[1,2]Ruirui Su

[3]Aiyi Liu

[2,4]Ling Guo

[3*] Xinchun Wu

Research on Automatic Identification and Real-Time Monitoring Technology of Mental Health Status Based on Multilevel Neural Network

Journal of Electrical Systems

Abstract: - In this paper, the densely connected DenseNet is used as a feature extraction network to solve the problem of overfitting due to the increase of network parameters and small data samples, and the classifier uses Softmax for facial expression classification and localization. Aiming at the problem of lack of maximum attenuation in automatic identification, Soft-NMS algorithm is used instead of the traditional NMS algorithm to improve the detection accuracy. Design of remote mental health monitoring system based on B/S structure, including the analysis of the hardware structure of the Web server, sound signal module, power supply module, and other analysis, as well as personality traits, personalized testing, data transmission and so on. Software development psychology teachers, design evaluation results analysis, permission management and other modules. Through the above series of measures, the user's mental health can be effectively, accurately and safely remotely monitored and evaluated. The results show that the Soft-NM algorithm in this paper has a recognition rate of 90.14% in recognizing mental health conditions. When monitoring from 10 to 100 times, the accuracy of the system remains above 94%, up to 97% with little fluctuation. Moreover, the system in this paper takes less than 5.8s to run, which verifies the effectiveness and stability of multilevel neural networks in practical applications.

Keywords: feature extraction; automatic identification; mental health monitoring; B/S structure; multilevel neural network

1. INTRODUCTION

At the present stage, the pace of life is accelerating, social competition is becoming more and more intense, and people are paying more attention to education, life, emotions, and work [1-3]. Therefore, it is particularly important to develop an effective and accurate system for identifying and monitoring mental health status. Although psychological tests are widely used as standardized assessment tools in mental health surveys and individual assessments, the results obtained are not significant and many psychological problems remain undetected at an early stage [4]. There are many reasons for this result, such as failure to provide true and reliable information, poor validity and reliability of the test, complexity of the psychological problems themselves, and ineffective utilization of the information inherent in the test. An important reason [5-7].

In order to effectively utilize test data to improve the recognition rate of psychological problems, it is necessary to create a more scientific model for mental health status recognition. This study describes the structural features

[1] Faculty of Education, Beijing Normal University, Beijing 100875, China.

[2]Student Affairs Department, Beijing Institute of Technology, Beijing 100081, China.

[3*] Beijing Key Laboratory of Applied Experimental Psychology, National Demonstration Center for Experimental Psychology Education, Faculty of Psychology, Beijing Normal University, Beijing 100875, China.Email:xcwu@bnu.edu.cn

[4]Psychological Consultation Center, Zhengzhou No. 69 Middle School, Zheng zhou of Henan Province, 450007, China.

and parameters of the DenseNet network and the advantages of its application in mental health status recognition. A remote mental health monitoring system based on personality analysis is designed. Using B/S structure, the system design is divided into three parts: client, application, and database. After the client user logs in, personality analysis is performed by determining the dimensions and weights of personality traits. Module and personalized test module, using a variety of scales to check the user's mental health, and the user's personality traits and test results are converted into digital form and uploaded to the Internet. Psychology teachers use a unified model to calculate test result data and display it on a monitor. If there is any important information, an alarm is signaled, thus completing the remote monitoring of the user's mental health status. This method appears to be more scientific, simple and effective, in addition to increasing the accuracy of the mathematical model.

2. RELATED WORKS

Timely understanding of and intervention in people's mental health status is critical to providing effective support and assistance. Online intelligent testing systems can provide people with the opportunity to assess and measure their mental state autonomously through a flexible and convenient approach. Literature [8] reviews the history and current state of mental health in schools, emphasizing its central role in the care of children and adolescents. By analyzing scientific data and the evolution of policy practices, the review reveals the importance of collaboration between education and mental health systems, suggesting that a multilayered system of mental health support enhances academic and psychosocial functioning and reduces the risk of adverse outcomes. Literature [9] points to a surge in student mental health needs as the new crown epidemic pushes universities to shift to distance learning. Digital phenotyping, which utilizes smartphones to monitor symptoms, has become a new tool for universities to assess mental health. A review of 25 studies found that the method assesses sleep, exercise, and social interactions by collecting data on location, movement, and social interaction to aid in personalized care. The studies, though diverse, show the potential of data in mental health care. As research is harmonized and samples are expanded, university mental health centers may integrate it into clinical practice to improve service outcomes. Literature [10] suggests that faculty play a significant role in improving student retention and graduation rates, especially in mental health. The study found that faculty actively intervened to support student mental health by identifying issues and recommending resources. Teachers' experiences enriched the existing literature by identifying five key themes of teachers' role in promoting mental health among college students. Literature [11] identified student mental health as a concern in higher education, with the new crown epidemic exacerbating challenges. Students need to adapt to virtual learning, social distance and cope with economic uncertainty. This study examines the additional impacts and solutions of the new crown on the mental health of university students, discussing the impacts and strategies. Literature [12] uses a mental health monitoring model based on IoT and machine learning technologies that can accurately monitor students' physiological and behavioral changes. Literature [13] suggests that mental health has a significant impact on cardiovascular health, either promoting or hindering it. Available data support a clear association between mental health and CVD and its risk, and that interventions to improve mental health are beneficial to cardiovascular health. Health care providers should emphasize and screen patients for mental health status to more comprehensively assess and manage CVD and its risks. Literature [14] suggests that social actors who perceive multicultural decision-making processes to be fair may promote social identity, and thus mental health and well-being, among members of ethnic minorities. The study verified the positive effect of procedural fairness climate on increasing social identity through vignettes and self-report questionnaires and emphasized the importance of using procedural fairness to enhance the well-being of ethnic minorities. Literature [15] explored the impact of health-centered leadership style on employees' psychological well-being in the Malaysian context and revealed for the first time the mediating role of psychosocial safety climate in this context. Through PLS-SEM analysis, it was found that healthy leadership style positively promotes psychosocial safety climate, while safety climate is negatively related to psychological well-being. This suggests that healthy leadership style indirectly promotes employees' psychological well-being by creating a safe climate. Not only does it provide a new perspective for the field of leadership and health psychology, but it also fills the research gap on the mediating role of leadership effectiveness and psychosocial safety climate in cultural contexts. Literature [16] found that the American College of Sports Medicine released a best practices document to help sports medicine teams comprehensively care for athletes' mental health. The document focuses on the psychological factors, injury response, and the impact of the sports environment on the psyche of athletes, covering a wide range of disorders such as eating disorders, depression, anxiety, etc., with an emphasis on detection, management, impact, and prevention, using the SORT method of grading evidence.

