ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Scientific program design and long-term follow-up study of core strength training for professional athletes

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SUMMARY: *In high-level training, core strength programs need to measurably present trunk stability, muscle synergy, load adaptation, and long-term response. This paper presents a framework for computer-aided scheme design and tracking of core strength training for professional athletes. Twenty-four weeks of data including 38,640 training records, inertial measurements, surface EMG, plantar pressure, heart rate variability, video skeleton points, and coach-rated action labels were collected from 86 athletes in sprint, basketball, soccer, and combat sports. Based on SVR, BiLSTM and attention-enhanced TCN, the framework constructs an intelligent scheme generation module, a multi-modal execution monitoring module and a long-term effect prediction module. Experimental results show that the accuracy of action quality classification is 93.4%, the mean absolute error of core stability score is 4.8%, and the F1 value of fatigue risk warning is 0.89. Compared with the empirical scheme, the system reduces the manual review time by about 41.6%, and supports the data-driven adjustment of training load, action combination, recovery interval and cycle plan in the training micro-cycle, forming a continuous and traceable training management record.*

KEYWORDS: *Core strength training; Multi-modal monitoring; Time series prediction; Intelligent scheme generation*

1 Introduction

Core strength training for professional athletes is moving from single-session fitness testing to data-driven control. The core region is responsible for trunk stability, power transmission, anti-rotation control and special movement connection. Sprint starting, football changing direction, fighting dodge and throwing force all rely on the synchronous cooperation of deep muscle groups and peripheral muscle groups. Traditional training arrangements are mostly based on coach observation, stage testing and post-match review, which can judge the completion of movements, but it is difficult to record the trunk microswing, muscle activation delay, support pressure offset and fatigue accumulation trajectory in each training. Professional athletes have high training frequency, high confrontation intensity and short recovery window. If the core strength plan lacks a computable basis, it is easy to have rough load distribution, fixed action combination and lag of cycle adjustment. The involvement of computer perception technology, wearable devices and machine learning methods enables core training to be transformed into a continuous process that can be collected, modeled and predicted.

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https://doi.org/10.65102/is2026917
Published: 30 April, 2026

In the field of intelligent sports monitoring, Alghamdi proposed an athlete health prediction method based on wearable sensors and recurrent neural network, indicating that time-series physiological data can reflect the change of training state [1]. Tsilimigkras et al. studied training load analysis and injury risk assessment in soccer, and proved that the machine learning model can link external load, internal reaction and risk level [2]. Majumdar et al. proposed a multi-season machine learning framework to analyze the relationship between training load and injury of professional football players, providing a modeling path for cross-cycle tracking [3]. Pillitteri et al. analyzed the association between internal load response and recovery ability of U19 professional soccer players, and showed that recovery status could be included in training decision variables [4]. Rossi et al. sorted out the application boundaries of machine learning in competitive sports around sports injury prediction, emphasizing the influence of data quality, feature construction and model interpretation on training scenarios [5].

The core strength training of professional athletes has multi-modal characteristics. The activation intensity and synergistic order of transversus abdominis, oblique abdominis, erector spinae and gluteus medius could be presented by EMG signals. IMU data can record torso inclination, angular velocity and anti-rotation stability. Pressure sensing can capture the support area change, the load-bearing difference between the left and right sides, and the drift of the center of gravity. Video skeleton points are able to identify motion deviations in plank, dead bug training, medicine ball rotation, weight-bearing resistance to lateral flexion, and single-leg support. de Leeuw et al. proposed a personalized machine learning monitoring method for elite volleyball players, indicating that the individualized model is more suitable for the training management of high-level athletes than the unified threshold [6]. Patalas-Maliszewska et al. constructed a motion activity suggestion system based on inertial sensors and machine learning algorithms, which provides a reference for core training action recognition and training tips [7]. Seckin et al. discussed the concept, challenges and application opportunities of wearable technology in sports, showing that sensing devices have been able to support continuous recording in training sites [8]. De Fazio et al. summarized the use of wearable sensors and smart devices in exercise performance monitoring, indicating that rehabilitation parameters, exercise performance and training feedback can be integrated into the same data link [9]. Buisseret et al. studied the application of wearable sensors in motion analysis, indicating that movement posture, joint activity and body stability have a quantifiable basis [10].

Based on the above research basis, this paper designs an integrated technical path of intelligent scheme generation, execution monitoring feedback and long-term effect prediction for the core strength training scenario of professional athletes. The training protocol is no longer regarded as a fixed list of actions, but is represented as a structured sequence of action categories, load levels, durations, interval proportions, fatigue constraints, and specific requirements. Before training, the system read the athlete's history test, special position, injury record and recent recovery index to generate the core strength training combination. During training, IMU, surface electromyography, pressure distribution, heart rate variability and video skeleton point data were collected to judge the action quality, muscle group coordination and load adaptation status in real time. After training, the time series prediction model is used to analyze the core stability score, fatigue risk and cycle response trend, and the dynamic adjustment suggestion for the next training microcycle is formed. The path can transform the core strength training of professional athletes from experience arrangement to computer-aided closed-loop decision-making process.

The main contributions of this paper are embodied in three aspects. Firstly, a multi-source feature representation for core strength training is constructed, and action execution, muscle activation, support stability and fatigue state are integrated into a unified computing framework. Secondly, an intelligent scheme generation model is designed to match the training action combination with the special needs of athletes, recovery states and risk constraints. Thirdly, a long-term tracking prediction and program adjustment algorithm is established, and the change trend of core competence is identified by using continuous training records, and the reachable load adjustment basis is output for the coach. This research conforms to the cross direction of intelligent sports, data mining and human-machine collaborative training system, and also conforms to the technical orientation of Informatica that focuses on the combination of computing methods, information systems and practical applications.

2 Literature Review

In recent years, intelligent perception, temporal learning and sports data mining have gradually entered the research of competitive training. The goals of core strength training for professional athletes are not limited to abdominal strength values, but also involve trunk control, pelvic stability, left and right support balance, force delivery efficiency, and post-training recovery status. Core training actions usually present characteristics such as long duration, small pose variation, and hidden compensatory actions, which make it difficult to capture subtle differences by manual observation alone. The computer method can convert inertial sensing, surface electromyography, pressure distribution, heart rate variability and video skeleton points into trainable features, which provides a technical basis for training scheme generation, execution monitoring and long-term tracking. Jeong et al. studied the lateral head movement in the rhythmic movement and functional action test, and proposed a core stable state classification method, indicating that the trunk control ability can be identified by the motion trajectory features [11]. Rose et al. reviewed the application of inertial measurement unit in tele-health care, and pointed out that IMU can be used for knee and hip motor function monitoring and continuous state recording, providing reference for portable collection of professional athletes' training sites [12]. Moghadam et al. compared the prediction accuracy of various machine learning models for lower limb joint kinematics, dynamics and muscle force, proving that wearable sensor data can support muscle force and joint load estimation [13]. These studies provide a basis for the computational expression of core strength training, but vocational training scenarios also need to incorporate core muscle coordination, action task category, and cycle load response into the same analysis link.

In the direction of human-machine action recognition, the deep network model has formed a more mature technical route. Khatun et al. proposed a Deep CNN-LSTM model with self-attention mechanism for human activity recognition under wearable sensors, and the model can simultaneously extract local motion patterns and long-term and short-term temporal dependencies [14]. Dirgova Luptakova et al. proposed a Transformer-based human activity recognition method for wearable sensors, which uses the attention mechanism to deal with the long-distance correlation between multi-channel time series signals [15]. Koşar and Barshan designed a new CNN-LSTM structure to enhance the classification ability of wearable motion sensor data through multi-type feature extraction [16]. Mim et al. proposed GRU-INC method, which combined Inception structure, attention mechanism and GRU for complex activity sequence recognition [17]. Jameer and Syed proposed Deep SE-BiLSTM model and adopted intelligent optimization strategy for parameter fine-tuning to make the activity recognition performance of mobile terminal and wearable sensor data more stable [18]. Asghar et al. studied the classification and monitoring of arm training actions under wristband devices, indicating that lightweight machine learning models can be used for training action counting, category recognition and execution state recording [19]. These studies show that core strength exercises such as planks, rotation resists, weight rotations, one-leg braces, and dynamic bridge movements can be organized into recognizable movement sequences that are linked to movement quality scores and fatigue warnings.

