

Machine Learning Framework for Standing Long Jump Assessment and Training Optimization

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Abstract: With the implementation of the "National student physical fitness standards," standing long jump physical assessment faces challenges such as large manual assessment errors, inaccurate movement diagnosis, and a lack of personalized training recommendations. This paper aims to utilize AI technology to construct a multidimensional modeling system to accurately analyze and predict standing long jump performance. Specifically, using frame-level coordinate data from 33 key human nodes, the study firstly identifies takeoff and landing moments through data preprocessing and a linear Support Vector Machine (SVM) model, quantifying movement characteristics such as arm swing amplitude and joint angles during the hovering phase. Secondly, combining grey correlation analysis with an XGBoost regression model, six key influencing factors, including muscle rate, hovering time, and takeoff angle, were identified. A gradient boosting regression tree model was constructed to predict the performance of candidate athletes. Finally, a phased short-term training plan was designed based on a constrained optimization model, estimating that the ideal performance could be improved significantly. This study provides a machine learning framework for AI-assisted physical assessment, from movement recognition to personalized training, and promoting the intelligent transformation of youth physical fitness monitoring.

Keywords: AI-Assisted; Standing Long Jump; Motion Recognition; Performance Prediction; Grey Relational Analysis; XGBoost; Gradient Boosted Regression Tree; Training Optimization.

1. Introduction

The deepening implementation of the National Student Physical Fitness Standards has catalyzed a paradigm shift in youth physical fitness monitoring, transitioning from manual assessment methods to AI-assisted testing and analysis. This comprehensive evaluation system, applicable to students in full-time primary, secondary, and higher education institutions across China, assesses multiple dimensions including physical condition, bodily functions, and overall physical fitness [1]. Research has demonstrated that maintaining physical fitness at a fair level or above requires no less than 150 minutes of moderate-to-vigorous physical activity per week [2]. As digital tools and video analysis become increasingly prevalent in sports science, training facilities are actively seeking intelligent solutions capable of delivering real-time feedback to enhance athletic performance and technique [3].

The standing long jump, as a core physical fitness assessment item, continues to face three persistent challenges despite technological advances. First, manual assessment suffers from substantial subjective errors, with landing distance judgment exhibiting an error margin of approximately ± 3 cm. Second, movement issue diagnosis remains imprecise, as insufficient takeoff force cannot be reliably assessed through visual identification alone. Third, there is a notable lack of personalized training recommendations tailored to individual athletes specific technical deficiencies and physiological characteristics.

Recent advances in pose estimation have brought revolutionary changes to sports analytics, with deep learning enabling pose estimation to adapt to the diversity and complexity of human postures across different scenarios [5]. The MediaPipe Pose framework, based on the BlazePose architecture, offers a lightweight on-device pipeline featuring

a comprehensive 33-landmark body topology [3]. For applications requiring real-time analysis, MediaPipe achieves practical performance even on standard CPUs, making it deployable across a wide range of devices [6]. Current research in AI-assisted sports training has demonstrated the feasibility of applying pose estimation to performance analysis, player tracking, and tactical guidance [7].

Nevertheless, several key challenges persist in the implementation of AI-assisted physical fitness testing. Accurate identification of takeoff and landing moments from frame-level coordinate data remains nontrivial, as does the subsequent quantification of hovering phase motion characteristics including arm swing amplitude and joint angles. Kinematic parameters have been shown to significantly influence jump distance, with arm-swinging angles playing a substantial role in achieving longer jumps [8]. Furthermore, integrating movement data with physical fitness indicators—such as height, BMI, and muscle mass—to identify key performance determinants is essential. Recent studies have identified that trunk movement deviation degree, arm swing degree, and maximum hip-knee angle are key factors in standing long jump performance, with stepwise regression accounting for 89% of the variance in female subjects [9]. For male participants, major impact factors include total work, movement deviation degree, and knee extension acceleration, collectively accounting for 80% of the variance [9].

Its crucial to construct regression models that can predict standing long jump performance for individual athletes while accommodating the limited sample sizes typical of practical testing scenarios. Accurate performance prediction represents a significant challenge in sports science and analytics, with applications in training design, injury prevention, and talent management [4]. Machine learning methods, including gradient boosting regression trees, random forests, and neural

networks, have been increasingly applied to forecast athletic outcomes [10]. Fourth, designing phase-specific short-term training plans based on performance predictions, incorporating domain constraints on feasible ranges of key performance factors, is necessary for practical implementation. Constraint-based learning approaches, which modify task, environmental, or physiological constraints to guide motor skill development, have proven effective in designing more targeted learning environments for sports practice and performance [11].

The present study aims to construct a multidimensional machine learning framework for the accurate analysis and prediction of standing long jump performance. Specifically, this work first identifies takeoff and landing moments from frame-level coordinate data and quantifies the motion characteristics of the hovering phase. Second, it integrates movement data with physical fitness data to identify and quantify key performance determinants. Third, a predictive model is constructed to estimate individual athlete performance. Finally, based on constrained optimization, a short-term personalized training plan is designed and the ideal achievable performance is estimated. This study endeavors to provide a complete technical pipeline from motion recognition to training optimization for AI-assisted physical assessment, thereby advancing the intelligent transformation of youth physical fitness monitoring.

