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A neural network-based quantification of risk in large health investments and its applicability to international investment law

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ABSTRACT

The rapid development of the big health industry brings opportunities for investors, while the risks faced by the investment also increase day by day. This paper combines artificial neural networks and genetic algorithms to construct a risk evaluation model for big health investment based on GA-BP neural network, which provides a tool for analyzing and evaluating the risk of big health investment. The normalization function is used to standardize the model sample data, determine the learning rate, target error and other model parameters, and on the basis of the BP neural network, the genetic algorithm is used to optimize the connection weights and thresholds to achieve the quantitative function of the evaluation of the risk of big health investment. In order to verify the performance of the model to carry out large health investment risk quantification experiments, this paper's model convergence performance is better, the minimum Loss loss value is 0.37, the overall fluctuation is smaller. Compared with BP and PSO evaluation models, the risk evaluation accuracy of this paper's model is above 93.5%, and the comprehensive evaluation accuracy is higher than 91.1%, which can realize more accurate risk prediction, and its applicability in the international investment law has a high practical value.

Keywords: BP neural network, genetic algorithm, normalization function, big health investment risk, international investment law

1. Introduction

At present, China's population aging is increasing, entering the stage of "getting old before getting rich". General Secretary Xi Jinping has emphasized the establishment of the concept of big health and big health, which points out the direction for the development of big health industry in the context of population aging [1-3]. The big health industry is a collection of all health-related industries, covering

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medical, pharmaceutical, pension, fitness, health care and other categories [4]. Developed countries entered aging earlier and have accumulated rich experience in investing in big health industry. In this regard, China should learn from the experience of developed countries to promote the in-depth development of investment in big health industry [5-6].

On the other hand, with the continuous improvement of China's comprehensive national power, China's economy has also stepped into the forefront of the world, which is accompanied by the improvement of the national ability to pay and its emphasis on their own health. China's health industry has a huge market demand [7-9]. The continuous progress of science and technology, both at the world level and the national level, life sciences are constantly developing, and people have a deeper understanding of the mechanism of disease, which allows them to develop targeted innovative biotechnology, laying a solid foundation for the vigorous development of the health industry [10-12].

At the same time, the medical and health industry, as a sunrise industry, is related to all aspects of residents' lives, and it has the characteristics of large capital market capacity, high capital profitability, and large space for capital operation [13-14]. With the continuous development of the economy and the improvement of various systems, the state has increased the reform of the financing mechanism of the medical and health industry in order to continuously adapt to the growing demand for medical services of the residents [15-16]. The national policy especially emphasizes the need to encourage social capital to increase investment in social undertakings such as medical care and pension, to innovate financing methods and to broaden financing channels [17]. In the future, China's medical and health industry has great development potential, and in the process of innovating the financing mode of medical and health industry, attention should also be paid to the establishment and improvement of the internal control system system system of medical institutions, strengthening the risk management of the main body of financing, and improving the efficiency of financing [18-19]. The big health industry has become a popular option for investment in China at present. It is very important to analyze the current situation of investment in China's big health industry and the existing risks, and explore the corresponding risk control strategies to promote the high-quality development of the big health industry [20-21].

In this paper, BP neural network is combined with genetic algorithm to construct a risk evaluation model based on GA-BP neural network for big health investment, which helps investors and enterprises to better understand and cope with the risks they may face in big health investment and make more informed investment decisions. A three-layer neural network structure is used to determine the BP neural network and establish the nonlinear mapping relationship between input and output. The number of neurons in the input layer is determined according to the number of indicators in the evaluation index system, and the number of neurons in the output layer is also determined according to the form of evaluation results. The model sample data were normalized by normalization, and the model parameters such as learning rate and target error were determined. Then genetic algorithm was used to optimize its connection weights and thresholds. Through the design of the fitness function in the genetic algorithm, the quantification and assessment of the risk of big health investment are finally realized. Finally, the individual data of the big health investment fund is selected as the research sample to carry out the quantitative experimental analysis of the big health investment risk, to verify the application effect of the model in this paper, and to put forward the targeted optimization strategy of the practicality of the international investment law based on the perspective of the big health investment risk.

2. Principles of Artificial Neural Networks and Genetic Algorithms

2.1. Principles of Artificial Neural Networks:

1) The concept of artificial neural network. Artificial neural network (ANN) is a mathematical model that simulates the neural network of the brain to process the input information, it simulates the neural

network in biology, and abstracts the response mechanism of the human brain to external stimuli into a network topology, so as to realize the learning and processing of complex information [22]. Its network topology is a multilevel network composed of many neuron nodes, each layer contains many neuron nodes, and the neurons between the layers will be connected to complete the transfer of information and processing In addition, the information can also be stored in it, which makes the network information processing efficiency is high, and makes the network has a better generalization ability.

2) Characteristics of Artificial Neural Networks. ANN has many good characteristics such as fault tolerance, parallelism, nonlinear mapping etc. These good characteristics of ANN make it possible to have good performance in solving complex nonlinear problems.

3) The concept and principle of BP neural network. BP neural network is a kind of artificial neural network, it is a kind of multi-layer feed-forward neural network trained by error back propagation algorithm.BP neural network can be trained to learn the relationship between the data, realize the mapping between the inputs and outputs without the need to determine the function expression between the inputs and outputs, and then in the given input value assigned to the network to get the corresponding output more accurately.

The working process of BP neural network is mainly to input data to the input node of the neural network, the information from the input node to the hidden layer, after calculation and activation, the information from the hidden layer to the output layer to get the corresponding output. Then compare the output results with the desired output value, when the error between the two is large, according to certain rules, the error will be back-propagated back to the input layer layer by layer, and adjust the connection weights and thresholds between each layer by layer. Repeat the above process until the error meets the requirements, so as to realize the learning and processing of information.The working principle of BP neural network mainly includes the two processes of the stop propagation of information and the reverse transmission of error.

