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Research on the Application of CGAN in the Design of Historic Building Facades in Urban Renewal—Taking Fujian Putian Historic Districts as an Example

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Abstract: In recent years, artificial intelligence technology has widely influenced the design field, introducing new ideas to efficiently and systematically solve urban renewal design problems. The purpose of this study is to create a stylized generation technology for building facade decoration in historic districts, which will aid in the design and control of district style and form. The goal is to use the technical advantages of the conditional generative adversarial network (CGAN) in image generation and style transfer to create a method for independently designing a specific facade decoration style by interpreting image data of historical district facades. The research in this paper is based on the historical district of Putian in Fujian Province and facilitates an experiment of image data acquisition, image processing and screening, model training, image generation, and style matching of the target area. The research found the following: (1) CGAN technology can better identify and generate the decorative style of historical districts. It can realize the overall or partial scheme design of the facade. (2) In terms of adaptability, this method can provide a better scheme reference for historical district reconstruction, facade renovation, and renovation design projects. Especially for districts with obvious decorative styles, the visualization effect is better. In addition, it also has certain reference significance for the determination and design of the facade decoration style of a specific historical building. (3) Lastly, this method can better learn the internal laws of the complex district style and form to generate a new design with a clear decoration style attribute. It can be extended to other fields of historical heritage protection to enhance practitioners' stylized control of the heritage environment and improve the efficiency and capability of professional design.

Keywords: machine learning; conditional generative adversarial network (CGAN); historic district; facade design; decoration style; urban renewal

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1. Introduction

1.1. Research Background

Urban organic renewal is a comprehensive renewal that integrates material renewal, life improvement, cultural regeneration, and social activation. It combines both material and non-material forms of renewal, focusing on urban infrastructure renewal and cultural shaping. Historic districts have the typicality and integrity of the style, the authenticity of the remains, and the functionality of the space. They are precious resources of urban cultural value and personality and are the key drivers of the organic renewal of the city to maintain lasting vitality and sustainable development. In the face of changing cities, the renewal of historical districts often has more specific and complex requirements. While attempting to avoid the phenomenon of homogeneity in the appearance of districts, it has become difficult to establish a balanced framework that considers the goals and demands of multiple parties in the design of historic district appearance and form. As a key element in forming a specific architectural style, facade decoration is an important part of the style and form of the districts, and it is also the main level of the districts that directly conveys the urban cultural personality and humanistic memory to the outside world. The virtual–real relationship, door and window styles, decorative components, and colors on the facade all affect the final effect of urban renewal, especially the renewal of historic districts. At present, many historical buildings in the districts and modern buildings have great contradictions in their facade decoration styles, such as the Fujian Putian Historic Districts [1], which affect the engine role of the historical districts in urban development. Therefore, methods to coordinate the integration of architectural styles in the renewal of historic districts and accurately and efficiently improve the control of the layout, materials, and scale of decorative elements on facades in the process of street renovation have become more important present issues.

In this context, this study found that conditional generative adversarial network (CGAN) technology can provide convenience in this complicated work. It attempts to establish a systematic approach to automatically generate possibilities for stylized buildings in relation to historic districts. Additionally, this generation can be targeted at individuals or in batches, maximizing design efficiency. At the same time, it can also provide more references for repairing partially damaged historical building facades. At present, scholars have carried out research on machine-learning image generation and conversion to quickly decompose and analyze image elements [2] and, at the same time, use the machine-learning assimilation of the facade style to transplant it to buildings in different places [3]. This research is constantly being explored, has achieved initial results, and is gradually being explored in urban renewal design.

1.2. Literature Review

The transformation of historic districts should be based on a thorough understanding of their characteristics and protection value. Only when we fully understand that historic districts are an important support for the urban historical spatial pattern, a place for the inheritance of architectural heritage culture, a place for the continuation of characteristic functions, and an important carrier of diverse humanities [4] can the protection of historical districts be effectively implemented, promoting sustainability in the historic built environment and heritage conservation [5]. Some scholars have also pointed out that the effective use of historic districts is a complex decision, and multi-criteria decision analysis (MCDA) can make adaptive use of historical buildings [6]. Tunxi Old Street in Huangshan City, Anhui Province [7]; Pingyao Ancient City in Taiyuan City, Shanxi Province [8]; Ancient Street in Suzhou City, Jiangsu Province [9]; Sanfang Qixiang in Fuzhou City, Fujian Province [10]; and Zhongshan Road Historic District in Xiamen City [11] provide a summary of conservation practices. There are currently four main modes: space management and control, building renovation, functional development, and comprehensive governance. These districts are remodeled in a small-scale, gradual, and segmental manner, especially using the traditional renovation method of classifying and subdividing the building. However, this method requires that many people work together for a longer period of time and necessitates a larger project budget.

With the wide application of big data and artificial intelligence technology, the disadvantages of the district renovation model commonly used in the early stage of the project are gradually highlighted, and there is a wave of machine-learning-assisted production and life in various areas of the city. The generative adversarial network (GAN) is one of the methods of machine learning that was proposed by Professor Lan Goodfellow in 2014 [12]. It uses an artificial neural network as the framework to perform representation learning algorithms on data [13]. Due to the excellent potential of GAN in image generation, repair, recognition, and other processing [14], it was widely used in the fields of image, audio, and video in the beginning to improve processing efficiency [15]. For example, it provides an algorithm for generating images from text [16], enabling intuitive, scale-specific control over face images [17] and color mode conversion [18].

Due to the improvement in technology and the enhancement in computing power, a new model architecture version has been improved based on the research architecture of GAN, such as PadGAN, which is used to explore and optimize space and provide reference solutions [19]. SRGAN (Super-Resolution Generative Adversarial Network) is used for image super-resolution conversion [20], and CycleGAN [21] and Pix2pix are used for image-to-image synthesis and creation [22]. It is precisely because of GAN's efficient working ability and strong self-generation ability that it has begun to penetrate widely into the application of traditional engineering majors such as architecture and urban planning. In the evolution of urban texture [23], the generation and evaluation of architectural planes [24], the interior layout [25], the exploration of architectural space [26], the deep organizational structure analysis and judgment of specific architectural works [27], the reconstruction of architectural topography [28], and other aspects have huge advantages and can actively innovate based on design aesthetics and preferences [29], bringing a new working mode and experience to the design field.

At present, GAN has also shown amazing adaptability in exploring historical building protection. Using GAN to reconstruct the color model for images of damaged cultural relics can provide a more comprehensive and objective evaluation of the degree of damage to cultural relics [30,31], which provides a solution to strengthen the evaluation of painted images on historical building facades. At the same time, the powerful learning ability and computing power of GAN help to generate programmed architectural styles and assist in building facade renovation [32,33]. This type of application of predefined style labels in specific areas to form the overall style control and guidance is not only required to realize the stylized renovation of the facade decoration of historical districts, but it is also important for urban renewal and cultural inheritance. Given that the stylized decoration of building facades in historical districts involves the combination of various building components, the definition of elements, and cultural significance, it is far more special than ordinary buildings. Therefore, in order to balance the styles of old and new buildings in the district, the limitations and possibilities of GAN in the stylization of historic district facades still need to be continuously explored.

1.3. Problem Statement and Objectives

The facade decoration style involves multiple links of collection, arrangement, analysis, evaluation, and redesign of relevant elements. The two historical districts of Jimei School Village and Luofutian in Fujian are dynamic and continuous. Long-term urban construction has already greatly interfered with the decoration of building facades in the districts. Different building types appear in the same district, including modern reinforced concrete buildings, traditional residential buildings, and Western-style buildings. These building facade decoration elements often have their own characteristics in terms of materials and styles, which greatly increases the difficulty of manual on-site data collection, which is time-consuming and laborious, and the determination of style often involves the subjective judgment of the designer. In addition, because historical and cultural districts are very important urban cultural and tourism resources, national and local governments have been supportive of the transformation of the facades of the districts and have introduced various types of protection plans and other regulations in the form of guiding opinions and guidelines, such as the *Law of the People's Republic of China on the Protection of Cultural Relics* (revised in 2017) and the *Measures for the Preparation and Approval of Protection Plans for the Neighborhoods of Famous Historical and Cultural Towns and Villages* (2014). Local governments will also formulate more detailed regulations that meet local development needs under the broad framework of national regulations according to their own actual situation, such as the *Regulations on Protection of Famous Towns and Villages and Traditional Villages in Historic and Cultural Cities of Fujian Province* (2017) and the *Protection Plan for Historic and Cultural Cities of Putian City* (2019), as a way to check and promote the facade renovation of neighborhoods step by step and promote urban historical and cultural regeneration and vitality of the neighborhoods. Therefore, unlike the facades of ordinary districts, the facades of historic districts have complex architectural patterns and high renovation costs. The requirements for element identification, scheme design, and construction of the facade decoration style are very strict, and the general steps are "data collection-style selection-schematic design-site construction-result acceptance". In addition, the renovation of historic districts is more complex than that of ordinary districts, not only because of the large number of architectural elements but also because of the relatively complex property relations between public and private buildings in the district. Generally speaking, during neighborhood restoration or intervention, the government will conduct an inventory of the property rights in the neighborhood and form systematic written data in order to obtain the support of private property owners for the project. The appropriate amount of compensation or direct storage into public ownership will be reflected in the renovation costs. Such a process leads to a very close relationship between cost control and design during the renovation process. According to the MacLeamy Curve [34], if there is a change in the early style choice, the pre-project planning or design stage has the most impact on the work that comes after, and it is easy to lose money and pay a high price (Figure 1).

