NTIRE 2025 Challenge on Single Image Reflection Removal in the Wild: Datasets, Methods and Results

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Abstract

In this paper, we review the NTIRE 2025 challenge on single-image reflection removal (SIRR) in the wild. SIRR is a fundamental task in image restoration. Despite progress in academic research, most methods are tested on synthetic images or limited real-world images, creating a gap in real-world applications. In this challenge, participants are required to process real-world images that cover a range of reflection scenarios and intensities, with the goal of generating clean images without reflections. The challenge attracted more than 200 registrations, with 11 of them participating in the final testing phase. The top-ranked methods advanced the state-of-the-art reflection removal performance and earned unanimous recognition from the five experts in the field. The proposed datasets are available at `https://huggingface.co/datasets/qiuzhangTiTi/NTIRE2025-SIRR` and the homepage of this challenge is at `https://github.com/caijie0620/Reflection-Removal-in-the-Wild`.

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1. Introduction

SIRR is a critical task in image restoration, focusing on recovering the transmission layer T from an input image I with reflection contamination R caused by different reflective surfaces (e.g., transparent glasses).

Over the years, various techniques have been proposed to address the SIRR problem. Traditional methods typically rely on non-learning paradigms to mitigate the ill-posed nature of this problem [22, 32, 38, 44]. However, these methods usually rely heavily on prior knowledge to guide the recovery process, which can not generate well in real-world scenarios.

To address this issue, deep learning-based methods have been used to model the uncertainty of transmission estimation. Several of the most recent works are summarized in Tab. 1. For example, RobustSIRR [33] adopted a single-stage architecture, taking I as input and only outputting T. This method presents a robust transformer-based model for SIRR, integrating cross-scale attention modules, multi-scale fusion modules, and an adversarial image discriminator to improve performance. In another study, Zhu et al. [50] utilized a two-stage architecture, where the edge map was first estimated and then the final reflection-free output was reconstructed. This framework consists of RDNet and RRNet, in which RDNet leverages a pre-trained backbone with residual blocks and interpolation to estimate the reflection mask, while RRNet uses this estimation to assist the reflection removal process. Some studies used cascaded structures with more stages. [6] presented a LANet for SIRR.

	Methods	Venue	Scheme	Cross-stage fusion
Single-stage	YTMT [12]	NeurIPS 2021	$I \rightarrow [T, R]$	-
	RobustSIRR [33]	CVPR 2023	$I_{multiscale} \rightarrow T$	-
Two-stage	DMGN [9]	TIP 2021	$I \rightarrow [T_1, R]$ $[I, T_1, R] \rightarrow T$	Convolutional Fusion
	RAGNet [23]	Appl. Intell. 2023	$I \rightarrow R$ $[I, R] \rightarrow T$	Convolutional Fusion
	DSRNet [13]	ICCV 2023	$I \rightarrow (T_1, R_1)$ $(R_1, T_1) \rightarrow (R, T, residue)$	N/A
	Zheng et al. [48]	CVPR 2021	$I \rightarrow e$ $[I, e] \rightarrow T$	Concat
	Zhu et al. [50]	CVPR 2024	$I \rightarrow E_R$ $[I, E_R] \rightarrow T$	Concat
	Language-Guided [49]	CVPR 2024	$[I, Texts] \rightarrow RorT$ $[I, RorT] \rightarrow TorR$	Feature-Level Concat
Multi-stage	Chang et al. [1]	WACV 2021	$I \rightarrow E_T$ $[I, E_T] \rightarrow T_1 \rightarrow R_1 \rightarrow T_2$ $[I, E_T, T_2] \rightarrow R \rightarrow T$	Concat Recurrent
	LANet [6]	ICCV 2021	$[I, T_0] \rightarrow R_1 \rightarrow T_1$ $[I, T_1] \rightarrow R_2 \rightarrow T_2$ $\dots$	Concat Recurrent
	V-DESIRR [29]	ICCV 2021	$I_1 \rightarrow T_1$ $[I_1, T_1, I_2] \rightarrow T_2$ $\dots$ $[I_{n-1}, T_{n-1}, I_n] \rightarrow T$	Convolutional Fusion Recurrent

Table 1. **I**, **R**, **T**, and **E** represent the **I**nput, **R**eflection, **T**ransmission, and **E**dge map, respectively. The subscripts of **T** and **R** represent intermediate process outputs. The Absorption Effect e is introduced in [48] to describe light attenuation as it passes through the glass. The output $residue$ term, proposed in [13], is used to correct errors in the additive reconstruction of the reflection and transmission layers. Language descriptions in [49] provide contextual information about the image layers, assisting in addressing the ill-posed nature of the reflection separation problem.