(1) Forward propagation of information. The stop-direction propagation of information is mainly to pass the information from the input layer input, according to the calculation of connection weights to the hidden layer input through the activation function to get the hidden layer output, and then through the calculation of connection weights to the output layer to get the output value. Assuming that the input layer of the network has n neuron, the input variable of the network is set to $X=(x_1,x_2,\ldots,x_n)$. The layers of the neural network have connection weights between the layers, and their initial weights are randomly generated within a certain range. The information is input from the input layer and passed to the neural nodes in the hidden layer, let the input variable received by the hidden layer be $A=(a_1,a_2,\ldots,a_m)$. The input data will be processed when it is passed from the input layer neurons to the hidden layer neurons, the data received by the hidden layer neurons will be expressed as a_j, and its processing formula is:

$$a_j = \sum_i x_i w_{ij} \tag{1}$$

$$a_j = \sum_i x_i w_{ij} \tag{2}$$

Where w_{ij} represents the weights between the input layer to the hidden layer, which specifically means the connection weights between the i nd neuron in the input layer and the j rd neuron in the hidden layer, and x_i is the input value received by the i th neuron in the input layer. Then the activation function is used to activate the information and the value after activation is:

$$y_j = f(a_j) \tag{3}$$

(2) Error reverse transmission:

$$b_k = \sum_j y_j v_{jk} \tag{4}$$

Where v_{jk} is the connection weight between the hidden layer to the output layer, which represents the connection weight of the jnd neuron of the hidden layer and the krd neuron of the output layer. Then the information is activated by the activation function and the final network output value is:

$$o_k = f(b_k) \tag{5}$$

The above step is the forward propagation process of the BP neural network, which gives the output value of the network $O=(o_1,o_2,\ldots,o_z)$. Error Reverse Propagation first compares the output of the above network with the desired output value to get the error between the two.

Assume that the error variable is:

$$E(W) = \frac{1}{2}\sum_k (d_k - o_k)^2 \tag{6}$$

Where d_k is the desired output value of the network and E is the global error of the BP neural network, the global error is obtained and then the error is back-propagated to the layers and the connection weights between the layers are adjusted according to the error.

Calculate the error between the output layer and the hidden layer, then adjust the weights between the two layers according to the error, and derive the connection weights between the hidden layer and the neurons in the output layer:

$$\frac{\partial E}{\partial v_{jk}} = \frac{\partial E}{\partial o_k} \times \frac{\partial o_k}{\partial b_k} \times \frac{\partial b_k}{\partial v_{jk}} \tag{7}$$

Among them:

$$\frac{\partial E}{\partial o_k} = \frac{\partial}{\partial o_k}\frac{1}{2}\sum_k (d_k - o_k)^2 = -(d_k - o_k) \tag{8}$$

$$\frac{\partial o_k}{\partial b_k} = \frac{\partial}{\partial b_k} f(b_k) = f(b_k)(1 - f(b_k)) = o_k(1 - o_k) \tag{9}$$

$$\frac{\partial b_k}{\partial v_{jk}} = \frac{\partial}{\partial v_{jk}} y_j v_{jk} = y_j \tag{10}$$

So:

$$\frac{\partial E}{\partial v_{jk}} = -(d_k - o_k) * o_k * (1 - o_k)\, y_j \tag{11}$$

Because the direction of weight adjustment is inconsistent with the direction of gradient descent, the learning rate parameter η is introduced to regulate the strength of the error change, and the adjusted weights of the connections between the neurons of the output layer and the hidden layer are expressed in a mathematical formula as:

$$v_{jk'} = v_{jk} - \eta \frac{\partial E}{\partial v_{jk}} \tag{12}$$

Similarly, the connection weights of the input layer neurons and hidden layer neurons are adjusted according to the above steps:

$$w_{ij'} = w_{ij} - \eta \frac{\partial E}{\partial w_{ij}} \tag{13}$$

In summary, the working process of BP neural network can be summarized as the forward propagation of information and the reverse transmission of error, the above one iteration is that it has gone through a learning, after a number of iterations, the error is gradually reduced until the requirements can be met when the iteration can be stopped.

2.2. *Principles of genetic algorithm*

Genetic algorithms simulate the process of natural selection and biological evolution to find optimal solutions [23]. Based on the principle of survival of the fittest, genetic algorithm takes the potential solution of a problem as a population, selects individuals with high fitness values to preserve them with high probability, and after crossover, mutation and other operations, thus making the new individuals better than the original individuals, gradually iterating, mimicking the biological evolution in nature, and finally selecting the optimal individual as the optimal solution.

The basic operations of genetic algorithm are explained in detail as follows.

1) Selection. Selection is the process of preserving the better individuals in a population so that their genes can be passed on to the next generation. The selection operation calculates the fitness value of an individual and selects the individual with a higher fitness value to inherit its genes to the next generation with a higher probability, the purpose of this process is to keep the better solution in the population with a higher probability.

2) Crossover. Crossover operation reflects the idea of information exchange, the operation is to make two chromosomes crossover to produce a new chromosome, the chromosomes within the population will be randomly combined two by two, with a certain probability of the two chromosomes to crossover, to produce a new chromosome on the new chromosome on the new chromosome at the same time contains the characteristics of the two chromosomes mentioned above.

3) Mutation. Mutation operation is to mutate the genes on a chromosome with a certain probability. Generally the mutation of chromosomes is random, so that part of the coding data of any chromosome within the population is randomly changed to produce a new chromosome, which can increase the diversity of the population.

3. Risk evaluation model of big health investment based on GA-BP neural network

With the rapid development of the big health industry, the market competition is increasingly fierce. Based on the principles of BP neural network and genetic algorithm, this paper will promote the risk identification and assessment of the enterprise's big health investment management project by establishing a big health investment risk assessment model to help investors make a more informed investment strategy.

3.1. *Risk evaluation index system for big health investment*

1) Environmental policy risk. National policy and regulation risk U_1, macroeconomic fluctuation risk U_2, natural environment risk U_3.

2) Technology risk. Advancedness of technology U_4, Reasonableness of theoretical foundation U_5, Substitutability of technology U_6, Ease of imitation of technology U_7, Reliability of technology U_8, Applicability of technology U_9, Research and development conditions of technology U_{10}, Intellectual property protection U_{11}.

3) Management risk. Managerial quality and experience U_{12}, rationality of business organization U_{13}, scientific decision-making U_{14}.

