Research on composition analysis and identification of ancient glass products related modeling

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Abstract: In this paper, in order to solve the problem that ancient glass would be weathered by the environmental influence during the burial process, and its chemical elements would change accordingly, based on Chi-square test and Spearman correlation coefficient analysis, the relationship between the types of glass relics and chemical components was analyzed, and the corresponding relationship was obtained.Then, the glass relics were classified and predicted by decision tree and random forest algorithm, and the classification and prediction results were given.

Key words: Chi-square test, K-means clustering analysis, t-test mean, decision tree classification, random forest classification, Spearman correlation coefficient

1. Introduction

Glass is a testament to the friendly exchanges between China and the West along the ancient Silk Road.Ancient Chinese glass absorbed Western technology and was locally manufactured, similar in appearance to imported products, but different in chemical composition.The main component of glass is silicon dioxide.Because the choice of flux is different, the other main chemical composition of glass is also different.The known state-owned heritage glass is divided into lead-barium glass and potassium glass.In the long history, many precious ancient Chinese glass products were buried in the earth or exposed to the air, and were more or less weathered. The composition analysis of these cultural relics is conducive to the analysis of ancient Chinese glass products technology, which has a high research value.

Aiming at the research problems of ancient glass products, this paper analyzes the classification rules of high-potassium glass and lead-barium glass. Based on the classification problems, the principal components are used to subclassify the glass, and the rationality and sensitivity of the classification results are tested.

2. Glassware classification model

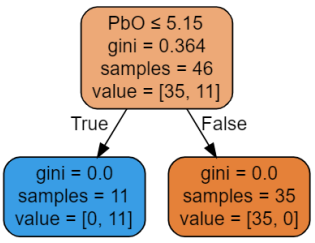
(1) Data preprocessing: the known data are merged, and the number, type, surface weathering and chemical composition content of the cultural relics are put into a table.

(2) the selection of parameters and indexes before data analysis: use of the classification of decision tree learning function of SPSSPRO software "comprehensive" table data is analyzed[1], the nominal variable selection type glass, glass types are also studied at the same time, quantitative variable selection the chemical composition, chemical composition is as the glass type parameters.Due to the large number of chemical components in the table and the small change in the content of some chemical components, it does not have high reference value, so we chose to abandon the chemical components with small reference value and reduce the index.In principle of index selection, we should select the chemical components with high content and big difference between the two types of glass as indicators.Combined with the solution results of the research background, silica and potassium oxide have a greater contribution to the weathering of high-potassium glass.Barium oxide and lead oxide have a greater contribution to the weathering of PB-barium

glass.Finally, we selected silicon dioxide, potassium oxide, lead oxide, barium oxide, four chemical components as indicators to analyze the classification rules of glass types[2].

(3) Data analysis: Taking glass type as the research object, silica, potassium oxide, lead oxide, barium oxide, four chemical components as indicators to analyze the classification rules of glass types[3].

(4) Using the four chemical components as indicators, the analysis results are as follows: the decision tree classification learning training sample 46, in which the lead oxide content lower than 5.355% is classified as high-potassium glass, and the lead oxide content higher than 5.355% is classified as lead-barium glass.The structure of decision tree is shown in figure 1[4].



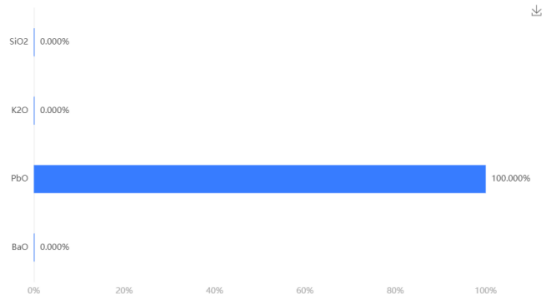


Figure 1 Decision tree structure Figure 2 The feature importance of each indicator of the model

(5) Model evaluation results: The accuracy of the test results of the test set based on decision tree classification learning reached 100%. Only lead oxide played a role in the glass type classification law, and the importance of the other three indicators was 0.The model evaluation results are shown in Table 1[5].

