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An Improved BP Neural Network-based Method for Predicting Health Status of Residents

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Abstract. *Intending to the current health status forecasting methods in the input of a wide range of influence indicators, leading to large prediction errors. This article designs a residential health status prediction method relied on optimized BP neural network. Firstly, chaos theory, dynamic weights, dynamic learning factors and Gaussian variation strategy are introduced into the Particle Swarm Optimization (PSO) technique, and the Improved PSO (IPSO) technique is adopted to optimize the updating strategy of weights and thresholds in the BP algorithm, so as to enhance the convergence rate and global enhancement ability of the traditional BP algorithm. Secondly, the influence indicators of residents' health status are selected and preprocessed, and the preprocessed influence indicators are downgraded to extract the principal components, and these principal components, which are linearly combined from the original indicators, are adopted as inputs to the optimized BP neural network model, with the residents' health status as the output, and the enhanced BP neural network is used to fit the nonlinear relationship between the principal components and inhibit the influence of irrelevant indicators on the fitting accuracy, for the goal of enhancing the accuracy of the forecasting. influence, thus improving the accuracy of forecasting. The experimental outcome implies that compared with the existing methods, the suggested method has lower MAE, MAPE, RMSE, RMSPE and R. The predicted health status of residents is almost the same as the actual status, which effectively improves the prediction accuracy.*
Keywords: BP neural network; Health status prediction; Particle swarm algorithm; Principal component analysis; Learning factor

1. **Introduction.** Recently, due to the economic level and social structure of human health to different degrees, the complexity and diversity of disease modalities, the health problems of the population are becoming more and more prominent. World health data show that hypertension, hyperlipidemia and many other diseases have a significant age trend, however, currently, the prevalence of our residents has increased exponentially

[1, 2]. On the one hand, residents shoulder the mission of national construction; on the other hand, residents bear the responsibility of old age and raising future generations, and their health affects the overall national quality [3]. With the advancement of national intelligent reform and the improvement of quality of life, people pay more attention to the early prevention of diseases, and machine learning methods play an important role in predictive modeling, which are now widely used in management, medicine and other multidisciplinary fields [4, 5]. Residents are the key population to improve the overall health of our country, and research on combining the health status of our residents with machine learning methods for health prediction is still lacking, and there is an urgent need for research to exploit the value. The research value of residents' health status prediction lies in identifying health risks in advance, optimizing the allocation of medical resources and promoting the formulation of public health policies, thus improving residents' health level and quality of life.

1.1. **Related work.** The main research of residents' health status prediction usually involves the application of statistics, epidemiology, data science and machine learning technology to analyze health data and predict the incidence of diseases, health trends and medical needs. Wang et al. [6] constructed a system of indicators affecting the health of the population and used ARIMA model to predict the underlying diseases. Hao et al. [7] firstly established a grey dynamic model by using the physical examination data of the population to predict the quality of health according to the physical examination status of the population. Zhang et al. [8] improved the grey model by using a Particle Swarm Optimization (PSO) technique to process the relevant value of the data of the urban and rural residents who are overweight and obese. Kim et al. [9] collected physiological information such as palm temperature and electrocardiogram, and detected autonomic function level, physiological age, blood pressure, etc., and predicted the health status by comparing with the normal physiological function graph, but the error was large. Kayacan et al. [10] used gray system theory to model the prediction of three body shape indicators, namely height, weight, and chest circumference. Morid et al. [11] established a database of residents' physical fitness and health monitoring data, and used the time series method to predict the development of physical fitness in the long term, while Bafjaish [12] used the simple Bayesian classification algorithm to construct a classifier of residents' physical fitness, and then classified the physical fitness and health status of the residents into groups in a detailed manner. Islam et al. [13] used Partial Least Squares (PLS) and SVM algorithms for feature selection and model optimization by collecting information on physiological indicators of female residents.

With the increasing flexibility of deep learning technology to utilize various complex feature approaches, more researchers have applied deep learning to the prediction of residents' health. Usama et al. [14] analyzed and trained a large amount of residents' behavioral data and physiological index data by building a recurrent Convolutional Neural Network (CNN) model to forecast the health status of residents. Nayeem et al. [15] implemented an MLP neural network model to predict the degree of disease of residents based on three hidden layers, but the prediction error was large. Divyashree and Divakar [16] analyzed a series of indicators affecting the health status, and then used decision making to forecast the health condition of the population. The BP neural network has become the most commonly used neural network due to its approximation ability. Samant and Rao [17] analyzed and trained a great quantity of behavioral data and physiological indicators of residents to forecast the health condition of residents. Mandala et al. [18] proposed a prediction method combining multiple influencing indicators with BP neural network, but the forecasting accuracy is not satisfactory. Lin et al. [19] designed a GA-BP neural network population health forecasting model using multiple factors affecting population health as prediction parameters and monitoring data.

