Retraction

Retracted: Research on Teaching Evaluation System Based on Machine Learning

Mobile Information Systems

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] A. Yang and S. Yu, "Research on Teaching Evaluation System Based on Machine Learning," *Mobile Information Systems*, vol. 2022, Article ID 9255064, 10 pages, 2022.

Research Article

Research on Teaching Evaluation System Based on Machine Learning

Aijun Yang[1] and Shuyan Yu [iD] **[2]**

[1]*Zhejiang Yuexiu University, Shaoxing 312000, Zhejiang, China*
[2]*Shaoxing University Yuanpei College, Shaoxing 312000, Zhejiang, China*

Correspondence should be addressed to Shuyan Yu; ysy@usx.edu.cn

Teaching evaluation, as a written measure of teachers' teaching work achievements, can motivate teachers to teach rigorously and work hard. However, the existing teaching evaluation system in China lacks sound standards and approaches. On the one hand, scientific research projects, funding, papers, etc. have become the criteria for measuring a teacher's performance, and this situation has contributed to the culture of quick success; on the other hand, the current teaching evaluation system is based on indicators of teaching quality achievements or subjective judgments of experts and subject groups, and these evaluation methods can only respond to some teaching quality from a one-sided perspective and cannot make a comprehensive, systematic, and scientific. The analysis and judgment of teachers' work cannot be made comprehensively, systematically, and scientifically. A good teaching evaluation system can not only help teachers distinguish the shortcomings of the current course teaching but also motivate them to make further efforts and devote themselves to the teaching tasks. In this paper, we hope to find a reasonable way to evaluate teachers' teaching work based on the proportion of different indicators and different influencing factors from machine learning, in view of the current unscientific evaluation methods that differentiate teachers' performance of various work indicators. Through experiments, it can be found that using gradient descent methods, we can obtain such a scientific model that can make a positive contribution to teaching evaluation.

1. Introduction

In recent years, with the continuous development of society and the progress of science and technology, education has become more and more important in the development of the country [1]. The main purpose is to cultivate more excellent and high-quality students for the society and the [2]country [3].

The main purpose is to cultivate more excellent and high-quality talents for the society and the country and to import fresh blood for the development and progress of the society and the country [4]. In recent years, due to the reform and development of education, the universities have inevitably expanded their enrollment, resulting in an increase in the number of teaching quality, and it is difficult for the teachers in charge to grasp the learning situation of every

teaching quality and give timely advice and help on teaching quality [5]. So it becomes very important to analyze the teaching quality data, predict the learning situation of teaching quality, and remind the abnormal teaching quality in time. The progress of technology makes teaching diversified, making students easy to be attracted by the teaching content, and many teaching quality can easily develop the idea of relaxing themselves when entering university, these will lead to teaching quality no longer studying hard and cannot acquire professional knowledge well during university, some teaching quality even cannot complete their studies successfully because they fail too many courses, and cannot get the degree and diploma, so it is necessary to analyze the examination results of teaching quality to understand its learning situation and to provide academic warning for teaching quality [6].

In the teaching process of higher education institutions, examinations have traditionally been an indispensable part of it. Examinations play the examination results of teaching quality represent the mastery of recent knowledge, which can be used to understand the mastery of the course and the ability to learn new knowledge, and to motivate teaching quality to learn [7]. Teaching quality results have always been one of the important indicators for schools and enterprises to assess the learning situation and ability of teaching quality, and examinations occupy a very important position in all types of school teaching. There is a lot of information in the data such as teaching quality examination results, and schools can adjust their teaching plans and carry out educational reforms in time through the information fed by teaching quality examination results, thus improving the quality of teaching [8] in [9] schools [10].

At present, the use of the teaching quality data information stored in the teaching management system of the school is still only some conventional and basic statistics, such as statistics on the average score of the course, the course failure rate, and the highest score of the course [11]. But these analysis results obtained are summaries of the courses that have been learned by the teaching quality, reflecting the learning situation of students in the past period of time, which can warn the teaching quality of unqualified grades, however, they do not provide early warning for future learning and cannot well motivate the learning of teaching quality [12]. So how to analyze these teaching quality data and what scientific and efficient methods to use to analyze teaching quality data and get the valuable information hidden in it, to achieve the monitoring and early warning of teaching quality learning, and then help teaching quality to improve their examination results has become an important research direction, the research goal of this thesis is to find the methods that can train an efficient and easy to understand academic early warning model. Machine learning is a key technology to exploit the value of data, and its close connection with big data exists [13]. The core of big data is to exploit the value of data, and the purpose of this thesis is to find simple and efficient machine learning algorithms to analyze teaching quality data, to make full use of the value of data in the school teaching management system, to predict the future learning of teaching quality, and to provide more valuable information [14].

At present, although "quality education" and "ability education" are gradually attracting attention, in terms of the actual education situation, knowledge, and intelligence education are still the core, main, and main content. The quality of teaching and learning is still measured and evaluated by academic achievement and even by schools [15]. The assessment of teaching quality is a relatively subjective process, but it has a profound guiding meaning for teachers' teaching work. In major universities, the importance people attach to teaching quality requires us to do scientific assessment of teaching so as to actively motivate teachers' work. Compared with the previous method of using simple statistics by expert panels to calculate teachers, in terms of content, it cannot comprehensively cover various possible factors affecting teachers' teaching quality; in terms

of rationality, it uses simple statistics and does not recognize that the proportions occupied by various influencing factors are different; in terms of simplicity, it does not get a calculation model that can be generalized among various disciplines [16].