It employs a reflection detection module which generates a probabilistic confidence map using multi-scale Laplacian features. The network is designed as a recurrent model that progressively refines reflection removal, where the Laplacian kernel parameters highlight strongly reflective boundaries to improve detection and enhance result quality.

Despite significant efforts and progress in deep learning, the lack of high-quality data has become an increasing bottleneck, limiting the full potential of models. Collecting large-scale, real-world reflection datasets is currently time-consuming and labor-intensive. Additionally, due to the variations in physical conditions in real-world environments, it is challenging to align transmission and blended image pairs accurately [43]. Recognizing the importance of high-quality data for the success of data-driven approaches, we propose a novel data collection protocol designed specifically to capture high-quality pairs of transmission and blended images. Based on this protocol, we have collected a new real-world, diverse, and pixel-aligned dataset, named OpenRR-1k. This high-quality dataset aims to advance research in reflection removal.

The goal of this challenge is to provide a platform for both industrial and academic participants to evaluate their models on real-world reflection removal scenarios, thus bridging the gap between academic research and practical photography.

This challenge is one of the NTIRE 2025[1] Workshop associated challenges on: ambient lighting normalization [37], reflection removal in the wild [42], shadow removal [36], event-based image deblurring [34], image denoising [35], XGC quality assessment [26], UGC video enhancement [31], night photography rendering [7], image super-resolution (x4) [2], real-world face restoration [3], efficient super-resolution [30], HR depth estimation [45], efficient burst HDR and restoration [15], cross-domain few-shot object detection [10], short-form UGC video quality assessment and enhancement [20, 21], text to image generation model quality assessment [11], day and night raindrop

[1] https://www.cvlai.net/ntire/2025/

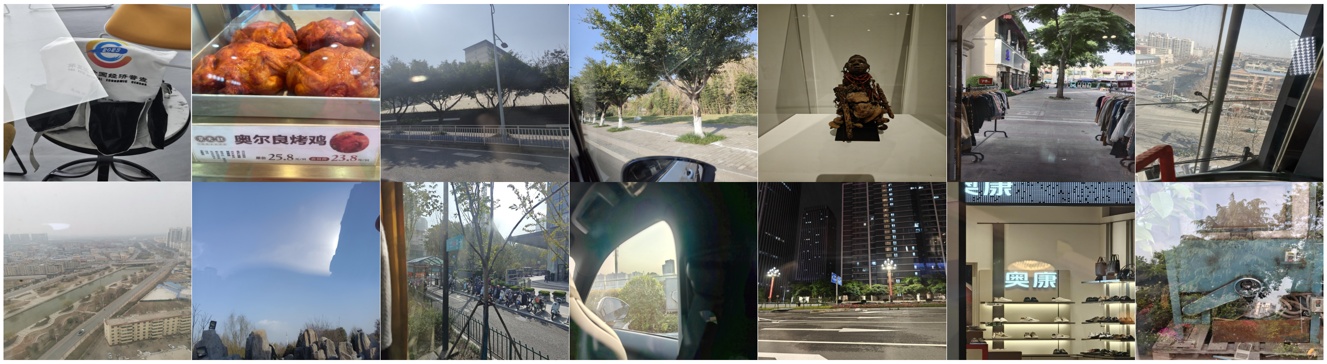

Figure 1. Overview of our OpenRR-1k dataset.

removal for dual-focused images [19], video quality assessment for video conferencing [14], low light image enhancement [27], light field super-resolution [41], restore any image model (RAIM) in the wild [25], raw restoration and super-resolution [4] and raw reconstruction from RGB on smartphones [5].

