Walchand College Of Engineering, Sangli

(An Autonomous Institute)

Department
of
Computer Science and Engineering

Title of the Project

Image Deblurring and Translation using GAN

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Department of Computer Science and Engineering
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CERTIFICATE

This is to certify that the Project Report entitled, "**Image Deblurring and Translation using GAN**" submitted by Ms. Priyanka Devendra Sadalage, Ms. Pooja Birappa Vhanzende, Mr. Parth Onil Shah, Ms. Shireen Ilahi Mujawar to Walchand College of Engineering,Sangli, India, is a record of bonafide Project work of course *" 5CS347" " Mini-Project-3"* carried out by him/her under my/our supervision and guidance and is worthy of consideration for the award of the degree of Bachelor of Technology in Computer Science & Engineering of the Institute.

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Acknowledgement

The acknowledgement page depicts the gratitude, respect and thankfulness of the student towards the people who helped him in pursuing the project successfully and ensured successful completion and implementation of the project. In this page, the author expresses his gratitude and concern by using praising and thanks giving words.
Acknowledgement Project Coordinator, Ass.Prof. Pawar A.S. for guidance.

Declaration

I hereby declare that work presented in this project report titled "**IMAGE DEBLURRING AND TRANSLATION USING GAN**" submitted by Ms. Priyanka Devendra Sadalage, Ms. Pooja Birappa Vhanzende, Mr. Parth Onil Shah, Ms. Shireen Ilahi Mujawar in the partial fulfillment of the requirementof the award of the degree of **Bachelor of Technology (B.Tech)** Submitted in the **Department of Computer Science & Engineering, Walchand College of Engineering,** Sangli, is an au- thentic record of my project work carried out under the guidance of Asst. Prof. Miss. Aprupa Pawar

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Project Title and Domain

Our project name is "**Image deblurrng and translation using gan".** Domain of our project is "Image Processing". Image processing is the science of manipulating digital images with computer means. This includes methods and algorithms to modify an image (resizing, filtering, registration…), improve the visual quality of an image (deblurring, denoising…) or analyze the information contained in an image (Fourier analysis, contour detection…)

Abstract

The proposed system is not only focused on Image deblurring but also it focused on night to day translation of image. Image deblurring is an important task in computer vision that aims to remove blur and restore the sharpness of an image and Image-to-image translation involves generating a new synthetic version of a given image with a specific modification, such as translating a summer landscape to winter or translating the night image to day. Blurring can be caused by various factors such as camera shake, motion blur, out-of-focus optics, or low light conditions. In recent years, Generative Adversarial Networks (GANs) have emerged as a promising approach for image deblurring and as well as for image translation. GANs are a type of deep learning model that can learn to generate realistic images by training a generator network to fool a discriminator network. There are various methods of GAN that can be used for image deblurring and image translation. Image deblurring using GANs involves training a generator network to take a blurry image as input and generate a sharp image as output. Image-to-image translation typically requires a large dataset of paired examples. These datasets can be difficult and expensive to prepare, and in some cases impossible, such as photographs of paintings by long dead artists. But the CycleGAN is a technique that involves the automatic training of image-to-image translation models without paired examples. This project will try to optimize the image deblurring and translation work using GAN to improve image quality by providing meaningful training object function. In this project we use the SR-GAN (Super Resolution Generative Adversarial Network) to sharpen the image and Cycle GAN to convert night image to day.

Keywords: Image deblurring, Generative Adversarial Network, SR GAN, Cycle GAN

Introduction

Nowadays, there is an increasing demand for images with high definition and fine textures, but images captured in natural scenes usually suffer from complicated blurry artifacts, caused mostly by object motion or camera shaking, and in Photographic images with high definition and exquisite detailed textures are preferred for their high visual quality. However, photographic images captured in natural scenes have complicated blurry artifacts in most occasions, blurry structures usually arise when moving objects are in the scene, and global blurs are caused by camera shaking or scene depth variation. And one another important point is, With the increasing crime rate, CCTVs are being implemented on roads, highways etc. But for them to be useful they need to be sharp and not blurry. Sometimes, images taken by CCTV are blurred and are not useful. Image deblurring is important because blurred images can negatively affect the quality, clarity, and usefulness of images in various applications. Deblurring is a task of restoring a blurred image to a sharp one, retriening the information due to the blur of image. Blurred images can be caused by a variety of factors, such as camera shake, motion blur, out-of-focus optics, or low light conditions. To overcome this problem, we can use "Super Resolution GAN" (SRGAN) for Image Deblurring. It is a type of GAN that is typically used for super-resolution tasks, where the goal is to generate high-resolution images from low-resolution images.