When we conduct teaching evaluation activities, the first thing we need to clarify is the teaching evaluation indicators, once we have clear indicators, teachers have a basis for comparison and reference in the daily teaching process, so we can see that teaching evaluation has a guiding function [17]. In this machine learning course, we can know that machine learning is different from the learning of previous courses, and its purpose is to make teaching quality learning how to make machines acquire by identifying and using existing knowledge. As an important research area of artificial intelligence, the research work of machine learning is mainly focused on three basic aspects of learning mechanism, learning methods, and task-oriented research.

2. Related Work

With the recent boom in technologies such as machine learning and artificial intelligence, more and more fields are adopting advanced techniques to study the available data and promote the progress and development of the field, such as computer field and business field. Nowadays, there is also an increasing interest in academic warnings based on the results of teaching quality test scores or analysis or on the results of analysis of some behavioral activities in the daily life and learning process of teaching quality. For example, [18] used artificial neural networks to analyze the data of final grades, midterm grades, and educational background of teaching quality to predict the passing status of teaching quality [19]. [20] described studies related to the use of data mining techniques for predicting the performance of teaching quality. [21] used data mining techniques to study the performance of teaching quality and they conducted two main studies, first, to predict the performance of teaching quality at the end of four years of study and second, to study the development of typical cases and combine them with the predicted results to provide timely warnings for teaching quality. In general, some foreign researchers have done a lot of relevant research in combining the current advanced data mining techniques and methods with university education for predicting the achievement and performance of teaching quality, and thus advancing the development of higher education.

[22] used a combination of feature selection and machine learning algorithms to analyze test scores, first using feature selection techniques to preprocess test scores, and then using decision tree algorithms to predict teaching quality test scores. [23] used multiple linear regression analysis to quantify the teaching quality test score data, analyzed the relationship between teaching quality English IV scores and teaching quality final scores, and constructed a multiple linear regression model for evaluating and predicting teaching quality scores. [24] used a decision tree algorithm to study the teaching quality test scores to warn the failed teaching quality, and he predicted the teaching

quality professional course grades by the teaching quality basic course grades, and teachers can focus on the teaching quality with poorer predicted grades according to the prediction results, so as to reduce the class failure rate and improve the teaching quality. [25] used the Ada Boost boosting algorithm to analyze the teaching quality data information of a junior high school to predict the teaching quality next examination results.

Many studies at this stage only predict whether there is a failure in a certain subject of teaching quality, in this paper, the prediction of teaching quality situation can better achieve the purpose of improving teaching quality of independent learning [26]. The study of academic early warning of teaching quality based on the data information of teaching quality can provide extremely informative suggestions for the reform of teaching evaluation and teaching work.

3. Research on Prediction of Teaching Quality Situation Based on Machine Learning

At present, the teaching quality assessment function is not yet available in the teaching management systems of universities, and they all only alert the teaching quality by counting the number of failed subjects, which has a lag and cannot provide early warning function. This section describes in detail the principles and steps of using the weighted plain Bayesian algorithm and the decision tree algorithm to analyze the teaching quality performance; first, we need to obtain the plain Bayesian graduation prediction model and the C4.5 graduation prediction model, and then use certain rules to combine the models obtained by the weighted plain Bayesian algorithm and the decision tree algorithm to obtain the WNB-C4.5 teaching quality prediction model [27]. The effectiveness of the obtained classification models is also evaluated experimentally, and the combined model is compared with the single model to obtain the best early warning model for teaching quality situation.

3.1. A Study on Early Warning of Teaching Quality Based on Plain Bayesian. The plain Bayesian algorithm is a very representative machine learning classification algorithm and a classical probabilistic-based classification method. With the features of simple and easy to understand principle and easy to implement, the plain Bayesian algorithm is therefore used in many fields. In the plain Bayesian algorithm, the individual feature attributes are considered to be independent of each other, and there is no interdependence between them. The n feature attributes in the experimental data set can be represented by $A_1, A_2, A_3, \cdots, A_n$. A sample data waiting for testing can be represented as $x = \{x_1, x_2, x_3, \cdots, x_n\}$, and the value of the category label of that sample corresponds to a value in the set C of category labels. If there are five feature attributes in the experimental data set, then the structure of the model of plain Bayes is shown in Figure 1:
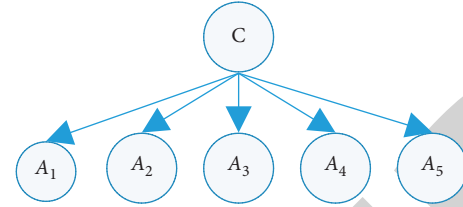

FIGURE 1: Schematic diagram of the structure of the plain Bayesian model.