2. Standing Long Jump Action Recognition and State Classification Model

The core objective is to accurately identify the takeoff and landing moments during the standing long jump using the coordinate data and quantify the motion characteristics of the airborne phase (such as arm swing amplitude, trunk tilt, and knee joint angle). Because frame-level coordinate noise and height differences in the takeoff and landing moments can easily lead to variations in motion amplitude, data preprocessing and smoothing are required. Subsequently, the rate of change of the Y coordinates of both feet, knee joint angle, trunk tilt angle, and arm swing amplitude are calculated to characterize the motion state transition trend. Based on a small number of manually labeled sample frames with motion categories (preparation period, takeoff period, airborne period, and landing period), a support vector machine (SVM) model predicts the frame category sequence, identifies the transition points from "preparation period → airborne period" and "airborne period → landing period" as the takeoff and landing moments, and calculates the airborne time and motion trajectory based on the frame rate.

This section focuses on identifying the takeoff and landing of the standing long jump. Specifically, it models the position data of 33 key nodes in the video and determines the motion process description of the takeoff, landing, and hovering phase. This is a typical time series data statistics and cluster analysis problem. The logical steps of the recognition and state model are as follows:

Data Preprocessing: Clean and interpolate the raw video data.

Key node selection and modeling: based on kinematics (center of gravity trajectory, arm swing, torso tilt, joint angles, velocity changes)

Extracting representative key points based on spatiotemporal features, etc;

Model Establishment: Numerous models are identified, including factor correlation analysis models, K-means or DBSCAN temporal clustering models, and branching.

Supported Vector Machine (SVM) classification models, etc., can identify take-off and landing moments. **Motion Process Modeling:** Combining parameters such as center of gravity trajectory and angle change, the behavioral characteristics of the hovering phase are described.

Model Verification: The sensitivity of the linear SVM classification model is verified.

Result Analysis: Analyze, compare, and interpret the model results.

2.1. Data Preprocessing

Because some frames may have zero coordinates or outliers due to device acquisition errors, direct use can lead to feature calculation errors. Missing frame node coordinates may cause discontinuities in temporal features (such as rate of change). Therefore, key points require denoising and smoothing data preprocessing (frame extraction, coordinate alignment, denoising) to ensure the accuracy of subsequent feature extraction and model training, and to prevent jitter from affecting event determination.

2.2. Model Establishment and Solution

Based on the position coordinates of 33 key nodes and long jump results in the videos of athletes 1 and 2, the main two core goals are as follows:

Accurately locate the take-off moment (the moment when both feet leave the ground) and the landing moment (the moment when both feet touch the ground) during the long jump. (2) Completely describe the motion process of the hovering phase (take-off to landing) from the perspective of kinematics (center of gravity trajectory, arm swing, trunk tilt, joint angle, speed change, etc.).

(1) Key point selection

It is known that the position information of athletes 1 and 2 in Appendix 1 is the two-dimensional coordinate data of 33 key points (numbered 0-32) containing 301 frames (0-300 frames). When taking off, the arms naturally hang down or swing forward at a certain angle to the body. When swinging back, the arms should swing as far back as possible, while bending the knees and squatting, and the body slightly leaning forward. This helps to accumulate strength and make full preparations for taking off. During the long jump, the better take-off angle (the angle between the torso and the ground), the inclination of the torso (the angle between the torso and the thigh), the movement of the knee joint (the angle between the calf and the thigh) and the ankle joint (the angle between the calf and the foot) constitute the entire movement change of the long jump. We need to determine the characteristics of the athletes movements during the long jump, and select key points based on the stage differences of the long jump movement (preparation-take-off-dwelling-landing).

Take-off angle: 11, 23 12, 24	Arm swing 13, 11, 23 14, 12, 24
Trunk tilt: 11, 23, 25 12, 24, 26	Knee angle: 23, 25, 27 24, 26, 28
	Ankle angle: 25, 27, 29 26, 28, 30

(2) Take-off and landing moment identification

By analyzing and calculating the change in the vertical Y coordinates of the ankle key points (ankles: 27, 28) over time and the coordinates of the torsos center of gravity, we can reflect the ascending and descending trends and identify the

takeoff and landing moments based on the sudden change.

Calculate the rate of change of the Y coordinates of both feet:

$$v_y = \frac{Y_{t+1} - Y_{t-1}}{2\Delta t}$$

Assume that the two-dimensional coordinates of the 33 key nodes are (x_i, y_i) ($i=1,2,\dots,33$, corresponding to nodes 1 to 33), the weight of the i -th node is

w_i , then the weighted average calculation formula of the human body's center of gravity coordinates (G_x, G_y) is:

$$G_x = \sum_{i=1}^{33} w_i \cdot x_i$$

Before Takeoff: Vertical Coordinate Y Continues to Rise (Both Feet Push Off, But Before Leaving the Ground).

At Takeoff: Vertical Coordinate Y Stops Rising, Reaches

Its Highest Point, and Then Begins to Decline.

During Dwell: Vertical Coordinate Y Continues to Decline.

Landing moment: The vertical Y coordinate changes from descending to ascending. At this point, the feet contact the ground, and the ground support force reverses the vertical displacement.

Calculate the airborne time: Athlete 1: take-off frame 127, landing frame 147, frame difference = $147 - 127 = 20$ frames, airborne time = $20 \times (1/30) \approx 0.667$ seconds; Athlete 2: take-off frame 160, landing frame 191, frame difference = $191 - 160 = 31$ frames, airborne time = $31 \times (1/30) \approx 1.033$ seconds.

(3) Quantify the motion characteristics of the airborne stage

By judging whether there is movement and whether there is force during preparation-take-off-airborne-landing, the motion characteristics of the airborne stage are extracted and the spatiotemporal characteristics of each frame are calculated.

