Image Quality Improvement using Deep Learning

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***Abstract*—Imagery data constituents a major portion of mobile network data usually for entertainment purposes. Photos captured my camera also may come out to be of bad quality. Low image quality decreases the production value of created content especially when seen on high-definition displays. There is a need for increasing the quality of these images which get degraded due to compression or original low resolution. Image enhancement is done using Generative Adversarial Network for image Super Resolution (SR-GAN). GAN has several benefits as compared to other techniques such as feature guidance and unpaired high resolution model training. Generative and Discriminative learning are used for training the model. The technique can produce perpetually satisfying enhancement in the sense of photo-realism. For the best result an upscaling of factor 4x is done. The hyperparameters are also optimized to obtain better results from the model. Final image is close to the original High resolution. The model was evaluated using loss function and peak signal-to-noise ratio. The project is implemented on Keras deep learning API on TensorFlow using python.**

***Index Terms*—Deep learning, image processing, tensorflow, super resolution, parameter optimization**

I. Introduction

Visual experience are important drivers in entertainment industry with imagery data consisting of 59% mobile internet traffic in 2017 according to [3]. This is further expected to rise to 79% till 2022. This growth is attributed to rise of display device among the general population. This has also raised the imagery content being generated by entertainers. To further fuel this growth, more and more imagery data is being in generated in high resolution. New mobile devices with camera capable of catching high resolution images have made their way into hands of many people. These devices also sport high resolution displays which prompts more usage of high-quality imagery data.

In turn the bandwidth for transmission of such data has still not matured to the extent of transmitting high resolution large size samples without down-scaling or disrupting the original quality. There is very high disparity of internet speed at present according to [15] with only small percentage of people enjoying high speed network. To mitigate this data compression techniques have been developed to increase efficiency in storing and transmitting data. While this extends the reach of the image, the same is loses visual appeal as result. This is more significant especially transmitting photo-realistic techniques. An end-to-end system where images can be compressed for transmission and then enhanced after reaching the destination can solve this problem. The quality of images can be improved as shown in figure 1 Sometimes the image captured are also of low quality. Camera used on unfavorable weather conditions produce hazy and degraded images. In real life events that cannot be repeated but need to be recorded often face this issue frequently. Low quality images also prove to be a challenge for vision-based tasks such an object detection, object picking bots, surface deformity and strain detection.

Fig. 1. Low Resolution and High Resolution

There are several machine learning techniques that can be employed to increase the image quality. This can be done by increasing the resolution of the image using neural networks. There are several machine learning techniques for single image super resolution. The [22] compares various representative techniques with various benchmarks and results. SR-GAN which is a generative adversarial network for image super resolution is one of the techniques which provide good result. Image super-resolution can also be implemented in video sources to improve their quality. This comes under real-time super resolution (RTSR) neural network which is often used in videogames, mobile video enhancement tools and dashboard camera.

Taking all this onto account, the research question in this paper is to find the usefulness of deep learning methods to obtain super resolved images use. For this Generative Adversarial Network for image super resolution is selected and implemented. An upscaling factor of 4x is desired to be achieved. The project is done using the Keras deep learning API running on TensorFlow.

The whole process is documented in the report with the goal of reproducing the whole project in this report. The report consists of the following sections as follows. Section II is a literature review of all the associated research papers and articles that were analyzed for this project. Section III is the whole methodological approach that was used for this project. Section IV is the evaluation and results of the model was implemented and finally Section V is the conclusion drawn from the project.

II. Related Work

There are various machine learning techniques that are available for image processing. Several technique performances were considered while deciding the desired technique for this project. [22] gave valuable insight on various parameters that were useful for this step. The study worked on classifying various techniques for Single Image Super Resolution(SISR). The study is comprehensive in regards for number of techniques verified but does not talk about application use for the same.

The project is implemented on Keras deep learning API on TensorFlow using python. TensorFlow is open-source machine learning developing and training model tool. Studies regarding deep learning were summarized for this project and hence in regard to that many related works were gone through. One of the most thorough work is a t he literature [8] which introduces a detailed insight on programming environment, high-level programming application interface and construction of complex input pipelines in a simple way. In-line with the previous work, [9] is next forward introducing advanced TensorFlow. As mentioned earlier, the paper uses Keras API, and the paper enumerates the limitations of such high-level API. New network layers and loss functions are not available in the high-level API which are being used by many research studies and papers. As such many new networks model which use the features cannot be constructed. To mitigate this, the literature introduces custom API for TensorFlow which solves the aforementioned problems. With this, custom callback functions, custom metric functions, custom loss functions and custom network layer can be used which was not possible as discussed earlier.

