

Research on Health Status and Early Warning Model of Cardiovascular and Cerebrovascular Disease of Old-aged Residents Based on Intelligent Algorithm

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Abstract

With the population aging trends and lifestyle changes of the elderly, cardiovascular and cerebrovascular disease becomes the number one health problem of the whole society. Compared with later treatment, early warning of disease is significantly better in both cost and effect. Machine learning method plays an important role in early warning model operation, and has been widely used in multi-disciplinary fields such as management, medicine and so on. In this study, the intelligent health monitoring system is used to collect data and analyze the health status of elderly residents. Based on Back-propagation Neural Network and Support-vector Machine method, the early warning model of cardiovascular and cerebrovascular diseases of elderly residents is constructed to provide a scientific basis for formulating relevant health intervention measures. Specifically, the paper constructs the indicators and evaluation model to evaluate the health status of elderly residents, collects 624 cases of health monitoring data, establishes the database, utilizes chi square test as well as rank sum test to determine significant indicators, and applies Matlab r2019b software to construct the BP neural network model for learning and prediction. This study finds that the nutritional intake, self-treatment of discomfort symptoms and the regulation of loneliness and depression need to be paid more attention. The final model can improve the accuracy and effectiveness of early warning of cardiovascular and cerebrovascular disease in the elderly group. We should strengthen normal health monitoring and build a multi-party, multi-dimensional and multi-form elderly health management system.

Keywords

Back-propagation neural network, early warning model, old-aged residents, cardiovascular and cerebrovascular disease.

1. Introduction

Health is the foundation of human survival. The outline of the “healthy China 2030” plan puts forward specific measures and requirements in key areas such as healthy behavior, chronic disease prevalence and intelligent health management^[1]. With the progress of medical research, great changes have taken place in the spectrum of human diseases since the 21st century. Chronic diseases represented by cardiovascular and cerebrovascular diseases have jumped to become the number one threat to human health^[2]. At present, the number of deaths caused by chronic diseases worldwide exceeds the sum of all other diseases. China’s Chronic Diseases Survey released by the World Bank shows that the prevalence of chronic diseases in China will continue to intensify from 2010 to 2030, and countries as well as individuals will bear heavy losses and burdens in the process of disease treatment^[3]. The report of the 19th national congress pointed out that we should base on the concept of great health, taking health-related social and psychological factors as a breakthrough, focusing on moving forward and paying

attention to the whole process of health [4], which fully reflects the state's attention to the health of whole nation.

With the deepening of population aging and the increasing number of empty nesters, disease prevention and treatment of the elderly has become the focus of the government. Chronic diseases such as hypertension and cardiovascular disease, as common diseases of the elderly, have also become the top priority in the field of medicine. According to the data of China's 7th National Census, China's population over 60 years old has exceeded 260 million, accounting for 18.7% of the total population, an increase of 5.44 percentage points compared with 2010 [5]. The decline of body organs in the elderly is obvious. Coupled with the unreasonable diet structure, the prevalence of chronic diseases in the elderly has become 4.2 times of the average level of the whole population in society, and the elderly has become the main population of chronic diseases [6]. Therefore, it is urgent and necessary to strengthen the prevention and control of chronic diseases in the elderly.

Health management based on disease monitoring and early warning is a new medical model that can effectively deal with chronic diseases. It takes individual residents or groups as the object, monitors, analyzes and evaluates their health, so as to provide targeted consultation and guidance [7]. In this process, it can fully mobilize the enthusiasm of individuals, institutions and society, make full use of existing health resources and maximize the effect of social health [8].

Under the background of national intelligent reform and big data promoted by the Internet, advanced technologies such as artificial intelligence provide more effective tools for early disease prevention. At present, the research of data mining and machine learning technology in the field of disease early warning has entered an extremely hot stage. As a machine learning algorithm, BP neural network has the ability of deep learning and artificial intelligence data processing. It can build a model in line with the data law through neural network and intelligently predict the location data. It has been widely used in management, engineering, medicine and other disciplines. Daniel J. Sargent E believes that in the field of big data, the prediction effect of machine learning algorithm is better than that of traditional multivariate statistics [9]. Qian Ling and others use neural network to predict diabetes, which proves that it is a good early warning method [10].

At present, there is still a lack of empirical research on disease prediction by combining the health problems of the elderly in China with intelligent methods, and the mining value is significant. Dao'ao Intelligent Technology Co., Ltd. has completed the real-time monitoring of heart rate, blood pressure, blood oxygen and other vital signs data based on pulse technology, developed corresponding hardware monitoring module products and realized small-scale mass production. Based on the support of the science and technology leading talent project in Xiangcheng District, Suzhou City, Jiangsu Province, China, this study collects health monitoring data for people over 60 years old in Suzhou, Nanjing and Beijing, analyzes the health status of elderly residents, explores and constructs an early warning model of elderly cardiovascular and cerebrovascular diseases in interdisciplinary fields, and improves the early warning effect through intelligent algorithms. The study aims to optimize the disease data analysis system of Dao'ao Intelligent Technology Co., Ltd., and provide new ideas for formulating health intervention measures for elderly residents and improving the overall health level.

2. Background and literature review

2.1. Chronic diseases and health assessment

2.1.1. Characteristics of senile chronic diseases and current situation of intelligent health management in China

Chronic diseases donot refer to a specific disease, but a general term of a common disease in modern society, including hypertension, hyperlipidemia, coronary heart disease, diabetes and

so on. These diseases are characterized by complex etiology, high prevalence, onset of concealment, long course of disease and low cure rate [11]. The World Health Organization defines chronic diseases as chronic non communicable diseases that can not form human to human transmission, develop slowly and last for a long time [12]. In China, chronic diseases refer to a group of diseases represented by cardiovascular and cerebrovascular diseases, diabetes, chronic obstructive pulmonary disease and malignant tumors. They are characterized by complex etiology, long treatment, damage to health and social harm [13].

