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Generative art methods for image creation

Ana Agić Cmrk[1], Nikolina Stanić Loknar[1], Lidija Mandić[1]
[1]University of Zagreb, Faculty of Graphic Arts, Croatia

Introduction

When speaking of generative art, there are several definitions that explain the creation of such art. One states that generative art is generated by a system that operates autonomously, and that artist may create the system itself, set parameters that influence image creation but ultimately the system creates the outcome (Tempel, 2017). Cao et al. in their paper define generative art as Artificial Intelligence Generated Content (AIGC), which refers to content generated by generative artificial intelligence (GAI) which can automate the creation of large amount of content in short period of time (Y. Cao et al., 2023). Content can be textual - conversational (as ChatGPT or Microsoft Gemini), it can be images (Dalle -2, Midjourney, Microsoft Designer, Stable Diffusion and many others) and video creation (as Open AI Sora or Runway ML). These tools allow designers, artists and enthusiasts to create art without technical knowledge. Historically, generative art has existed for some time, and its origins trace back to the mid-20th century. There were several artists who contributed to computer generated art, among prominent Vera Molnar, Harold Cohen, Herbert Franke and Manfred Mohr. Today all could not be possible without advancements in artificial intelligence, machine learning models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Denoising Diffusion Probabilistic Models (DDPMs). Besides these advancements in technology, ethical questions come into the picture, concerning originality of the text or image, authorship and changes in the design process. The aim of this paper is to explore technical aspects of several generative art algorithms, with visual examples of today's possibilities, and to explore possible future directions of generative art.

Generative Art CreationMethods

1. Generative Adversarial Networks (GANs)

Generative Adversarial Network (GAN) is an algorithm that consist of two neural networks which work in opposition – a generator and a discriminator. The generator attempts to learn from real data in order to create new data, while discriminator attempts to determine whether the input is from the real data space or not (Y. Cao et al., 2023). Figure 1 below depicts a simple GAN algorithm.

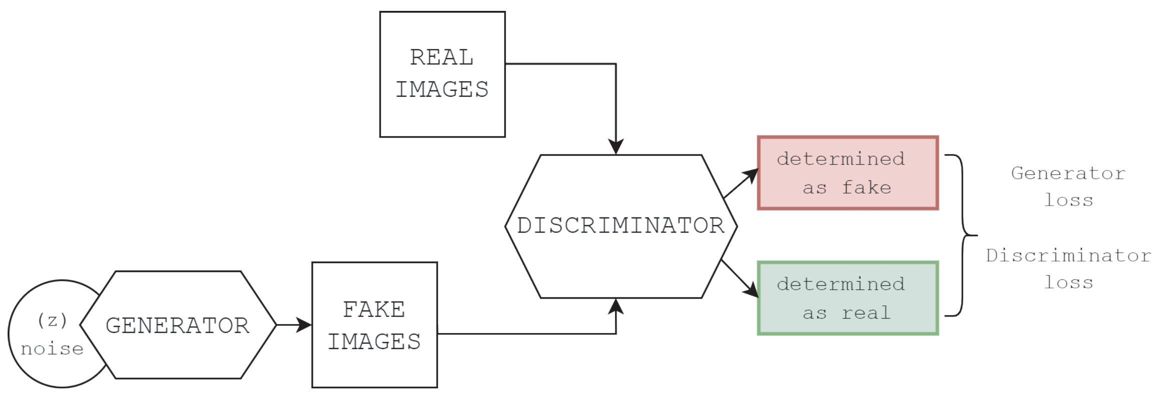


Figure 1

GAN network (adopted from Wang et al., 2021)

