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Investigating Architectural Style: Preservation and Innovation Utilizing AI - Rifat Chadirji's Dataset from Iraq as a Case Study

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Abstract Architecture is constantly evolving with the emergence of diverse technologies, in particular, the subject of architecture and artificial intelligence (AI). As such, this research focuses on architectural style utilizing Generative Adversarial Networks (GANs) and AI tools, especially in image-to-image technology. Further, the study examines StyleGAN 2-ADA, which can generate images as a general summary of the data input, besides DALL-E 3 and Midjourney AI tools to create images. This study analyzes AI models using local architectural data from the works of Rifat Chadirji, a renowned Iraqi architect (1926–2020) recognized for integrating modernist principles with traditional Iraqi architectural elements, resulting in a distinctive and influential style. The images of the facades were chosen for this research due to their extensive temporal range and the adaptability of their design approach. The research provides greater control over design outcomes using image-based inputs, addressing how architects can leverage AI tools to balance heritage preservation with innovation. Moreover, it offers practical insights into merging these tools into professional workflows and cultural applications. The methodology of this work has two main parts: generation and evaluation. In the generation process, the dataset was input into StyleGAN 2-ADA for image generation, whereas, in DALL-E 3 and Midjourney, the dataset was classified into subgroups before generating images. The evaluation process includes two methods. Firstly, the SSIM metric is applied to determine the structural similarity between the original and generated images. Further, the questionnaire was selected to investigate architects' opinions and assess attributes such as historical aspects, artistic elements, patterns, and materials, ensuring alignment with architectural standards. The results demonstrated that StyleGAN 2-ADA excels in tasks centered on retaining architectural heritage. On the other hand, DALL-E 3 proves to be a valuable tool for fostering innovation. Meanwhile, Midjourney provides a flexible method by balancing preservation and renewal.

Keywords Architectural Style, Artificial Intelligence, Rifat Chadirji, StyleGAN 2-ADA, DALL-E 3, Midjourney

1. Introduction

The advancement of computers has transformed scientific and practical levels. They were considered essential tools for expanding human boundaries [1]. Nowadays, AI applications are widely utilized across various fields. They become intellectual tools for assistance and creativity [2]. Studies in architecture show the use of AI to solve technical problems, providing knowledge and inspiration [3]. However, AI proposals are not integrated into the design without modification because they lack a connection to reality. Therefore, there is a crucial need to establish a link between the new tools and designers to improve future outcomes [2]. Architectural design today involves with many subfields, such as environmental experts and digital architects, to create the final product. As a result, architects are more adaptable to shifts in the design process [4] [5]. For example, some AI applications used in architectural design are Generative Segment Anything Models (SAMs) [6], Latent Diffusion Models (LDMs) [7], and Generative Adversarial Networks (GANs) [8].

GANs are Artificial Neural Networks (ANNs) inspired by biological neural networks. Consequently, they can train, learn, and create a creative generation. Moreover, they can also handle and analyze data quickly and accurately [9] [10]. On the other hand, data has constraints, especially in the field of architecture, such as limited data, data quality, and data classification. However, choosing the right data helps to train the model [11]. For instance, the Deep Convolutional Generative Adversarial Network (DCGAN) is an image generation algorithm. It analyzes and learns features and characteristics from data. As a result, it can identify specific patterns by selecting appropriate input data [12]. Moreover, previous studies have applied ANNs in architectural design, integrating data from inside and outside the architecture field, as in CycleGAN [13]. Furthermore, the data can represent an era or phase in which StyleGAN was used to create new designs by choosing the date of the Bauhaus style [14] [15].

