Automatic Extraction and Classification of Intangible Cultural Elements Using Reinforcement Learning Algorithm

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Abstract. This study focuses on enhancing the automated extraction and classification techniques for intangible cultural elements, thereby advancing their digital preservation and transmission. Recognizing the distinctiveness and intricacies of intangible culture, we introduce an original approach that integrates CAD (Computer-Aided Design) and RL (Reinforcement Learning) algorithms. Our method employs state-of-the-art image segmentation technology to identify intangible cultural elements and refine their categorization autonomously. Additionally, we leverage the adaptive learning capabilities of the RL algorithm to optimize the classifier's performance. In our experimental section, we've compiled a diverse dataset encompassing various intangible cultural elements and conducted a comprehensive comparative analysis. The findings reveal a substantial enhancement in both extraction accuracy and classification efficacy, affirming the method's efficiency and superiority. These results strongly indicate its potential for practical applications. Overall, our approach contributes innovative ideas and tools to the digital safeguarding and perpetuation of intangible culture, carrying significant theoretical and practical importance.

Keywords: Computer-Aided Design; Reinforcement Learning; Non-Legacy Culture; Element Extraction; Feature Classification
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1 INTRODUCTION

With the acceleration of globalization, intangible cultural heritage (ICH), as the precious wealth of human civilization, is facing unprecedented challenges of inheritance and protection. Cultural heritage images are an important component of human history and culture, documenting the styles, skills, and social changes of various eras. However, with the passage of time and differences in preservation conditions, many cultural heritage images have become blurred and incomplete, causing other problems and making it difficult to fully extract and understand the semantic information in them. The semantic enrichment of cultural heritage images, improving their information content and readability, has become an urgent problem to be solved. The rapid development of artificial intelligence technology has provided new possibilities for the semantic enrichment of cultural heritage images. Through techniques such as deep learning and computer vision, Abgaz et al. [1] automatically analyze, interpret, and enhance images to extract more semantic information. Based on the extracted features, use natural language processing (NLP) technology to perform semantic analysis on images. Generate descriptive text information by identifying objects, scenes, emotions, and other elements in the image. ICH not only carries a nation's historical memory and cultural genes but is also an important resource to promote cultural diversity and the development of human creativity. With the rapid development of digital technology, the protection and inheritance of cultural heritage are facing new opportunities and challenges. Belhi et al. [2] proposed a machine learning-based framework aimed at enhancing the digital experience of cultural heritage, making it more vivid, authentic, and interactive. Cultural heritage is an important carrier of human history and culture, recording the memory and wisdom of a nation. However, with the changes of the times and the acceleration of modernization, many cultural heritage sites are facing the danger of disappearance and forgetting. Therefore, how to protect and inherit cultural heritage so that it can shine with new vitality in the new era has become an urgent problem to be solved. The rapid development of digital technology has provided new possibilities for the protection and inheritance of cultural heritage. Through digital means, we can preserve and display cultural heritage in a digital form, making it easier to spread and share. Meanwhile, the application of artificial intelligence technologies such as machine learning can further enhance the interactivity and authenticity of cultural heritage digital experiences and enhance user engagement and immersion. However, due to the oral characteristics of intangible culture and the impact of modern lifestyle, many precious intangible elements are gradually disappearing, and effective protection and inheritance measures are urgently needed. Immersive virtual reality technology can provide users with an immersive experience, making them feel like they are in a traditional cultural environment. In industrial design, virtual reality technology can present intangible cultural elements to users in a more vivid and authentic way. Users can observe, interact, and experience the design details and cultural connotations of products through virtual reality devices. This immersive experience not only allows users to have a deeper understanding of the cultural value of the product but also stimulates their purchasing desire and interest in using it. Applying intangible cultural elements to industrial design can be achieved through shapes, colours, textures, and other aspects of design. For example, drawing on the shapes and patterns of traditional architecture, art, or handicrafts and applying them to product design to present a unique cultural atmosphere. In addition, intangible cultural elements can also be reflected through the selection of materials and processing methods. The use of traditional materials or traditional handicraft production methods can make the product more closely related to traditional culture, increasing its uniqueness and value [3].

In recent years, the rapid development of technologies such as CAD and RL has provided a new opportunity for the protection and inheritance of intangible culture. As an important technology for digitizing cultural heritage, cultural relic spectroscopy provides new means for non-destructive testing, identification, and digital reproduction of cultural relics. With the continuous progress of technology and the expansion of application scenarios, it is believed that cultural relic spectroscopy will play a more important role in the protection and inheritance of cultural heritage. At the same time, it is necessary to strengthen the research and application of cultural relic spectroscopy, continuously improve its accuracy and reliability, and contribute more to the digital protection and inheritance of cultural heritage. Cultural heritage is a precious treasure of human history and civilization, and cultural relics are important carriers of these heritages. However, due to factors such as time and environment, many cultural relics have suffered varying degrees of damage. In order to better protect and inherit this cultural heritage, advanced technological means are needed for research and restoration. As a non-destructive testing technology, cultural relic spectroscopy can obtain information on the internal structure and chemical composition of cultural relics without damaging them, providing strong support for the identification, protection, and digital reproduction of cultural relics [4]. Information modelling is a method of describing and expressing objects, scenes, or processes in the real world through digital means. In the field of intangible cultural heritage, information modelling can be used to construct digital models, preserving and displaying intangible cultural elements in a digital form. Reverse engineering technology, on the other hand, is a technique that involves measuring and analyzing existing products or objects to obtain their geometric shape, material properties, and other information in order to achieve replication, improvement, or innovation. Combining information modelling with reverse engineering technology can achieve digital replication and innovative application of intangible cultural elements. The digital architecture framework that combines the modelling of intangible cultural elements with reverse engineering technology has broad application prospects. It can be used not only for the protection and inheritance of cultural heritage but also to promote the innovative development of the construction industry, local economic prosperity, and cultural exchange [5]. Intangible cultural elements, such as traditional dance and handicrafts, often have rich dynamic and spatial characteristics. 3D technology provides a new way for the digital preservation and display of these elements. However, effectively extracting global features of intangible cultural elements from 3D data is a challenge. RNN, as a powerful sequence modelling tool, can handle time-dependent data. By combining attention mechanisms, RNNs can focus more on key parts of the sequence, thereby extracting more representative features. Han et al. [6] proposed an attention-based RNN model for learning 3D global features of intangible cultural elements. Firstly, we transform the 3D data of intangible cultural elements into a series of sequential views. Then, RNN is used to model these sequence views and capture their dynamic changes. On this basis, we introduce an attention mechanism to enable RNN to automatically focus on keyframes in the sequence, thereby extracting more representative global features. CAD is widely used in image processing, pattern recognition, and other fields, which can efficiently and accurately process and analyze a large amount of intangible cultural data. As an emerging machine learning framework, RL demonstrates immense promise in intelligent decision-making and self-directed learning, offering fresh insights for the automated categorization and recognition of intangible culture.

