

# 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.

## References

- [1] Eirikur Agustsson and Radu Timofte. Ntire 2017 challenge on single image super-resolution: Dataset and study. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 126–135, 2017. [1](#)
- [2] Pablo Arbelaez, Michael Maire, Charless Fowlkes, and Jitendra Malik. Contour detection and hierarchical image segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 33(5):898–916, 2010. [1](#)
- [3] Marco Bevilacqua, Aline Roumy, Christine Guillemot, and Marie line Alberi Morel. Low-complexity single-image super-resolution based on nonnegative neighbor embedding. In *British Machine Vision Conference*, pages 135.1–135.10, 2012. [2](#)

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	<b>0.8029</b>
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
SwinIR (Ours)	$\times 8$	DIV2K	<b>27.37</b>	<b>0.7877</b>	<b>25.26</b>	<b>0.6523</b>	<b>24.99</b>	<b>0.6063</b>	<b>23.03</b>	<b>0.6457</b>	<b>25.26</b>	0.8005
SwinIR+ (Ours)	$\times 8$	DIV2K	<b>27.47</b>	<b>0.7907</b>	<b>25.34</b>	<b>0.6546</b>	<b>25.03</b>	<b>0.6078</b>	<b>23.12</b>	<b>0.6499</b>	<b>25.42</b>	<b>0.8047</b>
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
SwinIR (Ours)	$\times 8$	DIV2K+Flickr2K	<b>27.55</b>	<b>0.7941</b>	<b>25.46</b>	<b>0.6568</b>	<b>25.04</b>	<b>0.6092</b>	<b>23.17</b>	<b>0.6547</b>	<b>25.55</b>	<b>0.8132</b>
SwinIR+ (Ours)	$\times 8$	DIV2K+Flickr2K	<b>27.59</b>	<b>0.7952</b>	<b>25.51</b>	<b>0.6588</b>	<b>25.08</b>	<b>0.6104</b>	<b>23.27</b>	<b>0.6581</b>	<b>25.73</b>	<b>0.8167</b>

