Understanding Generative Adversarial Networks (GANs): A Review

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***Abstract*—Generative Adversarial Networks (GANs) is an important breakthrough in artificial intelligence that uses two neural networks, a generator and a discriminator, that work in an adversarial framework. The generator generates synthetic data, while the discriminator evaluates the authenticity of the data. This dynamic interaction forms a minimax game that produces high-quality synthetic data. Since its introduction in 2014 by Ian Goodfellow, GAN has evolved through various innovative architectures, including Vanilla GAN, Conditional GAN (cGAN), Deep Convolutional GAN (DCGAN), CycleGAN, StyleGAN, Wasserstein GAN (WGAN), and BigGAN. Each of these architectures presents a novel approach to address technical challenges such as training stability, data diversification, and result quality. GANs have been widely applied in various sectors. In healthcare, GANs are used to generate synthetic medical images that support diagnostic development without violating patient privacy. In the media and entertainment industry, GANs facilitate the enhancement of image and video resolution, as well as the creation of realistic content. However, the development of GANs faces challenges such as mode collapse, training instability, and inadequate quality evaluation. In addition to technical challenges, GANs raise ethical issues, such as the misuse of the technology for deepfake creation. Legal regulations, detection tools, and public education are important mitigation measures. Future trends suggest that GANs will be increasingly used in text-to-image synthesis, realistic video generation, and integration with multimodal systems to support cross-disciplinary innovation.**

Keywords*—Generative Adversarial Networks (GANs), Mode Collapse, Deepfake, Synthetic Data, Training Stability

I. INTRODUCTION

Generative Adversarial Networks (GANs) is one of the fundamental innovations in the field of artificial intelligence that was first introduced by Ian Goodfellow in 2014 [1]. GANs uses a generative approach involving two neural networks, namely a generator and a discriminator, which interact in a competitive framework [2]. The generator serves to generate synthetic data that resembles real data, while the discriminator is tasked with evaluating the authenticity of the data by distinguishing between real data and data generated by the generator [3]. Through an iterative training process, GANs is able to generate highly realistic data, thus supporting various data-driven technology applications. This approach reflects significant advances in machine learning, especially in replicating and understanding the complexity of real-world data.

The main advantage of GANs lies in the adversarial training mechanism that enables unsupervised learning more effectively than conventional approaches. GANs have made significant contributions in various sectors, both in research and practical applications. In healthcare, researchers utilise GANs to generate synthetic medical images that resemble the original data, such as MRI and CT scans, which support the development of diagnostic models without violating patient privacy [4]. In the media and entertainment sector, GANs revolutionise the content creation process by creating nearreality images, videos and animations [5]. The gaming industry is using GANs to create more realistic virtual environments and textures [6]. The manufacturing sector is leveraging this technology to optimise product prototype design through synthetic data-driven simulations, ultimately improving production efficiency and innovation cycles. Future trends show that GANs are increasingly being used for applications such as text-to-image synthesis, where models are able to convert text descriptions into images, as well as video generation to automatically create realistic videos.

GANs have great potential, but their development faces various complex technical challenges. One of the main challenges is mode collapse, which is a condition where the generator produces a monotonous and less variable output [7]. Training instability is often a major obstacle, which makes generators prone to mode collapse due to imbalance with the discriminator [8]. Evaluation metrics such as Inception Score (IS) and Fréchet Inception Distance (FID) are also considered inadequate to thoroughly assess the quality of synthetic data. These challenges encourage researchers to develop new techniques that can stabilise training, increase data diversification and provide more reliable evaluation tools.

In addition to technical challenges, GANs also present significant ethical challenges. The technology can be used to create deepfake content, which is often used unethically in information manipulation [9]. There is a need to develop deepfake detection tools and regulations to limit the misuse of this technology. This article also makes a unique contribution by discussing GANs stabilisation strategies and their ethical implications in greater depth than previous reviews.

Various innovations have been developed to address the challenges of GANs. Architectures such as Conditional GAN (CGAN), Deep Convolutional GAN (DCGAN), Cycle GAN, Style GAN, Wassertian GAN (WGAN), Big GAN enable better control over the variation of the generated images as well as adaptation to various specialised applications. Other techniques such as progressive growing have been applied to increase the diversification of the generated data. The evaluation of synthetic data quality is also further enhanced by the use of more complex metrics, including human perception-based approaches.

This article aims to provide a comprehensive overview of GANs, covering their basic concepts, key architectures and applications in various sectors. It also discusses the technical and ethical challenges in the development of GANs and explores recent innovations that can improve the performance of this technology

II. Basic Concept of GANs

A. Basic Structure

GANs consists of two core components, namely generator (G) and discriminator (D), which work in an adversarial framework to generate synthetic data that resembles the original data. The main concept of GANs can be seen in Fig. 1.

