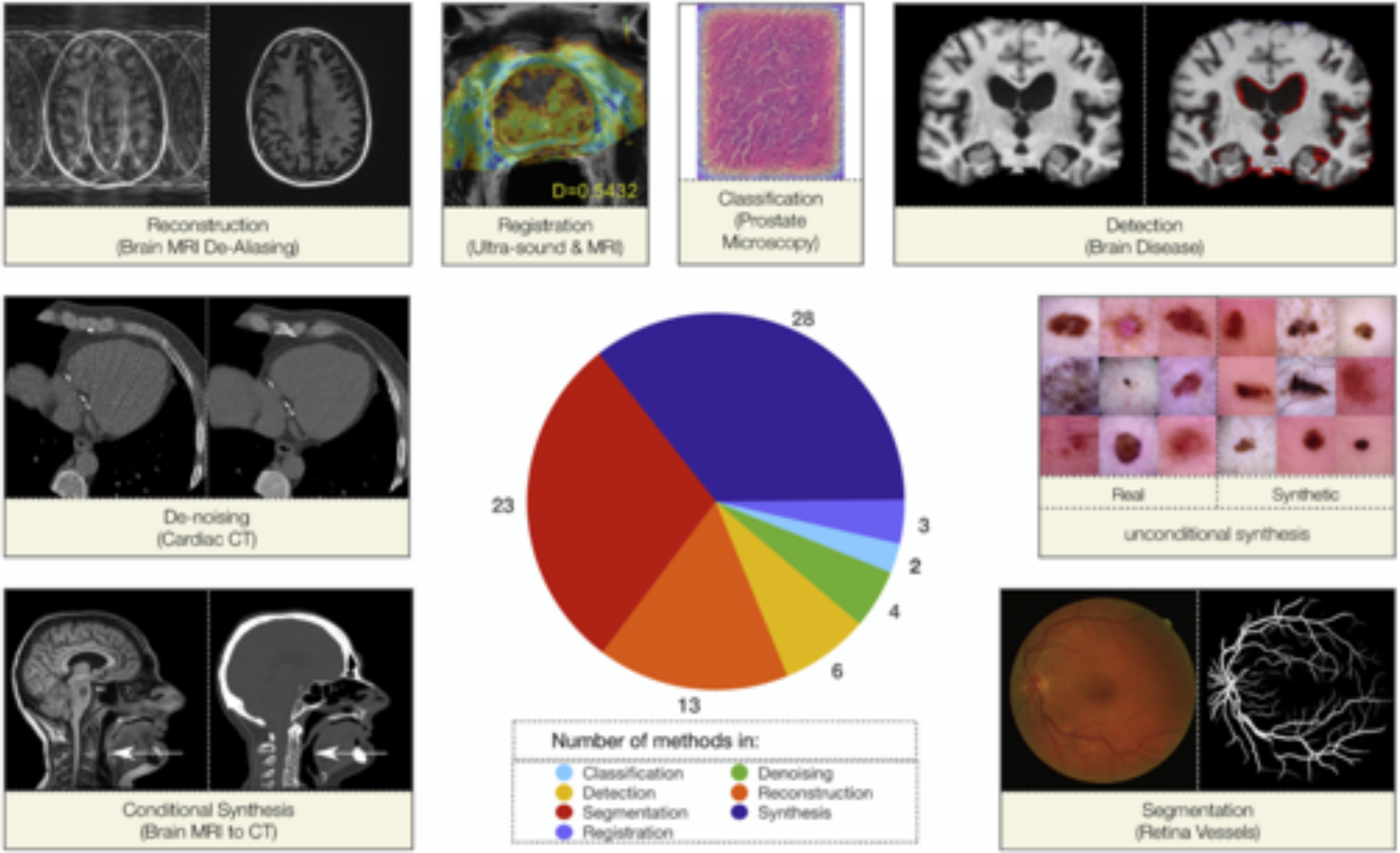
Applications of Generative Models

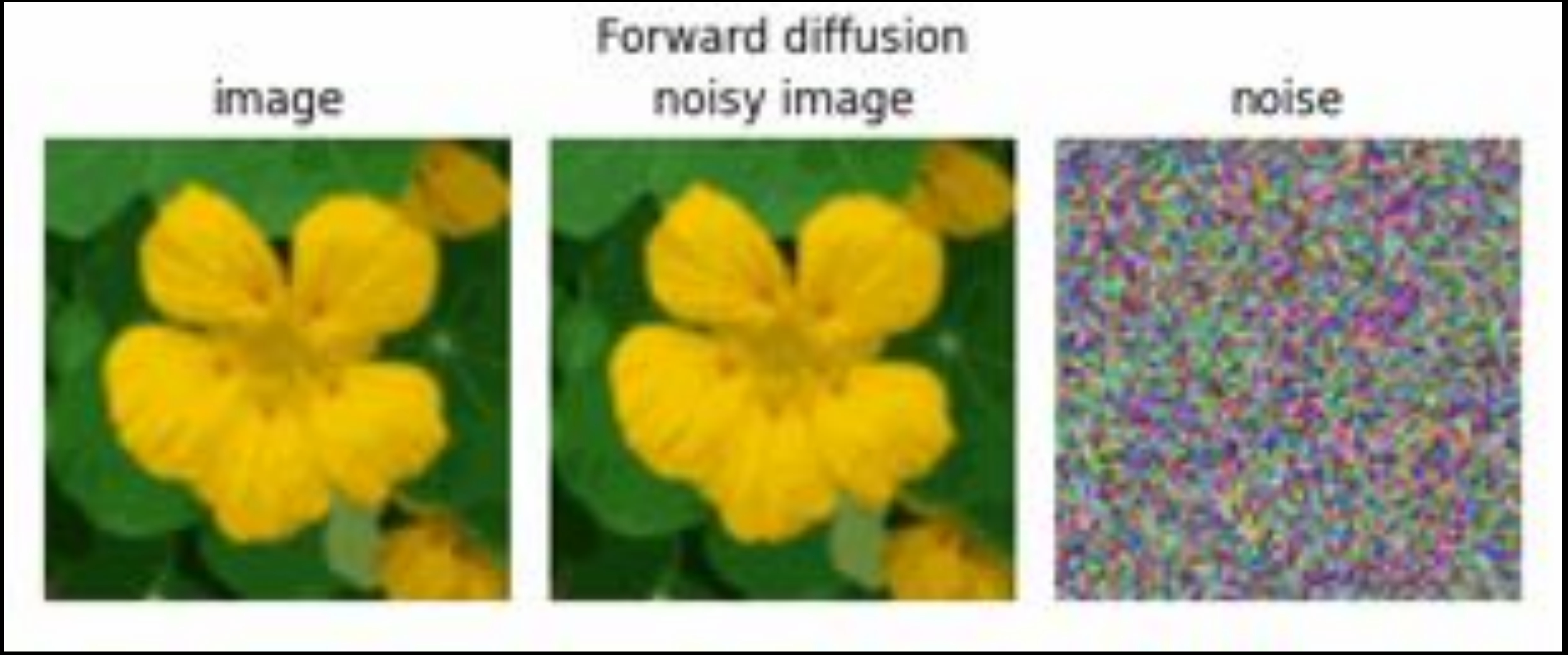


GANs for medical image analysis, 2020

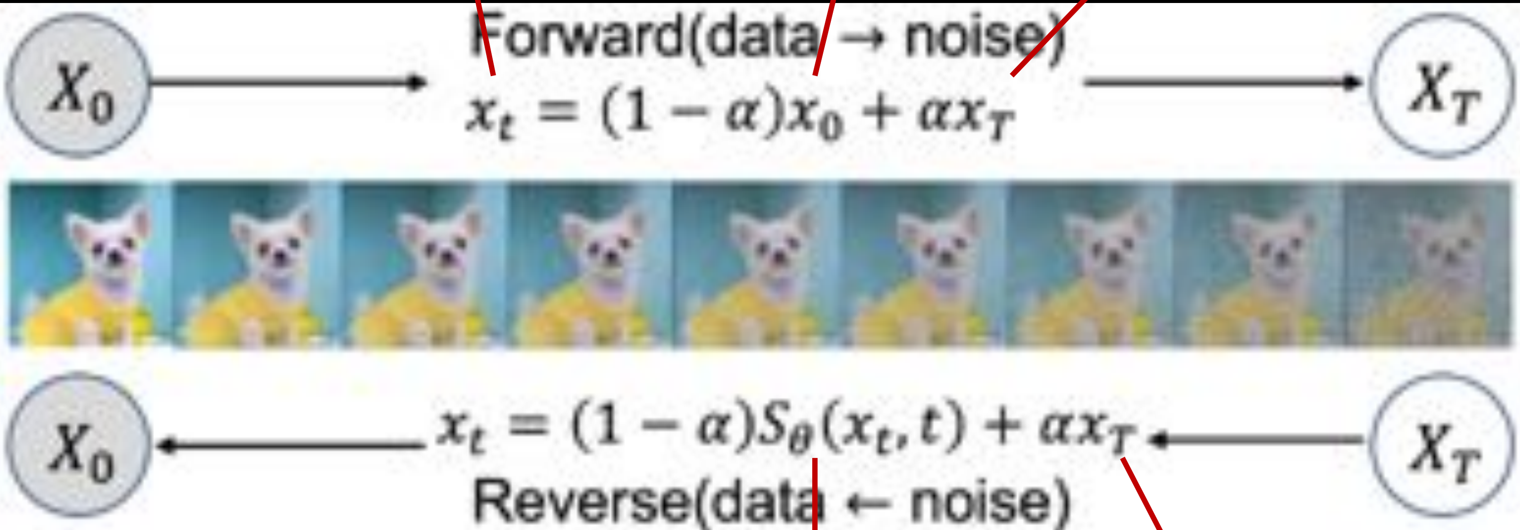
Probabilistic Diffusion Model

(the model you are probably using for
text to image generation)

Forward process: image to noise
Backward process: noise to image (we want to learn this)

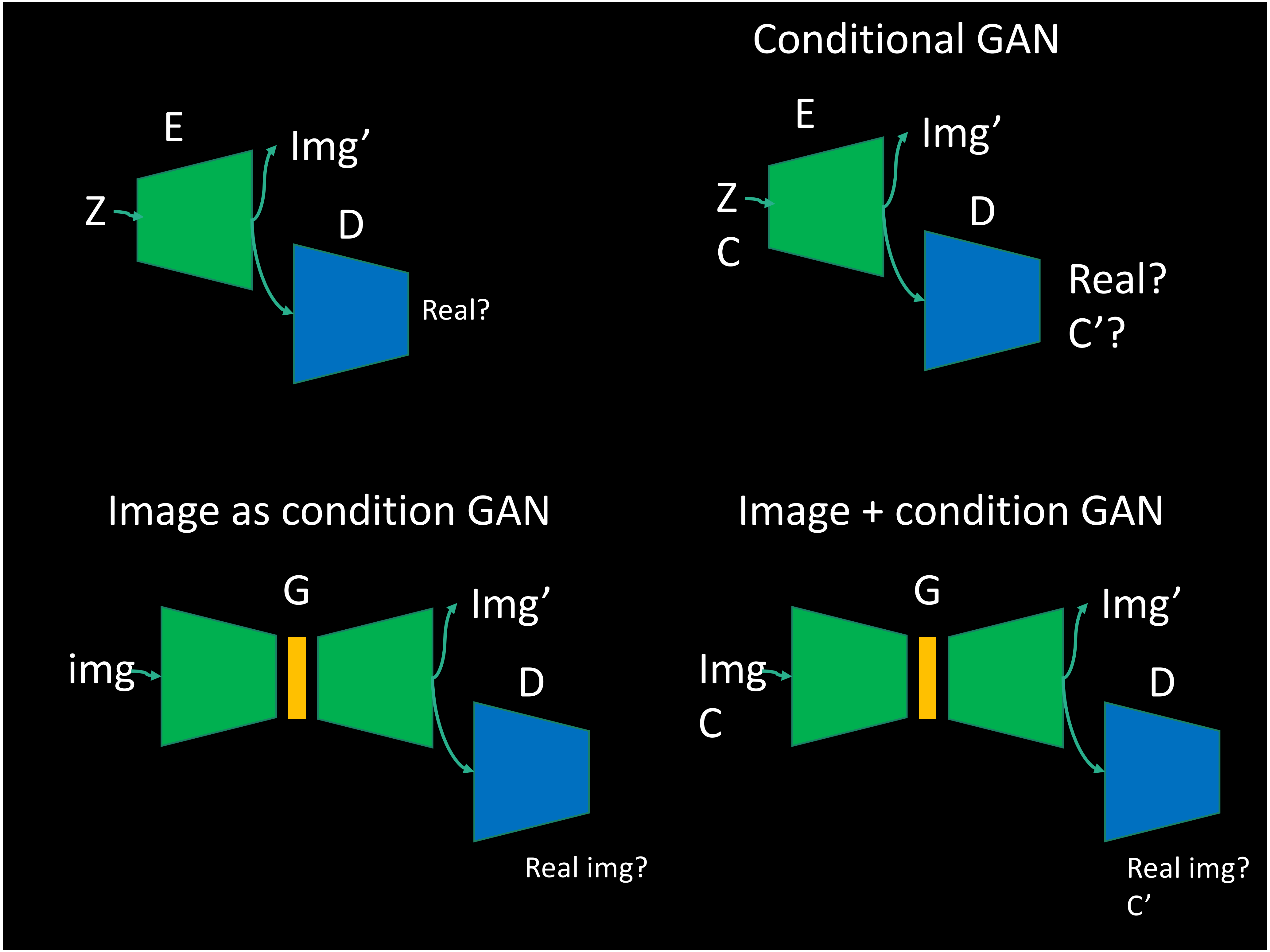


Noisy image Clean image Pure noise

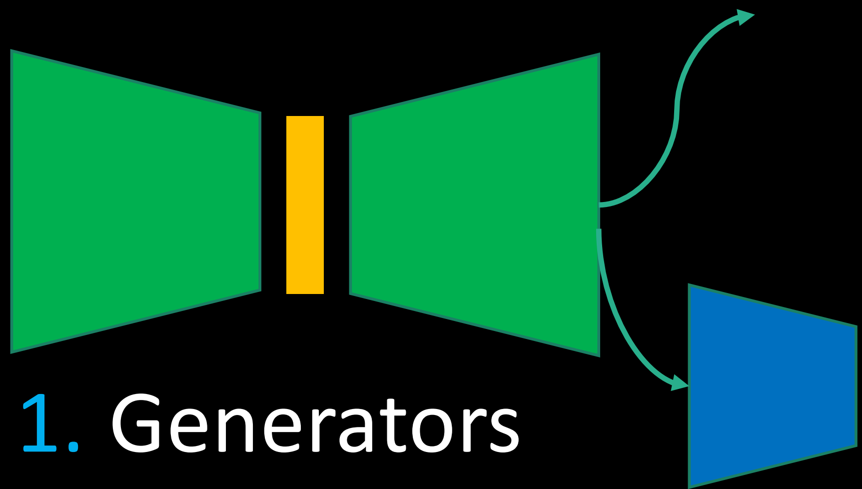


Denoising Model Pure noise

Learned using forward + backward process


Conditional GAN
E
Img’
Z
D
Real?
E
Img’
Z
C
D
Real?
C’?
Image as condition GAN
G
Img’
img
D
Real img?
Image + condition GAN
G
Img’
Img
C
D
Real img?
C’

Either way, both GAN or diffusion model can be described as:



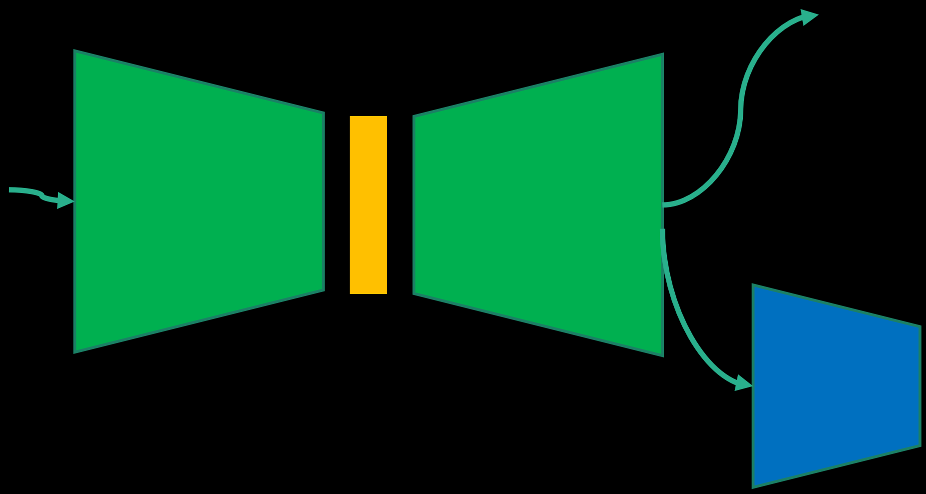
1. Generators

(GAN
or Diffusion)

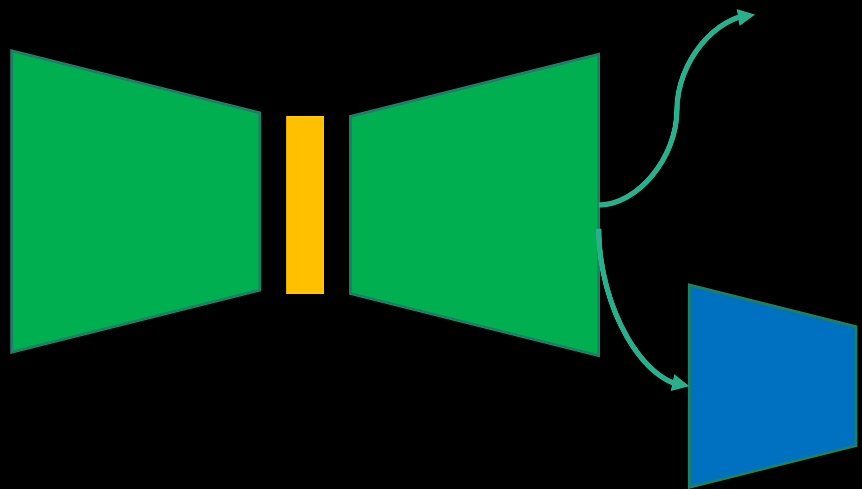
Either way, both GAN or diffusion model can be described as:

2\.

Input Image (x)
& Condition (c)



Either way, both GAN or diffusion model can be described as:



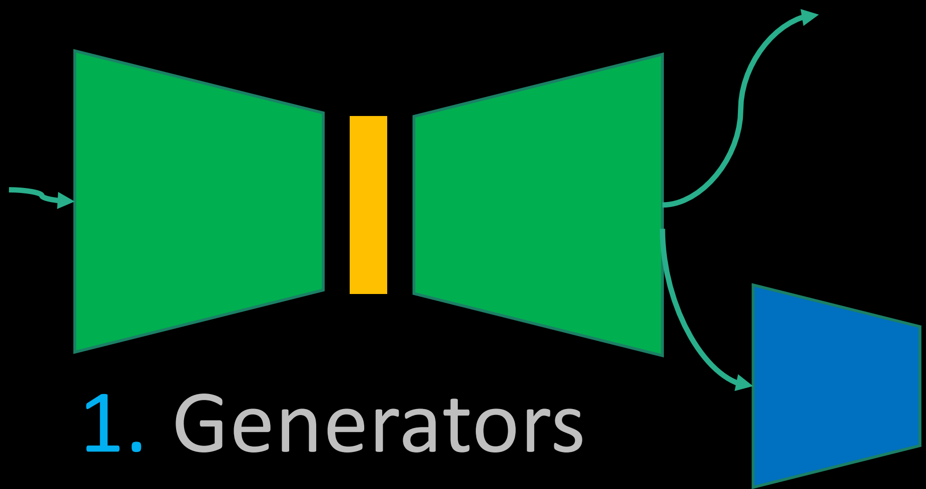
3.

A way to ensure conditions are met

GAN: discriminator

Diffusion: guidance

Either way, both GAN or diffusion model can be described as:



Let's first think about what kind of tasks can be defined as conditional image generation

(because most of time we want to *borrow* these techniques and bring them to our field)

Image as condition: super-resolution

Low resolution

High resolution

Image as condition: Image denoising

(a) Denoised (b) Original (c) Noisy

Image condition:

Super-resolutions / creating info at pixel level

Image as condition:

Inpaint / outpainting: creating info at image level

Image as condition:

Outpainting / uncropping

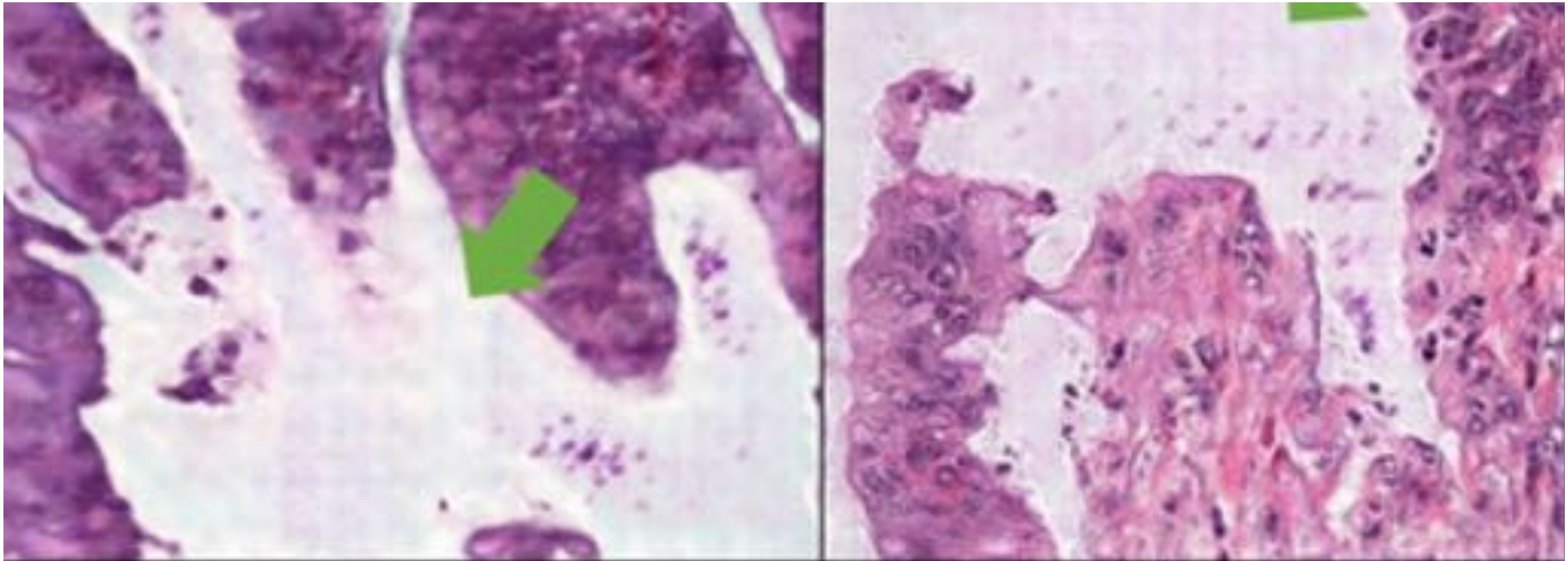
Image as condition:

Inpaint / outpainting: creating info at image level

Image as condition:

Only this is real

It created!
(w/ artifacts)



GAN artifacts

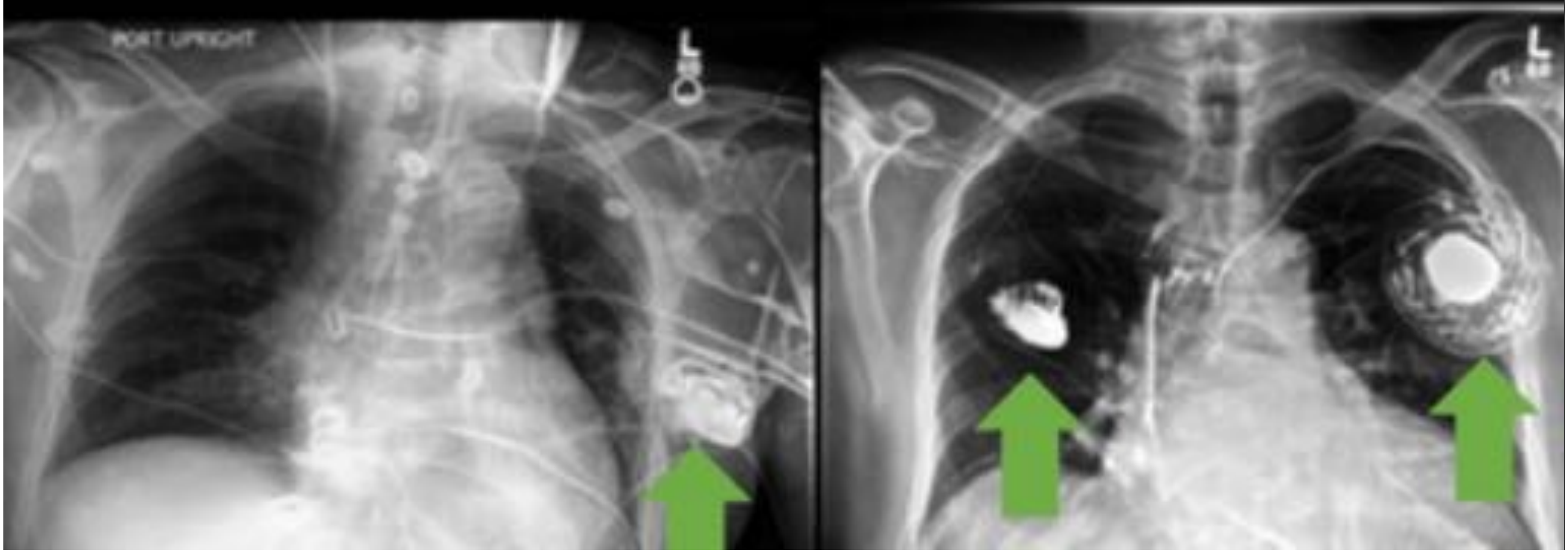
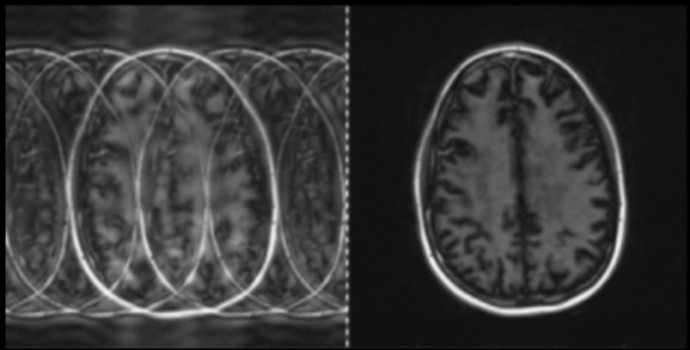
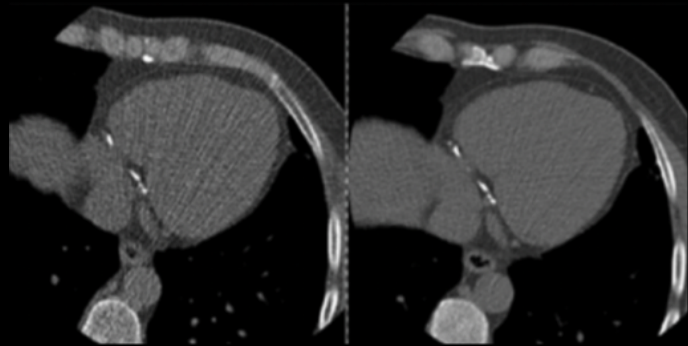


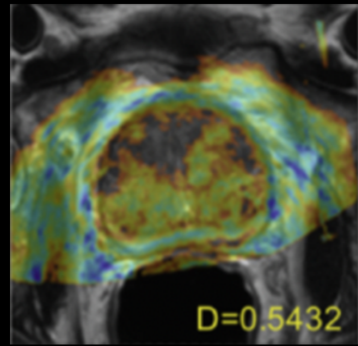
Image as condition:

Generate from segmentation info

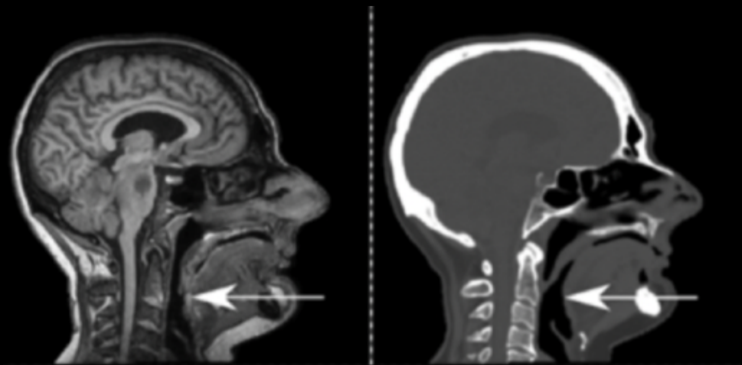
Image level (reconstruction (de-aliasing), de-noising, registration)

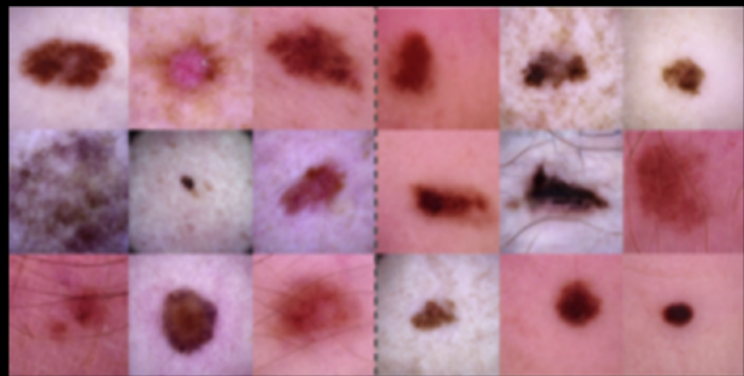




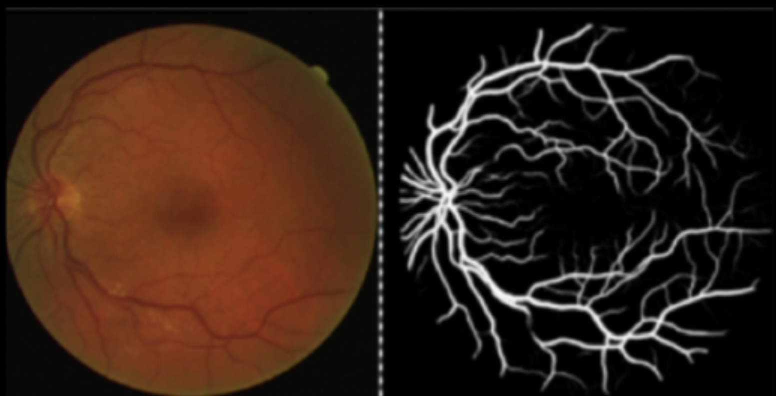


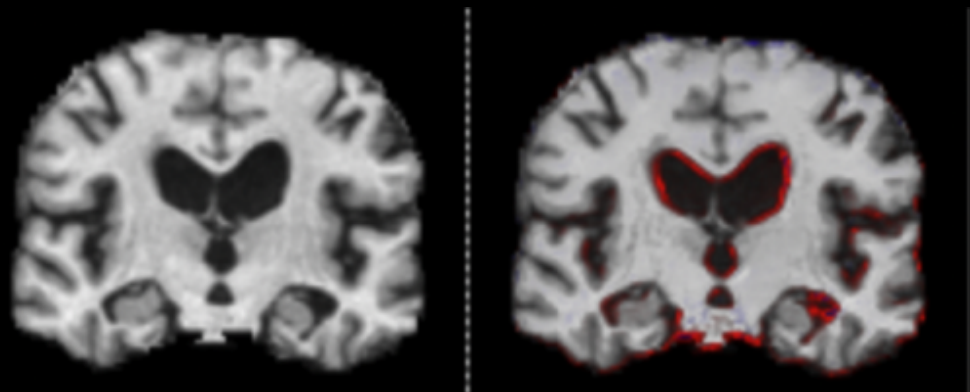
Synthesis





Downstream Tasks (Segmentation / Detection)

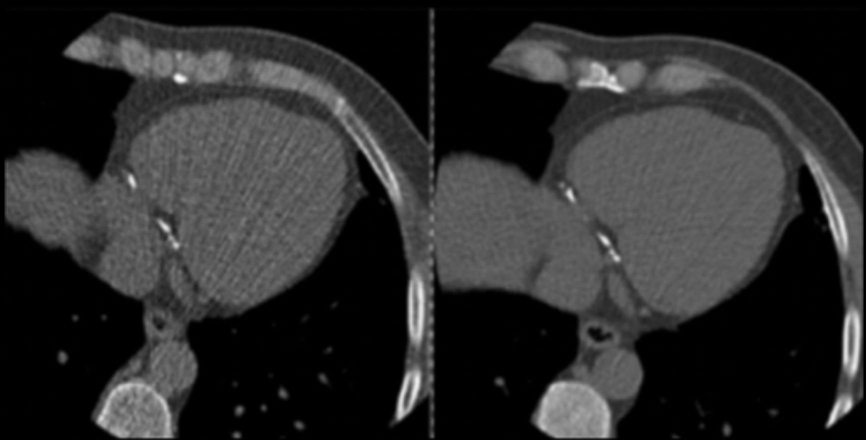




GANs for medical image analysis, 2020

Question 1:

"Can I frame our problem similarly to theirs?"



