Research Article

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Utilization of deep learning in ideological and political education

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Abstract: As society develops and educational needs continue to change, the traditional way of teaching ideology and politics is facing challenges in terms of efficiency and effectiveness evaluation. In response to the low efficiency of ideological and political education (IPE) methods and the difficulty in accurately and comprehensively evaluating students' ideological and political literacy and moral qualities, this article used the Long Short-Term Memory with Self-Attention Mechanism (LSTM-SAM) model to conduct experiments on the evaluation of IPE effectiveness. First, by collecting information on IPE from a research center of a certain university in 2023, and then using the LSTM (Long Short-Term Memory) model to catch the long-term dependencies of IPE, the learning trajectory and changing trends of students can be better understood. The self-attention mechanism was applied to dynamically learn and distinguish the importance of different parts in the input sequence, better weighting key features such as student learning behavior and participation level, thereby enhancing the accuracy and robustness of effectiveness evaluation. Finally, the splicing method was adopted to integrate the LSTM model and self-attention mechanism for the experiment, and the teaching efficiency of different teaching methods was statistically analyzed through a questionnaire survey. The test results indicated that the classification accuracy of the LSTM-SAM model reached 98.41%, which was 1.61% higher than the LSTM model. The teaching efficiency was the highest under the gamified teaching method, providing an effective method for evaluating the effectiveness of IPE and providing useful reference for optimizing teaching methods.

Keywords: ideological and political education, deep learning, teaching methods, LSTM model, self-attention mechanism, educational effectiveness

1 Introduction

In today's society, ideological and political education (IPE), as an important way to shape students' ideological and moral character and cultivate socialist core values, carries important historical missions and social responsibilities. However, with social changes and technological progress, IPE needs to adapt to the challenges of the new era and pay attention to the updating and diversification of teaching content. The current IPE methods generally face problems such as low teaching efficiency, insufficient student participation, and single teaching content, which seriously affect the actual effectiveness of IPE. Moreover, the existing evaluation methods for the effectiveness of IPE are often limited to superficial qualitative evaluations, making it difficult to objectively and comprehensively evaluate students' ideological and political literacy and moral qualities. This study applies deep learning (DL) to IPE, exploring more scientific and effective effectiveness evaluation ways to enhance quality and effectiveness of IPE, which has turned out to be an outstanding issue in current IPE studies and practices.

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For the past few years, with the increasing attention of the country to IPE, it has gradually been widely studied and has gained a large number of studies. With the development of integrated "online and offline" teaching, IPE has been integrated into daily teaching, and the teaching methods of blended teaching in ideological and political courses have gradually been explored, providing reference for future scholars to improve teaching efficiency [1–3]. The support vector regression method can be used to score the effectiveness of IPE, and the results prove the practicality and rationality of the evaluation method for IPE [4]. To tackle the issue of inaccurate differentiation of learners' learning status in IPE, the application of support vector machines (SVMs) and decision trees in online teaching quality evaluation is beneficial for improving classification accuracy [5]. Wang and other scholars used the CIPE (curriculum IPE) effectiveness evaluation system to evaluate the learning outcomes of students in IPE courses based on grades, improving the accuracy of outcome assessments [6,7]. The aforementioned scholars have made certain improvements in the evaluation of the effectiveness of IPE, but the accuracy of the evaluation is still low, and the research on teaching methods is not in-depth enough.

With the prevalence of DL technology, many scholars have begun to apply it to IPE, thereby improving the performance of effectiveness evaluation. The Long Short-Term Memory (LSTM) model has been applied to predict student classroom performance, improving the accuracy of prediction and providing a basis for comprehensive evaluation of IPE [8,9]. Zhang and other scholars used the Bidirectional Encoder Representations from Transformers – Bidirectional Long Short-Term Memory – Conditional Random Field model to predict the daily IPE learning situation of college students, and the findings indicated an accuracy of 91.09% [10]. A Deep Language Model for Text Question Answering model for teaching quality analysis was used to evaluate ideological and political learning, and the results showed that the student efficiency ratio reached 93.80% [11]. To tackle the issue of single and inaccurate evaluation methods, an artificial neural network algorithm based on artificial intelligence data mining was used to evaluate IPE. The results of the assessment showed that the test model agreed very well with the prior assessment results [12]. The aforementioned scholars have applied DL technology to evaluate the effectiveness of the education field, but the evaluation is not objective and comprehensive enough, and there is relatively little research in ideological and political classrooms. In summary, it can be seen that using DL methods to evaluate the effectiveness of IPE is feasible.

