Single Image Super Resolution for AI generated images

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Overview

- Problem statement
- Goal of the project
- Approach
- Result
- Limitations and Future work
- Reference

Problem Statement

The primary focus of this project is to create an efficient super-image resolution using GAN framework that maintains the quality of the generated images while reducing model complexity with computational efficiency. The goal of this project is to increase the sustainability and accessibility of GAN technology for real-time applications and users with constrained computational resources.

Goal of Project

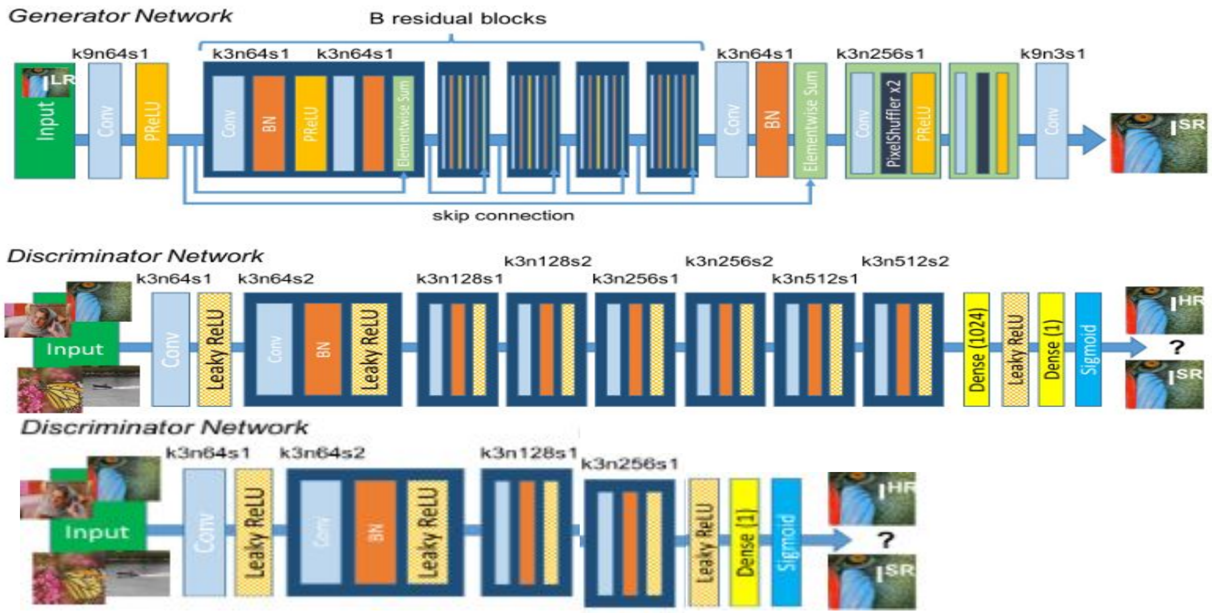
The goal of the project is to build an efficient and robust Image Super-Resolution Model which will be better than state-of-art model in terms of architecture complexity, performance, and with all these modifications giving results as efficient as the state-of-art models . Our main goal will be building a competitive model for the maximal improvement of the image resolution

Dataset

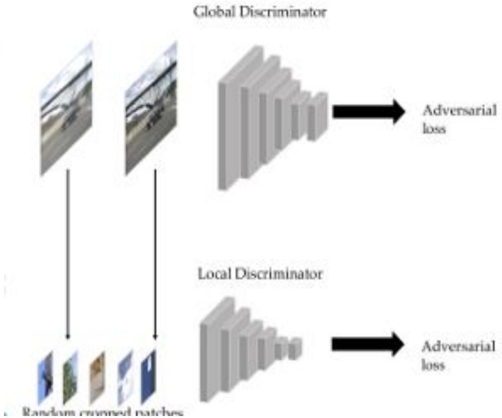
- The DIV2K dataset from Hugging Face, we will be training our model
- It has blur image and its ground-truth high resolution image
- We will be evaluating on the AI Generated low resolution images to improve the clarity for those images(CIFAKE).

- Our experimentations will also be on other datasets like DIV2K, kwenter Blur Dataset for the testing.

