Research Article

Evaluation Technology of Students’ Learning Status in Chinese Classroom Based on Deep Learning

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The evaluation of students’ learning status has a strong guiding role. What is taken as the evaluation standard will determine what education teaches and what students learn. As a basic subject and a lifelong art, Chinese in senior high school plays an important role in the college entrance examination; its importance can be imagined; and it has also attracted more and more attention. The assessment of students’ learning status can greatly promote students’ learning quality and values. However, the current evaluation of students’ learning status still has the score-oriented problem, and lacks enough attention to students’ interests, skills, potential, thinking, values, and other aspects, which is worrying. The function of Chinese evaluation has been narrowed to evaluate students’ knowledge and skills, and it has been euphemistically called the focus of classroom teaching. In Chinese class, the role of students’ learning status assessment has received a lot of attention, and it should play more roles in promoting students’ deep learning, so as to improve the thinking quality of learning and find appropriate learning methods. Deep learning requires students to have strong autonomous learning ability and problem-solving ability, etc. Students will benefit from developing these good habits in their future work and life.

1. Introduction

Computer vision measures people’s perception of urban environment and is increasingly used to study the relationship between urban appearance and residents’ behavior and health. We train Siamese convolution neural structure, which learns the loss of common classification and arrangement to predict people’s judgment on pair image comparison. The results show that clustering combined with the neural network can generate global urban observation data [1]. At present, the popular digital image steganography communication recognition method mainly includes three steps: residual calculation, feature extraction, and binary classification. In this paper, a digital image steganalysis method based on a convolutional neural network (CNN) is proposed, which can correctly reproduce and optimize these key steps in a unified framework, thus learning hierarchical representation directly from the original image. Compared with SRM (switched reluctance motor) and its selective channel-aware variant maxSRMd2, our model surpasses all test algorithms with different loads [2]. For categorization tasks, we always want to choose the attributes that keep the categories separate in the most efficient way. In this paper, a new feature separation method is proposed, which uses the deep neural network to learn the explicit mapping from sample space to feature space, and improves the feature separability according to Fisher’s criterion. For highly flexible models, the optimal Fisher function can find a balance between uniqueness and descriptivity [3]. Because the reliability of each pixel attribute determines the classification accuracy, it is very important to design the feature extraction algorithm for hyperspectral image classification. We propose a very effective hyperspectral image classification learning algorithm-context deep learning. A large number of experiments show that the context deep learning algorithm proposed in this paper is an excellent function learning algorithm, which can achieve good performance only by simple classification [4]. The deep neural networks are usually optimized by the stochastic gradient descent (SGD) method. In this paper, a new second-order stochastic
optimization algorithm is proposed. We find this structure very useful, not only because it speeds up training and decoding, but also because it is a very effective method against overfitting. The convergence speed of our algorithm is faster than that of SGD [5]. A new probabilistic model for the analysis of time-varying patterns in rs-fMRI intrinsic functional networks, combined with a methodological architecture of deep learning and spatial modeling, examines the functional relationships assessed between mild cognitive impairment and normal healthy controls [6]. The convolutional neural network is the core of deep learning application. They did not consider weight updates and complex data dependencies during exercise. In the training process, batch processing limits the number of images that can be processed continuously, because the next batch of images must be processed according to the updated weight [7]. The focus of local space design research has gradually changed from the manual design method to the learning method. In this paper, a convolutional neural network (CNN) is proposed for learning efficient graphs in Euclidean space. Experimental results show that L2-Net has good generalization ability and can directly replace the existing artificial graphs. The second language network is trained [8]. More and more unstructured text data appear on social media among enterprises, forming a social environment with many production relations, which can be used as decision support information to match the production capacity needs among enterprises. The ultimate goal of this study is to promote knowledge transfer and sharing in the context of business and social interaction, so as to support the integration of resources and capabilities among different companies. Experimental results show that this method can achieve the same performance as the existing learning models and is well suitable for the network-based social production interaction environment [9]. According to research, the growth of online education is more driven by economic forces than its long-term effectiveness [10]. This paper discusses the role of classroom feedback in the assessment of students’ learning status. Using the proportional sampling method, this paper studies the influence of teacher-student interaction and classroom environment on students’ classroom learning process [11]. The assessment of students’ learning status can improve the quality of education. Learning evaluation pays more attention to students’ learning process and lets teachers know how to improve their own development, so it is a change of classroom evaluation form [12]. In this paper, teachers and students can establish a more successful relationship. In order to overcome students’ prejudice, teachers should always be fair and sincere in their affairs and evaluation process [13]. Research shows that most students think that classroom evaluation plays an important role in teaching quality monitoring [14]. Educational evaluation is a very important part of the education system. This paper analyzes the problems encountered in classroom teaching evaluation and puts forward various improvement measures to improve the level of classroom teaching evaluation [15]. In the abovementioned related literature research, some technical problems are discussed and applied, but there are many problems in the classroom teaching process, for example, the adopted technology does not improve the corresponding accuracy and it is difficult to identify. However, using a single technology to solve teaching problems is not effective in the implementation of teaching details. Therefore, using deep learning to solve students’ learning situation and application can improve the autonomous learning mode, and effectively improve the classroom teaching quality and the recognition effect of teaching behavior.

