UniProcessor: A Text-induced Unified Low-level Image Processor (Supplemental Material)

Huiyu Duan[1,2], Xiongkuo Min[1,⋆], Sijing Wu[1],
Wei Shen[2,⋆], and Guangtao Zhai[1,2]

[1] Institute of Image Communication and Network Engineering,
Shanghai Jiao Tong University
[2] MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University
{huiyuduan,minxiongkuo,wusijing,wei.shen,zhaiguangtao}@sjtu.edu.cn

1 Distortion Bank

We adopt 30 commonly encountered distortions [10,11,18] with random levels for each type of degradation, to train our unified low-level image processor. Figure 1, 2, and 3 demonstrate the examples of the images degraded by various distortions with different levels. The details of each distortion type are explained below.

– ***JPEG Compression***: Applies standard JPEG compression.
– ***Gaussian Blur***: Filters the image with a Gaussian kernel.
– ***Lens Blur***: Filters the image with a circular kernel.
– ***Motion Blur***: Emulates motion blur by filtering using a line kernel.
– ***Color Diffuse***: Applies Gaussian blur on the color channels (a and b) in the LAB-color space.
– ***Color Shift***: Randomly shifts the green channel and blends it into the original image masked by a gray level map which is the normalized gradient magnitude of the original image.
– ***Color Saturate***: Multiplies the saturation channel in the HSV-color space by a factor.
– ***Gaussian Noise (RGB)***: Adds Gaussian white noise in the RGB color space.
– ***Gaussian Noise (YCbCr)***: Adds Gaussian white noise in the YCbCr color space.
– ***Impulse Noise***: Adds salt and pepper noise in the RGB color space.
– ***Multiplicative Noise***: Adds speckle noise in the RGB color space.
– ***Denoise***: Adds Gaussian noise and then applies a Gaussian blur filter to remove the noise.
– ***Over Bright***: Increases the brightness of the image by applying a non-linear curve fitting to avoid changing extreme values.

- ***Low-light***: Decreases the brightness of the image by applying a non-linear curve fitting to avoid changing extreme values.
- ***Mean Shift***: Shifts the mean intensity of the image by adding a constant value to all pixel values and truncating to the original value range.
- ***Resize Bicubic / Super Resolution (SR) Bicubic***: Downsamples the image and upsamples it back to the original size using bicubic interpolation. This is also a super-resolution task, which only downsamples the image using bicubic interpolation (the bicubic upsample process is inherently involved in the SR procedure).
- ***Resize Bilinear / SR Bilinear***: Downsamples the image and upsamples it back to the original size using bilinear interpolation. This is also a super-resolution task, which only downsamples the image using bicubic interpolation (the bilinear upsample process is inherently involved in the SR procedure).
- ***Resize Nearest / SR Nearest***: Downsamples the image and upsamples it back to the original size using nearest interpolation. This is also a super-resolution task, which only downsamples the image using bicubic interpolation (the nearest upsample process is inherently involved in the SR procedure).
- ***Resize Lanczos / SR Lanczos***: Downsamples the image and upsamples it back to the original size using lanczos interpolation. This is also a super-resolution task, which only downsamples the image using bicubic interpolation (the lanczos upsample process is inherently involved in the SR procedure).
- ***Sharpening (Unsharp Masking)***: Increases the sharpness of an image by using unsharp masking.
- ***Contrast***: Changes the contrast of the image by applying a non-linear Sigmoid-type curve on the RGB values.
- ***color Block***: Inserts randomly colored blocks at random locations in the image.
- ***Pixelate***: Makes a pixelate style for the image.
- ***Discontinuous (Non-eccentricity)***: Randomly offsets small patches in the image by small displacements.
- ***Jitter***: Randomly scatters image data by warping each pixel with small random offsets.
- ***Mosaic***: Emulates incomplete color samples output from an image sensor overlaid with a color filter array (CFA) by applying a CFA mask
- ***Irregular Black Mask***: Paints the image with randomly irregular black masks.
- ***Rectangle Black Mask***: Paints the image with randomly rectangle black masks.

Table 1: Details of the training and testing on 30 degradation-restoration tasks.

Degradation	Degradation factor	Training level	Testing (heavy)	Testing (middle)	Testing (slight)
JPEG comp.	quality factor	[5,96]	7	20	40
Gauss. blur	sigma	[0.1,5]	5	1	0.1
Lens blur	radius	[1,8]	8	4	1
Motion blur	kernel size	[12,28]	28	20	12
Color diffuse	amount	[1,12]	12	6	1
Color shift	amount	[1,12]	12	6	1
Color saturate	amount	[0.4,-0.4]	-0.4	0.1	0.4
Color saturate 2	amount	[1,9]	9	3	1
Gauss. noise	sigma	[0, 50]	50	25	15
GN (ycbcr)	amount	[0.0001, 0.003]	0.003	0.001	0.0001
Impulse noise	amount	[0.001, 0.03]	0.03	0.01	0.001
Multipli. noise	amount	[0.001, 0.05]	0.05	0.01	0.001
Denoise	sigma	[0, 50]	50	25	15
Over bright	amount	[0.1, 1.1]	1.1	0.4	0.1
Low-light	amount	[0.05, 0.8]	0.8	0.2	0.05
Mean shift	amount	[0.15, -0.15]	-0.15	-0.15	0
Bicubic resize/SR	scale	[2, 16]	16	4	2
Bilinear resize/SR	scale	[2, 16]	16	4	2
Nearest resize/SR	scale	[2, 16]	6	4	2
Lanczos resize/SR	scale	[2, 16]	16	4	2
Sharpening	amount	[1, 12]	12	3	1
Contrast imbal.	amount	[0.3, -0.6]	-0.6	0	0
Color block	amount	[2, 10]	10	6	2
Pixelate	amount	[0.01, 0.5]	0.5	0.1	0.01
Discontinuous	amount	[20, 100]	100	60	20
Jitter	amount	[0.05, 1]	1	0.2	0.05
Mosaic	constant	1	1	1	1
Irregular mask	amount	[0,20],[0,100],[0,30]	20,100,30	10,50,15	10,25,10
Block mask	amount	[0,10],[30,100]	10,[30,100]	5,[15,50]	5,[10,25]
Rain streak	amount	[1000,5000],[4,10],[3,8]	5000,10,7	2500,7,3	700,7,1
Snow streak	amount	[300,1000],[1,3],[1,4]	1000,4,1	500,3,1	250,3,1

- ***Rain Streak***: Adds rain streaks with random length, direction, thickness, blur level, to the image.
- ***Snow Streak***: Adds snow streaks with random length, direction, thickness, blur level, to the image.

Table 1 demonstrates the detailed distortions and corresponding levels used in our unified image processing setting. For various degradations, we train all tasks using one model with various degradation levels. For testing, we validate and compare the performance on the selected levels.

2 More Details of UniProcessor

2.1 More Details of Low-level Vision-language Instruction Tuning

Details of VQA data preparation. In order to enable the low-level vision visual question answering (VQA) ability of our UniProcessor, we construct a new VQA database, which includes over 70000 clean image patches and a distortion bank with 30 degradation types as aforementioned. For each [degradation], we impose it to the clean image and generate the questions and answers according to the following template.

Questions:

– What is the main factor that influences the quality of this image?
– What is the distortion in this image?
– What is the distortion level of this image?
– Please describe the quality and the distortion type of this image.
– Please describe the distortion type and the distortion level of this image.
– How is the clarity of the image?
– Is this image [random degradation]?

Answers:

– The main factor that influences the quality of this image is [degradation] artifacts.
– The distortion in this image is [degradation].
– The distortion level of this image is [level].
– This is a low-quality image. The distortion type of this image is [degradation] artifacts.
– The distortion type of this image is [degradation] artifacts, and the distortion level of this image is [level].
– The clarity of the image is [clarity].
– Answer [yes or no].

Specifically, the [degradation] represents the distortion type, the [level] means the degradation level description, the [clarity] means the clarity description according to the degradation level, the [yes or no] indicates the yes or no answer. Especially, we set three levels for the [level] item including “severe", “moderate", and “slight", and the specific option answer is from the specific parameter range. For [clarity] item, we also set three levels including “bad”, “not good”, and “good” according to the [level] option. The answer [yes or no] is based on whether the degradation type imposed to the image is consistent with the description in the question.

Details of Q-Former. Both of the instruction-tuned VQA module and the context control module contain the Q-Former. The functions of two Q-Formers are different. The Q-Former in the instruction-tuned VQA-module mainly focuses on extracting the instruction-aware embeddings to guide the LLM VQA behavior. The Q-Former in the context control module mainly focuses on extracting low-level subject-aware features for facilitating the manipulation prompt to control the processing behavior. However, the structure of the two Q-Formers is same. As shown in Figure 4, Q-Former is a trainable light-weight module to bridge the gap between a frozen image encoder and the following LLM or text-encoder. Q-Former consists of two transformer sub-modules including an image transformer that interacts with the frozen image encoder for visual feature extraction and a text transformer that functions as both text encoder and decoder. The learnable queries interact with each other as well as the text-tokens through self-attention layers and interact with the image embeddings through cross-attention layers. Different from BLIP-2 [5], the Q-Former in our UniProcessor aims to extract the most informative low-level related features for VQA and processing control.

Table 2: Results of VQA accuracy.

Model	InstructBLIP [1]	UniProcessor
Acc.	18.3	65.5

2.2 More Details of Degradation-aware Subject and Manipulation Representation Learning

Details of subject prompt and manipulation prompt generation. As shown in Figure 2 of the main paper, the context control module contains an image input and two text inputs including a subject prompt and a manipulation prompt. The function of the subject prompt is to disentangle and obtain the subject-related low-level features for the image, and the function of the manipulation prompt is to decide the manipulation behavior of the processor backbone. We generate the subject prompt following the template of:

- a low-quality image with [degradation] distortion.

The manipulation prompt contains the operations of:

- remove the distortion in this image.
- keep the image unchanged.
- remove the [degradation] distortion in the image.

Then these two prompts are fed into the context control module for generating context control embeddings.

2.3 More Details of the Processor Backbone

We follow the CSformer [3] to build the Processor backbone. To improve the efficiency of the network, we replace the Swin-transformer layer [7] using the convnext block [14]. Moreover, we further demonstrate the channel-attention module of the processor backbone in Figure 5.

3 More Experimental Results of Low-level VQA Tuning

Figure 6 qualitatively demonstrates the low-level VQA results of our tuned UniProcessor and InstructBLIP [1]. It can be observed that our UniProcessor can generate more accurate degradation-aware answers compared to InstructBLIP [1]. Specifically, InstructBLIP [1] cannot recognize the JPEG compression and the noise distortion well, and may answer "no distortion" for corresponding questions. Moreover, InstructBLIP [1] may have hallucinations and generate inconsistent answers, *e.g.*, it may answer "no" for distortion recognition but may give a level for the "level" question. Our tuned UniProcessor can overcome this defect, and generate more accurate answer. Moreover, we further conduct an experiment to validate the effectiveness of the low-level degradation-aware tuning strategy. As shown in Table 2, after instruction tuning, the accuracy of degradation recognition can be effectively improved.

Table 3: Comparison results for **30 degradations** with **middle** level on the CBSD68 dataset [8]. Our model outperforms other state-of-the-art models for almost all degradation types in terms of the three most commonly used evaluation metrics, *i.e.*, PSNR ↑, SSIM ↑ [13], and LPIPS ↓ [19]. The best results are colored in red.

