Synthesis Project

Literature Survey

Protecting Privacy while Improving Choroid Layer Segmentation in

OCT Images: A GAN-based Image Synthesis Approach

Image-to-Image Translation with Conditional Adversarial Networks

UNSUPERVISED REPRESENTATION LEARNING

WITH DEEP CONVOLUTIONAL

GENERATIVE ADVERSARIAL NETWO

https://github.com/amirhossein-kz/Awesome-Diffusion-Models-in-Medical-Imaging

Generative AI for Medical Imaging: extending

the MONAI Framework

https://docs.monai.io/en/latest/installation.html

https://github.com/Warvito/generative_oct/tree/main

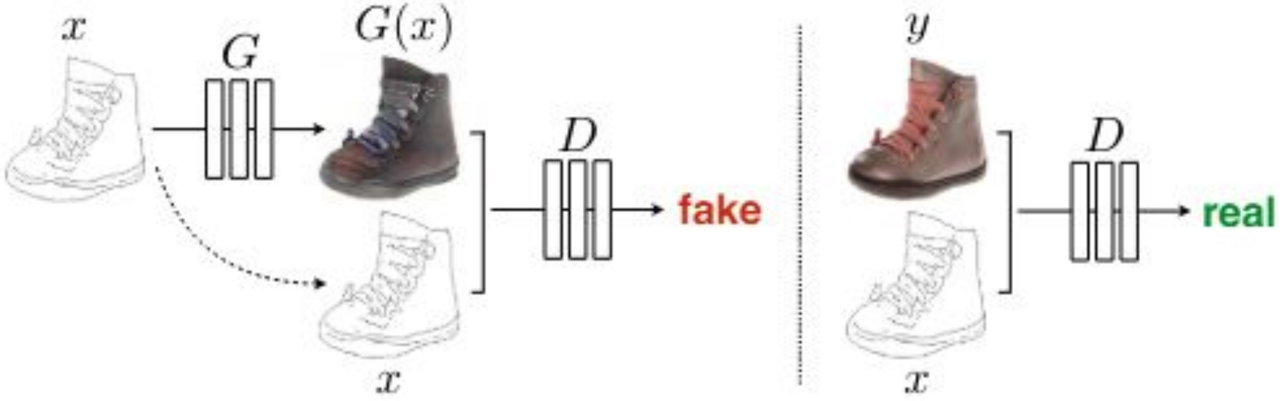
https://arxiv.org/pdf/2307.13125.pdf

RETINAL OCT SYNTHESIS WITH DENOISING DIFFUSION PROBABILISTIC MODELS

FOR LAYER SEGMENTATION

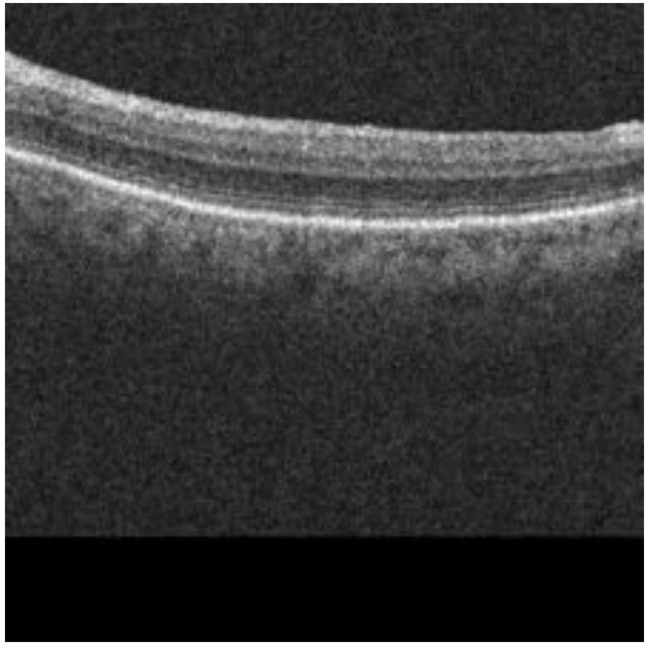
Unsupervised Denoising of Retinal OCT with Diffusion

