# Accelerating the Super-Resolution Convolutional Neural Network : Supplementary File

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**Abstract.** In this supplementary file, we first present more quantitative results for experiments that employed the 91-image dataset as the training set. SSIM and IFC [1] are reported. Then we follow the literature to compare with seven state-of-the-art super-resolution algorithms trained with different datasets. All results are evaluated in terms of PSNR, SSIM and IFC on the Set5 [2], Set14 [3] and BSD200 [4] datasets.

## 1 Experimental Results

### 1.1 Comparison Using the Same Training Set

We first compare our method with four state-of-the-art super-resolution algorithms – the super-resolution forest (SRF) [5], SRCNN [6], SRCNN-Ex [7] and the sparse coding based network (SCN) [8]. For fair comparison, all models are trained purely on the augmented 91-image dataset. All the implementations are based on the authors' released code. In addition to the PSNR values reported in the original paper, we also present the quantitative results of SSIM and IFC [1] in Table 1. As mentioned in the paper, the proposed FSRCNN outperforms other methods on PSNR values on most upscaling factors and datasets. From Table 1, we can also observe the same trend for SSIM. While for IFC, FSRCNN is slightly inferior to SRF, but is superior to SCN and SRCNN especially on $\times 2$ and $\times 3$.

**Table 1.** The results of PSNR (dB), SSIM and IFC [1] on the Set5 [2], Set14 [3] and BSD200 [4] datasets. All models are trained on the 91-image dataset.

| test dataset | × | SRF PSNR/SSIM/IFC | SRCNN [6] PSNR/SSIM/IFC | SRCNN-Ex [7] PSNR/SSIM/IFC | SCN [8] PSNR/SSIM/IFC | FSRCNN-s PSNR/SSIM/IFC | FSRCNN PSNR/SSIM/IFC |
|---|---|---|---|---|---|---|---|
| Set5 | 2 | 36.84/0.9554/**8.64** | 36.33/0.9520/7.56 | 36.67/0.9540/7.99 | 36.76/0.9545/7.32 | 36.53/0.9531/7.75 | **36.94/0.9552**/7.96 |
| Set14 | 2 | 32.46/0.9067/**8.20** | 32.15/0.9035/7.25 | 32.35/0.9061/7.69 | 32.48/0.9067/7.00 | 32.22/0.9049/7.44 | **32.54/0.9080**/7.59 |
| BSD200 | 2 | 31.57/0.9042/**7.57** | 31.34/0.9004/6.84 | 31.53/0.9036/7.19 | 31.63/0.9048/6.45 | 31.44/0.9025/7.03 | **31.73/0.9064**/7.14 |
| Set5 | 3 | 32.73/0.9098/**4.89** | 32.45/0.9040/4.32 | 32.83/0.9102/4.51 | 33.04/**0.9136**/4.37 | 32.55/0.9059/4.57 | **33.06**/0.9128/4.77 |
| Set14 | 3 | 29.21/0.8198/**4.48** | 29.01/0.8146/4.01 | 29.26/0.8210/4.17 | 29.37/0.8226/3.99 | 29.08/0.8169/4.25 | **29.37/0.8231**/4.37 |
| BSD200 | 3 | 28.40/08082/**4.90** | 28.27/0.8035/3.72 | 28.47/0.8010/3.84 | 28.54/0.8119/3.59 | 28.32/0.8061/3.97 | **28.55/0.8123**/4.04 |
| Set5 | 4 | 30.35/0.8601/**3.25** | 30.15/0.8522/2.90 | 30.45/0.8632/2.98 | **30.82/0.8728**/3.07 | 30.04/0.8490/2.73 | 30.55/0.8619/2.93 |
| Set14 | 4 | 27.41/0.7488/**2.93** | 27.21/0.7424/2.64 | 27.44/0.7509/2.70 | **27.62/0.7571**/2.71 | 27.12/0.7411/2.52 | 27.50/0.7509/2.64 |
| BSD200 | 4 | 26.85/0.7351/**2.60** | 26.72/0.7294/2.38 | 26.88/0.7369/2.42 | **27.02/0.7434**/2.38 | 26.73/0.7306/2.30 | 26.92/0.7378/2.35 |

### 1.2 Comparison Using Different Training Sets

We further compare with seven state-of-the-art algorithms trained on different datasets (following the literature), namely the neighbour embedding + locally linear embedding method (NE+LLE) [9], KK [10], the anchored neighbourhood regression method (ANR) [11], the adjusted ANR (A+) [12], SRF [5], SRCNN [6], SRCNN-Ex [7] and SCN [8]. The quantitative results of PSNR, SSIM and IFC [1] are shown in Table 2 and 3. As all the implementations are based on the authors' released code, the results may be slightly different from that reported in the corresponding paper. Our models FSRCNN and FSRCNN-s are trained on the 91-image and General-100 datasets. Note that the results of SCN are the same as in Table 1. As the authors do not release the training code, we cannot get the results (except PSNR) reported in the paper. Figure 1-4 show some reconstructed images on the BSD200 dataset with an upscaling factor 3.

