

# Diff-Plugin: Revitalizing Details for Diffusion-based Low-level Tasks

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This supplementary material is organized as follows. First, Sec. A details our network architectures. Then, Sec. B discusses some conceptions and method details mentioned in the main manuscript. Lastly, Sec. C elaborates on our experimental details.

## A. Network details

**Stable Diffusion.** Here we briefly review the Stable Diffusion (SD) [22] model we used as the base model. By default, we adopt the widely-used version 1.4 for experiments. SD performs the diffusion process in the latent feature space to reduce the computation cost and enable stable training. It first encodes a *pixel-space* image  $\mathbf{I} \in \mathbb{R}^{H \times W \times 3}$  into smaller *latent-space* image  $\mathbf{z}_0 \in \mathbb{R}^{H' \times W' \times d}$  via a pre-trained VAE [2] encoder  $Enc_V(\cdot)$ , such that  $\mathbf{z}_0 = Enc_V(\mathbf{I})$ . Normally, the  $H$  and  $W$  of the input  $\mathbf{I}$  is 512 in SD 1.4. The  $Enc_V(\cdot)$  performs three times down-sampling, resulting in the  $H'$  and  $W'$  are all 64, and finally apply a quantization operation and a reparameterization on the last layer results in  $d = 4$ . Then, at time step  $t$ , SD adds noise to latent  $\mathbf{z}_0$  to form noisy latent  $\mathbf{z}_t$ , which is fed to the diffusion model  $\epsilon_\theta$  for denoising. The architecture of SD is based on UNet [1] that consists of an encoder, a middle block, and a decoder. The denoised latent  $\mathbf{z}_0$  is finally reconstructed to the pixel-space  $\tilde{\mathbf{I}}$  via the decoder  $Dec(\cdot)$  in VAE, such that  $\tilde{\mathbf{I}} \approx \mathbf{I}$ .

**Task-Plugin.** Given an input image  $\mathbf{I}$ , we first adopt a vision encoder  $Enc_I(\cdot)$  (*i.e.*, CLIP-ViT-L/14 [19]) to extract general visual features of  $\mathbf{I}$ , such that  $\mathbf{F}_{clip}^v = Enc_I(\mathbf{I})$  and  $\mathbf{F}_{clip}^v \in \mathbb{R}^{256 \times 1024}$ . The Task-Prompt Branch (TPB) is a Multi-Layer Perception (MLP) network that distills the  $\mathbf{F}_{clip}^v$  to  $\mathbf{F}^p \in \mathbb{R}^{256 \times 768}$ . It comprises three MLP layers, each with 1024 units, and the final MLP layer reduces the feature dimension to 768.

To extract the task-specific spatial details effectively, we first capture the full image content information  $\mathbf{F}$  from the input image  $\mathbf{I}$ , utilizing  $Enc_V(\cdot)$  from SD. We set the variance in the reparameterization to zero and rely solely on the mean. Then Spatial Complement Branch (SCB) is then utilized to distill the vanilla  $\mathbf{F}$ . In SCB, we first employ an convolution layer with a kernel of  $3 \times 3$ , referred to as  $Conv_{in}(\cdot)$ , which is used for dimension adjustment. Then, SCB is structured with two sequential processing

units, each comprising a standard ResNet block followed by a standard Cross-Attention Block [22]. The output of the first unit serves as the input for the second. We adopt the same architecture setting as SD for ResNet and Cross-Attention Blocks. The time step  $t$  undergoes a dimension adjustment through an MLP layer to align with the spatial features, and then it is directly added into the ResNet and Cross-Attention Blocks. In terms of the output spatial features, SCB combines the output from the  $Conv_{in}(\cdot)$  layer, and the outputs from both processing units, into  $\mathbf{F}^s$ . While in the main manuscript, the spatial feature is represented by a single symbol  $\mathbf{F}^s$  for clarity and simplicity, it is important to understand that this symbol encapsulates the rich, multi-source spatial features.

**Plugin-Selector.** As depicted in Fig. 1, given a natural language sentence  $\mathbf{T}$ , Plugin-selector employs the pre-trained CLIP text encoder to derive a global textual embedding  $\mathbf{F}_{clip}^t \in \mathbb{R}^{768}$ . This embedding is then passed through the textual projection head, denoted as  $TP(\cdot)$ , to align visual embeddings and output text embedding  $\mathbf{q} \in \mathbb{R}^{768}$ . To calculate the similarity score  $s$  between the textual embedding  $\mathbf{q}$  and various Task-Plugin embeddings, we apply Max-Pooling to transform each Task-Plugin embedding from  $\mathbf{F}_i^p \in \mathbb{R}^{256 \times 768}$  to a reduced form of  $\mathbf{F}_i^p \in \mathbb{R}^{1 \times 768}$ . Then, we feed  $\mathbf{F}_i^p$  into a shared visual projection head  $VP(\cdot)$ , to obtain the textual-visual aligned multi-modality embedding  $v_i$ . After that, a cosine similarity function is used to calculate the distance between  $v_i$  and  $\mathbf{q}$ . Here, both the text and visual projection heads are a Fully Connected (FC) layer with input and output dimensions of 768.

**Placement of the injected spatial feature.** Since the last stage of the SD’s decoder contains three blocks, and  $\mathbf{F}^s$  consists of three parts of spatial features, we treat  $\mathbf{F}^s$  as residual features and add to these three blocks in the last stage of the SD’s decoder in the order of the three  $\mathbf{F}^s$  features. For each residual spatial feature, we append a zero-conv [39] layer for it and train them jointly with the Task-Plugin module.

## B. Discussion

“*Pre-defined mapping table*” in Line-215 of our main manuscript. As shown in Table 1, a mapping table outlines workflows for complex tasks that require multiple Task-

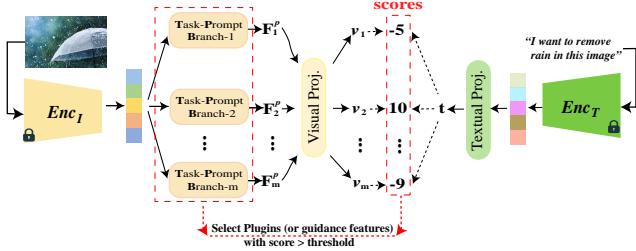


Figure 1. Schematic illustration of the developed Plugin-Selector.

Tasks	Workflow		
	1	2	3
Old photo restoration	Restoration	Colorization	Super-resolution
Adverse weather removal	Dehazing	Deraining	Desnowing

Table 1. Example of a pre-defined mapping table for complex low-level tasks that cannot be accomplished with a single Task-Plugin. Please note that workflows for complex tasks may vary from person to person, here are just a few examples.

Plugins. For instance, the workflow for old photo restoration may involve a sequence of steps: initially restoring damaged regions like scratches and noises, followed by colorizing the photo, and finally up-scaling the resolution. In adverse weather scenarios, we may first remove dense haze and then remove rain and snow, respectively.

**“TPB + SCB (Reconstruction)”** in Line-443 of our main manuscript. We train the Spatial Complement Branch (SCB) using a self-reconstruction denoising loss, where the Ground Truth (GT) is set to the input image during training. Subsequently, we fix the parameters of the reconstruction-based SCB and train only the Task Prior Branch (TPB). This variant tries to preserve the details in the input image through SCB first, and then handle the task-specific degradations via the visual guidance priors provided by TPB.

