Optimization Analysis of Physical Education Integration Teaching Based on Multi Support Vector Machines

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ABSTRACT The integration of sports and education serves as a core strategy for the coordinated development of youth well-being and academic growth in China's new era. Its core goal is to achieve a deep integration of sports education and cultural education, and cultivate composite talents with comprehensive qualities and sports skills. In the current practice of integrating sports and education, there are problems such as imbalanced teaching objectives, lack of personalized curriculum design, incomplete teaching effect evaluation system, and insufficient adaptability of integration strategies. Traditional qualitative analysis and single quantitative methods are difficult to accurately identify the core influencing factors in the teaching process, and cannot provide scientific and quantifiable decision-making basis for teaching optimization. Support Vector Machine (SVM), as an efficient machine learning algorithm, has significant advantages in small sample, high-dimensional, and nonlinear data processing. Multi support vector machine fusion models can better improve the accuracy and stability of prediction and classification. By incorporating wearable sensing and teachingprocess data into a multi-support vector machine algorithm, this research establishes a comprehensive "data collection —feature extraction—model training—effect prediction—strategy optimization" system to refine the physical education integration process.

INDEX TERMS sports-education integration,multi-support vector machine,teaching optimization,wearable sensing

I. INTRODUCTION

A. RESEARCH BACKGROUND

THE integration of sports and education is a vital measure for China to bridge the gap between athletic talent cultivation and basic education.

In 2020, the General Administration of Sport of China and the Ministry of Education jointly issued the "Opinions on Deepening the Integration of Sports and Education to Promote the Healthy Development of Adolescents", which clearly proposed to "promote the coordinated development of cultural learning and physical exercise for adolescents, promote their healthy growth, temper their willpower, and improve their personality"; In 2023, the "Opinions on Accelerating the Construction of a Sports Power" once again emphasized the need to "deepen the integration of sports and education, improve the system of youth sports events, and promote the improvement and efficiency of school sports"; In 2025, the Ministry of Education issued the "Guidelines for the Implementation of Integrated Sports and Education Teaching", which further clarified the teaching objectives, curriculum system, and implementation requirements of integrated sports and education, marking the transition of integrated sports and education from a policy level to a specific teaching practice level [1-3].

B. RESEARCH CONTENT AND TECHNICAL ROUTE

The main research content of this article includes:

1. Theoretical basis and indicator system construction: Sort out the relevant theories of sports education integration, support vector machines, and ensemble learning, and analyze the feasibility of applying multiple support vector machines to optimize sports education integration teaching; Identify the core influencing factors of integrated sports and education teaching, and construct a teaching evaluation index system and feature variable set.

2. Data collection and preprocessing: Conduct research on schools of different types and regions to collect practical data on the integration of sports and education teaching; Preprocess the raw data by cleaning, normalizing, and feature filtering, and construct model training and testing datasets.

3. Construction and training of multi support vector machine models: Construct a multi support vector machine integrated teaching effectiveness prediction model based on

Bagging, Boosting, and Stacking strategies; Select appropriate kernel functions and parameter optimization methods to complete model training and parameter tuning; Compare the predictive performance of different models and select the optimal model.

4. Research conclusion and outlook: Summarize the research results, point out the limitations of the research, and look forward to future research directions.

II. THEORETICAL BASIS AND DEFINITION OF CORE CONCEPTS

A. DEFINITION OF CORE CONCEPTS

Support Vector Machine is a machine learning algorithm based on statistical learning theory, mainly used for data classification and regression prediction [4]. For linearly separable datasets, SVM constructs the optimal classification hyperplane to maximize the interval between the hyperplane and two types of samples, thereby achieving data classification; For linearly inseparable datasets, SVM maps samples from low dimensional feature space to high-dimensional feature space through kernel functions, making the samples linearly separable in high-dimensional space, and then constructs the optimal classification hyperplane. The core advantage of SVM lies in its good learning performance in small sample situations, which can effectively avoid overfitting; High computational efficiency in high-dimensional data processing, without relying on the dimensionality of the sample; By selecting kernel functions, non-linear data can be effectively processed. The commonly used kernel functions include linear kernel functions, polynomial kernel functions, radial basis function (RBF), sigmoid kernel functions, etc. Among them, radial basis function has become the most commonly used kernel function due to its strong adaptability and few parameters [5].

Support Vector Machine (SVM) is a machine learning algorithm based on statistical learning theory, with core advantages in small-sample, high-dimensional, and nonlinear data processing, which is suitable for the sample characteristics and multi-dimensional indicator requirements of sports-education integration teaching [4]. In response to the nonlinear characteristics of the data in this study, the Radial Basis Function (RBF) is selected as the kernel function. It achieves linear separability by mapping low-dimensional features to high-dimensional space, with few parameters and strong adaptability, and has been effectively applied in the field of educational quantitative analysis [5]. Specific parameters are determined through subsequent grid search optimization. This study adopts SVM and its ensemble model with the core goal of solving the "small-sample, high-dimensional, nonlinear" effect prediction problem in sports-education integration teaching, rather than verifying the theoretical feasibility of the SVM algorithm itself. Therefore, the focus is on the application adaptation of the algorithm in specific research scenarios, rather than basic theoretical exposition.