The article's contribution is as stated below:

(1) In order to address the issue of insufficient comprehensive and accurate evaluation of the effectiveness of IPE, a self-attention mechanism was applied for experiments based on relevant data from a research center of a certain university.
(2) The influencing factors of the effectiveness of IPE were fully considered. Through data on student academic performance, self-evaluation, social activities, student behavior, and teaching methods of each class teacher, the comprehensiveness of the evaluation data of IPE effectiveness was ensured.
(3) The experiment evaluated the effectiveness of IPE by integrating LSTM and self-attention mechanism, improving classification accuracy, precision, and other performance. The on-site investigation method was adopted to evaluate the effectiveness of teaching methods, providing practical data reference for future scholars.
(4) This study achieved excellent predictive performance. By processing field data from a research center of a university, the Long Short-Term Memory with Self-Attention Mechanism (LSTM-SAM) model outperformed other models in terms of classification accuracy, highlighting its effectiveness in evaluating the effectiveness of IPE.

2 Utilization of DL technology in IPE

IPE refers to a form of education in which students are given political and ideological education in a planned and organized manner in educational activities, cultivating their correct political stance, worldview, and outlook on life, and promoting their comprehensive development [13–15].

IPE performs an essential function and significance in contemporary society. First, IPE helps to lead students to develop a right outlook on the world, life and values, and cultivate socialist core values [16].

Second, IPE helps to promote the core socialist values and inherit and develop the theoretical system of socialism with Chinese characteristics [17]. In addition, IPE helps to promote social stability and progress, cultivate students' sense of rule of law and social responsibility, and guide them to establish correct social moral concepts, improving their legal awareness and legal literacy and enhancing the level of social civilization and social harmony and stability. Finally, and more importantly, IPE helps to cultivate socialist builders and successors with comprehensive development in morality, intelligence, physical fitness, and aesthetics [18].

The application of DL technology in IPE [19,20] is very extensive, especially during the period of strong promotion of IPE classrooms in recent years.

Through DL models, suitable learning resources and teaching content can be recommended for students based on their learning characteristics and needs, improving learning efficiency and motivation. Second, in the analysis of learning behavior, DL models are used for profiling student learning action data and exploring student learning patterns, learning habits, and learning motivation, providing valuable references for teachers, and helping teachers better understand students, adjust teaching strategies, and improve teaching effectiveness. Third, in terms of teaching content recommendation, based on DL technology, students' learning behavior and interests are analyzed, and suitable IPE content and learning resources, such as articles, videos, and online courses, are recommended to stimulate students' learning interest and participation. Fourth, in the evaluation of teaching quality, DL techniques are used to assess students' academic behavior, such as homework grades and classroom participation, in order to objectively evaluate teaching quality and student attainment, and offer data support for instructional enhancements. In summary, it is evident that DL technology has a vast field of applications in IPE, which can help educators better understand students, optimize teaching processes, and improve teaching quality, thereby promoting the in-depth development and improvement of IPE.

This experiment mainly evaluates the effectiveness of IPE, because the goal of it is to cultivate students' ideological and moral qualities, and the effectiveness of IPE is often difficult to directly quantify and evaluate. After evaluating the effectiveness of IPE through DL models, a more objective and comprehensive understanding of students' learning and development in IPE can be achieved. Moreover, the evaluation of the effectiveness of IPE is crucial for educational reform and enhancement. By evaluating the effectiveness of IPE, existing problems and shortcomings can be identified in a timely manner, providing scientific basis for the improvement of educational and teaching work.

3 LSTM model and self-attention mechanism

3.1 LSTM model

LSTM is a DL model used for processing sequence data, particularly suitable for sequence data with long-term dependencies. By applying gating mechanisms, long-term dependencies can be effectively captured and remembered, resulting in better performance in processing sequence data. It is commonly used to solve the gradient vanishing and exploding problems that Recurrent Neural Network models are prone to when processing long sequences [21,22].

In the LSTM model, the input gate represents the input interface for structured data, which obtains new data from the outside and preprocesses the data simultaneously. The forget gate receives the memory information passed down from the previous unit and then selects the data with the strongest features based on the weight of the data, while forgetting the information with weaker features. The output gate mainly outputs the processed data.

The neural unit of LSTM first inputs data y_t, D_{t-1}, and K_{t-1} through the input gate at the previous time and then calculates the state of the memory unit through the forget gate function g_t and input gate function J_t. The calculation formula for the forget gate function is shown in the following [23]:

$$g_t = \beta(U_g[K_{t-1}, y_t] + c_g), \tag{1}$$

where β and U_g represent the weight coefficients, and c_g represents the bias.

