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# Image Completion and Image Super Resolution Using Generative Adversarial Network

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**Abstract -** *Deep learning AI is proven to get more and more accurate over the years. It can now learn without any human supervision and perform tasks with the precision of man himself. GAN is an evolving technology that has achieved excellent accuracy and seems to be progressing much more over time. Its various applications include image inpainting, video frame generation, language processing, and much more. This paper will explore the working of a GAN model and study more into what it is. We shall also look at two applications of GAN in detail.*

***Key Words*: Generative Adversarial Network, super-resolution, boundless, image-inpainting, Deep Learning**

## 1. INTRODUCTION

GAN was first introduced in 2014 by Ian Goodfellow and his colleagues. The basic idea was that of two models in constant competition, meaning one's loss is another's gain. This approach leads them to produce realistic, nondifferentiable protégées of the input. For example, if we were to input a video, the output would also be in the form of a video. GAN models are trained to identify patterns or similarities from the inputs, and they can create items that are very closely related to the input. GAN has proven itself in various difficult tasks such as improving resolution, generating facial expressions, and much more.
We shall look at the basic working of GAN and check out a basic algorithm of the same. We will also have a peek at two widely used GAN models that help us in altering images.

## 2. BASIC STRUCTURE OF GAN

### 2.1 Basics of GAN

Generative Adversarial Network is a part of deep learning that comprises two models: the Generator and Discriminator. It uses both these models to generate a realistic vision that can sometimes even fool the naked eye. Convoluted Neural Networks are used for both Discriminator and Generator. GAN is based on a zero-sum game, where the sum of both people's interests is zero, and one gains precisely what the other loses.

The Generator's main task is to identify, learn, and capture the input, a fixed-length random vector (from a Gaussian distribution). After training, the problem domain points will correspond to points in the multi-dimensional vector space. This will form the entire compressed data distribution representation. The generator model applies to aim to points during a chosen latent space. Such new points drawn from the latent space are often provided to the generator model as input and practice to generate new and different output examples. The Generator uses deconvoluted neural networks. The generator model is kept after training to generate more examples.

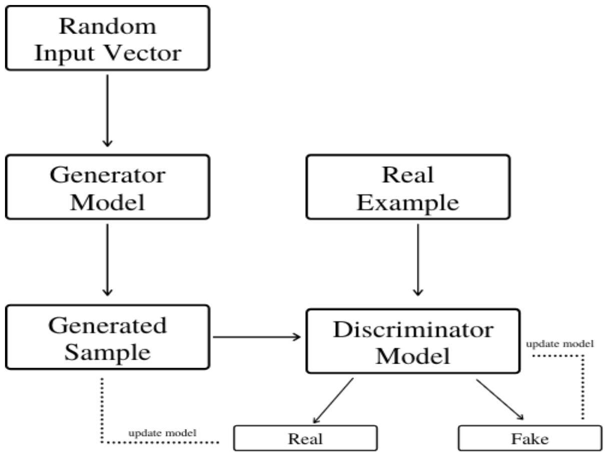


**Fig 1: A brief structure of GAN**

The Discriminator uses a convoluted neural network model and takes data from the domain, and it mainly classifies that data as real or fake. This is predicted using binary class. After training, the Discriminator is discarded, and only the Generator is used to generate the output. This Discriminator is given data from the Generator as well as the input to differentiate. The Discriminator is trained again based on how well it identifies the real and fake images. Subsequently, even the Generator is altered and made better on how well the Discriminator identified its outputs.

### 2.2 Mathematical model and Training Model

GAN can be viewed as an interaction between two unique models: the generator and the discriminator. Subsequently, each model will have its loss function. In this part, we should attempt to spur a natural comprehension of the loss function for each. Here are some terms to keep in mind before getting into the mathematical explanation.

x : real data; z : latent vector; $G(z)$ : fake data; $D(x)$ : Discriminator's evaluation of real data; $D(G(z))$ : Discriminator's evolution of false data; $Error(a, b)$: Error between a and b.

