

# Detecting and Avoiding Pitfalls in AI-Based Image ~~Reconstruction~~ Formation

= Acquisition, Preprocessing,  
Reconstruction, Postprocessing

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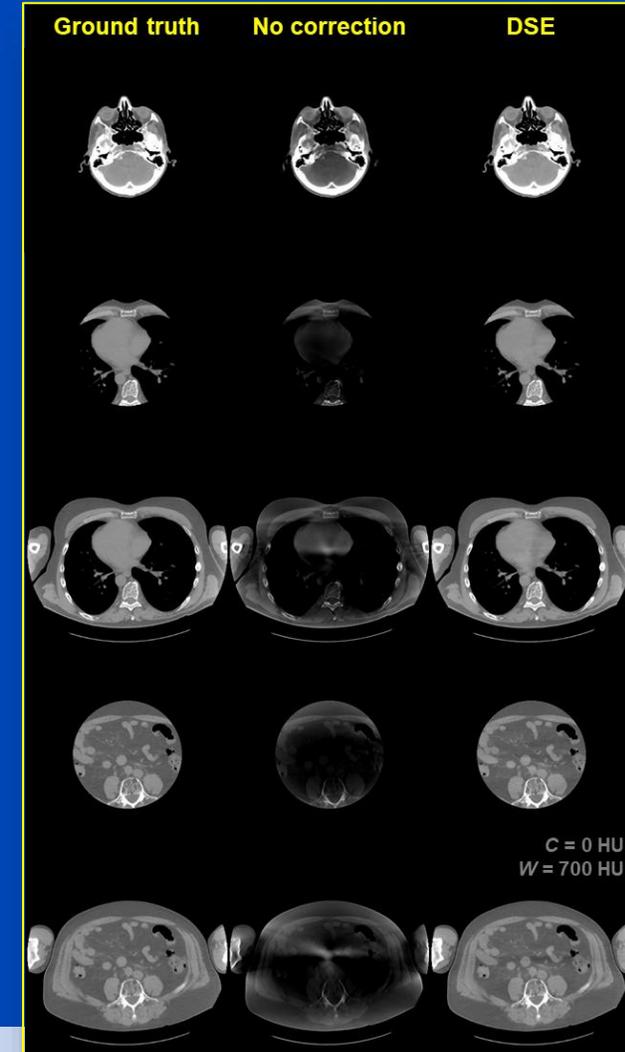
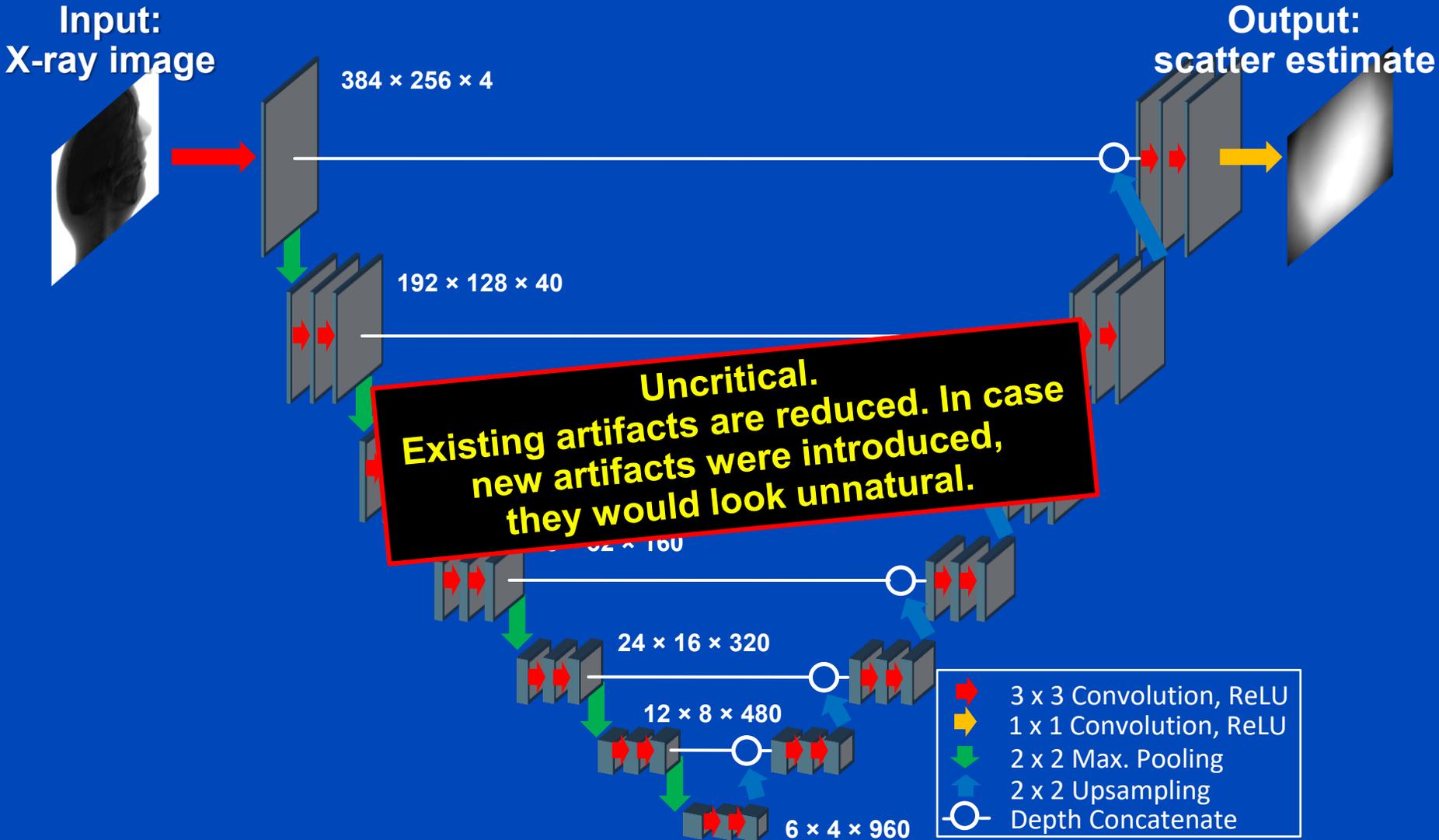
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Examples for