**How Diff-Plugin revitalizes details?** Providing an initial noise that contains the content of the original image is the most straightforward approach to maintain image details. Specifically, we first convert input images into their corresponding initial noise and then regenerate the images based on this noise. We show some examples in Fig. 2. It is evident that the inversion process, especially in complex images or regions, is unstable and often fails. Therefore, we seek a more stable way to ensure details, which is mainly achieved by SCB in our method.

In *Diff-Plugin*, we adopt the output of Task-Prompt Branch (TPB) as the query of the cross-attention layers in the diffusion model, learning task-specific visual guidance priors to handle unwanted degradations such as rain streaks and snowflakes. However, TPB alone cannot maintain intricate details at all. Even with the initial noise from DDIM Inversion, TPB effectively helps to capture large structured



Figure 2. Visualization of the results of first DDIM inversion and then reconstruction. The first and second rows show the input image and the reconstructed image, respectively.

scenes but falls short in preserving fine-grained details. To this end, we further introduce (*i.e.*, directly add) the output of Spatial Complement Branch (SCB) to the last stage of the diffusion model’s decoder. SCB plays a crucial role in detail preservation yet it struggles to remove unwanted degradations. Finally, combining both SCB and TPB can provide sufficient task-specific priors (*i.e.*, both visual guidance and spatial information) and thus ensures the fine-grained details preservation in the final output.

**“Multi-task setting”** in Line-476 of our main manuscript. In our experiments, we generate multi-task prompts for the eight low-level tasks by randomly pairing texts from two different tasks. For example: “*I want to remove rain and clear haze.*” and “*clear blur and enhance the lighting for this image*”. The use of the ‘\*’ symbol denotes that we enumerate the generation of all possible multi-task combinations for each task’s text. By default, we test two Task-plugins at the same time during evaluation, because scenarios requiring more than two Task-plugins are uncommon in practical applications. However, note that the Plugin-Selector’s functionality is not confined to just two tasks. Owing to our contrastive training paradigm and the strategy of randomly combining multi-task prompts for data augmentation, the Plugin-Selector can still handle combinations that involve more than two tasks.

**“Single + Non.”** in Line-481 of our main manuscript. We generate various text prompts for hypothetical, non-existent Task-Plugins and randomly combine them with prompts for existing Task-Plugins. Here are some examples of these non-existent Task-Plugin prompts: “*I want to conduct image classification*”, “*Can you help to add some haze in this photo?*”, and “***Introduce some moire pattern for this image***”.

## C. Experiments

### C.1. Datasets

**Task-Plugin:** The datasets for training and testing the Task-Plugin are listed in Table 2. For tasks like desnowing, dehazing, and deraining, we specifically excluded samples

Data \ Tasks	Desnowing	Dehazing	Deblurring	Deraining	Low-light Enhancement	Face Restoration	Demoireing	Highlight Removal
Train Datasets	Snow100K [11]	Reside [10]	Gopro [15]	Merged [36]	LOL [29]	FFHQ [8]	LCDMoire [35]	SHIQ [3]
	50,000	72,135	2,103	13,712	485	70,000	9,825	10,000
Test Datasets	Realistic [11]	RTTS [10]	RealBlur-J [21]	Real [26]	Merged	LFW [6, 27]	LCDMoire [35]	SHIQ [3]
	884	1375	980	122	350	1711	100	1000

Table 2. Dataset description for different low-level vision tasks. The merged refers to test data in these methods [5, 9, 13, 24, 25, 29].

with very low image quality (*e.g.*, those with extremely low resolution), small degradations that are barely visible, or instances where degradation dominates the entire image, leaving no other discernible content.

**Plugin-Selector:** To train the Plugin-Selector, we employ Chat-GPT to generate natural language sentences that mimic user input. Our approach is structured as follows:

1. **Sentence Structuring:** We deconstruct sentences into five distinct components: <begin>, <verb>, <article>, <noun>, and <end>. For example, ‘I want to remove the rain in this image’ is broken down into <begin>: ‘I want to’, <verb>: ‘remove’, <article>: ‘the’, <noun>: ‘rain’, and <end>: ‘in this image’.
2. **Task-Specific Keywords:** Each task is identified by unique <nouns>, with some overlap in <verbs> across different tasks. For example, ‘remove’ could apply to both ‘rain’ and ‘snow’. The segments <begin>, <article>, and <end>, are common across all tasks.
3. **Prompt Generation:** We first employ Chat-GPT to create task-specific sentence templates. For those incorrect examples, we eliminate them through manual review. Then, based on these templates, we employ Chat-GPT again, to produce appropriate text prompts for each task (*i.e.*, assemble different components).
4. **Dataset Creation:** For each task, we randomly select 750 prompts for training and 50 prompts for testing.

During training, these task-specific text prompts are combined with image samples corresponding to the task type to construct data pairs.

## C.2. Implementations

**Task-Plugin.** During the training phase of Task-Plugins, we set the training epochs based on the number of available samples for each task. Specifically, for tasks with fewer samples, *e.g.*, deblurring and low-light enhancement, we extend the training to 200 epochs. In contrast, tasks with a sufficient number of samples (*e.g.*, face restoration) are trained for 30 epochs. We employ the standard DDPM sampler with a time step of 1000 for training. For testing, we adopt the UniPC [40] sampler with 20 inference steps for faster inference.

**Plugin-Selector.** In the training phase of the Plugin-Selector, we randomly selected 5,000 sample pairs for each low-level vision task, conducting training over 200,000 it-

erations. The inference workflow of the Plugin-Selector is illustrated in Fig. 1. Given an input image and a corresponding text prompt, the Plugin-Selector determines the most appropriate Task-Plugins based on the computed visual-textual similarity score.

**Application.** Fig. 5 showcases a screenshot of our application interface. Our *Diff-Plugin* framework facilitates prompt-driven processing of low-level tasks and provides users the option to manually select their desired Task-Plugin. Please refer to our **demo video** for more details.

## C.3. Metrics

In evaluating our *Diff-Plugin*, we primarily focus on perceptual metrics like FID and KID, which are commonly used in the generative model domain [20, 22, 39]. These metrics are particularly suitable for assessing the visual quality and realism of generated images, especially in scenarios where ground truth (GT) is not available, such as with natural images. In addition, natural images often lack corresponding GT, rendering pixel-based comparison metrics like SSIM and PSNR impractical. To evaluate the FID and KID metrics, we use GT images from the training dataset as reference images for each low-level task. For example, we use 50,000 GT images from Snow100K [11] as the reference images to evaluate the predicted results on Realistic [11] according to FID and KID metrics. Following Parmar *et al.*[17], we opt for the CLIP vision encoder (ViT-B/32) instead of the Inception-V3 model.