The objective of the discriminator is to accurately name produced pictures as fake and exact information as real. Hence, we should take the following Loss function of the discriminator:

$$LD = Error(D(x),1) + Error(D(G(z)),0) \tag{1}$$

Here, we utilize an extremely nonexclusive, generic documentation for error to allude to some function that reveals the distance or the differences between the two functional parameters.

The generator's objective is to trick the discriminator so that it gets confused about labelling the images as real or fake.

$$LG = Error\ (D\ (G\ (z)),1) \tag{2}$$

We must be aware that the loss function is to be minimized. A typical loss function that is used in binary classification problems is binary cross-entropy. In classification tasks, the random variable is discrete; hence, the equation can be expressed as a summation.

$$H(p,q) = -\sum x \in \chi p(x) log q(x) \tag{3}$$

We can simplify this expression even further in binary cross-entropy since there are only two labels: zero and one. Binary cross entropy satisfies our goal in that it gauges how unique two appropriations are with regards to parallel order of deciding if an input data point is true or false. Applying this to the loss functions as shown in (1)

$$LD = -\sum x \in \chi, z \in \zeta log(D(x)) + log(1 - D(G(z))) \tag{4}$$

The same is applied for (2)

$$LG = -\sum z \in \zeta log(D(G(z)) \tag{5}$$

We have two loss functions with which to train the generator and the discriminator. The original paper by Goodfellow had the equation framed as a min-max game where the discriminator seeks to maximize the given quantity whereas the generator seeks to achieve the reverse. Mathematically,

$$\min_{G} \max_{D} log(D(x)) + log(1 - D(G(z)))$$
(6)

We define separate loss functions for the generator and the discriminator as we have done above. This is because the gradient of the function $y = logx$ is steeper near $x$ than that of the function $y = log\ (1 - x)$, meaning that trying to maximize $log\ (D\ (G\ (z)))$, or equivalently, minimizing $-log\ (D(G(z)))$ is going to lead to quicker, more substantial improvements to the performance of the generator than trying to minimize $log\ (1 - D(G(z)))$.

Now that we have defined the loss functions for both the discriminator and the generator, we try finding the parameters for the generator and the discriminator such that the loss functions are optimized. This corresponds to training the model in practical terms. In GAN, the generator and discriminator are trained separately. The quantity of interest can be defined as a function of and. Let's call this the value function

$$V(G,D) = E_{x \sim p_{data}}[log(D(x))] + E_{y \sim p_g}[log(1 - D(G(z)))] \tag{7}$$

We are more interested in the distribution modelled by the generator than. Therefore, let's create a new variable, $y = G(z)$, and use this substitution to rewrite the value function

$$V(G,D) = E_{x \sim p_{data}}[log(D(x))] + E_{y \sim p_g}[log(1 - D(y))] \tag{8}$$
$$= \int_{x \in \chi} p_{data}(x) log(D(x)) + p_g(x) log(1 - D(x)) dx$$

If the input data is (x), the task of the discriminator is to make $D\ (x)$ almost equal to 1. If the input is fake data $G\ (z)$ as mentioned above, the discriminator tries to make $D\ (G\ (z))$ close to 0, whereas G tries to get it closer to 1. Training the generator,

$$V(G,D) = E_{x \sim p_{data}}[log(D(x))] + E_{y \sim p_g}[log(1 - D(G(y)))] \tag{9}$$

We want the generator to be able to learn the underlying distribution of the data from sampled training examples. In other words, $P_{data}$ and $P_g$ should be as close to each other as possible. The ideal generator G is one where it can mimic p so well that it can make a compelling model distribution p. The final equation keeping in mind the zero-sum game is:

$$minGmaxD \int (D,G) = nE_{x \sim p_{data}}(logD(x)) + E_{y \sim p_g}(log(1 - D(g(z)))) \tag{10}$$

$$minGmaxD \int (D,G) = nE_{x \sim p_{data}}(logD(x)) + E_{y \sim p_g}(log(1 - D(g(z))))$$

### 2.3 Applications

GAN can be viewed as an interaction between two unique models: the generator and the discriminator. Subsequently, each model will have its loss function. In this part, we should attempt to spur a natural comprehension of the loss function for each. Here are some terms to keep in mind before getting into the mathematical explanation:

*1) Conditional GAN:* CGAN is a profound learning strategy where a contingent setting is applied, implying that both the generator and discriminator are adapted on a type of helper data, for example, class names or information from different modalities. Accordingly, the ideal model can take multi-modular planning from contributions to yields by taking care of it with various logical data. CGANs were exhibited to successfully integrate photographs from mark maps, remaking objects from edge maps, and colorizing pictures, among different errands (Image-to-image translation). CGANs can also be used in video generation to anticipate future casings in a characteristic video succession. CGANs use to create faces with explicit characteristics only from random noise.

