TUE-AM-161

Code repository

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Masked Image Training for Generalizable Deep Image Denoising

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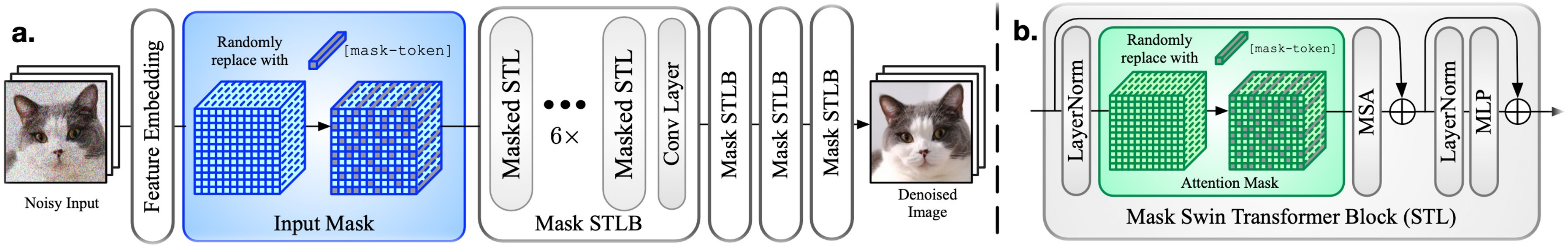
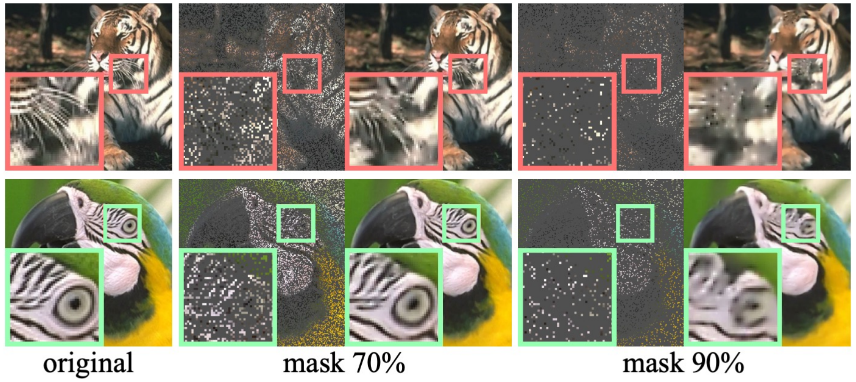
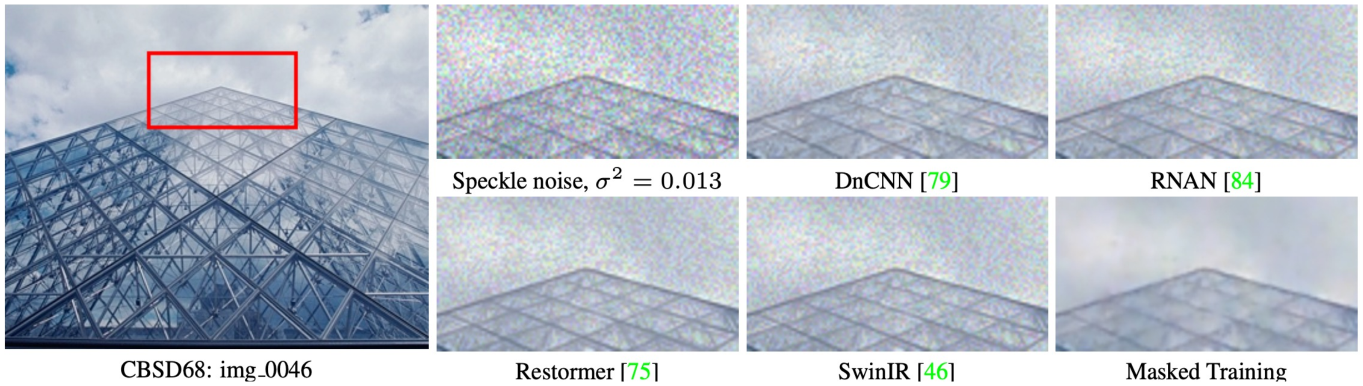
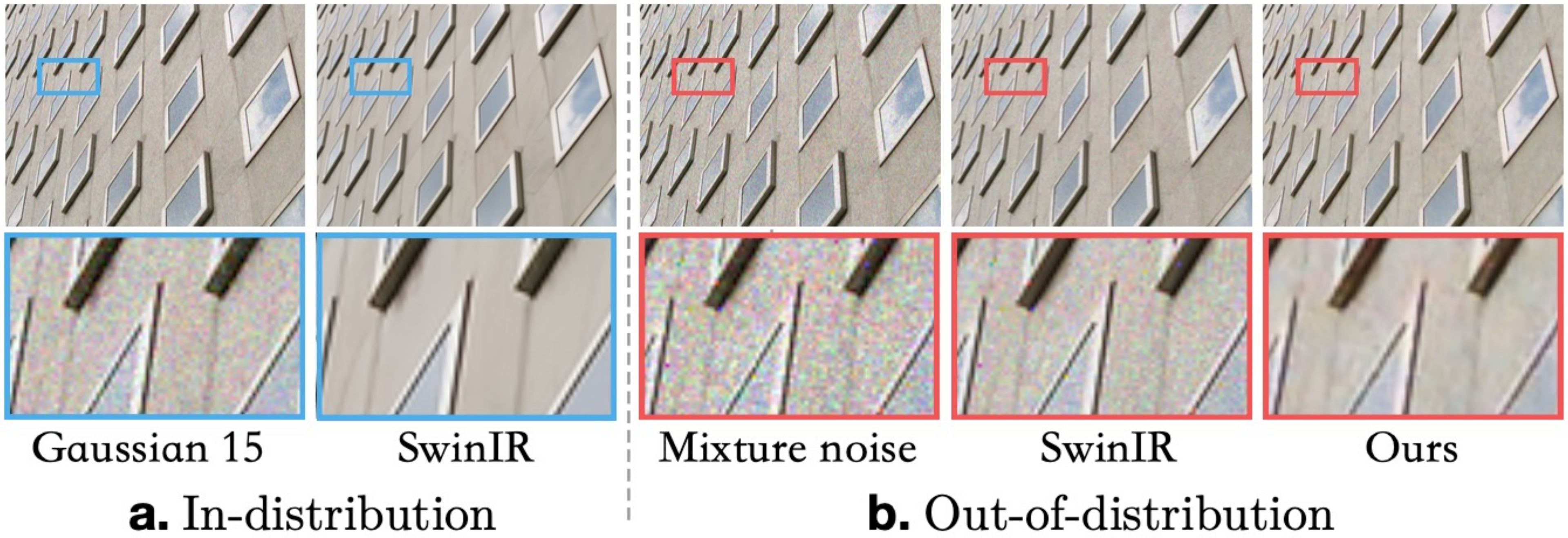
Quick Preview







