Deep-Learning-Rekonstruktion in der CT – Wo stehen wir in der Klinik?

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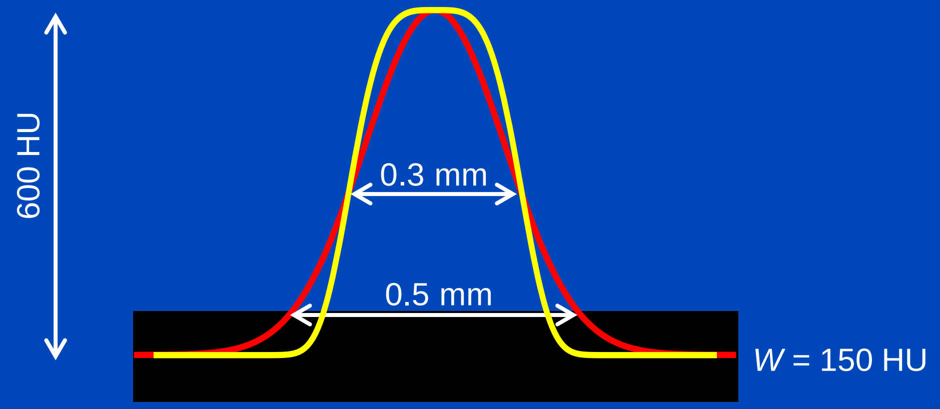
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Aim

- Introduce and discuss vendor-specific deep learning image reconstruction/restoration algorithms.
- Make aware of potential pitfalls of DL noise reduction algorithms.

Canon PIQE

- Precise IQ Engine (PIQE).
- Trained on data from Canon's Precision high spatial resolution CT
- Converts images from Canon's standard spatial resolution scanners (e.g. Aquilion ONE / PRISM edition) to look like high spatial resolution images.



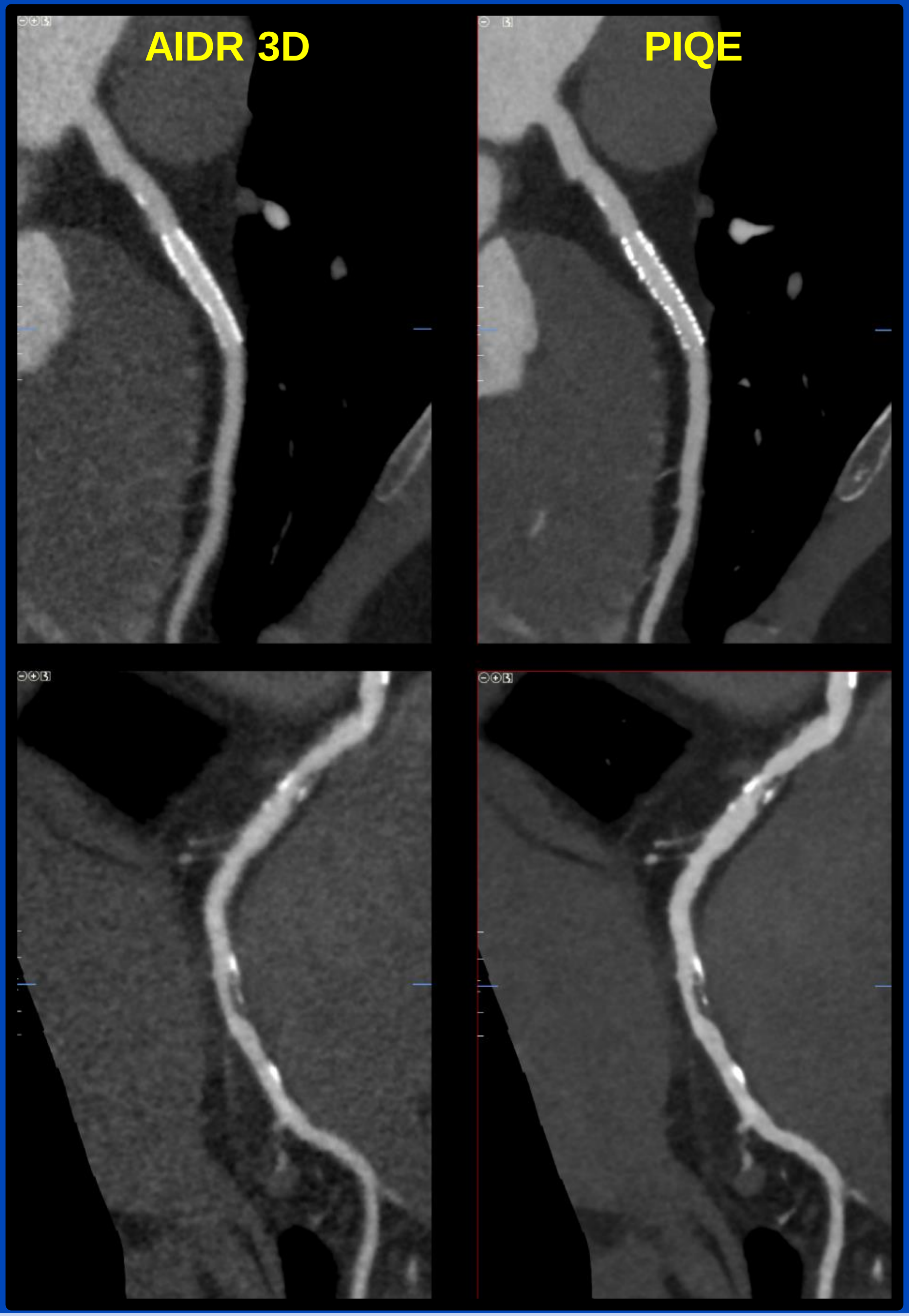
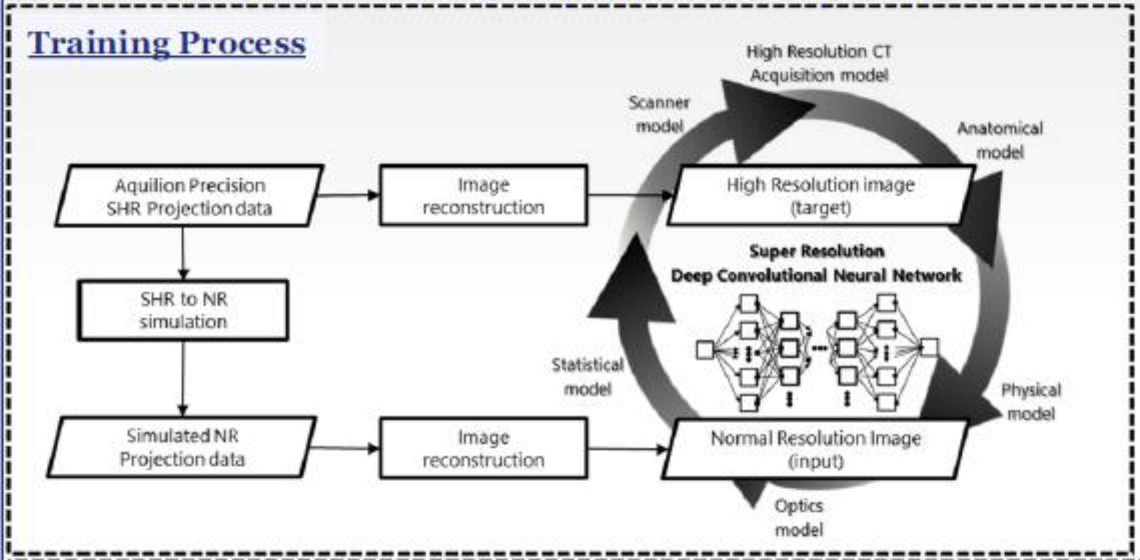
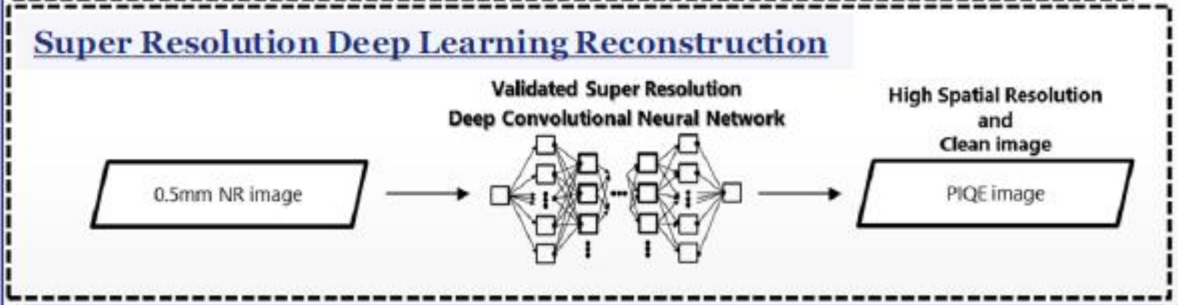


