iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** VII **Month of publication:** July 2021

DOI: https://doi.org/10.22214/ijraset.2021.37237

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VII July 2021- Available at www.ijraset.com

Super Resolution MRI Using Generative Adversarial Networks

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Abstract: This paper proposes a new frame for MRI Image Enhancement from a low-resolution (LR) image obtain from an early used MRI machine to generate a high-resolution (HR) MRI image. For this we use Generative Adversarial Networks, which have proven well in image recovery task. Here we simultaneously train two models which is Generative model that captures the data distribution in the LR MRI images, and a discriminative model that estimates the probability that a sample came from the training data rather than generator. For training generator, we have to maximize the probability of discriminator of making a mistake in comparing the fake image. For discriminator the adversarial loss uses least squares in order to stabilize the training and for generator the function is a combination of a least square adversarial loss and a content term based on mean square error and image gradient to improve the quality of generated images of MRI.

I. INTRODUCTION

In many medical applications like in MRI, CT scans, X Rays etc, or in the medical imaging where high-resolution images are required to facilitate early and accurate diagnosis of the diseases or any medical condition. But however due to economical, physical or technological limitations, like improving the machine to current technology or buying new machine is not feasible where machine cost is high or the situation where the body has to be still for generating a sharp image or a good resolution image.

So Super Resolution MRI using GANs is a tool that can bring improvement in the medical imaging where there is no chance or less chance of improvement in the machines. Our tool is based on Generating High resolution MRI images from the low-resolution MRIs produced from the earlier machines as according to the National Centre of Biotechnology Information (NCBI) survey majority of Indian Hospital, both private sector or government sector hospital owns older MRI machines i.e., of 1.2T or 1.5T MRI machines which are not capable of producing a high resolution and clear image. There is zero upgradation available to these older MRI machines, but with technology advancement we aim to provide a software-based solution to overcome this problem. So, to reduce these limitations with we propose this tool which aim to up sample the images produced by the older machines with a better resolution or we can a say it will produce a high-resolution image that can computationally add or details to the images.

Here we use Generative Adversarial Networks which work on generating a fake image and a discriminator for distinguishing it as fake or not from the given dataset. The training of generator is to produce an image which is similar to the image in the discriminator or to maximize the probability that the discriminator cannot discriminate between the two images. The image formed by the generator is of high resolution and with the help of least mean square error and the image gradient it will increase stability and the consistency in image formation and training.

II. RELATED WORKS

The generative adversarial network is a new technology which is developed in the year 2014 by Ina Goodfellow and not even a decade old, but is developed much from its creation to now in different field of imaging from photorealistic image. The early or the starting work are given as follow:

2014
Ian J. Goodfellow et. al.
General Adversarial Nets
Deep generative model which was earlier used had less impact due to difficulty in approximating intractable probabilistic computation. For this they proposed new generative model that sidestep these difficulties.in this framework, generative model is marked against adversary and discriminative model learns to determine whether a sample is from model distribution or data distribution.

They prepare a new framework in which they simultaneously train two models; generative model and a discrimination model. In the post modules generative model have less of an impact due to the difficulty of the approximating incontrollable and the result of the computation that arises. Its main generates the new images with some input dataset without any influence.

2015
Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks
Alec Redford et. al.
They introduced DCGANs to bridge the gap between success of CNN for supervised and unsupervised learning. Training on various datasets shows convincing evidence that our deep convolutional adversarial pair learn hierarchy of representation in both generator and discriminator, they also used learned features for task.
They proposed set of constraints un architectural topology of CGAN, makes them more stable to train in most settings, named it Deep Convolutional GAN(DCGAN), use of trained discriminator for image classification task. Visualize the filter learnt by GANs. They show that generators have interesting vector arithmetic properties allowing for easy manipulation of many semantic qualities of generated samples. It is a more stable set of architecture for training GANs. There were still some model instabilities remaining, further work needed to tackle the instability. They also thought that extending framework to another domain should be interesting

2016
Jiwon Kim et. al.
Accurate Image Super-Resolution using very Deep Convolutional networks.
In this they proposed a method in which they describe that by using a very deep convolutional networks increase the accuracy of the earlier methods and also improves visuals. This was the first time when the method of generating a high-resolution image from a low-resolution image. For this They basically increase the depth of neural network where details are not necessary and based on the which will look good while visualising