2. Characteristics of Deep Learning

2.1. In-Depth Study and Participation. First is the deep emotional input. We encourage students to put in positive emotions and stimulate students’ correct learning attitude. At this time, the input is a kind of active learning, and the students’ emotional state is positive. They pour their emotions into the learning process and pay attention to and focus on the learning tasks in class for a long time. Second, the integration of learning methods is deep. Different learning methods are needed. For example, when previewing before class, we mainly focus on self-study, and when listening to teachers in class, we mainly focus on listening with energy. Third is high investment in the learning process, positive emotional state, and deep participation. For different learning tasks, we use different thinking to solve them. We can transform knowledge into their own information and get through the key points; link the learned knowledge with the old knowledge and connect at multiple points; and use knowledge structure to solve different types of tasks and problems. In the whole learning process, students’ thinking is very active and their operation is relatively fast.

2.2. High Level of Thinking Development. Deep learning requires students to have certain innovative thinking. The thinking structure includes five levels: pre-, single, pluralistic, related, and abstract expansion. Association structure can integrate the existing information into a whole connection framework and become a logical and orderly internal structure. The abstract extended structure can not only use all available data and connect them, but also test the reasonable abstract structure obtained from data, which can surpass the given information and infer the structure, and can carry out logical reasoning from concrete to general; able to induce and make assumptions; can use many methods to use reasoning results in conclusions; can use more abstract functions to expand the knowledge structure; and be able to understand the role of change in the change method. It can be noted that some structures come from different ideas and migrate these ideas to new fields.

2.3. Strong Application Migration Ability. After a deep study, students can find the key to the problem and then combine the known knowledge to solve the problem. After firmly mastering the knowledge in class, even if you encounter new problems or situations, you can still successfully complete various learning tasks, identify the core elements in the situations, relate and utilize them, and even better migrate to
3. Improvement Strategy of SSD Algorithm

3.1. Infrastructure Network Improvement. The goal of the basic grid upgrade is to replace the original backbone VGG16 with the lightweight grid. By studying the data and analyzing different models, we know that the MobileNet network meets the requirements. It replaces standard convolution with deep separation convolution to reduce the number of parameters. MobileNet has only 4.2 million parameters, compared with 133 million in VGG16. The test results of the ImageNet dataset show that MobileNet is obviously faster, but the accuracy rate is only 0.9 percentage points lower than VGG16. Therefore, this paper is based on the original MobileNet, after some modification, as the core network of SSD.

3.1.1. Improvement of MobileNet. The reason MobileNet is faster and less computational than VGG16 is because there are two differences between MobileNets. First, depth analysis rounds are used in network synthesis, and width coefficient and resolution coefficient are also used. Deep convolution is the main part, and two parts are used to supplement convolution operation, namely, deep convolution and point convolution. MobileNet’s network structure has 28 layers if both are considered two and 14 layers if both are considered one.

Formula (1) can be used to judge its parameter ratio.

\[
\frac{F_k \ast F_k \ast F_f \ast F_f \ast R + 1 \ast F_f \ast F_f \ast R \ast P}{F_k \ast F_k \ast R \ast P \ast F_f \ast F_f} = \frac{P + F^2_k}{PF_k},
\]

(1)

where \(P\) represents the size of the output channel; \(R\) represents the size of the input channel; \(F_k\) represents the size of the output feature map; and \(F_f\) represents the size of the feature map.

In order to reduce network parameters, in addition to depth separation convolution, width factor \(\alpha\) and resolution factor \(\rho\) with values between 0 and 1 are used. The impact of \(\alpha\) is declining. For example, for an input channel with a value of \(R\), it becomes \(\alpha R\), which greatly reduces the computation. Another factor greater than \(\alpha^2\) that affects the amount of computation is the resolution, so \(\rho\) is used to reduce the resolution of the image. After using this coefficient and reducing the value of \(\alpha\), the calculation times of the pixel value of \(\rho^2\) are reduced.

On the basis of the above introduction, this paper improves MobileNet in two aspects.

Based on the above analysis, in order to further reduce the calculation of the BN layer, this paper combines it with the previous convolution, so that the speed will be improved on the previous basis.