Therefore, how to use mathematical tools to correctly and effectively utilize the information provided by the test to improve the identification of psychological problems in individual psychological assessments is an important issue facing the protection and promotion of mental health [17-19].

3. APPLICATION OF MULTILEVEL NEURAL NETWORKS

3.1 Model structure

Deeper semantic information can be extracted using deeper feature extraction networks, but as the network gets deeper, the parameters increase, which creates many difficulties in network optimization and experimental equipment [20-21]. In mental health recognition and monitoring, the number of samples in a separately generated dataset is small and training the network can easily lead to overfitting. Using DenseNet densely connected network as a feature extraction network can solve the above problems [22].

DenseNet borrows the concept of ResNet. Unlike the ResNet network, it is a completely new network architecture. The most intuitive difference between these two network architectures is the different transfer functions of each network module:

$$x_l = H_l\left(x_{l-1}\right) + x_{l-1} \tag{1}$$

$$x_l = H_l\left(\left[x_0, x_1, \cdots x_{l-1}\right]\right) \tag{2}$$

Equation (2) is the transfer function of the ResNet network, where the output of the first layer of the network is the output of the layer whose output has a nonlinear transformation. In DenseNet, the output of the first layer of the network module is the set of nonlinear transformations of the outputs of all the previous layers, and Figure 1 shows a multilayer network neural network model. The convolutions in each DenseBlock are connected, H meaning that BatchNorm and ReLU are used for each input and a k-dimensional 3 × 3 convolutional kernel is used to ensure that each node produces the same feature map, and k shows the thickness of the feature maps output by each convolutional layer. Comparisons with the thickness of the output feature maps of other networks can be in the hundreds or even thousands. The total thickness of DenseNet is only 32.

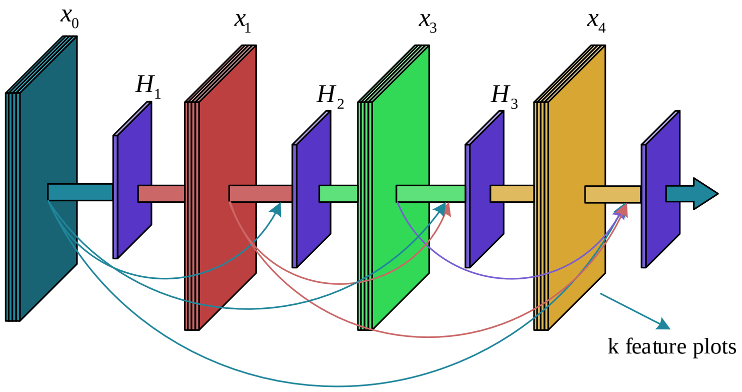

Figure 1 Multi-level neural network model

Because the dense connection of each module in the network can effectively utilize shallow and deep features, it can make the network efficient and narrow, and drastically reduce the network complexity and computation, the node parameters are shown in Figure 2. A four-layer DenseBlock 121 network is used as the feature extraction network, removing the fully connected layer and the classification layer, and combining the RPN and RoI pooling layers for full target identification and localization.

