Controlling Vision-Language Models for Multi-Task Image Restoration

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Project Page:
https://algolzw.github.io/daclip-uir/index.html

Multi-Task Image Restoration

Key Idea: Perform restoration across multiple tasks and datasets with a single model.

- Better generalization for different degradation types.
- Efficient deployment of real-world applications.

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Examples of Multi-Task Image Restoration

Image dehazing

Image deblurring

Face inpainting

JPEG artifact deduction

A Single Restoration Model for
All Degradations

Image desnowing

Low-light image enhancement

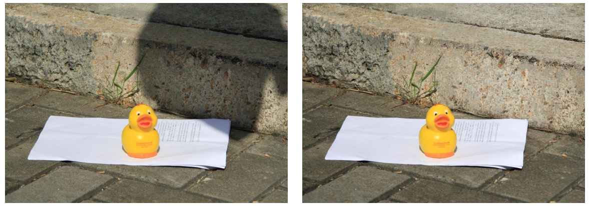

Image shadow removal

Image denoising

Image raindrop removal

Image deraining

Solutions and Challenges

Common solutions:

- Train individual modules for degradation classification
    - AirNet[1] trains an extra encoder to differentiate degradation types using contrastive learning.
    - PromptIR[2] employs a visual prompt module to guide the restoration for different tasks.
    - ***They are limited to a small number of degradation types and the specific datasets!***

Challenges:

- *Inaccurate prediction due to unbalanced datasets of different tasks.*
- *No proper way to utilize the degradation for image restoration.*

[1] Li, Boyun, et al. "*All-in-one image restoration for unknown corruption*". CVPR 2022.
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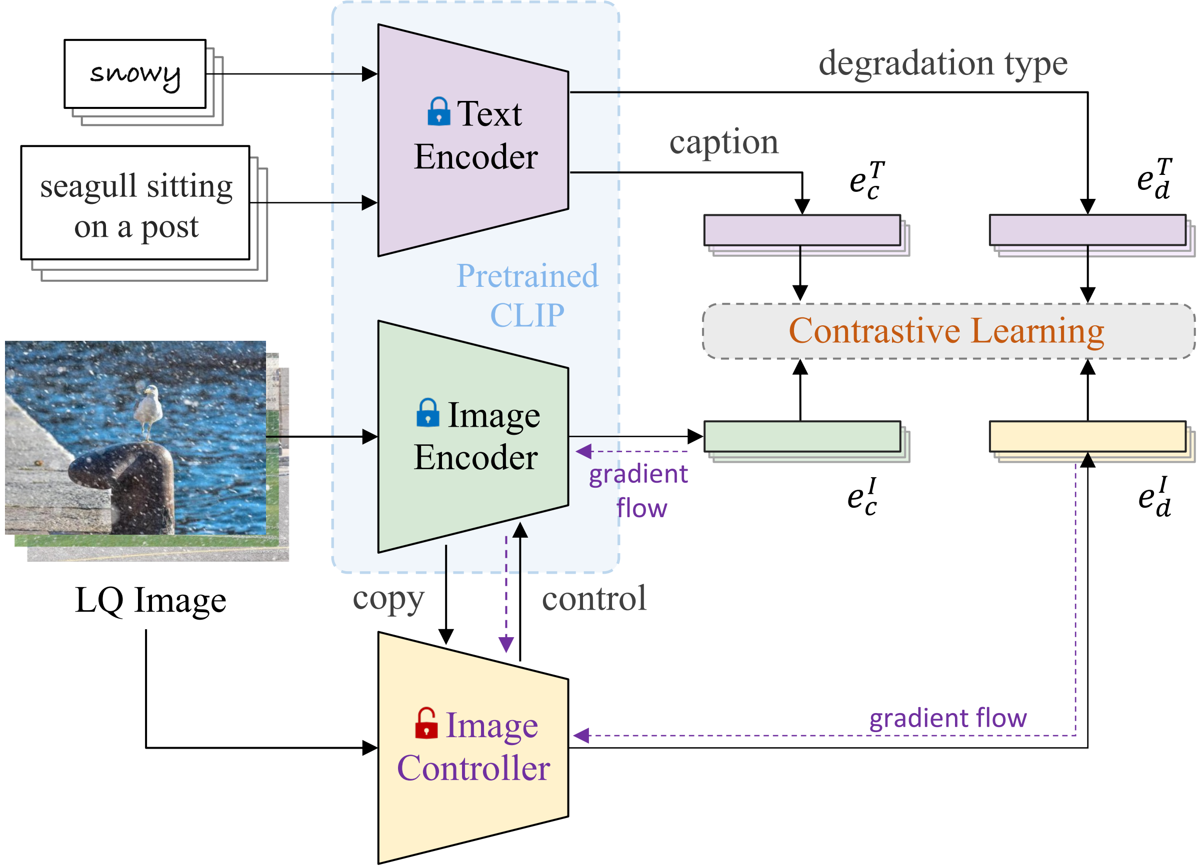
Degradation-aware CLIP (DA-CLIP)

- Controlling a pretrained vision-language model, i.e. CLIP[3], for:
  1. <u>*Degradation embedding*</u> prediction.
  2. <u>*Content embedding*</u> prediction.



