Predictive Model for Chinese Excavated Glass Based on Least Squares Method and BP-Neural Network

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Abstract. The ancient glass excavated in China proves that at least in the Warring States period more than 2,000 years ago, it was already possible to manufacture glass products with exquisite patterns. The antique Chinese lead-barium glass and potassium glass represent China's indigenous glass technology system, and their study has significantly contributed to the history of Chinese science and technology. To this end, this paper provides a physical examination of a group of more representative ancient Chinese lead-barium glass and potassium glass. Old glass is susceptible to weathering by composition and environment. Environmental factors mainly refer to the temperature, humidity, and time when storing glass. Therefore, the weathering products on the glass surface are determined by the glass composition, temperature, humidity, time, and atmosphere at the weathering time. The ratio of the chemical composition of the weathered glass will change and thus affect the judgment of the glass type. Therefore, this study developed partial least squares regression and PB neural network models to predict the chemical composition of lead-barium glass and potassium glass from a group of Chinese excavations.

Keywords: Antient Chinese glass · partial least squares regression · predictive model · PB neural network models

1 Instruction

1.1 Background

Most of the ancient glass was more or less weathered and produced weathering products due to the chemical stability of the glass components and the temperature, humidity, time, and atmosphere of the burial environment. There is also some shallow weathering, and the naked eye cannot judge the weathering products. The proportion of the overall chemical composition of the glass altered by weathering can impact the determination of glass types.

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1.2 Review of the Literature

In the study of the development of ancient Chinese glass, experts and scholars have conducted in-depth research on its introduction, growth, glass patterns, manufacture, and origin from various aspects using various methods [1]. Li Mo conducted material production process simulation experiments on relevant glass artifacts to infer the transformation process of glass artifacts into a molding process [2]; Li Yupu combed the development trajectory of ancient Chinese glass art along the historical timeline and explored the influence of technology, function, and style on the development of glass art [3]. Gan Fuxi explores the Chinese and foreign exchanges and technological exchanges of glass artifacts [4]; Dong Junqing et al. discuss the process and compositional content of glass artifacts from glass coloring [5]. Lu Shoulin made a qualitative analysis of the conservation of glass artifacts [6].

In contrast, there needs to be more research on the classification of glass categories. Nowadays, some scholars believe that since ancient glass composition is an essential basis for discerning the origin of glass and further exploring the old glass manufacturing process, they prefer to classify excavated glass artifacts from glass composition [7]. In terms of lead-barium glass, some scholars summarized and compared the lead isotope ratio characteristics to determine the lead-barium glass made locally in China [8]; some scholars compared glass artifacts excavated from different regions during the same period [9]; some scholars used laser exfoliation inductively coupled plasma emission spectroscopy to analyze ancient glass bead specimens and explore the significance of the “Silk Road” significance [10].

1.3 Our Work

In this study, typical correlation analysis was first used to treat the surface weathering of glass artifacts as one group and glass type, decoration, and color as another group to derive the correlation and model between them. The three corresponding dummy variables of ornament, style, and color were then subjected to systematic cluster analysis and regression to predict the chemical composition content of weathered sites before weathering. The K-means clustering algorithm was used to analyze the chemical composition of glass concerning decoration, color, and surface weathering. And the results of the K-means clustering algorithm were verified with the effect quantification table of the one-way ANOVA. The BP neural network was used to predict the type of another group of glass artifacts.

2 Building Mondel

2.1 Partial Least Squares Regression Prediction Model

A typical correlation analysis model was first developed to analyze the relationship between the surface weathering of glass artifacts and their basic information, i.e., glass type, decoration, and color. Using the principal component, surface weathering is divided into one group, and the essential information is divided into one group to find the relationship between the two groups. The specific steps are as follows.

2.2 K-means Clustering Algorithm

The glass's primary type and chemical composition are first classified by the K-means clustering method and the specific algorithm.