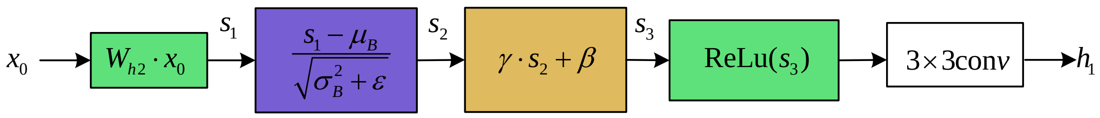

Figure 2 Node parameters

Table 1 shows the parameters of the DenseNet structure, where the network starts with a 7 × 7 convolutional layer and a 3 × 3 maximal pooling layer, followed by four dense blocks. The interior of each block consists of a number of 1 × 1 and 3 × 3 convolutional layers, the number of which is gradually increased by 6, 12, 24, and 16. Each dense block, except the last one, is followed by a pooling layer containing a 1 × 1 convolutional layer, which serves as a transition layer, and a 2 × 2 dielectric pooling layer, which is used to reduce the size of the dense blocks and the number of channels. The feature map so that the next dense block can be processed, and this design allows DenseNet to effectively utilize feature reuse to improve learning efficiency and network performance.

Table 1 DenseNet structural parameters

Structures	**Parameters**
Convolution Layer	7×7 conv, stride 2
Pooling Layer	3×3 max pool, stride 2

Dense block(1)	[1×1conv3×3conv] ×6
Connection Layer 1	[1×1conv]
	2×2 average pool, stride 2[1×1conv]
Dense block(2)	[1×1 conv3×3conv]×12
Connection Layer 2	[1×1conv]
	2×2 average pool, stride 2
Dense block(3)	[1×1 conv3×3conv]×24
Connection Layer 4	[1×1conv]
	2×2 average pool, stride 2
Dense block(4)	[×1conv3×3conv]×16

3.2 Non-extreme value suppression

NMS non-maximum fading is an important part of the detection process in practical applications of multilevel neural networks.FasterRCNN generates a set of detector frames $B=\{b_1,b_2,\cdots b_N\}$ and a corresponding set of detector frames S_i in an image.The NMS algorithm selects the detector frames prior to the maximum score and calculates the overlap with the remaining detector frames M in the set larger than this set IoU. The detector frames are suppressed if a threshold value of N_t is set. The formula for the NMS algorithm:

$$S_i=\begin{cases} S_i IoU\left(M,b_i\right)\prec N_t \\ 0 IoU\left(M,b_i\right)\geq N_t \end{cases} \tag{3}$$

Where the expression for IoU is: where the expression for 1 is:

$$IoU=\left(A\cap B\right)/\left(A\cup B\right) \tag{4}$$

Where A, B are two overlapping detection frames, the NMS algorithm will reset the detection frame that is adjacent to the detection frame and greater than a threshold. If the detected target appears in the overlapping region, the NMS algorithm will result in target detection failure and reduce the effectiveness of the detection model.

To solve this problem, Soft-NMS algorithm is applied to replace the traditional NMS algorithm. In this algorithm, the neighboring detection frames set the inhibition function according to the size of the overlap instead of setting their score to zero, which ensures the accurate recognition of neighboring targets.The Soft-NMS operational expression is:

$$S_i=\begin{cases} S_i IoU\left(M,b_i\right)\prec N_t \\ S_i\left(1-IoU\left(M,b_i\right)\right) IoU\left(M,b_i\right)\geq N_t \end{cases} \tag{5}$$

In this paper, we improve the front-end feature extraction network and end-end regressor of FasterRCNN detection algorithm, which is used to accomplish the facial expression detection in real environment, and the algorithm flow is shown as follows:

(1) A suitable image A is input and the image size is adjusted, and the output is a figure B of the specified size M × N.

(2) B is used as input to the feature extraction module, and a multilevel fusion feature map C is obtained by DenseNet.

(3) C serves as the input to the region proposal and 300 inputs are obtained using the sliding window method D. RPN uses border regression to change the generated users closer to the labeled frames.

(4) The mapping between suggested frames and feature maps E is obtained by using C & D as inputs for the sensed regions.

(5) Output E into two branches, classifier and regressor respectively, the classifier uses Softmax to classify and identify E and the regressor uses border regression Soft-NMS to further correct the border and finally classify the target and localize it.

4. MENTAL HEALTH STATUS IDENTIFICATION AND MONITORING REALIZATION

4.1 B/S structure

The B/S structure is a new platform model with a three-tier structure created based on network technology, and Figure 3 shows the architecture of the remote monitoring system for mental health conditions. The main server is broken down into a data server and multiple web servers, resulting in a three-tier structure of clients, applications and databases.