The calculation formula for the input gate is shown in the following:

$$J_t = \beta(U_\mathrm{v}[K_{t-1}, y_t] + c_\mathrm{v}), \tag{2}$$

where U_v represents the weight coefficient, and c_v represents the bias.

The calculation formula for the information of memory cells is shown in the following formula (3):

$$\bar{D}_t = \tan h(U_\mathrm{d}[K_{t-1}, y_t] + c_\mathrm{d}). \tag{3}$$

Finally, the output layer is calculated based on the state and output data of the memory unit, and the calculation formulas are shown in the following:

$$D_t = J_t \times \bar{D}_t + g_t \times D_{t-1}, \tag{4}$$

$$k_t = \beta(U_\mathrm{p}[K_{t-1}, y_t] + c_\mathrm{p}) \times \tan h(D_t), \tag{5}$$

where tanh represents the hyperbolic tangent function.

3.2 Self-attention mechanism

To further improve the behavior of the LSTM model, a self-attention mechanism is applied to optimize the LSTM. Self-attention mechanism is an attention mechanism used for processing sequence data, which enables models to dynamically focus on information at different positions in the sequence without being limited by the length of the sequence [24–26]. The self-attention mechanism allows the model to dynamically weight information from different positions when processing the input sequence to better capture long-distance dependencies and importance in the sequence. Incorporating the self-attention mechanism can help to focus on different positions and information in parallel, which improves the model's expressive and learning abilities. In addition, self-attention mechanisms typically integrate and process information through parameter mapping and fully connected layers, which can better utilize semantic information in sequences and improve the model's representation and generalization capabilities.

In the self-attention mechanism, it includes the self-attention force of the encoder, the attention of the connecting encoder, and the attention of the decoder. For multihead attention in self-attention mechanism, it uses multiple scaled convolutional attention as the basic unit, stacks them sequentially, and then uses value-weighted sum to determine the weight of values through the similarity function of the query. The formula for calculating weighted eigenvectors is shown in the following [27]:

$$\mathrm{Attention}(P, L, W) = \mathrm{Softmax}\left(\frac{PL^\mathrm{s}}{\sqrt{\mathrm{e}_\mathrm{l}}}\right), \tag{6}$$

where P denotes the query, L denotes the key, and W denotes the corresponding value.

Based on the aforementioned steps, the parameter matrix is mapped to P, L, and W for self-attention, and then, the results are connected and sent to the fully connected layer.

3.3 Model fusion

The steps for integrating the LSTM model and self-attention mechanism in this experiment are as follows:

(1) The LSTM model is used to model the input sequence data and obtain the output of the LSTM model.
(2) Then, the output of the LSTM model is used as the input of the self-attention mechanism, and the output of the LSTM model is weighted and summed using the self-attention mechanism to obtain the output of the self-attention mechanism.
(3) The output of the LSTM model and the output of the self-attention mechanism are concatenated in the feature dimension to obtain the fused output.

In the aforementioned steps, the self-attention mechanism calculates the attention weights between each position and other positions in the output of the LSTM model, and it applies these weights to the output of the LSTM model to obtain a new representation after weighted summation. It represents a new processing and extraction of LSTM model output, which integrates self-attention mechanism to analyze the significance of distinct locations, and has a richer and more comprehensive feature representation.

4 Experimental evaluation of the effectiveness of IPE

4.1 Experimental data

The data for this experiment come from the actual data of a research center of a certain university in 2023, including student academic performance, student self-evaluation, social practical activities, student behavior data, and teaching methods of each class teacher. Among them, student academic performance includes exam scores, homework scores, and classroom performance, in ideological and political courses; social practice activities include volunteer service, club activities, and internship practice; student behavior data include records of student behavior on campus and in society, including disciplinary situations, and moral behavior; the teaching methods include teaching method, group cooperative learning method, case study method, gamified teaching method, and problem-solving method. Based on the collected data from various aspects, the effectiveness of IPE is comprehensively evaluated, providing scientific basis for educational reform and improvement. A total of 30 college students are collected in the experiment, with a total of 3,090 pieces of data. The data partitioning method adopts the tenfold cross-validation method to partition the data, with 30% as the testing set and 70% as the training set. The experiment is conducted alternately, and the average of the results is taken as the final result of the experiment. Some of the test data are shown in Table 1.

