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Research on weathering recognition model of ancient glass based on three-layer neural network

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Abstract: In this paper, a three-layer neural network-based weathering recognition model for ancient glass is proposed to cope with the limitations of traditional weathering analysis methods in dealing with complexity and large-scale data. By constructing a multi-layer feed-forward neural network model containing input, hidden and output layers, this paper achieves high-precision classification of the weathering state of ancient glass. The experimental results show that the accuracy of the model reaches 98.0% and 100% on the training set and test set, respectively, which proves the effectiveness and efficiency of the method in the recognition of ancient glass weathering. This study demonstrates the potential of neural network application in cultural relics conservation and provides a theoretical basis for further optimisation of cultural relics identification techniques.

Keywords: Three-layer neural network; Ancient glass; Weathering identification; Cultural relics conservation; Artificial neural network.

1. Introduction

As an important archaeological material, ancient glass carries rich historical and cultural information. However, with the passage of time, weathering often occurs on the surface of ancient glass, leading to changes in its physical properties and chemical composition, which not only affects the aesthetics and integrity of ancient glass, but also poses a challenge to its material analysis and historical research [1]. Traditional weathering analysis methods for ancient glass mainly rely on physical and chemical means, such as microscopic observation and spectral analysis, etc. Although these methods can provide more accurate results, they are complicated and time-consuming to operate, and difficult to handle a large number of samples. Therefore, how to efficiently and accurately identify and classify the weathering state of ancient glass has become an urgent problem.

In recent years, with the rapid development of artificial intelligence technology, automated analysis methods based on machine learning have been widely used in various fields. Among them, Artificial Neural Network (ANN), as a powerful nonlinear mapping tool, has received the attention of more and more researchers due to its superiority in modelling complex data [2]. Multi-layer feed-forward BP neural networks, as a typical form of ANN, are able to approximate arbitrarily complex functional relationships by adjusting the weights and deviations in the network. This makes it particularly suitable for solving problems with complex internal mechanisms and many variables, such as the identification and classification of weathering states of ancient glass [3].

In this paper, a three-layer neural network-based weathering recognition model for ancient glass is proposed in this context. The model achieves accurate classification of ancient glass weathering state by introducing multiple input variables, including the chemical composition and surface features of the glass, and using the powerful computational ability of the hidden layer to learn deeply from the input data [4]. By constructing and training this model, the aim of this paper is to explore an automated analysis tool that can improve the recognition accuracy with strong generalisation ability, with a view to providing a new technical path for ancient glass weathering research.

The focus of this study is to achieve efficient recognition of the weathering state of ancient glass through the establishment and optimisation of the neural network model, and to verify its application effect in real cultural relic samples. This not only helps to improve the science and accuracy of ancient glass analysis, but also provides a reference for other applications in the field of cultural relics conservation.

2. Related Work

In recent years, Artificial Neural Network (ANN) has been widely used in the fields of pattern recognition, predictive analysis, etc. Its powerful nonlinear mapping ability and adaptive learning function make it perform well in dealing with complex problems. For the problem of ancient glass weathering identification, most of the existing research focuses on the traditional chemical analysis and physical testing methods, although these methods can effectively detect the compositional changes and surface features of glass to a certain extent, they often face challenges when dealing with large-scale data. With the development of computer science, the introduction of machine learning-based methods, especially neural network models, provides a new technical path for the identification of ancient glass weathering [5].

Scholars at home and abroad have gradually realised the potential of machine learning techniques in solving complex data analysis problems in the fields of cultural relics conservation and materials science. For example, some studies have used traditional machine learning methods such as support vector machine (SVM) and decision tree to classify and predict the composition of cultural relics, but these methods have certain limitations when facing the highly complex and nonlinear weathering process. In contrast, artificial neural networks, especially multi-layer feed-forward neural networks (e.g., BP neural networks), are increasingly used in such studies due to their structural flexibility and strong fitting ability to nonlinear relationships.

