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Research Article

Gated Recurrent Unit Framework for Ideological and Political Teaching System in Colleges

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College ideological and political education has always been the primary content of national spiritual civilization construction. The current teaching methods are more flexible, resulting in the quality of ideological and political teaching not being reasonably assessed. To address this problem, we propose a method for assessing the quality of ideological and political teaching based on the gated recurrent unit (GRU) network and construct an automatic assessment system for ideological and political teaching. We draw on the migration learning model to improve the loss function by using the generalized intersection set over the joint loss function to compensate for the shortcoming of the small number of ideological and political teaching datasets. We use a masking algorithm to enhance the local features of teaching data sequences for different classes of ideological and political teaching quality assessment metrics. In addition, we use the minimum outer matrix algorithm to extract the sequence features of different assessment dimensions to improve the accuracy of the model for the quality assessment of ideological and political teaching. To meet the quality assessment conditions of ideological and political teaching, we compiled and produced ideological and political teaching datasets according to the teaching data coverage. The experimental results proved that our method performed best in comprehensive quality assessment accuracy in ideological and political teaching, with the assessment accuracy rate above 90%. Compared with traditional machine learning methods and deep learning methods, our method has higher accuracy and better robustness.

1. Introduction

College ideological and political education has always been the primary content of national spiritual civilization construction. In the process of cultivating talents in colleges and universities, cultivating talents requires not only professional skills but also noble ideological and moral cultivation. We advocate personality education as the foundation and ideological and political education as the bricks and mortar. Personality is the stable psychological foundation for the formation of life values, and the role of ideological and political education is to regulate bad moral habits and establish correct values. At present, colleges and universities have opened courses in ideological politics for college students. In addition to a positive theoretical explanation from the classroom level, school teachers also deepen ideological and political work from the psychological perspective of students, so that ideological and political education is implicitly integrated into the life values of college students [1]. Civic education is in full swing, but the quality of civic education is an unknown quantity. To study the quality of civic education, we referred to a large body of literature in the field of educational effectiveness research and drew on its educational quality validation methods [2–4]. One of the most mainstream educational validity testing methods is meta-analysis, and related research has shown that meta-analysis can extract student benefit factors at the student level, which can be converted into educational validity weights. Changes in student achievement, changes in life habits, and changes in learning attitudes can all be introduced into a multilevel statistical model. Some studies have directly matched the weights of classroom, school, student, and teacher to obtain different levels of educational grading, and the link between educational grading and learning outcomes can be used as a reference for educational effectiveness. For effective ideological and political education, more perfect classroom performance in ideological and political courses, more enthusiastic teachers, more motivated students, and more interactive classrooms directly impact the quality of ideological and political education [5–7]. It has also been found that students' classroom performance also has a significant impact on the quality of ideological and political instruction, and the results of student thought quality tests administered during different academic years show that students' self-awareness in ideological and political courses has an indirect impact on the quality of ideological and political instruction [8, 9]. Currently, most researchers on the quality of ideological and political teaching and learning attempt to suggest a multidimensional assessment model that disperses assessment elements across the classroom and life, aiming to highlight the role of other influences on ideological and political teaching and learning in addition to mainstream civics.

In studies assessing the quality of ideological and political teaching, a large number of studies have attributed the factors that have the greatest impact on the quality of ideological and political teaching to the teachers themselves [10–12]. Some studies have indicated that teachers' teaching experience, educational height, and personality development all leave different impressions on students in the course, and the extent to which subject knowledge is imparted changes with students' impressions of the teacher. The degree of subject matter knowledge imparted also varies with students' impression of the teacher. In addition, students' learning methods and teachers' teaching methods have an indirect effect on the quality of teaching civics. This also reflects most of the classroom management problems of ideological and political teaching, teachers' teaching objectives development, and course structure planning reference. Issues such as students' performance in the classroom, the positive level of answering questions, the degree of completing assignments after class, and students' classroom feedback can reflect the quality of ideological and political teaching. The meta-analysis can synthesize teachers' teaching data to generate teachers' teaching effectiveness [13, 14]. For students, meta-analysis can also generate corresponding learning outcomes. Students' learning outcomes and teachers' teaching effectiveness are an important set of data for teaching quality assessment, and the results of a meta-analysis can provide feedback on the overall trend of teaching quality. The influencing factors of teaching quality evaluation are shown in Figure 1.