[3] Radford, Alec, et al. "*Learning transferable visual models from natural language supervision.*" ICML 2021.

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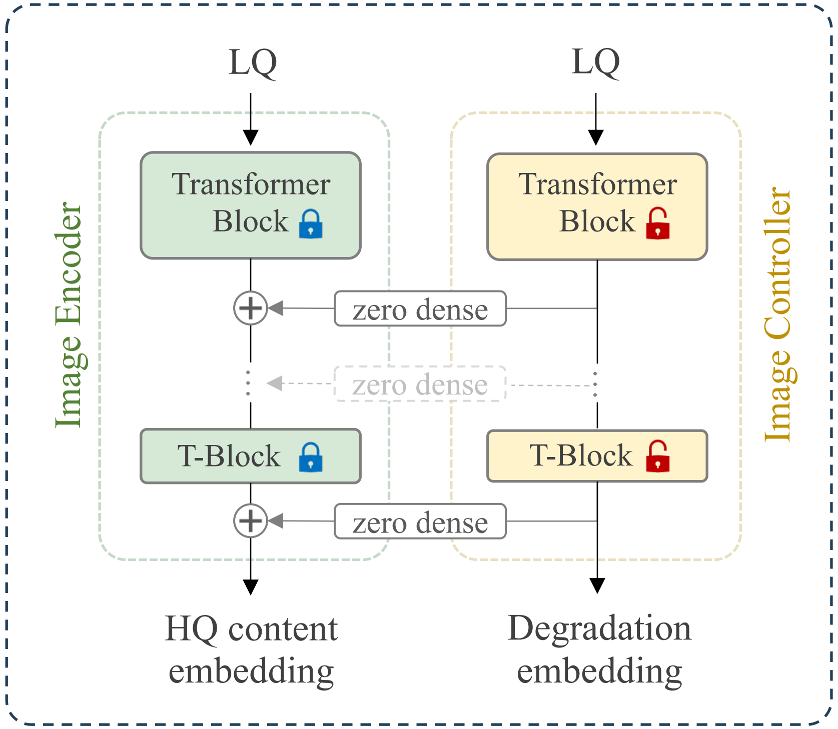

Example: Controller for ViT-based image encoder

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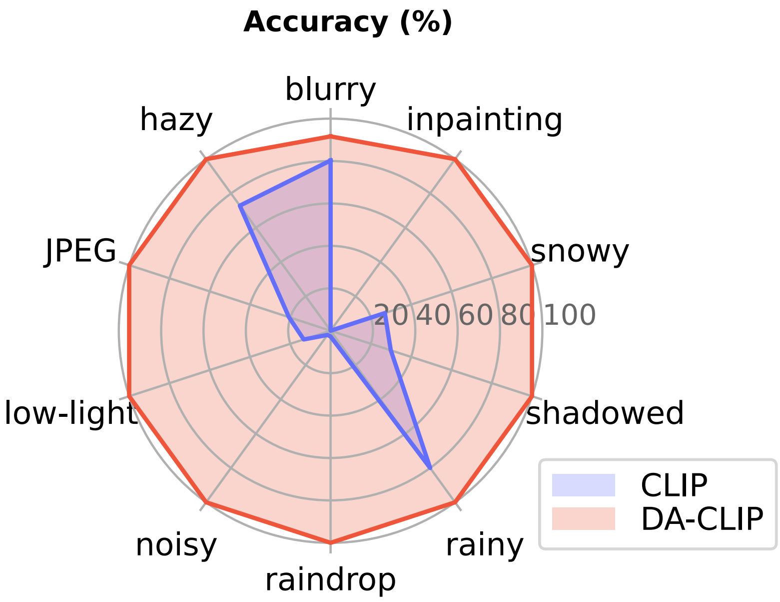

CLIP vs. DA-CLIP on 10 Degradation Types

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Image Restoration with DA-CLIP

