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URBAN MAP GENERATION IN ARTIST'S STYLE USING GENERATIVE ADVERSARIAL NETWORKS (GAN)

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Abstract

Artificial Intelligence is a field that is able to learn from existing data to synthesize new ones using deep learning methods. Using Artificial Neural Networks that process big datasets, complex tasks and challenges become easily resolved. As the zeitgeist suggests, it is possible to produce novel outcomes for future projections by applying various machine learning algorithms on the generated data sets. In that context, the focus of this research is exploring the reinterpretation of 21st century urban plans with familiar artist styles using different subtypes of deep-learning-based generative adversarial networks (GAN) algorithms. In order to explore the capabilities of urban map transformation with machine learning approaches, two different GAN algorithms which are cycleGAN and styleGAN have been applied on the two main data sets. First data set, the urban data set, contains 50 cities urban plans in .jpeg format collected according to the diversity of the urban morphologies. Whereas the second data set is composed of four well-known artist's paintings, that belong to various artistic movements. As a result of training the same data sets with different GAN algorithms and epoch values were compared and evaluated. In this respect, the study not only investigates the reinterpretation of stylistic urban maps and shows the discoverability of new representation techniques, but also offers a comparison of the use of different image to image translation GAN algorithms.

Keywords

Urban Map, Style Transferring, Generative Adversarial Networks, CycleGAN, StyleGAN.

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ABSTRACT

Artificial Intelligence is a field that is able to learn from existing data to synthesize new ones using deep learning methods. Using Artificial Neural Networks that process big datasets, complex tasks and challenges become easily resolved. As the zeitgeist suggests, it is possible to produce novel outcomes for future projections by applying various machine learning algorithms on the generated data sets. In that context, the focus of this research is exploring the reinterpretation of 21st century urban plans with familiar artist styles using different subtypes of deep-learning-based generative adversarial networks (GAN) algorithms. To explore the capabilities of urban map transformation with machine learning approaches, two different GAN algorithms which are cycleGAN and styleGAN have been applied on the two main data sets. First data set, the urban data set, contains 50 cities urban plans in .jpeg format collected according to the diversity of the urban morphologies. Whereas the second data set is composed of four well-known artist's paintings, that belong to various artistic movements. As a result of training the same data sets with different GAN algorithms and epoch values were compared and evaluated. In this respect, the study not only investigates the reinterpretation of stylistic urban maps and shows the discoverability of new representation techniques, but also offers a comparison of the use of different image to image translation GAN algorithms.

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ملخص

يعتبر الذكاء الاصطناعي مجالا قادرا على التعلم من البيانات الموجودة لتجميع بيانات جديدة باستخدام أساليب التعلم العميق. ويمكن حل المهام والتحديات المعقدة بسهولة باستخدام الشبكات العصبية الاصطناعية التي تعالج مجموعات البيانات الكبيرة. كما تقترح روح العصر، من الممكن إنتاج نتائج جديدة للتوقعات المستقبلية من خلال تطبيق خوارزميات التعلم الآلي المختلفة على مجموعات البيانات التي تم إنشاؤها. في هذا السياق، ينصب تركيز هذا البحث على استكشاف إعادة تفسير المخططات الحضرية للقرن الحادي والعشرين بأساليب فنية مألوفة باستخدام أنواع فرعية مختلفة من خوارزميات شبكات الخصومة التوليدية القائمة على التعلم العميق (GAN). من أجل استكشاف إمكانات تحويل الخرائط الحضرية باستخدام مناهج التعلم الآلي، تم تطبيق خوارزميتين مختلفتين من GAN وهما cycleGAN و styleGAN على مجموعتي البيانات الرئيسيتين. تحتوي مجموعة البيانات الأولى، وهى مجموعة البيانات الحضرية ، على ٥٠ مخططًا حضريًا لمدن فى ملفات jpeg تم جمعها وفقًا لتنوع الأشكال الحضرية. بينما تكونت مجموعة البيانات الثانية من أربع لوحات لفنانين مشهورين تنتمي إلى حركات فنية مختلفة. نتيجة لتدريب نفس مجموعات البيانات مع خوارزميات GAN المختلفة وقيم العصر تمت مجموعة من المقارنات والتقييمات. وفي هذا الصدد، لا تبحث الدراسة فقط في إعادة تفسير الخرائط الحضرية الأسلوبية وتظهر قابلية اكتشاف تقنيات التمثيل الجديدة، ولكنها تقدم أيضًا مقارنة بين استخدام خوارزميات GAN لترجمة الصور المختلفة.

الكلمات المفتاحية: الخرائط الحضرية، نقل الأنماط، شبكات الخصومة التوليدية، الشبكات التوليدية القائمة على الدورات، الشبكات التوليدية القائمة على الأنماط.

1. INTRODUCTION

The mass of information brought by the development of information and communication technologies can be easily processed and manipulated with artificial intelligence (Boden and Edmonds,2009). In this way, data can be used as design input, and unexpected situations and new forms of representation can arise. This paper presents an approach that uses Generative Adversarial Networks (GAN) algorithms to generate and transfer artist style to interpreted urban maps as a generative representation method.

