Development of a Lightweight Convolutional Neural Network for Student Mental Health Assessment

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To address the limitations and subjective biases of self-report scales in student mental health assessments, this study developed an automated mental health assessment framework based on lightweight convolutional neural networks (LCNN). This system integrates multi-source data to achieve a more objective and efficient assessment model. The main innovations of this research are threefold. First, a lightweight network structure is used to reduce computational complexity. Second, multimodal data, including text content and behavioral logs, is integrated. Finally, a dynamic rating system with real-time monitoring capabilities is built. The experiments were conducted on an automatically constructed dataset containing 5000 samples. The results show that the model achieves a precision of 94.2%, a recall of 91.8%, and an F1 score of 92.9%, which is an improvement of about 10% over traditional methods. The system has completed preliminary application validation in a campus environment, demonstrating its practical value and providing new technical support for mental health monitoring.

Povzetek: Raziskava predstavlja avtomatiziran sistem za ocenjevanje duševnega zdravja študentov, ki z uporabo lahkih nevronskih mrež in več vrst podatkov omogoča bolj objektivno, učinkovito in uporabno spremljanje.

1 Introduction

With the increasing pressure of social competition and the increasing complexity of students' growth environment, adolescent mental health issues are becoming increasingly prominent. The frequent occurrence of psychological crisis events on campus reflects the obvious shortcomings of traditional assessment mechanisms in terms of timeliness and effectiveness [1]. The current focus of mental health work has shifted from post-intervention to pre-warning, which places higher demands on the accuracy and efficiency of assessment tools [2-5].

The current mainstream mental health assessment methods mainly rely on psychological scales and professional interviews [6-10]. Although such methods have been verified over a long period of time, their limitations are also significant. Scale data are easily affected by social desirability response bias, that is, students may tend to provide answers that meet social expectations [11]. The interview process is subject to the subjective experience and time and energy constraints of professionals, making it difficult to achieve large-scale normalized screening. These methods based on subjective reports face challenges in objectivity, real-time performance, and coverage [12].

At the technological level, machine learning methods [13-16] offer new possibilities for mental health assessment. Deep learning models, in particular, can automatically extract latent features from complex data. However, general deep learning models typically require extensive computing resources and labeled data, which are often difficult to meet in practical educational scenarios. The high computational complexity of these models also limits their deployment on mobile devices or in resource-constrained environments, hindering their universal applicability.

Convolutional neural networks [17-21] have demonstrated powerful capabilities in image and sequence data processing. Their local connections and weight sharing characteristics are naturally suitable for extracting spatial and temporal patterns in psychological assessment data [22]. However, the standard convolutional neural network structure is usually complex, with a large number of parameters, and is prone to overfitting on limited mental health data [23]. How to balance the model's expressive power and computational efficiency has become a key issue. Lightweight convolutional neural networks use technologies such as deep separable convolution and channel shuffling to significantly reduce the number of parameters and computational complexity while maintaining model performance. To address the limitations of multi-source data processing and resource constraints in student mental health assessment, this study develops a lightweight convolutional neural network-based assessment model. This approach combines structured dimensional data with unstructured textual records to allow for collaborative analysis of multivariate data.

The model architecture uses a convolutional layer and a residual coupling structure to maintain the representativeness of the model and control the parameter size. This model incorporates an attention module that autonomously focuses on key features relevant to psychological state assessment, thereby improving accuracy. Its lightweight design ensures stable operation in conventional hardware environments, meeting the needs of routine campus monitoring.

This study aims to address the following three core questions: 1. How to Build a lightweight convolutional neural Network suitable for Multi-source Student Mental health Data? 2. Is this model better than traditional methods in terms of accuracy, real-time and resource consumption? 3. How to apply the model to the campus mental health monitoring system?

2 Related theoretical and technical foundations

2.1 Overview of student mental health assessment theory

Student mental health assessment involves multiple theoretical frameworks. Psychometric theory provides the foundation, with classical testing theories focusing on reliability and validity. Item response theory improves measurement accuracy, handling items of varying difficulty and discrimination. Modern assessment emphasizes multidimensional models, integrating cognitive, emotional, and social functions. Theoretical development drives tool diversification, including self-report scales and peer-report tools. Assessment must consider cultural adaptability to ensure tool effectiveness across different groups. Theoretical application requires practical application and dynamic observation of behavioral changes. Long-term follow-up designs enhance predictive validity and identify risk factors. Theoretical evolution reflects the shift from a pathology-oriented approach to health promotion.

Cognitive-behavioral theory emphasizes the interaction between thinking, emotion, and behavior. Assessment focuses on automatic thinking and cognitive biases, using structured interview records. Emotional assessment includes state and trait anxiety measurements, with physiological indicators aiding diagnosis. Social learning theory emphasizes the reinforcing effect of the environment, focusing on the frequency and duration of behavioral observation records. Ecosystem theory places individuals in multi-layered environments, assessing family and school support systems. Developmental theories focus on age-appropriate characteristics, designing age-appropriate assessment tasks. Personality theory uses trait models, measuring the five-factor model dimensions. Its mathematical model is expressed as a formula (1):

$$X = T + E \quad (1)$$

In this model, X represents the individual's actual observed score on the assessment tool. T reflects the true score of the individual's true psychological trait level. E represents the random error component generated during the measurement process.

