SRGAN

SUPER RESOLUTION USING GENERATIVE ADVERSARIAL NETWORKS

A Presentation by-
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SUPER RESOLUTION

- Image super-resolution is a technique of reconstructing a high-resolution image from the observed low-resolution image.
- Super resolution is 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

1.Proposed by Ian Goodfellow in 2014

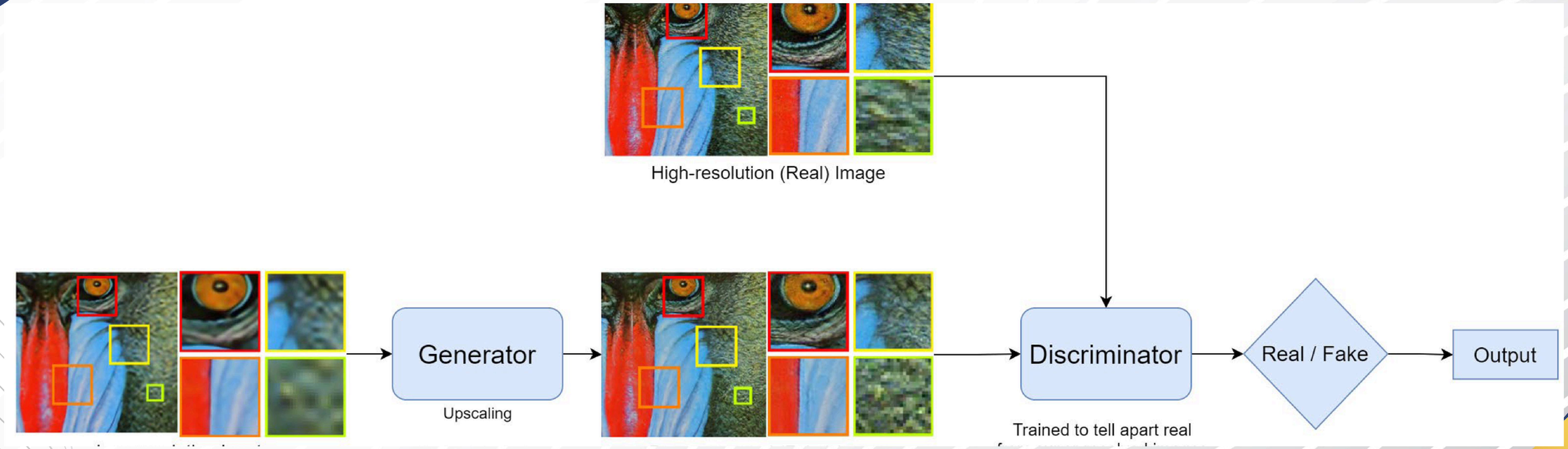
2.GANs are an architecture for automatically training a generative model by treating the unsupervised problem as supervised and using both a generative and a discriminative model.

3.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.

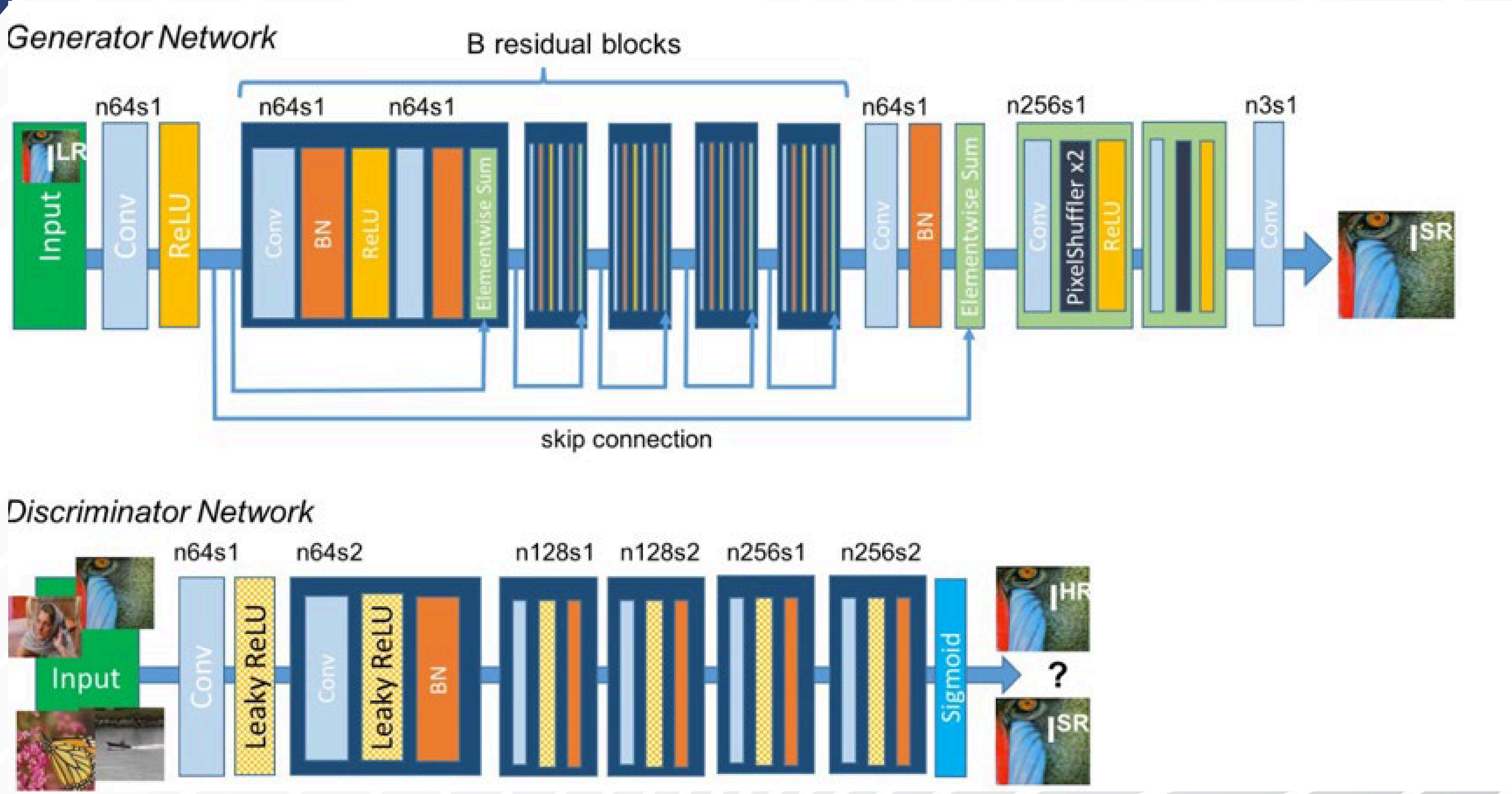
WHY SRGANS?