Table 1: Experimental data

Student	Class	Party member or not	Watching time of ideological and political courses (40 min)	Number of social welfare practices	Number of discussions participated	Test scores
Zhang	1	1	28	5	2	89.20
Wang	1	1	30	8	4	93.45
Li	1	2	16	2	1	82.14
Zhao	2	1	35	1	1	90.06
Liu	2	2	10	3	2	79.22
Chen	2	2	8	0	1	75.29
Huang	3	2	23	3	2	90.31
Xu	3	1	5	4	0	60.82
Zhou	3	2	2	0	0	64.77

In Table 1, the student's attributes, class, whether they are a party member, duration of ideological and political course viewing, frequency of social welfare participation, number of discussions, and exam scores in sequence are displayed. Among them, in the attribute of being a party member, 1 represents being a party member and 2 represents not being a party member.

From Table 1, it can be observed that there are certain differences in the viewing time and participation in discussions of students in ideological and political courses. Zhang has a viewing time of 28 min in ideological and political courses, while Wang has 30 min, which reflects the differences in students' learning attitudes and participation levels. At the same time, the frequency of social welfare and test scores also show diversity, reflecting the differences in social practice and academic performance among students. Furthermore, the party membership of students may have an impact on the effectiveness of their IPE. In Table 1, it can be seen that some students are party members, while others are not. By comparing the differences in viewing time, social welfare frequency, participation in discussions, and test scores between party member and non-party member students in ideological and political courses, the impact of party member identity on the effectiveness of IPE can be further analyzed.

4.2 Data preprocessing

To learn more about the data for the model, preprocessing is performed on the data, removing outlier data and supplementing it with the mean interpolation method. Missing values are also replaced with attribute mean [28,29]. The data is normalized to between 0 and 1, as shown in the following formula:

$$X = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \tag{7}$$

4.3 Experimental process

The design steps of the test flow of this test are shown in Figure 2, which are as follows:
(1) First, based on the collected data on student IPE, the data is processed for missing and outliers and normalized.
(2) Then, the LSTM model and self-attention mechanism are integrated for evaluating the effectiveness of IPE.
(3) A total of ten trials are run to comply with the results in order to evaluate the behavior of LSTM-SAM, LSTM, Random Forest, Decision Tree, and SVM in evaluating the effectiveness of IPE.
(4) The optimization of the model is carried out using the Adam (Adaptive Moment Estimation) gradient descent algorithm [30,31], with a learning rate initialized to 0.0001 and betas set to (0.9, 0.999).

LSTM-SAM is selected for comparison with LSTM, Random Forest, decision tree, and SVM based on the following criteria: first, LSTM-SAM is a DL model, while Random Forest, decision tree, and SVM belong to traditional machine learning (ML) methods. By comparing the performance of DL and traditional ML methods in evaluating the effectiveness of IPE, the advantages and disadvantages of DL technology in this field can be evaluated. Second, LSTM-SAM has strong memory and inference capabilities and incorporates self-attention mechanisms. Compared to them, Random Forests, decision trees, and SVM are ML algorithms based on simple models, which have lower model complexity. By comparing the performance of these models in evaluating the effectiveness of IPE, the balance between model complexity and performance can be evaluated.

4.4 Evaluation indicators

Accuracy:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \tag{8}$$

Precision:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{9}$$

Recall rate:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{10}$$

In this study, multiclassification is adopted as a whole. Among them, the actual positive class prediction is true positive, and passing is predicted as passing; the actual positive class is predicted as false negative, and passing is predicted as failing; the actual negative class is predicted to be false positive, and failing is predicted to be passing; the actual negative class prediction is true negative, and failing is predicted as failing.

4.5 Experimental results

4.5.1 Specific prediction results of LSTM-SAM model

Through the aforementioned steps, the effectiveness evaluation categories of IPE were divided into failed, pass, generally, good, and excellent, corresponding to scores of 0–60, 60–70, 70–80, 80–90, and 90–100 in sequence. Failed is represented by 1; Pass is represented by 2; Generally is represented by 3; Good is represented by 4; Excellent is represented by 5. The detailed test findings are shown in Table 2.

