Environmental Art Design Element Identification and Mining Based on Deep Learning

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Abstract. Identifying different design elements is a crucial step in environmental art design. These elements may include visual elements such as lines, shape, color, and texture or immaterial elements such as culture, history, and society. Data mining (DM) can help us find useful information hidden in a large amount of data. Deep learning (DL) possesses the capability to autonomously extract pertinent features from extensive datasets and discover the underlying structure and patterns within the data through hierarchical representations. From the change curve of the training accuracy and loss rate, the environmental art image classification method based on the integrated one-dimensional CNN showed good performance. This processing method not only helps to improve the quality and beauty of images but also provides more flexible and efficient solutions for a variety of image processing applications. Computer-aided design (CAD) systems can store and manage large amounts of design data, including design solutions, design elements, user feedback, etc. The combination with CAD technology further expands the application scope of DM in environmental art design.

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1 INTRODUCTION

Environmental art design is a wide-ranging field that spans multiple subdomains, such as architectural, interior, and landscape design. Practitioners in these areas must consider various elements like spatial configuration, material choice, light, and color usage, along with cultural and historical backgrounds, to devise designs that blend aesthetics and practicality while aligning with specific cultural and historical milieus. Rural environmental landscape planning and management are important means to achieve sustainable development and ecological protection in rural areas. However, due to the complexity and diversity of rural environments, this process faces many challenges. Chang [1] explored the application of deep learning algorithms and CAD (computer-aided design) technology in rural local environmental landscape planning and management and analyzed their potential advantages and challenges from the perspective of landscape and ecological engineering. Deep learning algorithms can automatically extract useful features from a large amount of data to classify, recognize, and predict rural environmental landscapes. For example, Convolutional Neural Networks (CNNs) have been widely used in image recognition and classification tasks, including automatic recognition of vegetation types, water distribution, land use, and other aspects of rural landscapes. The combination of deep learning algorithms and CAD can achieve seamless integration from data collection analysis to planning and design. Deep learning algorithms can extract valuable information from a large amount of data, while CAD can transform this information into specific planning and design. The combination of the two can greatly improve the accuracy and efficiency of planning while also helping to achieve more sustainable and eco-friendly rural environmental landscapes. The lakeside terrain design is an important component of landscape design. CAD technology can conveniently process and analyze terrain data, helping designers better understand the trends and characteristics of terrain. On this basis, designers can use CAD to accurately model terrain, simulate the effects of different design schemes, and provide a basis for final decision-making. Du [2] discussed the application of CAD-assisted intelligent technology in the design of lakeside landscape elements. This includes terrain design, plant configuration, water landscape design, and landscape architecture and elaborates on their advantages and challenges in practical projects. Plants are one of the important elements of the lakeside landscape. Using CAD technology, designers can easily carry out plant configuration design. By querying and selecting suitable plant species through a database and utilizing CAD drawing functions for planting design and layout, the efficiency and accuracy of the design have been greatly improved. Water features are the soul of lakeside landscapes. CAD technology can help designers establish and simulate water body models and precisely control the direction, depth, and velocity of water flow. Meanwhile, by utilizing the rendering function of CAD, designers can better showcase the visual effects of water feature design. With the ongoing evolution of computer technology, CAD has become an essential tool for modern environmental art design, aiding designers in crafting, refining, and optimizing design concepts more efficiently. The goal of residential landscape design is to create a comfortable, beautiful, and fully functional living environment. Density and proximity are important indicators for evaluating the effectiveness of residential planning, which are of great significance for improving the quality of life of residents and promoting community development. Traditional density and proximity evaluation methods are usually based on field investigations and empirical judgments, which have certain subjectivity and limitations. With the advancement of technology, the combination of deep learning algorithms and CAD technology provides new solutions for density and proximity assessment in residential landscape design. George et al. [3] explored the application of deep learning algorithms and CAD (computer-aided design) technology in evaluating density and proximity in residential landscape design in virtual reality (VR) and traditional simulation processes. In the practice of residential landscape design, the combination of deep learning algorithms and CAD technology provides strong support and guidance for designers. Through virtual reality technology, designers can preview and evaluate the density and proximity effects of design solutions in the early stages and discover and solve potential problems in a timely manner. This data- and analysis-based design method helps improve design efficiency and quality and reduces the cost of later modifications. Traditional CAD systems center primarily on the modeling and visualization of the design workflow but often struggle to glean valuable insights from vast design datasets to guide design decision-making and drive innovation. Hsu and Ou [4] explored the application of deep learning algorithms and computer-aided design (CAD) technology in sustainable landscape education, particularly in element recognition and parametric design assistance. By combining these two technologies, we can more effectively identify and utilize various elements in gardens, further promoting the Sustainability and ecological friendliness of garden design. Deep learning algorithms have significant advantages in image recognition and classification. By training deep neural networks, we can quickly and accurately identify various elements in gardens, such as vegetation, water bodies, terrain, etc. In addition, deep learning algorithms can also be used to identify specific plant species, pests, and diseases, providing data support for subsequent parameterized design assistance. CAD technology provides powerful design and visualization tools for landscape design. Through parameterized design, we can automatically adjust the relevant parameters in the design scheme, such as plant planting density, irrigation system layout, etc., based on the element information recognized by deep learning algorithms. This parameterized auxiliary design method can not only improve the efficiency of the design but also ensure the scientific and sustainable nature of the design scheme. Thankfully, the swift progress of DL algorithms has presented fresh viewpoints and techniques for data analysis and mining. DL adeptly extracts relevant features from large datasets and decodes the inherent structure and patterns within the data through hierarchical representations.

