# Cross-Cultural Examination of Intelligent Perception and Group Intention in Ceramic Appreciation Analysis

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**Abstract.** Ceramics have a critical position in the history of world cultural development and are the crystallization of art and science. As we all know, the development of Chinese ceramics has a long history and is representative of the primitive culture of the Chinese nation. Determining the source and dating of unearthed ceramics is essential in current archaeological work. With the combination of science and technology and archaeological research, the technical analysis of ceramic appreciation has gradually increased. At present, the research work on ancient ceramics in China mainly focuses on the determination of their composition and element content. This paper uses appropriate multivariate statistical methods to analyze ancient ceramics' chemical composition determination data. It proposes a ceramic intelligence method based on principal component analysis (PCA) and BP neural networks. A neural network parameter-while-drilling ceramic intelligent perception model; then, three different ceramic "three-in-one" rock samples were simulated through similar materials, and the unique ceramic manufacturing process was used to enter the test bench to obtain the drilling speed, rotation speed, and drilling pressure of the drilling rig, slewing pressure, slewing torque, mud pump pressure. And other six parameters while drilling. Finally, the theoretical model is trained and tested. The results demonstrate that compared with the traditional BP neural network ceramic intelligent perception model, the PCA-BP neural network ceramic brilliant perception method reduces the model calculation amount, and the accuracy of ceramic intellectual perception has been effectively improved.

**Keywords:** ceramics; archaeology; multivariate statistical principal component analysis; BP neural network; intelligence; Cross-Cultural.
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# 1 INTRODUCTION

China has a rich ceramic culture as one of the four ancient civilizations in the world and one of the earliest countries to fire and use pottery [3]. Ancient ceramics have practical value and form a unique artistic style in shape, decoration, glaze color, etc., reflecting the social environment, folk customs, and other times. They are an essential basis for people to study history and have the same importance as classics and other materials. value [19]. The development of Chinese ceramics can be roughly summarized as follows: the earliest pottery appeared in the early Neolithic Age; glazed pottery imprinted intricate pottery, and primitive porcelain were successfully fired in the Shang and Zhou dynasties; celadon porcelain was invented in the Han and Jim dynasties; and white porcelain was invented in the Sui and Tang dynasties. The emergence of glazed porcelain was a breakthrough, and the porcelain-making technology in the Song, Yuan, Ming, and Qing dynasties matured [25]. Among them are color-glazed porcelain, painted porcelain, and sculpture ceramics, brilliant achievements in Chinese science and technology history.

Pottery refers to the utensils made of clay or pottery clay after being kneaded into shape and fired. In the "History of Chinese Ceramics," it is pointed out: "Especially with the development of the agricultural economy and settled life, the storage of grains and the transportation of drinking water all require this new container-pottery, so it appeared in large numbers and became the Neolithic Age; The outstanding features of the earth have opened a new era in the history of human life." [23] Pottery is essential in Chinese archaeological research because it fuses clay, fire, and containers and represents two aspects of human knowledge and experience. A complex blend of separate domains [26].

Porcelain is made of stone, kaolin, quartz stone, mullite, etc.; the surface is covered with glass glaze or painted. China is the hometown of porcelain, and porcelain is an essential creation of the working people of Han nationality. "Five Miscellaneous Ancestors" records: "Today's kilns are called magnetic ware, and most of the Ci Zhou kilns are named after each other. For example, silver is called rice, and ink is called glutinous rice. And so on" [5]. At that time, replacing the kiln with a "ci kiln" was the most productive period of the Ci Zhou kiln. This is the earliest historical data to use the porcelain title so far.

The value of cultural relics is also gradually increasing with the development of history. Some people destroy mausoleums, dig tombs, and smuggle ancient ceramics for profit [14]. In addition, various regions in ancient times were closely connected, trade exchanges were frequent, and many ceramics were not produced in the land where they were made, which caused problems for archaeologists to cut off the source and date [1]. In addition, the phenomenon of imitating pottery and firing fake products also occurs from time to time. For example, Jingdezhen once imitated the painted pottery of the Tang Dynasty to learn the pottery craftsmanship of the Tang Dynasty. The finished ceramic product is shown in Figure 1.

