Medical Image Super Resolution

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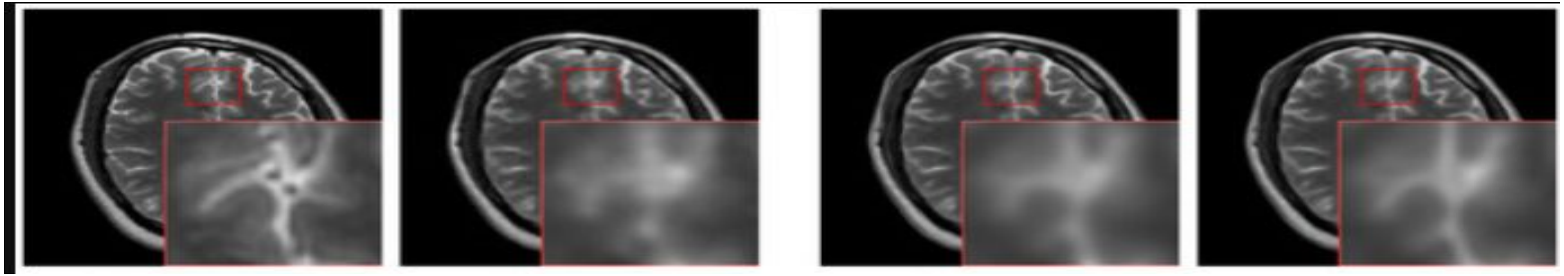
PROBLEM STATEMENT

- ❖ Validating existing image super resolution techniques over medical images.
- ❖ Observe the impact, specifically on the diseased region in the image.
- ❖ Change in the appearance (i.e - texture, brightness etc) of the disease region due to super resolution might lead to wrong interpretation by the radiologists.



Source: [Applied Sciences | Free Full-Text | Gradient-Guided Convolutional Neural Network for MRI Image Super-Resolution | HTML (mdpi.com)]

MOTIVATION

- Super Resolution plays a key role in medical imaging. Based on the statistics, it is found that on an average a radiologist, working 8 hours, reads 100 images which eventually leads to burnout. A high resolution image will not only reduce radiologists time but will also improve the decision accuracy.

LITERATURE REVIEW

- ❖ Existing super resolution techniques are proposed only on normal images(non-diseased images). Even if they are efficient, if they create any change in diseased region, they will be of no use in practical clinical setting.
- ❖ We are using Structure Similarity Index (SSIM) as our image quality evaluation metric because better sensitivity to detect distortions [1] and it is implemented to replicates human visual perception behavior which enables it to perform better on tasks that involve differentiating between a sample and a reference image.

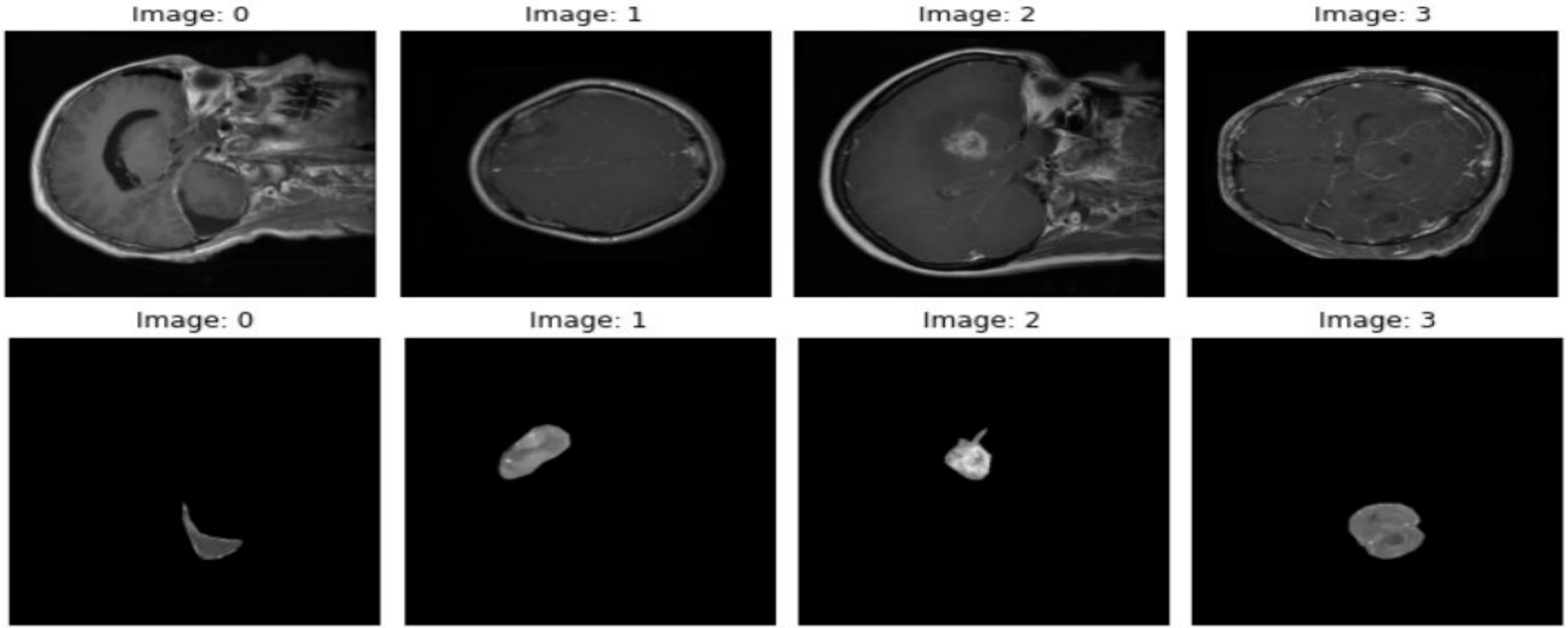
Implementations (Before December)

