Experimenting with MWCNN for Image Denoising

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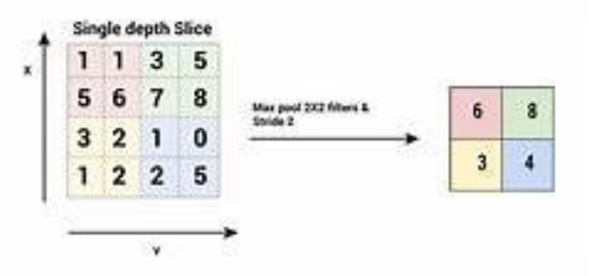
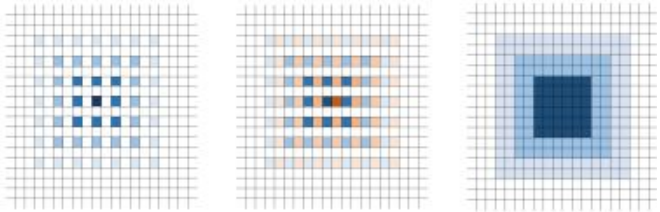
Problem Description

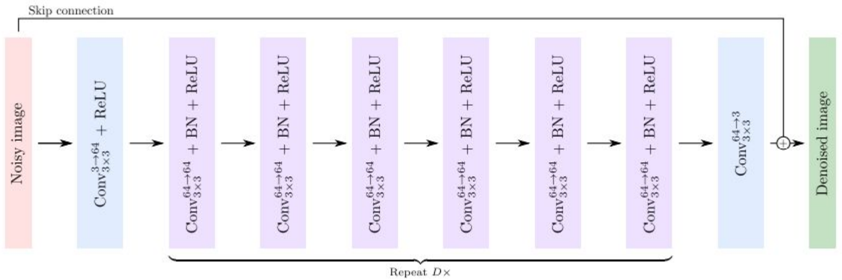
- CNNs use pooling layers to increase the receptive field while lowering computational complexity
- Cause information loss
- Dilated filter has been proposed to trade off between receptive field size and efficiency
- Gridding effect can cause a sparse sampling of input images with checkerboard patterns
- All in all, there is a need to find a method to increase receptive field without affecting efficiency or computational complexity.



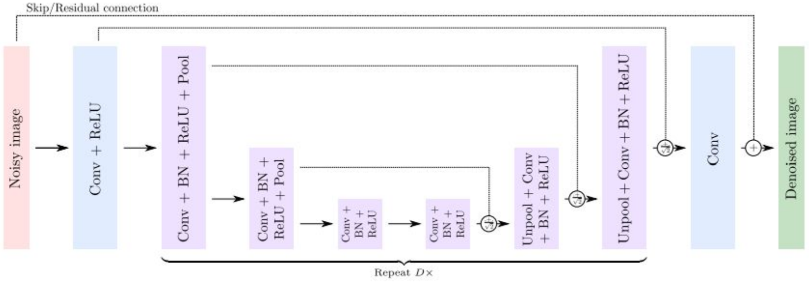


Other approaches

- FCN with symmetrical skip connections
- DnCNN architecture:



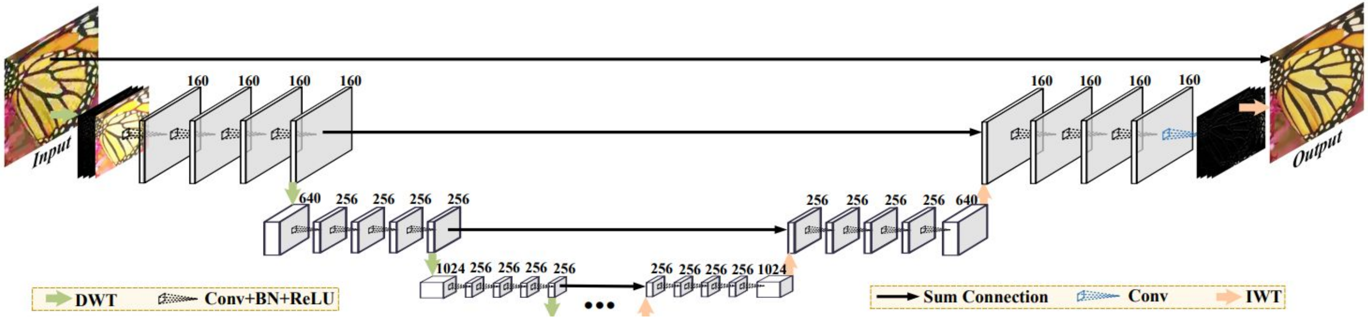
- UDnCNN architecture:



