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The Artistic Style Identification of CNN and Application in Architectural Interior Design

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Abstract. This article aims to study and construct an artistic style recognition model and explore its application in architectural interior design. Currently, to incorporate model content recognition that includes artistic styles into architectural design styles, this article constructs an enhanced comprehensive model recognition based on art networks. In terms of building the ability of target recognition, it has carried out artistic style recognition data processing. The model is based on convolutional layer images to extract deep features for architectural artistry training gradually. The model underwent refined image adaptive analysis during the adaptive learning optimization process of constructing cross-loss functions. In the process of optimizing the calculation of cross-function loss, this paper identifies the learning rate. The research results indicate that artistic style has a high degree of discrimination in the recognition process of architectural images. More than 95% accuracy was achieved in distinguishing different art styles. In the process of exploring the artistic interior analysis of architecture, it analyzed the fitting with high accuracy. The practice has shown that the involvement of cross-loss function research styles can provide a reference for designers in practical design.

Keywords: Artistic Style Identification; Convolutional Neural Network; Interior Design; Style Analysis
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1 INTRODUCTION

Under the strong promotion of relevant national policies, interior art design is rapidly developing with advantages such as a short construction period, low energy consumption, and low labor cost. Write the main program for two modeling methods, driving system family and self-built family, to automatically create models with given parameters and propose a parameterized method for creating openings for multi-opening shear walls [1]. From the perspective of interior art design, the parameterized design of prefabricated interior art design based on BIM achieves the linkage of information models in a three-dimensional form. From the perspective of energy conservation and emission reduction, currently, the calculation of carbon emissions in prefabricated interior art design mostly remains at the stage of calculation, statistics, and empirical calculation. According to the specifications for prefabricated interior art design, a reinforcement model for prefabricated components was established, and a function for generating reinforcement was used in RevitAPL [2]. The reinforcement program was written to automatically create reinforcement given the required parameters. At the same time, it also conforms to the development direction of BIM's positive design and conforms to the trend of the integration of information technology and industrialization in interior art design [3]. Taking prefabricated components of prefabricated shear wall structures as the research object, adopting the parameterized design concept and utilizing the powerful scalability of Revit modelling software for secondary development, a parameterized model is proposed and applied. Not only does it solve the problems of low modelling efficiency caused by model duplication and economic losses caused by design changes. By using the modelling method, the carbon emissions of prefabricated components can be unified, improving accuracy while also providing designers with more choices based on corresponding emission reduction strategies. The results indicate that parameterized modelling can achieve the modification of parameter linkage models, greatly improving efficiency [4]. By designing geometric models of different types of prefabricated components, establish a logical relationship between the insertion point and positioning point of the model. Based on existing parameterized models, write a program to automatically extract the engineering quantities of concrete and steel reinforcement. By inputting data information into modelling software, a model-based carbon emission measurement system was constructed to automatically calculate the carbon emissions of prefabricated components. By defining the boundaries of carbon emission measurement and using a carbon emission measurement model, a database of carbon emission factors and consumption quotas for prefabricated interior art design projects is established [5].

Given this backdrop, our study focuses on developing an artistic style recognition model utilizing CNN and exploring its potential applications in architectural interior design. The ultimate goal is to introduce innovative design concepts and techniques to the interior design sector. The deep learning architecture has significantly improved the accuracy and efficiency of indoor scene recognition in buildings, significantly reducing manual intervention and potential errors. The FCM algorithm is a clustering method based on fuzzy theory, which can discover uncertain and fuzzy clustering structures in datasets [6]. In the field of interior design, the boundaries between many design elements are not completely clear, but there is a certain degree of ambiguity and correlation. With the widespread application of 3D laser scanning technology, not only can external shape data of buildings be obtained, but also detailed point cloud data of indoor spaces can be obtained. "Covering the 3D natural resource database plate" and "Promoting the construction of 3D real scene databases". This poses new challenges to the processing, storage, and transmission of existing high-resolution 3D building model data. Realistic 3D models can be combined with basic geographic information data to serve urban planning, construction, management, and other aspects. The current main solution in academia is to use Level Of Detail (LOD) models to express 3D building models, and then use data organization and management methods that conform to the structure of 3D building models for data management [7]. As an important component of real-life 3D models, 3D building models have presented fine and complex data features and larger data volumes with the rapid development of data acquisition technology. A model simplification method that takes into account texture features has been developed by introducing texture features in the process of 3D building model simplification. Preserve important geometric and visual features of the model while minimizing the amount of data and complexity as much as possible. Realistic 3D is an important new type of infrastructure in the country, providing a unified spatial positioning framework and analytical foundation for Digital China. How to efficiently store, manage, query, and compute multi-resolution 3D building model data in large-scale urban scenes is also one of the challenges faced. Specifically, it includes a 3D building model mesh simplification algorithm based on "local vertex" texture features and a multi-resolution 3D building model data organization and management method based on global position grids [8]. In architectural interior CAD data, design elements usually exist in the form of graphics, lines, text, etc., and there may be complex spatial and attribute relationships between them [9]. Such a model requires strong feature learning and classification capabilities, which can adaptively learn various design elements in CAD data and accurately map them to predefined indoor feature spaces.

