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Retraction

Retracted: Smart Teaching Design Mode based on Machine Learning and its Effect Evaluation

Mathematical Problems in Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] Q. Su, "Smart Teaching Design Mode based on Machine Learning and its Effect Evaluation," *Mathematical Problems in Engineering*, vol. 2022, Article ID 9019339, 8 pages, 2022.

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Research Article

Smart Teaching Design Mode based on Machine Learning and its Effect Evaluation

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With the continuous progress of science and technology, the mode of smart teaching is more and more applied in the actual teaching process. Under the intelligent teaching system mode, teachers and students can jointly complete the construction of curriculum resources and classroom teaching tasks. This paper evaluates its application effect by introducing two examples of smart teaching. Among them, the evaluation effect of the academic teaching network system shows that the teaching network system based on machine learning is composed of three parts: model selection, data preparation, and modeling prediction. Moreover, it can greatly improve the prediction performance of the intelligent algorithm in the teaching mode by introducing the oversampling technology SMOTE algorithm (Synthetic Minority Oversampling Technique). To further verify the advantages of the smart teaching model, an example of social sciences teaching is introduced. The results show that the relevant predictive performance indicators in the computer engineering discipline are improved by using a combination of intelligent algorithms.

1. Introduction

In the process of development and progress of human society, it has been constantly researching the use of various machines [1, 2] to replace part of human labor to reduce labor costs, improve work efficiency, and increase productivity, which makes artificial intelligence come into being. The proposal of education modernization strategy has created conditions for smart teaching and promoted the development of smart teaching. The smart teaching design model [3, 4] opens a new model of smart teaching to guide the implementation of smart teaching [5] and lead students to achieve interdisciplinary learning, deep learning, and boundless learning. This can provide students with more choices, more personality, and more accurate wisdom teaching [6]. The use of artificial intelligence technology [7, 8] is not only a demonstration of teaching tools but also builds a new teaching ecology that is people-oriented, based on symbiosis, mutual establishment, and sharing. The biggest change brought about by the application of artificial intelligence technology [9, 10] is enabling teaching. The use of electronic lesson plans [10, 11] can avoid teachers' repetitive copying labor. The deep integration of artificial intelligence technology and smart teaching has brought unprecedented changes to teaching, but they are not easily combined.

The use of artificial intelligence technology [12, 13] has also brought about new changes in the teaching mode. A series of new smart teaching modes such as microlecture teaching [14, 15], MOOC teaching, flipped classroom teaching, and double-teacher classroom teaching has been born, which has changed our traditional topic-based teaching. The tactics-based classroom teaching model is well.

A large number of systematic studies have also been carried out at home and abroad on the related research on smarter teaching design. Among them, the relevant literature retrieval was carried out by taking the China National Knowledge Infrastructure (CNKI) academic journal database [16, 17] as an example. As shown in Figure 1, both the number of master's dissertations and academic papers in journals tend to increase with the increase of years [18, 19]. Among them, the frequency of cowords shows more: smart education, smart teaching design, design model, blended teaching, and educational optimal allocation of educational

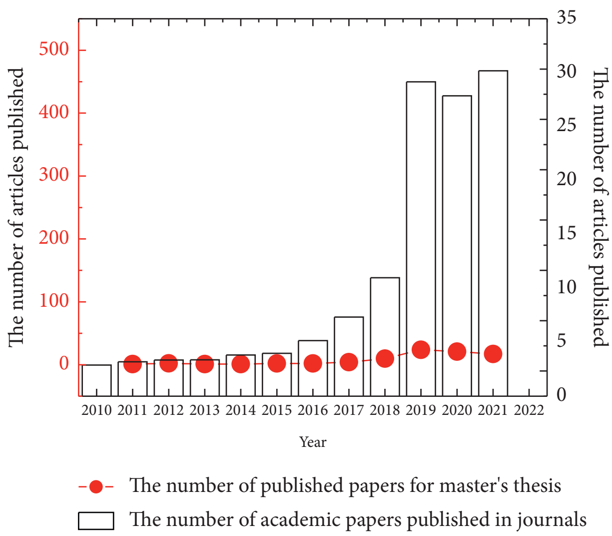

FIGURE 1: Comparison of the number of published papers on smart teaching design over the years.

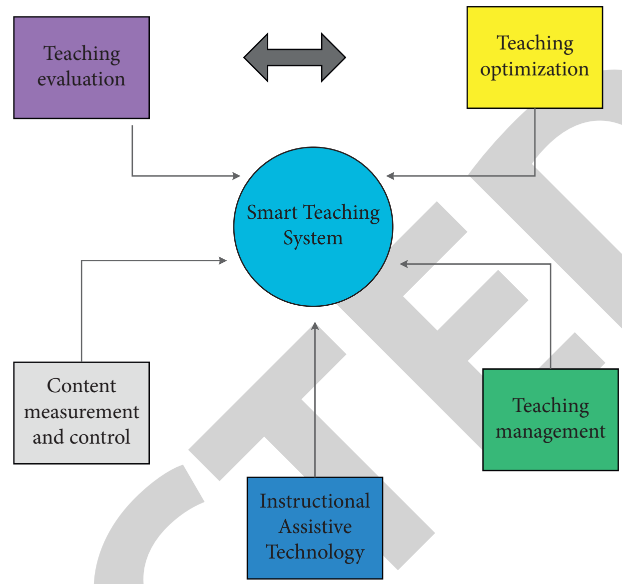

FIGURE 2: The construction process of today's smart teaching system.

resources. The overall change trend can be characterized as: they began to show an upward trend in 2016, reached the peak in 2019, and decreased slightly in 2020, showing a general trend [20, 21] of increasing year by year.

