Image Super-Resolutions

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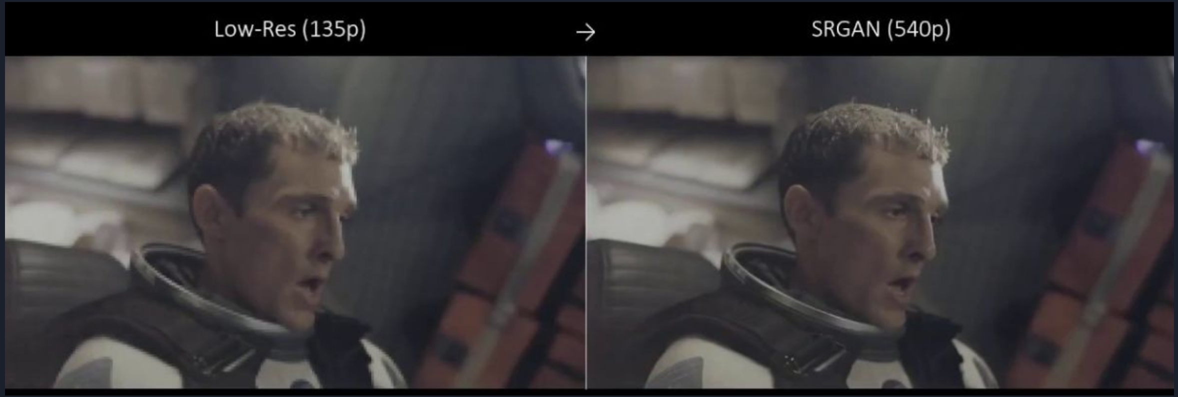
Context and Objectives

- **Motivation:** It is common to have blurred or pixelated images, and it is usually difficult get more optimal images. **Our objective** was to construct a model that can improve the resolution of any image by a factor of 4.



Milestones:

➔ Produce a Super Resolution x4 times the Low Resolution.

➔ Correct the use of MSELoss (instead of VGG Loss) with a more complex architecture.

➔ Construct a model that works for any test image.

Dataset

We started with BSD300.

- ➢ 200 variate Training images
- ➢ 100 variate Test images

We finally selected **DIV2K**

- ➢ **800 variate Training images**
- ➢ **100 variate Test images**

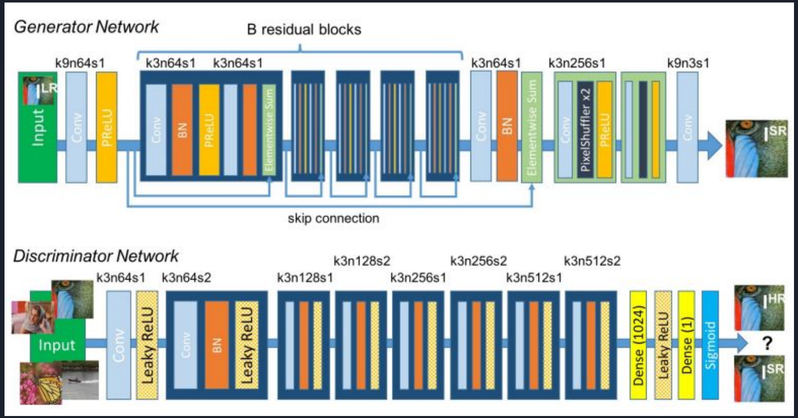
Center cropping of all the images:

- ➢ **64x64** for Low Resolution images
- ➢ **256x256** for High Resolution images

High Resolution

Low Resolution

Architecture

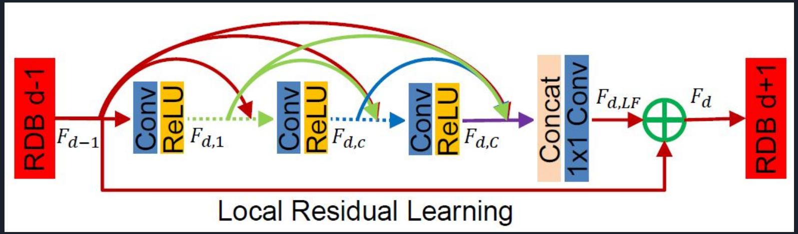


Basic SRGAN architecture:

- **Generator**
  - Convolutional+Parametric ReLU
  - 5 Residual Blocks
  - Batch Normalization
  - Upscaling Blocks with Sub-Pixel Convolutions
- **Discriminator**
  - Strided Convolutions
  - Fully Connected Layers

Improved with **Densely Connected Convolutional Networks** principle:

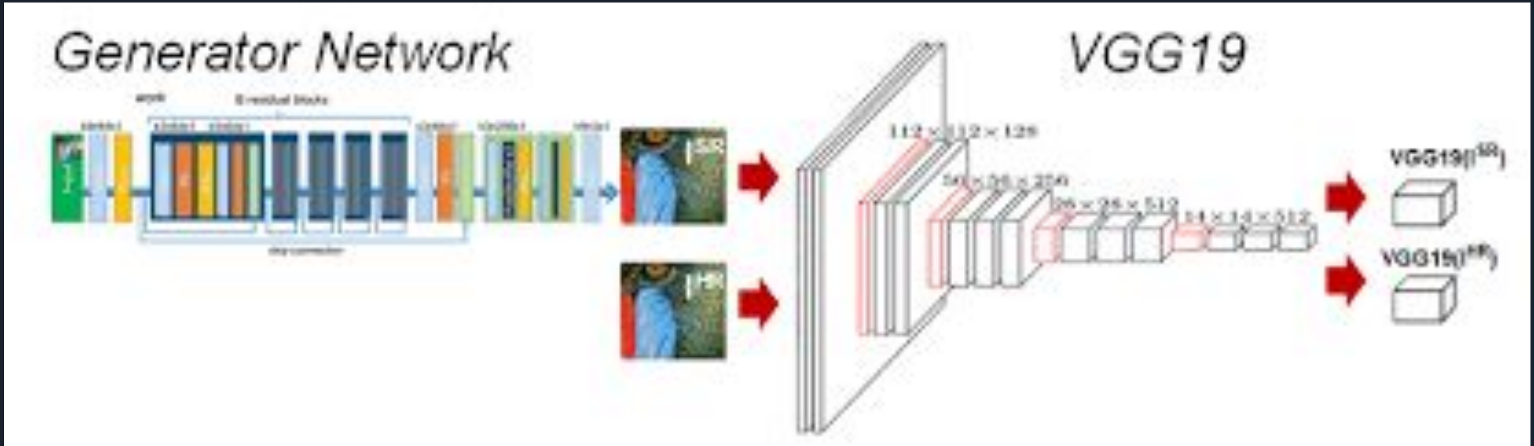
- Application of Densely Connected Residual Blocks
- Element-wise sum replaced with Weighted ‘concatenation’ of outputs



Use of VGG19 as Transfer learning for the discriminator:

Use a pre-trained VGG19:

- Input of the Discriminator
- Pre-processed VGG(HR)
- Less parameters



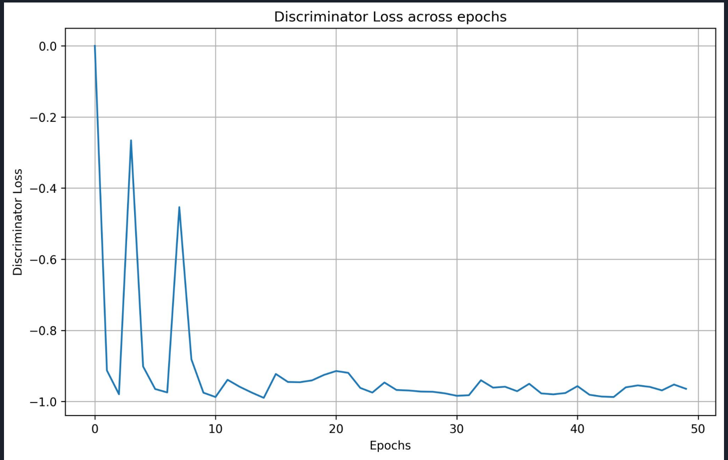
Training

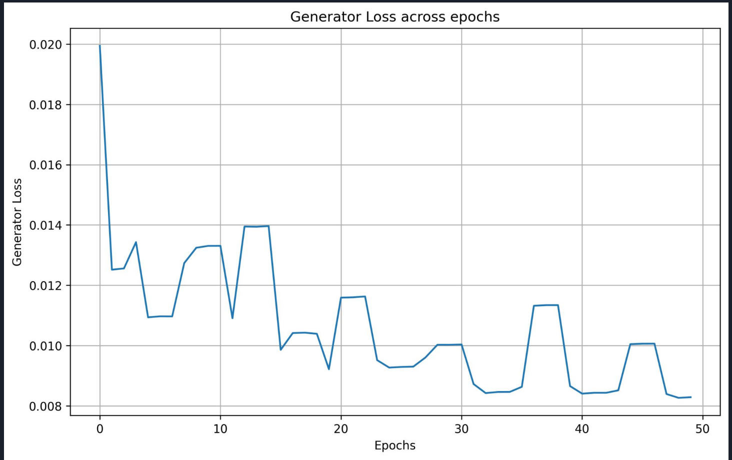
- Losses:
  - Content Loss: Pixel-wise loss (MSE versus VGG).
  - Adversarial Loss: Discriminator loss (Wasserstein versus BCE).
  - Perceptual Loss: Generator loss taking into account Content Loss and Discriminator feedback.

- Hyperparameters:
  - Learning Rate: Unique or one for each piece of the network.
  - Epochs: Computational time and diminishing returns.
  - Adversarial training: Regulating the race between Generator and Discriminator.
  - Batch Size: Usage of Batch Normalization or Instance Normalization in our architecture.

Results

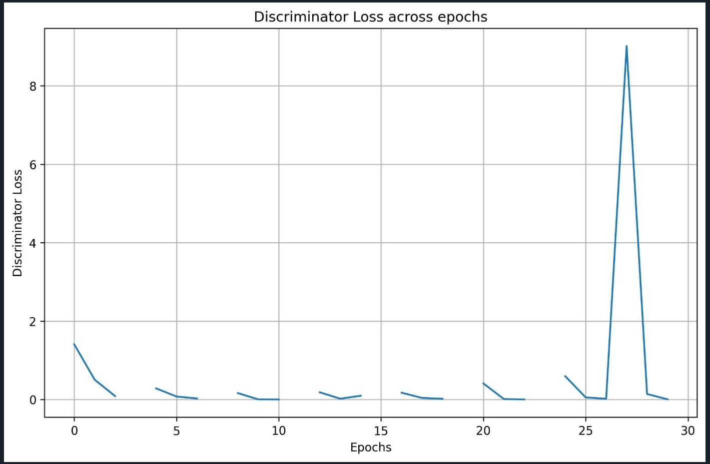
Metrics: Peak Signal to Noise Ratio (PSNR) and structural similarity (SSIM).

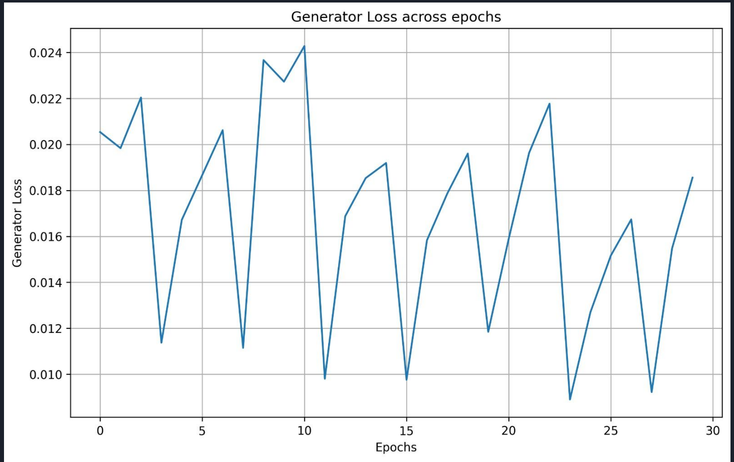




- Weighted Dense ResNet (WDRN) with VGG SRGAN 50 epochs:
  - PSNR = 29.23
  - SSIM = 0.739