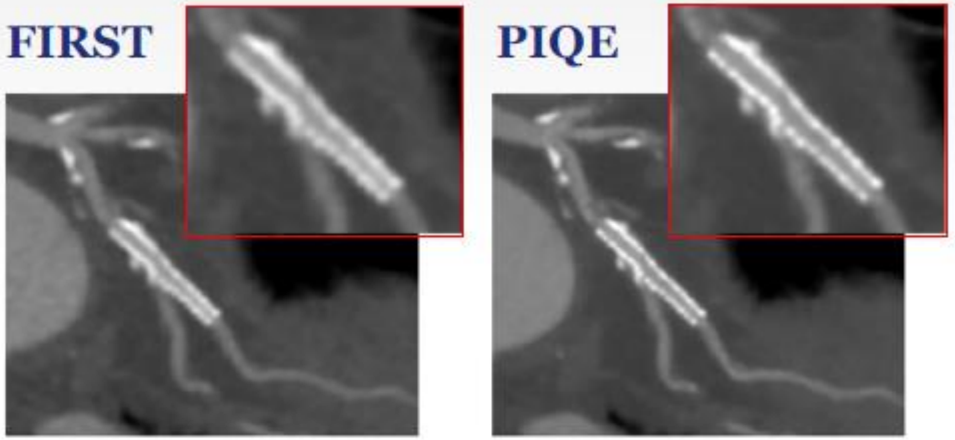
Image courtesy of Canon Medical Systems

The precise IQ engine (PIQE) network

European Radiology







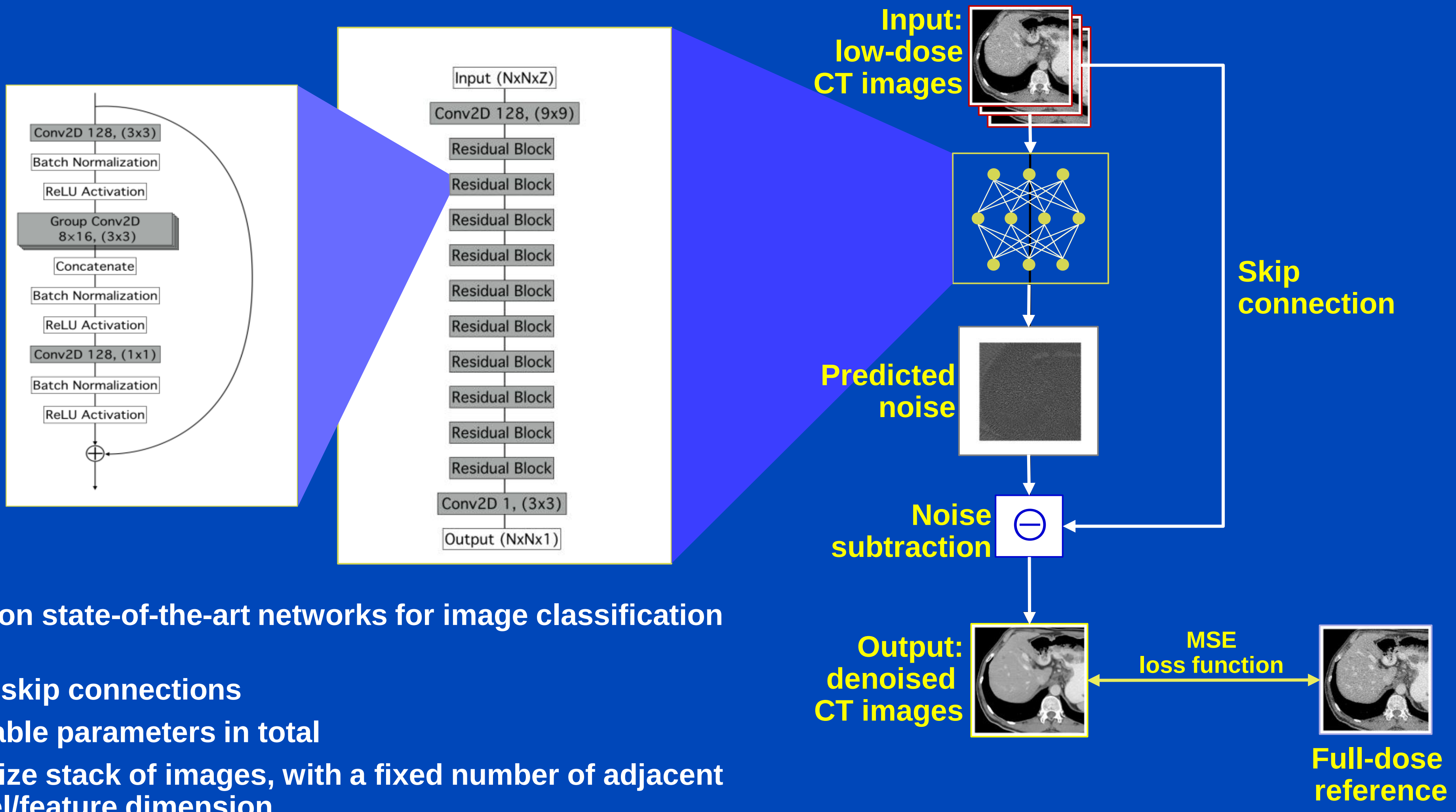
		Sensitivity (%, p-value)		Specificity (%, p-value)		Accuracy (%, p-value)	
Rev.1	FIRST	83.3	1.00	76.4	<0.05	77.1	<0.05
	PIQE	88.9		90.5		90.4	
Rev.2	FIRST	77.8	1.00	78.4	<0.05	78.3	<0.05
	PIQE	83.3		88.5		88.0	

Clinical Relevance Statement

With improvements in the diagnostic accuracy of in-stent stenosis, CT angiography could become a gatekeeper for ICA in post-stenting cases, obviating ICA in many patients after recent stenting with infrequent ISR and allowing non-invasive ISR detection in the late phase.

Eur Radiol (2023) Kawai H, Motoyama S, Sarai M et al.; DOI:10.1007/s00330-023-10110-7

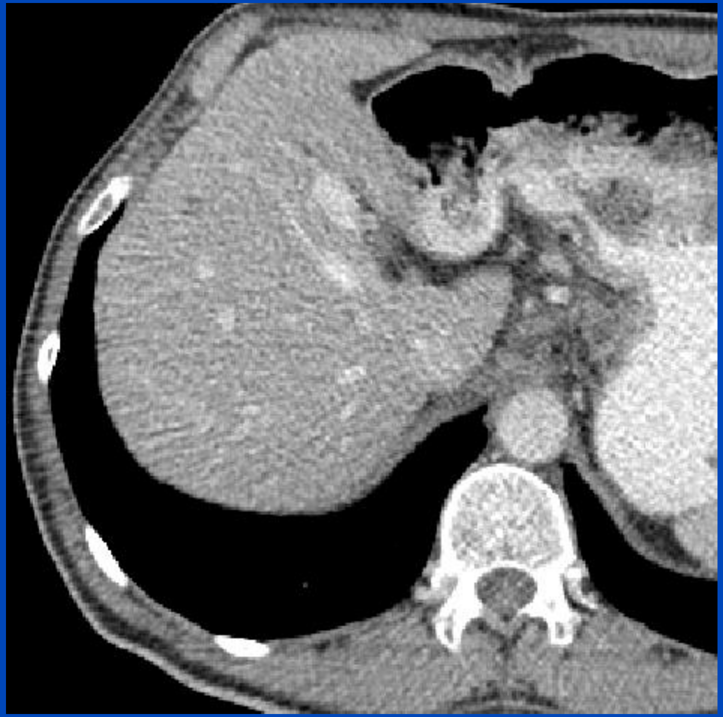
Noise Removal Example 1

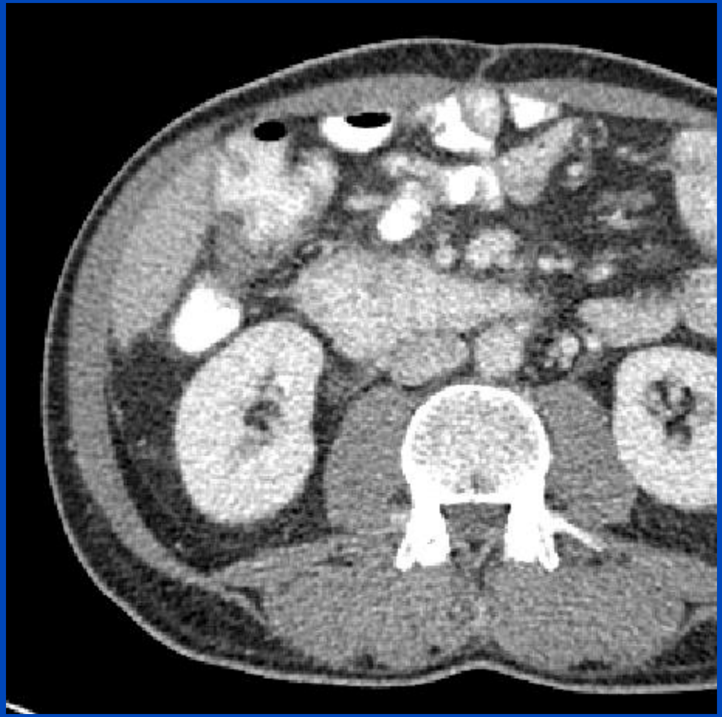


- Architecture based on state-of-the-art networks for image classification (ResNet).
- 32 conv layers with skip connections
- About 2 million tunable parameters in total
- Input is arbitrarily-size stack of images, with a fixed number of adjacent slices in the channel/feature dimension.

