Study on Early Warning and Adaptive Prediction Model of Hypoglycemia Risk in Diabetic Patients

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Abstract: With the improvement of people's living standard, the number of diabetic patients is increasing, which causes harm to human health. However, the aim of treating diabetic patients in clinical treatment is to stabilize blood glucose. If the future blood glucose concentration of patients can be predicted in advance, doctors can take effective measures to stabilize blood sugar before the occurrence of hypoglycemia, which will greatly reduce the harm caused by unstable blood glucose to patients. Therefore, early warning and adaptive prediction model of hypoglycemia risk in diabetic patients is studied. Hypoglycemia data of diabetic patients can be collected scientifically by studying the way of gaining hypoglycemia prediction data. Establishing the early warning and adaptive prediction model can help doctors and patients to reduce the incidence of hypoglycemia.

Keywords: Prediction model; Early warning of hypoglycemia; Diabetes; ARIMA model

1. Introduction

The improvement of the economic level has brought about a great material richness. People have more and more choices of food and more and more fine food processing. However, many people choose food in an irrational direction. A higher standard of living satisfies the normal nutritional needs of the human body to a great extent, but it also leads to a sharp increase in the number of patients with "illness of affluence" such as diabetes, which brings great suffering to patients and their families. At present, diabetes has caused a great harm to human's health. According to incomplete statistics, about 250 million people in the world's population suffer from diabetes, and China's current number of diabetic patients ranks first in the world and is increasing at a rate of about 3,000 cases per day[1]. The clinical symptoms of diabetes are often high or low blood glucose. Long-term hyperglycemia will cause harm to people's organs. Even worse, it can cause pathological changes, such as damage to the renal function of myocardial infarction caused by pancreatic dysfunction, decrease the resistance and aggravate cerebral infarction. Long-term hypoglycemia will destroy the human neural system, causing the retinal detachment, renal blood flow and reducing orientation recognition ability. More seriously, sudden hypoglycemia can result in increased heart rate, increased pulse pressure, or even fainting or death.

At present, the main plan of clinical treatment for diabetic patients is to stabilize blood glucose by inject insulin, but the insulin injected and the insulin produced by people are totally different in continuity. And drug reaction needs time to react, which makes it possible for the blood glucose level to be lower than the normal blood glucose level to produce hypoglycemia. If the patient's blood glucose level can be predicted in advance, then the doctor or the patient can take measures to stabilize the blood glucose in advance, so that the hypoglycemic event can be well controlled and the pain caused by blood glucose instability can be greatly reduced. There are two main methods used to stabilize blood glucose in modern clinics. One is taking medicines and the other is injecting insulin. But it takes a certain amount of time for drugs and insulin to work, so it will still lead to unstable blood glucose levels. Blood glucose prediction technology is an important method to solve this kind of problem, and it has been paid more and more attention by people. At present, a large number of scholars have engaged in the research of blood glucose prediction technology and made outstanding contributions.

2. The Construction of Adaptive Prediction Model

The current mainstream of blood glucose prediction research is based on the historical blood sugar level of diabetics. A prediction model is established by analyzing and studying historical blood glucose levels of patients. Using the combined predictive model, based on the patient's historical blood glucose levels, the ARIMA predictive model was used to efficiently reflect the changes in the patient's blood glucose levels and predict future values. Considering the influence of external events (food, exercise, drugs, etc.) on blood glucose fluctuations, BP neural network is used to correct the error [2]. At the same time, aiming at the impact of unexpected events on the irregularity of blood glucose, a discovery and processing algorithm is proposed to ensure the prediction accuracy, which greatly improves the prediction efficiency and accuracy. It can provide a more reliable reference for doctors and patients to take measures to stabilize the blood glucose and reduce the harm caused by hypoglycemia. Figure 1 shows the combined prediction model.

