



Bridging Global Context Interactions for High-Fidelity Image Completion

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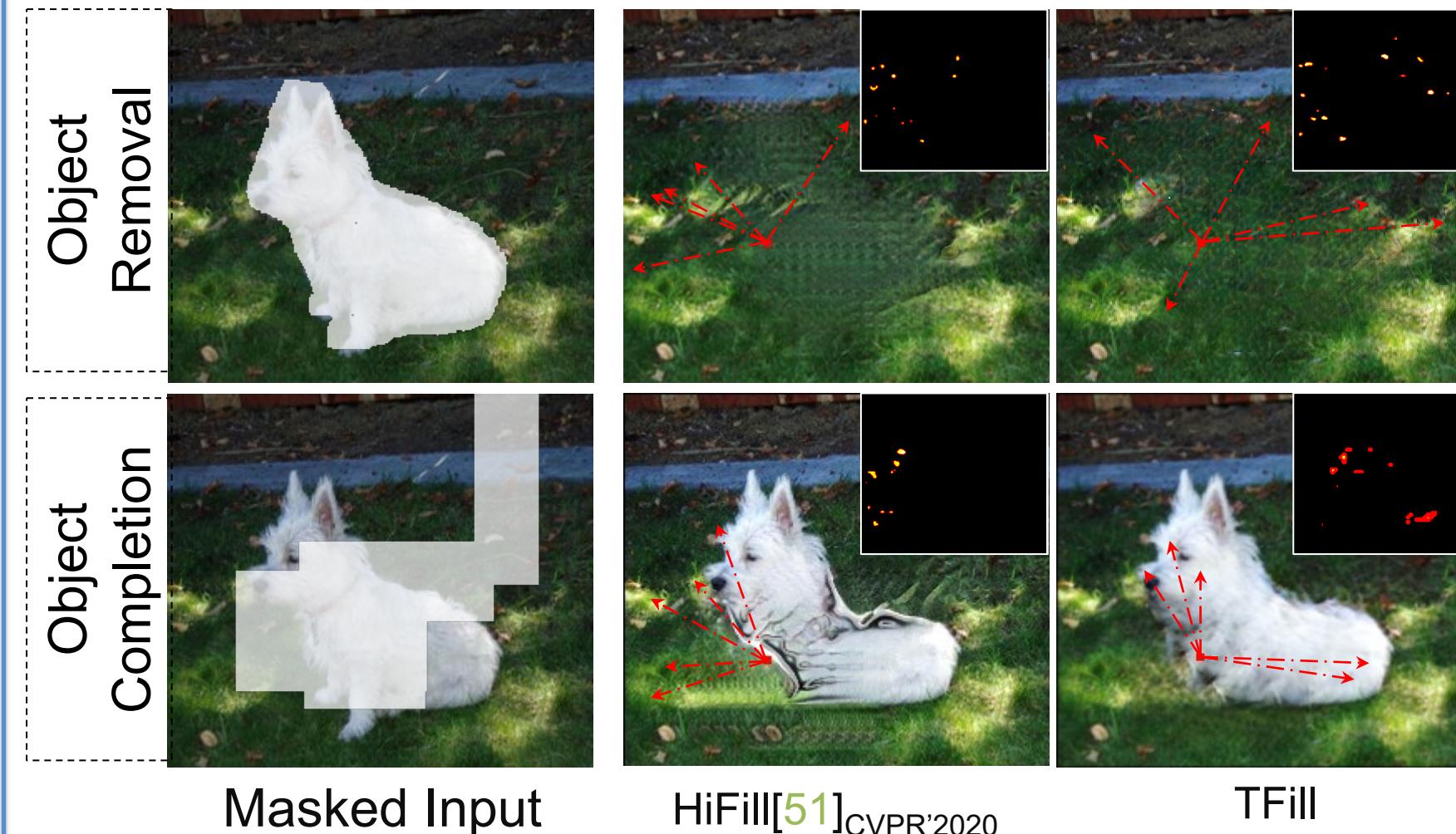
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Motivation

Goal: semantic image completion, *not* purely for removing objects

Challenge:

