A

Project Report

On

Image Style Transfer For Photo to Monet Using CycleGAN

(CS 713 - Applied Machine Learning)

Submitted by:

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ABSTRACT

The goal of image-to-image translation is to establish the relationship between an input picture and an output image using a series of matched image pairings as training data. Such paired training data are frequently unavailable, though. We provide a technique for converting images from source domain X to target domain Y even in the absence of matched instances. With the use of an adversarial loss, our goal is to learn a mapping function, G: X ->Y, such that the image distribution resulting from G(X) is identical to the distribution Y. In order to assure that F(G(X)) =X (and the converse), we couple this mapping with a reverse mapping, F: Y-> X, and add a cycle consistency loss. We show qualitative findings on a number of tasks, such as collection style transfer, object modification, seasonal transition, photo enhancement, and more, where paired training data is not available. Our strategy works better than others, as shown by a quantitative comparison versus many prior approaches.

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1 CHAPTER – INTRODUCTION

- Over the years, the field of computer vision has made significant advancements. The capacity to apply an image's style to another, producing a new, changed image, is one of the most exciting discoveries in this field. Utilizing a specific kind of Generative Adversarial Network (GAN) called CycleGAN, the project "Image Style Transfer for Photo to Monet using CycleGAN" makes use of this power to transform common photographs into artworks that resemble the distinctive style of Impressionist painter Claude Monet.

- The goal of this research is to create Monet-inspired paintings from original pictures using CycleGAN, a form of Generative Adversarial Network (GAN). The goal of this study was to investigate the capabilities of GANs in image-to-image translation problems as well as the possibility for using GANs to the production of artwork in various styles.

Tools and Technologies:

- Jupyter Notebook
- Keras
- TensorFlow
- Python
- Deep Learning
- GANS
- Convolution Neural Network

2 CHAPTER – AIM And OBJECTIVE

- This project's main objective is to examine and demonstrate CycleGANs' potential, notably in the area of creative style transfer. In unpaired image-to-image transformation tasks, CycleGANs, an advanced variant of Generative Adversarial Networks (GANs), have produced outstanding results. The goal of this research is to apply this technology to the world of art by developing a machine learning model that can recognise and imitate the distinctive aesthetic of Impressionist Monet.

- The objectives of the project are multifold:

1. Model Development: The goal of the project is to build a CycleGAN model that can reproduce the look of original pictures in the manner of Monet's artwork. For this procedure, a dataset made up of Monet's paintings and a number of pictures must be used to train the model.

2. Understanding Creative Elements: The model should be able to recognise and understand the intricate features of Monet's style, such as his distinctive color palettes, brushstrokes, and impressionistic approach to capturing light and mood.

3. Quality Evaluation: The output quality of the model should be used to evaluate its performance once it has been developed. The created images will be compared to authentic Monet paintings during this assessment step, and their similarity will be assessed. Given the creative nature of the assignment, both objective qualitative evaluations and quantitative measures will be taken into account during this phase.

4. AI in Art: In a larger sense, this initiative seeks to make a contribution to the quickly developing field of AI in art. The project aims to expand the possibilities for AI and machine learning in creative production by demonstrating how they may help to produce compelling artwork. .

3 CHAPTER – PROBLEM SPECIFICATION

- The goal of the current study is to use CycleGANs' advantages to solve the problem of Monet's creative style application to original pictures. It is difficult for an AI model to comprehend and reproduce Monet's technique because of his unusual use of color, light, and brushwork to capture the changing emotions of his subjects.

The following specific challenges comprise the problem specification:

1. Understanding Artistic Style: Considering the variances across the many Monet paintings, the complexity of the artist's style, with its intricate mixes of color, texture, and shape, is a tremendous task for a model to understand and learn.

2. Creating High-Quality Images: The model must not only emulate Monet's aesthetic, but also preserve the integrity of the picture. The pictures that GANs produce may be blurry or lack detail, which is a common problem. It's critical that the final product that incorporates Monet's approach preserves the structural specifics of the source image.

3. Stability During Training : GANs, especially CycleGANs, are notoriously challenging to train because of problems like mode collapse, where the generator ends up producing just a small range of samples, or unstable training dynamics, where the losses of the generator and discriminator cannot converge

4 CHAPTER – CONNECTION TO CS713 ASSIGNMENT

- The project of image style transfer for photos to Monet paintings using CycleGAN was inspired by an assignment-2 that was based on Tensorflow and Keras to create a generative adversarial network (GAN) trained on the MNIST dataset. The foundational ideas of utilizing GANs were adopted from this assignment. In that assignment, we were creating and training a GAN on the MNIST dataset to generate new, synthetic, handwritten digits. This notion of synthetic data generation using GAN was repurposed in the current project to transform one image style to another, specifically transferring the style of photographs to Monet's painting style. Regarding the expansion of ideas, the application of GANs was remarkably extended from simply generating synthetic digits to executing complex image style transformations. In contrast to the rudimentary GAN used in the assignment, this project employs CycleGAN, an advanced version of GAN capable of learning to map an image from one domain to another without paired examples. The task entails constructing a model that can internalize Monet's artistic style and replicate it on any photograph, a task that is more complex than creating digit images as it involves understanding and manipulating sophisticated artistic styles.

