Study on Key Risk Influencing Factors of TCM Supply Chain Based on BP Neural Network

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Abstract
Although China's TCM industry has made great development in recent years, there are still some problems in the planting, harvesting, processing, packaging and other related links of the TCM supply chain, which lead to difficult to control the quality risk of the TCM supply chain. Therefore, the author used Python programming language to establish the risk evaluation model of TCM supply chain and random forest model based on BP neural network, so as to obtain the application model tool of supply chain risk rating evaluation, the characteristic weight of 35 risk factors, the weight of the level index (each link of TCM supply chain risk measurement evaluation system). The study found that the top six evaluation indicators of the highest risk factors were"Imperfect origin infrastructure has an impact on quality control", "Farmers no specialized machinery and equipment for planting Chinese medicine affect the quality of Chinese medicinal materials", "lack of consciousness, cultural level and technical level affect the quality of Chinese medicinal materials", "Chinese medicinal materials or medicinal pieces transport unclean, cause medicinal materials pollution", "farmers harvest professional knowledge", "training professional and technical personnel, formulate policies and career promotion channels"; and cultivation of Chinese medicinal materialsThe processing link of Chinese herbal medicine occupies the largest weight in the supply chain. Government departments need to strengthen the control of these key risk factors and important links of the supply chain.

Keywords
TCM Supply Chain, BP Neural Network, Risk Factors

1. Introduction

General Secretary Xi stressed the need to follow the law of the development of TCM, inherit the essence, uphold integrity and innovation, and accelerate the modernization and industrialization of TCM. On October 26,2019, the CPC Central Committee and The State Council issued the Opinions on Promoting the Inheritance, Innovation and Development of Traditional Chinese Medicine, which is the first document on TCM issued by the CPC Central Committee and The State Council, clarifying the goals, key tasks and specific measures for the inheritance, innovation and development of TCM.

Although China's traditional Chinese medicine industry has made great development in recent years, there are still some problems in the supply chain of planting, harvesting, processing, packaging, storage, transportation, and sales of Chinese medicinal materials[1-2]. For example, in the planting link of Chinese medicinal materials, the abuse of chemical fertilizers and pesticides, herbicides and pesticides, the quality of seedlings, the technical level and cultural level of farmers, and the mechanization level of Chinese medicinal materials planting and harvesting are low[4-5]; In the harvesting link, farmers are random and shoddy, and farmers have insufficient professional knowledge of harvesting; in the primary processing link, artificial dyeing, weight gain, sulfur smoked herbs, farmers have insufficient knowledge of primary processing[6]; In the processing process, there is a lack of standards for processing accessories, the processing equipment is backward, the standards and gun rules need to be revised and gradually unified, and the processing workers lack of professionalism[7-11]; In the packaging process, the packaging specifications of TCM decoction pieces are chaotic, the packaging technology and packaging materials are backward, the packaging does not indicate the grade, source, name, origin, processing method, and the packaging label items are incomplete[12]; Storage link, backward storage infrastructure, backward storage and maintenance technology, lack of scientific and effective pest killing technology, and storage environment, transportation link, imperfect logistics standard system, and industry management is not in place[8]; In the sales link, the purchaser shall accept the professional technical level, testing equipment, and select legal and reliable decoction piece suppliers[13]. These problems make it difficult to control the quality risk of TCM supply chain.

The supply chain of Chinese herbal medicine is a complex network system, involving many enterprises with different targets. Its environment is unpredictable and more complex. The dynamics of the external environment always affects the information exchange between various nodes in the supply chain[14-19]This process increases the complexity and risk of the supply chain of Chinese medicinal materials, so it is necessary to evaluate the risk level of the supply chain, increase the understanding of the risk factors of each node in the supply chain, so as to control the risk of the quality of Chinese medicinal materials and ensure the safe and effective use of Chinese medicinal materials.