# AI IN CT IMAGE FORMATION

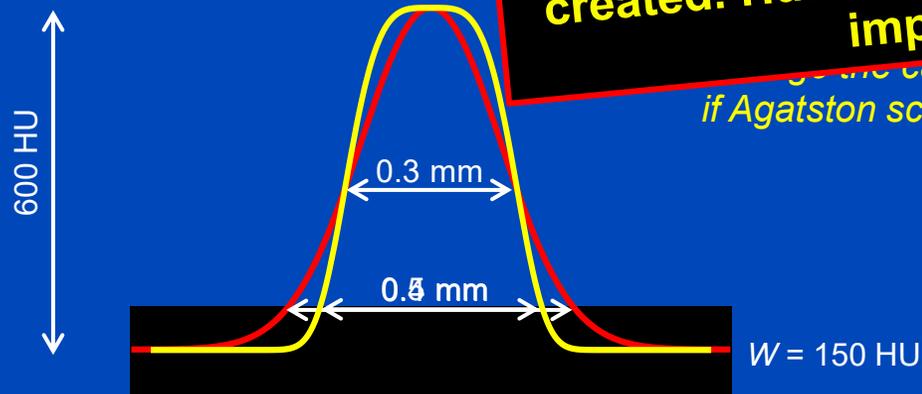
# Deep Scatter Estimation

## Network architecture & scatter estimation framework



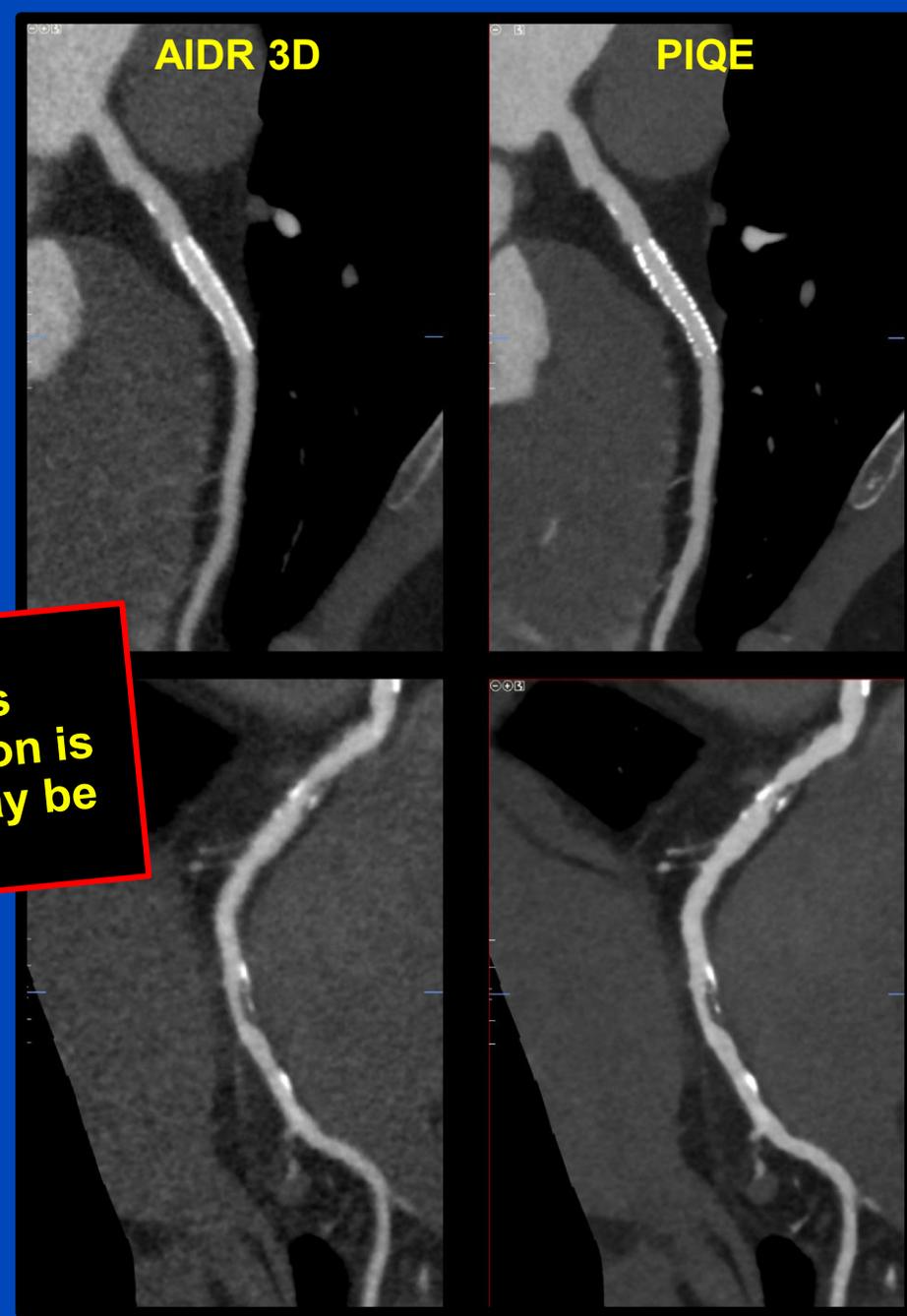
# Canon PIQE

- 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.



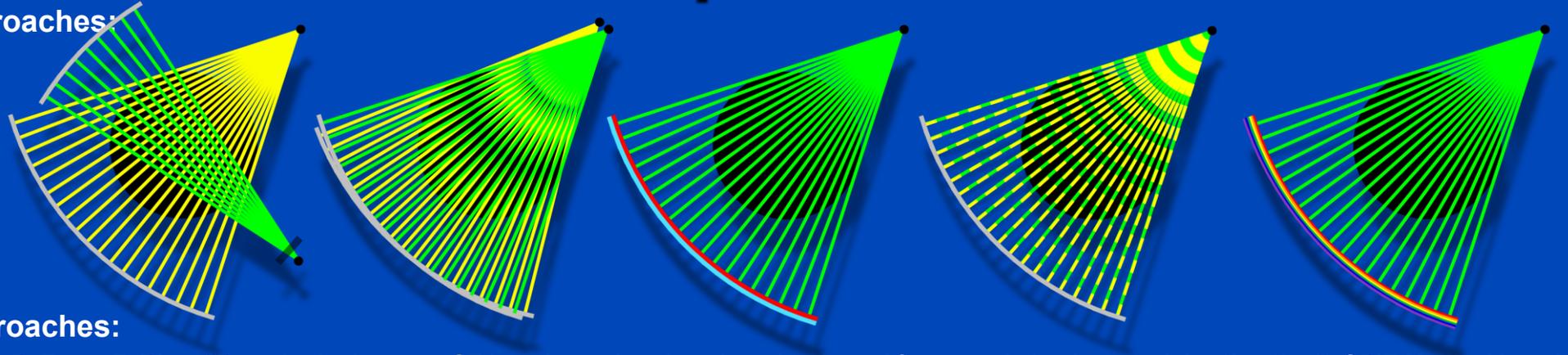
**OK.**  
Apparent spatial resolution is increased, but no new information is created. Human detectability may be improved.

*... of the calcium score, if Agatston scoring is used.*



# True and Fake Spectral CT

Existing true spectral CT approaches:



Existing fake spectral CT approaches:

[1] J. Ma, Y. Liao, Y. Wang, S. Li, J. He, D. Zeng, Z. Bian, “**Pseudo dual energy CT** imaging using deep learning-based framework: basic material estimation“, *SPIE Medical Imaging 2018*.

[2] W. Zhao, T. Lv, P. Gao, L. Shen, X. Dai, K. Cheng, M. Jia, Y. Chen, L. Xing, “A deep learning approach for dual-energy CT imaging **using a single-energy CT** data“, *Fully3D 2019*.

[3] D. Lee, H. Kim, B. Choi, H. J. Kim, “Development of a deep neural network for generating synthetic dual-energy chest x-ray images **with single x-ray exposure**“, *PMB 64(11)*, 2019.

[4] L. Yao, S. Li, D. Li, M. Zhu, Q. Gao, S. Zhang, Z. Bian, J. Huang, D. Zeng, J. Ma, “Leveraging deep generative model for direct energy-resolving CT imaging **via existing energy-integrating CT** images“, *SPIE Medical Imaging 2020*.

[5] D. P. Clark, F. R. Schwartz, D. Marin, J. C. Ramirez-Giraldo, C. T. Badea, “Deep learning based **spectral extrapolation** for dual-source, dual-energy x-ray CT“, *Med. Phys.* 47 (9): 4150–4163, 2020.

[6] C. K. Liu, C. C. Liu, C. H. Yang, H. M. Huang, “Generation of brain dual-energy CT **from single-energy CT** using deep learning“, *Journal of Digital Imaging* 34(1):149–161, 2021.

[7] T. Lyu, W. Zhao, Y. Zhu, Z. Wu, Y. Zhang, Y. Chen, L. Luo, S. Li, L. Xing, “Estimating dual-energy CT imaging **from single-energy CT** data with material decomposition convolutional neural network“, *Medical Image Analysis* 70:1–10, 2021.

[8] F. R. Schwartz, D. P. Clark, Y. Ding, J. C. Ramirez-Giraldo, C. T. Badea, D. Marin, “Evaluating renal lesions using **deep-learning based extension** of dual-energy FoV in dual-source CT—A retrospective pilot study“, *European Journal of Radiology* 139:109734, 2021.

[9] Y. Li, X. Tie, K. Li, J. W. Garrett, G.-H. Chen, “Deep-En-Chroma: **mining the spectral fingerprints in single-kV CT** acquisitions using energy integration detectors“, *SPIE Medical Imaging 2022*.

...

[19] T. Wang, C. Jiang, W. Ding, Q. Chen, D. Shen, Z. Ding, “Deep-learning generated synthetic **material decomposition images based on single-energy CT** to differentiate intracranial hemorrhage and contrast staining within 24 hours after endovascular thrombectomy“, *CNS Neurosci. Ther.* 31(1), 2025.

