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Design optimization of university ideological and political education system based on deep learning

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This study seeks to enhance the effectiveness and student engagement in university ideological and political education (IPE) by leveraging deep learning technology. Traditional IPE approaches often fall short in terms of flexibility and interactivity, resulting in diminished student participation. The advancement of deep learning technology offers new opportunities for IPE due to its powerful capabilities in feature extraction and pattern recognition. This research employs a CNN-LSTM hybrid model, integrating Convolutional Neural Networks (CNN) and Long Short Term Memory (LSTM). By analyzing students' learning needs and interests, personalized learning paths and resource recommendations are provided for them. Firstly, this paper introduces the research methods in detail, including deep learning algorithm and model design, as well as the optimization design process of IPE system. The hybrid model combines the advantages of CNN in feature extraction and the ability of LSTM in processing sequence data to realize accurate analysis of IPE data. In the discussion part of experiment and result analysis, the model is trained and verified by collecting multi-channel data related to university IPE and using high-performance server. The results show that CNN-LSTM hybrid model is superior to traditional methods such as SVM and random forest in accuracy, recall and F1 score. This proves the powerful ability of deep learning model in dealing with complex data and capturing the internal laws and relationships of data. This study optimizes the design of university IPE system through deep learning technology, which not only improves the pertinence and effectiveness of education, but also provides new ideas and directions for the application of deep learning in the field of education.

Keywords Ideological and political education system, Deep learning, Optimization, CNN-LSTM

With the rapid development of society and the continuous progress of information technology, the ideological and political education (IPE) of universities plays an important role in cultivating socialist builders and successors. IPE is not only related to students' moral concept and value orientation, but also the key link to shape their world outlook and outlook on life. However, the current IPE system is facing three dilemmas: first, the teaching method is characterized by "flooding", which is mainly based on one-way theoretical indoctrination and lacks personalized layered teaching strategies based on students' cognitive level and professional background[1]; Secondly, the utilization rate of learning behavior data is insufficient, and it is difficult for traditional questionnaires to capture students' real-time emotional feedback and attention changes, which leads to the teaching adjustment lagging behind the actual needs[2]; Thirdly, the form of classroom interaction is single, and the online learning platform mostly stays at the level of video playback and exercise testing, failing to build an immersive and gamified participation mechanism, and the students' cognitive involvement is below 65% for a long time[3]. These structural defects seriously restrict the effective breakthrough of IPE.

The iterative upgrading of AI technology provides a new paradigm for solving the above problems. Compared with traditional machine learning methods, deep learning constructs high-order feature representation through multi-layer nonlinear transformation, which shows its unique advantages in complex educational scenes. Among them, the CNN-LSTM hybrid model has attracted much attention because of its dual-mode processing ability: the convolution layer of convolutional neural network (CNN) can efficiently extract the spatial features in unstructured data such as students' micro expression and eye movement trajectory, and accurately identify the state of classroom participation; The long short term memory (LSTM) network is good at modeling the dynamic process of knowledge mastery over time, and capturing the long-term law of students' cognitive development

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through memory units[4,5]. This space-time feature fusion mechanism enables the system to dynamically generate a "one-person, one-policy" teaching scheme, such as automatically pushing the case enhancement module for groups with weak political sensitivity, and triggering the virtual reality scenario teaching for those who have difficulty in theoretical understanding, thus realizing the paradigm shift from "standardized supply" to "precise drip irrigation".

In this study, an intelligent IPE system is built based on the deep learning framework, focusing on solving three major pain points of traditional methods: first, digital portraits of students are established through multi-source heterogeneous data fusion; Secondly, CNN-LSTM model with enhanced attention mechanism is used to predict learning needs; Finally, a closed-loop optimization system of "evaluation-recommendation-feedback" is constructed.

The main contributions of this study are as follows:

(1) In this study, the deep learning technology is applied to the design of IPE system for the first time. Through the mixed model of CNN and LSTM (CNN-LSTM), the flexibility and interactivity of IPE system are significantly improved. This innovation not only brings a new technical path to the IPE field, but also provides a new solution to improve the educational effect and students' learning experience.
(2) In this study, a method of processing IPE data using CNN-LSTM hybrid model is proposed. The combination of CNN's advantages in feature extraction and LSTM's ability in processing sequence data enables the model to accurately analyze students' learning needs and interests.
(3) By collecting multi-channel data related to university IPE, this study realized the fusion of multi-source heterogeneous data and constructed the digital portrait of students. This method enables the system to understand students' learning situation and needs more comprehensively, and provides a data basis for accurate teaching.
(4) This study not only optimizes the design of university IPE system, but also provides new ideas and directions for the application of deep learning technology in the field of education. Through the exploration and practice of this study, it provides useful reference for introducing deep learning technology into other educational fields.

Literature review

In recent years, with the rapid development of information technology, university IPE has gradually merged with scientific and technological means, which has become an important way to improve the effectiveness of education. Scholars at home and abroad have carried out multi-dimensional research around this field, but there are still significant differences in theoretical depth and practical adaptability.

Technology-driven IPE mode transformation

From the international experience, European and American countries tried to introduce technologies such as virtual reality (VR) and augmented reality (AR) into civic education earlier, but their research focused on the superficial application of technical tools, lacking critical thinking on the internal relationship between educational goals and technical logic[6]. Although domestic scholars put forward innovative concepts such as "smart classroom" and "precise ideological and political thinking", some studies tend to be technological determinism, overemphasizing the optimization of algorithm model and ignoring the ideological attribute and value guiding function of IPE[7,8]. This separation leads to the "last mile" fracture between technological empowerment and the essence of education.

The educational application dilemma of deep learning

In the field of deep learning and education integration, there are three obvious limitations in the existing research, and there is tension between the data-driven paradigm and the humanistic attributes of IPE[9,10]. The prediction model of learning behavior proposed in reference[11] simplifies the complicated process of political identity into quantifiable indicators, and there is a risk of mechanized measurement of spiritual growth; The interdisciplinary knowledge transfer mechanism has not been established. At present, most of the algorithms are directly transplanted from the commercial field and fail to develop special feature projects for the political discourse system with China characteristics, resulting in semantic deviation between the model output and mainstream values; Personalized recommendation is alienated into information cocoon room. The experimental data in reference[12] shows that the recommendation system based on collaborative filtering may strengthen students' existing political cognitive tendency, which runs counter to the original intention of traditional IPE to eliminate cognitive bias.

