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Quantitative Mining and Genealogy Construction of Aesthetic Features of Ancient Chinese Porcelain Patterns Driven by Big Data

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Abstract: Porcelain, as a precious heritage in the treasure house of Chinese civilization, has become a key technology for promoting its protection and inheritance under the trend of digitalization and intelligence of cultural heritage. To improve the matching accuracy between the visual aesthetic features of ancient Chinese porcelain patterns and the corresponding textual information, this paper proposes a cross-modal entity alignment strategy based on pattern aesthetics within the visual-language pre-training framework. On this basis, a porcelain cultural knowledge graph platform based on big data is designed and developed, which integrates multiple core functional modules such as intelligent interactive questioning, speech synthesis, pattern aesthetic text generation, entity recognition, and relationship extraction. The actual system operation test shows that the average recognition accuracy exceeds 90% and the average response time is less than 5 seconds, verifying the efficiency and reliability of the system in practical applications.

Keywords: aesthetic characteristics; ancient porcelain; big data-driven; cross-modal entities

1 INTRODUCTION

Chinese culture has endured without interruption, and Chinese civilization boasts profound heritage. Only by systematically understanding the evolution of Chinese civilization can we effectively promote the innovative development and creative transformation of outstanding traditional culture in the modern context, thereby more solidly advancing the construction of socialist culture with Chinese characteristics. As an outstanding representative of traditional craftsmanship, ancient Chinese porcelain embodies profound cultural connotations through its minimalist aesthetic characteristics in its forms. Against the backdrop of the continuous deepening of the strategy to build a strong cultural nation, the minimalist aesthetic of porcelain forms has become an important medium for conveying traditional values. This paper first elucidates the cultural significance embedded in the minimalist aesthetics of ancient Chinese porcelain, then focuses on constructing the translation path of this aesthetic in the modern design context to promote the continuation of traditional craftsmanship spirit in contemporary times. The porcelain forms constructed through refined lines, small mouth, full shoulders, slender abdomen, and restrained feet, transform the core idea of "the great way is simple" in Eastern philosophy into perceptible visual symbols. The contraction and transition of contours not only derive from natural forms but also reflect the spiritual pursuit of restraint and self-discipline among ancient literati. Although ancient Chinese porcelain abandons elaborate decorations, it does not simply pursue formal simplification but strives for the ultimate expression of essential beauty, becoming a concrete carrier of the aesthetic ideal of "unity of form and spirit" through its concise visual language.

The knowledge system of ancient Chinese porcelain is complex, and research on its essence can be summarized into five categories: basic information, modeling characteristics, functional attributes, technological techniques, and cultural connotations [1]. Among them, basic information mostly comes from archaeological excavations and museum collections; modeling knowledge covers three major elements: vessel shapes, patterns, and colors, serving as a materialized carrier of function, craftsmanship, and cultural knowledge, occupying a central position in the overall knowledge framework. Currently, academic research on ancient Chinese porcelain has formed a relatively complete system and presented a clear developmental trajectory [2]. However, with the surge in data volume, issues such as inconsistent information representation and data silos have also emerged. Based on this, it is necessary to systematically review existing research approaches and strengthen the connections between different knowledge dimensions, thereby providing a reference for subsequent in-depth exploration.

As an important traditional field integrating historical depth and technological inheritance, the construction of knowledge maps for ancient Chinese porcelain culture not only needs to cover multidimensional information such as categories, techniques, and historical evolution, but also must take into account its interdisciplinary connections with history, archaeology, art, and materials science. Faced with the vast and diverse information of porcelain culture, how to achieve efficient integration has become a core issue of common concern to both academia and industry. This process not only relies on breakthroughs at the technical level but also requires a deep understanding and systematic organization of the essence of porcelain culture.

2 RELATED WORK

Currently, the classification of ancient porcelain in China mainly adopts two technical approaches: one is based on the analysis of the chemical composition of porcelain materials, and the other involves the use of digital images and machine learning methods for identification. In terms of chemical composition analysis, existing research has explored the correlation and patterns between the chemical composition of ancient porcelain and its raw material data [3], then applied models such as random forests, support vector machines, neural networks, and genetic algorithms to distinguish between raw material categories and the age of artifacts; another study used the chemical elements contained in porcelain as feature indicators [4] to construct neural network models for dating and classification. Some scholars have also utilized polarizing microscopes to observe the crystallization structure of glaze layers on porcelain fragments from different kilns [5], combined with X-ray fluorescence spectrometers to test the composition of the body and glaze of porcelain unearthed in Qinglong Town, thereby investigating the characteristics of raw material ratios. Additionally, laser-induced breakdown spectroscopy (LIBS) has been used for rapid identification of porcelain [6], enabling the differentiation of porcelain from different regions. However, these methods rely on specialized equipment, making them difficult to apply to large-scale data collection and may cause some damage to the artifacts.

With the popularization of digital photography equipment, more and more research has turned to image-based computational classification methods. Related achievements include: extracting and analyzing the contour features of ancient porcelain [7] to provide auxiliary means for identification; extracting color, size, and shape features from preprocessed porcelain images [9] to complete classification; using convolutional neural networks to recognize and categorize the base marks of Ming and Qing dynasty porcelain [10]; proposing a non-destructive classification method [11] that integrates color, edge contour, and decorative patterns for discrimination; exploring automatic authentication mechanisms by capturing local details of porcelain surface images [12] and combining image matching techniques; and other studies involving the capture of ancient porcelain images [13], extracting texture features and implementing classification with support vector machines. Most of the above research focuses on the overall contour shape of porcelain or visual attributes such as surface color, patterns, and designs.

In the field of knowledge graph technology, research focus has gradually shifted from static data processing to dynamic analysis of large-scale unstructured data, with greater emphasis on improving algorithm performance and expanding intelligent applications. This transformation indicates that the technology adaptability to complex real-time data environments is continuously enhancing, creating new possibilities for cross-domain integration. Some studies have conducted comparative analyses of related technologies such as multimodal data organization [14], pointing out that the deep integration of multimodal knowledge graphs and their representation methods with intelligent systems has become a frontier issue of common concern in both academia and industry. They argue that under the rapid growth of multi-source information such as text, images, and audio, how to efficiently integrate heterogeneous data and build knowledge graphs that support complex reasoning is a key direction for future development. Other scholars have pointed out that there are still issues in the representation and extraction of knowledge graphs [15], suggesting the establishment of evaluation mechanisms to ensure the accuracy and consistency of knowledge. In addition, some studies have attempted to combine knowledge graphs with other digital technologies to expand their capabilities, such as proposing an entity matching system for digital humanities [16], exploring the implementation of ontology knowledge in semantic networks [17], reviewing the current status of ancient book digitization research [18], building a Tang poetry knowledge graph service platform [19], developing the " Song Dynasty Academic Semantic Network " system [20], and constructing a specialized knowledge graph for Qing Dynasty sacrificial ritual vessels [21]. These practices not only drive innovation in technical methods but also broaden the application scope of knowledge graphs in cultural fields.