Another problem is, Cameras used in various applications such as surveillance, autonomous driving as Self-driving cars rely on cameras and sensors to navigate, but these devices may not perform well during low light conditions, and remote sensing may not be able to capture clear images during low light conditions. Therefore, there is a need to enhance the quality of such images to make them more useful for analysis and decision making. Image-to-image translation involves generating a new synthetic version of a given image with a specific modification, such as translating a summer landscape to winter or translating night image to day. Cycle GAN, a type of generative adversarial network, can be used to translate night images to day images. Training a model for image-to-image translation typically requires a large dataset of paired examples. But, the CycleGAN is a technique that involves the automatic training of image-to-image translation models without paired examples.

The proposed system will help in deblurring the image and also increase its sharpness. Along with image deblurring it will help to translation of image to night to day.

Problem Statement

“To design a system which help to image deblurring and image translation using GAN (Generative Adversarial Network)”

Literature Survey

1] Zhaohui Meng, Wenling Lu [2022] “Image Deblurring Based on Generative Adversarial Networks”, this paper proposes a deblurring algorithm based on generative adversarial networks. The model uses feature pyramid network as a framework instead of the multi-scale input, which effectively reduces the size of network and accelerates the training speed.

2] Gagandeep , Mrs. Narinder Kaur [2021] “Image Deblurring Using Generative Adversarial Networks” They develop a system that can perform deblurring task and without softening the image using Generative Adversarial Networks. A prototype system is developed and tested.

3] Jun-Yan Zhu, Taesung Park, Phillip Isola Alexei A. Efros [2020] “Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks”

Novelty

1. The existing GAN based systems either have image deblurring or translation but this proposed system contains both facilities. [1]
2. Another novelty is that we are going to implement image translation using unpaired dataset by using cycle gan. [3]

Objectives

Following are the few objectives that we are going to achieve-

1. To Study the required algorithms as per problem statement
2. To design the flow of system
3. To build the separate parts of system
4. To integrate all the parts together to form entire system
5. To analyze the accuracy and operational features of the system.
6. To validate the achieved data with real-time aspects.

Project Architecture

Working of Proposed system

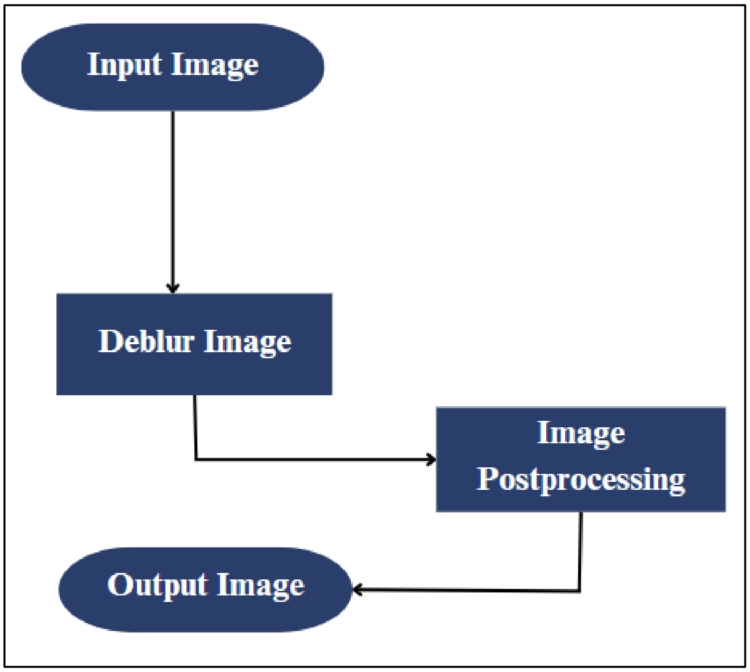


Fig. Flow Diagram of Proposed System

Above figure show how the Image Deblurring with GAN will actually work there are various steps so let's see one by one each step to understand the actual working of proposed system.

1] Input Image-

So very first step is taking the input from user i.e blur image that user wants to enhance.

2] Deblur Image-

In this step Image deblurring is done by using SR GAN

3] Image Post processing-

Then some post processing is done on image generated by SR GAN.