Question 3:

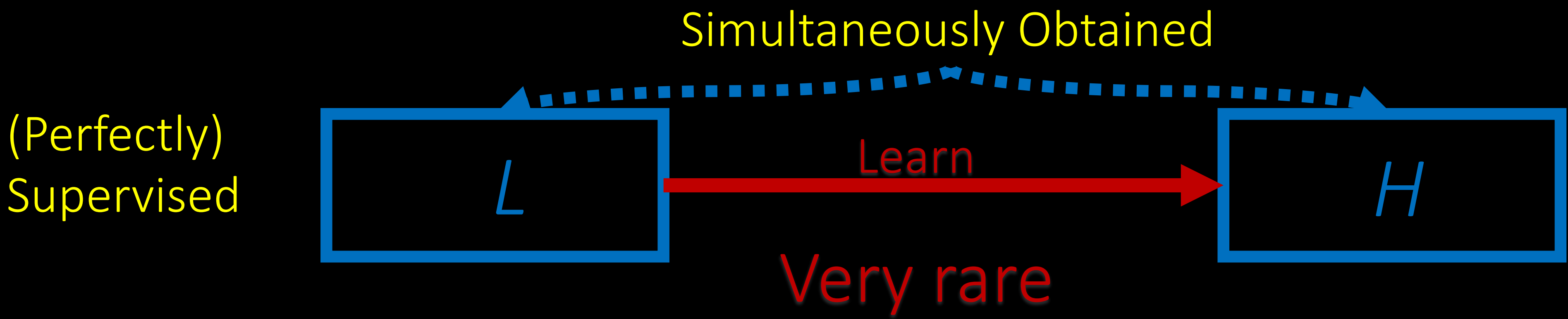
"How can you evaluate the results?"

Question 2:

“can I train it in a supervised manner

Or do I need to move to unsupervised learning?”

Most of time you have two domain, *L* and *H*



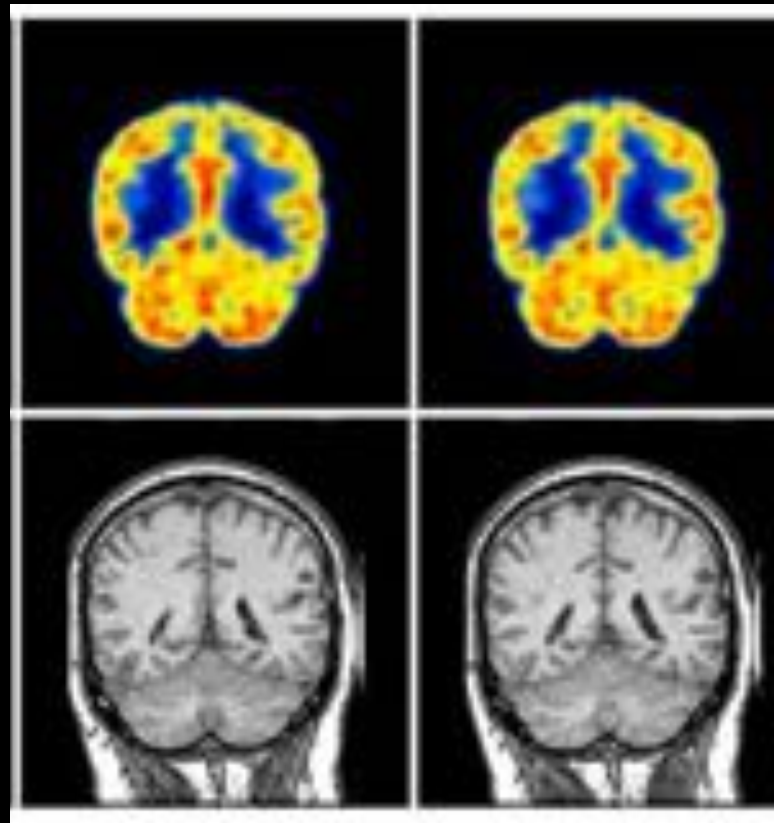
“True” Paired Dataset

CAI²R | Center for Advanced Imaging Innovation and Research

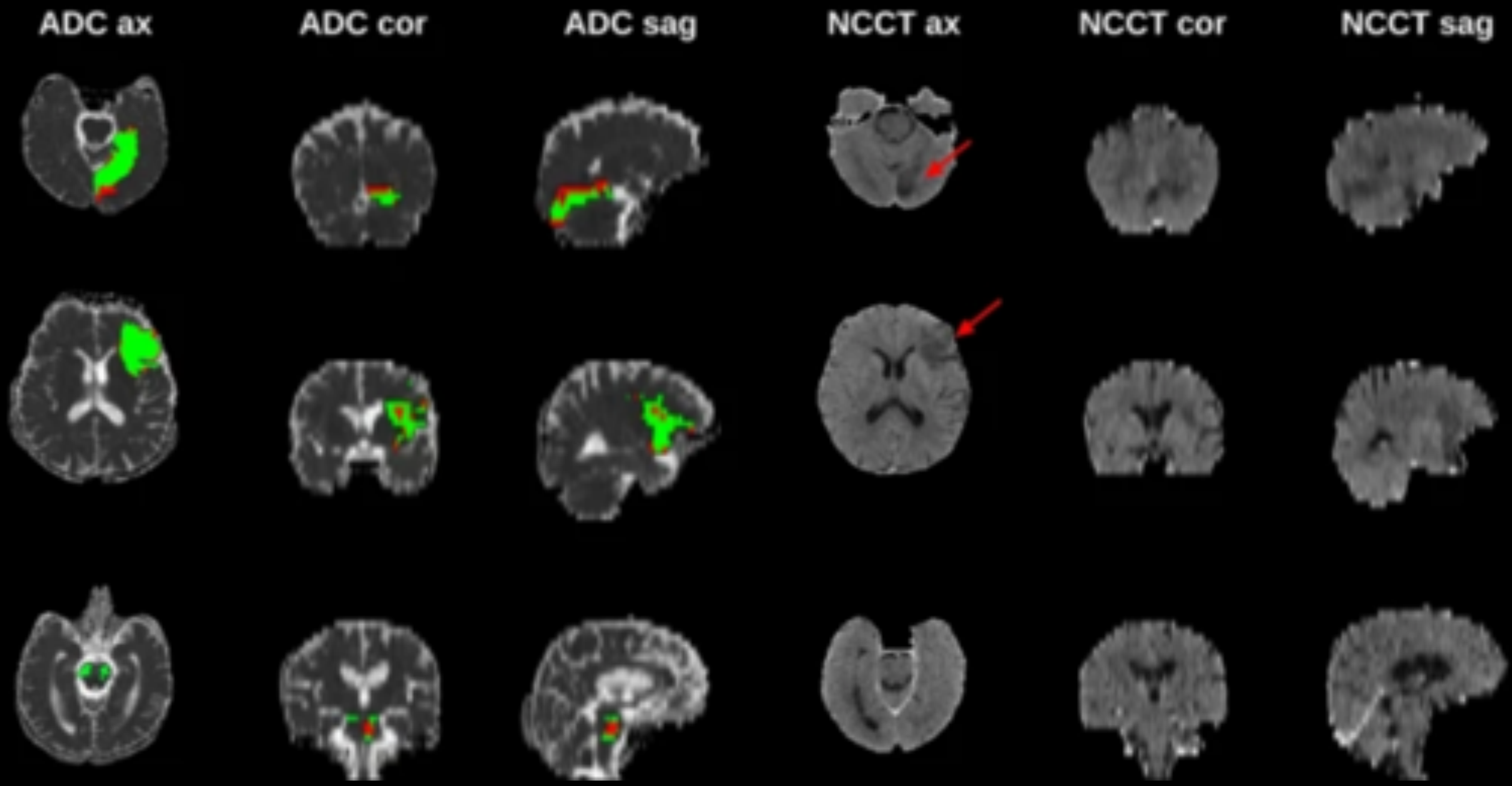
A National Center for Biomedical Imaging and Bioengineering

PET-MR Dataset

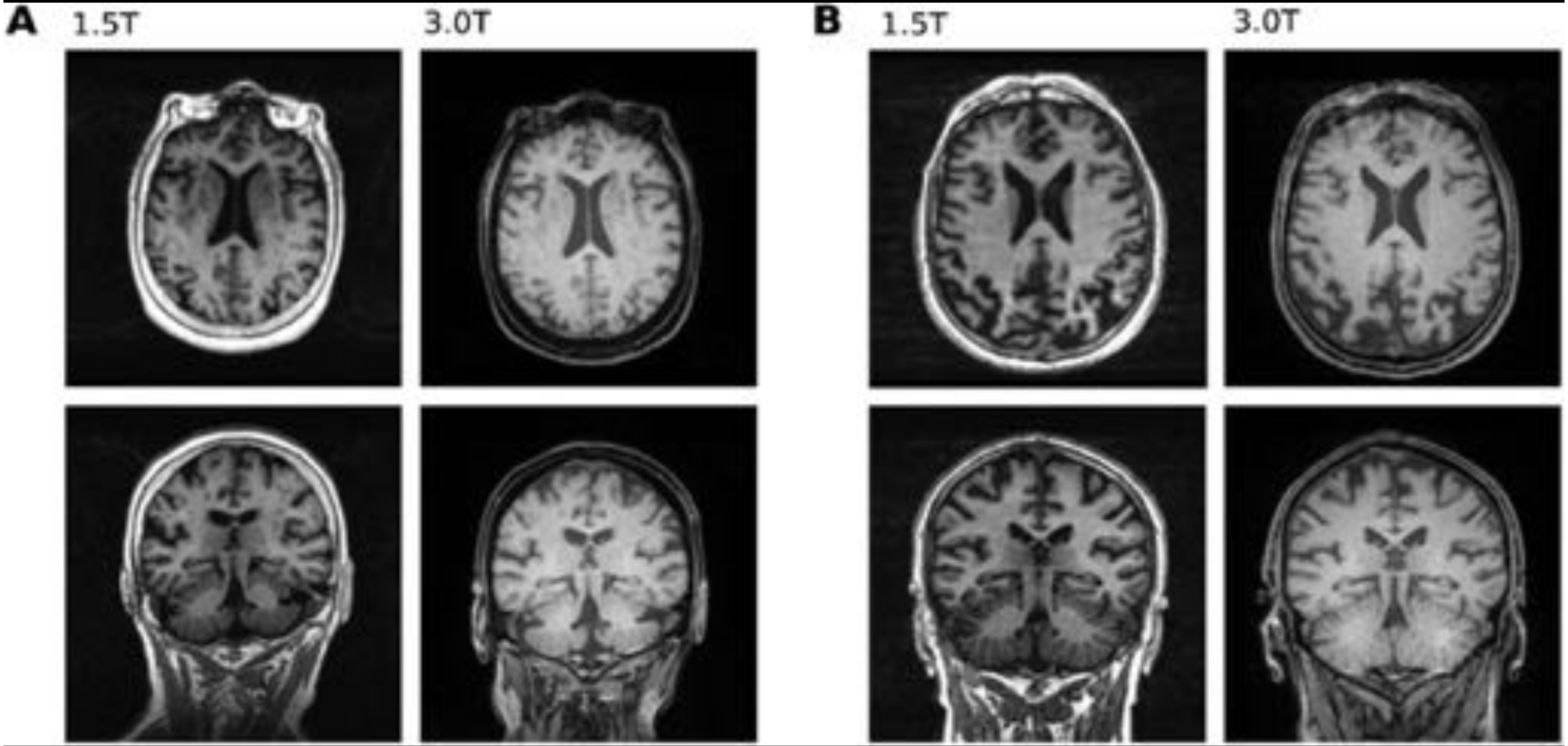
Simultaneously acquired positron emission tomography and magnetic resonance data of the brain, plus joint image reconstruction code.



"True" Paired Dataset



APIS: a paired CT-MRI dataset for ischemic stroke segmentation - methods and challenges



How do you approximate 3T > 1.5T?

Data Descriptor | Open access | Published: 27 July 2023

A paired dataset of T1- and T2-weighted MRI at 3 Tesla and 7 Tesla

Xiaoyang Chen, Liangqiong Qu, Yifang Xie, Sahar Ahmad & Pew-Thian Yap

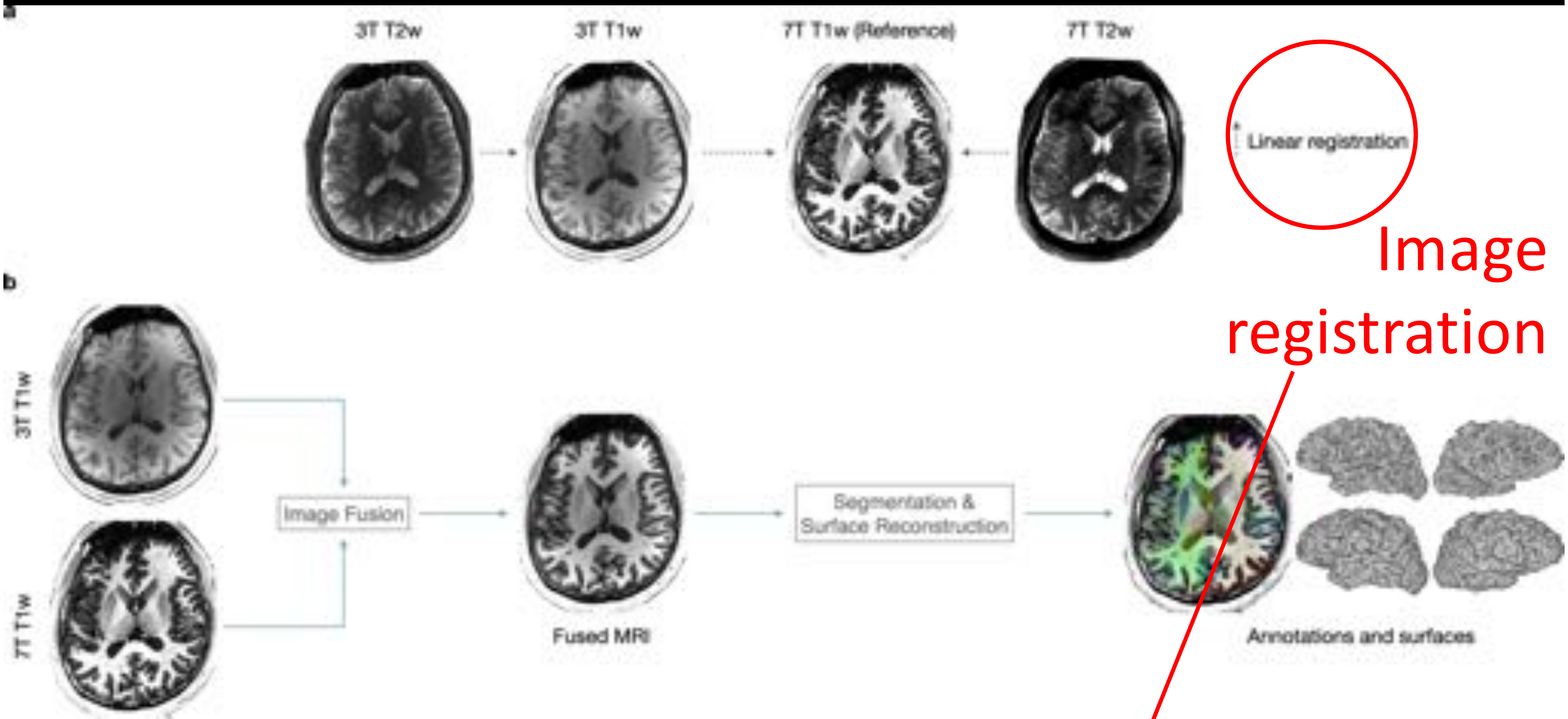
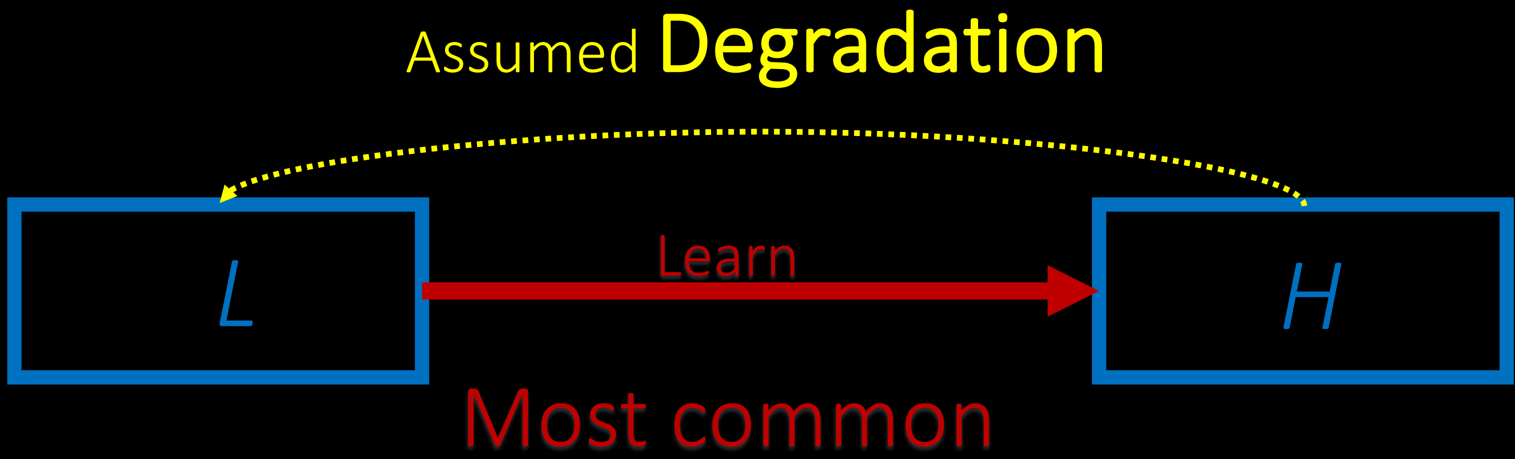


Image registration

Depends on how well they did it!

Supervised (w/ assumption)



“Safely Assumed” Paired Dataset

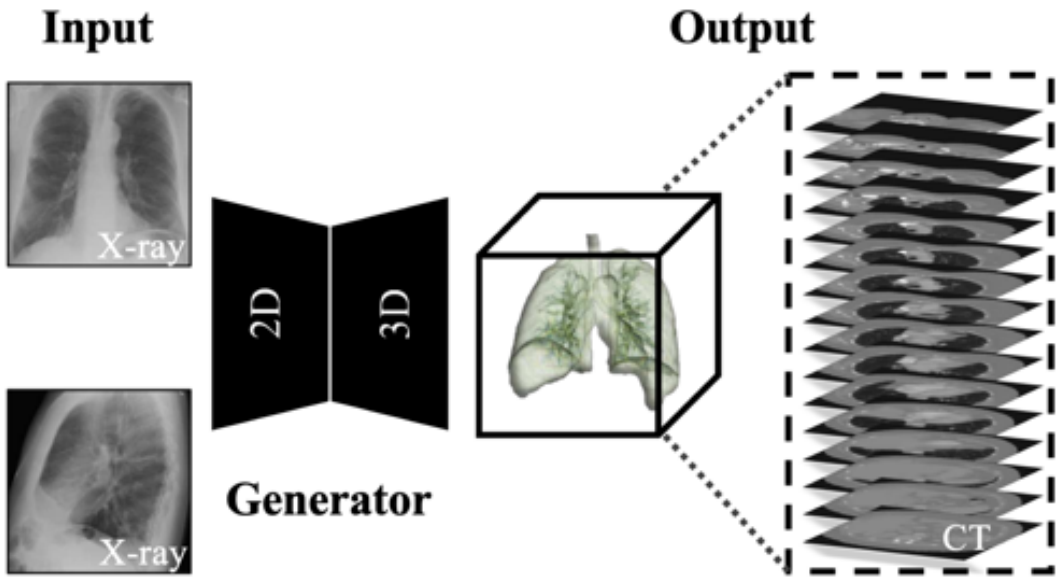


Figure 1. Illustration of the proposed method. The network takes 2D biplanar X-rays as input and outputs a 3D CT volume.

CT-Xray translation

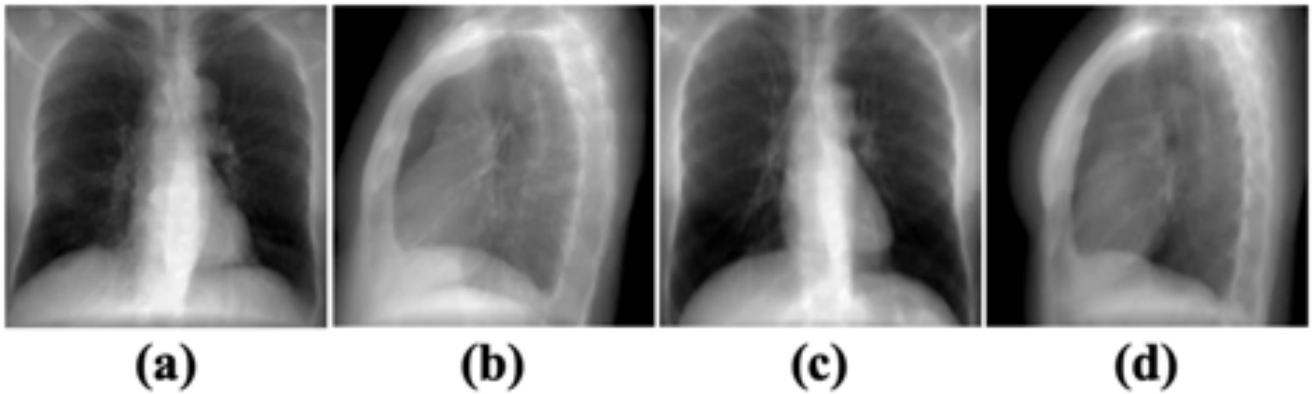
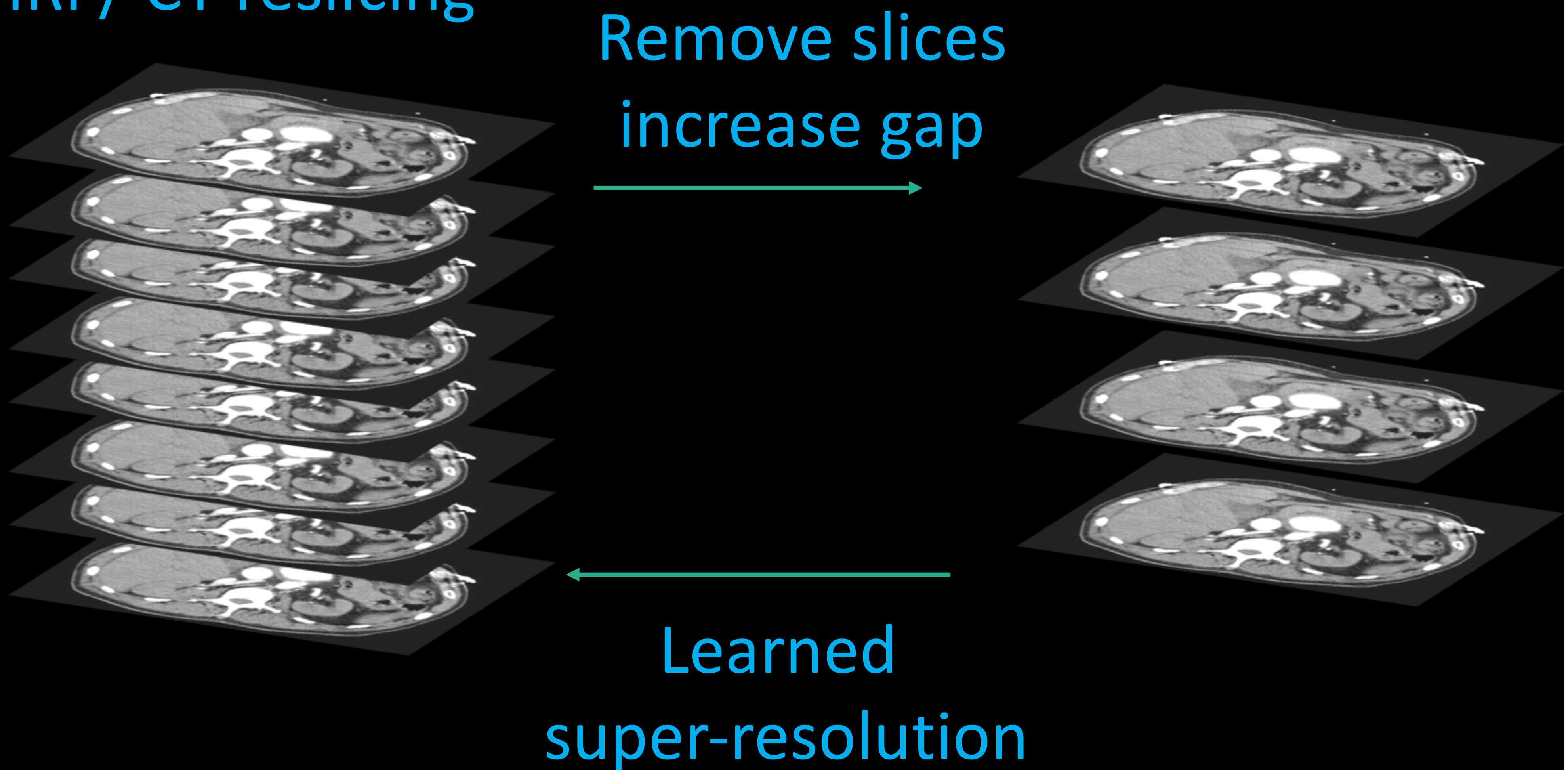


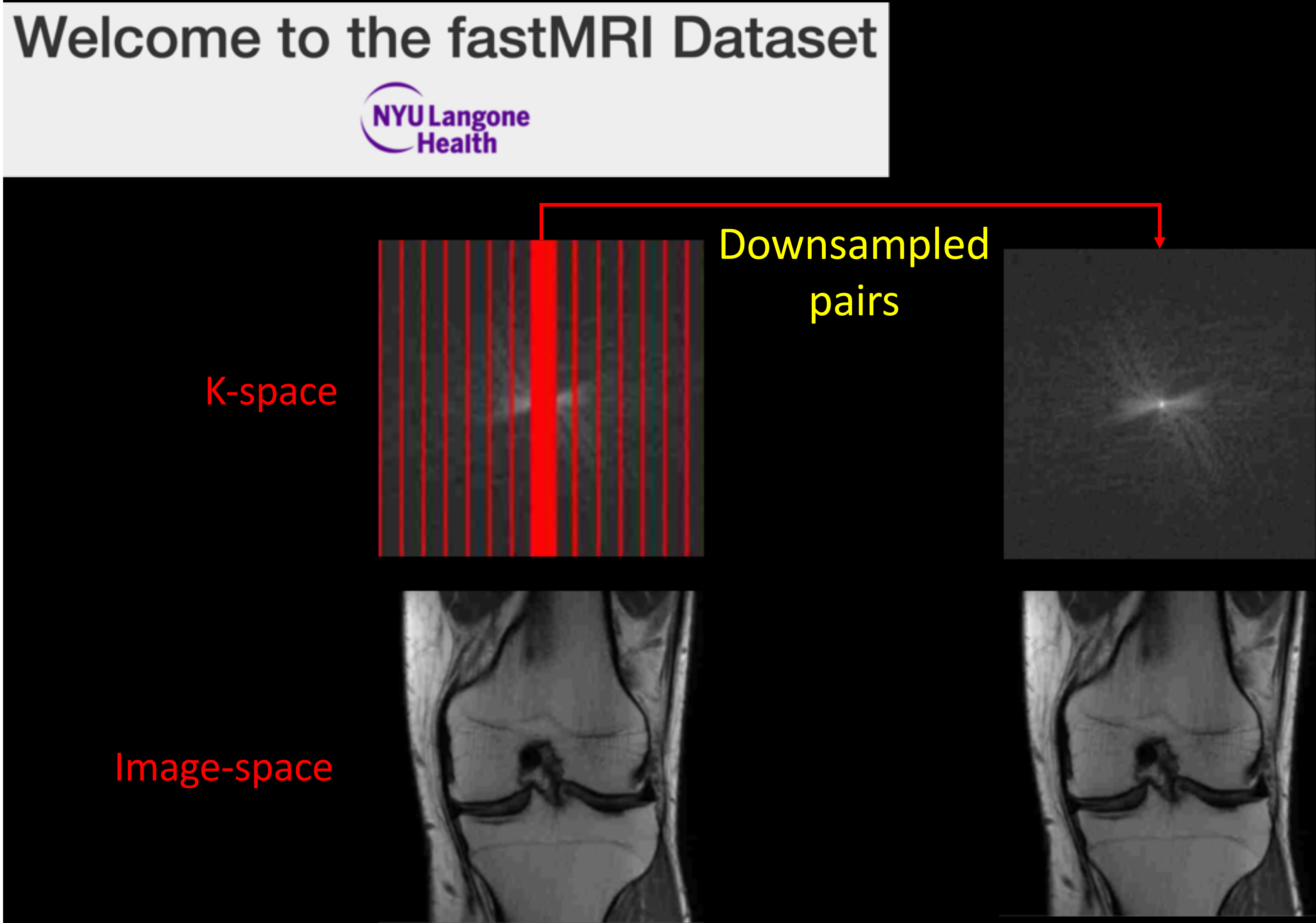
Figure 5. DRR [28] simulated X-rays. (a) and (c) are simulated PA view X-rays of two subjects, (b) and (d) are the corresponding lateral views.