Probabilistic Model

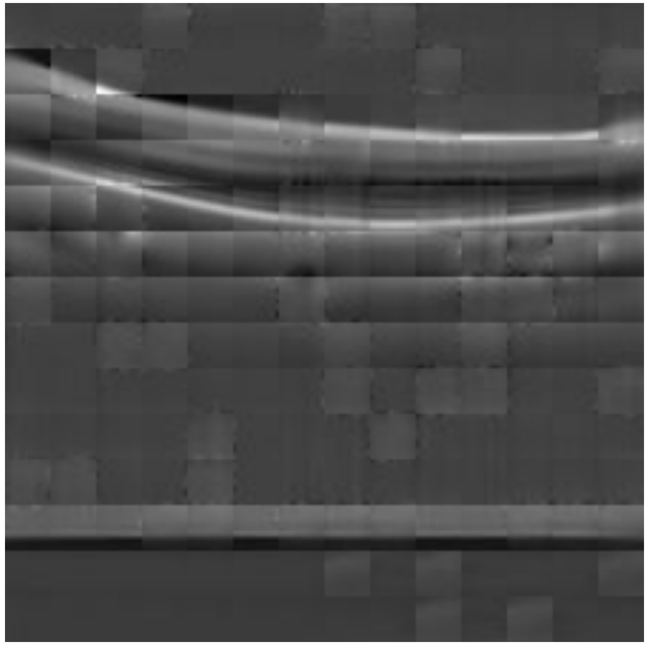


x
G
G(x)
D
fake
x
y
D
real
x

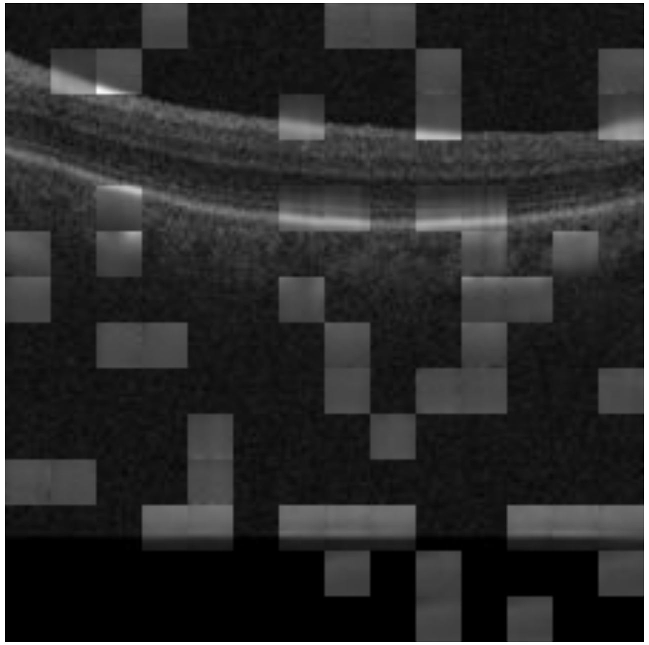
Reconstruction using Retfound



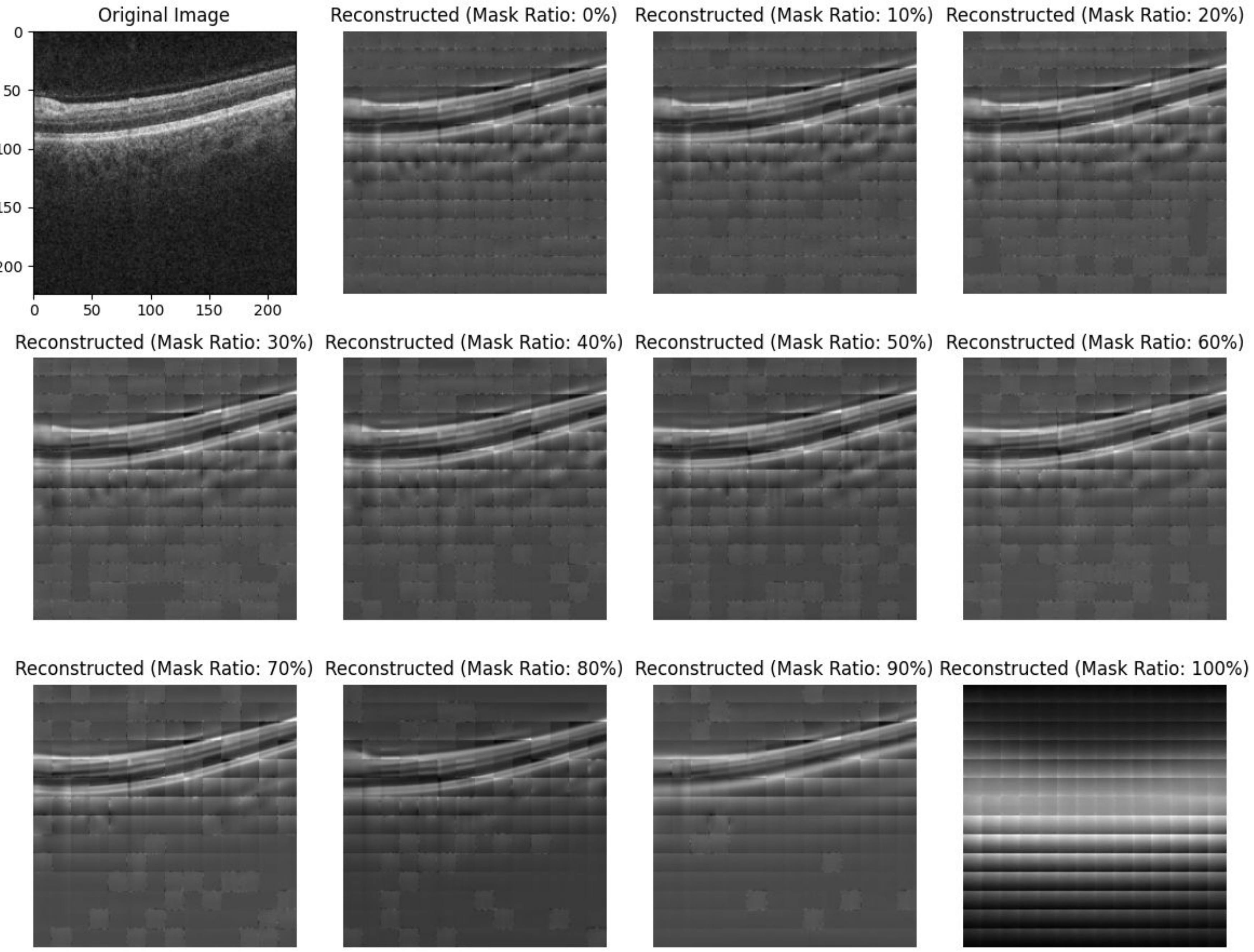
Original



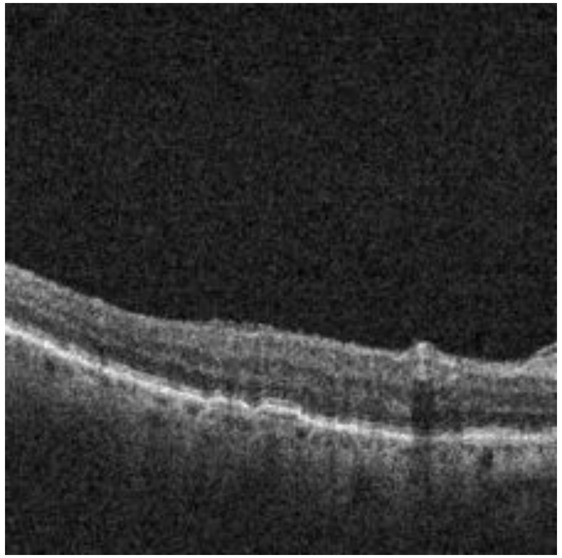
Reconstructed



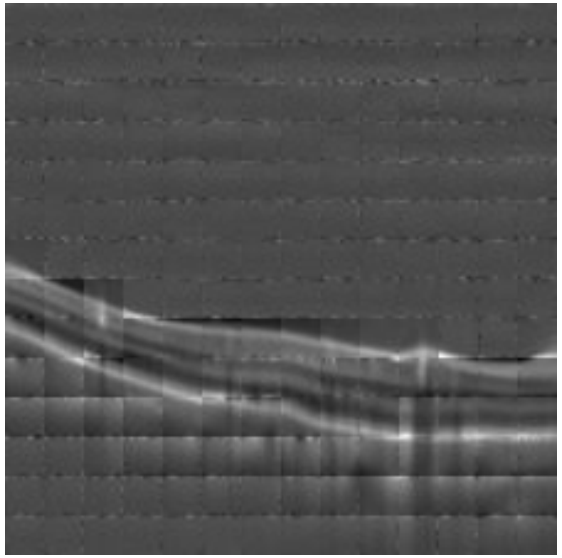
Replacing
Masked Patches


Original Image
Reconstructed (Mask Ratio: 0%)
Reconstructed (Mask Ratio: 10%)
Reconstructed (Mask Ratio: 20%)
Reconstructed (Mask Ratio: 30%)
Reconstructed (Mask Ratio: 40%)
Reconstructed (Mask Ratio: 50%)
Reconstructed (Mask Ratio: 60%)
Reconstructed (Mask Ratio: 70%)
Reconstructed (Mask Ratio: 80%)
Reconstructed (Mask Ratio: 90%)
Reconstructed (Mask Ratio: 100%)
0
50
100
150
200