The biggest difficulty in obtaining the posterior probability using Bayes' theorem is that the conditional probability of a class is the joint probability of all genera The joint probability on the properties, but it is difficult to obtain its value directly in the limited sample data [28]. In using the plain Bayesian, the classification is based on attribute independence and Bayes' theorem. For a given training data set, first, the joint probability of the input data and the output class is learned by assuming that each feature attribute is independent of each other; then, based on this model, we use Bayes' theorem to calculate the posterior probability of the samples to be classified. The category value that corresponds to the largest posterior probability is the final classification result of the sample to be classified. It is assumed that the feature attributes are independent of each other. The posterior probability is

$$P(c|x) = \frac{P(c)P(x|c)}{P(x)} = \frac{P(c)}{P(x)} \prod_{i=1}^{n} P(x_i \mid c), \tag{1}$$

where c is the value of a category in the set of classification results C. In the case of graduation prediction studies, there are only two categories, graduation and nongraduation, n is the number of feature attributes in the data set, x_i is the value of sample x on the ith feature attribute, and $P(c)$ is the probability that the sample category in the data set is c [29]. For each category, $P(x)$ is the same, so the Bayesian decision criterion based on the above equation can be known as the formula for plain Bayesian classification:

$$h(x) = \arg\max P(c) \prod_{i=1}^{n} P(x_i \mid c). \tag{2}$$

From the above equation, training the plain Bayesian classifier is to calculate the prior probability of each class and the conditional probability of each attribute using the data in the training data set. The formula for calculating the prior probabilities of the classes is shown below:

$$P(c) = \frac{|D_c|}{|D|}. \tag{3}$$

The conditional probability is calculated with respect to the type of data. If the data for the feature attributes are discrete values, the conditional probability is the ratio of the total number of x_i samples, D_{c,x_i} is the number of samples, and $|D_c|$ is the category label c in the training data set for the ith feature attribute value, with the following formula:

$$P(x_i \mid c) = \frac{\left|D_{c,x_i}\right|}{\left|D_c\right|}. \tag{4}$$

If the feature attributes are continuous type data, the conditional probability is assumed to obey the positive too according to the probability density function distribution, which is calculated as follows:

$$P(x_i \mid c) = \frac{1}{\sqrt{2\pi}\sigma_{c,i}} \exp\left(-\frac{\left(x_i - \mu_{c,i}\right)^2}{2\sigma_{c,i}^2}\right), \tag{5}$$

where $\mu_{c,i}$ is the mean on the ith characteristic attribute in category c and $2\sigma_{c,i}^2$ is the variance on the ith characteristic attribute in category c.

3.2. A Study on Teaching Quality Early Warning Model Based on Attribute Weighted Parsimonious Bayes. This prerequisite makes the algorithm have some uncertainty, and there are differences in the impact of each feature attribute on the graduation prediction, some features have a greater impact on the prediction result, while some attributes have a smaller impact on the prediction result. Since different attributes have different effects on the classification results, and there are correlations among the attributes, if we do not consider these effects and treat all feature attributes as having the same effect on the classification, and set all feature attributes as independent of each other, this will affect the quality of the teaching quality prediction model and reduce the accuracy of the prediction results. In order to improve the accuracy of model classification and increase its use value, the According to the different effects of different feature attributes on the classification results, based on the plain Bayesian algorithm, the Based on the plain Bayesian algorithm, we add a suitable weight to the different feature attributes according to their influence on the prediction results, and improve the prediction results' The correctness of the prediction results is improved by adding a weight to the attributes according to their influence [12].

When using the plain Bayesian algorithm with attribute weighting to obtain the prediction model of teaching quality, first, the influence of the attribute on the classification result should be determined according to the influence of the attribute on the classification result. The PBP algorithm is based on the influence of the attribute on the classification result, and then the weights of the attribute are used to. Then, the weighted Bayesian formula is adjusted by using the weight coefficients of the attributes to obtain the weighted Bayesian formula, which is defined as

$$h = \arg\max P(c) \prod_{i=1}^{n} P(x_i \mid c)^{w_i}, \tag{6}$$

where w_i represents the weight of the ith feature attribute, and the greater the influence of the feature attribute on the prediction result, the greater the corresponding weight of the attribute.

From the above (6), it can be seen that in the attribute weighting based plain Bayesian algorithm how to weight the

feature attributes are weighted and how to calculate the weights of each feature attribute with high quality and efficiency is a very important step. Therefore, the way to calculate the weights of each feature attribute becomes a key issue.

The information gain is often used in the decision tree algorithm to select the split feature attributes. In the information gain, the more information a feature attribute brings to the classification system, the more important the feature attribute is in the overall classification systemthe more important the feature is in the overall classification system. Therefore, in this section, the importance of a feature attribute is determined by the amount of information it brings to the system, and the weight of the feature attribute is determined by the amount of information it brings to the system. The information gain of feature attribute A is

$$Gain(D, A) = H(D) - H(D \mid A). \tag{7}$$

The empirical entropy and the conditional entropy in Eq. are calculated as follows:

$$H(D) = -\sum_{k=1}^{K} \frac{\left|C_k\right|}{\left|D\right|} \log_2 \frac{\left|C_k\right|}{\left|D\right|} H(D \mid A)$$

$$= -\sum_{j=1}^{m} \frac{\left|D_j\right|}{\left|D\right|} H(D_j) = -\sum_{j=1}^{m} \frac{\left|D_j\right|}{\left|D\right|} \sum_{k=1}^{K} \frac{\left|D_{j,k}\right|}{\left|D_j\right|} \log_2 \frac{\left|D_{j,k}\right|}{\left|D_j\right|}, \tag{8}$$

where $\left|C_k\right|$ is the number of samples belonging to C_k in the data set, K is the number of categories in the set C of categories, m is the number of attribute values in attribute A, $\left|D_j\right|$ is the number of samples in subset D_j, and $\left|D_{j,k}\right|$ is the number of samples in subset D_j whose sample category is C_k.