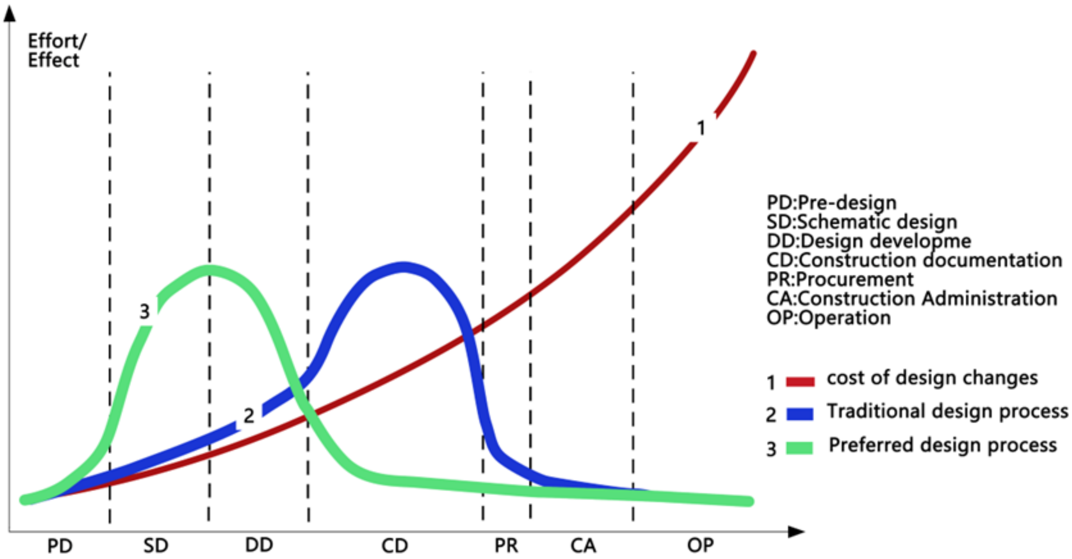

Figure 1. MacLeamy Curve's cost change during the project implementation phase can explain the importance of identification and selection of facade decoration styles in the early stage of the project for the cost control of the entire historical building facade renovation. (Image source: redrawn by the author; references are from As I, Pal S, and Basu P., Artificial intelligence in architecture: generating conceptual design via deep learning. International Journal of Architectural Computing, 2018, 16(4): 306–327).

In general, designers or engineers are frequently required to perform multiple complex tasks in order to solve the problem of stylized decoration of building facades in a district. The main problems focus on (1) the architectural image with a certain style or context for the area. It is necessary to investigate, record, and collect data on this facet, and this often involves thousands or even tens of thousands of historical building entities. (2) Classify and analyze the data to extract useful elements and symbols and their position information on the facade. Subjective judgments are inevitable. (3) Evaluate and determine the characteristics of these elements to recombine and design the stylized buildings of the relevant district facades in the renovation to ensure the integrity of the district style. However, in the face of huge amounts of data, timeliness is difficult to guarantee.

The objective of this research is to use CGAN technology to solve the above problems. The expected goals are as follows:

(1) Use CGAN to quickly identify, decompose, analyze, test, and evaluate the style attributes of the elements in the building facade images in the historic district;
(2) Independently generate facade schemes and realize accurate, rapid, and large-scale architectural facade stylization;
(3) Explore the effectiveness of CGAN in the renewal design of historic districts.

The above will minimize the workload of manual processing while updating the huge historical districts, avoid the influence of subjective human preference judgment, improve the work efficiency of designers, and contribute to overall cost control. At the same time, this process is more conducive to maintaining the consistency of regional architectural styles in urban renewal and the renewal design of historical districts.

2. Materials and Research Strategy

2.1. Study Area

Putian City, Fujian Province, is located on the southeast coast of China and is an important area along the world's Maritime Silk Road, with rich architectural and cultural heritage. Putian Yuanxiang has a strong clan culture, prosperous maritime trade, and frequent cultural exchanges between China and the West. Therefore, in Fujian, Putian can be seen everywhere in different styles of traditional Chinese architecture and Western-style buildings, and most of them are concentrated in the local historic district. In 2022, Putian City completed the late assessment of the declaration of China's National Historical and Cultural City and constantly promotes the renewal of historical and cultural districts to create architectural forms rich in Putian style.

Putian-style architecture, as a branch of the Minnan architectural style, is also an important addition to the Chinese regional architectural system. Its stylistic features are compatible with the characteristics of traditional architecture in Quanzhou, which focuses on external decoration and contains the grandeur and majesty of official mansions in Fuzhou, based on which it has formed its own unique architectural personality. The large number of Chinese people who have moved from Putian overseas also brought the architectural style of their hometown to foreign countries, becoming local Chinese businessmen overseas with Chinese spirituality in their homes. Putian-style architecture has also broken through the region's limitations to a larger stage. At the same time, most of the Putian-style buildings use a combination of brick, wood, and local materials and fit the natural aesthetic to adapt to the contemporary requirements of sustainable architecture development. Due to the rough, large-scale urban construction in the early days, the place we live in has gradually become a reinforced concrete arena, with thousands of cities and no characteristics. As a special area of urban cultural value, historic districts carry non-renewable historical information and face the most severe challenge of urban renewal. Organizing the urban context and transforming the current style of the historic district has always been the focus of attention from all walks of life. Fujian Putian has recently insisted on the combination of protection and utilization through continuous investment, revitalization of the functions of historical districts, repair of historical buildings, and renovation of street facades to improve the quality of historical districts. The related enthusiasm for conservation renovation has swept through all of Putian and Fujian Province while also playing out in other Chinese provinces and cities. By 2022, the number of historical and cultural districts in the country will exceed 1200 [1]. It is foreseeable that this will become a huge market in urban renewal.

The Putian Luomutian Historical and Cultural District (hereinafter referred to as "Luomutian") and the Xinghuafu Historical and Cultural District (hereinafter referred to as "Xinghuafu") are two representative provincial-level protected historical districts in Fujian Province (Figure 2). From the perspective of the main street interface, the downstairs section of Luomutian and Xinghuafu retains more original buildings but looks dilapidated due to the time it has existed. The two districts present a facade-style form rich in local characteristics in terms of shape, material, and spatial scale, but, at the same time, they both face the problem of decoration and transformation of the district facade.

