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Research Article

The Design of Adolescents’ Physical Health Prediction System Based on Deep Reinforcement Learning

Hailiang Sun¹ and Dan Yang ²

¹School of Physical Education, Shenyang Sport University, Shenyang, Liaoning 110102, China
²Sports Department, Suqian University, Suqian 223800, Jiangsu, China

Correspondence should be addressed to Dan Yang; 16113@squ.edu.cn

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According to the general recognition in the first half of the last century, hypertension was not considered a kind of disease, but was regarded as a compensatory response commonly seen in the elderly, and it would not occur to younger people. Because of this erroneous cognition, many young patients fail to pay attention to their own hypertension, fail to take correct and standardized treatment, and suffer from a series of complications caused by hypertension. This article summarizes the relevant factors that affect the patient’s future blood pressure from three directions: the basic characteristics of adolescent patients, the way they lower blood pressure, and the impact of the external environment. In order to make the model better fit the continuous data in the feature set of adolescents with hypertension, the structure of the internal components of the deep confidence network is optimized. Gaussian noise is introduced into the visible and hidden layers of the internal components of the network so that the stored information of the network changes from discrete to continuous during operation and improves the prediction accuracy of the blood pressure prediction model for adolescents with hypertension.

1. Introduction

The current health problems are getting younger and younger, with the emergence of adolescent hypertension becoming more serious. In the past, the demand of “getting the disease first, then treatment” has gradually changed to the demand of “early disease screening and prevention, early detection and early treatment, and personalized diagnosis”²; that is, medical services are required to detect, analyze, and evaluate the health of individuals in a timely manner, provide personalized health consultation and guidance, and prevent problems before they occur. However, the current limited medical resources and the level of medical services are still unable to meet the increasing needs of people, which may lead to aggravation and deterioration of the doctor-patient relationship. With the continuous emergence of research results of deep learning technology in disease prediction, which has accelerated the application of intelligent disease-assisted diagnosis systems in clinical practice, how to effectively ensure the health prediction of adolescents has become the focus of attention in this field. Early auxiliary diagnosis methods use traditional machine learning techniques such as Bayesian classifiers and artificial neural networks. However, traditional research methods have the limitations of insufficient feature extraction. Algorithms often extract lesion information in specific areas of the image as features, which cannot be used more comprehensively. The information predicts disease conditions. In the face of these massive physical health data, in order to obtain deeper information and dynamic monitoring of students’ physical health, as well as the research and analysis of the relationship between disease and physical health, deep learning methods must be used. The core of deep learning is to extract previously unknown, valuable, and implicit information from a large amount of raw data, as well as the processing process that this technology can be understood.
2.1.3. Body Mass Index. Body mass index (BMI) is calculated to measure the degree of body weight. Through in-depth mining of the adolescent health status follow-up data, the study found that, with the increase of the BMI index, the incidence of hypertension in overweight and obese people increased to 1.16 to 1.28 times that of healthy people.

2.1.4. Family History of Hypertension and Related Diseases. Family history of hypertension is one of the important risk factors for the onset of hypertension. In the primary follow-up management of adolescents with hypertension in my country, family history is an important management indicator. Including not only family history of hypertension, family history of coronary heart disease, family history of stroke, and family history of diabetes and other diseases closely related to hypertension are also included in the observation object.

In summary, it can be seen that there is a significant gap in the proportion of hypertensive groups among different genders and different age groups. Obese people and people with a family history of hypertension or family history of related diseases are high-risk groups of hypertension. According to current data, cardiovascular diseases are becoming younger and younger. Therefore, gender, age, BMI index for evaluating the degree of fatness, family history of hypertension, and family history of hypertension-related diseases should be included in the blood pressure prediction model of hypertensive adolescent patients [6–10].

