Research Article

Artificial Intelligence Technology and Its Application in Improving Thought-Politics Education

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As socialism with Chinese characteristics enters a new age, thought-politics education has also entered a new phase of development. Facing new opportunities and challenges, attaching importance to quality, pursuing quality, and improving quality have become the key directions for the development of thought-politics education. In the paper, a CNN-BiLSTM-based recommendation algorithm is proposed and combined with AI-related algorithms to be used in the task of improving thought-politics education. First, deep feature extraction in temporal and spatial dimensions by using LSTM and convolutional networks, respectively; then, by using multiscale attention fusion mechanisms to enhance the expressiveness of the features and make recommendations with the help of multilayer perceptron. Through extensive experiments, it is verified that the model has higher recommendation performance in this paper while maintaining higher real-time performance. It is tested on real data sets to verify that the model in the paper has better robustness.

1. Introduction

Nowadays, with the fast development, full integration, and widespread application of the new generation of network information technology represented by using mobile internet, internet of things, cloud computing, and artificial intelligence, humanity is gradually entering the “intelligent information era” of large-scale data mining, innovation [1], and application. The development and application of artificial intelligence and big data have become a new engine for economic transformation and growth and a new tool to reshape the country’s competitive advantage, and it has also become a new approach to improving national governance capacity in countries around the world. In recent years, our governments have been actively promoting carrying out the national big data strategy, accelerating the pace of building digital China, the application of artificial intelligence in various areas of the economy and society continues to advance in-depth, and the scientific value and social benefits are gradually highlighted. As the frontier of contemporary information technology development, the wide range of information resources, advanced information processing technology, and new thinking paradigm of big data empower the innovation and development of daily thought-politics education of college students and promote the intelligence of daily thought-politics education of college students.

When socialism with Chinese characteristics enters a new age, a range of new changes, which have led to new opportunities for both daily thought-politics education for college students, are occurring in the context of daily thought-politics education of college students, their goals and tasks, and the target audience of their work. In terms of new opportunities, on the one hand, the overall strengthening of the state’s leadership of thought-politics education in colleges and universities and the strengthening of the fundamental mission of “establishing moral education” in colleges and universities have brought a new historical opportunity for the daily thought-politics education of college students [2]. The national leaders emphasized that
from the overall height of achieving the great rejuvenation of the Chinese nation and the strategic height of realizing the party’s mission of governance and consolidating the party’s ruling position, they have made a comprehensive, profound, and systematic exposition of a series of issues such as the strategic status, duty, and mission, objectives and tasks, guidelines and principles, methods and paths, reform and innovation of thought-politics education work in colleges and universities at the National Conference on thought-politics work in colleges and universities, the Symposium for Teachers of Thought-politics Theory Courses in Schools, the Symposium for teachers and students of Peking University, and the National Education Work Conference. Importantly, it provides the scientific guidance and fundamental followings for the thought-politics education work of colleges and universities in the new period to develop a new situation and achieve new results. In addition, some relevant policies and regulations have been issued one after another, providing programs and planning paths for strengthening and innovating thought-politics work in universities. Under this situation, the daily thought-politics education of college students, which is the main position of thought-politics education for college students, will usher in new development opportunities. On the other side, the fast development of the new round of information technology revolution with digitalization, networking, and intelligence as its core features and its extensive integration with the economy and society have provided new vehicles and tools for the daily thought-politics education of college students. Currently, the new generation of network information technology represented by using mobile internet, Internet of things, cloud computing, and artificial intelligence is developing rapidly; digitalization, networking, and intelligence are prominent features but also the core of the emerging information technology. The development and application of new network media and new technology of big data provide new vehicles and tools for the day-to-day thought-politics education of students in the college.

