Implémentation d'algorithmes de type IA : exemples d'applications en imagerie biomédicale

Yannick Boursier
Centre de Physique des Particules de Marseille

Outline

1 - Biomedical imaging context : Computerized tomography (CT Scan)

2 - Convolutional Neural Networks (CNNs) for imaging

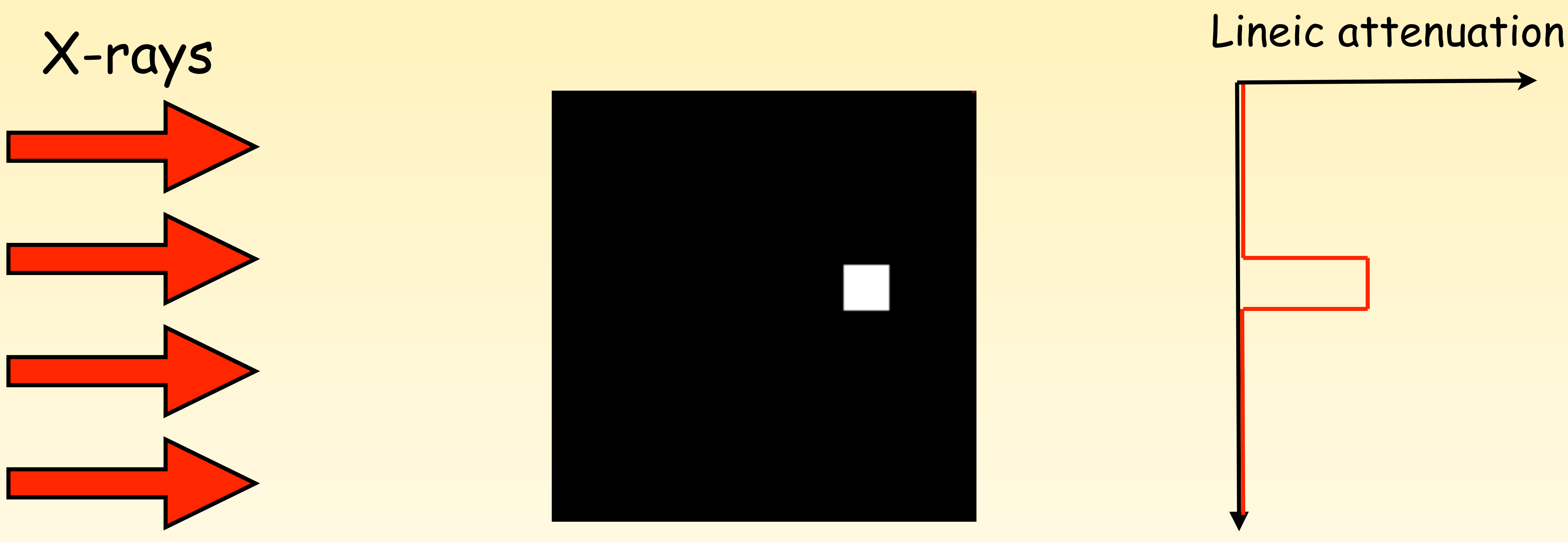
3 - Denoising issues

4 - Segmentation issues

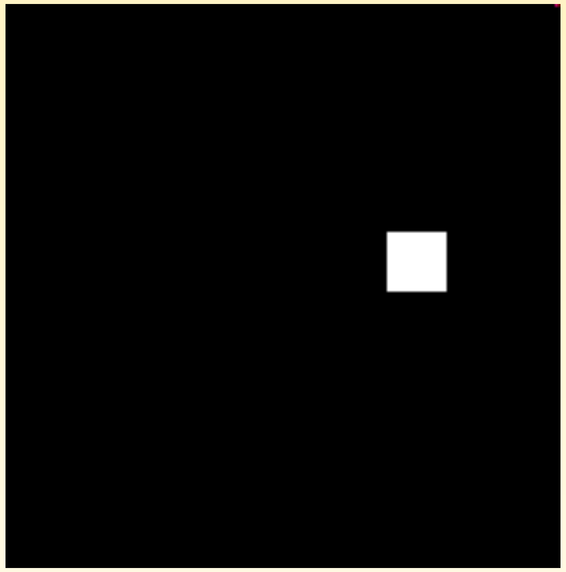
5 - Other issues

6 - Conclusion

Snapshot of standard tomography (CT)



Snapshot of standard tomography (CT)
2D sinogram



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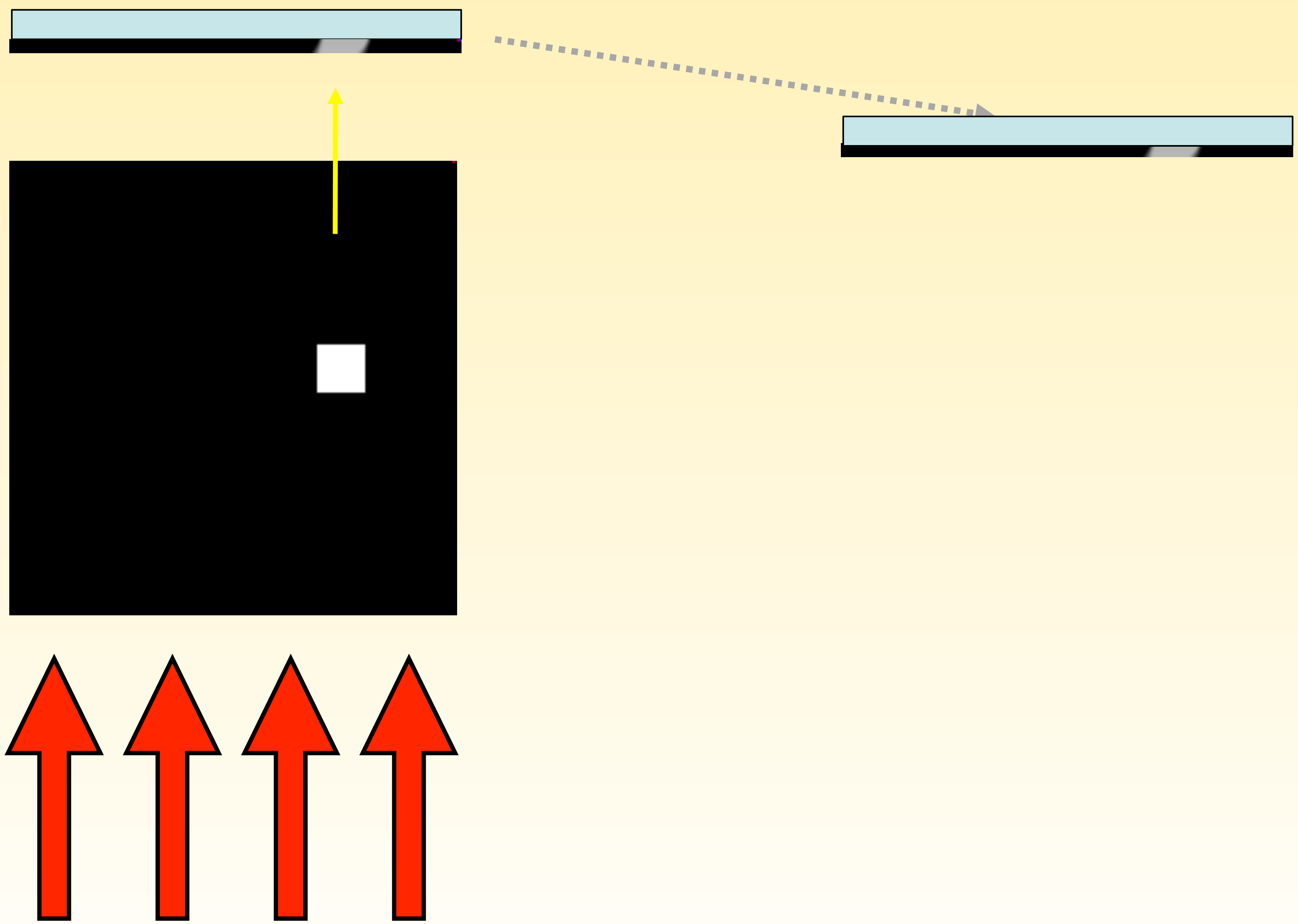

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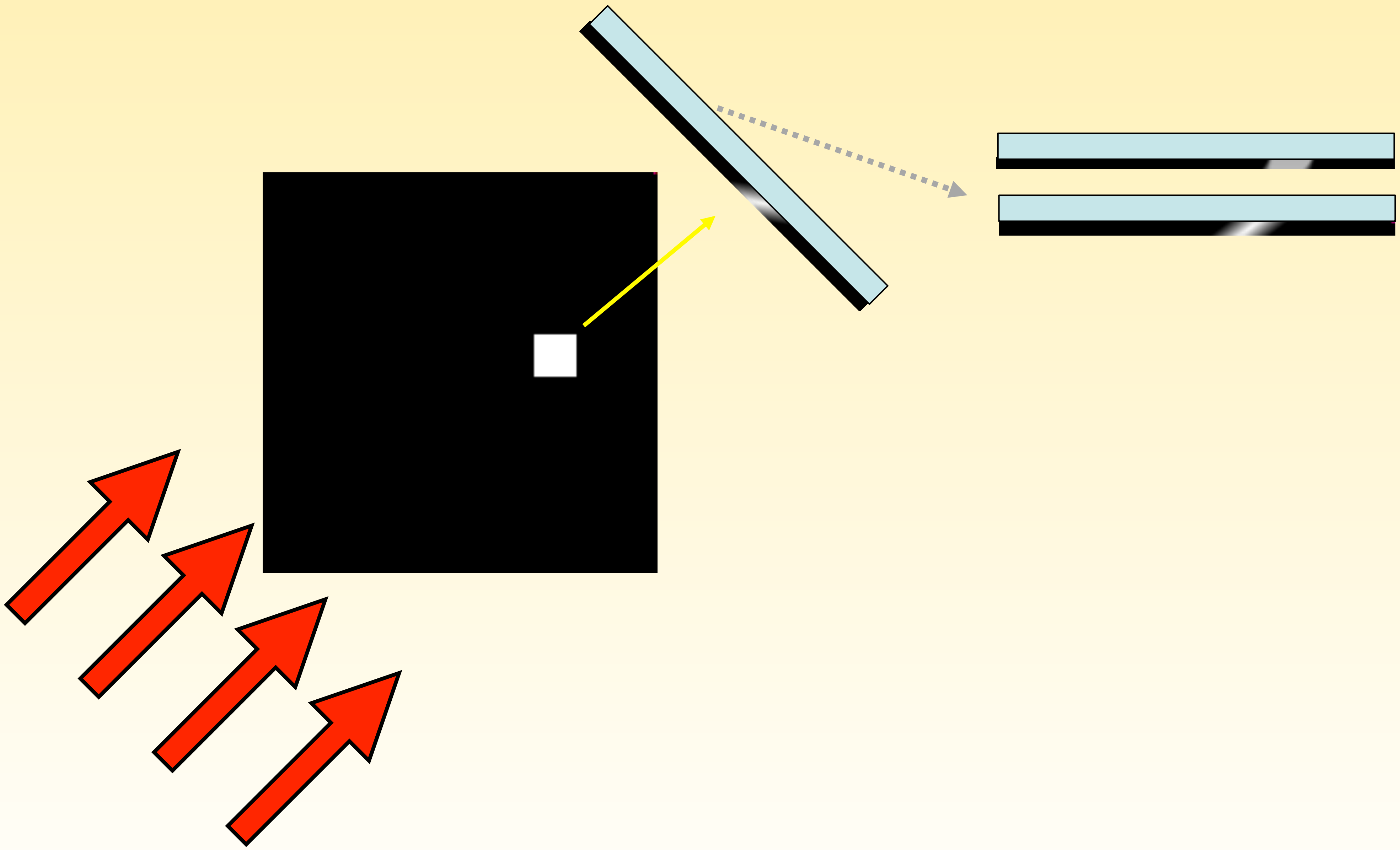

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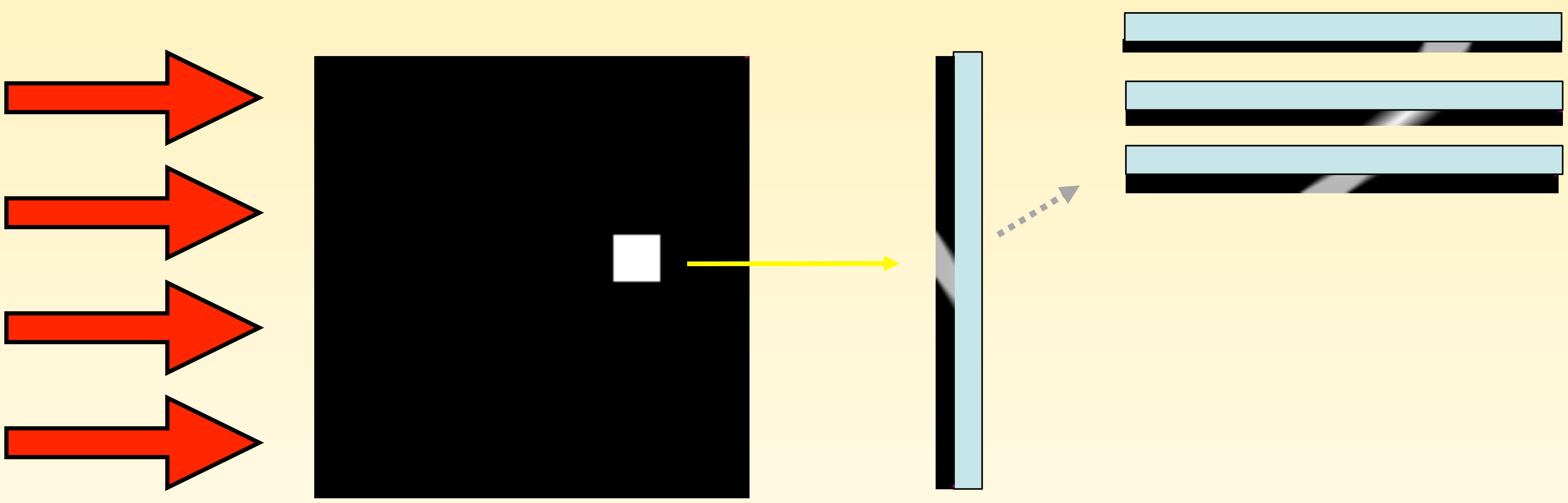

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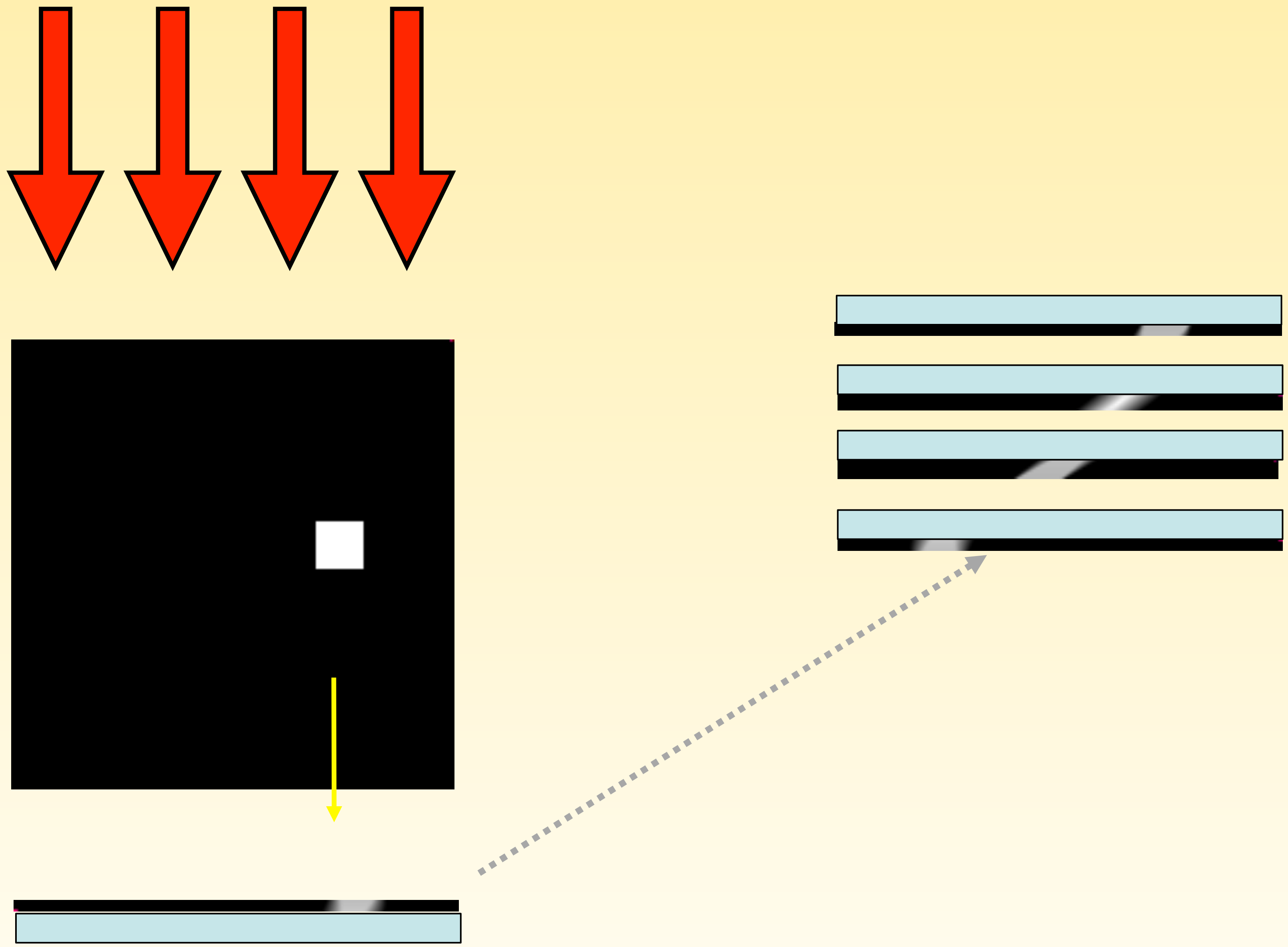

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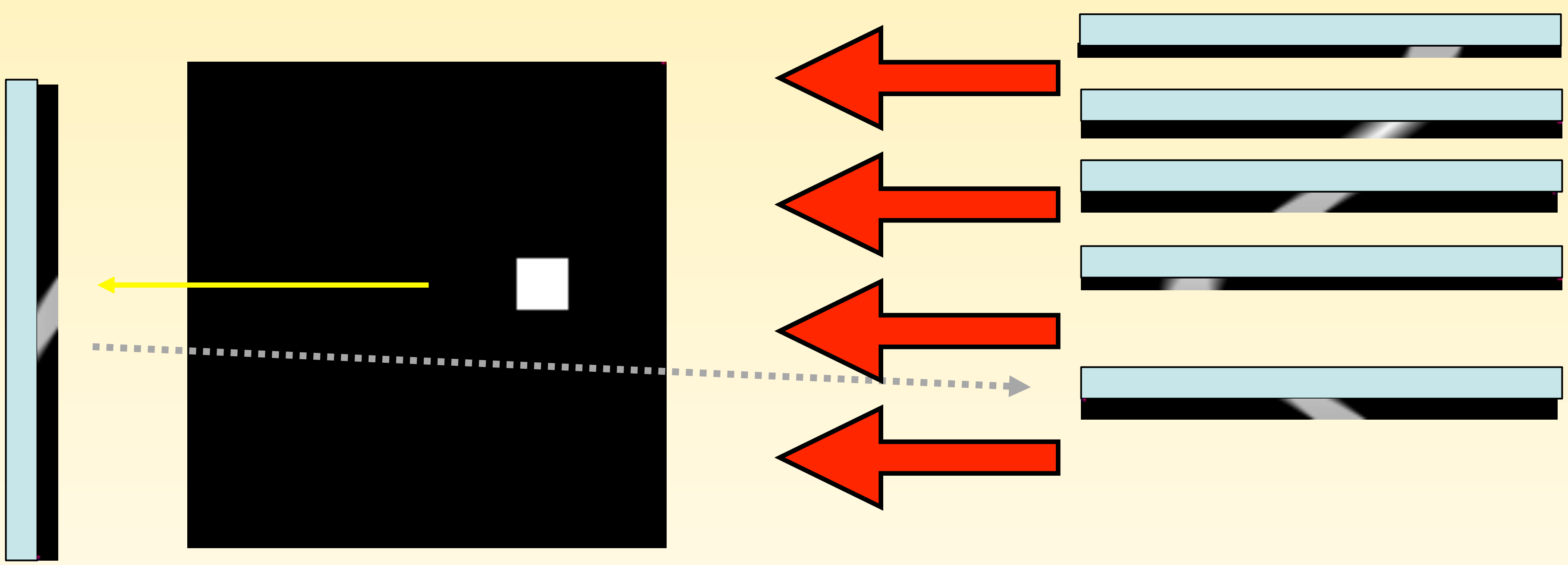

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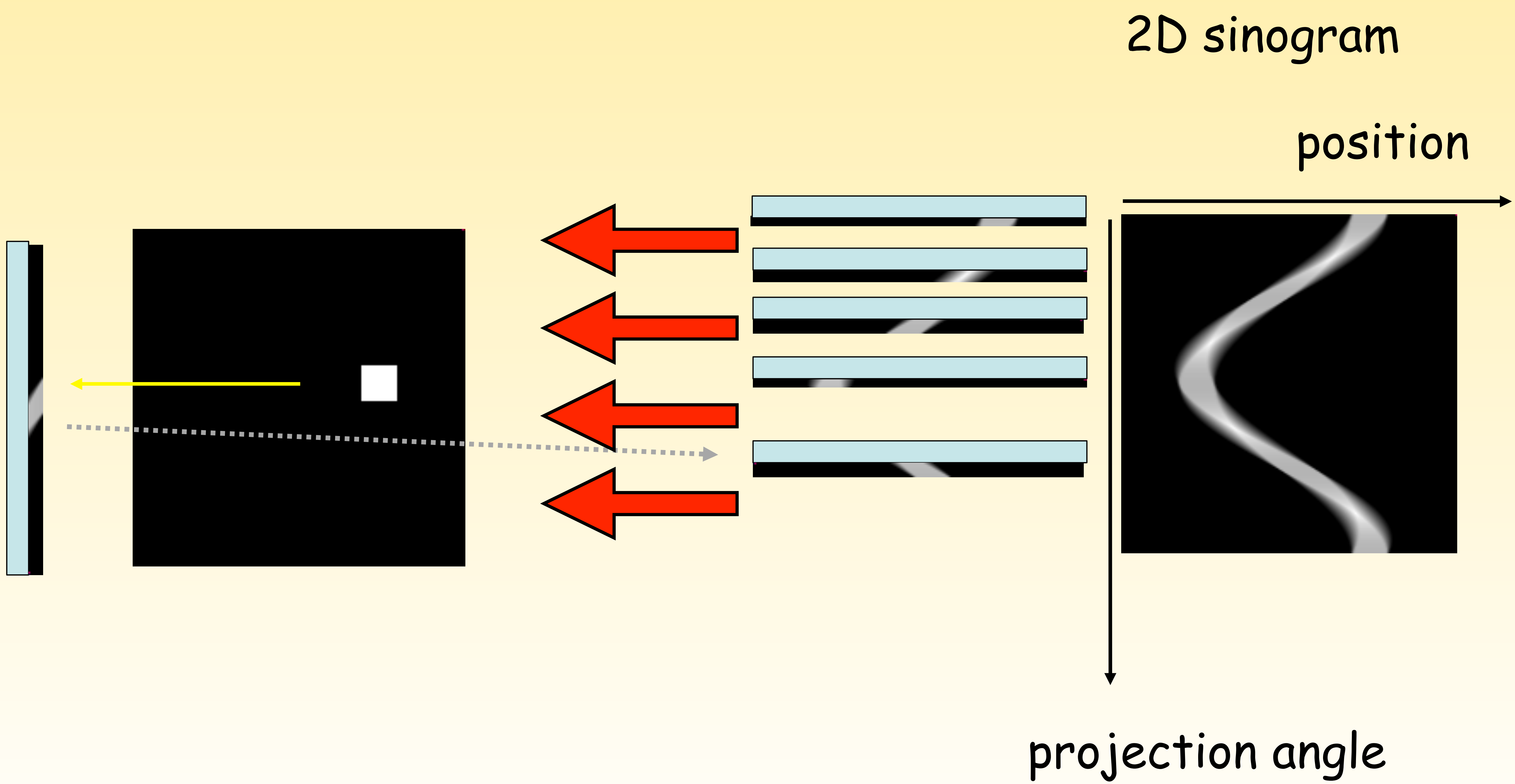
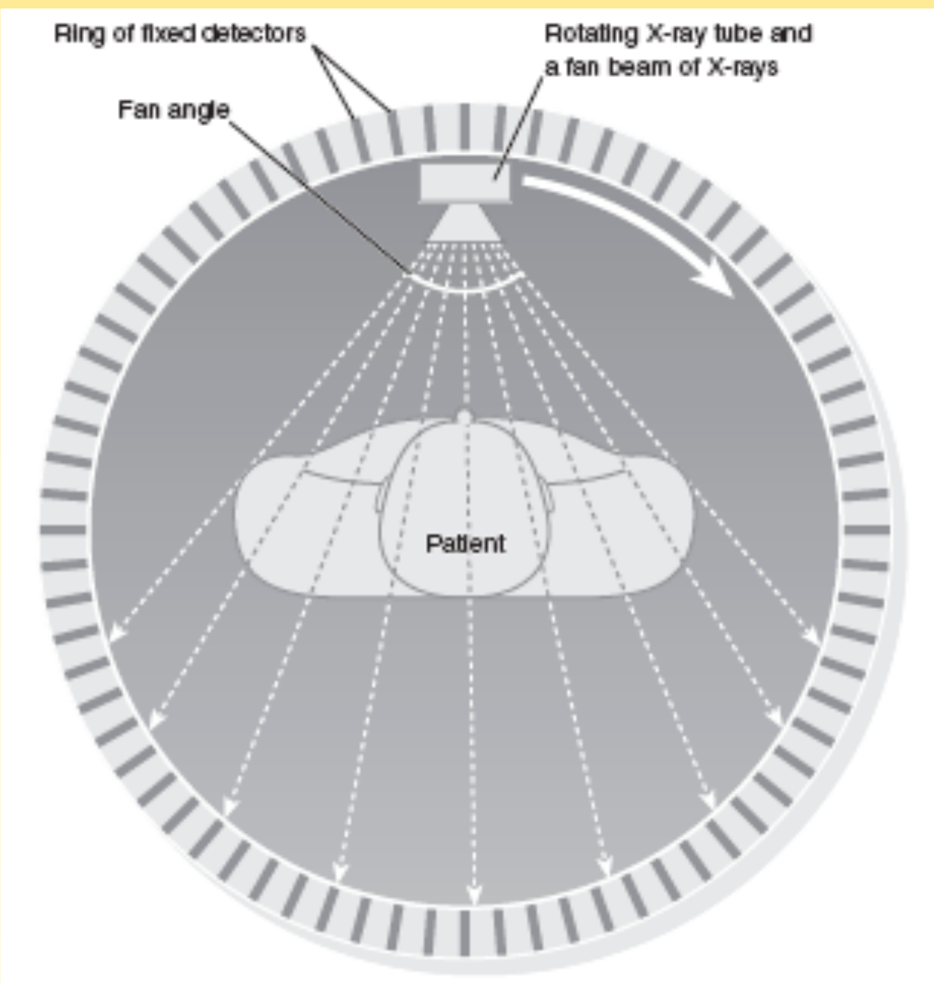
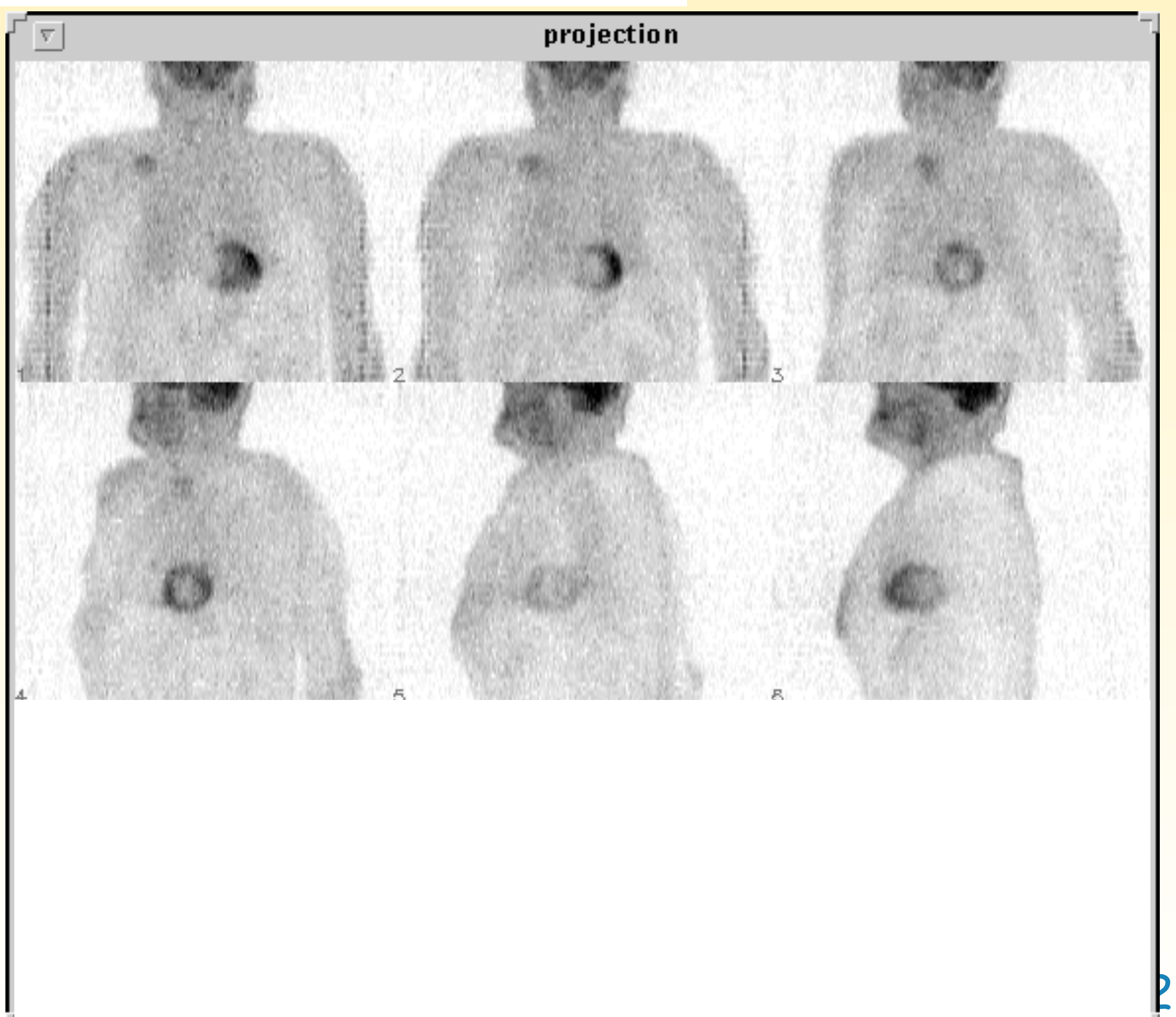