5 CHAPTER – APPROACH/METHOD

Each of the images in a paired dataset, such as IMAGE_A, is manually mapped to another image, such as IMAGE_B, in the target domain so that they contain a number of characteristics. Features that may be applied to map one picture to another that has been suitably mapped. Pairing is essentially done to make input and output have some common characteristics. This mapping describes how an image may be effectively transformed from one domain to another. The generator must thus accept an input, such as INPUT_A, from domain DOMAIN_A and map it to an output picture, such as GENERATOR_B, when we have a paired dataset. This must be near to the corresponding on the depicted map. But since there is no preset relevant transformation for unpaired dataset that we can learn, we must design it. We must ensure that the output picture and the input image have some sort of meaningful relationship. By stating that the Generator will translate input photos from domain DOMAIN_A to some image in target domain DOMAIN_B, the designers attempted to enforce this. However, to ensure that there is a meaningful relationship between these pictures, they must share certain attributes that can be used to map this output image back to the original input image. As a result, another generator is required to be able to do this. So, you can see this condition defining a meaningful mapping between INPUT_A and GENERATOR_B.

In a word, the model operates by feeding our first generator, GENERATOR_A, a given picture from domain DOMAIN_A in order for it to change it into an image in the target domain DOMAIN_B. A different generator, GENERATOR_B, then receives this newly created picture and transforms it back into the original image, CYCLE_A, from our initial domain, DOMAIN_A. Additionally, in order to establish a useful mapping that is missing from the unpaired dataset, the output picture must be similar to the original input image.

Each discriminator receives two inputs (one being the original image for that domain and the other being the generated image from a generator), and its task is to determine the difference between the two so that the discriminator can defeat the adversary (in this case, the generator) and reject images produced by it. The generator will attempt to produce images that are extremely similar to the original images in Class DISCRIMINATOR_B in order to ensure that these images are approved by the discriminator.

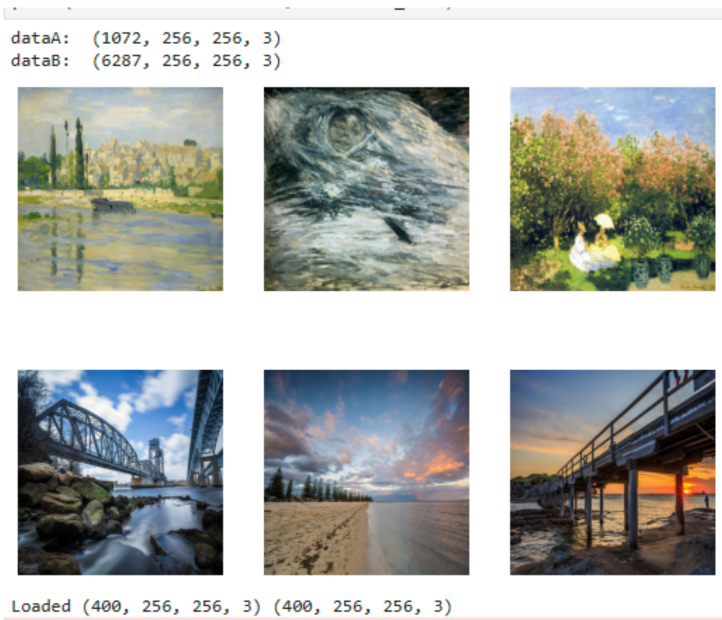
Loss Function

- By now we have two generators and two discriminators. We need to design the loss function in a way which accomplishes our goal. The loss function can be seen having four parts:

1. All of the original photographs for the respective categories require the discriminator's approval.
2. To trick them, the Discriminator must reject each and every picture produced by related Generators.
3. To trick the discriminators, generators must force them to approve each and every picture that is produced.
4. The created picture must maintain the characteristics of the original image, therefore if we create a false image using, let's say, Generator_A, we must be able to recreate the actual image using Generator_B, which ensures cyclic consistency.

