Multimodal Deep Learning and Reinforcement Learning Framework for Personalized Sports Training and Recovery Optimization

Zhang Shunchao[1], Niu Qing[2]
[1]School of Physical Education, Pingdingshan University, Pingdingshan City, 467000, Henan, China
[2]School of Mathematics and Statistics, Pingdingshan University, Pingdingshan City, 467000, Henan, China
E-mail: 3541@pdsu.edu.cn

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In this paper, an intelligent exercise training and recovery system based on multi-modal data fusion is proposed, which aims to optimize the training plan through an AI-driven model and predict the training load and recovery requirements in real time. The system integrates athletes' physiological signals, motion images and environmental data, totaling a data set of 800 athletes. The Xception model is used to extract the spatial characteristics of the moving image, and the BiLSTM model is used to analyze the dynamic characteristics in the time series data to achieve accurate prediction of training load and recovery time. On this basis, the deep deterministic policy gradient (DDPG) reinforcement learning algorithm is used to dynamically adjust the training intensity, duration and frequency based on real-time feedback. The experimental results show that when tested under different environmental conditions, the mean square error (MSE) of the training load prediction of the system is less than 0.05, the determination coefficient (R2) is close to 0.99, and the recovery time prediction is stable between 0.018 and 0.022 in the 10-fold cross-verification. The R2 value is as high as 0.98. Compared with the traditional training system, the injury rate of athletes in this system is significantly reduced, with an average injury rate of only 0.07, much lower than the traditional system of 0.12 to 0.22. Studies have shown that the system has a wide range of application potential, especially in high-intensity training and personalised training optimisation in complex environments.

Povzetek: Članek predstavi okvir za personalizirano športno vadbo in okrevanje, ki združuje multimodalne podatke, Xception-BiLSTM napovedni model ter DDPG algoritme. Ključna je integracija napovedi obremenitve, okrevanja in sprotne optimizacije.

1 Introduction

In recent years, with the rapid development of modern sports training [1-2], athletes' training effect and recovery process have received widespread attention. Traditional sports training usually relies on the experience of coaches and fixed training plans. However, these methods cannot personalize and dynamically adjust, which may lead to athletes overtraining or insufficient recovery, thereby increasing the risk of sports injuries [3-4]. Especially in high-intensity training, athletes' physical load and recovery needs are constantly changing. Therefore, evaluating the exercise load and recovery status in real time and accurately and dynamically adjusting according to the actual situation has become the key to improving the training effect and preventing sports injuries. With the advancement of wearable devices [5-6] and sensor technology, it has become possible to monitor and evaluate exercise training based on multimodal data [7-8]. For example, through real-time monitoring of multi-dimensional data such as heart rate variability (HRV), muscle oxygen content, EMG signal (EMG), and exercise trajectory, athletes' training load and recovery status can be comprehensively analyzed, to formulate personalized and optimized training strategies [9-10]. These technologies not only provide a scientific basis for dynamically adjusting the training plan but also significantly improve the accuracy and safety of training. Based on these technologies, this research aims to build an intelligent sports training and recovery system that integrates sports load prediction, recovery time prediction and training optimization functions to provide athletes with personalized training programs to improve training effectiveness and reduce injury risk, and lay a theoretical foundation for the future application of intelligent sports training systems.

The main contribution of this study is to propose an intelligent sports training and recovery system based on multimodal data fusion. Through accurate prediction of exercise load and recovery time, combined with the DDPG reinforcement learning algorithm, personalised training programs can be optimised, significantly improving athletes' training effect. By integrating physiological data, motion images and environmental data, the Xception-Bilstm model accurately predicts athletes' exercise load and recovery time. Based on these prediction results, the DDPG algorithm optimises dynamic load adjustment and recovery strategy during training. In this way, the system can automatically adjust the training load based on real-time feedback, so that the training intensity is always kept in the optimal range of the athlete, thereby avoiding the problem for overtraining or insufficient recovery and reducing the incidence of sports injuries.

This study proposed a training optimisation framework combining deep learning and reinforcement learning, filling the gap in the lack of personalised optimisation and load prediction in intelligent training systems. In addition, the model not only takes into account traditional physiological parameters but also integrates motion image data and environmental data, greatly improving the accuracy of load prediction and recovery time prediction. At the same time, the innovative application of the DDPG algorithm in this study can make targeted dynamic adjustments based on the predicted training load and recovery status, automatically optimize the training plan, further improve the training effect, and has strong application prospects and practical significance.

