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INTELLIGENT EVALUATION AND PREDICTION MODEL OF MENTAL HEALTH STATUS BASED ON DEEP LEARNING

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Abstract. In order to solve the problems of low efficiency and accuracy in traditional social psychological measurement techniques, the author proposes a deep learning based intelligent evaluation and prediction model for mental health status. The author combines multi parameter acquisition technology with deep learning algorithms and designs a psychological crisis testing algorithm based on a bipartite graph convolutional network model, using graph convolutional networks as the foundation. The algorithm is then embedded with a psychological testing instrument. The experimental results show that the accuracy of the BGCN undirected model is 88.52%, the accuracy is 86.21%, the recall is 66.56%, and the F1 value is 61.20%, all of which have performance advantages in model comparison. At the same time, with the increase of iteration times, the Loss change curve shows a stable downward trajectory, while the accuracy and F1 value curves show a large fluctuation amplitude in the early stage, a small fluctuation amplitude in the later stage, a fast decline speed in the early stage, and a stable trend in the later stage. This indicates that the model has the ability to conduct stable and accurate testing in the later stage of iteration. From the experimental results, it can be seen that this model can perform accurate psychological testing, which is conducive to the active development of social psychological testing.

Key words: Multiple parameters, Deep learning, GCN,BGCN, Psychological testing, Graph convolution

1. Introduction. Psychological health is an important component of health and also the foundation for the comprehensive development of individuals [1]. Scientific and efficient mental health assessment and intervention are prerequisites for effective psychological services [2]. However, traditional mental health assessments and interventions face significant challenges in terms of authenticity, effectiveness, and convenience when applied on a large scale [3].

With the rapid development of the current economy and society, people are constantly improving their quality of life while facing increasing pressure in their work, study, and life, which in turn has given rise to negative social phenomena and caused adverse social impacts [4]. At present, the application of mental health mainly revolves around physiological transaction detection and processing, including sign data detection and analysis, remote medical diagnosis services, real-time mobile ward monitoring, etc. However, there are relatively few applications in personal mental health testing, psychological counseling, and mental health message push [5]. The traditional methods of mental health assessment are mostly conducted through questionnaire surveys or face-to-face conversations, which have many shortcomings. At the same time, the accuracy of identifying individuals with psychological crises is seriously insufficient, and manpower is needed to supplement and distinguish the test results. Traditional methods of mental health assessment rely on the consultation and questionnaire surveys of doctors or psychological counselors. The diagnostic results generally depend on the experience of psychological researchers and the honesty of testers, and are easily affected by subjective differences, which may lead to misdiagnosis, missed diagnosis, inconsistent diagnosis before and after. In recent years, with the rapid development of artificial intelligence and big data technology, researchers have been able to more easily obtain richer multimodal data (such as speech data, text data, physiological data, etc.), and have also begun to try and use machine learning, deep learning and other methods in the field of artificial intelligence to characterize and model the relationship between these high-dimensional, unstructured, naturally generated data and their psychological state, achieve intelligent evaluation of psychological health status, and upgrade and replace psychological health intervention methods [6].

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2. Literature Review. Psychological state is not only a subjective feeling of an individual, but also an objective state that exists. Individuals with normal mental and psychological states and individuals with abnormal mental and psychological states have differences in their corresponding physiological parameters. By collecting physiological signals, these physiological differences can be detected and analyzed to determine whether an individual is in an abnormal state. Changes in mental and psychological states can cause changes in physiological signals, such as an accelerated heartbeat when a person is fearful. Physiological signals, due to their properties that are not easily concealed, can more objectively reflect the true mental state and psychological feelings. Monitoring changes in physiological signals has great practical significance in analyzing mental health problems. Therefore, identifying mental health problems based on physiological signals has gradually become a hot topic in the current field of mental health assessment research. Intelligent assisted diagnosis has been studied in various fields of mental health, classifying and diagnosing various psychological disorders, including anxiety, schizophrenia, depression, autism spectrum disorder, or attention deficit hyperactivity disorder. Lee, M. et al. analyzed the House Tree People Test (HTP), a widely used psychological test for drawing in clinical practice, which utilizes object detection techniques to extract more diverse information from images [7]. Zou, C. and others believe that the convenience of big data processing technology has played a huge advantage in many scenarios, and its deep learning can effectively mine different types of data in the dataset. Applying this method to the mining of psychological prediction datasets for legal misconduct can effectively prevent the occurrence of illegal behavior. Effective analysis of their psychological characteristics and emotional changes may pose hidden dangers, therefore it is necessary to extract such data in such situations [8]. Meng, Q. and others applied neural network algorithms of Bi LSTM and CNN models to study text data, and ultimately achieved high accuracy in psychological analysis experiments, providing a feasible solution for batch rapid analysis of psychological changes reflected in daily texts of basketball players [9].