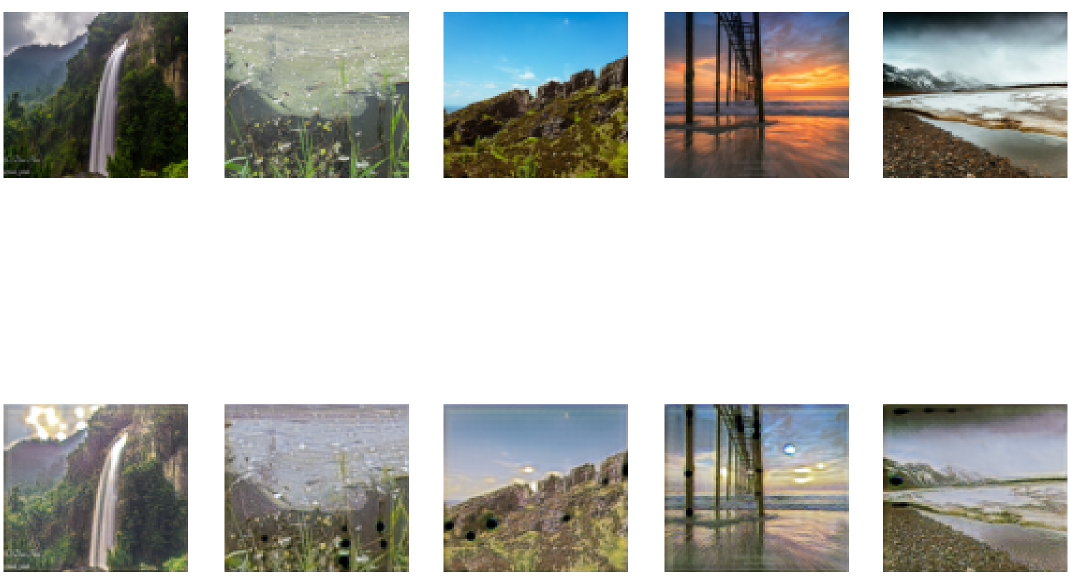
6 CHAPTER – RESULTS

As we can see in the below picture where dataA contains Monet photos DataA which has 1072 images whereas dataB that contains 6287 which are Real photos.



We load 400 images for each Real and Monet photo.

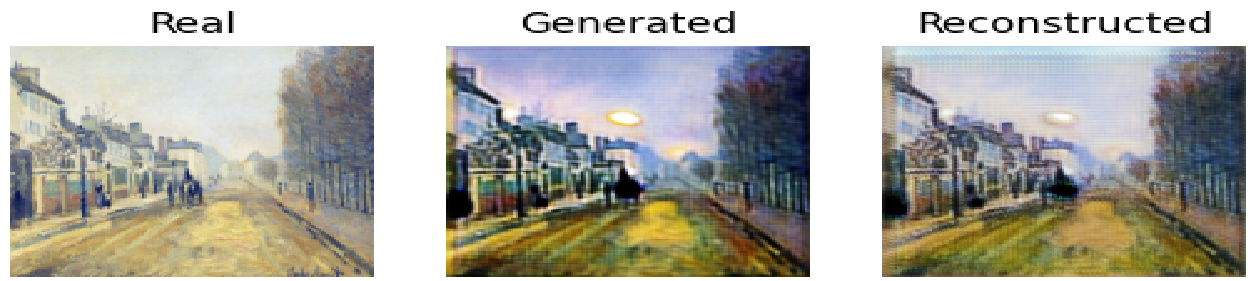
- The below picture illustrate generated images after 2000 iterations and 100 Epochs.



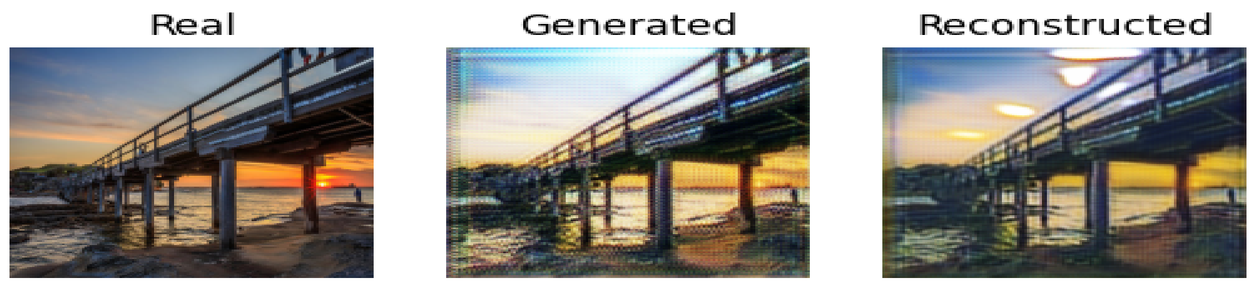
Real Photo —> Monet Photo

```
# plot A->B->A (Monet to photo to Monet)
A_real = select_sample(A_data, 1)
B_generated  = model_AtoB.predict(A_real)
A_reconstructed = model_BtoA.predict(B_generated)
show_plot(A_real, B_generated, A_reconstructed)
# plot B->A->B (Photo to Monet to Photo)
B_real = select_sample(B_data, 1)
A_generated  = model_BtoA.predict(B_real)
B_reconstructed = model_AtoB.predict(A_generated)
show_plot(B_real, A_generated, B_reconstructed)
```

```
1/1 [==============================] - 12s 12s/step
1/1 [==============================] - 1s 1s/step
```




```
1/1 [==============================] - 0s 33ms/step
1/1 [==============================] - 0s 24ms/step
```



