ISSN 2278-3091
Volume 11, No.3, May - June 2022
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse091132022.pdf
https://doi.org/10.30534/ijatcse/2022/091132022

Handwritten Digits Image Generation with help of Generative Adversarial Network: Machine Learning Approach

Bhavesh Rathi[1], Rajesh Kumar[2], Muhammad Waqas pasha[3], Bharat Kumar[4],Syed Ibrar Hussain[2], Um-e-Farwa [5]
[1] Department of Computer Science, University of Debrecen, Hungary.
Bhaveshrathi1995@gmail.com
[2]Department of Mathematics and Computer Science, University of Palermo, Italy
rajesh.kumar@unipa.it, syedibrar.hussain@unipa.it
[2,5]Department of Computing, Hamdard University Karachi, Pakistan
rajesh.kumar@hamdard.edu.pk
umefarwa.152@gmail.com
[3]Department of CCoCIS, Paf KIET Karachi, Pakistan.
Waqaspasha90@gmail.com
[4]Department of Computer Science, NEDUET, Karachi, Pakistan
Bharatkumar243@gmail.com

Received Date : April 18, 2022 Accepted Date : May 19, 2022 Published Date : June 06, 2022

ABSTRACT

In recent years, research into Generative Adversarial Nets (GANs) has increased dramatically. GAN was first proposed in 2014 and has since used in various real-time applications,Includes computer vision and natural language processing for approximately accurate results. Image composition is the most popular study of the many applications of GAN,Studies in this area have already shown the great future of using GAN for image composition.This article shows how to classify image composition methods, reviews different models of text-to-image composition and image-to-image conversionand provides some metrics and future research on image composition using GAN. I will explain the direction of in this paper. In current years, frameworks using Generative Adversarial Networks (GAN) have been very successful in many areas many areas, especially in image generation, asthey can create very realistic and crisp images and train on large datasets. However, successful GAN training can be very difficult if you need high resolution images. Text-to-image compositing, image-to-image conversion, face manipulation, 3D image compositing, and deep master printing are five interesting areas that can be applied to image compositing based on the state-of-the-art GAN technology described in this article. It presents a comprehensive analysis of current GAN-based imaging models, including their strengths and weaknesses. At the same time, recent rediscovery of deep learning and widespread interest in generation methods in the scientific community have made it possible to generate realistic images by learning the data distribution from noise. If the input data contains information about the visual content of the image, the quality of the generated image will improve.

Key words: GAN model, Machine Learning, Handwritten Digits

1.INTRODUCTION

Machine learning claims to uncover complex structural models to explain probability distributions across a variety of data sources found in AI applications: Natural photos,audio-audio waveforms, and symbols in a corpus of natural languages [10]. Machine learning algorithms have evolved to be able to compete with and even beat humans for severalprojects, such as image classification in ImageNet, due tocurrentpromotions in deep learning[9].The design and standard of images produced by generative techniques, especially generative hostile networks (GANs), have improved dramatically in the latest years. Despite latest efforts, there is still a lack of understanding of various aspects of the image composition process, including the origin of indefinitefeatures [18].Image composition is used in a variety of areas, including art, pictures, machine learning techniques. This is achieved through calculating the accurate saturation amount of consistency in the high-resolution picture. Despite the various proposed approaches, image composition remains a difficult problem. Machine learning applications benefit from the use of generative adversarial networks (GANs), which are game-theoretic generative models. GAN can generate realistic images and, thanks to competitive training and the power of deep networks, has made great strides in many images generation and manipulation models [17]. Good fellow etal. (2014) [10] proposed GANs as a fiction approach to train a generative model. Most of the cases, GANs.On the point of a genuine image (near to 1) or a forgery (close to 1).(Nearly 0). The losing function equation is written as under:

minG maxD Ex∈F [logA(x)] +Ex∈F [log (1 − A(H(w)))]

GAN pictures are often less fuzzy and more realistic than earlier generator model images. In an unconditioned generative model, they do not have control over the data modes created [17].

