www.cad-journal.net
Computer-Aided Design AND APPLICATIONS

Identification and Extraction of Environmental Art Design Elements Based on Computer Vision and Neural Network

Peng Jiao[1] and Wenyue Cao[2]

[1]Academy of Arts and Media, Shangqiu University, Shangqiu 476000, China, 000958@sqxy.edu.cn
[2]School of Arts and Media, Shangqiu University, Shangqiu 476000, China, caoyue929122@163.com

Corresponding author: Peng Jiao, 000958@sqxy.edu.cn

Abstract. This article adopts the method of combining theoretical analysis with empirical research. First of all, by consulting relevant literature and materials, we can deeply understand the basic principles and technologies of computer vision and NN (Neural network), as well as the types and characteristics of elements of CAD (Computer-aided design) and environmental artistic design. Then, combined with the actual needs and analysis results, an automatic identification and extraction and a thorough analysis and discussion of the results have been conducted. A comparative evaluation of the experimental outcomes reveals that the method introduced in this study outperforms other approaches in terms of precision, recall, and F1 score, thereby underscoring its exceptional merit and efficacy. The findings corroborate the preeminent performance of the proposed method in the context of element identification and extraction within CAD environmental art design. This is anticipated to advance research progressions in pertinent fields and furnish robust backing for practical implementations.

Keywords: Computer Vision; Neural Network; Computer-Aided Design; Environmental Art; Identification and Extraction of Design Elements
DOI: https://doi.org/10.14733/cadaps.2024.S18.160-174

1 INTRODUCTION

The main tasks of computer vision include image processing, image analysis, and image understanding. Landscape quality assessment is an important task in the fields of urban planning, environmental protection, and tourism development. Traditional landscape quality assessment methods often rely on manual observation and scoring, but this method is subjective and inefficient. It is widely applied in landscape quality assessment. Deep learning-based image segmentation algorithms can segment images into multiple regions based on the pixel information of street view photos and identify the objects and scenes corresponding to each region. This algorithm can extract rich visual information from images, providing strong support for landscape quality assessment.

Bianconi et al. [1] explored the application of machine learning in landscape quality assessment. We introduced the selection and implementation of image segmentation algorithms, as well as how to use these algorithms to extract landscape features and evaluate landscape quality. We can extract rich landscape features such as buildings, vegetation, roads, etc. These features can be used to evaluate quality indicators such as landscape diversity, coordination, and aesthetics. Specifically, we can use the extracted landscape features to construct a landscape quality assessment model. This model can automatically calculate the corresponding landscape quality score based on the input street-view photo images. This score can reflect the beauty, ecological value, and historical and cultural value of the landscape. Specifically, the basic principle of computer vision can be summarized as the following three steps: image acquisition: this is the process of transforming objects or scenes in the real world into digital images through cameras, scanners and other equipment. In environmental landscape conceptual design, designers usually use images to express design intentions. Deep learning techniques can process and analyze these images, extracting key design elements. Chen and Stouffs [2] plant species, terrain, water bodies, and other elements in images, providing designers with more comprehensive and in-depth design references. Environmental landscape design involves the correlation and interaction between multiple elements. Deep indication learning technology can provide designers with more accurate design suggestions by analyzing the correlation between spatial elements and understanding the relationships and interactions between elements. In environmental landscape design, structural design is a crucial link. Computer-assisted civil engineering and infrastructure can provide structural design support for designers, including structural analysis, structural optimization, etc. Through the application of computer-aided civil engineering and infrastructure, the safety and stability of structures can be more accurately evaluated, providing designers with more reliable design solutions. Environmental landscape design and construction are interrelated links. Computer-assisted civil engineering and infrastructure can help designers better understand and control the construction process, promoting coordination between design and construction. Through the application of computer-aided civil engineering and infrastructure, the construction process can be more accurately simulated, providing designers with more accurate design suggestions. In this process, we need to consider the influence of lighting conditions, equipment performance and other factors on image quality. Involving multiple disciplines, including landscape design, architecture, civil engineering, etc. Traditional landscape design methods often rely on the experience and intuition of designers, lacking objectivity and accuracy. With the gradual application of landscape design, designers are provided with more comprehensive and in-depth design references. Du [3] explored the application of CAD vision and neural network-assisted intelligence technology in landscape design. Through CAD visual technology, precise measurement and modelling of landscape design elements can be achieved; Neural network-assisted intelligent technology can achieve intelligent analysis and optimization of landscape design elements. In landscape design, designers need to identify and classify various elements. CAD visual technology can achieve automatic recognition and classification of these elements, improving the accuracy and efficiency of design. For example, CAD visual technology can be used to automatically recognize and classify plant species, providing designers with more comprehensive and in-depth design references. Image processing: After the digital image is obtained, it needs to be processed by a series of technical means, such as noise removal, image enhancement and feature detection, so as to improve the image quality and extract useful information. Environmental art design is a comprehensive design method that combines environment, art, and design. In environmental art design, designers need to identify elements with artistic value from a large number of design elements and integrate them into the design. However, traditional methods for identifying art and design elements often rely on the designer's experience and intuition, lacking objectivity and accuracy. Therefore, how can we achieve recognition of environmental art and design elements? Felbrich et al. [4] explored the process of recognizing environmental art and design elements. It introduces the design and implementation of an algorithm, as well as how to use this algorithm to identify environmental art and design elements. The algorithm can be trained and inferred on large-scale datasets without explicitly modelling data distribution. In the recognition of environmental art and design elements, we can apply distributed model-free deep reinforcement learning algorithms to the dataset of design elements and identify elements with artistic value by training neural network models. Image understanding: After obtaining and processing the image information, it is necessary to interpret and understand this information, such as target detection, image classification, scene understanding, etc. This usually needs to be done by building complex models. Environmental design is a comprehensive field that involves multiple aspects such as architecture, landscape, interior, etc. Computer vision can be used for image analysis and recognition, while neural networks can be used for feature extraction and classification. These technologies can help designers better understand and analyze the environment, thereby providing more accurate design recommendations. Halskov and Lundqvist [5] explored the applications of computer vision and neural networks in environmental design, particularly in the potential of spatial filtering and notification in design. We discussed how to utilize these technologies to improve the environmental design process, provide more accurate design recommendations, and increase the efficiency of design decisions. Computer vision has a wide range of applications in environmental design. Vision technology to analyze the appearance, structure, and details of buildings. Through image processing and recognition techniques, designers can extract the features and elements of buildings, providing more accurate data support for design. In addition, computer vision can also be used in landscape and interior design to help designers better understand and analyze the environment.