Structural defects of existing systems

Although academic circles have paid attention to data security and model interpretability[13–15], there is still a lack of critical reflection on the overall architecture design of IPE system. Most systems adopt the construction path of "technical superposition" instead of "deep integration"[16], which shows that independent functional modules are pieced together mechanically and the teaching process cannot be re-engineered; The design of man-machine cooperation mechanism is absent, and the teacher's main position in algorithm decision-making is weakened, which violates the basic principle of "educator-led-artificial intelligence-assisted"; The evaluation system tends to be single, relying too much on surface indicators such as click-through rate and length of stay, ignoring the deep evaluation of internalization of values[17].

Comparative analysis of existing research

Table 1 below compares and analyzes the existing related studies.

Research sources	Research contents	Main contribution	Limitations
Domestic research	Ideas such as "smart classroom" and "precise ideological and political thinking" are put forward.	Emphasize the application of intelligent means in IPE.	There is a tendency of technological determinism, ignoring the ideological attribute of IPE.
International studies	VR, AR and other technologies are introduced into civic education.	Explore the application of technical tools in IPE	Lack of critical thinking on the internal relationship between educational goals and technical logic.
Deep learning application	Optimizing IPE effect by using deep learning algorithm	Improve the educational effect and realize personalized teaching.	There is tension between data-driven paradigm and IPE's humanistic attributes, and the interdisciplinary knowledge transfer mechanism has not been established.
System architecture design	Explore the overall architecture design of IPE system	Pay attention to data security and model interpretability	Most of them adopt the path of "technical superposition" and lack deep integration.
Evaluation system	Establish IPE evaluation system	Pay attention to the quantitative evaluation of teaching effect	The evaluation system is single, ignoring the deep evaluation of internalization of values.

Table 1. Related studies are compared.

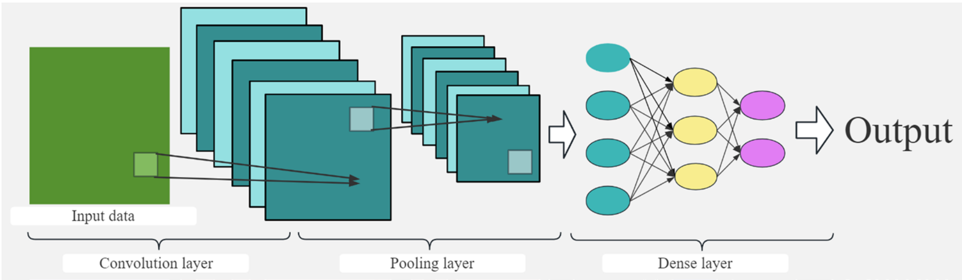

Fig. 1. Typical CNN network structure.

The existing research has made some progress in the integration of IPE and science and technology, but there are still many limitations and challenges. Future research should pay more attention to the deep integration of technology and education essence, and explore how to realize the innovative development of IPE through technical means. At the same time, we should strengthen the research on the evaluation system and establish a comprehensive and scientific evaluation mechanism to better guide the practice of IPE.

The breakthrough direction of this study
In view of the above theoretical blind spots and practical dilemmas, this study develops a deep learning model with ideological adaptability, and strengthens the analytical ability of core concepts through attention mechanism; Design a dynamic and balanced human-machine collaborative architecture to ensure the educational dominance and release the potential of technological empowerment. This systematic innovation can not only break through the bottleneck of existing technology, but more importantly, provide theoretical paradigm reference for the transformation and upgrading of ideological and political education paradigm in the era of artificial intelligence.

Research method
Deep learning algorithm and model design
The convolution layer in the convolutional neural network (CNN) can use several convolution kernels with different sizes to convolution data such as text vectors and capture local features with different granularity (as shown in Fig. 1). In the IPE scene, whether it is the micro-expression analysis of students or the processing of text content, the extraction of local features is very important[18]. For example, we can judge students' cognitive degree and attitude tendency to a specific topic from their local text characteristics such as words and sentence structure in the discussion, and CNN can accomplish this task efficiently[19]. For data involving spatial dimension, such as the identification of students' participation in class, the convolution layer of CNN can handle the spatial information well, and accurately identify whether students are in different classroom participation states, such as concentration, confusion and enthusiasm, thus providing a basis for the subsequent targeted teaching strategy formulation[20,21].

In the process of IPE, students' learning behavior and cognitive development are sequential and time-dynamic. Long Short-Term Memory (LSTM) is particularly good at modeling this kind of serial data, which can capture the dynamic process of students' knowledge mastery and the long-term law of cognitive development through memory units[22]. For example, analyze students' academic performance, online learning duration, homework completion sequence and other serial data in different time periods to predict students' future learning needs and possible difficulties. When dealing with students' long-term learning data, LSTM can remember the key information of the earlier stage and combine it with the follow-up information, which is very important for understanding the long-term process such as the evolution of students' ideas and the gradual formation of the value system, and is helpful to realize more accurate educational intervention and guidance[23,24].

Combining CNN's spatial feature extraction ability with LSTM's time series processing ability, we can realize the spatio-temporal feature fusion of ideological and political education data[25,26]. This integration mechanism enables the model to understand students' learning status and needs more comprehensively and deeply, such as taking into account students' real-time expressions (spatial characteristics) in class and their performance trends (time characteristics) at different learning stages, so as to dynamically generate personalized teaching programs and realize the transformation from "standardized supply" to "precise drip irrigation". CNN focuses on local and spatial features, while LSTM is responsible for sequence and temporal features, which complement each other and overcome the limitations of a single model in dealing with complex educational data[27]. This complementarity makes the model perform better in tasks such as analyzing students' learning behavior and predicting their learning needs. Compared with CNN or LSTM model alone, CNN-LSTM hybrid model can more accurately capture the inherent complex relationships and laws of data and provide more accurate and targeted support for the ideological and political education system.

In contrast, other deep learning models, such as the traditional feedforward neural network (FNN), lack the ability to deal with sequence data and local features effectively; Although the simple RNN (recurrent neural network) can process sequence data, it has shortcomings in the long-term dependence on capture and gradient propagation; Although transformer architecture performs well in processing long sequence data and capturing global dependencies, its computational complexity is high, and it may not be as efficient and targeted as cnn-lstm model in processing some IPE scenarios with obvious temporal and spatial characteristics and not a particularly large amount of data[28]. Therefore, considering the characteristics of IPE data and practical application requirements, it is reasonable and effective to choose CNN and LSTM to build a hybrid model to optimize the University IPE system.