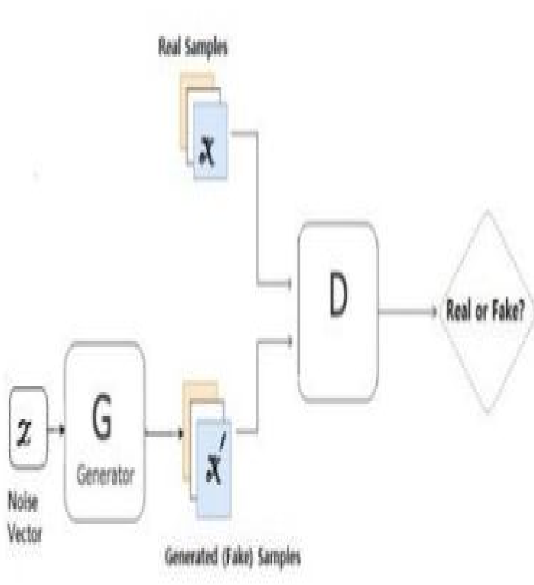

Figure 1: Structure of the Gan Model

Image production of complicated realistic settings with various objects and desired layouts is one of the important frontiers for computer vision. The presence of such algorithms will not only guide our designs for visual understandinginference systems but would also aid artists and users in terms of automatic picture production. Such algorithms, if effective, might fully replace visual search and retrieval engines.

2.LITERATURE REVIEW

The purpose of generative models is to produce new data points that are distributed in the same way as the training dataset. GANs are made up of two networks: the generators that make graphics from an image noise variable, and the learner, which learns from it. The discriminators are the secondary system.This distinguishes between genuine training pictures and those created by the generator. In other words, the discriminator D produces authentic pictures with D(x) = 1 and false images with D(x) = 0. To achieve the Nash equilibrium, the networks are antagonistically trained, which is an ideal state in which D(x) = 1/2 for each image x, suggesting that the discriminator is unable to differentiate between genuine and false samples [16].Nonetheless, the following factors are crucial for a successful Brain2Image process: 1) the premise that incoming brain signals preserve visual content information; 2) the capacity tointerpret and extract such visual material; and 3) the possibility to mix the first and second. A generation model that really can generate a distribution of data from limited and noisy inputs using the translated material [13].

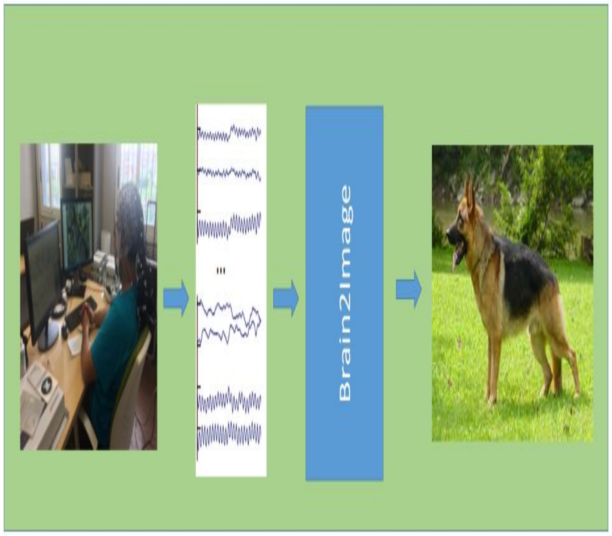

Figure 2: Our goal of this research is to have a subject look at an image while an EEG records their brain activity.