2. Construction of the risk measurement and evaluation system of Chinese herbal medicine supply chain

2.1. Construction of supply chain risk measurement and evaluation system

The author to "traditional Chinese herbal medicine planting", "Chinese herbal medicine harvest", "Chinese medicine processing", "Chinese herbal medicine processing", "Chinese medicine yinpian packaging", "logistics", Chinese herbal medicine "storage", "Chinese medicine yinpian / Chinese herbal medicine sales", "industry of traditional Chinese medicine", "Chinese herbal medicine supply chain" as a search term, search related literature, induction, sorting and summary. It also refers to the 2019 enterprise report of Tsujura Pharmaceutical Company, Guidelines on Cultivation, Collection and Processing of Medicinal Plants, and Manufacturing and Quality Management Standards (New Hanfang GMP) published by Japan Hanfang Pharmaceutical Association. Finally research visited Wenzhou sea crane pharmaceutical co., LTD., Zhejiang Huayu pharmaceutical co., LTD., and Zhejiang JingYueTang pharmaceutical co., LTD., issuing homemade questionnaire 95, consulting fixed number of year for 10 to 20 years related experts, finally proposed a contains 35 risk factors index quality risk evaluation system 2.BP neural network basic principle and structure

3. BP neural network basic principle and structure

3.1. The concept of the BP neural network

BP neural network is a multi-layer feed-forward neural network, which is mainly trained in two steps: forward propagation and error back propagation. It is the most widely used class of neural network. It has self-learning and adaptive characteristics, in the learning process can automatically extract the output mode and adaptive save network weight learning; robust to faults, local or partial damage has no obvious impact on the overall learning[21-23]. Therefore, it is able to better deal with multifactor, uncertainty and non-linear problems. Therefore, this study hopes to combine the BP neural network model to build the risk measurement evaluation model of the supply chain, so as to provide an application tool for the risk category evaluation of the supply chain in the later stage, so as to improve the risk control level and anti-risk ability of the supply chain.

3.2. Structure of the BP neural network

The BP neural network structure is divided into three layers, including the input layer, the middle layer (hidden layer) and the output layer[24-25]. The input layer mainly receives the input data, the implicit layer is mainly used to find out the potential rules in the sample, and the output layer mainly outputs the evaluation results, as shown in Figure 1.

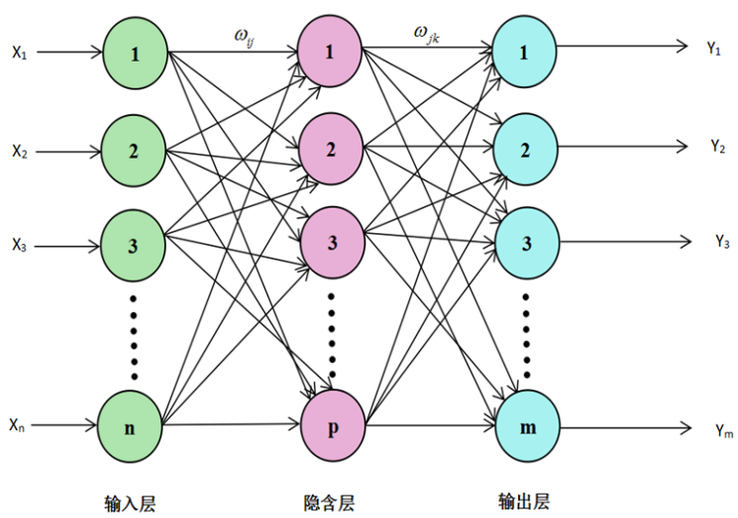


图 1：BP 神经网络结构图

3.3. The BP neural network algorithm

The algorithm training of BP neural network consists of two processes: forward propagation of input information and reverse transmission of error. The learning process of its algorithm is as follows:

3.3.1. The positive propagation process of the input information

Let the data of the BP neural network have n nodes in the input layer, p nodes in the hidden layer, and m nodes in the output layer. The weight between node i and node j is the Wij, The threshold of node j is bj[26]. Specific processes such as the formula (2.1) And formula (2.2).