NO Masking

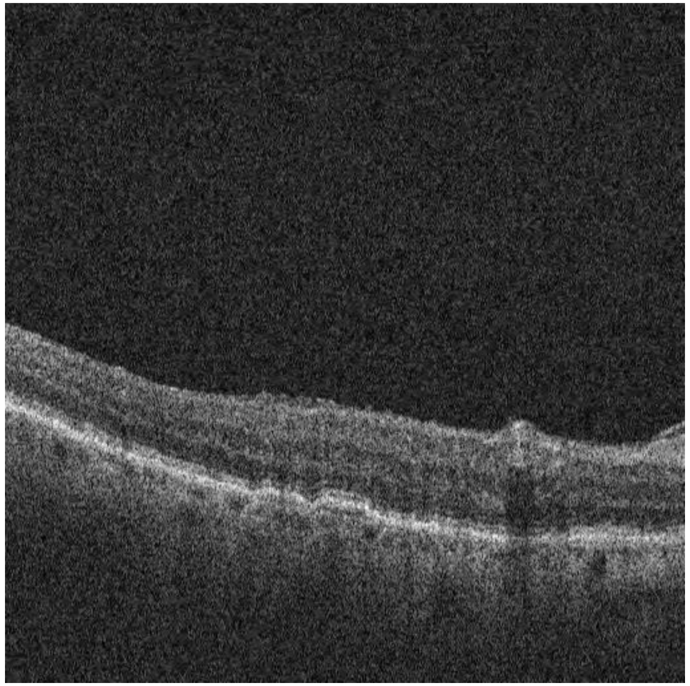


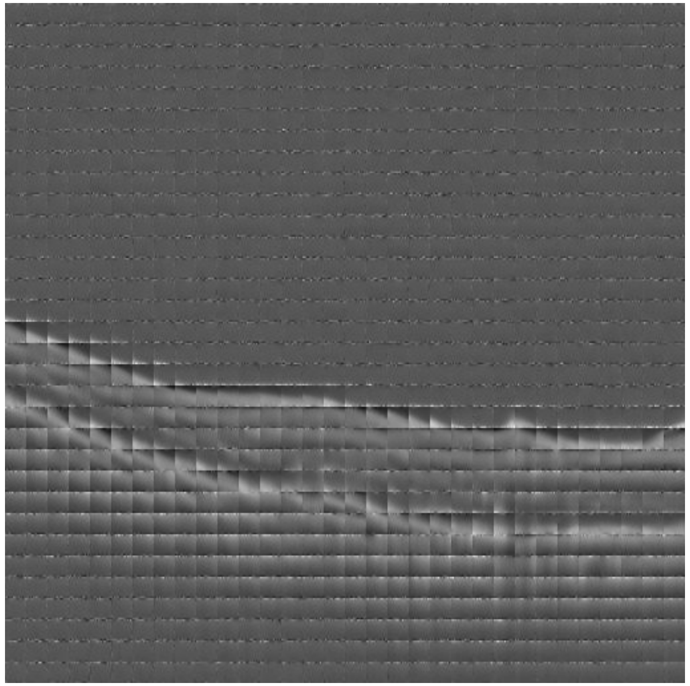
Original



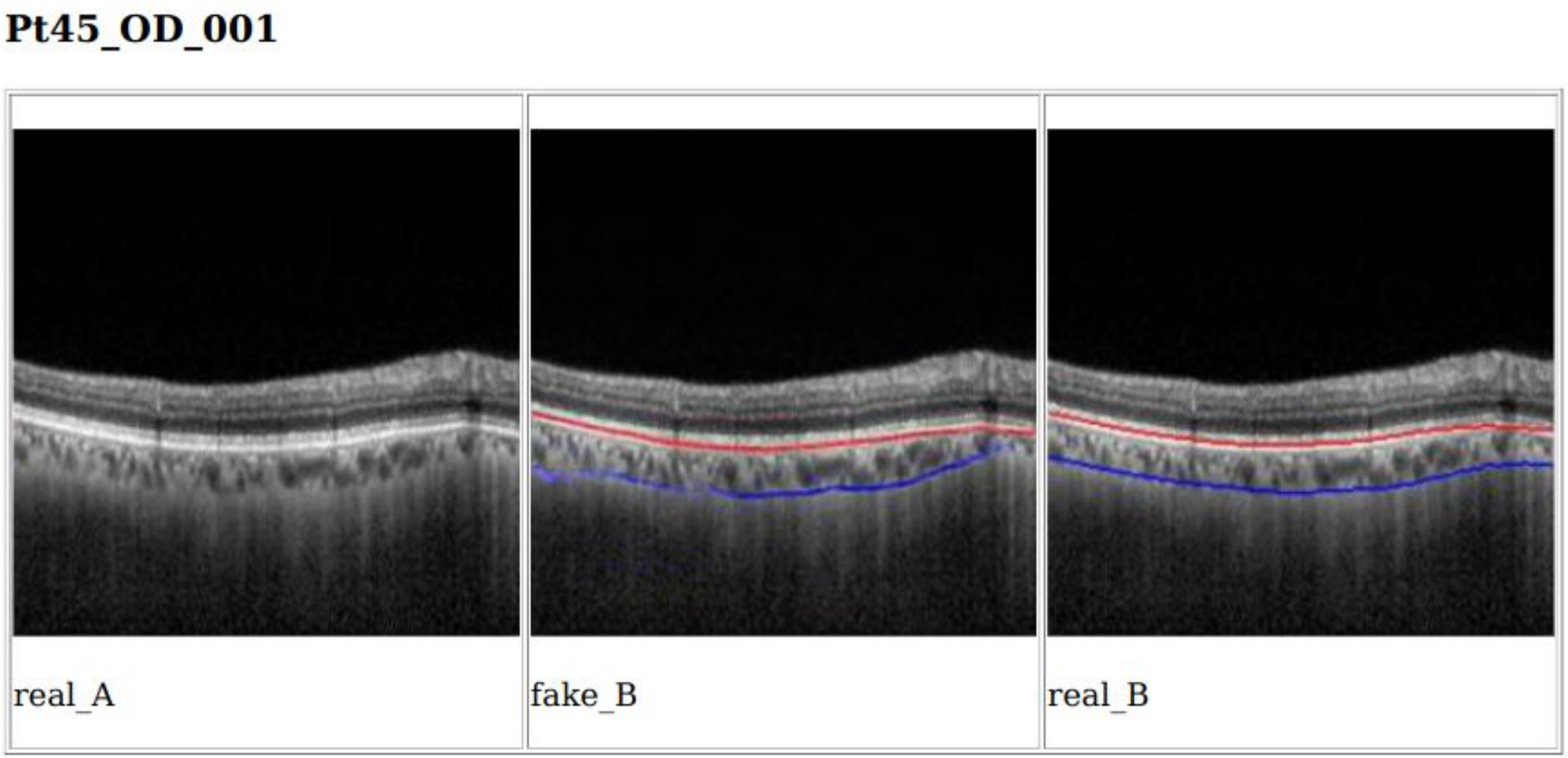
Reconstructed

512x512 Resolution