“Safely Assumed” Paired Dataset

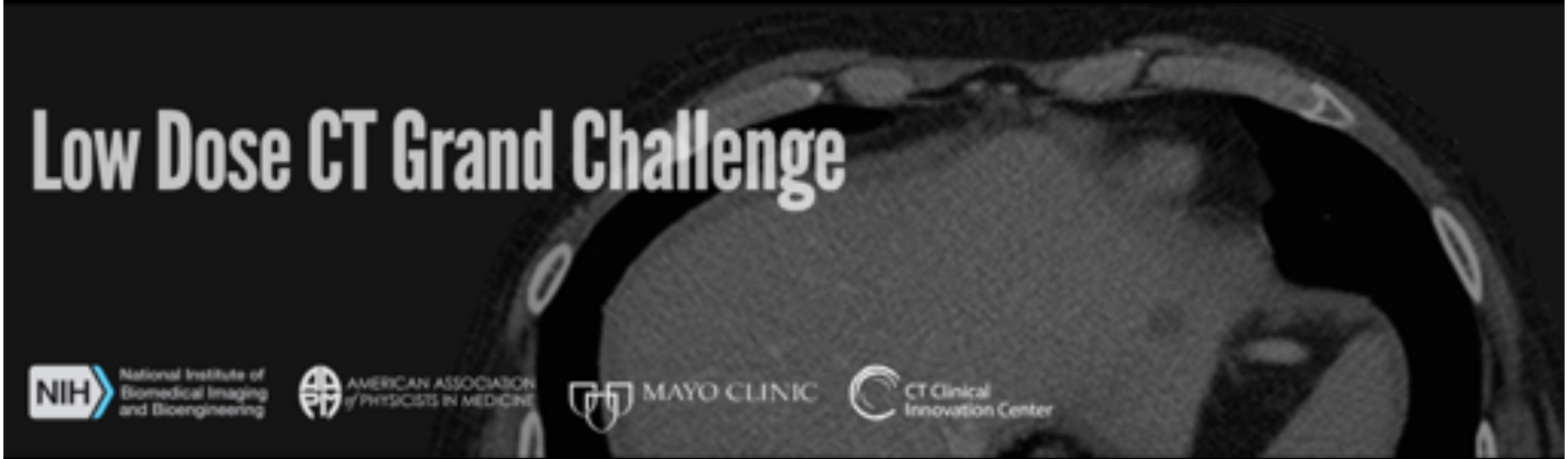
MRI / CT reslicing



“Safely Assumed” Paired Dataset

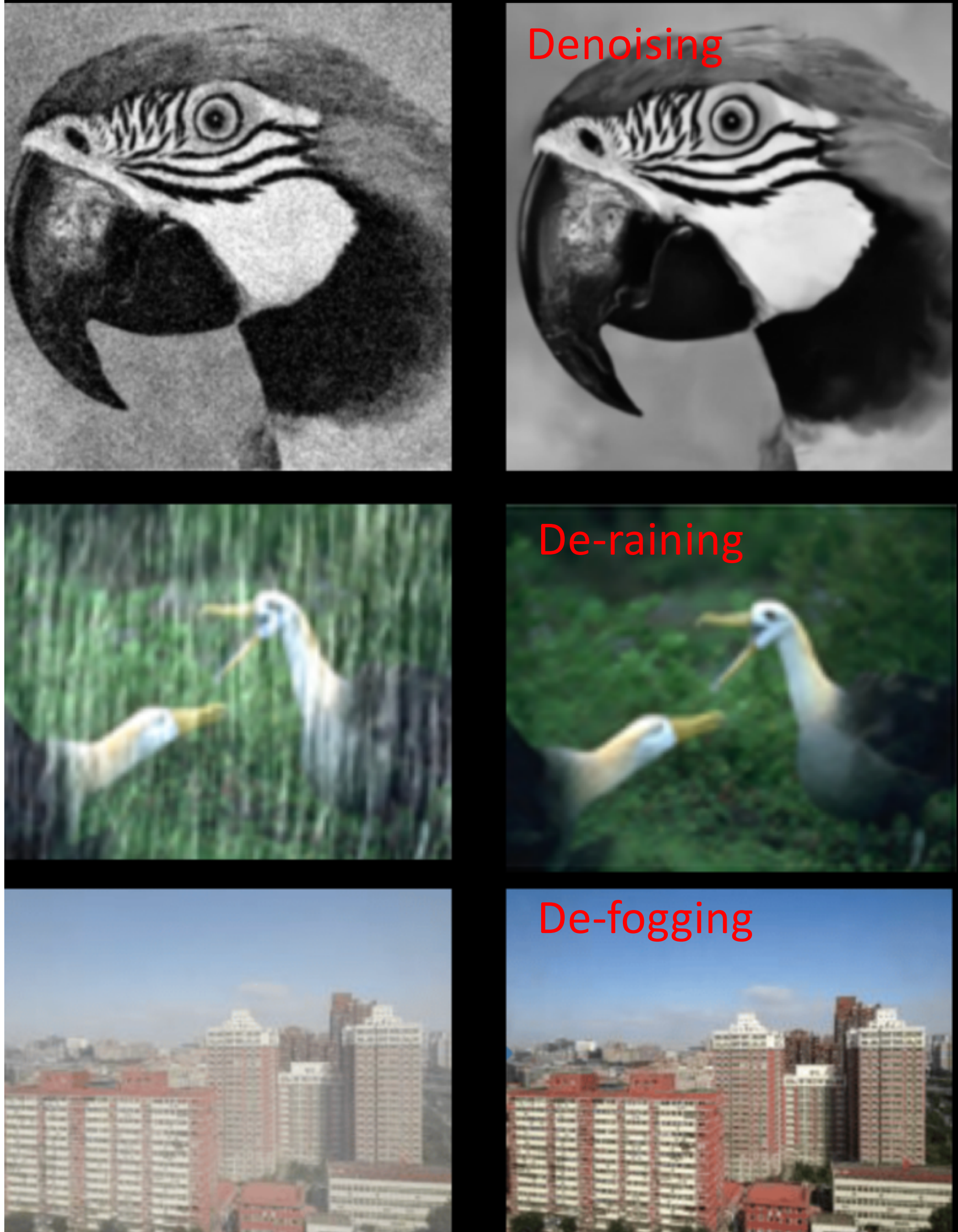


“Assumed” Paired Dataset



Noise Insertion to Simulate Reduced Dose Levels

Poisson noise was inserted into the projection data for each case in the library to reach a noise level that corresponded to 25% of the full dose (i.e. "quarter-dose" data were simulated)……….

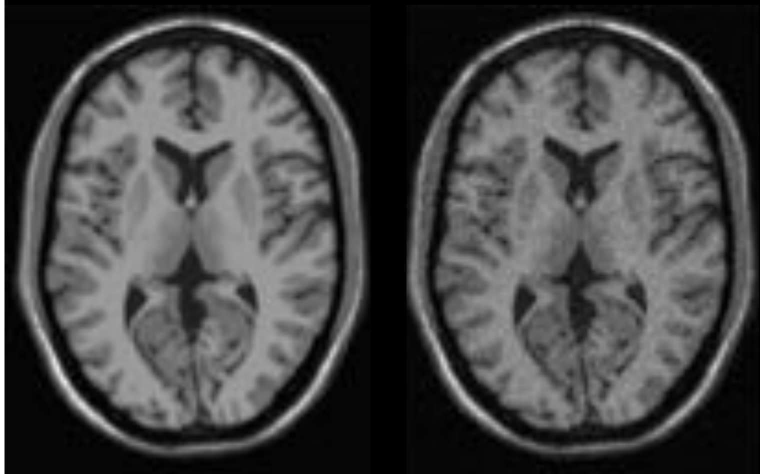


Some Degradation (H>L)

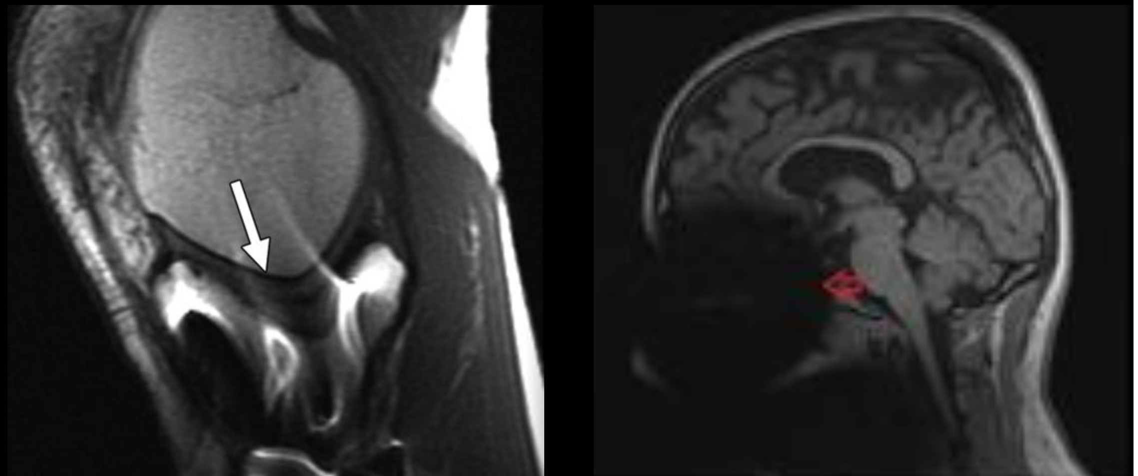
Is signal independent

Easier

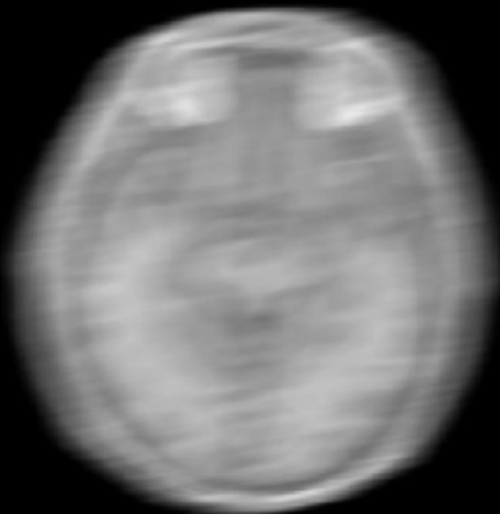
Some degradation is signal dependent



Add noise>

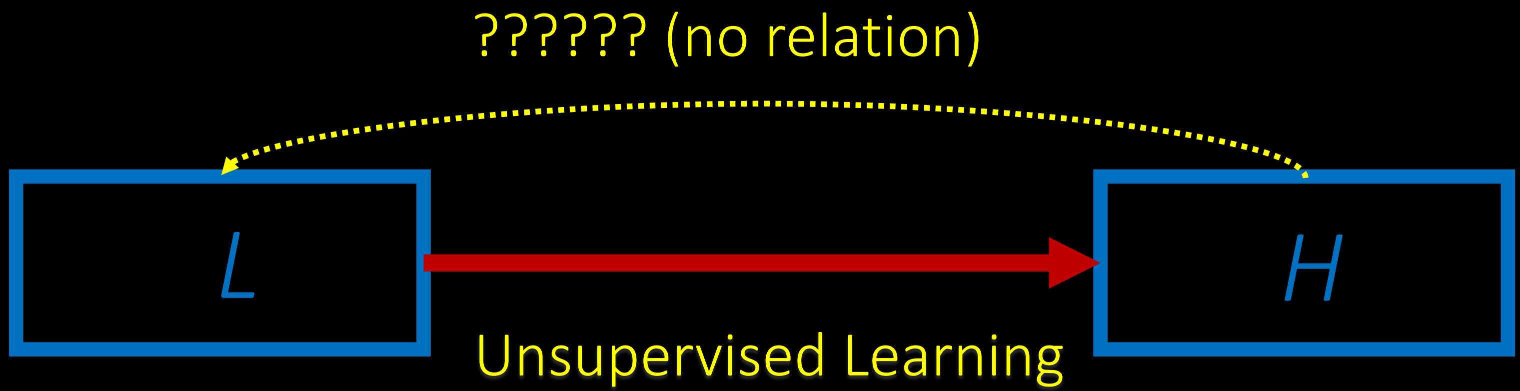


Add (signal + ???)



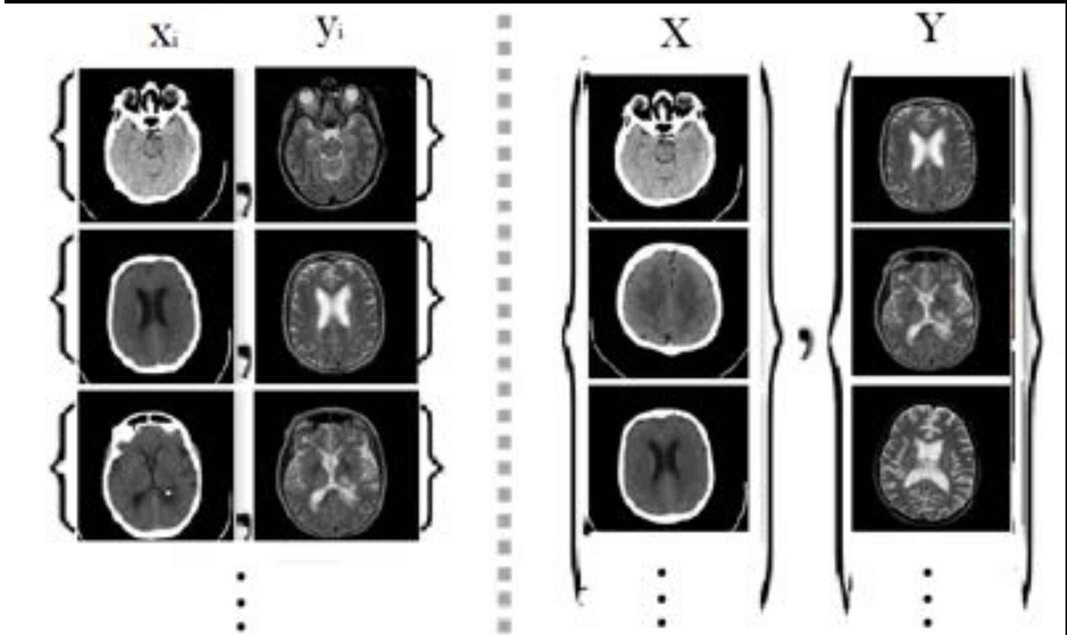
How do you approximate this?

Other times you don’t have relation between *L* & *H*



It’s very fun but
Good luck!

Paired Unpaired

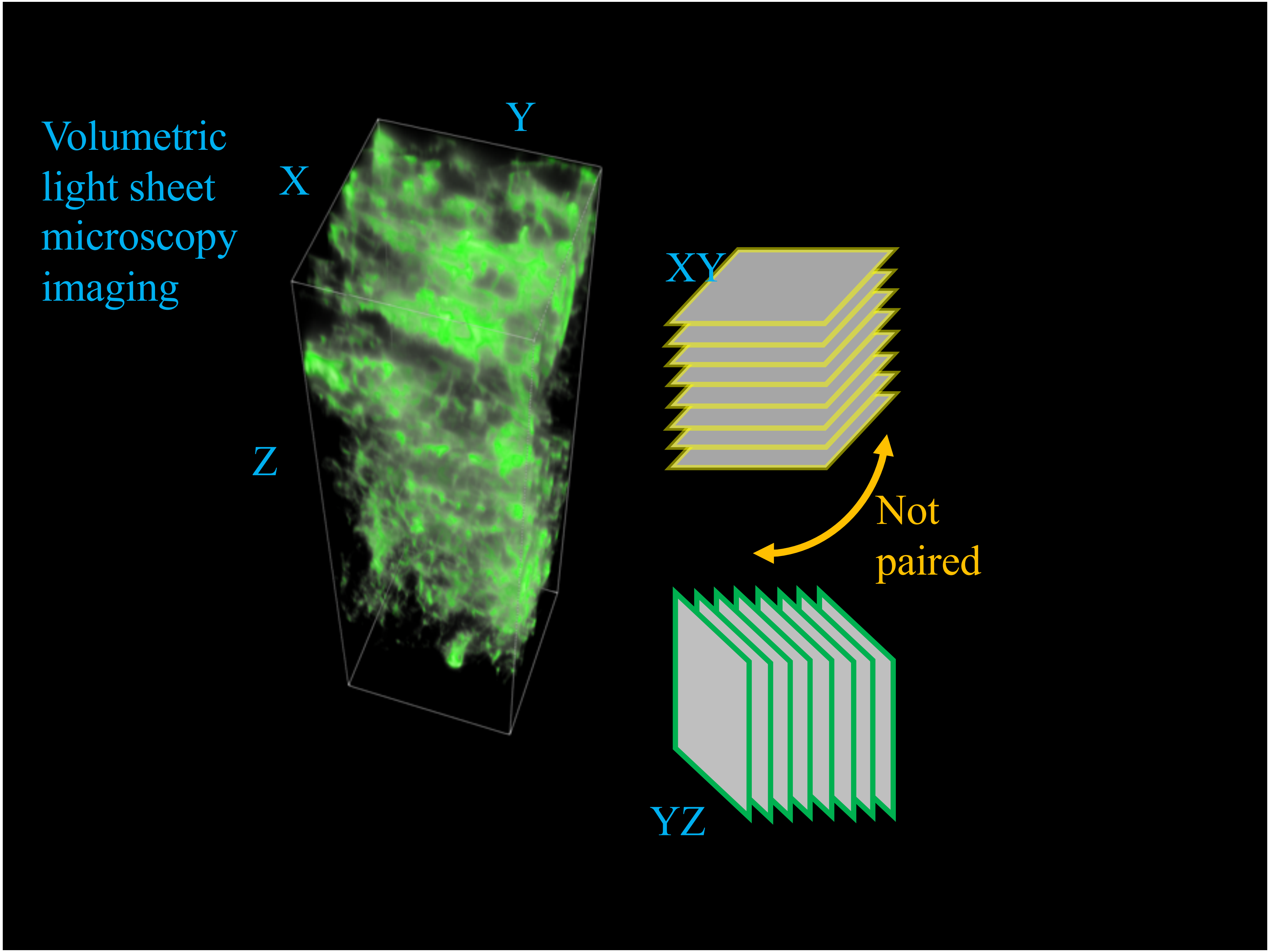


-Can’t take it simultaneously

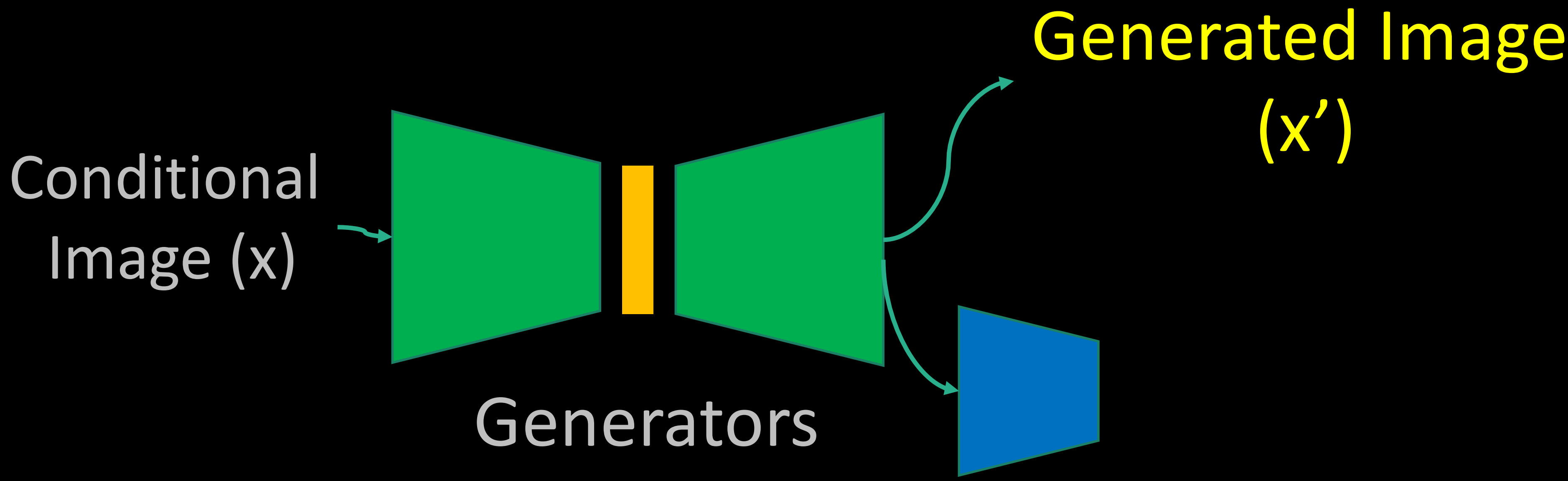
-Different sites/population

-Historical Data, Missing Data

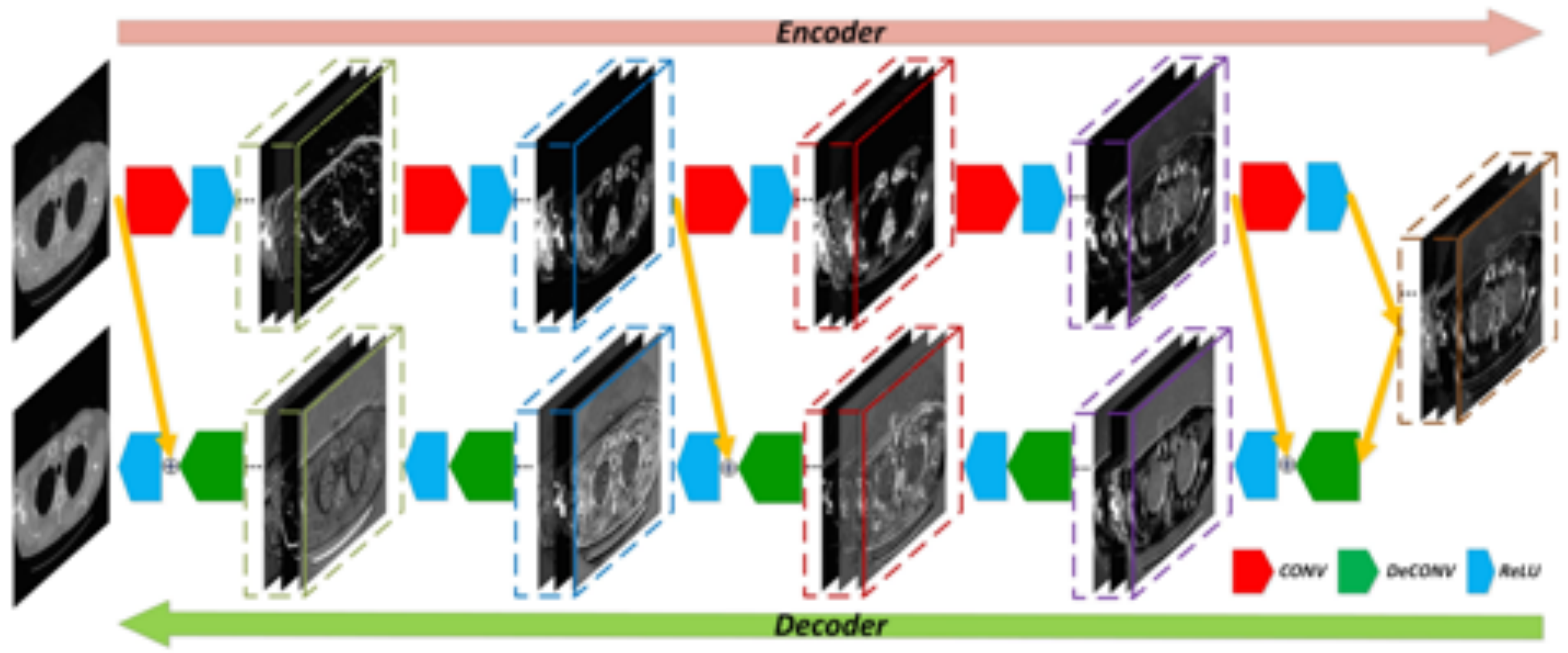
- (H>L) hard to assume


Volumetric light sheet microscopy imaging
X
Y
Z
XY
Not paired
YZ

Supervised Image-level

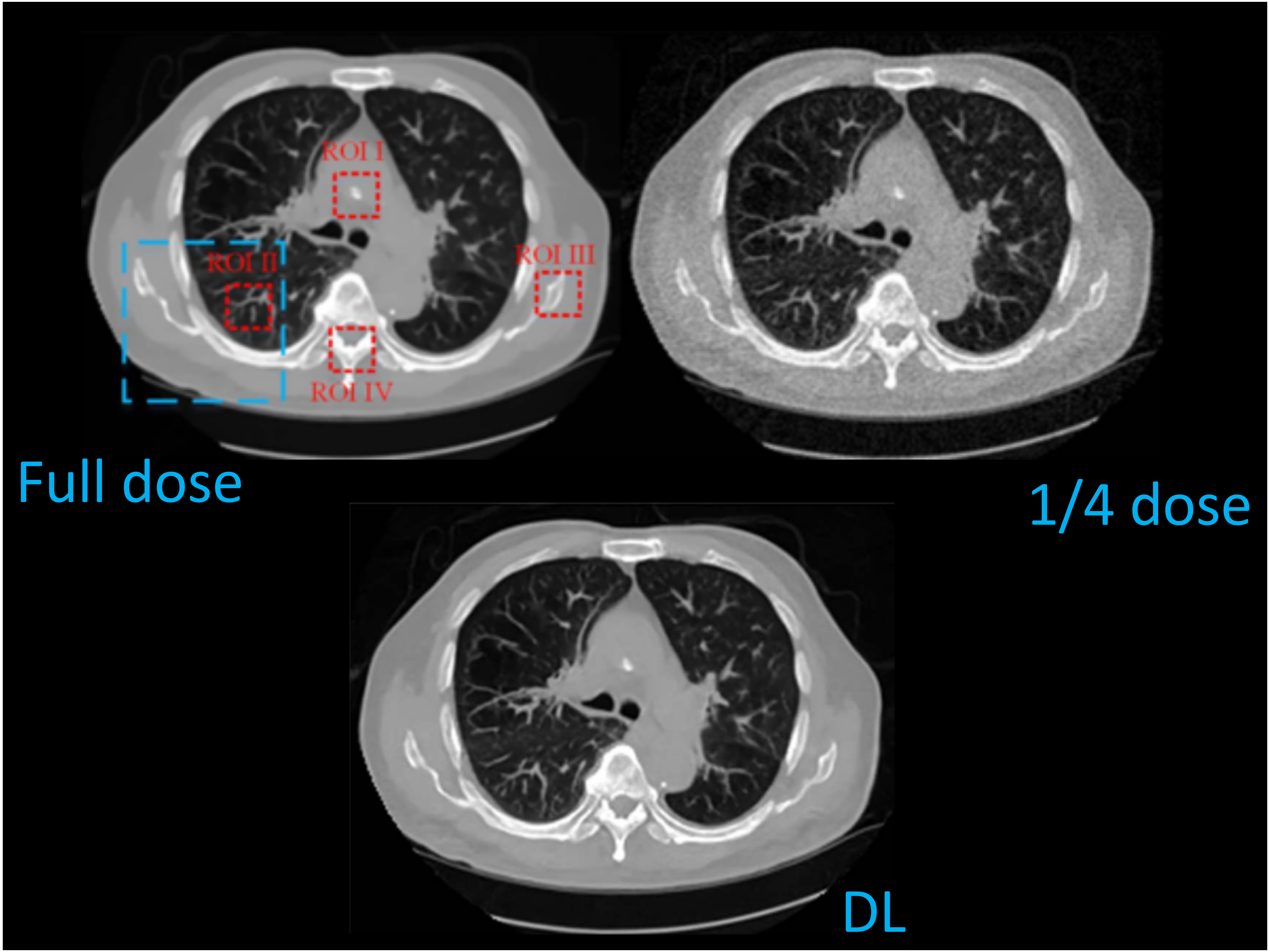


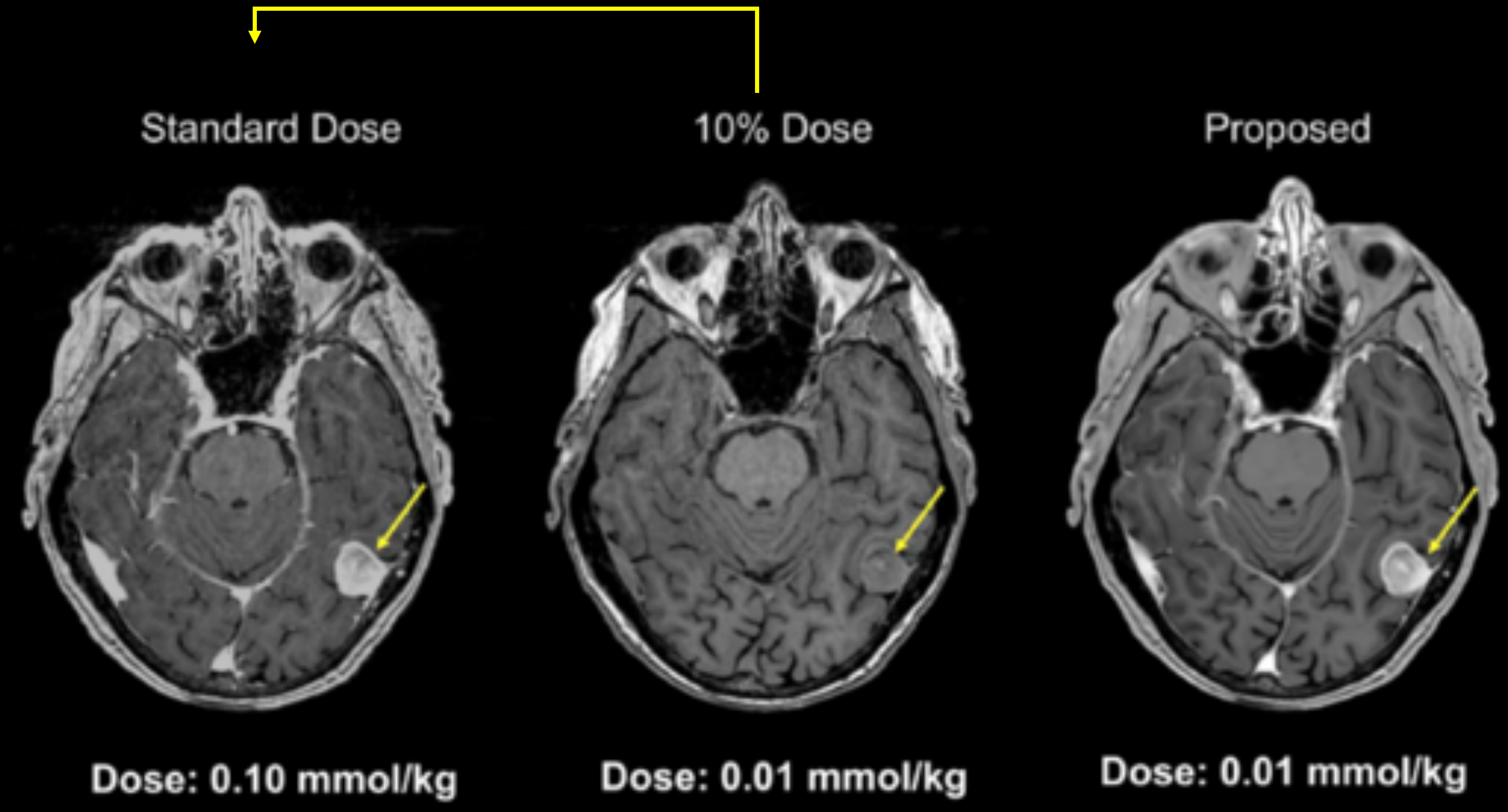
Supervised CT denoising



Q: what is this network?