Therefore, computer technology can be used to design a psychological testing instrument for individuals with sub healthy status in the social center. The graph convolutional model itself has high generalization ability and is more accurate in identifying and classifying information feature patterns. It can accurately classify structural information in model nodes and is very suitable for application in the field of psychological testing. Starting from this perspective, the research aims to design a psychological testing instrument based on multi parameter acquisition and bipartite graph convolutional neural network (BGCN), providing a practical approach for intelligent psychological testing.

3. Method.

3.1. Psychological testing method based on GCN algorithm. The author first uses Graph Convolutional Network (GCN) to represent the vectors of subjects by transmitting information similar to those between subjects, and based on this, identifies the psychological status of the subjects [10]. Unlike traditional machine learning models, the construction of GCN is based on graph structured data, so it requires an appropriate graph structure; At the same time, GCN also requires data features from traditional machine learning, therefore, it should consider the generation of node features in the graph structure. The psychological state testing framework based on GCN includes four parts: data layer, preprocessing layer, model construction layer, and prediction layer, as shown in Figure 3.1.

In Figure 3.1, the data layer collects data and parameters for psychological testing from different data sources, including evaluations of the psychological status of the subjects and records of psychological disorders; The preprocessing layer preprocesses the collected data, extracts the characteristics of the subjects from the processed data, and constructs a psychological similarity map of the subjects based on their psychological states. The characteristics of the subjects and the psychological similarity map of the subjects serve as the basis for constructing the GCN model; The model construction layer constructs a GCN model using training samples based on preprocessed subject characteristics and subject psychological similarity maps; The prediction layer uses the trained GCN model to identify and predict participants in psychological tests [11].

Regarding the relationship between subjects, the author constructs a psychological similarity map based on their psychological state. Set the psychological similarity between subject a and subject b to $S_{a,b}$, and set the threshold to ω. If the value of $S_{a,b}$ exceeds the threshold ω, it is considered that the psychological states of the two subjects are similar. Therefore, a relationship line is added between the two subjects. The author uses cosine similarity as the criterion for judging the psychological similarity and interval of the subjects. If the

