Composition Analysis and Identification of Ancient Glass Products

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Abstract. Based on the research on the rules of the classification of the two kinds of glass as the goal, take glass types as the dependent variable, the chemical composition content is the independent variable, and establish a model of decision tree classification, is based on chemical component content of glass type classification rule, then to analyze the chemical composition of each category, according to the laws of the elbow to calculate the clustering analysis, the optimal class number of k, the K-means clustering algorithm was used to subclassify the glass into K classes and quantify the types. The type was taken as the dependent variable, and the content of each chemical component was taken as the independent variable for decision tree classification. The sub-classification results based on the content of each chemical component and the chemical variables with significant effect on the sub-classification results were obtained. Perturbation was introduced to the chemical variables that had a significant effect on the subclassification results, and the subclassification changes after perturbation were studied to verify the sensitivity of the classification results. The results showed that the accuracy and sensitivity of the model were good.

Keywords: Ancient glass products, K-mean, factor analysis, sensitivity analysis.

1. Introduction

The history of glass development in China has been more than 2,000 years, and the Silk Road has closely linked the social economy and culture of different countries. In the composition detection of unearthed glass cultural relics, although the appearance of Chinese glass and foreign glass is similar, there is a big gap in composition. This paper divides the glass into high potassium glass and lead barium glass. However, ancient glass is easily weathered, which leads to changes in its composition. History is happening anytime and anywhere, and it is constantly passing, and historical relics and materials will help it to be truly preserved. Therefore, it is of great significance to study the protection of historical relics and reveal the law of human society development. In this paper, the classification rules of the two kinds of glass were analyzed according to the data, and the appropriate chemical composition was selected for each category to classify the sub-categories, and the specific classification method and results were given [1].

2. Classification rules of high potassium, lead and barium glasses

In this paper, the type of glass is quantified: high potassium glass is set to 0, and lead-barium glass is set to 1. Type as the dependent variable, the various chemical compositions of the two kinds of glass as the independent variables, the data as the training data in table 2 in attachment, the training model of decision tree classification, decision tree structure, in order to get high potassium, lead, barium glass for analysis in the classification of the basis, through the training set data a decision classification model, get the decision tree structure is shown in figure 1 [2].

Gini: Information gain.

Samples: Sample statistics.

Value: Type of classification.

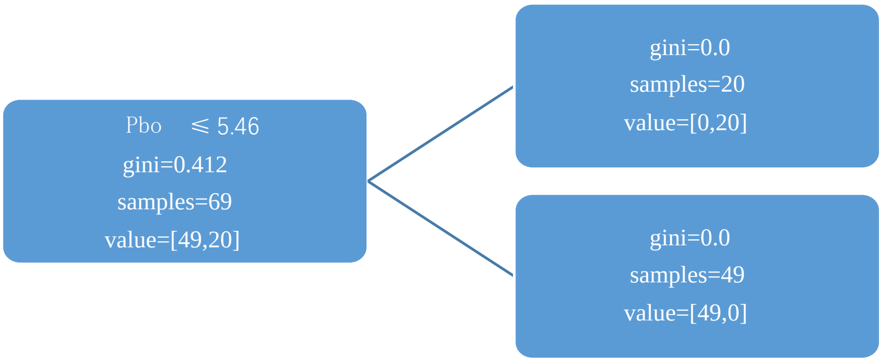

Figure 1. Decision tree structure

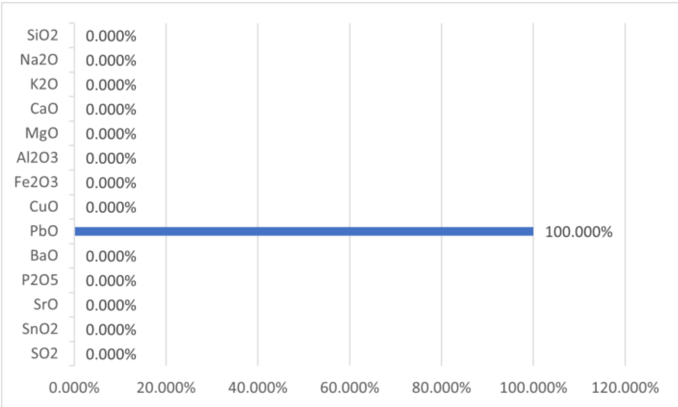

Figure 2. Schematic diagram of PbO content

Figure 2 shows that only one chemical component of lead oxide needs to be analyzed to classify the type of glass [3]. If the content of lead oxide is less than 5.46, it is high potassium glass. If the content of lead oxide is greater than 5.46, it is lead-barium glass.

