

## *Retraction*

# **Retracted: Research on Urban Renewal Public Space Design Based on Convolutional Neural Network Model**

## **Security and Communication Networks**

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## **References**

- [1] J. Wan and H. Shi, "Research on Urban Renewal Public Space Design Based on Convolutional Neural Network Model," *Security and Communication Networks*, vol. 2021, Article ID 9504188, 9 pages, 2021.

## Research Article

# Research on Urban Renewal Public Space Design Based on Convolutional Neural Network Model

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By establishing a database of urban space cases, machine learning algorithms and deep learning algorithms can be used to train computers to learn how to design urban spaces. Based on the basic concepts of machine learning and deep learning and their procedural logic, this paper explores the generation mode of traffic road network, neighborhood space form, and building function layout of urban space and uses the northern extension of the central green axis of the city as an application case to confirm its feasibility in order to seek a set of artificial intelligence-based urban space generation design method and provide a new idea for the innovative development of urban design methods.

## 1. Introduction

Urban physical space is a multilayered, open, and complex system. The factors that need to be considered for a good urban space design are not only numerous and interacting but also change from place to place and from time to time [1, 2]. For example, the site environment and culture, functional layout, and spatial form are also the space for social production, residents' living activities, and the regional carrier of the urban landscape. In the period of rapid urbanization, the rapid expansion of the city makes the spatial structure and characteristics of the city gain more and more attention. However, space of most cities lacks recognition and attractiveness, resulting in a dull image of the city and a lack of "connotation" [3, 4]. The following reasons have given rise to the phenomenon of "one city for all" to a certain extent: urban design elements have become more diversified, and more and more branches have been derived in terms of spatial topology, functional scope, and cultural connotation, and the information content that urban design needs to digest and cover has become more complicated. With the advancement of urbanization, the construction time of urban projects is getting more and more urgent, and the design cycle is constantly compressed. The lack of

experience and limitations of designers' thinking lead to deviations in the interpretation of spatial integrity and interaction of design elements, difficulties in obtaining complete information in a short time, and the lack of efficient information processing [5, 6].

Designers are constantly searching for designs that break through dilemmas and are personalized through an iterative approach to urban space design. Over the past century, theories of urban space analysis and design have emerged. With the evolution of the time, the breakthroughs in science and technology have also led to the development of innovative design methods [7, 8].

At this stage, the computer computing power has been greatly improved, and the rapid development and innovation of artificial intelligence technology, such as machine learning and deep learning, have made computers more intelligent. Can these new technologies make the design tools more innovative, not only to assist in obtaining better quality urban design but also to improve the design efficiency? This is a question worth considering. Therefore, this study explores this issue in order to use the emerging technologies to promote the development of innovative design methods to meet the needs of urban development.

The contributions of this paper are as follows:

According to the five elements, the urban spatial case database is set as three subdatabases so that the data information of urban architectural function layout can be reflected in the two-dimensional plan of different architectural functions through different colors.

The complexity of constructing urban public space evaluation system based on BP neural network model is proposed, including vector data based on point, line, and surface, street view data based on grid image, and language text data based on text.

Experimental simulation shows that the urban design scheme generated by machine learning and deep learning simulation is also a 2D image. This part automatically generates a 3D urban design model from the two-dimensional scheme drawings generated by simulation.

## 2. Related Work

The current research on urban public space using deep learning mainly focuses on street quality, street attributes, urban spatial imagery, etc., using image data from urban big data as the main data, supplemented by traditional geographic data, and machine learning methods such as manual scoring method,  $k$ -means clustering method, support vector machine, and convolutional neural network to explore the features and patterns existing in urban public space [9–12].

