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Research article

Prediction of fetal weight based on back propagation neural network optimized by genetic algorithm

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Abstract: Fetal weight is an important index to judge fetal development and ensure the safety of pregnant women. However, fetal weight cannot be directly measured. This study proposed a prediction model of fetal weight based on genetic algorithm to optimize back propagation (GA-BP) neural network. Using random number table method, 80 cases of pregnant women in our hospital from September 2018 to March 2019 were divided into control group and observation group, 40 cases in each group. The doctors in the control group predicted the fetal weight subjectively according to routine ultrasound and physical examination. In the observation group, the continuous weight change model of pregnant women was established by using the regression model and the historical physical examination data obtained by feature normalization pretreatment, and then the genetic algorithm (GA) was used to optimize the initial weights and thresholds of back propagation (BP) neural network to establish the fetal weight prediction model. The coincidence rate of fetal weight was compared between the two groups after birth. *Results:* The prediction error of GA-BPNN was controlled within 6%. And the accuracy of GA-BPNN was 76.3%, which were 14.5% higher than that of traditional methods. According to the error curve, GA-BP is more effective in predicting the actual fetal weight. *Conclusion:* The GA-BPNN model can accurately and quickly predict fetal weight.

Keywords: fetal weight; back propagation; neural network; genetic algorithm; prediction model

1. Introduction

In the health management of pregnant women, it is very important to predict the fetal weight accurately. Fetal weight is one of the important indicators to judge the development of fetus. The calculation of fetal weight in the middle of pregnancy can monitor whether the fetal development is normal [1]. The calculation of fetal weight in the late pregnancy has a guiding role in the mode of delivery. With the improvement of economic level and medical conditions, the incidence of macrosomia is also increasing year by year, accounting for nearly 10% of newborns [2]. The incidence of macrosomia is close to 70% due to the nutritional process of pregnant women. The following problems are the increase of dystocia and cesarean section [3]. However, fetal weight cannot be measured directly and can only be predicted according to the physical examination data of pregnant women.

The traditional fetal weight prediction model is based on the results of ultrasound examination. Shepard et al. [4] used biparietal diameter (BPD), abdominal circumference (FAC) and other parameters to calculate fetal weight directly. Using head circumference (HC), abdominal circumference (AC), femur length (FL) and other parameters, Hadlock et al. [5] predicted fetal weight through empirical formula obtained by regression analysis. MÖst et al. [6] believe that the traditional empirical formula is based on the results of single point prediction, which is easy to explain its significance. There results ignore the uncertain measurement in the prediction interval. Therefore, the conditional linear transformation model is proposed to predict fetal weight, and the uncertainty measurement of different prediction intervals is introduced into the prediction model to improve the fitness of the model. Due to the racial differences between different races, the measurement results also have great differences [7,8]. Therefore, the empirical formula prediction method needs to be adjusted according to the specific situation in the use process. It is difficult to establish a general empirical formula due to the differences of pregnant women in different areas, their own parameters and measurement methods, so the accuracy of empirical formula is low.

Farmer et al. [9] first proposed using artificial neural network to predict fetal weight. Based on the results of ultrasound examination, the physiological characteristics of pregnant women were added. Back propagation (BP) artificial neural network was used to predict fetal weight based on BPD, HC, AC, FL, maternal age, pregnancy times, birth times, height and other parameters. The results show that BP artificial neural network is better than traditional regression analysis. Mohammadi et al. uses artificial neural network to predict the weight of twin fetus [10]. Lu et al. used a new evaluation performance based on machine learning in the absence of ultrasound examination [11]. However, the above prediction models are based on single cross-sectional time of pregnant women or fetal examination parameter information, the prediction accuracy is still not high.

In this paper, based on the historical physical examination data of pregnant women from the beginning to the end of pregnancy, we established a model of continuous signs change of pregnant women, and used genetic algorithm to optimize back propagation neural network (GA-BPNN) to build a prediction model of fetal weight [12,13].

2. Materials and methods

2.1. Experimental grouping

A total of 80 pregnant women in our hospital from September 2018 to March 2019 were randomly divided into two group: control and observation group, 40 cases in each. Inclusive criteria: (1) regular prenatal examination; (2) have certain literacy and writing ability; (3) there are no interpersonal barriers. The study was approved by the Ethics Committee of The Third People's Hospital of HeFei. All the participants provided their written informed consent to participate in this study.