The main contributions and innovations of this research are reflected in the following aspects: First of all, an intelligent sports training and recovery optimization method based on multi-modal data fusion is proposed, making full use of athletes' physiological signals, motion images and environmental data, significantly improving the degree of personalization and prediction accuracy of the training plan. Secondly, combining the Xception and Bilstm models for deep learning analysis, extracting spatial features and time series features respectively, and realising the dynamic optimisation of the training plan through the DDPG algorithm solves the problem that traditional systems lack real-time adjustment capabilities. Finally, comparative experiments are used to verify the significant advantages of this system over traditional training systems, especially its outstanding performance in reducing the injury rate of athletes. These not only provide new theoretical support for intelligent sports training but also demonstrate its extensive potential in practical applications, laying a solid foundation for developing intelligent sports training systems in the future.

2 Related work

In the past few years, research on sports training and recovery has gradually received more and more attention, especially in refined training and personalized adjustment. Traditional training methods rely on the experience of coaches and fixed training plans. Although this method can guarantee the basic training effect, it cannot make real-time adjustments based on each athlete's unique physiological characteristics, training level and recovery status, which can easily lead to overtraining or insufficient recovery, increasing the risk of sports injuries [11-12]. In order to solve these problems, many studies have begun to explore the use of wearable devices [13-14] and sensor technology to monitor athletes' physiological signals in real time, such as heart rate, blood oxygen, muscle fatigue and other indicators, and also analyze athletes' posture and movement trajectory through video monitoring and other means. These technologies can provide more feedback information for the training process, and combined with artificial intelligence and machine learning technologies, more accurate evaluation of training load [15-16], recovery status and training effect. Based on data such as heart rate, acceleration and electromyography, existing studies have predicted exercise load through regression or neural network models and achieved certain results. At the same time, some progress has been made in the research on sports recovery in recent years, especially in evaluating the recovery level by monitoring athletes' physiological signals, including heart rate variability, muscle damage markers, etc. Many scholars have proposed different recovery prediction models. Despite this, there is still a lack of models that can accurately predict training load and recovery time, especially in the design and dynamic optimisation of high-intensity, personalised training programs. Existing research has not yet formed a systematic solution. Therefore, how to combine multimodal data with deep learning algorithms to achieve more accurate load prediction and recovery time evaluation has become an important direction in current research.

Although there has been some progress in related research, there are still many challenges in personalized optimization. Many AI-based sports training systems mainly rely on fixed training programs and lack dynamic adjustment functions for individual differences. Some studies have tried to use deep learning algorithms, such as convolutional neural networks and long short-term memory networks [17-18], to analyze athletes' training data and make certain predictions. However, most of these methods focus on a single data source or a fixed training load and fail to achieve deep fusion of multimodal data or establish a dynamic feedback mechanism between recovery needs and training load. In order to solve this problem, in recent years, reinforcement learning methods [19-20] have gradually been introduced into the research of sports training and recovery optimization. In particular, deep reinforcement learning has advantages in real-time decision-making and dynamic optimization, and has begun to be applied in personalized training systems. DDPG [21-22], as a reinforcement learning method suitable for high-dimensional continuous action space, has been widely used in recent years in robot control, autonomous driving, and other fields in recent years. It can optimise training strategies by interacting with the environment, adjusting training load and recovery time, and thus realise personalised training program design. Although reinforcement learning has broad application prospects in training load optimization, the current research on combining it with multimodal data-integrated load prediction and recovery time assessment models is still in its infancy, and there are relatively few related studies. Therefore, how to combine deep learning and reinforcement learning methods to use multimodal data to achieve accurate load prediction, recovery time assessment, and dynamic training optimization is still a challenging and urgent problem to be solved.

