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Generative Adversarial Networks for Visual Content: A Comprehensive Review of Image and Video Synthesis, Challenges, and Ethical Implications

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Abstract

Generative adversarial networks (GANs) represent a ground-breaking advancement in artificial intelligence, revolutionizing data generation and content creation. This systematic review critically analyses literature from 2019-2024, sourced from major databases like IEEE Xplore and Scopus, to go beyond descriptive surveys and provide a synthesized, critical evaluation. We identify a pivotal gap in the existing literature: a frequent disconnect between reporting technical advancements and examining their profound ethical and societal implications. Our analysis yields several integrated insights. First, while GAN applications predominantly excel in visual content generation with architectures like StyleGAN and BigGAN achieving remarkable progress in photorealistic image and video synthesis their efficacy is highly application-specific, revealing significant trade-offs in stability and diversity in domains such as medical imaging and real-time video processing. Second, persistent core challenges like training instability and mode collapse continue to drive architectural innovations; however, we critically examine how solutions like Wasserstein loss or minibatch discrimination demonstrate varying effectiveness and limitations across different tasks and datasets. Third, and most critically, we argue that ethical concerns, particularly regarding deepfakes and data bias, are not peripheral issues but are intrinsically linked to architectural choices and the quality of training data. The key contribution of this review is its novel, integrated framework for evaluating GANs, which concurrently assesses architectural efficacy, application-specific maturity, and associated ethical risks. This holistic and critical synthesis provides researchers with a nuanced reference and outlines clear, responsible directions for future GAN development, emphasizing the need for models that are not only more powerful but also more robust, fair, and accountable.

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1. INTRODUCTION

Over the last decade, artificial intelligence (AI) has made remarkable strides, enabling machines to perform complex human tasks, owing to the explosion of Big Data, algorithm optimization, and advances in computing power. With advances in artificial intelligence research, the ability of machines to mimic human behavior is increasing at an exponential rate [1] within this landscape. Generative Adversarial Networks have emerged as one of the most influential innovations, particularly in the field of generative modeling. "GANs, and the variations that are now being proposed, are the most interesting ideas in the last 10 years in ML."As noted by Lecun [2], Figure 1 illustrates the GAN Relationships with AL,ML & DL. GANs are unsupervised algorithms and a class of deep learning models that have transformed the field of generative modeling. They were introduced in 2014 by Ian Goodfellow [3] and have since gained significant attention and popularity because of their ability to generate high-quality synthetic data that closely resemble real-world data, such as images, music, and text. The architecture of GANs consists of two neural networks, the generator and discriminator, which engage in a competitive training process, leading to the iterative improvement of both models. The generator network attempts to produce synthetic samples that are indistinguishable from real data, whereas the discriminator network attempts to classify accurately whether a given sample is real or generated. Through this adversarial process, both networks improve their performances [4].

The generator learns to create increasingly realistic samples, whereas the discriminator is more adept at distinguishing real data from the generated data.

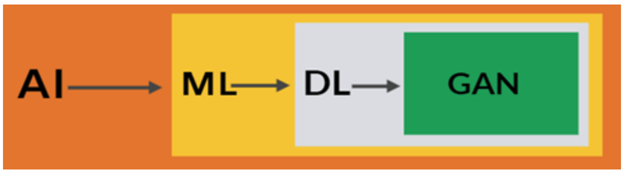

Figure 1. GAN Relationships with AL,ML & DL

The most well-known and prominent applications of GANs are in the field of image processing, including image generation, enhancement, and recovery. Recent studies demonstrated that GANs can produce synthetic data that are indistinguishable from real data, making them invaluable in areas where data scarcity is a concern. This adaptability sets GANs apart from traditional AI methods, which rely on predefined rules, allowing for greater innovation in generative tasks and opening the door to new horizons that are yet to be discovered [5]. Despite their remarkable capabilities, GANs face several challenges, including training stability, mode collapse, and the need for diversity in generated samples, which are critical areas of ongoing research [6].

Although a substantial body of the literature has reviewed Generative Adversarial Networks (GANs), a distinct and pressing research gap remains. Many existing reviews are either becoming dated, lacking coverage of the most recent architectural advancements (post-2021), or focusing predominantly on technical aspects without a balanced, in-depth integration of the critical ethical and societal implications that have gained urgency. Furthermore, many prior studies are narrative reviews that lack a transparent and reproducible methodology, making it difficult to assess their comprehensiveness and rigor.

The primary contribution of this review is to address this gap by providing a systematic and updated analysis of GANs. Unlike previous surveys, this study is based on a structured methodology for literature selection and analysis, ensuring comprehensive coverage and scholarly rigor. Our specific contributions are as follows:

- This provides a synthesized overview of the most impactful recent GAN architectures and their applications in visual content synthesis.
- Offers a critical analysis of persistent technical challenges and emerging solutions proposed in the latest research.
- Delivering an integrated examination of ethical implications, such as deepfakes and data bias, linking them directly to technical advancements.
- Outlining clear and informed directions for future research that bridge technical challenges with the need for responsible development."

Our goal was to explore the advantages of adversarial networks, as they have achieved impressive results in various fields and are becoming a hot topic in computer vision research. They essentially represent a machine learning approach that has been successfully used to train generative models through an adversarial method, involving two artificial neural network (ANN) models that learn their parameters through this adversarial process [7].

GANs facilitate a diverse range of applications, from image generation to creative domains, such as art, music, and style transfer to anomaly detection in real-time systems. Their revolutionary impact has the potential to transform industries by providing innovation and creativity tools. However, challenges remain, and understanding the challenges that affect the quality and diversity of the generated outputs and the underlying mechanisms of GANs is crucial for fully harnessing their potential. Some of the main points related to GANs are as follows.

- Data Generation: GANs make it possible to generate synthetic data that closely resembles real data [8]. This is particularly desirable when real data are scarce, expensive, or difficult to obtain. GANs have been used to create text, music, and video sequences.
- Creative applications: GAN are distinctive in that they have open horizons for unlimited possibilities in creative fields such as art, music, and design [9]. Artists, musicians, and creatives can now use GANs to create new and unique works of art or music, providing inspiration and pushing the boundaries of creativity.
- Data Augmentation: A highly sought-after feature is the use of GANs to augment training datasets by creating additional samples, as this helps improve the performance of machine-learning models trained on limited data [10].
- Anomaly Detection: GANs can be used to detect anomalies in data by comparing real samples with generated samples [11]. They can also create novel samples that deviate from the normal data distribution, aiding exploratory data analysis and novelty detection.

- Transfer Learning and Style Transfer: GANs have been used for transfer learning, where the knowledge learned from one interest or domain can be transferred to another interest or domain through a generator network. GANs also allow style transfer, whereby the style of one image can be applied to another, resulting in creative image transformations [8].

- Simulation and virtual environments: GANs have applications in simulating real-world environments, generating synthetic training data for robots, self-driving vehicles, and virtual reality applications, because they help create virtual worlds that closely resemble the real world, facilitating training and testing in a controlled environment.

Let us explain each component of the GAN [12]:

1. Generator Network: The generator network takes random noise or a latent vector as input and transforms it into synthetic data, which aims to learn the mapping from a latent space, generating realistic samples that resemble the training data distribution, such as images, music, or text. The generator is typically implemented as a neural network [13], often a deep convolutional neural network (CNN), in the case of image generation tasks. The generator output was a sample that perfectly captured the characteristics and patterns present in the training data. The generator focuses on reducing the discrepancy between the generated and real samples, which overcomes the discriminator and is unable to classify them as real.

2. Discriminator Network: The discriminator works as a binary classifier that differentiates between real data samples from the training dataset and counterfeit data samples generated by the generator. Similar to the generator, the discriminator typically performs as a neural network such as a CNN [14]. It takes real or generated input data samples and determines whether they are real or fake. The output here is a probability score that indicates the chance that the input sample is real, that is, belongs to the training distribution [15]. We can say that it aims to maximize its ability to correctly classify real and fake samples; on the other hand, the generator's goal is to minimize the discriminator's ability to distinguish between the two, which is exactly what we meant by using (a two-player zero-sum game) expression.

3. Training Process: The training of a GAN can be summarized as follows.

- Initialize and prepare the data. In this stage, both the G and D networks are initialized with random weights. A training dataset of real data samples was prepared.

- Generator training: G takes a random noise vector as the input. This noise vector contains random values and acts as a starting point for G's creation process. Using its internal layers and learned patterns, G transforms the noise vector into a new dataset such as a generated image.

- Discriminator Training: In this stage, D is trained on real data samples and synthetic data generated by G. It learns to precisely distinguish between real and generated samples [11].

- In adversarial training, GANs are trained using an adversarial training procedure, where G and D are trained simultaneously in a competitive manner. G is updated based on the feedback from D G to generate increasingly realistic samples to fool D, and D attempts to distinguish between real and fake samples. The generator aims to generate samples for which the discriminator is more likely to be classified as real.

- In iterative training, these steps are repeated, which allows both G and D to improve their performance.

Thus, the training process continues until the generator succeeds in generating synthetic samples that the discriminator cannot distinguish from the real data [16].

Our contributions in this paper are a comprehensive review of generative adversarial networks (GANs), which are currently among the most attractive topics in machine learning.

We examine the fundamentals of GANs and explore their underlying principles and training mechanisms. We highlight prominent applications of GANs across various domains. Moreover, we provide a critical examination of their industrial influences and potential, shedding light on their transformative impact on different sectors. Furthermore, we address the ethical and societal implications associated with the spread of GANs by considering both their positive contributions and potential challenges. We discuss the technical considerations and obstacles faced by GANs in recent years, including issues related to the training stability, mode collapse, and sample diversity. Finally, we shift our focus toward the future by discussing the horizons and directions for further research on GANs. We explore potential advancements and breakthroughs that could shape the field, offering insights into emerging trends and possibilities. Through this study, we aim to provide a comprehensive understanding of GANs, their current applications, and their promising prospects for the future.

The paper is organized as follows:

Section 2 details the systematic review methodology, outlining the search strategy, selection criteria, and the data synthesis process. Section 3 provides a foundational overview of GANs and discusses their significance, historical contexts, and evolutionary trajectories. Section 4 presents a critical analysis of the core GAN architectures and models and evaluates their trade-offs and application-specific suitability. Section 5 examines the applications of GANs through a maturity- and challenge-centric lens, moving beyond mere listing to a critical discussion of their real-world viability. Section 6 synthesizes the emerging challenges and recent solutions and offers a comparative analysis of their efficacy. Section 7 investigates the ethical and societal implications of GANs and explicitly links these concerns to their technical foundations. Finally, Section 8 discusses open issues and technical considerations, paving the way for future research. Section 9 presents the conclusions and integrates the key findings to provide a holistic perspective on the field.

2. REVIEW METHODOLOGY

This study was conducted as a systematic literature review to provide a comprehensive and structured analysis of the current landscape of Generative Adversarial Networks (GANs). The primary objective is to identify, evaluate, and synthesize the most significant recent advancements in GAN architectures, their dominant applications, persistent challenges, and critical ethical implications. To ensure transparency, reproducibility, and academic rigor, the review process adhered to a predefined protocol encompassing a systematic search strategy, explicit inclusion and exclusion criteria, and structured method for data analysis and synthesis.

The systematic approach outlined in our methodology aligns with the comprehensive development workflow shown in Figure 3, ensuring consistent evaluation across technical, applicational, and ethical dimensions.

2.1. Search Strategy

A comprehensive electronic search was performed to identify all the relevant peer-reviewed studies. The search was conducted across four major academic databases renowned for their extensive coverage of computer science, artificial intelligence, and engineering: IEEE Xplore Digital Library, ACM Digital Library, Springer Link, and Scopus. The search query was designed using key terms related to the core concepts of the review combined with Boolean operators to maximize both recall and precision. The primary search string used was: ("Generative Adversarial Network" OR "GAN") AND ("architect" OR "model" OR "survey" OR "review" OR "challenge" OR "application" OR "ethical" OR "deepfake*"). The search was confined to publications published between January 2019 and July 2024. This five-year timeframe was selected to capture the most recent and impactful developments in the field, focusing on the period following the initial establishment of fundamental GAN architectures and aligning them with the focus of recent surveys, such as those by [12, 17].

2.2. Inclusion and Exclusion Criteria

The study selection process was rigorously guided by pre-defined criteria to ensure the inclusion of high-quality, directly relevant literature.

Inclusion Criteria:

- Studies have introduced novel GAN architectures, models, or significant modifications (e.g., StyleGAN [18], CycleGAN [19], and WGAN [20]).
- Studies discussing the major and emerging applications of GANs focus on image and video synthesis [21, 22], facial manipulation [5, 23, 24], and data augmentation [25, 26].
- Studies have explicitly addressed fundamental challenges in GAN training and deployment (e.g., mode collapse and training instability) and proposed substantive solutions [27, 28].
- Studies have explored the ethical, societal, and legal implications of GAN technology [29, 30].
- Peer-reviewed journal articles and full-length conference papers published in English.

Exclusion Criteria:

- Studies not published in English.
- Short papers (typically fewer than four pages), abstracts, editorials, books, and dissertations.
- Duplicate publications of the same study.
- Studies where GANs were not the central focus.

2.3. Study Selection Process

The selection of studies was carried out using a multi-stage screening process to minimize bias.

1. Initial Search: The systematic search across four databases identified approximately 1,300 publication records.

2. Duplicates Removal and Screening: After removing duplicates, titles and abstracts of the remaining studies were screened against the inclusion and exclusion criteria. This step filtered the list into 240 potentially relevant papers.