Computer-aided design software has played an important role in mining environmental art elements in design. It not only improves the efficiency and accuracy of design but also provides designers with richer creative expression and implementation methods. Using CAD software, designers can quickly create 3D models and perform real-time environmental rendering. This helps designers to intuitively evaluate the visual effects of the design in the early stages, thereby better adjusting the design scheme. Some CAD software supports parametric design and generative design, making the environmental design process more intelligent. Designers can generate different design schemes by adjusting parameters, improving the diversity and innovation of the design. By combining virtual reality (VR) and augmented reality (AR) technologies, CAD software allows designers to conduct design evaluations and interactive experiences in a virtual environment, thereby improving the feasibility and user experience of the design. CAD software can integrate various data analysis tools to help designers optimize design solutions, such as energy efficiency, green performance, and so on [5]. The evaluation of environmental art images is of great significance for understanding the aesthetic value of artworks and enhancing the audience's appreciation experience. With the development of computer vision and deep learning technology, methods based on image classification and region segmentation have begun to be applied in the aesthetic evaluation of art images. Le et al. [6] explored how to use image classification and region segmentation techniques for the aesthetic evaluation of environmental art images. Classify environmental art images by training deep learning models such as Convolutional Neural Networks (CNN). The goal of classification is to classify images into different categories based on their content, style, color, and other characteristics. By classification, the aesthetic value of images can be preliminarily evaluated. Using image segmentation technology to divide environmental art images into multiple regions in order to analyze the characteristics and aesthetic value of each region in more detail. It combines the results of classification and regional segmentation to conduct a comprehensive aesthetic evaluation of environmental art images. The experimental results show that the method proposed in this article can effectively evaluate the aesthetic value of environmental art images. Identifying different design elements is a crucial step in environmental art design. These elements may include visual elements such as lines, shapes, colors, and textures, and they may also include immaterial elements such as culture, history, and society. Once the design elements are identified, the next step is to DM these elements to discover the patterns and trends. DM can help us to find useful information hidden in large amounts of data, such as the evolution of design style, the change of popular color, the change in user preferences, etc. This information has important implications for guiding design decisions and innovation. The introduction of the DL algorithm provides possibilities for the automatic identification of design elements. By educating the deep neural network model, computers can acquire the ability to autonomously learn and distinguish diverse design elements, thereby significantly enhancing the efficiency and precision of design element recognition. This article aims to discuss the integration of DL algorithms and CAD technology to foster more intelligent data recognition and mining in the realm of environmental art design. To accomplish this, we will initially delve into the pivotal elements of environmental art design and their influence on the design procedure, followed by exploring the utilization of DL algorithms to automatically recognize and extract these elements. Subsequently, we will elaborate on how to employ DM techniques to unearth concealed design patterns within the extracted design elements, ultimately presenting designers with a more exhaustive design reference.

The combination of DL algorithm and CAD technology can not only be applied to the identification of design elements and DM but also can further expand to the fields of automatic generation and optimization of design schemes. This approach can provide designers with a steady stream of design inspiration. Through the close combination with the CAD system, the generated design scheme can be directly imported into the CAD system for further improvement, realizing the seamless docking from data to design. This article studies the use of DL and CAD in the identification and DM, including the following innovations:

(1) This article combines the DL algorithm with CAD technology to explore the complementarity and synergy of the two in the field of environmental art design. While traditional CAD techniques focus on modeling and visualization, DL algorithms can automatically extract and mine useful information in design elements.

(2) This article employs DM techniques to thoroughly analyze the extracted design elements and uncover concealed design patterns and trends within the data. This approach assists designers in gaining a deeper comprehension of user requirements and market trends, thereby providing a more impartial foundation for making informed design decisions.

The paper initially outlines the backdrop and present status of environmental art design and CAD technology, followed by a discussion on the potential and applications of DL algorithms in identifying design elements and DM within the realm of environmental art design. Subsequently, the paper illustrates how the DL algorithm can be utilized to automatically recognize and extract design elements, as well as how DM technology can be leveraged to discern patterns within these design elements. Lastly, the paper verifies the practical efficacy of the generative model grounded in DL.