Table 1: The comparison of the key elements of the existing research

	Research method	advantage	Disadvantage
Traditional method	Relying on coach experience and fixed training plan, lack of real-time dynamic adjustment	Simple and easy, suitable for basic training scenarios	The lack of personalization and dynamic adjustment can easily lead to insufficient training or recovery, increasing the risk of sports injury
Zhang et al. (2022)	Use the attention mechanism LSTM network to predict game performance	Can effectively capture the dynamic characteristics in time series data, suitable for competition performance prediction	The data source is single, based only on competition data, and lacks the ability of multi-modal fusion
Sharp et al. (2022)	The impact of high-intensity multimodal training on healthy people	Comprehensively analyzed the multifaceted effects of high-intensity training and provided theoretical support	Lack of specific model design and algorithm implementation, can not be directly applied to personalized training optimization
Naureen et al. (2020)	Personalized training plan based on genetic testing	Provides a personalized training basis, which helps to accurately customize the training plan	Only focus on genetic data, not combined with other multimodal data, and the scope of application is limited
Wackerhage & Schoenfeld (2021)	Evidence-based personalized training plan and exercise prescription	Emphasize the scientific basis, which helps to improve the training effect and health level	Relying on existing research data, lack of intelligent dynamic adjustment ability
Gennarelli et al. (2020)	Psychological intervention promotes sports injury recovery	Provides proof of the effectiveness of psychological intervention and contributes to full recovery	Only focus on psychological factors, lack of comprehensive analysis of physiological data and environmental factors
Song et al. (2021)	Deep learning convolutional neural networks predict the risk of sports injury	The use of deep learning technology to improve the prediction accuracy, suitable for sports injury risk assessment	The data source is single, the generalization ability of the model is poor, and the reliability is doubtful.

3 Methods

3.1 Data collection and preprocessing

This research aims to solve the problem of overtraining or insufficient recovery caused by the lack of personalization and dynamic adjustment in traditional sports training through multi-modal data fusion and AI-driven optimization methods. Specific research objectives include: (1) Design and verify a sports load and recovery time prediction system based on the Xception-BiLSTM model to ensure its prediction accuracy under different environmental conditions (MSE<0.05, R2>0.95); (2) Use DDPG enhanced learning algorithm to achieve dynamic training optimization and reduce the injury rate of athletes to below 0.1; (3) evaluate the applicability of the system in a variety of training scenarios, especially in high-intensity training and performance in complex environments.

The research uses a multi-modal data fusion method to collect physiological data closely related to athletes' exercise load and recovery status from multiple data sources to assess their training load and recovery comprehensively. The system integrates various physiological signal monitoring methods, including heart rate, electromyography (EMG), breathing rate, and oxygen consumption. Each data source provides different information dimensions to describe the athlete's physiological state and sports performance accurately. As a key indicator, heart rate is monitored in real time through wearable devices such as smart bracelets or watches, and built-in photoelectric volumetric sensors are used to capture changes in blood flow and calculate heart rate. Electromyography is used to assess muscle load, fatigue, and recovery. Electrical signals of specific muscle groups are collected through surface or needle electrodes to reveal the muscle fatigue process at different training intensities. Breathing rate reflects the athlete's breathing burden and exercise intensity. At the same time, oxygen consumption directly measures aerobic metabolic capacity and training load to further to assess the athlete's endurance level and recovery needs. The comprehensive analysis of these multi-modal data provides a scientific basis for accurately predicting the training load and optimizing the recovery strategy [23-25].

This article collects data on 800 athletes, derived from joint research projects of multiple cooperative institutions, covering professional athletes and amateur sports enthusiasts, with high diversity and representation. The multimodal data generated by each athlete (including physiological signals, moving images, and environmental data) has undergone strict preprocessing and quality control to ensure its availability in model training.

The data collection of each athlete covers multiple training sessions, with a period of 8 consecutive weeks and 3-5 training sessions per week to ensure that the data is balanced between different temperature ranges (such as low temperature, medium temperature, and high temperature) and activity types (aerobic exercise, strength training, etc.).In addition, the collection of all human body data has been approved by the relevant ethics committees, and the principle of informed consent is strictly followed to ensure the privacy protection of participants. After the data is collected, it is processed anonymously, and the information related to personal identity is removed to ensure the security and compliance of the data. The collected physiological data are shown in Table 2.

Table 2: Physiological data display

Athlete No.	Heart rate (bpm)	Electromyography (mV)	Respiratory rate (breaths/min)	Oxygen consumption (L/min)	Exercise load (RPE)
001	130	0.85	25	1.2	7
002	145	1.1	28	1.5	8
003	120	0.75	22	1	6
004	155	1.3	30	1.8	9
005	135	0.9	26	1.3	7
006	140	1.05	27	1.4	7
…	…	…	…	…	…
800	150	1.25	29	1.7	8

Through the combination of accelerometer and gyroscope, the IMU can provide data on an athlete's cadence and stride. These two parameters are particularly important in running, walking, and any sports that require gait analysis. Cadence refers to the number of steps per unit time, while stride is the distance of each step. The athlete's physical condition and exercise efficiency can be reflected by monitoring the changes in cadence and stride. The collected motion data are shown in Table 3.

