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Precise GANs Classification Based on Multi-Scale Comprehensive Performance Analysis

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Abstract

GAN (Generative adversarial network) is a type of deep learning model that can generate fake data that looks real. GAN consists of two rival neural networks generator and discriminator. There are several types of GAN can be classified based on different criteria such as learning method, network architecture, application, and improvement of training. under the umbrella of learning methods, GAN can be categorized into three types, including unsupervised, semi-supervised, and supervised learning methods. Fully Connected GANs, Convolutional GANs, LAPGANs, AAEs, and Vari GANs are all subtypes of GANs that are distinguished by their respective network architectures, the quantity and composition of layers used in each style distinguishes it from the others. Application areas for GAN include computer vision and image processing, medical imaging, natural language processing, cyber security, and fault detection and tracking. In conclusion, GAN can be categorized in accordance with how training has progressed such as feature matching, probability percentages, regularization, choosing proper optimization, adding noise to discriminator, hyperparameters tuning, normalization, and weight normalization.

Keywords: GANs, GAN types, Unsupervised learning, Architecture, Stable training, Applications.

1. Introduction

Ian Goodfellow did come up with generative adversarial networks in 2014. Using two distinct duelling neural networks, this method lets computers make data that seems real. When GANs were first used, they made some amazing images; the fake images they made had the same quality as real images. GANs can turn scribbles into pictures [1]. The pairs' networks are trained at the same time to compete with one another as an art expert and a forger. In the GANs literature, the forger is referred to as the generator, and its job is to generate fake pictures that seem as legitimate as possible to fool the discriminator (art expert), who must distinguish both fake and genuine pictures [2]. Generator and discriminator networks are often constructed as multi-layer networks with convolutional and/or fully connected layers that use either multilayer perceptrons or filter banks with non-linear post-processing [3]; the network weights are learned by backpropagation in every iteration[4].Training networks need a loss function, as is the requirement with all deep learning systems, one loss function is for the generator, and another is for the discriminator. If the loss function gives a big value, the generator and discriminator networks adjust their weights and biases via backpropagation using one of several optimizers including stochastic gradient descent (SGD), Root Mean Square propagation (RMSProp), Adam, AdaGrad, and Adaptive Gradient algorithm (AGA). Therefore, both neural networks simultaneously learn [5]. It is possible to classify generative algorithms in terms of their relationship to either explicit or implicit density models. The models that constitute the distribution are defined and solved for in detail in explicit density estimation. The obstacles of computational tractability and learning from high-dimensional data are typical issues for this distribution. These generative models include the Markov chain approach (such as Boltzmann Machines), the Variational Autoencoder (VAE), and completely transparent belief networks. Constructing a model that can sample from the distribution without explicitly describing it is what implicit density estimation is about.

Generative models with implicit density include the popular generative stochastic network (GSN)[6] and generative adversarial networks (GANs)[7]. In particular, GANs have received a lot of interest as a unique class of deep generative models. This is due to the fact that they can be trained using backpropagation and do not need Markov chains for sampling, which means implicit density estimation is done by adjusting the weights of the generator and discriminant through training.

2. Training the Generator and the Discriminator

Obtaining genuine sample $\boldsymbol{x}$ at random from the provided training dataset, then obtaining a fabricated random noise $\boldsymbol{z}$ and creating a fictitious sample, x*, using the generator network, then Recognizing the distinction between x* and x using the discriminator network. Back-propagate attempts to decrease error by adjusting the biases and weights of the discriminator and generator [8]. See Fig. 1.

The Generator network uses random noise Z to create the images. The noise-generated images are saved as *G(z)*. Gaussian noise, which is a stochastic position in latent space, is often used as the input. A particular image's membership in a real distribution is determined by the discriminator network [9, 10]. GAN's loss function is based on a two-

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player minimax game, which is a zero-sum game with two neural networks competing against each other, two players are symbolized by two differentiable functions. D is the discriminator function with regard to their inputs x and weights Ө(D). G represents the generator function, whose input x and weights Ө(G) [11]. The loss functions are:

$$L(D,\theta(D)) = -Ex\sim pdata\,(x)\,[log\,D(x)] \quad (1)$$

for Discriminator

$$L(G, \Theta^{(G)}) = E_z\sim p_g\,[\log(1-D(G(z)))] \quad (2)$$

for Generator
Where the variable p_{data} indicates genuine data distribution, whereas the variable p_g indicates created data distribution.

Each competitor must account for its own loss function, D should be maximized by updating $\Theta^{(D)}$, and G should be minimized by updating $\Theta^{(G)}$. The loss functions of both competitors are depending upon that parameters of the other [15]. They are unable to update the other parameter and will continue to train unless a Nash equilibrium is reached [12, 13]. GAN is a minimax optimizer with the following loss function:

$$\min_{G}\max_{D} L(D,G)= \min_{G}\max_{D} \{Ex\sim pdata\,(x)\,[log\,D(x)] + Ez\sim pg(z)\,[log(1-D(G(z)))]\} \quad (3)$$

The first portion of equation (3) indicates that, given actual data, D maximizes the objective function. The latter signifies that, when fed with the produced data, D causes the output D (G (z)) to approach zero, while G's purpose is to bring the output D (from the generator) as near to one as possible. After the two models have been trained extensively enough, a Nash equilibrium is reached [14].

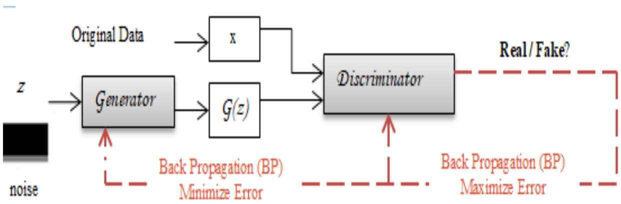

Fig. 1. Training the Generator and the Discriminator, where z denotes noise distribution, G (z) denotes the generator's samples, and x is a set of realistic data samples.

