A Hippopotamus Optimization Algorithm-Based Convolutional Neural Network Model for Mental Health Assessment Among College Students

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***Abstract*—The mental health of adult students is crucial not only for enhancing their learning experience and overall quality of life, but also for alleviating academic and employment-related anxiety. A significant challenge in developing effective online mental health support systems is the accurate assessment of students' mental health status. Current evaluation methods often lack precision and fail to integrate multifaceted data perspectives. To address these challenges, this study developed a psychological assessment system based on deep learning technology. The system aims to assess adult students' psychological states and provide appropriate support. Specifically, it utilizes a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) algorithm framework to evaluate students' psychological states by synthesizing image data, academic performance, and textual inputs. Furthermore, to enhance the accuracy of deep learning-based mental health assessment models, an improved hippopotamus optimization (IHO) algorithm was designed to optimize the hyperparameters of deep learning frameworks. By using the proposed multi-input single-output hybrid IHO-based LSTM-CNN framework (IHO-LSTM-CNN), the online mental health assessment module can accurately describe the psychological status of college students and provide personalized support to meet their specific needs. The final results indicate that the IHO-LSTM-CNN framework provides more accurate assessments than existing mental health assessment models, with an accuracy of 90.28%. This enhanced accuracy enables online community psychological support systems to deliver precise and effective psychological support to college students.**

Keywords*—Convolutional Neural Network; Long Short-Term Memory; hippopotamus optimization algorithm; mental health assessment; deep learning

I. INTRODUCTION

Amid growing global concern for mental health issues, researchers are designing generative artificial intelligence (AI)-based psychological support systems that utilize generative dialogue technology [1]. However, these systems often lack accuracy in assessing users' mental health status and consequently fail to provide high-quality, tailored psychological support [2]. Concurrently, higher education institutions and educational management departments are increasingly concerned about the rising prevalence of mental health problems among adult students. To address these specific challenges, an online community psychological support system powered by generative AI is designed. This system accurately assesses the mental health status of adult students based on their inquiry statements and basic information. Subsequently, leveraging the assessment results, it generates targeted psychological support statements to effectively address their mental health concerns.

The core goal of a generative AI-based network community psychological support system is to assess adult students' psychological states online, such as anxiety, depression, and stress levels, through non-invasive, continuous data collection and analysis. A core challenge for this online assessment system is accurately evaluating the psychological status of adult students based on available data. Specifically, since adult students' psychological data typically includes multimodal information (such as text, images, behavioral patterns, etc.), the evaluation model must effectively integrate these diverse inputs. Furthermore, the psychological state of adult students can fluctuate rapidly due to academic and family pressures, requiring algorithms to possess both short-term sensitivity and long-term trend prediction capabilities.

Current algorithms for mental health assessment primarily include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), traditional Random Forest algorithms, and expert rule-based systems [3]. Among these, CNN-based models excel at text sentiment analysis and image micro-expression recognition. However, CNN algorithms struggle to model dynamic changes in psychological states. They also demand large volumes of annotated data during processing, making the acquisition of psychological labels costly and subjective. In contrast, RNNs and Long Short-Term Memory Networks (LSTMs) can effectively capture the temporal evolution of psychological states. Nevertheless, their high model complexity can lead to overfitting, consequently reducing prediction accuracy. Finally, traditional Random Forest models are typically suitable only for small-sample static scenarios and struggle with unstructured data [4].

Another key challenge in generative AI-based network community psychological support systems is effectively using this technology to provide necessary psychological support for adult students. Current psychological support models primarily include those based on large language models (LLMs), knowledge graphs, and reinforcement learning [5]. LLMs can capture nuanced information through attention mechanisms and serve multicultural student groups on cross-border online education platforms. However, they may generate inaccurate

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psychological concepts and their responses often prioritize logical analysis over emotional warmth. Knowledge graph-based psychological support models offer strong professional accuracy, but suffer from long development cycles among other limitations. Reinforcement learning-based models can dynamically optimize support strategies through user feedback. However, during early training stages, the model may generate inappropriate suggestions.

To address the limitations in generative AI-based network community psychological support systems, this study proposes a psychological assessment model for adult students using CNN and LSTM algorithms. This model comprehensively analyzes adult students' behavioral expressions, academic performance, and textual interactions within the network community to accurately evaluate their mental health status. Furthermore, the system provides essential psychological support for adult students using a reinforcement learning algorithm. This reinforcement learning-based support model incorporates a two-layer filtering mechanism: 1) The first layer intercepts high-risk content using a rule-based system. 2) The second layer detects implicitly harmful content through a classifier. Additionally, when the psychological assessment model identifies a severely depressed mental health status, the support system initiates human counselor intervention. The architecture of the mental health assessment module is depicted in Fig. 1. The main contributions of this study are summarized as follows:

- A dual-layer architecture combining CNN and LSTM model has been developed, constructing a psychological assessment model for adult students. This model integrates multimodal data sources, significantly enhancing the accuracy of mental health assessment in educational settings.
- An improved hippopotamus optimization (IHO) algorithm incorporating a hybrid mutation strategy is proposed to optimize critical hyperparameters of CNN and LSTM, thereby enhancing model performance.
- An online psychological support model utilizing reinforcement learning algorithms has been designed, capable of providing personalized psychological support to large populations of adult students.
- The results showed that the HOA-LSTM-CNN model improved accuracy by an average of 20.65% compared to the other three commonly used emotion assessment models.

