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Design and Practice of Online Learning Performance Prediction Model Based on Multi-Algorithm Fusion

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Abstract

Based on the real online learning behavior data of students, this paper uses random forest, support vector machine, K-nearest neighbor, neural network and other algorithms to analyze various performance prediction models for learning status. Through multiple rounds of iterations and model testing, multiple algorithms are fused, and finally a multi-algorithm fusion prediction model based on accurate clustering is formed. The model is embedded in the CEN online learning platform to predict student grades in real time, verifying the effectiveness of the model. The research results show that the model can provide teachers and students with more accurate modeling methods and accurate performance prediction. The accuracy of the multi-algorithm fusion prediction model based on cluster analysis is significantly better than that of a single algorithm. The prediction results help teachers identify students' potential academic risks, thereby optimizing teaching plans and improving the quality and efficiency of online learning.

Keywords

Online Learning, Performance Prediction, Predictive Modeling, Multi-Algorithm Fusion

1. Introduction

In the context of digital transformation of education, large-scale online learning has become a key path to improve students' information literacy and digital capabilities (Gyekye, 2025). However, its teaching quality still faces significant challenges: there are significant differences in learners' prior knowledge levels (Kuang et al., 2025); the time-space separation characteristics inherent in online teaching lead to a serious lag in personalized teaching intervention (Gao & Lü, 2025); some students fall into cognitive difficulties and even suffer academic interruption because their abnormal learning behaviors are not identified in time (Wu et al., 2025). Therefore, using intelligent technology to dynamically analyze learning process data, build accurate academic risk prediction models, and implement targeted teaching interventions has become the core research and practice direction for optimizing the quality of online learning (Alalawi et al., 2024).

As an important link between learning behavior analysis and teaching intervention, academic performance prediction can identify high-risk students by mining multimodal learning data such as resource access trajectories, homework completion quality, and interactive participation, and provide a scientific basis for process-based teaching guidance (Tao et al., 2022; Feng et al., 2024). Existing studies have shown that single algorithms such as random forests, support vector machines, and neural networks have certain effectiveness in predicting grades (Chen & Zhai, 2023; Tin et al., 2024), but there are two key limitations: on the one hand, a single model is difficult to effectively handle the nonlinear characteristics of data and the heterogeneity of learners, and the prediction accuracy in different groups fluctuates greatly (Zhao et al., 2023); on the other hand, existing models focus on behavioral characteristics analysis and lack the integration of personalized factors such as cognitive style and emotional state (Aslam et al., 2024), and lack of differentiated modeling strategies for the mapping mechanism between the behavior and grades of different learning groups, which restricts the generalization ability of the model. For example, the discussion participation of active inquiry students is significantly positively correlated with their grades, while the frequency of homework submission of passive acceptance students has a more prominent impact on their grades. It is difficult for a unified modeling method to effectively capture the differences between these groups.

With the in-depth development of educational data mining and machine learning technology, multi-algorithm fusion provides a new solution path to break through the limitations of a single model (Ahmad et al., 2025; Malik et al., 2025). By integrating the core advantages of multiple algorithms, such as the feature screening ability of random forests and the sequential pattern recognition ability of neural networks, the model's fitting effect on complex learning patterns can be significantly improved (Yang et al., 2022; Junejo et al., 2025). However, current fusion strategies mostly adopt unified integration methods such as simple voting mechanisms and weighted averages, which ignore the heterogeneity of student groups in terms of learning styles and ability levels. That is, there are significant differences in the key influencing factors and algorithm adaptability of different groups, resulting in relatively limited improvement in the accuracy of the fusion model (Lagares Rodríguez et al., 2025). Therefore, it is urgent to build a multi-algorithm fusion model based on group segmentation, realize the classification of learner types through cluster analysis, and customize the algorithm combination strategy according to the characteristic distribution and learning mode of different groups to achieve a fundamental breakthrough in prediction efficiency.

Based on the above analysis, this study focuses on the need for accurate prediction of online learning performance, integrates educational data mining technology and machine learning methods, and is committed to solving the following core problems:

First, how to identify the learning behavior characteristics of heterogeneous student groups through cluster analysis?

Second, how to design a multi-algorithm fusion strategy based on clustering results to improve the accuracy of online learning performance prediction? What is the prediction performance of this fusion model in actual teaching scenarios?

2. Literature Review

2.1. Feature System for Learning Outcome Prediction

The effectiveness of the learning outcome prediction model essentially depends on the scientific nature and integrity of the feature system. Existing studies have constructed a hierarchical feature modeling framework based on learners' explicit behavioral trajectories, internal cognitive and emotional states, and multimodal data fusion. Its evolution path reflects the paradigm shift from single-dimensional description to multi-dimensional integration.