3. GAN Types and Classification

There are already hundreds of various GANs, and that number is rapidly growing. Different GANs are categorized in accordance with their respective learning methods, or GAN architectures or their application. Because of enhancements to the training network, new kinds have evolved to tackle previously intractable issues, one can name these types under an umbrella term: varieties GAN depend on the improvement of training.

3.1. Classification Based on Learning Strategies

Different GANs are categorized in accordance with their respective learning strategies: unsupervised, semi-supervised, and supervised learning methods [14]. See Figure 2.

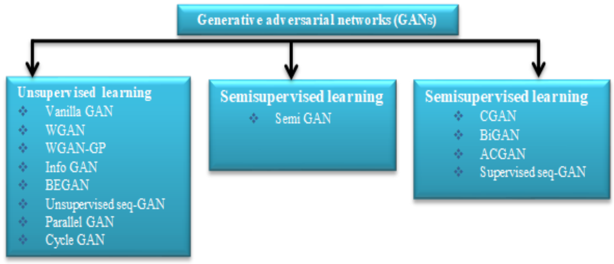

Fig. 2. GAN types classification based on learning methods.

3.1.1. Unsupervised learning

3.1.1.1. Vanilla GAN

This type is considered the first appearance of the GAN, which appeared in 2014, and is regarded as the simple type that was using the binary cross-entropy loss function. Iteratively adjusting weights and biases on every epoch until a discriminator and generator are accurately performed if the loss function produces more value than can be achieved using stochastic gradient descent (SGD) with backpropagation (Bp) The optimal value for generator is 0.5 when discriminator become unable to distinguish between fake or real data, Generator's value is determined by:

$$Generator = -\log 4 + 2 * JSD\,(Pdata(x)\,||\,Pg(x)) \quad (4)$$

where JSD is Jenson Shannon Divergence.

3.1.1.2. WGAN and WGAN-GP

"WGAN" is an abbreviation for the Wasserstein GAN, and "WGAN-GP" is an abbreviation for GAN-Gradient Penalty. As an alternative to the Jenson Shannon Divergence, the Wasserstein distance metric has been used. Weight clipping is a trouble in WGAN. To avoid it, use the Lipchitz constant, WGAN-GP is made by adding the gradient penalty term to the WGAN loss function [15]. A soft version of the restriction with only penalty for sample data on the gradient norm, So, here's what the loss function looked like [16, 17]:

$$LWGAN\text{-}GP = \min_{G}\left(\max_{w \in W} E_{x\sim pdata(x)}[D(x)] - E_{z\sim pg(z)}[D(G(z))]\right) + \lambda\, E_x\sim p_{data}\,[\|\nabla xD(x)\|-1)^2] \quad (5.a)$$

$$LWGAN - GP = Loss\ function\ WGAN + gradient\ penalty \quad (5.b)$$

The discriminator in WGAN does not give 0 or 1, instead it returns the Wasserstein distance, WGAN utilizes the root mean square propagation (RMSProp optimizer), which modifies the weights and biases of generator and discriminator for each iteration until discriminator is unable to distinguish between actual and artificial pictures. While, when using WGAN-GP, the Adam optimizer produces excellent sharp pictures [14]. Vanilla GAN, WGAN,WGAN-GP have same architecture are illustrated in figure 3.

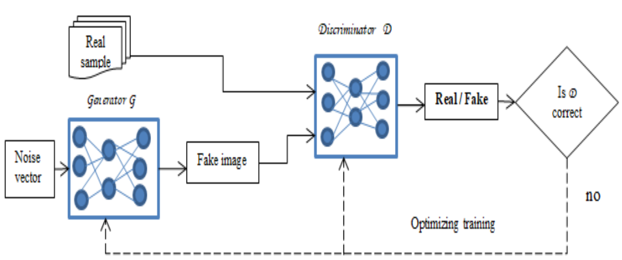

Fig. 3. Vanilla GAN, WGAN,WGAN-GP Architecture.

3.1.1.3. InfoGAN

InfoGAN stands for the semantic information (si) was added to noise, so the generator will receive information as well as the noise to create fake image, as shown in figure 4. SGD optimizer is used for adjusting weights and biases [18, 19]. The Wake-Sleep algorithm was included into InfoGAN. In the wake phase, we optimized and updated the lower limit of the generator log PG(x). During the sleep phase, designers update the auxiliary distribution Q by up sampling from a generator distribution rather than the actual data distribution [20], where loss function [21] :

$$\min_{G,Q}\max_{D} L_{InfoGAN}(G,D) = E_{x\sim pdata(x)}[\log(D(x)) + E_{n\sim pn(n)}[\log(1-D(G(n))] - \lambda \times LB(G,Q) \quad (6)$$

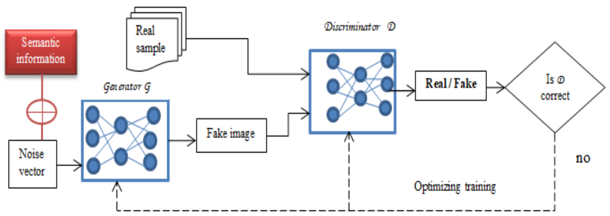

Fig. 4. InfoGAN architecture.

3.1.1.4. BEGAN

Boundary Equilibrium GAN is an acronym for this concept. This type of GAN utilized Nash equilibrium to achieve equilibrium. The architecture of *BEGAN* is identical to that of the original GAN, with just exception [23]: equilibrium preservation. The discriminator in BEGAN encodes pictures and can tell the difference between genuine and fake ones, while the generator performs the role of decoder as shown in figure 5. The loss function of D is:

$$LD = L(x) - ki * L(G(z)) \quad (7.a)$$

and to G is:

$$LG = L(G(z)) \quad (7.b)$$

the BEGAN to achieve equilibrium would use proportional control model [22]:

$$E[L(G(n))] = \gamma * E[L(r)] \quad (7.c)$$

where γ is the hyperparameter which gets the value 0 or 1.

$$Ki + 1 = ki + \lambda(\gamma k\, LD(x)) - L(G(z))) \quad (7.d)$$

where γ_k is a learning rate and k_i is an updating parameter that preserves formula, $k_0 = 0$.