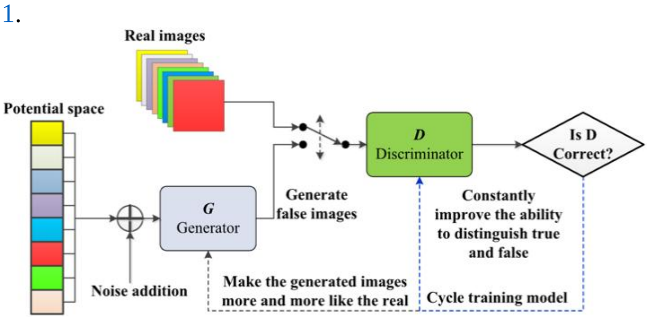

Fig. 1. The schematic of general GANs [10]

Based on Fig. 1, G is tasked with generating synthetic data based on random noise vectors that are transformed through neural networks into data with characteristics resembling the training dataset. G is continuously updated to produce increasingly realistic data that can fool the discriminator. The other component, the Discriminator (D), is a neural network designed to distinguish between real and synthetic data. Its main function is to provide a probabilistic evaluation of the input data, both from the original dataset and from the generator, to determine whether the data is real or fake. The dynamic interaction between these two components forms a competitive framework, where the generator and discriminator compete with each other to improve their respective performance in achieving an optimal equilibrium.

B. Training Process

GANs are designed to understand specific data distribution patterns, thus enabling the generation of synthetic data that resembles the original data for various real applications. During the training process, the generator uses feedback in the form of loss values provided by the discriminator to improve the quality of the data it generates [11]. The generator's loss value is calculated based on its ability to deceive the discriminator, i.e. by creating synthetic data that is perceived as real data by the discriminator. Conversely, the discriminator seeks to maximise its ability by increasing its accuracy in distinguishing between the original data and the synthetic data. Goodfellow described the GANs algorithm as a min-max game, where the value of the function V (D, G) is determined based on the standard GANs loss function [3].

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}\left[\log\left(1 - D\big(G(z)\big)\right)\right] \tag{1}$$

Where

$D(x)$	:	The probability given by the discriminator that x is the original data
$G(z)$	:	Data generated by the generator of noise z
$p_{data}(x)$	:	Original data distribution
$p_z(z)$	:	Noise distribution.

The generator generates synthetic samples $G(z)$ using a random noise vector z as input, while the discriminator evaluates the original samples x from the training data as well as the synthetic samples $G(z)$generated by the generator. The interaction between the two is governed by the objective function $V(D,G)$. In this context, p_{data} represents the original data distribution from which the real samples are taken, whilepz is the distribution from which the noise vector is sourced. The generator aims to minimise this function, while the discriminator seeks to maximise it. The loss function consists of two main components, namely the loss in the generator and the loss in the discriminator.

The GANs network is designed to achieve a Nash equilibrium within the framework of game theory due to its adversarial nature. During the training process, the generator and discriminator loss functions are used as the basis for gradient calculation, which is then applied to update the weights and biases of each network using the stochastic gradient descent (SGD) method. The training is assumed to take place without any internal or external optimisation loops, so both models are not expected to achieve full convergence. The optimisation process is performed iteratively with the aim of reaching an equilibrium point. At that point, the generator is expected to produce realistic samples that can fool the discriminator, while the discriminator gradually loses its ability to accurately distinguish between the original and synthetic samples. Fig. 2. shows the GANs architecture used to generate generative data.

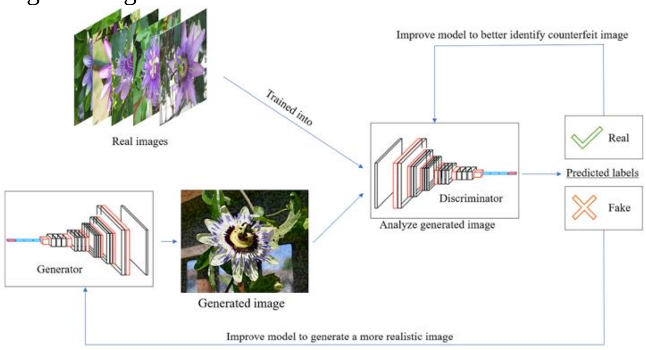

Fig. 2. A simple architecture of GANs [12]

C. Model Evaluation

The evaluation of the GANs model aims to assess the quality and diversity of the synthetic data generated. One of the key metrics is the Inception Score (IS), which measures the clarity and diversity of the data through Kullback-Leibler (KL) divergence [13]. IS is formulated as:

$$IS = exp(\mathbb{E}_x [D_{KL}(p(y|x)||p(y))]) \quad (2)$$

Where $p(y \mid x)$ is the probability distribution of predicted labels for synthetic data x, as given by the Inception model. p(y) is the marginal distribution of $p(y \mid x)$. DKL is the Kullback-Leibler divergence which measures the difference between two distributions.