The objective of this research is to facilitate the automated extraction and categorization of intangible cultural components utilizing CAD alongside the RL algorithm. This approach not only elevates the efficiency and precision of safeguarding and propagating intangible culture but also aids in delving deeper into its inherent worth and significance. By automating processes, we can more systematically organize and scrutinize intangible cultural resources, furnish scholars and researchers with convenient research tools, and enrich cultural and creative industries with diverse materials and inspiration. The principal innovations of this article are highlighted below:

(1) While traditional techniques for extracting intangible cultural elements often hinge on manual interventions and expert knowledge, resulting in inefficiencies and accuracy concerns, this article introduces CAD technology in a novel manner. Through image segmentation and feature extraction algorithms, the automatic recognition and streamlined extraction of intangible cultural elements are achieved, significantly enhancing both accuracy and efficiency.

(2) Historically, conventional machine learning algorithms have been employed to categorize intangible cultural elements, but their performance has been constrained by feature selection and model design limitations. In this article, an innovative adoption of the RL algorithm is presented. By constructing an agent and crafting a thoughtful state space, action space, and reward function, adaptive learning and optimal classification of intangible cultural elements are attained, thereby improving classification accuracy and generalization capabilities.

(3) Tailored to the demands of processing intangible cultural elements, this article constructs a comprehensive dataset enriched with diverse intangible cultural components and undertakes detailed experimental design and implementation based on this foundation. Through rigorous empirical demonstrations and comparative analyses, the efficacy and superiority of the proposed

methodology are corroborated, offering innovative approaches and resources for the digital preservation and propagation of intangible culture.

Furthermore, this study carries substantial practical application value. As artificial intelligence technology continues to evolve and gain traction, the intelligent preservation and propagation of intangible culture are poised to become a pivotal trend in future development. The methodologies and technologies introduced in this study can provide robust support and serve as references for related domains, fostering the seamless integration of intangible culture with modern scientific advancements and contributing to the broader objective of building a united human destiny.

The article is structured as follows: Initially, the research background and its significance are delineated, followed by a detailed exposition of the methodologies and techniques employed, including the automated extraction and classification algorithm for intangible cultural elements. Subsequently, the validity and feasibility of the proposed approach are substantiated through rigorous experiments, and the experimental findings are thoroughly analyzed and deliberated. Lastly, the article concludes with a comprehensive summary, highlighting research limitations and future prospects, thereby offering readers a holistic research perspective and fodder for further contemplation.

2 RELATED WORK

The combination of traditional arts, such as Peking Opera and modern technologies, such as computer-aided design and computer graphics, provides a new perspective for the visual design of Peking Opera scripts. Hou and Zhang [7] discussed the visual design of Peking Opera scripts, particularly the application of computer-aided design and computer graphics in this process, and analyzed their potential impacts and challenges. Beijing Opera, as a national treasure of China, has attracted countless audiences with its profound artistic heritage and unique performance forms. However, with the changing times, how to better integrate this traditional art form with modern technology has become a focus of attention for many scholars and artists. Computer-aided design and computer graphics, as important branches of modern technology, provide possibilities for the visual design of Peking Opera scripts. Through computer graphics technology, the characters, scenes, and other elements in Beijing opera scripts can be modelled and rendered in 3D, making them more vivid and realistic. Meanwhile, computer-aided design can help designers layout and design scripts more efficiently.

With the rapid development of digital technology, the protection and inheritance of Intangible Cultural Heritage (ICH) are gradually shifting towards the digital field. Reinforcement learning algorithms, as an advanced machine learning method, have shown great potential in automatically extracting and classifying elements of intangible cultural heritage. Hou et al. [8] summarized the latest progress of reinforcement learning algorithms in the field of digital intangible cultural heritage and explored the technical details and application prospects of implementing automatic element extraction and classification. Intangible cultural heritage is an important component of national culture and history, reflecting the diversity and creativity of human civilization. However, with the acceleration of modernization, the inheritance and protection of intangible cultural heritage face enormous challenges. Digital technology provides new means for the protection of intangible cultural heritage. Through digital means, automatic extraction and classification of intangible cultural heritage elements can be achieved, thereby providing convenience for their protection, inheritance, and research. As a unique traditional Chinese craft, blue printed fabric has rich and diverse patterns containing profound cultural connotations. Jia and Liu [9] proposed a blue-printed fabric classification method based on element extraction and convolutional neural network (CNN). It aims to achieve automatic classification of blue-printed fabrics with different styles and patterns. This method first extracts key elements of printed fabrics through image processing techniques and then uses CNN for feature learning and classification. With the development of modern technology, traditional blue-printed fabrics are facing market shocks and cultural inheritance challenges. Therefore, developing an efficient and accurate classification method for blue-printed fabrics is of great significance for protecting and inheriting this traditional craft. With the continuous progress of machine learning technology, its application in the field of culture and art is also becoming increasingly widespread. Liow et al. [10] explored how to use machine learning techniques to extract intangible cultural elements from art and design and classify them. Intangible cultural heritage is an important component of human civilization, including traditional handicrafts, performing arts, and festive activities. These elements often take artistic works and designs as carriers, inheriting the history and culture of the nation. However, with the rapid development of modern society, the inheritance of intangible cultural heritage faces many challenges. Machine learning, as a powerful data analysis tool, can help us extract intangible cultural elements from a large number of artworks and designs, classify them, and provide new ideas and methods for the protection and inheritance of intangible cultural heritage. Through image recognition and deep learning techniques, we can identify intangible cultural elements such as traditional patterns and colour combinations from art and design. Secondly, using natural language processing techniques, we can analyze descriptive texts of art and design, extract keywords and themes, and better understand the cultural connotations of the works. With the rapid development of information technology, the digital protection and management of intangible cultural heritage have become increasingly important. Chongqing, as a historical and cultural city, has abundant intangible cultural heritage resources. However, traditional methods of declaring intangible cultural heritage often suffer from low efficiency and cumbersome processes, making it difficult to meet the needs of modern society. Therefore, developing an efficient and convenient application interface is of great significance for the protection and inheritance of intangible cultural heritage. Deep learning, as a branch of machine learning, has powerful feature learning and classification capabilities. Through deep learning technology, we can automatically process and analyze data related to intangible cultural heritage, achieving automation and intelligence in the application process. Liu et al. [11] proposed a deep learning-based interface design scheme for Chongqing's intangible cultural heritage application, aimed at improving the efficiency and user experience of the application process and promoting the inheritance and development of intangible cultural heritage.