Table 3: Sports data display

Athlete No.	Acceleration (m/s^2)	Rotation angle (°)	Cadence (steps/minute)	Movement status
001	3.5	45	110	running
002	4.2	50	115	running
003	2.8	40	100	walk
004	5	60	120	running
005	3.8	55	108	running
006	2.5	35	95	walk
…	…	…	…	…
800	3.2	42	105	walk

Motion capture systems, such as Kinect, will be used to obtain sports image data of athletes. Kinect uses infrared sensors and depth cameras to capture athletes' movements and postures in real time, thereby providing high-precision three-dimensional spatial data. These data include athletes' limb postures, movement trajectories, and key point locations, which can accurately reflect the athletes' movement execution process. The image data obtained through the motion capture system can monitor the athletes' movement accuracy and trajectory in real time during training, helping to analyze movement patterns, posture stability, and movement optimization needs. The collected environmental data are shown in Table 4.

Table 4: Environmental data display

Time point (minutes)	Temperature (°C)	humidity (%)	Air pressure (hPa)	Wind speed (m/s)
0	22	50	1012	2.5
5	23	52	1011	2.3
10	24	55	1010	2.7
15	25	58	1009	3
20	26	60	1008	3.2
25	27	62	1007	3.5
30	28	65	1006	3.6
35	29	67	1005	3.8

In order to comprehensively evaluate the recovery level of athletes, this study used wearable devices to collect key data such as athletes' sleep quality and muscle recovery. Sleep quality is an important factor affecting athletes' recovery. Good sleep helps muscle repair and energy recovery, and reduces fatigue after training. Wearable devices, such as smart bracelets or sleep monitors, can monitor athletes' sleep cycles, deep sleep duration, sleep interruptions in real time to help assess their sleep quality. In addition, wearable devices can also be equipped with electromyography sensors to monitor muscle recovery after exercise, such as muscle electrical activity, muscle fatigue, and relaxation. These data can reflect the athlete's muscle recovery process and help the training team judge their recovery level.

There is unnecessary noise in physiological and motion data, which may come from sensor errors, environmental interference, etc. The low-pass filter can remove high-frequency noise and retain the main components of the signal. The formula is:

$$y(t) = \int_0^t h(t-\tau)x(\tau)d\tau (1)$$

In Formula 1, $x(\tau)$ is the original signal, $h(t)$ is the impulse response of the filter, and $y(t)$ is the filtered signal.

In order to avoid the dimensional differences between different data sources, the data is standardized. The formula is:

$$Z = \frac{X-\mu}{\sigma} (2)$$

Time series data is affected by random fluctuations, and smoothing can remove short-term noise. The moving average formula is:

$$y_t = \frac{1}{N}\sum_{i=t-N+1}^{t} x_i (3)$$

For time series data, the formula for linear interpolation is:

$$x(t) = x_1 + \frac{t-t_1}{t_2-t_1}(x_2 - x_1) (4)$$

Since multimodal data comes from different sensors, it has different timestamps, so data synchronization is required. Ensure that all data sources are aligned on the same time axis to avoid data alignment problems caused by time differences. For data with different timestamps, use interpolation to resample the time axis to ensure the data at each time point corresponds.

$$t_{aligned} = t_0 + \Delta t \cdot n (5)$$

In Formula 5, t_0 is the initial time, Δt is the time interval, and n is the sequence number of the sample. Resampling can ensure the time consistency of the data and avoid synchronization errors.

Through time synchronization technology, the image data generated by the motion capture system is aligned with the physiological signals collected by the wearable device and the external conditions recorded by the environmental sensor on the same timeline. Specifically, the interpolation method is used to resample data with different sampling frequencies to ensure that each data type corresponds at every point. This multi-modal data fusion method enables the system to comprehensively analyse the status of athletes, thereby providing more accurate input for training load prediction and recovery time evaluation.