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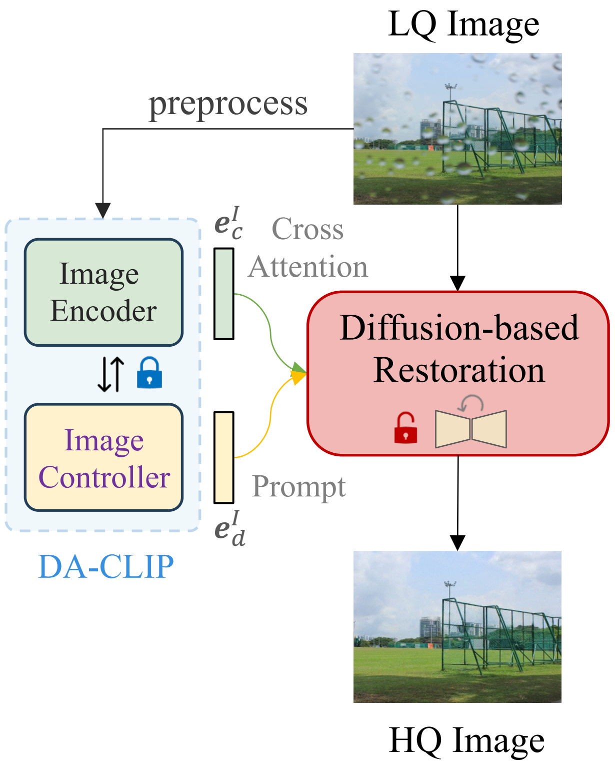
- Integrating *content embeddings* into U-Net with **cross-attention**.
- Integrating *degradation embeddings* into U-Net with **visual prompt**.



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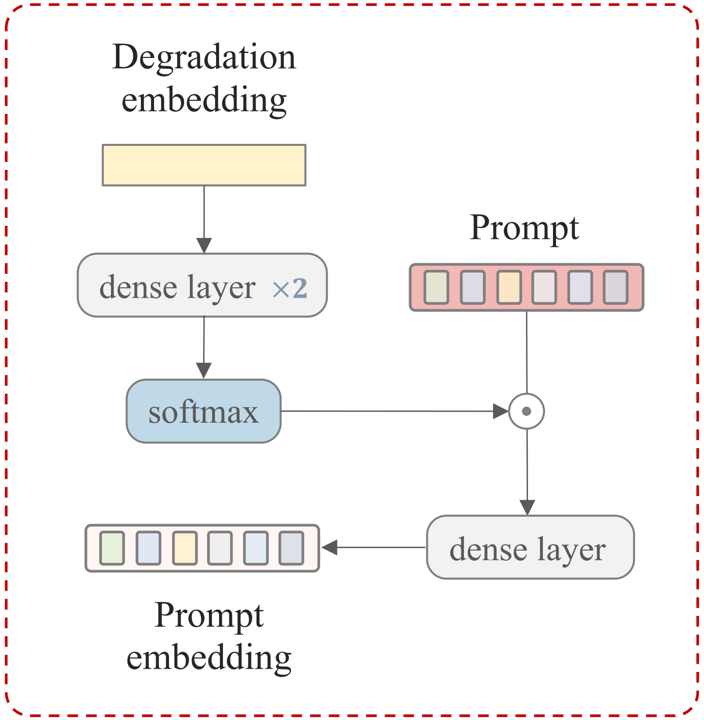

