

Based on BP neural network glass cultural relics chemical category and composition prediction model construction

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Abstract. The classification and prediction of chemical composition of glass cultural relics plays an important role in the study of cultural relics, and this paper obtains the chemical composition survey data of 58 groups of glass cultural relics, obtains the statistical law of the chemical composition content of glass cultural relics, and then builds a neural network prediction model of the chemical composition of glass cultural relics, and uses the chemical composition content of glass cultural relics as the training set and test set for building the prediction model. In this paper, the data is preprocessed and fed into the training set, so that the BP neural network model continues to learn, adjust the training parameters, and finally obtain the optimal prediction model. Comparing the predicted value with the real value shows that the BP neural network model has good accuracy. This experimental result verifies that the BP neural network combination model can effectively predict the category of glass cultural relics and predict the chemical content before and after differentiation, which provides an effective way for relevant departments in China to study the value of cultural relics.

Keywords: BP Neural Network, Predictive Model, Glass Artifacts, Chemical Content, Sigmoid Function.

1. Introduction

This paper studies the type and composition prediction of glass products, which has great application value and practical significance for exploring ancient glass cultural relics and identifying the categories of cultural relics in China. Ancient glass was affected by weathering, resulting in changes in the proportion of internal composition [1], which affected people's judgment on the type and chemical composition of excavated cultural relics glass. Therefore, based on the detection data of a batch of ancient glass products in China, this paper combines BP neural network to effectively predict the category and chemical composition of glass cultural relics [2-3]. Traditional forecasting methods are based on linear regression [4] and time series forecasting [5], and the analysis method has shortcomings.

2. Data processing of the chemical composition content of glass artifacts

2.1. Data cleaning

This paper cleanses the survey data of 58 groups of glass cultural relics. The data between 85%~105% of the component ratio and the total component ratio were regarded as valid data, so the analysis and summation data excluded the invalid data with a total component of less than 85%, and the valid data were preprocessed.

2.2. Analysis of glass artifacts based on the Wrenwhitney test

Table 1. Separate sample Mannwhitney test for glass composition and glass type analysis table

variable name	Variation	sample	median	standard deviation	statistics	P	median value difference	Cohen's d-value
silica (SiO ₂)	lead barium	40	36.82	17.998	42	0.000***	38.71	2.119
	high potassium	16	75.53	14.189				
	total	56	53.56	23.557				
Calcium Oxide (CaO)	lead barium	40	1.325	1.459	213	0.052*	3	1.035
	high potassium	16	4.325	3.296				
	total	56	1.63	2.342				
sodium oxide (Na ₂ O)	lead barium	40	0	1.811	361.5	0.345	0	0.269
	high potassium	16	0	1.145				
	total	56	0	1.651				
Aluminum oxide (Al ₂ O ₃)	lead barium	40	2.923	3.216	233	0.115	1.432	0.318
	high potassium	16	4.355	2.907				
	total	56	3.085	3.137				
Copper oxide (CuO)	lead barium	40	0.78	2.098	225	0.085*	1.135	0.199
	high potassium	16	1.915	1.362				
	total	56	0.988	1.913				
lead oxide (PbO)	lead barium	40	30.145	15.218	640	0.000***	30.145	2.481
	high potassium	16	0	0.482				
	total	56	20.38	19.451				
strontium oxide (SrO)	lead barium	40	0.305	0.246	566.5	0.000***	0.305	1.462
	high potassium	16	0	0.04				
	total	56	0.22	0.251				
potassium oxide (K ₂ O)	lead barium	40	0.145	0.292	103.5	0.000***	8.008	2.073
	high potassium	16	8.152	5.449				
	total	56	0.24	3.947				
magnesium oxide (MgO)	lead barium	40	0.6	0.649	276.5	0.416	0.05	0.236
	high potassium	16	0.65	0.674				
	total	56	0.625	0.654				
iron oxide (Fe ₂ O ₃)	lead barium	40	0.26	0.935	195	0.021**	0.2	0.611
	high potassium	16	0.46	1.29				
	total	56	0.325	1.076				