- [4] Hanting Chen, Yunhe Wang, Tianyu Guo, Chang Xu, Yiping Deng, Zhenhua Liu, Siwei Ma, Chunjing Xu, Chao Xu, and Wen Gao. Pre-trained image processing transformer. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 12299–12310, 2021. **1**
- [5] Tao Dai, Jianrui Cai, Yongbing Zhang, Shu-Tao Xia, and Lei Zhang. Second-order attention network for single image super-resolution. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 11065–11074, 2019. **2**
- [6] Chao Dong, Chen Change Loy, Kaiming He, and Xiaoou Tang. Learning a deep convolutional network for image super-resolution. In *European Conference on Computer Vision*, pages 184–199, 2014. **2**
- [7] Muhammad Haris, Gregory Shakhnarovich, and Norimichi Ukita. Deep back-projection networks for super-resolution. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 1664–1673, 2018. **1, 2**
- [8] Jia-Bin Huang, Abhishek Singh, and Narendra Ahuja. Single image super-resolution from transformed self-exemplars. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 5197–5206, 2015. **2**
- [9] Jiwon Kim, Jung Kwon Lee, and Kyoung Mu Lee. Accurate image super-resolution using very deep convolutional networks. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 1646–1654, 2016. **2**
- [10] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014. **1**
- [11] Wei-Sheng Lai, Jia-Bin Huang, Narendra Ahuja, and Ming-Hsuan Yang. Deep laplacian pyramid networks for fast and accurate super-resolution. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 624–632, 2017. **2**
- [12] Bee Lim, Sanghyun Son, Heewon Kim, Seungjun Nah, and Kyoung Mu Lee. Enhanced deep residual networks for single image super-resolution. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 136–144, 2017. **2**
- [13] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017. **1**
- [14] Kede Ma, Zhengfang Duanmu, Qingbo Wu, Zhou Wang, Hongwei Yong, Hongliang Li, and Lei Zhang. Waterloo exploration database: New challenges for image quality assessment models. *IEEE Transactions on Image Processing*, 26(2):1004–1016, 2016. **1**
- [15] David Martin, Charless Fowlkes, Doron Tal, and Jitendra Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In *IEEE Conference on International Conference on Computer Vision*, pages 416–423, 2001. **2**
- [16] Yusuke Matsui, Kota Ito, Yuji Aramaki, Azuma Fujimoto, Toru Ogawa, Toshihiko Yamasaki, and Kiyoharu Aizawa. Sketch-based manga retrieval using manga109 dataset. *Multimedia Tools and Applications*, 76(20):21811–21838, 2017. **2**
- [17] Yiqun Mei, Yuchen Fan, and Yuqian Zhou. Image super-resolution with non-local sparse attention. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 3517–3526, 2021. **1**
- [18] Ben Niu, Weilei Wen, Wenqi Ren, Xiangde Zhang, Lianping Yang, Shuzhen Wang, Kaihao Zhang, Xiaochun Cao, and Haifeng Shen. Single image super-resolution via a holistic attention network. In *European Conference on Computer Vision*, pages 191–207, 2020. **1, 2**
- [19] Ying Tai, Jian Yang, Xiaoming Liu, and Chunyan Xu. Memnet: A persistent memory network for image restoration. In *IEEE International Conference on Computer Vision*, pages 4539–4547, 2017. **2**
- [20] Radu Timofte, Eirikur Agustsson, Luc Van Gool, Ming-Hsuan Yang, and Lei Zhang. Ntire 2017 challenge on single image super-resolution: Methods and results. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 114–125, 2017. **1**
- [21] Xintao Wang, Liangbin Xie, Chao Dong, and Ying Shan. Real-esrgan: Training real-world blind super-resolution with pure synthetic data. *arXiv preprint arXiv:2107.10833*, 2021. **1**
- [22] Xintao Wang, Ke Yu, Chao Dong, and Chen Change Loy. Recovering realistic texture in image super-resolution by deep spatial feature transform. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 606–615, 2018. **1**

- [23] Xintao Wang, Ke Yu, Shixiang Wu, Jinjin Gu, Yihao Liu, Chao Dong, Yu Qiao, and Chen Change Loy. Esrgan: Enhanced super-resolution generative adversarial networks. In *European Conference on Computer Vision Workshops*, pages 701–710, 2018. [1](#)
- [24] Zhou Wang, Alan C Bovik, Hamid R Sheikh, and Eero P Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4):600–612, 2004. [1](#)
- [25] Changhoon Yim and Alan Conrad Bovik. Quality assessment of deblocked images. *IEEE Transactions on Image Processing*, 20(1):88–98, 2010. [1](#)
- [26] Roman Zeyde, Michael Elad, and Matan Protter. On single image scale-up using sparse-representations. In *International Conference on Curves and Surfaces*, pages 711–730, 2010. [2](#)
- [27] Kai Zhang, Yawei Li, Wangmeng Zuo, Lei Zhang, Luc Van Gool, and Radu Timofte. Plug-and-play image restoration with deep denoiser prior. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2021. [1](#)
- [28] Kai Zhang, Jingyun Liang, Luc Van Gool, and Radu Timofte. Designing a practical degradation model for deep blind image super-resolution. In *IEEE Conference on International Conference on Computer Vision*, 2021. [1](#)
- [29] Yulun Zhang, Kunpeng Li, Kai Li, Lichen Wang, Bineng Zhong, and Yun Fu. Image super-resolution using very deep residual channel attention networks. In *European Conference on Computer Vision*, pages 286–301, 2018. [1, 2](#)
- [30] Yulun Zhang, Yapeng Tian, Yu Kong, Bineng Zhong, and Yun Fu. Residual dense network for image restoration. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 43(7):2480–2495, 2020. [1](#)