*2)* Deep Convolutional GAN: DCGAN is likewise the best usage of GAN. It is made up of ConvNets instead of multi-layer perceptron's. The ConvNets are actualized without max pooling, which is supplanted by convolutional step. Likewise, the layers are not entirely associated. DCGAN can be used in the generation of anime characters. At present, artists physically draw characters with PC programming and at times on paper too. This is a manual cycle that generally takes a great deal of time. With DCGANs, new anime characters can be produced in significantly less time, consequently improving the inventive cycle. If there is a need to prepare a regulated AI model, an enormous dataset must prepare a decent model. DCGANs can help by expanding the current dataset, accordingly expanding the dataset's size needed for administered model preparation. This is called the augmentation of datasets. Wasserstein GAN model is one of the derivatives of DCGAN. We shall see image inpainting in detail in the further sections, where we use the same model to obtain the full image.


**Fig 2: Text to image translation by CGAN**

*3) Laplacian Pyramid GAN:* The Laplacian pyramid is a direct invertible picture portrayal comprising of a bunch of band-pass pictures, an octave separated, in addition to a low- recurrence remaining. This methodology utilizes various quantities of Generator and Discriminator organizations and various degrees of the Laplacian Pyramid. This methodology is principally utilized because it creates excellent pictures. The picture is down-tested from the start of each layer of the pyramid, and afterward, it is again up-scaled at each layer in a retrogressive pass where the picture secures some noise from the Conditional GAN at these layers until it arrives at its unique size.

*4)* Super Resolution GAN: SRGAN, as the name recommends, is a method of planning a GAN model in which a profound neural organization is utilized alongside an ill-disposed organization to create higher clarity pictures. This kind of GAN is precious in ideally up-scaling native low-goal pictures to upgrade its subtleties, limiting errors simultaneously. We will see its detailed application in the further sections.

## 3. LITERATURE SURVEY

Before exploring some of the widely used Generative Adversarial Network applications, we went through some published content to have a better understanding. Given below are the papers which we considered and the critical points we obtained from each.

**1. A Review: Generative Adversarial Networks**

- Authors: Liang Gong and Yimin Zhou (IEEE 2019).
- Overview: This paper emphasizes on the origin of GAN, its recent applications, extension variants, existing problems and some further applications. Mathematical training has also been explained in detail. The classification of GAN was one of the main highlights of the paper Applications of GAN in image and video like image generation, image-to-image translation, image super-resolution, video generation, video frame prediction, etc. It also has the advantages and disadvantages specified.
- Key takeaway**:** Classification and structure of GAN which is the main thing required before we start off with the implementation

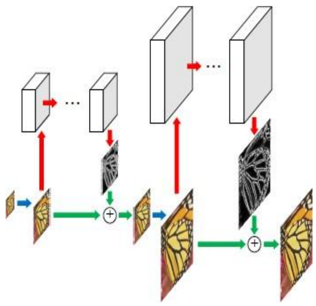

**Fig 3: Application of GAN using the Laplacian pyramid**

**2. Evolutionary Generative Adversarial Network**

- Authors: Chaoyue Wang, Chang Xu, Xin Yao, Dacheng Tao (IEEE 2018)
- Overview: There are some instances where GAN fails to deliver its purpose. Sometimes due to poor training model or sometimes due to instability of data. This particular paper proposes how GAN model can be made better. The authors have taken a completely different route as opposed to the traditional method and have introduced a

generator and discriminator. The quality of each generated material is evaluated and only the well-preserved generators are used for further operations.

