Denoising Fluorescence Microscopy Images with Machine Learning

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Gaussian-Poisson Noise in Fluorescence Microscopy Images

A signal-dependent noise observation model can be represented as:

$$z(x) = y(x) + \sigma(y(x))\zeta(x)$$

- z is the observed (recorded) signal
- y is the original (unknown) signal
- ζ is zero-mean independent random noise with standard deviation equal to 1
- σ is a function of y that gives the standard deviation of the overall noise component

In fluorescence microscopy images, the noise term is composed of two mutually independent parts: a Poisson signal-dependent component, η_p and a Gaussian signal-independent component, η_g.

$$\sigma(y(x))\zeta(x) = \eta_p(y(x)) + \eta_g(x)$$

Denoising Fluorescence Microscopy Images: A Two-Pronged Approach

- Image Segmentation using clustering algorithms
- Image Denoising using image-specialized deep learning methods

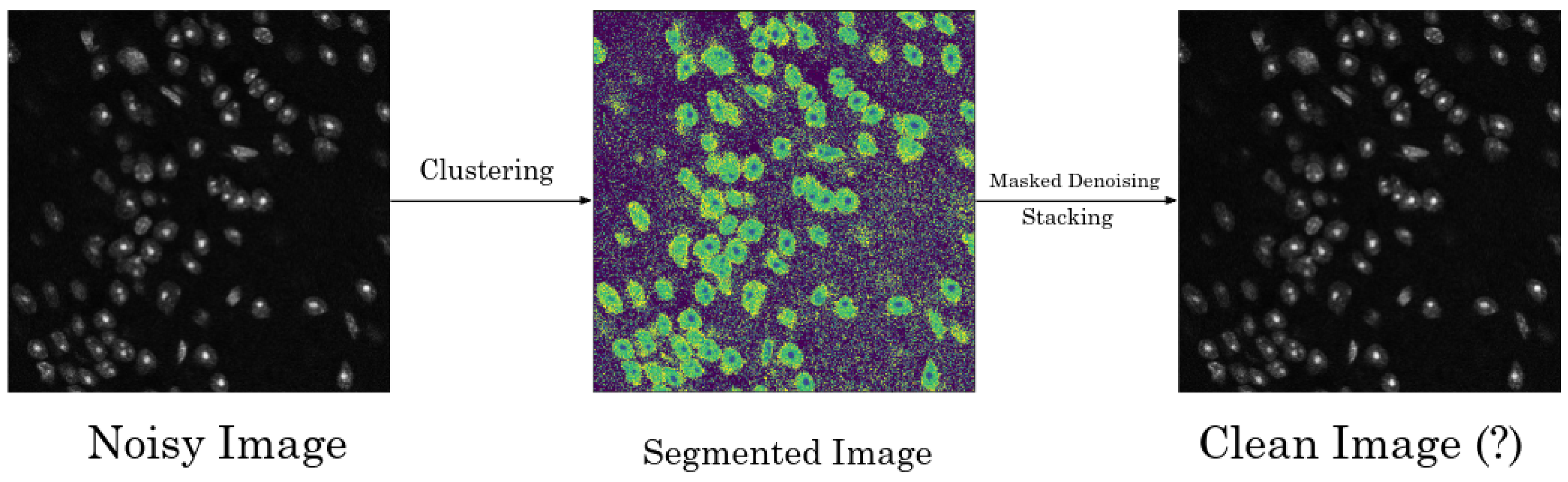


Figure 1. A Two-Pronged Approach to Denoising

Choice of Clustering Algorithm for Image Segmentation

Metric	K-means	DBSCAN	HDBSCAN
Silhouette Score	0.590	0.972	**0.975**
Davies-Bouldin Index	0.540	**0.381**	0.408
WSS Score	3.747	**0.771**	0.962

Cluster-Masking Enhances Denoising Performance of CNNs

- A CNN architecture was used to train two models: (i) on whole images and (ii) on clustered masks.
- CNN architecture: In → Conv. → MaxPool → Conv. → MaxPool → Dense → Out
- CNN$_{masked}$ marginally outperformed CNN$_{whole}$.

