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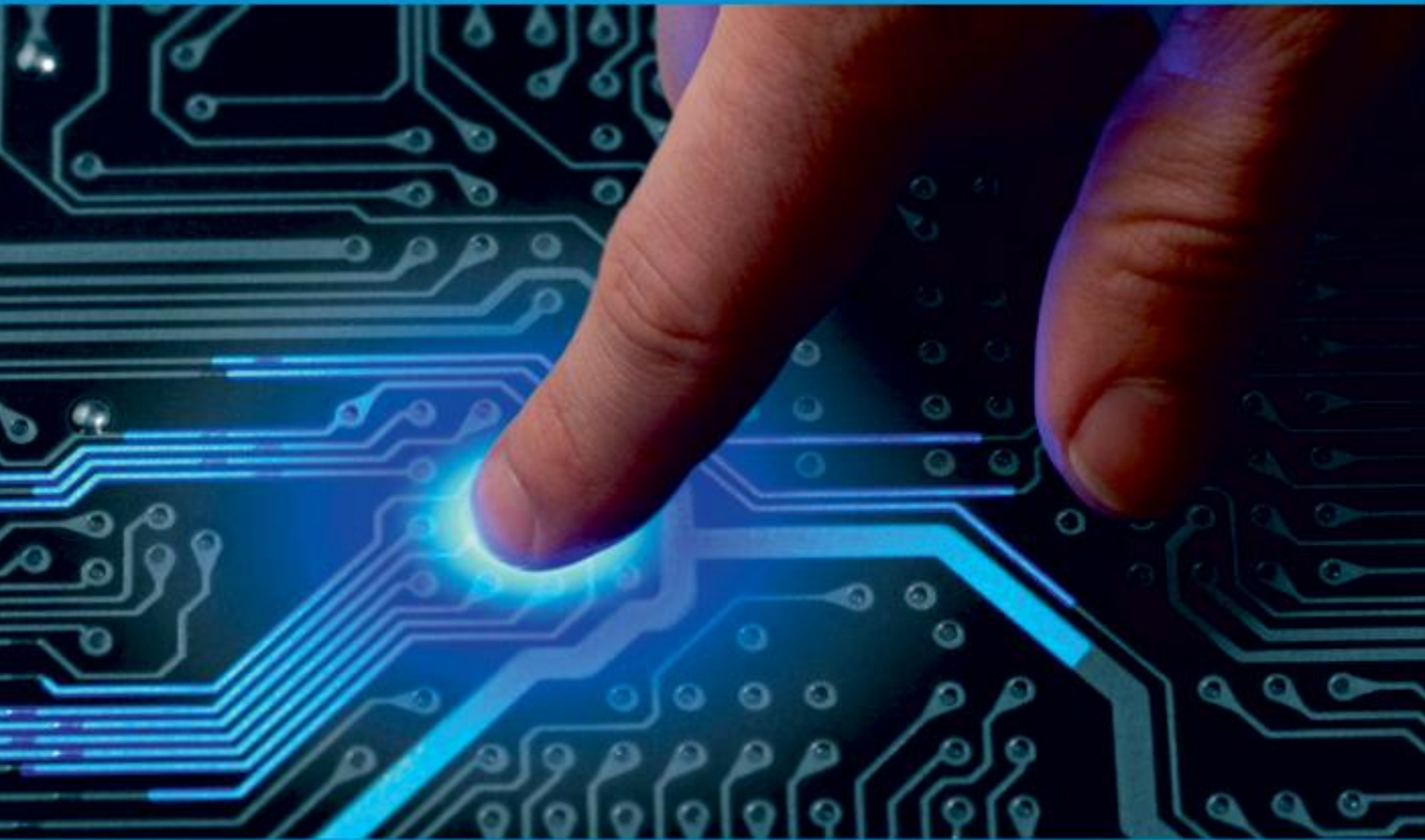

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GAN for Generating Hand-Written Digits

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ABSTRACT: Generative Adversarial Network (GAN) is a deep-learning (ML) model in which two parallel neural networks fight to become more accurate. Accounting backpropagation signals are used by these networks to learn. GANs have resulted in significant advances and outstanding performance in a variety of applications. The purpose of this study is to outline the benefits, drawbacks, and critical problems that GANs face in their successful deployment in a variety of applications. The primary goal of this study is to investigate and provide a comprehensive overview of the key applications of GANs, including image-to-image translation, Deepfakes, and GAN in generative written digit and face aging. This hands-on review study continues the generative digit; we discovered that by playing with learning rate ranging from 0.0001 to 0.0006 and simultaneously shifting between suitable boundary and its values, even if the model hits equilibrium by 20 epoch, it continues to learn and perfect in its progressive forms. Also, we try to comprehend and review that the model reaches an equilibrium state with some iteration losses of the generator and discriminator, and so the ML model is trained 50 epoch after where it will get the 0.06 difference in losses between D & G results.

