Attention2AngioGAN: Synthesizing Fluorescein Angiography from Retinal Fundus Images using Generative Adversarial Networks

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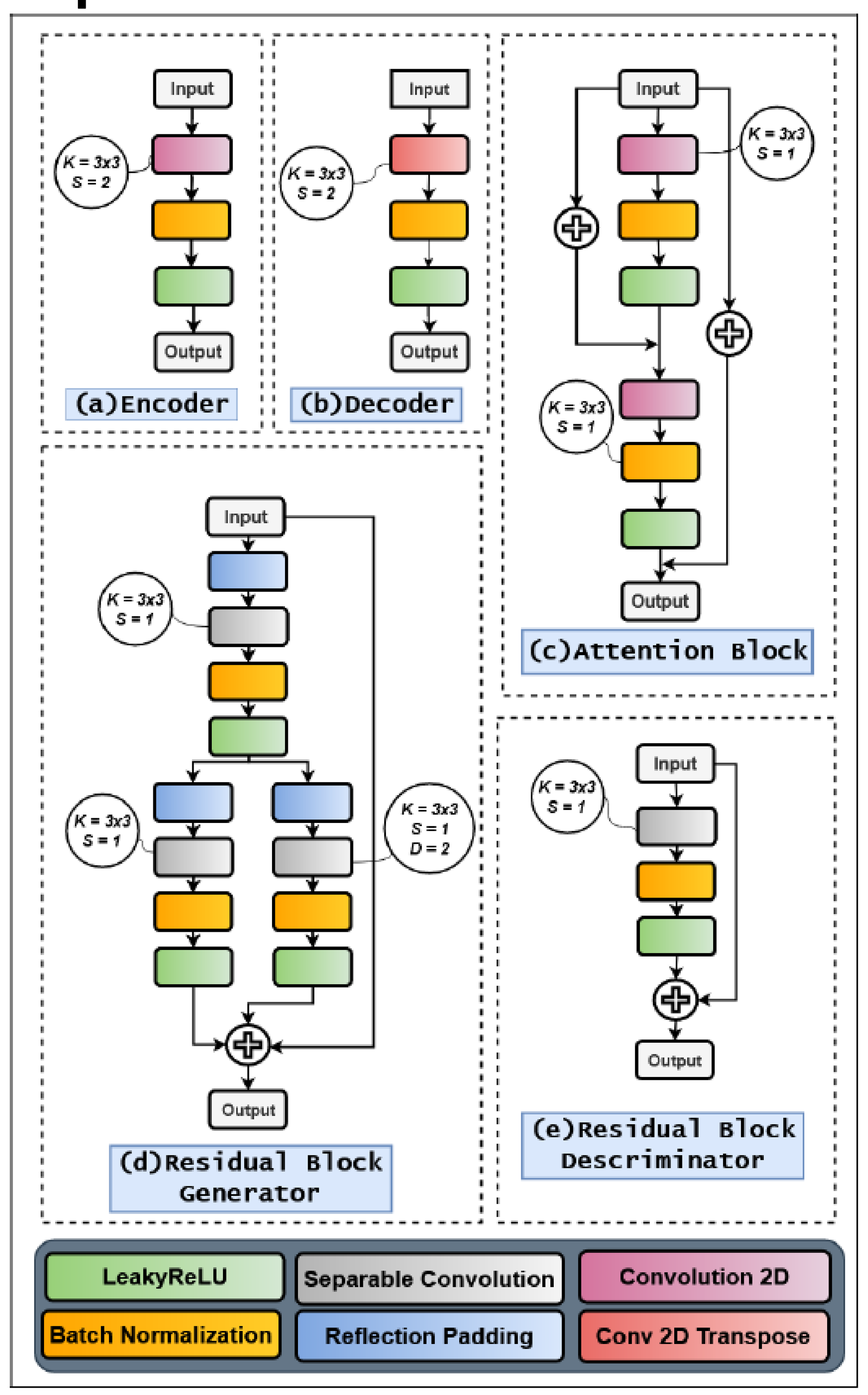
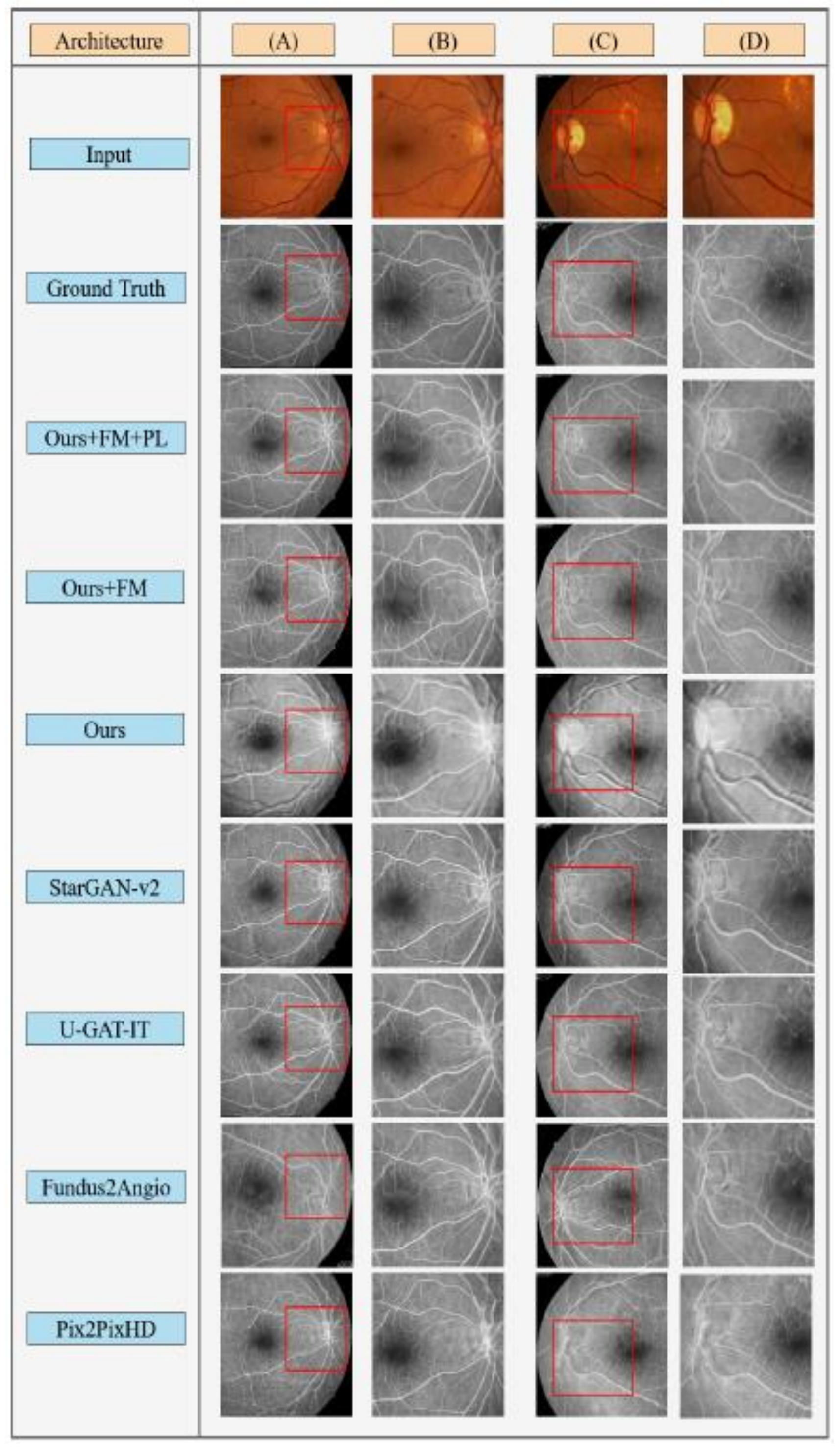
Introduction

