


# IMAGE DEBLURRING USING GAN

DSAN 6500 PROJECT

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# Dataset

## Original Dataset:

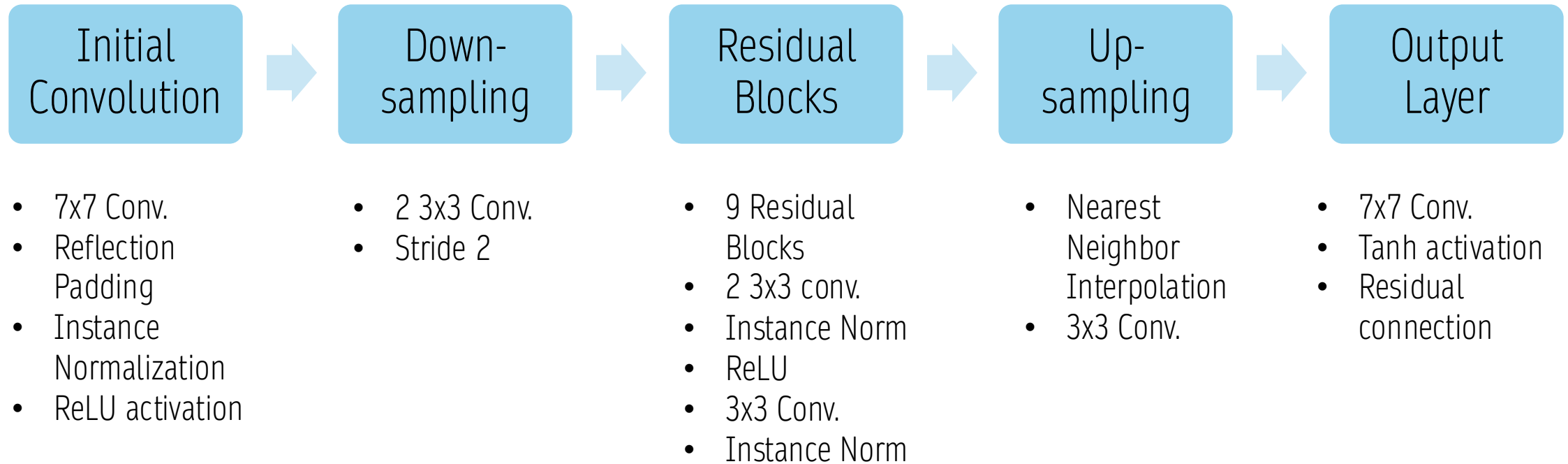
- [GROPRO Large](#)
- Size: 9.54 GB
- Total Images: 2103 (train), 1111 (test)
- Images are provided in pair format: One blurred and one corresponding sharp frame
- Original Resolution: 1280 x 720
- Common benchmark dataset for learning-based motion deblurring tasks