Conventional artistic style recognition techniques primarily depend on manually designed feature extractors, yet such methods struggle to handle intricate and fluctuating artistic styles effectively. Thanks to advancements in deep learning, particularly the widespread adoption of CNN, the precision of artistic style recognition has notably increased. Currently, multiple CNN-based artistic style recognition models have emerged and demonstrated impressive performance on public datasets. Nevertheless, their utilization in architectural interior design remains scarce, a void this study strives to bridge [10].

The core content of this study is to build an artistic style recognition model based on CNN and discuss its application in architectural interior design. The specific research contents include 1) collecting and sorting out data sets containing various artistic styles; 2) Design and implement an efficient CNN model for artistic style recognition; 3) Verifying the accuracy of the model through experiments; 4) The model is applied to the interior design of buildings, and the concrete design scheme is put forward and its effect is evaluated.

The innovations primarily manifest in the following ways: 1) Based on the traits of artistic style recognition, a novel CNN architecture has been devised to enhance recognition accuracy; 2) The application of CNN-based art style identification technology in the domain of architectural interior design offers fresh perspectives and techniques for interior decorating; 3) The practicality and effectiveness of the introduced approach have been validated through a real-world case study.

This article comprises five sections. Initially, the introduction outlines the research context, importance, current status, and article framework. Next, the theoretical foundations of CNN are explored, encompassing its core principles, evolutionary journey, key components, and capabilities. Following this, the third section delves into the intricacies of building an artistic style recognition model, spanning dataset curation, model conception and execution, training refinement, and an examination of experimental outcomes. The fourth segment explores how the artistic style recognition model is employed in architectural interior design, covering the proposal, enactment, and impact evaluation of design plans. Lastly, the conclusion encapsulates the significant accomplishments and contributions emerging from this study.

2 RELATED WORK

3D CAD (computer-aided design) technology also plays an indispensable role in the internal design of buildings. With the rapid development of augmented/virtual reality (AR/VR) technology, 3D CAD interior design data can be displayed and operated more intuitively and realistically. Extracting and transforming information from 3D CAD data in interior design, and applying it to AR/VR technology, can greatly optimize the design process and construction preparation. These pieces of information will be used to build highly realistic virtual indoor models, providing users with an immersive preview experience. Meanwhile, AR/VR technology can also be used for customer engagement and decision support. This helps customers better understand the creativity and intentions of designers, and improve customer satisfaction and design quality. In addition to basic geometric information such as room size, layout, and furniture placement, it is also necessary to extract and integrate attribute information related to interior design, such as material type, colour, texture, lighting effects, etc. By simulating the effects of different materials, colours, and textures, Tai and Sung [11] quickly tried various design solutions and obtained real-time feedback from customers. Customers can enter virtual indoor spaces through VR glasses or AR devices, experience the effects of different design schemes firsthand, and communicate and interact with designers in real time. Using AR/VR technology, Wu and Yan [12] conducted virtual assembly and simulation before actual construction. This not only provides designers with richer creative space but also provides owners and clients with a more intuitive and realistic preview experience. The traditional feature-based building image-matching method mainly extracts local key points of the image and calculates the descriptors of the key points to achieve image matching. Compared to directly comparing the pixel values of images, it has better robustness and matching accuracy. The commonly used traditional feature-based building image matching methods include the SIFT algorithm, SURF algorithm, ORB algorithm, etc. To solve the problem of selecting key points, this algorithm proposes the idea of selecting high-frequency areas in the image with human eyes, that is, selecting edges and corners with significant changes for detection. And estimate the direction of the local image around each key point, so that it has rotation invariance and scale invariance. The SIFT algorithm is an algorithm with scale invariance and rotation invariance, which searches for key points in different scale-spaces. By comparing the feature vectors of key points, the goal of image matching can be achieved.