The rest of this study is arranged as follows: In Section II, the models and algorithms related to this study are reviewed, and Section III mainly introduces the methodology of this study, including the mental health assessment model and psychological support system. Section IV presents the application results of the developed algorithms and models. Section V summarizes the entire text and provides future research directions.

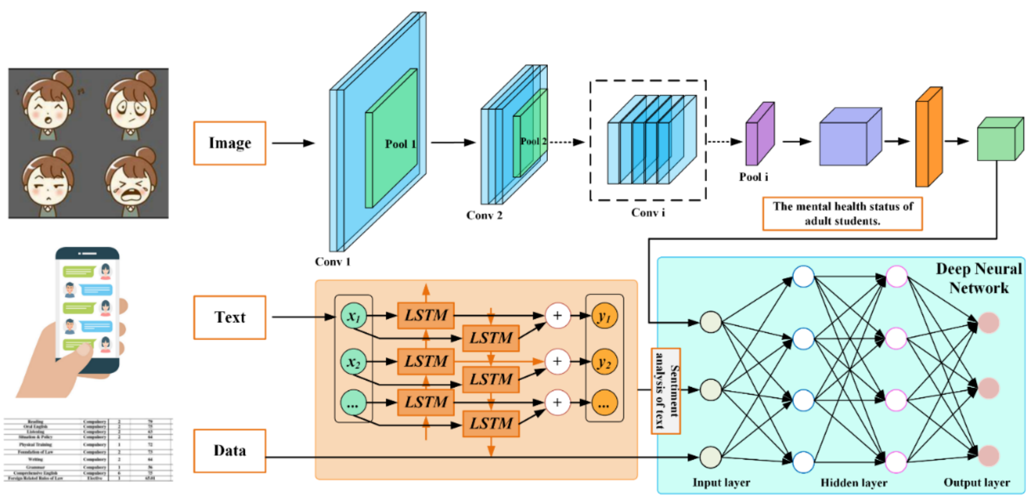

Fig. 1. The proposed framework for the mental health assessment system.

II. Related Work

The rapid development of multimodal models, machine learning, and reinforcement learning technologies has enabled the establishment of generative AI-based network community psychological support systems. In this study, the proposed online psychological support system predicts college students' mental health status using a hybrid CNN-LSTM framework, while generating psychological support dialogues through reinforcement learning models. Accordingly, this section provides a systematic review of mental health prediction models, psychological support systems, and heuristic optimization algorithms.

A. Emotion Prediction Based on Deep Learning

In [6], the authors summarize emotion classification methods based on speech data, and this study summarizes the application of deep learning techniques including convolutional neural networks (CNN), recurrent neural networks (RNN), and attention mechanisms in emotion analysis. Mou et al. [7] proposed a reader sentiment prediction framework based on news text content and comment data, which extracts news semantic features through a bidirectional Transformer encoder and synthesizes pseudo comment data using a generative model to expand the training data. Pordoy et al. [8] designed a transfer learning-based emotion recognition framework for facial emotion recognition in online education scenarios, which can combine adaptive strategies to transfer emotion analysis methods to specific educational scenarios. This study addresses the noise impact of lighting changes on image data in real classroom environments.

In [9], the authors proposed a speech emotion recognition technology for different accents, which integrates acoustic features and accent embedding vectors, and uses multi-task learning to optimize emotion classification and accent recognition tasks. This framework has been validated based on a mixed dataset containing English and Chinese dialects, providing a foundation for sentiment analysis of speech with accents. In [10], the authors developed a fake news detection model based on emotional features and proposed a multi-task learning model aimed at achieving news authenticity classification tasks and reader sentiment prediction tasks. This model is based on large-scale social media data and uses transfer learning algorithms to identify emotionally provocative language in fake news. In [11], the authors designed an end-to-end multimodal video emotion recognition system that integrates facial expressions, speech intonation, and text modalities, using a lightweight network architecture and cross-modal attention mechanism to analyze emotions in movie clips and video interviews.

B. Psychological Support Model Based on Reinforcement Learning

Generating psychological support for users based on sentiment analysis remains a significant challenge. In [12], the authors developed a moderation mediation model to investigate the impact of teacher support and family support on adolescents' psychological state during online learning. This study provides a theoretical basis for optimizing student psychological intervention strategies. In [13], the authors propose a deep learning framework for emotion recognition using deep neural networks, offering a foundation for the computable modeling of psychological phenomena. In [14], the authors developed a multimodal psychological support system for college students that utilizes facial image and voice data to recognize emotional states in real-time. Based on these recognition results, the system generates personalized virtual intervention scenarios. Experimental results demonstrated that this system significantly reduced users' psychological symptoms following intervention.

