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Computer-Aided Design AND APPLICATIONS

Extracting Cultural Elements of Intangible Cultural Heritage Based on Region-CNN Algorithm

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Abstract. Computer-aided design (CAD) technology provides a new possibility for the recording and presentation of ICH culture because it can generate high-precision digital models. Computer vision technology can identify, extract, and analyze the characteristic elements of ICH culture from massive images and videos. By analyzing the content extraction of neural network visual teaching, an application analysis of element extraction for digital cultural heritage has been constructed. Not only has it expanded the application of neural network elements, but it has also been well displayed on the digital table of material culture. The Faster R-CNN algorithm has been carefully evaluated through numerous experiments to identify the characteristics of material culture accurately. Data points were collected at different stages of the training results. The experimental results show that in the traditional testing and training stage, it has constructed a training model with high accuracy and fast convergence speed. By analyzing the quality of rendering speed. We created a high teaching quality effect. Therefore, the Faster R-CNN algorithm still provides strong algorithmic support in the inheritance of material culture.

Keywords: CAD; Computer Vision; Intangible Cultural Heritage; Cultural Elements; Visual Teaching
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1 INTRODUCTION

In today's era, there are countless forms of artistic expression. However, only digital art has successfully integrated traditional Chinese culture with modern electronic technology, demonstrating its unique charm. The establishment of this model not only greatly improves the efficiency of information processing but also makes digital art a new, widely participatory, and shareable form of art. The core goal of the digitalization process of digital art is to transform digital codes into substitutes for visual information. The ultimate goal of this process is to convert digital models into computer code, enabling the storage, high-speed analysis, and universal sharing of massive information. This innovation in digital art not only provides a new way for the inheritance and promotion of traditional Chinese culture, but also showcases the infinite possibilities of modern electronic technology. With the continuous development of modern society, there has been a gap in material culture. Many traditional patterns often cannot be effectively preserved in today's digital world. Therefore, inheritance is not limited to past models, but should keep up with the trend of the times and continuously expand its cultural and technological applications. By widely applying inheritance, we can increase the promotion of new vitality on the platform. The main difference between traditional culture and digital inheritance is first reflected in the media they use. In traditional cultural works, the sensitivity of an artist's brushstrokes to color and personal personality factors directly affect the presentation of the work [1]. Every traditional art and cultural work is unique because it contains a lot of hard work and skills. In contrast, digital artworks are created numerically based on electronic technology. Its works can be replicated because digital information can be infinitely replicated and transmitted. The differences in these media lead to their differences in different fields and commercial values. Notably, CAD and computer vision technologies hold significant potential for the digital safeguarding and promotion of ICH culture.

CAD technology offers highly precise digital models, paving new avenues for documenting and showcasing ICH culture. Barrile et al. [2] attempted to use digital narrative as a unique perspective for studying cultural. It conducted an in-depth analysis of the research background and current situation. It has been discovered that driven by cultural digitization strategies and emerging technologies, has unprecedented development momentum and opportunities. Based on the analysis of relevant concepts such as digital narrative and digital narrative, it analyzes the opportunities and challenges of inheriting digital narrative in China from the macro environment, technological environment, and new user needs. By analyzing the elements of digital narrative in typical cases, extract the elements of time, space, media, and the effect of digital narrative in the inheritance. And constructed a path for the inheritance of intangible cultural heritage from the perspective of digital narrative, including spatiotemporal scenes, interactive media, and narrative experiences. To provide a reference for the dissemination and enhancement of public awareness and deep participation in China. Meanwhile, computer vision technology can pinpoint, extract, and scrutinize characteristic ICH elements from a myriad of images and videos, enriching the digital representation of ICH culture. Digital storytelling, as an innovative application of digital technology in the field of inheritance, has gradually become an inevitable trend. In the field of inheritance, digital technology has broken the limitations of traditional inheritance methods through innovative applications, injecting new vitality into the inheritance and protection of intangible cultural heritage. With the rapid development of digital technology, its role in promoting inheritance has become increasingly significant. Bernardi et al. [3] comprehensively reviewed the research status inheritance and digital narrative in their in-depth research, and explored the close relationship between the two. It enables intangible cultural heritage to be presented to the public more vividly and intuitively, enhancing the dissemination effect and social influence. The use of digital information technology can optimize resource management methods, create intangible cultural heritage project archives to strengthen protection efforts, and use digital information systems for inheritance. Specifically, digital technology can optimize the storage methods resources by collecting a large amount of traditional textual information, collecting, processing, and forming a permanent database, laying a solid foundation, and improving the research level inheritance through various digital resources. Finally, digital technology can further analyze intangible resources and related data information, ensuring that intangible cultural heritage projects can be updated and improved in a timely and effective manner. This article introduces a CNN-based feature detection algorithm for ICH cultural elements. Faster R-CNN, a renowned deep learning algorithm, has demonstrated remarkable proficiency in image recognition and feature detection. By fine-tuning the Faster R-CNN framework's key parameters, we aim to simultaneously detect and identify ICH cultural elements, thereby enhancing identification accuracy and robustness.