Cultural landscape is an important component of human history and cultural heritage, including natural and artificial landscapes. In order to better protect and inherit these precious cultural heritage, advanced technological means are needed to record and display them. Point cloud 3D modelling is an efficient and accurate measurement and modelling technique that can be used to record detailed information on cultural landscapes. Herrero et al. [6] introduced the method of using point cloud 3D models to record cultural landscapes and demonstrated the application of geographic integration technology in landscape design through a garden case study. This model can accurately display the shape, size, material, and other information of cultural landscapes, providing strong support for subsequent landscape design and protection. Geographic information is a crucial reference in landscape design. Through geographic integration technology, geographic information can be combined with 3D models to provide designers with more comprehensive and in-depth design references. For example, geographic integration technology can be used to obtain information on terrain, topography, vegetation distribution, etc., providing designers with more accurate design suggestions. NN is a computational model that simulates the working mode of human brain neurons, aiming at processing complex information and pattern identification. Hu et al. [7] Through computer big data technology, it is possible to collect, process, and analyze landscape architecture design data, providing designers with more comprehensive and in-depth design references. The digital nonlinear design method can achieve flexibility and innovative design, improving the diversity and adaptability of design. And explore the advantages and challenges of digital nonlinear design methods in landscape architecture spatial form design. In landscape architecture design, computer big data technology can provide designers with more comprehensive and in-depth design references. The digital nonlinear design method can achieve flexibility and innovative design, improving the diversity and adaptability of design and providing designers with more accurate design references. It consists of a large number of neurons connected by weight, and each neuron receives the input signal, processes it and then outputs it to the next layer of neurons. The main types of NN include feedforward NN and RNN (Recurrent neural network). In the training stage, This is usually done by a mechanism called the backpropagation algorithm. In the prediction stage, NN uses the learned weights to predict the new input. This process is feedforward; that is, information starts from the input layer and reaches various hidden layers.

Landscape design and sustainable building environment are important components of modern urban planning. Traditional landscape design and sustainable building environment design methods often rely on the experience and intuition of designers, lacking objectivity and accuracy. These technologies can be applied to landscape design and sustainable building environment design to improve the accuracy and efficiency of design. Hussein et al. [8] explored the application of computer vision and neural network technology in sustainable architectural environments in landscape design.

We introduced the principles and characteristics of computer vision and neural network technology and explored how to apply them to landscape design and sustainable building environments to improve design accuracy and efficiency. In landscape design and sustainable building environment design, designers need to identify artistic elements from a large number of design elements and integrate them into the design. Through computer vision technology, design elements can be automatically recognized and classified, and features can be extracted using neural network technology. In this way, designers can classify and analyze design elements based on the classification results. Especially in the field of CAD environmental artistic design, how to effectively identify and extract design elements has always been the goal pursued by designers. The traditional method of identifying and extracting elements of CAD environmental artistic design mainly depends on manual operation, which is inefficient and makes mistakes easily. The method based on computer vision and NN can automatically identify and extract design elements, which greatly improves design efficiency. So as to improve design quality. Its innovations are as follows:

(1) The pre-trained CNN (Convolutional neural network) model is applied to the identification and extraction of elements in CAD environmental artistic design, and the spatial features and semantic information in the image are effectively extracted. This method takes full advantage of the powerful representation ability of the CNN model and improves the accuracy of identification and extraction.

(2) By means of transfer learning, the CNN model pre-trained on large-scale image data sets is transferred to CAD environmental artistic design. This method can not only make full use of the representation ability of existing models but also reduce the demand for a large quantity of labelled data and reduce the difficulty and cost of model training.

(3) PCA (Principal component analysis) and correlation analysis are used to reduce the dimension and select the extracted features to remove redundant and irrelevant features. This method ensures that the features input to the subsequent model are the most representative and relevant, thus improving the generalization ability and performance of the model.

(4) The data preprocessing is optimized in detail, including data cleaning, format conversion and data enhancement. These preprocessing steps ensure that the data input to NN is accurate, consistent and diverse, thus improving the training effect of the model and the accuracy of identification and extraction.

Firstly, this article describes the methods and steps of data preprocessing in detail. Then, the strategy of feature detection and selection based on CNN is emphasized. Finally, the superiority and the future work are prospected and suggested.