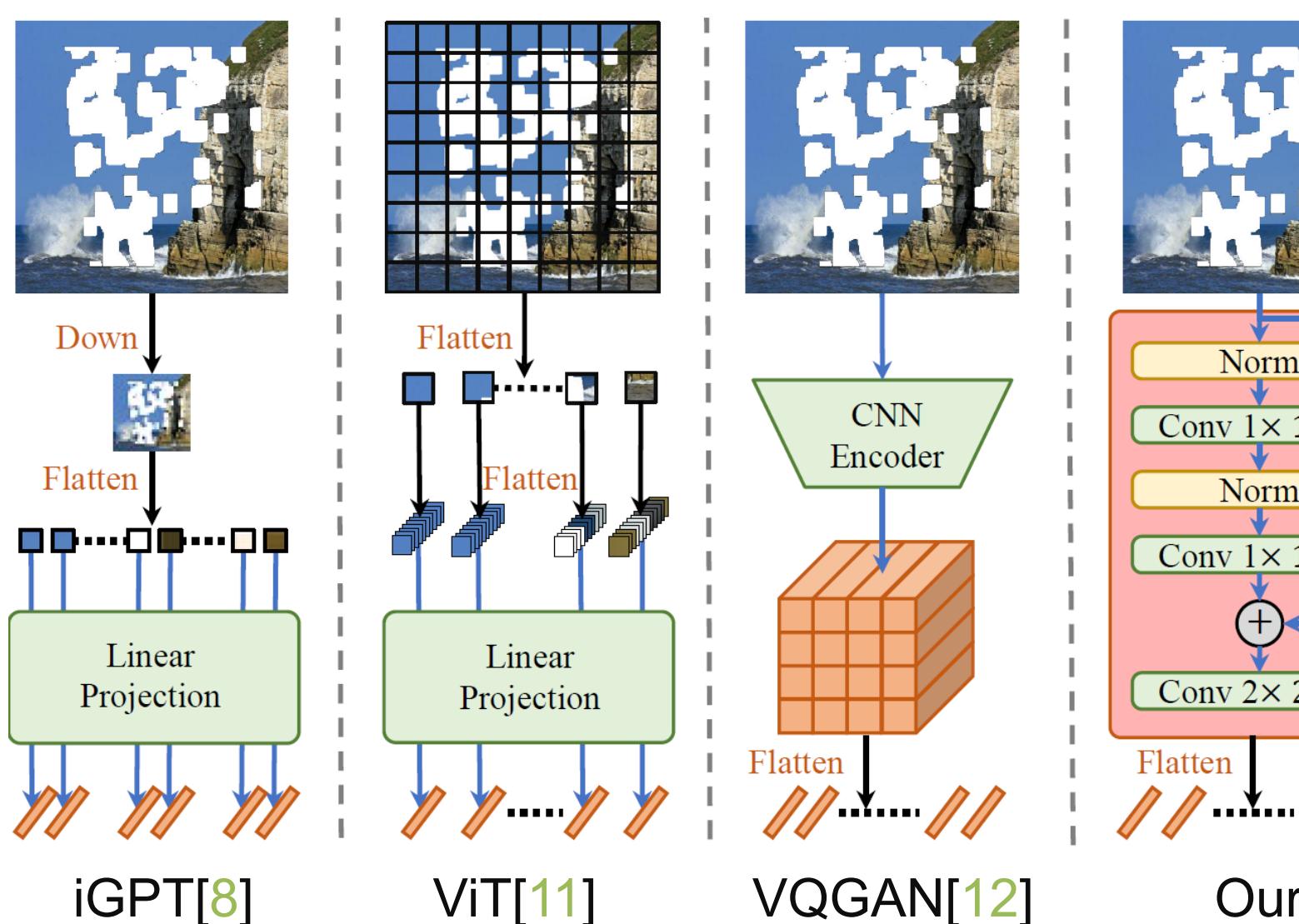
1. CNN gradually affected by neighboring pixels
2. Pixel-level attention requires expensive costs