Furthermore, when evaluating the accuracy of plugin selectors, in addition to using standard multi-label object classification metrics, we also introduce a strict zero-tolerance accuracy (ZTA) metric. This metric provides a sentence-level classification evaluation from a user-first perspective. It adopts a binary classification approach to ensure the utmost accuracy in determining the relevance of each sentence to the specified task. For instance, consider we have eight low-level vision tasks with assigned task IDs ranging from 0 to 7, corresponding to tasks (0) desnowing, (1) dehazing, (2) deblurring, (3) deraining, (4) low-light enhancement, (5) face restoration, (6) demoireing, (7) highlight removal. When a user inputs a prompt like “*Can you help to remove rain and enhance the brightness for this photo?*”, the Plugin-Selector generates similarity scores for each task, such as [-8.4, -15, -7.8, 19.1, 15.4, -3, -21.9, -



Figure 3. Visual results of our *Diff-Plugin* on multi-task processing. Here, we simply combine the ***restoration*** and ***colorization*** tasks to mimic the old photo restoration task.

	Desnowing Realistic [11]		Dehazing Reside [10]		Deblurring RealBlur-J [21]		Deraining real test [26]		Low-light Enhanc. merged low.		Face Restoration LFW [27]		Denoising LCDMoire [35]		Highlight Removal SHIQ [3]	
	FID ↓	KID ↓	FID ↓	KID ↓	FID ↓	KID ↓	FID ↓	KID ↓	FID ↓	KID ↓	FID ↓	KID ↓	FID ↓	KID ↓	FID ↓	KID ↓
Regression-based specialized models																
DDMSNET [38]	33.92	5.39	-	-	-	-	-	-	-	-	-	-	-	-	-	-
PMNet [32]	-	-	36.40	15.66	-	-	-	-	-	-	-	-	-	-	-	-
FSDGN [33]	-	-	34.58	14.10	-	-	-	-	-	-	-	-	-	-	-	-
MPRNet [36]	-	-	-	-	55.45	15.71	51.17	15.21	-	-	-	-	-	-	-	-
Restormer [37]	-	-	-	-	55.64	15.70	52.78	16.28	-	-	-	-	-	-	-	-
NeRCo [31]	-	-	-	-	-	-	-	-	48.47	10.96	-	-	-	-	-	-
CodeFormer [41]	-	-	-	-	-	-	-	-	-	-	19.94	7.09	-	-	-	-
VQFR [4]	-	-	-	-	-	-	-	-	-	-	19.28	6.72	-	-	-	-
UHDM [34]	-	-	-	-	-	-	-	-	-	-	-	-	29.59	1.45	-	-
SHIQ [3]	-	-	-	-	-	-	-	-	-	-	-	-	-	33.74	18.79	-
Diffusion-based specialized models																
WeatherDiffusion [16]	36.39	5.53	-	-	-	-	53.80	16.59	-	-	-	-	-	-	-	-
IR-SDE [12]	-	-	-	-	47.43	12.42	52.89	16.51	-	-	-	-	-	-	-	-
DiffIR [30]	-	-	-	-	55.78	15.88	-	-	-	-	-	-	-	-	-	-
DiffLL [7]	-	-	-	-	-	-	-	-	51.04	11.74	-	-	-	-	-	-
DR2 [28]	-	-	-	-	-	-	-	-	-	-	23.43/(17.46)	9.29/(5.76)	-	-	-	-
<i>Diff-Plugin</i> (ours)	34.30	5.20	34.68	14.38	51.81	14.63	50.55	13.84	48.98	11.73	20.07(18.46)	6.91(6.41)	29.77	1.75	12.58	6.37

Table 3. Quantitative comparisons to SOTAs (both regression-based and diffusion-based methods) on eight low-level vision tasks that need high content-preservation. KID values are scaled by a factor of 100 for readability. In face restoration, to ensure fairness, we apply the same post-processing [4] as DR2 [28] to our *Diff-Plugin* results. Metrics recalculated after this step are indicated in parentheses.

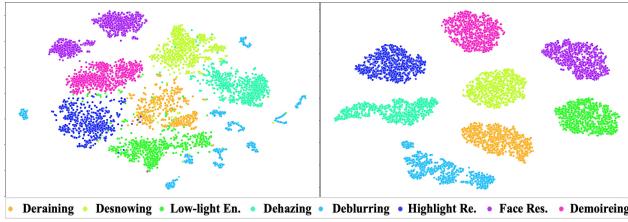


Figure 4. The t-SNE distribution of visual embeddings on the test set of different tasks before (*i.e.*, left sub-figure) and after (*i.e.*, right sub-figure) using the Task-Prompt Branch.

14.5]. Ideally, the Plugin-Selector should identify ‘deraining’ and ‘low-light enhancement’ as relevant tasks, which correspond to task IDs 3 and 4, respectively. The positive and negative classes thus should be [3, 4] and [0, 1, 2, 5, 6, 7], respectively. In the ZTA metric, binary classification is deemed correct only if the similarity scores for all positive classes exceed a threshold (*i.e.*, both 19.1 and 15.4 are greater than  $\theta = 0$ ), and the scores for all negative classes fall below the threshold. If these conditions are not met, the classification is considered incorrect. This metric, thus, embodies a zero-tolerance policy, strictly assessing the Plugin-Selector’s accuracy in identifying the correct task(s) based on user prompts.

#### C.4. More Internal Analysis

**Task-Plugin.** Fig. 4 displays a t-SNE plot illustrating the feature distribution map. In this analysis, we sampled 1,000 test images from each low-level vision task<sup>1</sup> and first fed

<sup>1</sup>Totalling 8,000 samples. For tasks with fewer than 1,000 test images, we repeated the available samples to reach 1,000.

them into  $Enc_I(\cdot)$ . The output from this encoder was then fed to various Task-Plugins, each responsible for extracting task-specific visual guidance priors based on the task type of the input images. It is obvious to see that the the distribution discrepancy among different low-level tasks is accentuated, indicating that the task-specific guidance priors are distinct and that the TPB has successfully learned these differences. This distinction is also advantageous for the Plugin-Selector, as it enhances the accuracy of visual-textual similarity scoring.

#### C.5. Visual Results of Multi-task Processing

In Fig. 3, we showcase additional visual results of multi-task processing using our *Diff-Plugin*. Specifically, we show how the old photo restoration task, particularly in face scenarios, can be simply decomposed into face restoration and colorization sub-tasks. The results illustrate our method’s capability to vividly rejuvenate old face photos.

#### C.6. Comparisons to SOTAs

**More quantitative comparisons.** We also compare our *Diff-Plugin* to several diffusion-based restoration methods, including WeatherDiffusion [16], IR-SDE [12], DiffIR [30], DiffLL [7] and DR2 [28]. The results are tabulated in Table 3 and we can see that our *Diff-Plugin* can still achieves competitive results compared to these specialized models, verifying its superiority.

**More qualitative comparisons.** We provide more visual comparisons of different low-level vision tasks in Fig. 6, Fig. 7, Fig. 8, Fig. 9, Fig. 10, Fig. 11, Fig. 12, Fig. 13.

