Evaluating the Robustness of a 4D STEM Autoencoder to Noisy Inputs

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Why Evaluate NN's Robustness to noisy inputs?

- Neural Networks can assist 4D STEM dataset analysis [2][3][4].
- Reduce damage to the specimen → send less electron beams [5] → larger noise to the dataset

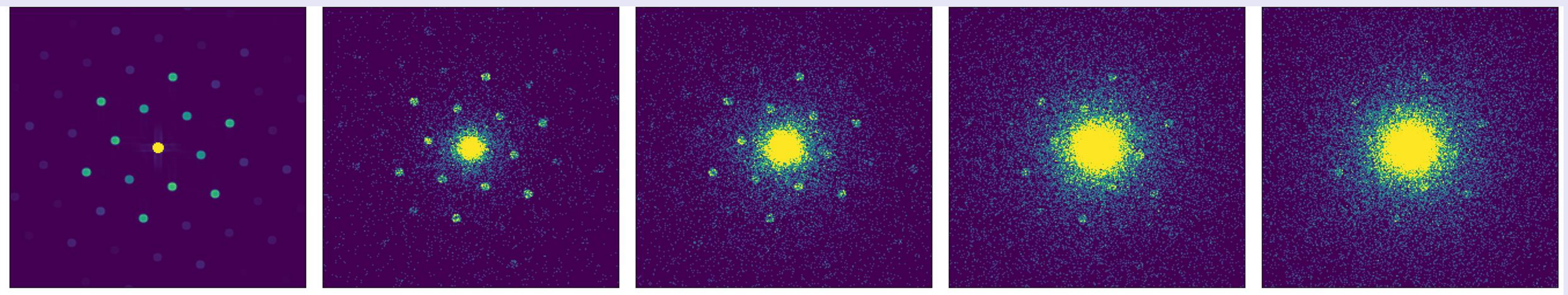
- What is the maximum noise level that the neural network can handle?
- How could we enhance the model's robustness?

CC-ST-AE

Data

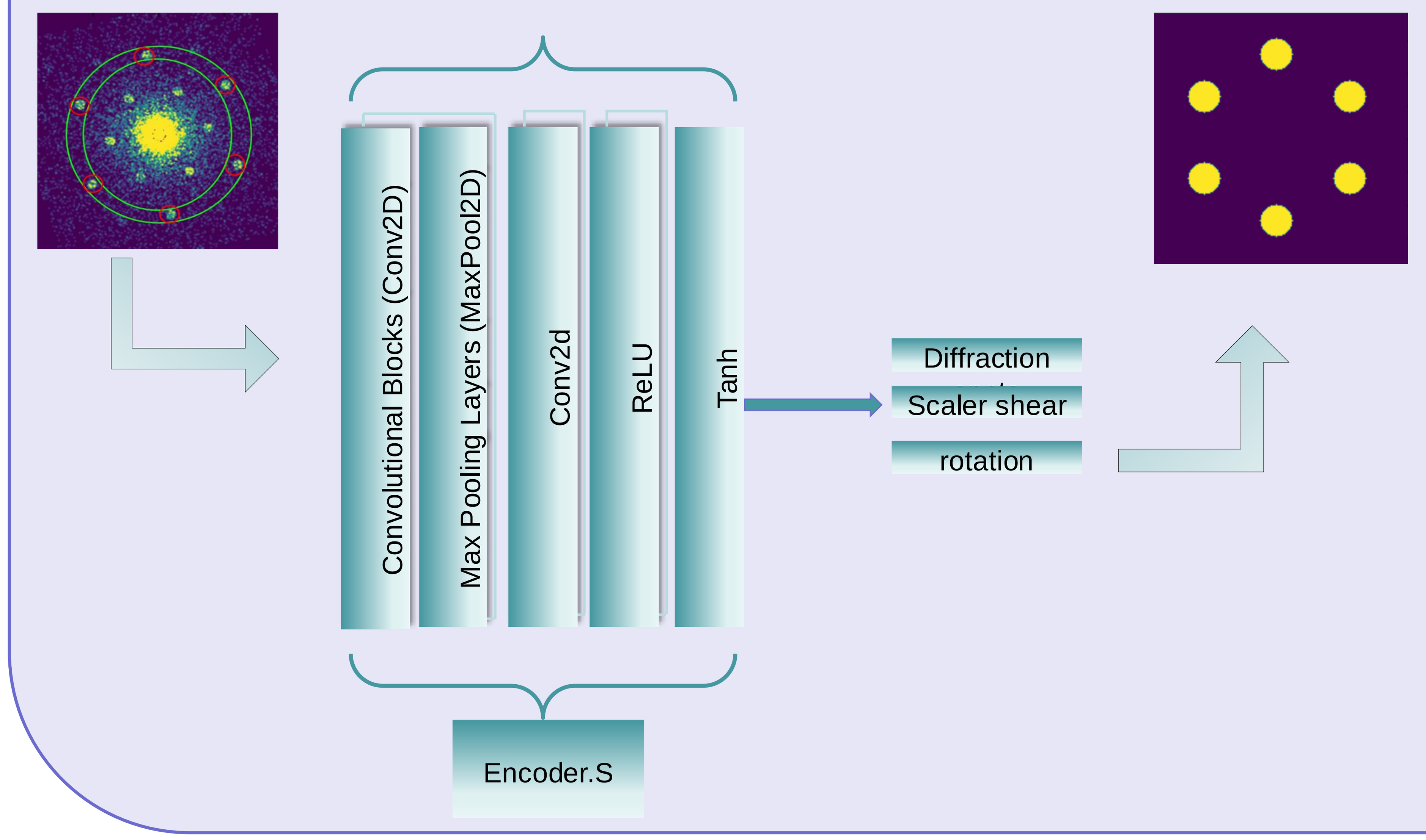
In material science, 4D Scanning Transmission Electron Microscopy (4D STEM) is a dataset of images formed by electrons passing through a thin specimen [1] that material scientists can learn some structural properties.