[14] elaborates on the evolving procedures in image processing from linear classifiers to neural networks. It also emphasizes on the slow rate of processing power evolution as compared to processing intensive techniques that have come up. The authors emphasize on the non-feasibility of some of the most accurate techniques due high storage costs or high computational needs and hence provide an alternate solution in upgrading the tensor algebra with respect to image class.

SR-GAN provides excellent super resolution performance as compared to another techniques. While there are more suited methods, they need paired high resolution image for model training. This is unrealistic in real world since low resolution images are hardly accompanied by high resolution counterpart and only low resolution samples are available for super resolution. The [12] is a feature guided unpaired SR-GAN implementation of such scenario and shows how GAN is flexible in that regard. This achieved by introducing a guidance module which forces the model to learn valid representation for super resolution.

SR-GAN capabilities are furthered emphasized in [11] which conducts hyperparameter tuning to present 4x upscaling factor which is useful for obtaining photorealistic images. This is done by training the model to differentiate between original photorealistic image and super-resolved image. This approach ensures that the super resolved are close to the original as much as possible. The approach uses perpetual loss function consisting of adversarial loss and content loss.

Tuning parameters in image processing algorithms are important to obtain good image reproduction. The [18] works on camera lens as well as image processing parameter optimization for best overall quality enhancement.

[16] gives insight on data driven optimization. Presence of uncertain variables in data makes parameter tuning but including these uncertainties make the model robust. The author use predefined confidence level in accordance of the data available, which makes the whole process computationally tractable while also being independent of the objective function.

To get better understanding of parameter optimization for this project, [4] proved to be valuable for giving insight. The research paper gives particular attention to Bayesian Optimization in regards of four fundamental strategies specifically, cost function transformation, parallelization, early termination, and diversification. This way the authors were able to achieve high Deep neural networks (DNN) benchmarks as compared to other techniques.

Image processing parameter optimization can also be done for specific detail in images also known as variational optimization. In [17], a new approach for single image dehazing is proposed. In real world, tiny particles in the atmosphere cause reflection and refraction which makes images hazy and degraded quality. These types of images have low contrast, faded colors, and few details. Image dehazing means enhancing contrast and improve color.

[20] is a research paper on image transformation using convolutional neural network review . The review contextualize quantitative image domain within deep learning advancement and leverage future development. The paper gave invaluable insight in regard to the project in deep learning study of image. This is in line as image processing application has various usage in all domain. Although the authors paid extra attention to medical imaging as their core interest and the usage of such techniques in healthcare.

Many image processing techniques are trained to operate on only greyscale images. This is not realistic as most image at present are full colored and there is hardly any black and white image that are available. In [1], the authors study the implementation of multilevel color image thresholding. The results put the model at par with state-of-the-art methods but with significantly better efficiency and decreased computational resources required.

The project uses SR-GAN technique which is Generative Adversarial Network in image Super Resolution. The model training is done using Generative and Discriminative Learning. For this purpose, literature which gave deep insight was taken into consideration while going the project. [19] is a comprehensive study of learning generative models with using discriminative approaches. The literature shows a variety of applications such as face modeling, denoising, non-photo-realistic rendering and texture modeling. These applications are direct consequences of image processing which is also the base for this project.

Another paper regarding the generative and discriminative model learning was considered while going through the project. [6] gives the perfect application for such type of models especially considering the algorithm of the generative and discriminative learning works. The distribution of data is vast but most of the content lack any useful information and not needs to be considered. An example of such is the space where 99.99% of space holds no information but only 0.001% of data is of interest to astronomy. The same is case in many other domains and as such this proportional imbalance is needed to be considered while training a model for these specific domains.

Parameter optimization is also conducted attain specific results. In [23] this approach has been treading to obtain image fusion on intensity-hue-saturation under generalized and adaptive approach. Till now only half of the fusion parameters were adaptive, but with this approach all fusion parameters are determined adaptively via two-step optimization procedure.

Another approach on parameter optimization is discussed in a [13], where interest based on region is considered to decrease the computational usage of the model. There has been lagging of hardware processing power as compared to techniques requiring computational resources which results in high processing time for complex machine learning procedures. To mitigate this the mentioned paper devises parameters that are specific for the region of interest. This is achieved by training several low performances for each specific parameter . While parallel operation may prove to be a little complex, the time saved, and the efficiency achieved compensates for the whole complexity.

