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Computer-Aided Design AND APPLICATIONS

Computer-Aided Architectural Style Identification and Landscape Design Teaching with Deep Learning

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Abstract. This article seeks to investigate the application efficacy of an architectural style recognition model, leveraging computer-aided design (CAD) and deep learning within the context of landscape design teaching. This article provides a detailed design and construction of the data style recognition concept for CAD deep learning models. Through platform-based data collection and training validation of deep learning, a target model training and validation method for architectural style was constructed to process the design platform. A comprehensive teaching comparison of landscape design was conducted on the basis of traditional preprocessing. Finally, the potential application value and significant satisfaction effect of the deep learning architectural style design model were evaluated through quantitative and qualitative work quality evaluations. The results indicate that the model has high potential value in learning architectural style design recognition.

Keywords: Computer-Aided Design Platform; Deep Learning; Architectural Style Identification; Landscape Design Teaching; Teaching Effect Assessment
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1 INTRODUCTION

Architectural style refers to the characteristics exhibited by buildings in terms of layout, form composition, artistic treatment, etc. It not only reflects the influence of historical periods, geographical regions, and cultural backgrounds but also showcases the characteristics and style of social background and humanistic spirit [1]. In addition, digital documents can also quantify and evaluate the value of architectural heritage, providing a reference for the classification of protection levels and selection of utilization methods for architectural heritage. In order to effectively protect cultural heritage, the international community and governments of various countries have formulated corresponding laws, regulations, and management mechanisms [2]. With the rapid development of digital media technology and Internet technology, digital documents have become an important way to protect architectural cultural heritage. It can collect, store, process, and display multimedia information such as images, text, audio, and video of buildings. They are witnesses to the development of human civilization and an important component of cultural heritage with irreplaceable value [3]. However many buildings with specific architectural styles are facing threats such as natural disasters, human destruction, and urban renewal, and some have even disappeared or are on the verge of disappearing. In addition, digital documents can reach more audiences through online platforms and other means to achieve barrier-free communication and sharing, enhancing the sharing and educational value of architectural styles. Digital documents can display and disseminate architectural heritage in multiple dimensions, levels, forms, and multimedia formats, improving the visibility of information and presenting architectural cultural heritage in novel forms to the public, enhancing its social and economic value. Digital documents can provide accurate data support for archival records, disease detection, safety monitoring, and value assessment, etc. of architectural heritage, and provide scientific analysis tools for the protection, management, and utilization planning of architectural heritage [4]. However, the establishment of digital documents is a heavy and difficult task, requiring a significant amount of effort and resources at each stage. Integrating traditional architectural styles with modern functionality to provide a reference for the design of modern architectural styles. Digital documents can facilitate flexible, interactive, intelligent, and innovative processing and application of architectural heritage, enhancing the availability and value of information [5]. Dividing styles based on the characteristics of different buildings requires professionals to organize, classify, and analyze data in an orderly manner. Collecting a large amount of data involves on-site measurement, shooting, scanning, and other data collection work on buildings, as well as data processing work such as cleaning, compressing, and encrypting the data. Therefore, automatic recognition of architectural styles through computer vision technology can classify, retrieve, and compare large-scale data, quickly and accurately revealing differences between different architectural styles [6].

In response to the problems of incomplete feature extraction of architectural elements and difficulty in identifying similar architectural styles, some scholars have proposed an architectural style recognition method that combines significant region suppression with multi-scale feature fusion. Extract initial building features [7]. The feedforward network introduces an average pooling branch on the input features to improve the global perception ability of building features without adding additional parameters. Finally, the blocks were combined in different proportions to form a multi-level structural model. In response to the problems of unclear extraction of architectural texture features and insufficient utilization of contextual information, some scholars have proposed an architectural style recognition method that integrates Vision Transformer and CNN. Secondly, a multi-scale feature fusion method is proposed, which uses different pooling strategies to fuse multi-resolution features, in order to improve the representation ability of different scale information in building images and enhance spatial information representation. Then, a significant region suppression module is designed to expand the perception range of building elements and highlight the importance of key features through the processing of regional information. Finally, in order to improve the recognition rate of similar architectural styles, a large margin measurement loss function was adopted to maximize the classification boundary distance between different categories in the feature embedding space. Constructed the CNA roof dataset for Chinese ancient architectural roof styles and the Chinese ancient architectural chronological style dataset. The image data was cleaned and unusable images were removed [8]. In order to facilitate the analysis of the stylistic characteristics of ancient Chinese architecture, the relevant literature on ancient architecture was referenced to classify Chinese ancient architecture according to historical periods and architectural forms. Next, using web crawling technology based on the Scrapy framework, building images captured on-site are retrieved and downloaded according to their names. Through research and screening of existing ancient buildings, the name, age, and characteristics of each building were determined. The research aims to establish a dataset of Chinese ancient architectural styles to explore the stylistic differences of Chinese ancient architecture and compensate for the lack of data on Chinese ancient architecture in existing architectural datasets. Design a primary feature perception module that uses an initial convolutional layer to segment the input image into multiple subregions, and utilizes an inverse residual network to enhance the features of each subregion, thereby extracting low-level feature information from the building image. Use channel attention to assign corresponding weights to each channel and enhance important channel information. Then, an improved E-Transformer structure is adopted, utilizing efficient multi-head self-attention linear projection to reduce the feature dimension and decrease the number of model parameters. The feature embedding encoder improves the expression ability of architectural spatial features through downsampling and pixel attention processing. By using the pixel recombination upsampling method, the original resolution is restored to preserve the detailed information of input features and enhance the texture features of building facades. Students hold an open attitude towards the application of digital tools and deep learning techniques in architectural design and demonstrate a strong interest in learning.