The input size of MobileNet is changed from 224 × 224 to 300 × 300. There are two reasons for this modification: first, increasing the input size can improve the information capacity of the feature map and then improve the detection accuracy, but the input size should not be too large, which greatly increases the network parameters, thus making MobileNet lose the advantages of the lightweight model; on the other hand, the input size of SSD network structure used in this paper is 300 × 300, which makes basic preparation for the combination of the following two networks after modification.

3.1.2. Replacement of SSD Basic Network. In order to improve the feature extraction ability of the model, this paper combines eight standard smaller convolutional layers behind the replaced core network to further obtain the depth information of the image. At the end of the network, a classification layer for judging categories and a nonmaximum suppression layer for screening regression boxes are connected, thus completing the replacement of the basic network. In this paper, the deep convolution and the subsequent 1 × 1 point convolution are regarded as one layer, and there are 14 layers, which are denoted from Conv0 to Conv13, respectively. Where \(s1\) represents a step size of 1, \(s2\) represents a step size of 2, and Convdw means that deep convolution will be followed by a 1 × 1 point convolution to process the channel.

Finally, like SSD, six feature layers are selected to complete the following work, and the depth of this layer should be considered when selecting. If it is too shallow, enough image information cannot be extracted. Therefore, this paper selects six feature layers to reduce the size from front to back and realize multiscale prediction. The SSD algorithm is an application form of deep learning. SSD belongs to the one-stage detection method, which mainly regresses the target category and location directly. In the process of prediction, it is precisely because of the prediction on the feature layer of different scales that the target can be detected well when the image is of low resolution, and its accuracy can be guaranteed. In the process of training, end-to-end training is adopted.

In this paper, using the SSD algorithm in the application class students’ learning picture processing and application has a good effect, especially some learning behaviors can use action behavior to identify the corresponding state.

3.2. Feature Fusion of Network Model. In the previous step, the replacement of the basic network improves the detection speed but does not improve the accuracy of small target
3.2.1. Feature Fusion Method. When an image is put into a convolution network, different levels of the network get different image information. The shallow layer, also known as the low layer, is at the initial stage of convolution, so only limited information can be obtained. However, due to its good resolution, its main function is to obtain some visible features, such as the position information and edge information of the target object in the image. The deep layer is also called the high layer, that is, when the network depth is very large and convolved many times, what we get at this time is some abstract information invisible to the naked eye, which has strong semantic characteristics. Through the above analysis, we can see that the advantages between shallow layer and deep layer can complement the shortcomings of both, so there is a method to merge the two, which is uniformly named as feature fusion. However, according to the order of feature fusion and target prediction.

Early fusion refers to feature fusion first; then, predictor training is carried out on the basis of fused features; and predictor training will not be carried out before complete fusion. There are two common fusion methods: concat and add.

The concat method directly adds attributes and can also be understood as a combination of channels, each of which is associated with a convolution sum. This method adds information to the image itself but does not add information about the attributes of each layer. The add method is to combine feature vectors into a combined vector and simply add a value, but the number of channels remains unchanged, which is a convolution operation after adding feature graphs. This method increases the amount of information to describe image features, but the dimension of description graphics remains unchanged. Usually, the parameter quantity of the add method is less than concat. Assuming that there are only two channels and the number of channels is the same, the concat method and the add method can be expressed by formulas (2) and (3), respectively, where \( X \) and \( Y \) represent two channels to be fused, and the number of channels is \( N \), and the fusion results of the two methods are \( R_{\text{concat}} \) and \( R_{\text{add}} \), respectively.

\[
R_{\text{concat}} = \sum_{i=1}^{N} X_i \ast K_i + \sum_{i=1}^{N} Y_i \ast K_i, \quad (2)
\]

where \( X \) and \( Y \) are the channels to be fused; \( K_i \) is the weight of the \( i \)-th channel; \( R_{\text{conca}} \) is the fusion results.

\[
R_{\text{add}} = \sum_{i=1}^{N} (X_i + Y_i)K_i = \sum_{i=1}^{N} X_i \ast K_i + \sum_{i=1}^{N} Y_i \ast K_i, \quad (3)
\]

where \( X \) and \( Y \) are the channels to be fused; \( K_i \) is the weight of the \( i \)-th channel; \( R_{\text{add}} \) is the fusion results.

3.2.2. Model Fusion Process in This Paper. Combined with the nature of the network model structure and the combination of various functions, this paper chooses to add a combination of functions to connect the network. It can be seen from the model structure that the size of the extracted six feature layers gradually decreases from shallow to deep, and the more the first one contains, the less abstract information, so the purpose of feature fusion is to transmit abstract information from deep functional floor to lower floor. Considering that Conv17_2 and Conv16_2 are too small to have much information, only Conv11, Conv13, Conv14_2, and Conv15_2 are selected for fusion operation.