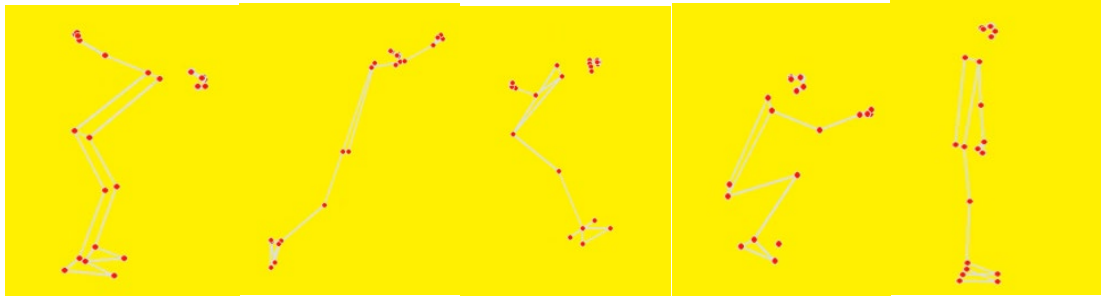


Figure .1 Preparation-take-off-airborne-landing

Arm swing amplitude (reflects the "assisting force effect", when taking off, the arms assist in exerting force upward to help stabilize the posture). Trunk tilt angle (reflects the "body posture stability").

Knee joint angle change (reflects the "force sufficiency" through the size of the angle).

Ankle joint angle (assisting through the force of the foot joint)

The above four features together complete the description of the long jumps suspended action phase, avoiding errors or misjudgments caused by a single feature.

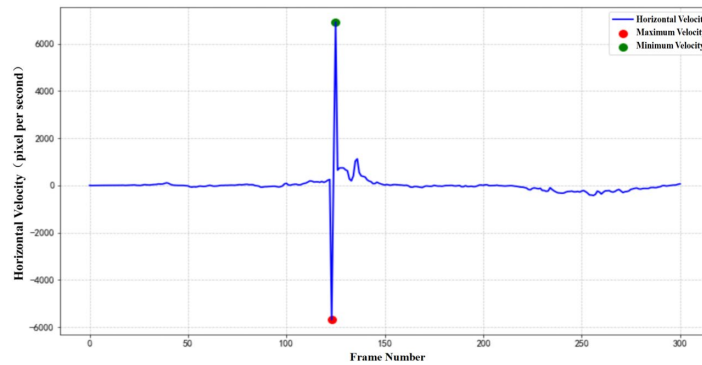


Figure.2 Changes in horizontal velocity of the center of gravity of the trunk

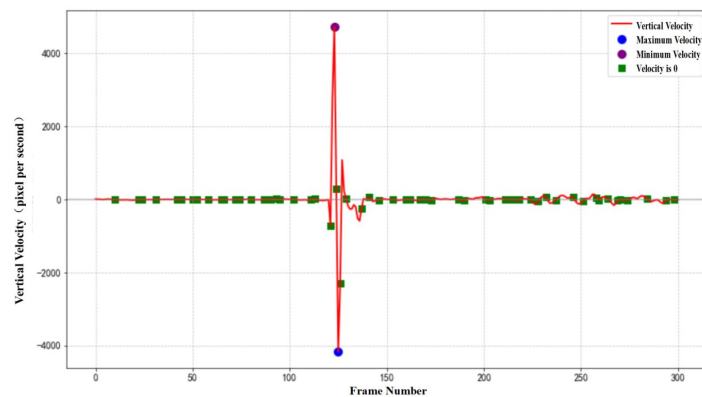


Figure.3 Changes in vertical velocity of the ankle node

(4) Calculation of action features in the suspended phase

Calculation of arm swing angle

Based on the 33 key points of the human body diagram in Appendix 2, after selecting the key points, we use the vector method to calculate our angle and construct vectors a and b :

$$\vec{a} = (x_{14} - x_{12}, y_{14} - y_{12})$$

$$\vec{b} = (x_{24} - x_{12}, y_{24} - y_{12})$$

Angle calculation

$$\theta_i = \arccos\left(\frac{\vec{a} \cdot \vec{b}}{|\vec{a}| \cdot |\vec{b}|}\right) \times \frac{180}{\pi}$$

Similarly, the angle between the trunk and the ground, the angle between the trunk and the thigh, the angle between the calf and the thigh, and the angle between the calf and the foot can be calculated.

