

# Supplementary for SwinIR: Image Restoration Using Swin Transformer

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<https://github.com/JingyunLiang/SwinIR>

## 1. Training and Evaluation Details

**Training.** For classical and lightweight image SR, following [29, 18, 17], we train SwinIR on 800 training images of DIV2K [1]. Some compared methods (e.g., [7], [23]) further use 2560 images from Flickr2K [20] for training, so we also train SwinIR on larger datasets (DIV2K+Flickr2K) to investigate whether SwinIR can further improve its performance. For fair comparison, we use  $48 \times 48$  and  $64 \times 64$  LQ image patches respectively in above two cases following the common settings. The HQ-LQ image pairs are obtained by the MATLAB bicubic kernel. The total training iterations and mini-batch size are set to 500K and 32, respectively. The learning rate is initialized as  $2e-4$  and reduced by half at [250K, 400K, 450K, 475K]. For  $\times 3$ ,  $\times 4$  and  $\times 8$  classical image SR, we initialize the model with  $\times 2$  weights and halve the learning rate as well as total training iterations. Unlike other Transformer-based models that often uses AdamW [13] optimizer with cosine learning rate decay strategy, we find that using Adam [10] optimizer with  $\beta_1 = 0.9$  and  $\beta_2 = 0.99$  leads to better performance.

For real-world image SR, we use the same image degradation model as BSRGAN [28] and train it on a combination of DIV2K, Flickr2K and OST [22]. The model is trained for 1,000K iterations for the PSNR training stage. The learning rate is halved at [500K, 800K, 900K, 950K]. For the GAN training stage, we train it for 600K iterations and the learning rate is halved at [400K, 500K, 550K, 575K]. Weighting parameters between  $L_1$  pixel loss, perceptual loss and GAN loss are 1, 1 and 0.1, respectively. Note that we use the same EMA strategy, USM strategy, perceptual loss and GAN loss as [21].

For denoising and compression artifact reduction, following [30, 27], we use random crops from the combination of 800 DIV2K images, 2650 Flickr2K images, 400 BSD500 images [2] and 4744 WED images [14]. The batch size is 8. The patch sizes are  $128 \times 128$  (window size is  $8 \times 8$ ) and  $126 \times 126$  (window size is  $7 \times 7$ ), respectively. We obtain noisy images by adding additive white Gaussian noises (AWGN) with noise level  $\sigma$ , and compressed images by the MATLAB JPEG encoder with JPEG level  $q$ .

The total training iterations and mini-batch size are set to 1600K and 8, respectively. The learning rate is halved at [800K, 1200K, 1400K, 1500K]. When  $\sigma = 15$  or  $q = 40$ , we train the model from scratch. When  $\sigma = 25/50$  or  $q = 10/20/30$ , we fine-tune from  $\sigma = 15$  or  $q = 40$ . Other details are the same as classical SR.

**Evaluation.** Following the tradition of image SR, we report PSNR and SSIM [24] on the Y channel of the YCbCr space. For image denoising, we report the PSNR on the RGB channel and Y channel for color and grayscale denoising, respectively. For compression artifact reduction, in addition to the Y channel PSNR and SSIM, we also report PNSR-B [25] that is specially designed for deblocking quality assessment. Particularly, we pad the image in testing so that the image size is a multiple of window size. We also find that using a sliding window strategy [4] to crop the image into patches can further improve the PSNR by  $0.02 \sim 0.03$ dB at the cost of longer testing time, so we do not use it for comparison.

## 2. Results on image SR ( $\times 8$ )

We show the comparison on classical image SR ( $\times 8$ ) in Table 1.

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Table 1: Quantitative comparison (average PSNR/SSIM) with state-of-the-art methods for **classical image SR ( $\times 8$ )** on benchmark datasets. Best and second best performance are in **red** and **blue** colors, respectively.

Method	Scale	Training Dataset	Set5 [3]		Set14 [26]		BSD100 [15]		Urban100 [8]		Manga109 [16]	
			PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
SRCNN [6]	$\times 8$	DIV2K	25.33	0.6900	23.76	0.5910	24.13	0.5660	21.29	0.5440	22.46	0.6950
VDSR [9]	$\times 8$	DIV2K	25.93	0.7240	24.26	0.6140	24.49	0.5830	21.70	0.5710	23.16	0.7250
LapSRN [11]	$\times 8$	DIV2K	26.15	0.7380	24.35	0.6200	24.54	0.5860	21.81	0.5810	23.39	0.7350
MemNet [19]	$\times 8$	DIV2K	26.16	0.7414	24.38	0.6199	24.58	0.5842	21.89	0.5825	23.56	0.7387
EDSR [12]	$\times 8$	DIV2K	26.96	0.7762	24.91	0.6420	24.81	0.5985	22.51	0.6221	24.69	0.7841
RCAN [29]	$\times 8$	DIV2K	27.31	0.7878	25.23	0.6511	24.98	0.6058	23.00	0.6452	25.24	0.8029
SAN [5]	$\times 8$	DIV2K	27.22	0.7829	25.14	0.6476	24.88	0.6011	22.70	0.6314	24.85	0.7906
HAN [18]	$\times 8$	DIV2K	27.33	0.7884	25.24	0.6510	24.98	0.6059	22.98	0.6347	25.20	0.8000
<b>SwinIR (Ours)</b>	$\times 8$	DIV2K	27.37	0.7877	25.26	0.6523	24.99	0.6063	23.03	0.6457	25.26	0.8005
<b>SwinIR+ (Ours)</b>	$\times 8$	DIV2K	27.47	0.7907	25.34	0.6546	25.03	0.6078	23.12	0.6499	25.42	0.8047
DBPN [7]	$\times 8$	DIV2K+Flickr2K	27.21	0.7840	25.13	0.6480	24.88	0.6010	22.73	0.6312	25.14	0.7987
<b>SwinIR (Ours)</b>	$\times 8$	DIV2K+Flickr2K	27.55	0.7941	25.46	0.6568	25.04	0.6092	23.17	0.6547	25.55	0.8132
<b>SwinIR+ (Ours)</b>	$\times 8$	DIV2K+Flickr2K	27.59	0.7952	25.51	0.6588	25.08	0.6104	23.27	0.6581	25.73	0.8167

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