With the rapid development of science and technology such as cloud computing, big data [22, 23], "Internet of Things+" and artificial intelligence [24, 25], artificial intelligence-based teaching optimization [26–28], teaching management, real-time tracking and evaluation of teaching process, educational resources, and technical services have become an important part of the development of modern education.

Through the platform of smart education, teachers and students can have equal access to knowledge, which is beneficial to solving the problem of information asymmetry between teachers and students in the teaching process. This novel education and teaching system can improve students' participation in course learning, cultivate students' assiduous spirit in professional learning, and discover students' positive and upward power.

Because of the differences and layers in the students' learning process, it is necessary to provide students with appropriate learning resources, tools, and services to adapt to their changing learning needs. Therefore, it is urgent to find a problem-solving model to solve the problem that the current teaching content does not match the professional development of students, so that the teaching system can achieve a new dynamic balance. Based on the above-given analysis and elaboration, the concept of smart teaching came into being.

2. Smart Teaching based on Smart Algorithms

With the support of massive data, the smart teaching system can be based on the real-time situation in the teaching process (such as students' learning interest, learning ability, attention status, and learning time). In this way, a learning plan can be formulated or adjusted, a personalized learning plan can be generated, new data can be continuously supplemented to the smart teaching model, and the system model can be updated in time. Compared with traditional teaching, the significant advantages of smart education include the following two aspects: (1) intelligent detection; (2) adaptive dynamic balance.

For the intelligent detection work, the specific workflow is described as follows: with the support of big data, data mining, and other technologies, it can learn from the latest research results of artificial intelligence development and build neural networks through deep learning. At the same time, it can provide a large amount of information about 'students' individual characteristics (cognitive ability, learning preferences, learning emotions, and learning styles), learning situations (learning time, learning space, learning partners, and learning activities), learning stages, learning progress, learning status, and, data perception. In this way, a model of student intelligence can be established. Through data terminal analysis and processing, personalized learning plans can be formulated for students, and appropriate learning resources and learning suggestions can be pushed.

For the adaptive dynamic balance work, the specific workflow is described as follows: due to the continuous development of professional knowledge and the complexity of the teaching system, the teaching process is changeable, dynamic and presents an open state. There are often situations that cannot be accurately predicted in the course of educational activities. Due to the continuous accumulation of students' knowledge and the availability of the latest research results, the original teaching plans and learning resources are inconsistent with the current learning needs. In addition, in view of the differentiation and hierarchy in the students' learning process, it is necessary to provide students with appropriate learning resources, tools, and services to adapt to the students' changing learning needs and solve the problem that the current teaching content does not match the students' professional development so that the teaching system achieves a new dynamic balance. Figure 2 shows the construction process of today's smart teaching system.

It can be seen that the smart teaching system mainly includes five main parts: teaching evaluation, teaching optimization, teaching management, teaching content operation, and evaluation. Moreover, the five parts complement each other, and a public teaching management system is established.

Under the intelligent teaching system mode, teachers and students jointly complete the construction of curriculum resources and classroom teaching tasks. Teachers are responsible for the teaching tasks of the basic theory and core algorithms of machine learning, and students are divided into groups (2–4 people/group) for the teaching tasks of other parts. Each group is responsible for the classroom teaching of a theme and the construction of related course resources. Lesson topics can be repeated if there are more groups. Classroom teaching focuses on the analysis of machine learning algorithms and application examples of different topics. Classroom organization emphasizes the flexibility and variety of interaction and organizational forms. This teaching mode mainly includes the cross-application of PPT lectures, blackboard lectures, seminars and analysis, interactive feedback, and classroom summaries.

Under this model, the assessment of the "Machine Learning" course adopts a combination of procedural examination and final examination. This teaching model will be evaluated throughout the whole process of course learning. Process assessment includes classroom attendance assessment, classroom performance assessment, and course task completion assessment. Teachers use the "scan code to sign in" function to conduct regular class attendance. The evaluation of course task completion mainly evaluates the students' independent completion of individual teaching tasks or participation in the completion of group teaching tasks.

In the process of theoretical teaching, it is necessary to consider changes in professional development and industry needs and refer to the application of advanced technologies in the field of work in engineering practice. At the same time, it is necessary to optimize teaching, refine teaching links, and further improve the effectiveness of teaching according to students' professional foundation and future expectations.