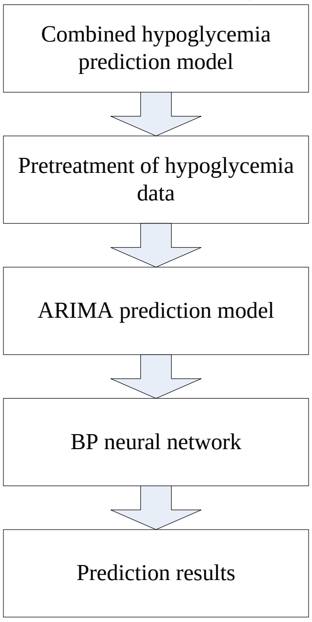

Figure 1. The diagram of combined hypoglycemia prediction model

2.1. Collection of hypoglycemia risk data

Blood glucose prediction is extremely important for doctors and diabetics. At present, the stable treatment of diabetes is mainly dependent on the injection of insulin. If the future blood glucose level can be obtained in advance, then the doctor and the patient can clearly know the injection time and the injection volume of insulin, and provide a good control effect on blood glucose control. At the same time, patients can adjust their diet and lifestyle in advance to reduce the occurrence of hypoglycemic events based on predicted values.

At present, in the research field of blood glucose prediction, there are generally two directions. One is to provide historical data directly to the patient; the other is to combine the blood glucose data provided by the patient with the human physiological model and apply a large amount of knowledge of physiology and pathology [3].

Some scholars engaged in this research believe that the patient's blood glucose data is directly collected, which reflects the most realistic blood glucose changes. Although human blood glucose is affected by factors such as human body mechanism, internal environment, diet, exercise, and drugs, these changes have been reflected in the dynamic changes of blood glucose. Therefore, the data collected directly by doctors has indicated the impacts of these factors. So the separate considering and analyzing is not needed. But in the process of collecting data, strict screening should be taken to data itself. As shown in table1.

Table 1. The requirements of collecting data directly

Data requirements	Data contents
More hypoglycemia data	Only by collecting enough data can we summarize the rules of blood glucose changes and build a predictive model.
Hypoglycemia data is continuing	The collected blood glucose data must be continuous, without breakpoints, and blood glucose collection is usually performed every five minutes.
The life of the collected patient is stable	Patients have stable eating habits and work habits, and huge changes can cause large fluctuations in blood glucose, which is not conducive to regular summarization and establishment of predictive models.
Use the same data collecting equipment	The physical characteristics of equipment from different manufacturers are generally different, so the noise and interference generated are often different, which is not conducive to the regular analysis of patients' blood glucose changes.

When making direct data hypoglycemia prediction, in addition to understanding the requirements of data acquisition, it is necessary to establish a neural network system that is compatible with it. This is because some scholars believe that the dynamic changes in blood glucose are affected by many factors in the field of blood glucose prediction research, such as internal conditions, diet, drug injections, emotions, etc. Therefore, they believe that the dynamic changes of human blood glucose are nonlinear. When the change of blood glucose is affected by external factors, the prediction effect obtained by using the linear prediction model will be worse than that obtained by the nonlinear prediction model. Fayrouz et al. proposed self-feedback neural network to predict human blood glucose [4].

Figure 2 shows that neural networks generally have three layers: input layer, hidden layer, and output layer. The input layer is used for data input; the hidden layer is used to process data, and the output layer is responsible for outputting data. Firstly, the neural network was trained using the historical blood glucose data collected directly, and the AIC criterion or the PSS criterion was used as the criterion of the prediction error. Then the neural network map was constructed.