With the continuous development of digital technology, group collaboration is playing an increasingly important role in cultural heritage protection, inheritance, and innovation. Lu et al. [12] utilized computer-aided design and computer graphics techniques to delve into the impact of group collaboration on the cultural heritage of social network relationships and demonstrated how to effectively analyze and visualize these relationships. Through this study, it was found that group collaboration plays an important role in the social network relationships of cultural heritage. Driven by group collaboration, the inheritance and innovation of cultural heritage are more active, and social network relationships are also closer. Meanwhile, the application of computer-aided design and computer graphics technology enables effective analysis and visualization of these relationships, providing strong support for the protection and inheritance of cultural heritage. Through computer-aided design and computer graphics technology, they not only successfully achieved digital protection and display of cultural heritage but also delved into the impact of group collaboration on the social network relationships of cultural heritage. As an important venue for cultural inheritance and exhibition, regional museums have always played an important role. However, in recent years, many museums have faced the challenge of declining visitor numbers due to various factors. At the same time, the rapid development of digital technology has brought new opportunities to museums. The digitalization of cultural heritage not only enriches exhibition content and enhances the visitor experience but also helps to attract more young audiences and increase museums' visibility and influence. Radosavljevi and Ljubisavljevi [13] explored the application of digital technology in museums in the central region and analyzed its potential to increase museum visits. The application of digital technology is extensive and profound. Firstly, virtual reality (VR) and augmented reality (AR) technologies provide viewers with an immersive visiting experience. Viewers can watch the reproduction of historical scenes or detailed interpretations of exhibits by wearing VR glasses or scanning AR logos on their phones. This interactive exhibition method not only attracts the interest of the audience but also deepens their understanding of cultural heritage. Cultural heritage is a treasure of national and ethnic history and culture. Protecting and inheriting these heritages is of great significance for maintaining cultural diversity and promoting social progress. With the development of technology, advanced technologies such as computer-aided design and reinforcement learning algorithms have provided new means for the protection and inheritance of cultural heritage. Saleh et al. [14] explored the importance of reinforcement learning algorithms based on computer-aided design in the design of high-quality cultural heritage products. The reinforcement learning algorithm is an algorithm that learns through trial and error, seeking the optimal decision strategy through interaction with the environment. In the design of cultural heritage products, reinforcement learning algorithms can help designers automatically adjust design parameters and optimize design schemes, thus achieving intelligent product design. Compared with traditional design methods, reinforcement learning algorithms have higher design efficiency and stronger optimization ability. Meanwhile, reinforcement learning algorithms can also adaptively adjust products based on user feedback and market demand, making them more in line with user needs and market trends.

Shen et al. [15] explored the possibility of developing a training system for intangible cultural elements based on virtual reality technology and elaborated on its design ideas, implementation methods, and potential value in the field of education. Intangible cultural elements, as an important component of human culture, carry rich historical, folk, and artistic values. However, due to the particularity of its inheritance methods and the impact of modern lifestyles, many intangible cultural elements are facing the danger of disappearing and forgetting. Therefore, developing an effective training system for intangible cultural elements is of great significance for the protection and inheritance of this valuable heritage. Virtual reality technology, with its characteristics of immersion, interactivity, and multi-perception, provides new possibilities for the training of intangible cultural elements. Through virtual reality technology, students can experience intangible cultural elements firsthand, gain a deeper understanding of their historical, cultural, and social background, and thus improve their learning effectiveness and interest. Intangible cultural heritage is an important component of culture, usually passed down from generation to generation through oral transmission. These elements are particularly prominent in architectural design, reflecting regional, ethnic, and historical characteristics. However, traditional architectural modelling methods often struggle to capture and reproduce these intangible cultural elements accurately. Immersive virtual reality technology, combined with a handheld user interface and direct operation, provides an innovative solution to this problem. In an immersive virtual reality environment, handheld user interfaces allow users to interact with the virtual world through intuitive gestures and actions. Compared to traditional mice and keyboards, this method is more in line with the natural way of human communication, providing a more immersive and authentic experience. Direct operation technology further simplifies the modelling process, allowing users to shape and adjust models directly in a virtual environment without the need for complex commands or menus [16].