Yang et al. designed a deep learning model based on an attention mechanism to address the psychological stress of college entrepreneurs. The model takes entrepreneurial diary text, social media behavior, and physiological sensor data as input parameters, and can predict anxiety and fatigue risk levels and provide real-time intervention recommendations [15]. In order to enhance the adaptability of normative software agents, Viana et al. [16] proposed a psychological intervention system based on meta models and reinforcement learning. Case studies have shown that this language has successfully intervened in children's psychological problems in the context of child companionship robots. In [17], the authors constructed an emotion state classification system based on multimodal data. This system can integrate Electroencephalogram (EEG) band energy data and achieve emotion classification through graph convolutional networks. In [18], the authors designed an adaptive psychological support system that can analyze user behavior logs, voice emotions, and physiological signals in real-time, dynamically generate personalized intervention strategies to reduce users' mental health problems.

C. Artificial Intelligence-Based Furniture Design System

In order to construct an artificial intelligence-based furniture design system, Luo et al. combined Capsule Networks with artificial rabbits optimization (ARO) algorithm and proposed a framework for optimizing Capsule Networks hyperparameters using the ARO algorithm, aiming to enable the furniture design system to more accurately capture users' emotional feedback in virtual environments [19]. Naulia et al. [20] proposed an improved metaheuristic algorithm based on mathematical principles, aimed at optimizing the weight parameters of deep convolutional neural networks. This improved metaheuristic optimization algorithm achieves intelligent adjustment of network parameters. Finally, the study tested the improved deep learning model on multiple standard datasets, demonstrating that the improved algorithm can effectively prevent overfitting of the deep learning model.

In [21], the authors combined the Beetle Antenna Search (BAS) algorithm with a CNN to develop an efficient imaging diagnostic model. This study is based on the BASO algorithm to optimize the hyperparameters of CNN, aiming to enable CNN to efficiently learn the features of medical images, while improving diagnostic accuracy and reducing the computational complexity of CNN. In [22], the authors used the Mountain Gazelle Optimizer (MGO) to optimize the parameters of artificial neural networks. The MGO algorithm is an optimization algorithm designed by researchers inspired by the foraging behavior of mountain gazelles. After testing, it has also shown good performance in parameter optimization of artificial neural networks.

III. Proposed Mental Health Assessment System

In this section, a network-based community psychological support system is designed utilizing automatic question answering technology. At present, research has tested the application of deep learning frameworks in the psychological assessment of college students and computer vision. The framework proposed in this study is different from the previous research. Specifically, the system comprises two core modules. The first module is a mental health assessment module based on CNN and LSTM. The second module is a psychological support module leveraging reinforcement learning. Fig. 2 illustrates the architecture of the reinforcement learning-based psychological support model. For the sentiment analysis system targeting adult students, it analyzes facial expressions conveying negative emotions using a CNN. Simultaneously, it performs sentiment analysis on texts generated by these students within the online community psychological support system using LSTM. Subsequently, based on the results from both the CNN and LSTM analyses, combined with the students' normalized performance data, a comprehensive evaluation is conducted using an artificial neural network.

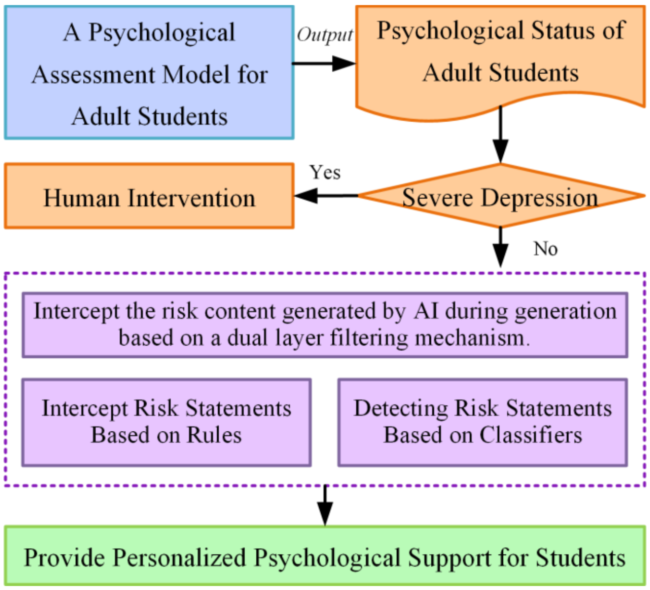

Fig. 2. A reinforcement learning-based psychological support model.

A. Hybrid LSTM and CNN (LSTM-CNN)-Based Mental Health Assessment System

The mental health assessment module adopts a deep CNN architecture, which includes multiple convolutional layers, pooling layers, and fully connected layers. This deep CNN takes pre-processed facial image data of adult students as input data, followed by multiple convolutional and pooling layers, and finally outputs the expression categories of adult students based on the classifier. The calculation formula for convolutional layers is as follows [Formula (1)]:

$$C_i = \sum_{k=1}^{K}\left[\left(w_i^k * Q_k\right) + O_i\right] \tag{1}$$

where, C_i is the $i-th$ feature map obtained through calculation. w_i^k is the $i-th$ convolution kernel on the $k-th$ channel. $*$ is the symbol for the convolution operation. Q_k is the input data on $k-th$ channel. O_i is the bias value.

