Development and Design of College Students Based on Deep Learning

Peng Li, Jinlong Zhao*

Changchun Humanities and Sciences College
Changchun China

*386423632@qq.com

Abstract. This study aims to develop a psychological counseling system for college students based on deep learning to improve the accuracy and intervention effect of mental health assessment through intelligent psychological assessment, personalized intervention and real-time data acquisition. The research methods include the construction of hybrid deep learning model, combining LSTM and CNN algorithm to process multimodal psychological data, using reinforcement learning to optimize personalized intervention strategies, and using distributed microservice architecture and efficient data storage technology to realize the system stability and high concurrent processing ability. The results show that the system performs well in user satisfaction, mental health improvement rate and system performance, has the potential for large-scale application.

Keywords: deep learning, psychological counseling system, personalized intervention, mental health assessment and intelligent assessment

1 Introduction

In recent years, with the increasingly prominent mental health problems of college students, how to effectively improve the efficiency and accuracy of psychological counseling services has become the focus of social and academic attention. In the face of the complex individual psychological state, the traditional psychological counseling model is often inadequate due to the lack of dynamic and real-time data support and personalized program. At the same time, deep learning, as a cutting-edge technology in the field of artificial intelligence, provides new solutions for the automated analysis and prediction of psychological data with its advantages in unstructured data processing, pattern recognition and adaptive learning. Deep learning can not only extract potential feature relationships from large amounts of mental health data, but also realize the intelligent design of individualized psychological interventions through multi-dimensional modeling of emotional, behavioral and cognitive data.

D. Hu et al. (eds.), *Proceedings of the 2024 5th International Conference on Modern Education and Information Management (ICMEIM 2024)*, Atlantis Highlights in Social Sciences, Education and Humanities 29,
https://doi.org/10.2991/978-94-6463-568-3_40

2 Technical Application of Deep Learning in Psychological Counseling

2.1 Optimization of Deep Learning Algorithm in Mental Health Assessment

In the mental health evaluation, the optimization of the deep learning algorithm is mainly reflected in the improvement of the evaluation accuracy, robustness and individualized prediction ability. Commonly used deep learning algorithms such as convolutional neural network (CNN), recurrent neural network (RNN) and Transformer architecture based on attention mechanism can effectively process multi-modal psychological data, including text, audio, image and other information sources. By modeling multilevel associations of the assessed data, these algorithms are able to accurately identify potential risks to mental health. At the same time, the hyperparameter optimization, regularization technology and model integration method of the algorithm further improve the generalization ability of the model, making its performance more robust in dealing with complex and changeable mental health data. In particular, the introduction of adaptive learning and transfer learning technology enables deep learning models to maintain high evaluation accuracy under the condition of small sample data or unbalanced data[1].

2.2 Application of Deep Learning Model in Emotion Recognition

As a core technology in the psychological counseling system, emotion recognition benefits from the wide application of deep learning in the field of natural language processing and computer vision. The emotion recognition model based on deep learning can accurately capture users emotion changes by analyzing multi-modal information such as language, speech and facial expressions. The long-and short-term memory network (LSTM) and the bidirectional RNN perform well in processing time-series emotional data, recognizing emotional fluctuations and subtle changes in continuous conversations. The expression recognition technology based on the convolutional neural network can assist the psychological counseling system to accurately judge the emotional state of individuals by capturing the changes of facial microexpressions[2].

3 Key Technology Development of Functional Modules

3.1 Implementation Method of Intelligent Psychological Evaluation Algorithm

The realization of intelligent psychological evaluation algorithm depends on the efficient modeling ability of multi-layer neural network in deep learning, especially the performance of convolutional neural network and recurrent neural network in processing multi-modal psychological data. In this module, psychological evaluation builds a hybrid model that uses CNN for the feature extraction of static mental data and RNN for the processing of time series data to capture the dynamic changes of users mental state. The input mental eigenvector is set as, through a multilayer convolution operation, where a convolution kernel, a bias term, and a nonlinear activation function. After obtaining the psychological feature map, the time dependence is modeled through the long-term and short-term memory network (LSTM), and the implied state is defined as, which represents the activation function. LSTM controls the forgetting and storage of information through the gating mechanism, capturing the long-term trend and short-term fluctuations of the mental state. Finally, the mental health score is output through the fully connected layer, whose 8BA1 formula is calculated as, which is the weight matrix and the bias term. The hybrid model not only improves the accuracy of the evaluation, but also adapts to the complex changes of the individualized psychological state[3].