2017
Photo-realistic single image super-resolution using a generative Adversarial network
Christian Lee et. al.
Till that date, it was the first framework capable of inferring photo-realistic natural images for 4× upscaling factors. To achieve this, they propose a perceptual loss function which consists of an adversarial loss and a content loss.
Our deep residual network is able to recover photo-realistic textures from heavily down sampled images on public benchmarks. The MOS scores obtained with SRGAN are closer to those of the original high-resolution images than to those obtained with any state-of-the-art method. A deep residual network SRRes-Net which produces the best results on previous public data sets (PSNR method used). Using extensive MOS testing, they have confirmed that SRGAN reconstructions for large upscaling factors (4×) are more photo realistic. They introduce the SRGAN for image super-resolution. In this they proposed a perceptual loss functions which consist of adversarial loss and a content loss. For generating a SR images, they use the SR algorithm in which minimization of the mean squared error b/w the recovered HR image and the ground truth is done.

2017
Deep generative adversarial neural networks for compressive sensing MRI
Morteza Mardani et. Al
MRI reconstruction is a severely ill-posed linear inverse task demanding time and resource intensive computation. So, in this they combine the compressed sensing analytics framework with the benefits from generative adversarial networks (LSGAN) to train a manifold of diagnostic quality MR images from historical patients and it also increases the reconstruction under a few milliseconds faster than the CS-MRI schemes.
To render with the ill posed linear inverse problem conventional compressed sensing incorporates the prior image information by means of sparsity regularization in a proper transform domain such as Wavelet. Propose GANCS as a data driven regularization scheme for solving ill posed linear inverse problems that appear in imaging tasks dealing with aliasing artifacts. Proposed and evaluated a novel network architecture to achieve better trade-offs between data consistency and manifold learning. Does not define the use in the field of 3D spatial correlations for improved quality imaging against patients with abnormalities. And variations in the acquisition model for instance as a result of different sampling strategies.

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2018
Brain MRI super resolution using 3D generative adversarial networks
Irina Sánchez, Verónica Vilaplana

In this work they propose an adversarial learning approach to generate high resolution MRI scans from the low-resolution images. Their architecture is based on the SRGAN model and adopts the 3D convolutions to exploit volumetric information. For discriminator they use the least square and for generator the uses the loss function and the least squares adversarial loss, and the content based on mean square error. In medical application high resolution images are required for early detection and diagnosis, but due to economical, technological or physical limitations it result into undesired resolution.

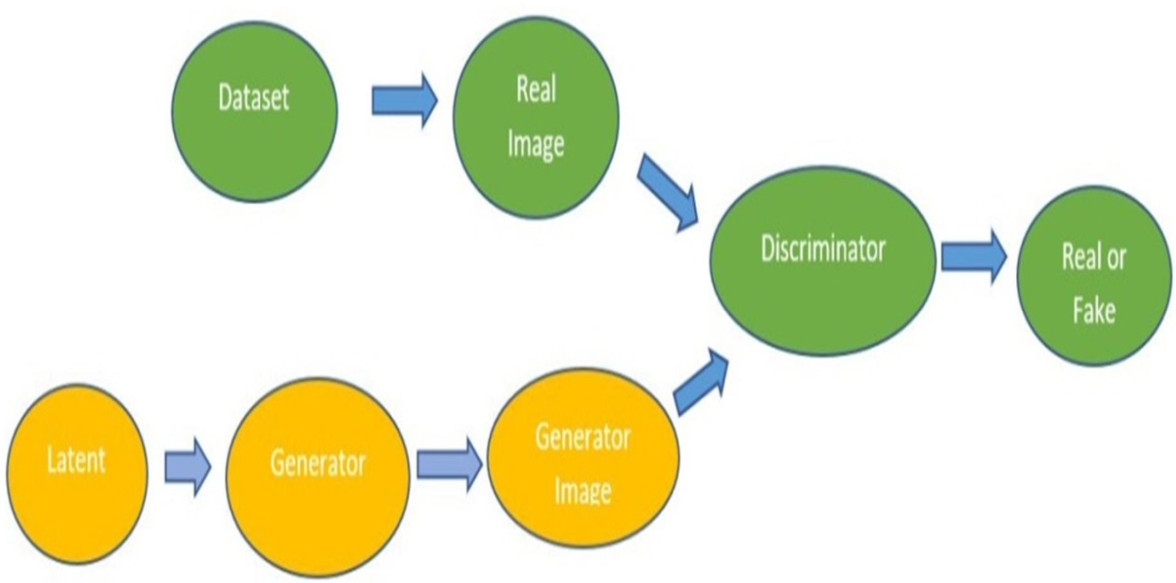
For this they propose an architecture for MRI super resolution that completely exploits the currently available volumetric information contained in MRI, the model is based on the SRGAN network and uses the adversarial loss and the least squares to stabilize the training and generator loss and uses the mean square and image gradient in order to improve the quality of image. Less dataset for the training and testing is used. A mean opinion score (MOS) test should be performed to evaluate the performance for this approach.

