



Experimenting with Image Priors in Super-resolution CNNs

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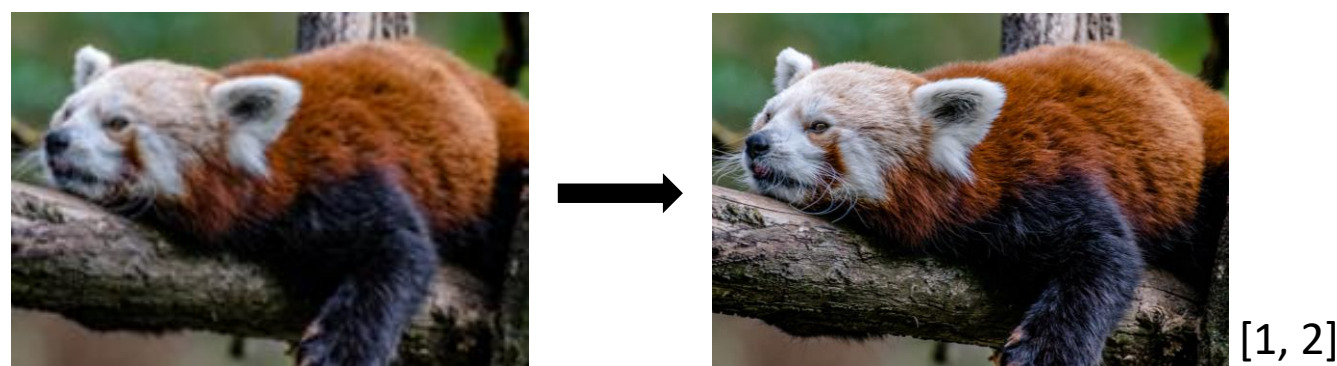
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Motivation

Image resolution can be enhanced from a single image using convolutional neural networks. This can be used for:

- Old personal photos
- Digital zoom
- Accelerated medical imaging

Goal: Given a low resolution image, output a high resolution version.



[1, 2]

Dataset

The Flickr2K dataset [1,2] is sampled into 128x128 high res image patches. Corresponding low res patches are then formed following:

$$LR = (HR * K(\sigma_{blur})) \downarrow + N(\mu \sigma_{add})$$

Then upsampled to size using bicubic interpolation (BI). These pairs are the input and labels for our model.



[1, 2]

References

- [1] B. Lim, S. Son, H. Kim, S. Nah, and K. M. Lee. Enhanced deep residual networks for single image super-resolution. In CVPR, pages 66–70, 2017.
- [2] R. Timofte and et al. Ntire 2017 challenge on single imagesuper-resolution: Methods and results. In CVPRW, pages 1110–1121, 2017.
- [3] C. Dong, C. C. Loy, K. He, and X. Tang. Learning a deep convolutional network for image super-resolution. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), 8692:184–199, 2014.
- [4] C. Dong, C. C. Loy, K. He, and X. Tang. Image superresolution using deep convolutional networks. IEEE Trans. Pattern Anal. Mach. Intell, 38(2):295–307, 2016.

