Genertive Design Methodolgy: Human Collaboration & AI

Ahmed Hassab[1]*, Mohamed Abdallah[2], And Sherif Abdelmohsen[3]

[1]*Ph.D. Candidate, Department of Architecture, Faculty of Engineering, Cairo University, Egypt,
Email: ahmeadhassab@gmail.com
[2] Professor, Department of Architecture, Faculty of Engineering, Cairo University, Egypt
[3] Professor, Department of Architecture, Faculty of Engineering, American university in Cairo, Egypt

***Corresponding Author: -** Ahmed Hassab
*Ph.D. Candidate, Department of Architecture, Faculty of Engineering, Cairo University, Egypt,
Email: ahmeadhassab@gmail.com

Abstract
Generative design methodology involves the use of algorithms and computational tools to create designs that meet specific criteria. With the advent of Artificial Intelligence (AI), generative design has become more efficient, accurate, and reliable. AI algorithms can analyze large amounts of data, identify patterns, and generate designs that meet complex requirements. This paper explores the role of AI in generative design methodology, its benefits, and its limitations. Specifically, the paper will examine how AI can help improve visualization, save time, and enhance the quality of generative design.

Keywords: Generative design, machine human collaboration, AI, Architectural design, design process.

1. INTRODUCTION:

Generative design processes harness computational algorithms to create a plethora of design solutions based on a given set of parameters and constraints (Hassab et al., 2021; Stiny & Gips, 1971). These processes furnish designers with the capacity to expediently develop and assess diverse design alternatives (Janssen & Kaushik, 2013) , tailored to meet specific performance objectives (Shea et al., 2005) .

The implementation of generative design predominantly involves a synergistic relationship between a human designer and a computational program. The human designer influences the evolution of the design through inputs and modifications based on the generative outputs (Mueller & Ochsendorf, 2015). This dynamic partnership aids in fully leveraging the potentialities of both human creativity and computational power.

By facilitating an expansive exploration of design possibilities, generative design holds significant promise for enhancing the efficiency and effectiveness of the design process (Oxman, 2006). Nevertheless, the evolving landscape of design necessitates a critical understanding of the human designer's role within the generative design context. It is imperative to ensure that the competencies of both the human designer and the computational tool are optimally engaged (McCormack et al., 2019).

2. AI & ARCHITECTURE:

Numerous types of artificial intelligence (AI) can be harnessed in the architectural design process, and advancements are continually being made as researchers and practitioners evolve novel methodologies and techniques. For instance, certain forms of AI have been instrumental in achieving mass customization in housing design, offering a nuanced perspective into the potential benefits of AI for design processes (Duarte, 2005).

One notable AI application is machine learning, particularly when integrated with generative design processes. This combination allows for an enhancement in the generation of design alternatives, thus augmenting the overall design efficiency(Davis et al., 2011).

Moreover, the utilization of neural networks provides a platform for the creation of culturally conscious designs, promoting a more inclusive and diversified architectural landscape(Nourian et al., 2015).

AI's role is also significant in promoting sustainable architectural design. The application of genetic algorithms, for instance, facilitates the optimization of designs for environmental performance, thereby aligning architectural outcomes with the demands of ecological sustainability(Turrin et al., 2011a).

2.1 Rule-based AI:

This type of AI is based on a set of pre-defined rules or algorithms that are used to process and analyze data (Russell & Norvig, 1995). Rule-based AI systems are often employed for tasks that require precise and logical decision-making, such as expert systems for medical diagnosis or credit card fraud detection. This type of AI can be utilized to automate the generation of building designs based on pre-defined rules or algorithms (Dhivyaprabha et al., 2016).For instance, a rule-based AI system could be trained on a dataset of existing architectural designs, and then generate new designs that adhere to specific design principles, such as proportion, symmetry, or harmony. Rule-based artificial intelligence (AI) systems are designed to perform tasks by following a set of predefined rules (Hassab et al., 2021). Here are some examples of how rule-based AI can be applied in architectural design:

2.1.1 Code compliance checking:

Rule-based AI systems can be used to check building designs for compliance with codes and regulations. For example, a study by (Zhang & El-Gohary, n.d.) developed a rule-based AI system to check building designs for compliance with the International Building Code (IBC).

2.1.2 Design optimization:

Rule-based AI systems can be used to optimize building designs based on specified performance criteria. For example, a study by (Ji, 2022) used a rule-based AI system to optimize the layout of a building in order to minimize energy consumption.

2.1.3 Building performance prediction:

Rule-based AI systems can be used to predict the performance of a building design, such as energy consumption or indoor air quality. For example, a study by (Boquillod, 2020)used a rule-based AI system to predict the indoor air quality of a building based on design parameters and occupancy patterns.