2 RELATED WORK

Forest landscape is an important component of natural ecosystems, with rich ecological and aesthetic value. Evaluating can help protect and restore the ecological environment and improve people's aesthetic experience. Traditional methods for evaluating often rely on manual observation and evaluation, which suffer from subjectivity and low efficiency. These technologies can be applied to the evaluation of the aesthetic quality of forest landscapes, improving the accuracy and efficiency of the evaluation. Jahani et al. [9] use computer vision and neural networks in the evaluation of aesthetic quality of forest landscapes, using machine learning methods to automatically recognize and evaluate forest landscapes. It introduces the principles and characteristics of computer vision and neural network technology and explores how to apply them to predict the aesthetic quality of landscape and other aspects. Computer vision technology can identify plant species, terrain and other elements in forest landscapes and classify and extract features from these elements through neural network technology. The computer-aided design method of parameterized models for visual and neural network landscape planning is a promising design method. The automatic recognition, classification, and optimization of landscape planning parameters through visual and neural network technologies. Parameterized models can achieve automation and intelligence in computer-aided design, reduce manual intervention and error rates, and improve design diversity and adaptability. In landscape planning, designers need to identify and classify various parameters. Visual technology can achieve automatic recognition and classification of these parameters, improving the accuracy and efficiency of design. Jia [10] uses visual technology to automatically recognize and classify elements such as terrain, plant species, and water bodies, providing designers with more accurate design references. It explores computer-aided design methods for parameterized models of visual and neural network landscape planning. Through visual and neural network technology, automatic recognition, classification, and optimization of landscape planning parameters can be achieved, improving the accuracy and efficiency of design. Gardens are an important component of urban planning, with multiple functions such as beautifying the environment, improving ecology, and improving quality of life. Bringing new opportunities and challenges to landscape design and management. Jing et al. [11] explored the application progress and prospects of machine learning technology in the field of landscaping. We introduced the principles and characteristics of machine learning technology and explored how to apply them to landscape design and management using machine learning technology to classify and extract features of plant species, terrain, water bodies, and other elements in gardens, providing designers with more comprehensive and in-depth design references. Meanwhile, machine learning. In the future, we can use machine learning technology to conduct more comprehensive and in-depth analysis and prediction of various elements in gardens, providing designers with more intelligent and automated design and management solutions. To intelligently analyze and solve various management problems in gardens, improving accuracy. 3D printing technology can quickly and accurately create complex landscape models, providing designers with more intuitive and precise design effects. Computer vision and neural networks play an important role in exploring 3D printing technology in CAD, providing designers with more efficient and accurate design tools and methods. Computer vision has a wide range of applications in the CAD exploration of 3D printing technology. Through computer vision technology, designers can accurately measure and evaluate 3D models, ensuring their accuracy and completeness. Meanwhile, computer vision can also be used for model optimization and improvement; improving vision can also be used for model rendering and visualization, providing intuitive and realistic design effects. Kim et al. [12] explored the potential of computer vision and neural networks in CAD exploration processes. We analyzed how to use these technologies to optimize landscape design, improve design efficiency and accuracy, and explored related challenges and future development directions. Computer vision has a wide range of applications in aerial gesture-based interaction. Through computer vision technology, devices can recognize and understand user gestures, thereby achieving control over the device. For example, users can use gestures to swipe the screen, select applications, adjust volume, and so on. Computer vision technology can also be used for gesture recognition and gesture tracking, improving the accuracy and efficiency of gesture recognition. Mich et al. [13] explored the application of computer vision and neural networks in the design space of mobile device interaction based on aerial gestures and speech. We discussed how to utilize these technologies to improve the interaction experience, provide more natural and intuitive ways of interaction, and explore relevant design spaces and methods. The design space for mobile device interaction based on aerial gestures and speech is a vast and complex field. Designers need to consider user habits, needs, and preferences, as well as device performance and limitations. At the same time, designers also need to consider how to integrate these two interaction methods together. Through visual and neural network technology, accurate prompts for the depth of the Lin Family Garden's artistic conception can be achieved, thereby improving tourists' experience of the depth of the illusion space. At the same time, it can also enhance the display of the connotation of garden culture and further promote the inheritance and development of Chinese classical garden culture. As one of the representatives of Chinese classical gardens, the Lin Family Garden has rich cultural connotations and artistic value. Through visual and neural network technology, cultural connotations and artistic values in gardens can be more accurately displayed. Tai [14] uses visual technology to identify and classify cultural relics and monuments in gardens and then uses neural network technology to perform deep learning and prediction on images, ultimately providing accurate depth cues for the painting environment. Visual technology can extract features and information from images and videos through analysis and processing. In the context of depth cues, visual technology can be used to identify and classify elements and scenes in images, thereby providing more accurate context depth cues [15].

Computer-aided collaborative design systems can play an important role. Firstly, through 3D modelling and lighting simulation techniques, designers can more accurately simulate the growth and colour changes of plants, thereby optimizing colour-matching schemes. Secondly, the system can also support collaborative design among multiple people, enabling better communication and collaboration among designers and improving the efficiency and quality of design. Finally, the system can also estimate and optimize material and maintenance costs.

By introducing an attention mechanism, the model can lay stress on the key areas of design elements and improve the accuracy of identification. However, there are still some problems in the existing methods, such as poor identification effect of complex design elements and incomplete information on extracted elements.

NN is expected to make a greater breakthrough. Especially with the wide application of advanced technologies such as CNN and RNN, we can expect the emergence of more efficient and accurate identification and extraction methods.

3 ANALYSIS OF ELEMENTS OF CAD ENVIRONMENTAL ARTISTIC DESIGN

3.1 Overview and Classification of CAD Environmental Artistic Design Elements

CAD environmental artistic design refers to the process of artistic design of indoor and outdoor spaces with the help of computer technology. This process involves a variety of design elements, such as spatial layout, colour matching, material selection, lighting settings and so on. These design elements together form the foundation of environmental artistic design, which is very important for designing a comfortable, beautiful, and practical space.

According to the design practice and research, CAD environmental artistic design elements can be divided into the following categories:

Spatial layout elements: including the division, organization, and streamlined design of space. These elements determine the basic structure and function of space.

Colour collocation elements: including hue selection, colour collocation, colour psychology application, etc. Colour has an important influence on the creation of space atmosphere and people's emotional experience.

Material selection elements: including the material determines the texture, touch and visual effect of the space.

Lighting setting elements: including light source selection, lighting layout, illumination design, etc. Lighting plays a key role in the lighting effect, atmosphere creation and visual guidance of space.

Decoration and display elements: including the selection and arrangement of furniture, curtains, carpets, artworks, etc. These elements can add personality and style to the space.

