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Training cGan Algorithm for Generating Architectural Layout Heat Map*

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ABSTRACT

The maps of the space layout have been considered by the architects as one of the first steps of the architectural design process. The theoretical framework of the high-performance architecture emphasizes that the topological and geometrical structure of these maps is adopted from the latent concepts. These concepts were formed under the influence of the subjective and objective variables. According to the research hypothesis, the space layout maps are subject to the latent patterns that are the basis for their formation. Using the computational strength for contributing to predicting the space layouts has always been a controversial issue in contemporary architecture and has been the prospect for future architecture. The current paper used the data-driven artificial intelligence methods for generating the heat maps of the space layout. Despite the conventional methods that try to define the layout plans based on the absolute mathematical relations, the designed method tries to take the spatial layout generator function from the experience of designing successful patterns with a designed based approach. Therefore, a set of 300 plans of the apartments in Tehran has been provided, and four types of different inputs have been supplied for training the artificial intelligence model. In the present research, cGan algorithm was used as one of the most efficient algorithms. This algorithm creates artificial intelligence and has been trained based on the provided layout patterns. This algorithm can regulate the mapping function to generate the target image based on the input image. After completing the process of training the cGAN model, the heat maps of the space layouts of 10 new apartments were tested. Also, the quality of the predicted answers was evaluated based on the predetermined five regulations. The suggested model based on the design-based approach is following modern construction technologies, such as the application of metadata, deep learning, machine learning, efficiency and smart consumption of energy, and energy-view optimization.

Keywords: Artificial Intelligence, High-Performance Architecture, Data-Oriented Design, Future Architecture.

* This paper is driven from the Ph.D. thesis of the first author entitled "A novel generative algorithm of architectural layout design (Based on hybrid cGAN algorithm & agent-based modelling)" conducted under the supervision of the second author, and advise of the third and fourth authors at Tarbiat Modares University in 2018.

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1. INTRODUCTION

Significant developments in contemporary architecture in Iran and the world indicate the emergence of new computing trends in the process of designing and executing architectural works (Caetano & Leitao, 2020). These technologies have been made available to designers based on the development of new computers (Mahdavinejad & Hosseini, 2019) and have created significant changes in the process of designing and executing architectural works. The introduction of computing technologies into the architectural design process has been challenging on the one hand (Mahdavinejad, 2014) and promising on the other. (Mahdavinejad, Zia, Larki, Ghanavati, & Elmi, 2014) to the extent that the interaction of high-quality computer capacities in architectural design has become an important topic in the literature (Pramanik, Mukherjee, Pal, Pal, & Singh, 2020). In other words, the advance in technology in practice has led to a more complex architectural design process (Ansarimanesh, Nasrollahi, & Mahdavinejad, 2019). Attempts to achieve form patterns (Hadianpour, Mahdavinejad, Bemanian, Haghshenas, & Kordjamshidi, 2019) and optimal orientation (Fallahtafti & Mahdavinejad, 2015), energy-view optimization (Pilechiha, Mahdavinejad, Rahimian, Cedemolla, 2020), more coordination with the site (Saadatjoo, Mahdavinejad, & Zhang, 2018) and the surrounding environment (Hadianpour, Mahdavinejad, Bemanian, & Nasrollahi, 2018), efficient building model (Javanroodi, Nik, & Mahdavinejad, 2019), the proportion of the mass and empty spaces (Mahdavinejad & Javanroodi, 2014) and coordination of form and geometry (Javidmehr & Hashempour, 2019), all of which have increased the applications of computers in the process of designing and executing architectural works.

The problem statement in this study is to explain an efficient model for the computational layout of the architectural space. In this problem, the purpose is to define an algorithm that can provide a layout (space layout), considering the geometrical and topological regulations. These regulations depend on the various subjective and objective factors that can be defined as the numerical objective functions, such as the architectural program, energy efficiency project, municipality regulations, design standards, the priorities of the employer, and so on. In contrast, the non-objective factors are related to the designer's opinion. These factors depend on the experience of the designer rather than the numerical regulations.