Teaching quality assessment is an important way to identify the effectiveness of education, and a variety of teaching quality assessment models have been studied in the field of educational effectiveness research, mainly using meta-analysis when it comes to teaching data analysis. All of these models cover multiple aspects of teaching and learning, including not only the interaction between students and teachers in the classroom, but also the teacher's preparation for the course, the teacher's mastery of the course, the student's completion of assignments at the end of the class, and the students' feedback on the course. Although different methods of assessing teaching quality use different data survey instruments, all teaching quality assessment models follow the following characteristics. Within the multivariate teaching quality framework, priority is given to the conceptual model of teaching quality, which also has limitations and is not comprehensive in its scope [15, 16]. Connections are established between scholars to integrate feedback on teaching quality with opinions among scholars to obtain recommendations on teaching quality weights.

The rest of the paper is organized as follows. Section 2 presents the history and research findings of teaching quality assessment research. Section 3 introduces the relevant principles and implementation details of the GRU-based ideological and political teaching quality assessment network. Section 4 shows the experimental datasets and the analysis of the experimental results. Finally, Section 5 summarizes our research and reveals some further research work.

2. Related Work

According to teaching effectiveness research, it was found that the model for assessing teaching quality is determined by multiple influencing factors. Researchers in the literature [17] have identified six inter-influential factors of teaching quality in teaching role assignment, which are course orientation, course structuring, classroom questioning, instructional modeling, instructional case application, and time management. The researchers also noted that the role of the teacher's teaching experience in the classroom directly influences the classroom learning environment and is a key indicator of classroom performance assessment. In the assessment of teaching quality in skill-based learning courses, the literature [18] suggests a more direct approach to assessing teaching effectiveness, such as structuring course instructional tests and theorizing skills assessment. Researchers in the literature [19] focused mainly on the degree of influence of the teaching model, and the authors framed the model for assessing teaching quality in terms of the ability of the teacher and students to interact and cooperate in the classroom. At the same time, the authors argue the interaction between different students and teachers in the same classroom as interrelated in terms of its contribution to the quality of teaching and learning in the whole course. To test this idea, researchers in the literature [20] adopted a control variable approach to verify the former idea based on the former. The experimental results showed that teaching quality was linearly associated with course instructional factors in stages and that efficient interaction between teachers and students during the effective teaching stage promotes the level of students' understanding of course knowledge.

Some researchers have defined five key indicators of instructional quality effectiveness: frequency, quality, stage, focus, and differentiation. These five indicators are derived from student feedback data from instructional assessments, teacher self-assessment data, and school ratings of classroom performance. Each of the five indicators corresponds to five dimensions of instructional effectiveness assessment, and each dimension can describe the function of an influencing factor in detail. For the quantitative characteristics

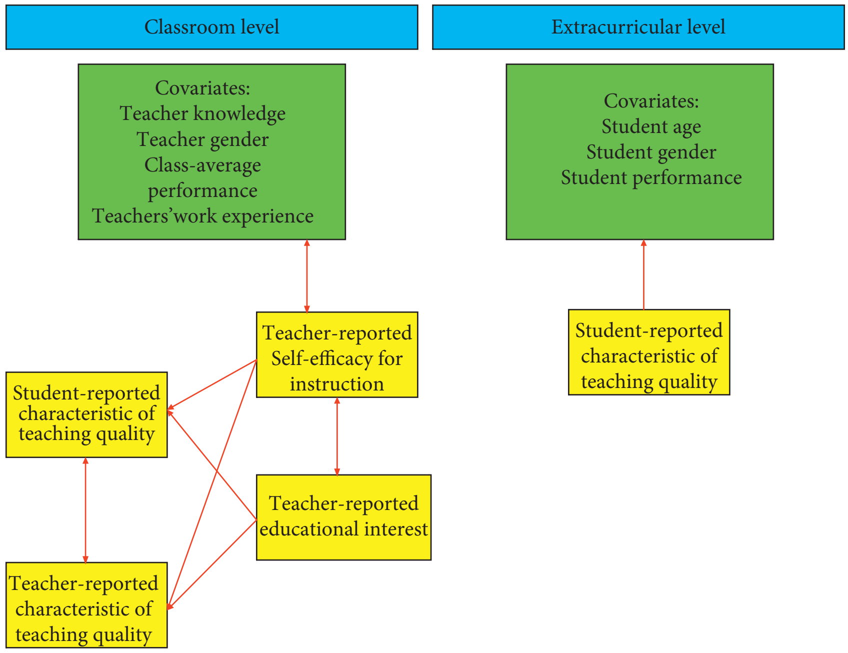

Figure 1: The influencing factors of teaching quality evaluation.

