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USING DEEP LEARNING TO GENERATE FRONT AND BACKYARDS IN LANDSCAPE ARCHITECTURE

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Abstract

The use of artificial intelligence (AI) engines in the design disciplines is a nascent field of research, which became very popular over the last decade. In particular, deep learning (DL) and related generative adversarial networks (GANs) proved to be very promising. While there are many research projects exploring AI in architecture and urban planning, e.g., in order to generate optimal floor layouts, massing models, evaluate image quality, etc., there are not many research projects in the area of landscape architecture - in particular the design of two-dimensional garden layouts. In this paper, we present our work using GANs to generate optimal front- and backyard layouts. We are exploring various GAN engines, e.g., DCGAN, that have been successfully used in other design disciplines. We used supervised and unsupervised learning utilizing a massive dataset of about 100,000 images of front- and backyard layouts, with qualitative and quantitative attributes, e.g., idea and beauty scores, as well as functional and structural evaluation scores. We present the results of our work, i.e., the generation of garden layouts, and their evaluation, and speculate on how this approach may help landscape architects in developing their designs. The outcome of the study may also be relevant to other design disciplines.

Keywords

deep learning, GANs, landscape architecture, artificial intelligence, outdoor design.

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ABSTRACT

The use of artificial intelligence (AI) engines in the design disciplines is a nascent field of research, which became very popular over the last decade. In particular, deep learning (DL) and related generative adversarial networks (GANs) proved to be very promising. While there are many research projects exploring AI in architecture and urban planning, e.g., in order to generate optimal floor layouts, massing models, evaluate image quality, etc., there are not many research projects in the area of landscape architecture - in particular the design of two-dimensional garden layouts. In this paper, we present our work using GANs to generate optimal front- and backyard layouts. We are exploring various GAN engines, e.g., DCGAN, that have been successfully used in other design disciplines. We used supervised and unsupervised learning utilizing a massive dataset of about 100,000 images of front- and backyard layouts, with qualitative and quantitative attributes, e.g., idea and beauty scores, as well as functional and structural evaluation scores. We present the results of our work, i.e., the generation of garden layouts, and their evaluation, and speculate on how this approach may help landscape architects in developing their designs. The outcome of the study may also be relevant to other design disciplines.

Keywords*:* deep learning, GANs, landscape architecture, artificial intelligence, outdoor design.

ملخص

يعد استخدام محركات الذكاء الاصطناعي في تخصصات التصميم مجالًا بحثيًا ناشئًا، والذي أصبح شائعًا للغاية على مدار العقد الماضي. وقد أثبت كل من التعلم العميق وشبكات الخصومة التوليدية GAN على وجه الخصوص أنهما واعدان للغاية فى هذا الإطار. وبالرغم من وجود العديد من المشاريع البحثية التي تستكشف الذكاء الاصطناعي في الهندسة المعمارية والتخطيط الحضري، من أجل على سبيل المثال إنشاء تخطيطات مثالية للفراغات، والنماذج الكتلية، وتقييم جودة الصورة، وما إلى ذلك، لا توجد العديد من المشاريع البحثية في مجال تنسيق المواقع وعلى وجه الخصوص تصميم مخططات الحدائق ثنائية الأبعاد. نقدم في هذه الورقة البحثية استخدام شبكات GAN لإنشاء مخططات أمامية وخلفية مثالية. نستكشف فى هذا الإطار محركات GAN المختلفة، منها على سبيل المثال، DCGAN، التي تم استخدامها بنجاح في مجالات تصميم أخرى. وقد تم استخدام التعلم الخاضع للإشراف وغير الخاضع للإشراف فى هذا البحث باستخدام مجموعة بيانات ضخمة من حوالي ١٠٠٠٠٠ صورة لمخططات الفناء الأمامي والخلفي، مع سمات نوعية وكمية، منها على سبيل المثال درجات للأفكار والجمال، بالإضافة إلى درجات التقييم الوظيفي والإنشائى. فى النهاية نقدم نتائج البحث، أي إنشاء مخططات الحدائق وتقييمها، ونتوقع كيف يمكن لهذا النهج أن يساعد مصممى تنسيق المواقع في تطوير تصاميمهم. قد تكون نتائج الدراسة ذات صلة أيضًا بتخصصات التصميم الأخرى.