1.2. **Contribution.** In summary, the existing research on the prediction method of residents' health status generally has the issues of more variables affecting indicators and low prediction accuracy, this paper designs the prediction method of residents' health status relied on optimized BP neural network. Firstly, to address the issue that traditional BP neural network falls under local improvement easily, dynamic learning factor and Gaussian variation strategy are introduced into PSO technique, and the improved PSO (IPSO) technique is adopted to improve the updating strategy of weights and thresholds in BP algorithm. Secondly, the indicators affecting the health status of residents are selected, normalized, and the processed indicators are subjected to principal component analysis, and then the four-layer topology of the optimized BP neural network is determined, and the extracted principal components are used as inputs to the optimized BP neural network and the residents' health status is used as outputs, and the enhanced BP neural network is suggested to inhibit the effects of irrelevant indicators on the fitting accuracy, so as to increase the prediction accuracy.

2. **Theoretical analysis.**

2.1. **BP neural network.** BP neural network is a feedforward network that uses error backpropagation to modify parameters [20, 21]. Figure 1 implies the framework of the neural network, which mainly includes input, output and obscured level.

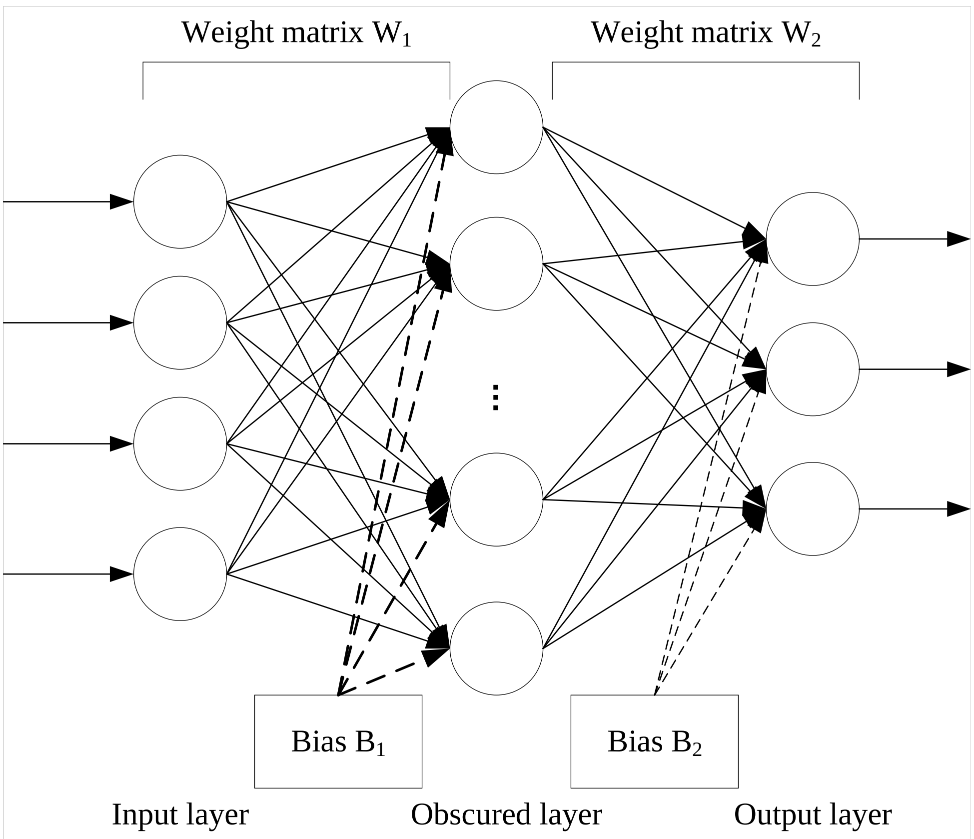

Figure 1. The network framework of the BP algorithm

A BP neural network can be composed of multiple obscured levels or a single obscured level, but in general, a single obscured level neural network can meet most of the prediction requirements. The BP neural network's input-output relation is represented by the following equation.

$$y = f\big[f(V_1x + A_1)V_2 + A_2\big] \tag{1}$$

where x and y are the input and output matrices, individually; f is the activation operation; V_1 and A_1 are the weights and biases between the input and obscured levels, individually; V_2 and A_2 are the weights and biases between the obscured and output levels, individually.

During the training process, the BP neural network modifies the weights and bias vectors through the back propagation of the error to make the error satisfy the demand. The principle of adjustment can be expressed by the following equation.

$$d\big[V_i(s+1)\big] = -\beta\wp_s + d\big[V_i(s)\big] \tag{2}$$

where $d\big[V_i(s+1)\big]$ and $d\big[V_i(s)\big]$ are the modification of the weight vector by $s+1$ and s iterations respectively; $\wp_s$ is the mean square error after the s iteration; β is the learning rate.

