

Research on Evaluation Model of Mobile Residential Space Based on Edge Intelligence

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Abstract:

With the rapid rise in the population, the demand for mobile residential space design has also increased accordingly. Residential spatial design has a complex design period, and requires higher labor. At present, the development of artificial intelligence and internet influences the architectural design of mobile residential space and work efficiency of designers in smart city applications. However, the usage of hand-crafted design features and error rate in residential space design is still high with traditional design techniques, which eventually leads to design inefficiency and reduced user satisfaction. The advent of edge-intelligence based on deep learning gave architectural design a new path. In this paper, we proposed Edge-based spatial adaptive graph Convolutional neural network (E-SAGCNN) approach for mobile residential space design prediction. Initially, data regarding Chinese residential building plan were collected. Residential space design features were automatically extracted by Recurrent Neural network-based Auto-Encoder (RNN-AE). The E-SAGCNN approach is trained over the residential space design features to generate the efficient mobile residential space design plan. The E-SAGCNN model is optimized by Butterfly optimization algorithm (BOA) to reduce the design error. The mobile residential space design plan generated using E-SAGCNN is stored in edge server for further applications. The proposed approach is compared with existing methods in residential space design planning. The results showed that the proposed model is effective in mobile residential space design compared to existing methods.

Keywords: Mobile residential space design edge-intelligence; recurrent neural network based auto-encoder (RNN-AE); edge-based spatial adaptive graph convolutional neural network (E-SAGCNN); butterfly optimization algorithm (BOA)

1 Introduction

Due to the proliferation of cloud computing, edge computing has become an essential part of the modern smart factory. From edge computing to edge intelligence: the evolution of AI-powered data analysis. Recent advancements in wireless systems allow for the unrestricted movement of employees, mobile shelves, and production facilities, thus data are gathered and processed using both wired and wireless methods in the smart factory [1]. Consequently, there is still a problem with wireless network connectivity in the industrial sector. As mobile and wireless communication

technology has become more widespread, many new possibilities have arisen for manufacturers. As new wireless networks rise to prominence in the smart industrial, a plethora of hierarchical mobility frameworks have evolved to accommodate them [2]. It is usual practice to classify mobile users into two categories when designing a wireless network: those who operate inside the same domain and those who operate across networks. These actions are compatible with the local mobility protocol and the global mobility protocol of the wireless network. Global mobility approaches keep the user linked to the factory regardless of where they happen to be, in contrast to local mobility protocols which work via distribution inside the domain.

Edge intelligence (EI) refers to the node-level processing, communication, and storage resources closest to the network's end users. The "edge," a metaphor for a certain location, is where new information is created and processed. Any form of edge requires a controller and a computer, plain and simple. Multiple studies have demonstrated that IoT and IIoT are quickly replacing devices that used to rely on less powerful CPUs [3]. These devices couldn't function without the help of artificial intelligence. Edge field data processing hardware enables the collection, analysis, consolidation, and application of smart data. These devices can perform ML and AI model analysis with the aid of edge computing. Traditional client-server architectures, which often use "double" or "thin" clients, are under threat from intelligent edges. The former are able to process, analyze, and secure data, while the latter are unable to do so. Information sharing, data processing, and data management are the cornerstones of edge intelligence [4]. Separate assembly lines may now coordinate their efforts through wired or wireless networks, made possible by intelligence located on the factory's perimeter. With this computing approach, a wide variety of devices and people (such as workers, supervisors, smart buildings, robots, sensors, and AGVs) can be linked. Inter-distributed computing allows for the collection, processing, analysis, and storage of vast volumes of data via fully networked edge intelligence systems. This local server setup may be used in conjunction with or as a replacement for cloud-based options. Edge servers, often called IIoT gateways, are widely used for edge computing [5]. A half rack, two blades, or an industrial embedded personal computer might all serve as examples of such gear. By bringing on-premises services into the cloud, edge computing businesses may gain access to computed insights. Intelligent edge control methods may be useful for local units and devices that are located near the edge. Edge intelligence may allow data to be processed locally, without the need to transfer it to a server or the cloud. As a result, we plan to implement edge-computable entities to prudently control the flow of information to mobile devices in motion across the smart factory.

Research on automated systems for designing and enhancing interior settings is urgently needed. The value of a well-executed interior design cannot be overstated, yet progress in this area has been sluggish [6]. The great majority of modern designs are created using quite basic procedures that provide subpar results and consume an exorbitant amount of designers' time. There are a few of issues, but the most glaring is the unintuitive user interface. There has been talk about how interior designers might provide better service to customers and spend less time on paperwork if the process of updating and enhancing designs for occupied spaces could be automated. It is possible that the space design process might be fully automated by incorporating simulation into it, greatly lowering the designer's effort while simultaneously increasing the efficacy and efficiency of the layout design. Hand-drawn layout often falls short of expectations because of the designer's inexperience and lack

of understanding. In contrast, layouts created with the help of a computer are often more effective [7]. This research was inspired by current developments in multi-intelligence decision-making technology, and its hardware and software ideas aim to improve the spatial arrangement of interior areas [8]. The tests prove that the system is the best in its class when it comes to energy efficiency and precision of its improvements. Improved rationale for attempting to better the indoor environment might be gained by further study of the indoor environment's hierarchical structure. There are no existing studies based on this research. Hence, this study proposed new idea for managing the mobile residential space design using Edge intelligence.

The following are some of the contributions that this research makes:

- Initially, information on the residential building plan in China was gathered for data collection.
- Recurrent Neural network-based Auto-Encoder (RNN-AE) is utilized to extract the residential space design features.
- To generate the efficient mobile residential space design plan, the E-SAGCNN approach is trained over the residential space design features.
- To reduce the design error, Butterfly optimization algorithm (BOA) is utilized to optimize the E-SAGCNN model.