- ❖ Disease Detection on Chest X-Ray images.
- ❖ Denoising Using Autoencoder on Chest X-Ray images.
- ❖ Implementing Efficient Sub-Pixel Convolution Neural Network (ESCN) on Chest X-Ray images.
- ❖ Dataset Used - **Chest X-Ray Images (Pneumonia)**

Implementations (After December)

- Brain tumor dataset obtained from figshare. This dataset contains 3064 T1-weighted contrast-enhanced images from 233 patients with three kinds of brain tumor: meningioma (708 slices), glioma (1426 slices), and pituitary tumor (930 slices) with **mask for tumor region**. This data is in matlab format and file consists of following fields: -
  - Patient ID
  - Label
  - Image Array
  - Tumor Border (It was generated by manually delineating the tumor border)
  - Tumor Mask

Implementations (Dataset)



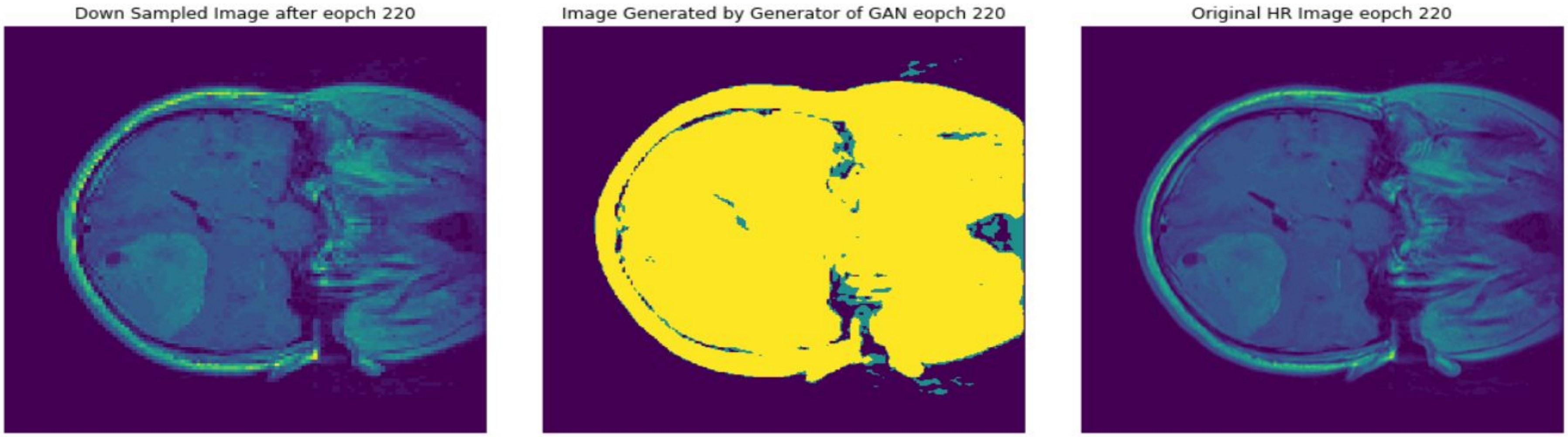
Implementations

- ❖ Implemented Single Image Super Resolution Generative Adversarial Network (SRGAN) on Brain Tumor Dataset [2].
- ❖ Implemented Super Resolution Using Efficient Sub-Pixel Convolution Neural Network (ESPCN) on Brain Tumor Dataset [3].
- ❖ Implemented custom Structure Similarity Index (SSIM) computation function for masked tumor region.
- ❖ The implementations are available at Github repository: Implementation Work

