Plan Generation with Generative Adversarial Networks: Haeckel's Drawings to Palladian Plans

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In this study the application of deep learning networks in architectural design is explored via experimental plan generation. With image processing abilities of deep learning networks such as GAN (generative adversarial network), training generative models with architectural visual data is possible. One type of GANs called CycleGAN is specially chosen for the purposes of this study because of its flexibility on visual datasets and low requirement of preliminary labor. In the scope of this study, 2D plans and visuals are selected as datasets to train the CycleGAN model. Instead of training the model with only one dataset of plans and let it generate similar but novel outcomes, in this study two datasets are used to experiment on translations into plan-like images from a different dataset. For the dataset that consists of plans, Palladio's plans are selected. Because the embedded spatial organizational data can be easily decoded and used as a training set for the CycleGAN algorithm, thanks to their potent and symmetrical representations on 2D. Second dataset is formed by Haeckel's microorganism drawings, in order to investigate new possibilities of spatial organization when they are emerged from the visual data of organism structures. Instead of original microorganism images, Haeckel's drawings are selected because of their idealized plan-like figures with rotational symmetry. The model was trained with these two datasets to perform image translation between them. Although the model can work both ways, this paper focused on and evaluated the translations from Haeckel's microorganism drawings to Palladian-like plans. Eventually the model translated Haeckel's drawings into plan-like images which shows the features of the forming patterns of Palladian plans. The outcomes can be beneficial and inspiring for the conceptual and preliminary design processes as well as studying the visual transformations between architectural and out of field visuals. This study, contributes to the field in terms of the application of AI methods -specifically GANs- in experimental plan generation tasks.

Keywords: AI in Architecture, CycleGAN, Deep Learning, Plan Generation, Spatial Image Processing.

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Çekişmeli Üretken Ağlar ile Plan Üretimi: Haeckel'in Çizimlerinden Palladyan Planlara

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Bu çalışmada, derin öğrenme ağlarının mimari tasarımdaki uygulamaları deneysel plan üretimi yoluyla araştırılmıştır. GAN (çekişmeli üretken ağ) gibi derin öğrenme ağlarının görüntü işleme yetenekleriyle, mimari görsel verilerle üretken modellerin eğitimi mümkündür. GAN türlerinden biri olan CycleGAN, görsel veri seti esnekliği ve ön işçilik gereksiniminin düşük olması nedeniyle bu çalışma için seçilmiştir. Bu çalışma kapsamında CycleGAN modelini eğitmek için veri seti olarak 2B planlar ve görseller seçilmiştir. Modeli yalnızca planlardan oluşan bir veri setiyle eğitmek ve benzer ancak yeni çıktılar ürettirmek mümkünken, bu çalışmada farklı bir veri setindeki görselleri plan benzeri görsellere dönüştürmek amacıyla iki veri seti kullanılmıştır. Planlardan oluşan veri seti için Palladio'nun planları seçilmiştir. Çünkü bu planların iki boyuttaki güçlü temsil dili ve simetrik özellikleri sayesinde, mekansal organizasyona dair gömülü veriler CycleGAN algoritması tarafından kolayca çözümlenebilir ve bir eğitim seti olarak kullanılabilir. İkinci veri seti ise, organik yapıların görsel verilerinden mekansal organizasyon oluşturma olasılıklarını araştırmak için Haeckel'in mikroorganizma çizimlerinden oluşturulmuştur. Haeckel'in çizimleri asıl mikroorganizma görselleri yerine, idealize edilmiş ve rotasyonel simetriye sahip plan benzeri figürler oldukları için seçilmiştir. Model, aralarında görsel dönüşüm yapmak için bu iki veri seti ile eğitilmiştir. Model her iki yönde de çalışabilmesine rağmen, bu makale Haeckel'in çizimlerinden Palladyan benzeri planlara dönüşümlere odaklanmış ve bu dönüşümlerin sonuçları değerlendirilmiştir. Çalışma sonunda model, Haeckel'in çizimlerini Palladio'nun planlarındaki biçimsel özelliklere sahip plan benzeri görsellere çevirmiştir. Sonuç ürünler, ön tasarım sürecine ve mimari ile alan dışı görseller arasındaki görsel dönüşümleri araştırma konusuna fayda ve ilham sağlayabilir. Bu çalışma, yapay zekâ yöntemlerinin -özellikle GAN'ların- deneysel plan üretimlerinde kullanımı açısından alana katkı sağlamaktadır.

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Anahtar Kelimeler: CycleGAN, Derin Öğrenme, Mekansal Görüntü İşleme, Mimarlıkta Yapay Zeka, Plan Üretimi.

1. INTRODUCTION

With the rapid increase in computer science developments especially in AI field, new architectural design approaches are a topic of discussion and exploration. Parametric design methods and computation have been used by architects for decades and the computer is considered as a partner instead of just the medium, more and more each day. But autonomy and adaptivity, which are features of AI methods, bring out new possibilities and discussions in architecture field. Shortly, autonomy is performing tasks without guidance and adaptivity is improving the performance by learning from the medium.

In this vast AI field, architectural design process can be approached in many ways. But particularly, 2D visual generation -plan generation- is focused on, in this study. In the context of 2D and 3D visual generation problems, a deep learning network -which is a subfield of machine learning that is a subfield of AI- called GAN mostly dominated the field since its proposal by Goodfellow et al. in 2014. GANs' popularity has been gained by their generative features which also show great potential for architectural image generation.