The CNN framework designed for facial expression analysis uses the following loss function for training data [Formula (2)]:

$$f\left(y_{prediction}\right) = \frac{1}{4\times N}\sum_n \left|y_{prediction}(n) - y_{ture}(n)\right| \tag{2}$$

where, $f\left(y_{prediction}\right)$ A is defined as the loss function. N is the number of adult students included in the test set. $y_{prediction}(n)$ is the test value, $y_{ture}(n)$ is the true value. When the test value is consistent with the true value, $\left|y_{prediction}(n) - y_{ture}(n)\right|$ =0; Otherwise, $\left|y_{prediction}(n) - y_{ture}(n)\right| = 1$.

This study is based on LSTM for sentiment analysis of text input by adult students in online community psychological support systems. Firstly, the original text undergoes a series of pre-processing steps and is transformed into dense vectors using word embedding techniques. On this basis, the mental health assessment system adopts a bidirectional LSTM network structure, which captures long-term dependencies of text through multiple LSTM layers, and finally outputs the emotions of adult students through fully connected layers. For the bidirectional LSTM network architecture, this study uses root mean square error (RMSE) as an additional evaluation metric; therefore, the EMSE metric of LSTM is defined as follows [Formula (3)]:

$$F_{RMSE} = \sqrt{\frac{1}{N}\sum_n \left(y_{prediction}(n) - y_{ture}(n)\right)^2} \tag{3}$$

where, F_{RMSE} is the EMSE metric of LSTM. $y_{prediction}(n)$ is the test value, $y_{ture}(n)$ is the true value.

B. Improved Hippopotamus Optimization Algorithm

In order to improve the performance of CNN, meta-heuristic optimization algorithms were used in works [21]-[22] to optimize the hyperparameters of CNN. Based on this idea, this study improved the HO algorithm with the aim of optimizing the hyperparameters of CNN and LSTM to enhance their prediction accuracy. At present, the HO algorithm has been widely applied in various fields such as intelligent transportation, logistics, and robotics [23].

In this study, the IHO algorithm provides an efficient group search strategy for hyperparameter optimization of CNN and LSTM. The search process of IHO first requires defining hippo individuals that contain multidimensional information, including key hyperparameters such as learning rate, batch size, number of convolution kernels, kernel size, dropout rate, and number of fully connected layer units. Among them, the size of the convolution kernel needs to be constrained to an odd number. Each hippo individual represents a set of hyperparameter combinations in the search space, and its continuous position vector is transformed into actual usable discrete parameter values through specific rules. In addition, the fitness function of CNN and LSTM hyperparameter optimization problems based on the IHO algorithm is also a challenge in the search process. The fitness function is the core content of the IHO algorithm optimization process. In the optimization process of the IHO algorithm, the initial solution is first generated based on hyperparameters of CNN and LSTM models, trained using hyperparameters corresponding to an individual of hippopotamus, and finally evaluated using test set accuracy.

In order to improve the convergence accuracy of the HO algorithm, the proposed IHO algorithm introduces a grey wolf optimization strategy based on the HO algorithm [24]. Therefore, in the search process of the IHO algorithm, the hippopotamus population first searches for the solution space of hyperparameters through the grey wolf optimization strategy. During each iteration, each individual of hippopotamus dynamically updates their speed and position based on the historical best position of the hippopotamus population. After the position update, it is necessary to determine whether the hyperparameters meet the boundary constraints based on their characteristics, such as limiting the size of the convolution kernel to an odd number. The following is the process of the IHO algorithm:

1) Initialization: Form a set of hippo individuals by combining the hyperparameters of CNN and LSTM. The hyperparameters of CNN include the number of convolution kernels, the size and stride of pooling kernels, and the learning rate. The hyperparameters of LSTM include the number of layers and learning rate of the recurrent neural network. In Formula (4), a set of initialized hippo individuals is defined.

$$G = \begin{bmatrix} g_1^1 & g_2^1 & \cdots & g_z^1 \\ g_1^2 & g_2^2 & \cdots & g_z^2 \\ \vdots & \vdots & \vdots & \vdots \\ g_1^l & g_2^l & \cdots & g_z^l \end{bmatrix} \tag{4}$$

where, G is a set of initialized hippo individuals. g_z^l is the z-th dimension of the l-th individual, representing a hyperparameter of CNN or LSTM.

