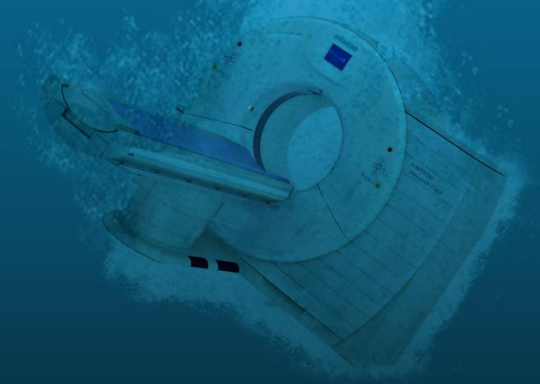
AI-Based Image Reconstruction: Basics, Vendor Implementations and Potential Pitfalls



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DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

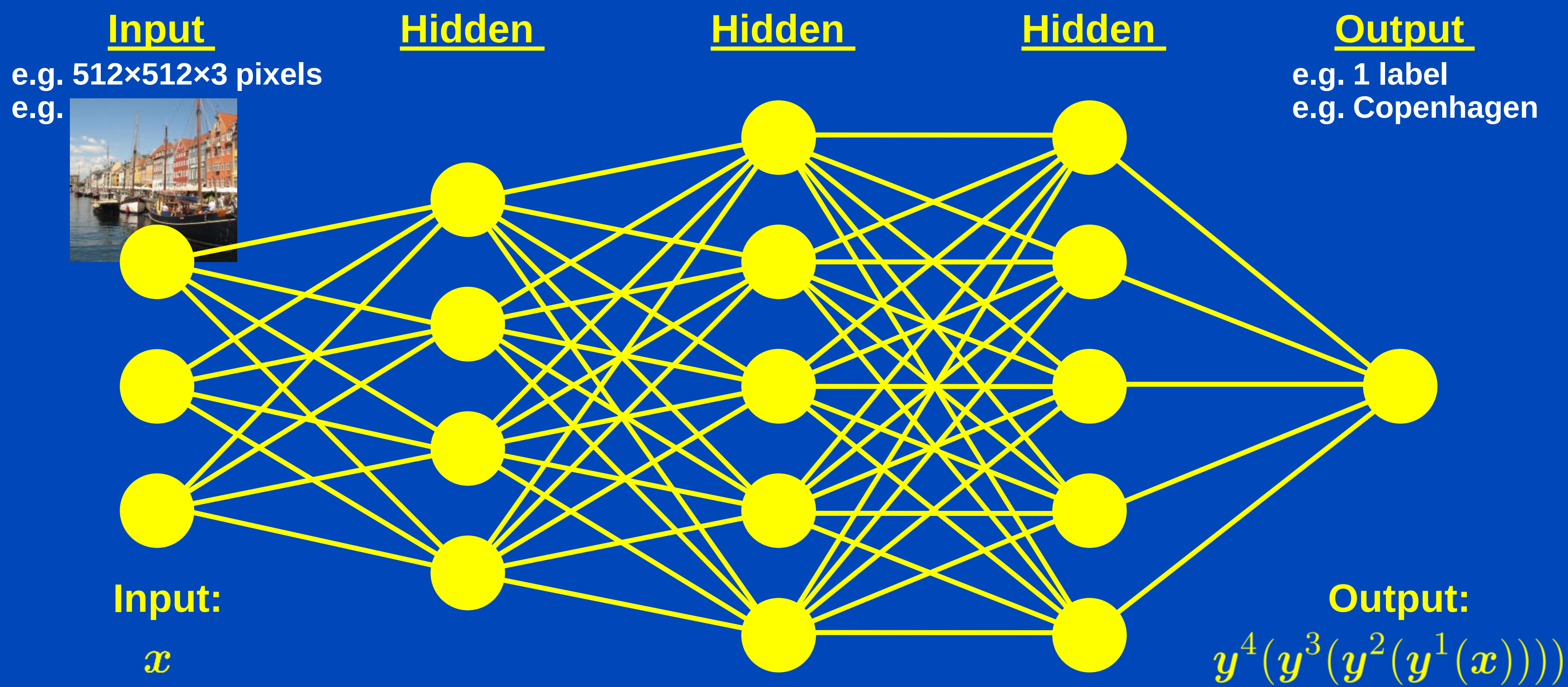
My Disclosures

Learning Objectives

- To learn that AI-based image reconstruction is mainly noise reduction
- To understand how AI-based image reconstruction works
- To learn about its dose reduction potential, and about potential pitfalls

Fully Connected Neural Network

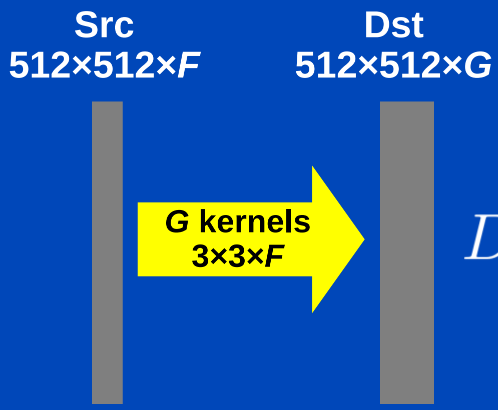
- Each layer fully connects to previous layer
- Difficult to train (many parameters in *W* and *b*)
- Spatial relations not necessarily preserved



$\boldsymbol{y}(\boldsymbol{x}) = \boldsymbol{f}(\boldsymbol{W}\cdot\boldsymbol{x}+\boldsymbol{b})$ with $\boldsymbol{f}(\boldsymbol{x}) = \big(f(x_1), f(x_2), \ldots\big)$ point-wise scalar, e.g. $f(x) = x \vee 0 = \mathrm{ReLU}$

Convolutional Neural Network (CNN)

- Replace dense *W* in $y(x) = f(W \cdot x + b)$ by a sparse matrix *W* with sparsity being of convolutional type.
- CNNs consist (mainly) of convolutional layers.
- Convolutional layers are not fully connected.
- Convolutional layers are connected by small, say 3×3, convolution kernels whose entries need to be found by training.
- CNNs preserve spatial relations to some extent.

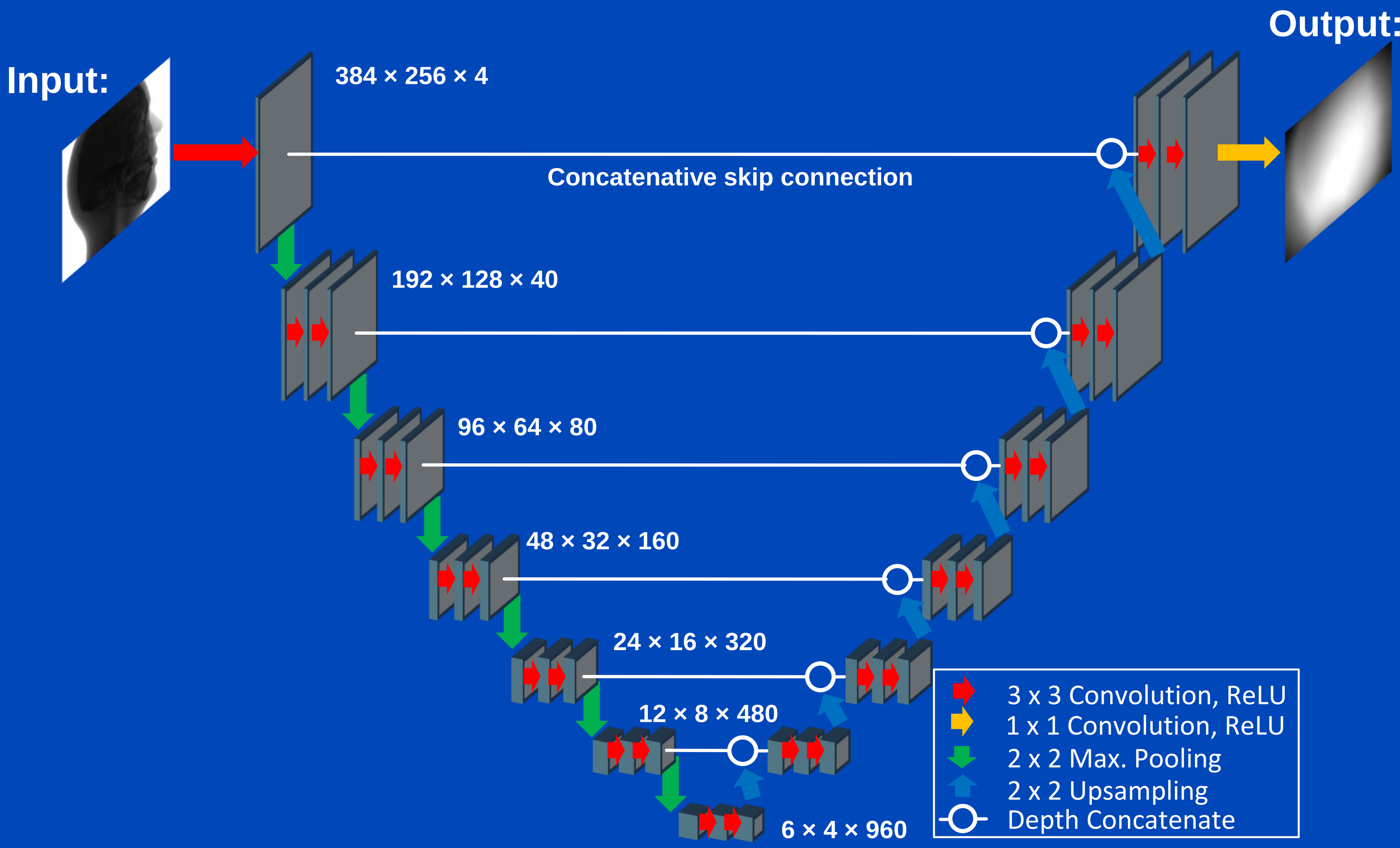


$$D_{i,j,g} = \sum_f S_{i,j,f} * K^g_{i,j,f} = \sum_{a,b,f} S_{i-a,j-b,f} K^g_{a,b,f}$$

Attention: No convolution in depth direction!

