# NTIRE 2017 Challenge on Single Image Super-Resolution: Dataset and Study (supplementary material)

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## Abstract

*This is a supplement to our paper, "NTIRE 2017 Challenge on Single Image Super-Resolution: Dataset and Study" [1]. We report results for the top challenge methods [10]: SNU_CVLab1 [6], SNU_CVLab2 [6], Lab402 [2] and HelloSR [10] in comparison with VDSR [5] and A+ [12]. We use the classic setup (bicubic downscaling) of the challenge and report PSNR, SSIM [9], IFC [8], and CORNIA [13] results computed on Y channel from YCbCr or directly on the RGB super-resolved image for $\times 2$, $\times 3$, $\times 4$ magnification factors. In addition to our newly introduced DIV2K dataset [1] we report also results for the most commonly used datasets in the recent literature: Set5 [3, 11], Set14 [14], B100 [7, 12], and Urban100 [4].*

## 1. DIV2K Test 100 images: quantitative results

In Tables 1,2,and 3 we report average quantitative results over DIV2K test 100 images for magnification factors $\times 2$, $\times 3$, and $\times 4$, respectively. Bicubic interpolation result is included for reference.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 36.38 | 0.953 | 8.11 | 13.4 | 34.93 | 0.948 | 8.22 | 13.0 |
| SNU_CVLab2 | 36.28 | 0.953 | 8.06 | 14.7 | 34.83 | 0.947 | 8.17 | 14.4 |
| Lab402 | 36.12 | 0.952 | 7.97 | 13.6 | 34.66 | 0.946 | 8.07 | 13.3 |
| HelloSR | 35.87 | 0.950 | 7.91 | 15.1 | 34.43 | 0.944 | 8.03 | 14.7 |
| VDSR[5] | 35.09 | 0.943 | 7.28 | 17.7 | 33.47 | 0.935 | 7.36 | 17.4 |
| A+[12] | 34.26 | 0.935 | 7.98 | 29.5 | 32.64 | 0.925 | 7.15 | 29.4 |
| Bicubic | 32.44 | 0.910 | 6.31 | 45.9 | 30.98 | 0.899 | 5.76 | 45.6 |

Table 1. Quantitative results on the test set of DIV2K with $\times 2$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 32.59 | 0.900 | 4.97 | 21.2 | 31.13 | 0.889 | 5.01 | 20.9 |
| SNU_CVLab2 | 32.49 | 0.899 | 4.93 | 22.2 | 31.04 | 0.888 | 4.97 | 21.9 |
| Lab402 | 32.29 | 0.896 | 4.80 | 22.8 | 30.83 | 0.884 | 4.83 | 22.5 |
| HelloSR | 32.20 | 0.895 | 4.78 | 23.4 | 30.74 | 0.883 | 4.82 | 23.1 |
| VDSR[5] | 31.48 | 0.881 | 4.40 | 27.0 | 29.89 | 0.866 | 4.43 | 26.9 |
| A+[12] | 30.89 | 0.869 | 4.61 | 40.3 | 29.32 | 0.852 | 4.26 | 40.3 |
| Bicubic | 29.66 | 0.837 | 3.67 | 58.3 | 28.20 | 0.821 | 3.43 | 57.9 |

Table 2. Quantitative results on the test set of DIV2K with $\times 3$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 30.56 | 0.853 | 3.39 | 26.4 | 29.09 | 0.837 | 3.41 | 26.2 |
| SNU_CVLab2 | 30.51 | 0.852 | 3.38 | 27.1 | 29.04 | 0.836 | 3.40 | 27.1 |
| Lab402 | 30.30 | 0.846 | 3.28 | 28.9 | 28.83 | 0.830 | 3.30 | 28.8 |
| HelloSR | 30.27 | 0.846 | 3.26 | 28.2 | 28.80 | 0.830 | 3.28 | 28.1 |
| VDSR[5] | 29.58 | 0.828 | 2.91 | 35.2 | 27.98 | 0.808 | 2.93 | 35.3 |
| A+[12] | 29.15 | 0.815 | 3.05 | 46.3 | 27.58 | 0.793 | 2.86 | 46.5 |
| Bicubic | 28.12 | 0.782 | 2.39 | 65.5 | 26.64 | 0.760 | 2.27 | 65.3 |

Table 3. Quantitative results on the test set of DIV2K with $\times 4$.