Our research is centered on the fundamental differences between artificial neural networks and AI platforms. Artificial Neural networks, like StyleGAN 2-ADA, rely on in-depth training on specific datasets. On the other hand, platforms such as DALL-E 3 and Midjourney rely on prior training on broad and non-specialized datasets. The data used in the research is a set of facades designed by the Iraqi architect Rifat Chadirji between 1950 and 1970. The images have different compositions but feature the main elements related to a specific style. The input images provide a novel approach because they can reduce dependence on pre-trained data. That offers limits and effective control over design outcomes. Therefore, the research seeks to investigate and assess these differences in which models are suited to achieving different design goals, like the conservation of heritage and innovation in design. Accordingly, the research provides an analytical framework that enables architects to choose the right tools according to their creative and practical needs, contributing to the advancement of artificial intelligence as an instrument in architectural design.

2. Artificial Intelligence Models

In recent years, numerous AI models and platforms are currently developed and used in architectural design to generate new and creative outcomes [16]. The following sections briefly define the tools used in this study, namely StyleGAN 2-ADA, DALL-E 3, and Midjourney. This choice depends on select models that transform image-to-image.

2.1. StyleGAN2-ADA

StyleGAN is a deep-learning algorithm with the potential to generate new configurations. It relies on data selection and organization to produce high-resolution images [14]. It was introduced by Nvidia in 2018 to create new images from a database of real-face images. It consists of two neural networks: the generator and the discriminator. The generator generates fake results of random noise; the discriminator is an algorithm that compares what is generated by the generator with the real database [15].

StyleGAN is one of the most advanced and powerful GAN networks in 2D image learning and generation. Compared to other GAN networks, StyleGAN has the potential to create fake images similar to the data you fed and mix image patterns. The generated images share similarities with the original ones but appear as new designs. It also provides a summary of the entire data in one format representing [17]. Moreover, StyleGAN utilizes an unsupervised algorithm based on image modeling [18]. Therefore, it controls the generated images based on their structure [19]. As a result, machine learning provides different perceptions from humans. It deals with specific values, disregarding cultural and functional aspects [15]. StyleGAN2-ADA is a type of StyleGAN and an advanced version of StyleGAN that can generate realistic images from small datasets [20]. Furthermore, it shows a greater convergence between the generated images and their source [18].

The StyleGAN Generator Model Architecture is illustrated in Figure 1, which is distinguished by a range of modifications to the generator network, as follows:

1- Baseline Progressive GAN (starts the process of generating from low resolution and gradually increases)
2- Addition of tuning and bilinear up sampling (adjusts parameters to improve model performance)
3- Addition of mapping network and AdaIN (style) (blends and controls style by disentangling the latent space, allowing each layer to be affected by different parts of the latent vector, and enabling control of various image parts)
4- Removal of latent vector input to the generator (improves stability in image generation)
5- Addition of noise to each block (focuses on image details without affecting the overall structure)
6- Addition Mixing regularization (generates diverse and realistic images by organizing to handle different style inputs across various layers) [21].

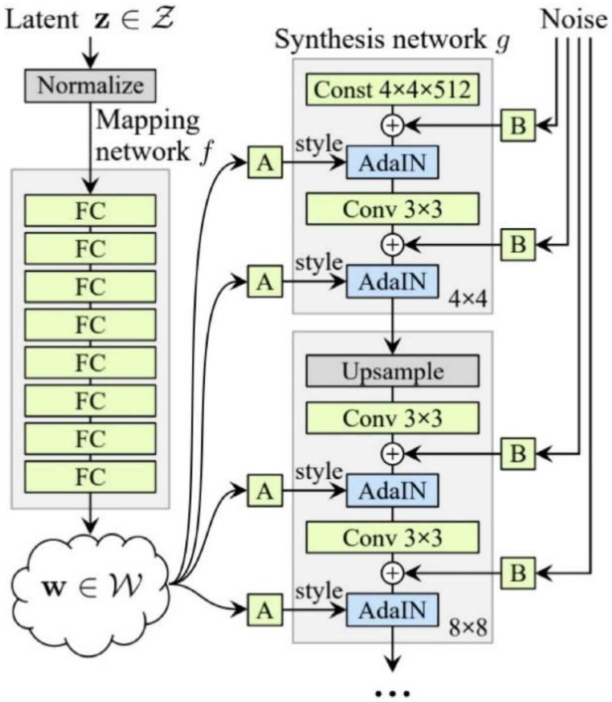


Figure 1. Architecture of the StyleGAN2-ADA Framework [21]