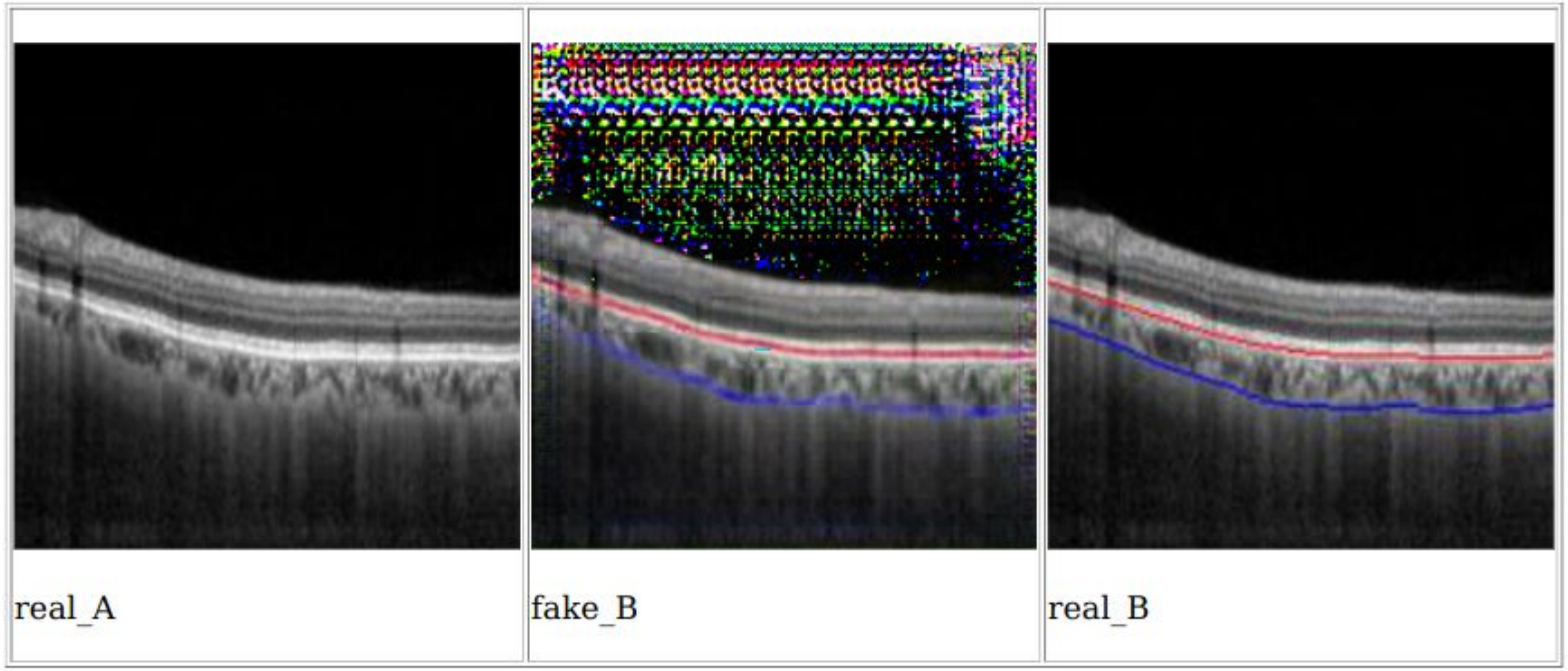


Pix2Pix GAN - ResNet based Generator



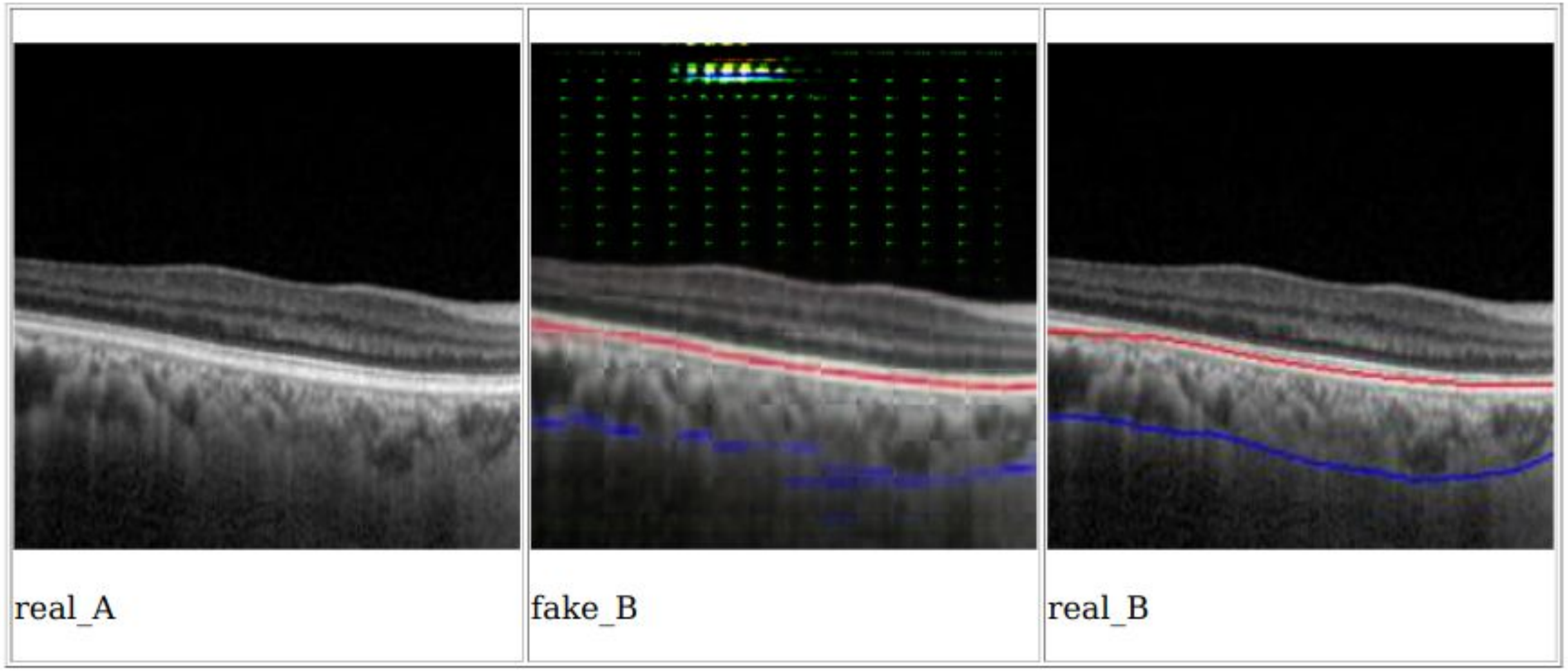
Pix2Pix with Retfound Model as Generator