Degradation	DRUNet [17] PSNR / SSIM / PIPS	MPRNet [16] PSNR / SSIM / PIPS	SwinIR [6] PSNR / SSIM / PIPS	Uformer [12] PSNR / SSIM / PIPS	Restormer [15] PSNR / SSIM / PIPS	PromptIR [9] PSNR / SSIM / PIPS	UniProcessor (Ours) PSNR / SSIM / PIPS
JPEG comp.	29.09 / 0.847 / 0.229	28.91 / 0.843 / 0.229	28.29 / 0.834 / 0.247	29.20 / 0.853 / 0.207	29.21 / 0.853 / 0.204	29.21 / 0.853 / 0.212	29.44 / 0.858 / 0.202
Gauss. blur	30.96 / 0.917 / 0.167	31.53 / 0.923 / 0.130	29.98 / 0.890 / 0.226	30.79 / 0.905 / 0.177	33.44 / 0.948 / 0.057	32.92 / 0.942 / 0.081	34.89 / 0.961 / 0.038
Lens blur	26.62 / 0.765 / 0.301	27.16 / 0.798 / 0.245	24.58 / 0.657 / 0.460	27.28 / 0.799 / 0.265	28.13 / 0.828 / 0.231	28.60 / 0.848 / 0.221	30.30 / 0.892 / 0.082
Motion blur	23.69 / 0.630 / 0.453	23.47 / 0.629 / 0.474	21.89 / 0.531 / 0.552	23.55 / 0.629 / 0.465	25.61 / 0.754 / 0.270	25.21 / 0.728 / 0.340	26.30 / 0.782 / 0.228
Color diffuse	24.13 / 0.903 / 0.162	27.38 / 0.943 / 0.112	26.29 / 0.936 / 0.115	28.76 / 0.948 / 0.098	28.07 / 0.949 / 0.105	28.39 / 0.950 / 0.107	29.96 / 0.956 / 0.093
Color shift	37.41 / 0.989 / 0.030	38.93 / 0.995 / 0.020	36.53 / 0.992 / 0.026	41.09 / 0.996 / 0.016	41.29 / 0.997 / 0.015	40.53 / 0.996 / 0.017	43.98 / 0.997 / 0.008
Color saturate	21.39 / 0.936 / 0.191	20.98 / 0.935 / 0.198	22.85 / 0.940 / 0.171	24.95 / 0.944 / 0.142	23.67 / 0.944 / 0.181	29.21 / 0.962 / 0.074	33.98 / 0.978 / 0.024
Color saturate	24.81 / 0.919 / 0.118	30.42 / 0.970 / 0.047	29.20 / 0.957 / 0.071	30.80 / 0.970 / 0.044	32.38 / 0.972 / 0.033	33.69 / 0.977 / 0.030	36.49 / 0.982 / 0.019
Gauss. noise	30.18 / 0.855 / 0.155	30.15 / 0.852 / 0.164	30.06 / 0.849 / 0.155	30.44 / 0.863 / 0.137	30.40 / 0.865 / 0.125	30.31 / 0.864 / 0.134	30.63 / 0.876 / 0.120
GN (ycbcr)	32.36 / 0.908 / 0.086	32.56 / 0.908 / 0.093	32.38 / 0.902 / 0.101	32.82 / 0.914 / 0.075	32.87 / 0.915 / 0.068	32.86 / 0.916 / 0.072	33.22 / 0.922 / 0.072
Impulse noise	44.28 / 0.996 / 0.004	45.53 / 0.996 / 0.002	44.77 / 0.995 / 0.005	43.95 / 0.996 / 0.003	47.85 / 0.998 / 0.001	47.98 / 0.998 / 0.001	48.59 / 0.998 / 0.001
Multipli. noise	34.25 / 0.944 / 0.055	34.82 / 0.949 / 0.050	34.81 / 0.948 / 0.049	35.01 / 0.951 / 0.043	35.21 / 0.952 / 0.035	35.24 / 0.954 / 0.039	35.64 / 0.957 / 0.040
Denoise	25.82 / 0.715 / 0.452	25.95 / 0.719 / 0.452	24.83 / 0.662 / 0.537	26.08 / 0.720 / 0.420	26.21 / 0.724 / 0.463	25.11 / 0.673 / 0.543	25.53 / 0.680 / 0.471
Over bright	17.50 / 0.902 / 0.076	20.20 / 0.924 / 0.060	21.03 / 0.925 / 0.062	21.41 / 0.939 / 0.049	26.31 / 0.971 / 0.024	26.47 / 0.976 / 0.017	29.33 / 0.983 / 0.009
Low-light	21.59 / 0.936 / 0.037	22.51 / 0.948 / 0.028	23.21 / 0.941 / 0.049	23.45 / 0.948 / 0.037	29.39 / 0.983 / 0.012	38.45 / 0.994 / 0.005	46.35 / 0.998 / 0.001
Mean shift	19.13 / 0.866 / 0.070	22.74 / 0.913 / 0.052	19.28 / 0.862 / 0.093	21.00 / 0.882 / 0.050	23.26 / 0.915 / 0.035	24.41 / 0.927 / 0.032	27.99 / 0.947 / 0.023
Bicubic resize	25.43 / 0.716 / 0.398	25.34 / 0.704 / 0.424	25.12 / 0.706 / 0.429	25.63 / 0.724 / 0.385	25.71 / 0.717 / 0.408	25.74 / 0.720 / 0.407	26.02 / 0.734 / 0.380
Bilinear resize	25.12 / 0.696 / 0.424	25.27 / 0.701 / 0.426	24.58 / 0.671 / 0.462	25.50 / 0.716 / 0.385	25.63 / 0.716 / 0.401	25.59 / 0.717 / 0.411	25.91 / 0.730 / 0.382
Nearest resize	23.58 / 0.662 / 0.370	23.21 / 0.650 / 0.384	23.20 / 0.652 / 0.413	23.55 / 0.668 / 0.394	23.50 / 0.665 / 0.384	23.52 / 0.665 / 0.371	23.73 / 0.674 / 0.360
Lanczos resize	25.45 / 0.721 / 0.417	25.43 / 0.713 / 0.437	25.15 / 0.713 / 0.434	25.65 / 0.721 / 0.408	25.67 / 0.718 / 0.417	25.74 / 0.719 / 0.421	25.98 / 0.733 / 0.389
Sharpening	29.75 / 0.924 / 0.087	31.50 / 0.948 / 0.051	27.63 / 0.870 / 0.135	30.88 / 0.937 / 0.072	32.41 / 0.965 / 0.043	32.77 / 0.968 / 0.036	33.39 / 0.974 / 0.028
Contrast imbal.	25.65 / 0.935 / 0.038	26.14 / 0.941 / 0.030	23.77 / 0.937 / 0.054	26.07 / 0.949 / 0.035	32.41 / 0.981 / 0.014	35.07 / 0.984 / 0.008	40.60 / 0.993 / 0.003
Color block	32.44 / 0.971 / 0.047	32.72 / 0.974 / 0.048	32.45 / 0.973 / 0.042	33.05 / 0.974 / 0.041	33.97 / 0.977 / 0.039	34.39 / 0.979 / 0.037	35.31 / 0.981 / 0.031
Pixelate	27.13 / 0.843 / 0.143	28.50 / 0.887 / 0.087	27.17 / 0.855 / 0.134	26.78 / 0.858 / 0.105	28.26 / 0.881 / 0.079	27.89 / 0.875 / 0.084	29.82 / 0.909 / 0.060
Discontinuous	28.55 / 0.934 / 0.047	28.58 / 0.937 / 0.038	27.10 / 0.928 / 0.052	26.83 / 0.922 / 0.058	31.33 / 0.952 / 0.041	29.11 / 0.941 / 0.035	32.02 / 0.957 / 0.038
Jitter	29.08 / 0.904 / 0.091	30.23 / 0.916 / 0.094	29.46 / 0.900 / 0.133	29.49 / 0.913 / 0.079	30.41 / 0.922 / 0.074	30.22 / 0.918 / 0.081	30.86 / 0.927 / 0.061
Mosaic	36.46 / 0.984 / 0.017	35.66 / 0.972 / 0.017	35.07 / 0.976 / 0.021	38.20 / 0.985 / 0.014	38.18 / 0.983 / 0.016	38.21 / 0.985 / 0.018	40.62 / 0.990 / 0.009
Irregular mask	33.06 / 0.971 / 0.035	35.02 / 0.978 / 0.029	33.23 / 0.973 / 0.033	34.46 / 0.975 / 0.030	34.73 / 0.976 / 0.028	36.44 / 0.979 / 0.027	38.51 / 0.981 / 0.022
Block mask	36.63 / 0.983 / 0.022	40.77 / 0.990 / 0.016	36.24 / 0.987 / 0.020	37.37 / 0.984 / 0.022	39.29 / 0.988 / 0.016	44.63 / 0.991 / 0.015	48.96 / 0.993 / 0.012
Rain streak	26.71 / 0.819 / 0.156	27.92 / 0.842 / 0.132	27.84 / 0.860 / 0.124	28.73 / 0.859 / 0.126	29.64 / 0.875 / 0.100	30.19 / 0.888 / 0.090	30.93 / 0.904 / 0.074
Snow streak	32.49 / 0.949 / 0.044	35.74 / 0.972 / 0.024	35.06 / 0.971 / 0.027	33.88 / 0.963 / 0.029	37.92 / 0.979 / 0.018	37.71 / 0.980 / 0.017	37.99 / 0.984 / 0.010
Clean image	41.23 / 0.990 / 0.009	53.36 / 0.999 / 0.001	39.31 / 0.995 / 0.006	40.98 / 0.987 / 0.014	49.17 / 0.997 / 0.002	62.24 / 0.999 / 0.001	80.16 / 0.999 / 0.000
Average	28.81 / 0.876 / 0.154	30.27 / 0.887 / 0.144	28.82 / 0.868 / 0.170	29.93 / 0.887 / 0.138	31.61 / 0.902 / 0.123	32.75 / 0.902 / 0.125	35.11 / 0.913 / 0.103

4 More Experimental Results of UniProcessor

Table 3, 4, 5, and 6 show the quantitative results of the proposed UniProcessor and other state-of-the-art image restoration models on CBSD68 dataset with middle level degradation, CBSD68 dataset with slight level degradation, kodak dataset with severe degradation, 750 image-net validation dataset with severe degradation, respectively. It can be observed that our UniProcessor achieves better performance in most cases. Moreover, we further show qualitative results of these state-of-the-art models for processing various degradations in Figure 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, and 23. These results qualitatively illustrate that our UniProcessor can well process these complex distortions with random levels using one model.

Table 4: Comparison results for **30 degradations** with **slight** level on the CBSD68 dataset [8]. Our model outperforms other state-of-the-art models for almost all degradation types in terms of the three most commonly used evaluation metrics, *i.e.*, PSNR ↑, SSIM ↑ [13], and LPIPS ↓ [19]. The best results are colored in red.

Degradation	DRUNet [17] PSNR / SSIM / PIPS	MPRNet [16] PSNR / SSIM / PIPS	SwinIR [6] PSNR / SSIM / PIPS	Uformer [12] PSNR / SSIM / PIPS	Restormer [15] PSNR / SSIM / PIPS	PromptIR [9] PSNR / SSIM / PIPS	UniProcessor (Ours) PSNR / SSIM / PIPS
JPEG comp.	31.28 / 0.901 / 0.139	31.09 / 0.897 / 0.133	30.18 / 0.885 / 0.140	31.27 / 0.902 / 0.127	31.38 / 0.904 / 0.119	31.33 / 0.902 / 0.131	31.60 / 0.907 / 0.118
Gauss. blur	41.23 / 0.990 / 0.009	53.36 / 0.999 / 0.001	39.31 / 0.995 / 0.006	40.98 / 0.987 / 0.014	49.17 / 0.997 / 0.002	62.24 / 0.999 / 0.001	71.05 / 0.999 / 0.000
Lens blur	31.60 / 0.931 / 0.125	32.69 / 0.942 / 0.100	31.63 / 0.931 / 0.134	31.97 / 0.935 / 0.119	35.71 / 0.966 / 0.038	34.95 / 0.962 / 0.047	38.09 / 0.983 / 0.009
Motion blur	24.41 / 0.675 / 0.396	23.99 / 0.668 / 0.402	22.93 / 0.591 / 0.472	23.91 / 0.647 / 0.424	26.64 / 0.801 / 0.222	26.57 / 0.788 / 0.270	28.51 / 0.853 / 0.140
Color diffuse	34.31 / 0.976 / 0.052	36.17 / 0.980 / 0.051	26.06 / 0.959 / 0.130	32.52 / 0.977 / 0.059	30.03 / 0.974 / 0.072	28.37 / 0.969 / 0.097	34.79 / 0.983 / 0.041
Color shift	37.41 / 0.988 / 0.021	41.15 / 0.997 / 0.011	39.07 / 0.995 / 0.015	40.67 / 0.994 / 0.015	43.07 / 0.998 / 0.011	42.65 / 0.998 / 0.011	46.07 / 0.998 / 0.004
Color saturate	24.49 / 0.959 / 0.093	24.45 / 0.962 / 0.090	24.88 / 0.958 / 0.098	25.98 / 0.953 / 0.082	27.03 / 0.966 / 0.072	29.75 / 0.972 / 0.051	37.82 / 0.992 / 0.009
Color saturate	39.18 / 0.988 / 0.009	46.50 / 0.996 / 0.002	29.87 / 0.967 / 0.031	36.67 / 0.981 / 0.018	44.33 / 0.996 / 0.002	46.99 / 0.997 / 0.001	34.21 / 0.991 / 0.015
Gauss. noise	32.91 / 0.916 / 0.085	32.90 / 0.913 / 0.092	32.84 / 0.911 / 0.090	33.10 / 0.918 / 0.080	33.17 / 0.921 / 0.063	33.16 / 0.921 / 0.071	33.48 / 0.926 / 0.069
GN (ycbcr)	37.26 / 0.967 / 0.025	38.38 / 0.971 / 0.016	38.45 / 0.973 / 0.021	36.99 / 0.970 / 0.019	39.23 / 0.974 / 0.014	39.32 / 0.976 / 0.012	39.74 / 0.978 / 0.015
Impulse noise	48.09 / 0.997 / 0.004	49.60 / 0.998 / 0.002	44.24 / 0.997 / 0.004	42.49 / 0.993 / 0.010	50.18 / 0.997 / 0.002	54.53 / 0.999 / 0.000	55.88 / 0.999 / 0.000
Multipli. noise	38.64 / 0.978 / 0.021	40.17 / 0.982 / 0.011	40.51 / 0.984 / 0.012	36.55 / 0.971 / 0.022	41.44 / 0.985 / 0.007	41.46 / 0.986 / 0.008	42.19 / 0.987 / 0.010
Denoise	26.42 / 0.751 / 0.398	26.73 / 0.760 / 0.381	25.35 / 0.696 / 0.473	26.53 / 0.749 / 0.390	27.15 / 0.773 / 0.378	25.72 / 0.721 / 0.465	26.16 / 0.719 / 0.407
Over bright	28.24 / 0.983 / 0.013	29.07 / 0.990 / 0.007	25.69 / 0.965 / 0.029	25.03 / 0.956 / 0.030	29.46 / 0.991 / 0.006	35.28 / 0.995 / 0.004	38.10 / 0.996 / 0.002
Low-light	31.08 / 0.987 / 0.011	33.12 / 0.995 / 0.003	32.03 / 0.986 / 0.014	31.69 / 0.987 / 0.014	34.73 / 0.994 / 0.004	40.07 / 0.998 / 0.001	41.43 / 0.998 / 0.000
Mean shift	41.23 / 0.990 / 0.009	53.36 / 0.999 / 0.001	39.31 / 0.995 / 0.006	40.98 / 0.987 / 0.014	49.17 / 0.997 / 0.002	62.24 / 0.998 / 0.000	38.30 / 0.990 / 0.004
Bicubic resize	28.67 / 0.880 / 0.161	29.42 / 0.886 / 0.156	28.95 / 0.872 / 0.215	28.90 / 0.865 / 0.210	29.14 / 0.878 / 0.114	29.12 / 0.881 / 0.105	29.48 / 0.873 / 0.204
Bilinear resize	28.36 / 0.857 / 0.223	28.26 / 0.848 / 0.249	27.46 / 0.817 / 0.305	28.09 / 0.833 / 0.231	28.79 / 0.860 / 0.150	29.21 / 0.873 / 0.158	28.80 / 0.849 / 0.228
Nearest resize	25.91 / 0.805 / 0.133	25.21 / 0.777 / 0.166	25.84 / 0.788 / 0.202	25.84 / 0.801 / 0.149	25.84 / 0.797 / 0.138	25.76 / 0.796 / 0.134	26.04 / 0.803 / 0.173
Lanczos resize	27.82 / 0.869 / 0.212	29.04 / 0.887 / 0.184	28.91 / 0.881 / 0.233	29.27 / 0.882 / 0.227	29.60 / 0.889 / 0.193	29.04 / 0.887 / 0.171	29.83 / 0.886 / 0.195
Sharpening	31.70 / 0.955 / 0.073	33.97 / 0.962 / 0.045	27.37 / 0.838 / 0.210	33.23 / 0.956 / 0.064	37.65 / 0.987 / 0.021	37.27 / 0.986 / 0.019	39.29 / 0.991 / 0.010
Contrast imbal.	25.65 / 0.935 / 0.038	26.14 / 0.941 / 0.030	23.77 / 0.937 / 0.054	26.07 / 0.949 / 0.035	32.41 / 0.981 / 0.014	35.07 / 0.984 / 0.008	40.60 / 0.993 / 0.003
Color block	35.75 / 0.984 / 0.022	37.08 / 0.990 / 0.019	35.44 / 0.988 / 0.019	35.80 / 0.984 / 0.022	36.70 / 0.988 / 0.017	37.23 / 0.991 / 0.017	41.11 / 0.993 / 0.011
Pixelate	29.04 / 0.899 / 0.114	31.76 / 0.951 / 0.031	30.23 / 0.939 / 0.045	28.80 / 0.930 / 0.057	30.10 / 0.940 / 0.044	30.34 / 0.940 / 0.046	32.89 / 0.956 / 0.024
Discontinuous	31.91 / 0.970 / 0.023	32.67 / 0.976 / 0.016	30.89 / 0.971 / 0.023	30.11 / 0.964 / 0.031	34.11 / 0.979 / 0.014	32.50 / 0.976 / 0.016	36.45 / 0.983 / 0.016
Jitter	33.49 / 0.976 / 0.018	38.53 / 0.989 / 0.007	33.73 / 0.982 / 0.015	34.08 / 0.979 / 0.017	37.16 / 0.990 / 0.006	39.39 / 0.992 / 0.004	40.11 / 0.992 / 0.006
Mosaic	36.46 / 0.984 / 0.017	35.66 / 0.972 / 0.017	35.07 / 0.976 / 0.021	38.20 / 0.985 / 0.014	38.18 / 0.983 / 0.016	38.21 / 0.985 / 0.018	40.62 / 0.990 / 0.009
Irregular mask	36.43 / 0.983 / 0.018	40.03 / 0.989 / 0.014	35.71 / 0.985 / 0.017	37.46 / 0.985 / 0.017	38.27 / 0.986 / 0.014	41.46 / 0.990 / 0.012	44.25 / 0.992 / 0.008
Block mask	38.61 / 0.988 / 0.012	45.14 / 0.997 / 0.006	38.00 / 0.992 / 0.009	38.86 / 0.989 / 0.013	43.23 / 0.995 / 0.006	47.51 / 0.996 / 0.005	52.17 / 0.998 / 0.002
Rain streak	26.00 / 0.795 / 0.197	27.99 / 0.846 / 0.155	28.18 / 0.868 / 0.129	29.90 / 0.892 / 0.077	30.07 / 0.866 / 0.118	31.01 / 0.897 / 0.083	32.68 / 0.935 / 0.043
Snow streak	34.72 / 0.970 / 0.029	38.17 / 0.984 / 0.015	37.17 / 0.983 / 0.017	35.61 / 0.976 / 0.022	40.23 / 0.987 / 0.011	40.18 / 0.989 / 0.010	40.54 / 0.991 / 0.006
Clean image	41.23 / 0.990 / 0.009	53.36 / 0.999 / 0.001	39.31 / 0.995 / 0.006	40.98 / 0.987 / 0.014	49.17 / 0.997 / 0.002	62.24 / 0.999 / 0.001	80.16 / 0.999 / 0.000
Average	33.11 / 0.932 / 0.085	35.79 / 0.939 / 0.075	32.14 / 0.925 / 0.100	33.08 / 0.933 / 0.082	36.02 / 0.948 / 0.059	38.13 / 0.948 / 0.062	39.76 / 0.954 / 0.055