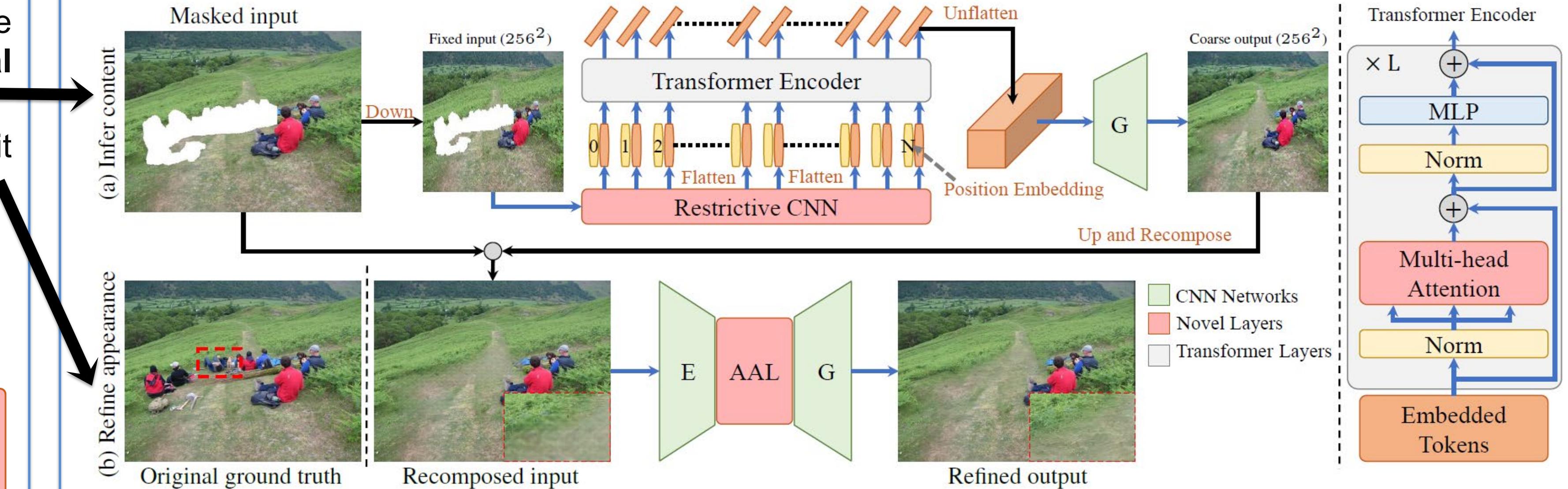
How to correctly model the disconnected context?

Key Insights

1. Propose a transformer-based framework with the **restrictive CNN** to correctly model the **global content** in each attention layer
2. Design a novel Attention-Aware Layer to exploit **global appearance information**



Pipeline: Two-stage Image Completion

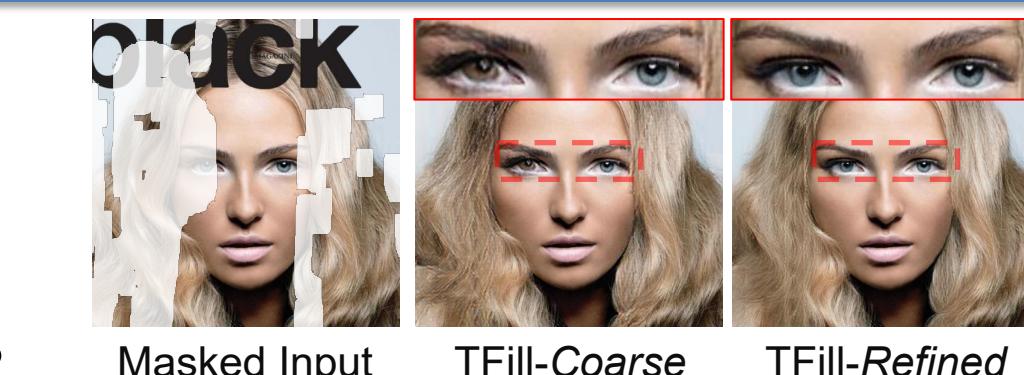


Tfill-Coarse: Global Content Inference

- Restrictive CNN:** embed patch visible context
Weighted Self-Attention Layer: bias visible token
CNN-based Decoder: generate tokens in parallel