KEYWORDS : Neural networks, Generative adversarial networks, loss function, Handwritten digit generation.

I. INTRODUCTION

An input vector, generator, and discriminator make up a basic model of Generative Adversarial Networks (GAN), Goodfellow et al. created the (GAN) In the subject of deep learning, it was first introduced. [1]. As a discriminative model referring fig.2 , convolutional neural networks have had a lot of success. These are very prominent in the field of computer vision, where they are commonly employed for image labelling and object recognition. Some tasks require you to create data points rather than discern between them. New data points based on a predetermined desired distribution. as an example, Make a picture of your room. The convolutional neural network's appearance isn't immediately apparent. The bedroom semantics should be captured by the model for this task. Beds, blankets, and pillows are all available. You must comprehend how each of these components, such as windows and doors, are interconnected in terms of connectedness and visual structure. [3] As they learn to imitate the distribution of data, GAN has immense potential for all wise and terrible people. In other words, GAN has been taught to construct a world that is strikingly similar to our own in every way, including pictures, music, language, and literature. They're golem artists all over the place, and their work is both astonishing and inspiring. The most obvious use of the Generative Adversarial Network is picture production [2]. It generates data that is indistinguishable from true and false which is based on current data. Information generation algorithms must be compared and contrasted with identification algorithms in order to comprehend GAN.

The classification of the supplied data is determined by the identification algorithm. GANs (Generative Adversarial Networks) are becoming a popular method for combining artificial intelligence with two competing neural networks in systems. A generator model and a discriminator model are included in the framework, and they participate in a game-like fashion. To produce dispersed data and estimate its probability, the generator model and the discriminator model are both trained simultaneously. Understanding GAN and Deep Convolutional Neural Network models trained in numeric or picture generation can also be highly intriguing. The discriminator is used as a loss feature by the generator, which adjusts its own parameters to provide realistic data. The discriminator, on the other hand, is responsible for updating the parameters in order to better discern between bogus and real data. In truth, it's a generative model that seeks to make fake money and can be compared to a gang of discriminate thieves. This model can be seen as a police attempt to apprehend a counterfeiter. This game of cat and mouse goes on until the system achieves equilibrium. This data generated by the generator after it has reached equilibrium appears so real that the discriminator can only guess at random. True or false is the generating data. As a result, the whole architecture resembles a two-player game. While the generator is attempting to make its objective function as less as possible , the discriminator is also attempting to minimize its own objective function. [2] Gan's are one of today's most attention-getting engineering concepts. Associate adversarial approach is used to train a pair of models in real time A generator ("the artist") referring to fig.1

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learns to make images that appear real, but a discriminator ("the art critic")referring to fig.2 learns to distinguish between actual and phoney photos.
GAN employs an unsupervised deep learning approach. Introduced in a 2014 study by Ian Goodfellow, Yoshua Bengio, and other University of Montreal researchers[1]. It employs two neural networks known as generator and mortal. They continue to corrode each other until they can pass genuine data.

In the upcoming paper, we have described about the literature survey(section-2) for four different application, Use of GAN for generating hand- written digits(sec-2.1),(sec-2.2) GAN for Deepfakes,(sec-2.3) GAN For Face Aging ,(sec-2.4) GAN For The Image-to-image Translation.We further dive deep into the Use of GAN for generating hand-written digits(sec-4) and reviewed some observations and obtained some insightful results.