3. Full-Text Assessment: The full texts of these 240 papers were thoroughly examined for eligibility. This involved assessing the technical contributions of architectural papers [18, 31, 32], relevance of application studies [33–35], and depth of analysis in challenge and solution papers [27, 28]. Studies that did not meet all criteria upon detailed review were excluded. This rigorous process resulted in a final corpus of 98 high-quality primary studies that formed the foundation for this systematic review.

2.4. Data Extraction and Synthesis

Data from 98 selected studies were systematically extracted and categorized using a structured framework. The extracted key information included the GAN model/variant name and year of proposal, core architectural innovations, primary application domains, specific challenges addressed, and ethical concerns raised. The data were synthesized as narrative and thematic. The extracted information was analyzed to identify dominant trends, map the technological evolution of GAN architectures, consolidate common challenges and their corresponding solutions, as discussed in previous studies [17, 27, 28], and build a coherent and critical discussion on the ethical implications highlighted in [29, 36, 37]. The results of this synthesis are presented in subsequent sections of this paper.

3. OVERVIEW OF GANS

Generative Adversarial Networks (GANs) have established a transformative paradigm in artificial intelligence, fundamentally changing the approaches to data generation and content synthesis. This section consolidates the core principles, significance, and evolutionary trajectory of GANs, setting the stage for critical architectural analysis to follow.

GAN networks have emerged with superior and unlimited advantages and promising progress in the field of artificial intelligence, as they breathe life into inanimate machines and enable them to simulate human behavior amazingly by developing models for the distribution of high-dimensional data. Thus, it provides advantages in both semi-supervised and unsupervised learning and addresses most of the limitations of the traditional methods.

The process of training GANs involves competitive learning, where the generator and discriminator networks compete with each other. The generator aims to generate synthetic samples that resemble the true distribution of the data, whereas the discriminator aims to correctly classify real and fake samples [38].

Thus, through this competition game, the performance of the networks is improved, allowing the generation of high-quality synthetic samples that are almost identical to the real distribution of the data.

3.1. The Significance

Generative Adversarial Networks (GANs) are considered one of the most significant advancements in artificial intelligence. Their most notable impact has been in the area of computer vision [39], where great advances have been made in challenges such as plausible image generation, image-to-image translation, facial attribute manipulation, and similar domains, primarily because of their exceptional ability to generate new high-quality data that resemble the original datasets. Their importance lies in addressing the critical challenges faced by researchers and developers, such as data scarcity and the high costs of data collection. GANs enhance creativity and innovation by allowing the creation of new content across various fields including art, design, and literature, thereby opening new horizons for human creativity.

Furthermore, GANs significantly contribute to improving the performance of machine-learning models by providing additional training data, which increases the accuracy and efficiency of these models [40]. Given their capacity to create realistic and precise data, GANs are also extensively used in image and video processing, enhancing visual experiences and helping companies develop engaging and lifelike content. The versatility of GANs in applications, from gaming and entertainment to healthcare and marketing, reflects the academic and industrial community's keen interest in their potential and aspirations for the future. This interest is well founded given their potential to transform our understanding of data generation and advance traditional methods in artificial intelligence.

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Only, by way of example and not limitation, in the fields of art, culture, literature, and poetry, generative adversarial networks have provided us with countless advantages, making art available and accessible to everyone at low prices, regardless of their backgrounds and abilities.

For example, GANs can make exact copies of the most difficult works [17] of art known worldwide, such as The Mona Lisa, or any paintings by famous painters, such as Leonardo da Vinci, Van Gogh, or others, which can be printed, displayed, and shared online. GANs can also design original and detailed artwork according to user preferences and tastes such as the color, style, or mood of the image. One of the most wonderful things we have achieved in the world of art, and by using the GAN, we can conjure the spirit of a famous singer who died decades ago, and the networks of generative competition summoned her to sing with her unique voice a new melody... Yes, it is a magical world that these networks have brought us into.

3.2. History and Evolution :

The concept of GANs was first introduced by Goodfellow et al. (2014). Their seminal paper, titled "Generative Adversarial Networks" presented a novel framework for training generative models. Since their introduction, GANs have undergone significant advancements and have been applied in various domains [41].

Over the years, researchers have developed numerous GAN variants and architectures to address these limitations and improve training stability. Some notable milestones in the evolution of GANs are as follows.

1. Conditional GANs: In 2014, shortly after the initial GAN framework was proposed, researchers extended GANs to include conditional information [42]. This has led to the development of Conditional GANs (CGANs), which allow for controlled generation by conditioning the generator on additional input variables.

2. Deep Convolutional GANs (DCGANs): In 2015, researchers presented DCGANs that merged deep convolutional neural networks into the GAN architecture. Compared to earlier GAN variants, DCGANs achieved significantly improved stability [43], and the resulting images were of high quality.

3. Progressive GANs that generate high-resolution images were introduced in 2017 [42]. They gradually increased the output resolution, starting with low-resolution images and gradually adding more details.

4. Cycle GANS: In 2017, cycle-consistent generative adversarial networks were used to solve image-to-image translation problems. This concept uses cycle-consistency loss to eliminate the use of target-domain data for training purposes [19].

5. Style GAN.: In 2018, StyleGAN was introduced, which allowed for fine-grained control over image synthesis by separating the generation of image content and style. StyleGAN produces highly realistic images and enables manipulation of specific attributes in the generated samples [18].

6. BIG GAN: This GAN was introduced in 2018, and focuses on generating high-quality and diverse images. BigGAN uses large-scale architectures [31] and advanced training techniques to achieve state-of-the-art image synthesis.

This progression from Vanilla GAN to sophisticated models reveals a clear evolutionary trajectory characterized by three key themes: (1) the pursuit of greater control over generated outputs, as evidenced by Conditional GANs and StyleGAN; (2) the continuous drive toward higher fidelity and resolution in synthetic content, demonstrated by Progressive GANs and BigGAN; and (3) persistent efforts to achieve improved training stability with innovations such as DCGANs and later architectural improvements.

Crucially, this evolution represents not merely technical refinement, but also significant conceptual shifts in generative modeling. The introduction of conditional information (CGANs) marked a transition from pure generative modeling to controllable synthesis, while the adoption of alternative loss functions, such as the Wasserstein distance (WGAN), constituted a paradigm shift in addressing training instability. Each architectural innovation has emerged as a direct response to the identified limitations, yet has often introduced new trade-offs in computational complexity, training requirements, or application specificity.

Notably, the development of GAN networks has progressed rapidly, and this development has led to a variety of research fields and vital applications [44].

This evolutionary trajectory reveals a consistent pattern: Each architectural innovation solves specific limitations while introducing new challenges. Vanilla GANs established the adversarial framework but suffered from instability, leading to convolutional improvements in DCGANs. The persistent issue of mode collapse motivated fundamental reforms in WGAN's loss function. Understanding this problem-solution continuum is crucial for anticipating future developments, suggesting that next-generation GANs will need to address the current trade-offs between generation quality, diversity, and computational efficiency through more fundamental architectural reforms.

In recent years, researchers have continually explored and developed new architectures, training techniques, and modern applications to push the boundaries of generative modeling and unlock the full potential of adversarial networks in various fields. Motivated by several factors, research on adversarial networks and image generation has flourished. Creative expression is one of the key drivers for studying adversarial networks because it offers a powerful tool for artists and designers to generate novel and visually captivating content [45].

Using adversarial networks, artists can delve into new artistic styles, create unique images, and produce visual effects that were previously difficult or impossible to manually achieve. The versatility of adversarial networks creates enormous possibilities for creativity [46]. Realistic content creation has been a major impetus in adversarial network research. This ability has major implications in industries, such as entertainment, advertising, and computer graphics, where the ability to create realistic visual content holds enormous value.

Adversarial networks can be used to create lifelike characters for video games, create photorealistic images of virtual environments, and produce high-quality visuals for marketing and promotional materials. Another key motivation lies in the realms of data augmentation and synthesis. Adversarial networks can generate synthetic data, aiding in the augmentation of training datasets for various machine learning tasks. By creating additional realistic samples, adversarial networks improve the generalizability and robustness of the models. Furthermore, in domains where data collection is arduous or costly, adversarial networks can synthesize data, enabling researchers to generate large amounts of synthetic data for training and evaluation [47]. The applications of adversarial networks extend to simulations and virtual environments. These networks can generate realistic textures, objects, and scenes to enhance the realism of simulations, virtual reality experiences, and computer games.

Immersive and interactive virtual environments created through adversarial networks closely mimic real-world scenarios, enriching the user experience and pushing the boundaries of realism in these applications. Research on adversarial networks has also led to advances in generative modeling.

Through the development of novel training techniques, architectures, and loss functions, adversarial networks have influenced and shaped the broader landscape of generative modeling. Researchers have explored adversarial networks to gain insights into training dynamics, stability, and convergence properties, thereby enhancing the effectiveness and efficiency of generative models beyond the scope of adversarial networks. The study of adversarial networks and image generation offers the opportunity to explore human perception and psychology. By generating images that align with human preferences, adversarial networks provide valuable insights into the underlying principles of visual aesthetics and human perception [48]. This knowledge finds applications in fields such as advertising, user interface design, and human-computer interaction, enabling the creation of visually appealing and user-friendly experiences that resonate with human perception.

Having established the historical context and fundamental principles of GANs, we now turn to a detailed examination of core architectures and models, analyzing how each addresses the evolutionary challenges discussed previously.

4. GAN CORE ARCHITECTURES AND MODELS

The evolution of GAN architectures represents a continuous endeavor to overcome fundamental challenges while expanding their generative capabilities. This section provides a critical examination of both the core components that constitute any GAN system and the specific architectural variants that define the field's progression, analyzing their respective strengths and limitations.

The basic architecture of a GAN is composed of a generator (G) and discriminator (D), which are two neural networks, and G gains the ability to produce believable data. The generated instances then become negative training examples for the discriminator. The Generator deceives the discriminator, which is responsible for accurately discriminating between generated and authentic data, by producing random noise samples. Realistic, high-quality samples are generated as a result of this competitive interplay, which propels both networks toward progress. GANs exhibit remarkable versatility as AI tools, as demonstrated by their widespread applications in image synthesis, style transfer, and text-to-image synthesis.

They have also brought about a revolution in generative modeling [13]. Through adversarial training, these models engage in a competitive dynamic until the generator becomes proficient in producing authentic samples, successfully outsmarting the discriminator approximately half the time. Therefore, GAN can be divided into three parts:

- Generative: Learn a generative model that describes how data are generated in terms of a probabilistic model.
- Adversarial: The word adversarial refers to setting up one thing against another. This means that in the context of GANs, the generative result is compared with the actual images in the dataset. A mechanism known as discriminator is used to apply a model that attempts to distinguish between real and fake images [10].
- Networks: Deep neural networks are artificial intelligence (AI) algorithms for training purposes.

Figure 2 shows the basic architecture of the GAN.

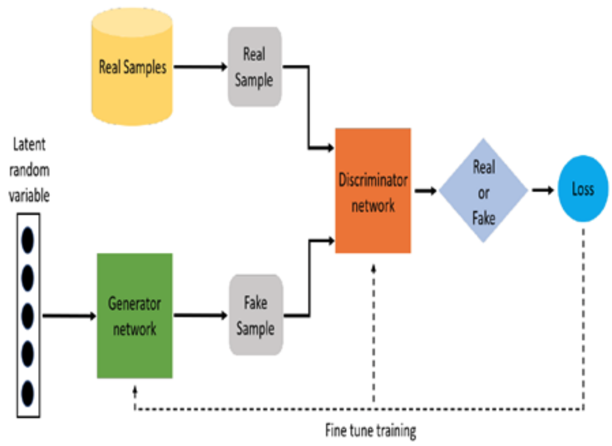

Figure 2. GAN Basic Architecture [49]

To provide a holistic understanding of how GAN components interconnect and where common challenges emerge throughout the development pipeline, Figure 3 presents a comprehensive workflow that maps the entire GAN lifecycle, from data preparation to societal impact. This flowchart serves as a visual guide to contextualize the architectural choices and technical challenges discussed in the subsequent sections.

This workflow demonstrates the intrinsic connections between technical design choices and their broader societal implications, highlighting the necessity of integrated ethical considerations throughout the development pipeline, rather than retrospective additions.

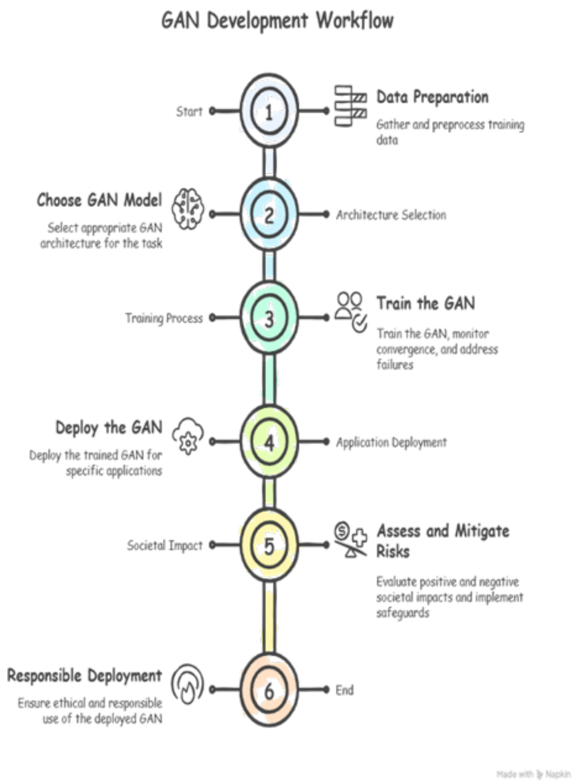

Figure 3. GAN Development Workflow: From Data to Responsible Deployment

4.1. Generator and Discriminator Components (Architectural Choices)

The design choices for the generator and discriminator components significantly influence training stability, output quality, and model convergence. Understanding these elements provides a crucial context for evaluating why different GAN variants exhibit markedly different behaviors.