Here, a 2D example is shown. Conv layers also exist in 3D and higher dimensions.

U-Net[1]



[1]O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. Proc. MICCAI:234-241, 2015.

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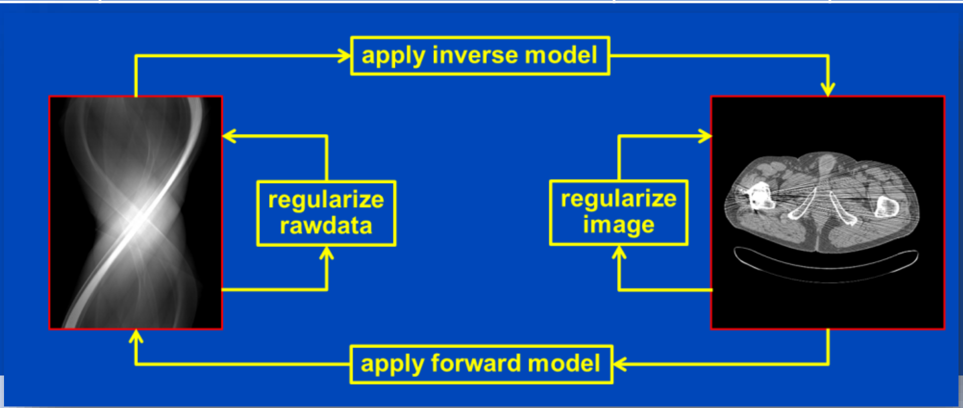
High-End and Mid-Range Systems 2023

CT-System	Rotation, Cone, Coll.	Max. Power, Anode Angle, Name, Max. mA @ low kV	Patient-specific prefilters	Detector Configuration, Type, Name	FOM, Reconstruction Matrix	Special Reconstruction Algorithms	Spectral	
Canon Aquilion ONE Prism Edition	0.275 s, 15°, 160 mm	100 kW, 10°, MegaCool Vi, 600 mA @ 80 kV	Ag, {0, *x*} mm	320 × 0.5 mm, EI, PUREViSION	50 cm, 512	iterative (AIDR 3D), deep (AiCE, PIQE)	fast TVS with DL	H
Canon Aquilion Precision Edition	0.35 s, 3.8°, 40 mm	72 kW, 7°, MegaCool, 600 mA @ 80 kV	none	160 × 0.25 mm, EI, PUREViSION	50 cm, 512, 1024, 2048	iterative (AIDR 3D), deep (AiCE)	2 scans	H
GE Revolution Apex Elite	0.23 s, 15°, 160 mm	108 kW, 10°, Quantix 160, 1300 mA @ 70+80 kV	none	256 × 0.625 mm, EI, GemStone Clarity	50 cm, 512		fast TVS or 2 scans	H
GE Revolution Apex Plus	0.28 s, 7.6°, 80 mm	108 kW, 10°, Quantix 160, 1300 mA @ 70 kV	none	128 × 0.625 mm, EI, GemStone Clarity	50 cm, 512	deep (TrueFidelity), SnapshotFreeze	fast TVS or 2 scans	M
Philips Spectral CT 7500	0.27 s, 7.7°, 80 mm	120 kW, 8°, iMRC, 925 mA @ 80 kV	none	2 · 128 × 0.625 mm, EI, NanoPanel Prism	50 cm, 512, 768, 1024	iterative (iDose)	sandwich	H
Philips Incisive CT	0.35 s, 3.9°, 40 mm	80 kW, vMRC	none	2 · 64 × 0.625 mm, EI	50 cm, 512, 768, 1024	iterative (iDose), deep (Precise Image&Cardiac)		M
Siemens Somatom X.ceed	0.25 s, 3.7°, 38.4 mm	120 kW, 8°, Vectron, 1300 mA @ 70+80+90 kV	Sn, {0, 0.4, 0.7} mm	2 · 64 × 0.6 mm, EI, Stellar	50 cm, 512, 768, 1024	iterative (ADMIRE)	split filter (Twin Beam) or 2 scans (Twin Spiral)	M
Siemens Somatom Force	0.25 s, 5.5°, 57.6 mm	2 · 120 kW, 8°, Vectron, 2 · 1300 mA @ 70+80+90 kV	Sn, {0, 0.6} mm	2 · 2 · 96 × 0.6 mm, EI, Stellar	50 cm/35 cm, 512, 768, 1024	iterative (ADMIRE)	DSCT	H
Siemens Naeotom Alpha	0.25 s, 5.5°, 57.6 mm	2 · 120 kW, 8°, Vectron, 2 · 1300 mA @ 70+90 kV	Sn, {0, 0.4, 0.7} mm	2 · 144×0.4 or 2 · 120×0.2 mm, PC, QuantaMax	50 cm/36 cm, 512, 768, 1024	iterative (QIR)	DSCT and PCCT	H

Premium Recon Algorithms 2023

Vendor	Algorithm	Additional parameters	Sinogram restoration	Image restoration	Full iterations	AI, Deep learning
all	FBP	-	✓	-	-	-
Canon	AIDR-3D enhanced FIRST AiCE PIQE	Body, Bone, Brain, Cardiac, Lung each with Mild, Standard, or Strong ?	✓ ✓ ? ?	✓ ✓ ✓ ✓	- ✓ - -	- - ✓ ✓
GE	ASIR, ASIR-V True Fidelity	0 – 100% (e.g. ASIR 30%) ???	✓ ?	✓ ✓	- -	- ✓
Philips	iDose IMR Precise Image&Cardiac	Levels 1 – 7 Soft, Routine, or SharpPlus ???	✓ ? ?	✓ ? ?	- ? ?	- - ✓
Siemens	IRIS SAFIRE ADMIRE QIR (PCCT-specific)	Strength 1 – 5 Strength 1 – 5 Strength 1 – 5 Strength 1 – 4	✓ ✓ ✓ ✓	✓ ✓ ✓ ✓	- ✓ ✓ ✓	- - - -



M. Lell and M. Kachelrieß. Recent and upcoming technological developments in CT. Invest. Radiol. Feb. 2020

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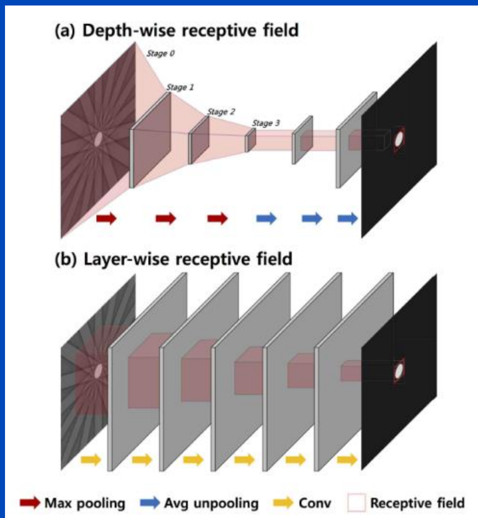
Dose Reduction by Sparse View Scanning and AI-Based Reconstruction