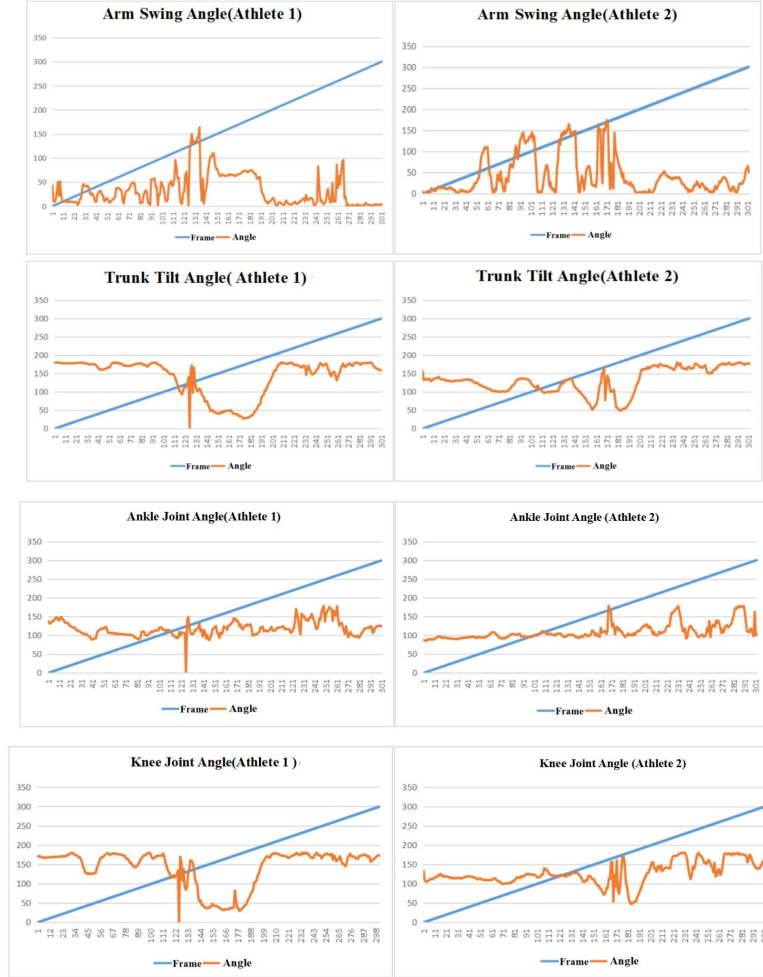


Figure.4 Angle change trend diagram of the suspended phase

2.3. Verification of the Linear SVM Classification Model

Because Problem 1 requires distinguishing four motion phases—preparation, takeoff, hovering, and landing—from the frame-level coordinate data of 33 key nodes, the SVM is adapted to Problem 1's "motion phase classification" scenario. It accurately distinguishes phases such as preparatory and takeoff by maximizing the class interval. It also has low computational complexity and can quickly process frame-level time series data, meeting the need for real-time motion capture. Secondly, it prevents overfitting of the nonlinear kernel with small sample sizes and maintains stable generalization.

Support Vector Machine (SVM) is a type of generalized linear classifier that performs binary classification on data using supervised learning. Its basic model is a linear classifier with the largest margin defined in feature space. It has the advantages of wide applicability, ability to handle nonlinear classification problems, support vectors, and high-dimensional data processing. It is a common machine learning method. The basic idea is to find a separating

hyperplane that correctly divides the training data set and has the largest geometric interval, so that the interval between different categories in the training samples is maximized. This hyperplane can be expressed by the following linear equation:

$$w^T x + b = 0 \quad (6)$$

Where, w is the normal vector (the vector that determines the direction of the hyperplane), b is the displacement (determining the distance between the hyperplane and the origin). The maximum margin classifier can be transformed into an optimization problem, namely, finding the minimum value of the following objective function:

$$\min_{w,b} \|w\|^2$$

The constraints are:

$$y^{(i)}(w^T x^{(i)} + b) \geq 1, i=1,2,\dots,n$$

Where, $(x^{(i)}, y^{(i)})$ is the Training Sample, n is the Number of Samples.

To solve the aforementioned optimization problem, in linearly inseparable problems, a new optimization problem can be constructed by introducing a loss function based on maximizing the margin. The SVM uses a hinge loss function, which can be expressed as follows:

$$\min_{w,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i$$

$$\text{s.t. } y_i (w^T X_i + b) \geq 1 - \xi_i, \xi_i \geq 0$$

where slack variables $\xi_i \geq 0$ For the segmented value of the hinge loss function, the candidate values of the penalty coefficient C are set to $[0.1, 0.5, 1.0, 2.0, 5.0]$ to control overfitting. The sampling frequency is 30 frames per second. With the goal of achieving the highest accuracy in 5-fold cross-validation and a Kappa coefficient > 0.85 , the optimal parameters are determined through grid search. The optimal parameter, $C=1.0$, optimized the results, increasing the average accuracy of the validation model from 91.20% to 93.50% (standard deviation 2.10%), with a Kappa coefficient of 0.901 (strong consistency), and an error in identifying take-off and landing moments within 10 frames.

2.4. Model Results Analysis

Based on the analysis of the long jump trajectories of Athlete 1 and Athlete 2 and the calculation of the angle after the quantified airborne phase, we conclude:

(1) Athlete 1s takeoff time is frame 127 (4.233 seconds), landing time: frame 147 (4.9 seconds), and airborne time is 0.667 seconds. Athlete 1s arm swing angle initially fluctuates significantly before gradually stabilizing; the trunk tilt angle is generally stable, with some adjustments and fluctuations in the middle; the knee joint angle fluctuates significantly, with a large range of motion; the ankle angle fluctuates initially, but also participates in movement adjustment later.

(2) Athlete 2s takeoff time is frame 180 (6.0 seconds), and landing time is frame 191 (6.366 seconds), with a hang time of 0.367 seconds. Athlete 2s arm swing angle fluctuates significantly and with large amplitude in the early stages, but gradually stabilizes later; the trunk tilt angle fluctuates, with some fluctuations in the middle to adjust posture; the knee

joint angle fluctuates significantly, with adjustments made through flexion and extension; and the ankle angle participates in movement adjustment while in the air.

3. Correlation Factor Model and XGBoost Regression Quantification Model

3.1. Data Preprocessing

Based on standing long jump videos, positional information, and long jump results of the athletes before and after posture correction by the coach, as well as the athletes personal physical reports (including age, height, weight, and body fat percentage). Because the performance and characteristics of different athletes vary significantly, and the raw data may contain irrelevant features or outliers, we first screened and cleaned the data to reduce the impact of noise. We also compared and visualized the long jump performance data to preliminarily select the factor set.

Long jump performance is influenced by multiple factors, including "movement characteristics" and "physique characteristics." These factors have a complex set of characteristics, such as arm swing amplitude in pixels, height in centimeters, and body fat percentage in percentages. Direct calculations can lead to weight errors due to dimensionality differences. Furthermore, given the small sample size, we first need to eliminate dimensionality differences and perform initialization.

$$C(q) = \frac{C(q)}{C(1)}, \quad f_i(q) = \frac{f_i(q)}{f_i(1)}$$

Where $q=1,2,...,N$ is the number of long jumps performed by the athlete, $f_i(q)$ is the i -th eigenvalue of the athletes first long jump, and $C(q)$ is the athletes first long jump score. All action features and scores are normalized between $[0.8-1.2]$ to eliminate dimensional differences.