الكلمات المفتاحية: التعلم العميق، شبكات الخصومة التوليدية، تنسيق المواقع، الذكاء الاصطناعى، تصميم الفراغات الخارجية.

1. INTRODUCTION

In recent years, various design disciplines have become interested in utilizing artificial intelligence (AI) in their design deliberations, such as studies on deep learning (DL) systems to generate novel floor layouts, or answer other design questions (As et al. 2018; Chaillou 2021; Huang and Zheng, 2018; Nauata et al. 2020). Our study explores artificial neural networks' (ANN) ability to produce landscape designs for small scale residential front-, and backyards. We used a large dataset of design imagery, made them machine-readable and created a workflow that predicts various landscape layouts from simple sketches.

Landscape architecture works at different scales and it has to deal with complex environmental issues. Even though there is a difference at various scales, there are common and essential design deliberations, which we can learn and extrapolate from smaller residential landscape projects.

Generative Adversarial Networks (GANs) proved to be the most efficient and effective ANN to respond best to our research goals. There are many projects that deal with novel applications of AI in the field of architecture, but in landscape architecture it is somewhat limited, and there is a need for such research in this area (Newton, 2018). In this study, we used open-source data and software alternatives to answer our main research question: 'Can we develop a design tool from AI-generated mechanism for residential landscape design?' (Figure 1.).

2. BACKGROUND

AI is becoming a popular tool among designers, for example, plugins and software tools such as Grasshopper are increasingly becoming more commonly used (Chaillou, 2022). The era of ours will be identified as 'Information Revolution' and AI-use will be more common in the future and will impact the life cycle of an architectural project (Cai et al. 2018). Decision making with statistical and data driven optimization tools, i.e., AI, is a popular research topic (Cai et al., 2018). The ability of AI to generate design has the potential to open up new possibilities and allow us to explore a larger part of the design space, which we previously were not able to do with traditional means. Neil Leach, for example, is expecting AI to be used not only in architectural design but also in other design disciplines (Leach, 2018). Others claim that AI-design samples are not as developed as human-designed artifacts (Cutellic, 2019). There is however a vast interest to learn and use AI in the design space, which we can clearly see from the large number of papers published in the field.

3. METHODS AND TOOLS

In this research, we tried to develop a mechanism that is helping landscape designers in their front and backyard garden designs. We used supervised deep learning processes and obtained a dataset from an extensive online repository, i.e., from Arcbazar.com, an online crowdsourcing platform for design projects. We selected designs that had beauty scores (given by platform users) that were higher than 5 (out of 10) (Dataset I). We then produced a twin dataset that was semantically separated (Dataset II). We used the existing Pix2Pix GAN, which uses the Dataset I and its semantic twin Dataset II, to develop a system that allows users to sketch some rough ideas (Garden Sketch) and is then able to generate novel garden designs.

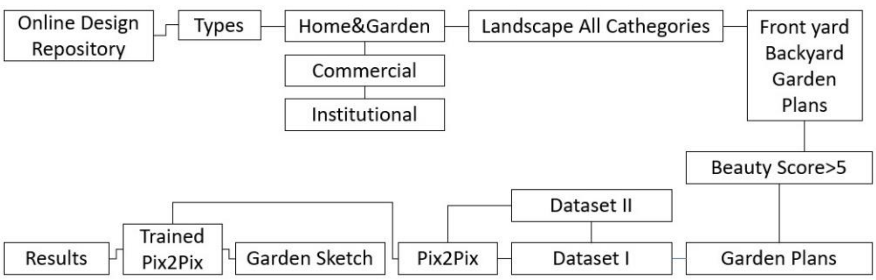

Fig.1: Workflow diagram of the study.