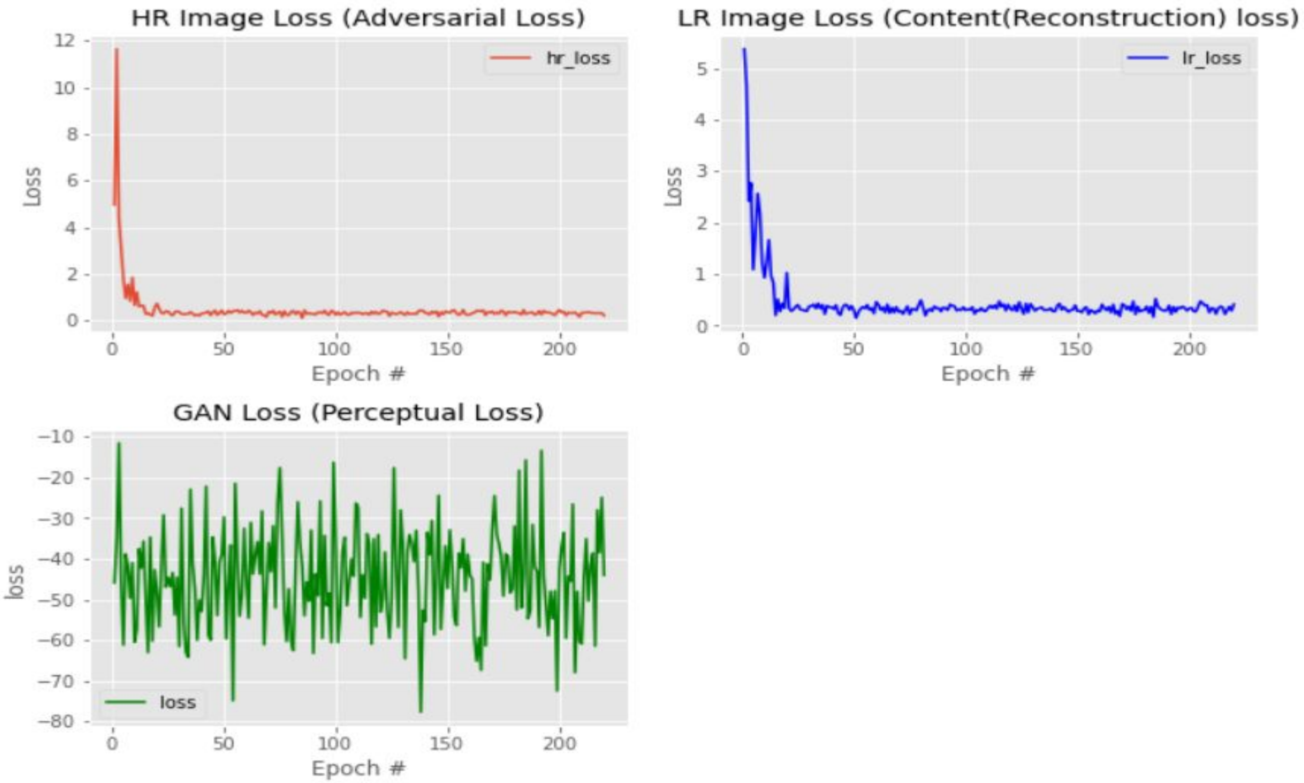
Results

- For SRGAN results are not upto expectations because of poor training of GAN network. The GAN was trained for 220 epochs because of 9 hr execution limitation at Kaggle. SRGAN needs to be trained for 20000 epochs to get good results, for which access to high computation GPU is required.
- For ESPCN results are obtained on complete image. And the results are satisfactory.