Table 5: Comparison results for **30 degradations** with **heavy** level on the Kodak24 dataset [4]. Our model outperforms other state-of-the-art models for almost all degradation types in terms of the three most commonly used evaluation metrics, *i.e.*, PSNR ↑, SSIM ↑ [13], and LPIPS ↓ [19]. The best results are colored in red.

Degradation	DRUNet [17] PSNR / SSIM / PIPS	MPRNet [16] PSNR / SSIM / PIPS	SwinIR [6] PSNR / SSIM / PIPS	Uformer [12] PSNR / SSIM / PIPS	Restormer [15] PSNR / SSIM / PIPS	PromptIR [9] PSNR / SSIM / PIPS	UniProcessor (Ours) PSNR / SSIM / PIPS
JPEG comp.	26.44 / 0.730 / 0.392	26.18 / 0.727 / 0.415	25.78 / 0.716 / 0.436	26.51 / 0.741 / 0.376	26.55 / 0.740 / 0.373	26.65 / 0.743 / 0.366	26.84 / 0.748 / 0.362
Gauss. blur	24.00 / 0.608 / 0.573	23.99 / 0.607 / 0.574	23.41 / 0.583 / 0.627	24.34 / 0.624 / 0.533	24.86 / 0.651 / 0.507	24.87 / 0.655 / 0.511	25.35 / 0.674 / 0.461
Lens blur	24.74 / 0.652 / 0.448	25.07 / 0.676 / 0.374	22.94 / 0.541 / 0.563	24.73 / 0.667 / 0.414	27.35 / 0.773 / 0.269	27.10 / 0.768 / 0.279	28.53 / 0.814 / 0.201
Motion blur	22.71 / 0.590 / 0.519	22.75 / 0.579 / 0.520	21.91 / 0.552 / 0.575	22.89 / 0.590 / 0.516	25.85 / 0.743 / 0.293	25.61 / 0.723 / 0.359	26.91 / 0.782 / 0.258
Color diffuse	20.81 / 0.868 / 0.240	23.17 / 0.889 / 0.201	21.44 / 0.885 / 0.215	23.56 / 0.897 / 0.188	23.86 / 0.902 / 0.181	24.32 / 0.901 / 0.179	25.80 / 0.921 / 0.153
Color shift	30.78 / 0.976 / 0.050	36.18 / 0.994 / 0.024	25.48 / 0.953 / 0.082	38.01 / 0.993 / 0.022	38.26 / 0.994 / 0.015	39.44 / 0.996 / 0.014	41.97 / 0.997 / 0.009
Color saturate	17.19 / 0.868 / 0.292	18.31 / 0.877 / 0.272	18.39 / 0.858 / 0.305	24.51 / 0.927 / 0.124	26.33 / 0.943 / 0.090	29.44 / 0.958 / 0.057	32.76 / 0.975 / 0.024
Color saturate	17.56 / 0.749 / 0.316	25.08 / 0.891 / 0.142	24.07 / 0.890 / 0.150	24.48 / 0.895 / 0.135	26.15 / 0.904 / 0.115	26.63 / 0.907 / 0.109	26.25 / 0.907 / 0.117
Gauss. noise	27.27 / 0.721 / 0.330	27.29 / 0.723 / 0.330	27.20 / 0.718 / 0.332	27.44 / 0.736 / 0.243	27.36 / 0.739 / 0.283	27.12 / 0.749 / 0.262	27.80 / 0.775 / 0.241
GN (ycbcr)	30.32 / 0.833 / 0.185	30.48 / 0.834 / 0.187	30.26 / 0.825 / 0.203	30.80 / 0.848 / 0.146	30.72 / 0.845 / 0.158	30.69 / 0.848 / 0.154	31.02 / 0.856 / 0.138
Impulse noise	40.20 / 0.986 / 0.012	40.86 / 0.989 / 0.010	39.19 / 0.989 / 0.011	39.28 / 0.982 / 0.014	42.16 / 0.992 / 0.008	42.83 / 0.992 / 0.007	42.97 / 0.993 / 0.003
Multipli. noise	30.54 / 0.858 / 0.168	31.09 / 0.869 / 0.152	30.95 / 0.863 / 0.164	31.40 / 0.879 / 0.115	31.35 / 0.877 / 0.127	31.27 / 0.881 / 0.124	32.19 / 0.896 / 0.111
Denoise	25.41 / 0.661 / 0.588	25.25 / 0.653 / 0.603	24.77 / 0.627 / 0.661	26.13 / 0.707 / 0.446	25.24 / 0.633 / 0.645	25.41 / 0.657 / 0.551	26.17 / 0.701 / 0.443
Over bright	12.92 / 0.730 / 0.296	17.07 / 0.808 / 0.231	16.20 / 0.808 / 0.212	17.67 / 0.838 / 0.182	19.93 / 0.874 / 0.160	20.73 / 0.874 / 0.161	22.36 / 0.895 / 0.124
Low-light	12.60 / 0.536 / 0.334	18.19 / 0.729 / 0.264	14.88 / 0.660 / 0.321	17.35 / 0.742 / 0.227	20.22 / 0.796 / 0.185	24.50 / 0.847 / 0.173	23.48 / 0.842 / 0.160
Mean shift	17.69 / 0.864 / 0.107	22.46 / 0.921 / 0.067	17.24 / 0.827 / 0.147	21.08 / 0.916 / 0.052	25.02 / 0.946 / 0.025	25.30 / 0.958 / 0.024	27.85 / 0.969 / 0.016
Bicubic resize	22.00 / 0.524 / 0.714	21.89 / 0.519 / 0.722	21.79 / 0.515 / 0.750	22.14 / 0.529 / 0.688	22.13 / 0.529 / 0.689	22.19 / 0.530 / 0.706	22.32 / 0.535 / 0.669
Bilinear resize	21.89 / 0.521 / 0.713	21.74 / 0.516 / 0.714	21.56 / 0.510 / 0.745	22.08 / 0.527 / 0.678	22.06 / 0.526 / 0.688	22.09 / 0.528 / 0.708	22.27 / 0.534 / 0.674
Nearest resize	22.38 / 0.611 / 0.479	22.55 / 0.612 / 0.498	22.48 / 0.602 / 0.521	22.61 / 0.615 / 0.483	22.67 / 0.618 / 0.473	22.73 / 0.621 / 0.460	22.85 / 0.627 / 0.429
Lanczos resize	22.04 / 0.522 / 0.729	21.94 / 0.519 / 0.731	21.88 / 0.515 / 0.755	22.13 / 0.526 / 0.707	22.16 / 0.528 / 0.695	22.19 / 0.528 / 0.712	22.32 / 0.533 / 0.675
Sharpening	23.87 / 0.899 / 0.110	23.47 / 0.889 / 0.116	22.99 / 0.889 / 0.114	23.85 / 0.911 / 0.091	23.72 / 0.896 / 0.119	24.34 / 0.924 / 0.084	24.91 / 0.937 / 0.069
Contrast imbal.	20.58 / 0.880 / 0.142	21.55 / 0.889 / 0.125	22.18 / 0.876 / 0.161	22.15 / 0.895 / 0.137	30.79 / 0.979 / 0.035	33.86 / 0.984 / 0.020	41.22 / 0.994 / 0.004
Color block	29.49 / 0.964 / 0.055	32.99 / 0.972 / 0.043	23.81 / 0.926 / 0.102	33.50 / 0.981 / 0.030	33.46 / 0.979 / 0.031	34.90 / 0.983 / 0.030	39.05 / 0.989 / 0.018
Pixelate	24.35 / 0.716 / 0.332	24.63 / 0.718 / 0.328	24.11 / 0.709 / 0.371	24.60 / 0.720 / 0.345	24.73 / 0.723 / 0.320	24.84 / 0.725 / 0.314	25.05 / 0.732 / 0.282
Discontinuous	27.11 / 0.939 / 0.054	27.79 / 0.932 / 0.044	22.33 / 0.896 / 0.110	26.64 / 0.943 / 0.051	32.61 / 0.967 / 0.023	31.33 / 0.960 / 0.023	35.32 / 0.975 / 0.021
Jitter	24.30 / 0.660 / 0.387	24.80 / 0.678 / 0.389	24.11 / 0.656 / 0.435	24.91 / 0.684 / 0.387	24.98 / 0.685 / 0.384	25.10 / 0.687 / 0.381	25.27 / 0.696 / 0.383
Mosaic	36.83 / 0.981 / 0.014	36.12 / 0.970 / 0.014	36.22 / 0.976 / 0.017	37.77 / 0.982 / 0.013	38.75 / 0.981 / 0.011	39.14 / 0.984 / 0.012	40.81 / 0.987 / 0.008
Irregular mask	28.46 / 0.939 / 0.093	30.70 / 0.949 / 0.080	24.00 / 0.907 / 0.130	30.39 / 0.952 / 0.068	31.25 / 0.953 / 0.075	31.71 / 0.955 / 0.074	33.27 / 0.961 / 0.057
Block mask	27.53 / 0.945 / 0.082	29.83 / 0.951 / 0.066	23.22 / 0.909 / 0.127	29.01 / 0.960 / 0.060	30.49 / 0.962 / 0.056	32.24 / 0.968 / 0.053	34.75 / 0.972 / 0.045
Rain streak	24.96 / 0.793 / 0.213	26.23 / 0.819 / 0.191	22.84 / 0.803 / 0.206	25.11 / 0.841 / 0.149	27.32 / 0.849 / 0.136	28.05 / 0.868 / 0.111	29.07 / 0.892 / 0.088
Snow streak	22.32 / 0.612 / 0.444	24.53 / 0.696 / 0.371	24.16 / 0.807 / 0.251	30.15 / 0.896 / 0.100	22.58 / 0.593 / 0.450	25.39 / 0.700 / 0.347	31.82 / 0.895 / 0.122
Clean image	32.28 / 0.972 / 0.035	36.57 / 0.958 / 0.028	23.40 / 0.932 / 0.088	34.49 / 0.982 / 0.023	42.33 / 0.996 / 0.004	46.60 / 0.997 / 0.002	69.15 / 0.999 / 0.000
Average	24.74 / 0.772 / 0.295	26.27 / 0.792 / 0.276	23.91 / 0.773 / 0.309	26.62 / 0.810 / 0.242	27.91 / 0.816 / 0.238	28.71 / 0.825 / 0.230	30.87 / 0.844 / 0.199

Table 6: Comparison results for **30 degradations** with **heavy** level on the imagenet validation set [2]. Our model outperforms other state-of-the-art models for almost all degradation types in terms of the three most commonly used evaluation metrics, *i.e.*, PSNR ↑, SSIM ↑ [13], and LPIPS ↓ [19]. The best results are colored in red.

