TRACK 02: SMART AND AGILE PLANNING: SMART CITIES AND REGIONS

METHOD FOR REFINED FUNCTION ZONING PREDICTION OF TOURIST TOWN URBAN DESIGN BASED ON BIG DATA AND CONDITIONAL GAN (1053)

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Abstract. Looking at the urban design of a tourist town, it is necessary to refine further the function zoning given by the urban plan. However, in the traditional urban design process, this step requires the designers to manually research for similar cases studies to analyze the spatial distribution relationships between businesses and geographical elements such as road networks, water bodies, and topography, which is not only time-consuming and laborious but also lacks reliability and accuracy. Therefore, this paper aims to propose a method that uses big data and conditional Generation Adversarial Network(cGAN) to obtain a POI-guided refined function zoning efficiently and accurately based on multiple proven precedents. Taking Nanjing's Tangquan Hot Spring Town as an example, this paper shows the process of acquiring and processing the dataset, building and training the model, and finally applying it to the target site and generating a preliminary urban design massing based on Rhinoceros and Grasshopper.

Keywords: Urban Design, Big Data, Conditional GAN, Function Zoning, Tourist Town Design.

1. Introduction

The decision-making process for the functional zoning of urban land has been complicated as it involves a large number of participants and contains multiple competing non-linear and non-additive objectives. This process requires rational resolution of the spatial dependence between plot functions and reference to the correlation between each type of function and the site basic conditions (Haque and Asami, 2014). In addition to employing functional zoning in master urban planning as a general guide, detailed plot-level function zoning and development intensity indicators are frequently required as references for detailed urban design in urban planning and design. The determination of a plot's refined function, zoning, and development intensity in the traditional urban design process typically rely on the urban designer's personal experience and the reference of a large batch of similar cases, which tests individual design ability and requires a lot of time and human resources.

For tourist towns, a refined function zoning of the plot plays a crucial role in the development of the town. A reasonable allocation of different types of buildings and corresponding development intensity in a short timeframe can help the town to function and develop well in the first place. On the contrary, we can see that delayed and unsupported zoning often affects the operation of the town at the beginning of its opening and reduces the probability of its subsequent success.

The above problems prompted the search for a newer solution. Modern information technology's continuous development and improvement have enabled new analyses that were previously unattainable due to a lack of data aggregation. Big Data and Artificial Intelligence enable a more comprehensive and rational approach to urban planning and design. Using big data and artificial intelligence can help designers improve the efficiency and accuracy of this process.

On the one hand, Big Data offers a fresh perspective on the planning and development of cities. The availability of such data suggests that it can be useful in making informed decisions to optimize resource use. On the other hand, using artificial intelligence models can provide scientific analysis for target site design based on available big data, which can help refine site design.

To provide reliable data support, this research introduces POI (Point of Interest) data as an important data basis for the functional zoning of the site where information on various functional facilities in urban space is distributed. This distribution implies the connection between urban functional zoning and the basic conditions of the site (Ye *et al.*, 2011).

For this research, the types of functional zoning required for tourist towns are relatively simple and clear, and the distribution relationship between each functional zoning and the local road network, natural environment, and other environmental conditions will largely affect the operation and use experience of the town. This research is based on the urban design of a tourist town, and this type of plot with clear development goals and relatively simple functional zoning is suitable as a preliminary experimental case for this research.

The objective of this research is to propose a method of applying big data and machine learning to try to master the POI distribution of a large number of cases similar to the target tourist town, to obtain a predicted POI distribution of the target town, and then guide the functional zoning refinement and subsequent urban design of the town.

2. Related Works

The development of computer science is providing an ever-growing assistance in the field of urban planning and design research. (e.g., Liang et al.(Liang *et al.*, 2018), 2018; Stevens, Dragicevic, and Roth-ley, 2007) (Stevens, Dragicevic and Rothley, 2007). Traditional planning methods usually use rule-based evolutionary mechanisms to make the corresponding decisions, such as cellular automaton models (CA) or multiagent-based models (MA). The drawback of these methods is that their corresponding rules and generation logic lack data support and rely heavily on human experience and subjective judgment. The completeness of their constraints largely determines the completeness of the computer-generated results.

Artificial intelligence tools aim to provide a reference tool for urban planners and designers. Machine learning uses artificial intelligence to enable systems to learn and adapt themselves without being explicitly programmed through prior experience (Baduge *et al.*, 2022).