- DUDnCNN architecture

Proposed approach

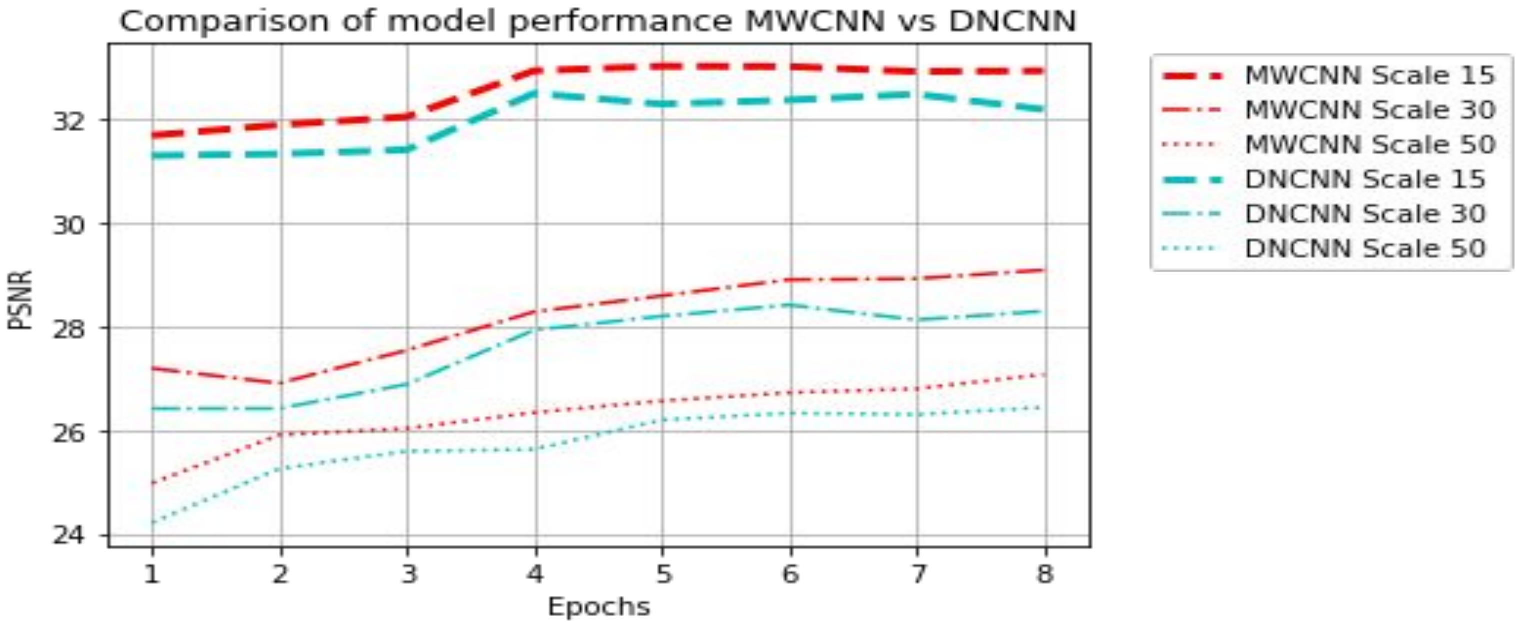
- Embed wavelet transform into CNN architecture to reduce the resolution of feature maps while at the same time, increasing receptive field
- Achieve better trade-off between receptive field size and computational efficiency.
- Based on U-Net architecture, and inverse wavelet transform (IWT) is deployed to reconstruct the high resolution (HR) feature maps



Experiments Performed...

