An Application of Graph Neural Network Model Design for Residential Building Layout Design

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Abstract—In the current process of residential building layout design, there are problems such as low design efficiency, excessive manual intervention, and difficulty in meeting personalized needs. To address these issues, a residential building layout design method based on graph neural network model is proposed to improve the intelligence level of residential building layout design. Firstly, the residential building floor plan layout design data are transformed into graph data suitable for graph neural network model processing. Then, deep learning techniques are used to analyse and identify the spatial distribution characteristics of the main functional areas in the space. Finally, the trained graph neural network model is applied to the actual residential building floor plan layout design and compared with the traditional method. The experimental results show that compared with the traditional computer-aided design method, the residential building floor plan layout design and optimisation method improves the completeness of the design scheme by about 2.3%, the rationality by about 3.6%, the readability by about 1.9%, and the effectiveness by about 10.3%. The method improves the efficiency and accuracy of residential building floor plan layout design, helps to shorten the design cycle and reduce the design cost, and helps to promote technological progress and sustainable development in the field of architectural design.

Keywords—Residential building layout plan; deep learning; GNN model; space utilization rate; resident comfort level; quantum particle swarm algorithm; Node2vec algorithm

I. INTRODUCTION

With the rapid development of social economy and the acceleration of urbanisation, the demand for residential buildings is increasing, and the floor plan layout design, as an important part of residential building design, directly affects the comfort, functionality and aesthetics of the residence [1]. The traditional floor plan layout design of residential buildings mainly relies on the experience and professional knowledge of designers, which is limited by the personal ability and experience accumulation of designers, and the design efficiency and accuracy are relatively low, and it is difficult to ensure the innovation and uniqueness of the design scheme [2]. In recent years, the development of artificial intelligence technology has provided new possibilities for residential building plan layout design [3]. Among them, the graph neural network (GNN) model, as a kind of neural network that can effectively process graphical data, has achieved remarkable results in the fields of computer vision, natural language processing, and recommender systems [4, 5]. However, in the field of residential building layout design, the application of GNN model is still in its infancy. Most existing research focuses on simple spatial relationship modeling, and there are still shortcomings in comprehensively considering various factors such as complex functional requirements, user preferences, and diverse building codes in residential buildings. In addition, how to build an efficient and accurate GNN architecture that can fully adapt to the special requirements of residential building layout design and achieve automatic generation and optimization of design schemes is still an urgent problem to be solved. The research aims to fill these research gaps by exploring the application of graph neural network models in residential building layout design, constructing more comprehensive and practical design models, and improving the quality and efficiency of residential building layout design, bringing new vitality and innovation to the field of residential building design. The study is divided into four parts: the first part is a summary of related studies; the second part is the design of the GNN model for residential building floor plan layout design, which is validated in the third part; and the fourth part is a summary of the whole study. The innovativeness of the study is mainly reflected in the following aspects The study of applying GNN to residential building floor plan layout design provides a new intelligent method for residential building floor plan layout design. Secondly, the study constructed a GNN model applicable to residential building floor plan layout design and optimised it with a large amount of training data, which improved the design efficiency and accuracy; finally, the GNN model was applied to actual design cases, which achieved significant design results.

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II. RELATED WORKS

GNN is a neural network that can efficiently process graphical data and automatically learn the structural and relational information in graphical data. Wang et al. proposed a quaternion-based social recommendation knowledge graph neural network, which reduces the parameters during training through the expressibility of quaternion and the weight sharing mechanism of the Hamilton product, and also employs explicit and implicit social relationship integration algorithms to solve the problem of users' social relationship data sparsity problem. Experimental results show that the model can achieve up to 85% recommendation accuracy in study [6]. Huang's group proposes a dynamic spatio-temporal graph neural network model (DSTGNN) to capture the dynamics and dependencies in traffic demand forecasting by constructing a spatial dependency graph. The results show that DSTGNN outperforms existing models in traffic demand prediction on two real datasets [7]. Rusek's group proposes a novel GNN-based network model to understand the complex relationships between topology, routing, and input flows, and to predict key performance indicators. The model was experimentally shown to be accurate up to 88% in predicting delay distribution, jitter and loss [8]. Lee et al. proposed a new human activity recognition model that combines a pre-trained model and a GNN to effectively overcome the sparsity of radar data. The results showed that the method achieved 96% accuracy in five different human activity classifications [9]. A related study proposes a scalable network slice digital twin based on the GNN model to capture intertwining relationships between slices and monitor end-to-end metrics. Experiments demonstrate that the method accurately reflects network behaviour and predicts latency in various topologies and new environments [10].

Graphic layout design is a design method to achieve an efficient, aesthetically pleasing and comfortable spatial environment by rationally arranging spatial elements. Li et al. proposed an attribute-conditional layout method for solving the problem of design element position and size in graphic layout design while considering element attribute constraints. The method was experimentally demonstrated to be effective in synthesising graphic layouts under different element attribute conditions and supports layout adjustment and original reading order preservation [11]. Murchie's group proposes a graphic design methodology based on the science of communicating vision and provides a high-level overview of terms related to layout, images, fonts, and colours. The method was able to increase graphic design satisfaction by 13% and helped to facilitate research collaboration between scientists and designers [12]. Stephan et al. used a mathematical planning approach to achieve optimal use of urban space by optimising car park layouts. The trade-off between high resolution and computational effort was explored by comparing orthogonal parking mixed integer programs at different resolutions. Experimental results show that the application of the optimised car park design scheme improves the effectiveness by 10% [13]. Boysen's team optimises the layout design of moving walkways through dynamic planning, which effectively improves the total travel time under several relevant extended constraints. The results showed that the method could reduce the total pedestrian travel time by 13% [14]. Wan team members targeted to propose a web page layout aesthetic assessment by automatically predicting the aesthetics of web page layouts based on an improved Adaboost algorithm. Experiments proved the superiority of the model in predicting the aesthetics of web page layouts [15].