### Diff-Plugin: Revitalizing Details for Diffusion-based Low-level Tasks

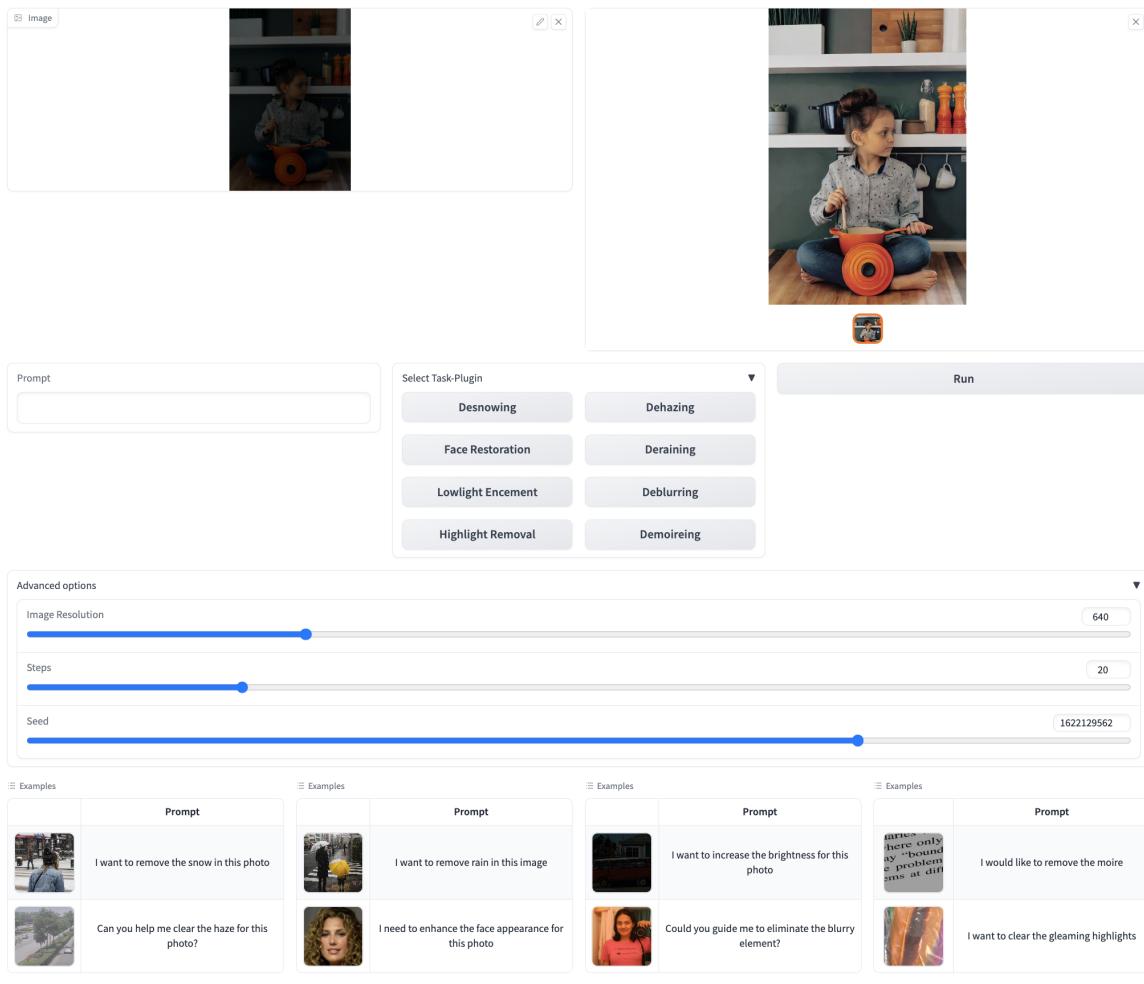


Figure 5. Demo interface diagram of our *Diff-Plugin* framework.

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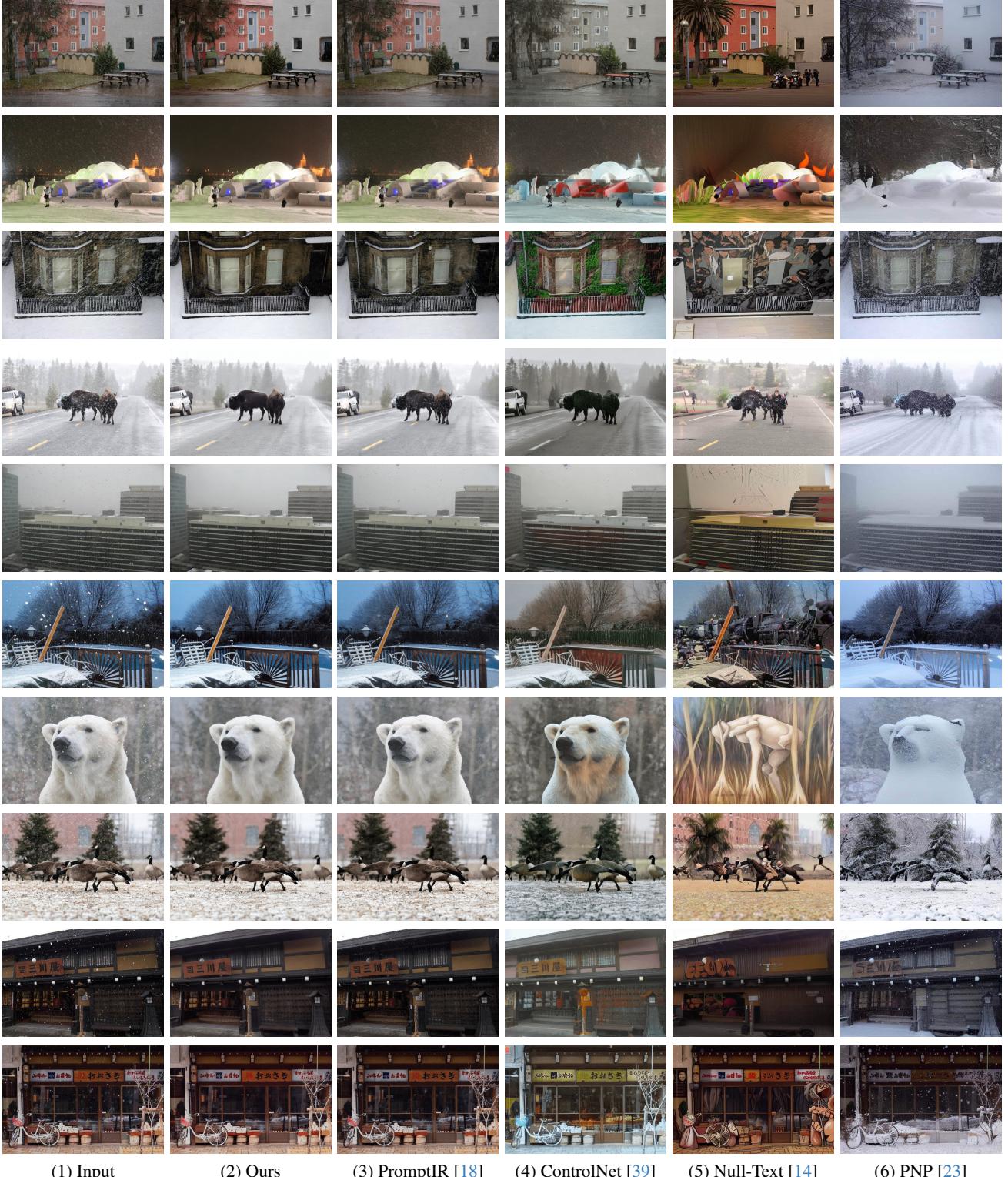


Figure 6. Visual comparisons of our *Diff-Plugin* with four representative approaches (one regression-based multi-task model in (3) and three diffusion-based models in (4)-(6)) on the ***desnowing*** task.

