RESEARCH ON INNOVATION OF DAILY IDEOLOGICAL AND POLITICAL EDUCATION FOR COLLEGE STUDENTS BASED ON DEEP LEARNING MODEL

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Reception: 12/11/2022 **Acceptance**: 04/01/2023 **Publication**: 31/01/2023

Suggested citation:

Z., Xianwei and Z., Yueyan. (2023). **Research on Innovation of Daily Ideological and Political Education for College Students based on Deep Learning Model**. *3C Tecnología. Glosas de innovación aplicada a la pyme, 12(1)*, 108-125. https://doi.org/10.17993/3ctecno.2023.v12n1e43.108-125

ABSTRACT

Various network information is mixed, which has a great impact education, with continuous development informatization. However, development of informatization has provided convenience for the daily ideological political education, effectively solved time and space limitation daily ideological, and sustainable development. Therefore, positively influence formation of college students' noble morality. The informatization education resources can be effectively integrated, and the utilization rate resources improved. Information resources of ideological and political education, we propose a complete block diagram of the daily ideological system of college students. First, design a complete interactive analysis questionnaire for college student's role of daily ideological and political education. Through questionnaire survey method, the survey and statistical weight scores were conducted to analyze the proportion of each indicator. Then, the framework of education in the network environment is adopted, which includes, class tutoring learning, class interactive learning, class in-depth study, process evaluation and feedback evaluation. Learn through a period of ideological and political education. Collect data as our training corpus. Finally, the training prediction model BERT-BiLSTM-CRF-based trained. Prediction of F1 BERT-BiLSTM-CRF -based can reach 91.09%.

KEYWORDS

Deep learning; ideological; political education; educational innovation; online education

https://doi.org/10.17993/3ctecno.2023.v12n1e43.108-125

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https://doi.org/10.17993/3ctecno.2023.v12n1e43.108-125

1. INTRODUCTION

Daily ideological, political education refers to political education activities that characterized by practicality, pertinence, and interactivity in addition to ideological and political theory courses [1-3]. Thematic education, campus culture, community activities, mental health education, social practice, financial aid education.

With development social informatization, daily ideological political education of college students has always been focus attention [4-6]. Exchanges and social information are numerous and complex [7]. The circulation of some information affects the formation of college students' ideological character. Today's daily ideological education guide cultivation morality through teachers' reasoning as in the past. Corresponding innovations and changes, which can positively affect the formation noble morality information resources [8]. Through the mining and utilization of new and modern network information resources in informatization, the informatization education resources can be effectively integrated [9].

At present, informatization and data, and various fields have begun to the industry [10-12]. Innovation work of college students, how times and develop scientifically data technology, deep learning technology to important issue faced [13-15]. Promote development of ideological and political education, so that content of daily ideological and political education is increasingly enriched and the means are increasingly perfected. Online resources for teaching have the following effects:

(1) The concept of mining resources, rejects information technology methods such as multimedia courseware for teaching [16].

(2) The information-based educational resources the information-based resources are simply applied to the daily ideological, and have not exerted the greatest effect [17].

(3) Information platforms are flooded complex information, and some unhealthy resources are also invisibly absorbed by students, which directly affects healthy development of college students' political education [18].

Data mining utilization of information resources high-quality information education resources play the growth [19]. Correct data helps to promote the cultivation of high morality and correct outlook on life and values for college students. It is required deep understanding of the importance of information resource mining and to carry out effective mining and utilization healthy education [20]. Through deep learning technology recommendation and prediction ultimately improve daily training program for college students.

Neural network gradually develops and matures [21-23]. Emergence word vectors can solve problem of data sparseness in high-dimensional space, and can also add more features. The classification and recognition method Bi-directional Long Short-Term Memory (BiLSTM)-based has improved accuracy compared with traditional methods [24]. In addition, many pre-training models such as Bidirectional Encoder Representations from Transformers (BERT), Long Short-Term Memory (LSTM) networks, Transformer, etc. have recently been used, combined with self-attention

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mechanism, transfer learning, etc. to improve classification accuracy methods [25]. BERT-BiLSTM-CRF classification method based on BERT and BERT-BiLSTM is compared with CRF, Convolutional Neural Network (CNN), LSTM and other methods, and obtained. Higher classification accuracy [26].

Therefore, we propose a training plan based on improving the recommendation and prediction through deep learning technology, ultimately. Among them, the main work is highlighted as follows:

(1) Design a complete set of interactive analysis questionnaires. Through the questionnaire survey method, the survey and statistical weight scores were conducted to analyze the proportion of each indicator.