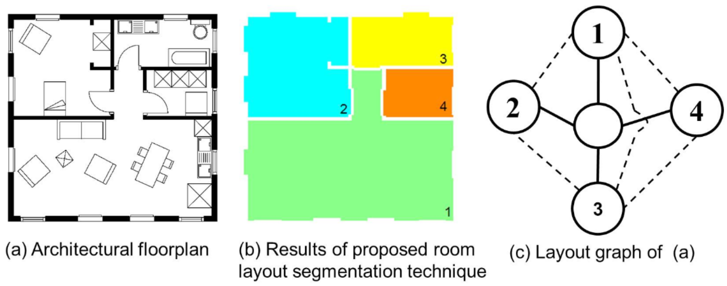


Fig. 1. A Simple Plan of an Apartment (Left), The Representation of the Space Allocation with Coloring (Middle). The Topological Relations of Spaces (Right)

In a simple plan of an apartment (Fig. 1), the representation of the space allocation was presented by coloring and the topological graph of the space relations. In the representation of the space allocation, geometrical and topological regulations have been observed. The dimensions of the rooms, their areas, and proportions are considered as geometrical regulations. The hierarchy of the space layout is also considered as a topological regulation. These two regulations are the result of subjective and objective factors.

2. RESEARCH METHOD

The methodological background of the research is based on an algorithmic approach to the architectural design process (Ziaee, Moztarzadeh, & Movahec, 2020). In addition to the formal aspects, computational architecture has also influenced the content aspects in the design process (Herthogs, Debacker, Tuncer, De Weerdt, & De Temmerman, 2019) and the execution of architectural works (Mahdavinejad & Refalian, 2011). Development of space syntax tools (Bassett, 2020), process optimization (Talaei & Mahdavinejad, 2019), social logic (Dousti, Varij Kazemi, & Behzadfar, 2018), and hybrid location (Hajian, Alitajer, & Mahdavinejad, 2020) provide new capacities for the research (Mahdavinejad & Shahri, 2015).

Based on the selected methodological model, it is assumed that each representation of color allocation in space reflects the topological and geometric rules of that space. These rules are the result of objective and subjective factors (Talaei, Mahdavinejad, & Azari, 2020) and are concepts hidden in the layouts of spaces (Rahbar, Mahdavinejad, Bemanian, & Davaie Markazi, 2019). Therefore, instead of using the rule-based optimization model, the data-driven prediction modeling method is used (Ziaee, Moztarzadeh, & Movahec, 2020). In particular, the conditional generative adversarial network (Isola, Zhu, Zhou, & Efros, 2017) is trained with a specific data set (Zhu, Park, Isola, &

Efros, 2017). Since the introduction of the generative adversarial network (GAN) in the Goodfellow article (Goodfellow, Pouget-Abadie, Mirza, Xu, Warde-Farley, Ozair, & Bengio, 2014) in 2014, different types of these networks have been proposed to solve various problems (Nisztuk & Myszkowski, 2019). Conditional generative adversarial networks or cGans are one of the important branches of research in this field (Rahbar, Mahdavinejad, Bemanian, & Davaie Markazi, 2020). In this research, the cGAN algorithm is trained with a specific data set. The cGAN can also be used to predict the probability of space allocation in a specific plan by providing space layout heat maps.

The main purpose of this study is to propose a practical method for predicting the layout probability of space allocation and to provide space layout thermal maps concerning data-driven processes. The generated drawings can be used in the early stages of design. These heat maps are by no means in the field of plan generation and indicate the possibility of the presence of space in an area of design. The architect uses these plans as a guide in the generation of architectural plans. The method and results related to various low-level features (pixel color of the input images of the artificial intelligence model) can be used in other architectural problems that are based on probabilities. Research innovations include:

- Generating a specific architectural layout data set for training artificial intelligence model and presenting a space layout prediction model based on data-driven principles
- Training cGAN to generate the heat maps of the space layout possibility
- Investigating the various low-level features of the input images of the artificial intelligence to achieve better results.

In the field of architectural layout design, we deal with "latent conceptual layers". In conceptual classification, each pixel of the source image is associated with the equivalent pixel in the destination image. However, in hidden concepts, there is no clear relationship between the source and destination pixels.

Here the question arises of how to define an algorithm that proposes the layout of the desired spaces based on the footprint (environmental) of the architectural space. In these cases, there is no more a direct relationship between the pixels of the two input and output images. Instead, the algorithm must decide on the space layout based on the topological and geometrical relations. In the current study, the conditional generative adversarial network algorithm was applied as the experiment axis and the process of simulating the human brain. The existing data are suitable for the purposes of dividing the spaces in the pixel correspondence algorithms. Therefore, a set of 300 exclusive data of apartments in Tehran was provided for the current study that will be explained in detail in the following sections.