To illustrate the good application effect of the smart teaching model, the following two application examples are used for classification research.

3. Research Design and Effect Evaluation-Example 1

The popularity and prosperity of social media have prompted more and more scholars to use social media to obtain and share academic information. Therefore, academic teaching network systems specially designed for scholars, such as Academia and Research Gate (RG), have also been born. This research takes RG as the object, and based on constructing an answer quality evaluation system and an

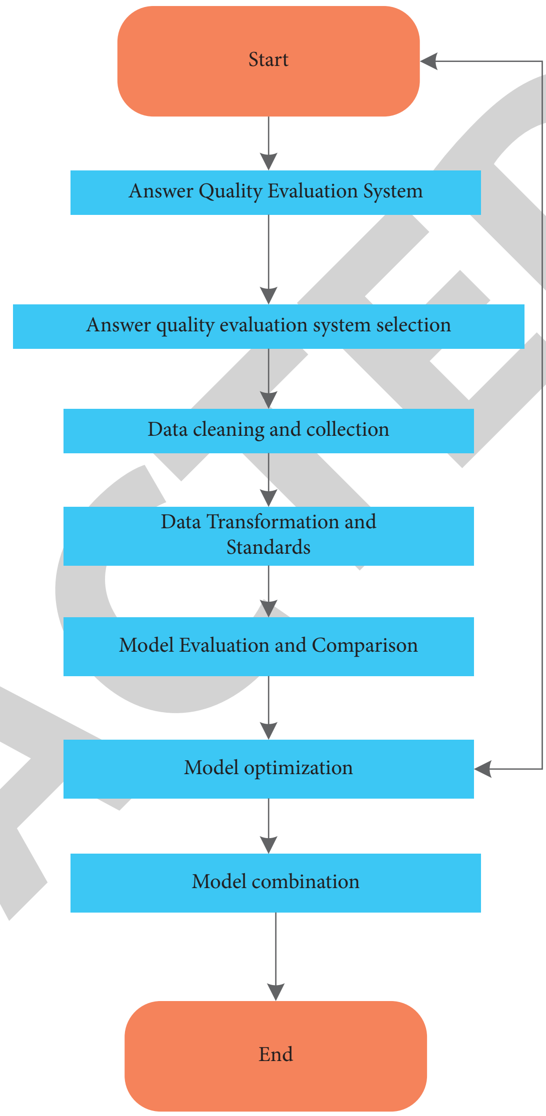

Figure 3: Research framework of intelligent evaluation of question and answer quality.

automatic evaluation model, an empirical study on the optimization of an academic teaching network system based on intelligent evaluation of Q&A (Question and answer system) quality is carried out.

Among them, RG is the most popular academic teaching network system today. Compared with other academic teaching network systems, RG has accumulated rich Q&A interactive data resources with the help of the Q&A function based on a large user group, which can support the research on intelligent evaluation of Q&A quality.

Compared with a manual evaluation of answer quality, machine automatic evaluation has all-round advantages such as fast speed, high precision, and low cost. It can meet the needs of academic teaching network systems to identify high-quality answers and optimize Q&A services.

Therefore, this paper adopts the machine learning method to realize the intelligent evaluation of the question and answer quality of the RG platform. The research framework of this paper consists of three parts: model selection, data preparation, and modeling prediction. The specific operation process steps are shown in Figure 3.

As shown in Figure 3, first of all, a quality evaluation system should be constructed according to specific problems, and an appropriate method should be selected by means of data processing. Then, we can start the data processing work. This part mainly includes data collection, data labeling, and data conversion. Finally, researchers can seek the best solution to a problem by optimizing and combining models.

Structured features refer to features that can be directly obtained from answer statistics. Similar to traditional web resources, the answers of the Q&A service of the academic social network platform are mainly presented in the form of text. Therefore, relevant indicators and methods suitable for analyzing the quality of traditional web pages can be applied to the evaluation of answer quality in academic question-answering services. Specifically, it includes the length of the text, the number of keywords, and the proportion of punctuation marks. The quantification of the structural features of the answer is simpler. With the help of word segmentation tools and text processing techniques, we can write python programs to perform statistics and quantification of metrics directly from the answer text.

Content features refer to the features contained in the text that can only be expressed after natural language processing. The answer content features are quantified as follows:

(1) *Question-Answer Theme Similarity*. High-quality answers and corresponding questions should belong to the same topic. We can use the LDA topic model to calculate the topics of the answers and their corresponding questions, respectively, and then analyze the topic similarity between the two.

(2) *Text Diversity*. This diversity is obtained by quantifying the word diversity of the answer text. The less the average number of words in the text, the stronger the word diversity of the answer. The calculation method of text diversity is as follows:

$$D_{dy} = \frac{\sum_i^n T_i}{n}, \tag{1}$$

where n represents the number of samples, T_i represents the quantitative index of diversity, which is a dimensionless number.