As in-line with the previous literature, [5] uses the same approach to classify specific parameters for emergency scenarios. This is done by using smaller datasets of regional value. The approach significantly reduces the image processing time by using an unmanned aerial system (UAS). Such optimization has various application where time is of the essence. The obtained results can be published in 3-D format on the web. This type of study is in benefit more for the end-user of the machine learning technique.

Model learning can be done by various approaches due to abundance of option available. In this project, generative and discriminative learning has been done. The generative approach solves the problem by providing a probabilistic value for each classification using bayes optimization rule to infer labels for category. The authors follow the same approach in [7] with more focus on the learning method rather than the application of the learning method. The authors also associate the generative and discriminative algorithm with human behavior with concurring that trend of categorizing objects into a category with higher probability. The paper suggests that human can be made to learn either generative or discriminative adaptation while making decision. The paper gave important inputs regarding the use of real life usage of computational techniques.

SR-GAN has been used for image processing for a very long time for it to show many underlying problems and inefficiencies. [10] shows an enhancement for this technique which reconstructs satellite images while being insensitive to noise as well. This is done by creating two images: one being intermediate high resolution which is sharp but a little eroded with noise and another which is enhanced mage contours. Then the model uses both images to construct imagery with high clarity and content. The results obtained were comparable to state-of-the-art super resolution techniques.

Another research [21] flows the advantages that GAN provides in image processing. DenseNet which is a type of convolutional neural network with dense connections between layers is a new implementation which has risen in usage across deep learning applications. The author introduced ultra-dense GAN (udGAN) for image SR where internal dimension is reformed in a 2-D matrix topology. This provides additional diagonal connections which in turn increase the number of pathways while with minimum layers usage. The authors are able to double the number of pathways which in turn provides exceptional reconstruction of images in super resolution. The paper further give input on the results achieved by extensive use of said technique on real world satellite imagery and show out-performance of stat-of the-art counterparts in quantitative and subjective measures.

Another approach is suggested in [2] that trains the model from unpaired high resolution and low resolution. The output from the previous is used as an input for the model which is trained for low to high GAN for image super resolution. The obtained is able to increase the quality of real-world images with far more better efficiency and less computational needs.

III. Methodology

CRISP-DM and KDD are the most widely utilized methodologies in this field. In this research, CRISP-DM is used. To determine how much does super resolution GAN find its relevance for upscaling images, it goes through six stages: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment.

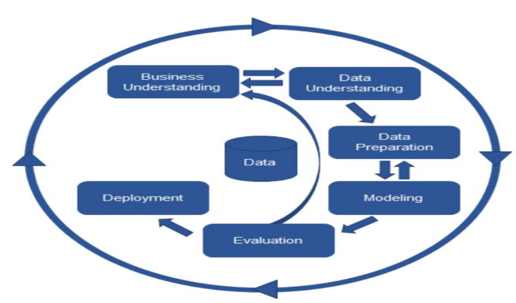

Fig. 2. CRISP-DM methodology

A. Business Understanding

This is the first and most important step in the CRISP-DM technique. The primary objective of this study is to analyse if super resolution GAN can suffice the need of image upscaling. Super-Resolution Generative Adversarial Network is a GAN technique for image super-resolution that is more engaging for the human perspective. It is made up of two neural networks 'Generator' and 'Discriminator'. By putting these two neural networks against one other, GAN learns a dataset's probability distribution. Upsampling is the process of turning a low-quality image to a high-quality image by increasing the details of the image. In upsampling more data is added to the image.The model is trained using a dataset that contains both low and high quality pictures of the same image. Risk in this study is that image processing consumes a lot of time and the performance depends on the machine speed.

B. Data understanding

To work efficiently on any dataset understanding the data is important. The second step of the CRISP_DM methodology is to understand data. A collection of images is acquired from Kaggle available for public use. It consists of various (100 considered) images having both high resolution and low resolution. The data is loaded, hyper parameters are defined. The batch size is defined as the number of pictures processed at once which is considered as 5 in this study. In contrast, with a text dataset, a batch size of 1000 or more can be considered. Epoch is defined as 500 for this learning to take place. One entire cycle through the training dataset is referred as as an epoch. It enables the model to re-adjust the model's parameters. Now the number of epochs have an effect on the time required to execute the task as well as if the number of epochs are substantially higher it will over train the model. It means,the output for the train dataset will be flawless but it will not function properly for the test or validation dataset. Keras is used as an interface for tensorflow as is user-friendly, modular and extensible. The low resolution images are of 96 X 96 pixels and high resolution images are of 384 X 384 pixels.