Bai et al. [13] used computer vision technology to construct a suitable convolutional neural network to identify street green view, street functional attributes, and pedestrian attributes in public space and made a preliminary exploration of quantitative research on urban public space based on visual big data. Using SegNet semantic segmentation network, Mukhina et al. [14] conducted a study on the view openness of road space, riverfront space, and open space in the central city of Tianjin using street scape image data. Sardar [15] established a cognitive model of urban imagery based on the theory of urban imagery and used an open deep learning service platform to analyze the image and text data of the city from the perspective of imagery structure, imagery type, and imagery evaluation and verified the scientificity and feasibility of the model using Chongqing as an example [16], while Kim et al. [16] also proposed a research model of urban imagery based on network image data, constructing a model which also proposed a research framework based on the composition of urban imagery elements, dominant direction, characteristic degree, and similarity of urban imagery as modules, and conducted an empirical study for 24 major cities in China [17]. Xie et al. [18] used SegNet semantic segmentation network to evaluate the spatial quality of street data and then used SDNA-based accessibility analysis to superimpose street quality and accessibility to study the quality measurement of street space at the human scale in depth and initially achieved a balance between large-scale analysis and refined measurement.

Compared with the research conducted using image and geographic data, domestic research on the quality of urban public space using social media and commentary platform data is relatively absent, and the research on the combination of urban public space and artificial intelligence is still at the

traditional visual level [19–21]. Research on the combination of urban public space and artificial intelligence has remained at the traditional visual level, using a variety of machine learning methods to conduct large-scale measurement and statistics on various visual elements such as greenery and architecture. The research on the combination of urban public space and artificial intelligence is still at the level of traditional vision, using a variety of machine learning methods to measure and count various visual elements such as greenery and buildings on a large-scale and supporting traditional geographic means for evaluation. The evaluation of urban public space is only limited to the physical appearance of space and lacks consideration of people's needs and emotions. Other aspects such as psychology and economics still need to be explored in depth.

## 3. Research Framework for Urban Spatial Generation Design

This study establishes an urban space case database based on the logical sequence of “learning-simulation.” Machine learning and deep learning are used as the basic design platform, while urban planning and design evaluation indexes are determined, and the final urban planning and design solutions are obtained through the interaction between designers and the design platform [22, 23]. The whole research process is divided into three parts, including the establishment of the urban space case database, urban space generation and scheme evaluation screening, and the generation of 3D urban design models.

*3.1. Establishment of Urban Space Case Database.* The spatial spectrum based on the spatial model of urban design can deconstruct the urban spatial structure. The basic types of spatial prototypes can be roughly divided into polycentric spatial patterns, grid tessellated neighborhoods, and circular circles radiating and axially related. The basic types of spatial prototypes can be roughly classified into polycentric spatial patterns, grid tessellated neighborhoods, circular circles radiating patterns, and axially related patterns [24, 25]. According to the classification of urban space cases, we collected several urban design proposals and established a database. The five elements of urban design are boundaries, roads, districts, nodes, and landmarks. Based on these five elements, the database of urban space cases is set into three subdatabases: urban traffic network information database, urban neighborhood spatial form database, and urban building functional layout database. The urban traffic network information is reflected by the two-dimensional plan of different levels of road traffic. The spatial patterns of urban neighborhoods are represented by 2D plans of buildings, squares, green areas, and other public spaces of different height distinguished by different colors. The data on the layout of urban building functions are represented by 2D plans with different colors to distinguish different building functions. The design and realization process of urban renewal public space is shown in Figure 1.