CNN stands as a pivotal model in deep learning, proficiently learning image feature representations from extensive training datasets. Intangible cultural heritage archives cannot be shelved and need to be deeply developed and widely utilized in order to realize their value. Digital technology has been applied to various aspects of information generation, storage, management, and development, and the development methods of intangible cultural heritage archives also urgently need to be transformed. From the information age to the data age, digital humanities, as an emerging research hotspot and research paradigm in a data-intensive scientific environment, can provide more inspiration for archives through its concepts, technologies, and methods. Challenor and Ma [4] combined the research advantages of digital humanities with intangible cultural heritage archives to create a way to archive. In fact, it has realized the deep excavation of information in intangible cultural heritage archives, promoting the development of intangible cultural heritage archives. In contrast to conventional image processing techniques, CNN excels in feature learning and abstraction, precisely capturing and identifying intricate image features. At present, both domestically and internationally are in a development stage. There is a lack of technical support and theoretical richness. The digital narrative of intangible cultural heritage in digital picture books. The narrative plot needs to attract readers' attention in a short period, and efficiently convey information, and the interaction method also needs to have a certain level of attractiveness and fun. How to make readers leave a deep impression after reading and the difficulty of understanding knowledge. Due to differences in ideological concepts between individuals and groups, it is often difficult to generate a strong interest in traditional visual intangible cultural heritage among consumers. Therefore, it is necessary to analyze the intrinsic motivation of consumers and find a clear and feasible entry point [5].

Faster R-CNN, a CNN variant, seamlessly integrates RPN and classifier, facilitating swift target detection and recognition. The innovative application driving force for humanities research, and connecting digital technology with humanities research for exploration and practice has become a trend. Digital humanities have emerged and played an important role, attracting increasing attention from the academic research community as an emerging discipline. Digital humanities provide a new research paradigm for academic research, and in a data intensive environment, digital resources with increasing content and types can be analyzed and processed through processing methods such as correlated data. Han et al. [6] achieved efficient research on traditional humanities. Its essence is to apply advanced and constantly developing digital technologies to traditional humanities research. Digital humanities provide new concepts, and technologies. It optimizes the integration and development of intangible cultural heritage archives from a technical perspective, and better realizes content mining and emotional expression from a humanistic perspective. In the endeavor to extract ICH cultural elements, we leverage the Faster R-CNN framework for automatic detection and identification of these elements in images, elevating the precision and efficiency of the extraction process.

The outcomes illustrate the algorithm's commendable accuracy and robustness, presenting a novel technical approach for the digital preservation and dissemination of ICH culture. Moreover, this algorithm can be integrated into visual teaching, enabling students to more intuitively grasp the distinctiveness and essence of ICH culture, thereby fostering a deeper appreciation and interest in traditional culture.

The contributions of this paper can be summarized as follows:

(1)Faster R-CNN introduced RPN, which replaced the traditional regional suggestion method, thus realizing end-to-end training and network structure.

(2) By using the "anchor" mechanism, RPN has realized multi-scale and multi-directional regional suggestions and enhanced the flexibility and accuracy of the model.

(3) FAST R-CNN incorporates RPN and Fast R-CNN, both utilizing identical convolution features. This approach not only cuts down computational load but also enhances feature detection efficiency.

(4) Faster R-CNN offers an end-to-end training capability, advancing from its predecessors in the R-CNN family. This allows for comprehensive network optimization, leading to performance enhancement.

This article introduces the value of ICH culture and the importance of protection, puts forward the shortcomings of traditional feature recognition methods, and then leads to the application of Faster R-CNN algorithm based on CNN in the feature detection of ICH cultural elements. Next, the paper expounds on the principle of the algorithm and the experimental results in detail, showing its advantages in accuracy and robustness. Finally, the application prospect of this algorithm in visualization teaching is discussed, with the aim of contributing to the inheritance and education of ICH culture.

2 RELATED WORKS

Many time-honored brands face the risk of losing their intangible cultural inheritance skills. They showcase the cultural characteristics and artistic charm of the Chinese nation uniquely, bringing rich and colorful experiences to our lives. Due to changes in market demand and the impact of modern production, some skills have gradually lost their original danger of being eliminated. However, due to the impact of modernization and talent loss, the intangible cultural heritage skills in time-honored brands face the risk of loss. Through digital means, intangible cultural heritage can break free from geographical and temporal limitations and be presented to the general public more vividly and intuitively. This digital inheritance method enables intangible cultural heritage to better integrate into contemporary society and be closely connected to people's lives. Through digital platforms, people can more conveniently understand and learn about intangible cultural heritage and feel its profound cultural connotations and artistic charm. This also injects cultural heritage, making it shine more brilliantly in the new era background [7]. Digital picture books, as a means of digital dissemination, utilize elements such as interactive storytelling, visual design, sound design, and interactive design. This can enable intangible cultural heritage to be presented intuitively and clearly to readers, becoming a new way and means of spreading intangible cultural heritage.