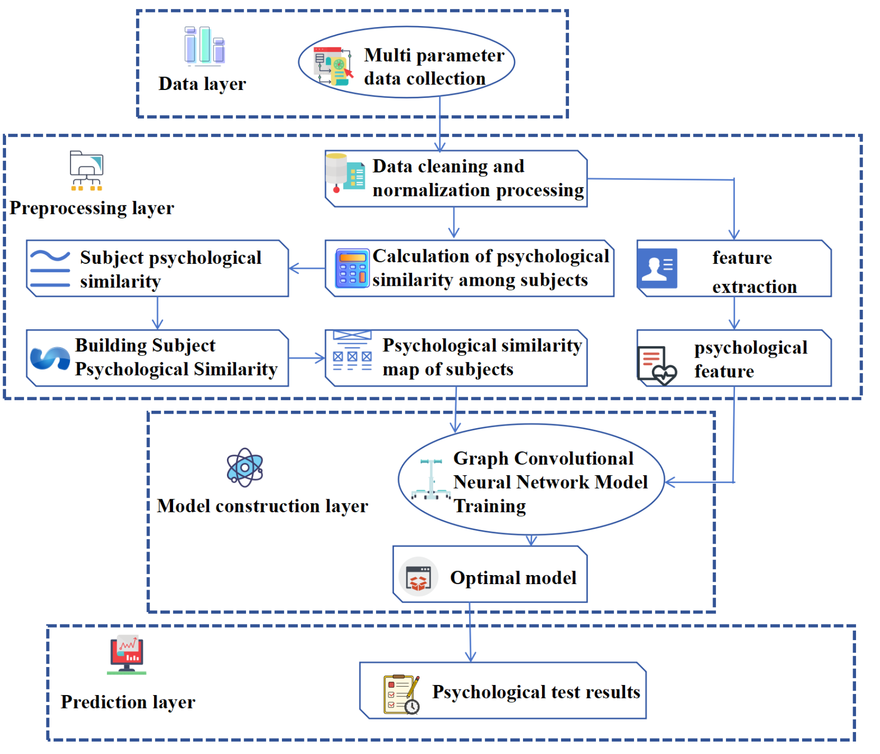

Fig. 3.1: GCN based psychological state testing framework

cosine value of two vectors is 0, it is considered that the two vectors intersect; When the cosine value of two vectors is greater than 0, it is considered that they are somewhat similar. The psychological similarity graph of the subjects is a symmetric undirected graph, which is an image where the edges between two points do not have their own directional definitions and need to be defined through cyclic variables [12]. The construction process is as follows: first, clean the collected psychological state data of the subjects to ensure the credibility and effectiveness of the data, and then use the Z-score normalization method to normalize the cleaned data, as shown in equation 3.1.

$$x' = \frac{x - \overline{x}}{\sigma} \tag{3.1}$$

In equation 3.1, x is the original data; x' is the result of normalization and follows a standard normal distribution; $\overline{x}$ is the average value of the original data; σ represents the standard deviation of the original data. After normalization, the psychological feature matrix of the subjects is obtained, and the cosine similarity between the sample data is calculated as shown in equation 3.2.

$$S_{a,b} \frac{X_a \cdot X_b}{||X_a|| \cdot ||X_b||} \tag{3.2}$$

In equation 3.2, $S_{a,b}$ represents the psychological similarity between subject a and subject b; X is the psychological characteristic matrix; X_a and X_b are the representation vectors of subject nodes S_a and S_b, respectively. When the psychological similarity between two nodes exceeds the threshold ω, it is considered that there is a certain degree of similarity between the two, and a psychological similarity graph T (S, U) is obtained. The elements in the i-th row and j-th column of its adjacency matrix M are calculated as shown in

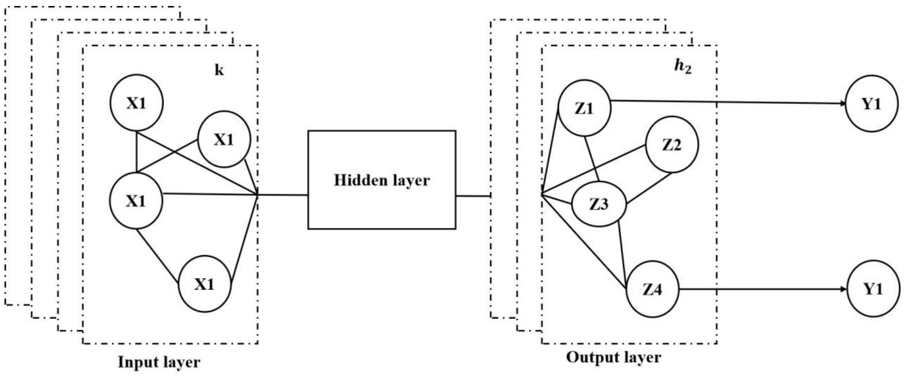

Fig. 3.2: Schematic diagram of model structure

equation 3.3.