$$H_j = \sum_{i=0}^{n-1} w_{ij} x_j \quad (2.1)$$

$$\boldsymbol{w} x_j = f(H_j) \quad (2.2)$$

In formula (2.1) and formula (2.2), HjDenotes the hidden layer input vector, xjFor the hidden layer output vector, and f is the activation function. With the activation function, the BP neural network takes the output from the previous layer as the input to the next layer. Common activation functions are the Relu function, and the softmax function. Relu functions have the advantages of being computationally efficient, allowing fast network convergence, and allowing back propagation. The softmax function can normalize the output value and convert all the output values into probability. The advantage of this function is that the output maps between (0,1), monotonically continuous, the output has limited range, optimized and stable, can be used as the output layer, and it is easy to guide. These two functions are commonly used as the activation function of the neural network. The expression of the Relu function is shown in formula (2.3) and the softmax function is shown in formula (2.4).

$$\mathrm{relu}(x) = \max(\mathrm{x}, 0) \quad (2.3)$$

$$\mathrm{softmax}(\mathrm{x})_i = \frac{\exp(\mathrm{x}_i)}{\sum_j \exp(\mathrm{x}_j)} \quad (2.4)$$

3.3.2. The reverse transfer process of the error

In BP neural networks, the error signal backates from the output layer to the input layer mainly based on the Widrow-Hoff learning rule. The learning rule reduces the error between the actual system output (output) and the desired output (target) by changing the weight of the connections between the neurons. Assuming that the output layer is m nodes, there will be an output error E when the actual neural network output is different from the expected output[27]. The mathematical expression for the output error E is shown in the formula (2.5).

$$E = \frac{1}{2} \sum_{i=1}^{m} (\mathrm{target} - \mathrm{output})^2 \quad (2.5)$$

4. Construction of the supply chain model of Traditional Chinese medicine based on BP neural network

The study mainly uses the Python programming language to create the TCM supply chain model based on BP neural network used in this study, in order to effectively analyze the risk level of the TCM supply chain quantitatively. The main programming ideas and running Python code are as follows:

(1) Import pandas, matplotlib and other data packets, as shown in Figure 1.

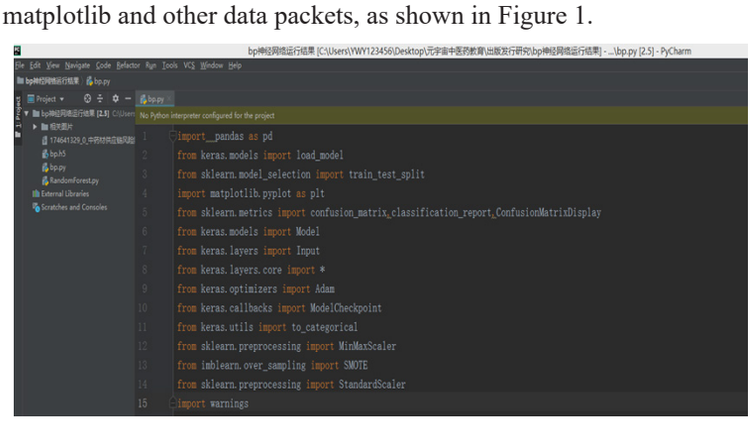


Figure 1. Import of the associated data packets

(2) Read the table (see Table 11: Quantitative processing results of the consequence severity of risk factors), and import the BP neural network input layer sample data (35 columns of risk factor values). The data were normalized to their range in the (0,1) interval. X and Y values are defined: X refers to 35 columns of risk factor values, and Y value refers to the risk measurement evaluation grade of the supply chain of Chinese medicinal materials. Here, the evaluation grade is divided into two categories: one is low risk [0-0.5), grade I; one is high risk [0.5-1), and the grade is. See Figure Figure 2 for the running code.

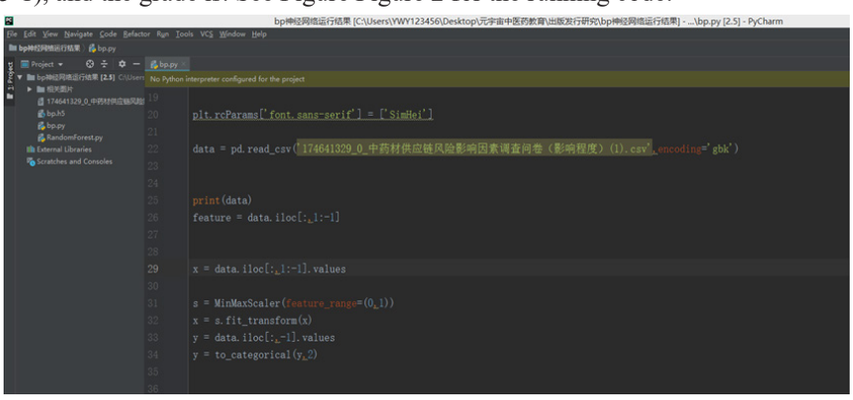


Figure 2 Import of the sample data from the input layer of the BP neural network

(3) The imported data samples are classified and divided into training set data samples and test set data samples. 20% of the data samples are used as test data. See Figure 3 for the running code.