- Key takeaway: The final outcome of this approach-EGAN (Evolutionary GAN) has been the basis of the main applications we have focused on. EGAN plays an integral part in image super resolution.

**3. Image Generation Using Different Models Of Generative Adversarial Network**

- Authors: Ahmad Al-qerem, Yasmeen Shaher Alsalman, Khalid Mansour (IEEE 2019 International Arab Conference on Information Technology (ACIT))
- Overview: There are many models of GAN. This particular paper checks out the differences between Multi-Agent Diverse Generative Adversarial Networks (MAD-GAN) that has only one discriminator and multiple generators, and Generative Multi-Adversarial Networks (GMAN) that has multiple discriminators and one generator. This paper gave a clear view of the working of a discriminator and generators and also has views on how to improve its efficiency. Here, image inpainting is shown using DCGAN and explains why this model does not give results as expected. Better models such as MAD- GAN and GMAN have proven to show better results according to the paper.
- Key takeaway: One of the main problems of GAN as seen in many research papers is that the model collapses. The solution to this problem is shown clearly in this paper. MAD-GAN is one of the most effective ways to keep the model from collapsing. This method has been used in the Image completion process.

**4. Emerging Applications of Generative Adversarial Networks**

- Authors: A YuXinyu (IOP conference series MEMA 2019)
- Overview: This paper deals with the emerging trends of deep learning and how GAN has come to existence. It also summarizes the multiple and exciting applications of GAN and its various models such as WGAN, StyleGAN, CycleGAN, WGAN and much more. Some known applications include Image to Image translation, text to image translation, Image super-resolution and much more. It also has a small section on how GAN can further be applied to get brilliant results. There is also a small part that covers the downside for GAN.
- Key takeaway: This paper was one of the essential ones that helped us pick an appropriate topic to work on. Everything has been explained in a non-complicated way to have a better impact on the readers.

**5. Progressive growing of GANs for improved Quality, stability and variation**

- Authors: Tero Karras, Timo Aila, Samuli Laine, Jaakko Lehtinen (Conference paper at ICLR2018)
- Overview: This paper mainly deals with the training approach of GAN models. Here, both the discriminator and the generator are grown progressively together. New layers are added gradually beginning with a low resolution. This method is proven to have better training and hence, better resolution when an image is trained with it. Celeb-A data set is used to train images. Celeb-A is a large scale dataset with 200,000 celebrity faces that are used mainly for training and testing image quality in GAN applications..
- Key takeaway: One of the main problems of GAN as seen in many research papers is that the model collapses. The solution to this problem is shown clearly in this paper. MAD-GAN is one of the most effective ways to keep the model from collapsing. This method has been used in the Image completion process.

**6. A Style Based Generator Architecture for Generative Adversarial Network**

- Authors: Tero Karras, Samuli Laine, Timo Aila (2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)
- Overview: This paper takes a new approach to StyleGAN, and proposes a new architecture that leads to an automatically learned, unsupervised separation of high-level features of the training images. There is also an excellent comparison between the old data and the newly generated data and the results are quite evident that the new data images are a lot more clearer than the trained ones. This paper also explores a way of image to image translation, that is style mixing. More experiments are done to show the differences in noise input in the images.
- Key takeaway: This paper shows the instability of the traditional GAN model and how the new architecture is used to provide better images.

**7. ESRGAN+: Further Improving Enhanced Super-Resolution Generative Adversarial Network**

- Authors: Nathanael Carraz Rakotonirina, Andry Rasoanaivo (2020)
- Overview: Enhanced Super-Resolution Generative Adversarial Network is one of the best ways to enhance image super resolution. It works no matter how bad the quality of the image is. Noise inputs are provided at some layers to increase the look of

the image making it more photorealistic. There is also comparison made between SRCNN, EnhanceNet, SRGAN with ESRGAN and ESRGAN+.