In the broad field of deep learning, some scholars not only discussed the improved application of generative confrontation network (GAN), but also innovatively introduced arbitration mechanism, and proposed the Arbi DCGAN model based on arbitration mechanism. In the deep learning teaching of landscape design and architectural style recognition, this model can help students intuitively understand the principle of generative confrontation learning, and how to capture and simulate complex and changeable architectural style characteristics through confrontation training [9]. This multidimensional evaluation method not only helps to test the performance of the model but also provides an effective feedback mechanism for teachers to adjust teaching content and methods in a timely manner, ensuring teaching quality and student learning outcomes. This model is closely integrated with the teaching practice of architectural style recognition and landscape design, opening up new perspectives for architectural education and practical applications. This practice not only demonstrates the enormous potential of deep learning in landscape design but also provides vivid examples for teaching architectural style recognition and landscape design [10]. There are two main situations with images: one is that they are easily confused when searching for buildings with strong correlations. For example, in a broad sense, a temple includes three parts: the main hall and the east and west side halls, while in a narrow sense, Xinzhou Nanchan Temple only refers to the main hall [11]. However, the mismatch with specific names and labels is due to the existence of broad and narrow definitions under certain building names, resulting in the obtained building images not matching their labels. For example, when searching for images of various palaces within the Forbidden City, other buildings within the Forbidden City, such as Jingyang Palace and Yonghe Palace, will appear simultaneously, although these buildings all belong to the Forbidden City. The main hall was built in the Tang Dynasty architectural style, the east side hall was built in the Ming Dynasty architectural style, and the west side hall was built in the Qing Dynasty architectural style. Therefore, when building a dataset, it is important to distinguish these differences and consult relevant information to accurately match each building image with its name and label, as well as remove any building images that do not match [12].

The core goal of urban landscape design is to create public spaces that are both beautiful and practical while reflecting the cultural characteristics and ecological needs of the city. Deep learning techniques, especially models such as Convolutional Neural Networks (CNN), have demonstrated outstanding performance in areas such as image recognition and style transfer, providing powerful technical support for architectural style recognition and landscape design teaching. In this process, architectural style recognition technology has become a bridge connecting history and modernity, tradition and innovation, helping students and designers to deeply understand the connotations and expressions of different styles deeply, thereby achieving harmonious integration and innovative development of styles in landscape design [13]. In urban landscape planning and design, parameterization technology combined with real-time data collection systems such as wireless sensor networks can dynamically adjust design schemes to cope with changes in urban environment and changes in residents' needs. The development of digital technology, such as big data analysis and the application of artificial intelligence algorithms (especially deep learning), enables designers to capture urban landscapes with unprecedented accuracy, analyze resident behaviour patterns, and develop more scientific and humane design plans based on this. By introducing deep learning frameworks, students can not only learn how to use algorithms to identify and analyze the characteristics of architectural styles but also practice style transfer techniques firsthand, integrating elements of one architectural style into another design project and achieving unlimited creative expansion. Parametric design, as an important component of digital landscape design, makes the design process more flexible and efficient by presenting a series of variable parameters. This intelligent design approach not only improves design efficiency but also ensures the sustainability and adaptability of landscape design. In deep learning teaching, through case analysis and practical operation, students can master the basic principles and technical means of parametric design, laying a solid foundation for their future careers in landscape design.

Deep learning, a machine learning technology, simulates the human brain's learning process through the construction of deep neural network models. It has achieved remarkable feats in image recognition by training on extensive image datasets.