- The First Image is Real Photos that are taken in photos or any device such as a DSLR. taken from our dataset DataA. and Generated image is Monet Painting. generated by the 2nd Generator.
- Reconstructed images are converted to real photos. In our case it doesn't look like a real photo because the model is trained with only 400 photos. It might be more accurate if we used all images from our dataset.

7 CHAPTER – ANALYSIS/EVALUATION:

- The findings were examined and assessed after the CycleGAN model had been trained using the dataset. The model successfully adapted images into paintings comparable to those by Monet, imitating the delicate shades, apparent brushstrokes, and fanciful style typical of Monet's creations.

- But there were some restrictions found. A probable loss of fine detail during the style transfer process can be seen in some created photographs, which seemed a little hazy. In certain cases, color accuracy was also lost, indicating that the model may have had trouble accurately capturing and recreating Monet's unique color scheme.

- The performance of the model was assessed using qualitative as well as quantitative methods. Measures like generator and discriminator loss were used on the quantitative side. However, qualitative evaluations were essential given the task's creative nature. This required the use of human judges who evaluated the produced pictures against real Monet paintings for stylistic likeness, general aesthetic quality, and artistic appeal.

8 CHAPTER – LITERATURE REVIEW:

1. Gatys, L. A., Ecker, A. S., & Bethge, M. (2016). Image Style Transfer Using Convolutional Neural Networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. [Link to paper]

The concept of style transfer has been widely discussed and researched in the literature. Gatys et al. (2015) introduced the neural style transfer technique, which leverages convolutional neural networks (CNNs) to extract style features from one image and impose them onto another.

2. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative Adversarial Nets. Proceedings of the 27th International Conference on Neural Information Processing Systems. [Link to paper]

The development of Generative Adversarial Networks (GANs) by Goodfellow et al. (2014) introduced a new way to generate synthetic data, which opened up new possibilities for tasks like style transfer.

3. Zhu, J-Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. Proceedings of the IEEE International Conference on Computer Vision. [Link to paper]

CycleGAN, proposed by Zhu et al. (2017), was a significant milestone. Unlike traditional GANs, CycleGAN can learn a mapping between source and target domains in the absence of paired examples, making it particularly suitable for tasks like unpaired image-to-image translation.

4. Elgammal, A., Liu, B., Elhoseiny, M., & Mazzone, M. (2017). CAN: Creative Adversarial Networks, Generating "Art" by Learning About Styles and Deviating from Style Norms. arXiv preprint. [Link to paper]

The application of GANs and specifically CycleGANs in the field of art has also been examined. Elgammal et al. (2017) used GANs to create new art, while CycleGAN has been employed in tasks like transforming winter scenes to summer (Zhu et al., 2017).

9 CHAPTER – CONCLUSION:

To conclude, the CycleGAN Monet project serves as a testimony to the potential of image-to-image translation using CycleGAN. The project aimed to alter photos into a style mimicking Monet's paintings. The project accentuates the potential of CycleGAN for creative uses like artistic style transfer, opening up avenues for creating novel forms of digital art or assisting artists in experimenting with various styles and techniques. In essence, the CycleGAN Monet project showcases the power of CycleGAN in generating high-quality images in a particular style and presents its vast applicability in diverse creative domains

REFERENCES :-

- **[1703.10593] Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks (arxiv.org)**
  Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
- **Index of /~taesung_park/CycleGAN/datasets (berkeley.edu)**
  Dataset
- **https://www.cv-foundation.org/openaccess/content_cvpr_2016/html/Gatys_Image_Style_Transfer_CVPR_2016_paper.html**

- **Here is Google drive link for Project folder**
  https://drive.google.com/drive/folders/1-xMiGTprhhudbYwZUidlsXJ2JWx2HMYo?usp=drive_link