$$
\begin{aligned}
X = \{x_1, x_2, \ldots, x_n\} C_i = f(W_i * X + b_i) W_I b_i f h_t \\
= \sigma(W_h \cdot [h_{t-1}, x_t] + b_h) \sigma SS \\
= soft\max(W_s \cdot h_t + b_s) W_s b_s
\end{aligned}
$$

3.2 Pre-processing Technology for Psychological Data Collection

The preprocessing technology of mental data collection is a key link to ensure the efficient operation of the mental health assessment system, because it needs to process multi-source and heterogeneous mental data, including text, speech, image and row 4E3A data. In order to improve the availability and consistency of the data, the preprocessing technology adopts multi-step processing such as normalization, denoising, missing value filling and feature extraction. Assuming the input dataset is, each data point is normalized with the formula is to map the data to the unity interval. Moreover, for noisy physiological signals and emotion data, wavelet transform, where the original signal and the wavelet basis function. For missing data, based on interpolation method or regression model, the nearest neighbor algorithm (KNN) is calculated with the nearest neighbor point, which is the nearest known data point. In the process of feature extraction, principal component analysis (PCA) is used to reduce the high-dimensional data. The covariance matrix is defined as, which is the mean of the data, and the previous principal components are selected to reduce the dimension to retain the maximum variance features. These preprocessing techniques ensure the accuracy and consistency of the mental data, providing high-quality input for subsequent deep learning algorithms.

$$
\begin{aligned}
D = \{d_1, d_2, \ldots, \quad d_n\} d_i \hat{d}_i = \frac{d_i - \min(D)}{\max(D) - \min(D)} W(f) \\
= \int_{-\infty}^{\infty} x(t) \psi(t - f) dt x(t) \psi(t) x_{\text{miss}}\, x_{\text{miss}} \\
= \frac{1}{k} \sum_{i=1}^{k} x_i x_\text{i} k \Sigma = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu)(x_i - \mu)^\top \mu m
\end{aligned}
$$

3.3 Model Training of Personalized Psychological Intervention Algorithm

The model training of personalized psychological intervention algorithm relies on the strategy optimization method of combining reinforcement learning (Reinforcement Learning, RL) with deep neural network, aiming to continuously adjust the intervention strategy through the users feedback and realize the highly personalized psychological intervention program. The model uses the deep Q network (DQN) in deep reinforcement learning. The state space includes the users psychological state, emotional response and behavioral data, and the action space includes different intervention programs, such as cognitive behavioral therapy, relaxation training, etc. The model maximizes the cumulative reward by optimizing the objective function, where the function is parameterized by the deep neural network and represents the future rewards that can be achieved by taking actions in the state. During the training, the historical data samples are stored and the neural network parameters are updated by minimizing the mean square error loss function, where the discount factor is the parameters of the target network. In order to accelerate the model convergence, the dual network architecture is adopted to update the parameters of the current network and the target network respectively to ensure the stability and convergence of the strategy[4].

$$
\begin{aligned}
& SAQ(s,a)QSa(s_t,a_t,r_t,s_{t+1})\mathcal{L}(\theta) \\
& = \mathbb{E}\left[\left(r_t + \gamma \max_a Q(s_{t+1},a;\theta^-) - Q(s_t,a_t;\theta)\right)^2\right]\theta\gamma\theta^-
\end{aligned}
$$

4 System Architecture Design and Technical Implementation

4.1 Design Scheme of the System Background Architecture

As shown in Figure 1, the background architecture of the system adopts distributed microservice design, combining Spring Boot and Kubernetes clusters to realize dynamic expansion and load balancing, and uses gRPC protocol to improve communication efficiency. In terms of database, the hybrid architecture of MongoDB and PostgreSQL is adopted. MongoDB improves the processing efficiency of unstructured data through the shard mode, and PostgreSQL processes structured data. Kafka Message Queuing is responsible for asynchronous task scheduling and high concurrent log processing, combined with Zookeeper clustering to implement service failover, and Redis cache is used to reduce database query pressure. Security is guaranteed by OAuth 2.0 and JWT, the data transmission adopts TLS encryption, and the system performance is monitored and optimized by Prometheus and Grafana in real time.