(3) *Answer Information Entropy*. From the perspective of information dissemination, information entropy can represent the value of information. High-quality answers are valuable information. Therefore, information entropy can reflect the quality of the answer to a certain extent. The answer information entropy can be calculated by formula (2), where P_i is the probability of each letter appearing in the information.

$$H = -\sum_i^n P_i \ln P_i, \tag{2}$$

where H represents the information entropy of the answer.

(4) *The Emotional Attitude of the Answer and the Subjectivity of the Answer*. High-quality answers are more emotionally inclined than average answers, and the respondent's attitude determines the degree of approval of the answer to a certain extent. Therefore, emotional attitudes and subjectivity and objectivity have an impact on the quality of answers. We can use the Text Blob package (a python library for manipulating text) to perform sentiment analysis and subjective judgments on the answer text. However, the emotional attitude and subjectivity of the answers are quantified by numerical results output by the program.

This paper selects the ID3 decision tree (Iterative Dichotomiser 3, ID3), Random Forest (RF), Support Vector Machine (SVM), and BP Neural Networks (BP Neural Networks, BP) in the automatic evaluation task of answer quality. The common model is to be constructed as the basis to realize the intelligent evaluation of the quality of the academic teaching network system.

As a classic classification algorithm, ID3 has average performance, but it runs fast and has strong model interpretability, which meets the requirements of the baseline prediction model. Therefore, ID3 is selected as the baseline prediction model in the manuscript. When a classification model outperforms ID3, the model is considered valuable and can participate in combined model predictions. At the same time, considering Random Forest (RF) is suitable for situations with relatively low data dimensions and high requirements for accuracy. Therefore, RF is also used in such studies. The Support Vector Machine (SVM) has a good performance in solving machine learning problems with small samples, so SVM is selected as the classification prediction model.

In addition, BP is one of the most common deep learning algorithms at present. It has a strong feature fitting ability and is suitable for situations where there is an inherent relationship between features. Therefore, BP is selected as the comparison model in the following paper.

First, the prepared data set is automatically divided into the training set and test set, and the division ratio is set to 80% of the training set and 20% of the test set. Second, the researchers used ID3, RF, SVM, and BP to train data for four algorithms. Finally, after tuning the parameters to optimize the model, researchers can use the precision, recall, and F1-score of the model on the test set to compare the performance of various algorithms. Among them, the precision rate represents the proportion of the number of correctly classified positive samples in the prediction results to the total number of positive samples in the prediction results. The recall rate indicates the proportion of the number of correct positive samples in the prediction results to the total number of true positive samples. Precision and recall are relatively common performance evaluation indicators. The values of the two indicators are proportional to the performance of the classifier. F1-score is the harmonic mean of precision and recall. This indicator comprehensively considers two numerical

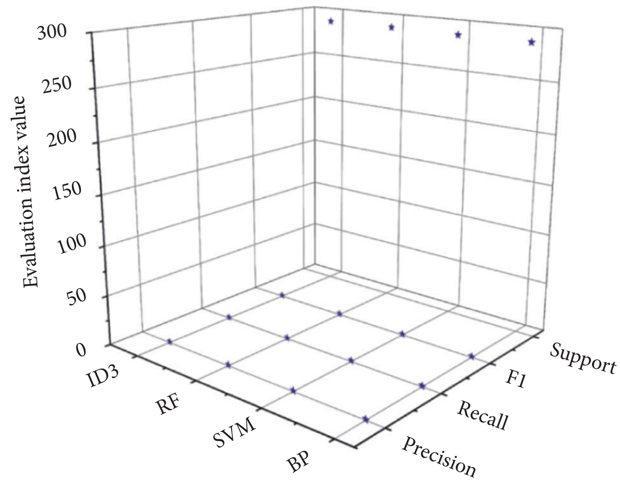

Figure 4: Performance of four classification models.

evaluation criteria and can conduct a more comprehensive evaluation of the effect of the classifier.

The performance of the four intelligent algorithm models is shown in Figure 4.

Comparing the above-given results, it can be found that when the four models classify and predict the answer quality of the RG question answering service, there is an imbalanced classification problem in which the classification results are shifted to the majority class; that is, classifiers tend to provide a severely imbalanced accuracy, with high accuracy for the majority class and very low accuracy for the minority class. This can easily lead to the failure of prediction and cannot get accurate results. The model cannot detect high-quality answers; that is, precision, recall and F1-score are all low.

The SMOTE algorithm (Synthetic Minority Oversampling Technique) uses a certain method to increase the number of samples of the minority class to a number similar to that of the majority class so that the ratio of the number of the two types of samples is in a relatively balanced state. It is suitable for situations where the amount of data are small and the labeled samples are unbalanced, which is consistent with the situation in this paper.

SMOTE algorithm is an improved scheme based on a random oversampling algorithm. It is a common method for dealing with unbalanced data and is unanimously recognized by academia and industry.

The SMOTE algorithm uses the KNN technology (K-Nearest Neighbor) to simulate the process of generating new samples. When generating samples, it is no longer a simple random copy of the original samples. Therefore, the new samples generated are more representative.