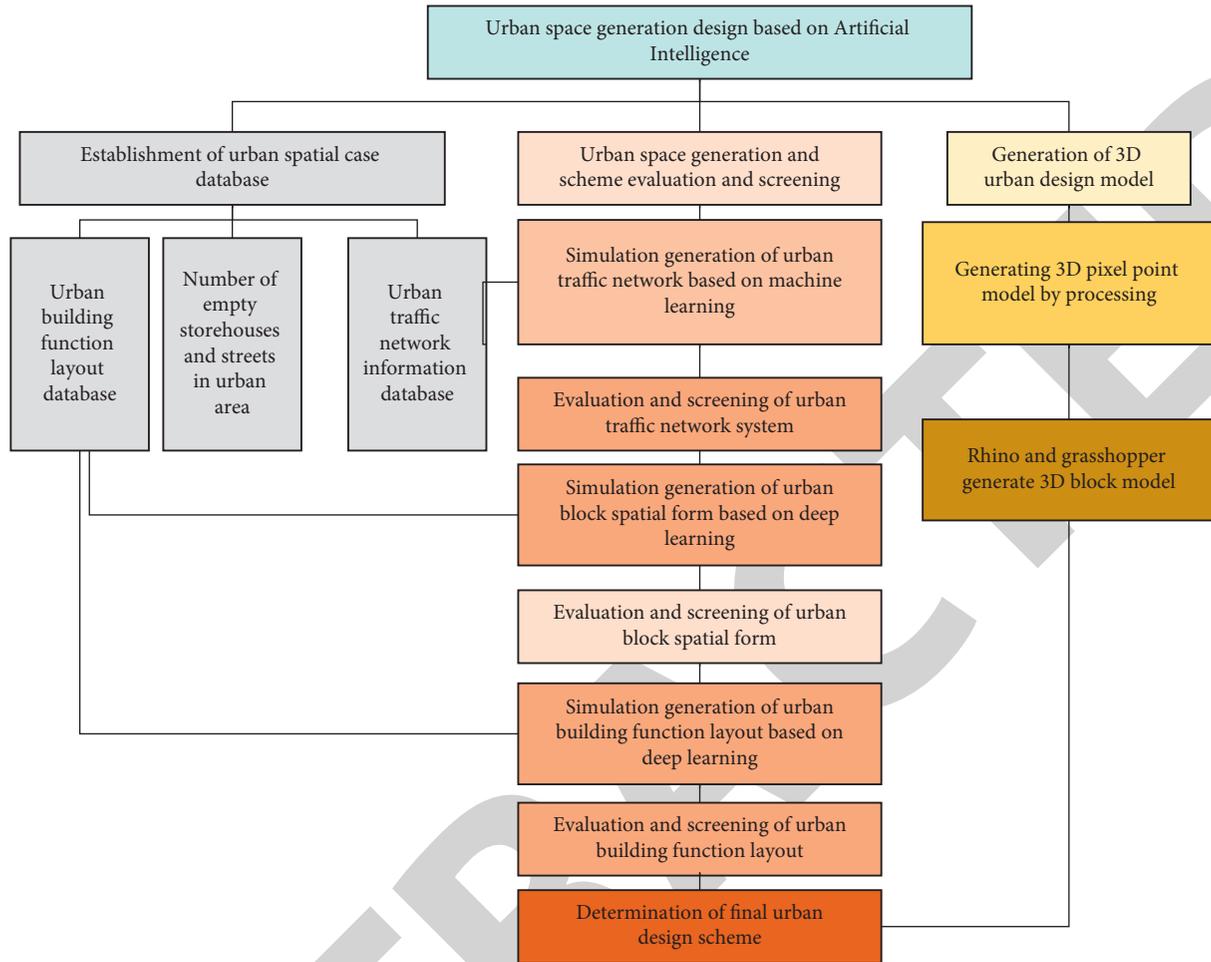


FIGURE 1: Research framework of urban space generation design.

3.2. *Data Acquisition and Preprocessing.* Due to the complexity of the urban public space evaluation system, the amount of data required for this study is relatively large compared to other studies [26]. In order to clarify the classification of each data, this paper divides all data into three categories: point-line surface-based vector data, raster image-based street scape data, and text-based language text data. The spatial map used is shown in Figure 2.

3.3. *Vector Data.* The specific process of urban space renewal is shown in Figure 3.

Source and acquisition of vector data such as roads and buildings are shown in Figure 4.

The OSM map is a comprehensive and detailed classification of the elements in the map of major cities in China. The elements in the OSM map required for this study are mainly administrative data, road network vector data, building vector data, and basic topographic data, as shown in Figure 5. After comparing and cross-validating with the data from the land management department, it was found that the vector data provided by the OSM maps are consistent in terms of accuracy and even have a higher degree of perfection [27, 28].

OSM data have a strict registration division for all roads (Table 1); for various types of roads, there are also

corresponding road attributes available for query; The main attributes contained in the road include nearly 50 attributes, such as road name, number of lanes, pavement material, maximum speed, height limit, etc. The road data is very large, so it needs a lot of manual annotation. Therefore, this paper only uses the geographic information of the road vector in the OSM map, the classification information of the road and the number of road lanes, and other general information to reduce the possibility of bias to the research results due to the incompleteness of some data [29, 30].