**Table 2.** The results of PSNR (dB), SSIM and IFC [1] on the Set5 [2], Set14 [3] and BSD200 [4] datasets. Following the literature, each model is trained using the specific dataset reported in the corresponding paper. The proposed FSCNN and FSRCNN-s are trained on both the 91-image and General-100 datasets.

| test dataset | × | Bicubic PSNR/SSIM/IFC | NE+LLE [9] PSNR/SSIM/IFC | KK [10] PSNR/SSIM/IFC | ANR [11] PSNR/SSIM/IFC | A+ [11] PSNR/SSIM/IFC | SRF [5] PSNR/SSIM/IFC |
|---|---|---|---|---|---|---|---|
| Set5 | 2 | 33.66/0.9299/6.10 | 35.77/0.9490/7.84 | 36.20/0.9511/6.87 | 35.83/0.9499/8.09 | 36.55/0.9544/8.48 | 36.87/0.9556/**8.63** |
| Set14 | 2 | 30.23/0.8687/6.09 | 31.76/0.8993/7.59 | 32.11/0.9026/6.83 | 31.80/0.9004/7.81 | 32.28/0.9056/8.11 | 32.51/0.9074/**8.22** |
| BSD200 | 2 | 29.70/0.8625/5.70 | 30.97/0.8955/7.07 | 31.30/0.9000/6.26 | 31.02/0.8968/7.27 | 31.44/0.9031/7.49 | 31.65/0.9053/**7.60** |
| Set5 | 3 | 30.39/0.9299/3.52 | 31.84/0.8956/4.40 | 32.28/0.9033/4.14 | 31.92/0.8968/4.52 | 32.59/0.9088/4.84 | 32.71/0.9098/**4.90** |
| Set14 | 3 | 27.54/0.7736/3.41 | 28.60/0.8076/4.14 | 28.94/0.8132/3.83 | 28.65/0.8093/4.23 | 29.13/0.8188/4.45 | 29.23/0.8206/**4.49** |
| BSD200 | 3 | 27.26/0.7638/3.19 | 27.98/0.7964/3.81 | 28.19/0.8016/3.49 | 28.02/0.7981/3.91 | 28.36/0.8078/4.07 | 28.45/0.8095/4.11 |
| Set5 | 4 | 28.42/0.8104/2.35 | 29.61/0.8402/2.94 | 30.03/0.8541/2.81 | 29.69/0.8419/3.02 | 30.28/0.8603/**3.26** | 30.35/0.8600/3.26 |
| Set14 | 4 | 26.00/0.7019/2.23 | 26.81/0.7331/2.71 | 27.14/0.7419/2.57 | 26.85/0.7353/2.78 | 27.32/0.7471/2.74 | 27.41/0.7497/**2.94** |
| BSD200 | 4 | 25.97/0.6949/2.04 | 26.52/0.7232/2.44 | 26.68/0.7282/2.22 | 26.56/0.7253/2.51 | 26.83/0.7359/2.62 | 26.89/0.7368/**2.62** |

**Table 3.** (Continue from Table 2) The results of PSNR (dB), SSIM and IFC [1] on the Set5 [2], Set14 [3] and BSD200 [4] datasets. Following the literature, each model is trained using the specific dataset reported in the corresponding paper. The proposed FSCNN and FSRCNN-s are trained on both the 91-image and General-100 datasets.