Fréchet Inception Distance (FID) is used to compare the original and synthetic data feature distributions in the Inception model feature space [14]. FID calculates the distance between the mean and covariance of the two distributions, which is formulated as:

$$FID = \left|\left|\mu_r - \mu_g\right|\right|^2 + \mathrm{Tr}\left(\Sigma_r + \Sigma_g - 2\left(\Sigma_r\Sigma_g\right)^{1/2}\right) \quad (3)$$

Where μ_r ,Σ_r is the mean and covariance of the original data features. μg, Σg is the mean and covariance of the synthetic data features. Tr is the trace of the matrix.

Metrics such as Kernel Inception Distance (KID) are also used to evaluate the similarity of the original and synthetic data distributions without the Gaussian assumption. KID is formulated as follows:

$$KID = E_{x\sim p_{data}, y\sim p_{gen}}[k(x,y)] \\ -E_{x,x'\sim p_{data}}[k(x,x')] - E_{y,y'\sim p_{gen}}[k(y,y')] \quad (4)$$

Where $k\ (x,\ y)$ is a kernel function to measure the similarity between the original data$x$ and the synthetic data y. Precision in GAN evaluation measures the extent to which the synthetic data generated by the generator really resembles the original data. Precision can be formulated as:

$$Precission = \frac{|Synthetic\ Data\ that\ Looks\ Like\ Real\ Data|}{|Total\ Synthetic\ Data|} \quad (5)$$

Recall measures the extent to which the generator covers all modes in the original data distribution, i.e., the success of the generator in generating data variations. Recall can be formulated as:

$$Recall = \frac{|Synthetic\ Data\ that\ Looks\ Like\ Real\ Data|}{|Total\ Synthetic\ Data|} \quad (6)$$

III. GANS VARIANTS AND ARCHITECTURE

A. Vanilla GAN

This architecture refers to the original GAN architecture proposed by Goodfellow and his colleagues in 2014 [1]. This architecture consists of only a generator network and a discriminator network. The architecture is based on an adversarial learning mechanism where both networks are trained iteratively in a min-max game process.

Although this architecture is simple, it has been the basis for many subsequent GAN developments. This adversarial learning principle has been applied in various generative applications, such as realistic image generation, image resolution enhancement, and synthetic data generation for training artificial intelligence models.

B. Conditional GAN (CGAN)

Conditional Generative Adversarial Networks (Conditional GAN) is an extension of the GAN architecture that allows controlling the output results by adding conditional information as input (Fig. 3). In wireless communications, Conditional GANs are used to model channel effects in a data-driven manner, providing a more accurate representation of dynamic channel conditions [15]. By adding the received signal from the pilot symbol as conditional information, the GAN can learn the relationship between input and output contextually.

One of the main advantages of CGAN in communication systems is its ability to efficiently bridge the Deep Neural Networks (DNN) of the sender and receiver. The conditional information derived from the pilot signal allows CGANs to learn the deep relationship between input and output, thus creating a model that understands the context of the communication channel [16]. With the ability to model channel effects, the gradient from the receiver DNN can be back-propagated to the sender DNN through the GAN. This process allows the sending DNN to iteratively learn to optimise the sending parameters to improve the decoding quality at the receiver side.

One of the major challenges in communication data processing is the high dimensionality of data, such as long sequences of symbols. To address this, the CGAN architecture uses a convolutional layer designed to reduce dimensional complexity without sacrificing important information [16]. This layer is designed to efficiently reduce the dimensionality of the data, while retaining the critical information needed to accurately model the communication channel. This approach makes CGAN effective at modelling a wide range of communication channel conditions, including channels with Gaussian noise, Rayleigh fading, and frequency selectivity. These capabilities make CGAN a highly adaptive model for end-to-end communication systems in dynamic environments. CGAN has been applied in various fields, including image-to-image translation and text-to-image generation, as well as used for data augmentation in machine learning [17].