3. Subclass division model

3.1. Calculation of clustering results based on the elbow rule

Eldow method: The calculation principle of Eldow method is the cost function, which is the sum of the distortion degree of each class. The distortion degree of each class is equal to the sum of the square distance between each variable point and its class center (the more compact the members of the class are, the smaller the distortion degree of the class is and the more dispersed they are) [4].

The calculation formula is as follows:

$$\sum_{i=0}^{n} min_{\mu_{i\epsilon C}}(||x_i - \mu_j||^2) \tag{1}$$

The results of the high potassium glass calculation are shown in Figure 3.

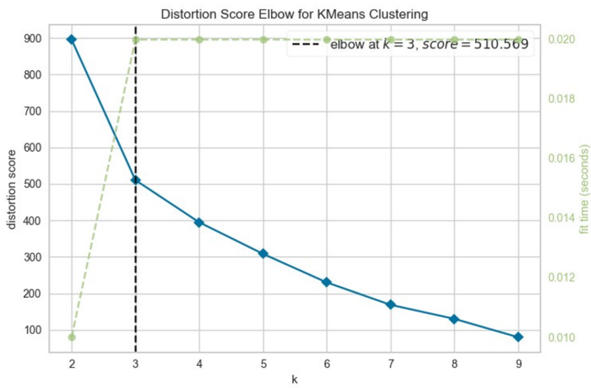

Figure 3. Calculation results of high potassium glass

As shown in Figure 3, it can be found that at the beginning, with the increase of K value, the distance within the cluster begins to decrease sharply. When K value is greater than 3, the distance reduction within the cluster begins to decrease significantly. At this time, this point is the point where the image slope changes most, and the optimal number of clusters for high-potassium glass is 3 [5].

For lead-barium glass, as shown in Figure 4, at the beginning, the distance within the cluster begins to decrease sharply with the increase of K value. When K value is greater than 5, the reduction of distance within the cluster begins to decrease significantly, and this point is the point where the image slope changes most [6], so that the optimal number of clusters for high-potassium glass is 5.

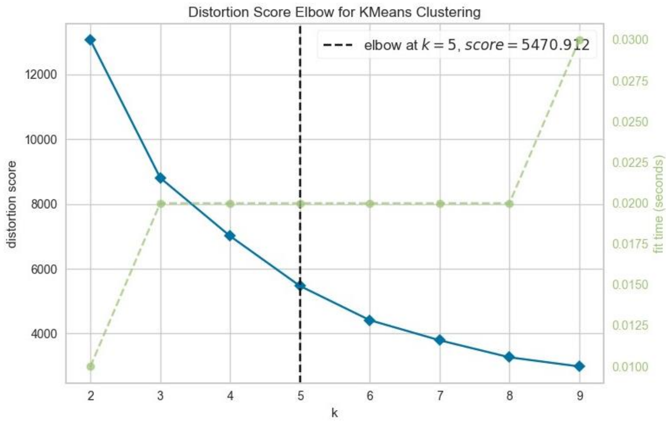

Figure 4. Calculation results of lead-barium glass

3.2. Results of K-means clustering algorithm

The results of cluster analysis of high potassium glass with cluster type 3 by K-means algorithm are shown in Table 1 [7].

Table 1. K-means algorithm clustering results for high potassium glass

type	High in potassium	High in potassium	High in potassium	High in potassium	High in potassium	High in potassium
SiO2	79.46	76.68	69.33	61.71	87.05	92.63
Na2O	0	0	0	0	0	0
K2O	9.42	0	9.99	12.37	5.19	0
CaO	0	4.71	6.32	5.87	2.01	1.07
MgO	1.53	1.22	0.87	1.11	0	0
Al2O3	3.05	6.19	3.93	5.5	4.06	1.98
Fe2O3	0	2.37	1.74	2.16	0	0.17
CuO	0	3.28	3.87	5.09	0.78	3.24
PbO	0	1	0	1.41	0.25	0
BaO	0	1.97	0	2.86	0	0
P2O5	1.36	1.1	1.17	0.7	0.66	0.61
SrO	0.07	0	0	0.1	0	0
SnO2	2.36	0	0	0	0	0
SO2	0	0	0.39	0	0	0
classification	0	0	1	1	2	2

The results of cluster analysis of lead-barium glass with cluster type 5 by K-means algorithm are shown in Table 2.