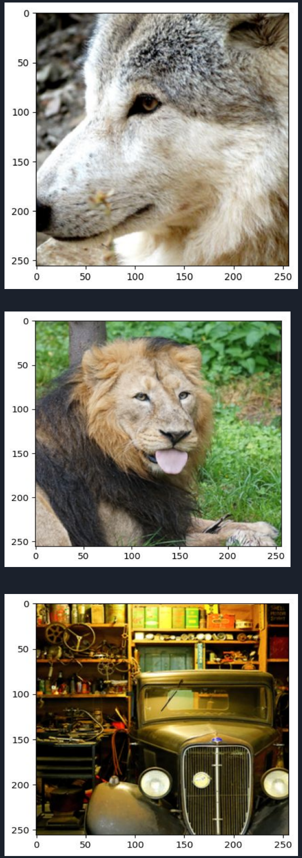
More Results (Second best model)



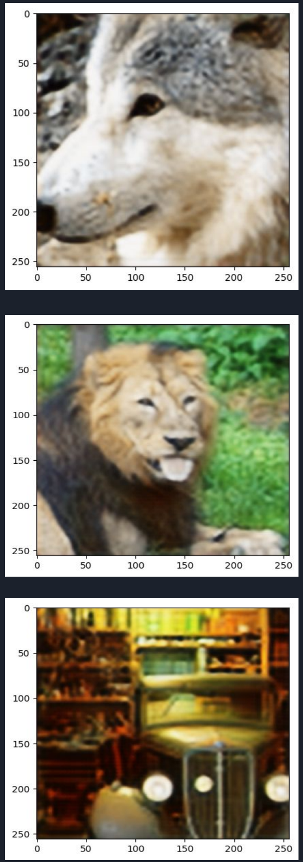


- Normal SRGAN 30 epochs:
  - PSNR = 29.21
  - SSIM = 0.731

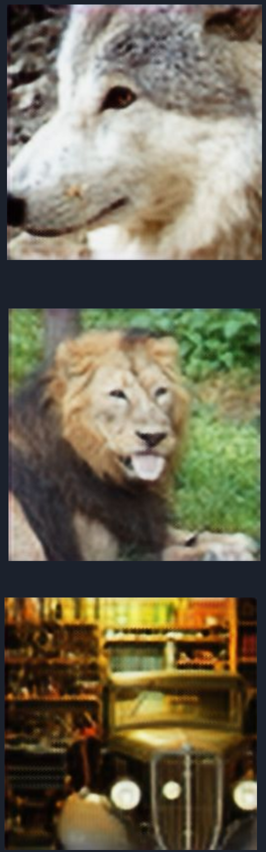
HR



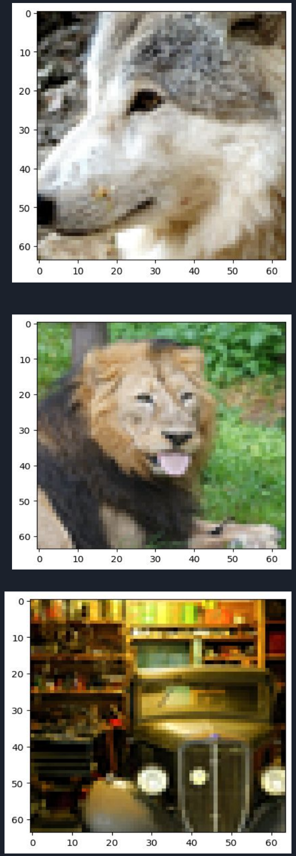
WDRN + VGG



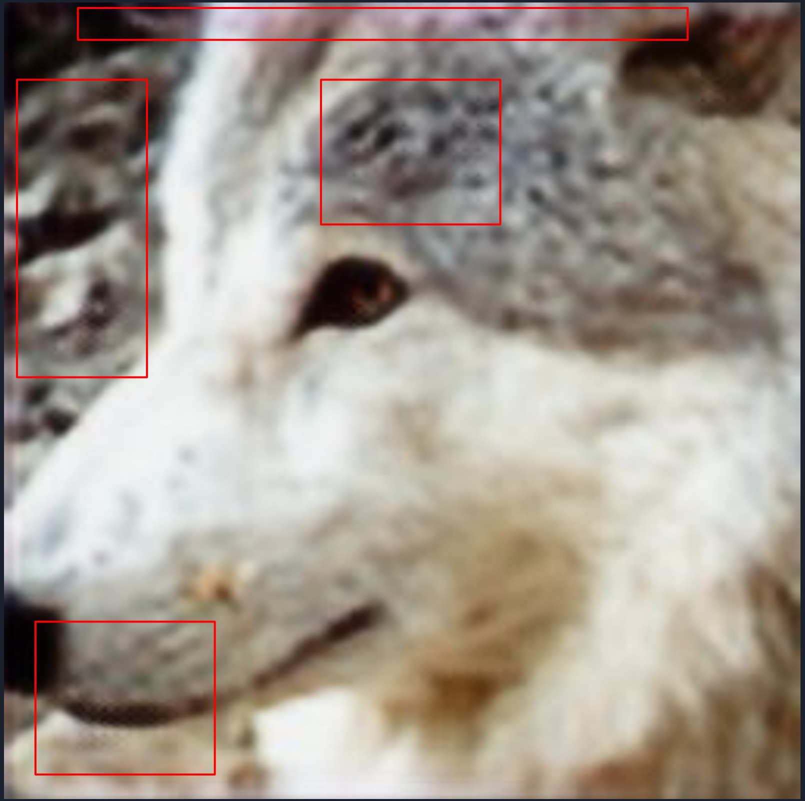
Normal



LR



COMPARISON BETWEEN WDRN AND THE ORIGINAL NETWORK



COMPARISON BETWEEN WDRN AND LOW RESOLUTION

Experiments

- Implementation of Densely Connected Blocks
  - Encouraging forward-pass nature of the model.
  - Experimentation with Weighted Dense Connections
- Wasserstein Loss
  - As discriminator loss
- VGG implementation
  - After the SR and HR images and before the Discriminator