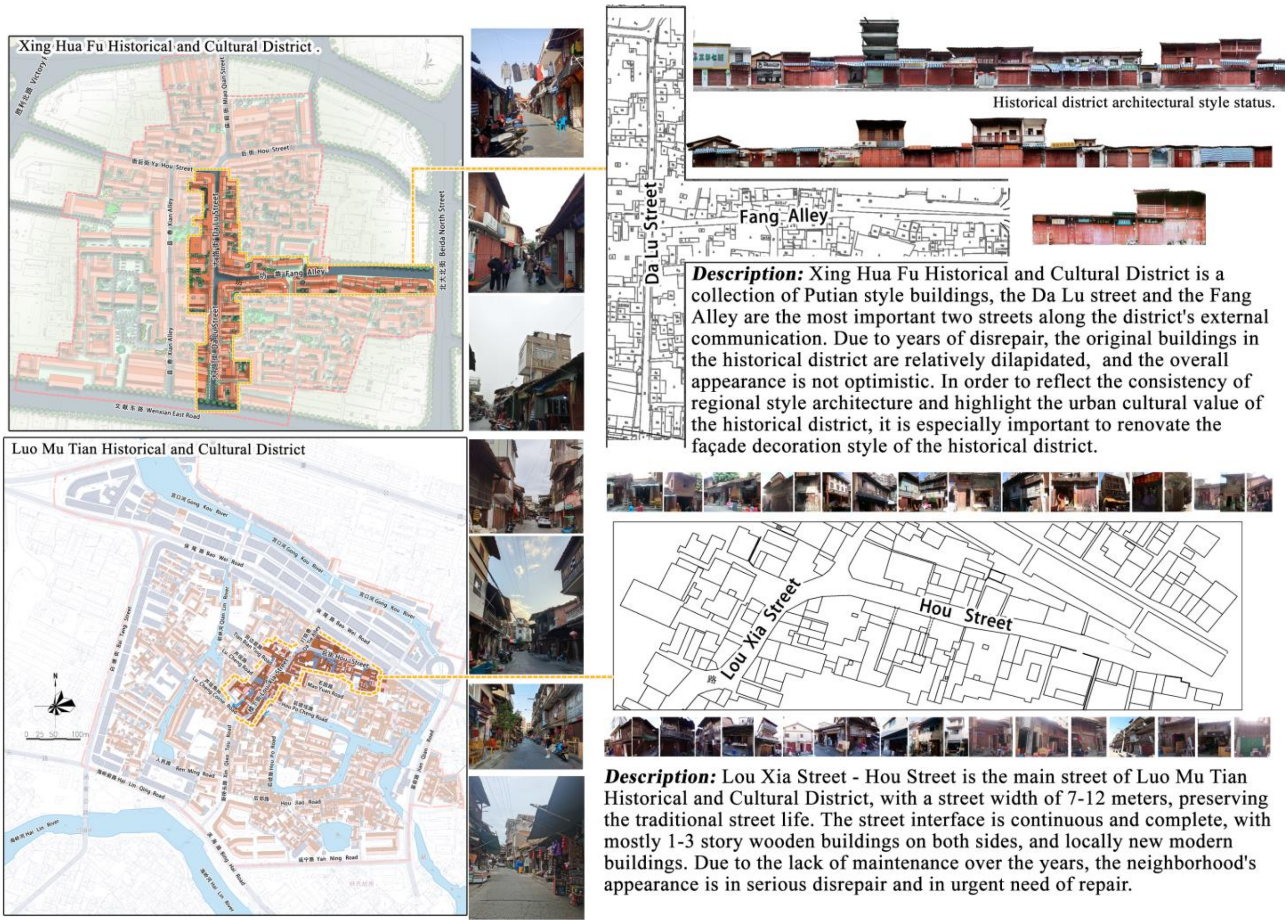

Figure 2. Putian Luofutian Historic and Cultural District and Xinghuafu Historical and Cultural District.

The facade decoration directly affects the external representation and cultural shaping of the district style and is the starting point and focus of the historical district renovation project. At present, the common ways to transform the facades of historic districts include the following: demolition of buildings that conflict with the historical features, downgrading of large high-rise buildings, and stylized micro-renovation of existing buildings. The former two are more difficult to implement due to large investments and the difficulty of unifying public opinions. Stylized micro-renovation has little impact on the status quo, requires less investment, achieves good results, and has become the main way to transform the style of the current neighborhood. Therefore, as early as 2014 and 2017, the official organization organized a general survey and identification of the architectural style elements of the two districts of Luomutian and Xinghuafu to evaluate and determine the style to be adopted for micro-renovation. However, it was difficult for the huge data collection and subjective style definition to be effectively promoted and recognized by relevant units for a while, and the project was repeatedly shelved. Situations such as this generally exist in the case of historical district renovation, and some relevant planning texts even directly apply the styles of other places, which cause irreversible mistakes and cultural value loss during urban renewal.

2.2. Methodology

This study explores the application of conditional generative adversarial networks in the stylization of facade decoration of historic buildings and takes Putian, Fujian, as an example to conduct empirical research. On the one hand, this study adopts CGAN technology to identify and generate the decorative style of historical districts through image generation, style transfer, and other work and to provide scheme design. On the other hand, this study also explores the adaptability of CGAN technology in historical district reconstruction, facade renovation, and renovation design projects, providing a better auxiliary basis. Especially for districts with obvious decorative styles, the visualization effect is better. At the same time, this study also provides a certain reference significance through the determination and design of the facade decoration style of a specific historical building. Therefore, this study has important practical value for enhancing practitioners' stylized control of the heritage environment and improving the efficiency and ability of professional design.

The research method based on CGAN consists of five steps: data acquisition, data processing, model training, model evaluation, and model application (Figure 3). The specific method is as follows:

(1) Data acquisition. The object of this study is to obtain the image data of building facades in the Putian Historic District, Fujian Province. Through several field investigations and interviews with villagers, we learned that the traditional wooden building facades in this area are the characteristic architectural features of this area. The materials and craftsmanship of the doors, windows, and walls of its building facades have unique local characteristics. However, at present, various architectural styles of wooden buildings and modern buildings are mixed together, failing to form a unified district style, and the status quo of district facades is relatively messy. Therefore, we photographed and collected 109 traditional wooden building facades as samples for machine learning in the Putian historical district buildings in Fujian. These samples are representative buildings with historical authenticity and site memory with high historical and cultural value. We took sample photos of these building facades to ensure the accuracy and completeness of the data and redrew each sample as a facade rendering with a consistent color style, which helped improve the reliability of the research results and their practicality.

(2) Data processing. After data collection, the data need to be preprocessed. First, clean and filter the data to remove noise and low-quality images to ensure the quality of the data. Second, label and classify the data, and classify the data according to the following three types of pictures:

(i) Building Exterior Profile (BEP): this shows the outline of the building, including elements such as the facade and roof of the building;
(ii) Label images of functional facade elements (Facial Semantic Labeling, FSL): mark various functional elements in building facades, including doors, windows, walls, columns, railings, and eaves, as well as their positions and sizes;
(iii) The final effect of the building facade (Building Exterior, BE): this aspect presents the final effect of the building facade, which can include elements such as color, texture, and details. Through this classification method, it can be prepared for the subsequent model training so that the model can more accurately analyze and identify the building facades of the historic district of Putian, Fujian.

(3) Model training. After the data processing is complete, it needs to be trained using a Conditional Generative Adversarial Network (CGAN) model. CGAN is a generative model that learns the mapping between input images and target styles during training. In this study, we used the CGAN model to generate images of historic building facades with a specific decorative style. Since the building facade contains many elements, the number of samples is limited. Therefore, in order to further improve the accuracy of the model, the task of building facade generation is split into two parts during the training process: that is, the generation from BEP to FSL and the generation from FSL to BE, and two models are trained for these two parts. This method of splitting tasks helps to improve the accuracy and stability of the CGAN model and increases the controllability of fine tuning. During the training process, we also need to choose an appropriate loss function and optimizer to improve the accuracy and stability of the model.