The average age of the observation group was (29 ± 2.5) years old; education background: 10 undergraduate students, 12 junior college students, 4 technical secondary school students, 8 senior high school students and 6 junior high school students; delivery times: 10 primiparas; 30 multiparas. The average age of the control group was (28 ± 2.7) years old, education background: 8 undergraduate students, 13 junior college students, 5 technical secondary school students, 6 senior high school students and 8 junior high school students; delivery times: 8 primiparas; 32 multipara women. There was no significant difference in age and parity between the two groups.

2.2. Prediction method

2.2.1. Control group

The medical staff roughly predicted the fetal weight according to the results of ultrasound and prenatal examination.

2.2.2. Research group

First, according to the data of electronic case records in our hospital, the GA-BP neural network model was established. The fetal weight was predicted according to the model results. From January 1, 2017 to December 31, 2017, 400 samples were randomly selected from all obstetric electronic medical records in our hospital. The eligible samples were singleton, no pregnancy syndrome, 22–43 years old, and received ultrasound examination within 72 hours before delivery.

2.3. Data preprocessing

Different times, institutions and contents of prenatal examination will lead to incomplete data of maternal physical examination, which will interfere with the training and prediction process of prediction model [14–16]. Therefore, the data preprocessing process is the key step to improve the quality of data [17]. In this paper, we first deal with the missing values of the original data and standardize the characteristics to form a continuous change model of maternal signs.

2.3.1. Input attribute parameters of prediction model

Table 1. Prediction model input attribute parameter list.

Parameter	Significance	Parameter	Significance
x_a	Age of pregnant women	x_{bpd}	Biparietal diameter of fetus
x_g	Number of pregnancies	x_{afi}	Amniotic fluid index
x_h	Height of pregnant women	$weight_{140}$	Weight on 140 d of pregnancy
x_p	Number of deliveries	$weight_{245}$	Weight on 245 d of pregnancy
x_w	Pre pregnancy weight	$weight_{210}$	Weight on 210 d of pregnancy
x_{ac}	Fetal abdominal circumference	$weight_{252}$	Weight on 252 d of pregnancy
x_{fl}	Fetal femur length	$weight_{175}$	Weight on 175 d of pregnancy
x_{hc}	Head circumference		

The historical examination data of pregnant women exist in electronic medical record system. We use the identity cards of pregnant women as the main index to extract the inspection data from early pregnancy to delivery, as well as the real weight of the fetus at birth, and form a sample set for weight prediction. Y is defined as the real weight set of the fetus, and X is defined as the input parameter set of the model. The set consists of 15 parameters, X= of which $\{\mathrm{weigh_t}\}$ represents the weight change of pregnant women at different times during pregnancy, and the significance of other parameters is shown in Table 1.

2.3.2. Missing value processing

A practical problem in the prediction model based on historical examination data is that the time and frequency of prenatal examination are not fixed, which will lead to the loss of weight series value [18–20]. In this paper, regression method is used to complete the missing weight series value. Based on the existing data set of pregnant women, the regression equation is established, the pregnant women with more than 5 records of production inspection are selected, and the weight values of different time (in days) of pregnant women are obtained. The regression equation is established for each pregnant woman as the data set. The regression equation adopts the quadratic fitting function. Given the data series $(x_i, y_{i)}$, where x_i is the days of pregnancy and $y_{i)}$ is the body weight of x_i. Let P(x) be the quadratic fitting function, the mean square error between the fitting function and the actual body weight series is obtained:

$$\frac{1}{m}\sum_{i=1}^{m}(P(x_i) - y_i)^2 \tag{1}$$

Through the above way, the maternal weight sequence set $\{\mathrm{weight_t}\}$ was obtained, and the missing value processing was completed.

2.3.3. Feature standardization

After data preprocessing and missing value processing, the input parameter set of the model is obtained, but different physiological parameters have different units and orders of magnitude. In order to eliminate the influence of different units and data levels on the prediction results of the model. Before the parameters are input into the network model, the data should be normalized to ensure that each parameter is in the same order of magnitude. The calculation method shown in Eq (2) is adopted for standardization, where x is the current eigenvalue, x_{min} is the minimum and x_{max} is the maximum value of the current eigenvalue, y is the normalized eigenvalue, and the data range after standardization is [−1,1].

$$\mathrm{y} = \frac{2(x - x_{min})}{x_{max} - x_{min}} - 1 \tag{2}$$

2.4. GA-BPNN fetal weight prediction model

The fetal weight prediction model is a three-layer BP neural network [21,22]. The initial weight and threshold of BP neural network are optimized by genetic algorithm according to the training objective function. The neural network model is studied by using error back propagation algorithm.