dimension, the authors chose frequency as the frequency of association between instructional effectiveness factors, thus achieving a quantitative role for each of the instructional effectiveness factors [21]. In matching individual instructional quality factors with the number of activities, it was found that cases of application of new knowledge were able to materialize the pedagogical theory and students were better able to understand this pedagogical approach. Such an approach can have a positive impact on the effectiveness of instructional quality. If too much time is spent on teaching examples of applications, it can create an illusion of a shift in the focus of learning for the students. That is why teachers need to structure the teaching phases. While grasping the course schedule, the course teaching methods should be reasonably arranged, and the centralized course model that pursues the course schedule should be avoided as much as possible, which will, on the contrary, produce negative effects on the classroom learning efficiency [22].

Most researchers have chosen the deep learning approach to evaluate teaching quality effectiveness research after comparing machine learning and deep learning approaches. Dynamic neural network models should be chosen as much as possible in the assessment models of teaching quality effectiveness, and dynamic neural network models can weigh the qualitative and nonqualitative characteristics of teaching quality factors. Researchers in the literature [23] found that for each neural network dimension of the instructional quality factors correspond to independent mathematical functional relationships, and for mapping associations between neural network dimensions and theories, dynamic neural network models can achieve single or multiple feature correspondences simultaneously. If all teaching quality assessment activities need to be completed according to expectations, the dynamic neural network model can generate corresponding teaching quality dimension assessment indicators at each stage, and according to the specific indicators, different neural network dimensions can be independently parameterized to obtain the expected values. Some researchers point out that the teaching quality assessment indexes of each neural network dimension are derived from a comprehensive functional assessment report, the index factors of each neural network dimension are independent of each other, the factors between dimensions do not influence each other, and the teaching quality factors of each neural network dimension will collaboratively govern the assessment trend of teaching quality according to the weight ratio when the overall teaching quality is assessed [24–26]. Each instructional quality assessment factor has a certain expectation of purpose fulfillment, and if an expectation corresponds to more than one purpose in an instructional course activity, the fulfillment rate of that expectation will decrease and the instructional quality assessment factor will be negatively affected [27, 28].

3. Method

3.1. Initial Structure. In the study of quality assessment of teaching of college and university civics, we conducted experiments between the machine learning model and the deep learning model, and the experimental results proved that the deep learning model was superior, so we finally chose the deep neural network model. We studied many neural network algorithms and conducted experimental validation, and finally we chose gated recurrent unit (GRU) as the network foundation. GRU is an upgrade of the RNN. GRU belongs to the algorithm of processing serial data, and in the quality assessment of college ideological and political teaching, GRU can obtain validity features from teaching data, also segment instances from the meta-analysis of classroom performance and student feedback, and mask the target features with different thresholds. The GRU algorithm is a two-layer algorithm: the first layer is to scan the instructional sample data to generate the weight factors, and the second layer is to output the instructional validity factor mask on the recurrent neural network branch. In the mask decoding process, we adopt the separation method to decode each instructional validity factor independently and cover all instructional validity dimensions accurately.

The GRU algorithm is obtained by optimizing based on the recurrent neural network, which aims to mine more feature information from instructional data sequences, and the authors use instructional effectiveness factor feature regions to replace the sequential traversal of data sequences. To prevent over-stacking the network, the GRU network borrows from the VGG network proposed by Google, and the authors propose a local memory unit network based on the VGG network with adaptive improvements to the GRU network. The biggest advantage of this network is that it uses a series of short-term memory units instead of the iterations of long- and short-term memory networks. The structure of the GRU network is shown in Figure 2.