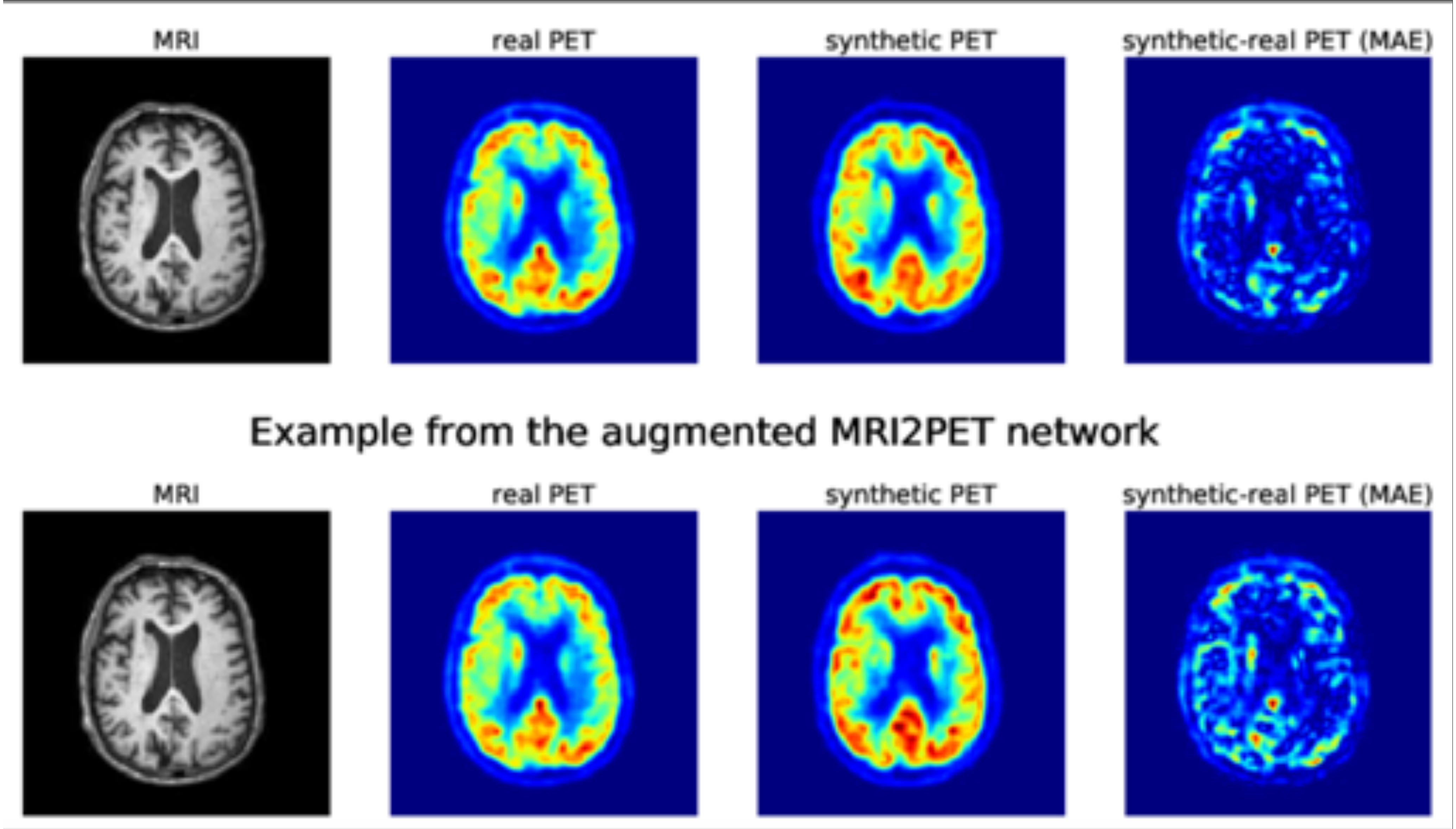
Low-Dose CT With a Residua
Encoder-Decoder
Convolutional Neural
Network


ROI I
ROI II
ROI III
ROI IV
Full dose
1/4 dose
DL

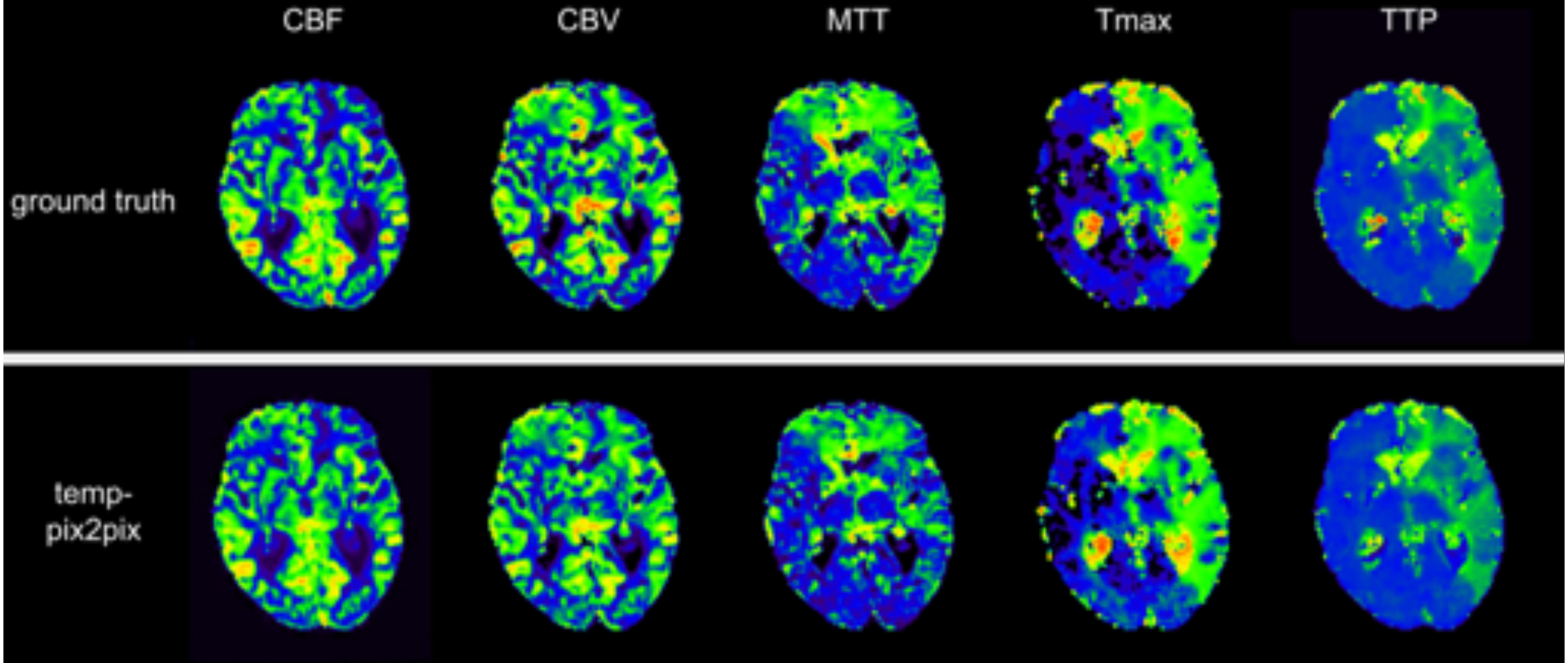


Use of AI to significantly reduce gadolinium dose

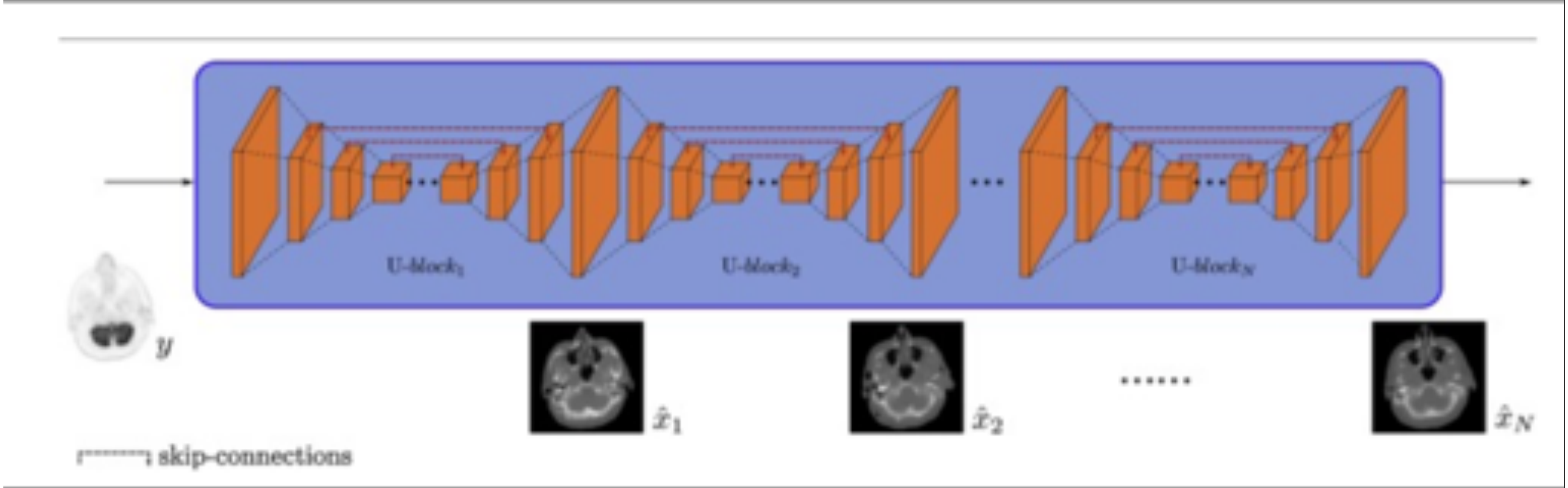
MRI2PET (paired)



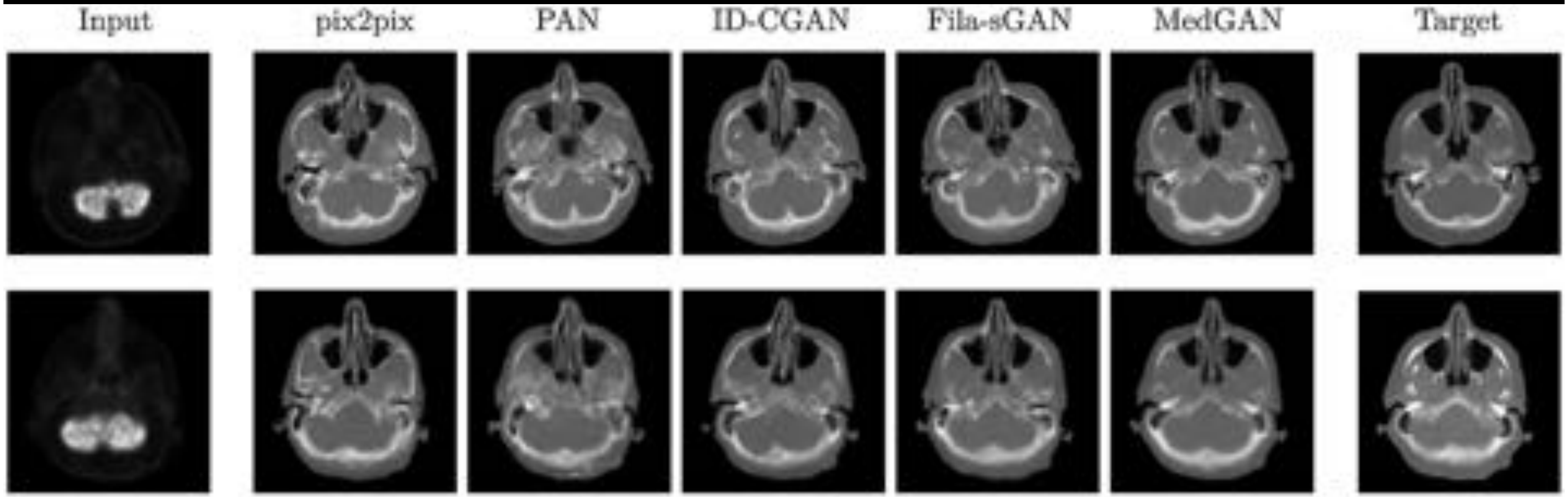
DSC-MRI to perfusion parameters



MedGAN

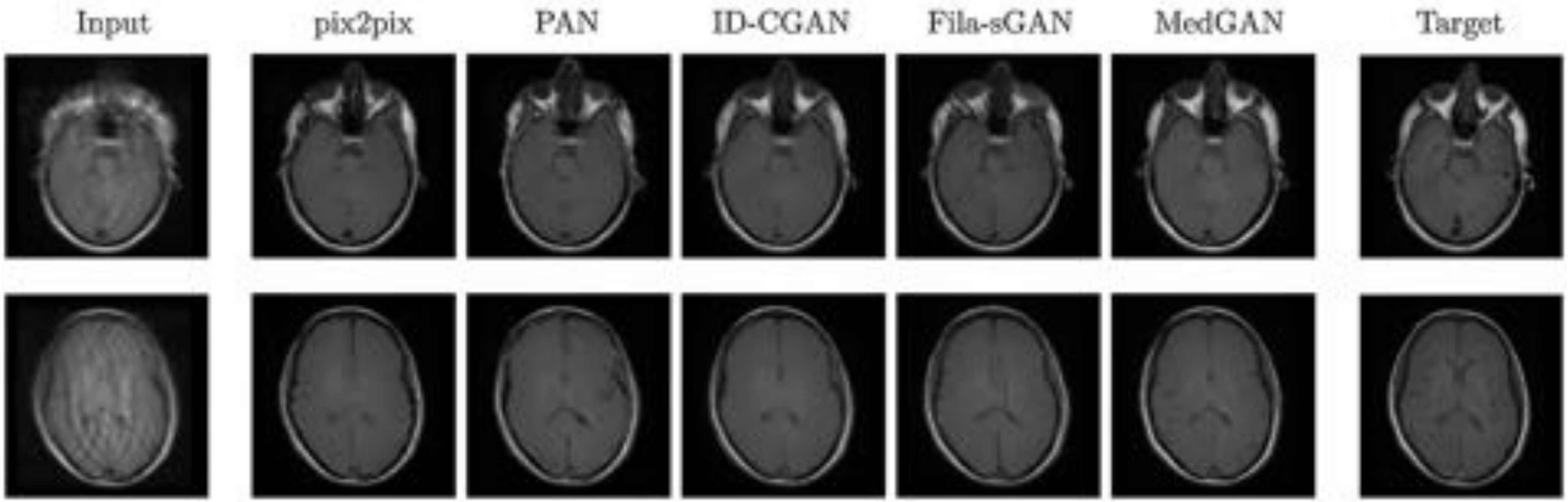


Q: what is this model?



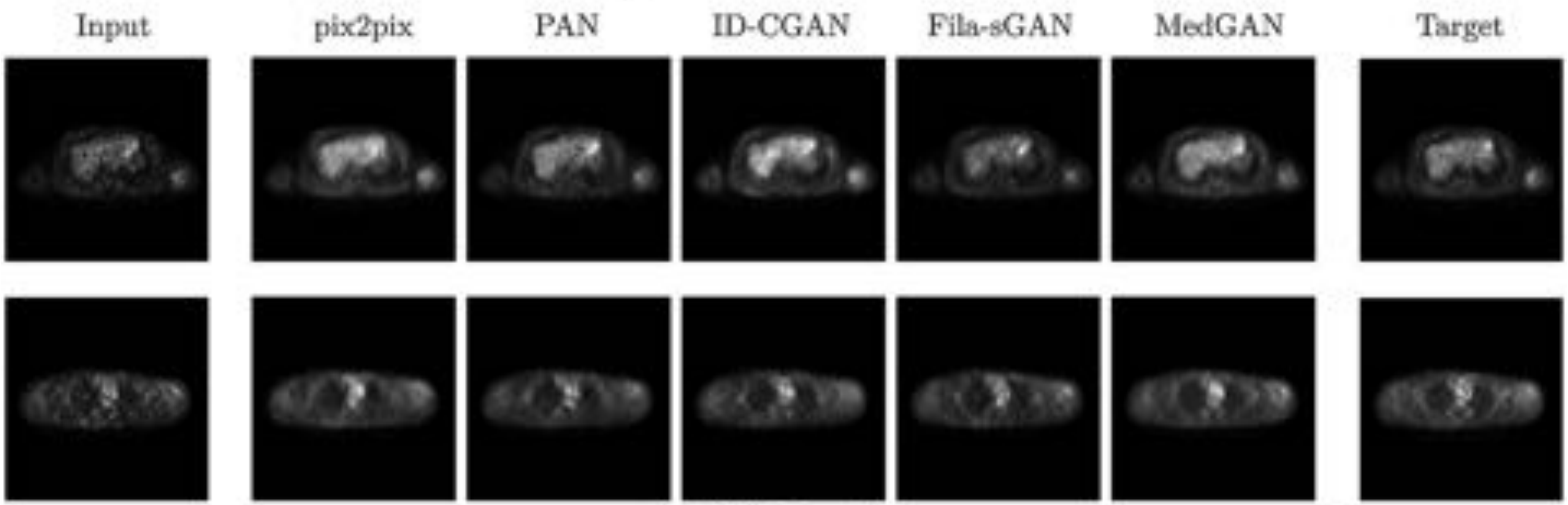
(a) PET-CT translation

By joint PET / CT scan



(b) MR motion correction

Imaging under resting + motion



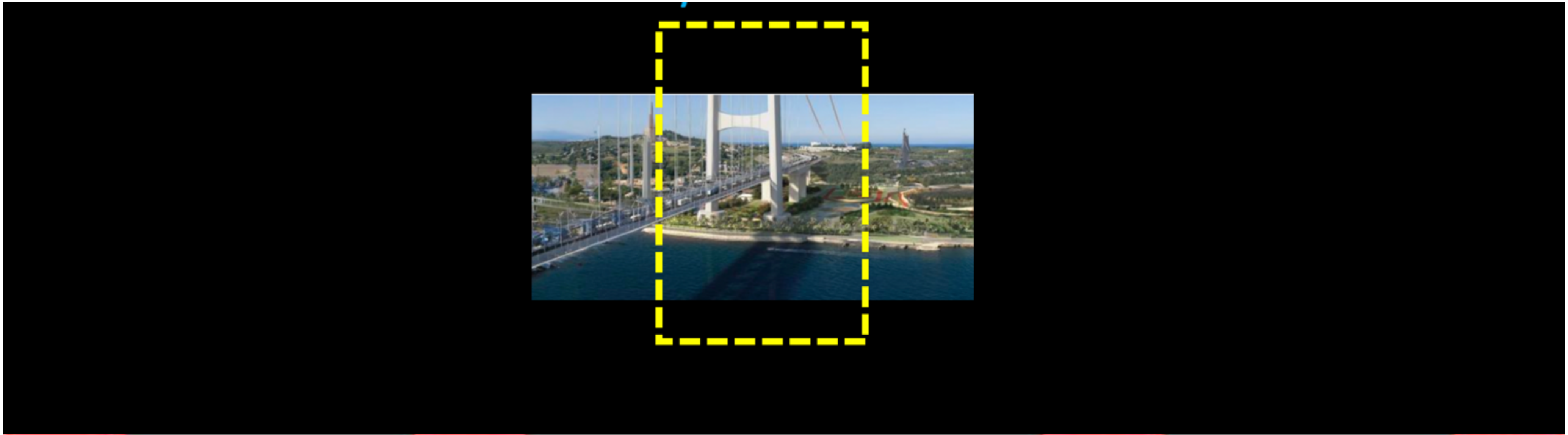
(c) PET denoising

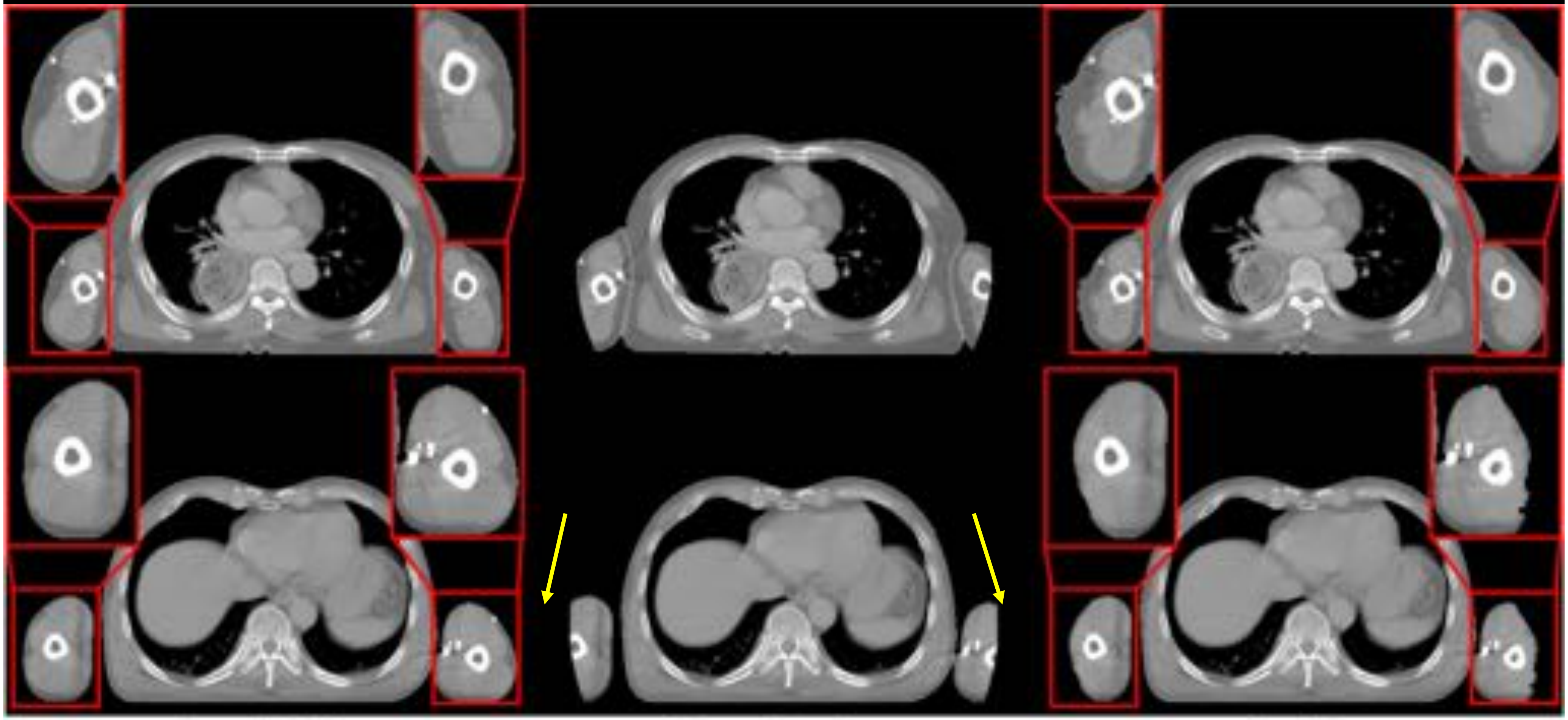
Reconstruction w/ 25% acquisition

Image to image summary:

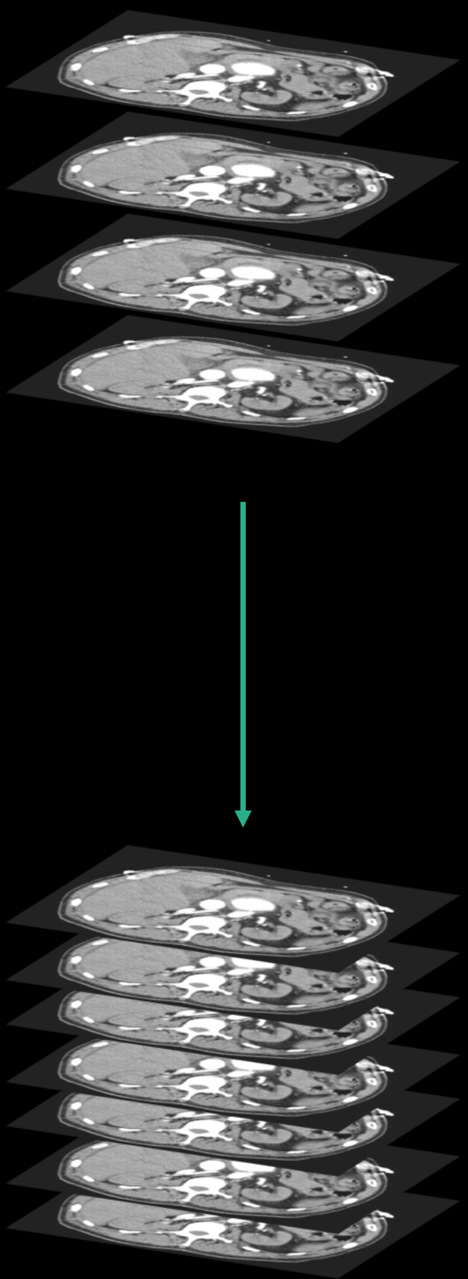
Find out if you can require paired dataset

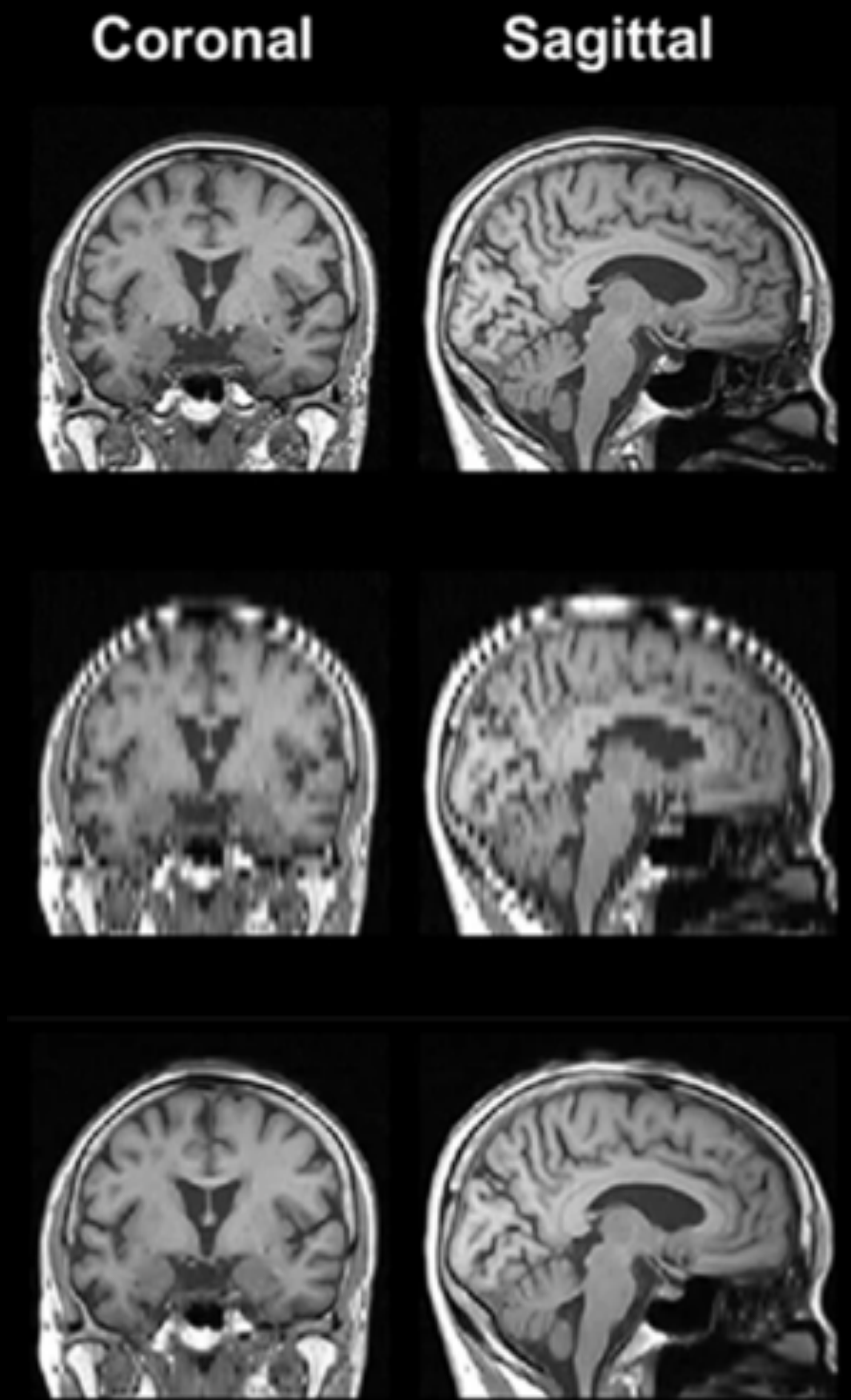
If not, how do people approximate the degradation?





Interslice inpainting





Other creative way to use image-to-image translation

Baseline (L) → Progress (H)

What make it look younger?

(observe the different can help explaining the process)

Progression Detection

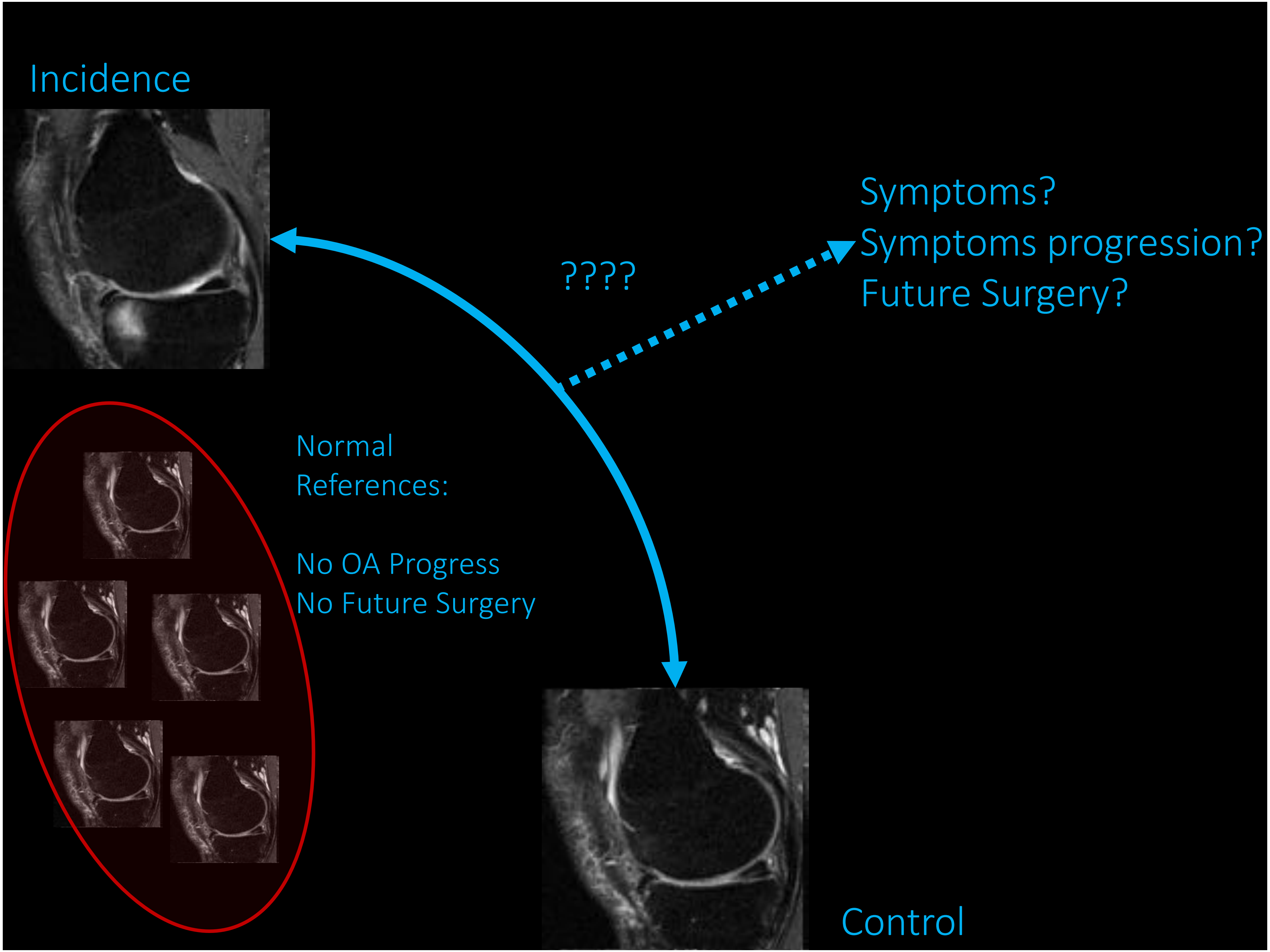
Incidence

????