Snapshot of standard tomography (CT)
3D sinogram





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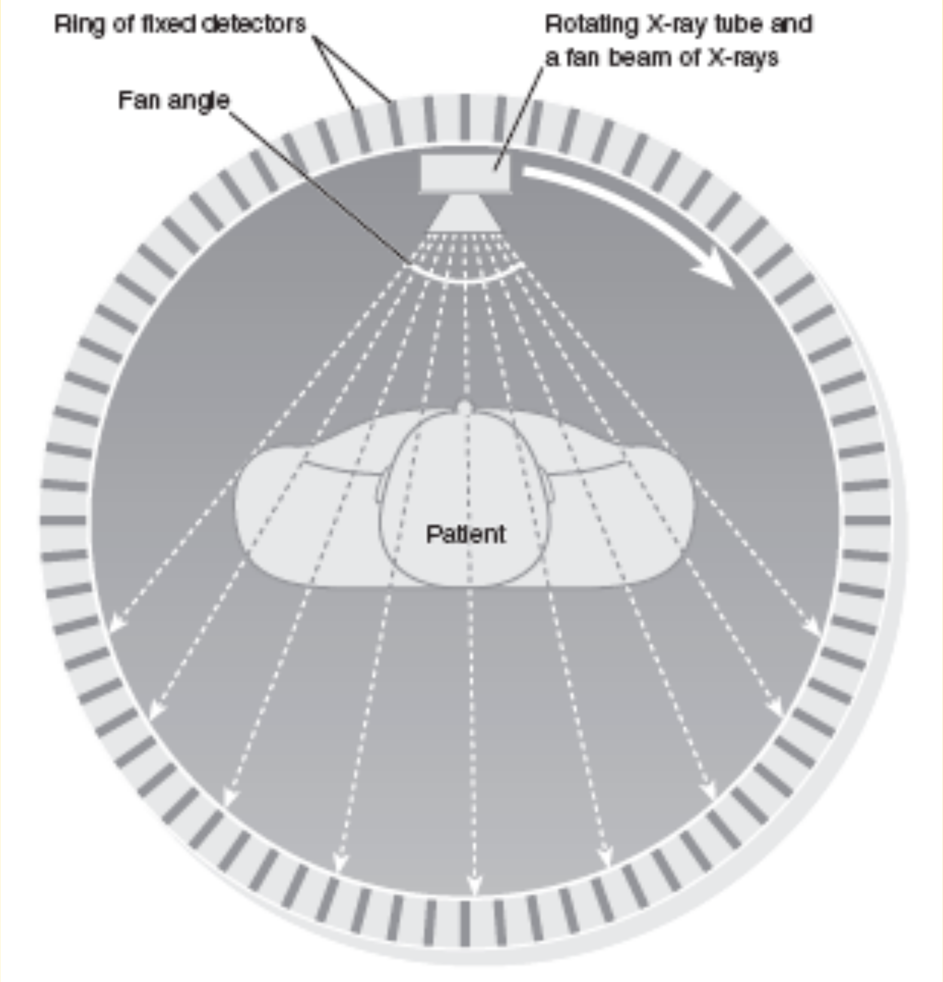
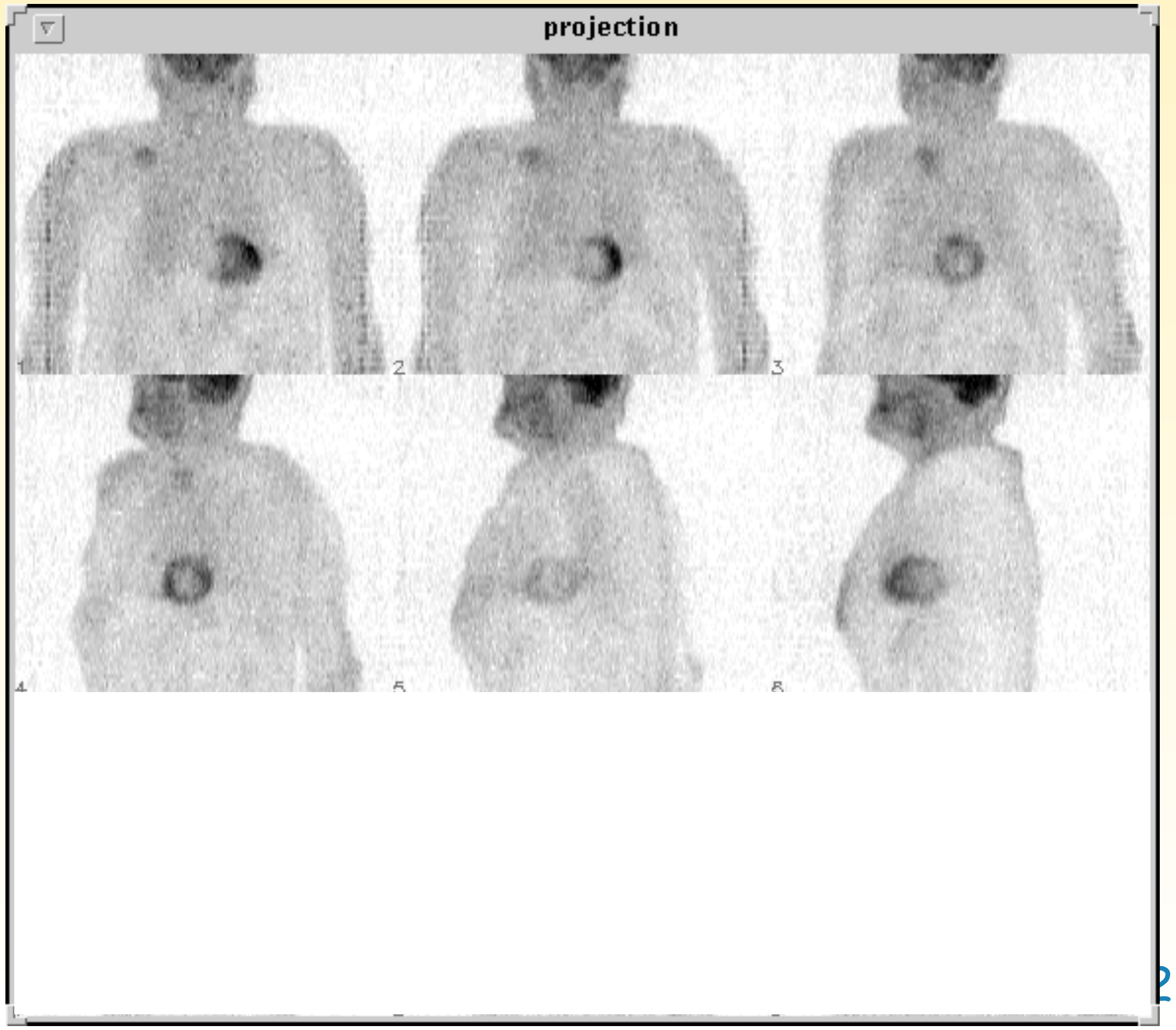
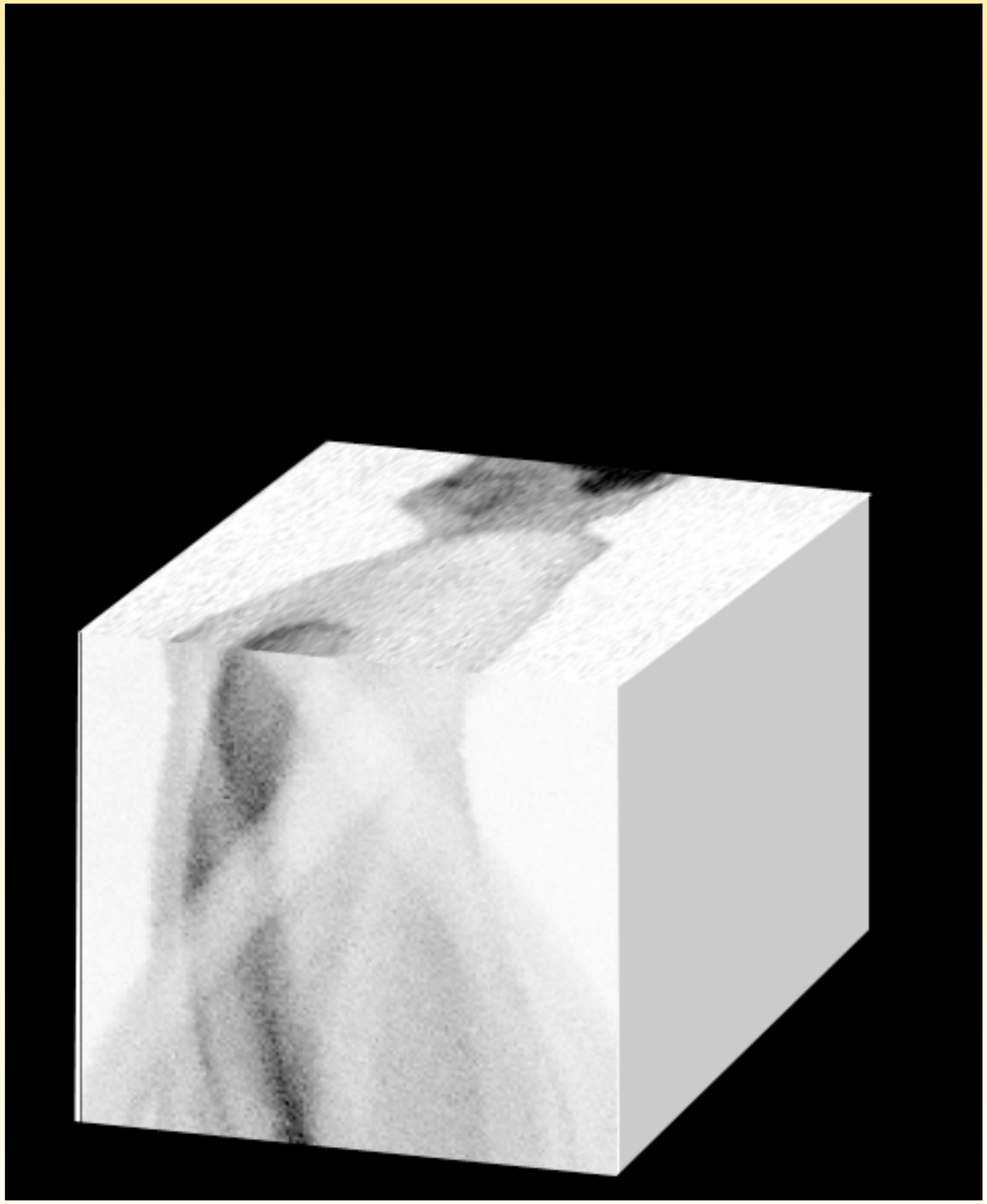
Snapshot of standard tomography (CT)
3D sinogram







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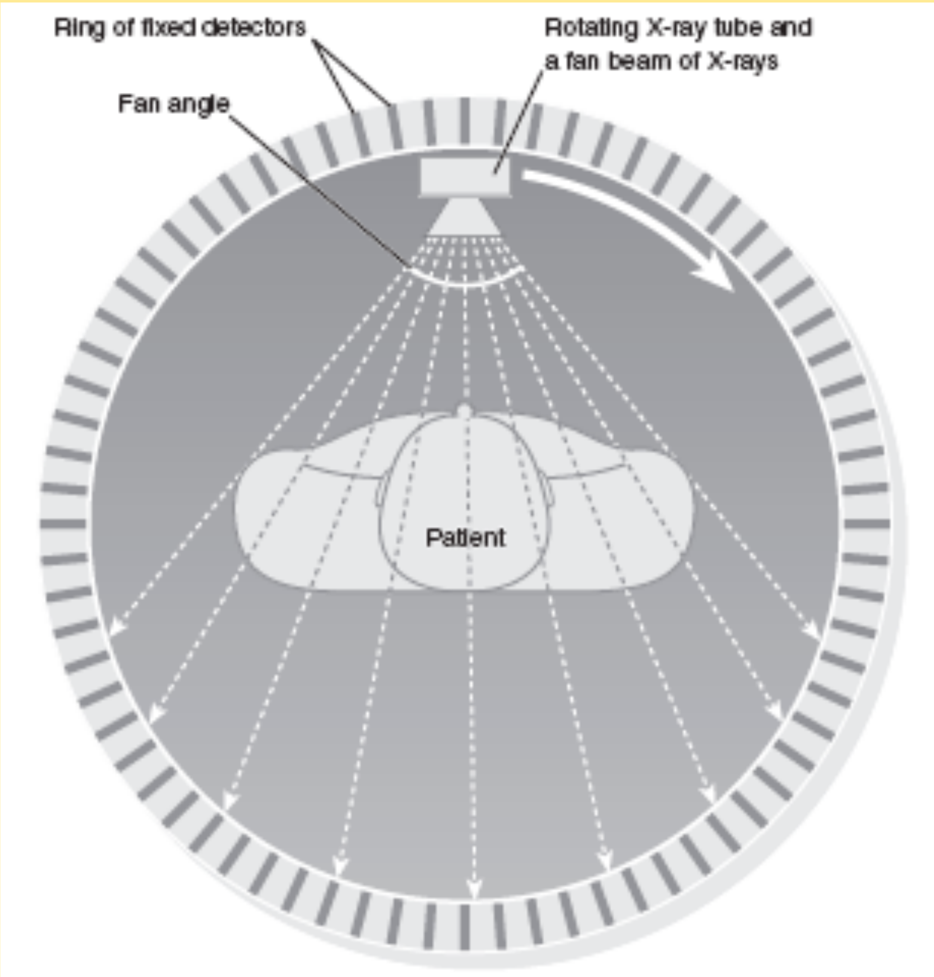
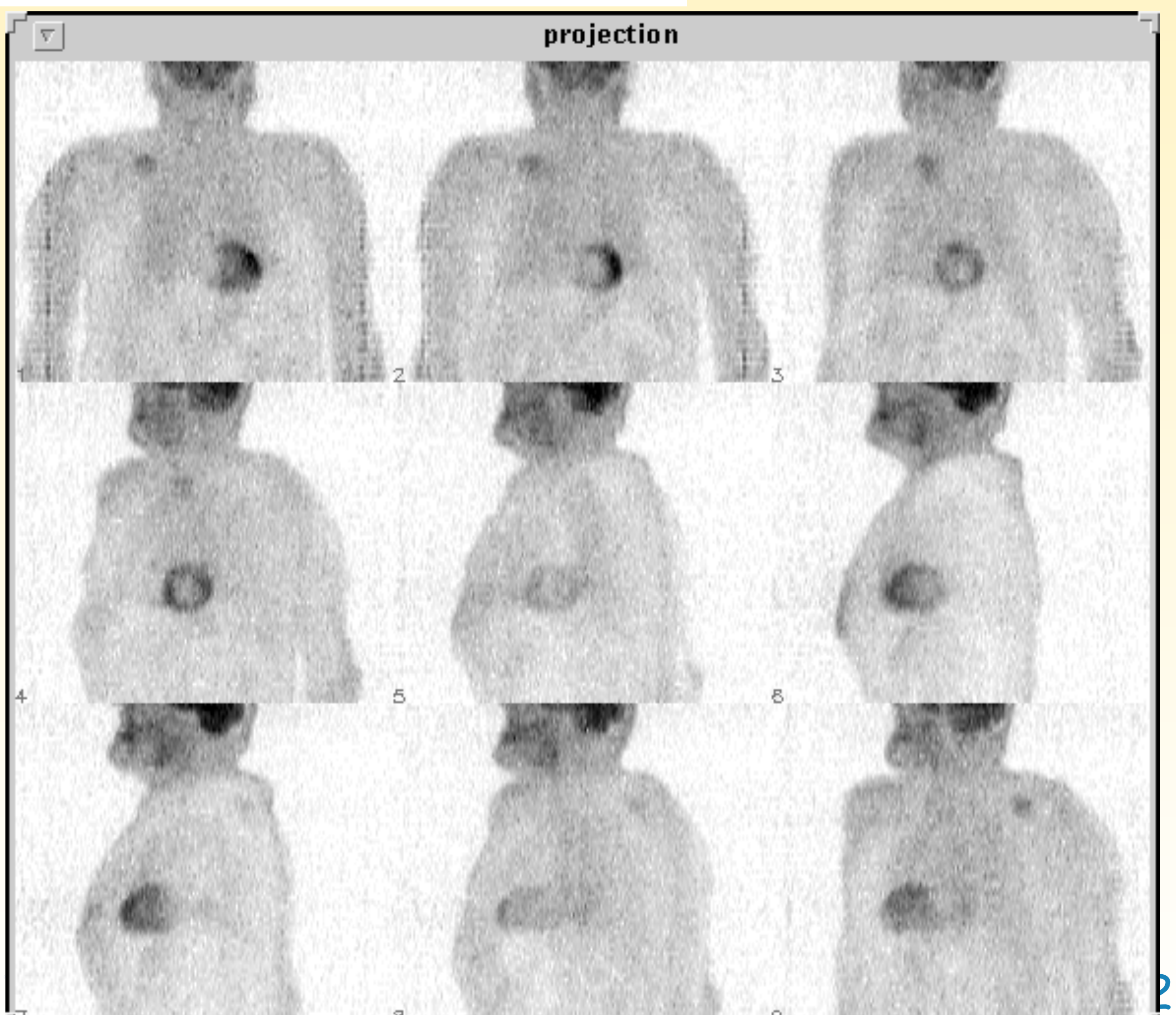
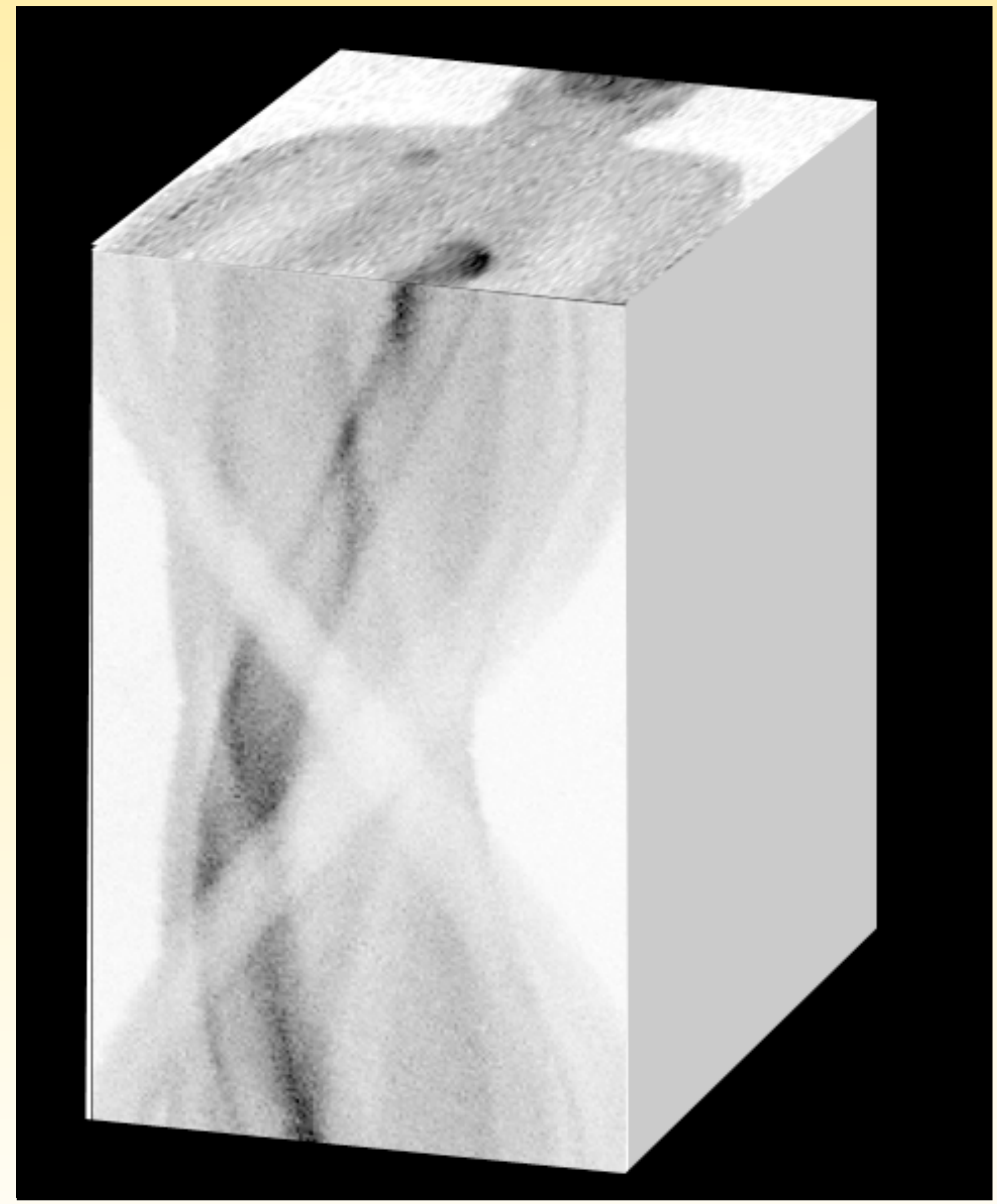
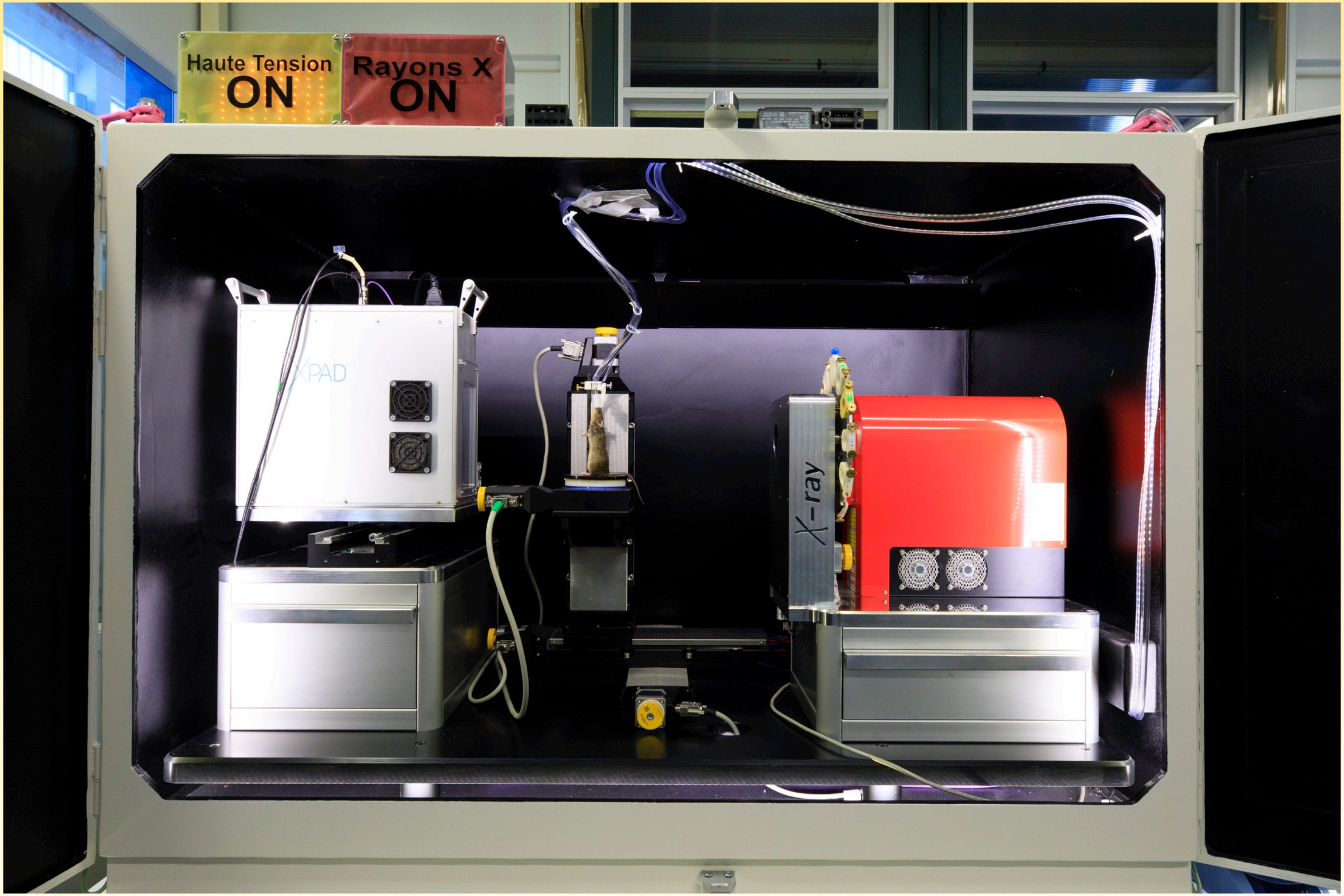