Table 1 Model evaluation results

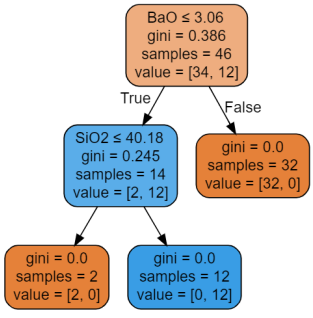
	Accuracy	Recall rate	Accuracy rate	F1
Traning Set	1	1	1	1
Test Set	1	1	1	1

The characteristic importance of each indicator of the model is shown in Figure 2.

(6) Further thinking and improvement of the model:

Although the accuracy of the above results reached 100%, only one of the four indicators selected was included in the consideration scope. In view of the small number of training samples of the model, the results of the model may be accidental, so we analyzed the data for several times after shuffling and recombination, and found that the results were still the same.In order to eliminate the possible contingency and find new classification rules to make the results more accurate, the lead oxide index was deleted and the remaining three indexes were used as parameters to analyze the classification rules[6].

The following results were obtained by using the three indexes to analyze the classification rule: barium oxide content more than 3.06% or barium oxide content less than 3.06% and silica content less than 47.645% were classified as lead barium glass, and lead oxide content less than 3.06% and silica content more than 47.645% were classified as high-potassium glass.The improved decision tree structure is shown in figure3[7].



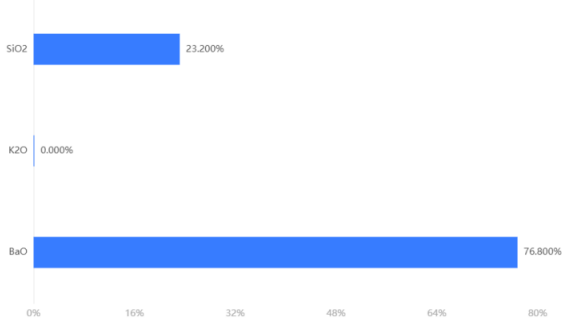


Figure 3 Improved decision tree structure Figure 4. The feature importance of each indicator of the new model

(7) Evaluation of the new model: the test result accuracy of the test set based on decision tree classification learning reached 100%, and silica accounted for 23% of the classification weight, barium oxide accounted for 76.8%, and potassium oxide accounted for 0%.The accuracy of the results is reliable[8].

Table 2 Evaluation results of the new model

	Accuracy	Recall rate	Accuracy rate	F1
Traning Set	1	1	1	1
Test Set	1	1	1	1

The characteristic importance of each indicator of the model is shown in Figure 4.

(8) Analysis results of classification rules:

The content of lead oxide lower than 5.355% is classified as high potassium glass, and the content of lead oxide higher than 5.355% is classified as lead barium glass.The content of barium oxide more than 3.06% or barium oxide less than 3.06% and silica less than 47.645% is classified as lead-barium glass, and the content of lead oxide less than 3.06% and silica more than 47.645% is classified as high-potassium glass[9].

3. Solving the classification model of glass products

For high potassium, the process of solving the sub-classification of lead-barium glass is as follows:

(1) Data preprocessing: the data in the "comprehensive" table were divided into two categories: high-potassium glass and lead-barium glass, which were respectively saved into the new table and named as "high-potassium" and "lead-barium".

(2) Cluster index - selection of chemical composition[10]

Considerations before selection: for the same type of glass, the content of each chemical composition is different and has differences. For example, the content of silica in high-potassium glass is high, and the content of sodium oxide is very low, or even there is no sodium oxide.In the process of clustering iteration, since the sodium oxide content of most high-potassium glasses is close to 0 or even 0, the sodium oxide content in the clustering center will always be near 0, which affects the clustering accuracy.Therefore, in the selection of clustering indicators, we will choose to discard such chemical components as sodium oxide.