- Fluorescein Angiography (FA) requires injecting exogeneous dye
  - might cause adverse effects ranging from nausea, to anaphylactic shock.
- To eradicate the need for FA we introduce an Attention-based Generative network to synthesize Fluorescein Angiography from Fundus images.

Proposed Blocks



Results



Results

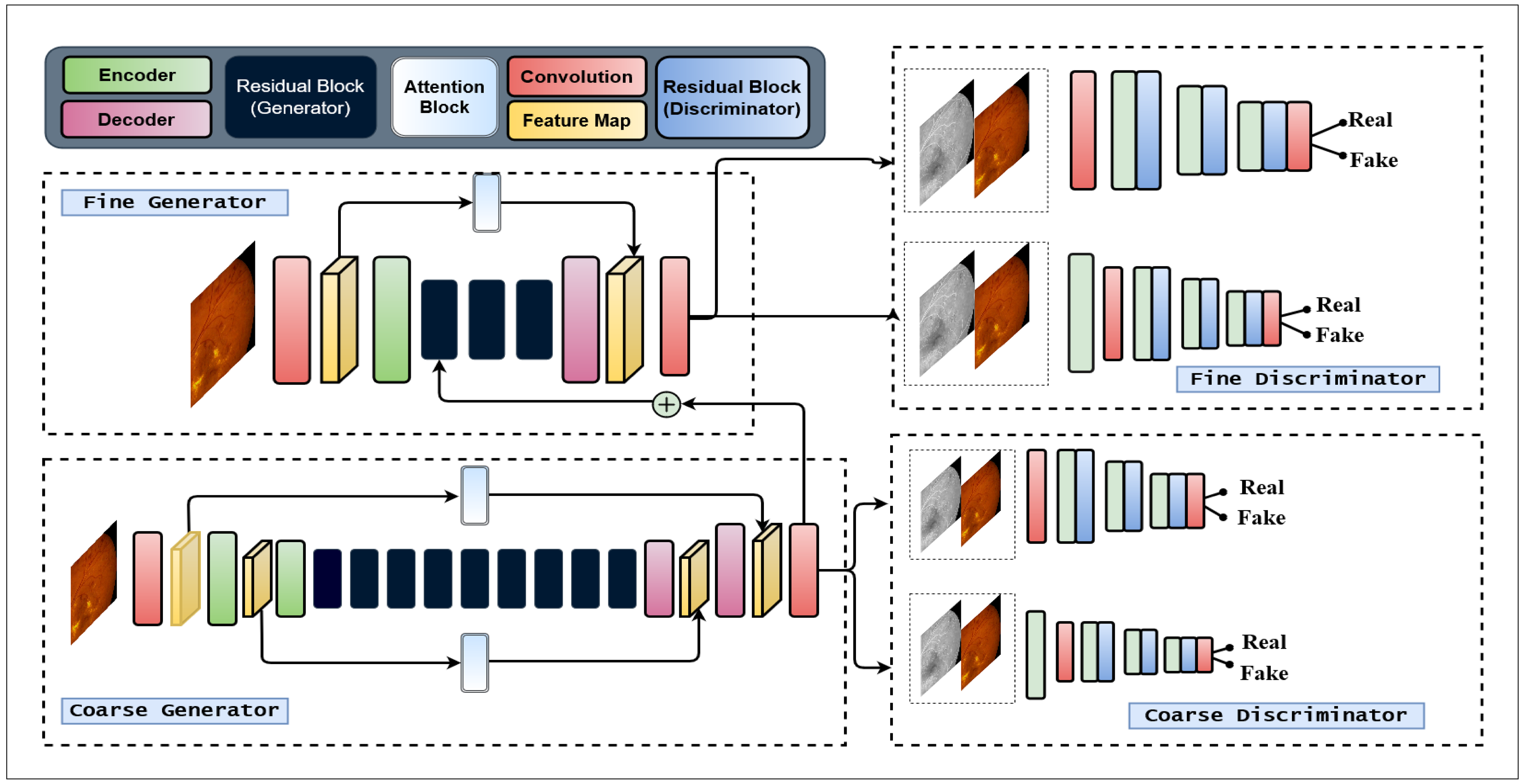
TABLE I
TEST RESULTS FOR DIFFERENT ARCHITECTURES

Fréchet Inception Distance (FID)						
Architecture	Orig.	Noise	Blur	Sharp	Whirl	Pinch
Ours + PL[1]+ FM[2]	24.6	21.6 (3.0↓)	30.0 (5.4↑)	25.6 (1.0↑)	40.0 (15.4↑)	24.9 (0.3↑)
Ours + FM[2]	**20.7**	**20.8** (0.1↑)	**23.5** (2.8↑)	**24.9** (4.2↑)	**27.8** (7.1↑)	**19.5** (1.2↓)
Ours	47.5	43.1 (4.4↓)	49.8 (2.3↑)	50.5 (3.5↑)	61.9 (14.5↑)	46.7 (0.8↓)
StarGAN-v2 [12]	27.7	35.1 (7.4↑)	32.6 (4.9↑)	27.4 (0.3↓)	32.7 (5.0↑)	26.7 (1.0↓)
U-GAT-IT [11]	24.5	26.0 (1.5↑)	30.4 (5.9↑)	26.8 (2.3↑)	33.0 (9.5↑)	29.1 (4.6↑)
Fundus2Angio [39]	30.3	41.5 (11.2↑)	32.3 (2.0↑)	34.3 (4.0↑)	38.2 (7.9↑)	33.1 (2.8↑)
Pix2PixHD [10]	42.8	53.0 (10.2↑)	43.7 (1.1↑)	47.5 (4.7↑)	45.9 (3.1↑)	39.2 (3.6↓)