- [1] J. Ma, Y. Liao, Y. Wang, S. Li, J. He, D. Zeng, Z. Bian, “**Pseudo dual energy CT** imaging using deep learning-based framework: basic material estimation“, *SPIE Medical Imaging 2018*.
- [2] W. Zhao, T. Lv, P. Gao, L. Shen, X. Dai, K. Cheng, M. Jia, Y. Chen, L. Xing, “A deep learning approach for dual-energy CT imaging **using a single-energy CT data**“, *Fully3D 2019*.
- [3] D. Lee, H. Kim, B. Choi, H. J. Kim, “Development of a deep neural network for generating synthetic dual-energy chest x-ray images **with single x-ray exposure**“, *PMB 64(11)*, 2019.
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- [9] Y. Li, X. Tie, K. Li, J. W. Garrett, G.-H. Chen, “Deep-En-Chroma: **mining the spectral fingerprints in single-kV CT** acquisitions using energy integration detectors”, *SPIE Medical Imaging 2022*.
- [10] S. Charyyev, T. Wang, Y. Lei, B. Ghavidel, J. J. Beitler, M. McDonald, W. J. Curran, T. Liu, J. Zhou, X. Yang, “Learning-based synthetic dual energy CT imaging **from single energy CT** for stopping power ratio calculation in proton radiation therapy”, *Brit. J. Radiol.* 95(1129), 2022.
- [11] J. Jeong, A. Wentland, D. Mastrodicasa, G. Fananapazir, A. Wang, I. Banerjee, B. N. Patel, “Synthetic dual-energy CT reconstruction **from single-energy CT** Using artificial intelligence”, *Abdom. Radiol.* 48 (11): 3537–3549, 2023.
- [12] Y. Li, X. Tie, K. Li, R. Zhang, Z. Qi, A. Budde, T. M. Grist, G.-H. Chen, “A quality-checked and physics-constrained deep learning method to estimate **material basis images from single-kV contrast-enhanced chest CT** scans”, *Med. Phys.* 50(6):3368-3388, June 2023.
- [13] S. Kim, J. Lee, J. Kim, B. Kim, C. H. Choi, S. Jung, “Conversion of **single-energy CT to parametric maps of dual-energy CT** using convolutional neural network”, *Brit. J. Radiol.* 97 (1158): 1180–1190, 2024.
- [14] Y. Koike, S. Ohira, S. Kihara, Y. Anetai, H. Takegawa, S. Nakamura, M. Miyazaki, K. Konishi, N. Tanigawa, “**Synthetic low-energy monochromatic image generation** in single-energy computed tomography system using a transformer-based deep learning model”, *J. Imaging Inform. Med.* (5): 2688–2697, 2024.
- [15] M. Lee, H. Lee, D. Lee, H. Cho, J. Choi, B. K. Cha, K. Kim, “Framework for dual-energy-like chest radiography image synthesis **from single-energy computed tomography** based on cycle-consistent generative adversarial network”, *Med. Phys.* 51 (2): 1509–1530, 2024.
- [16] Y. Gao, H. Xie, C. W. Chang, J. Peng, S. Pan, R. L. J. Qiu, T. Wang, B. Ghavidel, J. Roper, J. Zhou, X. Yang, “CT-based **synthetic iodine map** generation using conditional denoising diffusion probabilistic model”, *Med. Phys.* 51(9): 6246–6258, 2024.
- [17] Y. Gao, H. Xie, C.-W. Chang, J. Peng, R. L. J. Qiu, T. Wang, J. Roper, B. Ghavidel, J. Zhou, X. Yang, “**Iodine map synthesis from non-contrast CT** using diffusion model”, *SPIE Medical Imaging 2024*.
- [18] Y. Gao, R. L. J. Qiu, H. Xie, C. W. Chang, T. Wang, B. Ghavidel, J. Roper, J. Zhou, X. Yang, “CT-based **synthetic contrast-enhanced dual-energy CT** generation using conditional denoising diffusion probabilistic model”, *Phys. Med. Biol.* 69(16): 165015, 2024.
- [19] T. Wang, C. Jiang, W. Ding, Q. Chen, D. Shen, Z. Ding, “Deep-learning generated synthetic **material decomposition images based on single-energy CT** to differentiate intracranial hemorrhage and contrast staining within 24 hours after endovascular thrombectomy”, *CNS Neurosci. Ther.* 31(1), 2025.

Different fake DECT algorithms

Fake 1

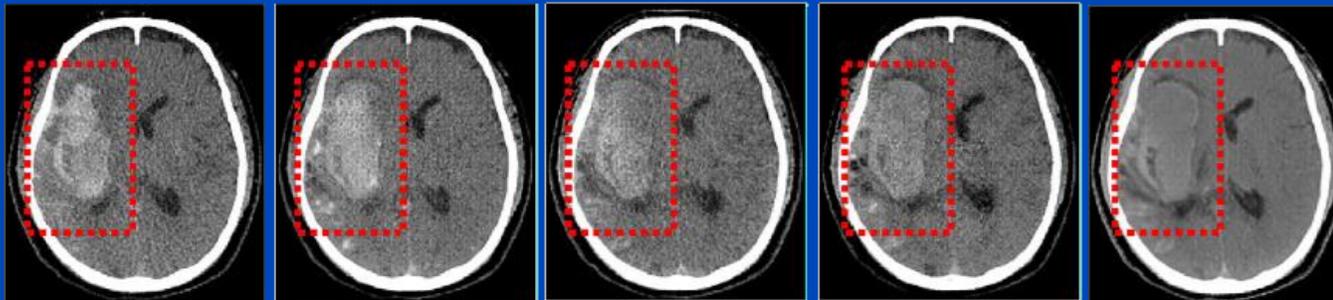
Fake 2

Fake 3

Fake 4

Fake 5

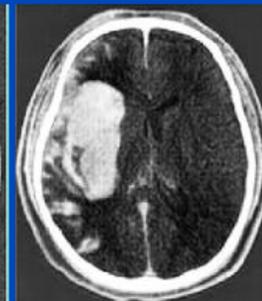
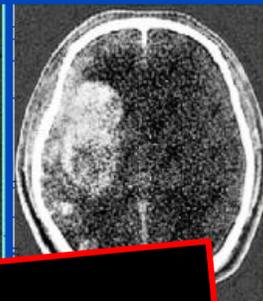
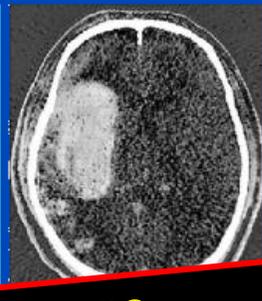
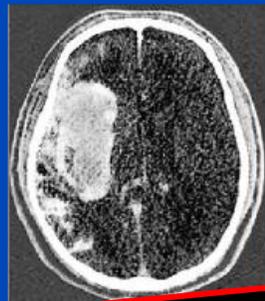
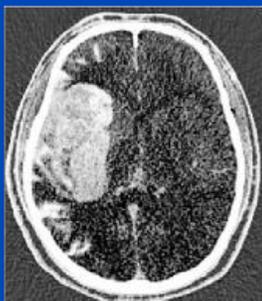
Intracranial Hemorrhage



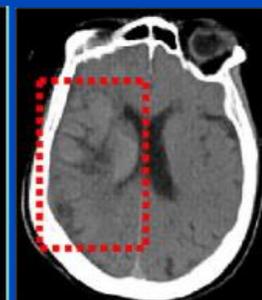
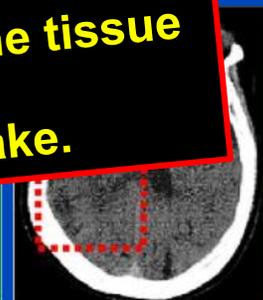
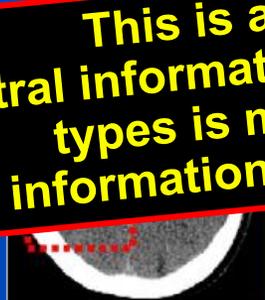
VNC (fake)

Iodine map (fake)

Single energy CT (non-fake)



Contrast Staining



VNC (fake)

Iodine map (fake)



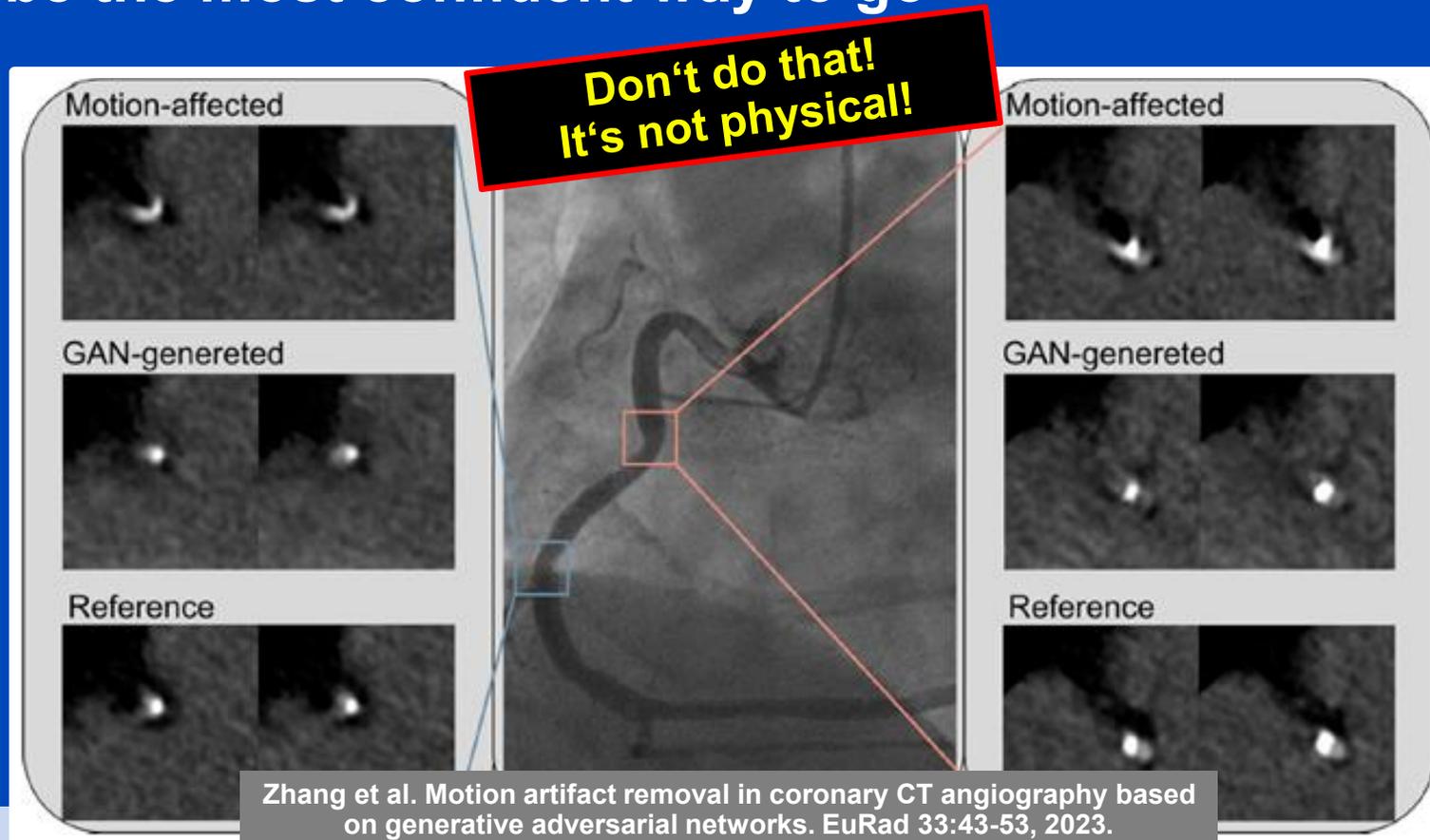
This is a no-go.  
No spectral information about the tissue types is measured.  
All information shown is fake.