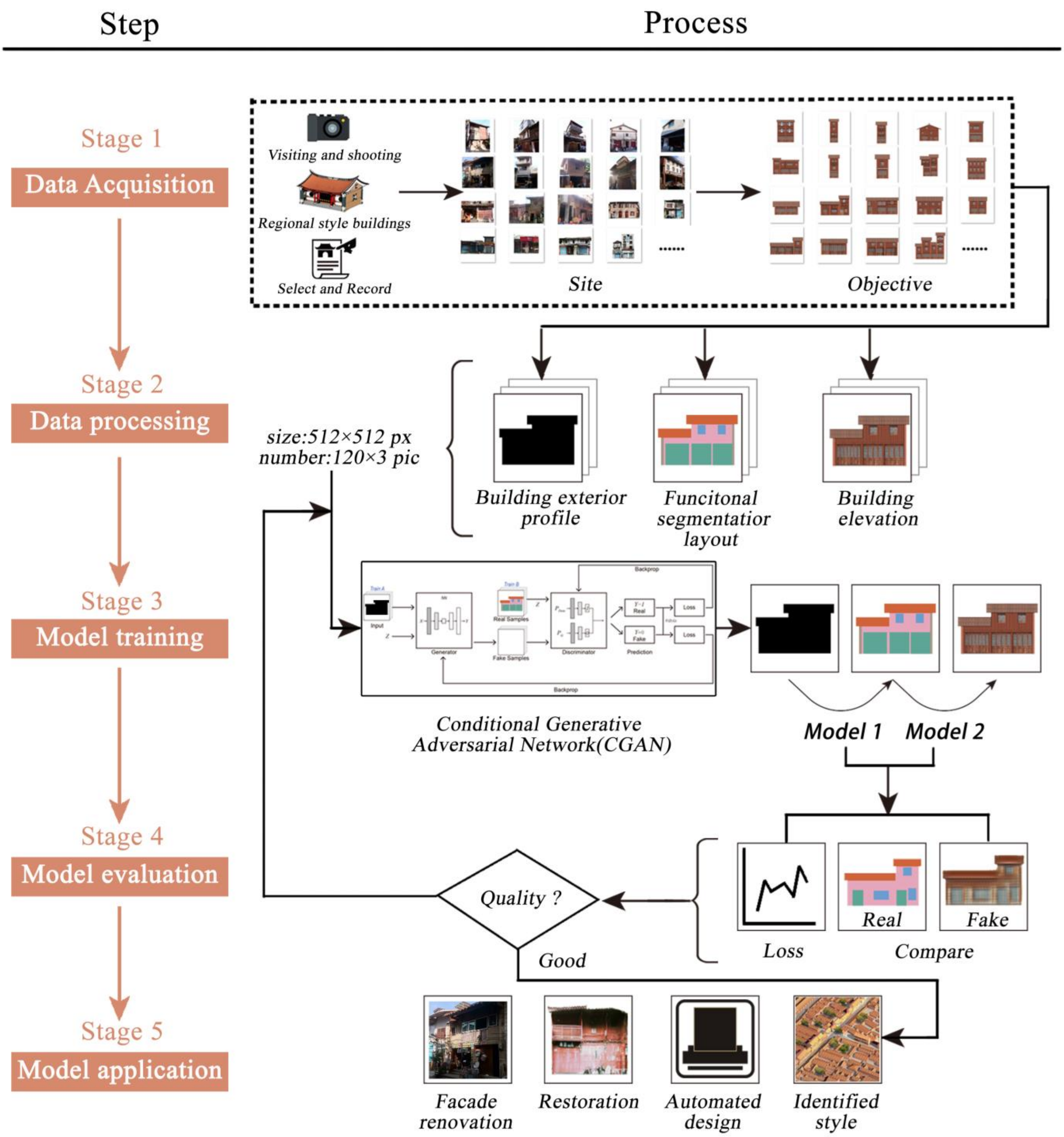

Figure 3. Research methodology flowchart.

(4) Model evaluation. In order to evaluate the performance of the trained CGAN model, a model evaluation is required. Commonly used evaluation methods include looking at the LOSS value in the training log and at the test pictures of each generation in the model iteration. The combination of these two methods can have a basic impact on the model's accuracy. If there are some problems, such as the generated image not matching the target style and obvious distortions, it can be adjusted and tested repeatedly by changing the loss function, increasing the training data, and adjusting the network structure. In addition, the performance and applicability of the model can be further improved by using methods such as human evaluation and user surveys to evaluate the model. The choice of

evaluation method can be determined in combination with specific application scenarios and research purposes.

(5) Model application. Finally, the trained CGAN model is applied to the stylized design of building facade decoration in the Putian Historic District, Fujian Province. Specific applications include the overall or partial scheme design of the façade; the determination and design of the facade decoration style of a single historical building; and the auxiliary basis for the reconstruction of historical districts, facade renovation and renovation design, and other projects. At the same time, this method can also be extended to other fields of historical heritage protection and restoration to improve the efficiency and capability of professional design.

2.3. Material Handling

The two historic districts of Luofutian and Xinghuafu in Putian, Fujian Province, selected in this study are the main gathering places of Fujian Minnan culture and overseas Chinese culture. This location has a collection of rich humanities, art, and architectural heritage, reflecting the strong regional characteristics of Puxian-style architecture. This study focuses on the facades of the main streets in the district. Hundreds of buildings are branded with the style of the times, and the old and new buildings are mixed. Among these buildings, 1–3-story buildings are the main ones, but there are also 4–5-story high-rise buildings due to poor protection in recent years, which affects the overall look and feel of the district, and the whole street faces the upcoming urban transformation. Therefore, it is important to evaluate the decorative style characteristics of building facades in districts as soon as possible. We selected well-preserved historical buildings in the district to ensure the quality and reliability of the image dataset. A total of 153 building facade images were taken, of which 44 samples were removed for reasons such as building occlusion or inappropriate shooting angles. There were 109 samples left for the experiment.

As shown in Figure 4, each experimental sample is divided into three types of pictures: BEP, FSL, and BE, and there are 109 pictures, respectively, totaling 327 pictures. These images have a uniform resolution of 512×512 pixels. According to the facade characteristics of different buildings, we marked each image with different colors in the corresponding facade elements and functional segmentation diagrams. These markings include turquoise for doors (R93, G166, and B149), blue for windows (R107, G157, and B208), orange for guardrails (R238, G163, and B36), and light red for walls (R230, G167, and B188). The roof is tan (R188, G133, and B43), and the columns are gray (R168, G149, and B135). Each facade image contains some or all of these six types of elements, depending on the actual situation. These markers aid in machine training and recognition.

2.4. CGAN Model

The Conditional Generative Adversarial Network (CGAN) is a network framework based on the Generative Adversarial Network (GAN). CGAN consists of two confrontational models: a generator and a discriminator(refer to Appendix A for the computer environment parameters of machine learning operation). Figure 5 shows the main principle of CGAN. The generator receives an input picture (Train A) and a random vector (Z) to generate a fake picture. At the same time, the discriminator marks another set of corresponding pictures (Train B) and random vectors as real pictures and marks fake pictures as 0. If the discriminator judges that the generated picture is fake, the discriminator will return the deviation value between the fake picture and the real picture to the generator, and the generator will be upgraded to generate a picture closer to the real picture. On the contrary, if the discriminator judges that the generated picture is real, then the discriminator will continue to learn from the training set to improve its recognition ability. Through confrontation training, the generator can finally generate fake pictures to achieve the goal of generating building elevations.