3. FINDINGS AND RESULTS

Conditional generative adversarial network algorithms or cGAN are the generative algorithms of artificial intelligence that consist of two rival networks. Its first network is a generative model called G which is responsible for generating the artificial data. The second network is a discriminative model called D, which is responsible for identifying the generated artificial data and the actual training data. The generator network function G creates a mapping function from a random primary vector called z and the input image x into an artificial output image. This function can convert the combination of any random vector and input image into an artificial output image. Discriminative network D can express the real and artificial recognition of the input image as a number. This number indicates the probability that the function G(x) is real or artificial. Each of these models has its objective functions. The final objective function of the cGAN algorithm can be represented by the following formula:

$$L_{cGAN}(G.D) = \mathbb{E}_{x.y}[logD(x,y)] + \mathbb{E}_{x.z}\left[\log\left(1 - D\big(x.G(x.z)\big)\right)\right]$$

In this equation, the G network tries to minimize the objective function, and the D network attempts to maximize the answer of the objective function. This competition is called the minimum-maximum game. Some of the researchers in the artificial intelligence area adds another function called the L2 distance function to the objective function. This function forces the generative network of G to produces more actual images and, at the same time, deceives the D network. Some other researchers also add the distance function of L1 to the main objective function and try to reduce the blurring effects of images. In the current study, the L1 distance approach was used to reduce the blurring of the produced layout plans. The formula of the L1 distance function and the final objective function is as follows:

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x.y.z}[\mathbb{I}y - G(x.z)\mathbb{I}_1]$$

$$G = arg\min_G \max_D \mathcal{L}_{cGAN}(G.D) + \lambda\mathcal{L}_{L1}(G)$$

The applied cGAN algorithm in the present study is the image to image translation that was implemented in the TensorFlow framework of google. This algorithm selected a U-Net network as the generative network of G, and used a classifying model of convolutional PatchGan. The final result is a discriminative network between zero and one, indicating the actual and artificial possibility of an image.

The training data of the artificial intelligence model in the current study is focused on the algorithmic production of heat maps of space layout probability in a predefined footprint. According to the training process of cGAN model, the data must consist of a pair of images. The first image defines the source, and the second image defines the purpose in the image to image translation algorithm. This set of training data is a significant part of the current study. Also, in this paper, the effectiveness of the low-level representational information on the created answers will be studied. Each training data of an input image is determined by an architectural area of an entrance door and windows. The output image is also a layout space map that is presented by using the colors that indicate various spaces. The first image was given to the algorithm as the x images. The second images were given to the algorithm as the actual images. The training process of cGAN is the optimization of the variable parameters of the generative model of G and a discriminative model of D. Therefore, the generative model can transfer the input images to the target image through a mapping function. In the current study, 300 plans of apartments in Tehran were provided as the training data of the artificial intelligence.

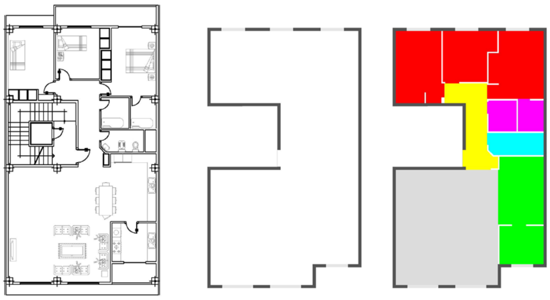


Fig. 2. Labeling the Architectural Plans for Training cGAN Model (Left: The Main Plan, Middle: The Input Image, Right: The Labeled Output Image)

The process of generating the training data of artificial intelligence in which every data includes two input and output images (Fig. 2). In the left image, the main plan of the apartment can be seen. The input image of the cGAN model was presented in the middle image. The terraces, stairs, and columns have been removed in this phase. The colors of RGB are actually the low-level values that the network is trained based on. In the process of training cGAN, the network learns how to turn an input image into an output image (Fig. 3). Four different types of the training data representation of the artificial intelligence model have been shown (Table 1).