2) Wolf pack hierarchical encirclement strategy: The IHO algorithm uses a wolf pack hierarchical encirclement strategy [24] to find the optimal solution, which is defined as follows [Formula (5) and Formula (6)]:

$$\begin{cases} g_z^l(a,new) = g_z^l(a) - A_1 \times D_1 \\ g_z^l(b,new) = g_z^l(b) - A_2 \times D_2 \\ g_z^l(c,new) = g_z^l(c) - A_3 \times D_3 \end{cases} \tag{5}$$

$$g_z^l(new) = \frac{1}{3} \times \left[g_z^l(a,new) + g_z^l(b,new) + g_z^l(c,new) \right] \tag{6}$$

where, A and D are random numbers on the [0,1] interval. $g_z^l(a)$, $g_z^l(b)$ and $g_z^l(c)$ are the vectors corresponding to the three best bounds currently generated.

3) Hippopotamus location update strategy: After completing the wolf pack hierarchical search, the IHO algorithm further explores the solution space based on the hippopotamus location update strategy, as shown in Formula (7).

$$g_z^l(new) = g_z^l + StepH \times \left(D\_hippe - g_{fe}^l \right) \tag{7}$$

$$StepH = \exp\left(-\frac{t}{T} \right) \tag{8}$$

where, $StepG$ is the stride of the dispersed search by the hippopotamus population, and D_hippe is the current optimal position of the hippopotamus individual. g_{fe}^l is the position of the female hippopotamus [see Formula (8)].

4) Avoiding natural enemies strategy: After completing the location update, the IHO algorithm further searches within a small range based on the strategy of avoiding natural enemies [see Formula (9)].

$$g_z^l(new) = g_z^l + r_\beta \times \left(g_z^l - g_{fe}^l \right) \tag{9}$$

where, r_β is the avoidance coefficient.

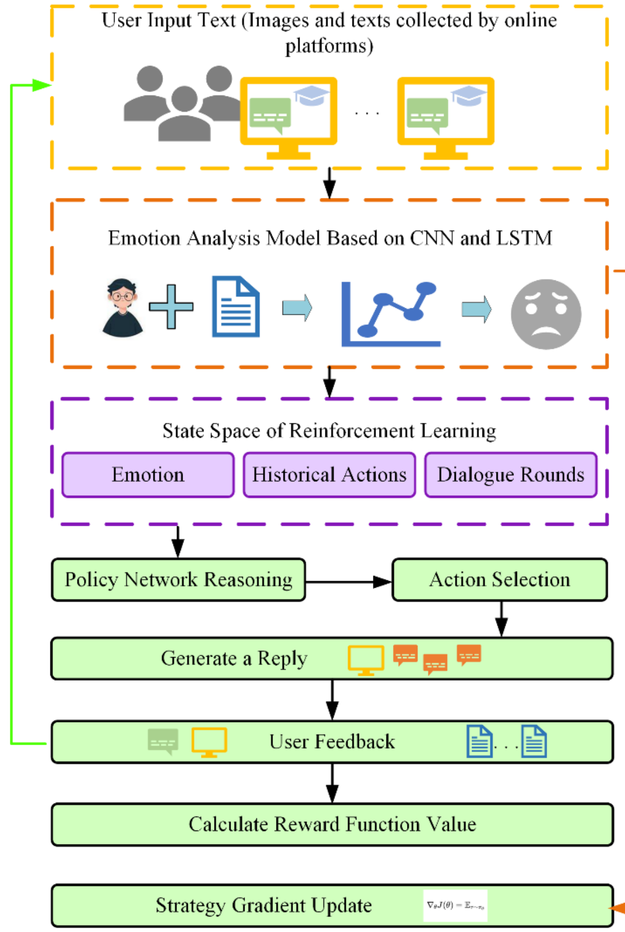

Fig. 3. A mental support system based on reinforcement learning.

C. *Reinforcement Learning-Based Mental Support System*

After evaluating the mental health status of students based on CNN and LSTM, a psychological support system was designed. As previously mentioned, a multidimensional state perception system based on CNN and LSTM has been constructed for mental health assessment. By integrating structured data (academic performance) and unstructured behavioral data (facial expressions, counseling texts, and frequency) of students in real-time, a personalized dynamic psychological profile has been formed for each user. The operational flowchart of the psychological support module is presented in Fig. 3.

The core of the psychological support system adopts a hierarchical reinforcement learning architecture, and a specialized knowledge base for psychological intervention strategies is designed at the action decision-making level. For example, when the user inputs "Final exam makes me breathless", the system first analyzes the user's psychological characteristics through the mental health status assessment module, and then activates a two-stage decision-making process:

- Surface semantic analysis based on LSTM is labeled as "academic stress" and "low mood".
- Cognitive bias detection identifies a tendency towards overgeneralization, and ultimately generates candidate action sets through strategy networks, such as mindfulness breathing guidance and psychological comfort.

Unlike conventional mental health question and answer systems, the proposed psychological support system innovatively introduces a psychological safety constraint layer: when calculating action weights, a dynamic coefficient adjustment mechanism is used to ensure that statements with high mental health risks inevitably trigger crisis intervention processes. The formula for calculating the action weight of the psychological support system is as follows [Formula (10)]:

$$DL_{action} = w_1 \times f_{cri} + w_2 \times f_{aes} + w_3 \times f_{acc} \tag{10}$$

where, w_1, w_2 ,and w_3 are weight coefficients, respectively. f_{cri} is the crisis index, f_{aes} is resource availability, and f_{acc} is user acceptance.