## 2. DIV2K Validation 100 images: quantitative results

In Tables 4,5,and 6 we report average quantitative results over DIV2K test 100 images for magnification factors $\times 2$, $\times 3$, and $\times 4$, respectively. Bicubic interpolation result is included for reference. Our computed results follow the protocol from the NTIRE 2017 Challenge [10] and use the provided codes by the top contenders also the publicly released models for VDSR [5] and A+ [12]. SNU_CVLab1 and SNU_CVLab1 provide comparable performance on DIV2K test dataset, while the results for SNU_CVLab1 are significantly better than those for SNU_CVLab2 on DIV2K validation dataset. This is likely because SNU_CVLab1 used DIV2K validation images for model training.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 36.82 | 0.950 | 8.07 | 10.4 | 35.39 | 0.943 | 8.18 | 10.1 |
| SNU_CVLab2 | 36.58 | 0.948 | 7.99 | 11.8 | 35.15 | 0.941 | 8.09 | 11.5 |
| Lab402 | 36.32 | 0.946 | 7.88 | 11.1 | 34.89 | 0.939 | 7.97 | 10.8 |
| HelloSR | 36.11 | 0.946 | 7.84 | 12.3 | 34.71 | 0.938 | 7.95 | 11.9 |
| VDSR[5] | 35.27 | 0.938 | 7.23 | 14.6 | 33.70 | 0.929 | 7.30 | 14.5 |
| A+[12] | 34.40 | 0.929 | 7.80 | 26.6 | 32.82 | 0.918 | 7.06 | 26.5 |
| Bicubic | 32.40 | 0.903 | 6.14 | 44.0 | 30.98 | 0.891 | 5.65 | 43.7 |

Table 4. Quantitative results on the validation set of DIV2K with $\times 2$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 33.33 | 0.899 | 4.99 | 17.1 | 31.90 | 0.887 | 5.03 | 17.0 |
| SNU_CVLab2 | 32.95 | 0.894 | 4.88 | 18.3 | 31.52 | 0.882 | 4.92 | 18.1 |
| HelloSR | 32.54 | 0.889 | 4.72 | 19.8 | 31.12 | 0.876 | 4.76 | 19.7 |
| Lab402 | 32.54 | 0.889 | 4.72 | 19.5 | 31.10 | 0.876 | 4.75 | 19.5 |
| VDSR[5] | 31.70 | 0.875 | 4.32 | 24.0 | 30.14 | 0.859 | 4.35 | 23.9 |
| A+[12] | 31.03 | 0.862 | 4.48 | 38.0 | 29.50 | 0.844 | 4.17 | 38.2 |
| Bicubic | 29.62 | 0.829 | 3.55 | 56.4 | 28.20 | 0.811 | 3.34 | 56.1 |

Table 5. Quantitative results on the validation set of DIV2K with $\times 3$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 31.29 | 0.853 | 3.43 | 22.5 | 29.85 | 0.836 | 3.45 | 22.5 |
| SNU_CVLab2 | 30.98 | 0.847 | 3.36 | 23.7 | 29.54 | 0.831 | 3.37 | 23.7 |
| HelloSR | 30.66 | 0.841 | 3.23 | 24.4 | 29.22 | 0.823 | 3.25 | 24.3 |
| Lab402 | 30.56 | 0.839 | 3.23 | 25.6 | 29.12 | 0.822 | 3.24 | 25.7 |
| VDSR[5] | 29.78 | 0.822 | 2.85 | 32.5 | 28.21 | 0.800 | 2.87 | 32.5 |
| A+[12] | 29.26 | 0.807 | 2.95 | 45.1 | 27.74 | 0.784 | 2.79 | 45.2 |
| Bicubic | 28.08 | 0.773 | 2.30 | 64.6 | 26.65 | 0.750 | 2.19 | 64.4 |

Table 6. Quantitative results on the validation set of DIV2K with $\times 4$.