In 2014, Ian Goodfellow proposed the structure of generative adversarial networks (Goodfellow *et al.*, 2020). That is, two multilayer perceptrons, a generator, and a discriminator are used to generate data and classify it as true or false based on the training data.

In November 2014, Mehdi Mirza and Simon Osindero proposed conditional GAN (CGAN) to place labels on the training data of generators and discriminators in the GAN structure (Goodfellow *et al.*, 2020). cGAN-based Pix2Pix model was proposed by Isola et al. in 2018 (Isola *et al.*, 2016), which is capable of learning from images to form an image to another image mapping relationship.

cGAN has already been applied to the field of site planning. For example, using reinforcement learning for urban texture studies (Peipei Jin,2022 (Jing, 2021)), for complete site planning design (CDRF 2020: Proceedings of the 2020 DigitalFUTURES pp 103-11 (Tian, 2021)), or for the forced-row design of settlements (Xinyu Cong, 2021 (SUN Cheng, 2021)). These studies demonstrate the feasibility of automatic site planning and design using methods such as cGAN with certain datasets.

POI information, roads, human activities and other information can provide rich quantitative data and decision support for urban development planning, commercial site selection, infrastructure layout, and other fields. By investigating the POI configuration of an area, urban planners can assess its function, vitality, and development (Cai et al., 2019 (Cai *et al.*, 2019); Gao, Janowicz, & Couclelis, 2017 (Gao, Janowicz and Couclelis, 2017); Lyu, Bertolini, & Pfeffer 2016 (Lyu, Bertolini and Pfeffer, 2016); Yue et al., 2017 (Yue *et al.*, 2017)). POI can be geographic information data and an important data link between data and urban planning.

When performing the above tasks or studies on urban areas, such as identifying urban functions, measuring vitality, and assessing development, it has become common to count the proportion or number of various types of POIs separately. For example, Liu and Long (2016) studied the main POI types that accounted for a large proportion of the POI within each region to determine the function of the region (Liu and Long, 2016); Yue et al. (2017) calculated the Hill number of an area from POI data to help people better understand the relationship between mixed use and community vitality(Yue *et al.*, 2017). Wu, Ye, Ren, and Du (2018) analyzed spatial-temporal effects of POI-based configurations on vibrancy and offered policy suggestions to improve resource utilization and design neighborhood rationally(Wu *et al.*, 2018).

The above work shows that it is feasible to use cGAN and big data for the prediction of sites. In this paper, we will build on the previous research by combining the advantages of big data and cGAN in their respective fields to enhance the data-based interpretation of image results while using big data for sample support.

3. Methodology

The synthesis workflow for this research uses a typical framework of data science processes and can be divided into three steps: data acquisition and processing, machine learning, and application in urban design (see Figure 1).