3.2 Difficulties and Problems in Identifying and Extracting Elements of Cad Environmental Artistic Design

In CAD environmental artistic design, the identification and extraction of design elements is an important but challenging task. As shown in Table 1, some main difficulties and problems are reflected.

Serial number	*Difficulties/problems*	*Describe*
1	Data complexity and diversity	The design data in the CAD environment includes various graphic elements, attribute information and relationships. How to accurately identify and extract design elements from these data is a key issue.
2	Semantic understanding	Design elements are rich in semantic information, such as

	and interpretation	spatial relations, style preferences, functional requirements, etc., which require designers' professional knowledge and experience for semantic understanding and interpretation.
3	Dynamics and variability	The design process is a dynamic process, and the design elements may be adjusted and changed at any time. How to identify and extract the latest design elements in real-time is a challenging problem.
4	Automation and intelligent requirements	With the continuous improvement of design efficiency and quality, the demand for automation and intelligence of the design process is also increasing. It is necessary to develop efficient and accurate automatic identification and extraction methods to meet the needs of modern design.

Table 1: Difficulties and problems.

In order to solve these problems and challenges, it is necessary to comprehensively use computer vision, machine learning, pattern identification, and other technologies to develop effective automatic identification and extraction methods. This will help to improve the design efficiency and promote the development and innovation of CAD environmental artistic design.

4 IDENTIFICATION AND EXTRACTION METHOD OF CAD ENVIRONMENTAL ARTISTIC DESIGN ELEMENTS BASED ON COMPUTER VISION AND NN

4.1 The combination of Computer Vision and NN

The integration of computer vision and neural networks is primarily manifested in the utilization of neural networks for image processing and comprehension. Among these, CNN is a type of neural network architecture particularly suited for handling image data. They extract localized features from images through convolutional operations and diminish the data's dimensionality via pooling operations. CNN has accomplished notable achievements in tasks within computer vision, such as image categorization and object detection. RNN constitutes an efficient model for processing video and other types of sequential data. These networks are adept at capturing temporal dependencies within a sequence, making them widely employed in tasks like action identification and video categorization. The architecture of GAN encompasses two neural networks, namely the generator and the discriminator. The generator is tasked with producing novel image data, while the discriminator endeavours to differentiate between the generated images and those that are authentic. GAN has demonstrated great ability in image generation, style transfer and other tasks. The combination of computer vision and NN provides a powerful tool and methodology for processing and understanding image and video data and has achieved remarkable results in various practical applications.

4.2 Data Preprocessing

This article presents an automatic identification and extraction. This method comprehensively uses image processing, CNN, pattern identification, and other technologies to realize automatic identification and extraction of design elements and improve design efficiency and quality.

Data preprocessing is a key step to ensure the effectiveness and accuracy of identification and extraction methods. In CAD environmental artistic design, the original data often has the characteristics of complexity, diversity, and high dimensions. Data cleaning is the primary task of preprocessing, and its purpose is to remove irrelevant, redundant or erroneous parts in the original data so as to ensure that the data input to NN is accurate and consistent. In the process of data collection or arrangement, duplicate design drawings or elements may appear. These data will not only increase the computational burden but also interfere with the training of the model. Therefore, this article uses corresponding algorithms or tools to detect and delete duplicate data. Moreover, some design elements or attributes may be missing in some data, which will lead to incomplete data. In this case, interpolation, deletion or estimation based on other related data can be used to deal with it. In addition, there may be noise or abnormal values in the data due to errors or other reasons in the acquisition process. These values will have a negative impact on the training of the model. By using filters, statistical methods or other noise reduction techniques, noise and outliers in these data can be effectively eliminated. Image preprocessing is shown in Figure 1.

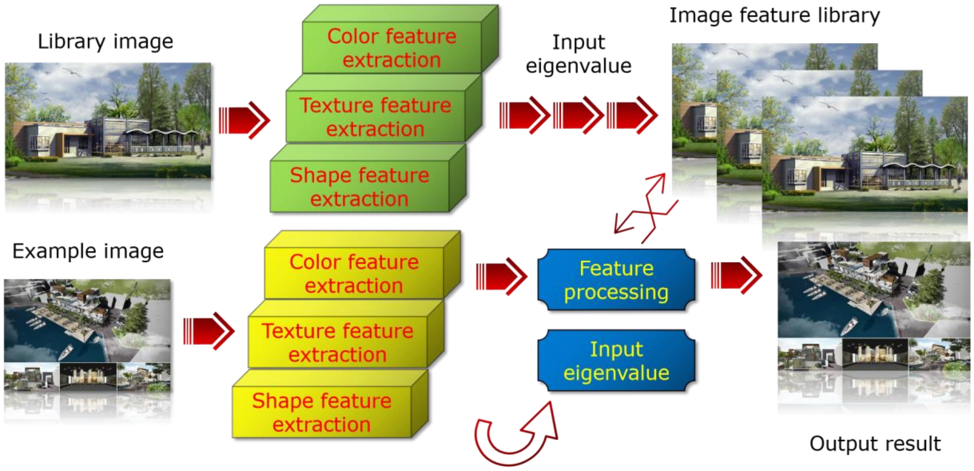

Figure 1: Image preprocessing.

The data in CAD systems are usually stored in proprietary formats, such as DWG, DXF, etc. These formats can not be directly processed by NN. Therefore, it is necessary to convert these data into common image formats, such as PNG, JPEG, and so on. In the process of conversion, we should lay stress on the following points: keeping the integrity of information, choosing the appropriate resolution, and optimizing the storage size. Data enhancement is a technology to expand the data set by transforming the original data. In CAD environmental artistic design, data enhancement is particularly important because it takes a lot of time and manpower to obtain and mark data. Common data enhancement methods include rotating and flipping: randomly rotating or flipping images can change the direction and layout of design elements, thus increasing the diversity of data. Zooming and cropping: By changing the size of the image or cropping part of its area, the observation effect under different viewing angles and resolutions can be simulated. Colour transformation: Adjust the brightness, contrast, saturation, and other colour attributes of the image to simulate different lighting and material effects.

