Research on the Problems of Ancient Glass Products

Jinye Xie*

Shanghai Technical Institute of Electronics&Information, School of Communication and Information Engineering, Shanghai, 201411 China

1637136625@qq.com

Abstract: This paper analyzes the relationship between the type, decoration, and chemical composition of ancient glass objects and their surface weathering in order to gain a deeper understanding and identification of the artifacts. First, the correlation between surface weathering and glass type, decoration, and color is analyzed. For lead-barium glass, a linear programming model was developed to predict the chemical composition content before weathering using a great likelihood function method. For weathered high-potassium glass, this paper found that the color of high-potassium glass was light when the chemical composition contained sodium oxide and dark when it did not contain sodium oxide. For the chemical composition of unweathered high-potassium glass and lead-barium glass, cluster analysis was used to classify the known samples. Then, the chemical composition of glass artifacts of unknown categories was analyzed and identified, using the use of distance function as a test function to give classification for samples of unknown types. Finally, to address the issue of correlation and variability of chemical compositions in different categories of glass artifacts, SPSSPRO was used to analyze the correlation between the chemical compositions contained in the two types of samples, and the results showed that the variability of phosphorus oxide free and sodium oxide between the chemical compositions of high-potassium glass and lead-barium glass was greater.

Keywords: Extremely Large Likelihood Function, Linear Programming, Cluster Analysis, Antique Glassware.

1. Introduction

The development of the Silk Road brought glass to ancient China, and in ancient times people continued to absorb technology and use local raw materials to improve the production of China's very historical representatives of glass artifacts, although similar in appearance, but because of the use of local raw materials to improve the composition of different elements, there is now a number of ancient glass products in China related data, archaeologists based on the chemical composition of the artifact samples and other means of detection have They are divided into two categories: high-potassium glass and lead-barium glass.

In this paper, we address the following main issues.

Question 1: What is the correlation between surface weathering, glass type, ornamentation, and color of glass artifacts? Is it possible to statistically determine the pattern of chemical content by whether the surface of the artifact is weathered, and finally predict ancient glass artifacts that are not weathered based on the data from the first weathering point test.

Question 2: Archaeologists have classified ancient glass products into high potassium glass and lead-barium glass, can you analyze what is the law why archaeologists classified them in this way. And for each category choose chemical analysis to subdivide it into a category with the same relationship, and give its division method and division results, and prove the rationality and sensitivity of the division method and results.

Question 3: Analyze and identify the chemical composition of unknown classes of glass artifacts and explain the sensitivity of the classification results.

Question 4: Analyze the relationship between the various chemical components in the glass artifacts according to the different categories and compare the differences between the chemical components of the different categories.

2. Model Assumptions

(1) Assuming the same size and mass of the glass artifacts examined in natural weathering.

(2) Assuming a linear relationship between the content of components in unweathered and weathered artifacts.

(3) Assuming the accuracy of each weathering point test data.

(4) It is assumed that the chemical elements tested do not generate new compounds due to natural weathering.

3. Model building and solving

3.1 Model building and solving (Question 1)

3.1.1 Analysis based on type, ornamentation and color

Firstly, missing counts were excluded for data processing. Secondly, we used the chi-square test from the literature [1-2] to analyze the information related to the surface weathering of the artifacts on type, ornamentation and color, respectively. The results of the chi-square test analysis showed that based on color and surface weathering, the significance p-value was 0.507, which did not present significance at the level, and the original hypothesis was accepted, so there was no significant difference for color and surface weathering data. Then based on the glass artifacts of "surface weathering, glass type, decoration, color" and other basic information in the cardinality test using SPSS, the results are shown in Table 1.