Approach



Generator Network
B residual blocks
k9n64s1
k3n64s1
k3n64s1
k3n64s1
k3n256s1
k9n3s1
Input
Conv
PReLU
BN
Elementwise Sum
PixelShuffler x2
skip connection
Discriminator Network
k3n64s1
k3n64s2
k3n128s1
k3n128s2
k3n256s1
k3n256s2
k3n512s1
k3n512s2
Leaky ReLU
Dense (1024)
Dense (1)
Sigmoid
?
Discriminator Network
k3n64s1
k3n64s2
k3n128s1
k3n256s1



Global Discriminator
Adversarial loss
Local Discriminator
Adversarial loss

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Approach

- Our approach is based on the Generative Adversarial Networks, where There is Generator and Discriminator. The Generators task is to generate fake images to fool the discriminator, where as the Discriminators task is to identify if the image generated is real or fake.
- The Architecture we have used is based on the SRGAN Model, where for B residual networks, B = 8 in our model
- In our approach instead of one discriminator, we will be using two discriminator. Where one discriminator is used for the whole image, and another one is used for chunks of images

Experiments

- Trained on 200 images
- Image input 96x96 low resolution image and output image size is 384x384
- num_epochs = 100, Adam Optimizer, Loss functions are L1 loss, VGG loss, BCE, MSE.
- Checkpoints are used to save the model weights.

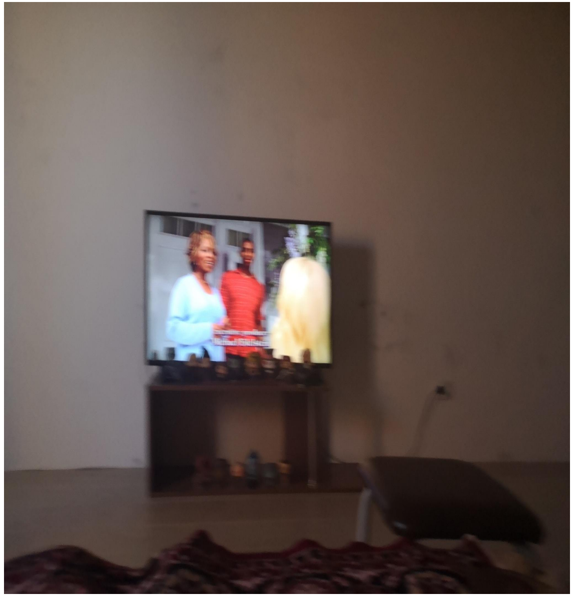
- On Base Model - Single Discriminator, Ran successfully for 58 epochs

- On Actual Model - Double Discriminator

Results:

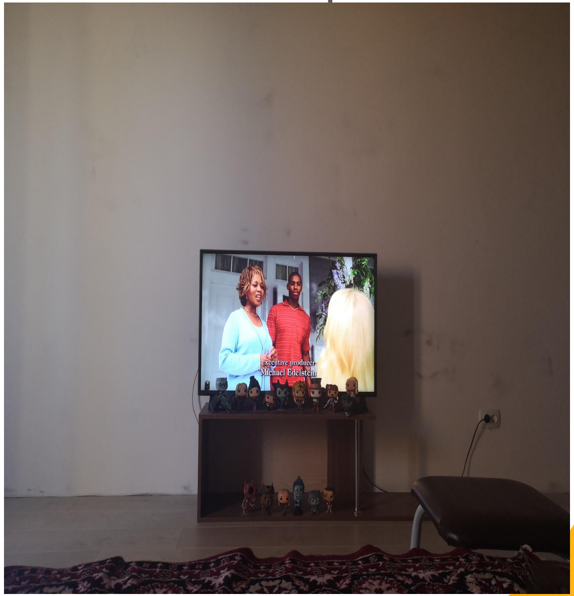
Initial Failed attempts:

Blur

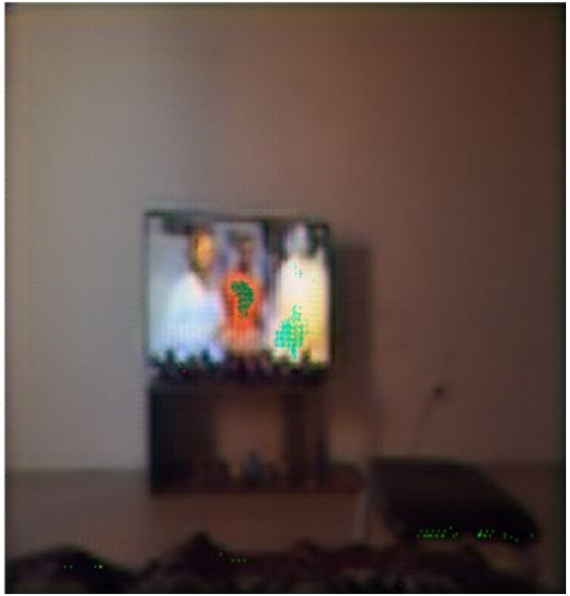


Prediction

Sharp

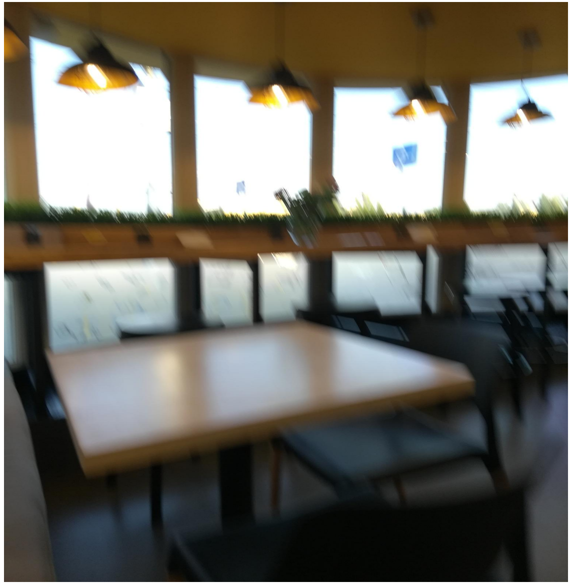


Initial Failed attempts:

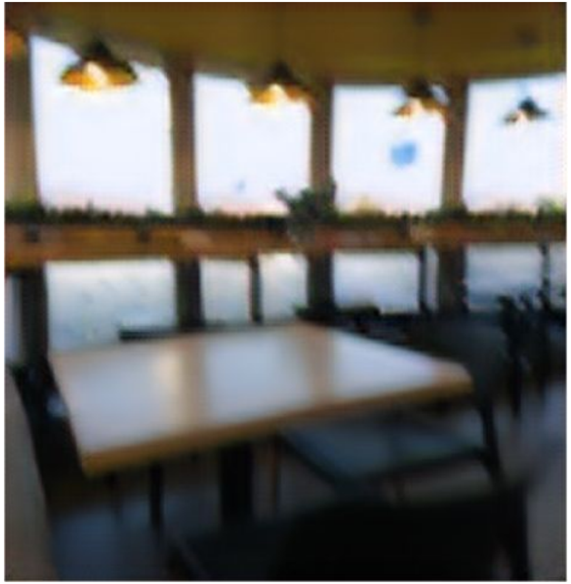


Improvements with the epochs

Blur

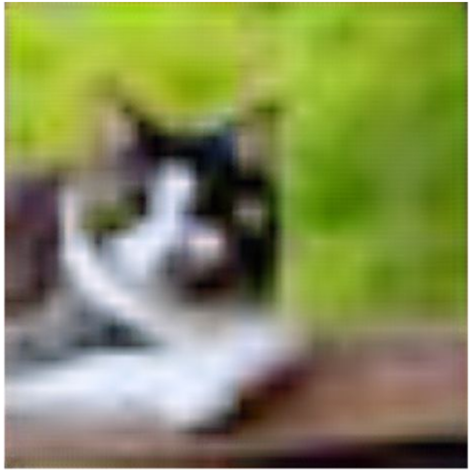


Predicted

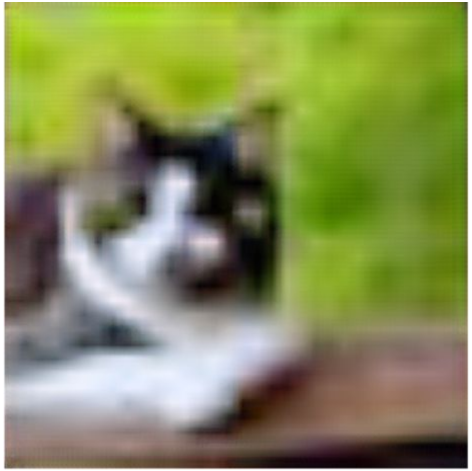


Sharp

Low resolution Low Resolution Resized 20 Epochs Predict 58 Epochs Predict

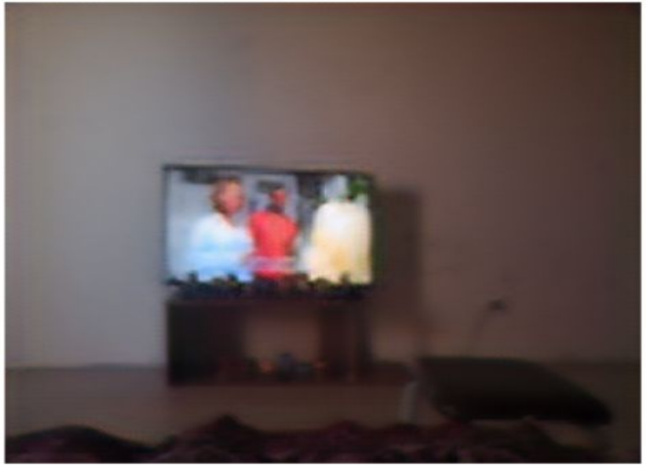


Single Discriminator(58 epochs)