2 RELATED WORK

Through virtual technology, designers can simulate and predict people's behavior patterns and preferences in landscape environments, thereby better carrying out low-carbon visual design. Lin et al. [7] focused on the role of low-carbon visual design based on virtual behavior preferences in landscape environments and how to use this design method to promote the formation of low-carbon lifestyles. Low-carbon visual design based on virtual behavior preferences refers to the use of virtual technology to simulate and analyze people's behavior patterns in landscape environments in order to design environments that are more in line with the concept of low-carbon living. This design method helps to improve the Sustainability and ecology of the landscape environment while also guiding people towards a low-carbon lifestyle. Landscape environment design can guide people to form a low-carbon lifestyle by creating a low-carbon and friendly environment. For example, reasonable planning of ecological elements such as green spaces and water bodies and increasing the use of renewable energy. Through reasonable landscape design, the utilization efficiency of land, water, and other resources can be improved, thereby reducing energy consumption and carbon emissions. For example, technologies such as rainwater collection and utilization, energy-saving lighting, etc., can be applied in landscape design. Cultural landscape restoration is an important means of protecting and inheriting cultural heritage. Design evaluation is a crucial link in the restoration process, which is of great significance for ensuring the quality of restoration and achieving sustainable protection of cultural heritage. Traditional evaluation methods are mainly based on expert experience and subjective judgment, which have certain limitations and subjectivity. The introduction of deep learning algorithms and CAD technology provides new ideas and methods for the evaluation of cultural landscape restoration design. In the restoration project of a historical monument, Lin et al. [8] used a combination of deep learning algorithms and CAD technology for design evaluation. Predictions and evaluations were made for different design schemes by analyzing historical data through deep learning algorithms. Meanwhile, CAD technology to establish high-precision models for visual analysis and quantitative evaluation. Finally, combining the prediction results of deep learning algorithms with the analysis data of CAD technology, the design scheme that best meets the repair goal was selected. With the development of digital imaging and big data technology, the demand for landscape similarity analysis of a large number of unclassified art images is increasing. Malik and Robertson [9] proposed a deep learning feature extraction method based on texture encoding for extracting landscape features in images and conducting similarity analysis. It uses different CNN models for feature extraction of art images and compares their performance. The experimental results show that using VGG16 and ResNet50 models can achieve good results. Secondly, we used different texture encoding methods to transform deep learning features and evaluated their performance. The experimental results show that the use of grayscale co-occurrence matrix (GLCM) and local binary mode (LBP) can achieve good results. Finally, we used the extracted texture encoding to perform landscape similarity analysis on unclassified art images and evaluated the accuracy of the analysis results. The experimental results show that the method proposed in this article can effectively recognize similar landscape images and has high accuracy. In the context of rural revitalization strategy, agricultural and cultural tourism, and local landscape design have become important means to promote rural development. Mao and Wenyan [10] explored the application of deep learning algorithms and computer-aided design (CAD) technology in agricultural, cultural tourism, and rural landscape design and analyzed their driving role in rural revitalization. The combination of deep learning algorithms and CAD technology helps to achieve scientific and refined agricultural, cultural tourism, and local landscape design. The application of this technology can not only improve the feasibility and Sustainability of design but also promote the development of the rural economy and the improvement of the ecological environment. Take a certain rural area as an example; it has abundant agricultural resources and beautiful natural scenery. By applying deep learning algorithms and CAD technology, the designer conducted a comprehensive analysis and design of the rural landscape. In the design, the local agricultural culture and natural resources were fully explored, and a unique agricultural cultural tourism route was created. Meanwhile, high-precision modeling and visualization of local landscapes were achieved through CAD technology, providing tourists with an immersive travel experience. This design method not only enhances the economic benefits of rural areas but also drives the development of local agriculture and cultural industries, providing strong support for rural revitalization. CNN is particularly suitable for processing image data, especially large images, and can automatically learn features in images to describe and classify them. Somrak et al. [11] used ALS-derived ancient Mayan settlement environments for visualized data CNN for structural classification, greatly improving our understanding of ancient civilization environments. Build a CNN model suitable for environmental visualization data. During the training process, it adopted transfer learning methods, using pre-trained CNN models as the foundation and fine-tuning the models according to specific tasks. It explores how to use CNN for structural classification by analyzing visual data of ancient Maya settlement environments. The experimental results indicate that CNN has significant advantages and application potential in processing environmental visualization data. The discovery and excavation of artistic elements in outdoor mountain and forest environments are of great significance for improving landscape quality and cultural value. Tzima et al. [12] explored how to utilize environmental element recognition and data mining techniques to enhance artistic discovery in outdoor mountain and forest environments. The outdoor environment of mountains and forests, as a precious natural resource, not only has ecological value but also contains rich artistic elements. These artistic elements include natural landscapes such as terrain, vegetation, and water bodies, as well as cultural landscapes such as historical relics and folk culture. However, due to the complexity of the environment and limited data, the discovery and mining of these artistic elements face many challenges. With the development of technology, environmental element identification and data mining have provided powerful tools to solve this problem. Take a certain mountainous area as an example; it boasts magnificent landscape paintings and rich folk culture. In order to better protect and develop the artistic value of this region, it has adopted environmental element identification and data mining techniques. Firstly, comprehensive data on mountainous areas was obtained through remote sensing technology and drones, and image recognition algorithms were used to automatically identify elements such as terrain, vegetation, and water bodies. A series of protection and development measures have been formulated to enhance the artistic quality and cultural value of the landscape in the region. Landscape design, as an important part of rural tourism development, requires the use of advanced technological means to achieve a more intuitive and vivid design presentation. The combination of deep learning algorithms and CAD technology provides new ideas and methods for the visualization of rural tourism landscape design. Deep learning algorithms can automatically extract useful features from a large amount of rural tourism landscape data, providing a more accurate reference basis for design. By training deep neural networks, the characteristics and patterns of landscape elements such as terrain, vegetation, and architecture can be identified, providing scientific guidance for design. Visualization methods have broad application value in rural tourism landscape design. By combining deep learning algorithms with CAD technology, designers can present design concepts and results more intuitively, improving communication efficiency and decision-making accuracy. Meanwhile, visualization methods can also provide tourists with an immersive experience, enhancing the attractiveness and competitiveness of rural tourism [13]. Landscape conservation art design involves the recognition, protection, and enhancement of the aesthetic, cultural, and historical values of natural and artificial landscapes. Traditional protection methods are often limited to on-site inspections and limited graphic and textual information, making it difficult to fully and deeply understand the rich connotations of landscapes. The immersive virtual reality technology based on spherical videos has brought revolutionary changes to this field. Wu et al. [14] explored the impact of immersive virtual reality technology based on spherical videos on the recognition and data mining of landscape protection art design elements. Through spherical video technology, we can obtain high-definition panoramic images and construct realistic virtual landscape models. This technology not only enables researchers to observe landscapes from various perspectives but also enables automatic recognition and classification of landscape elements. The immersive virtual reality technology based on spherical videos has brought unprecedented opportunities for landscape protection art design. It not only improves the recognition accuracy of landscape elements but also makes it possible to mine and analyze landscape data. This technology helps us to have a deeper understanding of the artistic value and cultural significance of landscapes, providing a scientific basis for landscape protection and design. Intangible artistic and cultural landscapes, as a combination of art and culture, have unique value and significance. However, due to their intangible characteristics, the analysis and design of such landscapes face many challenges. Wang [15] explored how to combine deep learning algorithms with computer-aided design (CAD) technology to analyze intangible artistic and cultural landscapes in order to reveal their deep characteristics and connotations. Deep learning algorithms can automatically extract useful features from a large amount of data and perform classification. By training deep neural networks, we can classify intangible artistic and cultural landscapes and identify their key features. Deep learning algorithms can be used to analyze semantic information and emotional expression in landscapes. By processing various data sources such as text, images, and audio, we can gain a deeper understanding of the cultural and artistic connotations conveyed by landscapes. By training deep learning models, we can predict the development trends of intangible artistic and cultural landscapes and achieve style transfer. This helps designers better grasp the direction of future development and create landscape designs that are more in line with the needs of the times.