| test dataset | × | Bicubic PSNR/SSIM/IFC | SRCNN [6] PSNR/SSIM/IFC | SRCNN-Ex [7] PSNR/SSIM/IFC | SCN [8] PSNR/SSIM/IFC | FSRCNN-s PSNR/SSIM/IFC | FSRCNN PSNR/SSIM/IFC |
|---|---|---|---|---|---|---|---|
| Set5 | 2 | 33.66/0.9299/6.10 | 36.34/0.9521/7.54 | 36.66/0.9542/8.05 | 36.76/0.9545/7.32 | 36.58/0.9532/7.75 | **37.00/0.9558**/8.06 |
| Set14 | 2 | 30.23/0.8687/6.09 | 32.18/0.9039/7.22 | 32.45/0.9067/7.76 | 32.48/0.9067/7.00 | 32.28/0.9052/7.47 | **32.63/0.9088**/7.71 |
| BSD200 | 2 | 29.70/0.8625/5.70 | 31.38/0.9287/6.80 | 31.63/0.9044/7.26 | 31.63/0.9048/6.45 | 31.48/0.9027/7.01 | **31.80/0.9074**/7.25 |
| Set5 | 3 | 30.39/0.9299/3.52 | 32.39/0.9033/4.25 | 32.75/0.9090/4.58 | 33.04/0.9136/4.37 | 32.54/0.9055/4.56 | **33.16/0.9140**/4.88 |
| Set14 | 3 | 27.54/0.7736/3.41 | 29.00/0.8145/3.96 | 29.30/0.8215/4.26 | 29.37/0.8226/3.99 | 29.08/0.8167/4.24 | **29.43/0.8242**/4.47 |
| BSD200 | 3 | 27.26/0.7638/3.19 | 28.28/0.8038/3.67 | 28.48/0.8102/3.92 | 28.54/0.8119/3.59 | 28.32/0.8058/3.96 | **28.60/0.8137/4.11** |
| Set5 | 4 | 28.42/0.8104/2.35 | 30.09/0.8530/2.86 | 30.49/0.8628/3.01 | **30.82/0.8728**/3.07 | 30.11/0.8499/2.76 | 30.71/0.8657/3.01 |
| Set14 | 4 | 26.00/0.7019/2.23 | 27.20/0.7413/2.60 | 27.50/0.7513/2.74 | **27.62/0.7571**/2.71 | 27.19/0.7423/2.55 | 27.59/0.7535/2.70 |
| BSD200 | 4 | 25.97/0.6949/2.04 | 26.73/0.7291/2.37 | 26.92/0.7376/2.46 | **27.02/0.7434**/2.38 | 26.75/0.7312/2.32 | 26.98/0.7398/2.41 |