The higher the value of information gain of attribute A means that attribute A has a greater influence on the final classification result when conducting the teaching quality warning study, and the more important it is in the classification. The information gain value of each attribute is calculated according to the formula, and the weight of each attribute can be obtained as follows:

$$W_t = \frac{Gain(A_t)}{\sum_{i=1}^{n} Gain(A_i)}. \tag{9}$$

Based on the principle of attribute weighted plain Bayesian algorithm, an early warning model of teaching quality situation is obtained and tested. The specific steps can be summarized as follows:

Step 1: Construct an experimental data set based on the obtained teaching quality data and process it to make the data meet the requirements of the algorithm, then divide the experimental data set into a training sample set D and a test sample set T.

Step 2: Calculate the information gain of each feature attribute in the training set based on the input training data.

Step 3: Based on the input training data, calculate the conditional probability of each feature attribute in the training data set and the prior Step3: based on the input training data, calculate the conditional probability of each feature attribute and the prior probability of each category in the training data set.

Step 4: Perform the weight calculation and calculate the weights of all feature attributes based on the information gain of feature attributes and the prior of each category and the conditional probabilities of all feature attributes obtained in Step2 and Step3, and then obtain the teaching quality prediction model.

Step 5: Perform teaching quality prediction model testing. The obtained graduation situation prediction model is tested using the test data set The model is tested, i.e., the teaching quality samples in the test data set are classified. And the output classification results are compared with the output classification results are compared with the real categories of the samples to analyze the model effect.

The specific process of obtaining a classification model based on attribute weighted plain Bayesian algorithm is shown in Figure 2.

3.3. A Study on Teaching Quality Assessment Based on Combined Decision Tree and Parsimonious Bayesian Algorithm

3.3.1. Basic Principles of Decision Tree and Plain Bayesian Combination Algorithm. When combining the classification results of the two classification models, it is based on the two models in the validation data set and the posterior probabilities of the two types of models, the probability that the test sample belongs to each category is calculated, and the category label with the maximum probability The category label that corresponds to the highest probability is the classification result. The probability of a sample belonging to each category is calculated as:

$$P(c|x) = \frac{A_{WNB} \times P(c|x)_{WNB} + A_{C4.5} \times P(c|x)_{C4.5}}{A_{WNB} + A_{C4.5}}, \quad (10)$$

where c is a category value, AWNB is the accuracy of the final obtained plain Bayesian classification model in classifying the validation data set, and AC4.5 is the accuracy of the final obtained Bagging-C4.5 decision tree classification model in classifying the validation data set. $p(c|x)$WNB is the classification result of the total obtained plain Bayesian classifiers for the samples to be classified is the proportion of classifiers of category c in the total classifiers. The calculation formula is as follows:

$$P(c|x)_{WNB} = \frac{1}{n} \sum_{i=1}^{n} Z_i,$$

$$Z_i = \begin{cases} 1, & R(T) = c \\ 0, & R(T) \neq c \end{cases}, \quad (11)$$

where n is the number of plain Bayesian classifiers and $R(T)$ is the classification result. C4.5 posterior probability $P(c|x)$ C4.5 of the decision tree classification model is similar to that of plain Bayesian.

3.3.2. Implementation of Combined Decision Tree and Plain Bayesian Algorithm. The research of the combined algorithm of attribute weighted plain Bayesian algorithm and C4.5 decision tree algorithm is carried out in two main phases as follows:

(1) Model Training Phase. In this phase, the model is trained using the acquired sample data using the weighted plain Bayesian algorithm and the Bagging-C4.5 algorithm, respectively. In this paper, data processing operations such as data feature extraction were performed on the data collected for teaching quality, and the data set required for the experiment was constructed and divided into training data set, validation data set, and test data set according to a certain ratio. Finally, the two models were combined according to certain rules to obtain the final prediction model of teaching quality. The process of the model training phase is shown in Figure 3:

The detailed steps for training the teaching quality test performance data using the attribute weighted plain Bayesian algorithm and C4.5 decision tree algorithm to obtain the classification model of ground teaching quality situation are as follows:

Step 1: Input training data and test data are inputs, and sample data in the training set are processed to standardize the data format so that they meet the requirements of the algorithm.

Step 2: The input training set is randomly sampled with put-back to obtain n subtraining data sets, and each subtraining data set contains 60% of the sample data in the original training data set.

Step 3: Use the obtained n subtraining data sets to train n weighted plain Bayesian classifiers, and then use the validation set data to evaluate the performance of the combined classifier of these n classifiers, and finally obtain the weighted plain Bayesian classifier and its performance evaluation result AWNB, i.e., the accuracy of the classifier.

Step 4: Train n C4.5 classifiers with the obtained n subtraining sets, and then evaluate the performance of the combined classifiers of these n classifiers with the validation set data, and finally obtain the C4.5 classifier and its performance evaluation result AC4.5, which is the accuracy of the C4.5 classifier.

Step 5: The output weighted plain Bayes classifier and C4.5 classifier, as well as the accuracy of the two classifiers AWNB and AC4.5 on the validation data set, are obtained for the teaching quality situation prediction model.

