# SUPER RESOLUTION USING GENERATIVE ADVERSARIAL NETWORKS

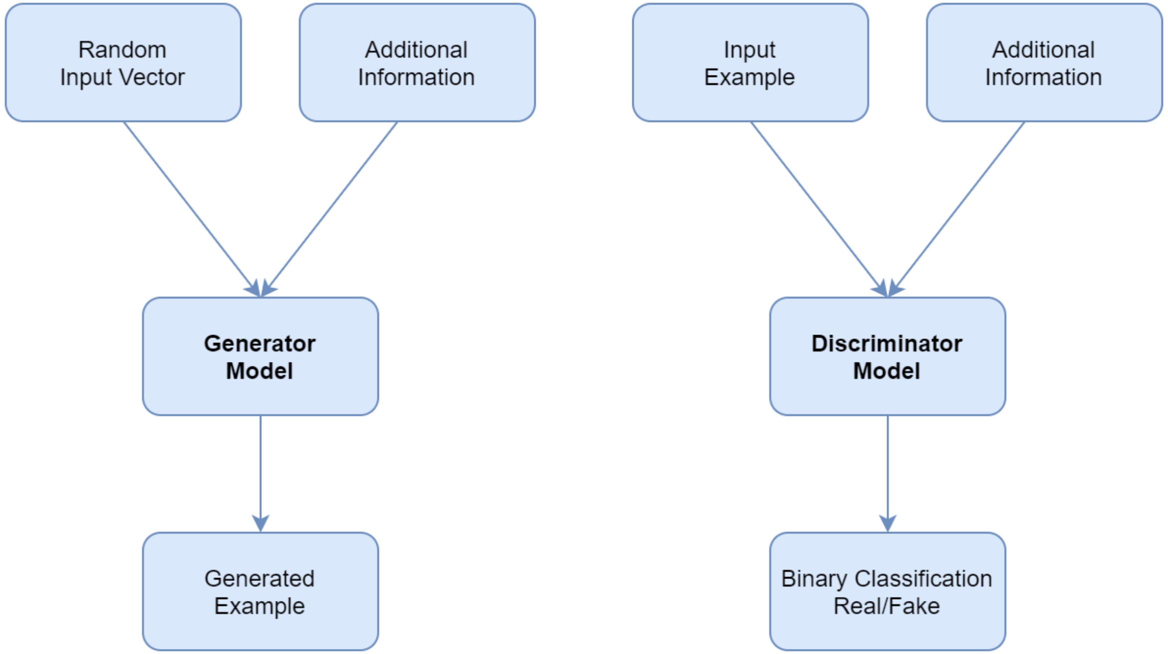
A Presentation by-
Asutosh Rath(1702070121)
Prabhakar Bisoyi(1702070122)
Subhasish Das(1702070125)

# SUPER RESOLUTION?

- Image super-resolution is a technique of reconstructing a high-resolution image from the observed low-resolution image.
- Super resolution are used in fields like surveillance, medical and media.
- Different Techniques used for super resolution are Interpolation techniques for up sampling (bilinear, nearest neighbor, bicubic),using CNNs ,SRResNets and SRGANs.

# Generative Adversarial Networks

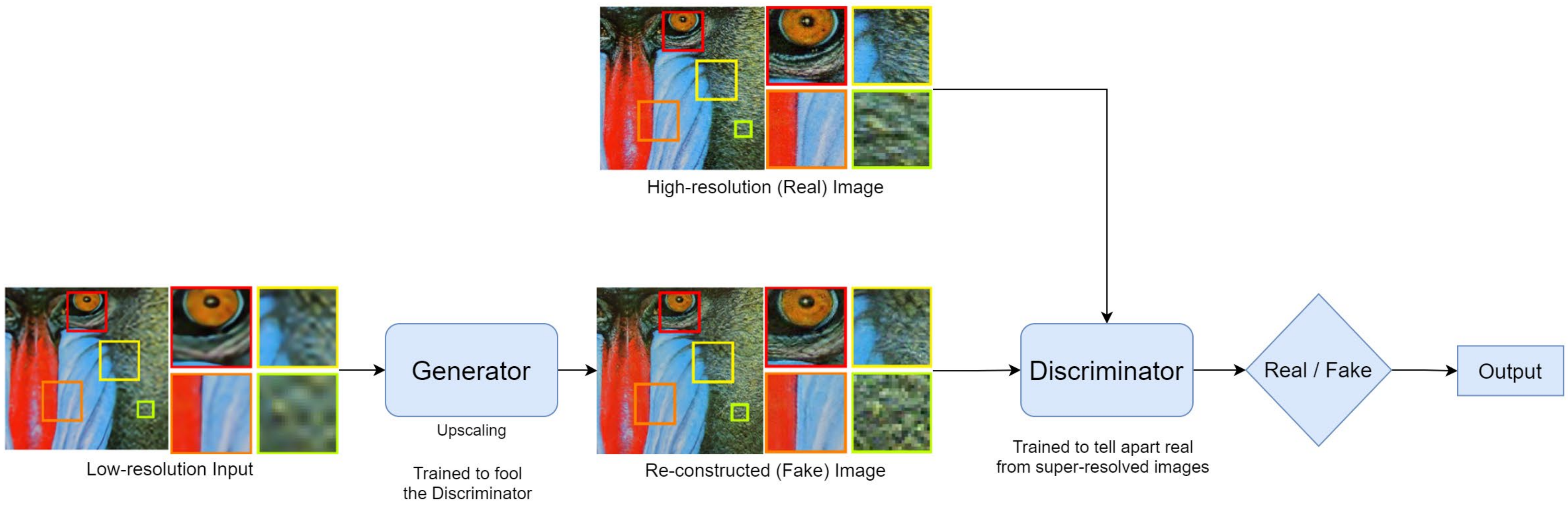
- Proposed by Ian Goodfella in 2014.
- GANs are an architecture for automatically training a generative model by treating the unsupervised problem as supervised and using both a generative and a discriminative model.
- GANs provide a path to sophisticated domain-specific data augmentation and a solution to problems that require a generative solution, such as image-to-image translation.