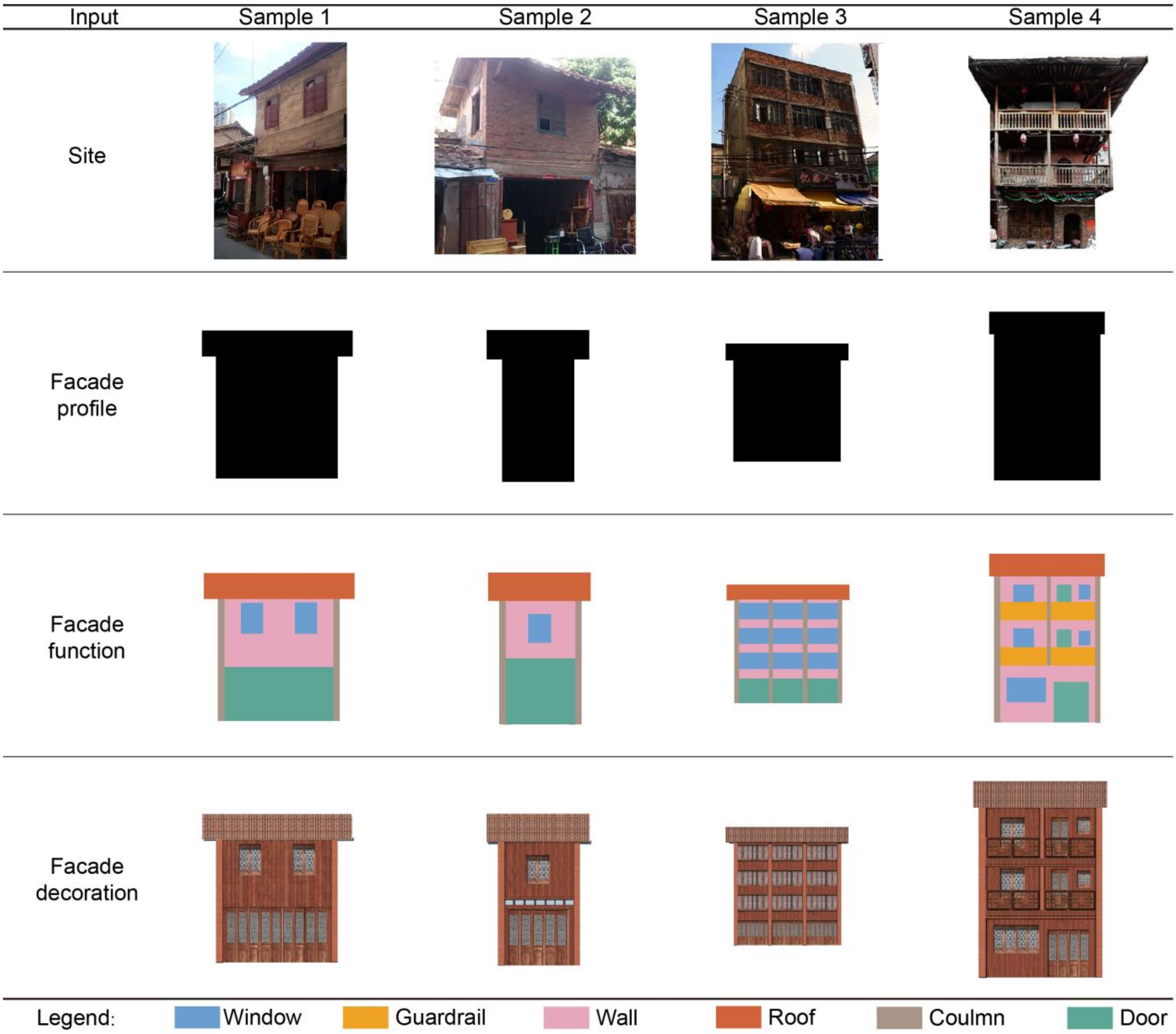

Figure 4. Experimental materials.

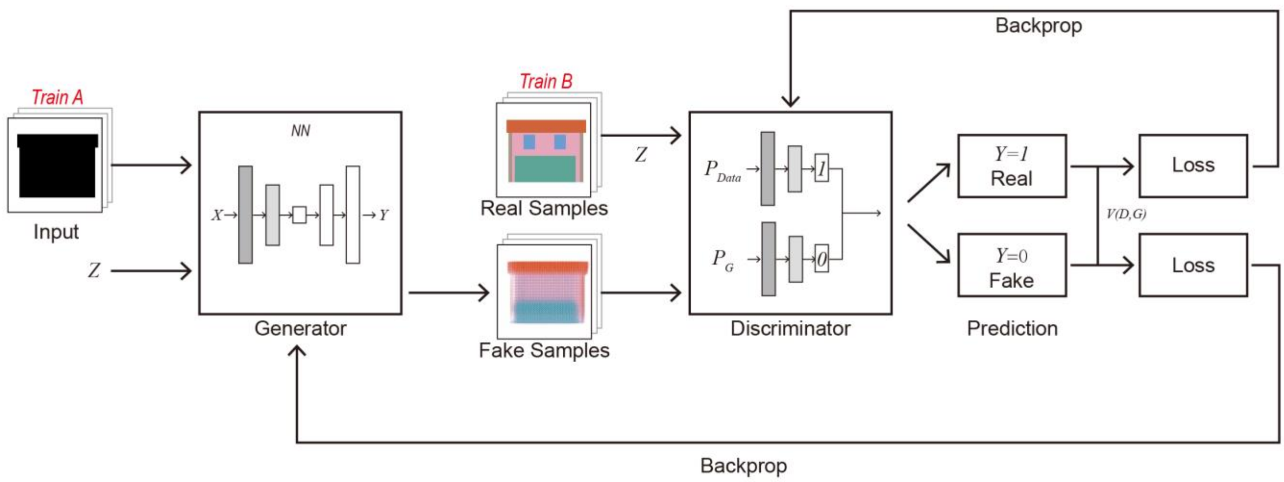

Figure 5. CGAN model framework.

3. Results

3.1. Model Evaluation

Two methods are used for model evaluation: (1) statistics and judgment of the size and trend of the LOSS value in the training log; (2) checking the quality of the test images of each generation in the model iteration. In the first method, the loss value of each generation model during the model training process is counted to make a line chart. Among them, Model 1 represents the weight model from BEP to FSL, and Model 2 represents the weight model from FSL to BE (Figure 6). The loss value includes five indicators, such as G_GAN, G_GAN_Feat, G_VCG, D_real, and D_fake, which, respectively, represent the following:

(1) G_GAN is the generator's confrontation loss, which measures how similar the image the generator generated and the real image are;
(2) G_GAN_Feat is the feature matching LOSS of the generator, which can help the generator generate more high-level features, such as texture and color, to make the generated image more realistic;
(3) G_VCG is a visual consistency LOSS, which forces the generator to generate images with visual consistency, that is, the similarity of each pixel in the image space;
(4) D_real and D_fake are the losses of the discriminator; D_real represents the probability that the real image is recognized as a real image by the discriminator, and D_fake represents the probability that the generated image is recognized as a fake by the discriminator.

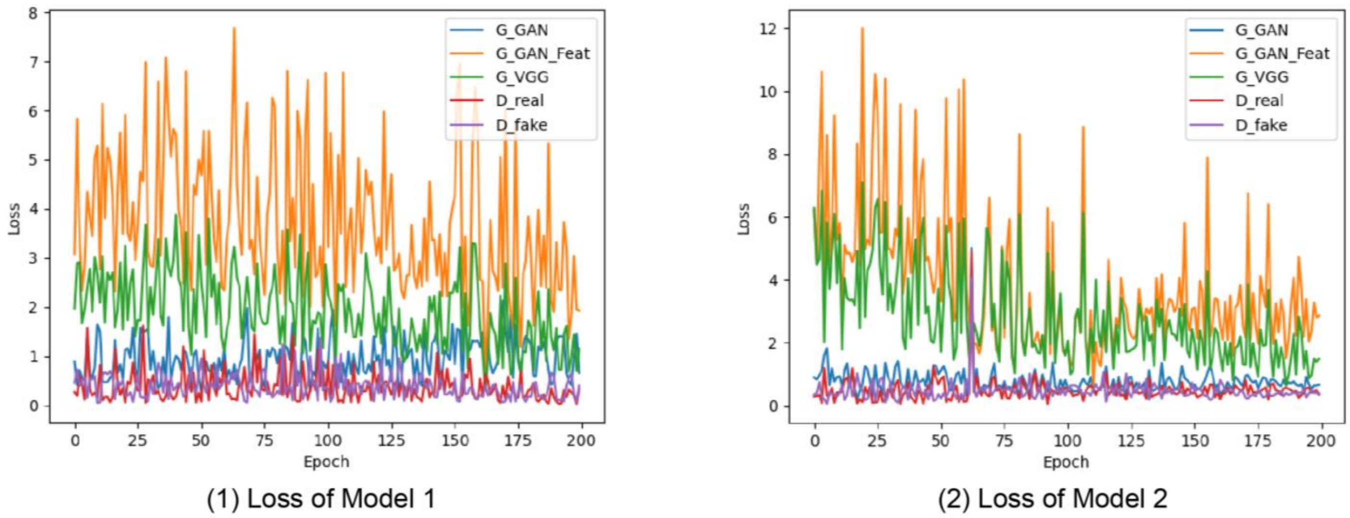

Figure 6. Model training log LOSS value statistics.

In the training of the CGAN model, the downward trend of the loss value is an important indicator. Generally speaking, the LOSS functions commonly used in training CGAN include the CGAN loss function, feature-matching loss function, and image reconstruction LOSS function, corresponding to the three indicators of D_fake, G_GAN_Feat, and G_VGG, respectively. In order to visually evaluate Model 1 and Model 2, the average value of the above three indicators can be used to calculate the slope, which is the rate at which the loss function decreases. It can be seen from the calculation that the slope of the loss value of Model 1 is -0.002, and the slope of the loss value of Model 2 is -0.010. Since the slope is negative, the loss value gradually decreases as the number of training steps increases. The slope of the loss value of Model 1 is closer to 0 than that of Model 2, indicating that the loss value of Model 1 decreases slowly during the training process, while the loss value decreases relatively quickly during the training process of Model 2. Therefore, the training effect of Model 2 is better than that of Model 1.