3.2 Model design

This study predicts athletes' training load and recovery needs based on the Xception-BiLSTM model. Xception is a variant of CNN that optimizes traditional convolution operations through deep separable convolutions, significantly improving the efficiency of the network. Google proposed the Xception model, which is a further improvement of the Inception network. Its core advantage lies in the use of deep separable convolutions, which divide traditional convolution operations into two steps: first, channel-by-channel convolution, and then, inter-channel convolution, thereby effectively reducing the amount of calculation while maintaining the efficiency of the convolution operation.

Given an input tensor X and a convolution kernel K, the standard convolution is calculated as:

$$Y = X * K (6)$$

Depthwise separable convolution decomposes the standard convolution into two steps: channel-wise convolution and point-wise convolution (1x1 convolution). Perform channel-wise convolution on the input tensor:

$$X' = X * K_d (7)$$

Perform a 1x1 convolution on X':

$$Y = X' * K_p (8)$$

Xception extracts the athlete's motion features from sports images, including the athlete's posture, trajectory, accuracy, etc. These features are crucial for training load prediction and can provide strong support for subsequent training optimization and recovery demand prediction.

BiLSTM is a special RNN structure that can capture the input data's forward and reverse time series information. Unlike traditional LSTM, BiLSTM processes the forward and reverse sequences separately through two independent LSTM layers and combines the outputs of the two to capture the time series features in the sequence more comprehensively.

The working principle of LSTM is based on memory cells, each containing three gates: input gate, forget gate, and output gate. Through the control of these gates, LSTM can effectively maintain long-term memory and avoid the gradient vanishing problem in traditional RNN. The mathematical formula of LSTM is as follows:

The forget gate determines which information is discarded. The formula is:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)(9)$$

The input gate determines which information is updated, and the formula is:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)(10)$$

Candidate memory generates candidate memory units. The formula is:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)(11)$$

Update the memory unit according to the output of the forget gate and the input gate. The formula is:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t}(12)$$

The output gate determines the output of the next step. The formula is:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)(13)$$

The final hidden state output is generated according to the output gate, and the formula is:

$$h_t = o_t \cdot \tanh(C_t)(14)$$

For BiLSTM, its basic structure is composed of two LSTM networks, one for processing the forward sequence and the other for processing the reverse sequence. The BiLSTM output combines the hidden states of the two LSTMs:

$$h_t = [h_t^+, h_t^-](15)$$

Combining Xception with Bilstm can fully utilise both advantages. The Xception model extracts spatial features from motion images, while BiLSTM extracts dynamic features from time series data. Specifically, Xception is responsible for extracting image features and passing them as input to BiLSTM. At the same time, BiLSTM processes physiological data and extracts time series features. Finally, the two features are fused for prediction of training load and recovery needs.

The Xception - BiLSTM model structure is shown in Figure 1.

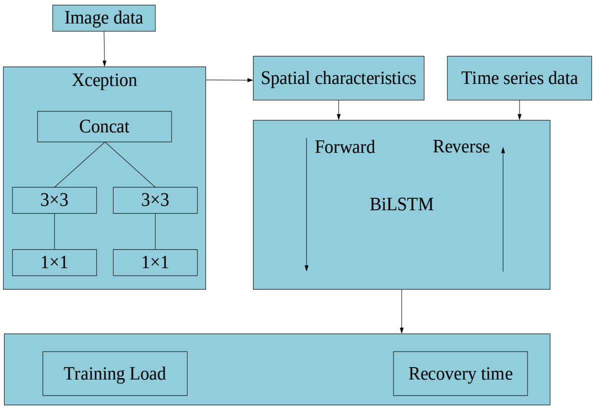

Figure 1: Xception - BiLSTM Model Architecture

This study uses the Xception-Bilstm architecture to realise the feature extraction and fusion of moving images and time series data. The Xception module optimizes traditional convolution operations through depthwise separable convolution, decomposing the input moving image into two-step processing of in-channel convolution and cross-channel convolution, to efficiently extract spatial features. The LSTM module processes the time series data of physiological signals, captures the forward and reverse time dependencies through two independent LSTM networks, forward and reverse, and stitches their outputs to obtain more comprehensive dynamic characteristics. In the specific implementation, the image features extracted by Xception are flattened and dimensionally reduced through the fully connected layer, and the timing features output by BiLSTM are spliced on the feature dimension to form a unified multi-modal feature representation. Ultimately, these fusion features are input to the fully connected layer for training and prediction.