The error is expressed using the Mean Square Error (MSE) among the true value and the forecasting value of the neural network. The MSE is computed as follows.

$$\wp = \frac{1}{m}\sum_{l=1}^{m}(y_l - y_{l,r})^2 \tag{3}$$

where m is the amount of training instances; y_l and $y_{l,r}$ are respectively the predicted value proportional to the l-th sample and the actual value of the l-th sample.

2.2. **Principal component analysis.** Principal component analysis (PCA) is a technique to decrease the data's dimensionality [22], which combines several related variables, eliminates duplicates, maximizes the number of new unrelated variables, and ensures that the new variables retain the information of the original variables, as follows.

(1) Normalize the raw data. Suppose that there are n index variables used in the PCA: $x_1, x_2, ..., x_m$, which is used to evaluate m objects, and x_{ij}, which is the j-th indicator of the i-th evaluation object. Single indicator values are converted to a standardized indicator $\tilde{x}_{ij}$ with the following expression.

$$\tilde{x}_{ij} = \frac{x_{ij} - \overline{x}_j}{s_j}, \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \tag{4}$$

(2) The eigenvalues and corresponding eigenvectors are computed. The eigenvalues of the correlation coefficient matrix R are $\mu_1 \geq \mu_2 \geq \cdots \geq \mu_n \geq 0$, the corresponding featured vectors are $w_1, w_2, ..., w_n$, and the n new indicator variable y_n consists of the featured vectors, where the initial chief ingredient is y_1, the second chief ingredient is y_2, and the n-th chief ingredient is y_n.

$$R = [r_{ij}]_{m\times n} \tag{5}$$

$$\begin{cases} y_1 = w_{11}\tilde{x}_1 + w_{21}\tilde{x}_2 + \cdots + w_{m1}\tilde{x}_n \\ y_2 = w_{12}\tilde{x}_1 + w_{22}\tilde{x}_2 + \cdots + w_{m2}\tilde{x}_n \\ \quad \vdots \\ y_n = w_{1n}\tilde{x}_1 + w_{2n}\tilde{x}_2 + \cdots + w_{mn}\tilde{x}_m \end{cases} \tag{6}$$

(3) The message donation [23] and cumulative donation [24] of featured value μ_j ($j = 1, 2, ..., n$) are calculated.

(4) The comprehensive score can be calculated and estimated in terms of the synthetical score value.

3. **Optimization of BP neural network.** Aiming at the issue that the traditional BP neural network is prone to partial improvement or slow convergence, this article introduces chaos theory, dynamic weights, dynamic learning factors and Gaussian variation strategy into the PSO algorithm, and uses the improved PSO technique to enhance the updating strategy of weights and thresholds in the BP algorithm. To enhance the convergence rate and universal improvement capability of BP algorithm, the steps in detail are as bellow.

In the iterative optimization process, the velocity and location of the particle are as bellow.

$$v_{ij}^{s+1} = \hat{u}v_{ij}^{s} + b_1 r_1 \left(q_{ij}^{s} - x_{ij}^{s}\right) + b_2 r_2 \left(p_j^{s} - x_{ij}^{s}\right) \tag{7}$$

$$L_{ij}^{s+1} = L_{ij}^{s} + v_{ij}^{s+1} \tag{8}$$

where, L_i and v_i denote the location and velocity of the i-th particle individually; q_i represents the extreme value of particle individual; p_i represents the extreme value of particle population; $\hat{u}$ is the inertia weight; j is the optimization space dimension; s is the amount of epochs; b_1 and b_2 are studying elements; r_1 and r_2 are unorganized numbers in $[0, 1]$.

The Tent mapping way is first adopted to initialize the PSO population, and the sequence of Tent chaotic mappings [25] is mapped to the search space so that it traverses the seek space to enhance the optimal search probability of the algorithm. Tent chaotic mapping sequence is a mapping method used in mathematics to generate chaotic sequences. It generates complex and seemingly random sequences through simple nonlinear transformation, which is often used in chaos theory research and some encryption algorithms.

$$x_{i+1}^{j} = x_{\min}^{j} + x_{i+1}^{j}\left(x_{\max}^{j} - x_{\min}^{j}\right) \tag{9}$$

For the goal of ensuring the global optimization as well as local enhancement capability of the PSO technique, the dynamic weighting [26] method is introduced to enhance the constancy of the method as well as the convergence speed, which can be expressed as bellow.

$$\hat{u}^{s} = \hat{u}_{\max} + \left(\hat{u}_{\max} - \hat{u}_{\min}\right)\left[\frac{2s}{s_{\max}} - \left(\frac{s}{s_{\max}}\right)^2\right] \tag{10}$$

where $\hat{u}^s$ denotes the inertia weight at the s-th iteration, $s_{\max}$ denotes the maximum amount of epochs, and $\hat{u}_{\max}$ and $\hat{u}_{\min}$ denote the upper and lower limits of the inertia weight.

