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Post-earthquake Emergency Supplies Prediction Based on BP Neural Network

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Abstract: The prediction of earthquake casualty population is a typical complex prediction system, which needs to comprehensively consider a variety of factors such as the earthquake damage itself, the population distribution in the affected area and its environment. Aiming at the prediction of emergency supplies in earthquake disasters, this paper collects historical earthquake data, including key factors such as magnitude, depth of epicenter, population density of the affected area, constructs the input layer of BP neural network, and utilizes the self-learning ability of the network for training to realize the prediction of the number of people injured in an earthquake, which in turn indirectly predicts the demand for emergency supplies. The experimental results show that the prediction model of the number of earthquake injuries based on BP neural network has excellent performance in prediction accuracy, and the operational coefficient of determination of the model R^2 reaches 0.93337, which indicates that the prediction results of the model have ahigh degree of correlation and accuracy with the actual values, and it is able to provide a more accurate and reliable reference for the rescue work of the emergency supplies after the earthquake.

Keywords: Bp neural network, Casualty prediction, Emergency supplies, Earthquake disaster.

1. Introduction

China, as a country located at the intersection of the Pacific Rim seismic belt and the Eurasian seismic belt, is prone to frequent earthquakes as a result of the frequent extrusion of the crustal plates. Earthquakes are one of the most serious natural disasters that China faces, and given the country's vast size, large population and dense urban distribution, the destructive power of a large-scale earthquake would be incalculable, with the potential to cause a large number of deaths and injuries as well as irreversible damage to property. Since the beginning of 2000 to 2023, just more than twenty years, China and its neighboring regions have experienced more than a hundred earthquakes of magnitude 6.0 or above, and each disaster is accompanied by heavy losses [1]. In particular, the occurrence of several major earthquakes in recent years has not only brought a deep shock to the people of the country, but also exposed many challenges in the process of disaster relief. After an earthquake, cities are instantly turned into ruins, roads are damaged and communication is interrupted, which brings great obstacles to rescue teams. In such emergencies, there is a need to quickly find trapped people and at the same time ensure that the basic needs of the victims are met. However, due to various unfavorable factors, such as the difficulty of obtaining information and the poor deployment of supplies, it is difficult for the relevant departments to accurately grasp the situation of the population casualties and the needs of the victims, which makes the supply of supplies a shortcoming in the rescue work, exacerbates the difficulty of the rescue work, and seriously threatens the survival and safety of the victims.

After the earthquake, the affected areas faced severe survival challenges, and were in urgent need of all kinds of emergency supplies to guarantee the basic living needs of the affected people. However, due to the suddenness and complexity of earthquake disasters, the mobilization and distribution of materials in the early stages often face many difficulties. On the one hand, the lack of resources such as manpower, financial resources and means of transportation makes the transportation and distribution of materials inefficient; on the other hand, the differences in the degree of damage in different disaster areas also lead to the diversity and variability of the demand for materials. If the materials are not properly distributed, it may not only lead to the backlog and waste of materials in some areas, but also cause serious shortage of materials in other areas, which may threaten people's lives and safety. Therefore, it is particularly important to make scientific and reasonable prediction and distribution of post-earthquake emergency supplies. This will not only help to improve the efficiency and fairness of the use of materials, but also provide strong support and guarantee for the subsequent emergency relief work.

2. Post-earthquake Emergency Supplies Forecasting Study

2.1. Identification of Data Indicators

The casualties caused by earthquakes are affected by a variety of parameters including, but not limited to, the magnitude of the earthquake, the exact time of the earthquake, the intensity of the fortification, the number of people affected by the earthquake, the severity of the destruction of the housing stock, and the level of economy in the area.