Ceramic identification in the traditional sense is also called "ophthalmology," which is mainly based on perceptual cognition and experience. The results of the determination of the authenticity, age, kiln mouth, value, and other characteristics of ceramics [2]. This method is highly subjective, and different people often come to different conclusions due to differences in practical experience. Using modern science and technology to judge the place and dynasties of ceramics can help improve the accuracy of the results [17]. The development of ancient ceramic identification methods can be divided into three stages according to the different research scope and detection techniques: old ceramic identification before the 1950s was mainly through contact with many natural objects, accumulated identification experience, passed it down from generation to generation, and was consistent with the "standard." to identify ceramics; since the 1980s, based on archaeological data, the scientific method of detecting ancient ceramic specimens has been introduced into the identification of ancient ceramics [13].

**Figure 1:** Tang dynasty ceramics.

In ancient ceramic identification research, the measurement and analysis of chemical element composition play an important role because it can provide information about the origin of ceramics, the type of raw materials, the origin, the evolution of its firing process, and product circulation [6]. A variety of methods can measure the chemical composition of ceramics. Classical wet chemical methods and emission spectroscopy were used in the early days. Later, atomic absorption spectroscopy, neutron activation, X-fluorescence, inductively coupled plasma emission spectroscopy, and mass spectrometry were applied. In addition, nuclear techniques using particle accelerators such as proton-excited X-fluorescence, synchrotron X-fluorescence, etc., are also used for this [4].

## 2 RELATED WORKS

At present, academic circles generally agree on the importance of studying the chemical composition of ancient ceramics. In addition to observing ceramic patterns, shapes, etc., it can be concluded that the dynasty, origin, and kiln mouth of the research on the chemical composition of ceramics have also promoted the development of ceramic identification [10]. The content of elements in the porcelain body and glaze has prominent regional characteristics, and most of these elements do not affect the appearance and quality of porcelain [15]. The main chemical elements in ceramics are silicon, aluminum, potassium, iron, calcium, sodium, magnesium, manganese, and titanium, and these chemical elements may change slightly in proportion and composition over time [11]. There are differences in the elements and mineral compositions contained in the land of different regions, and the locations of varying kiln systems and the firing methods of porcelain are also other. Therefore, even if the raw materials of the ceramics are the same, the element content will be different due to the various regions [24].

After a certain amount of data on the chemical composition of ceramics is obtained, the data analysis becomes the key to research. [21] pointed out that statistical methods such as scatter plots, pedigree plots, and mean analysis can be used to analyze these data. The origin of authentic Long Quan celadon and imitations of Long Quan celadon are analyzed and classified using the idea of discrimination in multivariate statistics, taking a small part of the sample for firing, measuring the content of chemical elements, and determining the origin of celadon according to chemical elements. Be classified [20]. The study concluded that in the current research on ancient ceramics, SPSS is usually used to perform descriptive statistical analysis, cluster analysis, discriminant analysis, and principal component analysis on component data.

Ancient Chinese ceramics have a history spanning more than 10,000 years, and innovations in porcelain-making technology in different dynasties and periods emerge one after another. It is precisely because of its long development history that ancient Chinese ceramics have a vast number of characteristics compared to other countries in the world, and their varieties are also complex and diverse, which will inevitably lead to the diversity of ancient ceramics data. Sex [9]. Multivariate statistical analysis is one of the practical statistical methods for dealing with multi-factor and multi-index feature problems, and its content is extensive. Amplifying, summarizing, and extracting the best angle of the required information is an essential part of identifying and analyzing ancient ceramics. [7].From the perspective of development trends, using statistical methods to analyze the characteristics of old ceramic samples has gradually become a hot issue in archaeological research. [8] In the comparative study of the chemical composition of the pottery of Bei Xin Culture and Shandong Longshan Culture, the multivariate statistical method of cluster analysis was used to measure the correlation coefficient between samples, and it was pointed out that cluster analysis has a broad range in archaeological research. However, the prerequisite is to be able to quantify the characteristics of archaeological culture. [18] From the perspective of the chemical composition elements of the original porcelain body and glaze, combined with multivariate statistical analysis methods such as principal component analysis, factor analysis, and cluster analysis. [16] Using X-ray fluorescence to analyze the composition of pottery fragments unearthed from the Shang Party Yangzi site and using SPSS software to carry out multivariate statistical analysis of the experimental data, the samples of different cultural periods belong to a class of their own. [22] compared the unearthed pottery pieces from the Shang computer room site and the San Group U point site and found that there may be cultural exchanges between the two places in the late Xavierian lower culture through the scatter plot drawn by principal component analysis.

