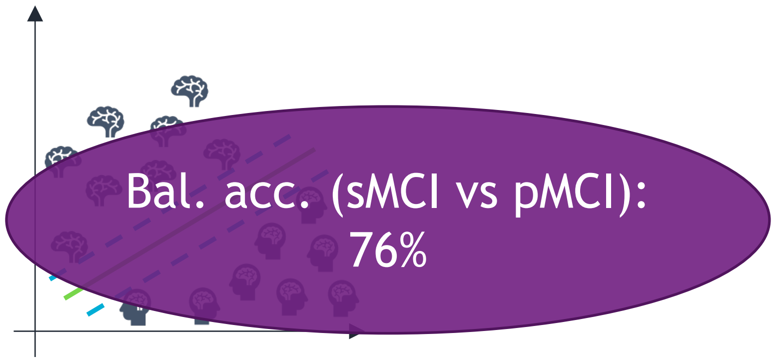
Bal. acc. (sMCI vs pMCI): -

3D Patch/ROI-based CNN



Bal. acc. (sMCI vs pMCI): 70% (patch) / 74% (ROI)

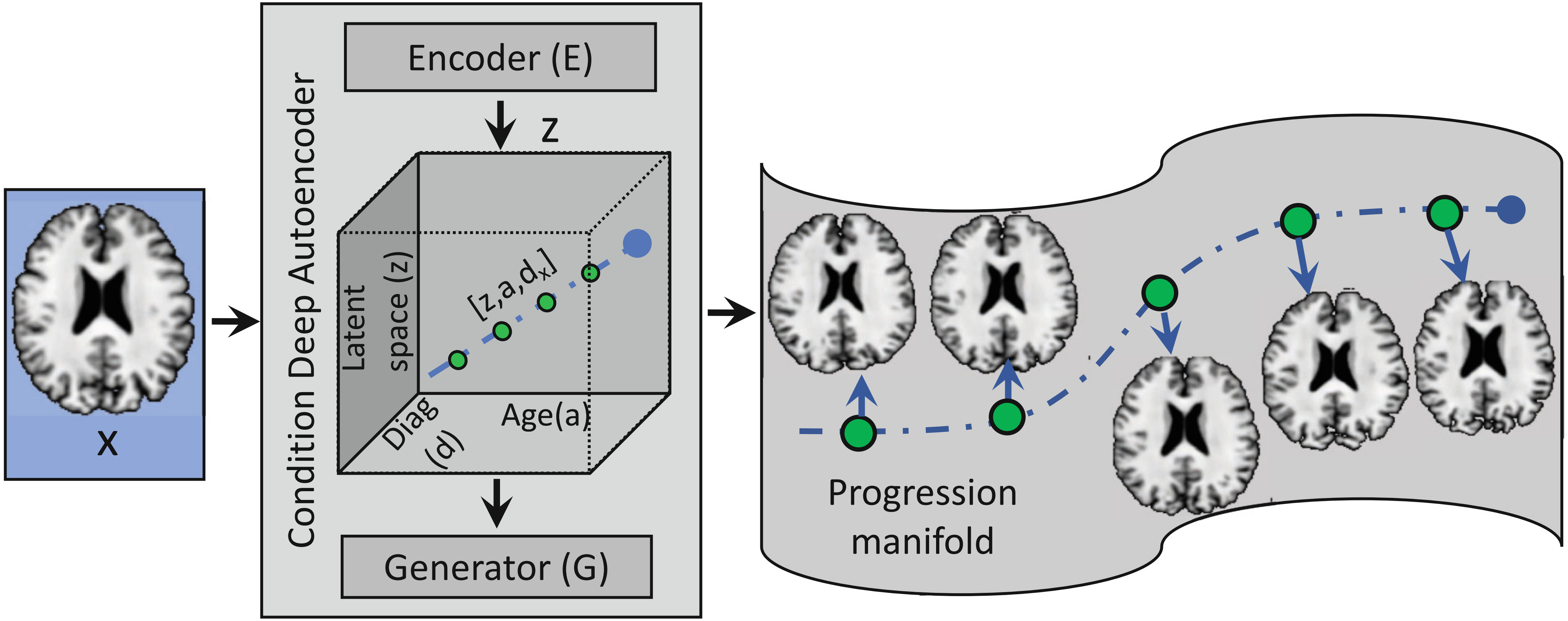