The aim of this paper is to construct a prediction method that can quickly provide a basis for decision-making in the mobilization and dispatch of emergency supplies in the early stages of an earthquake. Therefore, the selected data needs to meet the requirements of rapid access and easy analysis. After comprehensive consideration of various aspects, this paper selects the following seven parameters [2] as the key indicators for assessing the number of earthquake casualties: the magnitude, the time of the earthquake, the intensity of defense, the intensity of damage, the number of people affected, the destruction of housing, and the local economic development level, and the specific content of each predictive indicator is described below.

(1) Magnitude

The magnitude of an earthquake is a classification of the magnitude of the energy released by the earthquake source. The greater the magnitude, the greater the energy released by the source, and the greater the impact on the surface structure. The greater the magnitude, the greater the destructive power to the surface structure and buildings on the ground, and therefore, the greater the possibility of casualties. Therefore, the possibility of casualties is also greater.

(2) Time of occurrence

According to the analysis results of relevant literature, the number of casualties in earthquakes occurring between 0:00 a.m. and 6:00 a.m. is relatively high, so this paper marks this time period as 2, and other times as 1.

(3) Intensity of defense

Intensity of defense reflects the ability of buildings to resist the damage caused by seismic waves, which directly determines the stability and safety of buildings in earthquakes. In an area with a high intensity of defense, buildings may be less damaged in an earthquake, thus reducing the risk of casualties.

(4) Damage Intensity

Damage intensity is the actual observed degree of damage caused by the earthquake to the ground and buildings, and also directly reflects the actual impact of the earthquake, which is closely related to the casualties. Generally speaking, the higher the damage intensity, the more serious the casualties.

(5) Affected Population

The affected population refers to the group of people who are affected and may suffer casualties in an earthquake, and is one of the important indicators for assessing earthquake casualties. Densely populated areas tend to cause greater casualties in earthquakes. In addition, data on the affected population can be collected and organized by statistical departments or related organizations, and the data is relatively accurate and reliable.

(6) Destruction of housing

Housing is a basic place for people to live, and the degree of damage to housing directly affects people's life safety and quality of life, and heavy housing destruction often leads to a large number of casualties. Housing destruction refers to the extent of housing damage in an earthquake, including collapse, cracks, etc., which can be obtained through on-site investigation, remote sensing technology and feedback from residents.

(7) Level of economic development

The level of local economic development has a certain correlation with earthquake casualties. Regions with higher levels of economic development usually have better infrastructures and emergency response capabilities, and are able to respond more effectively to earthquake disasters and reduce casualties.

2.2. Data Processing

2.2.1. Data Standardization

Data standardization can scale the data to a uniform range of scales, reducing the differences between variables and facilitating the convergence of machine learning algorithms. Especially in BP neural network, its training process based on gradient descent method is very sensitive to the scale of input data. The standardization process can accelerate the adjustment process of weights and improve the training efficiency of the model, and the following are the specific steps of data standardization.

(1) Calculate the mean value

For all the collected indicator data, first calculate the mean value of its data values, and the calculation formula is:

$$Mean = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

(2) Calculating the standard deviation

Average the square of the difference from the mean for each data point and then take the square root of that average, and the calculation formula is:

$$StandardDeviation = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\lambda_i - Mean)^2} \tag{2}$$

(3) Standardizing data

For each case data point collected, subtract the mean and divide by the standard deviation, and the calculation formula is:

$$StandardizedData = \frac{x_i - Mean}{StandardDeviation} \tag{3}$$

2.2.2. Calculate the Pearson correlation Coefficient Matrix

By calculating the Pearson correlation coefficients between each feature and the number of injuries, this subsection can clearly demonstrate the linear relationship between features such as magnitude, time of occurrence, intensity of defense, and population affected by the earthquake and the number of injuries, in order to better understand the impact of earthquakes on human casualties. The Pearson correlation coefficient helps to select the features that are most helpful in predicting the number of casualties and improves the accuracy of the model. The calculation formula is shown below:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{j=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{j=1}^{n}(y_i-\bar{y})^2}} \tag{4}$$

Where r_{xy} denotes the Pearson correlation coefficient between feature x and feature y, n denotes the number of observations, x_i and y_i denote the i th observation of feature x and feature y, respectively, and $\bar{x}$ and $\bar{y}$ denote the mean values of feature x and feature y, respectively.