(2) Model Testing Phase. This phase is to test the classification model obtained in the training phase using the samples in
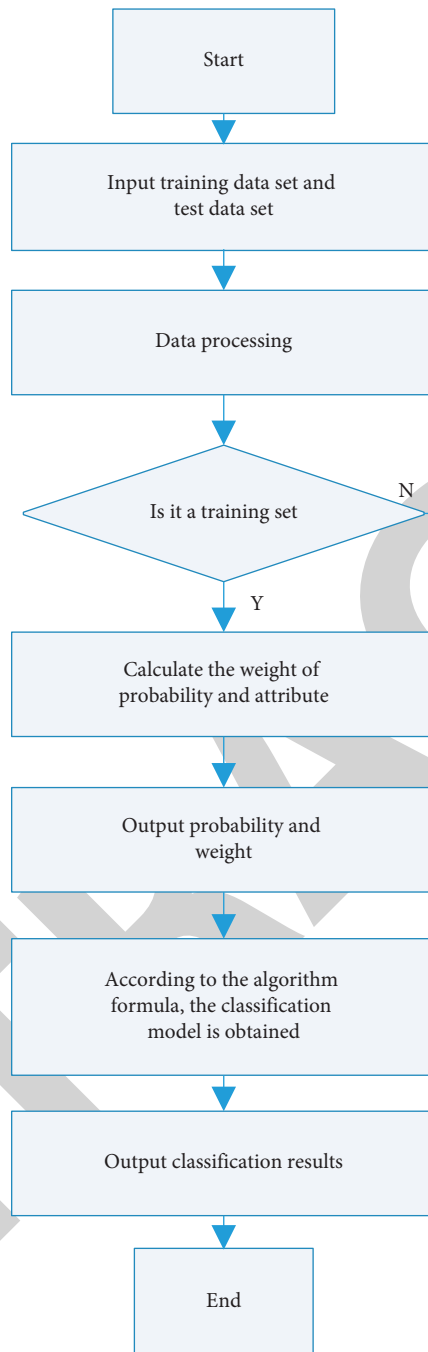
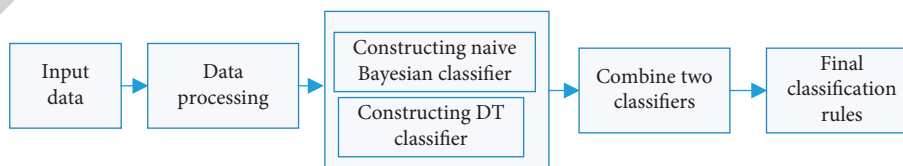Figure 2: Flow chart of weighted plain Bayesian algorithm.

Figure 3: Classifier training process.

the test data set. The sample data are substituted into the classification model obtained in the training phase to classify the samples to be classified; the classification results of the samples are compared with the real categories of the samples, and the performance of the model is evaluated. The specific process of the testing phase is shown in Figure 4:
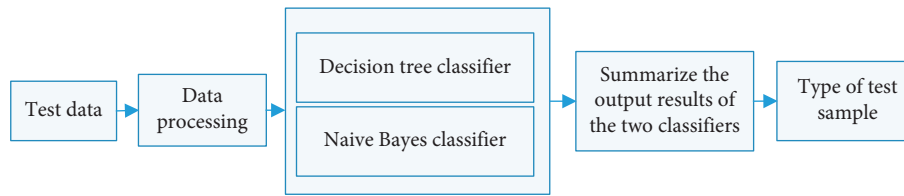
Figure 4: Classifier testing process.

The detailed steps for testing the ground teaching quality classification models obtained by the attribute weighted plain Bayesian algorithm and C4.5 decision tree algorithm are as follows:

> Step 1: Input test data, C4.5 classifier and plain Bayesian classifier and the accuracy of these two classifiers AC4.5 and AWNB and process the input test data so that the data meet the requirements of the teaching quality situation prediction model.

> Step 2: For each sample data x in the test data set, the n C4.5 weak classifiers in the training phase are combined into a strong classifier using the Bagging algorithm, and the sample data x is classified, and the probability $P(c|x)$ C4.5 that the sample data belongs to each category is counted.

> Step 3: For each sample data x in the test data set, the n plain Bayes classifiers in the training phase are used to classify the sample data x. The classification results are counted and the probability of the sample data belonging to each class $P(c|x)$WNB is calculated.

> Step 4: Calculate the probability that the sample data x belongs to each category according to Equation, and the category of the sample data x is the category label corresponding to the maximum probability.

> Step 5: Output the final classification results of all samples in the test set and count the accuracy of the classification results.

4. Experiments and Analysis of Results

4.1. Construction of Experimental Data Sets. The data used in this chapter are mainly extracted from the teaching quality data after the data cleaning operation, and the data set required for the experiment is constructed, which includes the training data required for training the model, the validation data required for evaluating the performance of the initial model, and obtaining the parameters and other information of the final model, as well as the test data set used for testing the final model. Generally, the raw data obtained cannot be directly applied to the experiments, and the format of the required data may be different in different cases, so it is necessary to process the data before using the established data set.