4.1.1. Generator Components

- Latent input layer: The generator uses a latent vector (a low-dimensional representation of the data) as the input. The size of this layer often depends on the dimensionality of the latent space [50].

- Hidden Layers: The generator uses multiple hidden layers, typically implemented as fully connected or convolutional neural network layers, to transform the latent input into a realistic data sample. These layers learn a complex mapping from the latent space to the data distribution.

- Output Layer: The output layer of the generator produces a generated sample, such as an image, audio clip, or text sequence. The size of this layer depended on the dimensionality of the desired output.

- Activation Functions: Hidden layers often use activation functions such as ReLU, tanh, or sigmoid to introduce nonlinearity and help the generator learn complex mappings.

- Normalization Layers: Techniques such as batch normalization or layer normalization may be used in the generator to stabilize training and improve performance [51].

- Loss Function: The generator is trained to minimize a loss function that measures the discrepancy between the generated samples and real data samples to fool the discriminator.

- Optimization Algorithm: An optimization algorithm, such as stochastic gradient descent or Adam, is used to update the generator parameters (weights and biases) during the training process to minimize the loss function.

4.1.2. Discriminator Components

- Input Layer: The discriminator takes either real data samples or generated samples from the generator as the input.

- Hidden Layers: The discriminator uses multiple hidden layers, often implemented as convolutional or fully connected layers, to learn the features that distinguish real from fake samples.

- Output Layer: The output layer of the discriminator produces a single scalar value, which represents the probability that the input sample is real (close to 1) or fake (close to 0).

- Activation Functions: The hidden layers of the discriminator often use activation functions, such as LeakyReLU or Sigmoid, to introduce nonlinearity and help the discriminator learn complex decision boundaries.

- Normalization Layers: Techniques such as batch normalization or layer normalization can also be used in the discriminator to improve stability and performance.

- Loss Function: The discriminator is trained to minimize a loss function that measures the classification error between real and fake samples to distinguish them accurately.

- Optimization Algorithm: An optimization algorithm, such as stochastic gradient descent or Adam, is used to update the discriminator parameters (weights and biases) during the training process to minimize the loss function [50].

The architectural interplay between the generator and the discriminator creates a delicate balance. An overly powerful discriminator can cause vanishing gradients, whereas a weak discriminator can provide an inadequate learning signal. This tension has driven many innovations in normalization techniques, loss functions, and training strategies, which we examine in subsequent sections.

4.2. GAN Models

Over the past decade, numerous generative adversarial network (GANs) models have been developed to address specific challenges and improve performance across a diverse range of applications [1]. The wide variety of GAN architectures stems from the need to overcome limitations, such as training instability, mode collapse, and lack of control over generated data, as well as to enhance the realism and quality of the outputs. Each model introduces innovative techniques to meet these goals.

The proliferation of GAN architectures represents a systematic response to core limitations, with each model introducing specific innovations that target specific weaknesses in the original framework.

4.2.1. Vanilla GANs:

The original GAN architecture, commonly referred to as Vanilla GAN, consists of two neural networks: a generator that produces fake data resembling real data and a discriminator that distinguishes between real and fake samples. Despite their simplicity and effectiveness, Vanilla GANs often suffer from issues such as mode collapse, where the generator produces limited variations in output and training instability [7].

While foundational, Vanilla GANs established an adversarial framework that subsequent models would strive to stabilize and enhance, highlighting the inherent tension between theoretical elegance and practical implementation.

4.2.2. Deep Convolutional GANs (DCGANs):

DCGAN marked a significant advancement by integrating convolutional layers into the GAN framework, significantly improving its effectiveness for image-generation tasks [52]. It also introduced techniques, such as batch normalization and strided convolutions, which enhanced the training stability and enabled the synthesis of higher-quality images. This architecture has laid the foundation for many subsequent GAN variants.

The DCGAN demonstrated that architectural inductive biases tailored for images (convolutions, batch normalization) could substantially improve stability, establishing a template that would influence most subsequent image-focused GANs.

4.2.3. Conditional GANs (CGANs):

Conditional GANs extend the original architecture by incorporating auxiliary information such as labels or data conditions into both the generator and the discriminator [53]. This allows the generation of data conditioned on specific attributes, such as generating images of a particular digit or class, making them highly useful in applications such as image-to-image translation, super-resolution, and style transfer.

CGANs marked a crucial shift from unconditional generation to controllable synthesis, addressing the need for targeted output generation that aligns with the practical application requirements.

4.2.4. Wasserstein GANs (WGANs))

WGAN introduced a new loss function based on the Wasserstein distance (Earth Mover's Distance), which significantly improved the training stability and mitigated issues, such as mode collapse. It also provides meaningful loss metrics that better correlate with the quality of the generated images, allowing the training of deeper and more complex networks [20].

By reformulating the adversarial objective using the Wasserstein distance, the WGAN addressed fundamental training instability issues, providing more reliable gradients and a meaningful training progress metric, although sometimes at the cost of increased computational complexity.

4.2.5. Cycle GAN

This is the most common GAN architecture and is generally used to learn how to transform images of various styles [19]. Designed for unpaired image-to-image translation, CycleGAN enables the transformation of images from one domain to another without requiring paired training examples. This architecture has been widely adopted in tasks such as style transfer, photo enhancement, and domain adaptation, and has produced remarkably realistic results.

CycleGAN's cycle-consistency loss enabled domain translation without paired data, significantly expanding its practical applicability, although it can struggle with geometric transformations and requires careful tuning to avoid artifacts.

4.2.6. Style GAN

Nvidia released StyleGAN in December 2018 and proposed significant improvements to the original generator architecture models. StyleGAN can produce high-quality photorealistic photos of faces [18]. StyleGAN introduced a new generator architecture that enables explicit control over different levels of image features, resulting in highly realistic and disentangled images. It allows for "rough" control over the style and attributes of generated images, achieving state-of-the-art results in facial synthesis and beyond.

Table 1. Comparative analysis of core GAN architectures

Model	Core Innovation	Key Strengths	Inherent Limitations	Primary Use Cases
Vanilla GAN	Adversarial training framework	Conceptual simplicity theoretical foundation	Severe training instability, mode collapse	Educational purposes, baseline implementation
DCGAN	CNN architecture for GANs	Improved stability for images, foundational design	Limited to image data, moderate quality	Image generation prototyping
CGAN	Conditional generation via auxiliary data	Controlled output, multi-modal synthesis	Requires labeled data	Image-to-image translation
WGAN	Wasserstein distance metric	Training stability	Computational overhead	Reliable convergence tasks
CycleGAN	Cycle-consistency	Unpaired translation	Geometric distortions	Style transfer
StyleGAN	Style-based generator	High quality	Heavy computation	Face synthesis
BigGAN	Large-scale training	SOTA performance	Huge resources	Large-scale image synthesis

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StyleGAN's disentangled latent-space representation represents a quantum leap in controllability and quality, although its computational demands and complexity create barriers to widespread implementation.

The exceptional quality of StyleGAN-generated faces exemplifies how technical advancements can simultaneously enable creative applications and ethical risks. While artists gain powerful tools for digital content creation, the same technology also facilitates the creation of convincing deepfakes that challenge digital media authenticity. This duality underscores the necessity of integrating ethical considerations directly into architectural design decisions rather than treating them as afterthoughts.

4.2.7. BigGAN

BigGAN scales up the architecture and training datasets to generate high-fidelity, diverse images. By leveraging large models and extensive datasets, it produces highly detailed images across multiple categories [31], making it suitable for large-scale image synthesis tasks.

BigGAN demonstrated the power of scale in generative modeling, achieving unprecedented diversity and quality on complex datasets, although its resource requirements primarily limit accessibility to well-funded research institutions.

Table 1 showing the comparative analysis of core GAN Architectures.

This architectural evolution reveals a pattern of innovation in which solutions to fundamental problems (instability, lack of control, and limited quality) often introduce new trade-offs in complexity, computational requirements, or application specificity. Understanding these trade-offs is essential for selecting appropriate architectures for specific applications, a theme we explore in the following section on GAN applications.

To bridge the gap between theoretical architecture and practical implementation, Table 2 presents a systematic analysis of recent GAN models, framing each as a case study for problem solving. This compilation serves not merely as a catalog but also as a comparative framework that explicitly links architectural choices (the 'solution') to the specific limitations or tasks (the 'challenge') they aim to resolve. By organizing research in this challenge-solution paradigm, the table highlights the evolutionary trends and design patterns that characterize cutting-edge GAN development, thereby providing actionable insights for future model design.

Table 2 presents recent GAN models in existing research, outlining the specific challenges each model faces and the corresponding solutions proposed to address them.

Table 2. Comparative analysis of core GAN architectures

Year	Reference	GAN Model/Study	Key Challenge	Technical Solution / Contributions
2022	[33]	SCGAN: Generative Adversarial Networks of Skip Connection for Face Image Inpainting.	This paper addresses challenges in face image inpainting, such as incoherent inpainting edges and a lack of diversity in generated images. The study enhances image coherence and stability during training, leading to more realistic and diverse inpainted images.	Proposed A face inpainting method based on skip connections in GANs. The model incorporated skip connections to enhance inpainting ability and employed double discriminators to improve discrimination capacity.
2023	[54]	Infrared and Visible Image Fusion Using Generative Adversarial Network with Feature Complement Block.	This study addresses the challenge of effectively fusing infrared and visible images by proposing a generative adversarial network with a feature complement block. This approach enhances the extraction of complementary features, improving the quality and structural similarity of the fused images compared to existing methods.	The proposed method for infrared and visible image fusion utilizes a generative adversarial network with a feature complement block. It addresses the limitations of traditional and existing deep learning methods by extracting salient and detailed information from both types of images, enhancing complementary features, and incorporating a structural similarity loss function for improved fusion quality. By combining the strengths of infrared and visible images, the proposed method aims to achieve a more comprehensive and clearer representation.
2022	[55]	Enhancing the Resolution of Ancient Artworks Using Generative Adversarial Networks.	This paper addresses the challenge of restoring and preserving damaged or incomplete artworks through digital image inpainting. By utilizing Generative Adversarial Networks, it aims to enhance the originality and quality of input images, facilitating the long-term digital conservation of historical art.	Using GANs to enhance the resolution of ancient artworks. The GAN model successfully generated high-resolution images that closely resembled the original artworks, restoring fine details and improving clarity and visual quality.
2019	[56]	StarGAN-VC2: Rethinking Conditional Methods for StarGAN-Based Voice Conversion	This paper addresses the challenge of non-parallel multi-domain voice conversion, which requires learning multiple mappings without explicit supervision. By proposing StarGAN-VC2, it enhances the quality of converted speech and bridges the gap between real and converted outputs through improved conditional methods and network architectures.	Presented the advancements in the field of multidomain nonparallel voice conversion (VC) by rethinking conditional methods in StarGAN-VC. They have proposed two improvements: a source-and-target conditional adversarial loss for training objectives and a modulation-based conditional method for network architectures. These improvements have been incorporated into a new model called StarGAN-VC2.

2022	[57]	Image Super-Resolution using Enhanced Super Resolution Generative Adversarial Network.	This study addresses the challenge of recovering soft texture details in high-resolution image enhancement while maintaining consistency and quality. By introducing ESRGAN, it combines advanced loss functions and a deep residual network to improve the realism and detail of upscaled images, effectively addressing the shortcomings of existing methods.	Proposed an image enhancement technique using Enhanced Super Resolution Generative Adversarial Network (ESRGAN) to address the challenges associated with lower-resolution images. The ESRGAN method, trained on the DIV2K dataset, outperformed other models such as SRGAN, EDSR, and RCAN in terms of achieving high Peak signal-to-noise ratio (PSNR) performance.
2019	[32]	Self-Attention Generative Adversarial Networks.	This paper addresses the challenge of generating high-resolution images with coherent details by introducing the Self-Attention Generative Adversarial Network (SAGAN), which enables long-range dependency modelling. By allowing the generator and discriminator to utilize attention mechanisms across all feature locations, SAGAN significantly improves the quality of generated images, as evidenced by enhanced Inception scores and reduced Fréchet Inception distance.	(SAGANs) incorporate a self-attention mechanism into the GAN framework. The self-attention module effectively models long-range dependencies in images. Also demonstrates that applying spectral normalization to the generator stabilizes GAN training, and using TTUR speeds up the training of regularized discriminators. SAGAN achieves state-of-the-art performance for class-conditional image generation on the ImageNet dataset. The proposed model outperforms other GAN models, such as AC-GAN and SNGAN-projection, in terms of Inception Score, Intra FID, and FID metrics.
2022	[58]	Creating Objects for Metaverse using GANs and Autoencoders	This paper addresses the challenge of creating high-quality virtual objects for the Metaverse by proposing a model that combines Generative Adversarial Networks (GANs) with an Autoencoder. This approach enables the generation of diverse objects and enhances their quality through super-resolution, thereby facilitating a more immersive experience in virtual and augmented reality environments.	Enhance the connection between the Metaverse and the real world by generating realistic objects, with a focus on human faces. The approach combines the power of Generative Adversarial Networks (GANs) and Autoencoders and emphasizes the potential application of the generated images in Augmented Reality (AR) and Virtual Reality (VR) applications. By incorporating realistic objects, such as human faces, users can have a more immersive and authentic virtual experience within the Metaverse.