Then, to remain the method's global optimization capability and partial optimization capability, a dynamic learning factor is introduced into the particle velocity update equation.

$$\begin{cases} b_1^s = b_{1\_\max} - (b_{1\_\max} - b_{1\_\min}) \times \ln\left(1 + \dfrac{s(e-1)}{s_{\max}}\right) \\ b_2^s = b_{2\_\min} + (b_{2\_\max} - b_{2\_\min}) \times \ln\left(1 + \dfrac{s(e-1)}{s_{\max}}\right) \end{cases} \tag{11}$$

where $b_{1\_\max}$, $b_{1\_\min}$, $b_{2\_\max}$, and $b_{2\_\min}$ denote the maximum and minimum values of the learning factors b_1 and b_2, individually.

The introduction of Gaussian variation term in the particle individual term in the particle velocity update formula improves the capability of the method to jump out of the partial optimal solution. The particle velocity after the introduction of Gaussian variation term [27] can be expressed as bellow.

$$v_{ij}^{s+1} = \hat{u} v_{ij}^s + b_1 r_1 \left(q_{ij}^s - L_{ij}^s + l_1 G_i^s\right) + b_2 r_2 \left(p_j^s - L_{ij}^s\right) \tag{12}$$

$$G_i^s = l_2 G\left(\xi, \delta^2\right) \tag{13}$$

where l_1 and l_2 are random numbers in $[0, 1]$; G_i^s is the Gaussian variance; ξ is the mean; and δ^2 is the variance.

Subsequently, the enhanced BP neural network model is trained and optimized using the above IPSO algorithm in the following steps.

Step 1: Initialize the BP neural network, select nodes' amount of the input level, output level and obscured level of the network, and set the activation function after dimensionality reduction of the data. To avoid the model falling into an overfitting state, only k obscured levels are selected, and the number of nodes is chosen and adjusted through several trials. The amount of nodes is chosen as bellow.

$$g = \sqrt{k + n + c} \tag{14}$$

where g is the nodes' amount of the obscured level, k is the nodes' amount of the input level, n is the nodes' amount of the output level, and c is the conditioning factor.

Step 2: Use weights and thresholds as adaptation values, initialize the IPSO parameters, particle positions and velocities, set the number of iterations, inertia weights, learning factors, etc., and assign the particle values after each iteration to the weights and thresholds.

Step 3: Train and test the training sample data. The training is evaluated based on the Root Mean Square Error (RMSE) of the true and forecasting values, and the training is completed when the RMSE reaches the target convergence accuracy range or iterations' amount reaches the maximum.

$$R_{\mathrm{MSE}} = \sqrt{\frac{1}{r} \sum_{r=1}^{r} \left(y_p - y\right)^2} \tag{15}$$

where r denotes the training set number, y_p denotes the forecasting value, and y represents the actual value.

4. An optimized BP neural network-based method for predicting health status of residents.

4.1. **Selection and pre-processing of population health impact indicators.** Focusing on the issue that the existing health status influence indicators are numerous, which leads to large prediction errors, this article designs a prediction method of residents' health status relied on optimized BP neural network. Firstly, the influence indicators of residents' health status are selected and pre-processed, and secondly, the processed influence indicators are downgraded to extract the principal components; they are adopted as the enhanced BP neural network model's input, and the residents' health status is adopted as the output. The model structure is implied in Figure 2.

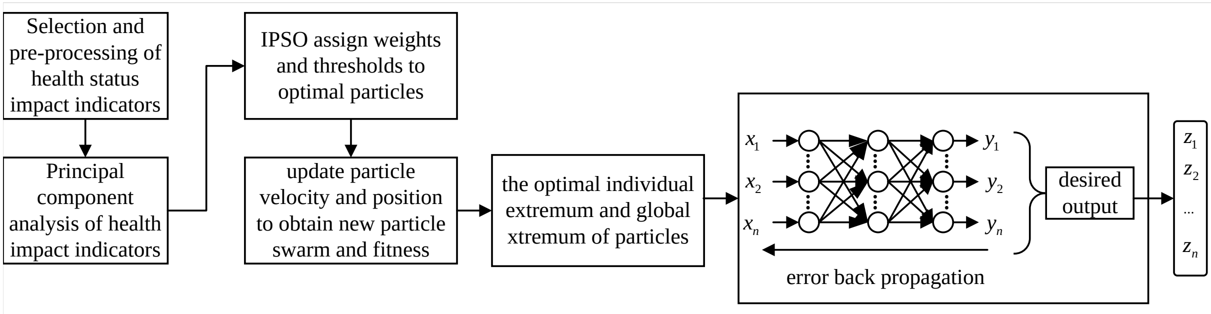

Figure 2. The entire model structure of the designed method

On the ground of existing studies, it can be concluded that health status indicators are selected relied on the four aspects of vital signs, mental state, eating habits and exercise behavior [28], and the indicators of influencing factors are obtained. The 40 influencing indicators, including body temperature, heart rate, blood oxygen saturation, respiratory rate, vigorous exercise, moderate exercise, sedentary, diet regularity, meat and vegetable mix, and frequency of eating sweets, were denoted as: $x_1, x_2, ..., x_{40}$, as the forecasting method's input data, and the residents' health status (healthy, sub-healthy, fever, and disease) as the output variable of the prediction model, denoted as y_1, y_2, y_3, y_4.