In summary, because of the existing research, this paper combines the multivariate statistical analysis method with identifying ancient, unearthed porcelain, analyzes the conventional identification method of unearthed pottery, and proposes that multivariate statistical analysis can be used for preliminary identification of excavated ceramics. Different from previous research results, this paper not only introduces the application of multivariate statistical analysis methods in the division of origin and culture of unearthed pottery but also proposes that multivariate statistical methods can be applied to the classification of unearthed pottery varieties and the classification of unearthed porcelain kiln families. Combining a variety of methods flexibly, the analysis is relatively comprehensive.

## 3 FEATURE EXTRACTION OF INK COLOR DISTRIBUTION IN THE MAIN DIRECTION OF CERAMICS

In addition to the shape of the line, the color of the ink is another important feature of Chinese ceramics. The painter can create a rich sense of color and draw scenery by transporting ink.

### 3.1 Main Direction Grayscale Map

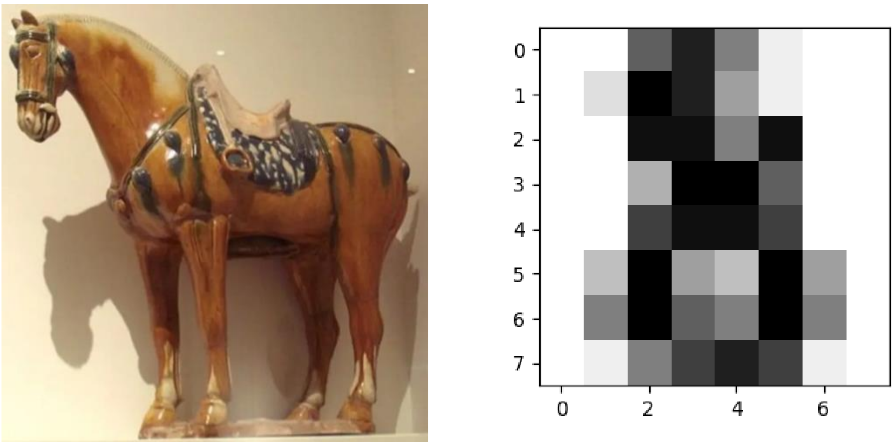
During $HOG$ feature analysis, the image is divided into $n$ grids of the same size: $cell_i, i = 1,2,\dots,n,$ As shown in the left figure of Figure 1. In general,$cell_i$ The partial image in is composed of several lines, and the directions of these lines are different. $cell_i$ The gradient direction histogram records the number of pixels in each gradient direction, namely $bin_j^{cell_i}, j = 1,2,\dots,m.$

Definition 1 In this paper, the gradient direction with the most significant number of pixels in grid $\mathrm{cell_i}$ is called the main direction of the grid mDirection $_{\mathrm{i}}$, the main direction of the ceramic.

$$\text{MainDirect} = \left\{ \text{mDirection}_i \mid \text{mDirection}_i \in \max\left\{ \text{bin}_j^{\text{cell}_i} \right\} \right\}, i = 1,2,\ldots,n, j, = 1,2,\ldots,m. \quad (1)$$

The combination of the main directions of all lattices constitutes the main direction of the ceramic. Through the research and analysis of ceramics, this paper believes that the lines in the main direction are the most critical lines in the grid area, which can best reflect the ink color characteristics of the painter's brush. As shown in the right image of Figure 1, the horse's mane in the grid area is drawn by lines in multiple directions, among which $\theta$ The number of pixels on the direction line is the largest, which can best reflect the characteristics of the ink used by the painter when he is using the brush.

Figure 2(a) is the original image of the ceramic, and (b) is the grayscale image of the main direction of the ceramic. It can be seen that the grayscale map of the main direction records the ink color information of the main lines, that is, the characteristics of the painter's pen.