Overseas, it is applied in museums, libraries, exhibition halls and Internet platforms, while domestically, it is applied through cultural tourism integration, community participation and industrial development. In addition, through searching databases both domestically and internationally, it was found that there is a lack of research conducted from a digital narrative perspective. Empowering the inheritance through digital narrative can provide more diverse presentation methods and promote the effectiveness of intangible cultural heritage inheritance. Masciotta et al. [8] explored how to use diverse presentation methods in visual picture books. To enable the public to better understand and feel the cultural connotations behind visual heritage, More and more people are paying attention to intangible cultural heritage, exploring its profound cultural connotations and artistic charm. Its application in the inheritance of intangible cultural heritage has become increasingly widespread. Digital narrative, as an innovative way of inheritance, can vividly and intuitively showcase the charm of intangible cultural heritage, making inheritance work more efficient and convenient. This has laid a solid foundation for the inheritance of intangible cultural heritage and created a favorable environment for its development in the digital age. The awakening of cultural confidence and deeply rooted in people's hearts, gaining broader social recognition and support. The positive empowerment of digital media is a way to enhance user experience needs. The cross-integration of various industries and media also provides more possibilities for the inheritance of intangible cultural heritage digital narratives. Nishanbaev et al. [9] analyzed the geographic spatial semantic web survey of cultural heritage.

As a new research paradigm, studying digital humanities itself has positive theoretical significance. Faced with the rapidly changing digital and even data-driven environment, Poux et al. [10] found it difficult to explore the deep value of research objects using traditional development methods. The development of archives of digital humanities has enriched the paradigm of digital humanities research at the application level. The successful integration of digital humanities and archival work has been achieved through related projects, but there is relatively little research. Taking intangible cultural heritage archives as samples, and introducing digital humanities to promote theoretical research in the field of archives will also have a profound impact on the research and use of digital humanities in archival studies. Intangible cultural heritage is a cultural heritage based on humanity and a living memory of human civilization. It emphasizes human skills and experience, with a human centered approach. Its prominent features are non-material and dynamic nature, making it prone to being left unattended, destroyed, or even disappearing. Material cultural heritage archives refer to the original records directly formed by social organizations or individuals in the series of intangible cultural heritage activities, which have preservation value for the country and society. It includes recording intangible cultural heritage activities or physical, written, or audio-visual archives preserved by inheritors. Rinaldi et al. [11] proposed that intangible cultural heritage archives tend to be broadly defined, starting from the entire process of formation, development, development, and utilization. It will preserve archives with preservation value to achieve the inheritance of culture and national spirit. Its specific content is not within the scope of this article, so it will not be discussed in detail. Intangible cultural heritage archives actually provide a solidified carrier for various elements of intangible cultural heritage activities, and provide better data support and evidence for the implementation of various work.

The concept and technology of digital humanities are highly compatible with the development and value realization archives. Strengthening the connection between intangible cultural heritage archives and digital humanities can not only enrich the practical connotation of digital humanities, but also realize the value of intangible cultural heritage archives. In their research, Selmanović et al. [12] fully demonstrated humanities in the development archives. By designing creative and meaningful digital picture books, we aim to convey the unique value and rich connotations of intangible cultural heritage to more people. This not only improves the efficiency and value of archive utilization, but also better realizes the important value of intangible cultural heritage archives. They have successfully digitized intangible cultural heritage archives by utilizing digital humanities methods and technologies, enabling them to be better preserved and disseminated. The audience's expectations and recognition of traditional culture are increasing day by day, and traditional culture is gradually moving toward its rise. These studios collaborate with major brands to provide rich creativity and services in the design field. The application of digital illustration technology in these industries is becoming increasingly widespread, creating character images that not only enhance brand awareness but also bring a brand new visual experience to the audience. Digital traditional text technology plays an indispensable role in this, and the colorful art style has become a new trend. Digital ink painting has quietly become a part of our daily lives, and its presence can be seen everywhere. More and more artists are beginning to engage and engage in this emerging industry, injecting new vitality into the Chinese illustration industry. Illustrators break free from the constraints of traditional painting methods and cleverly integrate traditional Chinese cultural elements into digital ink painting, showcasing the core culture with Chinese national characteristics. In addition, digital illustration is also showing a new face in the market. By integrating traditional Chinese cultural festival elements into it, a new market direction has been formed. For example, major museums extensively use traditional illustration elements on the packaging of their surrounding products, making them not only artistic but also imbued with profound cultural aesthetics [13].

