Computer Vision Project

Topic Image Super Resolution

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Team Vision21

Members

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Paper Implementation:

Image Super-Resolution Using Deep Convolutional Networks

Paper By:

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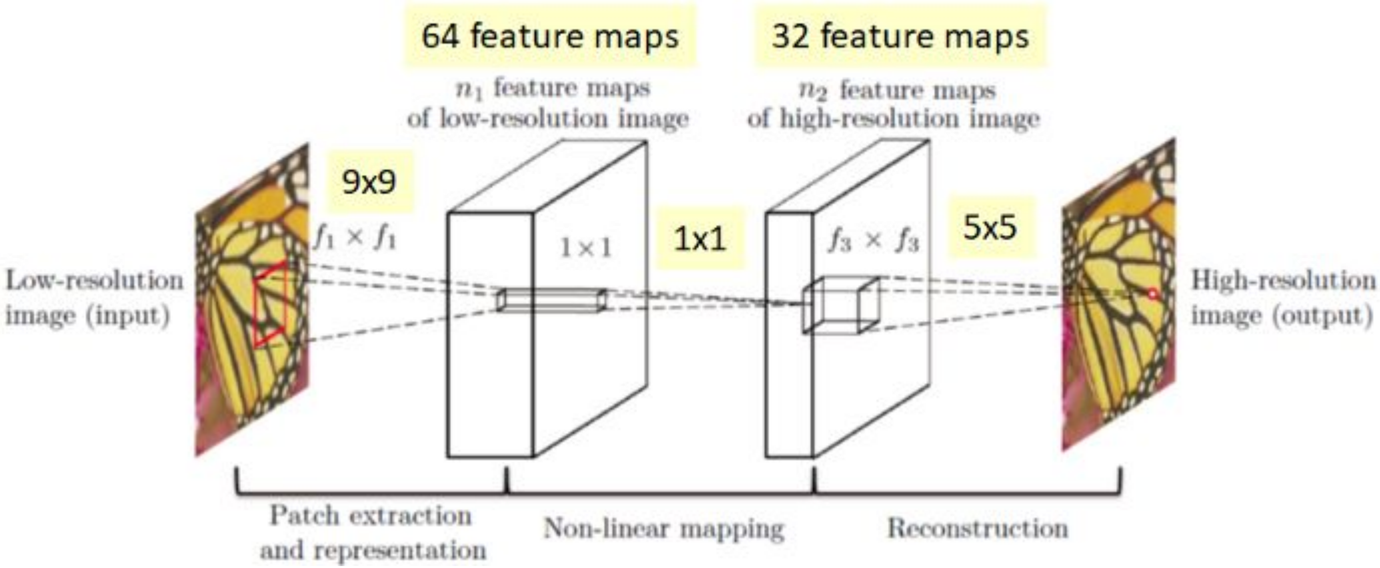
2. Objectives

- **Implement algorithm** given in paper and test it on images.
- **Compare algorithm** to **classic CV methods** including:
    - Yang, J., Wright, J., Huang, T.S., Ma, Y.: Image super-resolution via sparse representation. IEEE Transactions on Image Processing 19(11), 2861–2873 (2010)
    - Chang, H., Yeung, D.Y., Xiong, Y.: Super-resolution through neighbor embedding. In: IEEE Conference on Computer Vision and Pattern Recognition (2004)
    - Kim, K.I., Kwon, Y.: Single-image super-resolution using sparse regression and natural image prior. IEEE Transactions on Pattern Analysis and Machine Intelligence 32(6), 1127–1133 (2010)
    - Timofte, R., De Smet, V., Van Gool, L.: Anchored neighborhood regression for fast example-based super-resolution. In: IEEE International Conference on Computer Vision. pp. 1920–1927 (2013)

2. Objectives (cont'd)

- Use metrics such as PSNR, SSIM, IFC, NQM, WPSNR, MSSSIM for comparison with classic CV methods.
- Try variations of algorithm as given in paper by varying depth of network, number of channels and other hyperparameters. Compare results based on output quality and time taken.
- Visualize and interpret the channels learnt.

3. Method overview



3. Method overview (cont'd)

- This paper illustrates the use of CNN's for image super-resolution.
- The basic version of this algorithm uses a 3-layer CNN.
- Dataset to be used: ImageNet
- Input will be made as a part of preprocessing, in which the images of ImageNet will be converted to lower resolution images. This is sent to feed-forward network.
- Output will be original high resolution image.
- Loss function: MSE loss
- Iterations and other hyperparameters: to be tested as part of experiment.