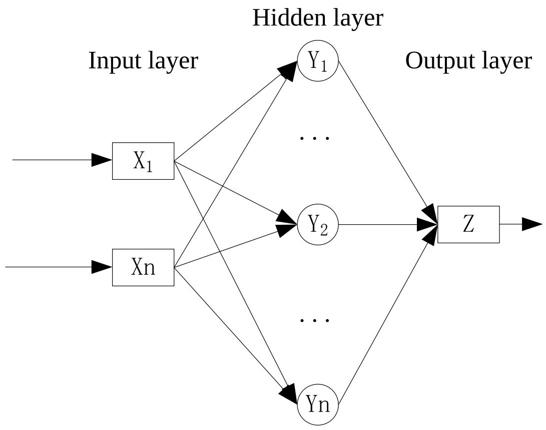

Figure 2. Neural network diagram

2.2. Physiological data acquisition

Directly collecting hypoglycemia data and human body physiological model prediction methods, mainly using the data provided by doctors, and then comprehensive consideration and analysis to establish a human blood glucose prediction model, predicting future blood glucose values or applying low blood sugar warning technology. At present, most of the direct collection data and the prediction methods of human physiological models mainly consider the main factors affecting the blood glucose fluctuation of the human body, namely, diet, amount of exercise and insulin injection, and use one or more of them to predict the future blood glucose prediction[5].

In order to pursue the accuracy of prediction, many scholars at home and abroad have tried to take into consideration all the factors that affect the fluctuation of human blood glucose. There are many factors affecting the fluctuation of blood sugar in the human body, such as diet, exercise, drug injection, mood swing, insomnia, weight, etc., all of which can affect the blood sugar fluctuations of the human body. The main factors are the first three. Claudio Cobelli et al. analyzed various factors affecting human blood glucose, classified the factors affecting human blood glucose fluctuations, and proposed that blood glucose fluctuations can be influenced and controlled from multiple aspects, as shown in Figure 3.

2.3. Hypoglycemia risk data processing

Whether the combined forecasting model can achieve the desired effect, the most basic is to ensure that the blood glucose data of the collected patient is close to the true value of blood glucose. Because the equipment that collects data is mostly physical equipment, coupled with the human body's physiological noise and some electromagnetic and electronic interferences, this results in certain differences between the collected low-glucose data and the patient's real blood glucose value. This causes certain difficulties and disturbances in the prediction of blood glucose. Therefore, the hypoglycemia prediction data must be processed to remove noise and make the collected data as close as possible to the true value. Therefore, it lays a solid foundation for the accuracy of the combined prediction model. In this paper, the wavelet transform is used to smooth the collected blood glucose data of patients. The specific preprocessing is shown in Figure 4.

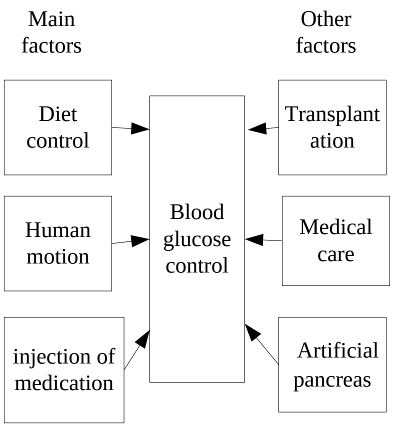

Figure 3. Control factors of blood glucose fluctuation

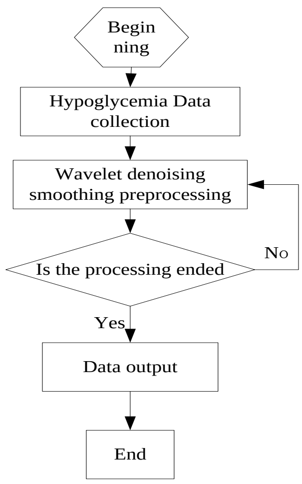

Figure 4. Blood glucose data preprocessing flow chart

In the process of blood glucose data preprocessing in Figure 4, the wavelet denoising method used in this paper is the threshold denoising method. First, wavelet decomposition is performed to determine a wavelet function and the number of decomposition layers. Then the high-frequency coefficients are quantized and finally the wavelet is reconstructed. Using the wavelet to process the historical blood glucose data of the collected patient, the signal is first decomposed by the wavelet. Usually the useless signal is the noise in the higher frequency range, so the decomposed high-frequency signal can be processed by the threshold selection method. Then the signal is reconstructed by wavelet to complete the noise reduction of the acquired signal. The data obtained by the final reconstruction is the denoised data.

The idea of constructing ARIMA model is: If the time series to be processed is non-stationary, differential processing is performed until the time series becomes stationary; Then use the ARMA(p, q) model to model the smooth time series, and then use the inverse transformation to get the original time series. In the treating process, it depends on the characteristics of the autocorrelation map and the partial autocorrelation map and related functions to determine which model the random sequence fits to, and finally determine the order and parameters of the model. Figure 5 shows the basic flow of the ARIMA model.