## 3. Set5 images: quantitative results

In Tables 7,8,and 9 we report average quantitative results over Set5 images for magnification factors $\times 2$, $\times 3$, and $\times 4$, respectively. Bicubic interpolation result is included for reference.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 38.18 | 0.961 | 8.33 | 17.6 | 36.06 | 0.946 | 8.43 | 17.2 |
| SNU_CVLab2 | 38.12 | 0.961 | 8.29 | 17.4 | 35.99 | 0.945 | 8.40 | 17.1 |
| Lab402 | 37.97 | 0.960 | 8.18 | 17.8 | 35.86 | 0.944 | 8.28 | 17.6 |
| HelloSR | 37.82 | 0.960 | 8.14 | 18.1 | 35.72 | 0.944 | 8.25 | 17.6 |
| VDSR[5] | 37.46 | 0.958 | 7.77 | 17.9 | 35.14 | 0.941 | 7.85 | 17.7 |
| A+[12] | 36.55 | 0.954 | 8.25 | 26.6 | 34.28 | 0.934 | 7.54 | 27.1 |
| Bicubic | 33.64 | 0.930 | 5.94 | 42.3 | 31.74 | 0.908 | 5.61 | 42.4 |

Table 7. Quantitative results on Set5 with $\times 2$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 34.80 | 0.930 | 5.48 | 19.7 | 32.82 | 0.908 | 5.51 | 19.7 |
| SNU_CVLab2 | 34.73 | 0.929 | 5.44 | 21.1 | 32.75 | 0.907 | 5.48 | 20.6 |
| Lab402 | 34.46 | 0.927 | 5.27 | 20.0 | 32.48 | 0.904 | 5.30 | 19.6 |
| HelloSR | 34.46 | 0.928 | 5.30 | 20.9 | 32.46 | 0.903 | 5.32 | 20.6 |
| VDSR[5] | 33.69 | 0.922 | 4.92 | 18.0 | 31.54 | 0.895 | 4.94 | 17.8 |
| A+[12] | 32.70 | 0.910 | 4.85 | 32.6 | 30.63 | 0.881 | 4.63 | 33.2 |
| Bicubic | 30.41 | 0.869 | 3.51 | 54.1 | 28.63 | 0.838 | 3.41 | 54.1 |

Table 8. Quantitative results on Set5 with $\times 3$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 32.64 | 0.901 | 3.88 | 23.7 | 30.73 | 0.873 | 3.89 | 23.7 |
| SNU_CVLab2 | 32.61 | 0.900 | 3.88 | 25.1 | 30.71 | 0.872 | 3.89 | 24.9 |
| HelloSR | 32.35 | 0.898 | 3.76 | 23.6 | 30.43 | 0.868 | 3.76 | 23.4 |
| Lab402 | 32.27 | 0.897 | 3.74 | 26.5 | 30.36 | 0.867 | 3.75 | 26.5 |
| VDSR[5] | 31.42 | 0.885 | 3.39 | 23.0 | 29.33 | 0.851 | 3.40 | 23.1 |
| A+[12] | 30.35 | 0.863 | 3.18 | 39.9 | 28.37 | 0.826 | 3.09 | 39.8 |
| Bicubic | 28.42 | 0.812 | 2.29 | 61.3 | 26.69 | 0.774 | 2.24 | 61.2 |

Table 9. Quantitative results on Set5 with $\times 4$.

## 4. Set14 images: quantitative results

In Tables 10,11,and 12 we report average quantitative results over Set5 images for magnification factors $\times 2$, $\times 3$, and $\times 4$, respectively. Bicubic interpolation result is included for reference.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 34.14 | 0.920 | 8.18 | 11.2 | 32.09 | 0.898 | 8.28 | 11.1 |
| SNU_CVLab2 | 34.01 | 0.920 | 8.12 | 12.2 | 31.97 | 0.898 | 8.21 | 12.0 |
| Lab402 | 33.95 | 0.919 | 8.01 | 10.9 | 31.90 | 0.897 | 8.10 | 10.7 |
| HelloSR | 33.70 | 0.918 | 8.00 | 12.7 | 31.68 | 0.895 | 8.09 | 12.7 |
| VDSR[5] | 33.17 | 0.912 | 7.55 | 14.9 | 31.00 | 0.885 | 7.61 | 14.7 |
| A+[12] | 32.43 | 0.904 | 7.89 | 25.7 | 30.34 | 0.876 | 7.43 | 25.8 |
| Bicubic | 30.33 | 0.869 | 5.96 | 42.4 | 28.52 | 0.842 | 5.71 | 42.4 |