(a) Original image (b) Main direction feature extraction

**Figure 2:** Main direction grayscale map.

### 3.2 Feature Extraction Based on Main Direction Grayscale Map

Through the study of many ceramics and the experimental analysis as follows, the "five colors" in the five colors of ink correspond to the following value ranges in the gray value: [0- 50] corresponds to "focus" in ink color; [51-101] corresponds to ink "dense"; [102-152] corresponds to ink "heavy"; [153-203] corresponds to ink "light"; and [204-255] corresponds to the ink color "Qing." That is, $cell_i$ the color of the pixel in the main direction $\text{mDirection}_{i,}$ is divided into five categories, denoted as

$$F_j = \{f_j(x,y)\}j, = 1,2,\ldots,5, \quad (2)$$

If $(x_k^j, y_k^j)$ is the coordinate position of pixel $f_k^j$ in $F_j$, and $(\overline{x_j}, \overline{y_j})$ is the center position of all pixels in $F_j$, then

$$(\overline{x_j}, \overline{y_j}) = \left(\frac{1}{num_j}\sum_{k=1}^{num_j} x_k^j, \frac{1}{num_j}\sum_{k=1}^{num_j} y_k^j\right). \quad (3)$$

From the above formula, we can get the center positions of the five types of ink colors: $cell_i$, medium coke, dark, heavy, light, and clear: $(\overline{x_j}, \overline{y_j}), j = 1,2,\cdots,5$. This paper proposes to use the relative positions of the five types of ink, coke, dark, heavy, light, and clear, to represent the distribution of ink colors, that is, the centers of various ink colors. The distance between is defined as follows.

$$\mathrm{dist}_{j1} = \sqrt{\left(\overline{x_j}, \overline{x_1}\right)^2 \left(\overline{y_j}, \overline{y_1}\right)^2} \tag{4}$$

Among them, $j = 1,2,\cdots,5$.represents the distance from the center of the remaining four types of ink colors (dense, heavy, light, clear) $F_j$ to the center of the first type of ink color (charred ink) $F_1$.

This paper defines the distribution characteristics of ink color in the main direction as follows:

$$\mathrm{color}_d\mathrm{ist}=[\mathrm{dist}_{21}, \mathrm{dist}_{31}, \mathrm{dist}_{41}, \mathrm{dist}_{51}], \tag{5}$$

And use the vector color ist to describe the ink color distribution characteristics of the line. This paper is based on the description of the main direction grayscale.

1. PCA-BP Neural Network ceramic intelligent sensing method

The brilliant PCA-BP neural network ceramic perception model comprises two independent algorithms: the PCA algorithm and the BP neural network. The PCA algorithm can retain the original data features to the greatest extent while extracting the main features; the BP neural network is based on the output information and expected output. The error value of the data is obtained by continuously adjusting the weights and thresholds of the network to get the best output information. Taking the principal component feature vector extracted by PCA as the input parameter of the BP neural network can make the feature more obvious and improve recognition accuracy. The network structure of the PCA-BP neural network ceramic intelligence model is shown in Figure 3.

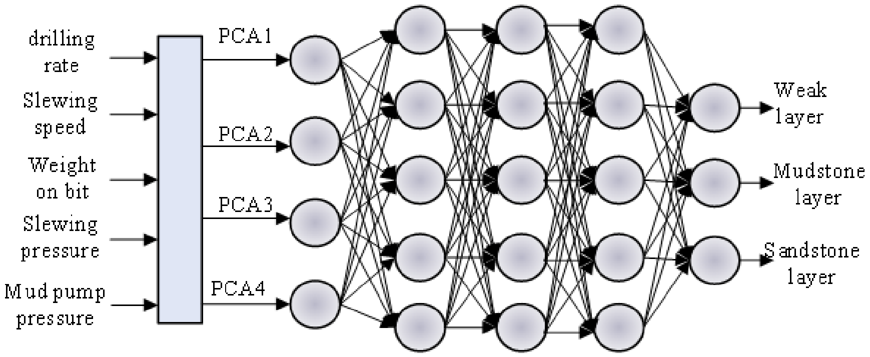



**Figure 3:** PCA-BP neural network ceramic intelligence model network structure.

2. Using the ceramic manufacturing process, enter the test bench to obtain the drilling speed, rotation speed, weight on the bit, rotation pressure, rotation torque, and mud pump pressure. Six kinds of sensitive data are used while drilling parameter data by preparing rock samples. After eliminating the invalid data, select the practical data. The parameter data while drilling is used as the data source and divided into training and test sets.