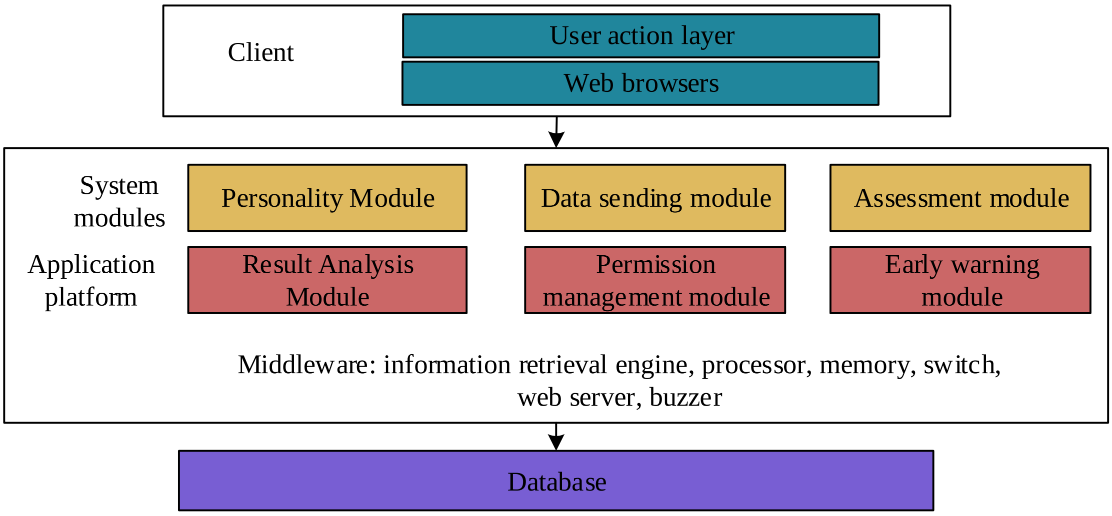

Figure 3 Architecture of the remote monitoring system for mental health status

According to the system architecture, the hardware platform of the health remote monitoring system is designed, including the data collector, Web server, monitor, buzzer alarm module, power supply module and control center. The system hardware structure is shown in Fig. 4, with the Web server, sound signal module and power supply module in the system hardware structure. As follows:

(1) The Web server used in this system adopts the latest SunFireT1000 server, which belongs to the octa-core 32-thread processor for computer networks and database systems, and is able to realize the functions of the whole server on a single chip. It can also support a variety of software to run directly, with certain advantages.

(2) In order to discover the user's psychological condition in time, the buzzer alarm module is designed to be composed of a buzzer and an alarm indicator, etc. [23]. Using microcontroller output electric power to drive the alarm indicator, using the power driver tube to drive the buzzer, and the microcontroller electric power level to determine whether the buzzer alarm sound. If there is important information is given timely reminder, so that the user can get timely psychological counseling.

(3) The designed mental health remote monitoring system uses different power supply circuits such as 5V, analog 3V, etc., and realizes the power supply design with the help of low voltage boost DC/DC converter. The chips used in the power supply module all use DC/DC converters to increase the supplyable voltage, and to prevent damage to the chip due to current influx, the chip operates in current mode pulse width modulation mode.

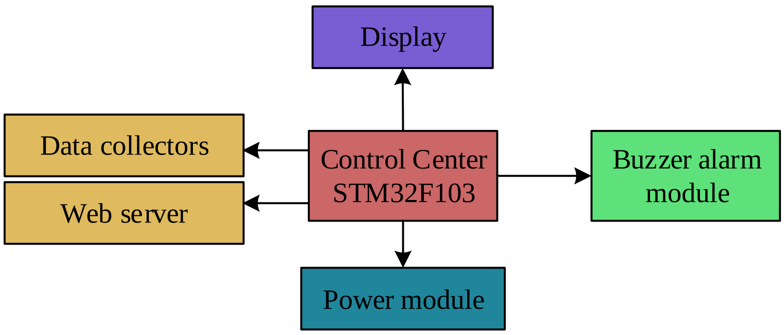

Figure 4 System hardware structure

4.2 System software design

The mental health status remote monitoring software designed in this paper is developed using MSP430F149 system, which mainly includes personality trait module, personality test module, data sending module, psychological teacher assessment results analysis module, and permission management module.

4.2.1 Personality Profile Module

Personality traits are important factors affecting the mental health status, therefore, in this paper, the personality traits module is added to the design of the monitoring system to analyze. The personality traits module consists of the user's personality traits dimensions and the values of different dimensions together. Mental health monitoring and user personality traits are categorized into five types: pleasantness, cautiousness, joyfulness, emotionality, and independence. Each personality trait dimension is used to represent the different personalities of that user, so as to analyze the impact of personality traits on mental health status [24-26].

Different values are assigned to the personality trait dimensions with the value unit set to [0, 1]. Each number represents the behavioral pattern of different individuals. Different values represent different degrees of influence of personality traits on mental health in order to better understand the influence of personality traits on mental health and to calculate the weights of individual dimensions of personality traits. The method of testing parameter significance in multiple linear regression analysis was used to test the data on the dimensions of personality traits by F . The magnitude of the F value determines the degree of influence. The weights were calculated using the following formula:

$$Q = \frac{F_i}{\sum_{i=1}^{5} F_i} \tag{6}$$

Where, Q describes the weight values, F_i describes the personality trait observations, and i describes the personality trait categories, which in total are categorized in this paper into 5 categories: pleasantness, cautiousness, joyfulness, emotionality, and independence.

4.2.2 Personalized Test Module

After registering and logging into the system, the user selects mental health-related content for testing in the scale testing interface, including anxiety self-assessment scale, depression self-assessment scale, thinking ability test and learning anxiety assessment. After the test, the data will be imported and saved in the database.

4.2.3 Data transmission module

After the client user assessment is finished, it will show whether the data needs to be uploaded or stored, display the assessment data information in digital form, compress the data that needs to be stored and upload it to the network, and complete the data sending.