2023	[59]	Lightweight Spiking Generative Adversarial Networks for IoT Applications	This paper addresses the challenge of efficiently representing datasets for IoT applications using Spiking Generative Adversarial Networks (SGAN). By improving training speed, accuracy, and power efficiency, the proposed algorithm enhances the performance of IoT systems compared to traditional networks, demonstrating significant advancements in hardware implementation.	They proposed SGAN (Spiking Generative Adversarial Networks) based on FPGA for Intelligent Edge Applications. They proposed that one way to build good dataset representations was by training Spiking Generative Adversarial Networks (SGANs) and networks as sensory data for unsupervised tasks.
2022	[34]	A Novel License Plate Image Reconstruction System using Generative Adversarial Network.	This paper addresses the challenge of reconstructing poorly captured images of vehicle license plates to enhance their quality for recognition purposes. By proposing a two-stage deep learning algorithm utilizing YOLOv4 for detection and Pix2Pix for reconstruction, it effectively transforms blurred and unclear license plate images into readable formats suitable for computer vision applications.	The work addresses the problem of license plate reconstruction in parking lot management systems. They proposed a two-stage algorithm based on deep learning techniques to reconstruct poorly captured license plate images. The first stage utilizes a YOLO-based transfer learning model for license plate detection, while the second stage employs a Pix2Pix model, a type of Generative Adversarial Network (GAN), for license plate reconstruction.
2021	[60]	Extreme Low-Resolution Activity Recognition Using a Super-Resolution-Oriented Generative Adversarial Network.	This paper addresses the challenge of activity recognition in extremely low-resolution videos, which lack sufficient detail for effective analysis while preserving privacy. By introducing a super-resolution-driven generative adversarial network, it enhances low-resolution images to improve recognition performance, demonstrating superior results compared to existing methods.	The work aims to address the limitations of extremely low-resolution videos by enhancing the resolution of the input frames. This is achieved through the use of a generative adversarial network (GAN) that is specifically oriented toward superresolution. The activity recognition component focuses on analysing the super-resolved video clips to recognize human activities.
2022	[61]	Realistic Face Masks Generation Using Generative Adversarial Networks.	This paper addresses the challenge of emotion recognition in the context of masked faces, which has become critical due to the COVID-19 pandemic. By proposing a generative adversarial network model for realistic face mask generation and employing image inpainting techniques, it enhances existing emotion recognition models and improves their performance on datasets featuring masked individuals.	Presented a novel approach for generating realistic face masks using a GAN-based image inpainting model. The integration of a face detection model enhanced the accuracy of mask localization. The authors acknowledged the limitations of existing face datasets and the impact of input image resolution on the quality of generated masks. Despite these challenges, the study highlighted the feasibility of using generative image inpainting models for face mask generation tasks.

2023	[62]	Context-based Image Inpainting with Improved Generative Adversarial Networks	This paper addresses the challenge of inpainting large missing regions in images while ensuring both global and local consistency in the generated content. By introducing an improved Generative Adversarial Network with specialized discriminators and dilated convolutions, the model effectively repairs defective images, producing visually coherent results that maintain the integrity of surrounding areas.	Proposed a novel approach for image inpainting using an improved generative adversarial network (GAN). The proposed model incorporates a global and local context discriminator to ensure both global and local consistency in the generated images. Additionally, Wasserstein loss was introduced to enhance the training of the generator. To improve the efficiency of the model, the authors replaced part of the standard convolution with dilated convolution, which helped to expand the receptive field of the model. This lightweight design allows for faster processing and better scalability.
2023	[63]	Application of a Deep Generative Model for Diversified Video Subtitles Based on Generative Adversarial Networks.	This paper addresses the challenge of generating diverse and contextually relevant subtitles for video content through the use of generative adversarial networks (GANs). By emphasizing generation diversity and optimizing the descriptive quality of the generated content, the proposed model enhances the intuitive understanding of images and videos, facilitating better textual retrieval and applications in cross-field scenarios.	After discussing the limitations of current subtitle generation models and algorithms, emphasized the need for improvement in diversity by using GANs as the framework for constructing the subtitle generation model. They introduced a different optimization scheme that focuses on both intragroup and intergroup differences. The proposed method effectively improves the diversity of image subtitle generation while maintaining the quality of the generated subtitles.
2021	[64]	Efficient Geometry-aware 3D Generative Adversarial Networks	This paper addresses the challenge of generating high-quality, multi-view-consistent images and 3D shapes from collections of single-view 2D photographs. By introducing a hybrid explicit-implicit network architecture that improves computational efficiency and image quality, the proposed method synthesizes high-resolution images in real time while producing accurate 3D geometry, overcoming limitations of existing 3D GANs.	The proposed method for 3D-aware image synthesis, which combines an efficient explicit-implicit neural representation, a pose-aware convolutional generator, and a dual discriminator, represents a significant advancement in the field. This approach successfully achieves photorealistic image synthesis while incorporating 3D awareness and high-quality unsupervised shape generation.

2023	[65]	Effects of Different Generative Adversarial Networks on the Face Generation Task.	This paper addresses the challenge of generating realistic human faces using various generative adversarial network (GAN) variants, specifically DCGAN, WGAN-GP, and PGGAN. While the generated images resemble real human faces, the study highlights limitations in performance due to computational constraints and discusses the ethical implications of face generation technology, emphasizing the need for responsible development in this rapidly evolving field.	They started discussing their experimental results of generating faces using DCGAN, WGAN-GP, and PGGAN on the CelebA-HQ 128*128 dataset, revealing several key findings. Then, they offered PGGAN as the most capable model, although it required extensive training time and hardware resources, making it challenging to achieve desired performance under limited conditions.
2023	[35]	Single Image Deraining with Generative Adversarial Network	This paper addresses the challenge of single image de-raining, focusing on the recovery of image details that current methods often fail to preserve. By proposing a rain removal algorithm based on a generative adversarial network (GAN) that incorporates a U-net architecture and high-level semantic loss, the method effectively enhances detail recovery in de-rained images, demonstrating significant improvements on standard datasets.	They invented a rain removal method based on GAN. They designed a feature conversion module (FCM) based on half-instantiated normalization layers and residual structures to remove rain streaks and restore the raindrop-corrupted spatial information. To better recover semantic information, they introduced high-level semantic loss to the training process and pre-trained parameters to compute the difference between feature maps extracted from the ground truth and the derained image.

The architectural innovations discussed in the previous section enable diverse practical applications. This section examines how these technical capabilities translate to real-world use cases, while considering their implementation challenges and societal implications.

5. APPLICATIONS OF GAN

Generative Adversarial Networks (GANs) have gained prominence in various fields. They enable the generation of high-quality synthetic data, which is particularly valuable for training machine learning models [23]. This capability is essential in scenarios in which real data are scarce, expensive, or ethically challenging to obtain.

While Table 3 chronologically catalogues GAN applications, our analysis through the integrated framework proposed in this review reveals varying maturity levels and distinct ethical risk profiles across different domains. Image synthesis and facial operations have reached a production-ready status in entertainment and digital media, whereas medical imaging and real-time video processing applications remain largely experimental because of robustness concerns and regulatory constraints. This critical assessment moves beyond mere enumeration to evaluate real-world viability and responsible deployment considerations for each application category.

Recent advancements have led to diverse applications in areas such as health care, art, and finance. In healthcare, GANs are used for medical imaging to enhance diagnostic capabilities. The synthetic images generated by GANs can aid in training algorithms to detect diseases more accurately. However, these medical imaging applications must address critical privacy concerns, as synthetic data generation risks potential patient data leakage and requires robust anonymization safeguards to protect sensitive health information.

In addition, GANs facilitate the creation of personalized treatment plans by simulating various patient responses and optimizing therapeutic strategies. In the realm of art, artists employ GANs to create unique and innovative works by blending human creativity with machine-generated designs. When applied to facial generation and manipulation, these capabilities raise significant identity protection concerns, necessitating the development of ethical frameworks that balance creative freedom with privacy rights.

Furthermore, in finance, GANs are used for fraud detection and risk assessment by generating synthetic transaction data. They also help develop realistic market simulations, enhance product designs, and optimize pricing strategies.

Overall, GANs are transforming various industries by improving data accessibility and enabling sophisticated analysis. Their ability to create realistic simulations fosters innovation and enhances the decision-making processes. As the research progresses, new applications and improvements in GAN architectures are expected. These advancements may lead to improved accuracy, efficiency, and broader adaptability across sectors. The ongoing exploration of ethical considerations will also shape the future landscape of GAN usage, ensuring responsible deployment [66]. This includes addressing concerns about data privacy, potential biases in generated outputs, and implications of deep fakes [67].

As technology continues to evolve, collaboration among artists, developers, and ethicists is crucial. Establishing guidelines and frameworks for responsible use will help mitigate these risks. Furthermore, enhancing the interpretability of GANs will facilitate greater transparency in their application. This enables users to understand the underlying processes and their potential limitations. Additionally, expanding educational resources on GAN technologies will foster awareness and proficiency among developers and end-users [68].

Increased knowledge promotes innovative use while minimizing risks. Ultimately, fostering a collaborative environment will drive responsible advancements in GAN applications by maximizing. While the common applications of GANs can be classified stereotypically, such as talking directly about their applications in fields such as marketing, industry, biology, and business, we have preferred in our study not to divide the applications in this manner. This is because all these fields share a fundamental reliance on GAN's main product, which is image and video as a core component of their processes.

Therefore, in this study, we focus on the advantages of GAN alone and thus reflect their impact on all these areas. In today's world, visual content–primarily images and videos–has become the dominant mode of communication and expression. The ability to capture, manipulate, and generate visual data has enriched various applications across the computing landscape. From social media platforms to medical diagnostics [69], the emphasis on visual representation has transformed how we perceive and interact with information. This visual-centric approach not only enhances user engagement but also facilitates a deeper understanding of complex concepts through clear and compelling imagery. As a result, the integration of image and video manipulation technologies is essential for driving innovation and improving the efficacy of applications across diverse fields, including entertainment, education, and healthcare. GANs excel in their ability to generate, create, manipulate, and process images and videos in an artistic manner. This unique characteristic makes them powerful tools that focus on both creative and technical aspects [70].

Regardless of the application domain, the essence of these networks remains in how they enhance image quality, generate new content, or perform artistic modifications. Thus, focusing on image- and video-related applications more accurately reflects the nature of GANs and highlights their impact across various fields by improving visual experiences and imaging techniques.

Our framework-based analysis demonstrates that GAN applications cannot be evaluated solely based on technical merits. The most technically advanced applications (e.g., facial manipulation) often carry the highest ethical risks, whereas less mature applications (e.g., medical imaging) offer significant societal benefits but face technical and validation barriers.

This tension between capability and responsibility highlights the need for an integrated evaluation approach chosen in this review, where architectural efficacy, application-specific maturity, and ethical implications are assessed concurrently rather than sequentially.

Accordingly, we will proceed to explain the applications of GANs from this perspective. GANs have several practical real-world applications, successfully addressing numerous tasks, including sequential data, computer vision, and image processing.

As systematically categorized in Table 3, GAN applications span diverse domains, from creative image synthesis to practical data augmentation. The predominance of image-related applications (seven out of 20 studies) underscores GANs' primary strength in visual content generation, while the consistent research output in facial operations (six studies from to 2019-2024) highlights both the technical maturity and associated ethical challenges in this domain.

Many tasks have been successfully solved using GANs, including the creation of images from descriptions [32, 71]. Examples of such tasks are:1.High-resolution image extraction from low-resolution images [72];2.Object detection [17], 3.Retrieval of images containing a given pattern; 4. Facial attribute manipulation [73], 5. Generation of digital artistic images [74] [74]; 6.Anime character creation [75–77]; 7. Image-to-image translation [78]; 8. Innovation of new approaches to content production in the metaverse to fill the gaps in their development [79] and many more [80].

As mapped in our development workflow (Figure 3), the transition from architectural selection to application deployment reveals how specific GAN variants naturally excel in particular domains, with StyleGAN dominating facial applications, whereas WGAN is essential for stable medical imaging implementations.

Table 3 summarizes the most important types of GAN applications identified in our systematic review, categorized by the application domain and publication year.

The categorization in Table 3 reveals several important trends in GAN applications. Image generation and synthesis remain the most active research areas with consistent publications from 2020 to 2024. Facial operations show sustained interest, particularly in 3D face reconstruction and the detection of GAN-generated faces. Video-related applications, while less numerous, demonstrate a growing maturity from basic synthesis to comprehensive frameworks. Emerging applications in data augmentation and privacy enhancement highlight GANs' expanding utility of GANs beyond pure content creation to practical data-centric solutions.

Table 3. Categorization of GAN Applications by Domain and Year.