Table 2: Part of experimental results

Student	Prediction category	Actual category	Student	Prediction category	Actual category
Zhang	4	4	Chen	3	3
Wang	5	5	Huang	5	5
Li	4	4	Xu	1	1
Zhao	5	5	Zhou	1	1
Liu	4	3			

In Table 2, overall, this model achieved a good evaluation of the effectiveness of IPE. Zhang*'s actual category was Good, and the prediction was also Good at this level. Moreover, as can be seen from the test data, the student studied ideological and political courses for up to 28 min and participated in social welfare discussions five times. He also frequently participated in classroom discussions on ideological and political topics. According to Wang*'s prediction results, the actual category was Excellent and the predicted category was Excellent. For specific data, the learning time was as long as 30 min; the number of social welfare practices was 8; the number of discussions was 4; the written test score reached 93.45 points. However, the model also has some erroneous predictions. Liu*'s actual performance in IPE learning was Generally, but this model predicted that it was Good. This may be due to the student's good performance in parameters such as social welfare frequency and participation in discussions, which leads to prediction errors. Overall, the LSTM-SAM model in this experiment achieved good results in evaluating the effectiveness of IPE.

4.5.2 Comparison of performance evaluation of IPE effectiveness using LSTM-SAM model with ten experiments

To analyze the behavior of IPE effectiveness assessment in each fold, the LSTM-SAM model for IPE effectiveness evaluation under ten experiments was displayed, as shown in Figure 1.

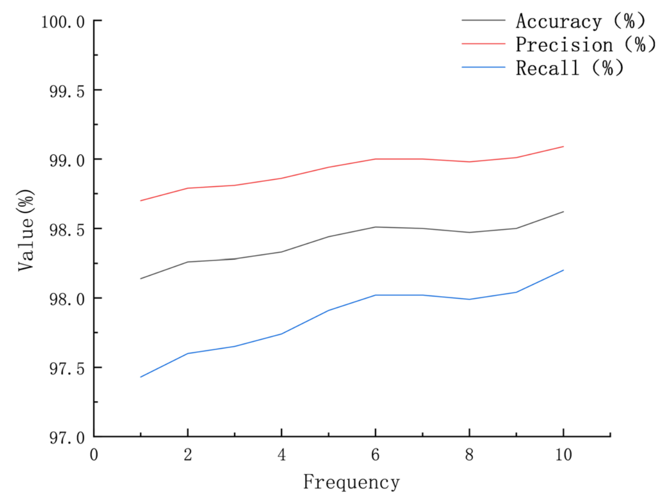

Figure 1: Performance evaluation of IPE effectiveness using the LSTM-SAM model.

In Figure 1, as a whole, it can be seen that the accuracy, precision, and recall of the effectiveness evaluation of IPE all steadily increased from 1 to 10 experiments, with an average accuracy of 98.41%, an average precision of 98.92%, and an average recall of 97.86%. In summary, it can be seen that the LSTM-SAM model has achieved good performance in evaluating the effectiveness of IPE.

4.5.3 Confusion matrix for effectiveness evaluation results

The confusion matrix for different classification of learning outcomes in IPE is shown in Figure 2. The horizontal axis represents the prediction type: from left to right, it is Failed, Pass, Generally, Good, Excellent;

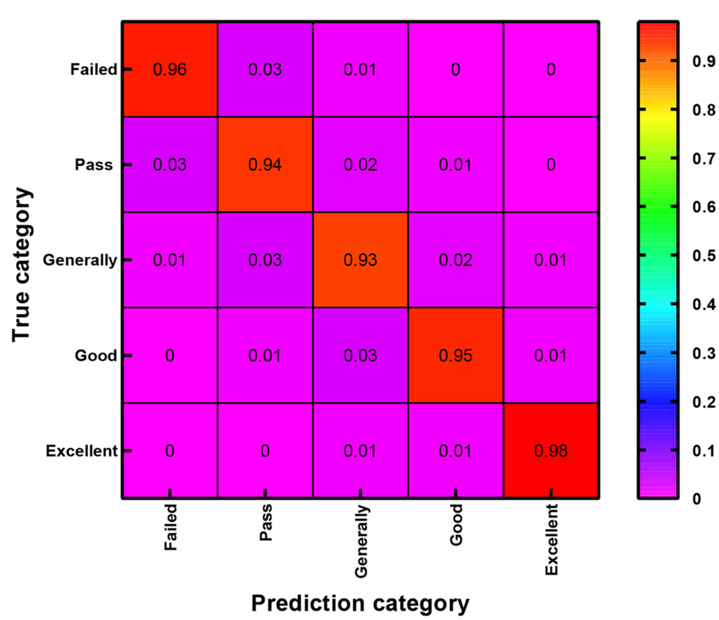

Figure 2: Confusion matrix of effectiveness evaluation results.