Generalization Problem of Denoising Networks



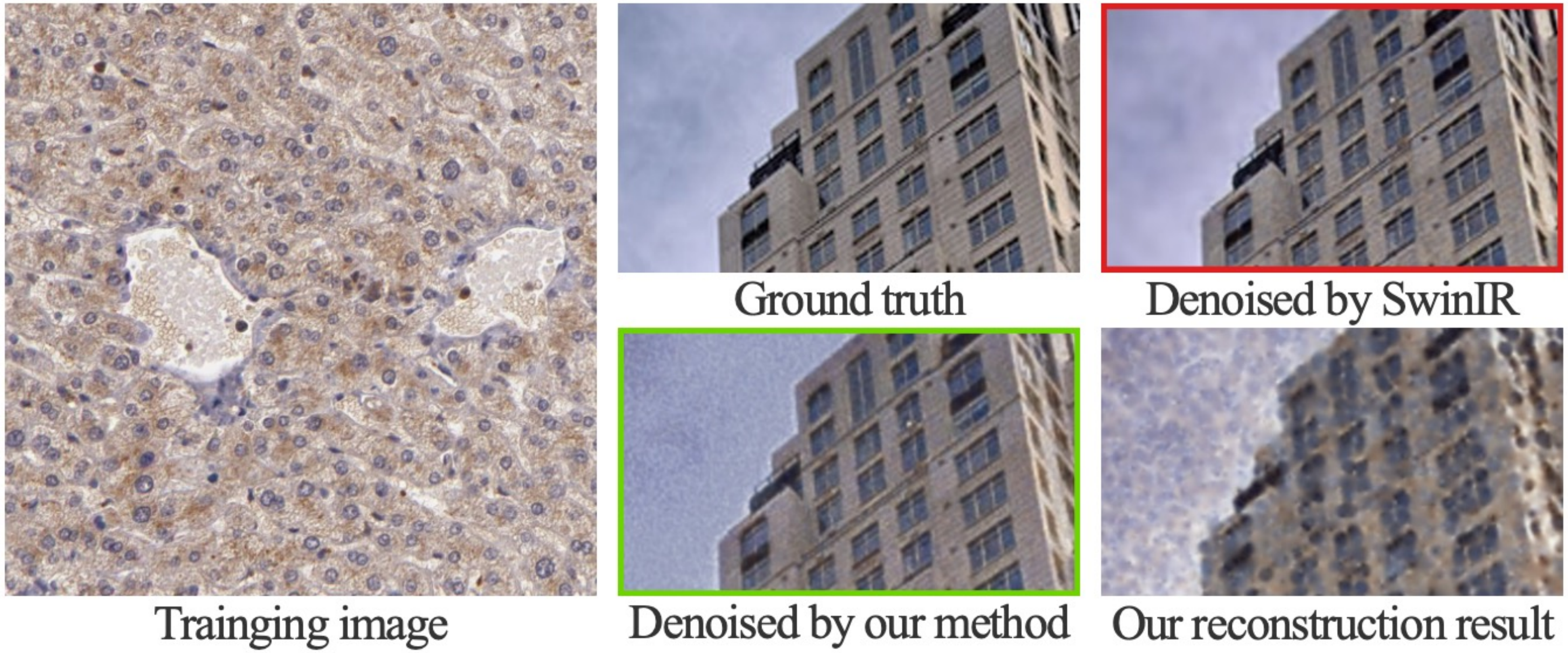
SwinIR

in-distribution noise: outstanding performance.
out-of-distribution noise: a huge performance drop.