Selection of chemical components: we first cluster all chemical components as indicators, set the cluster number to 2, and get the clustering results. Then we eliminate the chemical components that are significantly different from the divided categories, and get the indicators for the final clustering.

The difference results of each index and classified category of high-potassium cultural relics in the first clustering are shown in Table 3. When the P value is greater than 0.05, it can be considered that the component is significantly different from the classified category, which will affect the clustering accuracy.It should be omitted.Therefore, the final selection of high potassium index is silica, potassium oxide, calcium oxide, alumina, iron oxide.

Table 3 Difference results of various indexes and classification of high-potassium cultural relics clustering

	Cluster category (mean standard deviation)		F	P
	Category 1(N = 9)	Category 2(N = 9)		
SiO2	89.663±7.119	63.624±3.558	96.333	0.000***
Na2O	0.0±0.0	0.927±1.427	3.796	0.069*
K2O	1.986±3.22	10.818±2.37	43.917	0.000***
CaO	1.327±1.419	6.363±2.64	25.408	0.000***
MgO	0.437±0.593	1.133±0.672	5.435	0.033**
Al2O3	2.764±1.67	7.349±2.346	22.809	0.000***
Fe2O3	0.408±0.748	2.312±1.643	10.013	0.006***
CuO	1.492±1.136	2.819±1.565	4.233	0.056*
PbO	0.139±0.333	0.41±0.64	1.271	0.276
BaO	0.219±0.657	0.579±1.001	0.814	0.380
P2O5	0.533±0.451	1.523±1.652	3.007	0.102
SrO	0.008±0.023	0.048±0.051	4.516	0.050**
SnO2	0.262±0.787	0.0±0.0	1	0.332
SO2	0.0±0.0	0.136±0.205	3.923	0.065*

Table 4 shows the difference results of indicators and classification of the first clustering of lead-barium cultural relics. Similar to high-potassium cultural relics, the final indicators selected for lead-barium cultural relics are silica, sodium oxide, calcium oxide, alumina, lead oxide, phosphorus pentoxide, and strontium oxide.

Table 4 Difference results of various indexes and classification types of lead and barium cultural relics clustering

	Cluster category (mean standard deviation)		F	P
	Category 1(N = 28)	Category 2(N = 21)		
SiO2	24.915±9.204	57.49±9.133	151.314	0.000***
Na2O	0.172±0.527	1.881±2.4	13.423	0.001***
K2O	0.163±0.336	0.188±0.172	0.095	0.759
CaO	2.731±1.715	1.142±0.964	14.522	0.000***
MgO	0.602±0.671	0.704±0.581	0.31	0.580
Al2O3	2.62±1.498	5.064±3.888	9.278	0.004***
Fe2O3	0.68±0.87	0.624±1.065	0.04	0.842
CuO	2.415±2.992	1.165±1.273	3.215	0.079*
PbO	43.448±10.93	19.884±6.462	77.121	0.000***
BaO	12.377±9.949	7.975±4.621	3.526	0.067*
P2O5	4.916±4.253	1.128±1.909	14.425	0.000***
SrO	0.442±0.269	0.223±0.2	9.803	0.003***
SnO2	0.047±0.138	0.073±0.288	0.183	0.671
SO2	1.269±4.063	0.174±0.799	1.473	0.231

(3) Results of cluster analysis

High-potassium cluster analysis results: As shown in Table 5, there were significant differences in each index and classification category, and the clustering results were highly reliable.