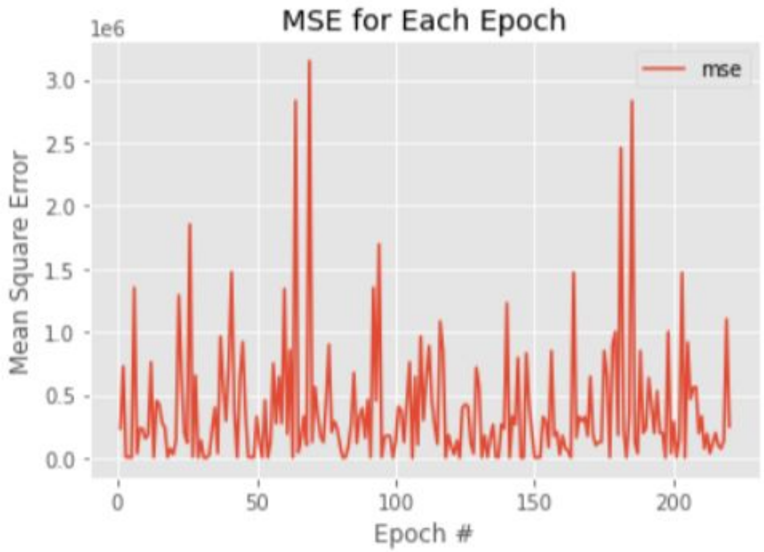
SRGAN - Results

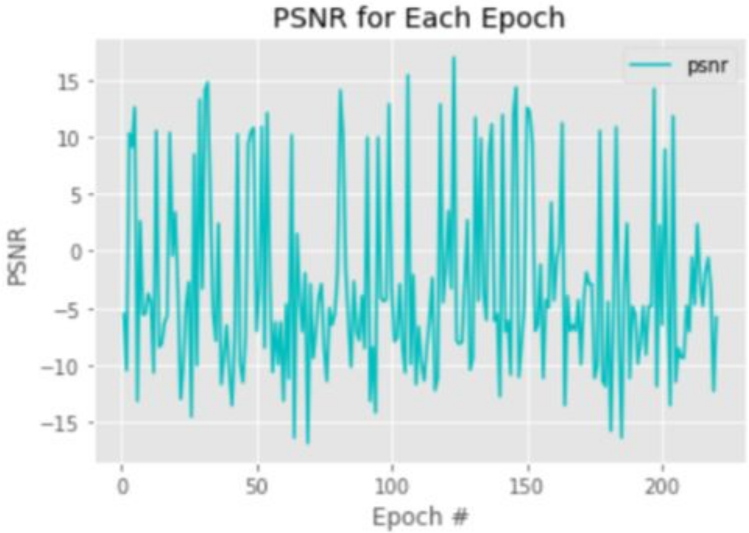


SRGAN - Loss/Evaluation Metrics

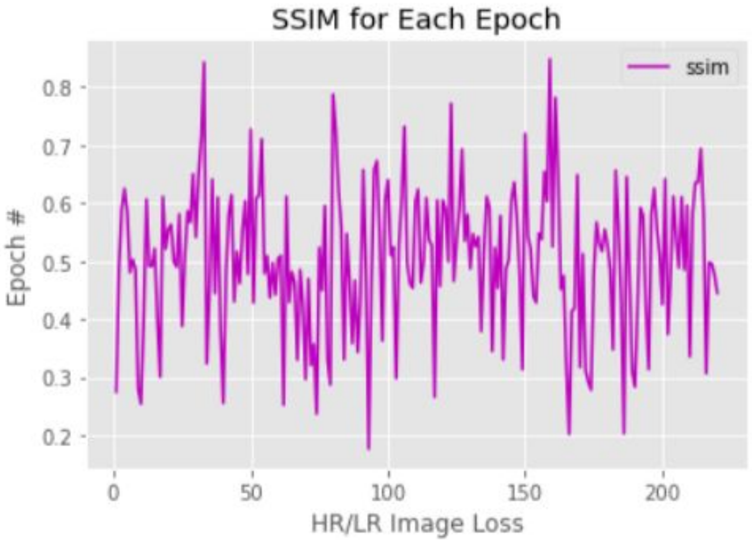


SRGAN - Loss/Evaluation Metrics





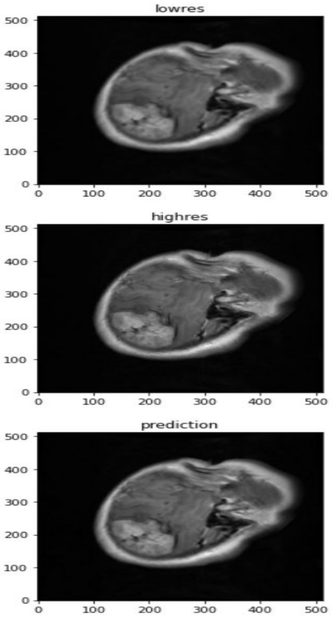
SRGAN - Loss/Evaluation Metrics




```
Avg. PSNR and Std for Generated Images: -3.2142207011183617 8.06920084913721
Avg. SSIM and Std for Generated Images: 0.5053453908957586 0.12482326044687929
Avg. MSE and Std for Generated Images: 382011.11467383127 494227.1688465232
```