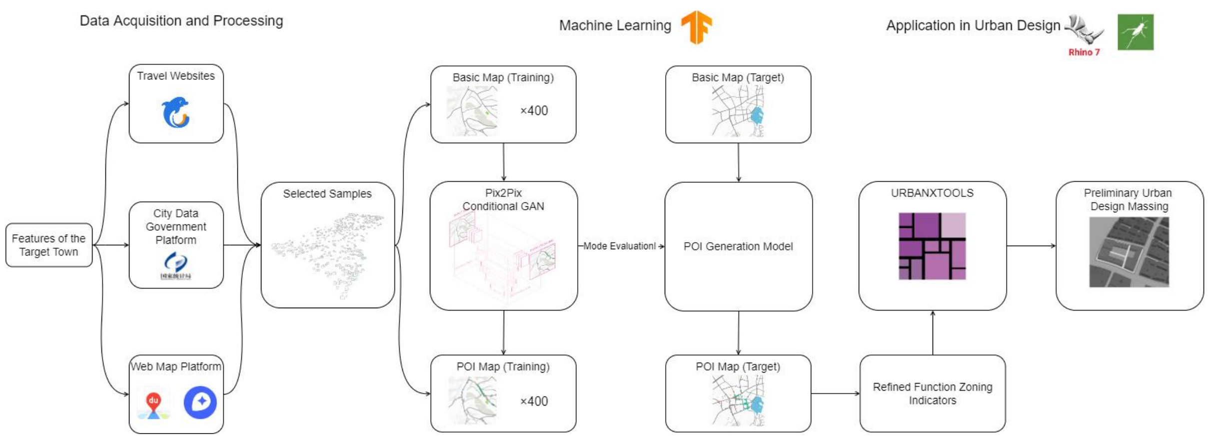


Figure 13. Research workflow

3.1. Data Acquisition and Processing

The data used in this research are all sourced from open-source platforms, including travel websites, city data government platforms, and web map platforms. Firstly, to get samples for subsequent machine learning, the preliminary samples are retrieved from the travel website by the characteristic keywords of the target town. Then, they are selected by their similarity to the target town in terms of urban development index and their ratings on travel websites. For each selected sample, a 1 km square map PNG image of the town center containing basic natural environment information and road net (Basic Map), and a map PNG image with additional POI marking points (POI Map) are created through web map platforms (Mapbox). Finally, paired Basic Map and POI Map are used as input for the subsequent machine learning.

3.2. Machine Learning

The machine learning model in this research uses the Pix2Pix pipeline to construct a translation from Basic Map to POI Map.

The Pix2Pix model consists of two parts: a generator, and a discriminator. The condition is concatenated with Gaussian noise as the input to the generator and again with the output of the generator as the input to the discriminator ('Pix2Pix Tutorial with Tensorflow', no date). Additionally, the model's objective function is the sum of the GAN loss, the binary cross entropy, and the l1 criterion between the generated image and the ground truth (see Figure 2).

In this research, the input image of the Basic Map is represented as a 256-pixel by 256-pixel image; the ground truth image is the same image appended with POI information distinguished by different colors. For the tourist towns we focus on in this research, we selected three POI: hotel, shop, and food. Similar approaches can be used for other POI types as well.

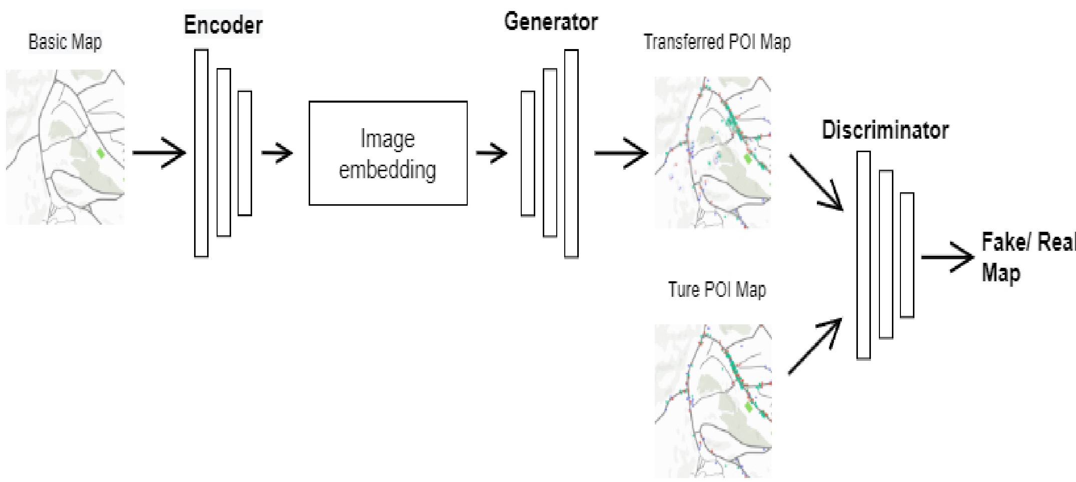


Figure 14. Pix2Pix architecture

3.3. Application in Urban Design

After the training of the model, the Basic Map of the target town center is input into the model to get the corresponding POI Map, and then transformed into a refined function zoning guide. In the generated POI Map, the plots to be refined and visualized are selected based on the initial zoning given by urban planning, and the number of POI in each selected plot is counted using OpenCV. The results of the count are translated into inputs (FAR, building density, mix ratio) for the UrabanXTools[13] plugin to generate POI-based urban design massing in the Rhinoceros window. This result serves as a guide to the refined function zoning of the target.

4. Case Study: Tangquan Hot spring Town in Nanjing

The proposed workflow was applied to the urban design of Tangquan hot spring town around Nanjing, Jiangsu Province, China (hereinafter referred to as Tangquan). The research was assisted and guided by designers who carried out the actual urban design work in Tangquan.