In order to further sort out the correspondence between the existing calculation methods and the core strength training research in this paper, the relevant literature can be summarized according to the type of technology, the content that can be used for reference, and the application position of this paper. In this way, the supporting role of different algorithms and sensing methods in training state recognition, action quality evaluation, fatigue trend judgment and dynamic adjustment of the scheme can be clarified, as shown in Table 1.

Table 1: Articulation of related calculation methods to the core strength training study in this paper

Literature Source	Computational Method	Transferable Element	Relevance to This Study
[11]–[13]	Core stability classification, IMU monitoring, machine learning prediction	Converting posture, joint, and muscle force data into training features	Supporting core stability scoring and training load quantification
[14]–[18]	CNN-LSTM, Transformer, GRU, SE-BiLSTM	Processing multi-channel wearable time-series signals	Supporting core training action recognition and fatigue trend judgment
[19]	Wrist-worn sensing and action classification	Identifying training action categories and execution counts	Supporting training process monitoring and automatic recording
[20]–[21]	Movement quality assessment and review of sensing technologies	Linking movement quality, sensor acquisition, and training feedback	Supporting program adjustment and long-term follow-up analysis

Movement quality evaluation research has further pushed core strength training from action recognition to action diagnosis. Swain et al., who conducted research on the assessment of movement quality by wearable devices and consumer-level technologies, emphasized that the judgment of movement quality should not stop at the completion of movements, but should also combine movement stability, rhythm consistency and feedback interpretability [20]. Venek et al. reviewed the application of sensing technology in recreational sports and professional sports, and pointed out that the sensing system can evaluate the quality of human movements from the aspects of posture, rhythm, impact and coordination [21]. For professional athletes, the value of core strength training is reflected in the power transfer and body control of specific movements. If only the number of training sessions and completion time are counted, the system cannot identify details such as lumbar compensation, pelvic deflection, uneven left and right support, and delayed core activation. In this paper, movement quality, muscle coordination and load response are jointly used as training tracking indicators, and each training movement is recorded into the athlete's personal cycle profile.

According to the existing literature, wearable sensing, activity recognition and exercise quality assessment have a high algorithm foundation, but professional athletes still need a computing framework closer to the logic of special training. Common human activity recognition mostly classifies daily actions such as walking, sitting and standing, and going up and down stairs as objects, with clear boundaries and large differences in categories. The movements in core strength training are more nuanced, with many exercises having similar appearance but distinct differences in muscle activation sequence, trunk rotation resistance, and support stability. Training data from professional athletes also has strong individual variability, varying load tolerance across events, positions, injury histories, and stages of the season. It is difficult for a unified threshold or a single classification model to fully describe the training state, and the training scheme needs to consider the action library, individual characteristics, training objectives and risk constraints at the algorithm level.

3 Methods

3.1 Intelligent scheme generation model for core strength training of professional athletes

The generation of core strength training program for professional athletes does not take the fixed action list as the starting point, but the current state of the athlete, the special demand and the position of the training cycle as the input. The system wrote plank, anti-rotation push-pull, medicine ball rotation, load-bearing lateral flexion, single leg stable support and dynamic bridge into the core training action library, and configured muscle group dominance relationship, posture stability requirements, load interval, recovery interval and taboo conditions for each type of action. Athlete-side inputs included core stability scores for the last three weeks, semG equalization, trunk angular velocity fluctuations, center of pressure drift, heart rate variability, and subjective fatigue rating. The model generates a single training scheme through feature normalization, action matching and risk constraint, so that the scheme has the properties of computable, reviewable and traceable.

Fig. 1 is used to illustrate the complete computational path from state input to program output for a core strength training program for a professional athlete. On the left is the athlete's basic information and training cycle information, including special events, position and role, recent training load, core stability test results and recovery status. The middle part is the model calculation layer, which completes the multi-modal state coding, action library matching, load constraint calculation, fatigue risk verification and scheme sorting in turn. The right side is the output layer of the scheme, which generates the combination of core training actions of the day, action sequence, number of groups, retention time, intergroup interval and risk tips. After the training is completed, the system writes the execution results into the cycle record archive module to provide continuous samples for subsequent long-term effect prediction and scheme dynamic adjustment.

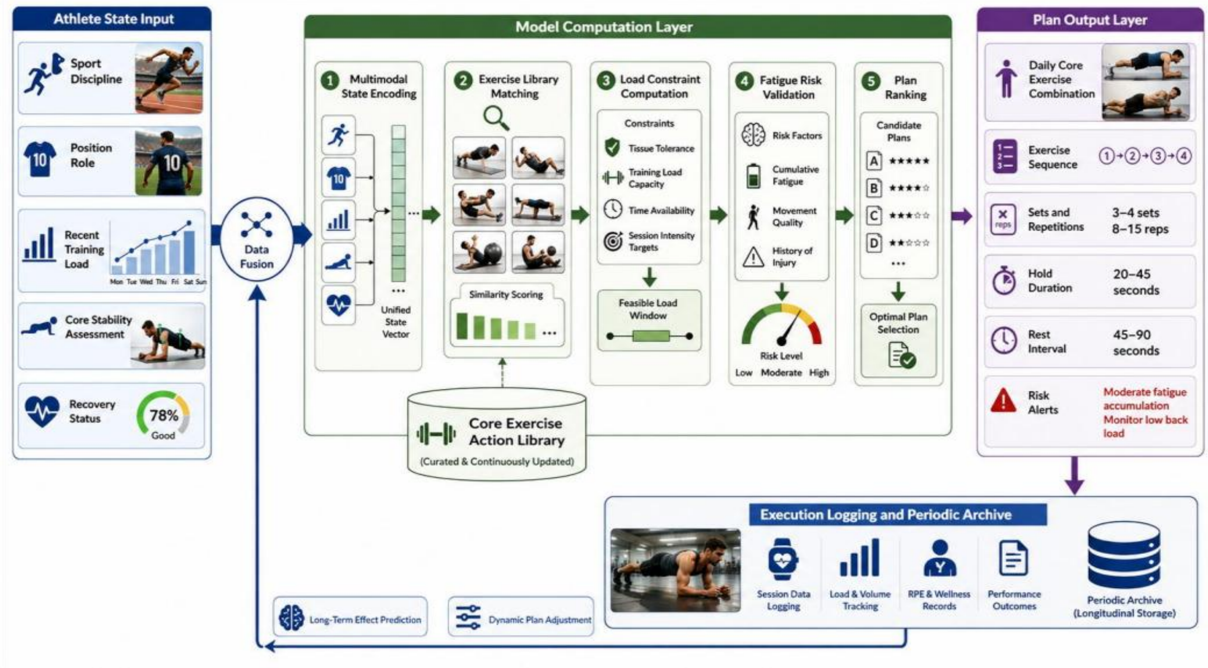

Figure 1: The generation process of an intelligent program for core strength training for professional athletes

In order to match the training action with the current ability of the athlete, the system first calculates the action fitness matrix and forms the basic weight value of the scheme generation, as shown in the following equation:

$$S_{i,j} = \sigma\left(\lambda_1 C_i + \lambda_2 M_i - \lambda_3 R_i + \lambda_4 Q_j - \lambda_5 D_{i,j}\right) \tag{1}$$

where $S_{i,j}$ represents the fitness of the i athlete to the j type of core training movement; C_i stands for core stable base value; M_i represents the level of EMG synergy; R_i indicates near-term fatigue risk; Q_j represents the action quality requirement; $D_{i,j}$ represents the gap between the individual state and the action requirement. The formula is used to screen out the training actions that are suitable for entering the candidate pool of the scheme, and avoid relying only on empirical judgment for action selection.