ESPCN - Results

PSNR of low resolution image and high resolution image is 36.8538
PSNR of predict and high resolution is 37.6489
Mean Squared Error of predict and high resolution is 13.4185
SSIM of predict and high resolution is 0.7692

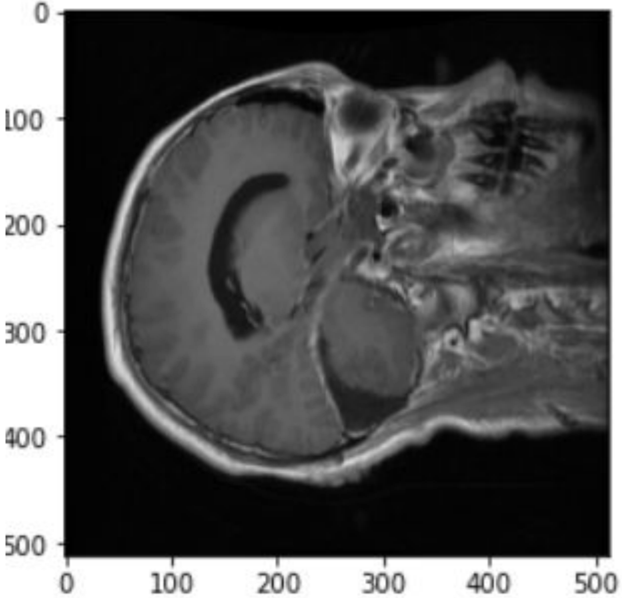


Avg. PSNR of lowres images is 33.3881
Avg. PSNR of reconstructions is 35.6307
Avg. MSE of reconstructions is 31.4046
Avg. SSIM of reconstructions is 0.7385

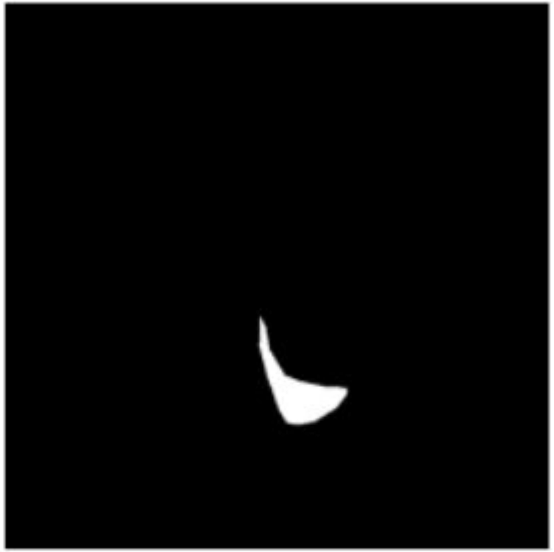
Future Work

- ❖ Train SRGAN for 20000 epochs. And calculate SSIM for diseased region and normal region separately.
- ❖ Calculate SSIM separately for diseased regions and normal region to more accurately estimate our results.