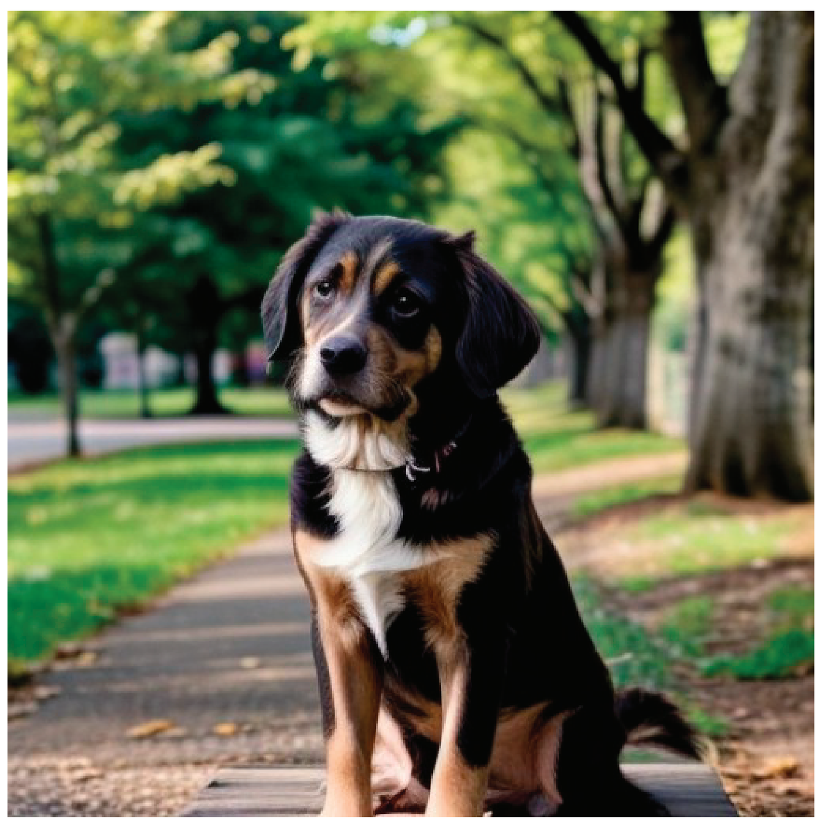


Figure 2

GAN image created from Artbreeder

2.Variational Autoencoders (VAEs) are a type of generator based on probability and include a latent space. Variational means that this technique uses Bayesian machine learning – variational Bayes (Foy, 2021). This feature makes them different from classical autoencoders which are not capable of producing new data, but they are similar because of encoder and decoder (Doersch, 2016). Autoencoders use a fixed (deterministic) latent code to map the input to, while Variational Autoencoders will replace this with a (Gaussian) distribution (Wenzel, 2022). VAEs work by compressing data into latent space (via encoder) where data is now presented as vectors and then the decoder reconstructs the data from the latent space and generates new data. Figure 3 depicts a simple VAE algorithm.

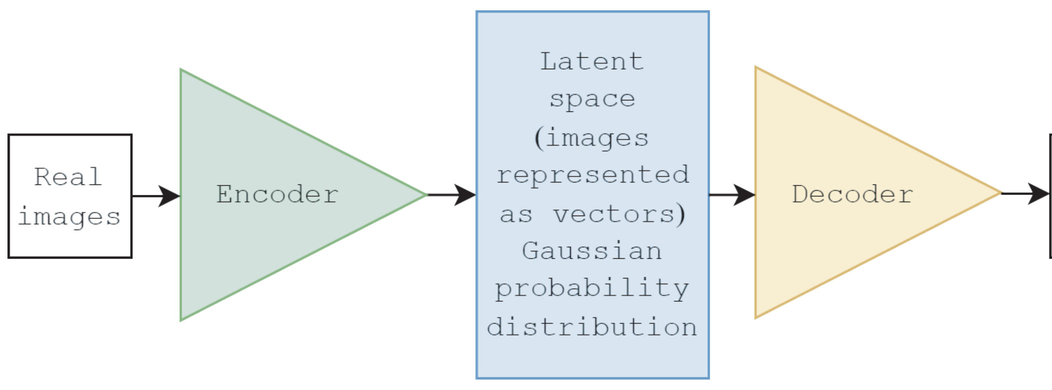


Figure 3

Simple VAE algorithm

At the end of encoder, we got samples of data, but presented in a probability distribution, allowing for meaningful interpolation between data samples. After this latent space, the samples of data (vectors) can pass through the decoder which are then passed through the neural network (Foy, 2021). Decoder converts data back into original form, reconstructing them from a lower-dimensional latent space into a higher-dimensional data domain. Figure 4 depicts image reconstruction using VAE algorithm.