In order to control the core training load at the safety boundary, the model combines the action intensity, duration and recovery coefficient into constraint values and incorporates them into the scheme, as shown in the following equation:

$$L_t = \sum_{j=1}^{m} p_{t,j}\left(I_j T_j\right) \cdot \frac{1}{1 + \rho G_t} \tag{2}$$

Here, L_t represents the comprehensive load of the t training;$p_{t,j}$ indicates whether the action is selected into the scheme; I_j denotes the intensity of the action; T_j is the duration of the action; G_t denotes the recovery state. Let ρ denote the recovery inhibition coefficient. The formula ensures that the high-intensity action will not be continuously accumulated when the recovery is insufficient, and ensures that the program generation results are in line with the season training rhythm of professional athletes.

In order to characterize the core stability gain in the training program, the system fuses torso swing, EMG synergy and pressure offset to form a comprehensive score calculation result, as shown in the following equation:

$$B_t = \eta_1(1 - A_t) + \eta_2 E_t + \eta_3(1 - P_t) + \eta_4 H_t \tag{3}$$

where B_t represents the expected revenue of the scheme; A_t represents the normalized value of torso swing; E_t represents the coactivation value of core muscle groups; P_t represents the pressure center offset value; H_t represents the specific action correlation degree. This formula links core stability training to specific performance, so that the program does not only pursue the number of movements completed, but also focuses on the quality of stability control and power transfer.

In order to avoid the scheme only pursuing single intensity, the model incorporates fatigue accumulation, recovery interval and risk threshold into the comprehensive penalty function index item, as shown in the following equation:

$$\Omega_t = \mu_1 F_t^2 + \mu_2 \max(0, L_t - \tau_i) + \mu_3 U_t \tag{4}$$

Here, Ω_t represents the risk penalty of the scheme. F_t represents fatigue accumulation level; τ_i denotes the individual load threshold of the athlete; U_t stands for action compensation mark; μ_1 to μ_3 represent the weights of different risk factors. This formulation is used to depress the ranking of training schemes with obvious features of insufficient compensation and recovery.

In order to generate the training sequence that can be executed in a continuous cycle, the model takes the maximum total benefit and the minimum risk as the joint objective function in the overall calculation, as shown in the following equation:

$$\Pi^* = \arg\max_{\Pi} \sum_{t=1}^{T} (B_t - \Omega_t + \delta Z_t) \tag{5}$$

Here, Π^* denotes the sequence of optimal kernel training schemes. T is the length of the training period. Z_t represents the scheme diversity score; Let δ denote the action change weight. The objective function connects the single training session with the cycle planning, so that the system can generate the core strength training plan suitable for professional athletes while ensuring the continuity of the load.

After the scheme generation, the system synchronously saves the action source, the parameter version, and the sensor calibration status. Each output scheme contains four types of content: main training action, auxiliary stabilizing action, centrifugal control action, and recovery action, and the training records are indexed by athlete number and microcycle number. The coach can view the source of the weight for which the action was selected, and the model recalculates the remaining action combinations, keeping the training objective and risk constraints consistent. In this design, the output of the algorithm is not separated from the training site, and the core strength training scheme is limited by data, rules and manual review. The model does not directly substitute for coach judgment, but converts movement quality, load intensity, and fatigue risk into comparable calculations. If the athlete is in the pre-race reduction period, the system reduces the proportion of high-load anti-rotation action and increases the low-impact stability control task. In the strength development stage, the system increased the proportion of weight-bearing rotation and dynamic support movements, and constrained the recovery time between groups.

3.2 Intelligent monitoring and feedback mechanism of core strength training execution process

Intelligent monitoring of the execution phase of core strength training requires transforming the action completion process into a continuous computable state. Torso swing, muscle activation sequence, center of pressure drift, and heart rate load change synchronically during the training of professional athletes, such as plank, anti-rotation push-pull, weight-bearing rotation, dynamic bridge, and one-leg stable support. The system writes IMU, semG, plantar pressure, heart rate variability, and video skeleton point data into the same time window and generates action quality, stability deviation, fatigue risk, and feedback ratings for each training set. This process makes the training scene not only record the number and duration, but retain the details of each action execution.

In order to ensure the time consistency of different sensors in the same action window, the system performs delay correction and window resampling on each channel data to form a computable training segment, as shown in the following equation:

$$\tilde{x}_{r,t} = \psi_r(x_{r,t-\Delta_r}) + \epsilon_r \tag{6}$$

Here, $\tilde{x}_{r,t}$ denotes the correction value of the r sensor at time r; $x_{r,t-\Delta_r}$ denotes the original sample after delay compensation; Let ψ_r denote the resampling mapping function; Let ϵ_r denote the device noise term. This formulation is used to eliminate the sampling misalignment between EMG, pose, and pressure data so that force variation, support variation, and pose variation in the core training action can enter the same calculation window.

On the synchronized multimodal sequence, the system uses attention fusion to calculate the training state representation to avoid a single sensor anomaly directly affecting the action judgment results, as shown in the following equation:

$$z_t = \sum_{r=1}^{R} a_{r,t}\, u_{r,t}, \quad a_{r,t} = \frac{\exp(\, q_t^{\top} A_r u_{r,t})}{\sum_{s=1}^{R} \exp(\, q_t^{\top} A_s u_{s,t})} \tag{7}$$

Here, z_t represents the fusion state vector of the t window. $u_{r,t}$ denotes the r sensing feature; $a_{r,t}$ denotes the attention weight of this channel; q_t represents the current action query vector. A_r represents the channel mapping matrix. The formula can adjust the key channel weights according to the action type. For example, anti-rotation training pays more attention to trunk angular velocity and plane pressure drift, and dynamic bridge training pays more attention to the activation sequence of gluts and erector spinae.

In order to characterize the stability level of the torso in core training, the model combines the Angle fluctuation, angular velocity mutation and pressure center shift into the stability deviation, as shown in the following equation:

$$V_t = \kappa_1 \mathrm{Var}(\theta_t) + \kappa_2 \|\omega_t - \omega_{t-1}\|_2 + \kappa_3 \|c_t - \bar{c}\|_2 \tag{8}$$

where V_t represents the stability deviation; Let θ_t denote the sequence of torso inclination angles; Let ω_t denote the angular velocity sequence; c_t represents the trajectory of the pressure center; $\bar{c}$ represents the personal stability support center; κ_1 to κ_3 denote the weight coefficients. The larger the index, the more significant swing, compensation, or support offset in the core control of the athlete, the system will reduce the difficulty of the subsequent movement or extend the recovery time between groups.

Muscle group synergy is another input to judge the quality of core strength training. The system calculates the synergy index based on the activation ratio of target muscle group and auxiliary muscle group, as shown in the following equation:

$$E_t = \exp\left(-\left|\frac{g_{p,t}}{\bar{g}_p} - \frac{g_{s,t}}{\bar{g}_s}\right|\right) \cdot \frac{g_{p,t}}{g_{p,t} + g_{s,t}} \tag{9}$$

where E_t represents the core muscle synergy index; $g_{p,t}$ denotes the activation strength of major core muscle groups; $g_{s,t}$ denotes the activation strength of auxiliary muscle groups; $\bar{g}_p$ and $\bar{g}_s$ represent individual baselines. The formula can not only identify the insufficient activation of the target muscle group, but also find the excessive dependence on the hip flexors and the superficial lumbar and dorsal muscles and other compensatory phenomena, so that the training feedback is closer to the real state of the action execution of professional athletes.