To enable the model to have the ability to screen high-quality answers, the manuscript uses SMOTE to change the phenomenon of “labeled sample imbalance” from the data level for the above-given prediction problems. This improves the prediction of high-quality answers. The comparison of the training set and test set before and after using the SMOTE algorithm is shown in Figures 5 and 6.

Comparing the above-given results, it can be found that after using the SMOTE algorithm to optimize the model

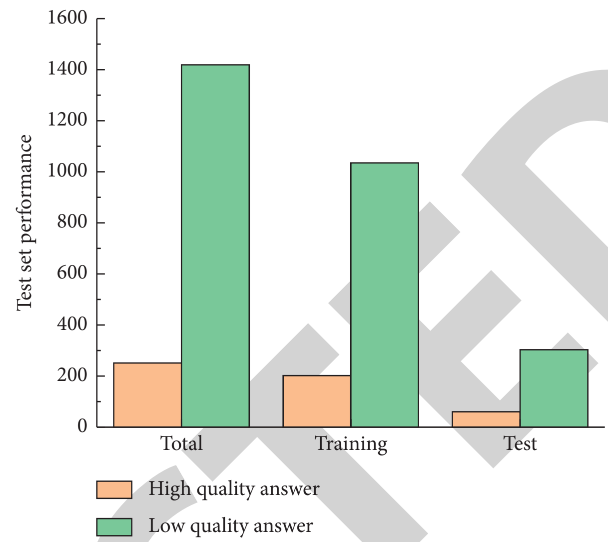

Figure 5: Original dataset.

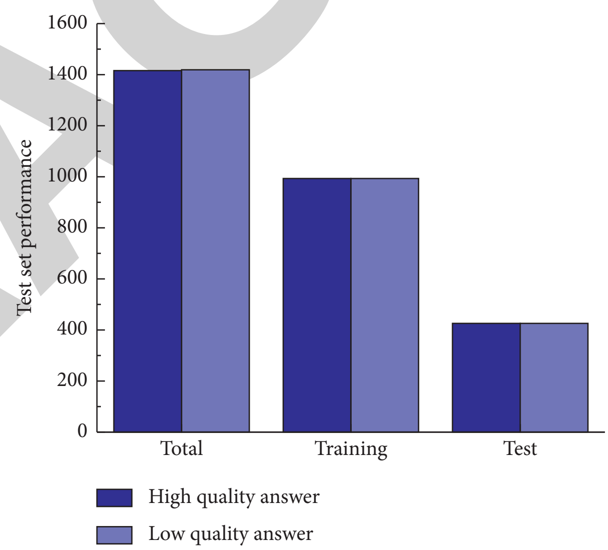

Figure 6: Prediction performance after SMOTE oversampling.

performance, the four models have greatly improved the precision and recall rates of high-quality answer classification, which can meet the needs of high-quality answer screening.

Specifically, the performance of the ID3 decision tree is poor compared to other types of algorithms; the performance of random forest and BP neural network is better and closer. The SVM model performed the best. Its performance is significantly better than other classification algorithms, with the highest precision, recall, and F1-score.

4. Research Design and Effect Evaluation-Example 2

In order to further illustrate the application prospects of machine learning methods in higher education, this section introduces a computer engineering discipline for verification. Taking a computer forecasting course in a certain period in Jiangsu Province as an example, this paper studies the forecasting advantages of machine learning in this field.

The calculation material contains monthly averages of 130 climate system indices. Among them, there are 88 items of the atmospheric circulation index. There are 16 other indexes, mainly including cold air, typhoon, and other indexes. The time scale is January 1980-December 2020. If there is a missing test, the factor is directly eliminated.

Statistical methods make full use of the laws of historical data and select factors with clear physical meaning and significant correlation for modeling. Machine learning emphasizes learning rules from historical data to make inferences and predictions on new data. Different from traditional statistical methods, machine learning is good at dealing with nonlinear problems. It takes advantage of machine learning to discover and extract new interconnected signals from the Earth system.

In this paper, the Random Forest algorithm is used for recursive feature elimination to select predictors. For comparison, we also model using multi-layer feedforward neural networks, support vector regression, and natural gradient boosting. We use these artificial intelligence methods to prove the application of intelligent algorithms in social sciences.

When modeling, select a sample set corresponding to the start-up time and mode. Among them, 30 samples in the training set are used for training and cross-validation, and 10 samples in the test set are used for independent testing.

The experimental performance of a computer engineering software in Jiangsu was comprehensively evaluated by the trend anomaly comprehensive score (Ps) and the spatial anomaly correlation coefficient (ACC). Among them, Ps can be expressed as follows: the trend anomaly comprehensive score (*Ps*) and spatial anomaly correlation coefficient (ACC) were used to evaluate the summer precipitation in Jiangsu. Among them, *Ps* can be expressed as follows:

$$Ps = \frac{N_0 + P_1 \times N_1 + P_2 \times N_2}{N + P_1 \times N_1 + P_2 \times N_2} \times 100, \tag{3}$$

where N is the total number of stations. In this paper, $N = 96$, $P_1 = 0.5$, $P_2 = 1.0$. N_0 is the sum of the number of stations with the same sign or different sign from the forecast and the actual anomaly, but the difference is only one level.

