MOTIVATION

- In machine learning and neural networks, most solutions require the trained models to approximate the original image using patterns observed from other images in the entire image set. Deep Image Prior (DIP) is an outlier; it recovers images without training data.
- In this project, we intend to leverage both DIP and traditional rule-based methods to form a new image recovery pipeline. We observe, compare, and analyze their performance.
- The early stopping point is a key concept in DIP. We are curious about what factors may affect it.

RELATED WORK

- Ulyanov et al. (2018) [1] proposed a powerful and effective method for imaging processing called Deep Image Prior (DIP). Our project will be mainly based on evaluating and extending the DIP algorithm by using different image preprocessing methods.
- Several methods were investigated to stop DIP iterations before fitting to noise and thus prevent from overfitting, most of which requires the clean image as an input. However, in real-world examples, clean images can be hard to retrieve, and it slightly contradicts the non-training objective of DIP.
- At the same time, many extensions can be made based on the idea of DIP. Bredell et al. came up with an idea that uses Wiener deconvolution to guide DIP for better performance on image deblurring. We may want to extend this idea and use different methods of denoising and deblurring to compare the results.

PROPOSED METHOD & EXPERIMENTAL RESULTS

In our project, we plan to investigate the mechanism and effectiveness of DIP, as well as potential improvements.

- Task 1. If we manually denoise/deblur the image before training it with deep neural networks, will the result be better? To obtain the answer, we plan to utilize different image denoising/deblurring methods as preprocessing for the corrupted input image to the DIP and compare the final results.
- Task 2. In the experimental setup, we plan to gather a variety of images and add the same noise to them, and observe the PSNR curve for possible patterns.

Our results show that when preprocessed with Wiener deconvolution or denoising neural networks, the performance is higher in terms of both maximum PSNR and convergence speed compared to standalone DIP. Also, the convergence speed does not correlate significantly with noise levels, but rather the image content frequency.

REFERENCES