Through the above preprocessing steps, the original CAD environmental artistic design data can be transformed into high-quality and standardized data sets, which provides strong support for the subsequent NN training, identification, and extraction tasks.

4.3 Model Construction and Optimization

In CAD environmental artistic design, the purpose of feature detection is to obtain spatial features and semantic information related to design elements from preprocessed image data. By simulating the processing mode of the human visual cortex, it can effectively extract spatial features, texture information and so on from images. In this study, the pre-trained CNN model is selected for feature detection. The model has been pre-trained on a large quantity of image data sets and has strong feature representation ability. The initial training example is utilized for the establishment of the first node, and the connection weights W_1 W_2 are configured accordingly:

$$W_1 = E(1) \tag{1}$$

$$W_2 = T(1) \tag{2}$$

$$W_1 = [w_1(1), w_1(2), w_1(3), \ldots,, w_1(n)]^T \tag{3}$$

$$W_2 = [w_2(1), w_2(2), w_2(3), \ldots,, w_2(n)]^T \tag{4}$$

The pre-trained CNN model can be applied to this study through transfer learning. In this article, the preprocessed CAD environmental artistic design image is input into the pre-trained CNN model, and the feature map of the image in each convolution layer is obtained by forward propagation. These feature maps contain spatial features and semantic information in images, which can be used as the basis for subsequent classification and identification tasks. The detailed stage of convolution and pooling of CNN is shown in Figure 2.

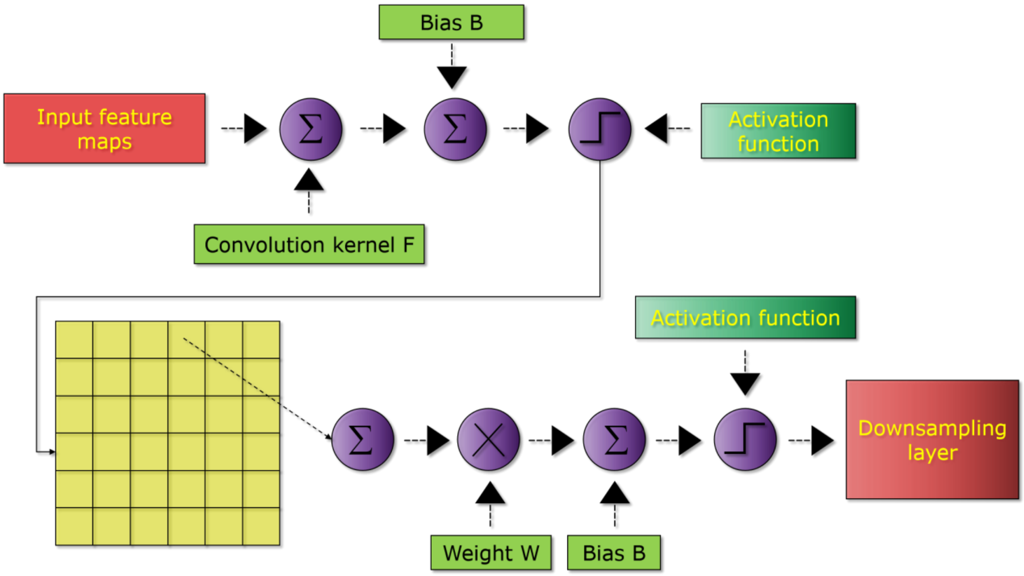

Figure 2: Convolution and pooling stage of CNN.

After CNN feature detection, a large quantity of image features can be obtained. However, there may be redundant and irrelevant information in these features, which will interfere with the subsequent model construction. Therefore, feature selection is needed to remove redundant and irrelevant features and keep the most representative features. In this study, statistical methods are used to select features and correlation analysis is used to reduce and select the extracted features. PCA is a commonly used dimensionality reduction method, and a new set of orthogonal features, namely principal components, can be obtained by linear transformation of the original features. These principal components are sorted according to the magnitude of variance, and the first few principal components can be selected as representative features. Through PCA dimensionality reduction, redundant information in the original features can be removed, and the most representative features can be retained. Correlation analysis is a method to measure the correlation between features. In this study, the correlation coefficient between each feature and the design elements is calculated and sorted according to the correlation coefficient. By setting a threshold, features with a correlation coefficient greater than the threshold can be selected as representative features. Through correlation analysis, features unrelated to design elements can be removed, and the most relevant features can be retained.

On the basis of feature detection and selection, this study constructs an identification and extraction model based on NN. The specific model structure includes an input layer receiving preprocessed image data, which are used to learn and express the characteristics of design elements. Output layer: output the results of identified and extracted design elements.

$$X = [x_1, \ldots, x_{n1}]^T \tag{5}$$

For the expected output vector:

$$T = [t_1, \ldots, t_{N3}]^T \tag{6}$$

Among them, k it represents which training mode.

$$y_h^k = f\left(\sum_{i=1}^{N1} w_{ih} x_i^k + \theta_h\right) \tag{7}$$

$$o_s^k = g\left(\sum_{h=1}^{N2} w_{hs} y_h^k + \theta_s\right) \quad k = 1,2,3,\ldots,N \tag{8}$$

Figure 3 shows the identification and extraction of elements of CAD environmental artistic design based on CNN.