III. PROPOSED METHOD

Our main aim is to improve the overall perceptual quality for SR. In this section, we first describe our proposed network architecture and then discuss the improvements from the discriminator and perceptual loss. At last, we describe the network interpolation strategy for balancing perceptual quality and PSNR.

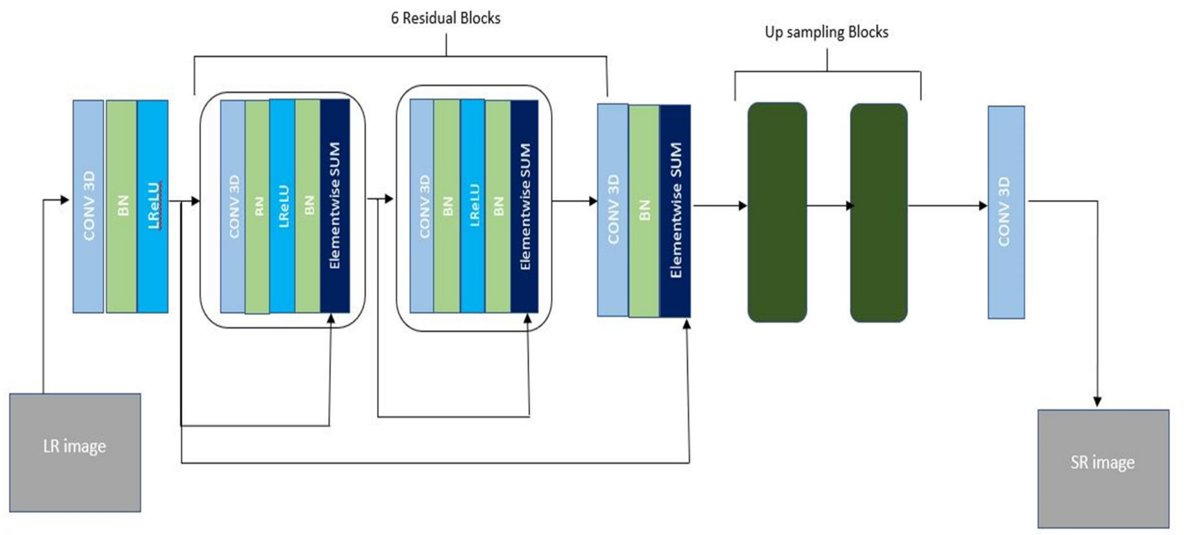
A. Generative Adversarial Networks

Generative Adversarial Networks, or GANs for short, are an approach to generative modelling using deep learning methods, such as convolutional neural networks.
Generative modelling is an unsupervised learning task in machine learning that involves automatically discovering and learning the regularities or patterns in input data in such a way that the model can be used to generate or output new examples that plausibly could have been drawn from the original dataset. GANs are a clever way of training a generative model by framing the problem as a supervised learning problem with two sub-models: the generator model that we train to generate new examples, and the discriminator model that tries to classify examples as either real (from the domain) or fake (generated). The two models are trained together in a zero-sum game, adversarial, until the discriminator model is fooled about half the time, meaning the generator model is generating plausible examples.