Artists produce artworks in many corners of the cities they live in, or they visit. However, many of them have not found a chance to express the plan of that city with their own style. One aspect of this work within the scope of the machine learning exploration is to show what a city plan would look like if it were tried to be represented in the style of an artist. Since besides the conventional visualization tools, machine learning has a great potential to be used in the research area of cultural and architectural heritage for understanding the built environment in the digital realm with the idea of inserting new interpretations to the existing urban map characteristics (Tamke et al, 2018). However, it significantly important to highlight the limits of the scope of the research in terms of as generation method of the visual mediums, to avoid any misinterpretations and speculations that might be associated urban morphological and planning studies, which requires broad investigations to make a statement.

As presented in the future sections of the paper, the proposed method of machine learning explorations has clear boundaries for to create a digital map collection of contemporary urban plans in the styles of the well-known artists from variety of artistic movements. Thus, it could be further used in multi-media environments as a dataset collection to identify and highlight various urban features and characteristics through various styles of the artists. Although it is possible to see such studies in this field in the literature of architectural visualization and representation, there is no precedent study on the urban map generation in the styles of various artistic movement through the exploration of machine learning methods and tools.

Another aspect of this study is to emphasize and explore the diversity that occurs when different image2image translation GAN algorithms. Different epoch and batch values have been tested in this exploration for the representation. All machine learning models have been trained on the Google Colab, thanks to the availability of a higher Graphics Processing Unit (GPU) as an advantage of cloud computing. Generative adversarial network (GAN) model framework has been selected as the generation method for this research since it is designed to learn and generate image data, that neural networks may produce fictitious and high-quality data (Goodfellow et al. 2014). In GAN, one algorithm generates, the other evaluates, and the cycle continues until the discriminator no longer distinguishes the image that can be produced by Generator as real or fake. In this research, two different GAN algorithms of of cycleGAN and styleGAN have been trained with five different data sets to evaluate their potentials for stylistic urban map projections. To increase the diversity of the work, 4 different artist's data sets were generated. The dataset belonging to the urban maps was obtained manually from the Snazzy Maps platform, and the other four datasets belonging to the artists were taken from the data provided by Berkeley AI Research as open source (Berkeley AI Research, 2022). The results of running the same data sets with different GAN algorithms and epoch values were compared and evaluated. In this respect, the study not only shows the discoverability of new representation forms but also offers a comparison of the use of different algorithms. The discussion includes generative adversarial networks, dataset creation, and results.

1.1 About the Generative Adversarial Networks

A Convolutional Neural Network (CNN) is a Deep Learning system that can take an input image, assign relevance such as learnable weights, biases, etc. to various aspects/objects in the image, and distinguish between them (Saha, 2018). When compared to other classification methods, the amount of pre-processing required by a CNN is significantly less. Through the application of suitable filters, a CNN can capture the spatial and temporal dependencies in an image (Saha, 2018). Because of the reduced number of parameters involved and the reusability of weights, the architecture performs superior fitting to the picture dataset. To put it another way, the network can be trained to recognize the image's sophistication. When Convolutional Neural Networks are trained on object recognition, they build an image representation that becomes increasingly explicit as the processing hierarchy progresses (Gatys et al 2015). As a result, as the network's processing hierarchy progresses, the input image is transformed into representations that care more about the image's real content than its exact pixel values.

In machine learning, generative modeling is an unsupervised learning task that entails automatically detecting and learning regularities or patterns in input data so that the model may be used to produce or output new examples that could have been drawn from the original dataset (Brownlee, 2019). These GANs generate new images using image inputs rather than a random data distribution as a source. Style transfer, colorizing, in painting, super resolution, future state prediction, object transfiguration, photo editing, enhancement, pose morphing, data augmentation, and many more areas of machine learning and computer vision can all be addressed by image-to-image GANs (Saxena and Teli, 2021). The GAN model architecture involves two sub-models: a generator model for generating new examples and a discriminator model for classifying whether generated examples are real, from the domain, or fake, generated by the generator model (Hui et al, 2018). The CycleGAN is an extension of the GAN architecture that involves the simultaneous training of two generator models and two discriminator models. The first generator receives photos from the first domain and creates images for the second domain, while the second generator takes photographs from the second domain and generates images for the first domain (Brownlee, 2019). The generator models are then updated using discriminator models to judge how realistic the generated images are.

The StyleGAN's GAN architecture differs from the CycleGAN by the inherent generator model. The generators implemented in the styleGAN architecture uses a mapping network to map points in latent space to an intermediate latent space. Thus, the intermediate one can control the generated style at each point, and it introduces the noise as a source of variation at each point as well in the generator model (Amirian et.al. ,2021).

2. COLLECTING AND PROCESSING THE DATASETS

For the purposes of this research, two different types of data sets have been collected: First the urban data set that consists of manually collected 1000 map images from 50 cities. Secondly, the artists' paintings data sets that have been separately constituted for the training process of the algorithms in terms of Van Gogh, Cézanne, Monet, and Ukiyoe from the CycleGan data repository.