3.1 Data Preparation

The success of DL is dependent on the quality of training data; therefore, we created our dataset from a large database management system (DBMS) of an online design repository. The DBMS has more than 300,000 design images such as plan drawings, section drawings, diagrams, and computer renderings. We picked high-quality projects from the DBMS, i.e., fully developed garden plans. All projects were evaluated by platform users on functional and aesthetic design criteria, i.e., 1 is worst, 10 is best, and we selected projects that were 5 and above.

3.2 Queries in DBMS

In order to filter relevant data from the DBMS, we used the following selection criteria:

- We only used top-view plan drawings, i.e., we did not use section drawings, perspective drawings or diagrams.
- We only picked front and backyard design projects.
- We selected projects that had more than 100 votes, i.e., were evaluated by more than 100 users.
- We filtered projects which were scored on average 5 or more (on a 1-10 scale).

(Figure 2).

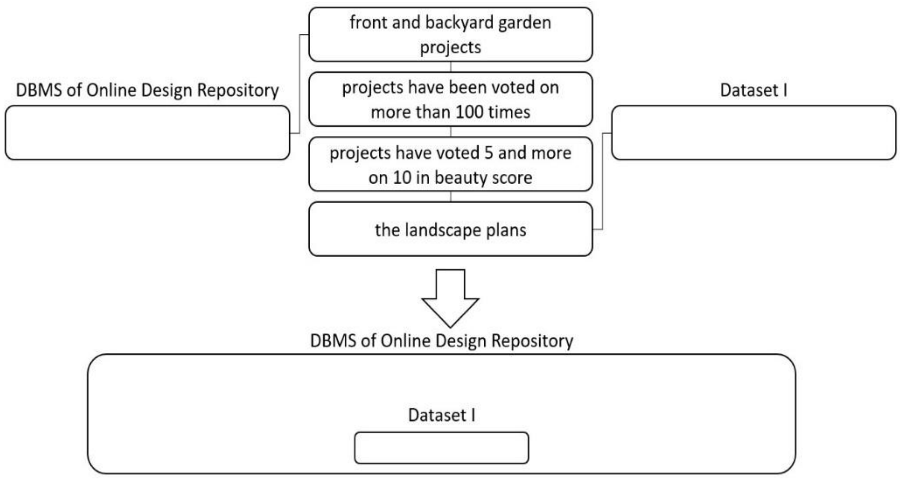

Fig.2: Queries in DBMS of Online Design Repository.

The dataset has an attribute table and contains different scores in terms of aesthetics, function, and other qualitative and quantitative aspects. After that we semantically segmented that data and created a twin dataset (Dataset II) (Figure 3, 4.). We used Dataset I and Dataset II to train the Pix2Pix GAN engine, with the aim to produce front and backyard designs from a rough sketch. There are studies that try to relate architectural design with deep learning processes using a similar number of examples and similar algorithms (Huang and Zheng, 2018).

Fig.3: Dataset I – we used garden layout designs from an online design repository, i.e., landscape designs acquired from Arcbazar.com's online crowdsourcing platform.

The workflow process requires the semantic segmentation of Dataset I. We manually produced each project sample according to the following protocol: a.black: roads zones, b.grey: buildings zones, c.green: softscape zone, d.orange: hardscape zone, e.blue: water bodies. (Fig.4)