2. NTIRE 2025 SIRR Challenge

2.1. Overview

Single Image Reflection Removal in the Wild is one of the NTIRE 2025 associated challenges (https://www.cvlai.net/ntire/2025/). The objectives of this SSIR challenge are as follows:

- To establish a benchmark for SIRR in the wild, incorporating real-world images with ground-truth reference across various scenarios, along with both objective and subjective evaluation metrics.
- To promote SIRR research, emphasizing models with strong generalization for real-world images.
- To bridge the gap between academic research and industrial application.

2.2. Challenge Rules

In order to ensure fairness and achieve equitable comparisons to the greatest possible extent, the following competition rules are formulated: (1) Method reproducibility is a must. (2) The method is expected to take a reflection-contaminated image as input and produce a reflection-free image as output. (3) Each participant is allowed to join only one team. Each team is allowed to submit only one algorithm for the final ranking. (4) The final ranking is decided on the basis of the reported performance in terms of quantitative metrics and subjective scores.

2.3. Challenge Phases

There are two phases in the challenge: (1) development and validation phase, (2) testing phase.

Development and Validation Phase: Participants have access to both training and validation data (see Sec. 2.4 for dataset details). The training data comprises 800 paired images. Each pair consists of an input blended image I and its corresponding ground-truth transmission image T. Similarly, the validation data contain another 100 pairs of data samples, but only the input blended images are provided to the participants. Participants can upload their results to the validation server to calculate PSNR and SSIM metrics and receive feedback.

Testing Phase: The organizers provide an additional set of 100 testing images without ground-truth reference. Participants have access to these reflection-contaminated images to generate their final results. Note that the ground-truth images remain inaccessible to the participants throughout this phase. Participants can submit their results to the test server and email their code/results and fact sheets to the organizers. Organizers execute the provided code to verify the reflection removal results, then combine both quantitative metrics and subjective feedback from experienced practitioners to determine the final ranking. The final ranking is shared with all participants at the end of the challenge.

2.4. Datasets

In many practical scenarios, the acquisition of precisely aligned ground-truth images is very difficult. Researchers typically rely on the utilization of props such as glass and cloth in their methodologies. After capturing the blended images, they construct reflection pairs (e.g., (I, T), $(I, I - R)$, etc.) by either removing the glass or blocking the background or reflection light with light-absorbing black velvet cloth [16–18, 39, 46, 50]. For example, Li et al. [18] obtained transmitted images by manually removing the glass. More recently, Zhu et al. [50] proposed a new data collection pipeline that involves blocking all reflection lights generated by the surrounding environment. However, these methods often suffer from uncontrollable environmental factors (such as wind or equipment vibrations), which can induce misalignment and color discrepancies between reflection pairs, thereby undermining the quality of the data obtained.

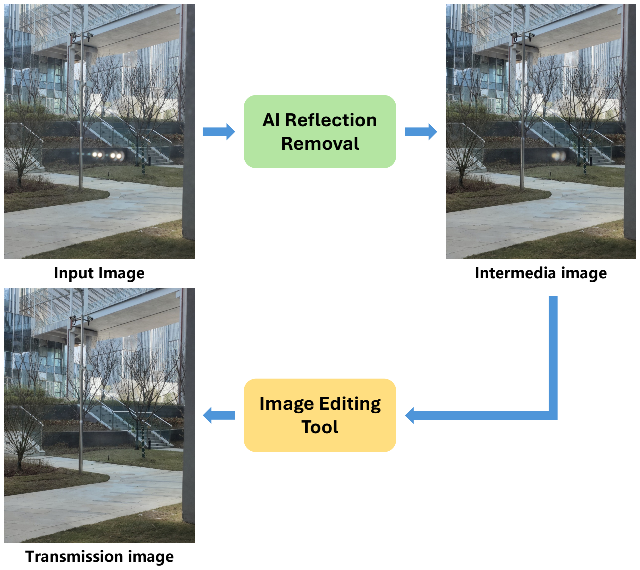

Figure 2. Visualization of paired data generation pipeline for reflection removal.