In terms of explicit behavioral characteristics, early studies focused on mining interaction logs on online learning platforms, covering core behavioral indicators such as resource access frequency, task completion quality, and social collaboration intensity et al. (Borna et al., 2024). The large-scale feature-derived bidirectional long short-term memory neural network (LFD-BiLSTM) model proposed by Yang et al. (2025) achieved a high prediction accuracy of 92.57% by extracting clickstream data. Some scholars have also found that the effective viewing time of video resources is significantly positively correlated with academic performance (Chen et al., 2020). With the formation of a hybrid learning ecosystem, cross-platform data integration has become a new research orientation. Chango et al. (2021) integrated online learning trajectories with offline classroom behavior data to construct an "online-offline" behavior feature matrix, which increased the accuracy of early prediction of learning outcomes by 18%, highlighting the modeling advantages of multi-scenario behavior data fusion.

As important dimensions of the feature system, the research on cognitive and emotional characteristics has undergone a methodological evolution from static representation to dynamic modeling. Early studies relied on static variables such as demographic characteristics and prior knowledge levels (Bilal et al., 2022), but such indicators have limited explanatory power for dynamic psychological mechanisms such as motivation activation and fluctuations in self-efficacy during the learning process. In recent years, individual difference variables such as learning style and metacognitive strategies have been gradually incorporated into the feature system. Li (2023) found that integrating emotional features can effectively improve the accuracy of online learning performance prediction by constructing a BiLSTM text sentiment classification model based on the self-attention mechanism. Ban et al. (2022) found through cluster analysis that the weight of discussion participation of active exploratory learners on academic performance is 2.1 times higher than that of passive receptive learners, highlighting the regulatory effect of cognitive style differences on learning outcomes.

In the field of multimodal data fusion, researchers have attempted to integrate multi-source heterogeneous information, such as behavioral logs, cognitive diagnostic data, and emotional computing results to construct a three-dimensional feature space. For example, Song et al. (2020) conducted a study on course grade prediction and early warning based on multi-source teaching data, such as taught professional courses, unit tests, and mobile teaching data. Kord et al. (2025) proposed a multimodal method based on educational data mining technology, integrating course planning recommendations with student grade prediction functions. Although such research has broken through the analytical boundaries of single behavioral data, there are still theoretical gaps in the dynamic tracking of knowledge construction paths and the characterization of deep features such as the neural mechanisms of emotional state evolution. A linkage prediction framework of "behavioral performance-cognitive processing-emotional regulation" has not yet been formed, making it difficult to reveal the complex causal network of learning outcomes.

2.2. Research Progress on Algorithm Fusion Based on Group Segmentation

Traditional academic performance prediction research mostly uses a single algorithm or a simple integration strategy, and the model's effectiveness is subject to the implicit influence of the heterogeneous characteristics of the student group. In recent years, algorithm fusion research based on group segmentation has gradually emerged, promoting the paradigm shift of prediction models from "unified modeling" to "differentiated adaptation". During this transformation, the algorithm fusion strategy has undergone an evolution from simple integration to intelligent adaptation. Early studies mainly used shallow integration methods such as stacking models and voting mechanisms to improve the generalization ability of the model through multi-level algorithm stacking (Yu & Liu, 2022; Shayegan & Akhtari, 2024). Du et al. (2022) combined random forests with XGBoost algorithms to increase the prediction accuracy to 82.4%; however, this type of unified integration method ignores the significant differences in students' learning styles, ability levels and other dimensions, resulting in differentiation in the adaptation effect of the model in different groups, especially in segmented scenarios such as high-risk student identification. There is a problem of prediction bias amplification. Cutting-edge research introduces cluster analysis technology to divide learners into groups based on their characteristic distribution and behavior patterns, and designs customized algorithm combinations based on the cognitive laws of different subgroups (Huang et al., 2024).

At present, research in this field still faces two core challenges. First, the theoretical basis of group division is weak. Most studies only cluster based on a single dimension, and fail to fully consider the interactive effects of multi-dimensional features such as cognition, emotion, and behavior, resulting in insufficient validity and reliability of group classification; second, the algorithm adaptation mechanism lacks systematic theoretical support. Existing studies mostly rely on empirical trial and error to determine the algorithm combination strategy, and have not yet formed an algorithm selection framework based on learning science theory. Therefore, building a group recognition model that integrates multi-dimensional psychological and behavioral characteristics, and an algorithm adaptation mechanism based on cognitive diagnosis theory, have become the key path to break through the current research bottleneck. In general, existing research shows a dimensional expansion from explicit behavioral description to implicit psychological modeling in the construction of feature systems, and a paradigm evolution from universal modeling to precise adaptation in algorithm design, but has not yet established a closed-loop linkage mechanism of "feature representation-group classification-algorithm adaptation".

3. Research Design

3.1. Research Process Design

This study adopts a three-stage progressive research framework of "construction-verification-application" with a research cycle of 1 year. The first two stages are based on historical course data to build and verify the optimization of the model, and the third stage verifies the application effect of the model in the actual teaching environment to ensure the practicality and effectiveness of the research results. The research process of this study is shown in **Figure 1**.

In the model construction stage, the final grades of completed courses will be used as the dependent variable, and the learning behavior data at a specific time point in the online platform, other academic performance, students' self-efficacy, attitude motivation and other emotional measurement results will be used as independent variables to construct an academic performance prediction model. Among them, the dependent variable (students' final grades) is composed of the final examination grades and process evaluation grades, of which the final examination grades account for 60% and the process evaluation accounts for 40%, which can more objectively reflect the students' academic level.