The processing process is as follows:

Step1. Input the number of clusters to be divided into k, and the data set Z containing n clustered objects. Step2. Output k clusters. Step3. Select any k objects from the dataset Z as the initial cluster centers. Step4. Compared with the last calculated clustering center, if the clustering center is different, continue Step2; otherwise, output the clustering result. Step5. Use Fisher's discriminant analysis for dimensionality reduction, and derive the classification models of high potassium glass and lead-barium glass by discriminant function. Therefore, it is necessary to set the sample centers of high potassium glass and lead-barium glass. Step6. Derive the inter-class scattering matrix and the maximum class spacing. Step7. The intra-class scattering matrix of high potassium glass and lead-barium glass. Step8. Construct the energy function. Step9. Discriminate the classes to which the new data points. Step11.Then use a systematic clustering algorithm similar to the model combined with the elbow rule to classify high potassium glass and lead barium glass, respectively.

2.3 BP Neural Network Model

BP neural network is one of the most widely used learning algorithms nowadays. Because the unit of chemical composition has been a percentage, all data have a range of values between (0, 1), there is no need for data pre-processing. The specific steps are as follows.

Step1. Select the initial values.

Step2. Derive the outputs of the neurons in the implicit and output layers.

Step3. Find the error of the neurons in the output layer, which is less than the set error, and all patterns are less than the set error, then the learning can be stopped; otherwise, return to Step 1.

Step4. If the error of the output layer neurons is not less than the set error, this calculates the implied layer error and corrects the weights, and returns to Step 1.

2.4 Spearman Correlation Coefficient

The correlation between the chemical composition content of two glass artifacts is obtained by finding Spearman's correlation coefficient between the chemical composition content of each type of glass artifact separately. The specific construction process is as follows. Spearman's correlation coefficient is as follows.

$$\rho = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2(y_i - \overline{y})^2}} \tag{1}$$

where n is the sample size, p is the correlation coefficient, and the two variables are x and y respectively.

3 Results and Discussion

3.1 Regression Analysis

Using SPSS24 yielded a typical correlation coefficient is 0.482, the eigenvalue is 0.302, and a p-value is 0.004. From its p-value of 0.004, it is clear that the correlation between typical variables is significant at the significance level of 0.05 again. The typical correlation model thus established was.

$$Y = 1.074x_1 - 0.295x_2 + 0.694x_3 \tag{2}$$

where Y is the typical variable surface weathering, x_1, x_2 and x_3 are the random variables type, color, and ornamentation, respectively.

3.2 Cluster Analysis

This study used SPSS24 to perform K-Means cluster analysis with 2 clusters for the variable's ornamentation, color, and surface weathering, yielding a p-value of 0.140 for adornment, 0.000 for color, and 0.400 for surface weathering.

The discriminant function of the model:

D = 28.16 - 0.161 × SiO_2 - 1.575 × Na_2O + 0.985 × K_2O - 0.039 × CaO + 0.461 × MgO 1.204 × Al_2O_3 - 2.179 × Fe_2O_3 + 1.991 × CuO - 1.639 × BaO - 0.431 × P_2O_5 + 4.043 × SrO + 0.08 × SnO_2 + 1.484 × SO_2

A factor analysis was performed with SPSS24, and the quantified analysis of the effects table was obtained as follows Table 1.

The partial Eta square is generally used to denote the effect size thresholds of 0.01, 0, 25, and 0.14 for small, medium, and large effect sizes, while Cohen's f values represent the thresholds of 0.1, 0.25, and 0.4 from large to small.

Systematic clustering in SPSS24 was applied to classify the two glasses, in which the division of high potassium glass and the subclassification of tall potassium glass and lead-barium glass into three and four categories, respectively, are shown in the following Table 2.

3.3 Neural Network Prediction

The neural network prediction results were derived by Matlab2018b. MSE is the mean squared error, which is the average value of the sum of the squared errors of the prediction training set and the test set, and the smaller the value, the better. Here, MSE is approximately equal to 0, which means almost no error. At the same time, R value is a measure of the correlation between the output and the target, i.e., an R of 1 indicates a close correlation, and 0 indicates no relationship. Here the R-value is approximately equal to 1, and the test set and training set are closely related. The above results surface that this BP neural network model is suitable for predicting the type of location glass artifacts belonging to.

Among the final predicted results, A1, A3, A4, and A8 are all unweathered, and A2, A5, A6, and A7 are weathered.