Table.1. Results of chi-square test analysis

Title	Name	Ornamentation C	A	B	Total	X^2	Correction X^2	P
Type	High Potassium	6	6	6	18			
	Lead Barium	22	14	0	36	13.886	13.886	0.001***
Total		28	20	6	54			
Color	Blue-Green	3	6	6	15			
	Pale Blue	10	10	0	20			
	Purple	4	0	0	4			
	Dark Green	7	0	0	7			
	Deep Blue	0	2	0	2	38.109	38.109	0.001***
	light green	3	0	0	3			
	Black	0	2	0	2			
	Green	1	0	0	1			
Total		28	20	6	54			
Surface weathering	No weathering	13	11	0	24			
	Weathering	15	9	6	30	5.747	5.747	0.056*
Total		28	20	6	54			

For these three chi-square test results, we hypothesize:(1) type is overwhelmingly dominant in the artifact surface weathering data and we should discuss both types separately; (2) the significance of ornamentation on surface weathering is too low and the factor of ornamentation can be ignored; (3) the significance of color on surface weathering is of order of magnitude relative to color, and its non-significance comes from the great difference in type. In the discussion of artifact subtypes, we focus on the factor of color.

We set $P_{LC}(c)$ as the surface weathering probability of lead-barium artifacts with respect to color, and $P_{PC}(c)$ as the surface weathering probability of high-potassium artifacts with respect to color [3].

The likelihood function of F_{LC} is expressed as follows:

$$F_{LC} = \prod_{\text{Weathered lead cultural relics}} P_{LC}(c) \prod_{\text{Unweathered lead cultural relics}} \left(1 - P_{LC}(c)\right) \tag{1}$$

The first multiplication means that the weathering probability corresponding to the color of all the lead-barium artifacts that have weathered is multiplied by all, while the second multiplication means that the unweathered probability corresponding to the color of all the lead-barium artifacts that have not weathered is multiplied by all.

Similarly, we obtain the likelihood for F_{PC} $P_{PC}(c)$ as follows:

$$F_{PC}=\prod_{\text{Weathered potassium cultural relics}} P_{PC}(c) \prod_{\text{Unweathered potassium cultural relics}} \left(1-P_{PC}(c)\right) \tag{2}$$

The first multiplication means that the weathering probability corresponding to the color of all the lead-barium artifacts that have weathered is multiplied by all, while the second multiplication means that the unweathered probability corresponding to the color of all the lead-barium artifacts that have not weathered is multiplied by all.

For equation (1), the surface weathering probability distribution of lead barium glass to color is obtained as shown in Table 2.

Table.2. Surface weathering probability of lead barium glass to color

Color	Black	Blue-Green	Green	Pale Blue	light green	Deep Blue	Dark Green	Purple
Probability distribution	1	0.5	0	0.8	0.8	0.7	0.665	0.5

For equation (2), the surface weathering probability distribution of high potassium glass to color was obtained as shown in Table 3.

Table.3. Surface weathering probability of high potassium glass to color

Color	Black	Blue-Green	Green	Pale Blue	light green	Deep Blue	Dark Green	Purple
Probability distribution		0.5	0	0		0		

The probability distribution of the blanks in the above table is due to the absence of these colors in the high potassium glass samples.

3.1.2 Analysis based on chemical composition

In order to study the statistical pattern of the content of components in artifacts with and without weathering, we set

$Per_{LB}(i)$ is the composition content of lead-barium artifacts before weathering, where i=1, 2,... ,14 represent the content of 14 components in Figure 2, respectively

$Per_{LA}(i)$ is the composition content of lead-barium artifacts after weathering, where i=1, 2,... ,14 represent the content of 14 components in Figure 2, respectively

$Per_{PB}(i)$ is the content of components of potassium artifacts before weathering, where i=1, 2, ... ,14 represent the content of 14 components in Figure 2, respectively

$Per_{PA}(i)$ is the content of components of potassium artifacts after weathering, where i=1, 2,... ,14 represent the content of the 14 components in Figure 2, respectively