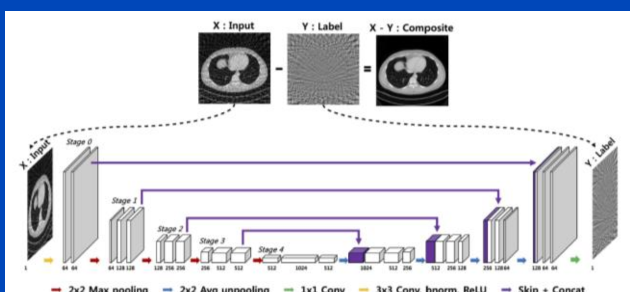
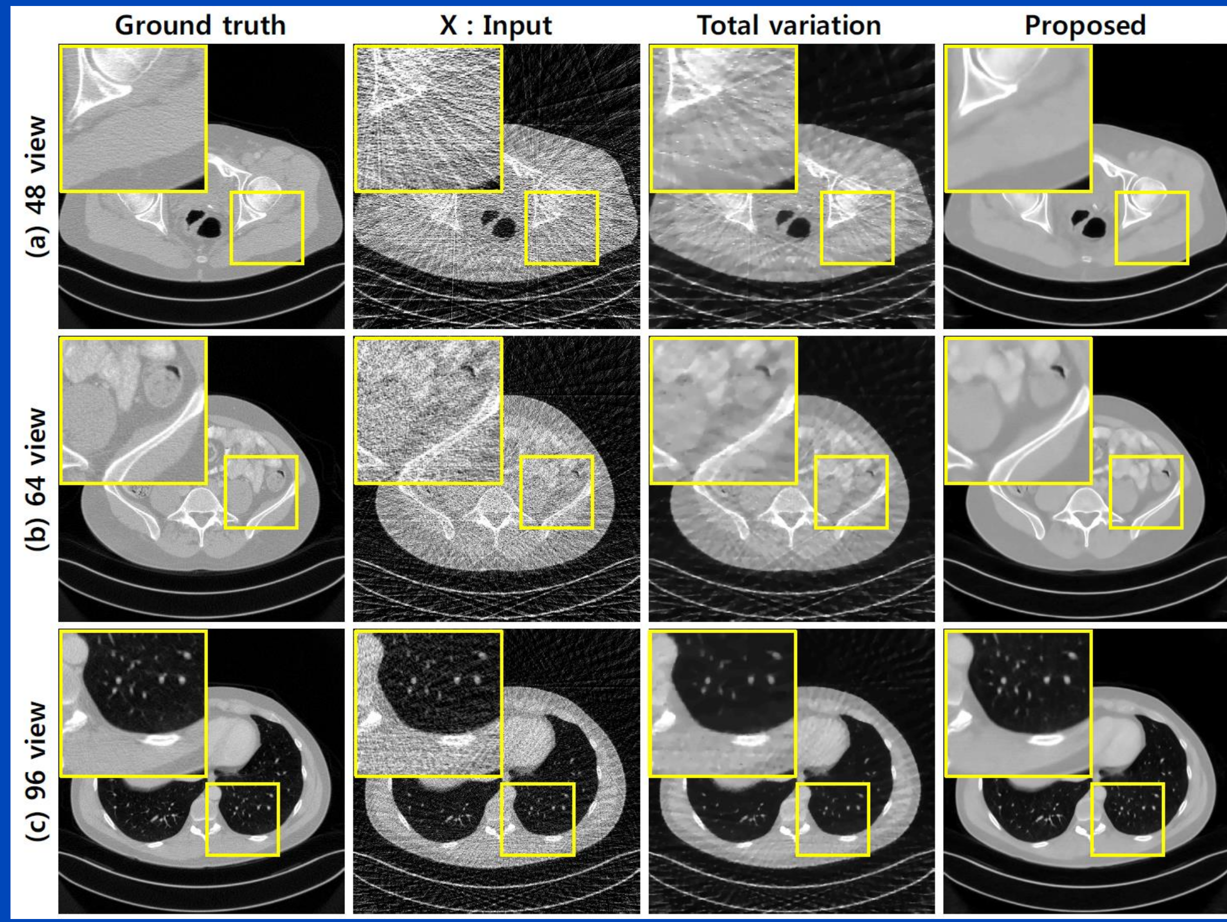
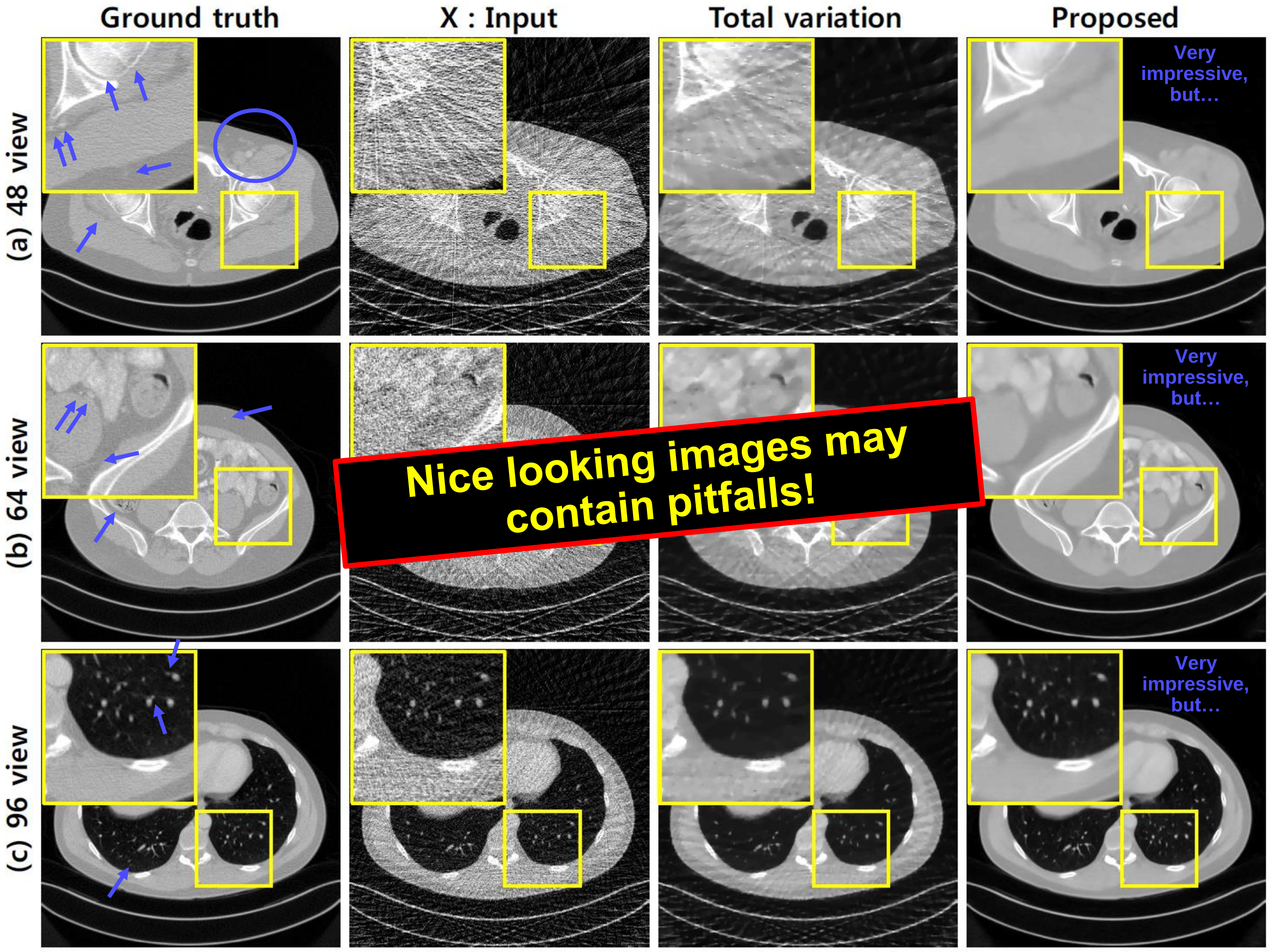
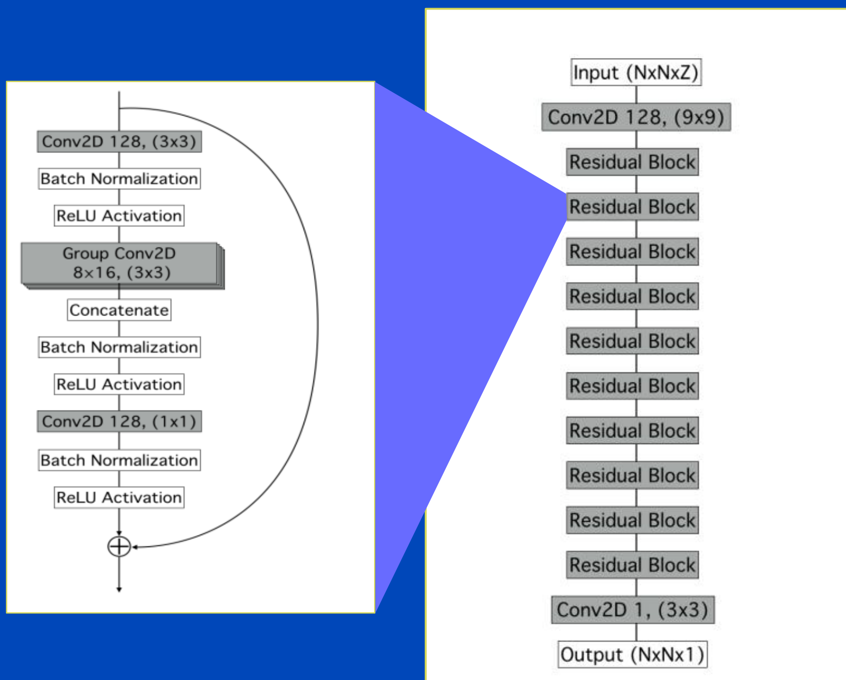