To adapt to the particularity of the field of mental health, the reinforcement learning based psychological support system adopts a three-stage progressive training program. In the stage of building basic abilities, the LSTM model is pre-trained based on a large amount of structured interview data, enabling it to accurately identify many types of psychological problems such as depression and anxiety. In the reinforcement learning stage, safety training is achieved through personalized simulation environments, mainly constructing various personality prototypes of college students, such as perfectionists and social anxiety sufferers. Professional psychological counselors control the simulator to generate dialogues containing poor mental health levels, and the mental health support system learns intervention strategies in this environment. In addition, the key innovation of the system lies in the dual track reward mechanism, which adds an effectiveness reward item in addition to the regular user satisfaction reward. If students perform the respiratory guidance exercises recommended by the system and there is a decrease in catastrophic expressions in subsequent conversations, additional rewards will be given.

According to Fig. 3, the reinforcement learning-based psychological support system needs to update the gradient of the algorithm, and the gradient update formula is shown below [see Formula (11)]:

$$\beta_{t+1} \leftarrow \beta_t - \xi \times \frac{E_t}{\sqrt{V_t} + \pi} \tag{11}$$

where, β_t is the gradient of the reinforcement learning algorithm, E_t and V_t are momentum estimates after deviation correction.

IV. Results and Discussions

In this study, the facial expression data, academic performance data, and text data from online communities of 450 students are collected as datasets. In these datasets, the ratio between male and female students was 1:1, and the average age of adult students was 20.6 years old. The training set used data from 390 students, while the testing set used data from 60 students.

For the proposed emotion analysis framework for college students, the effectiveness of the IHO algorithm-based CNN (IHO-CNN) module emotion classification was first demonstrated. To ensure fairness, Enzyme Action Optimization (EAO) [25] and Particle Swarm Optimization (PSO) [26] were used to optimize the hyperparameters of the CNN model, and the optimization results were compared with the proposed IHO-CNN model.

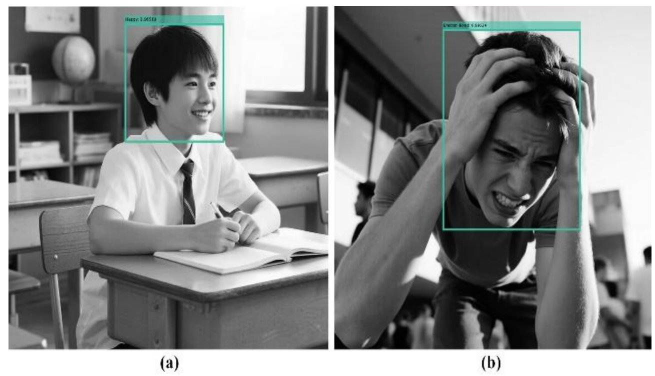

Fig. 4. Expression analysis results based on IHO-CNN model.

Fig. 5. Emotion analysis results based on IHO-CNN model.

Specifically, for the emotional categories of college students, five categories of emotional states are set: excitement, happiness, boredom, fatigue, and anxiety, and named them Category-1, Category-2, Category-3, Category-4, and Category-5, respectively. Fig. 4 shows the facial expression recognition results of the IHO-CNN model. Fig. 5 shows the confusion matrix of the expression classification problem based on IHO-CNN, while Fig. 6 shows the confusion matrix of the expression classification problem based on basic CNN. Table I shows the facial expression classification results of 1IHO-CNN, EAO-CNN, PSO-CNN, and basic CNN models. Fig. 7 visualizes the accuracy of the above data.

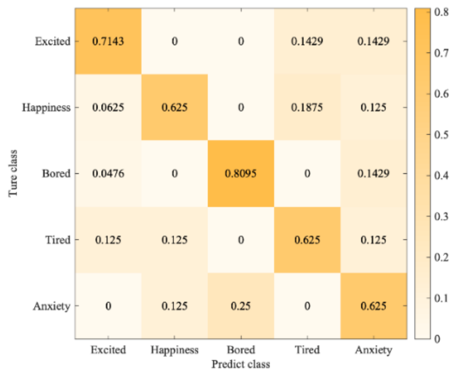

Fig. 6. Emotion analysis results based on CNN model.

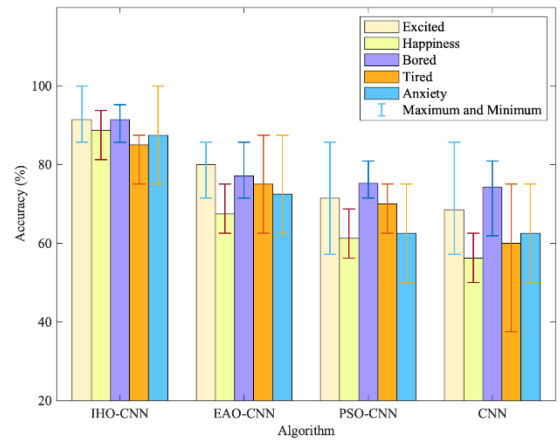

Fig. 7. The accuracy of emotion analysis based on different models.