The research on intelligent health management of elderly patients with chronic diseases in China is still in the exploratory stage, and its development presents diversified characteristics [14]. In terms of organizational themes: ① taking the hospital as the main body, connect the physical examination system, smart hospital system and mobile monitoring equipment to realize the integrated service and information-based health management of physical examination and health management, such as the smart health management center of Shenzhen People's Hospital [15] and Sichuan Provincial People's hospital [16]. ② Taking the community as the main body, the regional information sharing platform is used to realize data sharing and business collaboration among medical institutions at all levels. The community family doctor team provides routine health management for patients with chronic diseases. The hospital supports the community health service center in real time in terms of two-way referral and technical guidance, so as to realize the whole process management of patients, such as the "Shanghai Health cloud" platform in Shanghai [17]. ③ Business model with enterprises as the main body provides home health management services through health sensor terminals, data analysis platforms and mobile communication software, such as the "SPDC smart house" of Shanghai Xingjing Medical Technology Co., Ltd. In terms of service content, professional physical examination, health monitoring, health assessment, health education and online consultation are common. In terms of business model, it mainly includes convalescence + physical examination, insurance + medical health, chain physical examination, health cloud platform, o2o integrated operation and so on [18].

2.1.2. Health assessment

According to the definition of the World Health Organization, health status assessment mainly includes: People's birth and growth environment, work and living status, neighborhood relations, wealth level, education and position, racial discrimination, social and medical insurance status, government medical security policy, social attitude towards smoking and drinking, age and stress status. The impact of these factors on human health is either positive or negative, which can be divided into four aspects: demographic factors, behavioral factors affecting health status, psychological and emotional factors and family factors.

Among them, demographic factors mainly include age, income, economic status, nutritional level, educational background and so on. In people of different ages and income levels, their awareness of personal health management and ability to prevent facial diseases will affect the quality of life. The environmental and economic aspects of health remain long-term and difficult challenges [19]. One of the biggest challenges to improve China's overall health level is the untimely disease prevention and loneliness of all ages, especially the elderly, due to the mismatch between the burden of medical expenses, the allocation of health resources and the demand and supply of medical insurance.

The unhealthy behaviors affecting the health status of the elderly can be summarized as follows:

① diet: unreasonable diet structure, single nutritional composition or lack of necessary nutritional elements, poor cooking habits (heavy oil and salt), poor eating habits (overnight dishes) and so on [20]; ② Smoking and drinking [21]; ③ Sports: there is the behavior of living indoors for a long time, and there is a lack of various forms of activities including walking and moderate sports [22].

In terms of psychological emotion, depression and loneliness are common serious psychological problems among elderly patients with chronic diseases in the community [23]. Alexithymia, also known as "inability to express emotion" or "emotional dyslexia", is an emotional cognitive disorder caused by the impairment of individual emotional cognition, regulation and processing. On the one hand, the elderly are limited by their educational level, resulting in poor emotional expression; On the other hand, influenced by Chinese traditional culture, in order to avoid the burden of care for their children, the elderly are used to hiding their true feelings, which is more likely to produce alexithymia [24]. Studies have shown that patients with alexithymia have impaired ability to describe and elaborate personal feelings, and it is difficult to distinguish physical and emotional feelings, which hinders the accuracy and effectiveness of the treatment of psychological disorders such as depression, resulting in a high level of depression [25]. Loneliness refers to the painful emotional experience caused by the gap between the desire for social communication and the actual level. It is an important influencing factor of depression in the elderly [26][27]. Some studies have shown that people with high emotional disorder will think that their situation is very embarrassing in interpersonal communication because of their lack of ability to process emotional information and emotional expression, which intensifies the lonely experience [28].

Family factor refers to the family history composed of parents and other relatives, which has a certain impact on the offspring suffering from specific diseases. Cardiovascular diseases, diabetes and other chronic diseases have obvious family heredity. Family factors usually start from four metabolic changes, namely blood pressure, body weight, blood glucose and blood lipid metabolism, resulting in different disease risks. When behavioral and demographic factors are the same, but individuals have different prevalence rates, family factors play a major role in pathogenesis. The investigation of family history of major diseases is the key content to correctly evaluate and predict health status.

2.2. Artificial intelligence algorithm and disease early warning model

2.2.1. Three classical models for disease prediction in medical field

Disease is a result of many factors. At present, there are three kinds of classical modeling methods in the research of disease prediction in the medical field, including time series model, grey prediction model and neural network model. Among them, the first two are more inclined to predict the trend after analyzing the disease situation in a period of time, while the third one neural network model is to carry out individual or group disease early warning after learning the current data and summarizing the internal correlation and characteristic laws of the data.

ARIMA model is a time series prediction method based on calculus and sequence statistics theory. It is mainly used to predict the future development trend of data with time characteristics. It has the advantages of simple operation and good data processing ability, but it is generally only suitable for short-term prediction and fail to reflect the internal correlation between multiple factors. Many scholars have used the first mock exam to study epidemic diseases, such as Feng Dan's prediction of influenza like illness using the ARIMA model [29] and Liu Wei's prediction of the trend of tuberculosis using time series model [30].

The grey prediction model was first proposed by Professor Deng Julong in 1982. This method introduces the concept of systematic gray, which overcomes the limitations of traditional prediction models based on mathematical statistics and typical probability distribution to a certain extent, but it still cannot ensure the long-term stable prediction accuracy. Wu Xiaoqing and others used the model to predict the incidence trend of leprosy [31], while Li Guijiao predicted the incidence of viral hepatitis in Zhongshan City, Guangdong Province [32].

Neural network model is a learning algorithm based on the principle of brain and nervous system. Its advantage is to deal with non-normal nonlinear, fuzzy and noisy data, and learn the responsible nonlinear relationship between variables through the network. The model is

composed of many processing units arranged at different levels, and the purpose of learning is achieved by adjusting the internal connection relationship of the network. Neural network model has the advantages of strong data calculation and learning ability and good prediction effect on big data. However, this method has high professional requirements, difficult modeling, and there is an unobservable process of black box operation. Among many neural network models, BP neural network has become the most commonly used neural network because of its good approximation ability. Ma Yuxia and others used artificial neural network to predict the incidence of hypertension induced by meteorological factors^[33]. Gao Wei proved that BP neural network is suitable for the task of diabetes risk analysis^[34].