4) Market Risk. Demand of potential customers U_{15}. Market share U_{16}. Market entry barriers U_{17}. Frequency of new product introductions U_{18}. Marketing ability U_{19}.
5) Production risk. Supply of raw materials U_{20}, production equipment U_{21}, production personnel U_{22}, realization risk U_{23} There are both qualitative and quantitative factors in each risk indicator $U_1 \sim U_{23}$ affecting the investment risk of the project, and even if they are quantitative factors, their scales vary greatly. Therefore, for each risk indicator $U_1, U_2, \ldots, U_{23}$, an expert scoring method is used for evaluation. The scoring is divided into five levels (low (1.0), low (0.7), average (0.5), high (0.3), and high (0.1)).

3.2. Neural Network Approach to Risk Evaluation of Large Health Investments

In order to avoid the phenomenon of output saturation, the sample data of the training model need to be normalized. The normalization function is chosen to transform the input data into between [-1, 1] by the mapminmax function in Matlab, and the function expression is shown in Equation (14).

$$y = (y_{\max} - y_{\min}) \frac{x - x_{\min}}{x_{\max} - x_{\min}} + y_{\min} \tag{14}$$

where x and y are the values before and after data normalization, $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the input data, $y_{\min} = -1, y_{\max} = 1$ respectively.

3.2.1. BP Neural Network Structure Determination:
1) Determination of the number of layers of BP neural network [24]. The BP neural network structure includes three parts: input layer, hidden layer and output layer. In this paper, a typical BP neural network with three layers is chosen to establish the nonlinear mapping relationship between input and output, i.e., one input layer, one hidden layer and one output layer.
2) Determination of the number of neurons in the input layer. Generally according to the problem to determine the number of neurons in the input layer, the problem of the various influences is the neurons of the input layer, the number of neurons and the sample data dimension to maintain consistency, the number of neurons in the input layer of this paper has 9.
3) Determination of the number of neurons in the output layer. The number of nodes in the output layer is determined according to the output data dimension. The health value of the big health investment evaluation results is divided into five levels. Since all the index data are input into the neural network model, the final output evaluation result is a healthy value, so the number of neurons in the output layer is set to 1.
4) Determination of the number of neurons in the hidden layer. There is no mature theory or standard to solve the problem of determining the number of nodes in the implicit layer, and the optimal number can only be obtained by referring to the empirical formulas determined in previous studies as well as multiple experiments:

$$m = \sqrt{l + n} + a \tag{15}$$

where n represents the number of neurons in the input layer, l represents the number of neurons in the output layer, a is a constant between 1 and 10, and m is the number of neurons in the hidden layer:

$$m = log_2 n \tag{16}$$

where m is the number of neurons in the hidden layer and n represents the number of neurons in the input layer:

$$m = \sqrt{nl} \tag{17}$$

where m is the number of neurons in the hidden layer, n represents the number of neurons in the input layer, and l is the number of neurons in the output layer.

3.2.2. Selection of model parameters:

1) Selection of initial weights and thresholds. In order to speed up the learning rate of the neural network, the initial weights and thresholds should ensure that the initial net input of the neurons is close to zero. The initial weights are generally randomly assigned between [-1, 1] to avoid the sum of the weighted inputs being in the saturation region of the activation function, which can speed up the convergence of the network.

2) Selection of learning rate. The role of the learning rate controls the amount of weights and thresholds adjusted in each network cycle training, which determines the learning speed of the network, we need to select a suitable learning rate to ensure optimal network training. The learning rate is generally constant during the training process.

3) Definition of error. The appropriate expected error is very important in network training. Too large an error threshold leads to accelerated convergence of the network, the end of the iteration of the number of training is too small, if the error threshold is too small the training time is elongated, it is also possible that the network does not converge to the appropriate value.

4) BP neural network function determination. The functional form of the BP neural network constructed in this paper is $net = nevff(P, T, S, TF, BTF, BLF)$, where, P input data matrix, output data matrix, S number of nodes in the hidden layer, TF node transfer function, BTF activation function, BLF network learning function.

5) Activation function. BP neural network algorithm requires that the activation function must meet the conditions of continuous differentiable, the activation function can be divided into two categories of nonlinear function and linear function. Logarithmic S-function logsig and tangent S-function tangsig are the two most common nonlinear functions used as activation functions.

6) Error functions [25]. There are many formulas for calculating the error in BP neural networks, of which the standard BP algorithm error, the global cumulative error of the BP algorithm and the mean square error MSE are the three most commonly used methods.

(1) Standard BP algorithm error.The network starts to calculate the error after inputting a sample, and the connection weights of neurons in each layer are adjusted according to the error, after which the next training sample is trained. The disadvantage of this method is that the output error of the next training sample will not be reduced with the amount of adjustment of the last connection weights, increasing the number of network iterations is also prolong the network training time, using formula (18) for calculation:

$$E_p = \frac{1}{2}\sum_{k=1}^{m}(d_k - o_k)^2 \tag{18}$$

(2) Global cumulative error of BP algorithm.The overall error is calculated after inputting all the training samples, and the connection weights of the neurons in each layer are adjusted according to the overall error. However, the error of each input sample does not decrease with the decrease of the calculated overall error, which is calculated using Equation (19):

$$E = \frac{1}{2}\sum_{P=1}^{P}\sum_{k=1}^{m}(d_k^p - o_k^p)^2 \tag{19}$$

(3) Mean square error of the BP algorithm:

$$MSE = \frac{1}{mp}\sum_{p=1}^{p}\sum_{k=1}^{m}(d_k^p - o_k^p)^2 \tag{20}$$

where p denotes the number of learning samples, m denotes the number of neurons in the output layer, d_k^p denotes the desired output, and o_k^p denotes the actual output.