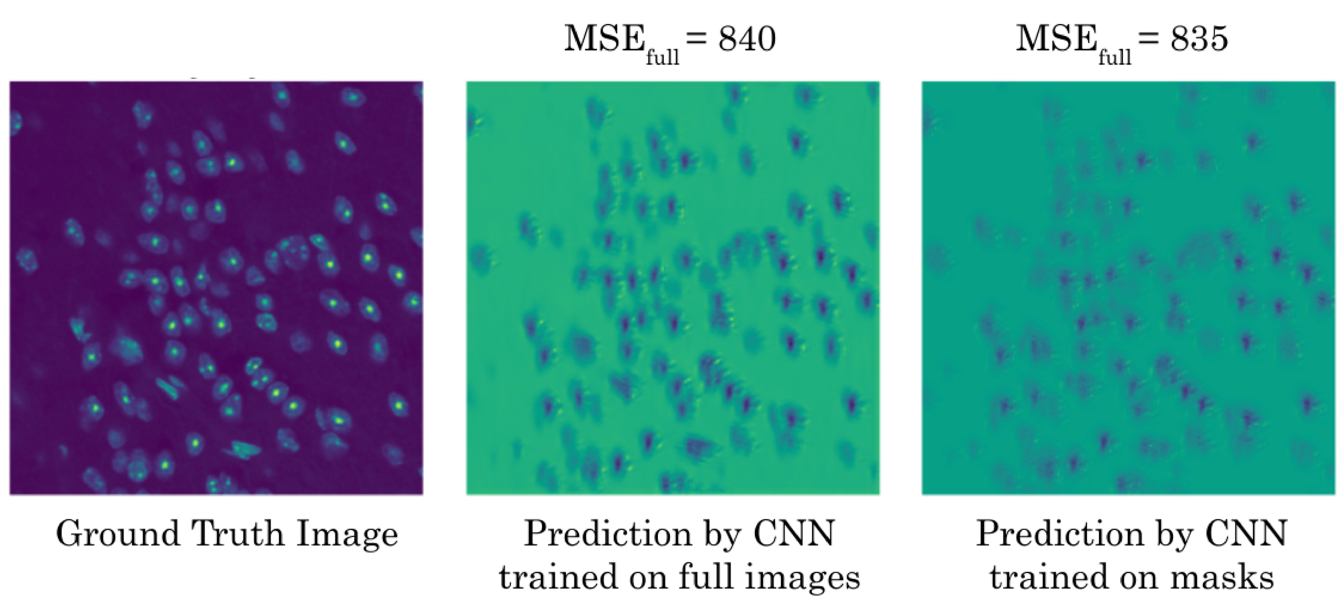


Figure 2. Illustrative Example of CNN$_{masked}$ Outperforming CNN$_{whole}$

Image Denoising Architecture

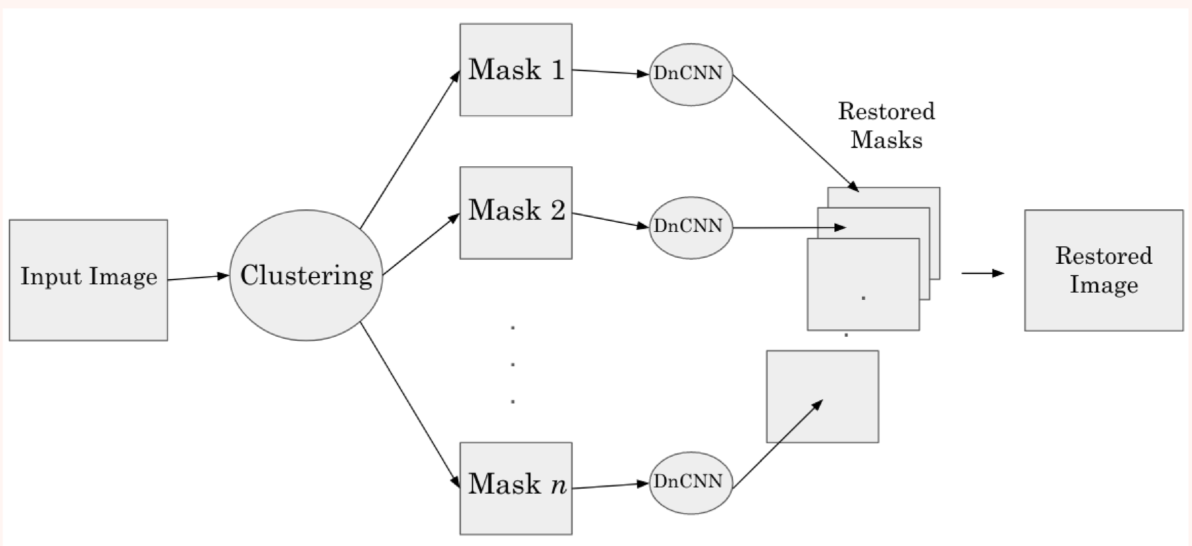


Figure 3. Proposed Model Architecture

- A denoising architecture is proposed: considering that masking is beneficial to eliminating noise.
- Literature survey: For deep learning approaches to denoising, DnCNN is optimum. [1]

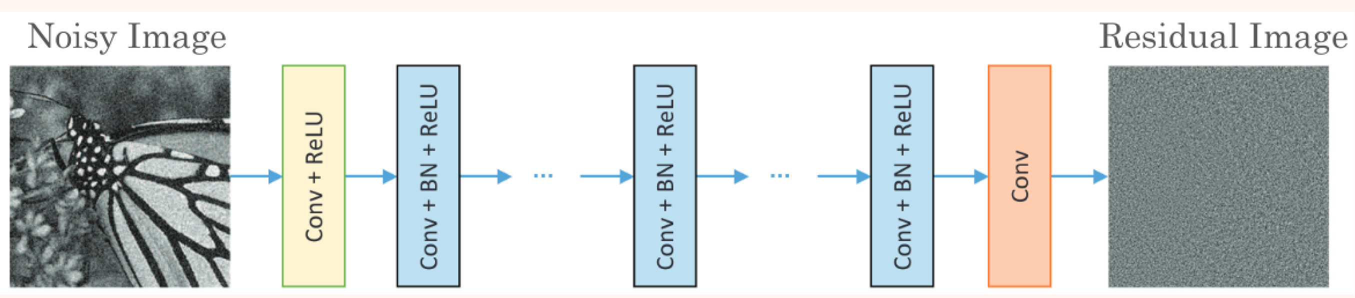


Figure 4. DnCNN Model Architecture

- DnCNN invokes Batch Normalization and Residual Learning to help training & boost denoising.

Image Denoising Model in Action

- The metrics used for accessing the quality of restored images were Peak Signal to Noise Ratio (PSNR) and Structure Similarity Index Measure (SSIM).
- It was found that these metrics were mostly unperturbed by image segmentation prior to denoising.
- Change in model architecture is suspected to have played a role.

Change of Course: Do Clusters Capture Noise?

