

## Research Article

# Deep Convolutional Neural Network and Weighted Bayesian Model for Evaluation of College Foreign Language Multimedia Teaching

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In colleges and universities, teaching quality evaluation is an integral part of the teaching management process. Many factors influence it, and the relationship between its evaluation index and instructional quality is complicated, abstract, and nonlinear. However, existing evaluation methods and models have flaws such as excessive subjectivity and randomness, difficulty determining the weight of indicators, easy over-fitting, slow convergence speed, and limited computing power, to name a few. Furthermore, the evaluation index system focuses primarily on teaching attitude, material, and methods, rarely taking into account preparation prior to teaching or the teaching situation throughout the teaching process, resulting in an incomplete evaluation. As a result, learning how to construct a model for objectively, truly, thoroughly, and accurately assessing the teaching quality of colleges and universities is beneficial not only to improving teaching quality but also to promoting scientific decision-making in education. This paper develops a teaching assessment model using a deep convolutional neural network and the weighted Naive Bayes algorithm. Based on the degree of influence of different characteristics on the assessment outcomes, a method to estimate the weight of each evaluation characteristic by employing the related probability of class attributes is proposed, and the corresponding weight is assigned for each evaluation index, resulting in a classification model ideal for teaching assessment that promotes standardization and intelligibility.

## 1. Introduction

With the continued development of higher education [1–4], determining how to fairly evaluate the teaching quality [5–7] of colleges and universities, promote the perfection of teaching objectives, and improve the teaching quality of colleges and universities is the key to furthering educational reform [8, 9], and it is also an urgent problem that needs to be solved now. As a result, evaluating teaching quality in colleges and universities has become an important part of the teaching management process [10], and researching methods or models for assessing teaching quality in colleges and universities has become a hot topic for scientific and standardized education and teaching.

Artificial neural network [11–14] is a nonlinear system [15] composed of many computational neurons which can be adjusted in different ways from layer to layer. It has the advantages of nonlinear ability, self-organization and self-learning ability, large-scale parallel processing, and so on. In the 1940s, McCulloch and Pitts [16] first proposed the mathematical model of neurons and became the forerunner in the study of artificial neural networks. Many new theories and algorithms of artificial neural networks have been proposed successively as a result of a large number of scholars joining the research, such as the perceptron model [17], back-propagation algorithm [18], Boltzmann machine [19, 20], unsupervised learning [21], and supervised learning [22–24], and their theoretical research and information

processing ability have improved and improved. Artificial neural networks have been applied to problems that cannot be solved by traditional methods and models as a mathematical model to deal with computation and have achieved good results in practice.

The back-propagation neural network (BP neural network) is a multilayer feedforward network that uses the back-propagation approach for training [25]. The goal of a BP neural network is to use the gradient descent method [26] to rectify error signals generated during forward propagation until the accuracy target is satisfied or the number of iterations is reached. Hecht-Nielsen [27] then showed that a BP network with a hidden layer may approximate a continuous function within any closed interval, meaning that any three-layer BP neural network can complete any mapping from  $N$  to  $M$  dimensions. Although the BP neural network has strong information processing and nonlinear mapping capabilities, it has some flaws, such as slow convergence speed and a tendency to fall into minimum values during the training process, making it ineffective in dealing with complex high-order abstraction problems. However, the multilayer perceptron with multiple hidden layers is a deep learning structure, which can be used to solve more complex and abstract nonlinear problems. After the publication of the research results of Geoffrey Hinton and Salakhutdinov [28], the academia and industry have set off a boom in the research of deep neural network, and the layer number and scale of neural network models have been greatly improved compared with the previous ones.

The main contributions of this paper are as follows:

- (1) To solve the problem of evaluating teaching quality in colleges and universities, promote continuous improvement of teaching goals, and promote scientific decision-making in education, this paper proposes a method based on a deep convolutional neural network and a weighted Bayesian model, all of which can help to improve teaching quality
- (2) This paper proposes to use convolutional neural networks to identify classroom behaviors and to use the weighted Bayesian incremental learning method to solve the problem of new samples arriving in batches. Through this strategy, it is not necessary to retrain the old sample data, and only need to adjust the model parameters according to the new sample data

The structure of this article is organized as follows. Section 2 presents the related work. Section 3 provides the details of the proposed method. Section 4 discusses the simulations and experiments, and Section 5 presents the conclusions.