GAN, generative adversarial network, includes two different units with different tasks but work together as a team. These models are called generator and discriminator. Generative model generates novel outcomes by learning from the dataset. The discriminator on the other hand, evaluates the outcomes from the generator in order to get a good enough result in the end, by eliminating the inadequate outcomes. After these evaluations and many training repetitions the outcomes get better and appear as real as possible (Goodfellow et al, 2014). After the proposal of GAN, many types of it emerged such as CycleGAN (Zhu et al, 2017) and pix2pix (Isola et al, 2017).

In the scope of architectural plan generation with GANs, the embedded spatial organizational data can be decoded and learned by the network and used to build a generative model. This model can perform the task of novel plan generation without a guidance with its autonomous ability. The process is mostly performed by the trained model but the selection of data is done by the user and is crucial because the input directly affects the model and the outcomes as a consequence. These networks learn from the data by recognizing the forming patterns and develop their own generative model accordingly. Therefore, the dataset should be formed carefully to serve the purpose of the study. Following the selection of the datasets, a preliminary work to prepare the data for the training is also necessary. In example, for the supervised training of conditional adversarial networks such as pix2pix labelling the distinguished parts of the images and pairing the images in the datasets are needed for image to image translation (Isola et al, 2017). However, there are also unsupervised methods such as CycleGAN –cycle consistent adversarial network- which is proposed by Berkeley AI Research Lab. and does not require labelling or image pairing (Zhu et al, 2017). CycleGAN only requires datasets to resemble each other for sufficient outcomes. In this way, CycleGAN distinguishes from the other GAN types by its low requirement of labor and flexibility on datasets. A CycleGAN model which is trained by two different datasets, transform the images from the fist dataset to the second dataset-like images and, vice versa. The model can work both ways in terms of translation with the same datasets. However, without image pairings and labelling, CycleGAN has some constrains on the outcomes and does not give elaborate results.

For the image to image translation purposes of this study, firstly the focus was on selecting the proper datasets. The study is planned around the task of image translation between architectural visuals and organism visuals in order to see the spatial formations when they are emerged from natural forms. For both datasets, selecting data within the same style or context was important. Thus, the architectural visual dataset is composed of Renaissance architect Palladio's architectural plans due to their potent representation and symmetrical organizations on 2D that make them prone to be easily decoded and used for the training by CycleGAN algorithm. The architectural visual data is taken from Palladio's book "I Quattro libri dell'architettura" (The Four Books of Architecture) that is written in 1570. Second dataset is formed by the visual data of microorganism structures. However, instead of using the visual data of original microorganism structures, zoologist and marine biologist Ernst Haeckel's drawings are selected because of their idealized figures. The images are taken from Haeckel's book "Kunstformen der Natur" (Art Forms of Nature) that firstly published in 1899 and consist of hundreds of microorganism and animal drawings. In selection process, the figures that have rotational symmetry are chosen in order to achieve a matching dataset which has organized and plan-like images for the Palladian plan dataset.

The purpose of building an image to image translation model with natural and architectural forms requires a network that is flexible on datasets. Because identical image pairings between datasets and element labelling was not the case for the datasets in question since one of them consists of architectural plans and the other one consists of microorganism drawings. Moreover, the dataset images have some restrictions in both quality and quantity because of time and hardware limitations, as well as original image qualities. In this case, Palladian plans dataset consists of 100 and Haeckel's drawings dataset consist of 105 images in 256*256 pixels size and grayscale setting. Considering these constraints, a CycleGAN algorithm which is an unsupervised learning method is selected in order to train the model and generate plan-like visuals from microorganism images by accepting the possible visual restrictions on the outcomes. Also, although the resemblance of the datasets is enough for CycleGAN in general, the only resemblance of the datasets of this study is their symmetrical and organized figures. Thus, the model would not be able to generate clear and rigorous Palladian plans. Another reason for this is, without supervising, the model would not possibly be trained on the spatial relations and functions of the plans. Thus, an elaborate visual generation, such as realistic plans in this case, is not possible. The model however, even without knowing the context, would be able to learn from the features of the images such as the forming principles of the lines, how these lines repeat, collide and surround the void areas, if these features are clear and distinguishable enough, which is the case for Palladio's plans. With this much information, the model in question is expected to generate plan-like visuals from microorganism figures by image to image translation. Eventually, the outcomes, the differences on formations and training values are evaluated.

1.1 Related Works

Recent related work differs from each other in terms of the GAN type they use and the aim of their studies. On Table 1, the difference on their preference on datasets can be seen as well. The authors selected proper datasets to train their GAN models and generated novel outcomes out of the model (Zhao et al, 2021; Çeliker et al, 2020; Balcı et al, 2020; Uzun et al, 2020; As et al, 2018).

Authors	Year	Study	GAN types	Datasets
Zhao, C. W., Yang, J., & Li, J. T.	2021	Generating the layouts of hospital emergency departments	DCGAN, pix2pix, CycleGAN	A selection of hospital emergency departments' layouts
Çeliker, Y. E., Efendioğlu, G. & Balaban, Ö.	2020	Exploring new spatial formations	CycleGAN	Modern interior and sci- fi movie visuals
Balcı, O., Terzi, Ş.B. & Balaban, Ö.	2020	Generating game maps	CycleGAN	Satellite images and game maps.
Uzun, C., Çolakoğlu, M. B., & İnceoğlu, A.	2020	Generating Palladian plans	DCGAN	Palladio's original plans and Palladian plans generated with Palladian grammar rules
As, I., Pal, S., & Basu, P.	2018	Generating conceptual design	InfoGAN	Architectural drawings in axonometric and graph view

Table 1: Some of the related works.