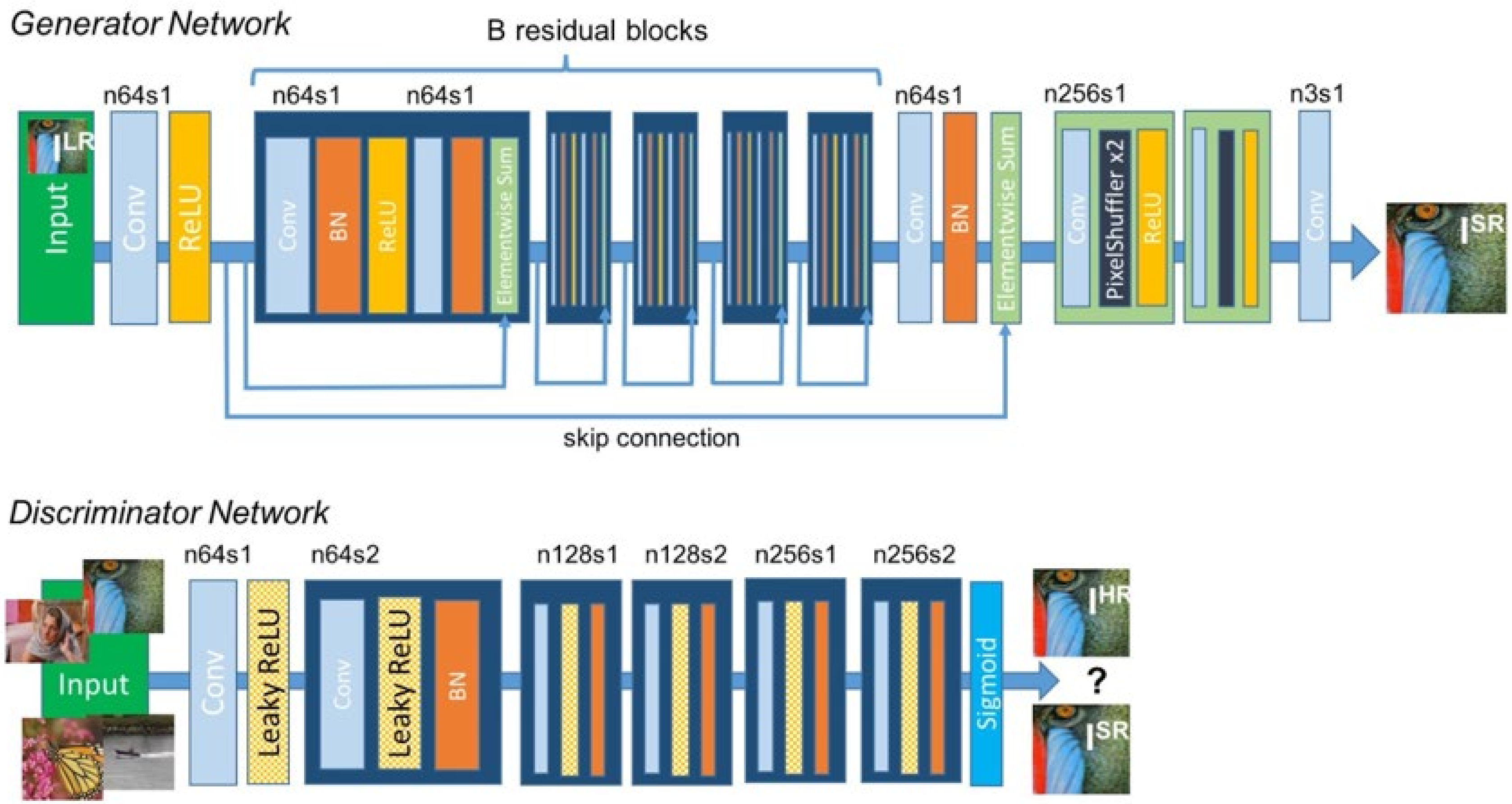
# Why SRGANS?

- Super-resolution GANs apply a deep network in combination with an adversarial network to produce higher resolution images.
- SR GANs tend to produce images which are more appealing to humans with more details compared to an architecture built without GANs.
- Most of the approaches for Image Super-Resolution till now used the MSE (mean squared error) as a loss function, which results in high texture details of the image are averaged to create a smooth reconstruction. To overcome this GANS use a perceptual loss function that consists of an adversarial loss and a content loss.