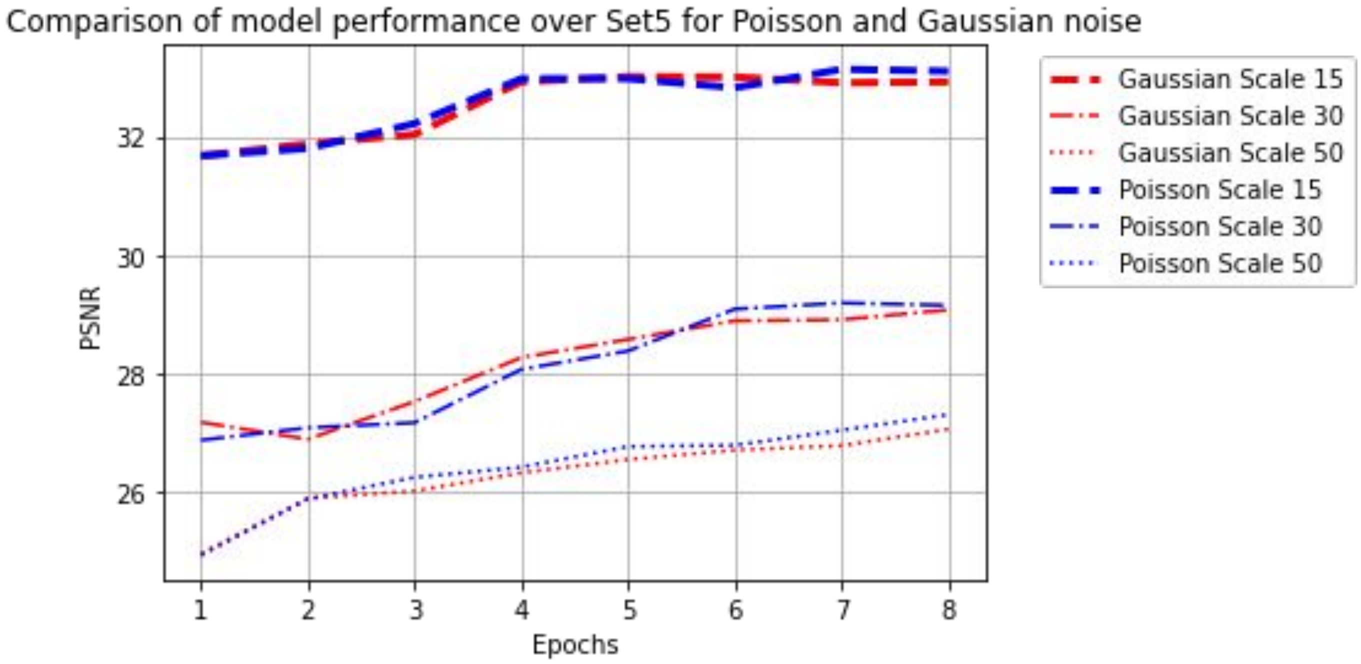
1. Models with and without Wavelets - Denoising PSNR comparison
    a. Comparing DnCNN, DUDnCNN vs MWCNN
2. Effect of noise level
    a. Gaussian sigma 15 vs sigma 50
    b. Poisson sigma 15 vs sigma 50
3. Effect of different noises
    a. Gaussian vs Poisson
4. Results with different Wavelets
    a. Haar Wavelet
    b. Biorthogonal 2.4
    c. Symlet 5
    d. Daubechies 5

Results | Training MWCNN Vs DNCNN



DnCNN trained for 80 epochs, plotted every 10th epoch in figure.