This investigation seeks to enhance the structure of university IPE systems by employing deep learning technology. To realize this objective, the research introduces a hybrid model that synergizes CNN with LSTM, capitalizing on CNN's prowess in feature extraction and LSTM's competence in managing sequential data[29,30]. Figure 2 provides an illustration of this concept.

Using CNN-LSTM hybrid model to process IPE data. Firstly, preprocess the collected IPE related data. This includes text cleaning, word segmentation, stop words removal and other steps to ensure the quality and consistency of data. In addition, word embedding technology Word2Vec is used to convert text data into vector representation, which is convenient for the input of deep learning model[31,32].

Word2Vec is a language model, which is used to learn semantic knowledge from a large number of text corpus in an unsupervised way. Its main purpose is to transform words in natural language into mathematical vectors so that computers can understand and process them. Word2Vec can transform words into vectors to represent them, so that the relationship between words can be quantitatively measured and the relationship between words can be mined. Word vectors generated by Word2Vec can capture the semantic information of words, such as words with similar meanings have similar vectors.

There are two main ways to realize Word2Vec model: CBOW (Continuous Bag-of-Words) and Skip-gram. The training of CBOW model can be carried out by using open source libraries such as Gensim. Predict the head word through the context word[33]. Skip-gram model predicts the contextual words around it through the head word, see in Fig. 3.

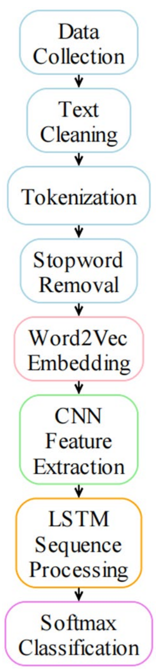

Fig. 2. The process of using CNN-LSTM mixed model to process IPE data.

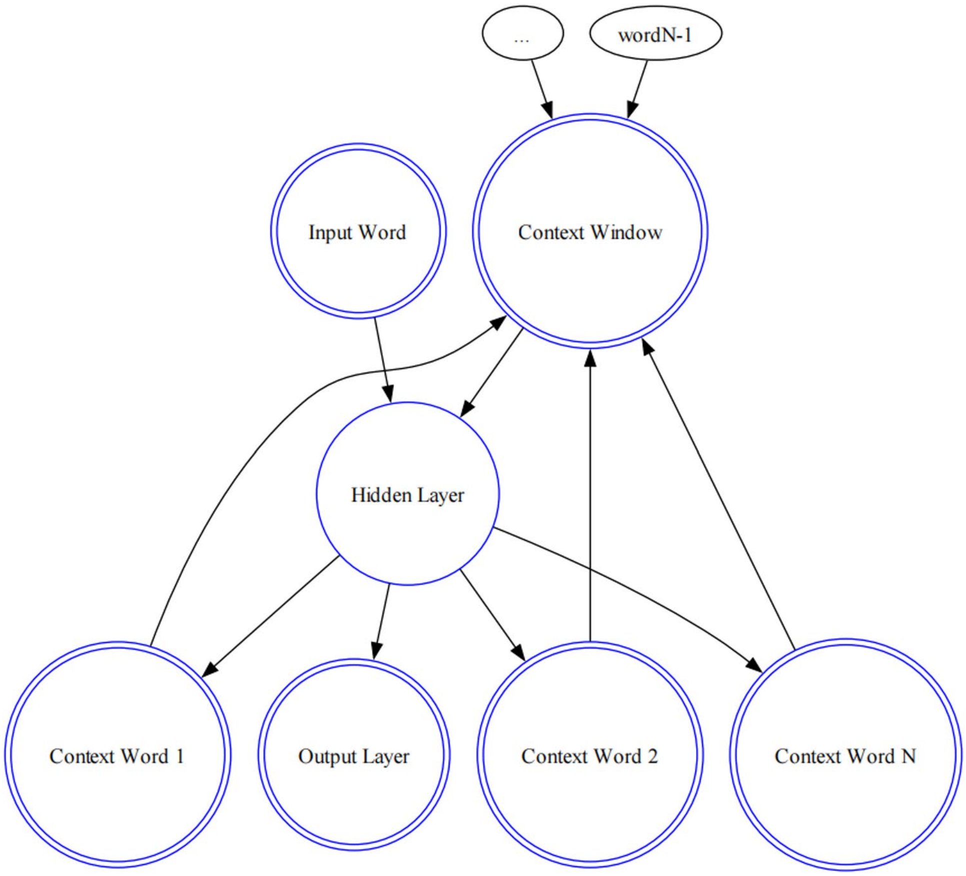

Fig. 3. Word2Vec language model structure.

Word2Vec is used to convert the text into a vector, and the original text is preprocessed, including word segmentation, stop words removal, stemming and other operations. Collect all the words in the preprocessed text to build a vocabulary. Each word in the vocabulary is assigned a unique integer identifier. The preprocessed text is converted into training data, in which each training sample consists of a central word and its surrounding context words. Use training data to train Word2Vec model. After the training is completed, the corresponding word vectors are obtained by querying the words in the vocabulary. Word vectors generated by Word2Vec are widely used in natural language processing, including word similarity calculation, text classification, part-of-speech tagging, named entity recognition, machine translation, text generation and so on. When using CNN-LSTM hybrid model to process IPE data, it is an important preprocessing step to convert text data into vector representation through Word2Vec, which can help deep learning model to better understand and process text data[34].

The input layer receives the preprocessed text vector as input. The convolution layer uses several convolution kernels with different sizes to perform convolution operations on text vectors to capture local features with different granularity (Fig. 4).

The mathematical expression of convolution operation is:

$$c_i = f\left(W \cdot x_{i:i+h-1} + b\right) \tag{1}$$

Where, c_i is the feature map after convolution operation, W is the weight matrix of convolution kernel, $x_{i:i+h-1}$ is the subsequence from position i to $i+h-1$ in the input text vector, b is the offset term, and f is the activation function ReLU.

The pooling layer performs maximum pooling operation on the feature map output by the convolution layer to extract the most important features and reduce the dimension[35]. The mathematical expression of maximum pooling is:

$$p_i = \max\left(c_{2i-1}, c_{2i}\right) \tag{2}$$

Where p_i is the output after pooling operation and$c_{2i-1}, c_{2i}$is the output of the adjacent convolution layer.