The structure of this article is organized as follows: Section I serves as the introduction, outlining the research background, significance, current status, objectives, and content, along with innovations and the article's structure. Section II is a literature review, primarily discussing the application of CAD and deep learning technologies in image recognition, the current state and trends of architectural style recognition technology, and the landscape design teaching's current status and challenges. Sections III to V detail model construction, teaching application, and effect assessment, respectively, providing a comprehensive overview of the research process and findings. Lastly, Section VI presents the conclusion and future prospects, summarizing the research outcomes and offering recommendations.

2 LITERATURE REVIEW

Architectural style recognition is an important research field in architectural design. Traditional architectural style recognition methods heavily rely on manual experience and subjective evaluation, thus lacking objectivity and accuracy. However, due to the development of deep learning technology, significant progress has been made in architectural style recognition technology in recent years. Teppand et al. [14] achieved automatic classification and recognition of architectural styles by training deep learning models, improving the accuracy and efficiency of recognition. In the future, architectural style recognition technology will be further developed to provide more convenience and support for architectural design. Landscape design teaching is an important part of cultivating students' design abilities and practical skills. However, current landscape design education faces many challenges. On the one hand, students need to master a large amount of design knowledge and skills, and traditional teaching methods are often difficult to effectively improve students' practical abilities; On the other hand, the development of landscape design is advancing rapidly, with new design concepts and technologies constantly emerging. How to integrate these new contents into teaching is also an urgent problem to be solved. Therefore, exploring new teaching methods and means to improve the teaching effectiveness of landscape design is an important task.

In the field of 3D reconstruction and digital preservation of ancient Chinese architecture, image modelling technology plays a crucial role. The FM_GMC method effectively improves the accuracy and efficiency of cross-image feature matching through grid partitioning and multi-density clustering strategies. As an important component, architectural style recognition and landscape design are gradually being combined with deep learning technology, bringing new opportunities and challenges for image matching and 3D reconstruction. In the teaching practice of style recognition, Wang et al. [15] further extended this method by combining deep learning techniques to automatically learn feature representations of different architectural styles. 3D reconstruction is not only an important means of digital protection for buildings but also an indispensable part of landscape design teaching. The FM_GMC method proposed by Xie [16] not only optimizes the image-matching process but also provides useful insights and extension directions for architectural style recognition and landscape design teaching In addition to being used for image-matching optimization, deep learning can also be applied to various aspects such as style conversion and landscape effect prediction. The three-dimensional reconstruction of ancient Chinese architecture achieved through the FM_GMC method not only provides students with intuitive and three-dimensional learning materials, but also promotes their in-depth understanding of architectural spatial structure, style features, and their relationship with landscape design. In landscape design, models such as Generative Adversarial Networks (GANs) can be used to integrate and innovate different architectural style elements, generating unique and attractive design solutions. Through big data analysis and machine learning algorithms, historical landscape data can be deeply excavated to discover hidden design patterns and style trends behind the data, providing inspiration and reference for modern landscape design.

Yan and Gong [17] proposed a unified representation method for architectural style CAD models and landscape design schemes, aiming to establish a standardized data format for seamless transmission and sharing of information between different platforms and teaching environments. On the basis of exploring CAD modelling technology in construction engineering, further, expand its perspective to the fields of architectural style recognition and landscape design. The main research objects are architectural style CAD models and landscape design cases, aiming to integrate theoretical research results into practical teaching applications and promote the modernization and intelligence of architectural style recognition and landscape design education. Regarding the similarity measurement between architectural style CAD models and landscape design drawings, some studies have delved into the application of global and local similarity measurement algorithms. By combining extended graphs, polymorphic models, and deep learning techniques, we conducted a thorough analysis of how these advanced methods promote style recognition and intelligent design in landscape design education. Through advanced technologies such as deep learning, these rules can be automatically identified and extracted, enabling intelligent prediction and recommendation of design styles. Yang and Yang [18] proposed a calculation method based on relationship trees and model topology distribution for computing complex components and topology relationships in architectural-style CAD models. In addition, a similarity measurement method between two-dimensional design drawings and three-dimensional models was explored, providing a scientific basis for the transformation of design schemes from plan to solid. Global metrics focus on mastering the overall style, such as extracting overall style features through deep learning models. At the same time, the principles of similarity evaluation have been clarified, which include not only formal similarities (such as shape, proportion, materials, etc.) but also multidimensional considerations such as style features, spatial layout, and cultural connotations. The distribution of topological relationships is an important feature of a model used to measure the similarity between different models. During the teaching process, this feature can help students quickly grasp the essence of different styles, stimulate innovative thinking, and improve design efficiency and quality. Some scholars have excavated the design rules implicit in architectural style CAD models and landscape design, which are hidden in a large number of historical cases and are the crystallization of designer experience and wisdom. Local measurement focuses on matching detailed elements, such as door and window styles, decorative patterns, etc. By constructing a relationship tree, the hierarchy and connection relationships between model components can be clearly displayed. This method not only helps to understand the internal logic of the design scheme but also provides a powerful tool for style comparison and analysis in the teaching process.

