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Combine the network model to conduct dynamic monitoring and prediction of the mental health status of students

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In order to meet the needs of students' mental health management, this study designed and implemented a dynamic mental health monitoring and prediction system based on big data. Based on multi-dimensional data, a multi-source data collection framework is constructed, and a deep neural network model is combined to accurately classify and predict the trend of students' mental health state. The system has advantages in terms of classification accuracy, operational efficiency and data processing ability, enabling educational administrators to detect mental health risks in a timely manner. The system designed real-time data acquisition, index analysis, state evaluation and intervention suggestions and other functional modules, forming a closed-loop monitoring and feedback system. The differences in classification performance and the lack of generalization ability are also identified, and optimization paths, minority class sample enhancement, data diversity expansion and system performance optimization are proposed. It provides scientific tools and implementation paths for students' mental health management, and promotes the development of the field of dynamic monitoring of mental health.

Keywords: mental health; big data analysis; dynamic monitoring

1. INTRODUCTION

Students' mental health problems have attracted much attention in the social development and education system. Due to the rapid development of modern society, the psychological pressures and health problems faced by students have become increasingly complex. These problems affect students' academic performance and relationships, and have a profound impact on their long-term physical and mental health. The monitoring of mental health and timely intervention have gradually become the research direction in the field of education management and social health. Traditional mental health assessment methods rely mainly on questionnaires and clinical interviews, which are widely used in scientific research. However, the acquisition of data is a lengthy process and its comprehensiveness is limited. In large-scale educational institutions with greatly diverse student groups, it is difficult for traditional methods to achieve the goal of dynamic monitoring and real-time prediction. Students' mental health status is affected by many factors, such as academic pressure, family environment, social relations, etc. A single data source is unable to fully capture the complexity of mental health. With the development of information technology, the application of data mining, big data analysis and artificial intelligence provides a new perspective and means for students' mental health monitoring. These technologies enable the efficient integration of multidimensional data to analyze dynamic changes in students' mental health, and support personalized interventions [1]. The emergence of big data technology has made possible the real-time monitoring of large-scale student groups, providing a scientific basis for education administrators and policy makers.

Wu et al. discussed the impact of big data capability on value creation, pointing out that big data analysis can significantly optimize the decision-making process of

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enterprises and improve operational efficiency [2]. Qiao et al. evaluated the use of big data analytics and electronic health records in HIV prevention, treatment, and care, highlighting the potential of data-driven approaches to improve treatment outcomes [3]. Cornelli et al. examined the practices of Asian central banks in the application of big data and the impact of data-driven decision-making in the financial field in particular. Their description of the data collection and analysis processes also provided some inspiration for data-driven decision-making in mental health research [4]. Xu et al. reviewed the use of data in sustainable tourism and pointed out that big data can help optimize resource allocation [5]. By means of bibliometric analysis, Rialti et al. revealed the relationship between big data and dynamic capability, finding that big data plays an important role in improving organizational flexibility and responding to external changes [6]. Rooney et al. focused on ways to optimize school mental health services by utilizing data, pointing out that data monitoring and evaluation are crucial to improving the effectiveness of mental health interventions [7]. Ozota et al. studied the mental health law and its challenges in Nigeria, and found that the legal framework plays an important role in regulating and promoting mental health services. He proposed that by combining big data and law, the mental health service system could be improved [8]. da Costa et al. summarized the potential of real-time data monitoring in supporting dynamic life cycle inventory and described several application scenarios involving real-time data monitoring [9]. Roado-Solomon et al. proposed the application of data-driven approaches to deal with mental health and mental illness in organizations, emphasizing that data can help managers better understand employees' mental states, and intervene [10]. Andrade et al. discussed the mental health and mental health literacy of informal caregivers and proposed that the combination of mental health education and data monitoring can help improve individuals' health management ability [11]. Righetti et al. analyzed the impact of self-regulation on mental health in intimate relationships and pointed out that real-time data monitoring could assist in assessing and improving individuals' self-regulation process [12]. Petrokas and Kavaliauskas discussed the genetic monitoring of forest dynamics, and found that the application of big data monitoring provided technical inspiration for remote data monitoring in the field of mental health [13]. Maswanganye et al. reviewed the application of remote sensing technology in non-sustainable river monitoring and mentioned the advantages of spatial time series analysis of remote sensing data for water resources management [14]. Joung et al. proposed a data-driven dual service failure-monitoring method [15]. Harris et al. discussed how to achieve mental health equity for children and adolescents, and proposed a combination of data and policies to ensure the equity of mental health services [16].