Compared to paper picture books, mobile augmented reality has more forms of expression, such as rich media content such as sound, animation, and interaction, which can better attract readers' attention and also has subtle educational functions. Digital mobile enhancement design can achieve both tangible and intangible dissemination [14]. When exploring the path of dissemination and protection, we can see that mobile augmented reality technology is playing an important role with its unique advantages. This presentation method not only enriches the forms, but also enables the public to deeply experience and feel the spiritual connotations and cultural heritage contained in these cultural heritage. Yin et al.'s research fully demonstrates the enormous potential of mobile augmented reality technology. Digital illustration, as an emerging form of media, has its unique characteristics clearly defined in recent years. On this basis, it further explores the significance of combining traditional Chinese cultural and artistic elements with digital illustrations. This integration not only enhances the artistic value of digital illustration, but also makes traditional culture shine with new brilliance in modern society. It has injected new vitality into the inheritance and promotion of traditional Chinese culture at the tangible level of dissemination. This fusion not only opens up a unique path with Chinese style for digital painting. It not only allows the audience to intuitively feel the information conveyed by the screen, but also has the advantage of non-destructive transmission, allowing information to be accurately and accurately transmitted to every audience. Through design innovation, these cultural treasures are presented in a brand new way to the public, guiding more people to approach, understand, and recognize their value and charm. Zhang et al. [15] constructed a bamboo weaving virtual experience system, allowing people to simulate the production process of bamboo weaving in a virtual environment, and understand the historical origins, technical characteristics, and cultural connotations of bamboo weaving.

3 METHODOLOGY

Digital media provides rich forms of expression and promotion through multimedia methods. Through the Internet, digital media can quickly spread the stories, skills, cultural values and other contents of intangible cultural heritage to all parts of the world, so that more people can understand and appreciate this valuable cultural heritage. Secondly, digital media has the characteristic of cross-temporal and spatial communication, which can break through the limitations of geography and time, and achieve dissemination. In addition, the interactive nature of digital media intangible cultural heritage. This multimedia presentation method increases the public's awareness and interest in it. Viewers or users can interact with intangible cultural heritage through online platforms, participate in inheritance activities, and express their opinions and feelings. Digital media plays a crucial role in the data management of intangible cultural heritage. The cross-temporal dissemination method enables these cultural heritages to transcend the limitations of time and space, allowing more people to have the opportunity to access and understand them. This digital management approach has also opened up new avenues for the dissemination of intangible cultural heritage. This ensures that these precious cultural heritages are effectively inherited and recorded. Through digital means, we can organize, classify, store, and retrieve relevant data. The expansion of this mode of communication not only enriches people's cultural perspectives, but also promotes communication and integration between different cultures, helping to build a more diverse and inclusive cultural environment. Through linear regression models, we can predict or estimate the shared convolutional layer y 'based on given image characteristics and parameter inputs. This relationship can be expressed by an equation, where y '=w1x1+w2x2+b, where w1 and w2 are weights and b is deviation, both of which are scalars. These weights and biases are the parameters of the linear regression model, which describes the linear relationship between input and output. It should be noted that there is usually some error between the predicted result y 'and the actual parameter y, as the model is a simplified representation of the real world and cannot fully capture all complex factors. For cultural images of intangible cultural heritage, preprocessing is a crucial step. We will size and standardize the input images to ensure they meet the input requirements of the model, thereby improving the stability of the model. In addition, in order to enrich the diversity of training data and enhance the generalization ability of the model, we also applied data augmentation techniques such as random cropping and rotation to expand our training dataset. However, the model still has broad application value in problems such as graph parameter prediction, as it can help us understand and predict the basic relationship between input and output.

These networks, pre-trained on extensive datasets like ImageNet, exhibit robust feature detection capabilities. We have selected ResNet-50 for this role, as it strikes a harmonious balance between performance and computational efficiency. The mechanics of ICH cultural element extraction are illustrated in Figure 1.

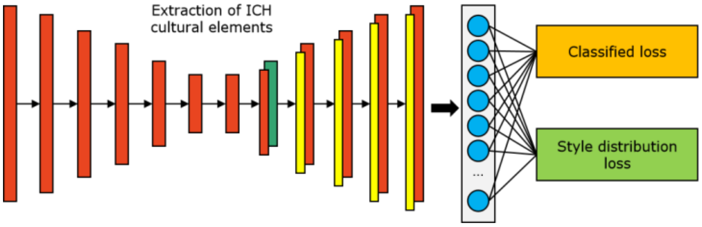

Figure 1: The principle of ich cultural element extraction.

The RPN, a pivotal element of Faster R-CNN, is responsible for producing potential regions of interest. RPN operates by sliding a compact convolutional network over the feature map, thereby creating a sequence of anchor points. The intersection ratio between these anchor points and the actual target frame determines whether an anchor point qualifies as a positive or negative sample. Subsequently, a classification layer and a bounding box regression layer predict the category and positional adjustments for each anchor point. During training, optimization of the classification layer employs the cross entropy loss function, while the bounding box regression layer utilizes the Smooth L1 loss function.