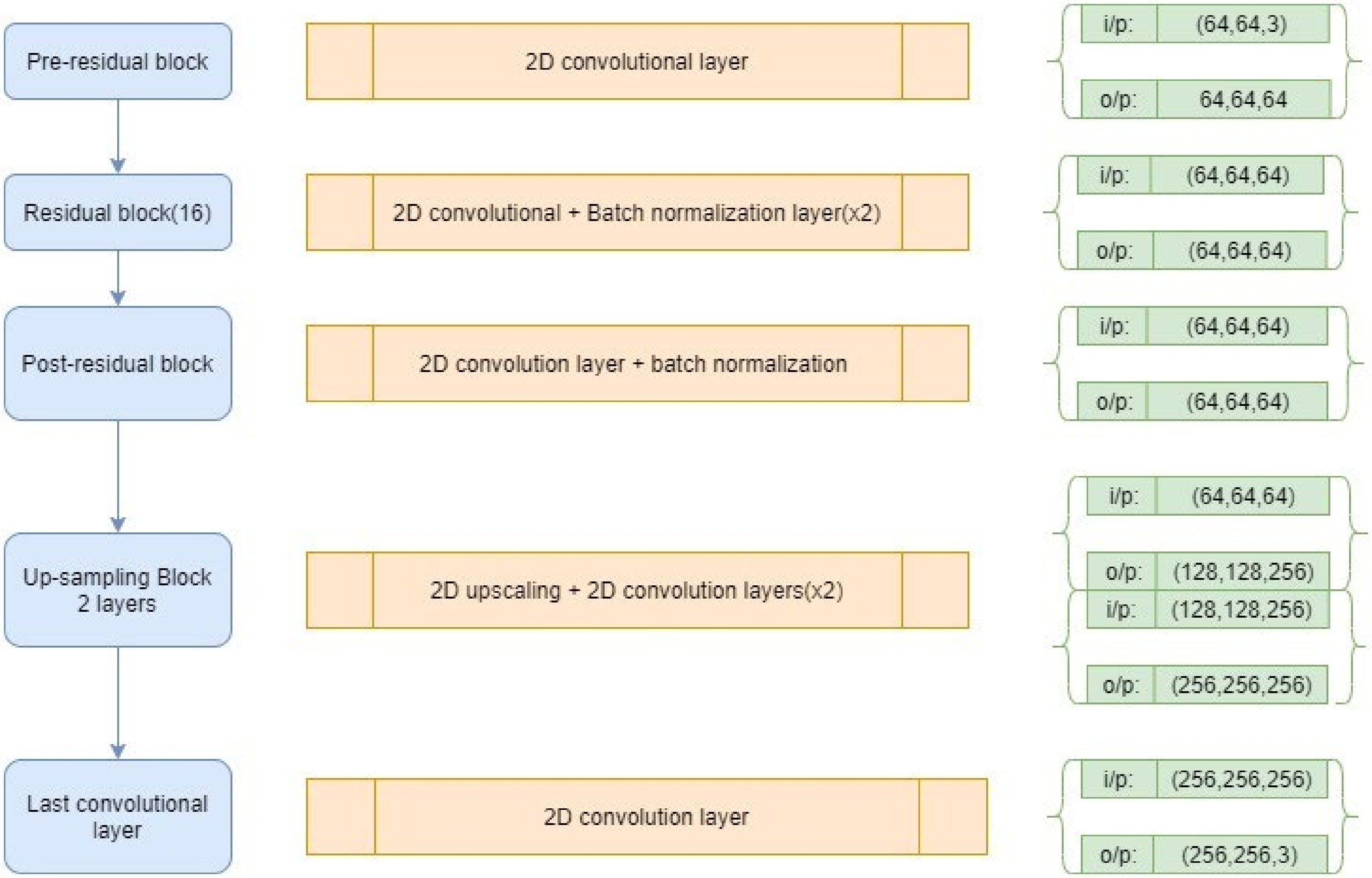
# Project overview



# SR-GAN Architecture



# Architecture Generator



# Architecture Discriminator

| Layer name | Input shape | Output shape |
|---|---|---|
| Input layer | (256, 256, 3) | (256, 256, 3) |
| 2D Convolution layer | (256, 256, 3) | (256, 256, 64) |
| 2D Convolution layer | (256, 256, 64) | (128, 128, 64) |
| Batch normalization layer | (128, 128, 64) | (128, 128, 64) |
| 2D Convolution layer | (128, 128, 64) | (128, 128, 128) |
| Batch normalization Layer | (128, 128, 128) | (128, 128, 128) |
| 2D Convolution layer | (128, 128, 128) | (64, 64, 128) |
| Batch normalization layer | (64, 64, 128) | (64, 64, 128) |
| 2D Convolution layer | (64, 64, 128) | (64, 64, 256) |
| Batch normalization layer | (64, 64, 256) | (64, 64, 256) |
| 2D Convolution layer | (64, 64, 256) | (32, 32, 256) |

# Loss functions

The objective function for SRGANs is called the perceptual loss function, which is a weighted sum of the two loss functions, as follows:

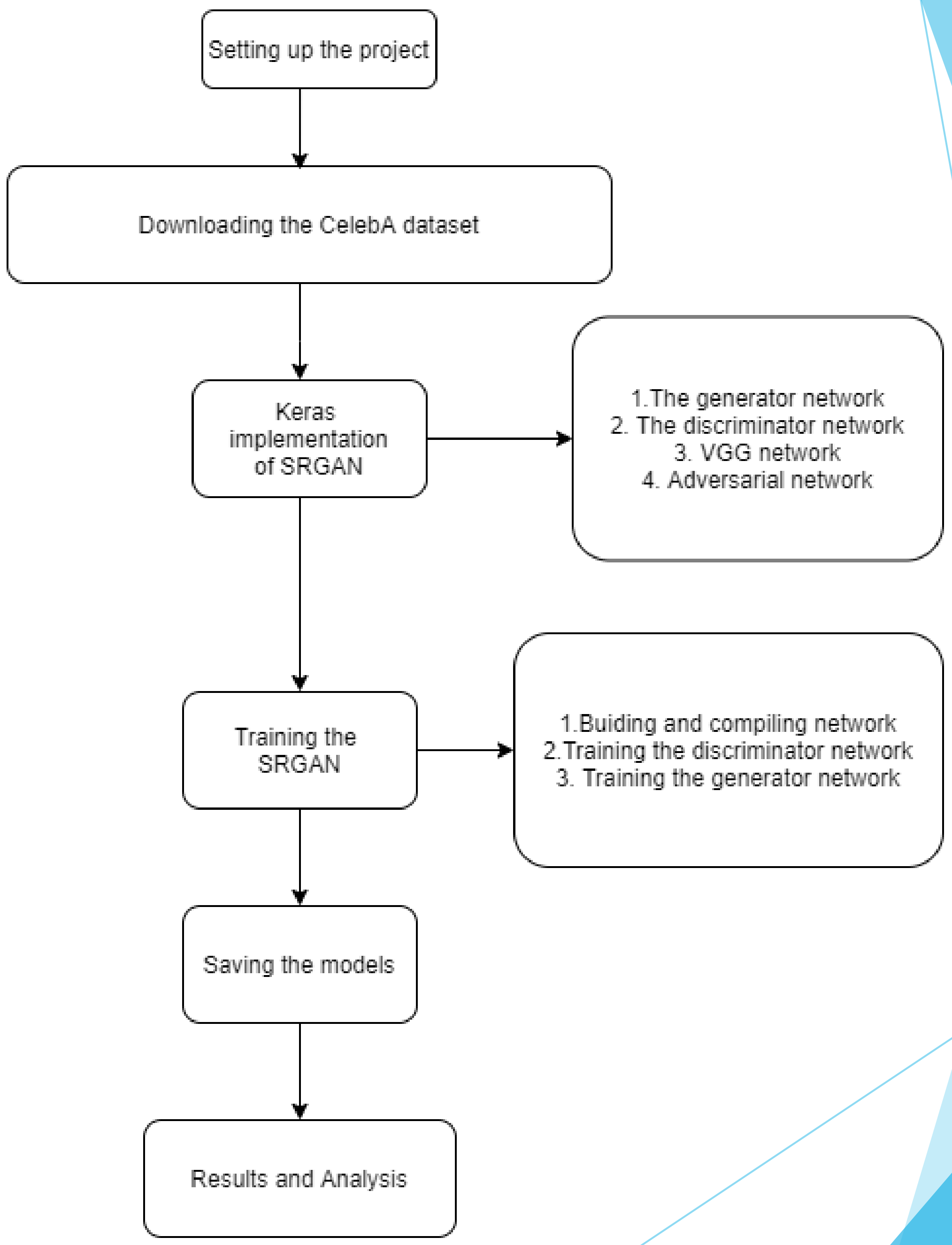
- **Content loss:** There are two types of content loss, as follows:
  - Pixel-wise MSE loss
  - VGG Loss
- **Adversarial Loss:** The adversarial loss is calculated on the probabilities returned by the discriminator network.

