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Research on the Hybrid Teaching Mode of Mechanical Fundamentals in the Context of Artificial Intelligence

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Abstract: The purpose of this study is to explore the innovation and application of mechanical foundation teaching mode in the context of artificial intelligence, and to improve students' learning efficiency and understanding ability through a hybrid teaching mode, which combines online and offline teaching methods. In the experiment, by comparing and analyzing the differences between traditional teaching mode and blended teaching mode in student learning effectiveness, the superiority of blended teaching mode in mechanical foundation courses was obtained. At the same time, this study also pointed out the problems and solutions in the implementation of blended learning mode, providing strong theoretical support and practical guidance for the optimization of future teaching modes. In the experimental stage, we explored the effectiveness of Long Short Term Memory (LSTM), Recurrent Neural Network (RNN) and Gated Recurrent Unit (GRU) in educational technology applications through four experiments. In the benchmark performance evaluation experiment, the accuracy based on the LSTM model was 75%, the recall was 80%, and the F1 score was 77%. In the second learning path recommendation effectiveness evaluation experiment, the LSTM model improved the average score of students by 15 points in recommending learning paths. In the evaluation experiment of improving learning motivation and participation, the learning motivation score based on the LSTM model was 90 points, and the participation score was 92 points. From the above experimental data conclusions, it can be seen that the LSTM model has great potential in educational technology applications, especially in designing personalized learning paths, improving learning motivation and engagement, and promoting long-term learning outcomes.

1. Introduction

With the rapid progress of artificial intelligence technology, its application in the field of education has begun to receive widespread attention. In the face of the current situation where traditional education models cannot fully meet the needs of modern education, especially in stimulating students' learning interests and meeting their personalized learning needs, this study focuses on exploring the application of LSTM model, RNN algorithm, and GRU algorithm in blended learning models, with the aim of proposing more effective personalized learning solutions for the field of educational technology.

In this study, the performance of LSTM, RNN, and GRU in educational technology applications was evaluated through four experiments, particularly their roles in personalized learning path recommendation, enhancing learning motivation and engagement, and enhancing long-term learning outcomes. The experimental research results indicate that although GRU slightly outperforms LSTM in certain performance indicators, LSTM has significant advantages in enhancing students' learning motivation, engagement, and long-term learning outcomes. These results not only provide theoretical support for educational practice, but also point out directions for future research and development of educational technology.

This article first introduces the background and importance of the research, followed by a detailed description of the experimental design, methods used and model selection, as well as the process of evaluating model performance using dataset data. In the experimental stage, by comparing and analyzing various indicators of LSTM, RNN, and GRU in educational technology applications, this article delves into the advantages and potential application value of the LSTM model. The final conclusion section provides suggestions for future research directions. The full text has a clear structure and rigorous logic, with the aim of presenting readers with a comprehensive and in-depth study.

2. Related Works

In response to the limitations of traditional teaching methods, many researchers at home and abroad have begun to explore more effective teaching strategies. For example, based on elaborating on the connotation of flipped classroom, Liu Dong discussed the practical value of flipped classroom in economic law teaching, and summarized the process and steps of flipped classroom application in economic law teaching, as well as the combination of common teaching methods [1]. Hu Chunyi et al. used the course "Principles and Interface Technology of Microcomputers" as an example, and constructed a flipped classroom teaching model based on the results oriented education concept, relying on the teaching platform to systematically sort out the logical relationship between course objectives and teaching design, and optimize teaching content [2]. Deng Huiji explored the flipped classroom teaching model from the perspective of MOOC, sincerely hoping that vocational colleges can use rich MOOC resources as the basis and create a more inclusive and free teaching environment through online platforms in the actual teaching process, in order to implement the flipped classroom teaching method [3]. Mascaro D J introduced the implementation of a comprehensive, hands-on, project-based teaching method for computer programming for freshmen majoring in mechanical engineering at the University of Utah. He also described the structure and content of the course, including the nature of the competition, and explained how to achieve the integration and synchronization of course content [4]. In order to meet the needs of production, teaching, and research talents, Gao S explored the complexity, interdisciplinary nature, and fast technological update speed of this course in the context of the new engineering discipline [5]. In order to improve the traditional teaching method of the course "Fundamentals of Mechanical Design", Luo S Z had taken measures such as integrating teaching resources, reforming teaching content, teaching methods, and assessment methods [6]. Lv X discussed the current practical situation of teaching computer fundamentals courses and the requirements for adopting a blended learning mode in a network environment. He proposed an effective strategy for implementing blended learning in computer basic courses in a network environment [7]. Piedade J' s research aimed to analyze how pre service informatics teachers use robots to design learning scenarios, teach programming fundamentals, and enhance students' computational thinking skills [8]. Rui Xiaoguang proposed a curriculum reform plan called "New Mechanical Fundamentals" to address the problems in industrial design. This plan is based on the principle of combining the teaching content of mechanical fundamentals with industrial design courses [9]. Shu Xin proposed the suggestion of incorporating the "Three Sex Experiment" teaching model into the mechanical foundation teaching of technical colleges, aiming to better cultivate talents with innovative spirit [10]. However, these studies have different focuses and have not yet formed a unified and efficient teaching model framework, especially in the teaching of mechanical foundation courses. The application effects of these methods still need to be verified.