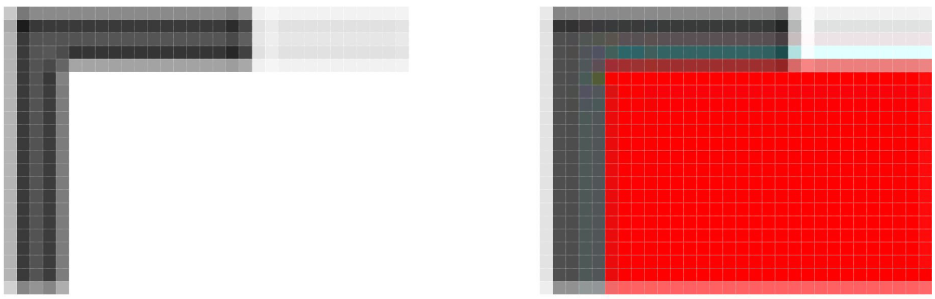
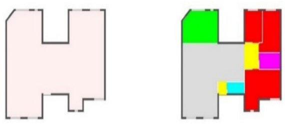
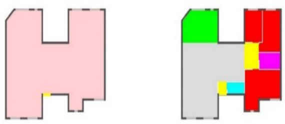
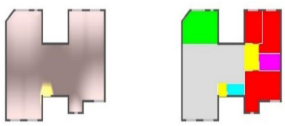
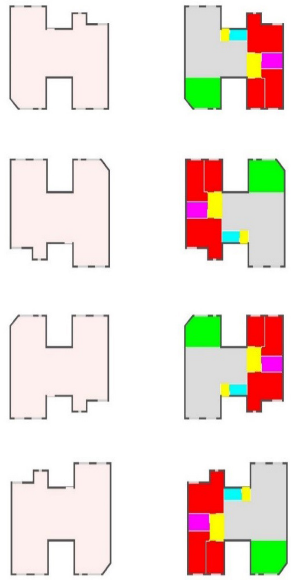


Fig. 3. Training the Correspondent Pixels in cGAN

Table 1. Four Different Types of Training Data to Test Their Efficiency in Space Layout Prediction

Row	Low-Level Features Descriptions	The Sample of Pair Images for Training the Artificial Intelligence Model of Cgan
1	Use cream color for the interior space and mark the front door with a thick black line	
2	Use a dark cream color for the interior space and mark the front door in yellow	
3	Use of gradient colors to emphasize the place of receiving natural light and determine the entrance space by creating a yellow color gradient at the entrance door	

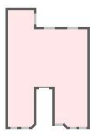
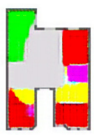
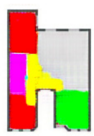
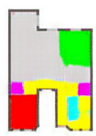
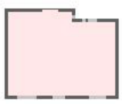
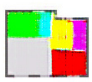
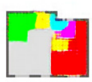
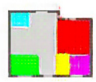
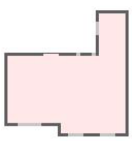
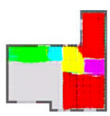
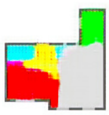
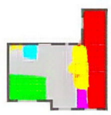
Row	Low-Level Features Descriptions	The Sample of Pair Images for Training the Artificial Intelligence Model of Cgan
4	Using the data augmentation techniques, in this method, each plan is mirrored in two main directions and the number of training data has increased up to 4 times.	

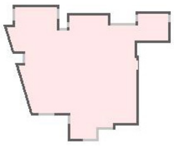
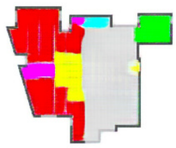
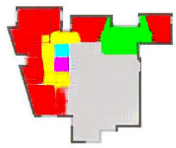
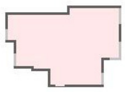
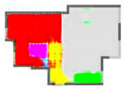
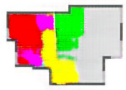
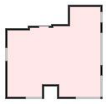
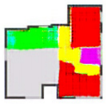
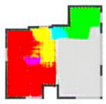
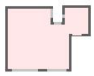
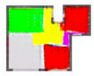
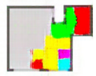
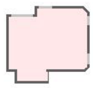
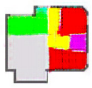
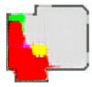
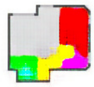
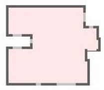
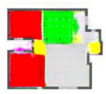
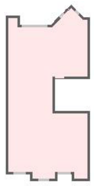
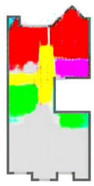
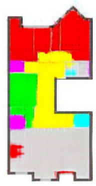
A part of the training data set is presented (Table 1), in which the dimensions of each apartment correspond to its area. The perimeter wall of each plan is adjusted based on the thickness of 20 cm so that there is no difference in wall thickness between the training data. The cGAN model is trained separately on all four sets. Training of the artificial intelligence model of cGAN is a significant part of the research accomplishments. According to the provided four types of training data, the process of training the artificial intelligence model has been implemented four times. Each one of the trained models can generate artificial space layout plans.