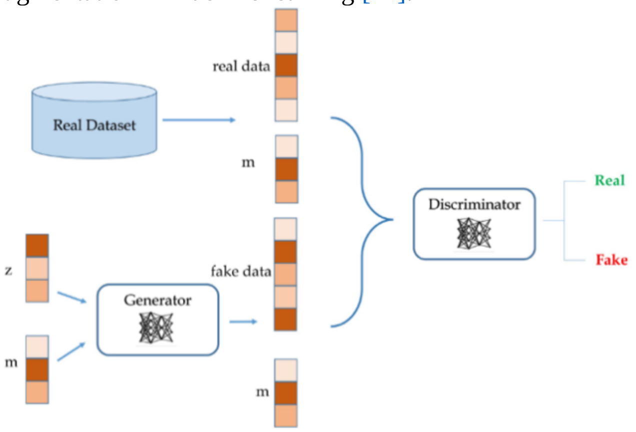

Fig. 3. Conditional GAN architecture [16]

While offering significant advantages, CGAN implementation faces several challenges. One of them is the need for high-quality condition labels, which are often difficult to obtain in practice. Training stability remains an issue, as CGANs must achieve a balance between generators and discriminators in the learning process. Nevertheless, research continues to focus on improving the CGAN architecture, including the development of more stable and efficient optimisation methods. With its vast potential and flexibility, CGAN remains a very important generative tool in many modern applications.

C. Deep Convolutional GAN (DCGAN)

Deep Convolutional Generative Adversarial Networks (DCGANs) are a development of convolutional network architecture designed for unsupervised learning [18] (Fig. 4). DCGANs integrate convolutional networks (CNNs) into the GAN structure by applying certain architectural constraints to improve training stability and the quality of the resulting representation. In DCGANs, the generator is responsible for creating synthetic data that resembles the real data, while the discriminator is responsible for distinguishing between the real data and the generated data. Through this adversarial interaction, DCGANs are able to learn the hierarchy of visual representations in depth, covering details such as texture, shape, and inter-object relationships.

The main advantage of DCGANs lies in its ability to learn data representations without explicit labels, making it an effective tool for unsupervised learning. During training on various image datasets, DCGANs proved to be able to deeply understand visual structures at both the generator and discriminator levels [19]. The resulting representations include details such as texture, shape, and patterns of relationships between objects, all of which are obtained without human intervention in the labelling process.

DCGANs also show great flexibility by applying the learnt features to various new tasks, such as image classification or analysis [20]. This capability proves that the generated features can serve as a generalised image representation. With its ability to generate high-quality data and understand data structures, DCGANs opens up new opportunities in the development of computer vision technology based on unsupervised learning.

Despite their significant advantages, DCGANs still face several challenges, such as the need for optimal training stability and the risk of mode collapse, where the generator fails to generate sufficient data variation [21]. To address these issues, recent research has focused on architectural innovations and more efficient optimisation techniques. As such, DCGANs continue to be one of the leading approaches in unsupervised learning and visual data-driven technology development.

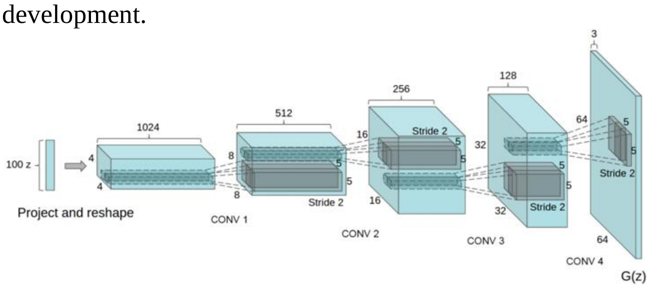

Fig. 4. DC GAN architecture [22]

D. Cycle GAN

Cycle-Consistent Generative Adversarial Network (CycleGAN) is a deep learning model designed to perform image transformation between two domains without requiring corresponding image pairs [23] (Fig. 5). In contrast to traditional GAN models, CycleGAN uses cycle consistency loss, which ensures that the transformation from the origin domain to the target domain, then back to the origin domain, retains the main characteristics of the original image [24]. This architecture makes CycleGAN ideal for tasks such as artefact removal, image quality enhancement and visual style adjustment.

In medical applications, retinal fundus image processing, CycleGAN is used to remove artefacts, including haze, glare, eyelash shadows and uneven lighting, which often reduce the quality of fundus images and increase the risk of misdiagnosis [25]. Using CycleGAN, such artefacts can be removed automatically without losing important information in the retinal image. This process improves the automatic quality evaluation (AQE) of the resulting images, demonstrating the success of this technique in improving image quality. CycleGAN is widely used in image style transfer, including visual style adjustment and image quality enhancement, demonstrating its versatility in various image processing applications [26].

CycleGAN still faces several challenges, such as limited image resolution and the need to preserve fine details in image transformation. Therefore, recent research has focused on developing techniques that improve image resolution and maximise the preservation of visual details, especially for high-precision applications such as medical image analysis. With continued innovation, CycleGAN has great potential to become one of the key tools in deep learning-based image processing, supporting needs across industries ranging from healthcare to digital art.