$$M_{i,j} = \begin{cases} S_{a,b}, S_{a,b} > \omega \\ 0, S_{a,b} \leqslant \omega \end{cases} \tag{3.3}$$

The GCN model is abstractly represented as f (X, M), and its antecedent propagation is shown in equation 3.4.

$$G^{l+1} = \delta(\tilde{C}\tilde{C}^{-\frac{1}{2}}\tilde{M}\tilde{C}^{-\frac{1}{2}}G^l W^l) \tag{3.4}$$

In equation 3.4, H^l is the hidden feature matrix of the th layer; W^l is the weight matrix of the th layer neural network; δ is the activation function; $\tilde{M} = M + I_N$ is the new adjacency matrix, I_N is the N-dimensional identity matrix, and N is the number of subjects. The schematic diagram of the model structure is shown in Figure 3.2.

In Figure 3.2, k represents the dimension of the input feature vector X_i; h_2 represents the hidden feature vector Z_i dimension of the final output, and the result Y_i is obtained through Softmax classification. By calculating matrix $M = \tilde{C}^{-\frac{1}{2}}M\hat{C}^{-\frac{1}{2}}$ in advance, the forward propagation formula of the two-layer graph convolution model can be obtained as shown in equation 3.5.

$$f(X, M) = softmax(MReLU(MXW^{(0)})W^{(1)}) \tag{3.5}$$

The author chooses the ReLU function as the activation function, and its formula is shown in equation 3.6.

$$ReLU(x) = \begin{cases} 0, x \leqslant 0 \\ x, x > 0 \end{cases} \tag{3.6}$$

3.2. Design of a psychological testing instrument based on multi parameter acquisition and BGCN . In order to improve the testing accuracy and generalization of the model, the author set the tested individuals and testing metrics as two types of nodes in the convolutional network, with pairwise connections between the nodes forming a bipartite graph. A psychological testing method based on BGCN was designed. The two types of nodes have different properties, but they can be connected to each other, thereby reducing the coupling between nodes and ultimately improving the generalization and accuracy of the model. The architecture of BGCN based psychological testing method is similar to GCN, with the main difference being the construction of graphs and the training and testing of models. Assuming the set of indicators for psychological testing is P, the set of nodes for the subjects is R, and the set of edges in the bipartite graph formed by connecting the two is O, with the corresponding set of edge weights being W [13,14]. From this, the bipartite graph $T'(P, R, O, W)$ can be obtained as shown in Figure 3.3.

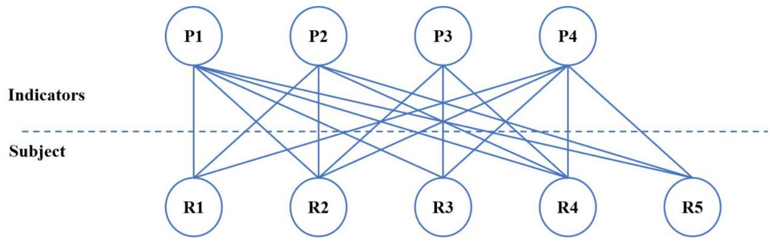

Fig. 3.3: Bipartite diagram

In Figure 3.3, subject node R_i and indicator node P_j are connected to each other, and the value of edge weight W is set based on the test indicator. Convert the judgment results obtained based on psychological testing indicators into numerical values. If there are n indicators that meet the degree of conformity, use the integer of the interval $[0, n-1]$ to represent the psychological status of the subjects based on the degree of conformity of the indicators. In practical situations, the subject bipartite chart cannot directly incorporate the transformed weight matrix, so it is necessary to standardize the weights of each indicator uniformly. There are two ways for the author to construct a bipartite graph. For an undirected graph $T_u(P, R, O, W)$, the edge weight set W directly corresponds to the values in the standardized weight matrix M; For directed graph $T_d(P, R, O, W)$, the edge weights of node R pointing to node P are set to equal values, and the edge weights of node P pointing to node R are set to the processed weight matrix M'. Assuming that the hidden features of the subject nodes are influenced by the indicator nodes, the degree of influence depends on the indicator matrix M of the subject nodes. When the influence of two types of nodes on each other is the same, an undirected graph is used. When the influence of each subject node on the indicator node is the same, a directed graph is used [15].