PIXSCAN-FLI



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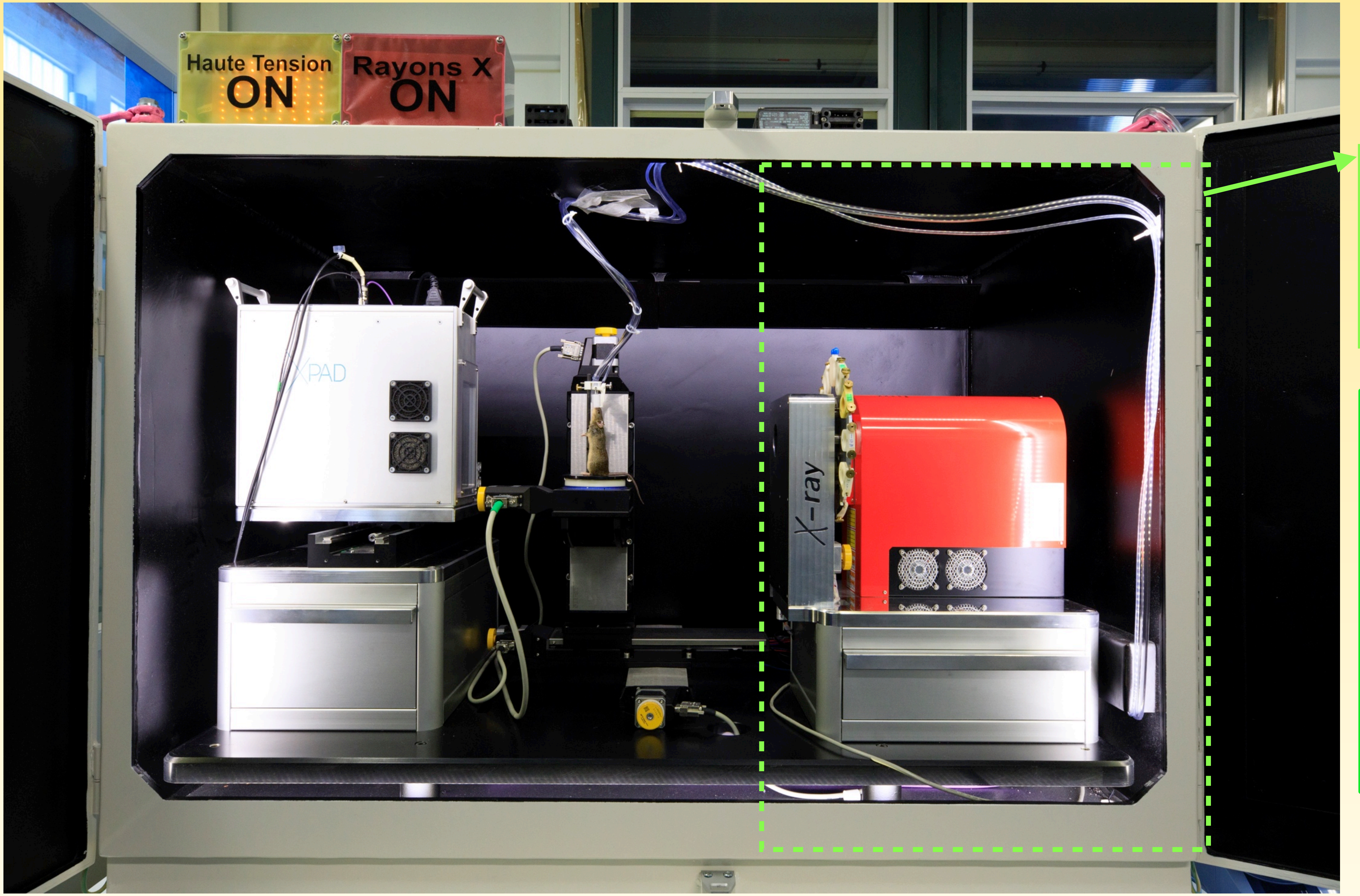
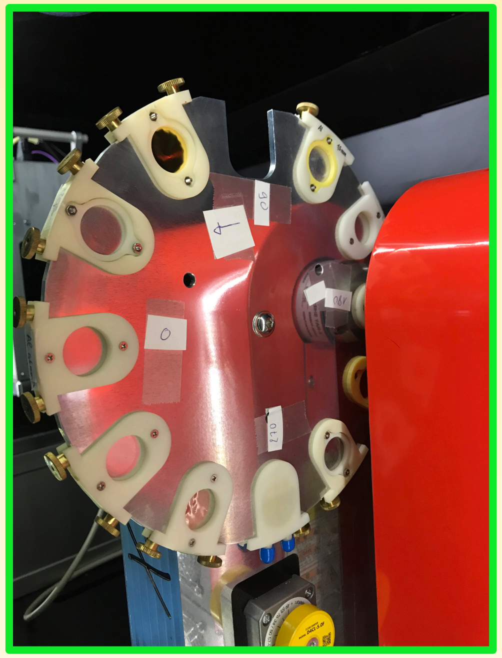


Source block

W anode (150 kVp)
Wheel filters



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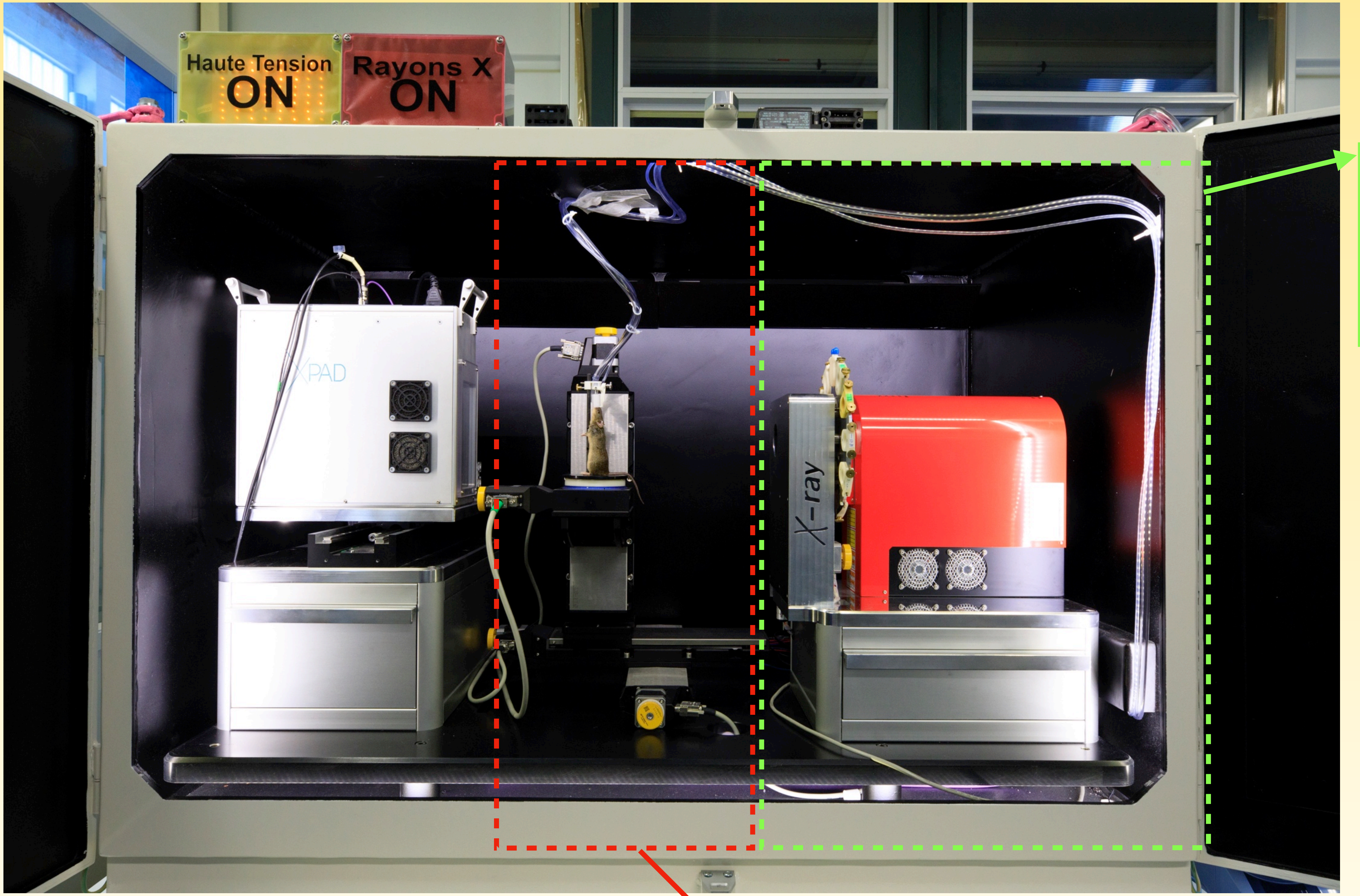

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Wheel filters

Animal block
Vertical rotation axis
Acquisition mode: shoot and step or continuous rotation
Gas anesthesia: isoflurane

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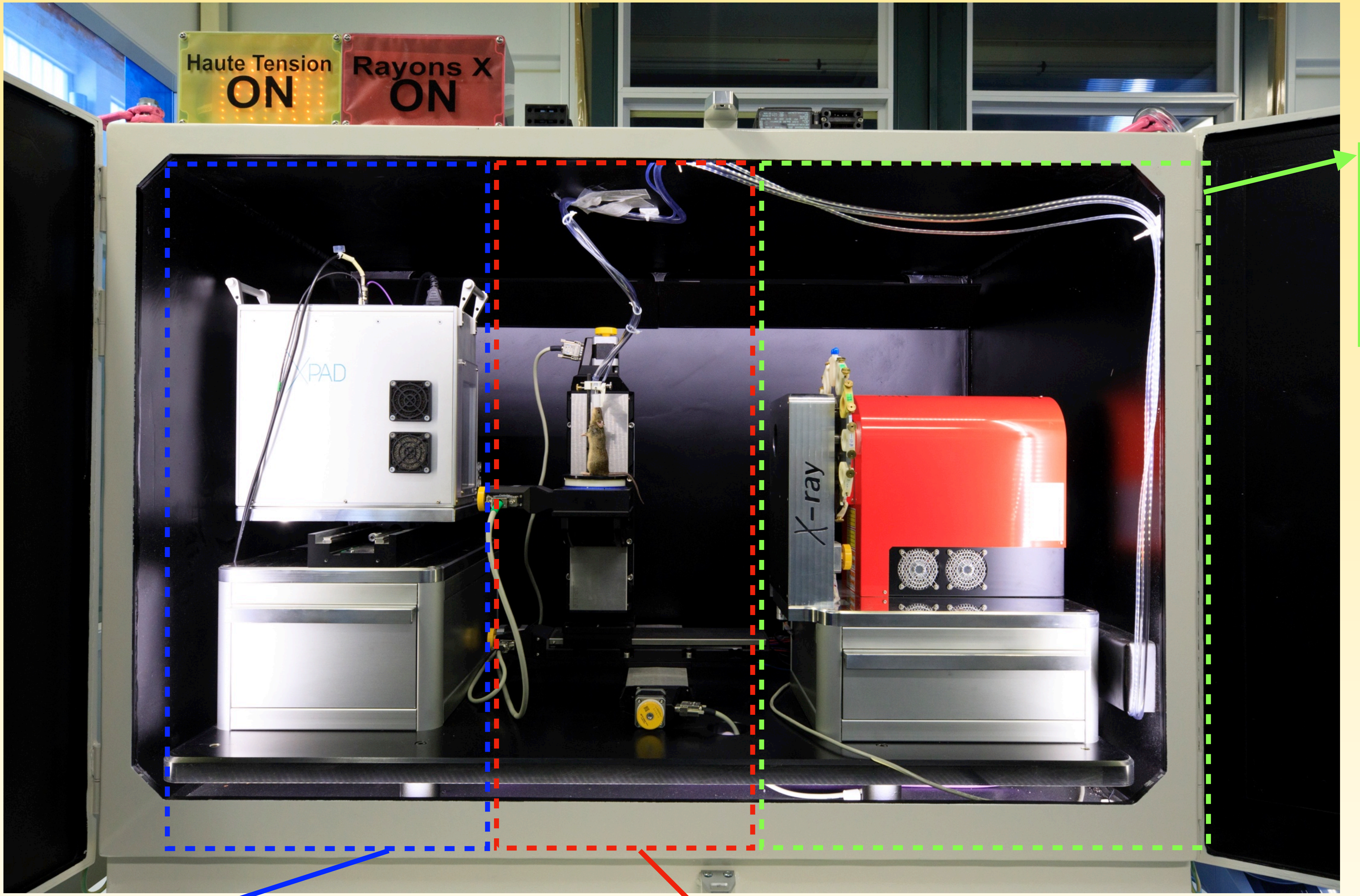

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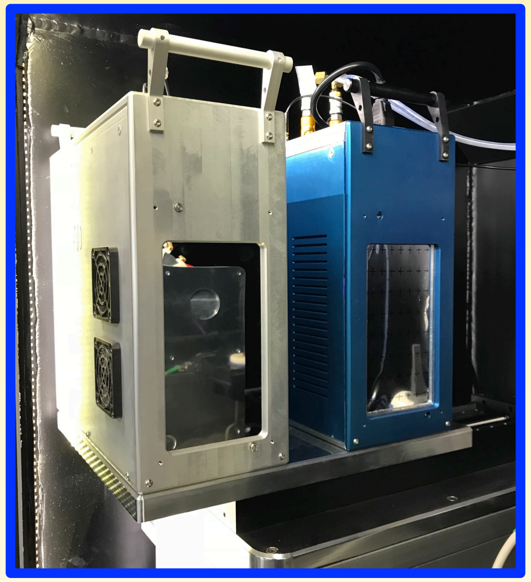
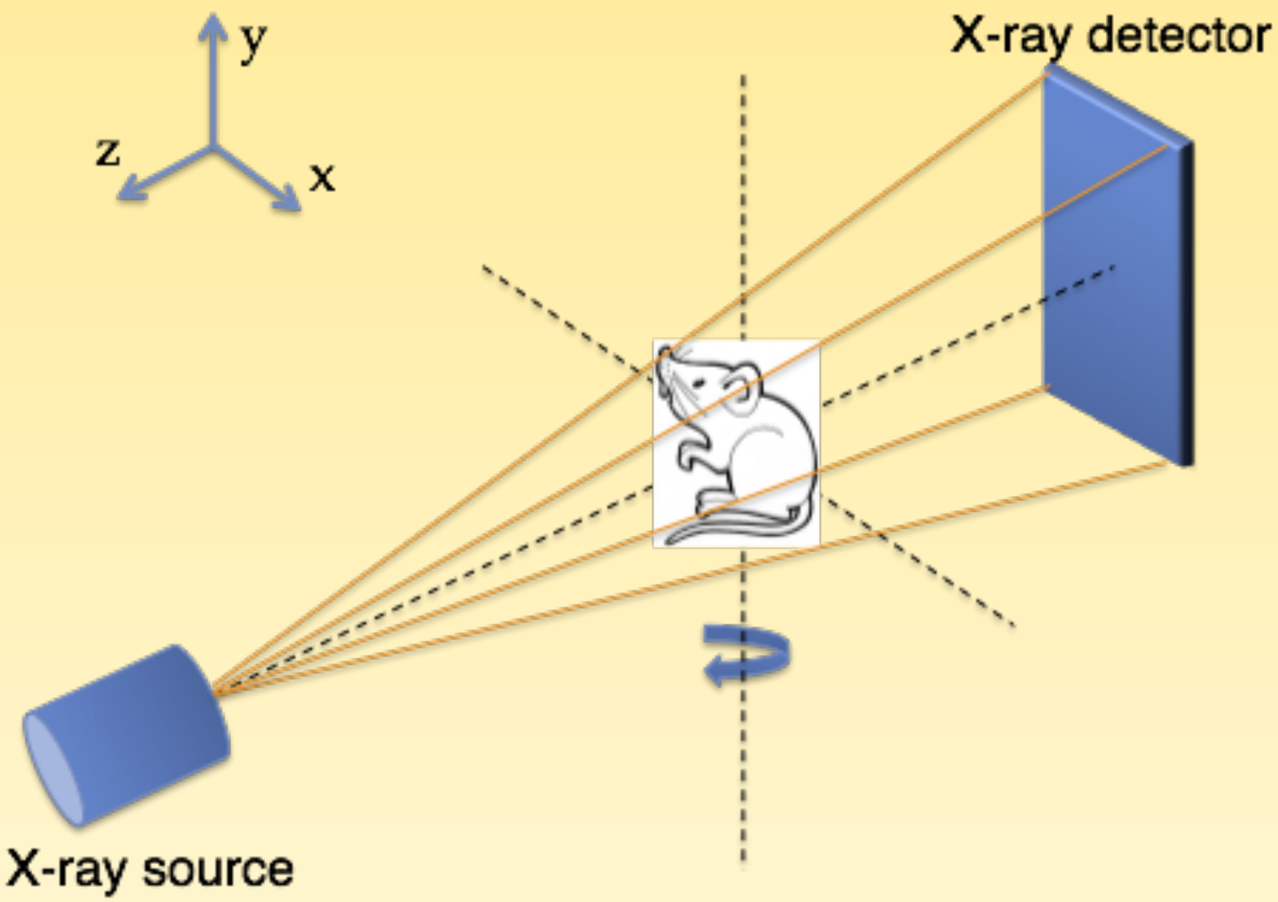


Detector block
Two cameras
Resolution of 85 µm/voxel

Animal block
Vertical rotation axis
Acquisition mode: shoot and step or continuous rotation
Gas anesthesia: isoflurane

In vivo X-ray imaging at CPPM



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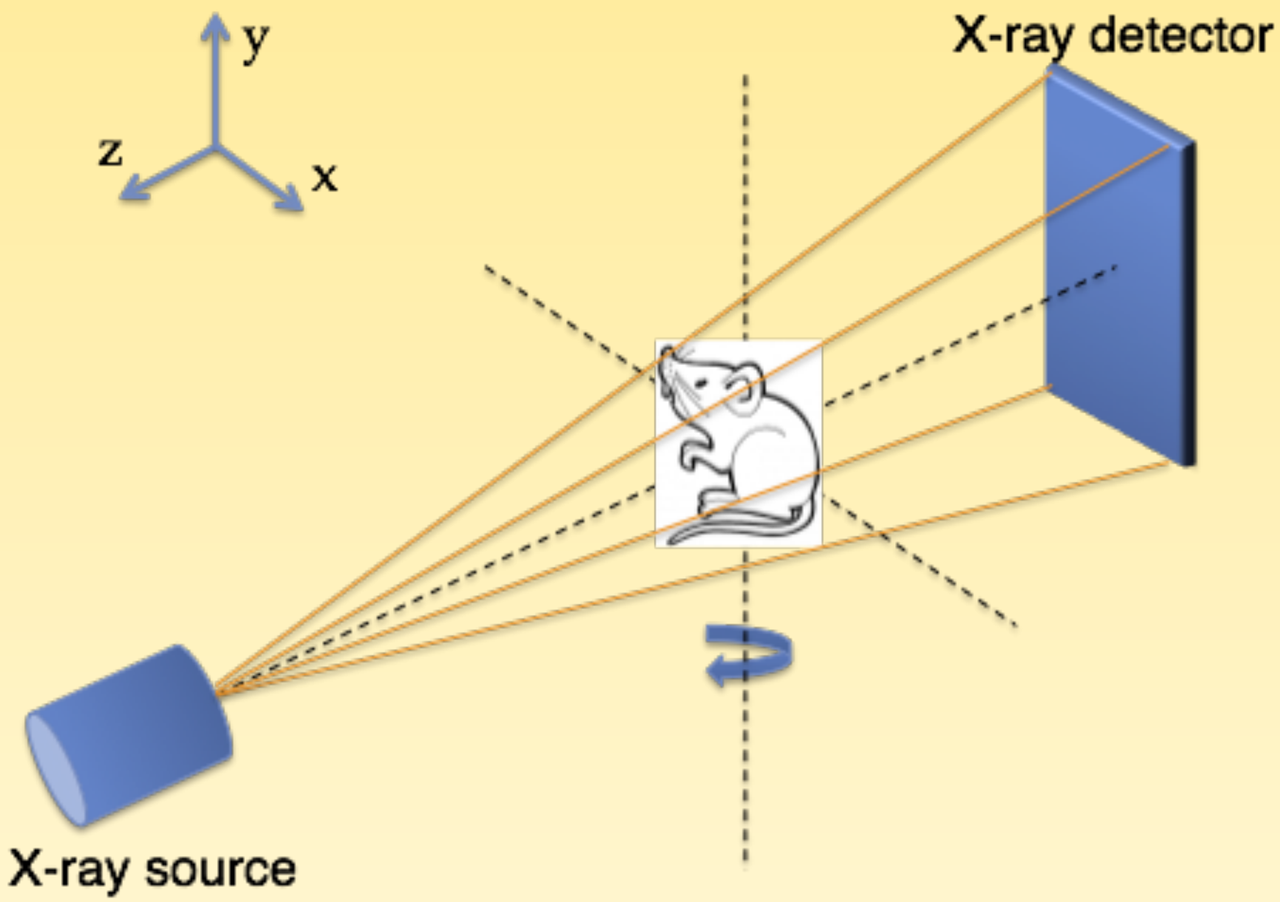

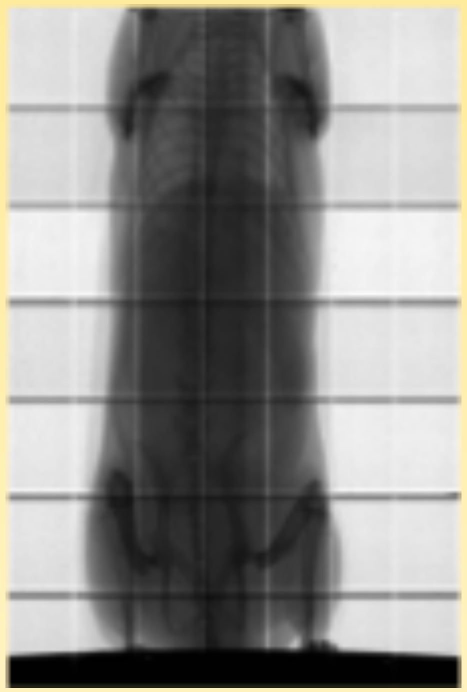

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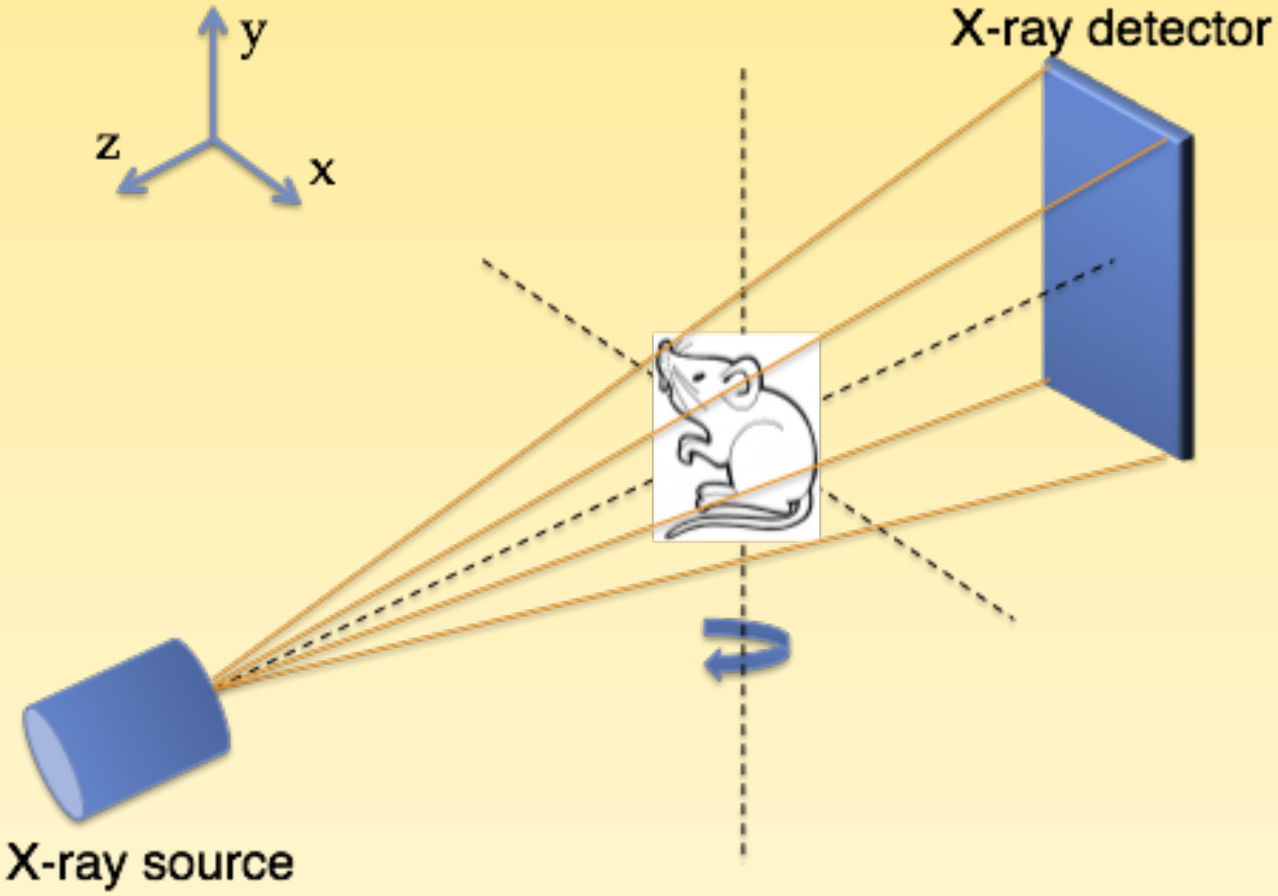

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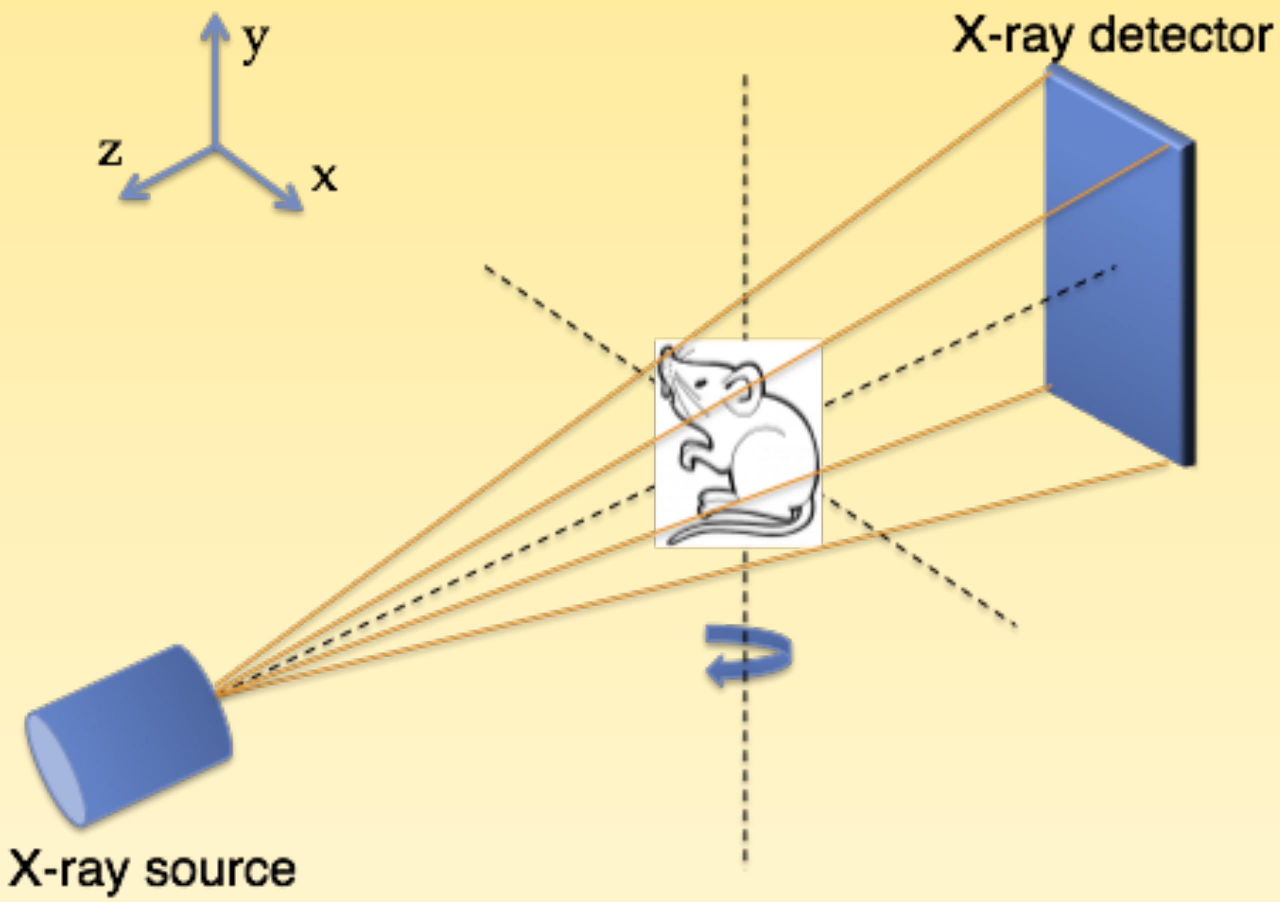