In recent years, a series of breakthroughs have been made in the intelligent and informatized research of ancient porcelain. For example, some scholars have explored the specific application of 3D printing technology in the inheritance of porcelain culture [22], providing new approaches for the protection and promotion of such cultural heritage; other studies focus on the reconstruction and dissemination mechanisms of porcelain symbol systems under the digital background [23], adapting to the needs of contemporary cultural communication; based on artificial intelligence technology, the recognition of image features of ancient porcelain shapes and patterns has been achieved [24], with precise identification and classification accomplished through deep learning and other methods; there are also studies analyzing the advantages of digital technology in the design, production, and dissemination of porcelain products [25], proposing specific implementation strategies; starting from practical design issues, the potential of digital media technology in porcelain creation is discussed [26]; image processing using Python and OpenCV, employing the SIFT algorithm to extract pattern feature points, and achieving image search through matching calculations [27]. Meanwhile, using the style transformation based on the patterns of blue and white porcelain as the experimental object, comparisons were made among rapid style transformation, direct style transformation, and pre-processing style transformation. The superiority of the pre-processing method in the pattern reconstruction task was verified. Another study combined traditional identification methods with computer technology [28, 29]. Using BP (Belief Propagation), RBF (Radial Basis Function), and Elman neural networks, the age of blue and white porcelain was predicted, providing a scientific basis for the identification of Jingdezhen porcelain from the Yuan, Ming, and Qing dynasties, and proposing a new method for ancient porcelain authentication based on convolutional neural networks, expanding the application paths of artificial intelligence in this field.

Overall, in recent years, the study of ancient Chinese porcelain has made significant progress in the direction of intelligence and informatization, covering the multi-dimensional integration of artificial intelligence and porcelain culture, the digital and intelligent transformation of porcelain products, as well as cross-domain innovation between traditional craftsmanship and modern technology. These achievements not only inject new momentum into the inheritance and promotion of porcelain culture but also provide theoretical and technical support for industrial upgrading. However, systematic information research in this field remains weak, with related resources being scattered and poorly integrated. Despite the long historical accumulation and profound cultural connotations of porcelain art and craftsmanship, comprehensive and in-depth information sorting remains insufficient. This fragmented status quo not only poses difficulties for academic exploration but also, to some extent, hinders the sustainable development of the field. Therefore, it is imperative to strengthen the systematic integration and in-depth mining of information on ancient Chinese porcelain culture to promote its inheritance, innovation, and sustainable development in contemporary society.

3 QUANTITATIVE STUDY OF ANCIENT CHINESE PORCELAIN BASED ON CLASSIFICATION ATLAS METHOD DRIVEN BY BIG DATA

3.1 Classification Coding and Feature Extraction

During the classification coding and feature extraction phase of Ming and Qing blue-and-white porcelain vases, the primary goal is to convert the physical characteristics of the porcelain into quantifiable and comparable data for deeper analysis and research. According to archaeological typology, specific codes are assigned to different porcelain shapes, styles, and features, forming a systematic coding system for shape classification and variation, as shown in Tab. 1.

Table 1 Classification of fractional coding systems

Type coding	Fractional coding
A type	I type
B type	II type
C type	III type
D type	IV type
E type	V type
F type	VI type

In feature extraction, key physical characteristics are extracted from each porcelain sample. These include dimensional features, shape features, and pattern features. Shape features encompass the mouth, neck, shoulder, body, foot, and ear. During the analysis of shape features, it was found that the body of the vessel is the main part, and its form and decoration can reflect the cultural characteristics and aesthetic trends of a specific period. Moreover, the body exhibits the most diverse morphological variations, and its shape directly influences the functional use of the vessel. At the same time, the body's shape also demonstrates the development of ceramic-making techniques, as different body shapes require different techniques to achieve. Therefore, the body can serve as an important reference for studying the advancement of ceramic technology. It largely determines the overall shape and aesthetic appeal of the vessel, so the body is chosen as the starting point for classifying and categorizing the vessel.

The coding system for the mouth, neck, ears, shoulders and feet, except for the abdomen of the vessel shape, is shown in Tab. 2. In the modeling part coding system shown in Tab. 2, detailed classification and coding of different parts can standardize the recording and analysis of the morphological characteristics of porcelain. In the table, porcelain is divided into multiple parts such as the mouth, neck, ears, shoulders, and feet. Each part has a different shape and corresponds to a specific code, such as A, b, c, d, e, etc. It also facilitates a systematic understanding and comparison of the characteristics of different porcelain pieces in research, discovers the connections and differences among porcelain pieces of different periods and styles, as well as their significance in historical and cultural contexts. This holds significant value for the protection, inheritance and innovation of traditional cultural heritage.

Table 2 Coding system for body part designations

Oral area: a	Neck: b	Ear: c	Shoulder: d	Feet: e
Paddle a1 Long neck	Long Neck b1	Have ears c1	Sloping Shoulder d1	Lap foot e1
Lip a2	Neck tie b2	Earless c2	Fengjian d2	Ring foot outside-stroke e2
Price a3	Short Neck b3		Folded Shoulder d3	Polygonal ring foot e3
Straight mouth a4	Melon-shaped neck b4		Flat shoulder d4	Oval ring foot e4
Open a5	Straight neck b5		d5	Two-layer ring foot e5
Garlic Head a6	Slender neck b6			Internal dig ring foot e6
Nozzle a7 Mouth	High Neck b7			
Rinse a8	Melon-shaped neck b8			
Other (sub-port, flower port) a9				

3.2 Quantitative Analysis of the Shape Curves of Ancient Chinese Porcelain

The analysis of the contour curves of the same category of vases is of great significance for the study of the design inheritance and innovation of blue and white porcelain vases in the Ming and Qing dynasties. By analyzing the contour curves of bottles of the same category, the design changes and development trends of blue and white porcelain in different periods can be revealed. This is helpful for understanding design decisions in a historical context and the influence of time on artistic styles. Analyzing the contour curves can help understand the cultural characteristics and aesthetic concepts of each period, and thereby gain insights into how these cultural elements influence the design of porcelain. Different contour curves reflect the evolution of porcelain-making techniques. Through comparative analysis, the innovative points of porcelain-making techniques and the impact of technological changes on the shaping of vessels can be discovered.