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.

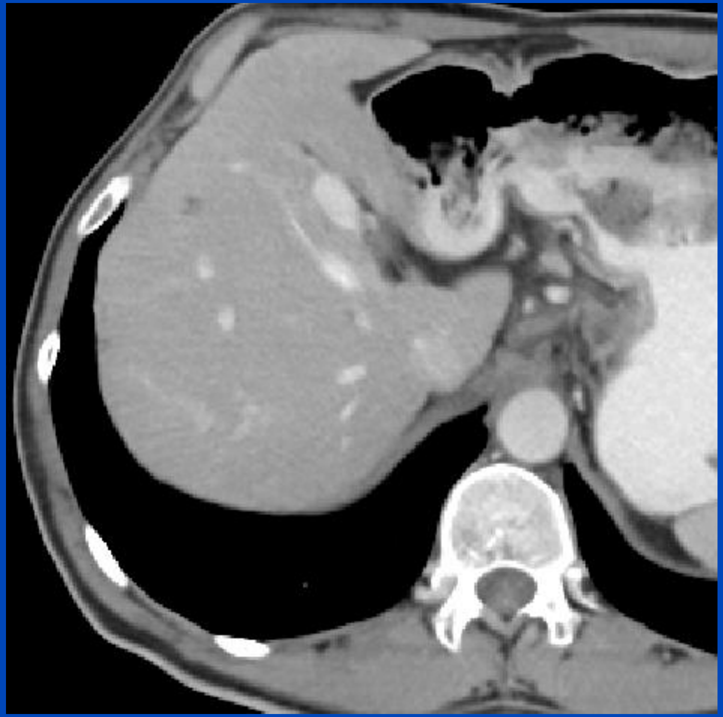
Noise Removal Example 1

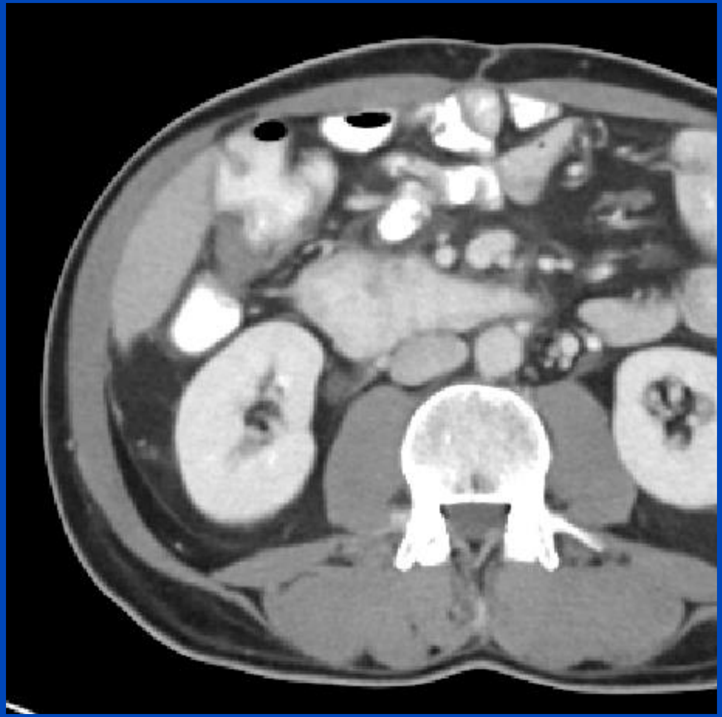




Low dose images (1/4 of full dose)

Noise Removal Example 1

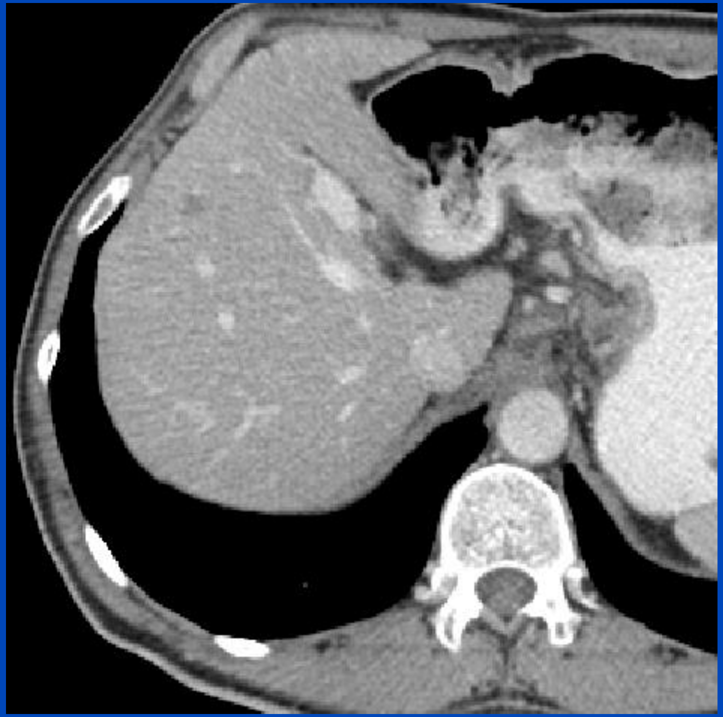


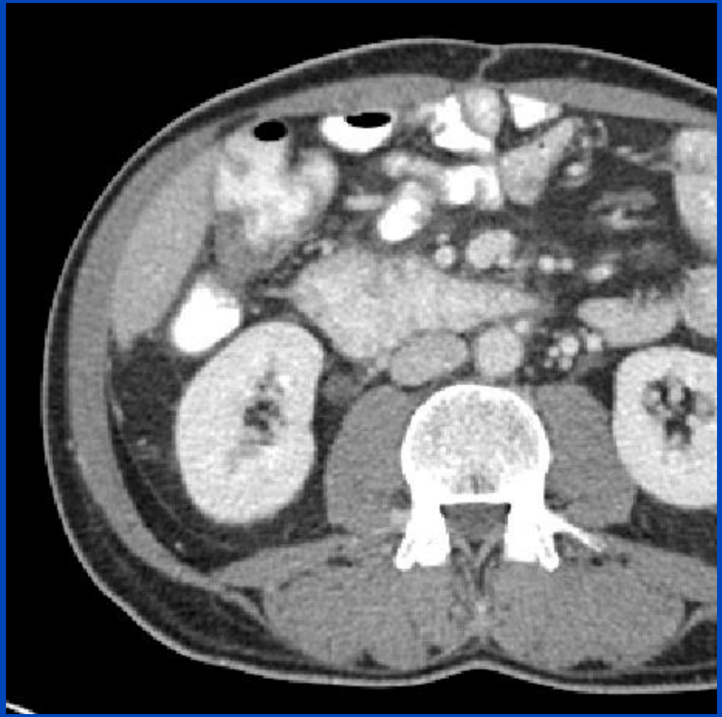


Denoised low dose

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 1

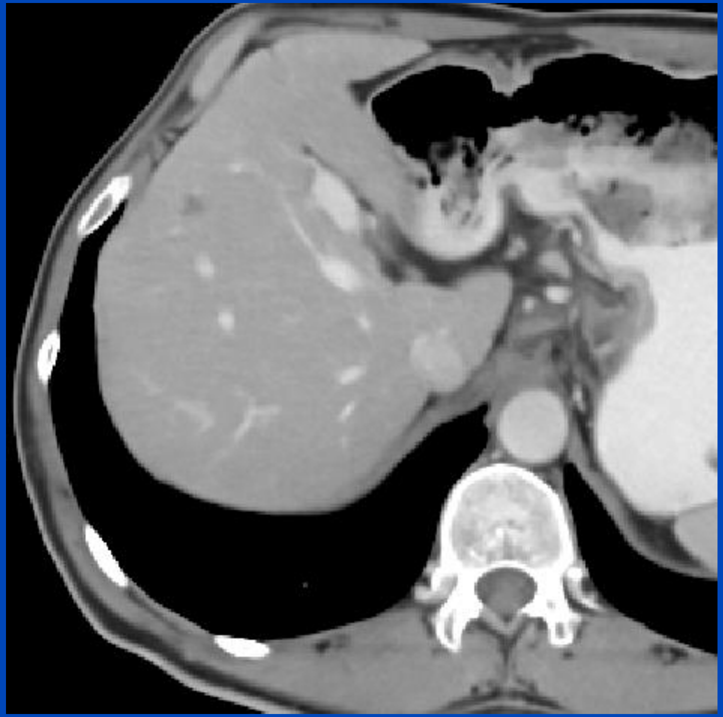




Full dose

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.