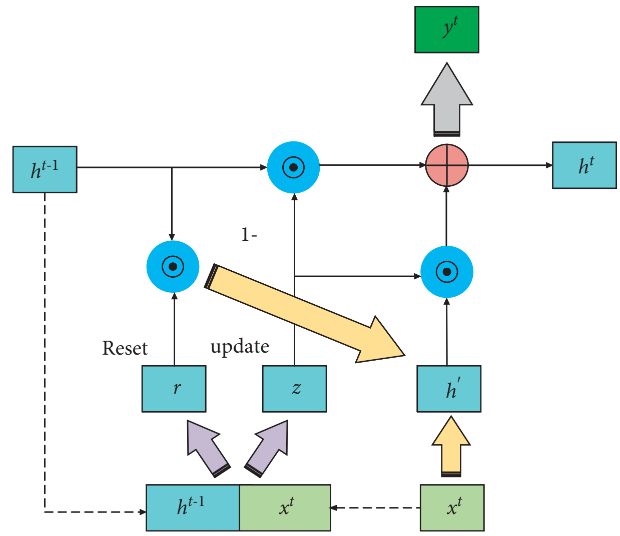

Figure 2: GRU network.

Each instructional effectiveness factor is modeled using a conditional probability distribution, where the final instructional effectiveness factor depends on the length of the sequence, and different sequence lengths correspond to different conditional probability distributions. The mathematical expression is as follows.

$$p(x_t|x_1,\dots,x_{t-1}) = g(h_t). \tag{4}$$

In the literature [29], it was found during experiments that recurrent neural networks are prone to long-term dependencies in the process of training data sequences. Due to the specificity of the recurrent neural network structure, the problem of gradient disappearance often occurs during the training process, which makes the method less variable in gradient amplitude changes and more difficult to optimize the network structure. For data with a long sequence length, its long-term dependence on exponentially smaller is not conducive to the learning of new sequence features at a later stage. To solve this problem, some researchers try stochastic gradient descent to reduce the dependence on a gradient. Other researchers have used the gradient cropping method to circumvent the gradient disappearance problem. Some researchers have also used the second-order method to normalize the gradient vector to prevent the occurrence of gradient explosion and reduce the sensitivity of the network structure to the gradient method by using the same growth pattern of the second-order derivative as the first-order derivative [30]. The GRU algorithm is similar to the LSTM algorithm, but the structure of the two is significantly different, as shown in Figure 3.

An efficient activation function has been found in the approach of sequence feature capture optimization of recurrent neural networks. Researchers found a nonlinear implementation of affine transform and gated units that take local recurrent units or activation functions in an independent direction, called gated recurrent units. All gated cyclic units do not cause long-term dependencies when extracting features in sequences of variable length. In

3.2. Mathematical Principles. RNN is a kind of feedforward neural network, which retains the advantages of a feedforward neural network and adds local feature processing network to efficiently identify data sequences of different lengths. Given a set of data sequences $x = (x_1, x_2, \dots, x_T)$, the relationship between the front and back layers of the hidden layer state of the RNN has the following mathematical equation.

$$h_t = \begin{cases} 0, & t = 0, \\ \phi(h_{t-1}, x_t), & \text{otherwise}, \end{cases} \tag{1}$$

where ϕ denotes a nonlinear function. In the above mathematical equation, we use a combination of logistic sigmoid and affine transform to calculate ϕ, avoiding the problem of forwarding transmission difficulties due to data redundancy. Furthermore, assuming that the output of RNN is $y = (y_1, y_2, \dots, y_T)$, and the length of this data sequence is also varied according to the input data sequence, then h_t has the following mathematical expression.

$$h_t = g(Wx_t + Uh_{t-1}), \tag{2}$$

where g represents the smoothed bounded function, and in the actual calculation, we adopt the hyperbolic tangent function as the bounded function. Assume that at the specified state h_t, the recurrent neural network outputs a new set of elements of the data sequence, the probability distribution of the elements can be represented according to the special symbols inside the model, the special symbols inside the model can be mapped to feature sequences at different lengths, and the matched sequence probabilities in the mapping have the following mathematical expressions.

$$p(x_1,\dots,x_T) = p(x_1)p(x_2|x_1)p(x_3|x_1,x_2)\cdots p(x_T|x_1,\dots,x_{T-1}). \tag{3}$$

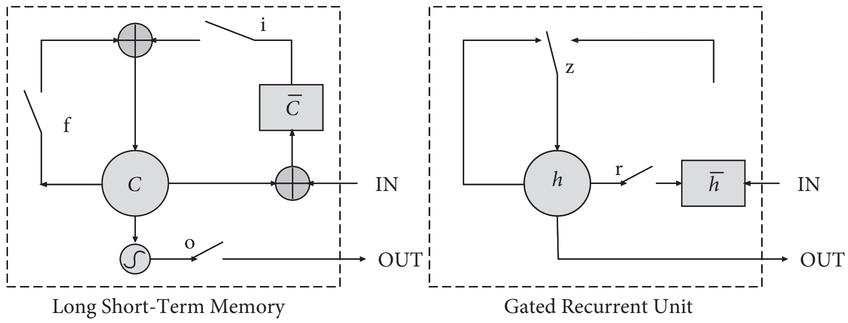

Figure 3: Structural differences between LSTM and GRU.

addition, GRU algorithms are often used in machine translation and speech recognition studies in addition to being able to process data sequences [31, 32].