Although existing literature provides case studies of various teaching methods, their specific application in mechanical foundation teaching is still insufficient. Although methods such as flipped classroom and project-based teaching have solved some of the problems in traditional teaching to a certain extent, their effectiveness in improving students' comprehensive application ability and combining theory with practice is still limited. In view of this, this study proposes to adopt a blended learning model, which aims to comprehensively improve students' learning efficiency and application abilities by fully utilizing online teaching resources and closely integrating offline practical activities.

3. Methods

3.1 Introduction to the Principle of LSTM Algorithm

The LSTM model is a special model based on RNN improvement, mainly used to solve long sequence tasks that RNN models are not good at, and can solve the gradient vanishing problem in long sequence tasks. It is very powerful in handling tasks related to temporal order and is widely used in various fields. In recent years, many scholars have improved the LSTM model and proposed many excellent neural network models, making LSTM one of the important foundational models in research [11-12].

In the structure of LSTM cells, there is something called a memory cell that only interacts with a small amount of information, allowing it to maintain its cellular state for a long time without being easily forgotten or altered. In addition, LSTM has three unique gate structures, including forget gates, input gates, and output gates, which is another notable feature of LSTM. The forget gate is responsible for determining which information to discard from the cellular state. The forgetting gate can be represented by formula (1):

$$\mathrm{f}_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

In formula (1), f_t represents the activation vector of the forget gate, σ is a function, W_f is the weight matrix related to the forget gate, h_{t-1} is the hidden state of the previous time step, x_t is the input of the current time step, and b_f is the bias term of the forget gate. The function of the input gate is to update the cell state. The final output gate is responsible for determining the value of the next hidden state. The hidden state contains information about the previous input and is also used to predict the next input. This process can be represented by (2) and (3).

$$\mathrm{o}_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{2}$$

$$\mathrm{h}_\mathrm{t} = o_t * \tanh(C_t) \tag{3}$$

In formulas (2) and (3), reference can be made to formula (1), where o_t represents the output gate at time step t and h_t represents the final hidden state. C_t is the cell state at time step t. tanh represents the hyperbolic tangent activation function. Through this structure, LSTM can effectively maintain long-term dependency relationships, avoiding the problems of gradient vanishing and exploding faced by traditional RNN. This makes LSTM particularly suitable for application scenarios that require consideration of long-distance contextual relationships between input data, such as language models, sequence prediction, speech recognition, and other fields [13].

3.2 LSTM Network Architecture Design

In the research of hybrid teaching mode for exploring mechanical foundations in the context of artificial intelligence, the data collection and preprocessing stage directly affects the efficiency of training LSTM models and the reliability of results. In response to the specific needs of this study, this article has captured some student learning data online as a dataset, which is used for training and testing the research model. The following is a detailed dataset of 100 students, as shown in Table 1:

Table 1: Dataset details

Student ID	Learning Hours	Homework Submissions	Discussion Participation	Score Improvements
1	11.0753	13	7.3709	1.7113
2	13.6678	8	9.8756	1.5211
3	5.4823	10	8.5497	5.1199
……	……	……	……	……
100	6.4106	12	9.7435	5.9114

In the dataset of Table 1, the collection mainly focuses on learning duration, homework submission, discussion participation, and score improvement. Datasets are usually a mess with missing values, outliers, and even inconsistencies, which requires data preprocessing to improve data quality and analysis effectiveness. Firstly, it is necessary to clean the collected data and eliminate incomplete, incorrect, or abnormal data records. Considering the diverse types of data collected, data standardization is used to eliminate the impact of different scales. In this study, Z-score standardization was used to process video viewing time. Among them, Z-score standardization can be achieved using formula (4):

$$Z = \frac{(X - \mu)}{\sigma} \tag{4}$$

In formula (4), the original data is X, μ and σ are the mean and standard deviation of the data, and the standardized data is Z. Missing values are inevitable in the collected data. This study adopted the method of deleting records containing missing values. Through the above data collection and preprocessing steps, a clean, standardized, and informative dataset can be obtained before the experiment begins, laying a solid foundation for constructing personalized learning path recommendation models using the LSTM algorithm.