4. Goals

- To build a network for image super-resolution.
- To survey classic CV methods for image super-resolution and compare it with SRCNN.
- To try variations of the proposed network by changing hyperparameters and analyzing the results.

5. Previous Timeline

- **Mid Evals:** Implement SRCNN and validate the results.
- **End Evals:** Review classical algorithms and present comparison results.

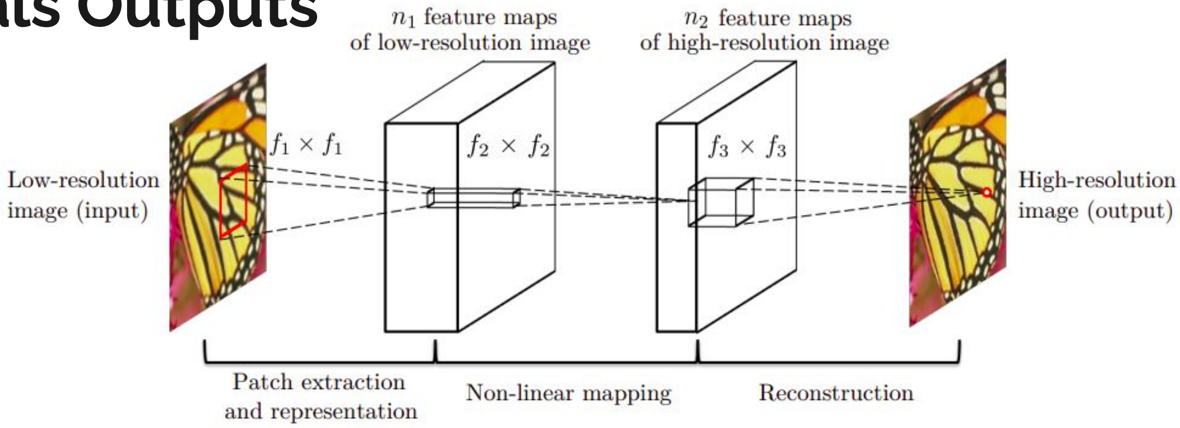
Current Progress

- SRCNN model implemented and trained.
- Model working is validated based on performance.
- The results we are getting are comparable(slightly better) to the original paper. And we are trying to improve it.

Data used

- 91-image train set mentioned in the paper is used.
- Set-5 and Set-14 test sets yield coherent results

