Research Article

Mental Health Education in Primary and Secondary Schools Based on Deep Learning

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Strengthening the mental health education of primary and middle school students is a key measure to lead their healthy growth. This paper takes mental health early warning as the starting point to carry out research on mental health education in primary and secondary schools. Aiming at the defect that the existing methods cannot effectively warn the mental health of primary and secondary school students, this paper proposes a mental health early warning research method based on the deep learning models. The method firstly obtains the mental health data of college students through the symptom self-rating scale. Then, a mental health prediction model combining convolutional neural networks (CNN), deep residual networks (ResNet), and long short-term memory (LSTM) is adopted. Through in-depth processing and analysis of mental health data, the mental health status of students can be determined. Experiments show that this method can effectively improve the accuracy of mental health early warning compared with the currently commonly used mental health early warning methods.

1. Introduction

With the increasingly fierce social competition, the primary and secondary school students are facing multiple pressures such as learning and interpersonal relationships, and mental health problems frequently occur [1–3]. Traditional mental health monitoring methods are relatively passive and inaccurate. People need to actively seek consultation with a psychiatrist and conduct tests to determine whether they have a disease. The main methods of diagnosis and treatment used by doctors are the form of communication and questionnaires, and the results of diagnosis are affected by the subjective judgment of doctors to some extent [4–6]. It is worth noting that the effect of traditional mental health monitoring methods in the prevention of mental health diseases depends greatly on the degree of people’s attention to mental health. And there is a lack of suitable biomarkers to quantify the degree of mental disease development and the effect of drugs. With the development of artificial intelligence technology, researchers have begun to predict mental health through intelligent algorithms and analyze people’s emotions and psychological states through analysis of human biological signals, facial expressions, body language, and other aspects. Judging from the existing literature, most of the currently used mental health early warning systems are based on traditional machine learning algorithms, such as back propagation (BP) neural network and decision tree algorithm, which require a large amount of calculation, and the accuracy of early warning is not high. In recent years, new artificial intelligence algorithms represented by deep learning have developed rapidly. From the reported results, deep learning models can dig deeper into the internal structure of data and obtain more reliable results than traditional machine learning algorithms [7–10].

Based on the background of mental health prediction, this paper carries out research on mental health education of primary and secondary school students. First of all, the mental health data of primary and middle school students is collected in the form of symptom self-rating scale, which is usually a high-dimensional data set, as the basic basis for mental health prediction. On this basis, a mental health prediction model combining convolutional neural networks (CNN), deep residual networks (ResNet), and long short-term memory (LSTM) is designed. CNN can effectively
extract the hidden features of high-dimensional data, but recurrent networks can learn historical information. Research shows that recurrent networks are more suitable for processing time series, and combining CNN and recurrent networks can take advantage of both. Reference [11] uses a convolutional LSTM to identify the original time series data of the signal, and its model performance exceeds the simple LSTM model in terms of recognition ability. Reference [12] used the deep network built by CNN and LSTM to classify and identify vibration signals. On the basis of previous research, this paper proposes a mental health state prediction method based on ResNet combined with LSTM [13–16]. Taking the collected mental health data of primary and middle school students as the model input, the 1DCNN network is used to extract the signal feature information, and the ResNet improves the model training depth to avoid the disappearance of the model gradient. Then, the LSTM network learns the feature information and finally realizes the classification and prediction of mental health status [17–20]. The method proposed in this paper can effectively combine the advantages of different deep learning models, thereby further improving the reliability of the final prediction results. Experiments are carried out based on the collected data sets, and the results show that the proposed method has higher prediction accuracy than traditional machine learning methods.