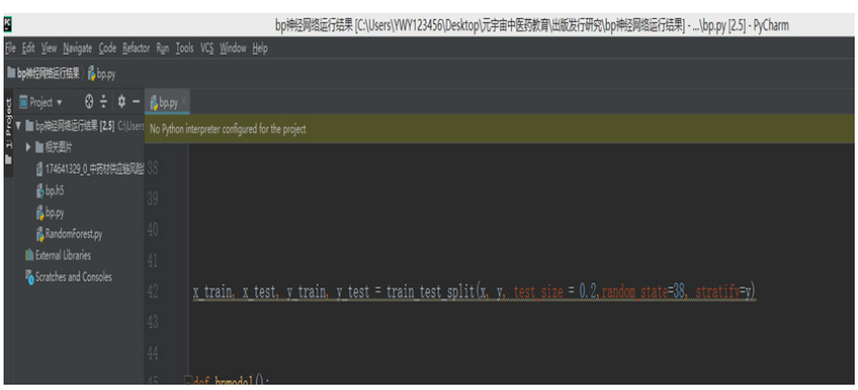


Figure 3. Classification of the data samples

(4) Design of the structure of the BP neural network. Since there is no systematic theoretical explanation for the selection of network structure, the network structure is mainly selected based on previous experience to determine the number of nodes of input layer, implied layer and output layer level. The input layer is 1 layer, the number of nodes is 35; the hidden layer is 3 layers, the first layer has 6 nodes, the second layer is 12, the third layer is 34, the activation function is relu; the output layer is 1 layer, 2 nodes, and the activation function is softmax. See Figure Figure 4 for the specific structural design.

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 35)                0
_________________________________________________________________
dense_1 (Dense)              (None, 6)                 216
_________________________________________________________________
dense_2 (Dense)              (None, 12)                84
_________________________________________________________________
dense_3 (Dense)              (None, 34)                442
_________________________________________________________________
dense_4 (Dense)              (None, 2)                 70
=================================================================
Total params: 812
Trainable params: 812
Non-trainable params: 0
_________________________________________________________________
```

Figure 4 Structure design of Chinese herbal medicine supply chain model based on BP neural network

(5) Neural network model training was conducted. The training sample set used in the study is 35 risk factor index values and 95 risk measurement evaluation levels of the TCM supply chain. There are 76 evaluation data for each risk factor, a total of 2736 data. The training target value is the risk measurement evaluation results of the TCM supply chain. The number of model training is 1000 times, and the training function used during the training is m. It (including forward transmission training and reverse transmission training process), optimizer is Adam function, cross entropy loss function is categorical_crossentropy. The Adam optimizer defines the way the parameters are updated by dynamically adjusting the learning rate for each parameter according to the first and second moments of the gradient of the loss function for each parameter. The categorical_crossentropy function characterizes the distance between the actual output (probability) and the expected output (probability), that is, the smaller the value of the cross-entropy, the closer the two probability distributions are. The specific parameters to be set are: β1=0.9, β2=0.999, ε=10^(-7). When the number of network training times exceeds the set maximum number, the network training is initially completed, and the algorithm can be terminated. See Figure 5 for the running code.