The formula for calculating ACC is

$$\mathrm{ACC} = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(o_i - \overline{o})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2 \sum_{i=1}^{n} (o_i - \overline{o})^2}}, \tag{4}$$

where n is the number of stations, and x_{i} and o_{i} performance indicators and monitor actual values in computer software applications, respectively. $\overline{x}$ and $\overline{o}$ represent the average value corresponding to the values tested by computer software, respectively.

To reduce the randomness of the machine learning algorithm in the modeling process, this paper adopts three different machine learning methods including multilayer feedforward neural network, support vector machine, and decision tree ensemble for modeling.

In the process of neural network prediction, the more hidden layers, the stronger the model data representation ability, and the easier it is to cause overfitting. Therefore, this paper only uses two hidden layers, and the number of neurons does not exceed the number of predictors. The expression of the prediction algorithm is

$$P_k = g_2\left[\sum_{j=1}^{m} w_{kj} g_1\left(\sum_{i=1}^{n} w_{ji} x_i + w_{j0}\right) + w_{k0}\right], \tag{5}$$

where x_i is the input value of node i; P_k is the output value of the node; g_1 is the activation function of the hidden layer; g_2 is the activation function of the output layer.

In the process of determining the number of neurons in the hidden layer, it is necessary to analyze the input and output of the network.

$$m = \sqrt{n + l} + a, \tag{6}$$

where n, l, and m represent the number of nodes in the input layer, the hidden layer, and the output layer, respectively.

In the BP neural network structure, two transfer functions are required to ensure data transfer. The sigmoid activation function is used to complete the information transfer at different levels. The sigmoid activation function can be expressed as follows:

$$f(n) = \frac{1}{1 + \exp(-n)}, \tag{7}$$

where n represents the number of samples collected, and $f(n)$ represents the function value related to the neural network calculation.

Support vector regression is an extension of support vector machines. The algorithm constructs a hyperplane or a set of hyperplanes in a high-dimensional or finite-dimensional space through a kernel function to minimize the distance between the data and it. The main expression can be,

$$\begin{aligned} f(x) &= \sum_{i=1}^{L} (a_i - a_i^*) K(x, x_i) + b, \\ K(x, x_i) &= e^{-\|x - x_i\|^2 / 2\sigma^2}. \end{aligned} \tag{8}$$

Here, L is the number of support vectors, x_i is the predictor, and σ is the parameter that controls the width of the Gaussian kernel parameter.

The Decision tree is a classification and regression algorithm in machine learning. For regression problems, the goal of the algorithm is to minimize the squared error of dividing the same category, but it is also easy to cause overfitting, which can be overcome by the decision tree ensemble method. The random forest and natural gradient boosting tree used in this paper belong to the decision tree ensemble algorithm.

In the internal node of the random forest, the data set is divided into two independent sets repeatedly, and the

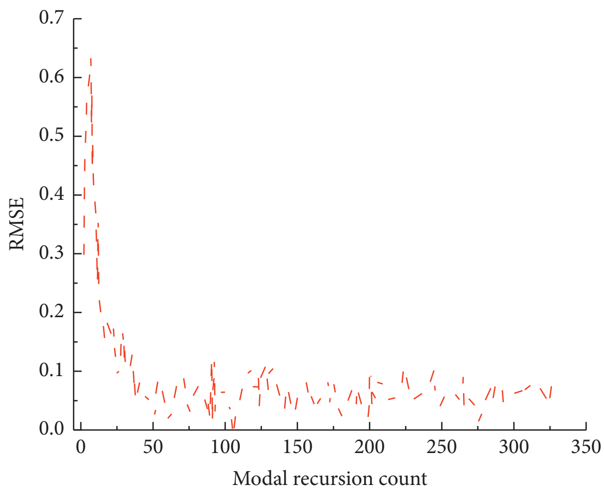

FIGURE 7: The RMSE corresponding to the number of factors of different EOF patterns selected by the machine learning method initialized.

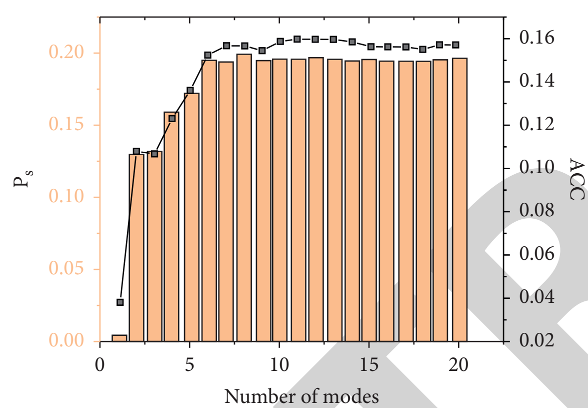

FIGURE 8: Cross-validation scores and correlation coefficients with prediction performance for different EOF modes.

internal variance of the set after each classification is calculated. The importance of prediction factors is determined according to the variance difference of the set before and after classification. The larger the variance difference, the higher the importance of the factor. The characterization equations of variance and variance contribution rate are as follows:

$$\delta(i) = \frac{1}{n}\sum_{i=1}^{n} c_i(t)^2 - \left[\frac{1}{n}\sum_{i=1}^{n} c_i(t)\right]^2,$$
$$\lambda(i) = \frac{\delta(i)}{\sum_{i=1}^{N} \delta(i)}, \quad (9)$$

where $\delta(i)$ and $\lambda(i)$ represent the variance and variance contribution rate corresponding to the i-th training data set, respectively.