Pt45_OS_000_003

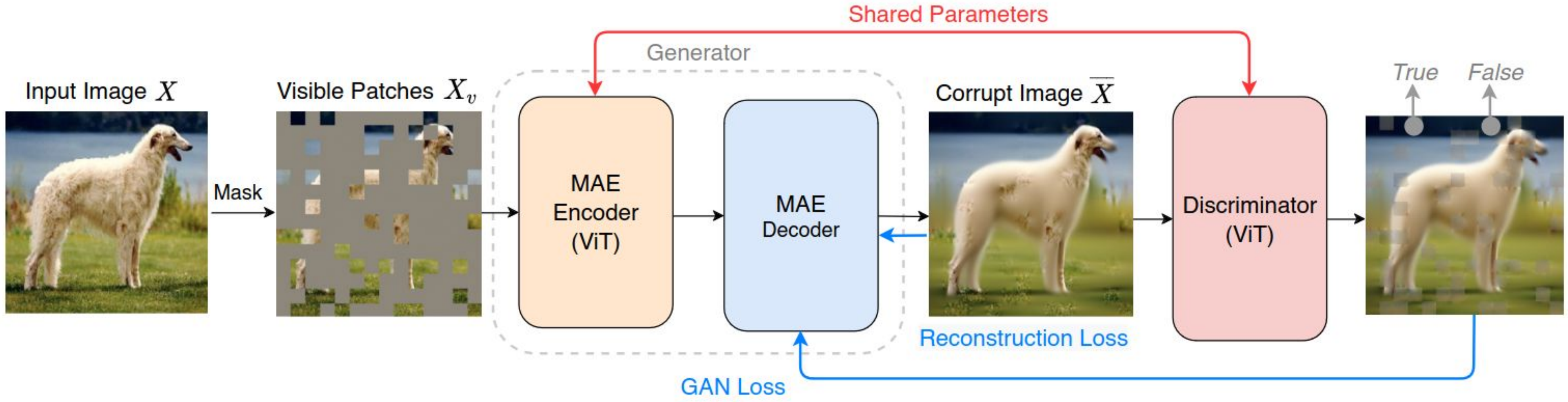


Retfound Model as Generator (with tanh non-linearity)