Figure taken from T. Wang, C. Jiang, W. Ding, Q. Chen, D. Shen, Z. Ding, "Deep-learning generated synthetic material decomposition images based on single-energy CT to differentiate intracranial hemorrhage and contrast staining within 24 hours after endovascular thrombectomy", CNS Neurosci. Ther. 31(1), 2025.



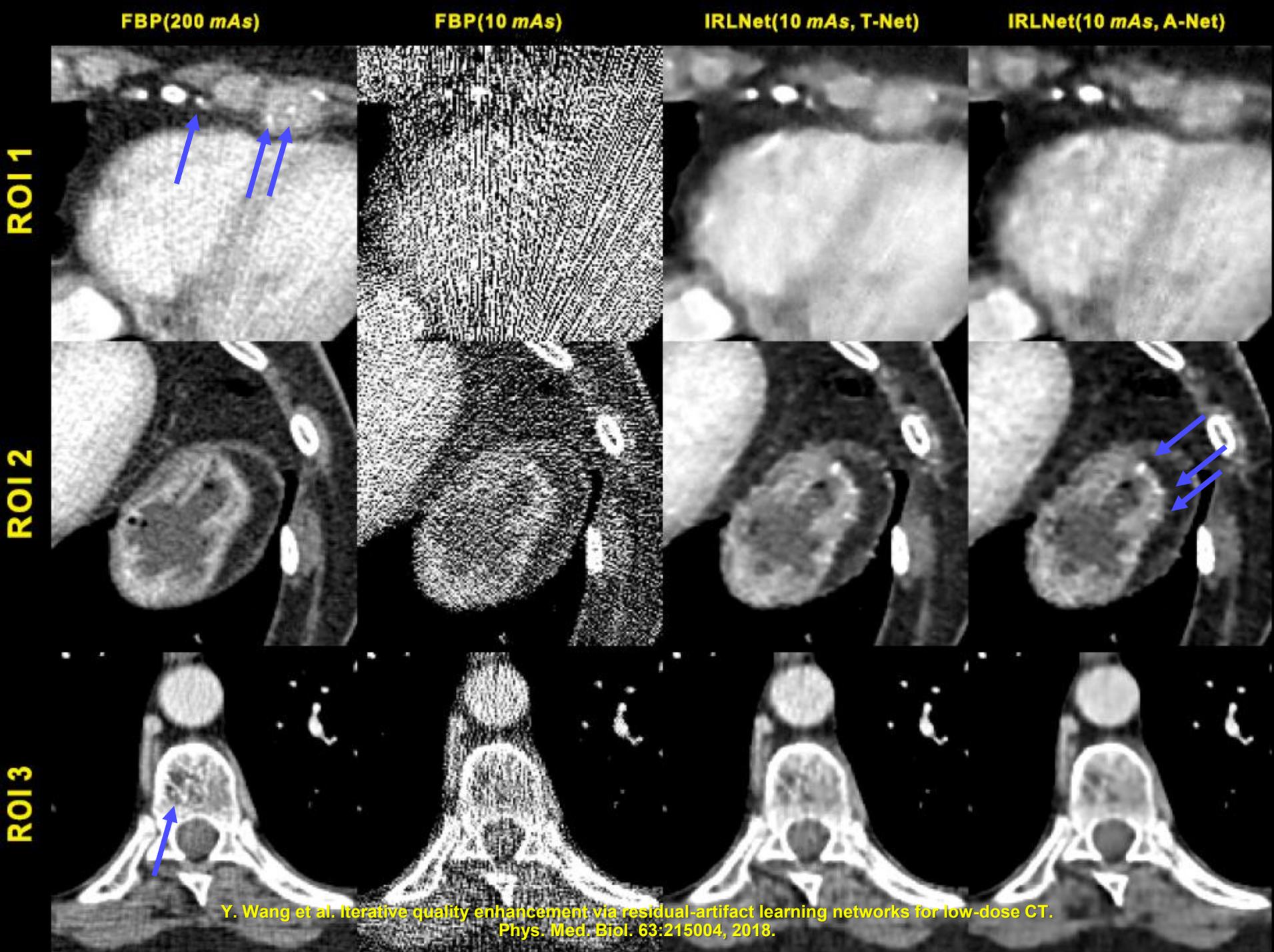
# Deep Cosmetic Motion Artifact Reduction

- Image-based correction = cosmetic correction = similar to pic beauty and others
- May not be the most confident way to go



Minimize pitfalls: User action, when in doubt

**COMPARE WITH NON-AI IMAGES**



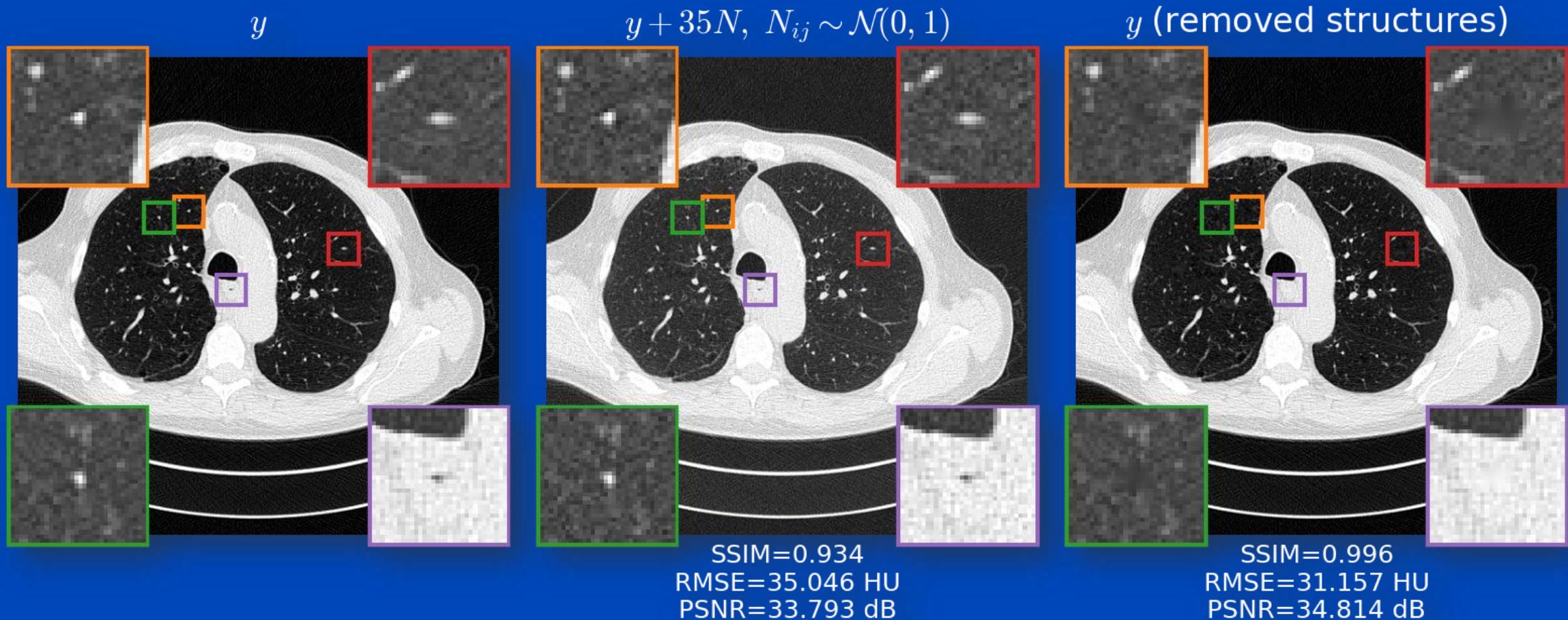
Y. Wang et al. Iterative quality enhancement via residual-artifact learning networks for low-dose CT. Phys. Med. Biol. 63:215004, 2018.