2. Method Description

2.1. 1DCNN. CNN is a feedforward neural network with representation extraction and learning capabilities. It is mainly composed of convolutional layers, pooling layers, and fully connected layers. It has been widely used in two-dimensional data classification problems such as image recognition. The convolution layer extracts features from the input data through the convolution kernel and continuously fits the local hidden features of the data during the training process. The pooling layer performs downsampling and dimension reduction processing on the data to complete parameter sparseness and reduce the amount of data. Due to the large size of the input data and the convolution kernel and many network parameters such as weights and biases, the parameter sharing method is commonly used to reduce the number of network free parameters and speed up the network training process. The time domain data of the interference signal discussed in this paper is one-dimensional time series data, so a 1DCNN is used, and whole basic formula is as follows:

\[
Z_{k}^{l+1} = \sum_{u_{k}} \left[ Z_{k}^{l} \times \omega_{k}^{l+1}(x) \right] + b_{k}^{l}, \tag{1}
\]

where \(Z_{k}^{l}\) and \(Z_{k}^{l+1}\) are the convolution input and output of the \(l+1\) layer; \(b_{k}^{l}\) is the deviation; \(\omega_{k}^{l+1}\) is the convolution kernel of the corresponding node of the \(l+1\) layer, and \(M\) is the set of convolution kernels.

The max pooling formula is

\[
s_{k} = \max \left( y_{k}(hn-1), y_{k}(hn) \right), \quad n = 1, 2, \cdots, \frac{m}{h}, \tag{2}
\]

In equation (2), \(h\) represents the pooling step size, and \(m\) is the number of elements in the sequence \(y_{k}^{l}\). After multi-layer convolution and pooling operations, the extracted multicolored deep-level feature sequences are integrated into one column in the flat layer, which lays a data foundation for subsequent time series feature extraction.

2.2. ResNet. With the increase of the number of layers of the CNN model, there will be problems such as loss of features and incomplete information between multiple hidden layers, resulting in disappearance of gradients and reduced network performance. The main approach of residual networks to address this problem is to add linear direct paths while convolutions handle nonlinear transformations. Its basic unit structure is shown in Figure 1.

It can be seen from the figure that between the input \(x_{l}\) and the output \(x_{l+1}\), the two convolutional layers in the middle are set up with cross-layer connections. The input of the shallow layer is directly connected to the end position. Since the weight of the direct cross-layer connection is 1, so in the process of layer-by-layer mapping, the problem of network gradient disappearance caused by the nonlinear processing of the convolution layer \(F(x_{l})\) being less than 1 can be avoided. Through the residual operation, the network performance cannot be degraded while increasing the depth.

2.3. LSTM. Recurrent neural network (RNN) is a deep learning algorithm often used in processing complex sequence data. The network takes sequence data as input and performs recursive processing in the evolution direction of the sequence. A neural network in which all cyclic units are connected in a chain can be used to process the information of the sequence structure. It reflects the transmission and accumulation of information from the front to the back in the time dimension and can expand the time characteristics. The state of the hidden layer of the RNN at each moment is determined by the current input and the state of the previous hidden layer at the same time, the memory capacity is limited, and it is easy to cause the problem of gradient disappearance. The LSTM network introduces forgetting gate, input gate, and output gate unit on the basis of the conventional cyclic neural network to control the state iteration of the LSTM unit and controls the memory information. The acquisition of input information and the transmission of output information are obtained through the gate coefficient, improving the classification network.

The difference between LSTM and general RNN is mainly in the calculation of the hidden state of the recurrent network. The basic structure of LSTM is shown in Figure 2. At time \(t\), the state of the LSTM unit \(C_{t}\) is determined by discarding the useless information of the unit and retaining some useful information. The state of the hidden layer \(h_{t}\) at this moment is determined by the useful information selected by the output gate \(C_{t}\). The calculation process is as
2.4. Procedure of Mental State Evaluation. In this paper, a mental health prediction model based on the combination of CNN, ResNet, and LSTM is constructed. Based on the mental health data of primary and secondary school students, the mental state and health level are judged. The basic process of the proposed method is shown in Figure 3, and the main steps are described as follows.

Step 1. Since the input of the LSTM layer is sequence data, the mental health data is firstly folded and input to the subsequent network layers.

Step 2. Through a convolution and two residual block operations and then through the maximum pooling layer and the flat layer, the dimension of the data is reduced.

Step 3. Sequence expansion of the output data of the flat layer is performed. And the two-layer LSTM layer is input to extract time series information, and finally, the extracted features are obtained.

Step 4. The Softmax function is employed to output the probability value. The type of mental state is determined according to the probability distribution, and the correct rate according to the label is output.