B. FEASIBILITY ANALYSIS OF APPLYING MULTIPLE SUPPORT VECTOR MACHINES TO OPTIMIZE INTEGRATED PHYSICAL EDUCATION TEACHING

The multi support vector machine algorithm can be effectively applied to the optimization research of integrated physical education teaching, and its feasibility is mainly reflected in the following aspects:

The characteristics of blended learning data: blended learning data has small sample size, high dimensionality, and nonlinearity, and SVM has significant advantages in processing small sample and high-dimensional data. Kernel functions can effectively handle nonlinear data, and multi SVM ensemble models can improve the generalization ability of the model, highly adapting to the characteristics of blended learning data [6].

III. CONSTRUCTION AND FEATURE EXTRACTION OF EVALUATION INDEX SYSTEM FOR INTEGRATED SPORTS AND EDUCATION TEACHING

A. PRINCIPLES AND METHODS FOR BUILDING AN INDICATOR SYSTEM

1) Principles for Constructing Indicator System

To ensure the scientific, comprehensive, operable, and targeted evaluation index system of integrated sports and education teaching, the construction process follows the following five principles:

1. Principle of comprehensiveness: The indicator system should comprehensively cover all aspects and core elements of integrated sports and education teaching, including teaching resources, curriculum design, student characteristics, teaching implementation, effectiveness evaluation, etc., to avoid missing key influencing factors.

2. Principle of scientificity: The selection of indicators should be based on relevant theories of sports education integration and education teaching. The definition of indicators should be clear and accurate, and the quantification method of indicators should be scientific and reasonable to ensure that the indicators can truly reflect the actual situation of sports education integration teaching.

3. Principle of operability: Indicators should be able to be quantitatively collected through methods such as questionnaire surveys, field research, and data statistics, avoiding selecting indicators that are difficult to quantify or collect, and ensuring the availability of data.

4. Targeted principle: The indicator system should be tailored to the characteristics of integrated physical education and cultural education, highlighting the integration of physical education and cultural education, and avoiding similarity with the evaluation indicator system of single cultural teaching or single physical education teaching.

5. Hierarchical principle: The indicator system should be divided into different levels, such as primary indicators and secondary indicators (feature variables), with clear hierarchy and rigorous logic, which facilitates subsequent feature extraction and model construction.

2) Method for Constructing Indicator System

This article uses a combination of literature analysis and expert interviews to construct an evaluation index system for integrated sports and education teaching. The specific steps are as follows:

1. Literature analysis: Systematically review relevant research results on integrated sports and education teaching, teaching effectiveness evaluation, and education quantification analysis at home and abroad, collect influencing factors and evaluation indicators of integrated sports and education teaching, and preliminarily construct an indicator system framework.

2. Expert interviews: Select 20 experts for in-depth interviews, including 5 experts in the research of sports education integration policies, 5 experts in physical education, 5 experts in basic/higher education, and 5 experts in machine learning and quantitative analysis of education. Solicit experts' opinions on the preliminary indicator system framework, and screen, modify, and supplement the indicators.

B. CONSTRUCTION OF EVALUATION INDEX SYSTEM FOR INTEGRATED SPORTS AND EDUCATION TEACHING

Based on the above principles and methods, this article constructs an evaluation index system for integrated sports and education teaching, which includes 5 primary indicators and 18 secondary indicators (core feature variables). At the same time, the quantification methods and assignment ranges of each secondary indicator are clarified, providing standards for subsequent data collection and feature extraction [7]. The specific indicator system is shown in Table 1.

Note: 1 The weights of each primary indicator are determined through the Analytic Hierarchy Process (AHP), and after consistency testing, CR<0.1, Reasonable allocation of weights; 2. The target variable E1 (comprehensive effect of integrated sports and education teaching) is obtained by weighting and summing four indicators: the improvement rate of cultural course grades, the improvement rate of sports skills, the improvement rate of students' physical and mental qualities, and the score of integrated adaptability, with weights of 30%, 30%, 20%, and 20%, respectively; 3. All feature variables are normalized and assigned values within the range of 0-10, which facilitates subsequent model training [8].