Ours

out-of-distribution noise:
maintains a reasonable denoising effect

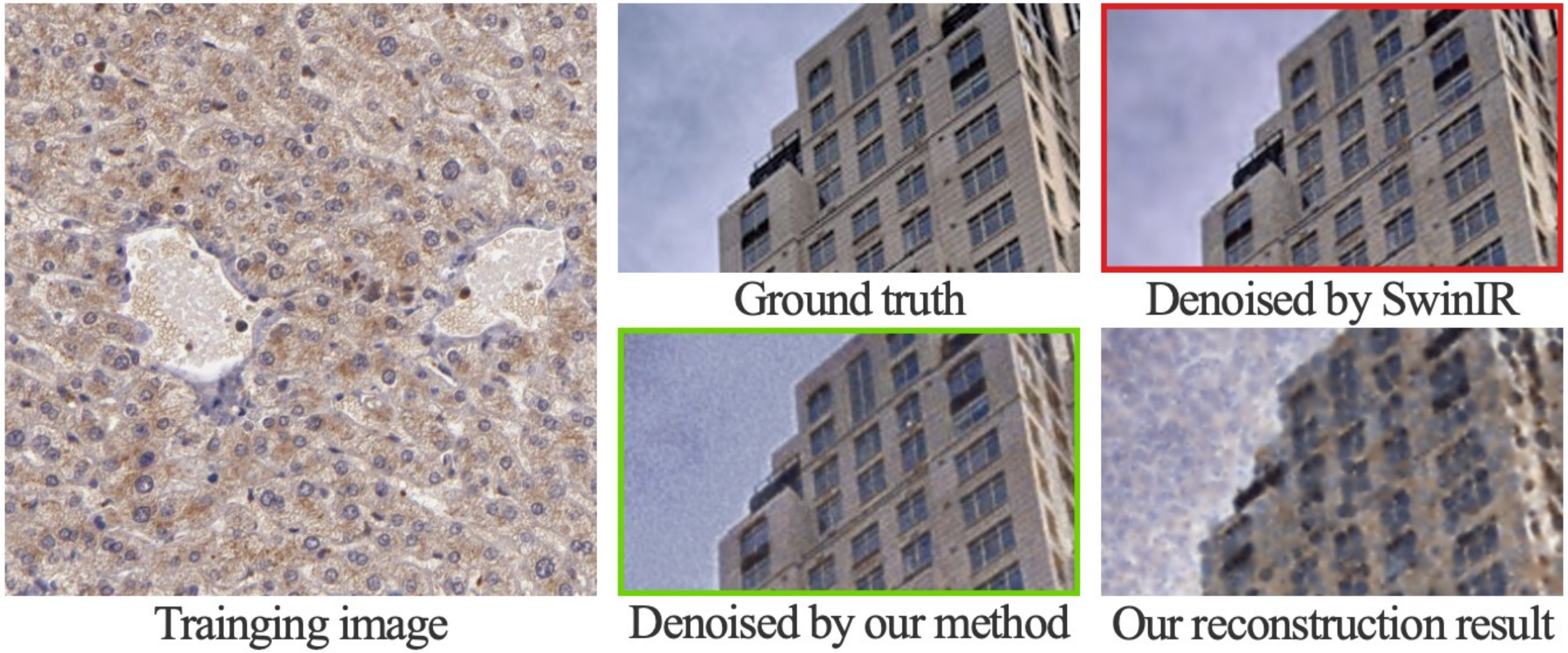
Motivation



Training noise type: Gaussian noise
Training image type: Immunohistochemistry images

Testing image type: Natural image

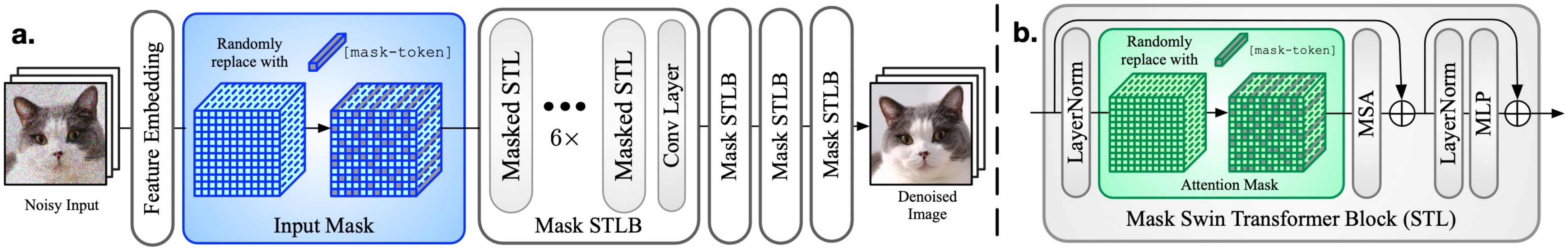
Motivation



Reason for the poor generalization ability: the training method makes the model *focus on overfitting the training noise instead of learning the image reconstruction.*

Instead, we want the model to *learn to reconstruct the texture and structure of the images, rather than focusing only on noise.*

Method: Masked Training



The Input Mask randomly masks out the feature tokens, and complete the masked information during training ⟶ explicitly constructs a challenging **inpainting problem**.

The Attention Mask. There is **inconsistency** between training and testing, we can narrow the gap between training and testing by performing the same mask operation during the self-attention process.