#### 4. Convolutional Neural Network Model Construction, Training, and Prediction

Among the convolutional neural networks in the CV domain [31], the author subdivides into two networks for the data required in this paper. The data of spatial visual perception factor and the data of spatial basic attributes in the previous paper are computed separately using the work of each network. The data of spatial visual perception factor and the data of spatial basic attributes in the previous paper are computed using each network (Figure 6).

After studying urban street scape data acquired in the previous section, the network selected for this study must

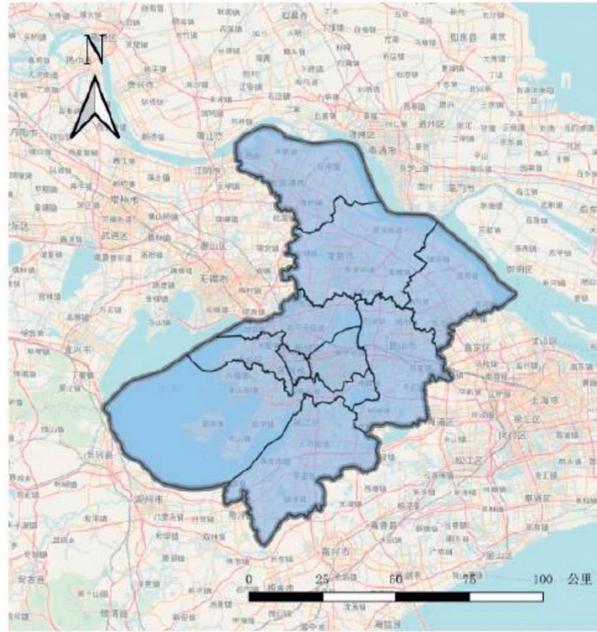


FIGURE 2: Map showing the scope of the study.

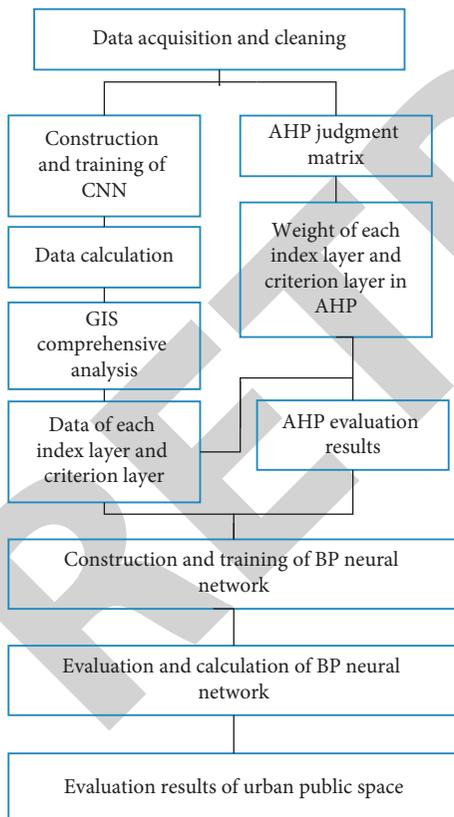


FIGURE 3: Flow chart of urban public space evaluation in the city.

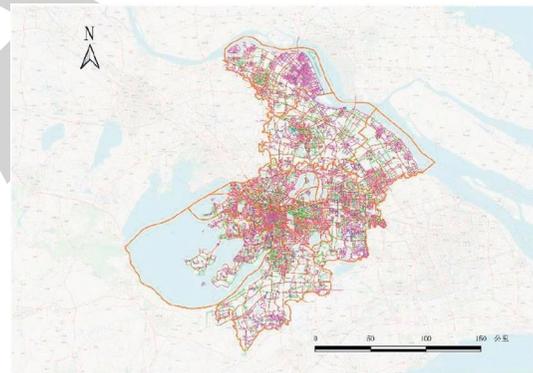


FIGURE 4: Types of urban roads.