4.2.4 Module for analyzing the results of the psychological teacher assessment

Reasonable design of the psychological teacher role to analyze the assessment results. When the psychological teacher logs into the system, selects the client user number, synthesizes the user scale assessment results and the user's personality trait dimension, and uses the unit model to calculate the test results. After the calculation is completed, the display is used to show the changes in the user's assessment and view the user’s mental health status.

4.2.5 Rights management module

According to the security rules designed by the system, the permissions of test users, psychology teachers and system administrators are set, and the different users are managed transparently. The administrator can maintain and manage user rights, user parameters, test contents, etc.

When logging into the system during system operation, both user name and password must be successfully recognized to log into the system. If there are more than 3 consecutive incorrect operations, the user will not be able to log in to the system and restart the system within 0.5 hours. Based on the analysis of the above monitoring software modules, Figure 5 shows the process of remote monitoring of mental health status. Through the steps of user registration and login, personality trait assignment, scale assessment, data transmission, data deletion, and unit model calculation, the remote monitoring and assessment of users' mental health status is realized. The whole process is well-designed and clear, which can effectively protect the user's privacy and data security, and at the same time provide the user with accurate mental health assessment results.

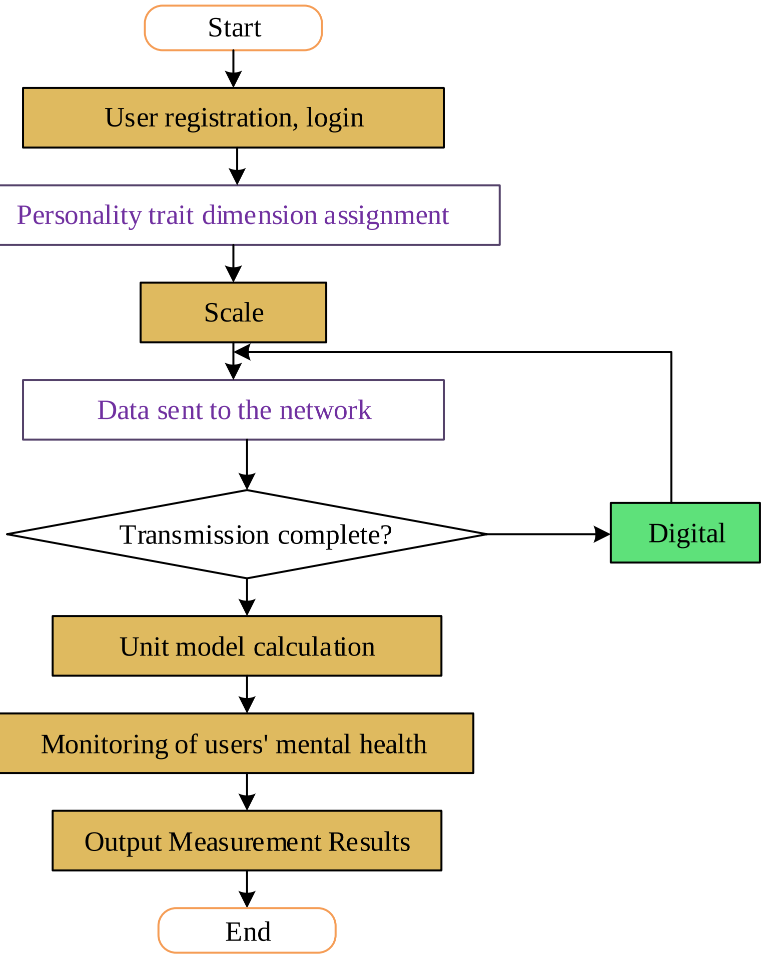

Figure 5 Process of remote monitoring of mental health status

5. MULTI-LEVEL NETWORK AUTOMATIC IDENTIFICATION AND REAL-TIME MONITORING EFFECT

5.1 Recognition accuracy

The JAFFE database was utilized to validate the previous algorithm using the method of cross validation. The relevant data were randomly divided into five parts, one for subsequent testing and all the rest for sample training. ResNet and DenseNet were used to represent the feature extraction networks to implement the training, respectively, and the maximum value of each method was used to implement the operation to facilitate data processing. Table 2 shows the mental health status recognition rate, and ResNet demonstrates good performance with its modest feature bit number of 2478 and high recognition rate of 87.79%. This is due to the fact that ResNet's residual connectivity mechanism helps to alleviate the problem of gradient vanishing or gradient explosion in the deep network, which improves the training efficiency and generalization ability of the model.DenseNet's recognition rate is lower than ResNet's 79.81%, although it has more feature bits 7980.DenseNet+SoftNMS, with a relatively small number of feature bits 1180 achieved the highest recognition rate of 90.14%. This indicates that the introduction of SoftNMS produces a significant improvement in the performance of DenseNet, and SoftNMS enables the model to more accurately identify mental health states by optimizing the decision-making mechanism in the classification process.