2.3. Constructing a BP Neural Network Prediction Model

2.3.1. Model Structure Identification

From the theoretical point of view, when the transfer function of the hidden layer of the three-layer BP neural network utilizes the S-type function, and the transfer function of the output layer adopts the linear function, it is able to approximate the arbitrary continuous function with arbitrary accuracy. Based on this, the BP neural network used in this paper contains three layers, specifically the input layer, a hidden layer and the output layer. Moreover, the transfer function between the input layer and the hidden layer is a linear activation function, while the transfer function between the hidden layer and the output layer is a sigmoid activation function.

(1) Determine the number of neurons in the input layer

After various studies, the seven indicators of earthquake magnitude, occurrence time, defense intensity, damage intensity, affected population, housing destruction and local economic development level are selected as the input parameters of the model, so the input layer neurons are determined to be seven.

(2) Determine the output layer neurons

In this paper, the number of people injured in the earthquake is chosen as the output of the network, so the output layer neuron is 1.

(3) Determine the hidden layer neurons

The determination of the number of hidden layer neurons is not standardized and is often based on the volume of samples collected and human experience. Setting the number of nodes too little may result in the model prediction accuracy not being able to meet the expected goal, while setting too much may improve the accuracy to a certain extent, but the overly complex model is prone to fall into the dilemma of overfitting. Therefore, in this paper, the implicit layer node settings are determined by the principle of trial-and-error algorithm, and the number of nodes ranges from 8 to 20, and the number of neurons in the implicit layer is determined to be 17 through the experiments of multiple model training and observation of the error.

(4) Other parameter settings of the model

Smaller batch sizes usually speed up training and help the model generalize better, but may also lead to unstable training, therefore, the number of data samples used for training in each batch was set to be 3. In addition, a higher number of loops may help the model learn more information, but may also lead to overfitting. Therefore, it was specified that the model was changed to run 500 cycles.

2.3.2. Steps to Build a BP Neural Model

BP (Back Propagation) neural network, proposed by scientists led by Rumelhart and McClelland in 1986, aims to solve the problem of multilayer neural network implicit layer connection weights learning, is a multilayer feed-forward neural network, whose core feature lies in the training through the back propagation of error algorithm. The sample data is input from the input layer, and is continuously calculated forward according to the parameters set in each layer until it reaches the output layer, and the back propagation is carried out according to the error between the output value and the expected value, and the weights and thresholds of the connections between the layers are adjusted and updated until the final output result meets the expected value. The structure of the BP neural network with three layers studied in this paper is shown in figure 1.

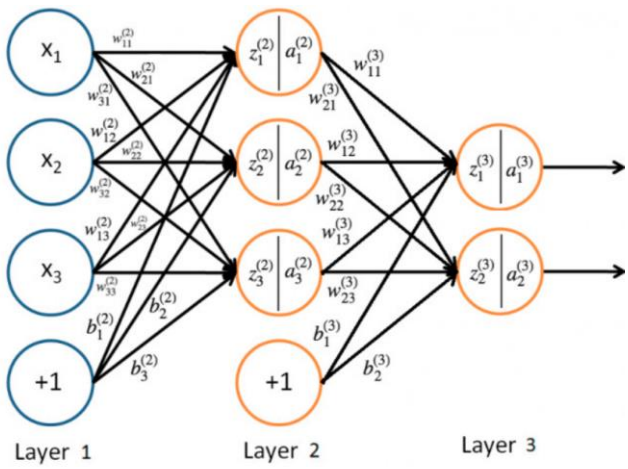

Figure 1. BP neural network structure diagram

The construction steps of the BP neural network model are as follows:

(1) Forward propagation

The output corresponding to the ith input layer node is:

$$a_i^0 = x_i \tag{5}$$

The inputs and outputs of the jth node of the hidden layer are:

$$I_j = \sum_{i=1}^{n} w_{ij} a_i^0 + \theta_j \tag{6}$$

$$a_j^1 = f(I_j) \tag{7}$$

(2) Objective function of BP network

Assuming that there are N samples, the error of the input and output corresponding to the ith sample is:

$$E_i = \frac{1}{2}\sum_{k=1}^{m}(d_{ik} - y_{ik})^2 \tag{8}$$

$$E = \sum_{i=1}^{N} E_i = \frac{1}{2}\sum_{i=1}^{N}\sum_{k=1}^{m}(d_{ik} - y_{ik})^2 \tag{9}$$

In the above two formulas, m is the number of output nodes, d_{ik} is the kth expected value of the ith sample, and y_{ik} is the kth neural network predicted output value of the ith sample.

(3) Gradient descent method is used to train the network, and the weight coefficient update formula is:

$$\Delta W = -\frac{\mu}{N}\frac{\partial E}{\partial w} \tag{10}$$

(4) Adjusting the weights and thresholds for each layer of the network:

$$W^{(l)} = W^{(l)} - \frac{\mu}{N}\sum_{i=1}^{N}\frac{\partial E_{(i)}}{\partial W^{(l)}} \tag{11}$$

$$b^{(l)} = b^{(l)} - \frac{\mu}{N}\sum_{i=1}^{N}\frac{\partial E_{(i)}}{b^{(l)}} \tag{12}$$

Where is the rate of change of $\frac{\mu}{N}$, i.e., the step size; $\frac{\partial E_{(i)}}{\partial W^{(l)}}$ is the derivative of the error equation.

2.3.3. Performance Evaluation Indicators

Performance evaluation metrics play a vital role in evaluating BP neural networks, which can help researchers understand the performance of the model for model optimization, comparing different models, and decision making, as well as reflecting potential problems in the model, such as overfitting or underfitting. Evaluation metrics usually use mean square error, mean absolute error, and coefficient of determination, as shown in the following equations:

(1) Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{13}$$

(2) Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{14}$$

(3) Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{15}$$

In the three evaluation indicator formulas above, n is the sample size, y_i is the true value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the average of the true values.

2.4. Estimated Material Requirements

(1) Daily consumables

According to CDC data, the minimum daily requirement per person in an emergency is 4183kJ (1000kcal) of energy and 1000ml (1kg) of drinking water. In this paper, bread, which is a representative of daily consumable relief foods, is stipulated to be about 1000 kcal for 500g of bread among the common bread types. Therefore, the total weight of food consumed by the general population in an emergency is 1.5kg/d.

(2) Common medicines

This paper focuses on the impact of the number of injured people on the demand for rescue supplies in the drug category, abstracting it into routine medical supplies and first aid supplies, such as bandages, anti-inflammatory drugs, iodine vapors, tetanus, and so on. They are packaged into one-person portions and distributed to the injured in the disaster area, stipulating that the demand of each injured person is fixed at 120g/d.

3. Case Studies

The purpose of this section is to demonstrate, through an example analysis, how the constructed prediction method can quickly predict the emergency supplies required by the victims at each disaster site when responding to a large-scale earthquake, so as to provide a reference for the rapid and effective mobilization and supply of emergency supplies in the first time after the earthquake. To this end, the 7.0 magnitude earthquake that occurred in Ya'an, Sichuan Province on April 20, 2013 was chosen as a case study in this chapter [3]. This earthquake is a major natural disaster that occurred in China in recent years, and we will use the constructed principal component BP neural network earthquake casualty prediction model and the method of estimating the demand for earthquake emergency supplies to analyze the demand for emergency supplies in the severely affected areas in the earthquake.