In regard to students' mental health, this paper establishes a dynamic monitoring and prediction system based on big data, and evaluates and predicts students' mental health status in a more scientific and comprehensive way. The current mental health assessment model has limitations in dynamic monitoring and individualized prediction, as it cannot be easily adapted to the complex and changeable characteristics of students' mental health problems. The goal is to integrate multidimensional data sources, build a dynamic monitoring system, use data modeling and machine learning technology to achieve accurate prediction of mental health status, and provide a basis for intervention for education administrators. Our approach includes the collection of multi-dimensional data related to mental health, taking into consideration variables such as study, life and mood. The data is cleaned, and processed using normalization technology. In the modeling process, the performance of different algorithms is compared, the optimal model is selected and the adaptive architecture is designed. The hierarchical training method is used to improve the stability and generalizability of the model. Combining a dynamic monitoring function and a prediction algorithm, a monitoring system for students' mental health is developed. The research will help effect the transformation of the mental health field from static assessment to dynamic and real-time monitoring, provide strong support for the early detection and intervention of students' psychological problems, and provide a scientific basis for the formulation of relevant policies.

2. MATERIALS AND METHODS

2.1 Research Data

2.1.1 Data Source and Feature Description

The data sources for this study are: records from education management systems (EMSs), student questionnaire results, psychological counseling records, and external data resources related to mental health. The EMS data contains students' basic information, academic performance, attendance record, course arrangement, etc., and indicates students' academic pressure and learning behavior pattern. The questionnaire survey data provide information such as students' self-perception and psychological state, which supplements the objective information in the EMS data. Psychological counseling records the problems, evaluation and conclusions pertaining to students who have obtained such counseling. This data indicates the severity of the individual student's psychological state. External data include the family's financial status, the community environment, Internet usage behavior, etc. By integrating these data, a dynamic portrait of students' mental health is constructed from multiple dimensions, as shown in Table 1 below.

2.1.2 Sample Selection Criteria and Screening Methods

The selected sample comprised middle school students in a certain province of China, in different grades, and from urban and rural regions and school types to ensure the diversity and representativeness of data. The selection criteria were: the student is between 12 and 18 years old, has a complete EMS record, has undergone at least one questionnaire or mental health assessment, and relevant external data is available. During the screening process, subjects with a high rate of missing data, inconsistent information or records with obvious outliers were eliminated. After screening, the

Table 1 Examples of data sources.

Data Source	Data Type	Description
Education Management System Data	Objective Data	Academic performance, course schedules, attendance records, etc.
Questionnaire Survey Data	Subjective Data	Self-reports, social support, mental state, etc.
Psychological Counseling Records	Annotated Data	Counseling issues and assessment conclusions
External Socioeconomic Data	Environmental Data	Family economy, community environment, internet behavior

Table 2 Description of variables.

Variable Name	Data Type	Description
Academic Pressure	Continuous Variable	Quantified based on grades and attendance records
Mental Health Score	Categorical Variable	Classified according to questionnaire results
Social Support Index	Continuous Variable	Reflects the level of social support of students
Family Economic Level	Categorical Variable	Classified using external data

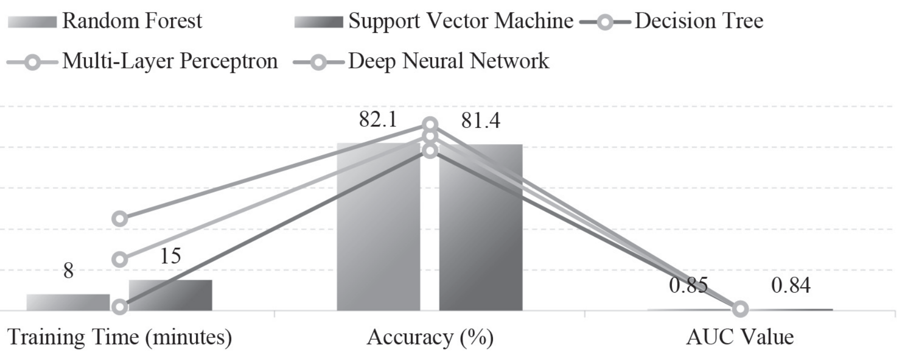

Figure 1 Comparison of different models and performance evaluation indicators.