## Preprocessing:

- Resized to 256x256
- Normalized pixel values to the range  $[-1,1]$

# Architecture

## Generator Network

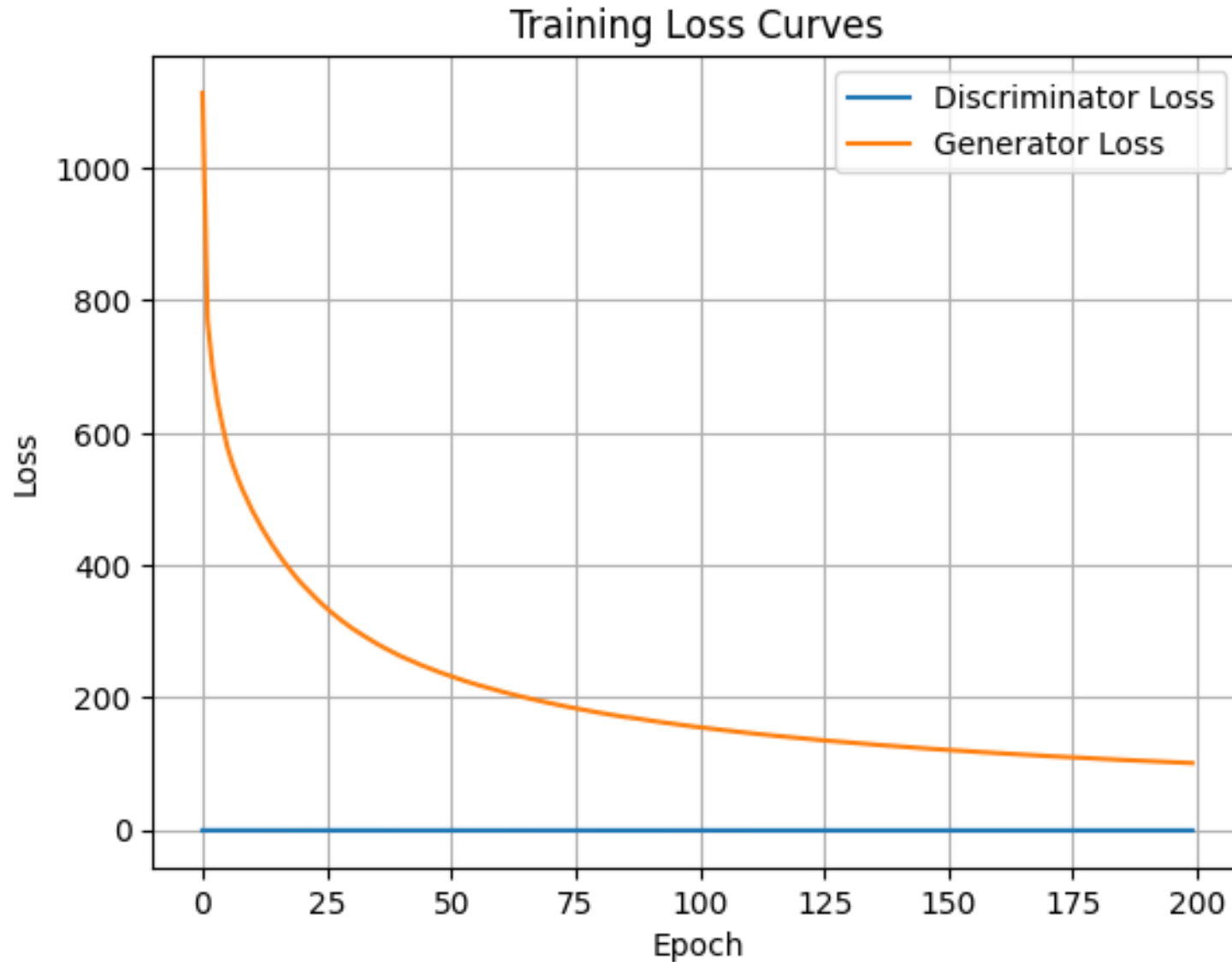


# Architecture

## Discriminator Network

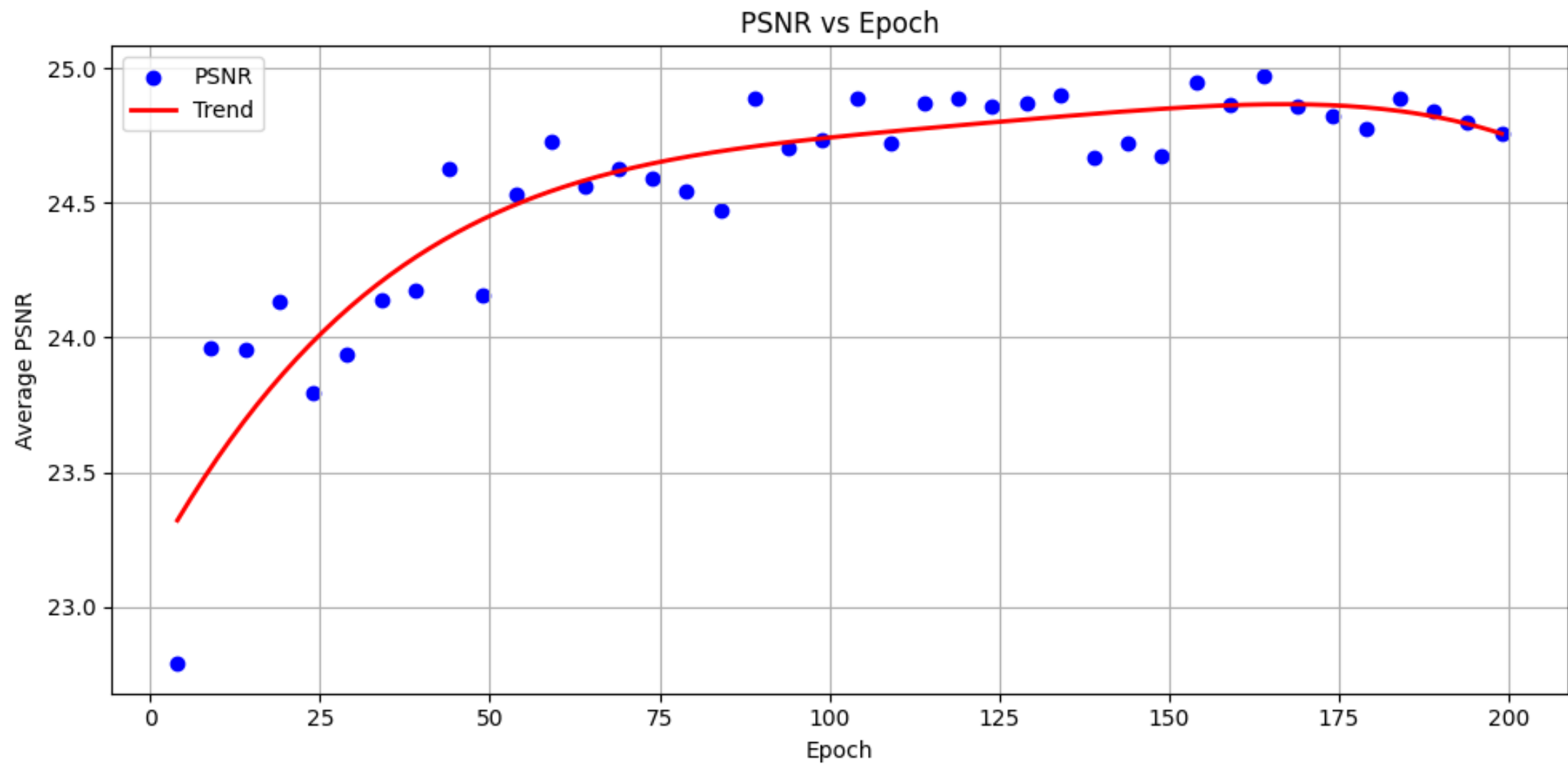
- The discriminator follows a PatchGAN design, evaluating image realism at the patch level rather than classifying the whole image.
- It takes either a real sharp image or a deblurred image from the generator and passes it through a series of 5 convolutional layers with increasing filter sizes.
- Each convolution is followed by LeakyReLU activations and Batch Normalization (except the first).
- Instead of a single output, the model outputs a grid of probabilities, where each value corresponds to the "realness" of a specific image patch.
- A final fully connected layer maps this grid into a single probability, predicting whether the input is real or generated.