Table 10. Quantitative results on Set14 with $\times 2$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 30.73 | 0.848 | 5.00 | 18.3 | 28.87 | 0.817 | 5.02 | 18.3 |
| SNU_CVLab2 | 30.63 | 0.846 | 4.95 | 17.8 | 28.76 | 0.816 | 4.98 | 17.8 |
| Lab402 | 30.49 | 0.843 | 4.82 | 18.7 | 28.63 | 0.812 | 4.84 | 18.8 |
| HelloSR | 30.45 | 0.843 | 4.83 | 18.3 | 28.58 | 0.812 | 4.86 | 18.4 |
| VDSR[5] | 29.89 | 0.832 | 4.45 | 21.1 | 27.90 | 0.794 | 4.47 | 21.2 |
| A+[12] | 29.28 | 0.820 | 4.47 | 34.4 | 27.36 | 0.783 | 4.30 | 34.4 |
| Bicubic | 27.63 | 0.775 | 3.43 | 56.7 | 25.94 | 0.739 | 3.33 | 56.5 |

Table 11. Quantitative results on Set14 with $\times 3$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 28.94 | 0.788 | 3.42 | 22.7 | 27.15 | 0.753 | 3.43 | 22.8 |
| SNU_CVLab2 | 28.88 | 0.787 | 3.40 | 23.4 | 27.09 | 0.751 | 3.41 | 23.4 |
| Lab402 | 28.73 | 0.783 | 3.32 | 25.4 | 26.94 | 0.747 | 3.33 | 25.4 |
| HelloSR | 28.72 | 0.783 | 3.31 | 24.4 | 26.93 | 0.747 | 3.32 | 24.5 |
| VDSR[5] | 28.11 | 0.768 | 2.97 | 26.8 | 26.20 | 0.724 | 2.99 | 26.8 |
| A+[12] | 27.43 | 0.751 | 2.92 | 40.6 | 25.62 | 0.708 | 2.84 | 40.7 |
| Bicubic | 26.08 | 0.703 | 2.22 | 63.6 | 24.46 | 0.662 | 2.18 | 63.4 |

Table 12. Quantitative results on Set14 with $\times 4$.

## 5. B100 images: quantitative results

In Tables 13,14,and 15 we report average quantitative results over Set5 images for magnification factors $\times 2$, $\times 3$, and $\times 4$, respectively. Bicubic interpolation result is included for reference.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 32.33 | 0.902 | 7.29 | 14.3 | 30.95 | 0.893 | 7.36 | 14.2 |
| SNU_CVLab2 | 32.28 | 0.901 | 7.26 | 15.8 | 30.90 | 0.892 | 7.33 | 15.7 |
| Lab402 | 32.18 | 0.900 | 7.21 | 14.8 | 30.80 | 0.891 | 7.27 | 14.6 |
| HelloSR | 32.09 | 0.899 | 7.17 | 15.7 | 30.71 | 0.890 | 7.25 | 15.5 |
| VDSR[5] | 31.81 | 0.895 | 6.90 | 16.4 | 30.41 | 0.885 | 6.95 | 16.3 |
| A+[12] | 31.13 | 0.884 | 7.19 | 29.0 | 29.71 | 0.872 | 6.65 | 29.0 |
| Bicubic | 29.48 | 0.843 | 5.53 | 47.7 | 28.12 | 0.828 | 5.21 | 47.5 |

Table 13. Quantitative results on B100 with $\times 2$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 29.28 | 0.811 | 4.23 | 23.8 | 27.90 | 0.793 | 4.24 | 23.8 |
| SNU_CVLab2 | 29.23 | 0.810 | 4.20 | 25.1 | 27.85 | 0.791 | 4.22 | 25.2 |
| Lab402 | 29.10 | 0.807 | 4.15 | 25.6 | 27.71 | 0.788 | 4.17 | 25.6 |
| HelloSR | 29.07 | 0.806 | 4.12 | 25.2 | 27.68 | 0.787 | 4.13 | 25.2 |
| VDSR[5] | 28.74 | 0.797 | 3.92 | 27.1 | 27.32 | 0.777 | 3.93 | 27.2 |
| A+[12] | 28.23 | 0.783 | 3.95 | 39.6 | 26.82 | 0.761 | 3.75 | 39.7 |
| Bicubic | 27.12 | 0.738 | 3.10 | 60.3 | 25.76 | 0.713 | 2.98 | 60.0 |