In summary, existing research on GNN has achieved significant results in various fields such as social recommendation, transportation demand prediction, network performance indicator prediction, and human activity recognition, demonstrating the powerful ability of GNN to process graphical data structures and relational information. In terms of graphic layout design, although there are various methods such as attribute conditional layout, design based on scientific communication vision, mathematical programming optimization of parking lot layout, dynamic programming of mobile sidewalk layout, and aesthetic evaluation of webpage layout, these studies mostly focus on specific types of layout design or specific optimization objectives. At present, there is a lack of an effective model that deeply applies the powerful graphic data processing capabilities of GNN to residential building layout design, and fails to fully utilize GNN to explore the complex structural and relational information between residential building spatial elements to achieve more comprehensive, intelligent, and universal optimization of residential building layout design. Therefore, the study proposes a GNN model for residential building layout design, aiming to provide intelligent methods for residential building layout design and promote technological progress in the field of architectural design.

III. GNN Model for Residential Building Layout Design

This paper discusses the data acquisition, pre-processing and analysis of residential building floor plan layouts using BIM technology. A layout design method based on GNN and deep learning is proposed to improve space utilisation and occupant comfort. Finally, the quantum particle swarm algorithm is used to optimise the layout design and transform it into a composite model to further enhance the design.

A. Spatial Data Processing of Residential Building Plan Layout

Residential building floor plan layout data acquisition and pre-processing is an important part of the BIM field, which involves the digital modelling of building space and provides basic data for building design, construction and operation [16]. Before carrying out the residential building plan layout, the functional area spatial data need to be collected and processed in order to extract the distribution characteristics of the layout space. The spatial data processing process of residential building plan is shown in Fig. 1.

The data format of spatial layout information mainly includes the location, size, and shape of building floor plans and related functional areas. Specifically, the data will include information such as the coordinates, area, and shape of each functional area. The input of the model is raw spatial data, and the output is processed and analyzed spatial distribution feature information. During the processing, it may be necessary to replace the classification code to adapt to the new data structure and analysis requirements. Finally, the processed data will be verified to ensure its quality [17]. The information entropy of spatial distribution characteristics of the main functional area is shown in Eq. (1).

$$\delta = -\sum_{i=1}^{n}\left(\frac{S_n}{S_0}\right)\ln\left(\frac{S_n}{S_0}\right) \tag{1}$$

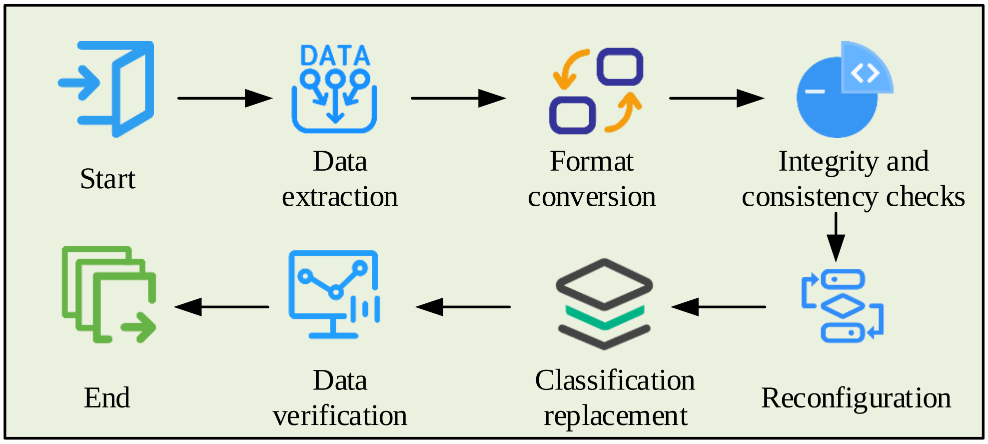

Fig. 1. The data processing process of residential building floor plan space.

In Eq. (2), the measure of spatial functional area land is η and the number of its types is N. The measure of spatial functional area land use can be realised by calculating the equilibrium degree, which takes the value range of [0, 1]. If the equilibrium degree is 0, it means that the use of land in the functional area is unbalanced; if the equilibrium degree is 1, it means that the use of land has reached the ideal equilibrium state. Through this metric, the development of land in the spatial functional area can be better understood and assessed [19]. The morphological characteristics of the main functional zone distribution of the building plan contain shape rate and compactness, and the shape rate of each functional zone is shown in Eq. (3).

$$\lambda = \frac{S_1}{L^2} \tag{3}$$

In Eq. (3), the shape rate of each functional area is λ, the area of the functional area region is S_1, and the length of the region is L. Shape rate is an important indicator to describe the morphological characteristics of the distribution of the main functional area, if the value is small, it means that the area shows obvious belt-like characteristics; if the value is large, it indicates that the distribution of the main functional area in the area is block-like. The compactness of the main functional area is shown in Eq. (4).

$$\mu = \frac{S_1}{S_1^{'}} \tag{4}$$

In Eq. (4), the compactness of each functional area is μ, and the minimum external circle area of functional area is $S_1^{'}$. Subsequently, the study analyses and identifies the spatial distribution characteristics of the main functional zones in the space through the deep neural network technology, and the deep neural network of spatial distribution of the main functional zones in the building plan is shown in Fig. 2.