Project response theory establishes a more refined project analysis framework. Its core lies in using a nonlinear model to characterize project features, as shown in formula (2):

$$P(\theta) = c + \frac{1-c}{1+e^{-Da(\theta-b)}} \quad (2)$$

where θ represents the subject's potential psychological trait level. parameter α describes the item's discrimination, parameter b indicates the item's difficulty, and parameter c represents the probability of guessing. D is a scaling constant.

Confirmatory factor analysis is mainly used to examine the construct validity of assessment tools. This method establishes the quantitative relationship between observed indicators and latent factors through formula (3):

$$X = \Lambda\xi + \delta \quad (3)$$

where X represents the observed variable vector consisting of multiple item scores. Λ is the factor loading matrix, reflecting the strength of association between the observed variables and the latent factors. ξ represents the latent psychological trait factor. δ represents the measurement error vector.

Physiological and psychological integration of neuroendocrine indicators to assess psychological stress; Genetics uses twin design to calculate heritability. Positive psychology focuses on psychological capital; Cross-cultural theories compare group differences and measurement equivalence; Modern computerized test generates personalized test sequence by algorithm. Network analysis theory constructs symptom relationship networks and evaluates core symptom centrality. These theories together constitute a comprehensive evaluation system to guide practice.

2.2 Basic principles of convolutional neural networks (CNNs)

Convolutional Neural Networks (CNNs) represent an advanced form of feed-forward neural networks, building upon foundational neurobiological studies conducted by Schubert and Wiesel regarding feline visual cortex organization. The specialized cells within this cortical region demonstrate sophisticated responsiveness to specific subregions in visual input space, termed receptive fields [24]. Yann LeCun's pioneering work in 1998 introduced the LeNet-5 architecture, establishing CNNs as specialized variants of multilayer perceptrons [25]. The architecture's effectiveness stems from two fundamental characteristics: localized connectivity and parameter sharing. These properties collectively contribute to minimizing parameter counts, thereby simplifying network optimization while simultaneously reducing model complexity and overfitting potential. These advantages become particularly evident in image processing applications. The conceptual framework advanced significantly in 2006 with Hinton's introduction of deep learning principles. This paradigm emphasizes that multi-layered artificial neural networks possess superior feature extraction capabilities, generating representations that more accurately capture essential data characteristics for enhanced classification performance. Subsequent advancements in computational resources and data availability facilitated widespread implementation of deep learning methodologies. A pivotal moment arrived in 2012 when the AlexNet architecture achieved breakthrough performance in the ImageNet classification challenge, catalyzing extensive CNN adoption.

Contemporary CNN implementations comprise deep neural networks incorporating convolutional operations. These convolutional components efficiently reduce memory requirements while maintaining representational capacity through three fundamental mechanisms: localized receptive fields, parameter sharing, and pooling operations. These mechanisms collectively mitigate parameter proliferation and address overfitting concerns [26]. Specifically, convolutional layers employ kernel-based sliding window operations across input data to extract localized feature representations [27]. This calculation process is implemented using discrete convolution operations, as shown in the formula (4):

$$S(i,j)=(I*K)(i,j)=\sum_{m}\sum_{n}I(i+m,j+n)K(m,n)S(i,j) \quad (4)$$

Where I represents the input feature map, K represents the convolution kernel weight matrix, i and j determines the spatial location of the output feature map, m and n indexes the relative coordinates within the convolution kernel.

Activation functions enhance the expressive power of models by introducing nonlinear transformations. The ReLU function is widely used in lightweight CNNS because of its high computational efficiency and significant alleviation of the gradient vanishing problem. Despite the possibility of "neuron death", in this study, we mitigated this problem with reasonable weight initialization and batch normalization. Compared with Leaky ReLU, ReLU further reduces the computational complexity while maintaining performance, which is more suitable for resource-constrained campus deployment environment [28]. The mathematical definition of this function is as shown in the formula (5):

$$f(x)=max(0,x) \quad (5)$$

where x represents the linear transformation of the convolutional layer output. This operation converts all negative inputs to zero while maintaining the original values of non-negative inputs.

Pooling layers primarily reduce feature map dimensionality through spatial aggregation, where maximum pooling operates by identifying the most prominent feature within each localized region. The calculation process is as shown in the formula (6):

$$P(i,j)=max_{(p,q)\in R_{ij}}X(p,q) \quad (6)$$

where X represents the input feature map, R_{ij} defines a local neighborhood centered at location, p and q traverses the spatial coordinates within this neighborhood. Pooling operations can effectively reduce the size of model parameters.