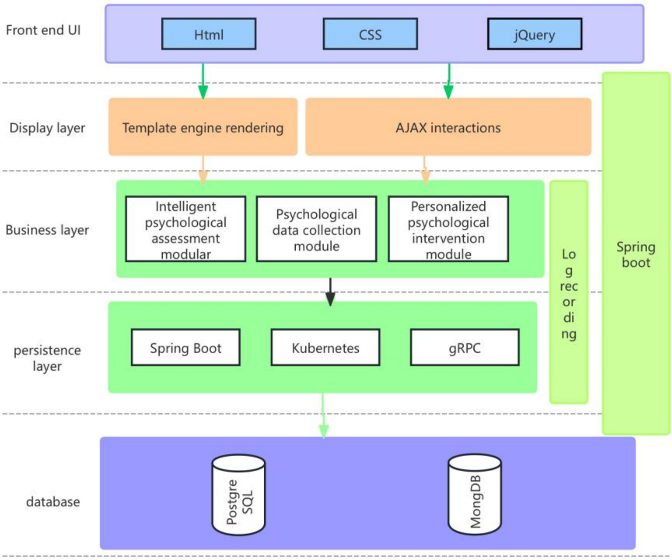

Fig. 1. System architecture design diagram.

4.2 Implementation Mechanism of Data Storage Technology

Data storage uses a hybrid architecture, combining PostgreSQL and MongoDB to cope with diverse psychological data. PostgreSQL For structured data storage, support ACID transaction, partition table and indexing technology, improve query efficiency and data consistency. MongoDB Processing unstructured data, achieving linear expansion with document storage and horizontal sharding, and ensuring high availability through the Replica Set architecture. Redis acts as a cache layer to accelerate high-frequency data reading, and adopts the master and slave replication and sentinel mode to ensure stability and recovery ability.

5 Platform Development and Testing

5.1 Integration Test of the Platform Functional Module

The integration test of the platform functional modules mainly passes through the multi-dimensional test process, such as unit test, integration test, system test and stress test, to ensure the stable interaction and performance among the modules. In the integration test stage, the platform conducts quantitative analysis of the test results of key modules to ensure the stability and performance of each module in the actual interaction scenario. In the prediction of mental health score, the intelligent psychological evaluation module keeps the error within 2.8% through the optimization of LSTM model, thus meeting the requirements of high-precision evaluation.

5.2 Platform Application Effect Evaluation

Through the actual user feedback data, the platform shows excellent application effect in multiple dimensions. In the user satisfaction survey, 88.5% of users were satisfied with the psychological assessment and intervention functions of the platform, exceeding the expected target. The results of the mental health improvement rate showed that the mental health score of users using the platform increased by 16.2% on average, which indicates that the personalized intervention module of the platform can effectively adjust the intervention strategies through the reinforcement learning algorithm and effectively improve the mental health level of users. The system performs well in terms of response time and concurrent processing capability, with an average response time of 460ms, well below the standard requirement of 500ms, thanks to the efficient synergies of the background Redis cache and Nginx reverse agents. Moreover, the stability of the platform under high concurrency scenarios was highly validated[5].

6 Conclusion

The paper explores the application of deep learning techniques in the development and design of educational systems for college students. The paper outlines various technological applications that support student learning and personal development, focusing on how deep learning algorithms can optimize the analysis of student data and enhance personalized learning experiences. The study also discusses the development of a platform that integrates educational data and learning patterns to assist students and educators in making informed decisions about academic progress and career paths.

Acknowledgement

2024 Scientific Research Project of Jilin Provincial Education Department (Special Employment, Entrepreneurship and Student Management), and research on the operation mechanism of "Deep integration of Internship and Employment" in private universities: JJKH20241716JY

References

1. Process analysis of depression facial expressions, actions, and their psychological integration changes based on deep learning algorithms [J] Yuan Qinmei; Yang Qiao; Zhang Jun; Liu Bowen; Shuai Jianwei; Cao Yuping. Chinese Journal of Clinical Psychology, 2023 (01): 23-45.
2. Chinese Science and Technology Policy Text Classification: An Enhanced TextCNN Perspective [J] Li Munan; Wang Liang; Lai Huapeng. Research on Technology Management, 2023 (02):45-56.
3. Psychological problems and mechanism construction of college students in the post epidemic era (review) [J] Wu Jiujun. Chinese Journal of Health Psychology, 2023 (08):111-132.

4. Challenges and Responses to Mental and Psychological Issues in the Post Pandemic Era [J] Su Sizhen; Gongyi Miao; Zhao Yimiao; Ni Shuyu; Shi Le; Bao Yanping; Lu Lin. Journal of Sichuan University (Medical Edition), 2023 (02):142-146.
5. Application of Text Classification Based on PSO-SVM in Insurance Precision Marketing [J] Wan Ping; Li Lizheng; Lou Feng; Wang Cheng. Systems Engineering, 2023 (05): 23.