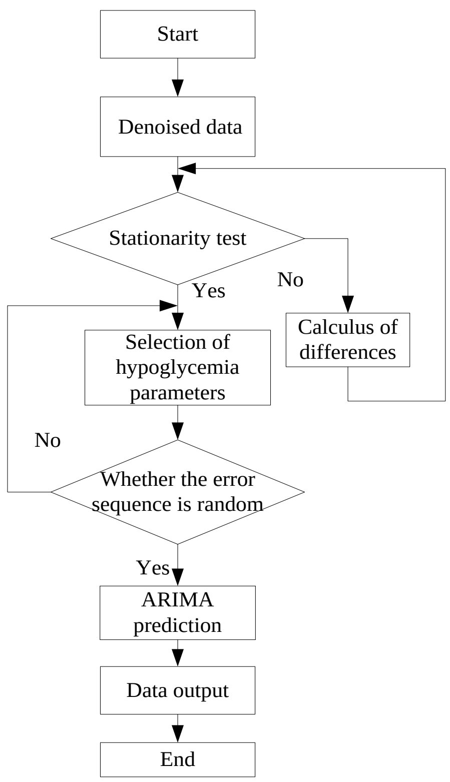

Figure 5. The process of ARIMA modeling

From Figure 5, the process of modeling is mainly divided into the following steps. First is data preprocessing. Before the establishment of a time series model to analyze the dynamic changes of the patient's blood glucose, it is necessary to perform certain operations on the dynamic data, remove special samples that do not conform to statistical laws, and test the basic statistical characteristics of the obtained data to ensure that the time series model of the established blood glucose data has high reliability and certain confidence, at the same time, it can meet the accuracy requirements[6]. Secondly, the stability test. To establish an ARIMA predictive model to predict future changes in blood glucose in patients, it is necessary to ensure that the time series of blood glucose values are stable, because stationarity is a prerequisite for time series modeling. There are two aspects that need to be considered in the test for stability: on the one hand, to verify whether the variance and mean value of the time series composed of blood glucose values are constant; On the other hand, it is verified whether the correlation function of the time series composed of blood glucose values is only related to the time interval and has nothing to do with the position at which the endpoint is located. Analyzing the human dynamic blood glucose changes, blood glucose sequence is a non-stationary time series, so it should be differentially processed, that is:

$$\Delta^{p,d} x_{\beta} = y_{\beta} \tag{1}$$

Where (p, d) represents the difference coefficient, $\Delta = \frac{1}{2} + \alpha$ is the difference operator, and α is the post-addition operator. After differential processing, the blood glucose sequence becomes a stationary time series: $\begin{pmatrix} \cdots 1 \cdots & \cdots 0 \cdots \\ \cdots 0 \cdots & \cdots 1 \cdots \\ \cdots 0 \cdots & \cdots 0 \cdots \\ \cdots 1 \cdots & \cdots 1 \cdots \end{pmatrix}$, Then the ARIMA(p, d) model of the blood glucose sequence is:

$$\lambda(B) + \Sigma \Delta^{d} = \chi(B)\left(\frac{1}{2} + \alpha\right)^{p} \tag{2}$$

Finally, the independence test. Independence is also a basic requirement for time series modeling, which means that the collected patient history data must be independent and must comply with the independence rules.

2.4. Adaptive prediction of hypoglycemia risk

The error diagnosis of the prediction model is mainly accomplished through the BP neural network. BP neural network is a nonlinear, complex, dynamic system. It has the ability to self-learn and self-organize the processing of data and information, and has the ability to adapt to uncertain regular systems.

There are various factors affecting human blood glucose, such as diet, exercise, insulin injection, etc. The influence of these factors on blood glucose is non-linear. BP neural network can be used to grasp the influence of nonlinear factors on human blood glucose by analyzing the error analysis of ARIMA prediction model prediction results.