The classification of environmental landscape art media is an important issue in the field of art, which involves the accurate identification and classification of environmental landscape artworks from different media (such as oil painting, watercolor, photography, etc.). With the development of deep learning technology, the use of deep convolutional neural networks (CNNs) for image classification has achieved great success. Yang and Min [16] explored how to use deep convolution methods to classify environmental landscape art media. The deep convolutional method is an image classification method based on convolutional neural networks. It extracts different features from the image by using different filters in the convolutional layer and gradually abstracts and extracts advanced features from the image through layer-by-layer convolution and pooling operations. In the classification of environmental landscape art media, deep convolutional methods can be used to train classifiers to achieve automatic classification of artworks from different media. It uses annotated datasets of environmental landscape artworks to train convolutional neural network models, enabling them to automatically extract features of different media artworks and classify them. Apply the trained model to practical environmental landscape art classification tasks and optimize and improve it as needed. Landscape environment design is a comprehensive art that involves multiple fields, such as planning, architecture, landscaping, sculpture, etc. Color, as an important element in landscape environment design, is of great significance in creating atmosphere, expressing themes, and enhancing overall effects. The computer-aided collaborative design system, with its efficient and precise characteristics, provides new possibilities for the color application of landscape environment design. The computer-aided collaborative design system provides strong support for the artistic color effect of landscape environment design. By combining digital technology and network technology, designers can more efficiently plan and select colors, collaborate in real-time, and preview effects. This not only improves design efficiency but also enables better reflection and implementation of artistic color effects in landscape design. This system achieves real-time collaboration among designers through digital and network technologies, improving design efficiency and effectiveness. Zhang and Deng [17] discussed how the artistic color effect of landscape environment design can be better presented in a computer-aided collaborative design system. Most studies focus only on the identification of specific design elements or applications in specific design areas, lacking a comprehensive and unified framework to handle multiple design elements and cross-domain applications. This article employs state-of-the-art DL algorithms combined with unsupervised learning techniques to extract useful features and mine deep design patterns and trends from a large amount of unannotated design data.

3 ENVIRONMENTAL ART DESIGN ELEMENT IDENTIFICATION AND DM

As a highly creative and technical field, environmental art design also benefits from the integration and application of these technologies. In particular, the combination of DL and CAD technology provides powerful tools and methods for the identification of environmental art design elements and DM. Traditional design element identification mainly relies on the expertise and experience of designers, which is conducted by observing and analyzing design cases. This approach is inefficient and easily influenced by subjective factors. The introduction of the DL algorithm provides possibilities for the automatic identification of design elements. By training deep neural network models, computers are allowed to learn and identify different design elements automatically. Specifically, a large quantity of annotated design element data can be used to train a CNN model so that it can automatically extract the features in the image and classify them. Once the model training is completed, it can be used to identify new design elements. The CNN structures identified by the environmental art design elements are shown in Figure 1.