2.2.2. Back-Propagation neural network (BP neural network)

As a prospective interdisciplinary research, disease early warning is often combined with machine learning algorithm. BP neural network model is recognized as a machine learning algorithm with good data approximation ability. This method was proposed by Rumelhart and McClelland in 1986. BP neural network is composed of multiple neurons. Its basic structure includes three parts: input layer, output layer and hidden layer. It mainly realizes the learning mode through the hidden layer. After each learning, the information and results are stored in the network. Specifically, BP neural network can obtain and adjust the model through two learning methods: signal forward propagation and error back propagation, so as to achieve the optimal prediction effect, as shown in Figure 1.

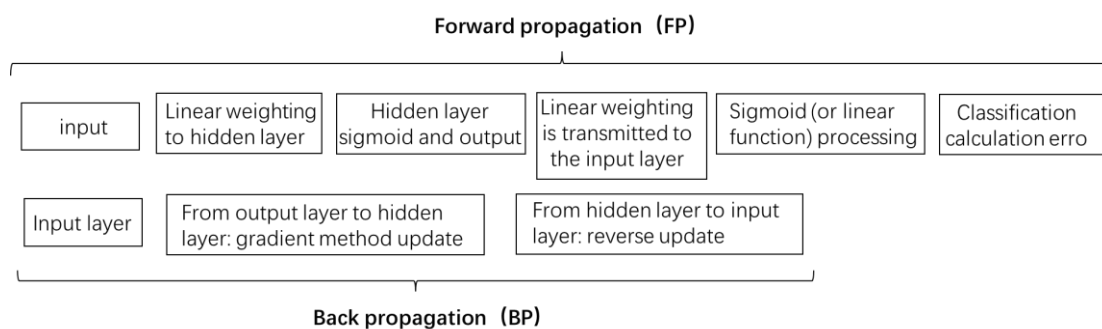


Figure 1: Forward and back propagation of BP neural network

Compared with traditional methods, BP neural network does not need any assumptions and has no special requirements for data types. It can solve various types of data and variables such as nonlinear, non-normal and discrete. It is the most widely used and mature neural network model with the best prediction effect at present. In the hidden layer part, the optimal number of neurons and hidden layers can be found through multiple experimental comparisons.

3. Methodology and data

3.1. Research object and category

This research data is based on the horizontal subject of the Science and Technology Leading Talent Support Plan of Xiangcheng District, Suzhou City, Jiangsu Province, China. Under the background of intelligent big data, based on the concept of providing chronic disease health monitoring for the elderly group, formulating health management path and realizing residents' personalized management, the project team selected 30 communities in three different cities (Suzhou, Nanjing and Beijing) as a source of random sampling. A total of 624 elderly residents were randomly selected as the survey objects during the period from March 2021 to October 2021. The inclusion criteria were: ① age ≥ 60 years old; ② It is the resident of the survey community (residence time ≥ 1 year); ③ Interested or agreed to participate in the survey after communication; ④ The investigation is clearly stated, and there is no cognitive impairment or other major diseases that make it impossible to conduct a complete investigation.

3.2. Survey tools

3.2.1. Evaluation model

The project team has constructed a health status evaluation index system and designed a questionnaire according to the index system through expert consultation and literature research in the early stage. This evaluation index system is based on three perspectives of physiology, psychology and society. Therefore, it is suitable for China's elderly residents. The main body of the questionnaire includes two modules: basic information and health monitoring. The basic information involves general characteristics such as name, age, gender and residence. Health monitoring involves living habits, emotional cognition, physiological information indicators, etc. The relevant physiological information indicators are collected through the monitoring module developed by Suzhou Dao'ao Intelligent Technology Co., Ltd. In this study, the questionnaire and monitoring module are used as research tools, and the basic information of residents and the corresponding indicators of health monitoring section are used to sort out and establish the health status evaluation model of elderly residents, as shown in Figure 2.

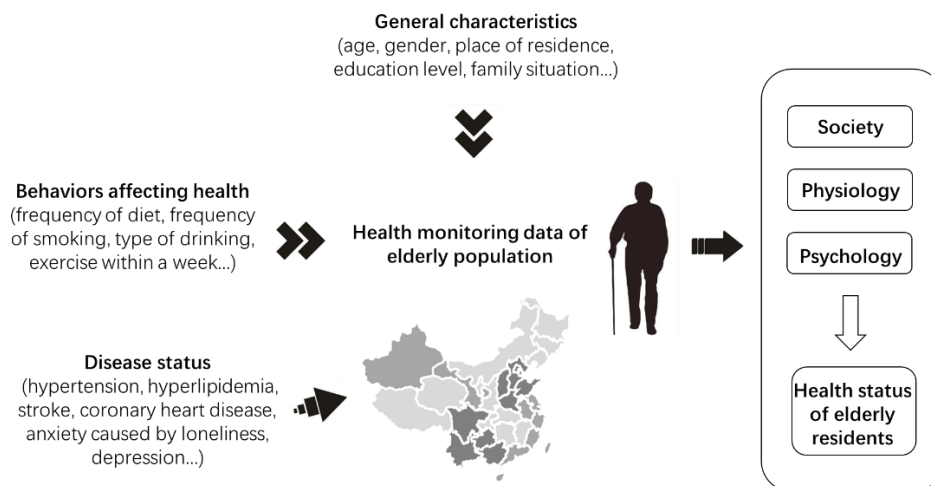


Figure 2: Evaluation model of health status of elderly residents

3.2.2. Evaluation index

The primary indicators of this study are the general characteristics, behaviors affecting health status and disease status of elderly residents. The specific contents and evaluation methods of secondary indicators are as follows:

General characteristics

A total of 10 indicators including city, age, gender, education level, family type, marital status, living status, family per capita monthly income, medical insurance expense reimbursement and religious belief were included.

Behaviors affecting health status

Include smoking frequency, whether there are people around smoking, passive smoking frequency, drinking frequency, drinking type, drinking years, whether there is physical discomfort untreated and corresponding times in a week, whether there is moderate exercise and days of moderate exercise in a week, whether there are walking and walking days in a week, whether there are long-term indoor and living days in a week, meals, breakfast There are 27 indicators in total, including morning meal, lunch, afternoon meal, dinner, night snack, frequency of eating sweets, frequency of eating fruits, frequency of drinking sugary drinks, meat and vegetable collocation, dietary preference, special diet, etc.