In the research conducted by Zhao et al. (2021), three different GAN types are used to train generative models for layout generation and the results are compared. They focused on generation of plans from a dataset of plans, instead of translation to plans from another set of data. Thus, the authors used 120 hospital emergency departments' layouts to train the model. According to them, CycleGAN was the most applicable one for the layout generation in terms of the flexibility on datasets and low requirement of labor, also the generation of proper and applicable results.

The researches Çeliker et al. (2020) and Balcı et al. (2020) resemble to this study in terms of the GAN type they use and their approach. Both studies used CycleGAN to perform image to image translation with the model that is trained by two different but similar datasets. Çeliker et al. trained the model with modern interior and science fiction movie interior visuals and evaluated the results of the translations from modern interior visuals to sci-fi movie atmospheric visuals. Balcı et al. on the other hand, studied in a bigger scale and focused on maps in their studies. They trained their model with two datasets which are formed by real satellite images and game maps and evaluated the outcomes of the translations from satellite images to game maps.

Another study that is conducted by Uzun et al. (2020) focused on automating the plan generation process with a DCGAN model that is trained by Palladio's original plans and another set of Palladian plans which is generated with the Palladian grammar rules, as a case study. Eventually, the authors evaluated the efficacy of the DCGAN model for architectural plan generation. They stated that the DCGAN model which was trained by Palladio's original plans were not successful in terms of proper plan generation due the heterogenous data. However, the second DCGAN model that is trained by the dataset which is formed by Palladian grammar rules, showed better quality results because of the homogeneous data.

2. STUDY

The proposers of CycleGAN, Zhu et al. (2017), offered different image to image algorithms with their network. In this study, one of their CycleGAN algorithms, called "Summer to Winter Yosemite", is used. The existing algorithm and datasets of Summer to Winter Yosemite are changed according to the needs of the study. It is trained by two datasets formed by Palladio's architectural plans and Haeckel's microorganism drawings in order to perform translations from microorganism drawings to plan-like visuals.

First dataset consists of 105 images of Haeckel's microorganism drawings while second dataset consists of 100 images of Palladio's architectural plans. Dataset visuals, obtained from books, cleaned and prepared manually one by one in a 256*256 pixels size and grayscale setting (**Figure 1 and 2**).

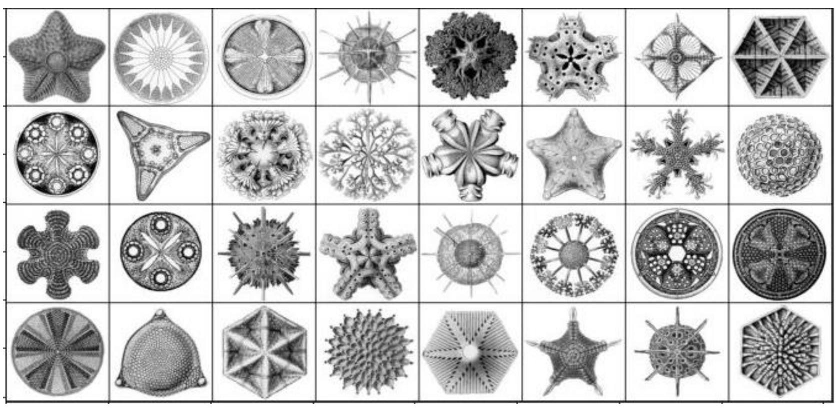


Figure 1: Some of Haeckel's microorganism drawings in the first dataset.