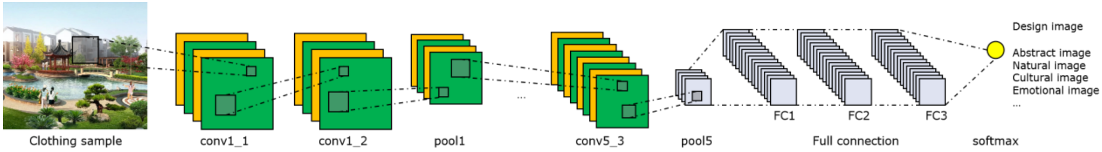

Figure 1: The CNN structure identified by the environmental art design elements.

The combination with CAD technology makes the identification of design elements more accurate. The CAD system can provide high-precision design models and data and provide rich training samples for the DL algorithm. In addition, the CAD system can also accurately annotate and locate the design elements so as to provide more accurate learning objectives for the DL algorithm. The spatial structure characteristics of environmental art are obtained through the operation of multiple convolution-pooling methods. Then the next full connection layer is carried out. The output information obtained from the whole connection layer is taken as the input and output of gated recurrent unit (GRU) module. The CNN _ GRU network model is shown in Figure 2.

In environmental art design, DM can help us to find useful information hidden in a large amount of design data, such as the evolution of design style, popular color changes, user preferences, etc. By training a deep neural network model, we can automatically extract useful features in the data and discover the intrinsic connections and regularities between the data.

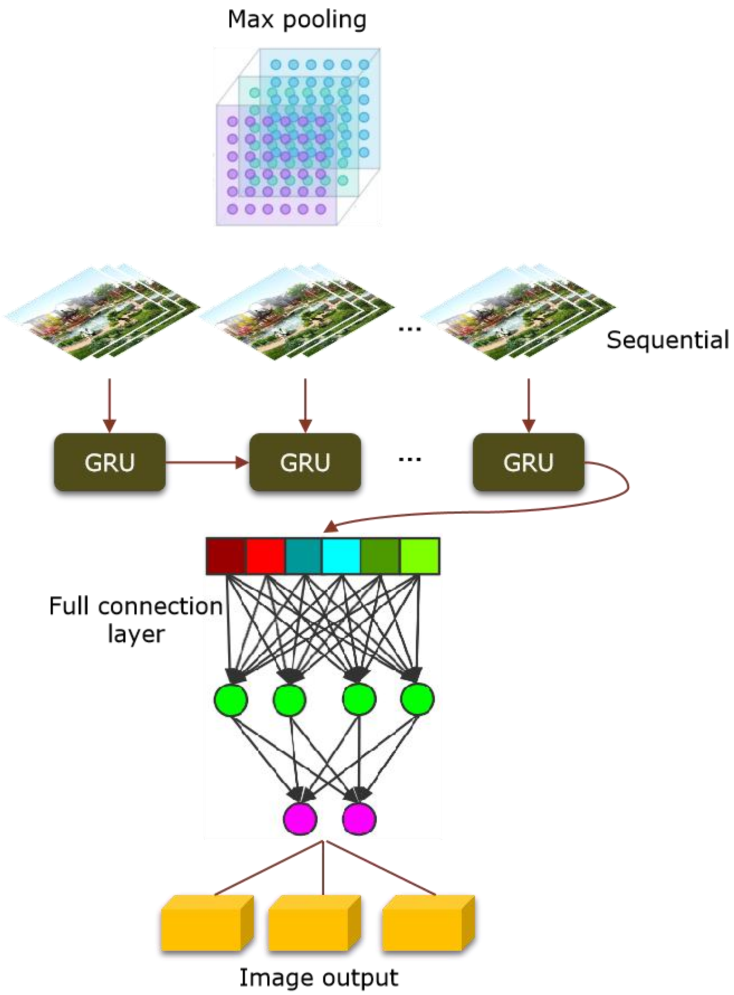

Figure 2: The CNN _ GRU network structure.

The combination with CAD technology further expands the application scope of DM in environmental art design. The CAD system can store and manage a large amount of design data, including design schemes, design elements, user feedback, etc. These data provide a rich data source for the DM. By combining the DL algorithm and the CAD technology, these data can be automatically analyzed and mined to discover hidden laws and trends. Image x_i is the information of all pixels in a picture and the category it is is y_i. Through the scoring function and activation function $f \; x_i, W$, the scoring s_j of different categories to which x_i belongs can be obtained. Then, the loss function of x_i for category prediction can be expressed as:

$$L_i = \sum_{j \neq y_i} \max \; 0, s_j - s_{y_i} + \Delta \tag{1}$$

The $\max \; 0, -$ function serves as a threshold centered around zero and is commonly referred to as the loss function of broken leaves. The objective of incorporating the support vector machine (SVM) loss function into neural networks is to ensure that the score of the accurate prediction outcome is notably higher than that of the incorrect prediction, with a minimum difference of Δ. If this criterion is fulfilled, the loss value is deemed zero, indicating a correct prediction. Otherwise, the loss is computed. In Softmax, the score mapping function remains unaltered, while the corresponding loss function is defined as follows:

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_{y_j}}}\right) \tag{2}$$

In a one-dimensional function, the slope represents the instantaneous rate of change of the function at a specific point. Gradient, on the other hand, is a broad term used to describe the slope of a function, and it is represented as a vector rather than a scalar. Within the input space, the gradient (or derivative) is comprised of a vector containing slopes across multiple dimensions. The formula for calculating the derivative of a one-dimensional function is given below:

$$\frac{df\ x}{dx} = \lim_{h\to 0}\frac{f\ x+h\ -f\ x}{h} \tag{3}$$

When a function involves multiple parameters, the derivative is referred to as a partial derivative. The gradient is a vector composed of partial derivatives in each dimension, representing the slope of the loss function in each respective dimension. Since the network aims to decrease the value of the loss function rather than increase it, the parameters within the network can be adjusted by moving in the opposite direction of the gradient.