Supposing that the number of layers in a convolutional layer is denoted as l, the subsequent layer comprises $l+1$ layers. To ascertain the sensitivity of the l layer, we must gather sensitivity samples corresponding to the pooling layer, ensuring that the sensitivity's dimension aligns with the output dimension of the convolutional layer.

$$\delta_j^l = \beta_j^{l+1}\ f'\ u_j^l \circ up\ \delta_j^{l+1} \tag{1}$$

Denoting the weight linked to the pooling layer, $up\ \cdot$ signifies the up-sampling process.

After RPN generates candidate regions, a Fast R-CNN detector is used to classify and precisely locate these regions. The Fast R-CNN detector initially employs the ROI Pooling layer to transform the feature map of each candidate region into a feature vector of uniform size. Subsequently, it utilizes a fully connected layer for classification and bounding box regression. Akin to the RPN, the Fast R-CNN detector relies on the cross entropy loss function and Smooth L1 loss function to refine both classification and bounding box regression tasks. Through collaborative training of the RPN and Fast R-CNN detectors, comprehensive feature detection and identification of ICH cultural elements become feasible.

This model has demonstrated its effectiveness in the artistic rendering of ICH. Its structure, clearly outlined in Figure 2, consists of a convolutional segment on top and an autoencoder segment below.

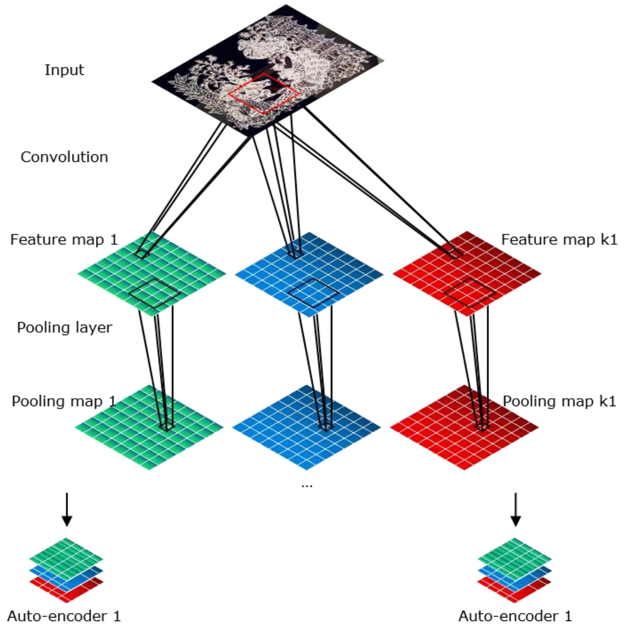

Figure 2: Structure of convolutional-automatic encoder.

A training sample, denoted as i_t, is arbitrarily chosen within the hyperplane constraint space. Herein, i signifies the inherent traits of the sample, whereas t embodies the extrinsic behavior of the sample, as exemplified in the given formula:

$$f\left(\omega, i_t\right) = \frac{\lambda}{2}\|\omega\|^2 + l\left(\omega, \left(x_{i_i}, y_{i_t}\right)\right) \tag{2}$$

The sub-gradient solution for the aforementioned formula is exemplified as follows:

$$\Delta_t = \lambda\omega_t - I\left[y_{i_t}\left\langle \omega_t, x_{i_i}\right\rangle < 1\right] y_{i_t} x_{i_i} \tag{3}$$

With $I\left[y_{i_t}\left\langle \omega_t, x_{i_i}\right\rangle < 1\right]$ representing the indicator function, the input comprises the user interest point dataset S, regularization factor λ, and sample external activity T. The one-cycle iteration can thus be described as:

$$\omega_{t+1} \le \omega_t - \beta_t \Delta_t \quad \beta_t = \frac{1}{\lambda_t} \tag{4}$$

In this context, $\beta_t = \frac{1}{\lambda_t}$ serves as an adaptive step factor that exhibits a negative correlation with the iteration count.

Due to the varying sizes and scales of ICH cultural elements within images, a multi-scale feature fusion approach is employed to bolster the model's scale invariance. We extract feature maps from multiple levels of the feature detection network and amalgamate them, thereby acquiring richer multi-scale information. Given that backgrounds often predominate in ICH cultural images, resulting in a significant imbalance between negative and positive samples, we dynamically choose high-loss negative samples from each training batch to enhance the model's discriminatory powers. This strategy aims to maximize the utilization of scarce positive sample data and bolster the model's ability to identify challenging samples.

Firstly, image acquisition and preprocessing of ICH cultural elements are carried out. Suppose you have a data set containing N images:

$$D = \left\{I_1, I_2, \ldots, I_N\right\} \tag{5}$$

Each image I_i has a set of corresponding ICH cultural element labels L_i. Pre-processing steps include scaling, cropping, flipping and so on to enhance the generalization ability of the model.

