Landscape Painter: Mimicking Human Like Art Using Generative Adversarial Networks

Yash Gogoriya, Oswald C and Abhijith Balan
National Institute of Technology, Tiruchirappalli, Tamil Nadu, India
{206122032, oswald, 406123001}@nitt.edu

Abstract

Generating paintings using AI has been an intriguing area of research and has posed significant challenges in recent years. Landscape painting is a type of man-made ecological art form which contributes to preserving the ecological integrity of the environment we live in. Generative AI based Painting constitutes a form of visual expression encompassing various elements like drawings, arrangement, and conceptualization. Existing generative models do not replicate the painting process followed by a human painter. A human artist creates artwork in various stages such as: Sketching, Outlining and Colouring. Current generative models frequently restrict the range and diversity of styles by depending solely on carefully selected datasets such as WikiArt and VanGogh. The proposed work intends to utilize scraping techniques to collect a wide range of comprehensive and diverse landscape paintings. The primary objective of this research is to apply various generative AI models to generate artwork that replicate a human painting process and encompasses various artistic themes and styles instead of relying on a particular one. Performance of our work has shown that the landscape painting generation into distinct sketch and color phases have proven to be effective, fun and realistic.

1 Introduction

Painting constitutes a form of visual expression that encompasses various elements like drawings, arrangement, and conceptualization. It serves as a means for artists to portray their viewpoints and understandings of the world surrounding them, encompassing genres such as still life, religious motifs, landscapes, surrealism, symbolism, historical occurrences, emotions, and politics etc.,. Some of the examples of different types traditional and folk art forms are Tanjore Painting, Madhubani Painting, Warli, Pattachitra and Kalamkari etc., (Kumar et al., 2018). Landscape painting encompasses various subgenres, such as rural and urban landscapes, seascapes, marine landscapes, ancient ruins, and forests, among others (Xue, 2021). Current machine art models do not replicate the process by which a human painter creates an artwork; rather, they rely primarily on pre-existing datasets such as WikiArt or VanGogh, which restricts the multiplicity and scope of the paintings that are generated (Choudhury, 2020). (Zhang and Yu, 2016) describes a method of generating Kandinsky art using generation of content and style images. This approach is limited to Kandinsky Art and is not applicable for other kinds of art forms. (Goodfellow et al., 2014) estimated generative models by means of an adversarial process. This approach fails to perform well in case of high resolution images and complex images. Some models are trained on small-scale traditional painting element, they cannot provide sufficient diversity for untrained categories. Our proposed method attempts to resolve few of the above mentioned limitations such as mimicking the human artistic style and not restricting the model to generate landscape painting from the dataset given during the training phase. It splits the image generation process into two phase: First being, Sketcher and other being colorize. Since, the images are scarped from various domains and model is trained accordingly the StyleGAN2 based model outperforms from CNN based DCGAN.

1.1 Key Contributions of our Proposed Work

- We created a dataset of different landscapes using web scraping methods from different sources witch is mentioned in Section 3.
- Design of the Sketcher phase using DCGAN and StyleGAN2 model.
- Design of the colorizer module which controls the coloring and other artistic effects of the Images.

- The main objective of the proposed work is to compare the Landscape paintings generated both the GAN models the DCGAN and StyleGAN2 based models. Based on the comparison, StyleGAN2 based model outperformed in Landscape Painting Generation which contributes to open domain Landscape Painting generation.

2 Related Work

(Xue, 2021) discusses method of generating Chinese Landscape painting using Sketch-and-Paint GAN (SAPGAN) where SketchGAN generates edge maps, and PaintGAN for subsequent edge-to-painting translation. (Gui et al., 2024) proposed DLP-GAN (Draw Modern Chinese Landscape Photos with Generative Adversarial Network) model to provide realism and to translate landscape images to modern painting using domain image translation framework with a novel asymmetric cycle mapping. (Andrade and Fernandes, 2020) used conditional GANs to generate satellite-images from historical maps. (Tian, 2021) proposed a site planning method using Conditional GAN known as Pix2PixHD and uses Urban GIS Data as dataset. Pix2PixHD GAN is used to learn the mapping from a site boundary geometry represented with a pixelized image to that of an image containing building footprint color-coded to various programs. (Han et al., 2018) proposed methodology to generate synthetic multi-sequence brain Magnetic Resonance (MR) images using Deep Convolutional Generative Adversarial Networks (DCGANs). Due to low resolution MRI images, it posed challenges to create synthetic images.