The discriminative network D can distinguish the real image from the artificial image. The generative model of G also tries to deceive the D discriminative network by producing artificial data similar to the real data. In the current research, the architecture of both networks was selected in accordance with the studies conducted by Isola (Isola, Zhu, Zhou, & Efros, 2017). The generative network of G is a U-Net network. Also, the discriminative network of D is a classifying network of PatchGan type that analyzes a small part of the image to distinguish if the image is real or synthetic. Therefore, it has a higher computational speed and provides the possibility of analyzing the images at larger scales.

The final production plans are presented (Table 2). The most important criterion for evaluating an artificial intelligence model is to examine the principle of which model has been able to better train the hidden rules of plan design.

Table 2. The Results Extracted From Examining the Models

Row	Entrance Plan	The First Taught Model	The Second Taught Model	The Third Taught Model	The Fourth Taught Model
1					
2					
3					

Row	Entrance Plan	The First Taught Model	The Second Taught Model	The Third Taught Model	The Fourth Taught Model
4					
5					
6					
7					
8					
9					
10					

All available training models (Table 2) are consistent with the training data provided (Table 1). The input plan column displays a set of ten plans tested on trained models. The produced artificial solutions should be evaluated based on topological and geometric criteria. In this regard, five criteria of straight-line design, space dimension, area proportions of spaces, entrance detection, and space layout logic have been analyzed on each model. The straight-line design criterion examines the quality of the results obtained in the field of drawing orthogonal lines of any space. It means that the trained model is capable of producing artificial data with orthogonal lines. The "dimensions of space" criterion examines the capability of the trained model in the generation of spaces with acceptable dimensions. The area proportions of spaces criterion test the proportions of the area of each space relative to other spaces. For instance, how much is allocated to the living space and how much to the bedroom space in a small apartment. The "Entrance Detection" criterion examines the models' ability to detect the entrance and place the entrance lobby in the correct location. The "space layout logic" criterion examines the capability of a model to create the proper topological structure. This topological structure also depends on the location of openings and windows (Table 3).

Table 3. Evaluation of Each of the Heat Maps Generated by cGAN Models

	The First Taught Model					The Second Taught Model					The Third Taught Model					The Fourth Taught Model				
	Designing straight lines	Dimensions of space	Area proportions	Entrance detection	Space layout logic	Designing straight lines	Dimensions of space	Area proportions	Entrance detection	Space layout logic	Designing straight lines	Dimensions of space	Area proportions	Entrance detection	Space layout logic	Designing straight lines	Dimensions of space	Area proportions	Entrance detection	Space layout logic
1	3	4	4	3	4	4	2	2	3	3	4	5	4	5	5	4	2	2	5	2
2	5	4	4	2	4	4	3	3	4	4	4	4	4	5	4	5	5	4	3	3
3	5	4	4	2	5	3	2	2	5	3	5	4	4	5	5	4	3	3	3	2
4	2	2	2	2	2	4	2	2	4	2	4	3	4	5	3	3	3	3	3	2
5	3	4	4	2	4	3	3	3	4	3	3	3	3	5	3	4	3	3	4	2
6	3	4	4	2	5	3	3	3	4	4	3	2	3	4	3	2	2	2	3	2
7	4	4	4	2	4	2	2	2	2	1	4	3	3	4	3	3	2	2	2	1
8	4	4	4	3	5	2	2	1	2	1	3	3	3	5	3	4	3	3	2	3
9	4	4	4	2	5	4	2	2	3	2	4	2	2	4	2	3	2	2	2	1
10	4	4	4	3	3	4	3	3	2	3	3	4	4	4	4	4	3	3	5	3
Avg	3.7	3.8	3.8	3.2	1.4	3.3	2.5	3.2	3.3	6.2	7.3	3.3	3.3	6.4	5.3	6.3	2.8	2.7	2.3	1.2

Ten heat space layout maps generated by four trained AI[1]models have been evaluated based on defined criteria (Table 3). It is a numerical evaluation on a scale of one to five, and five means the best state and one the weakest state.