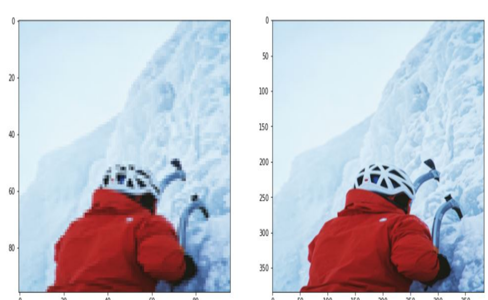

Fig. 3. Low resolution and High resolution image

It is important to understand the components of an image and what needs to be changed so as to validate the increase in quality. Image is made up of many digital values known as picture elements or in common term pixels. These pixels can be converted into pixel matrix which have unique numerical value for every pixel present in the image. Figure 5 is a pixel matrix of picture in figure 4. Hence any image can be

Fig. 4. Low Resolution Image

```
array([[[0.21176471, 0.32941176, 0.38823529],
        [0.24705882, 0.37647059, 0.44313725],
        [0.4       , 0.52156863, 0.57647059],
```

Fig. 5. Pixel matrix for Low Resolution

Low resolution images have smaller matrix as compared to high resolution. This is due to high pixel density for any detail present in the picture. For instance the wheel in figure 6 and figure 4 is identical but one has higher detail as compared to another. This is due to higher number pixels in figure 6 as compared to figure 4 for the same detail. This can also be seen in the respective matrix for the images.

C. Data Preparation

The data preparation step of CRISP_DM is the third stage that ensures that the data is clean. Firstly, it loads the data separately in the two different arrays from the given location. The steps carried out after for data preparation are normalizing, resizing and sampling. The next steps are to check size of data that we will be using for this experiment. As, seen from the below figure a dataset with 100 images of 384 X 384 pixels and 96 X 96 pixels is created in a 3 row array.

1) Resizing: It uses the OpenCV library function for resizing. By default, it resizes the height and width of the image. Depending on the necessity, the aspect ratio can be kept or not. By calculating width or height for a given height or width, the aspect ratio may be kept. The images are acquired from the location as specified and adjusted as per the shape defined.
2) Normalizing: The term "normalization" refers to a procedure that alters the range of pixel intensity values.

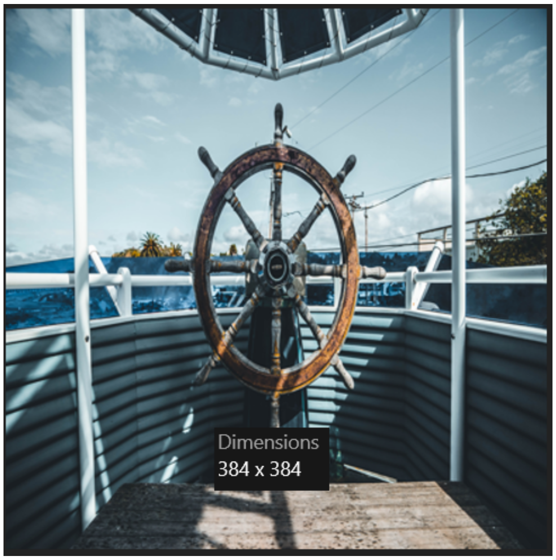

Fig. 6. High Resolution Image

```
array([[[0.17647059, 0.28627451, 0.34117647],
        [0.18431373, 0.29803922, 0.35294118],
        [0.18823529, 0.30196078, 0.35686275],
```

Fig. 7. Pixel matrix for High Resolution

```
HR_train, LR_train= get_data('E:/Project/Data')
HR_train.shape, LR_train.shape
```
```
((100, 384, 384, 3), (100, 96, 96, 3))
```

Fig. 8. Shape of the image dataset

The process of normalization is also known as ”contrast stretching” or ”histogram stretching”. Batch normalization is frequently employed to offset the internal covariate shift in order to train these deeper network designs quickly.