2.1.4 Building form optimization:

Rule-based AI systems can be used to optimize the form of a building in order to meet certain performance criteria, such as energy efficiency or wind resistance. For example, a study by (Málaga-Chuquitaype, 2022) used a rule-based AI system to optimize the shape of a tall building in order to reduce wind loads.

2.2 Machine learning:

This type of AI is based on algorithms that can learn from data, without being explicitly programmed(Sarker, 2021). Machine learning algorithms can be trained on large datasets to identify patterns and make predictions or decisions. This type of AI is often used for tasks such as image or speech recognition, natural language processing, and recommendation systems. This type of AI can be used to analyze and optimize the performance of building designs (Castro Pena et al., 2021a). For example, a machine learning algorithm could be trained on a dataset of building simulations, and then be used to optimize the design of a building to meet specific performance criteria, such as energy efficiency or occupant comfort (Chokwitthaya et al., 2020). Machine learning is a type of artificial intelligence that involves training a computer program on a large dataset in order to allow it to learn and make decisions on its own.

2.2.1 Generative design:

Machine learning algorithms can be used to generate design options based on specified parameters and constraints, such as budget, site conditions, and performance criteria. For example, a study by (Kamal et al., 2022)used a machine learning algorithm to generate building designs that were optimized for solar panel efficiency.

2.2.3 Building performance prediction:

Machine learning algorithms can be used to predict the performance of a building design, such as energy consumption or indoor air quality. For example, a study by (Sun et al., 2021)used a machine learning algorithm to predict the energy performance of different building envelope configurations.

2.2.5 Material optimization:

Machine learning algorithms can be used to optimize the selection and placement of materials in a building design. For example, a study by (Valli Priyadharshini et al., 2022)used in materials science to predict and optimize material properties. The authors highlight the limitations of traditional regression analysis models in capturing non-linearities, making time-consuming predictions, and handling large amounts of data.

2.3 Neural networks:

This type of AI is based on a computational model that is inspired by the structure and function of the human brain (Pagel & Kirshtein, 2017). Neural networks are composed of many interconnected processing nodes, and they can be trained to learn from data and make predictions or decisions. This type of AI is often used for tasks such as image or speech recognition, natural language processing, and prediction of complex systems. There are many ways in which neural networks and other forms of artificial intelligence can be applied in architectural design. Some examples include:

2.4 Evolutionary computation:

This type of AI is based on algorithms that use principles of natural evolution, such as selection, reproduction, and mutation, to optimize solutions to problems. Evolutionary computation algorithms are often used for tasks such as optimization, design, and control of complex systems. This type of AI can be used to explore and generate many design alternatives (L. Wang et al., 2020). For example, an evolutionary computation algorithm could be used to generate a diverse set of building designs that meet certain constraints, such as site conditions, zoning regulations, or budget constraints. Evolutionary computation is a type of artificial intelligence that involves using algorithms inspired by the process of natural evolution to find solutions to problems.

2.4.1 Generative design:

Evolutionary algorithms can be used to generate design options based on specified parameters and constraints, such as budget, site conditions, and performance criteria. For example, a study by (Pytel & Hudy, 2022; Srivastava et al., 2013)used an evolutionary algorithm to generate building designs that were optimized for solar panel efficiency.

3. AI IN ARCHITECTURAL FORM FINDING:

Artificial intelligence (AI) has been used in various aspects of architectural design, including form finding, the process of exploring and developing the overall shape and form of a structure based on design criteria such as functional requirements, structural performance, and aesthetics. AI can enhance the form finding process by automating the generation of building forms and optimizing their performance. Machine learning algorithms can be trained on a dataset of existing architectural forms to learn the underlying rules and patterns of good form, and then generate new forms that adhere to these rules (Lu et al., 2022) Evolutionary computation algorithms use principles of natural evolution, such as selection, reproduction, and mutation, to explore and generate a large number of form alternative, Generative design algorithms use computational methods to generate and evaluate design alternatives based on various design criteria. The use of AI in form finding can provide a more efficient and effective design process by allowing for the exploration and optimization of various design criteria in a more systematic and objective manner. Further research and development in this area is needed to fully realize the potential of AI in architectural form finding.