Assuming the indicator feature matrix is Q, $Q = I_D, I_D$ represents the D-dimensio- nal identity matrix; The subject feature matrix is E, which is a zero matrix of D and N, and the model feature matrix are horizontally connected; The bipartite graph convolutional neural network is represented as . The forward propagation formula for defining convolutional layers in bipartite graphs is shown in equation 3.7

$$\begin{cases} Q_k^{(l+1)} = \delta(\sum_{n \notin N_k} \alpha_{nk} E_n^{(l)} W^{(l)}) \\ E_n^{(l+1)} = \delta(\sum_{k \notin N_k} \alpha_{Kn} Q_k^{(l)} W^{(l)}) \\ X^{(l+1)=[Q^{(l+1)}||E^{(l+1)}]} \end{cases} \tag{3.7}$$

In equation 3.7, $Q^{(l)}$ represents the hidden feature of the l-layer indicator node; $E^{(l)}$ is the hidden feature of the -layer subject node; $a_{i,j}$ is the degree to which node j is affected by node i; $X^{(1)}$ is the hidden feature of layer l; $W^{(1)}$ is the neural network weight of the B-layer graph convolutional layer; N_i is the set of adjacent nodes i of a node. Unlike traditional convolutional neural networks, bipartite graph convolution requires two convolutions to transmit the information of the subject node back to that node. Therefore, the number of convolutions required to achieve node representation in this graph convolution method must be even. The two-layer graph convolution process is shown in Figure 3.4.

In Figure 3.4, on the l-th layer of graph convolution, the subject node first transmits feature information to the indicator node; On the l+1 layer graph convolution, the indicator node transmits feature information to the subject node. When training a model, if there are more parameters and fewer training samples, the model is prone to overfitting. In response to this phenomenon, the author added a Dropout layer after convolution of each layer of the graph. The Dropout layer improves model performance by preventing information transmission between hidden layer neuron nodes, and its information cannot be transmitted to the next layer. Then use the Softmax function to convert it into the classification probability of the subject, and use the negative logarithmic likelihood function as the loss function of the model. A psychological testing system based on multi parameter collection and deep learning should pay attention to the diverse needs of different subjects, as well as the common experience of the majority of subjects in their usage habits. Based on this principle, relevant techniques should

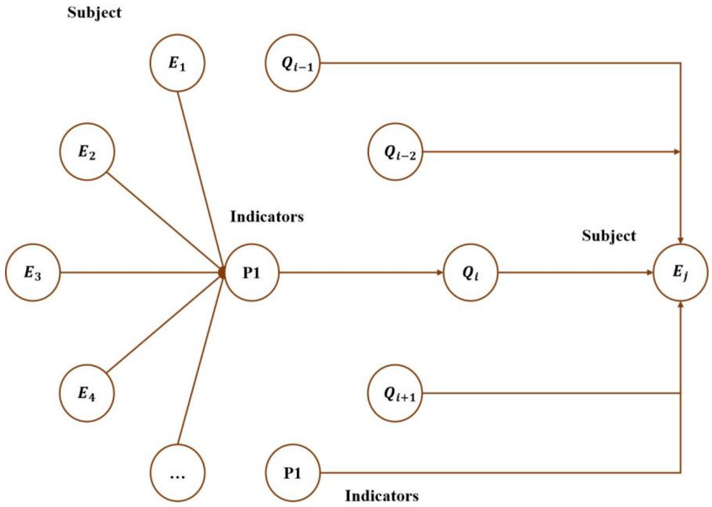

Fig. 3.4: Two layer graph convolution process

be used to set up the program layout. The author chose Myeclipse6.0 as the integrated development environment, MYSQL database, and J2EE as the network service environment. The actual operation of a psychological tester includes three parts: multi parameter collection, system analysis, and providing test results [16,18].