sample distribution covered key schools, ordinary schools and rural schools across the province, and the researcher ensured a balance of gender ratio, family backgrounds and other characteristics. The variable descriptions are shown in Table 2.

2.1.3 Data Cleaning and Pre-Processing

In the data cleaning stage, the missing value is processed, and the method of mean filling, mode filling or elimination is adopted according to the type of variable. The outliers are identified by box plot analysis and z-score standardized methods and then corrected or eliminated. For duplicate records of different data sources, unique identifiers (such as student numbers) are used for data dedication to ensure data integrity. In the pre-processing stage, different data formats are standardized, categorical variables are transformed into dummy variables, time variables are transformed into periodic features, and continuous variables are normalized to ensure the stability of model training. By means of the data partitioning strategy, the data is divided into training set, verification set and test set proportionally to build the high-quality data foundation required by the model.

2.2 Model Construction

2.2.1 Model Selection

For the model selection, the task characteristics and data attributes are combined to compare various models: decision tree, random forest, support vector machine (SVM), multi-layer perceptron (MLP) and deep neural network (DNN). Decision trees and random forests have the advantages of interchangeability, but their performance may be inadequate when dealing with high and complex data. Support vector machines (SVMS) perform well on small and medium-sized data and have high computational complexity. Multi-layer peppercorns and deep neural networks have advantages in dealing with high and nonlinear problems and are suitable for the big data background of this study. Deep neural network is chosen as the main model and random forest as the auxiliary analysis tool. The comparison and performance evaluation indicators for different models are shown in Figure 1 below.

2.2.2 Model Architecture Design

The deep neural network adopts a multi-layer architecture design, combining the functions of the input layer, hidden layer and output layer. The input layer receives

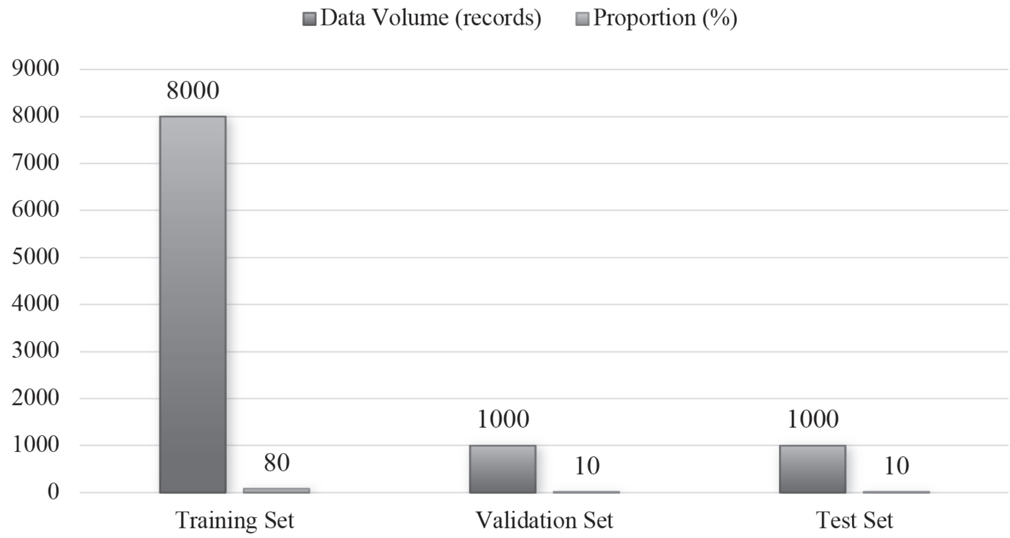

Figure 2 Data division ratio.