- Key takeaway: ESRGAN is the model we chose for a particular application of GAN- Image super-resolution. This paper was the basis of our approach

**8. Boundless: Generative Adversarial Networks for Image Extension**

- Authors: Piotr Teterwak, Aaron Sarna, Dilip Krishnan, Aaron Maschinot, David Belanger, Ce Liu, William T. Freeman(ICCV 2019)
- Overview: This paper deals with Image Inpainting and more importantly how to deal with an incomplete image. A model called Wasserstein GAN is used to complete images. This method can also be used in image distortion. Here the image extension is compared in 3 forms i.e. compare Deep-Fill(DF), PartialConv (PC), ours without conditioning (NCnd) with the main model.
- Key takeaway: Image extension using GAN with different baselines and panorama generation.

**9. Image Inpainting Based on Generative Adversarial Networks**

- Authors: Huaming Liu,Guanming Lu,Xuehui Bi, Jingjie Yan, Weilan Wang (2018 14th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD))
- Overview: This particular paper emphasizes on the need of image inpainting and how they are widely used in recent times. Traditional methods that have been used to do this process have been proved to be a little messy due to the fact that semantic repair cannot be done with accuracy due to insufficient sample resources. Deep Learning has some characteristics that can overcome this issue. GAN in particular can be used to constrain the repair process using neighborhood loss functions and gradient loss. This method proved to maintain the texture and clarity of the output.
- Key takeaway: Adding gradient loss constraint improves the quality of image to berepaired.

**10. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network**

- Authors: Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, Wenzhe Shi (2017 IEEE Conference on Computer Vision and Pattern Recognition)
- Overview: This paper focuses on SRGAN and how it is capable of producing photo-realistic image generation. A perceptual loss function which contains adversarial loss and content loss. The adversarial loss is responsible to make the image look realistic with the help of the discriminator. Mean Opinion Score testing is also done to check the scores of different images with different models. The result is that SRGAN had the highest score meaning it had the most photo-realistic image of all other methods.
- Key takeaway: How SRGAN can be used for super resolution and adversarial network architecture.

**11. Generate Desired Images from Trained Generative Adversarial Networks**

- Authors: Tero Karras, Samuli Laine, Timo Aila (2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)
- Overview: GAGAN is a method that is used to control the synthesis of an image with particular characteristics. To do this, a DNA pool of trained GAN models is introduced and evolved by a Genetic Algorithm (GA). By using AND, OR functions, GAGAN can further synthesize images with multiple specific attributes or single specific attributes. MNIST and Celeb A datasets are used to train and experiment the model
- Key takeaway: Using GAGAN to generate specific images from trained GAN model.

**12. Image Super-Resolution using a Improved Generative Adversarial Network**

- Authors: Han Wang, Wei Wu and Yang Su, Yongsheng Duan and Pengze Wang (IEEE 2019)
- Overview: SRGAN is used to increase the resolution of the image. This is the most proven method to generate super resolution photo-realistic images. However, this paper aims on how SRGAN works and how the model can be modified to obtain better results. An encoder block is fixed in the generator of the model to obtain much more clarity in the images. This also extracts crucial features of the image and can train it in a better way to synthesize a better resolution. The encoder block uses a simple encoder network to extract crucial information and it then joins this to the existing CNN. The parameters of CNN are reduced to simplify the distortion.
- Key takeaway: This method shows that super resolution images can be obtained with better clarity and higher resolution with the proposed model of attaching an encoder parallelly.

## 4. METHODOLOGY

### 4.1 Boundless GAN

Conventional image augmentation models that work on assorted datasets and safeguard significant level semantics and low-level picture structures and surfaces have wide uses in image altering, and PC illustrations. While inpainting has been widely discussed, in this paper, we found that it is trying to straightforwardly apply the best in class inpainting strategies to picture augmentation as they will, in general, produce hazy or dreary pixels with conflicting semantics. We apply semantic molding with the Generative Adversarial Network (GAN) and accomplish extraordinary subjective and quantitative outcomes on images with cognizant semantics and also outwardly satisfying tones and surfaces in the all-inclusive locales. We likewise show promising outcomes in extraordinary augmentations, including display age.