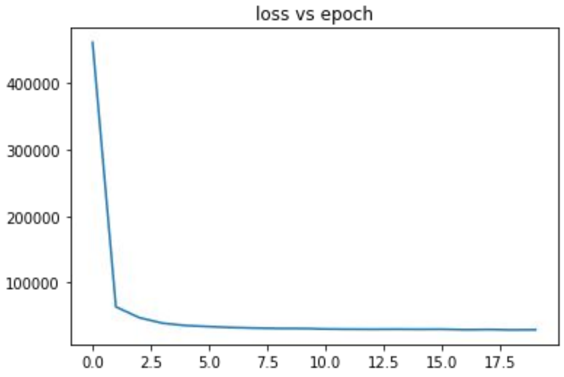
Mid-evals Outputs



Number of Epochs = 20

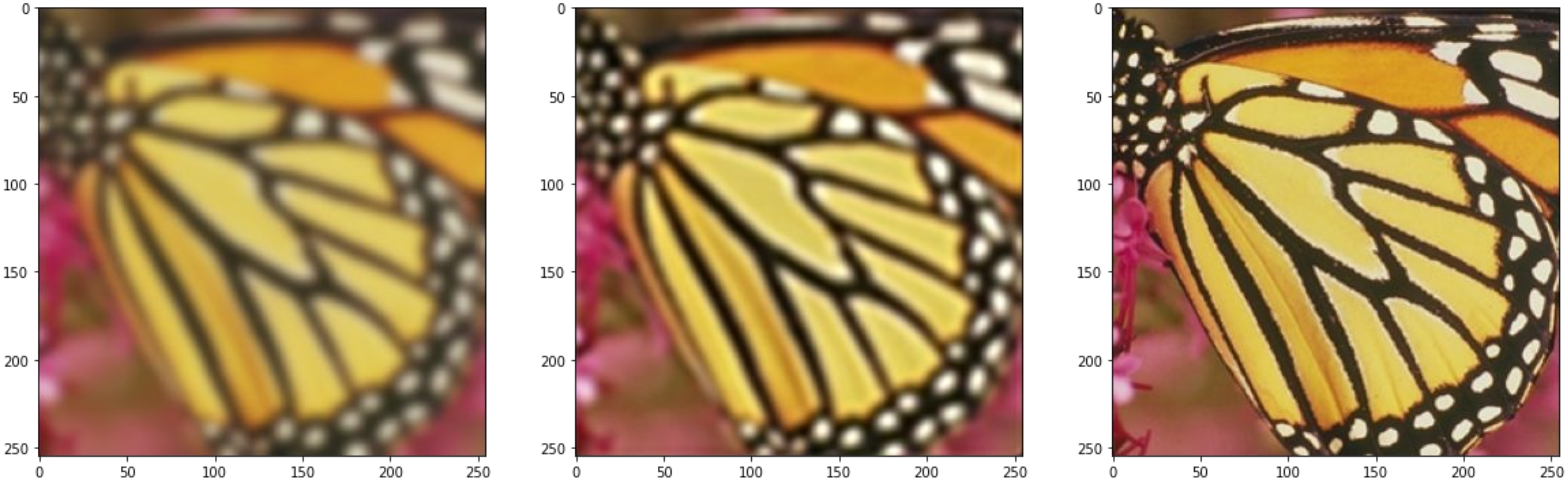
Learning rate = 1e-4

Loss Type = MSE



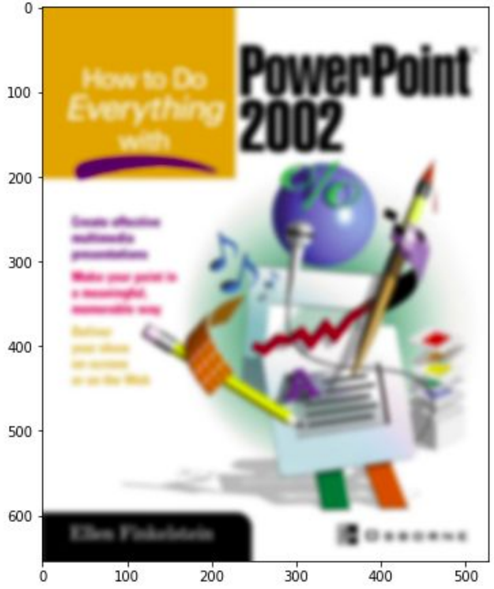
Test Image 1

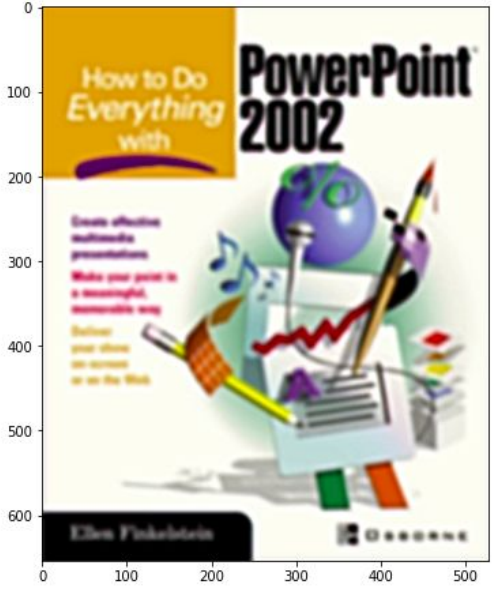
SRCNN PSNR: 27.95 dB
Our PSNR: 29.19 dB

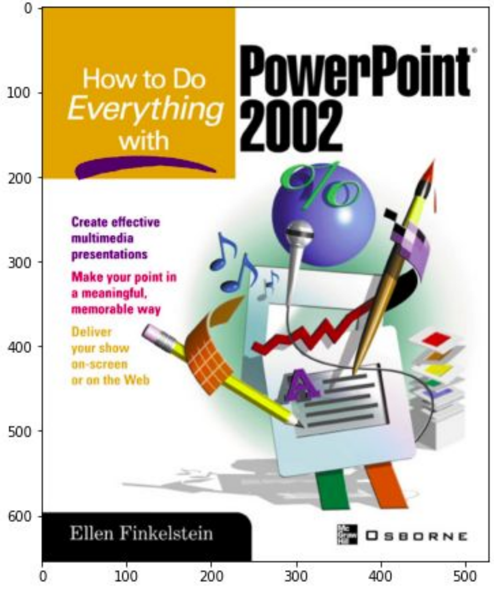


Test Image 2

SRCNN PSNR: 27.04 dB
Our PSNR: 30.54 dB

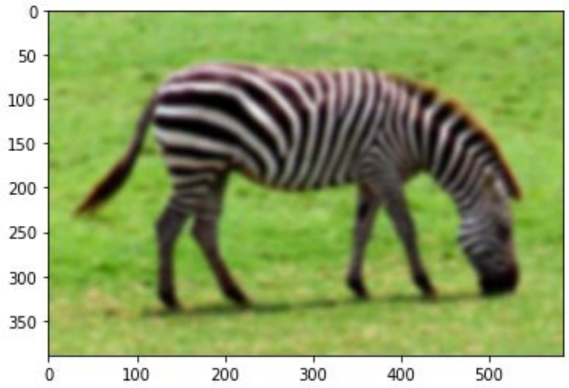