multi-dimensional feature data. The hidden layer uses a fully-connected structure, and each layer utilizes Lure activation functions and Dropout mechanisms to improve nonlinear modeling capabilities and reduce the risk of over fitting [17]. The output layer is set as the Soft max activation function for the multi-classification task to output the predicted categories of the students' mental health status. The loss function of the prediction model is as Equation (1).

$$L(y, \hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log \hat{y}_i + (1 - y_i)\log(1 - \hat{y}_i)) \quad (1)$$

2.2.3 Data Partitioning Method

The data is divided into training sets, verification sets and test sets in the ratio of 8:1:1. The training set is used to optimize the model parameters, the validation set is used to adjust the hyper parameters, and the test set evaluates the final performance of the model [18]. In order to maintain the balance of classification tasks, the proportion of all types of data should be consistent to avoid bias. Multiple random divisions further reduce chance. The proportion of data division is shown in Figure 2 below.

2.2.4 Model Implementation and Training Parameter Setting

Using the TensorFlow framework, the optimizer selects Adam, the initial learning rate is set to 0.001, and the convergence process is optimized by dynamically adjusting the strategy. The batch size is 64, the total number of training rounds is 50, and the early stop mechanism is set to terminate the training when the verification set performance does not improve for 5 consecutive rounds. Dropout rate is 0.5, which enhances the robustness of the model [19]. The model performance was evaluated by accuracy, AUC value, F1 value and other indicators, and the details of the performance were classified using confusion matrix analysis. For all types of mental health state, the performance of the model is balanced and therefore able to meet the needs of dynamic monitoring and prediction.

2.3 Implementation of Monitoring and Forecasting System

2.3.1 Functional Design of Dynamic Monitoring System

Based on multi-dimensional data fusion of dynamic monitoring system, a closed-loop structure of real-time acquisition, analysis, early warning and feedback is constructed. By integrating multi-source data such as education management system, a questionnaire survey and external environment data, the system realizes the dynamic acquisition and automatic update of students' mental health data. The monitoring module includes data collection, index analysis, state evaluation and dynamic feedback [20]. The data acquisition module is connected with the education management platform through the data interface. It collects the student behavior data in real time, and at the same time integrates the questionnaire results and external data resources at the same time. The indicator analysis module is based on predefined mental health indicators to assess students' performance in dimensions such as academic stress, psychological state, and social support. The status assessment module calculates the students' mental health status in real time through the classification algorithm, and transmits the results to the dynamic feedback module to support personalized intervention suggestions.

2.3.2 Process Design of Mental Health Prediction System

With a model-driven core, the mental health prediction system builds a complete process comprising data multiprocessing, model prediction, result interpretation and personalized intervention to predict the trend of students' mental health. The data multiprocessing module cleans, normalizes and performs feature engineering processing on the original data to generate high-quality input data. Based on the deep neural

Table 3 System function modules and descriptions.

Functional Module	Description
Data Collection	Real-time collection of student behavior, surveys, and external data
Indicator Analysis	Evaluates academic pressure, mental state, and other multidimensional indicators
Status Assessment	Classifies and outputs mental health status using classification algorithms
Dynamic Feedback	Provides personalized intervention suggestions and improvement paths
Data Multiprocessing	Cleanses, normalizes, and performs feature engineering on input data
Model Prediction	Uses deep neural networks to predict mental health status
Result Interpretation	Generates interoperable reports of prediction results
Personalized Intervention	Develops mental health support plans and behavioral adjustment recommendations

network architecture, the model prediction module inputs the current and historical data of students and outputs the predicted value and risk level of mental health status [21]. The results interpretation module combines feature importance analysis to generate explainable reports of prediction results to help educational managers understand the basis of prediction. The personalized intervention module generates personalized psychological support suggestions, psychological counseling programs and behavioral adjustment suggestions based on the predicted results. Students' mental health score is calculated with Equation (2).

$$S = \sum_{i=1}^{n} w_i \cdot f_i \tag{2}$$

S is the mental health score, represents the student's specific characteristic value (such as academic stress, social support, etc.), I is the weight of the corresponding characteristic, determined by model training. The function modules and description of the system are shown in Table 3.