Xie [13] introduced the definition, process, and commonly used techniques of image matching, dividing it into two categories: building image matching based on traditional features and building image matching based on convolutional neural networks. Such as fusing the SIFT features of traditional algorithms with ORB features, fusing the features of traditional algorithms with those of convolutional neural networks, and optimizing the search algorithm for extracted features. This algorithm is improved based on the SIFT algorithm and ORB algorithm, combining the SIFT algorithm with the ORB algorithm to extract different key points and improve matching accuracy. To improve the key points of traditional algorithms in the field of architectural image matching, increase the matching probability, and improve matching accuracy, the SO algorithm is proposed. These data not only cover basic information such as spatial layout and furniture decoration, but also complex sensory experience elements such as light, colour, and materials. By deeply analyzing the geometric features and spatial relationships of spatial layout, furniture placement, lighting, and colour, representative topological features are extracted. Prefabricated component reinforcement design is a key step in the parametric design process of prefabricated buildings. Traditional prefabricated component reinforcement design is mostly based on CAD drawings as a transmission medium applied in the preliminary design stage, construction drawing design stage, and detailed design stage. Therefore, based on the current research status, Xin and Daping [14] constructed a reinforcement model for prefabricated components by consulting relevant regulations and atlases of prefabricated buildings. The reinforcement design centred on drawings is not only prone to data loss throughout the entire process, resulting in incomplete or even non-compliant designs, but also consumes the energy of personnel at each stage in the processing of drawings. Complete the rapid creation of steel bar models to achieve adaptive adjustment of steel bar engineering and achieve parameter visualization.

Using Revit secondary development software to achieve parameterized reinforcement of prefabricated components not only improves the accuracy of the model but also enables timely adjustments when adapting to different component sizes. At present, it is still impossible to complete the 3D design modelling of the entire project solely using BIM software, which greatly weakens the application value of building informatization. Based on the structural characteristics of this project, Zhang et al. [15] studied parameterized modelling and carbon emission calculation models in the previous section, using actual engineering projects as examples. Apply the already written program to actual interior art design to achieve parameterized modelling of prefabricated components and steel bars in prefabricated shear walls. Through the secondary development of Revit, the existing parameterized model is used to obtain the engineering quantity, and the carbon emissions of prefabricated components are calculated according to corresponding rules. By debugging the program and using case studies to verify its feasibility, functional modules such as modelling, reinforcement, and carbon emissions, calculation can be integrated. By training classifiers, different indoor colours and styles can be classified into different categories, such as modern minimalism, Chinese classicism, Nordic style, etc. This not only helps designers quickly identify and understand different design styles but also provides convenience for subsequent element extraction and analysis. These features may include colour combinations, material textures, furniture shapes, etc., which together constitute the unique style and atmosphere of interior design. Based on the classification results, display specific indoor colour and style elements through visualization techniques. Preprocess and extract features from design data and use machine learning algorithms for pattern recognition and classification of the extracted features. Taking a certain interior design project as an example, Zhou [16] can use Auto CAD data for data mining. In this way, designers can have a more intuitive understanding of interior design cases with different styles, and draw inspiration and inspiration from them.

3 CONSTRUCTION OF ARTISTIC STYLE RECOGNITION MODEL

3.1 Design and Implementation of the Model

To train the artistic style recognition model, this section initially assembled a diverse dataset of artistic style images. These images were sourced from various public databases of artworks, museum archives, art exhibitions, and other avenues. Spanning different artistic epochs and movements—such as classical, modern, impressionist, cubism, and more—the dataset aims to bolster the model's generalization prowess. During data preprocessing, the images underwent consistent resizing, normalization, and potential data augmentation.

First of all, the input layer of the model should be able to accept images of appropriate size, which usually depends on the size and resolution of the images in the data set. In this article, the input image is set as an RGB image with 224*224 pixels, which is a common size and suitable for various pre-training models and transfer learning strategies. Then, this article designs several convolution layers to extract image features layer by layer. These convolution layers can effectively capture the local features of images by using small-sized convolution kernels (3*3) and gradually abstract higher-level feature representations through layer-by-layer convolution and pooling operations. The convolution layer formula is as follows:

$$O_{i,j} = f\ W \cdot X_{i-1,j-1} + b \tag{1}$$

Where $O_{i,j}$ represents an element on the convolved feature map, W represents the convolution kernel weight, $X_{i-1,j-1}$ represents an element on the input feature map, b represents the offset term, and f represents the activation function.

The formula of the pool layer is as follows:

$$P_{i,j} = f\ O_{i-1,j-1} \tag{2}$$

Where $P_{i,j}$ represents an element on the pooled feature graph, $O_{i-1,j-1}$ represents an element on the input feature graph, and f represents the pooled function.