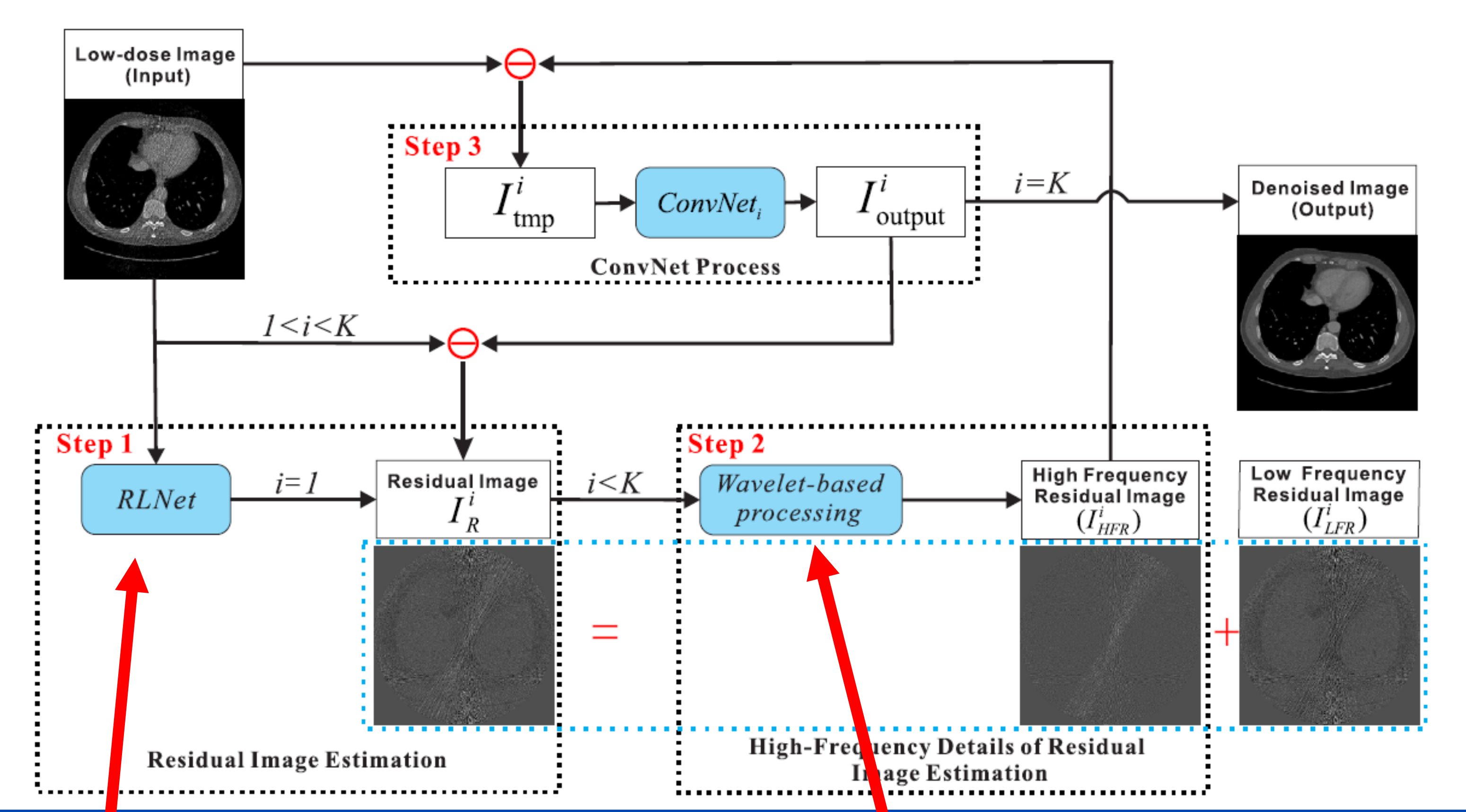
Noise Removal Example 1

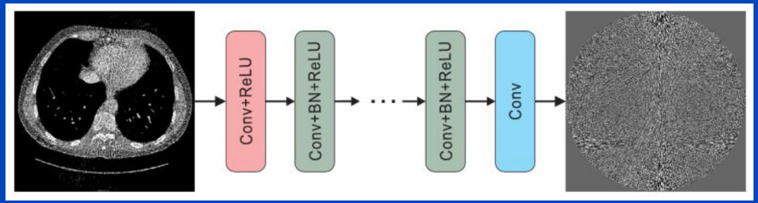


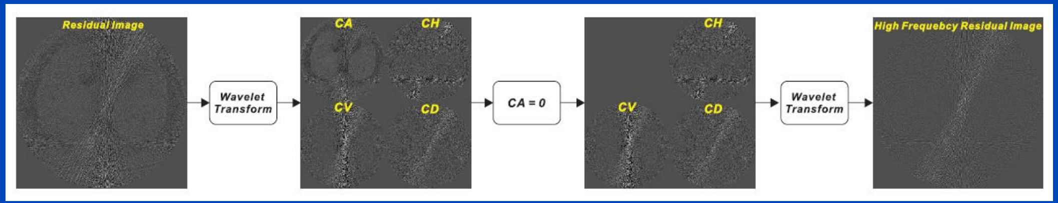
Denoised full dose

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.