Pt46_OD_030

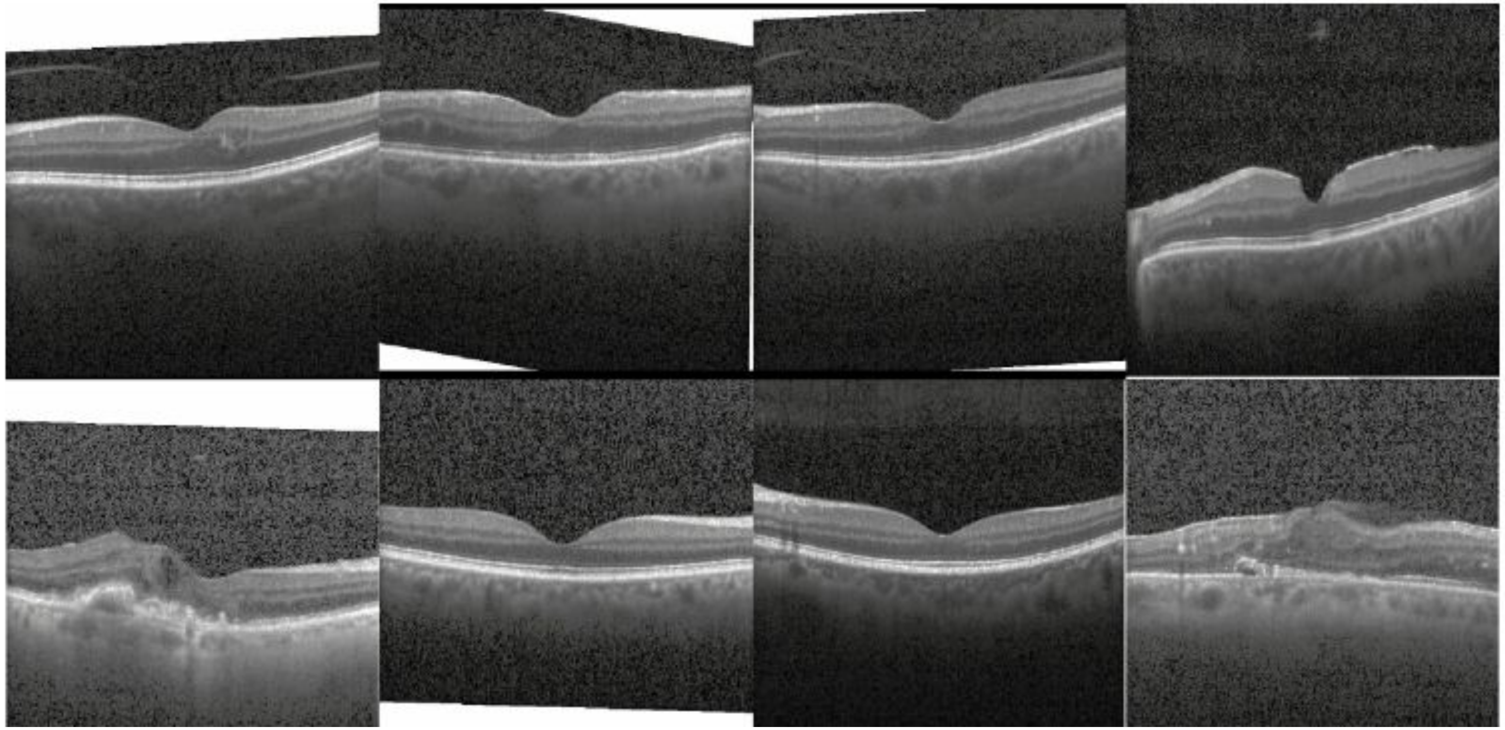


Masked Auto-Encoders Meet Generative Adversarial Networks and Beyond



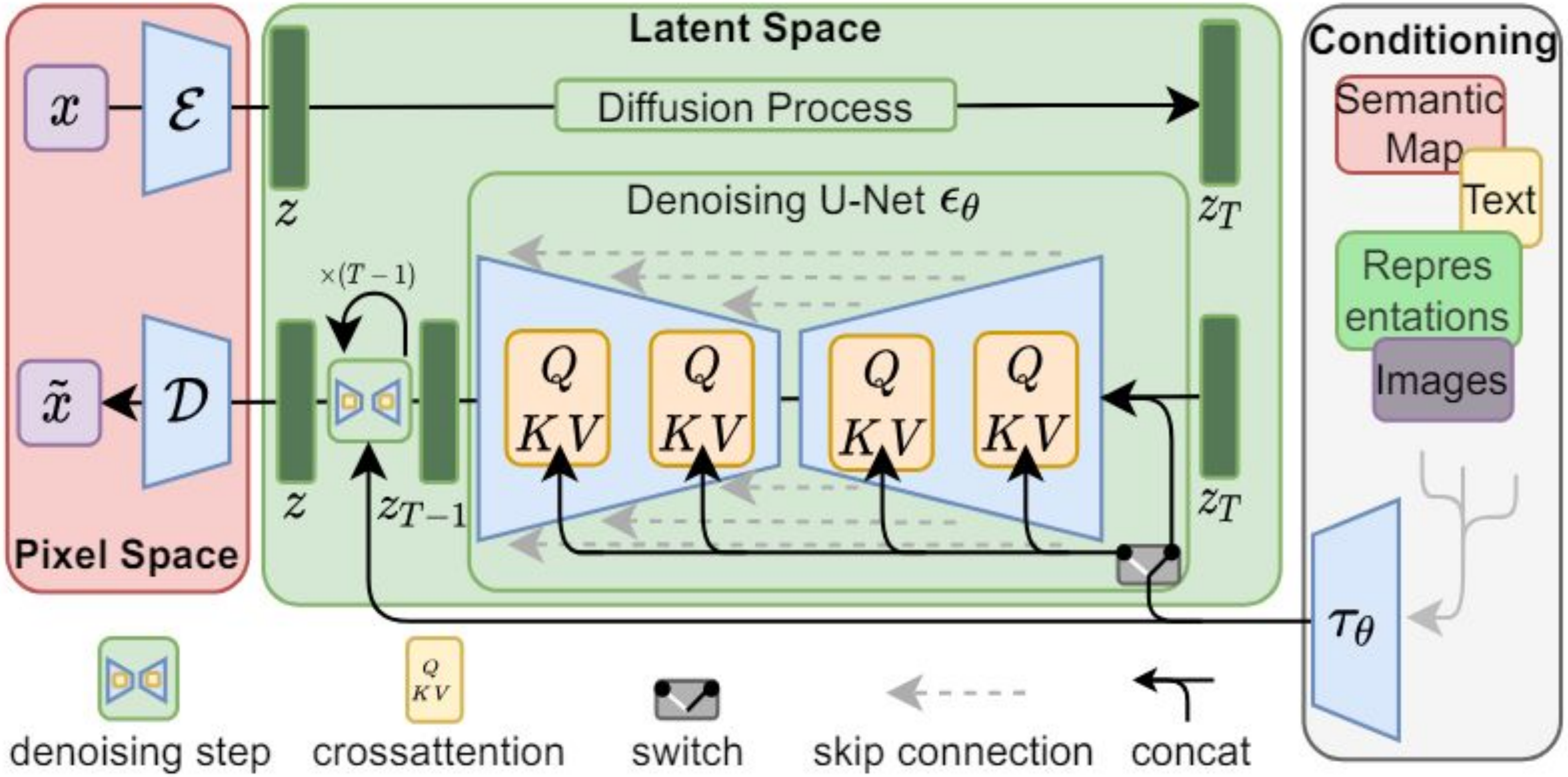
$$L_{gen}(X, \theta_{mae}) = L_{mae}(X, \theta_{mae}) + \gamma L_{adv}(X, \theta_{mae}).$$