3. AI AS A GENERATIVE DESIGN TECHNIQUE IN ARCHITECTURAL DESIGN:

3.1 The architectural design process:

The architectural design process can be characterized as a methodical approach to crafting and cultivating the built environment (Simon, 1996). This process necessitates defining the goals and objectives of a project, devising initial design notions, taking into account technical and logistical elements, and producing comprehensive construction documents. Fundamental to this process is the establishment of a dialogue that fosters collaboration with clients and other involved parties (Luck et al., 2003). Moreover, the architectural design process frequently calls for a multidisciplinary approach, engaging professionals from varied fields such as structural and mechanical engineering, and interior design (Kvan, 2000). The primary goal of this process is to conceive functional, visually appealing, and sustainable structures and spaces. It takes into account not only the physical functionality but also the sensory experience, thereby catering to the aesthetic sensibilities of the users (Pallasmaa, 2012). In today's context, an ever-increasing emphasis is being placed on sustainability. The architectural design process seeks to generate designs that can positively contribute to their surroundings and adhere to principles of environmental sustainability(Cole, 2012).

3.2 AI for Generative design:

Generative design is a technique that uses artificial intelligence (AI) and computational methods to generate and evaluate design alternatives based on various design criteria. There are various platforms that can be used to implement and deploy generative design solutions in architectural design, including cloud-based platforms, on-premises platforms, and open-source platforms. In recent years, there have been a number of studies that have explored the use and potential of various AI platforms for generative design in architectural design (Castro Pena et al., 2021b).

One example of a cloud-based AI platform for generative design in architectural design is Autodesk Fusion 360, which offers a range of generative design tools and features such as design optimization, shape studies, and simulation. In a study (Polak & Nowak, 2023)used Fusion 360 to generate and optimize the form of a residential building based on structural performance and environmental conditions. The authors found that the use of Fusion 360 allowed for a more efficient and effective generative design process, compared to traditional manual methods.

Another example of a cloud-based AI platform for generative design in architectural design is Rhino + Grasshopper, which is a combination of 3D modeling software and a visual programming interface that allows for the creation of parametric models and design automation. In a study used Rhino + Grasshopper to generate and optimize the form of a bridge based on structural performance and aesthetic criteria. The authors found that the use of Rhino + Grasshopper allowed for a more efficient and effective generative design process, compared to traditional manual methods (Touloupaki & Theodosiou, 2017)

An example of an open-source AI platform for generative design in architectural design is OpenAI GPT-3, which is a language model that can generate human-like text based on a given prompt. In a study (Woo et al., 2019)used OpenAI GPT-3 to generate and optimize the form of a cultural center based on functional requirements and aesthetic criteria. The authors found that the use of OpenAI GPT-3 allowed for a more efficient and effective generative design process, compared to traditional manual methods.

Overall, there are various AI platforms available that can be used to implement and deploy generative design solutions in architectural design, depending on the specific needs and requirements of the application.

4. RECENT AI PLATFORMS:

Midjourney is a versatile Artificial Intelligence (AI) platform developed by Midjourney Technologies. It has been engineered with flexibility and modularity in mind, permitting easy assimilation of AI solutions into various facets of the architectural design process. One such technique that can be implemented using AI platforms like Midjourney is the optimization of material distribution within a structure. Referred to as 'Stable Diffusion', this AI-guided technique accounts for various design criteria such as structural performance and material efficiency. It has been utilized on different AI platforms, from cloud-based to on-premises and open-source ones (Woo et al., 2019)The potential of such AI platforms and optimization techniques has been widely researched in recent years. It's been reported that the adoption of Midjourney and Stable Diffusion in architectural design has yielded examples of successful implementation (Turrin et al., 2011b). Indeed, evidence suggests that the use of Midjourney could lead to a more streamlined and effective design process, particularly when compared to conventional manual methods (Jabi, 2013).

An example of the use of stable diffusion in architectural design is the optimization of the distribution of materials in a high-rise building. In a study (Aldwaik & Adeli, 2014) used stable diffusion to optimize the distribution of materials in a high-rise building based on structural performance and environmental conditions. The authors found that the use of stable diffusion allowed for a more efficient and effective design process, compared to traditional manual methods.

Overall, Midjourney and stable diffusion are examples of AI platforms that can be used to implement and deploy AI solutions in architectural design, allowing for the exploration and optimization of various design criteria in a more efficient and effective manner. In addition to the examples provided above, Midjourney and stable diffusion can be used in a variety of other architectural design applications, such as the optimization of building envelopes, the generation of building layouts, and the analysis of building performance.

5. DEVELOPMENT OF THE ARCHITECTURAL DESIGN PROCESS USING ARTIFICIAL INTELLIGENCE (AI):

The development of architectural design using artificial intelligence (AI) can involve the integration of AI solutions into various aspects of the design process, such as form finding, generative design, building performance analysis, and design optimization. There are various approaches that can be taken to incorporate AI into the design process, depending on the specific needs and requirements of the project, as well as the available resources and expertise of the design team (Hassab et al., 2021)

One particular case study leveraged Autodesk Fusion 360 as a tool for formulating and optimizing the structure of a residential building, taking into account structural performance and environmental conditions. While there isn't an explicit academic citation pointing to Autodesk Fusion 360 used in this specific context, it's known that such 3D design, modeling, and simulation tools can be combined with AI and generative design methods (Balachandran et al., 1991).