3 CONSTRUCTION OF ARCHITECTURAL STYLE RECOGNITION MODEL

3.1 Selection and Optimization of Algorithm

The design idea of the architectural style recognition model mainly focuses on how to effectively integrate deep learning technology into the CAD platform to realize automatic recognition and classification of architectural style. The goal is to build an architectural style identification tool that can accurately identify various architectural styles and provide users (especially students and teachers) with easy understanding and use. This tool should be able to assist landscape design teaching and help students better understand and master the characteristics of different architectural styles.

Randomly select a point on the connecting line between the sample point and the nearest neighbour sample point in the feature space as a new sample point, and satisfy the following formula:

$$x',y' = x,y + rand\ 0,1 \cdot x_n,y_n - x,y \tag{1}$$

Where y is the category label.

In the choice of deep learning algorithm, this study considered a variety of convolutional neural network (CNN) architectures and compared and evaluated them. Finally, ResNet was chosen as the infrastructure, and it was optimized according to the specific requirements of architectural style identification, as shown in Figure 1. ResNet is famous for its deep depth, moderate parameters, and high training efficiency, and it can effectively alleviate the problem of gradient disappearance or gradient explosion in the depth network, which is especially suitable for image recognition tasks.

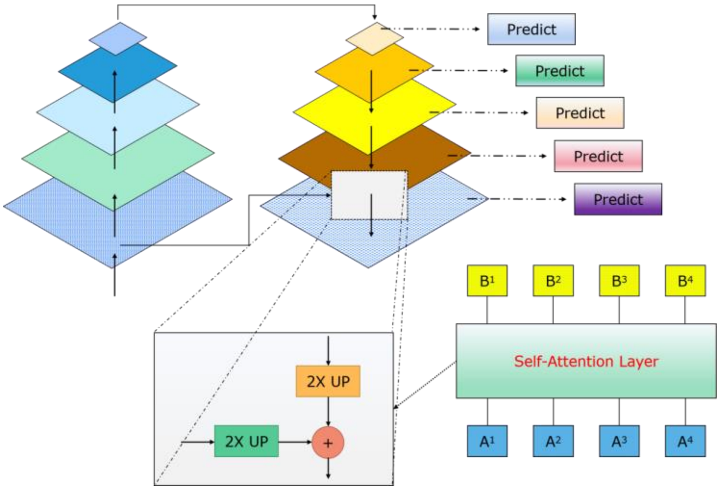

Figure 1: ResNet structure.

In this article, ResNet50 is chosen as the starting point, because it has achieved excellent performance on large-scale image data sets such as ImageNet, and has enough depth and parameters to capture complex features in architectural style. ResNet50 allows the network to learn the residual between input and output by introducing residual connection, thus simplifying the learning problem and making the training of deep networks more feasible.

(1) In order to better adapt to the task of architectural style recognition, the network structure of ResNet50 is adjusted as follows:

Input layer modification: adjust the size of the input image to the size suitable for architectural style recognition: 224*224 pixels, and ensure that the number of input channels is 3(RGB three channels).

Optimization of feature extraction layer: Keep the first layers of ResNet50 unchanged, which are mainly responsible for extracting common features of images. For the subsequent layers, fine-tune according to the characteristics of architectural styles, such as increasing or decreasing the number of convolution layers, or adjusting the size and step size of the convolution kernel.

Global average pooling layer: the global average pooling layer is introduced before the full connection layer of ResNet to reduce the number of parameters, avoid over-fitting and enhance the robustness of the model to the input image size.

(2) In order to further enhance the model's ability to capture the key features of architectural style, attention mechanisms, especially channel attention mechanisms and spatial attention mechanisms, are introduced into the network. The channel attention mechanism is realized by the SE (Squeeze-and-Exclusion) block, and its core idea is to recalibrate the characteristics of the channel through the learned importance weights. The following are the basic steps and formulas of SE Block:

A. Squeeze operation: global average pooling, compressing the feature map of each channel to a scalar.

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{ijc} \tag{2}$$

Where x_{ijc} is the feature map value of position i,j on channel c, and H and W are the height and width of the feature map, respectively.