Table:1 This shows experimental protocol's dimensions

Classification	50
The number of images in each class	70
The total number of images	3000
Order of visualisation	Sequence
Each image has its own time	1.0 s
Interval between courses	20 s
Count of Sessions	10
Duration of the session	400 s
Total time spent running	1500s

2.1 What is Generative Adversarial Network

Traditional definitions of generative models are algorithms that model data input distributions, p(x), or the combined distributions of input data and related objectives, p. (x, y). These models can sample from a feature, xxii, conditioned onanother feature, xxjj, using conditional inference. In the context of deep learning, generative models are models that produce data that appears realistic. We can sample from distributions of inputs, p(x), but conditional inference is not always achievable [16].

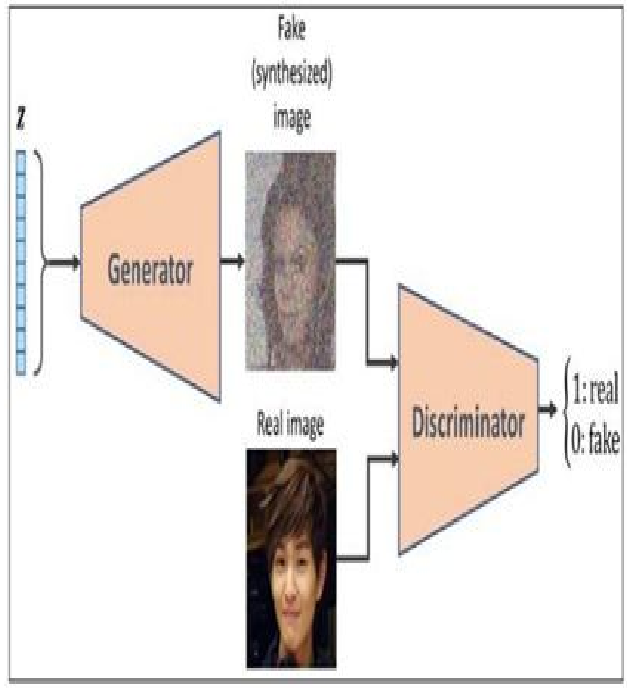

Figure 3: This is a Generative Adversarial Model

2.2 Understanding the loss functions of the generation and discrimination networks in a Generator Adversarial model

Because this study only employs, we'll look on every component's stochastic gradient descent using generation as well as 2 different decoders. In the above study, by lowering the reconstruction loss by lowering the reconstruction loss, we prepare the synthesizer Lr. The disappearance of the L2 norm function is used in this paper rather than the L1 norm loss function. Because it penalizes outliers, the L2 norm is ideal for inpainting tasks, but its resilience is inadequate. The loss of reconstruction is also significant