4] Output image-

Finally our output (deblur image) is ready which is given to user.

Post Processing:

Image Downscaling:

SRGAN produces a high-resolution output image that is larger than the input image. However, in some cases, it may be necessary or desirable to downscale the output image to a smaller size for various reasons such as reducing the computational complexity of downstream tasks or matching the size of the original input image. In such cases, we can use a resizing or downscaling operation during post-processing to achieve the desired output size.

Super Resolution GAN

Super-resolution is a process in which a high-resolution image from one or more low-resolution images is produces. Image super resolution is used to recover a high-resolution (HR) image from low-resolution. It required paired dataset of high resolution image and low resolution image. An illustration of image super-resolution can be seen in following fig.

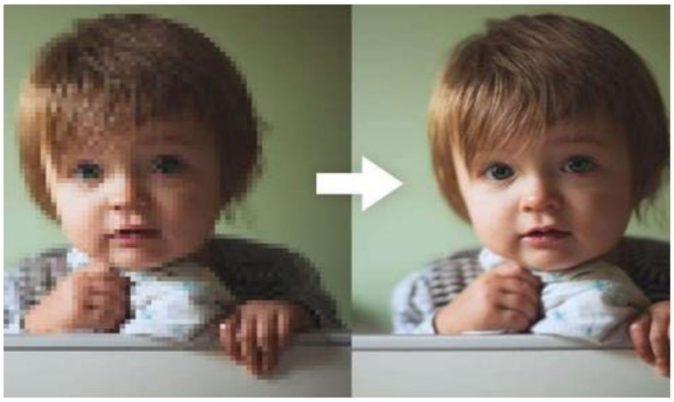
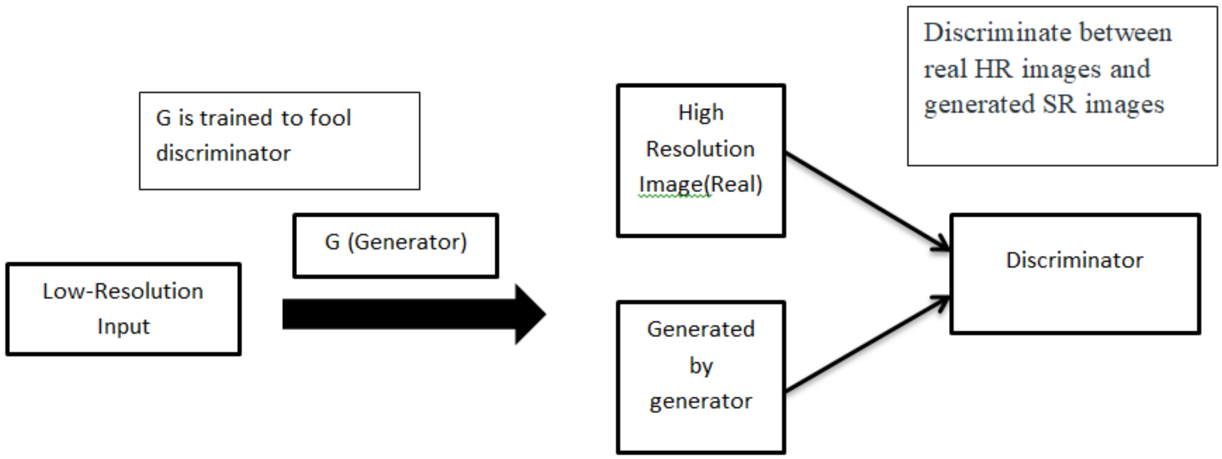


Fig. Illustration of Image Super Resolution

SRGAN is a generative adversarial network for single image super-resolution. It uses a “perceptual loss” function which consists of an adversarial loss (discriminator loss) and a content loss (generator loss). The adversarial loss pushes the solution to the natural image manifold using a discriminator network that is trained to differentiate between the super-resolved images and original photo-realistic images in simple word the Adversarial loss is the loss function that forces the generator to image more similar to high resolution image by using a discriminator that is trained to differentiate between high resolution and super resolution images.

Content loss is also known as VGG loss. It evaluate the image quality from its perceptual quality. It calculate the perceptual quality by comparing the features of generated image and ground truth image.

Architecture of SR-GAN



Super Resolution GAN contains two parts Generator and Discriminator where generator produces some data based on the probability distribution and discriminator tries to guess weather data coming from input dataset or generator. Generator than tries to optimize the generated data so that it can fool the discriminator.