The system inputs stability deviation, muscle group coordination, action rhythm and heart rate load into the quality evaluation layer together to form the execution quality result of the current action window, as shown in the following equation:

$$Q_t = \sigma(\beta_1 E_t - \beta_2 V_t + \beta_3 r_t - \beta_4 l_t + b_q) \tag{10}$$

Here, Q_t represents the action quality score; r_t represents movement rhythm consistency; l_t represents the heart rate load normalized value; b_q represents the bias term; Let σ denote the nonlinear activation function. Rather than simply judging whether an action is completed or not, the score provides orderable quality evidence for the coach side, so that differences in the execution of the same action on different athletes can be quantified.

When the execution quality deteriorates or the fatigue signal increases, the feedback module generates a hint level based on the risk probability and writes the feedback into the training record, as shown in the following equation:

$$P_t^{(k)} = \frac{\exp(A_k[Q_t, V_t, E_t, F_t, L_t, \Gamma_t] + b_k)}{\sum_{u=1}^{K} \exp(A_u[Q_t, V_t, E_t, F_t, L_t, \Gamma_t] + b_u)} \tag{11}$$

where $P_t^{(k)}$ represents the probability of the k feedback level; A_k represents the classification mapping parameter; F_t denotes fatigue state; L_t represents the current load; Let Γ_t denote the action compensation token. The formula converts the model judgment into three types of feedback: low risk reminder, action modification hint and pause review, so that the training site can complete the correction during the execution, rather than waiting for the end of the training to analyze.

In order to make the feedback reflect on the subsequent execution, the system calculates the adjustment amount for the next set of actions based on the gap between the current score and the target score, as shown in the following equation:

$$\Delta d_t = \mathrm{clip}\left(\alpha_1(Q^* - Q_t) - \alpha_2 \hat{F}_t - \alpha_3 \Gamma_t, -d_{max}, d_{max}\right) \tag{12}$$

where Δd_t represents the next set of training difficulty adjustments; Q^* represents the target quality score; $\hat{F}_t$ represents the short-term fatigue prediction value; Let Γ_t denote the strength of action compensation; clip is used to limit the adjustment amplitude. This formula ensures that feedback does not cause abrupt changes in training load, keeping movement difficulty, hold duration, and interval schedule within acceptable execution ranges for professional athletes.

After training, the system summarized the window-level monitoring results into action-level reports, recording the mass mean, stability fluctuation, muscle group coordination change, and feedback times for each group of actions. The coach side can view the video frame, EMG peak and pressure drift position corresponding to the abnormal window, and write a correction label after confirmation. The label flows back into the model parameter update process, making the recognition boundary of subsequent similar actions closer to the real execution state of professional athletes. The system also retains the device number, action version, and threshold source to ensure that each feedback can be traced back to a specific data segment, which is easy to review across training cycles. This recording method can reduce subjective judgment errors and maintain the continuity of athletes' training files, so that the feedback results can obtain more stable data support.

3.3 Long-term effect prediction and program dynamic adjustment algorithm of core strength training

The long-term effect prediction of core strength training was calculated using continuous training files. The core stability, muscle coordination, load bearing and fatigue recovery of professional athletes in different microcycles do not change linearly, and the single training score cannot directly represent the subsequent adaptation state. The system organizes the movement quality, stability deviation, EMG synergy, risk feedback, training load and recovery records of each athlete as a time series, and generates core training trends with weeks as the minimum prediction unit. The algorithm combined the temporal memory unit with the constraint optimization module to predict the capacity change in the future cycle, and then dynamically adjusted the action combination, load level, retention time and interval ratio. In terms of data organization, the system keeps the training date, microcycle position, special item, injury limit, and equipment calibration status, and writes the trainer correction label after each training to the same file. The data from different sources are uniformly numbered and entered into the prediction queue. The model can distinguish between temporary fluctuations and continuous decays, and avoid misjudging a single low score as a periodic decline.

In order to depict the continuation trend of core stability level across periods, the model inputs history score and fatigue recovery into the prediction layer together, as shown in the following equation:

$$\mathrm{m_t} = \tanh(\mathrm{A_1 s_t} + \mathrm{A_2 f_t} + \mathrm{A_3 m_{t-1}} + \mathrm{b_m}) \tag{13}$$

Here, $\mathrm{m_t}$ represents the training memory state of the t cycle. $\mathrm{s_t}$ represents the core stable score sequence; $\mathrm{f_t}$ represents the fatigue recovery feature; $\mathrm{m_{t-1}}$ represents the memory of the previous cycle; $\mathrm{A_1}$ to $\mathrm{A_3}$ represent the mapping parameters. $\mathrm{b_m}$ denotes the bias term. This formulation transforms the training effect from isolated ratings to a state representation with history dependence, enabling the model to recognize adaptation changes during successive training.

Fig. 2 shows the running link of the long-term effect prediction and scheme dynamic adjustment algorithm. On the left is the cycle training profile, which contains movement quality, stability deviation, fatigue record, and trainer correction labels. The middle part is the prediction calculation layer, which completes the time series state update, fatigue recovery estimation, risk probability discrimination and income evaluation in turn. On the right is the scheme adjustment layer, which outputs the action replacement, load change, group number correction and intermittent adjustment in the next microcycle. All adjustment results are saved synchronously with the athlete number, training phase and model version to ensure traceability of long-term tracking records.

Figure 2: Algorithm for long-term prediction and scheme dynamic adjustment of core strength training

In order to estimate the degree of fatigue recovery in the next training cycle, the current load, recovery interval and sleep quality are incorporated into the recursive calculation, as shown in the following equation:

$$\hat{f}_{t+1} = \rho f_t + \chi L_t - \varphi R_t - \upsilon u_t + \xi_t \tag{14}$$

Here, $\hat{f}_{t+1}$ represents the fatigue estimated value in the next cycle. L_t denotes the training load in this cycle; R_t is the recovery interval.u_t represents sleep and subjective recovery quality; Let $\rho,\chi,\varphi,\upsilon$ denote the regulation coefficients; Let ξ_tt denote the residual term. This formula is used to determine whether an athlete is qualified to enter higher load core training.

In order to identify potential risk states after continuous training, the system fuses stability prediction, fatigue estimation and compensation record generation probability, as shown in the following equation:

$$\hat{p}_{t+h} = \frac{1}{1 + \exp[-(c_1\hat{f}_{t+h} + c_2(1 - \hat{s}_{t+h}) + c_3\bar{\gamma}_t + c_4 e_t)]} \tag{15}$$

where $\hat{p}_{t+h}$ represents the risk probability of the h period in the future. $\hat{s}_{t+h}$ indicates the stability of prediction; Let $\bar{\gamma}_t$ denote the mean compensatory labeling; e_t represents the recent abnormal feedback times; c_1 to c_4 represent the weights. This formula unifies training status, execution quality and feedback records into risk judgment.

In order to generate a suitable adjustment amount for the next microcycle, the model performs constraint optimization among revenue, risk and action variation range, as shown in the following equation:

$$\Delta\pi_t^* = \arg\max_{\Delta\pi\in\mathcal{D}}[\hat{s}_{t+1} - \lambda\hat{p}_{t+1} - \mu||\Delta\pi||_1 - \nu H(\Delta\pi)] \quad (16)$$

Here, $\Delta\pi_t^*$ represents the adjustment amount of the optimal scheme. $\mathcal{D}$ denotes the set of optional adjustments. $||\Delta\pi||_1$ represents the amplitude of action and load variation; $H(\Delta\pi)$ represents the action structure disturbance value; Let λ,μ,ν denote the constraint weights. This formula ensures that the adjustment result will not deviate from the original training target, and also avoids excessive action changes in the same cycle.