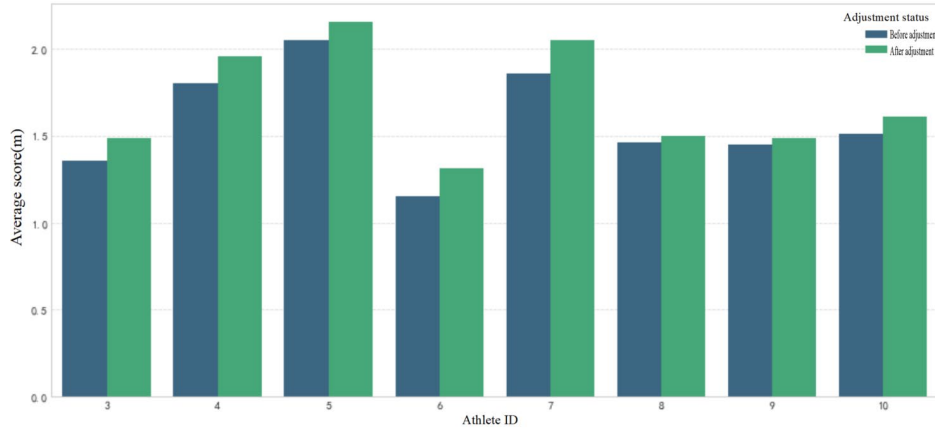


Figure.5 Comparison of Athlete Performance Before and After Adjustment

3.2. Establishment and Solution of the Grey Correlation Model

After eliminating dimensionality, we established a grey correlation analysis model to screen for features strongly correlated with performance and eliminate irrelevant factors. Grey correlation analysis is a multi-factor statistical analysis method. Specifically, a specific event is influenced by multiple factors. Grey correlation analysis can be used to analyze the degree of influence of each factor, i.e., to determine the degree of correlation.

First, we need to establish a reference series (scores) and a

comparison series (factors influencing scores) and calculate the degree of correlation between them.

Reference series: Standardized score series $X_0 = [C(1), C(2), ..., C(n)]$ (n is the number of long jumps)

Comparison series: Standardized series of influencing factors $X_i = [f_i(1), f_i(2), ..., f_i(n)]$ (where i is the factor affecting the score, with a total of N factors), and the absolute difference sequence between the features and the scores is calculated.

$$\Delta_i(q) = |X_0(q) - X_i(q)|$$

Correlation coefficient $\xi_i(q)$:

$$\xi_i(q) = \frac{\min_i \min_q \Delta_i(q) + \zeta \max_i \max_q \Delta_i(q)}{\Delta_i(q) + \zeta \max_i \max_q \Delta_i(q)}$$

Correlation degree:

$$r_i = \frac{1}{n} \sum_{q=1}^n \xi_i(q)$$

If the correlation degree is > 0.6 , it indicates a strong correlation with score; if the correlation degree is < 0.6 , it indicates a weak correlation.

