JAYPEE INSTITUTE OF INFORMATION TECHNOLOGY

MAJOR PROJECT

SYNOPSIS

Submitted to:-

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SUPER-RESOLUTION USING GENERATIVE ADVERSARIAL NETWORKS

INTRODUCTION:

Super resolution is the process of upscaling and or improving the details within an image. Often a low-resolution image is taken as an input and the same image is upscaled to a higher resolution, which is the output. The details in the high-resolution output are filled in where the details are essentially unknown.

Super resolution has varied applications in almost all digital image processing fields – satellite image processing, medical image processing and multimedia industry to name a few.[1]

In this project, we have tried to develop a Generative Adversarial Network (GAN) that will take a low-resolution image as an input and then super-resolve/upscale it four times.

WORKING:

GANs or Generative Adversarial Networks are Deep Neural Networks that are generative models of data. What this means is, given a set of training data, GANs can learn to estimate the underlying probability distribution of the data. This is very useful, because apart from other things, we can now generate samples from the learnt probability distribution that may not be present in the original training set. [2]

Generative Adversarial Networks are actually two deep networks in competition with each other. Given a training set ***X*** (say a few thousand high-resolution images), The Generator Network, ***G(x)***, takes as input a random vector and tries to produce images similar to those in the training set. A Discriminator network, ***D(x)***, is a binary classifier that tries to distinguish between the real high-resolution images according the training set ***X*** and the fake super-resolved images generated by the Generator. As such, the job of the Generator network is to

learn the distribution of the data in $\boldsymbol{X}$, so that it can produce real looking images and make sure the Discriminator cannot distinguish between images from the training set and super-resolved images from the Generator. The Discriminator needs to learn keep up with the Generator which is trying new tricks all the time to generate fake super-resolved images and fool the Discriminator.

Convolutional neural networks have been used for super resolution in the past but have some drawbacks like their input image is bicubic low resolution, which is an approximation of high-resolution image and because of this interpolated input they are not able to give state of the art result. The Super resolution CNN has three layers, so there is also a question that can more deep networks give better results? [3]

In this project, we have mainly used the concept of Generative Adversarial Networks but we have also used two deep learning concepts to reduce the number of parameters and train our network on a smaller dataset. The use of residual deep networks helped the network to learn better representations by using skip connections in the network. The use of transfer learning enabled us to train a big network with many parameters with the use of relatively smaller dataset by the use of a similar network with similar feature representations, VGG19 which was trained on larger dataset (approximately more than 1 million images) as compared to the DIV2K dataset. We have also used a perceptual loss function which consists of an adversarial loss and a content loss. The adversarial loss pushes our solution to the natural image using a discriminator network that is trained to differentiate between the super-resolved images and original photo-realistic images from the training dataset. In addition, we used a content loss motivated by perceptual similarity instead of similarity in pixel space (for this we used VGG19 pre-trained model to initialise the generator and calculate the content loss). [4]

CIRCUIT DIAGRAM:

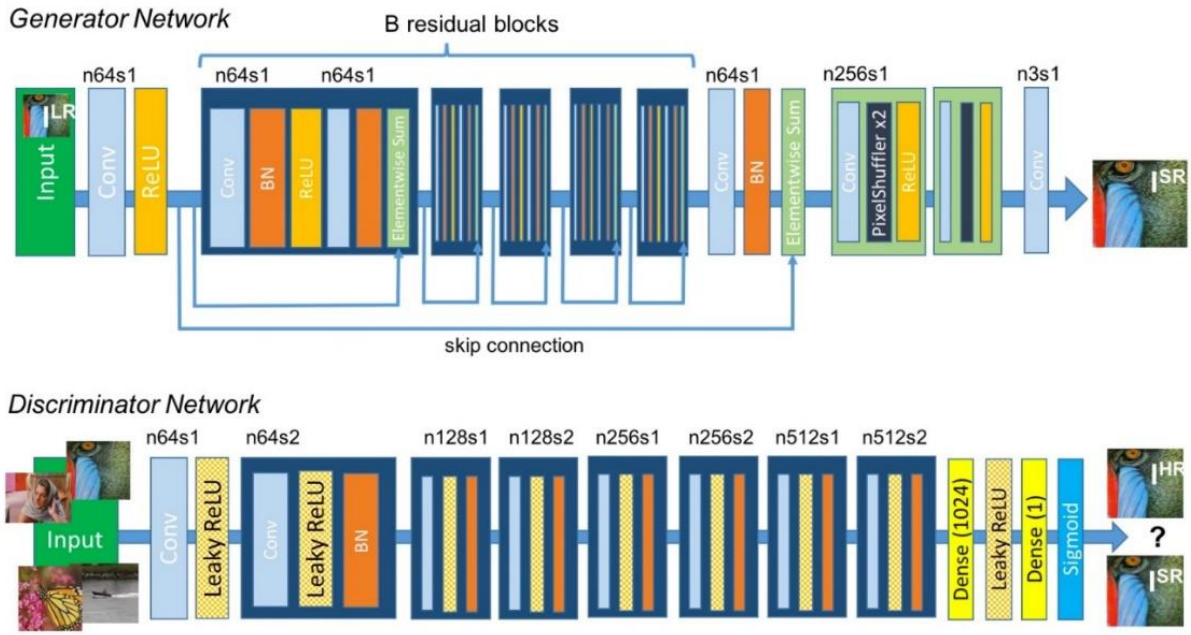

Fig.-1- SRGAN Architecture [4]

WORK STATUS:

Till Mid-Evaluation Viva, we have researched the topic extensively and have read the relevant literature by which we have learned that using Generative adversarial networks can improve the resolution of an image drastically [5],[6],[7]. We have trained the Super-resolution GAN on the DIV2K dataset and it has completed around 700 epochs.

By the end term viva, we have made progress with the training of SRGAN and we have also tried to do some experimentation with the methodologies followed for standard SRGAN and have got positive results[8]. Also, we have developed a web application based on Flask framework where you can upload an input picture and get a super-resolved picture as the output.

CONCLUSION:

This project has been able to give satisfactory results in upscaling low resolution images but due to paucity of resources it is not able to produce. state-of-the-art results. In the future, we will try to tweak the architecture of GAN to make the training process smoother and more efficient.

We have also developed a web application based on Flask framework where any novice can upload a low-resolution image and get a high-resolution output.

The detailed images generated by our model can be used in multiple fields where high-resolution images are indispensable to the research like in medical research, astrological studies etc.

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