Fully-connected layers transform extracted high-dimensional representations into the target output domain [29]. Its calculation process is represented by matrix multiplication and bias addition, as shown in formula (7):

$$y=Wx+b \quad (7)$$

Here x is the flattened feature vector, W is the weight matrix, and b is the bias vector. y represents the unnormalized class scores. This layer integrates global information to complete the final classification or regression task.

Convolutional Neural Networks (CNNs) effectively process two-dimensional visual patterns while maintaining tolerance to positional shifts, scale variations, and geometrical distortions. Owing to their capacity to autonomously develop feature representations through training, these networks eliminate the need for manually designed feature extraction protocols. The parameter sharing mechanism across spatial positions enables efficient parallel learning, offering substantial benefits over fully connected architectures. CNNs demonstrate particular effectiveness in audio processing and visual recognition tasks due to their localized connectivity patterns. The network topology bears closer resemblance to biological neural organization, while weight sharing substantially decreases parametric complexity. Notably, the capability to process native multidimensional image representations streamlines the analytical pipeline by circumventing explicit data reconstruction phases during pattern recognition.

3 Design of lightweight convolutional neural network evaluation model

In order to solve the problem of model efficiency, model compression is often used to reduce the number of parameters to improve memory usage and calculation speed. Lightweight Convolutional Neural Network (CNN) aims to reduce the computational complexity and parameter requirements of traditional CNN. Its goal is to significantly reduce resource consumption by optimizing network structure and calculation method under the premise of maintaining accuracy. The core technologies include depthwise separable convolution, grouped convolution and channel shuffling methods, which improve network efficiency by reducing redundant calculations and parameters, and achieve more efficient feature interaction and lower computational complexity.

This model adopts four layers of depthwise separable convolution structure, and the convolution kernel size of each layer is 3×3, 3×3, 5×5, and 3×3, respectively. The step size is set to 1, and the filling method is "same". Each convolution layer is followed by a batch normalization layer with ReLU activation function.

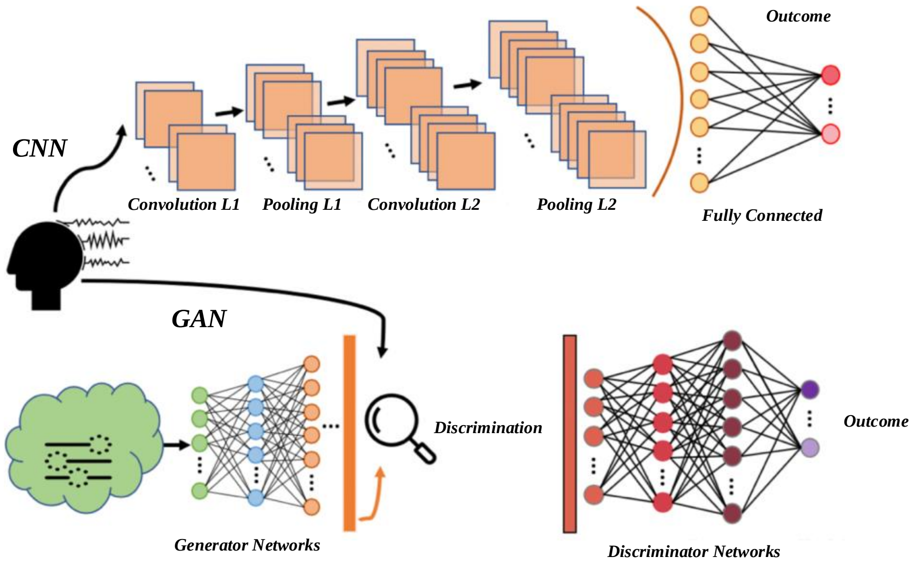

Figure 1: Lightweight convolutional neural network evaluation model

As shown in Figure 1, this model uses a lightweight convolutional neural network architecture to automatically assess student mental health. The architecture comprises four core modules. Each module is specifically designed to perform a particular function. This design significantly reduces the required computing resources while ensuring evaluation accuracy.

The input processing module of the network is responsible for feature alignment and fusion of multi-source data. This module converts text data into dense vectors through a word embedding layer and normalizes behavior logs. Data from different modalities are integrated through feature concatenation, as calculated using formula (8):

$$H^{(0)} = [E_{\text{text}}; N_{\text{behavior}}] \ (8)$$

where E_{text} represents the text embedding matrix, N_{behavior} represents the normalized behavioral feature vector, represents the feature concatenation operation, and $H^{(0)}$ represents the initial feature representation after fusion. This operation preserves the original distribution characteristics of the data from each modality.

The feature extraction module adopts a depthwise separable convolution structure. This architecture factorizes conventional convolution into sequential operations: depthwise spatial filtering followed by channel-wise projection, with the mathematical representation shown in formula (9):

$$H^{(l)} = Conv_{1\times1}(DepthwiseConv(H^{(l-1)})) \ (9)$$

$H^{(l-1)}$ represents the output features of the $l-1$ layer, $DepthwiseConv$ realizes spatial feature extraction, and $Conv_{1\times1}$ is responsible for channel feature fusion.