The **Perceptual loss function** is a weighted sum of the content loss and the adversarial loss, which is represented as the following equation:

$$l^{SR} = 1.0 * l_X^{SR} + 0.001 * l_{Gen}^{SR}$$

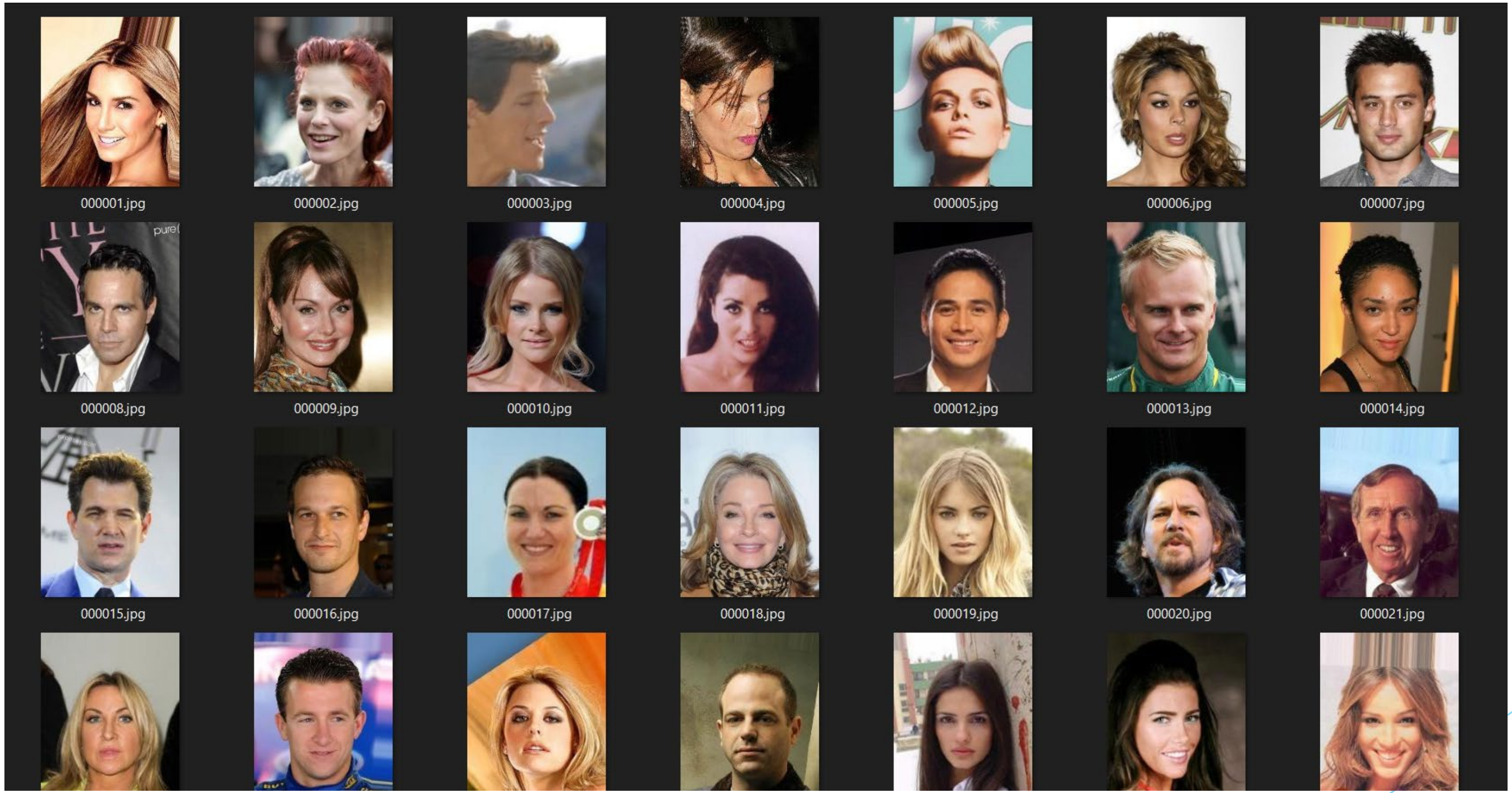
# Methodology

# FLOW CHART


Setting up the project
Downloading the CelebA dataset
Keras implementation of SRGAN
1.The generator network
2. The discriminator network
3. VGG network
4. Adversarial network
Training the SRGAN
1.Buiding and compiling network
2.Training the discriminator network
3. Training the generator network
Saving the models
Results and Analysis

# Dataset

- For this project we have used CelebFaces Attributes(CelebA) dataset. The dataset contains 202,599 faces of celebrities.



