Prediction Application of MLP Feedforward Neural Network Based on SNNS Neural Network Platform

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Abstract. Background: Rural disaster prevention and mitigation publicity behavior plays an important role in villagers' natural disaster risk resistance, but related research has not been quantitatively studied due to the availability of data. Objective: To study the influence mechanism of rural disaster prevention and mitigation publicity behavior and villagers' natural disaster risk resistance ability through index quantification. Method: Based on R The studio calls the SNNS neural network platform and uses the MLP feedforward neural network to predict the relationship between the two. Conclusion: Rural disaster prevention and mitigation publicity behavior can effectively promote the improvement of villagers' natural disaster risk resistance ability.

Keywords: disaster prevention and mitigation · villagers' natural disaster risk resistance · SNNS · MLP neural network

1 Introduction

The focus of disaster prevention and mitigation is to avoid disasters, avoid disasters, and prevent disasters [1]. The planning of disaster prevention and mitigation before disasters is particularly important. Since 1998, the "People's Republic of China Disaster Reduction Plan (1998–2010)", "National Comprehensive Disaster Prevention and Reduction Plan (2011–2015)", "National Comprehensive Disaster Reduction "Eleventh Five-Year Plan", "National Comprehensive Disaster Prevention and Reduction Plan (2011–2015)" The Disaster Reduction Plan (2011–2015), the National Comprehensive Disaster Prevention and Reduction Plan (2016–2020), and the National Comprehensive Disaster Prevention and Reduction Plan of the 14th Five-Year Plan have been successively promulgated. The "14th Five-Year Plan" National Comprehensive Disaster Prevention and Reduction Plan puts forward higher-level ideas and measures for the establishment and improvement of the national comprehensive disaster prevention and reduction system. Therefore, it is necessary for the publicity of disaster prevention and mitigation in rural areas.

My country is one of the countries most seriously affected by natural disasters. The impact of natural disaster risks on rural areas will be further amplified, which will affect

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rural agricultural income levels. However, the level of natural disaster risk management in my country's rural areas is not very optimistic. Due to the systematic characteristics of natural disasters, the natural disaster risk management in rural areas is not only dependent on itself, but also closely related to the development of natural disaster risk management systems and markets. Measuring the substantial impact of natural disasters on rural areas also has reference significance for the policy formulation of commercial insurance companies and relevant government departments.

2 Indicator Design and Method

The index system method is to select appropriate indexes according to the characteristics of the research area and natural disasters to construct an index system, and then use certain mathematical analysis methods to obtain a natural disaster risk resistance index representing the size of the natural disaster risk resistance. The steps are generally divided into constructing indexes. System, Normalization, Weighting and Aggregation. The method is applicable to a wide range, from large-scale international plans to small-scale village natural disaster risk resilience research [2]. A reasonable index system is the basis for accurately measuring natural disaster risk resilience, and the selection of indicators can be obtained by induction or deduction. At present, scholars have carried out unilateral or comprehensive measures of natural disaster risk resilience in the physical, social, economic, infrastructure, system, risk perception and other dimensions of natural disasters by building an index system. The disaster risk resilience index is mainly constructed through addition and subtraction and multiplication and division. Different natural disaster risk resilience index calculation methods lead to differences in results, and multiplication is more effective than addition and subtraction to reflect the synergistic relationship between the indicators [3]. The index system method is simple to operate, and the most important thing is the weighting of each index. The commonly used weighting methods for index weights include expert scoring method, entropy weight method, AHP, principal component analysis, multi-criteria analysis, random forest, etc. The biggest problem of the indicator system method is standardization. There is a lack of explanations for the rationality and necessity of the selected index factors. The problem that the weight is affected by human factors is the bottleneck in the practical application of the current research on natural disaster risk resilience [4].

Due to the availability of data, the relevant data for rural disaster prevention and mitigation propaganda work in this paper is based on a survey of an administrative village in Hubei Province. The ability to resist natural disaster risks is also obtained through research.

The specific network structure of MLPM is shown in Fig. 1 below.

Because the three-layer neural network can approach any nonlinear function, we choose the three-layer neural network model to construct. The steps are as follows:

① The hidden layer S-type activation function $g(x)$ takes the Sigmoid function in the form of:

$$g(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

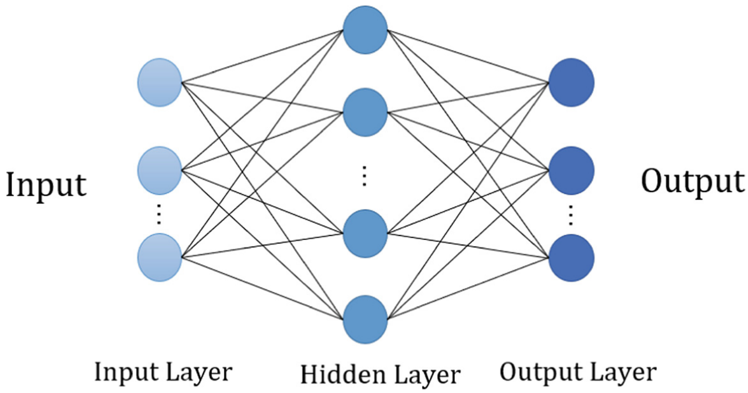

Fig. 1. Multilayer feedforward network

② The output H_j of the hidden layer is:

$$H_j = g\left(\sum_{i=1}^{n} \omega_{ij} x_i + a_j\right), i = 1, \cdots, n \tag{2}$$