The spatially relevant feature points of the residential building plan are extracted by deep neural network, and the functional area feature index parameters are calculated as shown in Eq. (5).

$$A = b + \frac{w}{r(s-w)} \tag{5}$$

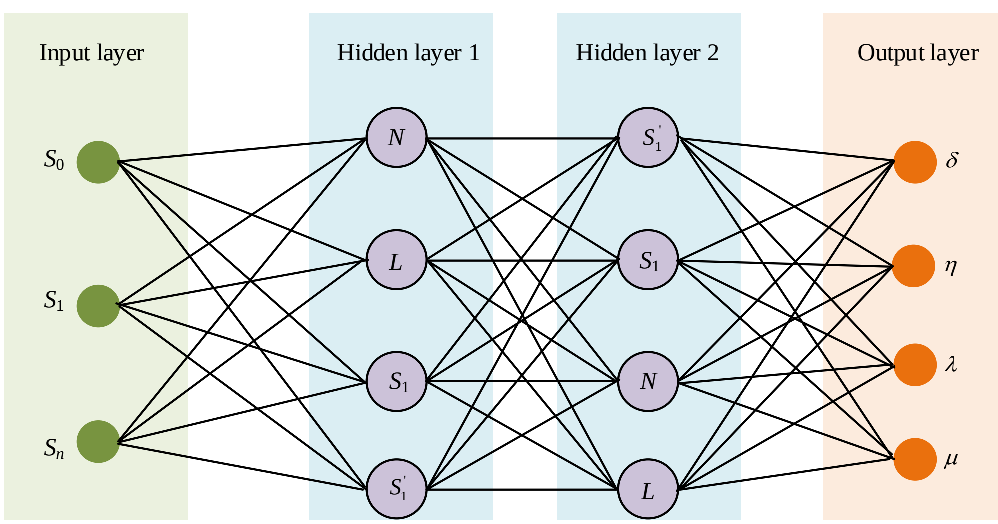

Fig. 2. Deep neural network for spatial distribution of main functional areas in architectural plans.

In Eq. (5), the feature indicator parameter is A, the upper limit value of feature is b, the optimisation coefficient of feature parameter is r, the distribution range is s, and the lower limit value of feature is w. The corresponding feature value index parameters are calculated and the results of the layout feature extraction of the functional area are evaluated. If the result exceeds the preset value range, it indicates that there is an abnormality in the feature extraction and it is necessary to carry out the extraction again. On the contrary, it can be considered that the layout feature extraction results are suitable for layout optimisation design, and the subsequent operations can be continued.

In summary, the study successfully extracted the spatial distribution characteristics of the main functional area by processing and analyzing spatial data using deep neural network technology. Then, using information entropy and spatial functional area land measurement methods, evaluate the development status of land in each functional area. In addition, by calculating the shape ratio and compactness of the main functional area, we have gained a better understanding of the development of the spatial functional area land. The research method not only improves the accuracy of residential building layout design, but also provides effective basis for subsequent layout optimization design.

B. Residential Building Layout Design and Optimisation Methods

Unlike traditional deep learning models, GNN acquires information about graph data by learning the relationships between nodes [20]. The mathematical representation of the graph structure is shown in Eq. (6).

$$G=\langle V,E\rangle \tag{6}$$

In Eq. (6), the graph structure is G, the set of nodes of the graph structure is $V=[v_1,v_2,\ldots,v_i]$, and the set of all edges of the graph structure is $E=[e_{11},e_{12},\ldots,e_{ij}]$. The radius subgraph of the nodes is shown in Eq. (7).

$$v_i^{(r)}=(V_i^{(r)},E_i^{(r)}) \tag{7}$$

In Eq. (7), the subgraph of node v_i within the radius r is $v_i^{(r)}$. The radius subgraph of an edge is shown in Eq. (8).

$$e_{ij}^{(r)}=(V_i^{(r-1)}\cup V_j^{(r-1)},E_i^{(r)}\cup E_j^{(r)}) \tag{8}$$

In Eq. (8), the subgraph of edge e_{ij} within radius r is $e_{ij}^{(r)}$. After random initialisation by supervised learning, the node radius subgraphs and edge radius subgraphs are trained by backpropagation. The node embedding representation is updated as shown in Eq. (9).

$$v_i^{(t+1)}=\sigma(v_i^{(t)}+\sum\nolimits_{j\in N(i)}h_{ij}^{(t)}) \tag{9}$$

In Eq. (9), the node embedding is denoted as $v_i^{(t)}$, the Sigmoid function is σ, and the set of neighbours of the node is $N(i)$. The hidden neighbour vector is $h_{ij}^{(t)}$ and its calculation is shown in Eq. (10).

$$h_{ij}^{(t)}=f\left(W_{neighbor}\left[v_j^{(t)},e_{ij}^{(t)}\right]^T+b_{neighbor}\right) \tag{10}$$

In Eq. (10), the nonlinear activation function of the neural network is f, the hidden neighbour weight matrix is $W_{neighbor}\left[v_j^{(t)},e_{ij}^{(t)}\right]^T$, the neighbour offset vector is $b_{neighbor}$, and the edge embedding vector of node $v_i^{(t)}$ and node $v_j^{(t)}$ at time t is $e_{ij}^{(t)}$. The edge embedding vector is updated as shown in Eq. (11).

$$e_{ij}^{(t+1)}=\sigma(e_{ij}^{(t)}+f\left(W_{side}\left(v_i^{(t)},v_j^{(t)}\right)+b_{side}\right)) \tag{11}$$

In Eq. (11), the edge vector update weight matrix is $W_{side}\left(v_i^{(t)},v_j^{(t)}\right)$ and the edge embedding vector offset vector is b_{side}. The final output obtained is shown in Eq. (12).

$$y_{build}=\frac{1}{|V|}\sum\nolimits_{i=1}^{|V|}v_i^{(t)} \tag{12}$$

In Eq. (12), the final output is y_{build} and the number of all nodes is $|V|$. The loss function for residential building prediction is shown in Eq. (13).

$$loss=\sqrt{\frac{1}{m}\sum\nolimits_{i=1}^{n}W_{reg}(y_i-y_{build})} \tag{13}$$

In Eq. (13), the loss function is $loss$, the regression weight matrix is W_{reg}, the actual score of the samples is y_i, and the number of samples is m. The Node2vec algorithm is an unsupervised machine learning model based on graph embedding, which represents similarity or proximity between nodes by sampling their neighbours in a random wandering manner and mapping the nodes to a high-dimensional space. The Node2vec algorithm borrows from the word2vec algorithm in natural language processing, considering each node in the graph as a word in the text and a sequence of nodes as a sentence in the text. The algorithm mainly solves the problem of how to generate a sequence of nodes starting from an initialised node. The optimisation objective of the Node2vec algorithm is shown in Eq. (14).

$$\max_f \sum\nolimits_{v\in V}\log\Pr(N_s(u)|f(u)) \tag{14}$$

In Eq. (14), the node mapping function is $f(u)$ and the set of nearest neighbour points of a node is $N_s(u)$. The GNN-based residential building plan layout design model is shown in Fig. 3.