In order to ensure that the long-term prediction results can be updated with new data, the model uses a weighted loss function to continuously correct parameter boundaries and suppress drift, as shown in the following equation:

$$\mathcal{J}(\Theta) = \sum_{t=1}^{T}\omega_t\,|\hat{s}_t - s_t| + \lambda_c\sum_{t=1}^{T}\mathrm{CE}\,(\hat{p}_t, y_t) + \lambda_r||\Theta - \Theta_0||_2^2 \quad (17)$$

where $\mathcal{J}(\Theta)$ represents the model training loss; Let ω_t denote the period weight; s_t denotes the true stable score; y_t represents the risk label.Θ_0 is the initial parameter. Let λ_c,λ_r denote the balance coefficients. The loss function takes into account prediction error, risk classification and parameter stability, making the model suitable for inter-cycle training data update of professional athletes.

In order to evaluate the comprehensive benefits after dynamic adjustment, the system combines core stability gain, fatigue reduction and execution consistency into the final index, as shown in the following equation:

$$G_t = \zeta_1(\hat{s}_{t+1} - s_t) + \zeta_2(f_t - \hat{f}_{t+1}) + \zeta_3 q_t - \zeta_4\hat{p}_{t+1} \quad (18)$$

Here, G_t represents the benefit of scheme adjustment; q_t represents execution consistency. $\hat{p}_{t+1}$ represents the risk probability in the next period; ζ_1 to ζ_4 represent the index weights. This formulation is used to compare the actual value of different adjustment schemes so that the training plan focuses on both core capability growth and preserves recovery and safety boundaries.

After the model output, the coach can view the basis of each adjustment and confirm the action replacement or load change. The system will write the confirmed plan into the next cycle training record to form a long-term training file that can be reviewed. In continuous application, the algorithm does not directly override coach judgment, but provides quantifiable candidate alternatives and risk evidence, making the source of long-term arrangements for core strength training clearer and reachable.

4 Results and discussion

4.1 Core strength training program generation and implementation effect analysis

In this paper, 86 professional athletes were selected as samples, covering four categories of sprint, basketball, football and combat, and 38,640 core strength training records were formed after continuous tracking for 24 weeks. IMU posture, surface EMG, plantar pressure, heart rate variability, and video skeleton point data were collected by the system, and the instructor score was used as the action quality label. The data was divided into training set, validation set and test set according to 7：1：2, and the experimental environment was Python3.10, PyTorch2.1 and RTX4090 platforms. The comparison methods include empirical scheme, fixed load scheme, SVR recommendation scheme and the intelligent scheme generation model of this paper. The evaluation indicators include action quality classification accuracy, core stability scoring error, F1 value of fatigue risk, feedback delay and manual review time.

To compare the adaptation differences of different schemes in core training, Fig. 3 presents five normalized indicators using radar charts. The scores of core stability, muscle group coordination, load adaptation, fatigue control and action completion quality of the experience scheme were 0.72, 0.68, 0.61, 0.58 and 0.70, respectively. The fixed load scheme is 0.75, 0.71, 0.66, 0.63 and 0.73, respectively; The SVR scheme reached 0.83, 0.79, 0.78, 0.76 and 0.81, respectively. The corresponding indexes of the proposed model are 0.91, 0.88, 0.87, 0.85 and 0.90. The data show that the advantages of the proposed model in load adaptation and fatigue control are more obvious, indicating that the intelligent scheme generation is able to adjust the action combination according to the athlete's state, rather than following the fixed training structure.

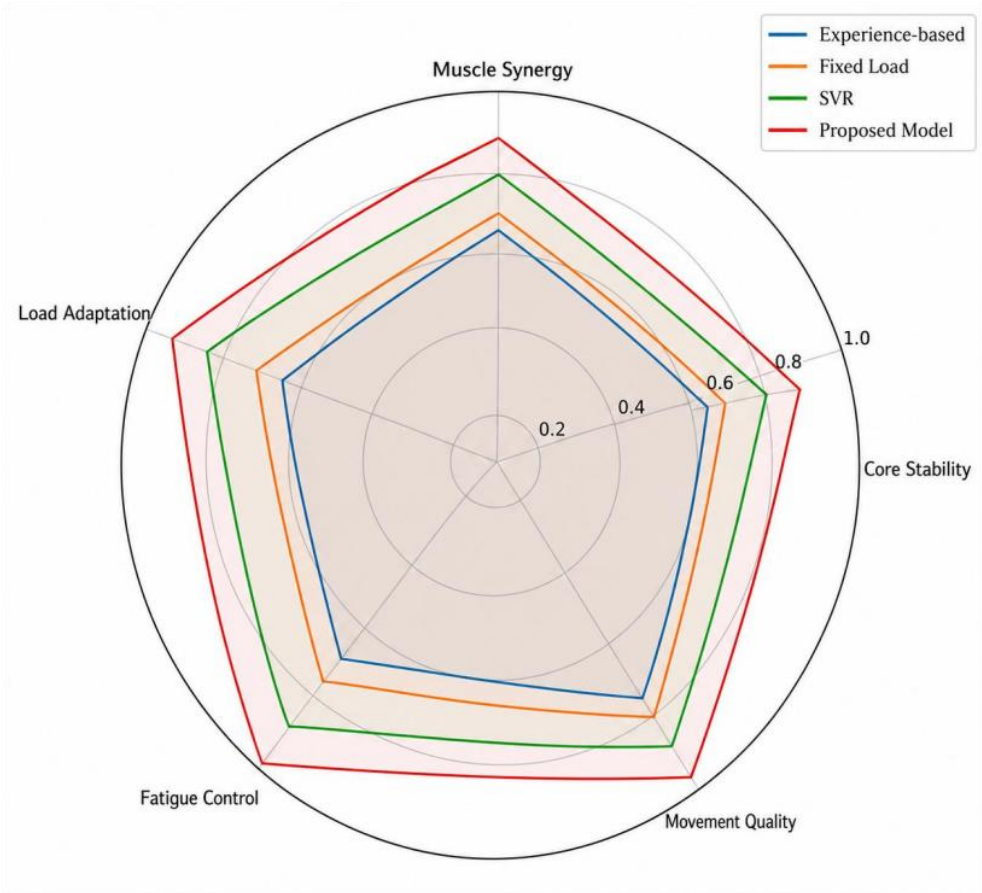

Figure 3: Radar chart of fitness for different core strength training programs

To analyze the differences in the execution of core training actions among athletes in different events, Fig. 4 uses heat maps to show the ratings of four types of athletes on five types of actions. The scores of sprinters in plank support, anti-rotation push-pull, weight-bearing rotation, dynamic bridge and single leg stable support were 88.6, 91.2, 86.4, 84.7 and 90.5. Basketball players 85.3, 87.8, 88.9, 86.6 and 87.1; For football players, 84.9, 88.5, 89.4, 87.2 and 86.8; For fighters, it was 87.5, 89.1, 92.3, 90.6 and 88.4. The quality distribution of the core training movements was affected by the special events, which was

92.3 in the weight-bearing rotation and 91.2 in the anti-rotation push-pull for the fighters and sprinters.