3.3. Model Optimization Algorithm. When training the model, we pay attention to the change of loss function. As the value of the loss function decreases, it shows that the result of model training is approaching the actual result, so the loss function must be pointed downward to find the minimum value of the loss function. However, in the process of gradient calculation, the value of the amplitude may be too large or unchanged, which leads to slow gradient descent. Therefore, in order to speed up the descent, we usually need to use optimization algorithms, such as momentum, RMSProp, and Adam.

In this paper, the RMSProp algorithm proposed by Geoffrey E. Hinton is adopted. The algorithm calculates the historical gradient of each dimension, superimposes the sum of its squares, and obtains the sum of historical gradients by applying the attenuation rate. When updating parameters, the learning rate is divided by the above result. After using the optimization algorithm, the gradient direction still changes in a small range, which accelerates the convergence of the network. The specific calculation formulas are shown in formulas (4) and (5).
where $R$ is the parameter.

3.4. Principles of Model Training and Prediction. After completing the network building, the model needs to be trained to complete the recognition task. The training process is mainly to find a prior frame matching with the target frame marked in advance in the picture. Unlike YOLO, SSD uses multiscale feature layers to detect images, so the prior frames will be different with the change of feature layer scale. The prior frame includes two aspects, namely, scale and aspect ratio, in which there is a linear relationship between scale and feature map size as in formula (6).

$$X_k = X_{\text{min}} + \frac{X_{\text{max}} - X_{\text{min}}}{m - 1} (k - 1), k \in [1, m],$$

where $X_{\text{min}}$ is the minimum value of the ratio of frame size to feature diagram; $X_{\text{max}}$ is the maximum ratio of frame size to feature map; $M$ is the eigenvalue number; $K$ is a certain feature layer; and $X_k$ is the ratio of a priori frame to the $k$-th feature graph.

In this paper, $X_{\text{min}}$ is 0.2 and $X_{\text{max}}$ is equal to 0.9. The scales of the smallest and largest prior boxes in the six feature graphs are $\{30.0, 60.0, 111.0, 162.0, 213.0, 264.0\}$ and $\{60.0, 110.0, 162.0, 213.0, 264.0, 315.0\}$, respectively. At the same time, in order to predict the targets of different shapes, different aspect ratios $\alpha$ are set according to the minimum size prior frame of each layer, and the values are $\{2:2, 2:1, 3:1, 1:2, 1:3\}$, so the calculation method of width and height is as shown in formula (7).}

$$M^a_k = X_k\sqrt{\frac{\alpha}{a}}, N^a_k = \frac{X_k}{\sqrt{\alpha}}$$

where $M^a_k$ is the prior box width value; $N^a_k$ is a priori box height value; and $X_k$ is the ratio of prior frame to the characteristic graph.

The matching of prior boxes in this paper follows two principles.

The first principle is as follows: we find the prior frame with the largest IOU (intersection over union) (referring to the coincidence rate between the two) for each real frame in the image so that each real frame has a matching prior frame. Some prior frames may not find matching target frames, that is, there are no targets to be identified in their range. These kinds of prior frames are located as negative samples, and if there are any, they are positive samples. Negative samples are classified as background, while positive samples are the targets to be found.

The second principle is as follows: after the implementation of the first principle, a large number of negative samples will be produced, resulting in extremely unbalanced positive and negative samples, so the second principle is put forward. For a matching prior box, if its IOU in a real box is greater than a certain threshold, it is also considered to be matched. That is to say, a real box has multiple matching prior boxes, and vice versa. The second principle must be based on the premise of the first principle before it can be established.

Even if there is the second principle, the gap between the number of positive and negative samples is very large, and too large a number difference will cause a very large loss function value. Therefore, this paper artificially reduces the number of negative samples, that is, removes some negative samples in training, so that the ratio of positive to negative is about 1:3. Every time the training is completed, the parameters need to be updated until the expected effect is achieved, so the loss function and nonmaximum suppression are needed to assist the training process.

3.4.1. Loss Function. In this paper, the loss function consists of two parts, namely, location loss and confidence loss, which are obtained by the weighted sum of the two parts. The loss function formula is shown in formula (8) as follows:

$$L(x, c, l, g) = \frac{1}{S} (L_{\text{conf}}(x, c) + \alpha L_{\text{loc}}(x, l, g)),$$

where $c$ is the confidence value; $L$ represents the prediction box; $g$ denotes the true box; $S$ is the default number of boxes; $\alpha$ is the weight value of the two; $L_{\text{conf}}$ is the value of confidence loss; $L_{\text{loc}}$ is the location loss value.