Disease status

Chronic disease status includes 13 indicators: hypertension, hyperlipidemia, coronary heart disease, cerebrovascular disease, diabetes, chronic gastritis, gastric ulcer, chronic obstructive

pulmonary disease, bronchial asthma, osteoporosis, cataract, glaucoma and other diseases. Family history includes 4 indicators: hypertension history, coronary heart disease history, stroke history and diabetes history. The psychological and emotional status includes both the degree of loneliness and the degree of depression.

In terms of specific measurement, the study used the international physical activity questionnaire (IPAQ) [35] to evaluate the exercise of the respondents, GAD-7 (7-item generalized anxiety disorder scale) to evaluate the anxiety caused by loneliness [36], and PHQ-9 (patient health questionnaire) to evaluate the depression status of the respondents [37]. The reliability and validity of GAD-7 and PHQ-9 in medical research have been confirmed by relevant studies at home and abroad [38][39]. The scales are in the form of Likert grade 4 score. The options of each item are set as follows: 0 = none at all, 1 = several days, 2 = more than half of the days, and 3 = almost every day. The general explanation of anxiety caused by loneliness is as follows: < 5 = no anxiety, 5 ~ 9 = possible slight anxiety, 10 ~ 13 = possible moderate anxiety, 14 ~ 18 = possible moderate and severe anxiety, > 18 = possible severe anxiety; The depression score is explained as follows: < 5 = no depressive symptoms, 5 ~ 9 = mild depression, 10 ~ 14 = moderate depression, 15 ~ 19 = moderate and severe depression, > 19 = severe depression.

3.3. Research method

Firstly, this study uses the literature research method to summarize and sort out the existing research literature, and constructs a theoretical model for the evaluation of the health status of the elderly. Secondly, the questionnaire survey method is used to collect data from the elderly residents of 30 communities in three cities in China. Finally, the BP neural network method is used to take the statistically significant indicators in the single factor analysis as the input variables, preliminarily building the disease early warning model.

4. Empirical analysis and results

4.1. General statistical analysis of survey data

In this survey, a total of 646 questionnaires were issued to collect the data of elderly residents. Excluding the data with a missing rate of more than 5%, 624 valid data were obtained, and the recovery effective rate was 96.59%. This data collection covers a total of 30 communities in Suzhou, Nanjing and Beijing. The number of research objects in the three cities are 222 in Suzhou, 198 in Nanjing and 204 in Beijing.

In terms of demographic characteristics of the investigated objects, among the 624 subjects, most of them are female elderly residents (435 cases, 69.7%), relatively few are male elderly residents (189 cases, 30.3%), and the ratio of men to women is 1:2.3. The average ages of men and women were 72.4 and 69.2 years, respectively. The marital status was mainly married with spouse (406 cases, 65.1%). From the perspective of educational level, there are 160 cases with bachelor degree or above, accounting for 25.6% of the total, and 464 cases with educational background including primary school and below, junior middle school, technical secondary school, high school and college, accounting for 74.4% of Chinese sports. From the perspective of medical expense reimbursement, 436 elderly residents used medical insurance reimbursement, accounting for 69.9%; There were 115 elderly residents at their own expense, accounting for 18.4% of the total; 73 elderly residents reimbursed medical expenses in other forms, accounting for 11.7% of the total.

In aspect of behavior affecting health status, the survey results were summarized from smoking, drinking, exercise and diet. The smoking rate of residents was 11.3%, which was characterized by that the smoking rate of men was significantly higher than that of women; The rate of passive smoking was 47.8%, and the frequency of passive smoking was mostly 1 ~ 2 days / week. The drinking rate of residents was 32.0%, of which the drinking rate of male elderly residents

(60.1%) was about three times that of female elderly residents (19.8%). The number of elderly residents engaged in various sports is more than half of the total. Most elderly residents can eat regularly, but the main problems are single diet structure and unreasonable nutrition ratio.

When it comes to prevalence, there were 538 elderly residents with chronic diseases, and the prevalence rate was 86.2%. The total prevalence of chronic diseases ranked three in the first place was hypertension (65%), diabetes mellitus (34.5%), and chronic gastritis (29.8%). Residents with a history of hypertension are the most, more than half of the total.

4.2. Construction and Empirical Study of disease early warning model based on BP neural network

4.2.1. Model overview

Because the data of the research object has the characteristics of non normal, complex variables, affected by many factors and large amount of data, we can not predict the data with simple linear regression. Therefore, we choose BP neural network suitable for processing fuzzy, nonlinear and noisy data for modeling. The main steps of building the model include: data preprocessing, data expansion, determination of input and output neurons, model parameter setting, number test of hidden layer neurons at hidden level, neural network training, test set and test the running results of the model. See Figure 3 for details.