Diffusion Models



generated using MONAI Framework - Latent Diffusion Models

Latent Diffusion Models



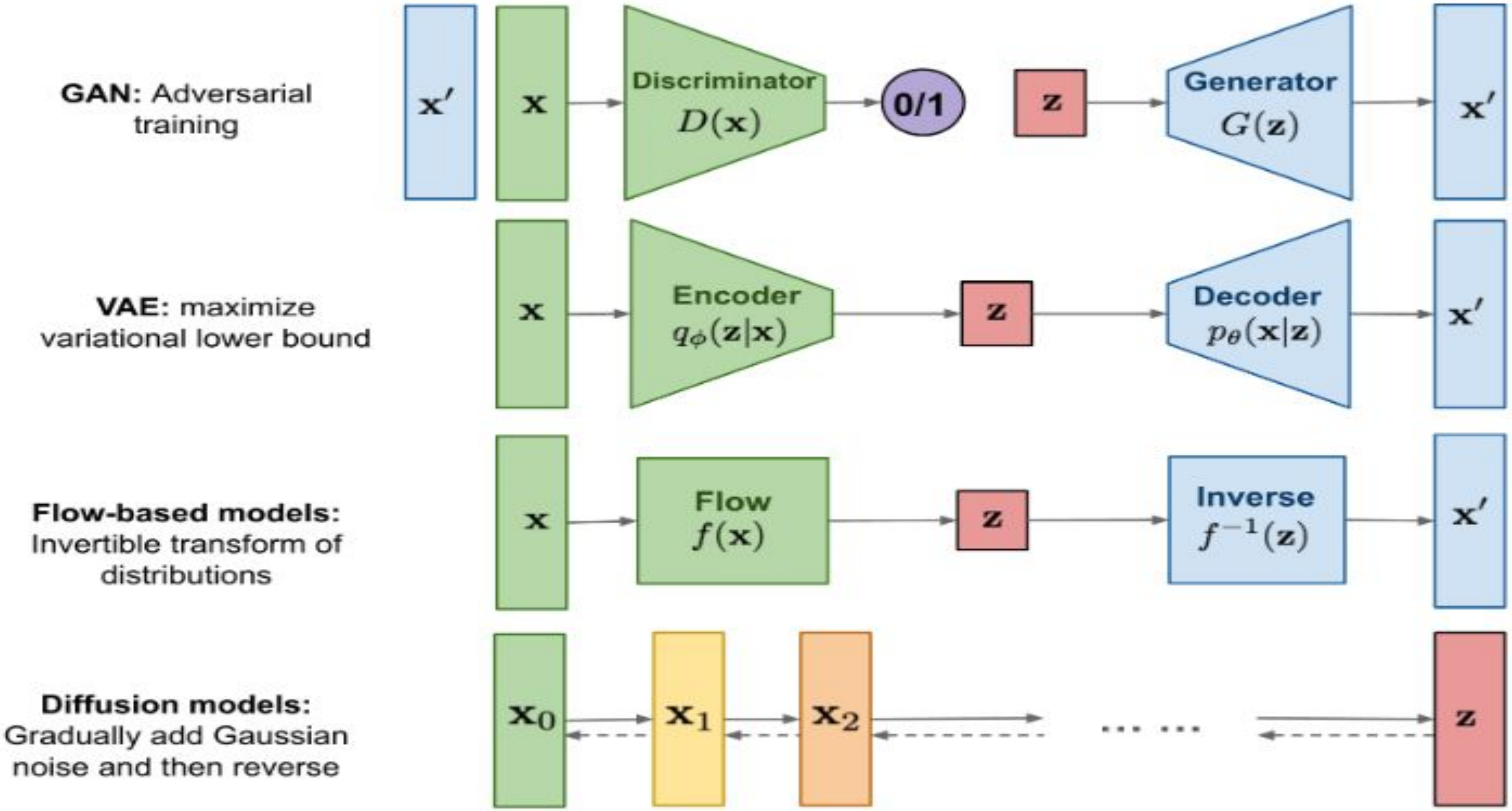


Fig. 1. Overview of different types of generative models.

Forward diffusion process

Given a data point sampled from a real data distribution $\mathbf{x}_0 \sim q(\mathbf{x})$, let us define a *forward diffusion process* in which we add small amount of Gaussian noise to the sample in T steps, producing a sequence of noisy samples $\mathbf{x}_1, \dots, \mathbf{x}_T$. The step sizes are controlled by a variance schedule $\{\beta_t \in (0,1)\}_{t=1}^T$.

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}) \quad q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=1}^T q(\mathbf{x}_t|\mathbf{x}_{t-1})$$

The data sample $\mathbf{x}_0$ gradually loses its distinguishable features as the step t becomes larger. Eventually when $T \to \infty$, $\mathbf{x}_T$ is equivalent to an isotropic Gaussian distribution.