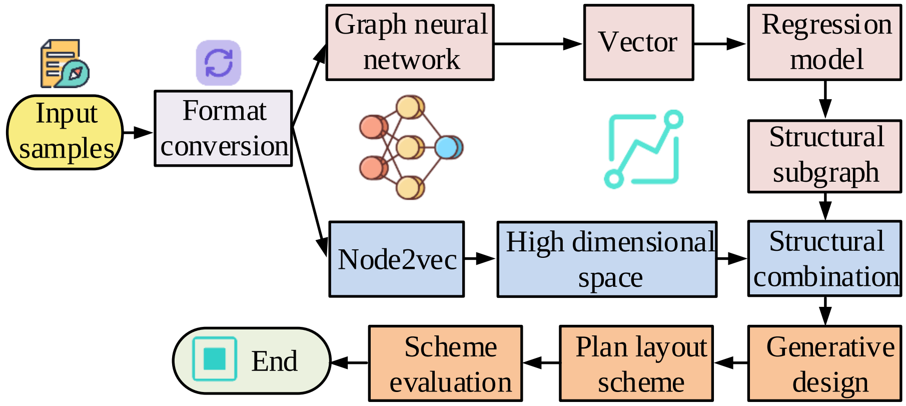

Fig. 3. A residential building layout design model based on GNN.

The residential building floor plan layout design model uses a graph data structure to encode and analyse building floor plans. The graph neural networks involved include Graph Convolutional Neural Networks (GCN) and Graph Attention Networks (GAN). In this model, nodes represent rooms, and node attributes include type, etc.; edges represent connectivity relationships between rooms, such as door connections, open connections, or vertical connections (e.g., stairs, ramps, or lifts). Through supervised learning, the model uses GNN to embed nodes and subgraphs to obtain the corresponding vector representation and the vector representation of the whole graph. Then, the linear regression model assigns weights to the subgraphs to minimise the error between the predicted score and the true score. After training, the subgraphs that have a high impact on the scores are extracted as good design elements. The unsupervised learning part uses the node2vec algorithm to map the sample graph into a high-dimensional space and visualise it to show potential relationships between nodes. This approach provides useful suggestions for subgraph combination, i.e., which nodes should be connected together in the final design. In the structure combination phase, the model identifies the basic modules (subgraphs) and then combines them into a new graph. This process can be achieved by adding new edges and additional nodes. Finally, the validity of the generated design solution is manually evaluated. After obtaining a new diagram that conforms to the design, the model converts the diagram into a residential building plan layout. Overall, the GNN-based residential building floor plan layout design model effectively integrates supervised and unsupervised learning, which helps to generate innovative and design-compliant floor plan layout solutions. The GNN structure used for subgraph construction is shown in Fig. 4.

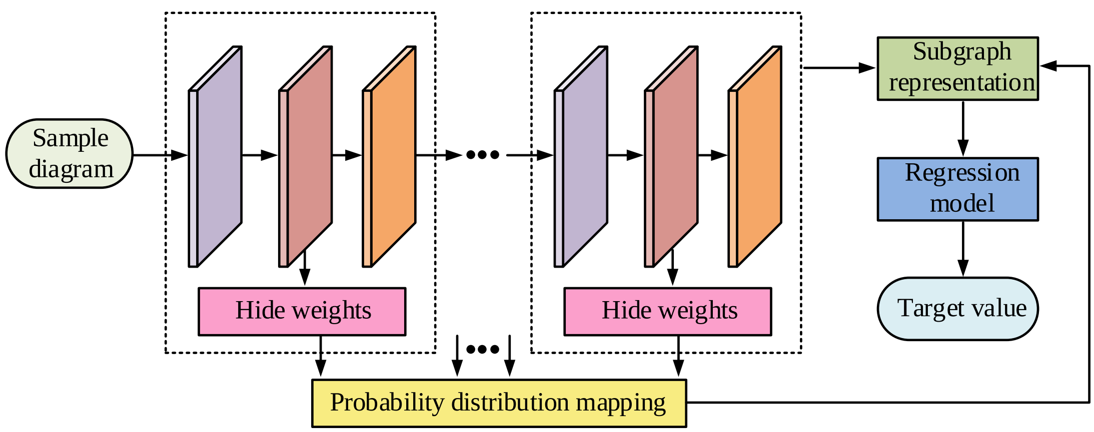

Fig. 4. GNN structure for subgraph construction.

Each layer of the GNN structure used to discover constructed subgraphs consists of neurons that hold real-valued representations of node attributes. In each layer, a convolutional operation processes the node attributes, multiplying the result by the hidden weights and mapping it to a probability distribution via a non-linear function to obtain a potential representation vector. The probability of each layer is related to the objective function score, and subgraph patterns are discovered by accumulating and remembering the neighbourhood contributions of the nodes. The subgraph vector is updated as shown in Eq. (15).

$$x_i^{(t+1)} = x_i^{(t)} + \sum_{j \in N(i)} x_{ij}^{(t)} \tag{15}$$

In Eq. (15), the subplot vector at the time of t is $x_i^{(t)}$ and the subplot vector at the time of $t+1$ after updating is $x_i^{(t+1)}$. The initialisation process of the subplot vector of the residential building plan is shown in Fig. 5.