3.3. Gated Recurrent Unit. Gated recurrent units (GRUs) were originally proposed by researchers in the literature [33]. The authors argued that each independent recurrent unit can correlate the dependencies between data sequences at different time scales during data sequence processing. Each cyclic unit is gated, and the gating method can regulate the flow of information within the unit on demand, and all gated units share a storage unit but do not share local feature information. During the processing of a whole data sequence, each gating unit acquires a segment of independent local sequence features, which will not overwrite the previous sequence features when new features are input, and the new features will be stored in the gating unit in parallel with the previous features. Suppose the GRU activation function is h_t^j at time t. The activation function of the previous layer is h_{t-1}^j, and the candidate activation layer is $\overline{h}_t^j$.

$$h_t^j = \left(1 - z_t^j\right) h_{t-1}^j + z_t^j \overline{h}_t^j, \tag{5}$$

where z_t^j represents an update gating unit that is capable of maintaining a superposition of activation function updates and stored sequences within the gating unit. The expression of the mathematical equation of the update gate is as follows.

$$z_t^j = \sigma\left(W_z x_t + U_z h_{t-1}\right)^j. \tag{6}$$

The processing means between the current state and the computed state of the new sequence is a linear summation operation, which is similar to the computation of the gating unit of the LSTM. All gating units in the GRU algorithm are in the visible state, and there is no unit controlling the hidden layer feature extraction in this algorithm structure, so the whole sequence processing is in the exposed state in this GRU algorithm unit. The mathematical principle between the features of the teaching data sequence is shown in Figure 4.

The expression of the $\overline{h}_t^j$ function for the candidate activation layer is shown below.

$$\overline{h}_t^j = \tanh\left(W x_t + U\left(r_t \odot h_{t-1}\right)\right)^j, \tag{7}$$

where r_t denotes the reset gate and $\odot$ represents a multiplication operation. When the reset gate is closed, r_t^j is close to 0. The reset gate generates a special symbol for each sequence as it processes the sequence, and in addition, the reset gate is special in that the gating unit internally allows the previous sequence characteristics to be forgotten and new sequence characteristics to be stored. The mathematical expression of the reset gate r_t^j is shown below.

$$r_t^j = \sigma\left(W_r x_t + U_r h_{t-1}\right)^j. \tag{8}$$

3.4. Teaching Quality Assessment System. Referring to a large number of teaching quality effectiveness studies, we choose the GRU network as the base network. We introduced the GIOU loss function to enhance the generalized feature extraction ability of the model for teaching quality effectiveness factors, and we also chose Compute Unified Device Architecture to accelerate the computational power of the model. To improve the teaching quality assessment system, we added a classroom data recording tool as the data source for later teaching quality classroom assessments. Data preprocessing is performed on the teacher-side, student-side, and school-side teaching data samples, then the local gating unit feature layer is obtained by convolutional transportation, then-candidate regions are extracted on the feature layer, and the candidate regions are pooled and convolved to extract features. We introduce the GIOU loss function after the pooling layer and set 3 threshold criteria for the GIOU loss function, which is trained iteratively by teaching quality feature update and CUDA model acceleration. Finally, we obtain the grade features, grade matching features, and classroom teaching effect feedback features for teaching quality assessment.