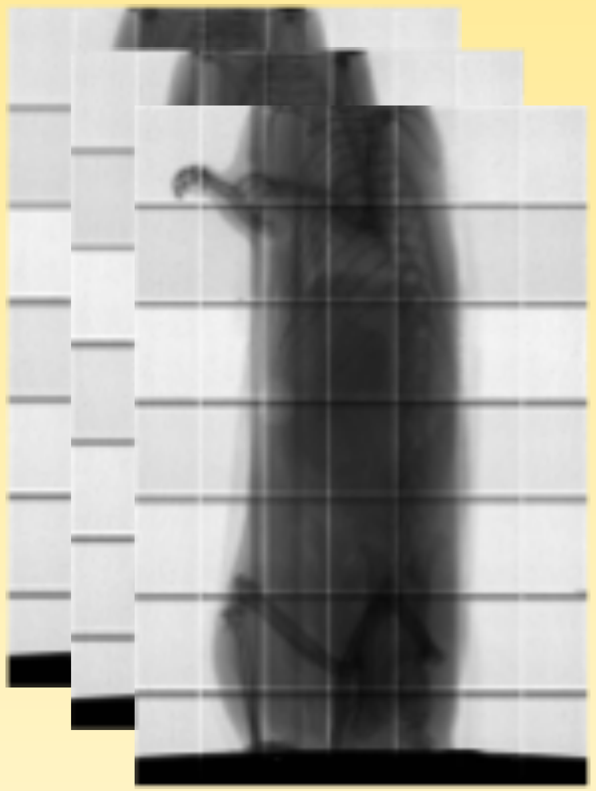

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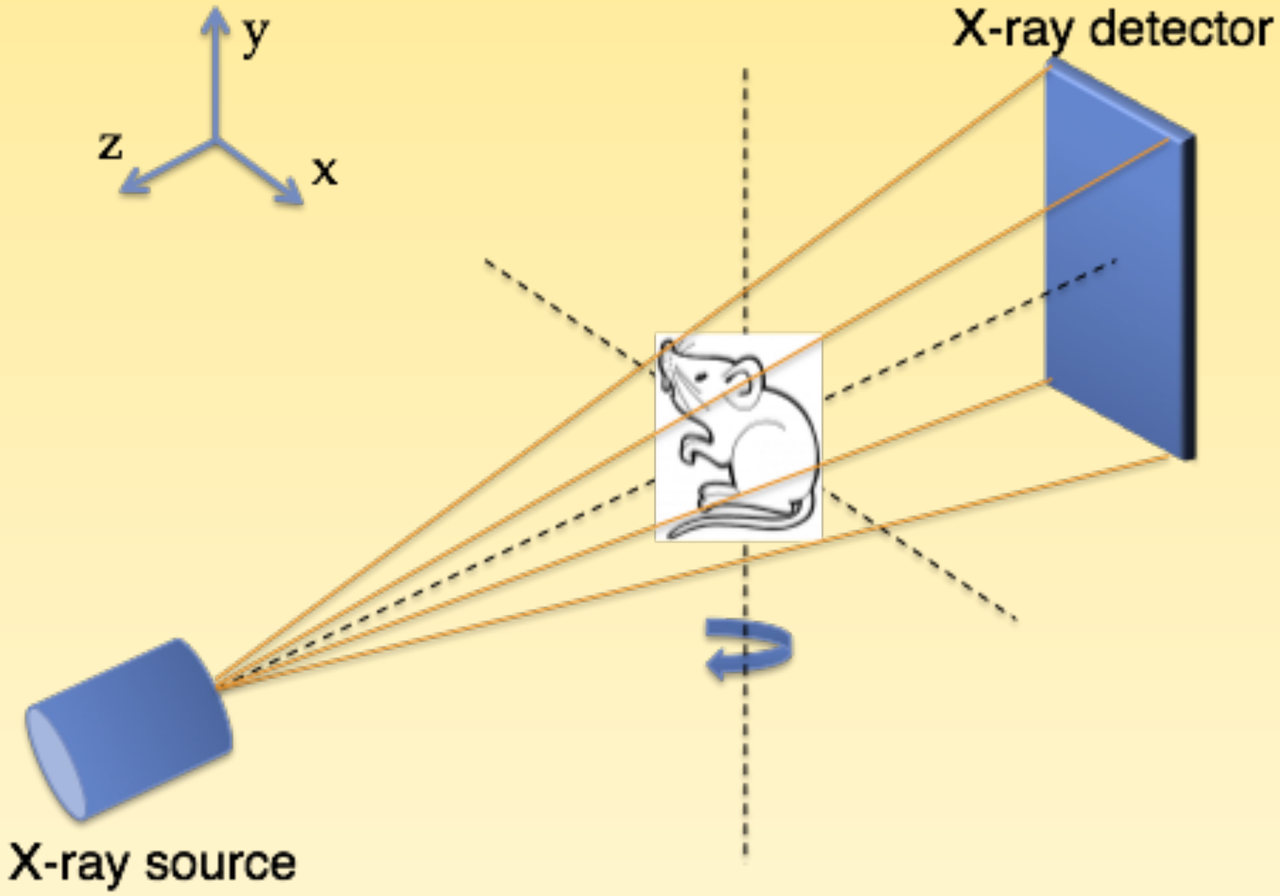

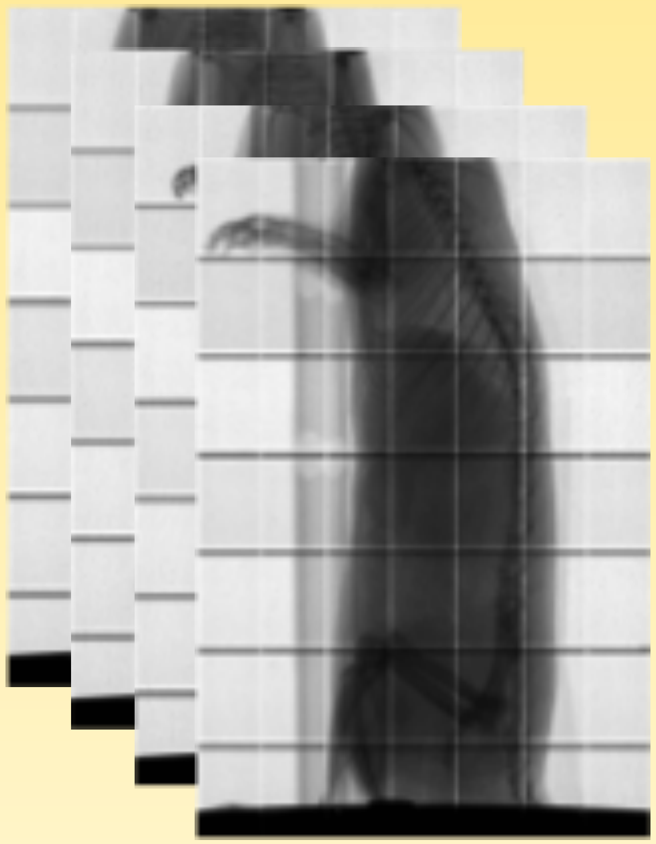

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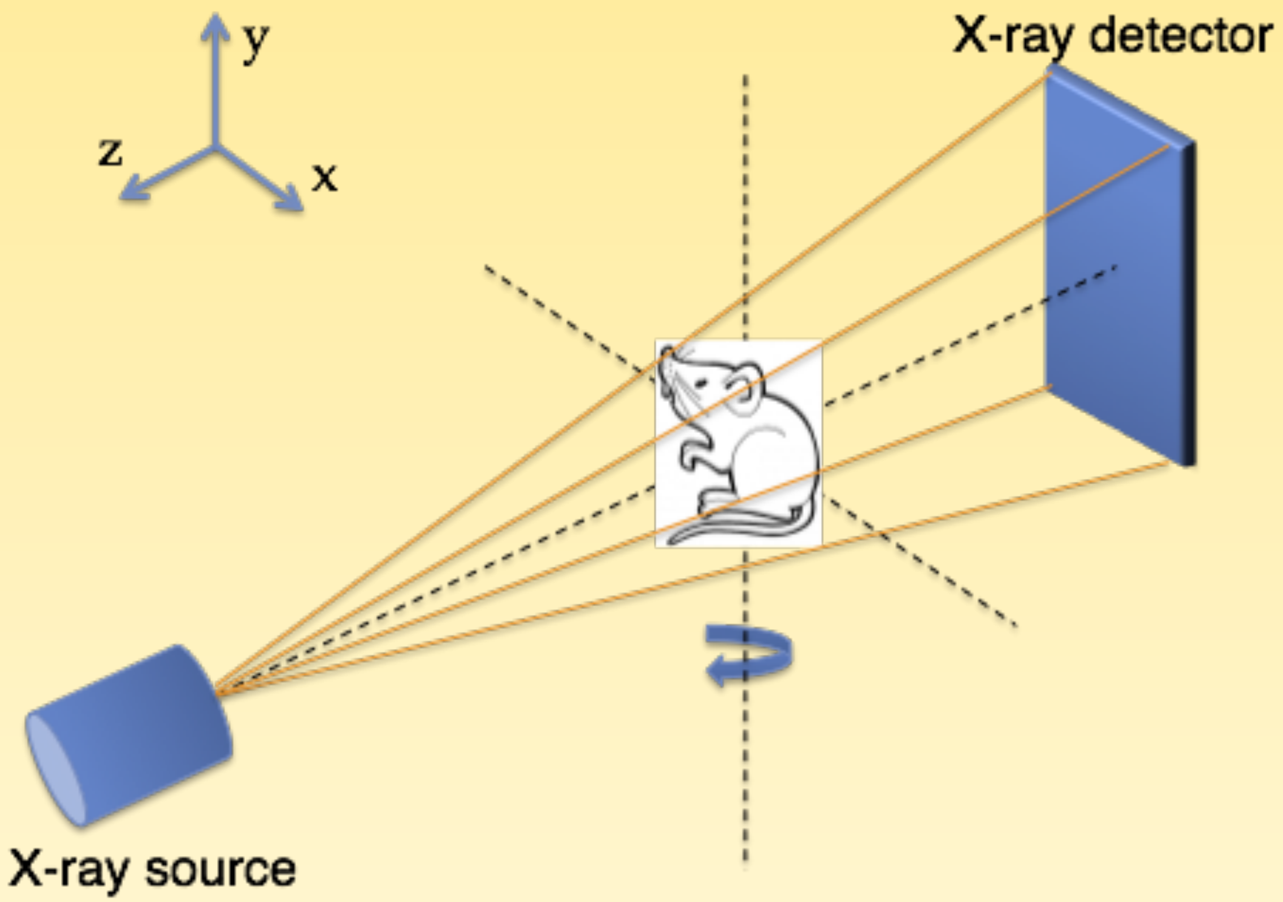

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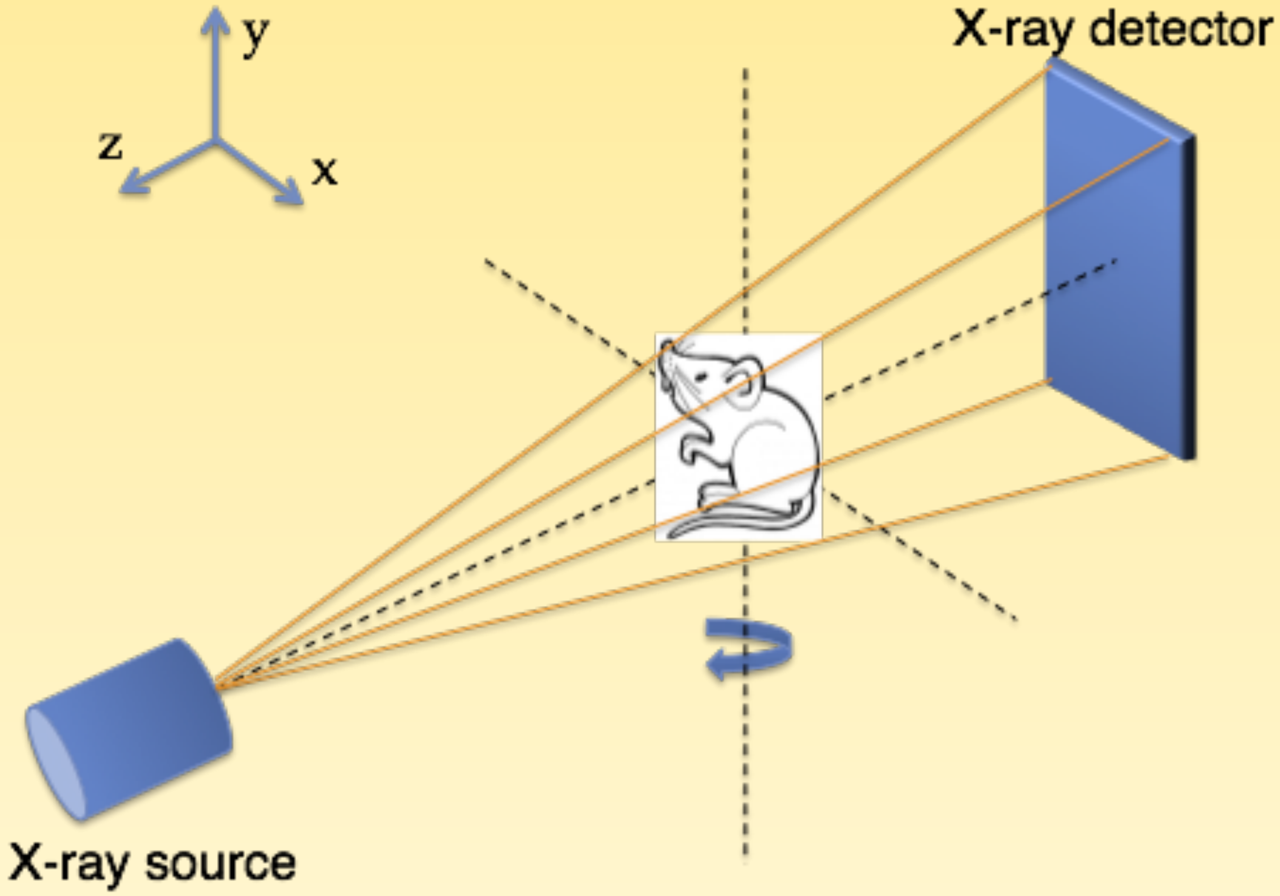

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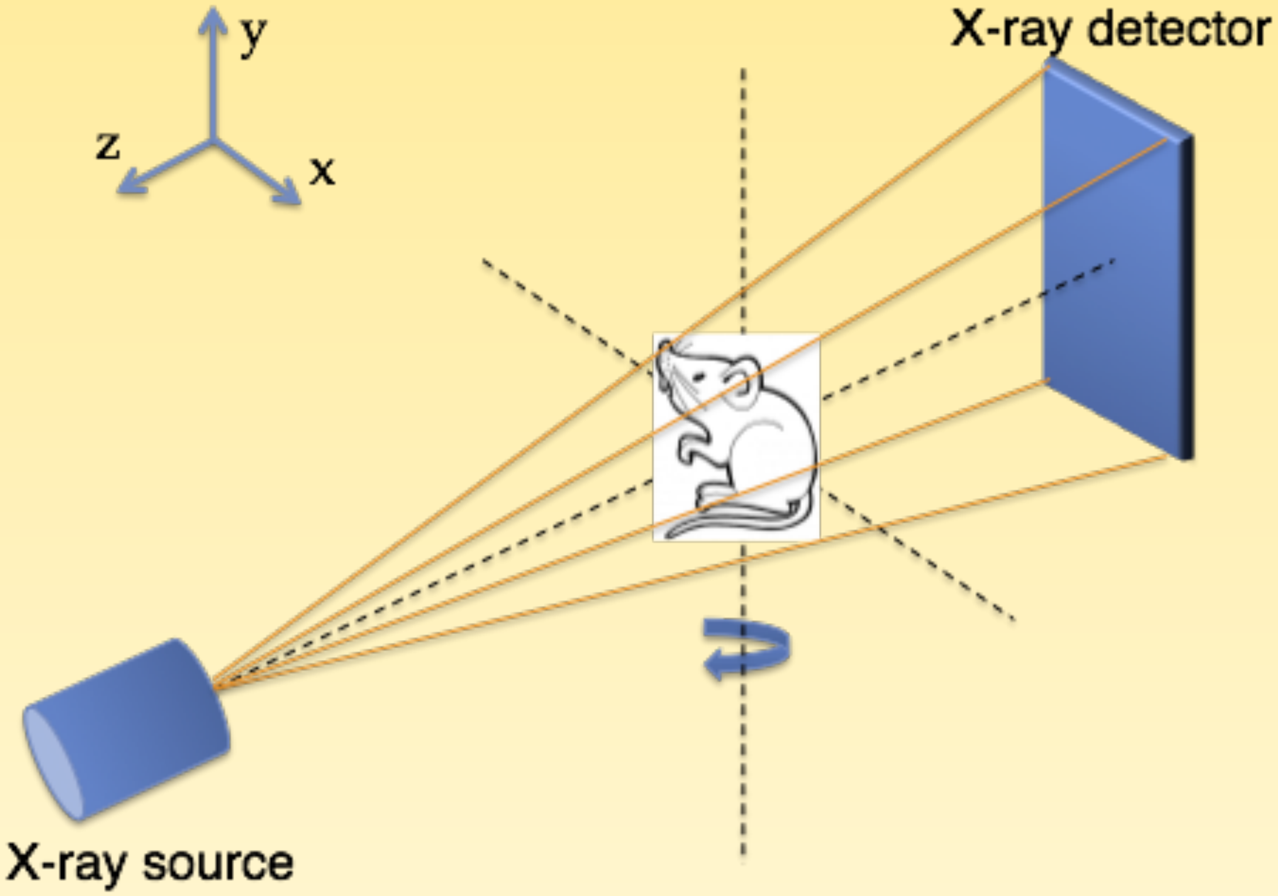

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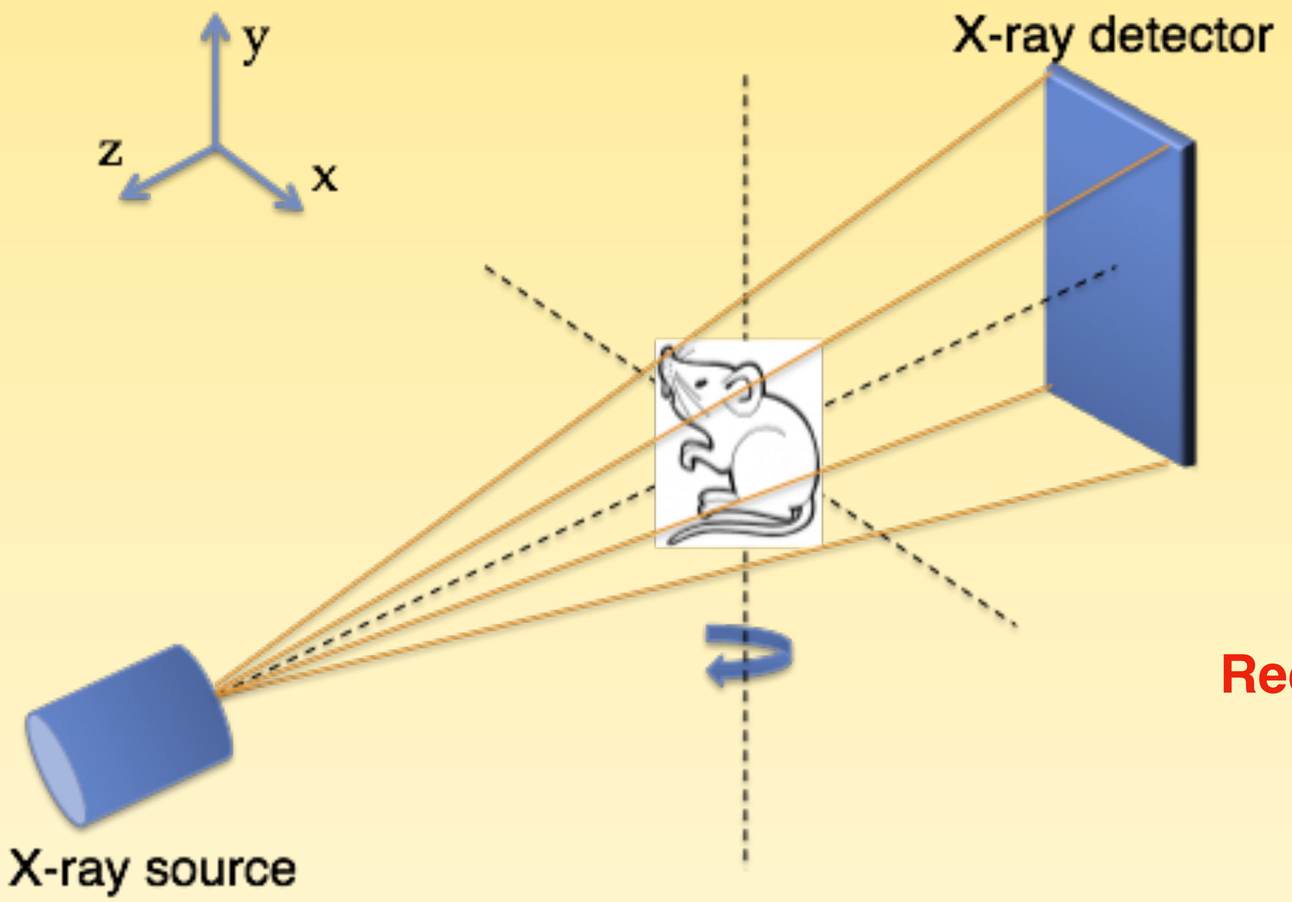
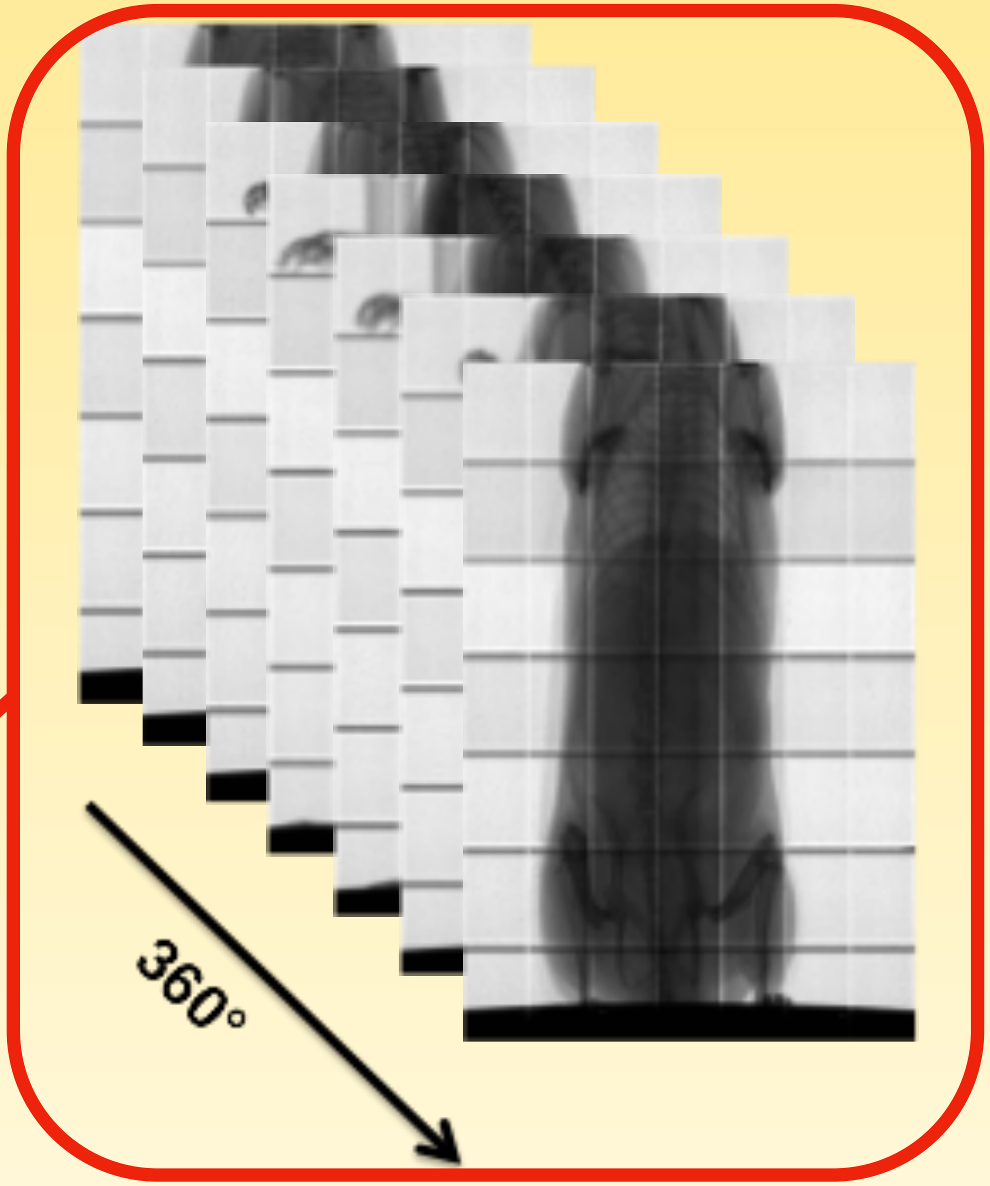


Reconstruction algorithm



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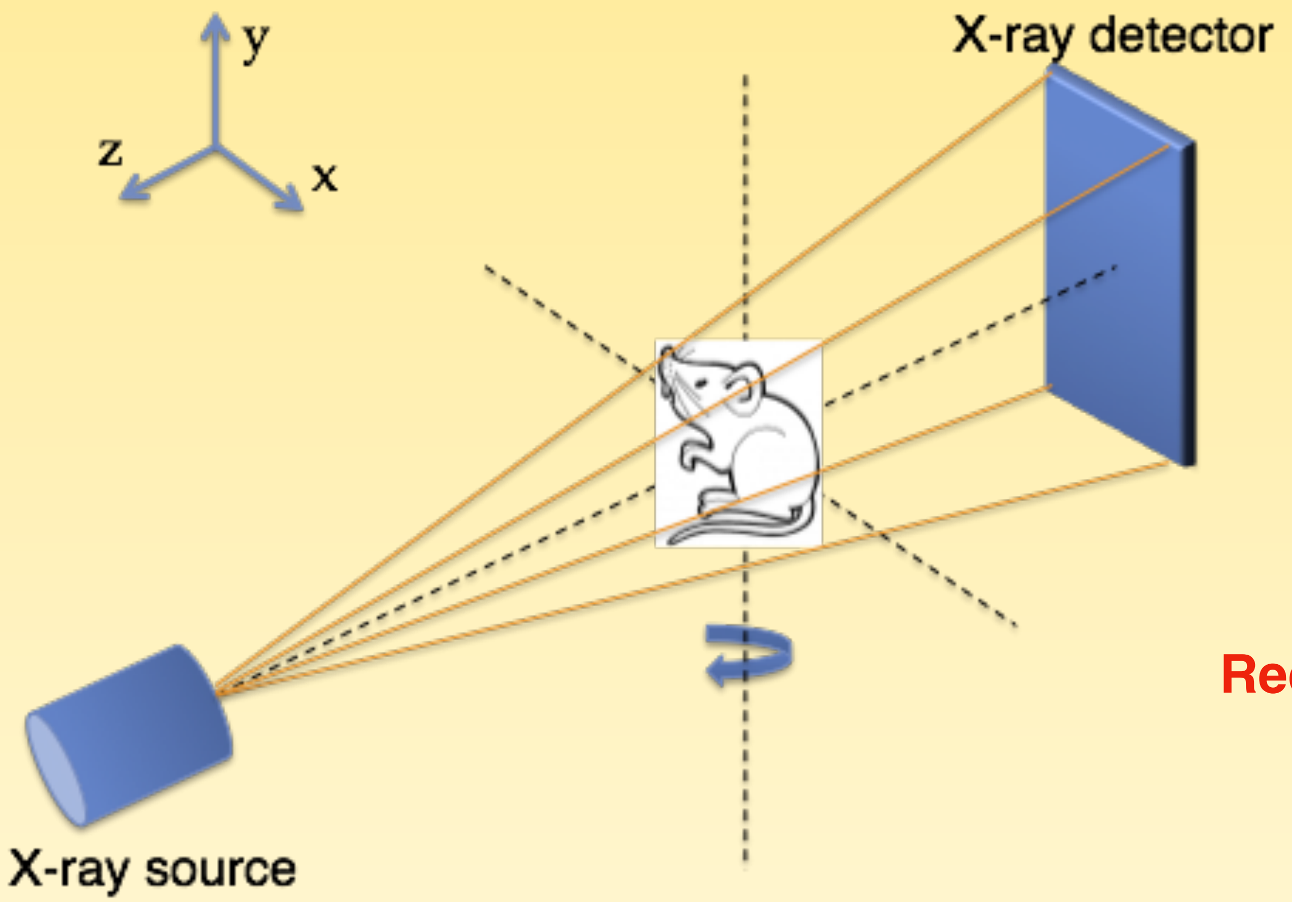