Let M, N be the correlation matrix for the presence or absence of weathering of lead and barium artifacts, respectively, that is

$$\begin{pmatrix} Per_{LA}(1) \\ \vdots \\ Per_{LA}(14) \end{pmatrix} = \begin{pmatrix} M_{11} & \cdots & M_{1,14} \\ \vdots & \cdots & \vdots \\ M_{14,1} & \cdots & M_{14,14} \end{pmatrix} \begin{pmatrix} Per_{LB}(1) \\ \vdots \\ Per_{LB}(14) \end{pmatrix} \tag{3}$$

and

$$\begin{pmatrix} Per_{PA}(1) \\ \vdots \\ Per_{PA}(14) \end{pmatrix} = \begin{pmatrix} N_{11} & \cdots & N_{1,14} \\ \vdots & \cdots & \vdots \\ N_{14,1} & \cdots & N_{14,14} \end{pmatrix} \begin{pmatrix} Per_{PB}(1) \\ \vdots \\ Per_{PB}(14) \end{pmatrix} \tag{4}$$

In the actual calculation, we choose the weathered artifacts and unweathered artifacts that look closer in the chart as the component content of the same artifact with or without weathering, respectively. For taking the minimum energy limit for M and N, we calculate M,N, as shown in Tables 4 and 5.

Table.4. M matrix

1.02	0	-0.448	-1.078	0	0.0469	-0.475	0	0.187	0	0	0	0	0.337
0	1.092	0	0	0	0	0	0.189	0		-1.126	0	0	0
0	0	0.9	0	0.13	0	0	0	0	0	0	0	-0.584	-0.33
0	0	0	0.5	0	0	0	0	0.881	0	-0.185	0	0	0
0	0	0	0	0.613		0		0.95	0	0	0	0	0
0	0	0	0	0	0.911	0	0	0.121	0	0	0	0	0
0.21	0	0	0	0	0	1.21		0	0	0	0	0	0
0.311	0	0	0.867	0		0.58	0.771	0.731	0.476	0	-0.707	0.337	0
0	0	0.261		0.596	0	0	0	0.812	0	0	0	0	0
0.337	-0.01	0	0	0	0	0	0	0.65	0.755	0	0	0	0
0.211	0	0	0	0	0	0.6	0	0	0	0.866	0	0	-0.156
0	0	0	0	0	0	0	0	0	0	0	0.637	0	0
0.338	0	0	0	0	0	0	0	0.597	0	0	0	0.935	0
0	0.417	-0.41	0	0.514	0.331	0	0	0	0.357	-0.51	-0.442	0	0.711

Table.5. N matrix

1.031	0	0	0	0	0	0	0	-0.536	0	0	0	0	0
-0.3	1.217	0	0.689	0	0	0.011	0	0.48	0	0.254	0	-0.143	0
0	0	1.776	0	0	-0.529	0	0	0	0	0.141	0	-0.416	0.062
0	0.413	0	0.8	0	0	0	0	0	0	0	0	0	0.718
0.245	0	0	0	1.056	0	0	0	-0.667	0	0	-0.875	0.017	0
0.37	0	0	0	0	0.975	0	0	0.564	0	0	0	0	0
0.856	0	0	0	0	0	0.42	0	0	-0.131	0	0	0	0
0	-0.136	0	0	-0.139	0	0	0.868	0	0	0	0	0	0.175
-0.097	0	-0.234	0	0	-0.789	0	0	0.462	0	0	-0.15	0	0
-1.069	0	0	0	0.351	0	-0.98	0	0	1.252	0	0	0	0
0	0	0	0	0	0	-0.099	-0.177	0	0	0.734	0	0	0
0	0	0	0	0	0	0	-0.412	-0.604	0	0	1.03	0	0
-0.42	0	-1.026	0.549	0	0	0	0	1.454	0	0	0	0.837	0
0.677	0	0	0	0	0	0	0	0	0	0	0	0	1.091

3.2 Model building and solving (Question 2)

3.2.1 Classification based on color and ornamentation

The ancient glass types with and without weathering were first filtered based on the integrated data and divided into four categories. Using excel statistics, the types of color and decoration of high potassium glass types and lead-barium glass types with or without weathering were obtained as shown in Tables 6 and 7.