Traditional machine learning methods in teaching quality effectiveness research are limited to the differences in available teaching feedback data, and no distinction can be made between staged and final teaching outcomes. This leads to a biased teaching quality assessment system, with the final teaching effectiveness accounting for the largest impact. To overcome this problem, we adopted a GRU gated unit-based recurrent neural network framework, which uses a masked gating structure that can reinforce the sequence features at the edges and can capture the local features of the sequences more comprehensively before storing them in each gating unit. Each sequence processing is divided into one stage, and the sequence features of each stage are stored in segments to avoid the loss of previous sequence features during the input

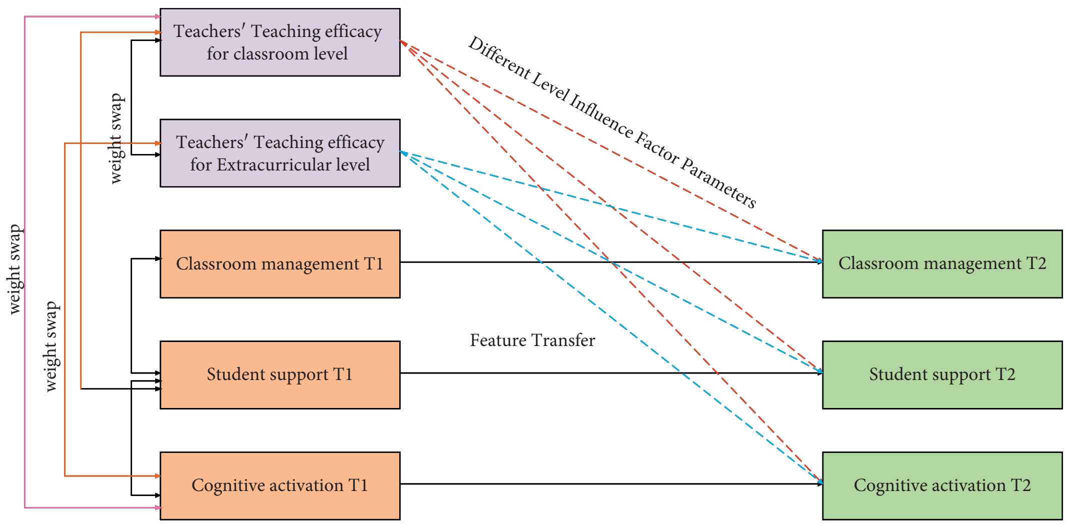

Figure 4: Structural differences between LSTM and GRU.

of new sequences. We also used the minimum external moment algorithm to accurately extract the sequence feature information of the teaching quality factor for independent segments. The detailed structure of the teaching quality assessment system is shown in Figure 5.

4. Experiment

4.1. Dataset. Current teaching effectiveness research does not have a systematic public dataset of teaching feedback. To validate our teaching quality assessment methods, we produced teaching quality feedback datasets supported by three dimensions: teacher, school, and student. To standardize the categories of teaching effectiveness assessment, we set up five main teaching quality assessment items in the early stage of teaching quality feedback dataset production, namely, teacher effectiveness (TE), student satisfaction (SS), classroom feedback (CF), course research (CR), and course size (CS). The detailed data preprocessing process is shown in Figure 6.

Teacher efficacy is the teacher's mastery of the course, the overall organization of the course, and the efficiency of the teacher's delivery, among other factors. Student satisfaction is only the level of satisfaction of the students who chose the course with the course and the instructor after taking the class. Classroom feedback refers to feedback and suggestions from students or the school about the problems of the course. Course research refers to the understanding and preparation of the course by the instructor before the course begins. Course size refers to the number of people who choose the course, which is often a direct indicator of the course's popularity and effectiveness. Different teaching effectiveness datasets were created according to the categories of teaching quality assessment indicators. Detailed information on the datasets is shown in Table 1.

4.2. Experimental Setting. To ensure the independence and stability of the ideological and political teaching quality assessment system, we configured an independent upper computer for the system, and all integrated systems were developed on the upper computer as the platform. In our experiments, we mainly configured the experimental environment of the Anaconda system. Considering the different requirements of the programming environment for the classroom interactive visual system and the teaching quality independent learning system, we configured multiple programming environments on the upper computer to suit different needs. In the construction of the ideological and political Teaching Quality Prediction Neural Network, we mainly use TensorFlow as the main framework. With the support of the powerful software community module, our teaching quality prediction network can be successfully built. The detailed training parameters are shown in Table 2.