During the training, A high-resolution image (HR) is downsampled to a low-resolution image (LR). The generator architecture than tries to upsample the image from low resolution to super-resolution. After then the image is passed into the discriminator, the discriminator and tries to distinguish between a super-resolution and High-Resolution image and generate the adversarial loss which then backpropagated into the generator architecture. The task of the discriminator is to discriminate between real HR images and generated SR images.

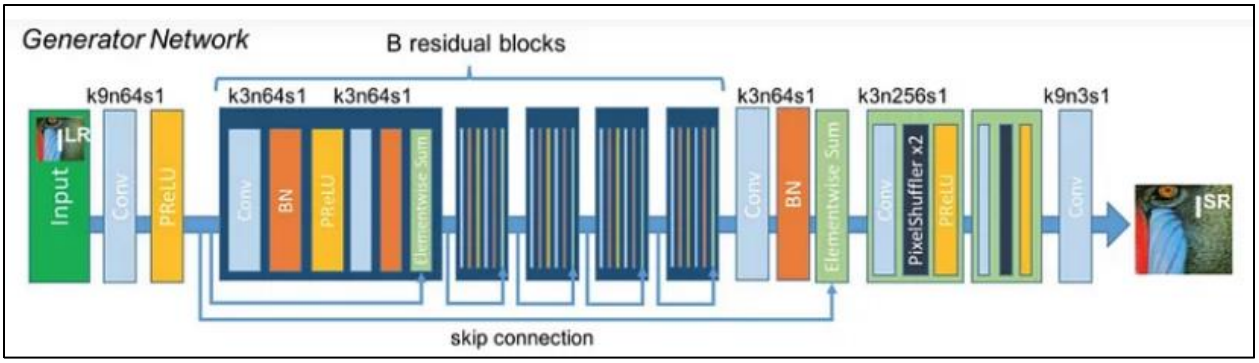
Working of SR GAN

SRGAN (Super-Resolution Generative Adversarial Network) is a deep learning model that can be used to deblur and enhance the resolution of images. The goal of a Super-Resolution GAN is to generate high-quality, sharp images from low-resolution and blurry images. To achieve this, the SR GAN framework uses two networks: a generator and a discriminator.

Generator-

The generator network is responsible for generating high-resolution images from low-resolution and blurry inputs. It is typically a deep neural network that takes in a low-resolution image as input and produces a high-resolution image as output.

In the case of image deblurring, the generator network is trained to remove the blur from the input image and generate a high-quality, sharp image as output. The generator network takes in a low-resolution and blurry image and upscale it to a higher resolution, while also removing the blur from the image.

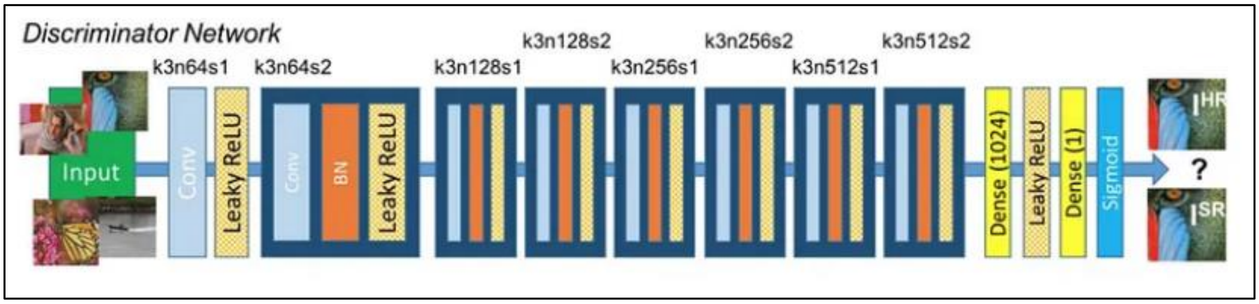


In the above fig there are B residual blocks (16), originated by ResNet. Within the residual block, two convolutional layers are used, with small 3×3 kernels and 64 feature maps followed by batch-normalization layers and ParametricReLU as the activation function.

The generator network is typically composed of convolutional layers, which are used to extract features from the input image, followed by a series of deconvolutional layers, which are used to upscale the image to a higher resolution. Additionally, skip connections can be used to pass information from earlier layers to later layers, which can help to preserve the details of the original image.