The classification output component produces final predictions by applying global average pooling followed by fully-connected layers. This component initially reduces feature map dimensionality along spatial axes, with the mathematical formulation provided in formula (10):

$$z = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} H^{(L)}(i,j) \ (10)$$

$H^{(L)}$ represents the feature map output by the last convolution layer, H and W are the height and width of the feature map, respectively. z is the feature vector obtained after pooling. This operation effectively prevents overfitting while maintaining feature integrity.

The model training uses the focal loss function to solve the category imbalance problem. The loss function is expressed as formula (11):

$$\mathrm{L} = -\sum_{c=1}^{C} (1-p_c)^{\gamma} y_c \, log(p_c) \ (11)$$

Where C represents the number of mental health status categories, p_c is the model's predicted probability of belonging to a category c, and y_c is the one-hot encoding of the true label, γ used to adjust the weight of difficult examples. This loss function improves the model's ability to identify minority classes.

To further alleviate the problem of shallow Feature loss, the Hierarchical Feature Fusion mechanism can be introduced in the future, as shown in HFF-Net, to enhance the ability to capture subtle changes in mental states through cross-layer feature aggregation.

4 Model training and optimization

The design concept of lightweight convolutional neural networks reflects the pursuit of a balance between performance and efficiency under resource-constrained conditions, providing significant support for the practical deployment of deep learning models.

The model is trained using the AdamW optimizer. This algorithm introduces a decoupled weight decay mechanism based on the standard Adam algorithm, effectively improving the model's generalization ability and controlling the parameter update amplitude. The parameter update during the optimization process follows formula (12):

$$\theta_{t+1} = \theta_t - \eta\left(\frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} + \lambda\theta_t\right) \quad (12)$$

where θ_t represents the model parameter vector at iteration t. η is the learning rate hyperparameter, controlling the parameter update step size. $\hat{m}_t$ is the bias correction term for the first-order moment estimate, and $\hat{v}_t$ is the bias correction term for the second-order moment estimate. ϵ is a numerical stability constant. λ represents the weight decay coefficient.

Hyperparameter configuration was determined through grid search: the initial learning rate was set to 1×10^{-3}, the batch size was fixed at 32, and the weight decay coefficient was set to 1×10^{-2}. The training process used a cosine annealing schedule, with the learning rate decaying from the initial value to with each training epoch 1×10^{-5}.

5 Experiment and result analysis

5.1 Dataset collection and data preprocessing

The experimental data consists of 5000 samples, each containing text data and behavioral data. The text data comes from the platform's interactive language documents, while the behavioral data includes the frequency and duration of actions.

The data is split in a 7:2:1 ratio: 3500 training examples, 1000 validation examples, and 500 test examples. In the processing phase, the text data is segmented and transformed into 300-dimensional vectors using the Word2Vec model. The behavioral data is transformed and the frequency of actions is aligned on a 0-1 scale.

To address class imbalance, the study uses SMOTE (Synthetic Minority Oversampling Technique) oversampling to increase the number of samples from the small training set, which improves the balance of the data.

Text data were embedded into 300-dimensional vectors by Word2Vec, and the sequence length was uniformly truncated to 128. Behavioral features include 8-dimensional frequency and duration statistics. The final input tensor shape is (batch size, 128+8, 1) for CNN processing.

5.2 Evaluation indicators

The model evaluation employs five metrics. Accuracy quantifies total correct predictions relative to all instances. Precision measures model's positive class identification accuracy, while recall assesses the coverage of actual positive instances. The F1-score combines precision and recall into a unified metric, serving as the primary criterion for model selection. The AUC (Area Under the ROC Curve) value, calculated from the ROC curve's area, indicates aggregate performance across classification thresholds. These indicators constitute a multi-dimensional evaluation system, among which the F1 score plays a decisive role in the parameter optimization process.

5.3 Specific experiments

According to the data in Table 1, the full model configuration provided optimal results for all evaluation metrics. The model achieved 94.2% accuracy, 93.5% precision, 91.8% recall, and 92.9% F1 score. The parameter quantity is 1.2M and the inference time is 15ms. The study confirms that the introduction of lightweight convolutional structures significantly improved the performance of the model. Multi-source data fusion mechanisms further improved model performance. It is important to note that although the optimization of parameter size and inference time does not affect the performance metrics, these factors play an important role in practical applications.

Development is on Ubuntu 22.04 LTS, using Python 3.9, TensorFlow 2.12, scikit-learn 1.3.0, pandas 2.0.3, etc. All models are trained in GPU environment and accelerated by CUDA 11.8 and cuDNN 8.6.