2.2. DALL-E

DALL-E 2 was created by OpenAI and launched in April 2022. It is an AI model based on natural language processing techniques with computer vision to generate images from textual descriptions. It is a tool for creative projects in design and art. Further, the platform interface is easy for text entry. DALL-E consists of Compact Language-Image pretrained (CLIP) embeddings, Principal Component Analysis (PCA) dimensionality reduction, and Generative Adversarial Networks (GANs) [22].

On the other hand, the DALL-E 2 model struggled with a poor connection in text and image coupling because it did not restrict the meaning of each word, leading to less coherent results. Therefore, DALL-E 3 addresses this issue by improving image labels within the training dataset [23]. Recently, enhancement in DALL-E 3 includes the capability of image-to-image conversion utilizing ChatGPT-4.

2.3. Midjourney

Midjourney is an AI tool created in February 2022 and became publicly available in June. Its popularity comes from online social networks after users shared images generated from their proposed prompts [24]. Midjourney has multiple applications in image generation, such as understanding artistic patterns, producing new forms, and exploring unique relationships. Accordingly, it offers artists and designers opportunities to visualize their ideas. The program is helpful for people who cannot draw or struggle to demonstrate their imaginative concepts [25] [26].

Table 1 shows the pros and cons of each of the AI models reviewed in the previous paragraphs.

2.4. AI Applications in Architecture

StyleGAN generates high-resolution images in the architectural field. For instance, it has contributed to enhancing the understanding of relationships between design elements and reshaping them to align with aesthetic and architectural requirements [15]. Moreover, it analyzes and reproduces design elements derived from rich databases [14]. In other applications, StyleGAN is used for visual experimentation by reconfiguring architectural patterns to expand visual understanding [27]. However, StyleGAN's uses in architecture face challenges, like the need for rich and high-quality datasets to ensure the accuracy of results. Despite these limitations, StyleGAN is a promising tool for forming more complex outputs and effectively merging them into professional practices.

AI tools, such as Midjourney and DALL-E 3, are experiencing increasing applications in architectural design. They bring a fundamental shift in exploring ideas and producing visual perceptions. Midjourney is focused on artistic aesthetics and creating context-rich visual scenes. As a result, it investigates preliminary ideas. Moreover, it is used in architectural education to uplift visual and creative thinking in students. DALL-E 3 is valuable for creating images from specific text. Therefore, it develops perceptions from imagination to realistic architectural features [28] [29].

Table 1. Comparison of AI Models: Pros and Cons

AI model	Pros	Cons
StyleGAN 2-ADA	- High ability to maintain the main elements of the original architectural style. - Flexibility in training with limited data.	- Requires programming and technical expertise. - Long training time is needed to achieve accurate results.
DALL-E 3	- High creative ability in creating new and innovative designs. - Easy use interface.	- A limited number of images are processed at a time. - Influenced by data entered by the user.
Midjourney	- Clear aesthetic results while maintaining design colors and ratios. - Suitable for initial stages of design.	- Depends on uncontrollable advance data, resulting in sometimes undesirable changes.

Although these tools offer creative benefits, they face challenges, such as the absence of spatial and structural coherence in some outputs, and generated images are not applied as final results. However, Midjourney and DALL-E 3 tools remain a promising role in the architectural design process. They can be further integrated into different design phases, enhancing architects' ability to innovate and interact with new complex architectural designs.

