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GAN and art: Facilitation of artistic production and expression based on artificial intelligence

Yihan Ran

School of Design, Jiangnan University, Wuxi, 214122, China

1051190205@stu.jiangnan.edu.cn

Abstract. The advancement of Artificial Intelligence has resulted in the investigation of its applications in a variety of sectors. The creation and depiction of artistic images as a tool for demonstrating human creativity and intellect has been a significant focus of Artificial Intelligence (AI) content generation. This study discusses picture generation approaches and highlights image creation principles as well as numerous varieties of Generative Adversarial Network (GAN). GAN models for image creation can inspire designers and artists, generate images that assist people grasp historical elements by imitating old artistic styles and cultural forms, and generate images of humans. GAN models for image generation can help designers and artists inspire their creativity, produce images that help people understand historical features by mimicking classic artistic styles and cultural forms, and produce images of people that provide intuitive access to information for communication and learning purposes. The application of GAN models in the field of art production is becoming increasingly sophisticated, and many novel applications are yet to be described and popularised. The article summarises the applications of artworks generated by GAN models, for one it can be applied as a thinking aid in art design and the creation of stylised artworks, while GAN-generated images can also help people GAN-generated images can also help people understand history, culture and other related knowledge, making profound art forms more common and popular. The article also analyses the potential hazards of GAN model-generated art images that are related to the passion and creative rights of the creators.

Keywords: artificial intelligence, GAN models, artistic expression, image generation.

1. Introduction

Artistic creation is a manifestation of human creativity and can assist in the visual presentation of ideas, history, education and other information that is difficult to understand directly in words [1]. The concept of computer-generated content has been around since the 1850s, when *Hummingbird* [2], a computer-generated artwork, became the winner of Computers and Automation magazine. Some of the early attempts focused on the use of computers to replicate human abilities related to artistic creation such as painting, music and literature [3]. Although there is a significant distinction between early works of art generated by artificially intelligent content and human creations, the process of development in these recent decades has seen the development of computers to an era where a higher level of artistic content and science and technology are interpenetrating and intermingling [4]. Digital art based Artificially Intelligent Content Generation (AIGC) is also advancing at an accelerating pace.

John McCarthy first used the phrase "artificial intelligence" (AI) in a conference in 1956 [5]. It is the process of using computers to simulate human thought and consciousness essentially endowing machines with the capacity to autonomously thought and create [6]. Artificial intelligence allows for machine learning and, contrary to the human brain, has better memory and computational speed than humans [7]. AlphaGo, a Go-playing robot created by Google (or Alphabet) that possesses "deep thinking," defeated the well-known Lee Sedol in the middle of a set, thrusting artificial intelligence technology into the spotlight. One of the subsets of machine learning, deep learning, uses a variation of Artificial Neural Networks (ANNs) to collect abstract concepts in a less abstract form. The Generative Adversarial Network (GAN) is a deep learning architecture that consists of a generator neural network and a discriminator neural network. The discriminator tells the difference between actual and bogus data, and the generator creates material that resembles input data. They compete in a closed feedback loop, raising the authenticity of generated content. GANs have diverse applications, such as image synthesis, data augmentation, and style transfer, improving machine learning model performance and addressing data scarcity [8]. With the help of continuous training and iteration of datasets, can even create high precision, out of things that do not exist, such as human faces [9].

As the technology of computer-generated art matures, related emerging industries, such as art stylization, are beginning to gain traction [10]. Art stylization as a cross-discipline is beginning to attract people from different specialist fields to come together and assist each other in the high-end technical areas of game design, computer vision, graphics development and multimedia information processing [11]. This development has expanded into many new forms of art applications in industries such as entertainment, customer service, education and marketing, which have made artworks more popular, universal and accessible in everyday life. Meta AI developed by Facebook can build a library of characters of children's drawings and animate them through image edge recognition. In addition, with the development of Midjourney and Stable Diffusion, the skills of text-generated images using computers have become more and more powerful, and the resulting artwork is now even highly original and subversive. The application of GAN models in the field of art creation is becoming increasingly profound, and many new forms of application have yet to be summarized and generalized.