3 About the Dataset

A vast array of extensive and varied data was meticulously gathered from a multitude of digital platforms, encompassing prominent sources such as Freepik (Landscape Painting Freepik), Pinterest (Landscape Oil Paintings by Craig Houston; Landscape Paintings by Mark VanderVinne), and Google images (Landscape Painting). Following the extraction process, a rigorous filtration procedure was implemented to eradicate any redundant entries, subpar resolution images, as well as any content that exhibited the presence of watermarks. To augment the dataset and improve its diversity, all images were horizontally mirrored by rotating them 180 degrees to the right. The dataset comprises a total of 5396 images.

4 Design of our proposed Landscape Painting Generation

The proposed work is novel from the existing literature where we generate human like artistic painting and does not rely on artistic features of particular dataset, instead it can generate diverse artistic features from different domains.

4.1 Architecture of our Proposed Work

The process of creating paintings will unfold in two distinct stages, namely the initial stage of sketch creation and the subsequent stage of coloring. The term "Sketcher" is employed to denote the first stage, while "Colorizer" is the designated term for the subsequent phase as shown in Figure 1. By employing advanced Deep Learning techniques, including Generative Adversarial Networkss and Convolutional Neural Networks, the system aims to learn complex features from the dataset and is able to produce artworks which looks like it is painted by a human artist. To accomplish the sketch generation step, the implementation of Deep Convolutional Generative Adversarial Networks (DCGAN) and StyleGAN2 is employed, while the coloring phase is achieved through the utilization of neural style transfer techniques. A Deep Convolutional GAN (DCGAN)

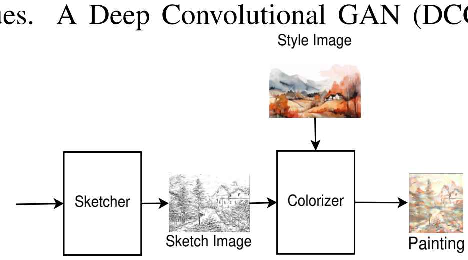


Figure 1: Sketcher and Colorizer block diagram of our proposed Landscape Painting Generation

uses convolutional networks to generate realistic images. It has two parts: a generator that creates images and a discriminator that distinguishes real from fake. StyleGAN2 is an improved GAN architecture that generates high-quality, realistic images with enhanced control over style. It separates image generation into layers, allowing finer control over features like texture and structure. The generator creates images with varying styles, while the discriminator refines their realism.

4.2 Sketcher Module

The primary phase of the undertaking comprises a Generator model entitled "Sketcher". Sketcher