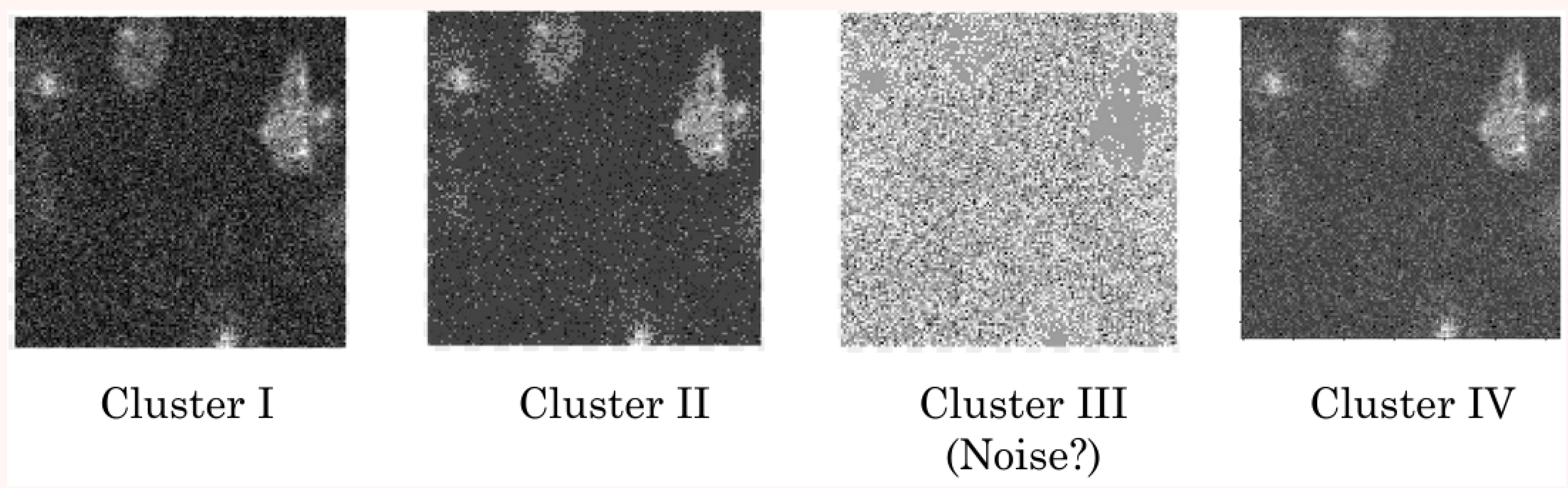
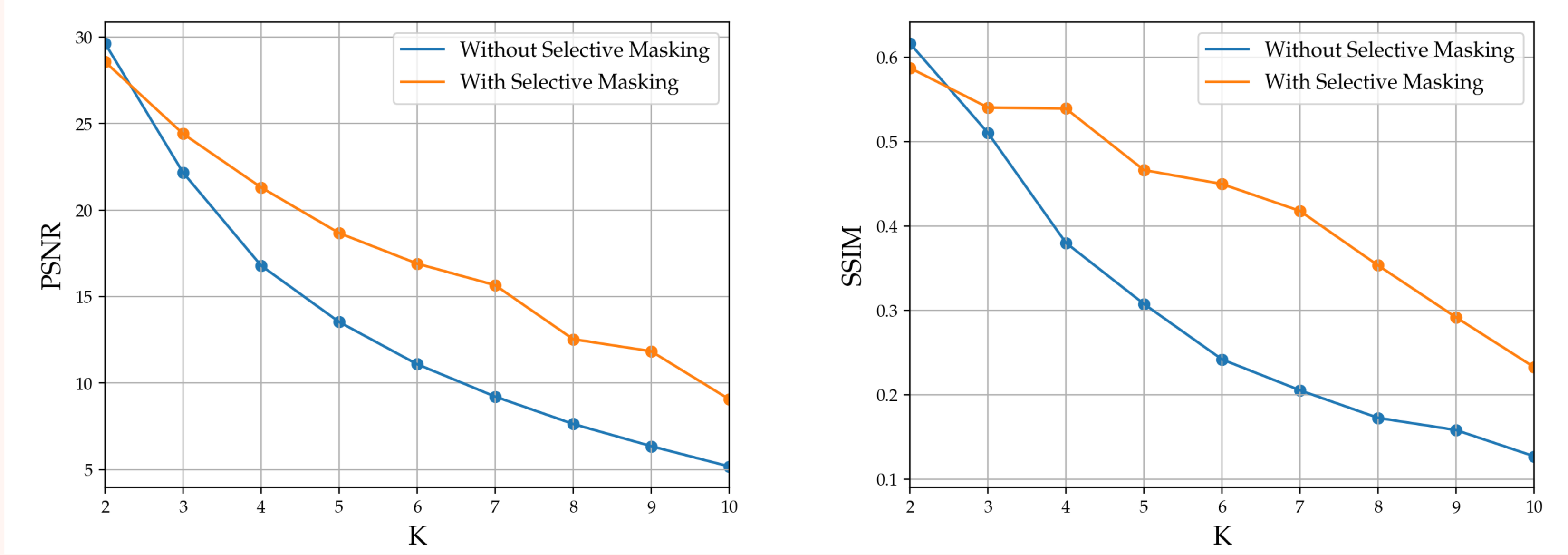