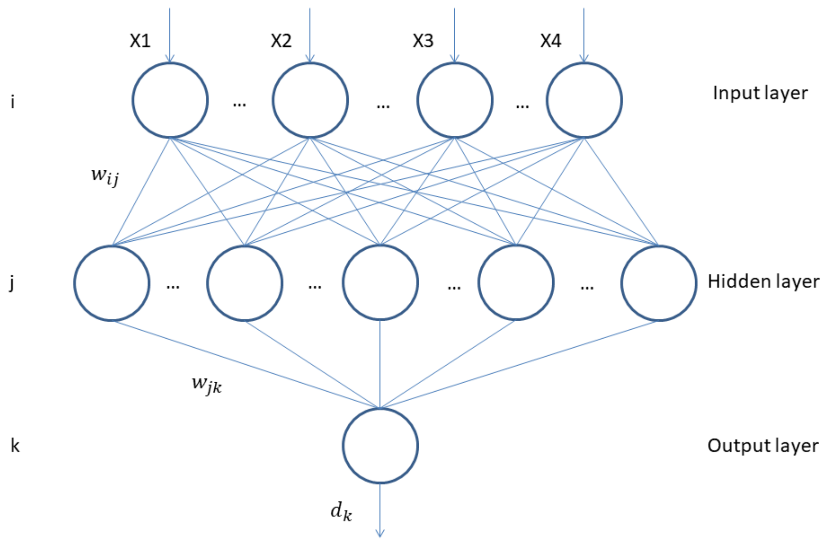

Figure 1. Structure diagram of three layer BP neural network.

In Figure 1, the input layer contains 15 neurons (physiological parameters), corresponding to$X = \{x_g, x_p, x_h, x_w, x_a, \{wirght_t\}, x_{hc}, x_{bpd}, x_{ac}, x_{fl}, x_{afi}\}$. The number of neurons in the hidden layer is n, and the output layer is a single neuron (fetal weight)

The common encoding method of genetic algorithm is real number encoding and binary encoding. The real number encoding has high accuracy and is easy to search in large space. Therefore, the real number encoding method is adopted in this paper. The encoding length is determined by formula (3):

$$\mathrm{L} = \mathrm{m} \times \mathrm{n} + \times \mathrm{l} + \mathrm{n} + \mathrm{l} \tag{3}$$

Where m is the number of neurons in the input layer, n is the number of neurons in the hidden layer and l is the number of neurons in the output layer. After completing the coding process and selecting the appropriate initialization population and fitness function calculation formula, the iterative process of genetic algorithm selection, crossover and mutation is carried out. When the iterative process meets the training goal or the number of iterations reaches the set goal, the iterative process is stopped. The optimal chromosome (i.e. initial weight and threshold of neural network) is returned as the result

Taking the return result of genetic algorithm as the initial weight and threshold of BP neural network, the neural network learning process is completed, and the optimal neural network structure is GA-BPNN fetal weight prediction model.

3. Results and discussion

The results show that the population size of genetic algorithm is 200, the crossover probability PC = 0.4, the mutation probability PM = 0.1, and the evolution algebra is 100. The learning rate of BP neural network is 0.016, the error precision is 1×10^{-3}, and the maximum number of iterations is 3000. The curve of fitness function value changing with evolution algebra is shown in Figure 2. It can be seen that the fitness function value of individuals has basically no change after evolution to 84 generations, and reaches the maximum value. The optimal chromosome value at this time is taken as the initial weight and threshold of BP neural network.