In the model verification phase, a two-dimensional verification strategy is used to ensure the robustness of the model. First, a longitudinal verification is conducted, where the constructed model is applied to different time points of the same course, and the temporal stability of the model is evaluated by comparing the predicted results with the actual final grades. Second, a horizontal verification is conducted, where the model is applied to other similar courses on the platform to test its cross-course generalization ability. Based on the feedback from the verification results, a multi-round iteration strategy is used to continuously optimize the model parameters and algorithm weights.

During the model application phase, the prediction models that have met the validation standards will be embedded in the teaching process of currently offered courses, realizing the functions of weekly regular performance prediction and risk warning. Through 1 - 2 semesters of application practice in different courses, the effectiveness and practical value of the prediction model in real teaching scenarios will be fully tested.

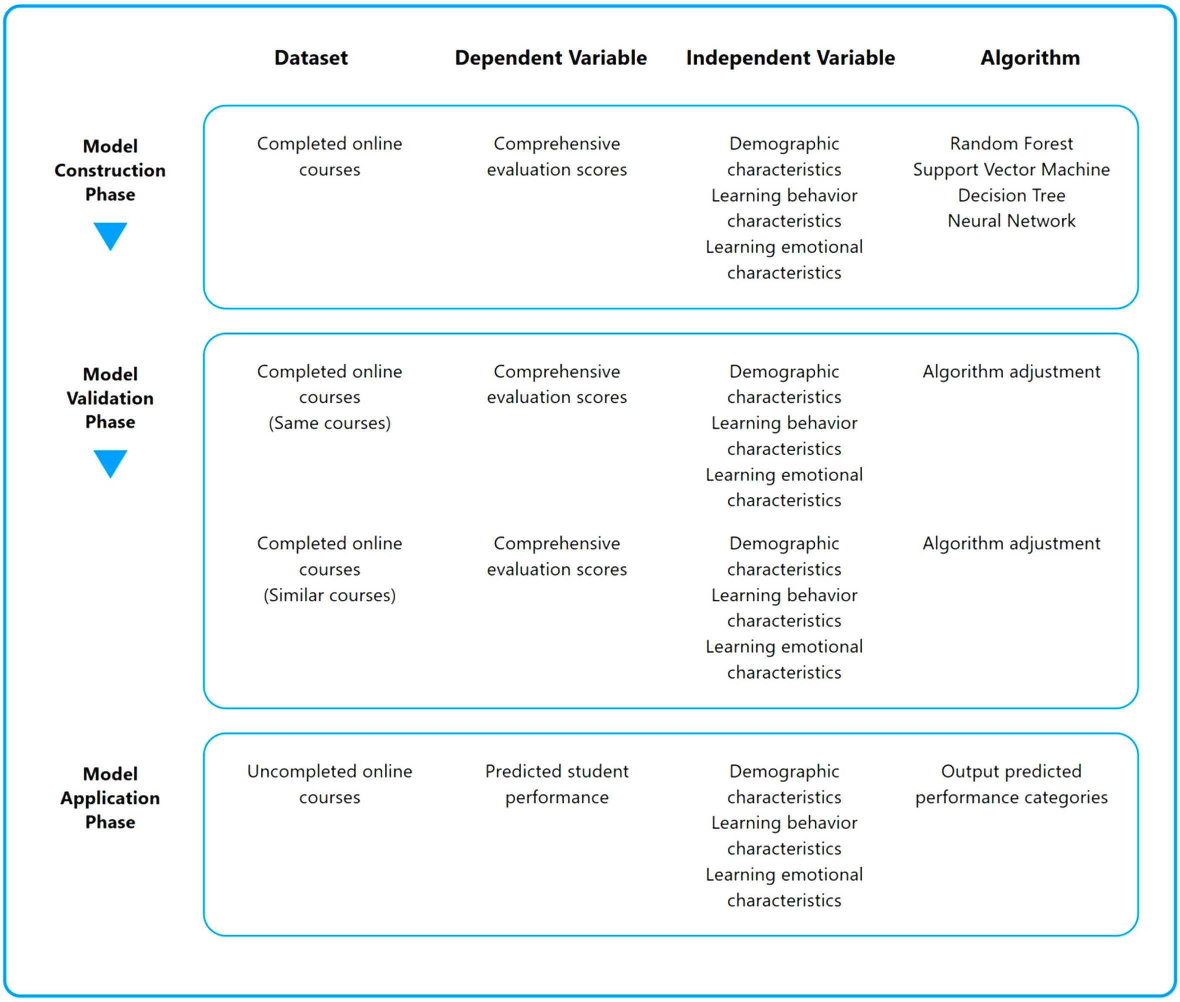

Figure 1. Research flow chart.

3.2. Research Tool Selection

1) Online Learning Platform (CEN)

This study is based on the school's computer basic course teaching platform (Computer Education Networks, referred to as CEN). The CEN platform is an integrated teaching and research platform developed by the school's computer public course teaching team, providing all-round support for university computer basic course teaching.