In this challenge, we designed a novel data collection protocol specifically designed to capture high-quality pairs of transmission and blended images. As illustrated in Fig. 2, our proposed data collection protocol consists of two main phases. During the first phase, we utilized proven effective AI tools to obtain ground-truth images instead of manually removing glass or light-absorbing black cloth. In this challenge, we adopted the AI-based reflection removal software integrated within the OPPO smartphone[2] to obtain the initial transmission results, since it is one of the few effective and widely used tools currently available on the market.

To guarantee the high quality of ground-truth transmission outcome, we further designed a refinement procedure aimed at eliminating any subtle residual reflections or artifacts that might appear. Specifically, we used professional image editing tools such as Photoshop and MeituPic. Through manual minor adjustments, the final images exhibit a high degree of quality, rendering them suitable for both training and evaluation purposes.

Following this protocol, we collected a total of 1,000 high-quality pairs of real-world images for this challenge and constructed our OpenRR-1k dataset. We implemented an 80/10/10 train-val-test split, selecting 800 image pairs for the training set, 100 image pairs for the validation set (OpenRR-1k$_{val}$), and 100 image pairs for the test set (OpenRR-1k$_{test}$). An overview of the OpenRR-1k dataset

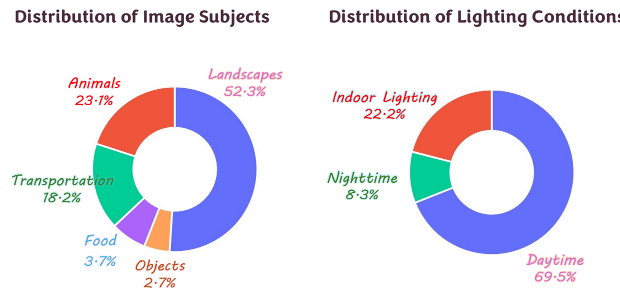

Figure 3. The category distribution of our OpenRR-1k dataset.

is presented in Fig. 1. In addition, Fig. 3 provides a comprehensive summary of the categorical composition of our OpenRR-1k dataset from two perspectives: image subjects and lighting conditions. In terms of image subjects, as illustrated in the left pie chart, the dataset can be systematically classified into five classes: animals, transportation, food, objects, and landscapes. Regarding lighting conditions, as depicted in the right pie chart, the dataset can be partitioned into three distinct scenarios: daytime, nighttime, and indoor lighting. Compared to existing open datasets, our dataset in this challenge not only encompasses more diverse scenarios, but also comprises **TRUE**, **GENUINE** reflection scenarios directly from real-world environments, without relying on artificial setups or simulated reflections. This helps the community to evaluate their models more effectively and gain a deeper understanding of the shortcomings in practical applications.

2.5. Evaluation Metrics

We evaluate the effectiveness of the models with both quantitative measures and subjective evaluation.

2.5.1. Quantitative Measure

Following prior arts [24], the PSNR, SSIM, LPIPS, DISTS and NIQE measures were utilized to conduct a quantitative assessment of the models, by leveraging image pairs with ground-truth reference[3].

2.5.2. Subjective Evaluation

We assessed the perceptual quality of the reflection removal results by visual examination. Specifically, we invited five experienced practitioners and conducted a comprehensive user study. The following criteria were taken into account during the evaluation:

- **Reflection removal cleanliness** (C): Both strong and weak reflections should be removed as completely and cleanly as possible without leaving residuals.
- **Artifacts** (A): Unintended removal or unnatural restoration should be avoided as much as possible.