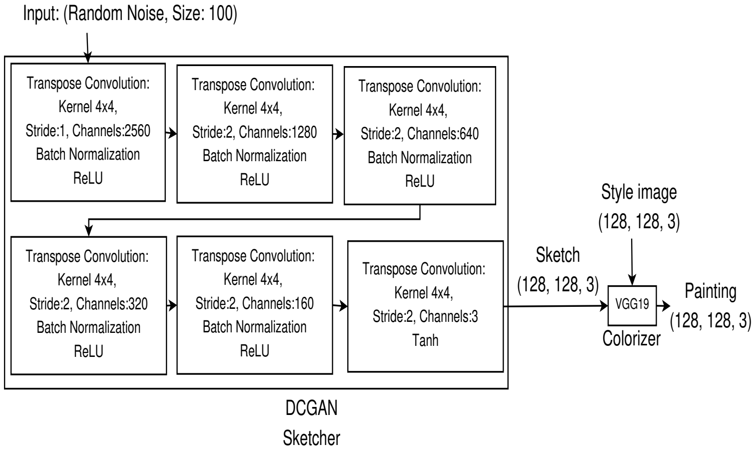


Figure 2: DCGAN based model for Sketching and Coloring

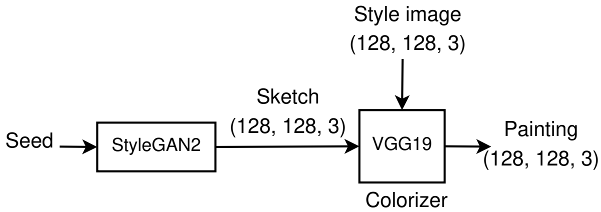


Figure 3: StyleGAN2 based model for Sketching and Coloring

is an innovative model that produces a depiction of a landscape. The utilization of the sketcher is realized through two distinct methodologies: the initial one being a Deep Convolution Generative Adversarial Network as shown in Figure 2, while the second one is known as StyleGAN2 as shown in Figure 3, an advancement of NVIDIA.

4.3 Colorizer Module

The Colorizer receives two images as input, namely a content image and a style image. The content image is sourced from the Sketcher, while the style image is provided externally to the Colorizer. The objective is to imbue the content image with the stylistic attributes present in the style image. To accomplish this objective, the Colorizer employs the Neural Style Transfer algorithm. Neural Style Transfer involves the utilization of a Deep Neural Network to produce artistic images. The content image is utilized to extract the structural characteristics, while the style image is employed to extract the stylistic features. Within this framework, two types of loss are defined: style loss and content loss. Style Loss is calculated using by constructing a feature space for each layer of the network to depict the correlation among the various filter responses. Content Loss quantifies the dissimilarity between the feature representations of the input base image (X) and the content image (Y) at a specific layer, denoted as L. Furthermore, a third image named as *style image* is introduced, and the algorithm endeavors to minimize both the style loss and content loss in relation to this image. VGG19 is utilized in Colorizer which is pretrained on ImageNet database.

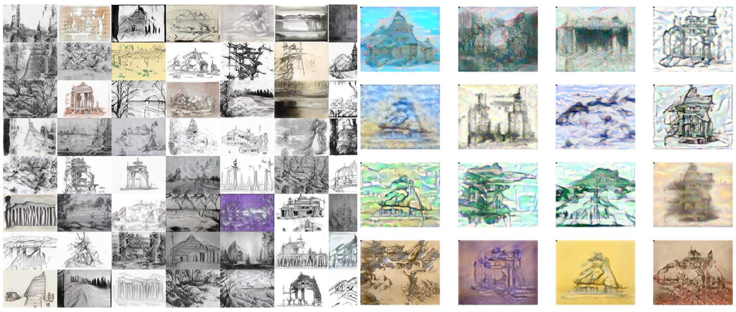
5 Experimental Results of DCGAN and StyleGAN based Approaches

Simulation is performed on an Intel i7 CPU with 32 GB Main Memory, NVIDIA RTX 3050 and 512 GB Hard Disk on Windows 10 Platform using Python and Anaconda tool. Throughout the duration of training the DCGAN Sketcher, noticeable improvements in the quality of sketches became increasingly apparent during each training phase as shown in Figure 4a and 4b. DCGAN based Sketcher was trained for 500 epochs. The colorizer adds the artistic features such as colors to sketcher images as shown in Figure 4b. Since, DCGAN is a CNN based model, the model fails to generate complex images and sharpness in images. StyleGAN2 underwent training on a dataset consisting of landscape sketches for a total of 1000 epochs. It is worth noting that the produced sketches demonstrate a notable degree of sharpness shown in Figure 5a and 5b. Despite the impressive visual quality, the model struggles to generate a diverse array of sketches.