The effective application of artificial intelligence and big data technology in the improvement of thought-politics education is beneficial to enrich the theory of thought-politics education for college students. Especially in the last few years, to enhance the thought-politics education of students in the college to achieve affinity in the context of anti-epidemic is especially the implementation of the professional ethics of college staff to care for students, which is the new requirement and development of the thought-politics education of students in the college in the new situation and new context. Secondly, it allows providing the diversified development needs of college students in the new age. College students entering the new era are more influenced and impacted by using the internet, have more ways and opportunities to contact new things, have more active thinking, more obvious personalized differences, more complex behavior patterns, and more diversified development needs for growth. With the assistance of big data technology and artificial intelligence technology, we are able to recommend positive cultural and educational columns to users in real time in the massive data, which can help meet the diversified development needs of college students in the new age [3]. It helps promote college students’ identification with thought-politics education. The most direct and obvious effect of thought-politics work in colleges and universities is to gain the acceptance and recognition of university students, which is related to whether the overall goal of thought-politics education can be achieved. The research study on enhancing the affinity of thought-politics education for college students in the new age will provide colleges and universities with the choice of paths, to build an intimate relationship with students in the education process, and also improve, to some degree, the identity of college students for thought-politics education. It also helps to build a harmonious and friendly campus environment in the new age of universities. The education system of colleges and universities is a unified organic whole. To improve the affinity of thought-politics education of college students in the new age, there is an urgent need for the joint efforts of many departments of colleges and universities and the whole education system. The whole staff, whole process, and all-round education mode is not only beneficial to optimize the relationship between teachers and students but also to the friendly collaboration between various organizational departments of the school, thus promoting the formation of a harmonious and friendly campus atmosphere and the construction of a harmonious and friendly campus environment.

Improving the thought-politics education of university students with the help of artificial intelligence technology is beneficial to promote the implementation of the establishment of the basic tasks of ethical education in colleges and universities. "The foundation of colleges and universities lies in the establishment of moral education." To establish morality is to use moral education to guide, sensitize, and motivate college students, to urge them to form correct moral concepts and excellent moral qualities, and to practice a good moral reality. We shape the people that are under the concept of “people-oriented” and “student-oriented” education; the university students will be shaped by using various educational methods, guided to become ideal, competent, and responsible newcomers of the times, and promoted to the overall development of all human qualities. In particular, in today’s rapidly growing network, how to accurately recommend positive cultural columns for colleges and universities to carry out the thought propaganda of the majority of young students, promote the core values of socialism, and help cultivate qualified socialist builders? As the main training ground for innovative talents, colleges and universities will become important participants, facilitators, and promoters under the wave of big data. As the most cutting-edge application of the new generation of information technology, the wide range of information resources, advanced information processing technology, and a new way of thinking contained in big data bring new impetus and space for the development and innovation of immediate, accurate, forward-looking and personalized daily thought-politics education for college students. Based on its resource advantages, technical advantages, and thinking advantages, big data has created a new space in cracking the lack of
information acquisition ability, weakened subject-object relationship, and ineffective education methods in traditional thought-politics education in colleges and universities. Demonstrating new values in meeting the diversity of needs for thought-politics education resources, the plurality of practice development, and the complexity of thinking transformation in universities. It brings new opportunities in providing strategic assets for thought-politics education in universities, exploring the laws of education, and grasping opportunities. It is a real need for the daily thought-politics education of college students to conform to the development of the times by using big data resources, technologies, and methods to promote the innovation of thinking, optimization of supply, improvement of methods, and reconstruction of paradigms, constructing a scientific, digital and intelligent daily thought-politics education system for college students, and promoting the transformation and upgrading of daily thought-politics education of college students to “accurate thinking and politics” and “intelligent thinking and politics. It is also an important growth point and strong impetus for the daily thought-politics education of college students to further improve its quality and efficiency and give it a new chance.

2. Related Works

In terms of thought-politics education, there is a lack of empirical evidence that professional scholars in China have paid due attention to and systematically studied the quality improvement of thought-politics education for college students. There is no chapter dedicated to “quality of thought-politics education” in any domestic thought-politics education textbook. The academic literature on systematic research on quality improvement of thought-politics education of college students has not been searched in the core journal paper database; in general, journals, although articles related to the quality of thought-politics education are abundant, many of them have made profound theoretical discussions on the issue, improving the quality of thought-politics education from different aspects; most of the articles are not directly related to this field, but only mention it in passing when discussing other topics, and there are very few specialized studies on it.