2 Evaluation of Design Space

Integrating and parameterizing various design aspects is at the heart of generative architecture, as is the exploration of new generative principles for the building of homes. It is required to extract design attributes and links between functions and spatial layouts in both a single home and an entire typical floor in order to go ahead with parametrically designed house design schemes. By collecting floor plans of common apartment types and analyzing the routines of real residents, we may get a better understanding of the connections between room functions and spatial design [9]. Parametric linkages between building components, room functions, and spatial layouts allow generative house design to rapidly acquire a huge number of design schemes that suit the required spatial qualities. Algorithms streamline the process of assessing the energy consumption of many design options, allowing for a better-informed decision on which is best. Research shows that increasing a building's efficiency throughout the planning stages yields the best results [10]. Saving money on energy bills could be possible without increasing construction costs if the building's form, spatial organization, and envelope are designed and optimized utilizing an appropriate green design and optimization technique early in the design process. Parametric algorithms have enabled the automation of several hitherto manual design stages. This method is often known as generative design [11].

The phrase "generative design" was used in the 1870s to describe a "technology capable of producing realistic answers to a given situation" [12]. The phrase "generative design" first used in the context of architecture around the turn of the century. The authors point out that generative designers, like architects, employ computer-aided generative systems [13]. To characterize their method of "automated development of a huge number of designs using an iterative algorithmic framework while respecting user-defined criteria and restrictions," designers Kallioras and Lagaros developed the term "generative design" [14]. Architects need the ability to swiftly adjust to changing

conditions in the era of the Third Technical Revolution, when information, social status, and design approach are growing at unprecedented rates. Generative design research is at the forefront of today's technology scene. Swarm intelligence, cellular automata, genetic algorithms, L-systems, and form grammars are the five generative design methods. Researchers here largely relied on preexisting game optimization algorithms rather than creating their own throughout the design process [15]. With the goal of creating high-quality, photorealistic block textures for use in architectural visualizations and city planning, the researchers created City Engine using a set of methods and a generative language [16]. Information gathered about Nanjing's building supplies was used to construct an analytical language for the design of inhabited environments. The research expert created a method to automatically generate novel designs by analyzing complex systems [17]. As an example, ArchiGAN might account for the curvature of the structure to give adaptable design options. In order to help cities and towns make the most of their plans for economic development and conservation, XKool developed a smart planning system. There is a dearth of scholarly research on the topic of generative design for low-energy, environmentally friendly homes [18].

Computer algorithms are becoming more popular tools for architects. The researchers in this body of work demonstrate the expanding focus on optimization methods for environmentally friendly building layouts [19]. Several elements, such as WWR, window material, structural material, shading devices, etc., were taken into account in order to achieve maximum efficiency [20]. Algorithmic optimization of a tourist center's facade may decrease the building load by 11% and the average PPD by 8.3%. The research experts determined that two commercial buildings in Brisbane and Hobart might each see a 19% and 26% reduction in their energy usage and carbon footprint if they adopted an ant colony optimization technique [21]. The cooling burden on the facade was significantly reduced by the use of parametric design and building energy modeling to adjust the shading system. None of these prior efforts dealt with computational manufacture and optimization of individual building components within the context of a larger architectural plan.

Different strategies for BOP optimization have been compared and contrasted in a number of scholarly articles. In their research for sustainable design strategies, the researchers compared the evolutionary algorithm to the Hooke-Jeeves (JS) pattern search technique. The findings show that JS is more susceptible to becoming caught in local minima caused by discontinuities in the objective function than GA is [22]. Next, the scholars looked at a variety of techniques, including coordinate search, many forms of particle swarm optimization (PSO), including a hybrid JS-PSO approach, the Nelder-Mead simplex algorithm, and the discrete Armijo gradient algorithm. The hybrid JS-PSO strategy often delivered the best minimum, but at a larger computational cost, compared to the results obtained by GA, which were extremely near to the ideal minimum, according to two numerical simulations carried out in three separate cities. The expert analyzed the computational cost and efficiency of GA, PSO, and SS while optimizing a building's envelope and choosing an HVAC system [22]. At once, GA recognized the optimal answer, but both GA and PSO were just as patient and diligent as SS in their pursuit of a solution. The researchers discovered that GA outperformed PSO and SS when optimizing the building envelope of residential buildings when there were more than 10 design variables [23]. The researcher shown that using integer or discrete design components might cause inconsistencies and failures in the simulated building's performance [24]. Edge relies on parameters and nonlinear equations whose values may be experimentally obtained; hence this is vital

information. These voids complicate the use of optimization methods like gradient-based pattern search [25]. Taking into account GA's many benefits, we have settled on employing it to optimize a single variable at a time.

3. Materials and Method

The major goal of this research is to develop a novel edge-intelligence based deep learning model for efficiently predicting the mobile residential space design plan. The proposed methodology of this approach is illustrated in Figure 1. First, the typical design plans regarding existing residential space schemes are collected from Chinese database. Then, the significant design features were extracted using RNN-AE to reduce the complexity of spatial design planning. The proposed E-SAGCNN algorithm generates reliable design schemes for mobile residential space in China. To decrease the error rate in design prediction, the proposed model is optimized by BOA. The generated design schemes for mobile residential space are sent to Edge server for storage. Upon user request, design schemes for mobile residential space are sent to the authorized users for usage.

3.1 Residential Space Plan Collection

To develop design prediction model for Chinese mobile residential space, existing residential space designs are required to compile the design characteristics. The data for this study is gathered from a database consisting of three hundred typical residential space plans in northern cities in China. Based on Chinese construction regulations and regional regulatory needs, the database of typical residential space layouts was collected.