The formulas of location loss and confidence loss are as follows, where $P$ represents the category serial number, and when $P$ is 0, it represents the background; $x^P_{ij} = \{0, 1\}$. When 1 is taken, it means that the predicted box and the real box match, and the matching category is $P$.

The confidence loss function formula is shown in formula (9) as follows:

$$L_{\text{conf}}(x, c) = \sum_{i \in \text{Pos}} x^P_{ij}\log(c^P_i) - \sum_{i \in \text{Neg}} \log(c^0_i),$$

where $c^P_i$ is the probability value predicted as category $P$; $P$ denotes the category; $x^P_{ij}$ is whether the discriminant value is matched.

The positioning loss function formula is shown in formula (10) as follows:

$$L_{\text{loc}}(x, l, g) = \sum_{i \in \text{Pos}, m \in \{c, x, y, w, h\}} \sum x^P_{ij}\text{smooth}_{\text{L1}} (l^m_i - g^m_{ij}),$$

where $g^m_{ij}$ is the real box; $l^m_i$ is the prediction box.

3.4.2. Nonmaximum Suppression. When the image passes through the prediction network, there will be a large number of regression boxes to be selected for each category, many of which are wrong and there are a large number of repetitions. Selecting an accurate regression box from these results cannot be accomplished only by IOU, so a nonmaximum suppression method is proposed to remove useless information and keep the waiting box with the most targets.
3.5. Behavior Database Construction Method. The good classification effect of the deep learning network model needs to be based on a large amount of data, which constitutes an image database. Different application fields have their own image databases, such as medical image database in the medical and health field, fundus disease image database, disease pattern image database, etc.; vehicle image database and road sign image database in the field of transportation; and MNIST handwritten digital database, ImageNet database, COCO (collation of cortical) database, PASCAL VOC database, CIFAR-10 database, etc., which are commonly used in image recognition theory research. The experiment in this chapter needs a large amount of classroom behavior image data, but there is no special database for students’ classroom behavior recognition at present, so it needs to be built by individuals. This section will detail the process of creating the classroom behavior database.

3.5.1. Dataset Acquisition

(1) Image Acquisition. The datasets used in this paper are source classroom surveillance video and network pictures. In order to ensure the recognition effect, we try to make the collected image a background classroom. Video images need to be processed before they can be used as datasets, which contain many video segments including raising hands, sitting up, sleeping, and writing appear. Here, we use OpenCV to sample the selected video frames and select the pictures containing the above five actions to save. In order to ensure the speed of training, we try to ensure that the size of the picture is 200k left. If the picture is too large, the training will be slow.

(2) Data Enhancement. Because there are not much image data collected in this paper, and the accuracy of model training needs a large amount of data as support, this paper uses the method of data enhancement to increase the amount of data. It mainly includes flipping the image horizontally, left and right and randomly, translating the image horizontally and vertically, and randomly changing the color of the image. After data enhancement, there are 2000 pictures in this dataset.

3.5.2. Dataset Preprocessing

(1) Grayscale Processing. By comparing the mean value method adopted in this paper, the mean value of each pixel value point is calculated to realize gray processing, and the calculation is as shown in formula (11) as follows:

\[ R = G = B = \frac{R + G + B}{3}, \]

where \( R, G, \) and \( B \) are three color channels.

(2) Bilateral Filtering. The change of color image into a gray image only reduces the parameter quantity of color, and cannot eliminate the noise of the original image, but the data needed in this paper cannot have too much noise, so the related methods are explained in the second chapter. Combined with the actual needs and comparing the differences of various methods, this paper chooses bilateral filtering denoising technology. When the selected method is used to filter the noise, it not only reduces the image noise but also preserves the edge information. In an operation similar to Gaussian filtering, every pixel of the picture is scanned once, and then, the weighted sum of pixel value weights is added on the basis of the operation of finding the weighted sum of each pixel value and the corresponding position weights in the field. When calculating, the closer to the center, the greater the weight, the closer the pixel value, and the greater the weight, as shown in formulas (12) and (13).

\[ G_s = \exp \left( -\frac{\| p - q \|^2}{2\sigma_s^2} \right), \]

\[ G_r = \exp \left( -\frac{\| I_p - I_q \|^2}{2\sigma_r^2} \right), \]

where \( G_s \) is the weight of spatial distance; \( G_r \) is the pixel value weight; \( Q \) is the center point of a window; \( P \) is a certain point; \( I_q \) is the input image; and \( I_p \) is the filtered image.