the vertical axis represents the actual category: from top to bottom, it is the same as the horizontal axis. As can be seen from the analyses in Figure 2, the percentage of samples actually belonging to the corresponding actual category predicted to be the highest was concentrated in Excellent, and the proportion of correctly predicted samples reached 98%, indicating a very impressive classification effect. The lowest concentration was in Generally, and the proportion of correctly predicted samples reached 93%, which was higher than the number of classification errors. Among them, 1% was incorrectly predicted as Failed; 3% was incorrectly predicted as Pass; 2% was predicted as Good; 1% was predicted as Excellent. Pass was difficult to classify, which was only 94%, with 3% predicted as Failed, 2% predicted as Generally, and 1% predicted as Good. Excellent was the easiest to detect and was more prominent compared to other analogical features, resulting in higher estimation accuracy and good classification performance for other categories.

4.5.4 Performance evaluation of IPE effectiveness using different models

For a closer look at the capability of the LSTM-SAM model, it was compared and analyzed with LSTM, Random Forest, decision tree, and SVM models, as shown in Figure 3.

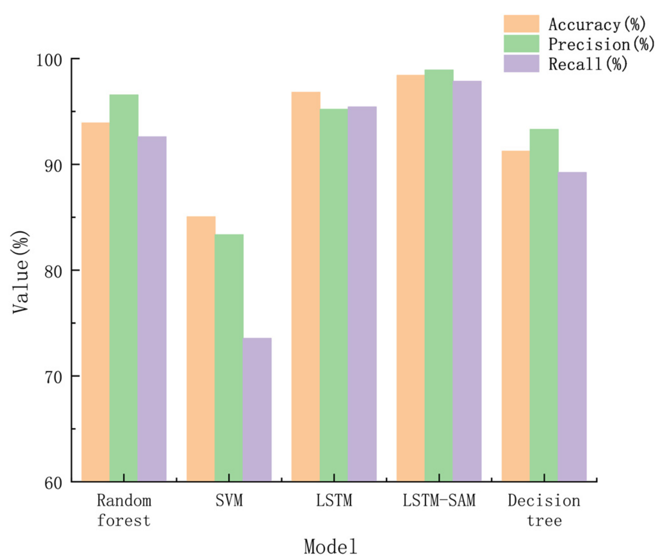

Figure 3: Evaluation of the effectiveness of IPE using different models.

In Figure 3, in terms of accuracy, the LSTM model achieved 96.80%; the LSTM-SAM model achieved 98.41%, an improvement of 1.61% compared to the LSTM model, indicating that applying self-attention mechanism can improve the classification performance of the LSTM model; the Random Forest model reached 93.92%; the decision tree model reached 91.25%; the SVM model had the worst classification accuracy, only 85.04%. In terms of precision, the LSTM-SAM model achieved 98.92%, an improvement of 3.72% compared to the LSTM model, indicating a significant improvement and confirming the classification behavior of the model with the application of self-attention mechanism. Next was the Random Forest model, which reached 96.55%, a decrease of 2.37% compared to the LSTM-SAM model. The SVM model only accounted for 83.34%. Regarding the recall rate, the highest was still the LSTM-SAM model, which reached 97.86%, an improvement of 24.3% compared to the SVM model. Overall, the LSTM-SAM model has better classification behavior in terms of accuracy, precision, and recall compared to the other four models, achieving good performance.

To further validate the analysis of the area under the curve (AUC) performance of this model, the specific receiver operating characteristic (ROC) curve comparison is shown in Figure 4.

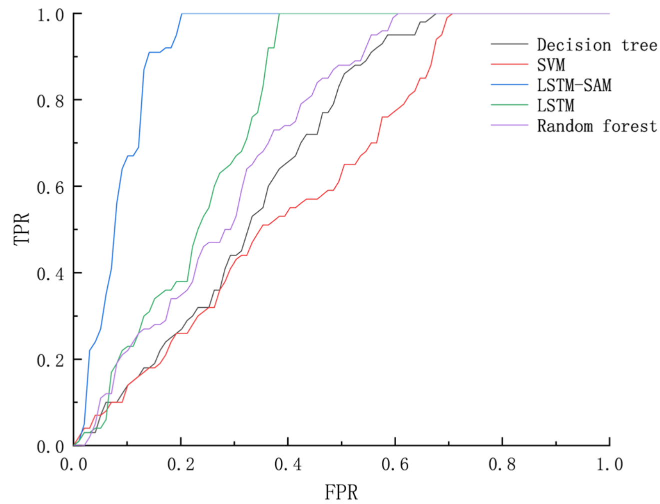

Figure 4: ROC curves of different models.