$Lr = k\ G(xm) - xk^2{}_2$

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 100)               2000
_________________________________________________________________
leaky_re_lu (LeakyReLU)      (None, 100)               0
_________________________________________________________________
dense_1 (Dense)              (None, 784)               79184
=================================================================
Total params: 81,184
Trainable params: 81,184
Non-trainable params: 0
_________________________________________________________________
```

Figure 4: The Function losses of the Gan Model

Unsupervised learning losses are required. GAN learning is becoming more common in so many tech fields; The generation has shown a lower unsupervised learning losses has greater having ability that replace its gaps. They use the Wasserstein GAN losses [19] along with new and existingdecoders for secure future. Wasserstein's GAN defeat as an unknown:

$\text{minimum}_B\ \text{maximum}_A S\ (B,\ A) = E_{x\sim pdata}(z)\ [I(y)] - E_{z\sim pz}(y)\ [E(I(y))]$

The following are the definitions of global and local discriminatory losses:

$M_{global} = F_{xc\sim pg}\ [Eg(xc)] - E_{x\sim pdata}\ [Eg(x)]$

$M_{local} = F_{mc\sim pg}\ [El(mc)] - E_{m\sim pdata}\ [El(r)]$

M_{global} and M_{local} represent global and local discriminator losses, respectively. The global and local discriminator functions are represented by Eg and El, respectively. The created region is represented by xc, whereas the full image is represented by mc. x and r represent the true picture from the true dataset and area The complete loss function is often formulated as having:

$N = N_r + \lambda 1 M_{local} + \lambda 2 M_{global}$

where**λ1**and **λ2**are weights used to balance the impacts of different losses [19].

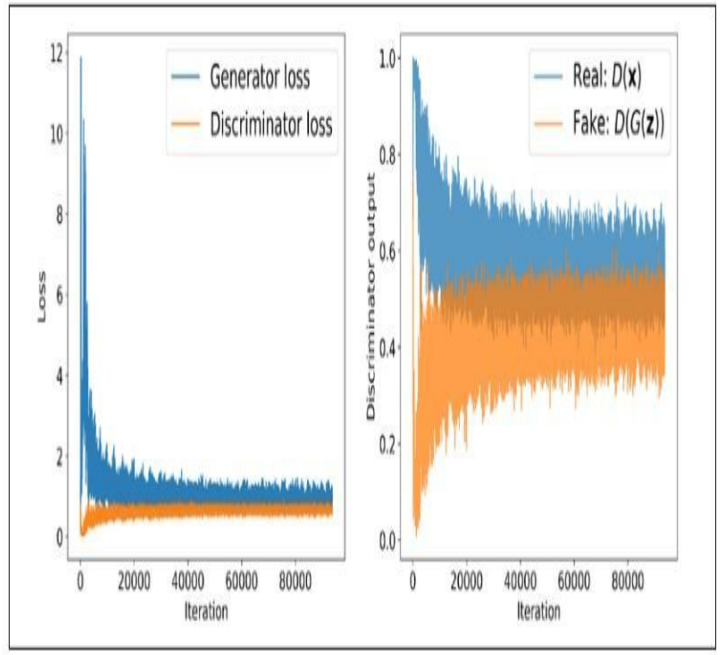

Figure 5: The Function losses of the Gan Model

2.3 A Train Method

This report discusses proposed picture contrast enhancement approach on trains. In each cycle, the dataset picture is destroyed using the tiny batch learning method. We start by masking a small sample of y pictures from the training examples with irregular gaps. After that, we acquire a small batch of masked photos (y), actual regions (o), and masks (n). Combination of elements is represented by zo = m x. The generation is again trained with L_r loss s days. We fix the generator after training it and use L_{global} and L_{local} to train discriminators t times. Finally, we train the consent with connection losses L. After entering x into the system, the expected pictures d is shown. We acquire the final inpainting pictures xii = y+ b by combining the masked regions of b and x. (0.05 m). Algorithm 1 may be used to illustrate the training method [19].**During iterations J 1lroin**

if J< r is true,

