

# Supplementary Materials for "Memory-Efficient Hierarchical Neural Architecture Search for Image Denoising"

## Appendix A. Visual results on BSD500, SIM1800 and Rain800

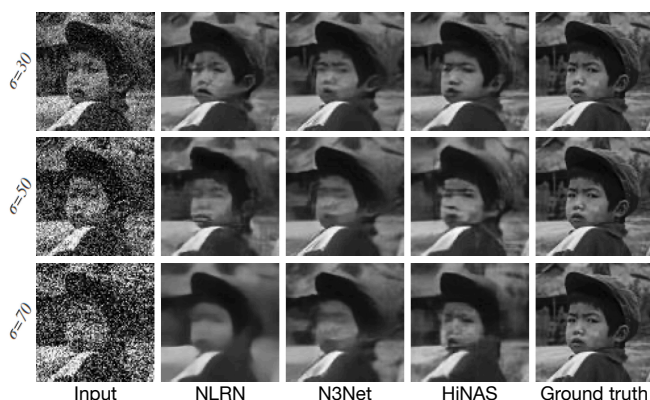


Figure 1: Denoising experiments on BSD500.

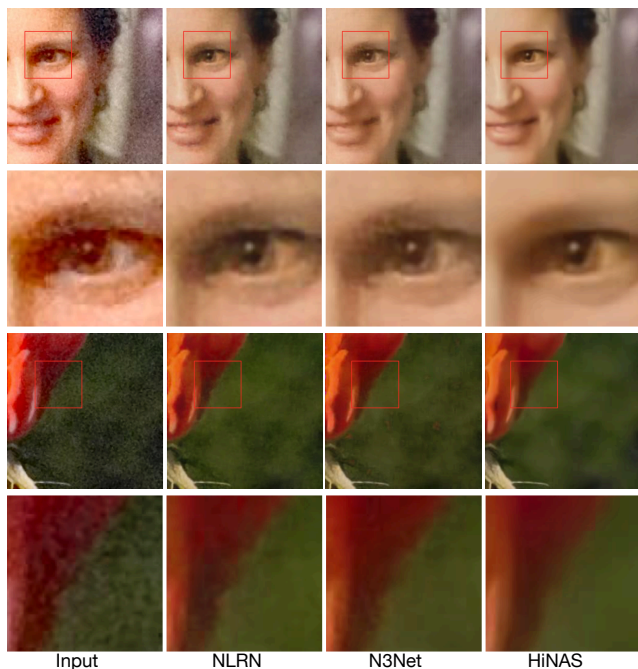


Figure 2: Denoising experiments on SIM1800.



Figure 3: De-raining experiments on Rain800.

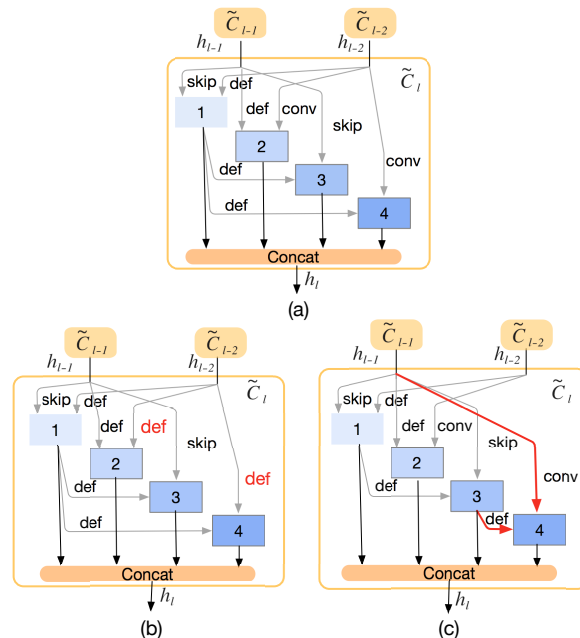


Figure 4: Architecture analysis for de-raining. (a) the detailed structures inside designed cell; (b) modified cell ( $R1$ ), where conventional convolution layers are replaced by deformable convolution layers; (c) modified cell ( $R2$ ), where the connection relationships between different nodes inside cells are changed.