(2) Adopt the framework in the network environment, which includes five aspects: class tutoring learning, class interactive learning, class in-depth study, process evaluation and feedback evaluation. Learn through a period of ideological and political education. Collect data as our training corpus.

(3) Design and propose CNN、CNN-CRF、LSTM、LSTM-CRF、BiLSTM、BiLSTM-CRF and BERT-BiLSTM-CRF. The experimental results are analyzed and discussed.

2. METHODOLOGY

2.1. INTERACTION ANALYSIS METHOD OF IDEOLOGICAL AND POLITICAL EDUCATION

Research application of new methods of data in ideological and political education. Deep learning analysis data method can predict and analyze the students' network thinking and behavior. Through mining and data to establish a deep learning model, it can realize the whole-process and full-sample analysis of individual students or groups, and realize personalized recommendation for innovation and reform[27-28]. We conduct online questionnaire surveys and statistical analysis through the following five aspects, is shown Table 1.

Table 1. Questionnaire

Student Group Category\Evaluation Proportion		Proportion of evaluation grades (%)					
		0	1	2	3	4	Weights
Different types of students	"985" college students	6.0	5.1	28.6	36.0	24.3	
	Non-"985" college students	3.1	6.0	27.4	38.1	25.4	
Students of different disciplines	Humanities	3.8	7.2	25.4	37.0	26.6	
	Social studies	3.8	6.0	28.7	34.7	25.8	
	Science and Engineering	1.9	7.9	25.4	40.0	24.8	
	Agricultural disciplines	2.9	6.1	41.2	25.8	23.0	
	Medical disciplines	1.8	4.5	29.7	37.9	26.1	

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Students of different ages	Undergraduate (freshman)	4.0	7.1	28.3	36.6	24.0
	Undergraduate (Sophomore)	4.2	6.9	29.1	20.8	29.2
	Undergraduate (Junior)	4.2	4.9	25.7	35.2	30
	Undergraduate (senior year)	2.9	13.8	23.3	23.9	36.1
	Postgraduate	3.0	6.9	27.7	38.1	23.4
	PhD student	2.5	4.8	27.5	36.3	29.8
Students with cadre experience (yes/no)	Officer experience (yes)	3.0	8.2	26.4	38.7	23.7
	Cadre Experience (No)	2.7	6.4	27.1	38.1	25.7
Political status	Party member (yes)	3.1	6.7	26.6	38.1	25.5
	Party member (no)	4.2	7.9	35.1	32.8	20.0

(1) College students' overall evaluation of campus cultural activities.

(2) The situation of the Party and Youth League organizations where different groups of college students are located to carry out organizational life. College students of different age groups, disciplines, and political outlooks have significant differences in the conditions of their party and youth organizations to carry out organizational life.

(3) The satisfaction evaluation of college students on the activities of the Party and Youth League.

(4) The development status education for college students.

(5) Participating in student associations and the satisfaction evaluation of student association activities.

2.2. FRAMEWORK OF IDEOLOGICAL AND POLITICAL EDUCATION IN THE NETWORK ENVIRONMENT

Effective use of network resources ideological and political educator. Improve work effectiveness is urgent. We build a set of ideological education work framework in the network environment, Fig 1.