Following each convolution layer, a batch normalization layer is incorporated to guarantee network training stability and rapid convergence. Batch normalization not only expedites the training procedure but also enhances the model's generalization capability to a certain degree. Refer to Figure 1 for a visualization of the CNN model structure.

The purpose of the content loss function is to preserve the content characteristics of the input image. It can be calculated by comparing the content image with the feature map of the generated image at a specific layer. Assuming that $I_{content}$ is the content image, I_{style} is the style image, I_{gen} is the generated style image, L_c is the content loss function, and $/LayerOutput$ represents the specific layer output of the network, then the content loss can be expressed as:

$$L_c = \frac{1}{N}\sum_{i=1}^{N}\ /LayerOutput_{content,i} - /LayerOutput_{gen,i}\ ^2 \tag{3}$$

Where N is the number of feature maps in a specific layer?

The style loss function aims to guarantee that the produced image bears a resemblance in style attributes to the reference style image. This is determined by contrasting the gradient of the feature map of the reference style image with that of the produced image at a designated layer.

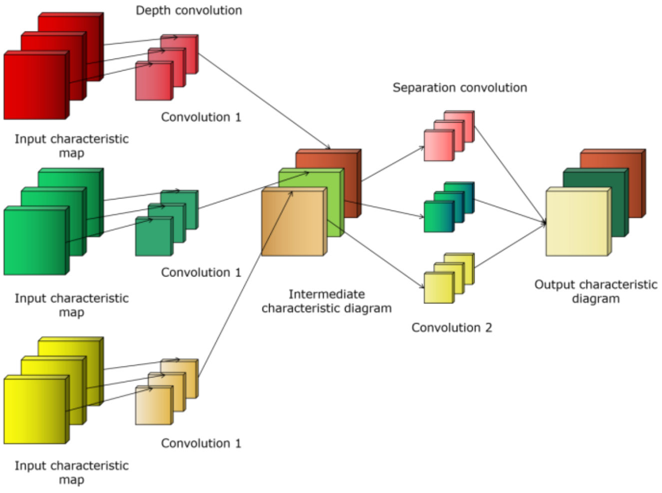

Figure 1: CNN model structure.

The formula for style loss L_s is as follows:

$$L_s = \frac{1}{M}\sum_{i=1}^{M}\frac{1}{CJ}\sum_{j=1}^{J} G_{style,i,j} - G_{gen,i,j}{}^{2} \quad (4)$$

Where G_{style} and G_{gen} respectively represent the Gram matrices of the style image and the generated image at a specific layer, C is the number of channels in the feature map, and J is the number of pixels in the feature map.

Total loss is a combination of content loss and style loss, and there is usually an adjustment factor λ to control the weight of both:

$$L = L_c + \lambda * L_s \quad (5)$$

In the training process, the gradient descent algorithm is used to minimize the total loss function. For each iteration, the weight W of the network is updated to:

$$W_{t+1} = W_t - \alpha * \nabla L\ W_t \quad (6)$$

Where α is the learning rate and ∇L is the gradient of the total loss function?

In the style loss function, the Gram matrix is used to compare the similarity of feature maps. For a feature graph F, its Gram matrix G is defined as:

$$G = F \cdot F^T \quad (7)$$

In this context, it represents matrix multiplication, while F^T denoting the transpose of F.

As the network depth increases, the maximum pooling layer gradually decreases the size of the feature map while preserving the most significant feature information. This approach not only cuts down on computational demands but also directs the model's focus toward the most pertinent sections of the image. Following the stacking of numerous convolution and pooling layers, a global average pooling layer is introduced. This layer effectively condenses each feature map into a solitary value, thereby significantly diminishing the model's parameter count and minimizing the chances of overfitting.

Furthermore, to bolster the model's classification prowess, a fully connected layer is appended after the global average pooling layer. The formula for the fully connected layer is given below:

$$F = f\ W * A + b \tag{8}$$

3.2 Model Training and Optimization

Based on the requirements and characteristics of 3D building model data, summarize the shortcomings and shortcomings of existing 3D building model simplification methods. A 3D building model mesh simplification algorithm based on "local vertex" texture features is proposed to address the issues of difficulty in preserving model details and easy texture distortion in 3D building model simplification. And based on complex 3D building model data, horizontal comparative experiments were conducted, and compared with other algorithms in terms of time, geometry, and image. The results showed the effectiveness and rationality of the algorithm proposed in this paper. So first, it is necessary to explain the model simplification strategy adopted here. This article specifically introduces the process of using texture feature information values and vertex curvature to optimize the folding cost of the QEM algorithm. The edge folding algorithm is an algorithm used for 3D mesh simplification. The basic operation is to merge an edge into a vertex and delete the triangles connected to the edge, thereby reducing the amount of data in the model and achieving the goal of mesh simplification. The research objective of this article is to improve the rendering efficiency of 3D building models by simplifying them and reducing their data volume while ensuring the appearance of the model. The basic idea is to define an error metric function to measure the cost before and after edge folding operations. Select the edge with the lowest cost for iterative operation until the simplification condition is met.