The second approach is to check the quality of the test images generated at each generation of the model iterations. Specifically, we selected the 1st, 50th, 150th, and 200th epochs in the model training process, generated test pictures, respectively, and compared them with real pictures to evaluate the degree of model restoration (Figure 7). Overall, the pictures generated after Model 1 and Model 2 training for 200 epochs are almost the same as the real pictures, and the accuracy is high. However, the results of Model 2 tested at the 50th epoch of training are already close to the real picture. However, Model 1 still has some errors in the 50th and 150th epochs, mainly reflected in the lack of accuracy in the size and position of the windows on the building facade. However, at the end of the 200th epoch, the results of the test pictures of Model 1 also reached the level of real pictures. Therefore, in general, although the training effect of Model 2 is better, Model 1 also shows good training effects and performance.

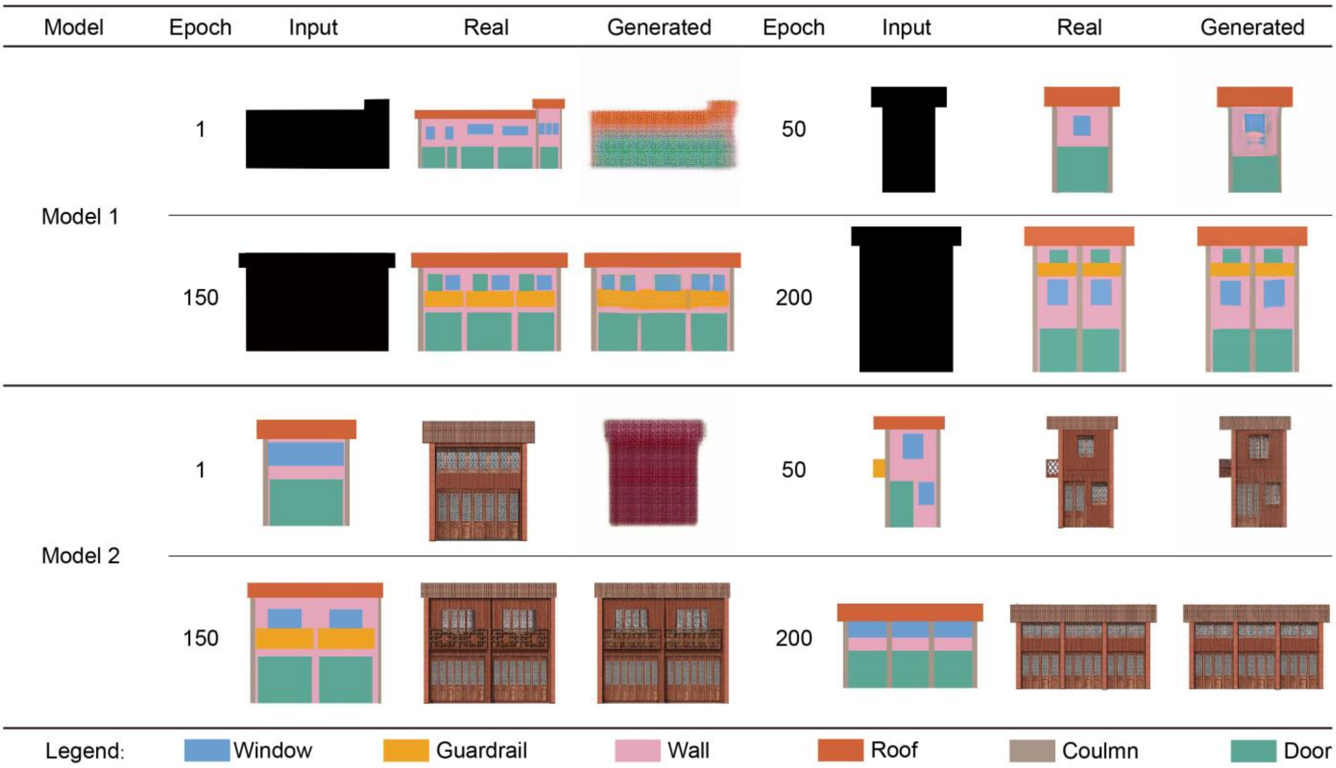

Figure 7. Testing the model's training process.

3.2. Model Testing

We randomly selected 20% of the pictures (22 pictures) from the 109 BEP training materials as further test samples to evaluate the performance of the trained models, Models 1 and 2. Specifically, we first input these BEP test pictures into Model 1 to generate FSL. Then, we inputted the generated FSL into Model 2 to generate BE and evaluated the quality of the generated image. As shown in Figure 8, we found that in Test 1, there was an error in the column in the middle of the building's facade. Model 1 did not generate columns coherently, causing subsequent models to continue this error. Additionally, in Test 2, the column in Model 1 was not connected to the eaves correctly in the middle part, but the generated result of Model 2 fixed this error. In Test 3, both Models 1 and 2 performed relatively well, with no obvious errors. In Test 4, the left and right sides of the eaves of the building facade generated by Model 1 showed color districts slightly beyond the building outline area, which made Model 2 unable to generate horizontal eaves. In general, Models 1 and 2 were relatively stable during the model-testing process, but there is still room for improvement. Especially for the generation of columns and eaves in building facades, higher accuracy is required, and in further applications, artificial correction may be required.

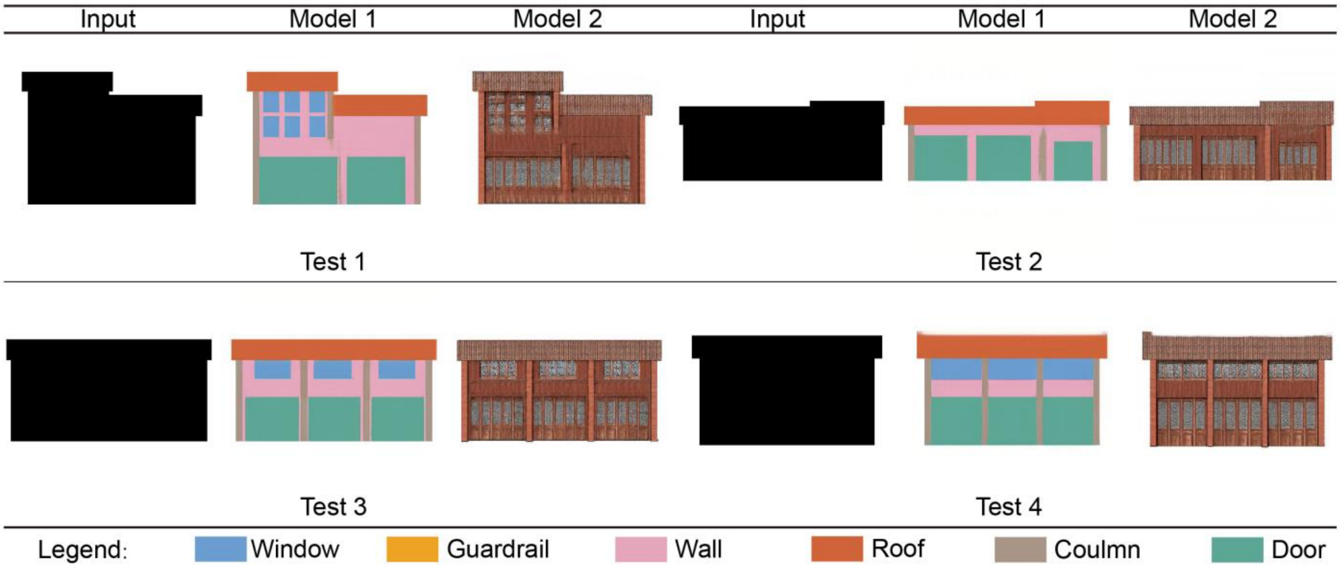

Figure 8. Model 1 and Model 2 used the training material to test the generation quality.

3.3. Model Comparison

In the field of deep learning, the performance comparison of models is usually based on the accuracy, efficiency, and robustness of their predictions. For the task of building facade appearance generation in this study, we evaluated the quality of both Model 1 trained in this study and the model [32] trained in previous studies when generating test images. Specifically, we found that in Tests 1 to 4, the Model 1 trained in this study was more stable and accurate than the model in previous studies when generating the architectural appearance (Figure 9). The reasons for this result are as follows:

(1) We adopted a more detailed training plan and divided the entire training process into three stages: the pre-training period, the simulated annealing period, and the stabilization period. In the pre-training period, the model was preheated with a small learning rate (0.0001) in the first 40 epochs of training so that the model could learn the characteristics of the data as soon as possible. In the simulated annealing period, the model was trained from the 41st epoch to the 150th epoch, and the learning rate was gradually increased (the upper limit is 0.001). The process of simulating the gradual heating up of the model helps the model find a better solution in a wider search space. In the stable period, the learning rate of the model was gradually reduced from the 151st epoch to the 200th epoch of training (the lower limit is 0.00005) so that the model could converge more stably and prevent overfitting.

