Analyzing the Effectiveness of CNNs and GANs in Supersampling MRI Scans

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Introduction

- Goal: Upscale MRI images
  - Input images: 25 x 25
  - Output images: 50 x 50
- Test image upscaling with different models
  - CNN
    - MSE loss, SSIM loss, SSIM and MSE combine, SSIM then MSE sequentially
  - GAN

Previous Work

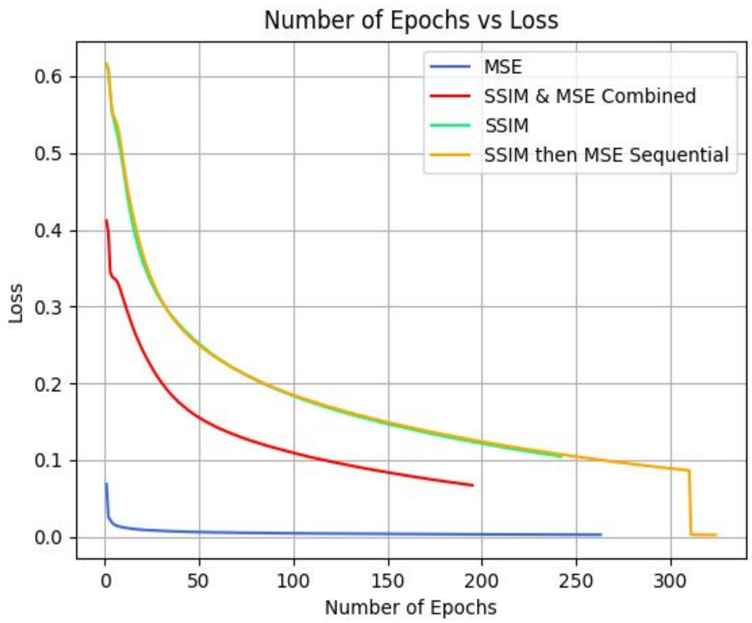
- SRCNN that learns end-to-end mapping between low- and high-resolution images [1]

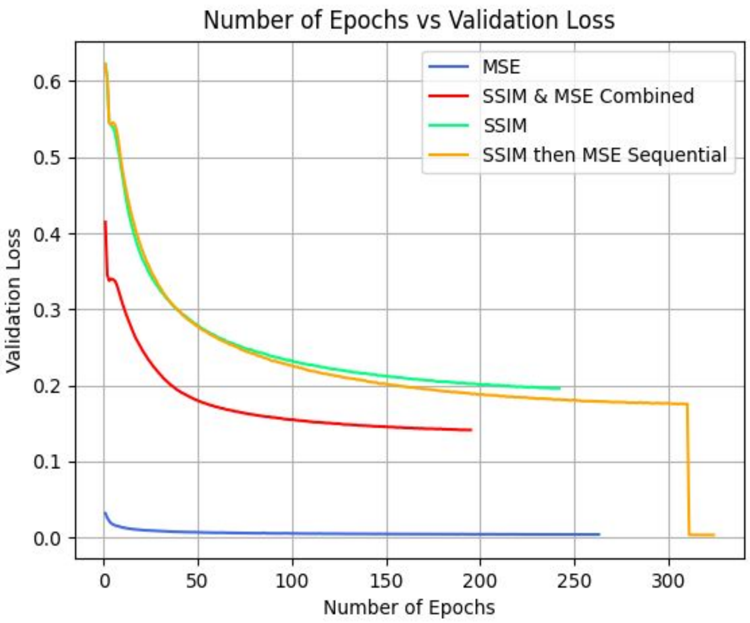
- First SRGAN using a perceptual loss function that consists of an adversarial loss and content loss [2]

CNN Architecture

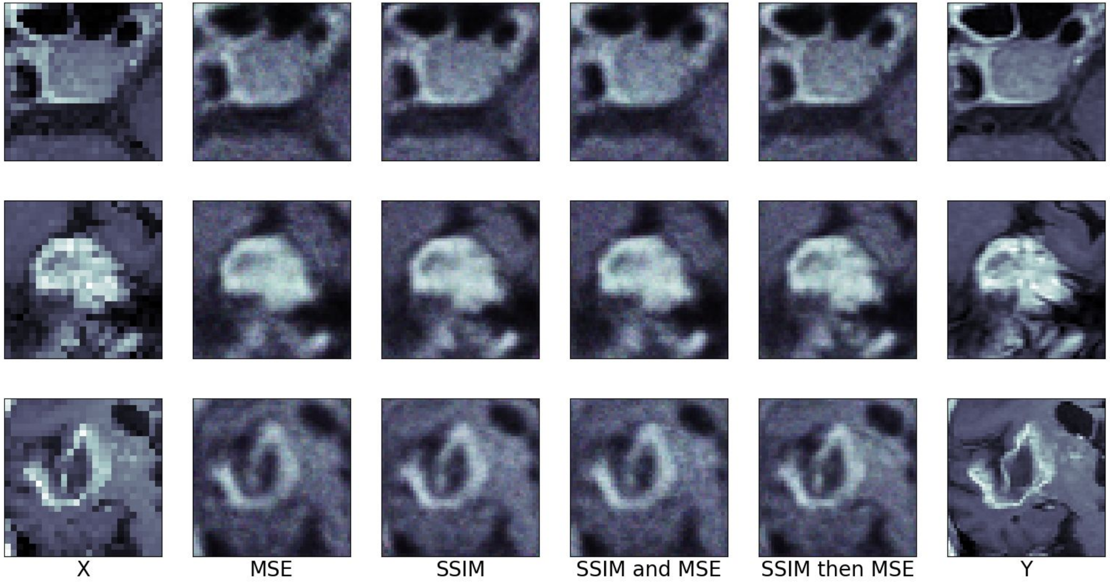
- 7 Layers
  - 4 Convolutional Layer
    - 128, 64, 64, 32
  - Flatten layer
  - Dense layer
    - 10,000 neurons
  - Reshape layer
    - Transform 10,000 to 50 x 50 x 4