Minimize pitfall: Let small structures be just as important as large structures

# **A NEW METRIC FOR SUBTLE DETAILS**

# Attention: Each Pixel May be Significant!

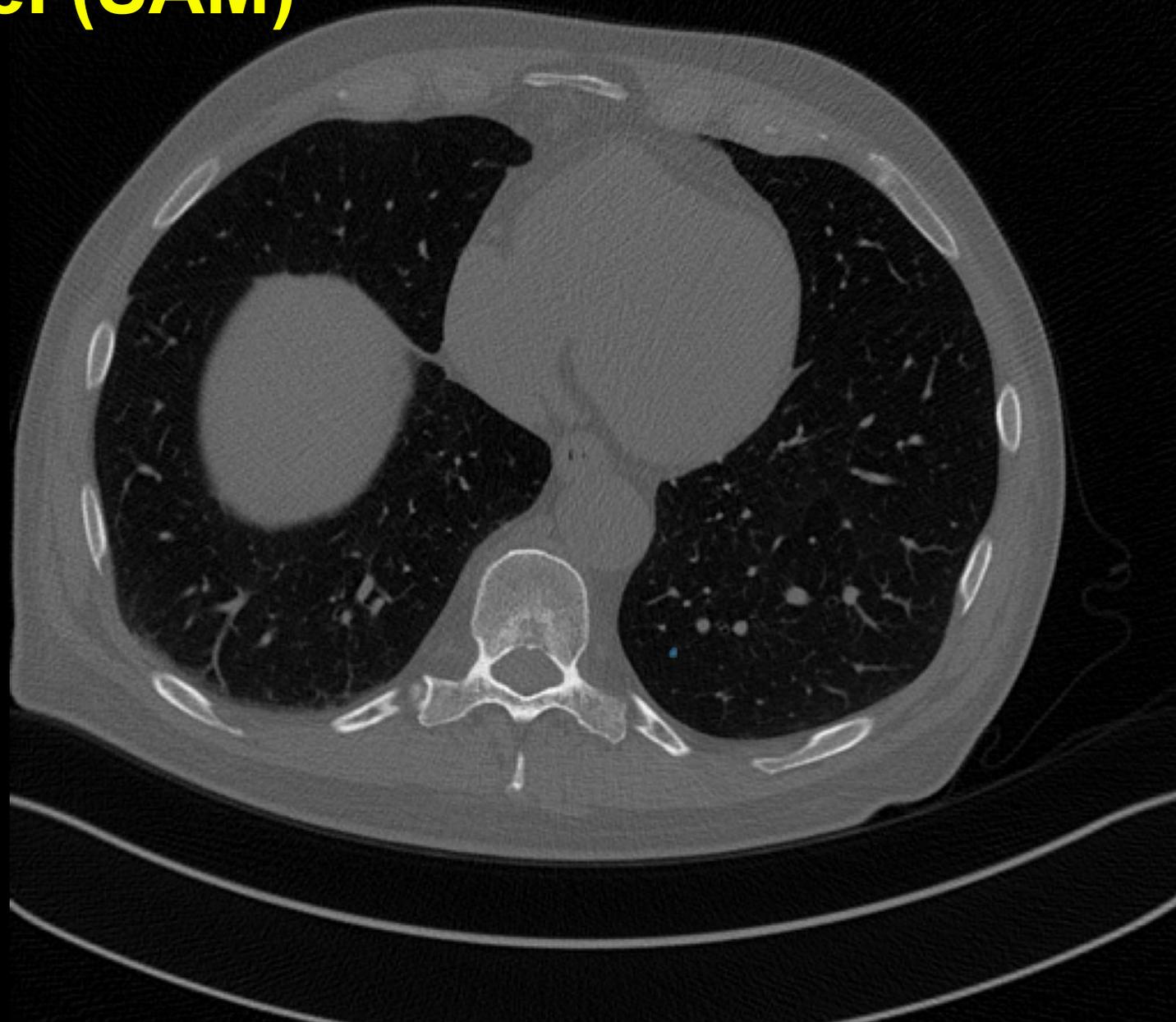
- MAE, PSNR, RMSE and SSIM\* are often used to quantify image quality, e.g. in loss functions or to rank algorithms.
- Alteration of a few pixels may mislead diagnosis.



\*SSIM also accounts in parts for the human visual system by using luminance, contrast and structure to estimate perceptual quality.

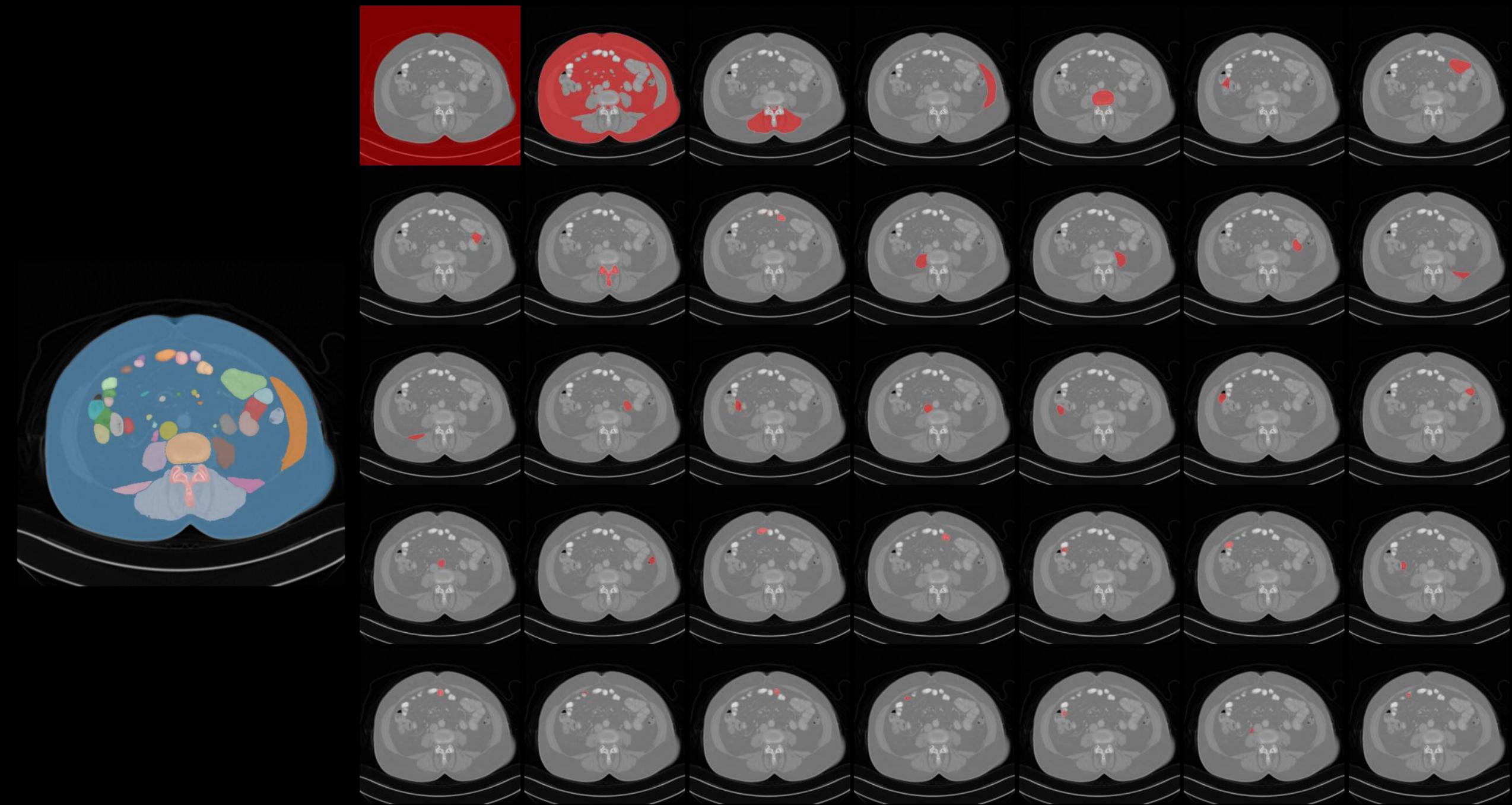
# Segment Anything Model (SAM)<sup>1</sup>

