Research Article

Research on the Application of a Universal Design Model for Urban Healthy Living Based on Artificial Intelligence Computing

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Along with the continuous improvement of living standard, people gradually improve the design quality of urban living space and require the living space to meet the standard of health design concept. This paper mainly focuses on the health concept of urban living space design, briefly elaborates on the health design concept of living space, and designs a soft furnishing layout model based on DBN according to the advantages of deep confidence network compared with BP neural network. The effect of the two models in the practical application of soft furnishing layout is explored, which is very important for the practical application.

1. Introduction

With the accelerating speed of urbanization, people’s requirements for the comfort, safety, and greenness of urban living space are gradually increasing [1]. It is found that whether the design of living space meets people’s health standards directly determines the degree of people’s dependence on living space and largely affects the physical and mental health of the occupants. However, the design of living space based on health concept, on the basis of living space design standards, highlights the health design elements of living space, which can maximize the satisfaction of people’s psychological, visual, and sensory requirements of living space and create a comfortable and healthy environment for people’s life [2].

In the design of the health concept of urban living space, on the basis of the design standard of the living place, the health design in the living place should be improved to the maximum extent, so as to ensure that people can feel the taste of health from various aspects such as vision, feeling, and touch and promote the development of the health design of urban living space, gradually improve the design quality of urban living space, and create a comfortable and warm environment for people’s life and study [3, 4]. Therefore, when designing the health concept of urban living space, the design should be based on residential design standards and should be designed with the health concept in all aspects, so as to add more comfort to the life of the occupants. In addition, the design of health concept includes the layout of living space, spatial scale, social space, and the treatment between indoor living space and natural environment [5, 6]. Different functions should be designed according to the different objects of use, and the interconnection and independence of each function should be considered, and different service facilities should be set up for different functions. For example, more sofas and chairs should be set in the public activities of family members to meet the needs of more people [7].

The health design of urban living spaces requires in-depth design in terms of comfort, safety, environmental protection, and neighborhood interaction [8].

In the safety design of urban living space, safety is a deep design based on the psychology of the occupants, which includes safety in a narrow sense and safety in a broad sense [9]. First of all, among the safety-related factors of residential buildings, the safety awareness and privacy protection of occupants are the focus of people’s attention. Therefore, when designing the health of living space, it is necessary to consider not only the physical scale of the residential space but also the psychological feelings of the occupants. On the premise of ensuring the physical safety of the occupants, the internal precautionary factors should be fully addressed. It
can be used to set up semi-private, semi-public, and public areas of living space to solve the privacy of the occupants, improve their security precautions, and make the occupants feel reliable and safe in the residence [10].

Indoor living environment refers to the designer’s use of space according to the nature of the occupants, through the use of the necessary architectural technology and artistic means, to construct an indoor space environment that meets both the functional use and the physiological and psychological needs of the occupants. Therefore, the design process needs to consider the relationship between people and the environment [11]. The relationship between people and the environment is mutual, and a healthy and complete indoor environment should not only have sufficient light and ventilation but also consider the occupants’ requirements for privacy, rest, and entertainment in the living environment. The social status of people includes public distance, social distance, personal distance, and intimate distance, and a healthy indoor living environment needs to meet different levels of social status so that people can live together harmoniously [12].

To sum up, in the design of healthy urban living space, it is necessary to design different living styles for different occupants in order to meet the comfort and suitability of residential space for the occupants and thus promote the sustainable development of healthy living space [13, 14].

2. The Use of Color in Interior Decoration

2.1. Color Selection from the Whole. The interior design industry in China has been developing rapidly as people’s demand for quality of life has increased and the emphasis on interior design has been on style, and the design education industry has also made great strides. In the interior design industry, there are inherent principles for choosing the color of a house. In the theory of interior decoration, the color of the interior of a house is determined by the overall needs of the client and the overall style of the design. A reasonable grasp of color can ensure a balanced design of the interior decoration style [15].

2.2. Color Selection in Line with the Function of the House. Regardless of the social and economic development, the purpose of housing construction is always to provide the residents with a place to complete their living and living requirements. In the construction of housing, the housing construction is generally divided into different functional areas to avoid the interference of different living functional areas with each other and reduce the functionality of the housing [16]. This requires the designers to have a certain psychological basis, to understand the psychological activities of the occupants under different functions and different behaviors, and to choose the color suitable for the behavior in the functional area, which can relatively promote the efficiency of the different behaviors of the occupants.

2.3. Color Matching to Ensure Focus. In the overall decoration of a house, the choice of colors should not only meet the overall style requirements but also ensure that there are different colors for each functional area, which requires different color choices in different areas. In fact, in the color selection and style design of architectural interiors, designers should ensure that the focus of the color is highlighted; whether it is a variety of different colors or different color schemes within the same area, the overall design should highlight the focus and meet the overall design style [17].