Because of the different dimensions of health indicators, training neural networks directly as sample data will lead to large errors. The normalization processing can convert the collected impact index data into numerical values within the range of $[0, 1]$, eliminate the errors between each index dimension, and thus enhance the accuracy of BP neural network forecasting. The normalized index equation is indicated below.

$$X_i = \frac{x_i - \min x_i}{\max x_i - \min x_i} \tag{16}$$

where X_i^* represents the data obtained after the standardization of the original data, and x_i represents the original data to be normalized; $\min x_i$ represents the minimum value in the data and $\max x_i$ represents the maximum value in the data.

The predicted results of the model are normalized data, and the data are unified within the range of $[0, 1]$, which cannot directly reflect the health status of the patients, so it should be de-normalized. The inverse normalized index equation is as bellow.

$$X^* = X_i * (\max x_i - \min x_i) + \min x_i \tag{17}$$

where X^* is the result of inverse normalization.

4.2. **Principal component analysis of indicators affecting the health of the population.** Due to the large number of indicators affecting the health status of the population, this article utilizes PCA to transform the 40 influencing indicators into several principal components, each of which is a linear mixture of the initial variables and each of which is disrelated with each other, which allows chief ingredients to be with certain excellent performance over initial variables.

One chief ingredient is not sufficient to stand for the initial 40 variables, so other principal components are sought, and the covariance of any two chief ingredients is zero. The method of deciding each chief ingredient is as bellow.

(1) Create a matrix R of correlation coefficients for each impact indicator variable after normalization in the previous section.

$$R = (r_{ij})_{m\times m} = \left(\frac{\sum_{l=1}^{n} \tilde{X}_{li} \cdot \tilde{X}_{lj}}{n-1} \right)_{m\times m} \tag{18}$$

where $i, j = 1, 2, ..., 40$, $r_{ii} = 1$ and r_{ij} are the correlations among the i-th index and the j-th index, and $\tilde{X}_{ij} = (X_{ij} - \overline{X}_j)/S_j$, $\overline{X}_j$ and S_j are the instance mean and instance standard divergence of the j-th indicator.

(2) Compute the featured value μ_m of the R, and the related featured vector w_m, where $w_j = (w_{1j}, w_{2j}, ..., w_{nj})^T$, made up of the eigenvector m novel index variables. Then, the corresponding principal component $y_1, y_2, ..., y_m$ is calculated by Equation (6).

(3) The information contribution rate and cumulative contribution rate of eigenvalue μ_j are calculated.

$$a_j = \frac{\mu_j}{\sum_{l=1}^{m} \mu_l}, \quad b_p = \frac{\sum_{l=1}^{p} \mu_l}{\sum_{l=1}^{m} \mu_l}, \quad Z = \sum_{j=1}^{p} a_j y_j \tag{19}$$

where a_j and b_j represent the message donation rate of the j-th ingredient and the cumulative donation rate of the chief component respectively. When b_p is close to 1, the initial p index variables are selected as p chief ingredients to replace the initial 40 index variables, in order that synthetical analysis can be performed on p chief ingredients, and Z in Equation (19) can be used to calculate the comprehensive score. The equation to obtain the p-th principal component Z_p is as follows.

$$Z_p = a_{p1}x_1 + a_{p2}x_2 + \cdots + a_{pp}x_p \tag{20}$$

where $\forall i$, there is an $a_{i1}^2 + a_{i2}^2 + \cdots + a_{ip}^2 = 1$.

4.3. **Prediction of population health status based on optimized BP neural network.** After obtaining p principal component indicators that affect residents' health status by PCA method, the BP neural network algorithm enhanced by IPSO in Section 3 predicts residents' health status. Specific steps are as bellow.

Step1: Build BP neural network. Determine the amount of network levels and the amount of nodes in all layers. A 3-layer BP neural network is constructed, in which the nodes' amount of the input layer is 3.

Step2: Select the parameters of the IPSO algorithm and initialize the population. The position L of the particle is initialized to $L_{ij}^{s+1} = L_{ij}^{s} + v_{ij}^{s+1}$ and the rate V is initialized to $v_{ij}^{s+1} = \hat{u}v_{ij}^{s}$.

Step3: Determine fitness function fitness to guide population search and calculate particle fitness value. The modulus of the difference matrix among the output value and the expected value forecasted by BP neural network is adopted as the fitness function. The equation is as bellow.

$$\mathrm{Err} = \mathrm{norm}(A - B, \beta) \tag{21}$$

where A is the output value matrix; B is the expected value matrix.