3) Sampling: In machine learning the model is trained on a small set of data and then it is said to be trained. It can be further explored for a big dataset. 2D convolution layer is used with input layer. This layer generates a tensor of outputs by convolving the layer input with a convolution kernel. Upsampling of images is done from height (h), width(w) , center(c) to (h*r, w*r, c/(r*r)) where r is scaling factor. The scaling factor is set to 4 by default.

D. Modelling

Deep networks are tough to train, but they do have the capacity to improve the network's accuracy, allowing for even more complex modeling mappings. GANs are a part of generative models family. Generic models, unlike auto - encoders, could generate new acceptable outputs from arbitrary encoding. GANs are taught to model input distributions by training two competitive (yet cooperating) networks termed generator and discriminator. The generator's job is to continually finding out new ways to make phony data or signals (audio, picture, and so on) that will deceive the discriminator. The discriminator, on the other hand, has been trained to discern between false and real signals. As training of the model progresses the discriminator finds it challenging to differentiate between synthetically generated images from the real images. Once the model is trained the discriminator can be eliminated and generator can be used to create new, real signals that are never been created before.

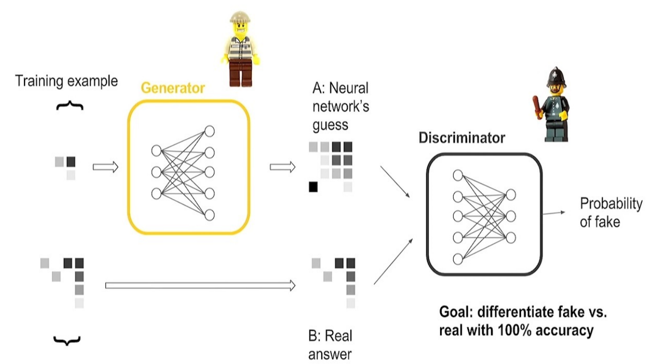

Fig. 9. GAN structure

The goal of this single image super resolution is to form a high resolution, super resolved image from the provided low resolution image. High resolution(HR) images are only available while the model is been trained. Final objective is to train a generation function G that predicts the HR complement of a given LR input picture. To obtain this goal the generator network is trained in feed-forward way.

Once the models have been shown to be a good fit for the original business problem, they are put into production. After the images are normalized, resized and sampled the model is implemented. The result of the model implemented is shown in the further sections.

```
G = get_G((96, 96, 3))
D = get_D((384, 384, 3))
vgg= get_vgg19()
```

Fig. 10. Model applied

IV. Evaluation and Results

The last steps of CRISP-DM methodology are evaluation and deployment. This section describes the different steps carried out for evaluating the implemented and discussion of the results

A. Project Evaluation

The project was able to reconstruct enhanced image after training. In figure 11 various regression of image in train while reconstruction can be seen.

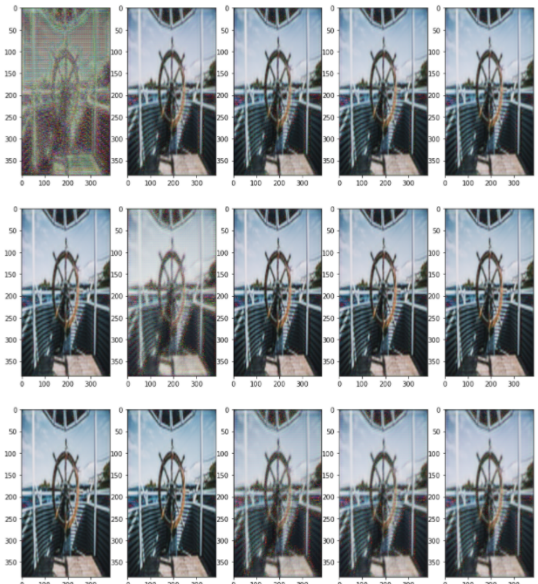

Fig. 11. Train Sample

In figure 16, the final result is obtained. The leftmost image is the original low resolution sample. As can be seen it is has very low pixel as compared to other two. Rightmost image is the high resolution sample which was used for model training. The center image is the reconstructed image. The image has a certain blur which due to over smoothing of the image. This is apparent characteristics of GAN model image processing.

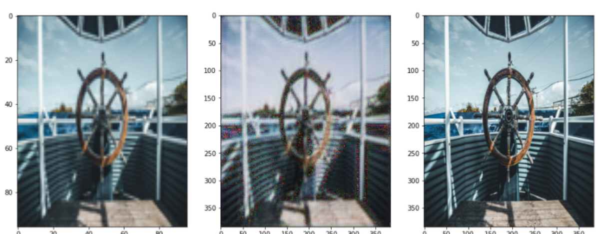

Fig. 12. Final Visual Result

The resulting image could have been enhanced using dense GAN which compensates for over smoothing of the resulting image.