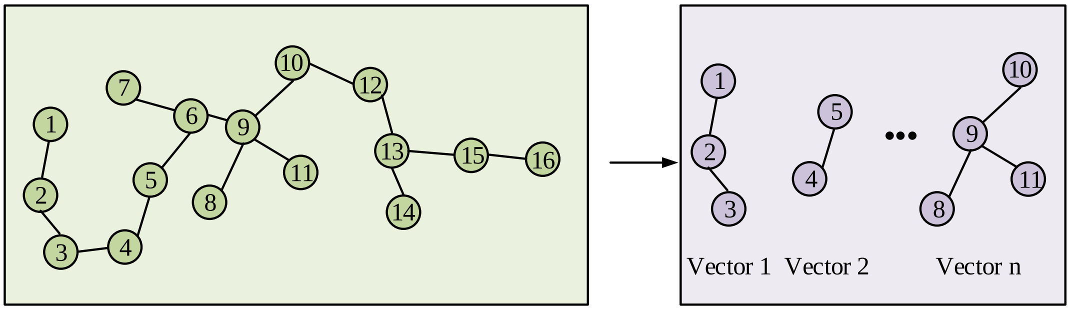

Fig. 5. The initialisation process of subgraph vectors in residential building plans.

The objective of the residential building floor plan layout design optimisation method is to maximise the space utilisation of the residential building while improving the comfort of the occupants, subject to the constraints [21]. The residential building floor plan layout design optimisation method is based on the quantum particle swarm algorithm, which achieves the goal by optimising two factors: the coordination of the layout design and the design cost. The optimisation model transforms the complex layout problem into the form of a composite model, which takes into account a variety of factors such as land type, functional area type, and adjacency. In the solution process, the optimal solution is searched by continuously updating the particle velocity and position, and the preset convergence conditions are satisfied. The final optimal layout design results obtained can be used to guide the actual residential building plan layout design.

IV. Analysis of the Application of Residential Building Layout Design Methods

The content of this chapter focuses on the analysis of data processing, feature extraction and application of design optimisation methods to residential building plan layout images. Firstly, the images in the ScanNet dataset are processed and converted. Then, the frequency and distribution features of different spatial types are analysed. Then, the GNN model performance is evaluated by experimenting different parameters using neural networks and Adam optimiser for training. Finally, the public space layout is optimised by quantum particle swarm algorithm.

A. Analysis of Data Collection and Pre-processing Effects

The experimental environment of the residential building floor plan layout design method includes the following: first, in the software environment, BIM software is used for data acquisition and pre-processing, such as Revit and AutoCAD. This software can help to acquire the relevant information of the building and to organise and process the data. It is also necessary to use deep learning frameworks, such as TensorFlow, PyTorch, etc., for data processing and analysis for model training and prediction. In terms of the hardware environment, we need to use a high-performance computer or server for data processing and model training. Specific configurations include high-speed CPU, high-capacity memory and high-performance graphics card to ensure the efficiency and accuracy of data processing and model training. The programming language uses Python as the main programming language, combined with the corresponding deep learning libraries and APIs of building information modelling software for data processing and model training. The storage device uses high-speed hard discs or solid-state hard discs as the data storage device to improve the data reading and writing speed and model training efficiency. The study selects residential building plan layout images as the raw data for data processing on the ScanNet dataset, and the data conversion processing effect is shown in Fig. 6.

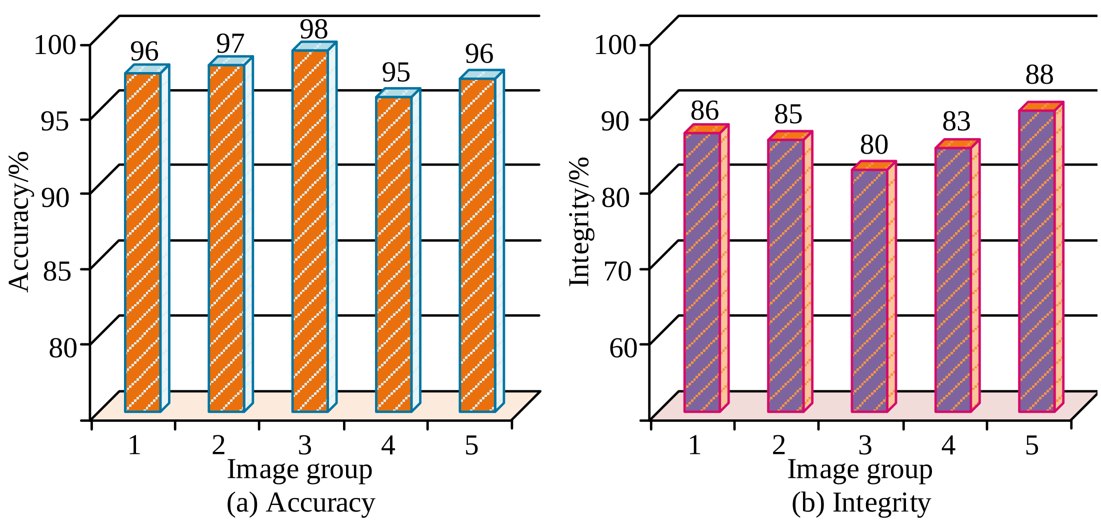

Fig. 6. Data conversion processing effect.

The image grouping in Fig. 6(a) is the random division of the 150 residential building floor plan layout image samples obtained from the ScanNet dataset into five groups of 30 sample images each shows the accuracy of the data conversion, with an average accuracy of up to 96.4%. It indicates that there are very few errors and deviations in the data conversion process, and most of the image samples can maintain a high degree of consistency and accuracy in the conversion process. Fig. 6(b) shows the completeness of data conversion, and the average completeness can reach 84.4%. In the data conversion process, the important information and features of the overall sub-image samples can be retained and reproduced. Comprehensively, the effect of data conversion processing is quite remarkable, with excellent performance in both accuracy and completeness indicators, which lays a solid foundation for further data analysis and processing. The study will contain 24 of the 30 data samples for training and cross-validation, using grid search to adjust the combination of hyperparameters, and the other 6 samples as a test set. The results of feature extraction for residential building plan layout images are shown in Fig. 7.