Note 2: The target variable E1 (comprehensive effect of sports-education integration teaching) is calculated by a mixed quantification method that prioritizes objective data with subjective evaluation as a supplement:

Core objective indicators (weight ratio 80%): Improvement rate of cultural course grades (35%), improvement rate of sports skill tests (35%), all data from the school's academic affairs system and standardized skill tests, completely objective and quantifiable;

Optimized subjective correlation indicators (weight ratio 20%):

Integration adaptability (10%): Quantified through objective data such as "increase rate of class course participation" and "quality of interdisciplinary homework completion", no longer relying on subjective scoring;

Physical and mental qualities (10%): Quantified based on physiological data (e.g., heart rate variability, exercise endurance) collected by smart sensors, combined with objective scores of the standardized mental health scale (SCL-90), reducing human subjective judgment.

C. SELECTION AND OPTIMIZATION OF CHARACTERISTIC VARIABLES

The 18 secondary indicators constructed are the initial feature variables of integrated physical education teaching. In order to reduce the computational complexity of the model and improve its prediction accuracy, it is necessary to screen the initial feature variables, eliminate redundant and irrelevant feature variables, and retain the core feature variables. This article uses a combination of analysis of variance (ANOVA) and mutual information method for feature screening. The specific steps are as follows:

1. Analysis of variance: Calculate the F-value and P-value between each initial feature variable and the target variable (comprehensive effect of integrated sports and education teaching), screen out feature variables with $P<0.05$, and eliminate redundant variables that are not significantly correlated with the target variable.

2. Mutual information method: Calculate the mutual information value between the selected feature variable and the target variable. The larger the mutual information value, the stronger the correlation between the feature variable and the target variable; Simultaneously calculate the mutual information values between feature variables and eliminate feature variables with high redundancy (mutual information values>0.8) [9].

3. Determination of core characteristic variables: Combining the results of analysis of variance and mutual information method, 15 core characteristic variables were ultimately retained, and 3 redundant variables (A4, B5, D4) were removed. The core characteristic variables include A1, A2, A3, B1, B2, B3, B4, C1, C2, C3, C4, D1, D2, D3 [10].

Determination of core characteristic variables: Combining the results of analysis of variance and mutual information method, 15 core characteristic variables are retained, and 3 redundant variables (A4, B5, D4) are removed. On this basis, 3 standard teaching control variables ("teacher teaching experience", "class size", "teaching duration") are added, forming a total of 20 comprehensive feature variables for model training.

D. CORRELATION ANALYSIS OF CHARACTERISTIC VARIABLES

In order to further analyze the relationship between core feature variables and avoid the influence of multicollinearity on model training, this paper uses Pearson correlation coefficient to conduct correlation analysis on 15 core feature

TABLE 1. Evaluation Index System of Sports-Education Integration Teaching

First-Level Indicator	Weight (%)	Secondary Indicator (Feature Variable)	Variable Code	Quantification Method	Value Range
Teaching Resource Dimension (A)	20	Perfection degree of sports teaching venues and facilities	A1	On-site research scoring, comprehensive evaluation based on facility compliance and utilization rate	0-10
		Integration degree of cultural and sports teaching resources	A2	Expert scoring, comprehensive evaluation based on resource sharing rate and adaptability	0-10
		Teaching fund input (sports + cultural integrated teaching)	A3	Per capita fund input, Unit: Yuan/person	0-10
		Adaptability of teaching equipment and information resources	A4	On-site research + questionnaire survey, comprehensive evaluation based on student and teacher satisfaction	0-10
Curriculum Design Dimension (B)	25	Integration degree of cultural and sports courses	B1	Expert scoring, evaluation based on the degree of curriculum content integration and class hour coordination	0-10
		Synergy of curriculum objectives (culture + sports)	B2	Expert scoring, evaluation based on whether objectives take into account both cultural learning and sports skill improvement	0-10
		Personalization and hierarchical design degree of curriculum content	B3	Questionnaire survey, evaluation based on recognition of students and teachers	0-10
		Integration of curriculum evaluation system	B4	Expert scoring, evaluation based on whether evaluation covers multi-dimensional assessment of culture and sports	0-10
		Proportion of practical courses (in integrated courses)	B5	Data statistics, practical course hours / total integrated course hours	0-10
Student Trait Dimension (C)	25	Students' sports foundation level	C1	Sports skill test, evaluation based on compliance rate and comprehensive score	0-10
		Students' cultural learning ability	C2	Ranking of cultural course scores, evaluation based on the percentage of grade ranking	0-10
		Synergy of sports foundation and cultural learning ability	C3	Correlation analysis, quantified by the correlation coefficient of the two	0-10
		Students' interest in sports-education integration teaching	C4	Questionnaire survey, evaluation based on student interest scores	0-10
Teaching Implementation Dimension (D)	20	Teachers' comprehensive ability (culture + sports)	D1	Expert scoring, comprehensive evaluation based on teachers' cultural teaching ability, sports teaching ability and integrated teaching ability	0-10
		Integration and diversity of teaching methods	D2	Classroom observation + questionnaire survey, evaluation based on teachers' teaching methods and student recognition	0-10
		Implementation degree of hierarchical teaching and personalized guidance	D3	Classroom observation + questionnaire survey, evaluation based on implementation frequency and effect	0-10
		Efficiency of teacher-student interaction in the teaching process	D4	Classroom observation, comprehensive evaluation based on interaction frequency and quality	0-10
Effect Evaluation Dimension (E)	10	Comprehensive effect of sports-education integration teaching	E1	Multi-dimensional weighted summation, the target variable for model prediction	0-100

variables, and calculates the correlation coefficient r between feature variables. The range of correlation coefficient values is [-1,1], and the closer | r | is to 1, the stronger the correlation between the two feature variables; |R |<0.6 indicates that there is no significant multicollinearity between the feature variables, making it suitable for model training.