Table.6. High potassium glass color and pattern types

Glass Type	Whether weathering	Ornamentation	Color
High Potassium	Weathering	B	Blue-Green
	No weathering	A, C	Blue green, light blue, dark blue

Table.7. Lead barium glass color and decoration type

Glass Type	Whether weathering	Ornamentation	Color
Lead Barium	Weathering	A, C	Black, blue-green, light blue, light green, dark green
	No weathering	B	Dark blue, light blue, dark green, light green, purple, green

Based on the analysis of the classified data, it can be seen that most of the high potassium glasses show darker colors when weathering, as shown in Table 8.

Table.8. Color appears when high potassium glass is weathered

Cultural relic number	Ornament	type	color	surface weathering	Cultural relic sampling point	**(SiO_2)**	**(Na_2 O)**
02	A	high in potassium	pale blue	weathering	02	36.28	0
07	B	high in potassium	Teal	weathering	07	92.63	0
08	C	high in potassium	purple	weathering	08	20.14	0
08	C	high in potassium	purple	weathering	08 Severe weathering point	4.61	0
09	B	high in potassium	Teal	weathering	09	95.02	0
10	B	high in potassium	Teal	weathering	10	96.77	0
12	B	high in potassium	Teal	weathering	12	94.29	0
22	B	high in potassium	Teal	weathering	22	92.35	0
27	B	high in potassium	Teal	weathering	27	92.72	0

And when the lead barium glass is weathered, the surface weathering shows light coloration.

Table.9. The color of lead barium glass appears when weathering

Cultural relic number	Ornament	type	color	surface weathering	Cultural relic sampling point	**(SiO_2)**	**(Na_2O)**
11	C	lead barium	pale blue	weathering	11	33.59	0
19	A	lead barium	pale blue	weathering	19	29.64	
25	C	lead barium	pale blue	weathering	25 Unweathered Points	50.61	2.31
28	A	lead barium	pale blue	weathering	28 Unweathered Points	68.08	0
29	A	lead barium	pale blue	weathering	29 Unweathered Points	63.3	0.92
40	C	lead barium	pale blue	weathering	40	16.71	0
42	A	lead barium	pale blue	weathering	42 Unweathered Point 1	51.26	5.74
42	A	lead barium	pale blue	weathering	42 Unweathered Point 2	51.33	5.68
43	C	lead barium	pale blue	weathering	43 part 1	12.41	0
43	C	lead barium	pale blue	weathering	43 part 2	21.7	0
44	A	lead barium	pale blue	weathering	44 Unweathered Points	60.74	3.06
48	A	lead barium	pale blue	weathering	48	53.33	0.8
51	C	lead barium	pale blue	weathering	51 part 1	24.61	0
51	C	lead barium	pale blue	weathering	51 part 2	21.35	0
52	C	lead barium	pale blue	weathering	52	25.74	1.22
53	A	lead barium	pale blue	weathering	53 Unweathered Points	63.66	3.04
54	C	lead barium	pale blue	weathering	54	22.28	0
54	C	lead barium	pale blue	weathering	54 Severely Weathered Points	17.11	0
58	C	lead barium	pale blue	weathering	58	30.39	0

The content of lead oxide and barium oxide generated during the firing process of high potassium glass is relatively high. In the process of firing potassium glass, it is fired and synthesized with a high potassium content such as quicklime as a combustion accelerant [4-6]. So the lead and barium oxide in lead-barium glass is higher than the lead and barium oxide in potassium glass. And vice versa. For this reason, for the category of high potassium glass, the analysis of the content of sodium oxide situation, it is concluded that when containing sodium oxide high potassium glass color is light color, when not detected containing sodium oxide high potassium glass surface shows a dark color, the results are shown in Table 10.