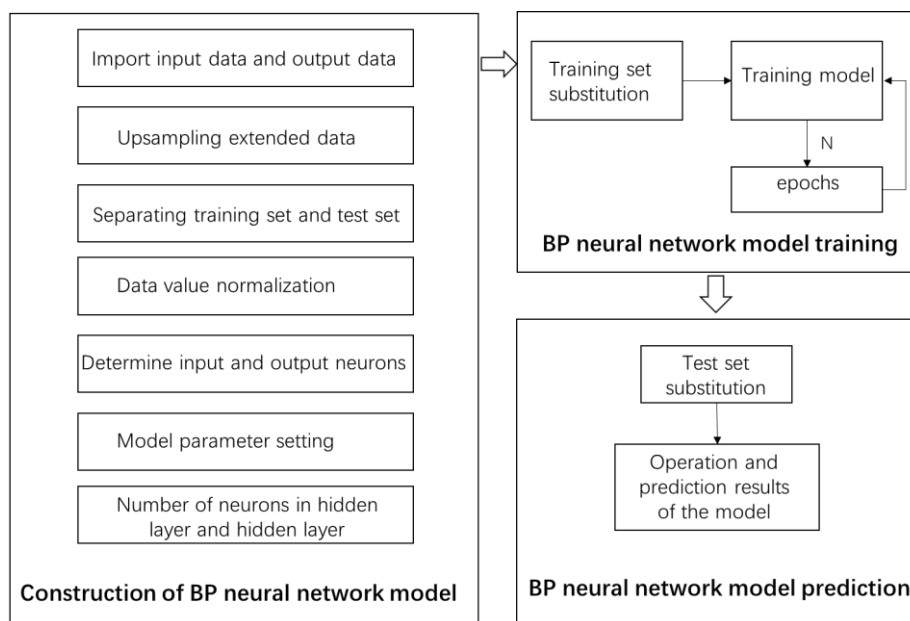


Figure 3: Flow chart of BP neural network modeling

4.2.2. Data preprocessing

We manually integrate the original data into excel format that can be called by MATLAB r2019 software. The input variable data is named beginning with *input-*, and the binary output variable data of disease or not is named beginning with *output-*. Read and call the input data and output data in the software to complete the data preprocessing.

4.2.3. Data expansion and set construction

In MATLAB, the number and proportion of 1 (sick) and 0 (not sick) in the output data are calculated by code. In the output data of this study, 1 accounted for 86.2% (538 cases) and 0 accounted for 13.8% (86 cases). The two types of data showed an unbalanced situation. Sample imbalance will lead to too few classification features of 0 and insufficient learning level, resulting in over fitting phenomenon. In order to balance the data set, this study conducted up sampling to balance the total number of samples in each category and improve the prediction

accuracy. First, we calculate the number of 1 and 0 in the output data, which are recorded as n_1 and n_0 , and get the proportion of 1 in the total, which is recorded as p ; According to the probability calculation, the number of centralized sampling from the original data is recorded as N_s . Algorithm is $N_s = \text{int}64((n_0 - n_1)/p)$. Next, we start up sampling, generate random integers with Randi function, extract and expand the sample set without changing the original data, so as to balance the number of 1 and 0 samples after sampling, and the total amount of expanded data is 1091. The expanded data set is scrambled to generate random sequence, and the input data set and output data set are separated.

Sufficient training set is the basis of building BP neural network with good performance. Theoretically, the larger the scale of training samples, the more the training model can reflect the essential law of samples. But in fact, the number of samples is limited, and too large training set is easy to lead to too much noise, affecting the network accuracy and training speed. Therefore, according to the actual situation, for the expanded 1091 samples, 80% of the data are randomly separated as the training set for the autonomous learning of neural network. The remaining 20% of the data is used as a test set to verify the accuracy of the early warning model. Considering the different dimensions and units of different characteristic variables, this study normalizes the data to enhance the convergence and reduce the training error. Normalization usually sets the data to vary between (0,1) or (-1,1). The following are common formulas:

$$x_a = \frac{x - x_{min}}{x_{max} - x_{min}} (0,1);$$

$$x_b = \frac{2(x - x_{mid})}{x_{max} - x_{min}} (-1,0)$$

Notes: X_a and X_b are original values, and x_{mid} , x_{min} and x_{max} are intermediate values, maximum values and minimum values respectively.

4.2.4. Input and output neurons in networks

Based on univariate analysis, 9 general characteristic factors such as gender, age, marital status, education level and living status, 25 behavioral factors affecting health status such as smoking frequency, whether someone around smokes, drinking frequency, drinking years, type of exercise and rationality of diet structure, as well as family history, anxiety caused by loneliness Depression degree and other 6 prevalence factors, a total of 40 statistically significant variables in univariate analysis were used as input variables. Whether the elderly residents have chronic diseases is taken as the output variable corresponding to the input variable. According to the determined input variable and output variable patterns, a BP neural network model composed of 40 input neurons, one output neuron and several hidden layers is built. As shown in Figure 4.

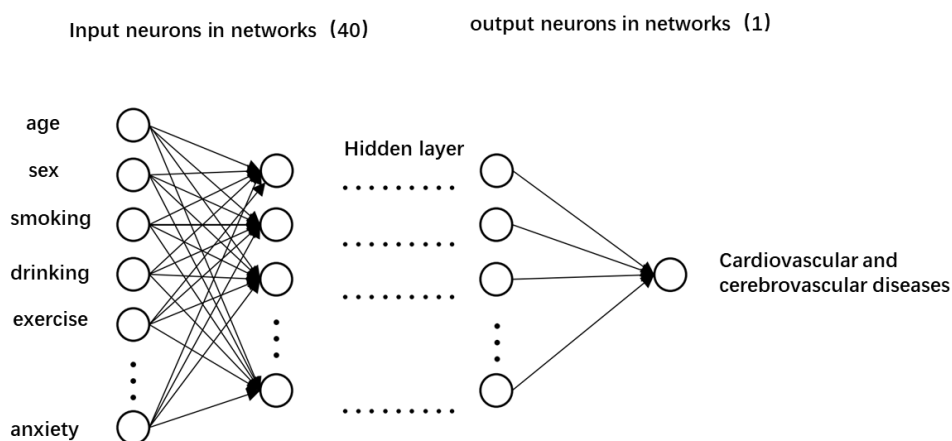


Figure 4: Basic structure diagram of BP neural network model

4.2.5. Model parameter setting

After completing the data operation, start to build the BP neural network. It is necessary to set the parameters of the model, such as constructor, training function, training set, verification set, test set and iteration times.

Construct function: the function of MATLAB (r2019b) is the `patternet` () function, which is used to construct BP neural network. The input neurons, output neurons, hidden layer and hidden layer neurons are written into functions, and the `patternet` () function is used to construct the neural network.

Training function: select the `trainf` training function with fast convergence speed and not easy to fall into local optimization for training, so as to reduce the computational complexity and shorten the training time.