Given the development and widespread use of GAN models, AI-generated artwork can be believed to have a wide range of citation areas and value, however, additional study and summarization are required to find potential application prospects and scenarios, as well as to comprehend the limitations of these art-making tools. A number of other studies have reviewed applications of GAN models, including text generation, but the value of applications for artistic creation has not been adequately summarized. This review paper will review the educational value of artworks generated by deep learning models.

The article will be structured as follows. Section 2 of the article will introduce the typical GAN models used for image generation and their basic principles, Section 3 will analyse the applications and limitations of GAN in the creation and presentation of art, finally a final conclusion will be presented in Section 4 based on the analysis of the article.

2. Method

2.1. Overview of the method

The image generation model has a long iterative process. The Variational Auto-Encoder is a generative network structure proposed by Kingma et al. in 2014 that is based on Variational Bayes (VB) inference. The VAE is based on an auto-encoder in which the image encoding potential vectors follow a Gaussian distribution to form the pictures, but the resultant image is blurry. DeepMind introduced PixelCNN in 2016, which is a representative model of Autoregressive models. The Autoregressive model was developed from slender regression in regression analysis and is mostly used for sequential data generation, such as text content and speech content. The Generative Adversarial Network (GAN), suggested by Ian J. Goodfellow et al. in their paper Generative Adversarial Nets, presented at the NIPS conference in October 2014, is a landmark presence of generative models.

2.2. Models

The GAN model is a neural network consisting of a generator and a discriminator that collaborate in a min-max game to create fresh content. The generator network is used to generate fake samples with content that has a similar distribution to the real data and is improved to interfere with the discriminator's judgement [12]. Concurrently, the discriminator attempts to differentiate between authentic and generated sample data Both networks undergo adversarial training using back-propagation techniques, where the generator and discriminator strive to outdo each other. As they compete, the two neural networks improve their errors until the fake data generated by the generator is indistinguishable from the original real data, producing a novel sample output. The workflow of the procedure can be found in Figure 1.

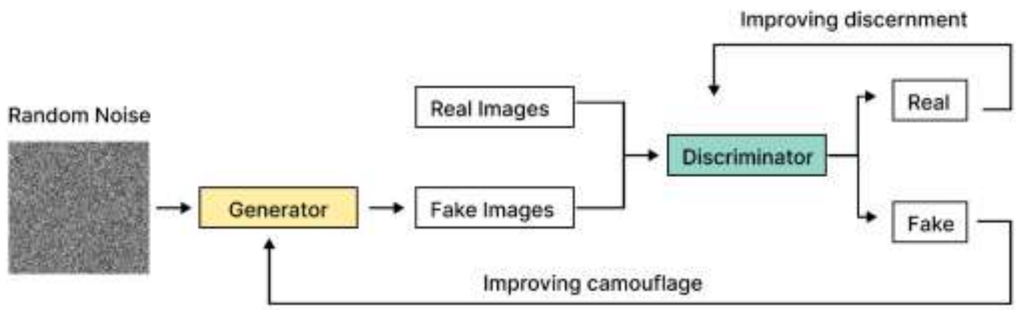

Figure 1. The basic framework of the GAN model.

Many more ascending algorithmic studies and functional iterations have been derived from the basic GAN model, and this paper will mainly analyse the variants of GAN related to artistic creation.

2.2.1. CycleGAN

CycleGAN was created to prevent the Generator from learning to generate spurious data that is deceptive. Therefore, it is crucial to ensure that the output image from the generator maintains a high degree of similarity to the original image, thereby preserving the essential features of the original image [13]. To achieve this objective, based on the GAN model, CycleGAN adds a new Generator to the model process, which can take the image output from the first Generator as input information to output an image that is as similar as possible to the original input image, and in this way prove that the output information from the first Generator retains a large amount of the original Otherwise, it is assumed that the first Generator could have faked the output. To improve the ability of CycleGAN to process images, there is also research rising into this area, such as the Asymmetric CycleGAN model [14], a model that can better handle the task of panning unpaired and asymmetric images.