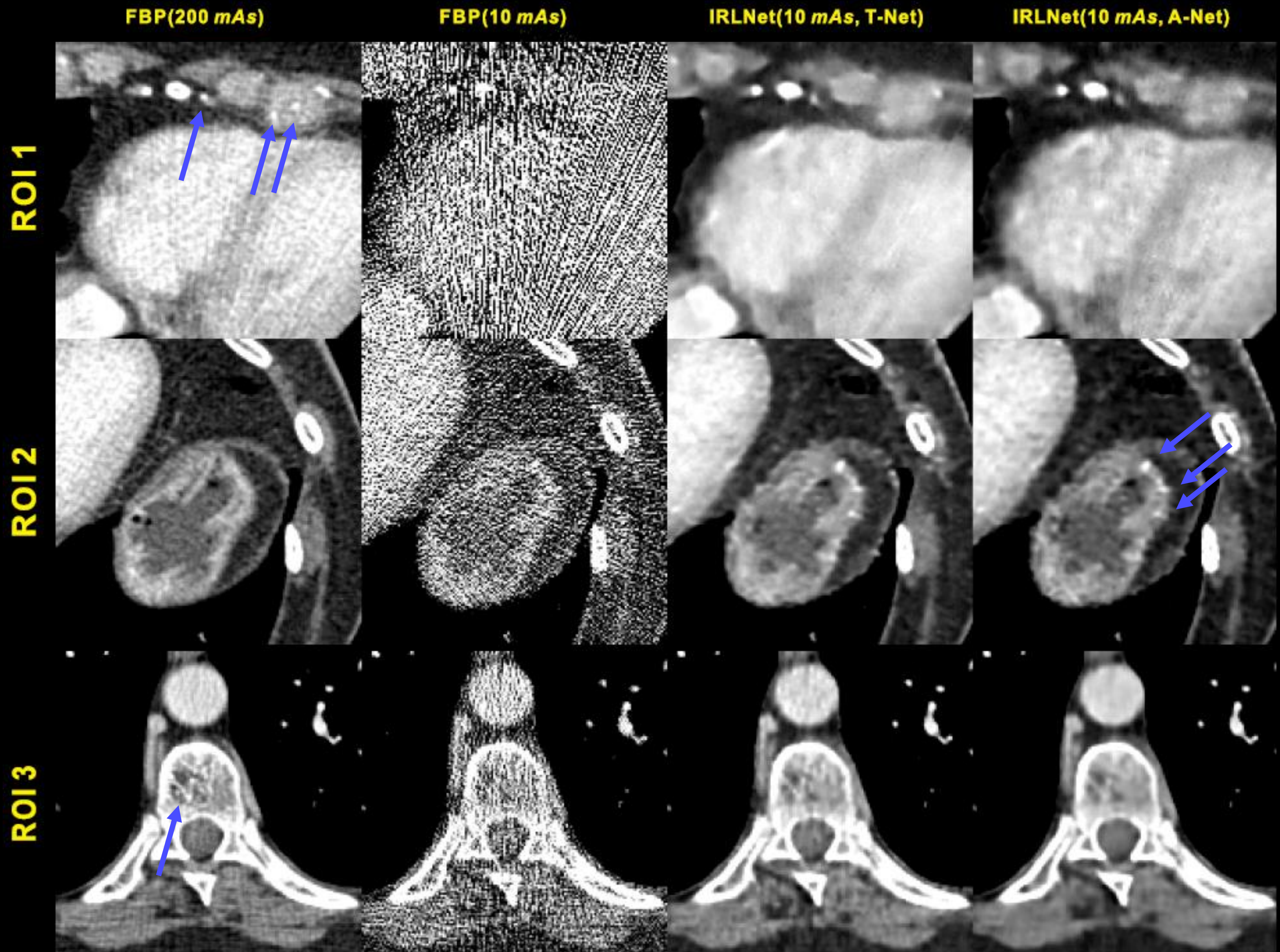
Noise Removal Example 2

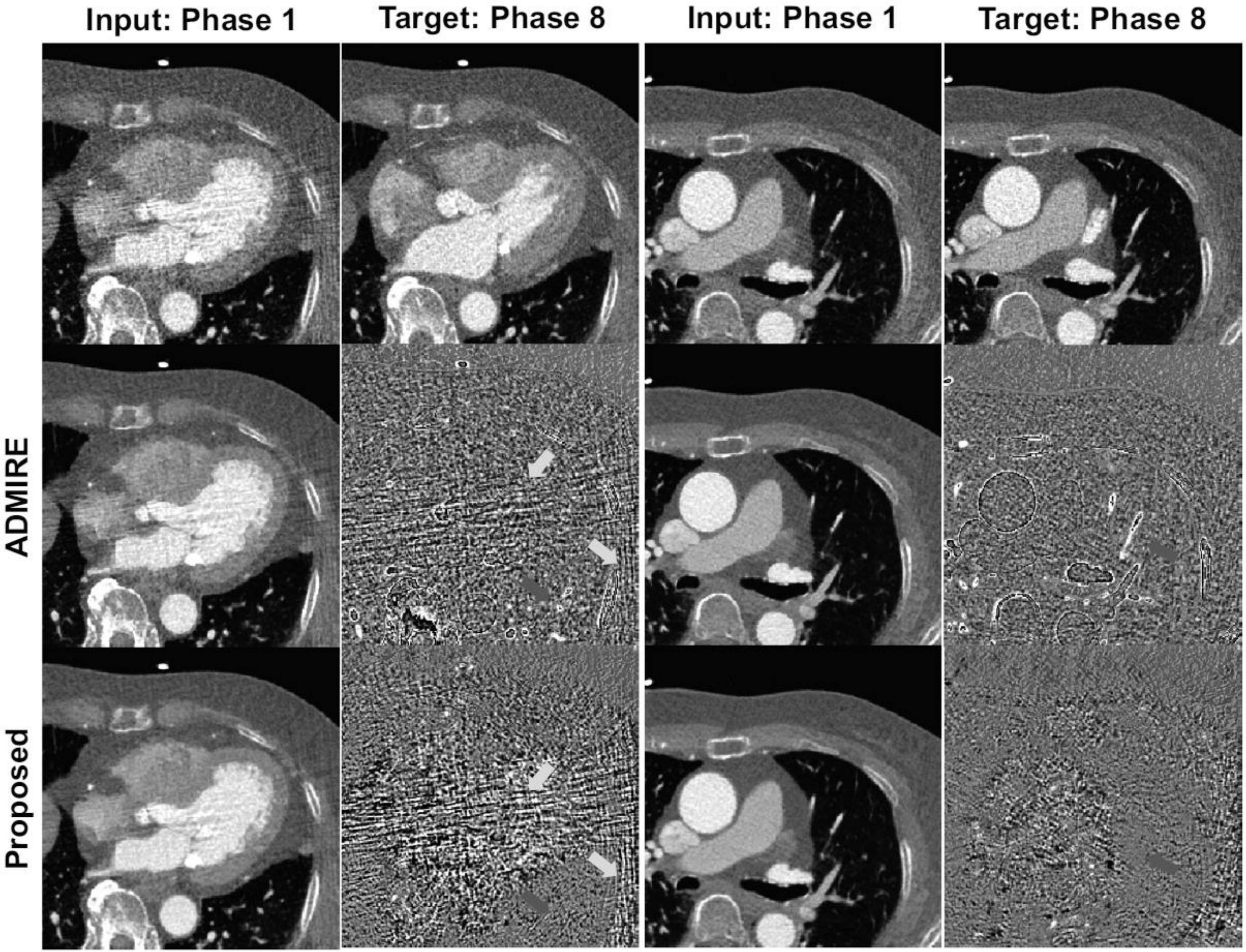






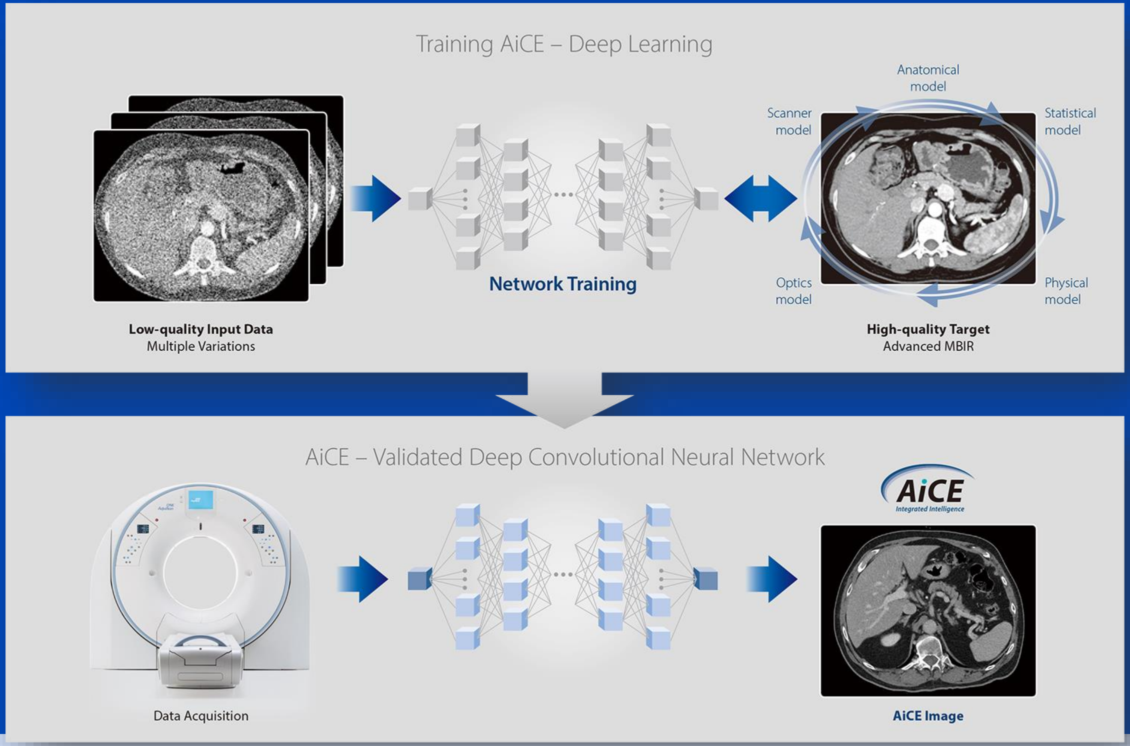
Y. Wang et al. Iterative quality enhancement via residual-artifact learning networks for low-dose CT.
Phys. Med. Biol. 63:215004, 2018.


FBP(200 mAs)
FBP(10 mAs)
IRLNet(10 mAs, T-Net)
IRLNet(10 mAs, A-Net)
ROI 1
ROI 2
ROI 3


Input: Phase 1
Target: Phase 8
Input: Phase 1
Target: Phase 8
ADMIRE
Proposed

Noise Removal: Canon's AiCE

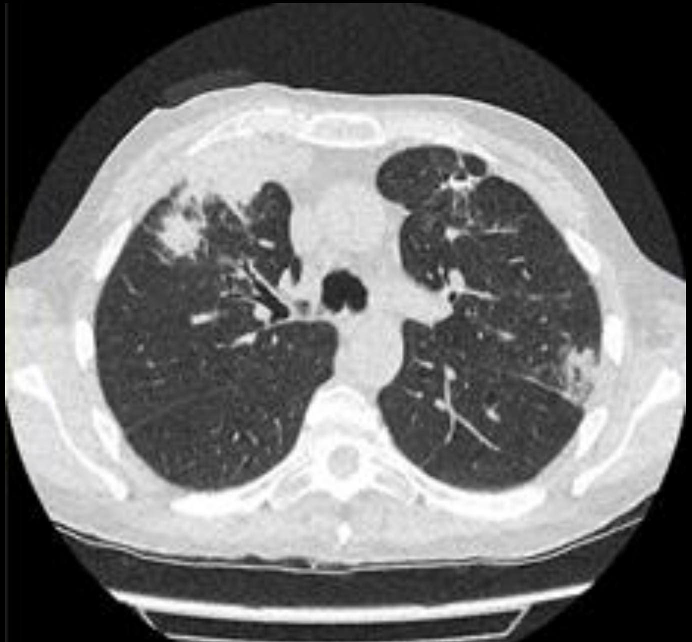
- Advanced intelligent Clear-IQ Engine (AiCE)
- Trained to restore low-dose CT data to match the properties of FIRST, the model-based IR of Canon.
- FIRST is applied to high-dose CT images to obtain a high fidelity training target