Intangible Cultural Heritage (NHF) is an important carrier of the history and culture of a country and nation. Protecting and inheriting these heritages is of profound significance for maintaining cultural diversity and promoting sustainable development. However, the implementation of intangible cultural heritage policies often faces various challenges, such as insufficient public awareness of their value, silence in policy implementation, and loss of memory. In recent years, reinforcement learning algorithms have made significant progress in the field of artificial intelligence, providing new perspectives for solving these problems. Reinforcement learning algorithms can help us understand the reasons why intangible cultural heritage policies encounter silence. Silence may stem from the public's lack of understanding, trust, or concern towards policies. Through reinforcement learning algorithms, Toji [17] simulated public behaviour in different contexts, analyzed which factors led to the phenomenon of silence, and formulated corresponding intervention measures. Xiao [18] discussed how to apply these technologies to sports and cultural centers, build an intelligent system to improve operational efficiency, optimize user experience, and promote innovative development of sports culture. Train historical data using machine learning algorithms to predict future passenger flow and resource demand, thereby achieving rational scheduling and optimized allocation of resources. Based on user interests and behavioural data, build a personalized recommendation system to recommend suitable sports events, activities, and related products to users. By monitoring and analyzing the safety data of the sports and cultural center in real-time, potential safety hazards are identified, and timely warnings are given to improve the level of safety assurance. The combination of machine learning and big data has brought tremendous changes and development opportunities to the sports culture center. By building intelligent systems, we can improve operational efficiency, optimize user experience, and promote innovative development of sports culture. However, in practical applications, we also need to pay attention to and solve issues such as data security and algorithm interpretability.

Intangible cultural elements refer to those intangible forms of cultural heritage, such as traditional handicrafts, folk activities, oral traditions, etc. These elements carry rich historical and cultural connotations and are important resources in the field of design. Collaborative design, as an emerging design model, emphasizes teamwork and multi-party participation, providing a broader perspective for the design of intangible cultural elements. Traditional computer-aided design improves design efficiency through technological means, providing technical support for the design of intangible cultural elements. Zhou et al. [19] explored the application of collaborative design and traditional computer-aided design in the design of intangible cultural elements and analyzed their respective advantages and limitations. Collaborative design emphasizes teamwork and multi-party participation, achieving collaboration and integration of the design process by sharing design resources and information. In the design of intangible cultural elements, collaborative design can promote communication and cooperation among experts in different fields and jointly explore and inherit intangible cultural elements. Meanwhile, collaborative design can also enable designers to have a deeper understanding of user needs and market trends, thereby designing products that better meet market demands. With the rapid development of urbanization, protecting and inheriting architectural heritage has become particularly important. In order to effectively identify and manage this precious architectural heritage, Zou et al. [20] proposed a machine learning-based method for identifying regional architectural form features and conducted empirical research using provincial architectural heritage as an example. This method aims to use machine learning algorithms to extract the morphological features of architectural heritage, thereby achieving automated recognition and classification. Architectural heritage is an important component of urban history and culture, recording social development and cultural changes in different periods. However, with the advancement of urbanization, much of the architectural heritage faces the risk of being demolished or renovated. Therefore, how to effectively identify and protect this architectural heritage has become an urgent problem to be solved. The article collected architectural heritage image data from multiple regions within the province and preprocessed and extracted features. Then, the support vector machine algorithm was chosen to construct a building heritage recognition model, and the model was trained and optimized using the training dataset.

3 AUTOMATIC EXTRACTION AND CLASSIFICATION OF INTANGIBLE CULTURAL ELEMENTS

CAD, or Computer-Aided Design, leverages computers and their graphic capabilities to assist designers in their work. This encompasses various domains like machinery, electronics, and architecture. Within the cultural sphere, CAD plays a pivotal role in digitally preserving cultural heritage, building virtual museums, and facilitating the creation and duplication of artistic pieces. The progression of CAD technology has shifted from 2D drawings to 3D modelling. Initial CAD systems centred on 2D graphics, but with technological advancements, 3D CAD systems have become prevalent in design. In culture, CAD ensures the long-term digital preservation of heritage while enhancing viewer engagement with more immersive experiences.

RL is a machine learning approach aimed at teaching agents to devise strategies through environmental interactions, ultimately maximizing cumulative rewards. Its fundamental components are states, actions, rewards, and policies. Agents perceive environmental states, choose actions, and refine their policies based on environmental feedback rewards to optimize performance. RL algorithms can be categorized into value-based methods, policy gradient methods, and model-based approaches. In image processing and pattern recognition, RL finds applications in target detection, image segmentation, and face recognition. By carefully crafting reward functions and state spaces, RL algorithms can autonomously learn and enhance their performance in these tasks. Scholars have conducted extensive research on extracting and categorizing intangible cultural elements. Early efforts primarily centred on manual feature extraction and designing traditional machine learning classifiers. The data used in this study mainly comes from images and texts related to intangible culture. Image data includes photos, patterns and high-definition scanned images of works of art of various non-legacy projects, which directly show the visual characteristics of non-legacy culture (Figure 1).