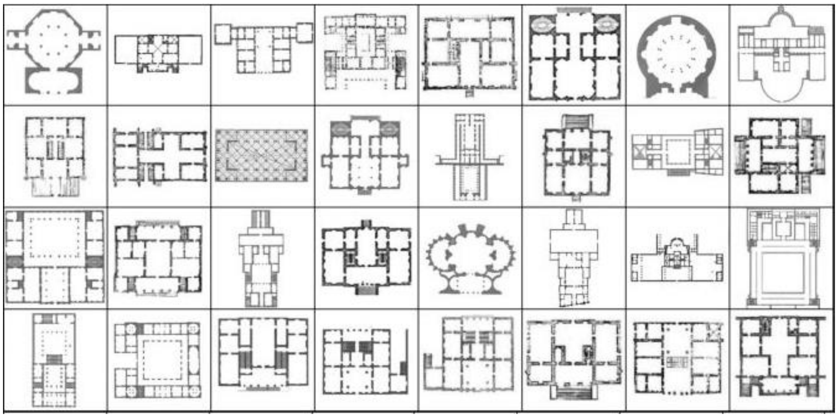
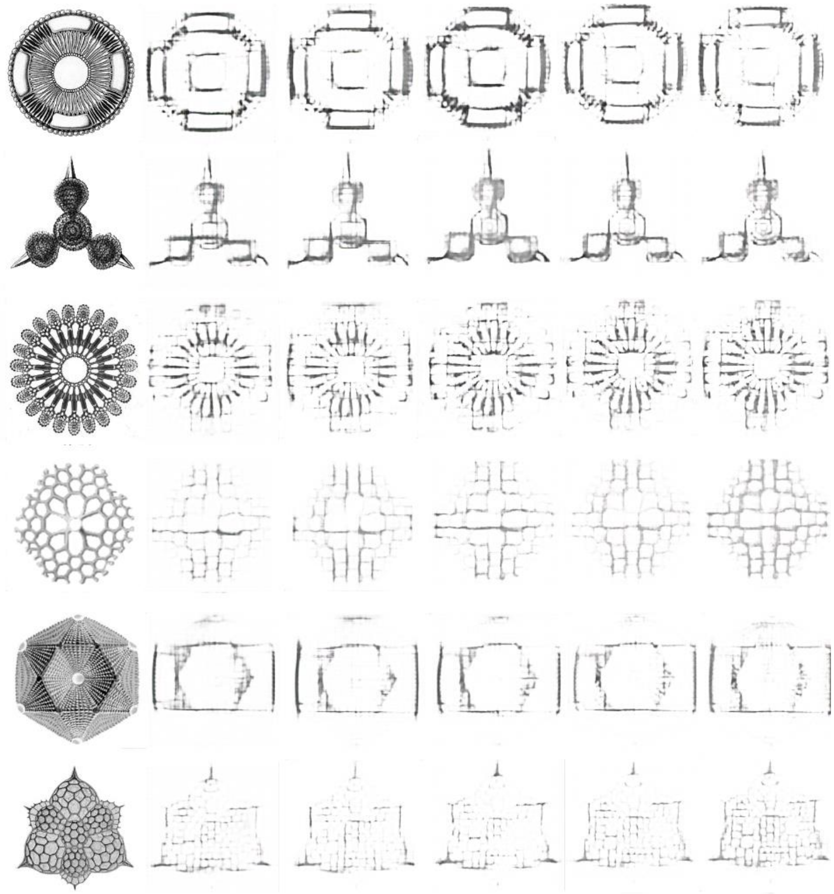


Figure 2: Some of the Palladio's plans in the second dataset.

For the training, the dataset images are needed to be split into two as training and test sets by 4 to 1 ratio. The training set is used to train the model and test set is used to test the trained model. Then the algorithm is trained by these datasets by decoding the visual formation principles and patterns on the images. Eventually the trained model translated the images from the first dataset which is formed by Haeckel's selected drawings into the images which follows the forming principles of the visuals from second dataset that is formed by Palladio's plans.

Algorithm is run many times with different batch size and number of epochs to see the difference in results and reach a satisfying training point. Python programming language and Google Colab notebooks are used for the process. After each generation, the outcomes are evaluated while considering their training values within both objective and subjective perspectives. On **Figure 3**, image translation from microorganism drawings to plan-like visuals can be seen after different number of epochs (**Table 2**). 1 epoch refers to 1 training of the whole dataset. However, many iterations are needed to train the whole dataset. The dataset was split into batches to train one by one. The batch size for the training in this study was 16.



original 200 400 600 800 1000

Figure 3: The results of the translation from microorganism drawings to plan-like visuals with Palladio's plan dataset, with gradually increasing epochs. 1000 epochs in total.

Table 2: Number of epochs and loss values of discriminator and generator for the outcomes on Figure 3.

n_epochs	200	400	600	800	1000
d_X_loss	0.3056	0.1851	0.1389	0.3908	0.0315
d_Y_loss	0.1850	0.4289	0.1777	0.2405	0.0913
g _loss	3.2833	4.9128	4.3460	3.7329	3.9413

Table 2 shows the loss values after the trainings. These loss values for discriminator and generator are used by the model to change the weights for their functions to optimize the outcome. Discriminator tries to be better at distinguishing real images which are from the dataset and fake images which are generated, while the generator tries to be better at generating more realistic images and fooling the discriminator. The loss graphic can be seen on **Figure 4** shows the fluctuations on training losses while the generator and discriminator try to get better at their tasks. It can be seen that while the discriminator

losses (blue and red lines) decreased in the end of the training with 1000 epochs, the generator loss (green line) showed a slight increase in the end which means there can be a better training point with more reasonable and satisfying visuals. However, the visual outcomes also need to be evaluated in terms of the visual quality and expectancy in order to achieve a good training point.

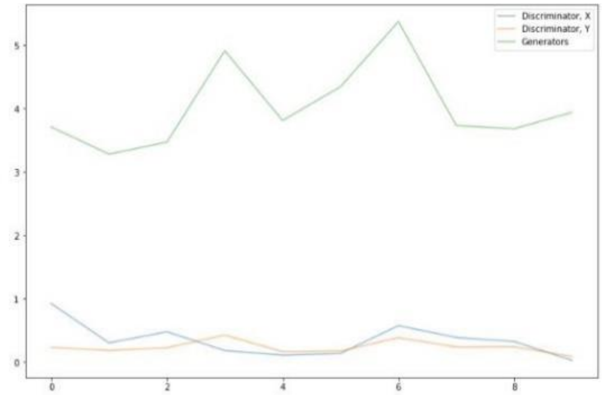


Figure 4: Training losses graphic generated with the algorithm for the outcomes on Figure 3.