$$L\left(y, \hat{y}\right) = -\sum_{i=1}^{C} y_i \log\ \hat{y}_i \tag{9}$$

Among them:

$\hat{y}$ is the probability that the ture tag is i (which means 1 in $one-hot$ coding and 0 in other cases);

$\hat{y}_i$ is the probability that the model predicts to be a class i.

The adaptive learning rate optimization algorithm can automatically regulate the learning rate of parameters based on the model's training status. Among the most widely utilized algorithms is Adam (Adaptive Moment Estimation).

The updated formula of the Adam optimization algorithm is:

$$\text{Parameter} = \text{Parameter} - \alpha \frac{\text{Gradient}}{\sqrt{\text{Gradient square average}} + \in} \tag{10}$$

Among them:

a is the learning rate;

Gradient is the gradient of the loss function to the current parameter;

$\sqrt{\text{Gradient square average}}$ is the square root of the first moment estimate of the gradient;

$\in$ is a very small number to prevent division by zero.

3.3 Art Style Recognition Experiment

After the model training is completed, a series of experiments are needed to verify the performance of the model. This includes evaluating the test set and calculating the accuracy, error and recall of the model. Furthermore, visual tools such as the confusion matrix and ROC curve can be used to further analyze the recognition ability of the model in different artistic styles.

The accuracy of the model is shown in Figure 2.

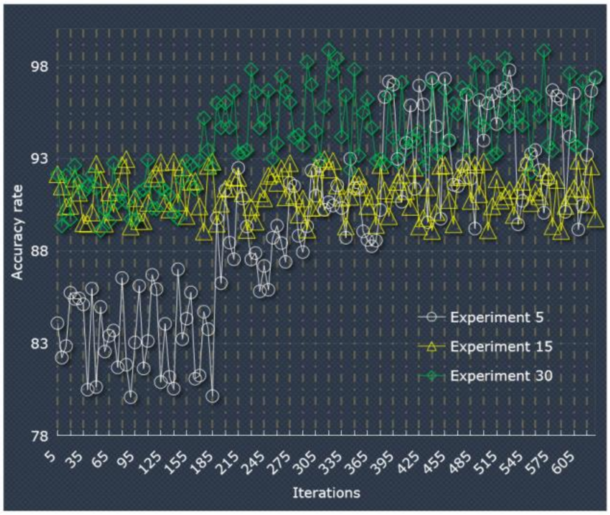

Figure 2: Accuracy of the model.

As shown in Figure 2, the model achieves a high accuracy of more than 95% in the task of artistic style recognition. This data strongly shows that the model can accurately identify and classify different artistic styles. High accuracy means that the model has excellent identification ability for the internal characteristics and nuances of different artistic styles, which is very important for the artistic style identification system. The error of the model is shown in Figure 3.

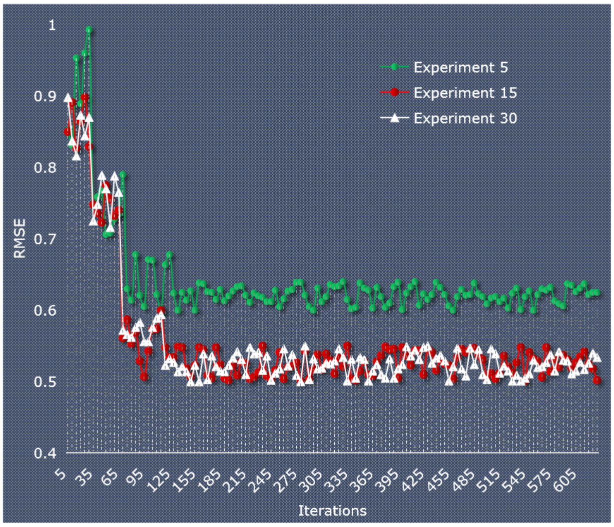

Figure 3: Error of the model.