  - Pre processed
- Dropout
  - To reduce overfitting
  - Different values
- Batch size
  - Problems
  - Instance Norm

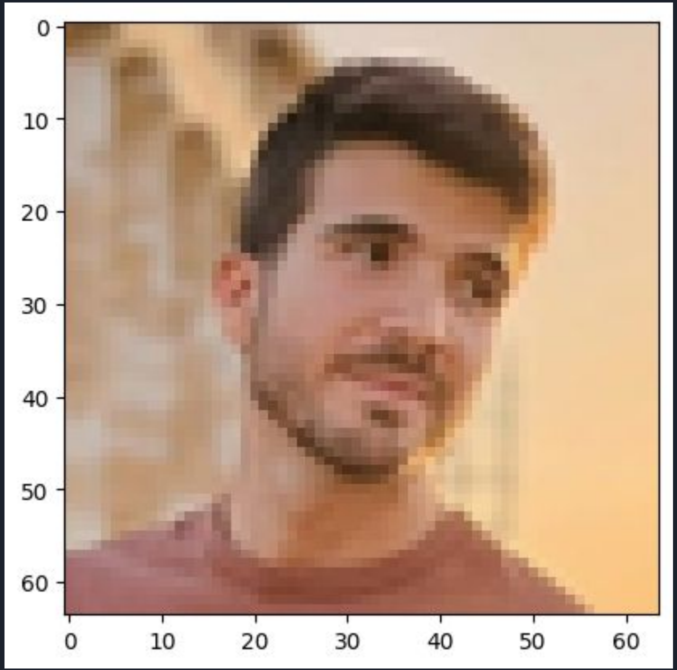
Possible extensions

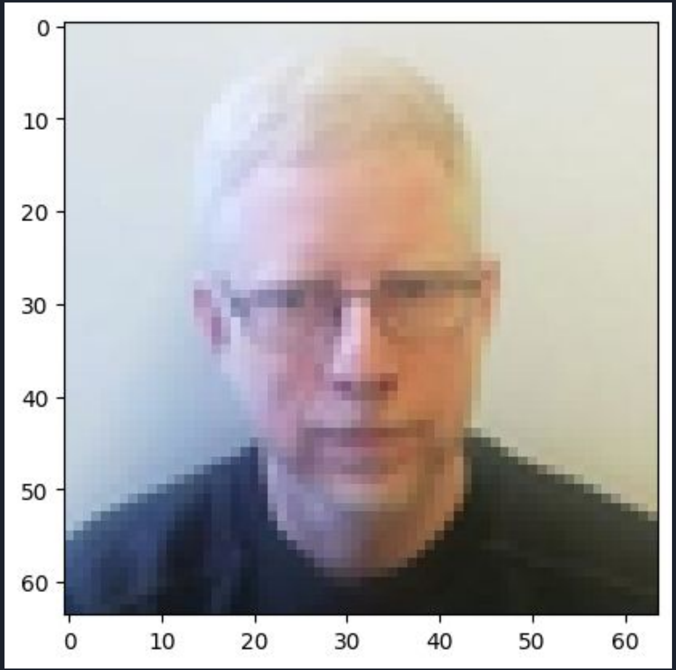
- Use a bigger dataset
- Use all possible crops of the same dataset (up to 10K)
- Adapt state of the art model with usage of hybrid attention blocks and transformers (HAT-L).
- Weighted dense Connections
  - Fine-tune the hyper-parameter “b”
  - Add modifications
- Expand the amount of layers of the Generator
- Change the content loss from MSE to VGG loss
- Modify the alternative training
- Experiment in a Cluster or local machine with more RAM (batch size, dataset size…)