Table 2. K-means algorithm clustering results for lead-barium glass

type	Lead barium	Lead barium	Lead barium	Lead barium	Lead barium
SiO2	37.36	20.14	63.66	30.39	17.11
Na2O	0	0	3.04	0	0
K2O	0.71	0	0.11	0.34	0
CaO	0	1.48	0.78	3.49	0
MgO	0	0	1.14	0.79	1.11
Al2O3	5.45	1.34	6.06	3.52	3.65
Fe2O3	1.51	0	0	0.86	0
CuO	4.78	10.41	0.54	3.13	1.34
PbO	9.3	28.68	13.66	39.35	58.46
BaO	23.55	31.23	8.99	7.66	0
P2O5	5.75	3.59	0	8.99	14.13
SrO	0	0.37	0.27	0.24	1.12
SnO2	0	0	0	0	0
SO2	0	2.58	0	0	0
classification	0	1	2	3	4

The visual analysis of classification results is shown in Figure 5.

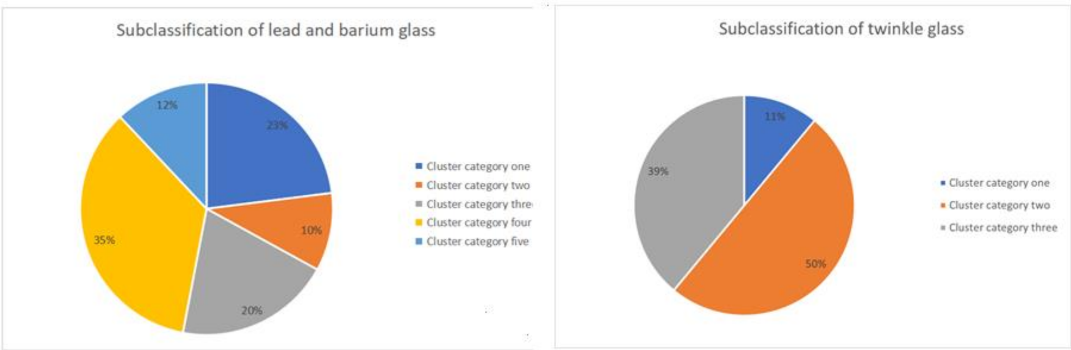

Figure 5. Result of subclass division

The data after clustering of the two types of glasses were used as the training set, and the decision tree classification model was trained. The decision tree structure was the basis for the sub-classification of high-potassium glass and lead-barium glass. The decision tree structure of the high potassium glass subclassification is shown in Figure 6.