2.2.2. StarGAN

When the mapper needs the images to interact and transform across n domain, it is necessary to train an additional $2 \times C_n^2$ Generators for n ranges, based on the design idea of CycleGAN. StarGAN is therefore designed to achieve the effect of transforming information within all domains into each other using a single Generator [15]. The Discriminator's task is to determine if the image is from the true image or one generated by the Generator, as well as to distinguish the domain from which the image comes. StarGAN is tiny and efficient, and it can convert between many styles.

2.2.3. StyleGAN

As the Generator of the GAN model generates images based on the effects of random noise to create the output of the image, it does not achieve categorical control over the image being generated, leading to the introduction of StyleGAN model. This model redesigns the architecture of the GAN's Generator and proposes a new way to control the image synthesis process. This Generator can simply isolate an

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image's high-level properties, such as pose and identity, and the isolated features are specified and blended and interfered with. Compared to the original GAN model, StyleGAN introduces a mapping network, Affine Transformation (A) and Adaptive Instance Normalization (AdaIN) and adds a noise vector (B) to produce high quality images without human supervision and can automatically separate different high-level attributes of the image while maintaining the overall features [16].

2.2.4. CartoonLossGAN

As the GAN model's development progressed, researchers began to explore its application in the field of artistic visual style, rather than solely focusing on image information representation. Since CycleGAN learns one artist's style intelligently at a time, training in multiple styles can lead to huge computational costs. CartonnLossGAN generates smooth cartoon surfaces from the input images and smoothly shades them [17]. The generated grey scale image of the cartoon style is compared with the grey scale image of the input image, so that the colour information is not disturbed and a similar effect to that of a sketch can be achieved.

3. Application and discussion

The continuous development of GAN models allows the generated images to be taken to a more advanced level of application. Within the realm of artistic creation, GAN models for image generation can assist designers and artists in stimulating their creative endeavors, producing images that help people understand historical features by imitating classic artistic styles and cultural forms, and creating images of people that provide an intuitive way of accessing information for communication and learning purposes.

3.1. Application of GAN in art production

The GAN model helps designers and artists to generate artworks as a reference through simple sketch lines. For instance, the researchers have proposed a GAN Sketching model based on StyleGAN, which can generate a variety of different drawings simply by the user having to improve on the sketch content [18]. GAN models can also help design practitioners and artists to quickly transform styles and demonstrate new techniques with the help of machine learning. The CycleGAN-based Chinese ink painting generation model is a stylised image that can be directly generated in the style of ink and wash [19]. Recent releases of image generation models such as DALL-E 2, Imagen, Stable Diffusion and many more have ushered in a new era of image generation, achieving unprecedented levels of image quality and model flexibility. This provides designers and art creators with greater inspirational references and creative ideas, with AI-assisted design and creation becoming a new area of development.

3.2. Application of GAN in art expression

GAN models can learn from existing art styles and quickly generate images with a specific style. When people provide images related to traditional painting styles, the GAN model generates images based on a new presentation of traditional artistic expressions, which can effectively assist people to understand the relevant history and culture. Zhang et al. used the GAN model to study the digital demonstration of traditional art form of Chinese seal carving. They used deformation algorithms to modify seal characters and compute layout parameters using databases and knowledge, preserving the art of seal carving in the digital age and giving seal carving art a theoretical and practical reference for its revival and innovation [20]. Furthermore, Moreover, GAN models have also demonstrated efficacy in generating character models that offer a heightened sense of immersion when individuals communicate with other characters in specific settings such as the history classroom and counselling room. In the music course experiment conducted at MIT, the generated character models allow students to feel in conversation with the cello player during the lesson, stimulating the students' desire to explore and understand Bach's music, and this generated character model is more attractive to learners [8].