SVM



Bal. acc. (sMCI vs pMCI): 76%

Longitudinal image prediction

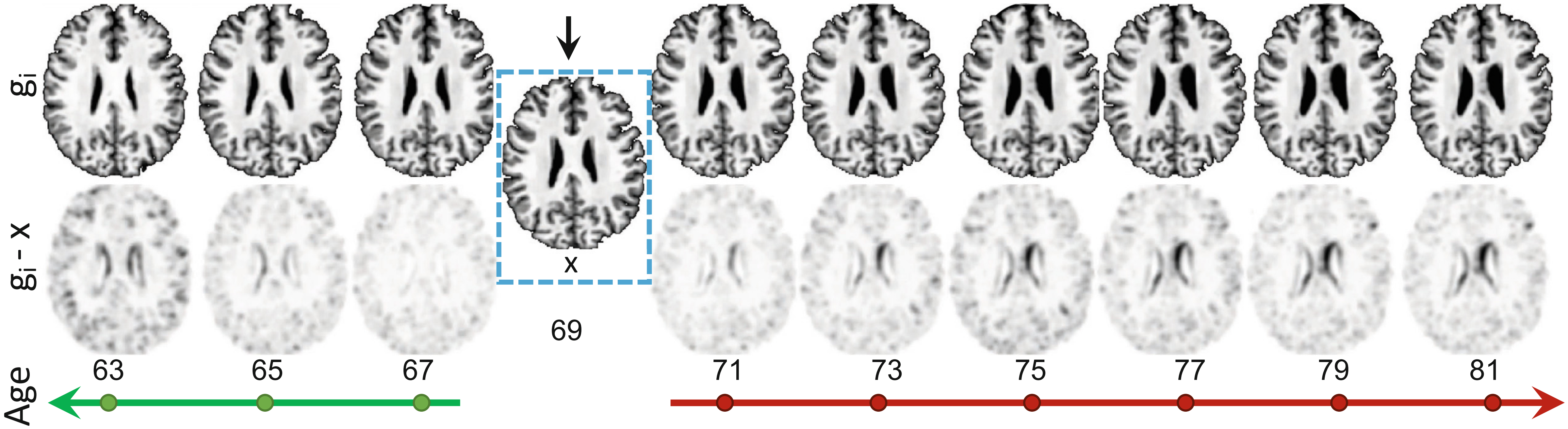
Generation of images that mimic disease progression