The generator is trained using adversarial training, where it is encouraged to generate high-quality images that are similar to the ground truth high-resolution images. The generator is trained to minimize the difference between the generated and ground truth images using a loss function, such as mean squared error or perceptual loss.

Discriminator



The discriminator network is responsible for distinguishing between generated images and real high-resolution images. It is typically a convolutional neural network that takes in an image and produces a binary output indicating whether the image is real or fake.

In the case of Super-Resolution GAN for image deblurring, the discriminator is trained to distinguish between the high-quality, sharp images generated by the generator and the ground truth high-resolution images. The discriminator network takes in an image and produces a probability score indicating the likelihood that the image is real.

The discriminator is also trained using adversarial training, where it is encouraged to correctly classify real and fake images. The discriminator is trained to maximize the difference between the probability scores of the real and generated images using a loss function, such as binary cross-entropy.

Adversarial Training

The generator and discriminator networks are trained in an adversarial manner, where they are pitted against each other in a game-like setup. The generator is trained to produce high-quality images that can fool the discriminator, while the discriminator is trained to correctly distinguish between real and fake images.

During training, the generator is fed with low-resolution and blurry images and generates high-resolution images. The discriminator is then fed with both the generated and ground truth high-resolution images and is trained to correctly distinguish between them. The generator is then updated based on the feedback from the discriminator and the process is repeated until the generator can produce high-quality images that are similar to the ground truth high-resolution images.

In summary, the generator and discriminator networks in Super-Resolution GAN work together in an adversarial setup to generate high-quality, sharp images from low-resolution and blurry images. The generator is responsible for generating high-resolution images while the discriminator is responsible for distinguishing between real and fake images. Adversarial training is used to train both networks in an iterative process until the generator can produce high-quality images that are similar to the ground truth high-resolution images.

Cycle GAN

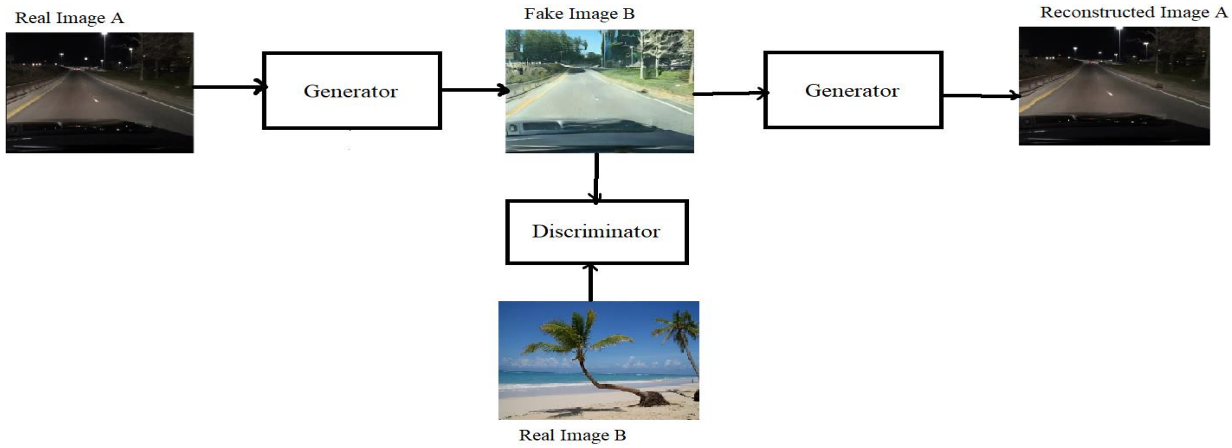
Cycle GAN is a GAN architecture that can be used for image-to-image translation tasks. It uses a cycle-consistency loss that encourages the generator network to produce consistent outputs.

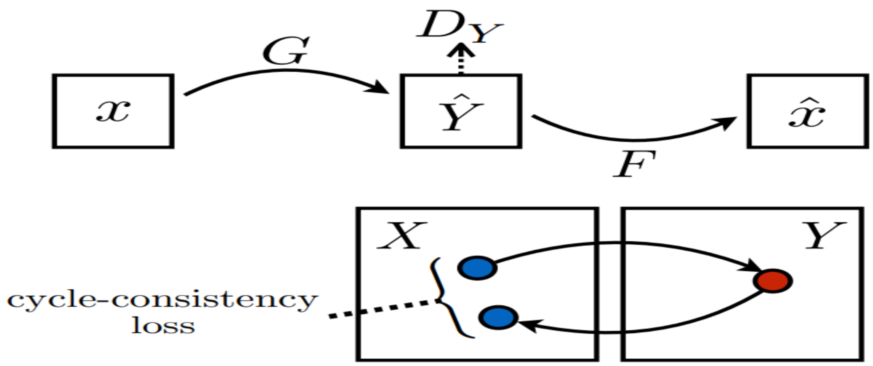
In CycleGAN, there are two mapping functions, one that maps images from domain X to domain Y, and another that maps images from domain Y to domain X. The cycle consistency loss is calculated by comparing the reconstructed images generated by these two mapping functions to the original images. Specifically, it measures the difference between the original image and the image reconstructed from the mapped image.