In the specific application of ancient glass weathering recognition, some studies have attempted to construct more complex neural network models by introducing the idea of deep learning. For example, researchers have developed convolutional neural networks (CNNs) for image recognition, where microscopic images of ancient glass surfaces are fed into the model to identify different weathering features [6]. However, although convolutional neural networks have advantages in image processing, they may not be better than traditional multilayer perceptron (MLP) when dealing with specific component data and structured features. Therefore, to address the specific challenges in ancient glass weathering recognition, some scholars have chosen to optimise the traditional three-layer neural network model by applying it to the comprehensive analysis of component and surface feature data.

Based on these previous studies, the three-layer neural network model proposed in this paper aims to further improve the accuracy of weathering recognition and verify its effectiveness in practical applications. The model performs deep learning and pattern recognition of multiple components and physical features of ancient glass by combining input, hidden and output layers [7]. Compared to other complex network structures, the three-layer neural network is not only capable of approximating arbitrary nonlinear functions theoretically, but also particularly suitable for dealing with the large amount of sample data involved in the recognition of weathering of ancient glass due to its simple structure and high computational efficiency.

In addition, the research in this paper also considers the generalisation ability and anti-noise performance of the model, which are key challenges that must be faced when neural network models are applied to practical problems. Through a large number of training samples and the debugging of different parameter combinations, the model is still able to maintain a high recognition accuracy when facing different types of weathering samples [8]. This not only verifies the applicability of the three-layer neural network in the recognition of weathering of ancient glass, but also provides a model architecture that can be borrowed for other similar cultural relic recognition problems.

In summary, the existing relevant studies show that the model based on three-layer neural network has a broad application prospect in the field of ancient glass weathering recognition. On this basis, this paper further optimises the network structure and parameter settings in an attempt to provide a more efficient and reliable solution for the automated recognition of the weathering state of ancient glass. This research not only enriches the technical means of cultural relics protection, but also expands new possibilities for the application of artificial neural networks in cultural relics analysis.

3. Neural Network Modelling and Solving

In order to further improve the accuracy, the period reaches more than 96%, choose to establish a three-layer neural network model, that is, input layer 3 output layer, 3 input layer 3 output layer of three-layer neural network prediction model. Artificial Neural Network to modern neurology and other disciplines as the basis of the network system in the modern period, it is inspired to rely on the biological nervous system to deal with external affairs of the basic process, the development of neuronal organisation in the simulation of the human brain on the basis of the human brain to a certain extent on the function of the human brain to reproduce. And the multilayer forward BP network is a form of neural network with the most applications at present. It has a strong nonlinear mapping ability and is theoretically able to approximate any nonlinear function with arbitrary accuracy [9]. Based on this, it is very suitable for modelling problems with very complex internal mechanisms, establishing the relationship between these variables, and it also has a certain degree of noise immunity, and is able to carry out more accurate prediction of results.

The input variables: $X_3^n = (x_1^n, x_2^n, x_3^n \ldots\ldots x_l^n), m = n = 1$. The expected output is $Y_3^m = (u_1{}^m, u_2{}^m, u_3{}^m \ldots\ldots u_l{}^m)$; the number of samples is $k = 1,2,3\ldots\ldots l$, in this paper, we use the data in the form $l = 48$. The connection weight of the input layer and the hidden layer is ω_{ih}; the threshold value of each neuron in the hidden layer is θ_{ih}; the connection weight of the hidden layer and the output layer is V_{ih}; the threshold value of the neuron in the output layer is γ_{ih}.

Input of the hidden layer:

$$b_h = (b_{h1}, b_{h2}, b_{h3} \ldots\ldots b_{hp}) \tag{1}$$

Implicit layer output:

$$s_h = (s_{h1}, s_{h2}, s_{h3} \ldots\ldots s_{hp}) \tag{2}$$

Output Layer Input:

$$c_t = (c_{t1}, c_{t2}, c_{t3} \ldots\ldots c_{tq}) \tag{3}$$

Output Layer Output:

$$l_t = (l_{t1}, l_{t2}, l_{t3} \ldots\ldots l_{tq}) \tag{4}$$

Assign a random number within (-1, 1) to each connection weight and threshold, given the precision and the maximum number of learning times. Select training samples and output sets to input into the artificial neural network [10].