The percent anomaly of observed precipitation in summer in Hunan from 1981 to 2010 was decomposed using empirical orthogonal function analysis (EOF). All the candidate climate factors and the top 10 modal time

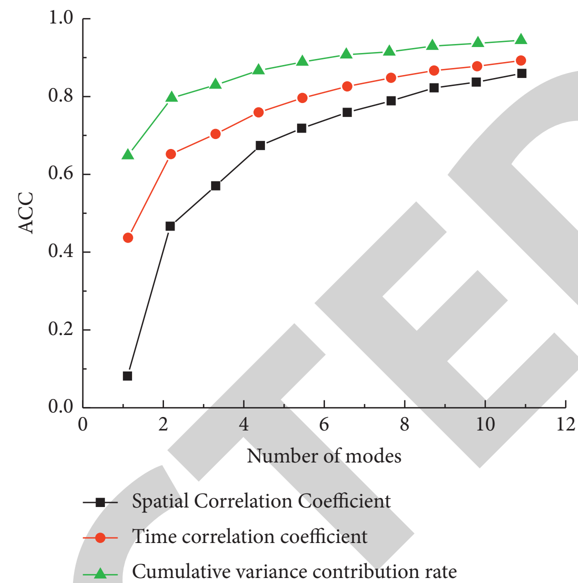

FIGURE 9: Cumulative variance contribution rate and abnormal correlation coefficient and temporal correlation coefficient of top 1–10 EOF modes.

coefficients are separately and recursively removed. Figure 7 shows the root mean square error of the top 10 modes reported in May after removing factors by recursive feature elimination. As shown in Figure 7, when the number of factors reaches a certain threshold, the error tends to level off.

Figures 8 and 9, respectively, show the results of five cross-validations of computer course prediction performance for the top 1–20 different empirical orthogonal function analysis (EOF) models. The ACC and Ps scores are the averages of the representative performance of the individual predictions.

Combined with the correlation coefficient of the cumulative variance contribution rate and prediction performance of different EOF models shown in Figure 9, the more EOF models, the better the application advantages of artificial intelligence technology in computer engineering.

5. Conclusion

(1) The AI-assisted system is only an auxiliary teaching tool, and the focus of smart teaching design must always be on students. Information technology products should focus on the use of interactive links and make full use of intelligent technology. This can improve student participation, save time in presentations, and improve teaching quality.

(2) Taking the example of RG as an example, the specific application of intelligent teaching design based on machine learning is expounded. And, through the performance test of various intelligent algorithms, its effect is systematically evaluated. The results show that by using machine learning methods, combined with technologies such as SMOTE, the selection of high-quality answers can be effectively achieved.

(3) Taking a prediction subject of computer engineering as an example, it proves the application effect of machine learning in the teaching of social science subjects. The evaluation results show that the prediction model based on machine learning has good prediction performance for computational engineering.

Data Availability

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

Conflicts of Interest

The author declares that there are no conflicts of interest.

Acknowledgments

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References

[1] N. Lavesson, "Learning machine learning: a case study," *IEEE Transactions on Education*, vol. 53, no. 4, pp. 672–676, 2010.

[2] A. Zhang and X. Feng, "The concept analysis of smart teaching," *Nurse Education Today*, vol. 112, Article ID 105329, 2022.

[3] X. Xu, Y. S. Wang, and S. J. Yu, "Teaching performance evaluation in smart campus," *IEEE Access*, vol. 6, pp. 77754–77766, 2018.

[4] X. Xu, D. Li, M. Sun et al., "Research on key technologies of smart campus teaching platform based on 5G network," *IEEE Access*, vol. 7, pp. 20664–20675, 2019.

[5] Z. Li and H. Wang, "Intelligent Guiding Model Based on Environment Perception and Posture Recognition," in *Proceedings of the 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA)*, pp. 1152–1155, Coimbatore, India, September 2021.

[6] L. Castro, M. A. Castro-Nogueira, and M. A. Toro, "Assessor teaching and the development of the capacity to innovate and to imitate," *Journal of Theoretical Biology*, vol. 472, pp. 88–94, 2019.

[7] M. Z. Latif, I. Hussain, R. Saeed, M. Qureshi, and U. Qureshi, "Use of smart phones and social media in medical education: trends, advantages, challenges and barriers," *Maqsood Acta Informatica Medica*, vol. 27, no. 2, p. 133, 2019.

