Super Image Resolution Using General Adverserial Network

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***Abstract*—Using deep learning and General Adversarial Network models in order to convert a low resolution image to an image of the desired higher resolution. An image may have a lower resolution due to a smaller spatial resolution i.e. due to a result of degradation. The task of super image resolution is of crucial importance. We are often faced with situations where in we are needed to work with high resolution images. However high resolution images are often expensive in terms of memory and computation. The process of converting low resolution images to high resolution images helps in solving the problem the high resolution images possess. Low resolution images can be converted to high resolution images by using deep learning, GAN networks giving us the output that is desired.**

***Key Words*—GAN, Image Resolution, Bicubic, Deep Learning, Computer Vision, Mean Square Error, Perceptual loss, Training, SRCNN, Image Denoising, Pixel Shuffler, Transpose Convolution, Sub Pixel Convolution**

I. Introduction

High-resolution (HR) image reconstruction from single low-resolution (LR) image is one of the important computer vision applications. Using deep learning models, general adversarial networks we convert the low level image resolution image to the high level image resolution. This is an important problem faced in various vision domains. We will be working on static image super resolution model. For uses such as increasing the resolution while watching videos, playing games we need a much better and faster technique to achieve our purpose of increasing the resolution of images. We do have few algorithms like Bicubic interpolation, SRCNN using Subpixel Convolution, SRCNN using transpose convolution model and General Adversarial Networks available to solve the problem of image resolution at a static scale. However, each of the algorithm have its own set of advantages and disadvantages which we will discuss in the subsequent sections.

II. Literature Survey

Considering the existing work in the field of super image resolution and which implemented as of now by us is bicubic interpolation and SRCNN model.

A. Bicubic Interpolation

Bicubic interpolation is one the traditional and old approach used for the improving the image resolution. So, bicubic interpolation is a 2D approach for enhancing and expanding digital pictures utilising cubic splines or other polynomial techniques. It is widely employed by retouchers and editors when upscaling or resampling a picture in computer image editing software. When we interpolate a picture, we're really warping the pixels as they go from one grid to the next.Bicubic interpolation is not just used for scaling images, but video display as well.

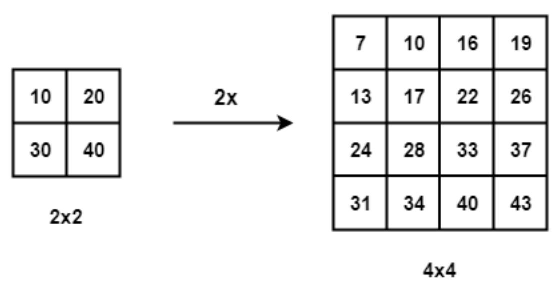


Figure-1 : Bicubic Interpolation

B. SRCNN Model

SRCNN is a deep convolutional neural network that learns how to translate low-resolution pictures

to high-resolution images from start to finish. As a consequence, we may utilise it to improve the picture quality of photographs of low resolution.
SRCNN consists of the following four operations:

1) Pre-processing: Up-scales Low-Resolution image to desired High-Resolution Image size using interpolation techniques.
2) Feature Extraction: Extracts a set of feature maps from the up-scaled low resolution image.
3) Non-linear mapping: Maps the feature maps representing low resolution to high resolution patches.
4) Reconstruction: Produces the high resolution image from high resolution patches.

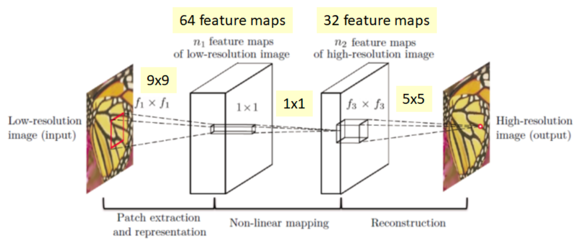
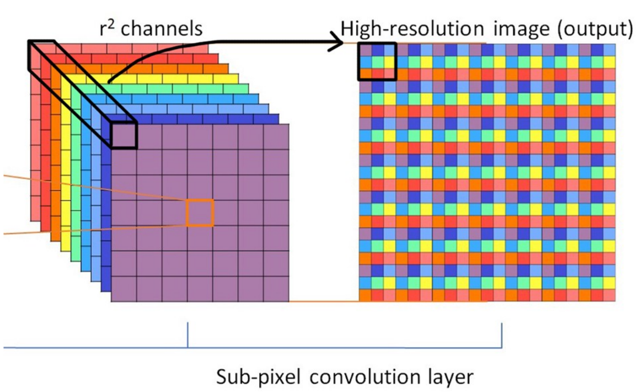