At present, the platform carries more than 30 basic computer courses, with more than 40,000 registered users and more than 3000 concurrent users per semester. The platform has developed high-quality online course resources with micro-videos as the core for each course, and automatically records each student's online learning information, including detailed behavioral data such as the start time, end time, and operation type of each study. To ensure data quality, the system has a built-in irregular detection mechanism to interrupt the learning time of students who are no longer online in time, effectively eliminating invalid "brushing time" behavior. At present, the CEN platform has stored more than 3 million high-quality online learning behavior records, providing a solid data foundation for this study.

2) Tools for Building Performance Prediction Models

This study uses a combination of multi-level analysis tools to ensure the scientific nature of the modeling process and the reliability of the results. First, Statistical Product and Service Solutions (SPSS) is used for basic statistical analysis, including correlation analysis and regression analysis. Second, IBM SPSS Modeler is used for professional clustering analysis, to build a single prediction model and realize the classification of research objects. Finally, Waikato Environment for Knowledge Analysis (Weka) is used to build a multi-algorithm fusion model, and the model quality is comprehensively evaluated and verified.

3) Self-Learning Ability and Self-Efficacy Measurement Tools

In order to accurately understand each student's learning style, attitude, motivation and level of autonomous learning ability, the researchers introduced the LASSI scale and the general self-efficacy scale into this study, and integrated the measurement functions of these two aspects of students into the CEN platform, so as to obtain each student's learning ability data and efficacy information at the beginning of each semester.

a) LASSI Learning Strategy Scale

The application level of learning strategies is an important measure of individual learning ability, one of the important factors that restrict learning effects, and a sign of whether one can learn. Weinstein et al. compiled the Learning and Study Strategies Inventory (LASSI) in 1987, which is widely used to test the level of learning strategies. The LASSI scale has 10 subscales, and this study selected three of them: attitude, motivation, and autonomous learning strategies. This scale is an internationally recognized authoritative scale, and its reliability and validity have been verified by many scholars.

b) Self-Efficacy Scale

This study primarily referred to the Adult Online Learning Self-Efficacy Scale developed by Li et al. (2015), which was appropriately modified based on the actual teaching conditions of this course. The scale divides self-efficacy into three dimensions: learning ability self-efficacy, learning volition self-efficacy, and learning technology self-efficacy. Using a Likert 5-point scoring method, the scale was measured to have an internal consistency coefficient (Cronbach's alpha) of 0.747

for its items, a KMO value of 0.657, and a Bartlett's test p-value of 0.000, indicating that the scale has good reliability and validity (Ma et al., 2024).

3.3. Data Source and Preprocessing

In order to accurately present the specific learning situation of students, the performance prediction model designed in this study collects data from four aspects: basic information of students, learning behavior characteristics, learning emotional characteristics and learning results characteristics. Basic information of students mainly includes gender and major. Learning behavior data mainly relies on the CEN online learning platform, which accurately records every learning behavior data and test result data of students. Learners' learning activities include reading electronic teaching plans, watching relevant teaching resources, completing class activities, participating in forum discussions, submitting personal homework, etc. Among them, teaching resources are the core content of learners' online learning, including teaching PPT, micro-videos and test questions. Learning emotional characteristics uses a fusion of learning motivation questionnaire and self-efficacy questionnaire. The process of student performance prediction is relatively complicated and easily affected by special values, so it should be processed accordingly. First, the collected data is cleaned case by case, removing the data of students who have selected courses but have not participated in any course learning, the data of students who have not participated in weekly course learning, and all the data of teachers; secondly, check the integrity of the information and remove the features such as names that are not related to the learners' academic performance. After the above operations are completed, the relevant data are normalized according to Equation (1).

$$X = \frac{X - \min}{\max - \min} \tag{1}$$

According to the distribution of grades and the difficulty of the course, students' grades are classified as follows: those with scores ≤ 70 are classified as Low, which means that students are at great risk of academic failure; those with scores 70 < scores ≤ 85 are classified as Middle, which means that learners at this level basically do not face the risk of academic failure; those with scores 85 < scores ≤ 100 are classified as High, which means that learners at this level are very unlikely to face the risk of academic failure. The selection of research subjects follows the principles of time progression and course coverage. First, learners of the "Information Processing Foundations" course in 2021 were selected as the research subjects in the model construction stage. Then learners of the "Information Processing Foundations" course in 2022 and learners of the "Statistical Software and Applications for Social Sciences" course in 2023 were selected as the research subjects in the model verification stage, and their grade data and online learning behavior data were used as the basis for model effect testing and iterative optimization.

4. Exploration and Construction of Learning Performance Prediction Model

4.1. Initial Construction of the Learning Performance Prediction Model—Baseline Model

In the initial stage of model building, the "Foundations of Information Processing" course that had been completed in the spring of 2021 was selected as the research object, and the final computer-based test scores and online learning behavior data for the entire semester were used as the basic basis for model construction.