The preprocessed image set D is input into the pre-trained CNN, and the feature representation is extracted. Suppose the pre-trained CNN is:

$$F : R^{H\times W\times 3} \to R^C \tag{6}$$

RPN consists of two convolution layers named φ_1 and φ_2 respectively. The potential target areas generated by RPN are classified and regressed. This can be achieved through a fully connected layer, named F_{cls} and F_{reg}. The output of the classifier is $p_{cls}\left(b_i\right)$ and $p_{reg}\left(b_i\right)$, respectively represents the classification probability and regression parameters of the bounding box.

$$L_{cls} = -\sum_{i=1}^{B}\left[y_{cls}\left(b_i\right)\log\left(p_{cls}\left(b_i\right)\right) + \left(1 - y_{cls}\left(b_i\right)\right)\log\left(1 - p_{cls}\left(b_i\right)\right)\right] \tag{7}$$

Regression loss can be expressed as:

$$L_{reg} = \sum_{i=1}^{B}\sum_{j=1}^{4}\left[y_{reg}\left(b_i, t_j\right)\log\left(p_{reg}\left(b_i, t_j\right)\right) + \left(1 - y_{reg}\left(b_i, t_j\right)\right)\log\left(1 - p_{reg}\left(b_i, t_j\right)\right)\right] \tag{8}$$

Among them, $y_{cls}\ b_i$ and $y_{reg}\ b_i, t_j$ respectively represent the classification label of the i -th bounding box and the label of the regression target, and $p_{cls}\ b_i$ and $p_{reg}\ b_i, t_j$ respectively represent the predicted classification probability and regression probability.

$$w_{t+1} = w_t - \alpha \frac{\partial L}{\partial w_t} \tag{9}$$

Where w_t represents the parameters of the model at time t, and a is the learning rate. The trained model is applied to the detection and recognition of ICH cultural elements in unknown images.

4 RESULT ANALYSIS AND DISCUSSION

4.1 Result Analysis

The ICH model, as shown in Figure 3, is meticulously crafted using cutting-edge 3D solid drawing techniques. This technology can accurately simulate various physical reactions of light on the surface of objects, including complex optical phenomena such as reflection, refraction, and scattering. To meet this demand, various advanced graphics rendering technologies have been adopted in the research, among which ray tracing technology is the most critical. Thanks to the application of ray tracing technology, our rendering engine can generate highly realistic and refined images. At the same time, the ICH model presents an unprecedented level of visual realism, as if placing people in a real three-dimensional space. This rendering technology not only brings stunning visual effects to ICH models but also opens up new avenues for the development of 3D solid rendering technology.

(a) The model built by Faster R-CNN

(b) The model built by traditional methods

(c) Stippling generated by image

Figure 3: ICH model rendered by 3D entity.

In optimization algorithms for numerical solutions, mini-batch stochastic gradient descent is widely used in deep learning. In each iteration, a small batch consisting of a fixed number of training data samples is randomly and uniformly sampled. Its algorithm is very simple: first select an initial value of a set of model parameters, such as randomly selecting. Then calculate the derivative (gradient) of the average loss of data samples in a small batch concerning model parameters. In each iteration, a small batch consisting of a fixed number of training data samples is randomly and uniformly sampled. Next, the parameters will be updated and iterated multiple times, so that each iteration may reduce the value of the loss function. The essence of optimization algorithms is to find the optimal loss function value between the predicted model and the actual training model, that is, the optimal parameter setting. Finally, the product of this result with a pre-set positive number is used as the reduction of the model parameters in this iteration.

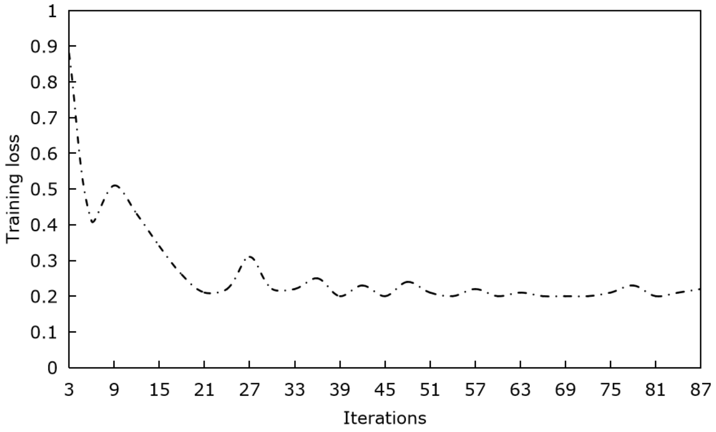

Figure 4: Training results of the algorithm.

In Figure 4, the experimental results clearly demonstrate that the training convergence speed of the algorithm introduced in this article surpasses other algorithms, exhibiting superior performance. To evaluate the algorithm's performance more thoroughly, we conducted tests on the retrieval time of ICH images with varying numbers of images and nodes. Figure 5 displays the outcomes of these experiments.