(2) We adopted a learning rate decay strategy that uses cosine annealing to decay the learning rate. Specifically, the learning rate slowly decreased during the last 25% of training. Then, with the help of the cosine function, the learning rate gradually decayed to a smaller value (the decay rate of the cosine function was 0.5). In addition, techniques such as batch normalization (batch size 32) and dropout (probability 0.5) were used in this study to prevent overfitting.

(3) In this study, the training data were screened and expanded to increase their diversity and quantity, which helps to improve the generalization ability and robustness of the model.

Compared with the performance of Model 2 trained in this study and the model [32] trained in previous studies when generating test pictures, due to the different training samples, different building facade appearances were presented. In contrast, the appearance of building facades trained using samples from the Putian Historic District, Fujian Province, is simpler in facade decoration. They were mainly composed of wooden walls and red tile roofs without too many facade decoration patterns, and the building had fewer terraces (Figure 10).

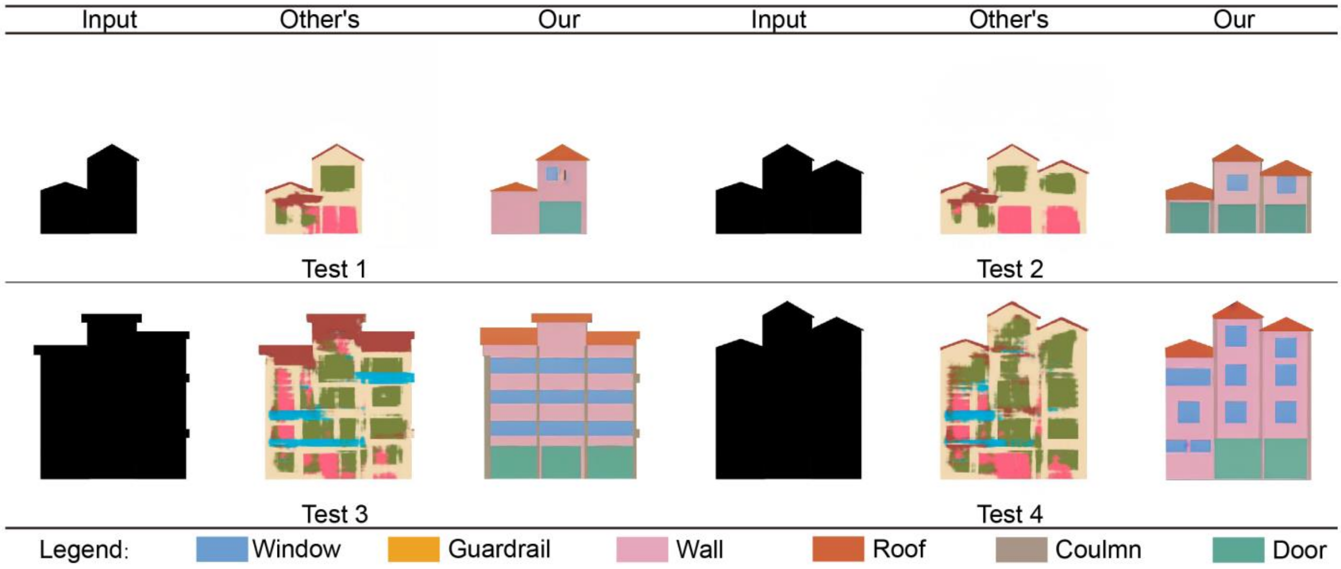

Figure 9. Comparison of Model 1 in this study with models from previous studies.

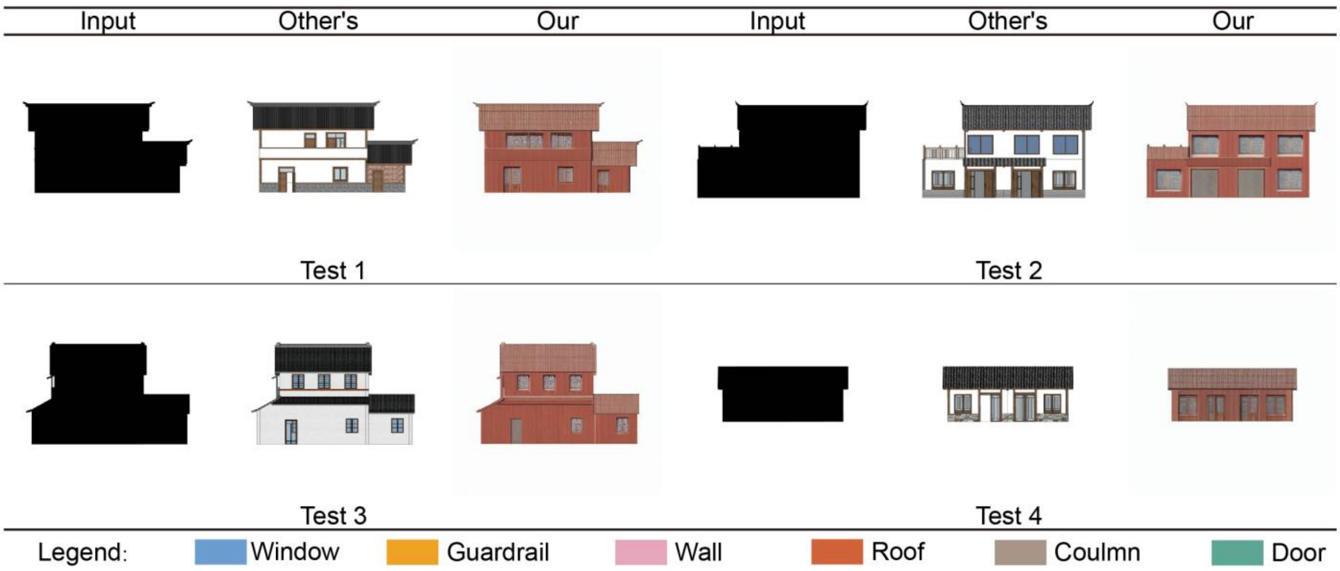

Figure 10. Comparison of Model 2 in this study with models from previous studies.

4. Discussion: Application of Model and Design of Historic District Scheme

4.1. Model Application

After model training, we applied the model to the building exterior renovation design project of the Putian Historic District in Fujian. The project includes two parts: the overall scheme design of the facade and the renovation of the facade. The buildings that need to be renovated cover different types of single-story, double-story, and multi-story buildings. Figure 11 presents some of the building facades generated by the model. In addition, based on the results generated in Figure 11, professionals can refer to the results generated by the model for architectural 3D modeling (Figure 12). Overall, the model achieves building appearance generation, unifying the building's facades into the same style without obvious errors. Although the results generated by the model are of certain reference, it should be noted that the facade elements generated by the model are relatively singular. In practical application, it is also necessary to consider the physical environment of the site, such as sunlight and wind flow, as well as the specific needs of users to further supplement and optimize the opening and decoration of the building facade. Therefore, the model cannot replace the designer to complete all the design work.

Figure 11. Application of models according to field conditions on site.