Training set, verification set and test set of the network: 65% (709 pieces) of the overall data are called to train the BP neural network. Through learning and summarizing the complex laws and relationships between input neurons and output neurons in the data, the BP neural network participates in the model training process in the whole process; 15% (164 pieces) of data are used to verify the network. After each training, the accuracy of the model is tested through the verification set and the parameters are adjusted in real time; Test the model with 20% (218 pieces) of the data, compare the real data results of the test set with the predicted results in the model, and test the effectiveness of the prediction model in terms of prediction error. The data of training set, verification set and test set are generated randomly. The following is the specific code:

```
net.divideParam.trainRatio=65/100;
```

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net.divideParam.valRatio=15/100;net.divideParam.testRatio=20/100.
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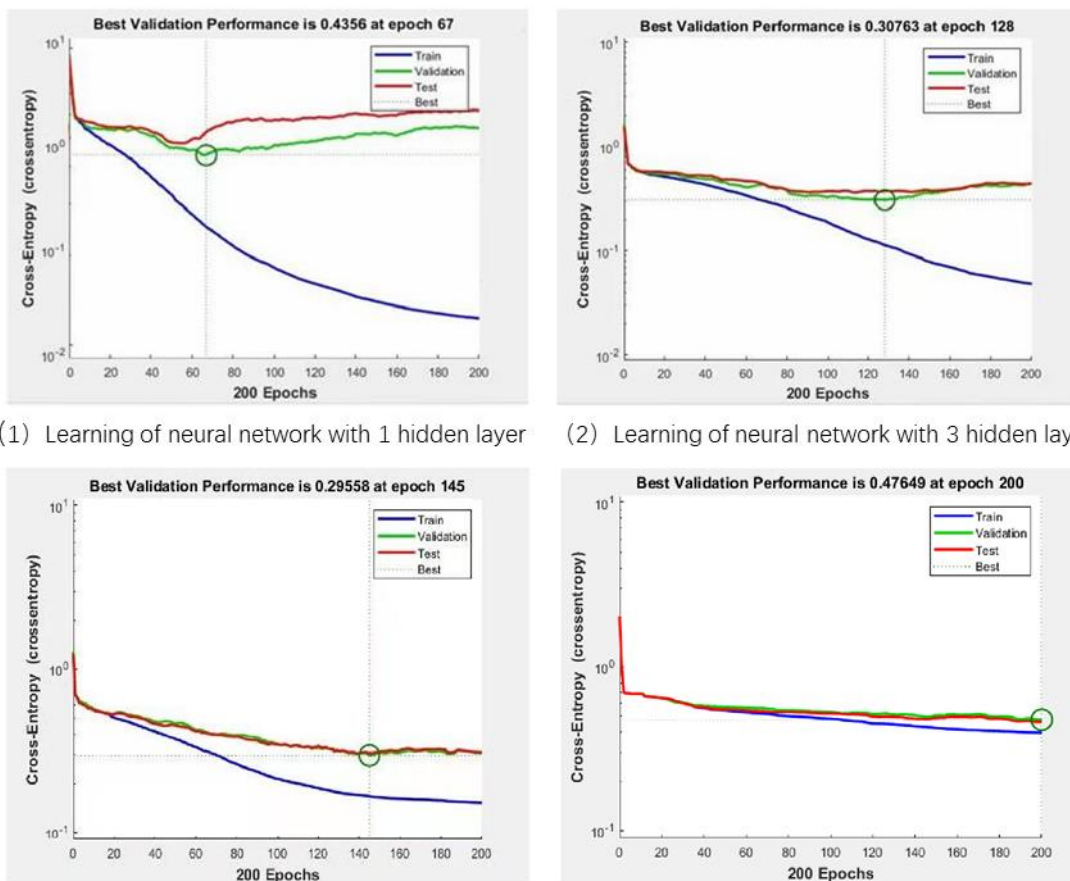
Training times: the number of training times indicates the maximum number of times that the error on the tolerable verification set is not reduced during the training process. When it reaches this number, it will quit the training. The training times of this study were set to 200 times, and the training was terminated after reaching this number.

4.2.6. Determination of the number of hidden layers and neurons

In this study, the number of neurons was preliminarily determined according to the empirical formula. The following is the reference formula: $\sum_{i=0}^n c_A^i > k$, $A = \sqrt{n + b} + \alpha$, $A = \log_2 n$. Where, A is the number of neurons in the hidden layer, n is the number of input neurons, i is an integer between 0 and n , k is the number of samples, and b is the number of output neurons, α Take any integer between 1 and 10.

For the location of hidden layer, this study evaluates the influence of different number of hidden layers and the number of neurons on the effect of neural network model. The specific test plan is as follows: it has been determined that the input neuron in the neural network is 40 and the output neuron is 1. It is expected to set the neural network into four structures containing 1, 3, 5 and 7 hidden layers to learn the health status data of middle-aged and elderly residents in this study, and compare the learning effects of the neural networks with the above four structures on the same data, Select the most appropriate number of hidden layers and neurons. The test results are as follows: when the hidden layer is 1, the hidden layer contains 16 neurons, and the training time is 17 seconds. The verification set error is the lowest at the 67th training, which is 0.4356. The accuracy of training set is 90.6%, the accuracy of verification set is 83.7%, the accuracy of test set is 84.0%, and the comprehensive accuracy is 88.3%; When the hidden layer is 3, the number of neurons in hidden layer is set to 30, 16 and 7 according to the formula, and the training time is 31 seconds. The verification set error is the lowest at the 128th training, which is 0.30763. The accuracy of training set is 96.9%, the accuracy of verification set is 90.9%, the accuracy of test set is 90.1%, and the comprehensive accuracy is 94.4%; When the hidden

layer is 5, the number of neurons in the hidden layer is set to 36, 24, 16, 10 and 4 according to the formula, and the training time is 47 seconds. The error of the verification set reaches the lowest at the 145th training, which is 0.29558. The accuracy of the training set is 96.8%, the accuracy of the verification set is 90.5%, the accuracy of the test set is 91.0%, and the comprehensive accuracy is 94.6%; When the hidden layer is 7, the number of neurons in the hidden layer is set to 36, 30, 24, 16, 10 and 4 according to the formula, and the training time is 1 minute and 12 seconds. The verification set error reaches the lowest at the 200th training, which is 0.47649. The accuracy of the training set is 84.3%, the accuracy of the verification set is 80.2%, the accuracy of the test set is 80.9%, and the comprehensive accuracy is 83.0%. As shown in Figure 5.