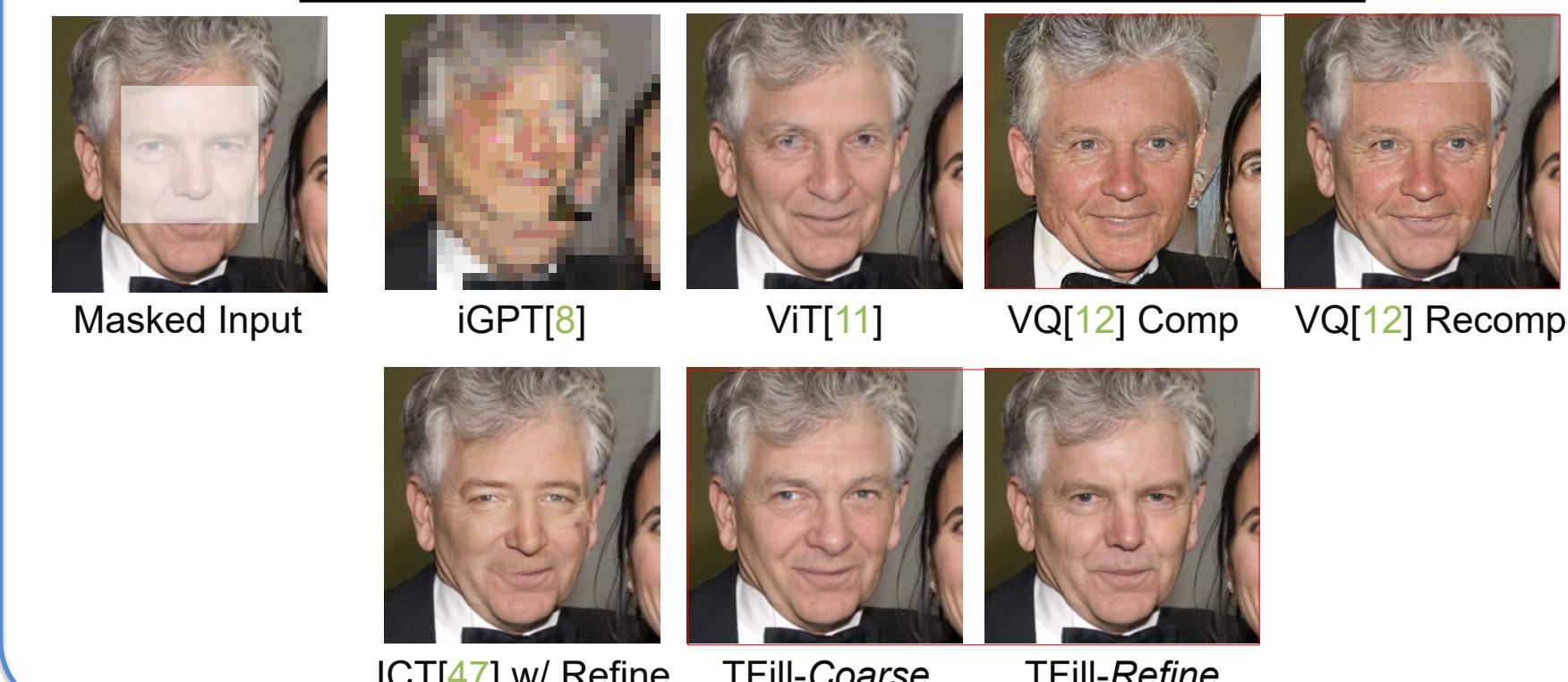
Tfill-Refined: Global Appearance Refinement