2.4 Paths and Suggestions

2.4.1 Build a Closed-Loop Collection of Mental Health Data

The construction of a closed loop of mental health dataset needs to integrate multiple data sources and ensure the comprehensiveness and accuracy of data through a standardized collection and feedback mechanism. Closed-loop data collection covers students' academic, life, psychological counseling records and other internal data, as well as the family's financial status, social environment and other external data. The basis of the closed loop is a real-time acquisition system that dynamically updates data with the help of IoT (Internet of Things) devices, online questionnaires and education management systems. Feedback mechanisms are an important part of the closed loop, early warning systems and report generation tools that deliver data analysis results to students, parents, and school administrators to achieve the linkage of data and behavior. The closed-loop model drives continuous improvement based on dynamic monitoring to provide long-term support for the prevention of mental health problems.

2.4.2 Improve the Generalization Performance of the Prediction Model

The generalizability of the prediction model directly determines the application outcomes in an actual scenario. To improve the generalization performance, it is necessary to consider: model design, data enhancement and training optimization. In the model design, the balance complexity and computational efficiency of the network structure are optimized to avoid overfitting. Data enhancement is expanded by increasing the diversity of the training data set to cover more manifestations of mental health problems, introducing simulation data and multi-regional data. In terms of training optimization, a regularization term, dynamic learning rate adjustment strategy and cross-validation technology are applied to improve the stability and adaptability of the model. The performance evaluation of the model should be based on a multi-dimensional index system, including accuracy, recall rate and AUC value, to ensure that the model's performance is balanced when predicting different mental health states.

2.4.3 Developing Psychological Intervention Path Suggestions

The goal of mental health monitoring and prediction is to achieve effective intervention, and the design of psychological intervention path starts from two perspectives: individuation and feasibility. Individualized interventions need to be tailored to students' mental health status, sources of academic stress and levels of social support. For students at high risk, internal psychological counseling resources are combined with off-campus professional support institutions to implement joint intervention. In terms of feasibility, interventions need to be adapted to the available resource and cultural background of schools. For schools with limited resources, the intervention coverage was extended by training teachers to

Table 4 Distribution of mental health statuses of samples.

Status Category	Sample Size	Proportion (%)
Healthy	6000	60
Sub-Healthy	3000	30
Abnormal	1000	10

take on psychological support roles. The dynamic adjustment mechanism of a psychological intervention path uses the data feedback of the monitoring system to update the intervention plan in real time to ensure the effectiveness and sustainability of the intervention.

2.4.4 Build a Dynamic Evaluation Index System for Mental Health

The dynamic evaluation index system is the basis of mental health monitoring. Hence, the construction of the system should take multiple dimensions as the core, such as students' academic pressure, emotional state, social support and behavior. The indicators for each dimension need to be evaluated by experts to determine the specific quantitative standards. Academic stress can be statistically analyzed based on academic performance and learning time, and emotional state can be evaluated by combining psychological questionnaires with behavioral data. The dynamic nature of the index system is due to its continuous improvement as data accumulates and analysis needs change. The weights of evaluation indicators were determined through model analysis and expert opinions, reflecting the impact of different dimensions on mental health. The dynamic evaluation system can provide a scientific basis for the evaluation of students' mental health, which is an important reference tool for educational management decision-making. Through the integrated path of data closed-loop, model optimization, intervention path and dynamic evaluation, the mental health monitoring and prediction system realizes the optimization of the entire chain from data collection to intervention implementation, ensuring the long-term support of students' mental health.

3. RESULTS AND DISCUSSION

3.1 Results

3.1.1 Data Distribution and Descriptive Statistics

The sample data covered multi-dimensional characteristics such as students' academic performance, emotional state, family economic level and social support index. The sample comprised 1000 students, covering different schools and grades in urban and rural areas, with ages ranging between 12 and 18 years, with a male to female ratio of nearly 1:1. Descriptive statistics show that mental health status presents significant differences, with healthy status accounting for about 60% of the samples, sub-health status 30%, and abnormal state 10%. The analysis of mean and standard deviation of each dimension shows that emotional state and academic pressure have the most significant influence on mental health state. The identification and classification of health status are obtained with Equation (3).

$$P(C_k|x) = \frac{P(x|C_k)P(C_k)}{P(x)} \tag{3}$$

The equation calculates the classification probability of a mental health state through Bayesian theory, which combines the characteristic conditional probability and prior probability of the sample, and identifies the students as healthy, sub-healthy or abnormal state. The distribution of mental health statuses of the sample is shown in Table 4 below.