barium oxide (BaO)	lead barium	40	8.965	7.235	629.5	0.000***	8.965	1.592
	high potassium	16	0	0.864				
	total	56	6.67	7.573				
tin oxide (SnO2)	lead barium	40	0	0.228	330	0.714	0	0.237
	high potassium	16	0	0.59				
	total	56	0	0.365				
sulfur dioxide (SO2)	lead barium	40	0	2.023	288.5	0.287	0	0.267
	high potassium	16	0	0.165				
	total	56	0	1.719				
Phosphorus pentoxide (P2O5)	lead barium	40	1.13	3.639	391	0.197	0.485	0.683
	high potassium	16	0.645	1.039				
	total	56	0.865	3.262				

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

As shown in Table 1, by exploring the classification of glass with high potassium versus lead barium based on its chemical composition, this paper concludes that the content of lead oxide and barium oxide in lead barium glass is significantly higher than that of high potassium glass, and the content of potassium oxide in high potassium glass is significantly higher than that of lead barium glass, which paves the way for the improvement of data and the following.

2.3. Refine the data with a predictive model based on the mean square difference value

The chemical composition of different types of glass products before weathering is a_{ij} , which represents the chemical composition of the sampling point of the cultural relic j in the i -th test.

$$A_i = \frac{1}{n} \sum_{i=1}^{i=n} a_{ij} \tag{1}$$

It shows the average chemical content of high potassium glass and lead barium glass before weathering

Similarly, the chemical composition of different types of glass products after weathering is b_{ij} , which represents the chemical composition of the j -th cultural relic sampling site in the i -th test.

$$B_j = \frac{1}{n} \sum_{i=1}^{i=n} b_{ij} \tag{2}$$

It shows the average chemical content of high potassium glass and lead collar glass, respectively. This can be obtained by comparing the chemical composition of each sampling point:

$$C_j = \frac{(A_j - B_j)}{B_j} * 100\% \tag{3}$$

$C_{j=1.....m}$ (m means there are m chemical components, $j=1.....14$)

Through data processing, the change law and C_j value of high potassium glass and lead barium glass before and after the change were obtained, and the data before weathering could be predicted according to the weathered data, and the information data was further improved.

3. Fundamentals of BP neural networks

3.1. The structure of BP neural network

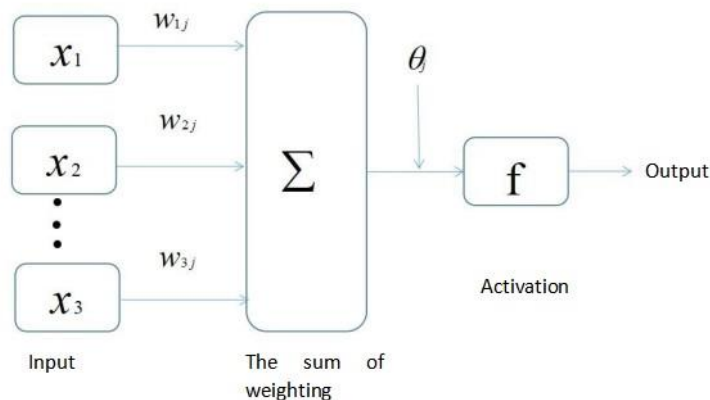


Figure 1. Basic schematic of a BP neural network

BP neural network is a multi-layer feedforward neural network trained according to the error reverse propagation algorithm. It is widely used because of its advantages of high classification accuracy, strong distribution processing ability, strong distributed storage and learning ability, full approximation of complex nonlinear relationships, and associative memory function.

BP neural network consists of three parts: input layer, hidden layer and output layer. Its essence is to train a multilayer feedforward network with backpropagation according to error, and uses gradient exploration technology to minimize the mean square error between the actual output value of the network and the expected output value.