3. Dataset Selection: Rifat Chadirji's Architectural Works

The study aims to analyze how AI models handle architectural-style datasets. The data represents the style of the renowned Iraqi architect Rifat Chadirji. He is an Iraqi architect and writer, who was born in 1926 in Baghdad and died in 2020 in the United Kingdom. He graduated from Hammersmith School of Arts and Crafts in London in 1952, and he is famous in England and Arab countries for his projects and manuscripts. He authored a collection of books in Arabic on architecture and represented within a cognitive framework. His work exhibits complex formations that subtly conceal modern features [30]. His projects varied between industrial projects, landscapes, gardens, and furniture. He worked as a consultant to the Secretary of Baghdad. Also, he commissioned several pioneer architects to contribute to several projects, such as Le Corbusier (Sports Hall) and Walter Gropius (University City) [31].

His work reflects the influence of Le Corbusier's and Mondrian's drawings, but he heavily derived work from Iraqi traditional architecture and themes [32]. He designed intricate roof structures that featured complex and innovative formations which concealed modern features. This architectural approach resembles sculpture, featuring sculptural blocks of buildings with symbolic expressions. It combines concrete with traditional local materials such as bricks and works to solve environmental problems through light control [30].

Unlike studies that adopt converging designs such as plans or interior design [13] [33], Rifat Chadirji's works represent a rich collection of architectural designs spanning 20 years. These works have unique architectural features that reflect the designer's style, with a clear evolution of this style over time. The designs are characterized by the diversity between different buildings. They provide an opportunity to examine how AI models handle data that belongs to one architectural style but have various compositions.

4. Case Study

The data selected for our research consists of various projects designed by Rifat Chadirji. The data was utilized in two case studies to generate images. In the first case study, the entire dataset was processed utilizing StyleGAN2-ADA. Based on the results of the initial case study, a specific subset of images featuring high-rise buildings was selected for the second case study. Subsequently, the dataset was input into StyleGAN2-ADA, DALL-E 3, and Midjourney.

4.1. The First Case Study with StyleGAN2-ADA

The data preparation for StyleGAN2-ADA involved using images from the book called ‘Building Index: Rifat Chadirji’ [34], which features a collection of his projects. The images were scanned directly from the book to ensure high resolution, as those extracted from the PDF version lacked sufficient quality for the study. A dataset of 500 images was compiled, and the images were subsequently resized to dimensions of 1024 × 1024 pixels, in order to satisfy the high-resolution requirements of StyleGAN2-ADA, which are essential for achieving optimal results.

4.1.1. Results of the First Case Study with StyleGAN2-ADA

The images generated from the entire data to StyleGAN2-ADA lack clarity and fail to reflect a clear connection with the original dataset. This issue stems from diverse types of input data because it includes high-rise buildings, low-rise buildings, and monumental buildings, as shown in Figure 2.

Figure 2. The results of the first case study with StyleGAN2-ADA.

4.2. The Second Case Study with StyleGAN2-ADA

The data selection lies in the gathering, classification, and analysis of its interrelationships [34]. Accordingly, the dataset was organized into high-rise building categories featuring common elements, with 106 images selected from the original dataset. Then, the high-rise building dataset was divided into smaller sets. Midjourney accepts 20 images per group, while DALL-E 3 could process 10 images in each image-to-image generating process, as shown in Figure 3.

4.2.1. Methods

4.2.1.1. Generation Methodology

The dataset was processed using three different AI models, StyleGAN 2-ADA, DALL-E 3, and Midjourney.

StyleGAN2-ADA

In AI, 'big data' means large and complex datasets [35]. However, in architecture, there is often a need for models that can handle more limited datasets, such as StyleGAN [20]. This model is especially adept at performing continuous conversion between two or more styles with high accuracy, supporting resolutions up to 1024 [14]. As a result, it is well suited to our chosen dataset. For our research, StyleGAN2-ADA-PyTorch was configured, and the training process was conducted over 9 hours on Google Colab, A collection of images was generated as shown in Figure 4.

Input the whole dataset (106 images) into StyleGAN2-ADA.

Input data into DALL-E 3 (10 consecutive images) in each generating process.

Input data into Midjourney (20 consecutive images) in each generating process.