Results | MWCNN | Training Gaussian Vs Poisson

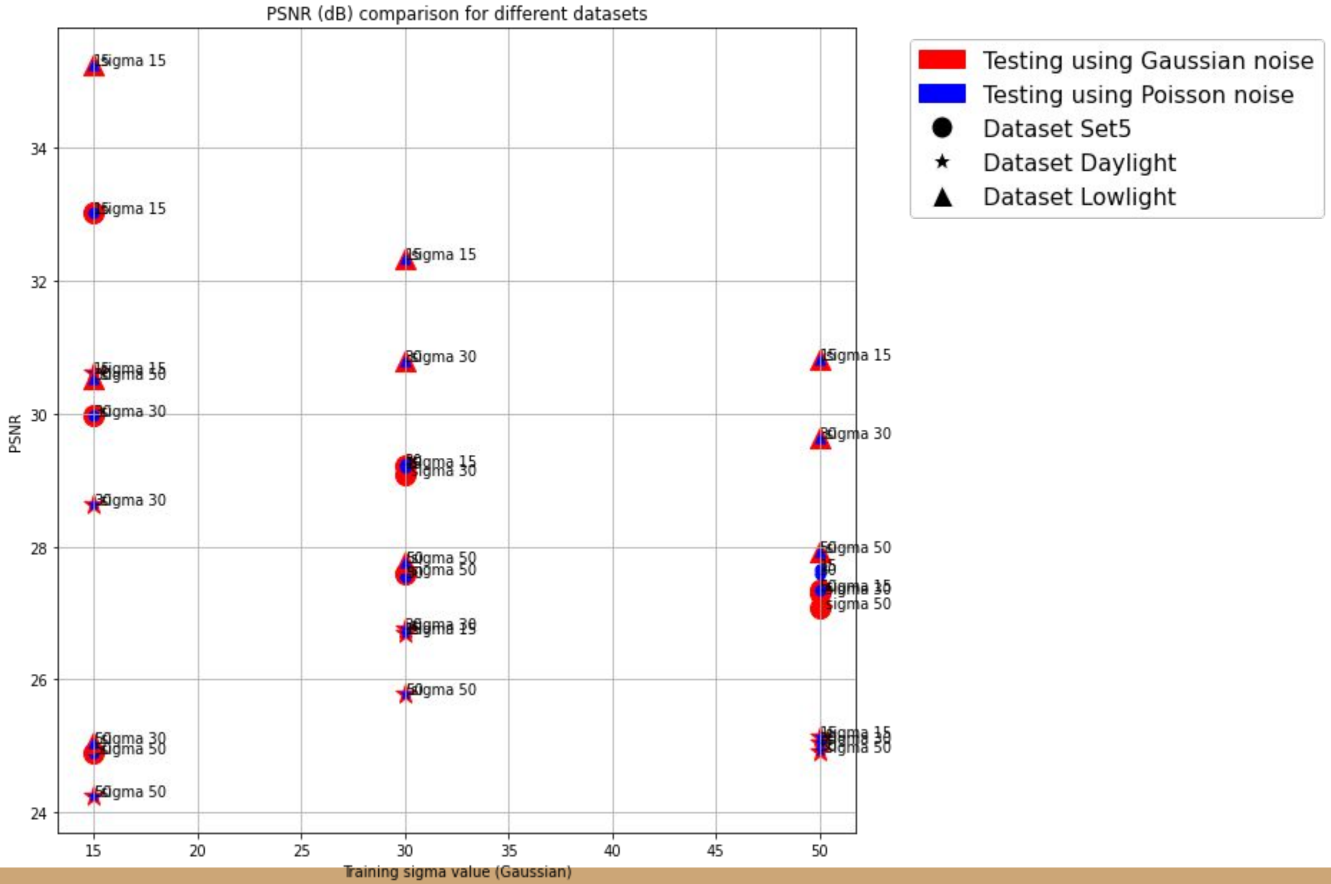


Training MWCNN over different Noise distribution, similar performance

Results | MWCNN | Test

Network Training with Gaussian Sigma =	Noise added to test	TestSet:Set 5			TestSet:Daylight			TestSet:Lowlight		
		15	30	50	15	30	50	15	30	50
15	Gaussian	33.0	30.0	24.9	30.6	28.6	24.2	35.2	25.1	30.5
30		29.2	29.1	27.6	26.7	26.8	25.8	32.3	30.8	27.8
50		27.3	27.3	27.1	25.1	25.1	24.9	30.8	29.6	27.9
15	Poisson	33.0	30.0	24.9	30.6	28.6	24.2	35.2	30.5	25.1
30		29.2	29.2	27.5	26.7	26.8	25.8	32.3	30.8	27.8
50		27.7	27.6	27.3	25.1	25.1	24.9	30.8	29.6	27.9