Application Domain	Year	Reference
Image Generation & Synthesis	2020	[81]
	2020	[82]
	2021	[83]
	2021	[21]
	2022	[84]
	2023	[85]
	2024	[86]
Facial operations	2019	[24]
	2020	[87]
	2021	[22]
	2022	[5]
	2023	[88]
	2024	[23]
Video Prediction and Synthesis	2020	[89]
	2020	[90]
	2021	[91]
	2022	[92]
	2023	[93]
Data Augmentation	2023	[94]
	2023	[95]
ART and Creation	2023	[96]
Enhance privacy	2021	[25]

A critical examination of these applications using our integrated lens revealed several key insights. First, the dominance of image generation and facial manipulation applications underscores GANs' exceptional capability of GANs in visual content synthesis; however, this strength amplifies ethical concerns regarding deepfakes and digital identity. Second, the emergence of video synthesis applications, while promising, faces significant challenges in terms of temporal consistency and computational demands, which limit current practical deployment. Third, applications in sensitive domains such as healthcare and privacy enhancement demonstrate GANs' potential for societal benefit, but require rigorous validation frameworks and ethical safeguards. This maturity-risk duality is central to our framework's evaluation approach.

The applications discussed reveal both the potential and limitations of current GAN technologies. We now analyze the fundamental challenges that continue to constrain their wider adoption and effectiveness across different domains.

6. EMERGING CHALLENGES AND RECENT SOLUTIONS IN GANS

The technical challenges in GAN training are not merely abstract research problems; they have direct implications for real-world applications and end users. Training instability, for instance, translates to longer development cycles and higher computational costs for AI developers, limiting the accessibility of GAN technology to small research teams and startups. Similarly, mode collapse does not just represent a theoretical limitation; it results in a reduced diversity of synthetic medical images, potentially leading to biased diagnostic models that fail to generalize across diverse patient populations. By understanding how these technical challenges impact practical deployment, researchers can prioritize solutions that address both algorithmic improvements and real-world usability.

The training failure points identified in Figure 3, particularly the mode collapse and unstable gradients, represent persistent bottlenecks that directly impact application reliability and deployment scalability across all domains discussed in this review.

This section highlights the significant challenges that accompany the training and deployment of GANs, including mode collapse, instability, and evaluation metrics. In addition, we will explore innovative solutions proposed by researchers to address these issues and enhance the robustness and reliability of GAN applications. Although numerous studies have catalogued GAN challenges, our systematic analysis reveals critical patterns in solution efficacy and application-specific limitations. The persistent nature of issues such as mode collapse and training instability, despite a decade of research, underscores fundamental tensions in adversarial learning paradigms that require more than incremental architectural fixes.

By providing insights into both challenges and solutions, this section aims to contribute to a deeper understanding of how to effectively leverage GANs in diverse fields.

GANs present a range of challenges that researchers are striving to overcome. Although some of these challenges have been met with effective solutions, others remain unresolved and continue to pose significant questions in the field. This section discusses these challenges, outlines the strategies that have been developed to address various issues, and highlights the open problems that require further investigation.

The authors in [27] summarized the GAN design and optimization solutions proposed for handling two main GAN challenges: mode collapse (MC), nonconvergence, and instability (NC&I). They then presented proposed solutions for handling the addressed GAN challenges. The study presented a summary table of GANs (approximately 67 models of GANs) and proposed design and optimization solutions for addressing two main GAN challenges: mode collapse (MC) and nonconvergence and instability (NC&I).

The authors in [97] [97] identified three common challenges during training: the vanishing gradient problem, where the generator fails if it is not as capable as the discriminator, and the mode collapse problem, where the generator gets stuck, producing the same set of instances because the discriminator gets trapped in a local minimum. Researchers have proposed solutions to address these challenges, including the use of Wasserstein loss to address vanishing gradients and mode collapse, as well as modeling the objective of the generator in coherence with the optimal discriminator. Furthermore, the introduction of noise to the discriminator inputs and the utilization of novel regularization techniques have been demonstrated to facilitate the convergence and stability of GANs. The authors in [28] focused on two major problems in training: model collapse and nonconvergence, and the latest solutions to these issues. Model collapse solutions include introducing conditional generation (CGANs, InfoGAN, and ACGAN), which conditions the generator on additional information to better control the generated modes. The proposed non-convergence and instability solutions include the use of new probability distances and divergences, such as the Earth-Mover distance in Wasserstein GANs (WGAN), which provide continuous and differentiable gradients to stabilize the training. Other variants, such as LS-GAN and RWGAN, further improved the WGAN approach.

The authors of [17] addressed the principal difficulties encountered with GANs. Mode collapse is a phenomenon in which a generator network fails to produce a diverse range of outputs, resulting in a loss of information. Several solutions have been proposed for this purpose.

including the balancing of the discriminator's outputs, use of multiple GANs, and alteration of the distance metric used to compare distributions. Training instability and saddle points are additional challenges that must be addressed. Potential solutions include the utilization of results from nonlinear systems theory, addressing issues with the Jacobian matrix, and applying second-order optimizers. Evaluation of generative models is a crucial aspect of this field. The proposed solution includes the introduction of a novel metric, designated as the 'neural net distance,' to address the limitations associated with the conventional approach to evaluating the performance of generative adversarial networks (GANs).

Our comparative synthesis of these proposed solutions revealed significant efficacy variations across domains. Although Wasserstein loss has demonstrated remarkable success in stabilizing image generation tasks, its performance in time-series data remains inconsistent [98]. Similarly, minibatch discrimination effectively addresses mode collapse in high-diversity datasets but introduces substantial computational overhead that limits real-time applications. This domain-dependent effectiveness highlights the need for context-aware solution selection, rather than a one-size-fits-all approach.

The key challenges in time series GANs are discussed in [98] are:

1) Training Stability - addressing issues like vanishing gradients and mode collapse requires changes to the architecture or loss function;

2) Evaluation–Qualitative assessment of generated time series data is difficult compared to images, but quantitative approaches using two-sample tests can be leveraged.

3)Privacy risk-de-identified data can still be re-identified using additional information; therefore, alternative methods are needed to protect sensitive health data and comply with stricter privacy regulations. The authors of [99] proposed the TextControlGAN model as a solution to the limitations of conventional GANs in text-to-image synthesis. It incorporates a regressor to learn conditional text features more effectively, utilizes data augmentation, and optimizes the discriminator training, resulting in significant performance improvements.

The authors in [100] identifies two main challenges in fake license plate recognition (LPR) using Generative Adversarial Networks (GANs): the limitations posed by small datasets and the texture sticking problem. Small datasets hinder the training of robust models, leading to a poor performance in generating realistic images. In addition, texture sticking affects the dynamic quality of the generated content, resulting in inconsistencies during video generation. To address these challenges, this review discusses various enhancements in GAN architectures, including pix2pix_GAN, CycleGAN, and StyleGAN2-ADA, which can effectively synthesize high-quality license plate images. Adaptive data augmentation techniques have also been introduced to stabilize the GAN training and mitigate texture sticking. These advancements have significantly improved the accuracy and robustness of fake LPR systems, enabling better generalization across diverse license plate styles and backgrounds.

6.1. Critical Evaluation of Solution Efficacy

Our framework-based evaluation of the cited solutions provided several critical insights. First, solutions addressing training instability (e.g., WGAN and spectral normalization) have achieved more consistent success across domains compared to mode collapse mitigation techniques. Second, there exists an often-overlooked trade-off between solution complexity and practical deployment ability. While sophisticated approaches such as unrolled GANs [101] offer theoretical advantages, their implementation complexity hinders widespread adoption. Third, the evaluation metrics themselves pose challenges; quantitative improvements in scores, such as FID, do not always translate to qualitative improvements in real-world applications.

Furthermore, our analysis identifies the gap between the algorithmic proposals and real-world constraints. Many solutions demonstrate efficacy on curated benchmark datasets but struggle with the data heterogeneity and resource constraints of production environments. This underscores the need for additional application-grounded validation methodologies in future GAN research.

The integration of Generative Artificial Intelligence (GAI) into the Internet of Things (IoT) ecosystem introduces significant challenges, including high processing resource demands, energy efficiency concerns, latency management, large data volumes, and privacy issues. To overcome these obstacles, the authors in [102]proposed solutions such as edge computing, stream processing, and distributed architectures to enhance real-time processing and resource optimization. Additionally, efficient compression and model optimization techniques can facilitate GAI functionality in resource-constrained devices, whereas real-time feedback mechanisms can help reduce energy consumption. Establishing strong cybersecurity policies and ethical frameworks is also crucial for ensuring data privacy and building user trust in GAI applications within IoT systems.

The authors in [26] discussed several challenges related to imbalanced datasets, including data imbalance, which leads to biased model performance, and class imbalance, which makes it difficult for algorithms to generalize. Additional issues include noisy data that complicate model training and a lack of hybrid approaches that combine GANs with other advanced techniques. To address these challenges, this study suggests using Generative Adversarial Networks (GANs) for data preprocessing and GAN-based oversampling to enhance the minority class representation. It emphasizes the need for advanced architectures and tailored frameworks to improve performance, and introduces categorization mappings for structured analysis. Finally, it encourages future research to explore hybrid approaches that integrate GANs with other methodologies for better handling data imbalances.

This critical examination moves beyond cataloguing challenges in analyzing solution efficacy patterns and their practical implications. Despite extensive research, the persistent nature of these issues suggests that future breakthroughs may require the fundamental reconceptualization of adversarial learning rather than incremental improvements. Our analysis provides researchers with a nuanced understanding of not just what solutions exist, but also when and why they succeed or fail, enabling more informed algorithmic selections and targeted innovations.

7. ETHICAL AND SOCIETAL IMPLICATIONS

The rapid advancement of AI-generated media, such as deepfakes and synthetic voices, has significant ethical and societal implications. Our integrated framework reveals that these ethical concerns are not merely byproducts but are intrinsically linked to specific architectural characteristics of GANs. The features that enable photorealistic generation, such as high-fidelity output in StyleGAN or seamless domain translation in CycleGAN, directly amplify their potential for misuse. This technical-ethical interdependence necessitates a co-design approach in which ethical considerations inform architectural choices from the outset.

Our workflow (Figure 3) explicitly connects technical capabilities to societal impacts, demonstrating how architectural choices enabling high-fidelity generation simultaneously amplify ethical risks, necessitating the co-design of technical and ethical safeguards from the initial development phases.

Although these innovations offer new opportunities for creativity and accessibility, their misuse threatens information integrity, personal privacy, and public trust. This duality underscores the urgent need for robust legal and regulatory frameworks that can mitigate risks without stifling innovation [29]. Current global regulatory efforts are fragmented and inconsistent, leaving gaps in addressing the complexities of AI-generated content. This lack of oversight raises important questions regarding accountability and individual rights. Therefore, balanced governance strategies are essential for navigating these risks while fostering innovation in this evolving landscape.

As the capabilities of GANs continue to evolve, it is crucial to proactively address their ethical and societal implications to ensure the responsible and beneficial use of this transformative technology [36]. Collaborative efforts between researchers, industry leaders, policymakers, and the public are essential in shaping the future of GANs and ensuring that their development aligns with ethical principles and societal well-being.

7.1. Bias in AI-Generated Content:

The outputs of GANs reflect and amplify the biases present in the training data. This raises concerns about fairness and representation in generated content, particularly in sensitive areas such as facial recognition and media portrayals [30]. Architectural analysis revealed specific bias amplification mechanisms: the discriminator's feedback loop in traditional GAN architectures can reinforce majority patterns in training data, systematically disadvantaging underrepresented groups. Furthermore, the latent space organization in models such as StyleGAN, while enabling fine-grained control, may encode and perpetuate social stereotypes if the training data reflect historical biases. Addressing these issues requires both algorithmic interventions (e.g., fairness-aware loss functions) and architectural modifications that explicitly model and mitigate bias propagation.

Addressing these biases requires the implementation of strategies to ensure diverse and representative datasets, along with ongoing monitoring and evaluation of the generated content to identify and mitigate potential biases. Researchers are exploring techniques for bias detection and correction in order to promote equity and inclusivity in AI-generated media.

7.2. Limited Engagement with Existing Research

Engaging with the current literature is essential for understanding the ethical implications of GANs and for guiding future developments. Numerous studies have explored the societal impacts of deepfakes and biases in AI-generated content, emphasizing the need for comprehensive ethical frameworks [103]. By synthesizing the findings from existing research, stakeholders can better navigate the complexities of AI governance and develop informed policies that address both the opportunities and risks associated with generative technologies.

7.3. Impact on Content Authenticity

7.3.1. Detecting Deepfakes.

The highly realistic synthetic media generated by GANs, commonly known as "deepfakes," pose significant challenges in verifying the authenticity of online content, images, and videos. This raises concerns about the potential of malicious actors to create false or misleading content that could be used to spread disinformation, manipulate public opinion, and undermine trust in digital media. The development of robust deepfake detection algorithms and technologies is crucial for addressing this challenge and preserving the integrity of the digital information [104].

The deepfake detection landscape reveals an architectural arm-race. As GAN generators evolve to produce more temporally consistent videos with fewer artifacts, detection methods must advance beyond surface-level analysis. Our framework suggests that sustainable solutions may lie in architectural transparency—building verifiable constraints into generator designs, rather than relying solely on post-hoc detection. The EU's Digital Services Act exemplifies the regulatory recognition that technical and governance solutions must co-evolve to effectively address this challenge.

Researchers are exploring various techniques, such as analyzing subtle inconsistencies in facial expressions, voice patterns, and metadata, to distinguish authentic content from deep fakes [105]. However, as GANs continue to evolve, the ability to create increasingly convincing deepfakes may outpace the development of detection methods, creating an ongoing "arms race" that requires continuous innovation and vigilance.