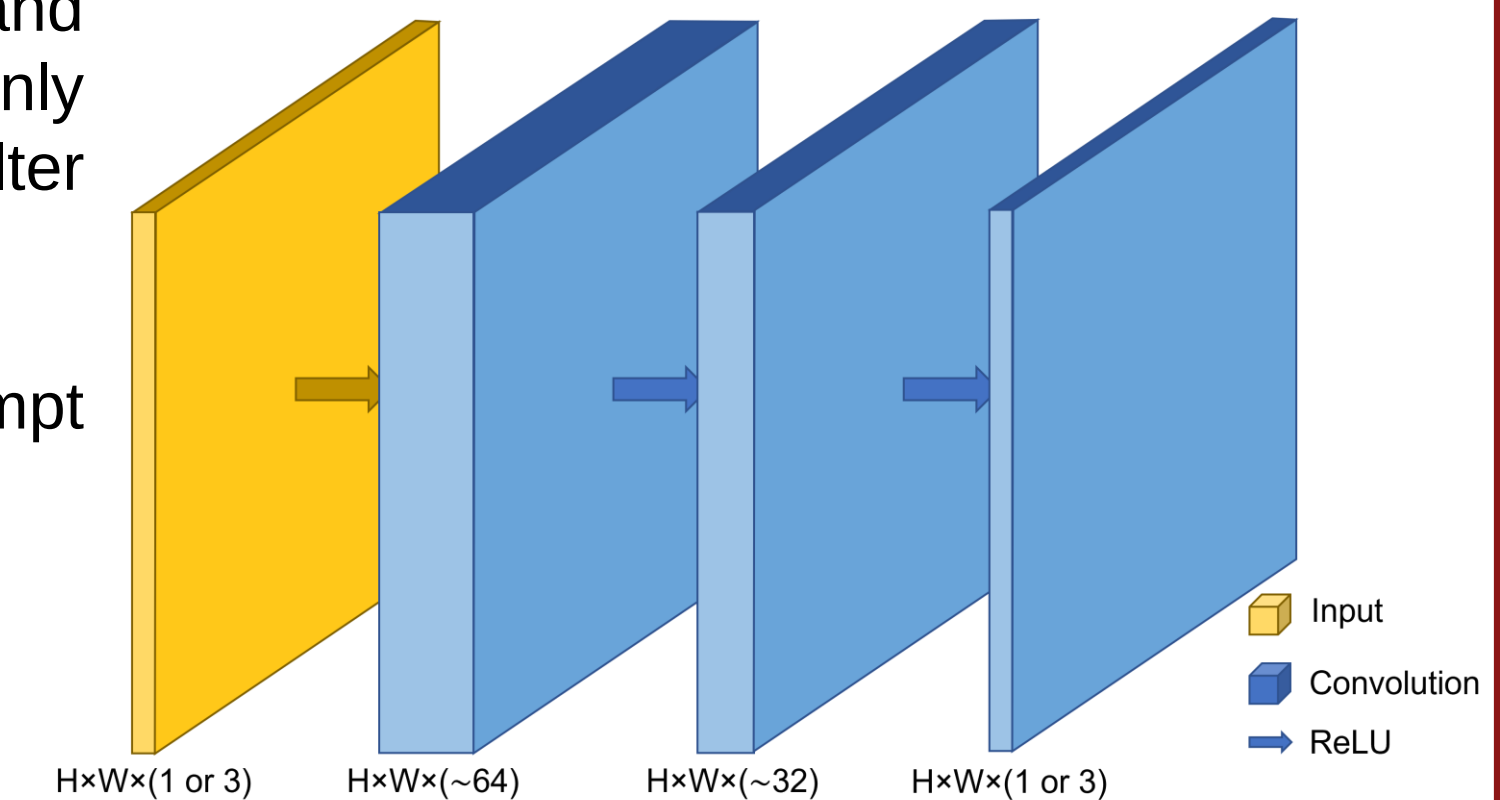
Methods

An SRCNN was implemented with 3 convolutional layers and ReLU activation [3, 4]. Networks were trained on luminance-only and full RGB data sets. Randomized search of filter hyperparameters was made.

Anisotropic total variation was included in loss function in attempt to speed up training.

$$TV = \frac{\lambda}{N} \sum_{i,j,k,c} (D_x \hat{y}^{(i)})_{jkc}^2 + (D_y \hat{y}^{(i)})_{jkc}^2$$

$$Loss = MSE \text{ or } MSE + TV$$



Results and Discussion

Training Results:

- Best models trained with MSE and MSE+TV compared
- MSE+TV model learns slightly faster

Quantitative Results:

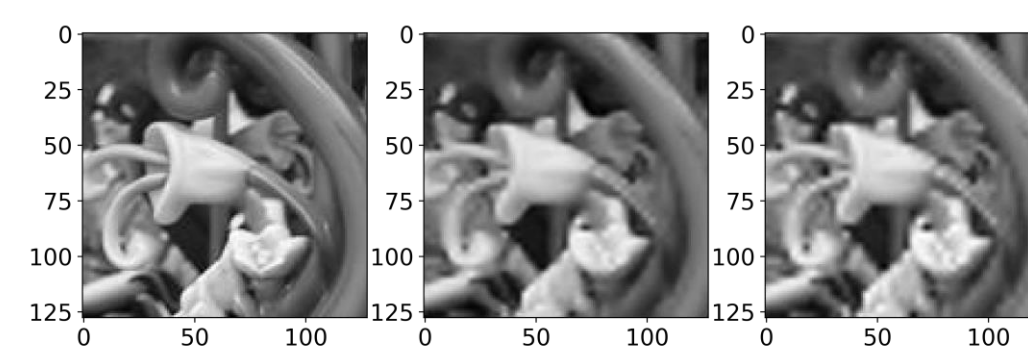
- SRCNN improves baseline by 3-4 dB
- SSIM is slightly improved (<0.1)