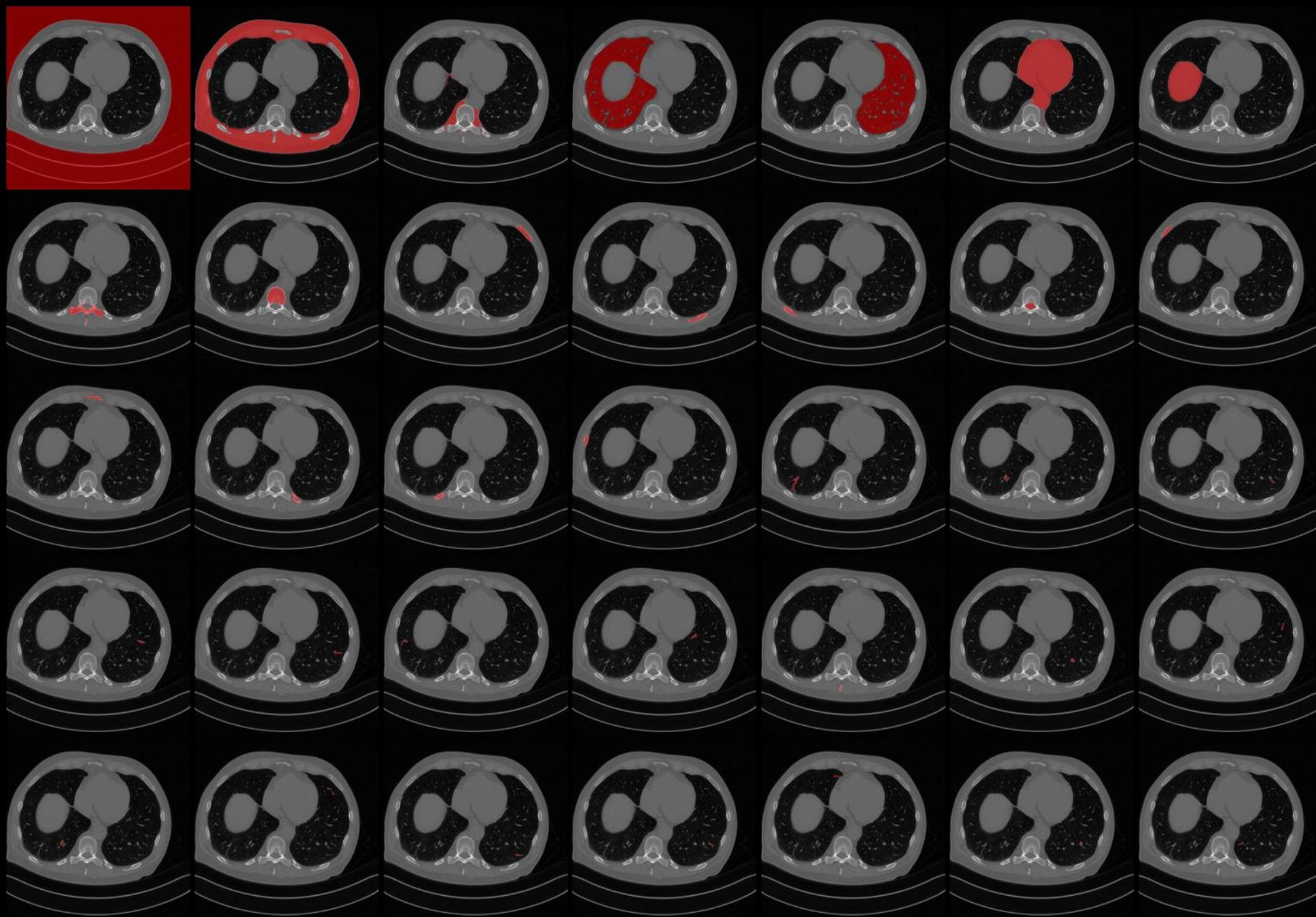
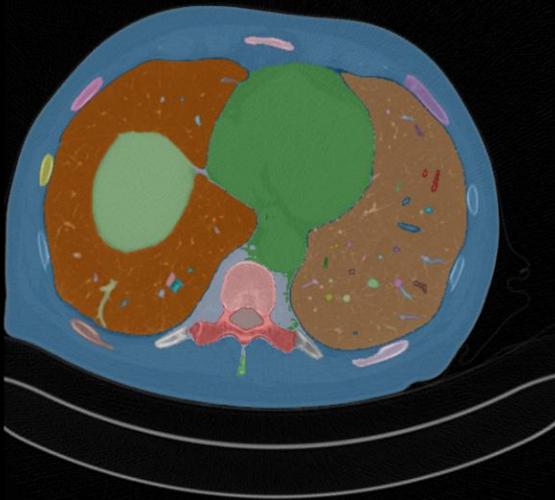
- SAM can automatically segment all structures in an image by predicting masks for all points on a grid.
- Many works proposed tuned versions of SAM for medical image segmentation<sup>2</sup>
- To make our metric work, we need to apply SAM
  - to the ground truth image
  - or to the denoised image
  - or to the noisy image.
- In the following, SAM is applied to the GT image.



<sup>1</sup>Kirillov, Alexander, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, et al. 2023. "Segment Anything." arXiv.

<sup>2</sup>Ma, Jun, Yuting He, Feifei Li, Lin Han, Chenyu You, and Bo Wang. 2024. "Segment Anything in Medical Images." *Nature Communications* 15 (1): 654.





# Segment RMSE (SRMSE)

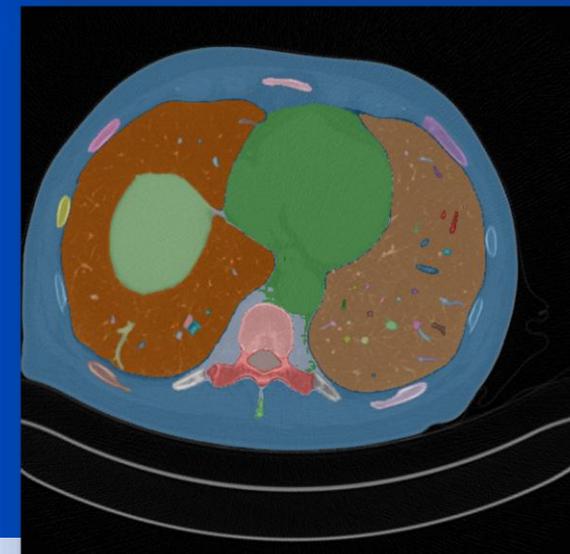
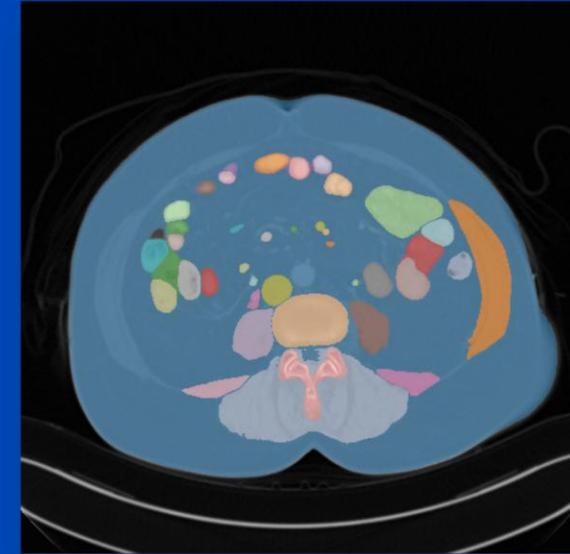
- Assume  $S$  segments from SAM for a given patient volume.
- Represent each segment by a binary mask volume  $m^{(s)} \in \{0, 1\}^N$  with  $N$  being the number of voxels.
- Define the segment-wise root mean square error between two images  $x$  and  $y$ , and segment  $s$ :

$$\text{SRMSE}(x, y; s) = \sqrt{\frac{\sum_{n=1}^N m_n^{(s)} (x_n - y_n)^2}{\sum_{n=1}^N m_n^{(s)}}}$$