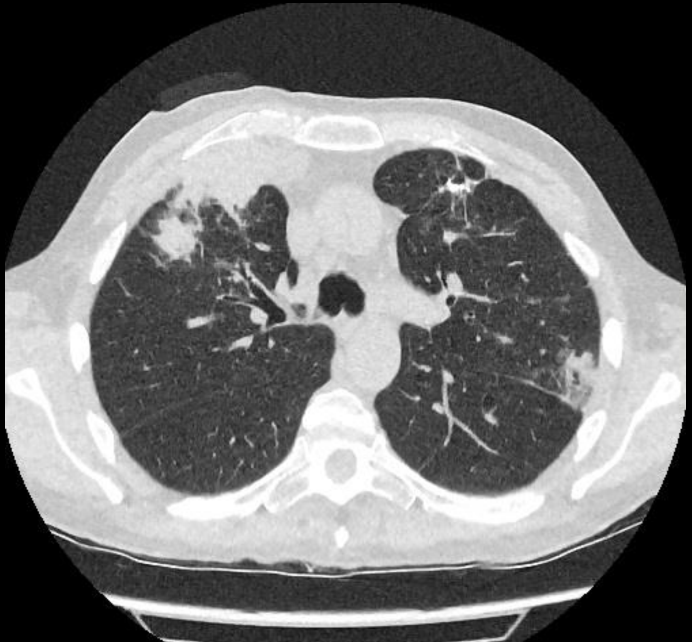
K. Boedeker. AiCE Deep Learning Reconstruction: Bringing the Power of Ultra High Resolution CT to Routine Imaging. Whitepaper, Canon, 2019.

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


FBP FC52 (analytical recon)


AIDR3De FC52 (image-based iterative)


FIRST Lung (full iterative)


AiCE Lung (deep learning)

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 either
  - FBP images to match the properties of Veo, GE's model-based IR (arXiV-Paper by GE)
  - sinograms to match the properties of FBP (white paper by GE)
- No information in how the training is conducted for the product implementation.

Ground truth training data are CT images reconstructed by FBP that can faithfully represent the scanned object.

ervised Training

ining process includes training, validation, and testing, which
pervised by GE Healthcare CT image quality experts and
nced radiologists.

g starts with an objective task and selection of the training data,
ncludes the input data to the neural network and the corresponding
ed output data. For each scanned object, both a high-dose,
se dataset and a low-dose, high-noise dataset are acquired. Images
tructed with the high-dose dataset produce the ground truth. The
gine is applied on the low-dose datasets to produce an estimation
econstructed images. Since the ground truth is known, it is used as
ning target for the deep learning-based reconstruction engine.

The training process is outlined below:

- The DLIR engine generates the output image from an input sinogram that is acquired with low radiation dose
- The features of the temporary output image are compared to the ground truth image to find the differences in terms of image noise, noise texture, low-contrast resolution, high-contrast spatial resolution, and other metrics
- Millions of parameters representing the DNN are fine-tuned through embedded backpropagation based on those differences. The goal of this parameter optimization is to reduce the difference between the DLIR output and the ground truth images

2.5D DEEP LEARNING FOR CT IMAGE RECONSTRUCTION USING A MULTI-GPU IMPLEMENTATION

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[eess.IV] 20 Dec 2018

ABSTRACT

While Model Based Iterative Reconstruction (MBIR) of CT scans has been shown to have better image quality than Filtered Back Projection (FBP), its use has been limited by its high computational cost. More recently, deep convolutional neural networks (CNN) have shown great promise in both denoising and reconstruction applications. In this research, we propose a fast reconstruction algorithm, which we call Deep Learning MBIR (DL-MBIR), for approximating MBIR using a deep residual neural network. The DL-MBIR method is trained to produce reconstructions that approximate true MBIR images using a 16 layer residual convolutional neural network implemented on multiple GPUs using Google Tensorflow. In addition, we propose 2D, 2.5D and 3D variations on the DL-MBIR method and show that the 2.5D method achieves similar quality to the fully 3D method, but with re-

streaking artifacts caused by sparse projection views in CT images [8]. More recently, Ye, et al. [9] developed method for incorporating CNN denoisers into MBIR reconstruction as advanced prior models using the Plug-and-Play framework [10, 11].

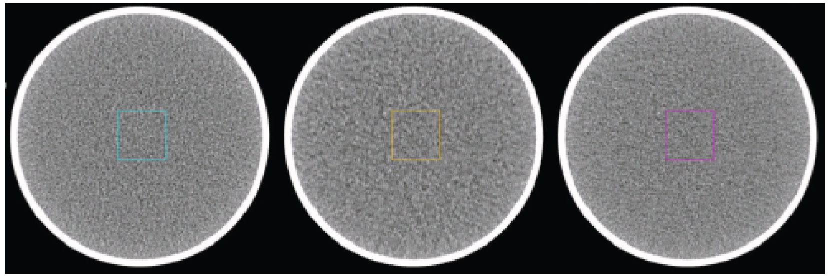
In this paper, we propose a fast reconstruction algorithm, which we call Deep Learning MBIR (DL-MBIR), for approximately achieving the improved quality of MBIR using a deep residual neural network. The DL-MBIR method is trained to produce 3D reconstructions that approximate true MBIR images using a 16 layer residual convolutional neural network implemented on multiple GPUs using Google Tensorflow. We present three implementations of DL-MBIR corresponding to processing the data in 2D, 2.5D and 3D. While the 3D processing is shown to offer the best fidelity to MBIR reconstruction, it requires 3D convolutions that increase computation