2.4. Color Selection of Furniture and Decorations. In addition to the choice of color for the walls and soft furnishings to ensure the overall decoration style, the appropriate choice of furniture in the actual decoration process can also ensure the unity of the building decoration style. In addition to the walls, furniture and curtains occupy the largest space in the house decoration, and the choice of color and shape of these furniture items can make the design of the room more prominent and ensure the focus of the design [18].

3. Model Design

3.1. Model Structure. A deep confidence network [19] is a probabilistic generative model with a deep network structure, using a similar structure to that of traditional neural networks, containing an input layer, an implicit layer, and an output layer. The network structure is a multilayer perceptron network composed of multiple restricted Boltzmann machine network structures, with full connectivity between two adjacent layers, and the neural units in each layer are independent states and not connected to each other [20, 21].

In this paper, the advantages of DBN over BP neural network are considered comprehensively, and a soft furnishing layout network model based on DBN is designed, and the model structure is shown in Figure 1. The training process of neural network can be seen essentially as the process of neural network simulating the work of human brain, and the network learns the features of training data so as to achieve the function of prediction, for learning features from the whole network structure, from abstract to concrete, and the features become more relevant as the learning of features continues. The implicit layer is mainly for learning and extracting the features in the data; if the number of implicit layers is too small, then the prediction result of the model is not better than the traditional neural network, and if the number of implicit layers is too many, it will cause the problem of workload growth of the whole network, and the learning efficiency of the whole network will be reduced, so this paper determines the number of implicit layers of the network as three layers.

The DBN model combines a multilayer RBM structure with a supervised learning BP neural network to improve the performance of the overall model. However, the RBM network can only optimize the connection weights and biases of each layer of the network model but cannot guarantee that the parameters of the whole network model are optimal, so a supervised learning BP neural network is added to the top layer of the network structure to optimize the parameters of the whole network structure. The network parameters are preprocessed by RBM, and then the entire
DBN model is fine-tuned by BP neural network to optimize the network structure so that different types of data features can be learned [8].

3.2. Model Training. The training process of the DBN-based soft-fitting layout model contains the training process of RBM and the training process of DBN. For the training of RBM, the contrast scattering method (CD) is used to prevent the model from obtaining local minima, and the model training time can be reduced at the same time [11], and the specific training steps are as follows:

(1) Initialize the connection weights of the visible and hidden layers of the model, initialize the biases of the neural units in the hidden and visible layers, and set the number of hidden layers, the number of nodes in the hidden layer, and the learning rate and the number of training rounds of the model.

(2) Input the training data through the neural unit states of the visible layer and calculate the neural unit states of the implicit layer of the model according to the following equation:

\[ P(h_{j=1}|v, \theta) = \sigma \left( b_j + \sum_{i=1}^{n} v_i w_{ij} \right) \]  

(1)

(3) The neural unit states of the visible layer of the model are reconstructed according to equation (1) from the neural unit states of the implicit layer of the model calculated in step (2).

\[ P(v_{j=1}|v, \theta) = \sigma \left( a_j + \sum_{j=1}^{m} h_j w_{ij} \right) \]  

(2)

(4) Calculate the connection weights and biases of the model at time \( t + 1 \) by updating the connection weights \( w_{ij} \) between the visible and hidden layers, the bias \( a_j \) of the visible layer neurons, and the bias \( b_j \) of the hidden layer neurons for time \( t \) using equation (2).

\[
\begin{align*}
W^{t+1} &= W^t + \eta \left( p(H^0 = 1|V^0, \theta') (V^0)^T - p(H^1 = 1|V^1, \theta') (V^1)^T \right), \\
\alpha^{t+1} &= \alpha^t + \eta (V^0 - V^1), \\
b^{t+1} &= b^t + \eta \left( p(H^0 = 1|V^0, \theta') - p(H^1 = 1|V^1, \theta') \right).
\end{align*}
\]  

(3)

(5) By iteratively executing steps (2) and (3), the training is stopped when the number of training rounds is set or reached, and the parameters of the network model are the optimal values learned at this time.

The training structure of DBN is shown in Figure 2. The specific training process is as follows:

(1) The RBM layer is trained by CD algorithm [9] in a layer-by-layer greedy manner to calculate the structural
parameters of the model, and the hidden layer of the RBM in the third layer is connected to the BP neural network to obtain the initial output data of the model, which ends the forward training phase of the model, and this process can be regarded as the initialization of the parameters of the deep confidence network.