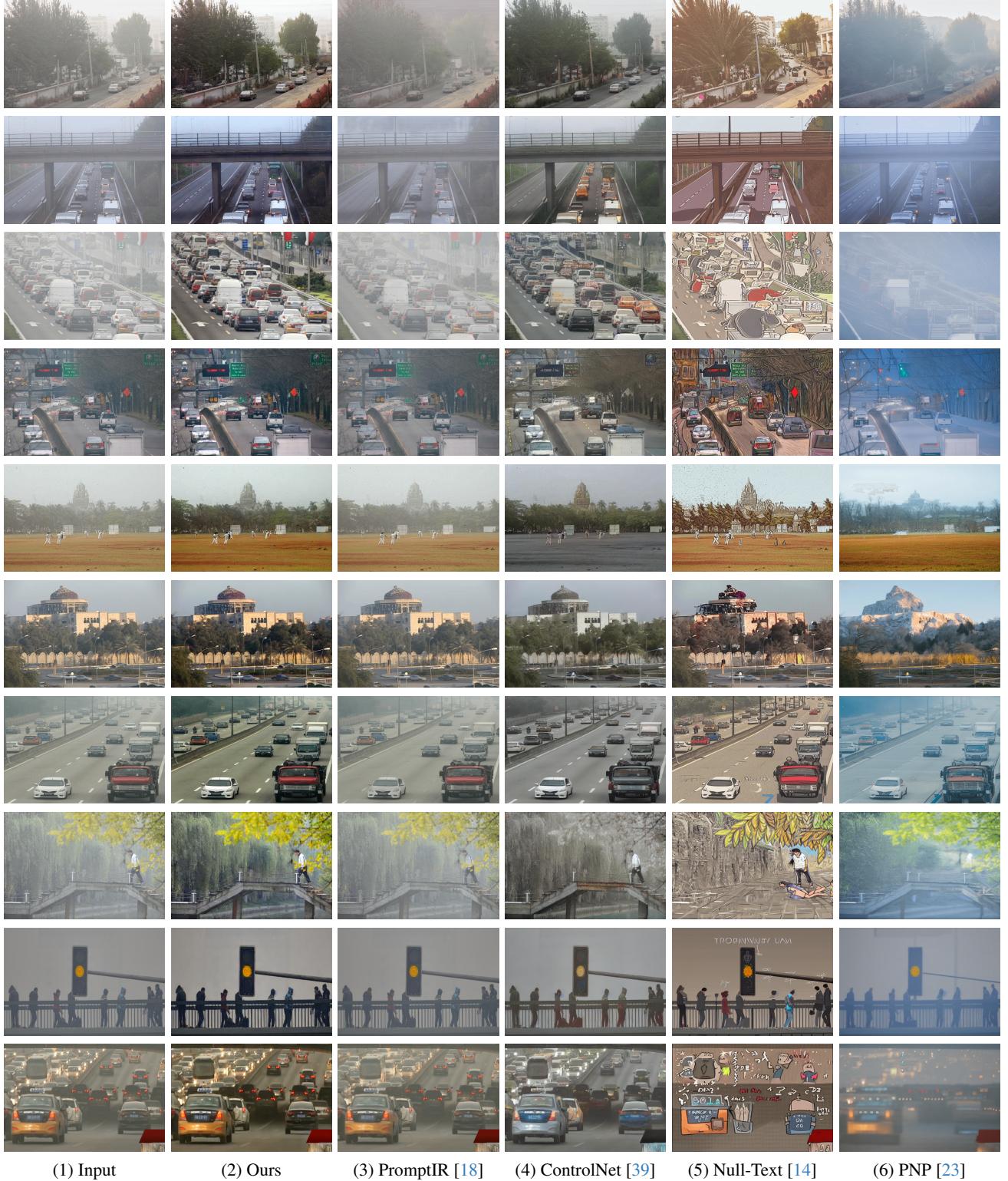


Figure 7. Visual comparisons of our *Diff-Plugin* with four representative approaches (one regression-based multi-task model in (3) and three diffusion-based models in (4)-(6)) on the ***dehazing*** task.