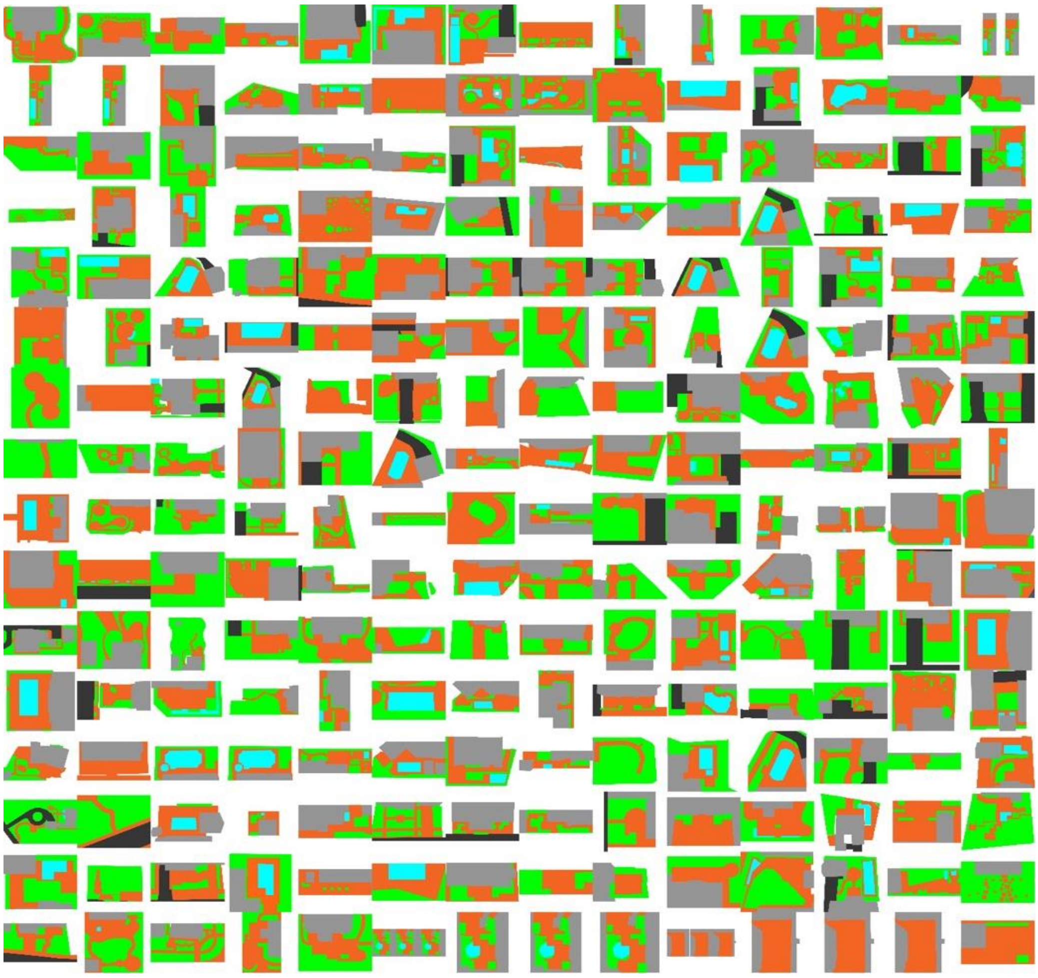

Fig.4: Dataset II – the semantic segmentation of the original landscape design samples.

3.3 Utilizing Pix2Pix GAN

Pix2Pix is a conditional GAN (cGAN), where the generation of the output image is dependent on an input image (Brownlee, 2019). The discriminator must decide if the target is a realistic transformation of the source image after being given both the source and target images. Through adversarial loss training, the generator is driven to produce believable images in the target domain. L1 loss is calculated between the manually created picture and the desired output image. This is method of updating the generator which encourages the generator model to provide accurate translations of the source image (Isola, et al., 2018). The Pix2Pix GAN has been explored on a variety of image-to-image translation tasks, including translating maps into satellite photos, black and white photos into color, and product drawings into actual product photos. The Pix2Pix model uses U-Net based architecture for the generator, and PatchGAN classifier for the discriminator. U-Net is based on an encoder-decoder network architecture that consists of four encoder blocks and four decoder blocks – which are connected (Tomar, 2021). PatchGAN is a type of discriminator for GANs that penalizes structure at the scale of local image patches (Isola, et al., 2018). A deep convolutional neural network that conducts image categorization serves as the discriminator, especially conditional image-classification. It forecasts the chance that the target image is a true translation of the source image or a false one based on the input of both the source image and the target image. The model creates a target image from a source image. This is accomplished by first downsampling or encoding the input image to a bottleneck layer then upsampling or decoding the bottleneck representation to the size of the output picture (Isola, et al., 2018). According to the U-Net design, skip-connections are introduced to create a U-shaped pattern between the encoding levels and the appropriate decoding layers.