Table.10. Effect of sodium oxide on color development

Cultural relic number	Ornament	type	color	surface weathering	Cultural relic sampling point	**(SiO2)**	**(Na2O)**
02	A	high potassium	pale blue	weathering	02	36.28	0
07	B	high potassium	Teal	weathering	07	92.63	0
08	C	high potassium	Purple	weathering	08	20.14	0
08	C	high potassium	Purple	weathering	08 Severe weathering point	4.61	0
09	B	high potassium	Teal	weathering	09	95.02	0
10	B	high potassium	Teal	weathering	10	96.77	0
12	B	high potassium	Teal	weathering	12	94.29	0
22	B	high potassium	Teal	weathering	22	92.35	0
27	B	high potassium	Teal	weathering	27	92.72	0
01	C	high potassium	Teal	no weathering	1	69.33	0
03	A	high potassium	Teal	no weathering	03 Part 1	87.05	0
03	A	high potassium	Teal	no weathering	03 Part 2	61.71	0
04	A	high potassium	Teal	no weathering	04	65.88	0
05	A	high potassium	Teal	no weathering	05	61.58	0
06	A	high potassium	Teal	no weathering	06 Part 1	67.65	0
06	A	high potassium	Teal	no weathering	06 Part 2	59.81	0
13	C	high potassium	pale blue	no weathering	13	59.01	2.86
14	C	high potassium	pale blue	no weathering	14	62.47	3.38
16	C	high potassium	pale blue	no weathering	16	65.18	2.1
18	A	high potassium	dark blue	no weathering	18	79.46	0
21	A	high potassium	Teal	no weathering	21	76.68	0

3.2.2 Classification of subclasses based on chemical composition

The composition content of the unweathered case of the more two types of glass was analyzed by MATLAB for clustering [7-8] to obtain the division of high potassium glass classes as shown in Figure 1.

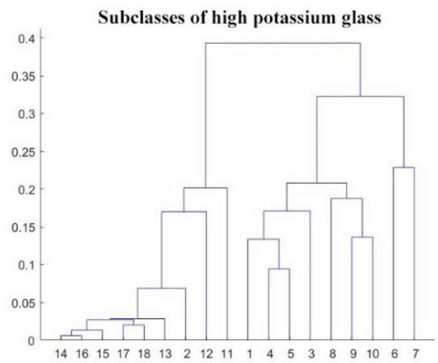

Figure 1. Clustering results of high potassium glass

From Figure 1, we obtain:

Sample classes of unweathered high-potassium glass PB: 1, 3, 4, 5, 6, 13, 14, 16.

Weathered high potassium glass samples PA: Other high potassium glass samples and the subcategories of lead-barium glass, as shown in Figure 2.

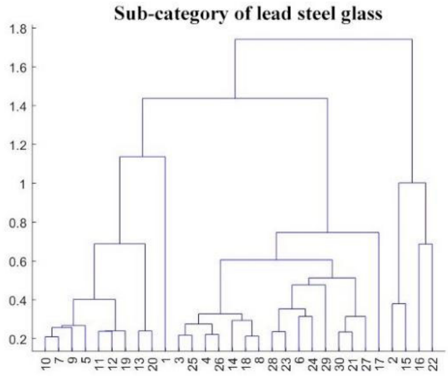

Figure 2. Clustering results of lead barium glass

From Figure 2, we obtain:

Unweathered lead barium glass sample class LA: 8, 24, 26

Weathered lead barium glass sample class LA: Other

3.3 Model Building and Solving (Question 3)

We start by defining a few functions.

DPA is the distance function from sample Y to PA

$$DPA(Y)=\left(\sum_{Z\in PA}\left(\sum_{i=1}^{14}(y_i-z_i)^2\right)\right)$$

DPB is the distance function of sample Y to PB

$$DPB(Y)=\left(\sum_{Z\in PB}\left(\sum_{i=1}^{14}(y_i-z_i)^2\right)\right)$$

DLB is the distance function from sample Y to LA:

$$DLA(Y)=\left(\sum_{Z\in LA}\left(\sum_{i=1}^{14}(y_i-z_i)^2\right)\right)$$

DPB is the distance function from sample Y to PA:

$$DLB(Y)=\left(\sum_{Z\in LB}\left(\sum_{i=1}^{14}(y_i-z_i)^2\right)\right)$$

Also set:

$$m(Y)=\min\left\{DPA(Y),DPB(Y),DLA(Y),DLB(Y)\right\}$$

We calculated the artifact sample from $DPA(Y),DPB(Y),DLA(Y),DLB(Y)$, as shown in Table 11.