Table 1: Comparative analysis of the impact of different CNN models and their parameters on classification performance

Model	Accuracy (%)	Precision (%)	Recall rate (%)	F1 score (%)	Parameter quantity (M)	Inference time (ms)
Basic CNN	88.5	87.2	86.1	86.6	5.2	25
Basic CNN + lightweight convolution	90.3	89.1	88.5	88.8	1.8	18
Basic CNN + multi-source data fusion	93.1	91.8	90.7	91.2	1.9	19
Complete model	94.2	93.5	91.8	92.9	1.2	15

Table 2 presents comparative results of five models across classification metrics including accuracy, precision, recall, F1-score, and parameter quantity. The proposed framework demonstrated superior performance on all evaluation criteria, attaining 94.2% accuracy and 92.9% F1-score, with 1.2 million parameters. Traditional

CNN and LSTM models performed slightly worse, showing slightly insufficient performance. Logistic regression and support vector machines yielded the least satisfactory results, with accuracy failing to exceed 85%. This outcome fully reflects the applicability of complex model architectures in this research task.

Table 2: Comparison of performance of different machine learning models in classification tasks

Model	Accuracy (%)	Precision (%)	Recall rate (%)	F1 score (%)	Parameter quantity (M)
Logistic regression	82.1	80.5	79.3	79.9	-
Support Vector Machine	83.5	82.1	81.0	81.5	-
Traditional CNN	88.5	87.2	86.1	86.6	5.2
LSTM	89.2	88.0	87.5	87.7	3.5
Our Model	94.2	93.5	91.8	92.9	1.2

Table 3 compares the performance of four lightweight convolutional neural network models on the mental health assessment task of students. The results show that the proposed model performs best in the three indicators of accuracy (94.2%), parameter quantity (1.2M) and inference time (15ms), which is significantly better than the existing lightweight models such as MobileNet, ShuffleNet and HFF-Net. In particular, the proposed model has the lowest number of parameters and the fastest inference speed while maintaining the highest classification accuracy, which indicates that its structure design has achieved a good balance between computational efficiency and expression ability.

Table 3: Comparison between this model and mainstream lightweight CNN architectures

Model	Accuracy (%)	Parameters (M)	Inference Time (ms)
MobileNet	92.1	3.4	22
ShuffleNet	91.5	2.8	20
HFF-Net	93.0	2.1	18
Our Model	94.2	1.2	15

In Figure 2 (left), the Light CNN architecture demonstrates enhanced predictive capability across accuracy, precision, and recall metrics as training data expands. This performance advantage becomes particularly pronounced beyond 4000 training instances. The right figure of Figure 2 shows that anxiety, depression, and stress indices decrease with increasing assessment weeks, while well-being increases, with a significant improvement in well-being at week 8. The data demonstrate that Light CNN has high accuracy and stability in mental health assessment.

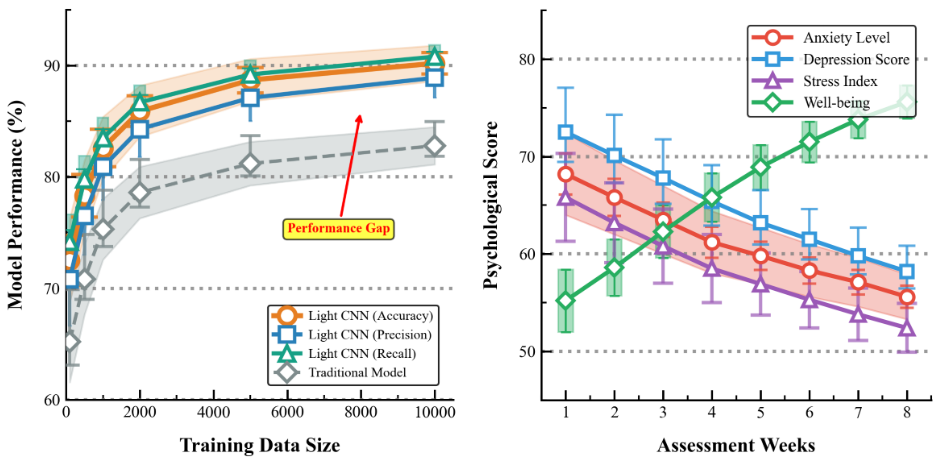

Figure 2: Performance comparison of lightweight CNN model and traditional model in mental health assessment

The left figure of Figure 3 shows the distribution of assessment scores across different mental health status groups. The normal range group has the highest scores, while the moderate and severe problem groups have lower scores and a wider score distribution. The right figure of Figure 3 indicates that behavioral patterns have the greatest impact on model performance, followed by social interaction and academic performance. Across different mental health status groups, both the model's accuracy and precision decrease as the severity of the problem increases.