TABLE I. THE FACIAL EXPRESSION CLASSIFICATION RESULTS OF IHO-CNN, EAO-CNN, PSO-CNN, AND BASIC CNN MODELS

Model	Parameters of the optimization algorithm	Index	Category-1	Category-2	Category-3	Category-4	Category-5
IHO-CNN	Population size=30	Average value	91.43%	88.75%	91.43%	85.00%	87.50%
	Iteration times=50	Maximum value	100.00%	93.75%	95.24%	87.50%	100.00%
	Dimension=3	Minimum value	85.71%	81.25%	85.71%	75.00%	75.00%
EAO-CNN	Population size=30	Average value	80.00%	67.50%	77.14%	75.00%	72.50%
	Iteration times=50	Maximum value	85.71%	75.00%	85.71%	87.50%	87.50%
	Dimension=3	Minimum value	71.43%	62.50%	71.43%	62.50%	62.50%
PSO-CNN	Population size=30	Average value	71.43%	61.25%	75.24%	70.00%	62.50%
	Iteration times=50	Maximum value	85.71%	68.75%	80.95%	75.00%	75.00%
	Dimension=3	Minimum value	57.14%	56.25%	71.43%	62.50%	50.00%
CNN	-	Average value	68.57%	56.25%	74.29%	60.00%	62.50%
	-	Maximum value	85.71%	62.50%	80.95%	75.00%	75.00%
	-	Minimum value	57.14%	50.00%	61.90%	37.50%	50.00%

From the above data, it can be seen that during the testing process, the accuracy of the IHO-CNN model in five categories of facial expression classification tests was 91.43%, 88.75%, 91.43%, 85.00%, and 87.50%. Compared with EAO-CNN, PSO-CNN, and basic CNN models, the IHO-CNN model has higher classification accuracy.

This study also introduces the effectiveness of the proposed IHO-LSTM model in analyzing the emotions of text generated by college students. To demonstrate the benefits of IHO-LSTM in improving the prediction accuracy of baseline LSTM models, the IHO-LSTM model was compared with EAO-LSTM and baseline LSTM models. The loss function curves of IHO-LSTM, EAO-LSTM, and baseline LSTM are shown in Fig. 8. Table II shows the average loss function and 95% confidence interval (95% C.I.) of the three models mentioned above. Fig. 9 shows the RMSE curves of the three models.

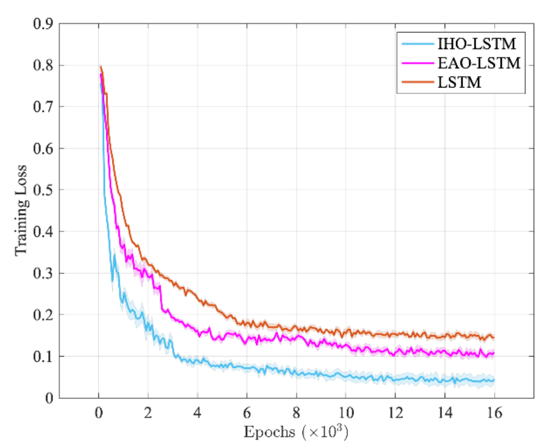

Fig. 8. The loss function curves of the models (shaded area is 95% C.I.).

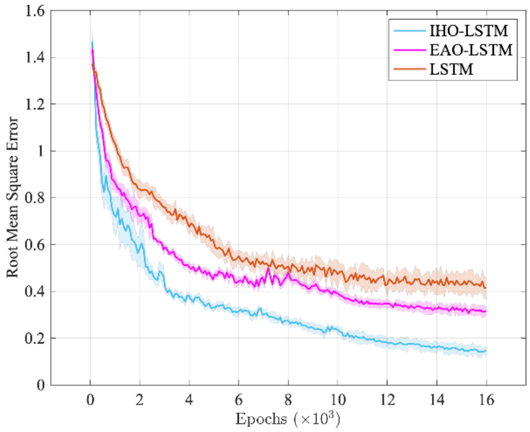

Fig. 9. The RMSE curves of the models (shaded area is 95% C.I.).