After seeing the first results, a third dataset is included to this experimental phase in order to see the differences that datasets can cause on the visual outcomes. Instead of Palladio's plans dataset, another dataset that is formed by 100 random plans taken from an online source (ArchDaily, 2017) is used to train the model with Haeckel's drawings. The purpose was to train the model with a plan dataset that is not homogeneous and does not have potent representation features like Palladio's plans have. In comparison to the potent representation of Palladio's structures with load bearing thick walls and void areas they surround, the random plans obtained have much lighter structures and are kept as they are with all their furnishings. The images are prepared in 256*256 pixels size and grayscale setting (**Figure 5**).

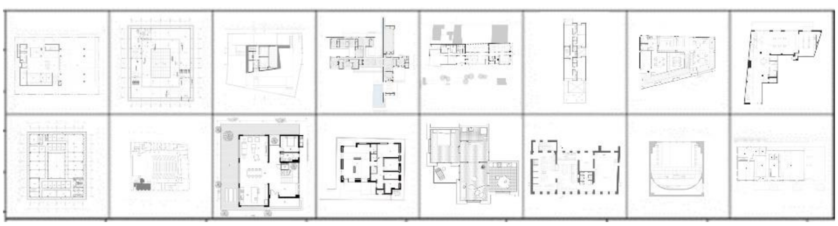


Figure 5: Some images from random plans dataset.

The training happened this time for the datasets of random plans and Haeckel's microorganism drawings. The visual results were not satisfying in comparison to the previous training with Palladio's plans. Because the random plan dataset consists of heterogeneous data which are plans with not much symmetry and weak representation with their light structures (**Figure 6**). **Table 3** shows the number of epochs and loss values for this training. Although the loss values reached similar points with the previous training with Palladio's plans dataset, the outcomes were not successful in terms of visual quality. This shows the importance of evaluation of the results in both objective and subjective manners in this study as well as using proper datasets to train the CycleGAN algorithm.

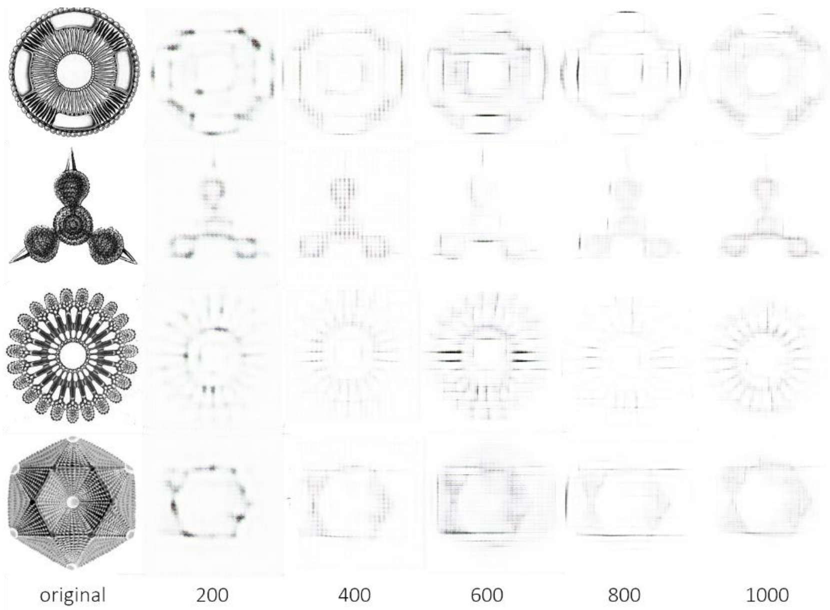


Figure 6: The results of the translation from microorganism drawings to plan-like visuals with random plan dataset, with gradually increasing epochs. 1000 epochs in total.

Table 3: Number of epochs and loss values for the outcomes on Figure 6.

n_epochs	200	400	600	800	1000
d_X_loss	0.4470	0.4132	0.4341	0.2480	0.1658
d_Y_loss	0.3111	0.3556	0.0745	0.1157	0.1989
g _loss	3.8440	4.6403	3.6422	3.7899	3.9976

After this experiment, more trainings are done with Palladio's plans and Haeckel's drawings datasets with a greater number of epochs in order to achieve a better training point (**Figure 7 and 9**).

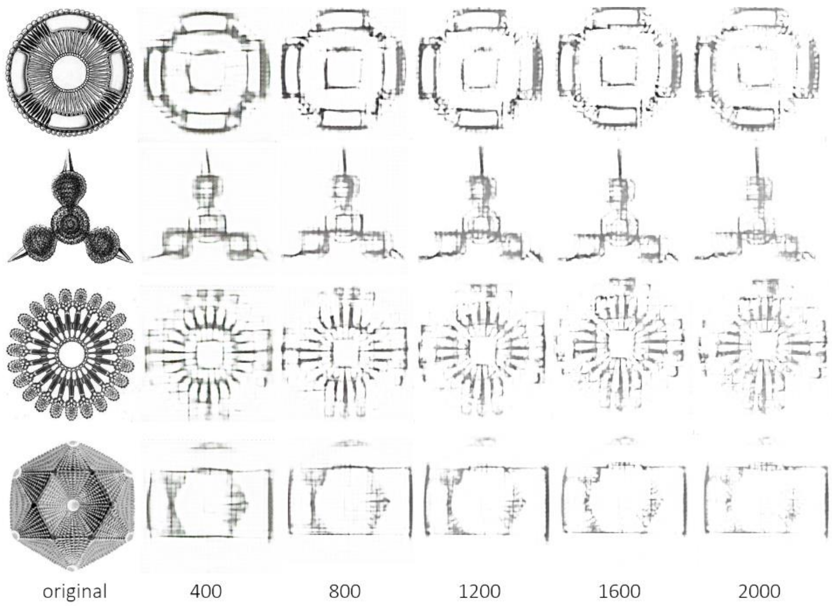


Figure 7: The results of the translation from microorganism drawings to plan-like visuals with Palladio's plan dataset, with gradually increasing epochs. 2000 epochs in total.