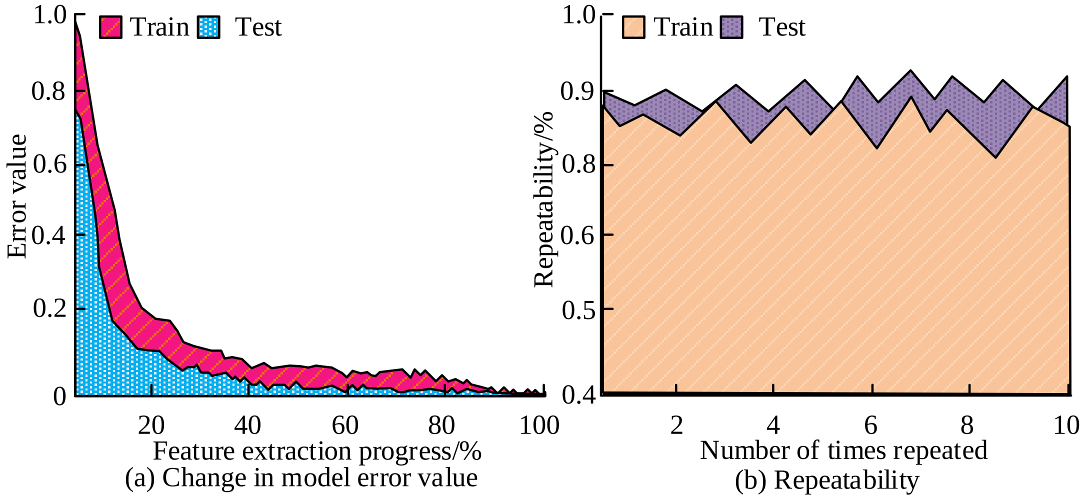

Fig. 7. The effect of feature extraction on residential building layout images.

Fig. 7(a) shows the variation of error values of residential building floor plan layout image feature extraction, and the error values of training and testing tend to be stable in the range of 0-0.01. Fig. 7(b) shows the repeatability test results of residential building floor plan layout image feature extraction, and the repeatability averages of training and testing are 84% and 89%, respectively. The results show that the effect of residential building floor plan layout image feature extraction is more significant, and the accuracy and repeatability are excellent. The results of the sample room type frequency statistics are shown in Fig. 8.

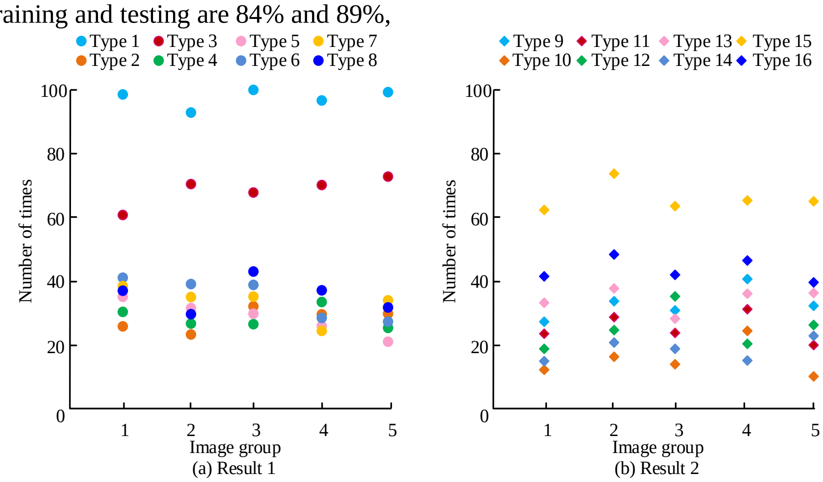

Fig. 8. Sample room type frequency statistics results.

In Fig. 8(a), types 1-8 represent bathroom, bedroom, corridor, kitchen, living room, dining room, parking room and laundry room, respectively. In Fig. 8(b), types 9-16 represent guest rooms, balconies, storage rooms, entrances, studies, master bedrooms, second bedrooms, and bathrooms, respectively. The frequency ranges of different types of spaces are not exactly the same, with bathrooms appearing most frequently, followed by corridors, and to a lesser extent, balconies. With regard to the information entropy of spatial distribution characteristics, the internal spatial distribution of residential buildings presents a high degree of randomness and diversity. In the spatial functional area land metric, functional areas such as bedrooms and living rooms occupy larger areas, while parking rooms and laundry rooms have smaller areas.

Regarding the shape rate of each functional area, kitchen and bathroom show a more regular shape, while bedrooms and living rooms are more irregularly shaped. The main functional areas such as bedrooms and living rooms are more compact, while dining rooms, laundry rooms, etc. are less compact.

B. Analysis of the Application of Residential Building Layout Design and Optimisation Methods

When evaluating the application effect of residential building layout design and optimization methods, a comparative evaluation method was used in the experiment to compare the proposed optimization method with computer-aided design (CAD) and poster tools. Nonprofessional and professional users were invited to evaluate the completeness, rationality, readability, and effectiveness of the three design tools. The study uses customised data and parameter settings to train neural networks to solve architectural design problems. Also, the Adam optimiser was used for training and different parameters such as subgraph radius and edge vector dimensions were chosen for the experiments. The effect of different parameters on the GNN model is shown in Fig. 9.