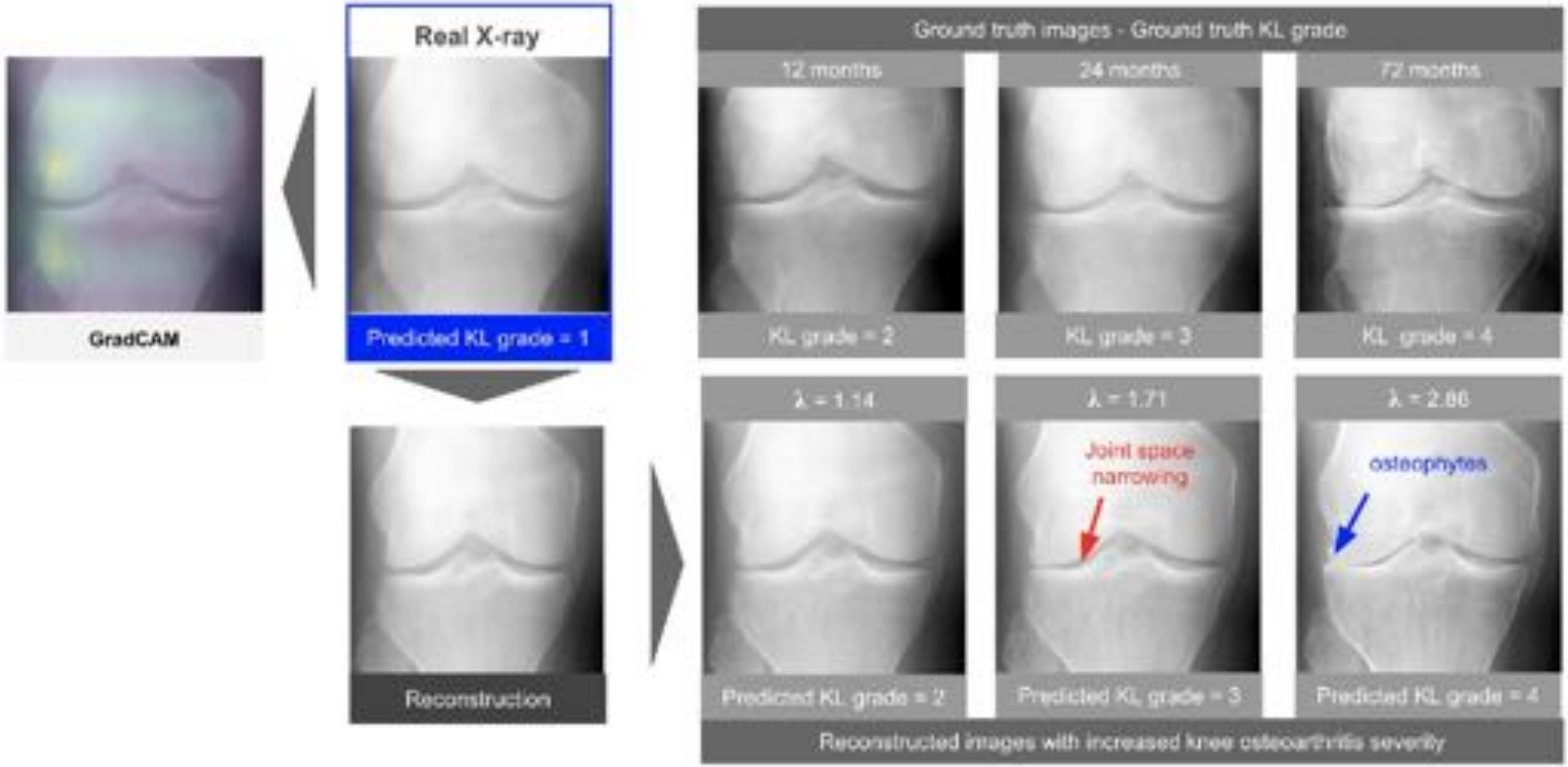
"Normal References"

Control

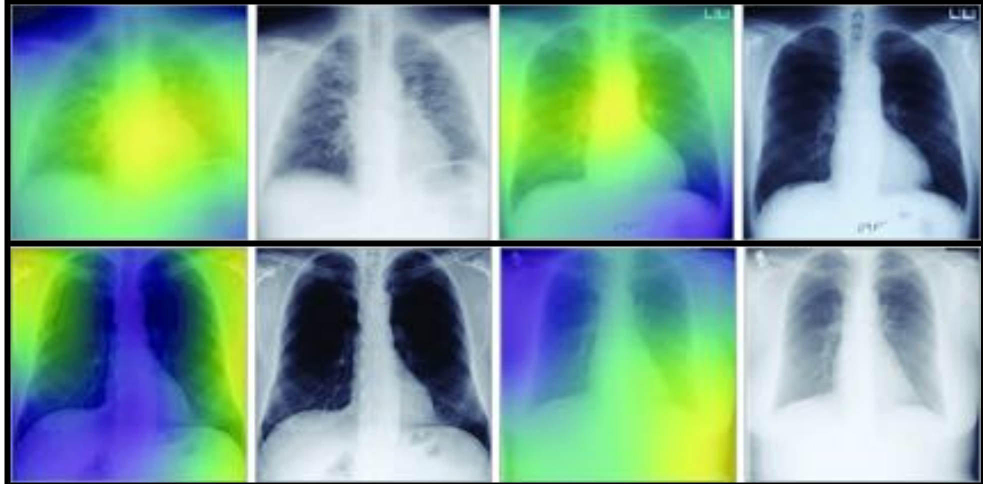
Gladiator 2 is coming out now
Please google it

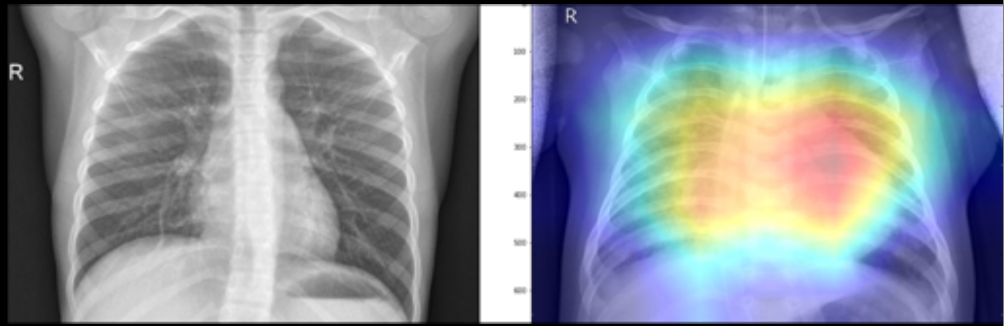

Incidence
Symptoms?
Symptoms progression?
Future Surgery?
????
Normal
References:
No OA Progress
No Future Surgery
Control

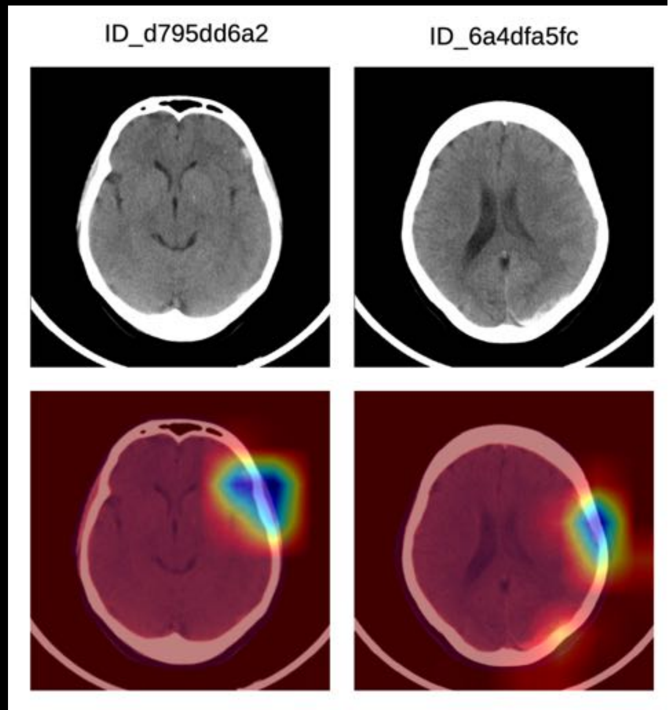
Using StyleGAN for Visual Interpretability of Deep Learning Models on Medical Images



“Explainable AI”

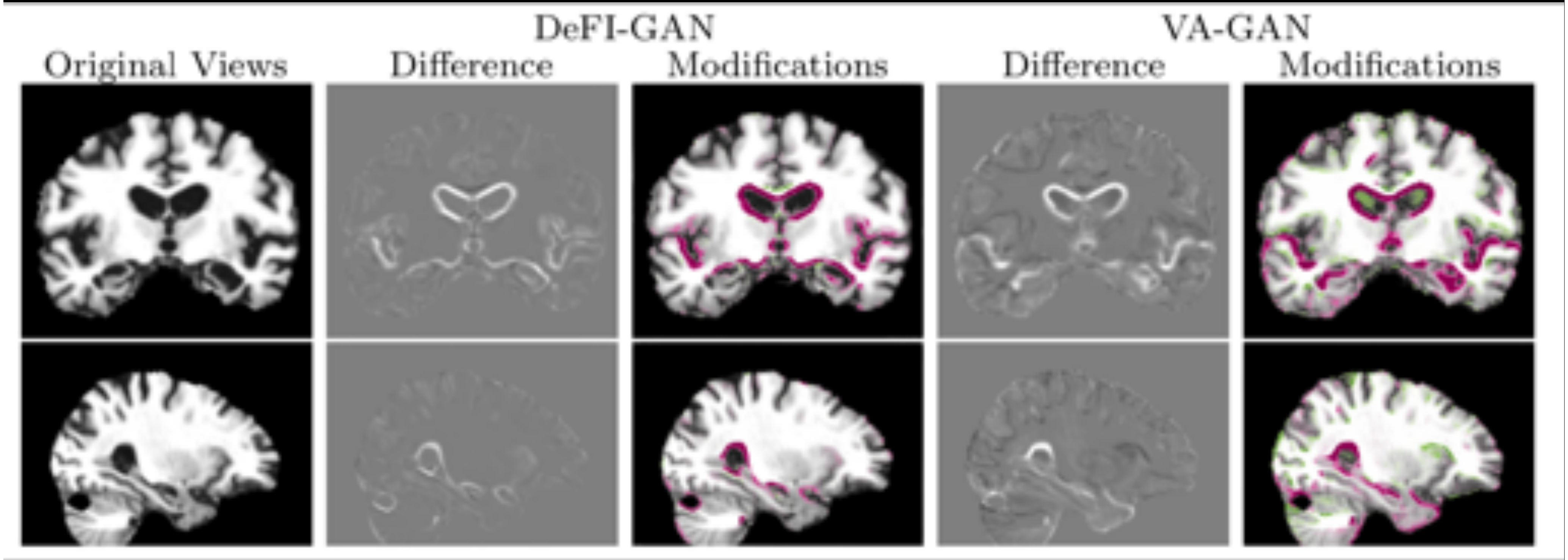






(paired) Progression Detection

Baseline (L) → Progress (H)



Interpretation of Disease Evidence for Medical Images Using Adversarial Deformation Fields, 2020

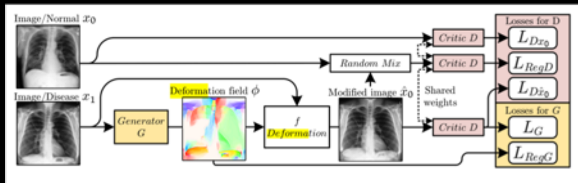
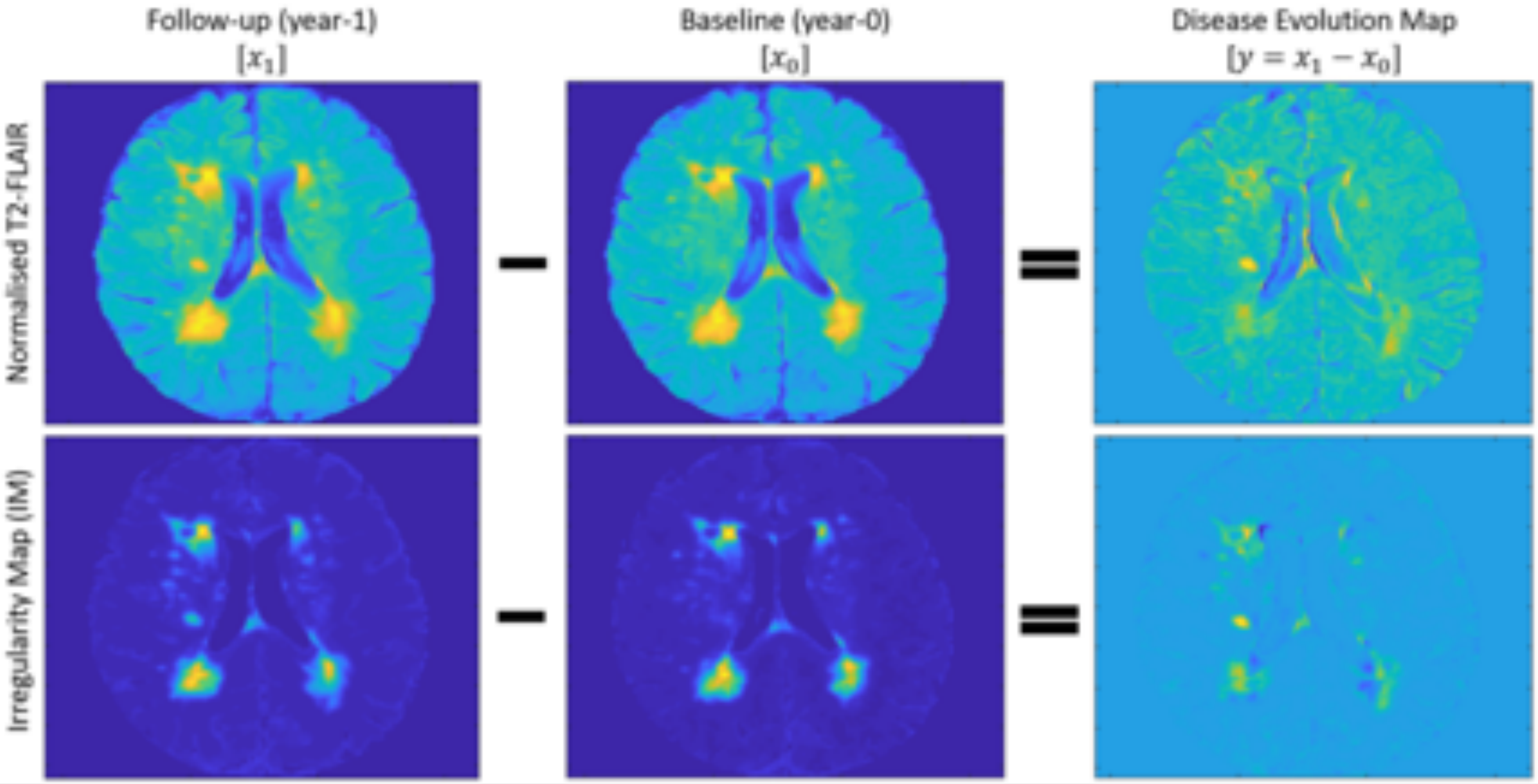


Fig. 1. Overall model architecture. The terms L_{Dx_0}, $L_{D\hat{x}_0}$, and L_G are WGAN losses, whereas L_{RegD} penalizes the gradient of D, and L_{RegG} penalizes the complexity of ϕ.

(paired) progression detection



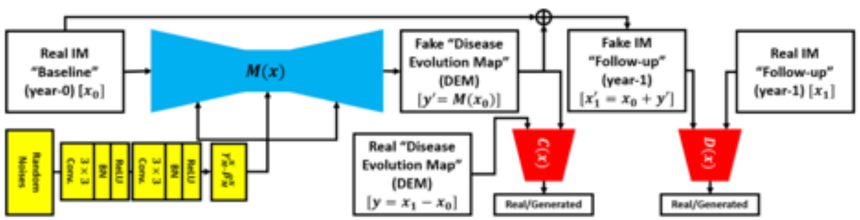


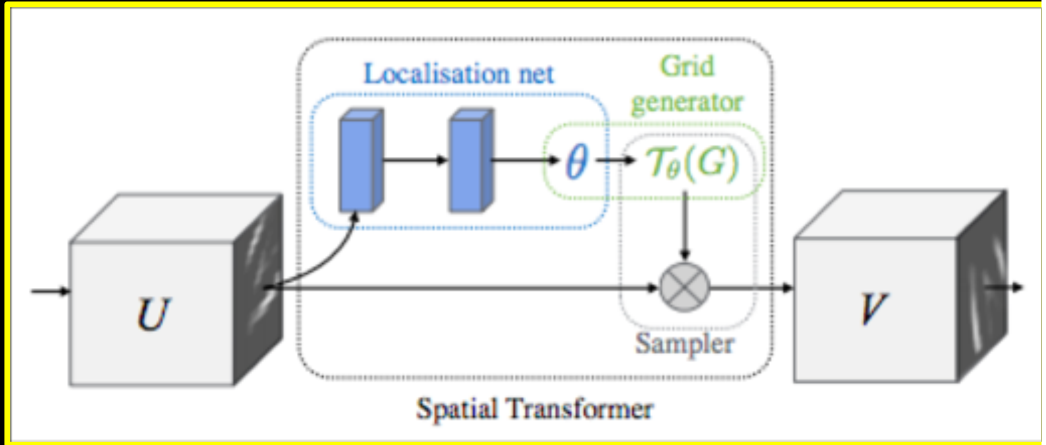
Fig. 2: Schematic of the proposed DEP-GAN with 2 discriminators (critics).

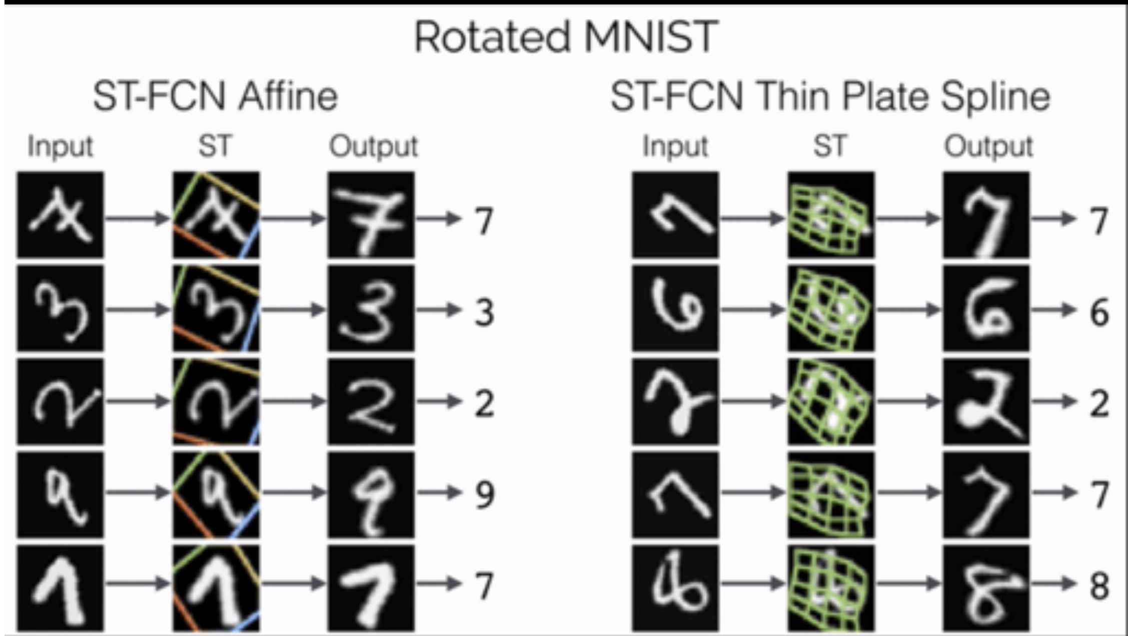
Predicting the Evolution of White Matter Hyperintensities in Brain MRI using Generative Adversarial Networks and Irregularity Map (2019)

Imaging Registration by Spatial Transformation

Baseline (L) → Progress (H)

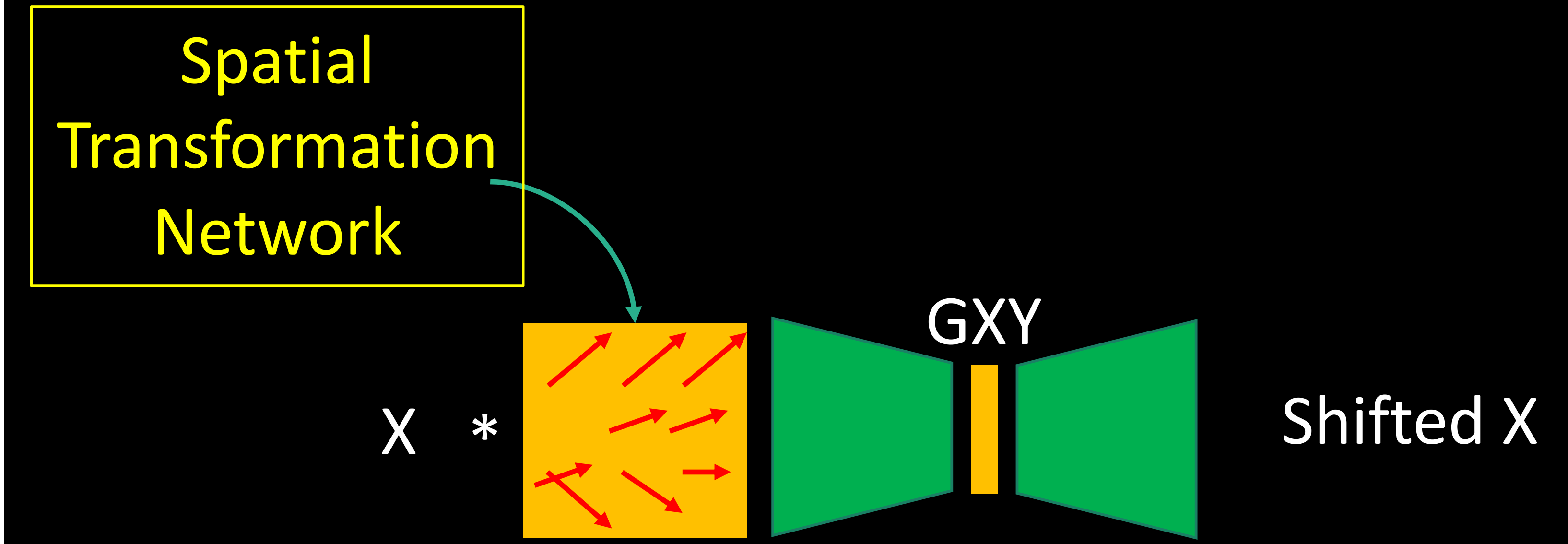
Spatial Transformation Network

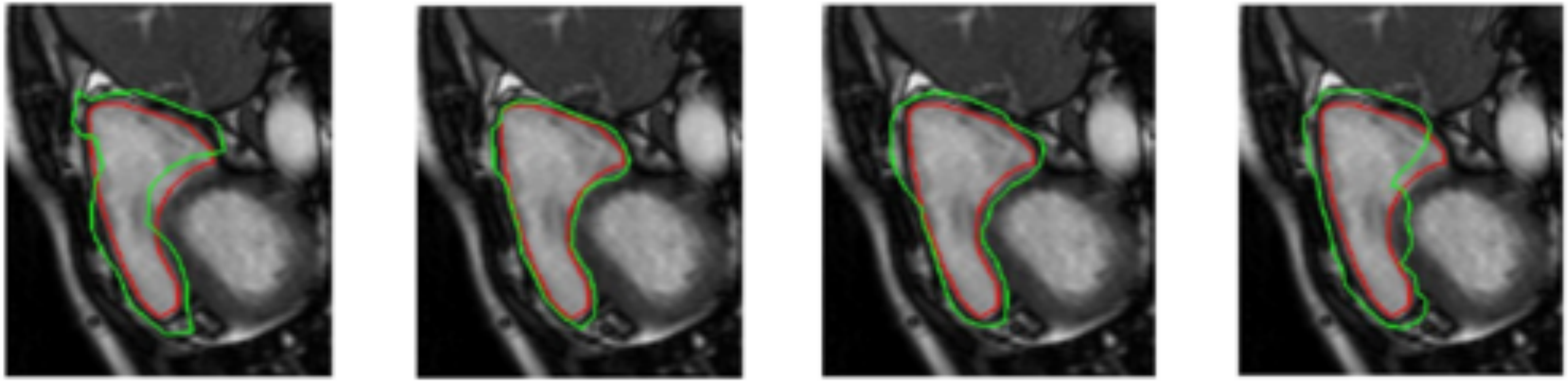




Pixels can only move around

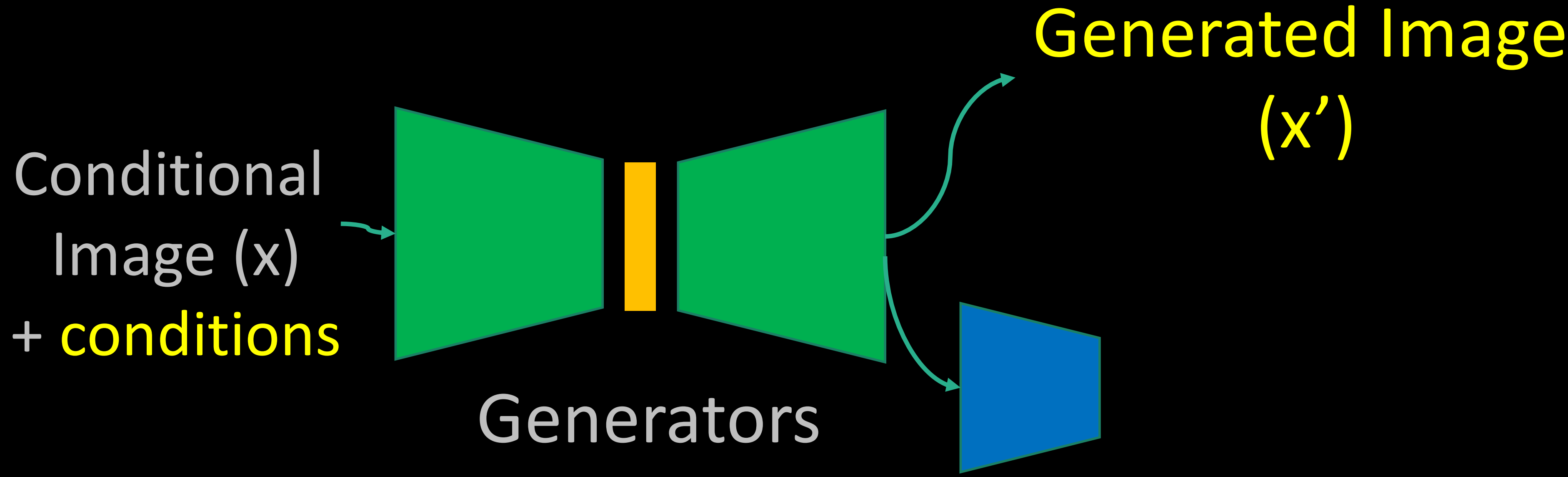
Imaging Registration by Spatial Transformation





ELASTIC REGISTRATION OF MEDICAL IMAGES WITH GANS

Synthetize images by class condition



Benign / Tumor
Type A/ Type B
Normal / Abnormal…

Most of times we use it to fight

- lack of data
- data imbalance /shifting

What's the main goal:

- accurately reflect the class condition
- diversity

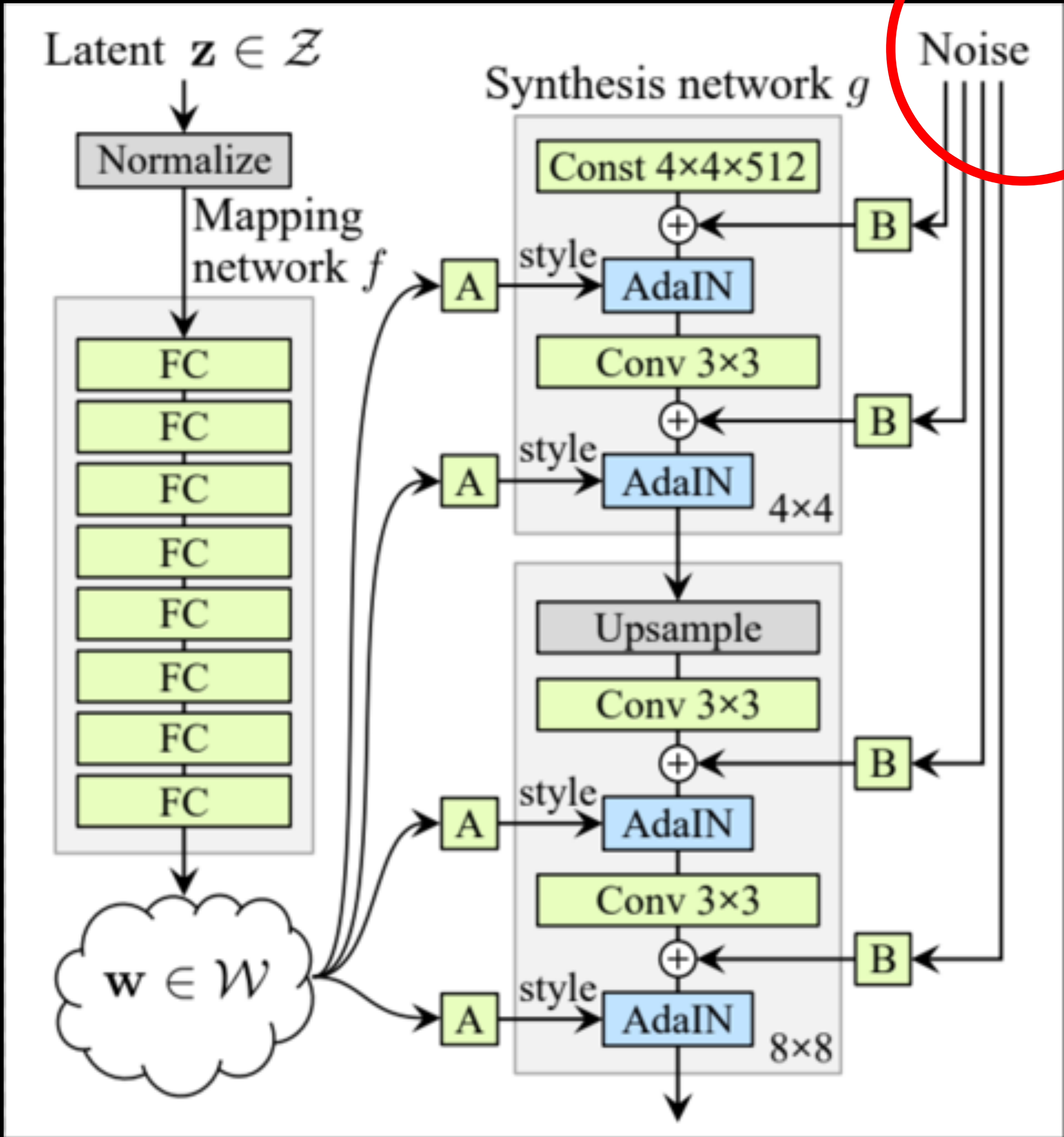
(because we want to approximate real-world's distribution)

Older Models

More diversity
More details
Multi-scaling etc...