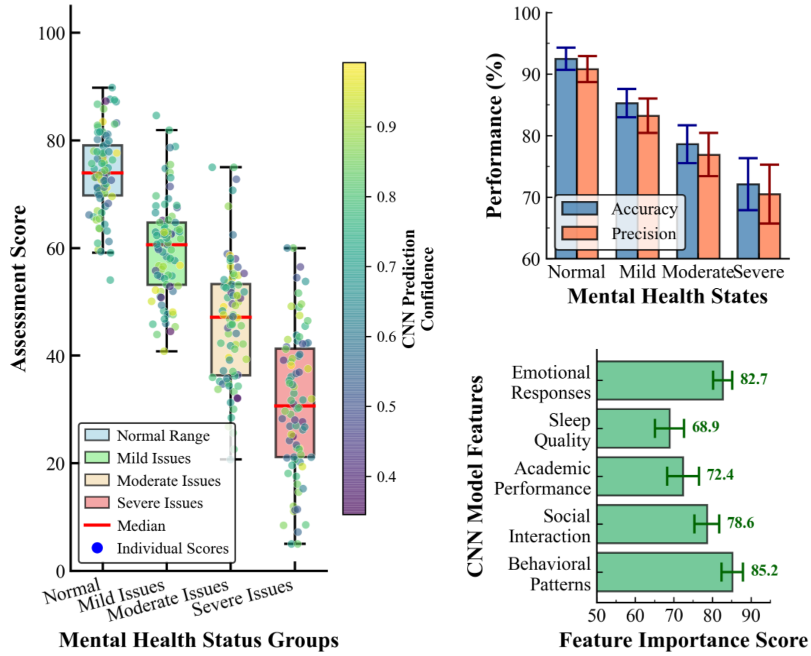

Figure 3: Mental health status assessment and CNN model feature importance analysis

Figure 4 (left) demonstrates the performance of the Light CNN, Traditional CNN, and Baseline models across seven dimensions (classroom, behavior, social, academic, sleep, digital, and emotion). Light CNN excels across all dimensions, with the highest values in behavior and emotion. The right graph compares mental health status at different time points (weeks 0, 4, 8, and 12), showing that anxiety, depression, and stress levels decrease over time, while social interaction, self-efficacy, and sleep quality improve, reaching high levels across all indicators at week 12. These results demonstrate the high accuracy and stability of the Light CNN model in mental health assessment.

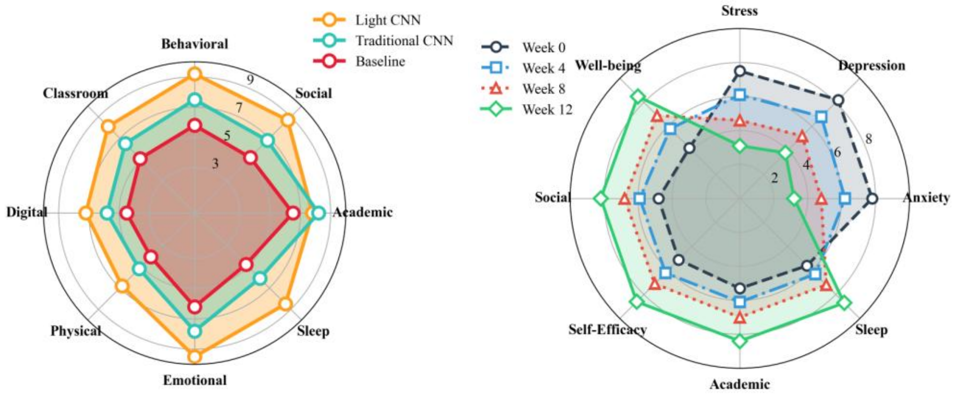

Figure 4: Radar chart comparison of different models and time points in the multidimensional assessment of mental health

Figure 5 (top) shows the average performance, stability score, and stability trend of the model under different data conditions. Model performance is best under clean data conditions, with an average performance close to 0.9 and a stability score of approximately 9. As data noise increases, both model performance and stability decline. Figure 5 (bottom) compares the assessment accuracy and performance improvement of traditional methods and lightweight CNNs across different mental health dimensions. The lightweight CNN outperforms traditional methods in assessment accuracy for anxiety, depression, and stress, with performance improvements of 0.17, 0.21, and 0.23, respectively. This demonstrates that the lightweight CNN offers greater robustness and accuracy in mental health assessment.