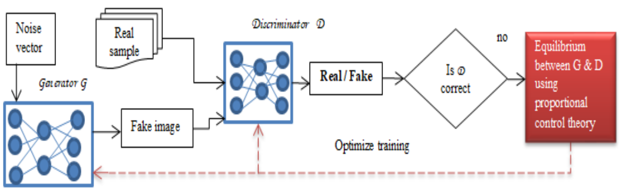

Fig. 5. BEGAN architecture.

3.1.1.5. Sequential GAN

Continually employing GAN with unsupervised learning, but the architecture of GAN has changed slightly**.** In this type of GAN, we will note that there are two generators and two discriminators. The noise is entered to Generator1 and the output is fake image1 that will enter to Generator2 to create fake image2 in sequential, while Discriminator1 and Discriminator2 is examine the fake image1 and fake image2 respectively, as shown in Figure 6.

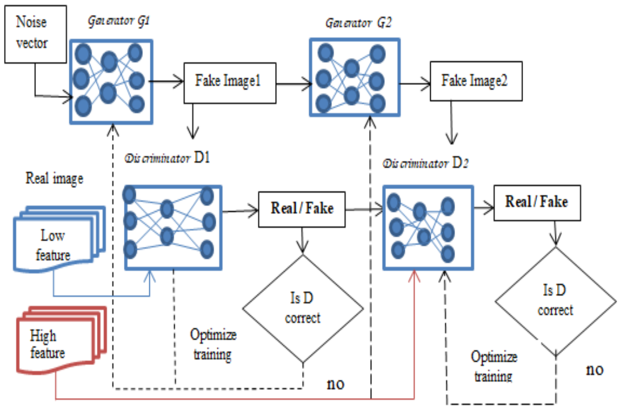

Fig. 6. Unsupervised sequential GAN architecture.

3.1.1.6. Parallel GAN

parallel GAN means that the four networks—two generator networks and two discriminator networks work in "parallel" to produce many images at the same time, see Figure 7, as though two GAN networks were communicating and operating in simultaneously [23].

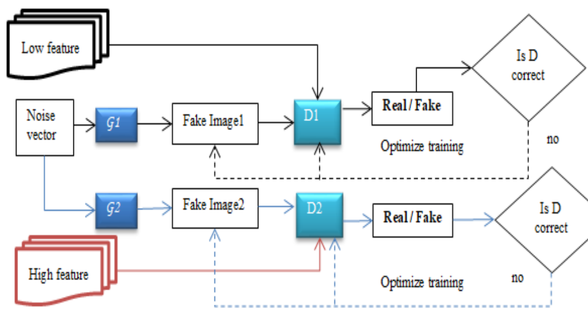

Fig. 7. Parallel GAN architecture.

3.1.1.7. Cycle GAN

Cycle GAN also have two generators and two discriminators, the first generator1 used noise vector to produced feature map that will be considered an input to generator2 Which then makes fake images as shown in Figure 8. It is worked with image-to-image translation [24]**.**

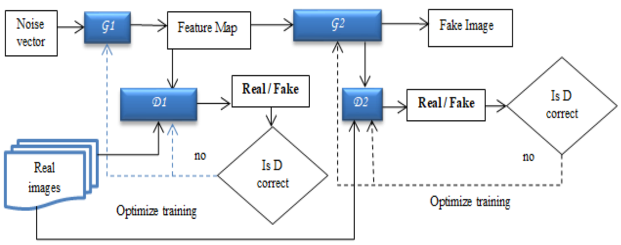

Fig. 8. Cycle GAN architecture.

3.1.2. Semi Supervised Learning
Semi-supervised learning means that the discriminator, in contrast to the Generator, be trained with labels. An example of such type is the Semi GAN**,** in this type, the discriminator network will be given a label with real sample, and this is a supervised learning characteristic. As for the generator, only noise is given without label, and this is the unsupervised learning. Thus, the GAN resulting from this architecture is semi-supervised [25] as shown in figure 9.

The loss function for generator and discriminator [26-28]:

$$LsemiGAN(D) = Ex{\sim}pdata(x)\ [log\ (D(x|c))] \qquad (8)$$

where c is a class label

$$LsemiGAN(G) = Ez{\sim}pg(z)\ [log(1\_ D(G(z)))\ ] \qquad (9)$$

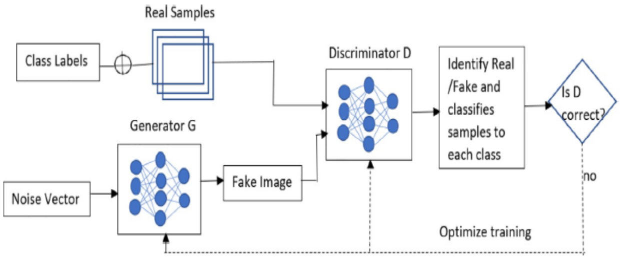

Fig. 9. Semi GAN.

3.1.3. Supervised Learning
These types of GAN learn in a supervised way, which means having labels with data.

3.1.3.1. BiGAN
BiGAN is short for bidirectional GAN [29]. The encoded image distribution, noise, and real data were used to train the discriminator as shown in Figure 10, BiGAN used SGD and backpropagation to update the weights at each iteration to make discriminator works correctly [30].

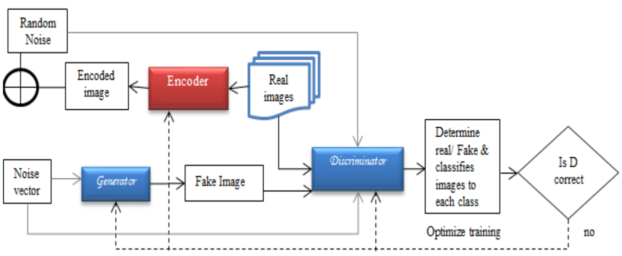

Fig. 10. BiGAN structure.