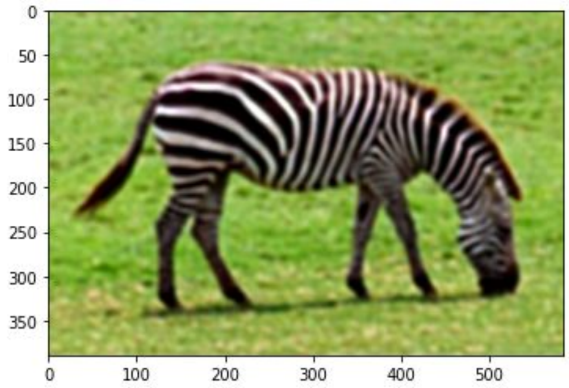


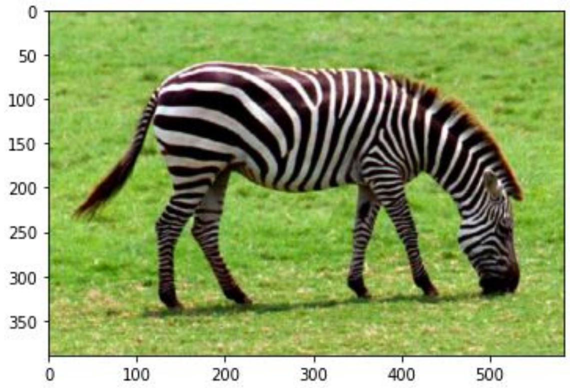


Test Image 3

SRCNN PSNR: 29.29dB
Our PSNR: 29.54dB

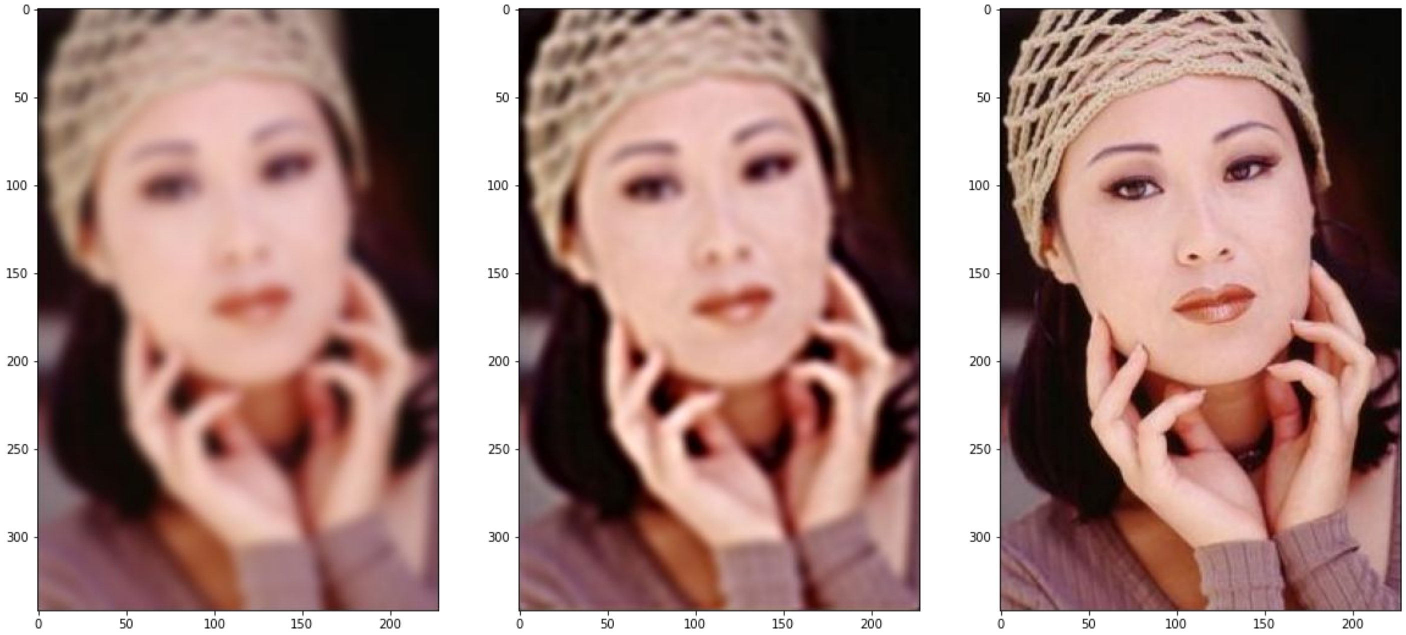






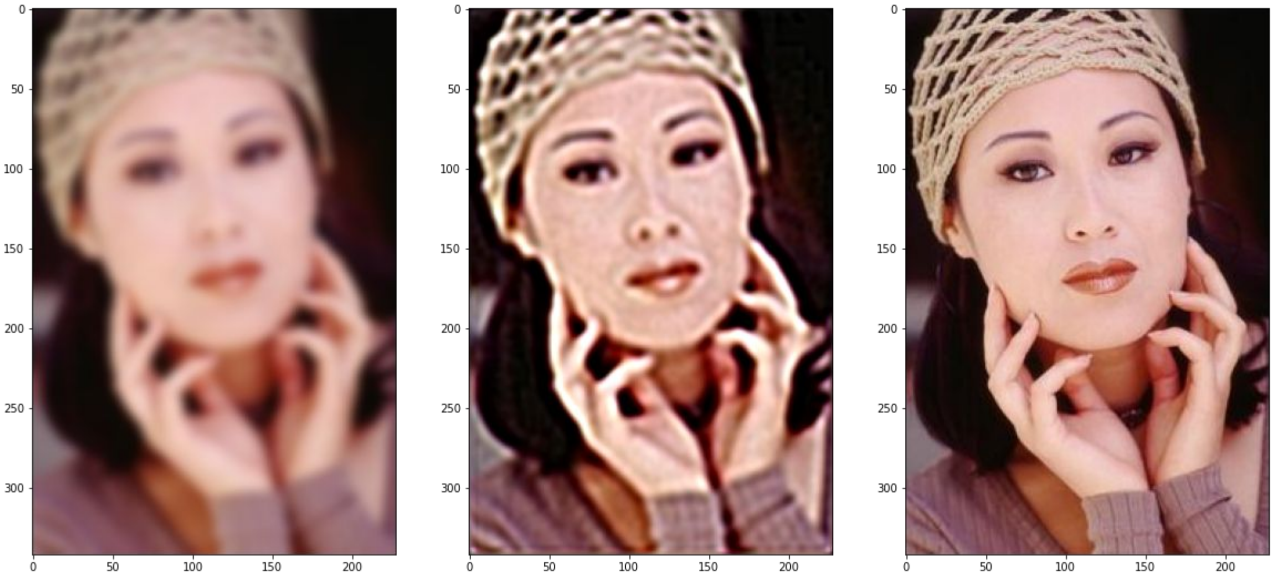
Test Image 4

SRCNN PSNR: 30.16dB
Our PSNR: 31.20dB



Additional Observations

- We also ran the model results on same image twice, which does not provide any improvement in quality or PNSR.



New PSNR: 29.48dB
Original PSNR: 31.20dB

Additional Observations

- We also increased the depth of the CNN model making it containing 6 layer as follows :
  - Layer 1 : 3 x 128
  - Layer 2 : 128 x 256
  - Layer 3 : 256 x 512
  - Layer 4 : 512 x 256
  - Layer 5 : 256 x 128
  - Layer 6 : 128 x 3
- This took a lot of training time with slightly better but not much improved results.
  - Δ $PSNR_{avg}$ = + 0.153dB

Thank You.