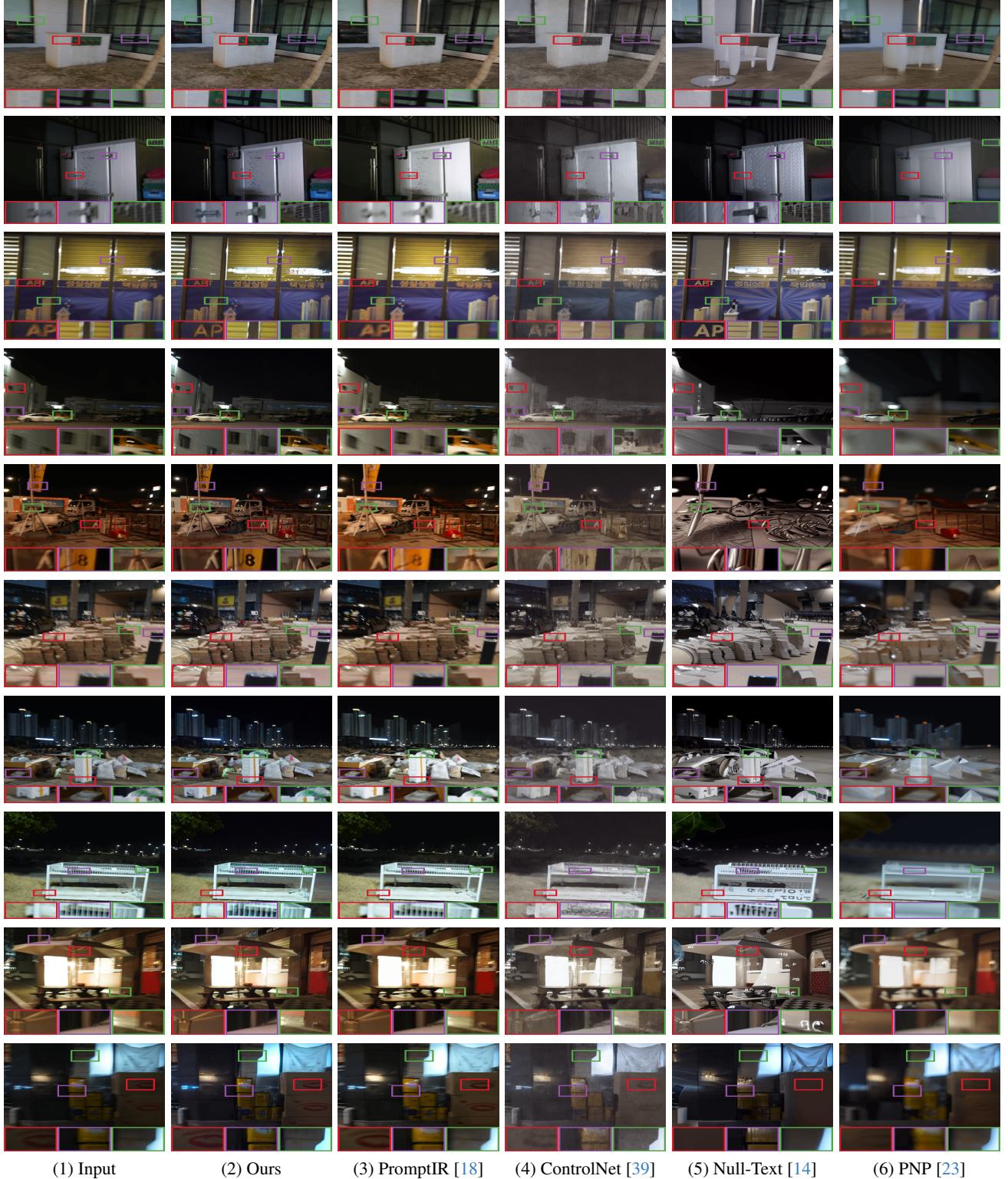


Figure 8. Visual comparisons of our *Diff-Plugin* with four representative approaches (one regression-based multi-task model in (3) and three diffusion-based models in (4)-(6)) on the **deblurring** task. Magnified regions are provided for clarity

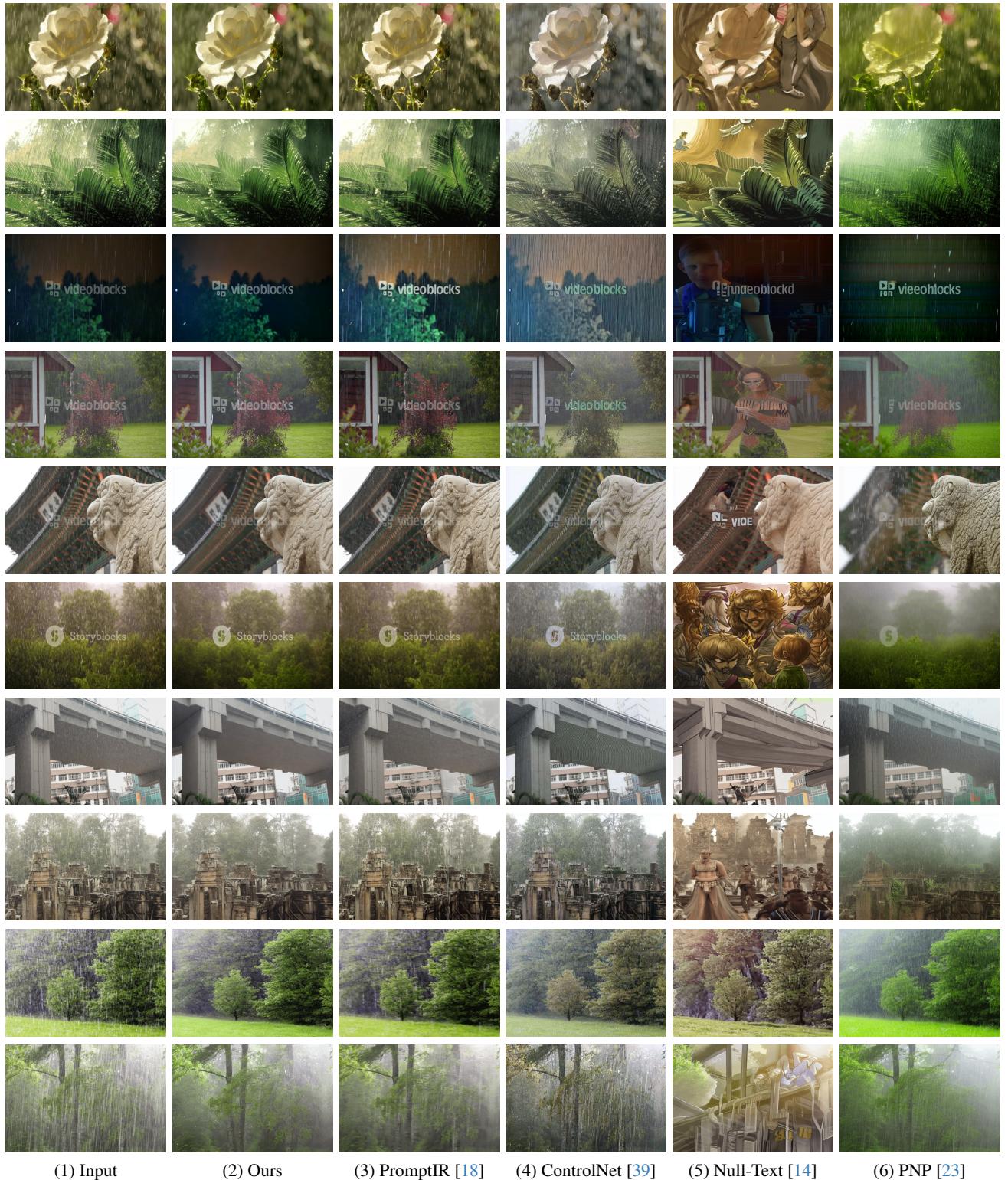


Figure 9. Visual comparisons of our *Diff-Plugin* with four representative approaches (one regression-based multi-task model in (3) and three diffusion-based models in (4)-(6)) on the ***deraining*** task.