3.1.3.2. CGAN
Conditional GAN (CGAN) is the simplest type which is the same as vanilla GAN with a small difference is the addition class label to both generator and discriminator network [31]. CGANs with classifier predictions may be used for automatic image labeling, with the generator producing the tag vector distribution based on image characteristics [9].

3.1.3.3. ACGAN
ACGAN is short for *Auxiliary Classifier GAN* [32]. The architecture of the ACGAN like CGAN with a slight difference that the class label is add to noise vector then enter to generator [14]. See Figure 11. To understand the variance. The SGD also used to update the weights for both G and D until the discriminator does its job.

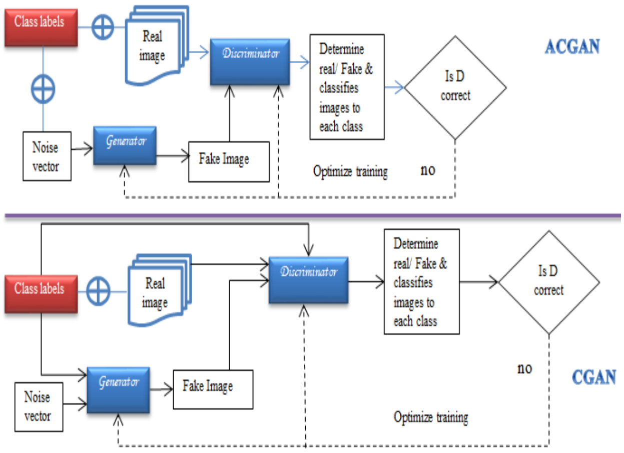

Fig. 11. Comparison ACGAN and CGAN.

3.1.3.4. Supervised sequential GAN
Supervised sequential GAN have two discriminators and two generators in sequential [33], when real sample is input to encoder to produce encoded image that will consider as input to the first generator, then the output is fake image1 which is enter to the second generator to create the fake image2, while the first discriminator has three inputs: (noise vector, encoded image, and fake image1) to determine whether it is genuine or counterfeit, and classifies a sample for each class, the second discriminator also has three inputs: (noise vector, encoded image, and fake image2) as shown in Figure 12. [34, 35].

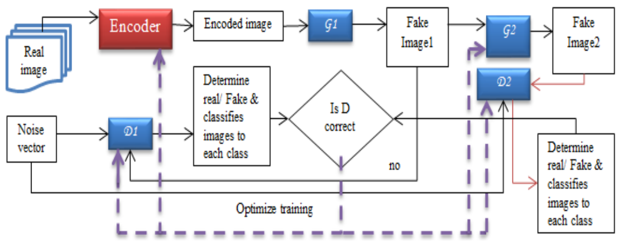

Fig. 12. Supervised sequential GAN structure.

Table 1 shorten a comparison between different types of GANs based on learning method, This table illustrate the basic types of learning method: supervised, semi-supervised, and unsupervised learning, and shows different criterions for comparison like loss function, optimizing algorithm, distance metric, activation function, and the gaps appeared in such type as well as the year of first appearance of this GAN.

Table 1. Comparison of different GANs based on learning method.

GAN	Learning Method	Optimizer Algorithm	Distance Metric	Loss Function	Activation Function	Gaps	Year Of Appearance

Vanilla GAN	**Unsupervised**	BP + SGD	JSD	Binary cross entropy Loss + min-max game theory	ReLU	For the first few iterations of back propagation, no learning will occur because when the distributions of the genuine image and the artificial image do not overlap, the JSD between the two values becomes log 2, and derivative log 2 equals zero, as expected [36].	2014 [1]
WGAN		RMS prop	Wasserstein distance	Kantorovich-Rubinstein duality loss [37, 38]	ReLU+ leaky or ReLU+ tanh	When using the Lipchitz constant, weight clipping cause low-resolution image creation [39].	2017 [5]
WGAN-GP		Adam	Wasserstein distance	Kantorovich-Rubinstein duality loss + penalty term	ReLU+ leaky or ReLU+ tanh	1. Nash equilibrium is difficult to achieve [40]. 2. Due to the fact that the gradient penalty is calculated for each data sample individually, Batch Normalization cannot be employed.	2017 [5]
Info GAN		SGD	JSD	Binary cross entropy + variational information regularization	ReLU	1. λ hyperparameter must tune precisely to produce image of high quality [21]. 2. The reciprocated information has been added to a generator that will replace the important data attributes while learning is going on.	2016 [5]
BEGAN		Adam	Wasserstein distance	Auto encoder loss	ELU	Nash equilibrium is hard to attain[41].	2017 [41]
Unsupervised seq-GAN		RMS prop	KLD + JSD	conversion loss + Binary cross entropy	ReLU	Nash equilibrium is hard to attain [42].	2018
Parallel GAN		SGD	JSD	Binary cross entropy	ReLU	Nash equilibrium is quite difficult to reach [43, 44].	2016 [23]
Cycle GAN		Batch normalization	JSD	Binary cross entropy loss + cycle consistency loss	ReLU+ sigmoid	It is challenging that image-to-image translation because of the many factors to be taken into account, such as color, texture, geometry, etc.[45].	2018 [5]
Semi-GAN	**Semi-supervised**	SGD	JSD	Binary cross entropy Loss	ReLU	The generator can't make more realistic pictures to trick the discriminator because it has been trained with labels In contrast to the generator, which is trained without a class label. [46]	2017 [28]
CGAN	**Supervised**	SGD	JSD	Binary cross entropy	ReLU	Stability in training is lacking[47, 48].	2014[5]
BiGAN		SGD	JSD	Binary cross entropy	ReLU	The real image test that is provided to the encoder should be clear, as well as the data distributions can't be too complicated or it won't work well[49, 50].	2016 [50]
ACGAN		SGD	JSD	Binary cross entropy	ReLU	Stability in training is lacking [51]	2017[5]
Supervised seq-GAN		RMS prop	KLD + JSD	Binary cross entropy, conversion loss, autoencoder loss	ReLU	If the encoder isn't provided with a high-quality, genuine sample, it won't be able to produce convincing fake images.[52]	2018 [42, 53]

3.2. Classification based on Network Architecture
When viewing the architecture of the generator and discriminator neural network, we notice that there are multiple types of GANs [54], that differ in terms of the sorts and numbers of layers used in each type, and they can be divided into five basic types [2, 9].