2.2. Deep Belief Network

2.2.1. Related Principles. As the number of layers of traditional neural network models increases, the training process becomes more and more difficult, and it is easy to fall into local extremes, which leads to the prediction effect of the deep model inferior to the shallow structure. The lack of learning algorithms suitable for deep neural networks became a major and difficult problem that hindered the development of neural networks at that time. This problem was solved in 2006. Professor Hinton of the University of Toronto proposed a deep network model that is trained by layer-by-layer initialization—deep belief net (DBN). The emergence of this deep network structure makes it feasible to train deep neural networks. Due to the excellent feature learning ability and nonlinear problem processing ability of the DBN model, it has been widely used in the field of data prediction. The network structure of the traditional DBN model is shown in Figure 1. It is composed of multiple Bernoulli-Bernoulli restricted Boltzmann machines (BB-RBMs) and a linear regression layer composition. Multiple RBM units are stacked, the output of the previous RBM unit is the input of the next unit, and the last RBM unit is connected with a linear regression layer to form the deep structure of the entire network [11].

Data prediction using the DBN model is mainly divided into two stages: unsupervised learning stage and supervised learning stage. The unsupervised learning stage refers to the unsupervised training of each RBM unit in the order from top to bottom in the network structure. When all RBM units in the DBN network are trained, the unsupervised learning process of the DBN is also completed. After the unsupervised learning stage is completed, the DBN model usually uses the same error backpropagation algorithm as the BPN model to fine-tune the network parameters and complete the supervised learning of the network. The BB-RBM unit in the
2.2.2. Basic Algorithm. Taking the BB-RBM unit as shown in Figure 2 as an example, the energy it possesses can be defined as

\[ E(V, H|\theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{i=1}^{m} b_i h_i - \sum_{i=1}^{n} \sum_{j=1}^{m} v_i w_{ij} h_j. \]  

(1)

In the formula, \( \theta = \{w_{ij}, a_i, b_j\} \) represents the parameter space to be sought. According to the energy function of the traditional DBN model is an undirected graph model with full connections between layers and no connections within the layers. The whole unit is divided into a visible layer and a hidden layer, as shown in Figure 2. The process of unsupervised training of the BB-RBM unit can be regarded as the process of extracting the characteristics of the input sample data by the DBN network. When performing unsupervised training, each BB-RBM unit is regarded as a separate system, with 1 representing the active state of its internal nodes and 0 representing the inactive state. The goal of unsupervised training is to find appropriate weights \( w_{ij} \), visible layer bias \( a_i \), and hidden layer bias \( b_j \) and make the input sample have the lowest energy in the system. When the system energy reaches the lowest, the current BB-RBM unit fits the data characteristics of the input sample to the greatest possible extent from the perspective of probability. Therefore, when the unsupervised training is completed, the output of the BB-RBM unit at this time can be regarded as the high-order feature representation of the input features [12–14].

The process of unsupervised training is as follows:

1. Calculate the state distribution probability of nodes in the hidden layer \( H_0 \) according to the original input \( V_0 \) of the visible layer of the current BB-RBM unit [15–19]:

\[ P(h_j = 1|\theta, \theta) = \sigma \left( \sum_{i=1}^{N} v_i w_{ij} + b_j \right). \]  

(4)

In the formula, \( \sigma(x) \) represents the activation function. According to the state distribution probability of \( H_0 \), perform Gibbs sampling to obtain the state information of the nodes in \( H_0 \).
2.3. Evaluation Index for the Accuracy of Adolescent Blood Pressure Prediction. At present, the American Association for the Advancement of Medical Devices (AAMI) standard is used internationally to evaluate whether a blood pressure meter is qualified. According to the AAMI standard, the maximum error allowed by the instrument used for blood pressure measurement is 5 mmHg. Therefore, this article also uses ±5 mmHg as the criterion to evaluate the prediction accuracy of the blood pressure prediction model for adolescents with hypertension; that is, when the model predicts blood pressure and the patient’s actual blood pressure value is within 5 mmHg, it is judged here that the prediction result is accurate; otherwise, it is judged as inaccurate. Define it as the model prediction accuracy $\text{Acc}$:

$$\text{Acc} = \frac{m}{n} \times 100\%.$$  

In the formula, $n$ represents the sample size, and $m$ represents the number of samples whose prediction error is within the criterion. The higher the prediction accuracy, the higher the accuracy of the model for predicting the patient’s blood pressure [21, 22].

3. Establishment of a Predictive Model for Adolescents’ Physical Health

3.1. Data Preprocessing. Data preprocessing is the process of processing the collected raw data into a high-quality dataset that meets the needs of research goals. Good data preprocessing can effectively improve the efficiency of subsequent data modeling and data analysis. This article analyzes the influencing factors of the blood pressure of adolescent patients, conducts a series of data preprocessing works on the collected outpatient follow-up original records and weather original records of adolescent patients with hypertension, and establishes a high-quality dataset of characteristics of adolescent patients with hypertension. The overall process of the work is shown in Figure 3 [23].