Experiments

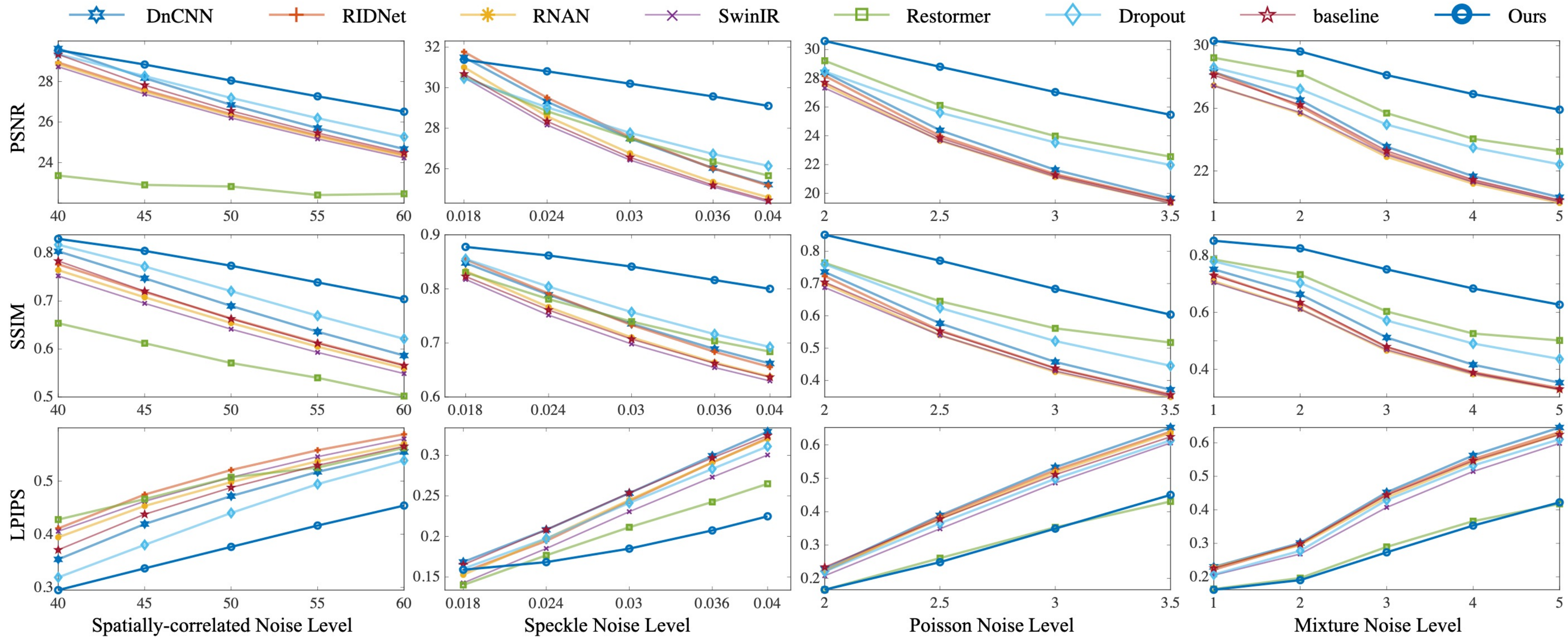


Figure 10. Performance comparisons on four noise types with different levels on the Kodak24 dataset [25]. All models are trained only on Gaussian noise. Our masked training approach demonstrates good generalization performance across different noise types. We involve multiple types and levels of noise in testing, the results cannot be shown here. More results are shown in the supplementary material.