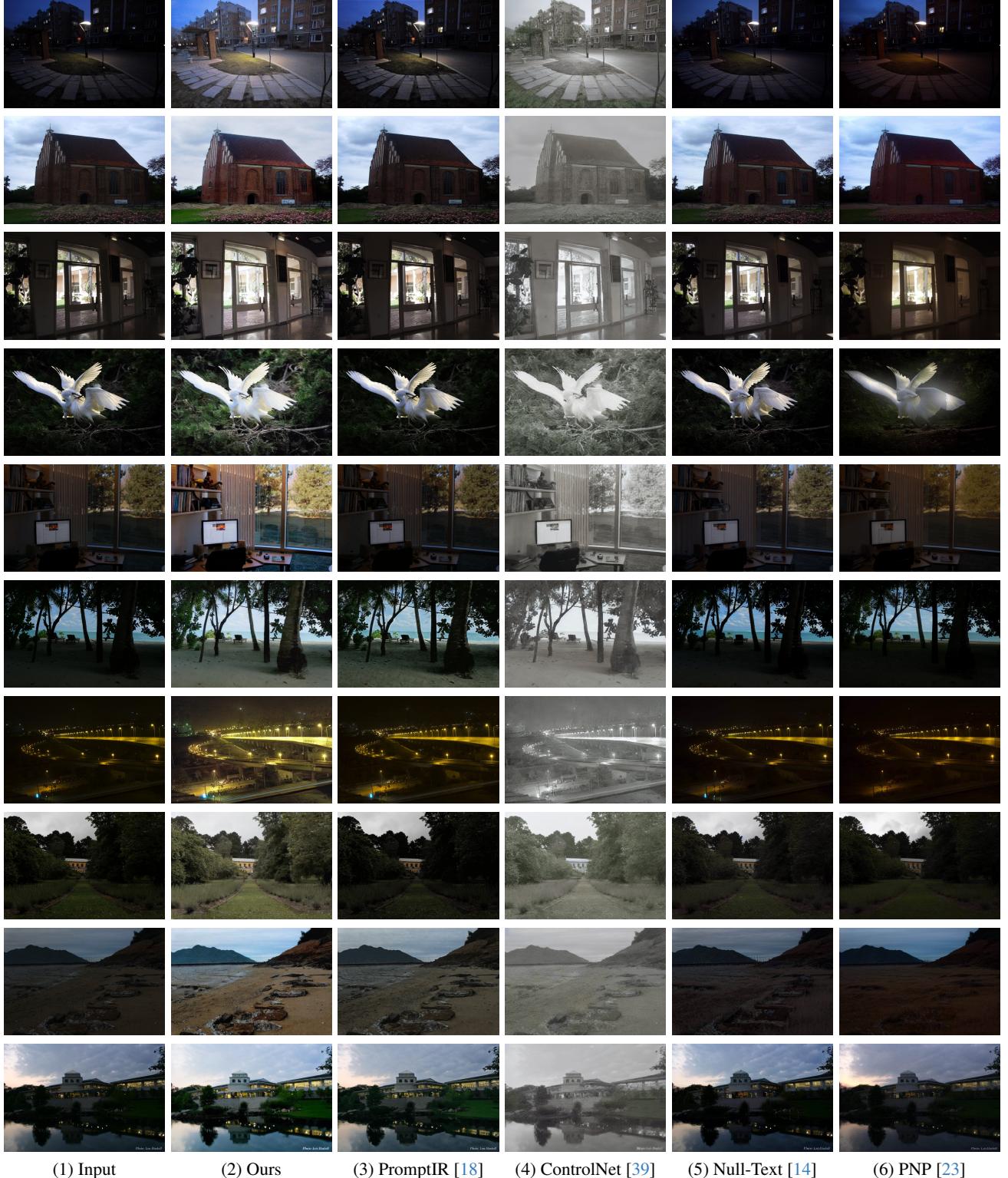


Figure 10. Visual comparisons of our *Diff-Plugin* with four representative approaches (one regression-based multi-task model in (3) and three diffusion-based models in (4)-(6)) on the ***low-light enhancement*** task.

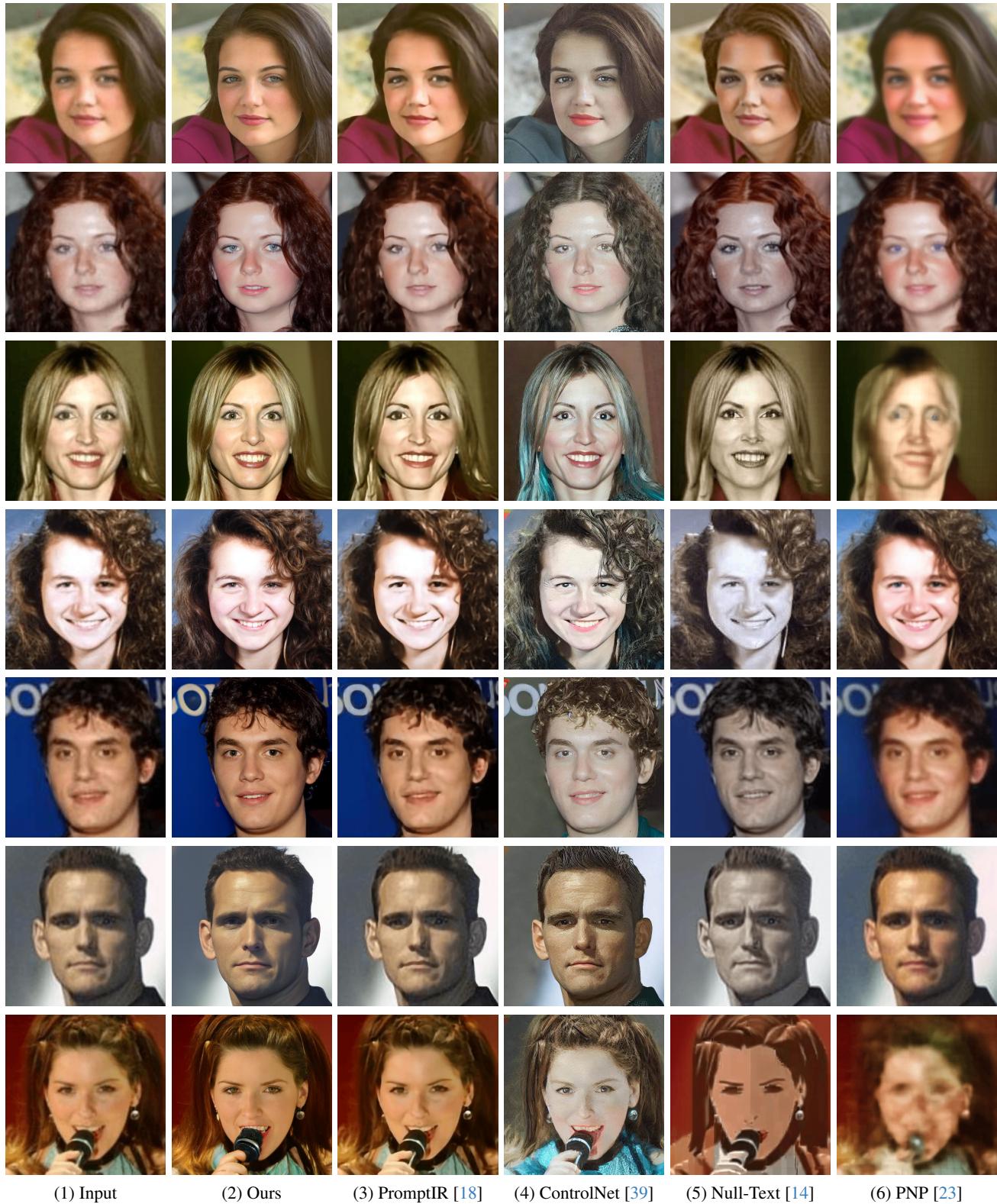


Figure 11. Visual comparisons of our *Diff-Plugin* with four representative approaches (one regression-based multi-task model in (3) and three diffusion-based models in (4)-(6)) on the ***face restoration*** task.