3.2. Experimental Environment. The experiment uses a personal computer, and the detailed configuration is shown in Table 1.

3.3. Adolescents’ Physical Health Prediction Model Based on the DBN

3.3.1. Predictive Model Process. For the DBN-based blood pressure prediction model for adolescents with hypertension, its hidden layer structure is also related to the final prediction accuracy of the model. Moreover, because the DBN model has one more unsupervised learning process than the BPNN model, the selection process of the network structure of the DBN model is often more complicated than that of the BPNN model. At present, there is still no complete theoretical basis for the selection of the number of hidden layers of the DBN model and the number of nodes in each hidden layer. Therefore, this article sets up multiple groups of controlled trials to determine the optimal number of nodes from top to bottom and establish a blood pressure prediction model based on the DBN for adolescents with hypertension.

3.3.2. Model Performance Evaluation. The overall model construction process is shown in Figure 4. The specific steps are as follows:
Randomly select 10,000 records in the characteristic dataset of adolescent patients with hypertension as the training sample set of the DBN model, and the remaining 3762 records are used as the test sample set of the DBN model.

Considering the performance of the experimental equipment and the risk of overfitting, the maximum number of hidden layers of the DBN hypertensive adolescent blood pressure prediction model is set to 3; the value set of the number of hidden layer nodes $\emptyset$ is set to \{10, 20, 30, 40, 50, 60\}; the initial value is set to 10; the maximum number of iterations for supervised training is set to 1000; the maximum number of iterations for unsupervised training is set to 5000.

Initialize the RBM unit. Set the learning rate of its unsupervised training $e1 = 0.5$; the activation function uses the sigmoid function; the visible layer bias $a$, the hidden layer bias $b_j$, and the connection weight of the hidden layer and the visible layer $w_{ij}$ are initialized to the interval (0, 0.1) value in range.

Randomly extract the training sample set samples, and unsupervised training of the current RBM unit is carried out according to the CD algorithm.

After reaching the maximum number of iterations, the unsupervised training ends. Construct a logistic regression layer with 2 nodes as the output layer of the network, which are used to predict diastolic blood pressure and systolic blood pressure, respectively. Connect the regression layer node to the hidden layer node of the current RBM unit, and initialize the connection weight between the hidden layer and the output layer $w_{ij}$ and the bias $b_j$ corresponding to each node in the output layer to be in the interval (0, 0.1). For random values, perform the supervised training of the DBN model according to the same error backpropagation algorithm as the BPNN model, and update the network parameters $w_{ij}$, $b_j$, $w'_{ij}$, and $b'_j$.

After the supervised training is completed, input the test sample dataset into the DBN-based blood pressure prediction model for adolescent hypertensive patients, and record the blood pressure prediction results of the DBN model under the current structure for the hypertensive adolescent patients in the test set.

Take the set value of the number of nodes in the next hidden layer in the set $\emptyset$, and repeat Steps 3 to 6, until all the values in $\emptyset$ are traversed. Establish a DBN hypertensive adolescent blood pressure prediction model with the same number of hidden layers and a different bottom RBM unit structure, and determine the bottom RBM unit structure with the best prediction effect of the DBN model under the fixed number of hidden layers according to the prediction results, which is the current optimal structure of the RBM unit.

Add a hidden layer, and judge whether the number of added hidden layers is greater than the preset maximum value. If it is not exceeded, remove the logistic regression layer of the DBN model, add a new RBM unit, and use the hidden layer of the previous unit as the visible layer of the new unit. The initial value of the number of nodes in the hidden layer of the new unit is also set to 10. Return to Step 3, and establish DBN models with different hidden layer structures; if it exceeds, compare the results of the DBN model predicting the patient’s blood pressure under different hidden layer structures, and select the model with the highest prediction accuracy. Finally, according to the above steps, the prediction accuracy is increased.
The results of the DBN model for the patient’s diastolic and systolic blood pressure under different hidden layer structures are obtained, as shown in Table 2. From the experimental results in Table 2, it can be seen that when the hidden layer of the DBN-based hypertensive adolescent blood pressure prediction model is changed from one layer to two layers, the prediction accuracy of systolic blood pressure and diastolic blood pressure is significantly improved, indicating that, in hypertension, in the problem of blood pressure prediction in adolescent patients, the deep network has a better complex relationship mapping than the shallow network.