[8] V. Oyefusi, P. Toto, and P. Leslie, "Get SMART! Teaching students geriatric health-related goal setting," *Journal of the American Geriatrics Society*, vol. 67, pp. S321–S322, 2019.

[9] J. Aguilar, M. Sánchez, J. Cordero, P. Valdiviezo-Díaz, L. Barba-Guamán, and L. Chamba-Eras, "Learning analytics tasks as services in smart classrooms," *Universal Access in the Information Society*, vol. 17, no. 4, pp. 693–709, 2018.

[10] S. N. Wang, "Smart data mining algorithm for intelligent education," *Journal of Intelligent and Fuzzy Systems*, vol. 37, no. 1, pp. 9–16, 2019.

[11] K. Walsh, "Getting SMART about STUDENT TEACHING," *Educational Leadership*, vol. 75, no. 8, pp. 38–42, 2018.

[12] M. J. Sanders, R. Bruin, and C. T. Tran, "How to make a standard inhaler device into a "smart" inhaler that teaches technique," *Journal of Aerosol Medicine and Pulmonary Drug Delivery*, vol. 31, no. 2, p. A14, 2018.

[13] J. M. Liang, W. C. Su, Y. L. Chen, S. L. Wu, and J. J. Chen, "Smart interactive education system based on wearable devices," *Sensors*, vol. 19, no. 15, p. 3260, 2019.

[14] M. Jou and J. Y. Wang, "A reflection of teaching and learning cognition and behavior in smart learning environments," *Computers in Human Behavior*, vol. 95, pp. 177-178, 2019.

[15] S. Streiter, J. Loewenthal, S. Berry, and A. W. Schwartz, "Better together: promoting geriatrics education across residency specialties with a pilot peer teaching exchange," *Journal of the American Geriatrics Society*, vol. 67, no. 10, pp. E1–E3, 2019.

[16] H. Mohamed and M. Lamia, "Implementing flipped classroom that used an intelligent tutoring system into learning process," *Computers & Education*, vol. 124, pp. 62–76, 2018.

[17] M. Hasanipanah, R. Naderi, J. Kashir, S. A. Noorani, and A. Zeynali Aaq Qaleh, "Prediction of blast-produced ground vibration using particle swarm optimization," *Engineering with Computers*, vol. 33, no. 2, pp. 173–179, 2017.

[18] H. Nguyen, X. N. Bui, and H. Moayedi, "A comparison of advanced computational models and experimental techniques in predicting blast-induced ground vibration in open-pit coal mine," *Acta Geophysica*, vol. 67, no. 4, pp. 1025–1037, 2019.

[19] M. C. Alvarez-Herault, A. Labonne, S. Toure et al., "An original smart-grids test bed to teach feeder automation functions in a distribution grid," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 373–385, 2018.

[20] I. Jang, D. Lee, J. Choi, and Y. Son, "An approach to share self-taught knowledge between home IoT devices at the edge," *Sensors*, vol. 19, no. 4, p. 833, 2019.

[21] Y. Zhao, R. l. Shan, H. l. Wang, X. Tong, and Yh Li, "Regression analysis of the blasting vibration effect in cross tunnels," *Arabian Journal of Geosciences*, vol. 14, no. 18, p. 1925, 2021.

[22] A. Eltom, W. Elballa, N. Sisworahardjo, R. Hay, and G. Kobet, "Smart distribution course for 21St century power sector workforce," *IEEE Transactions on Power Systems*, vol. 33, no. 5, pp. 5639–5647, 2018.

[23] L. S. Huang, J. Y. Su, and T. L. Pao, "A context aware smart classroom Architecture for smart campuses," *Applied Sciences*, vol. 9, no. 9, p. 1837, 2019.

[24] Y. C. Gong, Z. J. Wang, G. Y. Xu, and Z. Zhang, "A comparative study of groundwater level forecasting using data-driven models based on ensemble empirical mode decomposition," *Water*, vol. 10, no. 6, p. 730, 2018.

[25] H. Wang, H. Bai, Y. Zhao, D. Wang, X. Wang, and S. Wang, "The removal method of the blasting vibration signal trend item and noise," *Shock and Vibration*, vol. 2021, pp. 1–10, Article ID 1645380, 2021.

[26] R. Hasan, S. Palaniappan, S. Mahmood, B. Shah, A. Abbas, and K. Sarker, "Enhancing the teaching and learning process using video streaming servers and forecasting techniques," *Sustainability*, vol. 11, no. 7, p. 2049, 2019.

[27] M. S. Günbatar and H. Bakırcı, "STEM teaching intention and computational thinking skills of pre-service teachers," *Education and Information Technologies*, vol. 24, no. 2, pp. 1615–1629, 2019.

[28] Y. Zhao, R. L. Shan, and H. L. Wang, "Research on vibration effect of tunnel blasting based on an improved Hilbert-Huang transform," *Environmental Earth Sciences*, vol. 80, no. 5, p. 206, 2021.