3.1.2 Results of Model Training and Testing

After 50 rounds of training, the deep neural network model achieves high classification accuracy and AUC value on the test set. During the training process, the model converges quickly during the first 10 rounds and tends to be stable. The loss curve of the verification set shows that the model does not overfit. The classification accuracy is the best for the healthy state samples, and the classification of sub-health and abnormal states is slightly inaccurate. The confusion matrix analysis of the model shows that the recall rate of healthy states is 95%, while the accuracy rate of abnormal states is relatively low. The accuracy of the model is calculated with the following Equation (4).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

Where *TP* and *TN* are the number of true positives and true negatives of the classification, and *FP* and *FN* are the number of false positives and false negatives, respectively. The model training and testing results are shown in Figure 3 below.

3.1.3 System Performance Evaluation

System performance is evaluated in terms of: processing speed, resource consumption and predictive timeliness. In the test, the system's prediction time for each record was 0.45 seconds on average, and the total time spent on data processing and model reasoning was controlled to within 1 second. When processing batch tasks consisting of 1000 records, the system performed stably, and the processing time increased linearly according to the data size. The resource consumption of CPU and memory is low, thereby meeting the application requirements of the school education system. The evaluation results for the system's running performance are shown in Figure 4 below.

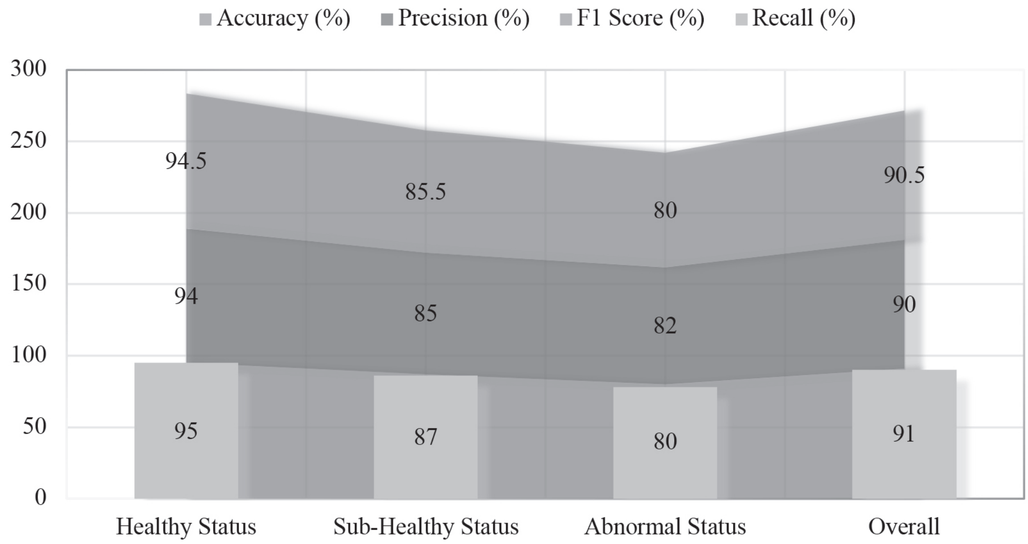

Figure 3 Model training and testing results.