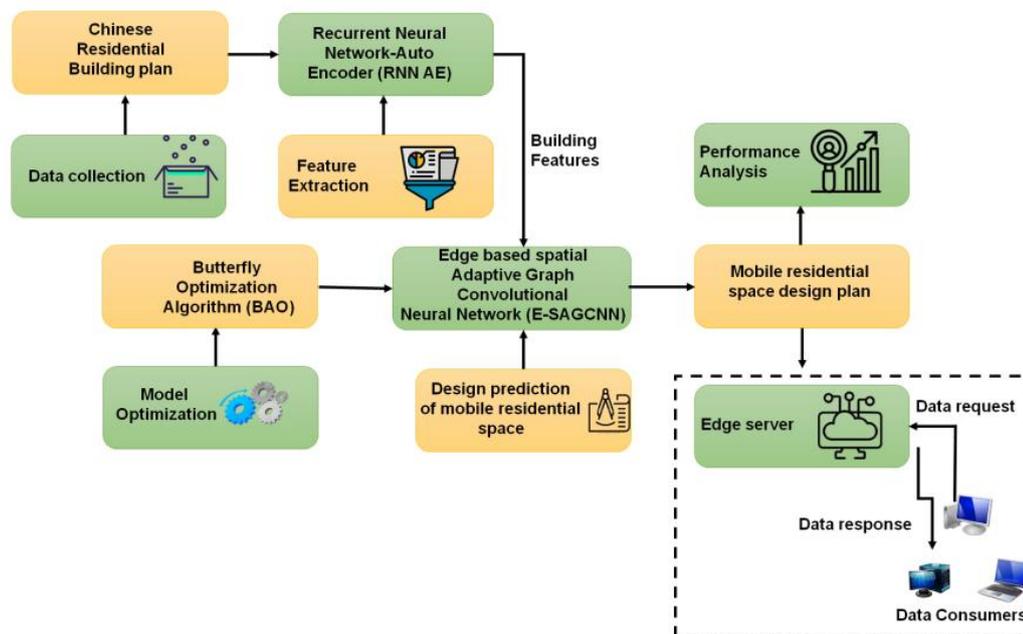


Figure 1: Mobile residential space design framework based on edge intelligence and deep Learning

3.2 Design feature extraction using recurrent neural network based auto-encoder (RNN-AE)

In mobile residential space design prediction, using original residential space data reduces prediction performance since these data include a greater level of irrelevant information. Instead of feeding

original residential space data to edge-intelligence based deep learning model, significant features extracted from the original residential space data can be used. To automatically extract significant residential space design features, RNN-AE is employed in this paper. An encoder and a decoder make up the RNN-AE. The encoder is made up of four RNN layers, and each RNN unit has the same number of hidden neurons as features in each feature category. Fig. 2 depicts the RNN AE layout.

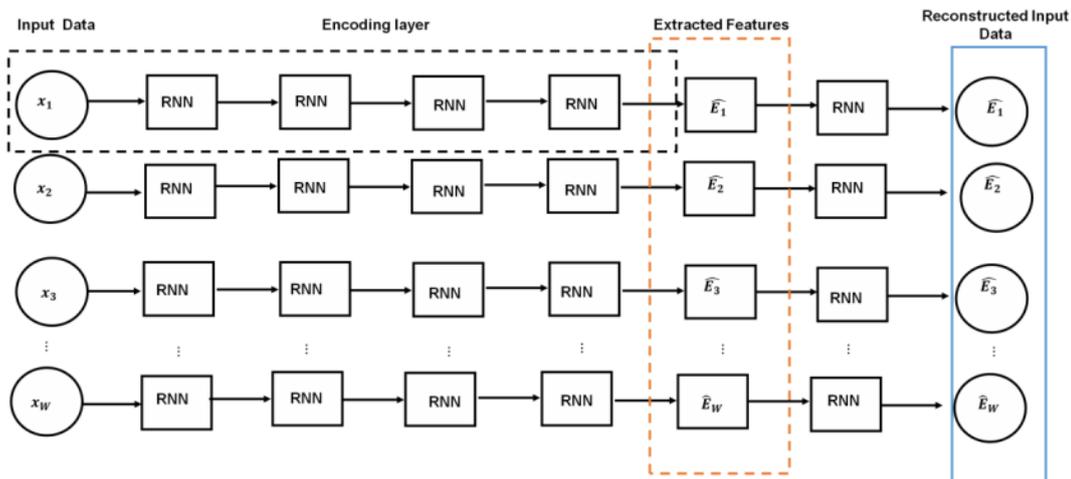


Figure 2: Layout of RNN AE

Hidden states are learning parameters in RNNs. These hidden states serve as the basis for a key to manage data for mobile residential spaces. They are updated throughout training using both the previous and most recent data. The hidden layer of conventional RNN updates the hidden state of current residential space design by Eq. (1).

$$g_w = \tanh (T_g g_{w-1} + T_x x_w + a_g) \tag{1}$$

Where w denotes the time, g_w and g_{w-1} represent the current and previous hidden state correspondingly, T_g and T_x mean the weight matrices for hidden state and input residential space data respectively, x_w is the input residential space data at time ‘w’, and a_g means the bias. The general output of RNN layer is defined by Eq. (2).

$$e_w = T_{ge} g_w + a_e \tag{2}$$

Where e_w means the output of RNN layer, g_w means the hidden state, T_{ge} represent the weight matrix, and $a_e^{(Enc)}$ denotes the bias.

But in our RNN-AE, the previous cell state d_{w-1} is also utilized in addition to g_{w-1} and x_w for updating the hidden state. In the encoding layers of RNN-AE, the dimensions are reduced, and the features are extracted. The current hidden state of the encoding layer is defined by Eq. (3).

$$g_w^{(Enc)} = RNN \left(x_w, g_{w-1}^{(Enc)} d_{w-1} \right) \tag{3}$$

Where $g_w^{(Enc)}$ and $g_{w-1}^{(Enc)}$ mean the current and previous hidden states of the encoding layer correspondingly, x_w is the input residential space data at time ‘w’, d_{w-1} means the previous cell state.

The output of the encoding layer at specific time is defined by Eq. (4). The output of the encoding layer denotes the set of significant mobile residential space design features.

$$e_w = T_{ge}^{(Enc)} g_w^{(Enc)} + a_e^{(Enc)} \tag{4}$$

Where e_w means the output of encoding layer, $g_w^{(Enc)}$ means the hidden states of the encoding layer, $T_{ge}^{(Enc)}$ represent the weight matrix, and $a_e^{(Enc)}$ denotes the bias for encoding layer.

The extracted mobile residential space design features obtained from encoding layer of RNN-AE are fed to the decoder. The decoding layer of RNN-AE consists of a single RNN layer. In the decoding layer, the dimensionally reduced design features are used to reconstruct the mobile residential space design data. The current hidden state of the decoding layer is defined by Eq. (5).

$$g_w^{(Dec)} = RNN \left(e_w, g_{w-1}^{(Dec)} d_{w-1} \right) \tag{5}$$

Where $g_w^{(Dec)}$ and $g_{w-1}^{(Dec)}$ mean the current and previous hidden states of the decoding layer correspondingly, e_w is the input residential space design feature at time 'w', d_{w-1} means the previous cell state.