4.1. Dataset

Sample Acquisition. The data were obtained from open-source platforms, including travel websites (Trip.com), city data government platforms (National Bureau of Statistics of China), and web map platforms (Baidu Map and Mapbox). To obtain Basic Map and POI Map image pairs of similar, high-quality samples that can be used as a machine learning database, we conducted a search based on the characteristics keywords of Tangquan, a selection based on the economic data of the surrounding cities and the town's rating, and a map image interception of the selected samples. For targeting Tangquan, we selected a total of 10 keywords to search on Trip.com, and a total of 3,464 preliminary samples were obtained. Subsequently, 400 samples were selected by comparing the similarity of the average urban development index of surrounding towns (in the 200 km radius) to the target town and their ratings on Trip.com (whether they were higher than 4 stars). These selected samples were used to generate image pairs of the Basic Map and POI Map to be used as the training set for machine learning.

Data Processing. To use the Pix2Pix model to learn the POI distribution characteristics of the selected samples for the refined function zoning prediction required a central Basic Map of each selected sample and a POI Map image made on this basis. We used the address to coordinate conversion function provided by Baidu Map to obtain each sample's initial central coordinates, retrieved the three types of POI within a 5 km square, and then used the geometric center of all three types of POI to create a modified center. Following that, a Basic Map image of 1 km2 of each sample was obtained in Mapbox using the coordinates of the modified center. The Basic Map contained map information related to refined function zoning prediction, including roads, water, greening, and terrain, which were represented by different colors, respectively. The POI Map was based on the Basic Map and was marked in three colors with three types of POIs: hotels, stores, and food. Finally, for input to the Pix2Pixmachine learning mode, both Basic Map

[13] UrbanXTools, developed by CAUPDxUrbanXLab of Tongji University, can rapidly generate rudimentary spatial models for urban design projects. The spatial model will be complied with superior plans and regulations('UrbanXTools', 2021).

and POI Map images were processed into 256 * 256 pixel PNG format (see Figure 3).

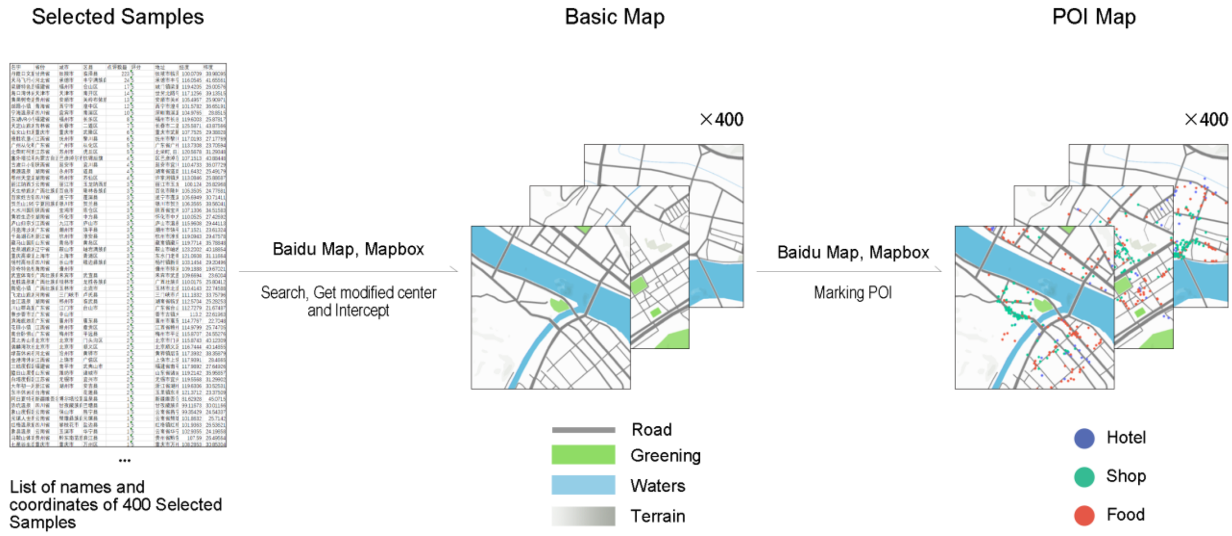


Figure 15. Data processing

4.2. Model Building and Training

To prepare a dataset for Pix2Pix training, we prepared a dataset composed of training images (Basic Map) and predicted images (POI Map) laid side-by-side as image pairs.

The model was trained in TensorFlow 2.1.0 environment with NVIDIA GeForce RTX 3070 GPU acceleration. The training data consists of 400 pairs of Basic Map and POI Map (see Figure 4).