```
m = bpmodel()
Adam(learning_rate=0.00001,beta_1=0.9, beta_2=0.999, epsilon=1e-08, amsgrad=False,)
m.compile(optimizer='Adam', loss='categorical_crossentropy',
          metrics=['acc'])


checkpoint = ModelCheckpoint('bp.h5', monitor='val_acc', verbose=1, save_best_only=True,mode='max',period=1)
# history = m.fit(x_train, y_train,validation_data=[x_test,y_test], epochs=1000, batch_size=3,callbacks=[checkpoint])
```

Figure 5. Training of the BP neural network model

(6)To predict and evaluate the model. The prediction results show that 9 of the predicted values of low risk level are true, and 4 of the predicted values of high risk level are true. The prediction results are shown in Figure 6. The value of the model accuracy is 0.6842, and the evaluation results are shown in Figure 7.

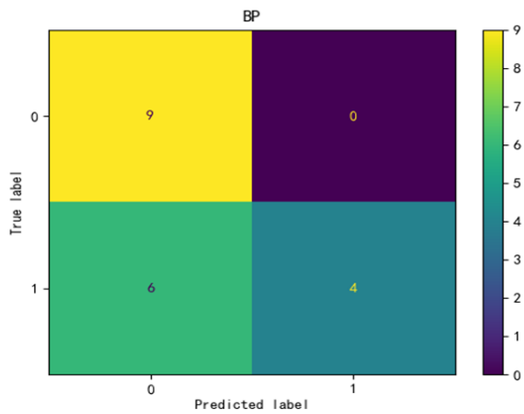


Figure 6. Model prediction results

	precision	recall	f1-score	support
0	0.6000	1.0000	0.7500	9
1	1.0000	0.4000	0.5714	10
accuracy			0.6842	19
macro avg	0.8000	0.7000	0.6607	19
weighted avg	0.8105	0.6842	0.6560	19

Figure 7. Results of the model evaluation

5. Construction of the random forest model

5.1. Rationale of the random forest model

Random forest was first proposed by Leo Breiman et al. Scholars in 2001, which is a relatively classical algorithm in the field of machine learning. Compared with other algorithms, it has the advantages of high prediction accuracy, unfavorable overfit, high tolerance to outliers and noise, and not susceptible to collinearity among variables, and is widely used in biomedical, marketing, risk prediction and other fields[29]. This algorithm is composed of multiple decision trees. He can produce multiple training sets by randomly sampling the sample information with the help of the bagging algorithm, and then use the decision tree as the base classifier for each training set, and according to the results of the majority vote of multiple trees as the final prediction value[30]. It can not only be used for classification, regression and prediction, but also for importance analysis. The so-called importance analysis refers to taking the best variables selected in the decision tree as the classification nodes, so as to order the variables of importance[31]. Therefore, this study wants to use the random forest model to rank the risk influencing factors of the TCM supply chain, so as to determine the key risk influencing factors of the supply chain.