As illustrated in Figure 3, the model's RMSE (root mean square error) consistently stays around 0.52, indicating a relatively low value. This low RMSE demonstrates the stability and reliability of the model's predictions. The minimal error rate signifies a small disparity between the predicted outcomes and the actual labels during artistic style recognition, further validating the model's effectiveness and precision. Regarding the recall of the model, refer to Figure 4 for details.

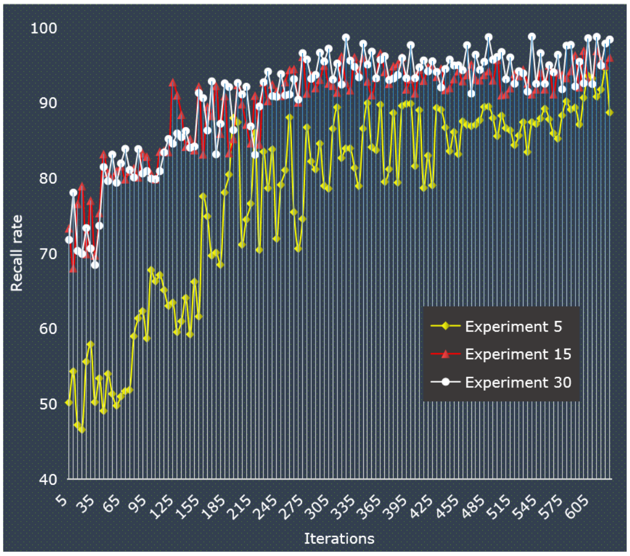

Figure 4: Recall of the model.

As shown in Figure 4, the recall of the model exceeds 97%. This means that the model can correctly identify the most relevant examples, that is, the model will hardly miss any real positive samples when identifying artistic styles. The high recall reflects the excellent ability of the model to find all relevant samples, which is very important to ensure the comprehensiveness and accuracy of artistic style recognition. The confusion matrix is shown in Table 1.

True Style vs. Predicted Style	*Abstract Art*	*Classical Art*	*Impressionism*	*Modern Art*	*Romanticism*
Abstract Art	93	2	1	3	1
Classical Art	1	96	1	2	0
Impressionism	0	1	98	1	0
Modern Art	0	0	0	100	0
Romanticism	1	3	2	0	94

Table 1: Confusion matrix.

In this confusion matrix, rows represent the real artistic style, and columns represent the artistic style predicted by the model. The bold numbers on the diagonal represent the number of correct predictions of the model (that is, the case where the real style is consistent with the prediction style). Off-diagonal numbers indicate the number of model mispredictions.

From this confusion matrix, we can see the performance of the model in identifying different artistic styles:

Abstract art:

Correct prediction: The model correctly identified 93 samples of abstract artistic style. This shows that the model has a good ability to identify and understand the main features of abstract art, such as non-figurative graphics, bold use of colours and freedom of composition.

Misprediction: Two samples were misjudged as classical art, one as impressionism, three as modern art and one as romanticism.

Classical art:

Correct prediction: the model correctly identified 96 samples of classical art style, which shows that the model has a good ability to capture the main characteristics of classical art.

Misprediction: One sample was misjudged as abstract art, two as modern art and one as impressionism. These misjudgments stem from some common features or similarities between these styles, which leads to confusion in distinguishing models.

Impressionism:

Correct prediction: the model correctly identified 98 samples of the Impressionist style, showing the strong recognition ability of the model to the Impressionist style.

Wrong prediction: one was misjudged as classical art and one was misjudged as modern art. The artistic characteristics of Impressionism overlap with some other styles, so it is difficult to distinguish the models accurately in some cases.

Modern art:

Correct prediction: The model correctly identifies 100 samples of modern art styles, which shows that the model has a very good understanding of the main characteristics of modern art.

Misprediction: No samples were misjudged.

Romanticism:

Correct prediction: the model correctly identified 94 samples of romantic style, indicating that the model has a certain ability to identify the basic characteristics of romanticism.

Misprediction: One sample was misjudged as abstract art, three as classical art and two as impressionism.

In the task of artistic style identification, each style is regarded as a positive category and other styles as a negative category, to draw a ROC curve for each style, as shown in Figure 5.