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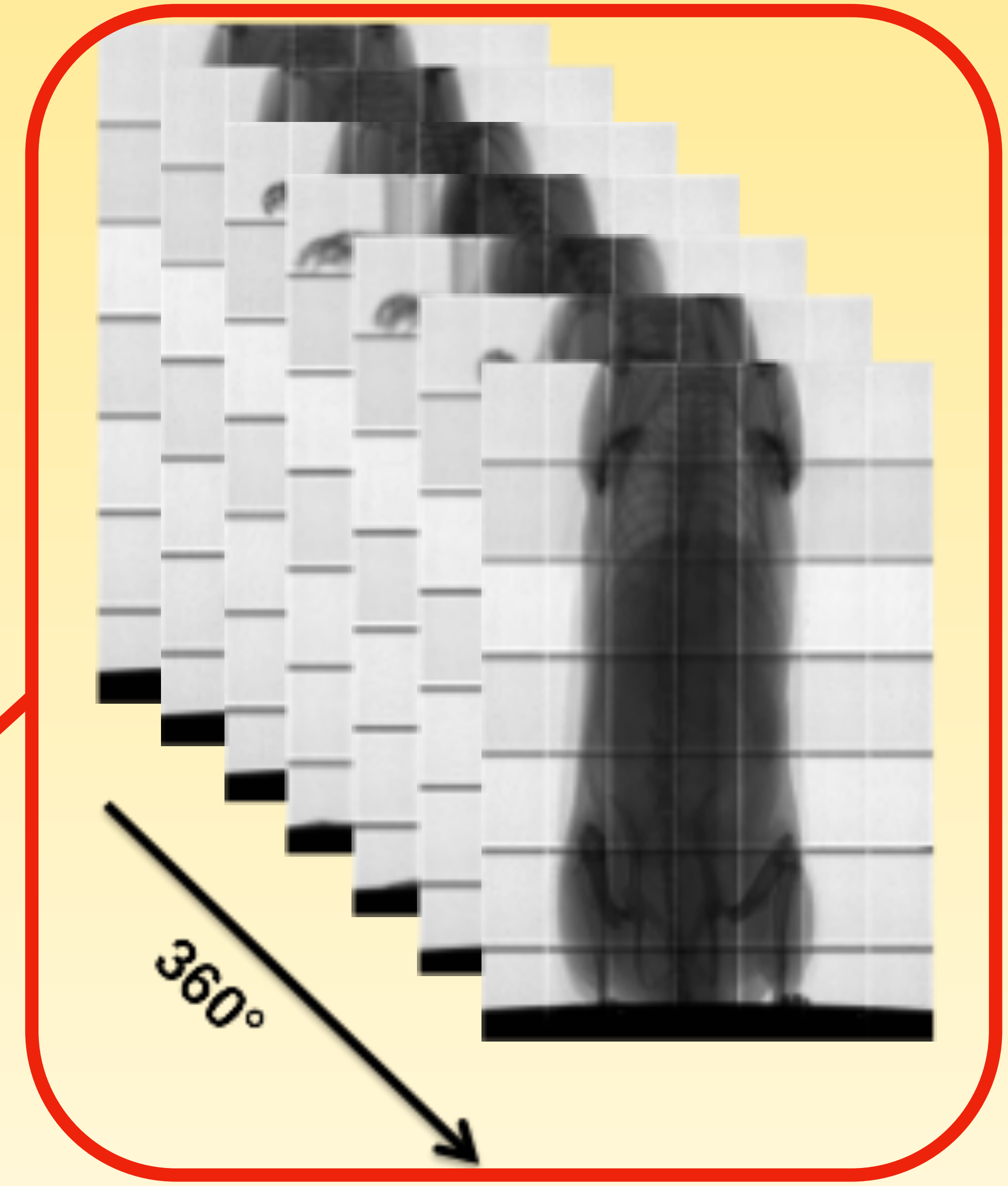

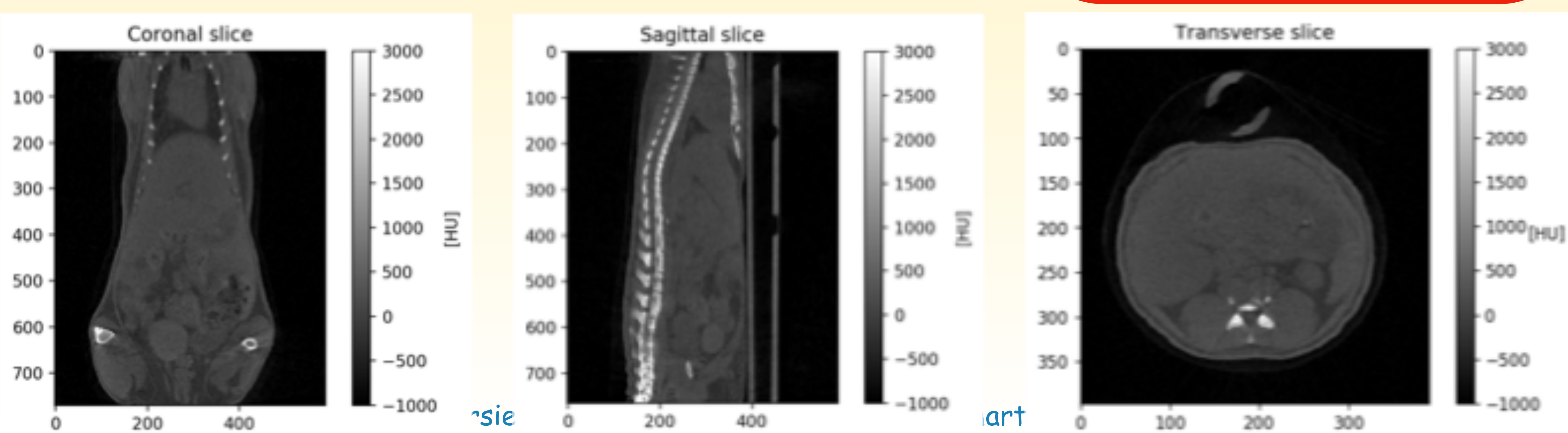

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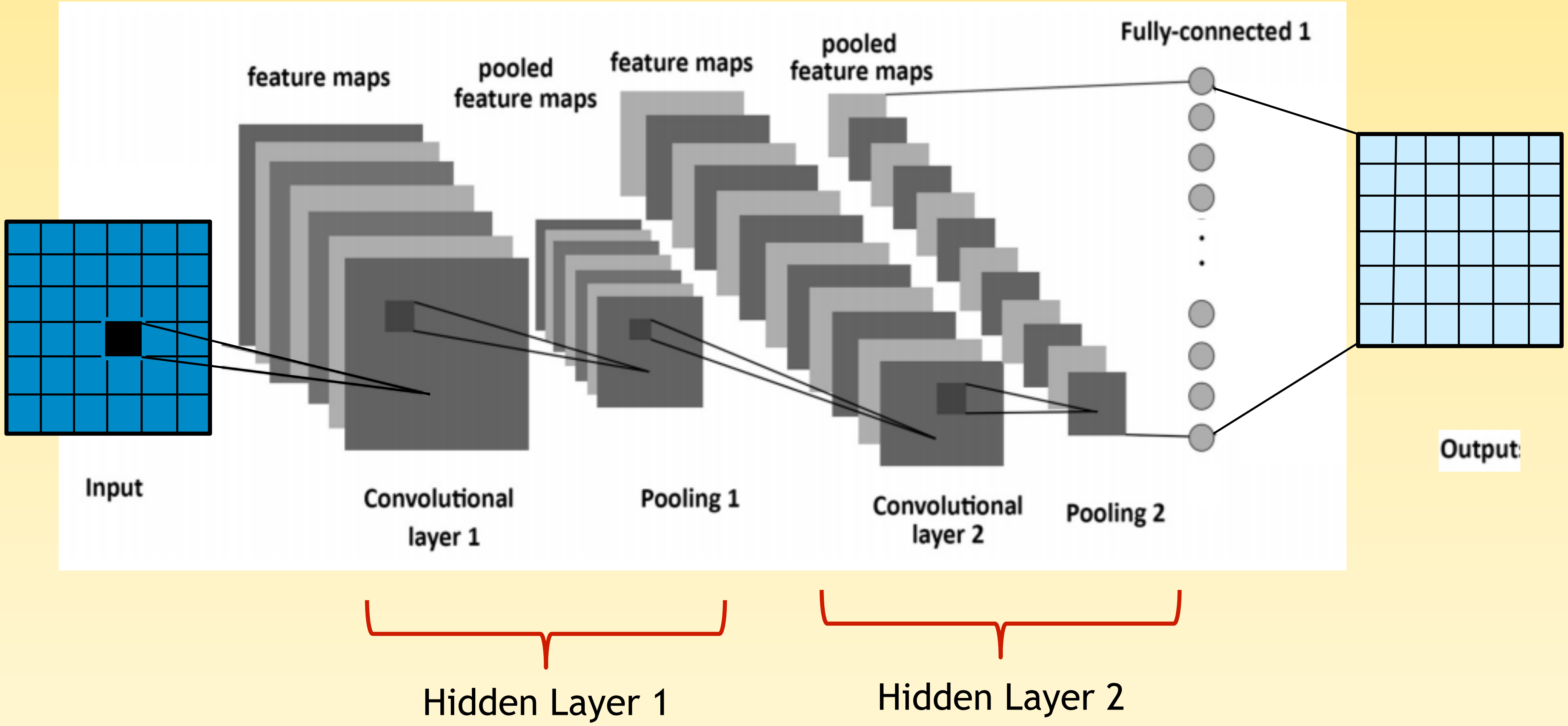
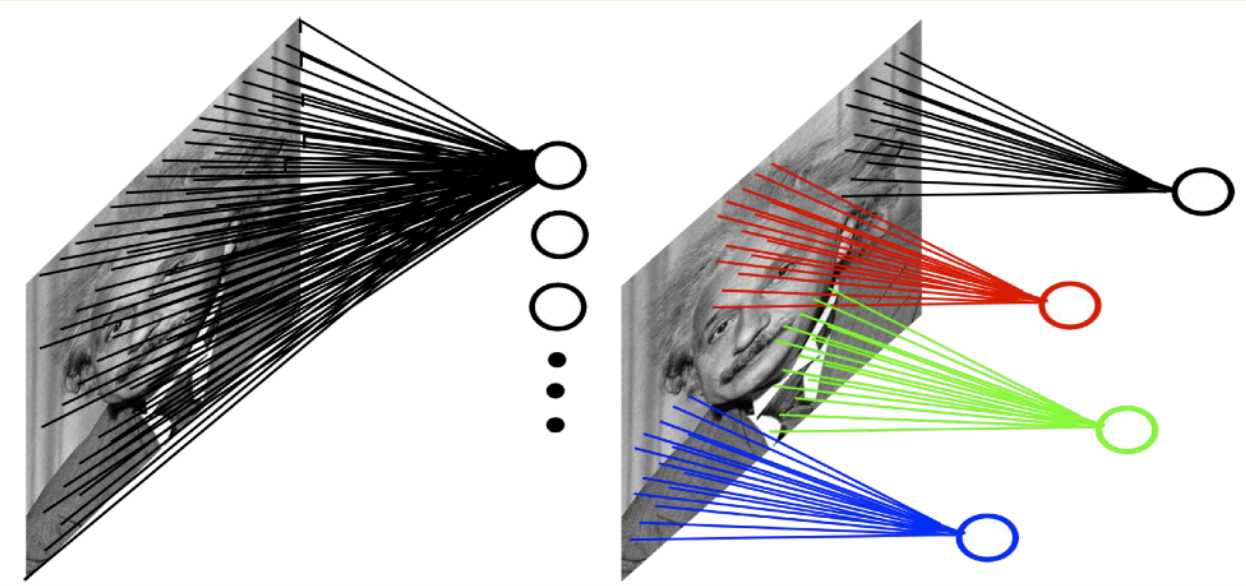
Convolutional Neural Networks (CNNs)



- Motivation: exploit the spatial structure of data
- Layers locally connected



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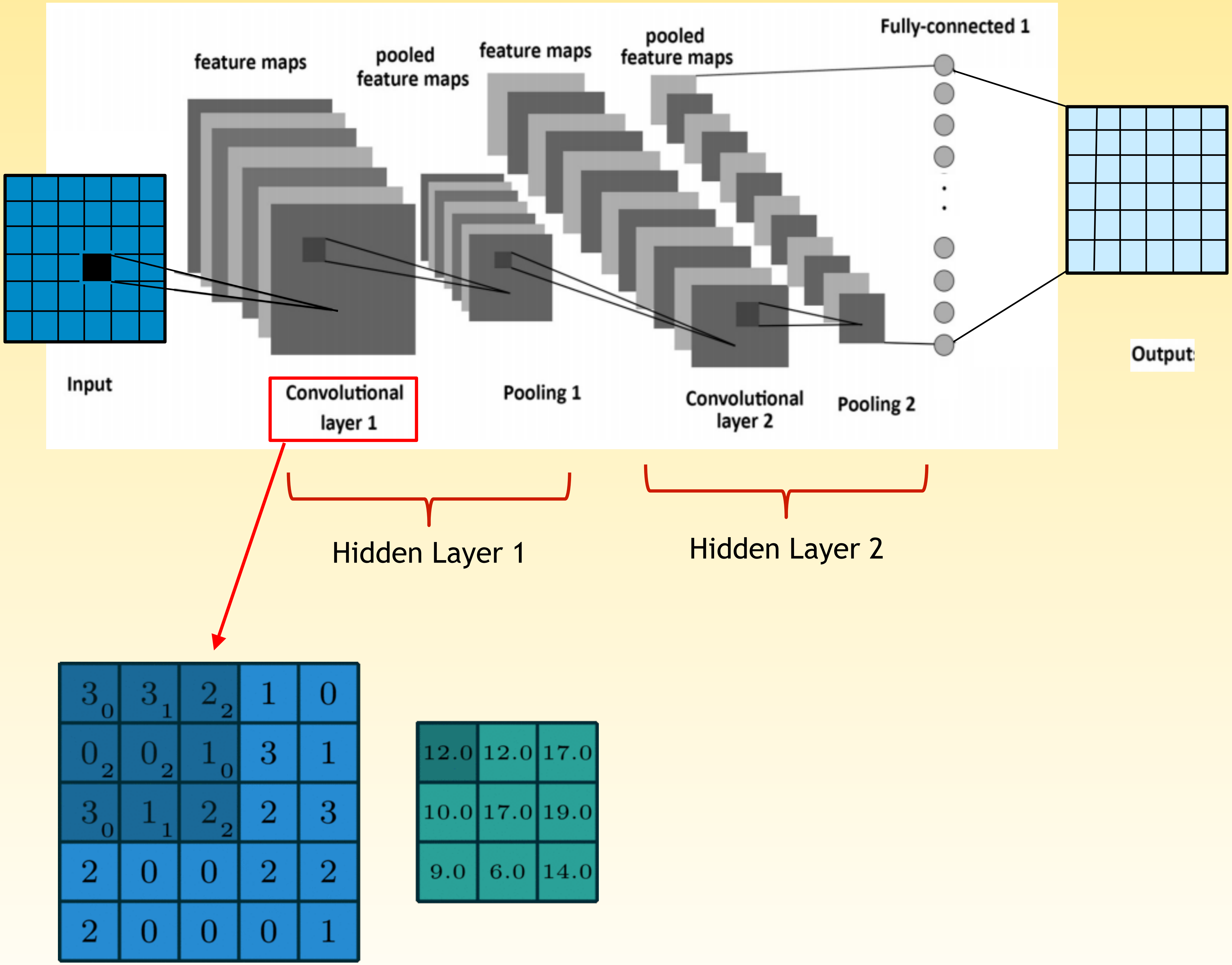

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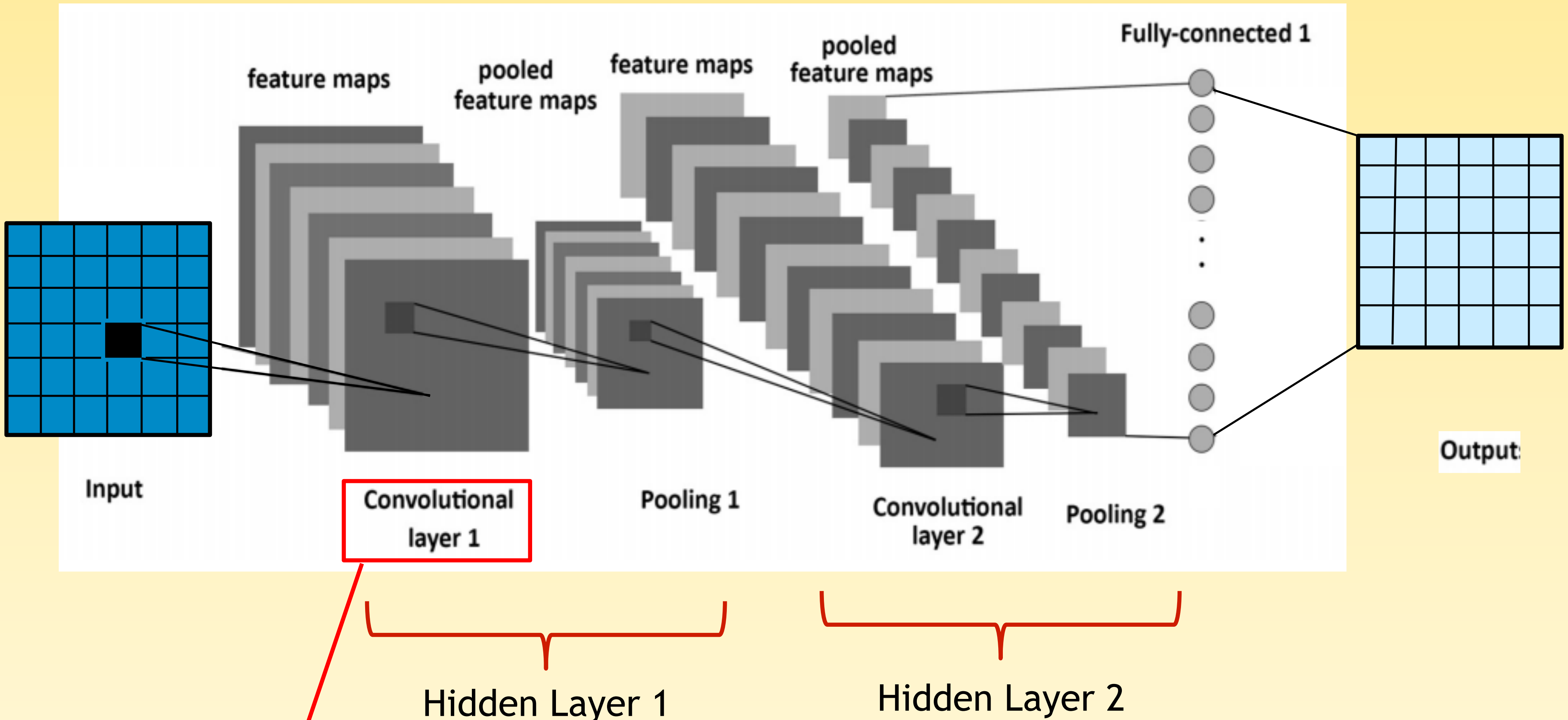
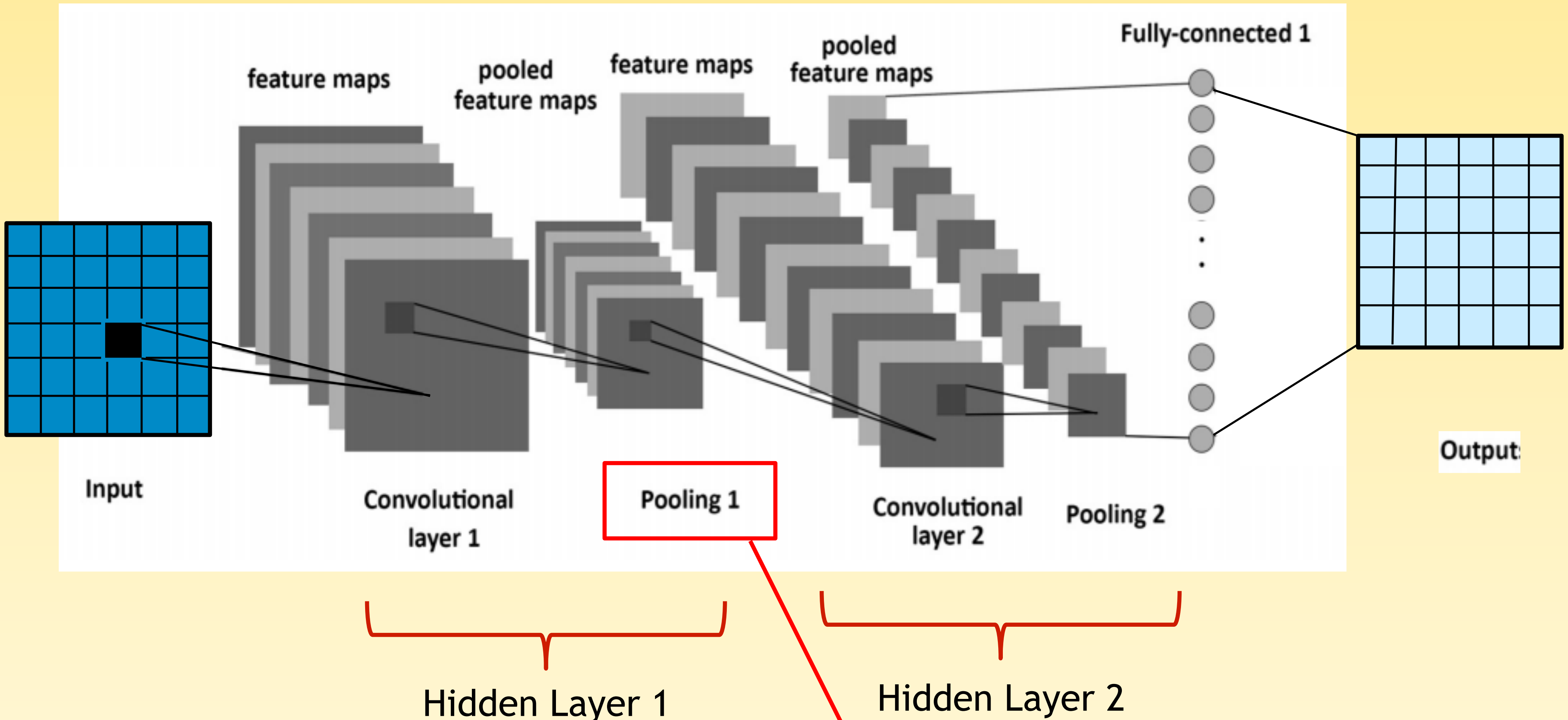
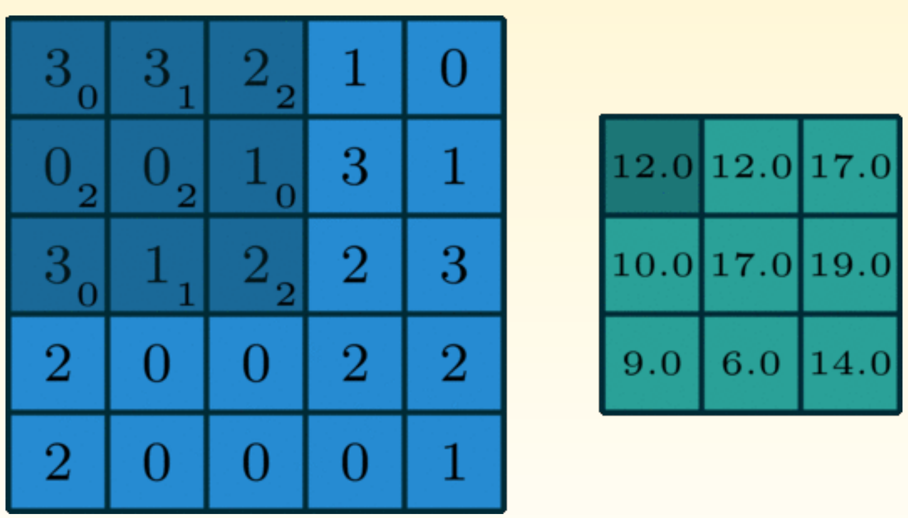


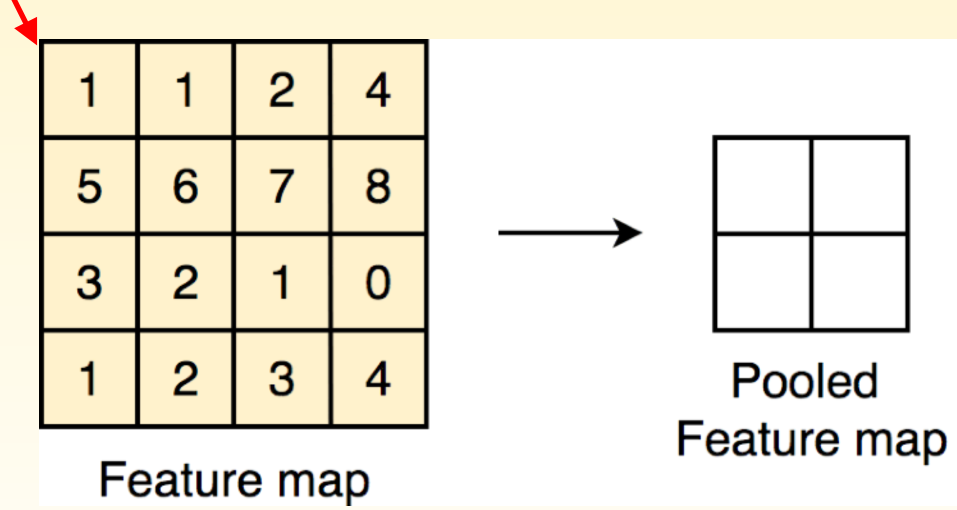
3_0	3_1	2_2	1	0
0_2	0_2	1_0	3	1
3_0	1_1	2_2	2	3
2	0	0	2	2
2	0	0	0	1

12.0	12.0	17.0
10.0	17.0	19.0
9.0	6.0	14.0

Convolutional Neural Networks (CNNs)