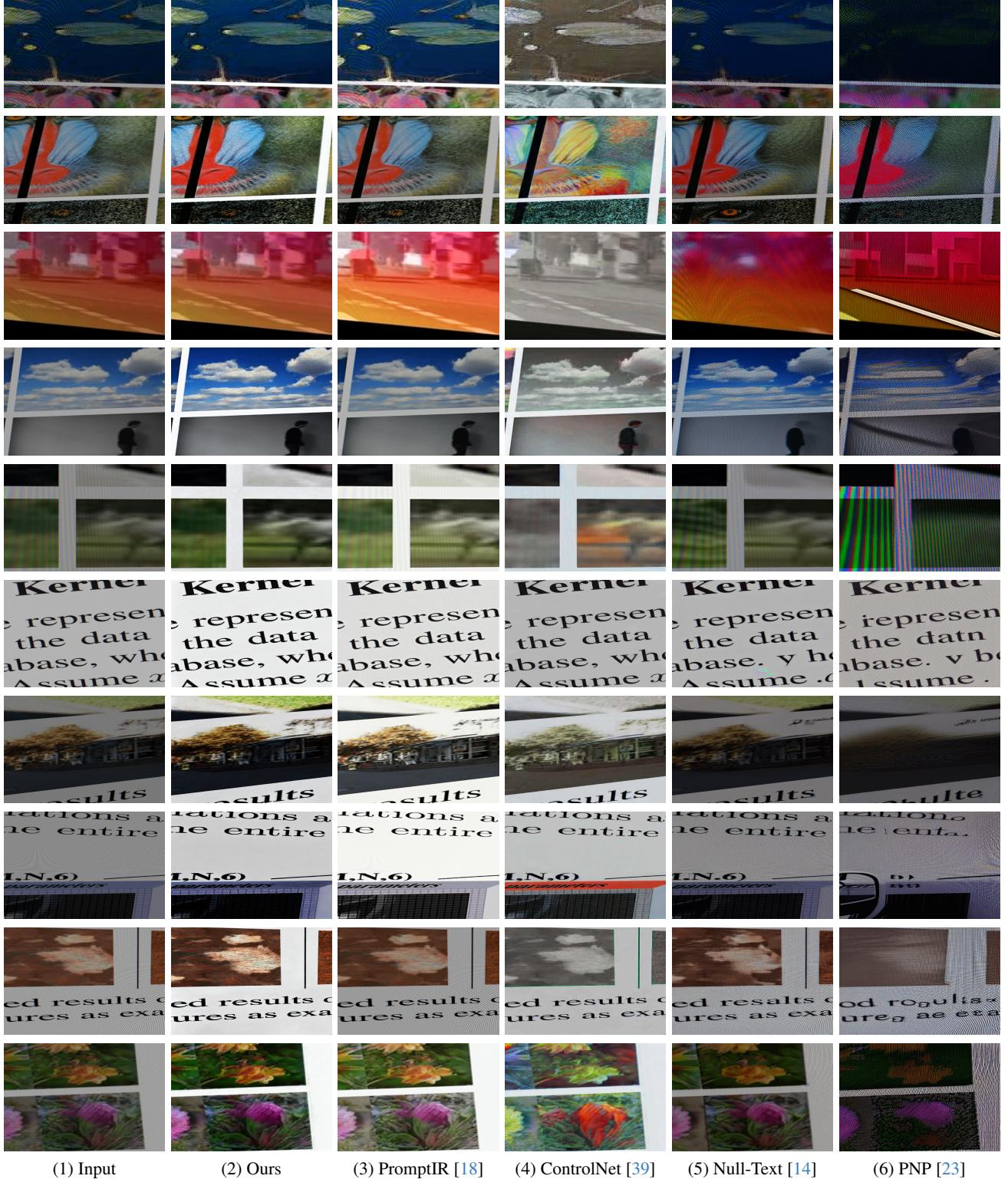


Figure 12. Visual comparisons of our *Diff-Plugin* with four representative approaches (one regression-based multi-task model in (3) and three diffusion-based models in (4)-(6)) on the *demoireing* task.

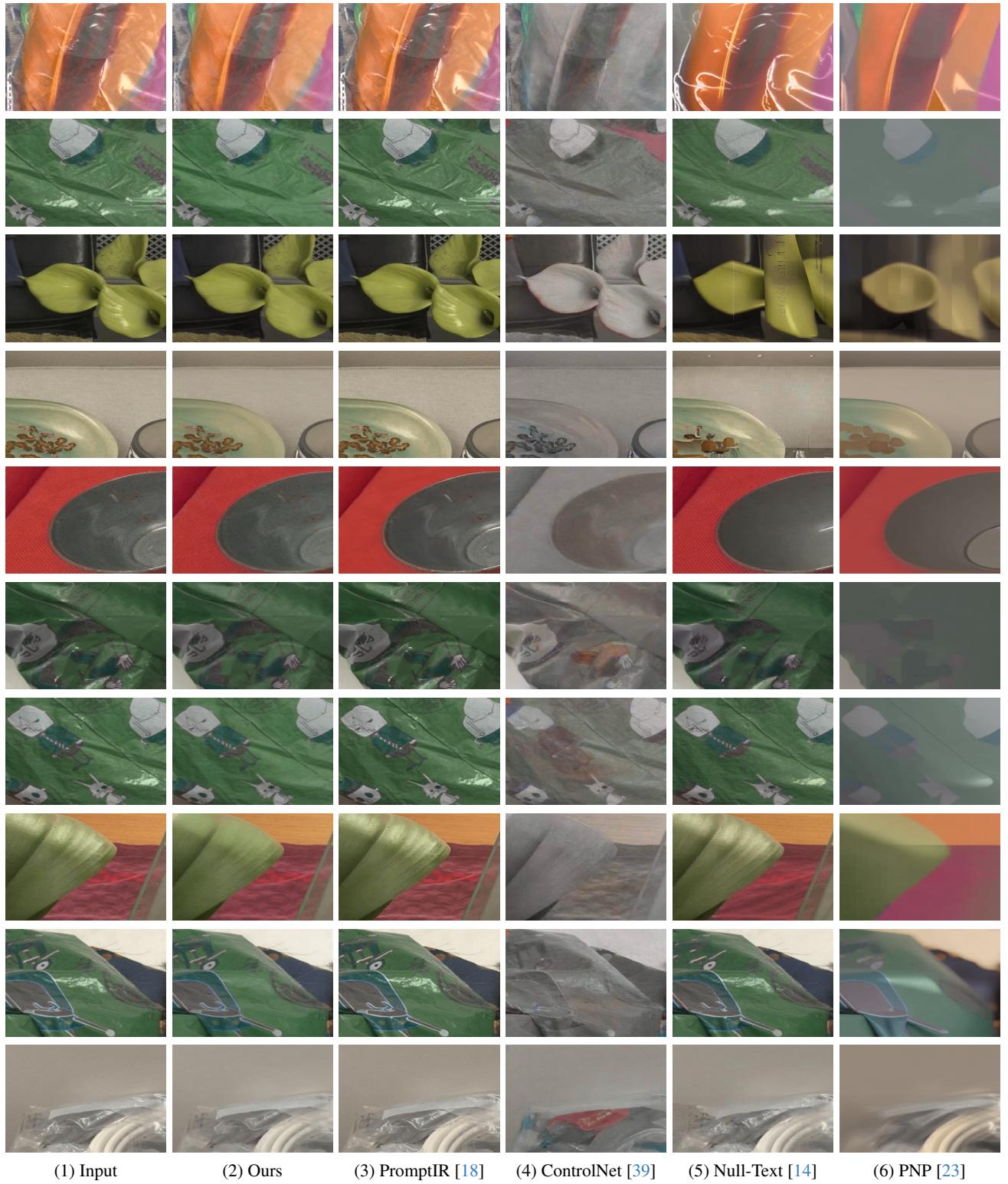


Figure 13. Visual comparisons of our *Diff-Plugin* with four representative approaches (one regression-based multi-task model in (3) and three diffusion-based models in (4)-(6)) on the ***highlight removal*** task.

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