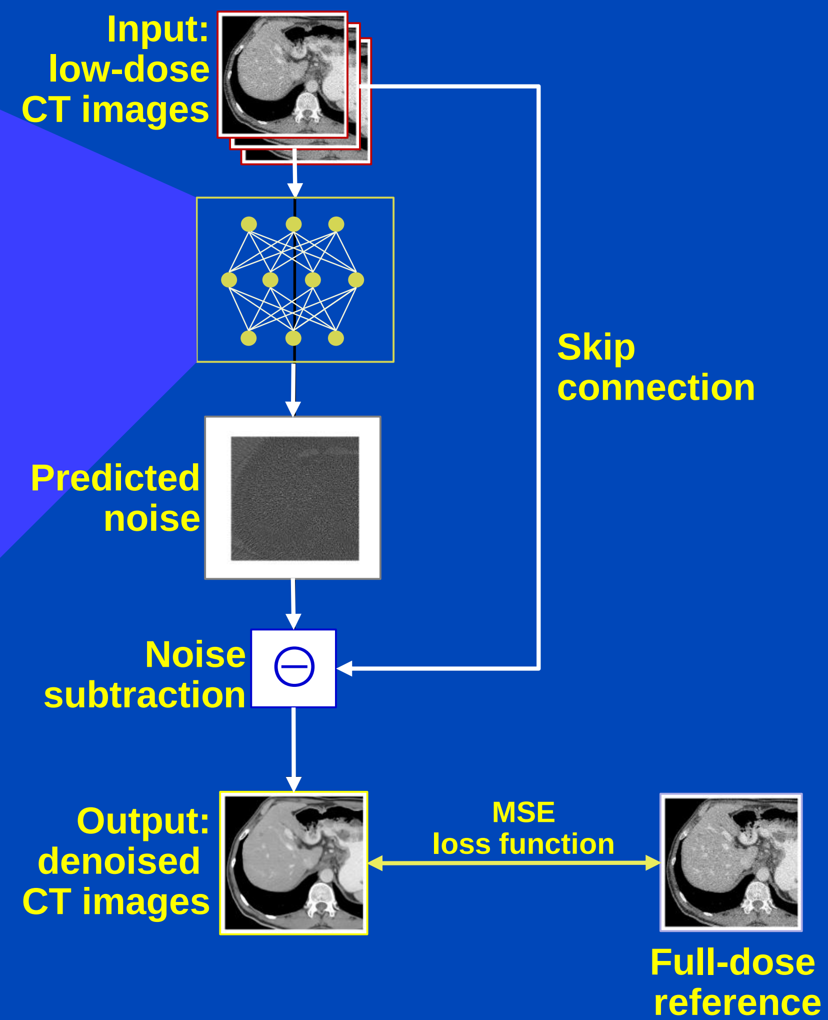
Figure 1. The proposed deep residual learning architecture for sparse view CT reconstruction.




Ground truth
X : Input
Total variation
Proposed
(a) 48 view
(b) 64 view
(c) 96 view
Very impressive, but…
Very impressive, but…
Very impressive, but…
Nice looking images may contain pitfalls!

Noise Removal Example

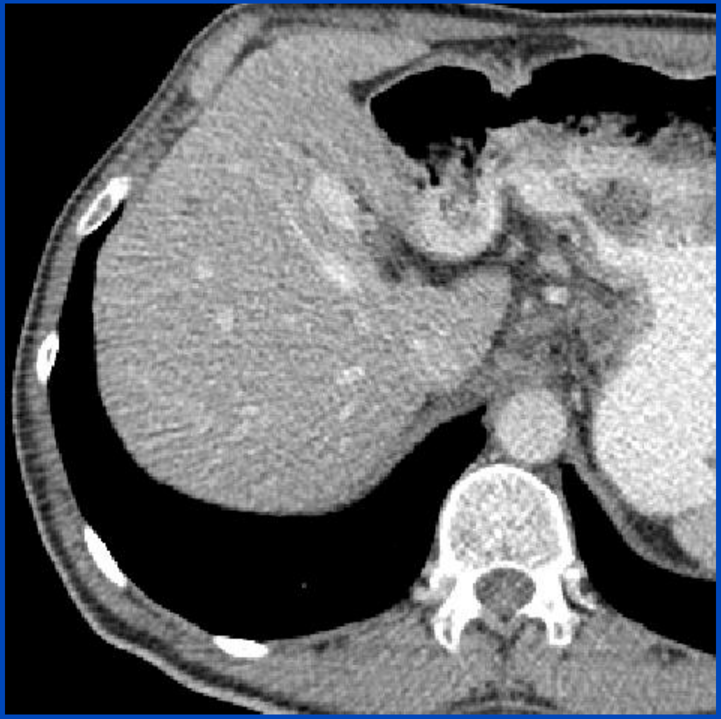


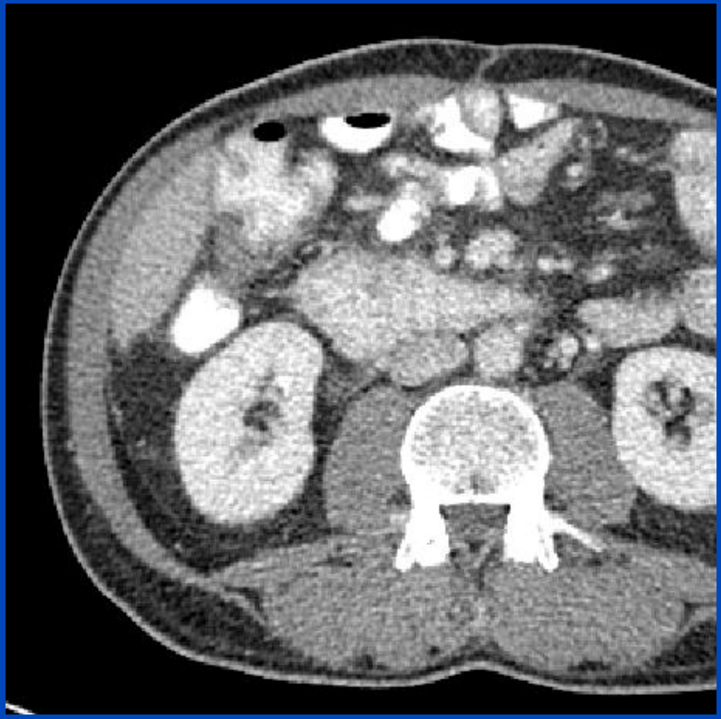


- Architecture based on state-of-the-art networks for image classification (ResNet).
- 32 conv layers with skip connections
- About 2 million tunable parameters in total
- Input is arbitrarily-size stack of images, with a fixed number of adjacent slices in the channel/feature dimension.

Andrew D. Missert, Shuai Leng, Lifeng Yu, and Cynthia H. McCollough. Noise Subtraction for Low-Dose CT Images Using a Deep Convolutional Neural Network. Proceedings of the 5th CT-Meeting: 399-402, 2018.

Noise Removal Example





Low dose images (1/4 of full dose)

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Noise Removal Example

Denoised low dose

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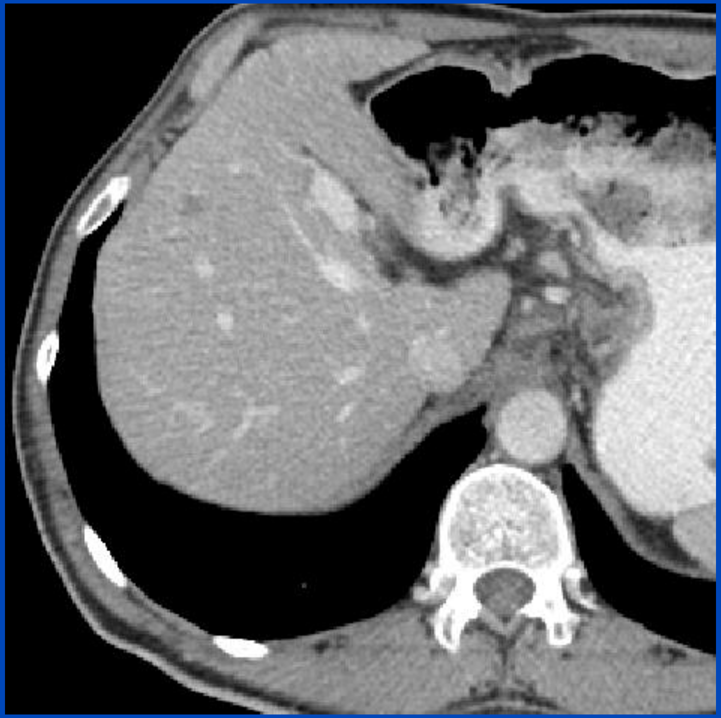
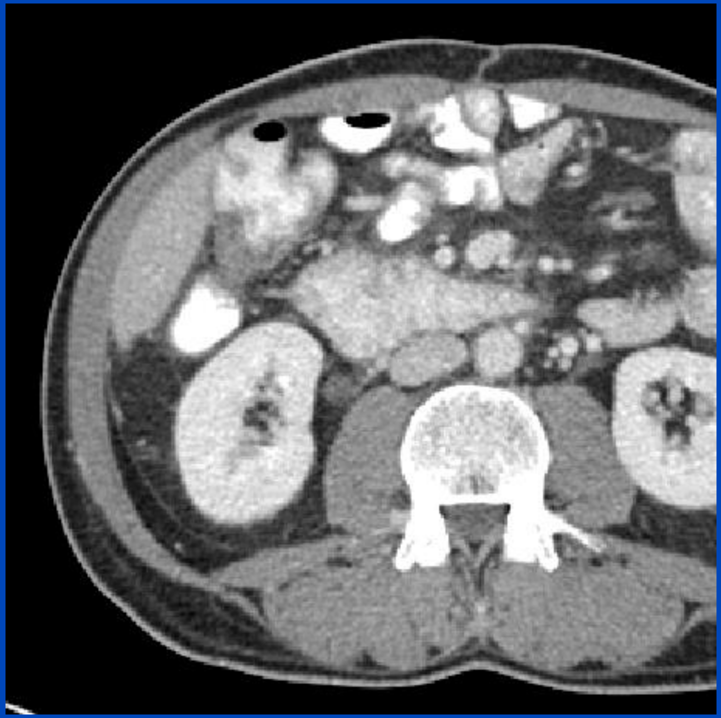
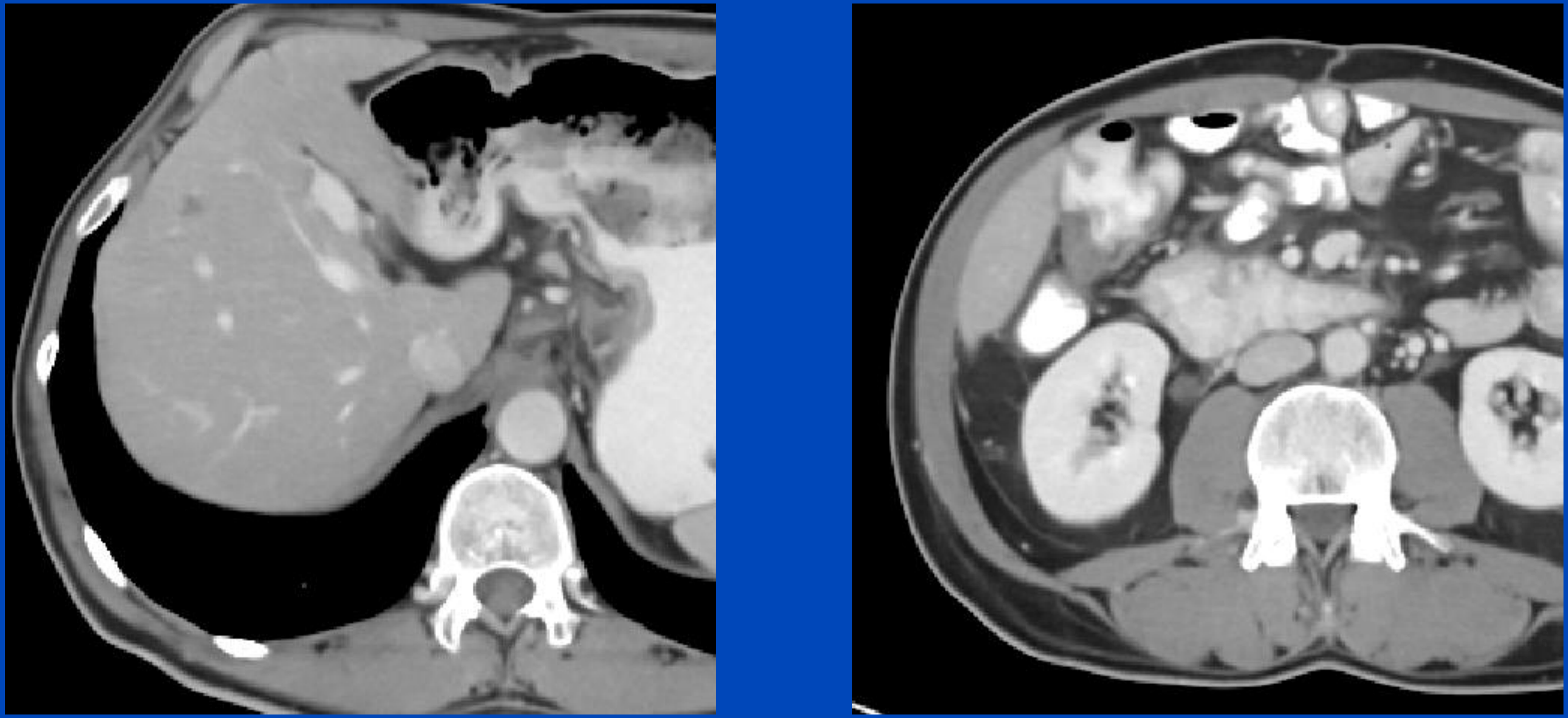
Noise Removal Example