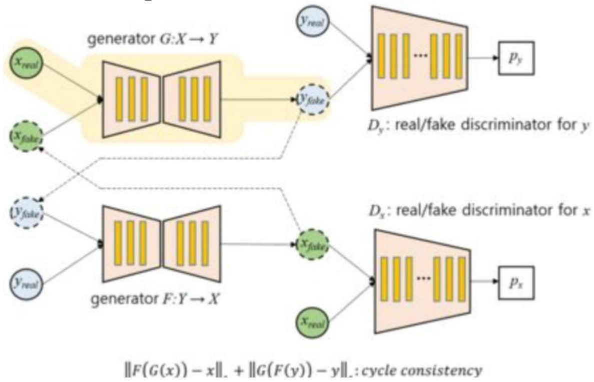

Fig. 5. Cycle GAN architecture [27]

E. Style GAN

StyleGAN is an innovative generator architecture in GAN inspired by the style transfer literature (Fig. 6). It is designed to separate high-level attributes, such as pose and identity (especially when trained on human face data), from stochastic variations in the generated images, such as texture spots or hair elements [28]. This approach allows StyleGAN to provide intuitive control over image synthesis at multiple scales, thus increasing flexibility in generating images with more natural variations.

StyleGAN's main advantages lie in its ability to improve the quality of image distributions generated based on traditional metrics, provide better interpolation, and separate latent factors more effectively. With this architecture, the variables that affect image variation can be manipulated separately, enabling the creation of realistic and controlled synthetic images [29]. To evaluate the interpolation quality and separability of latent factors, StyleGAN introduced two new methods that can be adopted by other generator architectures [30].

As part of its development, StyleGAN is equipped with a highly variable and high-quality human face dataset, which supports the training of models to produce realistic facial images. Through this approach, StyleGAN sets new standards in image synthesis, makes significant contributions to generative research, and opens up new opportunities in a wide range of application areas. Through a combination of innovative architecture, new evaluation metrics, and the use of quality datasets, StyleGAN sets a new standard in image synthesis. The model makes significant contributions to research in the generative field and opens up vast opportunities for various applications, including visual content creation, precise image editing, and the development of more realistic virtual reality technologies.

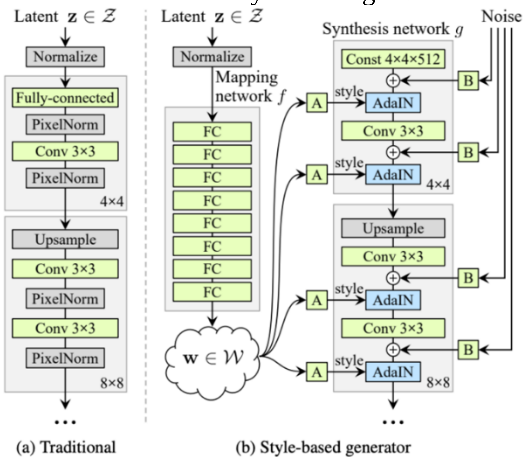

Fig. 6. Style GAN architecture [31]

F. Wassertian GAN (WGAN)

Wasserstein GAN (WGAN) is a variant of GAN designed to overcome the challenges of training stability and mode collapse in traditional GAN (Fig. 7). WGAN replaces the probability-based loss function with the Wasserstein distance (Earth Mover's Distance), which is more stable and effective to optimize [32]. This distance is used to measure the difference between the real data distribution and the generated data distribution, thus providing a more informative gradient signal during the training process.

The main advantage of WGAN lies in its ability to train the generator more stably, including in situations where the discriminator performs very well. To maintain the Lipschitz constraint, WGAN uses a weight clipping technique keeps the model in the optimal solution space. This technique has limitations such as producing suboptimal gradients. In further development, variants such as WGAN-GP (Gradient Penalty) introduce regularization instead of weight clipping, which improves efficiency and produces high quality and stable models [33]. The WGAN approach and its variants have been widely applied in various fields, including image synthesis, distributional data modelling, and other applications that require high stability in generative model training. These approaches not only improve training efficiency, but also produce more stable and high-quality models.

G. Big GAN

BigGAN is an evolved GAN architecture designed to generate high-resolution and high-diversity images from complex datasets such as ImageNet [34] (Fig. 8). By training GANs at a scale that has never been attempted before, BigGAN is able to overcome the challenges of training instability that often occur in large-scale data processing. One of the key innovations in BigGAN is the application of orthogonal regularization to the generator, which enables the application of the truncation trick [35]. This technique provides finer control over the trade-off between sample fidelity (quality) and variation by reducing the variance of the generator input.