3. The PCA algorithm is used to calculate the training set, solve the correlation matrix, construct and select the first p principal components whose cumulative contribution rate is greater than 85%, and input their eigenvalue vectors into the BP neural network using 4-10-10. The BP

neural network structure of 10-3 conducts multiple pieces of training on the input data, in which the hidden layer is composed of 3 layers with ten neurons in each layer.

4. After completing the training, save the PCA-BP neural network ceramic intelligent perception model and import the test set data into the model for validity verification.

# 4 APPLICATION EXAMPLES

## 4.1 Calculation Results and Analysis

To calculate the PCA-BP neural network ceramic intelligent perception model, first construct the sample matrix of the training set data, then standardize the sample matrix, and finally solve the correlation coefficient matrix through the PCA algorithm to obtain the eigenvalue, contribution rate, and cumulative contribution rate of each principal component; see Table 1.

| *Principal component* | *Characteristic value* | *Contribution rate /%* | *Cumulative contribution rate /%* |
|---|---|---|---|
| *1* | *2.5782* | *42.9665* | *42.9665* |
| *2* | *1.3698* | *22.8283* | *65.7943* |
| *3* | *1.0656* | *17.7618* | *83.5563* |
| *4* | *0.5974* | *9.9544* | *93.5106* |
| *5* | *0.2812* | *4.6847* | *98.1952* |
| *6* | *0.1084* | *1.8048* | *100.0000* |

**Table 1:** Principal component analysis results of training set samples.

Using the traditional BP neural network, a conventional BP neural network-based ceramic intelligent perception model is established. Three hidden layers are set; each layer has ten neurons; the number of iterations is 1000; the learning rate is 0.02; and the final error value is 1%. Using Python, the software trains the traditional BP neural network ceramic intelligence model many times, saves the model after training, and imports 60 sets of test set parameters into the model for validity verification. The perception accuracy rate of the traditional BP neural network ceramic intelligence model is 86.7%. See Table 2.

As can be seen from Figure 4, the traditional BP neural network ceramic intelligence model needs 57 times to reduce the error value to 1%. In comparison, the PCA-BP neural network ceramic intelligence model only needs 23 times to reduce the error to 1%. It shows that the PCA-BP neural network ceramic intelligence model not only improves the accuracy of ceramic intelligence but also simplifies the model's network structure and reduces the model's computational load.

## 4.2 Analysis of Results

The algorithm program was written to verify the algorithm's effectiveness in this paper based on the Visual Studio platform combined with the OpenCV open-source image processing library. The number of works created by ceramic artists in their lifetimes is limited, so the number of Chinese ceramics available for classification is relatively tiny compared to natural images. Currently, the experimental datasets used for classifying and identifying medium ceramics in the literature are generally dozens of pieces, and there is no standard dataset for medium ceramics. In this paper, the data from the literature is used as the experimental data set. This dataset contains five representative painters from the Yuan Dynasty to modern times [27].

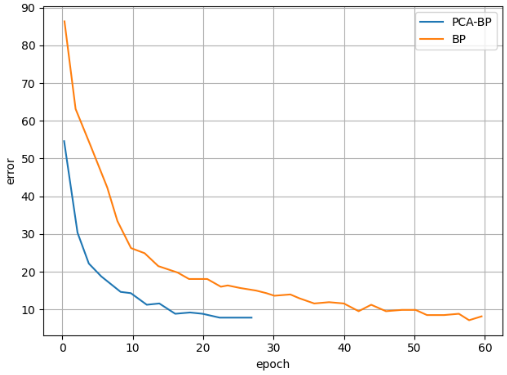



**Figure 4:** Error analysis of two models.

In this paper, the recall and precision evaluation algorithms are used. After using the algorithm in this paper to classify and identify Chinese ceramic painters, the average precision rates of the three experimental data sets are 0.97, 0.94, and 0.91, and the average recall rates are 0.97, 0.93, and 0.97.91, as shown in Tables 2 to 4. Experiments show that the algorithm in this paper can effectively classify the ceramics of different painters' styles. Further analysis shows that the maximum difference between the average recall rate and the average precision rate in the results of the three experimental schemes is 0.06, which indicates that the algorithm in this paper has good robustness.