3.1. Data Collection

3.1.1. Yaan Earthquake Data

According to the China Earthquake Network, at 8:02:46 Beijing time on April 20, 2013, an earthquake with a magnitude of 7.0 occurred in Lushan County, Ya'an City, Sichuan Province, at a depth of 13 kilometers, with a maximum intensity of 9 degrees, and affected an area of about 18,682 square kilometers. The latest situation of the earthquake damage coming from the Ya'an City Earthquake Relief Command shows that as of 12:00 on the 23rd, the number of deaths in the city has reached 173, 22 are missing, and the number of injuries has reached 10,974, of which 968 are serious injuries [4]. Specific data on the damage in Ya'an is shown in Table 1.

Table 1. Statistics on the damage in Ya'an

Region	Magnitude	Occurrence Time	Fortification Intensity	Damage Intensity	Affected Population	Destroyed Housing	GDP/ billion	Number of Injured	Number of Deaths
Yucheng	7	1	7	7	356800	125579	12.51	1109	15
Lushan	7	1	6	9	112000	127710	2.65	5537	120
Baoxing	7	1	6	6	58954	57731	1.91	2503	26
Tianquan	7	1	7	7	155200	18705	3.78	811	5
Mingshan	7	1	6	7	279900	14000	5.74	607	2
Yingjing	7	1	7	7	149000	7865	4.36	341	2
Shimian	7	1	6	6	124400	899	5.88	39	2
Hanyuan	7	1	6	6	325000	807	6.07	35	1

3.1.2. BP Neural Network Training Set Data Collection and Processing

In this paper, 39 earthquakes of magnitude 6 or above that occurred in China in the past 30 years are selected as the training sample set based on news reports, thesis data, and the "National Center for Sharing Earthquake Science Data", etc. Table 2 shows some of the statistical information of the earthquakes.

Table 2. Training set data

Region	Magnitude	Occurrence Time	Fortification Intensity	Damage Intensity	Affected Population	Destroyed Housing	GDP/ billion	Number of Injured	Number of Deaths
Lixian	6.1	1	7	8	103054	36500	0.63	359	30
Panzhihua	6.1	2	7	8	130311	7455	5.16	145	5
Ninglang	6.2	1	7	7	127870	17500	10.74	208	5
Dangxiong	6.6	1	8	8	899	171	3.84	19	9
Jiangyou	8.0	1	7	7	870000	200000	2.87	19278	437
Zitong	8.0	1	6	7	312807	16517	1.33	2489	25
Youxian	8.0	1	6	7	450000	112987	14.25	482	85
Xiaojin	8.0	1	6	8	79982	12888	12.73	452	27
Fucheng	8.0	1	7	8	545465	38298	1.48	2038	86
Luojiang	8.0	1	6	8	203000	24596	5.07	307	19
…	…	…	…	…	…	…	…	…	…
Lasa	6.1	2	7	9	130300	7466	12.18	132	5
Lijiang	7.0	1	7	7	1075000	959000	5.18	16912	309
Ludian	6.1	1	7	8	130311	7455	0.34	145	5

After the collected data were processed according to the standardization method in section 2.2.1, the data in the data table were converted to standard normal distribution as a way to eliminate the difference in magnitude between different features [5], which is beneficial for the training of the network. Some of the data after the standardization process is shown in Table 3 below.