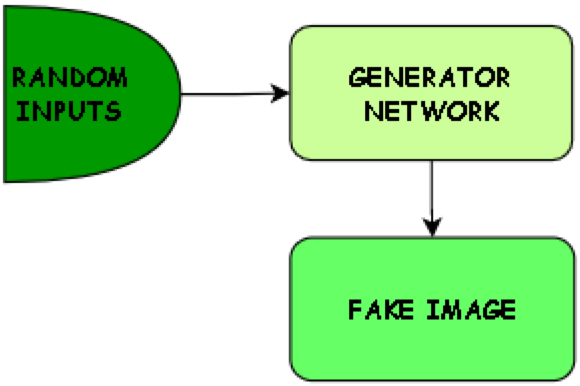

fig 1 : Generator Network

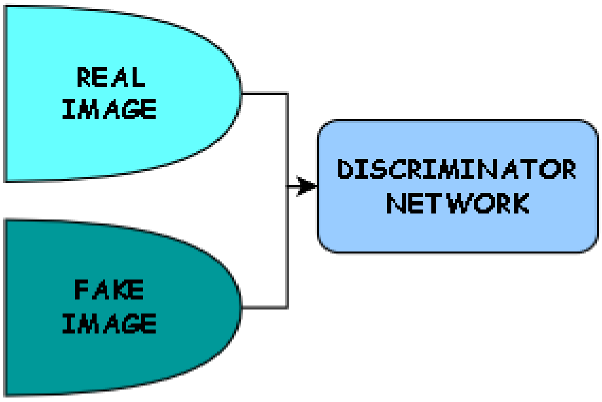

fig 2 : Discriminator Network

II. LITERATURE SURVEY

GAN is basically a technique of producing artificial dataset based on training dataset like training dataset. GANs are used in various sectors such as Technology, Bioinformatics, Medical science, Security control, Entertainment, Surveillance, Forensic art, etc. There are different types of GANs and they are used in different applications. DC GAN is deep most widely used, powerful and multilayered convolutional network. CGAN is used when some conditional information has to be provided to generators input and discriminator. Cycle-GAN is used in image translation.

2.1 Use of GAN for generating hand- written digits : Goodfellow et al. suggested the GAN for the first time in 2014. The generator and discriminator were two types that make up this system. The discriminator was used as a loss function by the generator, which adjusts its parameters to provide more realistic-looking data. [2] The generator and discriminator are two models that make up GAN. The discriminator is used as a loss function by the generator, which adjusts itselfs parameters to provide more real looking data. Discriminator, on the other hand, adjusts itselfs parameters to better distinguish bogus data from actual data[3]. The MNIST dataset served as the basis for our earliest tests. We employed the handwritten digit dataset to demonstrate the extent of our architecture to generate digits rather than the character dataset of one's handwriting. For this purpose, we used the ASCII value of the digits 0 to 9. The great range of writing styles results in variances in the generated images of the same digit. We expected that such variances will be minimal for a given style of writing, and that the generator network will be significantly more precise in duplicating that style of writing. [3] On the MNIST dataset, we put our DCGAN to the test. MNIST is a collection of 70000 annotated handwriting digits, ranging from 0 to 9, that is used as a testbed for classifiers and, in our instance, generative models. Non-parametric approaches can't generate realistic duplicates from hand-written digits, but they're simple enough (and with enough data) for a GAN to produce fascinating results. The outcomes we reported are primarily qualitative because our goal was to create realistic visuals. [4] Meanwhile, the database was loaded into the discriminator in such a way that it can discriminate or match real images and identify them in relation to the database, and the generator updated its parameters generating more realistic images in order to deceive discriminator into believing they are real. The discriminator, also, changes its parameters to distinguish bogus data from actual data. GAN

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finds the Minimax optimization method, in which the generator and discriminator are the two players, by updating their parameters in turn to minimise the generator loss and maximise the loss of the discriminator. [5] The discriminator can easily categorise the images generated by the generator as false or real in the early phases of training, but after a few epochs of training, the images generated by the generator become more difficult to classify. The images that were generated were at random during the beginning of the training process, as you can see. But when the training progressed, the generator learnt how to distribute the data , and after around 20 epochs, certain generated digits began to resemble genuine data, as seen in the diagram below.