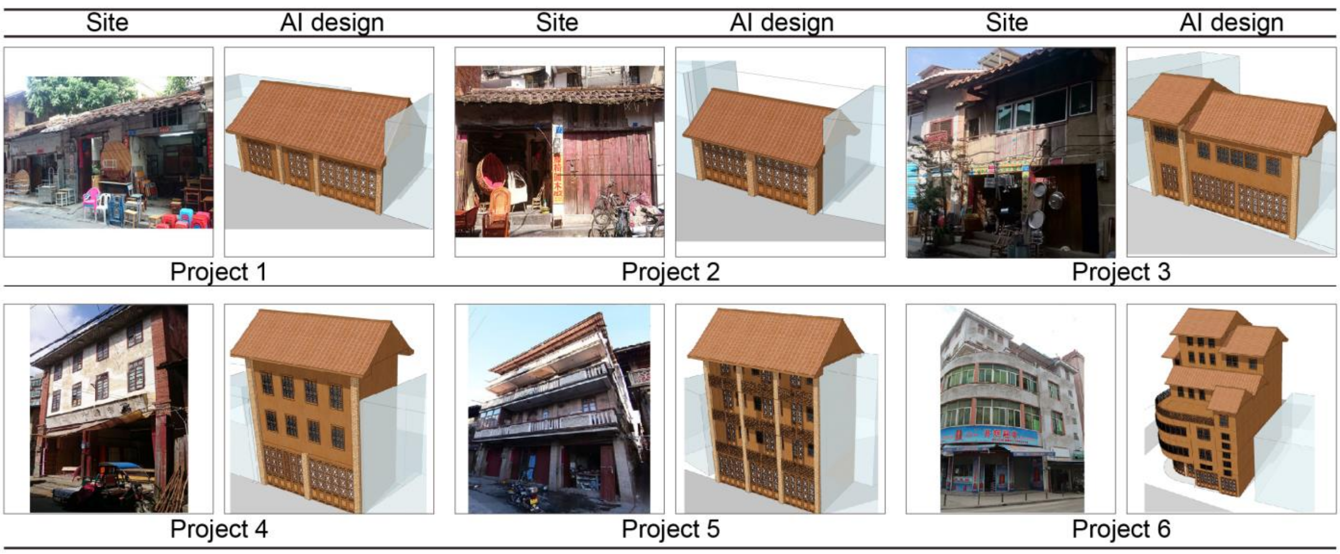

Figure 12. The 3D model effect of the model's application result.

4.2. Application of Multi-Scheme Generation

In addition to enabling facade generation for specific objects, the model can generate multiple different results by varying the noise input in the CGAN model. In CGAN, the noise input is a random vector, and different images can be generated by changing the noise vector. We also selected a building outline map in the historic district of Putian, Fujian Province, as a conditional input to ensure that the generated images are all in the same scene, but the design schemes can be different. When generating images using the CGAN model, we used multiple different random noise vectors to obtain various design options (Figure 13). By comparing the design schemes generated by different noise vectors, we found that this method can provide infinite new ideas and inspirations for the design of building exteriors. At the same time, the optimal design scheme can also be selected according to user preferences and needs.

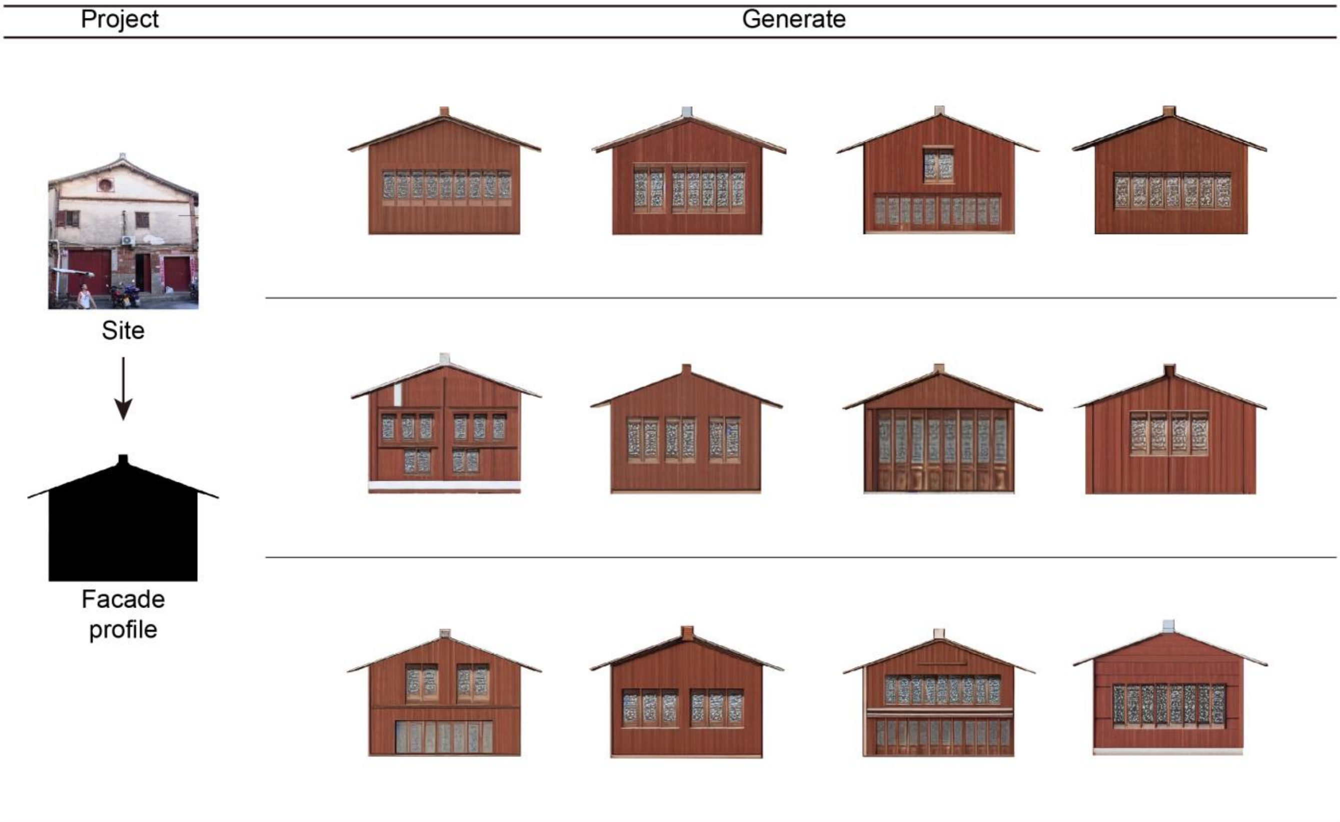

Figure 13. Multiple results generated by the model under the same building outline.

5. Conclusions

The purpose of this research is to explore the application of generative adversarial networks (CGAN) in the stylization of historical building facade decoration and take Putian, Fujian, as an example. China's urbanization rate exceeded 60% in 2019, and it has entered the post-urbanization era in an all-around way. Urban renewal has also transformed from large-scale incremental development to gradual stock quality improvement. As a place where the city's cultural atmosphere is concentrated, renovating its facade decoration style involves a wide range of areas and complex relationships, which has become an important issue for urban renewal. This study uses CGAN to construct a generative method for the stylization of building facades in historic districts and provides a design strategy for the current unified problem of historical building facade styles. The experimental results show the following:

(1) For the facade decoration of historic buildings in Putian, Fujian, which is full of regional characteristics in this study, CGAN demonstrated great comprehension ability and computing potential and completed the classification, analysis, and style reconstruction of facade decoration elements. These results demonstrate that CGAN is effective for element processing in building facade images.

(2) The resulting images independently generated by CGAN were similar to the real image, which shows that CGAN can batch and uniformly process the stylization of historical building facades and helps to guide the aesthetics of architectural facade decoration styles in historical districts.
(3) CGAN is able to extract unspecified facade decoration styles using the provided image dataset and transplant them to new buildings through the style transfer capability, showing good results. This will help designers provide more choices in the decision-making of facade decoration style and can play a role in correcting some subjective judgments.

However, as far as the current application scenarios are concerned, the CGAN method still has certain limitations and deficiencies, including the following: (1) CGAN mainly optimizes facade decoration and generates design styles. This is very important in terms of the cultural connotation of the district. (2) It is unclear how we can construct more interesting labels in the data set so that CGAN can generate more novel design variants. (3) At present, CGAN has shown strong advantages in the preliminary design of the project. Further extending it to the learning and control of the whole project, including the inspection of the construction process and the calibration of the final results, is yet to be completed. These issues will become the focus of CGAN's continuous improvement in its application to historical districts. Therefore, future research can continue to explore how to optimize the model's structure and algorithm to further improve the generation effect and training efficiency. At the same time, the conditional generative confrontation network can be applied to the protection of cultural heritage in other fields, providing more technical support and methods for the protection and reuse of cultural heritage.

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Data Availability Statement: The original code of the program cannot be released yet because our program is being used in other research. The training set for the machine learning for this article can be found online at https://data.mendeley.com/datasets/hp95rw6m6p/1 (accessed on 27 April 2023).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Machine learning environment configuration: the operating system is Windows 11 (X64), the Cuda version is 11.5, the deep-learning framework is Pytorch, the graphics card is a GeForce GTX 3070 (16G), and the processor is an AMD Ryzen 9 5900HX (3.30 GHz).

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