Table 3. Standardized processing of training set data

Region	Magnitude	Occurrence Time	Fortification Intensity	Damage Intensity	Affected Population	Destroyed Housing	GDP/ billion	Number of Injured	Number of Deaths
1	-2.286	-0.549	0.483	-0.194	-0.546	-0.427	-0.024	-0.560	-0.425
2	-2.13	-0.549	0.483	-0.194	-0.553	-0.372	0.989	-0.557	-0.425
3	-1.506	-0.549	2.526	-0.194	-0.880	-0.467	-0.263	-0.567	-0.424
4	0.677	-0.549	0.483	-0.194	1.361	0.632	-0.439	0.442	-0.338
5	0.677	-0.549	-1.558	-0.194	-0.075	-0.377	-0.721	-0.438	-0.421
6	0.677	-0.549	-1.558	-0.194	0.278	0.153	1.628	-0.543	-0.409
7	0.677	-0.549	0.483	0.483	-0.676	-0.397	1.351	-0.544	-0.420
8	0.677	-0.549	-1.558	-1.558	0.524	-0.257	-0.693	-0.461	-0.409
9	0.677	-0.549	-1.558	-0.194	-0.359	-0.333	-0.041	-0.552	-0.422
10	0.677	-0.549	0.483	-0.194	-0.723	-0.421	1.149	-0.567	-0.407
…	…	…	…	…	…	…	…	…	…
37	0.677	1.77	0.483	1.447	0.442	0.268	-0.253	1.382	1.851
38	0.677	-0.549	0.483	1.447	0.180	0.094	0.962	1.166	0.799
39	0.677	-0.549	0.483	1.447	-0.237	-0.112	0.216	0.259	0.539

3.2. Analysis of experimental results

3.2.1. Forecast of earthquake injuries

BP simulation experiments are carried out using the above standardized processed data, the dataset contains 39 seismic case samples, and all the later simulation experiments use the data after this processing. Firstly, the Pearson correlation coefficient between the data is calculated and the correlation heat map is plotted as shown in figure 2 below.

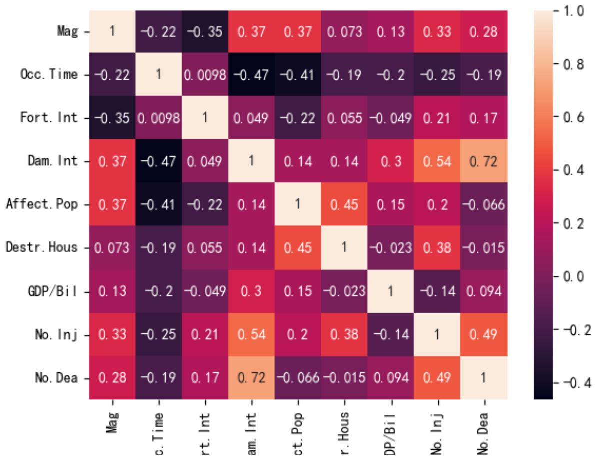

Figure 2. Heat map of Pearson's correlation coefficient

For the BP neural network model parameters are set as shown in Table 4 below.

Table 4. Model parameters

Training Epochs	Batch Size	Learning Rate	Number of Neurons	Hidden Layer Activation Function	Output Layer Activation Function
500	3	0.01	17	Linear	Sigmoid

The loss function curve for the output of the algorithm is shown in figure 3.

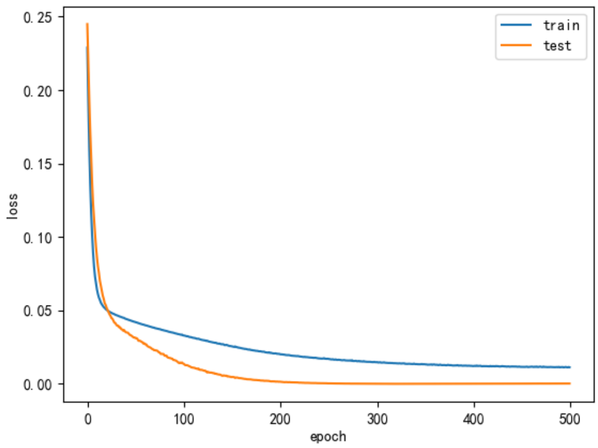

Figure 3. Graph of loss function

The loss function pictures visualize the change in loss during training and testing of the two different models. It can be seen from the figure that with the increase of training rounds, the loss of both the training and testing sets is gradually decreasing, which indicates that the model is gradually learning and optimizing its performance. The metrics of this prediction model are shown in the table below.