Compact or m pictures are instances of this. (x •>, x2>,...,x'"> from training set Q.,, (:k:). On every framestochastic occlusion processing was used to create a dataset of 112 covered pictures (zi •>, zi(2),.•., zi'">) and a dataset of m real regions before they were masked (13>, s2l,....s'"'>).

To receive m created photos, enter micro-batch or n masked photographs zi 1>, zi(2l,...,zi(m) to the generator. Update the generator with reconstruction loss using (H(y'),:y:' (Eq.3).

otherwise

....,:x y:('") to the global autoencoder

Compact or n completed regions d•l, d2>,...d'"l) and n actual regions e(ll e2>,...,e'"> u>

Classifier Generation Network loss updates local autoencoder and global autoencoder (Eq.5 and Eq.6).

if j >t + I is true then

To receive ni produced photos, enter micro or m covered pictures o(ll, o2>....,o(n) into the synthesizer. Local autoencoder (d•>, d2>....,d'">) discriminates created pictures, whereas global autoencoder (e•>, e2>....,e'">) discriminates finished regions (:;;I>,:;;3>,...,:;;Cm).

To the combined approach, implement combined losses (Eq. 7).

if end if while

Algorithm.1 : Algorithm for Training Data Set

2.4 The Experiment of Handwritten Digits images Produced by Using Generative Adversarial Network

The explanation for that is that the false instances didn't really look anything like the actual results, making the distinction between the two rather straightforward. As the training advances, the generator will grow better at synthesizing realistic pictures, culminating in probability of both actual and false samples approaching .50[16].

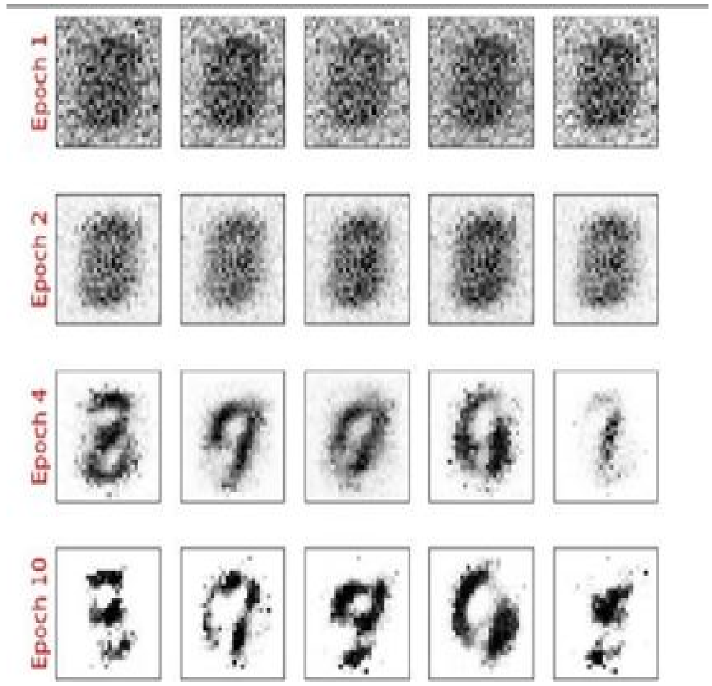

Figure 6: This is a produced images by Gan Network

We may also watch how the generator's outputs, or created pictures, evolve over time. We came up with several instances by reaching the create.samples() function after each epoch and saved them in a list data structure [16].

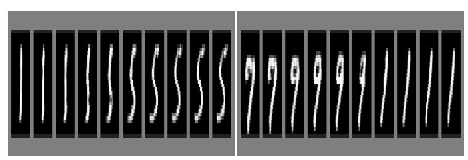

Figure 7: The Sample of the Handwritten Digits

Table 2: Log-likelihood estimate using the Parzen window

	Pictorial frameworks featuring strong directedness	**Unsupervised high pictorial architectures**	**Classification methods which produce**	**Modelling of adversary**
Train	Reasoning is essential during program. .	Reasoning is essential throughout program. MCMC was used to predict the clustering functional gradients.	Assured power production compromise among both combining and rebuilding	The generators and the discriminators are in sync 'Helvetica'
Assumption	Approximation reasoning was discovered.	Variation-based reasoning	MCMC-based reasoning	Approximation reasoning was discovered.
Sample	There does not have any difficulty	A Sequence is needed.	A Sequence is needed.	There does not have any difficulty
Evalua1ingp(x)	Intractable. AIS can be used to approximate	Intractable. AIS can be used to approximate	Nol is well-represented. may be estimated using the Parzen density method	Nol is well-represented. may be estimated using the Parzen density method