7.3.2. Trustworthiness of Generated Content.

As GANs become more advanced, the distinction between synthetic and real-world content may become increasingly blurred, making it difficult for individuals and institutions to discern the trustworthiness of the generated content. This can have far-reaching implications in areas such as journalism, education, and decision making, where the reliability and credibility of information are paramount. Misinformation or manipulated content generated by GANs can lead to the spread of false narratives, erode public trust, and undermine the foundations of democratic institutions. Establishing clear guidelines, standards, and transparency measures around the use of GANs and synthetic media can help foster trust and accountability in the digital landscape [106]. This may involve the development of content provenance mechanisms, digital watermarking, and other verifiable authentication techniques.

7.4. Regulations and Control Mechanisms

7.4.1. Intellectual Property Rights.

The ability of GANs to generate highly realistic and unique content raises complex questions regarding intellectual property rights and ownership. Determining the rightful owner of generated content, addressing issues of copyright infringement, and establishing appropriate licensing frameworks will be crucial to ensuring the fair and ethical use of GAN-generated content [36]. Policymakers and industry leaders must collaborate to develop comprehensive regulations and guidelines that balance innovation, creativity, and the protection of intellectual property rights. This may involve the creation of new legal frameworks or adaptation of existing intellectual property laws to accommodate the unique challenges posed by generative AI technologies [29]. Failure to address these issues may lead to a legal and ethical quagmire, stifling the growth and adoption of GANs and limiting their potential societal benefits.

7.4.2. Data Privacy and Ownership.

The training of GANs often requires large datasets that may include personal or sensitive information, raising concerns about data privacy and ownership. Ensuring the ethical and responsible use of data in GAN development, as well as establishing clear guidelines for data collection, storage, and usage, is essential to protect individual privacy and maintain public trust [107]. Engaging with stakeholders, including data subjects, researchers, and policymakers, is crucial in developing robust data governance frameworks that address the unique challenges posed by the widespread adoption of GANs. This may involve the implementation of strict data privacy regulations, establishment of data trusts or cooperatives, and empowerment of individuals to have greater control over their data. Failure to address these data privacy and ownership concerns could lead to a significant erosion of public trust, as well as legal and ethical challenges that could hinder the responsible development and deployment of GANs.

7.4.3. Ethical and Legislative Responses

The ethical implications of AI-generated media manipulation underscore the urgent need for effective regulatory frameworks that prioritize transparency, accountability, and social responsibility. As technologies, such as deepfakes, pose serious threats to privacy, reputation, and the integrity of information, governments and international organizations are increasingly recognizing the necessity for comprehensive regulations [37]. The European Union's AI Act exemplifies this proactive approach by categorizing high-risk AI applications and enforcing strict guidelines that mandate transparency regarding identity and consent, particularly in the sphere of audiovisual media.

In the United States, the DEEPFAKES Accountability Act represents a legislative effort to address urgent ethical issues, specifically, criminalizing malicious deepfakes that can lead to deception and defamation. This act not only captures the public's growing concern over the misuse of AI-generated media, but also demonstrates a legislative framework that confronts ethical dilemmas by emphasizing accountability for creators and distributors of harmful content. These laws seek to deter malicious use and encourage ethical practices within the technological community.

Real-world case studies further illustrate ethical challenges and regulatory responses in this evolving landscape. For instance, the rapid dissemination of a deepfake video during the 2020 U.S. presidential election highlights the critical need for robust content moderation practices. This incident underlined the effectiveness of regulatory frameworks such as the Digital Services Act (DSA), which aims to mitigate harm by imposing obligations on digital platforms to monitor and manage manipulated content. The blackmail and reputational damage resulting from such media manipulation have prompted significant discussions about creating more rigorous legal responses capable of holding content creators accountable for their actions [108]. UNESCO's Recommendation on the Ethics of Artificial Intelligence calls for global cooperation and uniform standards that can adapt to regional variations in media regulation, emphasizing that ethical considerations must be at the forefront of any international response to AI-generated media manipulation. By advocating common ethical standards, this initiative seeks to navigate the complex landscape of AI governance while safeguarding fundamental rights.

7.5. Technical Accountability and Governance

Our analysis underscores the need for technical accountability frameworks spanning the entire GAN lifecycle. From dataset curation to model deployment, each architectural decision carries ethical implications that must be documented and auditable [29, 36]. We propose three pillars of technical accountability:

1. Architectural Transparency: Documenting design choices that influence ethical outcomes (e.g., discriminator architecture impacting bias amplification)

2. Provenance Tracking: Implementing technical mechanisms to track data lineage and model genealogy

3. Impact-by-design: Integrating ethical impact assessment directly into the model development workflow

These technical measures complement regulatory frameworks by providing enforceable mechanisms for accountability [37].

The ethical landscape of GANs reveals a complex interplay between their technical capabilities and societal impact. Our integrated framework demonstrates that ethical risks cannot be treated as externalities, but must be addressed through technical design choices, governance mechanisms, and regulatory frameworks operating in concert. The most pressing challenge lies in balancing innovation with responsibility-developing GAN architectures that advance the state-of-the-art while incorporating ethical safeguards by design.

Future research must focus on developing technically grounded ethical frameworks that provide practical guidance for architects and developers [107]. This includes standardized impact assessment methodologies, bias detection integrated into training pipelines, and transparency mechanisms that make ethical considerations visible and actionable throughout the development lifecycle.

8. OPEN ISSUES AND TECHNICAL CONSIDERATIONS

GANs face several significant technical issues that must be addressed for effective deployment. Our systematic analysis reveals that many "solved" challenges in GAN research resurface in new contexts, indicating deeper fundamental issues in adversarial learning. Although architectural innovations have addressed specific symptoms, the root causes of instability and mode collapse persist, suggesting the need for paradigm-level rethinking rather than incremental improvements.

8.1. Ensuring Training Stability

One of the key issues in working with generative adversarial networks (GANs) is ensuring training stability. The core GAN framework pits a generator network against a discriminator network in an adversarial game, which can lead to unstable training dynamics and issues, such as mode collapse, where the generator becomes stuck, producing a limited variety of samples [28]. Researchers have developed novel architectural approaches to address these issues. A viable way to obtain a GAN to address these two issues is to redesign the network architecture to create a more powerful model. Select the best optimization techniques or modify an appropriate objective function. In recent years, these strategies have led to the proposal of numerous GAN versions with different properties.

Many studies have focused on GANs, and previous results have introduced various GAN designs and training strategies for these problems.

8.1.1. Novel Architectural Approaches.

Researchers have developed novel architectural approaches to address these issues. Wasserstein GANs (WGANs) modify the GAN loss function by replacing the standard Jensen–Shannon divergence with the Wasserstein distance [109], which provides a more stable training signal. Spectral normalization GANs (SNGANs) use spectral normalization to constrain the Lipschitz constant of the discriminator, thereby stabilizing the gradients during training.

8.1.2. Regularization Techniques.

In addition to these architectural innovations, regularization techniques have proven effective for stabilizing GAN training [110]. One key technique is the gradient penalty, which is used in WGAN-GP. The gradient penalty regularizes the discriminator by penalizing its gradient norm, thereby encouraging it to have a low Lipschitz constant. This helps to prevent the discriminator from becoming too strong relative to the generator, which can lead to unstable gradients and training collapse. Other regularization methods, such as feature matching, historical averaging, and path length penalty, have also been explored to improve the GAN stability and performance. The choice of architectural design and regularization approach often depends on the specific GAN application and the dataset. Although WGANs and SNGANs represent significant advances, our analysis reveals context-dependent limitations. Although theoretically elegant, the WGAN's Wasserstein distance imposes computational burdens that limit scalability to high-resolution domains. Similarly, spectral normalization enhances stability but may constrain the model capacity, potentially sacrificing expressiveness for reliability. This stability-expressiveness trade-off remains a fundamental tension in GAN design that warrants further investigation [51].

8.2. Mode Collapse

This is one of the main problems of GANs, in which the generator outputs only a few modes and does not represent the range of data distribution [17]. This phenomenon occurs when the generator learns to produce a limited set of samples, leading to a lack of output diversity. This problem reduces the quality of the output images by preventing the model from accurately reflecting the entire data distribution. Another strategy that prevents the creation of comparable samples is feature matching [111], which aligns the generator to produce outputs with the characteristics of the discriminator's middle layers. Because the discriminator may view several samples in a minibatch at once and is therefore less likely to be tricked by the generator with only a few modes, minibatch discrimination enhances the diversity. Unrolled GANs extend the concept of adversarial training by considering a few steps in the optimization process to minimize the chances of the generator outsmarting the discriminator [28]. The objectives of multi-objective GANs, which are included in the training process, are diversity and novelty, which make the generator search for more outputs and minimize mode collapse. Several techniques have been developed to address this problem.

8.2.1. Mini-batch Discrimination:

This allows the discriminator to look at several samples simultaneously, thereby encouraging the generator to produce a broader variety of outputs [27].

8.2.2. Unrolled GANs

This enables the generator to anticipate the discriminator's response, helping reduce repetitive outputs [101].

Our framework evaluation indicates that minibatch discrimination excels in large-scale settings, but struggles with limited data scenarios. Conversely, unrolled GANs offer theoretical guarantees, but face practical implementation challenges in memory-intensive applications. The optimal solution appears to be highly dependent on the data characteristics and computational constraints, underscoring the need for adaptive rather than one-size-fits-all approaches.

8.3. Computational cost

The computational cost is a critical challenge in training GANs because they require high computing resources and can be time-consuming [27]. Solutions include:

8.3.1. Distributed Training

Cloud computing resources or multiple graphics processing units (GPUs) were utilized to accelerate the training process.

8.3.2. Optimized Model

Design: Reducing the number of required parameters, which decreases the time and costs associated with training

8.4. Ethical Use and Misuse Potential

In addition to technical considerations, the ethical use and potential misuse of GANs are vital issues that must be addressed [29]. On the one hand, GANs have shown great potential in beneficial applications such as data augmentation, superresolution, and realistic media generation. However, they also enable the creation of "deepfakes," highly convincing fake media that can be used to spread misinformation. The responsible development and deployment of GAN technology require careful weighing of these trade-offs, and we provide more details on the ethical considerations and potential misuses of GANs, which are broken down into two key areas:

8.4.1. Deepfakes and Manipulations.

One of the most concerning potential misuses of GANs is the creation of "deepfakes," highly convincing fake media, such as images, videos, or audio, that can be used to spread misinformation and disinformation [37]. DeepFakes leverages the impressive generative capabilities of GANs to produce fabricated content that can be difficult to distinguish from real content. This technology could be weaponized to create fake news, political propaganda, revenge porns, and other malicious content intended to deceive and manipulate people. The proliferation of deepfakes poses significant risks to individual privacy, democratic processes, and public trust in media.

institutions. Effective detection and mitigation strategies are crucial to address this emerging threat.

8.4.2. Biased Data Generation.

GANs, similar to other machine learning models, are heavily dependent on the quality and representativeness of the training data to which they are exposed. If the training data used to develop GANs contain biases, stereotypes, or underrepresentations of certain groups, the generated content may perpetuate and amplify these biases.

This can lead to the creation of content that reinforces harmful societal biases related to gender, race, ethnicity, age, and other characteristics [112]. This bias can manifest in the generated images, text, or audio produced by GANs. The responsible development of GAN systems requires careful consideration of the data used for training, as well as the implementation of fairness and bias mitigation techniques to ensure that the generated content is inclusive and unbiased.

And for the solutions

The research community and industry leaders must work collaboratively to do the following:

- Robust deep fake detection and attribution methods have been developed to identify and mitigate the spread of manipulated media.
- Ethical guidelines and best practices for the development and deployment of GANs should be established with an emphasis on the responsible use and mitigation of potential harm.
- Investing in research on fairness, bias, and inclusivity in generative AI systems ensures that they create content that is representative and unbiased.
- Policymakers, civil society, and the public should be encouraged to raise awareness and inform policies that regulate the use of GANs and other generative technologies. By proactively addressing these ethical considerations, the research and development community can unlock the tremendous potential of GANs, while minimizing the risk of misuse and negative societal impacts.

8.5. Fundamental Trade-offs and Future Directions

Our integrated analysis identified several irreducible trade-offs that define the GAN research landscape.

1. Quality vs. Diversity: High-fidelity generation often compromises sample diversity, creating persistent tension in evaluation metrics [12].

2. Stability vs. Expressiveness: Techniques that ensure training stability frequently limit the model capacity and creative potential.

3. Theoretical Guarantees vs. Practical Efficiency: Methods with strong theoretical foundations often prove computationally prohibitive in real-world applications.

4. Architectural Complexity vs. Interpretability: As GAN architectures grow more sophisticated, their interpretability and debuggability correspondingly decrease.

These trade-offs suggest that future breakthroughs may require moving beyond the current adversarial paradigm toward hybrid approaches that combine the strengths of GANs with complementary generative modeling techniques [17].

In brief, we summarize the most important challenges and issues facing generative adversarial networks as follows:

1. Training Stability: The adversarial nature of the GAN framework can lead to unstable training dynamics, mode collapse, and gradient instability. Novel architectures such as Wasserstein GANs (WGANs) and spectral normalization GANs (SNGANs), as well as regularization techniques such as gradient penalties, are required to improve training stability.

2. Mode Collapse: This occurs when the generator produces a limited variety of outputs, failing to capture the full diversity of the training data. Techniques, such as minibatch discrimination, feature matching, and improved sampling methods, have been explored to address mode collapse and enhance sample diversity.

3. Hyperparameter sensitivity: GANs are vulnerable to small changes in training configurations, leading to significant differences in performance. The development of more robust and stable GAN training procedures as well as better hyperparameter initialization and tuning methods is an active area of research.