Table 2 Mental health status identification rate

Network model	**Raw feature bits**	**Recognition rate**
ResNet	2478	87.79%
DenseNet	7980	79.81%
DenseNet+SoftNMS	1180	90.14%

Human facial expressions are categorized into seven most basic expressions such as happy, surprised, sad, etc., and the network models are tested by using the test set of the types of expressions mapped by each psychological emotion, and the test results of different network models are shown in Table 3. The recognition results of the multilevel neural network then ranges from 90.1%-98.2, anger reaches 90.1% and happy reaches 98.8%. Between 72.8%-87.4% for ResNet and DenseNet, which further verifies that the proposed model can better recognize the mental health state.

Table 3 Test results of different network models

Network Models	**Anger**	**Disgust**	**Fear**	**Happiness**	**Sadness**	**Surprise**
ResNet	76.2%	72.8%	79.3%	81.8%	79.8%	83.1%
DenseNet	80.1%	74.8%	83.6%	87.4%	84.3%	86.9%
DenseNet+SoftNMS	90.1%	94.8%	93.6%	98.8%	94.6%	98.2%

5.2 Real-time monitoring of performance

The mental health status of 10 employees in different positions in a company was monitored, and the statistics of the system monitoring results are shown in Table 4. There are some differences between the system output results and the actual results, but the differences are relatively small. This indicates that the system has some accuracy in monitoring the psychological state of employees, but there is still room for improvement. For the majority of employees, such as numbers 1, 2, 4, 5, 6, 7, 8, and 10, the differences between the positive and negative psychological percentages output by the system and the actual results ranged from 0.01% to 0.05%, which shows a high degree of accuracy. For a few employees, such as numbers 3 and 9 there is a slightly larger difference between the system output of positive psychological percentages and the actual results, 0.03% and 0.01%, which is due to the sensitivity of the system algorithm in these particular cases or data input errors.

Positive psychological percentages of employees are generally high, with a high of 88.29% for number 10 and a low of 32.25% for number 1, indicating that overall the employee population is in a more positive or balanced psychological state. The percentage of negative psychology is relatively low, with a high of 67.75% for number 1 and a low of 11.71% for number 10, which further confirms that the overall psychological state of the employee group is favorable. However, it should also be noted that employees numbered 1 and 3 have relatively high negative psychological percentages, which requires attention to the changes and causes of their psychological status. In response to the discrepancy between the system output results and the actual results, the system algorithm can be further optimized to improve the accuracy of monitoring. Strengthen the calibration and quality control of the input data of the system to reduce the errors caused by data input errors. Regularly calibrate and maintain the system to ensure its long-term stable operation and accurate monitoring. Based on the results of system monitoring, the organization can more accurately identify employees in need of psychological care and take appropriate measures for intervention and support. Through the establishment of mental health files and regular tracking and monitoring, trends in the psychological state of employees can be detected in a timely manner and preventive measures can be taken in advance. Strengthen employee mental health education and training to improve employees' understanding of mental health and self-protection ability.

Table 4 Statistics of system monitoring results

Serial number	Positive psychology		Nnegative psychology	
	System output results	Actual results	System output results	Actual results
1	32.26%	32.25%	67.74%	67.75%
2	44.92%	44.90%	55.08%	55.10%
3	56.38%	56.35%	43.62%	43.65%
4	66.91%	66.92%	33.09%	33.08%
5	68.59%	68.56%	31.41%	31.44%
6	72.36%	72.33%	27.64%	27.67%
7	78.51%	78.50%	21.49%	21.50%
8	75.96%	75.92%	24.04%	24.08%
9	75.15%	75.16%	24.85%	24.84%
10	88.24%	88.29%	11.76%	11.71%

In order to further validate whether the provided system can effectively monitor the mental health of the company's employees in the work. The system was compared with a student mental health monitoring system utilizing IoT and machine learning techniques. The experiments and 10 employees were analyzed and the accuracy of mental health condition monitoring is shown in Table 5. Ideal accuracy, as the ideal target for monitoring accuracy, represents the expectation that the monitoring results perfectly match the actual situation. The accuracy of this system was always maintained at a high level of 94% or more, up to 97% with less fluctuation, during the increase of monitoring frequency from 10 to 100 times. It shows that the system can maintain stable performance with high reliability and accuracy at different monitoring frequencies. When the number of monitoring times is 10 times, the accuracy of this system is close to the ideal value of 97%-98%, which shows the efficiency of multilevel neural network and the ability to effectively utilize the data.

Table 5 Accuracy of mental health status monitoring

Number of monitoring sessions/times	Ideal accuracy (%)	Accuracy of the system (%)	Comparison system accuracy (%)
10	98	97	89
20	97	96	88
30	97	96	90
40	96	94	89
50	96	95	92
60	95	95	90
70	95	94	90
80	96	95	92
90	96	96	89
100	95	95	90

Then the running elapsed time of the mental health condition monitoring system is used as an indicator, and the running time of the system is shown in Fig. 6. Multi-level neural network has obvious advantages in running time-consuming, the time-consuming fold is always in the lowest level, not higher than 5.8 s. The running time-consuming of the physical network technology is under 9.0 s, while the running time-consuming of machine learning is the highest, and the time-consuming is as high as more than 10 s along with the increasing number of experiments. This indicates that the overall framework of the monitoring system designed using B/S structure in this paper is more effective and reduces the system running time consumption.