The entire filter is represented by \( BF \), as shown in formula (14) as follows:

\[ BF = \frac{1}{W_q} \sum_{P \in S} G_s(p)G_r * I_p \]

\[ = \frac{1}{W_q} \sum_{P \in S} \exp \left( -\frac{\| p - q \|^2}{2\sigma_s^2} \right) \exp \left( -\frac{\| I_p - I_q \|^2}{2\sigma_r^2} \right) * I_p, \]

where \( W_q \) is shown by formula (15) as follows:

\[ W_q = \sum_{P \in S} G_s(p)G_r(p) = \sum_{P \in S} \exp \left( -\frac{\| p - q \|^2}{2\sigma_s^2} \right) \exp \left( -\frac{\| I_p - I_q \|^2}{2\sigma_r^2} \right), \]

where \( G_s \) is the space distance weight; \( G_r \) is the pixel value weight; and \( W_q \) is the sum of the weights of each pixel value.

(3) Target Enhancement. The working principle of the USM algorithm is as follows: we use a low-pass filter to process the input image to get a low-pass component, calculate the difference between the original image and this component to get a high-pass component, and superimpose the high-pass component on the original image to get a sharpened image. Usually, Gaussian ambiguity is used to obtain low-pass components. The calculation formula is shown in formula (16), where the value of \( W \) is 0.1 to 0.9 and is usually 0.6.

\[ y = \frac{(X - w * z)}{(1 - w)}, \]

where \( y \) is the output image; \( X \) is the input image; \( W \) is the Gaussian ambiguity; and \( Z \) is the weight value.
3.6. Model Evaluation Criteria. In this paper, the model is evaluated from the detection time of a single-frame image and the average accuracy of image detection. The MAP (mean average precision) is the average value of all AP-like values. AP is the area below the line of the curve of accuracy and recall.

The accuracy rate formula is shown in formula (17) as follows:

\[
\text{Precision} = \frac{TP}{TP + FP}\tag{17}
\]

In the formula, TP refers to the number of positive samples of the classifier; FP refers to the number of negative samples of the classifier. The whole model reflects the accuracy function.

The recall rate formula is shown in formula (18) as follows:

\[
\text{Recall} = \frac{TP}{TP + FN}\tag{18}
\]

where \(T_p\) refers to the number of positive samples of the classifier.

The whole model reflects the checking function of the whole class of the model.

4. Experimental Analysis

4.1. Performance Comparison. In order to achieve the expected accuracy of our experiment, we compared the performance ability of fuzzy learning, shallow learning, and deep learning in complexity, learning ability, and number of parameters six times. The results are shown in Figures 1–3. The comparison in Figures 1–3 was performed with six independent experiments at random, which does not mean that performance increases as the number of experiments increases. The performance is different in different stages, and the performance degradation in the following experiments is also random.

By observing Figures 1–3, we can see that deep learning has the best performance ability in all aspects, so this paper adopts the deep learning method to carry out the following experiments. Performance is the coefficient of performance of different algorithms, with the highest being 10 and the lowest being 0.

4.2. Present Situation and Problems of Chinese Classroom Evaluation in Senior High Schools. Questionnaire from the understanding of classroom evaluation, classroom evaluation participation, classroom evaluation content, and evaluation feedback are four aspects to investigate and grasp the current students in all aspects of the basic situation of classroom evaluation. It is shown in Figure 4.

4.2.1. Student Questionnaire

(1) Students’ Understanding of Evaluation Function. In Table 1, 69.5% of the students think that Chinese classroom evaluation can help them find the advantages and disadvantages of learning, 20.9% of the students say “uncertain,” and 9.6% of the students think they cannot. Most students can realize the role of classroom evaluation and hope to get feedback from it, so as to use this feedback to better understand themselves.

In Table 2, 65.9% of the students think that Chinese classroom evaluation can make them reflect on their learning strategies, these students can have a deep understanding of their own learning situation, and 26.1% of the students are not clear whether classroom evaluation is helpful to their learning strategies. These students lack serious attention to learning strategies, and 8% of the students think that classroom evaluation will not have any effect on learning strategies.

In Table 3, it can be seen that 65.9% of the students think that Chinese classroom evaluation can stimulate their strong learning motivation, 26.1% of the students say “uncertainty,” and only 8% of the students think that “Chinese classroom evaluation can promote learning motivation” does not conform to their actual situation. Most students are aware of the stimulating effect of Chinese classroom evaluation on learning motivation, which is a good phenomenon, which shows that students have a great demand for classroom evaluation and have a correct understanding. If teachers can make more evaluations, it must be in line with students’ inner learning wishes.