Prompt for degradation embeddings

Dataset Construction

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HQ Image

LQ Image

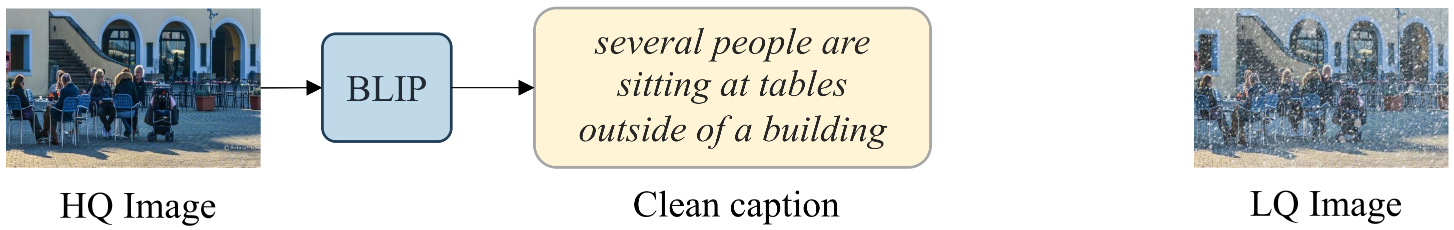
Dataset Construction

HQ Image

BLIP

LQ Image

Dataset Construction



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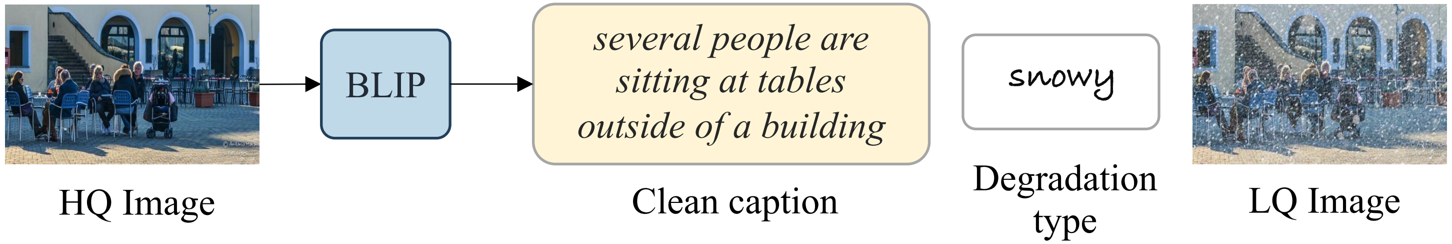

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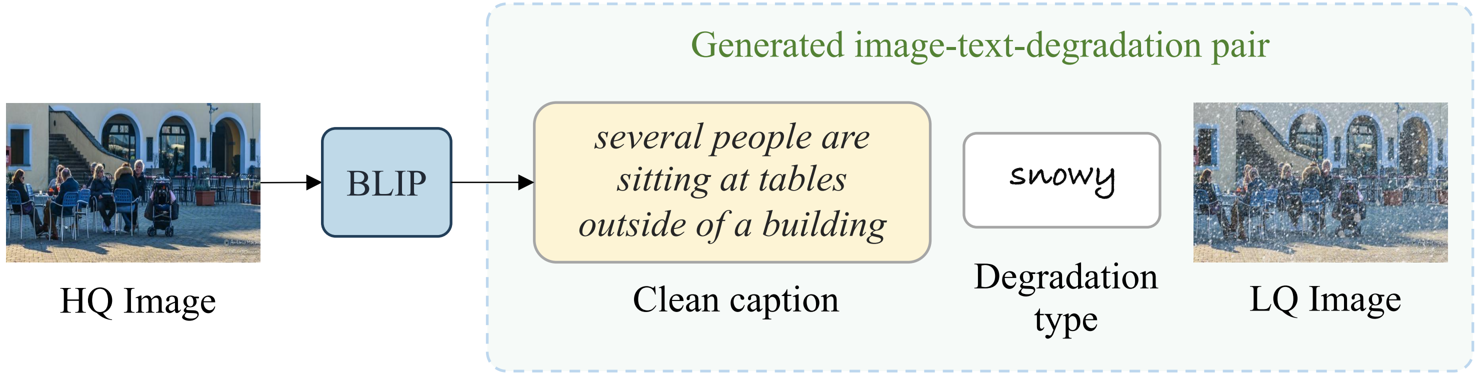

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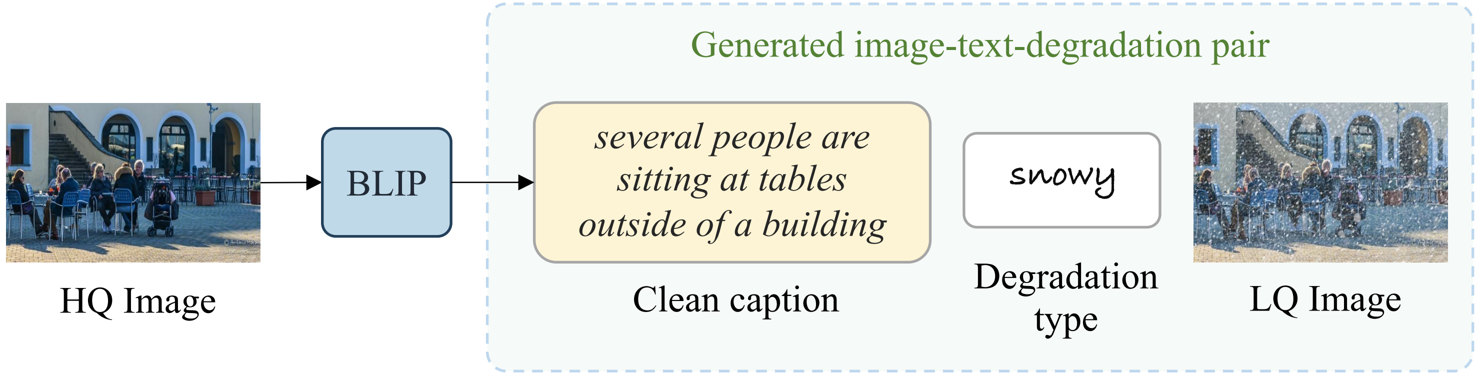


Table 1: Details of the collected training and testing datasets with different image degradation types.