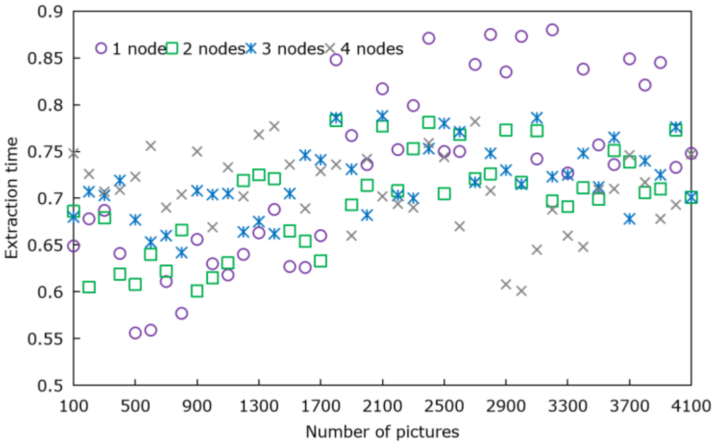

Figure 5: Time consumption of feature detection.

In scenarios involving numerous images, multiple nodes can operate simultaneously, with each handling a portion of the image set. This parallel approach considerably reduces total processing time, especially in fast-response retrieval situations where the advantages of multi-node parallel processing are even more pronounced. However, adding nodes also increases hardware and operational expenses. Therefore, it's crucial to balance processing speed and cost in real-world applications. For situations requiring extensive image processing, strategically increasing the number of nodes can boost efficiency, while for those involving fewer images, optimizing a single node's performance might be more cost-effective. As shown in Figure 6, on the premise of achieving the same rendering quality, the rendering time of this model is obviously lower than that of traditional methods.

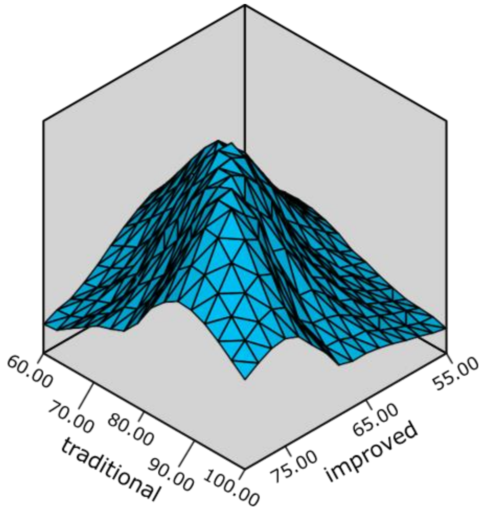

Figure 6: Rendering efficiency of different methods.

According to Figure 7, compared with the traditional method, the rendering quality of the model in this article is improved by about 15%. This improvement in quality may be reflected in more realistic colors, finer details and more accurate lighting effects.

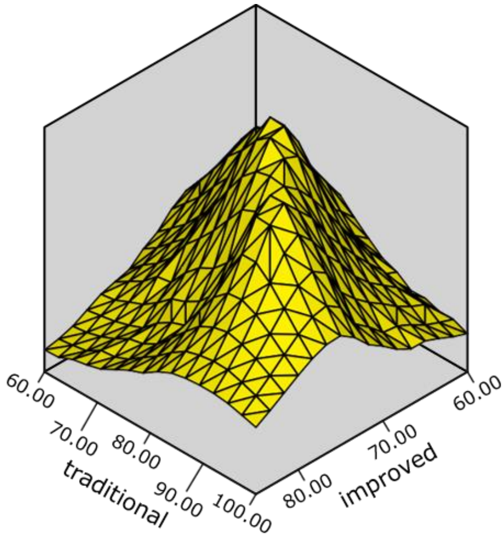

Figure 7: Rendering quality of different methods.

4.2 Discussion

In order to achieve precise localization of specific objects in images, we introduce the Faster R-CNN deep learning architecture. In addition, to further improve the generalization ability of the model, we also adopted data augmentation techniques such as random cropping and rotation to expand the training dataset, enabling the model to better cope with various complex situations. The core of this process lies in the shared convolutional layer used by Fast R-CNN, which effectively extracts image features and provides key information for subsequent classification and localization. In order to ensure the stability of the model and the consistency of the input, we preprocessed the input intangible cultural heritage cultural images. The preprocessing steps include adjusting the image size to meet the input requirements of the model, and standardizing to eliminate differences between different images. To accomplish this task, we employed a pre-trained deep convolutional neural network (CNN) as the feature extractor. In summary, by adopting the Faster R-CNN deep learning architecture, preprocessing images, and using pre-trained deep CNNs for feature extraction. It cleverly combines RPN with a Fast R-CNN detector to achieve automatic extraction, classification, and localization of candidate regions in the image. Feature detection networks play a crucial role. Its task is to extract advanced feature representations from preprocessed input images. These CNNs have been trained on a large amount of image data, so they can accurately capture key information in the image, providing strong support for subsequent object detection. This technology is of great significance for the protection and inheritance of intangible cultural heritage, helping us better understand and appreciate this valuable cultural heritage.

5 CONCLUSIONS

This study examines the utilization of an ICH cultural element extraction algorithm, utilizing Faster R-CNN, within visual education. The findings indicate that this algorithm excels in recognizing and locating ICH cultural elements, bolstering the visualization instruction of ICH culture.