3.3. Genetic Algorithm Optimization of BP Neural Networks

Genetic Algorithm Optimization The part of genetic algorithm in BP neural network is the process of selecting the optimal initial weights and thresholds. The specific steps are shown below.
1) Select the way of genetic algorithm to encode the initial weights and thresholds of BP neural network, determine the number of genetic algorithm population, and initialize the population.
2) Design of the fitness function. The initial weights and thresholds of the BP neural network optimized by the genetic algorithm must be the individuals with the highest fitness in the population, and also the individuals that make the network training accuracy the highest. The inverse of the error function is used as the fitness function for evaluating the individual fitness, as shown in Equation (21):

$$F = \frac{1}{1+MSE} = \frac{1}{1+\frac{1}{mp}\sum_{p=1}^{p}\sum_{k=1}^{m}(d_k^p - O_k^p)^2} \tag{21}$$

3) Maximum number of iterations. The suitable number of iteration termination can be determined based on when the value of the fitness function remains constant. The maximum number of iterations selected in this paper is 500.
4) Genetic operations:

(1) Selection operation. The method used for selection operation in this paper is roulette method. The probability of being selected as the next generation of the population is proportional to the fitness of the individual, where the probability of individual i being selected for the next generation is calculated according to the formula:

$$P_i = \frac{F_i}{\sum_{i=1}^{N} F_i} \tag{22}$$

(2) Crossover operation. The method used for selection operation in this paper is arithmetic crossover operation. Two X and Y are randomly selected from the parent chromosomes for crossover operation, based on the formula two chromosomes are crossover operation with a preset crossover probability:

$$x' = x_k(1-b) + y_k b \tag{23}$$

$$y' = y_k(1-b) + x_k b \tag{24}$$

(3) Mutation operation. The method used for mutation operation in this paper is non-uniform mutation. In the case of non-uniform mutation, the amount of variation in chromosomes varies non-uniformly with the number of evolutionary generations. The mutation operation is for a component x_k in a chromosome $X = (x_1, x_2, x_3, \ldots x_m)$ according to the formula mutation x'_k.

Finally, the genetic operation is looped until a new individual is produced that satisfies the compliance conditions and outputs the optimal weights and thresholds of the BP neural network.

4. Empirical Measurement and Analysis of Risk in Large Health Investments

In order to verify the effectiveness of the big health investment risk evaluation model constructed in this paper in the application of big health venture investment, this section will take the individual data of big health investment funds as the research sample to carry out the quantitative analysis of big health investment risk.

4.1. Data preprocessing for the large health investment sample

4.1.1. Data sources. The main data of this paper is the return volatility data of quantitative health investment funds, followed by the return volatility data of Shanghai and Shenzhen stock markets and traditional investment funds. In this paper, we analyze a number of individual samples of health investment funds as an entry point, and the selected quantitative fund name code and number are shown in Table 1.

Table 1 Fund name and code

Number	Fund code	Fund name
Fund1	030143.OF	Luban China Healthcare Equity Fund C Class
Fund2	013037.OF	Great Wall Healthcare A Fund
Fund3	011321.OF	Guotai Healthcare Equity Fund C Class
Fund4	001915.OF	Baoyin Healthcare Hong Kong and Shanghai Stock Fund
Fund5	000711.OF	Jarr Medical Healthcare Equity Fund
Fund6	000960.OF	China Merchants Pharmaceutical Health Industry Equity Securties Investment Fund
Fund7	011876.OF	Jing Shun Chang Cheng Medical Health
Fund8	001919.OF	Debon health and flexible allocation of mixed funds
Fund9	000369.OF	Fidelity Global Healthcare Index Securities Investment Fund A Class
Fund10	002708.OF	Morgan Stanley Healthcare Mixed A Fund
Fund11	516820.OF	Medical innovation ETF
Fund12	001645.OF	Guotai Healthcare Equity Fund A Class
Fund13	159929.OF	Huatai Zhongjin China securities medical health ETF
Fund14	016280.OF	Fidelity Global Healthcare Index Securities Investment Fund C Class RMB Shares
Fund15	016281.OF	Fidelity Global Healthcare Index Securities Investment Fund A Class USD Cash Shares
Fund16	009414.OF	Bank of China health stock securities investment fund
Fund17	020459.OF	Ping an pharmaceutical selection stock type securities investment fund C
Fund18	018529.OF	Hubao health mixed securities investment fund C
Fund19	004050.OF	Huaxia new jinsheng mixed securities investment fund A
Fund20	001898.OF	EFG health theme flexible allocation of hybrid securities investment fund

4.1.2. Data descriptive statistics:

1) Absolute Return Levels and Characteristics. This section will describe the basic statistical characteristics of the sample big health investment funds, get the summary table specifically as shown in Table 2. From the description of health investment funds, its absolute return performance is not outstanding, the average daily return of the fund are very low, in line with the low return investment characteristics of the fund products, the level of return of individual funds have good and bad, of which the worst return performance of the fund for the Cathay Health Equity C, the average daily return of -0.0765%, the best performance of the fund for the GF Global Healthcare Index Securities Investment Fund, the average daily return of 0.0743%. The best performing fund was GF Global Healthcare Index Fund with an average daily return of 0.0743%. From the overall view of the sample, the absolute range of daily return fluctuations of health investment funds is narrower, which is more suitable for ordinary investors with low risk tolerance.

The skewness and kurtosis of the return distribution show the characteristics of the fund's return distribution. If the skewness S is between -0.5 and 0.5, the distribution is quite symmetric, and vice versa, the distribution is less symmetric; if the kurtosis K is close to 0, the distribution is normal. If the kurtosis K is close to 0, the distribution is normal. If K>0, the distribution is high and narrow peaks, and the degree of dispersion is low. If K<0, the distribution is low broad peaks with a high degree of dispersion. The skewness of the sample funds is more discrete and the kurtosis is greater than 0. Therefore, it can be preliminarily judged that the distribution of the returns of the large health investment funds is not symmetrical, and the phenomenon of sharp peaks is more obvious, and the returns are around 0 in most of the periods.