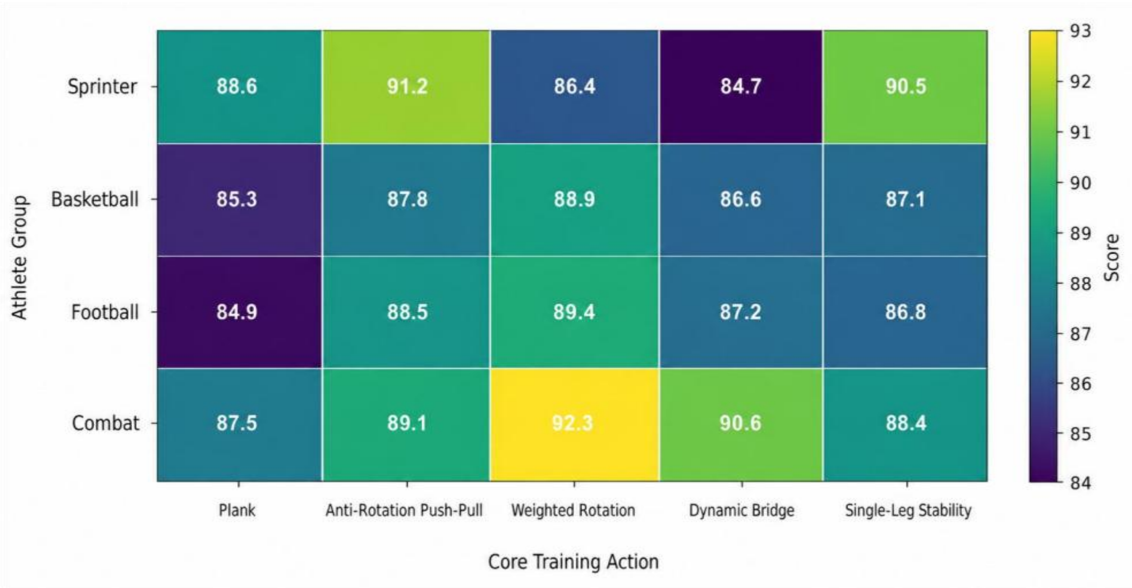

Figure 4: Heatmaps of core training action quality scores for different items

Table 2 compares the performance of different models in the training scheme generation task. The action quality classification accuracy of the model in this paper reaches 93.4%, the core stability score MAE is 4.8%, the F1 value of fatigue risk is 0.89, and the feedback delay is 41ms. Compared with the SVR recommendation scheme, the accuracy of the proposed model is increased by 5.9 percentage points, the MAE is reduced by 2.6 percentage points, and the F1 value is increased by 0.10. Compared with BiLSTM, the accuracy is increased by 2.2 percentage points and the feedback delay is reduced by 8ms, indicating that the model maintains a good balance between accuracy and response speed in the training field.

Table 2: Performance comparison of different models in the core strength training scheme generation task

Model Method	Accuracy / %	MAE / %	F1	Delay / ms
Empirical Rule	82.1	9.6	0.71	18
SVR Recommendation	87.5	7.4	0.79	36
BiLSTM	91.2	5.6	0.85	49
Attention-TCN	92.6	5.1	0.87	43
Proposed Model	93.4	4.8	0.89	41

To observe the influence of intelligent monitoring feedback on manual review, boxplots are used in Fig. 5 to present the distribution of review duration for the four types of schemes. The Q1, median and Q3 of the empirical scheme are 166s, 184s and 205s, respectively. The fixed load schemes are 142s, 161s and 183s. SVR schemes are 111s, 126s and 144s. In this paper, the models are 94s, 107s and 123s. Compared with the empirical scheme, the model in this paper reduces the median review time from 184s to 107s, with a reduction of 41.8%, which is consistent with the conclusion that the manual review time in the abstract decreases by 41.6%.

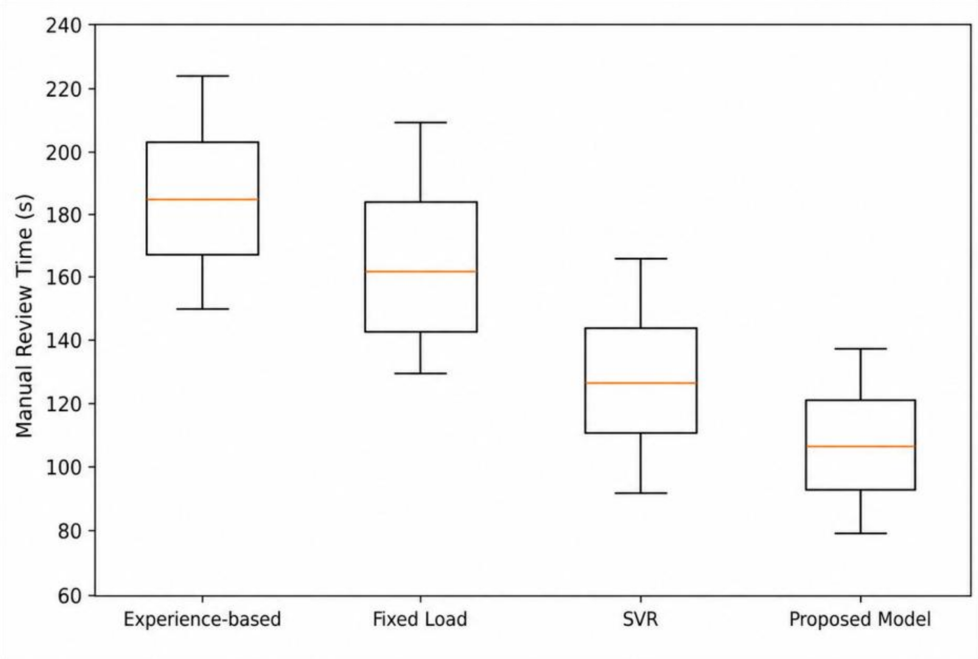

Figure 5: Box plots of manual review time under different schemes

Ablation experiments are used to examine the contribution of each module to the training effect, and Table 3 focuses on the performance decay after structural changes of the model. After removing the EMG collaborative input, the F1 value decreased from 0.89 to 0.82. After removing the center of pressure feature, MAE increased from 4.8% to 6.3%. After removing the dynamic feedback module, the review time increased from 107s to 139s. The results show that the EMG collaboration is more sensitive to fatigue risk identification, the pressure center characteristics have a more obvious impact on the core stability score, and the dynamic feedback module directly affects the efficiency of the training site review.

Table 3: Core strength training intelligent scheme generation model ablation experiments

Model Setting	Accuracy / %	MAE / %	F1	Review Time / s
Without EMG Synergy Input	90.1	5.9	0.82	128
Without Center-of-Pressure Feature	90.8	6.3	0.84	124
Without Video Skeleton-Point Input	91.0	5.7	0.85	119
Without Dynamic Feedback Module	91.6	5.3	0.86	139
Complete Model	93.4	4.8	0.89	107

In order to further judge the stability of the execution effect, Fig. 6 shows the distribution of the core stability score in the test set using violin plot. The mean value of the fixed load scheme is 82.4, and the standard deviation is 6.8. The mean of SVR scheme is 86.7, and the standard deviation is 5.1. The mean value of attention TCN scheme is 89.3, and the standard deviation is 4.4. The mean value of the proposed model reaches 91.6, and the standard deviation is reduced to 3.2. The score distribution of the model in this paper is more concentrated, and the tail of low scores is significantly narrowed, indicating that the core training plan generated by the model has more stable execution performance in athletes of different events.