The first trained model has received the best evaluation in terms of space dimensions, space area proportions, and space layout logic, and the third, fourth and second models are in the next ranks, respectively. In the first trained model, a monotonous cream color was used for the interior space, and a thick black line indicates the entrance door. The results of this model indicated that this model has performed better in simulating smooth lines than other models and has also been more successful in positioning bedrooms next to windows than other models. It also has a toilet and a bathroom in a place that does not need windows. However, this model is much weaker in detecting the entrance space than the third model.

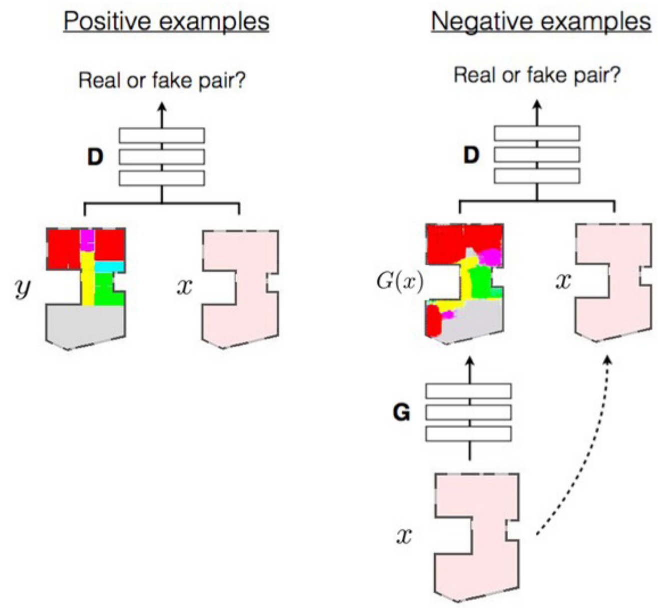


Fig. 4. The Training Process of cGAN for mapping the Input Plan Image to the Output Space Layout Plan Image

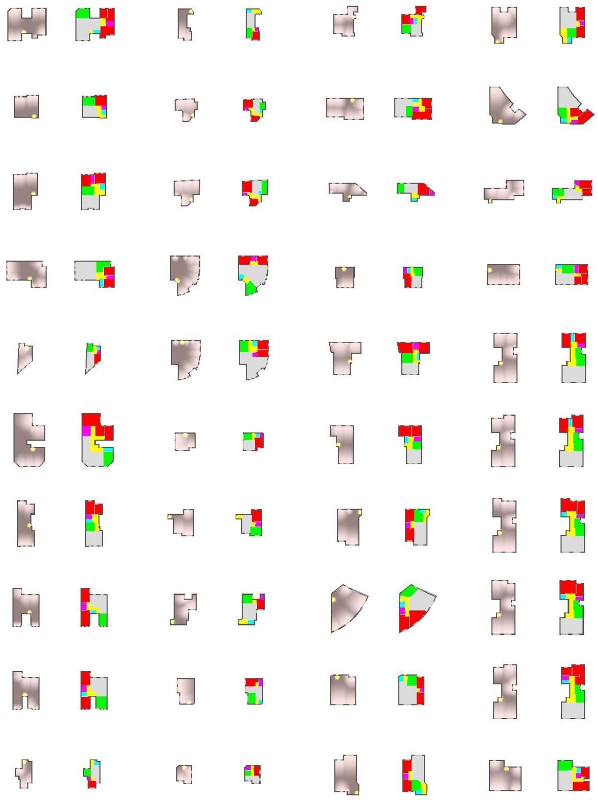
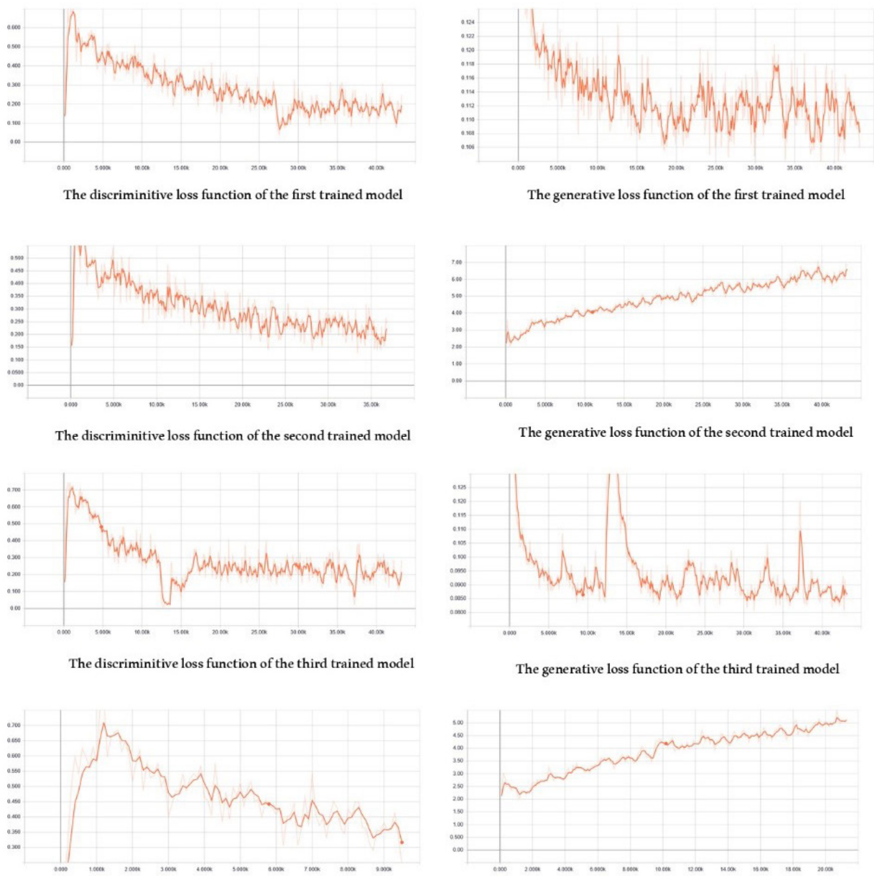