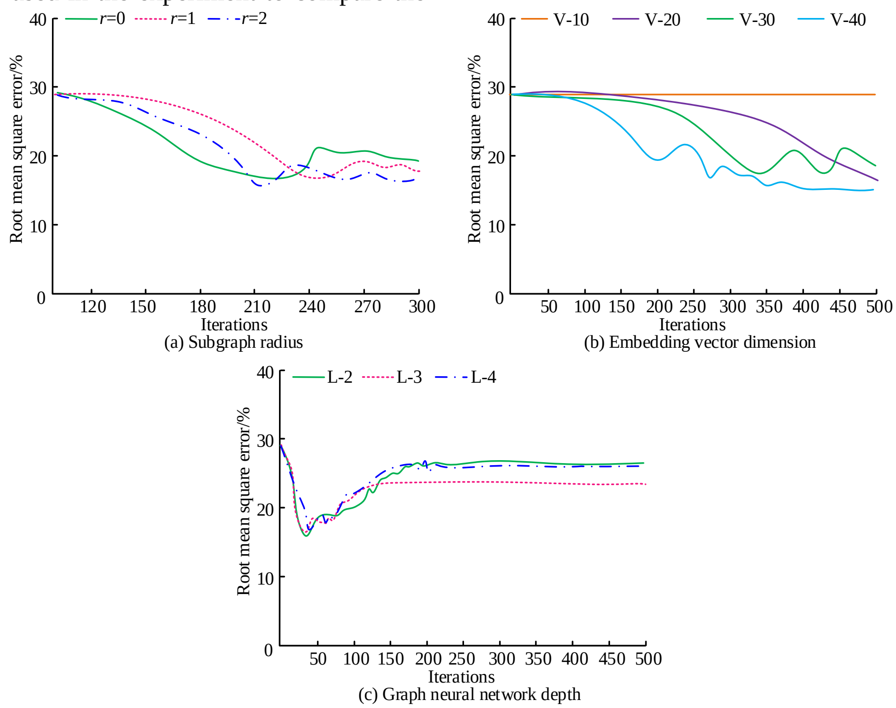

Fig. 9. The impact of different parameters on GNN models.

Fig. 9(a) shows the results of the effect of subgraph radius on the model performance, and it can be seen that the root mean square error of the model can be minimised up to 18.3% when the subgraph radius is 2. Fig. 9(b) shows the results of the effect of vector dimension on the model performance, and it can be seen that the root-mean-square error of the model can be minimised up to 16.9% when the vector dimension is 40. Fig. 9(c) shows the results of the effect of GNN depth on model performance, as can be seen that the model stabilises with a minimum root mean square error of 23.6% at a GNN depth of 3. With the current model setup, a subgraph radius of 2, a vector dimension of 40, and a GNN depth of 3, the smallest root-mean-square error can be obtained, resulting in optimal model performance. The sample room type vector space projection is shown in Fig. 10.

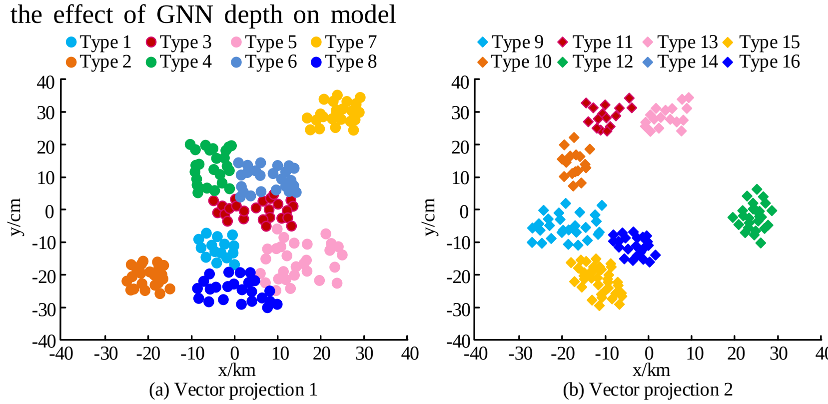

Fig. 10. Sample room type vector space projection.

Fig. 10(a) shows the space vector projections for types 1-8, i.e., bathroom, bedroom, corridor, kitchen, living room, dining room, parking room and laundry room. Fig. 10(b) shows the space vector projections for types 9-16, i.e. guest room, balcony, storage room, entrance, study, master bedroom, second bedroom and bathroom. It can be seen that clusters such as bedrooms and bathrooms are closer to each other, forming a larger category, while kitchens and dining rooms are closer to each other. In addition, clusters such as guest room, bathroom and second bedroom are very close to each other. The optimisation of the residential building floor plan layout design is shown in Fig. 11.

In order to verify the effectiveness of the GNN based residential building layout design and optimization method proposed in the study (marked as Method A), the GCN and GAT models were used as baselines in the experiment, and the intelligent generative method based on genetic algorithm (marked as Method B) and the layout optimization method based on particle swarm optimization (marked as Method C) published in 2023-2024 were compared. The comparison results of different methods are shown in Table I. Table I shows that Method A outperforms the baseline models GCN and GAN in all indicators, and compares Method B with Method C. Compared to the baseline model, the performance of method A has significantly improved, with its root mean square error reduced by nearly half, accuracy increased by about 10%, and F1 value increased by about 6%. Compared with the methods proposed in 2023-2024, Method A leads by about 4% in accuracy and F1 score, demonstrating higher overall performance. This indicates that the GNN based method for residential building layout design and optimization has significant advantages and application potential.

TABLE I. COMPARIING RESULTS OF DIFFERENT METHODS

Method	Root mean square error/%	Accuracy/%	F1 value/%
GCN	20.3%	83.1%	89.3%
GAN	25.1%	80.3%	87.3%
Method A	10.7%	93.2%	95.1%
Method B	13.7%	90.2%	91.3%
Method C	16.1%	89.3%	90.8%

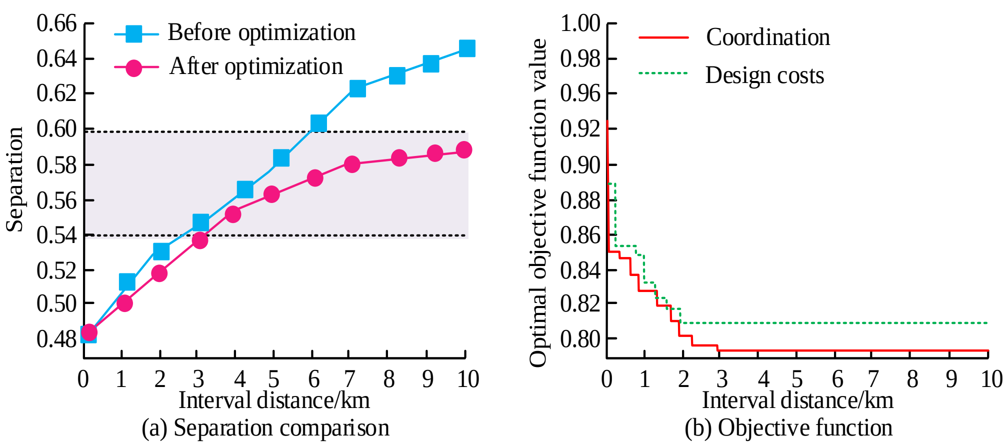

Fig. 11. Optimization of residential building layout design.