[2]https://www.oppo.com/en/newsroom/stories/coloros-15-launch-ai/

[3]The script of this measure is available at: https://github.com/caijie0620/Reflection-Removal-in-the-Wild

Rank	Team name	Subjective Score↑	PSNR ↑	SSIM↑	LPIPS↓	DISTS↓	NIQE ↓
1	X-Reflection	4.328125	33.7606	0.9685	0.0298	0.0212	3.7011
2	AIIA	4.324375	32.4062	0.9611	0.0381	0.0285	3.7610
3	Okkk	4.289375	33.5411	0.9674	0.0334	0.0224	3.7606
4	MVP Lab	4.281250	33.3140	0.9682	0.0321	0.0224	3.7375
5	KLETech-CEVI	4.169625	31.7977	0.9601	0.0401	0.0271	3.7315
6	ACVLab	4.089375	32.6355	0.9662	0.0377	0.0277	3.7981
7	i am a bug	3.795000	32.4648	0.9603	0.0454	0.0334	3.5814

Table 2. Quantitative results on Single Image Reflection Removal Challenge.

Figure 4. Qualitative results on Single Image Reflection Removal Challenge.

- **Overall image quality** (Q): The output image should have better image quality (including color fidelity, texture, sharpness, detail preservation, exposure, and contrast) than the input reflection-contaminated image. Additionally, the final result should be visually acceptable and satisfactory to users.

The final score (S) is determined by calculating the weighted average of the three criteria mentioned above.

$$S = 0.25C + 0.25A + 0.5Q \tag{1}$$

2.5.3. Final Evaluation

First, we selected the top seven teams based on their quantitative performance scores 2.5.1 across 100 testing images during the testing phase. Subsequently, we conducted a comprehensive user study to evaluate the perceptual quality of their results. Finally, the final rankings were determined solely by the subjective scores 2.5.2.

3. Challenge Results and Analysis

The challenge attracted 200+ registrations, with 63 of them submitting results during the testing phase, resulting in a total of 280 submissions. Finally, 11 teams submitted the testing phase results (including model outputs, codes, and fact sheets). We conducted a subjective evaluation of the top seven teams based on their performance. Brief descriptions of the methods used by participating teams are provided in Sec. 4 and **supplementary material**, while detailed team information is included in Appendix A.

3.1. Quantitative Results

Tab. 2 presents the performance metrics for the top seven teams. The results reveal several interesting observations. Team X-Reflection achieved the highest subjective score (4.328125) and demonstrated superior performance on most objective metrics, including PSNR (33.7606), SSIM (0.9685), LPIPS (0.0298), and DISTS (0.0212). Notably, the subjective scores for the top four teams exhibited minimal variation, with only a 0.046875 difference between the first and fourth positions, suggesting that human evaluators perceived these results as qualitatively similar despite variations in objective metrics.

The results also highlight interesting trade-offs between different evaluation criteria. For instance, team AIIA secured the second position in subjective evaluation despite having a lower PSNR (32.4062) compared to teams ranked below them. This discrepancy underscores the complex relationship between mathematical fidelity metrics and perceptual quality assessments. Similarly, team "i am a bug" ranked last in subjective evaluation while achieving the best NIQE score (3.5814), further emphasizing that optimization for specific objective metrics does not necessarily translate to enhanced perceptual quality.

3.2. Qualitative Analysis

Fig. 4 provides visual comparisons of the results produced by the competing methods. The qualitative evaluation reveals that top-performing approaches effectively address diverse challenging scenarios.

Visual inspection confirms that higher-ranked methods preserve finer details in the transmission layer while effectively suppressing artifacts from the reflection layer.

4. Challenge Methods

Due to space limitations, we only describe the top two participating teams and their proposed methods here, while the remaining teams are detailed in the **supplementary material**.

4.1. Top Two Teams

4.1.1. X-Reflection

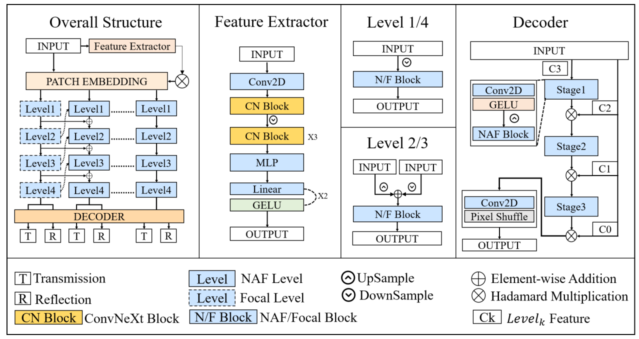

Figure 5. An overview of RDNet+ for Single Image Reflection Removal.