Table 5 Cluster analysis results of high potassium groups

	Cluster category(mean standard deviation)		F	P
	Category 1(N=9)	Category 2(N=9)		
SiO2	89.663±7.119	63.624±3.558	96.333	0.000***
K2O	1.986±3.22	10.818±2.37	43.917	0.000***
CaO	1.327±1.419	6.363±2.64	25.408	0.000***
Al2O3	2.764±1.67	7.349±2.346	22.809	0.000***
Fe2O3	0.408±0.748	2.312±1.643	10.013	0.000***

Table 6 Cluster center coordinates

Types of clustering	Central value - silica	Central value - Potassium oxide	Central value - Calcium oxide	Central value - alumina	Central value - Iron oxide
1	89.663	1.986	1.327	2.764	0.408
2	63.624	10.818	6.363	7.349	2.312

The cluster center coordinates are shown in Table 6. According to the component contents of the cluster center coordinates, the first cluster is named as the high silica content class, and the second cluster is defined as the low silica content class.

The corresponding cultural relics of the high potassium category after clustering are shown in Table 7.

Table 7 Cluster center coordinates

Cultural relic number	Type	Cluster type	Surface weathering	Sampling point of cultural relics	SiO_2	Na_2O	K_2O	CaO	MgO	Al_2O_3	Fe_2O_3	CuO	PbO	BaO	P_2O_5	SrO	SnO_2	SO_2
07	High potassium	The first kind	Weathered	07	92.63	0	0	1.07	0	1.98	0.17	3.24	0	0	0.61	0	0	0
09	High potassium	The first kind	Weathered	09	95.02	0	0.59	0.62	0	1.32	0.32	1.55	0	0	0.35	0	0	0
10	High potassium	The first kind	Weathered	10	96.77	0	0.92	0.21	0	0.81	0.26	0.84	0	0	0	0	0	0
12	High potassium	The first kind	Weathered	12	94.29	0	1.01	0.72	0	1.46	0	1.65	0	0	0.15	0	0	0
22	High potassium	The first kind	Weathered	22	92.35	0	0.74	1.66	0.64	3.5	0.35	0.55	0	0	0.21	0	0	0
27	High potassium	The first kind	Weathered	27	92.72	0	0	0.94	0.54	2.51	0.2	1.54	0	0	0.36	0	0	0
01	High potassium	The second kind	Unweathered	01	69.33	0	9.99	6.32	0.87	3.93	1.74	3.87	0	0	1.17	0	0	0.39
03	High potassium	The first kind	Unweathered	03部位1	87.05	0	5.19	2.01	0	4.06	0	0.78	0.25	0	0.66	0	0	0
04	High potassium	The second kind	Unweathered	04	65.88	0	9.67	7.12	1.56	6.44	2.06	2.18	0	0	0.79	0	0	0.36
05	High potassium	The second kind	Unweathered	05	61.58	0	10.95	7.35	1.77	7.5	2.62	3.27	0	0	0.94	0.06	0	0.47
06	High potassium	The second kind	Unweathered	06部位1	67.65	0	7.37	0	1.98	11.15	2.39	2.51	0.2	1.38	4.18	0.11	0	0
13	High potassium	The second kind	Unweathered	13	59.01	2.86	12.53	8.7	0	6.16	2.88	4.73	0	0	1.27	0	0	0
14	High potassium	The second kind	Unweath ⚠ 1	14	62.47	3.38	12.28	8.23	0.66	9.23	0.5	0.47	1.62	0	0.16	0	0	0
16	High potassium	The second kind	Unweathered	16	65.18	2.1	14.52	8.27	0.52	6.18	0.42	1.07	0.11	0	0	0.04	0	0
18	High potassium	The first kind	Unweathered	18	79.46	0	9.42	0	1.53	3.05	0	0	0	0	1.36	0.07	2.36	0
21	High potassium	The first kind	Unweathered	21	76.68	0	0	4.71	1.22	6.19	2.37	3.28	1	1.97	1.1	0	0	0
59	High potassium	The second kind	Unweathered	06部位2	59.81	0	7.68	5.41	1.73	10.05	6.04	2.18	0.35	0.97	4.5	0.12	0	0
69	High potassium	The second kind	Unweathered	03部位2	61.71	0	12.37	5.87	1.11	5.5	2.16	5.09	1.41	2.86	0.7	0.1	0	0

The results of lead and barium cluster analysis are shown in Table 8.The clustering results showed that there were significant differences in each index and classification category, and the clustering results were highly reliable.