Table 2 Basic statistics of the big health investment fund

Number	Average income(%)	Minimum value(%)	Maximum value(%)	Skewness(S)	kurtosis(K)
Fund1	-0.0096	-4.8946	3.8115	-0.5439	1.407
Fund2	0.0442	-7.0369	4.8406	-0.5997	2.4197

Fund3	-0.0765	-4.0834	3.5995	-0.2678	0.2176
Fund4	-0.0423	-5.2792	5.8371	-0.0254	0.0581
Fund5	0.0542	-6.5192	3.9117	-0.8399	3.0096
Fund6	-0.0098	-5.6996	4.9556	-0.2511	0.3726
Fund7	-0.0646	-6.1756	4.2902	-0.5765	1.4082
Fund8	0.013	-4.4578	0.8701	-6.1208	76.9876
Fund9	0.0743	-7.2393	4.047	-1.1161	3.5916
Fund10	-0.007	-5.2395	3.3629	-0.6459	1.7575
Fund11	0.0687	-6.8783	5.7872	-0.475	1.7819
Fund12	0.0316	-6.8182	3.1928	-1.1272	4.0748
Fund13	-0.0052	-6.5603	3.5491	-0.7259	1.6519
Fund14	-0.0732	-14.0812	3.8667	-2.5896	21.7759
Fund15	0.0581	-6.1974	4.2699	-0.7628	2.5516
Fund16	0.0088	-6.3191	5.0089	-0.5399	1.1275
Fund17	0.0644	-7.4662	4.2408	-1.1057	4.6174
Fund18	-0.0074	-4.4749	3.3019	-0.5982	1.2488
Fund19	0.0423	-5.5859	7.1058	-0.0762	3.2522
Fund20	-0.0266	-5.7391	4.3272	-0.3787	0.6025

2) Comparison of Overall Return Ability. The average of the statistical characteristics of the sample funds represents the overall performance of this type of fund, which is then compared and analyzed with the performance of traditional investment funds, China's large-cap and small- and mid-cap stock markets, as shown in Table 3. In terms of return performance, the returns of large health funds are significantly better than traditional actively managed funds, and also better than direct investment in the stock market, large-cap and small- and medium-cap stock index market performance, the overall downward movement of the stock market during the sample period, during the same period of the traditional funds and stock market returns are negative, while the returns of the large health funds are positive, with an average daily return of up to 0.0064%, the large health funds during the market During the market downturn, the returns of health funds are relatively firm, reflecting the stability of strategic stock picking investment. From a single sample, the average daily returns of 15 out of 20 large health funds exceeded those of traditional investment funds, and their return performance was stronger than that of traditional active stock picking funds.

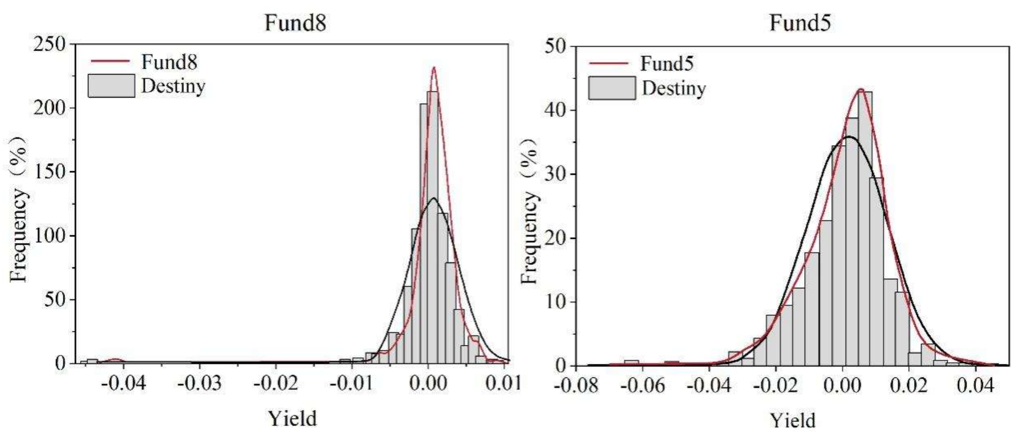
However, in terms of the volatility of returns, the minimum daily returns of large health funds are lower than those of traditional actively managed funds and the large-cap stock market, and similar to that of the small-cap stock market, so the risk of daily volatility loss of large health investment funds should be higher. In terms of the skewness and kurtosis of the return distribution, the return distribution of traditional funds and the stock market differs from the normal distribution, while the difference is even greater for large health funds, and the kurtosis of the return distribution is the most prominent, and combined with the positive average return of the sample funds, the returns of large health investment funds should be in the positive return range close to zero most of the time.

Table 3 Comparison of overall income ability

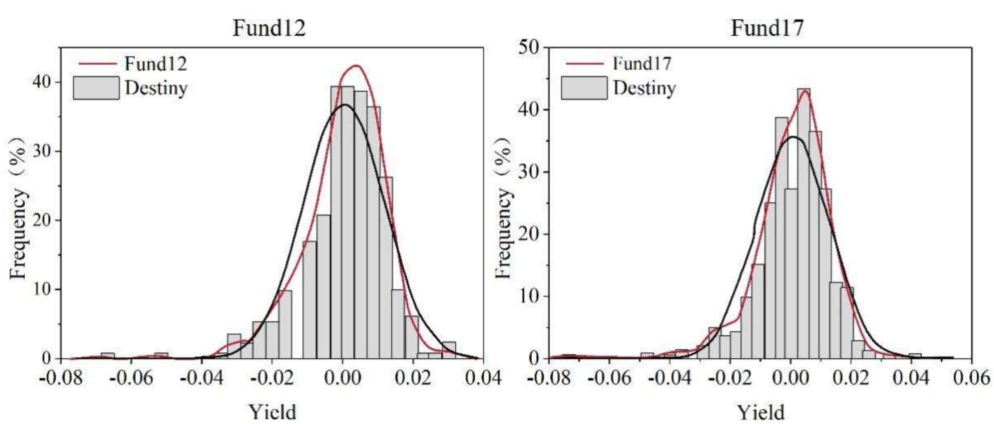
Type of investment	Income mean(%)	Minimum valu(%)	Maximum value(%)	Skewnes s	kurtosi s
Sample mean	0.0064	-6.3377	4.2087	-0.9686	6.6961
Traditional fund	-0.017	-5.3385	4.2561	-0.2884	0.5297
Small and medium market	-0.0026	-6.6856	3.8062	-1.0249	3.7468

