
OCTDiff: Bridged Diffusion Model for Portable OCT Super-Resolution and Enhancement

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1 A Appendix

2 A.1 Additional Results

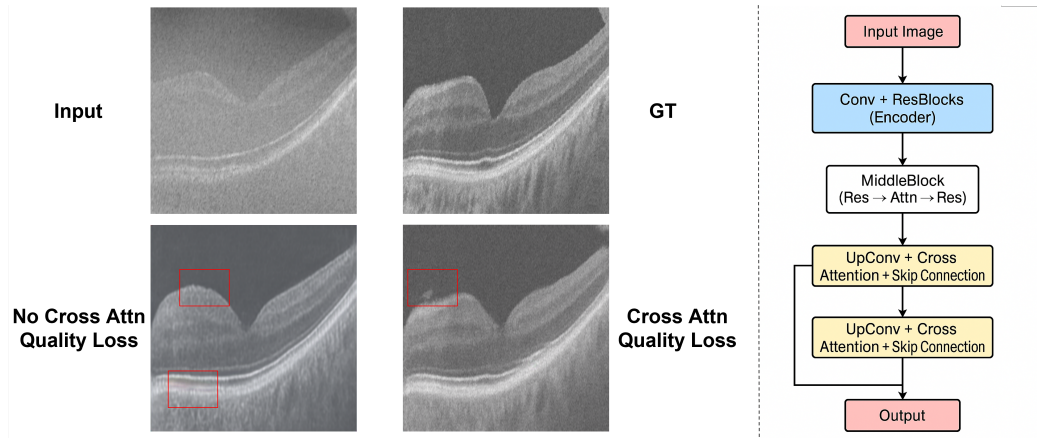


Figure 1: Example of an OCTDiff-generated image with and without the MSCA block. The loss function implemented contains the quality score term. Right side: a block depiction of MSCA.

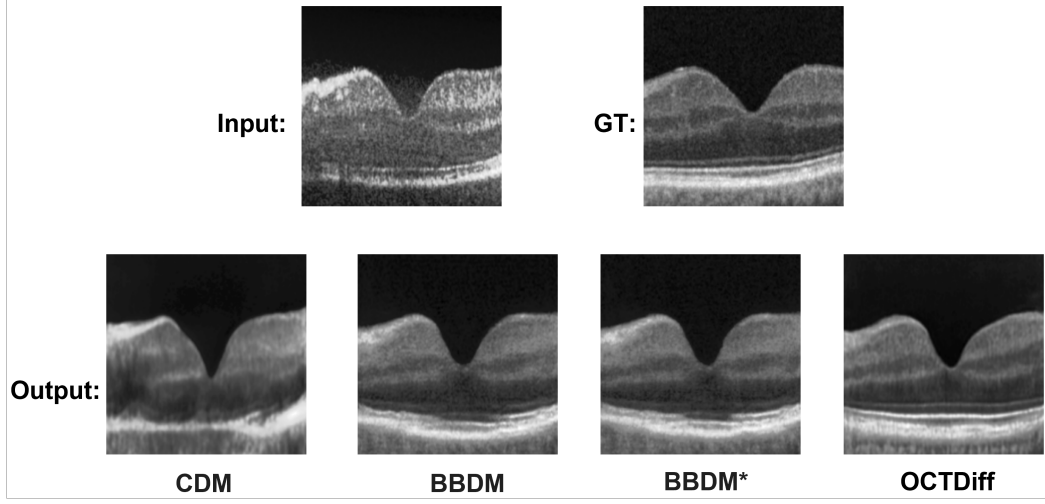


Figure 2: Another example comparing LDM, BBDM and OCTDiff outputs. The input image is normalized and histogram-matched with GT for better presentation. BBDM*: the BBDM model implemented with exactly the same strategy and hyperparameters as OCTDiff (including learning rate, optimizer, batch size and quality-loss).

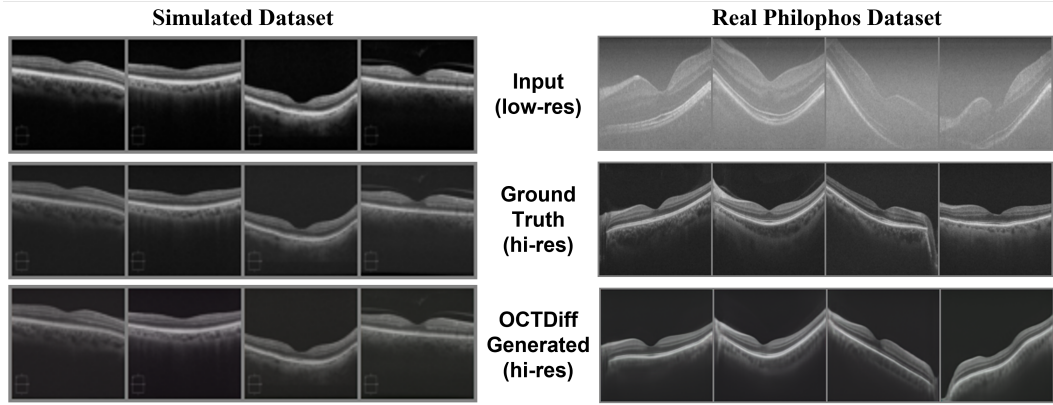


Figure 3: Results without doing image registration on the input low-resolution images, while the rest of the experiments are the same. Left: Results on Simulated Dataset; Right: Results on Philophos Dataset. From top to bottom rows: Input low-resolution images from portable OCT; Ground Truth high-resolution images from commercial OCT; OCTDiff generated images. Each row contains 4 independent examples for each dataset result.