As shown in Tables 2 to 4, compared with MHMM, the C4.5 decision tree method, and Fusion, the classification results of the algorithm in this paper are better; that is, the algorithm in this paper can more effectively describe the artistic style characteristics of different painters' ceramics, and the recognition accuracy is higher. It can also be seen from the experimental results that when the number of painters to be identified increases, the classification accuracy of each algorithm will decrease. In this paper, the algorithm's accuracy decreases slowly, reflecting better robustness.

This paper takes Table 2 as an example to analyze the misclassified ceramics. The line shape characteristics and main direction ink color distribution characteristics of ceramics can effectively represent the artistic style of ceramics. Therefore, the algorithm in this paper can correctly identify most of the typical ceramics of the painter and only cause errors in identifying a small number of non-mainstream works.

| | *The algorithm in this paper* | | *MHMM* | | *C4.5* | | *Fusion* | |
|---|---|---|---|---|---|---|---|---|
| | *P* | *R* | *P* | *R* | *R* | *R* | *P* | *R* |
| *Huang Gong Wang* | *1.01* | *0.94* | *0.92* | *1.01* | *0.89* | *0.71* | *0.98* | *0.95* |
| *Zheng Banqiao* | *0.95* | *1.01* | *1.01* | *0.91* | *0.76* | *0.91* | *0.95* | *0.98* |
| *Average value* | *0.98* | *0.98* | *0.97* | *0.96* | *0.83* | *0.81* | *0.97* | *0.97* |

**Table 2:** Classification results comparison of 2 artists.

| | *The algorithm in this paper* | | *MHMM* | | *C4.5* | | *Fusion* | |
|---|---|---|---|---|---|---|---|---|
| | *P* | *R* | *P* | *R* | | *P* | *R* | *P* |
| *Xu Bei Hong* | *0.99* | *0.92* | *0.90* | *0.99* | *0.56* | *0.59* | *0.94* | *0.90* |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Wu Chang Suo* | *0.94* | *0.88* | *0.77* | *0.81* | *0.68* | *0.61* | *0.90* | *0.94* |
| *Huang Gong Wang* | *0.95* | *1.01* | *0.84* | *1.01* | *0.88* | *1.01* | *0.93* | *0.91* |
| *Zheng Banqiao* | *0.87* | *0.92* | *0.85* | *0.84* | *0.71* | *0.72* | *0.91* | *0.91* |
| *Average value* | *0.95* | *0.92* | *0.87* | *0.83* | *0.73* | *0.72* | *0.92* | *0.92* |

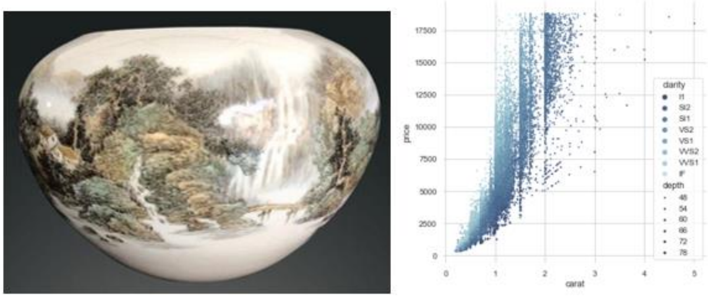
**Table 3:** Classification results comparison of 4 artists.

| | *The algorithm in this paper* | | *MHMM* | | *C4.5* | | *Fusion* | |
|---|---|---|---|---|---|---|---|---|
| | *P* | *R* | *P* | *R* | | *P* | *R* | *P* |
| *Xu Bei Hong* | *1.01* | *0.94* | *0.78* | *1.01* | *0.69* | *0.66* | *0.94* | *0.97* |
| *Wu Chang Suo* | *0.82* | *0.88* | *0.90* | *0.81* | *0.78* | *0.86* | *0.89* | *0.87* |
| *Huang Gong Wang* | *1.01* | *1.01* | *1.00* | *0.81* | *0.76* | *0.76* | *0.95* | *1.00* |
| *Zheng Banqiao* | *0.88* | *0.87* | *0.74* | *0.61* | *0.64* | *0.61* | *0.91* | *0.90* |
| *Wang Meng* | *0.88* | *0.87* | *0.84* | *1.00* | *0.71* | *0.70* | *0.78* | *0.73* |
| *Average value* | *0.92* | *0.92* | *0.86* | *0.85* | *0.72* | *0.70* | *0.89* | *0.90* |