Dataset	Blurry	Hazy	JPEG	Low-light	Noisy	Raindrop	Rainy	Shadowed	Snowy	Inpainting
#Train	2 103	6 000	3 550	485	3 550	861	1 800	2 680	1 872	29 900
#Test	1 111	1 000	29	15	68	58	100	408	601	100

Experiments

Degradation-Specific Image Restoration

a) Deraining
b) Low-light enhancement
c) Deblurring
d) Dehazing

Table 2: Quantitative comparison between our method with other state-of-the-art approaches on four different *degradation-specific* datasets. The best results are marked in boldface.

Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
JORDER	26.25	0.835	0.197	94.58
PReNet	29.46	0.899	0.128	52.67
MPRNet	30.41	0.891	0.158	61.59
MAXIM	30.81	0.903	0.133	58.72
IR-SDE	31.65	0.904	0.047	18.64
Ours	**33.91**	**0.926**	**0.031**	**11.79**

(a) Deraining results on the Rain100H dataset.

Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
EnlightenGAN	17.61	0.653	0.372	94.71
MIRNet	**24.14**	0.830	0.250	69.18
URetinex-Net	19.84	0.824	0.237	52.38
MAXIM	23.43	**0.863**	0.098	48.59
IR-SDE	20.45	0.787	0.129	47.28
Ours	23.77	0.830	**0.083**	**34.03**

(b) Low-light enhancement on the LOL dataset.

Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
DeepDeblur	29.08	0.913	0.135	15.14
DeblurGAN	28.70	0.858	0.178	27.02
DeblurGANv2	29.55	0.934	0.117	13.40
MAXIM	**32.86**	**0.940**	0.089	11.57
IR-SDE	30.70	0.901	0.064	6.32
Ours	30.88	0.903	**0.058**	**6.15**

(c) Deblurring results on the GoPro dataset.

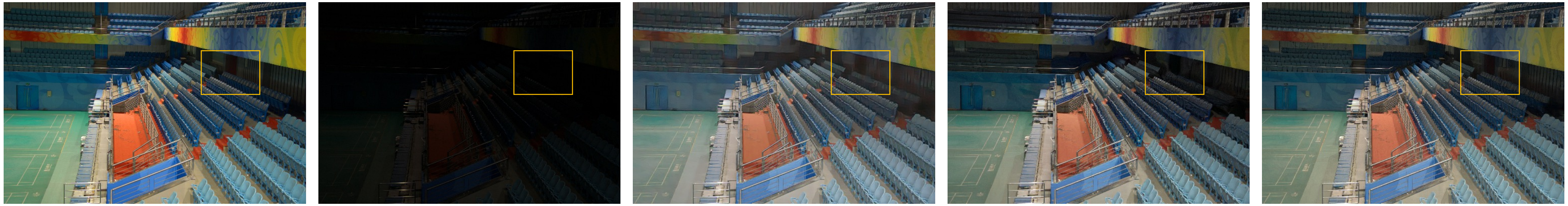
Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
GCANet	26.59	0.935	0.052	11.52
GridDehazeNet	25.86	0.944	0.048	10.62
DehazeFormer	**30.29**	**0.964**	0.045	7.58
MAXIM	29.12	0.932	0.043	8.12
IR-SDE	25.25	0.906	0.060	8.33
Ours	30.16	0.936	**0.030**	**5.52**

(d) Dehazing results on the RESIDE-6k dataset.

Degradation-Specific Image Restoration

a) Deraining b) Low-light enhancement c) Dehazing d) Deblurring

HQ Image | Rainy Image | MPRNet | IR-SDE | Ours



HQ Image | Low-light Image | URetinexNet | IR-SDE | Ours

Comparison of our method with other approaches on different degradation-specific tasks.

Degradation-Specific Image Restoration

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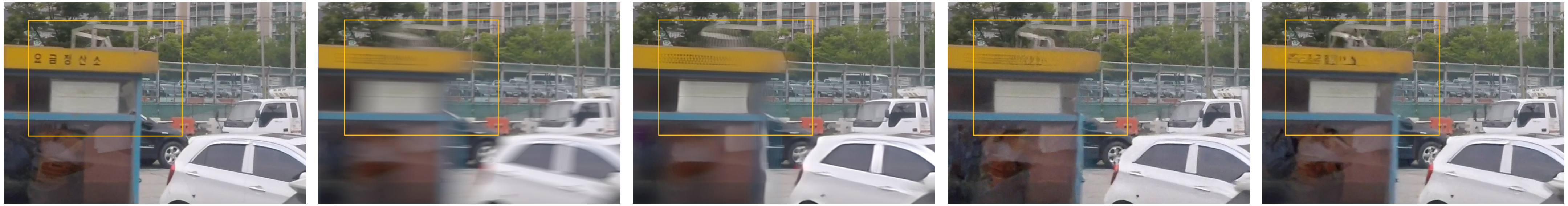
HQ Image | Rainy Image | DehazeFormer | IR-SDE | Ours