Figure 5. Illustrative Example of Potential Noise in a Cluster

- Some clusters may contain what appears to be only noise.
- Eliminating those clusters can hasten as well as improve the denoising process.

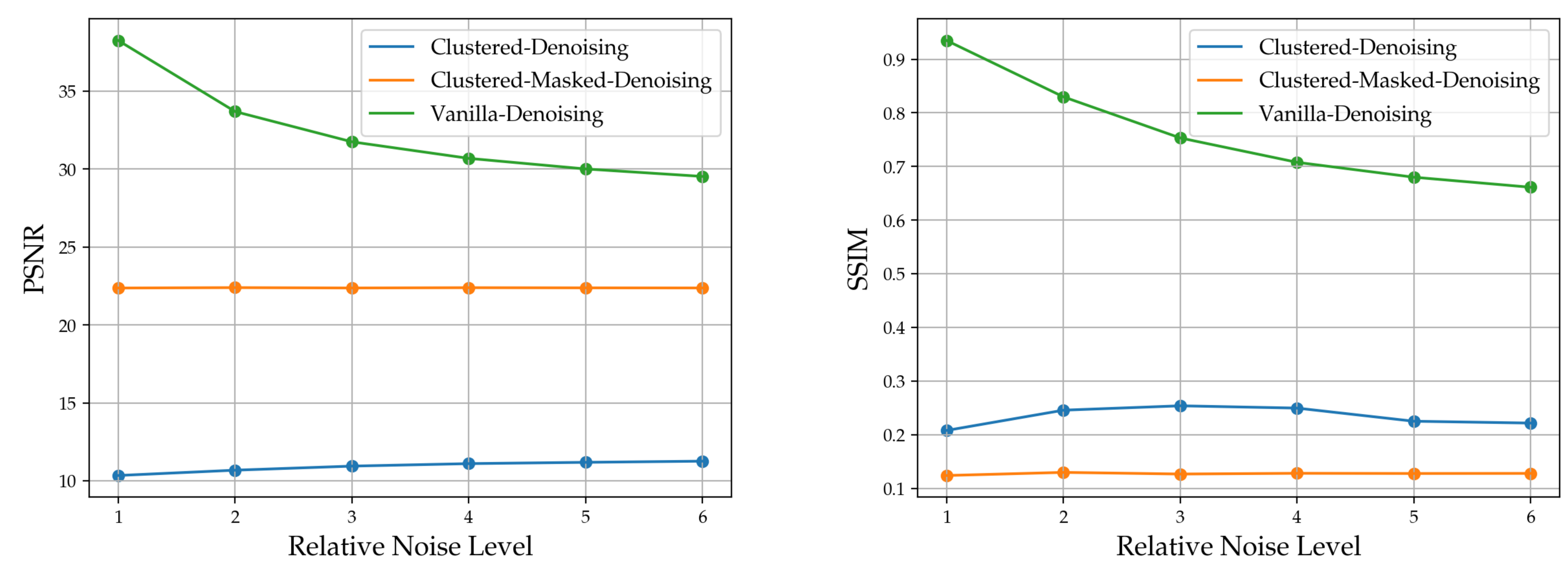


(a) PSNR as a function of number of K-means clusters (b) SSIM as a function of number of K-means clusters

Figure 6. Effect of Selective Masking on Image Quality Indices

- Pertinent question: Why does increase in K lead to a decay in image quality indices?