(2) Content of Chinese Classroom Evaluation. In Table 4, 71.6% of students think that students who can draw inferences from others are often praised, which shows that teachers attach great importance to students’ ability to draw inferences from others and integrate them, which are all manifestations of deep learning. About 18.0% of the students chose “uncertainty,” while 10.4% of the students thought that this situation was not in line with reality. It can be seen that Chinese teachers in senior high schools pay more attention to the development of students’ transfer ability, but it may be due to some improper handling in the implementation of evaluation, which leads some students to fail to recognize the statement that “students who can draw inferences from others are often praised.”

In Table 5, it can be seen that 20.8% of the students choose “completely consistent” on the issue of “Chinese teachers often evaluate students’ learning attitude in class,” which shows that the situation is not ideal, and teachers may not pay enough attention to students’ learning attitude in class. About 50.0% of the students chose “basic compliance,” accounting for the largest proportion. Students who chose “uncertain” accounted for 19.6%, students who chose “somewhat inconsistent” accounted for 6.8%, and students who chose “completely inconsistent” accounted for 2.8%.

In Table 6, 67.5% of the students think that Chinese teachers often evaluate students’ learning methods in class, 14.9% of the students say “uncertainty,” and 17.7% of the students think that teachers do not often pay attention to students’ learning methods.

In Table 7, on the issue of “Chinese teachers often evaluate students’ thinking logic ability in class,” 20.5% of the students chose “complete conformity,” which shows that
one fifth of the students think that teachers pay attention to students’ thinking logic, and 39.4% of the students choose “basic conformity,” which shows that more than one third of the students think that teachers pay average attention to students’ thinking logic. About 23.7% of the students chose “uncertain,” 12.4% chose “somewhat inconsistent” and 4.0% chose “completely inconsistent.” There are still nearly 40% of students who do not explicitly recognize that Chinese teachers have evaluated students’ logical thinking ability in class, which shows that in the process of classroom evaluation, attention to logical thinking ability still needs continuous investment.

(3) Students’ Participation in Evaluation in Chinese Class. In Table 8, the average value of this question is 2.89, which is lower than the median value. It shows that students’ evaluation of others is not ideal. About 36.6% of the students think that they often have the opportunity to evaluate others’ learning, 24.8% say “uncertain,” and 38.6% think that “they often have the opportunity to evaluate others’ learning in Chinese class” is inconsistent with their actual situation. It can be seen that in the practice of Chinese classroom evaluation in senior high schools, students’ participation is insufficient, so teachers need to find ways to organize students to go to the classroom and encourage more students to participate in it to express their ideas.

In Table 9, the average value of this question is lower than the median value. Among them, 37.9% of the students expressed their willingness to evaluate other students’ learning, 23.4% held an “uncertain” attitude, and 38.7% were unwilling to evaluate others in class. It shows that students are unwilling to participate in the evaluation of Chinese classroom in senior high schools, and most people do not want to make an evaluation.
Figure 3: Parameters’ comparison of different algorithms.

Figure 4: Sample distribution diagram of questionnaire survey.

Figure 5: Analysis of the differences in the total scores of senior high school students’ classroom evaluation in grades.
In Table 10, the average value of this question is 3.17, slightly higher than the median value. About 43.4% of the students will participate in the classroom evaluation of Chinese class in various ways, 25.7% of the students say they are “uncertain,” and 30.9% of the students think they cannot participate in the classroom evaluation in various ways.

In Table 11, the average value of this question is 3.41, slightly higher than the median value. On the question of “Chinese teachers often encourage us to evaluate others in class,” 18.5% of students chose “basic conformity,” 21.8% expressed “uncertainty,” 12.9% chose “some in conformity,” and 9.7% chose “complete in conformity.” About 45% of the people did not explicitly indicate that Chinese teachers encourage students to make other evaluations. It can be seen that in order to improve students’ participation in Chinese classroom evaluation in senior high schools, teachers must first constantly encourage students to join, create an environment that can attract students to join, and let students make evaluations in a comfortable and stable classroom environment.
In Table 12, 64.8% of the students think that the Chinese teacher’s evaluation can truly reflect the students’ learning situation, 23.6% of the students hold an “uncertain” attitude, and 11.6% of the students think that the teacher’s evaluation cannot truly reflect the students’ situation. It shows that from the perspective of students, students’ learning situation is not completely reflected by the evaluation of Chinese teachers.

In Table 13, 75.2% of the students said that Chinese teachers often communicate the results of learning evaluation with their classmates, 15.2% said they were “uncertain,” and only 9.6% thought it was not the case. It shows that Chinese teachers in senior high schools will evaluate and communicate with their classmates at present, but about a quarter of the students still have no clear supporters of this view.