1) Screening of Characteristic Variables

The selection of factors affecting students' performance directly affects the accuracy of the prediction modeling of academic performance, and some students' learning behaviors will significantly affect their academic performance. Among the numerous learning behavior data, which variables should be included in the prediction model is particularly critical (Zhao et al., 2019). This study uses a double screening strategy to systematically screen each variable. First, SPSS is used to calculate the Pearson correlation coefficient r between all individual features and academic performance. The calculation formula is as Equation (2). The correlation coefficient represents the linear correlation between the feature and academic performance.

$$r = \frac{\sum_{i=1}^{n}(x_i - x)(y_i - y)}{\sqrt{\sum_{i=1}^{n}(x_i - x)^2}\sqrt{\sum_{i=1}^{n}(y_i - y)^2}} \tag{2}$$

The ranking is based on the size of the correlation coefficient. The larger the value, the stronger the correlation between the feature and academic performance. Secondly, with the help of IBM SPSS Modeler uses information gain filters to filter out unimportant features. The information gain IG (S, A) is calculated as Equation (3), where H (S) represents the entropy of the sample set S.

$$IG(S,A) = H(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} H(S_v) \tag{3}$$

The obtained value > 0.95 means that the feature is very important for the prediction of learning performance, the value ≤ 0.95 means that the effect of the feature on the prediction of learning performance is relatively marginal, and the value < 0.9 means that the feature has no obvious effect on the prediction of learning performance. The feature screening results of the combination of the two tools are shown in **Table 1**.

It can be seen that the ranking results of the two methods are slightly different, and the number of topics submitted to the discussion area is also close to the level of "important" variables. Therefore, the first six variables in **Table 1** are used as independent variables for predictive modeling.

2) Baseline Model Construction Strategy

The processed data were divided into training set and test set in a ratio of 7:3, and the baseline model for academic performance prediction was constructed using random forest, support vector machine, K-nearest neighbor, neural network and other algorithms. The random forest algorithm improves the prediction accuracy by constructing multiple decision trees and taking the average value. Its prediction function is as Equation (4), and the model was mainly tested using IBM SPSS Modeler.

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b\left(x\right) \tag{4}$$

Table 1. Filter results based on IBM SPSS statistics and IBM SPSS modeler features.

SPSS Analysis	Feature Name	Pearson Correlation Coefficient	IBM SPSS Modeler Analysis	Feature Name	Value
Mutually Close	Regular Homework and Grades	0.431	Important Variable	Regular Homework and Grades	1.000
	Self-Directed Learning Strategies	0.371		Number of Platform Check-Ins	1.000
	Level of Self-Efficacy	0.321		Platform Online Time	0.996
	Platform Online Time	0.181			
	Number of Platform Check-Ins	0.176		Self-Directed Learning Strategies	0.837
	Number of Discussion Forum Topics Submitted	0.161		Level of Self-Efficacy	0.812
Not Relevant	Number of Submitted Jobs	0.100	Margin Variable	Number of Discussion Forum Topics Submitted	0.807
				Number of Submitted Jobs	0.685
	Micro Video Viewing Time	0.078		Micro Video Viewing Time	0.547

3) Quality Analysis of The Baseline Model and Actual Prediction Results

a) Quality Analysis of Prediction Results

After modeling based on the above algorithms and implementing prediction on the test set, the accuracy rate is used as the main evaluation index, and its calculation formula is as Equation (5). The prediction performance of the four algorithms is shown in Table 2. Among the four algorithms, the random forest algorithm has the highest accuracy, followed by the support vector machine algorithm. Therefore, the models constructed by the above two algorithms are preliminarily applied to the CEN platform to test the effectiveness of the models.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Table 2. Prediction accuracy and error rate of modeling with four algorithms.

Algorithm Name	Prediction Accuracy	Prediction Error Rate
Random Forest	65.561%	34.441%
Support Vector Machine	64.015%	35.985%
K-nearest Neighbors	61.925%	38.075%
Neural Networks	58.675%	41.325%

b) Analysis of Actual Application Effects

The initial model was applied to the CEN platform to predict the academic performance of students in the 2022 "Information Processing Foundation" course and the 2023 "Statistical Software and Applications for Social Sciences" course. The results showed that the accuracy of the initial model prediction was 63 % and 58.2 %, respectively, which was obviously insufficient. Compared with the research of other scholars, the accuracy of this prediction result was lower (Mou & Wu, 2017), and it failed to achieve a good prediction effect.

By analyzing the prediction principles of each model, it was found that the effectiveness of using different models is not the same. For example, although the random forest algorithm introduces randomness and is not easy to overfit, if the number of decision trees is too large, it will lead to an increase in the time and space used for training, causing the model to run too slowly; and the support vector machine algorithm has multiple parameters that need to be adjusted. The selection of these parameters has a great impact on the classification results and requires repeated debugging. If the selection is inappropriate, it will lead to deviations in the classification results. In order to solve the above problems, the researchers considered whether the single models can be integrated to make up for their respective advantages and disadvantages, so that the integrated model is more suitable for actual teaching scenarios.