The reconstructed mobile residential space design data (\hat{x}_w) resulted by decoding layer of RNN-AE is defined by Eq. (6).

$$\hat{x}_w = T_{\hat{g}_w}^{(Dec)} g_w^{(Dec)} + a_{\hat{x}}^{(Dec)} \tag{6}$$

Where \hat{x}_w means the output of decoding layer, $g_w^{(Dec)}$ means the hidden states of the decoding layer, $T_{\hat{g}_w}^{(Dec)}$ represent the weight matrix, and $a_{\hat{x}}^{(Dec)}$ denotes the bias for encoding layer.

The loss 'N' of RNN-AE based design feature extraction is defined as the total of mean squared error existing between the input residential space design data and the reconstructed residential space design data. The loss of RNN-AE is determined by Eq. (7).

$$N = \sum_w (x_w - \hat{x}_w)^2 \tag{7}$$

Where N denotes the loss, x_w denotes the input residential space design data to the RNN-AE, and \hat{x}_w means the reconstructed residential space design data.

3.3 Prediction of mobile residential space design by Edge-Based Spatial Adaptive Graph Convolutional Neural Network (E-SAGCNN)

E-SAGCNN is employed to generate efficient plan for mobile residential space design. Compared with traditional algorithms, the advantage of proposed model is that it avoids the complex processing. The reconstructed residential space design data obtained from RNN-AE are sent as input to E-SAGCNN for training. Initially, residential space design plans are processed by Convolutional operation. The convoluting kernel of size $k \times l$ for Convolutional operation is defined by Eq. (8).

$$T = \begin{bmatrix} t_{11} & t_{12} & \dots & t_{1l} \\ t_{21} & t_{22} & \dots & t_{2l} \\ \dots & \dots & \dots & \dots \\ t_{k1} & t_{k2} & \dots & t_{kl} \end{bmatrix}_{(k \times l)} \tag{8}$$

The process of convoluting design plan V is to multiply each t in the convolutional kernel T with the corresponding pixel v in the original design plan V to be covered and then summed. This process is defined by Eq. (9)

$$y = t_1 v_1 + t_2 v_2 + \dots + t_{kl} v_{kl} = \sum_{l=1}^{kl} t_l v_l = T^w V \tag{9}$$

Where t denotes the kernel value, v represents the pixel value, V means the residential design plan, and T denotes the Convolutional kernel matrix.

For an unprocessed design image with a convolution kernel of l, after ‘e’ convolution operations, the size of the output spatial design image is defined by Eq. (10).

$$I = [l - e] + 1 \tag{10}$$

Where I is the size of spatial design image after Convolutional operation, l denotes the size of convoluting kernel, and e means the number of Convolutional operations, Equation (11) specifies the dimensions of the final design image as a function of the convolutional step size, which is the slide's distance between two successive points.

$$I = \left\lfloor \frac{l-e}{u} \right\rfloor + 1 \tag{11}$$

Where u represents the step size, l the convoluting kernel's size, and e the number of iterations of the convolutional process.

Residential space design images suffer severe data loss at the image's boundaries if they are zoomed out, however this may be remedied by inserting "fake" pixels into the image's margins. If we assume that the fill pixel, is I then l becomes l+2i and the output image dimensions are given by Eq. (12)

$$I = \left\lfloor \frac{l+2i-e}{u} \right\rfloor + 1 \tag{12}$$

Where ‘i’ denotes the fill pixel. A valid convolution or the same convolution may be used to fill a pixel. After a proper Convolutional procedure, the resulting image will be scaled down as shown in equation 12. Kernel size is taken into account in Eq. (13) for the processed image acquired using the same Convolutional procedure.

$$\left\lfloor \frac{l+2i-e}{u} \right\rfloor + 1 = l \tag{13}$$

The result of the same Convolutional procedure on the processed picture will be scaled according to Eq. (14).

$$I = \frac{(l-1)u-l+e}{2} \tag{14}$$

Graphs are used as a storage medium for the processed data on residential space design that was acquired through the Convolutional method. Vector representations of nodes and subgraphs, as well

as global vector representations of graphs, are obtained by embedding them in a graph neural network layer. Eq. (15) modifies the vectors of subgraphs.

$$v_p^{(w+1)} = v_p^{(w)} + \sum_{q \in L(p)} v_{pq}^{(w)} \tag{15}$$

After the training is complete, we will be able to isolate subgraphs that have a significant bearing on the final score and constitute a solid design. Every single sample plot is then shown after being transferred to high-dimensional spaces. Finally, the plan for the design of mobile residential space is shown in the output layer of E-SAGCNN.

3.4 Butterfly optimization algorithm (BOA)

The E-SAGCNN methodology is optimized with the help of the Butterfly optimization algorithm (BOA). In 2019, Arora and Singh presented BOA, a novel meta-heuristic optimization method that mimics the nectar-seeking and mating behavior of real butterflies. For purposes of BOA, it is believed that butterflies produce a scent of a certain strength. This aroma is connected to the solution's objective function is defined in Eq. (16), and may be computed as follows:

$$e_p = d \times P^b \tag{16}$$

where e_p stands for the fragrance, P for the stimulus strength, d and b for the constant. BOA consists of a startup phase, iteration phases, and a termination phase. The initialization process creates the parameter settings and population. The iteration process includes two sub-steps: a global search and a local search. The mathematical formulation for the global search phase is as follows:

$$V_p(w + 1) = v_p(w) + (o^2 \times h^* - V_p(w) \times e_p) \tag{17}$$

the w^{th} butterfly's location is represented by V_p , the iteration number is w, $o \in [0,1]$ is a random integer, h^* is the global optimum, and e_p is the fragrance. The formulation of the local search phase is as follows:

$$V_p(w + 1) = v_p(w) + (o^2 \times V_q(w) - V_m(w)) \times e_p \tag{18}$$

Where V_p and V_m refer to the q^{th} and m^{th} butterflies in the population respectively. In BOA, the equations (17) and (18) from the previous paragraph are solved as follows:

$$\begin{cases} V_p(w + 1) = v_p(w) + (o^2 \times h^* - V_p(w) \times e_p) \text{ if } o < I \\ V_p(w + 1) = v_p(w) + (o^2 \times V_q(w) - V_m(w)) \times e_p \text{ otherwise} \end{cases} \tag{19}$$

where I is a constant between 0 and 1 (refer Equation (19)). By solving the following Eq. (20), we may get a new value for d.

$$D(w + 1) = d(w) + 0.025 / (d(w) \times \text{MaxIter}) \tag{20}$$

In this case, MaxIter is the maximum allowed number of iterations. The design plan which is generated using the proposed method is stored in the edge server. If the customer requests for the plan, the edge server will send the required plan to the customer.