When the network continues to deepen and the hidden layer increases to 3 layers, the blood pressure prediction accuracy rate of the DBN model decreases. This may be due to the accumulation of overall network errors and overfitting; when the number of layers is 2 and the number of nodes is 30 and 10, the model predicts the patient’s diastolic blood pressure and systolic blood pressure with the highest accuracy, which are 85.41% and 75.84%, respectively. Therefore, the network structure of the DBN-based blood pressure prediction model for adolescents with hypertension is finally determined to be four layers, and the number of nodes in the two hidden layers is 30 and 10 from the input layer to the output layer.

4. Adolescents’ Physical Health Prediction Model Based on the Improved Deep Belief Network

The fully continuous deep belief network model that uses the adaptive distance estimation algorithm for supervised learning is defined as FCDBN-Adam; the fully continuous deep belief network model that uses the stochastic gradient descent algorithm for supervised learning is defined as FCDDN-SGD; a deep artificial neural network model that has the same network structure as the above two models and uses an adaptive distance estimation algorithm for supervised learning is defined as ANN-Adam; it uses a stochastic gradient descent algorithm for supervised learning depth. The trust network model is defined as DBN-Adam. The settings of each model are shown in Table 3. Explore whether the FCDBN-Adam hypertensive adolescent blood pressure prediction model proposed in this article has higher accuracy and stability than other deep models in the face of different types of hypertensive adolescent patients.

4.1. Different Age Groups. Age is one of the important factors that affects the blood pressure level of patients. With the increase of age, the body’s immunity decreases, and the body’s ability to control blood pressure becomes worse. As a result, older adolescents with hypertension bear a higher risk of disease than younger patients. Considering that the blood pressure levels of hypertensive adolescents of different ages have different influences on the factors affecting their blood pressure levels, the characteristic dataset of hypertensive adolescents is now grouped by age (see Table 4 for grouping results) to explore in this article whether the established blood pressure prediction model for adolescents with hypertension can reveal the changes of blood pressure caused by the affected factors in patients of different ages.

100 samples were randomly selected from each group to form test samples, and the remaining samples were used as training samples to test the performance of each deep neural network model in Table 3 in the face of patients of different ages. The results are shown in Figures 5 and 6.

It can be seen from the prediction results of the blood pressure level of patients of different age groups in Figures 5 and 6 that the four models predict the diastolic blood pressure with 85.41% and 75.84% accuracy, respectively. The prediction accuracy of the FCDBN-Adam model is significantly higher than that of the other models. This shows that the fully continuous deep belief network model has better prediction performance and stability than the other models in the prediction of blood pressure level of patients of different ages.
pressure level of patients of different age groups under the premise that the number of training samples given by each age group is different. The above accuracy rate did not show a significant difference, but in predicting the systolic blood pressure level of patients, it may be due to the influence of a special undiscovered systolic blood pressure influencing factor. In the prediction of the pressure level, the prediction accuracy of each deep neural network model has decreased slightly, and the FCDDN-Adam model proposed in this paper can still maintain a prediction accuracy of more than 80%, which exceeds the other three deep models.

4.2. Different Follow-Up Cycles. The follow-up physicians set up different follow-up cycles for the patients according to the severity of the condition of the adolescents with hypertension. Patients with mild illness have a longer follow-up period, while patients with severe illness have a relatively shorter follow-up period. Moreover, the follow-up period can reflect the length of time the patient continues the current antihypertensive treatment. Long-term drug interventions and lifestyle interventions are likely to change the law of influencing factors on the blood pressure level of patients. Therefore, the characteristic dataset of adolescents with hypertension is now grouped according to the length of the follow-up period. See Table 5 to explore in this article whether the established blood pressure prediction model for adolescents with hypertension can reveal the changes of blood pressure caused by the affected factors in patients with different follow-up periods.

100 samples were randomly selected from each group to form test samples, and the remaining samples were used as training samples to test the performance of the deep neural network models in Table 3 in the face of patients with different follow-up periods. The results are shown in Figures 7 and 8.