- Super-resolution GANs apply a deep network in combination with an adversarial network to produce higher resolution images.
- SRGANs 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 being 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.

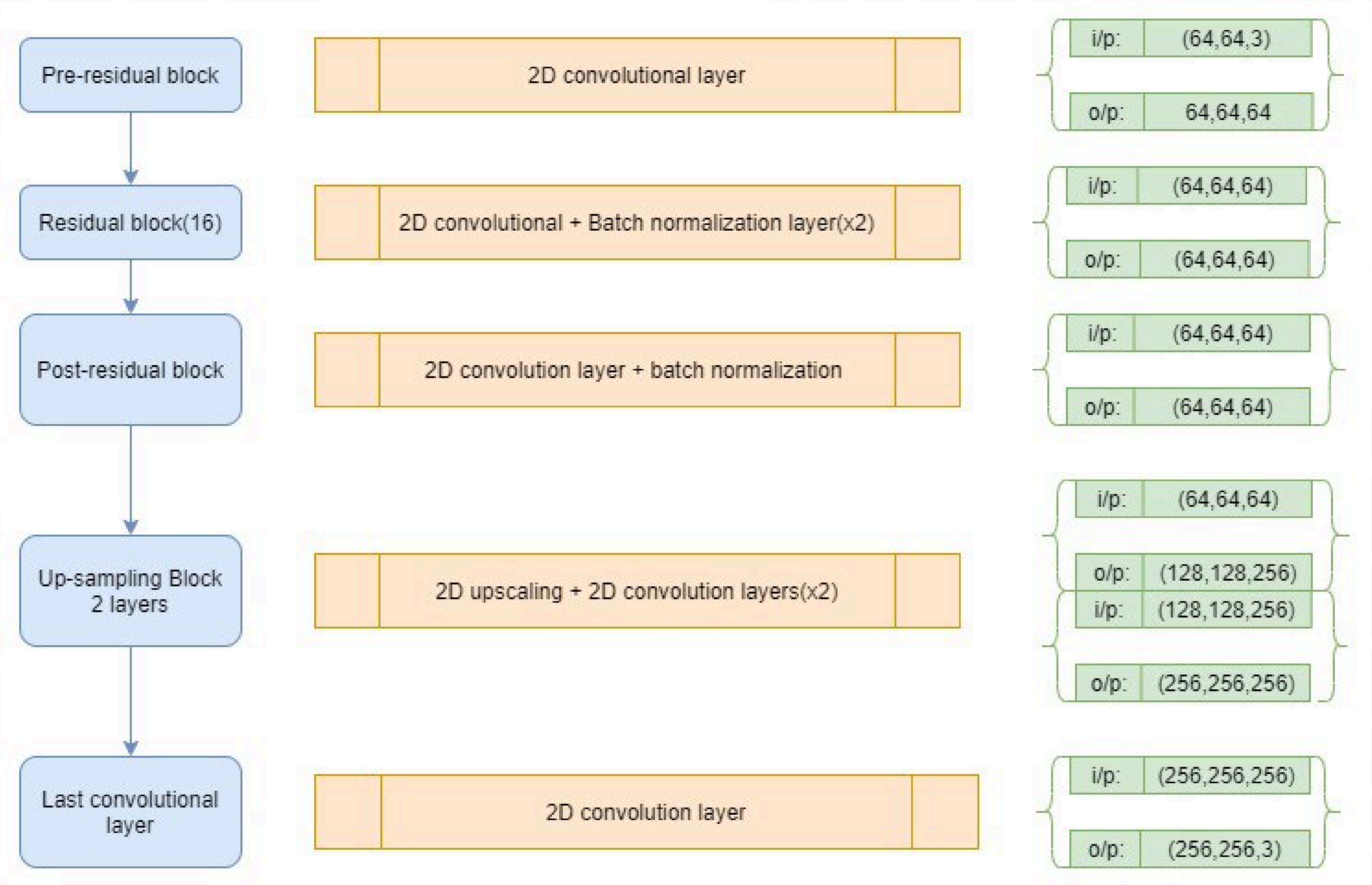
Project Overview



SR-GAN ARCHITECTURE



ARCHITECTUREGENATOR



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)