HQ Image | Low-light Image | DeblurGAN-v2 | IR-SDE | Ours

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Unified Image Restoration

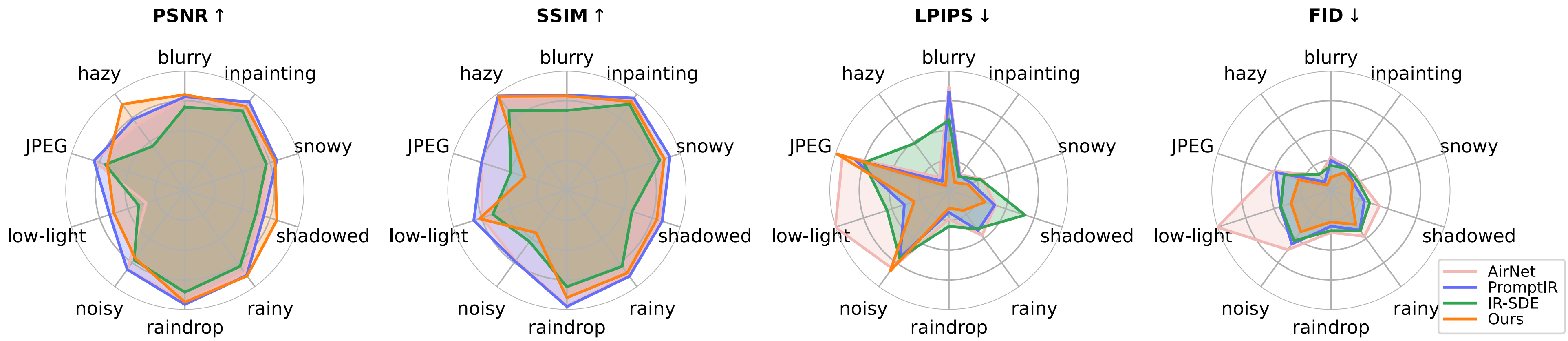

Table 3: Comparison of the average results over ten different datasets on the *unified* image restoration task.

Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
NAFNet	26.34	0.847	0.159	55.68
NAFNet + Degradation	27.02	0.856	0.146	48.27
NAFNet + DA-CLIP	**27.22**	**0.861**	0.145	47.94
Restormer	26.43	0.850	0.157	54.03
AirNet	25.62	0.844	0.182	64.86
PromptIR	27.14	0.859	0.147	48.26
IR-SDE	23.64	0.754	0.167	49.18
Ours	27.01	0.794	**0.127**	**34.89**

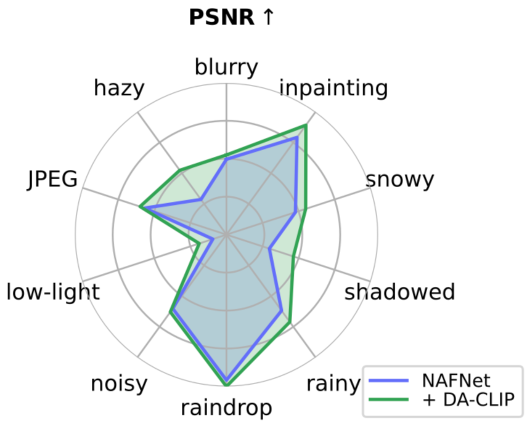

Figure 7: NAFNet with DA-CLIP for *unified* image restoration.