Noise-Robustness of Image Denoising Protocols

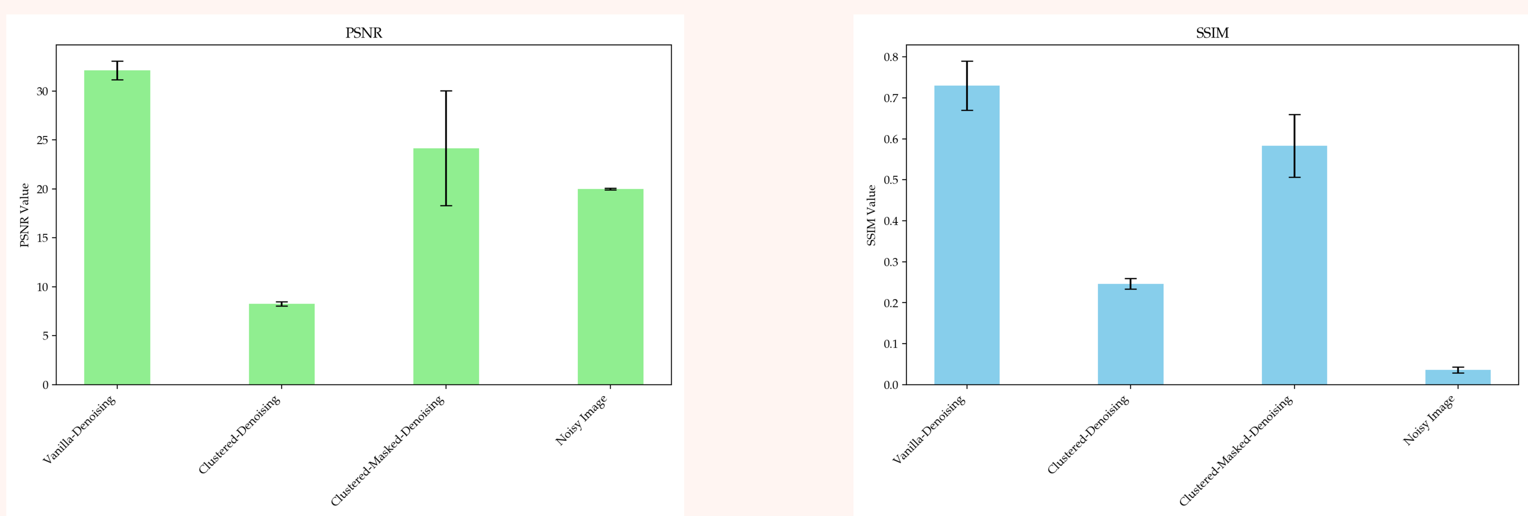


(a) PSNR Robustness to Noise (b) SSIM Robustness to Noise

Figure 7. Robustness of Image Quality Indices to Nose Levels

- Models which incorporate clustering are robust to varying noise-levels.

Closing Remarks



(a) PSNR Trends (b) SSIM Trends

Figure 8. Performance of Different Denoising Protocols

- Masking can improve denoising performance of CNNs. Influenced by model architecture.
- Clustering can potentially segregate noise from signal.
- Clustering prior to denoising turns the model robust to noise.

References

[1] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising," *IEEE transactions on image processing*, vol. 26, no. 7, pp. 3142–3155, 2017.