## 2. Related Work

The United Kingdom, the United States, and Japan were among the first to begin and propose important ideas and methodologies, such as multiple intelligence theory, con-

structivism theory, and the Taylor evaluation model, in terms of teaching quality evaluation research. An American educationalist's book, *Introduction to Psychological and Social Measuring*, provided a theoretical foundation for the standardization of educational measurement and marked the maturation of educational measurement. In Russia, the most common assessment approaches are state-based assessment, school-based self-assessment, and self-supervision evaluation based on social competitiveness. The Japanese government proposes the "dual-track assessment model," which calls for a pluralistic, objective, and transparent evaluation system that incorporates both internal and external reviews. Currently, the teaching quality evaluation index system at colleges and universities is mostly focused on teaching attitude, material, and procedures, which are quantified as input feature vectors of applicable methodologies and models. Analytic hierarchy process, multivariate statistical analysis, fuzzy comprehensive evaluation, fuzzy hierarchy analysis, correlation analysis, ID3 algorithm, support vector machine, BP neural network model, and so on are some of the extant assessment methods and models. Literature [29] proposed an enhanced Apriori method for mining teaching system data to assess college and university teaching levels. A BP neural network is used to create a training quality evaluation model in the literature [30], demonstrating that the BP neural network approach is highly operational. It not only simplifies the evaluation process but also addresses some of AHP's flaws, such as subjectivity and randomness. Ge Chun et al. [31] used a genetic algorithm to select the best individual and set the optimal weight and threshold value for the BP neural network. Data training improved the accuracy of the classroom teaching quality rating.

## 3. Methodology

*3.1. Classroom Behavior Recognition Based on Convolutional Neural Network.* This section creates a classroom behavior recognition model using convolutional neural networks. The initial layer of the network model is the input layer of  $512 \times 512$  student classroom behavior photographs. The second, fourth, and sixth layers all use convolution, followed by the maximum pooling layer. Image features are extracted using the second to seventh layers. The full connection layer is the eighth and ninth layers, and the output layer is the last. 0.001 is the learning rate, RELU is the activation function, and BATCH\_SIZE is 100. The detailed network model structure is shown in Figure 1.

In the convolutional neural network model layout, the picture input is followed by the convolutional layer and the pooling layer, which alternate. After the convolution calculation, the convolutional layer will add the obtained result to the offset item and then activate the function with ReLU to get the feature map. Then, the dimension of the feature map will be reduced through maximum pooling. The convolution kernel is  $3 \times 3$ , and the maximum pooling runs through these convolution and pooling procedures three times before being input into the two full connection layers. In the full connection layer, nonlinear changes are also carried out at first, and then, the Dropout layer is

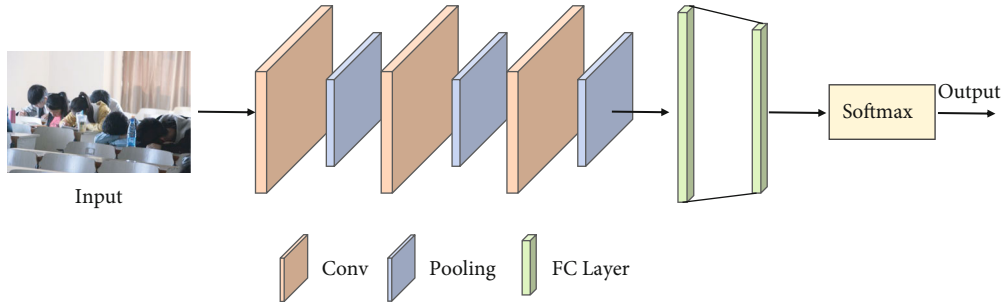


FIGURE 1: Schematic diagram of classroom behavior recognition model based on convolutional neural network.

added, and the loss rate is set at 0.4 to convert its feature graph into one-dimensional data. Finally, Softmax classifier is used to output the probability value of the predicted image.