4. Results and Discussion

The effectiveness of an E-SAGCNN-created mobile residential space plan is discussed in this section. The performance of the proposed method is analyzed and compared with certain existing methodologies such as “Multi Intelligent Decision Making (MIDM) approach” [26], “Parametric generative algorithm (PGA)” [27], “Sensitivity analysis and genetic algorithm (SA-GA)” [28]. Design accessibility means that the mobile residential space design we made with the help of our proposed method can be used, understood, and navigated by users with different levels of skill. Figure 3 and Table 1 depicts the accessibility comparison of the proposed methodology with the conventional methodology. Figure 3 clearly shows that the proposed methodology is easily accessible to people of various levels when compared to conventional methods.

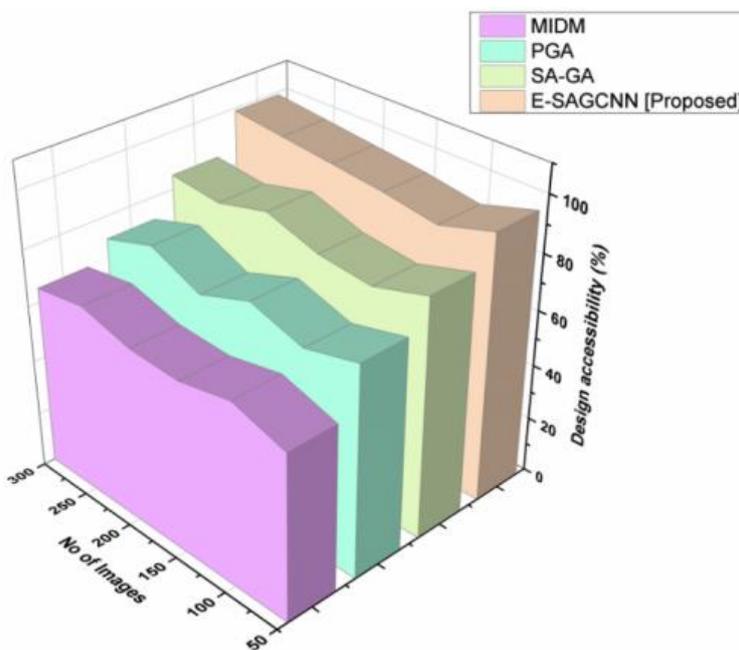


Figure 3: Design Accessibility

Table 1: Computation analysis of design accessibility

No of Images	Methods			
	MIDM	PGA	SA-GA	E-SAGCNN [Proposed]
50	60	76	86	96
100	66	71	80	90
150	62	77	82	93
200	63	70	88	95
250	68	78	83	97
300	65	72	85	99

From Figure 3 and Table 1, it is evidently proved that the design accessibility of the proposed work is more when compared to the existing works. On an average of 300 images, the proposed work possess 99% of accessibility while the existing MIDM possess 65%, PGA with 72% and SA-Ga with 85%.The overall amount spent on designing and implementing a mobile residential space design is

referred to as implementation costs. The proposed approach's implementation costs are contrasted with those of the traditional methodology in Fig.4 and Table 2. Fig.4 demonstrates unequivocally that, in comparison to traditional approaches, the proposed methodology incurs much lower implementation costs.

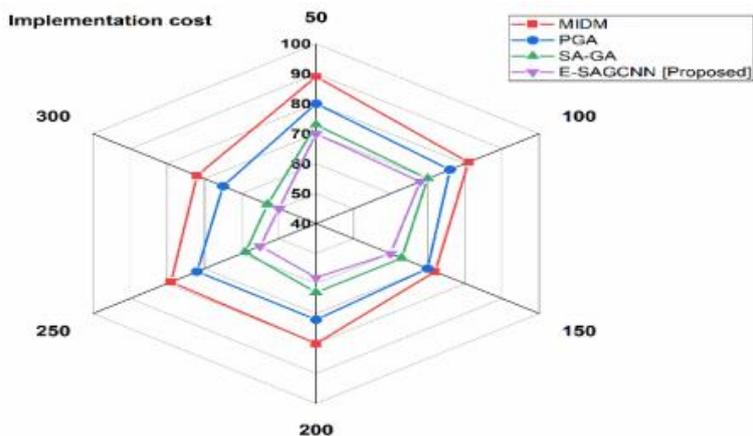


Figure 4: Implementation Cost

Table 2: Computation analysis of implementation cost

No of Images	Methods			
	MIDM	PGA	SA-GA	E-SAGCNN [Proposed]
50	89	80	73	70
100	81	76	70	68
150	72	70	63	60
200	80	72	63	58
250	79	72	59	55
300	72	65	53	50

The implementation of the proposed work is much easier when compared to the existing work and possess minimal computational cost as illustrated in Table 2 and Figure 4. The proposed work exhibits a computation cost of 50ms for 300 images while the existing MIDM, PGA and SA-GA experiences 72ms, 65ms and 53ms respectively. The design accuracy of a generated mobile residential space refers to how accurate the design is. The concept of "trueness" describes how close a value is to either the actual value or a reference standard. Fig. 5 and Table3 provide a comparison between the proposed method's accuracy in design and the traditional techniques' accuracy in design. Fig.5 makes it abundantly evident that the proposed technique has the highest design accuracy in comparison to the traditional methods.