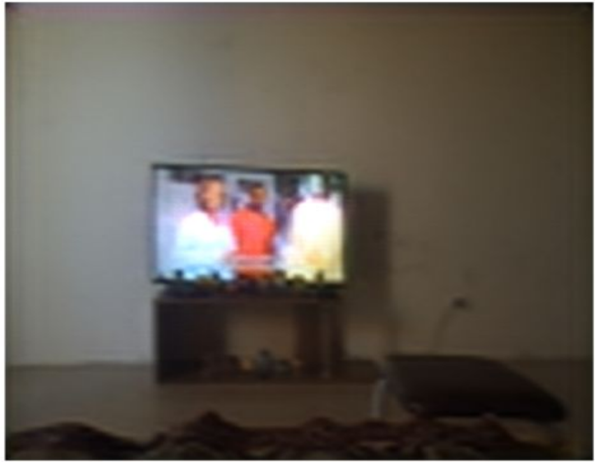


Double Discriminator(6 epochs)

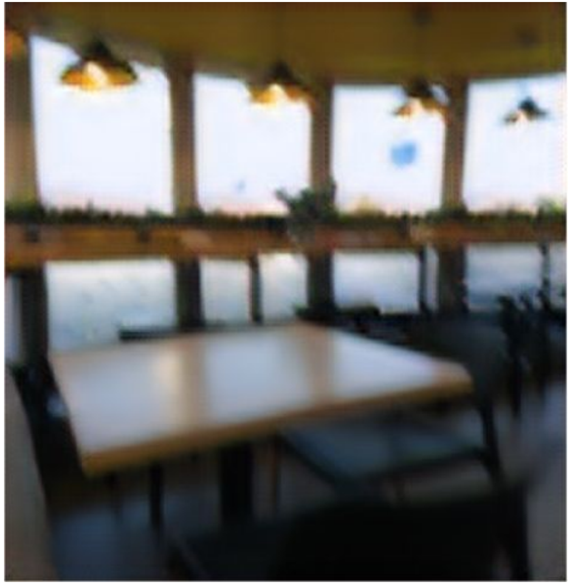
Single Discriminator(58 epochs)



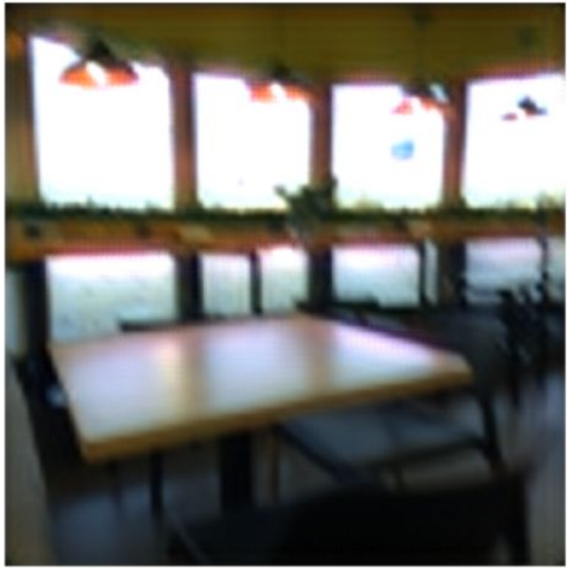
Double Discriminator(6 epochs)



Single Discriminator(58 epochs)



Double Discriminator(6 epochs)



Evaluation Metrics

	Base Model (Single Discriminator)	Base Model_V2 (Double Discriminator)	SRGAN	SRCNN
Peak Signal to Noise Ratio(PSNR)	22.97	22.44	29.4	30.07
Structural Similarity Index(SSIM)	0.63	0.68	0.84	0.86

Limitation and Future Work

- We have only used 200 images for training purposes due to the computational constraints
- The image resolution can also be increased further and the model can be designed such that it is faster than ours by removing/modifying some blocks in the architecture.
- Double discriminator technique and selection of the patches for the images can also be improved.
- Efficiency of the model can also be improved further.
- Could also reduce some parameters to be system requirement friendly

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References

[1] https://redirect.cs.umbc.edu/courses/graduate/691cv/lectures/17_image-synthesis.pdf

[2] Honggang Chen, Xiaohai He, Linbo Qing, Yuanyuan Wu, Chao Ren, Ray E. Sheriff, Ce Zhu,Real-world single image super-resolution: A brief review, Information Fusion, Volume 79, 2022,Pages 124-145, ISSN 1566-2535, https://doi.org/10.1016/j.inffus.2021.09.005.

[3]Blur dataset (kaggle.com)

[5]https://paperswithcode.com/dataset/cifake-real-and-ai-generated-synthetic-images