5.2. Construction of the random forest model

The study also used the Python programming language to create the random forest model used in this study to effectively determine the key risk influencing factors of the TCM supply chain. The main programming ideas and running Python code are as follows:

(1)Import pandas, numpy and other data as in Figure 8.

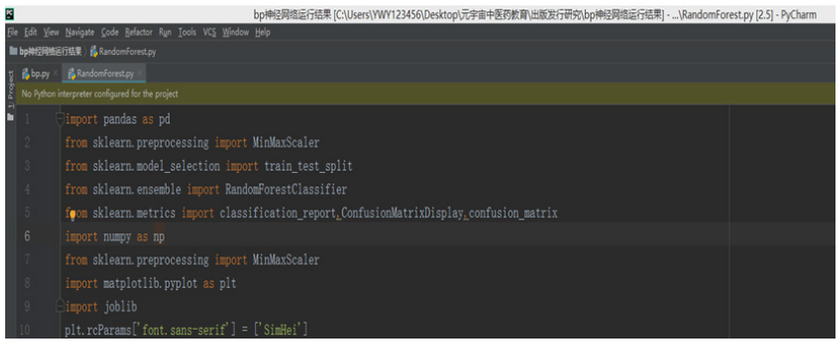


Figure 8. Import of related data packets

(2) Read the table (see Table 11: Quantitative processing results of the consequence severity of risk factors), and import the BP neural network input layer sample data (35 columns of risk factor values). The data were normalized to their range in the (0,1) interval. X and Y values are defined. X refers to 35 columns of risk factor values, and Y value refers to the risk measurement evaluation level of the supply chain of Chinese medicinal materials. See Figure 9 for the running code.

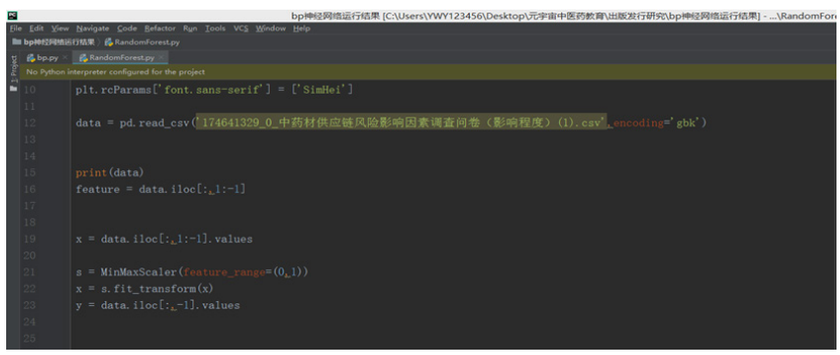


Figure 9. Import of the sample data

(3) The imported data samples are classified and divided into training set data samples and test set data samples. 20% of the data samples are used as test data. See Figure Figure 10 for the running code.



Figure Figure 10 Figs. Classification of the data samples

(4)Random forest models were designed, mainly through the RandomForestClassifier function. See Figure Figure 11 for the running code.



Figure Figure 11. Establishment of the random forest model

(5)Conduct the random forest model training. The training sample set used in the study is 35 risk factor index values and the risk measurement evaluation grade values of 95 Chinese herbal medicine supply chain. Each risk factor has 76 evaluation data, a total of 2736 data. Model is mainly used in the training process. The fit function is used for the training. After model training, 35 risk factors were ranked by importance and dimensionality reduction. The model training run code is shown in Figure 12,35 risk factor feature weights are shown in Figure 13, and the importance weight ranking of 35 risk factors is shown in Figure 14.



Figure Figure 12. Training of the Random Forest model