n_epochs	400	800	1200	1600	2000
d_X_loss	0.3263	0.2723	0.2792	0.1931	0.1454
d_Y_loss	0.1636	0.1028	0.2311	0.3464	0.1014
g _loss	3.7101	3.9390	3.5056	3.9218	3.2578

Table 4: Number of epochs and loss values for the outcomes on Figure 7.

Table 4 shows the number of epochs and loss values for the training. The loss graphic which shows the fluctuations can be seen on **Figure 8**. It can be seen on graph that all of the three loss values decreased in the end of the training with 2000 epochs. However, the visual results differ in terms of visual quality and satisfying the expectancy.

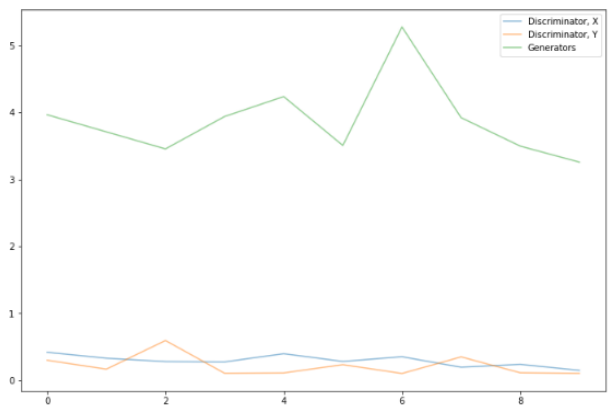


Figure 8: Training losses graphic generated with the algorithm for the outcomes on Figure 7.

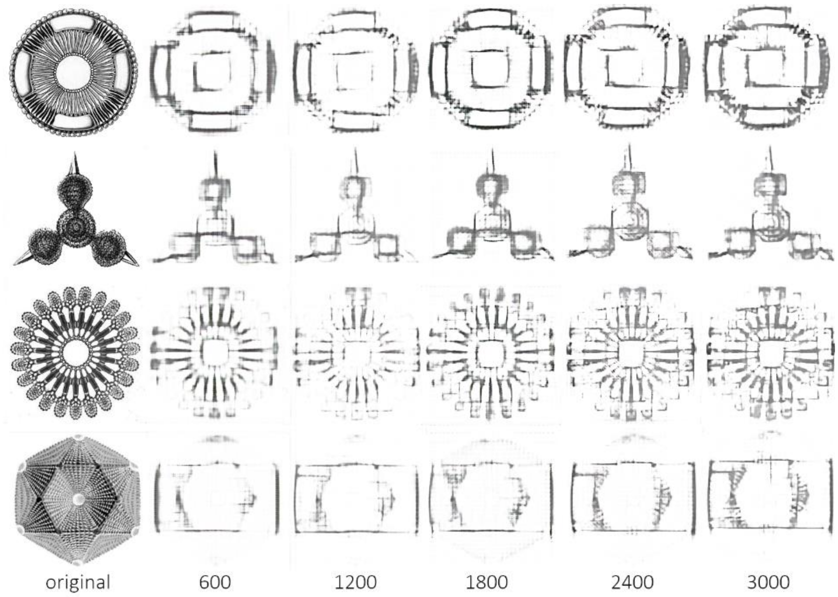


Figure 9: The results of the translation from microorganism drawings to plan-like visuals with Palladio's plan dataset, with gradually increasing epochs. 3000 epochs in total.

Table 5: Number of epochs and loss values for the outcomes on Figure 9.

n_epochs	600	1200	1800	2400	3000
d_X_loss	0.2641	0.3065	0.4385	0.7124	0.4070
d_Y_loss	0.1507	0.0705	0.3223	0.2969	0.3538
g _loss	4.2142	3.9209	3.6080	2.9825	4.2599

Figure 9 shows slightly better visual outcomes in terms of visibility of the structures and spaces after more training with greater amounts of epochs. However, it can be seen that the visual quality optimized after the half of the process and then decreased through the end. **Table 5** shows the number of epochs and loss values for this training. The related loss graphic can be seen on **Figure 10**.

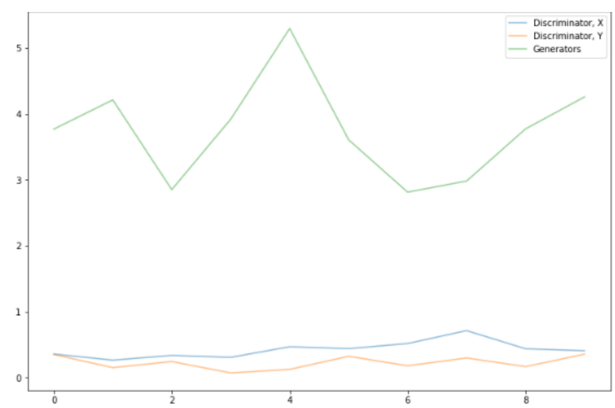


Figure 10: Training losses graphic generated with the algorithm for the outcomes on Figure 10.