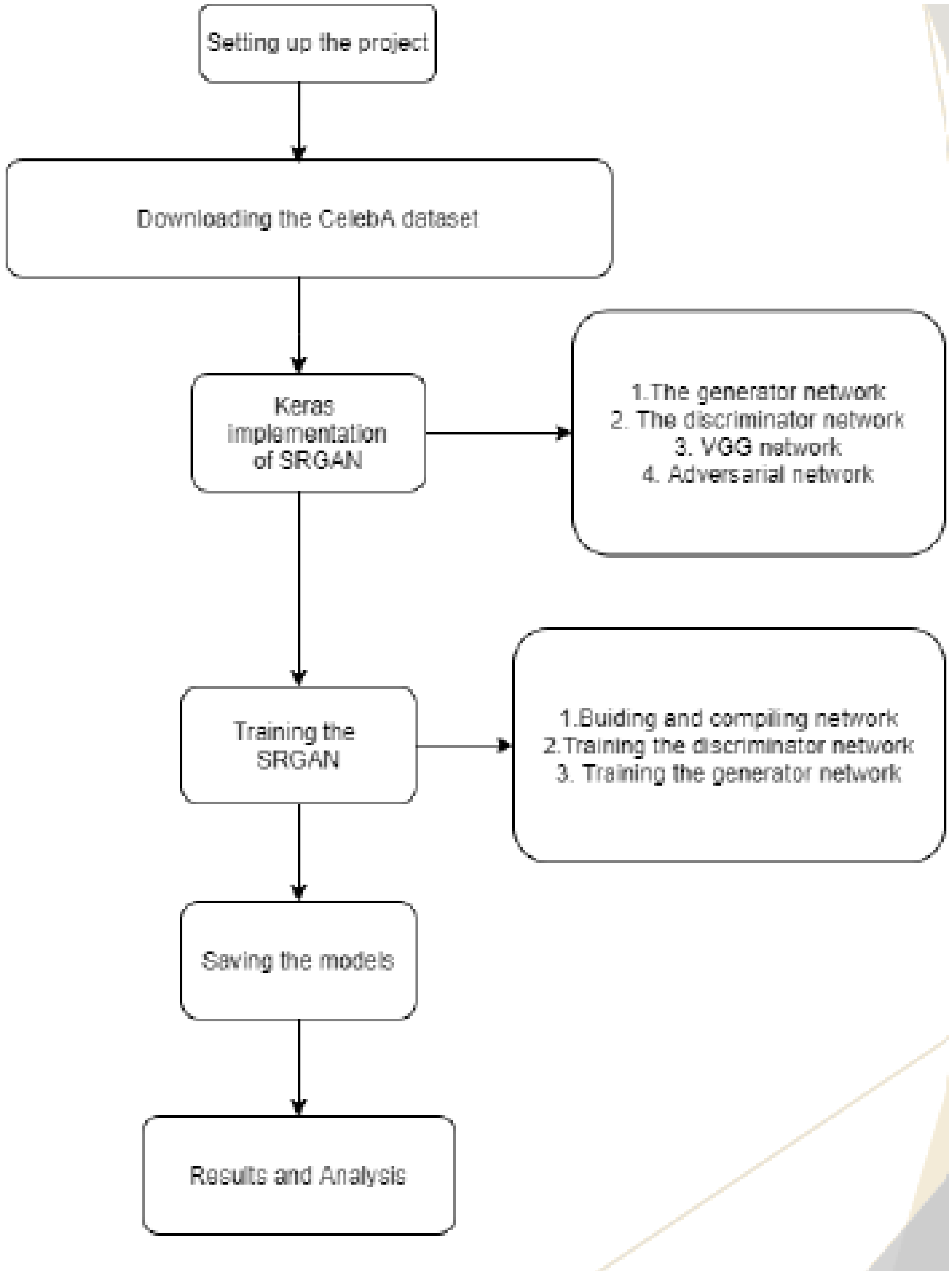
LOSS FUNCTIONS

The objective function for SRGANs is the perceptual loss function, which is a weighted sum of content loss and adversarial loss.

- Content Loss: Can be Pixel-wise MSE loss or VGG Loss.
- Adversarial Loss: Calculated from the probabilities returned by the discriminator. The perceptual loss is represented by the equation: lSR=1.0∗lXSR+0.001∗lGenSR

METHODOLOGY

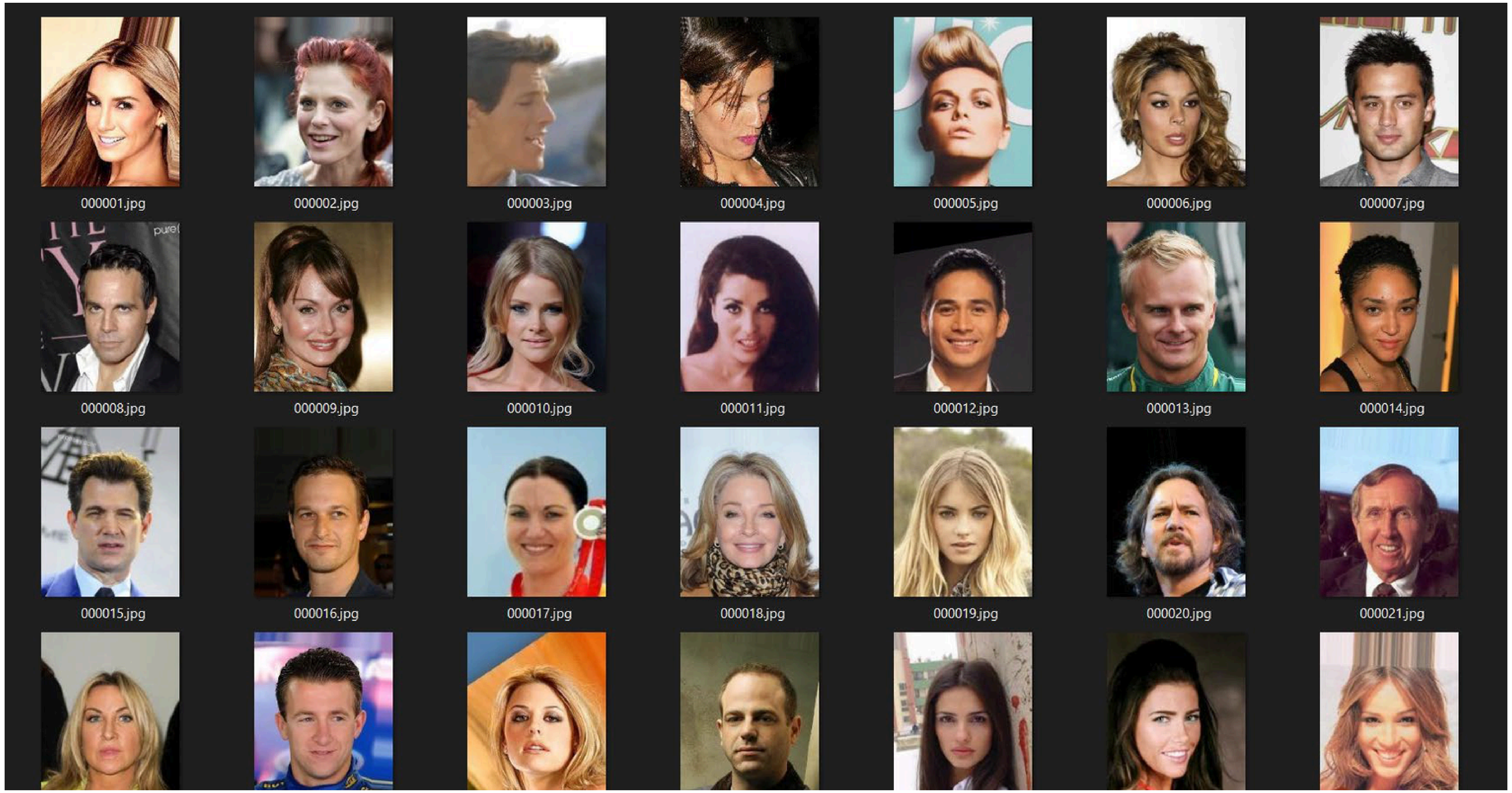
FLOW CHART



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 CelebFacesAttributes(CelebA) dataset. The dataset contains 202,599 faces of celebrities.