(2) In the training process of the forward pass phase, the model structure parameters of the RBM layer reach the optimum of the connection weights and bias of each layer, but not the optimum of the parameters of the whole network model, so the network model parameters are updated through the BP network. The output of the BP network is calculated through training, and the error is calculated based on the output value and the true value of the sample data, and the network structure parameters of the RBM are updated layer by layer [5], and the adjustment algorithm used is the conjugate gradient calculation method, which continuously adjusts and predicts the weights and bias matrix of the model and stops training when it meets the number of training rounds set by the network.

4. Experimental Analysis of DBN-Based Soft Furnishing Layout Model

4.1. Evaluation Metrics. In this paper, two different evaluation metrics are introduced to measure the performance of the deep confidence network model for soft furnishing layout design prediction. The two evaluation metrics are mean squared error (MSE) and mean absolute error (MAE). MSE and MAE are used to evaluate the model from the perspective of prediction error of soft furnishing layout, which reflects the error of the whole model prediction and can indicate the level of model prediction ability. The calculation formula of evaluation index is as follows:

\[
\text{MSE}(y, \tilde{y}) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \tilde{y}_i)^2, \quad \text{MAE}(y, \tilde{y}) = \frac{1}{n} \sum_{i=1}^{n} |y_i - \tilde{y}_i|.
\]  

4.2. Experimental Setup. This experiment uses the soft furnishing layout dataset after feature engineering processing. According to the soft furnishing design characteristics and room structure, the experiment divides the dataset into two categories, which are bedroom dataset and living room dataset. After processing the dataset with feature engineering, the bedroom dataset is divided into a mouth-type dataset and an L-type dataset according to the room structure, and the living room dataset is divided into a vertical hall-type dataset and a horizontal hall-type dataset according to the room structure. The datasets of each part are trained separately, and the experimental results shown by the evaluation metrics are used to analyze the effect of the deep confidence network-based soft furnishing layout model on soft furnishing layout prediction.

4.3. Analysis of Experimental Results. The experimental results were divided into 4 parts according to the dataset, namely, mouth-shaped bedroom, L-shaped bedroom, vertical hall living room, and horizontal hall living room. The MAE and MSE evaluation metrics were introduced using the mouth-shaped bedroom dataset as training data, and Table 1 shows the results of the layout prediction evaluation metrics of the deep confidence network-based soft furnishing layout model for the mouth-shaped bedroom. Compared with the evaluation indexes of the BP neural network model, the bed x-coordinate MAE is reduced from 7.063625 to 0.282644, MSE is reduced from 68.723175 to 0.133098, and the evaluation indexes of other parameters are also very small, and the prediction effect has been improved substantially. Overall, the deep confidence network model has a better prediction effect on the soft furnishing layout of the mouth-shaped bedroom, and the experimental results perform better than the BP neural network model. Figure 3 shows the MAE evaluation index of the mouth-shaped bedroom, and Figure 4 shows the MSE evaluation index of the mouth-shaped bedroom; it can be seen from the figure that there is a significant convergence after 5 iterations of the network, the convergence speed is better than the BP neural network model, and the overall MAE and MSE evaluation indexes after 30 iterations are smaller than those the BP neural network model.

Table 2 shows the prediction results of L-shaped bedroom soft decoration layout parameters. Figure 5 shows the MAE evaluation index of the L-shaped bedroom, and Figure 6 shows the MSE evaluation index of the L-shaped bedroom, from which it can be seen that the MAE index stabilizes after 3 iterations of the network, and the MSE stabilizes after 5 iterations of the network. Although the convergence speed is slightly worse than that of the BP neural network model, the trend of all the parameter evaluation indicators decreases steadily, and there is no problem of obvious differentiation of the evaluation indicators of the BP neural network model.

4.4. Model Practical Application Test. In order to verify the prediction performance of the DBN soft furnishing layout model designed in this paper in real applications and to

| Table 1: Mouth-shaped bedroom assessment index. |
|-----------------------------------------------|
| Parameter            | MAE     | MSE     |
| bed_poiind_x         | 0.282644| 0.133098|
| bed_poiind_y         | 0.262455| 0.135302|
| bed_vec_x            | 0.146789| 0.000823|
| bed_vec_y            | 0.118812| 0.001985|
| Wardrobe_point_x     | 1.248489| 0.038538|
| Wardrobe_point_y     | 0.158600| 0.002989|
| Wardrobe_vec_x       | 0.127318| 0.000420|
| Wardrobe_vec_y       | 0.018882| 0.000553|