- Using the set of all SRMSEs, define

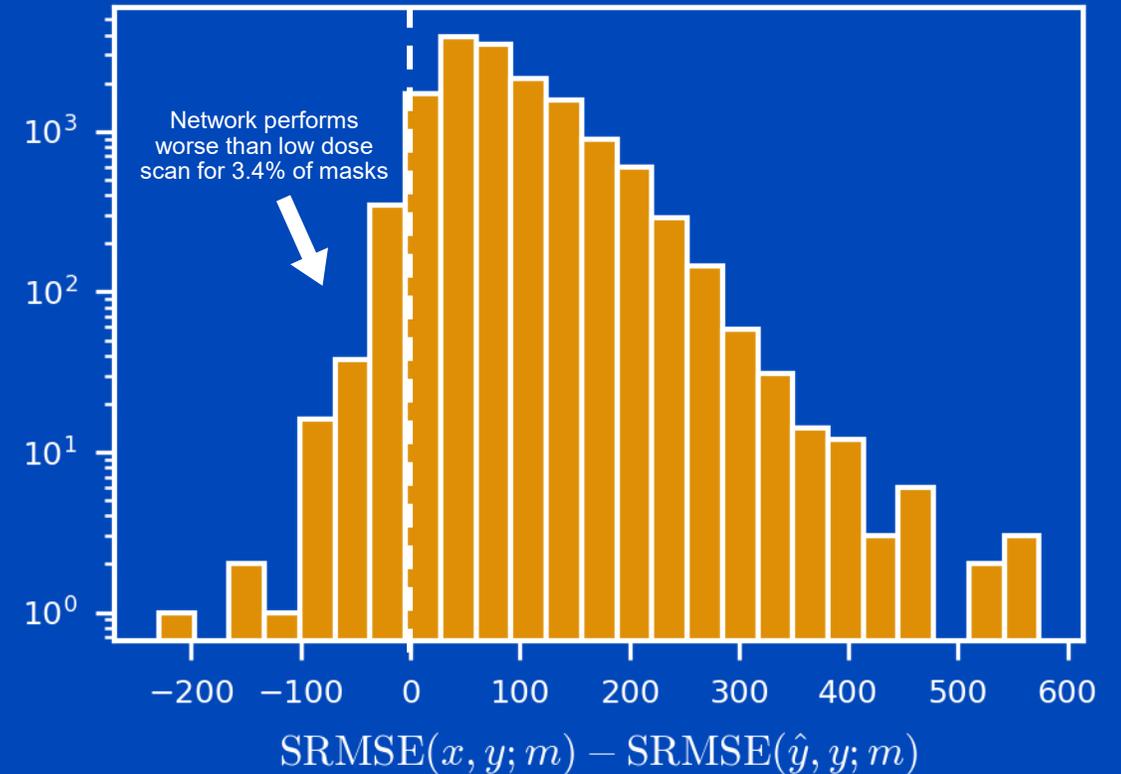
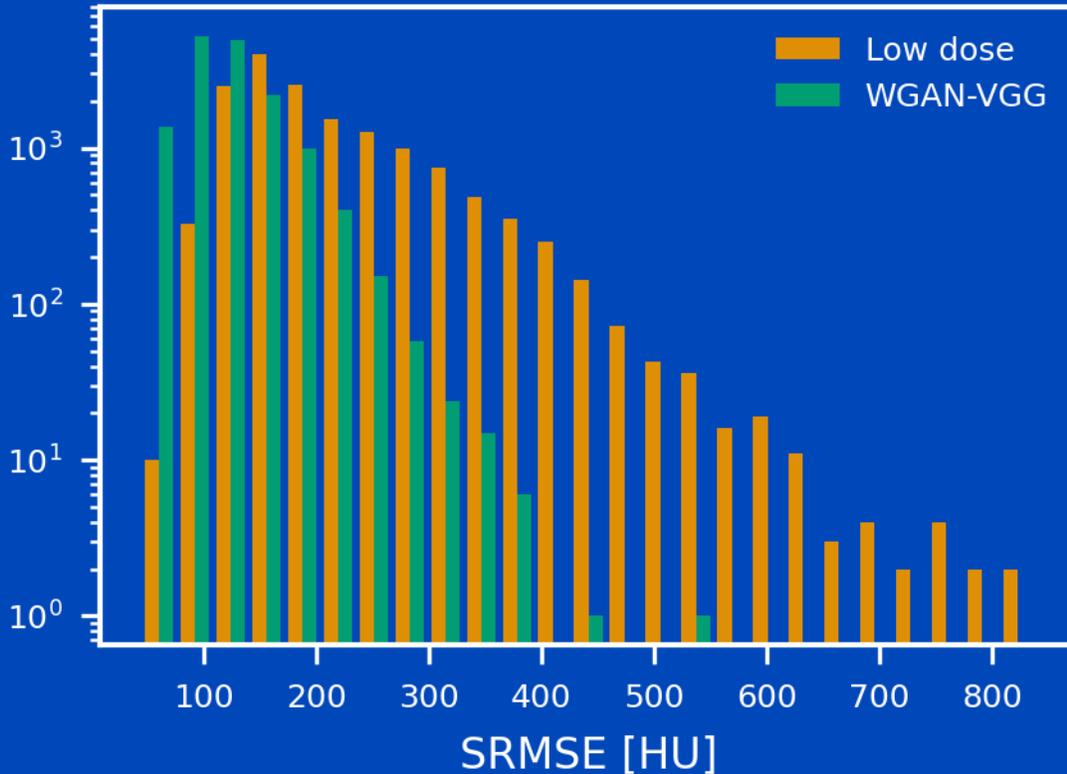
$$\text{MeanSRMSE}(x, y) = \frac{1}{S} \sum_s \text{SRMSE}(x, y; s)$$