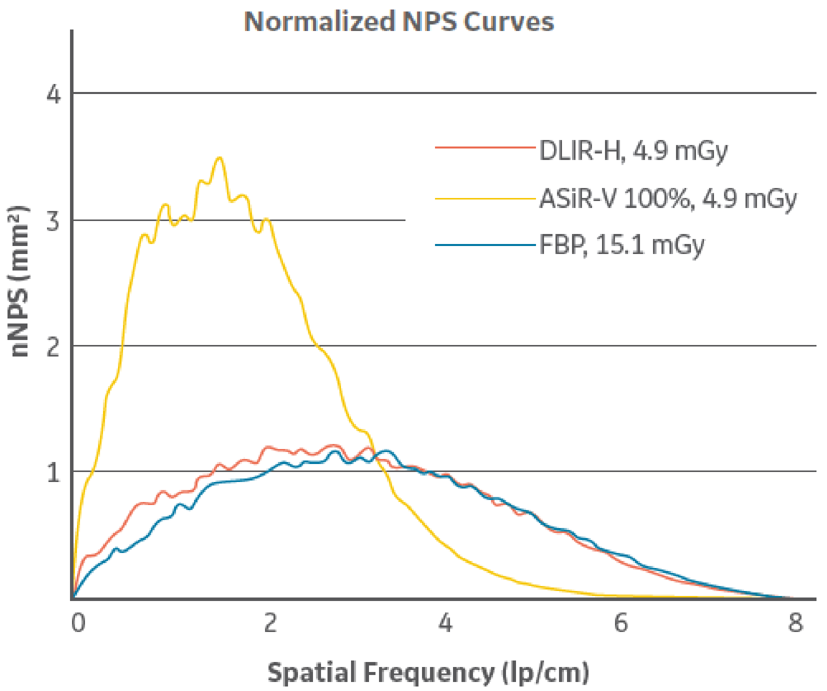
Noise Reduction: GE's True Fidelity

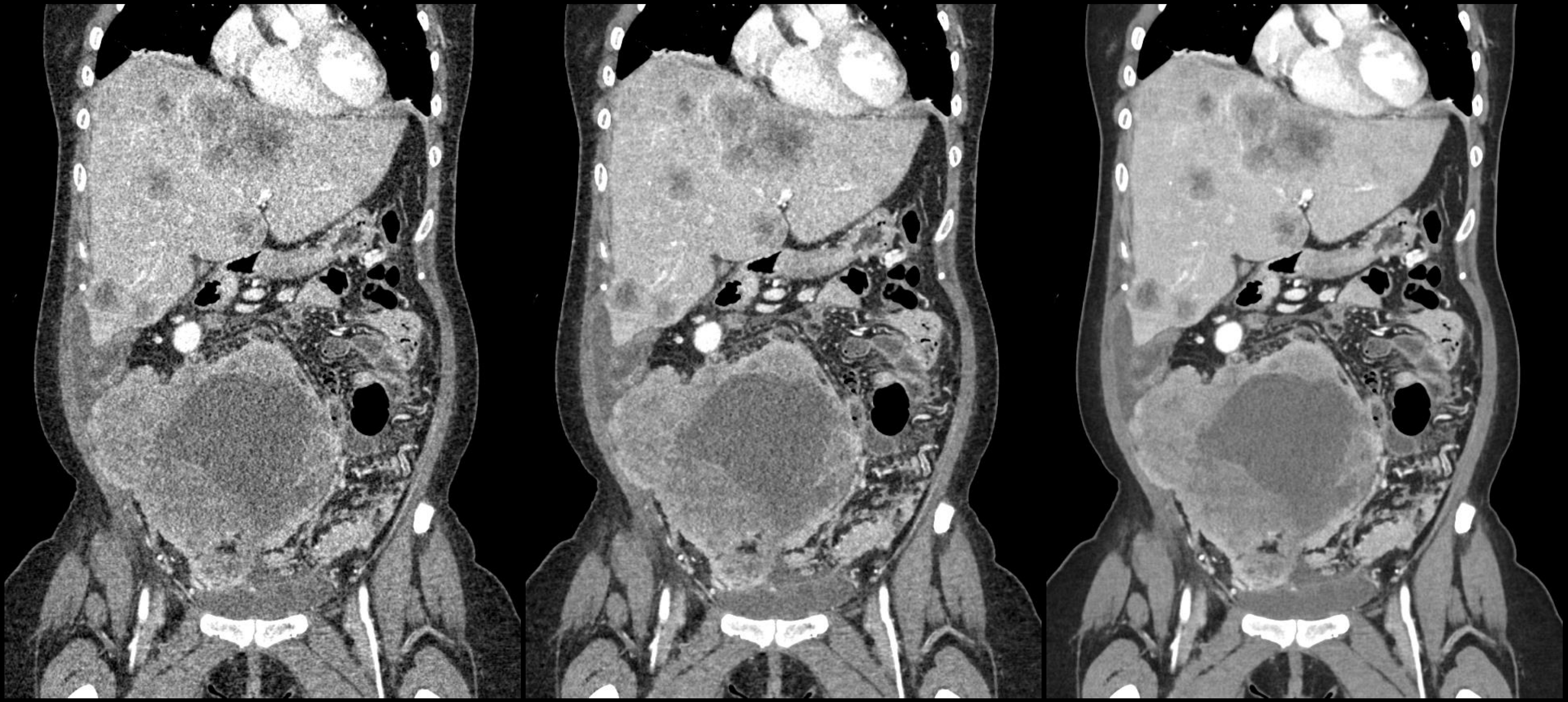
- Based on a deep CNN
- Trained to restore low-dose CT data to match the properties of high quality FBP datasets.
- Said to preserve noise texture and NPS

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, 15.1 mGy | ASiR-V 100%, 4.9 mGy | DLIR-H, 4.9 mGy





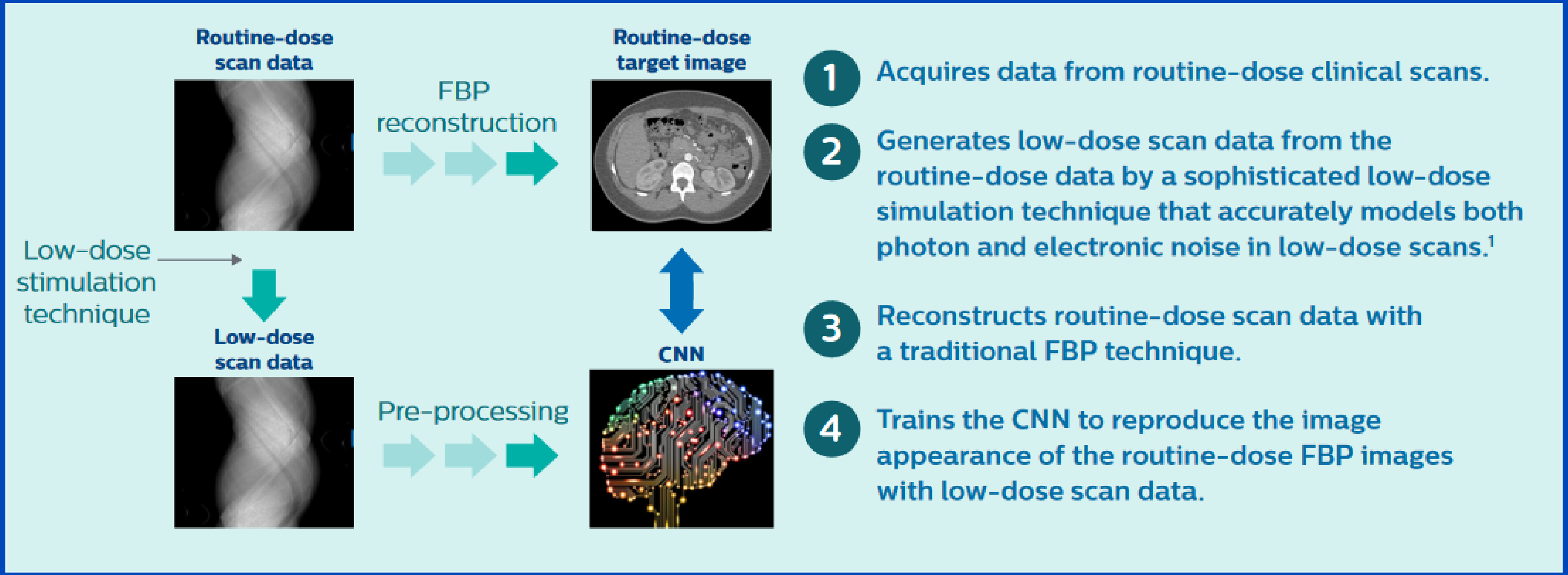


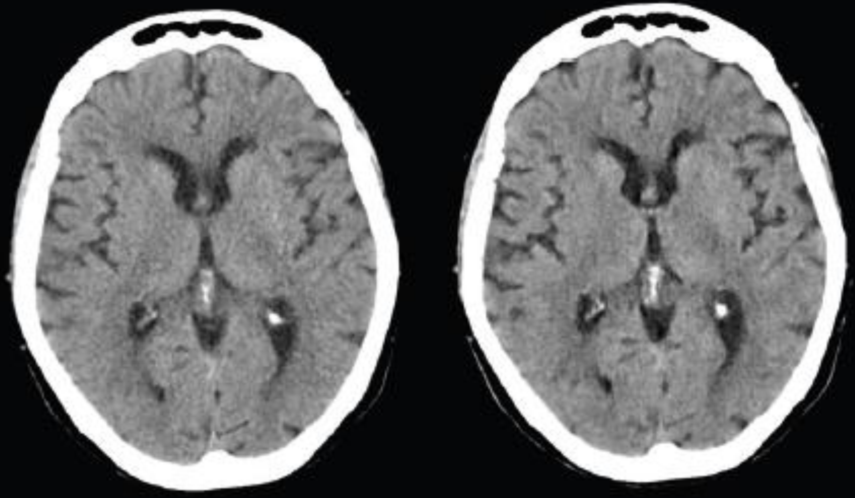
FBP | ASIR V 50% | True Fidelity

Courtesy of GE Healthcare

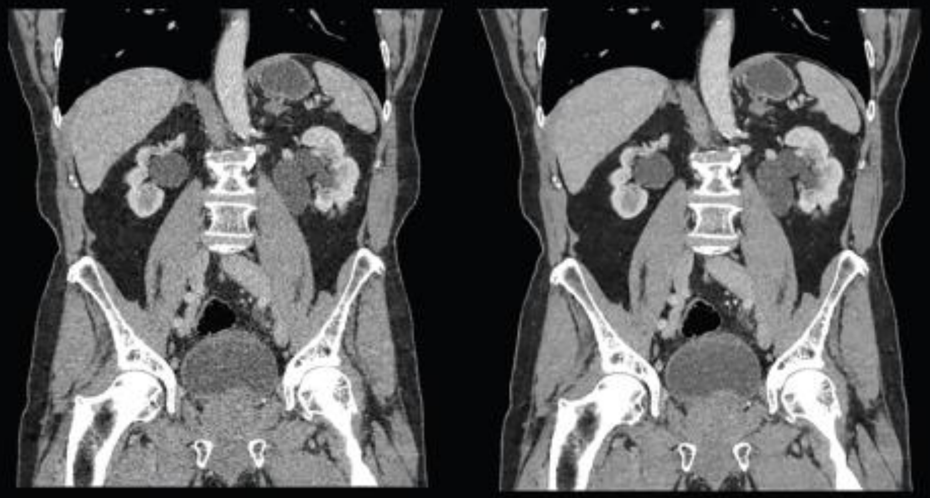
Noise Removal: Philips' Precise Image

- 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.