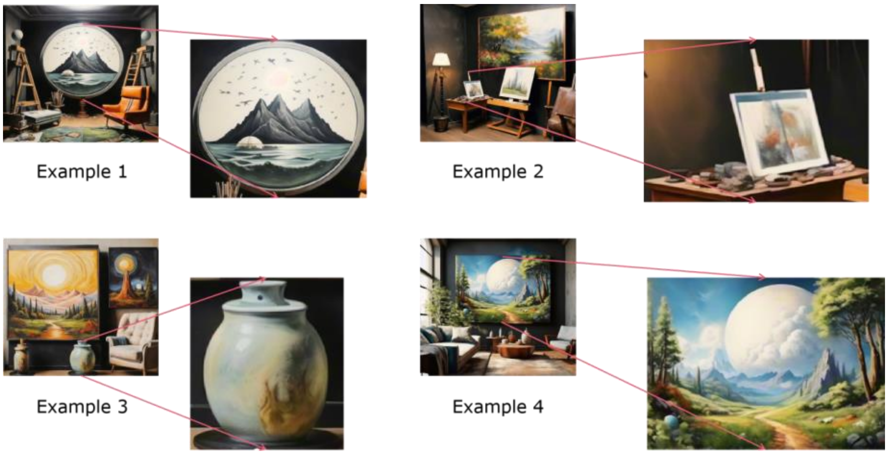

Figure 3: Identification and extraction of CAD environmental artistic design elements based on CNN.

In addition, in order to optimize the performance of the model, the following strategies are adopted in this study:

Loss function design: design appropriate loss functions according to the task requirements, such as cross-entropy loss, mean square error loss, etc.

Selection of optimization algorithm: select the optimization algorithm suitable for the model and use regularization technology to prevent the model from over-fitting.

Model evaluation and selection: assess the performance of the model through cross-validation and regularization technology and select the model with the best performance for subsequent experiments.

5 SIMULATION EXPERIMENT AND RESULT ANALYSIS

With the aim of validating the efficacy of the introduced approach for design element identification and extraction, an array of simulation experiments have been conducted within this investigation.

Subsequently, a comprehensive analysis and discussion of the outcomes have been undertaken. The experimental environment is as follows: TensorFlow, a DL framework based on Python, is used in this section, and the experiment is carried out. In order to train and assess the model, this study uses three open CAD environmental artistic design data sets: Dataset A, Dataset B and DataSet C. These three data sets contain labelling information on various design elements, such as spatial layout, colour matching, material selection and so on. Optimization is carried out according to the above methods, and training is carried out on the training set. During the training stage, the loss and accuracy of the model are recorded so as to observe the training situation of the model. When the model achieves the best performance on the verification set, the model parameters are saved and assessed on the test set. The specific statistics of the data set are shown in Table 2.

Dataset	*Design element category*	*Number of training set samples*	*Number of verification set samples*	*Number of test set samples*
Dataset A	Space Layout, Color matching, Material selection	5000	1000	2000
Dataset B	Space Layout, Color matching, Material selection, Lighting setting	8000	2000	3000
Dataset C	Space Layout, Color matching, Material selection, Lighting setting, Decoration and furnishings	10000	3000	4000

Table 2: Dataset statistics.

The identification and extraction model based on NN is constructed. In the training stage, cross-validation and regularization techniques are used to adjust the superparameter and select the best model. Moreover, In order to prevent over-fitting, the L2 regularization technique is adopted, and the regularization coefficient is set to 0.0001. The network model training is shown in Figure 4.

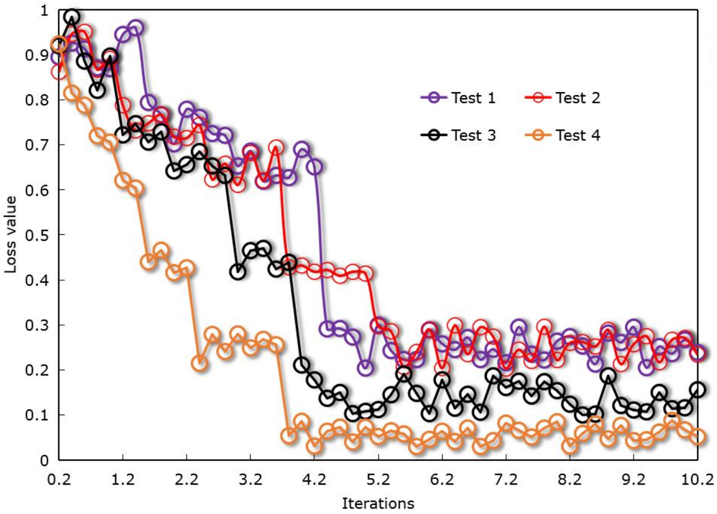

Figure 4: Network model training situation.

As the quantity of training iterations progresses, the trend observed in the change of the loss function indicates a gradual reduction in the model's loss value, leading to stability. This is evident in the model's increasing capability to discern the distributional patterns and feature representations within the data during the training phase, thereby enhancing its ability to fit the data. The consistent convergence of the loss function towards stability serves as an indication that the model is neither overfitting nor underfitting and exhibits commendable generalization prowess.

After a series of experiments, the identification and extraction results of the proposed method on various data sets are obtained in this section. Specific performance indicators are shown in Table 3.

Dataset	*Design element category*	*Accuracy rate*	*Recall rate*	*F1 value*
Dataset A	Space Layout	92.3%	89.6%	90.9%
	Colour matching	87.5%	84.3%	85.9%
	Material selection	90.2%	87.4%	88.8%
Dataset B	Space Layout	91.8%	90.1%	90.9%
	Colour matching	89.3%	92.7%	90.5%
	Material selection	93.9%	88.7%	91.2%
	Lighting setting	91.3%	90.2%	90.7%
Dataset C	Space Layout	92.7%	94.1%	93.7%
	Colour matching	88.5%	92.7%	90.9%
	Material selection	89.4%	88.6%	88.2%
	Lighting setting	90.7%	89.4%	90.1%
	Decoration and furnishings	92.8%	91.6%	92.1%

Table 3: Performance indicators of experimental results.