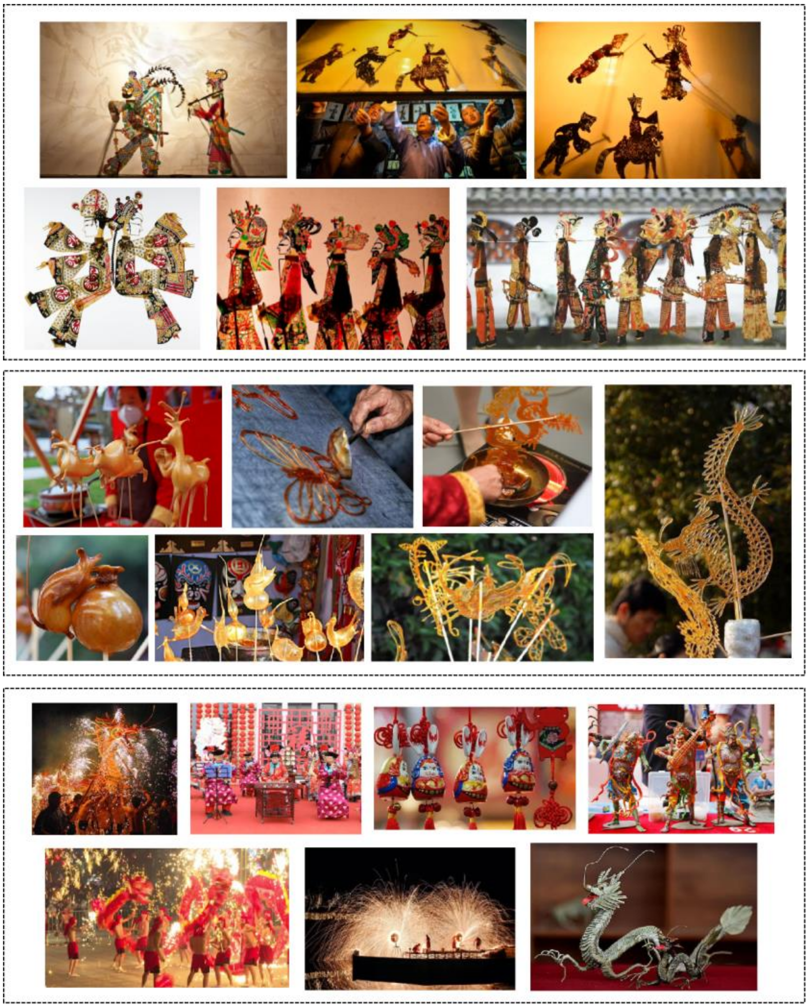

Figure 1: Overview of non-legacy projects.

Text data includes the description, historical background, production technology and so on of intangible items, which provides necessary supplements and explanations for image data. In the data preprocessing stage, firstly, the image data is cleaned and sorted, and the low-quality, repetitive and irrelevant images are removed to ensure the validity and accuracy of the data. For text data, this article carries out natural language processing operations such as word segmentation and word removal to extract key information, which provides a basis for subsequent feature extraction and classification algorithm design.

3.1 Automatic Extraction Method

The automatic extraction of intangible cultural elements utilizing CAD predominantly involves two distinct phases: image segmentation and feature extraction.

Image segmentation refers to the partitioning of a digital image into distinct sub-regions, often corresponding to objects or surfaces within the image. This process proves crucial for extracting intangible cultural elements as it facilitates the identification and isolation of key components. In this study, a semantic segmentation network rooted in DL is employed for precise image segmentation. Designed to comprehend and dissect all image components, particularly those pertaining to intangible cultural elements, this network meticulously analyzes the image to segment it into meaningful regions closely linked to specific cultural features.

Beyond mere pixel-based division, this DL-driven semantic segmentation network delves deep into image content, leveraging the capabilities of a deep neural network. Through rigorous training, the network gains proficiency in identifying key markers of intangible cultural elements, enabling precise localization and delineation within complex image backgrounds. This ensures a clear and accurate representation of the elements' positions and boundaries within the image.

Remarkably, this semantic segmentation network exhibits strong adaptability and generalization, effectively tackling challenges like varying illumination, angular shifts, and occlusions. Leveraging its robust feature extraction and pattern recognition abilities, the network consistently achieves accurate segmentation of intangible cultural elements. This technology proves invaluable for the digital preservation and perpetuation of intangible culture, laying a solid foundation for subsequent image analysis and manipulation. The underlying network architecture is visualized in Figure 2.

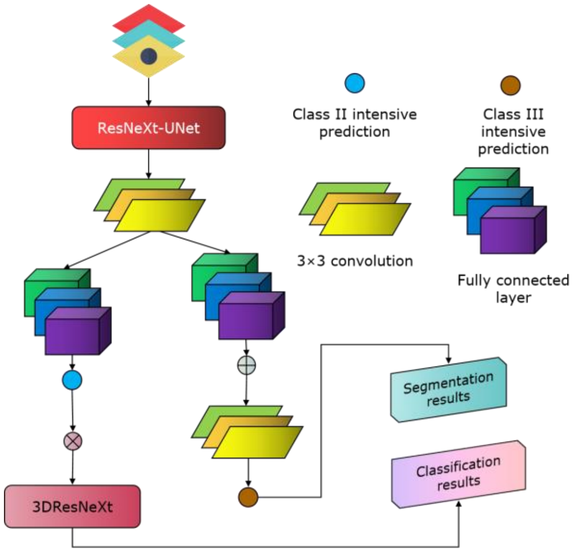

Figure 2: Network model.

In this article, the bilateral filtered boundary image f_{edge} in R,G,B space is converted into r,g chromaticity space to obtain the bilateral filtered boundary chromaticity image f_{echr} :

$$f_{echr}^{r}=\frac{f_{edge}^{R}}{f_{edge}^{R}+f_{edge}^{G}+f_{edge}^{B}} \tag{1}$$

$$f_{echr}^{g} = \frac{f_{edge}^{G}}{f_{edge}^{R} + f_{edge}^{G} + f_{edge}^{B}} \tag{2}$$

Mathematically speaking, data space, feature space, and category space are interrelated, and kernel processing methods can realize nonlinear transformations between them. Suppose there is a mapping function that reveals the internal relationship between data space and feature space, and we will call it ϕ. The core function of the kernel function is to realize the inner product transformation between vectors:

$$(x_i, y_i) \to K(x_i, y_i) = \phi(x_i) \cdot \phi(y_i) \tag{3}$$

$$\int g(x)^2 dx < \infty \tag{4}$$

For any raw data function $K(x_i, y_i)$, any function $g(x)$ $g(x)$ is not always 0. This article uses the average pixel grayscale values of C significant peak regions in the image grayscale histogram as the initial C clustering centers. By utilizing the statistical properties of image grayscale histograms, the calculation formula for various clustering centers can be simplified as follows:

$$v_i = \frac{\sum_{j=l_i}^{h_i} jH(j)}{\sum_{j=l_i}^{h_i} H(j)} \tag{5}$$

v_i represents the cluster center of Class i; l_i, h_i respectively represent the lower and upper limits of the grayscale level of image pixels in the i th peak region; $H(j)$ represents the value of the grayscale level in the grayscale histogram of the image.

Feature extraction is to identify and measure information from the region after image segmentation so as to facilitate subsequent classification and identification. In the feature extraction stage, this article uses computer vision and image processing technology to extract features representing intangible cultural elements from the segmented image area. These characteristics encompass low-level attributes like colour, texture, and shape, along with high-level traits acquired via DL models. These diverse features are capable of accurately portraying the visual distinctiveness and semantic significance of intangible cultural elements, thereby offering robust assistance to subsequent classification algorithms.