4.3. Analysis of Experimental Results. To verify the effectiveness of our ideological and political teaching quality assessment system, we compared machine learning methods and deep learning methods. Among the machine learning methods, we chose the RF [34] algorithm, and among the deep learning algorithms, we chose the RNN algorithm [35] and the LSTM [36] algorithm. To ensure the independent validation relationship between methods, we conducted five sets of experiments during the training process and independently validated each group of methods for different teaching efficiency assessment metrics. The test results of each method were directly input into the statistical calculation part of the dataset, and the final evaluation results were obtained by balancing the total number and quality of the dataset. In the first phase of the experiment, we validated all teaching quality feedback datasets and compared the efficiency of our methods with those of other methods. For method testing efficiency metrics, we chose recall (R) and precision (P) as general evaluation metrics, where X_{TP} denotes the correctly assessed teaching quality data, X_{FN} denotes the teaching quality data without any features acquired, and X_{FP} denotes the incorrectly assessed teaching quality data. The experimental results are shown in Table 3.

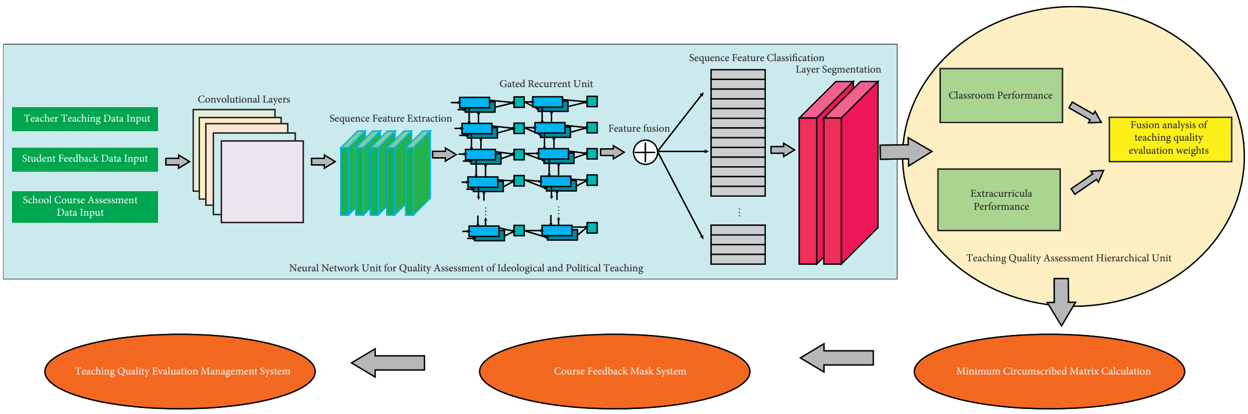

Figure 5: Ideological and political teaching quality evaluation system.

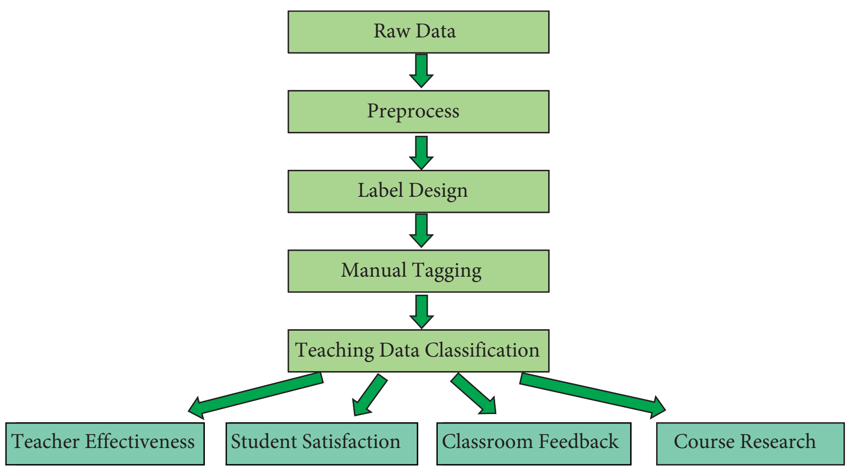

Figure 6: Data preprocessing process.

Table 1: Teaching effectiveness dataset classification and quantity.

	Train	Test	Total
TE	2993	1358	4351
SS	3651	2630	6281
CF	3412	1921	5333
CR	2978	1874	4852
CS	3021	1635	4656

Table 2: Experimental parameter settings.

Parameter	Value
Learning rate	0.001
Decay rate	0.001
Momentum	0.8
Epoch	130
Iterations	1000
Dropout rate	0.5

The X_{TP} in the experiment indicates the readiness rate for qualitative assessment per 500 samples of instructional feedback data. The experimental results in Table 3 show that the RF method has the highest number of instructional validity misclassifications, accounting for one-fifth of the total. The recall rate is only 64.1%, which is not very accurate.