Figure 3. The dataset of high-rise buildings designed by Rifat Chadirji [33]

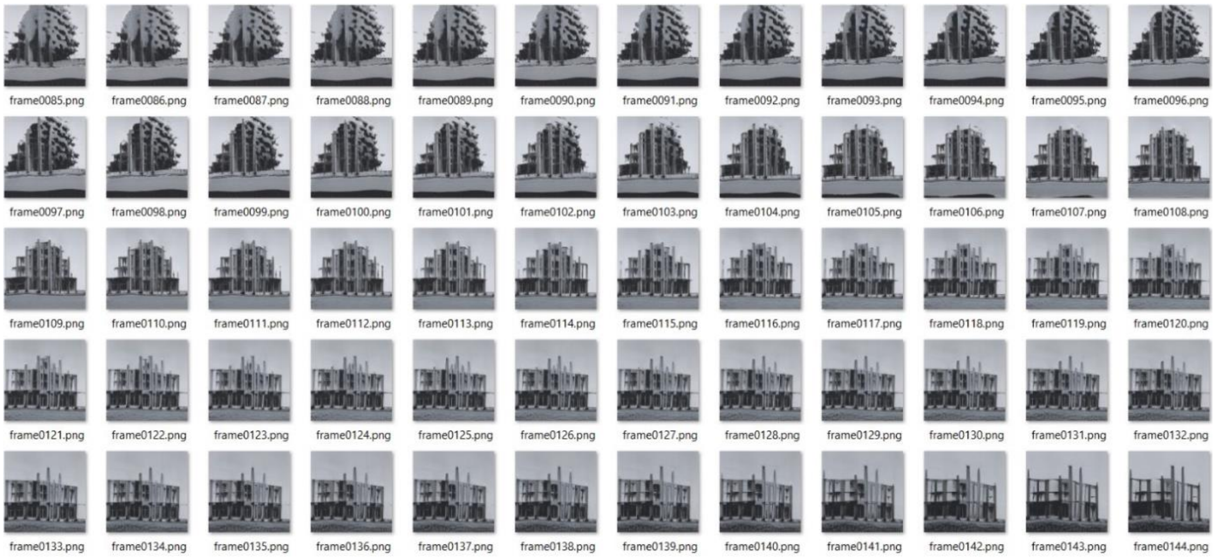


Figure 4. Images generated by StyleGAN2-ADA

DALL-E 3

The platform has constraints and capabilities in processing input data. Therefore, the data was organized into ten groups because of the limitation of data entry. Each subset contains ten images. DALL-E 3 was utilized in conjunction with ChatGPT-4, using its interface to input images.

Midjourney

For the Midjourney generation process, the data is divided into 20 images per experience, representing the platform's maximum acceptance number of images. This procedure repeats five times to cover the entire dataset.

4.2.1.2. Evaluation Methodology

The evaluation process is significant because it leads to achieving specific objectives. Some methods are applied to evaluate images, such as using the FID (Fréchet Inception Distance) standard to measure visual similarity between original and generated images [35], as well as SSIM (Structural Similarity Index) to evaluate the similarity of compositions [13]. Since our research focuses on measuring features that reflect the architectural style, comparing the features seen in both the original data entered and the data generated by AI models, two evaluation methods were implemented: SSIM and human assessment.

1. Image Analysis and Evaluation using the SSIM Metric

The Structural Similarity Index (SSIM) is a measure used to assess the quality of digital images. It compares the overall structure of the original image to the modified or reconstructed image. SSIM analyzes the structural similarity between local areas in images, making it more sensitive to differences observed in the human eye. It gives results ranging from 0 to 1, as one refers to the complete matching of images. Therefore, it provides an integrated method for evaluating image quality in practical application contexts.

The evaluation process in this research is conducted in two phases. Firstly, three pairs of images were chosen from an original image and its corresponding generated image. The selection method relies on choice-specific pairs located at the start, middle, and end for balance.

Secondly, this procedure aims to measure the structural similarity between the two images using the SSIM index. Through this comparison, conclude the extent to which each model can produce images that preserve the visual structure and details found in the original image. That allows the accuracy and efficiency of the different models scientifically and objectively.