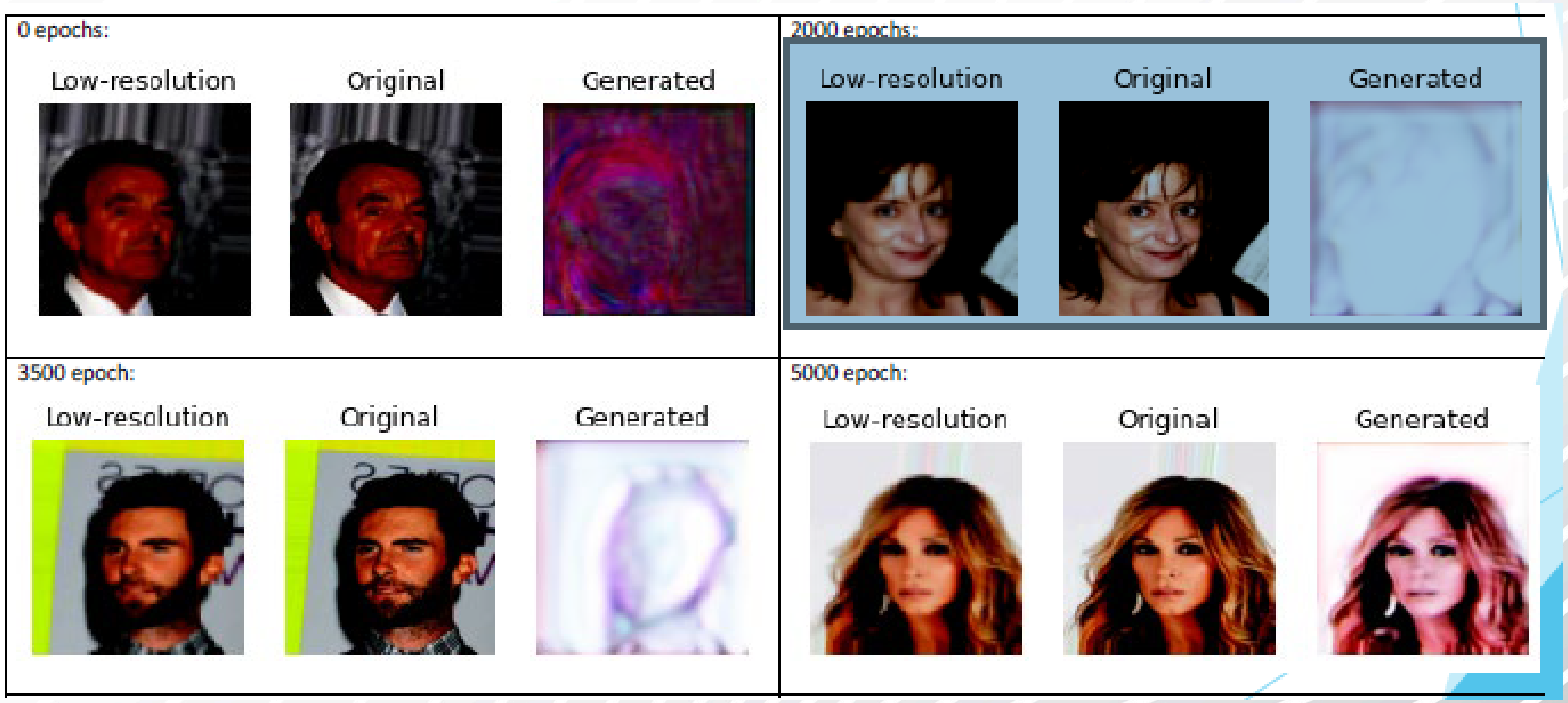
Results

1. RUN TIME ANALYSIS
PLATFORM (IDE): GOOGLE COLAB
NO. OF EPOCHS: 20,000
RESULT: IMAGES PER 500 EPOCHS
TOTAL RUN TIME: 8H 15MIN 36SEC
TOTAL NO. OF RESULTANT IMAGES: 20