Ravi et al., MICCAI, 2019

Longitudinal image prediction

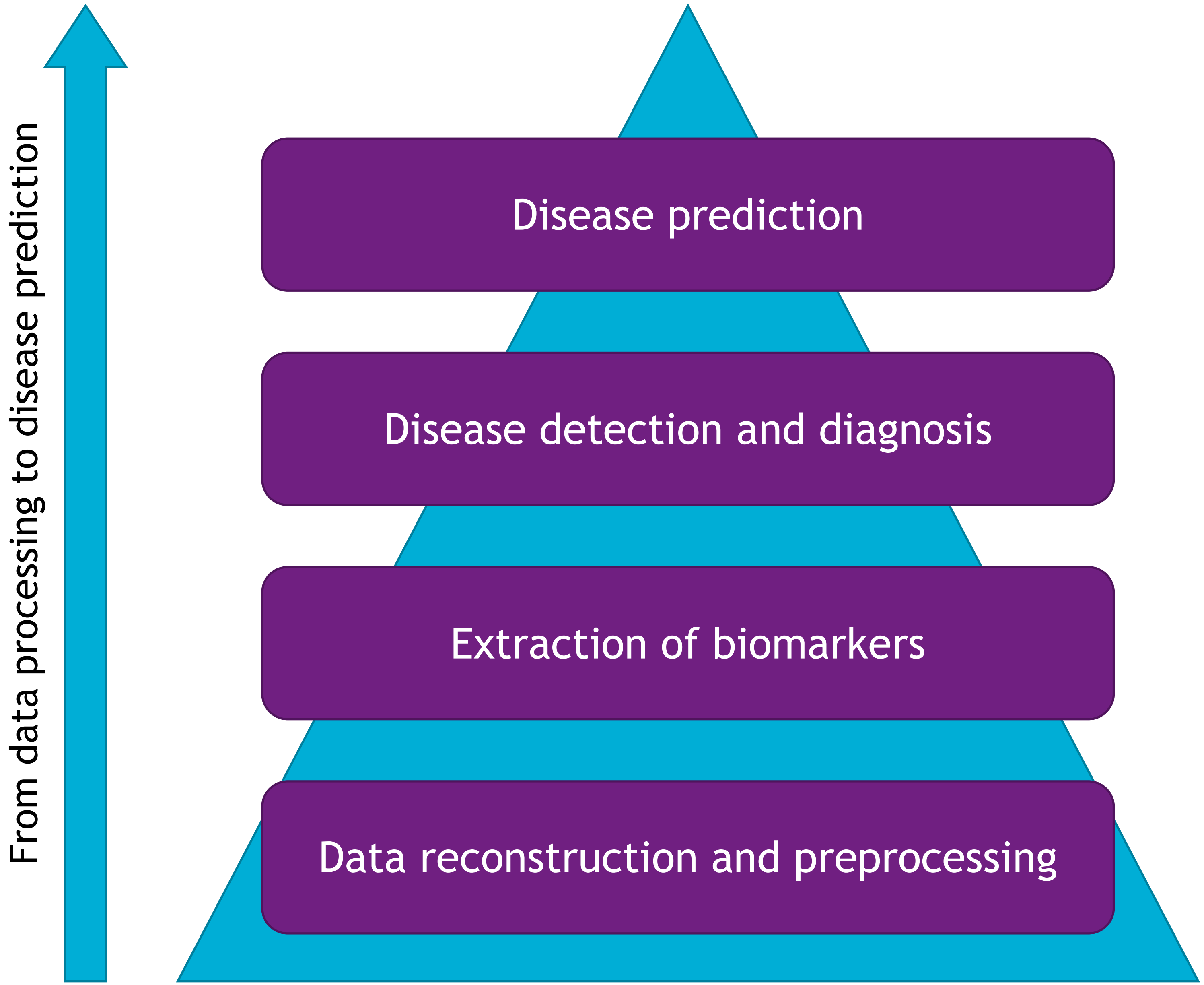
Generation of images that mimic disease progression