In a study published in the journal Engineering Structures in 2021, (Kim et al., 2021)used Rhino + Grasshopper to generate and optimize the form of a bridge based on structural performance and aesthetic criteria. The authors found that the use of Rhino + Grasshopper allowed for a more efficient and effective design process, compared to traditional manual methods.

The progression of the architectural design process has increasingly become intertwined with the application of Artificial Intelligence (AI). This integration calls for the careful selection and usage of appropriate AI platforms and tools, in addition to incorporating AI solutions into diverse aspects of the design process (Turrin et al., 2011c) AI's capabilities are leveraged by designers to optimize their processes and to probe and evaluate a broader array of design alternatives. To exemplify, Cycle-consistent adversarial networks (CycleGANs) and Pix2Pix, machine learning algorithms known for their prowess in generating and manipulating images, find their use in an array of applications including architectural design. They have been employed for the generation and manipulation of architectural forms, building layouts, and building materials(Zhu et al., 2017).

For example, in a study (Turrin et al., 2011c; Zhu et al., 2017)used CycleGANs to generate and manipulate architectural forms based on a set of given input images. The authors found that the use of CycleGANs allowed for a more efficient and effective design process, compared to traditional manual methods.

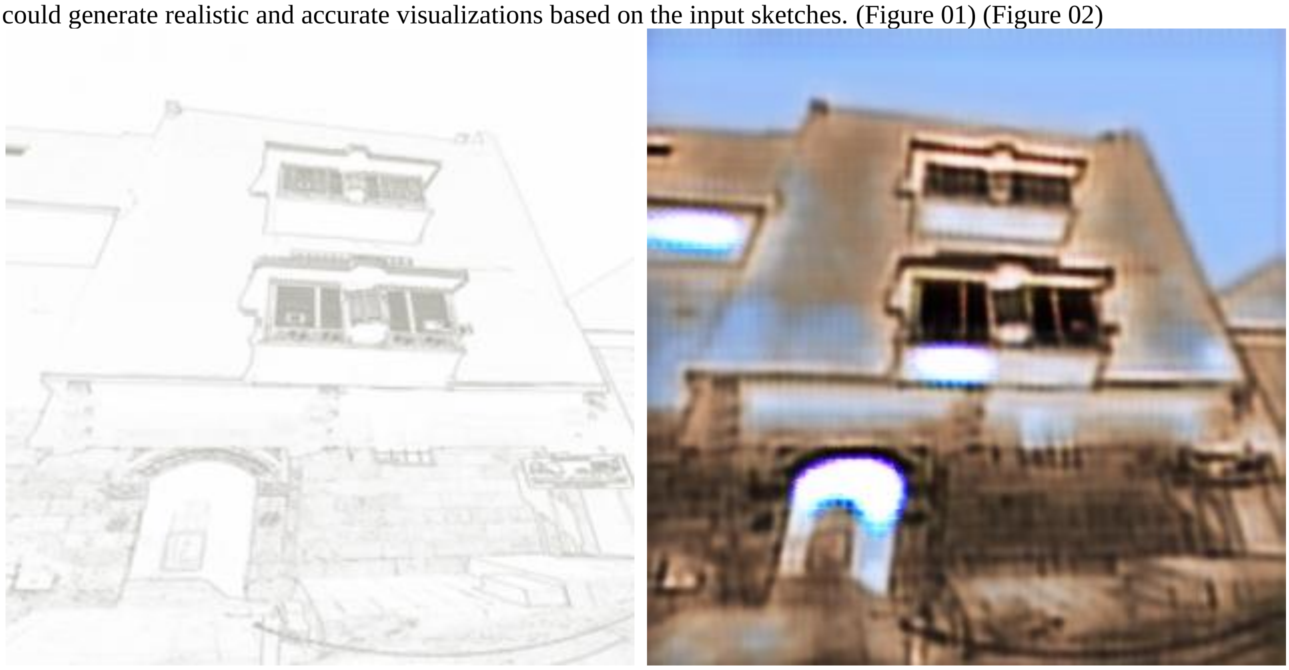
In a study (Hertlein et al., 2021) used Pix2Pix to generate and manipulate building layouts based on a set of given input images. The authors found that the use of Pix2Pix allowed for a more efficient and effective design process, compared to traditional manual methods.