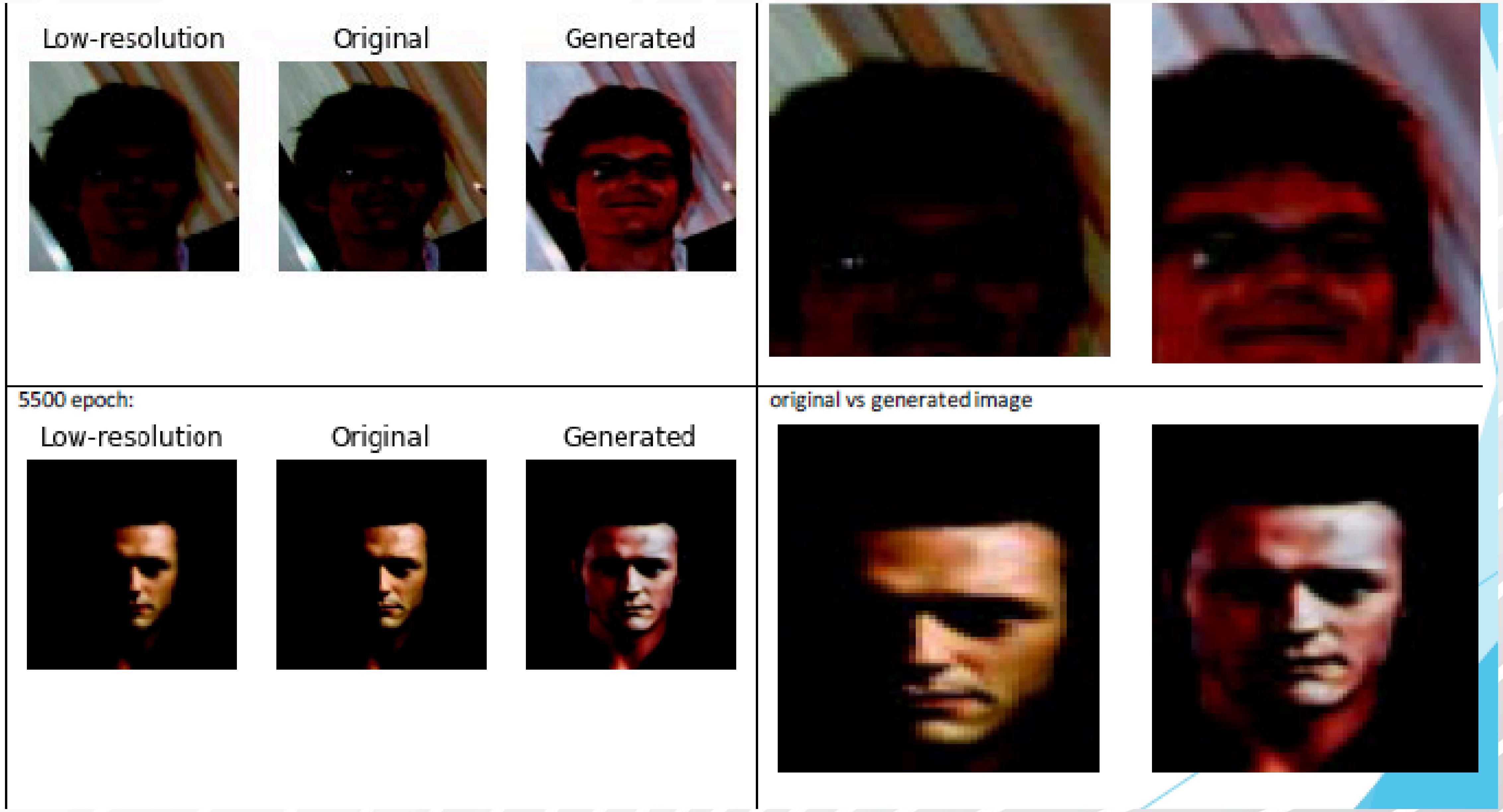
VISUALISATION OF RESULTANT IMAGES

Afterlargenumberofepochsthegeneratorwillstartgeneratinggoodimages.Astheno.ofepochsincreasesgeneratedimagequalityincreases.

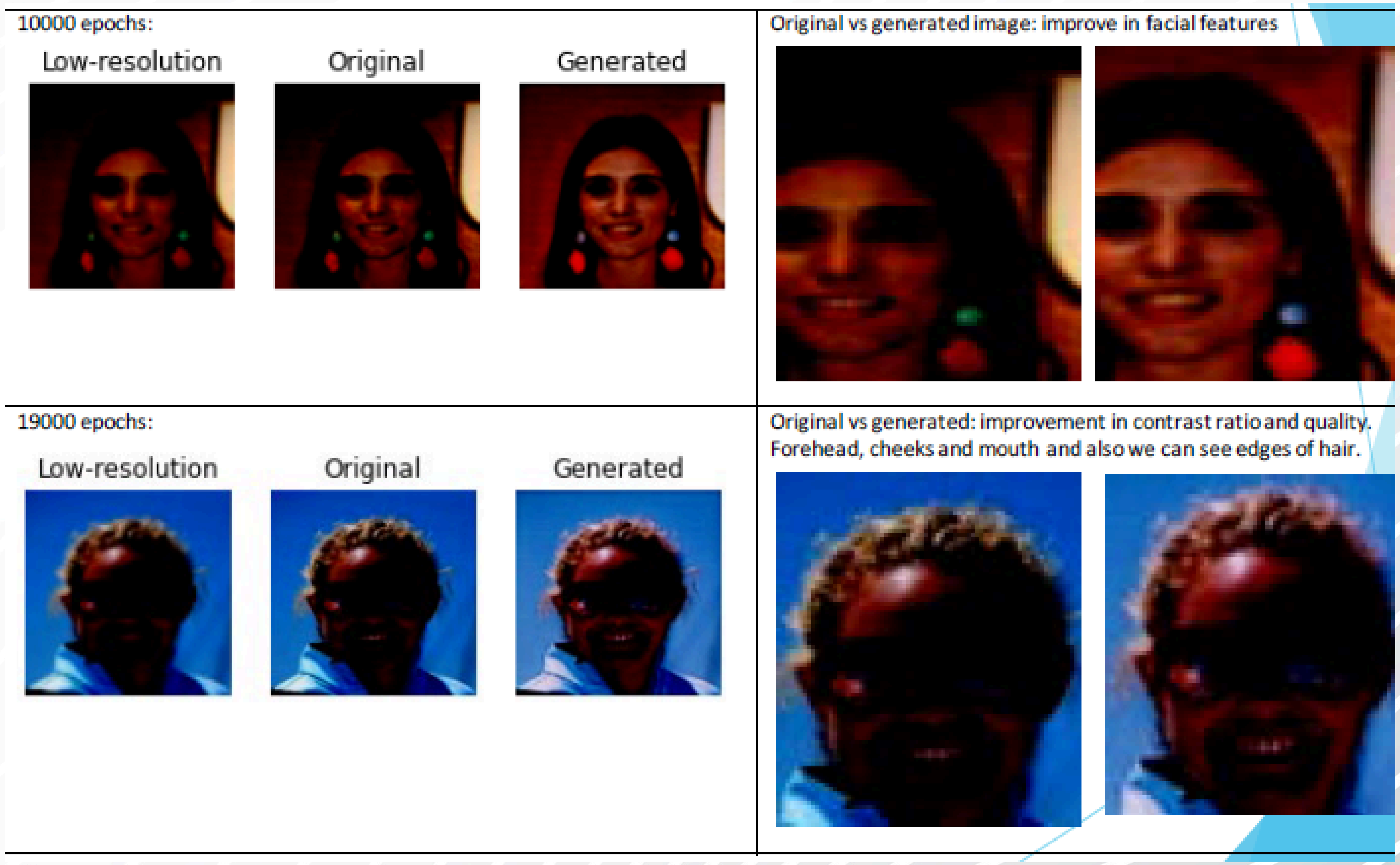
A)0-5000epochs:outlineandfaintoutlineoforiginalimageisproducedbygenerator.