Table 5. Performance evaluation indicators

Evaluation Metrics	Experimental Values
MSE	1.56954
MAE	0.00404
R^2	0.93337

The output values predicted by the model and the real test set target values are reduced to the original scale by a specific scaling transformation for more intuitive comparison and analysis. Figure 4 shows the predicted and actual graphs after reduction to the original scale.

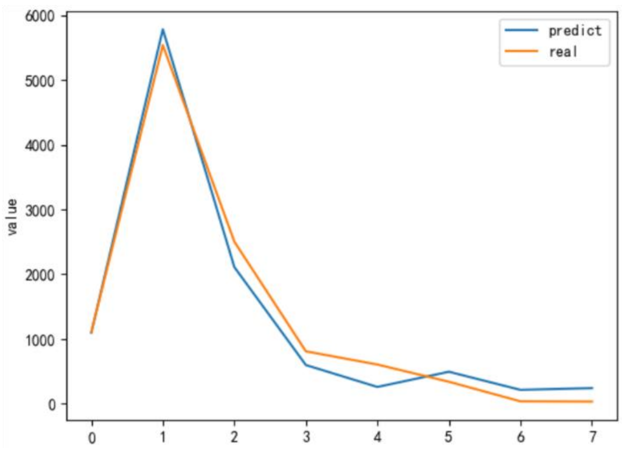

Figure 4. Comparison of predicted and actual values

In order to visualize the comparison between the model data and the real values, the specific data are organized into the following table.

Table 6. Statistics of predicted and real values

Region	Actual Value	Predicted Value
Yucheng	1109	1098
Lushan	5537	5780
Baoxing	2503	2110
Tianquan	811	699
Mingshan	607	560
Yingjing	341	495
Shimian	39	52
Hanyuan	35	45
ToTal	10982	10839

3.2.2. Forecasting of Requirements for Emergency Supplies

Based on the data projected in section 3.2.1, the demand for emergency supplies is calculated, and the demand for daily consumables as well as general pharmaceuticals in each region is shown in the following statistical table:

Table 7. Forecast of emergency supplies

Region	Daily Consumables (t)	General Pharmaceuticals (kg)
Yucheng	535.2	131.7
Lushan	168	693.6
Baoxing	88.4	253.2
Tianquan	232.8	83.8
Mingshan	419.8	67.2
Yingjing	223.5	59.4
Shimian	186.6	6.2
Hanyuan	186.6	5.4
Total	2040.9	1300.7

4. Summary and outlook

China is in an earthquake-prone area, and earthquake disaster, as a serious natural disaster, has caused serious economic losses and also seriously jeopardized people's lives. It is of great significance to predict the number of injuries for the first time after the earthquake and reasonably to provide data reference to the related organizations of emergency rescue.

In this paper, after analyzing many factors affecting earthquake casualties, according to the principle of being able to obtain direct or using rapid assessment methods for the first time after the earthquake, seven parameters such as the magnitude, the time of the earthquake, the seismic intensity, the intensity of earthquake damage, the affected population, the collapse of buildings, and the level of economic development are selected as the indicators for predicting the number of people injured in each affected point of the earthquake. In addition, the article constructs a three-layer BP neural network model and divides the collected samples into training sample sets and test sample sets. By continuously training and testing the samples, it proves that the network meets the error requirements and verifies the reasonableness of the constructed model. The experimental results of the model show that the coefficient of determination R^2 reaches 0.93337, proving that the neural network model has high accuracy in predicting the target variable.

Although the BP neural network model constructed in this paper achieved high accuracy in predicting the number of injuries of people at earthquake-affected sites, the data used in this paper may be limited by factors such as sample size, data quality and coverage. The complexity and diversity of earthquake hazards may result in some important influencing factors not being included in the model, thus affecting the predictive ability of the model. In addition, although the model achieved high accuracy on the training set, its generalization ability on unknown data or newly occurring seismic events has not been fully validated. Therefore, in future research, it is necessary to improve the predictive ability and generalization performance of the model by collecting more and more comprehensive seismic hazard data, including real-time and historical data, as well as integrating data from different sources.

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