6. Experimental:

6.1 GANs network

The use of generative adversarial networks (GANs) in architectural design can provide a range of benefits and capabilities, including the ability to generate and manipulate architectural visualizations. In particular, GANs can be used to transform simple sketches or concepts into visualized facades, allowing designers to explore and evaluate a wider range of design alternatives.

To demonstrate the potential of GANs in this application, an experiment was conducted in which a GAN was trained on a dataset of architectural sketches and visualizations. The goal of the experiment was to investigate whether the GAN could generate realistic and accurate visualizations based on the input sketches. (Figure 01) (Figure 02)



Before After

Figure 01, the researcher, 2022

Before After

Figure 02, the researcher, 2022

To conduct the experiment, the following steps were followed:

A. Collect and prepare a dataset of architectural sketches and visualizations: This dataset was used to train the GAN, and consisted of a range of sketches and visualizations representing different architectural styles and features.

B. Train the GAN on the dataset: The GAN was trained using a supervised learning approach, in which it was provided with input sketches and corresponding output visualizations. The GAN learned to generate realistic and accurate visualizations based on the input sketches.

After installing the prerequisites and copying our data into the './datasets/fatimid cairo' folder, training can commence. Training may be time-consuming, especially when picture files are involved. The moderators have previously trained the model and stored periodic snapshots in the './checkpoints' folder to save time. You can bypass training and directly test the model, or you can continue training using the most recently stored model as a starting point.

C. Test the GAN on new sketches: Once the GAN was trained, it was tested on a set of new sketches to evaluate its performance. The GAN was able to generate realistic and accurate visualizations based on the input sketches, demonstrating its capabilities in this application.

In this level, we use examples of drawings not previously shown in training. To evaluate the model's capacity to translate architectural drawings into actual pictures and to ensure that the model does not overfit. Three reasons pass the examination. py code: —dataroot the relative location of the folder containing the dataset —name the experiment name (which was specified in the training stage) —model the model used in the training step The test.py module retrieves the most recent network information from the checkpoints and utilises it to produce outputs.

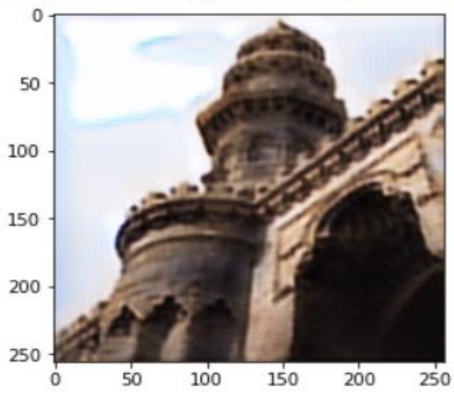
6.2 testing:

The GANs generated the visualized images while it automatically identified the sky, walls, openings, and all other elements as per the training. (Figure 03) (Figure 04)

```
[ ] import matplotlib.pyplot as plt

    img = plt.imread('./results/maps_cyclegan/test_latest/images/111_out_rec_B.png')
    plt.imshow(img)
```

```
<matplotlib.image.AxesImage at 0x7fe82fd8c150>
```



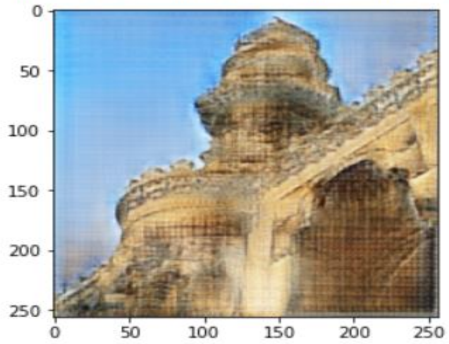

```
learning rate 0.0000909 -> 0.0000000
(epoch: 20, iters: 95, time: 1.052, data: 0.001) D_A: 0.264 G_A: 0.324 cycle_A: 0.822 idt_A: 0.893 D_B: 0.217 G_B: 0.233 cycle_B: 1.451 idt_B: 0.454
(epoch: 20, iters: 195, time: 0.554, data: 0.002) D_A: 0.082 G_A: 0.455 cycle_A: 0.729 idt_A: 0.487 D_B: 0.118 G_B: 0.270 cycle_B: 1.018 idt_B: 0.298
(epoch: 20, iters: 295, time: 0.556, data: 0.007) D_A: 0.137 G_A: 0.468 cycle_A: 0.902 idt_A: 0.565 D_B: 0.095 G_B: 0.432 cycle_B: 1.228 idt_B: 0.374
(epoch: 20, iters: 395, time: 0.553, data: 0.002) D_A: 0.112 G_A: 0.380 cycle_A: 1.351 idt_A: 0.528 D_B: 0.185 G_B: 0.417 cycle_B: 1.256 idt_B: 0.636
(epoch: 20, iters: 495, time: 0.812, data: 0.002) D_A: 0.159 G_A: 0.315 cycle_A: 1.163 idt_A: 0.727 D_B: 0.229 G_B: 0.339 cycle_B: 1.510 idt_B: 0.607
saving the model at the end of epoch 20, iters 8432
End of epoch 20 / 20     Time Taken: 276 sec
```