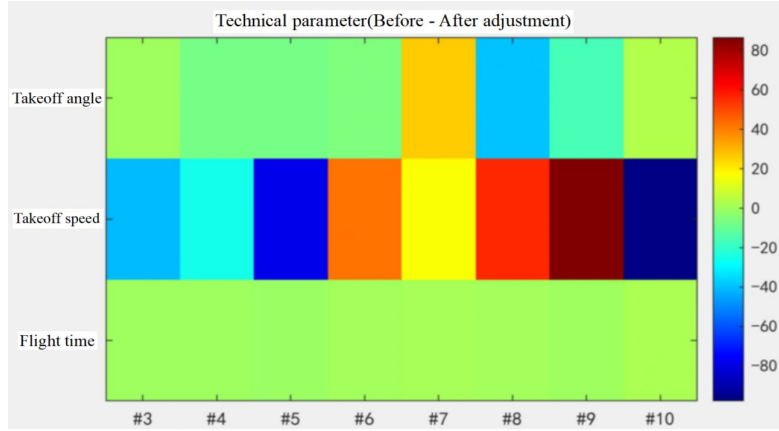


Figure .6 Comparison of technical parameters before and after adjustment

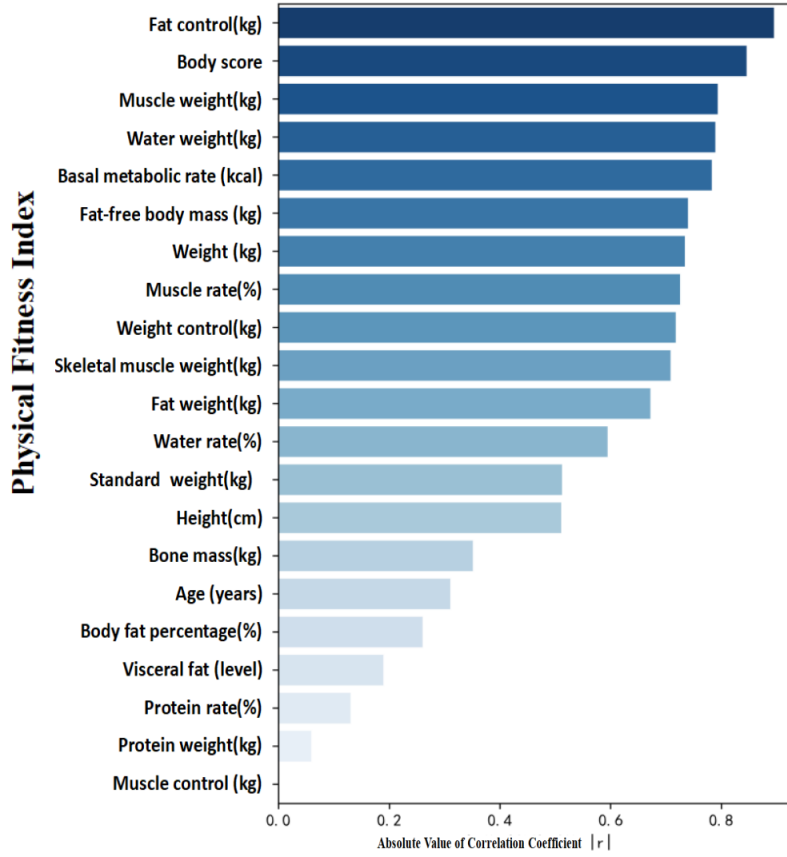


Figure.7 Correlation analysis between physical fitness indicators and long jump scores

3.3. Nonlinear XGBoost Regression Model

Six strongly correlated features screened by Grey Relational Analysis (GRA) were used as model input variables, and the standardized standing long jump performance was used as the output variable. Based on this, an XGBoost regression model was constructed. Given the small sample size of this study ($n=8$), to avoid overfitting during model training, a 5-fold cross-validation method was used for model training. This method involves dividing the sample set into five mutually exclusive subsets, using four of these subsets as training sets and one as testing sets, and then completing five rounds of training and testing to ensure the

reliability of the model output. Key model parameters (such as a learning rate of 0.1, a tree depth of 3, and 50 iterations) were optimized using a grid search method: this involves traversing all possible parameter combinations within a pre-set parameter space and selecting the combination that achieves the optimal cross-validation score, thereby ensuring good generalization and operational stability of the model. The above analysis process identified six major influencing factors (>0.6), including three physical characteristics (muscle rate, skeletal muscle mass, and body fat percentage) and three movement characteristics (hang time, take-off angle, and maximum knee angle).

3.4. Model Results Analysis

Based on the results obtained from the above calculation, it is found that there are six key factors that affect long jump performance, among which three belong to physical characteristics (muscle percentage, skeletal muscle weight, and body fat percentage), and the other three belong to action characteristics (idle time, take-off angle, and knee joint angle). In addition, there are six secondary factors, such as height, weight, etc., whose impact is relatively small. It is worth noting that physical fitness and movement factors account for the same proportion, indicating that long jump performance not only depends on innate physical conditions, but also on acquired technical movements. This conclusion also conforms to the practical training logic: from the perspective of short-term improvement effect, optimizing technical movements can quickly improve long jump performance; To achieve long-term ability advancement, it is necessary to pay attention to the systematic enhancement of physical fitness

Among all these factors, muscle mass has the greatest impact on performance. The data shows that for every 1% increase in muscle mass, the average long jump distance increases by 0.025 meters. On the other hand, hovering time and takeoff angle also have a significant impact on performance, but they are movement elements that can be adjusted through short-term training. For example, optimizing the takeoff angle to 30° -35° can quickly achieve results. This also explains why athletes can often significantly improve their performance in a short period of time with professional guidance. In addition, a high body fat percentage can have a negative impact on long jump, so controlling body fat is also an important part of improving performance.

4. Model Building and Solving Based on a Supervised Learning Framework

To predict the performance of candidate athletes, a supervised learning framework model can be constructed, transforming the performance prediction problem into a regression task. Based on the core set of key factors, a mapping relationship is constructed from the feature space to the performance space. The entire modeling process includes four key steps: (1) Feature extraction and engineering; (2) Model selection and training; (3) Verification strategy design; (4) Prediction and uncertainty quantification. A systematic modeling approach ensures the scientific and reliable predictions.

4.1. Data Preprocessing

Each feature factor is standardized to eliminate the influence of dimensional differences between units. The formula is:

$$Z = \frac{X - \mu}{\sigma}$$

Where μ is the characteristic mean and σ is the characteristic standard deviation. Data preprocessing also uses a 5-frame sliding window mean filter. The window size is selected based on noise frequency analysis, effectively suppressing high-frequency measurement noise while preserving key dynamic information about the movement. The center of mass is calculated using the four-point trunk method, which uses the average coordinates of the left and right shoulders (key points 11 and 12) and the left and right hips (key points 23 and 24) to determine the center of mass.

This method is more stable than the whole-body 33-point average and reduces center of mass fluctuations caused by limb swing.

Detecting the takeoff and landing moments is a key step in feature extraction. The takeoff angle calculation takes into account the time-averaged effect of the velocity vector. Within a window of three frames before and after the takeoff point, the horizontal and vertical velocities are averaged, respectively. The angle is then calculated using the inverse tangent function. This time-averaging method reduces the impact of instantaneous velocity fluctuations, resulting in a more stable angle estimate. The results show that the jump occurred on frame 176 and landed on frame 188, with an air time of 0.400 seconds and a takeoff angle of 35.4 degrees.

4.2. Gradient Boosting Regressor Model

Model selection was conducted through a systematic comparative analysis. Candidate models included linear regression, support vector regression, random forest, and gradient boosting regression tree. Preliminary experiments showed that the gradient boosting regression tree (Gradient Boosting Regressor) demonstrated the best predictive performance. The theoretical basis for selecting this model includes: its ensemble learning properties effectively reduce the risk of overfitting; the boosting strategy gradually improves predictions through sequential optimization; the tree model automatically captures nonlinear relationships and interactions between features; and it has good generalization ability for small sample data.