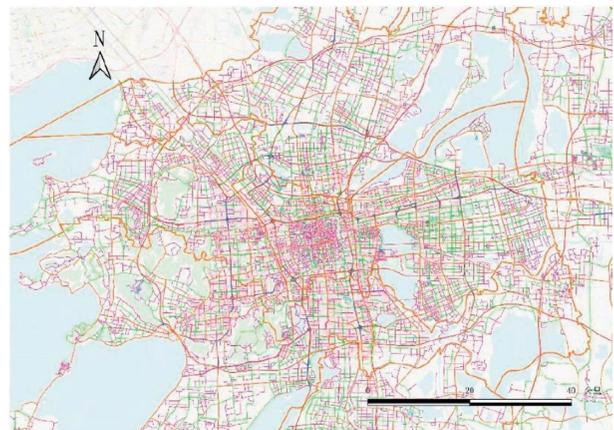


FIGURE 5: Types of roads in the central city.

contain the following features if it is to be used for semantic segmentation: first, it has a high sensitivity to the scale of the elements. In addition to the traditional one-point-two-point or three-point perspective, the elements in each street scene image, such as buildings, vegetation, roads, and pedestrians,

will have different levels of scaling, and since the perspective type of the street scene image taken by the street scene acquisition vehicle is a more special spherical perspective,

TABLE 1: OSM map road classification table.

Road category	Road subclass
	Expressway, national highway, provincial highway, trunk road, secondary trunk road, branch road, unclassified road, and road in residential area
Connecting road (ramp)	Freeway ramp, national highway provincial ramp, trunk ramp, secondary trunk ramp, and branch ramp
Pedestrian road	Footpath (impassable by motor vehicles), roads, steps, and corridors for horses
Special road	Living roads, service roads, pedestrian roads (for motor vehicles), agricultural and forestry trails, bus lanes, racetracks, and roads under construction

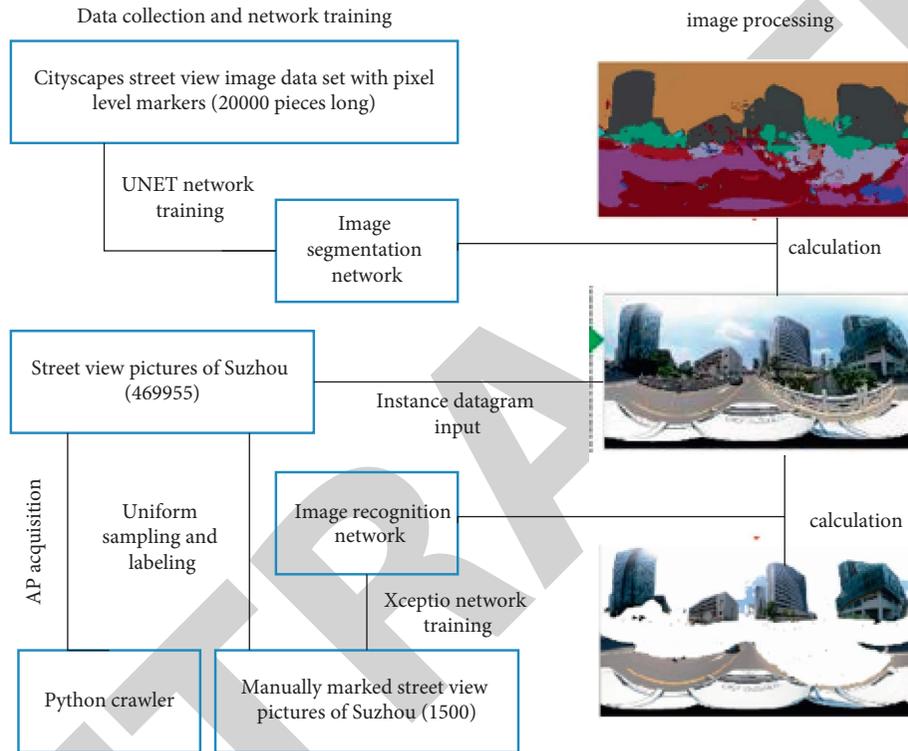


FIGURE 6: Flow from data collection to calculation of picture elements.

the elements in the spherical perspective image have changes such as oblique cut, deformation, and distortion in addition to scaling changes, which requires the selected CNN to be very sensitive to the changes of the scale and shape of data features, and consider the changes of training data in the training process, so that the robustness and accuracy of the model in practical calculation can be enhanced [32, 33].