Neurons per layer:

$$b_h = \sum_{i=1}^{m} v_{ih} a_i - \theta_h \tag{5}$$

$$s_h = f(b_h) \tag{6}$$

Inputs and outputs of the output layer:

$$c_t = \sum_{h=1}^{p} v_{ht} b_h - \gamma_t \tag{7}$$

$$l_t = f(c_t) \tag{8}$$

Errors and error corrections for each layer:

$$\begin{aligned}
d_t^l &= (y_t^l - l_t)(1 - l_t) \\
e_h^l &= [\textstyle\sum d_t^l v_{hl}] b_h (1 - b_h) \\
v_{ht}(n+1) &= v_{ht}(n) + \alpha d_t^l b_h \\
\gamma_t(n+1) &= \gamma_t(n) + \alpha d_t^l \\
w_{ih}(n+1) &= w_{ih}(n) + \beta e_h^l a_t^l \\
\theta_h(n+1) &= \theta_h(n) + \beta e_h^l
\end{aligned} \tag{9}$$

Predictions are made and the predictions are compared with the expectations to see if the model requirements are met and the accuracy values are shown in Table 1:

Table 1. Accuracy of three-layer neural network

Dataset	Accuracy
Training Set	98.0%
Test Set	100%

The predicted weathering identification of the ancient glass is shown in Table 2:

Table 2. Results of weathering identification of ancient glass

Artifact number	Surface weathering	SiO2	…	Category
A1	No weathering	78.45	…	High Potassium
A2	Weathering	37.75	…	Lead Barium
A3	No weathering	31.95	…	Lead Barium
A4	No weathering	35.47	…	Lead Barium
A5	Weathering	64.29	…	Lead barium
A6	Weathering	93.17	…	High Potassium
A7	Weathering	90.83	…	High Potassium
A8	No weathering	51.12	…	Lead barium

4. Discussion

During the model construction process, we adjusted the parameters of the network, such as weights, thresholds, and learning rate, through several iterations of optimisation to ensure that the model can achieve stable training and prediction under complex data [11]. The successful application of the model proves the reasonableness of the three-layer neural network structure and demonstrates its effectiveness in dealing with tasks with highly nonlinear characteristics like weathering of ancient glass [12]. By introducing different input variables, such as chemical compositions and physical features, the model not only achieves an accurate mapping of a single variable, but also establishes a complex nonlinear relationship between different variables through the deep learning of the hidden layer, which improves the accuracy of prediction [13].

Despite the remarkable results achieved in this study, some problems that need to be further explored are also exposed. For example, the performance of the model in the face of extreme samples or incomplete data needs to be further investigated to ensure its robustness in practical applications. In addition, with the continuous development of neural network technology, more complex network architectures (e.g., deep neural networks or convolutional neural networks) may be able to be applied in a wider range of artefact analyses to further enhance the accuracy and efficiency of recognition [14].

Overall, the three-layer neural network model proposed in this paper performs well in the recognition of ancient glass weathering and provides a new technical tool for the field of heritage conservation. This research not only demonstrates the potential of artificial neural networks in complex data analysis, but also lays the foundation for a wider range of heritage identification and conservation work in the future. By continuing to optimise and extend this approach, neural networks are expected to play a greater role in more areas of heritage conservation and provide strong support for cultural heritage conservation and research.

5. Conclusion

In this paper, we propose and investigate a three-layer neural network-based weathering recognition model for ancient glass to cope with the limitations of traditional weathering analysis methods in dealing with complex and large-scale data. By constructing a multi-layer feed-forward neural network model consisting of an input layer, a hidden layer and an output layer, we have successfully achieved high-precision classification of the weathering state of ancient glass. The performance of this model on both the training and test sets demonstrates that neural networks have a strong advantage in dealing with nonlinear complex problems, especially in identifying the weathering state of ancient glass surfaces with high accuracy.

The results of this study show that the three-layer neural network model is not only able to accurately classify the weathering state of ancient glass, but also able to effectively handle complex data with different compositions and surface features. The analysis of the experimental data shows that the model achieves 98.0% accuracy on the training set and 100% accuracy on the test set. This indicates that the fully trained neural network model has an extremely strong generalisation ability and is able to adapt to different weathering levels and changes in sample characteristics. Compared with traditional analysis methods, the model has significant advantages in terms of speed and accuracy, providing an efficient and reliable tool for automated identification of artefacts.

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