TABLE II. THE TEXT SENTIMENT CLASSIFICATION RESULTS OF THE MODELS

Index	Model	Average value	The upper bound of 95% C.I.	The lower bound of 95% C.I.
Loss Function	IHO-LSTM	0.0449	0.0507	0.0391
	EAO-LSTM	0.1093	0.1162	0.1023
	LSTM	0.1454	0.1540	0.1369
RMSE	IHO-LSTM	0.1472	0.1721	0.1224
	EAO-LSTM	0.3168	0.3367	0.2969
	LSTM	0.4136	0.4606	0.3666

Experimental data shows that LSTM models optimized based on IHO algorithm have significant advantages in classification accuracy. Experimental data shows that the IHO-LSTM model exhibits significant advantages in both the loss function and RMSE key indicators. Firstly, during the 10 runs, the average loss function of IHO-LSTM was the lowest, at 0.0449. The average loss function values of EAO-LSTM and benchmark LSTM models are 0.1093 and 0.1454, respectively. In addition, the 95% C.I. of the loss function of IHO-LSTM does not overlap with the EAO-LSTM and benchmark LSTM models, which confirms the statistically significant performance improvement of the IHO-LSTM model. Meanwhile, the narrowest confidence interval width of IHO-LSTM indicates that its performance estimation is stable and reliable. In addition, compared with the baseline LSTM model, the RMSE corresponding to IHO-LSTM decreased from 0.4136 to 0.1472, and the performance of IHO-LSTM improved by 64.41%.

Based on the above two analyses, combined with students' academic performance and other data, the IHO-LSTM-CNN model, EAO-LSTM-CNN model, PSO-LSTM-CNN model, and LSTM-CNN model were comprehensively evaluated. Aiming to provide an accurate emotion recognition model for online emotional support systems for college students. Specifically, the data of 450 students were scrambled, and 60 students' data were randomly selected as the test set each time, for a total of 6 test sets.

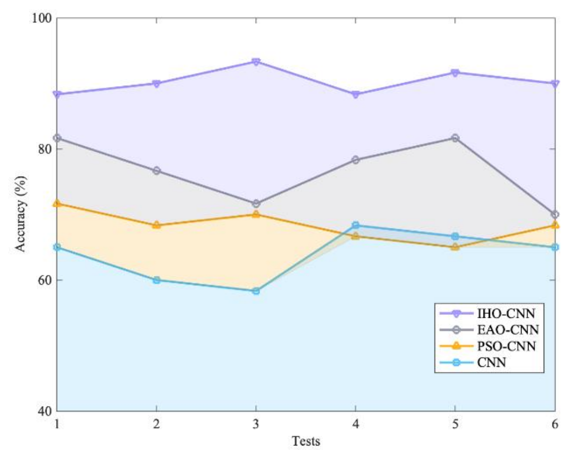

Fig. 10. The accuracy of all the models in 6 tests.

TABLE III. THE RESULTS OF THE MODELS IN 6 TESTS

Tests	Test-1	Test-2	Test-3	Test-4	Test-5	Test-6	Average Value
Model	***Accuracy***						
IHO-LSTM-CNN	88.33 %	90.00 %	93.33 %	88.33 %	91.67 %	90.00 %	90.28 %
EAO-LSTM-CNN	81.67 %	76.67 %	71.67 %	78.33 %	81.67 %	70.00 %	76.67 %
PSO-LSTM-CNN	71.67 %	68.33 %	70.00 %	66.67 %	65.00 %	68.33 %	68.33 %
LSTM-CNN	65.00 %	60.00 %	58.33 %	68.33 %	66.67 %	65.00 %	63.89 %

Fig. 10 shows the accuracy of four models in six independent tests (Test-1 to Test-6). Table III shows the test results of four models in six independent tests. The average accuracy of the four models provided in Table III over six independent tests reliably reflect the overall performance of the models. Firstly, IHO-LSTM-CNN significantly outperforms other models in accuracy, with an average accuracy of up to 90.28%. And consistently performed the best in six tests, with Test-3 reaching a peak of 93.33%. In contrast, the average accuracies of EAO-LSTM-CNN, PSO-LSTM-CNN, and LSTM-CNN are 76.67%, 68.33%, and 63.89%, respectively. Specifically, the accuracy of IHO-LSTM-CNN improved by 13.61% compared to EAO-LSTM-CNN, 21.95% compared to PSO-LSTM-CNN, and 26.39% compared to the base model LSTM-CNN, highlighting the significant advantages of IHO-LSTM-CNN.

Secondly, this improvement remained consistent across all tests. For example, in Test-2, the accuracy of IHO-LSTM-CNN was 13.33% higher than that of EAO-LSTM-CNN, 21.67% higher than that of PSO-LSTM-CNN, and 30.00%

higher than that of LSTM-CNN. This indicates that IHO-LSTM-CNN not only has superior performance, but also strong robustness. However, other models, especially LSTM-CNN, have significant fluctuations in accuracy.

V. CONCLUSION

To accurately assess the mental health status of adult students and alleviate their academic anxiety, this study developed an online psychological assessment system based on deep learning. Specifically, an IHO-LSTM-CNN hybrid framework was constructed to optimize the hyperparameters of LSTM and CNN using the IHO algorithm, significantly improving the performance of LSTM based text sentiment analysis and CNN based facial expression classification models. Experimental verification shows that the proposed hybrid IHO-LSTM-CNN framework achieves an accuracy of up to 90.28%, which is a breakthrough improvement compared to existing mainstream models. The hybrid IHO-LSTM-CNN framework can more accurately characterize students' psychological states and provide personalized and highly reliable intervention evidence for online psychological support communities. In future research, we will validate the performance of the system on a larger scale of cross-cultural data.

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