Sharply increasing trend of the generator loss value can be seen on the graph in the end of the process which also corresponds to the quality decrease on the visuals. The training experiments with greater amounts of epochs stopped from this point because of the decrease trend in both visual quality and loss values. After the experiments on training with different number of epochs it is seen that the points in between 2000-3000 epochs was optimal for the generated visuals.

3. DISCUSSION

In this study, the algorithm is trained with the Palladio's plans' load bearing walls and the spaces defined by them without knowing the functions and relations of these elements and spaces. However, the embedded data about forming these spaces is revealed partly on these 2D images which appear to have dark and thick lines which have symmetrical setting and surround the white and perpendicular areas. This data used to transform the microorganism drawings into plan-like visuals. When the outcomes are evaluated, it can be seen that, the model translated the images from the Haeckel's microorganism drawings dataset into the images which follows the forming principles of the visuals from Palladio's plan dataset. The trained model turns the organic curvilinear lines into linear lines as it is learned from Palladio's plans (**Figure 11**). Also, the lighter shades of gray and voids in Haeckel's drawings turned into empty spaces; and darker shades of gray are kept as filled areas or lines. However, if the darker and filled area is big, then the algorithm also turned it into void areas. Because the Palladian plans does not have that big filled areas.

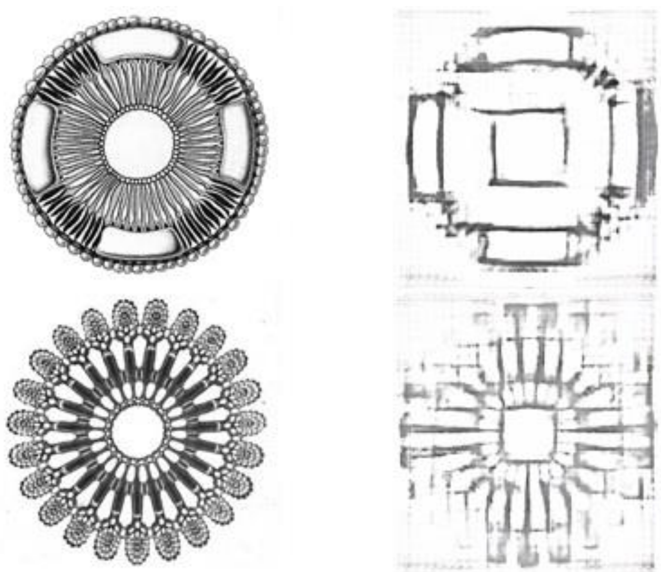


Figure 11: The results of the training with 2100 epochs. Translation from microorganism drawings (on the left) to plan-like visuals (on the right).

The results also showed limited visual quality which was expected due to the constraints of the study such as low quality of the original dataset images, difference of the formations on images in two datasets, limited potentials of unsupervised training as well as limited time and hardware. It is seen that the quality and the quantity of the content of datasets are crucial. Meticulously prepared images with higher resolution and potent expression on 2D give better results in terms of training the CycleGAN model. Pixels size could be increased to get more satisfying visual quality, however then the visual data which needs to be processed will also increase and thus the amount of time for the training will increase and more computer processing power will be needed. Low requirement of labor and time was important for. Therefore 256*256 pixels size is selected because it gives results with good enough resolution for the scope of the study.

From the training with random plans dataset, it can be seen that unclear and faded images which consist of mostly non-symmetrical plans with lighter structures than Palladio's, resulted in unsatisfying outcomes. The difference between Palladio's plans with their potent symmetrical expressions and randomly gathered heterogenous plans without any common style was the reason for that unsuccessful training. Comparison of this training with random plans and the training with Palladian plans dataset showed the importance of introducing decent and proper datasets to the CycleGAN algorithm for training, in terms of visual quality and also coherence in style (**Figure 12**).

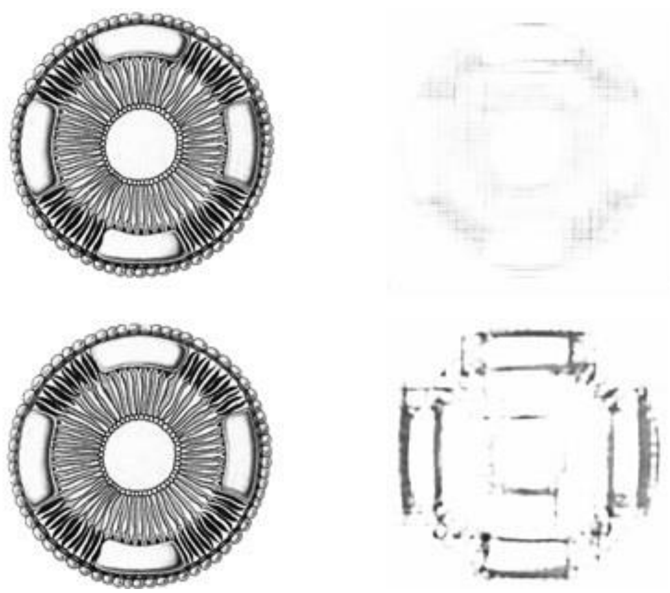


Figure 12: The outcome of the training with random plans above and with Palladio's plans below.