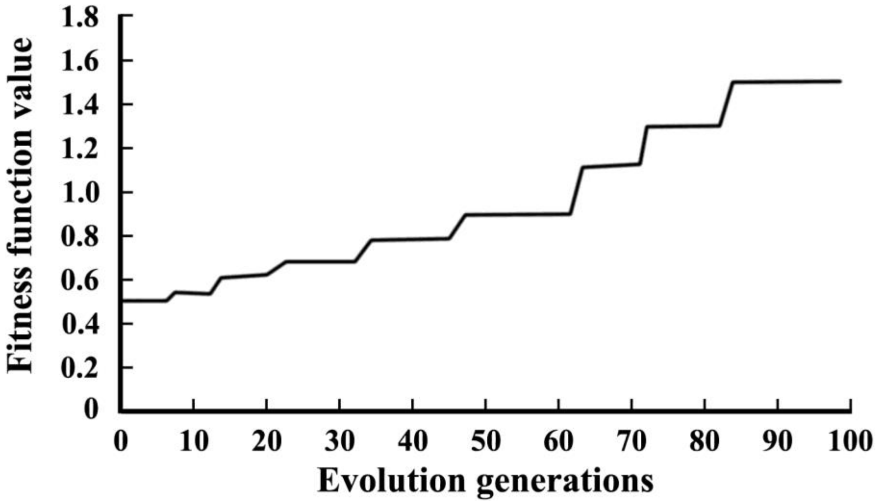

Figure 2. Variation curve of fitness function value.

In this paper, two indexes are used to measure the performance of the prediction model. The first is mean relative error (MRE), which can better reflect the reliability of the measurement. Let m be the number of samples and MRE be the mean relative error.

$$\mathrm{MRE} = \frac{1}{m}\sum_{i=1}^{m}\frac{|actual-predict|}{actual} \tag{4}$$

Another criterion is that the error between the predicted value and the actual value of fetal weight is within ± 250 g, which means that the prediction is accurate, so as to calculate the accuracy of the prediction model. The experimental results of this paper are discussed through the above two criteria. It can be seen from Table 2 that the error of GA-BP prediction of fetal weight is controlled within 6%.

Table 2. Prediction of fetal weight by two methods.

Method	Average relative error	Accuracy
Traditional method	7.58 ± 0.67	61.4 ± 4.2
GA-BPNN	5.86 ± 0.43	76.3 ± 5.1

Table 3. Two methods of fetal weight prediction error statistics.

Method	MiRE	MaRE	MRE
Traditional method	1.31	9.14	7.26
GA-BNPP	0.36	6.52	5.38

The statistics of fetal weight prediction errors of traditional method and GA-BPNN models are shown in Table 3. Among them, MiRE is the minimum relative error, and MaRE is the maximum relative error, and the training error curve of traditional method and GA-BPNN is shown in Figure 3.

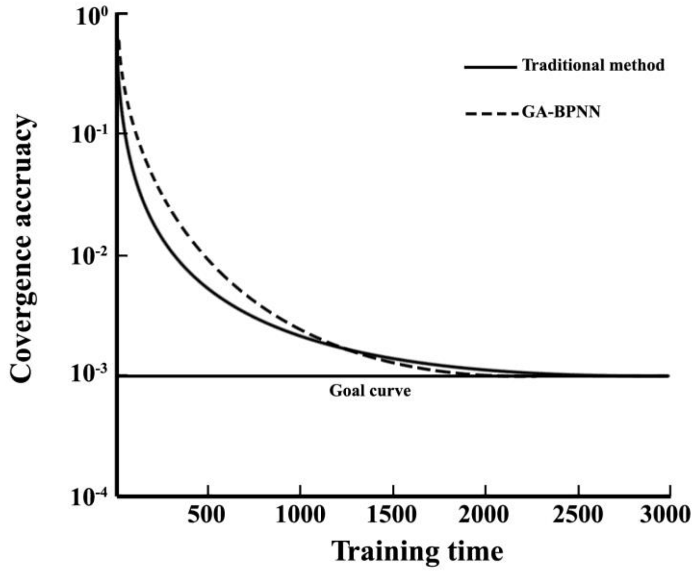

Figure 3. Traditional method and GA-BPNN training error curve.

From the results in Table 3, it can be seen that the accuracy of prediction of GA-BPNN is higher than that of traditional method, and the prediction results of GA-BPNN are closer to the actual fetal weight value. From Figure 3, it can be seen that the convergence speed of GA-BPNN is faster than that of traditional method, and the model performance is better.

4. Conclusions

In this paper, a prediction model of fetal weight based on Genetic Algorithm Optimized BP neural network (GA-BPNN) is proposed. Based on the historical physical examination data of pregnant women, a continuous change model of physical signs is established. Then the initial weights and thresholds of BP neural network are optimized by genetic algorithm to establish a prediction model of fetal weight. The experimental results show that the GA-BPNN fetal weight prediction model not only accelerates the convergence speed of the model, but also improves the prediction accuracy of fetal weight by 14.5%. Future work can further consider the time series characteristics of maternal physical examination data, improve the fetal weight prediction model, so as to further improve the accuracy and practicability of the model.

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Conflict of interest

The authors declared that there was no conflict of interests.

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