2.1. Urban Dataset

For the Urban dataset generation, the base map template had been created using the Snazzy Maps website, which allows user to define their own style for the maps, by using the Google Maps data. From the interface, 1000 map images have been collected without labels or signs and have low contrast and saturation values. The location of each map was chosen from different characterized urban morphologies on purpose, to see variety of urban characters under various artist styles. Therefore, we have manually collected 20 map images from 10 countries' 5 most populated cities, from Europe, Asia, North and South America (Table 1). The original images were 1920*1080 pixels, therefore a batch resizing and cropping processing operations have been applied. In order to maintain the images into 256*256 pixel sizes by keeping the aspect ratio, which approximately shows a 10,2 km2 area, by Python code using Numpy and PIL libraries. In the end, we have generated an urban dataset that contains 1000 images in suitable pixel size, RGBA color mode, and .png format. Examples of this data set (2%) can be seen from Figure 1 (Fig.1). The data have separated into train_urban and test_urban folders that the train_urban folder contains 80% of the total data, whereas test_urban has %20 which equals 200 map images.

Table 1: The location of the map images that constitutes the urban dataset.

Country	Cities
Turkey	Istanbul, Ankara, İzmir, Bursa, Antalya
Germany	Berlin, Hamburg, Cologne, Munich, Stuttgart
Italy	Florence, Genova, Milan, Naples, Rome
Spain	Barcelona, Bilbao, Madrid, Sevilla, Valencia
Netherlands	Amsterdam, Eindhoven, Maastricht, Rotterdam, Utrecht
Brazil	Brasilia, Fortaleza, Rio de Janeiro, Salvador, Sao Paulo
Japan	Hiroshima, Kyoto, Nagasaki, Osaka, Tokyo
Russia	Kazan, Moscow, Novosibirsk, Samara, St. Petersburg
U.S.A	Boston, Chicago, Los Angeles, Miami, New York City
Egypt	Alexandria, Aswan, Cairo, Luxor, Sharm El-Sheikh

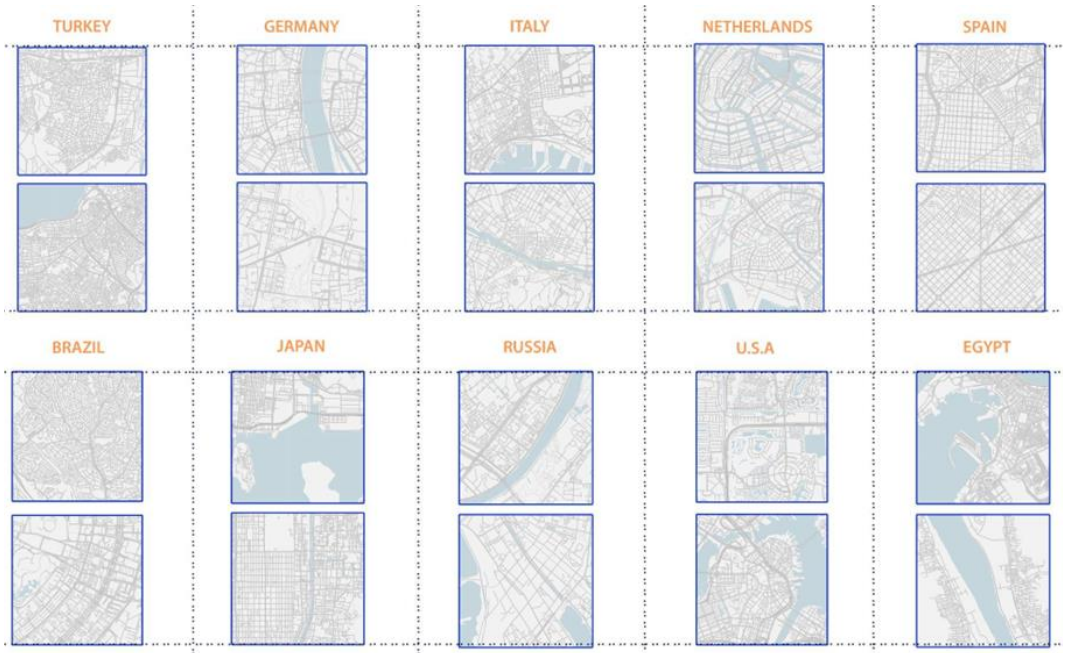

Fig.1: Urban Dataset example map images from 10 different countries

2.2. Artist Paintings Dataset

In order to apply different artist styles to urban layouts, we collected datasets from the CycleGAN repository. The selection criteria for the artist's painting besides the availability issue of the data was the artistic movements that they are belong in to.

The art works of well-known pioneer artist of the Impressionism, who were Van Gogh, Monet, Cezanne, has been included in the data sets; whereas Ukiyo-e's paintings has been consciously added to data set from the Japonisme style, which has strong connections and influence on impressionism, to embrace the complexity within the dataset. The selection of the impressionist artworks was critical at that point of the research, since the movement pioneers generally depicts the landscape and the contemporary life by capturing the rapid pace of contemporary life and the fleeting conditions of light (Nesic, 2022). Thus, that kind of constant transformation represented on the artworks has been elaborated conceptually as in a similar manner of the urban fabric, which is constantly subjected to the alterations within different time frames.

All painting dataset containing the artworks of the artists mentioned above have been subjected to a series of batch image processing operations, to maintain 256*256 pixels, in RGB color mode, jpg formatted images. Each of the datasets had been separated into train and test folders likewise the urban dataset. The examples from the artists' datasets can be seen in Figure 2 (Fig.2).