We initially trained the model with 224 images and with ReLU (rectified linear) activation function. If the input is positive, the ReLU will output the input directly; if it is negative, it will output zero. The images are resized into 512X512 pixels in order to be able to use them for training. After resizing images, we paired them for training. Initial data contained 224 garden images and 224 sketches that was generated based on the garden images.

4. CASE STUDY

For this case study, we used residential garden designs, e.g., front and backyards that were gathered from an extensive online repository on Arcbazar.com, an online crowdsourcing platform for design projects. The projects were all part of residential landscape design competitions and were dealing with real-world residential landscape design challenges. The projects are all located within the United States.

There are many different uses for the DBMS content used in the study. A learning process has been developed, which is akin to traditional design approaches in landscape architecture. Similar to the human design learning process, we applied supervised deep learning and identified traditional landscape components, such as water bodies, green zones as softscape zone, and non-green uses as hardscape zone, buildings, and driveways, in the dataset.

Fig.5: Training pair of images. Semantic segmentation (left) and ground truth (right) of training data.

The results were promising. The system was able to construe various landscape designs based on entirely new sketches.

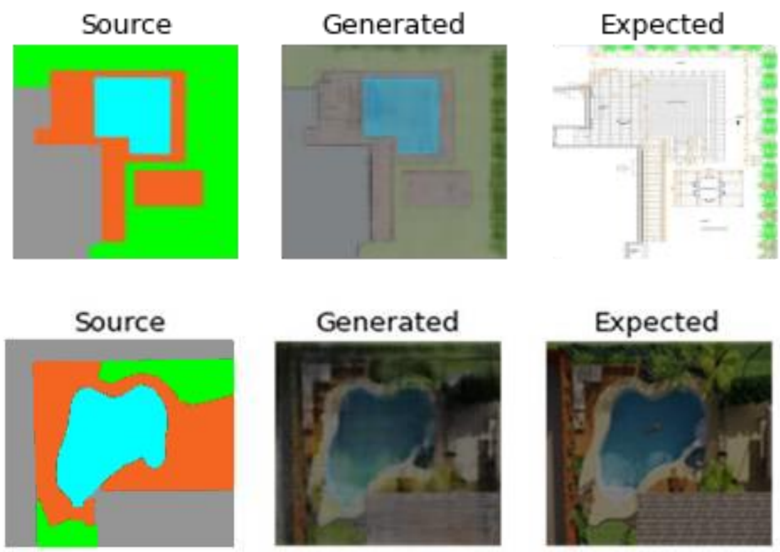

Fig.6: Training results of Pix2Pix model.

As can be seen from figure 6, the left side of the images are input images to the system and the right side are ground truth images -- after epoch 200, which is the final epoch of training. In the middle of the images, the generated results by the system according to input are given.

The similarity between expected images and generated images have shown that system can successfully generate landscape plans after training completed.