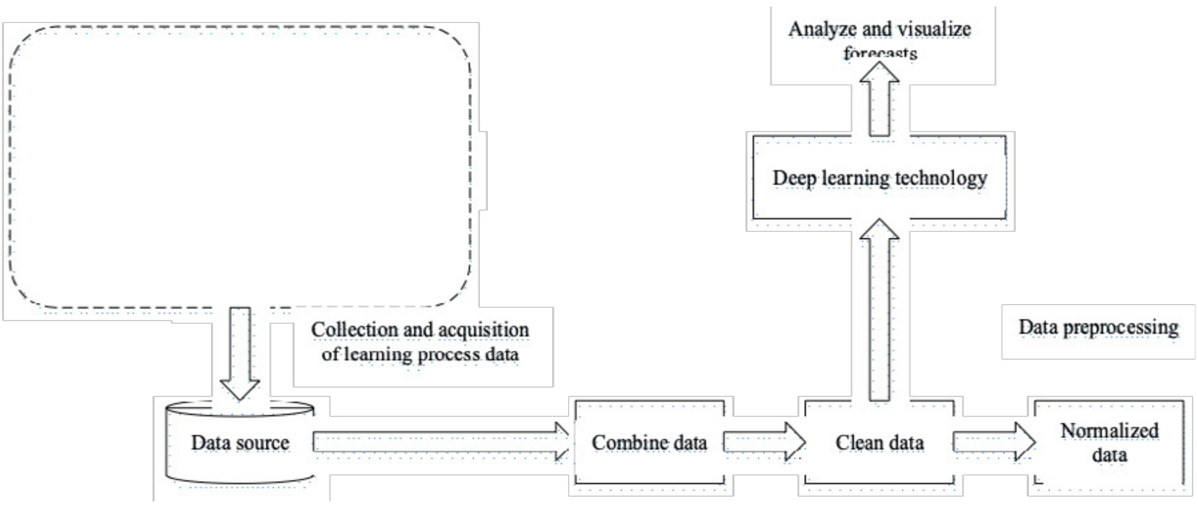

Figure 1. Network Environment

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(1) Pre-class tutoring: Pre-class tutoring is the preparatory work for classroom teaching. The key point of tutoring learning is to use the ideological education and teaching materials provided by teachers to allow students to independently find out the ideological tasks and difficulties of the study unit, so that classroom listening is more targeted. The method is to use the "online ideological and political education" or "Communist Youth League ideological education" video function module of the network to issue the pre-class autonomous learning content (the content can be discussion or divergent thinking, etc.) to each student or each group.

(2) Interactive learning in class: Questionnaires about students' difficult points, and then use the questionnaire survey module to interact with students. At the same time, teach knowledge points by watching and other methods.

(3) In-depth study after class: In-depth study after class refers to an important process in which teachers use question answering discussions or tests to conduct complementary learning with students after class teaching. Through this stage, consolidate achieve the teaching purpose of in-depth understanding and further improvement.

(4) Process assessment and evaluation: Assessment and evaluation refers to the process in which teachers need to evaluate the teaching link in a timely manner, which can be carried out by using the assessment question bank (note that this process is the data automatically generated by the system). Teachers only need to give praise to students with outstanding performance and good learning effect motivate other students.

(5) Feedback or evaluation: Students give feedback on the pre-class, after-class, and assessment. Final calculation ratio is converted into a score, in which we divide the percentile system into four grades, 0~20, 20~40, 40~60, 60~80 and 80~100, and collect the information in Table 1 and the selected courses. Information such as name and viewing time are used as a corpus.

2.3. BERT-BILSTM-CRF CONSTRUCTION

Language preprocessing, a language task for classification, has been a hot research topic. Compared with traditional language models, it is more conducive to classification for classification tasks. Collected in this paper contains text and scores. For the mixed text of text and scores, corresponding features are extracted in the first layer. BERT-BiLSTM-CRF framework is shown in Fig 2. Divided into 4 layers:

(1) BERT and normalization layer. BERT can represent polysemy, and the corpus is pre-trained by BERT, as shown in Fig 3. At the same time, normalization is performed for the score features, and the value range of all features is between [0, 1].

(2) Second layer: BiLSTM layer. BiLSTM uses forward-LSTM and backward -LSTM to capture the contextual features of the text.

(3) Third layer: Attention layer, which different levels of contextual information, assigns different weights to it, and captures the latent semantic features between texts.

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(4) Fourth layer: CRF to ensure the predicted labels. CRF to decode and label the output results, and extract and classify entities.