SRCNN Results			BI Base Results		
Model	PSNR	SSIM	Set	PSNR	SSIM
Luminance MSE	28.59	0.78	RGB	24.35	0.73
Luminance MSE+TV	28.49	0.78	Luminance	24.70	0.71
RGB MSE	27.47	0.75			
RGB MSE+TV	27.95	0.76			

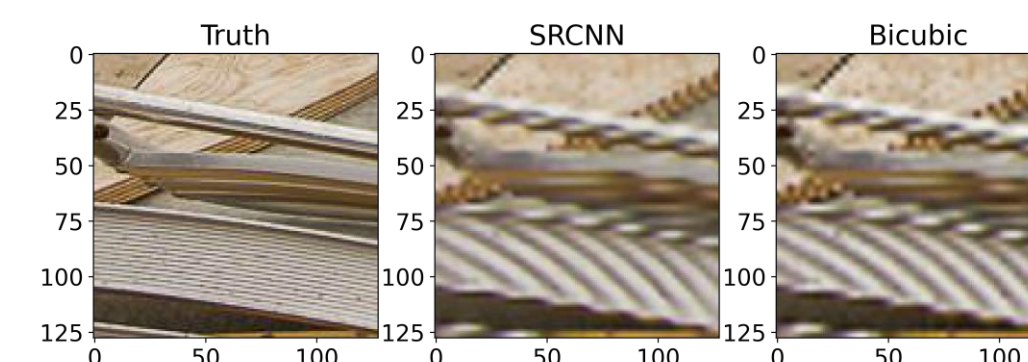
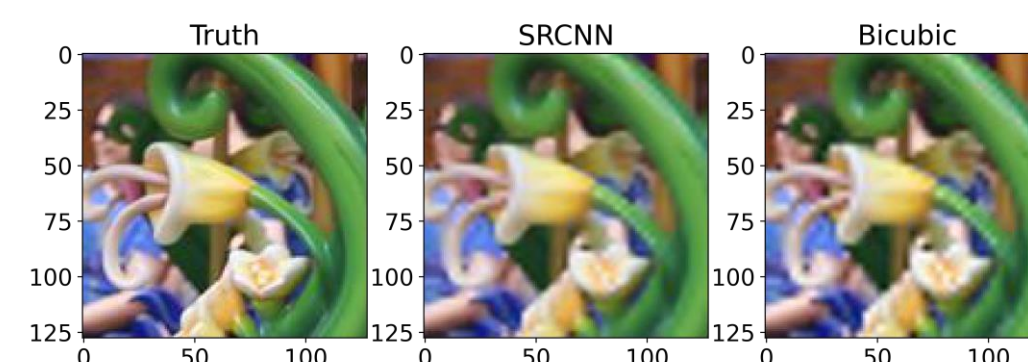
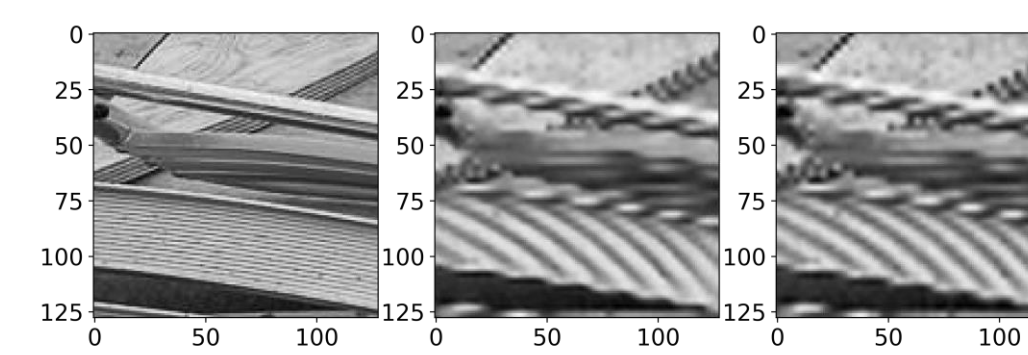
Visual Results:

- SRCNN sharpens edges while reducing noise
- SRCNN improves upon BI baseline images
- SRCNN cannot handle high aliasing

Successful Luminance-Only Result



Aliased Luminance-Only Result



Successful Full RGB Result