Modeldesign	Almost all models are extremely difficult.	Multiple properties necessitate careful design.	Any differentiable functions are technically permissible. .	Any differentiable functions are technically permissible.

Table 3: The Generative Model Challenges

Model	MNIST	TFD
DBN[3]	150 +- 5	1915+-70
Stacked CAE[3]	125+-2.0	2120+-55
Deep GSN[6]	230+-1.5	1900+-40
Adversarial nets	240+-2.5	2100+-30

3. RESULTS

Inside this step, we built a very basic GAN system with just one fully - connected convolution layers for the classifiers. While preparing the GAN model on the Mnist, they can obtain encouraging, although not yet satisfactory, results with the fresh character recognition. Adding convolutional layers toour GAN model for working with picture data might further boost results[16].

Visual inspection proved to be a quick and intuitive way to detect image quality improvements. The two-time update rule [15], one-sided label smoothing [15], and replacing transposed convolutions with a combination of convolutions and upsampling [15] all resulted in noticeable improvements. While visual inspection may not be able to detect finer improvements, it worked well for the purposes of this project given the state of the developed model [15].

The findings include examples of synthetic images and a expert's quantitative assessment of their realism. On an Nvidia GeForce GTX 1080, each 128x128 (64x64) sequence took about 2 hours to train [6].

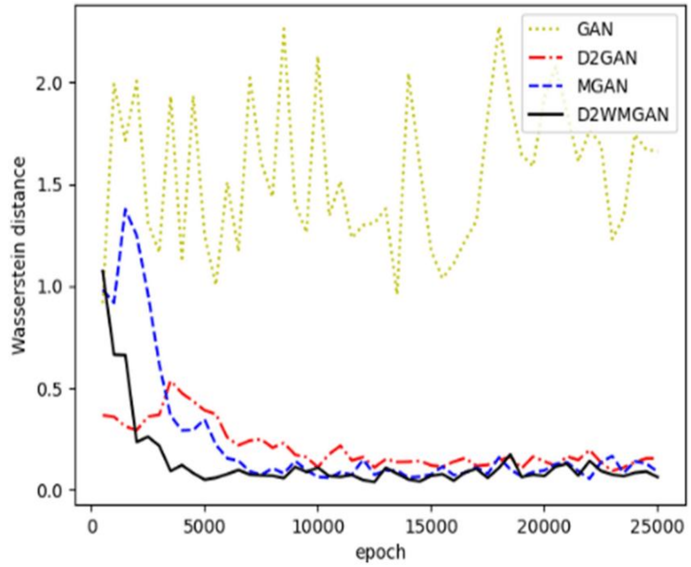

Figure 8 : The Distance of the Handwritten Digits

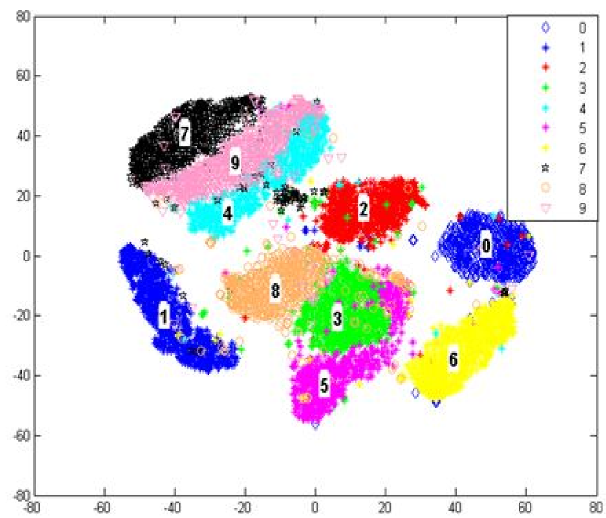

Figure 9: The Visualization of the Handwritten Digits

4. CONCLUSION AND FUTURE WORK

For document deblurring, we presented a novel model that employs cycle-consistent adversarial networks. CycleGAN is adapted to the task of text image deblurring in our proposed "Blur2Sharp CycleGAN" architecture. Because CycleGan has the property of cycle-consistency, we can both deblur and blur sharp images. We don't need the ground-truth sharp images because we're using unpaired images as our training dataset. Based on our previous experience, we can successfully deblur an unpaired image dataset using Cy-cleGAN [7].We did not need the human free hand drawing to precisely follow the three enhanced styles throughout testing, even though we added three new sketch styles to the sketch drawing. We put the proposed framework through rigorous testing to establish its benefits. In the upcoming years, we plan to examine more robust learning algorithm as well as new application situations. Although the result is true to the original drawing, new quantitative assessments showing "perceptional" consistency among a (poorly drawn) raw drawing and our produced picture (e.g., Figure 6) may be required, which is a separate topic and challenging challenge [21].We see in future decades that Generative Adversarial Network works in the field of Artificial Intelligence, Cyber security, Network Security. It will provide better performance and accuracy as compared to the past decades.