3.2.1. Fully Connected GANs
Fully connected neural networks (dense) were employed for both the generator and discriminator in the original GAN architectures. Three relatively straightforward image datasets—MNIST, CIFAR-10, and the Toronto Face Dataset (TFD)—were used to test this type of design [1, 9]. This type called also vanilla GAN.

3.2.2. Convolutional GANs
It is also called Deep Convolutional GANs (DCGAN) because it uses the CNN layers instead of using dense hidden layers; these layers include polling, convolutions, batch normalization, and ReLU(Rectified linear unit) and LeakyReLU activations, three datasets were used to test this new architecture: Imagenet1k , CIFAR10 and LSUN datasets[55]. Adam optimizer, learning rate of 0.0002, momentum term β1 =0.5 —all these used in DCGAN to stabilize training. See Figure 13, which illustrates the architecture of the DCGAN's generator.

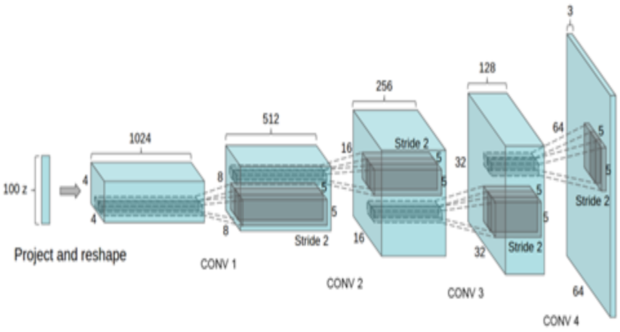

Fig. 13. Architecture of the DCGAN's generator.

3.2.3. Laplacian Pyramid of Adversarial Networks (LAPGAN)

In this architecture, upsampling and/or downsampling are used to produce high-resolution images. A Laplacian pyramid architecture consisting of a cascade layer of convolutional networks is used to generate images from coarse to fine[56].

In order to prepare the picture for generative adversarial networks, it is first downsampled by a factor of N at each layer, and then upsampled in reverse order at each layer until it is the same size as before[57, 58]. Laplacian pyramid is used Gaussian pyramid at each layer as shown in Figure 14.

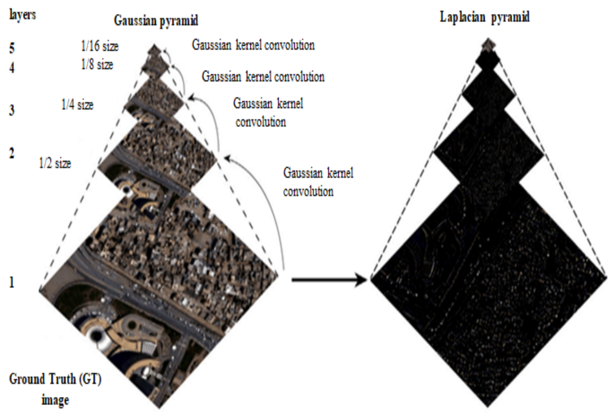

Fig.14. Laplacian pyramid is used Gaussian pyramid at each layer.

3.2.4. Adversarial Autoencoders (AAE)

Autoencoders are non-linear "encoder" and "decoder" networks, using backpropagation with unsupervised learning, the encoder and decoder parameters can be learned from the difference between the created image and the original image[59, 60]. In 2015 Makhzani et al. [60] suggested AAE that is the encoder trains to transfer the data distribution to the prior distribution, while the decoder trains to transfer the given prior to the data distribution using a deep generative network. Show Figure15 that illustrate x and latent vector z were entered to encoder while p(z) is the prior distribution and the q(z/x) is encoding distribution that will enter to decoder to get p(x/z) which is decoding distribution.

3.2.5. Vari GAN

Vari GAN is an abbreviation of variational GAN, Zhao et al. [61] in 2018, it was foreseen that cloth images would be created in a coarse-to-fine progression, with the overall appearance of the object serving as the first inference to style, followed by the creation of a coarse cloth image with a different style in low resolution, and finally, the creation of a fine cloth image in high resolution. The coarse and fine image generators used encoders and decoders, but the fine image generator also used U-net in a double way. U-Net is a type of CNN network that looks like a letter U(symmetric shape) [62]. Table 2 shorten a comparison between different types of GAN based on network architecture, This table shows different criterions for comparison like learning method, network architecture, optimizer algorithm, activation Function, year of appearance and gaps.

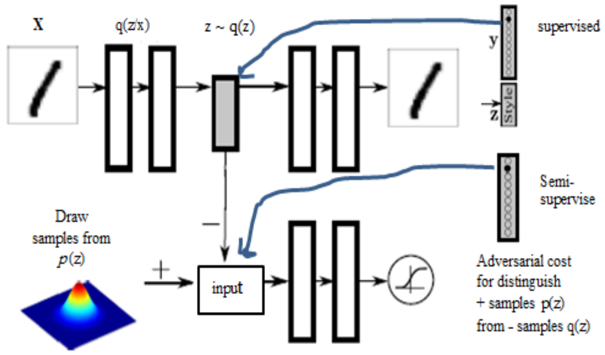

Fig. 15. An unsupervised AAE architecture becomes supervised when style and label are added, and semi-supervised when label is added with discriminator input. The upper line is a conventional autoencoder that synthesizes x given z, and the bottom line is a discriminator that is used to estimate whether a sample comes from the autoencoder's concealed code or a user-specified sampled distribution.

3.3. Classification based on Application

GANs are an incredibly great generative model for producing samples that seem realistic. Due to these benefits, GAN is used in several artificial intelligence (AI) and computer vision (CV) applications.