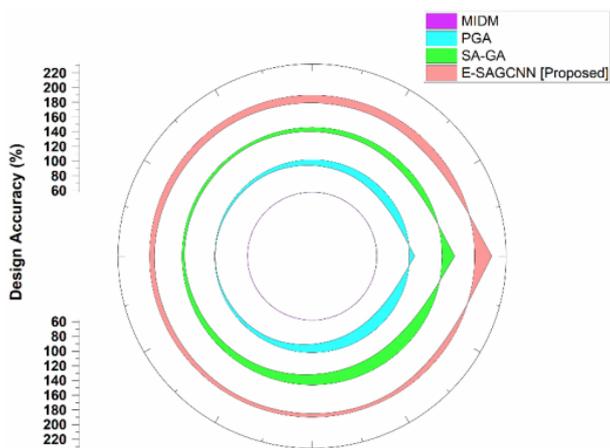


Figure 5: Design accuracy
Figure 5: Design accuracy

Table 3: Computation analysis of design accuracy

No of Images	Methods			
	MIDM	PGA	SA-GA	E-SAGCNN [Proposed]
50	58	65	75	81
100	65	72	85	89
150	70	79	89	91
200	72	85	90	94
250	65	78	82	96
300	58	65	72	98

The accuracy of the proposed work is more when analyzed against the existing MIDM, PGA and SA-GA. The proposed method of E-SAGCNN exhibits 98% of accuracy while the existing MIDM, PGA and SA-GA experiences 58%, 65% and 72% of accuracy which is very low for a range of 300 images. The term "energy consumption" refers to the total amount of energy needed to finish a mobile residential space design. Multiplying the number of power units used over a certain time period is a standard way to express energy consumption. Fig.6 and Table 4 compare the proposed technique to the existing approaches in terms of its energy usage. Clearly, the energy consumption of the proposed approach is lower than that of the conventional method, as shown in the Fig.6.

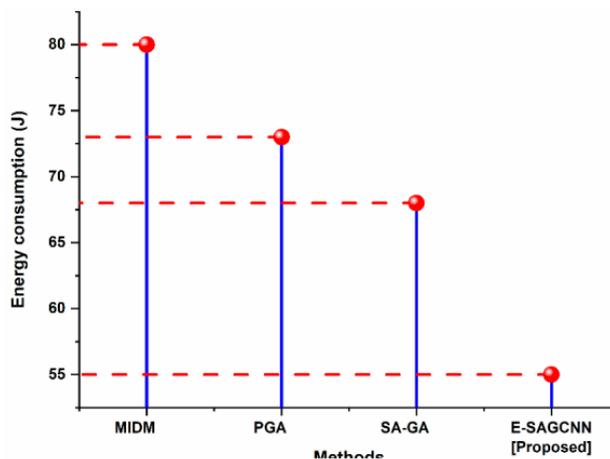


Figure 6: Energy Consumption

Table 4: Computation analysis of energy consumption

Methods	Energy Consumption (J)
MIDM	80
PGA	73
SA-GA	68
E-SAGCNN [Proposed]	55

Energy consumption of the system determines the life time of the system. In this way, the proposed work consumes a reduced energy of 55J while the existing methods consumes 80J by MIDM, 73J by PGA and 68J by SA-GA methodologies. The term "Design Reliability" refers to a set of techniques used by engineers to make their mobile residential space design as reliable as possible. Function, usage conditions, and acceptable risk at various times should all be spelled out in detail in order to describe the dependability criteria. A comparison of the proposed method's dependability to that of more traditional approaches is shown in Fig.7 and Table 5. Fig.7 clearly demonstrates how the proposed solution outperforms the status quo in terms of design dependability.

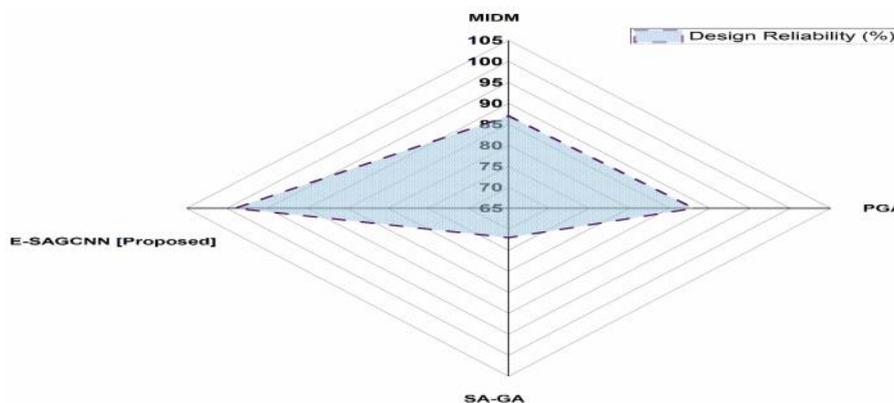


Figure 7: Design reliability

Table 5: Computation analysis of design reliability

Methods	Design Reliability (%)
MIDM	87
PGA	88
SA-GA	72
E-SAGCNN [Proposed]	99

The time required to carry out a planning operation is referred to as the "planning time". Fig.8 and Table 6 displays a planning time comparison of the proposed method with that of the conventional methods. Fig.8 clearly shows that the proposed method computes lesser time for planning an operation when compared to traditional methods.