2.1. Study on the Theoretical Basis of Daily Thought-Politics Education for University Students. Theoretical foundation research mainly focuses on the conceptual connotation, current characteristics, content system, main principles, and basic laws of daily thought-politics education of college students, which aims to systematically construct and professionally develop the daily thought-politics education of college students.

Definition of the connotation of daily thought-politics education for college students. There are three main tendencies in defining and interpreting the connotation of the concept of daily thought-politics education for college students: one is to focus on the “subject” [4]. This view emphasizes that the daily thought-politics education of college students refers to the educational activities organized and carried out mainly by student staff, such as counselors. For example, literature [5] believes that daily thought-politics education of college students refers to various educational activities organized and carried out by college student staff, such as counselors and class teachers, according to the Party’s educational policy and the requirements of carrying out thought-politics education work in colleges and universities, from the law of students’ cognitive development and in response to different students’ thought reality, with dormitories, class groups and grade work as the carrier. Literature [6] focuses on the “everyday” statement. This viewpoint defines daily thought-politics education for college students as a form of education other than classroom teaching in thought-politics theory courses, emphasizing the “daily” nature. Literature [7] points out that the daily thought-politics education of college students refers to the thought-politics education activities that are often carried out on weekdays, penetrates the daily study and life of college students, and plays a subtle role in the overall development and healthy growth of college students, with the characteristics of regularity, extensiveness, continuity, latent and permeability. Literature [8] focuses on the “carrier” saying, “This viewpoint focuses on the daily thought-politics education carried out by various carriers such as party and group organizations, social practice, campus culture, and network management”. For example, according to literature [9], the daily thought-politics education of college students is “the most basic and important way to carry out thought-politics education and daily management for students with the carrier of party and group organizations, association organizations and classes.

In addition, the issue of effectiveness has always been the central issue in the study of daily thought-politics education of college students. The researcher mainly explores the strategies and paths to enhance the effectiveness of daily thought-politics education of college students from the aspects of the education concept, education content, education method, team building, and education mode. (1) Update the concept of education. Literature [10] points out that “people-oriented” is the educational concept and methodological principle that must be adhered to improve the effectiveness of daily thought-politics education of college students. Literature [11] points out that respecting the equality of personalities in educational philosophy and realizing the transformation of subject-object dichotomy to the intersubjectivity relationship is the way out of the dilemma of daily thought-politics education of college students. (2) Enrich the education carrier. Literature [12] explored the use of various carriers such as party and caucus organizations, club activities, class collective construction, campus culture, social practice, and network management in the daily thought-politics education of college students to enhance their effectiveness. For example, in terms of cultural carriers, it is pointed out that the spirit of Jinggang Mountain and Qilu culture are used as carriers to carry out daily thought-politics education for college students. In terms of network carriers, it is pointed out that microblogs, new media, WeChat, self-media, public numbers, and APP
2.2. The Function of Deep Learning in Enhancing Thought-Politics Education. Recently, achievements of deep learning in natural language processing and computer vision have led the recommendation field to take notice of the robust tool, and scholars have begun to explore the methods of using deep learning so as to improve some of the insurmountable weaknesses of today’s recommender systems, such as data sparsity, cold starts, and poor interpretability. Particularly, the advent of CNN and RNN has been a great success in many natural language processing tasks. So, people started to experiment with deep learning methods, DeepCoNN, D-Attn, etc., to mine user preferences and make recommendations from the user’s perspective, which can be directly applied to predictive scoring [25]. DeepCoNN is composed of two parallel neural networks with CNN as the basic model, learning the representation of the learner and the thought-politics-cultural preferences of interest, respectively, and connecting the two sections at the top of the network to see the interaction, which demonstrates the validity of user-focused texts on thought-politics education for alleviating the sparsity problem.