In the ROC curve of Figure 4, the closer the curve is to the upper-left corner, the better the performance of the model. The closer the curve is to the diagonal, the poorer the behavior of the model. The point in the upper-left corner indicates that the model can achieve both high true positive rate and low false positive rate at a good threshold, representing an ideal working point. In Figure 4, it can be seen that the SVM model's curve was closer to the diagonal in the experiment, with the smallest corresponding AUC of only 0.64, indicating the worst predictive performance of the model. For the LSTM-SAM model experiment, the curve was closer to the upper-left corner, corresponding to the maximum AUC, reaching 0.90, indicating better performance in evaluating the effectiveness of IPE. In addition, the LSTM model also reached 0.81; the Random Forest model reached 0.74; the decision tree model only reached 0.68. The overall image shows part of fitting, which is caused by the model overfitting the features of the training set, resulting in the inability to generalize to unseen data. Overall, it can be seen that the LSTM-SAM model achieves the best classification performance.

4.5.5 Efficiency of different teaching methods

The teaching methods of ideological and political classes can directly affect the cultivation of students' ideological and political literacy and moral qualities. Appropriate teaching methods can build a great environment for learning, inspire students' interest and motivation in learning, and promote the comprehensive development of their thinking abilities. By flexibly applying various teaching methods, not only can teaching effectiveness be improved, but also the effectiveness of IPE can be evaluated and enhanced, building a strong foundation for the holistic growth and well-being of students. Teaching methods usually include traditional teaching methods, group cooperative learning, case study, gamified teaching, and problem-solving. The questionnaire survey was adopted to collect the teaching methods of 320 teachers, ensuring the coverage of all methods in the data. A total of 303 pieces of data were collected, and statistics were conducted from four aspects: improvement rate of academic performance, mastery of knowledge, improvement of ideological and political literacy, and student interest in learning, as shown in Table 3.

Table 3: Efficiency of different teaching methods

Teaching method	Learning performance improvement rate (%)	Knowledge mastery (%)	Improvement level of ideological and political literacy (%)	Students interest in learning (%)
Teaching method	15.25	80.76	10.05	61.28
Group cooperative learning method	20.57	83.39	17.70	73.34
Case study	26.91	92.53	21.28	78.42
Gamified teaching method	32.52	97.92	25.09	82.93
Problem solving	22.74	88.35	19.51	76.26

The specific steps of the questionnaire survey were as follows:

(1) First, a questionnaire targeting teaching methods was designed, including traditional teaching methods, group cooperative learning methods, case studies, gamified teaching methods, problem-solving methods, and other common teaching methods.
(2) The designed questionnaire was distributed to 320 teachers through email, online survey platforms, or paper methods to ensure coverage of all teaching methods in the data.
(3) The completed questionnaires by teachers were collected to ensure that each questionnaire was filled out completely and accurately. When collecting data, attention should be paid to ensuring the privacy and information security of the respondents, as well as the timeliness and completeness of questionnaire collection.
(4) The collected data were statistically analyzed from the aspects of academic performance improvement rate, knowledge mastery level, ideological and political literacy improvement level, and student learning interest level. Statistical methods and data visualization tools were used to process and display the data, in order to obtain relevant conclusions and insights.

In Table 3, in terms of the rate of growth in academic performance, the teaching method had the lowest score, only 15.25%, followed by group cooperative learning method, which only reached 20.57%, and the highest score was gamified teaching method, which reached 32.52%. From the perspective of knowledge mastery, gamified teaching method and case study method were relatively high, reaching 97.92 and 92.53%, respectively. From the viewpoint of ideological improvement and political literacy, the group cooperative learning method reached 17.70%, and the gamified teaching method reached 25.09%, which was 15.04% higher than traditional teaching methods. From the perspective of student interest in learning, gamified teaching method reached 82.93%; problem-solving method reached 76.26%; the lowest was the teaching method, which was only 61.28%. Overall, it can be observed that college students prefer gamified teaching methods, while they are less interested in traditional teaching methods.

In this experimental data, Class 1 adopted a gamified teaching method; Class 2 adopted a case study approach; Class 3 adopted the traditional teaching method. Compared with experimental data, it can be seen that from the perspective of student attribute parameters such as exam scores, the teaching efficiency of using gamified teaching method was generally higher, and the improvement of ideological and political literacy and academic performance of college students was faster, resulting in better results. Therefore, it is recommended to apply gamified teaching methods or case studies for Class 3 to improve teaching efficiency.