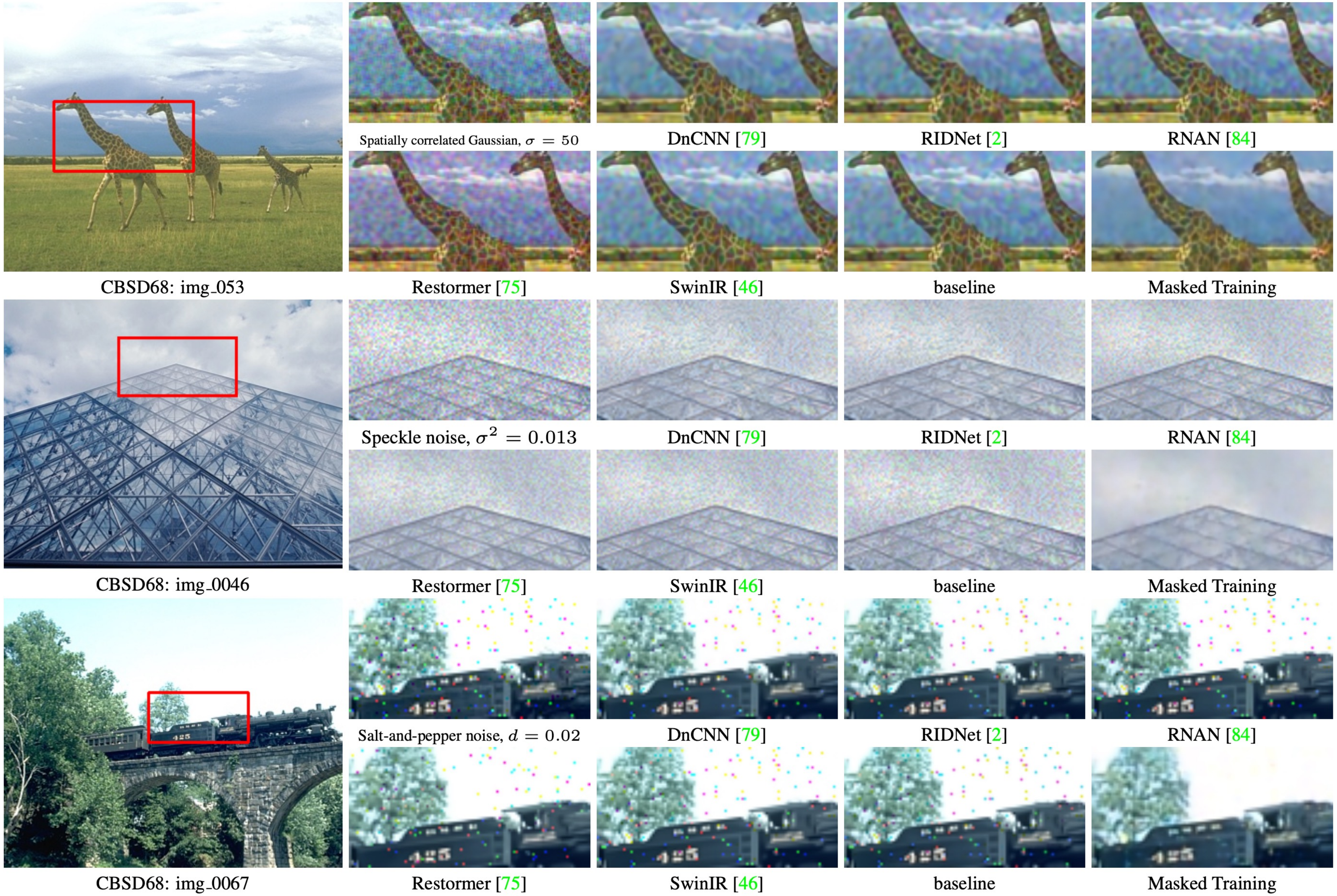


Figure 7. Visual comparison on out-of-distribution noise. When all other methods fail completely, our method is still able to denoise effectively. Please refer to the supplementary material to see more visual results.