The focus of the attention mechanism is to learn a weight to identify the degree of importance, and it has been widely used for natural language processing since its introduction, achieving state-of-the-art results in machine translation, reading comprehension, and speech recognition, as well as other areas. Thus, attention mechanisms receive attention in the field of recommendation and start being used for building recommendation algorithms that enhance thought-politics education. NARRE uses attention mechanisms to learn textual representations of different cultures of thought, to better model users and interests, predict interests, and generate explanations. Unlike the D-Attn word-level attention mechanism, NARRE uses a two-channel attention mechanism. Inspired by transformer, MPCN proposes a new pointer-based learning scheme without using RNNs and CNNs and relying entirely on attention mechanisms, which allows for deep textual interaction between the learner and the thought-politics culture of concern, with excellent results.

The development of NLP has contributed greatly to the application of text in the area of recommendation. Pre-trained language models have evolved rapidly since they were proposed, resulting in lots of great approaches such as feature-based Elmo and fine-tuning-based OpenAI GPT. However, these language models are all unidirectional, limiting the representational power of pretraining. So, literature [26] proposed a bidirectional pretraining model, BERT, which reads the entire text at once using Transformer’s Encoder and this allows the model to learn based on both sides of the word and thus grasp more accurately the meaning expressed by the word in the sentence. Thus, BERT is naturally bidirectional, with a high generalization capability, and provides a good basis for downstream tasks.

In summary, this paper combines techniques such as CNN and LSTM in deep learning to construct recommendation models and apply them to the educational work of ideology and politics, which will greatly facilitate the rapid mining of columns such as education and culture of interest to learners in the massive data, quick reading to locate the knowledge of interest and real-time attention. Meanwhile, it is beneficial to enhance the cognitive ability of people's
3. Methodology

The recommended model of thought-politics education culture with artificial intelligence in this paper includes features extracted from the spatial dimension by using convolutional neural networks and temporal features extracted from the temporal dimension by using bidirectional long and short-term very easy neural networks, multiscale fusion based on the attributes of both features, and deep recommendation by using fused features. Section 3.1 gives the theory of convolutional neural networks; then, the process of feature extraction from the temporal dimension by long- and short-term memory neural networks is presented in Section 3.2; subsequently, a scale fusion attention is introduced in Section 3.3. Finally, Section 3.4 gives the strategy for computing the prediction scores and generating recommendations.

3.1. Convolutional Neural Network. The basic structure of a convolutional neural network [27] is composed of an input layer, a pooling layer, a fully connected layer, a convolutional layer, and an output layer. The convolution layer is an inner product of the embedding vector and the filter matrix. The pooling layer pools each feature map obtained from the convolution layer. Numerous studies by scholars have confirmed that the maximum pooling approach can extract better features and better results compared to the mean pooling, and current studies are using the maximum pooling approach. The fully connected layer takes the output features of the pooling layer as input and activates them by the activation function to obtain a feature vector of fixed dimension. CNNs are outstanding in classification problems, but there are few results in recommendation algorithms, mainly because the recommendation is a regression problem and the goals of the two are different. In the recommendation algorithm for text data, scholars fused CNN with a classical recommendation algorithm to build a hybrid recommendation model to achieve more accurate recommendation results. The structure of the convolutional network is given in Figure 1.

3.1.1. Input Layer. In the neural network, the embedded data have low dimensionality and can map discrete sequences into continuous vectors. Here, the input layer is used to convert the textual information of the learning resource into an embedding matrix, where each row in the matrix is a clause element, which can be expressed as equation (1).

\[
D = \begin{bmatrix}
    w_{11} & \cdots & w_{1i} & \cdots & w_{1m} \\
    w_{21} & \cdots & w_{2i} & \cdots & w_{2m} \\
    \vdots & \ddots & \vdots & \ddots & \vdots \\
    w_{n1} & \cdots & w_{ni} & \cdots & w_{nm} \\
\end{bmatrix},
\]

where \( m \) indicates the dimensionality of the embedding, \( n \) indicates the number of words, and \([w_{i1:m}]\) indicates the vector form of the \( i \)-th word.