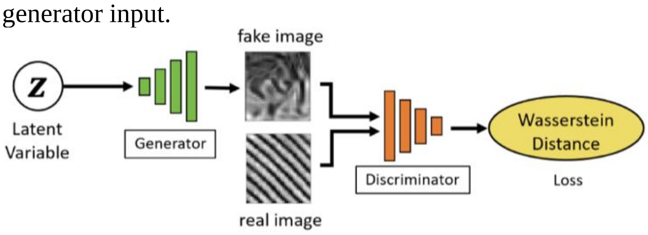

Fig. 7. Wassertian GAN architecture [32]

BigGAN introduces architectural modifications that significantly improve performance in class-based conditional image synthesis. When trained on the ImageNet dataset with a resolution of 128×128, BigGAN achieved an IS score of 166.5 and FID of 7.4, which is a great improvement compared to the previous model (IS 52.52 and FID 18.6) [36]. These achievements make BigGAN a new standard in largescale image synthesis, with the ability to produce highly realistic and varied images. This innovation opens up new opportunities in generative modelling research, especially for applications that require high quality in visual data. This includes fields such as digital art, augmented reality, and data-driven visual exploration.

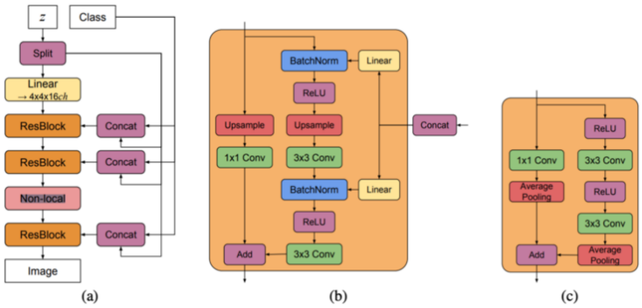

Fig. 8. BigGAN architecture [36]

IV. GANs Applications

A. Image Processing

One of the main applications of GANs is image generation, where the model generates synthetic images that resemble the original data. The generation of realistic human faces by StyleGAN is an example of this application, which generates images of individuals that do not exist in the real world. GANs are also applied in image-to-image translation, as in CycleGAN, which transforms images from one domain to another without requiring the same data pair [37].

In the field of super-resolution images, GANs play an important role through models such as SRGAN (SuperResolution GAN), which is capable of increasing image resolution while maintaining high visual detail [38].This technology is useful for improving image quality in applications such as medical image processing.

In the field of image restoration, GANs is used in image inpainting, which is the reconstruction of missing or damaged parts of an image [39]. This technology is useful for recovering old image archives or incomplete medical images. GANs is also applied in image data augmentation, which creates synthetic data to improve the performance of machine learning models, especially when the original dataset is limited [40].

In the creative industry, GANs open up new opportunities in generating innovative designs. GANs has been used to create new patterns in clothing design, architecture, and digital art, which are difficult to design manually [41]. With these innovations, GANs continues to expand its application in various fields that require high creativity and accuracy.

B. Healthcare Industry

One of the main applications of GANs is in medical image synthesis. GANs generates synthetic image data, such as MRIs, CT scans, or X-rays, that resemble the original data. This synthetic data is very useful for training machine learning models, especially since it can increase the size and diversity of the dataset without violating patient privacy [42]. GANs are also used to generate additional data on rare medical conditions, thus overcoming the problem of dataset imbalance in diagnostic model development [43]. GANs is applied in image augmentation, which improves the accuracy of diagnostic models by introducing new variations in the training dataset.

GANs play an important role in medical image restoration (image inpainting), where they reconstruct parts of a medical image that are missing or damaged due to artefacts or device interference. This technology ensures more complete and high-quality medical data, which is crucial for further analysis and diagnosis [44].

In the field of medical imaging, GANs are used to enhance the low resolution of medical images to high resolution. This technology makes it easier for doctors to analyse images more accurately, for example to detect diseases or identify small structures that were previously difficult to see [45]. GANs is also applied in medical image registration, which aligns images from different modalities, such as combining MRI and CT scan images for more comprehensive analysis.

With these various applications, GANs supports efficiency, accuracy, and innovation in the healthcare industry. It continues to be an essential tool in the modern era, especially in the face of new challenges and opportunities in medical imaging.

C. Audio and Video

In the audio field, GANs are used for sound synthesis, where models such as WaveGAN and MelGAN produce realistic audio, including music, speech, and sound effects. This technology is applied in the creation of AI-based voices for virtual assistants, voice-over in videos, or the creation of realistic sounds for simulations in games [46]. GANs is also used in speech enhancement, which improves audio quality by removing noise, improving the smoothness of the voice, or reconstructing missing parts of the voice [47]. In text-tospeech (TTS) applications, GAN produces a more natural sound by preserving intonation, emotion, and expression [48].