3.3 Model Training and Optimization

The goal of training the LSTM model in this article is to adjust the weights within the network by learning labeled sample data, with the aim of making the model's prediction results as close as possible to the true values, thereby reducing errors and achieving ideal results. In this process, adjusting different network weights will lead to different degrees of error in the model. This article will use something called a loss function to measure how large the prediction error is when the network weights are set differently. When dealing with regression problems, the value of this loss function is usually represented by Mean Absolute Error (MAE) or Mean Squared Error (MSE). The average absolute error refers to the average of the absolute values of all sample errors, which can avoid the cancellation of positive and negative errors between the predicted and actual values of different samples. However, there is a problem with functions containing absolute values, which is that they cannot be differentiated at certain points, which is not good for model optimization. Therefore, the LSTM model in this article chooses mean square error as the loss function, which not only facilitates differentiation and gradient calculation, but also reflects the model loss situation corresponding to different network weights during the optimization process [14].

Next, the model gradually adjusts its parameters through multiple rounds of iterative training to minimize the loss function. In each round of training, we divide the dataset into multiple batches, and the LSTM model will be trained batch by batch, which helps improve the efficiency and stability of model training. By monitoring the performance on the validation set, if there is no significant improvement in performance within several consecutive iterations of training, terminate the training process in advance. Finally, this article adopts a strategy of dynamically adjusting the learning rate. When the loss of the model stops decreasing, the learning rate is reduced to finely adjust the model parameters, thereby achieving better training results.

Through the above training and optimization process, the LSTM model in this article can effectively learn and predict students' learning behavior and its relationship with academic performance improvement, providing solid algorithm support for personalized learning path recommendation in blended learning mode [15].

4. Results and Discussion

4.1 Benchmark Performance Evaluation

In this benchmark performance experiment, the performance of the LSTM model, RNN algorithm, and GRU algorithm on personalized learning path recommendation tasks was evaluated. In the experiment, the performance of these three models in accuracy, recall, and F1 score were compared, and the data of these three indicators were plotted to visually display the performance differences of each model.

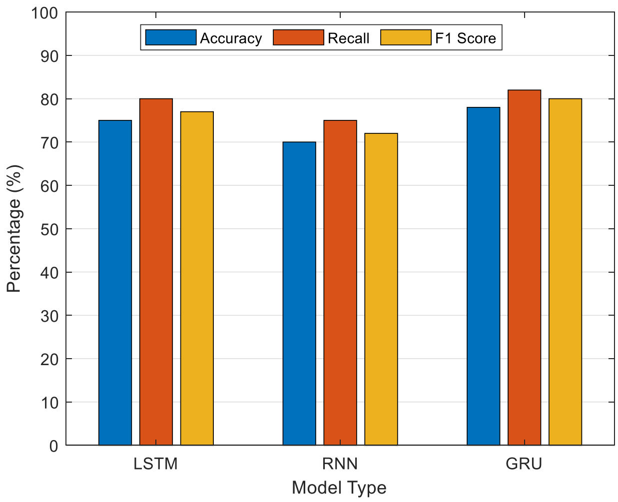

Figure 1: Benchmark performance evaluation

From Figure 1, it can be seen that the accuracy of LSTM reached 75%, the accuracy of RNN was 70%, and the accuracy of GRU was 78%. In terms of recall rate, LSTM reached 80%, while RNN reached 75% and GRU reached 82%. In terms of F1 score indicators, LSTM reached 77%, RNN reached 72%, and GRU reached 80%. From the above data conclusion, it can be seen that although the GRU algorithm is slightly better than LSTM in certain indicators, the LSTM model provides balanced and robust performance in the overall experiment. The specific situation is shown in Figure 1:

4.2 Evaluation of the Effectiveness of Learning Path Recommendation

This experiment evaluated and compared the performance of LSTM model, RNN algorithm, and GRU algorithm in personalized learning path recommendation systems. In the experiment, the focus was on the performance of three models in the two key indicators of student average score improvement and student satisfaction after recommendation. The performance values of the three models on these two indicators were plotted to visually demonstrate the performance differences. The specific data details are shown in Figure 2:

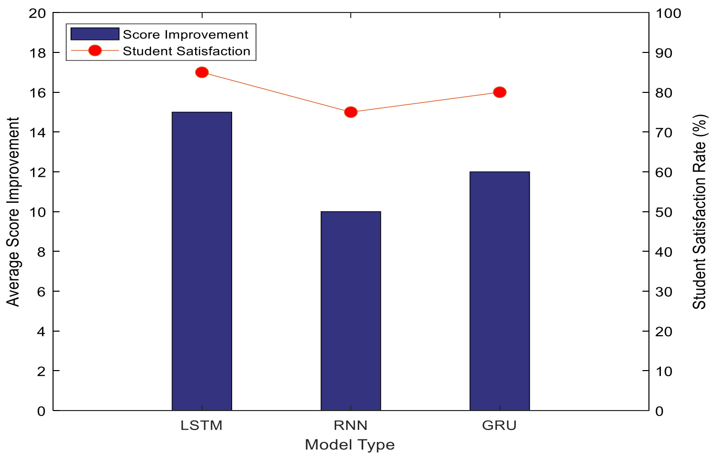

Figure 2: Evaluation of the effectiveness of learning path recommendation

From Figure 2, it can be seen that the learning path recommended based on the LSTM model can improve students' grades by an average of 15 points, while other GRU and RNN algorithms have achieved an average improvement of 12 points and 10 points, respectively. In terms of student satisfaction evaluation indicators, the average satisfaction rate based on the LSTM model reached 85%, while the student satisfaction rates for GRU and RNN were 80% and 75%, respectively. From the data conclusion, it can be seen that the LSTM model has a unique ability in understanding student learning needs and optimizing learning path recommendations.

4.3 Evaluation of Improving Learning Motivation and Participation

In the learning motivation experiment, the effectiveness of LSTM, RNN, and GRU models in enhancing student learning motivation and engagement was evaluated and compared. In the experiment, the average improvement scores of each model on learning motivation and participation were quantified to visually demonstrate the potential of each model in educational technology applications. Drawing the values of these two indicators into a graph to visually display the performance differences of each model.

From Figure 3, it can be seen that the average score of learning motivation based on the LSTM model was 90 points, and the average score of participation was 92 points. The learning motivation and participation scores of the RNN model were 80 and 78, respectively. Based on the GRU model, the scores were 85 and 88 respectively. From the above data, it can be seen that the LSTM model has a strong ability to stimulate students' interest in learning and participate in teaching activities. The specific data situation is shown in Figure 3:

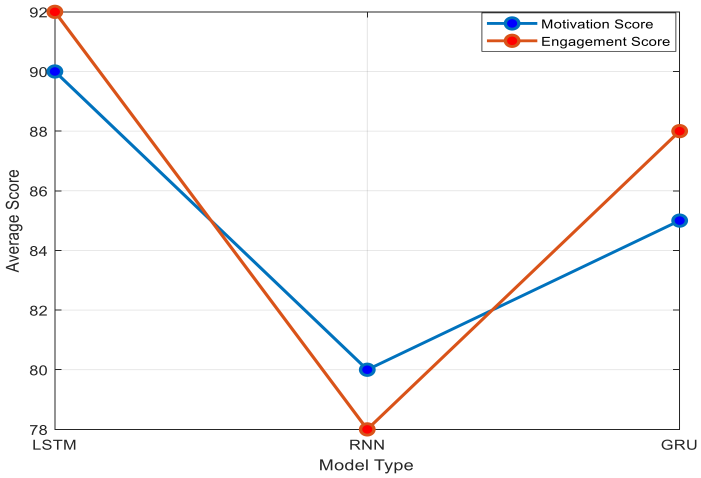

Figure 3: Assessment of Improving Learning Motivation and Participation

4.4 Long Term Learning Effectiveness Evaluation

In the long-term learning effectiveness evaluation experiment, the experiment compared three different artificial intelligence models: LSTM, RNN, and GRU. The experiment compares the impact of these models on the improvement of students' average grades within a semester, and then selects the most effective model to promote long-term learning for students. The long-term learning assessment can be represented by formula (5):

$$\text{LLE} = \alpha \cdot \Delta S + \beta \cdot E + \gamma \cdot P \tag{5}$$

In formula (5), ΔS represents the improvement of students' academic performance before and after learning, their participation during the learning period is E, P represents their persistence in the long-term learning process, and α, β, γ is the weight coefficient. The specific data details are shown in Table 2:

Table 2: Evaluation of Long Term Learning Effectiveness

Model	Average Score Improvement
LSTM	8
RNN	5
GRU	7

From the data in Table 2, it can be seen that the LSTM model achieved an average improvement of 8 points in promoting students' long-term learning, which is higher than other models. It can be seen that the LSTM model has unique advantages in processing long-term learning sequences and maintaining information flow.

5. Conclusion

In this study, the performance of algorithms such as LSTM in educational technology was evaluated through four experiments. The LSTM model not only effectively improves students' learning motivation and participation, but also makes an important contribution to enhancing their long-term learning outcomes. These findings provide strong theoretical and practical basis for designing personalized learning paths in blended learning models, and also demonstrate the enormous potential of LSTM in the field of educational technology. Although this study has made some progress, it still faces some limitations, such as the generalization ability of the model and the need for further testing of its adaptability in teaching scenarios. Future work can include exploring more diverse datasets and testing these models in offline teaching environments to further improve model structure and learning algorithms, enhance their performance and applicability in educational technology applications. In addition, studying the possible applications of other advanced artificial intelligence technologies in the field of education is also an important future research direction.

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