Table 14. Quantitative results on B100 with $\times 3$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 27.74 | 0.744 | 2.79 | 29.1 | 26.36 | 0.719 | 2.80 | 29.5 |
| SNU_CVLab2 | 27.72 | 0.743 | 2.79 | 29.7 | 26.34 | 0.718 | 2.80 | 30.0 |
| Lab402 | 27.59 | 0.738 | 2.76 | 31.1 | 26.21 | 0.712 | 2.77 | 31.3 |
| HelloSR | 27.58 | 0.738 | 2.73 | 30.7 | 26.20 | 0.712 | 2.73 | 30.9 |
| VDSR[5] | 27.20 | 0.724 | 2.54 | 34.3 | 25.78 | 0.697 | 2.55 | 34.6 |
| A+[12] | 26.74 | 0.709 | 2.51 | 46.7 | 25.33 | 0.680 | 2.41 | 46.7 |
| Bicubic | 25.87 | 0.666 | 1.95 | 67.6 | 24.50 | 0.636 | 1.89 | 67.3 |

Table 15. Quantitative results on B100 with $\times 4$.

## 6. Urban100 images: quantitative results

In Tables 16,17,and 18 we report average quantitative results over Set5 images for magnification factors $\times 2$, $\times 3$, and $\times 4$, respectively. Bicubic interpolation result is included for reference.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 33.21 | 0.937 | 9.38 | -2.3 | 31.58 | 0.929 | 9.50 | -2.6 |
| SNU_CVLab2 | 33.09 | 0.936 | 9.27 | -0.9 | 31.45 | 0.928 | 9.38 | -1.2 |
| Lab402 | 32.62 | 0.932 | 9.06 | -2.1 | 31.00 | 0.924 | 9.16 | -2.4 |
| HelloSR | 32.30 | 0.929 | 9.01 | -0.1 | 30.70 | 0.920 | 9.13 | -0.3 |
| VDSR[5] | 30.73 | 0.913 | 8.01 | 3.2 | 29.05 | 0.901 | 8.08 | 2.9 |
| A+[12] | 29.18 | 0.892 | 8.19 | 17.9 | 27.60 | 0.879 | 7.62 | 17.7 |
| Bicubic | 26.85 | 0.839 | 6.16 | 40.5 | 25.41 | 0.826 | 5.80 | 40.0 |

Table 16. Quantitative results on Urban100 with $\times 2$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 29.08 | 0.870 | 6.08 | 5.4 | 27.52 | 0.855 | 6.12 | 5.3 |
| SNU_CVLab2 | 28.98 | 0.868 | 5.99 | 5.9 | 27.42 | 0.853 | 6.03 | 5.8 |
| Lab402 | 28.46 | 0.858 | 5.71 | 7.3 | 26.91 | 0.842 | 5.74 | 7.3 |
| HelloSR | 28.37 | 0.856 | 5.71 | 7.7 | 26.83 | 0.840 | 5.75 | 7.6 |
| VDSR[5] | 27.10 | 0.826 | 4.91 | 12.6 | 25.49 | 0.807 | 4.93 | 12.5 |
| A+[12] | 26.02 | 0.796 | 4.80 | 30.7 | 24.49 | 0.776 | 4.58 | 30.5 |
| Bicubic | 24.43 | 0.733 | 3.59 | 54.4 | 22.99 | 0.712 | 3.45 | 53.8 |

Table 17. Quantitative results on Urban100 with $\times 3$.