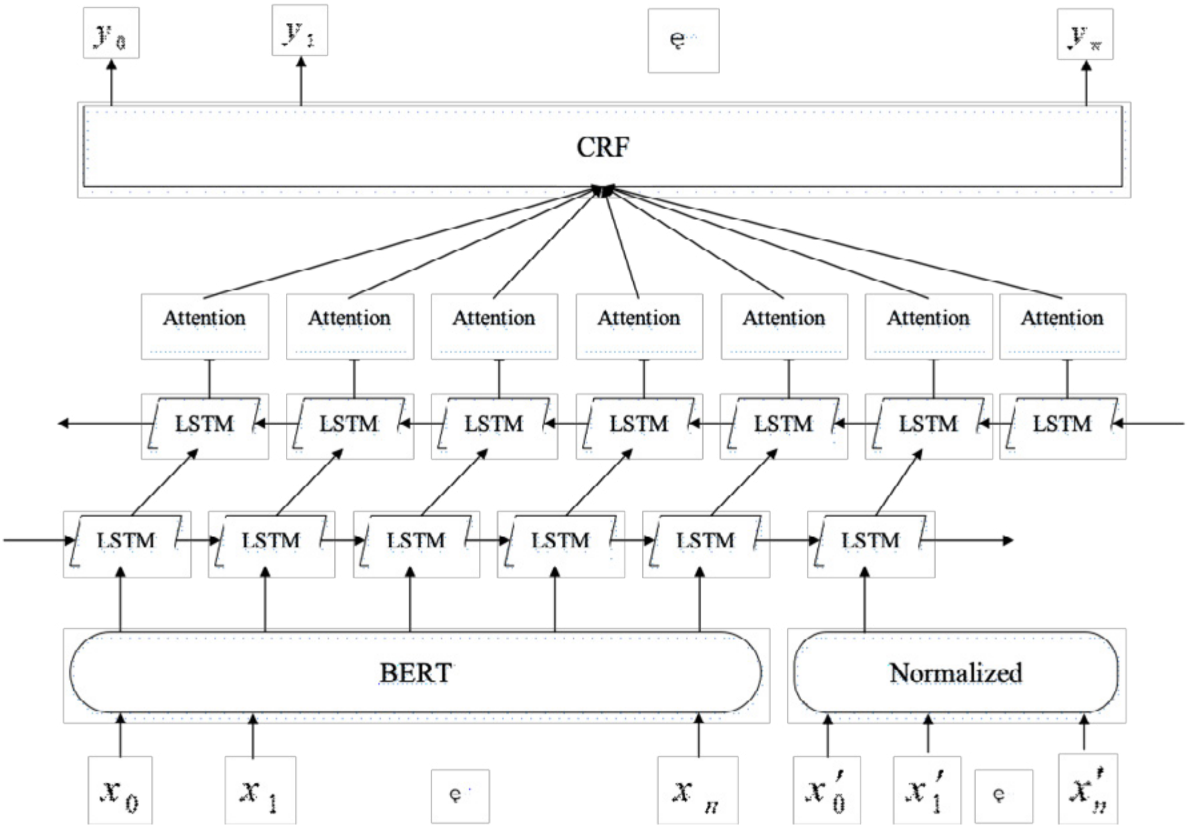

Figure 2. BERT-BiLSTM-CRF framework

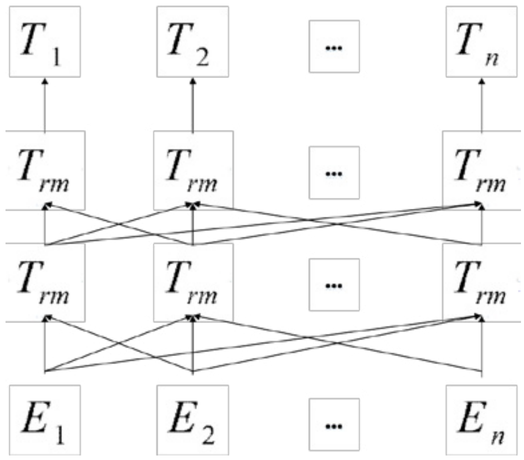

Figure 3. BERT's network structure

2.3.1. BERT AND NORMALIZATION

Language models through one-hot, Word2Vec, ELMO, GPT to BERT. However, module adopted in this paper performs pre-processing on sentences, according to the characteristics of Chinese word segmentation, the method of whole word Mask is applied to Chinese. In the whole word Mask.

Deep network based on "self-attention mechanism", and its encoder structure is shown in Fig 4. Do not have the ability to obtain the sequence of the entire sentence

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like RNN, so to solve this problem, Transformer adds position encoding before data preprocessing, and sums it with the input vector data to get the relative position.

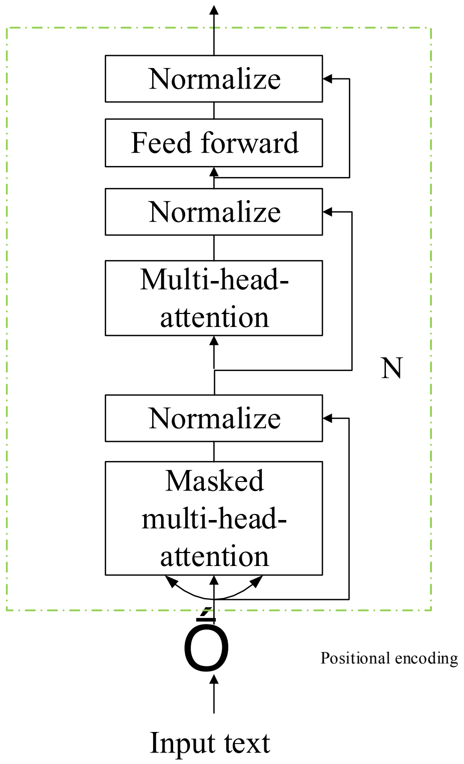

Figure 4. Transformer

First, word segmentation text sequence is obtained through word segmentation processing. Part of the word segmentation sequence is used for whole word Mask, in which a special mark [CLS] is added at the beginning of the sequence, and the sentences are separated by a mark [SEP].