Bulk market	-0.0466	-5.0687	4.2334	-0.433	1.1909

3) Normality test of return distribution. Four funds are randomly selected from the sample funds as an example, and the probability density distribution graph of the logarithmic returns of the big health investment funds is compared with the standard normal distribution (the black line in the graph), which is realized by relying on Python code programming, and the distribution graph is shown in Fig. 1. From the pattern in the figure, we can see that the yield distribution of the big health investment fund has the characteristics of right skewed peak, sharp peak, and thick tail, especially the characteristics of the sharp peak is obvious, the yield presents this state of low yield fluctuation agglomeration phenomenon, the reason for this, although the big health fund through the machine algorithmic strategy for selecting and buying and selling stocks, different from the traditional active investment funds to human experience judgment investment, but essentially The main investment assets are still stocks, and their yield is greatly affected by the stock market, while the stock market has the characteristics of convergence of trading behavior and limited liquidity, which determines the return on assets can be divided into two states, there are things that happen, there is a market for a few periods of time, the absolute value of the return is relatively large, which corresponds to the phenomenon of the “thick tail”. The absolute value of the return is relatively small in most of the peaceful periods, and the return is mainly concentrated around 0 due to the influence of the market balance arbitrage, which corresponds to the phenomenon of “sharp peaks”. In addition, since the return distribution of quantitative investment funds is skewed to the right of the peak, this also indicates that large health funds can more often than not obtain lower positive returns and have long-term investment value.



(a)Fund5 and Fund8



(b)Fund12 and Fund17

Fig. 1. Yield

In this paper, we will further adopt the common method of normality test, using skewness and kurtosis to construct the J-B statistic for normality test. It is generally believed that when the J-B statistic is greater than 6, it can be assumed that the unacceptable data follows a normal distribution. The test statistics of the sample fund are shown in Table 4. From the J-B test statistic of the sample data, only the J-B statistic of two funds, Cathay Healthy Stocks C and Baoying Medical Healthcare H.K.S.E. Stocks, is less than 6, and the J-B statistic of the rest of the sample funds is greater than 10, so the logarithmic return distributions of the sample funds do not obey the normal distribution, and there are skewed peaks and narrow peaks in the sample funds in general.

Table 4 J-B statistic

Fund number	J-B statistic	Fund number	J-B statistic
Fund1	47.47	Fund11	61.14
Fund2	109.36	Fund12	325.44
Fund3	5.05	Fund13	72.46
Fund4	4.01	Fund14	7515.09
Fund5	178.19	Fund15	132.44
Fund6	6.93	Fund16	36.53
Fund7	49.6	Fund17	393.19
Fund8	91153.89	Fund18	44.82
Fund9	268.16	Fund19	159.03
Fund10	71.41	Fund20	14.05

4.2. Experiment on Quantitative Evaluation of Risks of Large Health Investments

The experimental platform is WINDOWS7 platform, the test platform memory 32G, processor is 64-core processor. The parameters of the risk evaluation model for big health investment are shown in Table 5.

Table 5 Parameter value

Parameter type	Parameter value
GA group size	30
Mutation probability	0.4
Evolutionary frequency	10
Cross probability	0.6
Training step	1000
Learning rate	0.2
BP output neuron	14
BP Hidden layer	3
BP Output layer	1

180 sample data of big health investment funds are collected and organized, and the test and training are 40 and 140 respectively. Based on the big health investment risk ah evaluation index system constructed in this paper, the data collected in this section covers the six major risks of big health investment in environmental policy risk, technology risk, management risk, market risk, production risk, realization risk, and according to the risk factors are divided into five grades, level one to level five danger. The traditional BP model and particle swarm algorithm (PSO) model are selected to participate in the comparison, and the loss performance of the major health investment risk evaluation model is specifically shown in Figure 2. The number of iterations increases, although the BP model Loss loss performance gradually decreases, but after 300 iterations, the BP model Loss loss property can still have large fluctuations, compared with the other two evaluation models, the Loss

loss performance is poor. Compared with the BP evaluation model, the PSO evaluation model has less overall fluctuation, converges after 450 iterations, and the minimum Loss loss value is 0.37. The model with the best training performance is the model in this paper, which has the best convergence performance, converges after 400 iterations, and the Loss loss value is 0.28, which is the best performance at this moment.