Fig. 11(a) shows the results of the comparison of the separation degree of the spatial layout before and after the optimised design. Before the optimal design, the separation degree of each functional area is low, and there are some areas that are not effectively utilised. The separation degree of the functional areas after the optimal design is significantly improved and always within the permitted fluctuation range, which indicates that our proposed design method can effectively optimise the layout of the public space, making the spatial distribution of the functional areas clearer and avoiding the waste of space. Fig. 11(b) shows the results of the objective function solution, which shows a decreasing trend with the increase of the number of iterations. This is because in the quantum particle swarm algorithm, the particles are able to adjust and update all the particle information through quantum mechanics, maintaining the original position and velocity while choosing the appropriate velocity direction based on historical experience. This process of constantly searching and updating position information makes the particles gradually approach the optimal solution, thus optimising the layout of the main functional area of the public space. The evaluation of the application effect of the residential building layout design and optimisation method is shown in Fig. 12.

In Fig. 12, the study compares the proposed method for designing and optimising the floor plan layout of residential buildings with computer-aided design (CAD) and poster tools as a comparison in order to analyse the effectiveness of the application of the proposed method in the study. Fig. 12(a) shows the evaluation results for non-professional users and Fig. 12(b) shows the evaluation results for professional users. Compared with CAD and poster tools, the completeness of the residential building floor plan layout design and optimisation method is improved by about 2.3%, rationality by about 3.6%, readability by about 1.9% and effectiveness by about 10.3%.

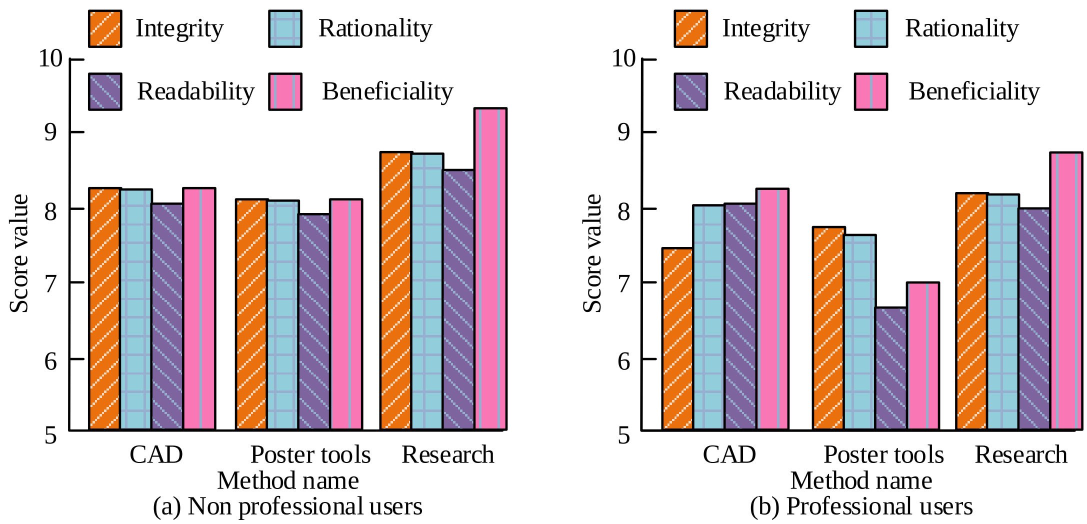

Fig. 12. Evaluation of the application effect of residential building layout design and optimisation methods.

V. Conclusion

In order to improve the space utilisation of residential buildings and the comfort of occupants, the study proposes a GNN-based method for designing and optimising the floor plan layout of residential buildings. The method analyses and identifies the spatial distribution characteristics of the main functional areas in the space through deep learning techniques. The study adopts the quantum particle swarm algorithm to optimise the layout of the public space, and transforms the complex layout problem into the form of a composite model to meet the preset convergence conditions and obtain the optimal layout design results. In the process of data conversion, the average accuracy can reach 96.4% and the average completeness can reach 84.4%, which lays the foundation for further data analysis and processing. The error value of the residential building floor plan layout image feature extraction is within the range of 0-0.01, and the repeatability averages for training and testing are 84% and 89%, respectively. Compared with the most advanced methods, the accuracy and F1 value of the GNN based residential building layout design and optimization method have been improved by about 4%, and its overall performance is better. Compared to CAD and poster tools, the effectiveness of the residential building floor plan layout design and optimisation method was improved by about 10.3%. The results indicate that the GNN-based residential building floor plan layout design and optimisation method has high applicability. This study has made multiple contributions in the field of residential building layout design. Firstly, the innovative application of Graph Neural Networks (GNNs) in residential building layout design provides a new intelligent design approach. Secondly, a GNN model adapted to the layout design of residential buildings was carefully constructed and optimized with a large amount of training data, significantly improving design efficiency and accuracy, effectively addressing the shortcomings of existing research in comprehensively considering multiple factors such as complex functional requirements, user preferences, and building standards of residential buildings. Thirdly, the successful application of the GNN model in practical design cases has improved the completeness, rationality, readability, and efficiency of the design scheme. It has shown outstanding performance in data conversion, image feature extraction, and other aspects. Compared with traditional CAD and poster tools, its efficiency has been significantly improved, effectively promoting technological progress and sustainable development in the field of architectural design. However, the study still has some limitations, such as the limited scope of data collection and the insufficiently fine setting of model parameters. Future research can collect data in a wider range and further optimise the model parameter settings to improve the performance and practicality of the layout design method.

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