Fig.2: Artist dataset examples and the total number of images contained in each dataset

3. TRAINING THE GAN MODELS: CYCLEGAN & STYLEGAN

3.1. CycleGAN

The CycleGAN is a technique that involves the automatic training of image-to-image translation models without paired examples and unsupervised learning is used to train the models using a set of images from the source and target domains that can be unrelated (Brownlee, 2019). The system can learn to capture features of one image collection and find methods to translate these features to other image collection in the absence of paired training examples (Chen et al., 2019). Cycle consistency is a further feature to the architecture that is used by the CycleGAN which is the idea that an image produced by the first generator may be utilized as the input for the second generator, whose output must resemble the original image and the output of the second generator may be fed into the first generator as input, and the output should equal the second generator's input (Zhu, et al., 2020). By including an extra loss to calculate the difference between the output of the second generator and the original image, and vice versa, the CycleGAN promotes cycle consistency. As a result, the generator models are regularized, directing image production in the new domain in the direction of image translation (Brownlee, 2019).

3.1.1. Van Gogh to Map & Map to Van Gogh

To test the model, the model initially trained with 60 epochs on the Google Colab platform. After the generation of first sample images and plotting the discriminator losses on the chart (Figure 3), the application continued by training it with 6000 epochs values.

For both applications the hyper parameters had been set the same as LR (Learning Rate) = 0.0002; Batch Size =16, except the epoch number. However, while training the model with 6000 epochs, we faced an interruption in the 5560th epoch due to the working time issue of Google Colab. The total, discriminator, and generator loss values, in the 10th and 5560th epochs of the application, are:

Epoch [10/ 6000] | d_X_loss: 0.4649 | d_Y_loss: 0.5561 | **g_total_loss: 10.3906**
Epoch [5560/ 6000] | d_X_loss: 0.1041 | d_Y_loss: 0.1751 | **g_total_loss: 3.6625**

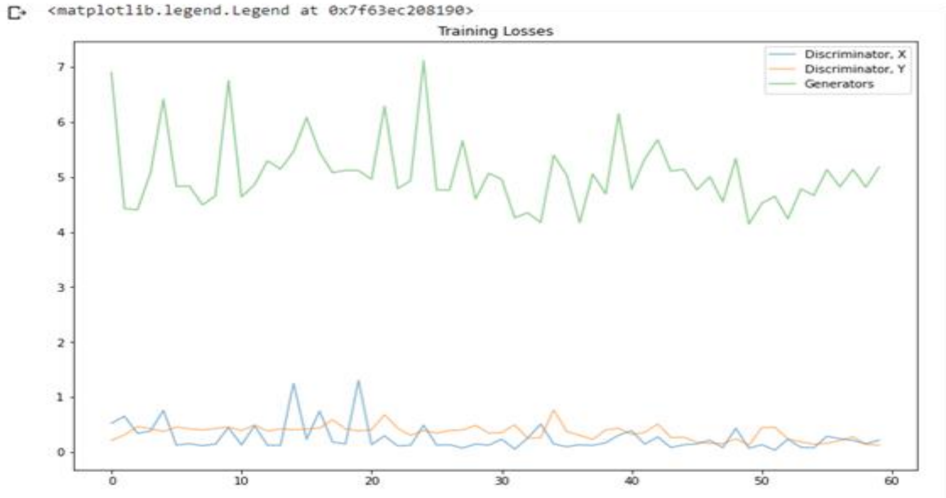

Fig.3: Training Losses with 60 epochs

The outputs of the training with 100th epoch and 5500th epoch can be seen below for both maps to painting (Figure 4 a & b), and paintings to map (Figure 5 a & b) applications.