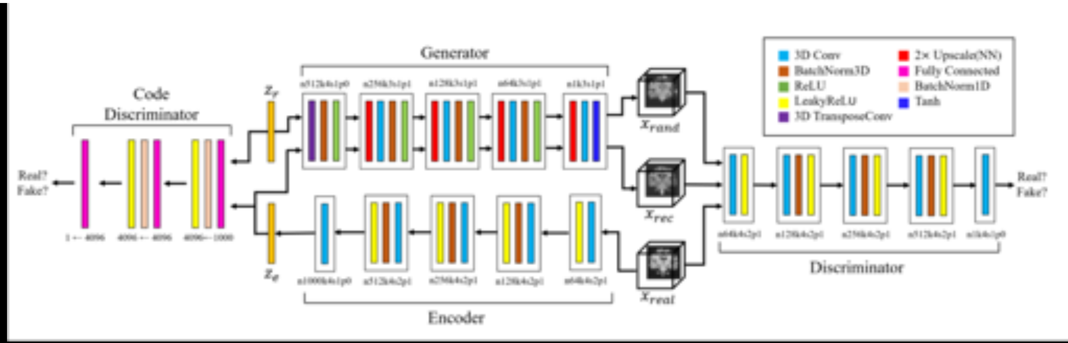
StyleGAN

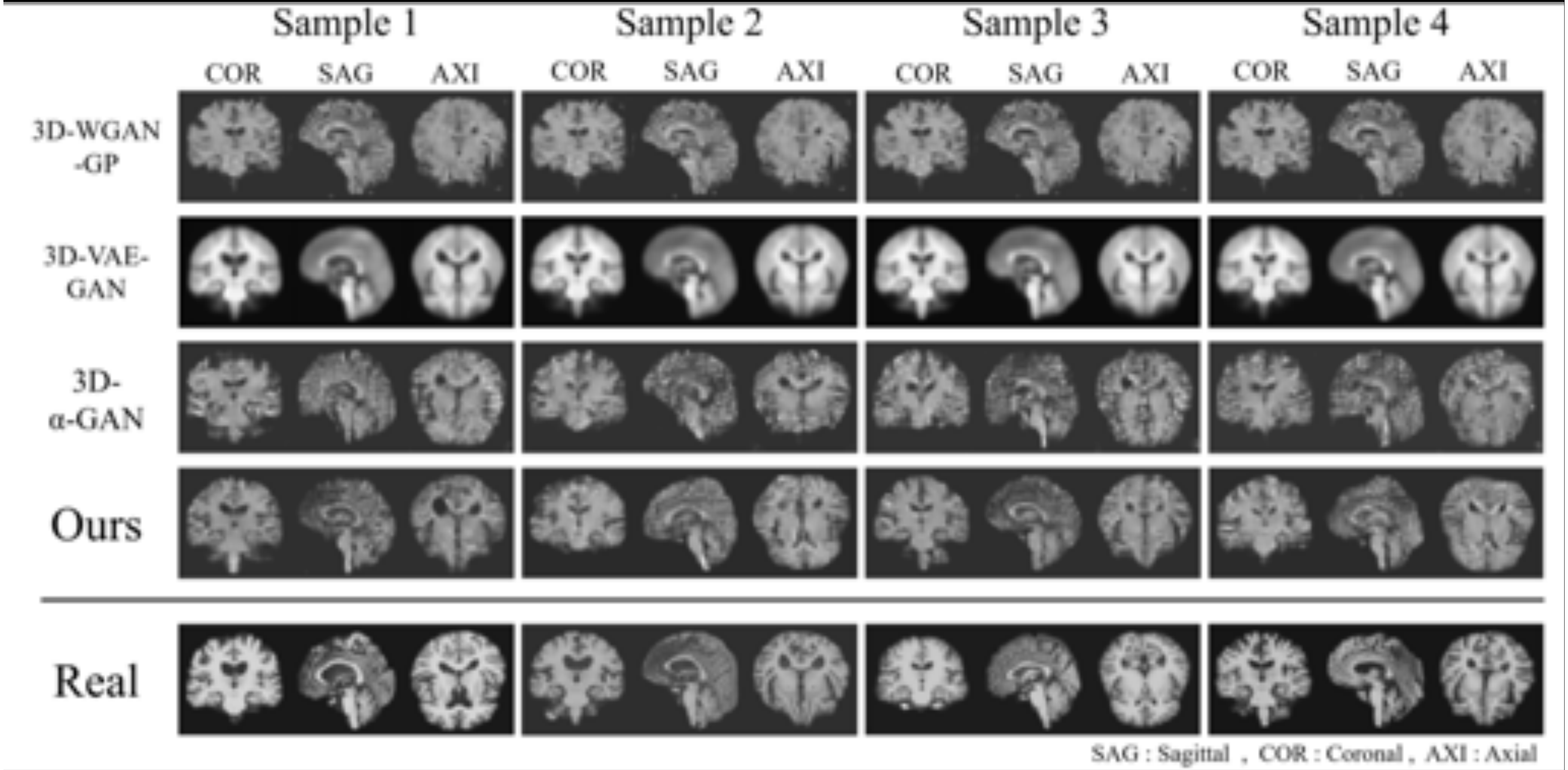
randomness



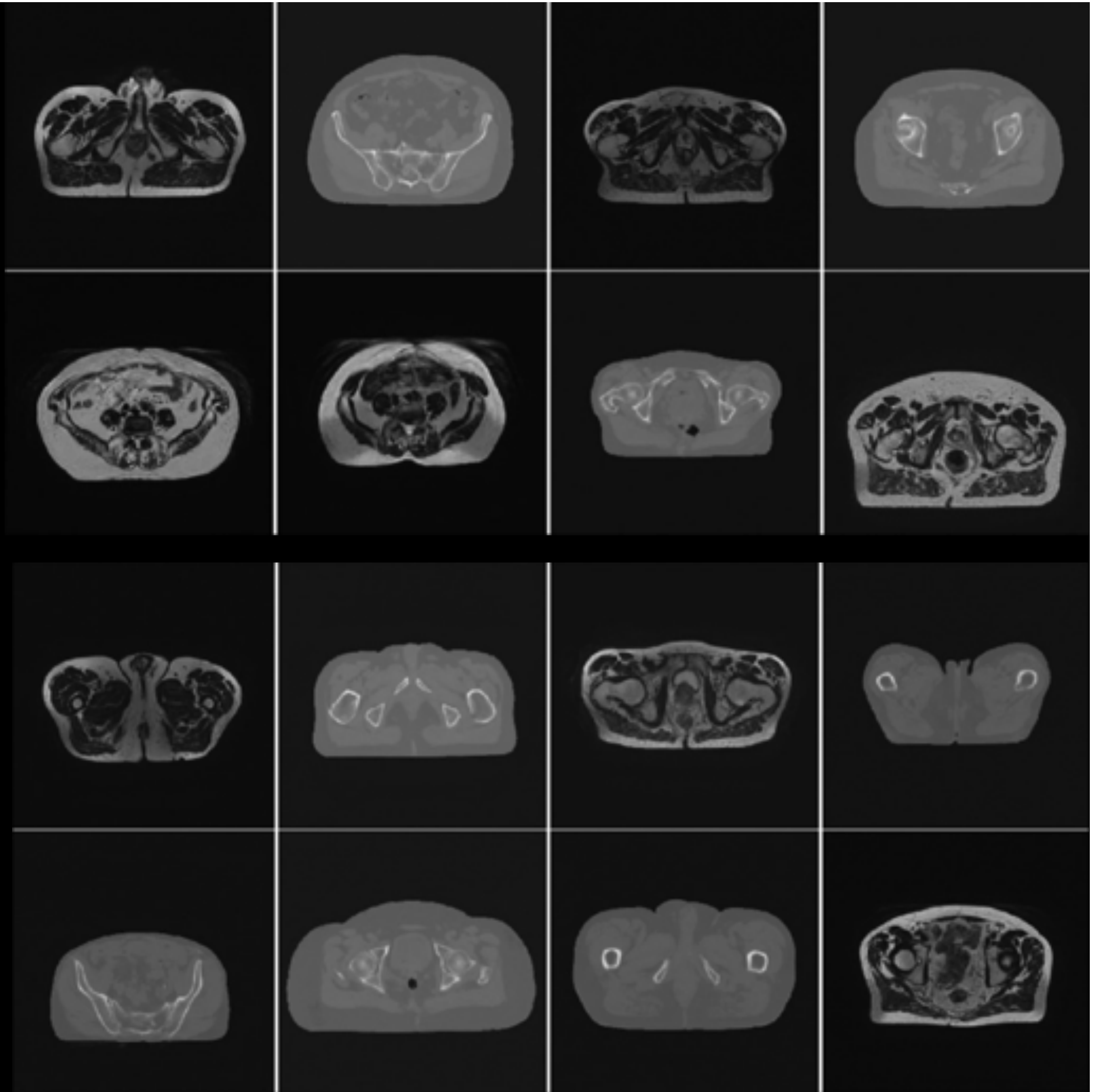
Stylecode

Generation of 3D Brain MRI Using Auto-Encoding Generative Adversarial Networks (2020)



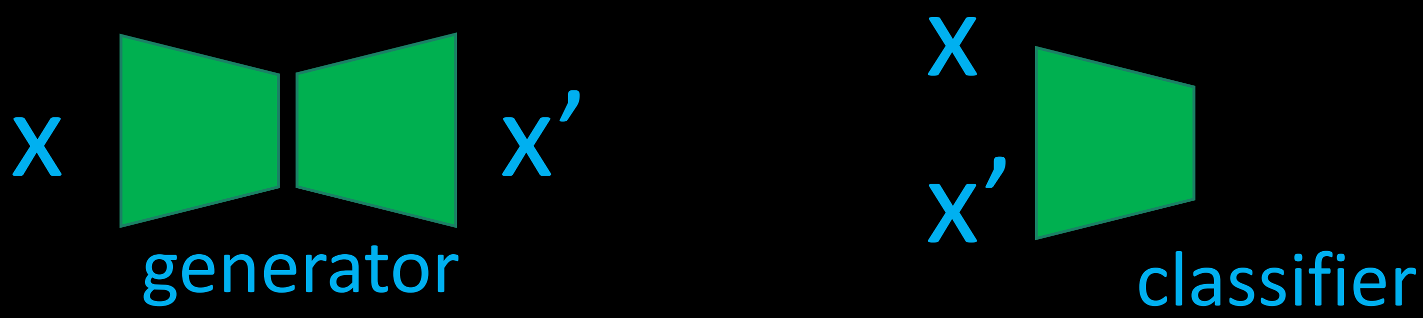


Result of stylegan

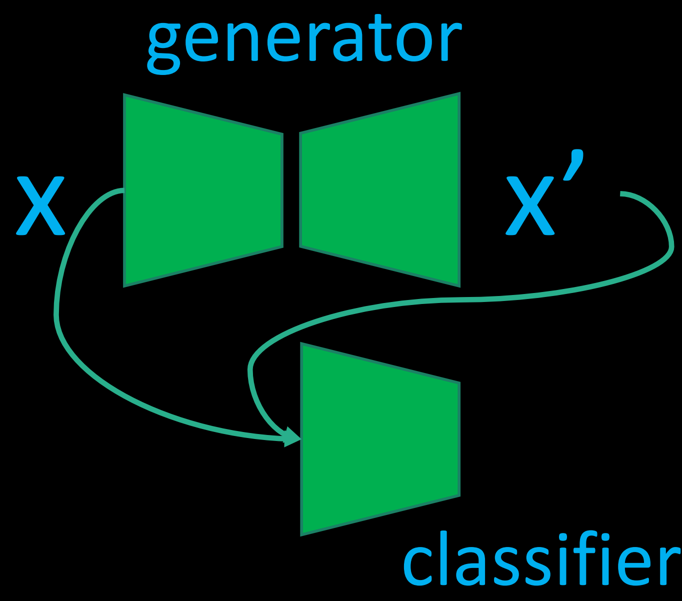


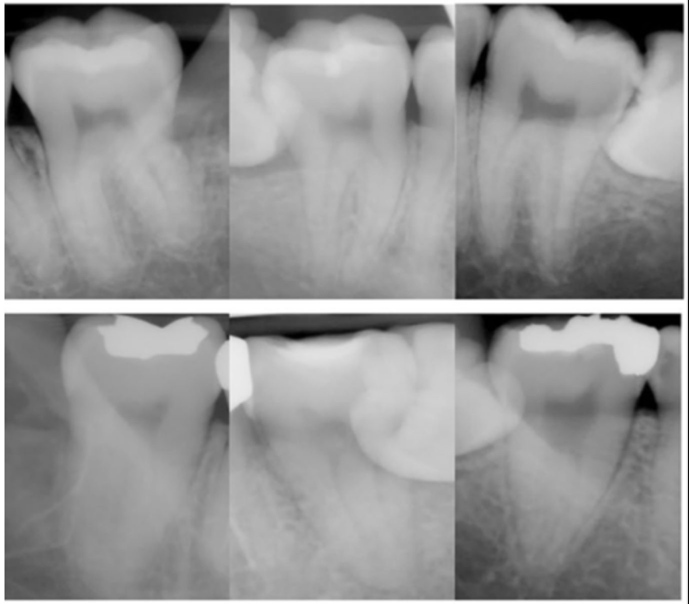
Generative model assisting classification:

2-stage:

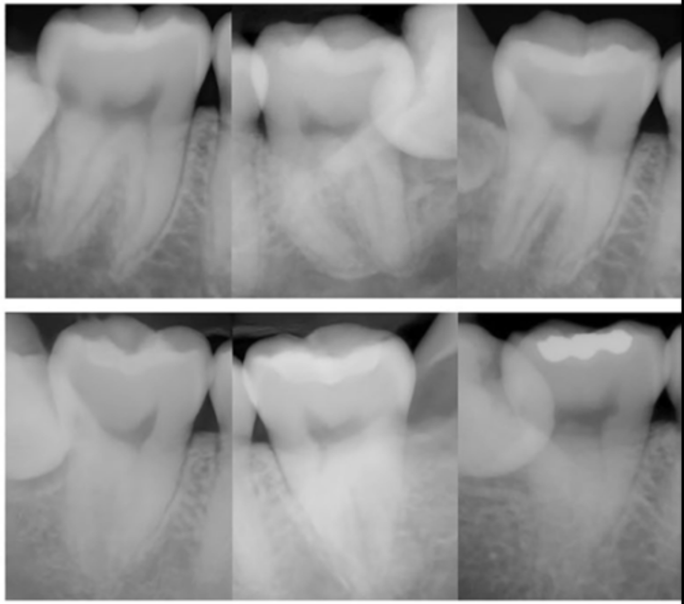


1-stage:

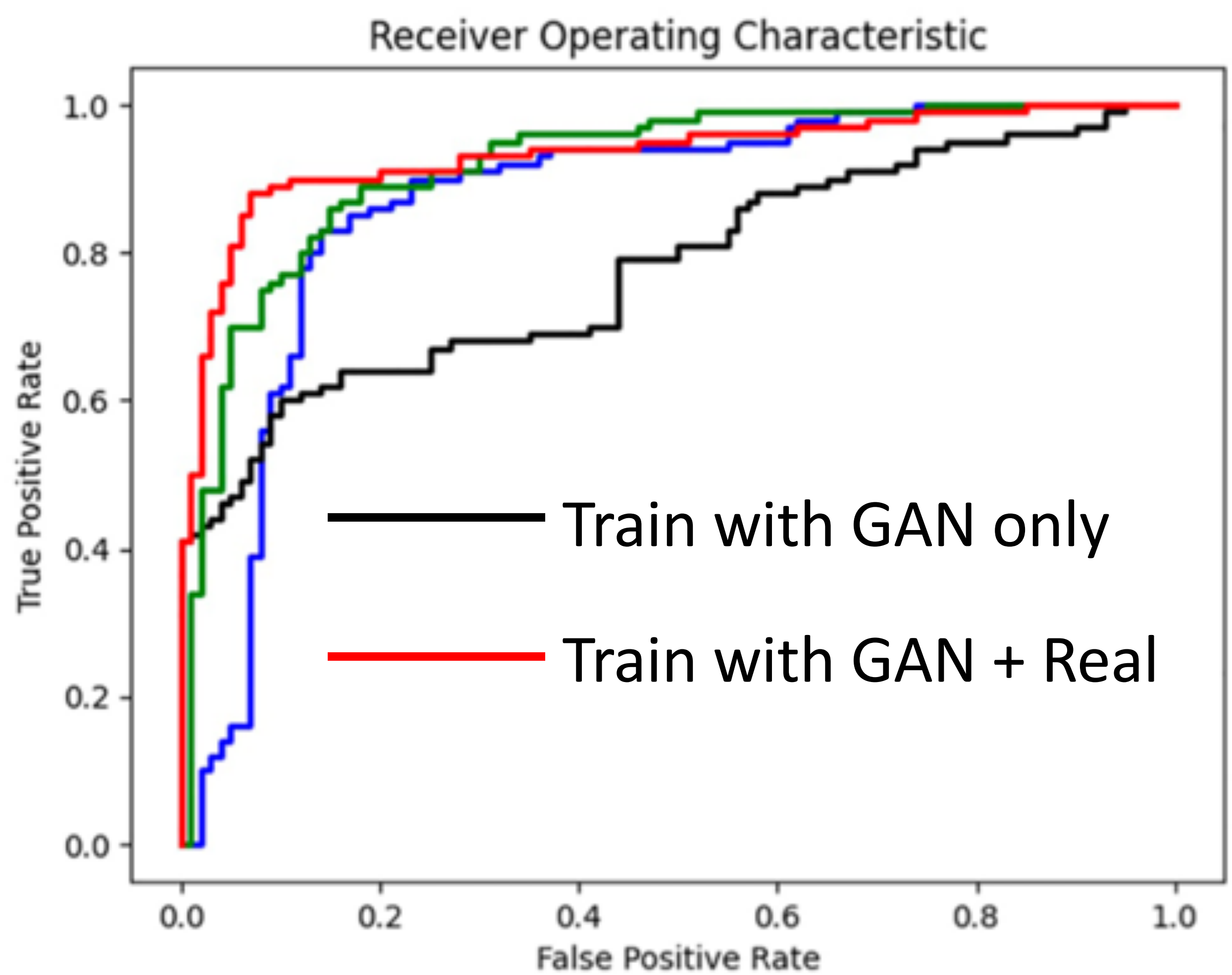




Real images

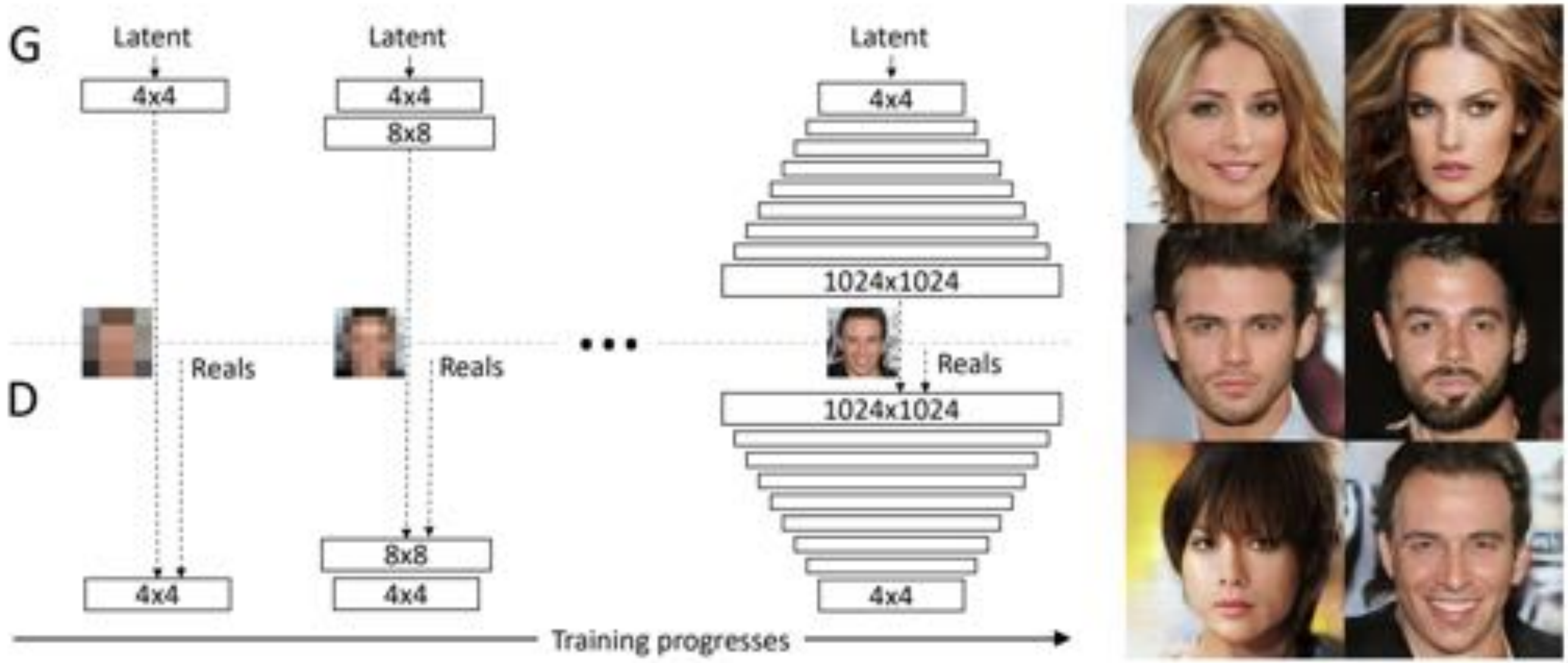


Generated images



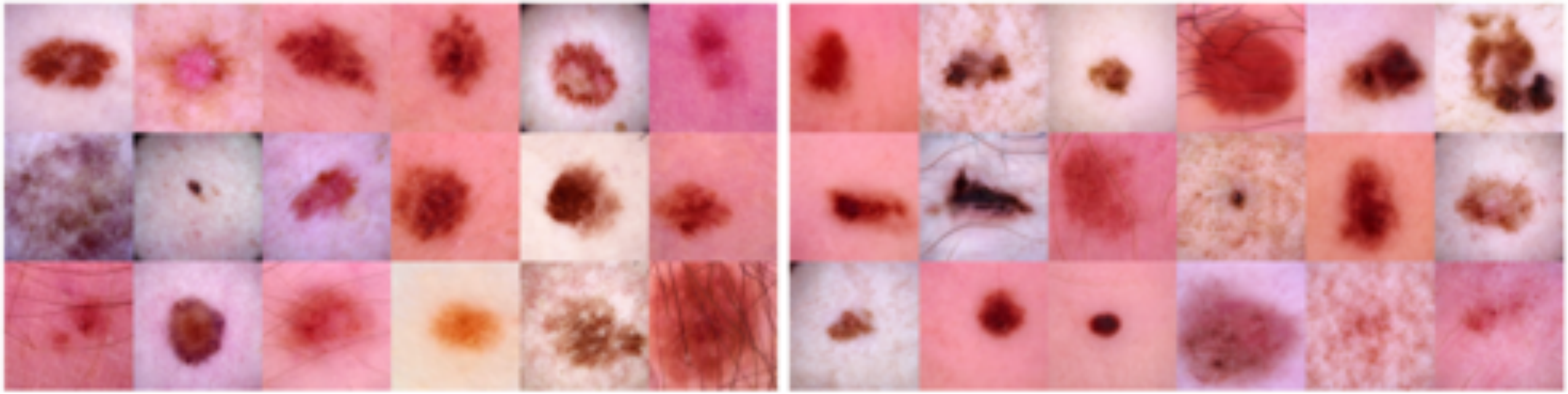
Looks real != helpful

You can also generate large dimensional image with progressive enlarging GAN

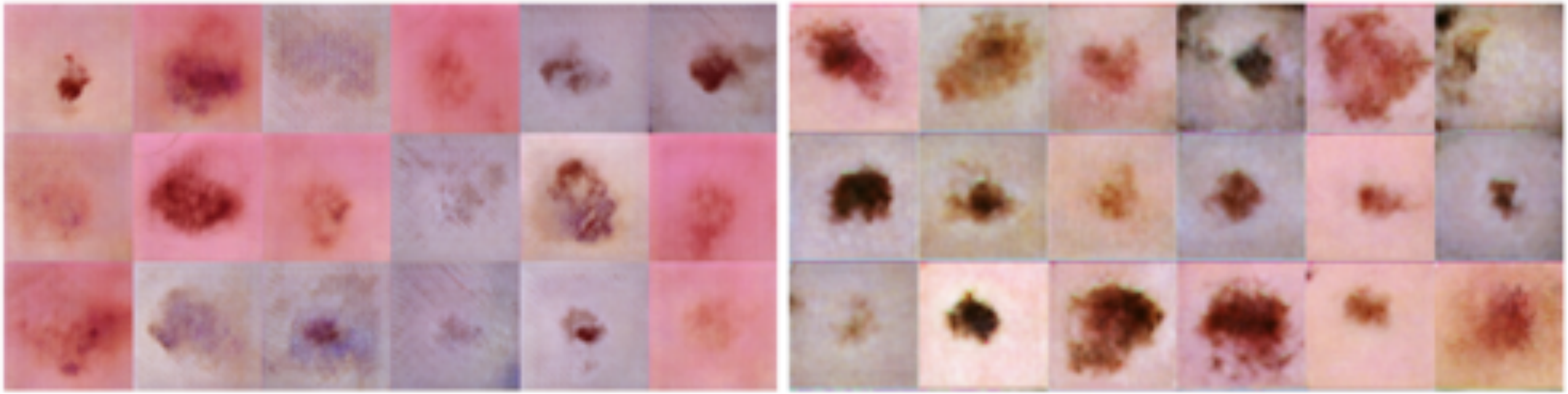


Synthetic Large Images

Generating Highly Realistic Images of Skin Lesions with GANs (2018)

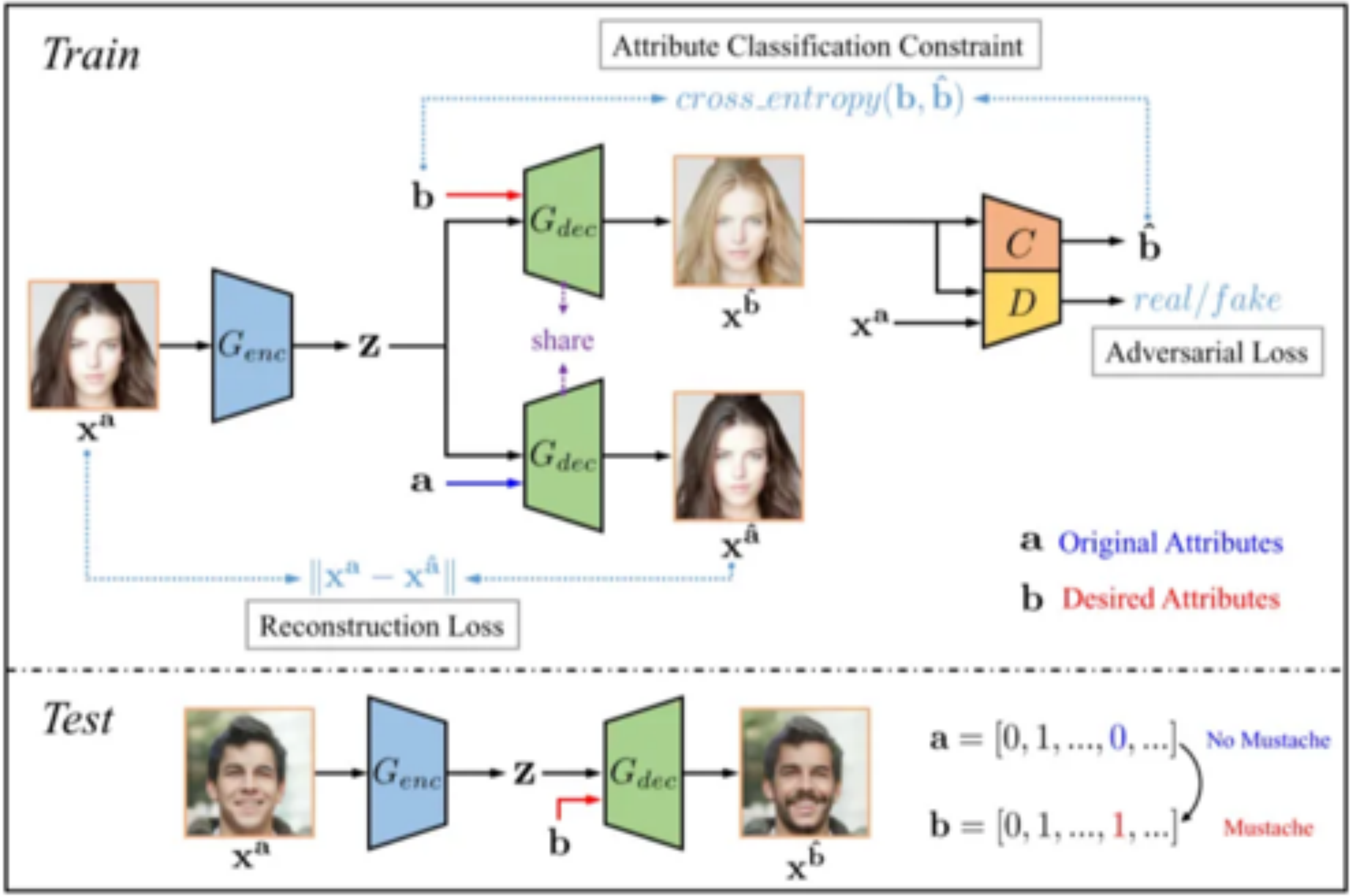


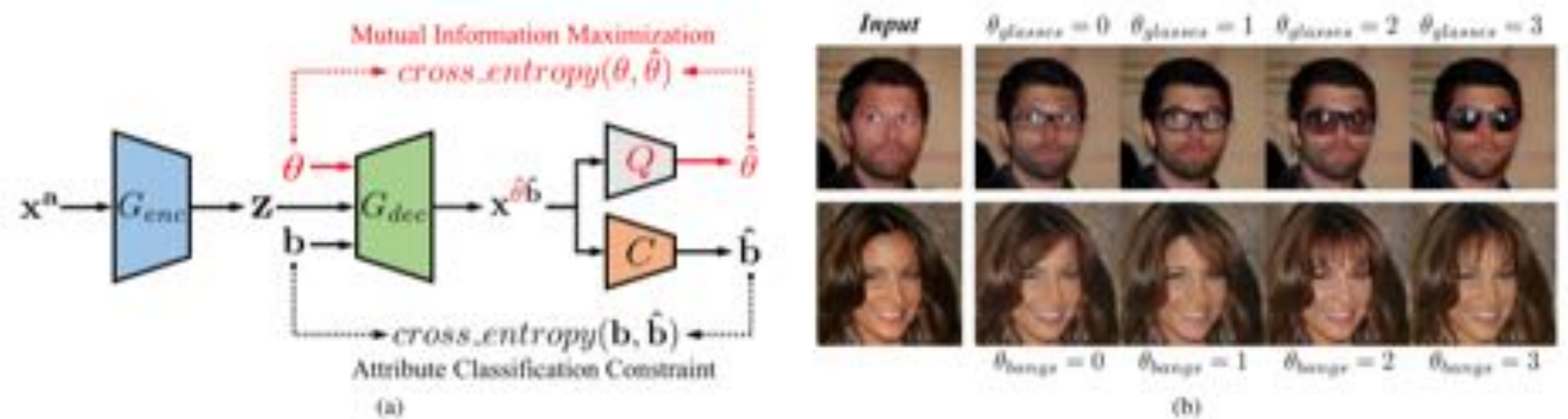
(a) Real Images (b) PGAN Samples



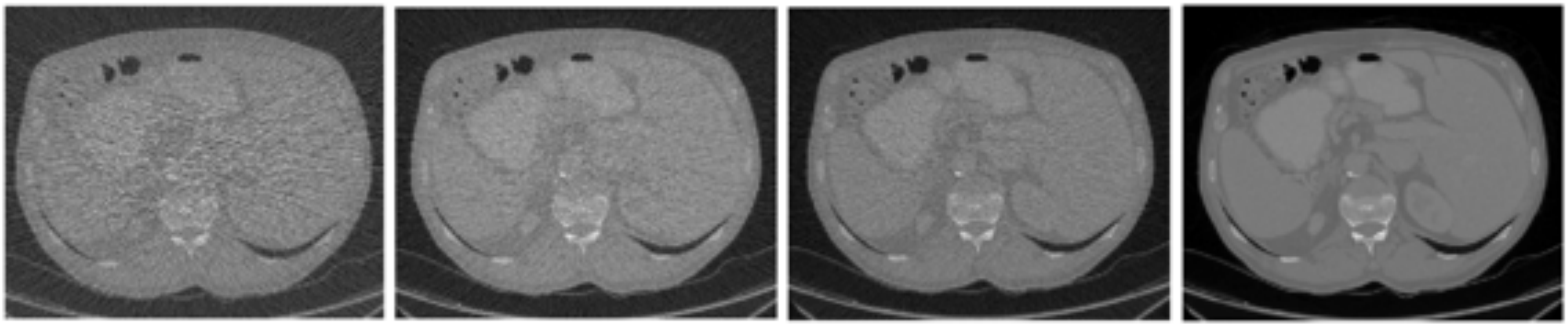
(c) DCGAN Samples (d) LAPGAN Samples

Editng GANs (fine-grained, feature specific)