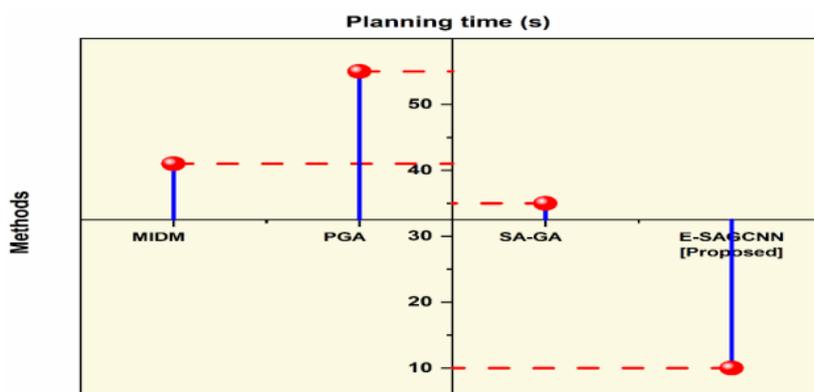


Figure 8: Planning Time

Table 6: Computational analysis of planning time

Methods	Planning Time (s)
MIDM	41
PGA	55
SA-GA	35
E-SAGCNN [Proposed]	10

The term "planning error" refers to either the inability to carry out a planned activity as anticipated (error of execution) or the selection of an inappropriate design plan for accomplishing a certain objective (i.e., error of planning). The proposed approach and the standard methods are compared with regard to their effect on planning errors, as shown in Fig.9 and Table 7. As can be seen in the illustration, the proposed technique results in less inaccuracy when calculating the plan for an operation than do the conventional methods.

Table 7: Computational analysis of planning error

Methods	Planning Error (%)
MIDM	33
PGA	25
SA-GA	16
E-SAGCNN [Proposed]	8

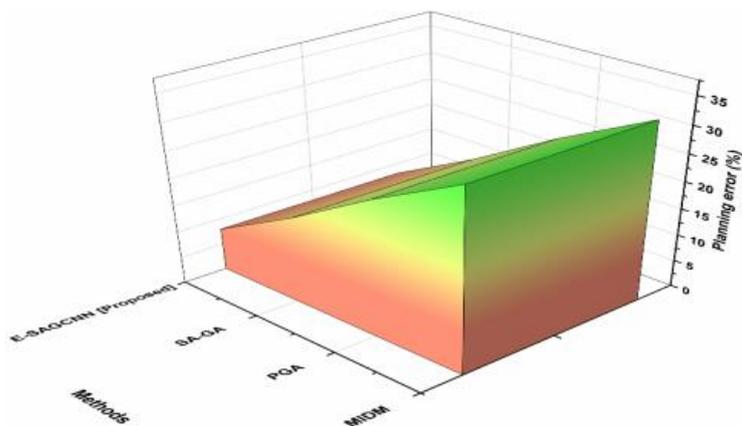


Figure 9: Planning error

Complexity is defined as the degree of uncertainty in the design of a mobile residential space in meeting functional requirements. A comparison of the complexity of the proposed technique with the standard methods is shown in Fig.10 and Table 8. The graphic illustrates how the proposed strategy reduces computational complexity in comparison to the status quo. The scalability of an artificial intelligence algorithm is impacted by its computational complexity in several manners. Initially, if an algorithm is excessively intricate, it could present challenges during its implementation on a sizeable scale. Secondly, if an algorithm is not easily scalable, it could pose difficulties in its training when dealing with an extensive dataset.

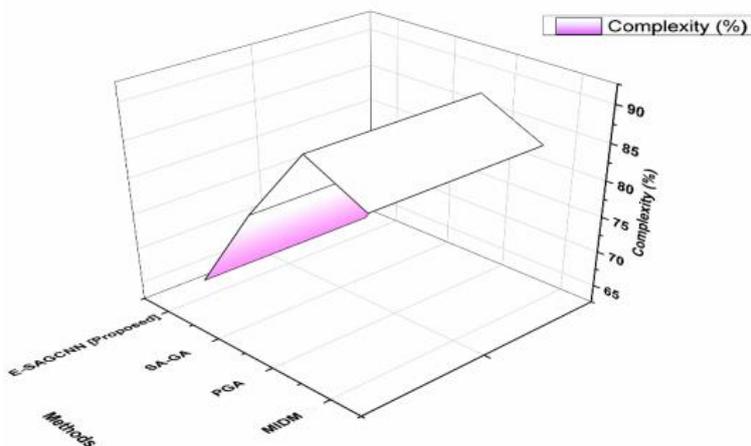


Figure 10: Complexity comparison

Table 8: Computational analysis of complexity

Methods	Complexity (%)
MIDM	85
PGA	89
SA-GA	78
E-SAGCNN [Proposed]	65

Artificial intelligence algorithm results in residential planning space division and moving line planning have been achieved, and have received high subjective evaluation results from the audience.

However, the edge intelligence based algorithm has integrated fields such as space art design, soft decoration design for the home, art for the home, construction design for decorations, and so on. This study provides a clear analysis of utilization of mobile residential design space in commercial building plan.

5. Conclusion

People's expectations for mobile residential space layout have increased as living circumstances have improved. However, the current mobile residential space design techniques have a number of drawbacks, and designing a new one will take a lot of time and effort. To address these issues, we developed edge-intelligence based deep learning model named E-SAGCNN to generate mobile residential space layout in this study. We compared the efficiency of the proposed model in mobile residential space layout planning with existing design algorithms. It is observed that E-SAGCNN predicts the mobile residential space layout with lesser energy, time, implementation cost, computational complexity, and design error. The proposed work exhibits a better performance with 99% of accessibility, computational cost of 50sec, 98% accuracy, 55J of energy consumption, 99% of design reliability, planning time and error with 10s and 8% and a complexity of 65%. Moreover, the mobile residential space layout generated by the proposed E-SAGCNN is highly accurate with less design errors. This might be due to RNN-AE based design feature extraction and E-SAGCNN model optimization by BOA. The study results proved that proposed model has provided an accuracy of 98%. The limitations of this research are utilization of less residential design images for the study. In the future, we must analyze the efficacy of the model with increased number of residential design images.