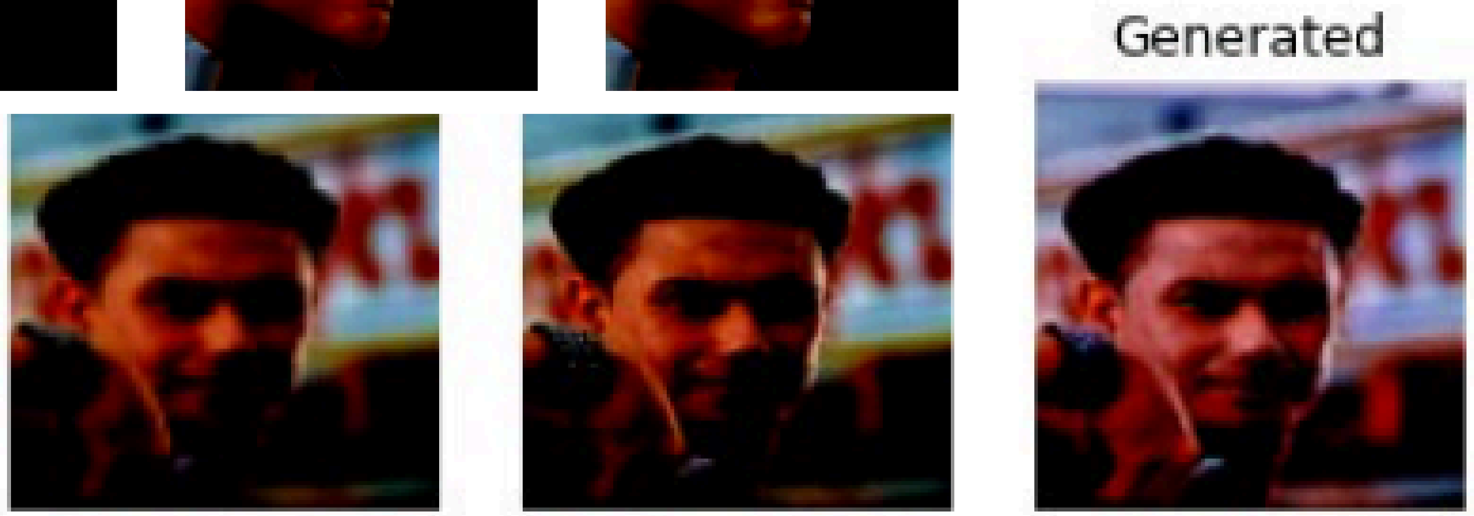
The resulting images exhibit improved edges and contrast ratios compared to the original image. As the number of epochs increases, the image features, such as edges and contrast ratios, enhance, and in some cases, noise levels decrease.



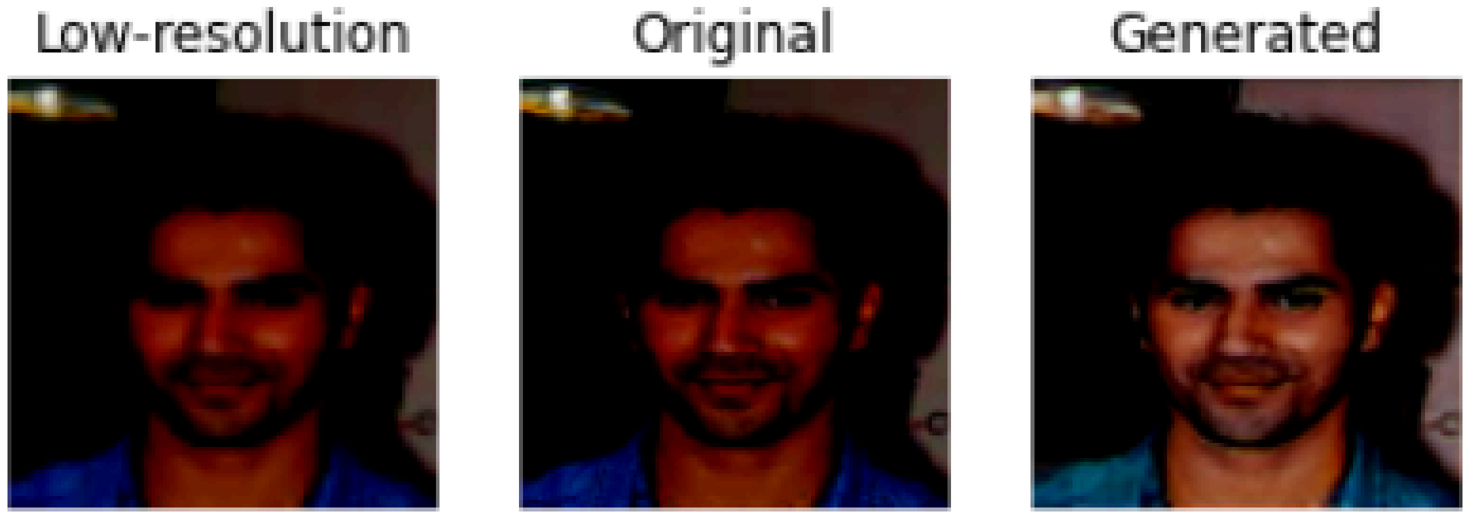
C) Resultant images with significant improvement