Full dose

Noise Removal Example



Denoised full dose

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Noise Removal Example

Denoised low dose

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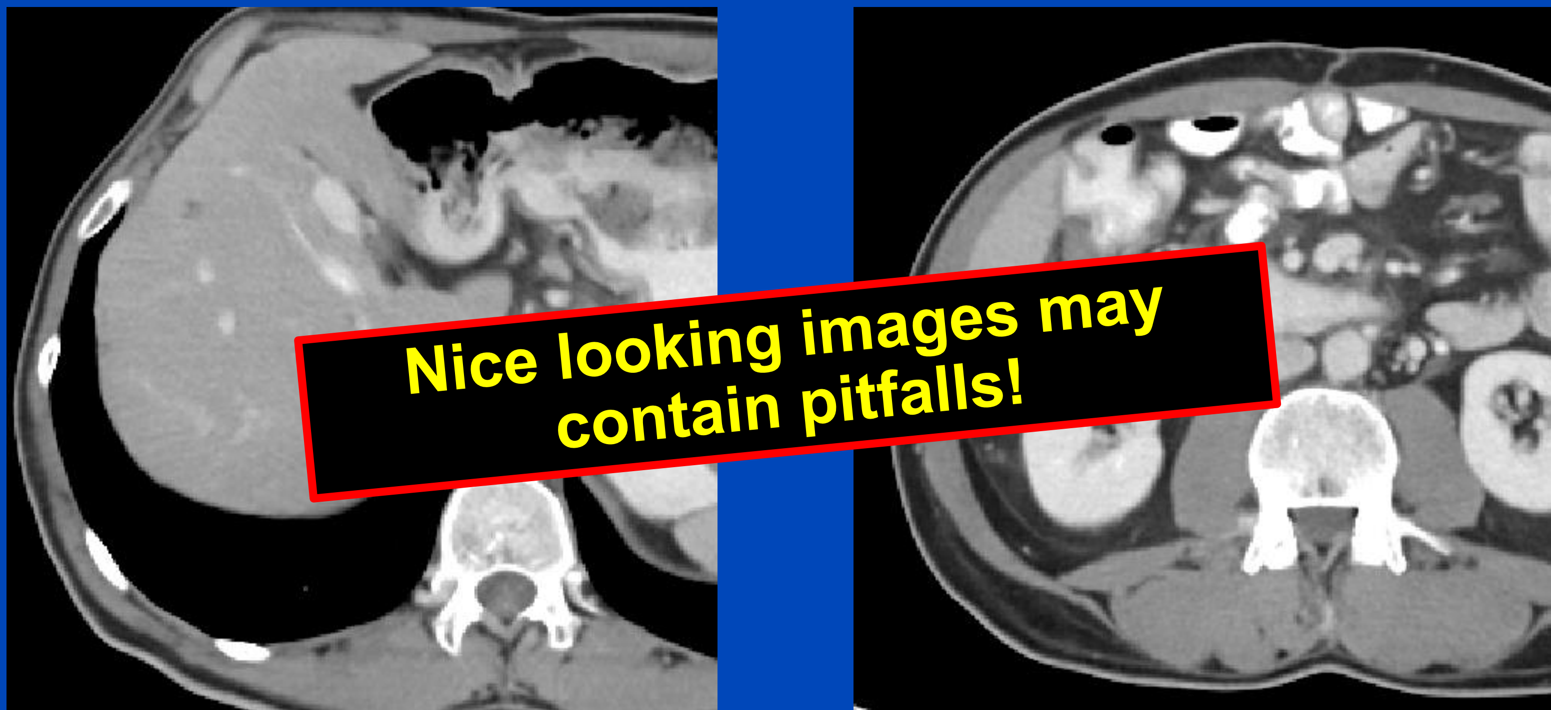
Noise Removal Example