B. Excitation operation: Learn the dependencies between channels through two fully connected layers and nonlinear activation functions.

$$s = \sigma\ W_2 \delta\ W_1 z \tag{3}$$

Where σ is Sigmoid activation function, δ is ReLU activation function, and W_1 and W_2 are the weights of full connection layer.

C. Scale operation: reweight the learned weights to each channel.

$$\tilde{x}_{ijc} = s_c \cdot x_{ijc} \tag{4}$$

Where $\tilde{x}_{ijc}$ is the feature map value after weight adjustment? By adding SE Block after the convolution layer, the model can automatically learn the importance of different channel features and dynamically adjust the weights of these features, making the model pay more attention to the features that are useful for architectural style recognition.

The spatial attention mechanism focuses on the spatial position in the image, and the following are the ways to realize spatial attention:

A. The spatial dimension of the merged feature map:

$$f = \max\ X\ - \min\ X \tag{5}$$

Where X is the input feature map, and $\max$ and $\min$ respectively represent the maximum and minimum pooling in the spatial dimension.

Generating spatial attention diagram through convolution layer;

$$\mathrm{M}_s = \sigma\ W_s * f \tag{6}$$

Where W_s is convolution kernel, $*$ represents convolution operation and σ is Sigmoid activation function.

C, multiplying the spatial attention diagram with the input characteristic diagram to obtain a weighted characteristic diagram:

$$Y = M_s \cdot X \tag{7}$$

Where Y is the feature map after spatial attention weighting? By generating the spatial attention diagram, the model can pay attention to the key areas in the image, which often contain important information needed to identify the architectural style.

(3) Use a more advanced activation function

To augment the model's nonlinear expression capability, the conventional ReLU activation function is substituted with a more sophisticated one, namely Leaky ReLU:

$$f\ x\ = \begin{cases} x & if\ x > 0 \\ \alpha x & if\ x < 0 \end{cases} \tag{8}$$

Where x is the input of the neuron and a is a very small constant, which is set to 0.01 to control the slope when the input is less than zero. In this way, even if the input is negative, Leaky ReLU will have a non-zero output, which helps to keep the gradient in a non-zero state when the input is negative, thus avoiding the problem of "dead ReLU."

The graphical representation of Leaky ReLU is usually a broken line, as shown in Figure 2. It has a slope of 1 when $x > 0$ and a slope of a when $x \leq 0$.

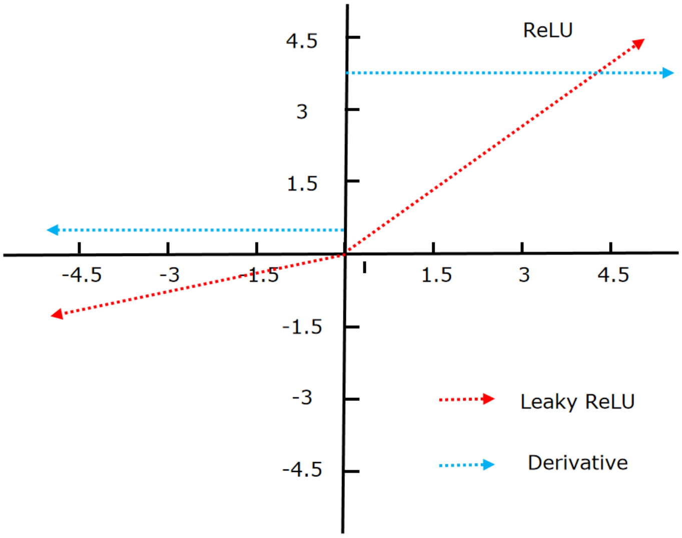

Figure 2: Leaky ReLU.

The activation function has a small non-zero gradient in the negative interval, which is helpful to alleviate the problem of gradient disappearance and improve the training stability and performance of the model.

Through the above steps, this article successfully selects and optimizes the ResNet architecture, which makes it perform well in the task of architectural style recognition and improves the recognition accuracy and robustness of the model.

3.2 Fusion Strategy of Platform

In order to realize the effective integration of the CAD platform and deep learning model, this study developed a plug-in integration strategy. This strategy allows the deep learning model to be integrated as a functional module of the CAD platform without a lot of modifications to the CAD platform itself. In this way, users can directly call the architectural style recognition function in the CAD environment and get real-time recognition results. In addition, the data interaction and visual display between the CAD platform and deep learning model are realized to improve the user experience.