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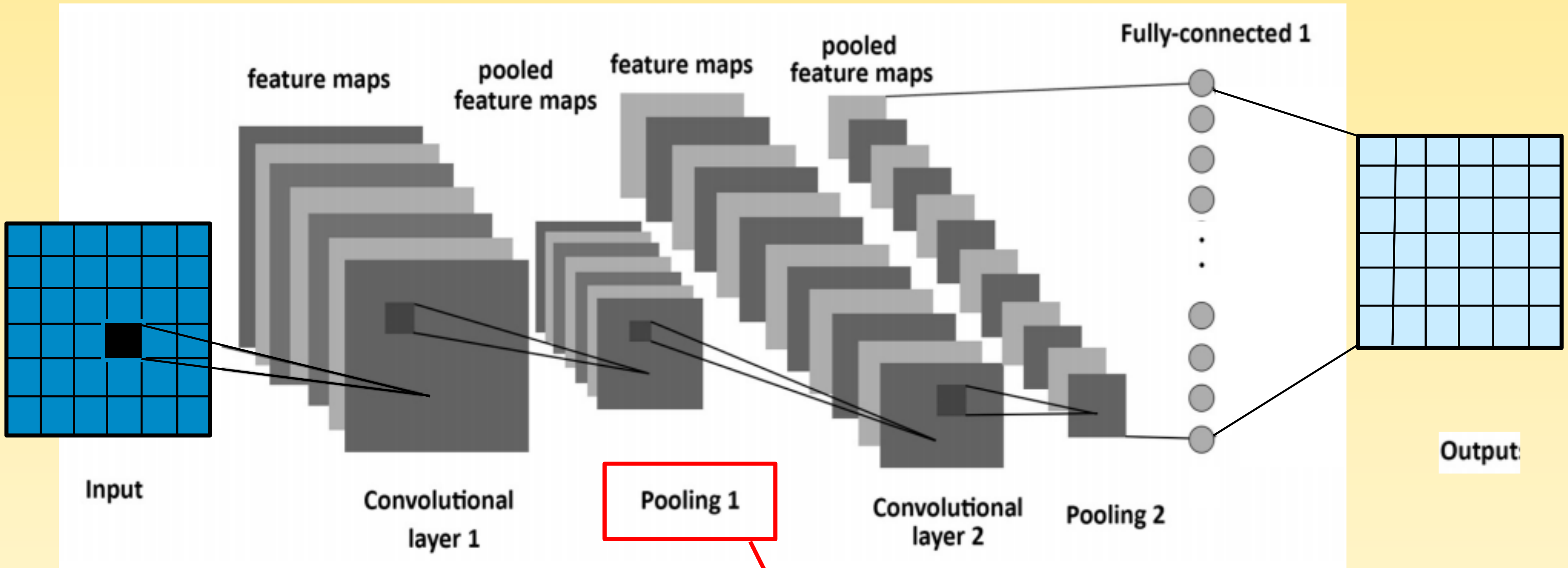
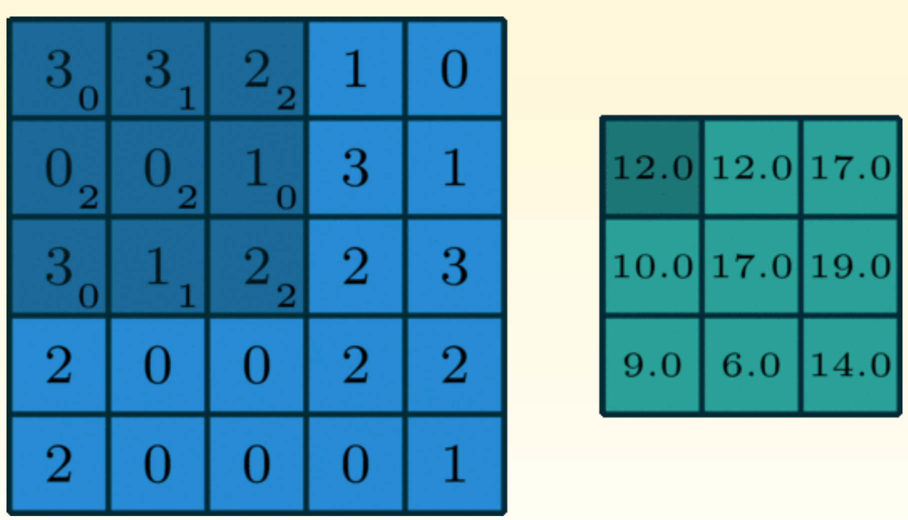
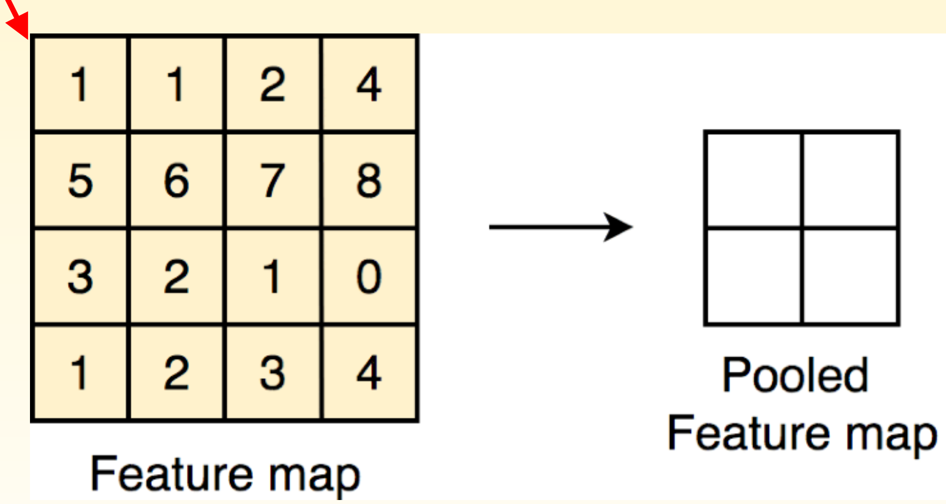


Hidden Layer 1

Hidden Layer 2





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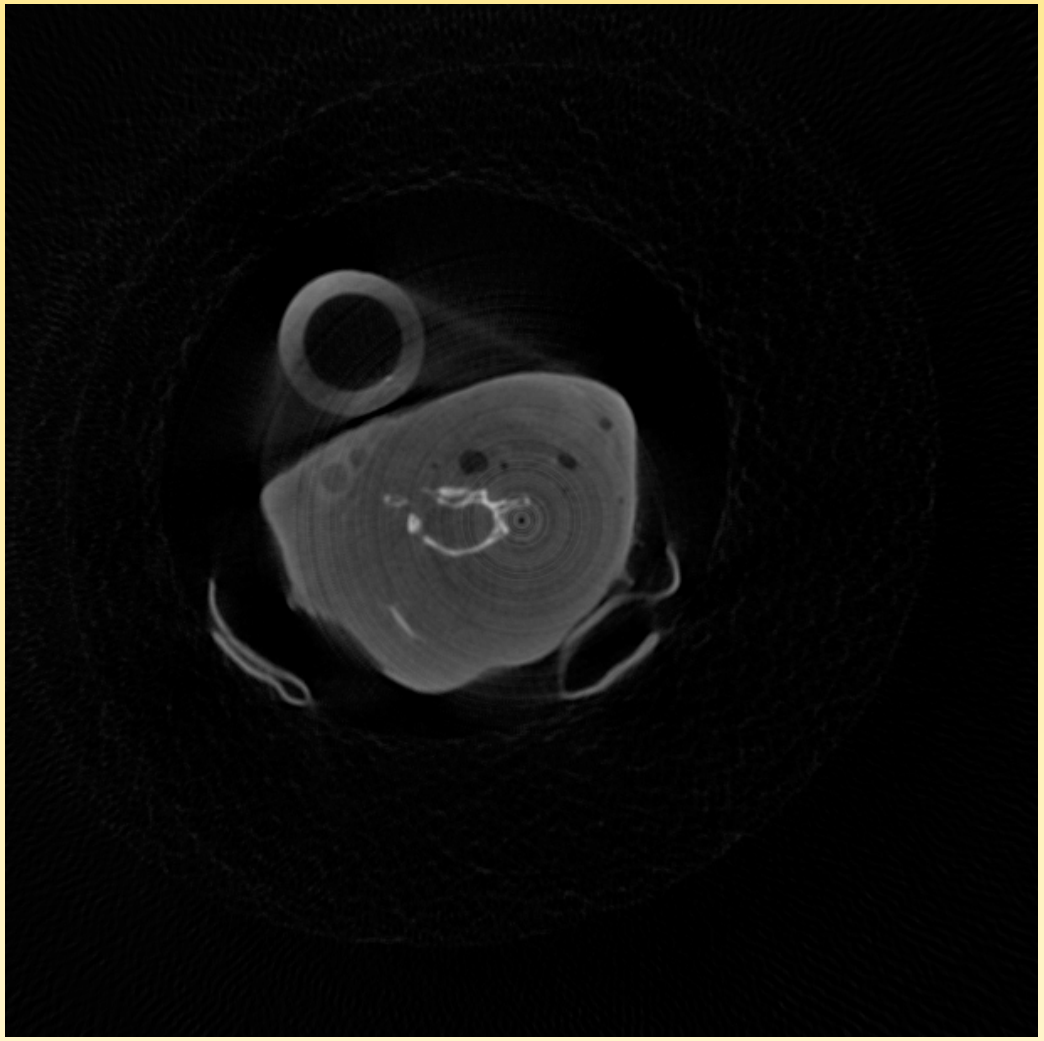
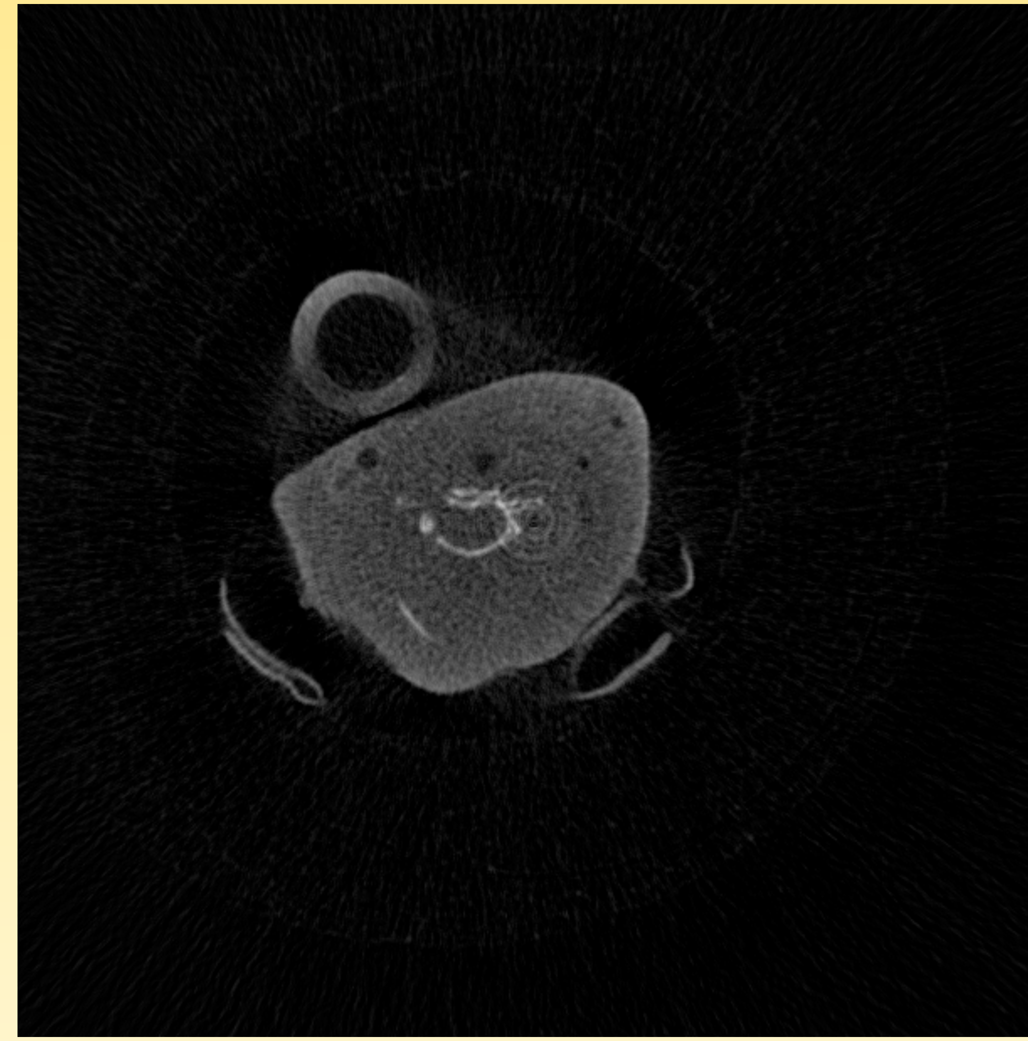
Noise in CT

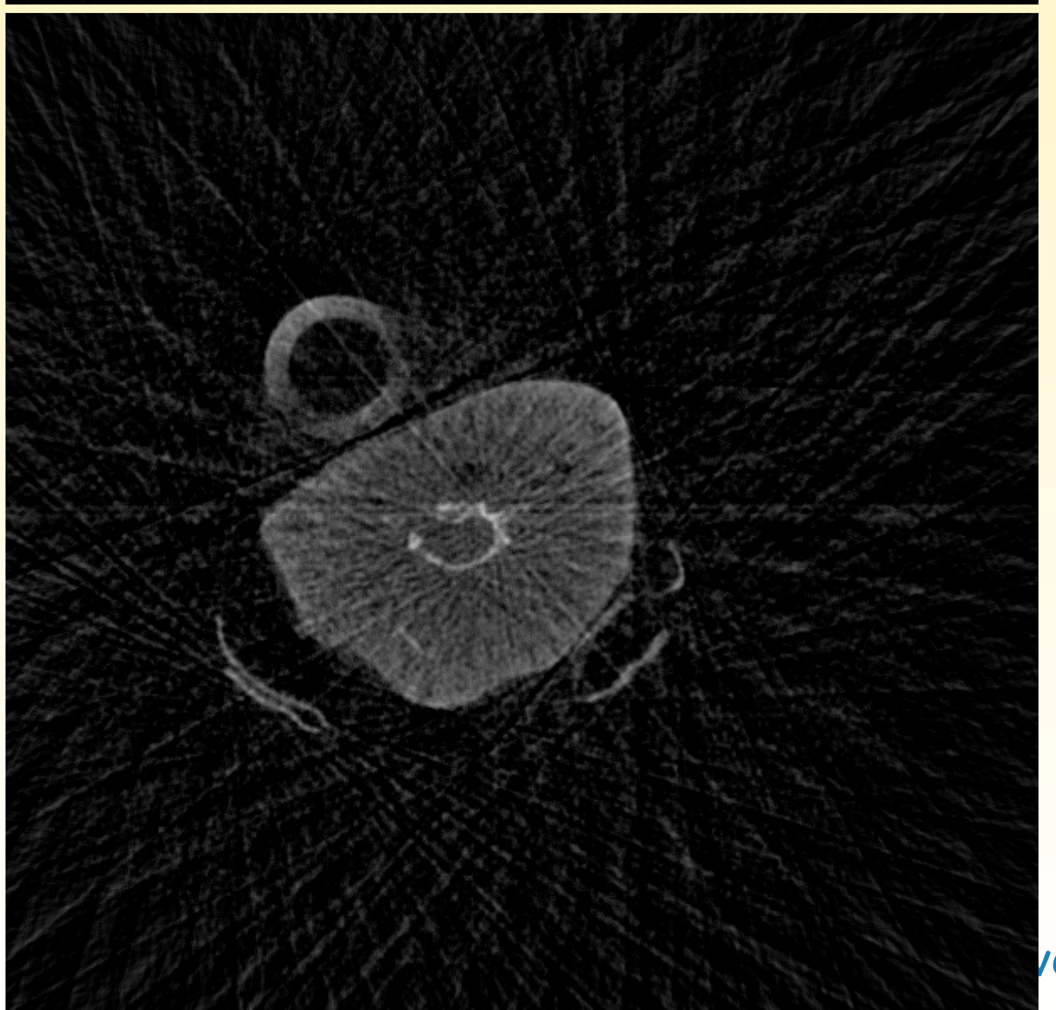




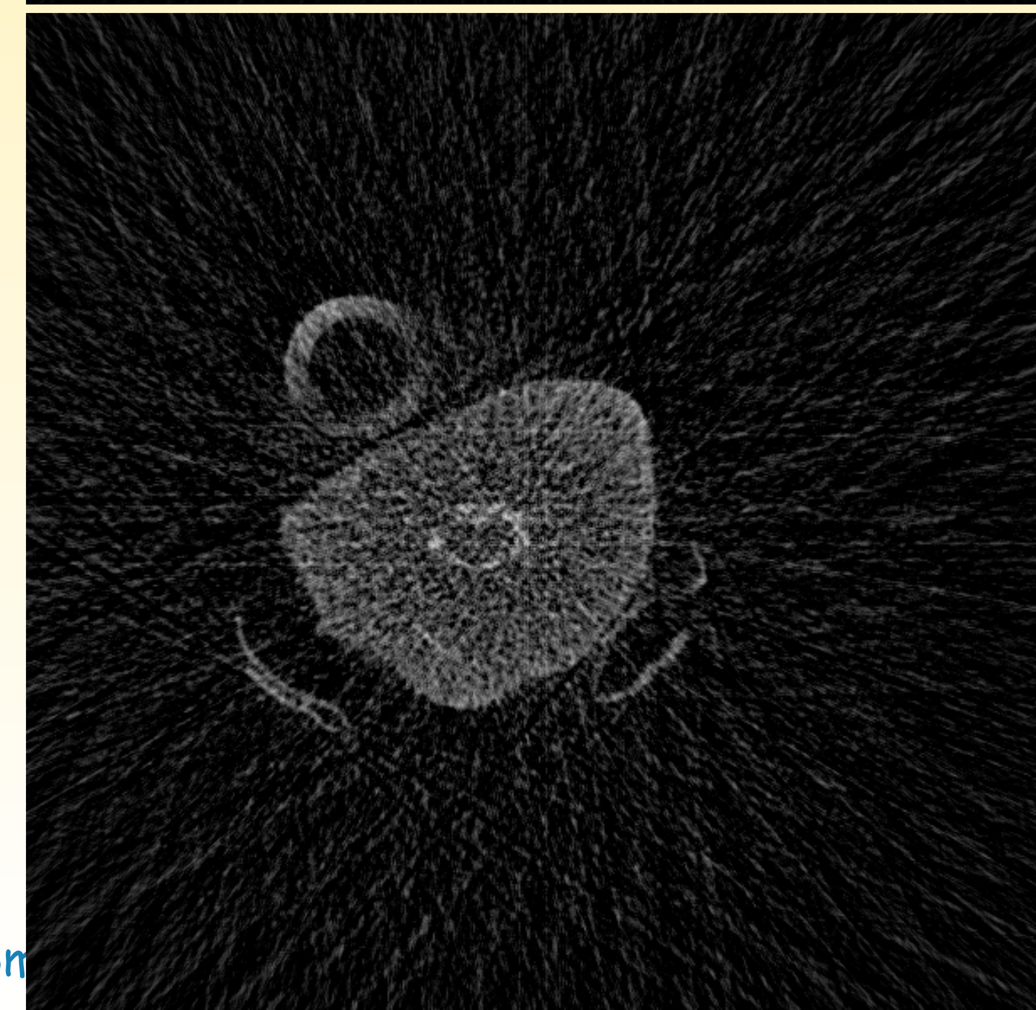
Transverse slice

FBP algo.
588 x 588 pix.

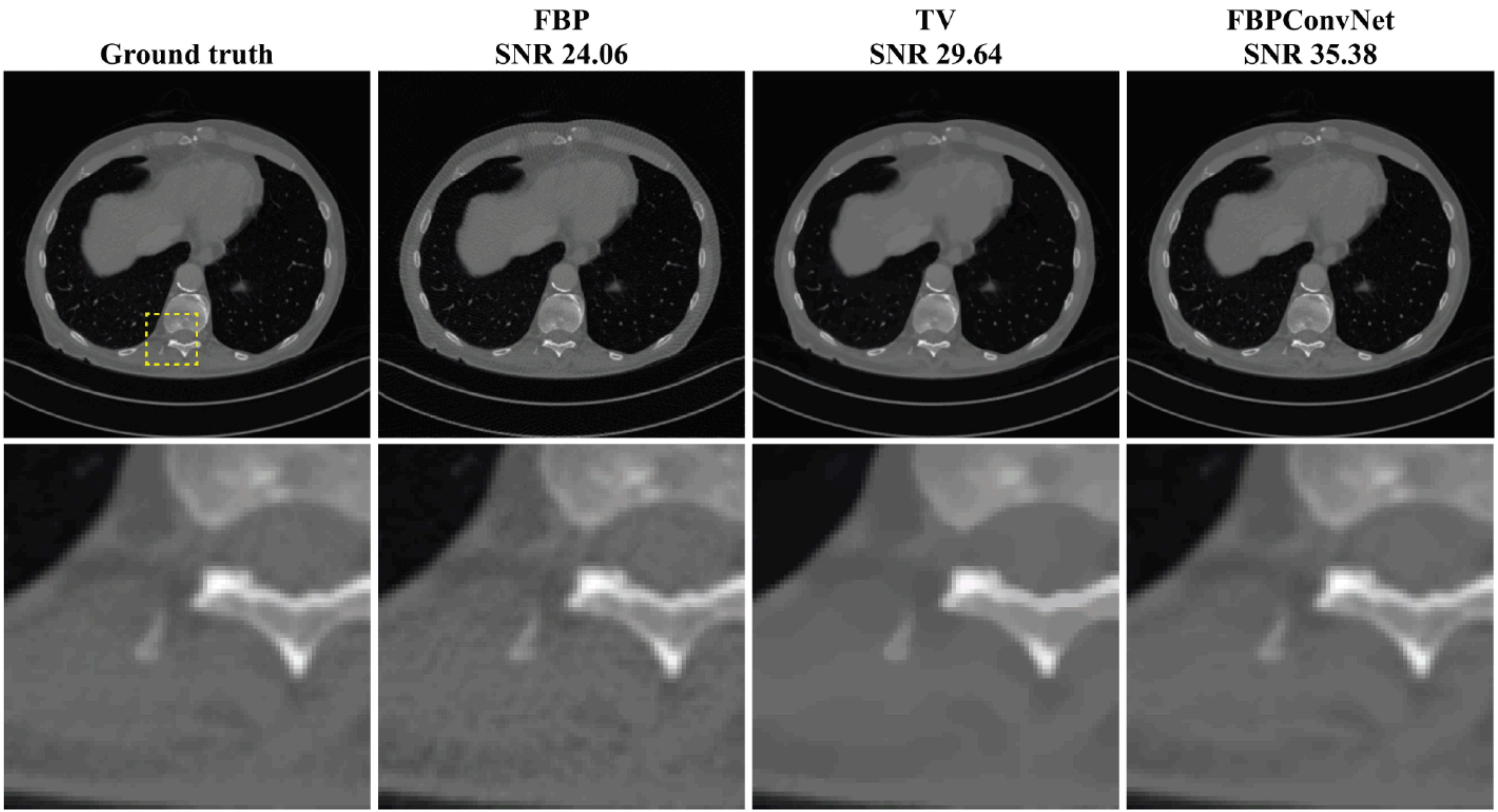
Angles/10
Radon noise



Dose/25
Gaussian noise



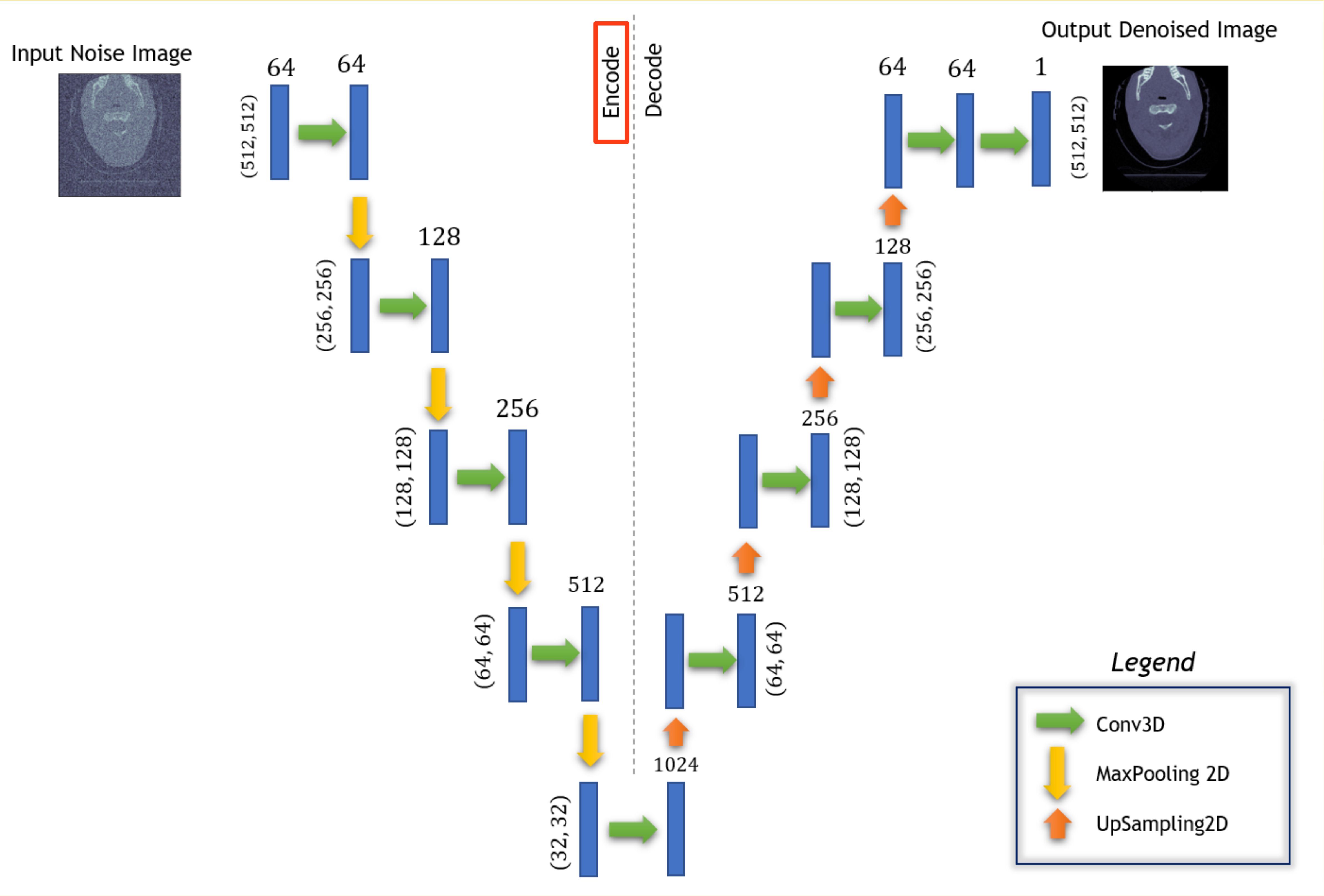
Why Deep Learning in CT Reconstruction ?



Reconstructed images of biomedical dataset from 143 views using FBP, TV regularized convex optimization [14], and the FBPConvNet.