Unified Image Restoration

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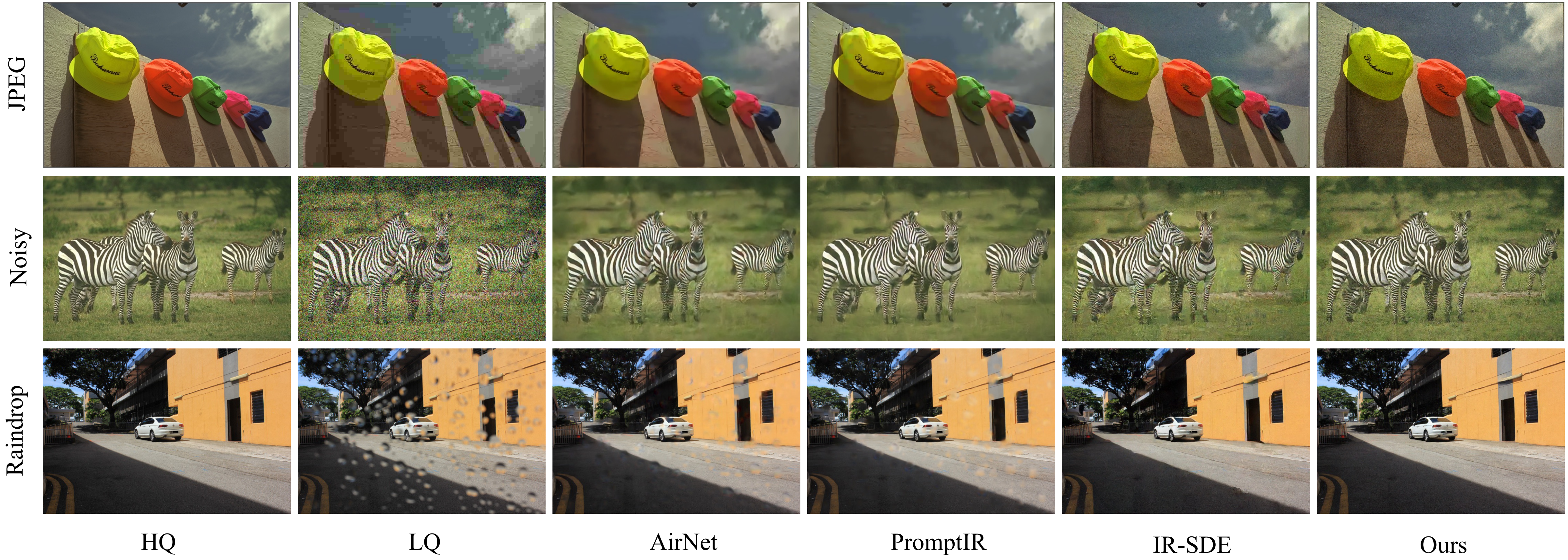
Comparison of our method with other approaches on the unified image restoration.



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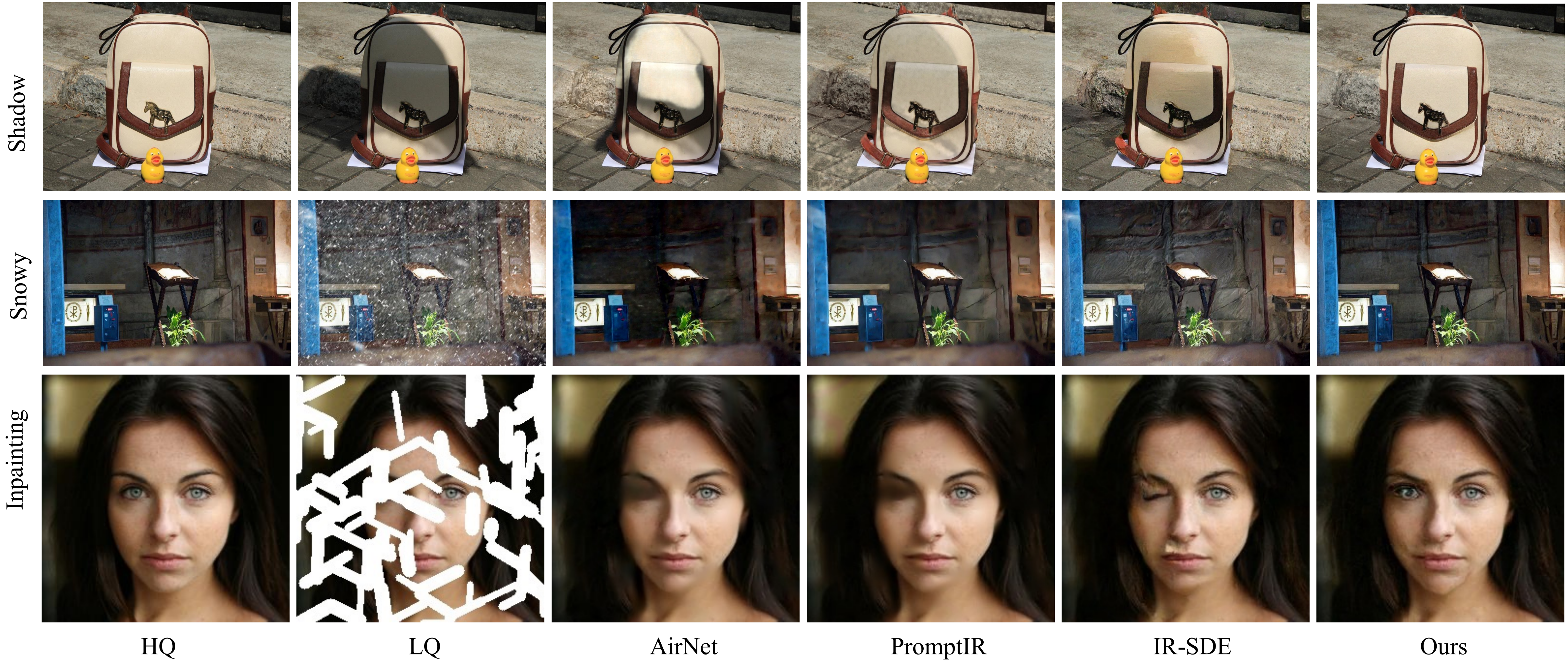