The workflow of the BP neural network is shown in Figure 6.

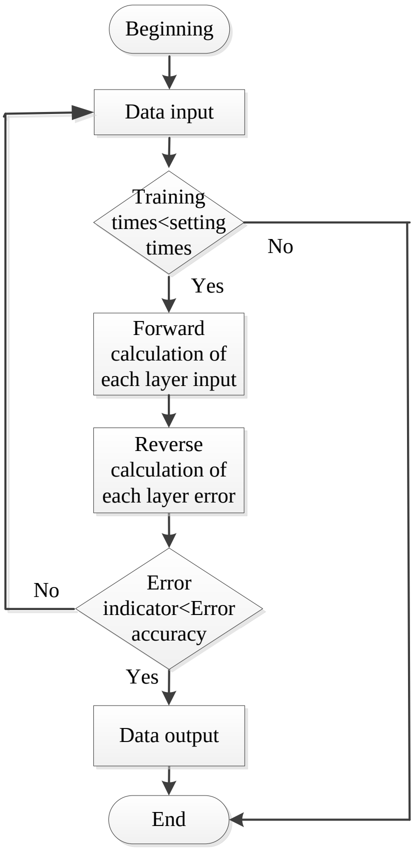

Figure 6. BP neural network detection flow chart

3. Experimental Analysis

In order to verify the validity of the design of the self-adapted predictive model for predicting hypoglycemia risk in patients with diabetes, a simulation experiment was designed and conducted. The experiment was conducted twice in total to test the stability of data collection in hypoglycemic patients (SSGPE) and the stability of predictive model prediction（RMSE）. In order to ensure the validity of the experiment, the traditional AR model was compared with the AR model method designed in this paper to observe the test results.

In the 2.1 and 2.2 experiments, the number of patients in the two experiments was the same, that is, 60 people. At the same time, the same detection equipment is used. The abscissa represents the number of patients; the ordinate represents stability, and the smaller the stability value, the more stable the model.

3.1. SSGPE Stability comparison

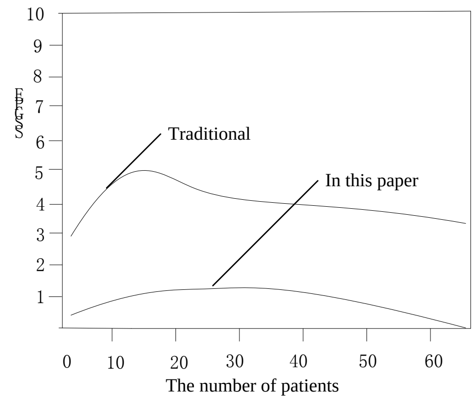

Figure 7. SSGPE Stability comparison chart

3.2. RMSE Stability comparison

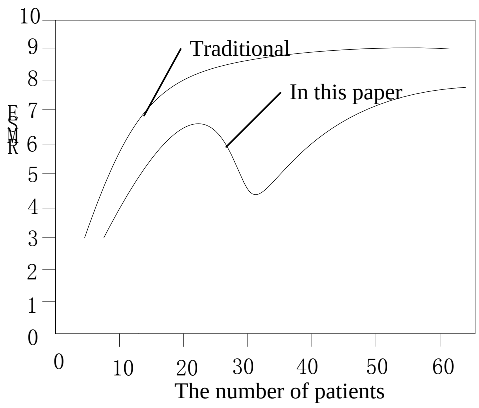

Figure 8. RMSE stability comparison chart

From the observation and comparison in Fig. 7 and Fig. 8, it can be found that the adaptive hypoglycemia prediction model designed in this paper is superior to the traditional AR hypoglycemia prediction model in the comparison experiments of SSGPE and RMSE stability. Therefore, it can be explained that the adaptive hypoglycemia prediction model designed in this paper is effective.

4. Conclusion

In summary, through the study of the adaptive predictive model of hypoglycemia risk in diabetic patients, it can be found that the establishment of this predictive model has a great effect on diabetic hypoglycemia patients and doctors. It makes a great contribution to the physical health and well-being of patients.

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