The correlation analysis results show that the absolute values of the correlation coefficients between the 15 core feature variables are all less than 0.58, indicating no significant multicollinearity and no further dimensionality reduction is required. They can be directly used as input feature variables for the multi support vector machine model to construct a prediction model for the effectiveness of integrated physical education teaching [11-13].

IV. DATA COLLECTION AND PREPROCESSING OF INTEGRATED SPORTS AND EDUCATION TEACHING

A. SELECTION OF RESEARCH SUBJECTS

To ensure the representativeness, comprehensiveness, and diversity of the research data, this article uses stratified sampling to select research objects, covering different regions and types of schools, including primary and secondary schools, vocational colleges, and ordinary universities, taking into account both economically developed and underdeveloped areas, urban and rural schools. The specific research subjects are as follows:

1. Regional distribution: Select schools from 12 provinces and cities, including the eastern region (Beijing, Shanghai, Jiangsu, Zhejiang), central region (Henan, Hubei, Hunan, Anhui), and western region (Sichuan, Shaanxi, Yunnan, Guizhou), to ensure data coverage of regions with different levels of economic development.

2. School types: Select 28 primary and secondary schools (10 primary schools, 10 junior high schools, 8 high schools), 12 vocational colleges, and 8 ordinary universities (3 teacher training schools, 3 comprehensive schools, and 2 sports schools), for a total of 48 schools.

3. Sample size: Each school selects 2-3 pilot classes for integrated physical education teaching, with each class serving as one research sample. A total of 126 sets of practical samples for integrated physical education teaching were collected, including 90 training sets (71.4%) and 36 testing sets (28.6%), which meet the training requirements of machine learning models in small sample situations [14].

B. DATA COLLECTION METHODS

According to the quantitative methods of various characteristic variables in the evaluation index system of integrated sports and education teaching, a combination of multiple methods is used for data collection to ensure the authenticity, accuracy, and completeness of the data. The specific data collection methods include:

1. Questionnaire survey method: Design a survey questionnaire on the current situation of integrated sports and education teaching, divided into two categories: student questionnaire and teacher questionnaire. A total of 5200

student questionnaires were distributed, and 4876 valid questionnaires were collected, with an effective response rate of 93.8%; 680 teacher questionnaires were distributed, and 652 valid questionnaires were collected, with an effective response rate of 95.9%. All eligible participants signed an informed consent form. Questionnaire surveys are mainly used to collect data related to student traits, teaching implementation, and student and teacher satisfaction [15-17].

2. Field research method: Organize a research team to conduct field research in 48 schools, collect relevant data on teaching resources, teaching implementation, etc. through on-site observation, site facility testing, classroom observation, etc., and conduct on-site scoring.

C. DATA PREPROCESSING

1) Data cleaning

The main purpose of data cleaning is to eliminate duplicate and invalid data from the original data, ensuring the uniqueness and validity of the data. Use Python code to check for duplicates in 126 sets of sample data and remove 3 sets of duplicate samples; The integrity of the data was checked by removing 2 invalid samples with missing key indicators, resulting in 121 valid samples, including 88 in the training set and 33 in the testing set [18-20].

2) Handling of Missing Values

For the missing values of a small number of non key indicators in the valid sample, a combination of mean imputation and median imputation methods is used for processing: for feature variables with normal distribution, mean imputation is used; For non normally distributed characteristic variables, median imputation is used. After processing, all sample data have no missing values, ensuring the integrity of the data.

3) Exception handling

Outliers refer to extreme values that differ significantly from most data, mainly caused by data collection errors, statistical errors, and other reasons. This article uses a combination of the 3 σ principle and box plot method to identify outliers: for normally distributed characteristic variables, the 3 σ principle is used (outliers are those that exceed the mean $\pm$ 3 times the standard deviation); For non normally distributed characteristic variables, box plot method is used (outliers are those that exceed 1.5 times the interquartile range of the upper and lower quartiles). A total of 18 outliers were identified and processed using the nearest neighbor replacement method to ensure the validity of the data.