[Jin et al., June 2017]

CNNs Autoencoder



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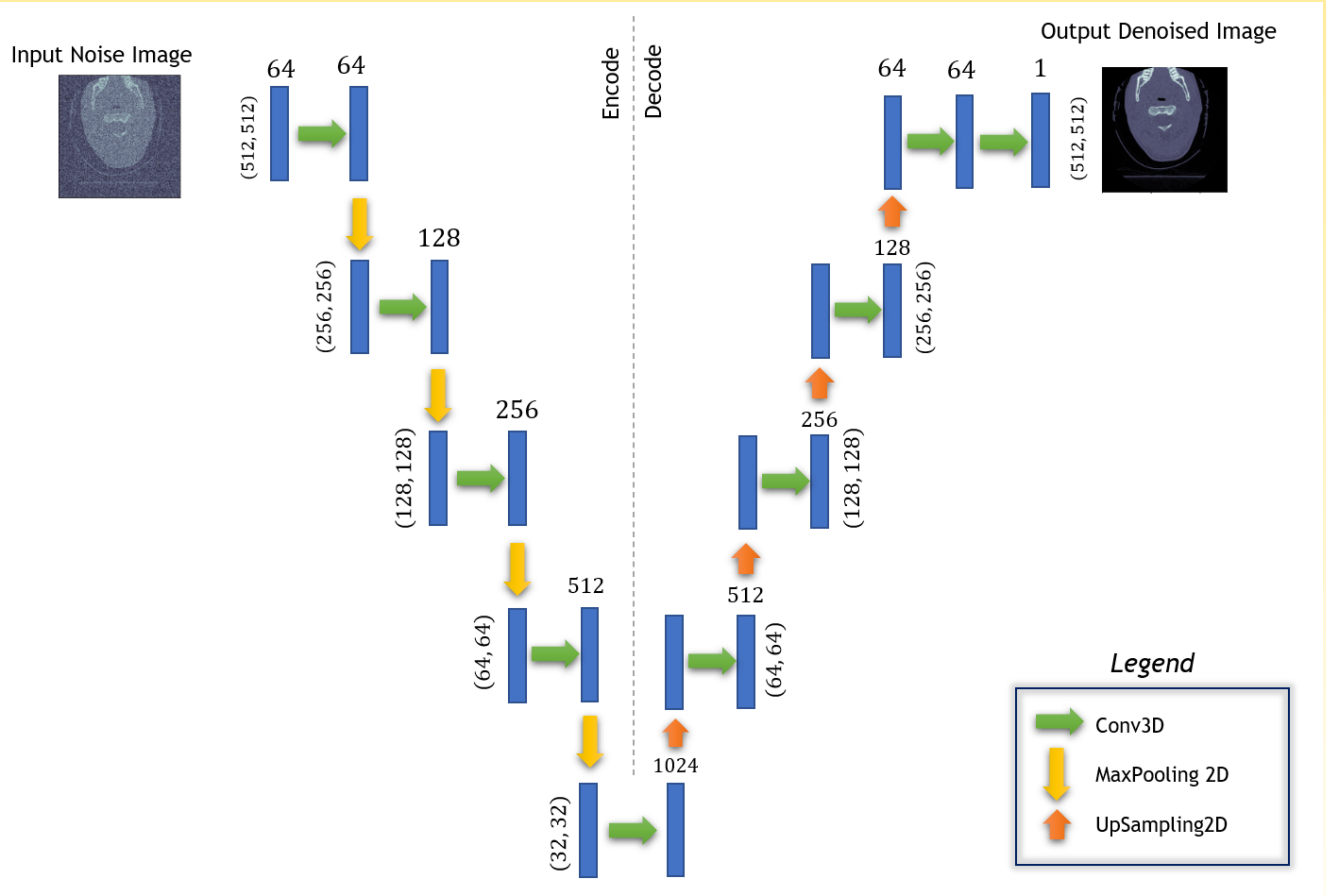

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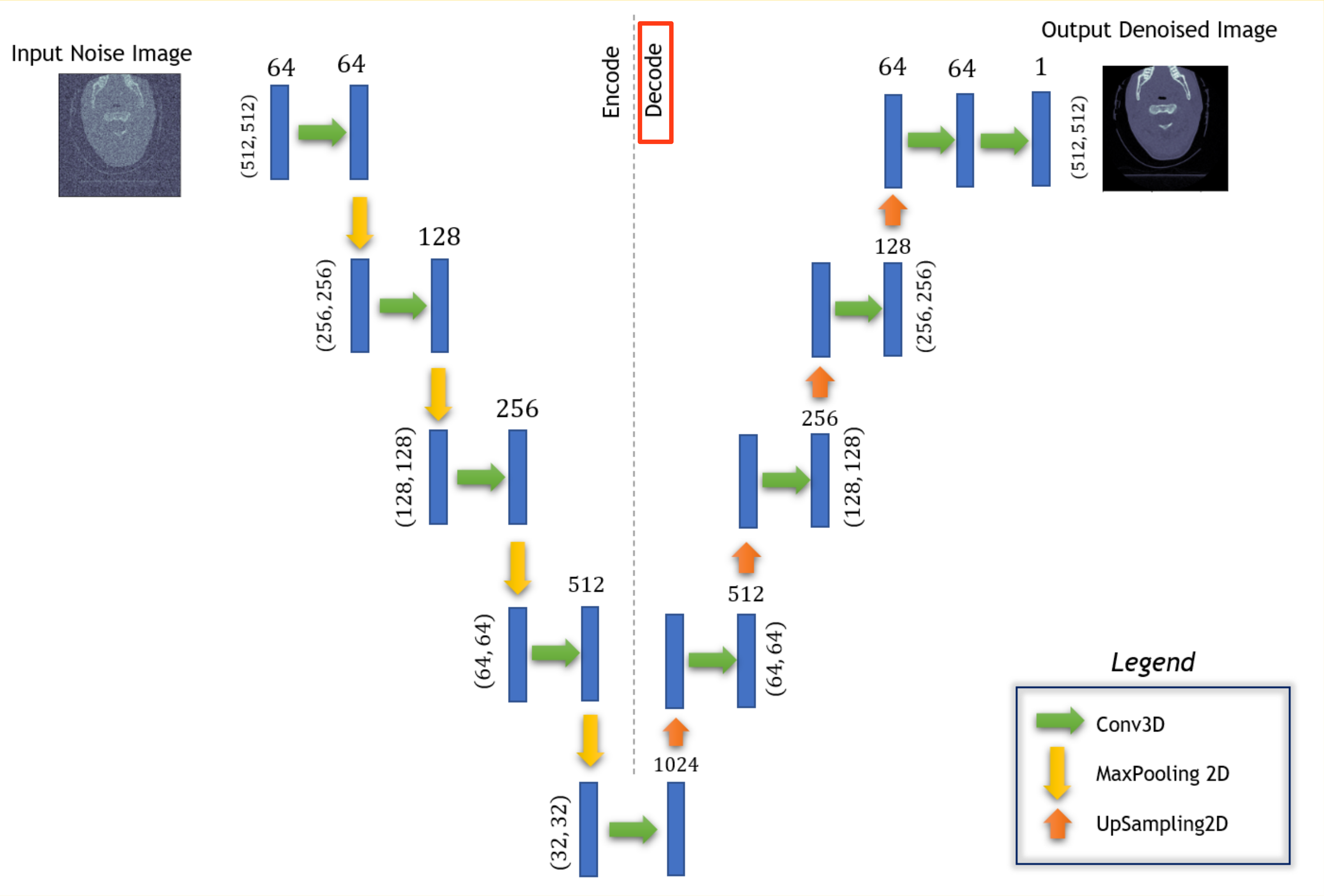
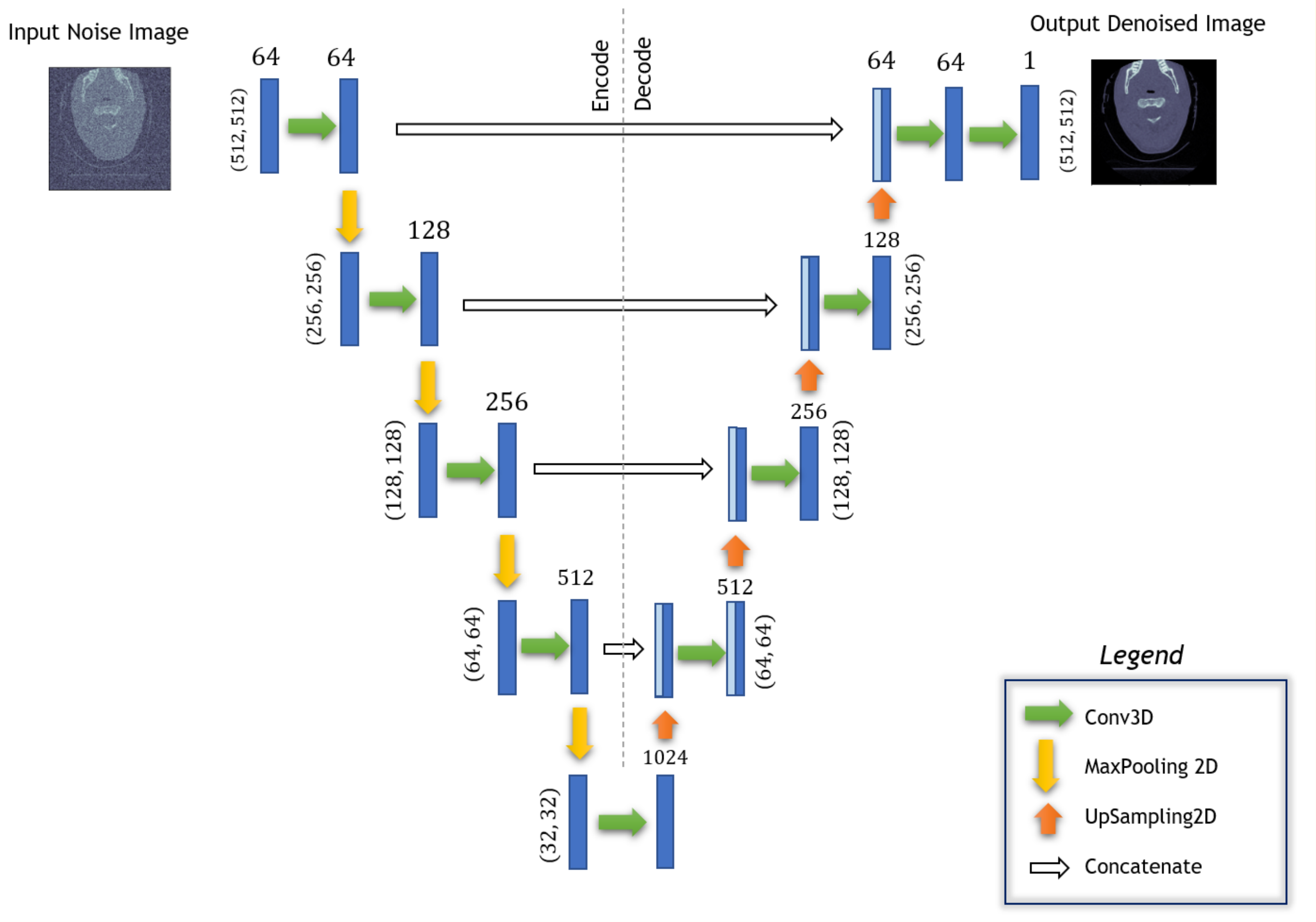


CNNs : The U-net network for denoising



CNNs : Implementation in Keras/Tensorflow

```python
from tensorflow.keras.activations import relu
from tensorflow.keras.layers import Input, Activation, Convolution2D, BatchNormalization, MaxPooling2D, \
    Conv2DTranspose, Concatenate, AveragePooling2D, Dense, Conv2D, SpatialDropout2D, Dropout, Flatten, concatenate, Reshape, UpSampling2D
from tensorflow.keras.models import Model
from tensorflow.keras import backend as K


def define_model (n,m):

    input_img = Input(shape=(n, m, 1))

    conv0 = Convolution2D(32, 3, padding='same', input_shape=[512,512,1], activation='tanh')(input_img) #(None, 512,512,32)
    conv0 = Convolution2D(32, 3, padding='same', activation='tanh')(conv0) #(None, 512,512,32)
    M0 = MaxPooling2D()(conv0) #(None, 256,256,32)


    conv1 = Conv2D(64, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(M0)
    conv1 = Conv2D(64, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(conv1)
    SD1 = SpatialDropout2D(30/64)(conv1)
    P1 = MaxPooling2D(pool_size=(2, 2))(SD1)#(None, 128,128,64)

    conv2 = Conv2D(128, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(P1)
    conv2 = Conv2D(128, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(conv2)
    P2 = MaxPooling2D(pool_size=(2, 2))(conv2)#(None, 64,64,128)
```

CNNs : Implementation in Keras/Tensorflow

```
conv4 = Conv2D(512, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(P3)
conv4 = Conv2D(512, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(conv4)#(64,64,512)
D4 = Dropout(0.5)(conv4)
P4 = MaxPooling2D(pool_size=(2, 2))(D4)#(32,32,512)#(None, 16, 16,512)

flatten = Flatten()(P4)
dense = Dense(512, activation='tanh')(flatten) #(None, 1024)

dense = Dense(256, input_shape=(512,), activation='tanh')(dense)#(None, 64)
reshape = Reshape((16, 16, 1))(dense) #(None, 8,8,1)

# up6 = Conv2D(512, 2, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(UpSampling2D(size = (2,2))(reshape))#(64,64,1024")
up6 = Conv2DTranspose(512, 2, strides = 2, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(reshape)
merge6 = concatenate([conv4,up6], axis = 3)
conv6 = Conv2D(512, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(merge6)
SD6 = SpatialDropout2D(150/512)(conv6)
conv6 = Conv2D(512, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(conv6)

# up7 = Conv2D(256, 2, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(UpSampling2D(size = (2,2))(SD6))
up7 = Conv2DTranspose(256, 2, strides=2, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(SD6)
merge7 = concatenate([conv3,up7], axis = 3)
conv7 = Conv2D(256, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(merge7)
#SD7 = SpatialDropout2D(25/256)(conv7)
conv7 = Conv2D(256, 3, activation = 'tanh', padding = 'same', kernel_initializer = 'he_normal')(conv7)
```

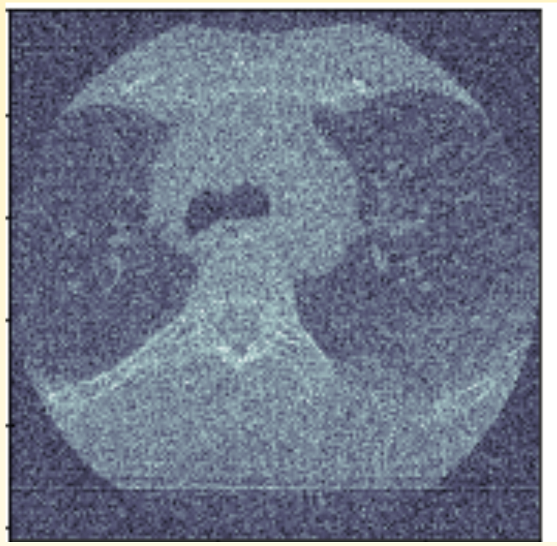
CNNs : The U-net network for denoising

Coding with Keras/Tensorflow, activation function for denoising: **tanh**

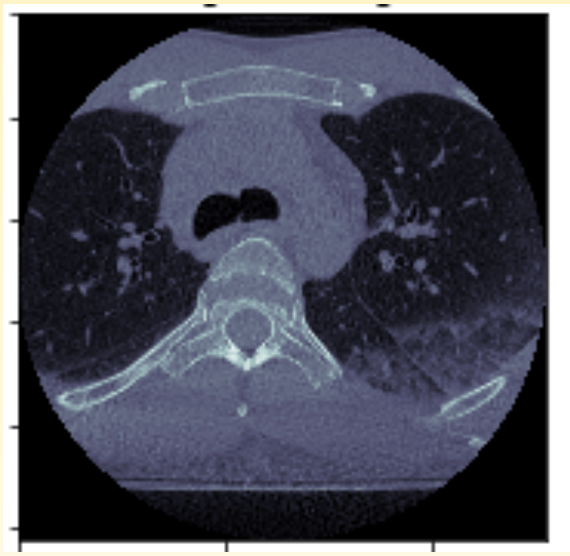
Hardware: GPU, **NVIDIA GeForce RTX 2080,** 11Go RAM, 4352 cores, 420 GFlops (double)

1 - Train the network with an as huge as possible database of couple of noisy/ground truth images.

Database : 600 couples of images of 512x512. Training time: 1h30 for 70 epochs.



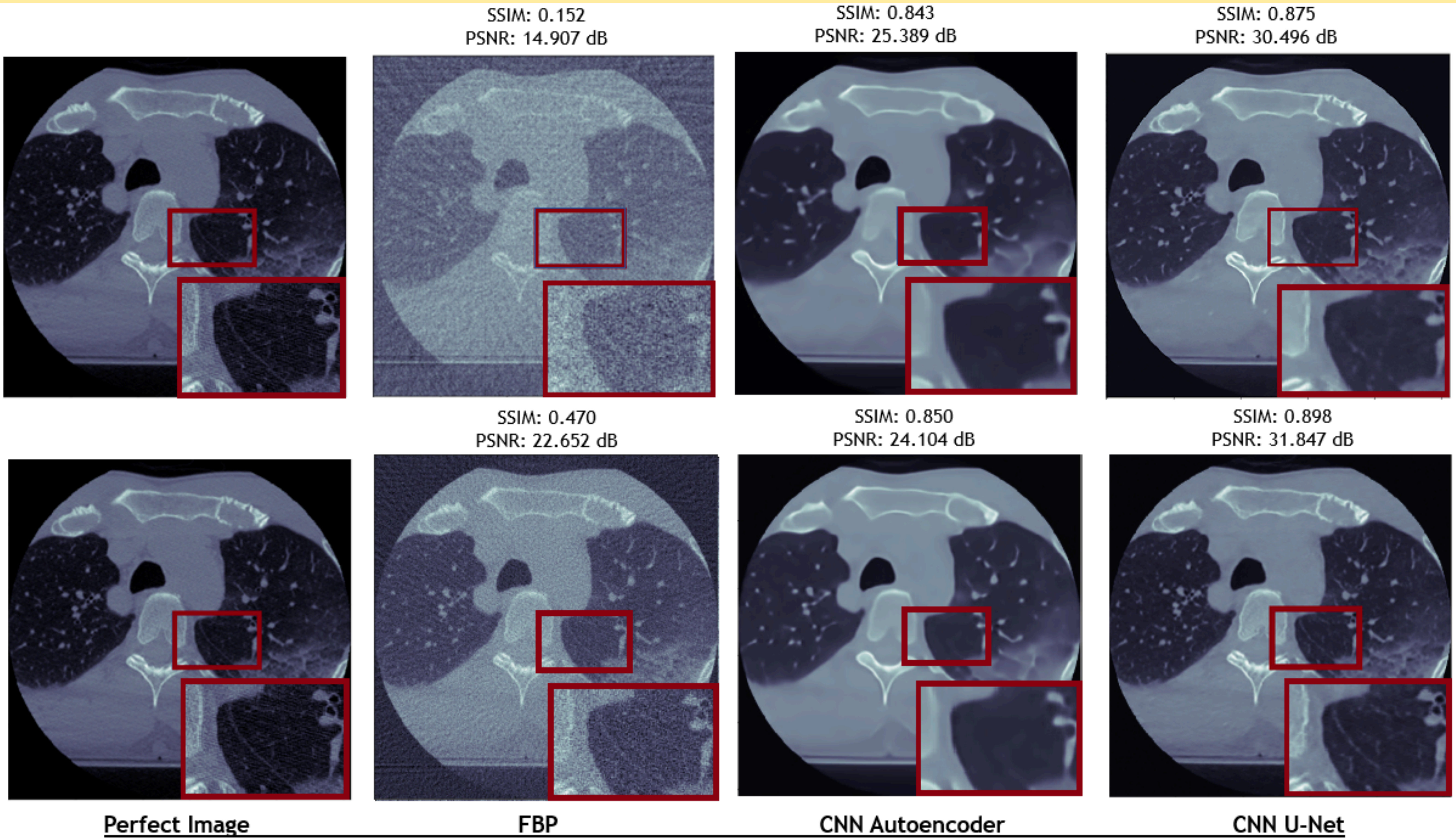
Input : noisy image



Output : perfect image

2 - Test performances of the network on unseen noisy images.
Prediction time : about 50ms

CNNs : The U-net network for denoising

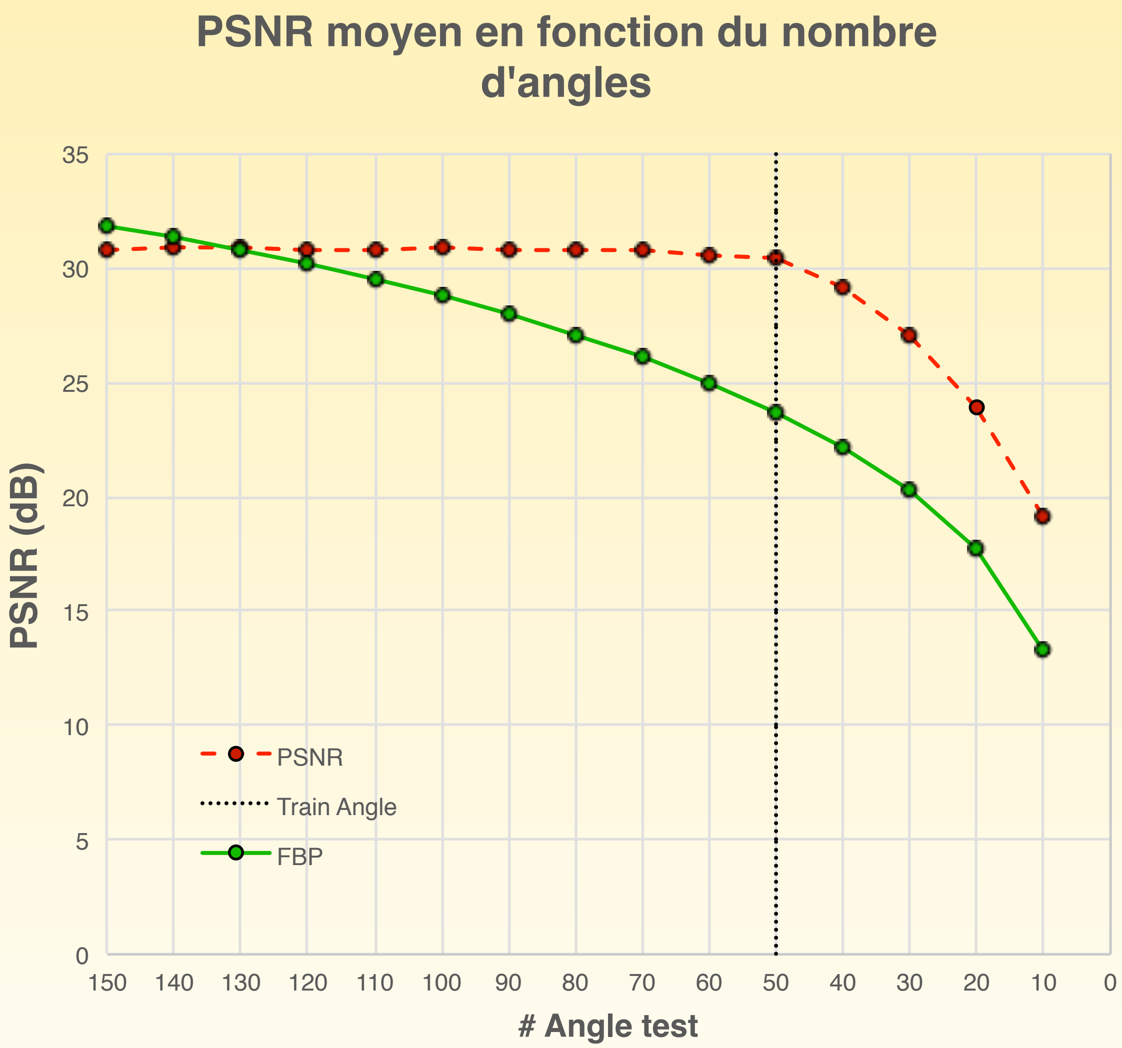


U-net Denoising approaches

Method

1 - Train the U-net with **very** noisy images (with **only** 50 projection angles).

2 - Test performances with images of any level of noise (results on 50 images).

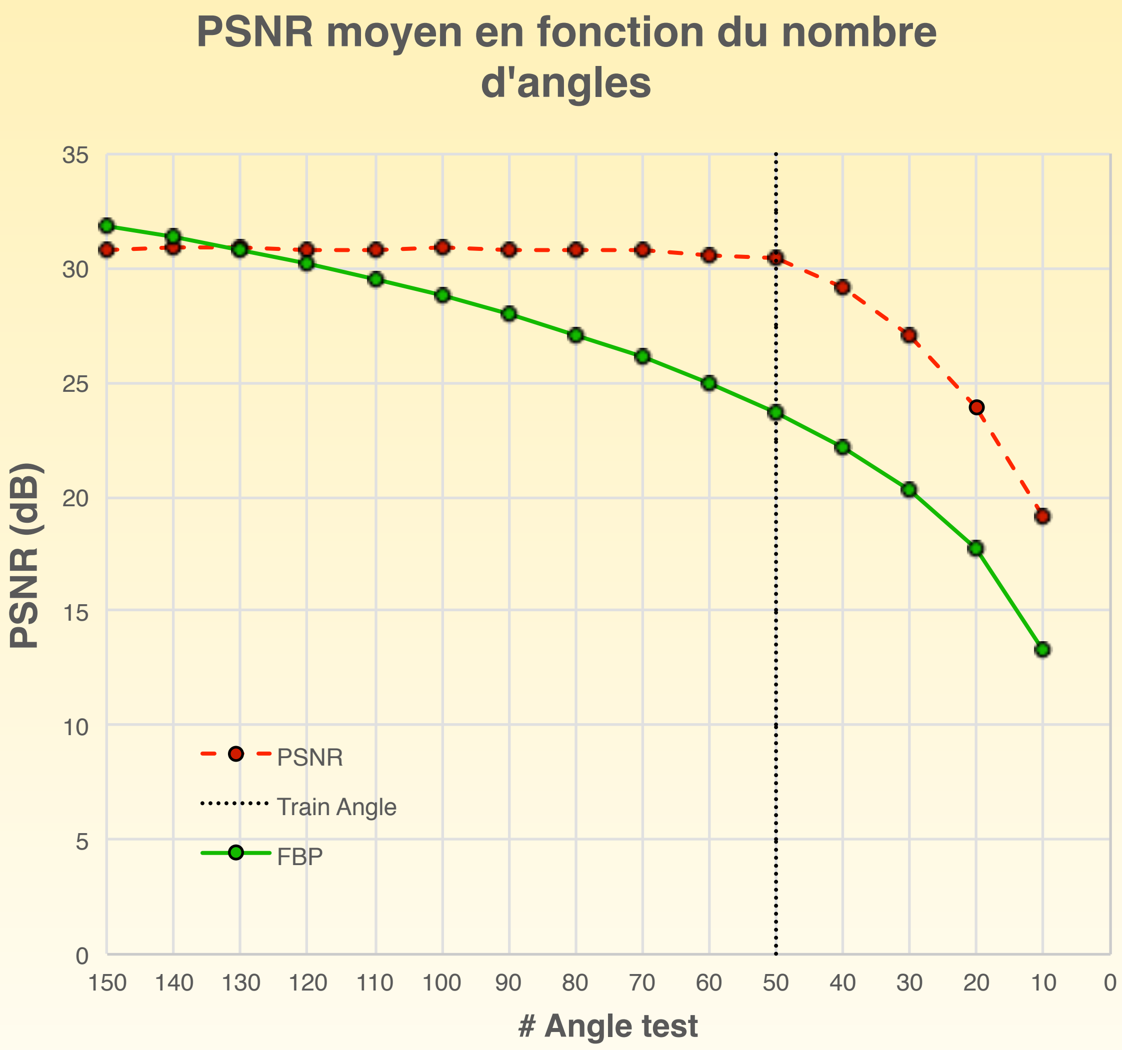


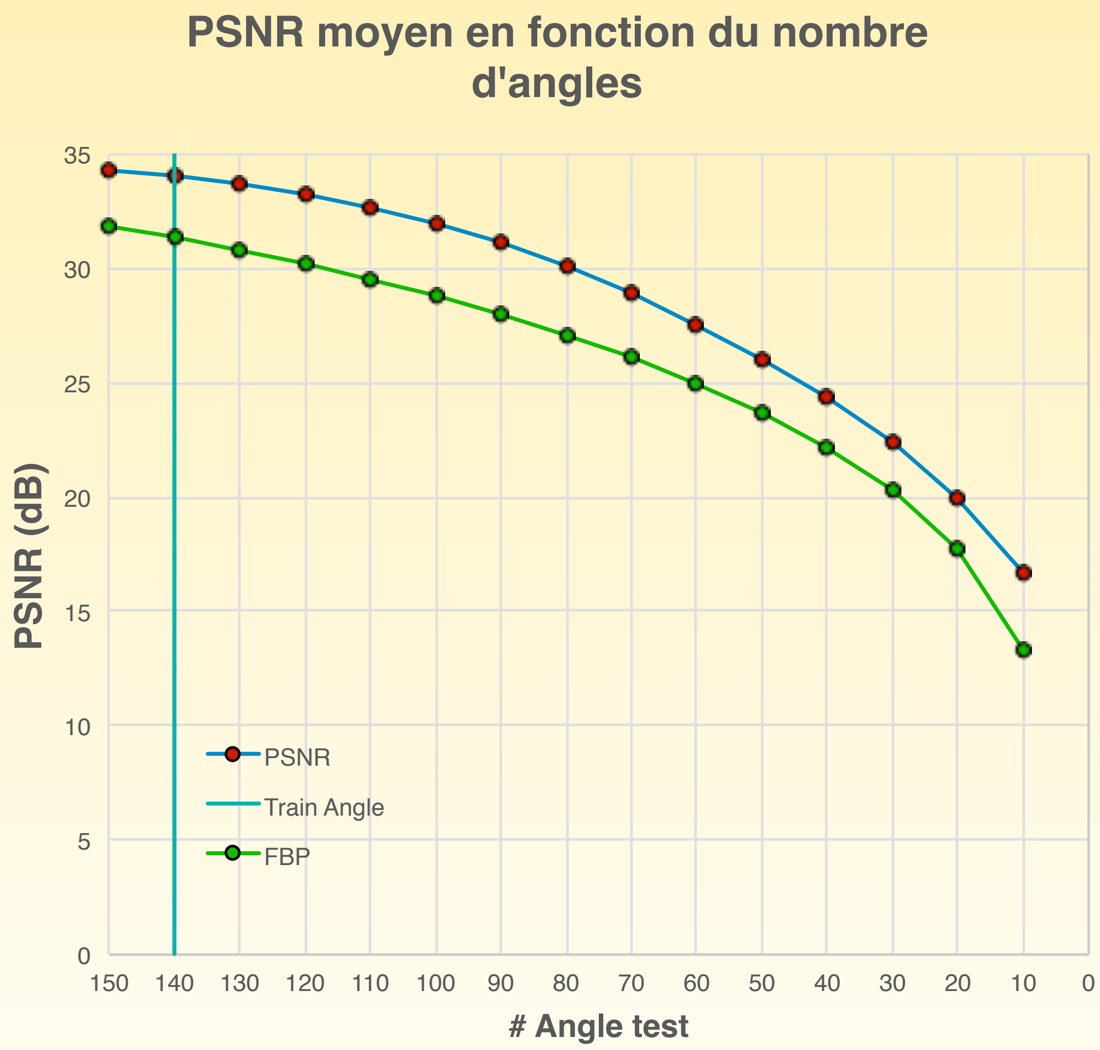
U-net Denoising approaches

Method

1 - Train the U-net with **hardly** noisy images (with 140 projection angles).

2 - Test performances with images of any level of noise.