3.1.2. Convolution Layer. Multiple convolution kernels of different sizes are used to make convolution operations on the embedding matrix, and the window size is the number of words covered by each convolution. In order to cover the whole word embedding vector, this paper sets the convolution size in the format of the number of words \( \times \) vector dimension. The convolution operation flow is shown in Figure 2.

3.1.3. Pooling Layer. The pooling layer is mainly used after the convolution layer so as to reduce the feature map dimension and the number of network parameters by a downsampling operation. Common pooling operations include average pooling and maximum pooling. The pooling operation can ignore small variations in the feature maps and improve accuracy while effectively avoiding the overfitting phenomenon. Assuming that the feature map
obtained in the \( t \)-th convolutional layer is \( M_t = [m_1, m_2, ..., m_j] \), the maximum pooling strategy is used to extract the maximum value for \( M_t \), \( p_t \) denotes the pooling result of the \( t \)-th convolutional layer, and the pooling operation can be expressed as equation (2).

\[
p_t = \max(M_t) = \max\{m_1, m_2, \ldots, m_j\}.
\]

3.1.4. Fully Connected Layers. The main role of the fully connected layer is to synthesize the previously extracted feature values and output a fixed-size feature vector. Suppose there are \( m \) neurons in the fully connected layer, and after the ReLu activation function, a fixed-size vector \( s \) is obtained, and it is the text feature vector of the learning resource. The calculation is shown in equation (3).

\[
F_i = \sigma(w_ip_i + b_i),
\]

where \( p_i \) denotes the output of the learning resource text information on the pooling layer, \( \sigma \) is the ReLu activation function, \( w_i \) denotes the weight, and \( b_i \) is the bias.

3.2. Bidirectional Long- and Short-Time Recurrent Neural Network. In the traditional recurrent neural network [28], the neurons between the layers are interconnected, which can preserve the short-range temporal features, but the gradient between the hidden layers is unstable, and there is the problem of gradient disappearance or gradient explosion. The long- and short-term temporal recurrent neural network structure allows the gradients to pass well through each hidden layer and can learn data with temporal characteristics such as text very well. The neurons of the LSTM structure learn only the information of the neurons in front of the layers, while the words before and after the words affect the semantic relations. Bidirectional long-term recurrent neural network (BiLSTM) combines two sets of long short-term recurrent neural networks with opposite learning directions, which can better understand the contextual semantics compared to LSTM. The LSTM neural network consists of four main elements: forgetting gate \( f_t \), input gate \( i_t \), memory unit \( c_t \), and output gate \( o_t \). The forgetting gate determines the retention of the previous state information in the memory unit, the input gate controls the input of the current moment information in the memory unit, and the memory unit updates the memory state according to the current input information; then, the output gate determines the output result of the memory unit for the next state. The calculation process can be expressed as shown in equations (4) to (9).

\[
f_t = \sigma(W_f[h_{t-1}, x_t] + b_f), \tag{4}
\]
\[
i_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \tag{5}
\]
\[
\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c), \tag{6}
\]
\[
c_t = f_t \ast c_{t-1} + i_t \ast \tilde{c}_t, \tag{7}
\]
\[
o_t = \sigma(W_o[h_{t-1}, x_t] + b_o), \tag{8}
\]
\[
h_t = o_t \ast \tanh(c_t), \tag{9}
\]

where \( W \) is the matrix multiplication operation, \( h_t \) denotes the state of the memory cell, \( x_t \) denotes the information input, \( b \) is the bias term of the function, \( \sigma(\cdot) \) is the sigmoid function, and \( \ast \) denotes the dot product operation.

The two-way long and short-term memory model is two sets of forward and backward LSTM models connected with sequential LSTM learning features \( h_t^{\text{forward}} \), inverse LSTM learning features \( h_t^{\text{backward}} \), and the two sets of LSTMs are connected into the final feature representation as shown in equation (10).

\[
T_t = h_t^{\text{bilstm}} = h_t^{\text{forward}} \oplus h_t^{\text{backward}}, \tag{10}
\]

where \( \oplus \) is the concatenation operator. This two-layer structure allows the BiLSTM model to fully learn the contextual information of words in the input sequence data.