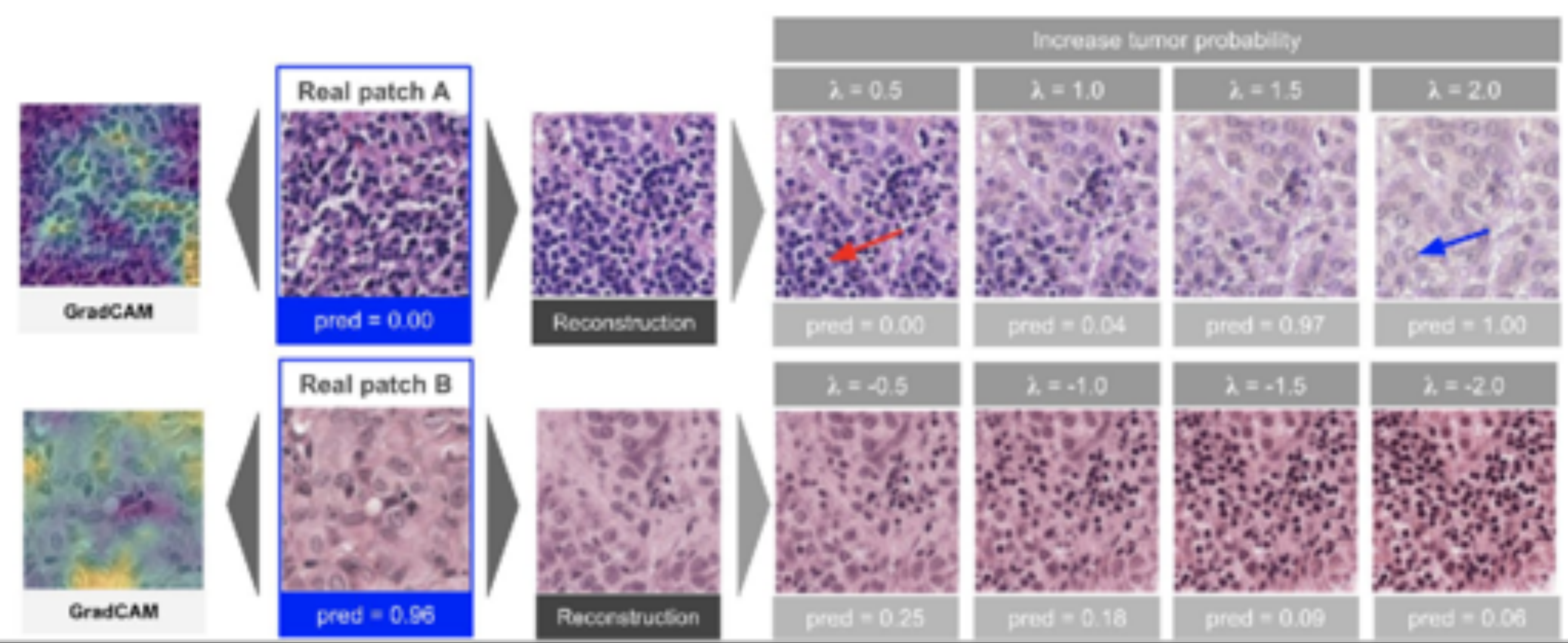


θ_1 θ_2 θ_3 θ_0



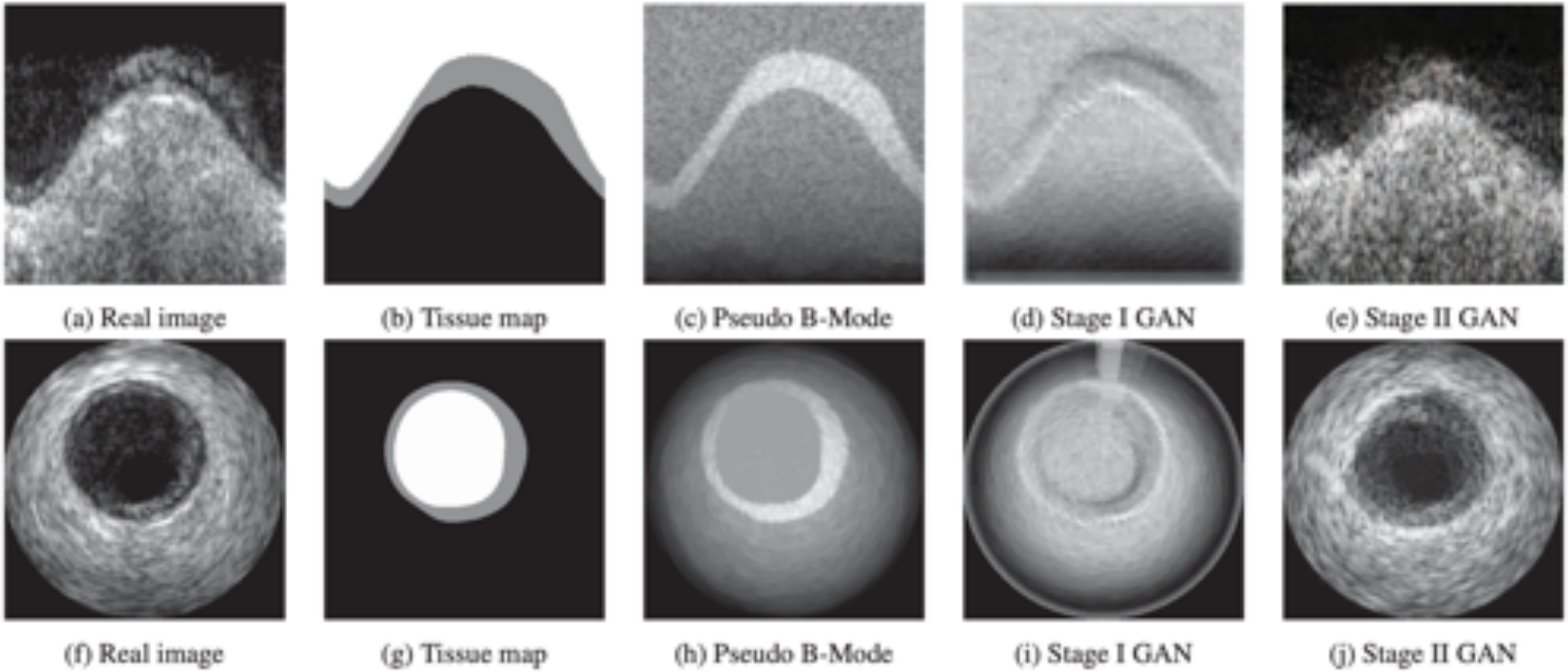
Different S/N ratio

Using StyleGAN for Visual Interpretability of Deep Learning Models on Medical Images



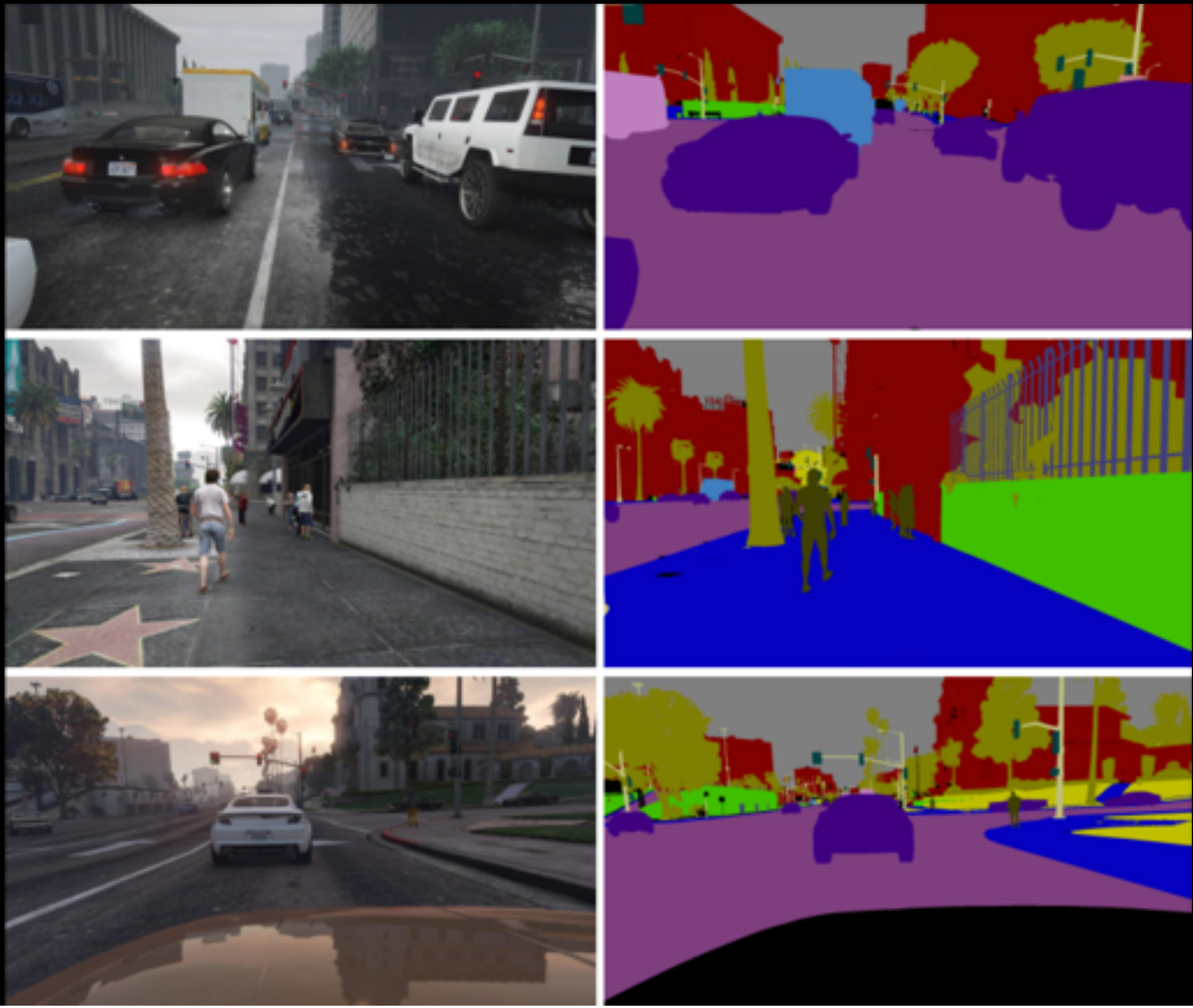
Different tumor prob.

Synthetic from segmentation

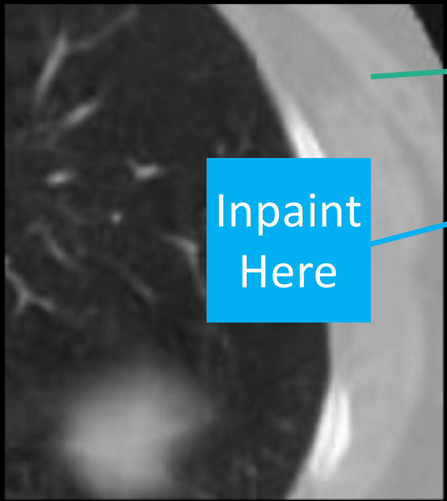


SIMULATING PATHO-REALISTIC ULTRASOUND IMAGES USING DEEP GENERATIVE NETWORKS WITH ADVERSARIAL LEARNING

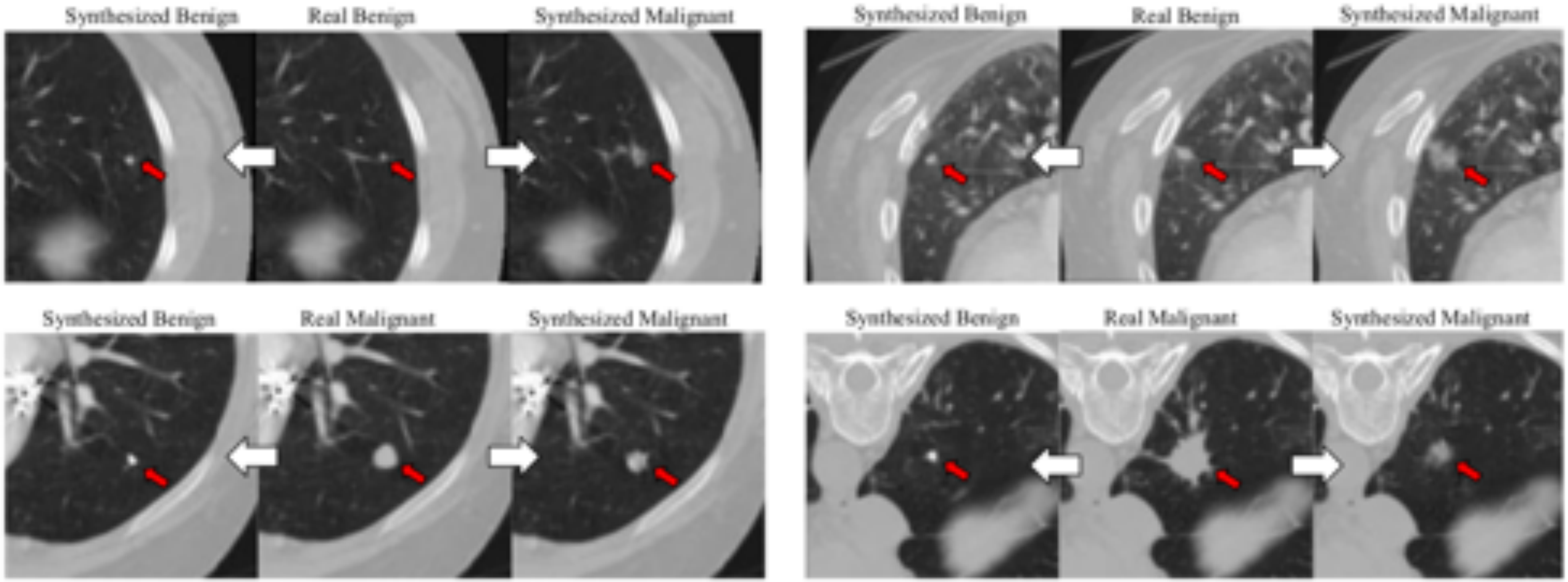
Synthetized from segmentation maps



A case for image + class condition

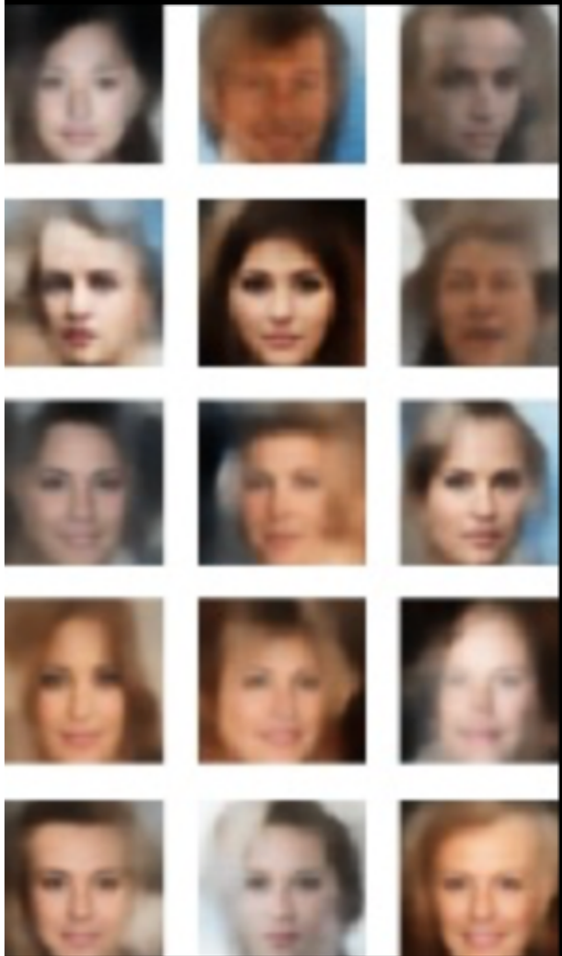


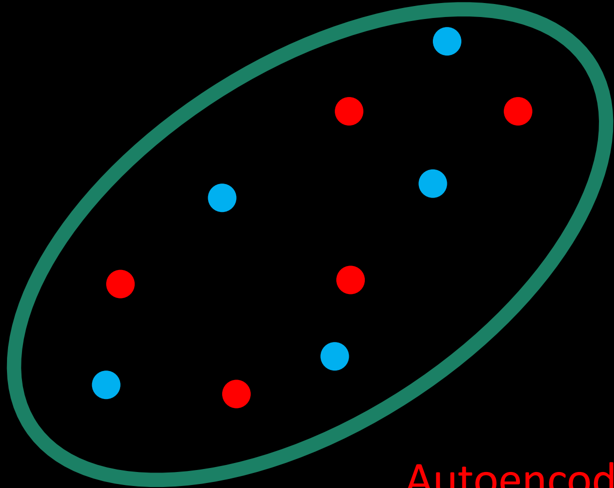
1. Image condition (neighboring structures)
2. Class condition (benign / malignant)



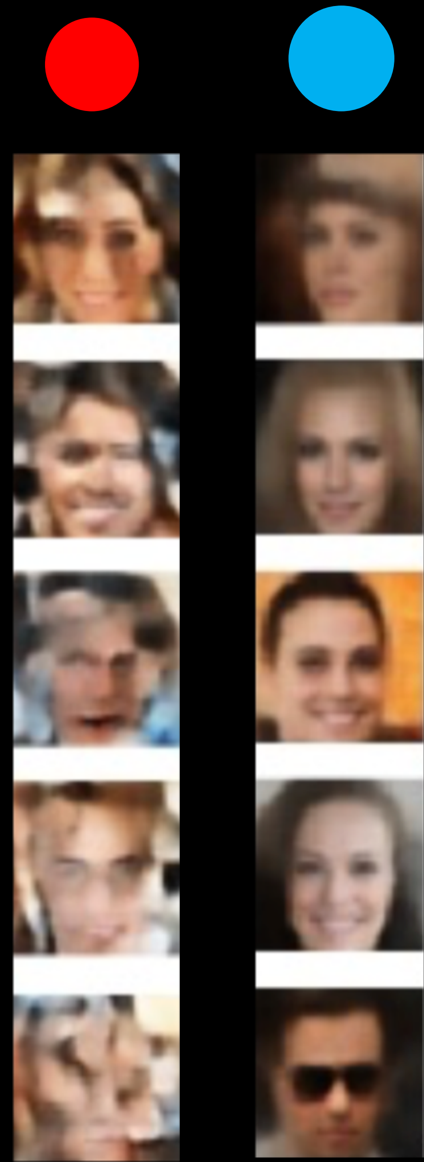
CLASS-AWARE ADVERSARIAL LUNG NODULE SYNTHESIS IN CT IMAGES (MICCAI 2020)

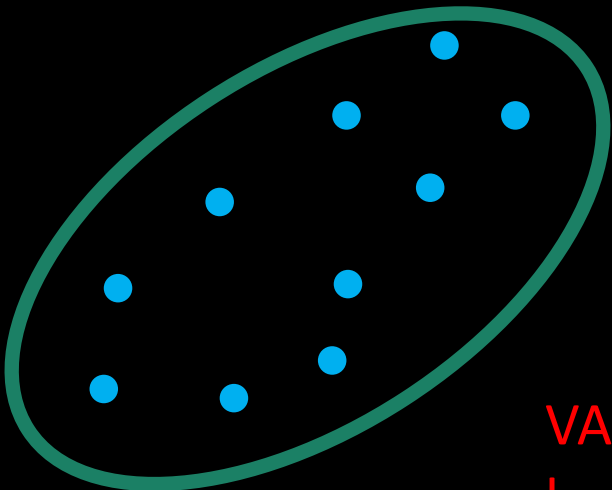
Anomaly Detection





Autoencoder

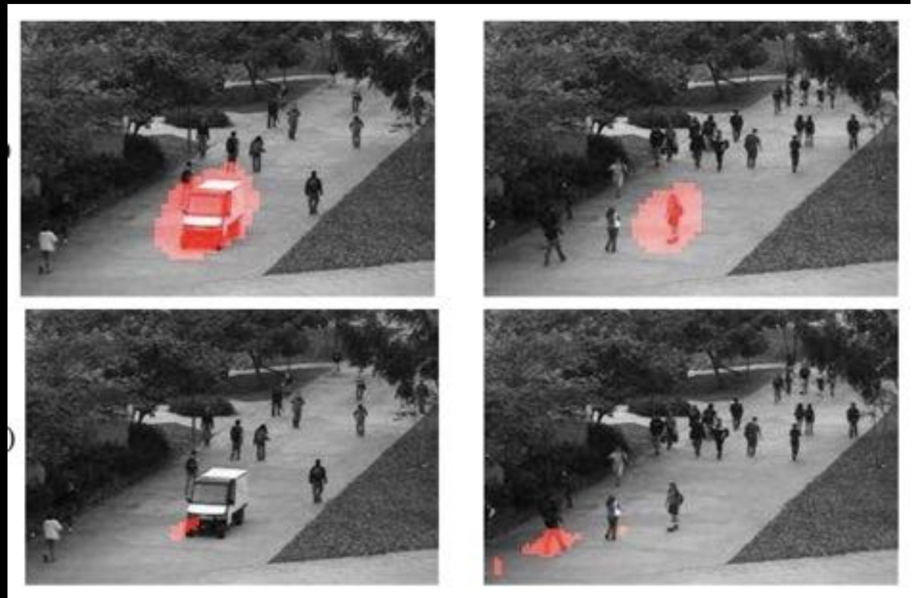


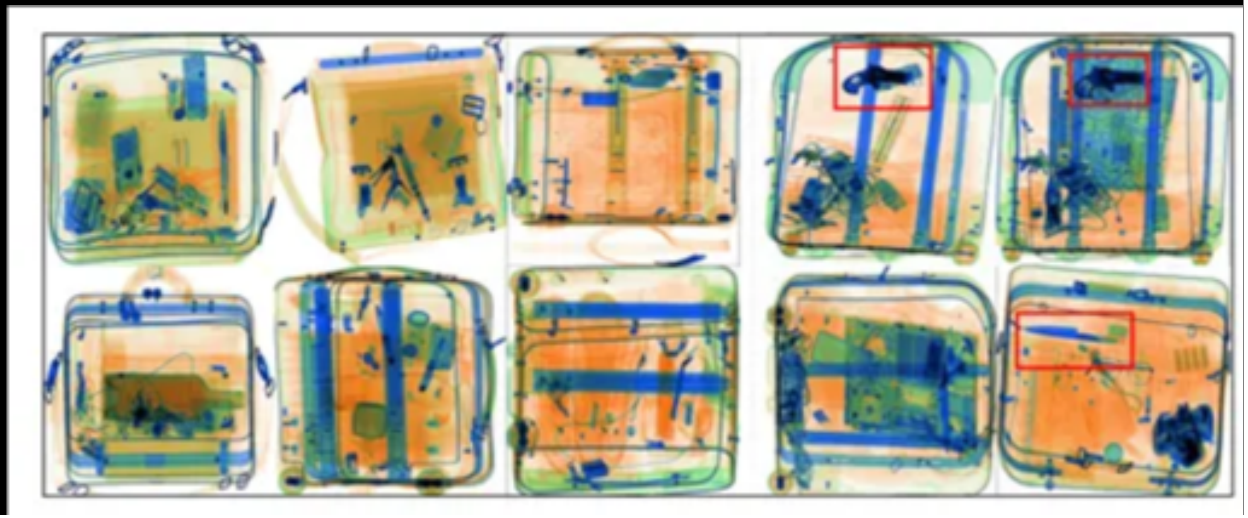


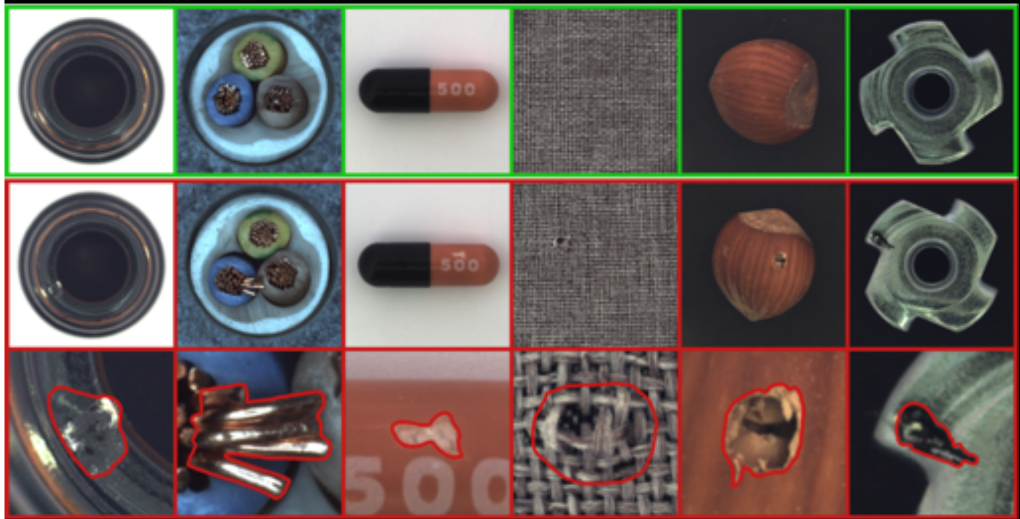
VAE: generative models
knows what “normal” looks like

Anomaly Detection

Fail cases are rare and difficult (expensive) to define

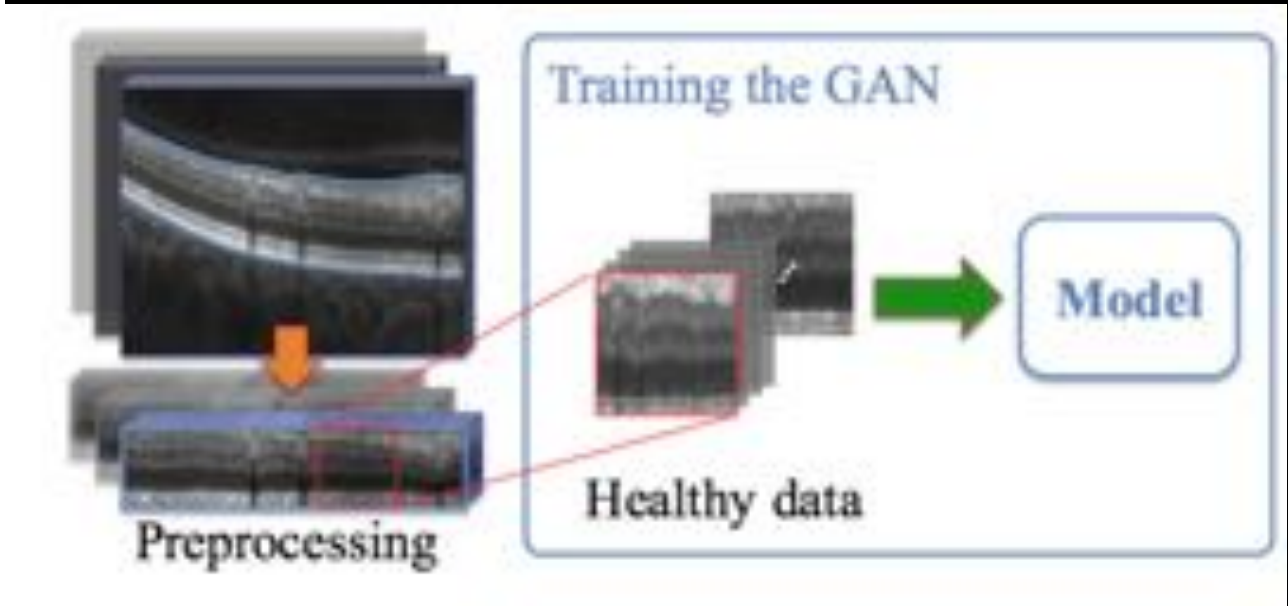


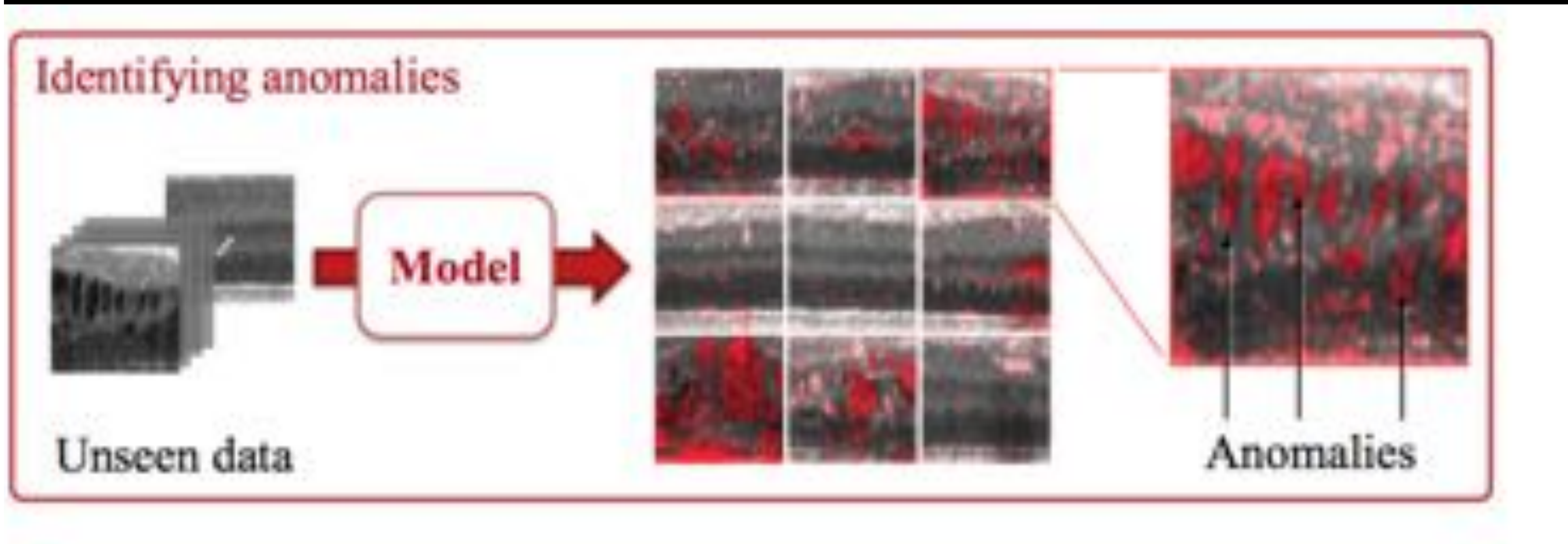


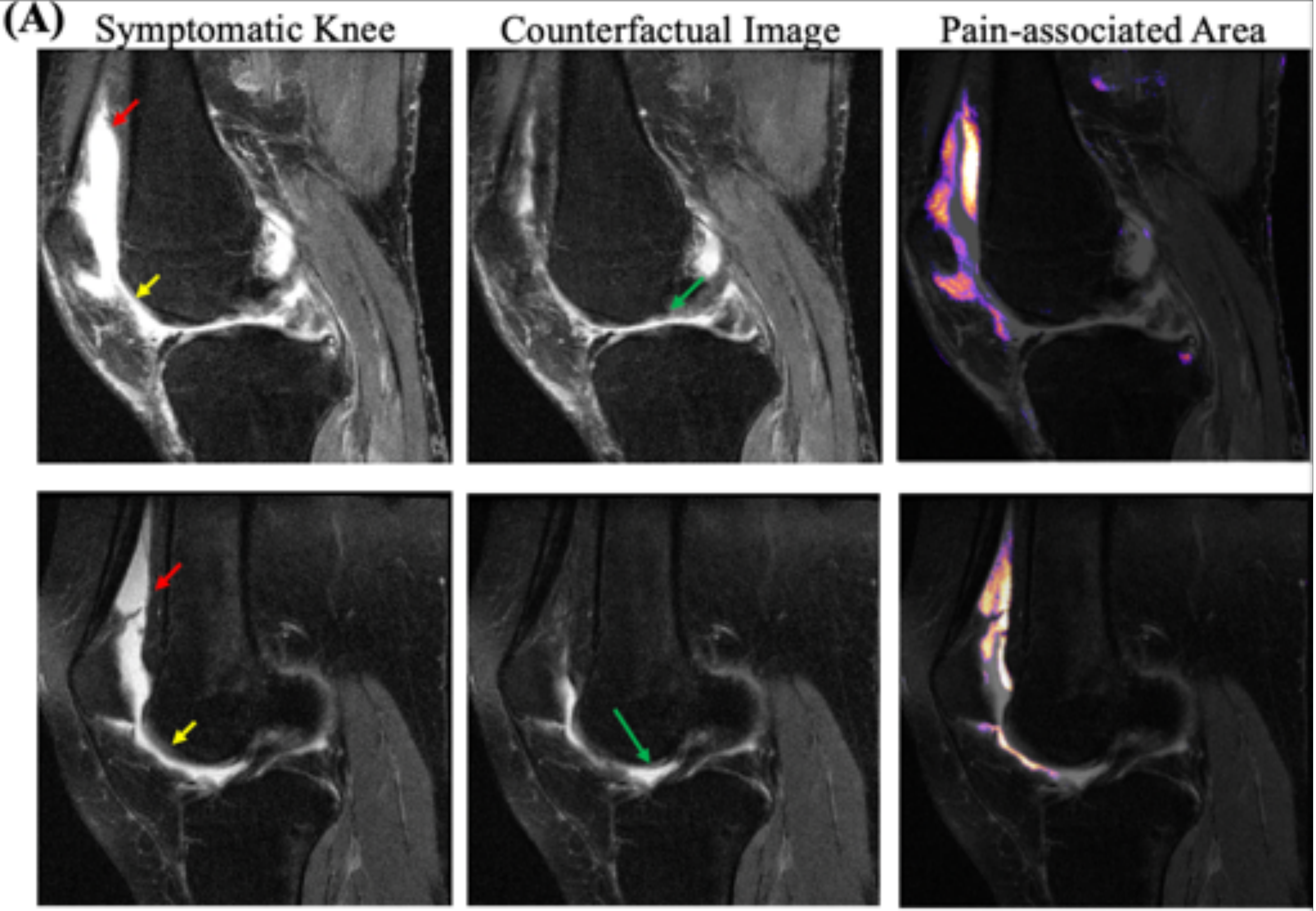


Anomaly Detection

f-AnoGAN: Fast unsupervised anomaly detection with generative adversarial network






(A)
Symptomatic Knee
Counterfactual Image
Pain-associated Area

Semi-supervised Learning

Cohort X, data w/ diagnosis, annotation etc.