Denoised low dose

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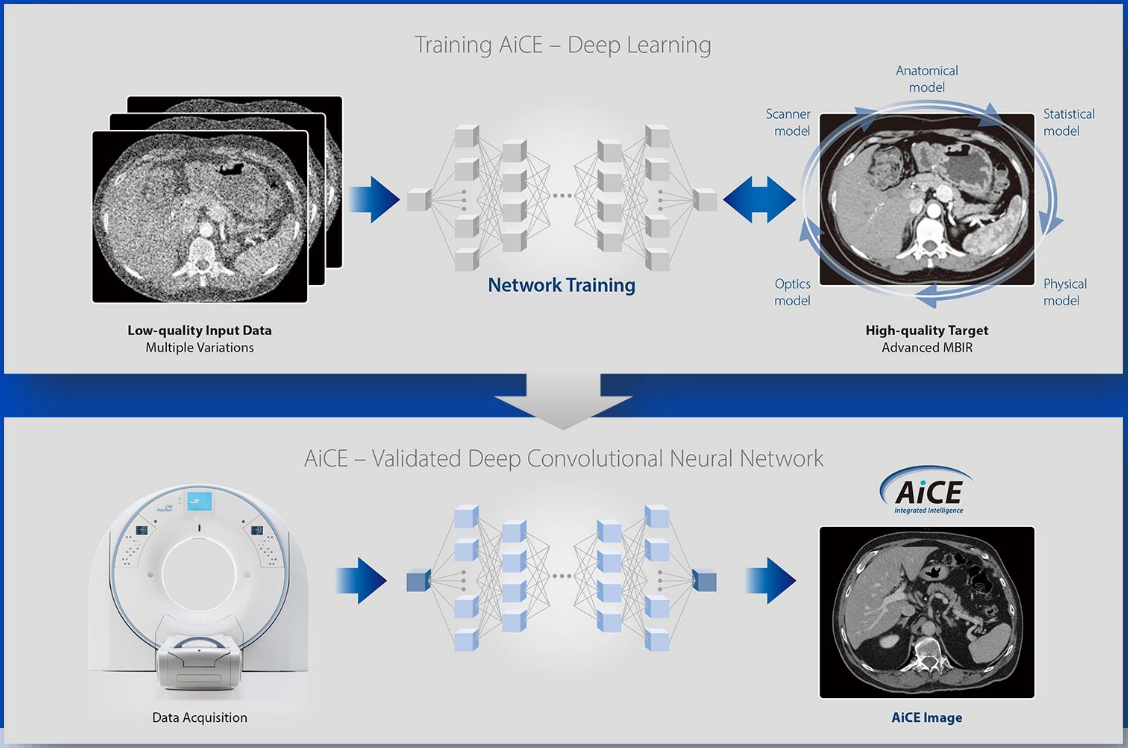
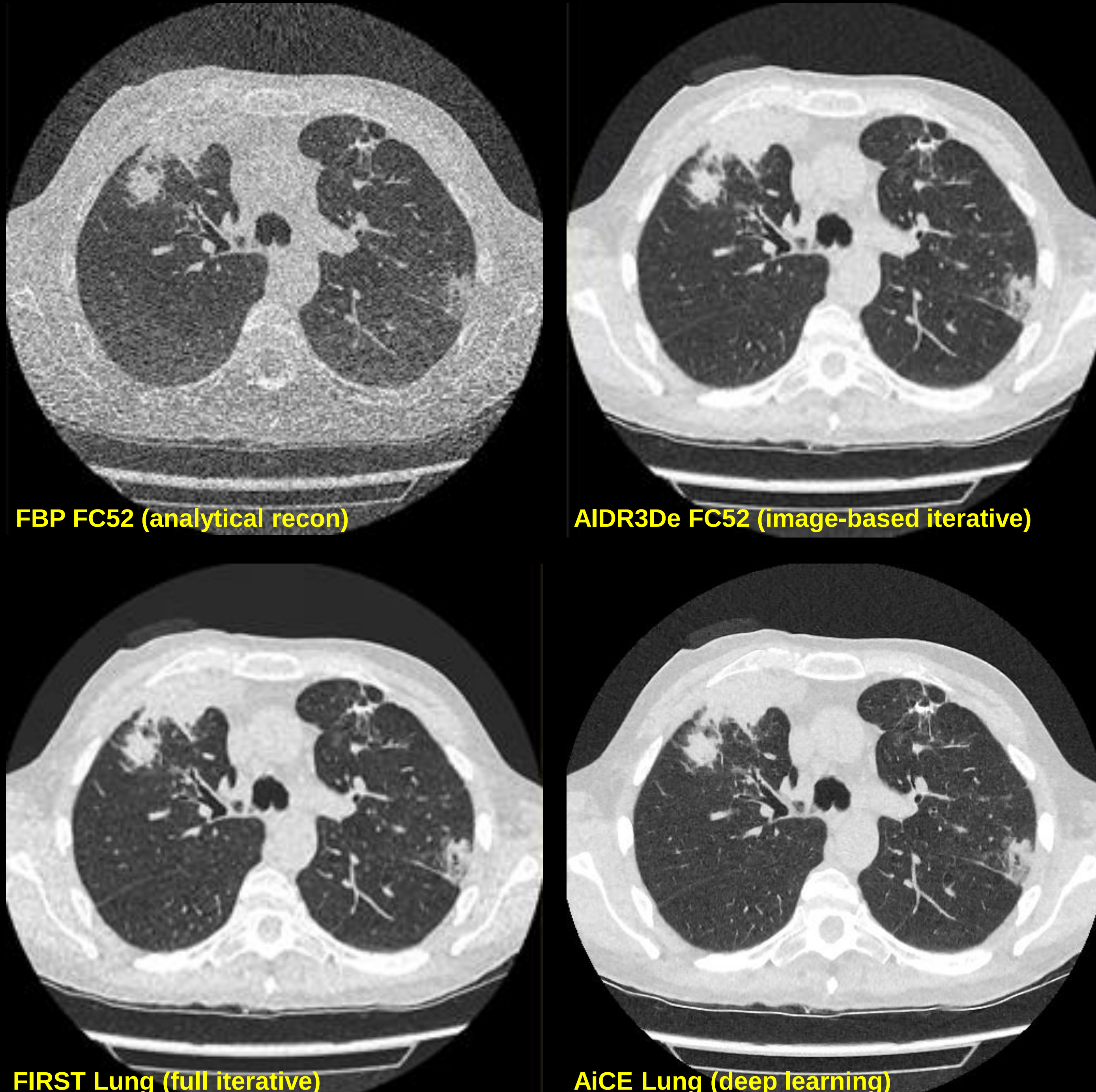
Canon's AiCE

- Advanced intelligent Clear-IQ Engine (AiCE)
- Trained to restore low-dose CT data to match the properties of FIRST, the model-based IR of Canon.
- FIRST is applied to high-dose CT images to obtain a high fidelity training target