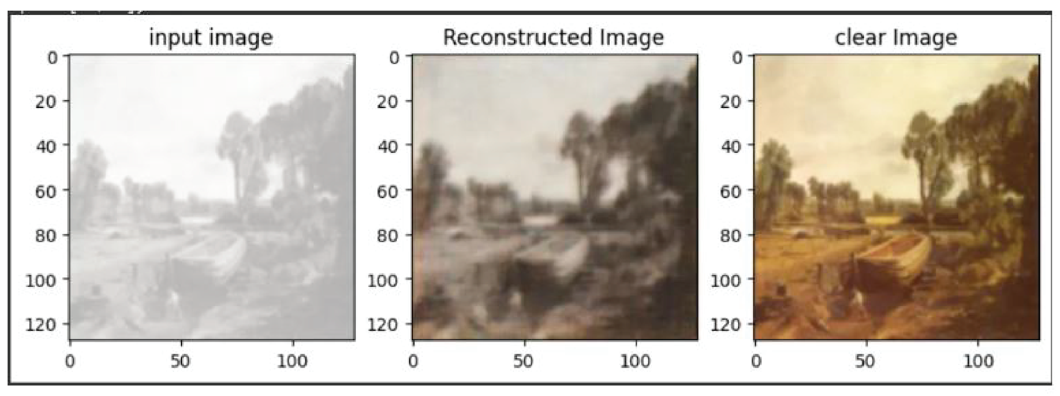
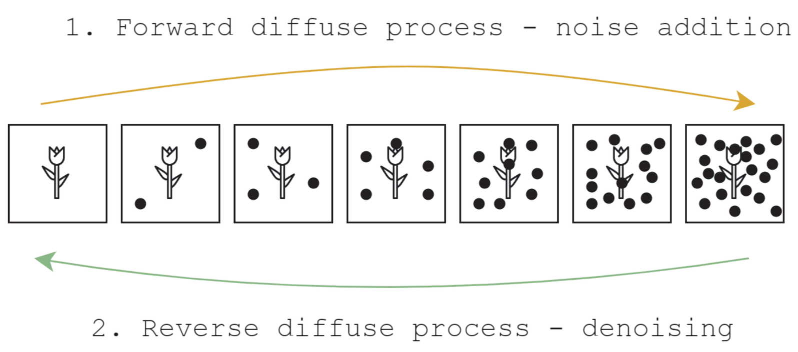


Figure 4 Image reconstruction using VAE algorithm

https://pub.aimind.so/image-restoration-using-deep-learning-variational-autoencoders-8483135bb72d

3 Denoising Diffusion Probabilistic Models (DDPMs)

Diffusion models are a class of generative probabilistic models that produce images through a process of gradual noise injection into the original data until it turns into the known noise distribution, before reversing this process with noise reduction (H. Cao et al., 2015). DDPM models make use of two Markov chains – one that adds noise to the data and other which converts data from the noise (Yang et al., 2024). Figure 5 and 6 depict a Denoising Diffusion Model algorithm and generated example. Models are trained on large image datasets, the larger the dataset, the better generated outcome.



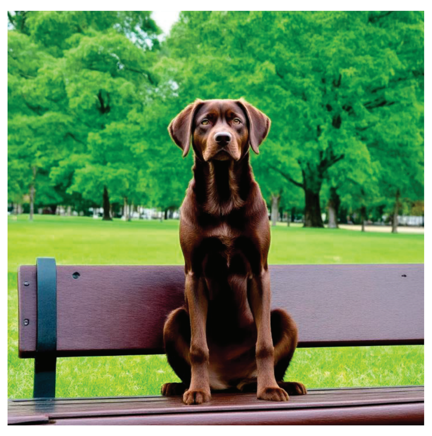


Figure 5 (left) and 6 (right)

Denoising Diffusion Model and generated example

Discussion / Conclusion

Three image generators explained; GANs, VAEs, DDPMs – Diffusion models. Generative models have several practical applications in graphic design, digital art, gaming industry and video generation. Some downsides of this text/image/video production are showing, as inability to recognize real from artificially generated content, especially as deepfake videos where fake news can be easily placed in order to spread misinformation. Also, problems with generating delicate and illegal content can be encountered. Finally, it is unlikely that generative image creation will slow down in progress, and rather than avoiding and resisting its presence we can use it as a supplement and use it responsibly.

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