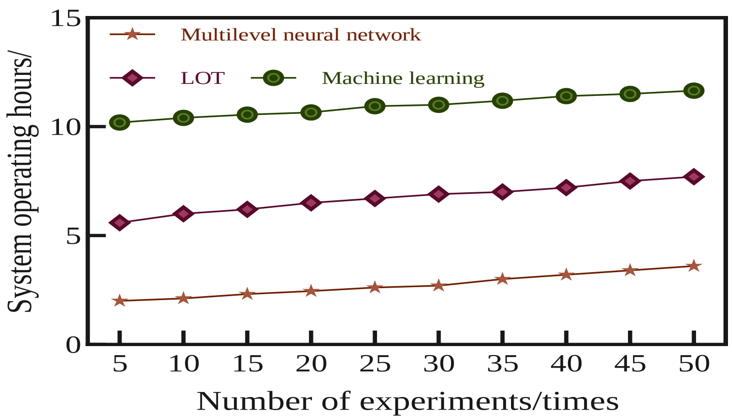

Figure 6 System Runtime

6. CONCLUSION

In this paper, the features of DenseNet network are utilized for more effective feature extraction and recognition of mental health status. By improving the Faster RCNN detection algorithm and using the Soft-NMS algorithm instead of the traditional NMS algorithm, the detection accuracy is improved. The remote mental health monitoring system is based on a B/S structure and aims to remotely monitor and evaluate users' mental health status. The results show that the combination of DenseNet+SoftNMS is used to achieve a mental health recognition rate of 90.14% with a feature number of 1180, which is better than ResNet and DenseNet, indicating that the mental health status can be recognized more accurately. In the face expression test, DenseNet+SoftNMS significantly outperforms in recognizing the accuracy of various mental states, such as anger reaching 90.1%, happy reaching 98.8%, etc. Monitoring of the employees of a company showed that the difference between the system output and the actual results was small. For most employees, the difference was between 0.01% and 0.05%. The overall psychological condition of the employees is good, but attention needs to be paid to the negative psychology of employees 1 and 3. Compared with the physical network technology, the accuracy of this system is above 94% and up to 97% with less fluctuation, but the fluctuation of the physical network technology system ranges from 88% to 92%, and the accuracy is significantly lower when the number of monitoring times is less. And the system in this paper is running time consuming under 5.8s, which verifies that this system has obvious advantages.

REFERENCES

[1] Wang, Y., Di, Y., Ye, J., & Wei, W. (2021). Study on the public psychological states and its related factors during the outbreak of coronavirus disease 2019 (COVID-19) in some regions of China. Psychology, health & medicine, 26(1), 13-22.

[2] Ojio, Y., Mori, R., Matsumoto, K., Nemoto, T., Sumiyoshi, T., Fujita, H., ... & Mizuno, M. (2021). Innovative approach to adolescent mental health in Japan: school-based education about mental health literacy. Early intervention in psychiatry, 15(1), 174-182.

[3] Gitonga, I., Desmond, D., Duda, N., & Maguire, R. (2022). Impact of connected health interventions on psychological wellbeing and quality of life in patients with cancer: a systematic review and meta-analysis. Psycho-Oncology, 31(10), 1621-1636.

[4] Logeshwaran, J., Malik, J. A., Adhikari, N., Joshi, S. S., & Bishnoi, P. (2022). IoT-TPMS: An innovation development of triangular patient monitoring system using medical internet of things. International Journal of Health Sciences, 6(S5), 9070-9084.

[5] Dutta, D., & Mishra, S. K. (2024). Bots for mental health: the boundaries of human and technology agencies for enabling mental well-being within organizations. Personnel Review, 53(5), 1129-1156.

[6] Vuorre, M., Orben, A., & Przybylski, A. K. (2021). There is no evidence that associations between adolescents' digital technology engagement and mental health problems have increased. Clinical Psychological Science, 9(5), 823-835.

[7] Fu, Z., Burger, H., Arjadi, R., & Bockting, C. L. (2020). Effectiveness of digital psychological interventions for mental health problems in low-income and middle-income countries: a systematic review and meta-analysis. The Lancet

Psychiatry, 7(10), 851-864.

[8] Hoover, S., & Bostic, J. (2021). Schools as a vital component of the child and adolescent mental health system. Psychiatric services, 72(1), 37-48.

[9] Melcher, J., Hays, R., & Torous, J. (2020). Digital phenotyping for mental health of college students: a clinical review. BMJ Ment Health, 23(4), 161-166.

[10] Kalkbrenner, M. T., Jolley, A. L., & Hays, D. G. (2021). Faculty views on college student mental health: Implications for retention and student success. Journal of College Student Retention: Research, Theory & Practice, 23(3), 636-658.

[11] Salimi, N., Gere, B., Talley, W., & Irioogbe, B. (2023). College students mental health challenges: Concerns and considerations in the COVID-19 pandemic. Journal of College Student Psychotherapy, 37(1), 39-51.

[12] Souri, A., Ghafour, M. Y., Ahmed, A. M., Safara, F., Yamini, A., & Hoseyninezhad, M. (2020). A new machine learning-based healthcare monitoring model for student's condition diagnosis in Internet of Things environment. Soft Computing, 24(22), 17111-17121.