Degradation	DRUNet [17] PSNR / SSIM / PIPS	MPRNet [16] PSNR / SSIM / PIPS	SwinIR [6] PSNR / SSIM / PIPS	Uformer [12] PSNR / SSIM / PIPS	Restormer [15] PSNR / SSIM / PIPS	PromptIR [9] PSNR / SSIM / PIPS	UniProcessor (Ours) PSNR / SSIM / PIPS
JPEG comp.	25.35 / 0.732 / 0.322	25.16 / 0.728 / 0.341	24.76 / 0.720 / 0.361	25.49 / 0.743 / 0.306	25.53 / 0.742 / 0.304	25.53 / 0.745 / 0.302	25.86 / 0.752 / 0.298
Gauss. blur	23.05 / 0.603 / 0.497	22.86 / 0.594 / 0.525	22.13 / 0.557 / 0.570	23.43 / 0.621 / 0.470	23.98 / 0.652 / 0.448	23.98 / 0.670 / 0.429	24.57 / 0.681 / 0.403
Lens blur	23.69 / 0.646 / 0.380	23.82 / 0.651 / 0.343	21.62 / 0.510 / 0.524	23.84 / 0.659 / 0.362	26.17 / 0.765 / 0.237	26.17 / 0.767 / 0.236	27.37 / 0.804 / 0.174
Motion blur	21.39 / 0.560 / 0.470	21.02 / 0.540 / 0.481	20.24 / 0.504 / 0.538	21.36 / 0.558 / 0.474	24.40 / 0.726 / 0.259	24.40 / 0.714 / 0.310	25.70 / 0.770 / 0.223
Color diffuse	20.46 / 0.807 / 0.239	22.00 / 0.831 / 0.210	21.31 / 0.826 / 0.217	23.73 / 0.850 / 0.185	22.67 / 0.845 / 0.193	22.67 / 0.848 / 0.185	25.02 / 0.869 / 0.164
Color shift	31.15 / 0.967 / 0.074	33.48 / 0.981 / 0.049	30.62 / 0.965 / 0.082	35.75 / 0.987 / 0.031	35.30 / 0.987 / 0.035	35.30 / 0.986 / 0.037	37.99 / 0.990 / 0.021
Color saturate	16.50 / 0.808 / 0.303	16.41 / 0.815 / 0.293	16.52 / 0.793 / 0.309	23.43 / 0.879 / 0.137	22.65 / 0.875 / 0.166	22.65 / 0.894 / 0.130	30.84 / 0.949 / 0.040
Color saturate	22.99 / 0.821 / 0.154	24.02 / 0.843 / 0.139	23.66 / 0.841 / 0.146	24.77 / 0.855 / 0.119	24.48 / 0.857 / 0.119	24.48 / 0.857 / 0.115	26.03 / 0.875 / 0.096
Gauss. noise	26.22 / 0.730 / 0.234	26.28 / 0.731 / 0.239	26.26 / 0.727 / 0.231	26.37 / 0.743 / 0.181	26.30 / 0.745 / 0.202	26.30 / 0.751 / 0.192	26.29 / 0.769 / 0.186
GN (ycbcr)	29.28 / 0.837 / 0.129	29.41 / 0.837 / 0.126	29.27 / 0.831 / 0.131	29.69 / 0.852 / 0.106	29.73 / 0.850 / 0.103	29.73 / 0.852 / 0.107	30.24 / 0.867 / 0.100
Impulse noise	37.88 / 0.979 / 0.014	39.06 / 0.985 / 0.009	37.23 / 0.973 / 0.022	38.29 / 0.981 / 0.010	41.16 / 0.989 / 0.007	41.16 / 0.990 / 0.005	41.08 / 0.990 / 0.004
Multipli. noise	29.08 / 0.850 / 0.130	29.71 / 0.861 / 0.117	29.57 / 0.854 / 0.121	30.00 / 0.872 / 0.096	30.08 / 0.873 / 0.095	30.08 / 0.875 / 0.096	30.74 / 0.889 / 0.088
Denoise	24.83 / 0.687 / 0.428	24.58 / 0.666 / 0.476	23.96 / 0.639 / 0.526	25.25 / 0.713 / 0.369	24.85 / 0.676 / 0.469	24.85 / 0.672 / 0.463	25.00 / 0.692 / 0.410
Over bright	15.14 / 0.705 / 0.259	17.16 / 0.753 / 0.222	16.82 / 0.761 / 0.204	19.09 / 0.810 / 0.167	19.14 / 0.812 / 0.160	19.14 / 0.835 / 0.142	22.02 / 0.857 / 0.115
Low-light	14.32 / 0.636 / 0.235	17.94 / 0.734 / 0.199	16.03 / 0.667 / 0.250	18.05 / 0.737 / 0.168	21.26 / 0.809 / 0.137	21.26 / 0.837 / 0.125	25.25 / 0.854 / 0.107
Mean shift	19.64 / 0.873 / 0.068	22.65 / 0.904 / 0.051	18.93 / 0.846 / 0.096	22.15 / 0.894 / 0.045	24.66 / 0.923 / 0.028	24.66 / 0.942 / 0.022	30.55 / 0.956 / 0.014
Bicubic resize	20.00 / 0.461 / 0.665	19.84 / 0.453 / 0.677	19.72 / 0.446 / 0.714	20.18 / 0.471 / 0.641	20.22 / 0.473 / 0.639	20.22 / 0.477 / 0.646	20.40 / 0.483 / 0.620
Bilinear resize	19.85 / 0.456 / 0.663	19.66 / 0.447 / 0.676	19.44 / 0.438 / 0.709	20.09 / 0.469 / 0.633	20.12 / 0.470 / 0.637	20.12 / 0.475 / 0.649	20.34 / 0.481 / 0.625
Nearest resize	21.53 / 0.599 / 0.410	21.46 / 0.599 / 0.438	21.18 / 0.585 / 0.460	21.57 / 0.604 / 0.422	21.59 / 0.608 / 0.412	21.59 / 0.610 / 0.406	21.84 / 0.617 / 0.387
Lanczos resize	20.01 / 0.458 / 0.682	19.90 / 0.452 / 0.683	19.86 / 0.447 / 0.714	20.15 / 0.467 / 0.659	20.22 / 0.471 / 0.644	20.22 / 0.474 / 0.650	20.40 / 0.480 / 0.6277
Sharpening	24.89 / 0.874 / 0.094	24.34 / 0.864 / 0.103	25.18 / 0.877 / 0.088	25.69 / 0.891 / 0.076	25.26 / 0.879 / 0.094	25.26 / 0.904 / 0.070	27.28 / 0.922 / 0.055
Contrast imbal.	21.86 / 0.881 / 0.113	21.86 / 0.881 / 0.109	22.46 / 0.865 / 0.133	22.25 / 0.886 / 0.112	26.47 / 0.945 / 0.057	26.47 / 0.956 / 0.041	37.64 / 0.990 / 0.007
Color block	26.39 / 0.902 / 0.127	25.60 / 0.902 / 0.134	26.01 / 0.896 / 0.125	27.11 / 0.916 / 0.106	27.16 / 0.917 / 0.107	27.16 / 0.923 / 0.102	28.06 / 0.927 / 0.092
Pixelate	24.06 / 0.729 / 0.261	23.92 / 0.727 / 0.271	23.71 / 0.720 / 0.296	23.98 / 0.732 / 0.280	24.11 / 0.734 / 0.261	24.11 / 0.737 / 0.258	24.41 / 0.742 / 0.242
Discontinuous	23.42 / 0.782 / 0.187	21.71 / 0.774 / 0.142	21.16 / 0.759 / 0.170	21.55 / 0.769 / 0.167	24.69 / 0.831 / 0.120	24.69 / 0.810 / 0.128	24.93 / 0.841 / 0.112
Jitter	23.71 / 0.669 / 0.320	23.73 / 0.678 / 0.336	23.27 / 0.657 / 0.371	23.98 / 0.685 / 0.335	23.96 / 0.686 / 0.333	23.96 / 0.689 / 0.333	24.23 / 0.701 / 0.340
Mosaic	33.47 / 0.960 / 0.020	33.05 / 0.946 / 0.020	32.52 / 0.947 / 0.025	34.22 / 0.957 / 0.021	34.61 / 0.959 / 0.019	34.61 / 0.961 / 0.020	36.04 / 0.967 / 0.013
Irregular mask	23.41 / 0.786 / 0.241	23.54 / 0.792 / 0.235	22.79 / 0.772 / 0.238	24.06 / 0.801 / 0.216	24.39 / 0.800 / 0.224	24.39 / 0.806 / 0.219	25.48 / 0.817 / 0.203
Block mask	24.34 / 0.838 / 0.212	24.72 / 0.842 / 0.206	23.75 / 0.825 / 0.209	25.15 / 0.849 / 0.194	26.03 / 0.849 / 0.196	26.03 / 0.854 / 0.192	27.71 / 0.858 / 0.186
Rain streak	23.91 / 0.776 / 0.140	24.45 / 0.802 / 0.124	22.43 / 0.787 / 0.137	24.40 / 0.823 / 0.102	26.55 / 0.844 / 0.088	26.55 / 0.854 / 0.077	28.30 / 0.883 / 0.063
Snow streak	23.04 / 0.671 / 0.327	23.59 / 0.707 / 0.293	24.57 / 0.773 / 0.228	29.50 / 0.892 / 0.080	22.12 / 0.654 / 0.340	22.12 / 0.753 / 0.239	29.48 / 0.881 / 0.101
Clean image	39.41 / 0.979 / 0.022	45.89 / 0.991 / 0.009	37.93 / 0.979 / 0.023	44.65 / 0.988 / 0.014	54.41 / 0.995 / 0.003	54.41 / 0.997 / 0.002	71.91 / 0.999 / 0.000
Average	24.20 / 0.752 / 0.263	24.78 / 0.760 / 0.259	23.90 / 0.743 / 0.280	25.60 / 0.780 / 0.228	26.38 / 0.789 / 0.223	26.38 / 0.797 / 0.216	28.84 / 0.817 / 0.191

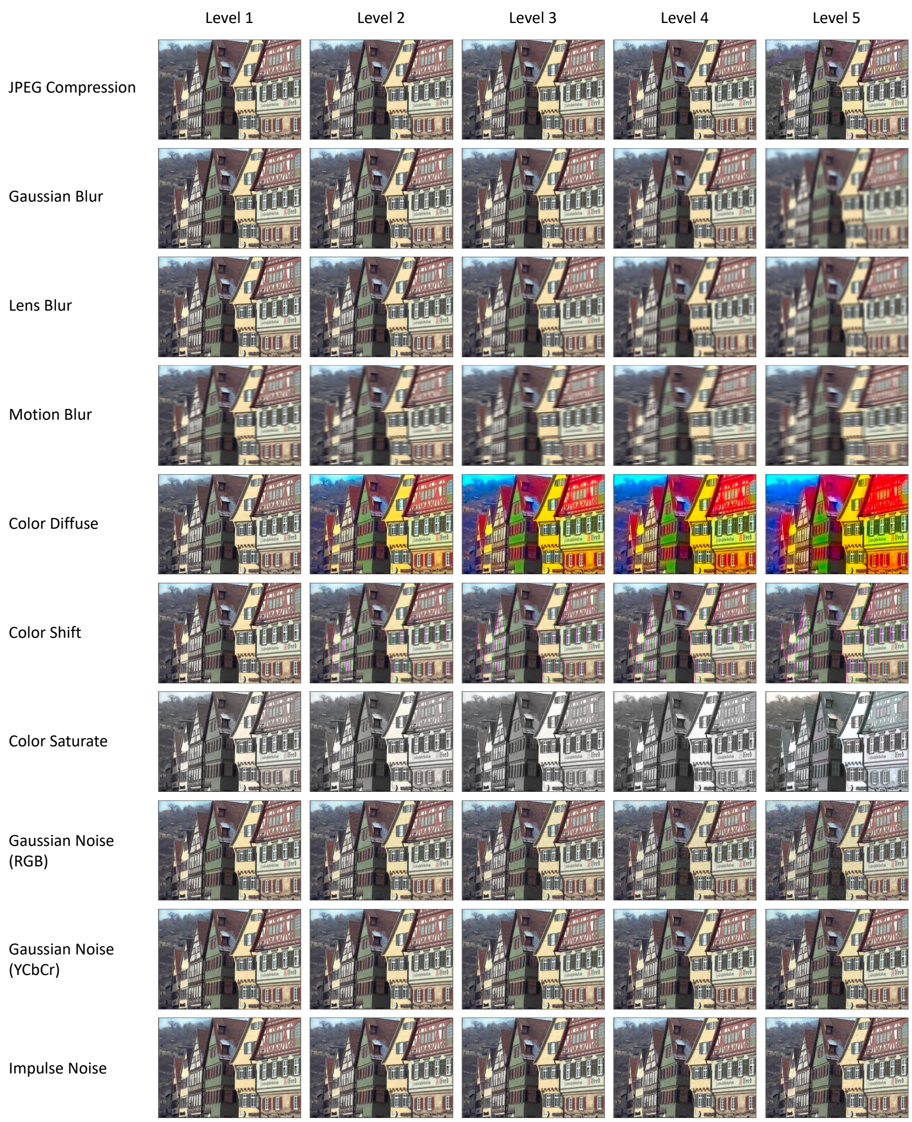

Fig. 1: An illustration of the degradations in the distortion bank. Better in zoomed-in view.