The procedure of data standardization involves scaling the data, ensuring that the standardized data falls within a narrow and predefined range. One of the most common standardization techniques is the Z-score method, which transforms the eigenvalues to conform to a standard normal distribution. The formula for this transformation is:

$$x' = \ x-\mu\ /\sigma \tag{4}$$

In this context, x and x' denote the features prior to and following normalization, respectively. μ Represents the sample mean, while δ signifies the sample standard deviation. Both of these values can be determined from the sample data. The z-score normalization method is highly effective when dealing with a sufficient quantity of samples, making it well-suited for processing contemporary scenarios characterized by abundant and noisy data. By incorporating z-score normalization, the average and standard deviation of the attribute A are normalized. Consequently, the value of normalized A, denoted as v, becomes v'. This value is computed using the following formula:

$$v' = \frac{v-\bar{A}}{\sigma_A} \tag{5}$$

Where the mean A is:

$$\bar{A} = \frac{\sum A}{n} \tag{6}$$

The standard deviation A is:

$$\sigma_A = \sqrt{\frac{\sum\ A-\bar{A}\ ^2}{n-1}} \tag{7}$$

After normalization, all variables will have a mean of 0 and a variance of 1. The interval scaling method involves utilizing the boundary values of feature data to confine the feature values within a specified range. In this article, we employ two maxima for scaling the feature data. The transformation function used is as follows:

$$x' = \frac{x - \min\ x}{\max\ x\ - \min\ x} \tag{8}$$

In this context, $\min\ x$ and $\max\ x$ are the minimum and maximum values of the sample data. This method effectively ensures that the data falls within the range of [0,1]. Binarization involves setting a threshold, denoted as T. Values exceeding T are assigned a value of 1, while values below T are assigned a value of 0. The formula for this process is expressed as follows:

$$x' = \begin{cases} 1, & x > threshold \\ 0, & x \leq threshold \end{cases} \tag{9}$$

DL algorithm has powerful feature extraction and classification capability, combined with high-precision data of CAD, which can realize high-precision identification and positioning of design elements. Mining a large amount of CAD data by DL can reveal design patterns and trends that are difficult to find by traditional methods, providing designers with deeper design insights. Combining the real-time modeling of CAD and the real-time analysis capability of DL, designers can provide real-time design feedback and optimization suggestions. The combination of DL and CAD is not only limited to the identification of design elements and DM but can also be extended to cross-field applications such as the automatic generation of design schemes and user preference prediction. Let's denote the gray value of a pixel and $g\ i,j$ represent the corresponding gradient value for that pixel. The gradient of any pixel in the image is then defined as follows:

$$g\ i,j\ = \sqrt{\left[f\ i,j\ - f\ i+1,j+1\ \right]^2 + \left[f\ i+1,j\ - f\ i,j+1\ \right]^2} \tag{10}$$

Set the projection center to be at the center of the image. The coordinate values of the image point A in the display user area, relative to the image center in the user area, represent its corresponding coordinate values in the image coordinate system.

$$A = \ x - lWidth / 2, y - lHeight / 2 \tag{11}$$

In this context, x,y it represents the coordinates of points A within the user area. $lWidth$ Denotes the length of the image while $lHeight$ signifies its height. To ensure accuracy in determining the coordinates of image points within the user area and minimize errors associated with mouse selection, a method of selecting and averaging over multiple iterations is employed. The formula used for this process is as follows:

$$x,y\ = \left(\sum_{i=1,n} x_i / n, \sum_{i=1,n} y_i / n\right) \tag{12}$$

4 RESULT ANALYSIS AND DISCUSSION

Environmental art images of different images were selected as experimental subjects, including Abstract image, Natural image, and cultural image. For each scale image, different numbers of nodes were used for identification and DM to observe the effect of the quantity of nodes on operational efficiency. As shown in Figure 3, in the case of a small image size, as the quantity of nodes in the image increases, as does the time required for image recognition. When the image scale is larger and larger, the identification efficiency of multiple nodes will show a significant increasing trend.

When processing small-scale images, increasing the number of nodes does not bring a significant efficiency improvement and may even lead to decreased efficiency. This is because the data amount of small-scale images is small; a single node can be processed quickly, and increasing the number of nodes will increase the overhead of communication and coordination. When processing large-scale images, the parallel processing of multiple nodes can significantly improve the operation efficiency and shorten the processing time. By comparing the performance of different methods when processing images of different sizes, we can find that the proposed environmental art design element identification and DM methods have significant advantages when processing large-scale images.