*A. Model*

Wasserstein GAN framework is used as a model. that has a generator network which is trained by the assistance of discriminator, which is trained accordingly. The generator, G has information comprising of the picture z with pixel esteems in the reach of [−1, 1], which has to be expanded,

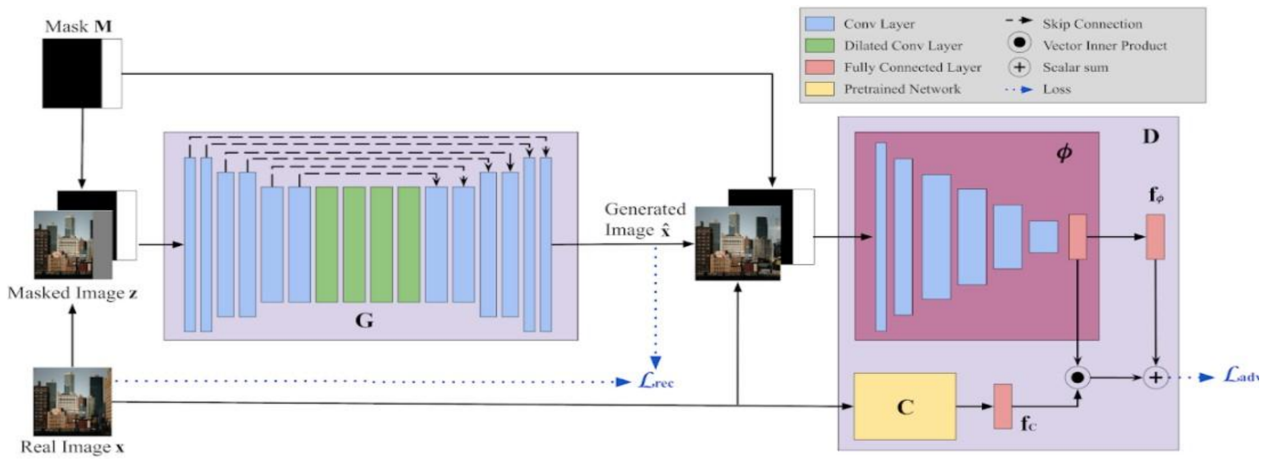


**Fig. 4: Model explaining Boundless GAN**

and a double cover M. Both z also, M comprises an area of known pixels and unknown pixels. Rather than inpainting systems, the distant locale pixels imparts a limit to the known area on just one side where, z is set to 0 in the unknown area, and M is set to 1 in the obscure district and 0 in the known district. The yield of G(z,M) of G has similar measurements as z and also, the loss of a pixel during preparation, utilizes this full yield. Notwithstanding, the last stage prior to taking care of the discriminator D is to supplant what the generator combined in the known locales and the pixels that are known.

*B. Training*

Reconstruction loss and Adversarial loss are combined and then the model is trained.

$$Lrec = kx - G(z,M)k \qquad (11)$$

Wasserstein GAN hinge loss is used for adversarial loss that defines the coarse prediction.

$$L_{adv,D}=E_{x\text{-}p(x)}\,[Re\,LU\,(1 - D\,(x\,,M,x)) + Re\,LU\,(1 + D\,(x\,,M,x))] \qquad (12)$$

Here, *ReLU* is the rectified linear unit function.

$$L_{total}=L_{loss}+\ \lambda L_{adv,G} \qquad (13)$$

The above equation is the equation for the total loss function λ is set to 10. The models are trained with the datasets of the top 50 classes of the Places365-Challenge dataset. These are then separated into spatial dimensions of 257x257 pixels.

*C. Predicted Output*

The main objective of Boundless GAN is to complete an incomplete image. According to the previous related work we have referred to, and after studying every outcome of such methods, we predict our output to be similar to the figure 5.

**Fig 5: Predicted output that shows image completion for 25%, 50% and 75% of the original image.**

## 4.2 SRGAN

This design intends to recuperate better surfaces from the picture when we upscale the input image, so that quality cannot be undermined. For example, there exists several techniques such as Bilinear Interpolation, which can be utilized to play out this assignment, yet they experience the ill effects of picture data loss and smoothing. The creators proposed two structures, SRResNet (one without GAN ) and another one as SRGAN (with GAN). It is presumed that SRGAN has a much better accuracy and produces picture all the more satisfying to eyes than SRGAN.