A sample input image with different noise level, i.e. intensity of background noise



Model

Qin et al. proposed a neural network structure called cycle-consistent-spatial-transforming auto-encoders (CC-ST-AE) to extract spatial parameters like crystallographic strain, shear, and rotation to understand material properties [3], [4].



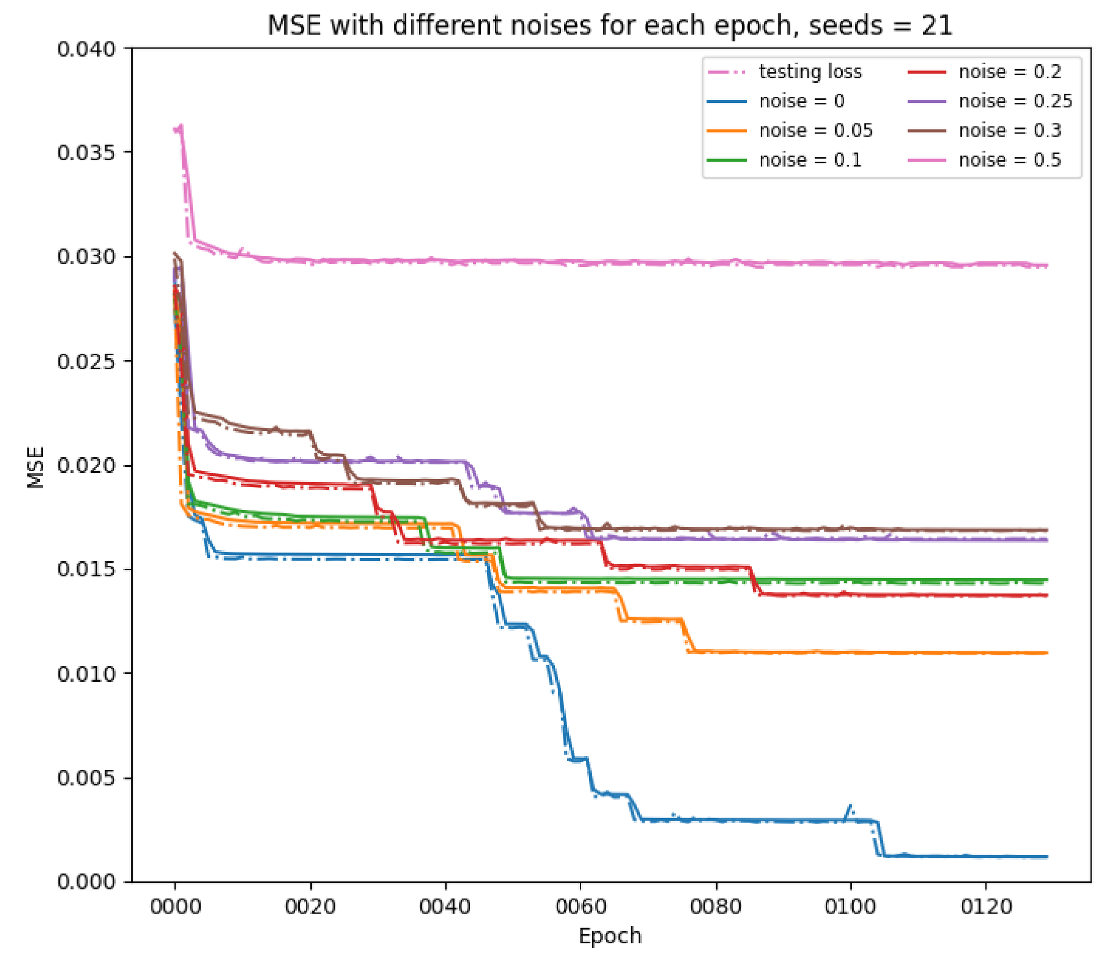
Results

Methods

Train and test the model with different noise levels to measure its robustness to noisy inputs.