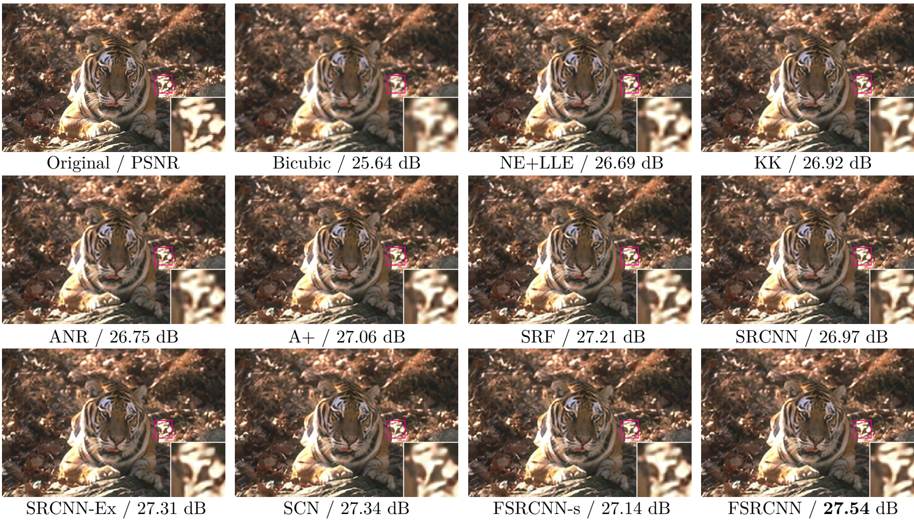


**Fig. 1.** The “108069” image from the BSD200 dataset with an upscaling factor 3.

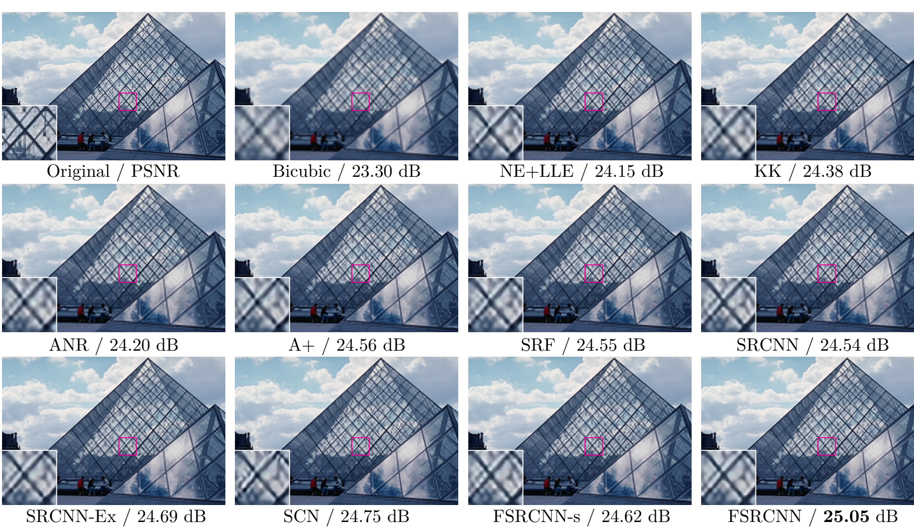


**Fig. 2.** The “223060” image from the BSD200 dataset with an upscaling factor 3.

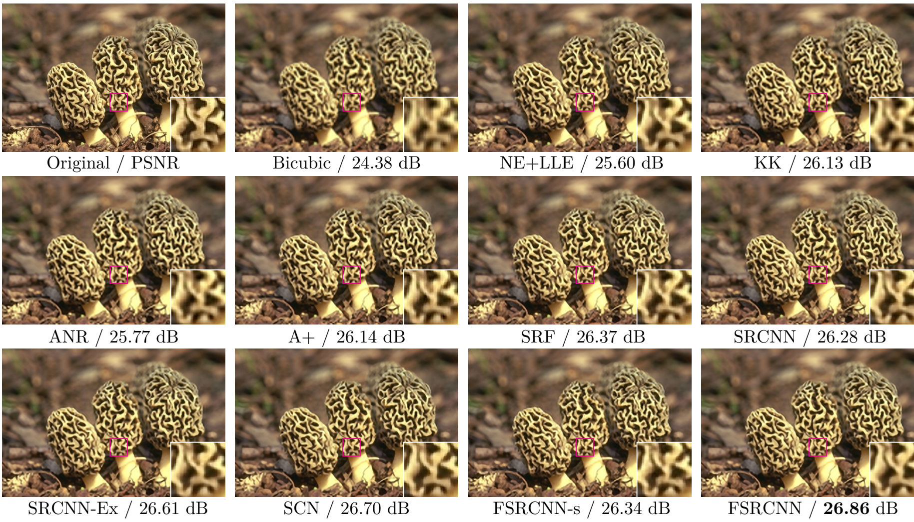


**Fig. 3.** The “208078” image from the BSD200 dataset with an upscaling factor 3.

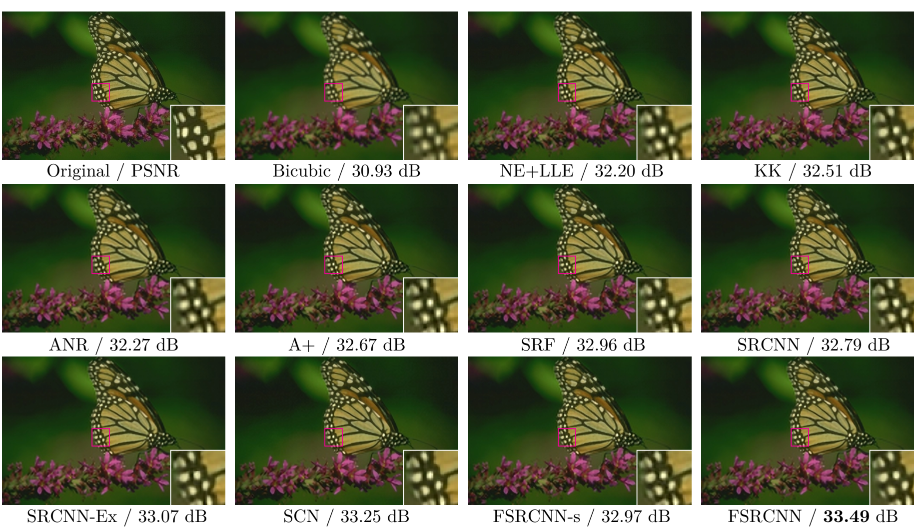


**Fig. 4.** The “35049” image from the BSD200 dataset with an upscaling factor 3.

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