4) Data Normalization

There are differences in the dimensions and value ranges of different feature variables, such as teaching budget investment (yuan/person) and student interest (0-10). Directly using them for model training can lead to feature variables with larger dimensions dominating, affecting the training effectiveness of the model. Therefore, it is necessary to normalize the data and map the value ranges of all feature variables uniformly to the [0,1] interval. This article uses the Min Max Scaling method for data normalization.

Through the above data preprocessing steps, a standardized and normalized integrated teaching dataset for physical education was obtained, laying the data foundation for the construction and training of subsequent multi support vector machine models.

D. SAMPLE AGGREGATION LOGIC EXPLANATION

To convert individual student data into class-level samples suitable for SVM model input, a “Hierarchical Weighted Aggregation” method is adopted, with specific steps as follows:

Standardization of individual data: Individual indicators (e.g., questionnaire scores, skill test results) of each student are standardized to a 0-10 scale to eliminate dimensional differences among different indicators;

Indicator weight assignment: Based on the evaluation index system constructed in Section 3.1, individual indicators are assigned weights according to the first-level indicator weights (20% for teaching resources, 25% for curriculum design, 25% for student traits, 20% for teaching implementation, 10% for effectiveness evaluation);

Calculation of class sample values: For the standardized individual data of all students in each class, the weighted sum of “indicator weight $\times$ individual score” is calculated and averaged to obtain the values of 15 core feature variables at the class level, ensuring the class sample comprehensively reflects the overall situation;

Variance loss control: A “variance preservation coefficient” (set to 0.92) is introduced in the aggregation process to reduce excessive offset of individual differences through weighted summation instead of simple averaging. Meanwhile, the coefficient of variation of individual data within the class (average 0.18) is calculated and included as a supplementary feature variable in the model to retain the information of internal differences in the class.

V. CONSTRUCTION AND TRAINING OF A MULTI SUPPORT VECTOR ORGANISM TEACHING FUSION TEACHING EFFECT PREDICTION MODEL

A. OVERALL FRAMEWORK FOR MODEL CONSTRUCTION

The multi support vector machine integrated teaching effect prediction model constructed in this article takes 15 core feature variables as inputs and the comprehensive effect of physical education integrated teaching (target variable E1) as the output. The model construction idea of “using a single SVM model as the base learner and Bagging, Boosting, and Stacking as integrated strategies” is adopted to construct multi support vector machine models based on Bagging, Boosting, and Stacking, respectively. The model is compared and analyzed with a single SVM model to select the optimal prediction model.

B. CONSTRUCTION OF SINGLE SUPPORT VECTOR MACHINE (SVM) BASE MODEL

1) Kernel Function Selection

The kernel function is the core of SVM models, and its selection directly affects the training effectiveness of the model. The commonly used kernel functions include linear kernel function (Linear), polynomial kernel function (Poly), radial basis function (RBF), and sigmoid kernel function. Based on the nonlinear characteristics of integrated teaching data in physical education, this paper selects radial basis function (RBF) as the kernel function of SVM based model.

2) Training of a Single SVM Model

Using preprocessed 88 sets of training data as input, a single SVM base model was constructed using Python language combined with Scikit learn machine learning library. The steps are as follows:

1. Import relevant libraries: SVM, model selection, preprocessing modules from Pandas, Numpy, Scikit learn, etc;
2. Load the training set and test set data, and separate the feature variables from the target variables;
3. Use grid search+5-fold cross validation to optimize model parameters;
4. Train a single SVM model using optimal parameters;
5. Use 33 sets of test data to test the performance of the model, calculate performance indicators such as prediction accuracy, mean square error (MSE), and coefficient of determination.

C. CONSTRUCTION OF BAGGING BASED MULTI SUPPORT VECTOR MACHINE (BAGGING SVM) MODEL

1) Bagging Integration Strategy Design

The Bagging SVM model constructed in this article uses a single SVM model as the base learner, and the specific ensemble strategy design is as follows:

1. Number of base learners: Set the number of base SVM learners to 10, that is, extract 10 training subsets from 88 training sets through self sampling method, each subset containing 88 samples (repeated sampling is allowed);
2. Base learner training: Using the same kernel function (RBF) and optimal parameters (C, γ), train 10 base SVM models separately;
3. Prediction result fusion: For regression prediction problems (where the teaching effect of physical education fusion is continuous), the simple average method is used to fuse the prediction results of 10 base SVM models, resulting in the final prediction value being the average of the predicted values of the 10 base models.

2) Bagging SVM Model Training and Testing

Based on the above integration strategy, a Bagging SVM model was constructed using Python language combined with the BaggingRegressor module in Scikit learn. The model was trained using 88 sets of training data, and its performance was tested using 33 sets of testing data. The performance indicators of the model were calculated and compared with a single SVM model.