In Fig. 1, the analysis diagram of Type A Type I is shown. The vertical axis is marked as the Height (Height / mm) of the vessel, and the horizontal axis is marked as the Width (Width / mm) of the vessel. The orange-yellow line represents the sample of the largest-sized vessel, the orange-red line represents the sample of the medium-sized vessel, and the red line represents the sample of the small-sized vessel. The following other analyses are the same as above.

Through the analysis of the contour line morphology, it is concluded that: (1) The sample contours have obvious differences: the maximum sample height is about 58 mm, the minimum height is about 6 mm, and the medium sample height is about 28 mm. The contour lines of large, medium and small-sized samples show the influence of size on the shape of the bottle body. The curvature and bending points of each line reveal that the shape will be adaptively adjusted when the size changes. (2) The sample morphology is adaptable: larger-sized samples are more bulging in the abdomen to maintain the proportion and visual balance of the bottle. Smaller-sized samples may be more slender or flat to accommodate their size limitations and ensure the stability of the bottle body. (3) Samples of different sizes may require different manufacturing techniques. For instance, large porcelain vases may require heavier materials and a longer firing process, while the production of small porcelain vases may pay more attention to details and refinement. (4) The difference in size may reflect the different uses of porcelain vases. Large-sized porcelain vases may be used for storage or display, while small-sized ones may serve as tableware or ornaments. Aesthetically, large-sized bottles may give people a sense of grandeur, while small-sized ones appear more delicate and endearing.

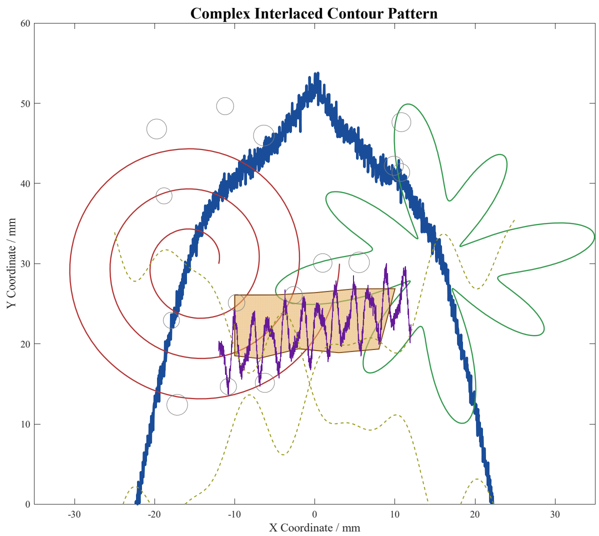

Figure 1 Type A Type I

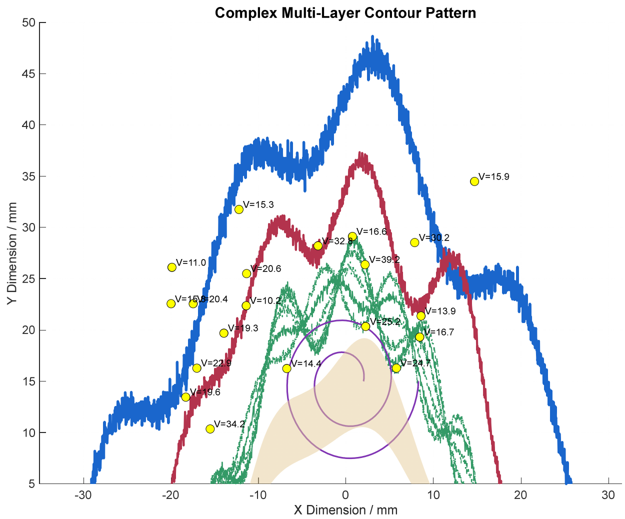

Figure 2 Partial analysis diagram of Type A Type I

The partial analysis diagram of Type A and Type I in Fig. 2 shows the partial analysis of the round-belted type of blue and white porcelain vase from the Ming and Qing dynasties. The different curves in the figure represent the widths of different parts of the porcelain vase, and the red dots indicate the width values of each part. From these data points, one can observe the contour changes of the porcelain vase and the width ratios of different parts of the vase. Based on the quantified data of local widths, it can be concluded that (1) the width variation of the curve at different heights is as follows: The widest part is usually the bottle belly section, while the widths at the bottle mouth and the bottle bottom are relatively narrower. The position of the widest point of the bottle belly moves upward as the height increases, indicating a gradually narrowing trend from the bottom to the top. (2) The smoothness of the curve reflects the fluidity of the bottle's contour. If the curve is smooth, it indicates that the shape of the porcelain vase is more rounded, while sharp turns of the curve may suggest that the vase body has more geometric features. (3) Analyze the aspect ratio of the bottle body by measuring the height and width of the curve. This proportional relationship helps to understand the overall shape and style of the porcelain vase, whether it leans more towards being slender or flat.

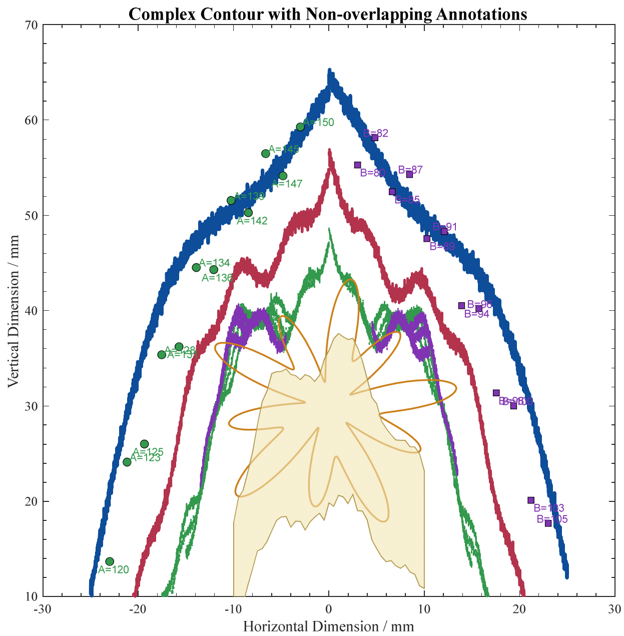

Figure 3 Type A Type II

According to the analysis in Fig. 3, it can be concluded that: (1) The characteristic of the long round abdomen style is an elegant curve, which gradually expands from the bottom to the middle section to form the widest abdomen, and then gradually narrows up to the neck and down to the bottom. The widest point is approximately located at the upward one-third from the bottom. This design is not only aesthetically pleasing but also stable. (2) Samples of different sizes maintain a consistent design language, with the main change being the scale. This indicates that this form is regarded as an ideal design and has been enlarged or reduced according to different needs or preferences. (3) From the perspective of the design evolution of the vessel shape, the design of the long round-bellied type may have evolved along with different functional requirements, while also adhering to the aesthetic standards of that time. The consistent proportions among different sizes reflect the possible combination of craftsmanship and standardized methods, which may be driven by both technological progress and market demand.