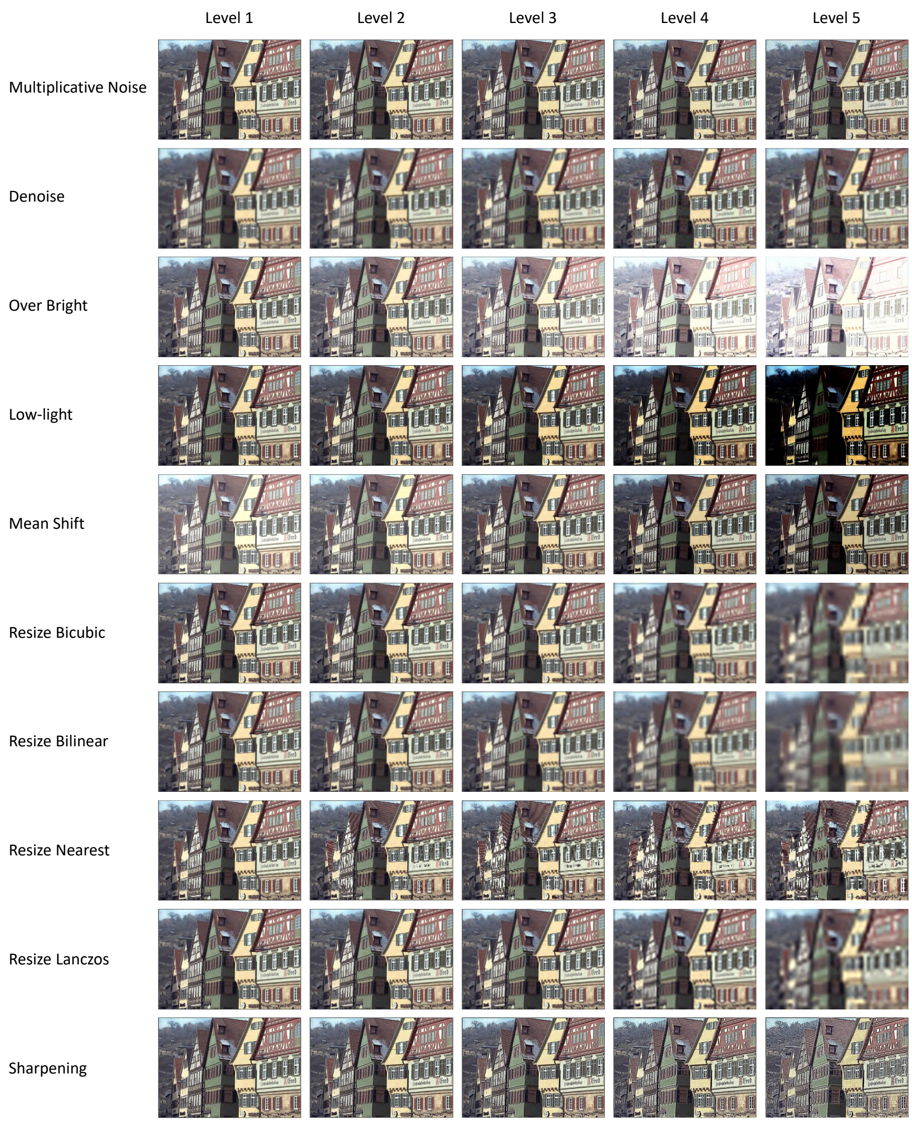

Fig. 2: An illustration of the degradations in the distortion bank (continued). Better in zoomed-in view.

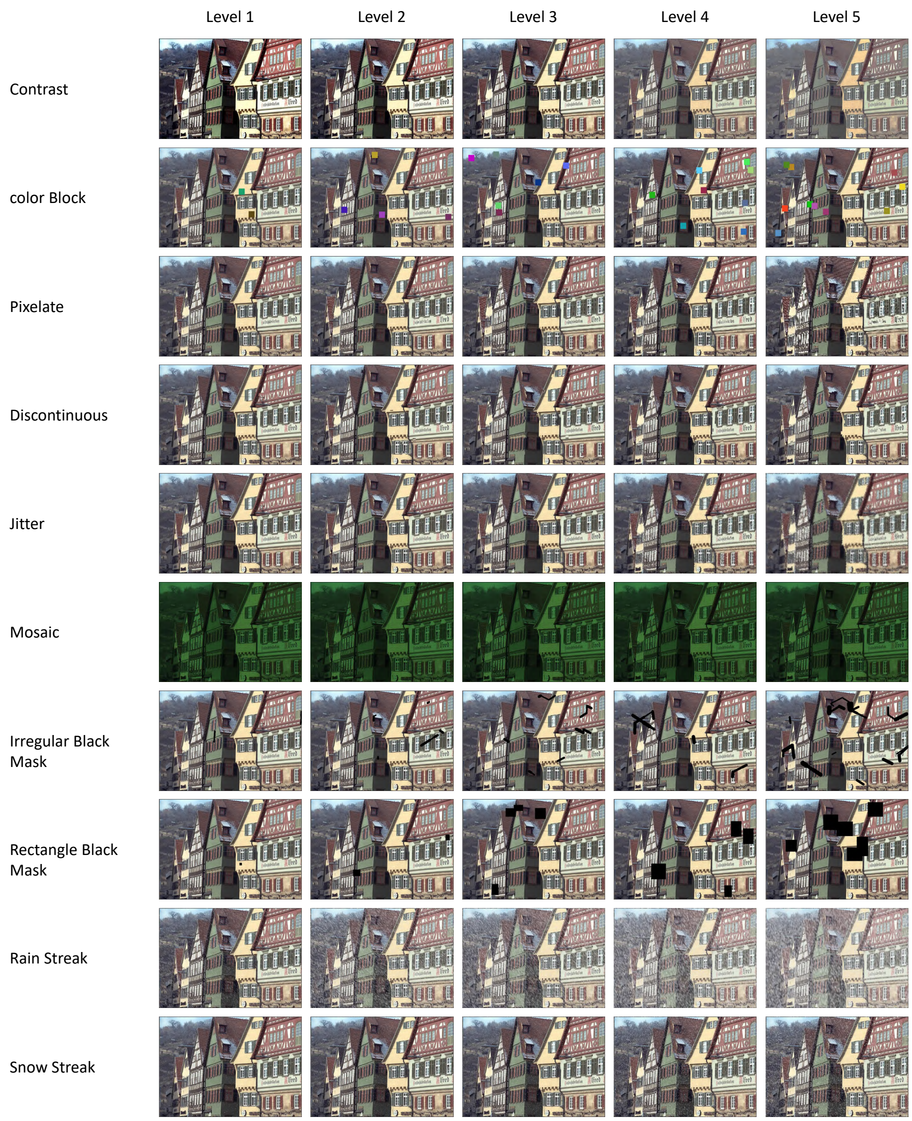

Fig. 3: An illustration of the degradations in the distortion bank (continued). Better in zoomed-in view.

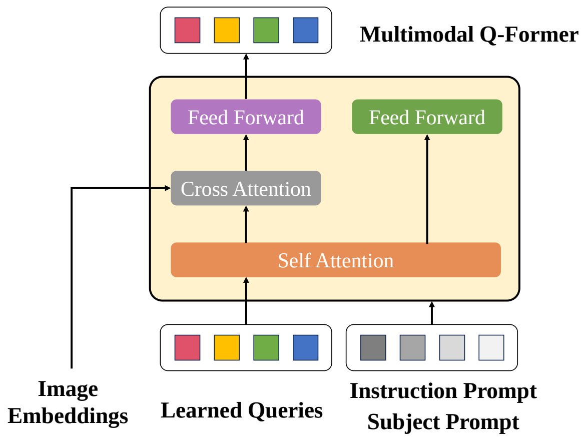

Fig. 4: The illustration of the Q-former.

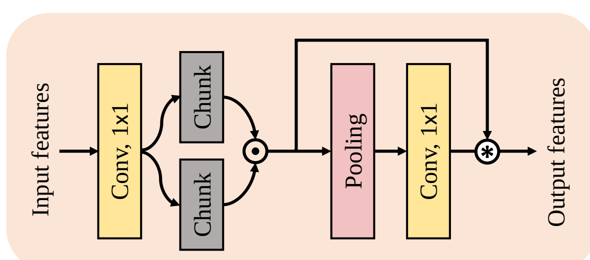

Fig. 5: The illustration of the channel-attention block.

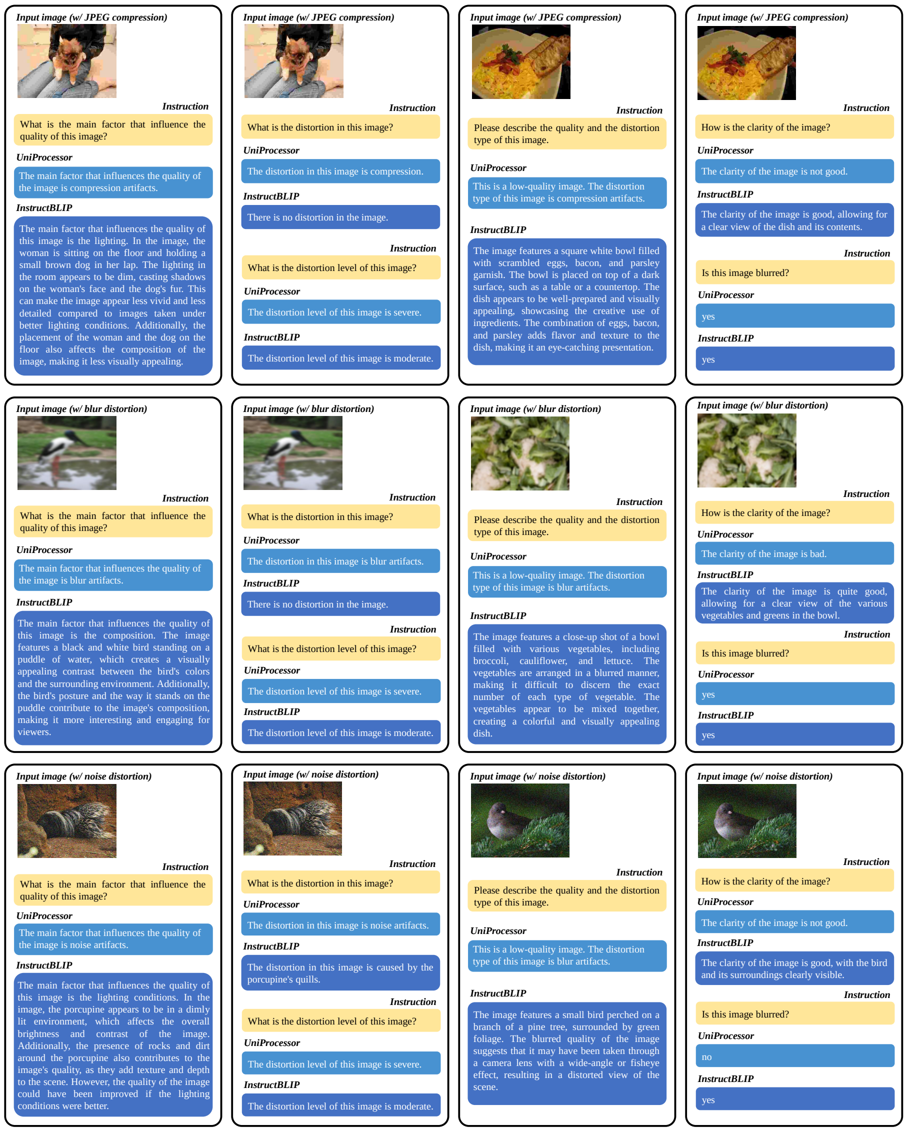

Fig. 6: Comparisons of low-level visual question answering performance between UniProcessor and InstructBLIP [1]. Our UniProcessor achieves better performance on the low-level degradation-aware VQA task.

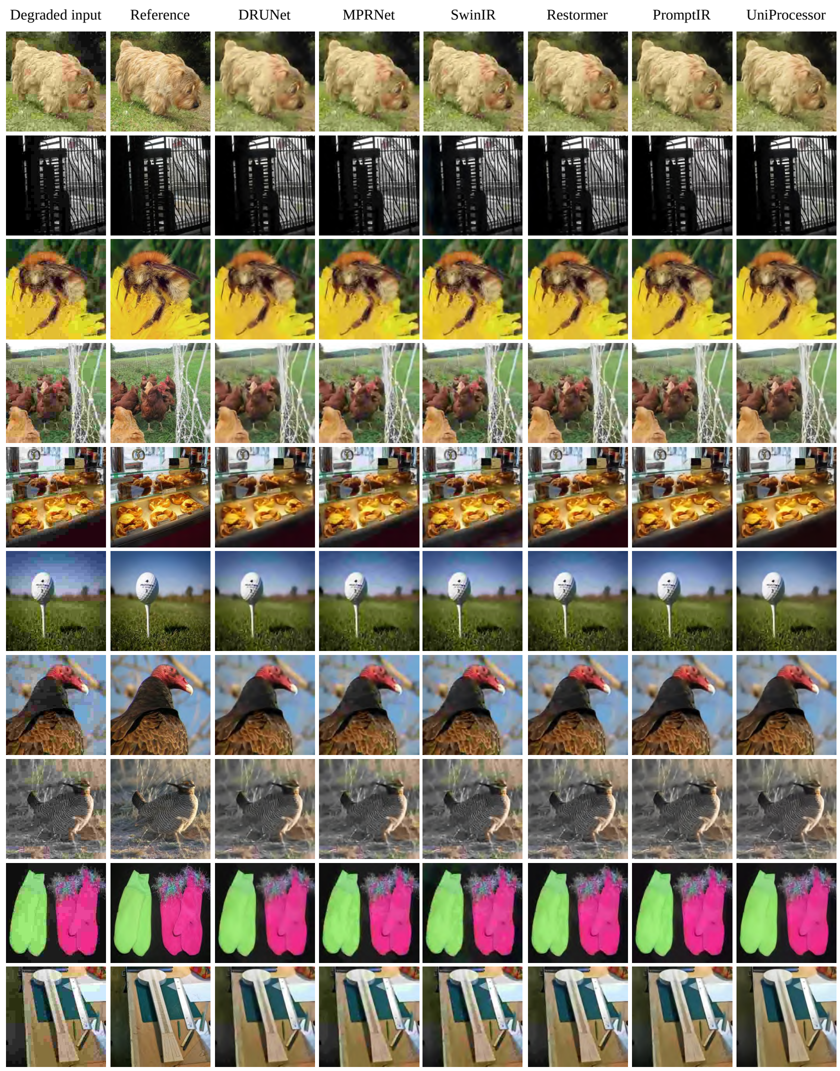

Fig. 7: Visual comparison of different methods on the task of removing JPEG compression.