3.3.1. Image-to-Image Translation

It is a method for acquiring the knowledge required to convert an image from one domain to another such as translate white and black image to color image, 2D image to 3D image [64]. General approaches in this translation are Cycle-consistent GAN (CycleGAN) and pix2pix uses [65]. CycleGAN have two generators and two discriminators. The generators in CycleGAN each take an image and convert it into a representation of a certain feature. The discriminators in CycleGAN ensure that only the desired characteristics are present in the translated images. This allows CycleGAN to be used with just two domains, with each generator in charge of one domain [24]. Figure 16 illustrate how that CycleGAN application .Pix2Pix have U-Net generator and PatchGAN discriminator. When U-Net do segmentation to image that is mean part of image is converted, there are applications of the Pix2Pix shown in figure 17 [66, 67].

Table 2. Types GAN based on networks architectures Comparison

Gan	Learning Method	Network Architecture	Optimizer Algorithm	Activation Function	Year Of Appearance	Gaps
Fully Connected GANs	Unsupervised	Multilayer perceptrons	SGD, BP	ReLU	2014	It work with simple image such as black and white image.
Convolutional GANs	Unsupervised	Convolutional networks	Adam optimizer	ReLU, LeakyReLU	2015	Although easy convergence occurs, training different images needs adjusting parameters and

						suffers from vanishing gradients. [11]
LAPGAN	Supervised	cascade of convolutional networks	_	_	2015	Although LAPGAN is easy to approach and provide step-by-step independent training, it must be trained under supervision [11].
AAE	Supervised, Semi-supervised unsupervised	Multilayer perceptrons	SGD, regularization, mini-batch	ReLU	2015	It is a model that takes the best features of both GAN and VAE (forgery and semi-supervised learning, respectively) and eliminates the worst features of neither (overfitting in VAE and high training instability in GANs) [63].
Vari GAN	unsupervised	Multilayer perceptrons, U-net (CNN)	Adam optimizer	ReLU or ELU	2018	There aren't many academic papers devoted to this format, generating realistic images conditioned on the given images [61].

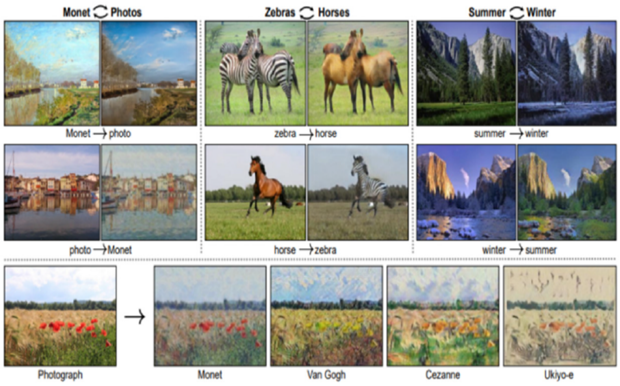

Fig. 16. Case study of Image-to-Image Translation by CycleGAN: Monet paintings to/from landscapes, Horses to/from zebras and, Summer to/from winter landscapes [65].

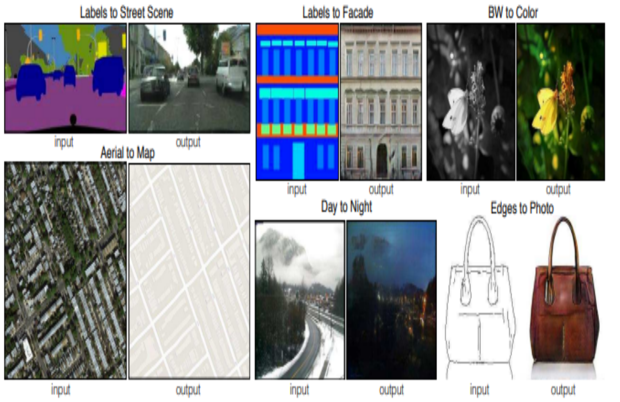

Fig. 17. Case study of Image-to-Image Translation by pix2pix: Labels to Street Scene, Labels to Facade, Aerial to Map ,Black and White to color photos, Sketch to photo, and day to knight [68].

3.3.2. Image Synthesis or Blending

Image synthesis, or blending, means that transferring visual characteristics like color, tone, texture, or style from one image to another and merging features from various images allows for novel synthesis, see figure 18. This is a type of can that needs a large and varied dataset to be able to generate new images, but in the case of the input images being few, it will cause overfitting and mode collapse [69].

Fig. 18. Case study Image synthesis or blending by DEff-GAN [69].

3.3.3. Application of GANs in Healthcare

In the medical field, GANs can help with issues such as health data generation, abnormality detection, and medical image segmentation [70].

3.3.3.1. Health Data Generation

Electronic health records (EHRs) are databases that hold medical records electronically. Full or partial exchange of EHR data is difficult due to privacy and regulatory concerns. For data scientists and researchers, acquiring EHR data is a major source of stress. Due primarily to legal issues, the wait time for EHR among data workers is extremely lengthy. It also slowed down the progress of most medicinal studies. To address the challenge of collecting high-quality EHR data, GAN can be used to generate convincing artificial data. There are no regulatory barriers to sharing high-quality fake data. And that will hasten the entire process of collecting data for medical studies. Synthetic patient medical data are generated by a medical adversarial network (medGAN) [71]. Figure 19 shows uses medGAN to improve the quality of the medical brain image.

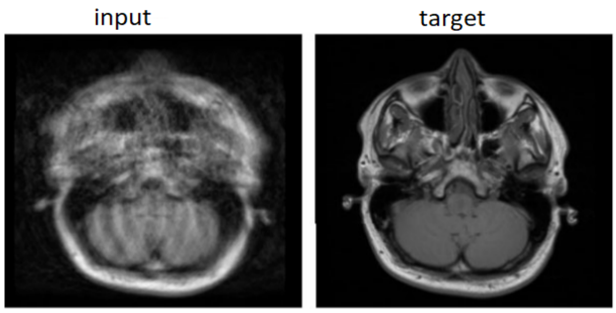

Fig. 19. Case study of health data generation by medGAN.