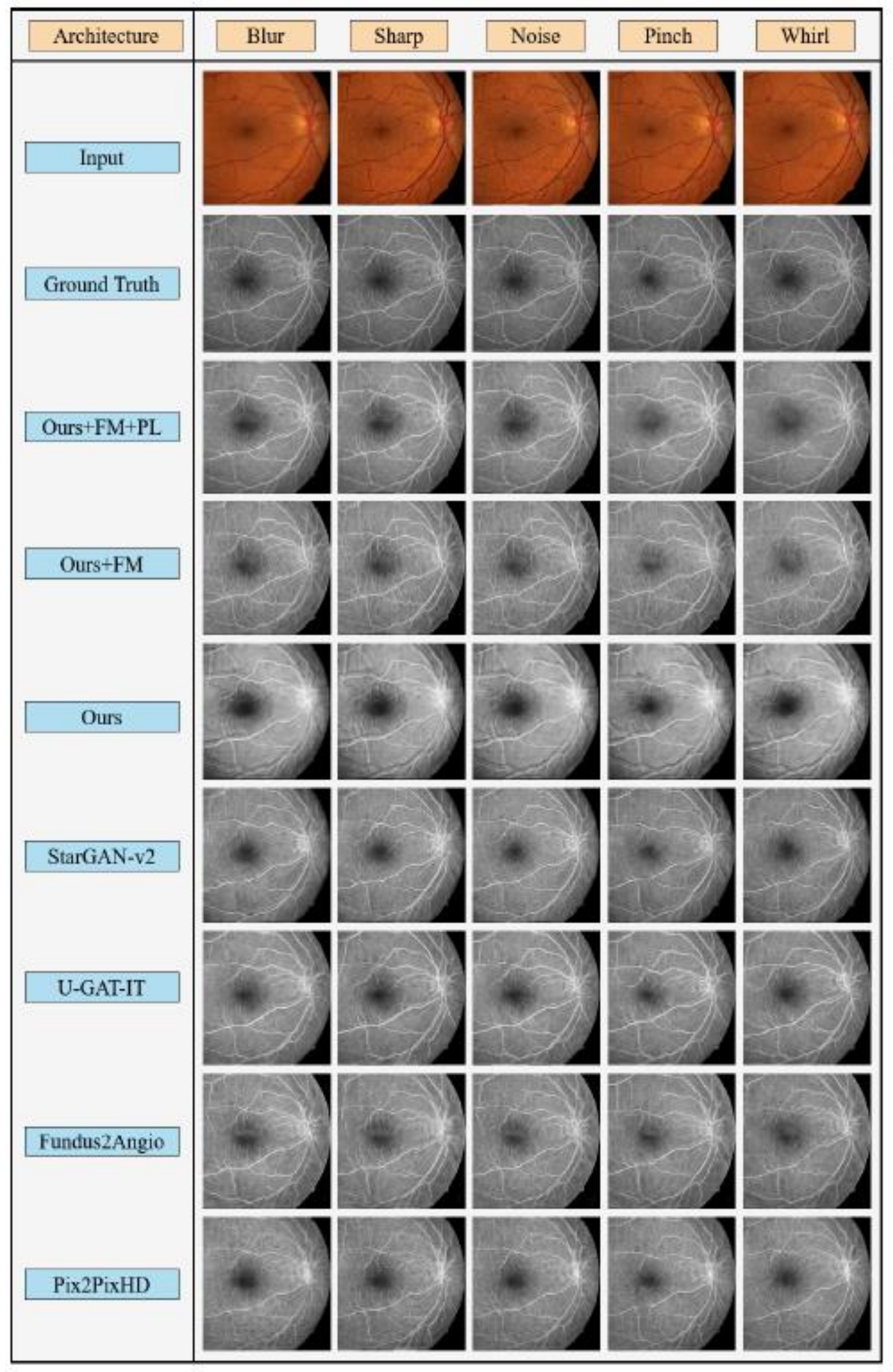
Kernel Inception Distance (KID)						
Architecture	Orig.	Noise	Blur	Sharp	Whirl	Pinch
Ours + PL[1]+ FM[2]	**0.00087**	**0.05045**	**0.00235**	**0.05162**	0.05390	**0.04575**
Ours + FM[2]	0.00392	0.05390	0.00505	0.05301	0.05657	0.05341
Ours	0.00595	0.05237	0.00617	0.05298	0.05613	0.05419
StarGAN-v2 [12]	0.00118	0.05274	**0.00235**	0.05331	0.05539	0.05271
U-GAT-IT [11]	0.00131	0.05610	0.00278	0.05533	0.05815	0.05719
Fundus2Angio [39]	0.00184	0.05328	0.00272	0.05267	**0.05278**	0.04985
Pix2PixHD [10]	0.00258	0.05613	0.00254	0.05788	0.06029	0.05838

[1] PL = Perceptual Loss; FM = Feature-Matching Loss
[2] FID: Lower is better; KID: Lower is better

The Proposed GAN architecture



Results



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