4.2. Second-Generation Prediction Model Based on Multi-Algorithm Fusion

Through Weka software, researchers try to organically integrate multiple single model algorithms, using random forest, support vector machine, neural network and other algorithms as the basic algorithms for building multi-algorithm fusion models, and as the basic classifiers for training multi-algorithm fusion. The core idea of using Stacking to perform model fusion is to train a meta-learner to combine the prediction results of multiple base learners as Equation (6). A performance prediction model based on multi-algorithm fusion was constructed for performance prediction. Stacking was used as a meta-classifier, and several other algorithms were fused as base classifiers. The prediction performance accuracy of the new model was 67.87 % and the error rate was 32.14 %. This accuracy rate was higher than that of the four single algorithm models, but the improvement effect was still not obvious enough.

$$\hat{y} = f_{meta}\left(h_1(x), h_2(x), \cdots, h_k(x)\right) \tag{6}$$

4.3. Multi-Algorithm Fusion Prediction Model of "Introducing Clustering Results"

The direct fusion of the four algorithms did not significantly improve the prediction accuracy. In exploring the underlying reasons, the researchers found that not all students are suitable for predicting their grades using a model that directly combines the four algorithms. Based on this, after reviewing the literature, the researchers believe that, given that different types of students have their own unique learning habits and learning abilities, the extreme values of individual students will have a greater impact on the results of grade prediction. Therefore, if students are clustered to form several distinct categories, and then independent multi-algorithm fusion grade prediction is carried out for different types of students (Li et al., 2023), which may significantly improve the prediction accuracy.

1) Classify The Research Objects Using K-Means Clustering Algorithm

With IBM SPSS Modeler software uses K-Means method to perform cluster analysis on the research objects. The objective function of K-Means algorithm is as Equation (7). According to the cluster analysis model summary in IBM SPSS Modeler, k = 6 configuration was selected because it yielded optimal cluster quality and more distinct, interpretative category profiles than nearby alternative configurations. Thus, all students were divided into 6 groups, which is justified by the validity criterion of high intra-cluster cohesion and low inter-cluster coupling. From the summary of the cluster analysis model, it can be seen that this classification uses 8 input variables, and each category has high coupling within it and low coupling between categories, so the clustering quality is good. Observe the specific distribution of each category, and summarize the characteristics of the 6 groups and name them according to the distribution of cells in the cluster, as shown in **Table 3**.

$$J = \sum_{i=1}^{n}\sum_{j=1}^{k} w_{ij} x_i - \mu_j^{\,2} \tag{7}$$

Table 3. The categories represented by the clustering results.

Category	Features	Name
Category 1	All indicators are the lowest	Refusing to make an effort
Category 2	Average in all indicators but high in performance	Actual efficiency
Category 3	All indicators are average and the performance is lower	Unequal pay-off
Category 4	All indicators are above average and the results are above average	Equal pay-back
Category 5	All indicators are high but the results are low	No return type
Category 6	Average in all indicators but very low performance	Extremely uneven payback

2) Constructing a New Performance Prediction Model Based on Clustering Results: Clustering Plus Multi-Algorithm Fusion Prediction Model

Based on the specific classification in **Table 3**, the student data are exported and named Category 1, Category 2, Category 3, Category 4, Category 5 and Category 6 respectively, so as to further conduct multi-algorithm fusion model experiments and observe the score prediction of students in different categories.

The classified data results were exported to form 6 data sets. The Weka software was used to predict the grades of the 6 data sets (i.e., 6 categories of students) using the multi-algorithm fusion model. Taking category 2 as an example, the data of category 2 was divided into training set and test set, and Stacking was used for integration. The algorithm structure was adjusted, and a multi-algorithm fusion grade prediction model based on clustering analysis was gradually constructed through iterative experiments. It was found that the prediction accuracy of the integrated model was 88.57%. Similarly, the researchers used the above model to predict the grades of the other 5 categories of students, and the prediction accuracy was significantly improved. The comprehensive accuracy of the grade prediction of all students was as Equation (8), and finally reached 83.43%. Based on the above research process, this study constructed a high-quality "clustering + multi-algorithm fusion" (Abbreviated as clu-MultiAlgo) grade prediction model. As shown in Figure 2.

$$\text{Accuracy}_{\text{overall}} = \frac{\sum_{i=1}^{6} n_i \times \text{Accuracy}_i}{\sum_{i=1}^{6} n_i} \tag{8}$$

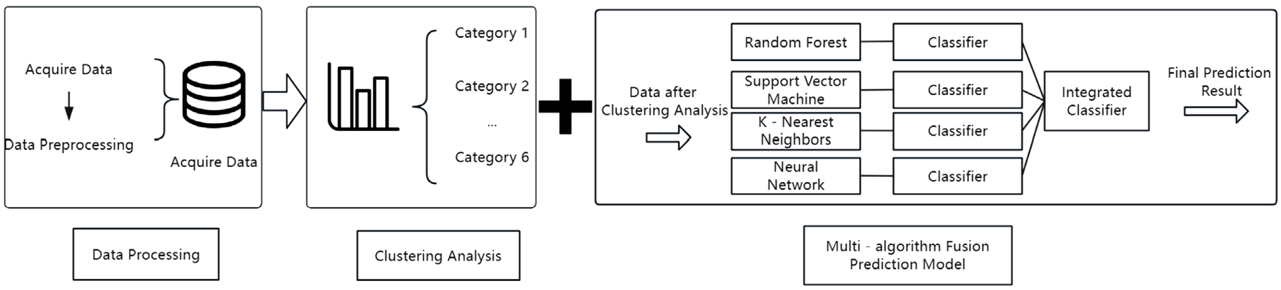

Figure 2. The clu-MultiAlgo performance prediction model.