3.3.3.2. Medical Image Segmentation

It is the method by which edges in a 2D or 3D medical image are identified automatically. Segmentation is a significant difficulty when dealing with medical images. The image must be segmented into relevant zones so that doctors can recognize tumors and other semantically related regions. Tumor detection and volume estimation are also completed following this segmentation process. The image must be segmented into relevant zones so that doctors can recognize tumors and other semantically related regions. Tumor detection and volume estimation are also completed following this segmentation process. Segmentation GAN (segAN)is Hybrid convolutional neural network & U-Net [72]. Figure 20 illustrate how segment tumor from medical image of brain.

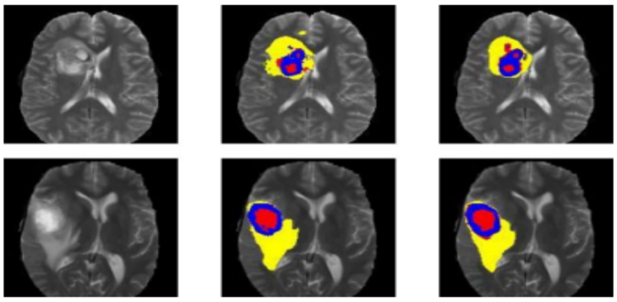

Fig. 20. case study of segmentation tumor of brain by segAN.

3.3.3.3. Abnormality Detection

Anomaly GAN(AnoGAN) is used to Find strange things in medical images, detect and classify image anomaly, or develop an image anomaly prediction system [73, 74]. The use of imaging techniques in medicine is crucial for the accurate diagnosis of many diseases. Automatic image analysis using deep learning is gaining popularity to help radiologists save time and effort in making diagnoses. Yet such approaches need the time-consuming and labor-intensive annotation of pictures, which is itself challenging, expert-heavy, and resource-intensive. Because of this, AnoGAN have been developed to aid radiologists in automatically detecting and localizing probable problems with minimal to no annotations as shown in figure 21 [75].

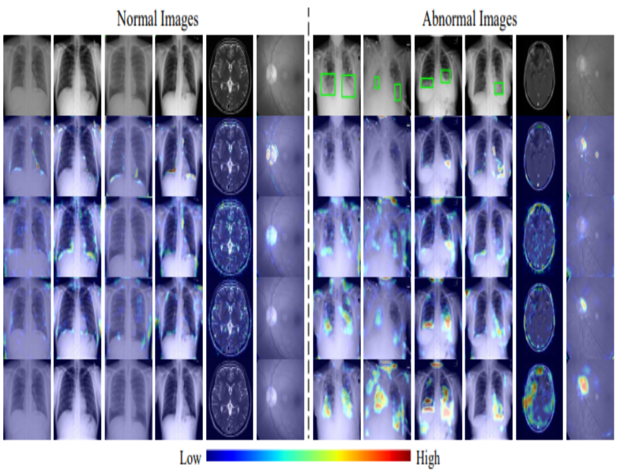

Fig.21. The anomalous areas are denoted by the green boxes [75].

3.3.3.4. Financial

By providing a new economics-based loss function for the generator, supervised learning may be applied to Generative Adversarial Networks. When applied to daily stock market data, Financial GAN (Fin-GAN) achieves higher Sharpe Ratios than a set of benchmarks while also generating distributional forecasts and uncertainty estimates. Profit-and-loss (PnL) metrics are typically used when making financial forecasts since they help choose which side of a transaction to take (buy or sell) [76].

There are several GAN kinds, each of which is utilized for a certain application[9, 77]. Table3 illustrates these applications and their branches and associates each GAN with the appropriate application and what the input and output dataset.

3.4. Classification Based on Training Improvement

The key problems with GAN training that causes instability, vanishing gradients, mode collapse, and convergence problems. This problems can be solved by techniques and/ or Stabilization Heuristics such as regularization, choosing proper optimization, normalization and noise injection [78]. The solution consider improvement for GAN which produce new types. The problems are the following.

3.4.1. Vanishing Gradients Problem

This problem means that the discriminator is active, it predicts confidently in real samples, which impacts the generator's trainability, so a discriminator may prevent the generator from learning the distribution of data. While the produced and original samples are too dissimilar in early training, an optimum discriminator does not supply enough information to the generator to proceed ahead [79]. In this situation, the generator's training is so slow that it may fail because the gradient for the Jensen-Shannon divergence disappears, to address this issue, many alternative loss functions and extended types of GANs, like the Wasserstein GAN, which use the Wasserstein distance, have been suggested [80], in addition improvement of min-max loss which has been recently suggested to address the vanishing gradient issue [5].

3.4.2. Mode collapse problem

This problem means that generator when it generates a real samples to the discriminator and learn repeatedly in every iteration, consequently, the generator only creates a small pool of samples, the diversity among generated samples is unsatisfactory [81]. **To solve** this problem there are several solutions such as the Wasserstein loss, gradient penalty (as in WGAN-GP) [82], unrolled optimization of the discriminator, using implicit variational learning [83], boosting generative models, balance the generator's and discriminator's training [84], mini-batch discrimination for discriminator and alleviate the over-optimization of the generator.

3.4.3. Convergence problem

This problem appear when the model parameters space of generator and discriminator are diverging, or oscillating behavior, It is challenging to train two GAN rival neural networks to produce a stable model because of the min-max game is neither convex nor concave. Finding the equilibrium called the Nash equilibrium (NE) between the generator and the discriminant is difficult because instead of reaching the global (NE), it approaches the local (NE) [85].

A generator creates samples that are significantly different from the original distribution and too simple for the discriminator to categorize, while the discriminator's loss quickly approaches zero. To solve this problem uses: regularization, noise addition to the discriminator, weight penalty, appropriate choice of the optimization function (such as the Adam optimizer), and selection and tweaking of the hyperparameters(e.g., batch size and learning rate), these solutions are a viable for remedy for the GAN convergence failure [84]. These three basic of training problems are often highly linked with each other and addressing them often takes character of a trade-off [78], as shown in figure 22.