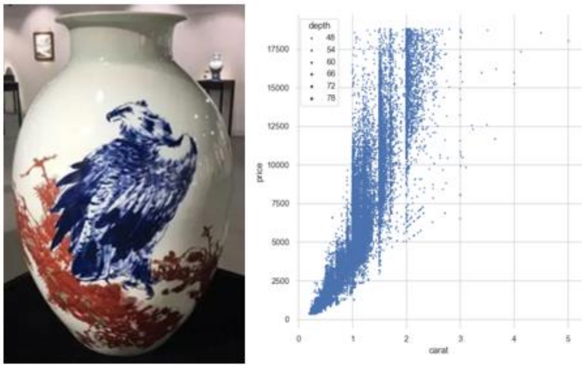
**Table 4:** Classification results comparison of 5 artists.

The main objects in the ceramics shown in Figure 5(a) are landscape paintings; the mountains and forests are drawn with heavy ink, and the water is removed with light ink and fine brushes. After the feature extraction of the algorithm in this paper, the grayscale image in the main direction is obtained, and only the mountains and forests drawn with heavy ink are retained. Figure 5(b) shows a backward eagle, and the grayscale image in the main direction only keeps the feathers and eagle tail with a heavier ink color. Most of the ceramics are eagle ceramics. When painting the eagle, the pen is solid and robust, and the ink is full and vivid. The streaks are all applied according to the shape and structure of the eagle. The ink color in the main direction is consistent. The main direction feature of the above two images only extracts the feature of heavy ink, which cannot reflect the consistency of ink color, so the experimental result of identification error occurs[12].

Compared with other ceramics, the character line shape in Figure 6 is more realistic. For the ceramics in the picture, after using the algorithm in this paper, the grayscale image in the main direction cannot reflect the ink color contrast between the main character and the flowers, so the identification is wrong.




(a) Incorrect classification of painting one and its gray image of the main direction




(b) Incorrect classification of painting two and its gray image of the main direction

**Figure 5:** Incorrect Classification Paintings of Wu Kang.

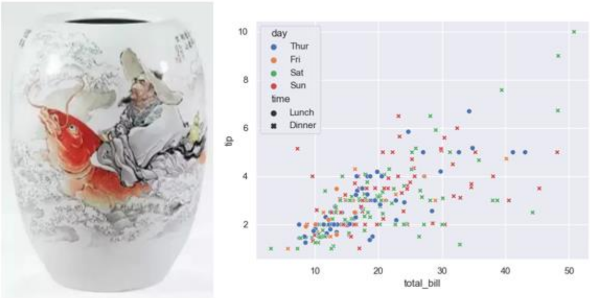



**Figure 6:** Incorrect classification painting of chang suo wu.

## 5 CONCLUSION

This paper proposes a ceramic intelligence method based on PCA and BP neural networks. First, a parameter-while-drilling ceramic intelligence model based on the PCA-BP neural network is constructed through theoretical analysis. In collecting experimental data for the "three-in-one" rock samples of three different ceramics, it is necessary to avoid factors that interfere with the quality of the analyzed images due to the digitization process of the ceramics. Interference factors include: 1) Due to the difference in hardware (such as acquisition equipment, display equipment, etc.) and ambient light, the digitized image of the ceramic is distorted compared with some colors in the local area of the original work. In digitizing ceramics, it is necessary to use high-precision and unified image acquisition equipment for collection in the same environment as much as possible and store digital images in the same size as the original ceramics as much as possible to ensure color consistency with the original ceramics. The cross-cultural dynamics of intelligent perception and group intention in ceramic appreciation is a multifaceted exploration that uncovers how diverse cultures perceive and value ceramic art. This endeavor encompasses understanding individual sensory and cognitive processes and collective interpretations within cultural groups.

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