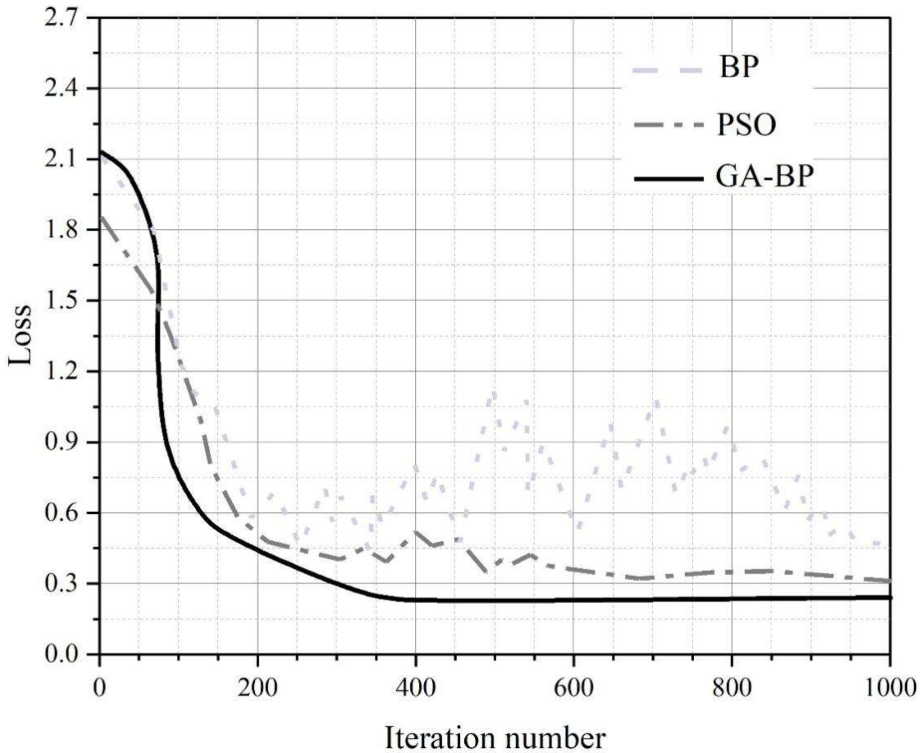
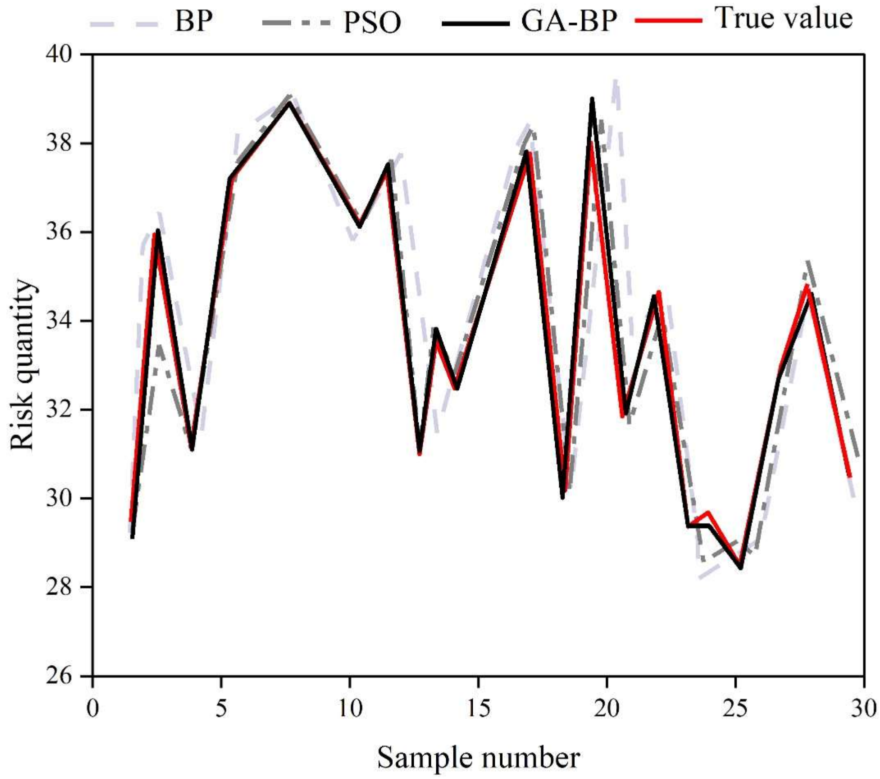
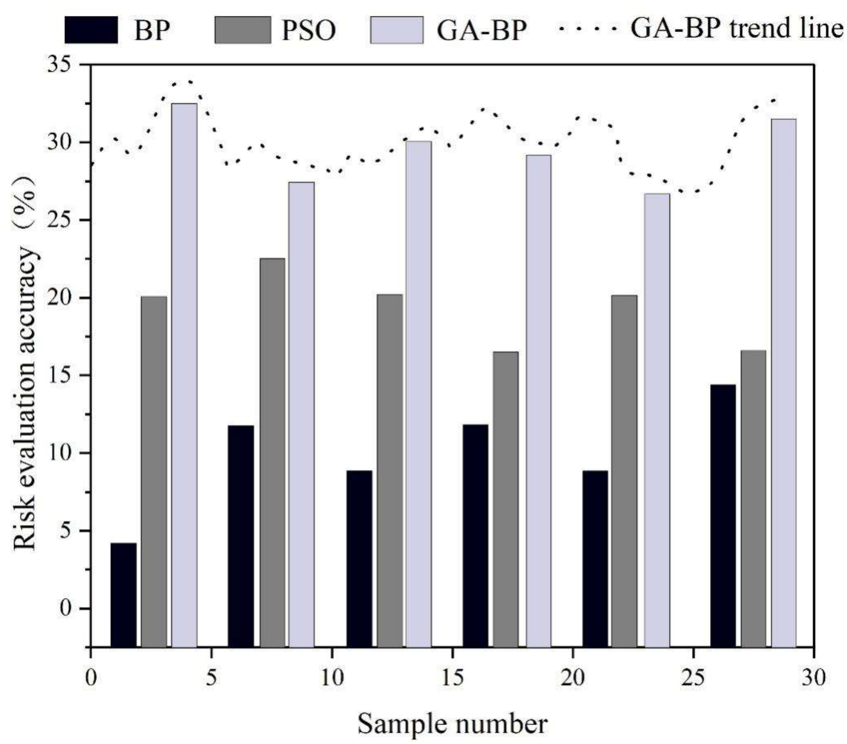


Fig. 2. Model loss performance

Thirty samples of risk indicators are selected for training to test the training effect of the three risk evaluation models of this paper's model, the BP evaluation model and the PSO evaluation model on the number of risks as well as the precision of risk evaluation, as shown in Figure 3. Figures (a) and (b) correspond to the model's risk prediction quantity and risk evaluation accuracy of big health investment, respectively. According to the results in Fig. (a), the BP risk model has the worst prediction of the number of risks within the sample data, and the predicted number of risks in sample numbers 5, 14 and 21 have obvious deviations from the actual values. Compared with the BP model, the PSO risk evaluation model curve is closer to the real value curve, but there is still some prediction deviation in individual sample data. The model in this paper predicts the sample risk most accurately, which is basically consistent with the real value curve of the sample risk. From the overall data trend of Fig. (b), the GA-BP evaluation model of this paper has the highest evaluation accuracy of sample risk, and the risk evaluation accuracy of the GA-BP risk evaluation model is above 93.5% in all 30 sample indicators. The PSO risk evaluation model has the second highest performance, and compared with the GA-BP risk evaluation model, there is a relatively obvious gap in the overall evaluation accuracy, and the evaluation accuracy of the PSO model is below 82.5%, while the traditional BP risk evaluation model has the worst performance. It can be seen that the model in this paper can more accurately predict the number of risks within the big health investment risk sample, and has better training performance and evaluation accuracy.