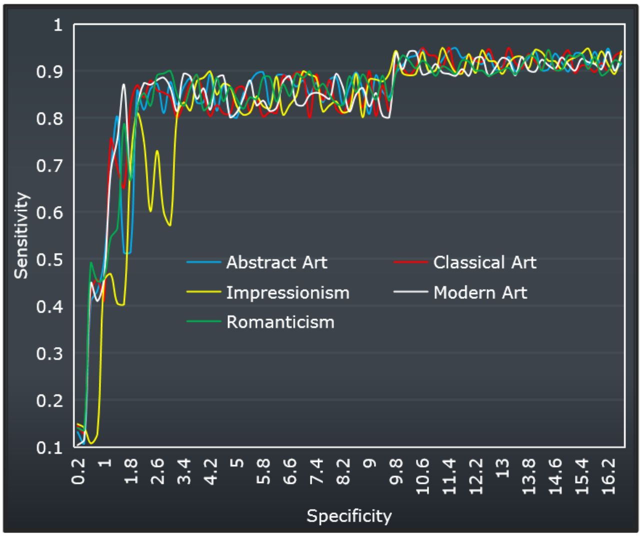

Figure 5: ROC curve.

The area under the ROC curve (AUC) is an important index to measure the performance of the classification model. The ROC curve of this model shows that the AUC value is high, close to 1. This shows that the model can maintain good classification performance under various threshold settings and accurately distinguish positive cases (target artistic style) from negative cases (non-target artistic style). A high AUC value means that the overall classification effect of the model is excellent. This makes the model in this article have high value and potential in practical application.

4 APPLICATION OF MODEL IN ARCHITECTURAL INTERIOR DESIGN

To demonstrate the practical application effectiveness of the artistic style recognition model in architectural interior design, this article chooses two representative design cases for analysis. Case 1: Show a modern minimalist living room design scheme, identify the modern elements in the reference image through the model, and integrate them into the design (Figure 6). Case 2: Show a bedroom design scheme with retro style, and identify the details of classical furniture and decoration through the model to create a unique retro atmosphere (as shown in Figure 7).

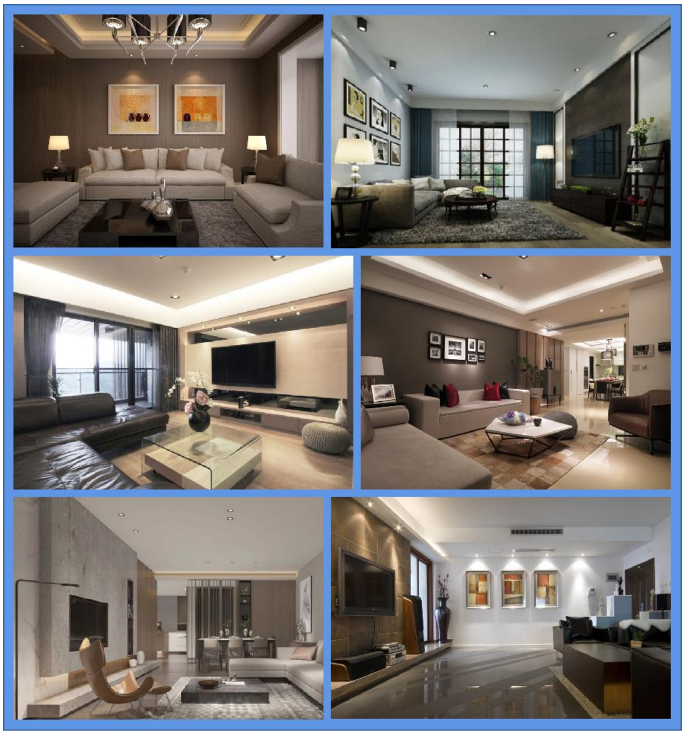

Figure 6: Living room design scheme (modern minimalist style).

In the case of the modern minimalist style, the artistic style recognition model is used to identify the modern elements in the reference image and integrate these elements into the design of the living room. Modern minimalist style is usually characterized by simplicity, freshness and functionality, emphasizing the openness and fluency of space.

Modern elements identified: Through model identification, features such as simple lines, monochrome or multicolour block combinations, and modern materials and decorations are extracted.

Design integration: These identified modern elements are then skillfully integrated into the living room design. For example, simple lines are used to decorate walls and furniture, and modern materials such as glass and metal are selected to enhance the modern atmosphere of the space. In addition, the colour choice is mainly neutral colour or cool tones, which conforms to the aesthetic of the modern minimalist style.

Overall effect: Finally, the living room design shows a spacious, bright and fully functional space, which not only meets the practical needs of modern life but also embodies the simple but not simple design concept.

Figure 7: Bedroom design (retro style).

In the case of retro style, the model is used to identify the details of classical furniture and decoration, to create a unique retro atmosphere in bedroom design.

Classical elements identified: The model identified the typical features of classical styles such as exquisite carving, retro colour matching, gorgeous fabric and classic furniture styles.