Table.11. Comparison of power load forecasting of 403 line

Unweathered group			Weathered group		
number	high potassium	lead barium	number	high potassium	lead barium
A1	16.720578	38.183179	A2	67.701104	28.574785
A3	55.143005	31.86715	A5	34.077151	43.856748
A4	43.671935	26.692407	A6	2.3112807	72.361891
A8	33.158136	19.364353	A7	4.6960071	70.347638

Where the colored data are the corresponding ones for each sample $m(Y)$.

Now, we define the classification function as follows.

$$F(Y)=\begin{cases} PA, & \text{if } \min(Y)=DPA(Y) \\ PB, & \text{if } \min(Y)=DPB(Y) \\ LA, & \text{if } \min(Y)=DLA(Y) \\ LB, & \text{if } \min(Y)=DLB(Y) \end{cases} \tag{5}$$

That is, we classify the sample in one of the four classes closest to it. Substituting the previously calculated values of $m(Y)$ into (5), we obtain the following classification results for the artifacts.

Unweathered high potassium class artifacts: A1

Weathered high-potassium artifacts: A5, A6, A7

Unweathered lead and barium artifacts: A3, A4, A8

Weathered lead and barium artifacts: A2

We used the method of [9] for a concise and efficient clustering L^2 distance analysis. The analysis shows that it can correctly discriminate the subclasses to which the samples belong when the samples of different classes do not change significantly even if the distances do not change. For example, among the chemical compositions of A4 and A5, only two items, iron oxide and phosphorus pentoxide, were significantly different, while the other 14 items were close to each other. However, we still classified them in different subclasses.

3.4 Model Building and Solving (Question 4)

We used SPSS for correlation analysis between chemical compositions based on 2 different types of data, selected for high potassium glass without weathering and lead-barium glass without weathering. When the variables were: {(high potassium) phosphorus pentoxide (P2O5), (lead barium) phosphorus pentoxide (P2O5)}; correlation type: {Spearman correlation coefficient}, the results are shown in Table 12.

Table.12. Table of correlation coefficients (1)

	(High potassium) phosphorus pentoxide (P_2O_5)	(Lead barium) Phosphorus pentoxide (P_2O_5)
(High potassium) phosphorus pentoxide (P_2O_5)	1.000 (0.000**)	0.771(0.072*)
(Lead barium) phosphorus pentoxide (P_2O_5)	0.771(0.072*)	1.000 (0.000**)

Table 12 illustrates the correlation of the chemical composition phosphorus pentoxide contained in the samples of different categories of glass artifacts.

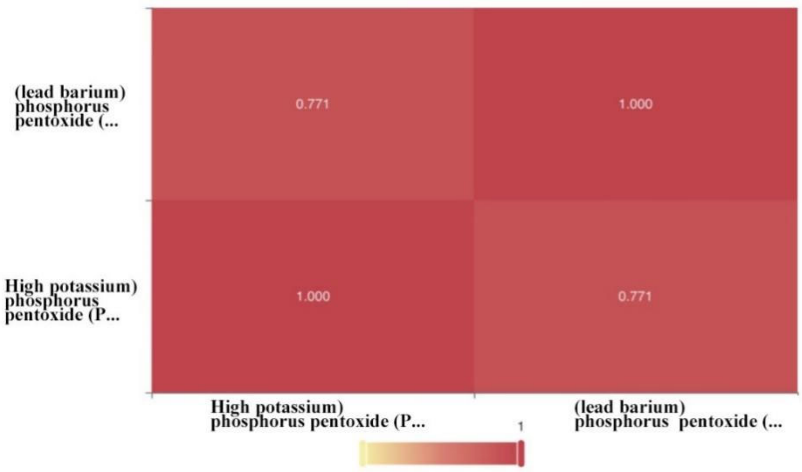

Figure 3. Heat map of correlation coefficient (1)

Figure 3 shows the value of the correlation coefficient in the form of a heat map, which indicates the magnitude of the value mainly by color shades.

When the variables are variable X:{(high potassium) alumina (Al_2O_3), (lead barium) alumina (Al_2O_3)}; correlation type:{Spearman correlation coefficient}, the results are shown in Table 13.