The experiments are implemented on Windows platform with Core I7 6800K processor and GTX1080TI graphics card, and the software part involves feature engineering and modeling and application with the help of sklearn, Keras, and TensorFlow modules in Python language.
compare the prediction effect of the BP neural network soft furnishing layout model in real applications, real bedroom and living room soft furnishing design data are used for soft furnishing layout prediction, and the prediction results are input to the dresser platform for visualization output through JSON files. The model predictions were compared with the real soft furnishing design data, and the application test was divided into four parts, namely, mouth-shaped bedroom, L-shaped bedroom, vertical living room, and

| Parameter         | MAE   | MSE   |
|-------------------|-------|-------|
| bed_point_x       | 0.512984  | 9.395217 |
| bed_point_y       | 0.104472  | 0.017197  |
| bed_vec_x         | 0.155106  | 0.006467  |
| bed_vec_y         | 0.065128  | 0.943446  |
| Wardrobe_point_x  | 0.943446  | 0.254954  |
| Wardrobe_point_y  | 0.408047  | 0.035467  |
| Wardrobe_vec_x    | 0.180931  | 0.052701  |
| Wardrobe_vec_y    | 0.157025  | 0.043023  |

Table 2: L-shaped bedroom assessment indicators.

| Feature name | Design scheme data | BP neural network prediction data | DBN forecast data |
|--------------|--------------------|----------------------------------|------------------|
| Bed point    | (−182.21, 184.58)  | (−182.21, 181.98)               | (−182.21, 183.18) |
| Bed orientation | (1, 0)          | (1, 0)                          | (1, 0)            |
| Wardrobe point | (−182.21, −157.11) | (−182.21, −156.58)       | (−182.21, −157.08) |
| Wardrobe orientation | (0, 1)       | (0, 1)                          | (0, 1)            |

Table 3: Comparison of soft furnishing layout data for portrait bedrooms.
horizontal living room. For each section, predictions were made by two network models, and the results were compared with the actual design solutions.

After the model output prediction results, the layout prediction of the mouth-shaped bedroom by the deep confidence network-based soft furnishing layout model and the layout prediction of the mouth-shaped bedroom by the BP neural network-based soft furnishing layout model were obtained. The comparative information of the design solution data and model prediction results are shown in Table 3. According to the results in Table 3, the prediction results of the deep confidence network-based soft furnishing layout model and the design scheme data are very small, and the prediction is closer to the real design scheme data than the BP neural network-based soft furnishing layout model,
and the performance of the deep confidence network model is better than that of the BP neural network model for the soft furnishing layout prediction of the orifice bedroom. The output of the BIM system shows the schematic diagram of the room structure of the orifice bedroom, the design plan is shown in Figure 7, the prediction plan of the BP neural network model is shown in Figure 8, the prediction plan of the DBN model is shown in Figure 9, and the 3D rendering of the DBN model is shown in Figure 10.

After the model output prediction results, the soft furnishing layout model based on deep confidence network predicts the layout of L-shaped bedrooms and the soft furnishing layout model based on BP neural network predicts the layout of L-shaped bedrooms. The deep confidence network-based soft furnishing layout model is also closer to the real design data, and the soft furnishing layout prediction performance for L-shaped bedrooms is better than that of
the BP neural network model. The output of dressing home BIM system shows the schematic diagram of L-shaped bedroom room structure. The design plan is shown in Figure 11, the prediction plan of BP neural network model is shown in Figure 12, the prediction plan of DBN model is shown in Figure 13, and the 3D rendering of DBN model is shown in Figure 14.

The results of the soft furnishing layout model based on the deep confidence network are similar to the data of the design scheme, and the prediction error of the sofa combination in the functional area of the living room is very small. Also, the layout prediction of the soft furnishing layout model based on deep confidence network is closer to the real design scheme data; although the BP neural network model predicts the soft furnishing layout of the vertical living room very well, it is slightly worse than the deep confidence network model. The output of the dressing house BIM system shows the room structure schematic and the design plan of the vertical living room. The prediction plan of the BP neural network model is shown in Figure 15, the prediction plan of the DBN model is shown in Figure 16, and the prediction 3D rendering of the DBN model is shown in Figure 17.

5. Conclusions

With the development of economy, people’s living standard has been improving, and people are gradually paying attention to the overall experience of living instead of just the comfort of the house. In this paper, we design a DBN-based soft furnishing layout model to meet the requirements of people’s house matching. Firstly, the design of the deep confidence network model is introduced to explore the effect of the model in the practical application of soft furnishing layout, which is very important for the practical application. The design style is determined according to the owner’s requirements, identity, and hobbies, and the color of each functional area of the room is selected separately using the psychological viewpoint to achieve the unity of function and decoration.

Data Availability

The dataset used to support the findings of this study is available from the corresponding author upon request.
Conflicts of Interest

The authors declare that they have no conflicts of interest.

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