Description: As shown in Fig. 5, we propose RDNet+, which is an improved version of our previous work, RDNet [47], by replacing the prompt generator with backbone-produced features as prompt. Additionally, we employ the model merging technology to obtain a more balanced model.

Implementation: In addition to the training dataset provided by the competition organizers, we add 7,643 synthesized pairs randomly sampled from the PASCAL VOC dataset [8], 90 real pairs from [46], 200 extra real pairs from the "Nature" dataset [18], and 13,700 synthesized pairs sampled from [46].

Our model is implemented using PyTorch and BasicSR [40] frameworks. We employ AdamW [28] optimizer with a learning rate of 0.0001 for the first 40000 iteration, and halved every 40000 iteration. The training is conducted on 8 NVIDIA GeForce RTX 4090 GPUs. Initially, we train with random-cropped patches of size 384. We used MSE, gradient, and VGG perceptual losses during training for 100000 iters. Subsequently, we increase the patch size to 448 and incorporate an additional adversarial loss for the remaining 50000 iterations. During testing, we perform test-time augmentation by flipping the input horizontally, vertically, and both horizontally and vertically.

4.1.2. AIIA

Description: In this study, we propose an innovative reflection removal framework, called DualPatchFusion-ReflectNet (DPF-ReflectNet), as illustrated in Fig. 6. This framework is designed to enhance model performance through three key technological breakthroughs:

1. Two-Stage Fine-Tuning with Progressive Patch Learning: Leveraging a pre-trained RDNet [47] as the backbone, we first conduct Stage-I fine-tuning on the competition training set with standard patch size (e.g., 256×256) to stabilize convergence. Subsequently, Stage-II fine-tuning

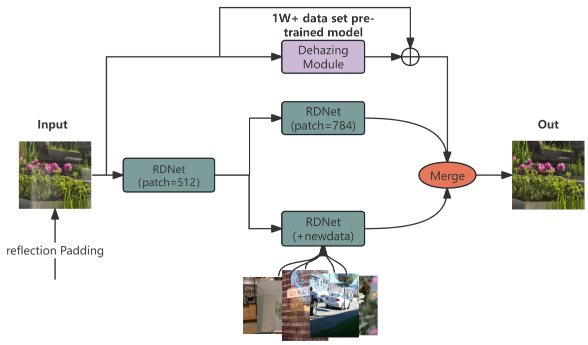

Figure 6. An overview of DualPatchFusion-ReflectNet for Single Image Reflection Removal.

employs enlarged patches (e.g., 512×512), enhancing the model's ability to capture global contextual priors while suppressing overfitting.

2. Cross-Domain Data Fusion for Robust Reflection Modeling: During Stage-II training, we augment the competition dataset with 10,000+ synthetic natural images and 1,200 real-world scene images (collected from public benchmarks). This hybrid dataset bridges the domain gap between synthetic and real reflections, improving generalization through adversarial training with a domain-adaptive discriminator.

3. Reflection-Aware Padding for Arbitrary-Size Inference: At test time, input images are padded to multiples of the network's receptive field using reflective padding, which mirrors edge pixels instead of zero-padding. This strategy eliminates boundary artifacts caused by conventional cropping while preserving structural continuity.

Final predictions are generated by averaging outputs from both fine-tuning stages, leveraging complementary features from different patch contexts.

Implementation: In this experiment, the training set used for the first stage of fine-tuning consisted of 780 images from the competition training set, with the remaining 20 images reserved for the validation set. In the second stage, we added 60 images selected from the "Real" [46] and "Nature" [18] datasets, while the test data was taken from the competition test set. For the first stage, the batch size was set to 2, and the initial learning rate was designed as 1e-4, which was reduced by half every 50 epochs, for a total of 200 epochs. In the second stage, the batch size was set to 4, and the learning rate was 1e-5 for training over 100 epochs. Throughout all stages, the decay factors $\beta_1 = 0.9$ and $\beta_2 = 0.999$ were used to update the Adam optimizer. All training was conducted on a single RTX 3090 GPU.

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