The LSTM layer receives the output of the pooling layer as the input of the sequence, and captures the long-term dependencies in the sequence through the LSTM unit (Figure 5).

The mathematical model of LSTM unit involves multiple gating mechanisms and cell state update, and the specific formula is as follows:

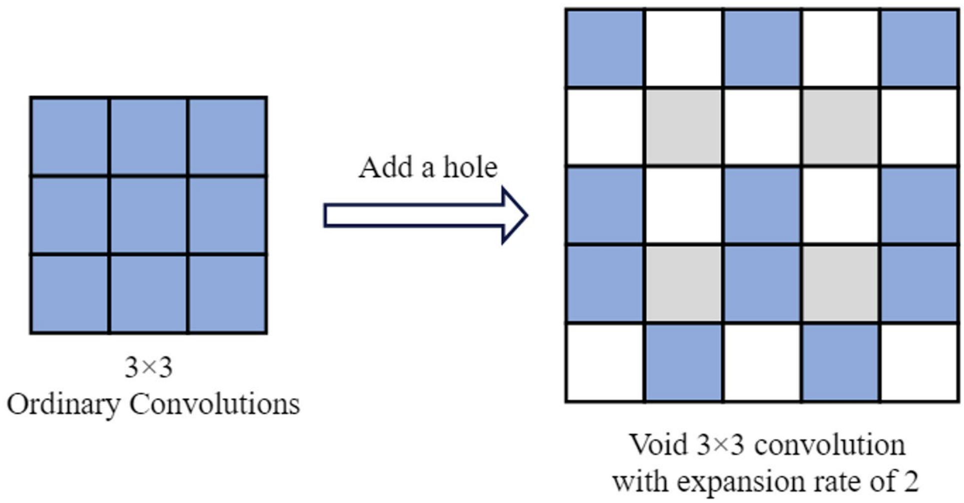

Fig. 4. Convolution transformation process.

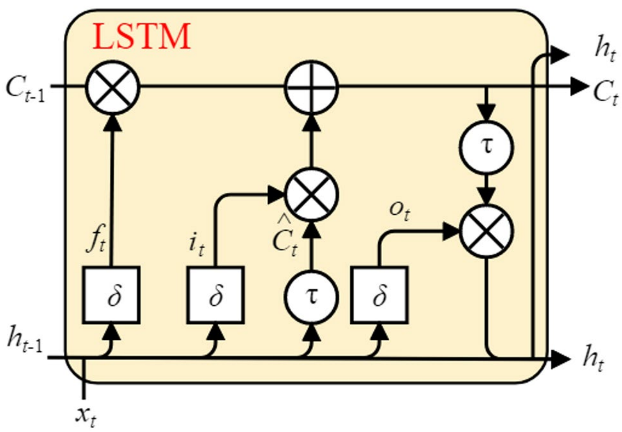

Fig. 5. LSTM structure.

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + b_i\right) \tag{3}$$

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \tag{4}$$

$$o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + b_o\right) \tag{5}$$

$$g_t = \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right) \tag{6}$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes g_t \tag{7}$$

$$h_t = o_t \otimes \tanh\left(c_t\right) \tag{8}$$

Where x_t is the current input,$h_{t-1}, c_{t-1}$is the hidden state and cell state at the last moment, W, b is the weight matrix and bias term, σ is the sigmoid activation function, and $\otimes$ is the element-by-element multiplication.

The output layer uses softmax function to classify the output of LSTM layer. The mathematical expression of the softmax function is:

$$P\left(y = j\,|x\right) = \frac{e^{x_j}}{\sum_{k=1}^{K} e^{x_k}} \tag{9}$$

Where *x* is the output vector of the LSTM layer, *j* is the index of category labels, and *K* is the total number of categories.

Back propagation algorithm and gradient descent optimizer are used to train the model. Adjusting model parameters by minimizing cross entropy loss function;

$$L = -\sum_{i=1}^{N} y_i \log\left(p_i\right) \tag{10}$$

Where N is the number of samples, y_i is the one-hot coding vector of real tags, and p_i is the probability distribution vector of model prediction. In the training process, early stop and regularization techniques are also used to prevent over-fitting, and the learning rate attenuation strategy is used to optimize the training process.

Optimal design process of IPE system

This study aims to optimize the design of university IPE system through deep learning technology. In order to achieve this goal, a mixed model combining CNN and LSTM is adopted. The architecture design of university IPE system is shown in Fig. 6.

First of all, university IPE-related data are collected from multiple channels, including lecture notes, students' homework, discussion forums, online test records, etc. These data cover all kinds of performances of students in the process of IPE, which is very important for establishing an accurate deep learning model.

The collected raw data needs a series of preprocessing operations to adapt to the input requirements of deep learning model. Pretreatment steps include text cleaning (removing irrelevant characters, punctuation marks, etc.), word segmentation (dividing the text into independent words or phrases), stop words removal (deleting common words that have little meaning to the text), stem extraction or word shape reduction (converting words into their basic forms), etc. In addition, the text data is transformed into vector representation by word embedding technology, so that the model can be understood and processed.

After preprocessing the data, a CNN-LSTM hybrid model is constructed. This model combines the advantages of CNN in feature extraction and the ability of LSTM in processing sequence data. Specifically, CNN layer is responsible for extracting local features from text data, while LSTM layer can capture long-term dependencies in text sequences. Through this hybrid architecture, the model can understand text data more comprehensively and extract information that is instructive to IPE.

The subsequent step involves employing the pre-processed data for model training. During this phase, both the backpropagation algorithm and the gradient descent optimizer are utilized to fine-tune the model's parameters, thereby minimizing prediction errors. Concurrently, measures to counteract overfitting and augment the model's generalization capabilities are examined, including the early stop technique (which halts training once validation error starts to increase) and regularization techniques (such as L1 and L2 regularization). Moreover, a learning rate decay strategy is implemented to dynamically adjust the learning rate, accelerating the model's convergence and enhancing the training outcome.