# Training



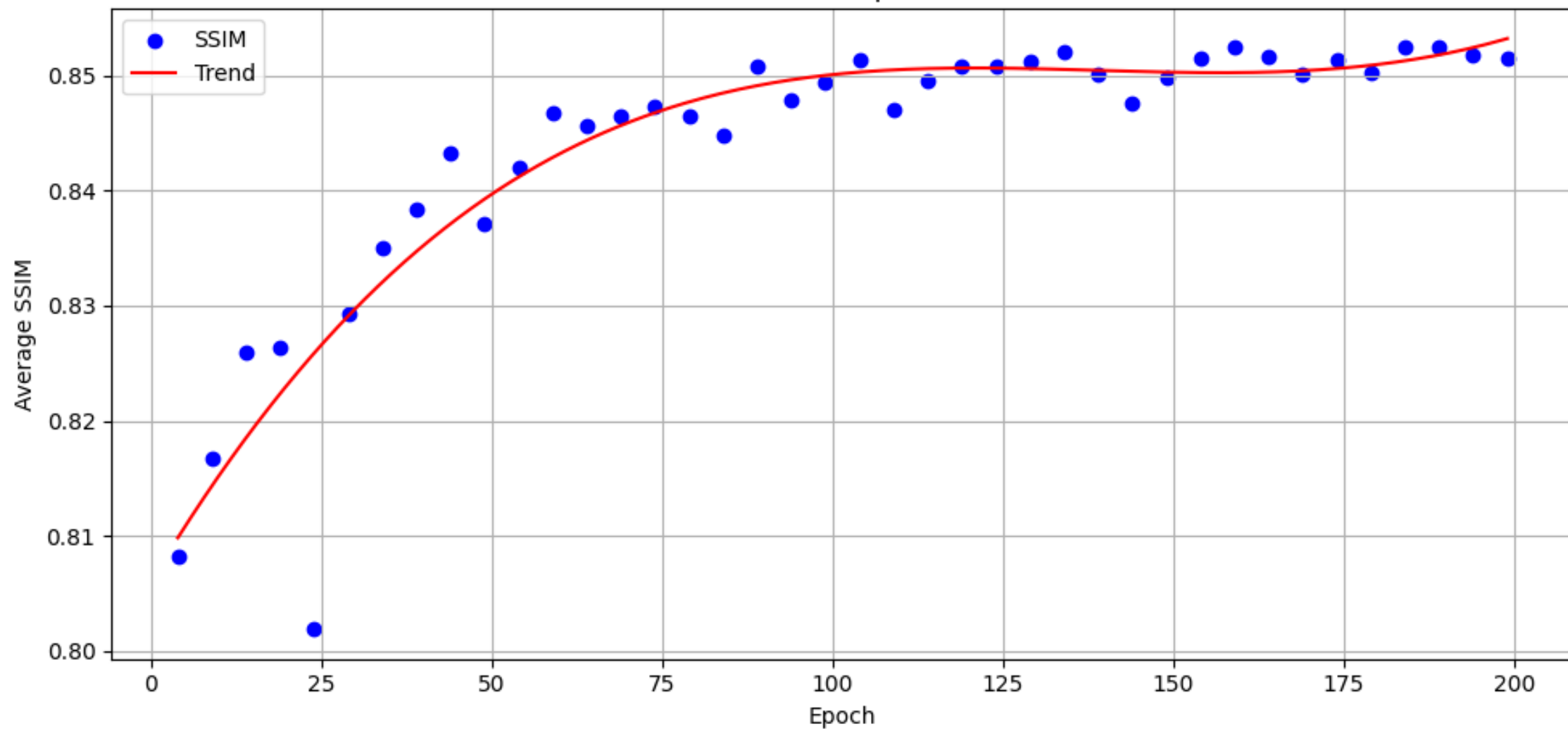
- Trained for 200 epochs
- Generator Loss: Weighted sum of
  - Perceptual loss (VGG16)
  - Wasserstein loss
- Discriminator Loss: Wasserstein Loss