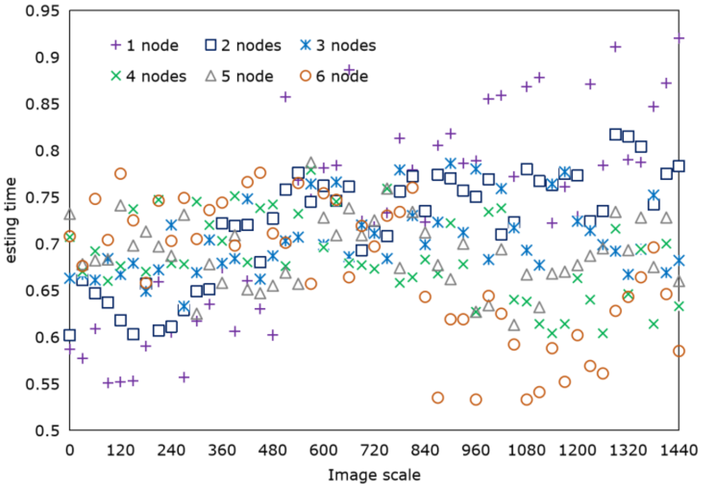

Figure 3: Image recognition consumption time for different quantities of nodes.

The algorithm execution time was tested, and the results are shown in Figure 4. Given the nature of the online task, where tasks are continuously submitted to or from the cluster, these dynamics make accurate estimation of energy consumption a challenge. Unlike batch tasks, in an online environment, there are already other tasks running in the cluster when new tasks are submitted to the cluster, meaning that the resource utilization of the cluster is dynamically changing.

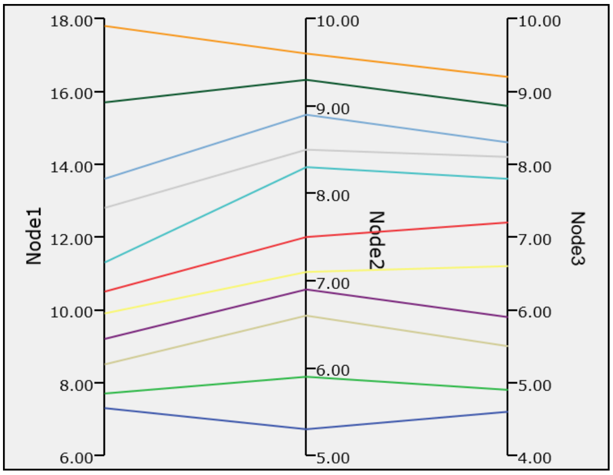

Figure 4: Processing time variation of the dataset.

Different types of tasks may have different energy consumption characteristics. For example, computationally intensive tasks may consume more CPU resources, while I / O intensive tasks may generate greater load on disk and network. Through a deep understanding and classification of the task characteristics, the energy consumption can be estimated more accurately. In an online task environment, energy consumption assessment with the task as the basic granularity is feasible and can provide a valuable reference for energy-saving strategies in clusters.

For the validation of the environmental art image classification method based on the integrated one-dimensional CNN, the dataset processed by the data balance was used to ensure the fairness and accuracy of the experiment, by setting control experiments, the advantages and disadvantages of this method over other methods. From the change curve of training accuracy and loss rate (Fig. 5 and Fig 6), this method showed a significant performance improvement in the early stage of training. At the beginning of the training session, the loss value decreases substantially. This usually means that the learning rate is set properly and the model is effectively performing the gradient descent process. Figure 5 shows CNN_ The training accuracy results of GRU. Figure 6 shows CNN_ The training loss rate result of GRU.

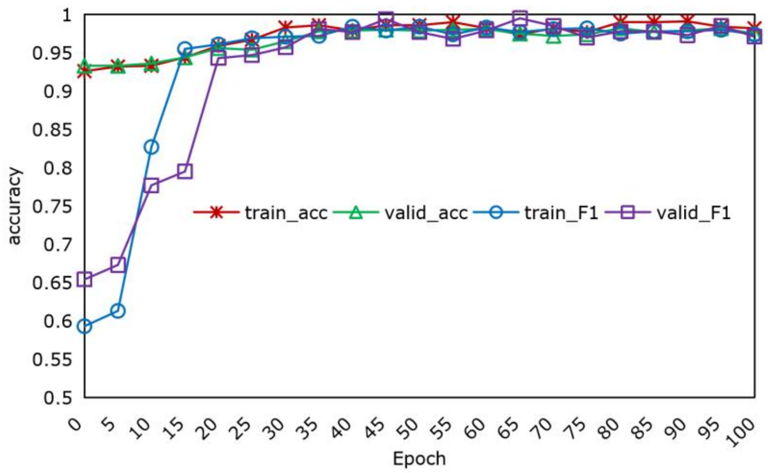

Figure 5: Training accuracy of CNN _ GRU.

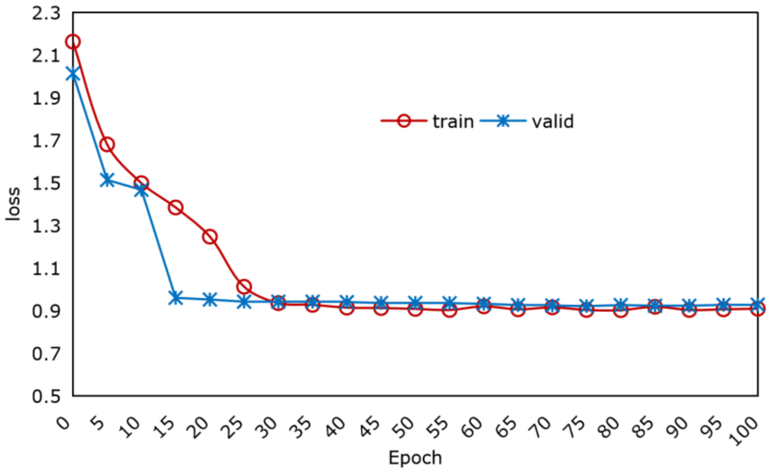

Figure 6: Training loss rate of CNN _ GRU.