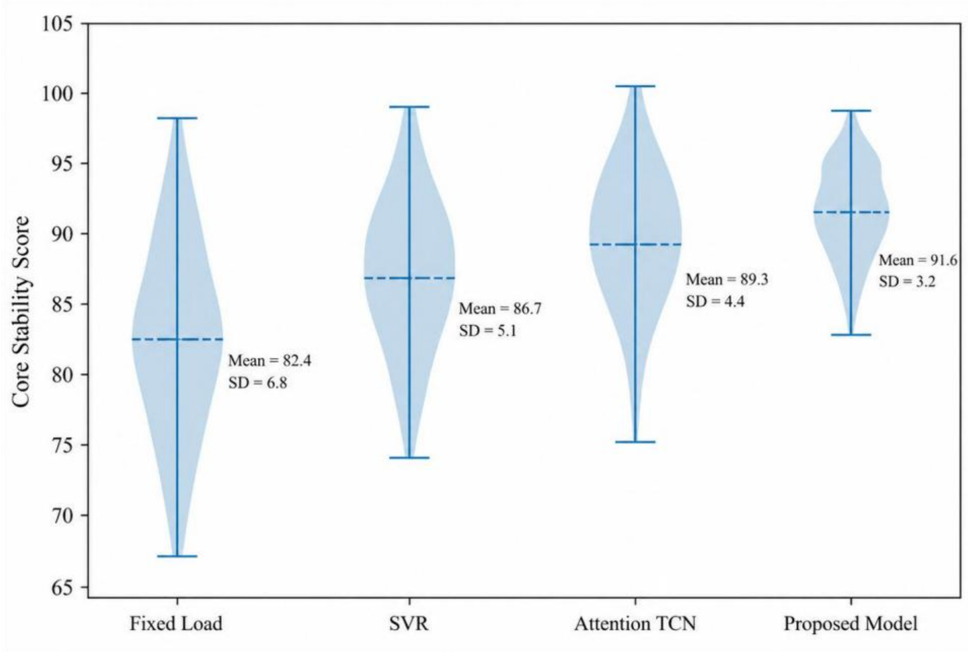

Figure 6: Violin plot of distribution of core stability scores for different schemes

The comprehensive chart results show that the proposed model can connect the core action library, individual athlete state, load constraint and training feedback into a continuous calculation process. The training scheme provides action adaptation basis, risk tips and reviewable execution records synchronously. The multimodal perception and timing model is suitable for the generation of core strength training programs for professional athletes, especially for the project scenarios with high training frequency, fine action quality requirements, and short recovery Windows.

4.2 Validation of long-term tracking effect of core strength training for professional athletes

Based on the previous test set, this experiment continued to carry out 24-week tracking verification. 86 professional athletes entered the same training management system according to their events, and the system collected the core stability score, fatigue risk, action quality, plan implementation rate and manual review time every week. Long-term tracking no longer only compares single training results, but examines the adaptation state of the intelligent scheme in successive microcycles. All the data were formed by the sensors at the training end, the coach score and the system log, with a total of 38640 tracking records. The model completed parameter calibration every four weeks, and the prediction window was set to the next two weeks.

To illustrate the change of the core stable state in different cycles, Fig. 7 uses an area trend plot to show the average rating of athletes in the four categories. In the fourth week, the scores of sprint, basketball, football and combat athletes were 84.1, 82.7, 83.5 and 85.2, respectively. At week 12, they increased to 88.6, 86.9, 87.4 and 89.1, respectively. At week 24, it reached 92.0, 90.8, 91.1, and 92.6. The data show that the scheme adjustment can maintain a stable upward trend under continuous tracking, and the score growth of combat and sprint events is more concentrated due to the higher demand for core anti-rotation.

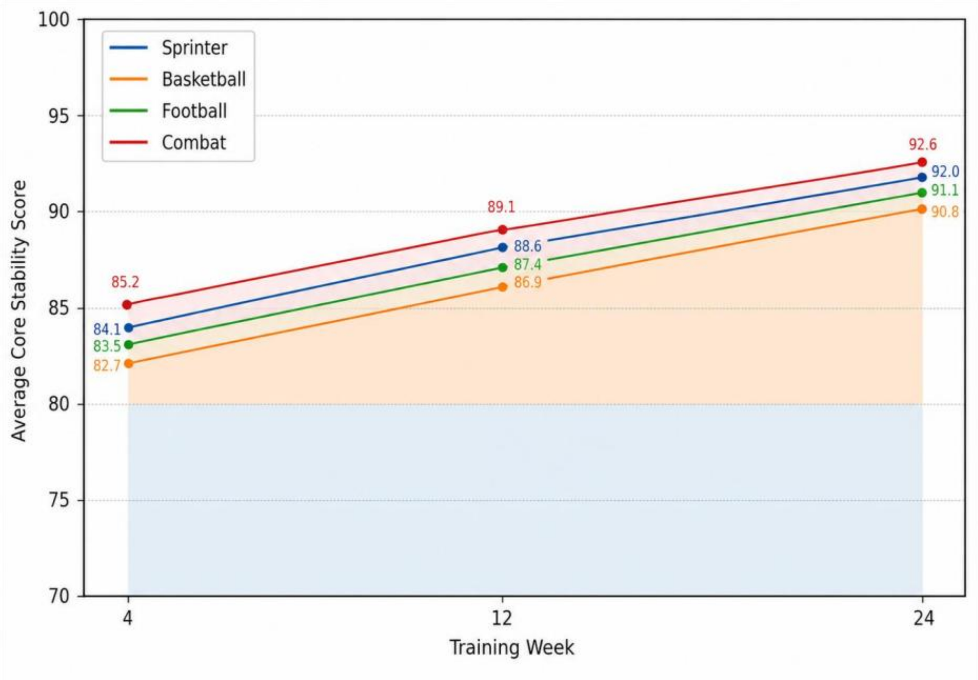

Figure 7: Trend plot of core stability score area at 24 weeks

Table 4 further compares the composite metrics of the four tracking stages. The core stability score increased from 83.9 in week 4 to 91.6 in week 24, the F1 value of fatigue risk increased from 0.81 to 0.89, and the manual review time decreased from 156s to 107s. The program execution rate stabilized above 92% after week 16, indicating that the dynamic adjustment algorithm did not cause execution interruptions.

Table 4: Indicators of core training effect in different tracking stages

Follow-up Stage	Stability Score	MAE / %	F1	Execution Rate / %	Review Time / s
Week 4	83.9	6.7	0.81	86.4	156
Week 8	86.5	5.9	0.84	89.1	138
Week 16	89.4	5.2	0.87	92.3	119
Week 24	91.6	4.8	0.89	93.7	107

To observe the long-term adaptation relationship between different items and different training actions, Fig. 8 uses heat maps to show the mean value of action quality at week 24. For sprinters, it is 93.1 in anti-rotation push-pull and 92.4 in one-leg stable support. Basketball players are 90.7 in dynamic bridge and 91.2 in weight-bearing rotation; Soccer player is 91.8 in one-leg stable support; The fighter reaches 93.5 in a weighted turn. The heat map shows that the model can form differentiated action combinations according to specific needs, and there is no convergence of the training structure of all items.

Figure 8: Heat map of core training action quality for different items at week 24

Table 5 presents the predictive ability of the long-term tracking model versus the baseline model. The proposed model has a MAE of 4.8%, a risk recall of 91.3%, and an F1 value of 0.89 within a two-week prediction window, which is better than SVR, BiLSTM, and attention TCN. The response delay is 41ms, which can still meet the immediate feedback requirements in the training field.

Table 5: Comparison of long-term tracking prediction model performance

Model	MAE / %	Risk Recall / %	F1	Delay / ms
SVR	7.4	82.6	0.79	36
BiLSTM	5.6	87.8	0.85	49
Attention-TCN	5.1	89.4	0.87	43
Proposed Model	4.8	91.3	0.89	41

To check whether the protocol adjustment was accepted by the training field, Table 6 counts the execution results of the four types of proposals: action replacement, load drop, interval extension, and recovery action insertion. A total of 624 motion replacement suggestions were proposed, and 572 were accepted, with an acceptance rate of 91.7%. There were 481 suggestions for load reduction, and 438 were accepted, with an acceptance rate of 91.1%. The acceptance rate of recovery action insertion reached 94.6%. These results show that the output of the system does not stop at the rating level, but can be fed into the actual training schedule of the coach.