Step4: Compare the current fitness of individual particles with the fitness before iteration. If the current fitness of the particle is better than the fitness before iteration, then update the individual extreme values. The velocity and location of the particle are refreshed by Equation (12) and Equation (13).

Step5: Judge whether the stop condition is satisfied. If the current amount of epochs has got the set upper limit, or the error has reached the set minimum error, then stop the iteration before proceeding to the next step, otherwise go to Step 4.

Step6: Update of the BP neural network's weights and thresholds adopting the particles' optimization trajectory. In this paper, we introduce the formula, the updated weights of the BP neural network, and update the threshold of the BP neural network using the dynamic learning factor of IPSO as bellow.

$$\Delta v_{jl} = trace()\theta_l^o y_j = trace()(d_l - o_l)o_l(1 - o_l)y_j \tag{22}$$

$$c_{jl} = b_1 c_j - |b_2 - b_1| c_j \times \left(\frac{l}{n_{\max}}\right) \tag{23}$$

where $trace() = zeros(p+1, n_{\max})$, p denotes the number of principal component indicators affecting health status, θ_l^o denotes the activation operation of level l, d denotes the desired output vector of level l, o_l denotes the output of layer l, and b_1 and b_2 are the dynamic learning factors of IPSO.

Step7: Substitute the optimal initial weights v_{jl} and threshold c_{jl} of IPSO search into the BP neural network, train the IPSO-optimized neural network with the training samples, and calculate the output vectors of each level of the network and the network error. The output of the j-th neuron h_j in the obscured level is as follows.

$$h_j = g\left(\sum_{l=1}^{k} v_{lj} x_l - c_j\right), \quad j = 1, 2, \ldots, 40 \tag{24}$$

where v_{lj} is the connective weight of the l-th neuron to the j-th neuron of the obscured level, x_l denotes the input vector of the l-th level, and c_j represents the threshold of the j-th neuron.

Thus, the output of the i-th neuron of the output level is obtained as follows.

$$z_i = g\left(\sum_{j=1}^{m} v_{ji} h_j - c_i\right), \quad i = 1, 2, \ldots, 40 \tag{25}$$

The error E among the expected value of the neural network and the actual output value y_i of the population's health status is as bellow.

$$E = \frac{1}{2}\sum_{i=1}^{n}\left(y_i - g\left(\sum_{j=1}^{m} v_{ji} g\left(\sum_{l=1}^{k} v_{jl} x_l - \theta_j\right) - c_{jl}\right)\right) \tag{26}$$

Through the setting of network weights and thresholds, the optimization problem of minimizing the error E is achieved until the error requirements are met, and the construction of the residents' health status forecasting model relied on enhanced BP neural network is completed.

5. **Performance testing and analysis.**

5.1. **Comparative analysis of forecast results.** For the goal of verifying the performance of the resident health status prediction method relied on optimized BP neural network, this article selects the resident health status network data of China Statistical Yearbook from 2011 to 2020. The dependent variable of the data set is the health status of the residents, and the independent variable is the index selected according to the principal component analysis. After sorting out the statistical results, MATLAB R2017b was used for mathematical statistical analysis. In this article, the resident health data samples were assigned into the training set and validation data set in terms of the ratio of 6:3:1. For the convenience of description, the prediction method suggested in this article was recorded as PHSBP, the method suggested in literature [14] was recorded as SACNN, and the method suggested in literature [18] was recorded as AOBPN, and the prediction outcome of these three methods were compared and analyzed. The training accuracy of all models is 0.001, the learning rate is 0.01, the maximum training times is 1 000, and the group length is 64.

In this paper, 40 sets of predicted health status data were selected for comparison, and the comparison of prediction accuracy is implied in Figure 3.