2.2 GAN for Deepfakes : With relatively little data and processing power, the average individual could make a film of a world leader confessing to a wrong practice/operation that could lead to an unanticipated constitutional crisis or worse societal unrest in the future. A military leader can make an inappropriate remark about racism causing civil disturbance in a combat zone, or a corporate leader who believes his revenues are poor which could cause a global market manipulation. Deep counterfeiting poses a major risk to our democracy, the nation's security and the society. [6]

DeepFake videos are currently divided into three categories. A head puppet is a video that synthesises the target person's full head and upper shoulders from the original head footage, giving the composite target the appearance of being the source. Second, traditional face-swapping entails generating a target movie in which the faces are swapped with those synthesized from the source but the facial expressions are preserved. The third part, lip-syncing, is all about generating a fake video by simply altering the target's lips so that they appear to be talking about something they aren't. [6]

There are a variety of models available. A level of documentation: Image completion, hyper-resolution, text-image generation, and frame-to-frame translation are only a few of the applications for which GAN architectural variants are available.The discriminator as well as the generator in the original GAN document were fully linked neural networks. To create higher quality images from lower resolution GAN input, Laplacian pyramid of adversarial networks is recommended. The invalidated neural network architecture is used for the first time in deep convolutional GAN. [7]

proposed the initial boundary balanced GAN with autoencoder architecture as a discriminator. The Radical GAN contains a series of progressive steps toward expanding the network architecture. This architecture, which is based on the progressive neural network concept initially proposed in BigGAN, which achieved the greatest performance on ImageNet dataset with characteristics of categorized flower photos), by figuring out how to change the flower's color while keeping the backdrop the same. This test yielded excellent findings as well. Shen et al. presented a new approach for processing proposed facial attributes based on residual image training. It stimulated procedures like training residual pictures, which are different from the original input image and its desired altered image. Instead of focusing on the full face, which contains many unnecessary and unimportant information, the suggested work concentrated on certain attribute sections of the face. They created a dual schema that allowed them to master two inverse property operations at the same time (one being a primitive operation and the other was a double operation). Discriminator classifies the reference and generates images to three groups for each face attribute operation. [8]

Celebrities and politicians, for example, might have had a significant amount of videos and photos available on internet, making them prime targets for deep fakes . When deepfake tactics were being used to make movies of international politicians with phoney speeches wrong reasons, it presented a threat to global security. Deepfakes were therefore used to incite political or religious tensions between countries, deceive the public and influence election campaigns, or create turmoil in the financial markets by fabricating fake news. In both criminal and civil trials, videos and images were frequently utilised as evidence. They could be used as evidence in a court of law if they were digital.[9]

Celebrities and politicians, for example, may have a significant number of videos and photos available on the internet, making them prime targets for deep fakes.. When deepfake tactics are used to create movies of international leaders with phoney speeches for falsification reasons, it poses a threat to global security. Deepfakes are thus used to incite political or religious stress among countries, deceive the citizens and influence election camps, or make turmoil in the financial market by fabricating false news. In both criminal and civil trials, videos and images are frequently utilised as evidence. Digital evidence can be used to introduce them as evidence in a court of law.[9]

In their current state, some DeepFake-based algorithms were limited in their ability to manage more than two domains (e.g., hair colour changes, gender, age, and multiple traits). Because they wanted to produce independent models for separate pairs of image domains, they had to develop separate models for separate pairs of image domains. Choi et al.

[10] used starGAN,(a GAN).The objective was to define an image to image translation model that could be scaled across several domains and had only one generator and discriminator. Deepfakes (combination of the words "deep learning" and "fake") was created by superimposing face images of target person over video of supply person to create a video of target character doing or elaborating things that the supply person will do or elaborate.

2.3 GAN For Face Aging : Generative adversarial networks are used to create fake images with high visual quality. GAN is capable of producing high-resolution images. Age synthesis is another term for face aging. Face aging is described as the artistic portrayal of a face image. Natural anti-aging and anti-wrinkle effects on the individual face[11]. In today's world, the human face is the most important biometric data. The human face ensures accuracy and trustworthiness. It may be used for a variety of purposes, including cross-age face recognition, information forensics, securities, and facial recognition. It also aids in the recovery of missing persons or children using old photographs. Face matching at the border is done using digital passports for security reasons.

Although face aging is a difficult process, there are many internal and extrinsic effects on the face due to facial variances such as illumination effects. The unique individuality of the face is kept in the face aging procedure, such as face geometry, skin colour, texture, and so on. Humans' facial traits alter as they get older.

Face aging refers to the appearance of a human face as it ages. Face aging must be combined with additional adjustments such as a beard, sunglasses, and a change in hair colour, as well as distinctive facial features, in real-life use. Natural picture production was being studied, but GAN made it achievable for the first time in 2014.