B. The Generator Model

The generator model takes a fixed-length random vector as input and generates a sample in the domain. The vector is drawn from randomly from a Gaussian distribution, and the vector is used to seed the generative process. After training, points in this multidimensional vector space will correspond to points in the problem domain, forming a compressed representation of the data distribution. This vector space is referred to as a latent space, or a vector space comprised of latent variables. Latent variables, or hidden variables, are those variables that are important for a domain but are not directly observable. We often refer to latent variables, or a latent space, as a projection or compression of a data distribution. That is, a latent space provides a compression or high-level concepts of the observed raw data such as the input data distribution. In the case of GANs, the generator model applies meaning to points in a chosen latent space, such that new points drawn from the latent space can be provided to the generator model as input and used to generate new and different output examples. After training, the generator model is kept and used to generate new samples.

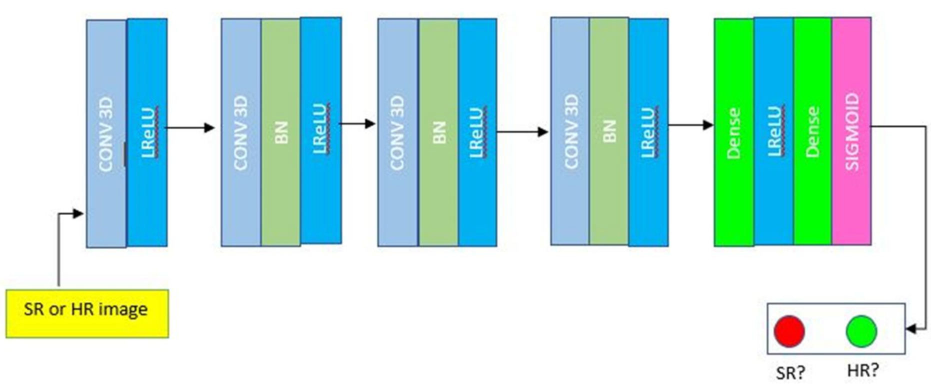


Generator architecture

C. The Discriminator Model

The discriminator model takes an example from the domain as input (real or generated) and predicts a binary class label of real or fake (generated). The real example comes from the training dataset. The generated examples are output by the generator model. The discriminator is a normal (and well understood) classification model.

After the training process, the discriminator model is discarded as we are interested in the generator. Sometimes, the generator can be repurposed as it has learned to effectively extract features from examples in the problem domain. Some or all of the feature extraction layers can be used in transfer learning applications using the same or similar input data.



Discriminator Architecture

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VII July 2021- Available at www.ijraset.com

D. SRGAN

Single image super-resolution by large up-scaling factors is very challenging. SRGAN proposed to use an adversarial objective function that promotes super-resolved outputs that lie close to the manifold of natural images. The main highlight of their work is a multi-task loss formulation that consists of three main parts: a MSE loss that encodes pixel-wise similarity, a perceptual similarity metric in terms of a distance metric defined over high-level image representation (e.g., deep network features), and an adversarial loss that balances a min-max game between a generator and a discriminator. The proposed framework basically favours outputs that are perceptually similar to the high-dimensional images. To quantify this capability, they introduce a new Mean Opinion Score (MOS) which is assigned manually by human ratters indicating bad/excellent quality of each super-resolved image. Since other techniques generally learn to optimize direct data dependent measures (such as pixel errors), outperformed its competitors by a significant margin on the perceptual quality metric.

E. Vanishing Gradient

The vanishing gradient problem is an issue that sometimes arises when training machine learning algorithms through gradient descent. This most often occurs in neural networks that have several neuronal layers such as in a deep learning system, but also occurs in recurrent neural networks. The key point is that the calculated partial derivatives used to compute the gradient as one goes deeper into the network. Since the gradients control how much the network learns during training, if the gradients are very small or zero, then little to no training can take place, leading to poor predictive performance.

The problem is that in some cases, the gradient will be vanishingly small, effectively preventing the weight from changing its value. In the worst case, this may completely stop the neural network from further training. As one example of the problem cause, traditional activation functions such as the hyperbolic tangent function have gradients in the range (0, 1), and backpropagation computes gradients by the chain rule. This has the effect of multiplying n of these small numbers to compute gradients of the early layers in an n-layer network, meaning that the gradient (error signal) decreases exponentially with n while the early layers train very slowly.