# Training



# Training

SSIM vs Epoch





# Results

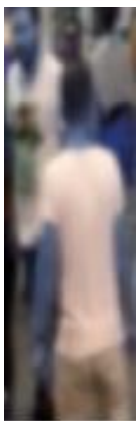
Blurred



Deblurred

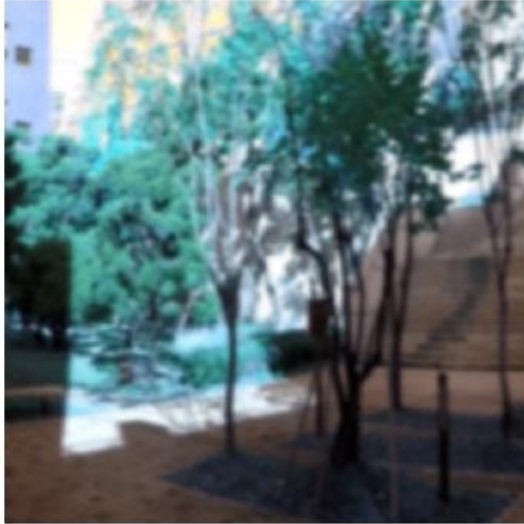


Target

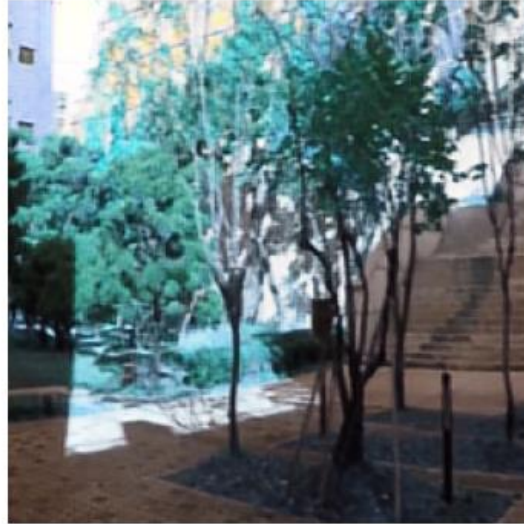


# Results

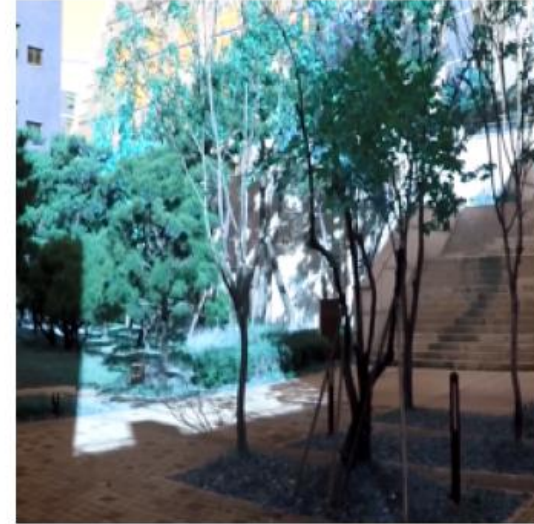
Blurred



Deblurred



Target



# Results

	Sun <i>et al.</i> (using CNN)	Nah <i>et al.</i> (Deep Multi-scale CNN)	Xu <i>et al.</i>	GAN
PSNR	24.6	28.3	25.1	26.42
SSIM	0.84	0.916	0.89	0.87

# References

Nah, Seungjun, Tae Hyun Kim, and Kyoung Mu Lee. "Deep multi-scale convolutional neural network for dynamic scene deblurring." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.

Kupyn, Orest, et al. "Deblurgan: Blind motion deblurring using conditional adversarial networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

Xu, Li, Shicheng Zheng, and Jiaya Jia. "Unnatural l0 sparse representation for natural image deblurring." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2013.

<https://machinelearningmastery.com/how-to-implement-wasserstein-loss-for-generative-adversarial-networks/>

<https://www.kaggle.com/datasets/lqzmlaq/gopro-large>