4.2. Analysis of Experimental Results. The experimental data used in this chapter are from the data of the teaching quality of the School of Information from 2004 to 2015 during the school years and the high school examination

results of the teaching quality. The learning process of teaching quality is gradual, and the learning situation and learning attitude of teaching quality, etc., change at different stages, then the performance data of teaching quality is also changed. The teaching quality at different times for teaching quality of early warning or different. In this paper, the examination data of teaching quality before that time point were collected at four different time points in combination with the data of teaching quality at the time of the teaching quality entrance examination for the graduation situation prediction study. The teaching quality data obtained at the four different time points were processed to make the experimental data meet the requirements of the algorithm used, and then the teaching quality prediction model was trained and tested using the identified research method and the processed teaching quality data. Some of the experimental results are shown in Table 1. A result value of 0 in the experimental results means that the teaching quality graduated as expected, and if the result value of 1 the teaching quality failed to graduate as expected. Judgment is the comparison of the real result with the predicted result, and the value represents whether the predicted result is correct or not. Based on the predicted result, the teacher can be alerted to the quality of teaching with a result value of 1, i.e., not graduating on time, and the teacher can be alerted to the possible problems of the quality of teaching in advance [15].

After completing the testing of the model, the obtained test results are analyzed and studied, and the output sample categories are compared with the actual categories of the samples to evaluate the performance of the model. In this paper, experiments are conducted on teaching quality data collected at four time points: the end of the first semester of the freshman year, the end of the first semester of the sophomore year, the end of the second semester of the sophomore year, and the end of the third academic year, e.g., the data collected at the end of the first semester of the sophomore year are the teaching quality freshman year and first semester of the sophomore year for each subject exam. The test results at these four time points were compared with the real results, and the correctness, recall, and accuracy rates were calculated, respectively. And the results were compared with the weighted plain Bayesian classification model and Bagging-C4.5 classification model. The results are shown in the following table:

In order to visualize the comparative effects of the prediction models of teaching quality obtained by the three different algorithms, the experimental results in the above table are shown in Figures 5–7.

Table 1: Performance evaluation results of the graduation scenario prediction model.

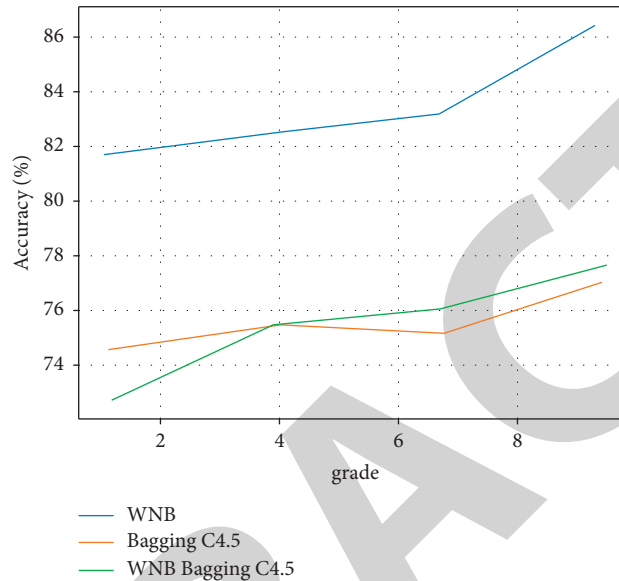|	WNB			Bagging-C4.5			Combined model		
	Correct rate	Recall	Accuracy rate	Correct rate	Recall	Accuracy rate	Correct rate	Recall	Accuracy rate
Bigger	74.4	68.9	76.7	72.8	64.5	75.6	81.6	83.3	80
Sophomore up	75.5	72.9	77	75.5	69.3	79	82.6	83.6	82
Sophomore down	75.3	74.6	76.7	76	76	77	83.3	84	82.9
Junior	77.3	74.6	78.8	78	76.	79.1	87.7	86.6	85.8

Figure 5: Comparison of graduation prediction correct rate.

Figure 5 shows the comparison of the correct rate of the weighted plain Bayesian algorithm, the Bagging-C4.5 algorithm, and the hybrid algorithm of these two algorithms. In Figure 5, the horizontal coordinate is the teaching quality data set collected at four different times, and the vertical coordinate is the correct rate of the prediction results; overall, the hybrid algorithm of the two algorithms has a significantly higher correct rate, and the correct rate of the other two methods is closer, and it can be seen from the above graph that the higher correct rate of the teaching quality prediction model with the change of the teaching quality data collection time is due to the increasing number of courses taken and the learning situation of teaching quality is becoming more and more obvious.

Figure 6 shows the comparison of the recall rates of the weighted plain Bayes algorithm, the Bagging-C4.5 algorithm, and the hybrid algorithm of these two algorithms. The recall of the hybrid algorithm of the weighted plain Bayesian algorithm and Bagging-C4.5 algorithm is overall significantly better than that of the single algorithm, while the recall of the weighted plain Bayesian algorithm and Bagging-C4.5 algorithm classification has some difference. And it can be seen from the above graph that the recall rate of the hybrid algorithm increases slightly with the change of data collection time, and the teaching quality data collected at the end of the junior academic year has the highest recall rate among the hybrid algorithms.
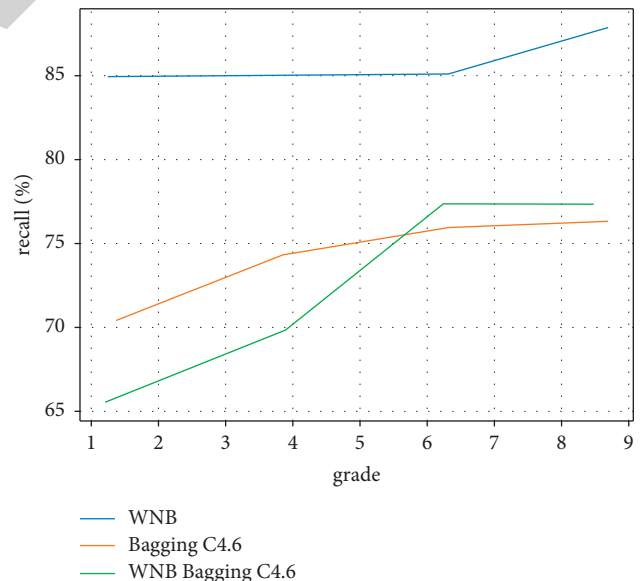

Figure 6: Comparison of graduation prediction recall rate.