U = 100 kV
CTDI = 0.6 mGy
DLP = 24.7 mGy·cm
D_{eff} = 0.35 mSv

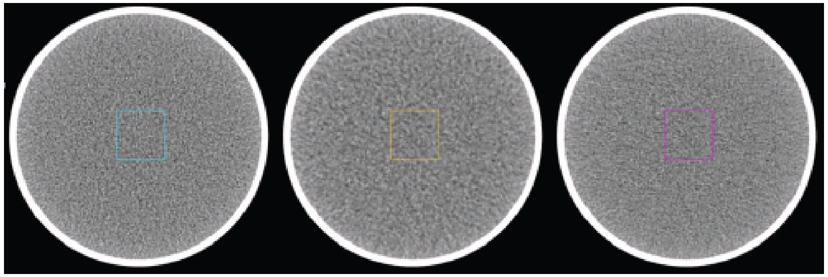


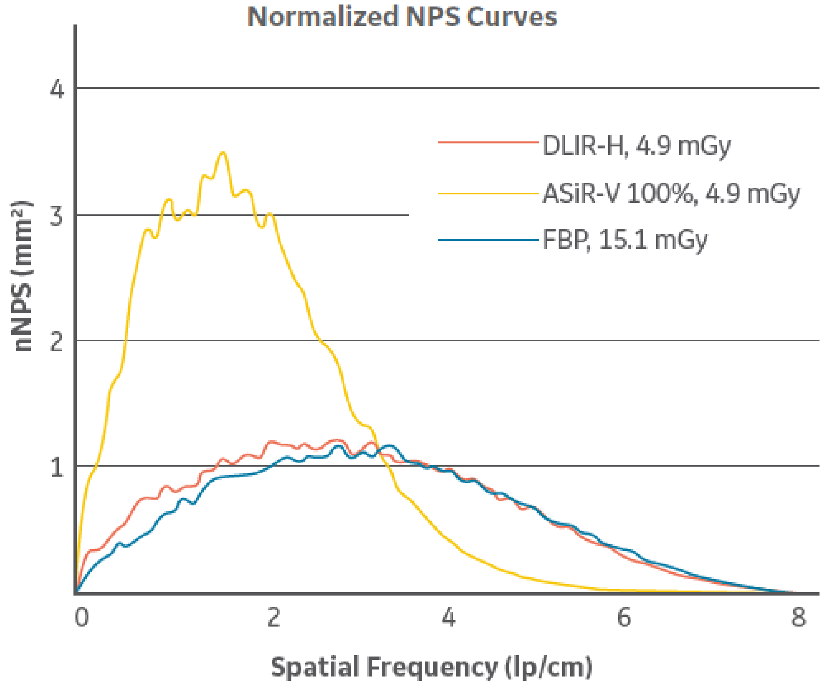
Courtesy of Radboudumc, the Netherlands

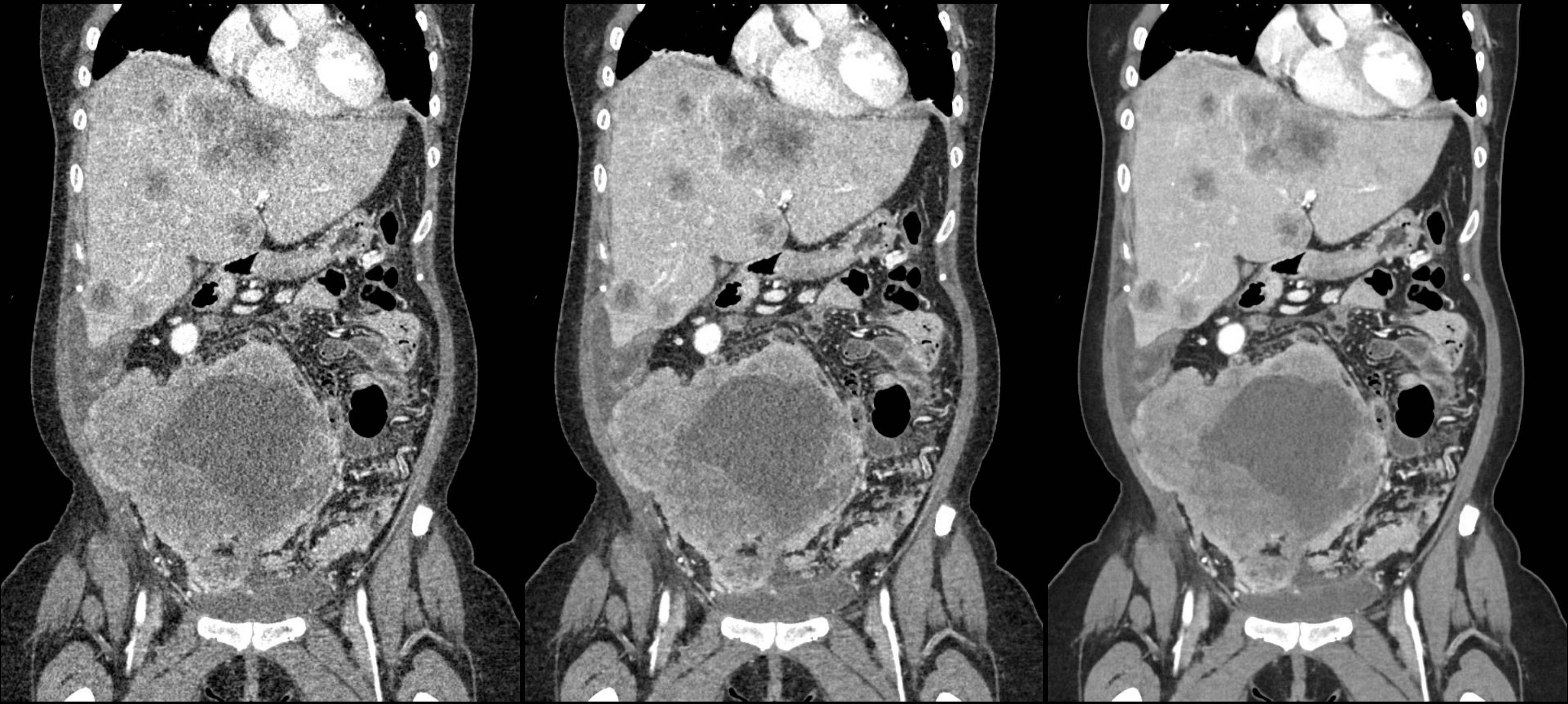
Noise Reduction: GE‘s True Fidelity

- Based on a deep CNN
- Trained to restore low-dose CT data to match the properties of high quality FBP datasets.
- Said to preserve noise texture and NPS

The 20 cm water phantom (GE Healthcare, WI, US) was scanned on Revolution CT with two CTDIvol levels: 4.9mGy and 15.1mGy, and 2.5 mm thick images were reconstructed using FBP, ASiR-V 100% and DLIR-H (Fig. 11a). ASiR-V 100% and DLIR-H were selected for the highest potential visible change in image texture relative to the FBP reference at higher dose, for a challenging setup to compare the impact of the iterative reconstruction and deep-learning technologies on image appearance. The normalized NPS curves (Fig. 11b) show that images of low-dose DLIR have the same NPS characteristics as the images of high-dose FBP, whereas iterative reconstruction produces results that are clearly different.