### 3.2. Evaluation Classification Model Based on Weighted Naive Bayes

**3.2.1. Naive Bayes.** A classification algorithm based on Bayes' theorem is known as Bayesian classification. The basic premise of classification is to learn a significant amount of training data in order to estimate the prior probability of each category and, then, calculate the posterior probability of a certain instance  $X$  belonging to different categories, and finally determine the instance as the class with the largest posterior probability. Suppose  $D$  is the training dataset,  $A = \{A_1, A_2, \dots, A_n\}$  is the attribute variable set, and  $n$  is the number of attributes.  $C = \{C_1, C_2, \dots, C_m\}$  is the class variable set,  $m$  is the number of categories, then a training sample can be expressed as  $\{x_1, x_2, \dots, x_n, C_j\}$ ,  $C_j$  means that the class label of the training sample is known, and a test sample  $X$  can be expressed as  $\{x_1, x_2, \dots, x_n\}$ , judge the test sample The probability of belonging to a certain category is calculated as follows:

$$p(C_j | X) = \arg \max_{C_j} \frac{p(X | C_j)p(C_j)}{p(X)}. \quad (1)$$

Naive Bayes (shown in Figure 2) is an effective classification algorithm in Bayesian classification methods. The classification model has the benefits of being simple to interpret, having a high computational efficiency, and being stable. In some cases, it outperforms decision-making and Classifiers like tree and SVM.

The root node  $C$  is the class variable, and the leaf node  $\{A_1, A_2, \dots, A_n\}$  is the attribute variable. The generic Bayes classification model is based on the Naive Bayes classification model, which does not impose attribute independence restrictions. In practice,  $p(X)$  is usually a constant, so the calculation equation of Naive Bayes is as follows:

$$p(C_j | X) \propto \arg \max_{C_j} p(X | C_j)p(C_j), \quad (2)$$

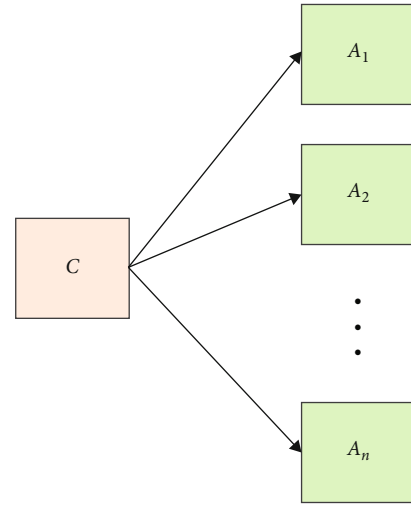


FIGURE 2: Schematic diagram of Naive Bayes.

where  $p(C_j)$  is the class prior probability, which can be learned through training data. The calculation equation is

$$p(C_j) = \frac{S_j}{S}, \quad (3)$$

where  $S_j$  represents the number of class  $C_j$  in the training sample and  $S$  represents the total number of training samples.

According to the assumption of conditional independence, the calculation formula of  $p(X | C_j)$  can be simplified as

$$p(X | C_j) = \prod_{i=1}^n p(x_i | C_j). \quad (4)$$

**3.2.2. Evaluation Attribute Weights Based on Weighted Naive Bayes.** In this paper, the Weighted Naive Bayes (WNB) classification algorithm is used to assign a reasonable weight to attributes based on their contribution to classification, which not only keeps the Naive Bayes algorithm fast but also reduces the impact of the attribute conditional independence assumption on the classifier's performance. The following is the formula for calculating it:

$$p(C_j | X) = \arg \max_{C_j} p(C_j) \prod_{i=1}^n p(A_i | C_j)^{w_i}, \quad (5)$$

TABLE 1: Comparative experiment results on the GTZAN dataset.

Times	1	2	3	4	5	6	7	8	9	10
SVM	0.71	0.70	0.71	0.69	0.71	0.71	0.73	0.68	0.71	0.70
NB	0.68	0.71	0.70	0.72	0.70	0.72	0.70	0.71	0.72	0.71
Ours (WNB)	0.75	0.76	0.73	0.74	0.73	0.74	0.74	0.73	0.74	0.75

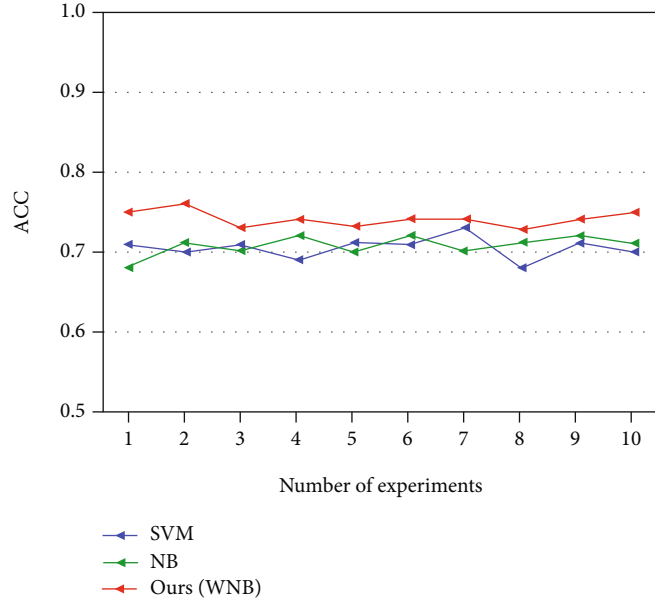


FIGURE 3: Comparison result of evaluation accuracy.

where  $w_i$  represents the weight of attribute  $A_i$ , which determines the importance of different attributes in the classification process. The larger the value of  $w_i$ , the more important the corresponding attribute  $A_i$  is for classification.