Discussion & Analysis

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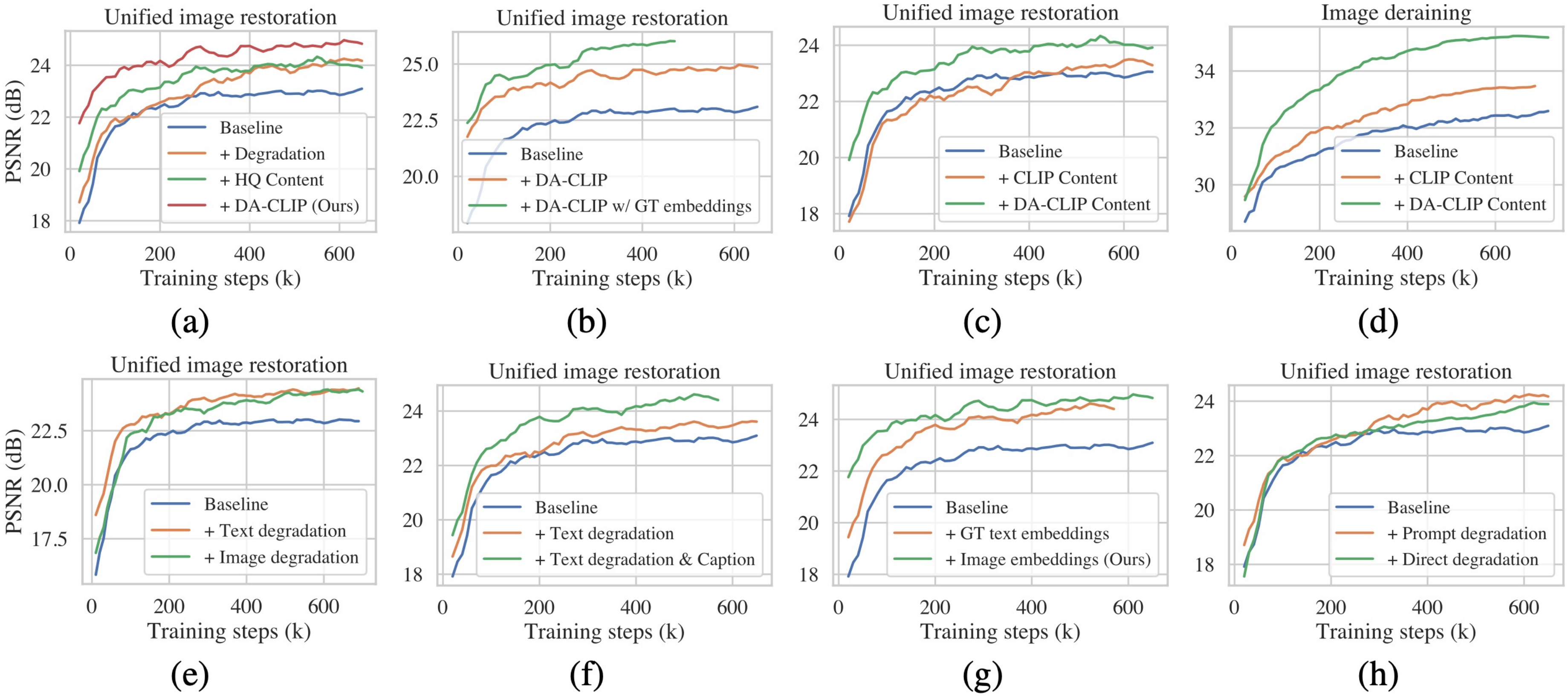

Summary

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- We present **DA-CLIP** to leverage pretrained vision-language models for image restoration.
- We use **cross-attention** and **visual prompt** to integrate embeddings into restoration networks.
- We construct **a mixed degradation dataset** with synthetic captions for DA-CLIP training.
- Our approach achieves highly competitive performance on diverse image restoration tasks.

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Follow-up Paper:
Photo-Realistic Image Restoration in the Wild with Controlled Vision-Language Models