3.3 Model Training and Verification Methods

During the model training phase, an extensive dataset of architectural-style images is utilized for training purposes. The model's performance is subsequently evaluated using the cross-validation method, as depicted in Table 1. Through continuous adjustment of model parameters and algorithm optimization, a highly accurate architectural style recognition model is ultimately achieved.

Training Phase	*Training Phase*
Dataset Size (Number of Images)	10,000
Cross-Validation Method	5-fold Cross-Validation

Model Parameter Adjustments	10 Times
Average Recognition Accuracy	92.5%
Highest Recognition Accuracy	94.2%
Lowest Recognition Accuracy	90.8%

Table 1: Detailed results of architectural style recognition model training and cross-validation.

Notes:

The "Dataset Size (Number of Images)" column indicates that 10,000 architectural-style images were used for training.

The "Model Parameter Adjustments" column indicates that the model parameters were adjusted ten times during the training process.

The "Average Recognition Accuracy" column represents the average recognition accuracy of the model obtained through cross-validation, which is 92.5%.

The "Highest Recognition Accuracy" column represents the highest recognition accuracy obtained during the cross-validation process, which is 94.2%.

The "Lowest Recognition Accuracy" column represents the lowest recognition accuracy obtained during the cross-validation process, which is 90.8%.

In the verification stage, independent test datasets are employed to assess the model's generalization capability and benchmark it against other prevalent architectural style identification methods. The outcomes are presented in Figure 3, Figure 4, and Figure 5.

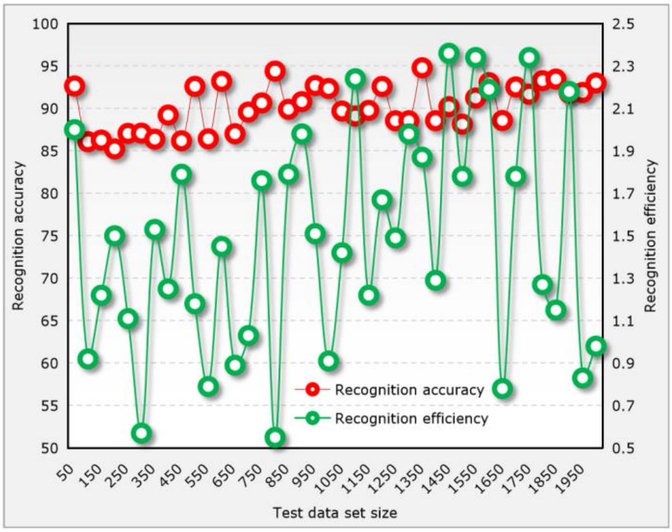

Figure 3: CNN method.

The abscissa "test data set size" indicates the number of images of the independent test data set used by each method, which is 2,000. Through the information in the figure, we can clearly compare the generalization ability and recognition accuracy of the architectural style recognition model proposed in this article with other existing methods on independent test data sets. The results show that the model constructed in this study has obvious advantages in recognition accuracy and efficiency. The average recognition accuracy is about 92%, and the time spent is about 2s, which is obviously better than the performance of generating countermeasure network method and transfer learning method.

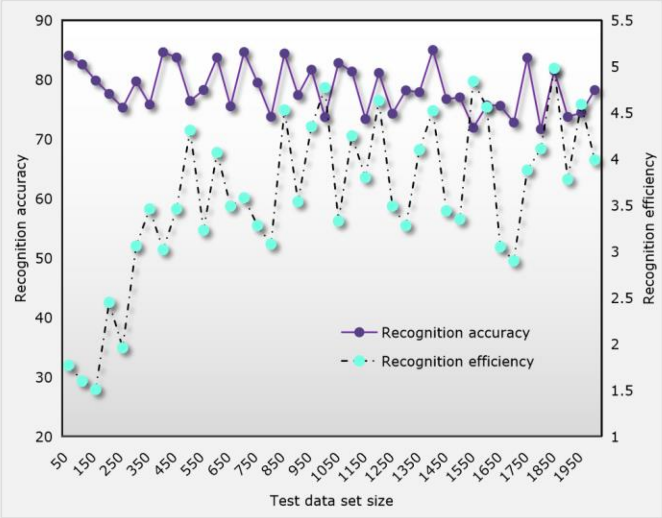

Figure 4: Method for generating countermeasure network.