(1) Learning of neural network with 1 hidden layer (2) Learning of neural network with 3 hidden layer
 (3) Learning of neural network with 5 hidden layer (4) Learning of neural network with 7 hidden layer

Figure 5: Learning of neural networks with different hidden layers

In terms of model learning, from the perspective of training time, the more hidden layers, the longer the time; In terms of accuracy, the accuracy of training set, verification set, test set and comprehensive accuracy of networks with 1 and 7 hidden layers are significantly lower than those with 3 and 5 hidden layers, which may be caused by over fitting caused by over training. Therefore, without increasing the network complexity and ensuring the training effect, this study selects the BP neural network structure with 5 hidden layers and the number of neurons in each hidden layer is 36, 24, 16, 10 and 4 respectively to establish the disease early warning model of elderly residents.

4.2.7. Operation and evaluation

On the basis of clarifying the data, parameters and network structure, the BP neural network model of this study has been determined. The view network command is executed in MATLAB r2019b software, and the model structure is shown in Figure 6.

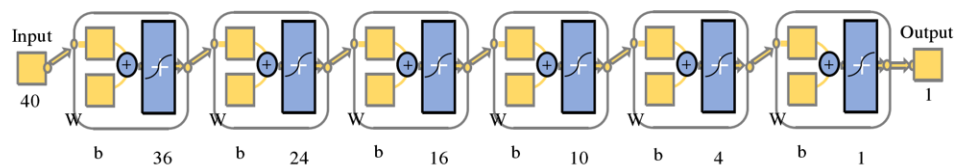


Figure 6: Structure of BP neural network model for disease prediction of the elderly residents. The trained BP neural network model is used to predict the test set data, and the output results are binary values, namely class 1 (sick) and Class 0 (not sick). According to the software display range, the prediction results of the first 100 cases of data in the test set are analyzed. It is found that the model output values of the test set samples are consistent with the real values, and the trained model has high fitting ability to the test data. Among them, the red dot is the predicted value and the blue circle is the real value, as shown in Figure 7.

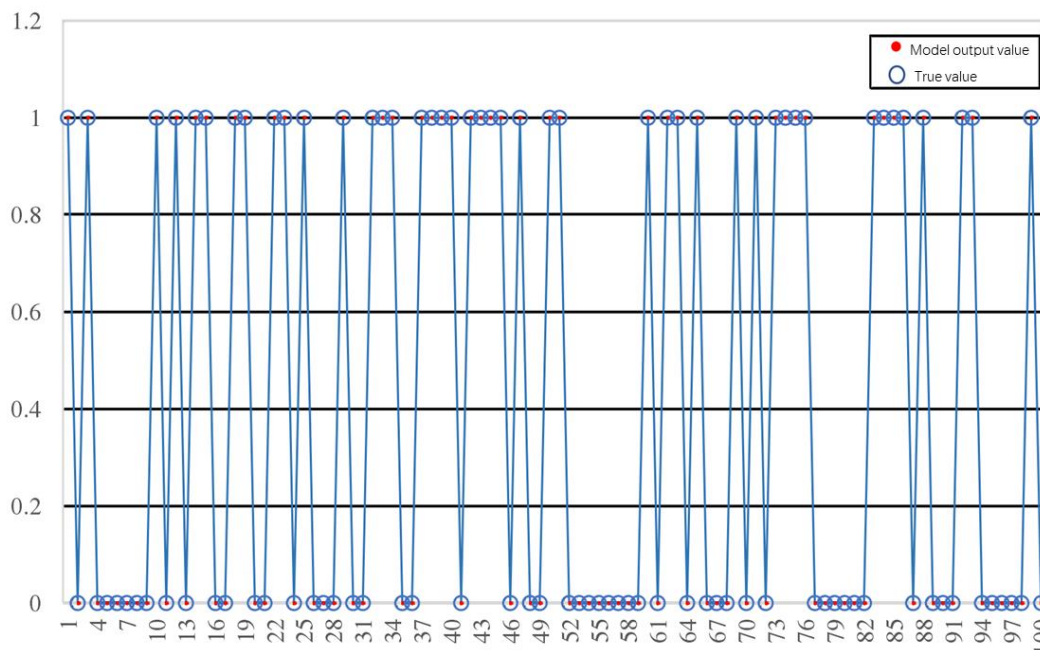


Figure 7: Comparison between the output value of neural network and the real value of the first 100 data in the test set

The confusion matrix is a measure of the quality of the BP neural network model. The output class in the matrix represents the real situation of the data, and the target class represents the prediction of the data. The confusion matrix of the prediction results of each set in this study is as follows:

In the training set, there were 338 elderly residents who were not ill, of which 336 samples had correct regression results (accounting for 47.4% of the total training), 2 samples had wrong prediction results (accounting for 0.3%), and the prediction accuracy of elderly residents who were not ill was 99.3%; There were 371 sick elderly residents, of which 350 samples were judged correctly (accounting for 49.4% of the total training set), 21 samples were judged incorrectly (accounting for 2.9%), and the prediction accuracy rate of sick elderly residents was 94.4%; A total of 686 samples in the training set were predicted correctly, and the comprehensive accuracy was 96.8%.

In the validation set, there were 70 non sick residents, of which 68 samples had correct predicted values (accounting for 41.9% of the total validation set), 2 samples were misjudged to be sick (accounting for 1.0%), and the prediction accuracy of non sick residents was 97.7%; There were 94 sick residents in total, of which 79 samples had correct predicted values (accounting for 48.2% of the total validation set), 15 samples were misjudged as not sick, the

ratio was close to 10% of the validation set, which was the highest among the four charts, and the prediction accuracy of sick residents was 84.5%, which was lower than that of the training set; 83 samples were verified to be correct, and the comprehensive accuracy rate was 90.1%. In the test set, there were 90 non sick residents, of which 88 samples were correctly predicted by the model (accounting for 40.8% of the total test set), 2 residents were misjudged as sick (accounting for 0.8%), and the prediction accuracy of non sick residents was 98.2%; There were 128 sick residents, of which 110 samples were correctly predicted by the model (accounting for 50.3% of the total test set), 18 residents were misjudged as not sick (accounting for 8.2%), the ratio was about 5% higher than that in the training set, and the prediction accuracy of sick residents was 85.9%; A total of 198 residents in the test set were correctly predicted, and the comprehensive accuracy was 91.0%, which was between the training set and the verification set. As shown in Figure 7.