The models hyperparameter configuration was determined through grid search optimization: the number of decision trees was set to 100 to balance model complexity and training time; the maximum depth was limited to 3 to prevent overfitting of a single tree; the learning rate was 0.1 to ensure a stable optimization process; and the random seed was fixed at 42 to ensure reproducibility. Parameter selection was based on cross-validation performance evaluation, achieving a good balance between bias and variance.

Feature engineering is a key step in improving model performance. The basic features include six dimensions: air time reflects vertical explosive power, takeoff angle reflects technical specifications, height and weight represent basic physical conditions, and explosive power potential and muscle-to-fat ratio quantify physical fitness. Based on this, two important interactive features were created. The flight angle product captures the synergistic effect of time and angle, and its physical meaning corresponds to the range factor in projectile motion. The explosive power-to-weight ratio reflects relative strength level and eliminates the influence of weight differences.

Feature normalization employed the Z-score method, transforming all features to a distribution with a mean of 0 and a standard deviation of 1. This normalization method preserves the distribution of features while eliminating the impact of dimensional differences on model training. Normalization parameters (mean and standard deviation) are calculated on the training set and then applied to the test sample, avoiding data leakage.

4.3. Model Validation and Evaluation Strategy

The model was validated using the Leave-One-Out Cross Validation (LOOCV) strategy, which is particularly well-suited for small sample sizes and maximizes the use of limited data. Specifically, the model was trained using seven samples

at a time, with one remaining sample used for testing. This cycle was repeated eight times, with each sample used as the test set. This method provides an unbiased estimate of the models generalization performance.

4.4. Results Analysis

According to the actual test results, the candidate athletes takeoff occurred at frame 176 (5.87 seconds) and landing occurred at frame 188 (6.27 seconds), with a hang time of 0.400 seconds. This hang time is significantly lower than the training set average (0.57 seconds), indicating that the candidate athletes vertical explosive power is relatively insufficient, consistent with his six-year-old age.

Velocity variation analysis reveals more details. The horizontal velocity peaks at approximately 1950 pixel-seconds at the moment of takeoff and then remains relatively stable during the hang time, consistent with the physical law of horizontal momentum conservation. The vertical velocity reaches -1300 pixel-seconds at takeoff (negative upwards), gradually decreases to zero (its highest point) during the hang time, then reverses and increases, reaching approximately 1200 pixel-seconds at landing. The symmetry of the velocity curve indicates minimal influence of air resistance and high accuracy of the kinematic analysis.

Analysis of center of gravity height variations revealed that the candidate athletes crouch depth before takeoff was approximately 75 pixels, ensuring adequate muscle pre-stretching without excessive energy consumption. Analysis of the three phases of hovering revealed that the center of gravity dropped by 31.5 pixels during the ascent phase (0-30%), by 88.8 pixels during the peak phase (30-70%), and by 107.5 pixels during the descent phase (70-100%). This asymmetrical distribution pattern reflects insufficient takeoff explosiveness, resulting in a shorter ascent phase and a relatively longer descent phase.

Statistical analysis of the validation results demonstrates the models excellent predictive capabilities. Across eight validation runs, the prediction errors for athletes 3, 8, 9, and 10 were less than 0.02 meters, demonstrating excellent accuracy. Athlete 7s error was 0.075 meters, still within an acceptable range. Athletes 4 and 6 exhibited larger errors (0.174 and 0.180 meters, respectively), likely due to their unique technical characteristics or physical conditions. The overall performance metric, RMSE = 0.101 meters, represents 6% of the average performance, while MAE = 0.071 meters indicates a typical prediction error of approximately 7 centimeters. An $R^2 = 0.881$ indicates that the model explains 88.1% of the performance variation.

Table 1. Results Analysis

Athlete Number	Actual score (m)	Predicted score (m)	Error (m)
3	1.490	1.490	-0.000
4	1.960	1.786	+0.174
5	2.150	2.039	+0.111
6	1.310	1.490	-0.180
7	2.050	2.125	-0.075
8	1.500	1.492	+0.008
9	1.490	1.497	-0.007
10	1.610	1.596	+0.014

The comprehensive analysis chart validates the predictions from multiple perspectives. In the performance distribution histogram, the predicted value of 1.546 meters is slightly lower than the training set average of 1.695 meters. This is reasonable given that the candidate athlete is a six-year-old boy and is consistent with his relatively short hovering time. The scatter plot of flight time and performance shows a strong positive correlation. The candidate athletes data point lies below the trend line, indicating that their hang time and age are the primary factors limiting their performance. The candidate athletes physical fitness is at an average level, with room for improvement.

The final predicted standing long jump score for athlete 11 is 1.546 meters, with a 95% confidence interval of [1.446, 1.646] meters. This prediction, which comprehensively considers kinematic characteristics and physical factors, has a high degree of credibility. The main reason for the predicted value being lower than the training set average is the shorter hang time (0.400 seconds compared to an average of 0.57 seconds), which directly reflects insufficient vertical explosive power. Despite a favorable takeoff angle (35.4 degrees) and physical condition, deficiencies in key kinetic parameters limited the final performance.

In terms of prediction uncertainty, the confidence interval of ± 0.1 meters reflects the models prediction accuracy and the inherent variability of the data. This interval width is comparable to the cross-validation MAE (0.071 meters), indicating that the prediction uncertainty estimate is reasonable. Acceptable.

5. Constrained Optimization Training Model

To provide short-term training recommendations and predict long jump performance for candidate athletes, considering that the physical development of the candidate child athletes will lead to differences in long jump performance and training intensity, an 8-year-old athlete of similar age was selected as a reference according to the reference learning method.