F. ReLU

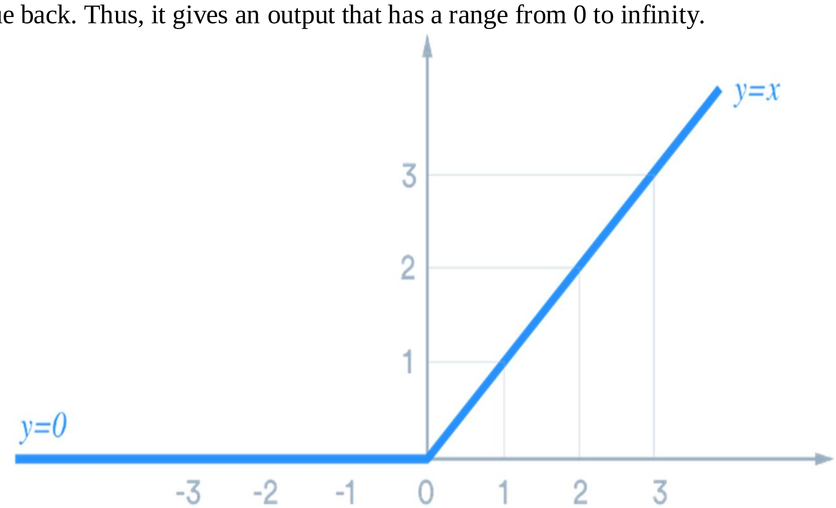
The rectified linear activation function or ReLU for short is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. It has become the default activation function for many types of neural networks because a model that uses it is easier to train and often achieves better performance.

ReLU stands for rectified linear activation unit and is considered one of the few milestones in the deep learning revolution. It is simple yet really better than its predecessor activation functions such as sigmoid or tanh.

G. ReLU Activation Function Formula

$f(x)=\max(0,x)$

ReLU function is its derivative both are monotonic. The function returns 0 if it receives any negative input, but for any positive value x, it returns that value back. Thus, it gives an output that has a range from 0 to infinity.



H. Leaky ReLU

Leaky ReLU function is an improved version of the ReLU activation function. As for the ReLU activation function, the gradient is 0 for all the values of inputs that are less than zero, which would deactivate the neurons in that region and may cause dying ReLU problem.

Leaky ReLU is defined to address this problem. Instead of defining the ReLU activation function as 0 for negative values of inputs(x), we define it as an extremely small linear component of x. Here is the formula for this activation function

f(x)=max (0.01*x, x).

This function returns x if it receives any positive input, but for any negative value of x, it returns a really small value which is 0.01 times x. Thus, it gives an output for negative values as well. By making this small modification, the gradient of the left side of the graph comes out to be a non-zero value. Hence, we would no longer encounter dead neurons in that region.

I. Image Gradient

Image gradients are used as a measure of image sharpness. The gradient at any pixel is the derivative of the DN values of neighbouring pixels. The mean gradient is the contrast between the details and clarity of the image.

$$\overline{G} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \sqrt{\frac{\Delta I_x^2 + \Delta I_y^2}{2}}$$

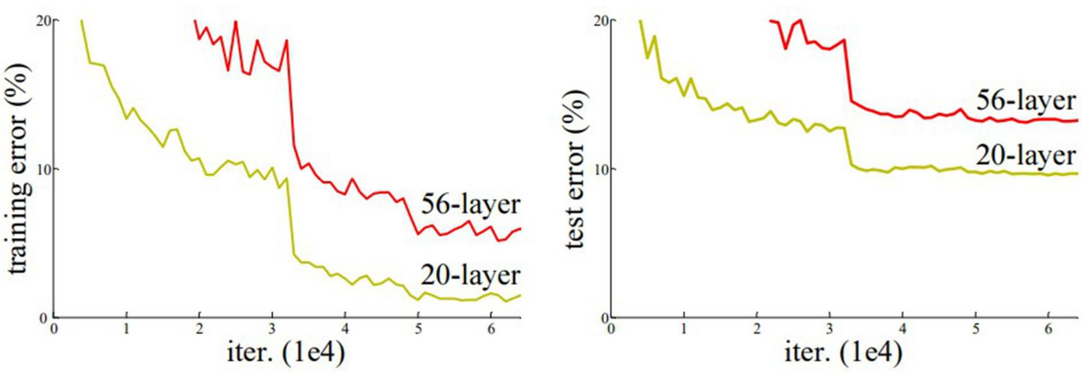
$$\Delta I_x = X(i+1, j) - X(i, j)$$

$$\Delta I_y = X(i, j+1) - X(i, j)$$

And, ΔIX and ΔIy are the horizontal and vertical gradients per pixel.