Table 1. Effect quantification analysis table

Analysis item	Difference between groups	Total variance	Bias Eta square	Cohen's f-value
SiO_2	18645.985	39318.008	0.474	0.950
Na_2O	0.694	187.896	0.004	0.061
K_2O	554.008	1038.129	0.534	1.070
CaO	28.257	369.164	0.077	0.288
MgO	0.339	28.061	0.012	0.111
Al_2O_3	15.39	637.685	0.024	0.157
Fe_2O_3	6.695	91.769	0.073	0.281
CuO	0.457	332.957	0.001	0.037
PbO	15545.030	26273.799	0.592	1.204
BaO	1457.863	4801.946	0.304	0.660
P_2O_5	78.112	840.712	0.093	0.320
SrO	1.481	4.848	0.306	0.663
SnO_2	0.051	7.520	0.007	0.083
SO_2	7.748	481.045	0.016	0.128

Table 2. Subclassification of the two types of glasses

Subclassification of high potassium glass	Glass artifact number	Lead-barium glass sub-category	Glass artifact number
High potassium I	09, 12, 10, 22, 27, 03	Lead barium I	08, 26, 24, 11, 20
High potassium II	18, 21	Lead barium II	08, 26
High potassium III	01, 04, 14, 16, 03, 05, 13, 06	Lead barium III	34, 38, 30, 36, 02, 49, 51, 56, 57, 41, 50, 52, 43, 54, 39
		Lead barium IV	25, 55, 50, 42, 47, 23, 46, 49, 29, 44, 45, 53, 37, 28, 32, 35, 31, 33

3.4 Correlation Coefficients

The correlation coefficient table was derived using SPSS24, and the following Fig. 1 and 2 show the correlation coefficient heat map for the chemical composition content of high potassium glass and lead-barium glass.

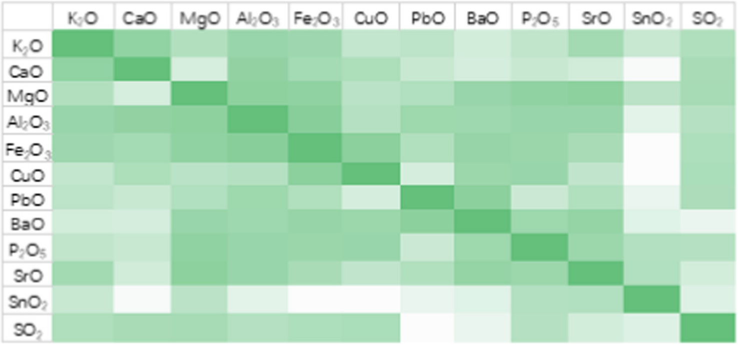

Fig. 1. Heat diagram of high potassium glass

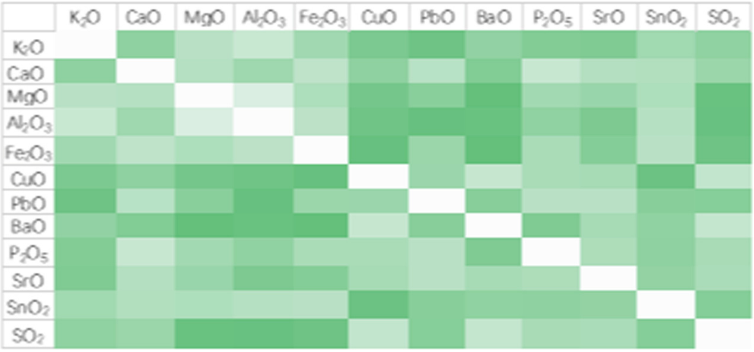

Fig. 2. Heat diagram of lead-barium glass

4 Conclusion

The typical correlation analysis was used instead of one-way ANOVA to make the correlation of the results more complete. Then, the independent variables were regressed with the chemical composition ratio by partial least squares, and the regression equation was used to predict the chemical composition content of weathered sites before weathering. The K-means clustering algorithm was used to first analyze the ornamentation, color, and surface weathering of glass and chemical composition, and only color was found to be significantly different between the categories divided by the cluster analysis, and only some of the chemical composition contents were significantly different between the categories when analyzed by chemical composition content. The systematic clustering algorithm combined with the elbow rule was used to subclassify the two types of glasses. Among them are three subclassifications of high potassium glass: high potassium class I, II, and III, and four subclassifications of lead-barium glass: lead-barium class I, II, III, and IV.

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