2. The Role of Human Evaluation in Design Validation

The questionnaire was applied to get a human perception of architects with experience or familiarity with artificial intelligence in architectural design. It relied on the Likert Scale to determine characteristics relevant to the architectural style [18]. The questions focused on the historical aspect, artistic elements, patterns, and construction materials (such as bricks and concrete). The approach prioritized these attributes based on the participants' expertise.

4.2.2. The Results

4.2.2.1. The Results of the Generation Processes

The results obtained from each AI model will be showcased through a series of image-to-image conversions, illustrating the transformation as follows:

Images generated by StyleGAN2-ADA demonstrate the model’s ability to preserve the general qualities of the original data, as shown in Figure 5. Changes in the generated images, such as the appearance and disappearance of some details, occur because the algorithm processes images as a set of pixels. Consequently, the generated images acquire new features.

The results from DALL-E 3 demonstrate a high degree of regeneration. Despite the original data's emphasis on height and some repetitive elements such as openings and arches, DALL-E 3 reconfigures these elements to generate new designs, as shown in Figure 6.

The results from Midjourney are understandable and preserve the general colors of the input images. Midjourney effectively simulates building height, ratios, and size while conserving the overall composition of the original dataset. However, it introduces adjustments to the finer details, as shown in Figure 7.

4.2.2.2. The Results of the Evaluation Processes

SSIM results showed a difference in maintaining structural similarity and accuracy in images generated by AI models, as shown in Figure 8. StyleGAN 2-ADA achieves the highest values across all measured standards (0.1260, 0.0891, 0.2188). It reflects superiority in producing higher quality images and higher structural resemblance. On the other hand, the performance of the DALL-E 3 came in second with relatively close results (0.1152, 0.0813, 0.1674). That indicates the efficiency of this system in producing competitive quality images with a slight difference from StyleGAN 2-ADA. Compared to Midjourney, it got the lowest values (0.0803, 0.0542, 0.0820). It showed a limited ability to maintain the structure and fine details.

The results of the human evaluating process showed that StyleGAN 2-ADA achieved 40% in the building body component, reflecting its ability to capture the overall shape. Concrete achieved 37.66%, while Brick, Pattern, and History ranged from 26.3% to 33.33%, reflecting accurate details. In contrast, the DALL-E 3 showed outstanding performance in the building body element at 41.16% and the pattern at 38.33%, while the history element recorded the lowest value at 14.33%, with the art element achieving 28.33%, indicating an average performance on the creative side. Midjourney outperformed the building body component by 60%. The concrete component achieved 38.8%, with a lower ratio of 27.5% history elements and a 34.5% pattern, while the art component achieved a high rate of 43%, reflecting its focus on visual creativity.