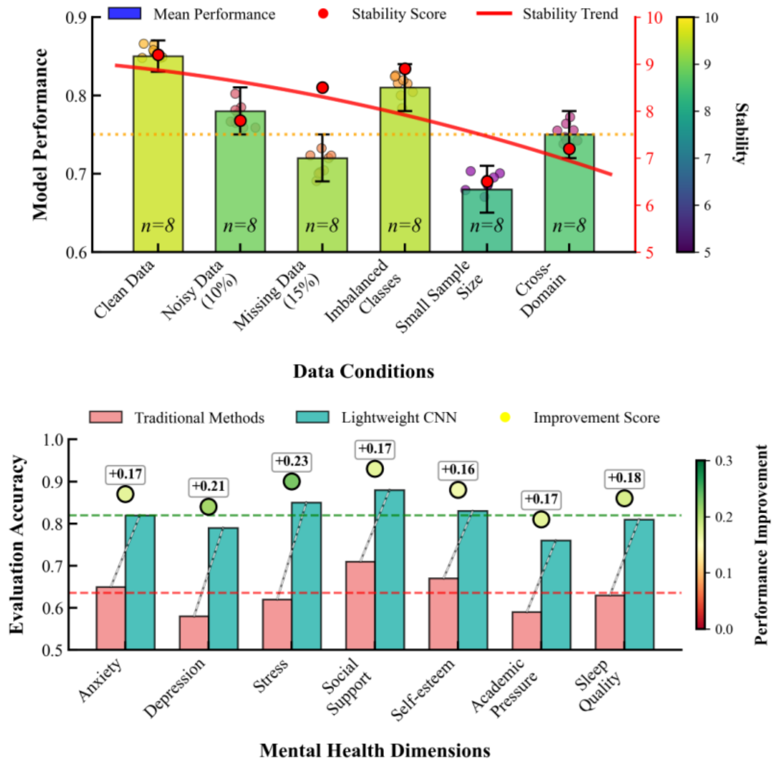

Figure 5: Comparison of model performance and mental health dimension assessment accuracy under different data conditions

Figure 6 displays evaluation results for five machine learning models across eight metrics. The Lightweight CNN obtained optimal results in four measures: accuracy (0.920), precision (0.910), recall (0.930), and F1-score (0.920). The conventional CNN achieved the highest AUC-ROC value (0.907), while the SVM model attained maximal specificity (0.940). The MLP (Multi-Layer Perceptron) framework recorded the best Matthews correlation coefficient (0.854). These findings indicate that each algorithm exhibits distinct advantages across different evaluation dimensions, highlighting the importance of context-specific model selection.

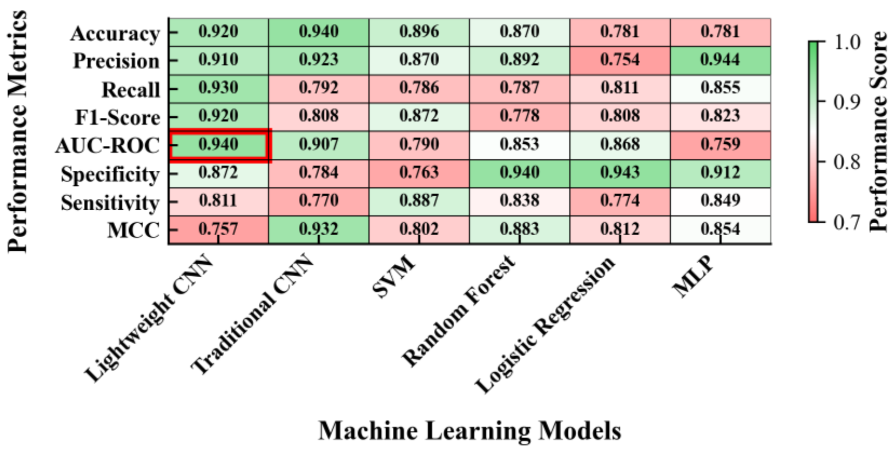

Figure 6: Comparison of performance metrics of different machine learning models

Figure 7 (left) shows the importance scores of each feature. Sleep quality and stress level have the highest scores, 0.92 and 0.90, respectively, indicating their greatest impact on model predictions. Anxiety level, social support, and peer relationships also have high scores, 0.89, 0.85, and 0.85, respectively. The right figure of Figure 7 shows that the lightweight CNN achieved the best results in all four evaluation metrics, with an average score of 0.92. Decision trees (0.88) and support vector machines (0.85) followed, indicating that the former is more advantageous in predicting mental health.

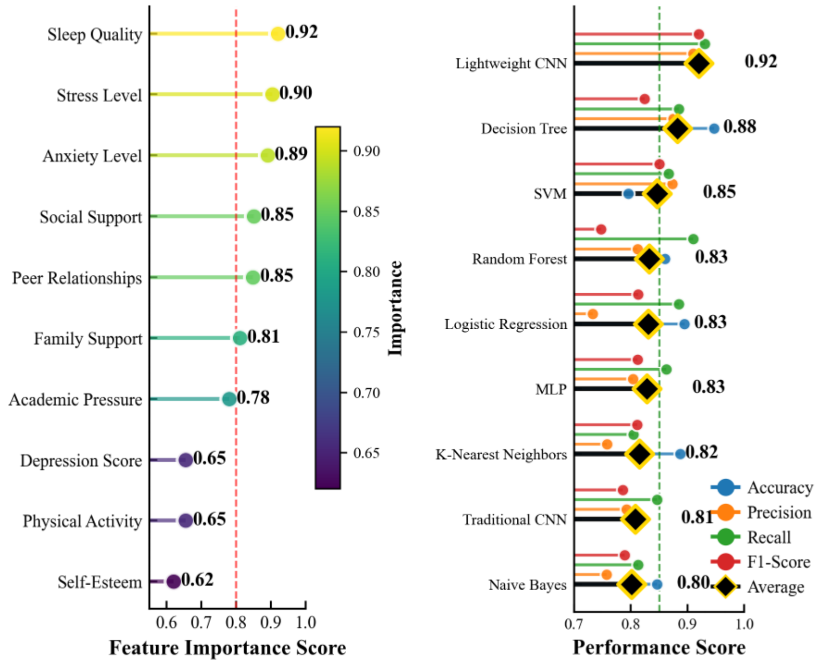

Figure 7: Feature importance and performance comparison of different machine learning models