In video, GANs play a key role in video generation and video editing. Models such as MoCoGAN are used to generate synthetic videos with realistic motion flow, useful for animation simulation or AI-based visual content creation [49]. GANs are also applied in super-resolution video, improving the quality of video resolution from low to high without losing important details [50]. In video editing applications, GANs enable frame interpolation, which creates additional frames to produce smoother, higher frame rate videos [51]. GANs also play a role in deepfake technology, which is used to alter or manipulate videos, whether for entertainment, training or simulation purposes [9].

D. Other Fields

GANs have a wide range of applications that go beyond image, audio, and video processing, making them a versatile technology for various fields. One of the main applications of GANs is in product design and manufacturing. GANs result in innovative new designs, such as the design of automotive products, electronic devices, or home appliances [52]. With GANs, companies optimise simulation-based designs, resulting in digital prototypes that speed up the product development process. GANs is also applied in material design, which helps generate synthetic material structures with specific properties, such as strength or flexibility, to support advanced materials research.

In the field of cybersecurity, GANs are used to detect threats and improve data security [53]. One application is in simulating security attacks to identify weaknesses in network systems, where GANs create synthetic attack scenarios to train threat detection systems. GANs are also used for data privacy enhancement, such as in anonymisation methods, where the original data is replaced by synthetic data that retains statistical characteristics without violating privacy [54].

In the education industry, GANs are used to produce interactive learning materials, such as AI-based 3D visualisations or virtual simulations for professional training [55]. This technology allows students to learn through realistic virtual environments, such as simulated medical operations or flight training.

In the field of environment and climate change, GANs have significant contributions in weather simulation and environmental impact modelling. They are used to predict the spread of pollution, simulate ecosystem changes, or analyse climate change impacts based on historical data [56]. These applications demonstrate the versatility of GANs in supporting innovation in various sectors, making it a relevant technology for solving real-world challenges.

V. Challenges of Using the GANs

A. Collapse Mode

Mode collapse is a significant challenge in GANs training, where the generator only generates data with limited variation, even though the original data has wide diversity [57]. This occurs when the generator focuses on a few modes of the original data distribution that provide low loss values, but ignores other modes. The resulting synthetic data thus becomes monotonous and does not reflect the overall distribution of the original data, reducing the effectiveness of the model in applications that require data variation, such as data augmentation or image synthesis.

Collapse mode is triggered by the training imbalance between the generator and the discriminator [7]. If one of the networks is too dominant, the learning process becomes unstable, and the generator tends to produce data that only mimics a fraction of the original data. The limited capacity of the generator network and the use of non-optimal loss functions, such as cross-entropy, exacerbate this phenomenon. If the generator adapts too quickly to the feedback from the discriminator, it will focus its efforts on only certain modes to minimise loss, at the expense of other modes.

B. Training Instability

Training instability is one of the major challenges in GANs development [58]. This phenomenon occurs due to the competitive nature of GANs, where generators and discriminators are trained simultaneously with opposing objectives. Instability arises when a balance between the generator and discriminator is not achieved, resulting in one of the networks becoming too dominant. If the discriminator is too strong, the generator struggles to produce realistic data as the feedback received becomes meaningless. If the generator is too dominant, the discriminator fails to distinguish real data from synthetic data, resulting in ineffective training.

This instability is also affected by vanishing gradient or exploding gradient problems, which occur when network parameter updates do not converge [59]. Loss functions such as cross-entropy are often not stable enough to cope with the competitive nature of GANs, causing training to fluctuate or even fail [60]. Inappropriate hyperparameters can also exacerbate training instability.

C. Quality Evaluation

Quality evaluation in GANs faces a number of challenges due to the complex nature of the synthetic data and the purpose of the model [61]. One of the main challenges is the difficulty in objectively assessing realism, as data quality is often subjective and dependent on the application context. Data that looks realistic in a particular domain, such as images of human faces, may not meet the standards in another domain, such as medical images. The absence of universal evaluation metrics adds to the challenge, as both IS and FID metrics have limitations [14]. IS focuses on the clarity and diversity of the data, but does not necessarily reflect the similarity of the distribution to the original data. FID is more reliable in comparing feature distributions, which can be influenced by the pre-trained models used to extract features.

Another challenge arises in measuring data diversity without losing realism. The phenomenon of mode collapse, where generators only produce data with limited variation, is often difficult to detect by standard evaluation metrics. Metrics such as Precision and Recall for GANs have been introduced to evaluate data realism and coverage, but their application still requires parameters customised to specific datasets [62]. Qualitative evaluations such as visual inspection by humans, while effective for certain tasks, tend to be time-consuming and inconsistent due to the subjectivity of judgement between individuals.