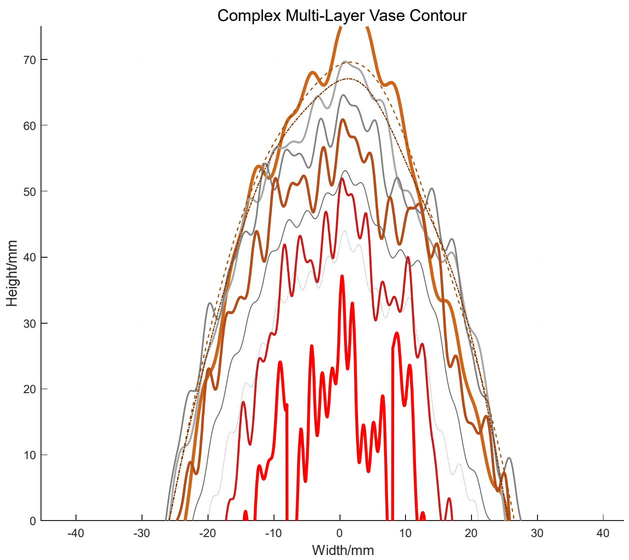

Figure 4 Type A Type III

According to the analysis in Fig. 4, it can be concluded that: (1) The shape characteristics of the blue and white porcelain with a spherical belly are that the bottom narrates, the belly then expands outward to form a distinct circle or nearly spherical shape, and then narrates towards the neck. This shape usually gives people a sense of balance and fullness visually. (2) From the perspective of the changing trend of the vessel's shape, samples of different sizes, while maintaining the basic feature of a spherical belly, will make some adjustments in details. This might reflect the requirements for size and proportion set by different uses or aesthetic standards. The spherical shape of the abdomen was maintained in all size samples, indicating that this form might have been very popular and widely used during the Ming and Qing dynasties. (3) From the perspective of the design evolution of the vessel shape, the spherical bellied blue and white porcelain may have undergone a transformation from practicality to decoration during the Ming and Qing dynasties. This transformation is reflected in the design differences of samples of different sizes. Large-sized porcelain may be more often used for display, while small-sized ones might be more convenient for daily use.

According to the analysis in Fig. 5, it can be concluded that: (1) The characteristic of the flat-bellied blue and white porcelain shape is that the lateral width of the abdomen is greater than the longitudinal height, and the shape is approximately flat or oval. This design appears relatively spacious visually. Generally, this shape helps to display larger areas of decorative patterns and also ensures the stability of the bottle body. (2) From the analysis of the trend of morphological changes, although the sample sizes are different, the basic shape of the flat-bellied type has been retained. This indicates that there is strict control over proportion and form in the design. The changing trend may indicate the consideration of specific uses and display effects during production. The flat abdomen provides more display space. (3) From the perspective of the evolution of vessel design, the flat-bellied design might have developed to meet specific display requirements or aesthetic preferences. It can better showcase complex patterns and is more stable when displayed.

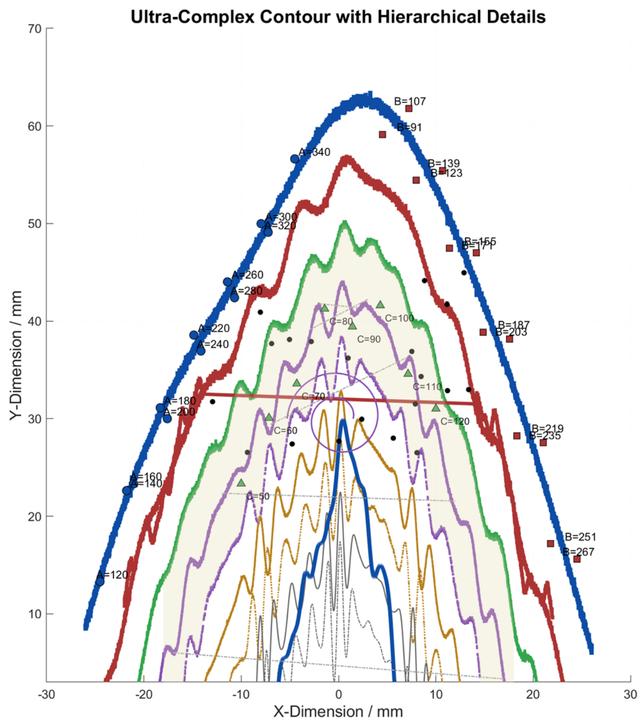

Figure 5 Type A IV and Type A V

3.3 Variable Analysis of Contour Curves of Ancient Chinese Porcelain

Fig. 6 shows the curves of multiple shapes of blue and white porcelain vases from the Ming Dynasty. The curves are presented in different colors, representing the various types of existing vessel shapes. By observing the aesthetic patterns of ancient Chinese porcelain, it can be concluded that (1) the curves show that the characteristics of Ming Dynasty porcelain are smoothness and elegance. The curve from the neck of the bottle to the shoulder gradually changes, showing a natural expansion from the neck to the abdomen. The overall shape of Ming Dynasty vessels is round. (2) The complex contour lines indicated the high maturity of the porcelain-making technology at that time, enabling the production of porcelain with various shapes. The Ming Dynasty was a peak period for the development of Chinese porcelain. These complex curves might be related to the cultural prosperity and aesthetic tastes of that time. The richness of porcelain forms may also reflect the symbol of social and economic status. The complex and delicate forms of porcelain might have been designed to meet the needs of different social classes. By analyzing these curves, it is possible to infer the morphological evolution of blue and white porcelain vases in the Ming Dynasty, as well as the possible cultural and social factors behind these evolutions. Each curve is a record of the aesthetics of its era, demonstrating the richness and diversity of history.