4.4. Preliminary Test of the Effectiveness of the "Clu-MultiAlgo" Prediction Model

The prediction model of "clu-MultiAlgo" achieved good prediction results (with an accuracy rate of 83.43%) on the data set based on the 2021 "Information Processing Foundation" course. To further test the generalization ability and stability of the model, the researchers applied this model to two new data sets, the 2022 "Information Processing Foundation" course (the same course in different years) and the 2023 "Statistical Software and Applications for Social Sciences" course (different courses in different years), and achieved good prediction results, with the correct prediction rate above 83%. It can be seen that after using K-Means cluster analysis, the accuracy of more appropriate performance predictions for students is significantly improved compared to the overall prediction accuracy of students.

5. Discussion and Analysis of the "Clu-MultiAlgo" Model

5.1. Identification of Heterogeneous Student Groups Based on Cluster Analysis and Construction of Multi-Algorithm Fusion Strategy

This study uses the K-Means clustering algorithm to systematically analyze multidimensional data such as learning engagement, cognitive strategy application, and self-efficacy level, and successfully divides six groups of students with significant behavioral differences. Among them, students who refuse to work hard show low values in all evaluation dimensions, and their lack of learning motivation and lack of self-management ability are clearly visible. Although the quantitative indicators of practical efficiency students are at a medium level, they have achieved breakthroughs in academic performance with efficient learning strategies and excellent time management skills. Students with unequal input and output show an imbalance between learning input and results, reflecting their potential defects in learning methods and cognitive strategies. Students with equal input and output maintain good coordination between indicators in each dimension and academic performance, representing a more ideal learning ecology. Although students with no return show high learning input, they are constrained by factors such as weak basic knowledge or improper learning strategies, and their learning results are not as expected; students with extremely uneven input and output show a sharp contrast between medium learning input and extremely low academic performance, and systematic learning diagnosis and intervention measures are urgently needed.

The cluster analysis model constructs a classification system through 8 key input variables. The categories formed show a high degree of cohesion, while the categories maintain a significant degree of separation, providing a solid data foundation for subsequent multi-algorithm fusion prediction. It is worth noting that the differentiated distribution characteristics of each characteristic variable in different categories, such as the outstanding performance of homework and grades in the actual efficiency-oriented student group, and the key role of the platform online time in the classification and identification of students who refuse to work hard, further confirm the effectiveness and reliability of cluster analysis in describing the heterogeneity of student groups.

Based on the results of cluster analysis, this study constructed a hierarchical multi-algorithm fusion prediction architecture, used the Stacking ensemble learning method, and used multiple algorithms such as random forest, support vector machine, neural network as basic classifiers, and deeply integrated the prediction results of each base classifier through the meta-learner. Taking the actual efficiency student group as an example, by scientifically dividing the training set and the test set, systematically carrying out algorithm integration, iterative experiments and parameter optimization, the prediction accuracy of the fusion model finally constructed reached 88.57%, which was significantly improved compared with a single algorithm. After implementing the same multi-algorithm fusion strategy for the remaining five types of student groups, the prediction accuracy of each category showed significant improvement, and the overall prediction accuracy of all student scores reached 83.43%, which was 15.57 percentage points higher than the traditional overall multi-algorithm fusion method. This strategy fully utilizes the homogeneity of the student group revealed by cluster analysis, and through targeted optimization of the training process, effectively integrates the technical expertise of different algorithms, successfully making up for the inherent limitations of a single algorithm.

5.2. "Clu-MultiAlgo" Model Mechanism Analysis and Teaching Intervention Practice

The "clu-MultiAlgo" model to achieve a significant improvement in prediction accuracy can be deeply analyzed from three dimensions. First, cluster analysis effectively reduces the interference of sample heterogeneity on the prediction model by accurately identifying and separating student groups with different learning behavior characteristics, making the data distribution within each subgroup more regular; secondly, based on the characteristic differences of students in different categories, differentiated algorithm parameter optimization strategies are formulated and implemented to ensure that each base classifier has the best prediction performance on the corresponding student group. Finally, the Stacking integration strategy uses the intelligent combination mechanism of the meta-learner to deeply explore the complementary characteristics between different algorithms and further improve the overall prediction accuracy of the model. In order to verify the generalization ability and stability of the model, the study applied the model to the data sets of the 2022 "Information Processing Foundation" course and the 2023 "Statistical Software and Applications for Social Sciences" course for testing. The experimental results show that in different years and different course backgrounds, the correct prediction rate of the model remains above 83%, which fully proves that it has strong generalization ability and application stability, and provides strong support for the promotion and application of the model in actual teaching scenarios.