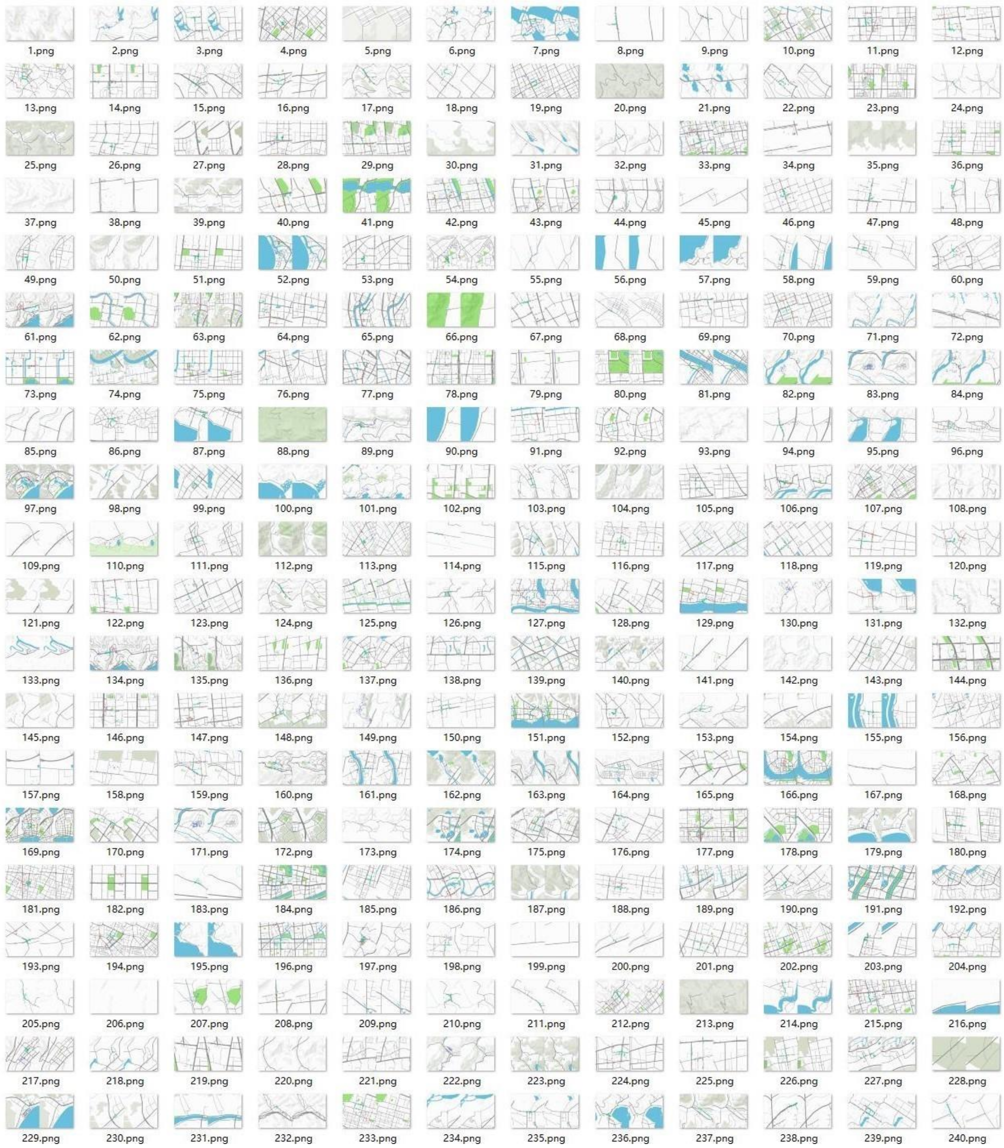


Figure 16. Training data batch example

4.3. Model Result and Evaluation

The initial result of the model was to realize the generation of images with POI distribution information from the tourist town map images containing only basic information such as roads, waters, greening, and terrain to guide the refined function zoning prediction. As the training proceeds, the model gradually identified the connection between the POI distribution and the elements in the Basic Map.

Several samples were used as test data to test the model in generating POI Map from Basic Map. It is worth noting that the final model predictions did not exactly match the ground truth images but converged to the results learned for all databases combined, indicating that the model's overfitting is controlled (see Figure 5).