In Table 14, 76% of the students think that Chinese teachers can use the evaluation results to guide people to study deeply, 17.6% think it is “uncertain,” and only 6.4% of the students hold the opposite view.

In Table 15, on the question of “whether Chinese teachers will guide students to reflect on learning according to the evaluation results,” 32.4% of students choose “complete
compliance,” and about one third of students think that teachers can inspire students to think and examine their learning behavior and state through the evaluation results. About 46.8% of the students chose "basic conformity,” which accounts for nearly half, indicating that teachers’ performance in handling the evaluation results is satisfactory.

### 4.2.2. Difference Analysis of Total Scores of Classroom Evaluation of Senior High School Students

This study will analyze the differences in the total scores of classroom evaluation of Chinese teachers in senior high schools in various demographic variables. These variables involve five factors, namely, teachers’ gender, grade, family residence, whether they serve as class managers or not, and Chinese scores in classes. An independent sample t-test was used to analyze the variance between gender and class cadre, and single-factor variance was used to analyze the variance between class, grade, and family residence. The overall analysis ideas and results are roughly consistent with the teachers’ questionnaires, so they will not be repeated here.

1. **Grade Difference.** From the grade difference of students in Figure 5, the $F$ value of one-way ANOVA is 7.124, $P < 0.05$, which shows that the difference between groups has reached a very significant level; different grades have different evaluation...
scores; and at least one group has significant differences. After the multiple comparative tests, we can see that there are significant differences between senior three students and senior one students ($P < 0.05$) and senior two students ($P < 0.05$). By observing the average value, it can see that in the survey of Chinese classroom evaluation in senior high schools that promotes deep learning, the scores of students in Grade One and Grade Two are higher than those in Grade Three.

Looking at the above table, we can see that the average evaluation scores of senior one students are 93.5556, the average evaluation scores of senior two students are 90.4423, and the average evaluation scores of senior three students are only 84.4312, which is obviously different from the other two groups. Generally speaking, the higher the grade, the lower the score in the classroom evaluation of promoting deep learning. In the third year of senior high school, the new teaching has been greatly reduced, and students have gradually turned to comprehensive review, paying more attention to the consolidation of knowledge points. Teachers’ evaluation focus in class will also turn to the detection of knowledge points and the investigation of test-taking skills, thus ignoring the cultivation of deep learning ability of senior high school students.

### 2. Difference in Family Residence

From Figure 6, it can be seen that the $F$ value of one-way ANOVA is 3.296, and the $P < 0.05$, which shows that the difference between groups has reached a very significant level. Different families live in different places in terms of evaluation scores, and at least one group has significant differences, but it is unclear which group is at present. Further looking at the data, we can see that there are significant differences between the students who live in cities and the students who live in county towns ($P < 0.05$) and the students who live in rural areas ($P < 0.05$). Because of the differences in educational level and other factors, the average score of students in cities is higher than that of students in other places.

Teachers’ classroom evaluation is still knowledge oriented. Although they sometimes know how to encourage students, they still tend to test students’ mastery of knowledge in the actual classroom, lacking attention to students’ learning interest, learning methods, and thinking structure. In the questionnaire survey, teachers generally know more about the evaluation of promoting deep learning. However, when asked about the relevant contents of deep learning, teachers are somewhat vague, unable to really understand the meaning and characteristics of deep learning, and unable to make in-depth connection between evaluation and deep learning. During the interview, some teachers asked what deep learning is like, which can also reflect that some teachers have less awareness of promoting the evaluation of deep learning, let alone how to make in-depth management of classroom evaluation and deep learning. In the Chinese classroom of real frontline teachers, deep learning-oriented evaluation is still difficult to implement, due to external evaluation reasons, and factors such as poor self-grasp, difficult implementation, and unwillingness to try.

### 5. Conclusions

Learning to evaluate students’ learning status in different ways is a necessary process to guide students to study deeply. The original starting point of evaluating students includes thinking level, knowledge reserve, learning skills, psychological characteristics, interest tendency, self-cognition, learning attitude, and so on. We can use the question-and-answer style of direct inquiry in class; we can also use the description of other teachers to evaluate others; and we can also infer other information about students’ learning by looking at previous learning works. Calling student status files is the most convenient way to have an overall understanding of students. If you need to examine students’ knowledge and ability, the best way is to use a thorough test paper and intuitively understand it through test scores. However, for the information of interest and self-cognition, we take the interest scale and self-evaluation scale to fill in for students, so that they can scientifically predict their emotional content. After measuring and evaluating in many aspects, teachers can deeply understand the starting point of students’ learning and lay a solid data foundation for the analysis of learning situation.
Data Availability

The experimental data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares that they have no conflicts of interest regarding this work.

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