# Training the models

# Results

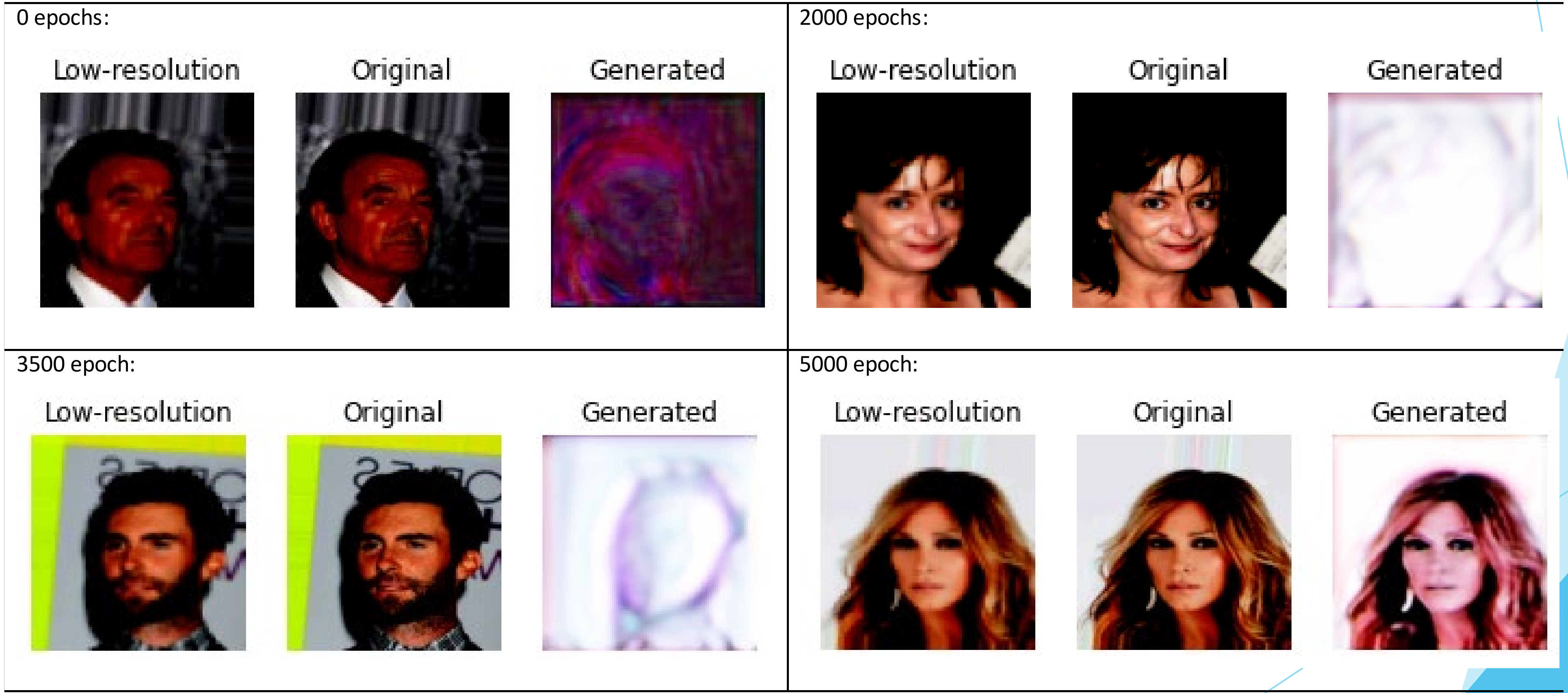
## 1. Run Time Analysis

| | |
|---|---|
| Platform(IDE) | Google Collab |
| No. of Epochs | 20,000 |
| Result | Images per 500 epochs |
| Start Time – End Time | 10.30am – 7.40pm |
| Total run time | 8h 15min 36sec |
| Total no. of resultant images | 20 |

## 2. Visualisation of Resultant Images

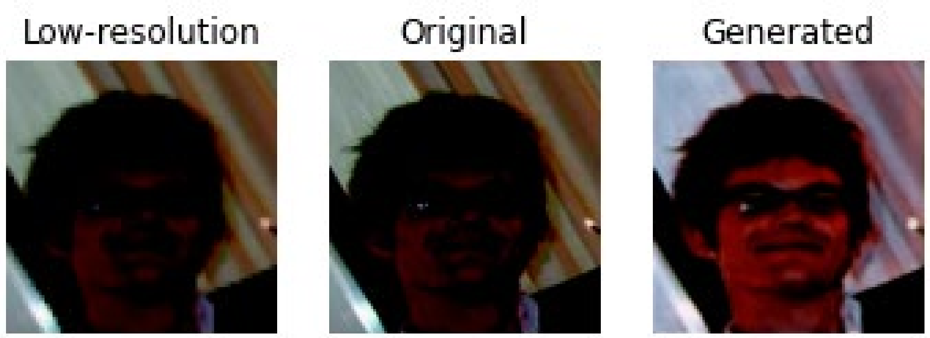
After large number of epochs the generator will start generating good images. As the no. of epochs increases generated image quality increases.

A) 0- 5000 epochs: outline and faint outline of original image is produced by generator.



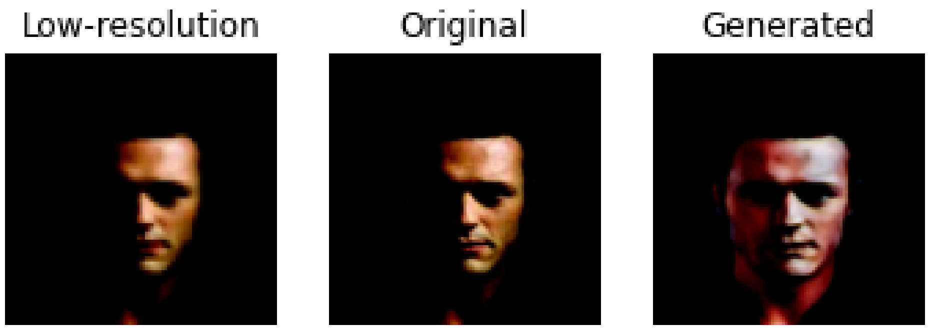
B) Resultant images with better edges and contrast ratio than that of original image. With increase in no. of epoch image features such as edges, and contrast ratio improved and in some cases noise decreased.

6000 epochs:

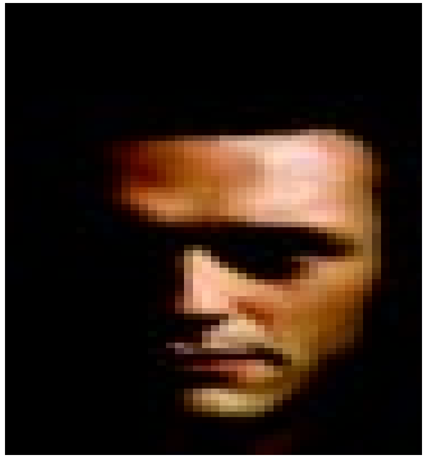


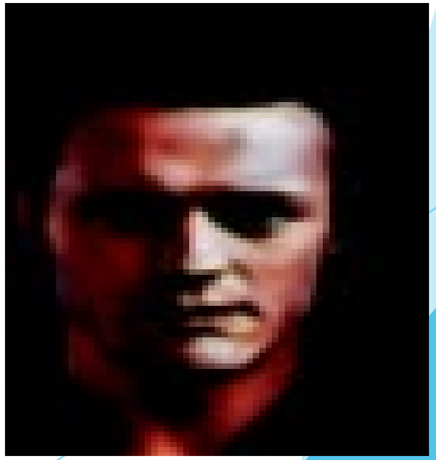

original vs Generated image

5500 epoch:



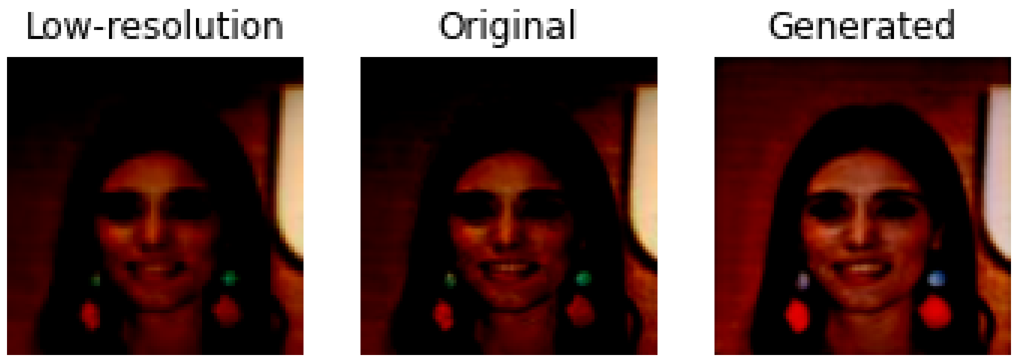

original vs generated image





## C) Resultant images with significant improvement.

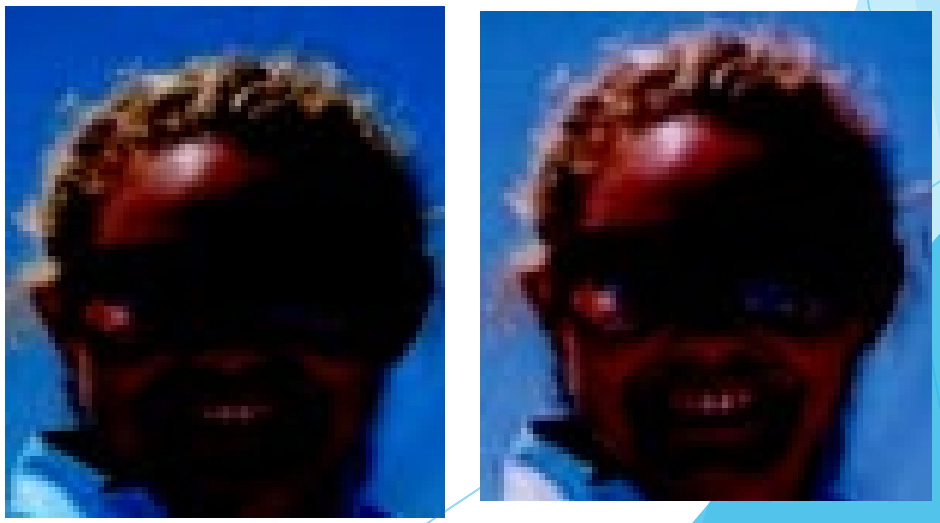
10000 epochs:



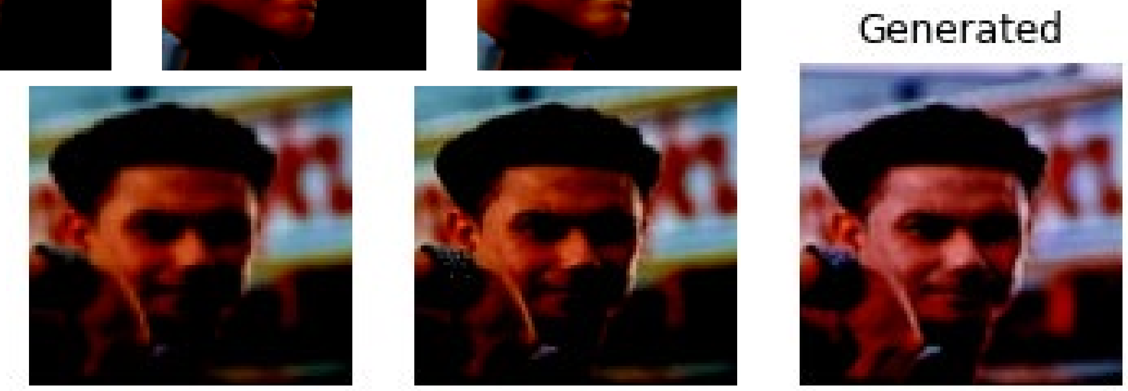

Original vs generated image: improve in facial features

19000 epochs:

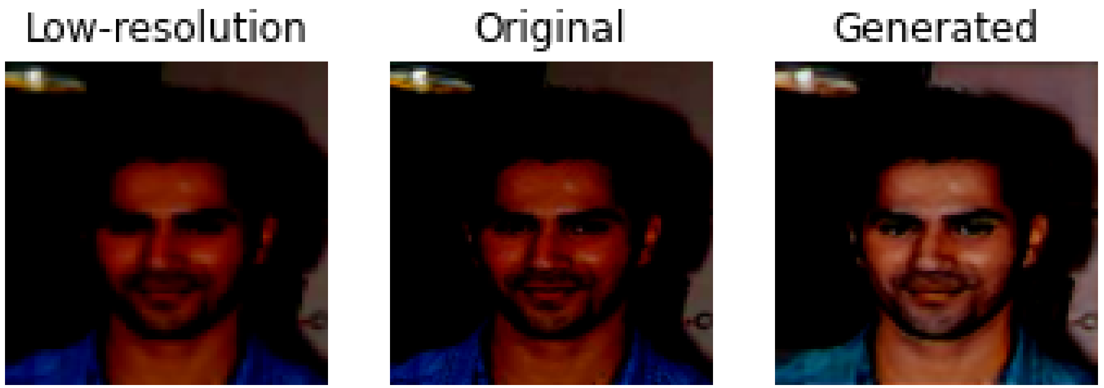

Original vs generated: improvement in contrast ratio and quality. Forehead, cheeks and mouth and also we can see edges of hair.




ır to that of original.

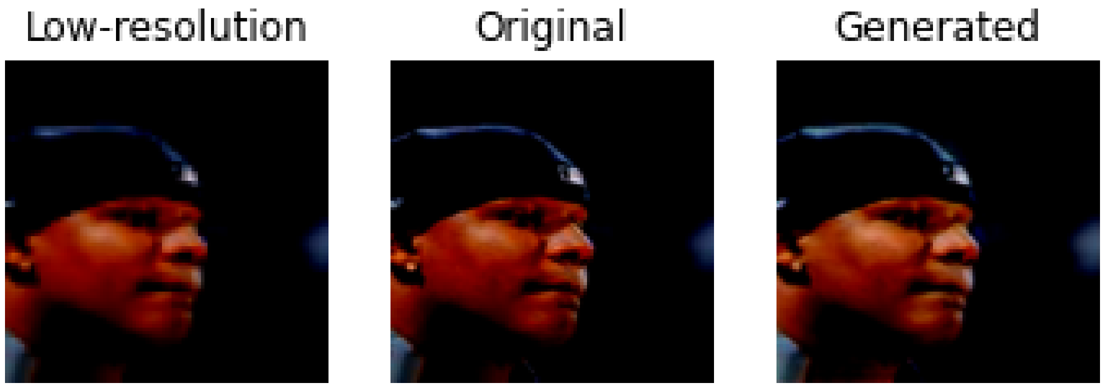



7000 epochs:



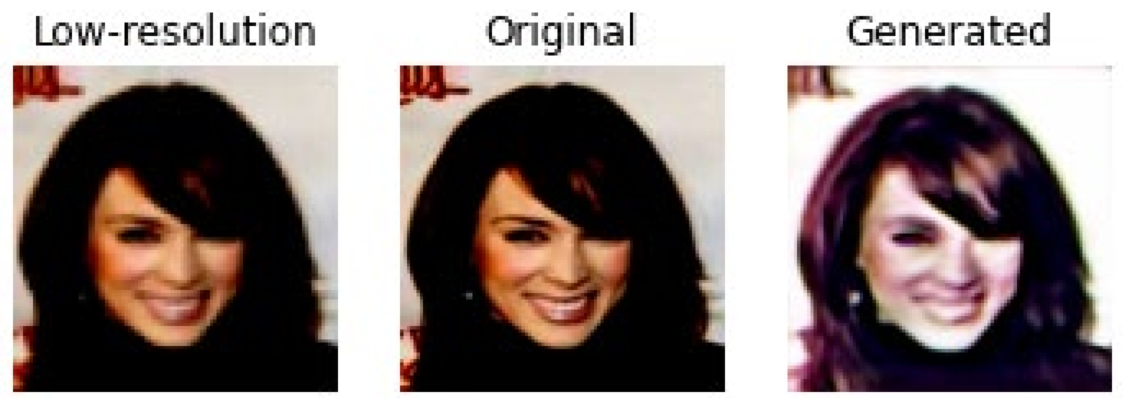

12500 epochs:


19500 epochs:

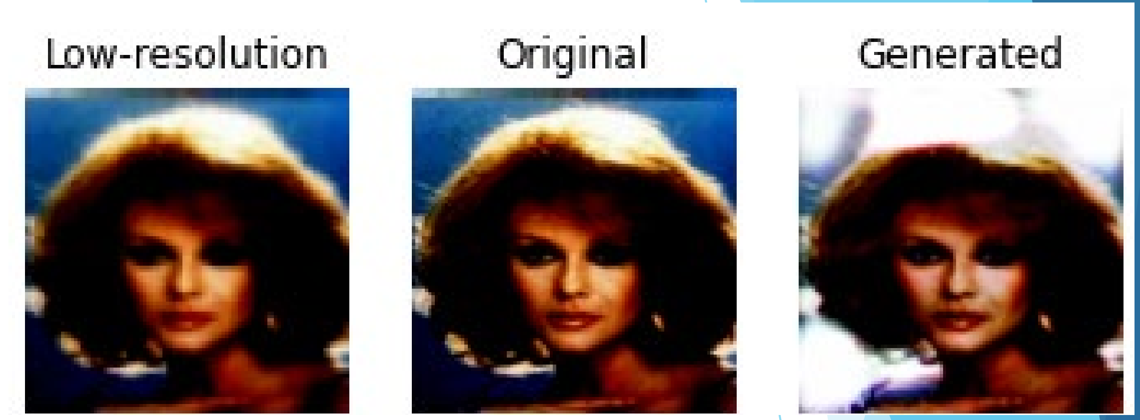


E) Sometimes generated images with degraded quality and alteration in pixel values.

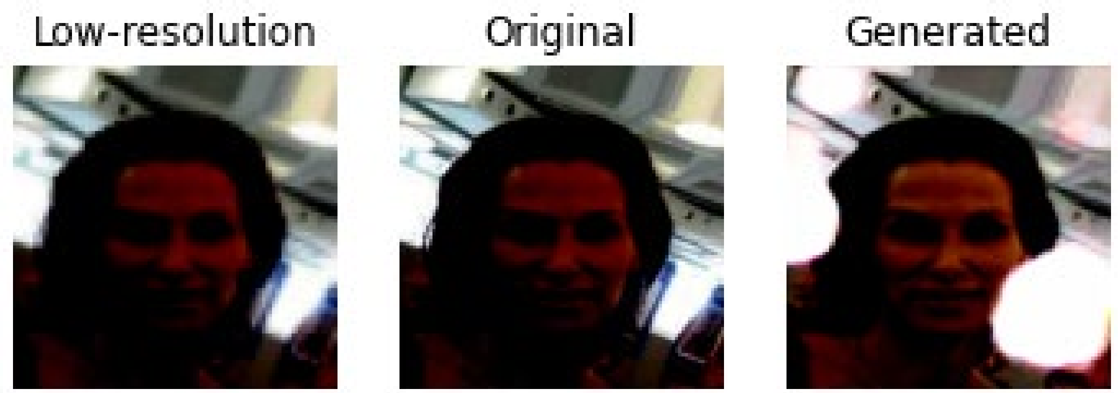
4500 epochs:



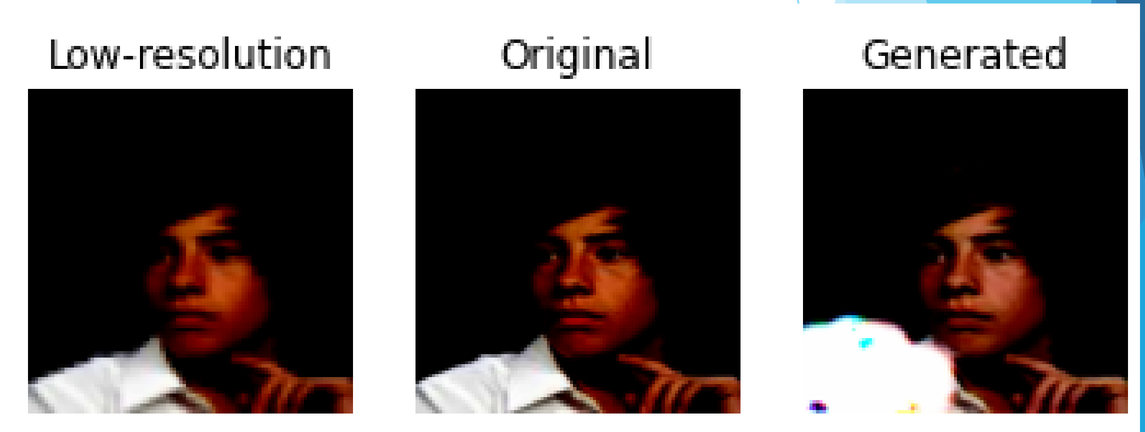

10500 epochs:




14500 epochs:



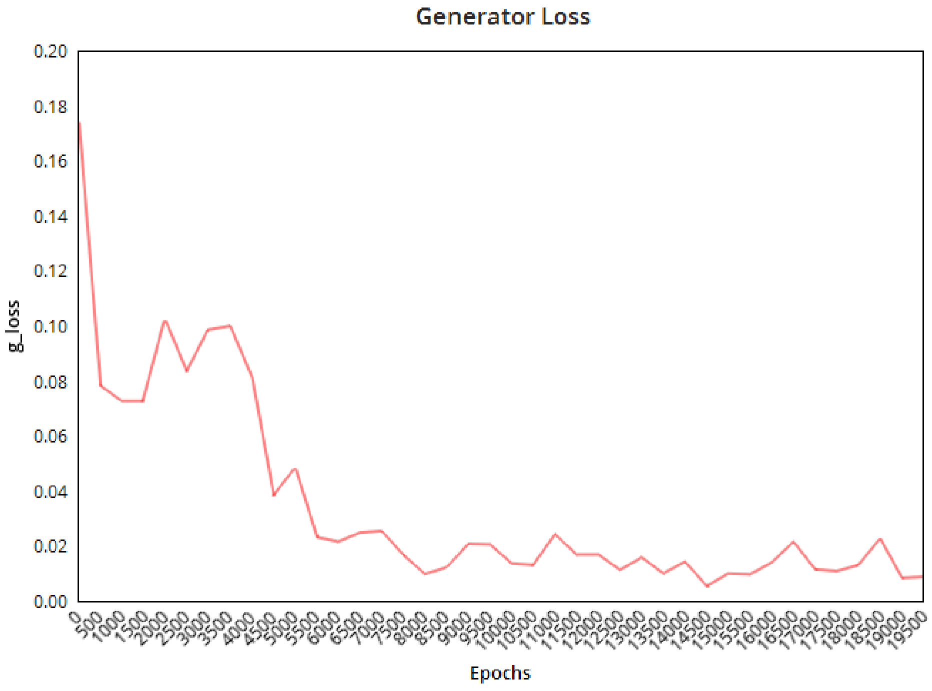

17500 epochs:

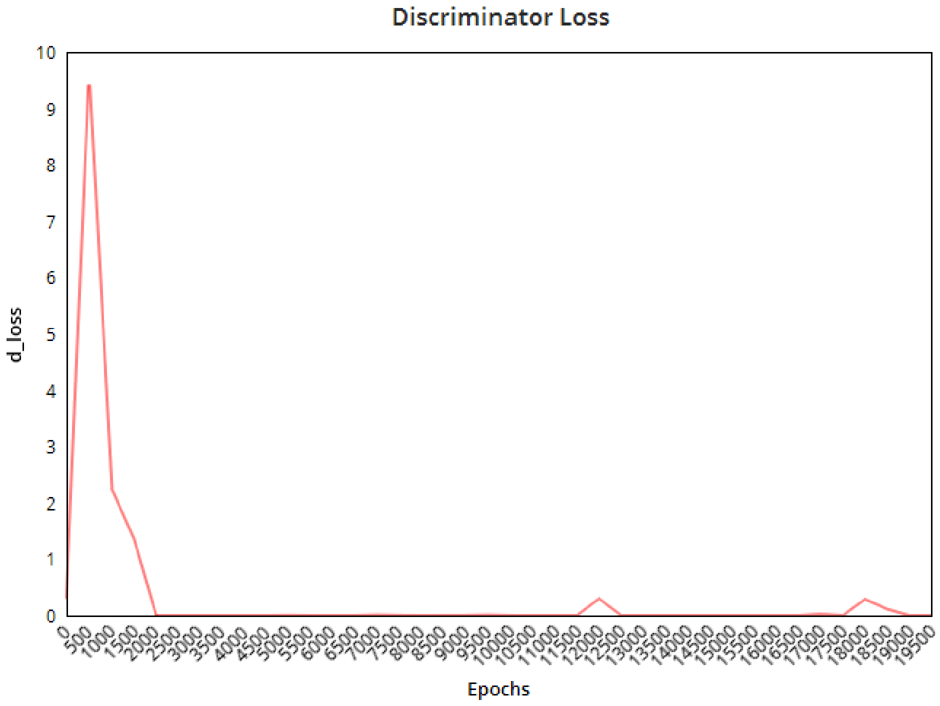



To generate really good quality images, we need to train the network for 30,000-50,000 epochs.

# 3. Loss Analysis

- The plots decide whether to continue training or stop. Here as we see losses are decreasing gradually.



# APPLICATION

- LR video images can be converted to high-definition images using SR techniques.
- Various medical imaging modalities can provide both anatomical information about the human body structure and functional information.
- Improvement in satellite images.
- Recovery of old photographs, image reconstruction.
- Automatic enhancement of picture quality in cameras by building software's based on training models.

# Advantages

- It can be used for 4 upscaling factors while also maintaining the realistic quality.
- It can recover photo realistic textures from heavily down sampled images.
- MOS(mean opinion score) obtained with SRGAN is close to those of original HR than any other methods.
- Model once trained can be used to generate SR any no. of times.

# Limitations

- Training may take time.
- High processing power requirement for generating training model.
- Some time data overfits. We need to check whether loss are converging with time or not
- Developing technology more research and work is needed in this field.

# Future Implementation

Scientists and researchers have developed various GANs that can be used to build commercial applications.

- Implementation in various fields such as game development, computer vision, machine learning and artificial intelligence.
- 3-D GANs for generating shapes, generate photo realistic images, turn painting to photos, image translations, images to map conversion etc.

# CONCLUSION

- SRGANs are comparative better technique for super resolution of images, videos than other techniques such as bicubic, CNN and deep neural networks.
- These data driven networks can be implemented in various fields to improve existing techs as well as make new technologies based on it.
- Significant improvement in the field of computer vision, ML,DL and AI.

# REFERENCES


1. Jason Brownlee, *Generative Adversarial Networks with Python (2020),* Course Hero, 24 Apr. 2020.

2. Ahirwar, Kailash. *Generative Adversarial Networks Projects Build next-Generation Generative Models Using TensorFlow and Keras*. Packt, 2019.

3. C. Ledig et al., *Photo-realistic single image super-resolution using a generative adversarial network*, in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 4681–4690.

4. *Large-Scale CelebFaces Attributes (CelebA) Dataset*, mmlab.ie.cuhk.edu.hk/projects/CelebA.html.

# Thank You