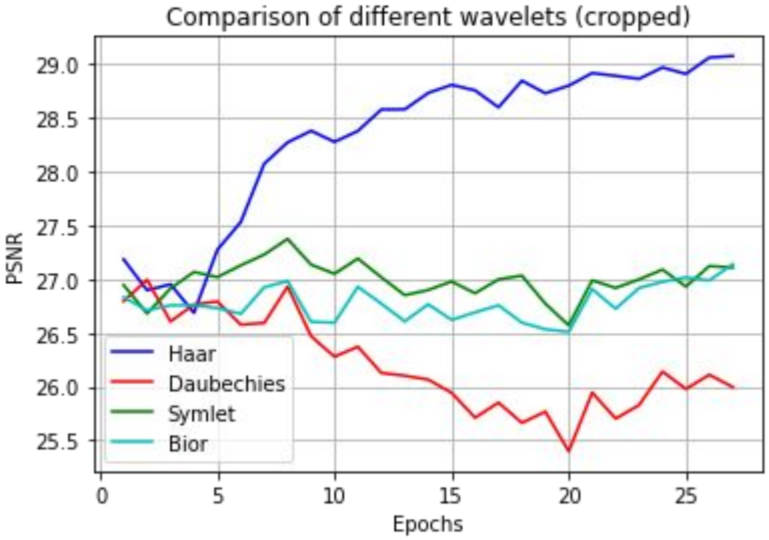
Results | MWCNN | Test

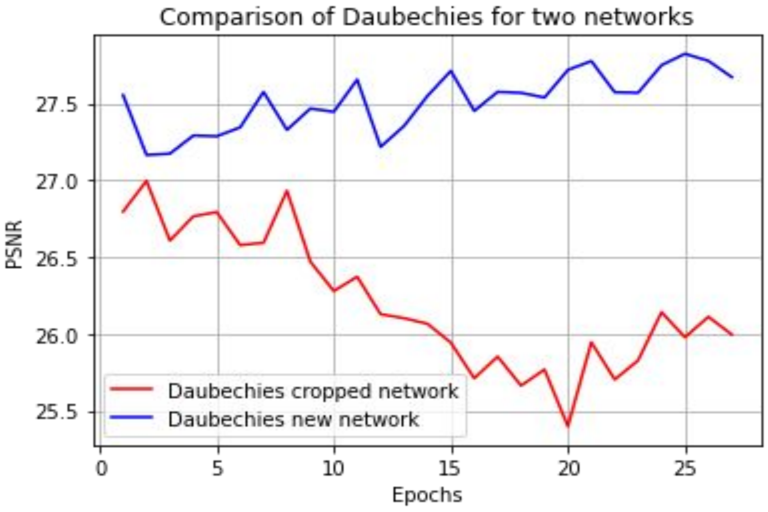


Testing various dataset under different noise distribution

Observation: It is optimal to train the network for moderate Noise level.