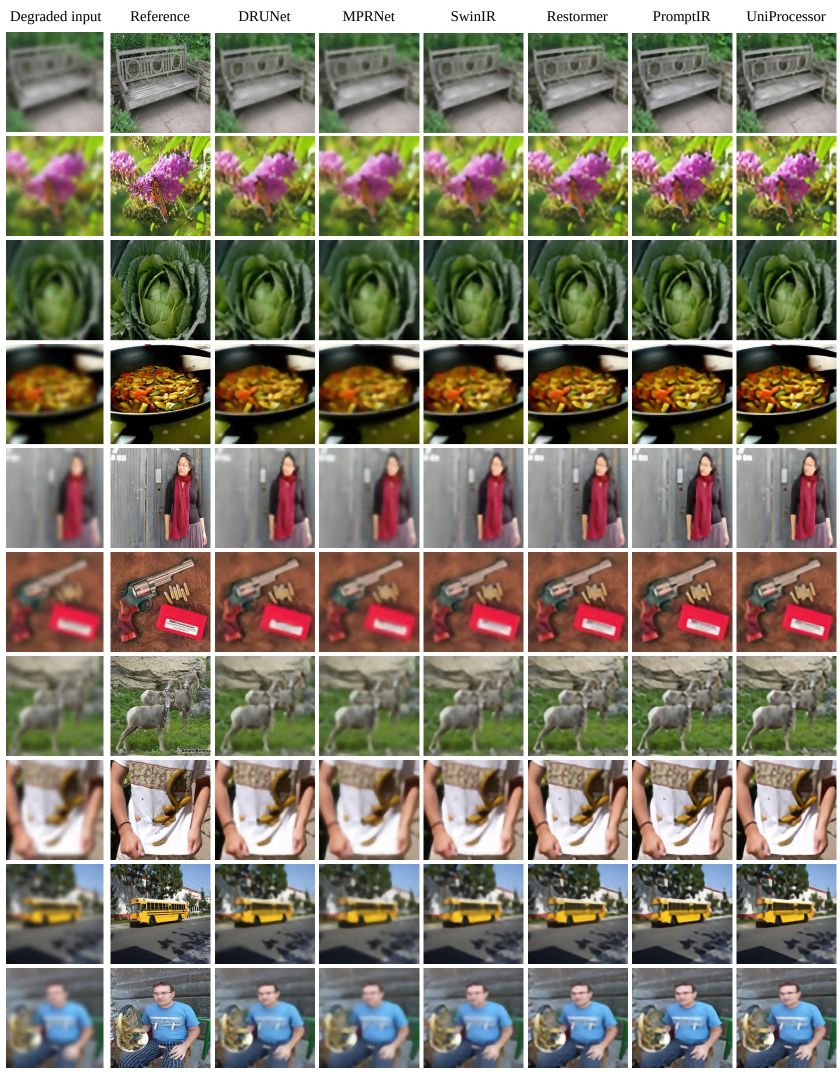

Fig. 8: Visual comparison of different methods on the task of removing Gaussian blur.

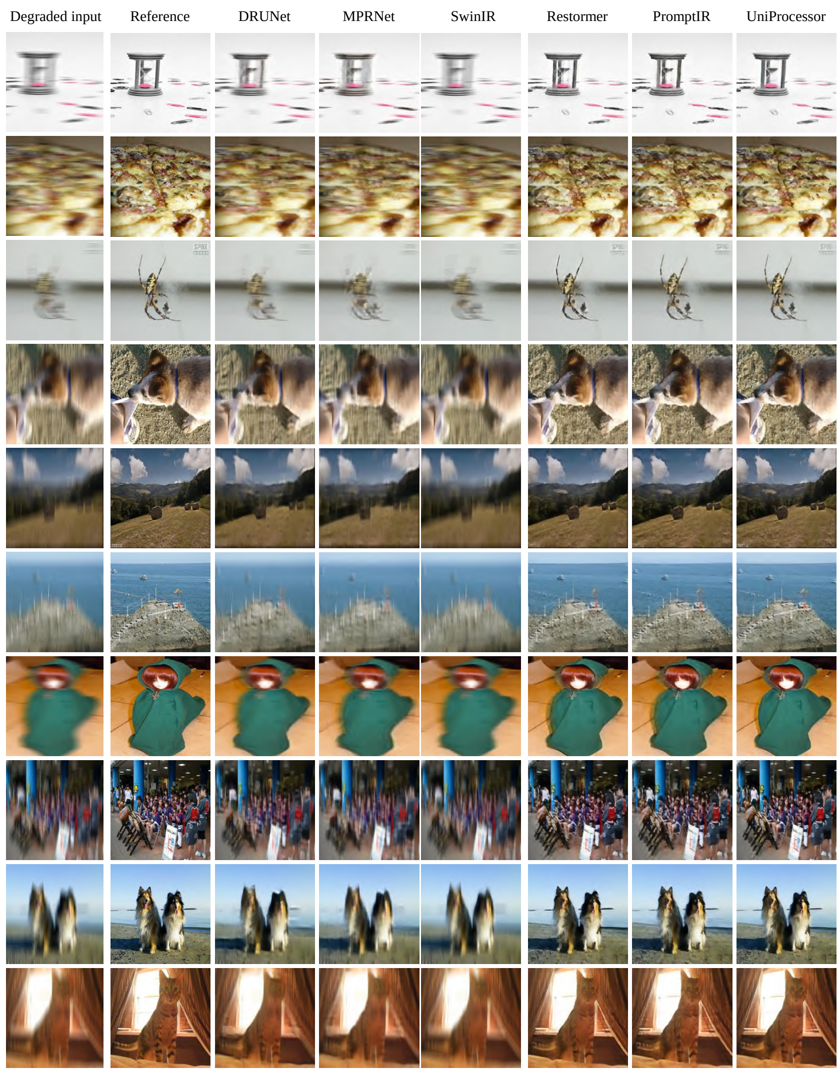

Fig. 9: Visual comparison of different methods on the task of removing motion blur.

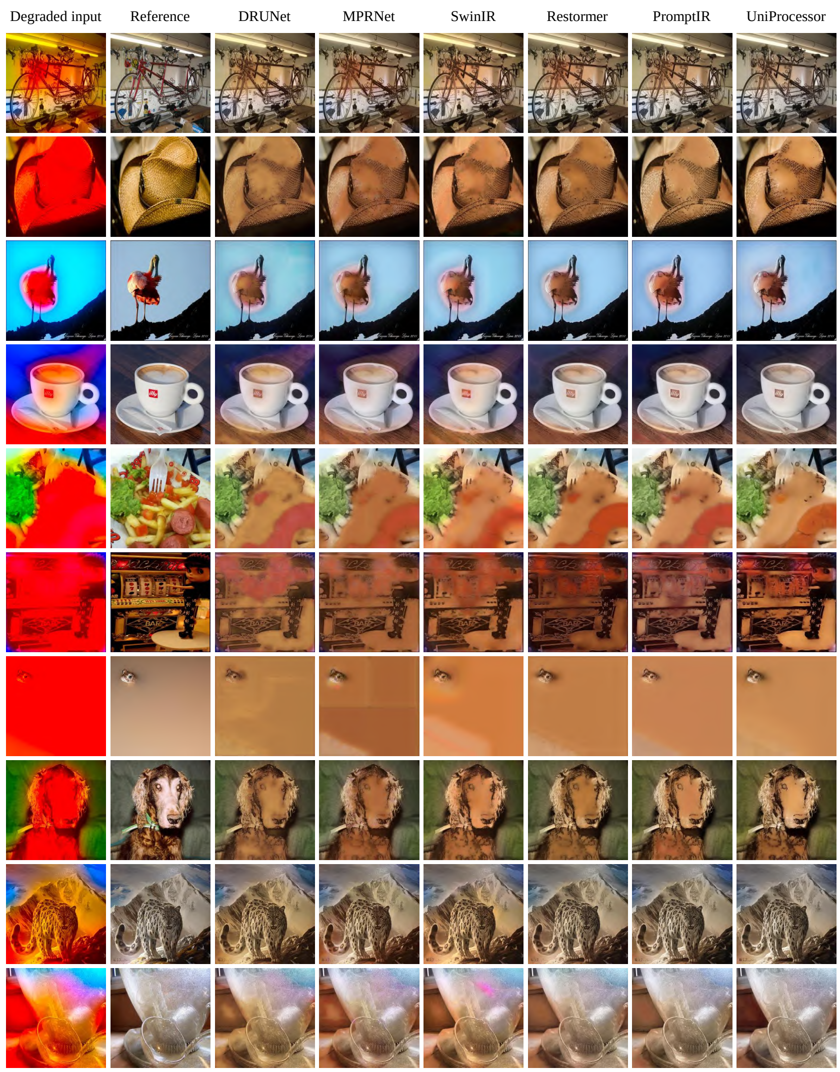

Fig. 10: Visual comparison of different methods on the task of removing color diffuse.

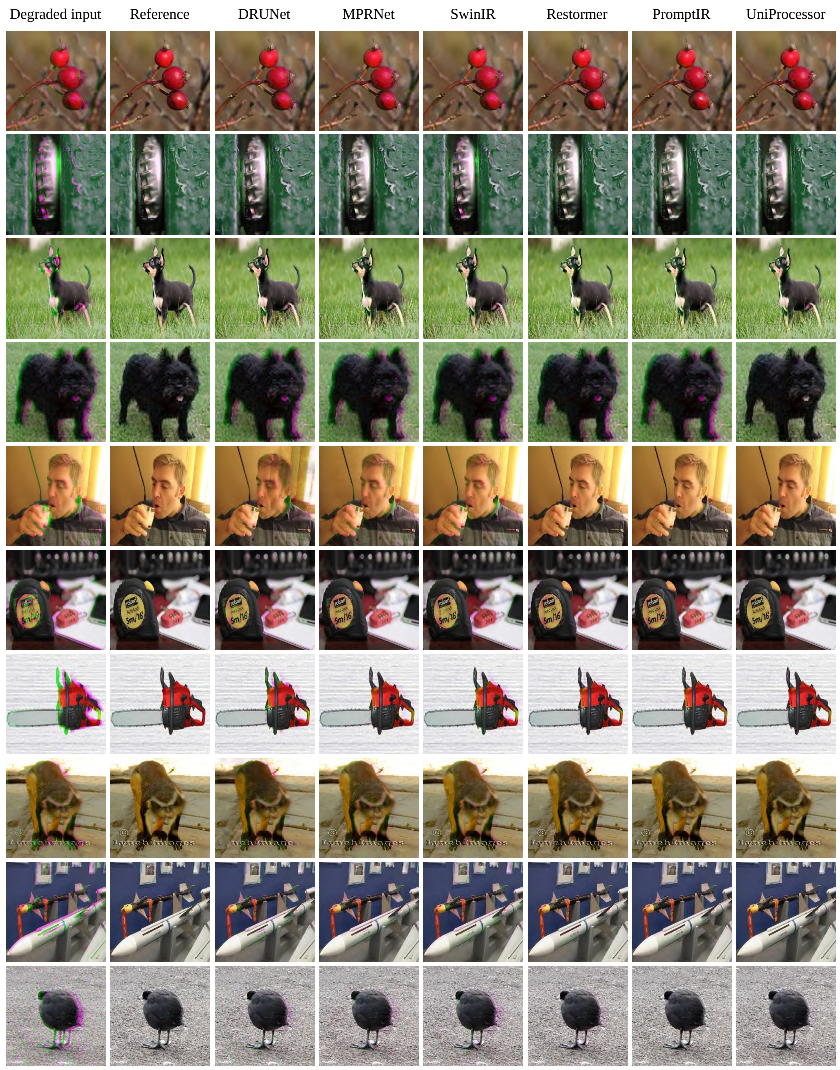

Fig. 11: Visual comparison of different methods on the task of removing color shift.

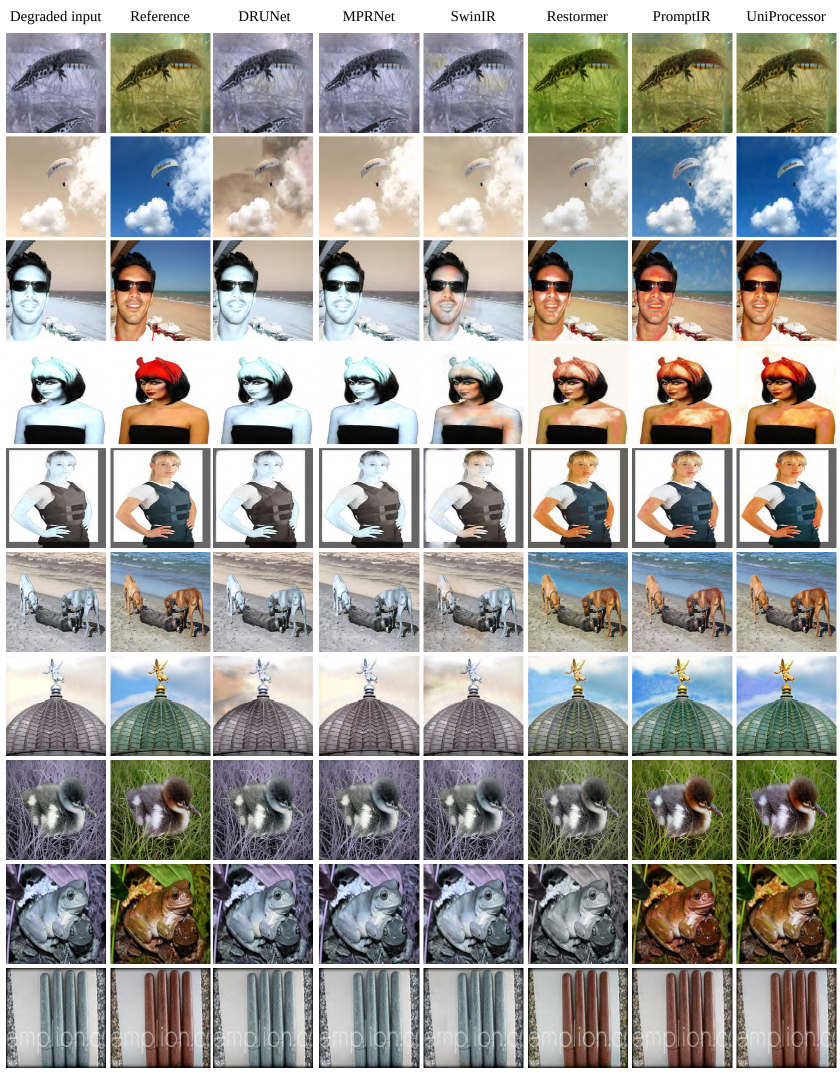

Fig. 12: Visual comparison of different methods on the task of removing color saturate.