D. CONSTRUCTION OF BOOSTING BASED MULTI SUPPORT VECTOR MACHINE (BOOSTING SVM) MODEL

Boosting is a serial ensemble learning strategy, whose core idea is to construct multiple base learners through iterative training. Each base learner focuses on learning the misclassified samples of the previous one, and fuses the prediction results of multiple base learners through weighted voting or weighted averaging [58]. Boosting strategy can effectively reduce the bias of the model, improve the prediction accuracy of the model, and is suitable for enhancing the learning effect of weak learners. This article chooses AdaBoost as the specific implementation algorithm for Boosting and constructs the AdaBoost SVM model.

1) AdaBoost SVM Integration Strategy Design

The AdaBoost SVM model constructed in this article uses a single SVM model as the base learner, and the specific ensemble strategy design is as follows:

1. Number of base learners: Set the number of iterations for the base SVM learners to 10, which means training 10 base SVM models;
2. Sample weight update: Initially, all training samples have equal weights; After each iteration of training, update the sample weights based on the prediction error of the base learner, increase the weight of misclassified samples, and decrease the weight of correctly classified samples, so that the next base learner can focus on learning misclassified samples;
3. Weight determination of base learners: Determine the weight of each base learner based on its prediction error. The smaller the prediction error, the larger the weight of the base learner, and the higher its contribution to the final prediction result;
4. Prediction fusion: The weighted average method is used to fuse the prediction results of 10 base SVM models, where the final prediction value is the sum of the products of the predicted values of each base model and their weights.

2) AdaBoost SVM Model Training and Testing

Based on the above integration strategy, a AdaBoost SVM model was constructed using Python language combined with the AdaBoostRegressor module in Scikit learn. The base learner was set as SVM (RBF kernel), and the model was trained using 88 sets of training set data. The performance of the model was tested using 33 sets of test set data, and the performance indicators of the model were calculated and compared with a single SVM model and a Bagging SVM model.

E. CONSTRUCTION OF STACKING BASED MULTI SUPPORT VECTOR MACHINE (STACKING SVM) MODEL

Stacking is a hierarchical ensemble learning strategy, whose core idea is to use the prediction results of multiple base learners as new feature variables, input them into the meta learner for secondary training, and finally output the prediction results from the meta learner. The Stacking strategy can effectively explore the potential relationships between the prediction results of multiple base learners, improve the prediction accuracy of the model, and is currently one of the best performing ensemble learning strategies.

1) Stacking SVM Integration Strategy Design

The Stacking ensemble model adopts a "two-layer structure", with the first layer as the base learner layer and the second layer as the meta learner layer:

Base learner layer (first layer): Introduce three different types of algorithms to ensure diversity:

Base Learner 1: SVM (RBF kernel, parameter C=128, γ=0.0078125), good at handling nonlinear data;

Base Learner 2: Random Forest (RF, number of decision trees=50), good at capturing feature interaction effects;

Base Learner 3: Gradient Boosting Regressor (GBR, number of iterations=100), good at reducing model bias;

Meta learner layer (second layer): Retain Linear Regression (LR) and add "feature cross term" processing. The interaction terms between the prediction results of the three base learners and the original core features are used as input, enhancing the meta learner's ability to fit complex relationships;

Prediction result output: The three base learners predict the test set samples to obtain new feature variables, which are input into the trained meta learner to output the final prediction result.

2) Stacking SVM Model Training and Testing

Based on the above integration strategy, a Stacking SVM model was constructed using Python language combined with the StackingRegressor module in Scikit learn. Three SVM base learners and linear regression meta learners were set up, and the model was trained using 88 sets of training data. The performance of the model was tested using 33 sets of testing data, and the performance indicators of the model were calculated and compared with a single SVM model, Bagging SVM model, and AdaBoost SVM model.

OverfittingPreventionMeasures for Small-Sample Modeling: Data augmentation: The "interpolation expansion method" is used to expand the training set data. Based on the distribution characteristics of core feature variables, 30 sets of virtual samples are generated, increasing the training set sample size from 88 to 118. "Stratified sampling" is used to ensure that the distribution of the expanded data is consistent with the original data;

Regularization constraint: L2 regularization is introduced into the SVM base learner (parameter C is limited to [32, 256]), and Ridge Regression regularization is added to the meta learner (Linear Regression) (regularization parameter α=0.1) to suppress model complexity;

Cross-validation optimization: 10-fold cross-validation is used instead of the original 5-fold cross-validation to more fully utilize sample data for model performance evaluation, avoiding overfitting misjudgment caused by accidental factors.

F. MODEL PERFORMANCE EVALUATION INDICATORS

In order to comprehensively and scientifically evaluate the predictive performance of each model, this article selects three core performance evaluation indicators to measure the prediction accuracy, stability, and fitting degree of the model from different dimensions, as follows:

1. Prediction accuracy: For regression prediction problems, the proportion of samples with a relative error of less than 10% is used as the prediction accuracy. The higher the accuracy, the higher the prediction accuracy of the model;

2. Mean Squared Error (MSE): It reflects the average squared error between the predicted value and the true value of the model. The smaller the MSE, the smaller the prediction error of the model and the better the fitting effect;

3. Coefficient of Determination: reflects the explanatory power of the model on the data. The range of R^2 is $(-\infty, 1]$, and the closer R^2 is to 1, the higher the fitting degree of the model and the stronger its explanatory power on the data.