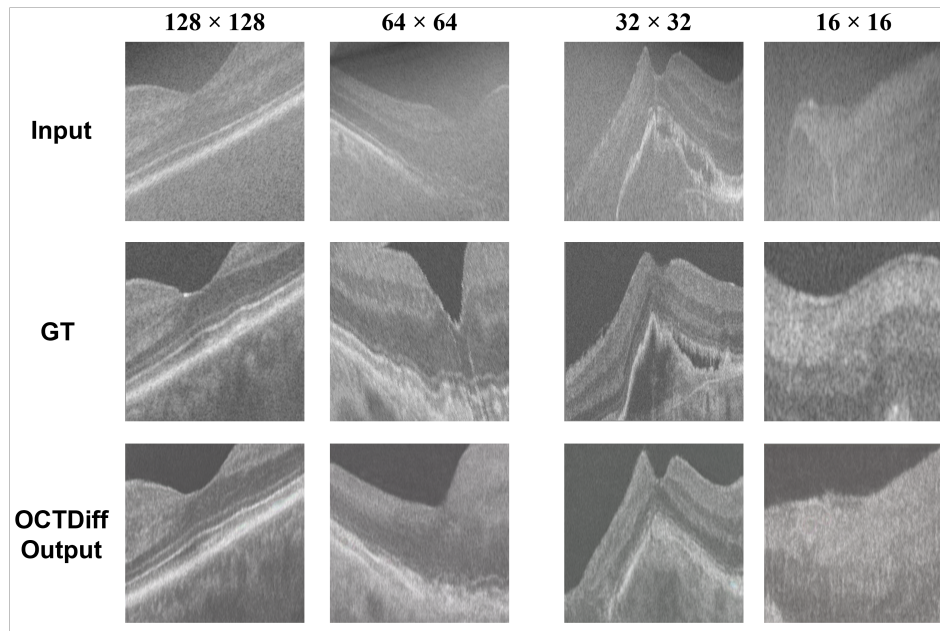


Figure 4: A set of generated image-patch examples using OCTDiff. From left to right: four image patches at resolutions of 128×128 , 64×64 , 32×32 , and 16×16 , respectively, revealing progressively more localized details.