The age-cGAN model is used to create this face aging model. It will create human faces within a specified age range. GAN stands for generative adversarial network with age condition [12]. It is made up of two networks: generator and discriminator . The CGANs generator lays hold of an put in image and a targeted age code and creates a face of the target age. The discriminator is intended to be unable to identify the generated face from genuine faces in the targeted age group [13]. Purpose of generators is to model the distribution of picture space. The discriminator's job is to tell the difference between real face images from the image distribution and the generator's fake ones. Both the generator and the discriminator are tuned iteratively against each other in this case. We supply conditional information at G's input and D's first convolutional layer. We've divided the population into six age groups: 0-18, 19-29, 30-39, 40-49, 50-59, and 60+. Reconstruction of the face: Although GANs are the most powerful generating models, they are unable to replicate tiny details such as accessories, backgrounds, and face details. With Age-cGAN [12], a natural put in facial picture can be approximated instead of precisely constructing again. As a result, generate first latent Approximations that are virtuous enough to give the optimization algorithm starters. In the majority of situations, the face's original identity is lost by 50%[12]. As a result, the accuracy of early latent approximations must be enhanced. Latent vector optimization has two major drawbacks: it makes reconstructions more blurry, and it focuses on unimportant elements like sunglasses, beards, and the background of input face photos, all of which have a substantial pixel impact but have nothing to do with a person's identification. Face recognition networks recognise identity in an input image. This face-aging method can be used to artificially augment face datasets. Face recognition technologies will be more robust in the future as a result of this. Furthermore, by merging "Pixelwise" techniques into a single optimization target, the face reconstruction and identity preservation can be improved even more. Future research will look at this.

2.4 GAN For The Image-to-image Translation : gan techniques have recently used in image-to-image translation, with promising conclusions. (cgan) were used in pix2pix [14] to develop a map from put in image to put out image; Cgan learned conditional model using pair images from the origin and destination domains. In the lack of paired examples, zhu et al. [15] devised Cyclegan for image-to-image translation challenges. Introducing two cycle consistent losses, it learned to map from a supply domain x to destination domain y (and same from both sides). Considering the same situation , discogan [16] dualgan [17] employed a unsupervised schooling approach for image-to-image translation, but their loss functions were completely different. zhang et al. have planned Harmonic gan. [18] Introduced abstraction smoothing for not paired image-to-image translation to ensure consistency mapping throughout the conversion.

Liu et al. [19] said that an unsupervised image-to-image translation network (unit) that supported linked GANS[20] and the sharing latent space , which states that the collection of similar images from various fields were mapped to similar latent .Going further, several image-to-image translation algorithms assumed that latent space of pictures had been divided into content space and method space, allowing multi-modal put outs to be generated. Huang et al.[21]

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stated a multimodal unsupervised image-to-image translation framework (munit) with two latent shows for style and content, respectively, until now.
The content coding of an image was merged with completely distinct style representations sampled from the destination fielfs to convert it to a different field.

Lee et al.[22] said that numerous image-to-image translation (drit) supported the disentangled illustration on not paired information that decomposes the latent space in 2: field-invariant content space capturing shared information and field-specific attribute space to supply multiple put outs giving a similar source. Branchgan was devised by.[23] to move a picture from one field to the other by utilizing the shared distribute of the two field' encoders. To execute multi-instance field-to-field image translation, Instagan [24] uses article segmentation masks as additional supervisors. By introducing context conserving loss, it protects the backdrop. However, because instagan relied on segmentation labels (i.e., pixel-by-pixel annotation) for training, it was limited in its applicability where such data was not available

III. METHODOLOGY

The typical GAN function and its loss, often known as the minimum & maximum loss, was in the in a paper titled "Generative Adversarial Networks" by Ian Goodfellow et al. in 2014.