In other words, the cycle consistency loss measures how much information is lost or distorted during the translation process. By minimizing this loss, the model can learn to perform more accurate and faithful image-to-image translations between the two domains, even when paired data is not available.

Day to night translation

Cycle GAN Architecture





In above image, consider x is the night image and it transform into day image using generator, Dy is discriminator which tells that Y hat is similar to Dy or not by considering the Y real images of day image. It produces output real or fake in terms of 0 and 1.

Now, it will again convert it into real image to calculate loss that is:

Cycle consistency loss = Reconstructed image – original image

In second diagram, X is converted into Y and again back to the X, by this we came to know how close these dots together, if they are very similar to each other then reconstruction quality is good.

Thus, the cycle GAN measure the cycle consistency loss.

Project Potentials

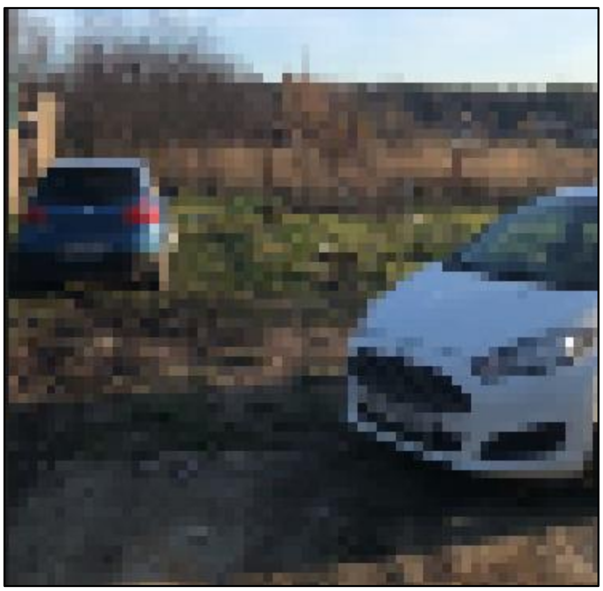
Following are the proposed system-

1. To convert the low resolution image to high resolution.
2. In CCTV camera for capturing more high quality video or image
3. In medical field to convert the blur image to sharp
4. To convert the Night image to day which is very useful where lights are low but high security is needed.

Find and Tune

To reach the final number of epoch for better result we train our model with different number of epoch and dataset and analyse the output. So first we train our system with 20 epoch and 1511 of dataset but efficiency is not that good. Then we train our system with 100 epoch and dataset of 1000 paired images are used its accuracy is better than 20 epoch so the basis of this we understand that if we increase the Epoch then it give us better output so then we train our system with 18000 epoch and dataset of 8 images its accuracy is better than previous two. And on final basis we decided to go with 16000 epoch and dataset of 80 images whose efficiency is best among all these models.