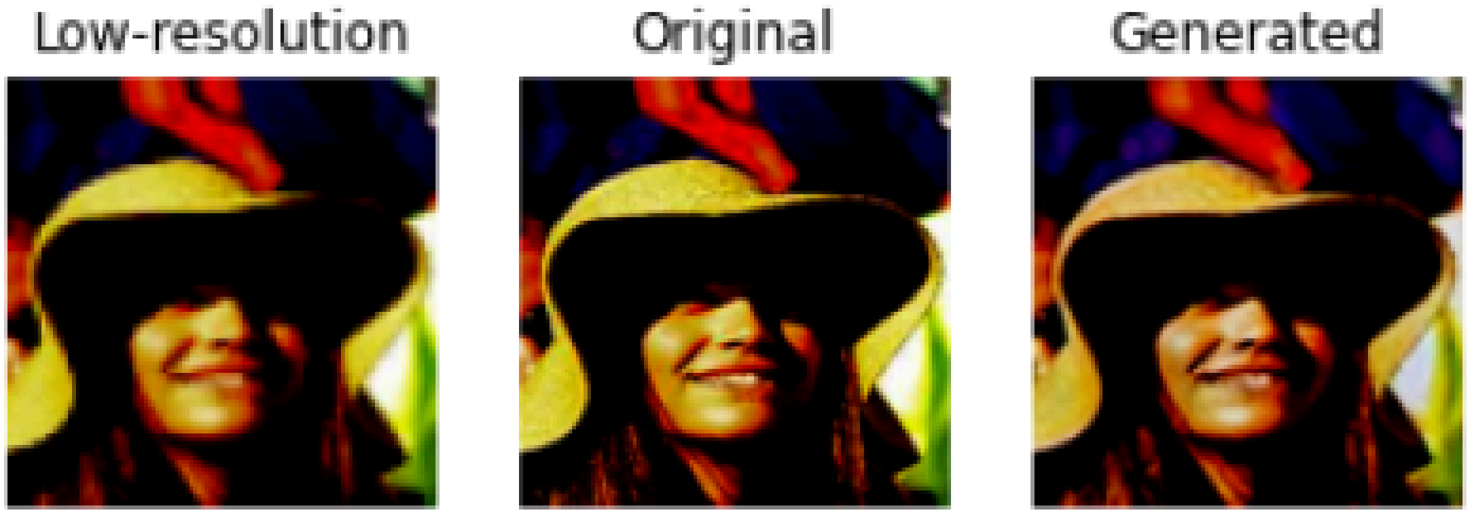
r to that of original.



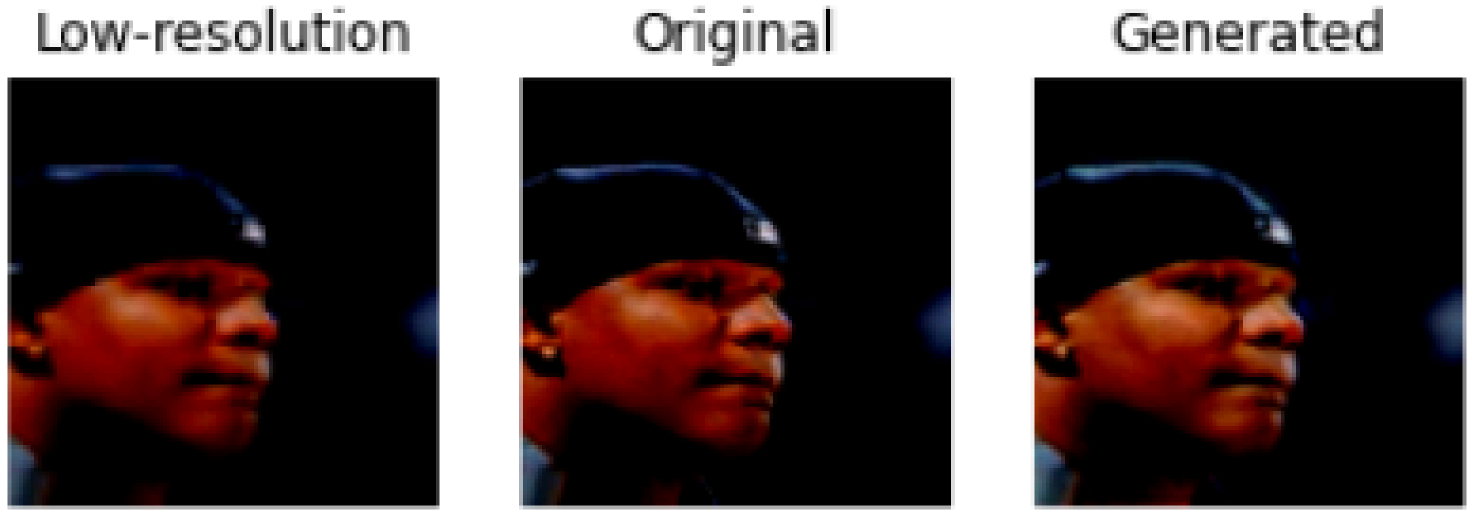
7000 epochs:



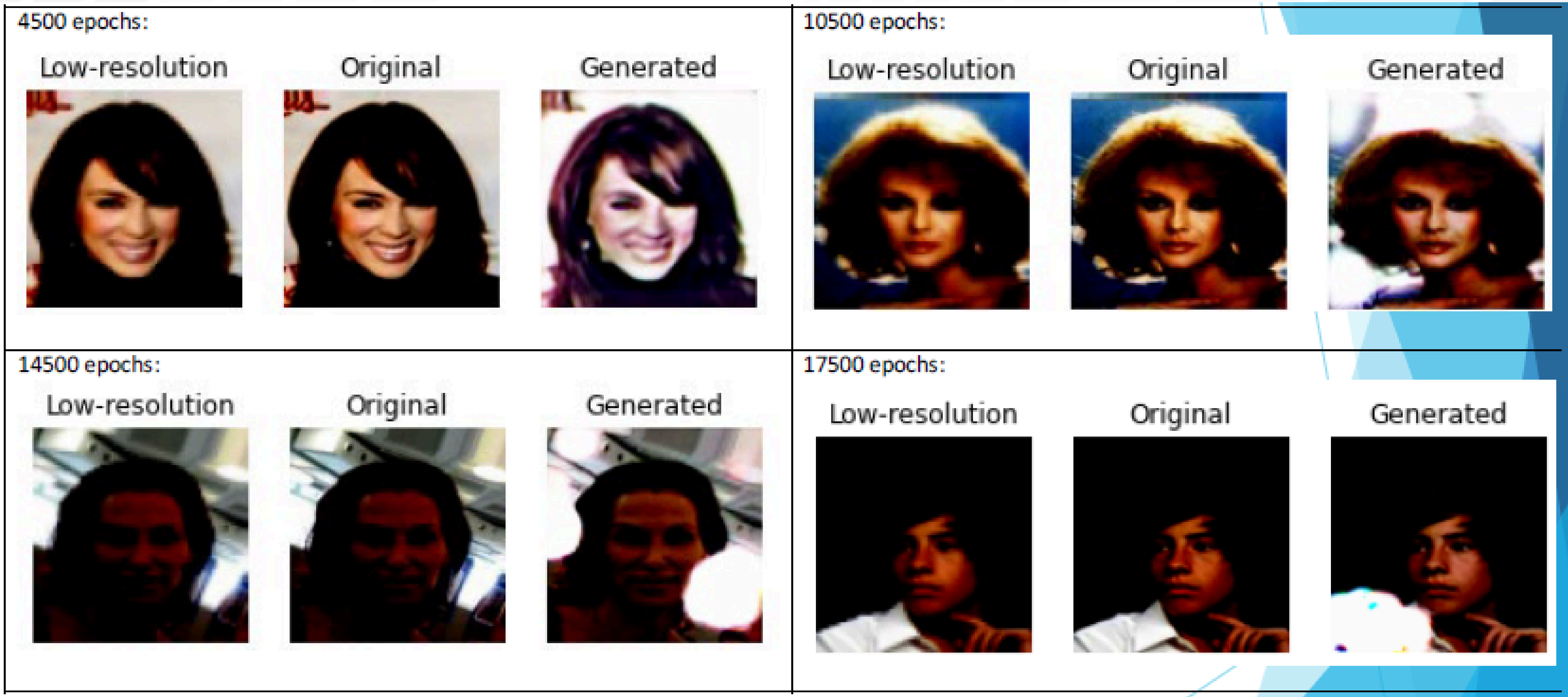
12500 epochs:



19500 epochs:

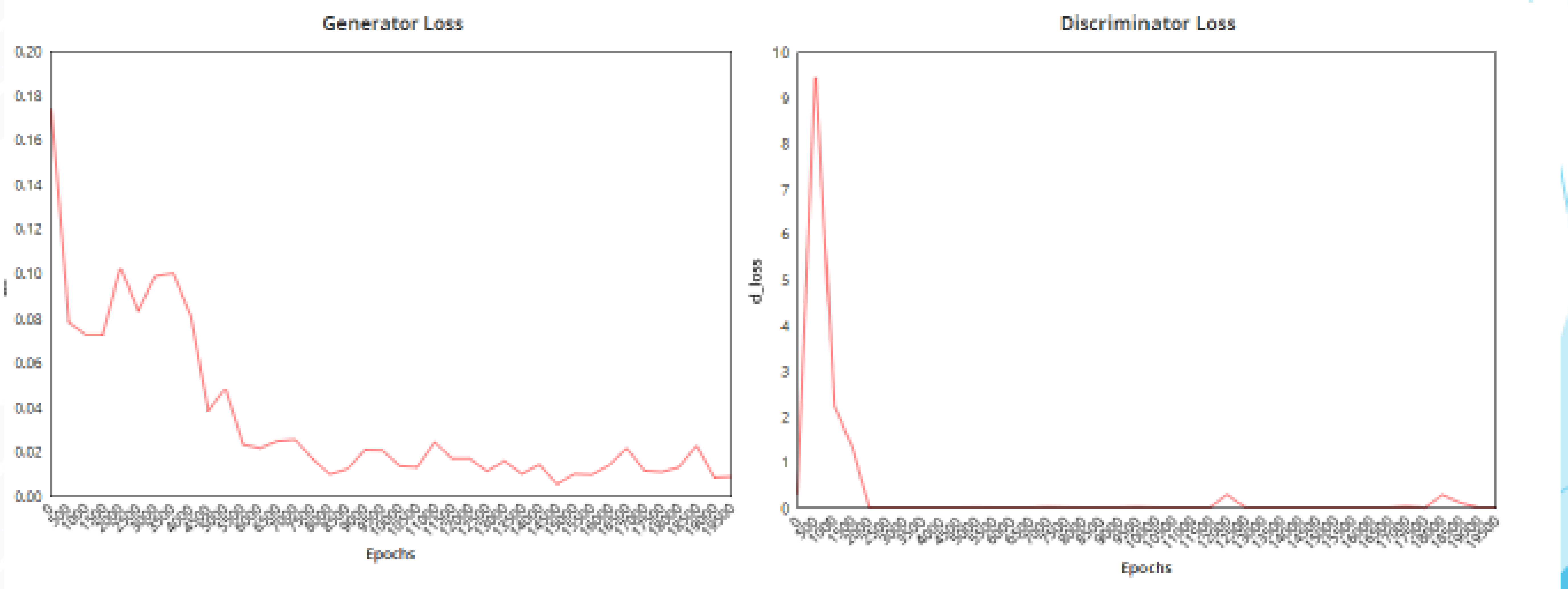


E) Sometimes generated images with degraded quality and alteration in pixel values.



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

3. Loss Analysis



APPLICATION

1.Converting low-resolution video images to high-definition.
2.Improving medical imaging for both anatomical and functional information.
3.Enhancement of satellite images.
4.Recovery of old photographs and image reconstruction.
5.Automatic picture quality enhancement in cameras.
Advantages

Advantages

- Can be used for 4x upscaling factors while maintaining realistic quality.
- Recovers photo-realistic textures from heavily down-sampled images.
- Achieves a Mean Opinion Score (MOS) closer to original high-resolution images than other methods.
- A trained model can be used to generate super-resolution images any number of times.

Limitations

- Training can be time-consuming.
- Requires high processing power.
- The model can sometimes overfit the data.
- It is a developing technology that requires more research.

Future Implementation

- Development of commercial applications using various GANs.
- Implementation in fields like game development, computer vision, and AI.
- Use of 3-D GANs for generating shapes, photo-realistic images, image-to-image translation, and more.

REFERENCES

- Brownlee, Jason. Generative Adversarial Networks with Python. 2020.
- Ahirwar, Kailash. Generative Adversarial Networks Projects: Build next-Generation Generative Models Using TensorFlow and Keras. Packt, 2019.
- Ledig, C., et al. "Photo-realistic single image super-resolution using a generative adversarial network." Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 4681-4690.
- Large-Scale CelebFaces Attributes (CelebA) Dataset. mmlab.ie.cuhk.edu.hk/projects/CelebA.html.

CONCLUSION

- SRGANs are a comparatively better technique for super-resolution than other methods like bicubic interpolation, CNNs, and deep neural networks.
- These data-driven networks can be implemented to improve existing technologies and create new ones.
- They represent a significant improvement in the fields of computer vision, machine learning, and AI.