3.2 Classification Algorithm Design

The design of an RL-driven classification algorithm tailored for intangible cultural elements primarily involves delineating the state space, action space, and reward function. The state space encompasses all potential states an agent may encounter while interacting with the environment. In our context, it's defined as a vector space comprising extracted features of cultural elements, where each state corresponds to a distinct feature vector encapsulating their visual traits and semantic nuances.

The action space, on the other hand, comprises all viable actions an agent can undertake. Here, it's outlined as a range of possible classification labels, including "folk dance," "traditional drama," and "traditional handicrafts." The agent's objective is to select the most apt label based on the prevailing feature vector. Furthermore, the reward function serves as the feedback mechanism, informing the agent about the efficacy of its actions. In our setup, it's crafted to provide positive reinforcement for accurate classifications and negative feedback for errors. This rewards-based approach guides the agent to refine its classification strategies and enhance overall accuracy.

By establishing these fundamental components—state space, action space, and reward function—we can forge an RL-powered classification algorithm tailored for intangible cultural elements. This algorithm is capable of autonomous learning and optimization, facilitating efficient and precise categorization. The algorithmic model operates within a supervised learning paradigm, facilitating end-to-end training. Its performance is evaluated using a loss function that quantifies the discrepancy between the correct labels and the algorithm's predictions, employing cross-entropy as the metric:

$$loss = -\sum_{i=1}^{e} y_i \log \hat{y}_i \tag{6}$$

In real-world applications, the error distribution across the network's weight space is highly intricate, exhibiting numerous peaks and valleys, also known as local minima. To address this, our article incorporates the preceding gradient into the weight modifier, introducing it as a momentum term:

$$\Delta w_{ji}\ n = -\eta \sum_{t=0}^{n} \alpha^{\eta-t} \frac{\partial \varepsilon\ t}{\partial w_{ji}\ t} = -\eta \frac{\partial \varepsilon\ n}{\partial w_{ji}\ n} - \eta \sum_{t=1}^{n} \alpha^{\eta-t} \frac{\partial \varepsilon\ t}{\partial w_{ji}\ t},\quad 0 < \alpha < 1 \tag{7}$$

The present gradient plays the most significant role in $\Delta w_{ji}\ n$ maintaining a consistent coefficient. Meanwhile, the influence of the prior gradient $\Delta w_{ji}\ n$ diminishes rapidly in correlation with $\alpha^{\eta-t}$. The formula for calculating the error is as follows:

$$E_p = \frac{\sum_t \ t_{pi} - o_{pi}\ ^2}{2} \tag{8}$$

t_{pi}, o_{pi} represent the expected output and actual calculated output of the network, respectively.

4 EXPERIMENTAL DESIGN AND IMPLEMENTATION

Establishing a reliable and effective experimental setting is paramount to guarantee seamless experimental progression and precise outcomes. Table 1 provides a comprehensive overview of the steps involved in creating this environment:

Computer performance requirements		*Programming language and development environment*	
CPU	High-performance	Programming language	Python
Internal storage	High-capacity	Reason for choice	Widely used in image processing, machine learning, and other fields, it has rich library support.
Storage device	High-speed	Exploitation environment	Install Python Interpreters, Related Libraries and Toolkits
Remarks	Choose a computer with high configuration to ensure fluency and stability when processing a large number of images and data.	Remarks	Configure the development environment for algorithm development, data analysis and visualization.

Table 1: Experimental environment.

Additionally, to substantiate the efficacy and practicality of the suggested approach, this article has devised a meticulous experimental plan. The primary components of this experimental design are outlined below:

Specific steps: firstly, preprocess the collected intangible cultural data, including image cleaning and labelling; then, use CAD technology to automatically extract the intangible cultural elements, including image segmentation and feature extraction. Then, the classifier is designed based on the RL algorithm, and it is trained and tuned. Finally, the performance of the classifier is evaluated on the test set and compared with the benchmark method.

Parameter setting: During the experiment, some key parameters need to be set, such as the threshold of the image segmentation algorithm, the parameters of the feature extractor and the learning rate of the RL algorithm. The setting of these parameters will directly affect the experimental results and performance. Therefore, it will be adjusted and optimized according to experience and actual situation, as shown in Table 2.

Parameter name	*Describe*	*Hypothetical value*
Threshold of image segmentation algorithm	The threshold used to distinguish different regions in the image affects the accuracy of segmentation.	0.5
Feature extractor parameters	Parameters that control the feature extraction process, such as filter size and step size, etc.	Filter size: 3*3, step size: 1
RL learning rate	Parameters that control the learning speed of agents during training.	0.001
Batch Size	When training the network, the number of samples used for training in each batch.	64
Epochs	The number of times the whole data set was traversed when training the network.	100
Discount Factor	Parameter in RL to weigh immediate reward and future reward.	0.99
Exploration Rate	Parameters for balancing exploration and utilization in RL	Initial value: 1.0, gradually decreasing to 0.01

Table 2: Parameter setting.

Evaluation criteria: In order to objectively evaluate the advantages and disadvantages of the experimental results, this article adopts a variety of evaluation indicators, including classification accuracy, recall rate, F1 score and so on. These indicators can reflect the performance of classifiers from different angles and provide us with a comprehensive evaluation basis.

Assessment Metrics: This article employs a diverse array of evaluation metrics, such as classification accuracy, recall rate, and F1 score, among others, to impartially assess the strengths and weaknesses of the experimental outcomes. These metrics offer insights into the performance of classifiers from various perspectives, thereby providing a holistic evaluation framework.

The cornerstone of any experiment is the dataset. Here's a comprehensive overview of dataset curation and manipulation:

Data Provenance: A plethora of intangible cultural data, encompassing public image databases, museum collection imagery, and artists' original works, has been amassed from various sources for this article. This extensive data compilation spans diverse types and genres of non-legacy projects, presenting a broad spectrum of research subjects.