Input Image-



Output Using Different Models-

Epoch-20,dataset- 1511

Epoch-100,dataset- 1000

Epoch-8000,dataset- 8

Epoch-16000,dataset- 80

Losses

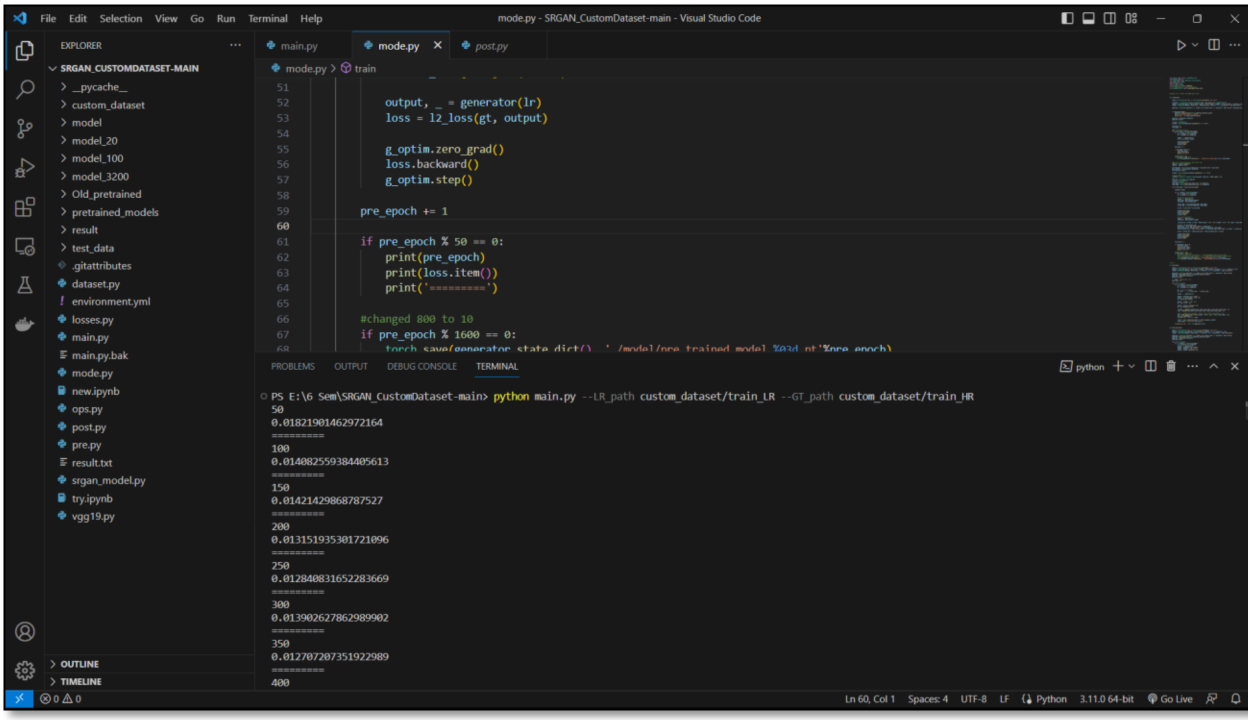
Perceptual Loss or MSE:

Perceptual loss focuses on capturing high-level perceptual similarity between images. It leverages pre-trained neural networks, such as VGG, to extract feature representations from the generated output and the ground truth image. The perceptual loss measures the difference between these feature representations, typically using metrics like Mean Squared Error (MSE) or L2 distance. By considering higher-level features, perceptual loss encourages the generated output to capture important structures, textures, and patterns from the ground truth image, rather than focusing solely on pixel-level accuracy. Perceptual loss helps to improve the visual quality and perceptual fidelity of the generated output, producing sharper and more realistic images.