CNN Loss Results





CNN Visual Results



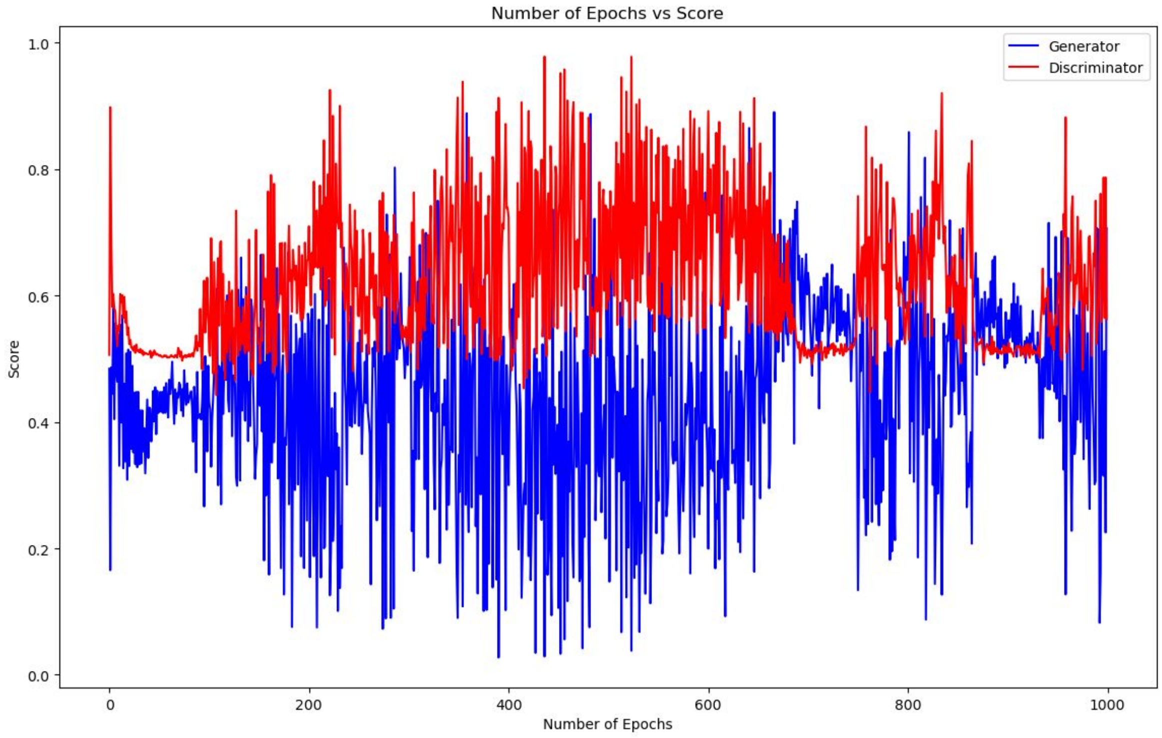
GAN Architecture

- Generator
  - 5 Convolutional Layers
  - 64, 32, 16, 8, 4
  - After each convolutional layer is a batch normalization layer and a ReLU activation layer.
  - After the first ReLU layer is a dropout layer.
  - After the second ReLU layer is an upsampling layer.

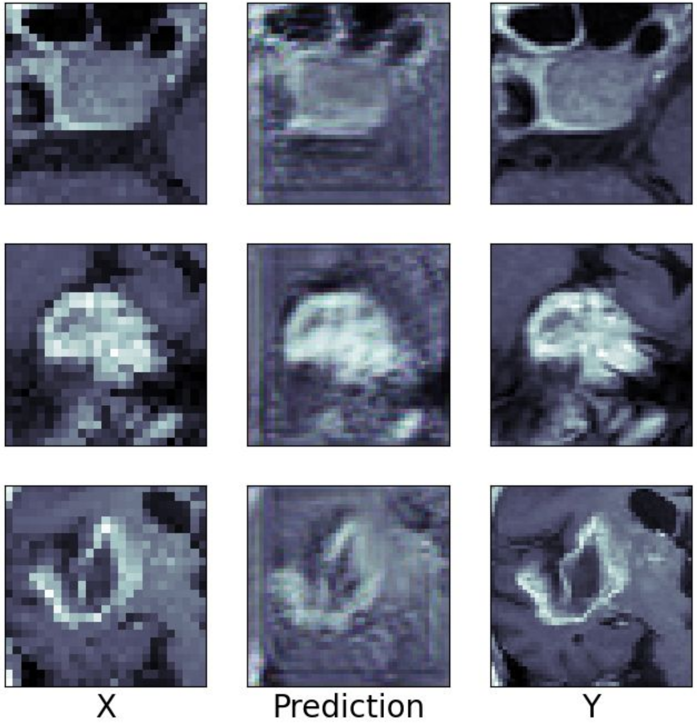
GAN Architecture

- Discriminator
  - 4 Modules
    - Convolutional Layer
    - Leaky ReLU Layer
    - Dropout Layer
  - 8, 16, 32, 64
  - Flatten layer
  - Dense layer with one neuron with sigmoid activation

GAN Scoring Results



GAN Visual Results



Conclusion

- All models were provided some form of image upscaling success
  - CNN with SSIM then MSE loss provided best results
- Future contributions
  - Testing more
    - Architecture designs
    - Hyper-parameters
    - Loss configurations
  - Finding more data for dataset