For score value, we use normalization processing. First, the distance digital feature (column) is regarded as the unit 1, and then we look at the ratio of the distance between x and the minimum value to the total distance. The final output is a percentage between [0,1].

$$\frac{X - Min}{Max - Min} \tag{1}$$

where Min and Max are the minimum and maximum values of the property, respectively.

$$\mathrm{Attention}(\mathrm{Q}, \mathrm{K}, \mathrm{V}) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

where, $\mathrm{Q}, \mathrm{K}, \mathrm{V}$ are word vector matrices, and d_k is the Embedding dimension.

The multi-head attention mechanism is projected through multiple different linear transformation pairs:

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$$\mathrm{MultiHead}(\mathrm{Q}, \mathrm{K}, \mathrm{V}) = Concat(head_1, head_2, \ldots, head_n)W^0 \quad (3)$$

$$head_1 = Attention(QW_i^Q, KW_i^K, VW_i^V) \quad (4)$$

where W is the weight matrix. Location information in different spaces.

ReLU and linear activation function form a fully connected feedforward network (FFN).

$$\mathrm{FNN(Z)} = \max(0, ZW_1 + b_1)W_2 + b_2 \quad (5)$$

where the output of the multi-head attention mechanism is denoted as Z, and b is the bias vector.

2.3.2. BILSTM

The relevant information of the previous moment cannot be used for the next moment. Recurrent Neural Networks (RNNs) have this capability. However, it is difficult to learn relevant information when the predicted points are far away from the dependent relevant information. LSTM can solve this problem very well and learn long-term dependency information. LSTM addresses the exploding or vanishing gradients that occur during RNN training. Unit structure is shown in Fig 5.