It can be seen from the prediction results of the blood pressure level of patients in different follow-up periods in
Figures 7 and 8 that, as the prediction time span increases, the prediction accuracy of each deep neural network model decreases, and the proposed method based on FCDBN-Adam is high. Compared with other models, the blood pressure prediction model for adolescent patients with blood pressure is more stable. The prediction accuracy of diastolic blood pressure is always above 90%, and the prediction accuracy of systolic blood pressure is maintained at about 85%. It has higher prediction accuracy and can predict well.

4.3. Result Analysis. Judging from the overall results of the four models for predicting the patient’s blood pressure, it can be seen that, under the same number of supervised training iterations, in terms of prediction accuracy, the FCDBN-Adam model is better than the FCDBN-SGD model. Among them, the Adam algorithm has a higher learning efficiency than the SGD algorithm; the prediction accuracy of the FCDDN-Adam model far exceeds that of the ANN-Adam model with the same structure, indicating that the deep belief network model can be better than the multilayer neural network model. Characterize the complex nonlinear relationship between the future blood pressure situation of the human body and its various influencing factors; the prediction accuracy of the FCDBN-Adam model is significantly higher than that of the DBN-Adam model, indicating that the traditional RBM unit inside the deep confidence network is replaced with a double-layer Gaussian structure. The GG-RBM unit can effectively improve the

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Table 5: Sample distribution of the characteristic dataset of adolescent patients with hypertension (grouped by the follow-up period).

| Group | Follow-up cycle                        | Number of samples |
|-------|----------------------------------------|-------------------|
| 1     | Within two weeks                       | 2900              |
| 2     | Two weeks to one month                 | 5700              |
| 3     | More than one month                    | 5000              |
prediction accuracy of the blood pressure prediction model for adolescents with hypertension.

To sum up, this article proposes a blood pressure prediction model based on FCDBN-Adam hypertensive adolescent patients. Although there are differences in the blood pressure prediction results of different types of hypertensive adolescent patients, the overall prediction accuracy of the model remains at a high level, and the prediction accuracy of diastolic blood pressure has reached about 85%, and the accuracy of predicting systolic blood pressure is over 90%, which is better than the other three deep neural network models. It can better characterize the complex nonlinear relationship between the future blood pressure of the human body and its various influencing factors. It is suitable as a model for predicting the blood pressure level of adolescents with hypertension under the complex influence of multiple factors.

5. Conclusion

This article first optimizes the internal units of the blood pressure prediction model for adolescents with hypertension based on the deep confidence network and uses a restricted Boltzmann machine (GG-RBM) unit with a double-Gaussian structure to replace the double-layer Bernoulli in the original model. The structure of the restricted Boltzmann machine (BB-RBM) unit has established a blood pressure prediction model for adolescents with hypertension based on the fully continuous deep confidence network (FCDBN). Experiments show that the improved model can better fit the characteristics of adolescent patients with hypertension and improve the accuracy of the model for predicting the blood pressure level of patients.

Secondly, considering the large number of input factors in the current model and the complicated selection process of the hidden layer structure, this paper designs a method based on the traditional network structure determination method to determine the number of hidden layer nodes in a fully continuous deep confidence network model based on reconstruction errors. The method of hiding the number of layers omits the step of supervised learning in the network structure selection process, saves the time cost of blood pressure prediction modeling for adolescents with hypertension, and enhances the scalability of the model.

Finally, this paper constructs four different types of deep neural network models, FCDBN-Adam, FCDBN-SGD, DBN-Adam, and ANN-Adam, respectively, and evaluates the blood pressure prediction accuracy of the four models in the face of different types of adolescents with hypertension. The experimental results show that the blood pressure prediction model for adolescents with hypertension based on FCDBN-Adam proposed in this paper performs best. In the face of different types of adolescents with hypertension, it can maintain a high prediction accuracy of patient blood pressure. The average prediction accuracy of diastolic blood pressure exceeds 90%, and the systolic blood pressure reaches about 85%. It is based on four types of deep learning. In the future, with the widespread application of the adolescent prediction system, it is believed that other adolescent diseases can also be well predicted.

Data Availability

The dataset can be accessed from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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