In the teaching practice of the SPSS Data Analysis course in the spring of 2024, based on the prediction results of the "clu-MultiAlgo" model, 83 students were assessed for academic risk, and 21 students in the academic warning state were successfully identified. For these students, teachers extracted LASSI scale data and self-efficacy data to comprehensively analyze their online autonomous learning ability and learning confidence level, and formulated personalized teaching intervention strategies based on this, including pushing adapted learning resources, academic risk warning through the WeChat platform, and urging students to complete learning tasks on the CEN platform. Through continuous tracking and analysis of the changes in the learning behavior of students at academic risk, it was found that insufficient online learning investment, especially the short online time of the platform, was the key factor leading to poor academic performance of some students; at the same time, some students with weak autonomous learning ability or improper learning strategies still faced high academic risks even if they invested more learning time. This finding points out the direction for the optimization of teaching intervention strategies. While paying attention to the improvement of students' knowledge and skills, teachers should pay more attention to the guidance of learning strategies, the cultivation of thinking methods and the improvement of self-efficacy, and effectively reduce the ineffective investment of students in the online learning process.

5.3. Model Application Value and Teaching Quality Assurance Mechanism

From the analysis results of the characteristic variables constructed by the "clu-MultiAlgo" model, the learning engagement of online students (including online learning time, quality and grades of regular homework, and number of times participating in topic discussions) showed a low positive correlation with the final academic performance, indicating that although learning engagement is an important factor affecting academic performance, it is not the only decisive factor. The study further found that students' autonomous learning ability, self-efficacy, and learning motivation attitude also have a significant correlation with the final academic performance, among which the level of self-efficacy and the effective application of autonomous learning strategies have a particularly prominent impact on students' academic performance. In fact, students with low levels of autonomous learning strategies and self-efficacy in a certain course usually have unsatisfactory grades in previous courses (Bai & Yu, 2023). Even if these students invest more online learning time in the current course, their final academic performance is often still difficult to reach the expected level. Therefore, teachers need to discover and focus on them in a timely manner, and provide personalized professional support in terms of learning methods, confidence building, and basic knowledge reserves.

Based on the above model analysis results, the teaching intervention for students with academic warning should adopt differentiated and precise strategies. Teachers need to conduct a comprehensive analysis from multiple dimensions such as students' online learning investment, autonomous learning ability and self-efficacy, and accurately identify the key constraints that affect the learning quality of each student, whether it is a weak foundation of knowledge and skills, lack of learning strategies and learning ability, or insufficient self-efficacy or learning motivation. Only based on the accurate judgment and deep understanding of this core information can teachers formulate targeted intervention measures for each student. Through in-depth tracking and analysis, it was found that insufficient online learning investment, especially the significantly low online learning time, is an important reason for some students to have academic risks. Another part of students with relatively weak autonomous learning ability or improper use of learning strategies, even if they show a high degree of learning investment, often fall into the academic risk group. For the former type of students, teachers should focus on providing special guidance on study time management and cultivation of study habits. For the latter type of students, in addition to paying attention to their progress in knowledge and skills, teachers should also provide necessary professional guidance in learning strategy optimization, thinking mode cultivation, etc., and pay more attention to the students' self-efficacy development level, and effectively reduce the phenomenon of ineffective investment in their online learning process by building learning confidence and improving learning efficiency.

The prediction results of the "clu-MultiAlgo" model provide important technical support and innovative paths for online learning quality assurance. In the process of using the results of grade prediction to carry out teaching intervention, teachers should continue to pay attention to the changes in students' process learning data, actively guide students to actively participate in various learning activities, continuously improve the quality of their homework, and guide students to actively carry out diversified exchanges and discussions such as teacher-student interaction and student-student collaboration, continuously optimize learning effects, and thus promote students' personalized and comprehensive development (Wang et al., 2022).

6. Conclusion

This study focuses on improving the quality of online learning. Based on educational data mining technology, it deeply analyzes learning behavior data and constructs a grade prediction model suitable for online courses. Aiming at the key problems of insufficient generalization ability of single algorithm model and neglect of learner heterogeneity by traditional multi-algorithm fusion strategy, this study integrates classic machine learning algorithms such as random forest, support vector machine, and K-nearest neighbor, and innovatively proposes a differentiated fusion modeling method based on cluster analysis. The experimental results show that after the K-means algorithm is used to segment the student groups, the average prediction accuracy of the multi-algorithm fusion model reaches 83.43%, which is about 17.87% higher than that of the single algorithm model, and significantly enhances the nonlinear fitting ability of the mapping relationship between learning behavior characteristics and grades. By accurately capturing the key influencing factors of different learning groups, this model provides data support for teachers to accurately identify academic risks and dynamically optimize teaching strategies, and also provides scientific guidance for students' personalized learning path planning. The research results not only verify the effectiveness of multi-algorithm fusion from the perspective of group segmentation, but also provide a replicable methodological reference for building an online learning support system of "data-driven-intelligent diagnosis-precise intervention" in the context of digital transformation of education.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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