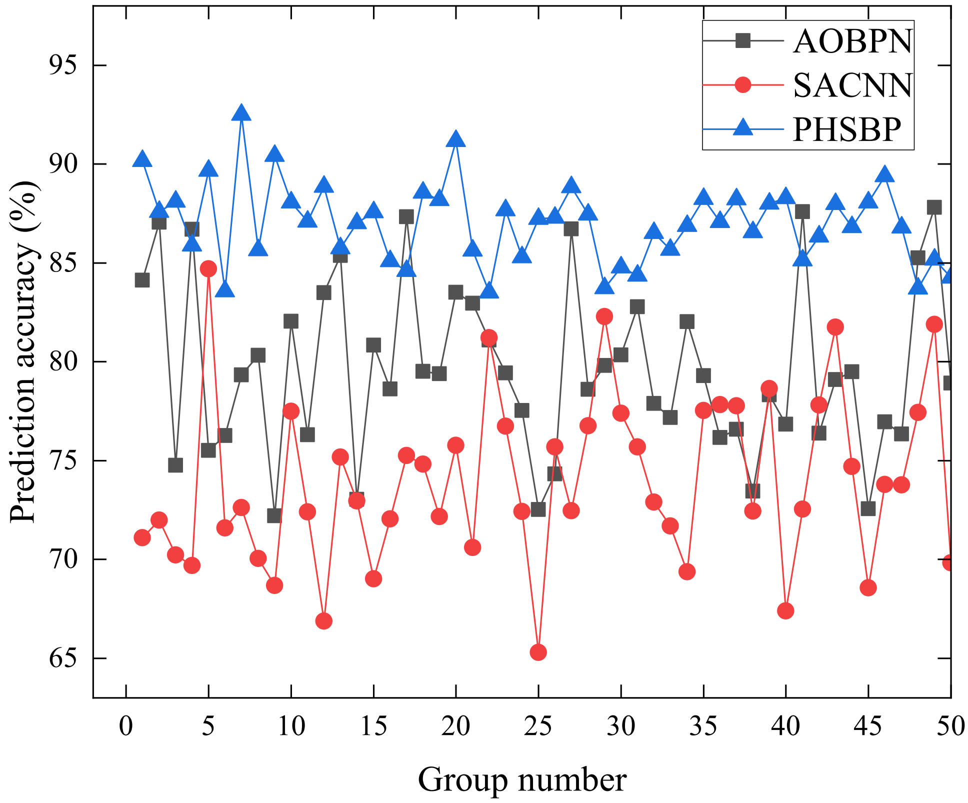

Figure 3. Accuracy results of different forecasting methods

As can be seen from Figure 3, the prediction accuracy of PHSBP method is the highest, reaching 92.5%, followed by that of AOBPN method, reaching 87.8%, and that of SACNN is the lowest, reaching 84.7%. In particular, when 10 groups of sample data were tested, the accuracy rate of PHSBP method was 90.7%, the accuracy rate of AOBPN method was 82.5%, and the accuracy rate of SACNN method was 77.9%. Therefore, PHSBP method had the best prediction performance.

In addition, the comparison curves of the forecasting errors of the PHSBP method with those of the SACNN and AOBPN methods are indicated in Figure 4. The prediction errors of the PHSBP method range from 0.05 to 0.4, with the largest error occurring in sample

19 and the smallest in sample 15. While the prediction errors of the AOBPN method range from 0.002498 to 0.937, with the maximum error of 0.937 occurring in sample 19 and the minimum error of 0.002498 in sample 26. In terms of the overall effect and the error interval, the prediction errors of the PHSBP method are smaller than those of the SACNN and AOBPN methods. AOBPN method. This is because the PHSBP method not only uses PCA to extract important indicator variables that affect the health status of residents, but also uses the IPSO method to enhance the BP neural network, which greatly reduces the forecasting error. The SACNN method, on the other hand, uses the CNN method to predict the health status, which requires multiple convolution operations to calculate the results, resulting in a larger error. The AOBPN method takes multiple variables affecting health as inputs to the traditional BP neural network to predict the health status, but does not reduce the dimensionality of these variables or optimize the BP neural network, leading to a larger error result than the PHSBP method.