3.3. Multiscale Feature Fusion. The proposed attention mechanism is inspired by the human visual mechanism [29], and the basic idea is to weaken irrelevant information and increase the attention of focused information during the operation. In this paper, the time-dimensional features \( T \) and spatial-dimensional features \( F \) are fused by using the multiscale feature fusion attention mechanism as shown in Figure 3.

First, the matching matrices \( FA \) and \( FB \) between the temporal dimensional features \( F_i \) and the attribute features \( T_i \) of the spatial dimensional feature learning resource are calculated by using equation (11).

\[
\left\{ \begin{array}{l}
FA = F_i \times T_i^T, \\
FB = T_i \times F_i^T.
\end{array} \right. \tag{11}
\]

Then, the attention distribution weights \( w_1 \) and \( w_2 \) of the matching matrices are calculated by using the SoftMax function, respectively, and the weights \( w \) are multiplied with the individual scale feature matrices to obtain the attention
representation matrices $F'_i$ and $T'_i$, which is expressed as shown in equation (12).

\[
\begin{align*}
F'_i &= F_i \times w_1, \\
T'_i &= T_i \times w_2.
\end{align*}
\] (12)

Finally, a multiplicative gating mechanism is used to multiply the attentional representation with another single-scale feature for the corresponding elements to obtain the interscale mutual attention matrices $F_1$ and $F_2$, which is expressed as shown in equation (13).

\[
\begin{align*}
F_1 &= T_i \cdot F'_i, \\
F_2 &= F_i \cdot T'_i.
\end{align*}
\] (13)

The $F_1$ and $F_2$ are jointly operated to obtain the final multiscale fusion features, represented as shown in equation (14).

\[
F_s = F_1 \oplus F_2,
\] (14)

where (\times) denotes matrix row multiplication; (\cdot) denotes matrix dot product; and (\oplus) denotes Cat operation.

3.4. Predicting Scores and Generating Recommendations.

The abovementioned multiscale fused features $F_s$ are used as the input of the multilayer perceptron to predict the scores. Here, to achieve end-to-end optimization of the model in the paper, a cross-entropy loss function is used, and the weights of each layer are adjusted and determined by back-propagation. Finally, the prediction results are given quickly by mapping the activation function to the range $[0, 1]$. The calculations are shown in equations (15) to (17).

\[
X_i = w h_i + b,
\] (15)

where $h_i$ is the decoder output hidden vector. $X_i$ is the fully connected result.

\[
P(y \mid x) = \frac{e^{h(x, y)}}{\sum_{j=1}^{n} e^{h(x, y)}},
\] (16)

where $x$ is the fully connected result, $y$ is the true description, and $P$ is the SoftMax function.

\[
L(\theta) = - \sum_{t=1}^{T} \log p(y^t \mid y_1^{t-1}).
\] (17)

where $\theta$ denotes the model cross-entropy loss balance parameter.

4. Experiments

The experimental running environment is ubuntu16 with 64G RAM and NVIDIA Tesla A100 GPU with 40G graphics memory; PyTorch deep learning framework supporting GPU acceleration is used, and the Cuda environment is NVIDIA CUDA 11.3 and the deep learning acceleration library of cuDNN.

In the experiments, the network was trained by using the stochastic gradient descent algorithm SGD with an initialized learning rate of 0.005 and a learning decay rate of 0.001, and the model training loss curve and accuracy curve are shown in Figure 4. The momentum factor is set to 0.8. In addition, to solve the model overfitting problem, Dropout is introduced to remove some neurons randomly, and Dropout takes the value of 0.5 in the paper. It can be seen from Figure 4 that when the number of model iterations Epoch is 40, the loss curves of both the training and test sets smooth out, and the loss values are below 0.06, indicating that the model has converged.