D. High Computing Needs

GANs are known to have very high computational requirements, which is a major challenge in their development and implementation. The competitive nature of the GAN architecture causes the generator and discriminator to be trained simultaneously in an adversarial framework. This training process requires intensive iterations to achieve a balance between the two networks, which requires computationally powerful hardware, such as GPU or TPU [63].

The modern GANs model BigGAN, which is designed to generate high-quality and high-resolution images, requires large memory and high computing power to handle a significant number of parameters and complex operations such as convolutions and normalisations [34]. The use of large batch sizes, in BigGAN, adds to the computational burden. Large batch sizes are necessary to improve gradient estimation during training, but directly increase GPU memory consumption.

The forward pass and backpropagation processes that occur in the generator and discriminator alternately double the computational requirements compared to traditional machine learning models [64]. Spectral normalisation and gradient penalty training stabilisation techniques also increase computational complexity [65].

E. Ethics and Safety

One of the main issues is the misuse of GANs technology to generate misleading content, such as deepfakes, which can be used to create fake videos or images that are difficult to distinguish from the origina [9]. Deepfakes raise concerns in various sectors, including politics, national security, and individual privacy, as they can be used to spread disinformation or attack one's reputation. GANs can also be used to create fake data that resembles real data, such as identity documents or signatures, which can potentially be misused in fraud or cybercrime [66].

From a privacy perspective, GANs present risks related to data anonymity. Although GANs are often used to generate synthetic data that protects individual privacy, the model may inadvertently remember specific data from the training dataset [67]. This may pose a risk of sensitive information leakage, especially in applications involving medical data or personal information. The use of GANs for specific purposes, such as improving the quality of medical images, may also pose ethical challenges if there is no transparency on how the data is used and processed.

VI. Solutions and Innovation

A. GANs Stabilisation Technique

One widely used technique to address the stabilisation problem of GANs training is the Wasserstein GAN (WGAN), which replaces the conventional cross-entropy loss with the Wasserstein distance. This approach produces more stable gradients and supports training consistency [33]. The application of gradient penalty in WGAN-GP regulates gradient changes to prevent extremes, which reduces the risk of mode collapse and improves the quality of the resulting synthetic data.

The spectral normalisation technique controls the largest spectral value in the weight matrix in the generator and discriminator to prevent gradient explosion, resulting in more controlled training [68]. In this way, gradient explosion is prevented, resulting in more controlled training. Mini-batch discrimination allows the discriminator to evaluate the diversity in a batch of synthetic data, which encourages the generator to produce more diverse data [69]. This technique is very effective in overcoming the problem of lack of data variety due to mode collapse. Additional approaches such as progressive growing introduce data gradually, which can improve training stability, especially for high-resolution data [70].

B. Training Strategy

GAN training requires specialised strategies to maintain stability and efficiency. Training balance between the generator and discriminator is a top priority, which is achieved by setting the update ratio and using adaptive learning rates as in Adam's algorithm. Batch normalisation maintains gradient stability and accelerates convergence [71].

Regularization techniques, gradient penalty in WGANGP and spectral normalization, help prevent gradient instability [33]. Progressive growing introduces data from low to high resolution, which is effective in StyleGAN models. To ensure data diversity, mini-batch discrimination encourages the generator to produce more varied data.

C. Development of Advanced Evaluation Metrics

Accurate evaluation metrics are key to assessing the quality and diversity of data generated by GANs. IS and FID are widely used evaluation standards, but both have limitations, such as reliance on pre-trained models and lack of ability to measure the diversity of data distribution [14]. To address this, metrics such as Precision and Recall assess the realism and coverage of synthetic data, while Kernel Inception Distance (KID) offers a more flexible alternative to FID. Metrics such as the Multi-Scale Structural Similarity Index (MS-SSIM) evaluate data diversity, and the Perceptual Path Length (PPL) assesses the smoothness of the latent space [72]. The development of more holistic metrics enables more accurate evaluation of GANs, supporting the improvement of synthetic data quality and diversity for various applications.

D. Efficiency Improvement

One approach to creating a lightweight GANs is to use pruning and quantisation. Pruning removes less important parameters or connections in the network, thus reducing the model size without sacrificing significant performance [73]. Quantisation reduces the numerical representation of parameters from a higher precision format to a lower precision format, which reduces memory requirements and speeds up inference [74].

Another technique is to use more efficient architectures, such as MobileGAN or LiteGAN, which are specifically designed to run on limited hardware. MobileGAN, uses simpler convolutional blocks such as depthwise separable convolutions to reduce computation [75]. Training with knowledge distillation allows smaller models (student) to learn from large models (teacher), thus maintaining output quality with much smaller model sizes [76].

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