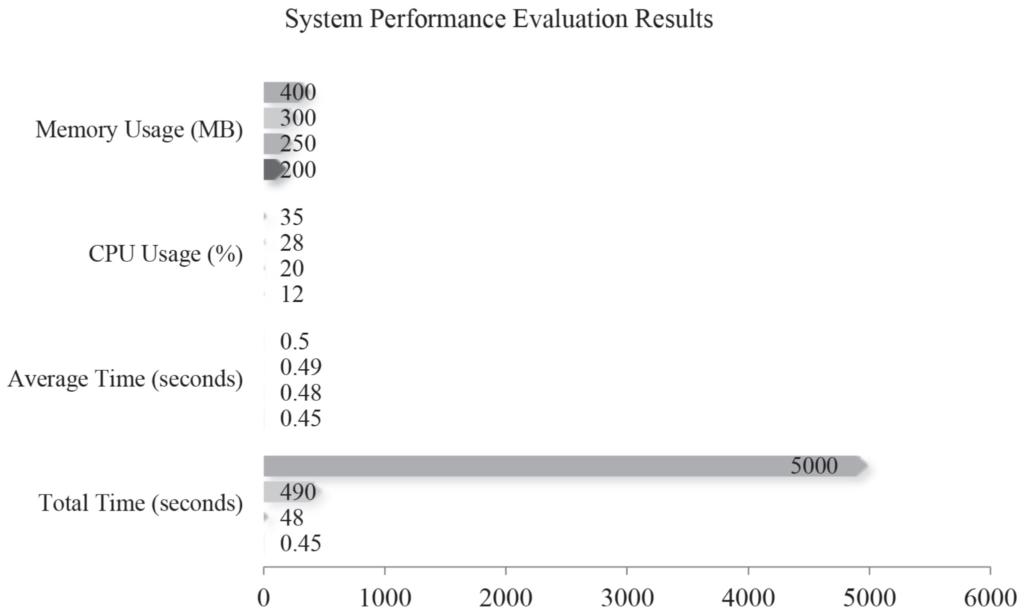

Figure 4 Results of system performance evaluation.

3.2 Discussion

3.2.1 Problem Summary

The students' mental health dynamic monitoring and prediction system based on big data has reached a high level in regard to classification accuracy and operation efficiency, but there are still several problems that need to be addressed and overcome. The classification performance of different mental health statuses is different. The classification of health status is good, with the recall rate and accuracy rate both higher than 90%, while the classification accuracy of sub-health state and abnormal state is relatively low. The recall rate for the abnormal state is low, and the model is unable to fully capture the characteristics of a few class samples. The lack of diversity of data sources affects the generalizability of the model. The sample data in this study was derived mainly from a single region, covering different schools and student groups. However, the performance of the model declines when applied to groups with more diverse socioeconomic backgrounds and cultures. The system performance is excellent in single prediction and small-scale batch tasks, although there is still room for the optimization of resource consumption and response time in large-scale concurrent task processing.

3.2.2 Optimization Suggestions

In terms of model improvement, using the original deep neural network, a few class sample enhancement techniques were applied, such as the SMOTE algorithm. The model was retrained with other mental-health-related data by means of transfer learning to improve the classification ability of the model for sub-health and abnormal states. In terms of data expansion, the diversity of sample data should be increased. In particular, the sample should comprise the data for students from different regions and cultural backgrounds, and the generalizability of the model could be improved by combining cross-regional samples. In terms of system optimization, the introduction of distributed computing architecture will improve the concurrent processing capability of the system, optimize the algorithms of data reading and model reasoning, and reduce the resource consumption and response time of the system under high-load scenarios.

4. CONCLUSION

Based on the demand for dynamic monitoring and prediction of students' mental health, this study constructed a monitoring and prediction system based on big data to realize the dynamic analysis and classification prediction of mental health status. By integrating education management system data, questionnaire survey results and external environment variables, the study built a comprehensive data collection framework, and adopted a deep neural network model to improve the classification and prediction of students' mental health status. The experimental results show that the system performs well in terms of classification accuracy and operational efficiency, and can meet the actual needs of mental health monitoring.

However, there is still room for improvement in the classification of different mental health state categories, especially in the recognition of abnormal states. Combined with the suggestions for improving model optimization and data extension, it is expected that the prediction ability and generalizability of the system will be further enhanced. At the same time, the dynamic monitoring and intervention path proposed by the study provides scientific decision-making support for educational administrators and practical programs for students' mental health management. Future studies can continue to expand the diversity of data sources, optimize the processing capacity of the system, and explore the implementation effects of different interventions to provide richer support for applications in the field of mental health.