(a)The number of predictions for major health investment risks



(b)Evaluation accuracy of major health investment risk

Fig. 3. Performance of major health investment risk forecasting

Combined with the risk evaluation index system of big health investment constructed in this paper, the evaluation results of three risk evaluation models in six risk indicators of environmental policy risk, technology risk, management risk, market risk, production risk and realization risk are finally counted, and the statistical results are shown in Table 6. From the data in the table, it can be seen that there are differences in the number of risks and the degree of risk impact of different sample data, and the evaluation accuracy of the three risk evaluation models also has a big difference. Comparison of the three models, this paper's model has the highest evaluation accuracy of the risk of big health investment, the evaluation accuracy is higher than 91.1%, followed by the PSO model, the evaluation accuracy is higher than 78.5%, and the worst performance is the BP model, the evaluation accuracy is basically not higher than 80%. It can be seen that the GA-BP big health investment risk evaluation model proposed in this paper has the highest comprehensiveness and meets the requirements of big health investment risk investment.

Table 6 Statistics of the risk assessment of major health investments

Risk assessment type	Sample number	Accuracy		
		BP	PSO	GA-BP
Environmental policy risk	1	73.1	83.6	95.9
	2	74.4	85.4	97.6
	3	78.9	81.1	96.2
	4	79	90.6	95.4
	5	80	89.7	91.1
Technical risk	1	79.9	82.1	96
	2	74.5	78.5	94.8
	3	75.9	81.3	95.4
	4	75	82.7	96.5
	5	79.3	82.1	96.8
Management risk	1	82.3	84	96.2
	2	74.5	87.7	95.5
	3	70.5	80.1	95.3
	4	70	80.6	97.7
	5	76.9	86.8	97
Market risk	1	72.6	91.3	95.7
	2	79.1	84.7	93.6
	3	80.7	85.8	97.2
	4	74.7	86.1	93.7
	5	76.1	89.4	99.1
Production risk	1	70.8	85	95.6
	2	73.4	81.9	97.7
	3	76.8	89.8	93.2
	4	72.7	83.4	98.7
	5	78	87.5	91.7
Cash risk	1	79.3	82.5	96.9
	2	70.9	80.2	95.7
	3	76	78.7	94.3
	4	79.2	80.2	98
	5	78	85.6	92.3

5. Strategies for Optimizing the Applicability of the International Investment Law

In the context of economic globalization, large health investments between countries are becoming more frequent, and country-to-country large health investment relationships are being brought under the constraints of international investment law. The significance of optimizing the applicability of international investment law to big health ventures is to provide a more balanced and predictable legal environment that supports public health objectives and sustainable development. This not only helps protect the propriety of big health investors, but also ensures that states have greater autonomy and flexibility in formulating and implementing public health policies. To this end, this chapter proposes pragmatic optimization strategies for international investment law from the perspective of big health investment risks.

1) Balancing the rights and interests of host and investor countries. In view of the imbalance between the interests of investors and the right to regulate of host countries in international investment treaties, in order to meet the requirements of sustainable development, international investment law should be revised with the starting point of balancing the rights and interests of host countries and investor countries. What kind of way to respond to social change or development is adopted in the international investment law, whether to further explore the developmental and inclusive interpretation, formulate a list of exceptions, or to properly balance the many conflicting interests and considerations, which is an important thinking to balance the rights and interests of the host country and the investing countries under the realistic and feasible countermeasures.

2) Increase the transparency of the application of the law. In the context of global environmental governance, we cannot rely solely on the laws and policies promulgated by one country, but must also rely on the joint discussions of all countries to formulate relevant legal norms and increase the transparency of the application of laws, so as to better coordinate the international investment in health and environmental protection. It is clear in the provisions that the health investment measures taken in accordance with such health investment policies will not violate the requirements of the international investment law, thus greatly increasing the transparency of the application of the international investment law, and thus promoting the coordinated development of international health investment.

3) Inject the concept of sustainable development. Injecting the concept of sustainable development into international investment law can help resolve the contradiction between international investment law and environmental regulation, and also provide policy space for host countries and investor countries to realize the goal of sustainable development in health investment. Attempts can be made to eliminate factors unfavorable to the realization of sustainable development goals in terms of regulation and institutional design, critique and deconstruct the relevant substantive rules and the investor-host country investment arbitration mechanism, impose regulations on investors to protect the environment and increase the procedures for sustainability impact assessment to promote the sustainable development of international investment in health, so as to gradually promote the development and change of international investment law in the context of global environmental governance. This will gradually promote the development and change of international investment law in the context of global environmental governance.

6. Conclusion

In order to realize the scientific quantification and evaluation of the risk of big health investment, this paper selects the neural network as the theoretical foundation of this research, combines the BP neural network with the genetic algorithm, builds a big health investment risk evaluation model based on GA-BP neural network, and carries out the quantitative evaluation experiments of the risk of big health investment, in order to validate the performance of this paper's model and the application of the performance. Before formally carrying out the experimental analysis, the big health investment sample data are preprocessed. The average daily return of large health investment funds generally exceeds that of traditional investment funds, but the volatility of returns is greater, and the risk of daily volatility loss is higher than that of traditional actively managed funds and large-cap stock markets. More often than not, large health investment funds can obtain lower positive returns, with long-term investment value, and the distribution of logarithmic returns do not obey the normal distribution. The traditional BP and PSO evaluation models are chosen as comparisons, and the performance of this paper's model in quantifying and evaluating the risk of large health investment is discussed in depth. In the model training, the training performance of this model is better than that of BP and PSO evaluation models, the overall fluctuation of the Loss loss is smaller, and it tends to converge after 450 iterations, with the minimum Loss loss value of 0.37. 30 risk index samples are selected for the training, and the risk evaluation accuracy of this model is more than 93.5%, whereas the evaluation accuracy of the PSO model is less than 82.5%, and the BP model has the worst performance. The BP model performs the worst. In the comprehensive statistical analysis of six risk indicators, namely, environmental policy risk, technology risk, management risk, market risk, production risk, and realization risk, the evaluation accuracy of PSO model and BP model is higher than 78.5% and 68.5% respectively, while the evaluation accuracy of this paper's model is higher than 91.1%, which is a higher comprehensive performance in the quantification and assessment of risk of big health investment.

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