B. Model Evaluation

1) The model is evaluated using the Loss function values for Mean Square Error (MSE) chart. MSE is the sum of squared values of the target values with respect to target variable.
Figure 14 is the Mean Squared Error Loss Function Graph per Epoch from 0-50. This is compared to the 15 which is a graph of Loss function.

$$MSE = \frac{\sum_{i=1}^{n} (y_i - y_i^p)^2}{n}$$

Fig. 13. Mean Square Error

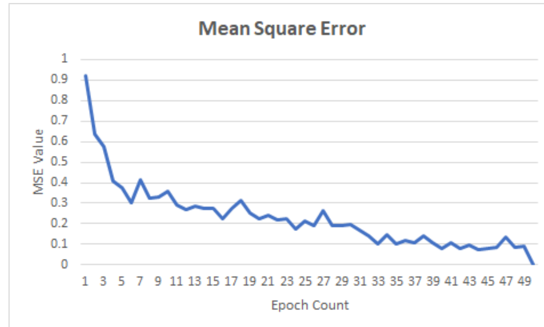

Fig. 14. Mean Squared Error Loss Function Graph per Epoch from 0-50

The graphs shows similar line and thus can be concluded that there is no penalty while doing back propagation.

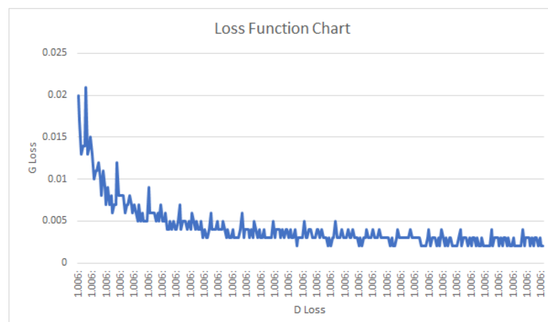

Fig. 15. Loss Function Graph

2) Another evaluation metric for image processing is Peak signal-to-noise-ratio (PSNR). It is defined as the maximum possible value of the signal as compared to the power of noise that effects the quality of the image. The ratio of these two value gives the PSNR.

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

Fig. 16. Peak Signal-to-noise ratio formula

As can be seen in figure 17 which is the code snippet and value in python file, the PSNR value for the model is **17 dB**. Although it is considered that higher PSNR offers higher quality, in image processing this is not the case due to human perception of visual appeal.

C.

The SR-GAN model came to hold the following advantages and disadvantages as per literture review and project findings.

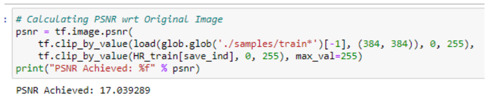

Fig. 17. Peak Signal-to-noise ratio

1) Advantages:

- GAN trained discriminator is a a classifier which is useful for image processing and is able to genrate both discriminator and generator.
- GAN can be feature guided for unpaired training of model without necessity of high-resolution counterpart.
- GAN also features very high upscaling factor as compared to other techniques. In this project, the super resolution of 4x factor was obtained.
- GAN also has the ability for modeling data distributions at very high optimization rate.

2) Disadvantages:

- The techniques tend to generate blurry and over-smoothed super resolved images but can be improved via dense deep-learning.
- One of the most serious drawback of GAN is the lack of intrinsic metric for evaluation. This prove to be serious issue during this project.
- It is unable to predict the density of an image.

V. Conclusions and Future Work

In this project the objective of enhancing the quality of the image via Generative Adversarial Network image Super Resolution (SR-GAN) was successfully implemented. The reconstruction image was obtained of sufficient quality. The model was evaluated using Peak signal-to-noise-ratio ad loss function. The limitations and advantages SR-GAN model was discussed for reasoning of model choosen.

The applied technique can be used on videos rather than single image. There is already work done on this domain under Real Time Super Resolution(RTSR). Such techniques are being used in steaming services and videogames. With arrival of 8K displays, the scaling factor of 4x may not hold much value for much longer. Higher scaling factor without holding the computational needs back also can be done. Another area of interest is the us of dense Networks in GAN which will increase the performance of already optimized techniques.

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