Assuming a specific instance  $X$ , when the attribute  $A_i$  of  $X$  takes the value  $a_k$ , for the category  $C_j$ , the calculation formula of the correlation probability  $p(A_i | rel)$  and the irrelevant probability  $p(A_i | noel)$  of the attribute  $A_i$  with respect to  $C_j$  is as follows:

$$p(A_i | rel) = \frac{\text{count}(A_i = a_k \wedge C_j)}{\text{count}(A_i = a_k)}, \quad (6)$$

$$p(A_i | noel) = 1 - p(A_i | rel), \quad (7)$$

where count represents the statistical number. When the attribute  $A_i$  value is  $a_k$  and belongs to the  $C_j$  category, the attribute weight calculation formula is as follows:

$$w(A_i, a_k, j) = \frac{p(A_i | rel)}{p(A_i | noel)}. \quad (8)$$

Therefore, the specific calculation formula of the WNB classification algorithm is as follows:

$$p(C_j | X) = \underset{C_j}{\operatorname{argmax}} (C_j) \prod_{i=1}^n p(A_i | C_j)^{w(A_i, a_k, j)}. \quad (9)$$

Finally, based on the specific value of each characteristic, the weight value of the likelihood associated with the current category label is chosen for computation, and the result value of each category is compared. The greatest value corresponds to the highest category in the classification.

## 4. Experiments and Results

**4.1. Experimental Setup.** The hardware configuration of the experimental environment is as follows: CPU is Intel E5-1607V3 quad-core 3.1GHz, graphics card is RTX2070 (8G), memory is 16G, and operating system is Windows10. The experimental simulation uses a framework based on TensorFlow 1.9.0, and the programming language is implemented using Python 3.5 and MATLAB R2017b. The learning rate of the model in this paper is 0.01, the number of iterations is 2000, and the batch size is 10.

**4.2. Dataset.** The student evaluation data used in the experiment comes from real data in the educational administration management system of a university. The back-end database management system of the educational administration management system of the school uses Oracle as the database management system. The student evaluation database of the school stores the data from the second half of 2004. Up to the first half of 2020, there are a total of 16 school years and 32 semesters of all teaching evaluation data, and a total of 222,190 student evaluation records. Student

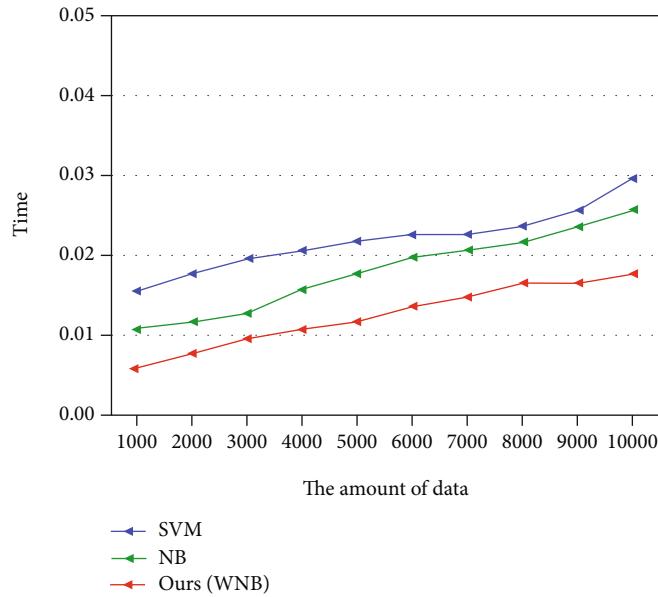


FIGURE 4: Comparison result of time.