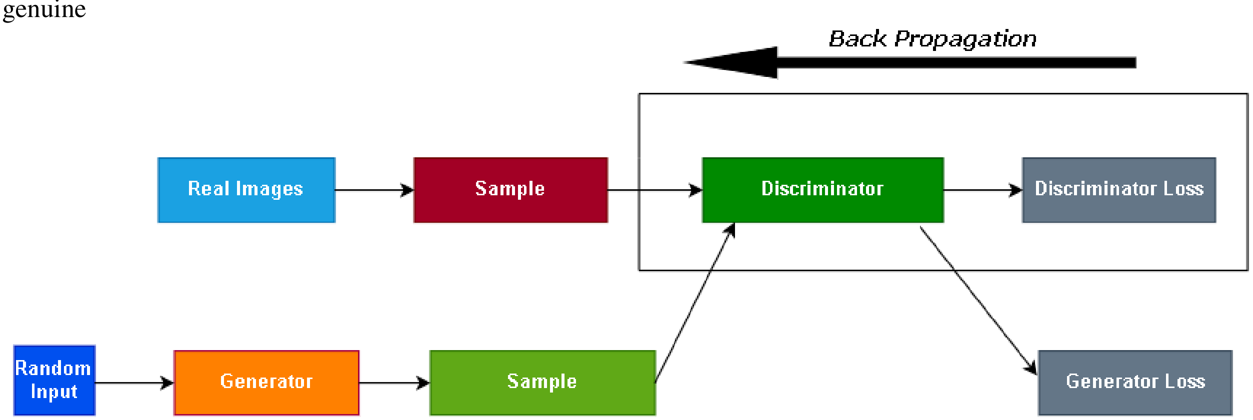
$$E_x\,[log\,log\,(D(x))\; + E_z\left[log\,log\,\left(1 - D\left(G(z)\right)\right)\right]]\quad \text{------ Eq. 1}$$

This function is minimised by the generator, whereas it is maximised by the discriminator. This description of the loss seems effective when seen as a min-max game. In actuality, it saturates for the generator, which means that if it does not match up with the discriminator, generator will frequently stop training. The loss of the discriminator and loss of generator sections of the loss function of standard GAN and can be further divided.

3.1 Loss Of The Discriminator: Referring to fig.3 below, Discriminator identifies both the genuine and false information from the generator while it is being taught**.**By maximizing the below function, it penalises itself for misclassifying real information as fake or fake scenario (made by the generator) as true**.**

$$\nabla_{\theta_d}\frac{1}{m}\sum_{i=1}^{m}\quad [log\,D(x^i) + log(1 - D(G(z^i)))]\quad \text{------ Eq. 2}$$

From referring to the above Eq. 2 ,Maximize log(1-D(G(z)) would assist in accurately identifying the fake picture that comes from the generator, whereas log(D(x)) is referring to to the chance that generator is correctly identifying the genuine



Architecture of Generator model-fig. 3

3.2 Loss Of Generator: As it is taught, the generator samples at random noise and produces an put outs. The put out is passed via discriminator, which determines whether its "Real" or "Fake" depending on discriminators ability to distinguish the two. The generating loss is calculated using the discriminator's categorization; it is rewarded if it fools the discriminator; otherwise, it is punished. The following Eq. 2, equation is minimizing to train the generator, maximizing log(1-D(G(z)) would assist it accurately classify the fake picture that emerges from the generator.

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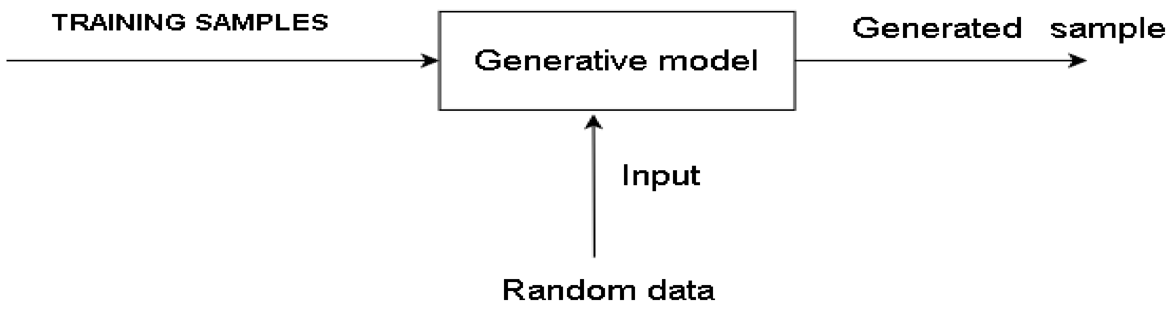
$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \quad log(1 - D(G(z^i))) \quad \text{------ Eq. 3}$$