| Method | computed on Y from YCbCr | | | | computed on RGB | | | |
|---|---|---|---|---|---|---|---|---|
| | PSNR | SSIM | IFC | CORNIA | PSNR | SSIM | IFC | CORNIA |
| SNU_CVLab1 | 26.88 | 0.808 | 4.31 | 10.7 | 25.36 | 0.789 | 4.32 | 10.7 |
| SNU_CVLab2 | 26.83 | 0.807 | 4.26 | 10.9 | 25.30 | 0.787 | 4.28 | 11.0 |
| Lab402 | 26.37 | 0.792 | 4.04 | 13.1 | 24.86 | 0.772 | 4.06 | 13.1 |
| HelloSR | 26.32 | 0.792 | 4.01 | 13.4 | 24.82 | 0.771 | 4.03 | 13.4 |
| VDSR[5] | 25.13 | 0.750 | 3.32 | 21.5 | 23.57 | 0.725 | 3.33 | 21.6 |
| A+[12] | 24.31 | 0.718 | 3.17 | 39.5 | 22.81 | 0.692 | 3.06 | 39.3 |
| Bicubic | 23.11 | 0.656 | 2.35 | 63.4 | 21.67 | 0.629 | 2.28 | 63.0 |

Table 18. Quantitative results on Urban100 with $\times 4$.

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## References

[1] E. Agustsson and R. Timofte. Ntire 2017 challenge on single image super-resolution: Dataset and study. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, July 2017.

[2] W. Bae, J. Yoo, and J. C. Ye. Beyond deep residual learning for image restoration: Persistent homology-guided manifold simplification. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, July 2017.

[3] M. Bevilacqua, A. Roumy, C. Guillemot, and M. line Alberi Morel. Low-complexity single-image super-resolution based on nonnegative neighbor embedding. In *Proceedings of the British Machine Vision Conference*, pages 135.1–135.10. BMVA Press, 2012.

[4] J.-B. Huang, A. Singh, and N. Ahuja. Single image super-resolution from transformed self-exemplars. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2015.

[5] J. Kim, J. Kwon Lee, and K. Mu Lee. Accurate image super-resolution using very deep convolutional networks. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.

[6] B. Lim, S. Son, H. Kim, S. Nah, and K. M. Lee. Enhanced deep residual networks for single image super-resolution. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, July 2017.

[7] D. Martin, C. Fowlkes, D. Tal, and J. Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In *Computer Vision, 2001. ICCV 2001. Proceedings. Eighth IEEE International Conference on*, volume 2, pages 416–423. IEEE, 2001.

[8] H. R. Sheikh, A. C. Bovik, and G. De Veciana. An information fidelity criterion for image quality assessment using natural scene statistics. *IEEE Transactions on image processing*, 14(12):2117–2128, 2005.

[9] H. R. Sheikh, M. F. Sabir, and A. C. Bovik. A statistical evaluation of recent full reference image quality assessment algorithms. *IEEE Transactions on image processing*, 15(11):3440–3451, 2006.

[10] R. Timofte, E. Agustsson, L. Van Gool, M.-H. Yang, L. Zhang, et al. Ntire 2017 challenge on single image super-resolution: Methods and results. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, July 2017.

[11] R. Timofte, V. De Smet, and L. Van Gool. Anchored neighborhood regression for fast example-based super-resolution. In *The IEEE International Conference on Computer Vision (ICCV)*, December 2013.

[12] R. Timofte, V. De Smet, and L. Van Gool. A+: Adjusted anchored neighborhood regression for fast super-resolution. In D. Cremers, I. Reid, H. Saito, and M.-H. Yang, editors, *Computer Vision – ACCV 2014: 12th Asian Conference on Computer Vision, Singapore, Singapore, November 1-5, 2014, Revised Selected Papers, Part IV*, pages 111–126, Cham, 2014. Springer International Publishing.

[13] P. Ye, J. Kumar, L. Kang, and D. Doermann. Unsupervised feature learning framework for no-reference image quality assessment. In *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*, pages 1098–1105. IEEE, 2012.

[14] R. Zeyde, M. Elad, and M. Protter. On single image scale-up using sparse-representations. In J.-D. Boissonnat, P. Chenin, A. Cohen, C. Gout, T. Lyche, M.-L. Mazure, and L. Schumaker, editors, *Curves and Surfaces: 7th International Conference, Avignon, France, June 24 - 30, 2010, Revised Selected Papers*, pages 711–730, Berlin, Heidelberg, 2012. Springer Berlin Heidelberg.