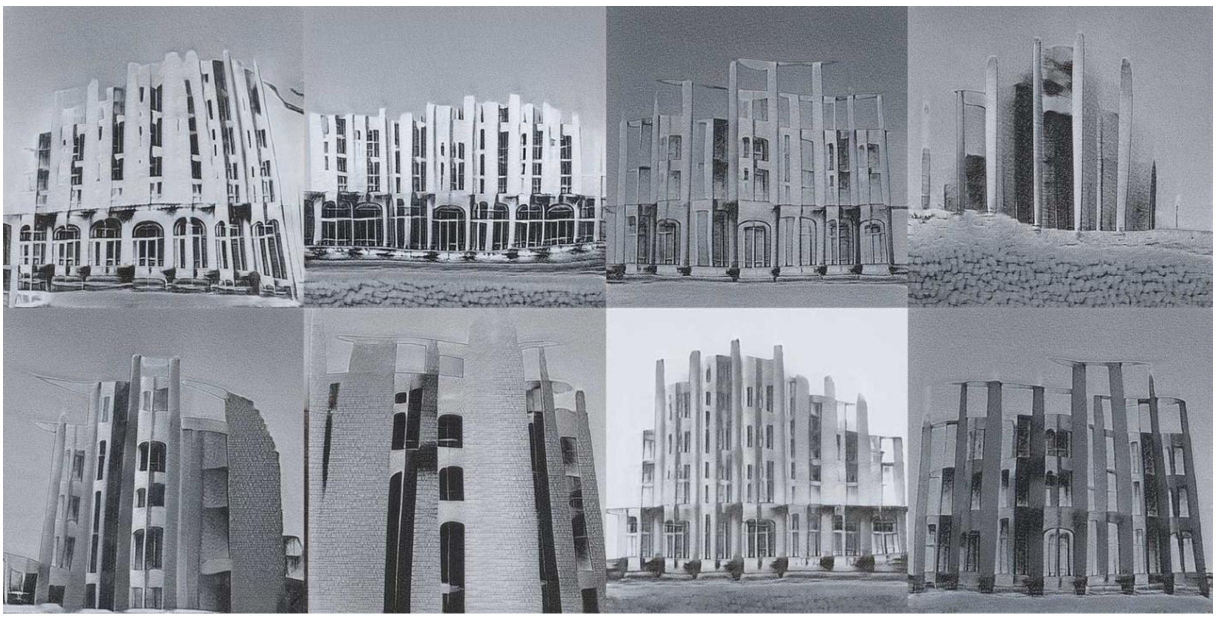


Figure 5. The most important outputs of StyleGAN2-ADA training

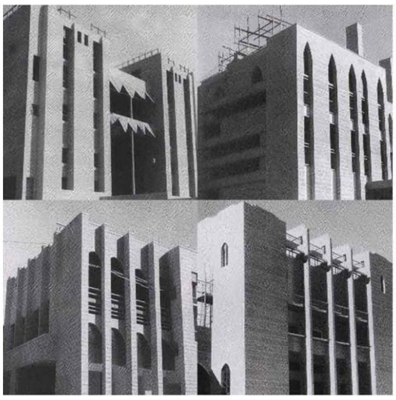
(No.1-10) (No.11-20) (No.21-30)

(No.31-40) (No.41-50) (No.51-60)

(No.61-70) (No.71-80) (No.81-90)

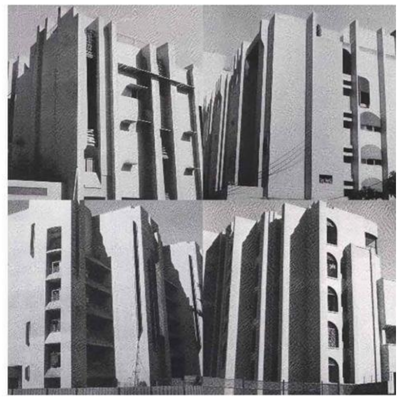
(No.91-100)

Figure 6. Images created by DALL-E 3



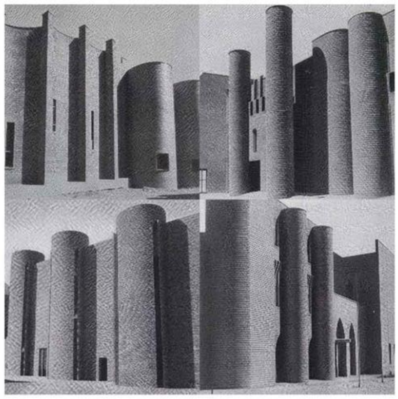
(No.1-20)

(No.21-40)



(No.41-60)

(No.61-80)



(No.81-100)

Figure 7. Images created by Midjourney

original StyleGAN 2-ADA original DALL-E 3 original Midjourney

SSIM= 0.1260 SSIM= 0.1152 SSIM= 0.0803

Figure 8. Comparison of Original and AI-Generated Architectural Designs with SSIM Metrics

5. Discussion

Based on SSIM results, StyleGAN 2-ADA can maintain structural optical elements and fine detail. It is an efficient choice in applications that require high visual quality and accurate resemblance to input. While DALL-E 3 remains a promising option with powerful performance. Midjourney outputs may be more suitable for applications that do not require strict structural accuracy.