Fig. 5. A Part of the Third Trained Data Set



The discriminitive loss function of the first trained model

The generative loss function of the first trained model

The discriminitive loss function of the second trained model

The generative loss function of the second trained model

The discriminitive loss function of the third trained model

The generative loss function of the third trained model

The discriminitive loss function of the fourth trained model

The generative loss function of the fourth trained model

Fig. 6. Optimization Diagram of Generative Loss Function and Discriminative Loss Function by Trained cGAN Models

Regarding the cGAN algorithm training process (Fig. 4), the generative loss function and discriminative loss functions of all four trained models are represented in Figure 6. The discriminative network of D also seeks to improve its detection ability so that it could detect the real and fake images properly. Therefore, the more successful the discriminative network, the lower is the value. This process of optimization of the variable parameters of the two networks is implemented by the defined numbers of epochs. Examining the diagrams, it is revealed that in the second and fourth models, the diagram is of the incremental generative loss network, and the discriminative network diagram is decreasing. It indicates that in these trained models, the generative network has not been well trained, and a desirable artificial intelligence model has not been created. In these two models, the generative network is not able to produce near-realistic images. However, in the first and third training models, the generative loss value is reduced. Therefore, it indicates the improvement of the generative algorithm during the training process. By considering the obtained numbers, we can see the number 0.08 for the generative loss function of the third trained model after 200 epochs (training loop), which in comparison with the first model of 1.2, indicates the relatively better quality of the third model than the first model. In general, based on the visual findings and evaluation of criteria and evaluation of optimization diagrams, the third model can be evaluated as the best model in terms of generation capacity of heat layout maps.

4. CONCLUSION

The research results confirm the main research hypothesis practically in the efficiency of the cGAN algorithm in generating the heat maps of space layouts. In this regard, using the cGAN artificial intelligence has been successful practically. The research results of the training models indicate that the artificial intelligence of cGAN is trained better in the space topological relationships than the geometrical regulations. Therefore, it is useful for designers in the initial phases of the design. This matter is of considerable significance in the larger projects such as hospital, airport, and all the projects that have complicated topological relations, and can present the initial idea of the space layout based on the trained data. In other words, in the future architecture scheme, paying attention simultaneously to all the influential factors on the process of architectural design is significant. The important point in this process is the algorithmic presentation for understanding the previous design experiences. The experience-based design or data-driven design can help the design group in many of the design issues.

END NOTE

1. Artificial Intelligence

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