Generalization Analysis

Training curve

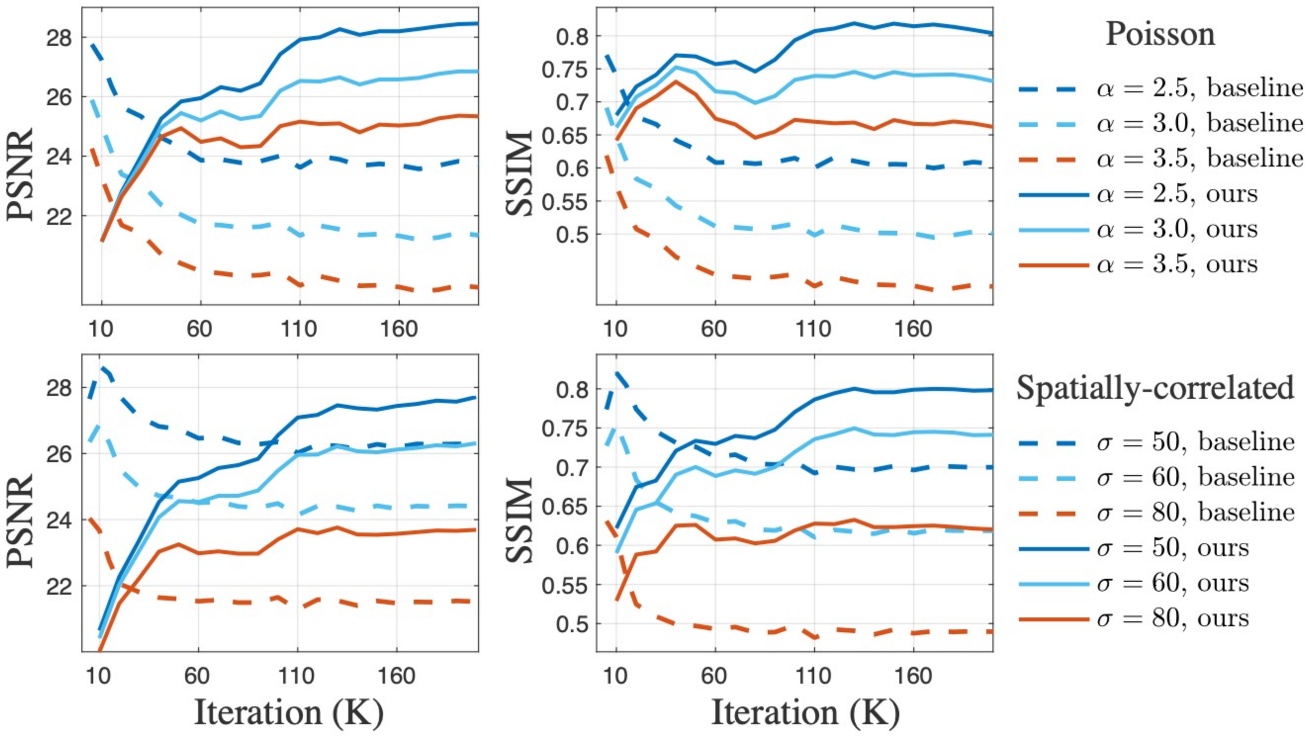


Figure 12. The testing curves on different noise types and levels.

The models are trained using only Gaussian noise.
Testing on other noise type.

Generalization Analysis

Feature Distribution

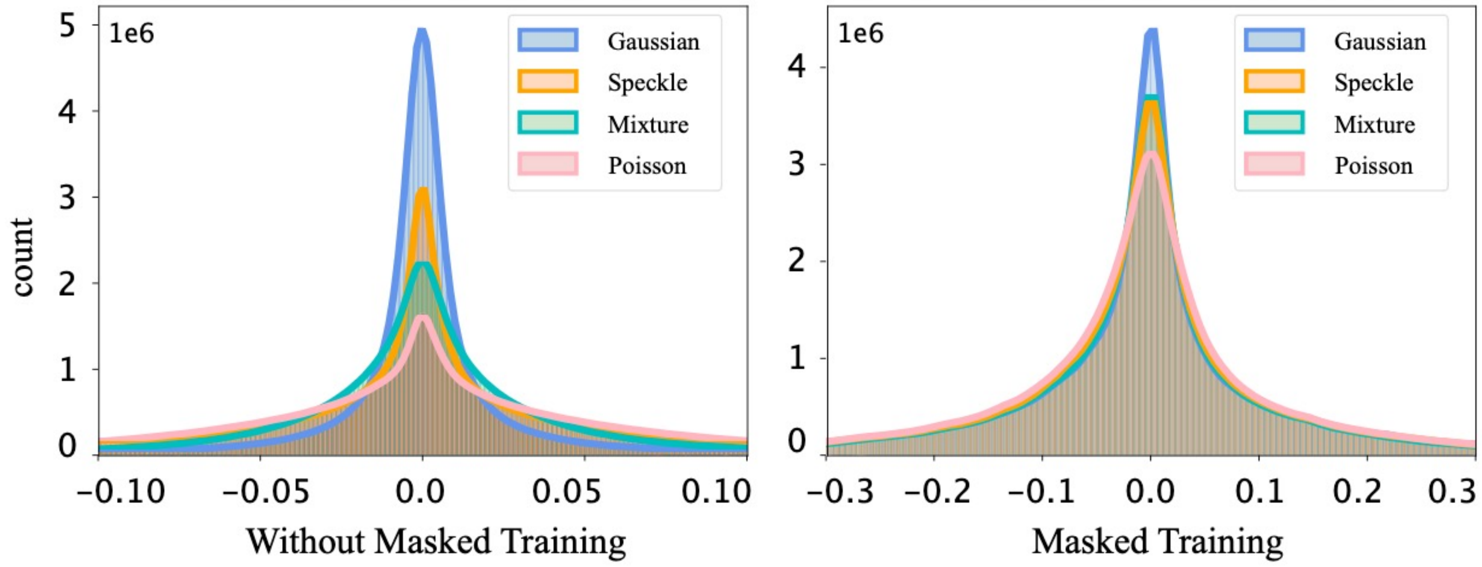


Figure 14. The distribution of baseline model features is biased across different noise types. Our method produces similar feature distributions across different noise.

Thank you for watching