After the training, the deep learning model is integrated into the existing IPE system. The prediction results of the model are provided as auxiliary information to teachers and education administrators to help them understand students' learning situation and needs more comprehensively. For example, the model can predict students' learning performance in an ideological and political course, thus providing personalized teaching suggestions for teachers; At the same time, the model can also analyze students' online communication data and find potential problems and puzzles, so that education administrators can intervene and provide help in time. In

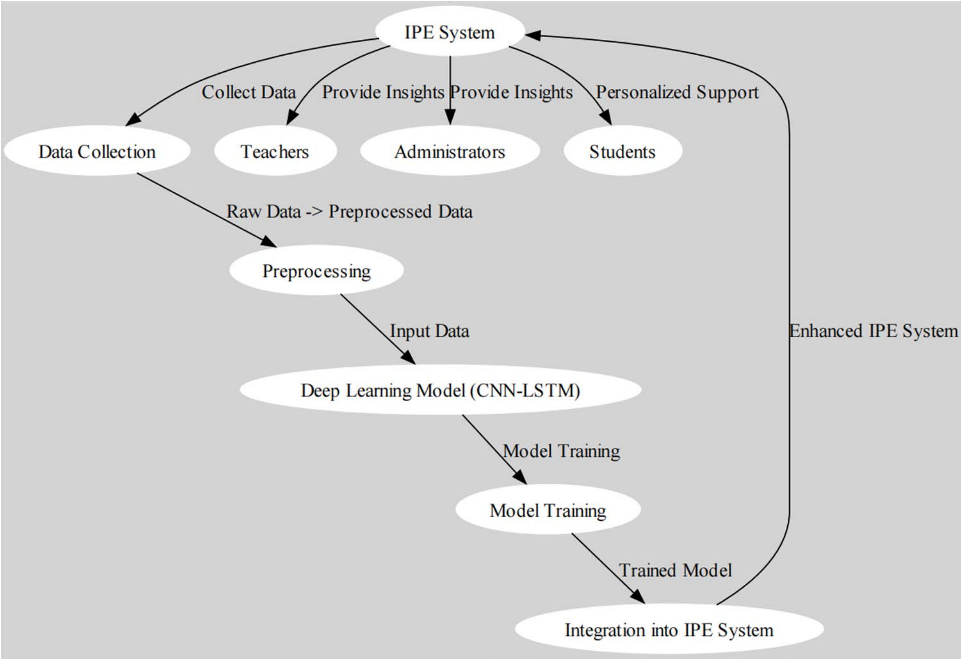

Fig. 6. Architecture of university IPE system.

this way, the deep learning model can effectively improve the intelligent level of IPE system and provide students with more accurate and personalized learning support.

Experimental setup

Data set

This study uses a multi-channel data set related to IPE from universities, including lecture notes, students' homework, exchange records in discussion forums and online test scores. The data set is about 5GB in size and contains millions of records, covering thousands of students' learning behaviors, interactions and test scores. This data set shows a high degree of diversity in many dimensions, such as the diversity of data sources, the diversity of students' backgrounds and the diversity of learning behaviors.

Clean the text, remove irrelevant characters and punctuation marks, and keep the useful text information for model training; Use Chinese word segmentation tools to cut the text into independent words or phrases, and delete stop words to reduce noise data; Convert words into basic forms and express them uniformly through stem extraction or morphological reduction; Word2Vec technology is used to convert the processed text data into vector representation.

Hyperparametric optimization of CNN-LSTM model

In order to optimize the performance of CNN-LSTM hybrid model, the method of combining grid search and random search is used to optimize the superparameter. Grid search is an exhaustive search method, which traverses all hyperparametric combinations within a specified range and finds the optimal solution. Random search is to randomly select the combination of superparameters within a specified range for experiments. Although the optimal solution may be missed, the calculation cost is low and it is suitable for preliminary screening in a large range.

Adjust several key hyperparameters to optimize performance, including learning rate (0.0001 to 0.1), batch size (32 to 256), convolution kernel size (3 to 7), convolution layer number (1 to 3), LSTM layer number (1 to 2) and regularization intensity (0 to 0.1). After many experiments, the final superparameter values are: learning rate 0.001, batch size 128, convolution kernel size 5, convolution layer number 2, LSTM layer number 1 and regularization intensity 0.01.

Using 50% cross validation) protocol. The specific steps are as follows:

(1) Divide the data set into five equal parts at random.
(2) Each time, four copies are selected as the training set, and the remaining one is used as the verification set.
(3) The model is trained on each training set, and the performance is evaluated on the corresponding verification set.
(4) Repeat the above steps five times, and choose a different verification set each time.
(5) Calculate the average performance of five verifications as the final performance index of the model.

Data privacy and ethical issues

All student data are anonymized during the collection stage to prevent direct identification of individuals. Only collect the necessary data directly related to the research to avoid obtaining unnecessary personal information. In the process of data transmission and storage, encryption technology is used to protect its security. Before data collection, students are clearly informed of the purpose of collection and the way of use, and their consent is obtained. Through strict access control, it is ensured that only authorized researchers can access these data, further ensuring students' privacy and data security.

Experiment and result analysis

In this study, data sets collected from various channels related to IPE in universities are used, including lecture notes, student assignments, communication records in discussion forums and online test scores. After preprocessing these data, a comprehensive IPE data set is formed to train and verify the deep learning model.

The experimental procedure was conducted on a server boasting a high-performance GPU. The model's construction and training were facilitated by deep learning frameworks, notably TensorFlow and Keras. A thorough assessment of the model's performance entailed the use of accuracy, recall, and F1 score as principal evaluation metrics. These metrics offer a holistic representation of the model's precision, inclusiveness, and equilibrium in tasks related to classification and prediction.

During the training process of CNN-LSTM mixed model, it was observed that with the increase of training rounds, the loss function gradually decreased, while the accuracy of training set and verification set gradually improved, and finally reached a stable state. This shows that the training process of the model is effective, and there is no obvious over-fitting or under-fitting phenomenon (Figs. 7 and 8).

In the initial stage of training (the first few iterations), the value of loss function is relatively high, because CNN-LSTM hybrid model has just started to learn data, and the parameters have not been fully adjusted, so there is a big gap between the predicted results and the actual labels. After the 30th iteration, the value of the loss function entered a relatively stable stage with little fluctuation. This shows that the model has basically converged, and the improvement effect of parameter adjustment on loss function is no longer obvious. It is worth noting that the value of the loss function finally stabilized at about 0.00015, which shows the good performance of CNN-LSTM hybrid model on the training data set.