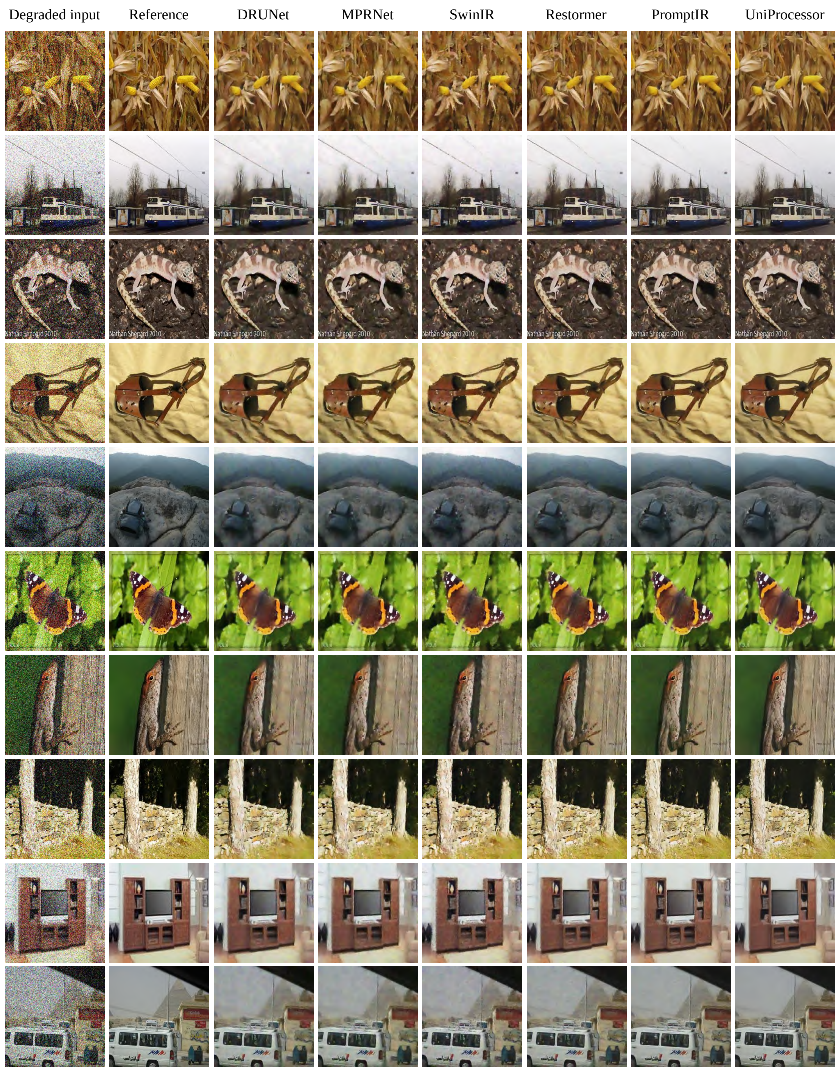

Fig. 13: Visual comparison of different methods on the task of removing Gaussian noise.

Fig. 14: Visual comparison of different methods on the task of removing over bright degradation.

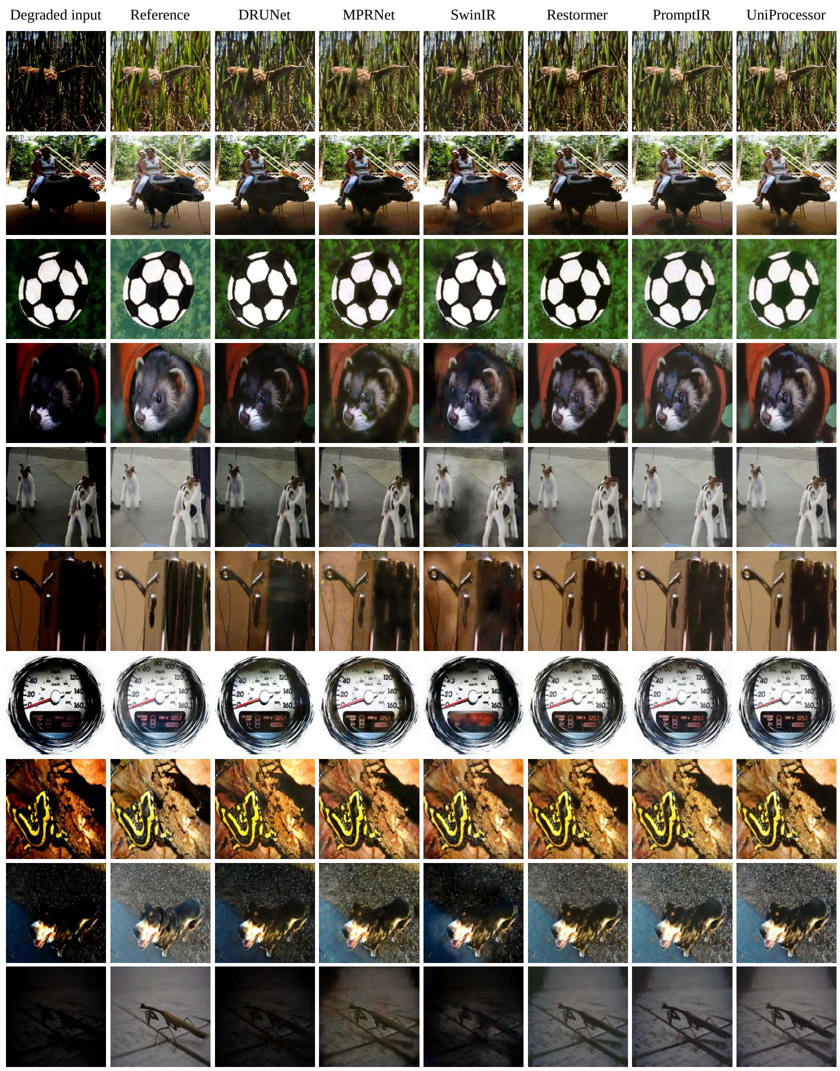

Fig. 15: Visual comparison of different methods on the task of removing over dark degradation.

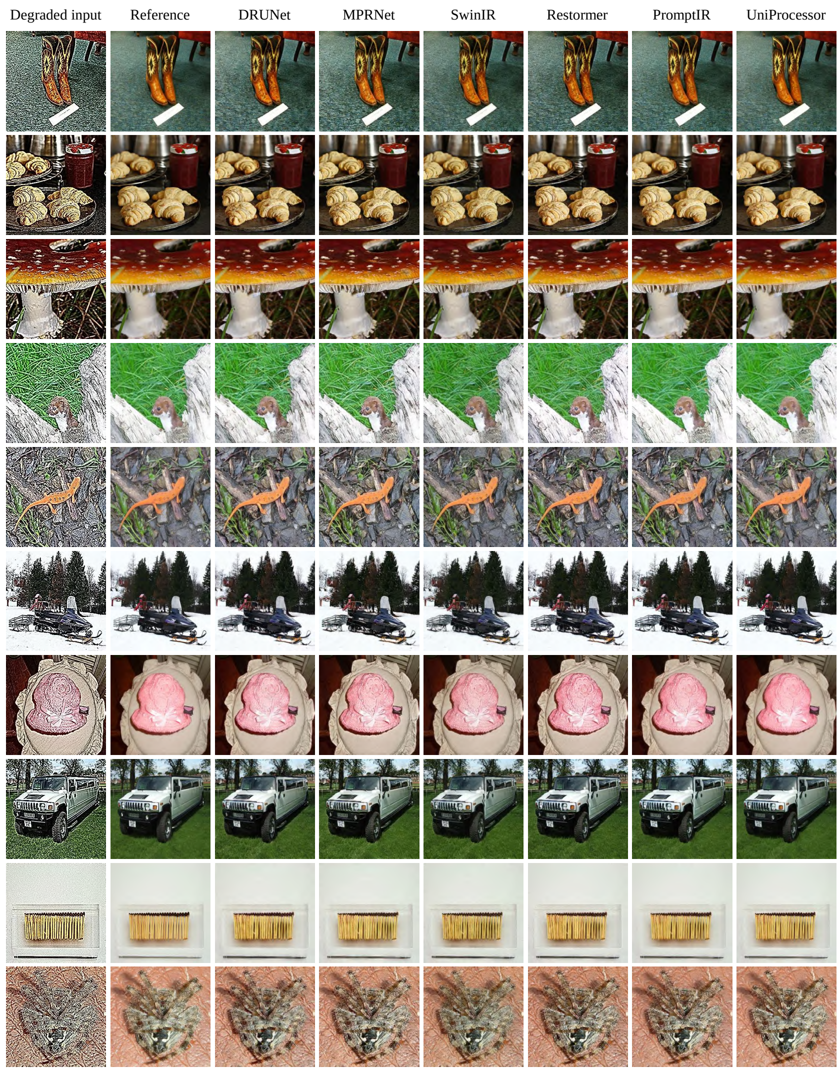

Fig. 16: Visual comparison of different methods on the task of removing over sharpening degradation.

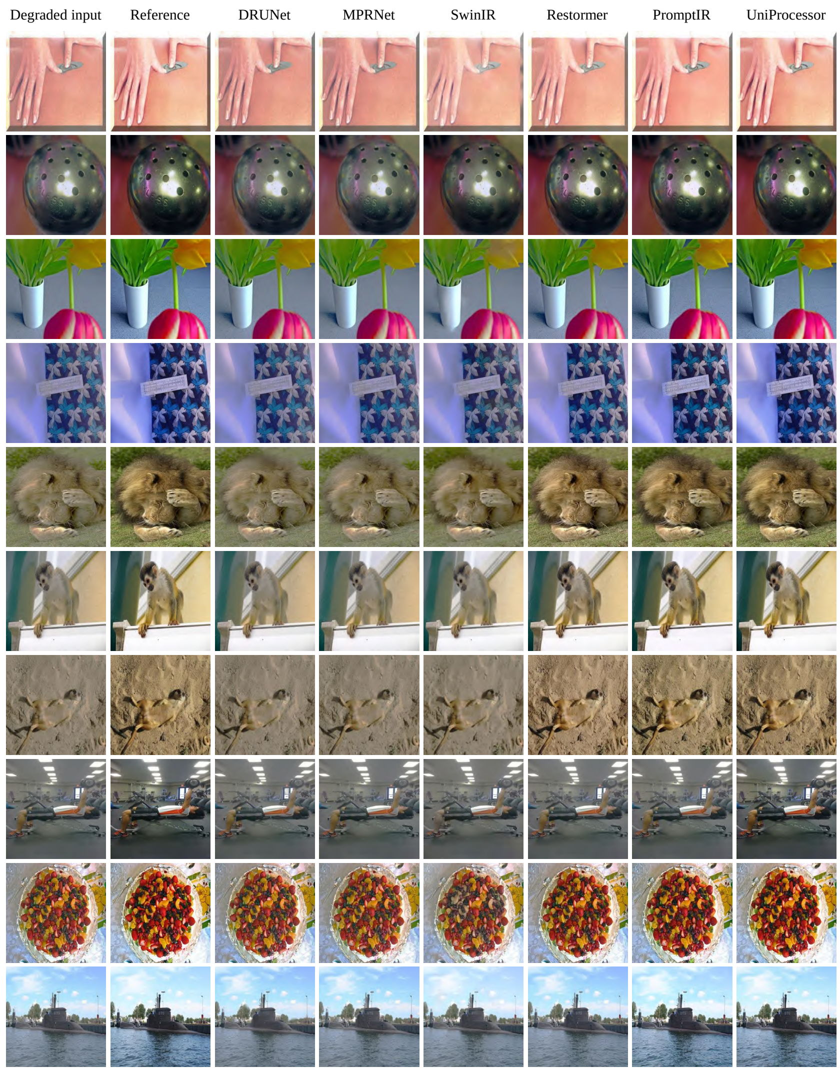

Fig. 17: Visual comparison of different methods on the task of removing contrast imblance degradation.

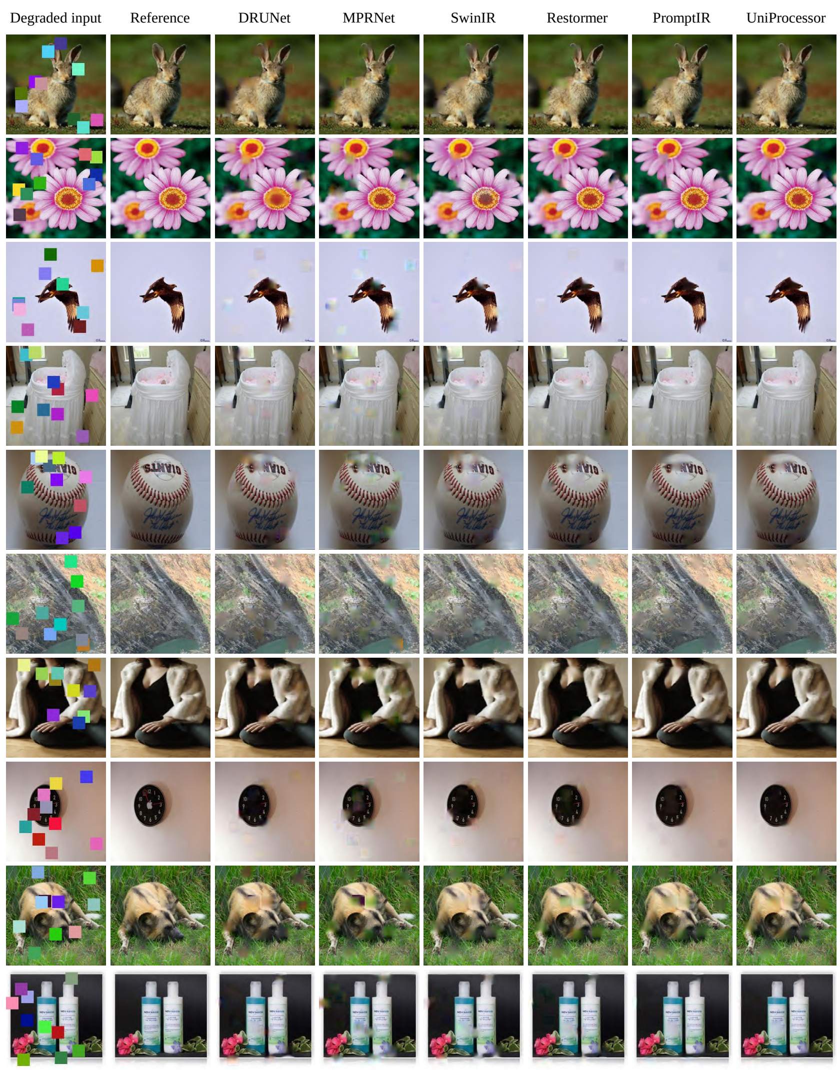

Fig. 18: Visual comparison of different methods on the task of removing color block.