4.1. The Results and Analysis of Experiments

4.1.1. Comparison of Recommended Effects. To prove the validity of the model in the paper, comparative experiments are conducted under the same environment and evaluation index. The traditional collaborative filtering recommendation algorithm User-CF [30] based on user play records, the Gram-based personalized recommendation algorithm Gram-CF [31] and the collaborative filtering recommendation algorithm FCNN-CF [32] based on user preference statistics are selected as the comparison models. And
accuracy rate AR (accuracy rate), precision rate PR (precision rate, PR), recall rate RR (recall rate, RR), and F1 value are used as evaluation metrics.

From Figure 5, it can be seen that the model in this paper has improved 1.78% (89.7% vs. 91.3%), 1.22% (90.2% vs. 91.3%), and 3.05% (88.6% vs. 91.3%) in terms of accuracy compared to the comparison models FCNN-CF, User-CF, and Gram-CF recommendation models, respectively; in terms of precision, the models in this paper improved by 2.60% (88.5% vs. 90.8%), 0.78% (90.1% vs. 90.8%) and 1.79% (89.2% vs. 90.8%), respectively; in terms of recall, the models in this paper improved by 1.67% (90.1% vs. 91.6%), 1.10% (90.6% vs. 91.6%), respectively. 91.6% and 2.58% (89.3% vs. 91.6%), respectively. In terms of F1, the models in this paper improved by 1.58 (88.9% vs. 90.3%), 2.38% (88.2% vs. 90.3%), and 0.22% (90.1% vs. 90.3%), respectively. The abovementioned experimental results verify that the model in this paper has good recommended performance. The reason for this is that this paper performs feature extraction from two dimensions, such as temporal and spatial, and fuses them to strengthen the expressiveness of the features, effectively suppress edge information, and enhance the learning ability of the model for detailed information.

4.1.2. Robustness Testing. Besides, to verify the robustness of the model in this paper, robustness tests are conducted under the same data and experimental platform and compared with three current mainstream models and the experimental results are shown in Figure 6. It can be seen that the advantage of this paper gradually comes to the fore as the number of recommended projects increases. In particular, when the number of recommendations reaches 25, the model in this paper is higher than 81% for both AR, PR, RR, and F1 metrics. The abovementioned data further verify the robustness of the model in this paper.
4.1.3. Recommended Real-Time Testing. Another requirement of the recommendation algorithm is that the model is real time. Here, to verify the real-time performance of the recommendation model in this paper, tests are conducted on the same data and environment. The results are shown in Figure 7. It can be seen that the model in this paper can achieve the recommended rate of 6.9 video/s, the FCNN-CF model can achieve the recommended rate of 6.1 video/s, and the User-CF model can achieve the recommended rate of 6.4 video/s, and the Gram CF model can achieve the recommended rate of 5.3 video/s. The abovementioned data show that the model in this paper can achieve a better recommendation success rate, mainly because this paper takes into account the personalized service of users and combines the attribute characteristics of learners and learning resources for a personalized recommendation.

4.2. Real-Life Example Analysis. The confusion matrix of this paper’s method in six sets of real data is given in Figure 8, where the rows of the matrix denote the real labels and the columns denote the human models generated by the model. From the confusion matrix, it can be concluded that the successful accuracy of generating human morphological models for the six testers in the six sets of experiments was 92.48%, 93.28%, 93.26%, and 93.57%, respectively. The
The abovementioned data show that the model in this paper tends to perform stably on multiple sets of experimental results and also has good real-time performance, which verifies that the model in this paper has good robustness.

5. Conclusion

In this paper, a recommendation algorithm is proposed in combination with artificial intelligence-related algorithms and applied to the task of enhancing the cognitive ability of thought-politics education, which will greatly facilitate the rapid excavation of the civic culture section of interest to learners in the massive data, quick reading to locate the knowledge of interest and real-time attention. Meanwhile, it helps to improve the cognitive ability of people's minds and has a positive effect on improving the quality of all people. Through testing in a variety of civics-related cultural columns, it is verified that the model in this paper has better real-time performance while maintaining higher detection accuracy and outperforms the mainstream comparison model in several indexes, which has a certain application value.

Data Availability

The datasets used during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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