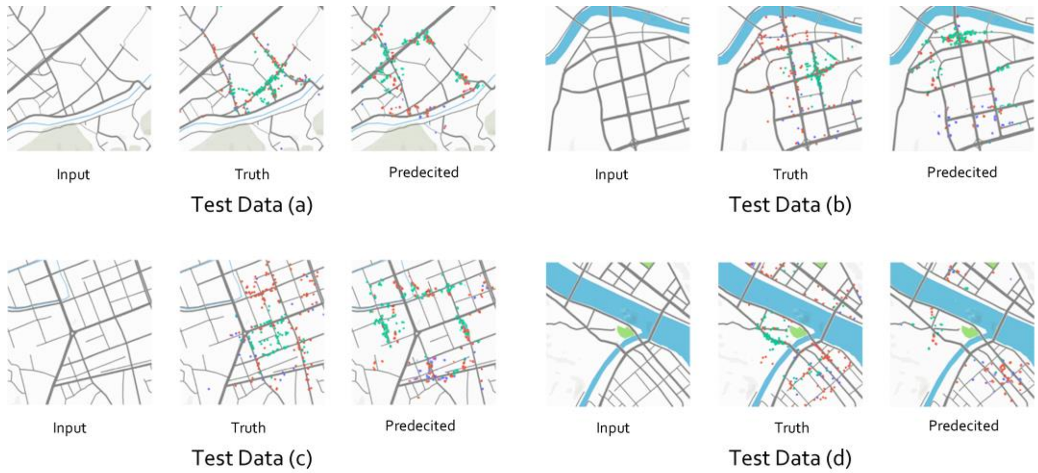


Figure 17. Model generation test example

As Tangquan was still in the undeveloped stage, the map platform did not have access to its planned road net. Therefore, after acquiring the map containing the natural environment information, the road net given by urban planning was attached in the same style as the training data to form the Tangquan Basic Map. We input the Basic Map of Tangquan into the trained Pix2Pix model and got the POI Map prediction of it (see Figure 6).

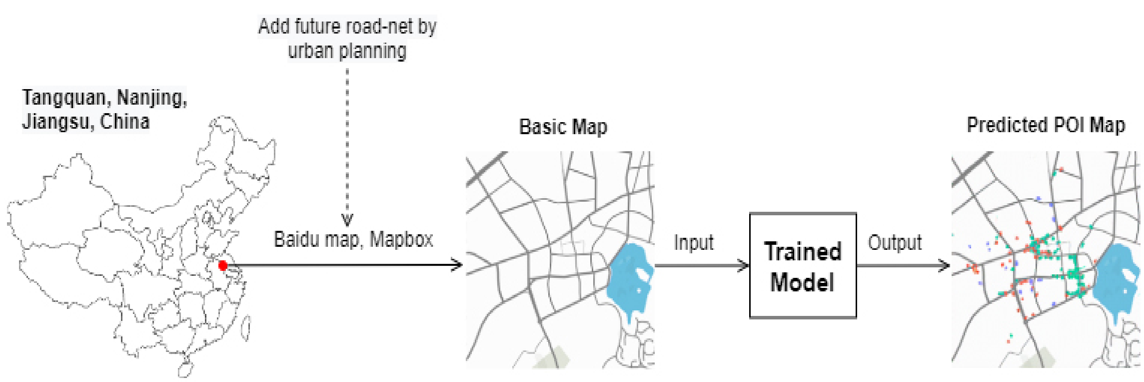


Figure 18. Training data batch example

4.4. Urban Design Application

To translate POI Map prediction into metrics useful for refined function zoning and to visualize them for designers, the types of POIs and the pixel number of each type of POI on each plot were counted, which determines the input values for the automatic massing generation program including building massing type, number, and volume ratio. This generated an urban design massing that can be easily referenced by designers.

Transformation of Images to Plot Indicators. The existing function zoning at the urban planning level of Tangquan could serve as the basis and prerequisite for refining the function zoning at the urban design level using the predicted POI Map. Based on the planned road network and the initial functional zoning, mixed commercial and residential land, commercial service facility land, and mixed commercial and office land (commercial-related) were selected as the plots for refining the functional zoning using the predicted POI Map. Then, the plots were numbered and the number of each type of POI[14] contained in the predicted POI Map was calculated for each plot using OpenCV (see Figure 7). The predicted numbers of three types of POI in each plot were plotted separately (see Figure 8). The number of the three POI in each plot and their ratio could indicate the development intensity of a specific building function (hotel, stores and food) and the mix ratio between them, as a reference for zoning refinement.