As shown in Figure 1, it can be seen that the BP neural network reflects the function mapping relationship from X to Y, which is a nonlinear function, and there are many factors that affect the prediction, and there is a nonlinear relationship between the data series of the chemical composition content of glass cultural relics [6], so the use of BP neural network to predict the chemical composition content of glass cultural relics has good applicability [7].

3.2. The training process of the BP neural network

(1) In this paper, the activation function of the BP neural network model is used as the Sigmoid function, and the specific formula is as follows:

$$\text{Sigmoid}(z) = \frac{1}{1+e^{-z}} \quad (4)$$

(2) The process of forward propagation, that is, entering variables into the input layer in the BP neural network, and finally outputting the results in the output layer [8]. First, the data is passed to the input layer and transmitted to the hidden layer, and the hidden layer initializes the weight and bias of the data for linear change, and then nonlinear processing through the Sigmoid function to obtain the output result of the hidden layer, and finally linear processing in the output layer to obtain the prediction result [9], the formula is as follows:

Hidden layer output H_j

$$H_j = \text{Sigmoid}(\sum_{i=1}^n W_{ij}x_i + a_j) \quad (5)$$

The output layer outputs O_k the predicted data values:

$$O_k = \sum_{j=1}^l H_j W_{jk} + b_k \quad (6)$$

(3) Backpropagation, that is, the neural network updates the weights through backpropagation so that the predicted value is closer to the true value. The gradient descent method is used to weight the

degree of influence on the error, and then update the weight. Error E represents the difference between the true value and the predicted value result, and the formula is:

$$E = \frac{1}{2} \sum_{k=1}^m (Y_k - O_k)^2 \tag{7}$$

To minimize the error function, minE, update the weight formula using gradient descent as follows:

$$W = W_{ij} - \eta \frac{\partial E}{\partial W_{ij}} \tag{8}$$

where η represents the learning rate and W_{ij} represents the link weight between the upper layer i neurons to the next layer of j neurons.

3.3. Experimental process of BP neural network

In this paper, the BP neural network combination model is used to predict the category and chemical content of glass cultural relics [10], as shown in Figure 2, and part of the glass cultural relics content data is used as a training set to learn and train the BP neural network model. The parameters of the BP neural network model are set to: BP training function of gradient descent, the training number is 1000 times, the learning rate is 0.01, and the minimum error of the training target is 0.00001. Through repeated training, when the hidden layer node is 10, the error is small, which is suitable for model training.

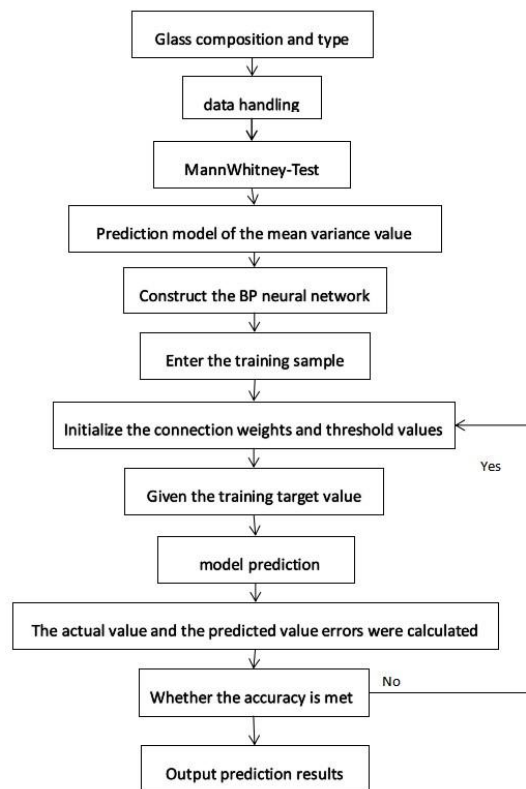


Figure 2. Neural network prediction flowchart

4. Results

4.1. Artifact category prediction results

In order to facilitate the identification of glass types, this paper uses high potassium glass as 1 and lead barium glass as 0. Predictions made by the Sigmoid function [10] allow predictions of cultural relics categories through BP neural networks, and some of the results are shown in Table 2.