Fig. 7 shows the curves of multiple shapes of blue and white porcelain vases from the Qing Dynasty. From the density and fluidity of the curves, it can be analyzed that (1) the porcelain forms of the Qing Dynasty were more diverse and delicate, which might reflect the highly developed porcelain-making techniques at that time. The curve not only varies complexly in the vertical direction, but also shows rich layers and details in the horizontal direction. (2) The fineness of the morphological change curves of Qing Dynasty porcelain may indicate the artistic pursuit of Qing Dynasty artisans in porcelain shaping. Its morphological changes were also closely related to functionality and might have been associated with the culture and aesthetics of that time.

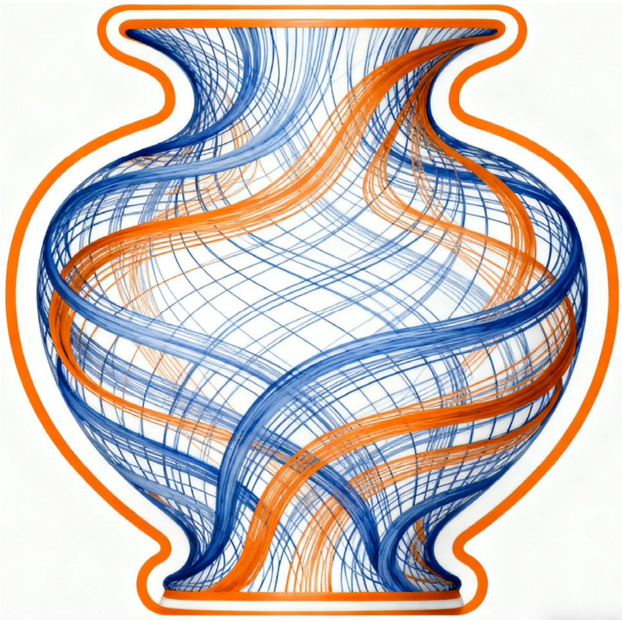

Figure 6 Outline curves of blue and white porcelain vases from the Ming Dynasty

Among the A-type vessel types, the representative A-type IV and A-type V vessel types are selected as examples. These ship-shaped structures have wide hulls, providing a relatively large flat space, which is highly suitable for displaying large continuous patterns, such as landscape paintings or long scroll story scenes. The patterns usually spread horizontally along the sides, with a balanced composition. Sometimes, border patterns are used to embellish the neck or the edge of the bottom. This layout not only highlights the decorative nature of the porcelain but also maintains visual balance, making the visual focus of the entire bottle evenly distributed.

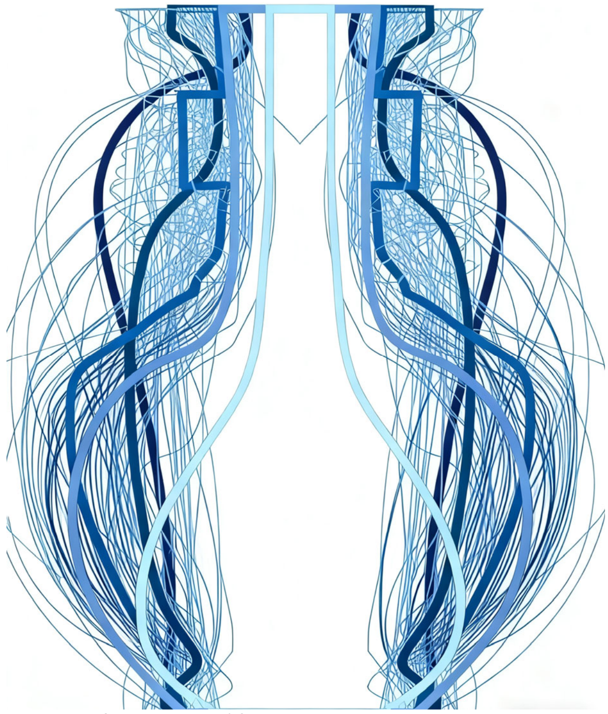

Figure 7 Outline curves of Qing Dynasty blue and white porcelain vases

4 CONSTRUCTION OF A CROSS-MODAL KNOWLEDGE GRAPH FOR THE DECORATIVE FEATURES OF ANCIENT PORCELAIN

4.1 Cross-Modal Entity Alignment Method Based on Multi-Feature Mapping

Mapping the features of different modalities into a unified feature space for alignment is the core of the cross-modal entity alignment task. This paper proposes a method based on the VLP (Variable Length Packet) model, namely the cross-modal entity alignment method IMFM-CMEA (Intrinsic Mode Function- Cellular Message Encryption Algorithm) for multi-feature mapping of aesthetic patterns on ancient Chinese porcelain. The overall structure of IMFM-CMEA is shown in Fig. 8. The encoders of ancient Chinese porcelain pattern aesthetics and text within it are initialized by the public VLP model, and the encoder parameters remain unchanged.

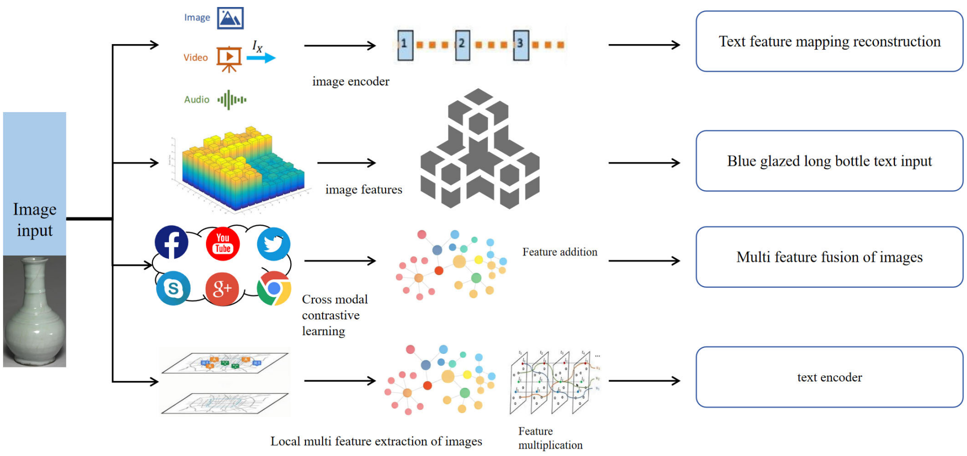

Figure 8 Structure Diagram of IMFM-CMEA

Specifically, for the given aesthetic of ancient Chinese porcelain patterns I, this paper extracts its local features in terms of contour, texture and color based on the digital aesthetic processing technology of ancient Chinese porcelain patterns. The pseudo-code of the extraction process is presented in Tab. 3 Algorithm 1.