4. Results and Discussion. The author proposes a psychological crisis testing algorithm based on a bipartite graph convolutional network model, and designs a chimeric application combined with a psychological tester. In the process of performance analysis, the author selected an experimental sample set containing 260 positive samples and 1000 negative samples. 20% of the selected samples were used as the test set, and the remaining 80% were used as the training set. At the same time, the model sets the dropout probability to 0.5, the number of hidden features to 80 and 30, and the learning rate to 1c-2. The training process of the model first requires parameter initialization, setting initial parameters for each layer of BGCN. Existing initialization methods, such as Xavier initialization, can be used. Then conduct model training, calculate the predicted values through forward propagation, and use appropriate loss functions (such as cross entropy loss) to measure the difference between the predicted values and the true values. On this basis, a gradient descent optimizer is used to update the model parameters to minimize the loss function [19]. The author mainly uses the method of effect comparison for analysis. The author selects four main indicators: Accuracy, precision, recall, and F1 value, and analyzes them from three dimensions: composition threshold, number of training rounds, and horizontal comparison of model performance. The parameter dimension analysis is shown in Figure 4.1.

From Figure 4.1, it can be seen that in terms of accuracy, when the composition thresholds are 0, 0.1, and 0.2, the accuracy of the model is 88.52%, 84.27%, and 82.14%, respectively. It can be seen that as the composition threshold increases, the accuracy of the model gradually decreases; In terms of accuracy, when the composition thresholds are 0, 0.1, and 0.2, the accuracy of the model is 86.21%, 82.34%, and 80.96%, respectively. It can be seen that as the composition threshold increases, the accuracy of the model also decreases continuously; In terms of recall, when the composition thresholds are 0, 0.1, and 0.2, the accuracy of the model is 55.25%, 62.48%, and 58.52%, respectively. It can be seen that there is a peak change in recall, with an increase in recall in the early stage and a decrease in recall in the later stage. The optimal value point is located at the composition threshold of 0.1; On the F1 value, when the composition thresholds are 0, 0.1, and 0.2, the F1 values of the model are 0.6679, 0.6335, and 0.6123, respectively. It can be seen that as the composition threshold increases, the F1 value of the model continuously decreases. Overall, an increase in composition threshold will lead to a decrease in model performance [20].

In practical psychological testing applications, it is normal to form a testing period, and the stability of the model after the testing period is very important. Therefore, the model designed by the author is very suitable

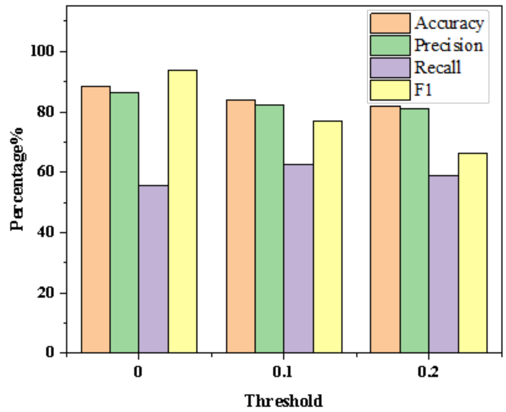

Fig. 4.1: Parameter dimension analysis

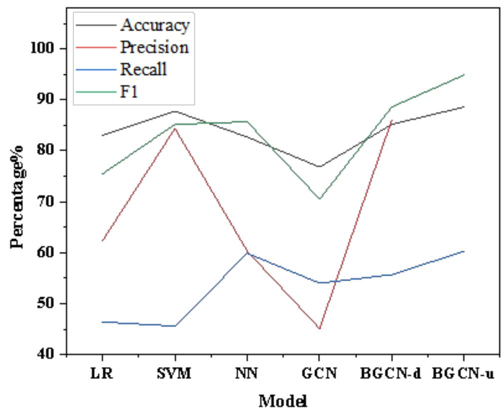

Fig. 4.2: Model Comparison Analysis

for application in psychological testing. The comparative analysis of the models is shown in Figure 4.2.