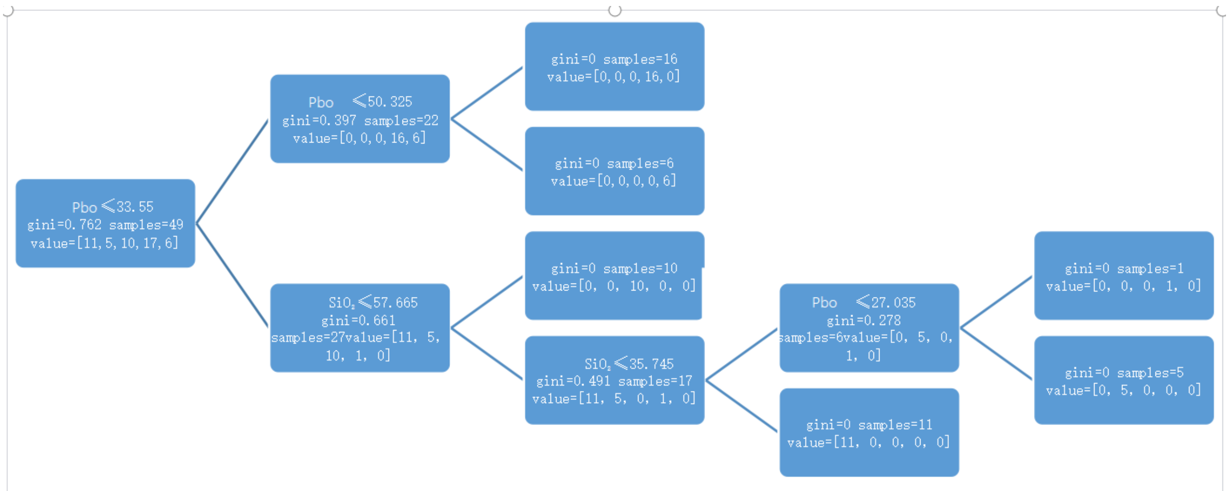

Figure 6. Decision tree structure of high potassium glass subclassification

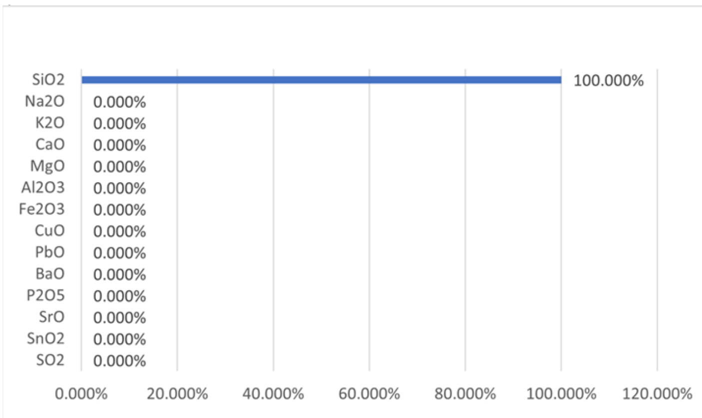

Figure 7. SiO_2 content map

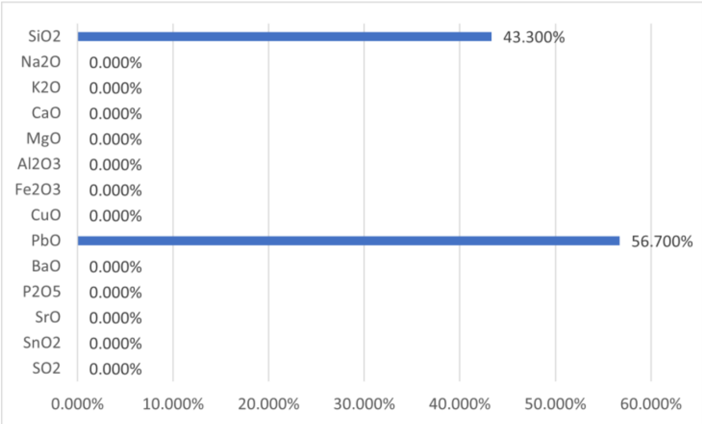

Figure 8. SiO_2 and PbO content map

The content of SiO2 is shown in Figure 7, and the content of SiO2 and PbO is shown in Figure 8. According to Figure 6-8, only the content of silica affects the sub-classification category of high-potassium glass: when the content of silica in the glass is less than 73.005, it is the sub-classification category 0; When the component content of glass silica was less than 89.7, it was classified as subclassification category 1. When the content of lead oxide in the glass is greater than 27.055 and less than 33.55, and the content of silica is greater than or equal to 35.475 and less than or equal to 57.665, it is the subclassification category 0; When the content of lead oxide in glass is between 27.035 and 33.55 and the content of silica is less than 35.475, it is classified as subclassification class 1; When the content of lead oxide in glass was less than 33.55 and the content of silica was more than 57.665, it was classified as subclassification class 2. When the content of lead oxide in glass was between 33.55 and 50.325, it was classified as subclassification class 3. Otherwise the subclassification category is 4 [8].

4. Sensitivity analysis

For high potassium glass, silica content plays a major role in the sub-classification of high potassium glass. If the classification result is not changed, the sensitivity of the model is poor by introducing 20%, -10%, 10% and 20% perturbation factors for silica content. If the classification results change, the sensitivity of the model is better [9].

For lead-barium glass, silica content and lead oxide content play a major role in the subclassification of lead-barium glass, and the perturbation factors of -20%, -10%, 10% and 20% are introduced to silica content and lead oxide, respectively. If the classification results are not changed, the sensitivity of the model for this component is poor. If the classification results change, the model is more sensitive for this component [10].

5. Conclusion

Based on the research on the rules of the classification of the two kinds of glass as the goal, take glass types as the dependent variable, the chemical composition content is the independent variable, and establish a model of decision tree classification, is based on chemical component content of glass type classification rule, then to analyze the chemical composition of each category, according to the laws of the elbow to calculate the clustering analysis, the optimal class number of k. The K-means clustering algorithm was used to subclassify glass into K classes and quantify the types. The elbow algorithm was used to calculate the optimal type of clustering to improve the accuracy of the clustering algorithm. The sub-classification results based on the content of each chemical component and the chemical variables with significant effect on the sub-classification results were obtained. Perturbation was introduced to the chemical variables that had a significant effect on the subclassification results, and the subclassification changes after perturbation were studied to verify the sensitivity of the classification results. The results showed that the accuracy and sensitivity of the model were good.

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