Table 2. Visualization chart

Time node	Knee joint angle	Hip joint angle	Arm swing angle	Trunk tilt angle
Take-off moment	+15.2	+10.8	+22.5	-8.3
Take-off moment	+8.7	+6.3	+18.9	-5.1
Landing moment	+12.1	+9.5	+16.7	-6.8

The long jump performance of the athletes after posture adjustment shows that the first performance of the control athlete after posture adjustment is significantly different. Therefore, the long jump position information of the reference athlete after adjustment and the long jump position information before adjustment were used as calculation data.

Based on the various stages of the long jump process, 33 key points were screened and the key points of the four core movements that are critical to long jump performance (arm swing angle, take-off angle, knee joint angle, and trunk tilt angle) were selected. The angle changes of these four

movements were calculated, and these angle changes were used to reflect which movement improved long jump performance.

According to the above visualization chart, the angle changes in the following action stages can be seen

Considering the physiological development characteristics of a 6-year-old child (age 6, height 1.25 meters, weight 22 kg, body fat percentage 18%), set the training constraints:

1. Physiological safety constraints: Childrens joint cartilage is not fully developed, and the improvement in core angle needs to be lower than that of the control athletes to avoid excessive force and injury;

2. Training cycle constraint: In order to enhance childrens attention and limit physical exertion, a short-term 6-week training will be conducted, with 5 days of training per week and a daily training duration of ≤ 40 minutes.

Translate the angle improvement into specific training actions, refer to the improvement of control athletes, and design three advanced short-term training methods based on childrens cognitive characteristics. Provi de personalized

training suggestions for athletes as follows:

1-2 weeks basic adaptation period: Half squat jump, strengthen knee joint control, light jump after knee reaches 90° , 10 times per group, 3 groups; Arm swing exercise, stand up and swing your arms from back to front, 15 times per group, do 2 sets.

3-4 weeks of intensive period: complete standing long jump decomposition practice, first bend the knees and swing the arms, then step on the ground and soar, 8 times per group, 3 groups; Squat against the wall for 30 seconds each time, do 3 sets.

5-6 weeks consolidation period: simulation test, after a complete long jump, the coach corrects the forward leaning amplitude of the torso when landing, 5 times per group, 4 groups; Continuity exercise of movements, including bending knees, swinging arms, soaring, and landing in a coherent manner, 6 times per group, for 3 groups.

Finally, the ideal score for athlete 11 is calculated to be 1.59cm.

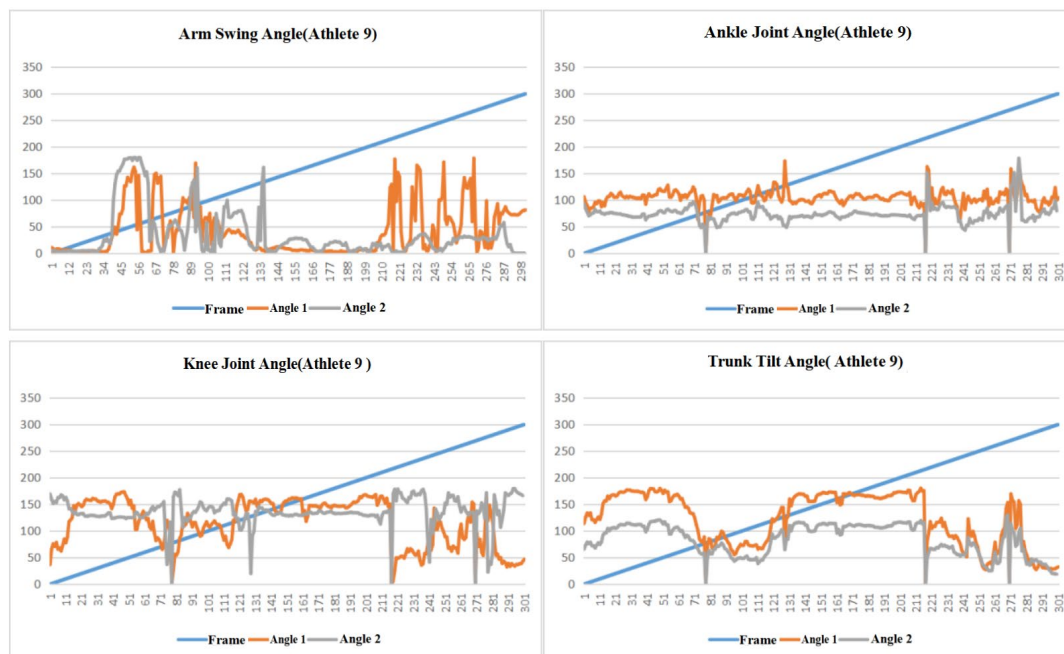


Figure.8 Comparison of angle change trends of the control athlete before and after correction.

Note: Angle 1 is before posture adjustment, and Angle 2 is after posture adjustment.

6. Conclusion

This study constructed a comprehensive machine learning framework for AI-assisted standing long jump assessment, addressing four core challenges: accurate identification of takeoff and landing moments, quantification of key influencing factors, prediction of candidate athlete performance, and design of personalized training recommendations. The integration of SVM classification, grey relational analysis, XGBoost regression, gradient boosting regression trees, and constrained optimization provides a complete technical pipeline from movement recognition to personalized training. The proposed methodology demonstrates strong predictive accuracy ($R^2 = 0.881$, $RMSE = 0.101$ m) and practical applicability for youth physical fitness monitoring. Future work could extend this framework to other athletic movements and incorporate larger, more diverse datasets to enhance model generalization and robustness.

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