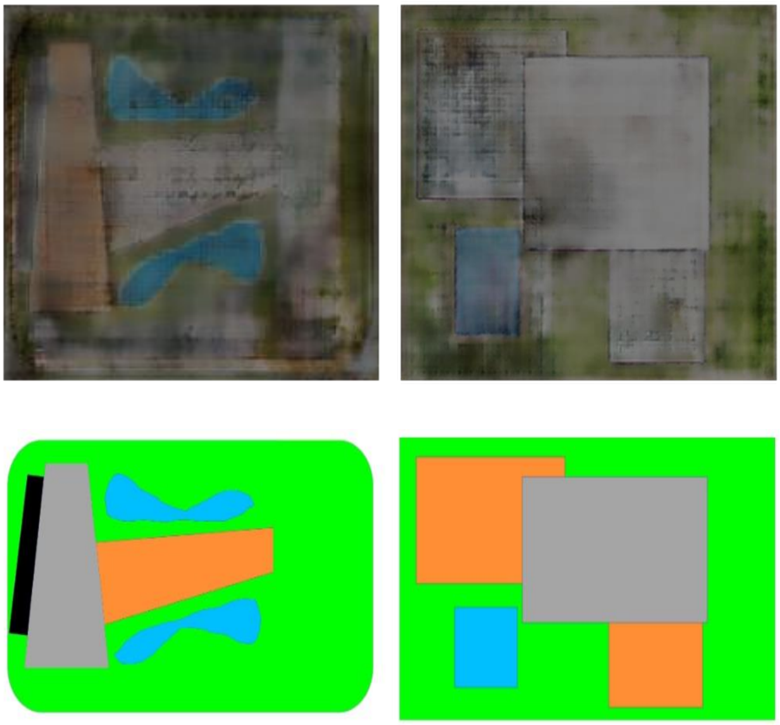

Fig.7: Generation of new images from new sketches.

The developed model with ReLU activation function is tested with new segmentation inputs as seen in figure 7. Images at the bottom of the figure 7 are input segmentation images and images at the top of the figure are newly generated landscape plans that are not included in training set.

After this first model, the pix2pix model was trained again with the mish activation function. Mish function is a novel self-regularized non-monotonic activation function, and it improves the performance of neural networks (Misra, 2019). We not only changed the activation function, but also skewd original images in order to increase the dataset. The final model was trained with 672 images.

4.1. Results

Our latest results were improved and have higher resolution. The model is trained with 200 epochs to improve the output. The training results have shown that Mish function and the additional data improved the first model.

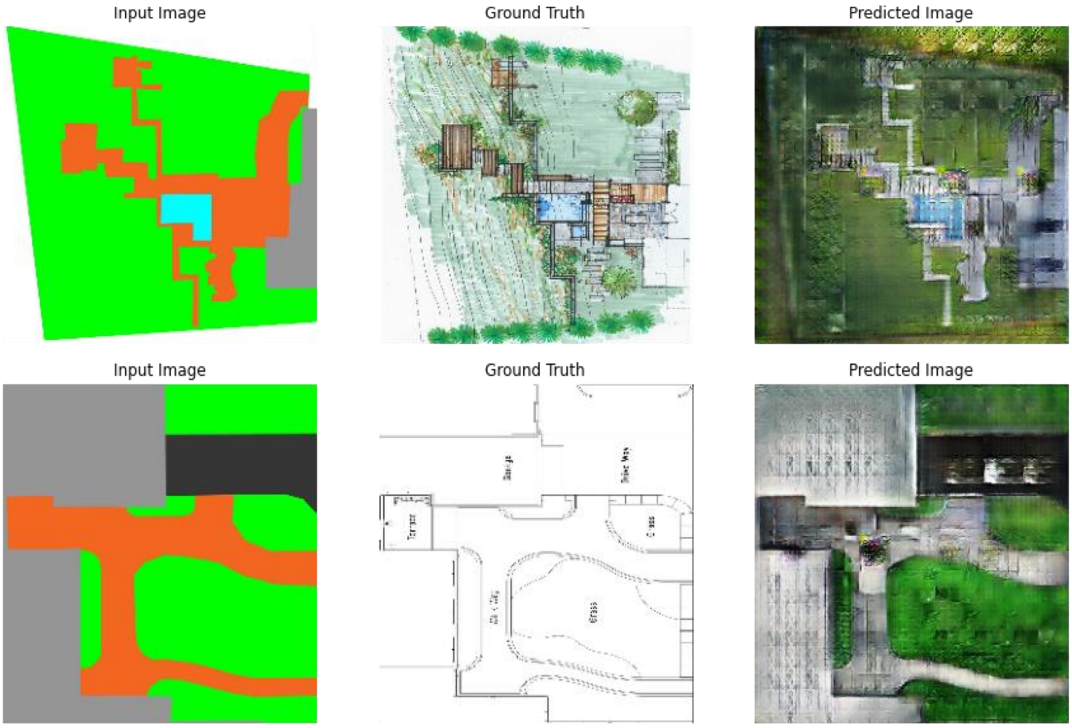

Fig.8: New training results.

Figure 8 illustrates some of the training results and one can notice the high accuracy in the predictions.