J. ResNet

Mostly in order to solve a complex problem, we stack some additional layers in the Deep Neural Networks which results in improved accuracy and performance. The intuition behind adding more layers is that these layers progressively learn more complex features. For example, in case of recognising images, the first layer may learn to detect edges, the second layer may learn to identify textures and similarly the third layer can learn to detect objects and so on. But it has been found that there is a maximum threshold for depth with the traditional Convolutional neural network model. Here is a plot that describes error% on training and testing data for a 20-layer Network and 56 layers Network.

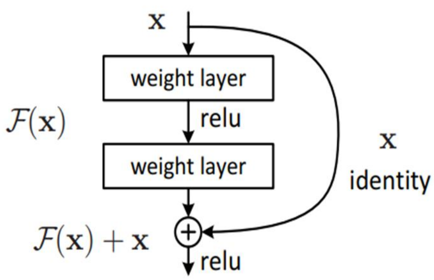


We can see that error% for 56-layer is more than a 20-layer network in both cases of training data as well as testing data. This suggests that with adding more layers on top of a network, its performance degrades. This could be blamed on the optimization function, initialization of the network and more importantly vanishing gradient problem. You might be thinking that it could be a result of overfitting too, but here the error% of the 56-layer network is worst on both training as well as testing data which does not happen when the model is overfitting.

K. Residual Block

In order to solve the problem of the vanishing/exploding gradient, this architecture introduced the concept called Residual Network. In this network we use a technique called skip connections. The skip connection skips training from a few layers and connects directly to the output.

The approach behind this network is instead of layers learn the underlying mapping, we allow network fit the residual mapping. So, instead of say H(x), initial mapping, let the network fit, *F(x):= H(x) – x* which gives *H(x):= F(x) + x*.



The advantage of adding this type of skip connection is because if any layer hurt the performance of architecture, then it will be skipped by regularization. So, this results in training very deep neural network without the problems caused by vanishing/exploding gradient. The authors of the paper experimented on 100-1000 layers on CIFAR-10 dataset.

There is a similar approach called "highway networks", these networks also use skip connection. Similar to LSTM these skip connections also uses parametric gates. These gates determine how much information passes through the skip connection. This architecture however has not provided accuracy better than ResNet architecture.

L. K space

The image of the MRI is formed using the k space and by applying Inverse Fourier transform we get the image of the scan. All point in k space contain little dot that represent the contrast and the voxel part of the MRI image. So, each point or the individual image space depend on all the points contained in k space. In these low spatial frequencies represents part of the object that change in a spatially slow manner. High spatial frequencies represent small structures whose size is on the same order as the voxel size (tissue boundaries).

M. Fourier Transform

The Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain equivalent.

The Fourier Transform is used in a wide range of applications, such as image analysis, image filtering, image reconstruction and image compression.

For a square image of size N×N, the two-dimensional DFT is given by:

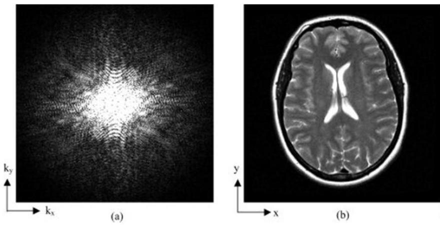
$$F(k,l) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f(i,j)\, e^{-\iota 2\pi \left(\frac{ki}{N} + \frac{lj}{N}\right)}$$

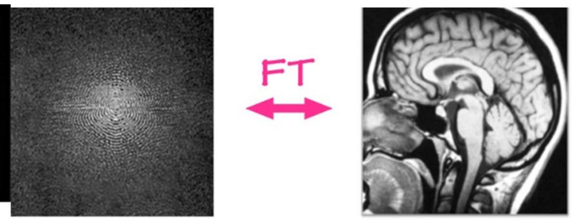
n a similar way, the Fourier image can be re-transformed to the spatial domain. The inverse Fourier transform is given by:

$$f(a,b) = \frac{1}{N^2} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} F(k,l)\, e^{\iota 2\pi \left(\frac{ka}{N} + \frac{lb}{N}\right)}$$

Where, $F(k,l) = \frac{1}{N} \sum_{b=0}^{N-1} P(k,b)\, e^{-\iota 2\pi \frac{lb}{N}}$