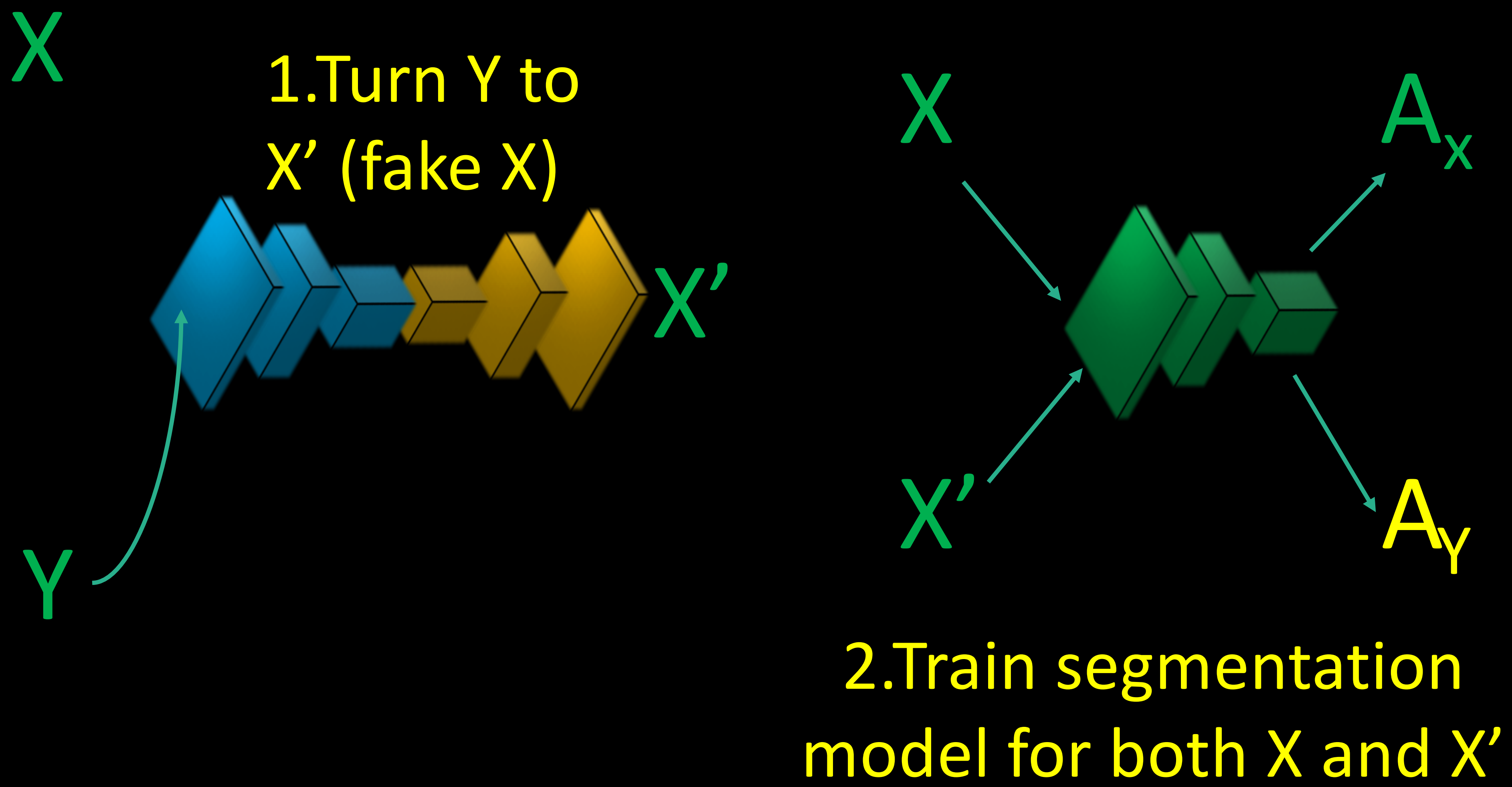
$$X \longrightarrow A_x$$

Cohort Y, more data, w/o diagnosis, annotation etc.

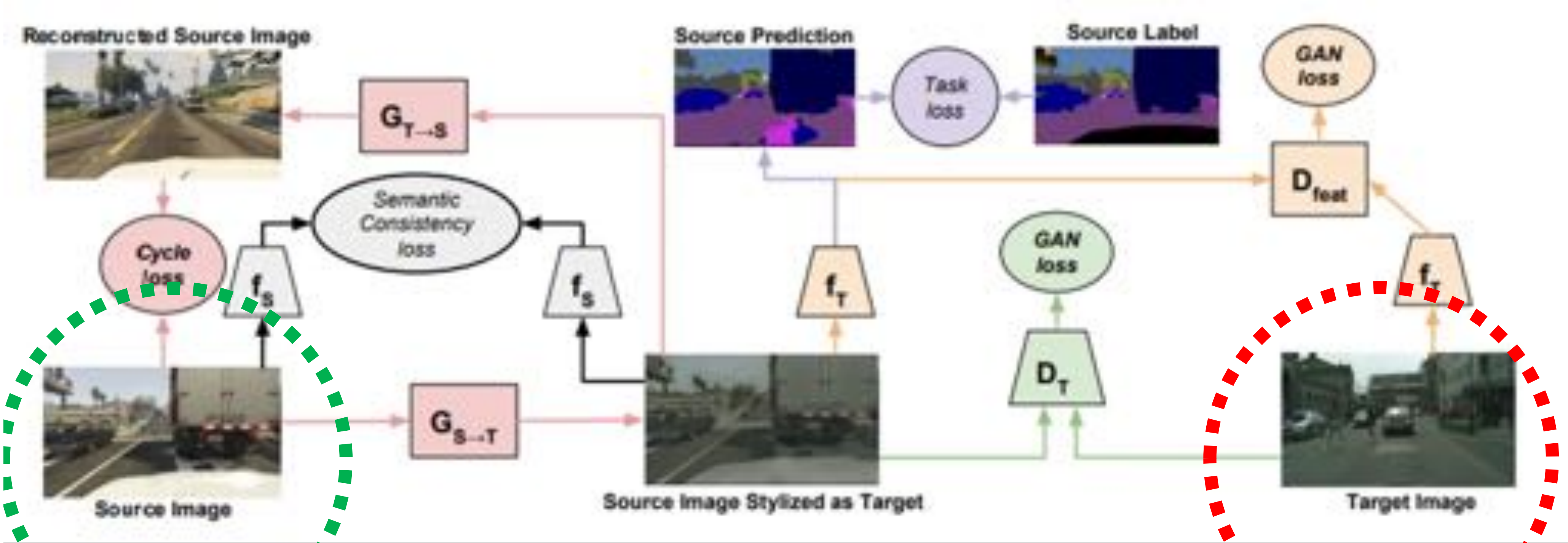
$$Y \longrightarrow ????$$

Semi-supervised Learning

Cohort X, data w/ diagnosis, annotation etc.

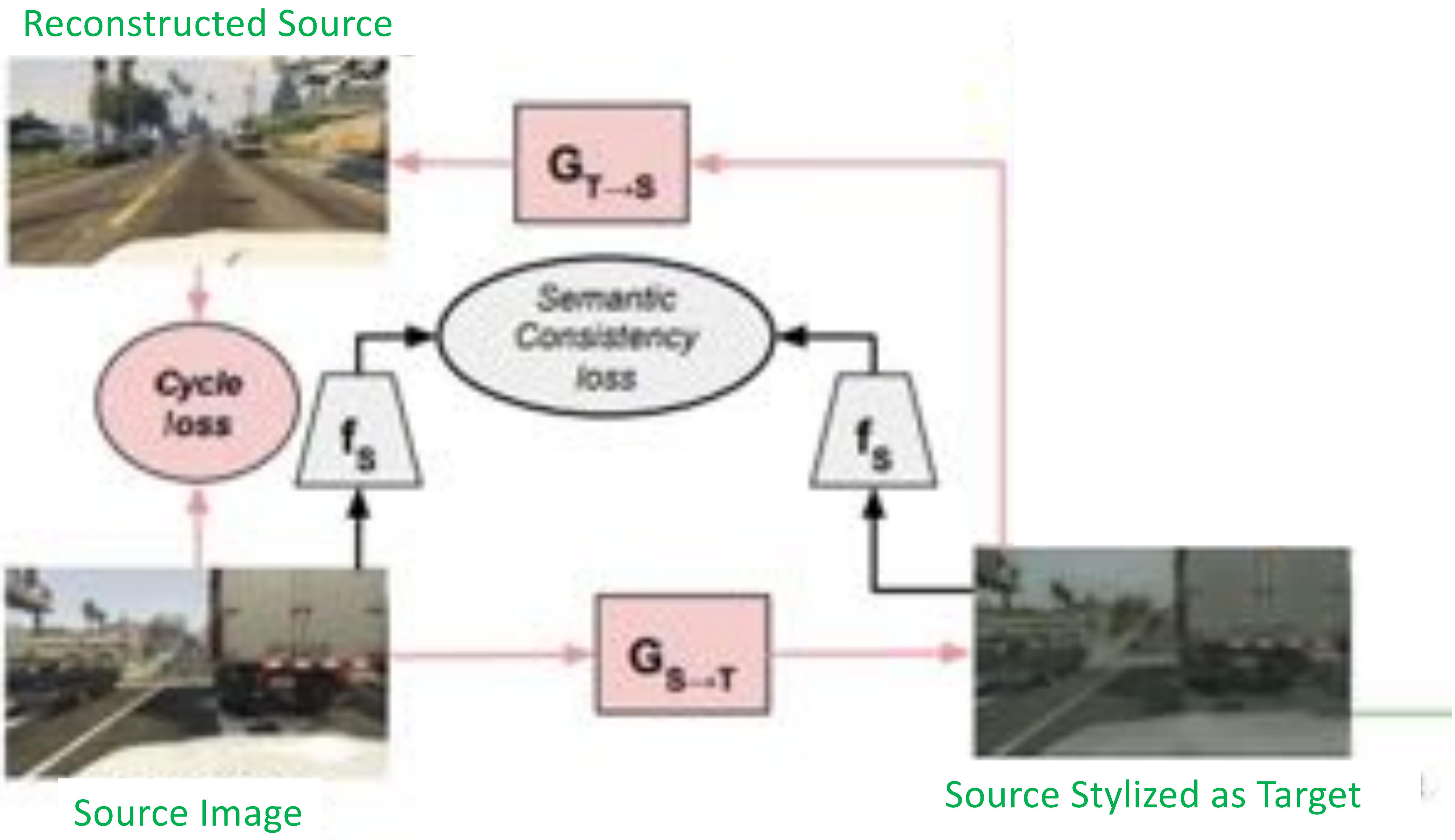


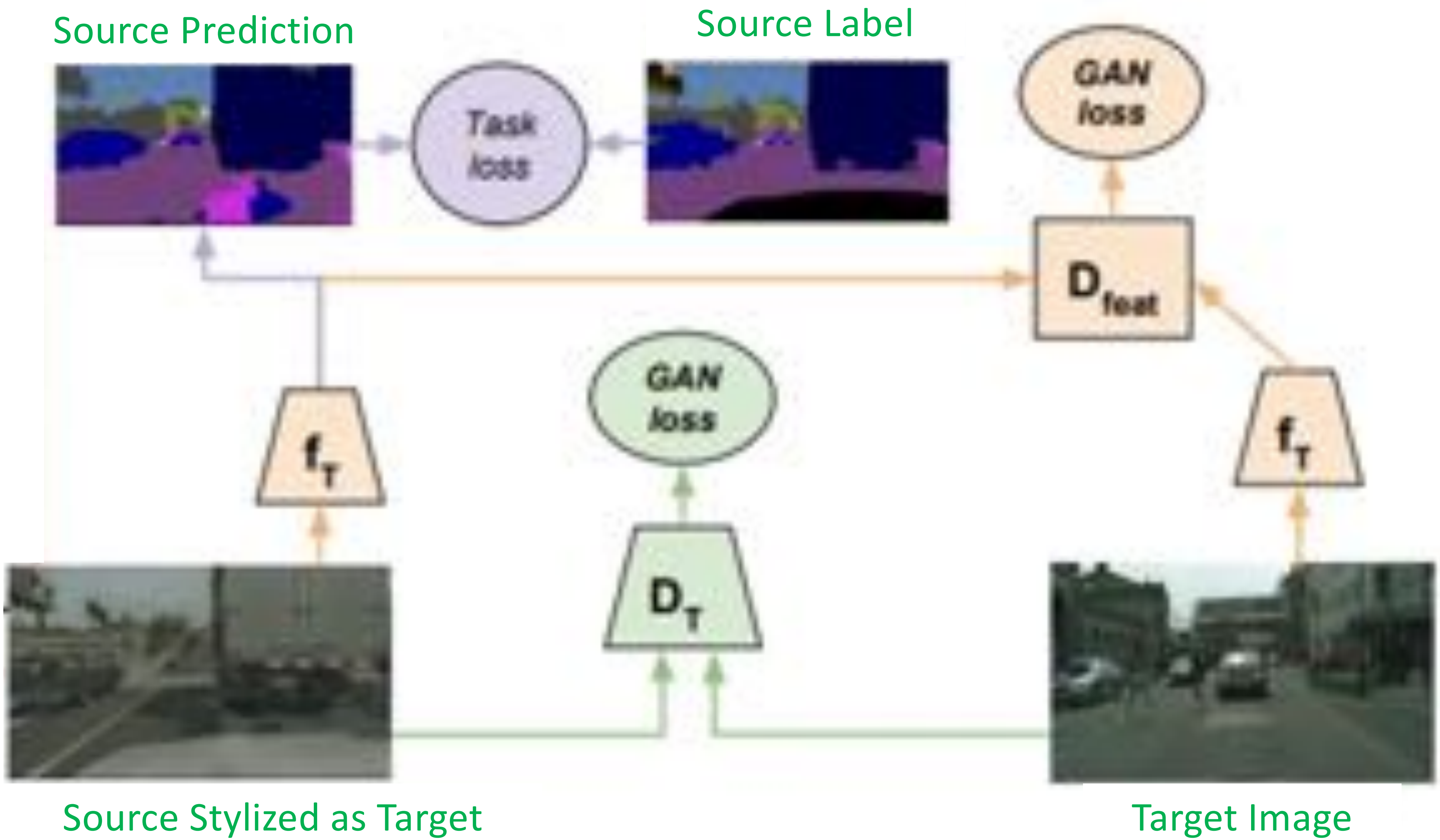
Semi-supervised Segmentation



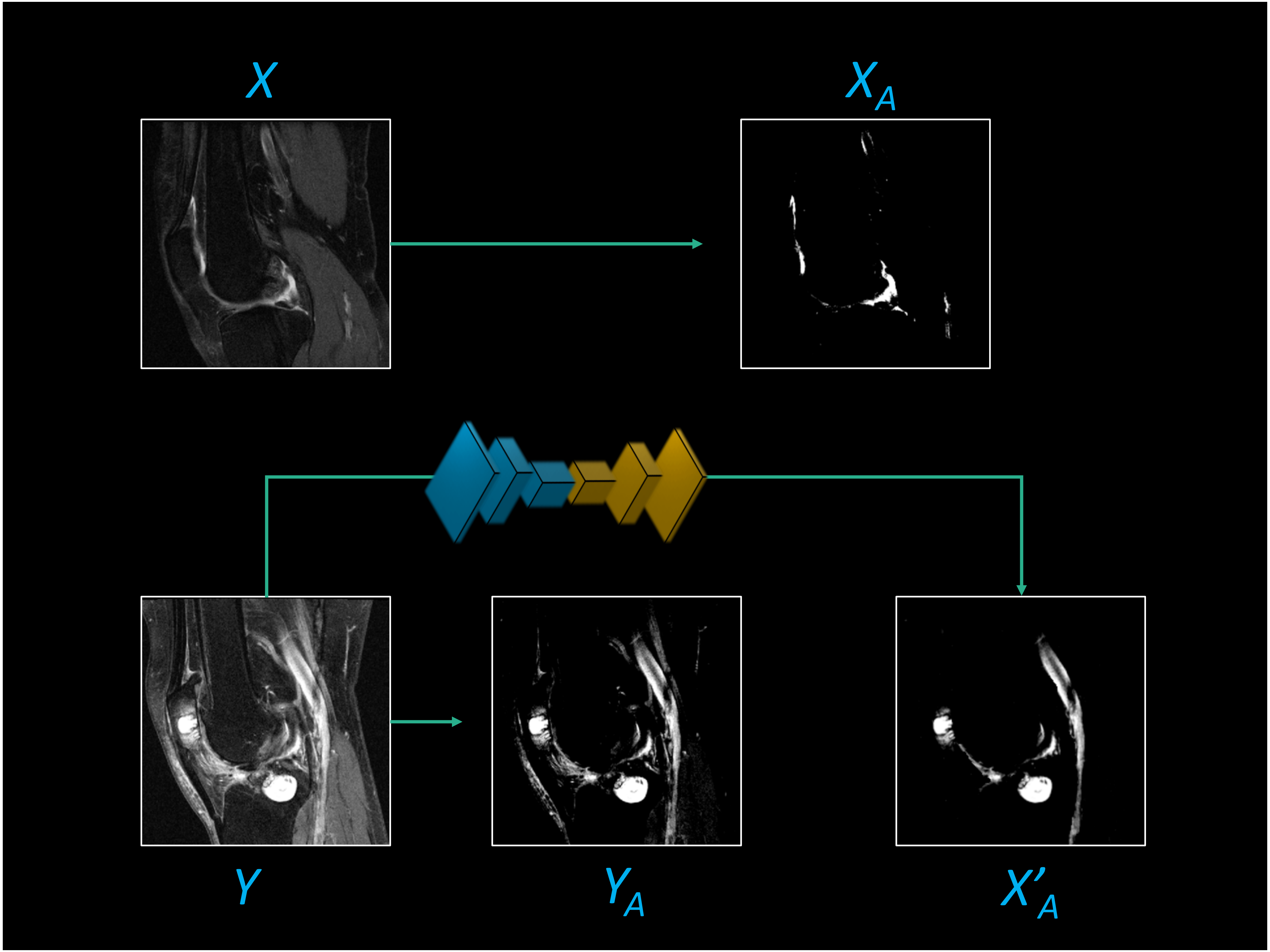
Real images with no annotation

From video games with free annotation


Reconstructed Source
$G_{T \to S}$
Semantic Consistency loss
Cycle loss
f_S
f_S
$G_{S \to T}$
Source Image
Source Stylized as Target



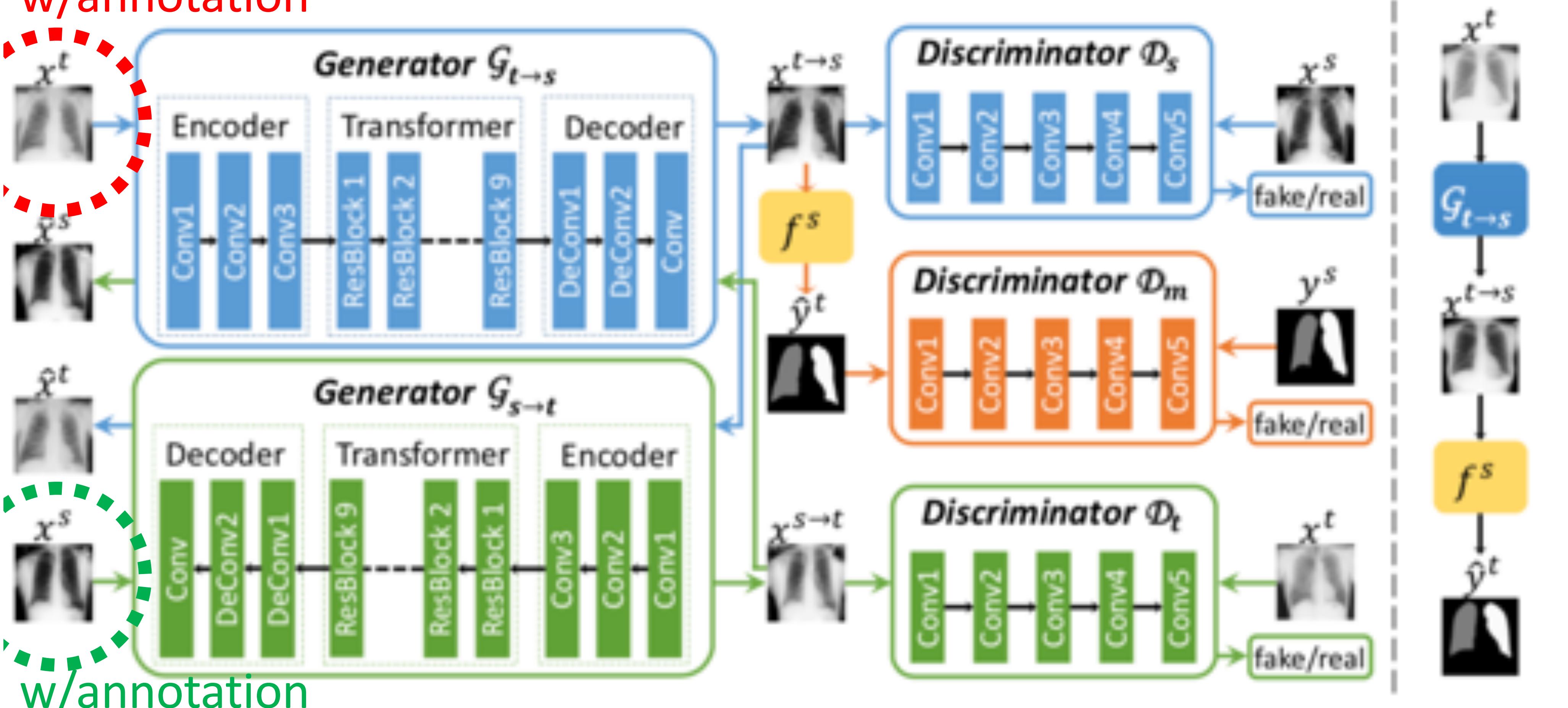
Source Prediction
Task loss
Source Label
GAN loss
D_{feat}
GAN loss
f_T
D_T
f_T
Source Stylized as Target
Target Image



X
X_A
Y
Y_A
X'_A

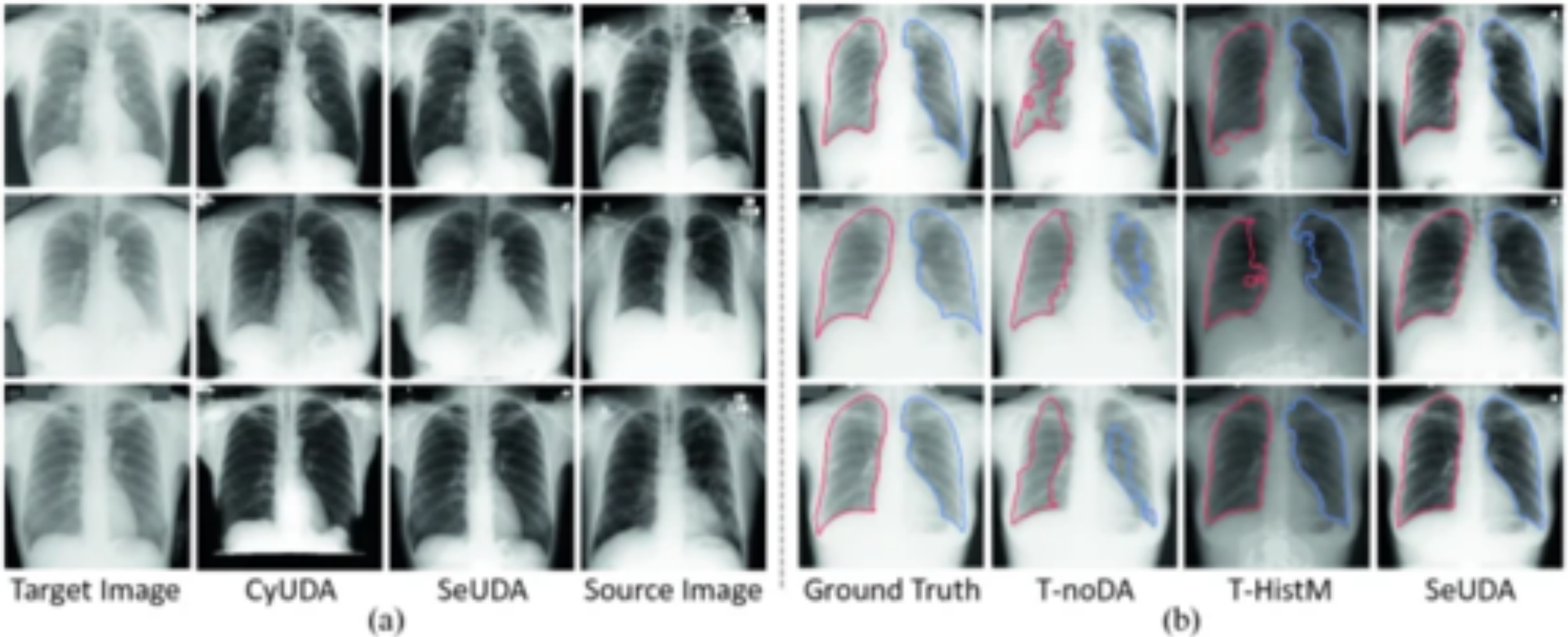
Semi-supervised Segmentation

w/annotation

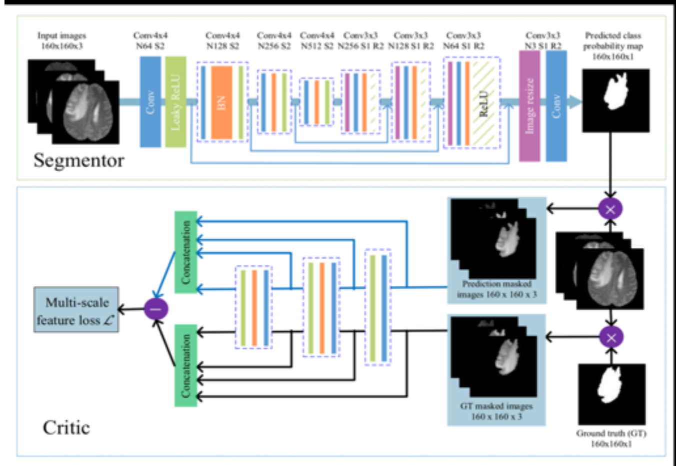


w/annotation

Semantic-Aware Generative Adversarial Nets for Unsupervised Domain Adaptation
in Chest X-ray Segmentation


Target Image
CyUDA
SeUDA
Source Image
(a)
Ground Truth
T-noDA
T-HistM
SeUDA
(b)

Semi-supervised Segmentation



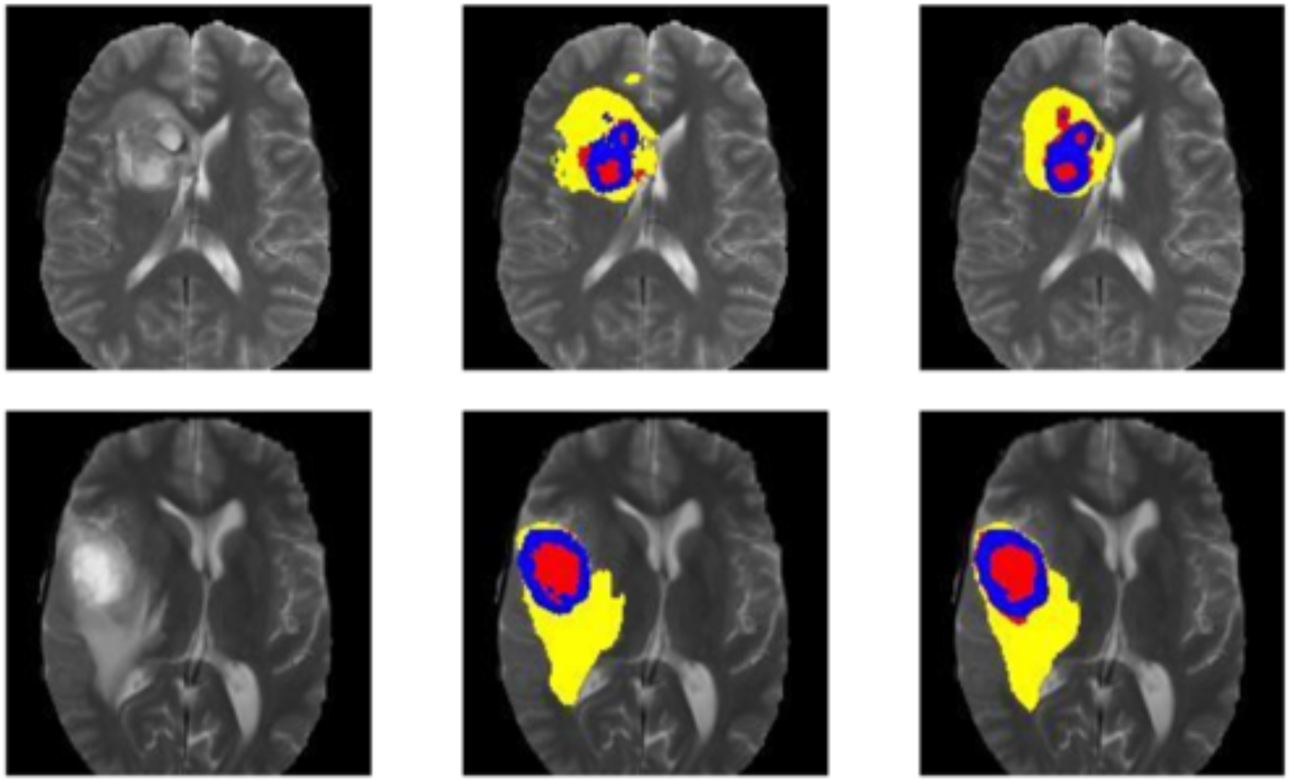


Fig. 3 Example results of our SegGAN (right) with corresponding T2 slices (left) and ground truth (middle) on BRATS validation set.

SegGAN: Adversarial Network with Multi-scale L1 Loss for Medical Image Segmentation (2017)

Semi-supervised Segmentation

GAN UNet Annotation