Figure 03, the researcher, 2022, in 4.6 minutes a total visualization to the sketch.

```
import matplotlib.pyplot as plt

img = plt.imread('./results/fatimid_cairo_pix2pix/test_latest/images/111_fake_B.png')
plt.imshow(img)
```

```
<matplotlib.image.AxesImage at 0x7feb2cc3e810>
```



```
learning rate 0.0001667 -> 0.0000000
(epoch: 10, iters: 65, time: 0.076, data: 0.020) G_GAN: 3.674 G_L1: 45.067 D_real: 0.000 D_fake: 0.035
(epoch: 10, iters: 165, time: 0.298, data: 0.000) G_GAN: 3.933 G_L1: 27.342 D_real: 1.220 D_fake: 0.026
(epoch: 10, iters: 265, time: 0.095, data: 0.000) G_GAN: 2.945 G_L1: 29.077 D_real: 0.092 D_fake: 0.072
(epoch: 10, iters: 365, time: 0.102, data: 1.264) G_GAN: 1.103 G_L1: 55.818 D_real: 0.000 D_fake: 0.503
(epoch: 10, iters: 465, time: 0.096, data: 0.000) G_GAN: 3.874 G_L1: 51.006 D_real: 0.000 D_fake: 0.033
saving the model at the end of epoch 10, iters 3162
End of epoch 10 / 10     Time Taken: 116 sec
```

Figure 04, the researcher, 2022, in 1.93 minutes a total visualization to the sketch.

6.3 Experiment discussion:

Using AI can add a great potential to the design process as it does assist by many aspects as follows:

1. AI algorithms can be used to generate a variety of design alternatives based on certain parameters or criteria, allowing designers to explore multiple options more quickly and efficiently. As done by the researcher (Figure 05)