Neurodegeneration simulation of a 69-year old ADNI participant

Ravi et al., MICCAI, 2019

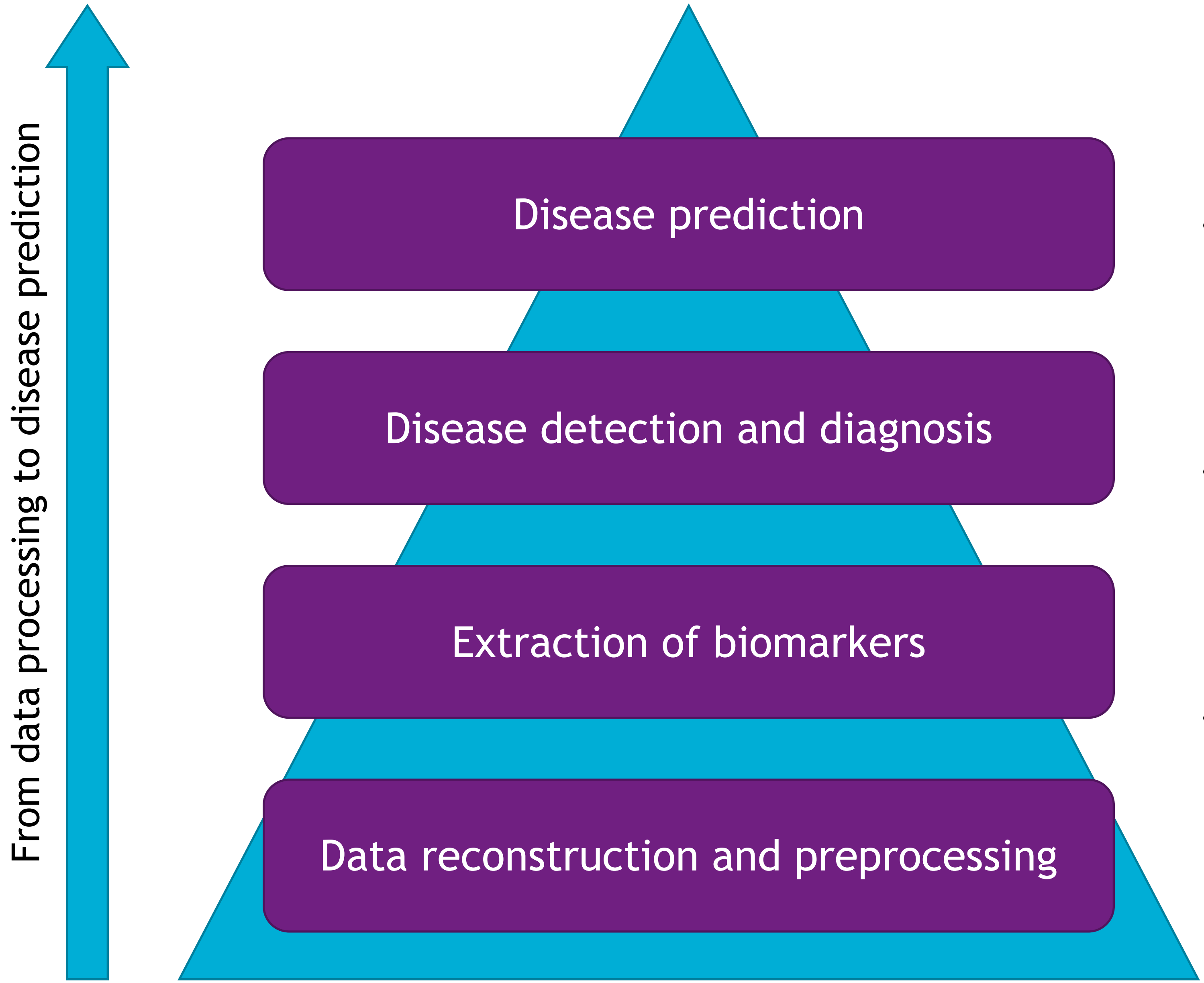
Deep learning for medical imaging



Challenges that currently prevent bringing DL to the clinic

- DL usually requires a large amount of data, which can be hard to collect for some medical applications.
- Research cohort specificities may prevent the application of models trained on such data to clinical cohorts.
- Algorithms are often black boxes, with poor interpretability of the decision-making process.
- Validating models accurately is crucial as the algorithms can very easily overfit the training data.

Deep learning for medical imaging



Further reading:

- Litjens et al., 2017. A survey on deep learning in medical image analysis. *Medical Image Analysis* 42, 60–88. doi:10.1016/j.media.2017.07.005
- Burgos et al., 2020. Deep learning for brain disorders: from data processing to disease treatment. *Briefings in Bioinformatics*. doi:10.1093/bib/bbaa310
- Zhou, S.K., Greenspan, H. and Shen, D. eds., 2017. *Deep learning for medical image analysis*. Academic Press. ISBN:9780128104088