From the change curve of the training accuracy and loss rate, the environmental art image classification method based on the integrated one-dimensional CNN showed good performance. Further validation of the effectiveness of this method requires more detailed experiments and analysis, including direct comparison with other methods and application to a wider range of datasets.

The efficiency of the environmental art image classification model of different methods was tested on the Matlab platform, the identification efficiency was evaluated by the running time, and the experimental results were calculated on the characteristic dimension reduction time of different environmental art images (Abstract image, Natural image, cultural image, Emotional image) were analyzed, which was helpful to understand the performance difference and application scope of each model. From the results in Table 1, different methods showed significant differences in running time and feature dimension reduction time when dealing with different types of environmental art imagery. This is due to the different optimization degrees and adaptability of different methods when processing different types of data. For the same method, the running time and the feature dimension reduction time are also different when handling different types of environmental art imagery. This may be due to the different complexity and feature distribution of different types of data, leading to the different performance of the same method when dealing with different types of data.

Environmental art imagery	*training sample*		*test sample*	
	RNN	*CNN*	*RNN*	*CNN*
Abstract image	8.24	8.18	8.22	5.79
Natural image	9.31	8.51	8.78	5.12
cultural image	8.95	8.48	8.85	4.37
Emotional image	7.66	7.55	7.47	5.56

Table 1: Dimonality reduction time of the environmental art feature classification model.

Based on the above conclusions, appropriate methods can be selected for different application scenarios and data types, and the model parameters can be optimized and adjusted to improve the efficiency of the image classification model of environmental art.

Through the observation and analysis of the results in Figure 7, we can deeply understand the influence of different content and style weight comparisons on the generated images. This influence is not only reflected in the color and details of the image but also reflects the interrelationship and boundary ambiguity between the content and the style in the image processing.

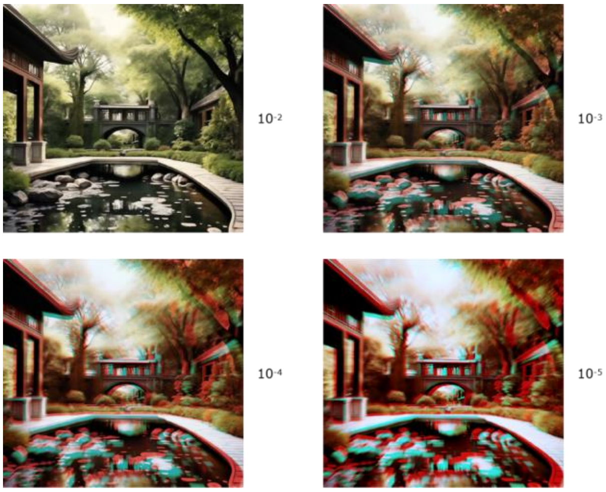

Figure 7: Different weights of different contents and styles.

When the weight of the style image is large, and the weight of the content image is small, the generated image is obviously dominated by the style image in color. In this case, the color of the generated image is very similar to the input style image, sometimes even to an almost consistent degree. However, this color similarity comes at the expense of detail. Due to the small weight of the content image, the generated image often loses serious losses in the detail performance, which may appear fuzzy, distorted, or lack hierarchy. Conversely, when the style image weighs less and the content image more, the generated image performs more and more well in detail retention. The increased weight of the content image enables the generated image to retain more of the detailed features of the original image, such as texture, shape, edges, etc. This retention of detail not only enhances the realism and clarity of the generated image but also helps to maintain its consistency with the original content image.

By flexibly adjusting the weight ratio of content and style, more diversified and personalized image processing effects can be achieved. This processing method not only helps to improve the quality and beauty of images but also provides more flexible solutions for a variety of image processing applications.

5 CONCLUSION

With the ongoing advancement of DL, artificial intelligence, and big data technologies, their applications in the domain of environmental art design are expanding rapidly, presenting designers with an array of unprecedented creative opportunities. Notably, in the identification of environmental art design elements and DM, these cutting-edge technologies exhibit immense potential and value. Environmental art design is a multifaceted and complex field that encompasses various subdomains such as architectural design, interior design, and landscape design. Traditional CAD systems primarily concentrate on the modeling and visualization aspects of the design process, often lacking the capability to extract insightful information from voluminous design data to inform design decisions and foster innovation. This article delves into the integration of DL algorithms and CAD technology to foster more intelligent data recognition and mining in the realm of environmental art design. The findings reveal that by adjusting the weight ratio of content to style, a more diverse and personalized range of image processing effects can be achieved. This method not only enhances the quality and aesthetic appeal of images but also offers more versatile and efficient solutions for various image processing applications. By analyzing and mining historical design data, insights into design style trends, shifts in user preferences, and the emergence or disappearance of popular elements can be gained. Such information plays a pivotal role in guiding design decisions, anticipating future design trends, and spurring design innovation.

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