From Figure 4.2, it can be seen that in terms of accuracy, the BGCN undirected model designed by the author has an accuracy of 88.52%, the BGCN directed model has an accuracy of 85.18%, and the GCN model has an accuracy of 76.21%. The model designed by the author has the highest accuracy, meanwhile, compared with traditional machine learning algorithms of the same type, the model designed by the author also has a significant accuracy advantage; In terms of accuracy, the BGCN undirected model designed by the author has an accuracy of 86.21%, the BGCN directed model has an accuracy of 65.10%, and the GCN model has an accuracy of 44.46%. Compared with traditional machine learning algorithms of the same type, the model designed by the author also has the highest accuracy; In terms of recall, the BGCN undirected model designed by the author has a recall rate of 66.56%, the BGCN directed model has a recall rate of 54.72%, and the GCN model has a recall rate of 54.61%. At the same time, compared with traditional machine learning algorithms of the same type, the designed model has the highest recall rate; In terms of F1 value, the BGCN undirected model designed by the author has an F1 value of 61.20%, the BGCN directed model has an F1 value of 55.14%,

Table 4.1: Comparative Analysis Results

Data samples	The output value of the author's method	Expert evaluation value	Operation time/s	Assessment Level
1	9.57	9.7	1.82	good
2	6.46	6.4	1.64	preferably
3	4.56	4.6	1.67	commonly
4	7.45	7.4	1.51	good
5	5.82	5.8	1.58	preferably
6	2.36	2.3	1.44	difference
7	9.16	9.2	1.70	good
8	8.05	8.0	1.88	good
9	4.36	4.3	1.73	commonly
10	9.62	9.5	2.07	good
11	5.68	5.6	1.81	preferably
12	1.03	1.0	1.87	difference
13	7.55	7.6	1.64	good
14	8.56	8.6	1.77	good
15	8.24	8.2	1.40	good

and the GCN model has an F1 value of 53.71 %, the F1 value of the model designed for comparison with traditional machine learning algorithms of the same type is also the highest. From this, it can be seen that the performance of the model designed by the author is superior in terms of accuracy, precision, recall, and F1 value. When applied in psychological testers, more accurate psychological test results can be obtained, which helps to achieve intelligent psychological state detection.

The comparative analysis of the evaluation results obtained by this method and the expert evaluation results is shown in Table 4.1. According to Table 4.1, it can be seen that the difference between the psychological health evaluation values of college students output by this method and the expert evaluation values is very small, which can effectively obtain the psychological health evaluation results of college students and has a fast calculation speed.

5. Conclusion. The author proposes a research on an intelligent evaluation and prediction model for mental health status based on deep learning. Nowadays, the number of mental illness patients is increasing day by day, and mental health has become an important issue in current social research. The author designed a psychological crisis testing algorithm for a bipartite graph convolutional network model, which is attributed to graph convolutional technology and multi parameter acquisition technology, to address the relatively low accuracy and efficiency of traditional psychological measurement techniques at the social level. The algorithm optimized the model from two aspects: accuracy and generalization. The research results show that when the composition thresholds are 0, 0.1, and 0.2, the model accuracy, precision, recall, and F1 value all show a gradually decreasing trend with the increase of the composition threshold. As the number of iterations increases, the Loss value variation curve of the model designed by the author shows a relatively stable downward trend, while the accuracy and F1 value variation curve shows a relatively fast upward trend in the early stage. At the same time, the fluctuation range is large in the upward range, indicating that most of the erroneous cases occur in this range. In the later stage, the overall change trajectory tends to be stable, and the fluctuation is significantly reduced, indicating that the model can conduct high accuracy testing with stability at this time. In addition, in algorithm comparison, the BGCN undirected model designed by the author has an accuracy rate of 88.63%, an accuracy rate of 86.31%, a recall rate of 66.67%, and an F1 value of 61.30%, which is the highest performance in both improved models of the same type and traditional models. It can be seen from this that the model designed by the author has superior performance and can be used for more reliable and accurate psychological testing.

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