And $P(k,b) = \frac{1}{N} \sum_{a=0}^{N-1} f(a,b)\, e^{-\iota 2\pi \frac{ka}{N}}$





N. PSNR

Peak signal to noise ratio (PSNR) is the ratio of the maximum possible power of an image to the power of distorting noise that affects the quality of the image representation. To find the PSNR, it is essential to compare that image to an ideal clean image with the maximum power. It is simply ratio between maximum powers of signal to noise**.**

PSNR is as follows:

$$PSNR = 10log_{10}(\frac{(L-1)^2}{MSE}) = 20log_{10}(\frac{L-1}{RMSE})$$

Where L= maximum intensity levels (min being 0)

And $$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(O(i,j) - D(i,j))^2$$

Where O = matrix data of original image,

D = matrix data of degraded image

m = no. of rows of pixels and i = index of that row

n = no. of columns of pixels and j = index of that column

O. SSIM

SSIM is used for measuring the similarity between two images. It is a method for finding the perceived quality of pictures, and digital images. The difference between this and other techniques is that those techniques approaches estimate absolute errors

$$\text{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

with:

- μ_x the average of x;
- μ_y the average of y;
- σ_x^2 the variance of x;
- σ_y^2 the variance of y;
- σ_{xy} the covariance of x and y;
- $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$ two variables to stabilize the division with weak denominator;
- L the dynamic range of the pixel-values (typically this is $2^{\#bits\ per\ pixel} - 1$);
- $k_1 = 0.01$ and $k_2 = 0.03$ by default.

SSIM is a new measurement tool that is designed based on 3 factors i.e., luminance, contrast, and structure.

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

with, in addition to above definitions:

- $c_3 = c_2/2$

Also, by putting all these in the first formula we, get:

$$\text{SSIM}(x,y) = \left[l(x,y)^\alpha \cdot c(x,y)^\beta \cdot s(x,y)^\gamma\right]$$

Setting the weights α, β, γ to 1, the formula can be reduced to the form shown above.

P. NRMSE

The root mean square error (RMSE) is the measure of the variations between values predicted by a model or an estimator and the values observed. The RMSE shows us the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences.

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{t=1}^{T}(x_{1,t} - x_{2,t})^2}{T}}.$$

Where, x1, t and x2, t are time series

And T is the no. of times. The NRMSE can be taken as a fraction of the total range that is typically resolved by the model.

$$\mathrm{NRMSD} = \frac{\mathrm{RMSD}}{\bar{y}}.$$

Ybar = average of observation value

Q. Adversarial Loss.

1) *Loss Function:* The standard GAN loss function described in the original paper by Ian Goodfellow et al. is given as:

$$E_x[log(D(x))] + E_z[log(1 - D(G(z)))]$$

Where, D(x) = the discriminator's estimate of the probability that real data instance x is real.

Ex = the expected value over all real data instances.

G(z) = the generator's output when given noise z.

D(G(z)) = the discriminator's estimate of the probability that a fake instance is real.

Ez = the expected value over all random inputs to the generator

2) *Discriminator Loss:* While the discriminator is trained, it categorizes both the real data and the fake data from the generator.

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(x^{(i)}\right) + \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)\right]$$

Where, log(D(x)) is the probability that the generator is doing right in classifying the real image.

3) *Generator Loss:* When the generator is trained, it samples random noise and produces an output from that noise. The output then goes through the discriminator and gets categorized as either “Real” or “Fake” based on the ability of the discriminator to tell one from the other.

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)$$

IV. ADVANTAGES AND DISADVANTAGES

This new framework comes with advantages and disadvantages relative to previous modelling frameworks. The advantages are that Markov chains are never needed, only backprop is used to obtain gradients, no inference is needed during learning, and a wide variety of functions can be incorporated into the model. The aforementioned advantages are primarily computational. Adversarial models may also gain some statistical advantage from the generator network not being updated directly with data examples, but only with gradients flowing through the discriminator. This means that components of the input are not copied directly into the generator’s parameters. The main advantage of our product is that it is very economical for users and disadvantage is that hardware requirement is very high.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VII July 2021- Available at www.ijraset.com

V. CONCLUSION AND FUTURE WORK

We have discussed the optimization and evaluation of generative image models. Different metrics can lead to different trade-offs, and different evaluations favour different models. It is therefore important that training and evaluation match the target application. An evaluation based on samples is biased towards models which overfit and therefore a poor indicator of a good density model in a log-likelihood sense, which favours models with large entropy. Such an analysis at least has the property that the data distribution will perform very well in this task. To summarize, our results demonstrate that for generative models there is no one-fits-all loss function but a proper assessment of model performance is only possible in the context of an application.