There are many other problems, such as **overfitting** of generator with the current discriminator, the feature matching is used to prevent this problem, or dropout regularization. **overconfidence** in the prediction of discriminator is also consider problem in training and the solution is used one-sided label smoothing. Table 4 shorten a comparison between different types of GANs based on improvement of GAN training, shows different criterions for comparison like problems of training, improvement, GAN name, advantage, and year of appearance.

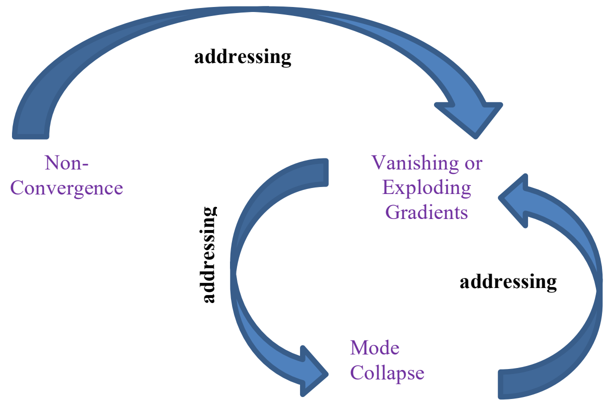

Fig.22. stability training problems.

Table 3. Types of GAN based on applications.

Applications	Branches	GAN name	Input	Output
Image processing and computer vision	Image synthesis or blending	Data-Efficient GAN (DEff-GAN) [69] Coupled GAN [86]	Two images or more	One image
	improve the image quality	SRGAN [5]	image	High quality image
	Image-to-image translation	CycleGAN [65] Pix2pix [68]	Image from source domain	Image in Target domain
Application of GANs in Healthcare	Abnormality detection	MADGAN [87] AnoGAN [75]	Medical Image (x-ray image).	Medical Image with annotations of diagnosis of the disease type.
	Medical image segmentation	SegAN[9] [72]	Medical image	Prediction & segmentation of tumor.
	Health data generation	medGAN [71]	(EHRs)/ Medical image Positron Emission Tomography(PET)	(EHRs)/ Medical image Computed Tomography (CT)
Natural Language Processing [88]	Text Generation	BFGAN	text	text
	Text -to-image translation	Stack GAN TAC-GAN	text	image
Cyber Security [89]	Security analysis Intrusion/Malware detection [90] Steganography	CGAN Vanilla GAN	Image + secret message	Secure Image Steganography
Fault Diagnosis and Monitoring	Smart grid fault diagnosis	GBSS [91]	diagnostic system	Analyzing two power grid situations to identify assaults and flaws
Finance	Predicting time series	Fin-GAN [76]	financial data	Forecasting buy or sell

Table 4. Improvement of GAN training.

Problems	Improvement		Gan name	Advantage (new feature)	Year
Overfitting problem	feature matching		McGAN	provide a stable training environment for GANs, reducing the loss between distributions significantly.	2017 [92]
	probability percentages		variational GAN	Uses in text, image generation and text style transfer. This model was stable training	2020 [93]
	Regularization		GAN	More stable, easy convergence	2017 [94]
Convergence problem	choosing proper optimization	stochastic Gradient descent (SGD)	Vanilla GAN	image generation	2014 [1]
		Root Mean Square propagation (RMSprop)	Seq2Seq GAN	generate video future predictions based on previous video for city	2020 [95]
		adaptive moment Estimation(ADAM)	CFC-GAN	address issues caused by a limited sample size, elevate the rate of convergence and generalizability of the model.	2021 [96]
	Adding noise to discriminator		PA-GAN	promotes healthy competition between the generator and discriminator, which in turn improves the performance of the generator.	2018 [97]
	Hyperparameters tuning		InfoMax-GAN, SSGAN	enhances the effectiveness of GANs in creating synthetic images, Prevention of Collapse Mode.	2021[98]
	Normalization	Batch Normalization (BN)	Fisher GAN	not need weight clipping, stable GAN, not hinder the discriminator's ability.	2017 [99]
		Weight	GAN	produce samples better quality as GAN models	2017

		Normalization(WN)		without normalization, train quicker & more stable than BN.	[100]
		Spectral Normalization	SC-GAN	Based on 3D conditional GAN, guarantee the training process is stable and the optimization converges.	2020 [101]
Vanishing gradients Mode collapse problem	mini-batch discrimination		Bayesian GAN	avoids mode-collapse for generator.	2017 [102]
	Use a different loss function like the Wasserstein distance.		WGAN	Use also norm clipping, weight normalization and batch normalization in discriminator.	2017[15]
	Gradient Penalty		WGAN-GP	Steadier production of new, high-quality data samples.	2022 [103]
	unrolled optimization		UGAN	several novel Internet of Things applications have been developed utilizing GAN.	2021 [104]

4. Conclusions

This article shows classified GAN types based on learning methods, architecture, application in different domains, and improvement of training. Different criterion for comparison between different types of GANs were illustrated based on learning methods, and showed different milestones for comparison like loss function, optimizing algorithm, distance metric, activation function, and gaps. The basic branches: supervised, unsupervised, and semi-supervised learning. Depending on the architecture of GAN can be further classified into five classes, each class different from anther in network architecture, learning method, optimizer algorithm, activation function, and gaps that suffer from it.

GAN has multiple types in various fields such as Healthcare, finance, Natural Language Processing, Fault Diagnosis and Monitoring, Cyber Security and computer vision. The paper showed the key problems that causes instability of the GAN: Convergence Vanishing gradients Mode collapse problems, and the types that appear when addressing this problem.

We observe that many researchers still continue to propose further types of GAN, this study, in our opinion, can assist researchers in choosing the best techniques for certain neural network topologies and in better comprehending the drawbacks of current techniques in order to create new techniques that address such drawbacks.

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