[13] Levine, G. N., Cohen, B. E., Commodore-Mensah, Y., Fleury, J., Huffman, J. C., Khalid, U., ... & American Heart Association Council on Clinical Cardiology. (2021). Psychological Health, Well-Being, and the Mind-Heart-Body Connection A Scientific Statement From the American Heart Association. Circulation, 143(10), E763-E783.

[14] Valcke, B., Van Hiel, A., Van Roey, T., Van De Putte, B., & Dierckx, K. (2020). Societal actors shape collective identities of minorities: procedural fairness climate effects on identification, subjective well-being and psychological health. Social justice research, 33(4), 379-405.

[15] Mirza, M. Z., Memon, M. A., & Dollard, M. (2023). A time-lagged study on health-centric leadership styles and psychological health: the mediating role of psychosocial safety climate. Current Psychology, 42(10), 8164-8175.

[16] Chang, C. J., Putukian, M., Aerni, G., Diamond, A. B., Hong, E. S., Ingram, Y. M., ... & Wolanin, A. T. (2020). Mental health issues and psychological factors in athletes: detection, management, effect on performance, and prevention: American medical society for sports medicine position statement. Clinical Journal of Sport Medicine, 30(2), e61-e87.

[17] Abdulkarem, M., Samsudin, K., Rokhani, F. Z., & A Rasid, M. F. (2020). Wireless sensor network for structural health monitoring: A contemporary review of technologies, challenges, and future direction. Structural health monitoring, 19(3), 693-735.

[18] Odgers, C. L., & Jensen, M. R. (2020). Annual research review: Adolescent mental health in the digital age: Facts, fears, and future directions. Journal of Child Psychology and Psychiatry, 61(3), 336-348.

[19] Steffens, N. K., LaRue, C. J., Haslam, C., Walter, Z. C., Cruwys, T., Munt, K. A., ... & Tarrant, M. (2021). Social identification-building interventions to improve health: A systematic review and meta-analysis. Health psychology review, 15(1), 85-112.

[20] Begum, N., & Mustafa, A. S. (2023). Multi-level graded facial emotion intensity recognition using MCANN for health care. Intelligent Decision Technologies, 17(2), 331-341.

[21] Montagni, I., Tzourio, C., Cousin, T., Sagara, J. A., Bada-Alonzi, J., & Horgan, A. (2020). Mental health-related digital

use by university students: a systematic review. Telemedicine and e-Health, 26(2), 131-146.

[22] Chakraborty, A., Banerjee, J. S., Bhadra, R., Dutta, A., Ganguly, S., Das, D., ... & Saha, G. (2024). A framework of intelligent mental health monitoring in smart cities and societies. IETE Journal of Research, 70(2), 1328-1341.

[23] Raviv, T., Smith, M., Hurwitz, L., Gill, T. L., Baker, S., Torres, S. A., ... & Cicchetti, C. (2022). Supporting school-community collaboration for the implementation of a multi-tiered school mental health program: The Behavioral Health Team model. Psychology in the Schools, 59(6), 1239-1258.

[24] Patelarou, A., Mechili, E. A., Galanis, P., Zografakis-Sfakianakis, M., Konstantinidis, T., Saliaj, A., ... & Patelarou, E. (2021). Nursing students, mental health status during COVID-19 quarantine: evidence from three European countries. Journal of Mental Health, 30(2), 164-169.

[25] Bakker, E. J., Kox, J. H., Boot, C. R., Francke, A. L., van der Beek, A. J., & Roelofs, P. D. (2020). Improving mental health of student and novice nurses to prevent dropout: A systematic review. Journal of Advanced Nursing, 76(10), 2494-2509.

[26] Dalton, L., Rapa, E., & Stein, A. (2020). Protecting the psychological health of children through effective communication about COVID-19. The Lancet Child & Adolescent Health, 4(5), 346-347.

ABOUT THE AUTHOR

Ruirui Su obtained a master's degree from Tsinghua University. And she studies a doctorate in Education at Beijing Normal University.She currently works at the Mental Health Education and Counseling Center of Beijing Institute of Technology. Her main research directions are clinical psychology and counseling, trauma psychology, and college student's mental health.

E-mail: 13488795281@163.com

Aiyi Liu was born in Beijing, China. She obtained a Ph.D. degree from the Faculty of Psychology at Beijing Normal University. Her main research directions are clinical psychology and counseling, trauma psychology, and adolescent mental health research.

E-mail: psylay@mail.bnu.edu.cn

Guo Ling was born in Zhengzhou, Henan Province, China in 1987.Her master's degree graduated from Beijing Normal University.She currently works as a psychological teacher at No. 69 Middle School in Zhengzhou City and studies a doctorate in education at Beijing Normal University.Her major research area is adolescent mental health education.

E-mail:guoling@mail.bnu.edu.cn

Xinchun Wu is a distinguished professor at Beijing Normal University, holding the title of Jing Shi Distinguished Professor. He serves as the Chair of the Psychology Degree Committee, a doctoral advisor at the Faculty of Psychology, and the head of the psychology discipline at the Zhuhai campus.

E-mail:xcwu@bnu.edu.cn