In order to comprehensively assess the performance of the proposed method in element identification and extraction in CAD environmental artistic design, this section compares and analyzes with other related methods. The traditional image processing method and the identification method are based on various methods, and the performance of the proposed method can be objectively assessed. The accuracy comparison of several methods is shown in Figure 5, the recall comparison is shown in Figure 6, and the F1 value comparison is shown in Figure 7.

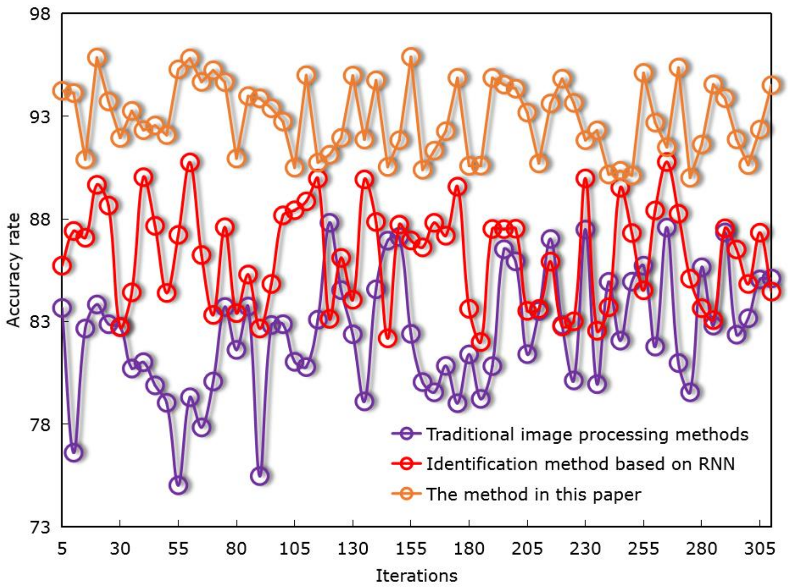

Figure 5: Comparison of accuracy rate.

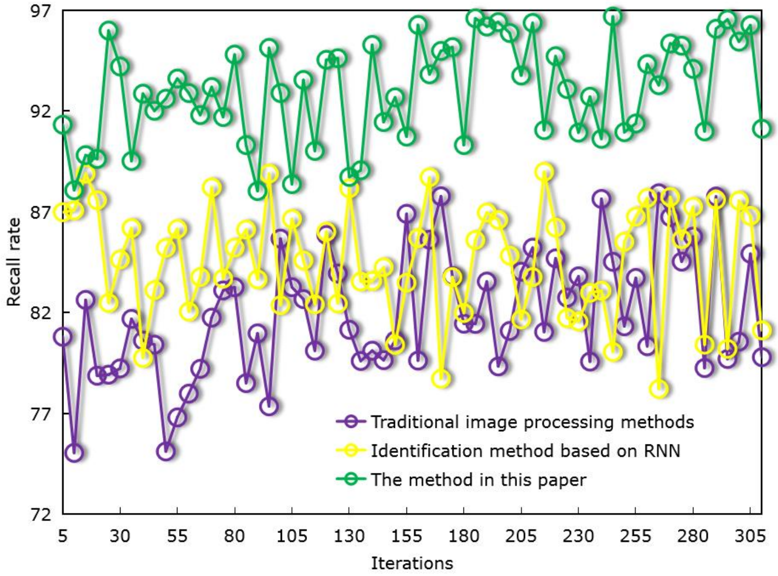

Figure 6: Comparison of recall rate.

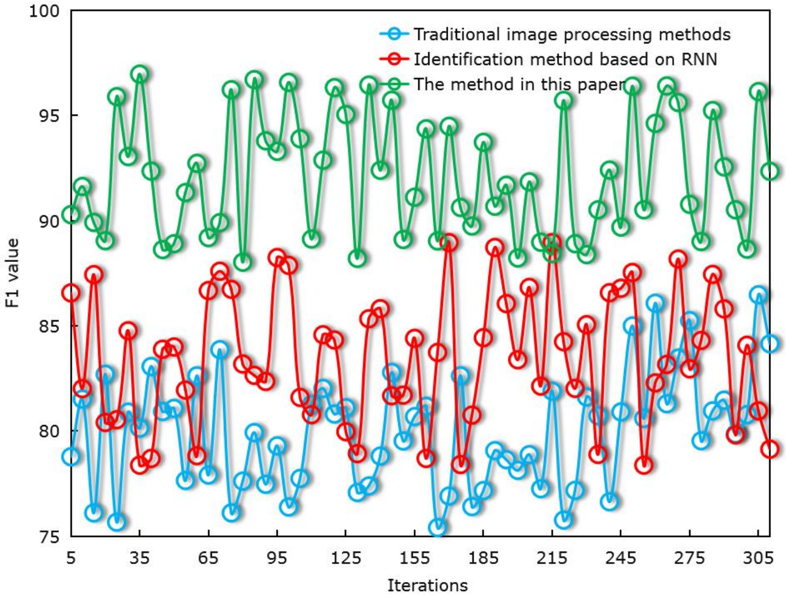

Figure 7: Comparison of F1 value.

It is evident that the introduced approach surpasses both conventional image processing techniques and identification methods reliant on RNN in terms of precision. This advantage can be attributed to the method's strategic integration of a pre-trained CNN model for feature detection, coupled with the utilization of statistical techniques for feature selection, which collectively enhances the model's classification precision. It can be observed from Figure 6 that the proposed method also performs well in the recall rate, which exceeds other comparison methods. This shows that the proposed method can effectively identify and extract design elements when processing positive samples and reduce the situation of missing detection. As can be seen from Figure 7, the proposed method also achieves the best performance in the value of F1.