4.5.6 Importance level of features

After the aforementioned experiment, the relevant data of ideological and political research on college students were analyzed for the importance of characteristic attributes, as shown in Figure 5.

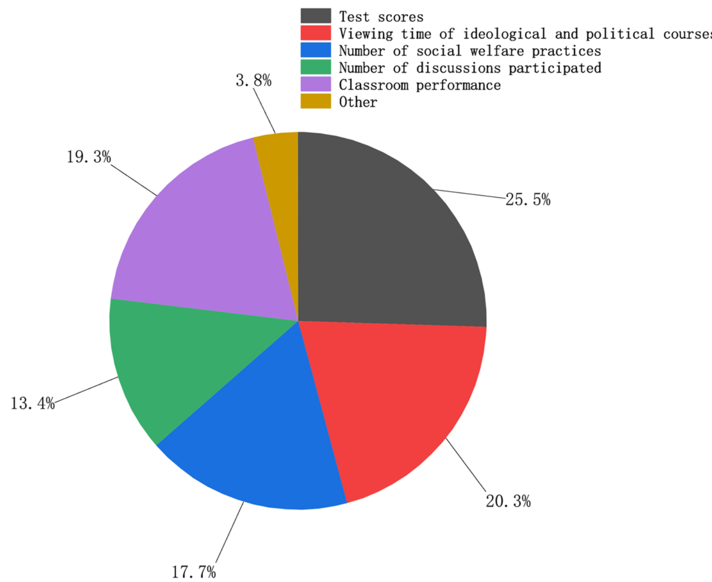

Figure 5: Importance level of features.

In Figure 5, it can be seen that the ideological and political exam score still accounted for the largest proportion, reaching 25.5%, followed by the viewing time for ideological and political courses, which also reached 20.3%, and the classroom performance reached 19.3%. In addition, the number of social welfare practices reached 17.7%, and the number of participation in discussions reached 13.4%. In summary, it can be seen that the importance of the characteristics of exam scores in IPE courses is the highest, and it has the greatest impact on the evaluation results. This may be because the current IPE evaluation system may focus more on students' academic performance, and test scores are one of the main indicators for evaluating students' academic level. In addition, the high proportion of test scores in feature importance analysis may also be limited by data collection. However, aspects such as classroom performance and the number of social welfare practices cannot be ignored.

5 Experimental discussion on evaluating the effectiveness of IPE

In the aforementioned experimental results, by investigating and analyzing the classification behavior of the distinct models in evaluating the effectiveness of IPE, the teaching efficiency of different teaching methods, and the teaching efficiency analysis of college students on IPE courses, the LSTM-SAM model showed high accuracy, precision, and recall in evaluating the effectiveness of IPE, proving its effectiveness in evaluating students' ideological and political literacy and moral qualities. In addition, the application of self-attention mechanism enhanced the LSTM model's attention and learning of important features, improving the performance of the model. Comparing the efficiency of different teaching methods, it was found that gamified teaching method and case study method had a more significant effect on improving students' grades and ideological and political literacy and were also more effective in stimulating their learning interests.

From the analysis of influencing factors, the superiority of the LSTM-SAM model mainly benefits from its combination of LSTM model and self-attention mechanism, which can better capture temporal information and important features in the data. The excellent performance of the LSTM-SAM model in evaluating the effectiveness of IPE may be due to its ability to effectively process temporal data and weight important features through self-attention mechanism, thereby improving the predictive behavior of the model. The impact of teaching methods mainly depends on the design and implementation of teaching methods. Gamified teaching methods and case studies can better stimulate students' learning interest and thinking ability. The reason why gamified teaching methods and case studies can improve students' academic performance and ideological and political literacy may be because these teaching methods can stimulate students' interest and improve their participation and thinking ability.

6 Conclusions

This article was based on time series data on IPE from universities and integrated the LSTM model and self-attention mechanism through concatenation for the effectiveness evaluation experiment of IPE. The experimental results showed that by applying a self-attention mechanism, the model can better understand the learning trajectory and changing trends of students and dynamically distinguish the importance of different parts in the input sequence, improving the accuracy and robustness of effectiveness evaluation. However, there are also some shortcomings in this study. Although the accuracy performance is good after applying self-attention mechanism, a lot of model parameters lead to unsatisfactory response speed. Therefore, future research would focus on lightweight optimization of the LSTM-SAM model to improve its efficiency and practicality through techniques such as model compression and parameter pruning.

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