REFERENCES

1. Chen C. Design of intelligent education decision support system based on big data analysis. Engineering Intelligent Systems. 2024; 30(4): 289–298.
2. Wu XB, Liang LP, Chen SY. How big data alters value creation: through the lens of big data competency. Management Decision. 2022; 60(3):707–734.
3. Qiao S, Li XM, Olatosi B, Young SD. Utilizing big data analytics and electronic health record data in HIV prevention, treatment, and care research: a literature review. AIDS Care. 2024; 36(5):583–603.
4. Cornelli G, Doerr S, Gambacorta L, Tissot B. Big data in Asian central banks. Asian Economic Policy Review. 2022; 17(2):255–269.
5. Xu FF, Nash N, Whitmarsh L. Big data or small data? A methodological review of sustainable tourism. Journal of Sustainable Tourism. 2020; 28(2):144–163.
6. Rialti R, Marzi G, Ciappei C, Busso D. Big data and dynamic capabilities: a bibliometric analysis and systematic literature review. Management Decision. 2019; 57(8):2052–2068.
7. Rooney ME, Burstein M, Acri M. Developing Optimized School-Based Mental Health Interventions: National Institute of Mental Health (NIMH) Priorities and Opportunities. School Ment Health. 2024; 16(3):919–923.
8. Ozota GO, Sabastine RN, Uduji FC, Okonkwo VC. Nigeria mental health law: Challenges and implications for mental health services. South African Journal of Psychiatry. 2024; 30:a2134.
9. da Costa TP, da Costa DMB, Murphy F. A systematic review of real-time data monitoring and its potential application to support dynamic life cycle inventories. Environmental Impact Assessment Review. 2024; 105:107416.
10. Rosado-Solomon EH, Koopmann J, Lee WYT, Cronin MA. Mental health and mental illness in organizations: A review, comparison, and extension. Academy of Management Annals. 2023; 17(2):751–797.
11. Andrade C, Tavares M, Soares H, Coelho F, Tomás C. Positive mental health and mental health literacy of informal caregivers: A scoping review. International Journal of Environmental Research and Public Health. 2022; 19(22):15276.
12. Righetti F, Duric M, Hofmann W, Finkenauer C. Self-regulation in close relationships. Personal Relationships. 2022; 29(4):674–698.
13. Petrokas R, Kavaliauskas D. Concept for genetic monitoring of hemiboreal tree dynamics in Lithuania. Land. 2022; 11(8):1249.
14. Maswanganye SE, Dube T, Mazvimavi D, Jovanovic N. Remotely sensed applications in monitoring the spatio-temporal dynamics of pools and flows along non-perennial rivers: a review. South African Geographical Journal. 2022; 104(4):427–445.
15. Joung J, Kim KH, Kim K. Data-driven approach to dual service failure monitoring from negative online reviews: Managerial perspective. 2021; 11(1):2158244020988249.
16. Harris TB, Udoetuk SC, Webb S, Tatem A, Nutile LM, Al-Mateen CS. Achieving mental health equity: Children and adolescents. Psychiatric Clinics of North America. 2020; 43(3):471–485.
17. Stange JP, Kleiman EM, Mermelstein RJ, Trull TJ. Using ambulatory assessment to measure dynamic risk processes in affective disorders. Journal of Affective Disorders. 2019; 259:325–336.
18. Lewinski AA, Jazowski SA, Goldstein KM, Whitney C, Bosworth HB, Zullig LL. Intensifying approaches to address clinical inertia among cardiovascular disease risk factors: A narrative review. Patient Education and Counseling. 2022; 105(12):3381–3388.
19. Osinska V, Matusiak KK, Kowalska M, Bednarek-Michalska B, Malak P. Distribution of date elements and its relationship to the types of digital libraries: Analysing aggregated metadata of a Polish large-scale distributed system. Journal of Librarianship and Information Science. 2019; 51(3):710–720.
20. Tamás M, Potocarova A, Konecna B, Klucar L, Mackulak T. Wastewater sequencing - An innovative method for variant monitoring of SARS-CoV-2 in populations. International Journal of Environmental Research and Public Health. 2022; 19(15):9749.
21. Waqas M, Xu SH, Hussain S, Aslam MU. Control charts in healthcare quality monitoring: a systematic review and bibliometric analysis. International Journal for Quality in Health Care. 2024; 36(3):mzae060.