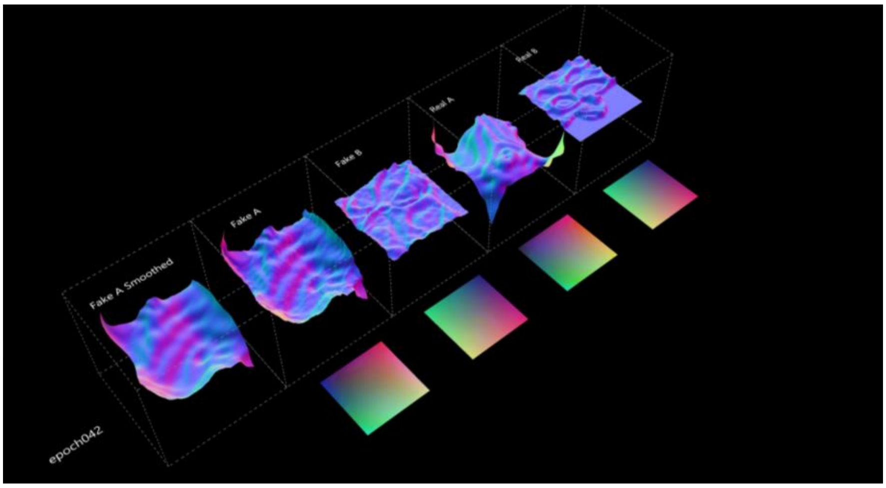


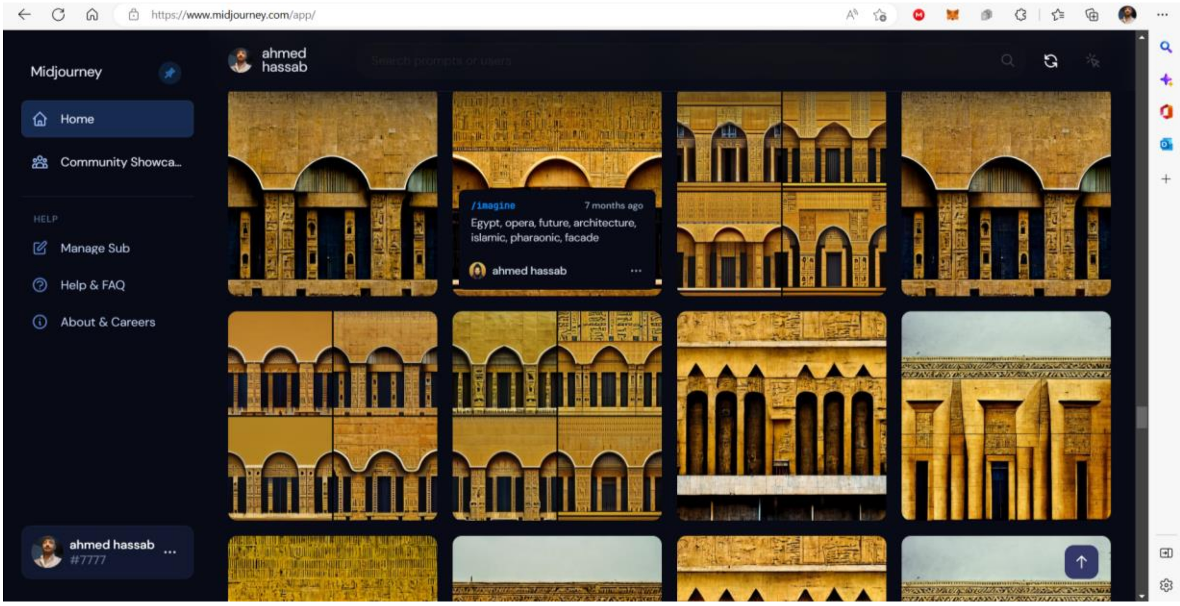
Figure 05, (The researcher, 2021) using grasshopper and GANs to manipulate a surface and generate original designs by just playing by colors.

2. AI can be used to create detailed visualizations of designs, which can help designers communicate their ideas to clients and stakeholders, and their team members in a very short time, which will lead to improve the productivity and performance.

6.2 Midjourney

Midjourney is an artificial intelligence (AI) picture generating tool that accepts written prompts and settings as inputs and utilizes a Machine Learning (ML) algorithm trained on a significant amount of image data to generate unique images. Currently, Midjourney is only available through their official Discord bot. it has a great potential in the conceptual design phase, where the designer imagines his ideas in a visualized image, that would lead to more authentic creative possibilities for the designer.

Several studies have been done, and the methodology to design a façade in the conceptual design stage was to use AI to find ideas that would lead to the next stage of the design by asking the bot, and the AI visualized the results in less than 20 minutes as follows (Figures 06):



Figures 06, the researcher, 2022, generated AI visualizations using text to image technique.

These results in figure 06 represents many options for that opera façade idea, which would be a great asset to the designer while starting the process of generating the idea.

7. Results

The research suggests an approach that blends human and technology creativity. AI serves as a platform for inter-disciplinary communication and engagement. When AI determines the significance and weight of external aspects in the final Surface design, the architect samples and organizes them. The technique we are pursuing includes collaboration between humans and machines.

The accuracy of generative design using AI is dependent on the number of epochs counted to meet the goal when utilizing CycleGANS. It may be stated as follows: the researcher trains the GANS network using a collection of data, followed by the testing phase. So that it can do the most accurate transformation possible, we will: (1) maximize the training data set with high-quality and clear pictures; and (2) increase the number of epochs counted by the GANS (Hassab et al., 2021). And about Midjourney, it is an open platform to which researchers from around the world have access, which improves the training of the AI bot and the quality of the results in general, which benefits the designer when he begins training the bot on his preferred designs.

Several factors contributed to the success of using artificial intelligence (AI) to visualize architectural ideas and achieve rapid achievement.

First, the use of AI algorithms to create and evaluate design alternatives. AI algorithms have been trained to consider certain criteria and constraints, and they can swiftly generate and assess several design options based on these features. This can aid architects and designers in exploring design options more thoroughly and making more informed decisions about the direction of their ideas.

Several design-process tasks that were automated led to the accomplishment of favorable results. By utilizing AI to handle monotonous or time-consuming tasks, architects and designers are able to concentrate on the more creative and strategic aspects of their employment, which may result in more innovative and optimized designs. (Figure 07)