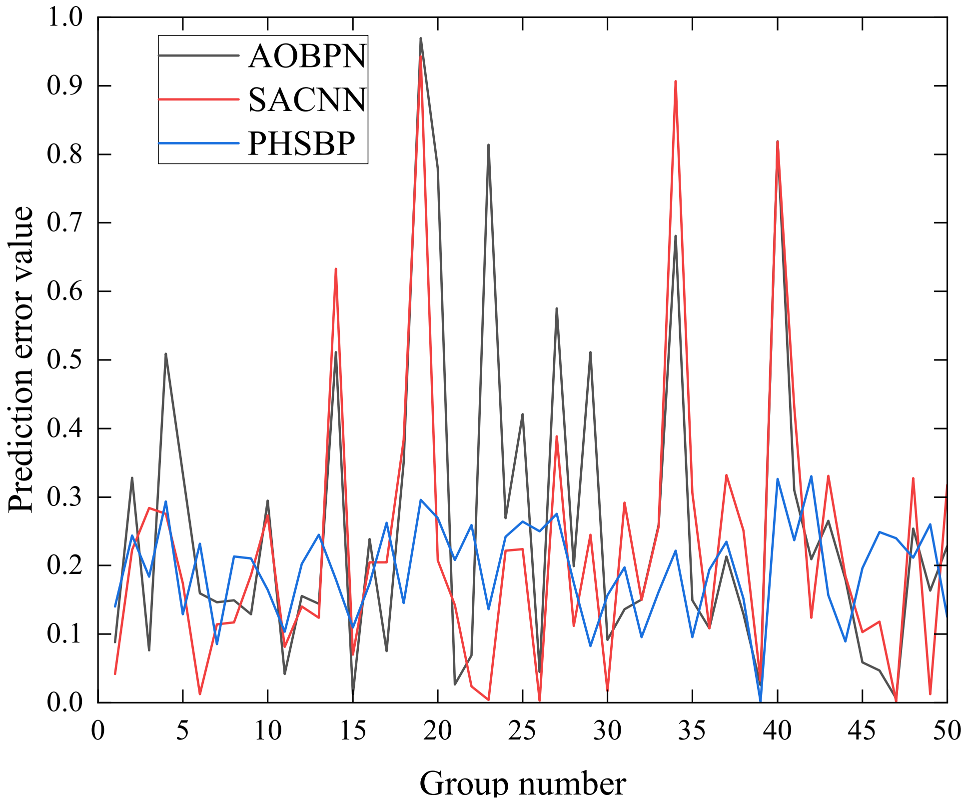

Figure 4. Prediction error results for different methods

5.2. **Comparative performance analysis.** Relied on the above analysis of the forecasting results, the experimental outcome is measured by five indicators: MAE, MAPE, RMSE, RMSPE and correlation coefficient R [29]. The results of the three model evaluation metrics are given in Table 1 and Figure 5.

Table 1. Comparison of prediction accuracy of different methods

Model	**MAE**	**MAPE**	**RMSE**	**RMSPE**	**R**
SACNN	0.2192	0.2461	0.2912	0.2328	0.7915
AOBPN	0.1528	0.1377	0.2036	0.1458	0.8627
PHSBP	0.0714	0.0528	0.0964	0.0762	0.9306

As shown in Table 4 and Figure 5, the accuracy evaluation indexes of PHSBP are significantly better than those of SACNN and AOBPN, in which the MAE and RMSPE of PHSBP are 0.0714 and 0.0762, respectively, which are reduced by 14.78% and 19.33% compared to SACNN, and 8.14% and 8.49% compared to AOBPN, which indicates that the forecasting method relied on the optimized BP neural network is more suitable for solving the issue of predicting the health condition of the population. Comparing the correlation coefficient R, the R value of PHSBP is 0.9306, which is 13.91% and 6.79% higher than that of SACNN and AOBPN, respectively, which indicates that the PHSBP method is effective in using the IPSO algorithm to enhance the convergence rate of BP neural network, and it has a better fitting effect for the prediction of health status of residents.

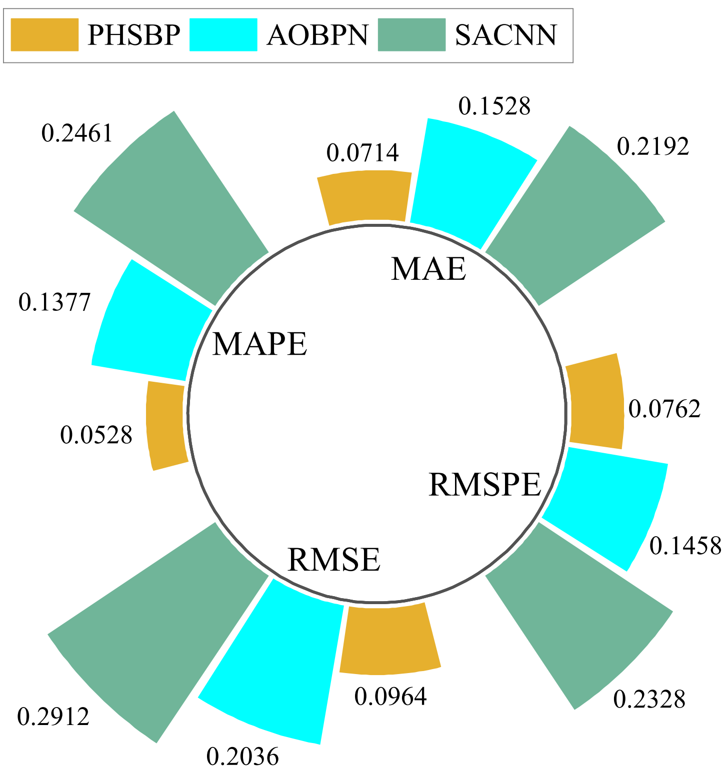

Figure 5. Comparison of the prediction performance of different methods

6. **Conclusion.** Focusing on the issue of unsatisfactory prediction accuracy of the existing health status prediction methods, this article designs a health status prediction method for residents relied on optimized BP neural network. Firstly, to address the issue that BP neural network is simple to fall into local optimum, chaos theory and dynamic learning factor are introduced into PSO technique, and the IPSO technique is adopted to update the weights and thresholds of BP algorithm. Secondly, the indicators affecting the health status of residents are selected, normalized, and the chief components are extracted from the processed indicators using PCA, which is used as the input of the optimized BP neural network, and the health status of the residents is used as the output, and the improved BP neural network is used to fit the non-linear relationship between the principal components, for the goal of enhancing the accuracy of the prediction. The experimental outcome indicates that the suggested method has a low forecasting error and high prediction accuracy, and can be better applied to the prediction of residents' health status.

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