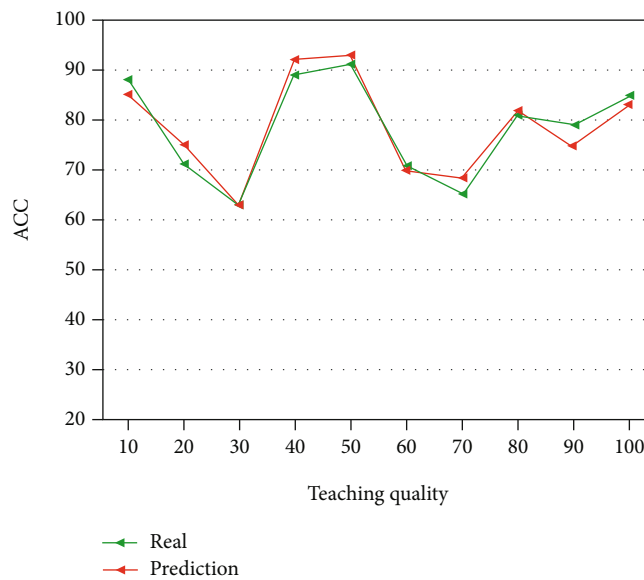


FIGURE 5: Comparison result of the prediction and real.

evaluation of teaching is organized and implemented in the form of an online evaluation of teaching. In order to ensure that every student must participate in the evaluation of teaching, the system has adopted a mandatory treatment. The system requires that the evaluation of teaching by students must be conducted in the time after the end of the course and before the examination of the course; otherwise, the scores of students who did not participate in the evaluation of the course refuse to enter the system.

4.3. *Evaluation Index.* This chapter determines the classification accuracy rate (Acc). The following is the procedure for calculating classification accuracy:

$$Acc = \frac{TP}{TP + FP} \tag{10}$$

4.4. *Experimental Results.* To conduct cross-validation testing, we randomly selected 70% of the data as the training set and 30% of the data as the test set. The classification accuracy of the NB and WNB algorithms was determined using ten cross-validation trials. The individual experimental outcomes are shown in Table 1 below.

As demonstrated in Figure 3, the average classification accuracy of the Naive Bayes algorithm on this dataset is 0.707, while the weighted naive Bayes approach is 0.741. The weighted naive Bayes algorithm has a greater classification

TABLE 2: Comparative experiment results on the GTZAN dataset.

Times	1	2	3	4	5	6	7	8	9	10
$lr = 0.1$	0.74	0.75	0.71	0.73	0.71	0.73	0.72	0.72	0.73	0.72
$lr = 0.001$	0.63	0.75	0.72	0.73	0.71	0.71	0.69	0.71	0.73	0.70
Ours ( $lr = 0.01$ )	<b>0.75</b>	<b>0.76</b>	<b>0.73</b>	<b>0.74</b>	<b>0.73</b>	<b>0.74</b>	<b>0.74</b>	<b>0.73</b>	<b>0.74</b>	<b>0.75</b>

accuracy than the regular naive Bayes algorithm on the instructional evaluation dataset.

It can be seen from Figure 4 that because the incremental model does not need to retrain and calculate the previously trained dataset, it only needs to classify and calculate the increased data, directly merge with the previous training value, and update the relevant parameters of the model, saving It saves time and improves the efficiency of the classification model. In addition, Figure 5 depicts a comparison between the predicted and actual results. The model's usefulness is demonstrated by the experimental results.

It can be seen from Table 2 that by setting the ablation experiment, we can clearly see that when the learning rate is set to 0.01, the model achieves the best performance. Therefore, we can determine the effectiveness of the hyperparameters of the model in this paper.

## 5. Conclusion

In colleges and universities, teaching quality evaluation is an integral part of the teaching management process. It is not only beneficial to increase teaching quality but also to encourage scientific decision-making in education, to learn how to develop an objective, actual, comprehensive, and accurate model to evaluate teaching quality in colleges and universities. This research develops a teaching assessment model using a deep convolutional neural network and the weighted Naive Bayes method. A method to estimate the weight of each evaluation characteristic by employing the related probability of class attributes is proposed based on the degree of influence of different characteristics on the assessment outcomes, and the corresponding weight is set for each evaluation index, so as to construct a classification model suitable for teaching evaluation, which is conducive to promoting the standardization and intelligence of teaching management in colleges and universities. We conducted a series of simulation, comparison, and ablation experiments. The results of the comparison experiments show that the method in this paper has achieved competitive performance. In addition, through ablation experiments, this paper further confirms the validity and superiority of the model in this paper.

## Data Availability

The data used to support the findings of this study are included within the article.

## Conflicts of Interest

All the authors do not have any possible conflicts of interest.

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