Table 6: Dynamic adjustment proposal execution results

Adjustment Type	Number of Suggestions	Number Accepted	Acceptance Rate / %	Average Adjustment Magnitude
Action Replacement	624	572	91.7	1.3 items
Load Reduction	481	438	91.1	8.6%
Rest Interval Extension	536	497	92.7	18 s
Recovery Action Insertion	352	333	94.6	1.1 sets

Fig. 9 presents the prediction errors of different models at week 24 using violin distribution plots. The average SVR error is 7.4%, and the tail of the distribution extends to 12.8%. The average error of BiLSTM was 5.6%, and the high error samples were concentrated in basketball and football projects. The average attention TCN is 5.1%. The mean error of the model in this paper is 4.8%, and the interquartile range is 3.6% to 5.7%. The error distribution is more concentrated, which indicates that the model has a more stable tracking ability for cross-project and cross-cycle state changes.

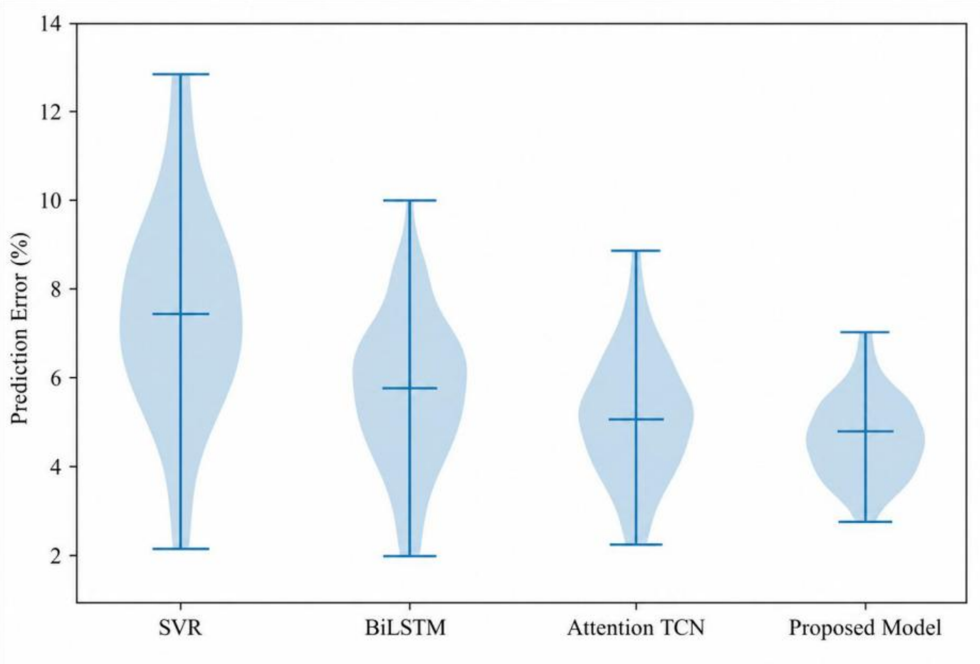

Figure 9: Violin distribution plot of long-term prediction error at week 24

The results of ablation experiments are shown in Table 7. After removing the periodic memory unit, the MAE increased to 6.1%, and the risk recall decreased to 86.2%. After removing the fatigue recovery estimation, the F1 value decreased from 0.89 to 0.83. After removing the scheme adjustment constraint, the proposal acceptance rate drops to 84.5%. The full model maintains a low error and a high proposal acceptance rate, which indicates that the long-term tracking effect depends on the combined effect of temporal memory, recovery estimation and constraint adjustment.

Table 7: Ablation experiments for long-term tracking models

Model Setting	MAE / %	Risk Recall / %	F1	Suggestion Acceptance Rate / %
Without Periodic Memory Unit	6.1	86.2	0.84	88.3
Without Fatigue Recovery Estimation	5.8	85.7	0.83	89.1
Without Risk Discrimination Layer	5.4	82.9	0.80	90.4
Without Program Adjustment Constraint	5.2	88.6	0.86	84.5
Complete Model	4.8	91.3	0.89	93.7

The 24-week tracking data show that the model can organize the action quality, stability deviation, fatigue feedback and load change in each training session into a continuous periodic state, and adjust the subsequent action combination, training intensity and recovery interval accordingly. At the end of tracking, the average core stability score reached 91.6, and the manual review time was reduced by 31.4% compared with the initial stage and 41.6% compared with the empirical scheme. These data show that the intelligent perception and timing prediction can stably record the details of the changes in the core strength training process of professional athletes, and provide a review basis for the coach to judge the training load, movement quality and recovery arrangement.

4.3 Discussion

The results of this paper show that the intelligent scheme generation model for core strength training can form a relatively stable execution effect in the training site of professional athletes. The motion quality classification accuracy of the model reaches 93.4%, the core stability score error is reduced to 4.8%, and the F1 value of fatigue risk recognition reaches 0.89, which indicates that the fusion of IMU posture, surface EMG, plantar pressure and video skeleton points can better describe trunk control, muscle group coordination and load response. During the 24-week tracking, the core stability score increased from 83.9 to 91.6, and the manual review time decreased from 156s to 107s, indicating that the action combination, load adjustment and recovery interval output by the model had continuous application value. Ablation results also show that EMG collaborative input has a great influence on fatigue risk identification, the pressure center feature is more sensitive to the stability score, and the dynamic feedback module is directly related to the review efficiency. There are differences in the thermal distribution of movement quality of athletes in different events. Sprinters have higher scores in anti-rotation push-pull, and fighters have outstanding performance in weight-bearing rotation, which indicates that the core strength training program cannot be generated only according to the uniform action template. The value of our approach lies in transforming empirical judgments in vocational training into computable records, enabling coaches to adjust training rhythms based on model evidence. It should be noted that the sensor wearing position, sweat interference and high-intensity confrontation action will still affect part of the signal stability, and a more refined calibration process and training site review mechanism are still needed in the future. In addition, as the long-term data continues to accumulate, the model's recognition of the athlete's individual training rhythm will be more stable. The scheme adjustment is no longer based on a single action score, but can refer to the association changes between season stages, recovery status and special tasks at the same time, so that the training management of professional teams can obtain a more continuous judgment basis.

5 Conclusion

This paper focuses on the design and long-term tracking of core strength training programs for professional athletes, and constructs a technical framework consisting of intelligent program generation, execution process monitoring and long-term effect prediction. The framework integrates the core action library, individual athlete states, training load constraints and feedback records into the same computing link, which makes the core strength training change from static arrangement to data-driven dynamic management. Multi-modal sensing data is used to describe trunk stability, muscle group coordination, support deviation and fatigue change. Time series prediction algorithm is used to identify periodic states. This path meets the needs of vocational training for continuous recording, fast feedback and reviewable decision, and also reflects the application value of computer models in sports training scenarios. There are still some limitations in this paper. The samples were mainly from fixed event types, and some extreme confrontation actions and high-pressure situations before the competition were insufficient coverage. Wearable devices may still produce signal drift in scenarios of high sweat, strong impact and fast body rotation. The depth of the model's integration of long-term injury history, psychological stress and schedule density needs to be strengthened. Future research can expand cross-project data sources, establish a more stable federated learning training mechanism, add a lightweight edge reasoning module, and improve the core stability evaluation by combining 3D motion capture and force platform data. The subsequent system can also develop an interpretable interface for the coach side to integrate algorithm judgment, training evidence, and human experience into the same operation process. On this basis, the core strength training of professional athletes can form a closed-loop path from state recognition, plan generation, on-site feedback to cycle correction, which provides more detailed technical support for high-level training management, and enhances the long-term continuity and traceability of training files.

Author's Profile

Junniao Meng was born in Zhengzhou, Hennan, China, Associate professor, in 1979. Graduated from Physical Education College of Henan University, A master's degree,Now She is working in the School of Physical Education of Zhengzhou Shengda University,His research interests are sports and health, and physical education reform.

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