Among them, the number of nodes in the input layer is n, ω_{ij} is the connection weight from the input layer node i to the hidden layer node j, a_j is the offset from the input layer to the hidden layer, X_i is the output value of the input layer node i, and $g(x)$ is the excitation function.

③ The output of the output layer O_k is:

$$O_k = \sum_{j=1}^{l} H_j \omega_{jk} + b_k, j = 1, \cdots, l \tag{3}$$

The output of the hidden layer is H_j, the number of nodes in the hidden layer is l, the weight from the hidden layer to the output layer is ω_{jk}, and the offset from the hidden layer to the output layer is b_k.

④ The global network prediction error function used to propagate errors through the network:

$$E = \frac{1}{2}\sum_{k=1}^{m} (Y_k - O_k)^2, \ k = 1, \ \cdots, \ m \tag{4}$$

In this formula, E is the global network prediction error, Y_k is the expected output, O_k is the actual output of the network, and m is the number of nodes in the output layer. The steepest descent method is used to minimize the objective function, that is, the weights and thresholds of each part of the system are changed proportionally by calculating the derivative of the error to the weight.

Next, this article introduces the RSNNS environment and MLP functions configured in this article. The Stuttgart Neural Network Simulator (SNNS) is a library containing many standard implementations of neural networks. This package wraps the SNNS functionality to make it available from within R. This function creates a multilayer perceptron (MLP) and trains it. MLPs are fully connected feed-forward networks, and probably the most common network architecture in use. Training is usually performed by error backpropagation or a related procedure [5].

3 Results

In this paper, the predicted results are compared with the actual results, and the correlation test between the predicted time series data and the original time series data is carried out, and the following results are obtained (Table 1).

Table 1. Summary table of results

Project	Disaster Prevention and Mitigation Publicity Behavior	Natural disaster risk resilience	Post-prediction natural disaster risk resilience
Disaster Prevention and Mitigation Publicity Behavior			
Pearson correlation coefficient	1	0.98***	0.97***
Significance (two-tailed test)		0	0
Number of samples N	31	31	31
natural disaster risk resilience			
Pearson correlation coefficient	0.98***	1	0.99***
Significance (two-tailed test)	0		0
Number of samples N	31	31	31
Post-prediction natural disaster risk resilience			
Pearson correlation coefficient	0.97***	0.99***	1
Significance (two-tailed test)	0	0	
Number of samples N	31	31	31

4 Conclusion and Discussion

This paper uses R studio Invoke the S NNS neural network platform and use the M LP feedforward neural network to perform predictive analysis on the relevant data obtained by the survey. The conclusion is drawn that the publicity behavior of rural disaster prevention and mitigation plays an important role in the villagers' natural disaster risk resistance ability. The suggestions are: follow-up should strengthen the publicity of disaster prevention and mitigation in rural areas to improve the villagers' ability to resist natural disaster risks.

References

1. Zhou, Bang, Yueguan Yan, Huayang Dai, Jianrong Kang, Xinyu Xie, and Zhimiao Pei. 2022. "Mining Subsidence Prediction Model and Parameters Inversion in Mountainous Areas" Sustainability 14, no. 15: 9445. https://doi.org/10.3390/su14159445
2. Perales Gómez, Ángel Luis, Lorenzo Fernández Maimó, Alberto Huertas Celdrán, and Félix J. García Clemente. 2020. "MADICS: A Methodology for Anomaly Detection in Industrial Control Systems" Symmetry 12, no. 10: 1583. https://doi.org/10.3390/sym12101583
3. Haque, C. Emdad, M. Abul Kalam Azad, and Mahed-Ul-Islam Choudhury. 2019. "Discourse of Flood Management Approaches and Policies in Bangladesh: Mapping the Changes, Drivers, and Actors" Water 11, no. 12: 2654. https://doi.org/10.3390/w11122654
4. Lin, Yu-Pin. 2014. "Environments: A New Cutting-Edge International and Interdisciplinary Scholarly Open Access Journal" Environments 1, no. 1: 1-3. https://doi.org/10.3390/environments1010001
5. Bergmeir, C. and Benítez, JM (2012), Neural Networks in R Using the Stuttgart Neural Network Simulator: RSNNS. Journal of Statistical Software, 46(7), 1-26.