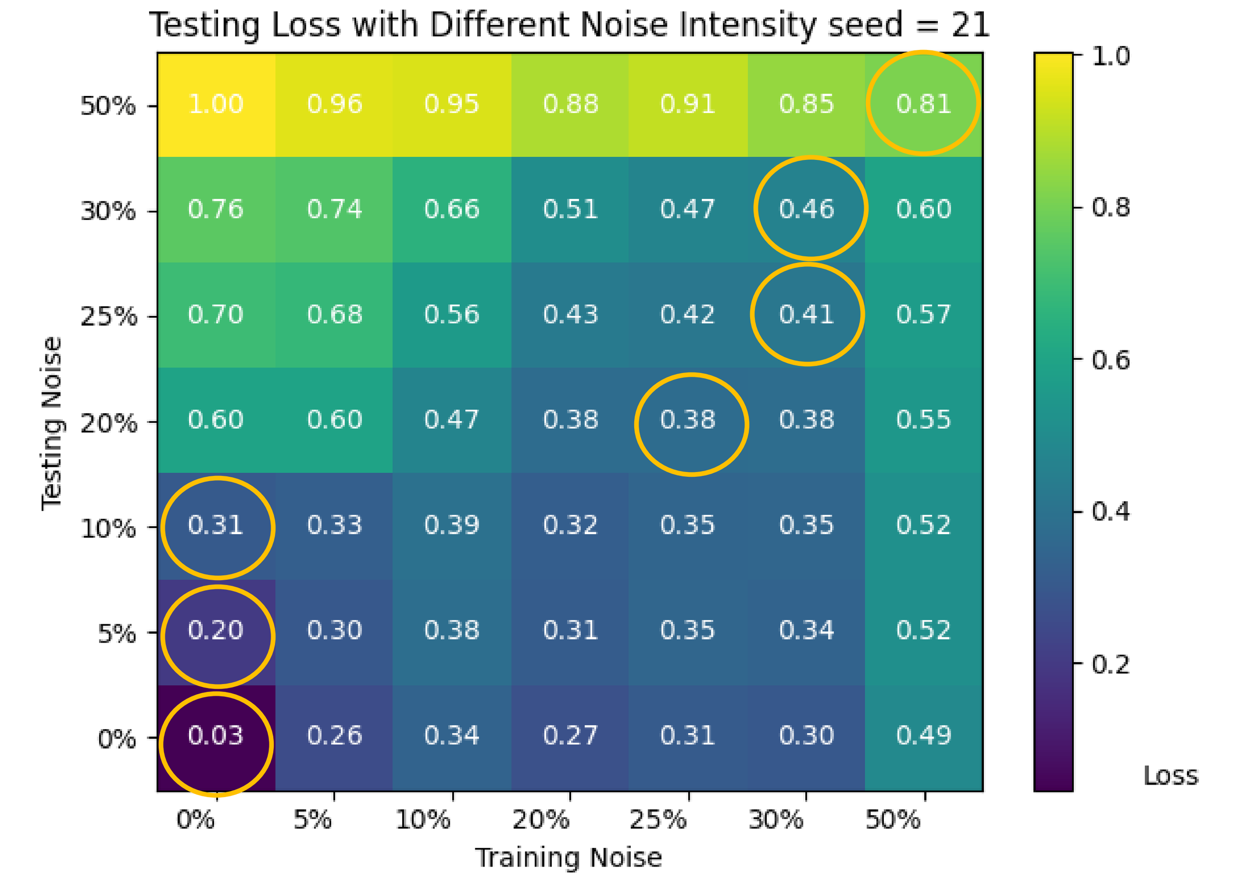
Takeaways #1

The larger the noise level is, the worse the model's trains.



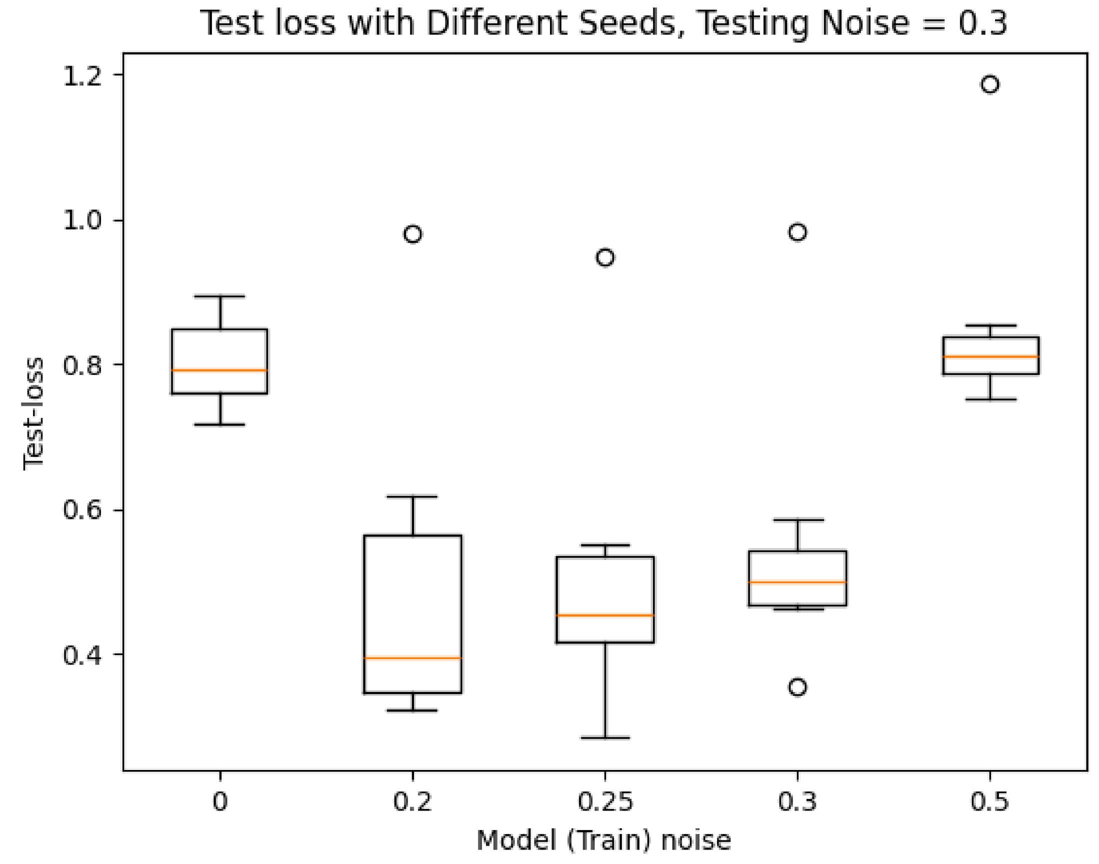
Takeaways #2

By injecting noise into the training set, we can improve the robustness of the model.



Takeaways #3

The model trained with the same noisy level as testing balances small spread with lower loss.



Future Work

- **Data augmentation with training with a combination of various noise levels**
- **Hyper-parameter tuning for the learning rate, seed, and batch size**
- **Explore techniques such as regularization, pruning, and quantization to make this suitable for edge deployment.**

References

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