(a) DCGAN without Colorizer (b) DCGAN with Colorizer

Figure 4: DCGAN based Image Generation

The amount of Loss over Epoch is depicted in Figure 6 which shows the loss of generator and dis-



(a) StyleGAN2 without Colorizer (b) StyleGAN2 with Colorizer

Figure 5: StyleGAN2 based Image Generation

criminator of GAN based Sketcher. Initially, the loss of the Generator rises and gradually diminishes over time. This observation indicates that the Generator is improving its ability to produce images that are indistinguishable from authentic ones. In contrast, the Discriminators loss is initially low and their gradually increases. This demonstrates that the Discriminator is becoming more proficient at discerning between genuine and counterfeit images. The decline in the Generators loss and the increase in the Discriminators loss signify positive progress in the training process. Figure 7 presents

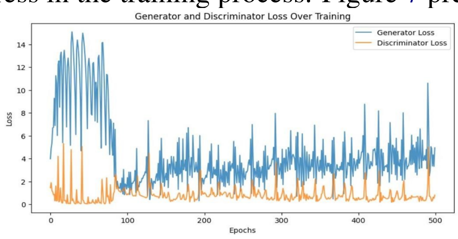


Figure 6: Generator and Discriminator Loss

a visual representation of the discriminators performance in the GAN based Sketcher. It illustrates the scores assigned by the discriminator to both real and generated (fake) samples throughout the training process. The real score signifies the discriminators ability to correctly identify authentic samples, with the goal of achieving higher scores. On the other hand, the fake score assesses the discriminators capacity to distinguish between generated samples, with lower scores indicating success.

Figure 7: Real And Fake Score

6 Conclusions and Future Directions

The partitioning of the landscape painting generation into distinct sketch and color phases has proven to be effective, resulting in realistic and interesting outcomes. Further investigation should concentrate on refining techniques that take into account lines and figures in the coloring process to enhance the overall quality of the generated artworks.

References

Henrique JA Andrade and Bruno JT Fernandes. 2020. Synthesis of satellite-like urban images from historical maps using conditional gan. *IEEE Geoscience and Remote Sensing Letters*, 19:1–4.

Mrinmoy Dutta Choudhury. 2020. *Automated Identification of Painters Over WikiArt Image Data Using Machine Learning Algorithms*. Ph.D. thesis, Dublin, National College of Ireland.

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial nets. *Advances in neural information processing systems*, 27:949–960.

Xiangquan Gui, Binxuan Zhang, Li Li, and Yi Yang. 2024. Dlp-gan: learning to draw modern chinese landscape photos with generative adversarial network. *Neural Computing and Applications*, 36(10):5267–5284.

Changhee Han, Hideaki Hayashi, Leonardo Rundo, Ryosuke Araki, Wataru Shimoda, Shinichi Muramatsu, Yujiro Furukawa, Giancarlo Mauri, and Hideki Nakayama. 2018. Gan-based synthetic brain mr image generation. In *2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018)*, pages 734–738. IEEE.

Sonu Kumar, Arjun Tyagi, Tarpit Sahu, Pushkar Shukla, and Ankush Mittal. 2018. Indian art form recognition using convolutional neural networks. In *2018 5th International Conference on Signal Processing and Integrated Networks (SPIN)*, pages 800–804. IEEE.

Landscape Oil Paintings by Craig Houston. https://www.pinterest.com/craighouston/landscape-oil-paintings/.

Landscape Painting. https://www.google.com/search ?q=landscape+painting.

Landscape Painting Freepik. https://www.freepik.com/free-photos-vectors/landscape-painting.

Landscape Paintings by Mark VanderVinne. https://www.pinterest.com/markvandervinne/landscape-paintings/.

Runjia Tian. 2021. Suggestive site planning with conditional gan and urban gis data. In *Proceedings of the 2020 DigitalFUTURES*, pages 103–113, Singapore. Springer Singapore.

Alice Xue. 2021. End-to-end chinese landscape painting creation using generative adversarial networks. In *Proceedings of the IEEE/CVF Winter conference on applications of computer vision*, pages 3863–3871.

Kang Zhang and Jinhui Yu. 2016. Generation of kandinsky art. *Leonardo*, 49(1):48–54.