Table 2. Prediction results for cultural relics categories

Relic number	Predicted value	Classify	silicon dioxide(SiO ₂)	Sodium oxide(Na ₂ O)	...	Tin oxide(SnO ₂)	Sulfur dioxide(SO ₂)
A1	1	High potassium	78.45	0	...	0	0.51
A2	0	Lead barium	37.75	0	...	0	0
A3	0	Lead barium	31.95	0	...	0	0
A4	0	Lead barium	35.47	0	...	0	0
A5	0	Lead barium	64.29	1.2	...	0.49	0
A6	1	High potassium	93.17	0	...	0	0
A7	1	High potassium	90.83	0	...	0	0.11
A8	0	Lead barium	51.12	0	...	0	2.26

4.2. Prediction results of chemical composition content before and after weathering of cultural relics

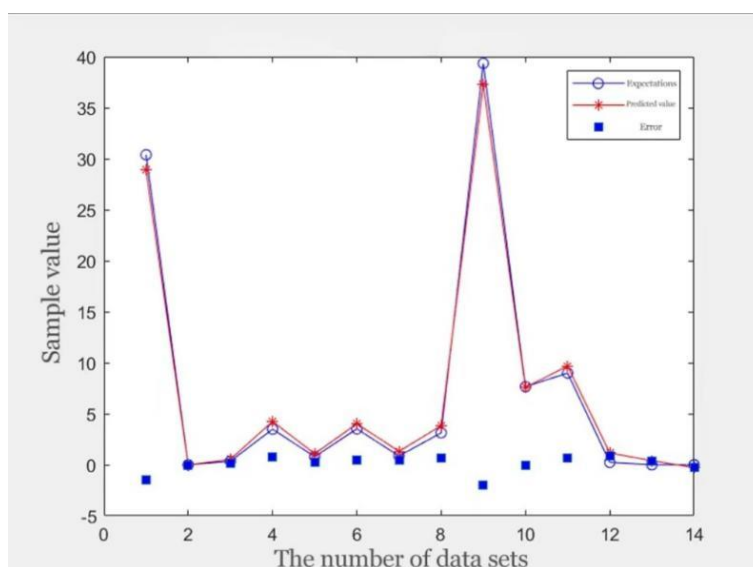


Figure 3. Comparison of predicted and actual values of cultural relics after weathering

As shown in Figure 3, it can be seen that the data before and after the weathering of cultural relics based on the BP neural network model is close to the real value. By testing the model, the average absolute error MAE between the true value and the predicted value is 0.62645, the mean square error MSE is 0.67938, and the rmse is 0.82425.

In summary, it can be concluded that the BP neural network model is used to predict the classification of glass cultural relics and the chemical composition content before and after weathering, so the BP neural network model can be used to predict the chemical composition content before and after the classification of cultural relics and weathering.

5. Conclusions

(1) When the traditional model is used to fit the chemical composition data series of glass cultural relics, some of the results have a large fitting error, so in order to solve the data fluctuation caused by external uncertain factors, the BP neural network is used to adjust the neural nodes, and finally obtain a more accurate prediction value of the chemical composition of glass cultural relics.

(2) The training and learning ability of BP neural network effectively avoids the defect of inaccurate prediction of the chemical composition content of glass cultural relics by external environmental factors, and solves the situation that the traditional prediction model is more accurate in the short term but cannot make long-term accurate prediction. It provides an effective way for the identification of glass cultural relics in China and the prediction of content before and after weathering.

(3) The BP neural network model proposed in this paper, after continuous optimization and training learning, makes the parameters optimal, and makes the simulation training results very close to the actual value, and finally controls the error rate well and ensures the effectiveness of the model. The BP neural network model solves the fluctuating influence of external environmental factors on the content of chemical composition of glass cultural relics, brings new ideas for the identification and weathering content prediction of glass cultural relics in China, and provides a reference basis for the prediction of the identification direction of cultural relics in China to a certain extent.

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