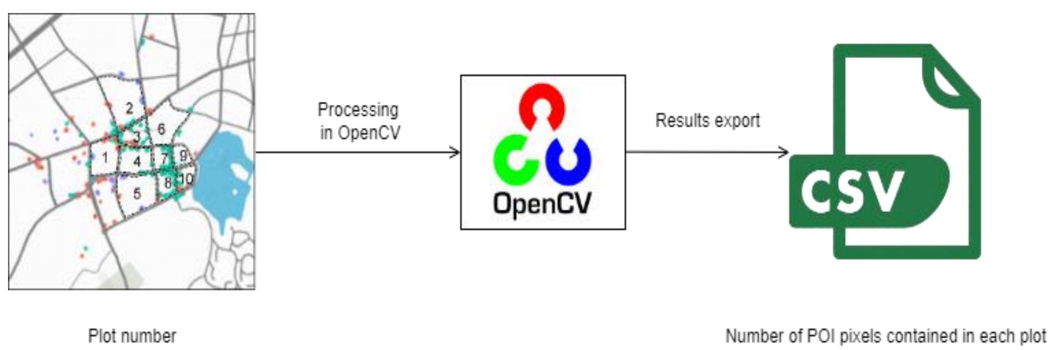


Figure 19. Processing predicted POI Map with OpenCV

[14] The number of POI is estimated by the number of pixels per type of POI.

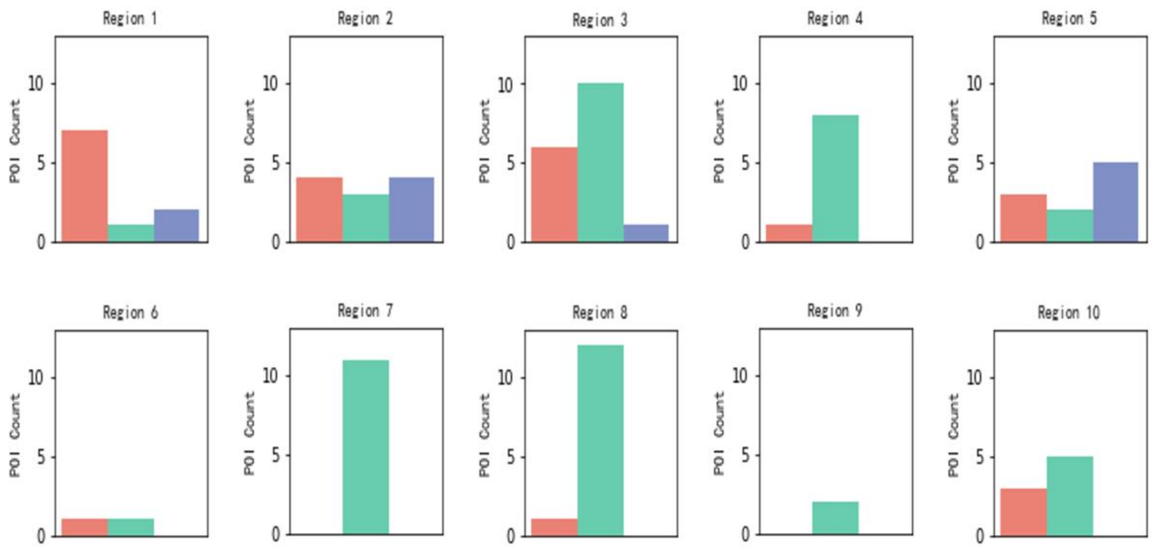
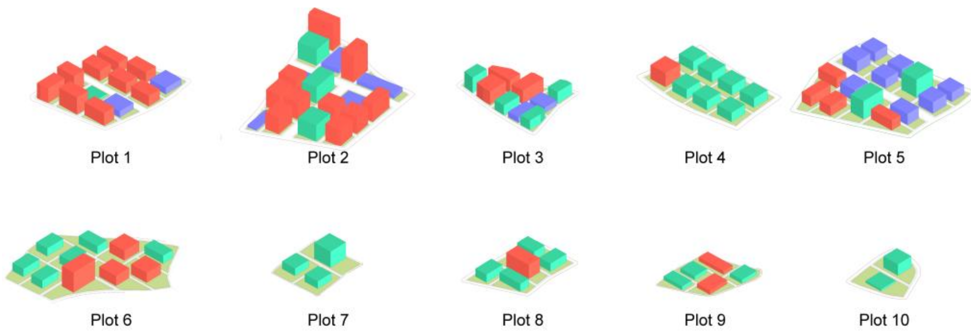


Figure 20. Predicted number of three types of POI in each plot

Visualization of POI-based massing in Rhinoceros and Grasshopper. UrbanXTools in Grasshopper was used to visualize the predictions into 3D volumes that designers can identify easily, and POI-based urban design massing was generated in Rhinoceros by controlling their FAR, building density and function mix ratio (see Figure 9). It is worth noting that the generated massing was based on the statistical results of POI number and common urban design criteria, and its goal is to provide designers a reference for the refined function zoning and corresponding development intensity, rather than to generate the final urban design massing results.