The second is to choose a CNN with a moderate number of layers that best matches the hardware ceiling. This is determined by the hardware of the local computer. Compared to lightweight CNN (e.g., AlexNet [34], with 8 layers), convolutional neural networks with a higher number of layers (e.g., ResNet [35], with 152 layers) have an exponential increase in training parameters, usually with higher resolution and larger batches, and also require a larger amount of video memory, but therefore, an important principle in selecting the network structure is to choose those networks that are close to the upper limit of arithmetic power and memory, but do not lead to memory overflow, i.e., the networks with the best results that the

current hardware can afford, so as to significantly increase the GPU usage and maximize the performance of the hardware.

The third requirement is the amount of training data. Since this training dataset only contains the Cityscapes dataset with 20,000 annotated images and the 1500 Suzhou Street View dataset with the author’s own annotations, from the perspective of deep learning, compared to ImageNet and other datasets with millions or hundreds of millions of images, the volume of the dataset used in this study is relatively small when selecting the network structure. Therefore, when selecting the network structure, we also consider those networks that are prepared for lightweight datasets and can obtain good results on small datasets.

## 5. Urban Spatial Generation

This study utilizes two core techniques of artificial intelligence: machine learning and deep learning. The machine learning algorithm uses the Python algorithm wave function

collapse (WFC) [36], which simulates the input image and generates similar images. Local similarity in machine learning algorithms is related to two aspects: first, each  $N$  (feature parameter)  $\times N$  pixel module of the output image appears at least once in the input image; second, the probability of each  $N \times N$  pixel module appearing in the output image is approximated by the probability of appearing in the input image [2, 4, 5]. The algorithm is mainly based on the model simulation studies of [3, 5]. By modifying the feature parameter  $N$ , different styles of simulated images can be generated. In contrast, the deep learning algorithm applies the image style transfer algorithm published by [31] and the neural plaque algorithm published by [7, 8]. The algorithm utilizes the Python language, which is used in this study due to the fact that the simulation speed of the image processor is considerably faster than the simulation speed of the central processor [6, 15]. The algorithm generates a new image by using multiple images, which depends on the original image with the original information and the given content annotated image, transferring the matching degree of the annotated patch information extracted from the style image to the target image, and the matching effect is related to the computational speed and the number of iterations  $I$ . Within a certain range, the higher the number of iterations  $I$ , the better the matching effect and the longer the computation time, but the matching effect does not improve after the number of iterations  $I$  reaches a certain level. By modifying the number of iterations  $I$ , different simulated images can be generated, such as the urban texture map shown in Figure 7, which is the clearest in this paper.

The information of the 3 subdatabases in the previous database are all 2D images, and the urban design solutions generated by machine learning and deep learning simulation are also 2D images, and this part is to automatically generate 3D urban design models from the 2D solution drawings generated by simulation.

As shown in Figure 8, different colored areas in the simulated 2D urban neighborhood spatial pattern map represent squares, greenery, and buildings of different heights, and the pixels of different colors in the simulated 2D urban neighborhood spatial pattern map are programmed with processing software to give different heights to generate a 3D pixel location model and derive 3D coordinate information for each pixel. These data are then imported into Rhino and Grasshopper software to generate a 3D block model from the 3D pixel location map, which is the final 3D urban design model.

As shown in Figure 8, the central green axis of Wenzhou city is a spatial landscape spine running from north to south and a center of public culture and public activities, covering four core functional areas: administrative and cultural area, leisure and living area, commercial and creative area, and urban green area. This study establishes an urban space case database, uses machine learning to generate road networks, uses deep learning to generate neighborhood spatial patterns and building functional layouts, and finally uses processing algorithms to generate 3D spatial models.