Table 3: Comparison of teaching quality assessment of different methods.

Method	X_{TP}	X_{FP}	X_{FN}	R (%)	P (%)
RF	284	113	79	64.1	75.9
RNN	346	62	50	88.1	83.4
LSTM	373	31	30	91.1	92.5
Ours	434	5	4	98.1	98.5

The efficiency of teaching quality assessment is slightly better than RNN and LSTM methods, but there is still room for optimization. Our method has only five teaching effectiveness misclassification data, and the accuracy of teaching quality assessment reaches 98.5%. This is superior to other methods, which shows the superiority of our method in the first phase of experimental validation. In the second phase of the experiment, we verified the details of each teacher's teaching data separately. The highest student feedback score was 100, the highest expert rating was 10, and the highest workload was 25. Education represents the teacher's academic background, with higher scores representing higher education. Before the start of the experiment, we performed a preprocessing operation on the teaching quality feedback data to standardize the input format and sampling frequency of teaching quality data to prevent the influence of data

Table 4: Comparison of teaching quality data for teachers with different experiences.

Teacher (experience)	Workload	Leadership (%)	Student feedback	Expert score	Education
1(2)	8	72.3	85	7	8
2(4)	12	81.2	89	7	8
3(5)	14	89.8	91	8	7
4(8)	20	93.5	96	9	4

Table 5: Comparison of the accuracy of ideological and political teaching quality assessment by different methods.

	Classroom part (%)	Extracurricular part (%)
RF	64	71
RNN	73	75
LSTM	74	84
Ours	89	93

discrepancies on the experimental results. The results of the second phase of the experiment are shown in Table 4.

The results of the second phase of the experiment showed that teachers with more teaching experience had a heavier workload, and teachers with more years of experience held more positions in the school and had more work issues. At the leadership level, teachers with more years of work experience had stronger leadership skills, performed better in their courses, and had higher student feedback scores for their teachers. At the expert rating level, teachers with more work experience scored higher on the teaching quality assessment, and despite a less academic background, work experience became a major factor in improving teaching quality.

In the third stage of the experiment, the accuracy of the Civic Education Teaching Quality Assessment System is verified in assessing teachers' civic education performance and work assessment performance. We divided the ideological and political education into two categories: the classroom part and the extracurricular part, where the classroom part includes teaching progress and students' ideological and political performance, and the extracurricular part includes students' after-class homework. The experimental results are shown in Table 5.

The experimental results from the third stage show that all methods have higher assessment accuracy in the extracurricular part of ideological and political teaching than in the classroom part. The accuracy of the extracurricular part is higher than that of the classroom part because many assessment details cannot be implemented in the extracurricular part, so the highest scores are taken in many aspects. The RNN and LSTM methods still need to be improved in the work of meta-analysis of data outside the classroom. Our method performs best in the quality assessment of ideological and political teaching and learning, outperforming RNN and LSTM methods.

5. Conclusion

In this paper, we propose a method for assessing the quality of ideological and political teaching based on the gated recurrent unit (GRU) network and construct an automatic ideological and political teaching assessment system. We draw on the migration learning model to improve the loss function by using the generalized intersection set over the joint loss function to compensate for the shortcoming of the small number of ideological and political teaching datasets. We use a masking algorithm to enhance the local features of teaching data sequences for different classes of ideological and political teaching quality assessment metrics. In addition, we use the minimum outer matrix algorithm to extract the sequence features of different assessment dimensions to improve the accuracy of the model for the quality assessment of ideological and political teaching. To meet the quality assessment conditions of ideological and political teaching, with the support of ideological and political teachers, students, and school administration teachers, we compiled and produced ideological and political teaching datasets based on the teaching data coverage. The experimental results proved that our method performed best in comprehensive quality assessment accuracy in ideological and political teaching, with the assessment accuracy rate above 90%. The assessment accuracy rate is the best performance in teaching outside of class. It proves that our method performs well both inside and outside the ideological and political teaching classroom. Compared with traditional machine learning methods and deep learning methods, our method has higher assessment accuracy and better stability.

Although our method performs best in experiments inside and outside the ideological and political classroom, there is still much room for improvement in the accuracy of ideological and political teaching quality assessment. In future research, we will try to add generative adversarial neural networks to the adversarial network as an auxiliary classification to optimize the reasonable segmentation of teaching data sequences of different dimensions and improve the robustness and generalization of the network.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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