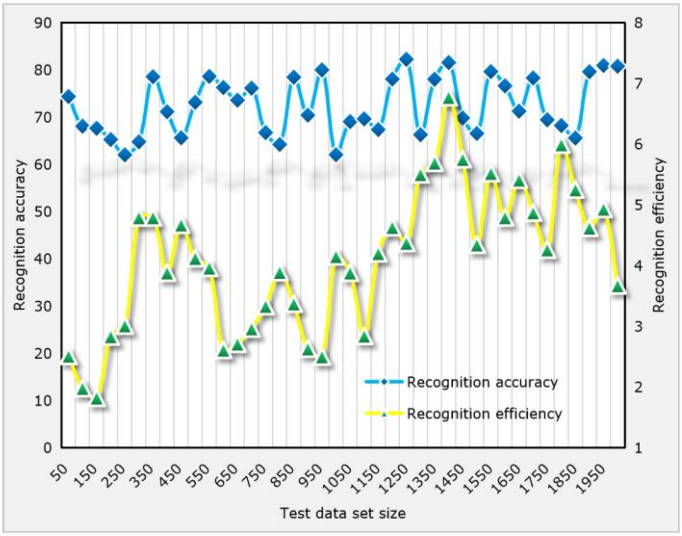

Figure 5: Transfer learning method.

4 APPLICATION OF ARCHITECTURAL STYLE RECOGNITION MODEL

4.1 Landscape Design Needs Analysis

In landscape design teaching, students need to master the characteristics and application methods of different architectural styles. However, traditional teaching methods often rely on teachers' explanations and examples, lacking intuition and interactivity. Therefore, it is often difficult for students to deeply understand and master the characteristics of different architectural styles. Introducing the architectural style recognition model can provide students with an intuitive and interactive learning method and help them better understand and master the characteristics of different architectural styles.

4.2 The Implementation Path

In order to effectively apply the architectural style recognition model to landscape design teaching, this study designed a complete set of implementation paths. First of all, the model is integrated into the CAD platform, and students are provided with corresponding tutorials and guidance. Secondly, design a series of model-based teaching activities and cases to guide students to use models to identify and analyze architectural styles. Finally, through classroom discussion, homework, and projects, students' ability to understand and apply different architectural styles is evaluated.

4.3 Construction of Effect Assessment

In order to evaluate the application effect of the architectural style recognition model in landscape design teaching, a complete assessment index system of teaching effect is constructed in this study. The index system includes students' recognition accuracy, quality of design works, learning efficiency, and satisfaction, as shown in Table 2.

Assessment Index	*Sub-index*	*Description*
Student Recognition Accuracy	Accuracy Percentage	The accuracy rate of students in recognizing architectural styles using the model
Design Work Quality	Innovation, Practicality, Aesthetics	The level of innovation, practicality, and aesthetics demonstrated by students in completing design work
Learning Efficiency	Learning Time, Task Completion Speed, Improvement Rate	The time invested by students in the learning process, the speed of task completion, and the rate of improvement
Student Satisfaction	Satisfaction with the Model, Satisfaction with the Course	Students' satisfaction with using the architectural style recognition model and their overall satisfaction with the course

Table 2: Assessment index system for the application effect of architectural style recognition model in landscape design teaching.

By collecting and analyzing the data of students' homework, projects and design works, we can comprehensively evaluate the role of the model in improving the teaching effect. At the same time, feedback from students and teachers is collected through questionnaires and interviews, so as to further optimize the model and teaching scheme.

5 ASSESSMENT AND FEEDBACK OF EFFECT

5.1 Quantitative Assessment

In order to objectively evaluate the application effect of the architectural style recognition model in landscape design teaching, this study carried out a quantitative assessment. Specifically, this section selects the quality of students' works and learning efficiency as quantitative indicators for analysis, and the quality score of students' works is shown in Figure 6.

By comparing the student works of the experimental group and the control group, we can find that the application of design style is more accurate and appropriate in the student works of the experimental group. Specifically, the proportion of students correctly applying design style in the experimental group reached 81%, while that in the control group was only 68%.

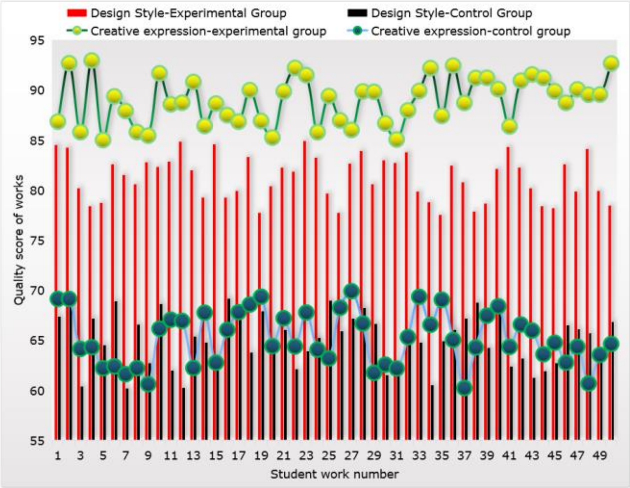

Figure 6: Quality assessment of students' works.