REFERENCES

1. A Survey of Image Synthesis and Editing with Generative Adversarial Networks. (2017). *TSINGHUA SCIENCE AND TECHNOLOGY vol. 22, no. 6, pp. 660-674.*
2. Aram You, J. K. (2022). Application of generative adversarial networks (GAN) for ophthalmology image domains: a survey. *Eye and Vision volume 9 Article number: 6.*
3. Bingqi Liu, J. L. (2021). Application of an Improved DCGAN for Image GenerationApplication of an Improved DCGAN for Image Generation.
4. Bo Zhao, L. M. (2019). Image Generation from Layout. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 8584-8593*.
5. Carl Vondrick, H. P. (2016). Generating Videos with Scene Dynamics. *Advances in Neural Information Processing Systems 29*.
6. Changhee Han, H. H. (2018). GAN-BASED SYNTHETIC BRAIN MR IMAGE GENERATION. *IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)* .
7. Hala Neji, M. B.-I. (2021). Blur2Sharp: A GAN-Based Model for Document Image Deblurring. *International Journal of Computational Intelligence Systems Vol. 14(1), pp. 1315–1321*.
8. Hao Tang, S. B. (2020). XingGAN for Person Image Generation. *arXiv:2007.09278v1 [cs.CV]* .
9. He Huang, P. S. (2018). An Introduction to Image Synthesis with Generative Adversarial Nets. *arXiv:1803.04469v2 [cs.CV]* .
10. Ian J. Goodfellow, J. P.-A.-F. (2014). Generative Adversarial Nets. *arXiv:1406.2661v1 [stat.ML]*.
11. Jyoti Islam, Y. Z. (2020). GAN-based synthetic brain PET image generation. *Brain Informatics volume 7, Article number: 3.*
12. K. Sarada, B. N. (2021). PHOTOS TO IMAGE TRANSLATION USING GANS: A REVIEW. *JETIR , Volume 8, Issue 6* .
13. Kavasidis, S. P. (2017). Brain2Image: Converting Brain Signals into Images. *In Proceedings of MM ’17, Mountain View, CA, USA, 9 pages*.
14. Little, C. (2021). Generative adversarial networks for synthetic data generation: A comparative study. *CONFERENCE OF EUROPEAN STATISTICIANS Expert Meeting on Statistical Data Confidentiality*.
15. Mattila, M. (2021). Synthetic Image Generation Using GANs – Generating Class-Specific Images of Bacterial Growth. *Cognitive Science LIU-IDA/KOGVET-G--21/010--SE*.
16. Sebastian Raschka, V. M. (2019). *Python Machine Learning.* Packt Publishing Ltd.
17. Shirin Nasr Esfahani, S. L. (n.d.). IMAGE GENERATION WITH GANS-BASED TECHNIQUES: A SURVEY. *International Journal of Computer Science & Information Technology (IJCSIT) Vol 11, No 5*.
18. Tero Karras NVIDIA, S. L. (2019). A Style-Based Generator Architecture for Generative Adversarial Networks. *arXiv:1812 sy.04948v3 [cs.NE]*.
19. YI JIANG, J. X. (2020). Image Inpainting based on Generative Adversarial Networks. *DOI 10.1109/ACCESS.2970169, IEEE Access*.
20. Yogita T Hambir, P. B. (2021). Facial Image Generation of Anime characters. *IJCRT Volume 9 ISSN: 2320-2882*.
21. Yongyi Lu, S. W.-W.-K. (2018). Image Generation from Sketch Constraint Using Contextual GAN. *arXiv:1711.08972 [cs.CV]*.