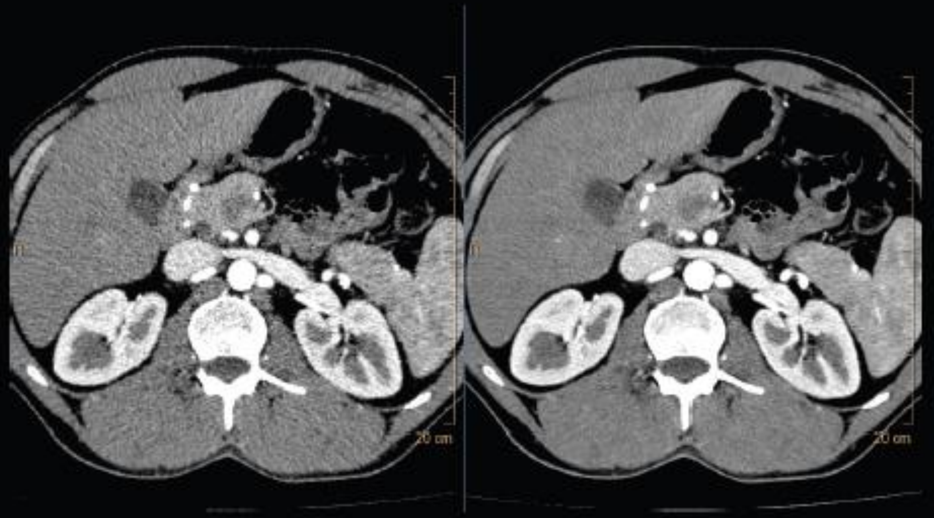


iDose^4 1.4 mSv   Precise Image 0.7 mSv



iDose^4 5.1 mSv   Precise Image 2.6 mSv

iDose^4 1.5 mSv   Precise Image 0.75 mSv

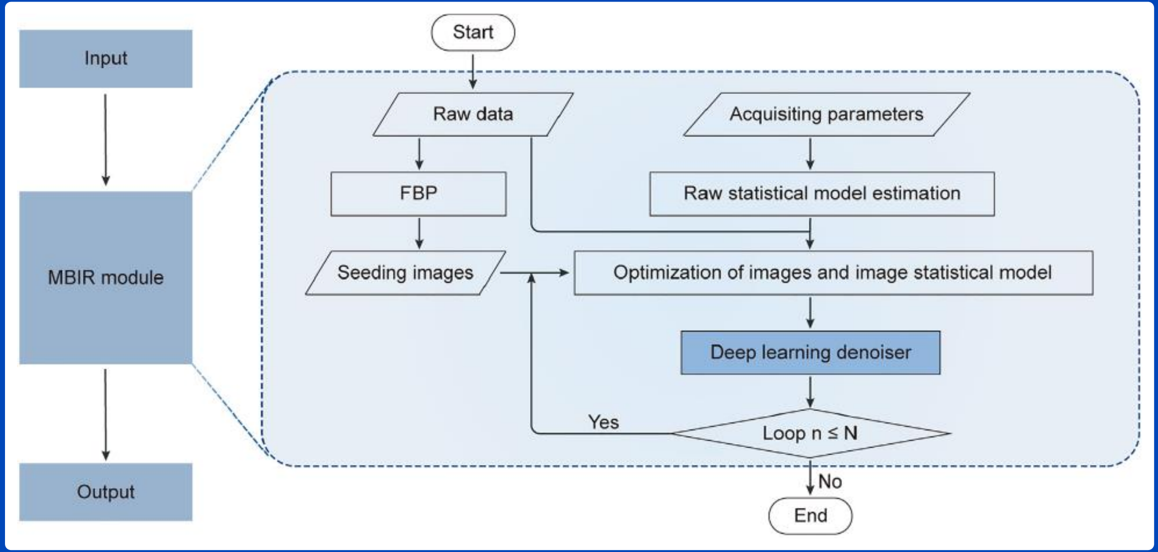


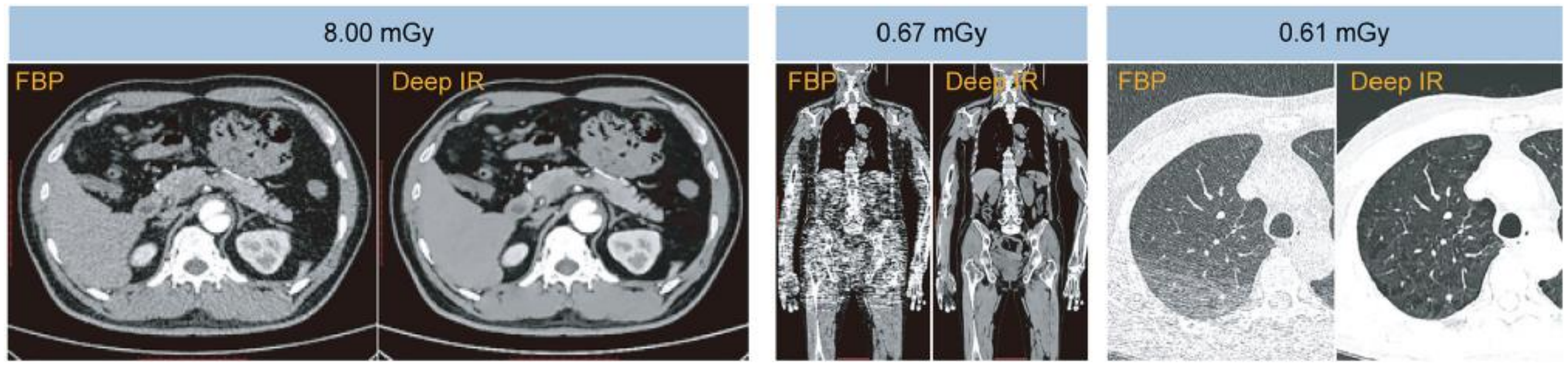
iDose^4 5.4 mSv   Precise Image 2.6 mSv

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

Noise Removal: United Imaging‘s Artificial Intelligence Iterative Reconstruction (AIIR)

- AIIR is an iterative reconstruction algorithm whose regularizer is replaced by a pretrained neural network
- AI regularization is done in each iteration step





Liao et al. Fast and low-dose medical imaging generation empowered by hybrid deep-learning and iterative reconstruction. Cell Reports Medicine (4), July 2023.

dkfz.

CT Vendor-Based DL Denoising Algorithms

Name	Vendor	Source	Labels	Comments
AiCE	Canon	Low dose AIDR3D images (by noise injection)	FIRST reconstruction of normal dose data	
True Fidelity	GE	Low dose rawdata/images (by noise injection)	FBP reconstruction of normal/high dose data	Probably uses BP layer. Said to preserve noise texture.
Precise Image	Philips	Low dose images (by noise injection)	FBP reconstruction of normal dose data	
-	Siemens	-	-	
AIIR	United	Low dose sinograms (by noise injection?)	Iterative reconstruction of normal dose data	Neural network regularizes IR

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Study	Topic	Dose Reduction	Assessment	Reconstruction	Vendor
Beregi et al., 2022	low-dose abdomen phantom	79%	objective	AiCE	Canon
Hirai et al., 2022a	low-dose multiphase hepatic	52%	objective, subjective	AiCE	Canon
Hirai et al., 2022b	low-dose pediatric 80 kV	54%	objective, subjective	AiCE	Canon
Jin et al., 2022	low-dose interstitial lung disease	62%	objective, subjective	AiCE	Canon
Loffroy et al., 2022	low-dose head & neck	43%	objective, subjective	AiCE	Canon
Sun et al., 2022	ultra-low-dose urolithiasis	75%	objective, subjective	AiCE	Canon
Yoshioka et al., 2022	low-dose contrast abdomen	40%	objective, subjective	AiCE	Canon
Awai et al., 2021	low-dose abdominal UHR	30%	objective, subjective	AiCE	Canon
Dillman et al., 2021	pediatric detectability	52%	objective, subjective	AiCE	Canon
Loffroy et al., 2021	cardiac CTA stroke	40%	objective, subjective	AiCE	Canon
Kalra et al., 2020	low-dose lesion detection	83%	subjective	AiCE	Canon
Song et al., 2024	low-dose chest, lung parenchyma	86%	objective, subjective	AiCe	Canon
Othmann et al., 2023	ultra-high-resolution Head and Neck	30%	objective, subjective	AiCe	Canon
Willemink et al., 2023	principles & prospects	71%	mixed	meta	many
Strigari et al., 2023	image quality phantom	96%	objective	Precise Image	Philips
Noel et al., 2024	lung phantom	25%-67%	objective	Precise Image	Philips
Deng et al., 2022	ultra-low-dose pulmonary nodules phantom	72%	objective, subjective	TrueFidelity	GE
Lee et al., 2021	pediatric chest & abdomen	63%	objective, subjective	TrueFidelity	GE
Funama et al., 2024	preoperative transcatheter aortic valve implantation	30%	objective, subjective	TrueFidelity	GE
Xi et al., 2024	colorectal cancer	75%	objective, subjective	AIIR	United

Conclusions

- Most DL reconstruction/restoration algorithms aim at noise reduction which can then be converted into a dose reduction.
- Substantial improvements in image quality or dose reduction are clinically seen.

Thank You!

- This presentation will soon be available at www.dkfz.de/ct.
- Job opportunities through DKFZ's international PhD or Postdoctoral Fellowship programs (marc.kachelriess@dkfz.de).
- Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.