3 A.2 Comparison of Generative Models

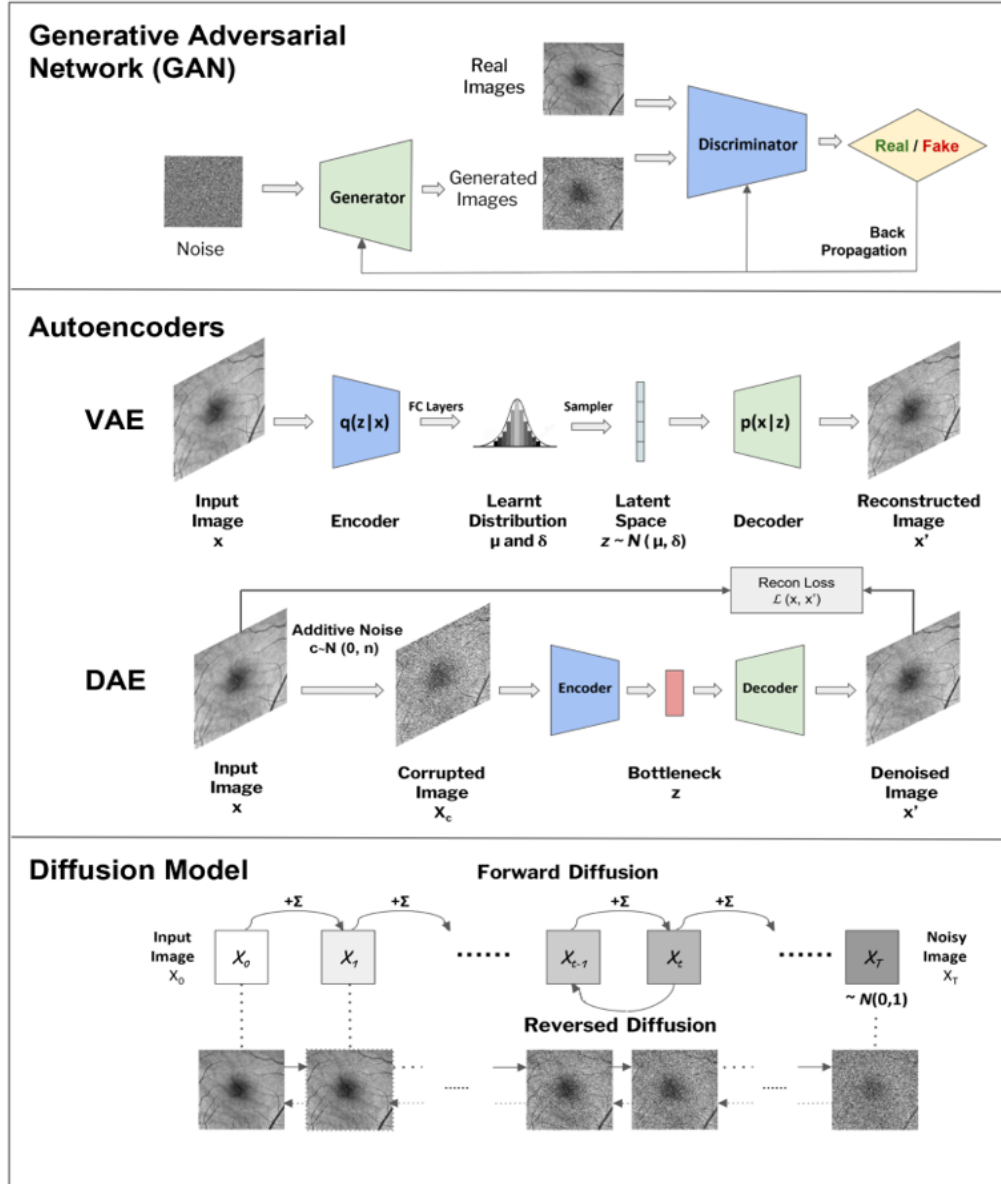
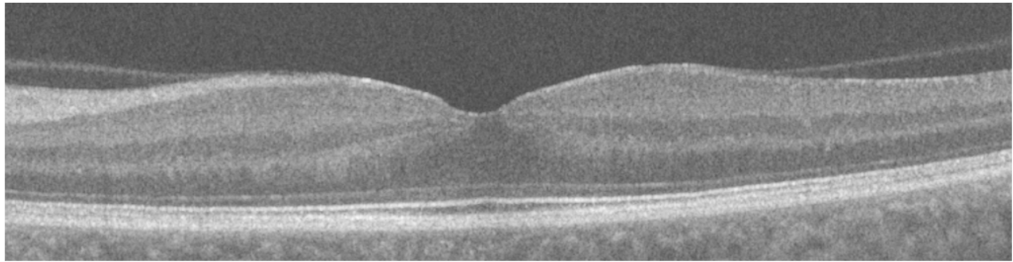


Figure 5: The depiction of three classes of image-generation AI models. From top to bottom: GAN; Autoencoders including VAE and DAE; Diffusion Model.

4 A.3 Quality Score Acquisition

1		
Score:	Reason (optional):	High quality image, well centered
9		

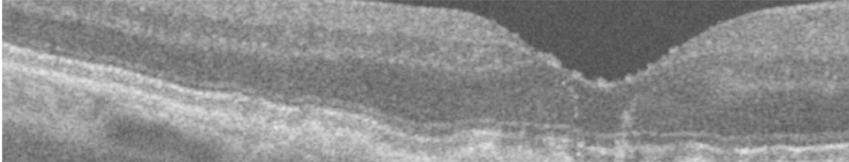
2		
Score:	Reason (optional):	Off center, cannot see nasal macula, cannot see choroid
2		

Figure 6: The slide shown to clinicians for consensus quality scores on high-resolution (target) images, which are used in regularizing the loss function. Top: an example of a scan scored 9/10; bottom: an example of a scan scored 2/10.

5 A.4 Extended Ablation Study

6 The focal-style loss function with the quality score as defined in Secion 3.3 as:

$$MSE_{focal} = \frac{1}{N} \sum_{i=1}^N \left(1 - S_{quality}^{(i)}\right)^{\gamma} \cdot (x_i - \hat{x}_i)^2 \quad (1)$$

7 where $\gamma < 0$ is a focusing parameter that controls the degree to which high-quality samples are
8 prioritized, usually being set in $[-2, -1]$. The quality score S is normalized to the range $(0,1)$.

9 We conduct an ablation on the impact of different γ values on results.

Table 1: Ablation study on the focal parameter γ . Evaluation is on Philophos Dataset.

γ	$W_{S=0.2}$	$W_{S=0.8}$	SSIM% \uparrow	PSNR \uparrow
-0.5	1.12	2.24	88.2	35.1
-1.0	1.25	5.00	91.8	35.7
-2.0	1.56	25.0	83.9	34.2

10 When the focal parameter γ becomes smaller (i.e., closer to -2), the weighting effect on high-quality
11 samples is significantly amplified. The model places much stronger emphasis on high-quality samples
12 when γ is smaller. Conversely, the weights assigned to lower-quality samples increase only slightly
13 across the range of $(-2,0)$. According to the comparison in table 1, we used $\gamma = -1.15$ to get the
14 best-performing result in the following experiments.