- AAL:** copy global context from both encoded and decoded features

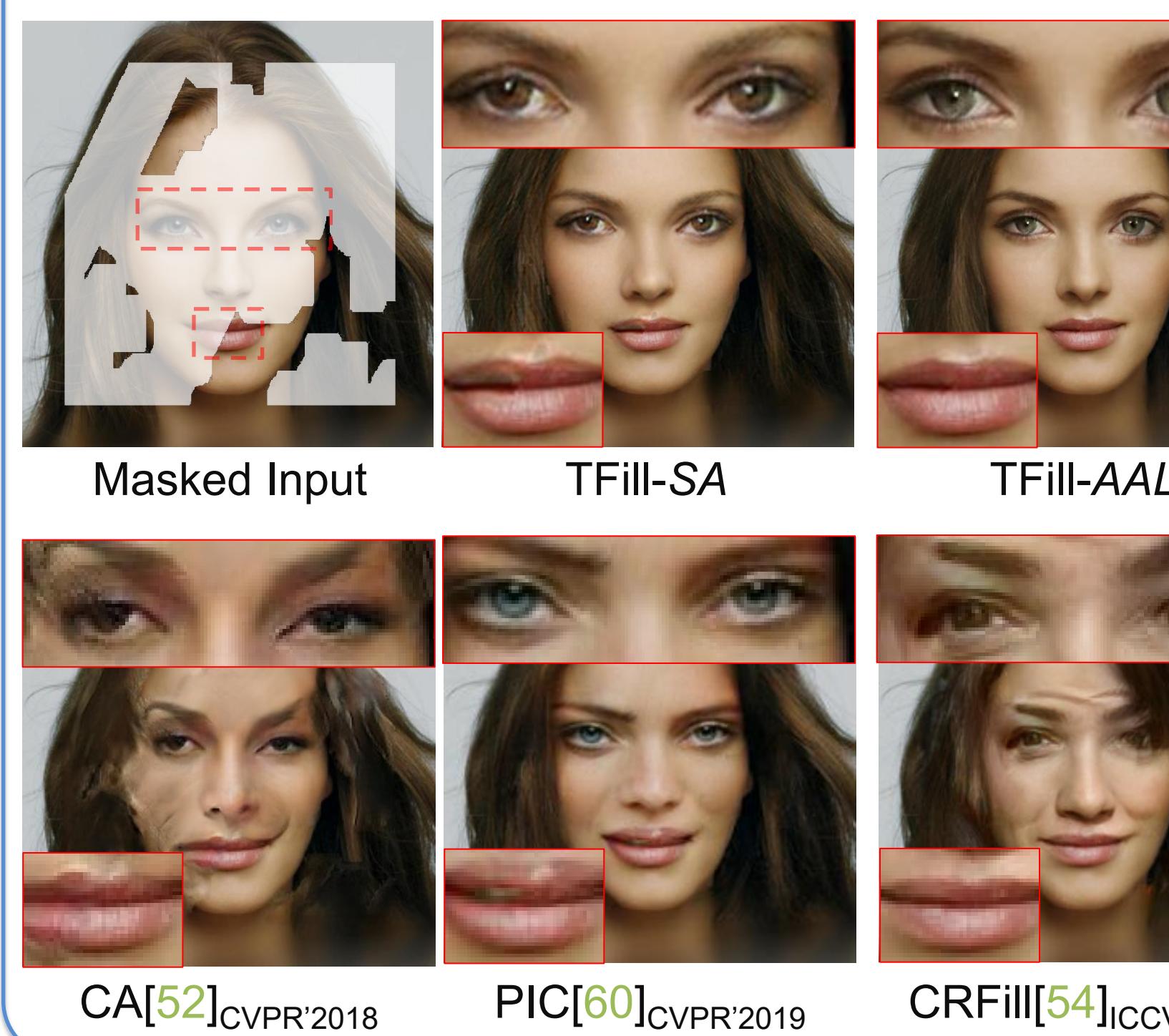


Analysis: Architecture of Tfill

Method	CelebA-HQ		FFHQ	
	LPIPS↓	FID↓	LPIPS↓	FID↓
CA [52] CVPR'2018	0.104	9.53	0.127	8.78
PIC [60] CVPR'2019	0.061	6.43	0.068	4.61
MEDFE [29] ECCV'2020	0.067	7.01	-	-
A Traditional Conv	0.060	6.29	0.066	4.12
B + Attention in G	0.059	6.34	0.064	4.01
C + Restrictive Conv	0.056	4.68	0.060	3.87
D + Transformer	0.051	4.02	0.057	3.66
E + Masked Attention	0.050	3.92	0.057	3.63
F + Refine Network	0.048	3.86	0.053	3.50



Analysis: Attention-Aware Layer



Overall Comparison with Other Methods