According to human evaluation, Midjourney mastered building bodies and creative elements. While DALL-E 3 shows a good balance of elements with a poor representation of historical references. In contrast, StyleGAN 2-ADA highlights the preservation of constructive materials with varied performance for the other elements. This variation reflects the different focuses of each model on architectural elements according to the desired goal.

The results of comparing SSIM and human evaluation process show the ability of AI models to represent certain visual and architectural elements, with variations in their respective focus. The two evaluations agree that StyleGAN 2-ADA has remarkable efficiency in maintaining fine details and constructive elements used distinctively in applications that require structural accuracy. On the other hand, there is a difference in the evaluation for the Midjourney model. It was considered less efficient in SSIM outcomes. While, in humans, it outweighed the representation of the building's body and creative elements. As a result, it focuses on producing more technically creative forms and losing structural accuracy. DALL-E 3 showed a balanced performance in both evaluations. It records good results in SSIM visuals and achieves human evaluation medium to good ability to represent different elements with an apparent weakness in the representation of the historical side. This variation reflects that AI relies on data-based training and visual detail analysis. Human evaluation depends on the perception of design contexts and precise architectural details.

As a result, training of the three models StyleGAN 2-ADA, DALL-E 3, and Midjourney, differs in processing the dataset, advantages, limitations, and applications in architecture. StyleGAN 2-ADA demonstrated a proficient ability to conserve the general proportions, materials, and architectural characteristics, achieving a high level of preservation. As a result, the model had the potential for recreating traditional architectural style, while DALL-E 3 and Midjourney demonstrated the ability to innovate and create new designs. DALL-E 3 provided higher refinement in the generated designs by adding new elements. Therefore, this feature helps to add aesthetic values to the design, especially at the initial design stages. Moreover, Midjourney maintains proportions, materials, and colors while adding new configurations inspired by the main elements for conserving style with some evolution.

The three models process the data differently. Therefore, the data has an impact on the generating process. StyleGAN 2-ADA can be trained on the dataset without external influence, with greater control over the results. In contrast, DALL-E 3 and Midjourney are affected by their pre-trained data. They present a challenge in maintaining style but offer an advantage when generating designs with new elements. In addition, the technical aspect is essential when using AI models. Training StyleGAN 2-ADA requires programming skills and AI systems. Architects should have expertise in the programming disciplines or collaborate with specialists to achieve optimal results. However, DALL-E 3 and Midjourney are easy to use and generate images without requiring technical expertise in AI.

In summary, the study indicates many possibilities for AI models. StyleGAN 2-ADA utilizes projects that require preserving the style, investing in historical data, and generating new designs. DALL-E 3 and Midjourney can be considered tools for inspiration and generation. They provide a wide range of options. They are trained on many datasets beyond architecture. As a result, the interdisciplinary overlap supports the creative process.

6. Conclusions

The intersection of architecture and artificial intelligence extends beyond the principles of speed and precision. It plays an active role in the creative process. Our study explores how AI models deal with datasets to generate innovative and original designs. Therefore, this study can help architectural offices and architects their designs have similar stylistic features, even with different configurations.

The study shows that each AI model adapted well to the dataset. StyleGAN2-ADA can train with an unspecified number of images but requires considerable time and expertise. In contrast, DALL-E and Midjourney accept a limited number of images. Comparatively, StyleGAN2-ADA results are close to the original architectural style, while DALL-E 3 introduced new formative relationships that could inspire continuous innovation in design, and Midjourney maintained main features with some modifications. Consequently, these platforms allow quick generation without requiring deep AI knowledge. As a result, they are different from more complex algorithms.

In conclusion, conservation and renewal depend on understanding the relationships between image elements. Moreover, the results highlight the potential of utilizing AI in image generation to preserve architectural styles, and it offers a range of design options. Additionally, future research could develop into uniting textual and visual data, expanding the scope of style exploration.

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