Dataset Assembly: During the dataset construction phase, the data undergoes sorting and labelling procedures. Each image is assigned corresponding category labels and attribute information. Subsequently, the dataset is partitioned into training, validation, and test sets in predetermined ratios, facilitating subsequent model training and performance assessments.

Data Refinement: To enhance data quality and applicability, a range of preprocessing techniques is employed. These methods significantly improve the visual aesthetics and feature representation capabilities of the images, laying a solid foundation for subsequent automated extraction and classification tasks.

5 EXPERIMENTAL RESULTS AND ANALYSIS

In this chapter, we delve into the experimental outcomes pertaining to the automated extraction and categorization of intangible cultural elements. Initially focusing on extraction proficiency, we have adeptly utilized CAD technology to extract these cultural elements precisely and efficiently. More precisely, the employed image segmentation algorithm adeptly isolates the cultural elements from their backgrounds, while the feature extraction algorithm adeptly captures prominent features such as colour, texture, and shape.

Regarding classification proficiency, this article employs a diverse array of evaluation metrics to holistically assess the classifier's performance. These include the ROC curve, recall rate, and F1 score. The comprehensive results are illustrated in Figures 3, 4, and 5, respectively.

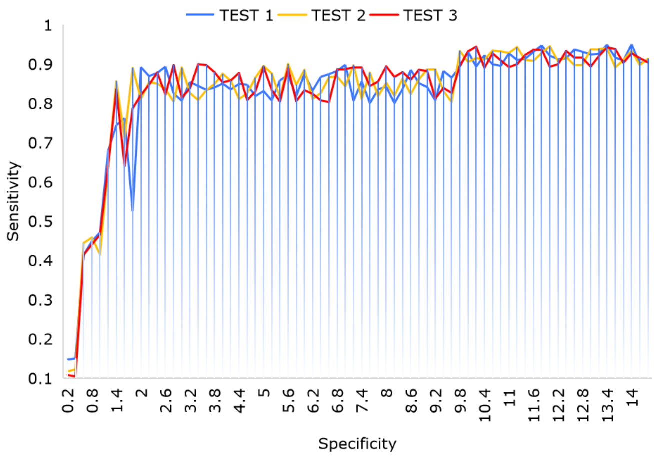

Figure 3: ROC curve.

Figure 3 illustrates the ROC curve of the present methodology. As evident from the depiction, the curve's proximity to the upper left corner signifies the classifier's remarkable proficiency in discriminating between positive and negative samples.

Figure 4 reveals that the methodology presented in this article has attained impressive recall rate outcomes. This signifies the classifier's proficiency in accurately recognizing intangible cultural elements, thereby minimizing missed detections. This achievement is profoundly significant for safeguarding and perpetuating intangible cultural heritage.

Figure 5 demonstrates that the F1 score remains consistently high. This indicates that the methodology presented in this article excels in both accuracy and recall, ensuring precise classification of intangible cultural elements into their respective categories.

The experimental outcomes described above underscore the remarkable classification accuracy achieved by the classifier rooted in the RL algorithm when tested on the dataset. This underscores the method's proficiency in identifying and distinguishing diverse intangible cultural elements. To facilitate a more comprehensive assessment of this approach, this article juxtaposes it against traditional methodologies with the comparative results presented in Figure 6.

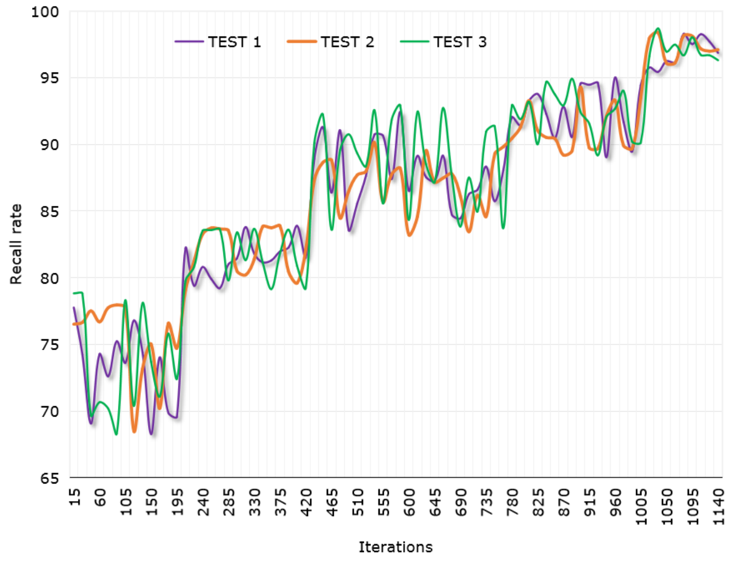

Figure 4: Recall rate.

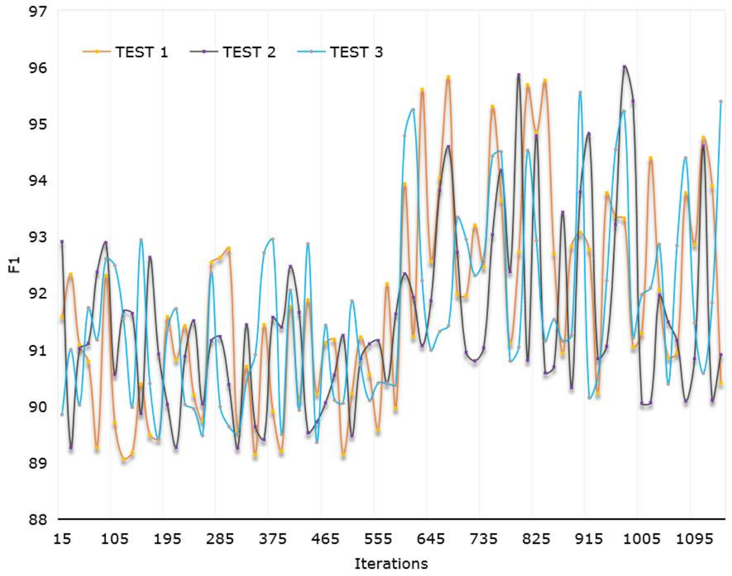

Figure 5: F1 score.