Figure 7 shows the comparison of the accuracy rates of the weighted plain Bayesian algorithm, the Bagging-C4.5 algorithm, and the hybrid algorithm of these two algorithms. From this figure, it can be seen that the recall rate of the hybrid algorithm of the weighted plain Bayesian algorithm and Bagging-C4.5 algorithm is higher than that of the
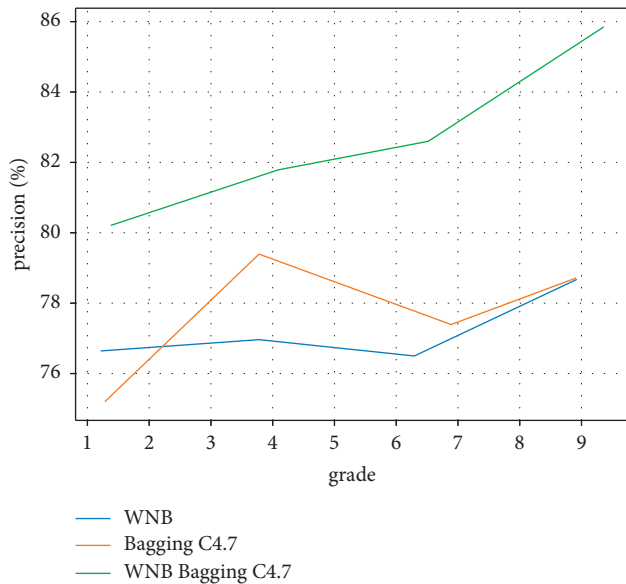
FIGURE 7: Comparison of graduation prediction accuracy rate.

attribute-weighted plain Bayesian algorithm and Bagging-C4.5 algorithm, while the accuracy rates of the classification of the weighted plain Bayesian algorithm and Bagging-C4.5 algorithm are more similar, except for the difference in the teaching quality data collected in the first semester of the sophomore year. The accuracy rate of the hybrid algorithm increased with the time of experimental data collection, and the accuracy rate of the teaching quality data collected at the end of the third year was the highest among the hybrid algorithms.

After the comparison, it can be seen that the hybrid algorithms of the weighted plain Bayesian algorithm and Bagging-C4.5 algorithm are generally better than the weighted plain Bayesian algorithm and Bagging-C4.5 algorithm in terms of correctness, recall, and accuracy.

5. Conclusions

This paper focuses on a study of prediction of teaching quality conditions. This study is another academic early warning study. The main focus of this study is to use a hybrid algorithm of weighted plain Bayesian algorithm and decision tree algorithm for student failure prediction. This chapter describes in detail the basic principles of the plain Bayesian algorithm, the weighting of attributes, and the method and steps of its integration with the decision tree algorithm. This chapter describes in detail the basic principles of the plain Bayesian algorithm, the methods and steps of attribute weighting, and the detailed steps of its combination with the decision tree algorithm. This chapter also designs experiments to verify the algorithm. The data set is first constructed and processed according to the specific situation, and then used to. The model is then trained and tested, its performance is evaluated, and the results are compared with those obtained by the weighted plain Bayesian and decision tree algorithms. The model performance is evaluated, and the results are compared

with the models obtained by the weighted plain Bayesian and decision tree algorithms.

Data Availability

The data set used in this paper is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

Acknowledgments

References

[1] V. Tserklevych, O. Prokopenko, O. Goncharova, I. Horbenko, O. Fedorenko, and Y. Romanyuk, "Virtual museum space as the innovative tool for the student research practice," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 16, no. 14, pp. 213–231, 2021.

[2] X. Bai and J. Li, "Applied Research of Knowledge in the Field of Artificial Intelligence in the Intelligent Retrieval of Teaching Resources," *Scientific Programming*, vol. 2021, Article ID 9924435, 2021.

[3] T. Zhang, "Design of English Learning Effectiveness Evaluation System Based on K-Means Clustering Algorithm," *Mobile Information Systems*, vol. 2021, Article ID 5937742, 2021.

[4] Y. Zhang, Y. Guo, J. Hu et al., "A teaching evaluation system based on visual recognition technology," in *Proceedings of the IOP Conference Series: Materials Science and Engineering*, vol. 782, p. 032101, Bristol,UK, March 2020.

[5] Y. Jiang and B. Li, "Exploration on the Teaching Reform Measure for Machine Learning Course System of Artificial Intelligence Specialty," *Scientific Programming*, vol. 2021, Article ID 8971588, 2021.

[6] X. Xu and F. Liu, "Optimization of Online Education and Teaching Evaluation System Based on GA-BP Neural Network," *Computational Intelligence and Neuroscience*, vol. 2021, Article ID 8785127, 2021.