Faster R-CNN demonstrates rapid convergence and proficient feature detection during training, forming a firm basis for the handling and examination of ICH cultural image data. In rendering tests, this model clearly outperforms traditional methods, enhancing both speed and quality. These strengths enhance the effectiveness of visual teaching, offering students a more immersive experience and fostering a deeper appreciation for ICH culture.

In conclusion, the Faster R-CNN-based ICH cultural element extraction algorithm holds immense potential in visual education. It elevates teaching quality, revitalizes the preservation of ICH culture, and encourages a younger audience to engage with traditional culture.

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REFERENCES

[1] Bae, S.; Jung, T.-H.; Moorhouse, N.; Suh, M.; Kwon, O.: The influence of mixed reality on satisfaction and brand loyalty in cultural heritage attractions: A brand equity perspective, Sustainability, 12(7), 2020, 2956. https://doi.org/10.3390/su12072956
[2] Barrile, V.; Fotia, A.; Bilotta, G.; De Carlo, D.: Integration of geomatics methodologies and creation of a cultural heritage app using augmented reality, Virtual Archaeology Review, 10(20), 2019, 40-51. https://doi.org/10.4995/var.2019.10361
[3] Bernardi, P.; Bertello, A.; Shams, S.-M.: Logics hindering digital transformation in cultural heritage strategic management: An exploratory case study, Tourism Analysis, 24(3), 2019, 315-327. https://doi.org/10.3727/108354219X15511864843876

[4] Challenor, J.; Ma, M.: A review of augmented reality applications for history education and heritage visualisation, Multimodal Technologies and Interaction, 3(2), 2019, 39. https://doi.org/10.3390/mti3020039
[5] Gonçalves, A.-R.; Dorsch, L.-L.-P.; Figueiredo, M.: Digital tourism: an alternative view on cultural intangible heritage and sustainability in Tavira, Portugal, Sustainability, 14(5), 2022, 2912. https://doi.org/10.3390/su14052912
[6] Han, D.-I.-D.; Tom, M.-C.; Jung, T.: Augmented reality smart glasses (ARSG) visitor adoption in cultural tourism, Leisure Studies, 38(5), 2019, 618-633. https://doi.org/10.1080/02614367.2019.1604790
[7] Liu, Y.: Evaluating visitor experience of digital interpretation and presentation technologies at cultural heritage sites: a case study of the old town, Zuoying, Built Heritage, 4(1), 2020, 14. https://doi.org/10.1186/s43238-020-00016-4
[8] Masciotta, M.-G.; Morais, M.-J.; Ramos, L.-F.; Oliveira, D.-V.; Sanchez, A.-L.-J.; González, A.-D.: A digital-based integrated methodology for the preventive conservation of cultural heritage: the experience of HeritageCare project, International Journal of Architectural Heritage, 15(6), 2021, 844-863. https://doi.org/10.1080/15583058.2019.1668985
[9] Nishanbaev, I.; Champion, E.; McMeekin, D.-A.: A survey of geospatial semantic web for cultural heritage, Heritage, 2(2), 2019, 1471-1498. https://doi.org/10.3390/heritage2020093
[10] Poux, F.; Valembois, Q.; Mattes, C.; Kobbelt, L.; Billen, R.: Initial user-centered design of a virtual reality heritage system: Applications for digital tourism, Remote Sensing, 12(16), 2020, 2583. https://doi.org/10.3390/rs12162583
[11] Rinaldi, A.-M.; Russo, C.; Tommasino, C.: An augmented reality cbir system based on multimedia knowledge graph and deep learning techniques in cultural heritage, Computers, 11(12), 2022, 172. https://doi.org/10.3390/computers11120172
[12] Selmanović, E.; Rizvic, S.; Harvey, C.; Boskovic, D.; Hulusic, V.; Chahin, M.; Sljivo, S.: Improving accessibility to intangible cultural heritage preservation using virtual reality, Journal on Computing and Cultural Heritage (JOCCH), 13(2), 2020, 1-19. https://doi.org/10.1145/3377143
[13] Trunfio, M.; Lucia, M.-D.; Campana, S.; Magnelli, A.: Innovating the cultural heritage museum service model through virtual reality and augmented reality: The effects on the overall visitor experience and satisfaction, Journal of Heritage Tourism, 17(1), 2022, 1-19. https://doi.org/10.1080/1743873X.2020.1850742
[14] Yin, C.-Z.-Y.; Jung, T.; Tom, D.-M.-C.; Lee, M.-Y.: Mobile augmented reality heritage applications: Meeting the needs of heritage tourists, Sustainability, 13(5), 2021, 2523. https://doi.org/10.3390/su13052523
[15] Zhang, L.; Wang, Y.; Tang, Z.; Liu, X.; Zhang, M.: A virtual experience system of bamboo weaving for sustainable research on intangible cultural heritage based on VR technology, Sustainability, 15(4), 2023, 3134. https://doi.org/10.3390/su15043134