3. Experiment and Analysis

3.1. Dataset Collection and Preprocessing. During the mental health data collection and preprocessing, the symptom self-assessment scale was distributed to 500 students in a middle school, and psychological data was collected. In order to quantify each student’s psychological state, the student’s mental health data structure was constructed as (student number, somatization, interpersonal sensitivity, obsessive-compulsive symptoms, depression, anxiety, terror, hostility, paranoia, psychosis, and others). In the experiment, 300 pieces of mental health data of college students were randomly selected as training samples, and the remaining 200 pieces of data were used as test samples. The collected mental health data structure of each student is represented as a one-dimensional column vector with 11 elements. Therefore, both training samples and test samples in the experiment can be represented by a one-dimensional column vector with 11 elements.

3.2. Result and Discussion. In this paper, a deep learning model is used to predict the mental health data of primary and secondary school students, and the proposed method is verified according to the collected data. The experiment compares and analyzes the method proposed in this paper with the traditional mental health prediction method based on BP neural network and decision tree model. Five experiments are carried out for each method, and the training samples and test samples used in each experiment are randomly selected. And the best early warning accuracy and average prediction accuracy of the five experiments are taken for the mental health status. Table 1 shows the prediction results of mental health status by various methods. It can be seen that the prediction accuracy of the proposed method is higher than that of the two contrasting methods. The reasons for this performance advantage can be analyzed from two aspects. One is the advantage of deep learning models. Deep learning algorithms can better process mental health
In this paper, a method based on symptom self-rating scale and deep learning is proposed for the psychological state assessment in the mental health education of primary and secondary school students. First, the mental health parameters of the students are obtained through the symptom self-rating scale, and then, the feature vector is constructed. Taking the feature vector as input, train a deep learning model combining 1DCNN, ResNet, and LSTM. The trained model can judge the students’ mental state and health level according to the results of the self-rating symptom scale of students, so as to provide improvement strategies for the targeted development of mental health education for primary and secondary school students. In the experiment, the proposed method is tested with relevant data and compared with the existing mental health prediction algorithms, and the results reflected the effectiveness of the method.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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[1] C. G. Brooker, J. M. Curran, A. James, and E. Readhead, “Developing and piloting an audit tool for mental health education and training: the National Mental Health Education Continuous Quality Improvement Tool,” Journal of Interprofessional Care, vol. 19, no. 3, pp. 280–293, 2005.
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Table 1: Comparison of performance of different methods.

| Method     | Average classification accuracy (%) |
|------------|-------------------------------------|
| Proposed   | 93.2                                |
| BP         | 87.1                                |
| Decision tree | 89.2                            |

Table 2: Performance of different methods at different repetitions (%).

| Method     | 10  | 15  | 20  | 25  | 30  |
|------------|-----|-----|-----|-----|-----|
| Proposed   | 93.5| 93.9| 94.1| 94.2| 94.1|
| BP         | 87.4| 88.1| 88.3| 88.3| 88.2|
| Decision tree | 89.3| 88.9| 89.1| 89.2| 89.3|

In order to further verify the robustness of the proposed method, the experiment further increases the number of repetitions, Table 2 gives the prediction accuracy under multiple different repetitions (10, 15, 20, 25, and 30). With the increasing number of experiment repetitions, the average prediction accuracy of various methods tends to be stable. From the results, the prediction accuracy of the method in this paper always maintains the highest level, reflecting its superior performance in mental health prediction.

4. Conclusion

In this paper, a method based on symptom self-rating scale and deep learning is proposed for the psychological state assessment in the mental health education of primary and secondary school students. First, the mental health parameters of the students are obtained through the symptom self-rating scale, and then, the feature vector is constructed. Taking the feature vector as input, train a deep learning model combining 1DCNN, ResNet, and LSTM. The trained model can judge the students’ mental state and health level according to the results of the self-rating symptom scale of students, so as to provide improvement strategies for the targeted development of mental health education for primary and secondary school students. In the experiment, the proposed method is tested with relevant data and compared with the existing mental health prediction algorithms, and the results reflected the effectiveness of the method.

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