Design application: These identified classical elements are used in bedroom design. For example, solid wood furniture with retro carving was selected, with gorgeous curtains and bedding, and warm walls and lights were used to create a warm and elegant atmosphere.

Overall atmosphere: through this design, the bedroom shows an elegant and comfortable retro style, which makes people feel as if they have crossed into a certain era in the past and enjoyed that quiet and luxurious life experience.

After applying the artistic style recognition model to architectural interior design, it is needed to evaluate the application effect. This includes the consistency assessment of design style, the assessment of space utilization and the survey of user satisfaction (Figure 8).

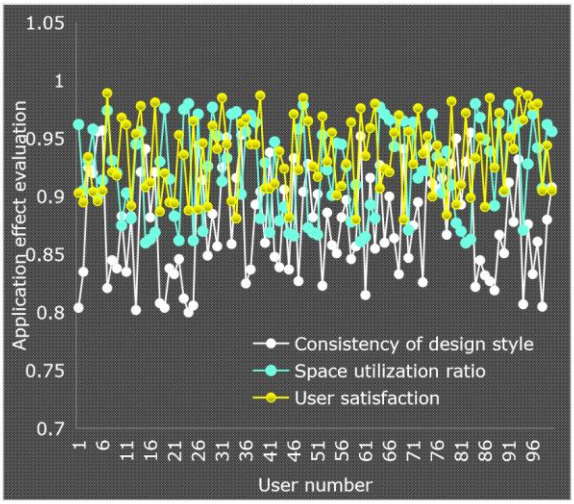

Figure 8: Application effect assessment.

The assessment results show that the design style is innovative, which shows that the artistic style recognition model can not only accurately capture and reproduce the traditional style, but also add novel elements to the design so that the final design scheme not only retains the essence of the original style but also injects inspiration into modern design. Furthermore, space utilization is an important consideration factor in interior design. The results in the figure show that the design scheme after applying the artistic style recognition model is excellent in space utilization. This means that designers not only pay attention to the presentation of style but also fully consider the rational planning and utilization of space when using models. In addition, user satisfaction is the key index to evaluate the success of the design. As shown in Figure 8, the average user satisfaction has reached more than 9.2 points, which is a very high assessment. This shows that users are very satisfied with the design schemes after applying the artistic style recognition model, and think that they are not only beautiful and generous, but also give full consideration to practicality and living experience.

Furthermore, it is also very important to collect user feedback, to understand the advantages and disadvantages of the model in practical application and provide direction for subsequent optimization and improvement (as shown in Table 2).

Feedback Number	*Feedback Content*	*Feedback Type (Advantage/Disadvantage)*	*Suggestions or Improvement Measures*
1	The model can accurately identify and apply artistic styles.	Advantage	None
2	The design scheme is innovative and meets personalized needs.	Advantage	None
3	Reasonable space planning and high utilization.	Advantage	None
4	Not enough refinement in certain details.	Disadvantage	Strengthen the processing and optimization algorithm of details.
5	The identification of certain special styles is not accurate enough.	Disadvantage	Increase training data for special style samples.
6	Hope the model can provide more design scheme options.	Suggestion	Develop diversified design scheme generation functions.

Table 2: User feedback collection table.

Through comprehensive assessment and user feedback analysis, the effectiveness and practicability of the artistic style recognition model in architectural interior design can be further verified. Furthermore, this feedback can also provide a useful reference for the application of the model in other fields.

5 CONCLUSIONS

In this study, a CNN-based artistic style recognition model has been successfully developed, and its initial application in architectural interior design has been investigated. Experimental outcomes reveal that the model attains high accuracy (exceeding 95%) and recall (surpassing 97%) in artistic style recognition tasks, effectively discriminating between various artistic styles. Additionally, the model exhibits a low error rate, with an RMSE of approximately 0.52, which is considered an ideal value. The confusion matrix further indicates that the model's performance in identifying distinct artistic styles exceeds 90%. Moreover, this paper presents practical application examples of the model in interior design, which have garnered widespread praise, demonstrating its effectiveness and practicality in real-world design scenarios.

Despite the progress achieved in this research, there are still limitations and areas for improvement. Therefore, this article offers the following recommendations for future studies: (1) Continuously expand and refine the dataset to enhance the model's recognition capabilities and generalization performance. Conduct an in-depth examination of model enhancement and optimization techniques to elevate its practical application performance. Further explore innovative ways to apply artistic style recognition technology in interior design, providing designers with more powerful and intelligent design tools and sources of inspiration.

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