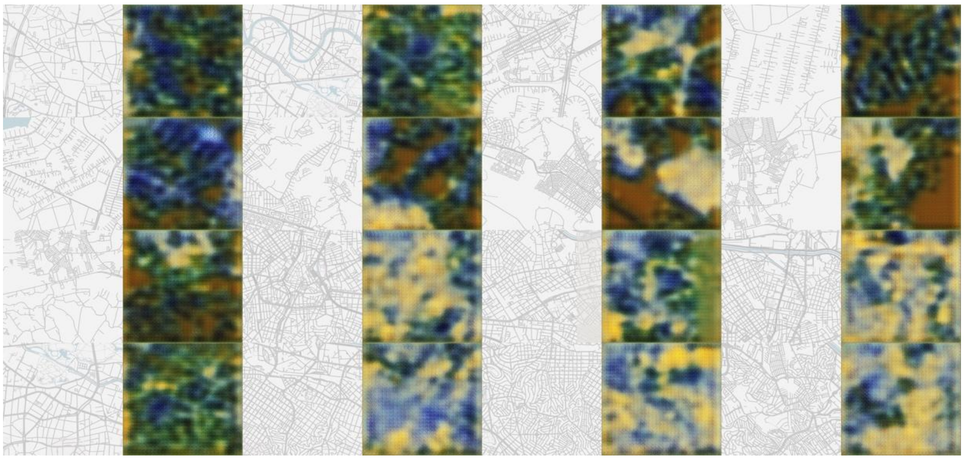

Fig.4(a): Map to Van Gogh Painting 100th epoch

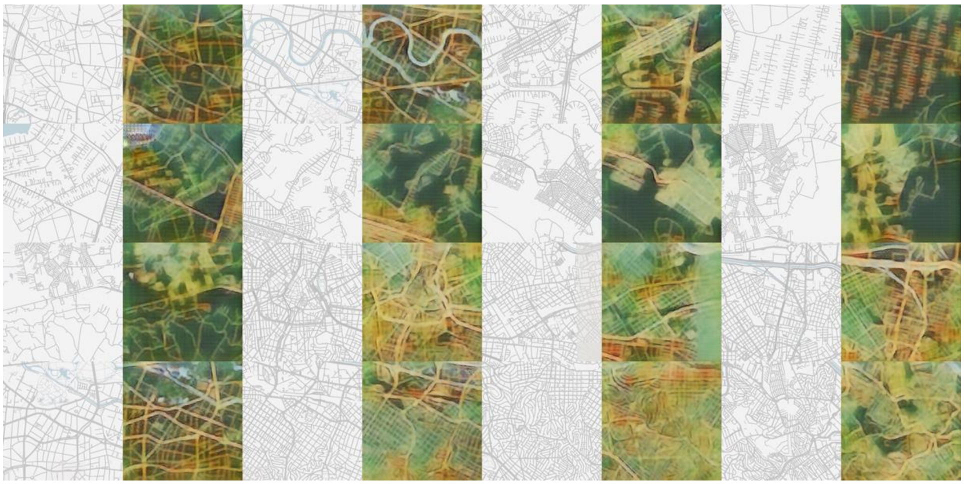

Fig.4(b): Map to Van Gogh Painting 5560th epoch

Fig.5(a): Van Gogh Painting to Map 100th epoch

Fig.5(b): Van Gogh Painting to Map 5560th epoch

3.1.2. Monet to Map & Map to Monet

Likewise, in Van Gogh's paintings application, the model was first trained with 100 epochs for the first trial. Then we have trained our model using the same hyper parameters as the previous application, but this time with a smaller number of epochs of 4000, to see the difference in between. The discriminator and total losses of the 10th and 4000th are:

Epoch [10/ 4000] | d_X_loss: 0.0395 | d_Y_loss: 0.4869 | **g_total_loss: 5.2189**

Epoch [4000/ 4000] | d_X_loss: 0.2004 | d_Y_loss: 0.2249 | **g_total_loss: 3.2786**

The output images for both Monet map to painting (Figure 6 a & b), and painting to map (Figure 7 a & b) can be seen from as well as the loss chart in Figure 8.

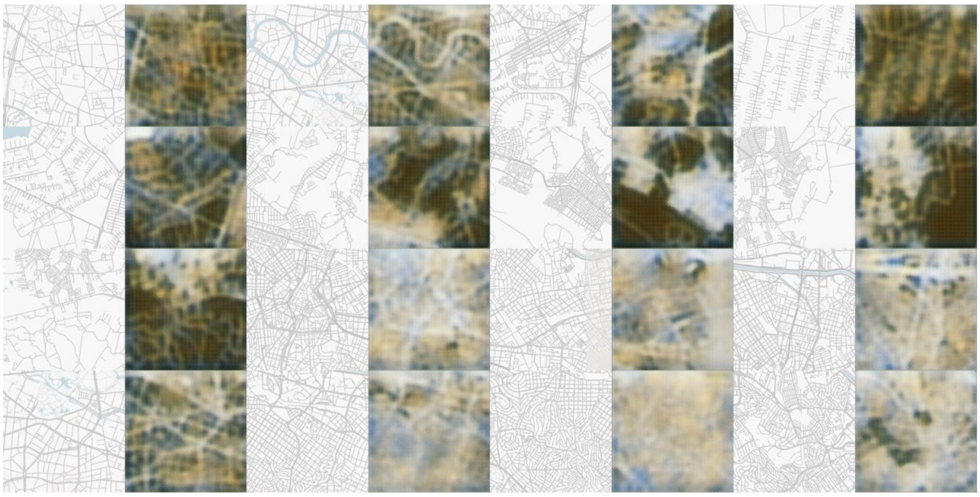

Fig.6(a): Map to Monet Painting 100th epoch

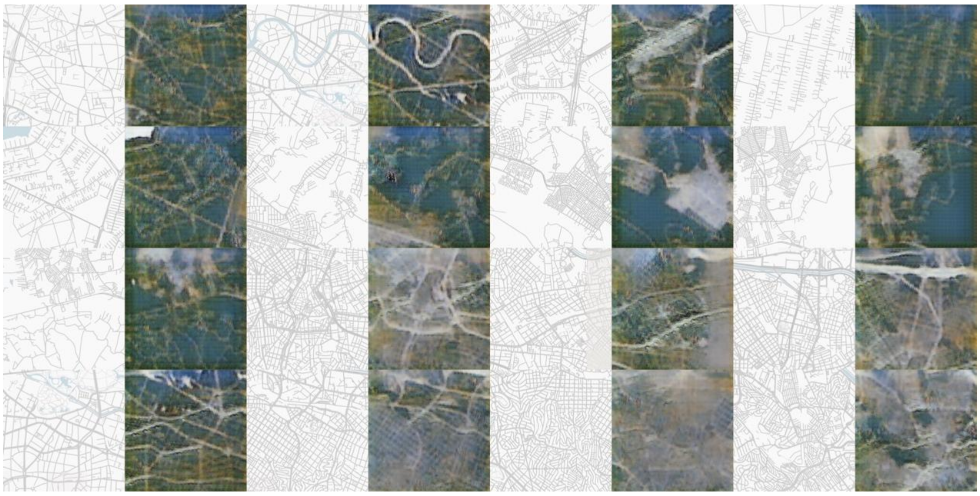

Fig.6(b): Map to Monet Painting 4000th epoch

Fig.7(a): Monet Painting to Map 100th epoch

https://digitalcommons.bau.edu.lb/apj/vol28/iss3/9
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Fig.7(b): Monet Painting to Map 4000th epoch