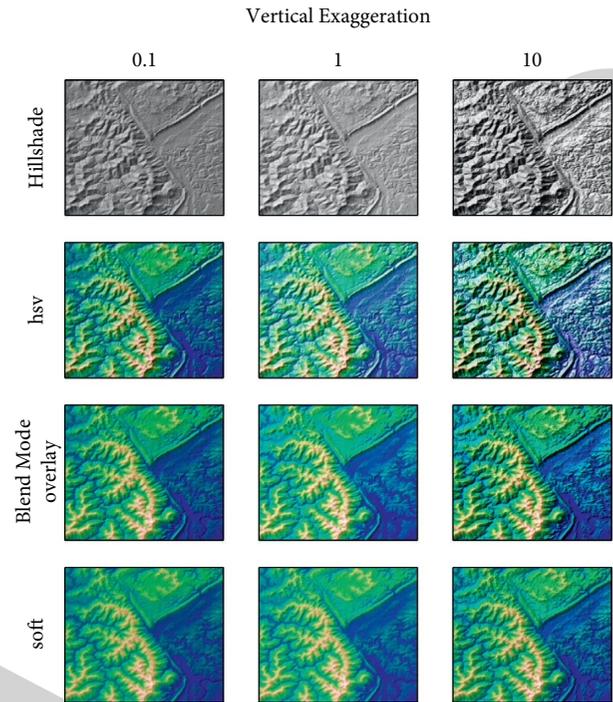


FIGURE 7: City texture map.

Overlay Blending Looks Best with Rough Surfaces

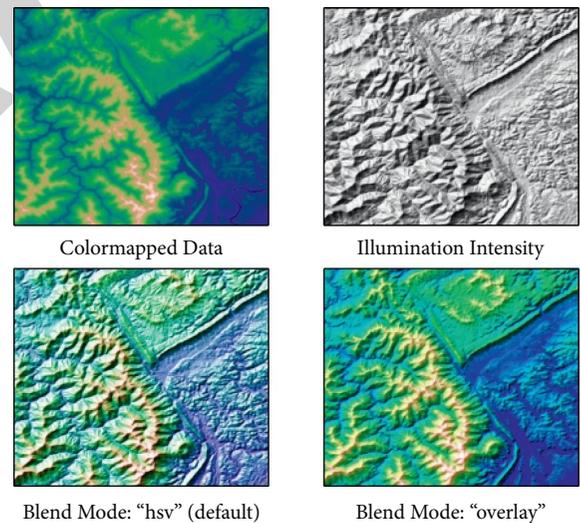


FIGURE 8: Geographical generation map.

The urban space case database is divided into 3 subdatabases. That is, each case contains three parts of information: urban traffic road network, urban neighborhood spatial form, and urban building functional layout, as shown in Figure 9.

As showed in Figure 10, urban traffic road network information is collected and organized in the case of road network material. The information of urban block form distinguishes buildings, squares, green areas, and other public spaces of different heights with different colors, and the building heights are divided into three categories: 1-to-3-story buildings, 3-to-8-story buildings, and buildings with

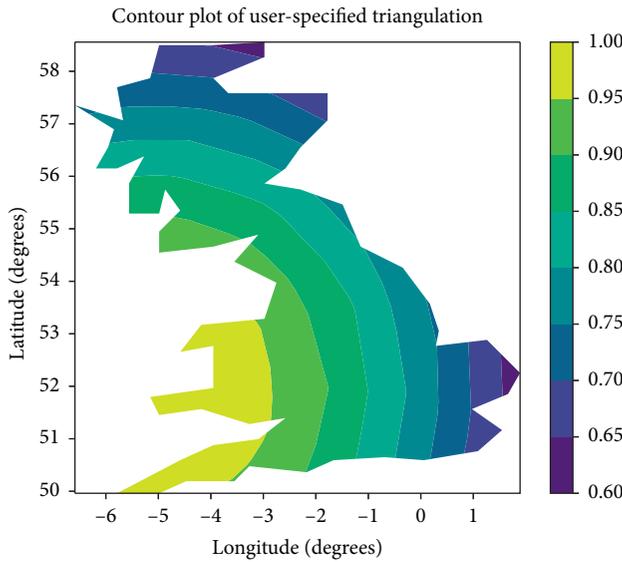


FIGURE 9: Heat map of urban land.

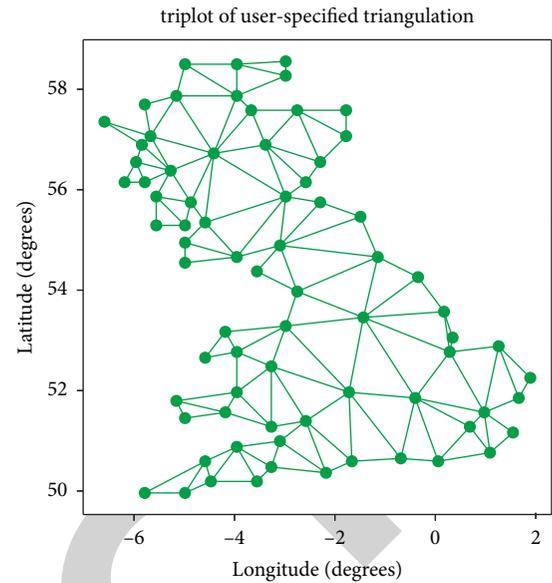


FIGURE 11: Deep learning-based urban neighborhood space.