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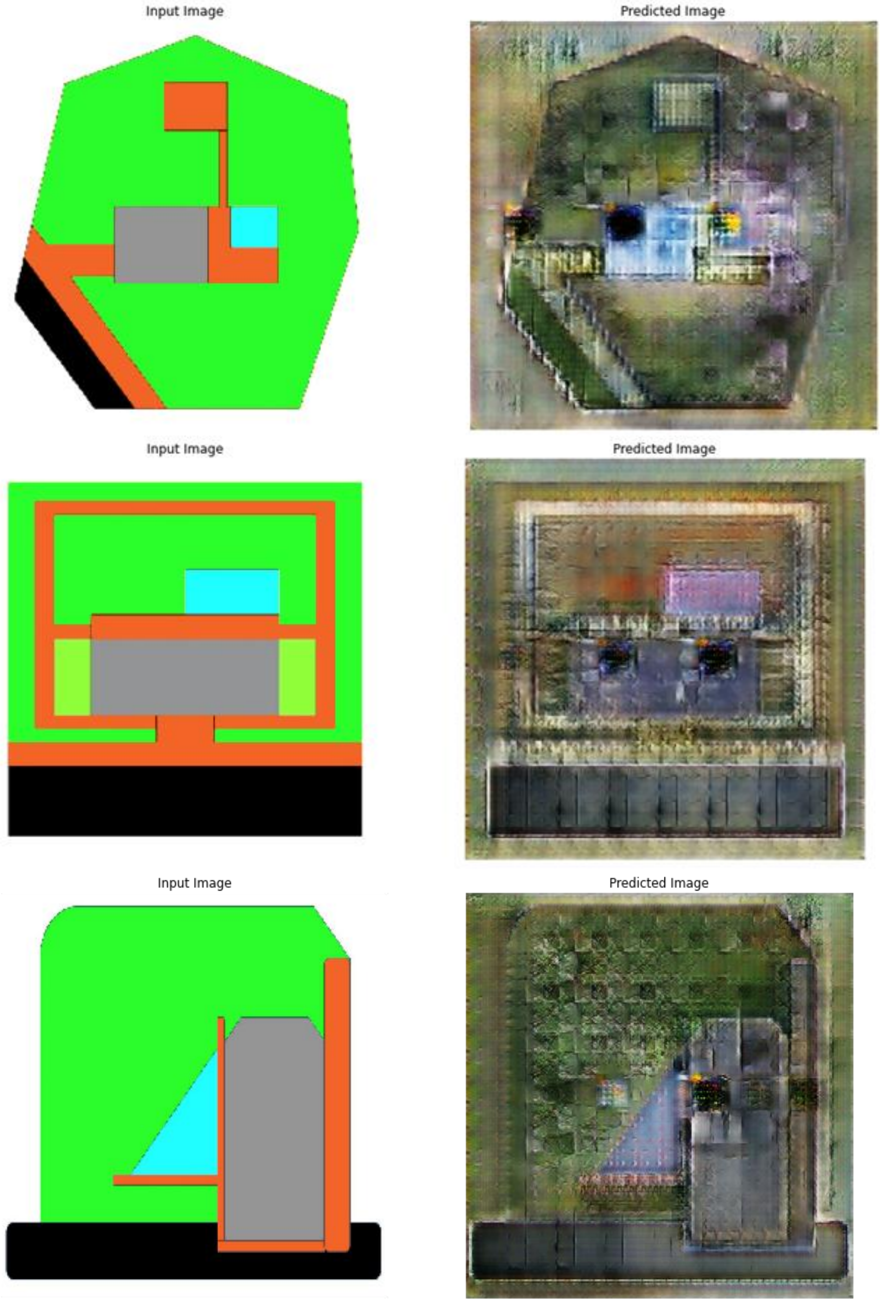

Fig.9: New generated results from new sketches.

The results demonstrated that our model is able to transform simple sketches into landscape plans. The design output can be obtained in seconds when a sketch is drawn.

4.2. Limitations

Firstly, the main limitation of this study is that the number of projects comprising our dataset is lower than it is usual to train such algorithms. Secondly, the image resolution of the output data is very low. We tried to overcome this limitation by increasing the image resolution from 256x256 to 512x512 pixels, adding a layer to the discriminator model and adding an addition to the decoder and encoder blocks.