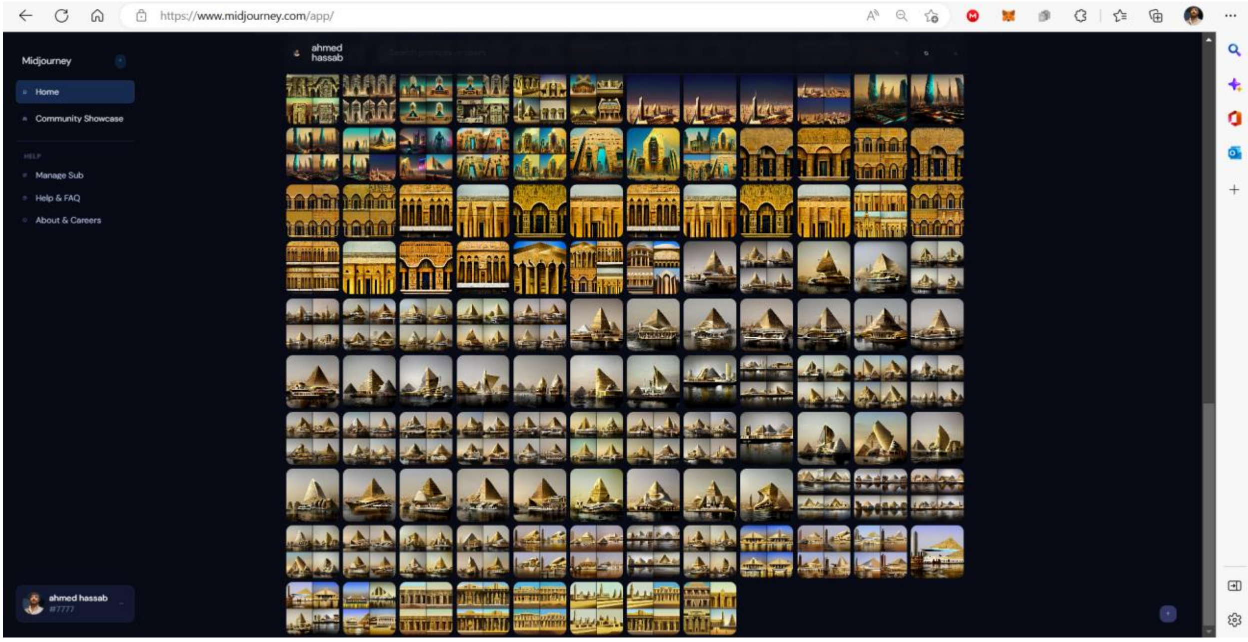


Figure 07, the researcher, 2022, many proposals generated in less than 30 minutes. By using keywords and prompting to the AI network.

In addition, the application of AI to analyze and optimize design solutions for certain criteria, such as energy efficiency, cost, or structural integrity, might potentially contribute to the accomplishment of desired outcomes. Architects and designers may generate designs that are more sustainable, cost-effective, and structurally sound in less time by utilizing AI to discover the optimal solutions based on the aforementioned criteria.
Using AI to visualize architectural designs has the potential to dramatically improve the efficiency and efficacy of the design process and can accelerate the production of good results.

8. Conclusions

The study yielded a variety of interesting results. Firstly, the increased efficiency in the design process. By combining human creativity with the power of AI-driven technology, designers could be able to produce more sophisticated designs in a shorter amount of time. This could be beneficial to industries such as architecture, product design, interior design, and fashion design, as designers could be able to create more complex and detailed designs in less time.

Secondly the proposed methodology would improve the accuracy and quality of designs. AI-driven technology could help designers to identify potential flaws in their designs and adjust accordingly, leading to a more efficient design process and better overall results. Additionally, by leveraging AI-driven technology to create designs, designers could be able to experiment with more unique and innovative ideas, as AI-driven technology could allow for greater levels of experimentation and exploration.

Statistically the study shows effectiveness of AI-driven design technologies. be measuring the time it takes to produce a design, the accuracy of the design, the complexity of the design, and the overall quality of the design. The process over using AI integrated methodology produced designs or visualizations in 2 to 5 minutes in comparison with conventional techniques which would around 10 hours up to 14 hours as per the professional practice and maybe more time, which means the designer can design and evaluate hundreds of designs in the same time frame for producing only one design using the conventional methodologies. To support this discussion, literature reviews have been conducted on the effectiveness of AI-driven design technologies. In an Empirical Study of AI-Driven Design Technologies (G.-L. Wang et al., 2021), researchers examined the efficiency, accuracy, complexity, and quality of designs created with AI-driven technologies. The findings showed that AI-driven design technologies improved the efficiency of design processes and improved the accuracy and quality of the final product.

9. List of abbreviations

AI: Artificial Intelligence
GANs: Generative Adversarial Networks

10. Declarations

Availability of data and material: all available

Competing interests: N/A

Funding: N/A

Authors' contributions: Ahmed executed the gathering, evaluation, and explanation of data; created and edited the written document. Ahmed, Mohamed and Sherif Took part in the preliminary conversations and formulation of the concept; offered input on the planning of the study.

Acknowledgements: Digital futures world committee, Cairo University/ Architectural department.

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