Similar to the loss function, the accuracy of CNN-LSTM mixed model is relatively low at the initial stage of training. This is because the model has not fully learned the characteristics of the data, and the prediction results are not accurate. After the 30th epoch, the accuracy of the model entered a relatively stable stage with little fluctuation. This shows that the model has basically converged and the prediction results tend to be stable. It is

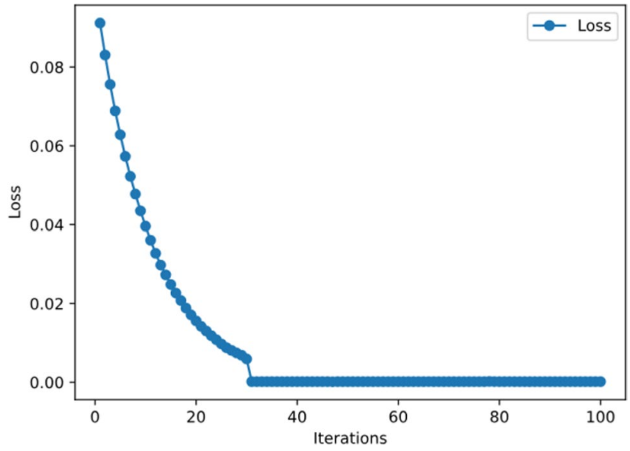

Fig. 7. Loss function of CNN-LSTM mixed model.

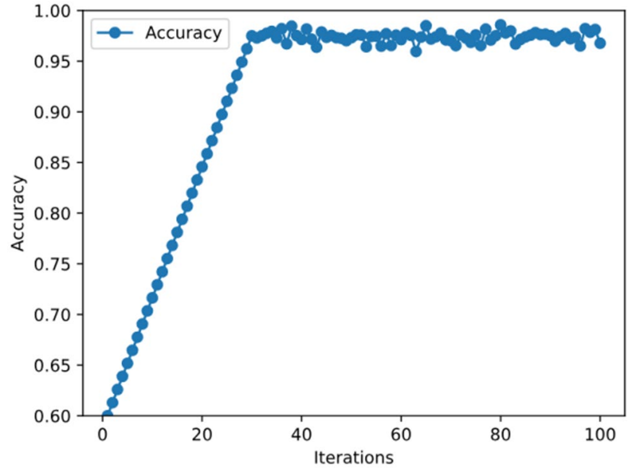

Fig. 8. Accuracy of CNN-LSTM mixed model.

worth noting that the accuracy of CNN-LSTM hybrid model is finally stable at around 97.5%, which shows the excellent performance of the model on training data sets.

Through 50% cross-validation, it is found that the average accuracy of CNN-LSTM mixed model is 91.5% and the standard deviation is 0.02, which shows that the model has good stability and generalization ability. Figure 9 shows the accuracy distribution of CNN-LSTM hybrid model in 50% cross-validation.

It can be seen from the figure that the accuracy distribution of the five cross-validation folds (Fold 1 to Fold 5) is relatively concentrated, and the median is close to 91.5%, which shows that the performance of the model in different data sets is stable and consistent. In addition, the accuracy distribution range of each fold is relatively narrow, which shows that the performance of the model does not fluctuate greatly in each verification. At the same time, there are relatively few outliers, and most of them are concentrated above the box, which means that the accuracy of CNN-LSTM hybrid model can reach or exceed the average level in most cases.

CNN-LSTM hybrid model has good generalization ability. The model not only achieves high accuracy on the whole, but also shows stability and consistency in different data division. This shows that the model can effectively learn useful features from the training data and maintain good performance on the unknown data.

Compared with traditional methods such as Support vector machine (SVM) and random forest (RF), CNN-LSTM hybrid model shows advantages in accuracy, recall and F1 score. Compared with traditional methods, the deep learning model can understand the inherent laws and complex relationships of text data more deeply. By automatically learning the hierarchical representation of data, the model can capture more useful information, thus improving the accuracy and reliability of prediction (Table 2; Fig. 10).

In the performance comparison and analysis, CNN model, with its excellent local feature extraction ability, has reached 0.90 in accuracy and 0.89 in F1 value, which significantly surpasses the traditional methods. The LSTM model improves the recall rate to 0.85 by virtue of its advantages of sequence modeling, but its comprehensive performance (F1 = 0.86) is still not as good as CNN's. The CNN-LSTM hybrid model, by combining CNN's feature extraction ability and LSTM's time series modeling ability, has achieved the greatest improvement in

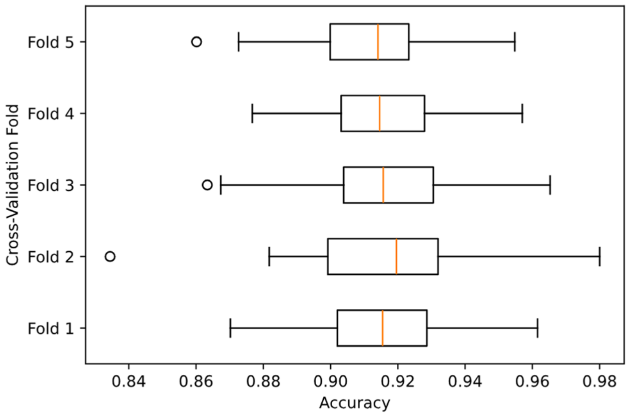

Fig. 9. Generalization ability of CNN-LSTM mixed model.

Model	Accuracy	Recall	F1 score
SVM	0.80	0.75	0.77
RF	0.85	0.80	0.82
CNN	0.90	0.88	0.89
LSTM	0.88	0.85	0.86
CNN-LSTM	0.95	0.93	0.94

Table 2. Performance comparison.

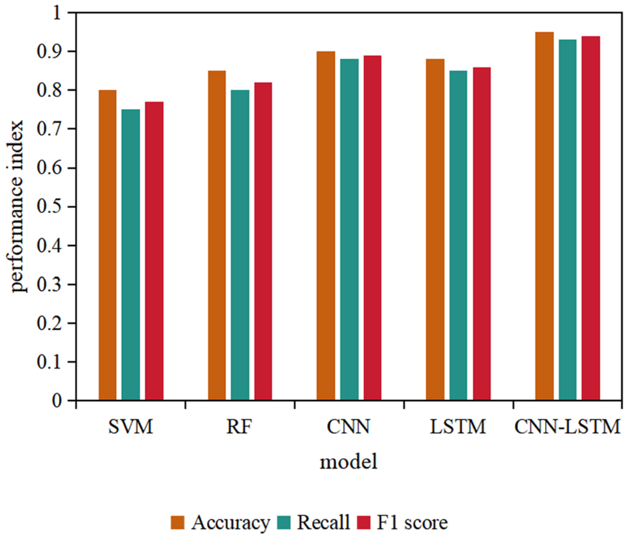

Fig. 10. Comparison of different models in accuracy, recall and F1 score.

accuracy, recall and F1 value (+5% accuracy, +8% recall and +8% F1 value) respectively, showing the best overall performance.