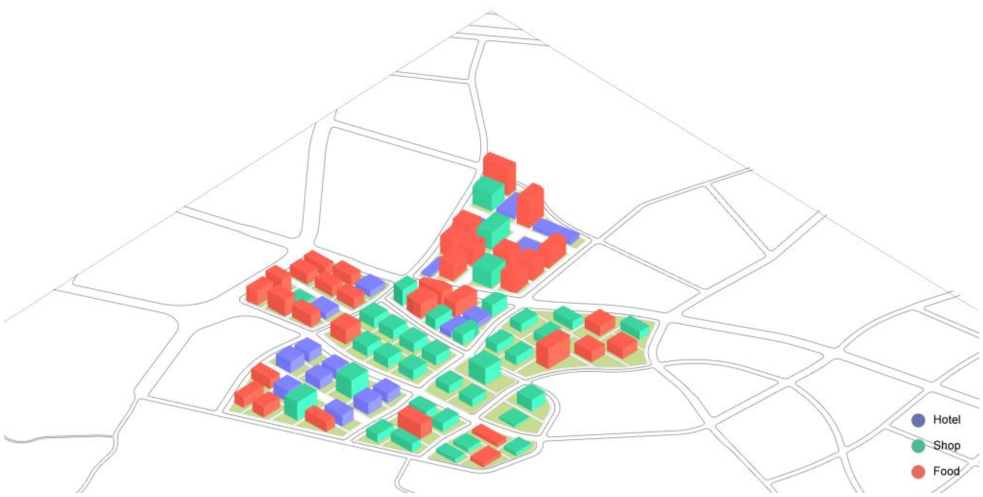


Figure 9. Visualization of POI-based massing

5. Conclusion

This research proposed a method to predict the POI distribution of a target tourist town based on big data and cGAN and to guide refined function zoning based on the predicted POI Map of the target town. In addition to presenting the method of predicting POI Map, this research also explored how to interpret the predicted results and translate them into urban design indicators to visualize urban design massing for reference.

5.1. Discussion and Contribution

This research illustrated a new methodological approach using Pix2Pix to predict graphical plot indicators and guide urban design function zoning refinement accordingly, which is made possible by the development of big data and machine learning. This approach is based on a large number of existing cases with their common features mastered in machine learning. This indicates that the prediction results generated by this method have a high reference value for designers. Furthermore, this method can significantly reduce the time and labor costs of function zoning refinement in the urban design process, which allows designers to address a greater number of design objects and iterate quickly in a shorter period.

The application of this method opens possibility of big data and machine learning assisted urban design. Predicting the distribution of possible POI guides the refinement of function zoning of targets in a bottom-up approach. Moreover, this method provides data support for urban design and streamlines the urban design process, which allows designers to devote more energy to urban design refinement.

5.2. Challenges and Future Study

Three factors should be taken into account in future research: a larger sample size with more extended models, network structure optimization, and a more thorough interpretation and translation of prediction results.

This research focused on tourist towns and applied the methodology to a specific design target. The advantage of this approach is that it focuses on a specific type and requires only a relatively small number of samples based on the characteristics of the target. The drawback is the inability of usage for more general targets. In other words, the model trained by cGAN corresponds to the target and cannot be directly applied to other types of targets. The model needs to be retrained using the same method for new targets of different types. Therefore, one possible evolution is to target more general targets and use larger sample sizes for training. Also, mapping relations related to the target type can be added to improve the specificity while ensuring the overall generality of the model. This evolution may avoid repetitive training of the model.

Another possible evolution is the optimization of network structure. For example, using DCGAN to improve the stability of GAN training and the quality of the generated results (Radford, Metz and Chintala, 2016), or using WGAN to improve GAN in terms of the loss function to solve the instability of training to some extent (Arjovsky, Chintala and Bottou, 2017).

Improvements could also be made to the interpretation of the predicted results. The number of POI contained in each plot can be counted in a more precise way, for example, by identifying POI centers based on color and then counting them. Also, a more systematic and supported approach can be used in translating statistical POI data into urban design indicators, such as by correlating with local urban design guidelines.

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