4. Evaluation: Assessing the performance of GANs, particularly in terms of sample quality and diversity, is challenging. Traditional metrics, such as the inception score and Fréchet inception distance, have limitations, and developing comprehensive frameworks for GAN evaluation remains an open problem.

5. Ethical Considerations: The potential for misuse of GANs, such as the creation of "deepfakes" for the spread of misinformation, is an important issue that must be carefully considered. The responsible development and deployment of GAN technology requires addressing these ethical implications and implementing appropriate safeguards.

6. Computational Cost: Training GANs can be resource-intensive and requires significant computational resources and time. Strategies such as distributed training and optimized model designs are essential for effectively managing these costs. Despite extensive research, the persistent nature of these technical challenges underscores the fundamental limitations of the current GAN paradigm. Our analysis suggests that incremental architectural improvements may have diminishing returns and that future progress may require the reconceptualization of adversarial learning. The integration of GANs with emerging approaches such as diffusion models, energy-based models, and neurosymbolic methods offers promising avenues for overcoming these limitations [42]. Moreover, the technical challenges discussed cannot be disentangled from the ethical considerations in Section 7. Issues in training stability directly impact model reliability in sensitive applications, whereas mode collapse affects fairness through a lack of diversity. This technical-ethical interdependence reinforces the necessity of our integrated framework, in which technical development and ethical considerations advance in concert rather than in isolation.

9. CONCLUSION

This systematic review advanced beyond descriptive surveying to provide an integrated framework that concurrently evaluates GAN architectures, application maturity, and ethical implications. Generative Adversarial Networks (GANs) have revolutionized the field of artificial intelligence, serving as powerful tools for data generation and creative applications across multiple domains. In this paper, we conducted a comprehensive review of the latest studies on GANs, examining all aspects of this cutting-edge technology. At the fundamental level, GANs aim to estimate the potential distribution of real data samples and generate new samples from this distribution. Their core concept revolves around the adversarial game between the generator and discriminator, functioning as two players in a zero-sum competitive setting.

Throughout this study, we discuss the most critical aspects of GANs, including their architectures, training techniques, and recent advancements. We highlighted their prominent applications in areas such as image synthesis, video prediction, and 3D object creation, demonstrating their significant impact on industry and research. Additionally, we examined the key challenges faced in training GANs, such as non-convergence, mode collapse, and issues related to ethical use and potential misuse.

The principal contribution of this study lies in its integrated analytical framework, which moves beyond technical cataloguing to critically examine how architectural choices inherently shape both performance capabilities and ethical risks. This holistic perspective reveals that solutions to technical challenges such as mode collapse and training instability have direct implications for fairness, accountability, and potential misuse. Our analysis identifies three critical research directions that must be pursued concurrently: (1) developing next-generation architectures that fundamentally reconceptualize adversarial learning beyond current paradigms, (2) establishing comprehensive evaluation metrics that assess technical performance alongside fairness and robustness, and (3) creating ethical-by-design frameworks that embed accountability directly into GAN architectures rather than treating it as an external constraint. In the future, continued innovation and exploration of emerging techniques promises to overcome current limitations and unlock new opportunities. This review provides researchers, practitioners, and policymakers with an integrated framework to navigate complex GAN landscapes. By emphasizing the intrinsic connections between technical capabilities and societal implications, we aim to foster development that advances not only what GANs can do but also how they should be developed and deployed, ensuring that these transformative technologies fulfill their potential while serving the broader interests of society.

REFERENCES

[1] D. G. P. Audichya and A. Singh, "Generative adversarial networks: Models and techniques - a review," in *IEEE World Conference on Applied Intelligence and Computing*, IEEE, 2022.

[2] A. O. Arik and B. O. Kose, "Data guardians: Empowering cybersecurity with generative adversarial networks," in *Enhancing Security in Public Spaces Through Generative Adversarial Networks (GANs)*, IGI Global, 2024, pp. 102–123.

[3] M. E. Laino, P. Cancian, L. S. Politi, M. G. D. Porta, L. Saba, and V. Savevski, "Generative adversarial networks in brain imaging: A narrative review," *J. Imaging*, vol. 8, no. 4, p. 83, 2022.

[4] A. Gunasekaran, "Generative adversarial networks: A brief history and overview," *J. Stud. Res.*, vol. 12, no. 1, 2023.

[5] A. Kammoun, R. Slama, H. Tabia, T. Ouni, and M. Abid, "Generative adversarial networks for face generation: A survey," *ACM Comput. Surv.*, vol. 55, no. 5, pp. 1–37, 2022.

[6] A. A. Nayak, P. Venugopala, and B. Ashwini, "A systematic review on generative adversarial network (gan): Challenges and future directions," *Arch. Comput. Methods Eng.*, pp. 1–34, 2024.

[7] P. Cobelli, S. Nesmachnow, and J. Toutouh, "A comparison of generative adversarial networks for image super-resolution," in *2022 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*, IEEE, 2022, pp. 1–6.

[8] T. Karras, S. Laine, and T. Aila, "A style-based generator architecture for generative adversarial networks," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019, pp. 4401–4410.

[9] I. Goodfellow et al., "Generative adversarial networks," *Commun. ACM*, vol. 63, no. 11, pp. 139–144, 2020.

[10] Z. Liu, T. Yuan, and B. Zeng, "Recent advances of generative adversarial networks," in *IEEE 2nd International Conference on Electronic Technology, Communication and Information (ICETCI)*, IEEE, 2022.

[11] L. Xu et al., "Tgan-ad: Transformer-based gan for anomaly detection of time series data," *Appl. Sci.*, vol. 12, no. 16, p. 8085, 2022.

[12] M. Megahed and A. Mohammed, "A comprehensive review of generative adversarial networks: Fundamentals, applications, and challenges," *Wiley Interdiscip. Rev. Comput. Stat.*, vol. 16, no. 1, e1629, 2024.

[13] J. Gui, Z. Sun, Y. Wen, D. Tao, and J. Ye, "A review on generative adversarial networks: Algorithms, theory, and applications," *IEEE Trans. on Knowl. Data Eng.*, vol. 35, no. 4, pp. 3313–3332, 2021.

[14] Y. Zhang, "Analysis of learning mechanism of generative adversarial network," in *2022 International Symposium on Advances in Informatics, Electronics and Education (ISAIEE)*, IEEE, 2022, pp. 59–63.

[15] R. K. Devi and M. A. Jerlin, "Generative adversarial networks: A comprehensive review," in *Generative Artificial Intelligence (AI) Approaches for Industrial Applications*, 2025, pp. 69–92.

[16] C. Shen, Y. Yin, X. Wang, X. Li, J. Song, and M. Song, "Training generative adversarial networks in one stage," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021, pp. 3350–3360.

[17] H. Alqahtani, M. Kavakli-Thorne, and G. Kumar, "Applications of generative adversarial networks (gans): An updated review," *Arch. Comput. Methods Eng.*, vol. 28, pp. 525–552, 2021.

[18] T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, and T. Aila, "Analyzing and improving the image quality of stylegan," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 8110–8119.

[19] Y. Wang, "A mathematical introduction to generative adversarial nets (gan)," *arXiv preprint*, vol. arXiv:2009.00169, 2020.

[20] P. Saxena, R. Gupta, A. Maheshwari, and S. Maheshwari, "Semantic image completion and enhancement using gans," in *High Performance Vision Intelligence: Recent Advances*, 2020, pp. 151–170.

[21] E. R. Chan, M. Monteiro, P. Kellnhofer, J. Wu, and G. Wetzstein, "Pi-gan: Periodic implicit generative adversarial networks for 3d-aware image synthesis," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021, pp. 5799–5809.

[22] M. Toshpulatov, W. Lee, and S. Lee, "Generative adversarial networks and their application to 3d face generation: A survey," *Image Vis. Comput.*, vol. 108, p. 104 119, 2021.

[23] S. Sabnam and S. Rajagopal, "Application of generative adversarial networks in image, face reconstruction and medical imaging: Challenges and the current progress," *Comput. Methods Biomech. Biomed. Eng. Imaging & Vis.*, vol. 12, no. 1, p. 2 330 524, 2024.

[24] B. Gecer, S. Ploumpis, I. Kotsia, and S. Zafeiriou, "Ganfit: Generative adversarial network fitting for high fidelity 3d face reconstruction," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019, pp. 1155–1164.

[25] Z. Cai, Z. Xiong, H. Xu, P. Wang, W. Li, and Y. Pan, "Generative adversarial networks: A survey toward private and secure applications," *ACM Comput. Surv. (CSUR)*, vol. 54, no. 6, pp. 1–38, 2021.

[26] U. Sirisha, C. K. Kumar, S. C. Narahari, and P. N. Srinivasu, "An iterative prisma review of gan models for image processing, medical diagnosis, and network security," *Comput. Mater. & Continua*, vol. 82, no. 2, 2025.

[27] D. Saxena and J. Cao, "Generative adversarial networks (gans) challenges, solutions, and future directions," *ACM Comput. Surv. (CSUR)*, vol. 54, no. 3, pp. 1–42, 2021.

[28] H. Chen, "Challenges and corresponding solutions of generative adversarial networks (gans): A survey study," in *Journal of Physics: Conference Series*, vol. 1827, IOP Publishing, 2021, p. 012 066.

[29] C. Uddagiri and B. V. Isunuri, "Ethical and privacy challenges of generative ai," in *Generative AI: Current Trends and Applications*, Springer, 2024, pp. 219–244.

[30] X. Fang, S. Che, M. Mao, H. Zhang, M. Zhao, and X. Zhao, "Bias of ai-generated content: An examination of news produced by large language models," *Sci. Reports*, vol. 14, no. 1, p. 5224, 2024.

[31] J. Donahue and K. Simonyan, "Large scale adversarial representation learning," *Adv. Neural Inf. Process. Syst. (NeurIPS)*, vol. 32, 2019.

[32] H. Zhang, I. Goodfellow, D. Metaxas, and A. Odena, "Self-attention generative adversarial networks," in *International Conference on Machine Learning (ICML)*, PMLR, 2019, pp. 7354–7363.

[33] Y. Zhang, Q. Zhang, M. Jiang, and J. Su, "Scgan: Generative adversarial networks of skip connection for face image inpainting," in *2022 Ninth International Conference on Social Networks Analysis, Management and Security (SNAMS)*, IEEE, 2022, pp. 1–6.

[34] V.-H. Phan, M.-Q. Ha, and T.-H. Do, "A novel license plate image reconstruction system using generative adversarial network," in *2022 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT)*, IEEE, 2022, pp. 222–228.

[35] N. Li, S. Zhou, P. Wang, and Y. Zhang, "Single image deraining with generative adversarial network," in *2023 IEEE International Conference on Mechatronics and Automation (ICMA)*, IEEE, 2023, pp. 2189–2194.

[36] S. A. Alajaji et al., "Generative adversarial networks in digital histopathology: Current applications, limitations, ethical considerations, and future directions," *Mod. Pathol.*, p. 100 369, 2023.

[37] P. Zlateva, L. Steshina, I. Petukhov, and D. Velev, "A conceptual framework for solving ethical issues in generative artificial intelligence," in *Electronics, Communications and Networks*, IOS Press, 2024, pp. 110–119.

[38] F. Ramzan, C. Sartori, S. Consoli, and D. R. Recupero, "Generative adversarial networks for synthetic data generation in finance: Evaluating statistical similarities and quality assessment," *AI*, vol. 5, no. 2, pp. 667–685, 2024.

[39] Z. Wang, Q. She, and T. Ward, "Generative adversarial networks in computer vision: A survey and taxonomy," *ACM Comput. Surv.*, vol. 54, pp. 1–38, 2021. DOI: 10.1145/3439723.

[40] P. Sharma, M. Kumar, and H. K. Sharma, "Gan-cnn ensemble: A robust deepfake detection model of social media images using minimized catastrophic forgetting and generative replay technique," *Procedia Comput. Sci.*, vol. 235, pp. 948–960, 2024.

[41] P. Sharma, *A brief history of generative adversarial networks*, 2022.

[42] S. Bengesi, H. El-Sayed, M. K. Sarker, Y. Houkpati, J. Irungu, and T. Oladunni, "Advancements in generative ai: A comprehensive review of gans, gpt, autoencoders, diffusion model, and transformers," *IEEE Access*, 2024.

[43] J. Jenkins and K. Roy, "Exploring deep convolutional generative adversarial networks (dcgan) in biometric systems: A survey study," *Discov. Artif. Intell.*, vol. 4, no. 1, p. 42, 2024. DOI: 10.1007/s44163-024-00138-z.

[44] H. K. Kılınç and Ö. F. Keçecioğlu, "Generative artificial intelligence: A historical and future perspective," *Acad. Platf. J. Eng. Smart Syst.*, vol. 12, no. 2, pp. 47–58, 2024.

[45] S. M. Razak and B. Jafarpour, "History matching with generative adversarial networks," in *ECMOR XVII*, vol. 2020, European Association of Geoscientists & Engineers, 2020, pp. 1–17.

[46] P. Purwono, A. N. E. Wulandari, A. Ma'arif, and W. A. Salah, "Understanding generative adversarial networks (gans): A review," *Control. Syst. Optim. Lett.*, vol. 3, no. 1, pp. 36–45, 2025.

[47] R. Bhat and R. Nanjundegowda, "A review on comparative analysis of generative adversarial networks' architectures and applications," *J. Robotics Control. (JRC)*, vol. 6, no. 1, pp. 53–64, 2025.

[48] Y. Li and Q. Zhang, "The analysis of aesthetic preferences for cultural and creative design trends under artificial intelligence," *IEEE Access*, 2024.