Table 3 Algorithm 1: local multi-feature extraction

Input: Aesthetic Patterns on Ancient Chinese Porcelain I
Output: Local multi-feature extraction results.
1) I ← U2-Ne (tI) // Subject extraction;
2) I ← Processing (I) // preprocessing;
3) dim S, P, C // define the shape, pattern and color of the vessel;
4) S ← Canny (I) //Canny operator;
5) P ← LBP (I) //LBP;
6) I ← HS (I I);
7) C ← GMMs (I) // Gaussian Mixture Model;
8）C ← RGB (C);
9）μS，μP，μC← Image Encode (rS，P，C);
10）return [μS，μP，μC]

4.2 Aesthetic of Patterns on Ancient Chinese Porcelain Integrates Multiple Features

The multi-feature fusion strategy of aesthetic patterns on ancient Chinese porcelain draws on the feature fusion strategy based on gating. During the training process, this strategy can automatically assign weights to each feature without the need for manual Settings. Specifically, the gated multi-fusion device first learns the appropriate fusion weights for each feature to integrate multiple features u, u^s, u^p and u^c of a given aesthetic of ancient Chinese porcelain patterns, calculated as:

$$u' = \mathrm{LN}_0(u) \oplus \mathrm{LN}_1(u^s) \oplus \mathrm{LN}_2(u^p) \oplus \mathrm{LN}_3(u^c) \tag{1}$$

$$z_i = \sigma_i\left(\mathrm{LN}_i\left(u'\right)\right) \tag{2}$$

In the formula, u' represents the result of the initial integration of multiple aesthetic features of ancient Chinese porcelain patterns. u as the initial embedding vector, it will generate the final embedding through forward propagation, then combine with the loss function to calculate the error, use backpropagation to obtain the gradient, and finally update iteratively using the optimizer to minimize the loss. LN stands for linear layer; $\oplus$ indicates splicing calculation; z_i represents the fusion weight corresponding to the aesthetic features of each ancient Chinese porcelain pattern, $i \in [0, 3]$, $z_i \in [0, 1]$; σ represents the sigmoid activation function.

Finally, when conducting feature fusion, the proportion of aesthetic features of each ancient Chinese porcelain pattern is determined by the fusion weight z_i, which is calculated as:

$$u^F = \sum_{i=0}^{M} \theta_i\left(\mathrm{LN}_i\left(\left(u^i\right)\right) \cdot z_i \tag{3}$$

In the formula, u^F represents the fusion result of multiple aesthetic features of ancient Chinese porcelain patterns. M represents the number of features to be fused, and $M \in [0, 3]$; θ represents the tanh activation function; u_i represents the features to be fused u, u^s, u^p and u^c.

Using the aesthetic features of ancient Chinese porcelain patterns to guide the reconstruction of text features v can make it closer to the aesthetic features μ of ancient Chinese porcelain patterns. Firstly, a multi-layer fully connected mapper is designed to convert the fusion feature u^F into the mapping feature λ. The conversion process is as follows:

$$\lambda = \phi\left(\eta\left(\mathrm{LN}\left(l, m, o, u^F\right)\right)\right) \tag{4}$$

In the formula, λ represents the mapping feature; φ represents the ReLU (rectified linear unit) activation function, where there is no ReLU in the output layer; η represents the dropout regularization technique, where there is no dropout in the output layer; l represents the number of fully connected propagation layers; m represents the number of hidden neurons in the middle layer; o represents the output dimension of the mapping feature.

Next, the mapping feature λ is fused with the encoded text T, and then it is input into the text encoder and calculated as:

$$v = f\left(\phi(T) \oplus (s, \lambda)\right) \tag{5}$$

In the formula, v represents the reconstructed text feature; $f(\cdot)$ represents a text encoder; φ indicates Tokenizer text encoding; T stands for text; s represents the scaling range of the mapping feature λ.

During the training process, the connection between the aesthetic feature u of ancient Chinese porcelain patterns and the text feature v is established, and the similarity between them is measured by calculating the cosine similarity between cross-modal features. Calculate the contrastive loss $LI \rightarrow T$ from the text to the aesthetic patterns of ancient Chinese porcelain, and calculate it as:

$$L_{T\rightarrow 1} = \frac{1}{N}\sum_{i=1}^{N} \log \frac{\exp\left(v_i^T u_i \tau\right)}{\sum_{j=1}^{N} \exp\left(v_i^T u_i \tau\right)} \tag{6}$$

v represents the index of the sample user, and t represents the index of the actual target item of the category. Calculate the contrast loss $LI \rightarrow T$ of the aesthetic and textual patterns of ancient Chinese porcelain, and calculate it as:

$$L_{T\rightarrow 1} = \frac{1}{N}\sum_{i=1}^{N} \log \frac{\exp\left(u_i^T v_i \tau\right)}{\sum_{j=1}^{N} \exp\left(u_i^T v_i \tau\right)} \tag{7}$$

4.3 Construction of Cross-Modal Knowledge Graphs

The complete construction framework of the cross-modal knowledge graph is shown in Fig. 9, which adopts a top-down construction approach. First, conduct ontology modeling at the pattern layer, that is, on the basis of a thorough analysis of the knowledge in the porcelain field, define the concept classes, hierarchical structure and attributes of the porcelain ontology. A fine pattern layer can support the construction of the data layer. First, collect the data required by the data layer from multiple sources, and then map them into an initial set of triples according to the rules and construct a text knowledge graph.

Furthermore, the IMFM-CMEA method is utilized to perform cross-modal alignment on the image data contained therein. Before this, a ChinaWare dataset containing image and text titles still needs to be created for the training of IMFM CMEA. Finally, the graphic and text data is mapped into a series of aligned cross-modal triplet knowledge and stored in the text knowledge graph.