References

- Densely Connected Convolutional Networks [DenseNets] (1608.06993.pdf (arxiv.org))
- Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network [SRGAN] (1609.04802.pdf (arxiv.org))
- Hybrid Attention Transformers [HAT-L] (2205.04437.pdf (arxiv.org))
- Wasserstein GAN (https://arxiv.org/pdf/1701.07875.pdf)

Thank You for your attention





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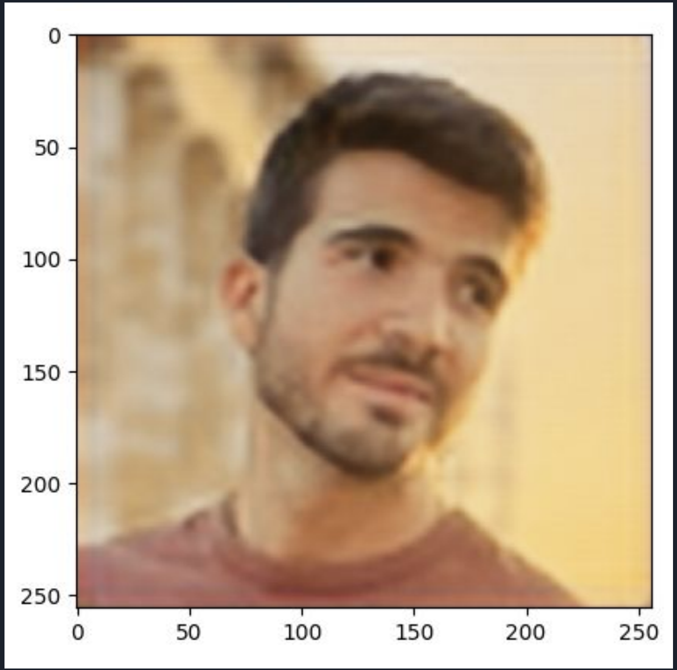

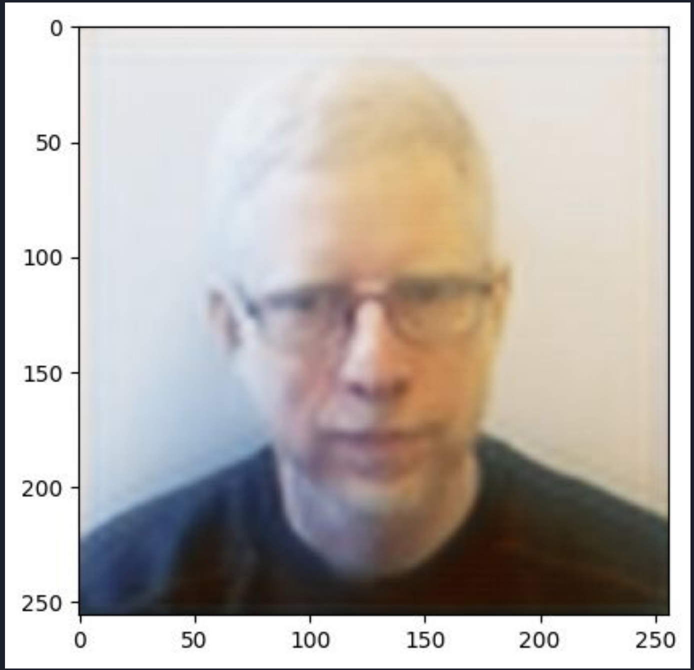

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