Figure-2 : SRCNN Model

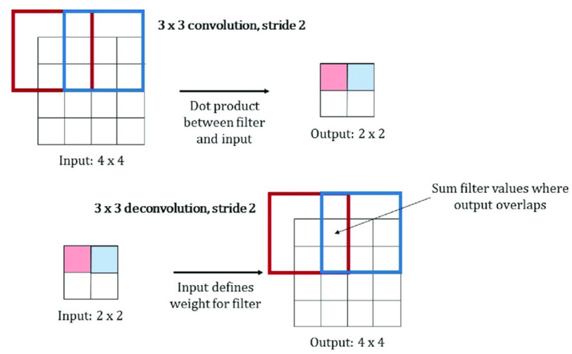
C. SRCNN using subpixel convolution

SRCNN using subpixel convolution uses the features extracted from the previous layers in order to increase the resolution of the image. This is done so by taking the depths of features and converting it into spatial data. Subpixel convolution works on a finer(pixel) level and thus leads to better results than transpose convolutions. The color shift is also less prominent as compared to the transpose convolution technique. (3) (4)



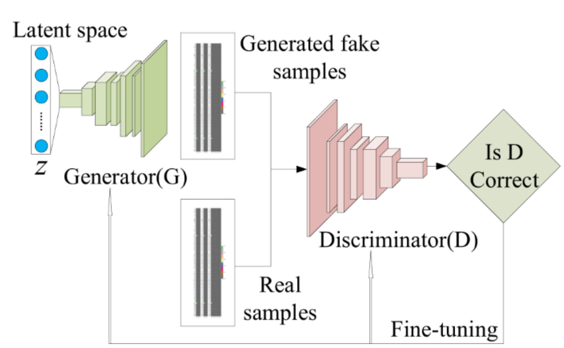
D. SRCNN using transpose convolution

SRCNN using transpose convolution is basically a deconvolution technique aimed at increasing the resolution of the image. Transpose convolution works on the basis of kernel operation. It strides over the entire image using kernel operation and increases the resolution of the image based on the factor by which we aim to achieve it. It sums all the values gained from the hadamard product of the kernel values and the image pixel values. (7)



E. GAN Model

Following the issues possessed by all of the previous techniques GAN model proved to be the best. GAN model has two networks in constant competition with each other to see wholl do better. The discriminator model aims to classify whether the image produced by the generator is of a desired quality or not. The moment the generator falsely classifies the generated image to be real our training would have said to be completed. (5) (6)



III. Implementation

We have implemented the models from different papers.

1) Image Denoising
2) SRCNN (Super resolution using convolutional neural network).
3) SRCNN using subpixel convolution
4) SRCNN using transpose convolution
5) GAN model

- Before moving to single image super image resolution it is important to work with comparitevly simpler models in order to understand the mechanism behind more complex models. Image denoising aims at reducing any noise from the image.
- We have recreated the paper on DNCNN which relates to image denoising. The noise has been introduced by us. The noise introduced is gaussian in nature. Our model as shown in results slide helps in reducing the noise which exists inside the image. The accuracy we have achieved is around 80 percent which is good for day to day usage.(1)
- Next we have created the paper on SRCNN which is the most basic paper which aims at super resolution. SRCNN first uses any interpolation technique in order to increase the resolution of the image to a rough scale. The rough values are then calculated again with the help of the convolutional neural network. The network aims to bring the partially resolved image as close as possible to the targeted high resolution image. The architecture follows a sequential structure to arrive at the desired output. (2)
- Following SRCNN we implemented various other models around SRCNN where in we did not upscale the image beforehand but had the model handle it. The first technique we used in order to achieve this was the SRCNN using transpose convolution. Transpose convolution is a deconvolution technique aimed at increasing the resolution of the image to a desired scale.
- In order to achieve better results we went on to look at increasing resolution from a pixel level detail. For that we used SRCNN with subpixel convolution. It aims to convert the depth of the filters learnt to spatial resolution which increases the resolution of the image. The process is known as depth-to-space convolution. (3) (4)
- Lastly due to issues faced from each of the following techniques we implemented a GAN model which gave a much better result than any of the previous techniques. (5) (6)

IV. Results

In the attached screenshots the original low resolution image depicts the image which we want to upscale by a factor of 2. The resolution of the image is 100 x 100. The high resolution image obtained will be of size 200 x 200.