[49] A. Dash, J. Ye, and G. Wang, "A review of generative adversarial networks (gans) and its applications in a wide variety of disciplines: From medical to remote sensing," *IEEE Access*, vol. 12, pp. 18 330–18 357, 2023.

[50] Z. Wang, Q. She, and T. E. Ward, "Generative adversarial networks in computer vision: A survey and taxonomy," *ACM Comput. Surv. (CSUR)*, vol. 54, no. 2, pp. 1–38, 2021.

[51] Z. Li et al., "A systematic survey of regularization and normalization in gans," *ACM Comput. Surv.*, vol. 55, no. 11, pp. 1–37, 2023.

[52] N. Pandey and A. Savakis, "Poly-gan: Multi-conditioned gan for fashion synthesis," *Neurocomputing*, vol. 414, pp. 356–364, 2020.

[53] T. DeVries, A. Romero, L. Pineda, G. W. Taylor, and M. Drozdzal, *On the evaluation of conditional gans*, arXiv preprint arXiv:1907.08175, 2019.

[54] R. Fang, "Infrared and visible image fusion using generative adversarial network with feature complement block," in *2023 6th International Conference on Electronics Technology (ICET)*, IEEE, 2023, pp. 133–138.

[55] R. Ashwini, R. Vani, and S. Suvitha, "Enhancing the resolution of ancient artworks using generative adversarial networks," in *2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA)*, IEEE, 2022, pp. 1081–1086.

[56] T. Kaneko, H. Kameoka, K. Tanaka, and N. Hojo, *Stargan-vc2: Rethinking conditional methods for stargan-based voice conversion*, arXiv preprint arXiv:1907.12279, 2019.

[57] R. Sarode, S. Varpe, O. Kolte, and L. Ragha, "Image super resolution using enhanced super resolution generative adversarial network," in *ITM Web of Conferences*, vol. 44, EDP Sciences, 2022, p. 03 054.

[58] T. P. A. Singh, "Creating objects for metaverse using gans and autoencoders," *Int. Res. J. Eng. Technol. (IRJET)*, vol. 09, no. 06, Jun. 2022.

[59] S. Park, B. Choi, P. Park, S. Kim, and K. Park, "A lightweight on spiking generative adversarial networks for iot applications," in *2023 International Technical Conference on Circuits/Systems, Computers, and Communications (ITC-CSCC)*, IEEE, 2023, pp. 1–4.

[60] M. Hou, S. Liu, J. Zhou, Y. Zhang, and Z. Feng, "Extreme low-resolution activity recognition using a super-resolution-oriented generative adversarial network," *Micromachines*, vol. 12, no. 6, p. 670, 2021.

[61] K. A. Butainy, M. Felemban, and H. Luqman, "Realistic face masks generation using generative adversarial networks," in *2022 14th International Conference on Computational Intelligence and Communication Networks (CICN)*, IEEE, 2022, pp. 90–95.

[62] M. Qian, B. Chen, and W. Chen, "Context-based image inpainting with improved generative adversarial networks," in *2023 3rd International Conference on Neural Networks, Information and Communication Engineering (NNICE)*, IEEE, 2023, pp. 311–315.

[63] L. Shen, "Application of a deep generative model for diversified video subtitles based on generative adversarial networks," in *2023 3rd Asia-Pacific Conference on Communications Technology and Computer Science (ACCTCS)*, IEEE, 2023, pp. 176–181.

[64] E. R. Chan et al., "Efficient geometry-aware 3d generative adversarial networks," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022, pp. 16 123–16 133.

[65] T. Dong, "Effects of different generative adversarial networks on the face generation task," in *2023 IEEE International Conference on Image Processing and Computer Applications (ICIPCA)*, IEEE, 2023, pp. 1051–1055.

[66] J. J. Huallpa, "Exploring the ethical considerations of using chat gpt in university education," *Period. Eng. Nat. Sci.*, vol. 11, no. 4, pp. 105–115, 2023.

[67] I. Masi, A. Killekar, R. M. Mascarenhas, S. P. Gurudatt, and W. AbdAlmageed, "Two-branch recurrent network for isolating deepfakes in videos," in *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part VII*, Springer, 2020, pp. 667–684.

[68] K. H. Teo et al., "Emerging gan technologies for power, rf, digital, and quantum computing applications: Recent advances and prospects," *J. Appl. Phys.*, vol. 130, no. 16, 2021.

[69] X. Yi, E. Walia, and P. Babyn, "Generative adversarial network in medical imaging: A review," *Med. Image Anal.*, vol. 58, p. 101 552, 2019.

[70] V. S. S. P. Reddy, S. L. M. A. R., and S. Kumar, *Enhancing image quality with super-resolution generative adversarial networks*, ResearchGate, 2024.

[71] O. R. Nasir, S. K. Jha, M. S. Grover, Y. Yu, A. Kumar, and R. R. Shah, "Text2facegan: Face generation from fine grained textual descriptions," in *2019 IEEE Fifth International Conference on Multimedia Big Data (BigMM)*, IEEE, 2019, pp. 58–67.

[72] X. Wang et al., "Esrgan: Enhanced super-resolution generative adversarial networks," in *Proceedings of the European Conference on Computer Vision (ECCV) Workshops*, 2018, pp. 0–0.

[73] S. Tulyakov, M.-Y. Liu, X. Yang, and J. Kautz, "Mocogan: Decomposing motion and content for video generation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018, pp. 1526–1535.

[74] F. Wang, "Generation of digital artistic images based on gans," in *2nd International Conference on Intelligent Design and Innovative Technology (ICIDIT 2023)*, Atlantis Press, 2023, pp. 438–444.

[75] S. Ruan, "Anime characters generation with generative adversarial networks," in *2022 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA)*, IEEE, 2022, pp. 1332–1335.

[76] Z. Yi, G. Wu, X. Pan, and J. Tao, "The research of anime character portrait generation based on optimized generative adversarial networks," in *2021 33rd Chinese Control and Decision Conference (CCDC)*, IEEE, 2021, pp. 7361–7366.

[77] J. Oshiba, M. Iwata, and K. Kise, "Automatic landmark-guided face image generation for anime characters using c2 gan," in *International Conference on Pattern Recognition*, Springer, 2021, pp. 236–249.

[78] X. Xing and D. Zhang, "Image-to-image translation using a relativistic generative adversarial network," in *Eleventh International Conference on Digital Image Processing (ICDIP 2019)*, vol. 11179, SPIE, 2019, pp. 121–127.

[79] R. Paliwal, "Generative artificial intelligence in metaverse era," *Int. Res. J. Mod. Eng. Technol. Sci.*, vol. 5, no. 09, 2023.

[80] D. Bau et al., "Seeing what a gan cannot generate," in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 2019, pp. 4502–4511.

[81] V. Sorin, Y. Barash, E. Konen, and E. Klang, "Creating artificial images for radiology applications using generative adversarial networks (gans)–a systematic review," *Acad. Radiol.*, vol. 27, no. 8, pp. 1175–1185, 2020.

[82] L. Wang, W. Chen, W. Yang, F. Bi, and F. R. Yu, "A state-of-the-art review on image synthesis with generative adversarial networks," *IEEE Access*, vol. 8, pp. 63 514–63 537, 2020.

[83] X. Mao and Q. Li, *Generative adversarial networks for image generation*. Springer, 2021.

[84] S. Xun et al., "Generative adversarial networks in medical image segmentation: A review," *Comput. Biol. Med.*, vol. 140, p. 105 063, 2022.

[85] V. L. T. de Souza, B. A. D. Marques, H. C. Batagelo, and J. P. Gois, "A review on generative adversarial networks for image generation," *Comput. & Graph.*, 2023.

[86] A. Purwanto, E. Utami, and D. Agustriawan, "A comprehensive literature review on generative adversarial networks (gans) for ai anime image generation," in *2024 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)*, IEEE, 2024, pp. 1–6.

[87] Z. Huang, S. Chen, J. Zhang, and H. Shan, "Pfa-gan: Progressive face aging with generative adversarial network," *IEEE Trans. on Inf. Forensics Secur.*, vol. 16, pp. 2031–2045, 2020.

[88] X. Wang, H. Guo, S. Hu, M.-C. Chang, and S. Lyu, "Gan-generated faces detection: A survey and new perspectives," in *ECAI 2023*, 2023, pp. 2533–2542.

[89] L. Jin, F. Tan, and S. Jiang, "Generative adversarial network technologies and applications in computer vision," *Comput. Intell. Neurosci.*, vol. 2020, 2020.

[90] F. B. Aissa, M. Mejdoub, and M. Zaied, "A survey on generative adversarial networks and their variants methods," in *Twelfth International Conference on Machine Vision (ICMV 2019)*, vol. 11433, SPIE, 2020, pp. 1006–1012.

[91] A. Sasithradevi, S. M. M. Roomi, and R. Sivaranjani, "Generative adversarial network for video analytics," in *Generative Adversarial Networks for Image-to-Image Translation*, 2021, pp. 329–345.

[92] N. Aldausari, A. Sowmya, N. Marcus, and G. Mohammadi, "Video generative adversarial networks: A review," *ACM Comput. Surv. (CSUR)*, vol. 55, no. 2, pp. 1–25, 2022.

[93] M. Hamza, S. U. Bazai, M. I. Ghafoor, S. Ullah, S. Akram, and M. S. Khan, "Generative adversarial networks (gans) video framework: A systematic literature review," in *2023 International Conference on Energy, Power, Environment, Control, and Computing (ICEPECC)*, IEEE, 2023, pp. 1–5.

[94] K. Silva, B. Can, R. Sarwar, F. Blain, and R. Mitkov, "Text data augmentation using generative adversarial networks–a systematic review," *J. Comput. Appl. Linguist.*, vol. 1, pp. 6–38, 2023.

[95] M. S. M. Yahaya and J. Teo, "Data augmentation using generative adversarial networks for images and biomarkers in medicine and neuroscience," *Front. Appl. Math. Stat.*, vol. 9, p. 1 162 760, 2023.

[96] S. Rani, D. Jining, D. Shah, S. Xaba, and P. R. Singh, "The role of artificial intelligence in art: A comprehensive review of a generative adversarial network portrait painting," in *International Conference on Intelligent Computing & Optimization*, Springer, 2023, pp. 126–135.

[97] M. P. Kumar and P. Jayagopal, "Generative adversarial networks: A survey on applications and challenges," *Int. J. Multimed. Inf. Retr.*, vol. 10, no. 1, pp. 1–24, 2021.

[98] E. Brophy, Z. Wang, Q. She, and T. Ward, "Generative adversarial networks in time series: A survey and taxonomy," *arXiv preprint arXiv:2107.11098*, 2021.

[99] H. Ku and M. Lee, "Textcontrolgan: Text-to-image synthesis with controllable generative adversarial networks," *Appl. Sci.*, vol. 13, no. 8, p. 5098, 2023.

[100] D. Habeeb, A. Alhassani, L. N. Abdullah, C. S. Der, and L. K. Q. Alasadi, "Advancements and challenges: A comprehensive review of gan-based models for the mitigation of small dataset and texture sticking issues in fake license plate recognition," *Eng. Technol. & Appl. Sci. Res.*, vol. 14, no. 6, pp. 18 401–18 408, 2024.

[101] J. Wang and L. Yao, "Unrolled gan-based oversampling of credit card dataset for fraud detection," in *2022 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, IEEE, 2022, pp. 858–861.

[102] N. Kumar, A. Aeron, and S. Kumar, *Generative ai empowerment in iot ecosystems: Review of real-time processing challenges and solution*, 2025.

[103] Y. Wang, Y. Pan, M. Yan, Z. Su, and T. H. Luan, "A survey on chatgpt: Ai–generated contents, challenges, and solutions," *IEEE Open J. Comput. Soc.*, vol. 4, pp. 280–302, 2023.

[104] T. Zhang, "Deepfake generation and detection, a survey," *Multimed. Tools Appl.*, vol. 81, no. 5, pp. 6259–6276, 2022.

[105] P. Edwards, J.-C. Nebel, D. Greenhill, and X. Liang, "A review of deepfake techniques: Architecture, detection and datasets," *IEEE Access*, 2024.

[106] M. Tschaepe, "Pragmatic ethics for generative adversarial networks: Coupling, cyborgs, and machine learning," *Contemp. Pragmatism*, vol. 18, no. 1, pp. 95–111, 2021.

[107] A. Sharma and R. Sharma, "Generative artificial intelligence and legal frameworks: Identifying challenges and proposing regulatory reforms," *Kutafin Law Rev.*, vol. 11, no. 3, pp. 415–451, 2024.

[108] J. Anderson, *Legal and regulatory frameworks for ai-generated*, 2024.

[109] P. Saxena, R. Gupta, A. Maheshwari, and S. Maheshwari, "Semantic image completion and enhancement using gans," in *High Performance Vision Intelligence: Recent Advances*, Springer, 2020, pp. 151–170.

[110] H.-Y. Tseng, L. Jiang, C. Liu, M.-H. Yang, and W. Yang, "Regularizing generative adversarial networks under limited data," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2021, pp. 7921–7931.

[111] M. Jaweed and R. F. Shaikh, "Optimizing generative ai by overcoming stability mode collapse and quality challenges in gans and vaes," *MSW Manag. J.*, vol. 34, no. 2, pp. 497–507, 2024.

[112] A. Abusitta, E. Aïmeur, and O. A. Wahab, "Generative adversarial networks for mitigating biases in machine learning systems," in *ECAI 2020*, IOS Press, 2020, pp. 937–944.