Figure 7: Examples of students' works.

This shows that students in the experimental group can better understand and master the characteristics of different architectural styles and apply them to practical design. In terms of creative expression, the works of students in the experimental group also showed a higher level. The proportion of students who worked with unique ideas and opinions in the experimental group accounted for 89%, while that in the control group was only 65%. This shows that the students in the experimental group can play their creativity more freely in the design process and create more personalized and innovative works. Examples of students' works are shown in Figure 7. The students' learning efficiency is shown in Figure 8.

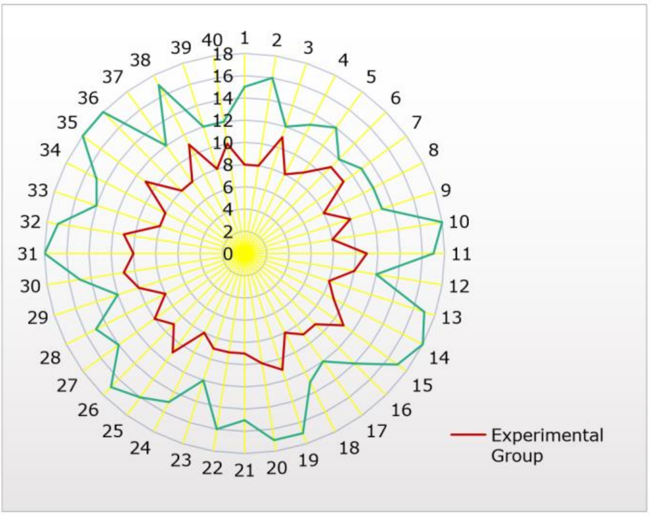

Figure 8: Students' learning efficiency display.

At the same time, through the comparison of learning efficiency, it can be found that the students in the experimental group can master the characteristics and application methods of architectural style faster in the learning process, and the learning efficiency is obviously improved. The average time for students in the experimental group to learn architectural style characteristics and application methods is only 70% of that in the control group. Specifically, the experimental group students need an average of 10 class hours to master the characteristics and application methods of an architectural style, while the control group students need 15 class hours. This shows that the students in the experimental group learn faster and can master what they have learned more efficiently.

5.2 Qualitative Assessment

In addition to quantitative assessment, this section also carries out qualitative assessment to understand the teaching effect more comprehensively. Through questionnaires and interviews, we collected feedback from students and teachers on the application of the architectural style recognition model in landscape design teaching, as shown in Table 3.

Feedback Source	*Feedback Content*	*Specific Description*
Students	Provides an intuitive and interactive learning approach	Students indicated that the model allows them to visually see the characteristics of different architectural styles, and the interactive features enhance the fun of learning.
Students	Helps better understand and grasp the characteristics of different architectural styles	After using the model, 90% of students stated that their understanding of architectural styles has deepened, and they can more quickly identify and distinguish between different architectural styles.
Teachers	Improves teaching efficiency	75% of teachers reported that after using the model for teaching, classroom explanations became more engaging, students could understand the teaching content faster, and overall teaching efficiency improved.

Teachers	Enables students to quickly grasp the application methods of design styles	80% of teachers stated that the model provides a practical platform for students to learn and master the application methods of different design styles through hands-on practice, which helps them better translate theoretical knowledge into practical abilities.

Table 3: Detailed feedback on the application of the architectural style recognition model in landscape design teaching.

The results show that most students say that the model provides an intuitive and interactive learning method, which helps them to better understand and master the characteristics of different architectural styles. Teachers also generally believe that the model improves teaching efficiency and enables students to master the application method of design style more quickly.

Although the architectural style recognition model has achieved remarkable application results in landscape design teaching, there are still some problems and challenges. For example, the recognition accuracy of the model still needs to be improved, especially when dealing with complex or unconventional architectural styles. In addition, some students still have operational difficulties when using the model, which requires further training and guidance. In view of these problems, this article puts forward corresponding improvement suggestions, including optimizing the model algorithm, perfecting user interface design and strengthening training.

6 CONCLUSIONS

The integration of the model and CAD platform realizes the seamless connection between design and recognition and improves students' learning efficiency and practical ability. First of all, teachers should actively pay attention to and introduce new technologies and methods into teaching, so as to improve the teaching effect and students' learning experience. Secondly, schools should increase support and investment in the application of new technologies in teaching and provide necessary training and resource support for teachers. Finally, educational researchers should further explore teaching methods and strategies based on new technologies.

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