Future Work

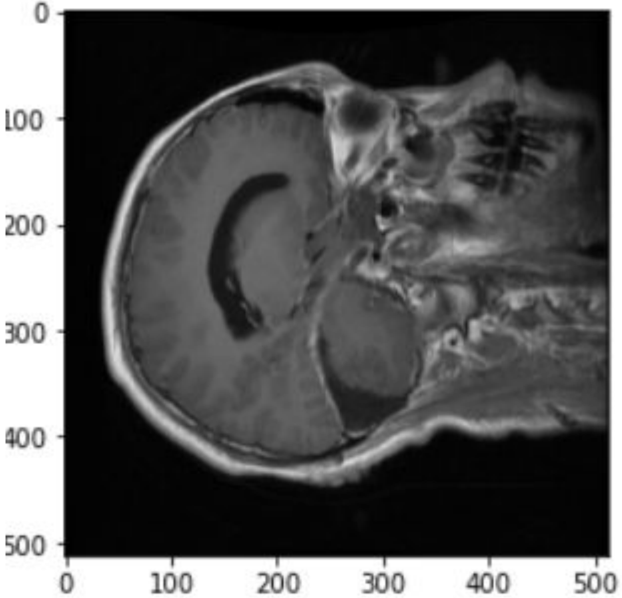


Original Image

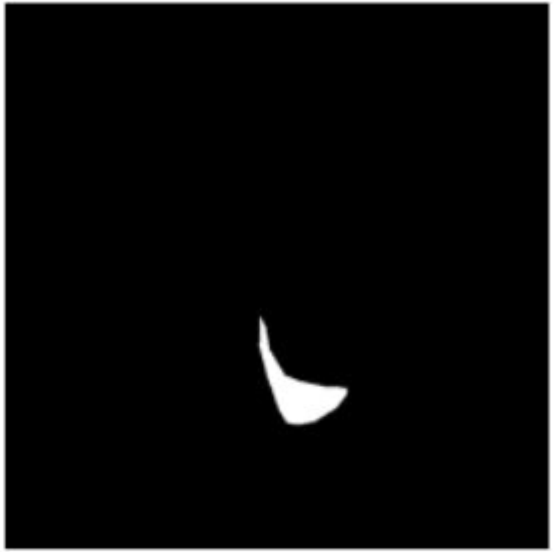


Tumor Region

Future Work

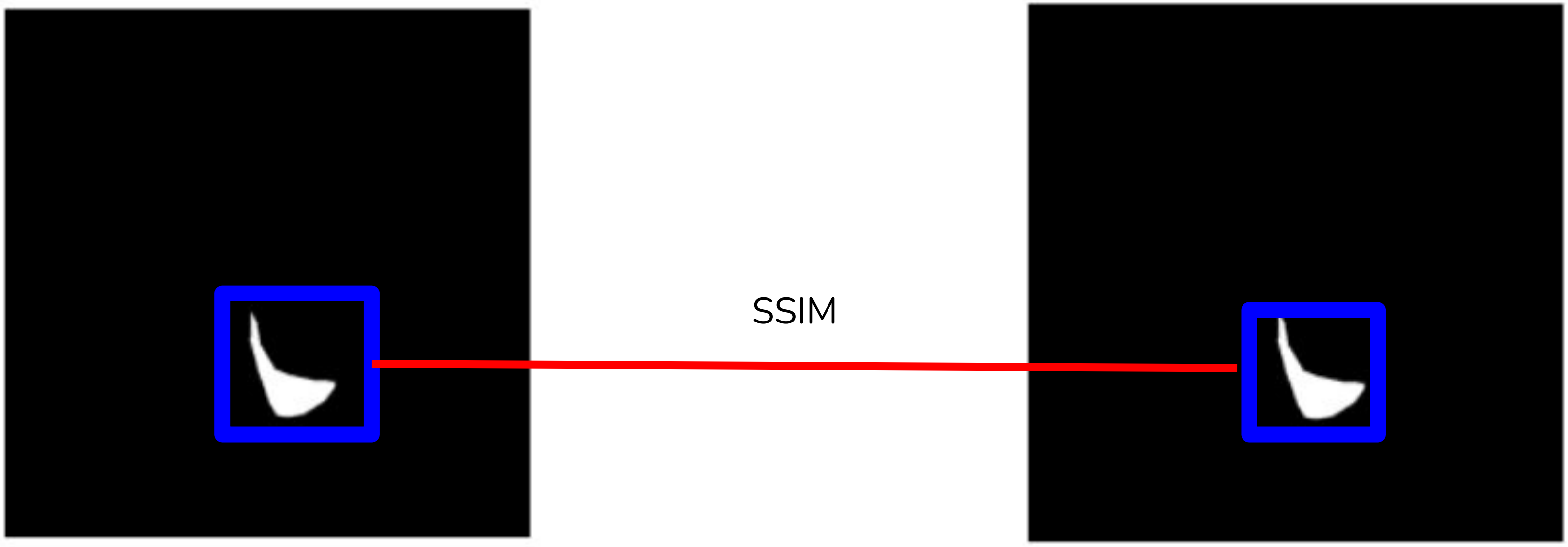


Generated HR Image



HR Image Tumor Region

Future Work



References

- [1] Alain Horé MOIVRE, Djemel Ziou “PSNR vs SSIM: imperceptibility quality assessment for image steganography” (2020).
- [2] Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, Wenzhe Shi “Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network” (2017).
- [3] Wenzhe Shi1, Jose Caballero1, Ferenc Huszar, Johannes Totz1, Andrew P. Aitken1, Rob Bishopl, Daniel Rueckert1, Zehan Wang1 “Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network” (2016)


THANK YOU :)