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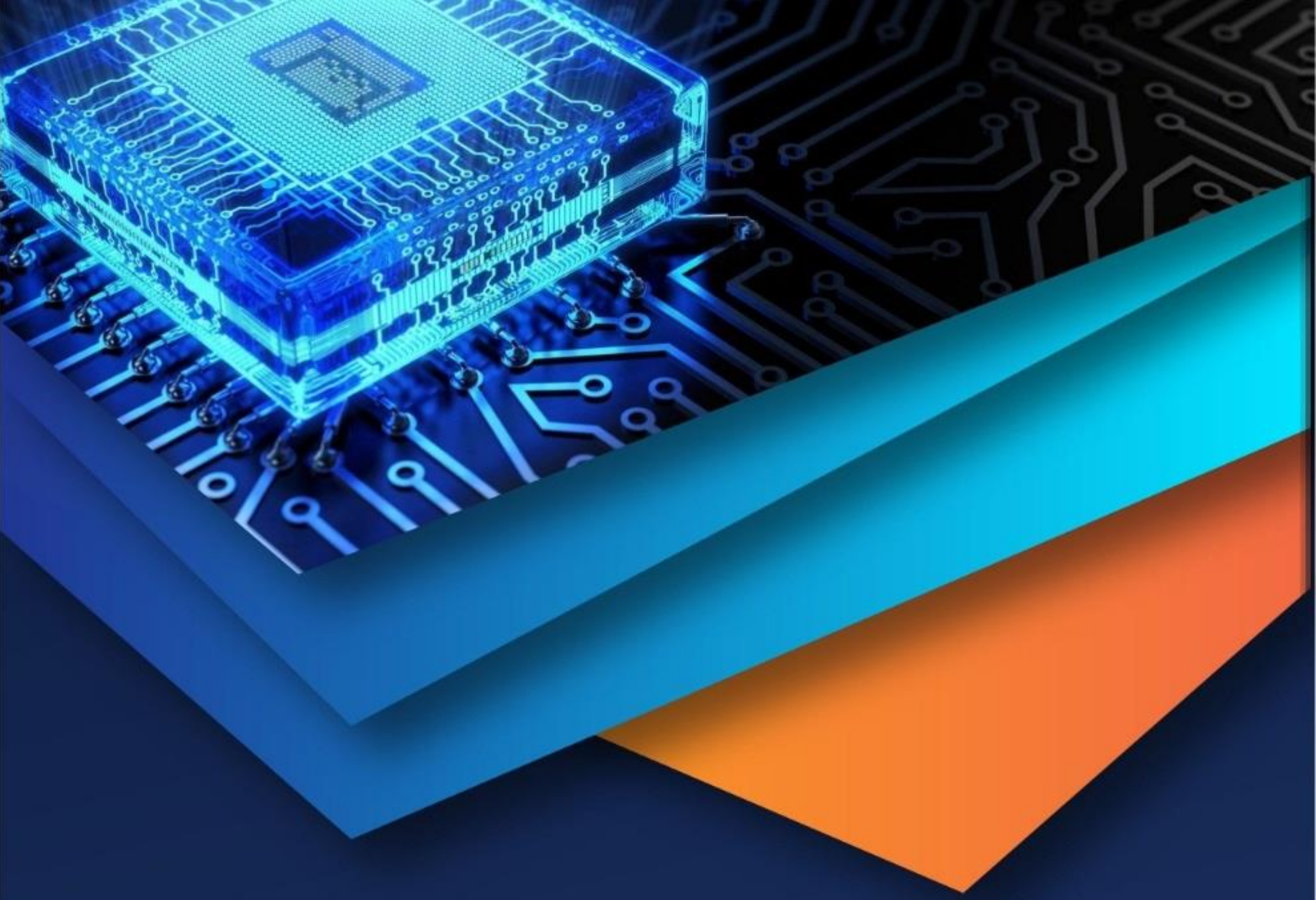

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