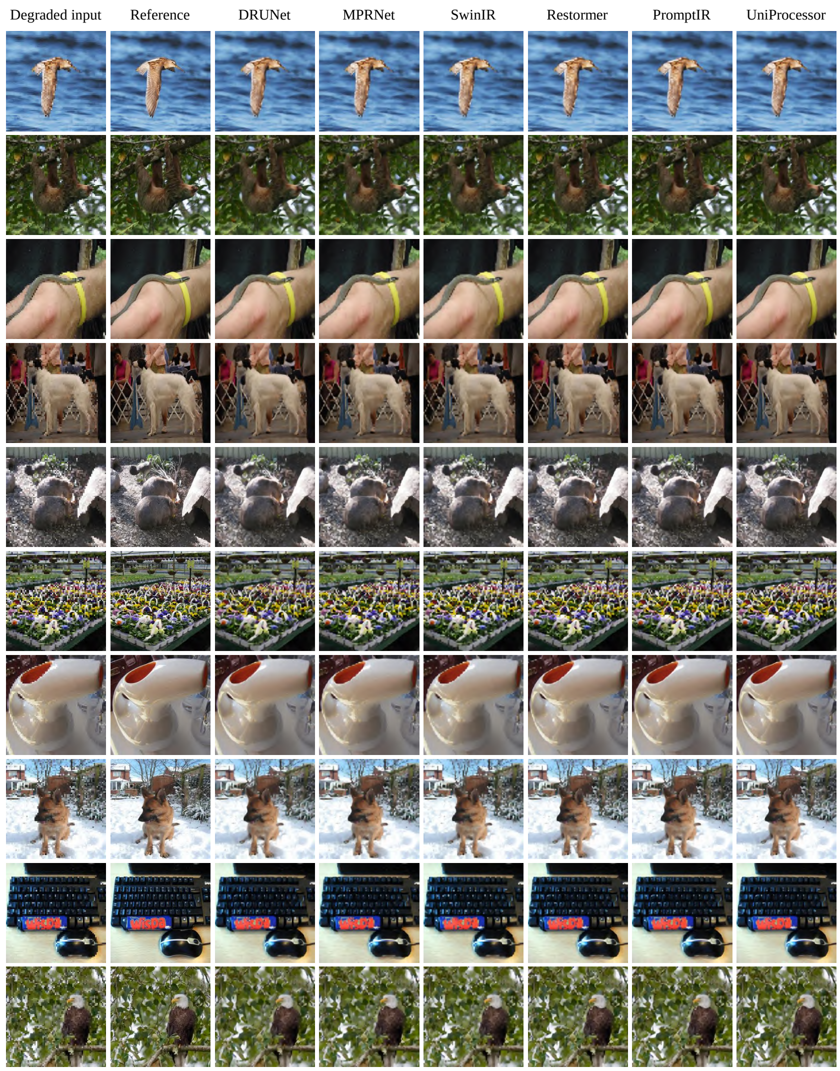

Fig. 19: Visual comparison of different methods on the task of removing pixelate degradation.

Fig. 20: Visual comparison of different methods on the task of removing discontinuous degradation.

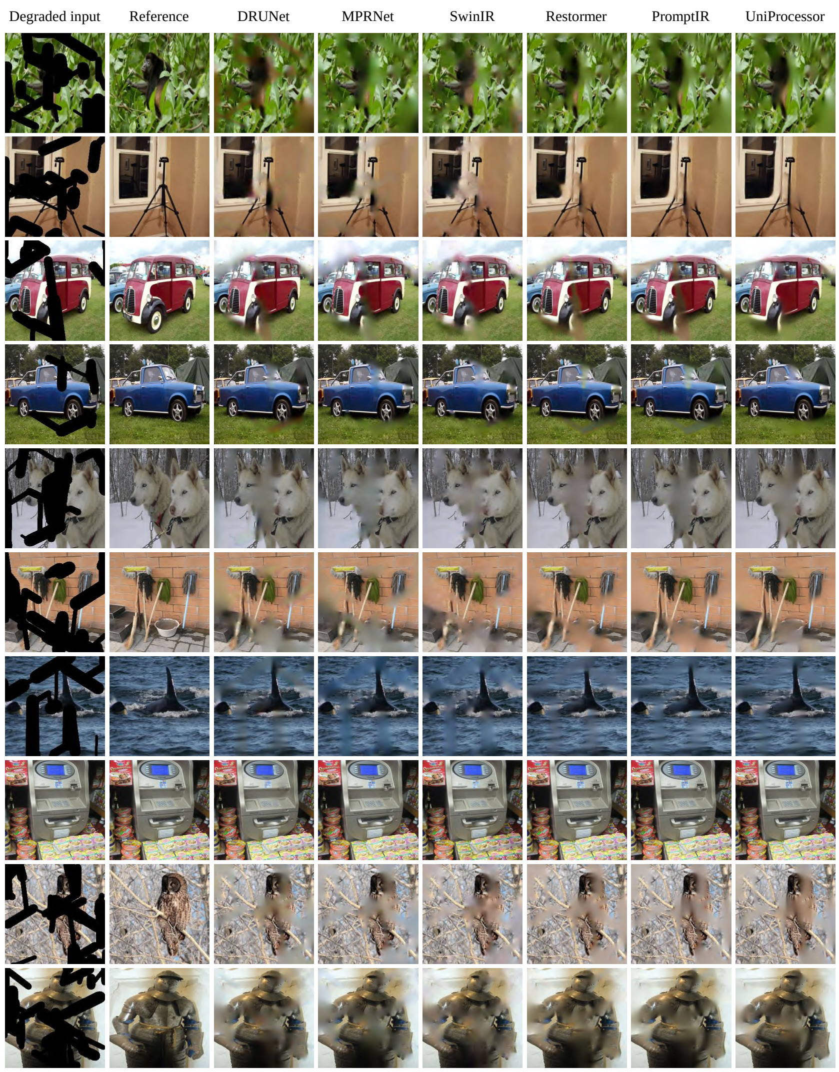

Fig. 21: Visual comparison of different methods on the task of inpainting.

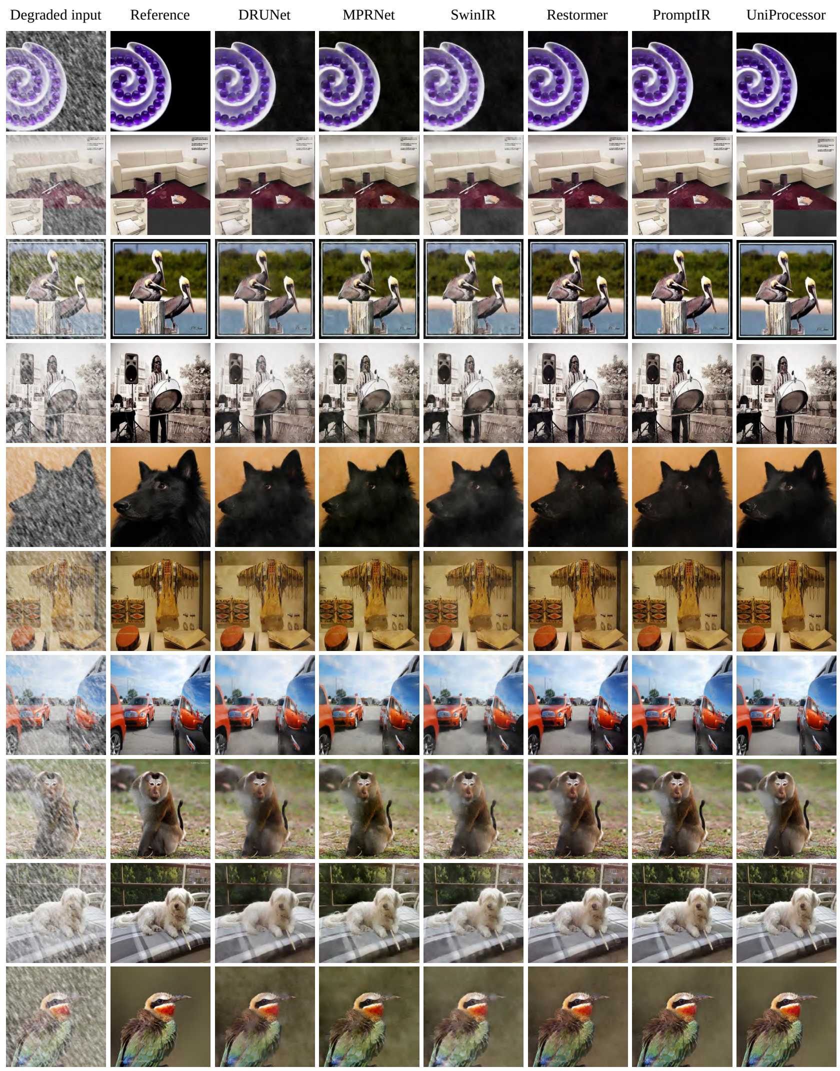

Fig. 22: Visual comparison of different methods on the task of single image rain removal.

Fig. 23: Visual comparison of different methods on the task of single image snow removal.

References

1. Dai, W., Li, J., Li, D., Tiong, A.M.H., Zhao, J., Wang, W., Li, B., Fung, P., Hoi, S.: Instructblip: Towards general-purpose vision-language models with instruction tuning. In: Proceedings of the Advances in Neural Information Processing Systems (NeurIPS) (2023) 5, 13
2. Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L.: Imagenet: A large-scale hierarchical image database. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 248–255 (2009) 8
3. Duan, H., Shen, W., Min, X., Tu, D., Teng, L., Wang, J., Zhai, G.: Masked autoencoders as image processors. arXiv preprint arXiv:2303.17316 (2023) 5
4. Franzen, R.: Kodak lossless true color image suite. http://r0k.us/graphics/kodak/ (1999), online accessed 24 Oct 2021 7
5. Li, J., Li, D., Savarese, S., Hoi, S.: Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. In: Proceedings of the International Conference on Machine Learning (ICML) (2023) 4
6. Liang, J., Cao, J., Sun, G., Zhang, K., Van Gool, L., Timofte, R.: Swinir: Image restoration using swin transformer. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV). pp. 1833–1844 (2021) 6, 7, 8
7. Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S., Guo, B.: Swin transformer: Hierarchical vision transformer using shifted windows. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV). pp. 10012–10022 (2021) 5
8. Martin, D., Fowlkes, C., Tal, D., Malik, J.: A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV). pp. 416–423 (2001) 6, 7
9. Potlapalli, V., Zamir, S.W., Khan, S., Khan, F.S.: Promptir: Prompting for all-in-one blind image restoration. Proceedings of the Advances in Neural Neural Information Processing Systems (NeurIPS) (2023) 6, 7, 8
10. Saha, A., Mishra, S., Bovik, A.C.: Re-iqa: Unsupervised learning for image quality assessment in the wild. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 5846–5855 (2023) 1
11. Suvorov, R., Logacheva, E., Mashikhin, A., Remizova, A., Ashukha, A., Silvestrov, A., Kong, N., Goka, H., Park, K., Lempitsky, V.: Resolution-robust large mask inpainting with fourier convolutions. In: Proceedings of the IEEE Winter Conference on Applications of Computer Vision (WACV). pp. 2149–2159 (2022) 1
12. Wang, Z., Cun, X., Bao, J., Zhou, W., Liu, J., Li, H.: Uformer: A general u-shaped transformer for image restoration. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 17683–17693 (2022) 6, 7, 8
13. Wang, Z., Bovik, A.C., Sheikh, H.R., Simoncelli, E.P.: Image quality assessment: from error visibility to structural similarity. IEEE Transactions on Image Processing (TIP) **13**(4), 600–612 (2004) 6, 7, 8
14. Woo, S., Debnath, S., Hu, R., Chen, X., Liu, Z., Kweon, I.S., Xie, S.: Convnext v2: Co-designing and scaling convnets with masked autoencoders. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 16133–16142 (2023) 5
15. Zamir, S.W., Arora, A., Khan, S., Hayat, M., Khan, F.S., Yang, M.H.: Restormer: Efficient transformer for high-resolution image restoration. In: Proceedings of the

IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 5728–5739 (2022) 6, 7, 8
16. Zamir, S.W., Arora, A., Khan, S., Hayat, M., Khan, F.S., Yang, M.H., Shao, L.: Multi-stage progressive image restoration. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 14821–14831 (2021) 6, 7, 8
17. Zhang, K., Li, Y., Zuo, W., Zhang, L., Van Gool, L., Timofte, R.: Plug-and-play image restoration with deep denoiser prior. IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI) **44**(10), 6360–6376 (2021) 6, 7, 8
18. Zhang, K., Zuo, W., Gu, S., Zhang, L.: Learning deep cnn denoiser prior for image restoration. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 3929–3938 (2017) 1
19. Zhang, R., Isola, P., Efros, A.A., Shechtman, E., Wang, O.: The unreasonable effectiveness of deep features as a perceptual metric. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 586–595 (2018) 6, 7, 8