3.3. Limitations of GAN applications in the art field
As the images generated by the GAN model are based on the features of existing reference images, this leads to limitations in the GAN's capacity to assist designers and artists in the creative process for stylistic representation. This leaves art creators vulnerable to plagiarism and style dependence, compromising the ability to create themselves and lacking the competitiveness unique to creators when compared to artificial intelligence. And due to the nature of GAN models based on existing images for creation, the original images used for artistic reference or character generation may be in danger of infringement or even invasion of personal privacy. However, it is imperative to highlight that GAN models should be used to enhance current practices of artistic creation and expression, rather than replacing current creative workers and infringe on the rights and passions of creators.

4. Conclusion
This article focuses on a growing and popular generative model, the GAN model, which is an extremely valuable and promising generative network in the field of neural networks and investigates the application of the GAN model to artistic expression and creation, taking artistic images as a starting point. The article explores the application of the model in the field of artistic creation and expression, focusing on the application of artistic image generation. The article reviews the classical variations of GAN models and their role in assisting designers and artists to create art and in helping users to understand and learn about art-related culture. It also analyses the potential hazards of GAN-based art applications in terms of creators' rights and enthusiasm. The application of this technology in the field of artistic creation requires additional regulations and guarantees to ensure that AI technology can truly assist creators in their creative work and disseminate content in an intelligent form.

References
[1] Morriss-Kay GM 2010 *The evolution of human artistic creativity* J Anat 216(2) pp 158-176
[2] Vincent J 2015 *A look back at the first computer art contests from the '60s: bullet ricochets and sine curve portraits*, The Verge
[3] Boden M A and Edmonds E A 2009 *What is generative art? Digital Creativity* 20 pp 21–46
[4] Wei X et al 2019 *Online Learning and Teaching Resource Management System Based on Virtual Reality Technology* Springer Singapore pp 103-115
[5] Yoav M and Ronit B 2019 *Introduction to artificial intelligence in medicine*, Minimally Invasive Therapy & Allied Technologies, 28:2 pp 73-81,
[6] Wang Y et al. 2018 *The key to the future development of interactive art-virtual reality technology* J Multimedia Inform
[7] Schiavoni F L and Gonçalves L L 2017 *From virtual reality to digital arts with mosaicode* Symposium on Virtual and Augmented Reality (SVR), IEEE (2017, November),
[8] Pataranutaporn P et al 2021 *AI-generated characters for supporting personalized learning and well-being* Nat Mach Intell 3 pp 1013–1022.
[9] Mirsky Y and Lee W 2021 *The creation and detection of deepfakes: a survey* ACM Comput. Surveys 54 pp 1–41
[10] Franke H W and Kurz I 1987 *The expanding medium: the future of Computer Art* Leonardo 20(4) pp 335-338
[11] Jiang P 2020 *Integration of Arts and Crafts in Artificial Intelligence Environment, Integration of Arts and Crafts in Artificial Intelligence Environment* IOP 1574(1) 012162
[12] Durgadevi M 2021 *Generative Adversarial Network (GAN): a general review on different variants of GAN and applications* 6th International Conference on Communication and Electronics Systems (ICCES) IEEE pp 1-8
[13] Zhu J Y et al 2017 *Unpaired image-to-image translation using cycle-consistent adversarial networks* Proceedings of IEEE International Conference on Computer Vision IEEE pp 2223-2232

[14] Dou H 2020 *Asymmetric CycleGAN for image-to-image translations with uneven complexities* Neurocomputing Volume 415
[15] Yunjey C et al 2020 *StarGAN v2: Diverse Image Synthesis for Multiple Domains* Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)
[16] Tero K et al 2019 *A Style-Based Generator Architecture for Generative Adversarial Networks* CVPR pp 4401-4410
[17] Dong Y et al 2022 *CartoonLossGAN: Learning Surface and Coloring of Images for Cartoonization* IEEE Transactions on Image Processing vol 31 pp 485-498
[18] Wang S et al *Sketch Your Own GAN* in 2021 IEEE/CVF International Conference on Computer Vision (ICCV) pp 14050-14060
[19] Xiang Z et al 2022 *Transparent Ink Wash Style for Free-Viewpoint Video Generation* APMAR
[20] Zhang K et al 2022 *Visual knowledge guided intelligent generation of Chinese seal carving* Frontiers of Information Technology & Electronic Engineering