References

- [1] Y. Z. YapingZheng, "Research on cloud-edge joint task inference algorithm in edge intelligence," *Journal of Computer Science*, vol. 32, no. 4, pp. 211–224, 2021.
- [2] Pandi Selvam, R., Jayasankar, T., Kiruba Buri, R., Maheswaravenkatesh, P. (2024). "Optimal Mixed Kernel Extreme Learning Machine-Based Intrusion Detection System For Secure Intelligent Edge Computing" *Reconnoitering the Landscape of Edge Intelligence in Healthcare* , pp.231-248.
- [3] F. Foukalas and A. Tziouvaras, "Edge AI for industrial IoT applications," *IEEE Industrial Electronics Magazine*, vol. 15, no. 2, pp. 28-36, 2021.
- [4] R. Firouzi, R. Rahmani, and T. Kanter, "Context-based reasoning through fuzzy logic for edge intelligence," *Journal of Ubiquitous Systems and Pervasive Networks*, vol. 15, no. 01, pp. 17–25, 2021.
- [5] V. Mittal, A. Tyagi, and B. Bhushan, "Smart surveillance systems with edge intelligence: convergence of deep learning and edge computing," in *Proc. Of ICICC*, New Delhi, pp. 1-5, 2020.
- [6] S. Premkumar and A. N. Sigappi, "Processing capacity based decision mechanism edge computing model for iot applications," *Computational Intelligence*, vol. 22, no. 4, pp.1-22, 2022.
- [7] N. Harth, C. Anagnostopoulos, and D. Pezaros, "Predictive intelligence to the edge: impact on edge analytics," *Evolving Systems*, vol. 9, no. 2, pp. 95–118, 2017.
- [8] M. Castiglioni, D. Ferraioli, N. Gatti, and G. Landriani, "Election manipulation on social networks: seeding, edge removal, edge addition," *Journal of Artificial Intelligence Research*, vol. 71, no. 21, pp. 1049–1090, 2021.
- [9] Md. Z. Uddin and E. G. Nilsson, "Emotion recognition using speech and neural structured learning to facilitate edge intelligence," *Engineering Applications of Artificial Intelligence*, vol. 94, no. 11, pp. 103775, 2020.
- [10] N. Ath. Kallioras and N. D. Lagaros, "DzAIN: Deep learning based generative design," *Procedia Manufacturing*, vol. 44, no. 12, pp. 591–598, 2020.
- [11] D. Newton, "Generative deep learning in architectural design," *Technology/Architecture + Design*, vol. 3, no. 2, pp. 176–189, 2019.

- [12] U.G. Lee, S.H. Kang, J.C. Lee, S.Y. Choi, U. Choi, and C.I. Lim, "Development of deep learning-based art learning support tool: using generative modeling," *Korean Association for Educational Information and Media*, vol. 26, no. 1, pp. 207–236, 2020.
- [13] Y. Malhotra, "AI, machine learning & deep learning risk management & controls: beyond deep learning and generative adversarial networks: model risk management in AI, machine learning & deep learning," in *Proc. of Armed Forces Communications and Electronics Association (AFCEA) C4I and Cyber Conference*, New York, pp.1-7, 2018.
- [14] H. Ishikawa, "Set-based design using deep learning network," in *Proc. of Design & Systems Conference*, Japan, p. 2401, 2020.
- [15] M. Padmaa, T. Jayasankar, S. Venkatraman, Ashit Kumar Dutta, Deepak Gupta, Shahab Shamshirband, Joel J.P.C. Rodrigues, "Oppositional Chaos Game Optimization Based Clustering with Trust Based Data Transmission Protocol For Intelligent IoT Edge Systems", *Journal of Parallel and Distributed Computing*, vol.164, 2022, pp.142-151. <https://doi.org/10.1016/j.jpdc.2022.03.008>
- [16] Q. Fu and H. Wang, "Aeroenginestate prediction based on generative adversarial networks and deep learning," *International Journal of Computer Aided Engineering and Technology*, vol. 15, no. 4, p. 486-500, 2021.
- [17] C. Chen, X. Zhao, and M. C. Stamm, "Generative adversarial attacks against deep-learning-based camera model identification," *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 5, pp. 99, 2019.
- [18] H. Tembine, "Deep Learning Meets Game Theory: Bregman-based algorithms for interactive deep generative adversarial networks," *IEEE Transactions on Cybernetics*, vol. 50, no. 3, pp. 1132–1145, 2019.
- [19] S. Kannan, Prabakaran. D, Dhenesh Kumar S and Shivaraj S, "A Deep Learning-Based Convolution Neural Networks to Forecast Wind Energy," *2023 International Conference on Recent Trends in Electronics and Communication (ICRTEC)*, Mysore, India, 2023, pp. 1-6.
- [20] X. Wang, Y. Song, and P. Tang, "Generative urban design using shape grammar and block morphological analysis," *Frontiers of Architectural Research*, vol. 9, no. 4, pp. 914-924, 2020.
- [21] I. Caetano, L. Santos, and A. Leitão, "Computational design in architecture: defining parametric, generative, and algorithmic design," *Frontiers of Architectural Research*, vol. 9, no. 2, pp. 287–300, 2020.
- [22] C.J. Lin, "The STG-framework: A pattern-based algorithmic framework for developing generative models of parametric architectural design at the conceptual design stage," *Computer-Aided Design and Applications*, vol. 15, no. 5, pp. 653–660, 2018.
- [23] C.J. Lin, "Developing narrative diagrams for algorithmic modeling of architectural parametric design," *Computer-Aided Design and Applications*, vol. 17, no. 2, pp. 447–457, 2019.
- [24] T. Wortmann and B. Tunçer, "Differentiating parametric design: digital workflows in contemporary architecture and construction," *Design Studies*, vol. 52, no. 41, pp. 173–197, 2017.
- [25] Y. Wan, "Research on the influence of theme restaurant interior design on users' consumption behavior based on the layout of interior environment space," *E3S Web of Conferences*, vol. 251, no. 45, p. 02025, China, 2021.
- [26] Y. Wu, "Architectural interior design and space layout optimization method based on vr and 5g technology," *Journal of Sensors*, vol. 2022, no. 1, pp. 1–10, 2022.
- [27] J. Dong and M. Ran, "Research on interior design and space layout optimization based on multi-intelligent decision-making," *Journal of Sensors*, vol. 2022, no. 3, pp. 1–10, 2022.
- [28] J. Zhang, N. Liu and S. Wang, "Generative design and performance optimization of residential buildings based on parametric algorithm," *Energy and Buildings*, vol. 244, no.1, p.111033, 2021.
- [29] F. Bre, A.S. Silva, E. Ghisi and V.D. Fachinotti, "Residential building design optimisation using sensitivity analysis and genetic algorithm," *Energy and Buildings*, vol. 133, no.1, pp.853-866, 2016.