*A. Model*

The generator design contains residual networks rather than deep convolution networks since residual organizations are anything but difficult to prepare and permits them to be significantly more profound to produce better outcomes. This is on the grounds that the residual network utilized a kind of association called skip associations. The goal of the input is expanded with both well-prepared convolution layers of sub-pixels. While preparing, a high-resolution picture (HR) is reduced to an image which is of a lower resolution (LR). The generator design then attempts to upscale the picture from a low goal to super-resolution(SR). After then the picture is sent into the discriminator, it then attempts to recognize a super-resolution and High- Resolution picture and create the antagonistic misfortune, which then back propagated into the generator design.

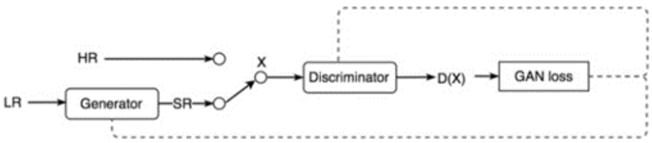


**Fig 6: Training model to implement SRGAN**

*B. Training*

The high-resolution pictures are accessible during training is subjected to Gaussian filter to obtain Low Resolution as output. It is then down sampled by factor. The SRGAN utilizes perceptual loss function (LSR) that constitutes the combined amount of two-loss segments: adversarial loss and content loss. This loss is significant for the exhibition of the G. There are two types of content loss which we shall be considering: pixelwise MSE loss for the SRResnet architecture

$$l_{MSE}^{SR} = \frac{1}{r^2WH}\sum_{x=1}^{rW}\sum_{y=1}^{rH}(I_{x,y}^{HR} - G_{\theta_G}(I^{LR})_{x,y})^2 \qquad (14)$$

Loss of different VGG layers is also taken as one of the content loss .This VGG loss is based on the ReLU activation layers of the pre-trained 19layer VGG network.

$$l_{VGG/i.j}^{SR} = \frac{1}{W_{i,j}H_{i,j}}\sum_{x=1}^{W_{i,j}}\sum_{y=1}^{H_{i,j}}(\phi_{i,j}(I^{HR})_{x,y} - \phi_{i,j}(G_{\theta_G}(I^{LR}))_{x,y})^2 \qquad (15)$$

Adversarial loss is the one that powers the G to picture close to high-resolution images with the help of a discriminator that is prepared to separate between HR and SR images.

$$l_{Gen}^{SR} = \sum_{n=1}^{N} -\log D_{\theta_D}(G_{\theta_G}(I^{LR}))$$

The final equation will be:

$$l^{SR} = l_{X}^{SR} + 10^{-3} l_{Gen}^{SR} \qquad (17)$$

Where the first element is the context loss and the second element is the adversarial loss and both together constitutes perpetual loss.

*C. Predicted Output*

After upscaling the image four times, we must obtain an output close to figure 7. The data is taken from ImageNet database and around 350 hundred images are trained to acquire maximum precision. We must note that the testing images do not come from the already trained samples. The down sampling factor, *r* is taken as 4.

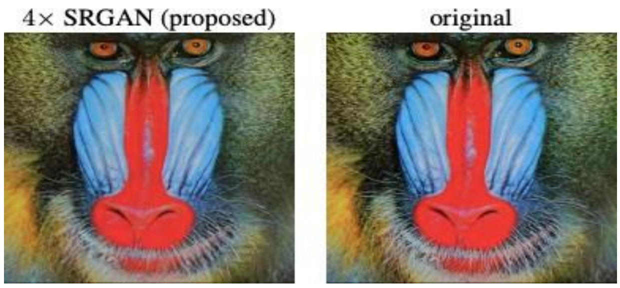


**Fig7: Output predicted after applying r as 4**

## 5. CONCLUSION

There are many factors that can be improved in GAN models. SRGAN can be achieved with another model called ESRGAN+. This has the basis of what we saw but only the generator loss functions are improvised to provide better results. Boundless GAN can be improved to make the output a lot better. Similarly, GAN is a growing field and there will always be scope for improvement and betterment. There are many fields in which GAN models are applied as seen above. This can be further taken care of.

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