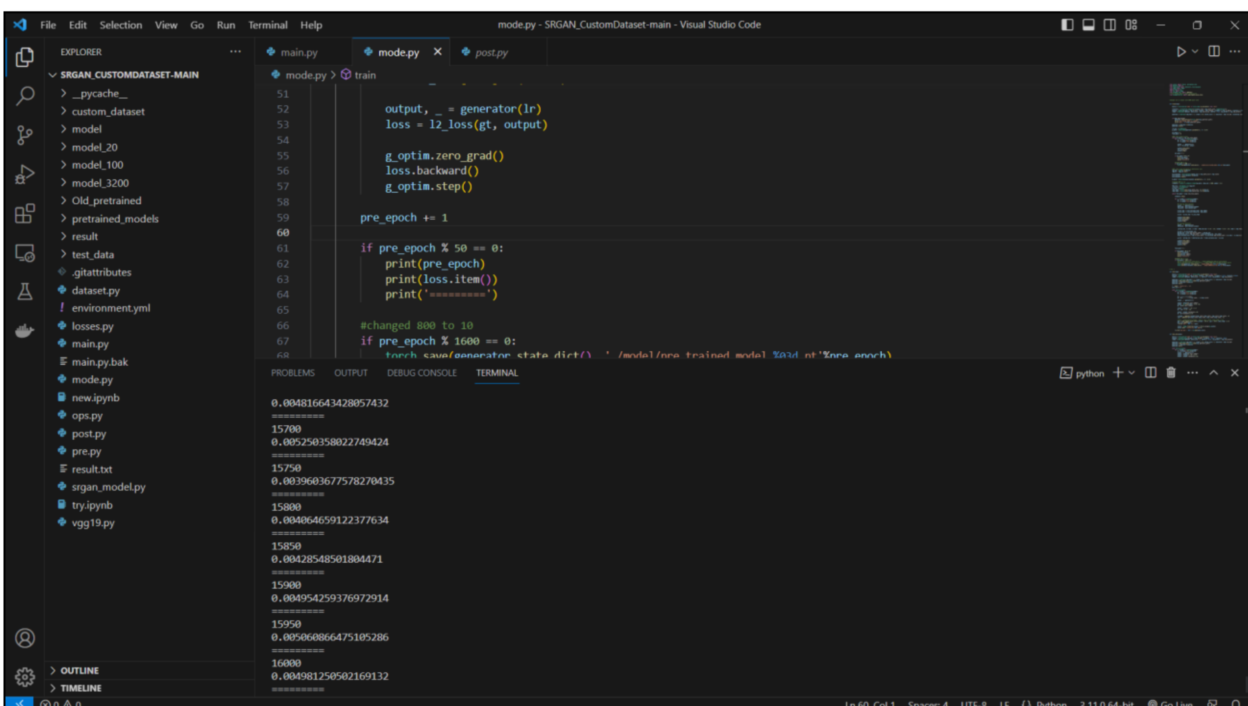
Formula and code for perceptual loss:

```
l2_loss = nn.MSELoss()
g_optim = optim.Adam(generator.parameters(), lr = 1e-4)

pre_epoch = 0
fine_epoch = 0

#### Train using L2_loss
while pre_epoch < args.pre_train_epoch:
    for i, tr_data in enumerate(loader):
        gt = tr_data['GT'].to(device)
        lr = tr_data['LR'].to(device)

        output, _ = generator(lr)
        loss = l2_loss(gt, output)

        g_optim.zero_grad()
        loss.backward()
        g_optim.step()

    pre_epoch += 1

    if pre_epoch % 2 == 0:
        print(pre_epoch)
        print(loss.item())
        print('=========')
```

Loss after 50 epochs:



Loss after 16000 epochs



Adversarial Loss

Adversarial loss is based on the principles of Generative Adversarial Networks (GANs). GANs consist of a generator network and a discriminator network that play a two-player minimax game. The generator aims to generate outputs that are indistinguishable from real data, while the discriminator's goal is to accurately classify between real and generated data. Adversarial loss is calculated based on the discriminator's predictions for the generated output. It encourages the generator to produce outputs that can fool the discriminator into classifying them as real. The adversarial loss is typically formulated using binary cross-entropy, where the generator seeks to minimize the loss, while the discriminator aims to maximize it. The adversarial training process helps the generator to learn the underlying distribution of the ground truth images and generate more realistic and visually appealing outputs.

```
## Training Discriminator
output, _ = generator(lr)
fake_prob = discriminator(output)
real_prob = discriminator(gt)

d_loss_real = cross_ent(real_prob, real_label)
d_loss_fake = cross_ent(fake_prob, fake_label)

d_loss = d_loss_real + d_loss_fake

g_optim.zero_grad()
d_optim.zero_grad()
d_loss.backward()
d_optim.step()

## Training Generator
output, _ = generator(lr)
fake_prob = discriminator(output)

_percep_loss, hr_feat, sr_feat = VGG_loss((gt + 1.0) / 2.0, (output + 1.0) / 2.0, layer = args.feat_layer)

L2_loss = l2_loss(output, gt)
percep_loss = args.vgg_rescale_coeff * _percep_loss
adversarial_loss = args.adv_coeff * cross_ent(fake_prob, real_label)
total_variance_loss = args.tv_loss_coeff * tv_loss(args.vgg_rescale_coeff * (hr_feat - sr_feat)**2)

g_loss = percep_loss + adversarial_loss + total_variance_loss + L2_loss
```

Result

SR GAN-

Input Image **Output Image**

CYCLE GAN-

Conversion of Zebra to Horse

Conversion of Horse to Zebra

Conclusion and Future Scope

This project introduces an image deblurring model based on generative adversarial network, which trains the network through generator and discriminator adversarial learning. The proposed system is capable to deblur the blur image and transform the image using cycle gan which is currently under process. Efficiency of SR GAN can be increase by increasing number of epoch and by training it with big dataset.

References

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[3] Jun-Yan Zhu, Taesung Park, Phillip Isola, Alexei A. Efros, Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, 24 Aug 2020