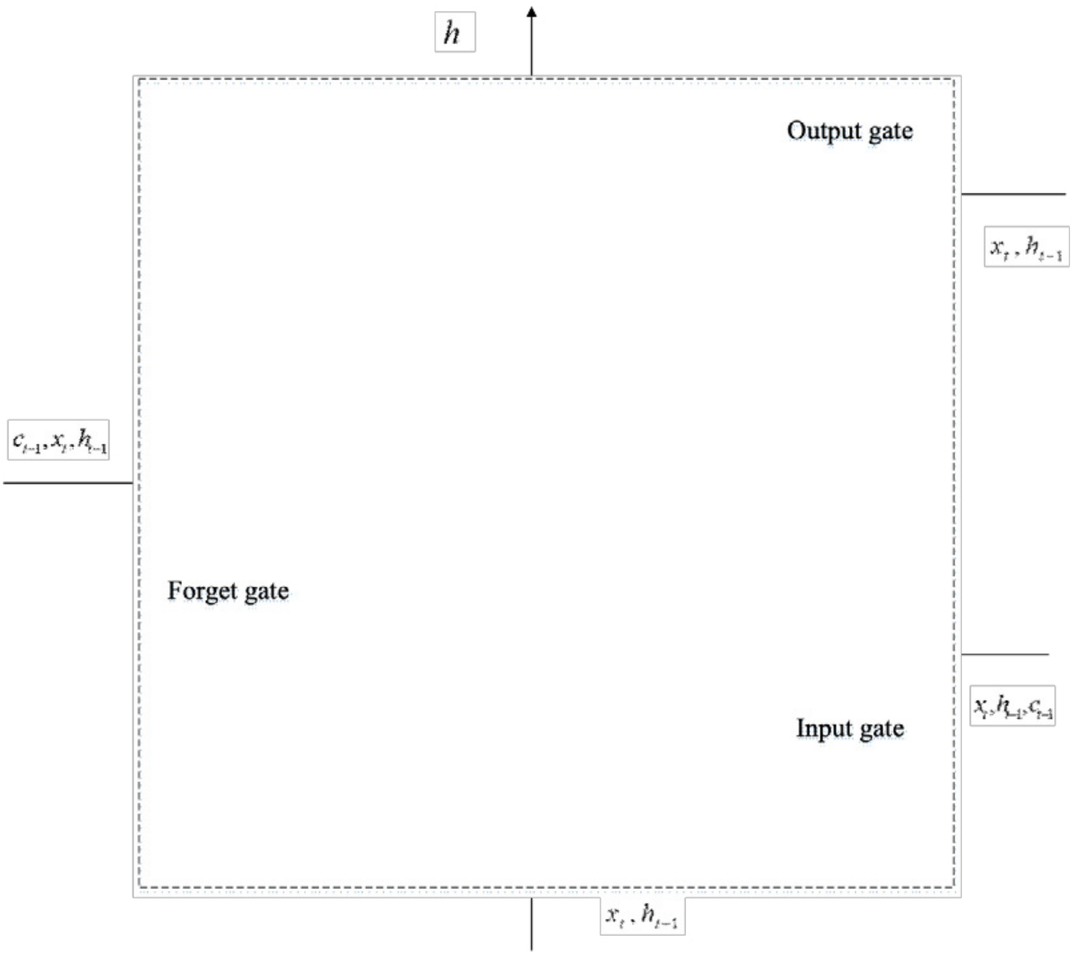

Figure 5. LSTM

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The common function of input and forgetting gate is to discard the useless sequence information. For entire structure, the result of multiplying the output gate. Its structure is expressed by the formula as follows:

$$i_t = \delta(W_i x_t + U_i h_{t-1} + b_i) \quad (6)$$

$$o_t = \delta(W_o x_t + U_o h_{t-1} + b_o) \quad (7)$$

$$f_t = \delta(W_f x_t + U_f h_{t-1} + b_f) \quad (8)$$

where x_t is the input text vector; δ is the sigmoid function; tanh is the activation function; i_t, o_t, f_t are the input gate, output gate and forget gate, respectively.

Unit of information stored is $cell_t$, where input gate and forget gate are not used to adjust the information cell.

$$cell_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (10)$$

where, $W_i, W_o, W_f \, and \, W_c$ are the weights of different gate control mechanisms on the input text vector x_t; U_i, U_o, $U_f \, and \, U_c$ are the weights of different gate control mechanisms on the hidden layer vector h_{t-1}; b_i, b_o, $b_f \, and b_c$ are bias vectors.

Unit information of forget gate and previous moment is stored in $cell_t$.

$$cell_t = f_t cell_{t-1} + i_t \widetilde{cell}_t \quad (11)$$

$$h_t = o_t \tanh(cell_t) \quad (12)$$

where, the hidden layer h_t is calculated by the output gate and the storage gate $cell_t$.

At the same time, input a word vector B output from the RERT pre-training language model to BiLSTM, X_t represents the input data at time t, $\overrightarrow{h_t}$, $\overleftarrow{\mathrm{h}_t}$ and $\overrightarrow{h_t} = (\overrightarrow{h_0}, \overrightarrow{h_1}, \ldots, \overrightarrow{h_t})$ and $\overleftarrow{\mathrm{h}_t} = (\overleftarrow{\mathrm{h}_0}, \overleftarrow{\mathrm{h}_1}, \ldots, \overleftarrow{\mathrm{h}_t})$.

Finally, the two are combined to obtain the output of BiLSTM at $h_t = [\overrightarrow{h_t}, \overleftarrow{\mathrm{h}_t}]$, and the forward and backward outputs of the LSTM unit at time t are spliced. Get a sequence of hidden states t_0 , t_1 , . . . , t_i.

$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \in R^n \quad (13)$$

where n represents the vector set.

2.3.3. ATTENTION MECHANISM

BiLSTM can obtain contextual information, but does not highlight the latent semantic correlation between current sequence feature information and contextual information. Therefore, an attention layer is added after the BiLSTM network to mine the latent semantic features between texts.

First, word vector sequence into BiLSTM to extract contextual features.

$$v_t = \tanh(h_t) \tag{14}$$

where, the attention weight is v_t; h_t is the feature vector output by the BiLSTM layer.

Then, the attention mechanism different weights to the different feature vectors of the text.

$$P_t = \frac{\exp(v_t)}{\sum_{t-1}^{n} \exp(v_t)} \tag{15}$$

attention weight probability vector is P_t.

Finally, contextual features and latent semantic features is generated.

$$\alpha_t = \sum_{t-1}^{n} P_t h_t \tag{16}$$

where, the attention weights are configured as α_t.