Table.13. Table of correlation coefficients (2)

	(high potassium) alumina (Al_2O_3)	(Lead barium) Aluminum oxide (Al_2O_3)
(high potassium) alumina (Al_2O_3)	1.000 (0.000**)	-1.000(0.000**)
(Lead barium) Aluminum oxide (Al_2O_3)	-1.000(0.000**)	1.000 (0.000**)

The data in Table 13 indicate a very strong negative correlation between the chemical composition of alumina in high potassium glass and the chemical composition of alumina in lead-barium glass.

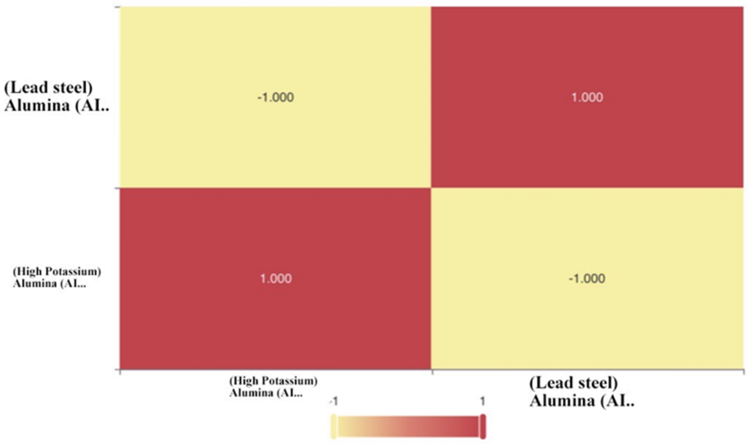

Figure 4. Heat map of correlation coefficient (2)

Figure 4 shows the value of the correlation coefficient in the form of a heat map, which indicates the magnitude of the value mainly by the color shades.

After that, Afterwards, a paired sample T-test [10] was performed between the two groups of different types of high potassium glass and lead-barium glass.

The results of the test are shown in Table 14.

Table.14. Comparison of power load forecasting of 403 line

Variable Name	Sample size	Average value	Standard deviation	Skewness	Kurtosis	S-W test	K-S test
(high potassium) silicon dioxide (SiO2) paired with (lead barium) copper oxide (CuO)	6	67.7	9.537	2.099	4.681	0.728(0.012**)	0.342 (0.393)
(high potassium) barium oxide (BaO) paired with (lead barium) magnesium oxide (MgO)	6	0.203	0.894	0.503	1.751	0.874 (0.244)	0.257 (0.742)
(high potassium) sulfur dioxide (SO2) paired with (lead barium) iron oxide (Fe2O3)	6	-0.243	0.517	0.971	0.948	0.929 (0.576)	0.223 (0.869)
(High Potassium) Strontium Oxide (SrO) Pairs (Lead Barium) Aluminum Oxide (Al2O3)	6	-3.638	1.655	0.348	1.852	0.921 (0.509)	0.237 (0.819)
(high potassium) tin oxide (SnO2) paired with (lead barium) lead oxide (PbO)	6	19.625	6.176	0.973	0.336	0.907 (0.418)	0.175 (0.975)

(High Potassium) Lead Oxide (PbO) Paired Lead Barium) Potassium Oxide (K2O)	6	0.048	0.636	1.032	1.768	0.929 (0.570)	0.239 (0.812)
(High potassium iron oxide (Fe2O3) paired with (lead barium) silicon dioxide (SiO2)	6	55.007	11.559	0.939	0.429	0.928 (0.566)	0.206 (0.917)
(High potassium) phosphorus pentoxide (P2O5) paired with (lead barium) sodium oxide (Na2O)	6	0.187	2.792	0.166	0.076	0.95 (0.744)	0.24 (0.810)
(high potassium) copper oxide (CuO) paired with (lead barium) tin oxide (SnO2)	6	2.95	1.485	0.014	0.124	0.995 (0.998)	0.135 (0.999)
(high potassium) aluminum oxide (Al2O3) paired with (lead barium) calcium oxide (CaO)	6	6.005	2.694	1.206	1.666	0.906 (0.411)	0.231 (0.843)
High potassium magnesium oxide (MgO) paired with (lead barium) phosphorus pentoxide (P2O5)	6	0.108	2.518	2.157	4.764	0.683(0.004***)	0.316 (0.488)
(high potassium) sodium oxide (Na2O) paired with (lead barium) barium oxide (BaO)	6	10.727	6.735	1.744	3.567	0.811(0.073*)	0.32 (0.475)
(high potassium) potassium oxide (K2O) paired with (lead barium) strontium oxide (SrO)	6	9.005	2.547	0.671	-0.19	0.965 (0.861)	0.151 (0.996)
(high potassium) calcium oxide (CaO) paired with lead barium) sulfur dioxide (SO2)	6	4.778	3.038	1.021	0.822	0.833 (0.113)	0.307 (0.526)