The identification accuracy of this method in the categories of design elements such as spatial layout, colour matching and material selection is over 90%, showing a high identification accuracy. In addition, the comparison results with traditional image processing methods and RNN-based identification methods also show the superiority and effectiveness of this method. The above results show that the identification and extraction method of CAD environmental artistic design elements based on computer vision and NN is effective and practical.

6 CONCLUSIONS

This article analyzes the types and characteristics of elements of CAD environmental artistic design. The basic principles and technologies of computer vision and NN are studied. An automatic identification and extraction method of CAD environmental artistic design elements based on computer vision and NN is developed. Ultimately, the feasibility of the proposed approach has been substantiated through rigorous simulation experiments. Drawing inferences from the experimental outcomes presented in this paper, several conclusions can be reached: The introduced method outperforms both conventional image processing techniques and identification methods relying on RNN in matters of accuracy, recall, and F1 score. This enhanced performance can be attributed to the strategic employment of a pre-trained CNN model for feature detection, which is further complemented by the incorporation of statistical methods for feature selection. Consequently, this methodological fusion elevates the model's capabilities in classification and identification. Moreover, the identification accuracy of this method in spatial layout, colour matching and material selection is over 90%, which shows a high identification accuracy.

The results of this study prove the important role of computer vision and NN in the task of identifying and extracting elements of CAD environmental artistic design. Through the comprehensive application of image processing, CNN, pattern identification, and other technologies, the identification effect of some complex and abstract design elements is not ideal, and the model and algorithm need to be further optimized. Future research directions can include improving the model structure, introducing more semantic information, and studying cross-domain transfer learning to improve the identification effect and application scope.

Peng Jiao, https://orcid.org/0009-0006-2687-0591
Wenyue Cao, https://orcid.org/0009-0005-9843-7714

REFERENCES

[1] Bianconi, F.; Filippucci, M.; Seccaroni, M.; Rolando, A.; D'Uva, D.: Machine learning and landscape quality. Representing visual information using deep learning-based image segmentation from street view photos, SCIRES-IT-SCIentific RESearch and Information Technology, 13(1), 2023, 117-134. http://dx.doi.org/10.2423/i22394303v13n1p117

[2] Chen, J.; Stouffs, R.: Deciphering the noisy landscape: Architectural conceptual design space interpretation using disentangled representation learning, Computer-Aided Civil and Infrastructure Engineering, 38(5), 2023, 601-620. https://doi.org/10.1111/mice.12908

[3] Du, J.: Application of CAD aided intelligent technology in landscape design, International Journal of Advanced Computer Science and Applications, 13(12), 2022, 1030-1037. https://doi.org/10.14569/IJACSA.2022.01312118

[4] Felbrich, B.; Schork, T.; Menges, A.: Autonomous robotic additive manufacturing through distributed model-free deep reinforcement learning in computational design environments, Construction Robotics, 6(1), 2022, 15-37. https://doi.org/10.1007/s41693-022-00069-0

[5] Halskov, K.; Lundqvist, C.: Filtering and informing the design space: towards design-space thinking, ACM Transactions on Computer-Human Interaction, 28(1), 2021, 1-28. https://doi.org/10.1145/3434462

[6] Herrero, T.-T.-R.; Arques, S.-F.; López, C.-M.-S.; Cabrera, M.-R.; Romero, J.-L.-M.: Documenting a cultural landscape using point-cloud 3d models obtained with geomatic integration techniques. The case of the El Encín atomic garden, Madrid (Spain), Plos one, 15(6), 2020, e0235169. https://doi.org/10.1371/journal.pone.0235169

[7] Hu, S.; Meng, Q.; Xu, D.; Katib, I.; Aouad, M.: The spatial form of digital nonlinear landscape architecture design based on computer big data, Applied Mathematics and Nonlinear Sciences, 7(1), 2021, 783-790. https://doi.org/10.2478/amns.2021.1.00069

[8] Hussein, H.-A.-A.: Integrating augmented reality technologies into architectural education: application to the course of landscape design at Port Said University, Smart and Sustainable Built Environment, 12(4), 2023, 721-741. https://doi.org/10.1108/SASBE-08-2021-0132

[9] Jahani, A.; Saffariha, M.; Barzegar, P.: Landscape aesthetic quality assessment of forest lands: an application of machine learning approach, Soft Computing, 27(10), 2023, 6671-6686. https://doi.org/10.1007/s00500-022-07642-3

[10] Jia, J.: Computer-aided design method of parametric model for landscape planning, Computer-Aided Design and Applications, 19(S3), 2022, 55-64. https://doi.org/10.14733/cadaps.2022.S3.55-64

[11] Jing, Z.; Ran, C.; Huichao, H.; Zhuang, S.: Application progress and prospect of machine learning technology in landscape architecture, Journal of Beijing Forestry University, 43(11), 2021, 137-156. https://doi.org/10.12171/j.1000-1522.20200313

[12] Kim, S.; Shin, Y.; Park, J.; Lee, S.-W.; An, K.: Exploring the potential of 3D printing technology in landscape design process, Land, 10(3), 2021, 259. https://doi.org/10.3390/land10030259

[13] Mich, O.; Schiavo, G.; Ferron, M.: Framing the design space of multimodal mid-air gesture and speech-based interaction with mobile devices for older people, International Journal of Mobile Human-Computer Interaction, 12(1), 2020, 22-41. https://doi.org/10.4018/978-1-6684-5295-0.ch028

[14] Tai, N.-C.: Effect of pictorial depth cues on the illusory spatial depth of the Lin family garden, Empirical Studies of the Arts, 41(2), 2023, 497-524. https://doi.org/10.1177/02762374221143725

[15] Xu, F.; Wang, Y.: Color Effect of low-cost plant landscape design under computer-aided collaborative design system, Computer-Aided Design and Applications, 19(S3), 2021, 23-32. https://doi.org/10.14733/cadaps.2022.S3.23-32