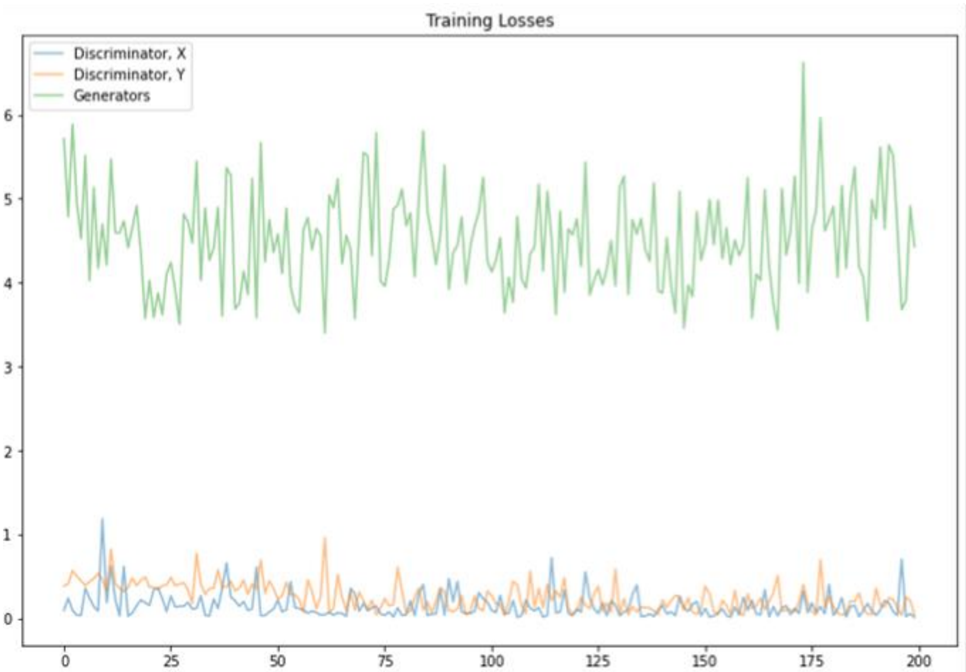


Fig.8: Training Losses of Monet to Map & Map to Monet application

3.1.3 Evaluation of the Outputs

When we try to evaluate the outputs of CycleGAN models on the same urban data set applied with two different sets of Van Gogh and Monet paintings, it is possible to say that the map to painting conversion had provided better results in terms of legibility of urban characteristics. As well as it can be seen from Figure 4(b) and Figure 6(b) the urban features are so clear that they could be seen as an aerial image painted by Van Gogh's and Monet's style. But also painting to map conversions are still valuable in terms of creating an urban texture out of the original paintings Figure 5(b) and Figure 7(b). However, the produced maps are not so readable as in the case of the map to painting, for detecting the urban grid and natural elements.

Secondly, when we compare the difference between each application on different artists' paintings, we can say that due to the different number of epochs applied, the resolutions of the generated images are various. One might say that the Van Gogh applications results are more prominent than the Monet one, especially in the painting to map conversions. At that point, it is important to note that a smaller number of epochs might not be the only reason for it. The reason can also be interpreted as the artists’ style is highly determinant for the legibility of the generated maps. Even if both artists are pioneers of the same artistic movement of impressionism, the personal style differences that can be seen clearly from their masterpieces have also been projected on this research’s outputs.

3.2. StyleGAN

The StyleGAN is a GAN extension that proposes significant changes to the generator model. These changes include the use of a mapping network to map points in latent space to an intermediate latent space, the use of the intermediate latent space to control style at each point in the generator model, and the addition of noise as a source of variation at each point in the generator model (Brownlee, 2019). In the styleGAN algorithm, a feature space that was initially created to capture texture information to get a representation of the style of an input image is employed (Gatys, Ecker, & Bethge, 2015). The filter responses in each layer of the network are used to create this feature space. It consists of the correlations between the various filter responses over the feature maps' spatial area. A stationary, multi-scale representation of the input image by adding the feature correlations of many layers, which captures the texture information but not the global layout is generated. In addition to producing stunningly photorealistic, high-quality images of faces, the resultant model also provides control over the style of the created picture at various degrees of detail by adjusting the style vectors and noise.