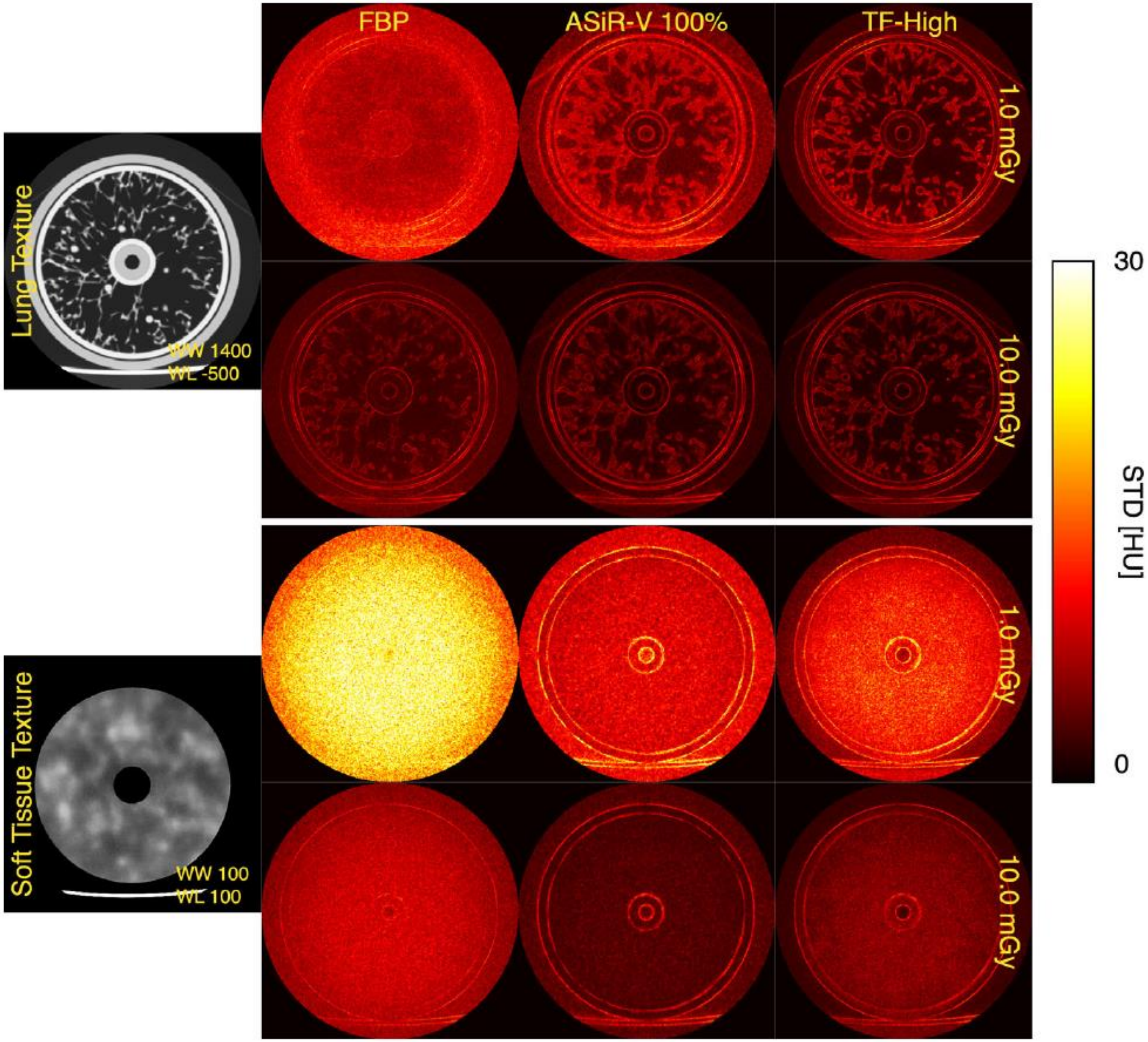






FBP ASIR V 50% True Fidelity

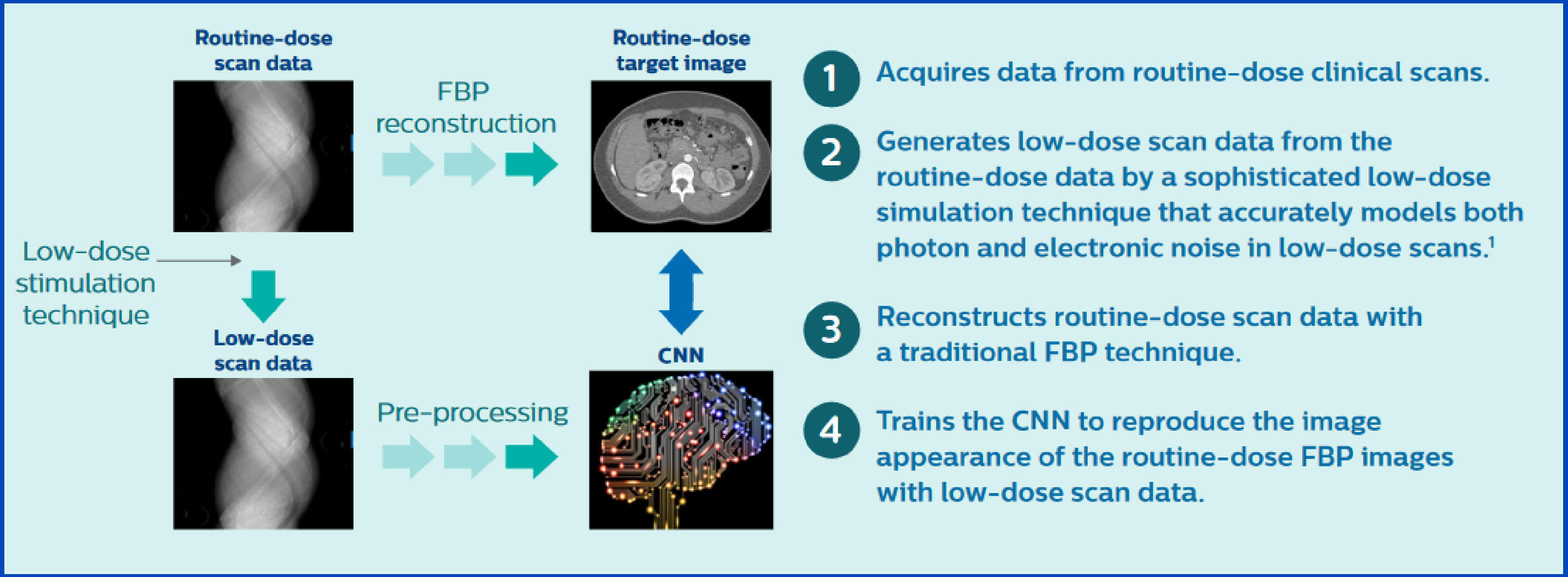
Courtesy of GE Healthcare

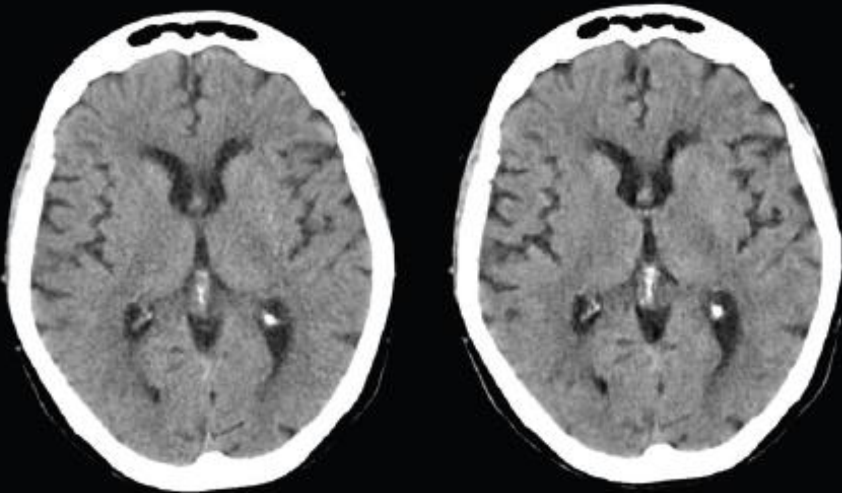


Solomon et al. Noise and spatial resolution properties of a commercially available deep learning-based CT reconstruction algorithm. Med. Phys. 47(9):3961-3971, Sept. 2020

Philips' Precise Image

- Noise-injected data serve as low dose examples while their original reconstructions are the labels. A CNN learns how to denoise the low dose images.

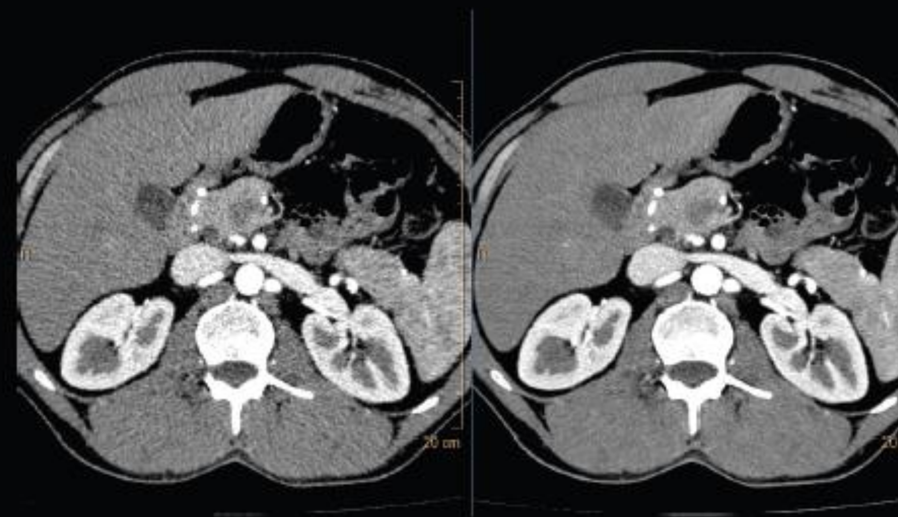




iDose^4 1.4 mSv | Precise Image 0.7 mSv

iDose^4 5.1 mSv | Precise Image 2.6 mSv

iDose^4 1.5 mSv | Precise Image 0.75 mSv



iDose^4 5.4 mSv | Precise Image 2.6 mSv

Taken from https://www.philips.com/c-dam/b2bhc/master/resource-catalog/landing/precise-suite/incisive_precise_image.pdf

Canon's PIQE

- PIQE (precise IQ engine) is trained to convert low resolution images into high resolution images
- Training data are taken from Canon's Precision CT that has small detector pixels (0.25 mm at iso).
- Claims:
  - Improved visualization of plaque
  - Reduction in blooming artifacts

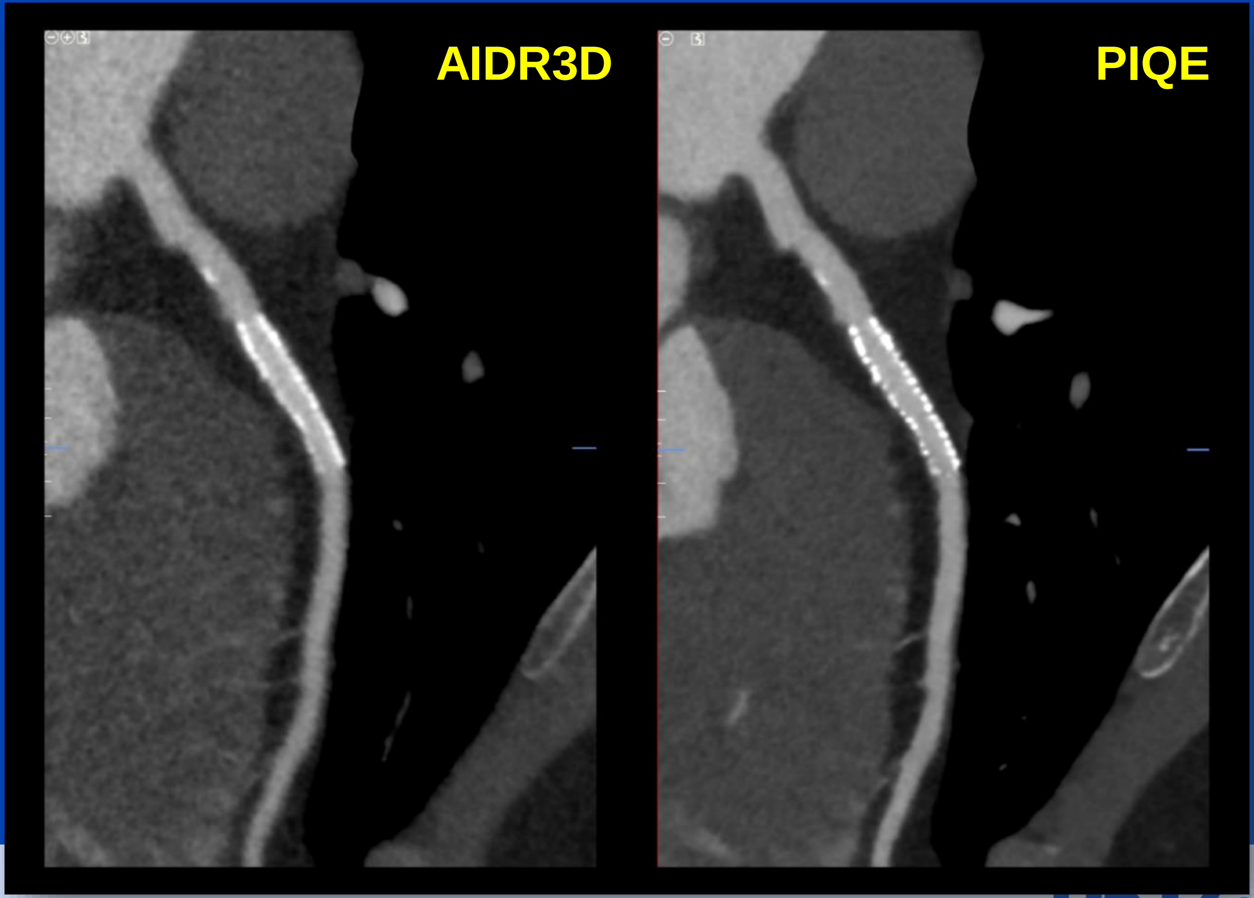


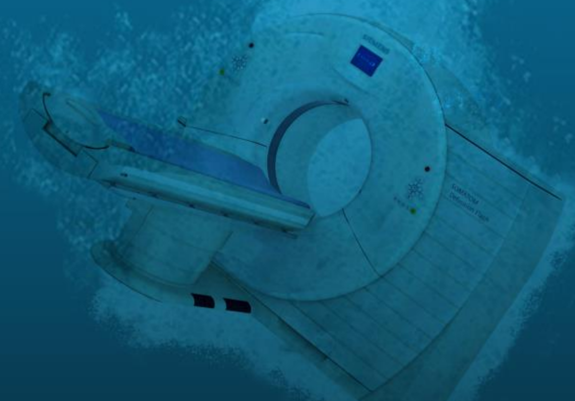
Image taken from at.medical.canon

Are the Methods Reliable?

- Studies about explainability of AI in CT image formation are more than sparse.
- Cosmetic corrections:
  - Unclear if noise reduction, artifact reduction etc. is removing/adding lesions. The whole process is a black box. Proofs do not exist.
  - Super resolution applications may only achieve the impression of higher spatial resolution: Two closely adjacent small lesions that appear as one blurry lesion in the original image, are they converted to two separate objects or just to one non-blurry lesion?
- Difficult, if not impossible, to perform quality assurance.

Take Home Points

- AI plays and will play a significant role in CT image formation.
- High potential for
  - Noise and dose reduction
  - Artifact correction
  - Real-time dose assessment (also for RT)
  - …
- Care has to be taken
  - Underdetermined acquisition, e.g. sparse view or limited angle CT, require the net to make up information!
  - Nice looking images do not necessarily represent the ground truth.
  - Data consistency layers and variational networks with rawdata access may ensure that the information that is made up is consistent with the measured data.
  - …



Thank You!

In case of questions or suggestions please write to marc.kachelriess@dkfz.de.