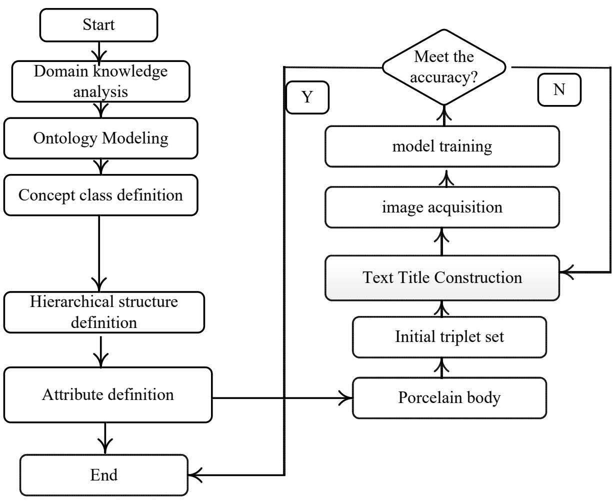

Figure 9 Construction framework of cross-modal knowledge graph

Intelligent question-answering module. This module conducts natural language understanding of users' questions based on large language models and combines the knowledge graph of ceramic culture for reasoning and response. Users can obtain various types of information in the field of ceramic culture, such as ceramic history, craftsmanship, and artists, by asking questions.

(2) Voice generation module. This module is based on speech synthesis technology, converting the system's text responses into voice feedback to the user, enhancing the interactivity of the system. The speech synthesis adopts a high-quality TTS engine to ensure the naturalness and smoothness of the speech output.

(3) Image generation module. Based on the user's description or requirements, the system can generate ceramic artworks or related images, helping users better understand the visual art of ceramic culture. This module is implemented by calling the API of the large model.

(4) Entity and Relation Extraction Module. The system can automatically extract entities and relationships from the text input by users and update them to the ceramic culture knowledge graph, ensuring the accuracy and timeliness of the graph content.

5 SIMULATION

The dataset used for the experiment was self-built and contains 21028 pairs of image-text. These data are divided into training sets, validation sets and test sets in proportions of 80%, 10% and 10% respectively.

The influence of four main hyperparameters in IMFM-CMEA on cross-modal alignment performance will be explored. Fig. 10 depicts the variations of MR Indicators of IMFM-CMEA in text-image and image-text alignment tasks under different values of four hyperparameters. The optional value range of hyperparameters is selected in accordance with the provisions in 4.1.3. When testing the influence of a certain hyperparameter, the other hyperparameters remain fixed and the following Settings are adopted: $l = 3$, $m = 128$, $o = 8$, $s = 0.5$.

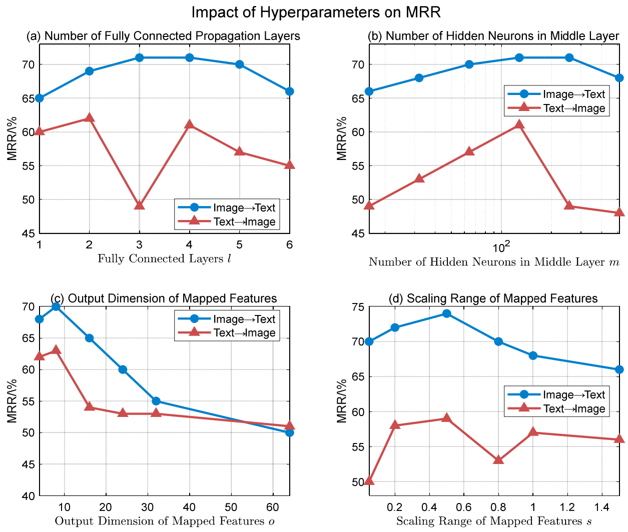

Figure 10 The influence of hyperparameter settings on the cross-modal alignment results

Overall, the text-image alignment task shows significant fluctuations, mainly due to the inherent diversity and ambiguity of text descriptions. These characteristics make the model more challenging when capturing images that match its content, so the text-image alignment task is more sensitive to the setting of hyperparameters.

The number l of fully connected layers in IMFM-CMEA affects the expression degree of feature fusion to mapping feature transformation. Fig. 10a shows that increasing the number of fully connected layers is not always beneficial for improving the cross-modal alignment performance of the model. The alignment effect of the model is the best when $l = 3$. Although the alignment result of the model is also close to the optimal when $l = 5$, increasing the number of layers also means an increase in the computational burden. When $l = 6$, the alignment effect of the model drops significantly, indicating that overly complex nonlinear relationships may interfere with the performance of the model.

The number m of hidden neurons in the middle layer also has an important influence on the feature expression ability of IMFM-CMEA. With the increase of m, the performance of the model in Fig. 10b shows an upward trend and peaks at $m = 128$. After exceeding this value, performance begins to decline, possibly due to overfitting caused by overly strong expressive power.

The output dimension o of the mapping feature is not necessarily the larger the better. Fig. 10c shows that as o increases, the model performance first rises and then falls, reaching the optimal state when $o = 8$. A larger o may lead to an increase in noise, thereby reducing the alignment performance of the model. For instance, when $o = 64$, the model's performance on the MR Metric is not as good as that with smaller dimension Settings.

The scaling range s of the mapping features also has a significant impact on the alignment results of the model. Fig. 10d shows that as s increases, the alignment effect of the model gradually improves and reaches the best when

s = 0.5. When s continues to increase to 0.8, the performance actually declines. This indicates that an overly large scaling range may cause excessive interference, thereby affecting the stability and accuracy of the model.

Fig. 11 clearly presents the cross-modal alignment results of IMFM-CMEA and zero-shot CN CLIPViT-B/16 in terms of the shape, pattern and color of porcelain. The first column shows the heat map of IMFM-CMEA. The second column shows the heat map of zero-shot CN-CLIPViT-B/16.

In the experiment, 15 representative porcelain features were selected for testing. Among them, 30 images of 5 vessel shapes, 20 images of 5 patterns, and 25 images of 5 colors were collected, and the average similarity scores between them and the corresponding text entities were calculated. It can be seen that the alignment results of IMFM-CMEA have clear boundaries and meet the expected requirements.

In the shape experiment, as shown in Fig. 11a, the average similarity score between the image of the ewer and the "Yuhuchun Vase" is second only to that of the ewer, and vice versa. This is because, in terms of appearance, most ewers are similar in shape to Yuhuchun vases. Compared with zero-shot CN-CLIPViT-B/16, IMFM-CMEA further enhances the distinction between the two shapes. The average similarity score between the patterns of ancient Chinese porcelain and the "Yuhuchun Vase" is also relatively high. Because the horizontally flipped images of the patterns of ancient Chinese porcelain are similar to those of the Yuhuchun Vase, IMFM-CMEA has a 17-point improvement over zero-shot CN-CLIPViT-B/16 in this regard. In addition, IMFM-CMEA has also made significant improvements in the alignment of the lotus leaf can image with the "lotus leaf can".