$$\text{MaxSRMSE}(x, y) = \max_s \text{SRMSE}(x, y; s)$$

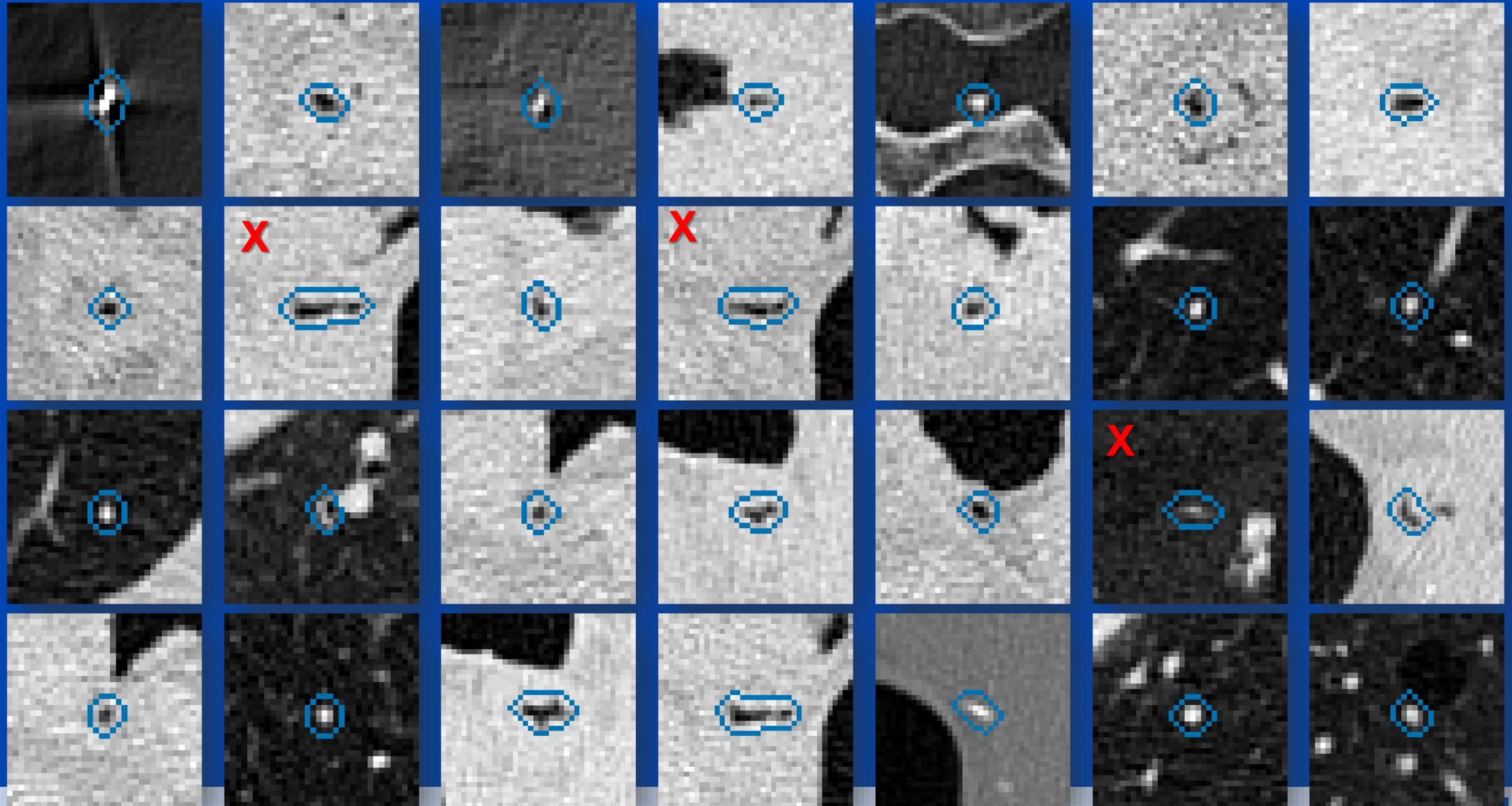


# Detecting Hallucinations

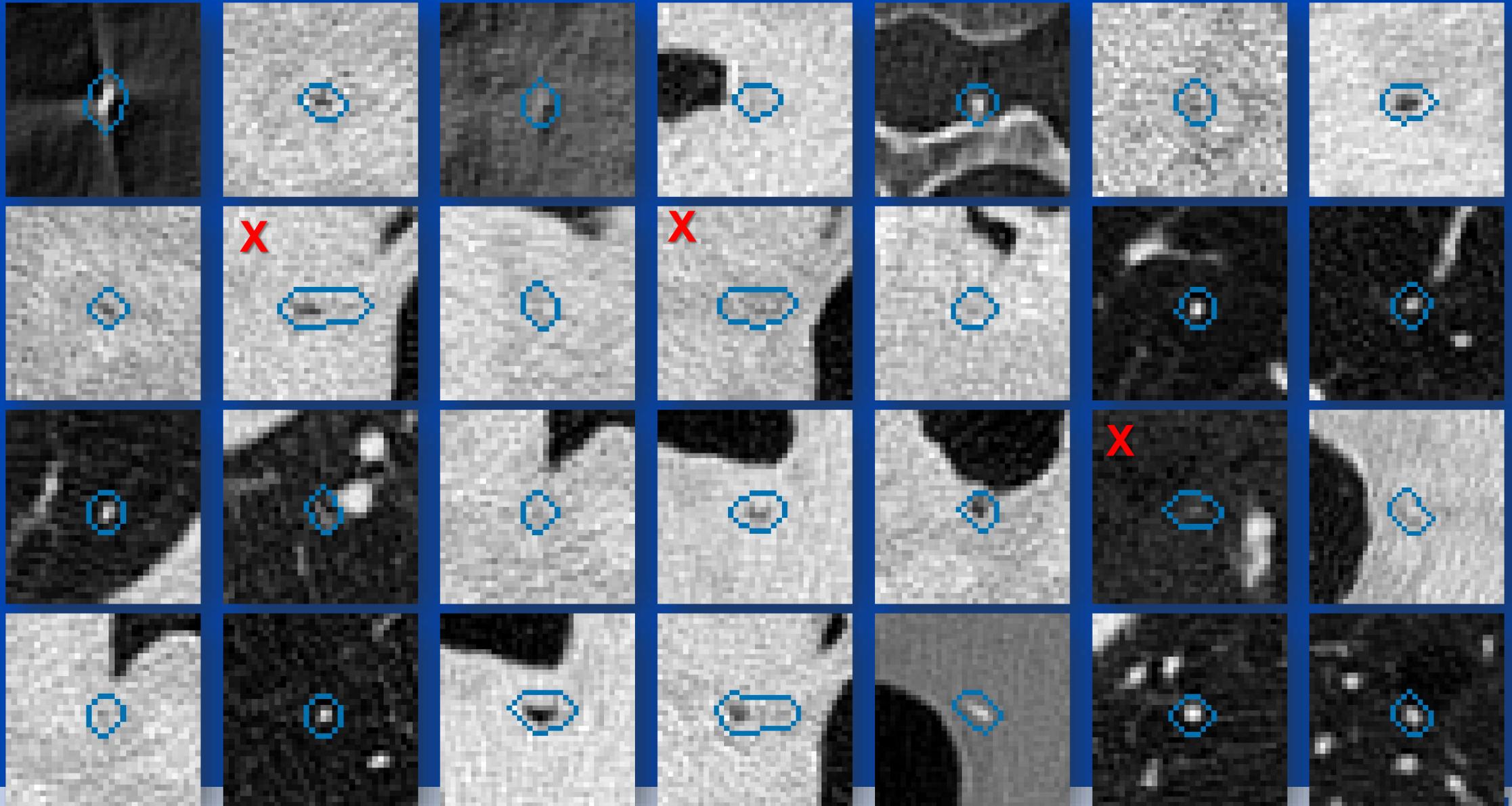
- Compare SRMSE of low dose scan ( $x$ ) with network prediction ( $\hat{y}$ )
- On a chest scan with 392 axial slices we have a total of 15,547 masks



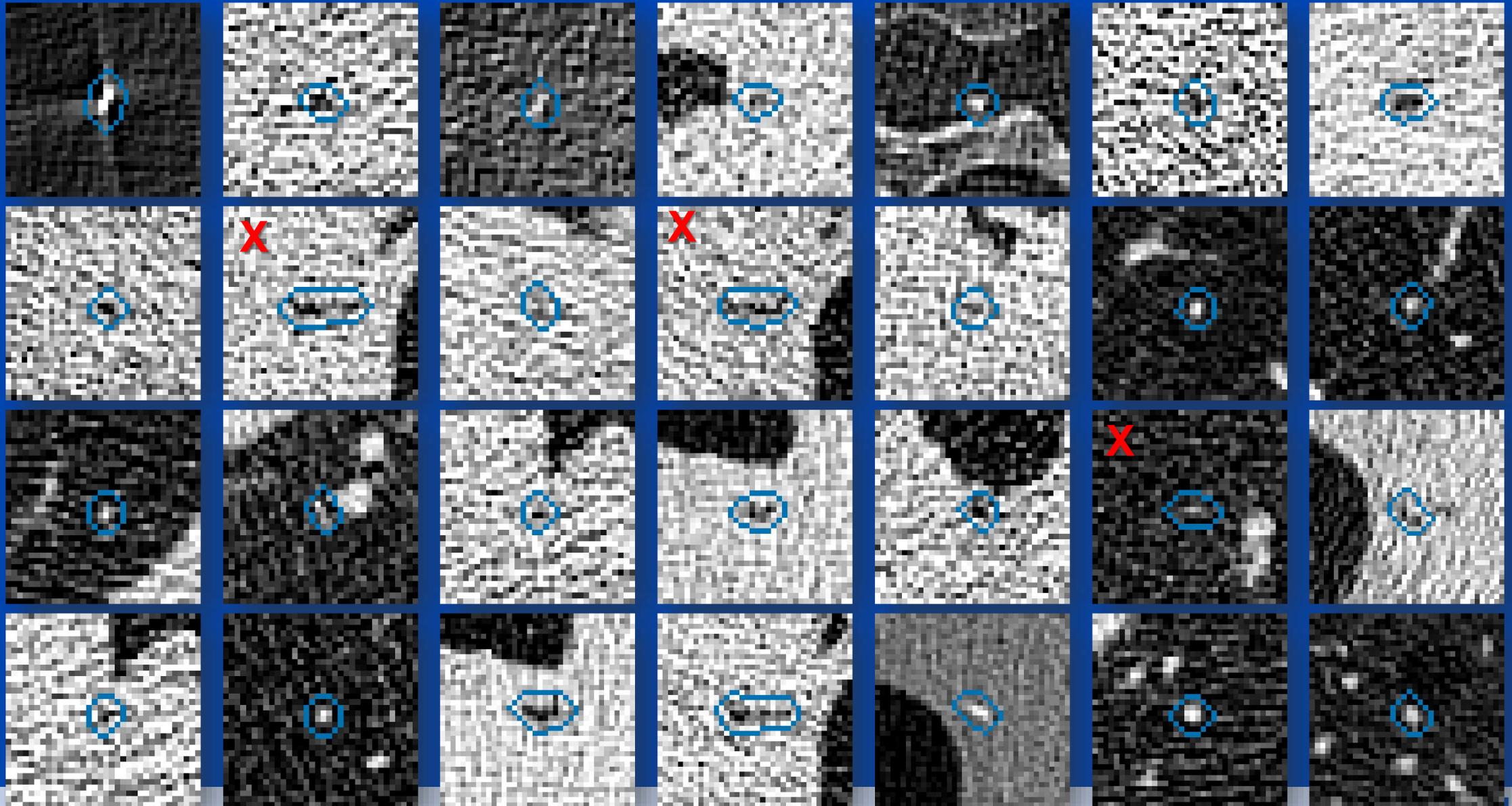
# High Dose Images



# Network Predictions (WGAN-VGG)



# Low Dose Images



# Conclusions

- **New metrics are needed to quantify changes in subtle details.**
  - Needed to evaluate the quality of AI-based algorithms.
  - Could become part of the loss function to train networks.
  - May help to determine the amount of dose reduction possible for a given algorithm.
- **Methods to detect hallucinations are required**
  - The new metric may help to do so.
  - Approaches exist that reconstruct hallucinations by analyzing the AI algorithms.

## Thank you!

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

<sup>1</sup>S. Bhadra, V. A. Kelkar, F. Brooks, and M. Anastasio. On hallucinations in tomographic image reconstruction. IEEE TMI 40(11):3249-3260, 2021.

<sup>2</sup>E. Eulig, J. Maier, B. Ommer, and M. Kachelrieß. Reconstructing and analyzing the invariances of CT denoising networks. Med. Phys. 52(1):188-200, January 2025.