As for model superiority verification, although CNN alone is good at capturing local features in data, it is not good at dealing with long-distance dependencies; In contrast, LSTM alone can deal with long-distance dependence in sequence information, but it lacks effective extraction of spatial features. In contrast, CNN-LSTM hybrid model not only makes up for their respective shortcomings, but also realizes more comprehensive text representation learning through multi-level feature fusion. The experimental results show that this hybrid architecture successfully combines the local perception characteristics of CNN and the global dependency modeling ability of LSTM, and shows stronger data representation ability and better generalization performance in text classification tasks.

Number of concurrent users	Average response time (ms)	Maximum response time (ms)	Response time distribution range (ms)
1	20	35	15–35
10	25	45	20–50
50	30	60	25–70
100	35	80	30–90

Table 3. Response time test results.

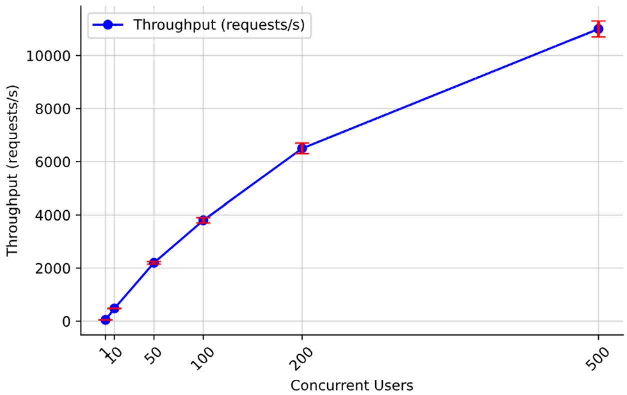

Fig. 11. Throughput test results.

This study also tests the performance of the optimized university IPE system to ensure that the system can run stably and efficiently in the actual operating environment and meet the needs of users. The test content mainly includes the response time, throughput and resource consumption of the system. Test environment: high-performance server, configured as multi-core CPU, large-capacity memory and high-speed storage equipment. Multiple computers with different configurations are used to simulate the concurrent access of different numbers of users. A stable LAN environment ensures that the influence of network delay and bandwidth is minimized during the test.

The response time test measures the time from sending the request to the server and returning the response by simulating the user submitting the request. It mainly focuses on the average response time, maximum response time and response time distribution.

Throughput test measures the number of requests that the system can handle per second by gradually increasing the number of concurrent users. This paper mainly focuses on the throughput performance of the system under different concurrent users.

The resource consumption test monitors the CPU, memory, disk and network bandwidth consumption of the server during the test. The main concern is whether the resource utilization rate of the system is reasonable under different loads, and whether there is resource waste or bottleneck.

From the data of the response time test, with the increase of the number of concurrent users, both the average response time and the maximum response time show an upward trend (Table 3). This reflects that when the system is faced with higher load, the speed of processing requests gradually slows down.

When the number of concurrent users is 1, the average response time is 20 milliseconds and the maximum response time is 35 milliseconds, which is a very fast response time, indicating that the system can quickly handle the request of a single user. When the number of concurrent users increases to 10, the average response time and the maximum response time increase to 25 milliseconds and 45 milliseconds respectively, but they are still within the acceptable range. With the number of concurrent users further increasing to 50 and 100, the average response time and the maximum response time increase significantly, reaching 30 milliseconds to 35 milliseconds and 60 milliseconds to 80 milliseconds respectively. This shows that in the case of high concurrency, the response speed of the system is affected to some extent. In addition, from the distribution range of response time, with the increase of the number of concurrent users, the distribution range is gradually expanded, indicating that the fluctuation of response time of the system under different loads is also increasing.

Figure 11 clearly shows the changing trend of the number of requests that the system can handle per second (that is, throughput) with the increase of the number of concurrent users.

When the number of concurrent users is small (such as 1 or 10), the throughput of the system is relatively low, 50 and 480 requests/second respectively. This may be because the system resources have not been fully utilized, or because the number of concurrent users is too low to fully display the processing power of the system. With the increase of the number of concurrent users (from 50 to 100), the throughput of the system has increased rapidly, from 2200 requests/second to 3800 requests/second. This shows that the system can effectively handle more concurrent requests, and within this range, the processing capacity of the system has been fully utilized.

testing phase	Number of concurrent users	CPU utilization (%)	Memory utilization (%)	Disk I/O(MB/s)	Network bandwidth (Mbps)	Is there a bottleneck
initial stage	1	5	10	0.5	10	no
Low load	10	20	25	2.0	50	no
Medium load	50	60	50	10.0	200	no
High load	100	85	75	20.0	400	no
Ultimate load	200	95	90	30.0	600	no

Table 4. Resource consumption test results.

When the number of concurrent users further increases (from 200 to 500), the throughput of the system still keeps growing, but the growth rate slows down. From 6500 requests per second to 11,000 requests per second, although the growth rate is still considerable, the growth rate is not as high as before. This may indicate that the system is approaching the limit of its processing capacity, or because other system resources (such as CPU, memory or network bandwidth) are beginning to become bottlenecks. With the increase of the number of concurrent users, the error gradually increases. This may be because in the case of high concurrency, the performance of the system fluctuates greatly, resulting in certain uncertainty of throughput data. However, from the overall trend, the error range is relatively small, indicating that the test results have certain credibility.

The results of comprehensive response time test and throughput test show that the system shows different performance characteristics when facing different loads. Under low load, the system can process the request quickly and keep a fast response speed; Under high load, although the response time of the system has increased, the throughput can still maintain a high level. This shows that the system has certain scalability and robustness, and can cope with the challenges of high concurrency scenarios to a certain extent.

However, it should also be noted that in the case of high concurrency, the response time of the system fluctuates greatly, which may have a certain impact on the user experience. Therefore, in practical application, it is necessary to further optimize the system architecture and algorithm to improve the stability and response speed of the system and ensure that it can still provide a good user experience under high load.