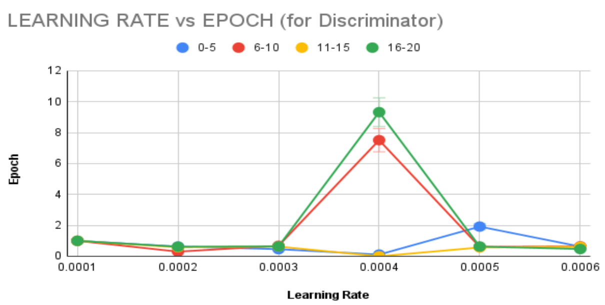
DCGAN- So far, we've looked at the GAN process; the DCGAN (Deep Convolutional GAN)is an extended VERSION of the GAN described above, with the addition of convolutional-transpose layers in the generator-discriminator framework. The discriminator is now created with strided convolution layers, batch normalizing, and Leaky Relu type activation functions, comparable to GAN, and the entire process is under the down sampling procedure. Similarly, the generator is made up of convolutional-transpose layers, and Relu and Tanh activation functions will be used. The input will be a latent space vector, such as z from the normal distribution, and the output will be in the desired pixel size. The pixels size for the final comparative output digital picture is 28x28x1 grayscale image. A convolutional layer will be present at each step, which will process the system using deconvolutions and convolutions, as well as activation functions, to change the positive and negative slopes classified during the process. In this approach, they can improve their performance by updating their parameters. For example, if the generated samples are fraudulent and not real, then back propagation will update the model weights to correct the error and generate real samples. [5] We can train a generative model generating new digits using a dataset of handwritten digits. During the training phase, we can tweak the model's parameters to minimize a loss function and learn the training set's probability distribution using an algorithm. After that, you can produce new samples using the model you've trained.

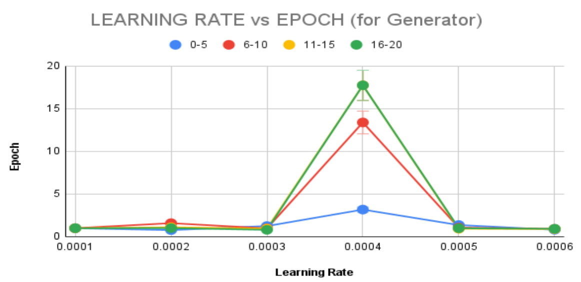


DCGAN Hand -generated System-Flow -Fig.4

Referring to figure. 4 above ,when the generator was generating new data instances, and the discriminator assesses them for reality; that is, the discriminator checks whether each sample of data it checks corresponds to the actual training dataset or not.
Meanwhile, the generator is generating new synthetic images for the discriminator to process. It does so in the hopes that they, too, will be recognised as genuine, despite the fact that they are not. The generator's objective is to generate presentable handwritten digits, allowing the user to deceive without being discovered. The discriminator's purpose is to recognise images generated by the generator as false. The discriminator can easily categorize the images generated by the generator as false or real in the early phases of training, but after a few epochs of training, the images generated by the generator become more difficult to classify.

The generating images were completely random at the start of the training process, as you can see. The generator is learning the distribution of the real data as the training goes, and after around 20 epochs, some generating digits begin to resemble real data.





Graph1-represents a comparison of x-axis(learning rate) vs y-axis (epoch) for discriminator.

Graph2 -represents a comparison of rate x-axis (learning rate) vs y-axis(epoch) for generators.

In the majority of cases, the user sets learning rates at random. At best, the user would gain an intuition about the proper value to use for determining learning rates based on previous incidents (or different types of learning material). When someone chooses a rate of learning and is training the model, they frequently just sit back and they have to wait for rate of learning to decrease for the model to tend to meet at a point over a time.

When the slope reaches a point , however, improving the loss of training becomes more difficult. The challenges of minimizing the loss, according to Dauphin et al, is due to fixed saddle points other than weak local minima. If during the process of training the model doesn't improve our loss, we'll change rate of learning every iteration using a function of cyclic " f," rather than utilizing a fixed value and gradually go on decreasing it. In terms of iterations, each cycle has a specified length. Using this technique, rate of learning can cyclically fluctuate between reasonable values of border. It's beneficial since increasing our learning rate allows us to move over saddle point plateaus more quickly if we get stuck in terms of loss generation.Here, loss generation is crucial because as far as the loss are generated the model is in the process of self-judgement and thus ultimately improvement.