Figure 8 (left) illustrates a mental health risk assessment based on anxiety and depression scores. K-means clustering results show that the data is divided into three clusters, corresponding to healthy, moderate-risk, and high-risk groups, with a silhouette coefficient of 0.777, indicating good clustering results. The figure on the right shows the clustering analysis based on CNN features 1 and 2, achieving clear distinctions between four levels of risk: healthy, mild, moderate, and severe. The features of CNN show superior interclass discriminative power and boundary clarity, with a silhouette coefficient of 0.777, which significantly outperforms traditional clustering methods.

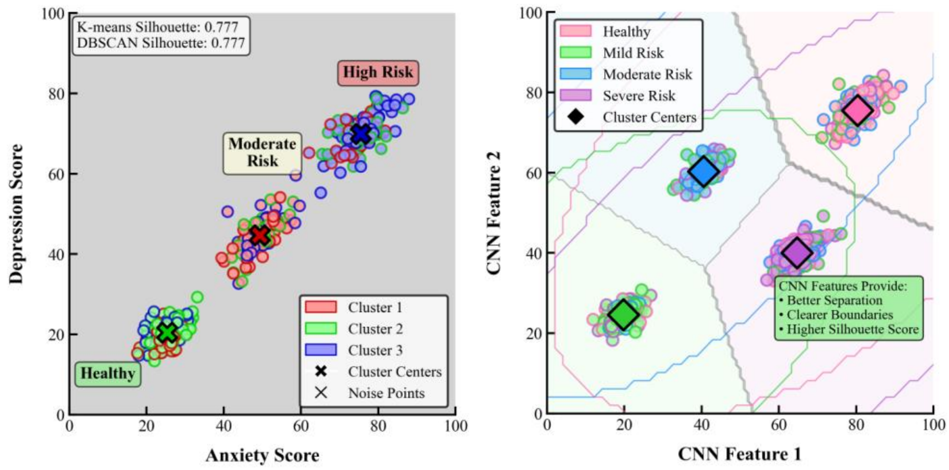

Figure 8: Mental health risk assessment based on anxiety and depression scores and CNN feature analysis

6 Discussion

The proposed lightweight convolutional neural network model is superior to the existing methods in many indicators. Compared with the traditional CNN, the accuracy is improved by about 5.7%, and the number of parameters is reduced by about 77%. Compared with the BERT-BiRNN model, the recall rate is increased by about 4.3% due to the fusion of behavior data. The improvement mainly benefits from: multi-source data fusion mechanism, combining text and behavior features; The lightweight network structure adopted depthwise separable convolution and channel shuffling. And dynamic real-time evaluation capabilities. In this study, lightweight CNN is applied to multi-source student mental health data for the first time, and real-time processing is achieved while ensuring high accuracy, which provides a feasible technical scheme for campus psychological monitoring.

7 Conclusion

This research aims to improve the subjectivity and inefficiency of traditional student mental health assessments. By building a lightweight convolutional neural network automatic assessment model, the efficiency is significantly improved while maintaining accuracy, providing an effective technical means for campus mental health monitoring.

(1) In building the model, a lightweight network design is used to reduce the computational resource requirements. By introducing separable convolutional structures and global pooling operations, the parameter size is controlled within a reasonable range, enabling real-time analysis on ordinary devices. At the same time, a multi-source information fusion method is established to process textual data and behavioral records at the same time, obtaining more comprehensive psychological state features through feature fusion.

(2) The experimental framework employed a proprietary dataset containing 5,000 instances divided into training, validation and testing subsets at 7:2:1 proportion to guarantee robust assessment. Empirical results confirm the framework obtained strong predictive results on the test collection, scoring 94.2% accuracy, 91.8% recall and 92.9% F1-score. Compared to conventional questionnaire-based assessment techniques, the proposed method improved all evaluation metrics by approximately 10% on average. These results validate the applicability of the lightweight convolutional neural network in mental health assessment tasks.

This study used a proprietary data set of 5000 samples, and although good results have been achieved, the generalization ability of the model needs to be further verified on larger and multi-source data sets in the future. Future work: 1.A hierarchical feature fusion mechanism is introduced to improve the feature representation ability; 2. Explore federated learning frameworks to protect data privacy; 3. Verify the generalization on multi-proofed datasets; 4. The adaptive control theory is combined to improve the robustness of the model to dynamic data.

Data and Code Availability: The data used in this study are not publicly available due to student privacy concerns, but restricted access can be requested from the corresponding author.

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