3.2.1 Cézanne to Map and Map to Cézanne

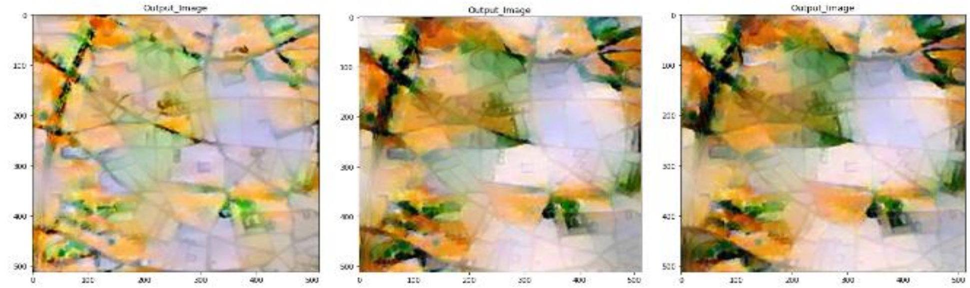
The StyleGAN model was trained with 10 epochs and 1000 iterations for each epoch. Losses in the first epoch and the last one was:

After epoch 1: Tot_loss: 6.7482, Sty_loss: 1.6912, Con_loss: 3.9273, Var_loss: 1.1297

After epoch 10: Tot_loss: 5.5615, Sty_loss: 0.9411, Con_loss: 3.4904, Var_loss: 1.13

The loss of the system has not changed drastically with different parameters; however, visual results seem promising and satisfying. The algorithm is run with painting to map transfer initially.

Fig.9: Style image and content image



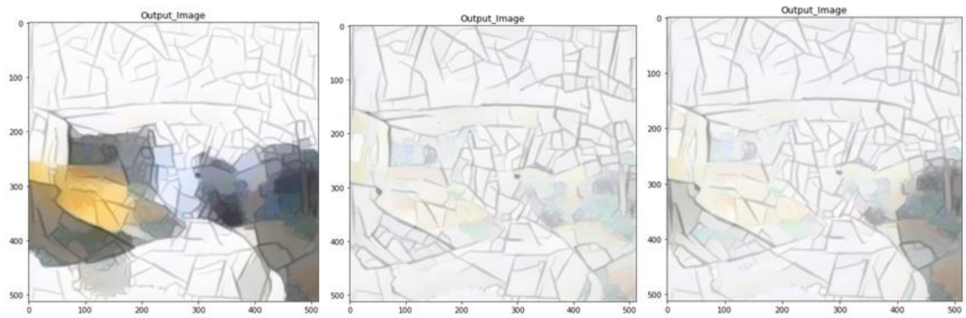
Epoch#1 *Epoch#5* Epoch#10

Fig.10: Cézanne to Map transfer

After trying the painting to map, the algorithm has ran in the opposite direction and transfer the map to painting to see the results. Even the system loss has not changed significantly, the results can be evaluated as promising new stylistic map features.

After epoch 1: Tot_loss: 5.314, Sty_loss: 0.9266, Con_loss: 3.388, Var_loss: 0.9993

After epoch 10: Tot_loss: 5.2411, Sty_loss: 0.8976, Con_loss: 3.3408, Var_loss: 0.9944



Epoch#1 *Epoch#5* Epoch#10

Fig.11: Map to Cézanne transfer

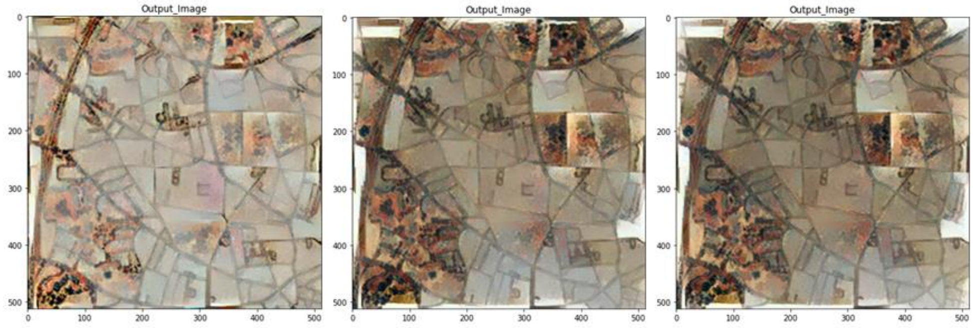
3.2.2. Ukiyo-e to Map and Map to Ukiyo-e

The StyleGAN model was trained with 10 epochs and 1000 iterations for each epoch. The losses are plotted similarly to previous training sessions with different artists.

After epoch 1: Tot_loss: 7.16, Sty_loss: 1.74, Con_loss: 3.98, Var_loss: 1.43

After epoch 10: Tot_loss: 5.31, Sty_loss: 0.92, Con_loss: 3.38, Var_loss: 0.99

Fig.12: Style image and content image



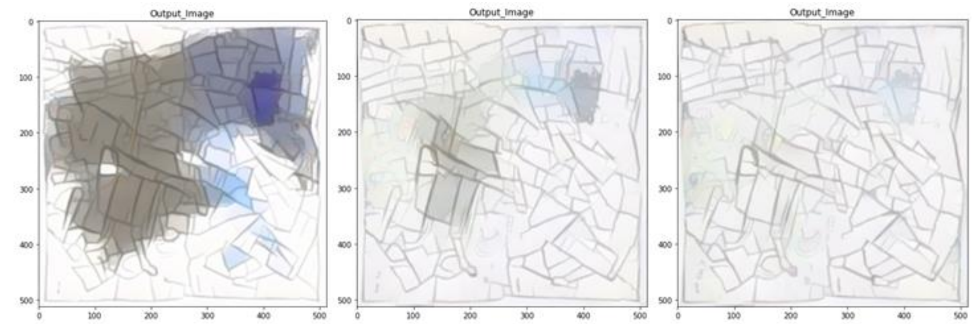
Epoch#1 *Epoch#5* Epoch#10

Fig.13: Ukiyo-e to Map transfer

Map to painting has run and the losses achieved like the Cézanne example.