2.3.4. CRF

CRF chooses conditional random fields for sequence labeling. Classification task, dependencies between adjacent labels. CRF can obtain an optimal prediction sequence through the relationship between adjacent tags. It can make up for the shortcomings of BiLSTM.

First, input any sequence $\mathrm{X} = (x_0, x_1, \ldots, x_n)$.

Then, number n words and the number of k labels. For prediction sequence $\mathrm{Y} = (y_0, y_1, \ldots, y_n)$, the score function:

$$\mathrm{S}(\mathrm{X}, \mathrm{Y}) = \sum_{i=0}^{n} A_{y_i, y_{i+1}} + \sum_{i=1}^{n} P_{i, y_i} \tag{17}$$

where, A_{ij} represents score; A represents transfer score matrix; The probability that the Y is generated is:

$$\mathrm{P}(\mathrm{Y} \mid \mathrm{X}) = \frac{e^{s(X,Y)}}{\sum_{Y \in Y_X} s(X, Y)} \tag{18}$$

Finally, decoder the largest score.

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$$\text{In}\left(\text{P}(\text{Y}|\text{X})\right) = \text{s}(\text{X},\text{Y}) - \text{In}\left(\sum_{Y \in Y_X} s(X,Y)\right) \tag{19}$$

$$Y^* = argmax\, s(X,Y)_{Y \in Y_X} \tag{20}$$

where, Y represents real annotation sequence; Y_X represents possible annotation sequences.

3. EXPERIMENTAL RESULTS AND ANALYSIS

3.1. DATASET AND TRAINING ENVIRONMENT CONFIGURATION

The corpus used in this experiment includes student names, place names, course names, and ages. The experimental data mainly comes from the daily ideological education storage data of a college from 2019 to 2022, including 502 electronic feedback questionnaires with a total of 16,465,469 words. The data in the electronic feedback questionnaire was 10% as the test set, 10% as the validation set and 80% as the training set. IData, the marked data will not be changed, and if there are missing features, 0 will be added.

Table 3. Experimental Environment and Hyperparameters

Category		configuration		configuration
Hardware	CPU	GTX 2080Ti	RAM	128GB
	GPU	E5-2650L V3-8	video memory	11GB
	operating system	Ubuntu 18.04		Linux 64
Software	Python	3.6.12	Tensorflow	2.2.0
	CUDA	11.0		
Parameter	Transformer layer	12	Hidden layer dimension	768
	optimizer	Adam	learning rate	0.001

Training process, Adam optimizer is used; learning rate is 0.001. At the same time, LSTM_dim is 200, batch_size is 64, and max_seq_len is 128. In order to prevent the overfitting problem. The specific hyperparameter settings and training environment configuration is shown in Table 3.

3.2. DATASET LABELING AND EVALUATION METRICS

The BIO system, which has 7 labels. In this paper, the recall rate R, precision rate P and F1 value are used to evaluate the performance of the model. The calculation methods of each evaluation index are as follows:

A is the total number of entities, and B is the predicted number.

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$$P = \frac{a}{B} \times 100\% \tag{21}$$

$$R = \frac{a}{A} \times 100\% \tag{22}$$

$$F_1 = \frac{2PR}{P+R} \times 100\% \tag{23}$$

3.3. RESULTS AND ANALYSIS

On the dataset, CNN、CNN-CRF、LSTM、LSTM-CRF、BiLSTM、BiLSTM-CRF and BERT-BiLSTM-CRF are used for performance analysis, are shown in Table 5.

(1) CNN model and the LSTM model, it can be seen that LSTM is better than the training dataset in this paper.

(2) CNN, LSTM model and CNN-CRF, LSTM-CRF model, it can be seen that after adding CRF module, the F1 value is improved. This is because CRF can take full advantage of the association of adjacent tags.

(3) LSTM-CRF and the BiLSTM-CRF. BiLSTM performs better than LSTM, because LSTM use the following information.

(4) BiLSTM-CRF and the BERT-BiLSTM-CRF, the F1 value improved, because the BERT deeply extract text semantic information and fully characterize polysemy.

(5) Among them, the attention mechanism makes the model focus more on finding input information more relevant to the current output, strengthens the latent semantic correlation between current information and contextual information, and improves the accuracy of prediction.