Table 8 Results of lead and barium cluster analysis

	Cluster category(mean standard deviation)		F	P
	Category 1(N=28)	Category 2(N=21)		
SiO2	24.951±9.024	57.49±9.133	151.314	0.000***
Na2O	0.172±0.527	1.881±2.4	13.423	0.001***
CaO	2.731±1.715	1.142±0.964	14.522	0.000***
Al2O3	2.62±1.498	5.064±3.888	9.278	0.004***
PbO	43.448±10.93	19.884±6.462	77.121	0.000***
P2O5	4.916±4.253	1.128±1.909	14.425	0.000***
SrO	0.442±0.269	0.223±0.2	9.803	0.003***

The cluster center coordinates are shown in Table 9.

Table 9 Cluster center coordinates

Types of clustering	Central value - silica	Central value - sodium oxide	Central value - Calcium oxide	Central value - alumina	Central value - Lead oxide	Central Value - Phosphorus pentoxide	Central Value - Strontium oxide
1	24.915	0.172	2.731	2.620	43.448	4.916	0.442
2	57.490	1.881	1.142	5.064	19.884	1.128	0.223

After clustering, the first type was named as low silicon and high lead class according to the component content of the cluster center coordinate, and the second type was defined as high silicon and low lead class.The corresponding species of each cultural relic of lead and barium species after clustering are shown in Table 10. Due to space limitation, only part of the data are listed in this paper.

Table 10 Corresponding species of cultural relics of lead and barium after clustering