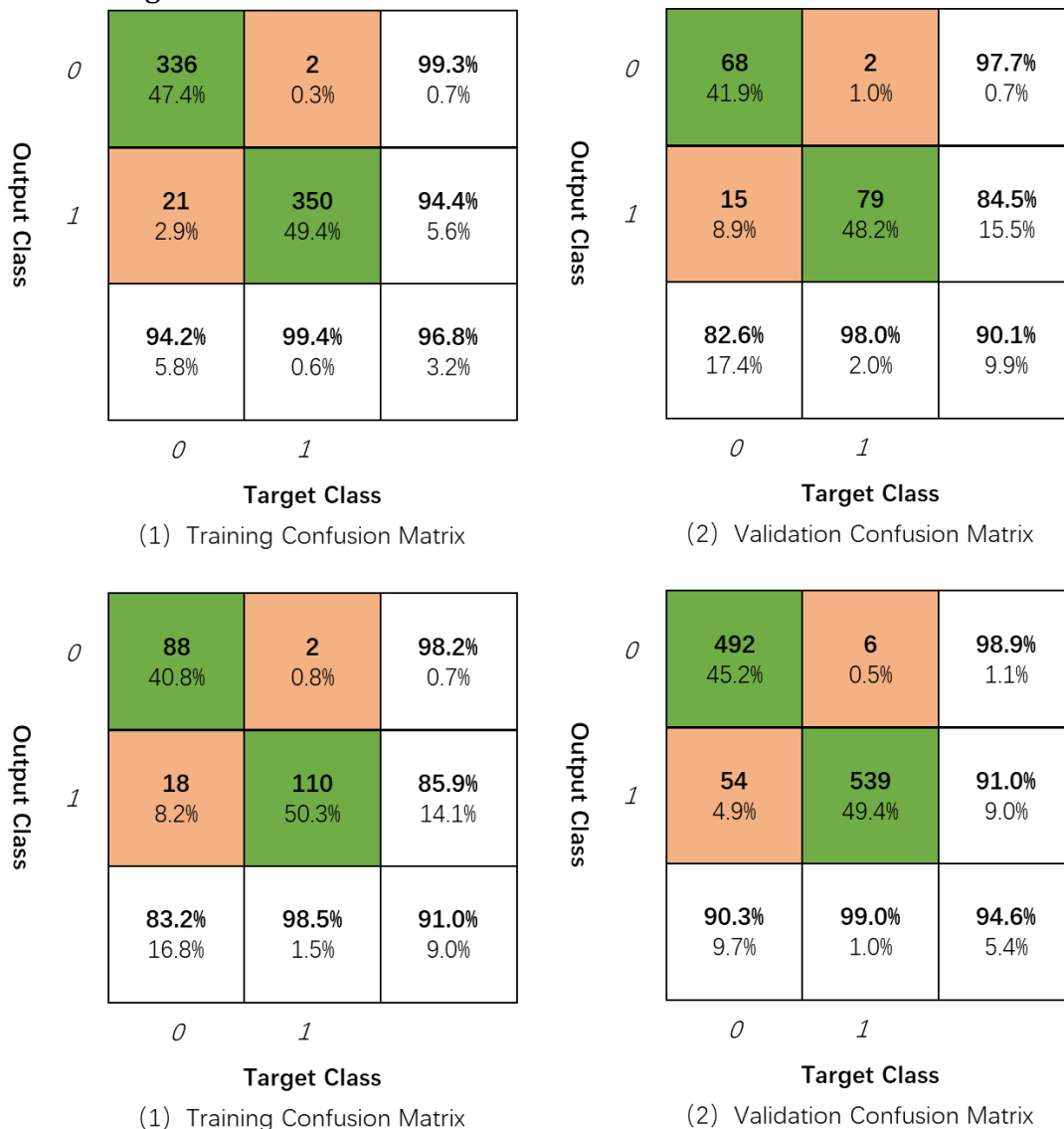


Figure 8: Confusion matrix of prediction results of BP neural network model

5. Conclusion

On the one hand, through the general characteristics and behavior research results affecting health status, this study concludes that the sample elderly residents in Suzhou, Nanjing and Beijing have serious problems in unreasonable diet structure, unhealthy eating habits, anxiety and depression caused by loneliness, such as active smoking, second-hand smoke intake,

drinking Moderate exercise and other aspects of good performance. Unbalanced diet and nutrition can easily lead to physical malnutrition. Salty diet will cause excessive burden on the heart and body. Anxiety and depression have a strong negative impact on the cardiovascular system.

On the other hand, this study establishes an early warning model of cardiovascular and cerebrovascular diseases in elderly residents based on BP neural network, and shows the application of the model, which provides artificial intelligence technical support for the prevention of chronic diseases in the elderly. In view of the great differences in the classification and pathogenesis of chronic diseases in the elderly population, this study focuses on cardiovascular and cerebrovascular diseases, pays attention to the early warning of cardiovascular and cerebrovascular diseases in the elderly population, has strong pertinence and high accuracy, and does not pay attention to the physiological indicators detected by the hospital, which is in line with the normalized health monitoring and disease early warning of the elderly population. The disease early warning model established in this study has enough sample size to support, and its health promotion effect on the elderly population is mainly reflected in the following points: first, the BP neural network model early warning the disease risk of the elderly population through health data, and the comprehensive accuracy is 90.1%; Second, the accuracy of the sample with the prediction result of disease is higher, and the probability of disease of the sample without the prediction result of disease is lower; Third, the early warning model makes it more feasible to move forward the gateway of chronic diseases such as cardiovascular and cerebrovascular diseases. The counterpart departments can take relevant preventive measures in advance with reference to the analysis results of the early warning model.

Acknowledgements

Science and technology leading talent plan of Xiangcheng District, Suzhou City, Jiangsu Province, China.

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