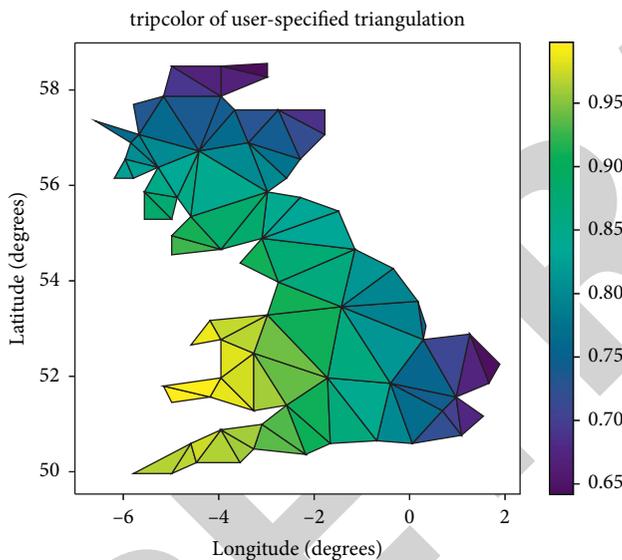


FIGURE 10: Regional map.

more than 8 stories. Building functional layout information divides the building functions into five categories: cultural and educational, commercial, residential, administrative office, and commercial and residential combination, and uses different colors to distinguish the building function types.

Extract information of urban traffic road networks from the database, and perform machine learning by using Python algorithm wave function collapse. Adjust feature parameters  $N$  (e.g., 3, 4, and 5) to generate multiple road networks, and then evaluate and filter the generated road networks to select the optimal urban traffic road network. The evaluation of urban traffic road networks mainly includes two aspects: time and space. First, in space, we should consider the overall construction level of regional traffic road network, road network accessibility, and road network density within

a certain range of the site, which is basically a static analysis. Second, in time, we should consider the operation time of the regional road network, motor vehicle speed, etc., and then make an evaluation of it. However, this study mainly stays in the program stage, so the evaluation of time cannot be judged, and only the evaluation of space can be made. This study determines the following evaluation indexes according to the systemic, independence, practicality, comparability, scientificity, and reliability principles: road network density, road network accessibility, and surrounding site fit.

As shown in Figure 11, among the three generated road network solutions, solution 1 has a suitable road network density, high accessibility, and high surrounding site fit; solution 2 has a high road network density, suitable accessibility, and low surrounding site fit; solution 3 has a high road network density, low accessibility, and low surrounding site fit. Therefore, this proposal is the optimal road network solution (Figure 11).

## 6. Conclusions

This study explores the feasibility of using machine learning, deep learning, and other related algorithms to train computers to learn urban space generation design, using the northern extension of the green central axis as an application case to confirm its feasibility. In this study, machine learning and deep learning are used for the first time to obtain urban space design solutions, and under the monitoring and selection of the designer, the preliminary solution is set mainly using artificial intelligence, and the final decision is made by the designer, in which both the efficient ability of artificial intelligence to process and produce information and the decision-making ability of the designer itself are required, fully reflecting the human-computer interaction.

Although the method explored in this study based on machine learning and deep learning image processing

algorithm can generate multiple solutions quickly and make the design more objective and scientific, the drawings generated by this method are not accurate enough because of the limitation of computer hardware and algorithm, and the drawings generated by deep learning have mixed areas of different colors. At the same time, the process of program evaluation and screening is still subjective, and the optimal program cannot be automatically screened by the computer. With the continuous improvement of computer program algorithm technology, the design algorithm of urban space generation using artificial intelligence will become more and more perfect, and the method of urban design will be constantly updated.

## Data Availability

The dataset used in this paper are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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