Table 5. Comparison of the effects of each model (/%)

Model	P	R	F_1
CNN	80.83	79.52	79.67
LSTM	81.59	82.18	81.37
CNN-CRF	81.16	80.87	80.15
LSTM-CRF	82.68	83.12	82.34
BiLSTM	83.48	83.12	83.02
BiLSTM-CRF	85.87	85.45	85.09
BERT-BiLSTM-CRF	91.63	90.56	91.09

At the same time, the time required for each model training round is also compared, as shown in Table 6. Traditional model is about 15 times that of the BERT-BiLSTM-CRF. Training time of the BERT-BiLSTM-CRF is the least among all models, indicating that the BERT of the whole word Mask has higher training efficiency. Compares and analyzes the update of the F_1 value in the first 25 rounds, as shown in Fig 6.

Table 6. Training time (/s)

Model	Time
CNN	1089
LSTM	1834
CNN-CRF	227
LSTM-CRF	392
BiLSTM	452
BiLSTM-CRF	351
BERT-BiLSTM-CRF	120

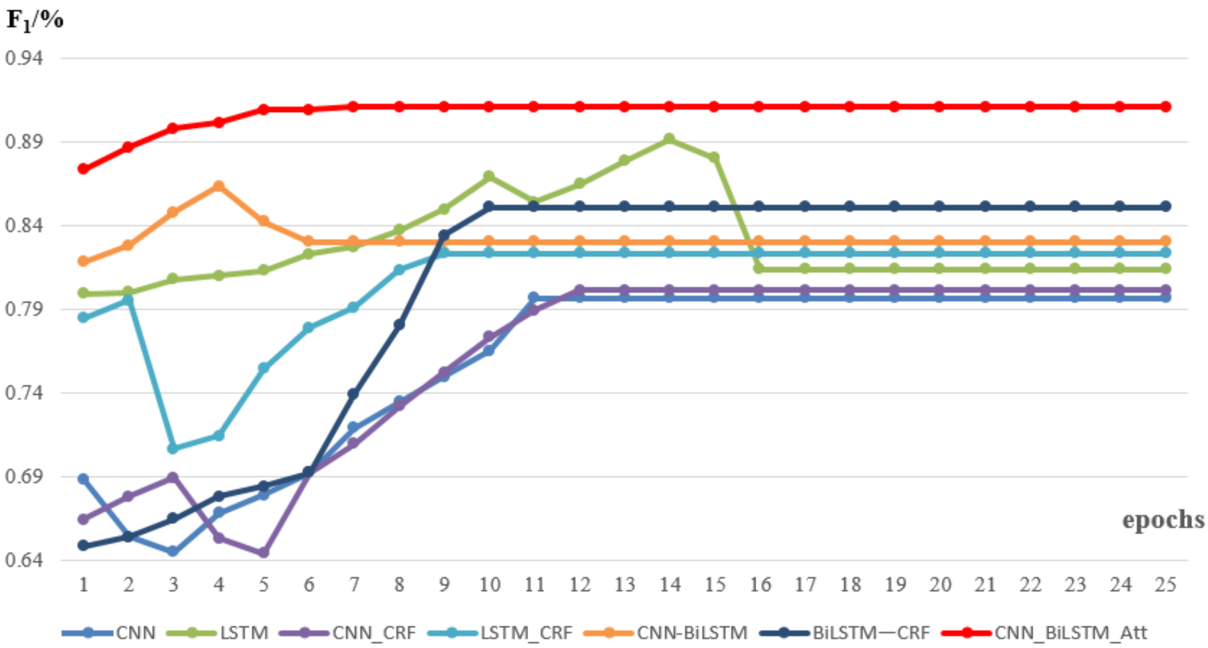

Figure 6. Experimental results

CONCLUSION

In this paper, information resources are used to positively influence the formation of college students' noble morality. Informatization education resources can be effectively integrated, and the utilization rate of the ideological and political education resources can be improved. (1) Design complete interactive analysis questionnaires for college students to evaluate the role of daily ideological and political education. Through questionnaire survey method, survey and statistical weight scores were conducted to analyze the proportion of each indicator.

(2) Adopt the ideological political education work framework, which includes five aspects: class tutoring, class interactive learning, class in-depth study, process evaluation and feedback evaluation. Learn through a period of ideological and political education. Collect data as our training corpus.

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(3) Design and propose CNN、CNN-CRF、LSTM、LSTM-CRF、BiLSTM、BiLSTM-CRF and BERT-BiLSTM-CRF. Experimental results are analyzed and discussed.

Finally, the training prediction model based on the BERT-BiLSTM-CRF model is trained and compared with other models. Experimental results show prediction accuracy based on the BERT-BiLSTM-CRF is the best. Deep learning prediction is only a reference direction, and practical application.

CONFLICT OF INTEREST

The authors declared that there is no conflict of interest

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