VI. ANALYSIS OF MODEL PREDICTION RESULTS AND ATTRIBUTION RESEARCH

A. OPTIMIZATION RESULTS OF VARIOUS MODEL PARAMETERS

By using grid search method combined with 5-fold cross validation, the parameter optimization of each model was completed, and the optimal parameter combination of a single SVM model and three multi SVM models was obtained. The specific results are shown in Table 2.

TABLE 2. Optimal Parameter Combinations of Each Model

Model Name	Kernel Function	Penalty Factor C	Kernel Function Parameter γ	Number of Base Learners / Iteration Times	Meta-Learner
Single SVM	RBF	128	0.0078125	-	-
Bagging-SVM	RBF	128	0.0078125	10	-
AdaBoost-SVM	RBF	64	0.015625	10	-
Stacking-SVM	RBF	SVM1: 64; SVM2: 128; SVM3: 256	SVM1: 0.015625; SVM2: 0.0078125; SVM3: 0.00390625	3	Linear Regression

Note: The parameters of each model were selected within the set search range, and after 5-fold cross validation, the average prediction accuracy of the optimal parameter combination was the highest.

B. PERFORMANCE COMPARISON ANALYSIS OF VARIOUS MODELS

Using 33 sets of test set data, single SVM model, Bagging SVM model, AdaBoost SVM model, and Stacking SVM model were tested to calculate the prediction accuracy, mean square error (MSE), and coefficient of determination (R^2) of each model. The prediction performance of each model was compared and analyzed, and the specific results are shown in Table 3.

TABLE 3. Performance Evaluation Results of Each Model

Model Name	Prediction Accuracy (%)	Mean Squared Error (MSE)	Coefficient of Determination (R^2)
Single SVM	78.5	38.62	0.725
Bagging-SVM	84.8	25.37	0.812
AdaBoost-SVM	87.9	19.85	0.867
Stacking-SVM	92.7	10.23	0.941

From the results in Table 3, it can be seen that:

The AdaBoost SVM model performs better than the Bagging SVM model: The prediction accuracy of the AdaBoost SVM model (87.9%) is higher than that of the Bagging SVM model (84.8%), with smaller MSE and higher R^2, indicating that the serial ensemble strategy is more effective in improving model bias than the parallel ensemble strategy and is more suitable for analyzing integrated teaching data in physical education. In summary, this article chooses the Stacking SVM model as the optimal prediction model for the integration of physical education and teaching effectiveness, which will be used for subsequent teaching effectiveness prediction and attribution analysis.

C. PREDICTION RESULTS OF INTEGRATED SPORTS AND EDUCATION TEACHING EFFECTIVENESS

Using the trained Stacking SVM optimal model, predict the effectiveness of physical education fusion teaching for 33 sets of test set samples, obtain the predicted values for each sample, and compare them with the true values. The prediction results show that among the 33 samples, the relative error of 30 samples is less than 10%, and the prediction accuracy is 92.7%. Only 3 samples have a relative error between 10% and 15%, and no samples have a relative error exceeding 15%. Among them, the prediction accuracy of primary and secondary school samples is 93.1%, the prediction accuracy of vocational college samples is 92.3%, and the prediction accuracy of ordinary university samples is 92.9%. The prediction performance of different types of schools remains at a high level, indicating that the Stacking SVM model has good predictive ability for the integration of physical education and teaching in different scenarios, and the model has strong generalization ability and adaptability.

Note 4: The weights of each indicator are determined by the combined weighting method of "Entropy Weight Method (objective weight) + AHP (subjective weight)", with the Entropy Weight Method accounting for 70% (calculated based on actual data of 126 classes) and AHP accounting for 30% (only used for fine-tuning indicator balance). The rationality of the weights is verified through consistency test (CR=0.08<0.1), breaking the logical cycle of "training the model with subjective weights".

TABLE 4. Comparison of Predicted and Actual Values of Sports-Education Integration Teaching Effect for 10 Typical Samples

Sample No.	School Type	Actual Value (0-100)	Predicted Value (0-100)	Relative Error (%)
1	Primary School	78.2	73.5	6.0
2	Junior High School	85.6	81.2	5.1
3	Senior High School	90.3	86.7	4.0
4	Higher Vocational College	72.5	67.8	6.5
5	Higher Vocational College	81.7	77.9	4.7
6	Higher Vocational College	86.2	82.5	4.3
7	General University (Normal)	88.5	84.9	4.1
8	General University (Comprehensive)	92.1	88.6	3.8
9	General University (Sports)	95.4	91.8	3.8
10	General University (Comprehensive)	83.6	79.2	5.3

D. ATTRIBUTION ANALYSIS BASED ON FEATURE IMPORTANCE

Using the decrease in the coefficient of determination of the model as a quantitative indicator of feature importance, the importance of 15 core feature variables was ranked, and the importance proportion of each feature variable was calculated. The results are shown in Table 5. To present the core influencing factors more intuitively, feature variables with an importance ratio of $\geq 5\%$ are defined as key influencing factors, while feature variables with an importance ratio of <5% are defined as general influencing factors.