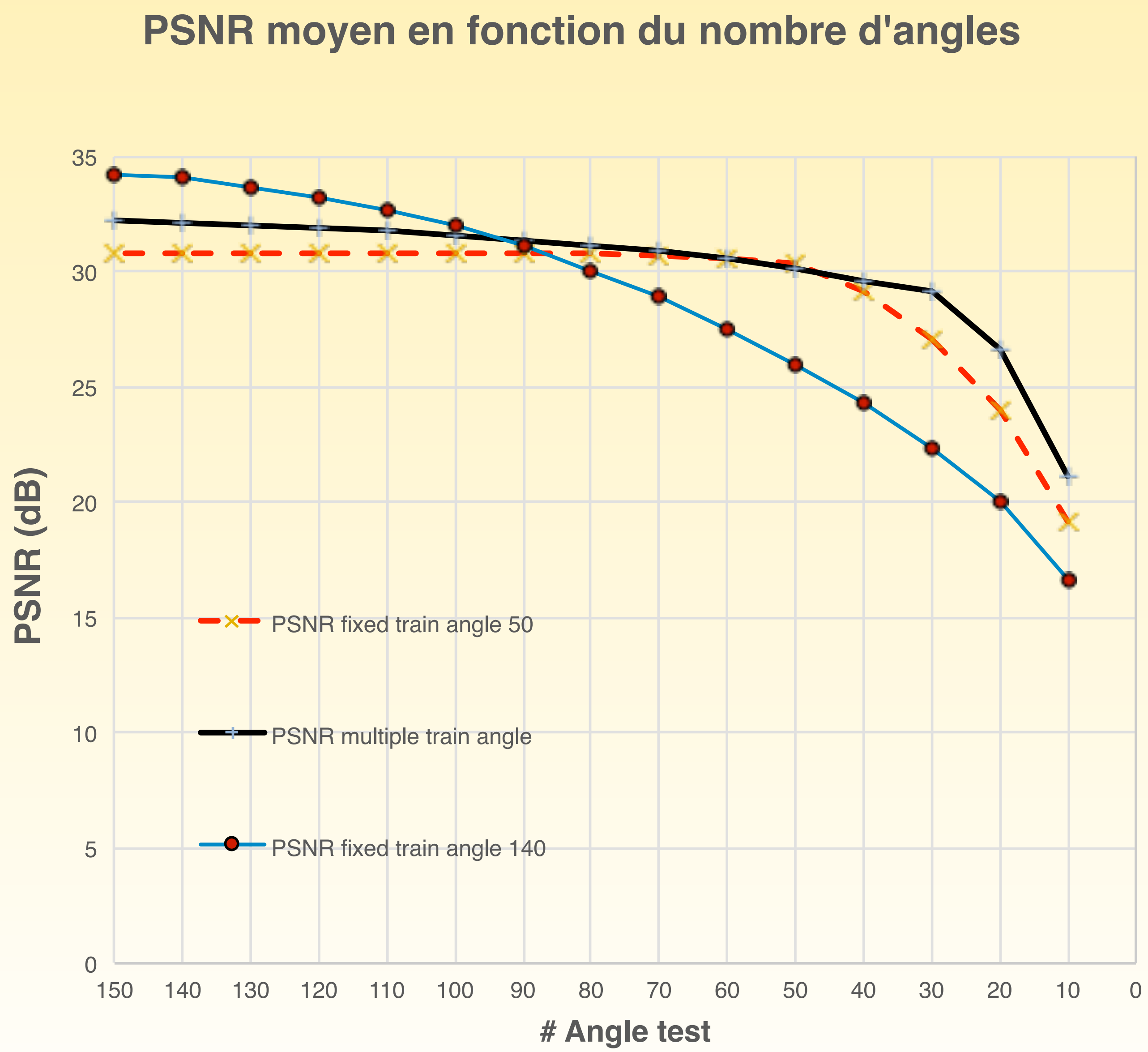
U-net Denoising approaches

Method

1 - Train the U-net with images of **any level of noise** :

20% of 30, 20% of 60, 20% of 90 , 20% of 120, 20% of 150 angles.

2 - Test performances with images of any level of noise.



Outline

1 - Biomedical imaging context : Computerized tomography (CT Scan)

2 - Convolutional Neural Networks (CNNs) for imaging

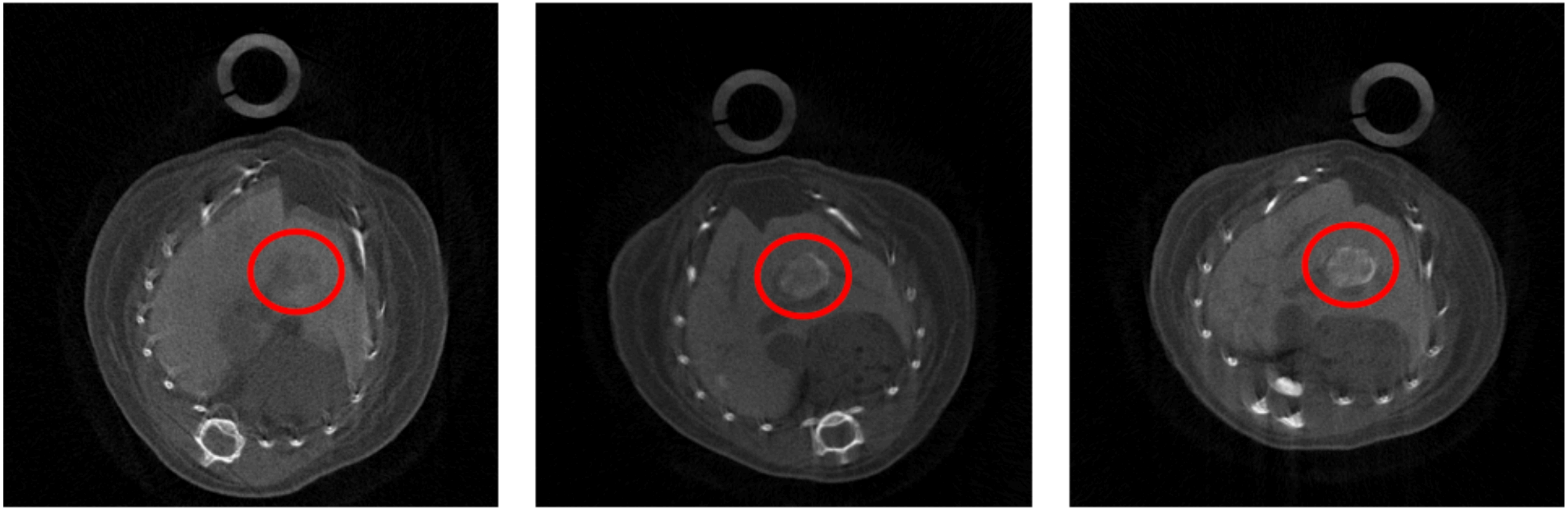
3 - Denoising issues

4 - Segmentation issues

5 - Other issues

6 - Conclusion

Why Deep Learning in CT segmentation ?

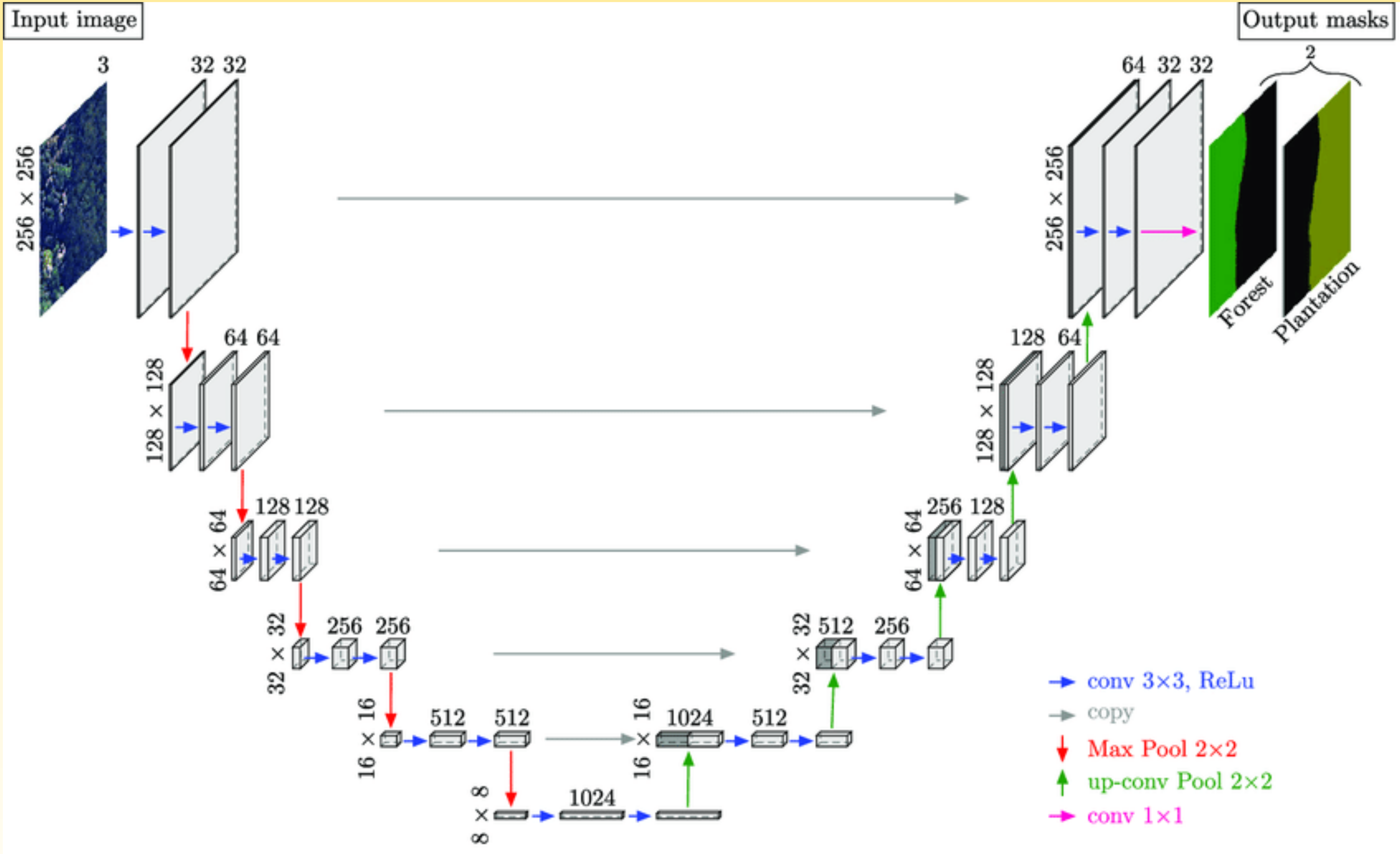


Scan 1 : 25/11/2020 Scan 2 : 03/12/2020 Scan 3 : 09/12/2020

Three transverse slices of the same mouse imaged at weekly intervals.

Different morphological classes/shapes of tumors

CNNs : The U-net network for segmentation



CNNs : Supervised segmentation

Coding with Keras/Tensorflow, activation function for segmentation:

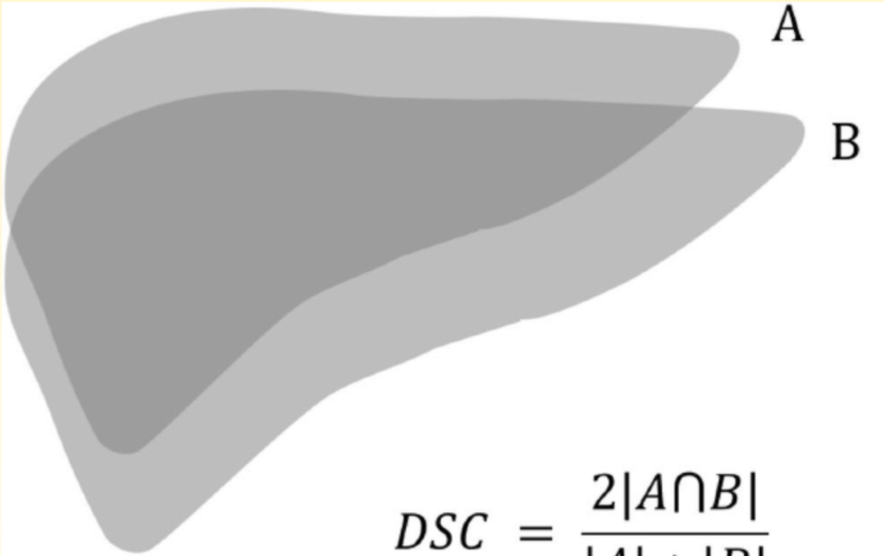
- **ReLu** then **softmax** or **sigmoid** (1 label) on the last layer.

Hardware: GPU, **NVIDIA GeForce RTX 2080,** 11Go RAM, 4352 cores, 420 GFlops (double)

1 - Train the network with a as huge as possible database of couple of images/manually segmentation.

Database : more than 10,000 couples of images of 512x512.
Training time: 1h30 for 50 epochs.

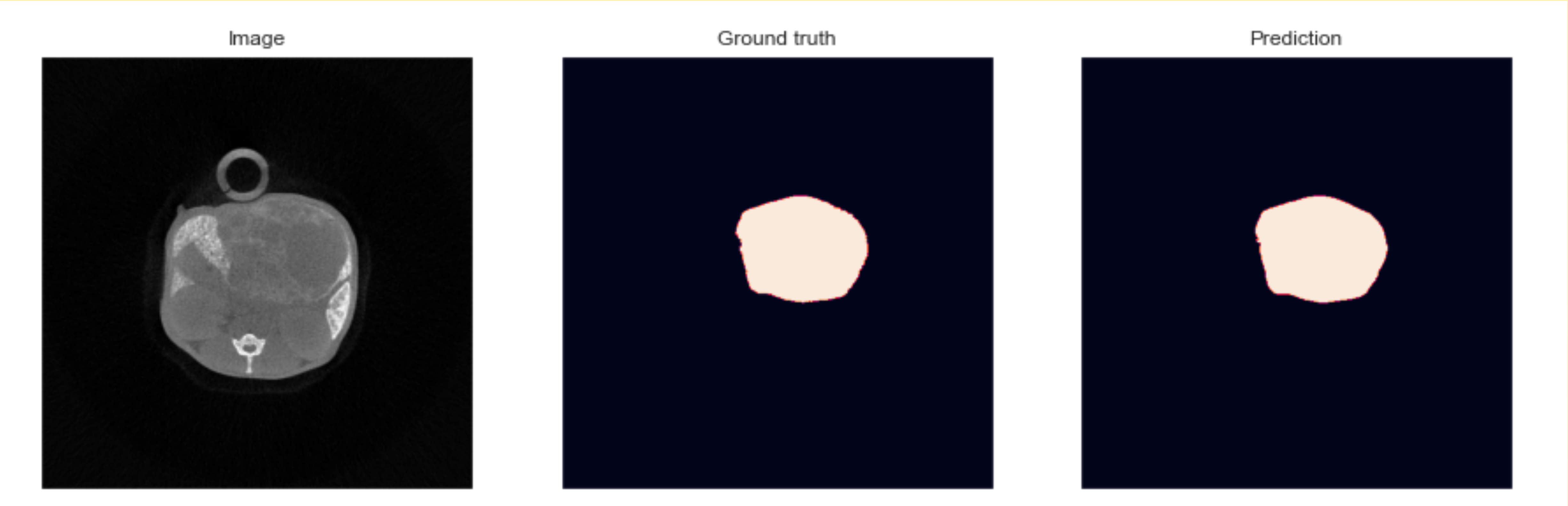
2 - Test performances of the network on unseen images with tumor.
Prediction time: about 50-100ms
Metric: DICE score in [0, 1].



$$DSC = \frac{2|A \cap B|}{|A| + |B|}$$

DSC: Dice similarity coefficient

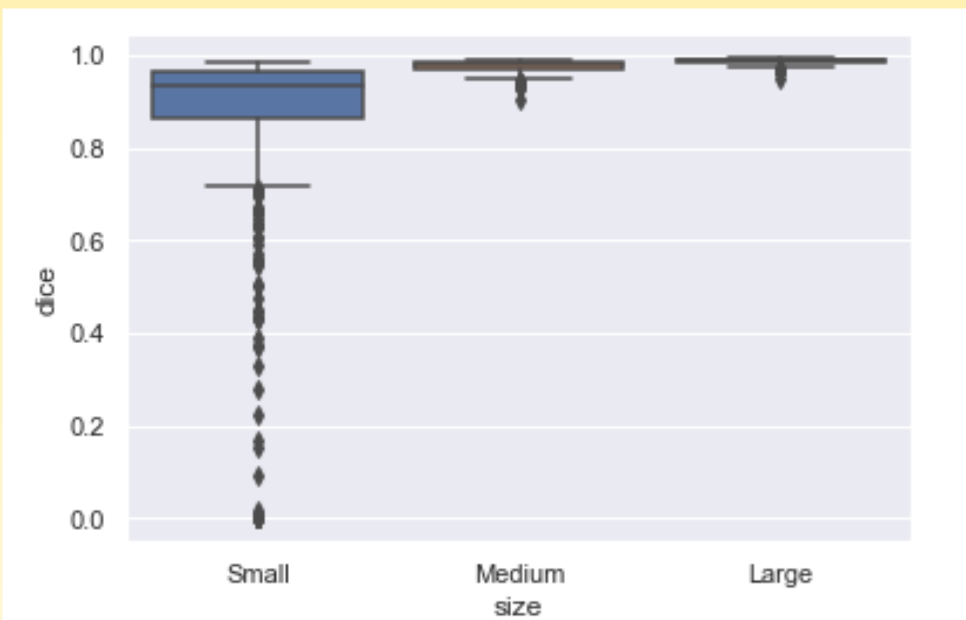
Deep Learning in CT Segmentation Liver / Tumor



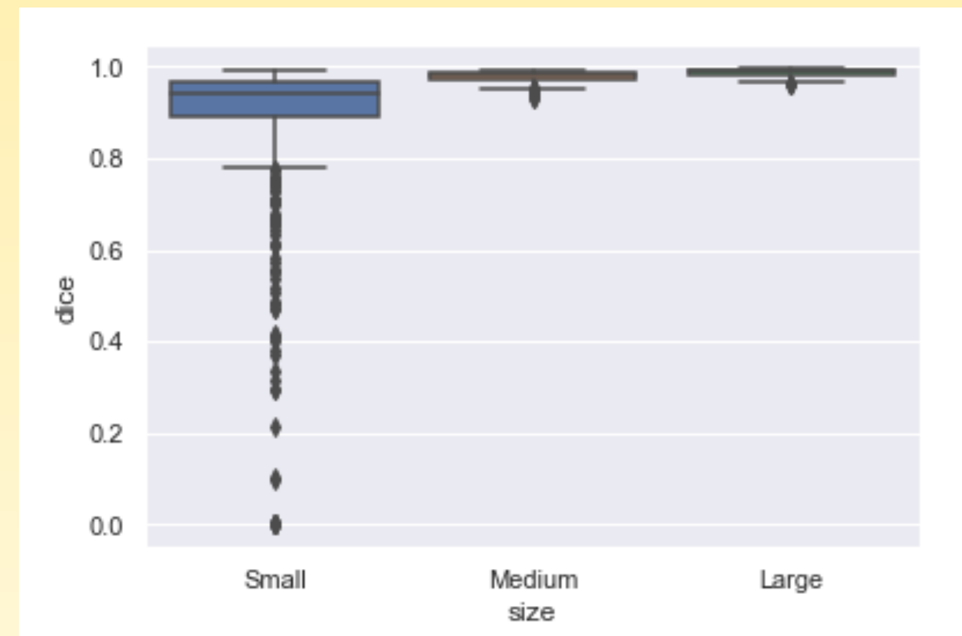
Deep Learning in CT Segmentation Liver / Tumor

DICE score as a function of tumor size:

Small: < 50mm²
Medium: 50 mm² < size < 100mm²
Large : > 100 mm²



Database with all tumors



Database with Stratification

	Réseau de référence	Stratification par taille
DICE moyen	0,916 +/- 0,157	0,929 +/- 0,132
DICE small	0,866 +/- 0,196	0,888 +/- 0,165
DICE medium	0,974 +/- 0,013	0,977 +/- 0,011
DICE large	0,987 +/- 0,008	0,987 +/- 0,006

Outline

1 - Biomedical imaging context : Computerized tomography (CT Scan)

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Numerous issues (only) in the context of CT

Not possible today to read everything.

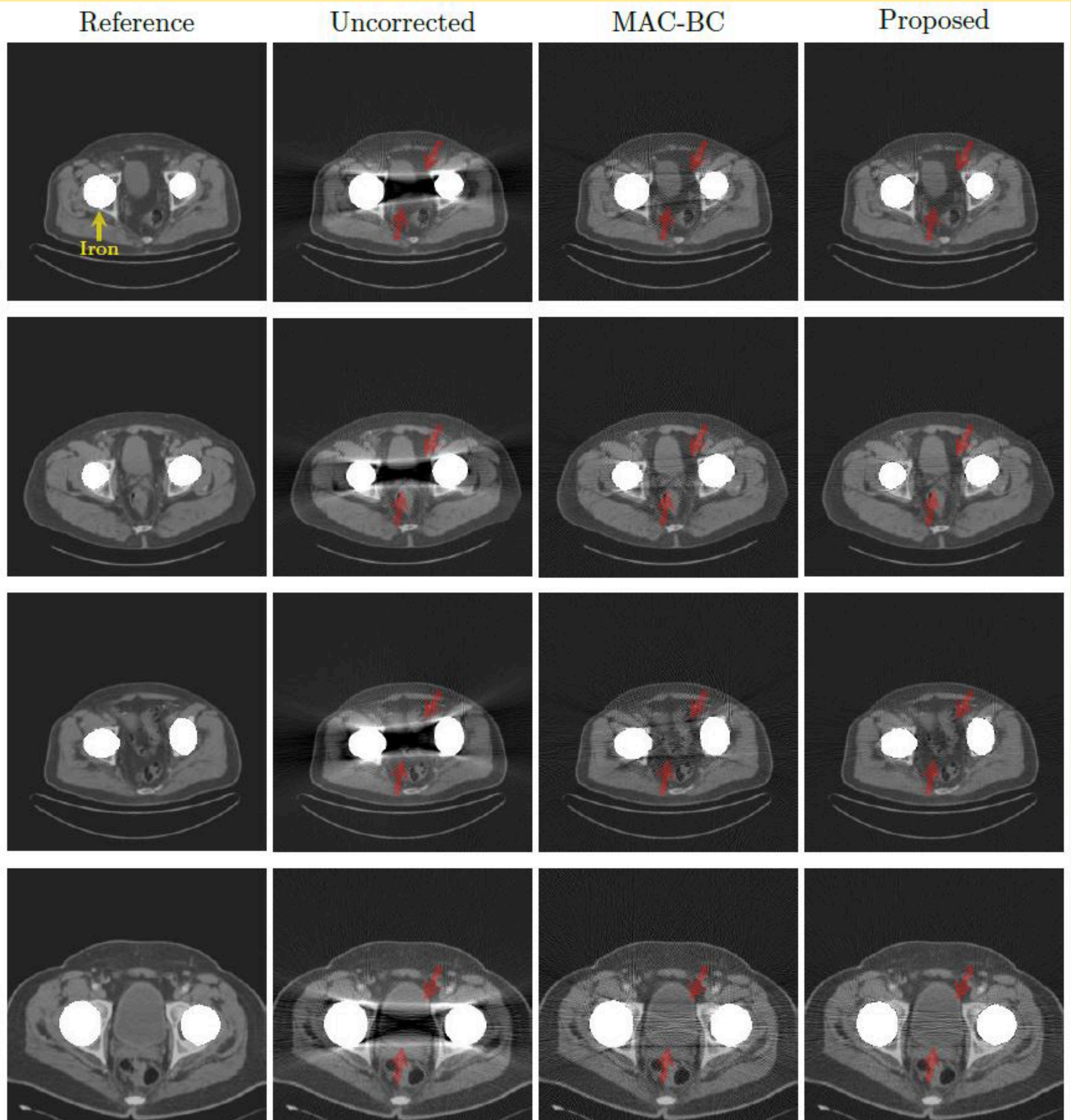
All the proposed methods were at least at the level of the gold standard in:

- Metal artifact reduction, [Park et al., Aug. 2017]
- Low Dose CT reconstruction, [Hammernik et al., Nov 2017]
- Scatter correction for spectral CT, [Xu et al., Jan. 2018]
- Monochromatic CT reconstruction, [Jin et al., June 2017]
- Material decomposition in spectral CT, [Lu et al., May 2018]
- Spectral distorsion corrections in spectral CT, [Touch et al., July 2016]
- CT segmentation with/without contrast agent
- CT registration

and…

- COVID-19 based detection in lung CT images
- …

Metal artifacts reduction



- [Park et al., Aug. 2017]

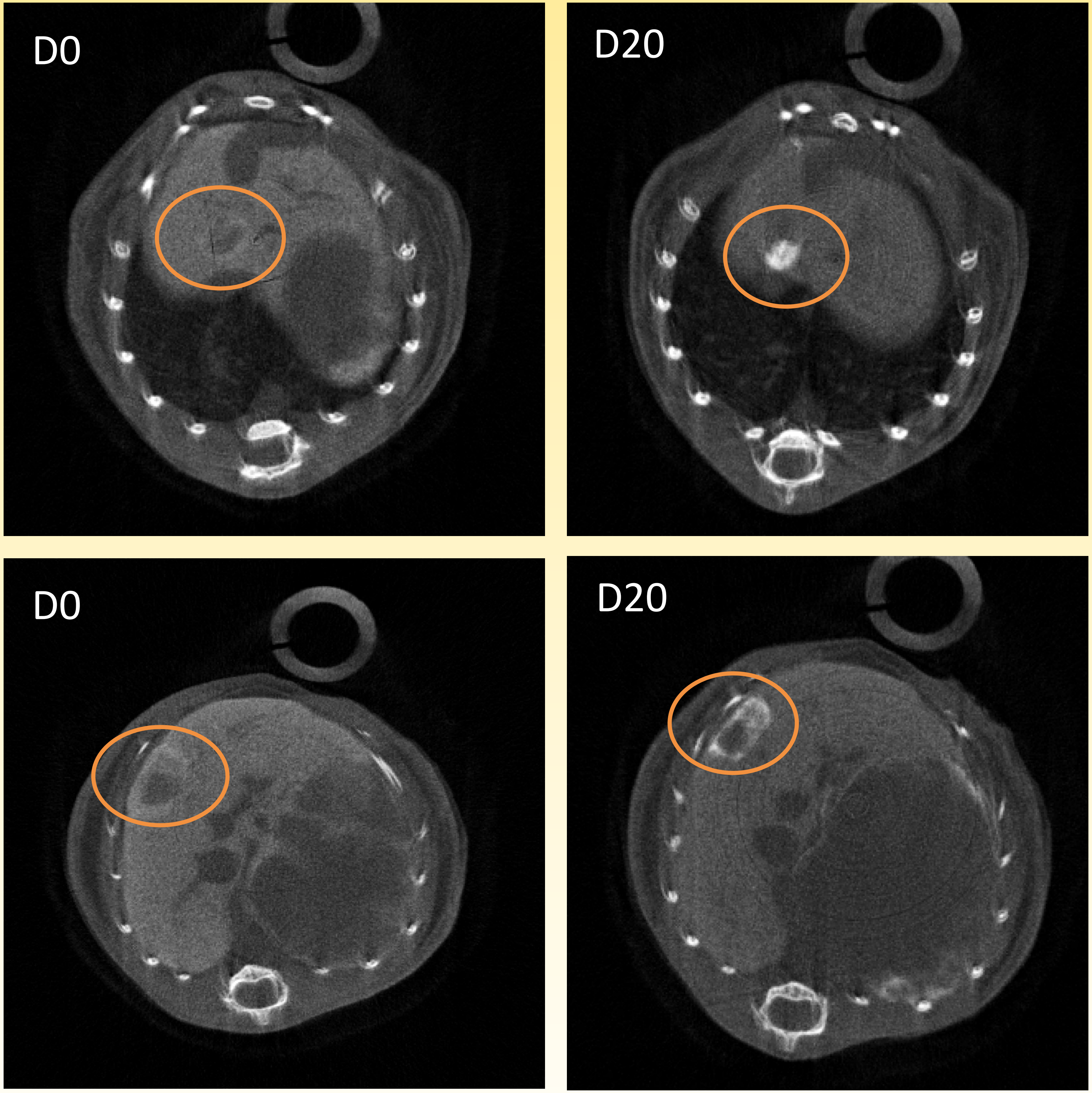
Data

Conclusions

CNNs based on U-net architectures appears to be efficient on numerous problems in biomedical imaging. Their use is everywhere.

Compare performances of GPUs vs. other hardwares for CNNs: are GPUs optimal ?

Can these U-net based CNNs be embedded closer to the sensor ?



Tumor evolution examples (at D0 in the left and D20 in the right)