The CycleGAN model does not require the datasets to be paired or labelled, however it requires them to resemble each other. The previous translation works, in example, were between modern interior images and sci-fi interior images, and satellite maps and game maps (Çeliker et al.,2020; Balcı et al.,2020). However, in this study the second dataset was out of field and the only resemblance between the datasets was the rotational symmetry of Haeckel's drawings and the mirror symmetry of Palladian plans. This also explains the translation limits of the visuals. The training repetitions showed some difference on the outcomes, but the model could achieve only these outcomes with the existing data. The loss values also showed this limitation. The model constantly checks the loss values and differs the weights of its functions in order to get better results. However, when the loss values are good enough for the model, then the weights don't change according to values. Instead, the discriminator decides with fifty percent chance whether the image is real or fake. This explains the fluctuations on the loss function graphs.

The low requirement of preliminary labor of CycleGAN is an advantage, especially non-requirement of labelling the images. However, the colorful images can cause some problems. Because similar colors on the images can be identified as the same kind of data by CycleGAN due to not labelling the data. Thus, this misreading can be seen on the outcomes. In the study of Balcı et al. (2020) in example, the algorithm mistakes the areas with similar color as same kind of data and trains the model according to that. Thus, this mistake can be seen on the generated images. In the scope of Balcı et al.'s study, the mistake occurred as reading the water and green areas on the maps as the same kind of data which resulted in interpreting the green areas as water on the visual outcomes and turning the green areas into sea on the generated maps. This specified problem, however, didn't occur in this study. Because the data images kept or translated to grayscale. Furthermore, digitally representing and processing grayscale images are easier and quicker than processing colorful images because of the lower amount of data. Also, only expectation from the generated outcomes in this study was to form filled and void rectangular areas to generate plan-like images. Therefore, checking the translation of different texture was not necessary.

The non-requirement of labelling the images was an advantage in terms of time and labor. However, it also constrained the image translation abilities of the model. With labelling, training the model on functions and relations of the spaces would be possible. But this training would not be possible with CycleGAN but another network with supervised learning method.

4. CONCLUSION

In this paper, an experimental study has been conducted by translating microorganism drawings into plan-like visuals with a CycleGAN model. The difference of it is that it is a study of image translation of idealized natural forms into architectural spatial organization with a deep learning network. The study is important because it shows the ability to train models with architectural data to perform within the forming principles of that data. This study demonstrates that the trained model can be trusted to generate within the forming principles of the datasets, as long as the forming patterns are decoded properly by the algorithm. Beyond being an example of usage of AI methods in architectural design, the study is also important in terms of generating architectural spatial formation from out of field visuals such as natural forms which have different forming patterns. This can be inspirational and useful for the conceptual design process as well as studying the visual transformations between architecture and out of field areas.

Apart from transformations, this study also shows the potential of an optimization tool. Taking the advantage of a tool to generate many novel architectural visual options which actually follows the established design principles as learned from the dataset can result obtaining optimized results. Moreover, these optimized results will be achieved in a short time. Otherwise manually conducting many options would take a significant amount of time and labor.

Another issue to point out is how will the design practice be affected with the developments in AI field. Moreover, which profession is going to dominate the design practice from now on with the developments in AI field? Architects should own this discussion themselves and be the leading force for these new dynamics. These dynamics will definitely question the established ways of design, research and practice. The researchers should contribute to this phase with many experimental studies which can lead to discoveries and discussions. This study, in example, can stimulate other researchers' minds for examining the architectural image processing, translation and generation possibilities with different datasets as well as experimenting with different scales other than plans which was the focus on this study.

This study can be developed further by experimenting with different datasets, enriching the current datasets or building a model with a different GAN algorithm. In the scope of this study's datasets, the Palladian plans dataset, in example, can be enriched with other Renaissance architects' works which follows the Palladian principles. Haeckel's drawings, on the other hand, have other possibilities since Haeckel have many other drawings which can form a matching dataset with a façade dataset, in example. After the unsupervised training for this study, a supervised training can be studied next which can let the labelling the spaces on plans according to their functions and training the GAN model with it. Thus, the outcomes of this trained model will form architectural spaces according to their functions. Experimenting on whether the model can decode the patterns of spatial organization according to spatial functions and relations of them can cause more discussions and stimulations.

This study also indicated the importance of the dataset collection part. In order to achieve satisfying outcomes, the model needs to be trained well with suitable datasets. In the scope of AI in architectural design studies, this is the responsibility of the architects and needs to be done carefully in order to achieve proper results. It appears that, in the future, the architects will be using some AI method tools to help them in the design process specially to achieve optimized results. Thus, the responsibility of gathering suitable content for the datasets and specially the selection of "good" designs mostly for the optimization models should be discussed more within the architectural design field. Because there are important questions appear like whose design or which design or design of the which part of the world will be represented and which will be left out.

In conclusion, this study as with the other deep learning studies in architecture field holds many possibilities for the parts that is inclined to automation, experimentation and exploration in the design process. These new possibilities will help architects in their research and practice more and more each day. The possibilities that the AI methods offer can help architect's mind to explore within the creative field as freely and widely as it can while leaving the computational and automated parts to the computers.

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