Cultural relic number	Type	Cluster type	Surface weathering	Sampling point of cultural relics	SiO_2	Na_2O	K_2O	CaO	MgO	Al_2O_3	Fe_2O_3	CuO	PbO	BaO	P_2O_5	SrO	SnO_2	SO_2
20	Lead barium	The second kind	Unweathered	20	37.36	0	0.71	0	0	5.45	1.51	4.78	9.3	23.55	5.75	0	0	0
24	Lead barium	The first kind	Unweathered	24	31.94	0	0	0.47	0	1.59	0	8.46	29.14	26.23	0.14	0.91	0	0
30	Lead barium	The first kind	Unweathered	30部位1	34.34	0	1.41	4.49	0.98	4.35	2.12	0	39.22	10.29	0	0.35	0.4	0
31	Lead barium	The second kind	Unweathered	31	65.91	0	0	1.6	0.89	3.11	4.59	0.44	16.55	3.42	1.62	0.3	0	0
32	Lead barium	The second kind	Unweathered	32	69.71	0	0.21	0.46	0	2.36	1	0.11	19.76	4.88	0.17	0	0	0
33	Lead barium	The second kind	Unweathered	33	75.51	0	0.15	0.64	1	2.35	0	0.47	16.16	3.55	0.13	0	0	0
35	Lead barium	The second kind	Unweathered	35	65.91	0	0	0.38	0	1.44	0.17	0.16	22.05	5.68	0.42	0	0	0
37	Lead barium	The second kind	Unweathered	37	60.12	0	0.23	0.89	0	2.72	0	3.01	17.24	10.34	1.46	0.31	0	3.66
45	Lead barium	The second kind	Unweathered	45	61.28	2.66	0.11	0.84	0.74	5	0	0.53	15.99	10.96	0	0.23	0	0
46	Lead barium	The second kind	Unweathered	46	55.21	0	0.25	0	1.67	4.79	0	0.77	25.25	10.06	0.2	0.43	0	0
47	Lead barium	The second kind	Unweathered	47	51.54	4.66	0.29	0.87	0.61	3.06	0	0.65	25.4	9.23	0.1	0.85	0	0
55	Lead barium	The second kind	Unweathered	55	49.01	2.71	0	1.13	0	1.45	0	0.86	32.92	7.95	0.35	0	0	0
62	Lead barium	The first kind	Unweathered	30部位2	36.93	0	0	4.24	0.51	3.86	2.74	0	37.74	10.35	1.41	0.48	0.44	0
63	Lead barium	The second kind	Unweathered	42未风化点2	51.33	5.68	0.35	0	1.16	5.66	0	2.72	20.12	10.88	0	0	0	0
65	Lead barium	The second kind	Unweathered	49未风化点	54.61	0	0.3	2.08	1.2	6.5	1.27	0.45	23.02	4.19	4.32	0.3	0	0
66	Lead barium	The second kind	Unweathered	50未风化点	45.02	0	0	3.12	0.54	4.16	0	0.7	30.61	6.22	6.34	0.23	0	0
02	Lead barium	The first kind	Weathered	02	36.28	0	1.05	2.34	1.18	5.73	1.86	0.26	47.43	0	3.57	0.19	0	0
08	Lead barium	The first kind	Weathered	08	20.14	0	0	1.48	0	1.34	0	10.41	28.68	31.23	3.59	0.37	0	2.58
11	Lead barium	The first kind	Weathered	11	33.59	0	0.21	3.51	0.71	2.69	0	4.93	25.39	14.61	9.38	0.37	0	0
19	Lead barium	The first kind	Weathered	19	29.64	0	0	2.93	0.59	3.57	1.33	3.51	42.82	5.35	8.83	0.19	0	0
23	Lead barium	The second kind	Weathered	23未风化点	53.79	7.92	0	0.5	0.71	1.42	0	2.99	16.98	11.86	0	0.33	0	0
25	Lead barium	The second kind	Weathered	25未风化点	50.61	2.31	0	0.63	0	1.9	1.55	1.12	31.9	6.65	0.19	0.2	0	0
26	Lead barium	The first kind	Weathered	26	19.79	0	0	1.44	0	0.7	0	10.57	29.53	32.25	3.13	0.45	0	1.96
28	Lead barium	The second kind	Weathered	28未风化点	68.08	0	0.26	1.34	1	4.7	0.41	0.33	17.14	4.04	1.04	0.12	0.23	0

4. Analysis of sensitivity and rationality of subclassification results

(1) The results of two cluster analyses showed that there were significant differences between the selected indicators and the classified categories, so the classified categories were strictly classified according to the content of chemical components of cultural relics.

(2) The data tables after subclassification were saved as "high potassium subclass Division" and "lead and barium subclass Division", and the data in the tables were trained by decision tree.The species after clustering were selected as the research objects, and the chemical components in the clustering step were selected as indicators.In other words, silica, potassium oxide, calcium oxide, alumina and iron oxide were selected as indicators for high-potassium classes.Lead barium selected silica, sodium oxide, calcium oxide, alumina, lead oxide, phosphorus pentoxide, strontium oxide as indicators.The decision tree classification analysis (this step is the same as the principle of analyzing the classification law of cultural relics) was carried out to obtain the accuracy of the model. If the accuracy is high, the model is reasonable.

The precision rate of high potassium subclass classification is shown in Table 11.

Table 11 Precision rate of high potassium subclass classification

	Accuracy	Recall rate	Accuracy rate	F1
Training set	1	1	1	1
Test set	1	1	1	1

The accuracy of lead and barium subclasses is shown in Table 12.

Table 12 Precision rate of lead and barium subclass division

	Accuracy	Recall rate	Accuracy rate	F1
Training set	1	1	1	1
Test set	0.952	0.952	0.955	0.95

The accuracy rate of the two training results is more than 90%, which indicates that the subclasses divided by this cluster analysis are relatively reasonable.