In contrast to conventional manual feature extraction techniques and traditional machine learning-based classification methods, our approach exhibits notable superiority in terms of extraction efficacy and classification precision.

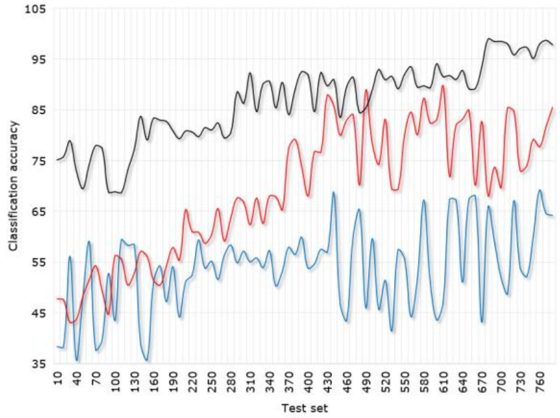

Figure 6: Classification accuracy (Compared with traditional methods).

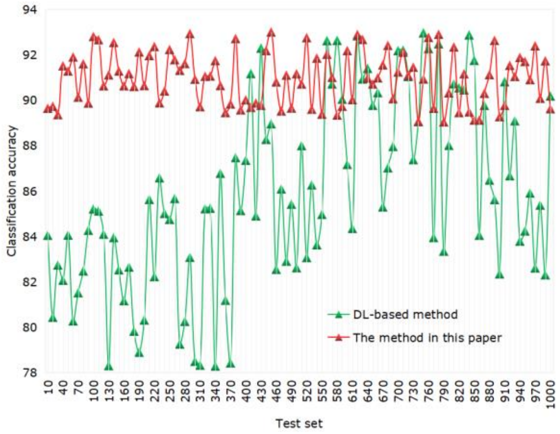

Figure 7: Classification accuracy (Compared with the DL method).

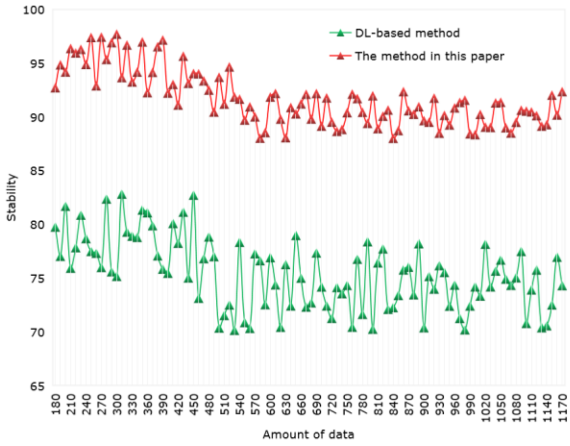

Figure 8: Algorithm stability.

This advantage primarily stems from the robust image processing capabilities of CAD technology and the remarkable efficiency of the RL algorithm in classification decision-making. Furthermore, this article delves into a comparative analysis with recently proposed DL-based extraction and classification methods for intangible cultural elements, with the findings presented in Figures 7 and 8.

Experimental outcomes indicate that this methodology possesses superior stability and generalizability while maintaining a high level of classification accuracy. Stability refers to the consistent and reliable performance of this approach across diverse scenarios, sources, and varying qualities of intangible cultural heritage (ICH) images. This aspect is crucial for ensuring reliability in practical applications, given the inherent diversity and complexity of ICH imagery. The RL algorithm, through its interactive learning process between the agent and the environment, can autonomously explore and refine the feature space. This enables the extraction of more distinctive and resilient features that not only capture the essence of known intangible cultural elements but also adeptly handle challenges posed by unknown ones. These advantages can be primarily attributed to the distinctive strengths of the RL algorithm in optimizing feature extraction and classifier design.

Drawing from the experimental findings, this article delves into a comprehensive discussion and interpretation. Firstly, regarding extraction effectiveness, the successful utilization of CAD technology owes to its well-developed capabilities in the domain of image processing. Precise image segmentation coupled with efficient feature extraction allows for the accurate capture of the distinctive traits of intangible cultural elements, thereby providing robust support for subsequent classification tasks. In terms of classification accuracy, the design of the RL algorithm facilitates adaptive adjustments in the classifier based on real-time feedback signals. This continuous optimization of the classification strategy, coupled with the rational definition of state space, action space, and reward functions, guides the agent toward learning the most appropriate classification decisions, further enhancing classification accuracy.

6 CONCLUSIONS

This study centers on the automated extraction and categorization of intangible cultural elements. Through the integration of CAD and RL algorithms, the efficient and precise handling of these elements is achieved. The research's key advancements and novelties are highlighted below:
Initially, this article adeptly incorporates CAD technology for the extraction of intangible cultural elements. By leveraging cutting-edge image segmentation and feature extraction techniques, the system facilitates automatic recognition and extraction of these elements. This innovation elevates both the efficiency and precision of the extraction process, laying a solid foundation for subsequent classification tasks.

Furthermore, this research uniquely employs the RL algorithm for the classification of intangible cultural elements. Through a thoughtful design of state space, action space, and reward function, an agent capable of adaptive learning and strategy optimization is developed. This agent excels in the efficient and accurate classification of intangible cultural elements. The experiment, conducted within a stable environment, utilizing a meticulous experimental design and leveraging a high-caliber dataset, confirms the method's effectiveness and practicality. The results demonstrate that this approach surpasses existing methodologies in terms of extraction efficacy and classification accuracy, offering a fresh perspective for the digital preservation and transmission of intangible culture.

Nevertheless, the findings also reveal certain limitations. For instance, in complex scenarios involving the extraction of intangible cultural elements, the image segmentation algorithm may occasionally produce incorrect segmentations. Additionally, the RL algorithm's training phase demands considerable computational resources and time. To address these challenges, we are committed to refining and optimizing our methodology in future investigations, aiming to attain even more favorable outcomes.

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