```
[0.04842202 0.020941   0.02842709 0.03510309 0.0278571  0.05744574
 0.0531135  0.03588095 0.0295335  0.04477052 0.03101199 0.01276265
 0.015803   0.02225223 0.0187157  0.01809365 0.02939404 0.0113667
 0.01951148 0.03873623 0.02093127 0.02736459 0.02494768 0.02463517
 0.0155623  0.0358429  0.01904002 0.03186694 0.03857044 0.04518648
 0.02477863 0.02069777 0.03719159 0.0136736  0.02056843]
```

Figure 13 35 characteristic weights of risk factors

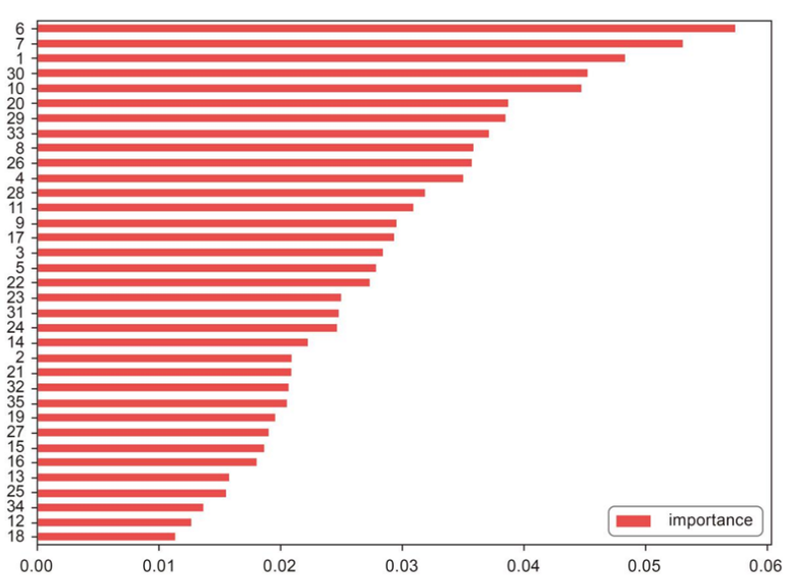


Figure Figure 14 Importance weight ranking of the 35 risk factors

(6) To predict and evaluate the model. The evaluation results show that the value of the model accuracy is 0.63, and the evaluation results are shown in Figure 15 and the running code in Figure 16.

	precision	recall	f1-score	support
0	0.62	0.56	0.59	9
1	0.64	0.70	0.67	10
accuracy			0.63	19
macro avg	0.63	0.63	0.63	19
weighted avg	0.63	0.63	0.63	19

Figure Figure 15. Results of the model evaluation

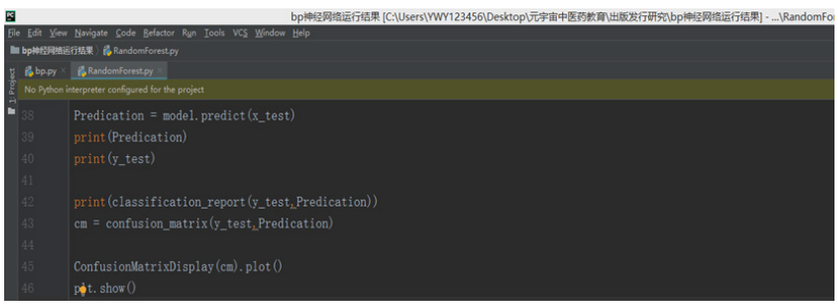


Figure 16 Model Prediction Assessment Run code

5.3. Calculation of the weight of the risk measurement evaluation system of TCM supply chain

By creating the random forest model used in this study through the Python programming language, the importance characteristic weights of 35 risk factors (secondary indicators) can be obtained, and adding the characteristic weights of each secondary index can get the weight of the primary index (each link of the risk measurement evaluation system of the supply chain of Chinese medicinal materials).

6. Conclusion

Based on the survey results of TCM Supply Chain Quality Management Questionnaire of TCM manufacturers, 35 risk factors were quantified and the random forest model used in this study was created through Python programming language, thus obtaining the importance feature values of 35 risk factors and ranking the importance weight of 35 risk factors (see Figure 13). According to the importance ranking results, we can know that the highest evaluation indicators of the top six risk factors are"Imperfect origin infrastructure has an impact on quality control", "Medicine farmers no specialized planting Chinese medicine machinery equipment affect the quality of Chinese herbal medicine", "medicine farmers insufficient consciousness, cultural level, technical level affect the quality of Chinese herbal medicine", "Chinese herbal medicine or decoction transport unclean, medicinal materials contaminated", "farmers harvest professional knowledge", "training processing professional and technical personnel, making policy and career promotion channel". These six high-risk factors are mainly distributed in the cultivation link of traditional Chinese medicinal materialsThere are three high-risk factors in the transportation of Chinese medicinal materials, harvesting and processing of Chinese medicinal materialsTraditional Chinese herbal medicine planting link. The study was also calculated from the following resultsThe weight of the first-level index (each link of the risk measurement and evaluation system of the supply chain of Chinese herbal medicine) can be seenChinese herbal medicine

planting links andThe processing link of Chinese herbal medicine occupies the largest weight, respectively0.3072,0.1739. Therefore, the government departments should will“Imperfect origin infrastructure has an impact on quality control”, "Medicine farmers no specialized Chinese medicine machinery equipment affect the quality of Chinese herbal medicine", "medicine farmers consciousness, cultural level, technical level affect the quality of Chinese herbal medicine", "Chinese herbal medicine or Chinese medicine yinpian transport unclean, cause medicinal materials contaminated", "farmers harvest professional knowledge", "training processing professional and technical personnel, making policy and career promotion channel" six highRisk influencing factorsconductKey control point of the supply chain, willChinese herbal medicine planting link,The processing link of Chinese medicinal materials, as the key control link, implements the key control of these factors and links. Regarding the evaluation of risk rating rating of TCM supply chain, this paper creates the evaluation model of BP neural network used in this study. By comparing the identification accuracy of random forest and BP neural network, the identification accuracy of BP neural network model is higher and better than the random forest model, which provides an application tool for the risk rating evaluation of the late supply chain, so as to improve the risk control level and anti-risk ability of the supply chain more effectively.

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