[7] Y. Guo, "University Classroom Teaching Model Based on Decision Tree Analysis and Machine Learning," *Mobile Information Systems*, vol. 2021, Article ID 6926013, 2021.

[8] C. Pong-Inwong and K. Kaewmak, "Improved sentiment analysis for teaching evaluation using feature selection and voting ensemble learning integration," in *Proceedings of the 2016 second IEEE international conference on computer and communications (ICCC)*, pp. 1222–1225, IEEE, Chengdu,-China, 2016 October.

[9] Y. Zhang, "English teaching evaluation system based on big data," in *Proceedings of the 2021 fourth International Conference on Information Systems and Computer Aided Education*, pp. 1321–1325, New Jersey,US, 2021 September.

[10] Q. Liu and Y. Peng, "A method of unstructured information process in computer teaching evaluation system based on data

mining technology," in *Proceedings of the 2013 International Conference on Communication Systems and Network Technologies*, pp. 688–692, IEEE, Gwalior,India, 2013 April.

[11] W.-x. Huang, X. Gao, N. Wang, Y.-c. Yang, and Y. Yan, "Teaching quality assessment system based on support vector machine technology," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 11, no. 11, pp. 4–8, 2016.

[12] C. Ma and P. Yang, "Research on classroom teaching behavior analysis and evaluation system based on deep learning face recognition technology," *Journal of Physics: Conference Series*, IOP Publishing, vol. 1992, , Article ID 032040, 2021.

[13] A. Dong and Q. Gao, "Framework of the teaching process based on machine learning and innovation ability cultivation in big data background," *Journal of Physics: Conference Series*, IOP Publishing, vol. 1992, , Article ID 042069, 2021.

[14] G. Wang, "Research on the construction of classroom teaching evaluation system based on artificial intelligence," in *Proceedings of the 2021 International Conference on Big Data Engineering and Education (BDEE)*, pp. 101–105, IEEE, Guiyang,China, 2021,August.

[15] C. An, "Student status supervision in ideological and political machine teaching based on machine learning," *E3S Web of Conferences*, EDP Sciences, vol. 275, , Article ID 03028, 2021.

[16] C. H. Cao, Y. N. Tang, D. Y. Huang, G. WeiMin, and Z. Chunjiong, "IIBE: An Improved Identity-Based Encryption Algorithm for Wsn Security," *Security and Communication Networks*, vol. 2021, Article ID 8527068, 8 pages, 2021.

[17] X. I. E. Tao, C. Zhang, and Y. Xu, "Collaborative parameter update based on average variance reduction of historical gradients," *Journal of Electronics and Information Technology*, vol. 43, no. 4, pp. 956–964, 2021.

[18] Y. Chen and L. B. Hoshower, "Student evaluation of teaching effectiveness: an assessment of student perception and motivation," *Assessment & Evaluation in Higher Education*, vol. 28, no. 1, pp. 71–88, 2003.

[19] P. Spooren, B. Brockx, and D. Mortelmans, "On the validity of student evaluation of teaching," *Review of Educational Research*, vol. 83, no. 4, pp. 598–642, 2013.

[20] G. Anderson, "Assuring quality/resisting quality assurance: academics' responses to "quality" in some Australian universities," *Quality in Higher Education*, vol. 12, no. 2, pp. 161–173, 2006.

[21] N. Denson, T. Loveday, and H. Dalton, "Student evaluation of courses: what predicts satisfaction?" *Higher Education Research and Development*, vol. 29, no. 4, pp. 339–356, 2010.

[22] L. Arthur, "From performativity to professionalism: lecturers' responses to student feedback," *Teaching in Higher Education*, vol. 14, no. 4, pp. 441–454, 2009.

[23] E. Blair and K. Valdez Noel, "Improving higher education practice through student evaluation systems: is the student voice being heard?" *Assessment & Evaluation in Higher Education*, vol. 39, no. 7, pp. 879–894, 2014.

[24] L. P. Steenkamp, R. S. Baard, and B. L. Frick, "Factors influencing success in first-year accounting at a South African university: a comparison between lecturers' assumptions and students' perceptions," *South African Journal of Antarctic Research*, vol. 23, no. 1, pp. 113–140, 2009.

[25] B. A. Friedman, P. L. Cox, and L. E. Maher, "An expectancy theory motivation approach to peer assessment," *Journal of Management Education*, vol. 32, no. 5, pp. 580–612, 2008.

[26] C. Steyn, C. Davies, and A. Sambo, "Eliciting student feedback for course development: the application of a qualitative course evaluation tool among business research students," *Assessment & Evaluation in Higher Education*, vol. 44, no. 1, pp. 11–24, 2019.

[27] G. Foster and S. Stagl, "Design, implementation, and evaluation of an inverted (flipped) classroom model economics for sustainable education course," *Journal of Cleaner Production*, vol. 183, pp. 1323–1336, 2018.

[28] L. McClain, A. Gulbis, and D. Hays, "Honesty on student evaluations of teaching: effectiveness, purpose, and timing matter," *Assessment & Evaluation in Higher Education*, vol. 43, no. 3, pp. 369–385, 2018.

[29] D. T. L. Shek, Z. Yang, C. M. S. Ma, and C. W. Y. Chai, "Subjective outcome evaluation of service-learning by the service recipients: scale development, normative profiles and predictors," *Child Indicators Research*, vol. 14, no. 1, pp. 411–434, 2021.