After epoch 1: Tot_loss: 6.61, Sty_loss: 1.54, Con_loss: 3.74, Var_loss: 1.37

After epoch 10: Tot_loss: 4.98, Sty_loss: 0.86, Con_loss: 3.15, Var_loss: 0.82



Epoch#1 *Epoch#5* Epoch#10

Fig.14: Map to Ukiyo-e transfer

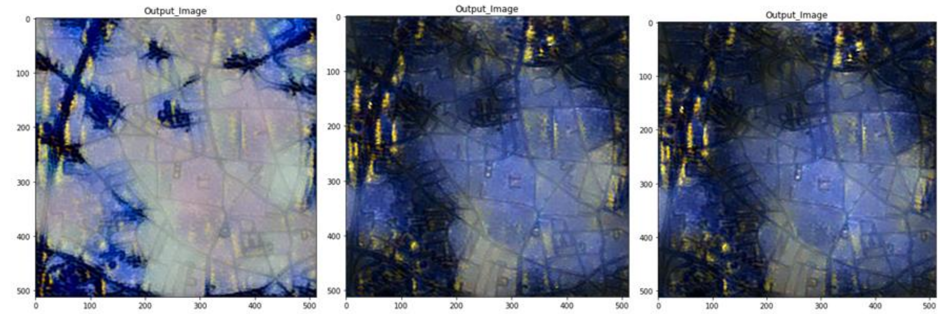
3.2.3. Van Gogh to Map and Map to Van Gogh

The last exploration was from Van Gogh dataset and the system loss results were like other attempts. The algorithm was run with 10 epochs and 1000 iterations for each epoch as previous attempts.

After epoch 1: Tot_loss: 8.34, Sty_loss: 1.72, Con_loss: 4.15, Var_loss: 1.78

After epoch 10: Tot_loss: 5.241, Sty_loss: 0.83, Con_loss: 3.481, Var_loss: 0.904

Fig.15: Style image and content image



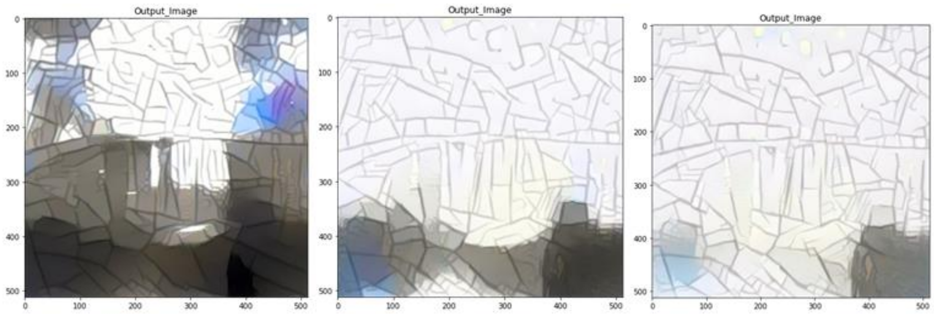
Epoch#1 *Epoch#5* Epoch#10

Fig.16: Van Gogh to Map transfer

Map to painting trial in Van Gogh dataset gave more promising results than other trials in the styleGAN algorithm. The losses are similar to previous attempts yet; visual results are more promising than Van Gogh to map attempt.

After epoch 1: Tot_loss: 7.267, Sty_loss: 1.902, Con_loss: 4.205, Var_loss: 1.612

After epoch 10: Tot_loss: 5.011, Sty_loss: 0.762, Con_loss: 3.338, Var_loss: 0.842



Epoch#1 *Epoch#5* Epoch#10

Fig.17: Map to Van Gogh transfer

3.2.4. Evaluation of the Outputs

When we try to evaluate the outputs of StyleGAN models on the same urban map applied with three different paintings of Cézanne, Ukiyoe, and Van Gogh, the map to painting style transfer provided improved results in terms of legibility of urban morphology as in the CycleGAN models. The one disadvantage of the StyleGAN algorithm is that it works with image pairing which means it only transfers the one image style, not the whole artist style. However, the map to painting transfers gave promising results for urban map generating in artists’ styles.

4. RESULTS AND DISCUSSION

After many failed attempts, Generative Adversarial Networks successfully learn and generate urban plans with chosen artist’s styles. By training datasets of different styles, various results have been achieved. In the context of the results, we believe that the model Map to Painting with cycleGAN algorithm is a more promising GAN model in terms of introducing a new type of representation, where you can see various artist’s touch in today's modern urban plans. Therefore, it is possible to say that it enables the user to generate map images that look like an aerial view, which are painted by an avant-garde artist, from basic figure ground maps of the cities.

Secondly, the painting to map outputs of the StyleGAN also values a lot, especially for the future research directions, in terms of generating new urban patterns in artists' style. However, in the styleGAN algorithm, the system does not train the whole paintings of the artists to apply the style to the map, it rather learns the style of the given painting and applies it to the map. So, rather than producing maps in an artist's style like in cycleGAN, it produces maps in paintings' style. As well as it can be seen from the outputs, the same content map image given to the algorithm produced various urban morphologies in various artistic styles depending on the used technique in the paintings. So, the generated painting to map images can provide a basis for further research agendas, which focus on the inquiry about the potentials and drawbacks of applying this methodology as a tool for urban planning applications.

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