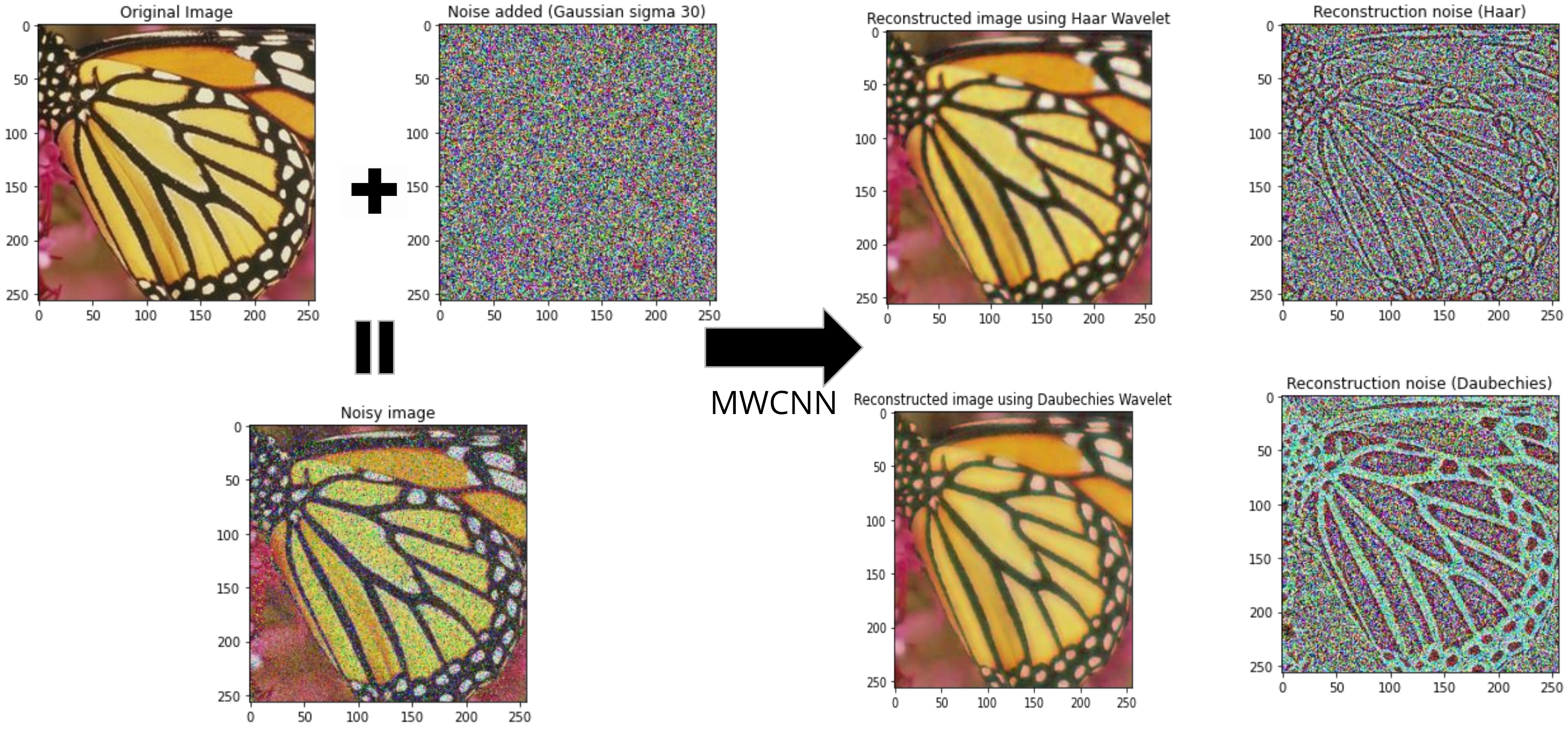
Results | MWCNN with different wavelets





- Left figure, Used db5,sym5 and bior2.4 (Length =10) , appropriately truncated after DWT/IDWT . Due to truncation loss of information is reflected in PSNR.
- Right Figure: Changed the underlying network dimension to enable DWT/IDWT output without truncation. Improvement in PSNR observed
- Haar performance is best under our use case .

Results | MWCNN with different wavelets



Conclusion

- Using wavelets definitely improves denoising PSNR as seen from the first plot.
- The model trained is noise invariant to some extent. Gaussian and Poisson noises are almost denoised to the same extent.
- For real life applications, training the denoising model for sigma 30 is ideal. Sharpening filters can then be used to try to reconstruct the edges.
- Haar wavelet is the better wavelet for Image denoising.

Thank you!