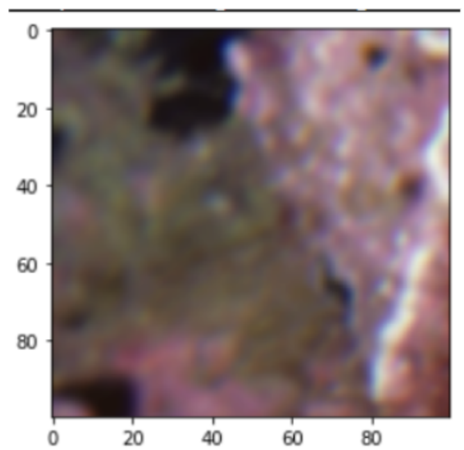


Figure-3 : Original Low Resolution Image

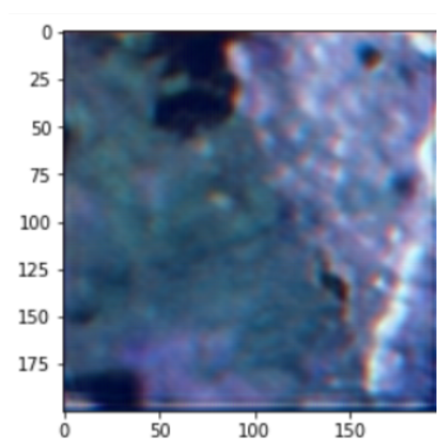


Figure-4 : Transpose Convoluted HR Image As visible the image suffers from a great amount of color shift as compared to the low resolution image.

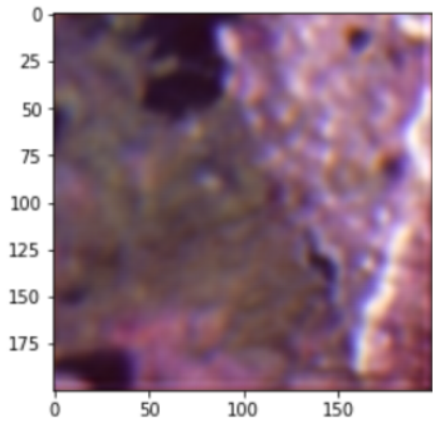


Figure-5 : Sub-Pixel Convolution HR Image The color shift is comparatively lower in the output obtained from the sub pixel convolution as compared to the transpose convolution.

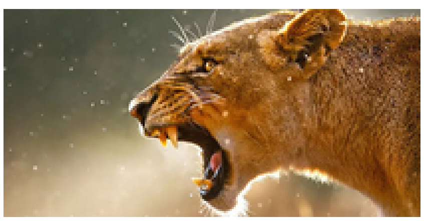


Figure-6 : Original Low Res Image To be passed to the GAN model (210 x 105)

Figure-7 : High Res Image received from the GAN model. As visible the color shift is much less prominent than the other models.

V. Conclusion

Throughout the entire journey we took to achieve the final results we found out that GAN'S provided the best results for the task of super image resolution among the other techniques we tried. The drawbacks of each method are described below.

1) Bicubic interpolation: Linear operation thus leading to loss of data
2) SRCNN (using transpose convolution): It leads to checkerboard artifacts which showcases blockiness of the images (not desired). Due to a lack of training colour shift can be prominently seen.
3) SRCNN (using transpose convolution): It can solve the problem mentioned above to a certain extent but highly refined images were not outputted. Due to a lack of training and resources the outputted images suffered from a color shift.
4) SRCNN (using subpixel convolution): The color shift that was prominent in the transpose convolution seems to be reduced to a great extent in the subpixel convolution. The reason being it looks at a much more detailed and finer manner than did transpose convolution.
5) GAN : On basis of all the techniques explored before this GAN's seemed to provide the best result as desired by us. Since the generator and the discriminator are in a constant competition the model keeps getting better and better in producing results that deceive the discriminator and thus leading to better outputs.

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