As can be seen from Table 4, with the increase of the number of concurrent users, the system's CPU utilization, memory utilization, disk I/O, network bandwidth and other resource consumption all show an upward trend, which is in line with expectations. As the load increases, the system needs to handle more requests, so it needs more computing resources, memory space, disk reading and writing, and network bandwidth to support these requests.

Specifically, in the initial stage, when the number of concurrent users is 1, the CPU utilization rate and memory utilization rate of the system are relatively low, which are 5% and 10% respectively, indicating that the system can effectively manage resources under low load and avoid unnecessary waste. At the same time, the use of disk I/O and network bandwidth is also at a low level, indicating that the system has little demand for storage and network resources at this time. With the increase of load, from the low load stage to the medium load stage, CPU utilization and memory utilization have increased significantly, but they are still within a reasonable range. This shows that the system can effectively use computing resources and memory to handle more requests. At the same time, the use of disk I/O and network bandwidth has also increased, but it has not become the main bottleneck.

In the high load stage, when the number of concurrent users reaches 100, the CPU utilization rate and memory utilization rate further increase, reaching 85% and 75% respectively. This shows that the system can still maintain high processing capacity under high load and make full use of computing resources and memory resources. At this time, the use of disk I/O and network bandwidth continues to increase, but it is still within a reasonable range, and there is no obvious bottleneck. In the extreme load stage, when the number of concurrent users increases to 200, the CPU utilization rate and memory utilization rate approach or reach the maximum, which are 95% and 90% respectively. This shows that the system is close to the limit of its processing capacity, but it can still maintain stable operation. At this time, the use of disk I/O and network bandwidth has reached a high level, but there is still no resource bottleneck or performance degradation.

The system can maintain reasonable resource utilization under different loads, and make full use of computing resources, memory, disk and network bandwidth to process requests. During the test, there is no waste of resources or bottleneck, which shows that the system has strong resource management ability and can cope with the challenges under different loads.

In the testing stage, this study mainly adopts the method of simulating user load to evaluate the performance. Due to the limitation of experimental resources and time, the maximum simulated user load we set is 500. This limitation means that our test results mainly reflect the system performance within this load range. Future research can further expand the simulated user load to evaluate the performance of the system under high concurrency. At the same time, we also notice that there may be more complicated factors in practical application, so we suggest to carry out more extensive testing and verification before actual deployment.

Discussion

CNN-LSTM model combines the advantages of CNN and LSTM, but it also has some limitations. Its main problems include high computational cost, high computational complexity and resource requirements due to the combination of two deep learning networks, and increased training time and hardware cost; The generalization ability of the model is insufficient, and it may not perform well in the face of new or different distribution data, which affects the accuracy and reliability in practical application; And there may be bias. If the training data is biased, it may lead to unfair recommendation results and affect the user experience and system credibility. In order to solve these problems, we can reduce the computational burden by optimizing the model structure and using distributed or edge computing technology. Increase data diversity and scale, adopt data enhancement technology and introduce regularization method to improve generalization ability; At the same time, by collecting more balanced data and introducing fairness constraints into the model, the bias is reduced to ensure the fairness and social acceptance of the system.

In practical application, the high computational overhead of CNN-LSTM model may lead to the delay of system response and affect the user experience. Insufficient generalization ability may lead to inaccurate recommendation and reduce the practicability of the system; The problem of prejudice may cause social controversy and damage the reputation of the system. These problems suggest that the limitations of the model must be carefully considered and effective measures should be taken to alleviate it when it is applied to practical scenarios such as university IPE.

In view of the above challenges, the improvement suggestions include continuously optimizing the model structure to improve the calculation efficiency and ensure that the system can run efficiently in the environment with limited resources; Strengthen data management and preprocessing to ensure the quality and diversity of data, thus enhancing the generalization ability and accuracy of the model; The fairness evaluation mechanism is introduced to regularly detect and correct the bias in the model to promote fairness and transparency. Although the research results show that CNN-LSTM model has significant potential in personalized education, it is still necessary to pay attention to computing resources, data quality and fairness in actual deployment, and consider the influence of the "black box" characteristics of deep learning model on interpretability and trust.

CNN-LSTM model is suitable for environments with abundant data and sufficient computing resources, such as large universities or educational institutions. However, in the case of limited resources, it may be necessary to simplify the model or adopt lightweight algorithms as an alternative. Future research should focus on developing more efficient model structure and optimization algorithm to reduce the calculation cost, while deepening data management and preprocessing technology to improve data quality and diversity. Paying attention to the interpretability and fairness of the model is very important to improve the credibility and acceptance of the system, and studying how to combine deep learning with modern educational technology is also an important direction to promote the innovation and development of IPE system.

Conclusion

Through in-depth discussion on the application of deep learning technology in the design optimization of university IPE system, this study reveals its great potential in improving educational effect, promoting students' participation and recommending personalized learning paths. Through comparative experiments and performance evaluation, this study proves the advantages of deep learning model in processing IPE data, analyzing students' learning behavior and providing personalized recommendations. Especially in the key indicators such as F1 score, accuracy and recall, CNN-LSTM hybrid model shows the performance far beyond the traditional methods. In this study, the CNN-LSTM hybrid model is integrated into the IPE system to realize the intelligent transformation of the existing system. This not only improves the pertinence and effectiveness of IPE, but also stimulates students' learning interest and experience by providing personalized learning paths and resource recommendations. This study emphasizes the importance of high-quality educational data in deep learning model training. It is suggested that more resources should be invested to collect more diversified and high-quality data, and fine pretreatment should be carried out to improve the training effect and generalization ability of the model. The investigation into optimizing the design of university IPE systems through deep learning introduces novel opportunities and challenges to the field, offering a thorough exploration and valuable insights for applying deep learning within education. Future studies can delve deeper into more sophisticated deep learning models and optimization algorithms, examining how deep learning can be integrated with other contemporary educational technologies to foster the ongoing innovation and evolution of the IPE system.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author Huan-huan Ding on reasonable request via e-mail 1002266062@ucsiuniversity.edu.my.

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Declarations

Competing interests
The authors declare no competing interests.

Ethical approval

The studies involving human participants were reviewed and approved by School of Management, Guangzhou Xinhua University Ethics Committee (Approval Number: 2022.06541200). The participants provided their written informed consent to participate in this study. All methods were performed in accordance with relevant guidelines and regulations.

Additional information

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