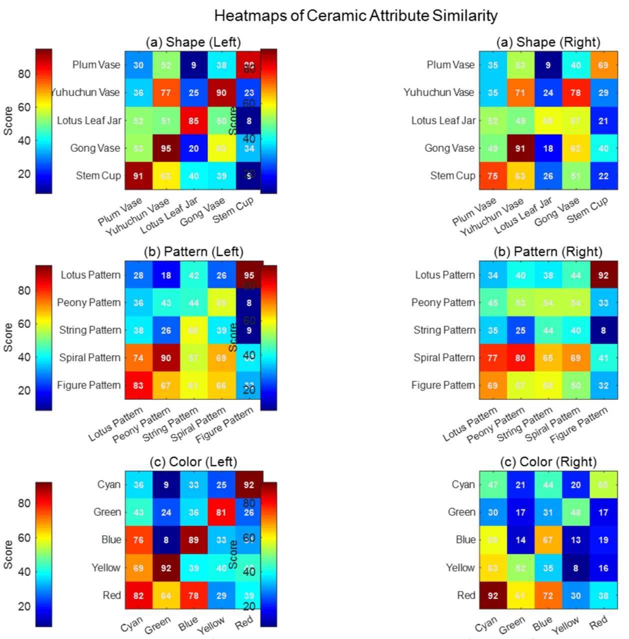

Figure 11 Visualization of cross-modal alignment results of IMFM-CMEA and zero-shot CN-CLIPViT-B/16 in terms of shape, pattern and color

Both IMFM-CMEA and zero-shot CN-CLIPViT-B/16 achieved relatively good alignment effects on human patterns in the pattern experiments, as shown in Fig. 11b, indicating that the models have a strong global cross-modal understanding ability. However, in the alignment of more detailed patterns such as lotus and chord patterns, IMFM-CMEA demonstrated a more outstanding local understanding ability. For instance, the average similarity score between the chord pattern image and "chord pattern" has increased by 16 points, and the average discrimination from the other four text entities has risen by 15 points.

In the color experiment, as shown in Fig. 11c, IMFM-CMEA significantly improved the cross-modal alignment effect of red and yellow, with the average similarity scores of red and yellow increasing by 37 and 33 points respectively. In contrast, there was an error in the alignment of cyan and green in zero-shot CN-CLIPViT-B /16, while IMFM-CMEA effectively corrected this deviation. Especially in the comparison of the second group of images with a greenish tint, not only was the recognition correct, but the average similarity score difference with cyan reached 23 points.

(1) Accuracy of intelligent question answering

In this test, 100 questions related to ceramic culture were randomly selected for systematic testing, covering multiple aspects such as the history, artists, craftsmanship, and types of ceramics. Test sample: 100 questions, covering ceramic art, history, ceramic products, masters, ceramic techniques, etc. Accuracy assessment: By manually marking the correct answers and comparing them with the responses generated by the system, the accuracy is evaluated. The accuracy rate of the system's question-answering is 96%, meaning that 96 questions were answered accurately. Only 4 questions had minor errors or were not detailed enough in their answers, mainly focusing on some less popular or specific ceramic knowledge fields. The system provides correct and informative answers regarding the historical background and the introduction of common ceramic artworks. However, the system's responses to some emerging ceramic artists and specific regional ceramic schools are somewhat lacking.

(2) Accuracy of voice generation

In the voice generation module, the system answers users' questions by converting text into voice. To test the quality of the system's voice output, 50 standard response texts were selected for text-to-speech conversion, and their clarity, fluency and naturalness were evaluated. Speech naturalness: 95% of the voice responses sound very natural, with smooth intonation changes and moderate speaking speed, meeting most speech synthesis standards. Voice clarity: 98% of the voice responses are clear and easy to understand, meeting the standards of speech synthesis. Only a few voices feel slightly stiff in some quick responses or longer sentences.

(3) Image generation accuracy

During the testing process, 50 descriptions related to ceramics (such as "blue and white porcelain vase", "Jingdezhen porcelain", "Modern ceramic art") were input, and the generated images were evaluated to see if they matched the descriptions. Consistency: 85% of the generated images exactly match the user's input description and conform to the visual style of ceramic art. Quality assessment: The quality of images varies between traditional porcelain (such as blue and white porcelain) and modern art porcelain. For traditional-style porcelain, the generated images are more detailed and in line with historical features, while for modern art-style images, there may be certain artistic differences or style deviations in the generated images.

6 CONCLUSION

In conclusion, the minimalist aesthetic features of the decorative patterns on ancient Chinese porcelain are not only the result of traditional craftsmanship and philosophical thinking, but also a cultural bridge connecting the past and the present. By extracting classic elements and combining them with modern needs, the cultural spirit can be conveyed. Ultimately, the ancient cultural relics of Chinese porcelain patterns have regained new vitality in contemporary society. Regarding the challenges of cross-modal entity alignment in ancient Chinese porcelain, this paper proposes a method for multi-feature mapping of images based on visual language models. Firstly, a series of local feature selection strategies were formulated for the visual features of ancient Chinese porcelain (including shape, pattern, and color), and the relevant features were extracted. Then, a multi-fusion device with a gating mechanism was designed to adaptively integrate multiple features of the image. Additionally, through a multi-layer fully connected network, the model was trained to map the fused features to an appropriate intermediate representation space to guide the text encoder to generate text features similar to the image features. Ultimately, the principle of cross-modal contrastive learning is utilized to optimize the model through the InfoNCE loss function. Experiments were conducted on the self-built ChinaWare dataset. The results show that in the text-image and image-text alignment tasks, compared with the benchmark method, the average recall rate MR Of IMFM-CMEA has increased by 3.2% and 7.5% respectively, demonstrating high accuracy. Finally, by applying technologies such as ontology modeling, data mining and cross-modal entity alignment (IMFM CMEA), a cross-modal knowledge graph of ancient Chinese porcelain containing 8949 nodes and 18211 relationships was successfully constructed. In the image generation module, when generating certain complex or specific style ceramic artworks, in the future, more advanced image generation technologies can be explored, such as the generation method combining style transfer and deep learning, to improve the quality and diversity of the generated images.

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