Note: ***, **, * represent 1%, 5%, 10% significance levels, respectively

The comprehensive analysis concluded that (high potassium) silicon dioxide (SiO2) paired with (lead barium) copper oxide (CuO) sample N < 5000, using the S-W test, the significance P-value was 0.012**, which showed significance at the level, and the original hypothesis was rejected, so the data did not satisfy the normal distribution, and its kurtosis (4.681) absolute value was less than 10 and skewness (2.099) absolute value was less than 3.

High potassium magnesium oxide (MgO) paired (lead barium) phosphorus pentoxide (P2O5) sample N < 5000, using the S-W test, the significance P-value is 0.004***, the level presents significance, the original hypothesis is rejected, so the data do not meet the normal distribution, its kurtosis (4.764) absolute value is less than 10 and skewness (-2.157) absolute value is less than 3.

All of the data satisfy the normal distribution except for these two groups, which do not satisfy the normal distribution.

4. Conclusions

This paper describes a procedural approach to classifying and identifying ancient glass. It expounds the in-depth study of ancient glass in the modern age of technological development. The excavation of ancient cultural relics is the focus of contemporary archaeologists' research. This paper analyzes the mechanism of glass through chemical composition analysis, starting from the chemical composition mechanism of different types of glass. The methods of linear programming, cluster analysis and T-test are designed, which have a positive effect on the identification and classification of historical relics for subsequent research.

References

[1] Scientific Platform Serving for Statistics Professional 2021. SPSSPRO. (Version 1.0.11)[Online Application Software]. Retrieved from https://www.spsspro.com.

[2] Mao Shisong, Wang Jinglong, Pu Xiaolong, et al. Advanced Mathematical Statistics (Second Edition) [M]. Beijing: Higher Education Press, 2006.

[3] Yang Xiaoping, Zhang Ruixiang, Yang Fuwei, Ma Qian, Liu Wei, Li Zhifeng. Research on Image Restoration Algorithm Based on Maijishan Grottoes Relics [J]. Journal of Longdong University, 2022,33(05):48-52.

[4] Li Yingli. Research on glassware unearthed in China from the 10th to the 12th century [D]. Liaoning Normal University, 2021.

[5] Ren Zhanzhan. Research on Glassware in Wei, Jin, Southern and Northern Dynasties, Sui and Tang Dynasties [D]. Soochow University, 2020.

[6] Zhang Jinping. Analysis and detection of cultural relics [J]. Southeast Culture, 2000, (03): 123-126+5.

[7] Huang Qinglan. Intrusion detection method based on cluster analysis and transfer learning [J]. Computer and Telecommunications, 2021, (03): 13-15+38. DOI: 10.15966/j.cnki.dnydx.2021.03.004

[8] Zhang Situo, Lin Xubin, Wu Liu, Liao Niandong. Power System C&C Threat Detection Based on Traffic Cluster Analysis [J]. Information Network Security, 2021, (S1): 173-176.

[9] Fu Jianhua, Cluster Analysis Based on Predicted Density and Sensitivity Analysis to Distance [D], Harbin University of Commerce, 2007.

[10] Fisher Box, Joan. Guinness, Gosset, Fisher, and Small Samples[J]. Statistical Science. 1987, 2 (1): 45–52.