In the subclassification rationality analysis step, the data table after subclass division is put into the decision tree classification learning model for training, and the trained model has a high accuracy.Therefore, we can use this model to analyze the sensitivity.Firstly, we modify the chemical composition of some cultural relics, and take the cultural relics with modified chemical composition as new cultural relics, and put them into the trained model for prediction. The categories before and after modification are compared. If the categories before and after modification are the same, the model is stable and the classification results are stable.

High potassium cultural relics mainly modified the composition of silica, potassium oxide and calcium oxide.Comparison of chemical composition and species of high-potassium cultural relics before and after modification: (There is no column of cultural heritage label in the prediction result, because the number of cultural heritage number will affect the clustering result.However, the

unmodified chemical composition content comparison can be used to judge the one-to-one correspondence between the two tables of cultural relics), as shown in Table 13.

Table 13 Results of high potassium cultural relics

Cultural relic number	Type	Cluster type	Surface weathering	Sampling point of cultural relics	SiO_2	K_2O	CaO	Al_2O_3	Fe_2O_3
10	High potassium	The first kind	Weathered	10	96.77	0.92	0.21	0.81	0.26
12	High potassium	The first kind	Weathered	12	94.29	1.01	0.72	1.46	0
14	High potassium	The second kind	Unweathered	14	62.47	12.28	8.23	9.23	0.5
16	High potassium	The second kind	Uneathered	16	65.18	14.52	8.27	6.18	0.42

The prediction results of the model are shown in Table 14.

Table 14 Table of model prediction results

Prediction Results	The first probability of prediction results	The second probability of prediction results	SiO2	K2O	CaO	Al2O3	Fe2O3
The first	1	0	86.77	0.92	0.21	0.81	0.26
The first	1	0	84.29	1.01	0.72	1.46	0
The second	0	1	65.47	12.28	8.23	9.23	0.5
The second	0	1	65.18	14.52	8.27	6.18	0.42

The compositions of silica, lead oxide, and barium oxide were mainly modified in lead-barium relics.The chemical composition and species comparison of lead-barium cultural relics before and after modification are shown in Table 15.

Table 15 Result Table of lead and barium cultural relics

Cultural relic number	Type	Cluster type	Surface weathering	Sampling point of cultural relics	SiO_2	K_2O	CaO	Al_2O_3	Fe_2O_3
10	High potassium	The first kind	Weathered	10	96.77	0.92	0.21	0.81	0.26
12	High potassium	The first kind	Weathered	12	94.29	1.01	0.72	1.46	0
14	High potassium	The second kind	Unweathered	14	62.47	12.28	8.23	9.23	0.5
16	High potassium	The second kind	Uneathered	16	65.18	14.52	8.27	6.18	0.42

The prediction results of the model are shown in Table 16.

Table 16 Model prediction results Table

Prediction Results Y	The first probability of prediction results	The second probability of prediction results	SiO2	Na2O	CaO	Al2O3	PbO	P2O5	SrO
The second	0	1	55.61	2.31	0.63	1.9	27.9	0.19	0.2
The first	1	0	24.79	0	1.44	0.7	27.03	3.13	0.45
The second	0	1	60.91	0	0.38	1.44	26.05	0.42	0
The second	0	1	55.12	0	0.89	2.72	20.24	1.46	0.31
The second	0	1	50.21	0	0	4.79	28.25	0.2	0.43

After two comparisons, the subclasses of the same cultural relics remained unchanged before and after modifying the chemical composition content, indicating the stability of the model.

5. Conclusion

In order to solve the problem that ancient glass would be weathered by environmental influence during burial and its chemical elements would change accordingly, this paper analyzed the relationship between the types of glass relics and their chemical components based on chi-square test and Spearman correlation coefficient analysis, and obtained the corresponding relationship.Then, decision tree and random forest algorithm are used to classify and predict the glass relics, and the classification and prediction results are given.

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