However, our aim was to illustrate that machine learning can be used as a design tool in the field of landscape architecture, and one should consider our work as a work-in-progress, which we hope to develop in our future research. We will take steps to improve the results by experimenting with different generative models such as the diffusion model. We choose the pix2pix algorithm because of it was easy to implement (and thus can be easier adapted within the landscape discipline), and it proved successful in generating promising results.

5. CONCLUSION

Our paper explored the use of AI in landscape architecture, particularly smaller residential garden design. We examined the ability and potential of AI as a design tool. The study has two main parts, first, use the DBMS of an online design repository to obtain the dataset and its preparation to make the source data machine-readable. The second part of the study uses this dataset to train Pix2Pix, which generates unprecedented residential garden designs. Indeed, our model was able to generate front and backyard designs from a simple sketch.

We also encountered some limitations. The technical limitations of the dataset were about plans produced by different designers, for this reason, plans have different plan languages, textures, colors, and styles. This caused a problem, and the source data was not uniform. It took us some time to manually adjust some of the projects, and others we had to omit. The study offers a glimpse into using AI for landscape designs, however, in the future we think the data can be much larger and contain richer information.

The need for an AI-aided design tool that has emerged in recent years has become one of the researches and software development goals in the world of technology and design. This need, which is the driving motivation of the research, is important in terms of understanding the work of artificial intelligence within the scope of landscape architecture. Thanks to the understanding AI learning and production capabilities in the software to be developed, the results of the study are important for more comprehensive and detailed research on this already new subject. This research deals with landscape architecture as the focus, however we argue that this system can be also used in the planning process at other scales related to the built environment.

Past studies on AI to generate for example floor plans provided important background work for this research. It is important to notice that AI approaches to different design disciplines are similar. Artificial intelligence studies of different disciplines using similar datasets show that AI-aided design tools are suitable for multi-disciplinary use. The approach of different disciplines to machine learning with similar structures allows us to rethink the perception, learning, and production of human-made design by artificial intelligence and to seek answers to more comprehensive research questions by producing much more comprehensive data sets. Our approach presented in this study has shown that ML applications can become useful tools for designers. Being able to quickly produce landscape plans from simple sketches can save time in the design process, as well as enable different alternatives to be explored.

In this paper, we demonstrated whether artificial intelligence can make a contribution to the discipline of landscape architecture, landscape planning, and their design processes. Inspite of the limiting factors in the deep learning process, such as the difference in the graphic languages of various designers in the data set, the results are promising. In recent years, the European Union's turn to artificial intelligence-supported tools and research such as the Green Deal makes it essential for designers, experts, and researchers to develop this field of research. The abundance of publications investigating the relationship between design and AI, also show the importance and future popularity of this topic.

Furthermore, the scope of this research can be expanded from residential landscape design to larger scale ecological approaches in the future. One of the goals in our future research is to use artificial intelligence in city wide ecological designs. For example, one could train Ken Yeang's 'Ecodesign' approach, which puts ecological sustainability before human needs and makes 'Land use/Land Cover' (LU/LC) data the basic input of the design. One could gather an appropriate data set of Yeang’s work and use supervised artificial intelligence to automate designs that fit his criteria. Based on LU/LC data, which is real earth and ecosystem data in satellite images, we can develop ecologically designed AI structures that aim for ecological sustainability. Indeed, this paper presents the first steps toward this larger goal and exploring the work of other tangent disciplines related to the field, will be the key to developing the AI-Aided Ecological Design tool.

In this paper, our main goal was to illustrate an AI approach for the conceptual design development of landscape architecture. Any design process consists of various subsequent phases, such as pre-design, conceptual design, design development, construction drawings, project implementation and operations. Conceptual design is perhaps the most important first step in the design process, where all processes and scenarios are developed. We hope that this research sets a small milestone in the use of AI in landscape architecture and help landscape architects develop their conceptual design schemes in the future.

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