Table 1

LR/Epoch	0-5	6-10	11-15	16-20
0.0001	1	1	1	1
0.0002	0.78	1.59	1.11	1.01
0.0003	1.25	0.98	0.95	0.81
0.0004	3.18	13.39	17.74	17.74
0.0005	1.37	1.07	0.94	1
0.0006	0.82	0.92	0.90	0.93

LEARNING RATE vs EPOCH FOR DISCRIMINATOR LOSSES

Table 2

LR/Epoch	0-5	6-10	11-15	16-20
0.0001	1	1	1	1
0.0002	0.63	0.30	0.58	0.62
0.0003	0.46	0.68	0.63	0.64
0.0004	0.11	7.51	0.00	9.32
0.0005	1.92	0.61	0.57	0.63
0.0006	0.63	0.64	0.62	0.47

LEARNING RATE vs EPOCH FOR GENERATOR LOSSES

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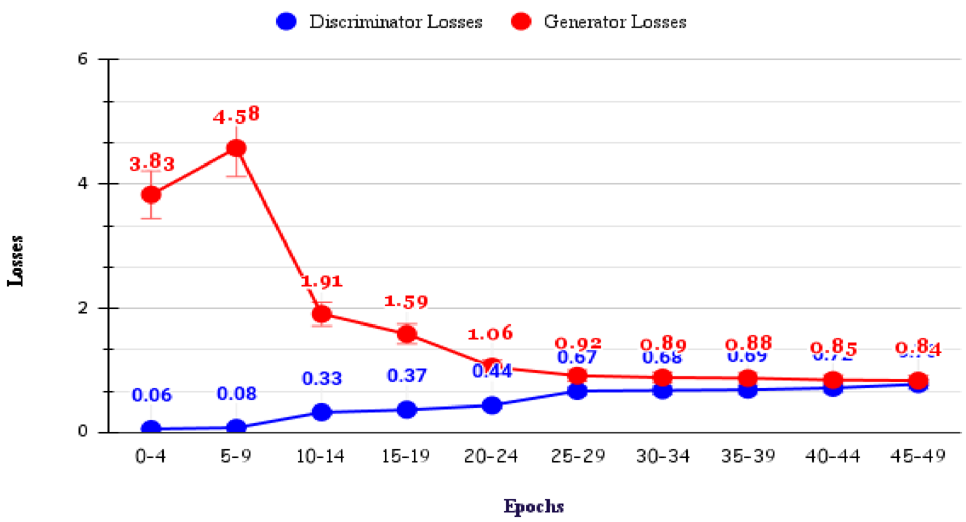

By evaluating the above chart we are able to understand that with some iteration losses of the generator and discriminator reach a equilibrium state where the losses created by the generator and the discriminator equally feed in each other thus this experimental model reached a point either of them could not fool each other and thus ml model(generator) is trained enough to satisfy the desire state of results.

Table 3

Epochs	D-LOSS	G- LOSS
0-4	0.06	3.83
5-9	0.08	4.58
10-14	0.33	1.91
15-19	0.37	1.59
20-24	0.44	1.06
25-29	0.67	0.92
30-34	0.68	0.89
35-39	0.69	0.88
40-44	0.72	0.85
45-49	0.78	0.84

EPOCH vs LOSSES

IV. CONCLUSION & FUTURE SCOPE

We discovered a method for creating our own generative adversarial networks. Before going into a use that generates pictures of written digits, we usually start with a toy example to familiarise ourself with the GAN structure. We also noticed that modifying certain mode's of the parameters had a major impact on the model's working, outcome, accuracy, and efficiency, and we eventually gained several critical insights from the hands-on experimentation. Despite the high quality of GANs, we found that machine learning libraries like PyTorch make implementation much easier by providing automatic differentiating and easy GPU setup. Even if the goal is to speed up the training process, developing effective, scalable parallel training algorithms is still worthwhile. These deep models are memory intensive and time costly during testing, making them unsuitable for deployment on mobile systems.
GANs are a hot issue in analysis, with a slew of new applications expected in the coming years. Throughout this project, we learned how to use a GAN model to generate pictures of written numerals. We also studied the difference

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between a discriminator and a generator, as well as how they're constructed and trained. DCGAN is still a realm of discovery and investigation that will undoubtedly aid in future applications, which will have a significant impact on our understanding of the most crucial components of the ml modelling technique and computer effective use.

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