## Appendix B. Architecture analysis for deraining

To further verify if HiNAS improves the accuracy by designing a proper architecture or by simply intergrating

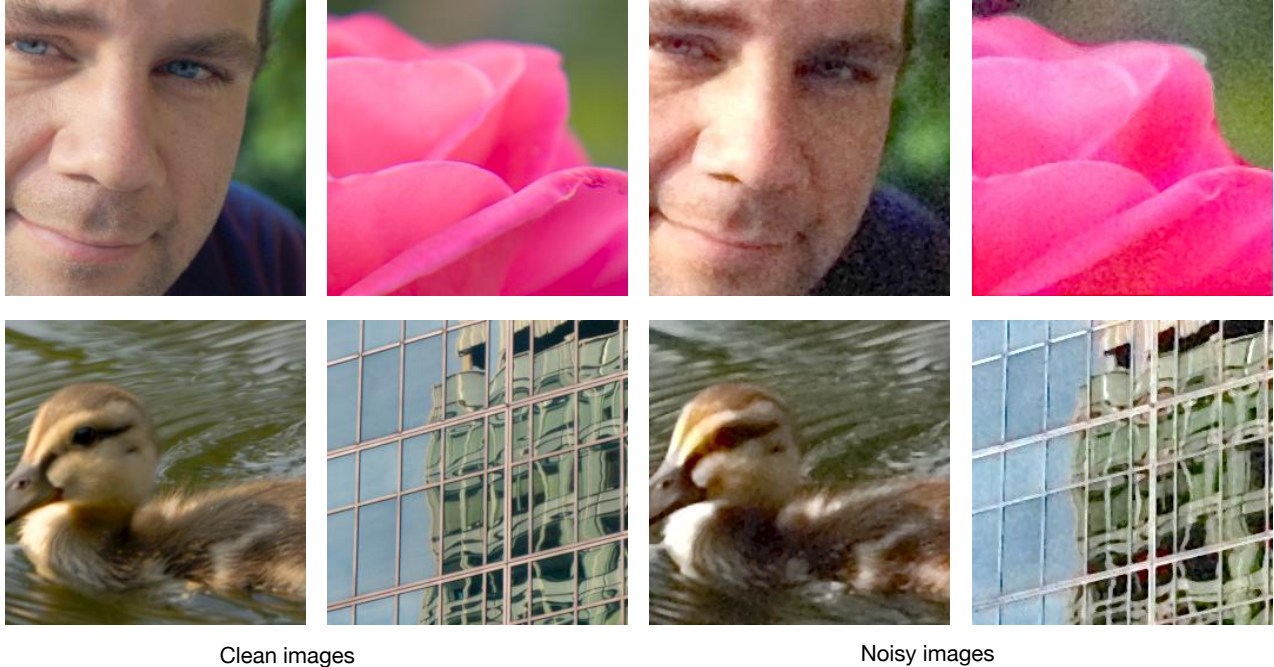


Figure 5: Some samples of SIM1800.

Methods	HiNAS	HiNAS, $R1$	HiNAS, $R2$
PSNR	<b>26.31</b>	21.48	25.69
SSIM	<b>0.8685</b>	0.6754	0.8416

Table 1: Architecture analysis.

various branch structures and convolution operations. We implemented two architecture analysis experiments on denoising on Rain800. Similarly, we modify the architecture found by our HiNAS in two different ways and then compare the modified architectures with unmodified architecture. The modifies we did are shown in Figure 4 and the comparison results are listed in Table 1, from which we can see that both modifications reduce the accuracy. Replacing convolution operation reduces the PSNR and SSIM by 4.83 and 0.1931, respectively. Changing connection relationships decreases the PSNR and SSIM to 25.69 and 0.8416, respectively.

### Appendix C. Denoising dataset SIM1800

The second denoising dataset SIM1800 is built by ourselves. By using the camera pipeline simulation method proposed in [2], we build this new denoising dataset SIM1800, which contains 1600 training samples and 212 test samples. Firstly, we use the camera pipeline simulation method to add noise to 25k patches extracted from MIT-Adobe5k dataset [1], then manually pick up 1812 patches which have the most realistic visual effects. This dataset

will be publicly released soon. Some examples of SIM1800 are show in Figure 5.

### References

- [1] Vladimir Bychkovsky, Sylvain Paris, Eric Chan, and Frédo Durand. Learning photographic global tonal adjustment with a database of input/output image pairs. In *Proc. IEEE Conf. Comp. Vis. Patt. Recogn.*, pages 97–104. IEEE, 2011. 2
- [2] Ronnachai Jaroensri, Camille Biscarrat, Miika Aittala, and Frédo Durand. Generating training data for denoising real rgb images via camera pipeline simulation. *arXiv: Comp. Res. Repository*, abs/1904.08825, 2019. 2