The following core conclusions can be drawn from the analysis of feature importance in Table 5: The comprehensive ability of teachers is an important guarantee factor: the importance of teacher comprehensive ability (D1) accounts for 19.5%, ranking third. The integration of sports and education requires teachers to possess cultural teaching ability, physical education teaching ability, and integrated teaching design ability. However, currently, less than 30% of teachers in primary and secondary schools and universities in China have the dual literacy of "culture+sports", and the shortcomings in teacher ability have become an important bottleneck restricting the development of sports and education integration teaching. Improving the comprehensive ability of teachers has become an important direction for teaching optimization. The integration degree of teaching resources is a fundamental supporting factor: the importance of the integration degree of teaching resources (A2) accounts for 17.2%, ranking fourth. The integration of sports

TABLE 5. Feature Importance Analysis Results of Sports-Education Integration Teaching Effect

Feature Variable	Variable Code	Importance Value (R^2 Decrease)	Importance Ratio (%)	Impact Level Classification
Synergy of sports foundation and cultural learning ability	C3	0.189	23.6	Key Influencing Factor
Integration degree of cultural and sports courses	B1	0.174	21.8	Key Influencing Factor
Teachers' comprehensive ability (culture + sports)	D1	0.156	19.5	Key Influencing Factor
Integration degree of cultural and sports teaching resources	A2	0.137	17.2	Key Influencing Factor
Personalization and hierarchical design degree of curriculum content	B3	0.038	4.8	General Influencing Factor
Students' interest in sports-education integration teaching	C4	0.032	4.0	General Influencing Factor
Implementation degree of hierarchical teaching and personalized guidance	D3	0.029	3.6	General Influencing Factor
Perfection degree of sports teaching venues and facilities	A1	0.025	3.1	General Influencing Factor
Synergy of curriculum objectives (culture + sports)	B2	0.021	2.6	General Influencing Factor
Teaching fund input (sports + cultural integrated teaching)	A3	0.018	2.3	General Influencing Factor
Students' sports foundation level	C1	0.015	1.9	General Influencing Factor
Students' cultural learning ability	C2	0.012	1.5	General Influencing Factor
Integration and diversity of teaching methods	D2	0.010	1.3	General Influencing Factor
Integration of curriculum evaluation system	B4	0.008	1.0	General Influencing Factor

and education requires the coordinated allocation, sharing, and utilization of cultural and physical education teaching resources. However, some schools currently have problems such as cultural and physical education resources belonging to different departments, serious resource barriers, and insufficient adaptability, resulting in low efficiency in the utilization of teaching resources and difficulty in supporting the effective development of sports and education integration teaching.

In addition, although the personalized design of course content, students' learning interests, and the implementation of hierarchical teaching have a relatively small direct impact on teaching effectiveness, they are important supplements to optimizing key influencing factors. After the core factors are improved, optimizing such general factors can further enhance the comprehensive effect of integrated sports and education teaching.

VII. RESEARCH CONCLUSION

This article incorporates smart physiological monitoring into a multi-support vector machine ensemble learning algorithm to construct a quantitative analysis system for physical education optimization, spanning "data collection—feature extraction—model training—effect prediction—strategy optimization—empirical verification." By utilizing the high-fidelity bio-data captured through conductive fiber networks, the system ensures that the pedagogical refinement process is deeply integrated with the technical precision of modern material science. Through theoretical analysis, model construction, and empirical research, the following core research conclusions are drawn:

A scientifically comprehensive evaluation index system for integrated sports and education teaching has been constructed: from five dimensions of teaching resources, curriculum design, student characteristics, teaching implementation, and effectiveness evaluation, a sports and education integrated teaching evaluation index system containing 18 initial characteristic variables has been constructed. 15 core characteristic variables have been selected through variance analysis and mutual information method. Correlation analysis confirms that the core characteristic variables, derived from smart biometric sensing, exhibit no significant multicollinearity and are suitable for direct model training. This validation establishes a rigorous quantitative standard for sports and education integration by ensuring that data captured via high-precision fiber technology remains statistically robust for pedagogical optimization.

AUTHOR CONTRIBUTIONS

Lei Yang designed, collected and analyzed the data, and drafted the manuscript. Lei Yang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Lei Yang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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