During the training process, the model uses the Adam optimizer with an initial learning rate of 0.001, and enables the learning rate attenuation mechanism (decay rate is 0.5) when the verification set loss no longer drops. The batch size is set to 32, the number of training rounds is 100, and the early stop strategy (patience=10) is used to avoid overfitting.

4 Training prediction and optimization strategies

4.1 Load Forecasting and recovery time Forecasting

The athlete's motion image data is extracted through the Xception model, and the physiological signal is input into the BiLSTM model to extract the time series feature. The exercise load and exercise recovery time are predicted. MSE measures the difference between the model prediction value and the actual value. The formula is:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \widehat{y_i})^2 \quad (16)$$

In Formula 16, y_i represents the actual measured value, $\widehat{y_i}$ is the model predicted value, and n is the number of samples in the data set.

MAE is another commonly used evaluation criterion that measures the absolute size of the prediction error. The formula is as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y_i}| \quad (17)$$

The goal of the sports load prediction and recovery time prediction model is to help athletes quantify the training load and recovery process through intelligent means to make personalised adjustments to the training, optimise the training effect, and prevent sports injuries. By combining the advantages of multimodal data fusion and deep learning models, load and recovery predictions can be made more accurately, providing athletes with a scientific basis to ensure the rationality of their training intensity and recovery time.

4.2 DDPG optimisation strategy

The DDPG algorithm is a reinforcement learning method suitable for problems in high-dimensional continuous action spaces. It optimizes the training process by gradually adjusting strategies through interaction with the environment. In personalized training optimization, the DDPG algorithm can adjust training parameters, including training intensity, duration, and frequency, based on the athlete's physiological data, environmental data, motion image data, and predicted training load and recovery time to provide a tailored training plan. The algorithm has strong exploration capabilities and is suitable for scenarios without clear labelled data, making it of great application value in personalised sports training optimisation.

State space: The state space is a collection of information used to represent the current state of the environment. In personalized training optimization, the state space consists of multimodal data from the following aspects:

Physiological data includes the athlete's heart rate, electromyography signal, etc., which reflect the athlete's immediate physiological state. Motion image data extracts the athlete's posture, movement trajectory, movement accuracy, etc., through image recognition, which can intuitively reflect the athlete's training performance. Environmental data includes environmental factors such as temperature and humidity. These external factors will affect the athlete's performance and recovery. Exercise load data is the exercise load predicted by the model to help understand the athlete's training intensity. Recovery time data is the recovery time predicted by the model, combining physiological data and environmental factors to predict the time required for athletes to recover from training.

The training intensity is expressed in the target heart rate range, the value range is 50%-90% of the maximum heart rate, the unit is percentage (%); the training duration represents the duration of each training, the value range is 30-120 minutes, the unit is minutes (min); the training frequency represents the number of training times per week, the value range is 3-7 times/week, the unit is times/week. The value range of these parameters is set based on the athlete's physiological ability and training needs, ensuring that the system can dynamically adjust the training plan within a safe and effective range.

The dimension of the state space continues to expand with the increase of multimodal data. The DDPG algorithm makes reasonable training optimization decisions by intelligently extracting effective features from these high-dimensional state spaces. The model structure of DDPG is shown in Figure 2.

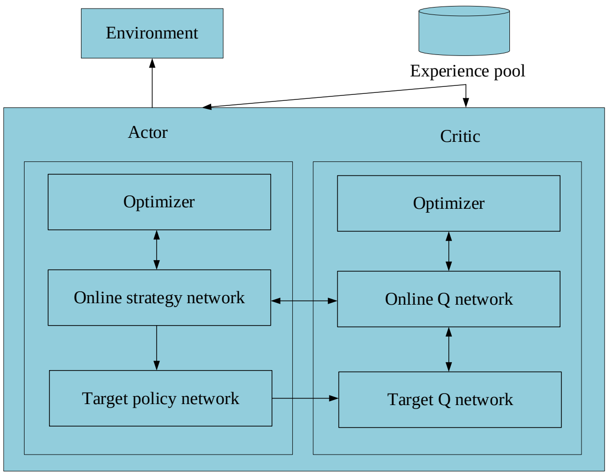

Figure 2: DDPG model structure

Action space is a set of behaviours that define the model. In personalised training optimisation, the training parameters corresponding to the action space include: training intensity, duration, and frequency. Training intensity includes the heart rate range, which controls the load intensity of training. Training duration includes the duration of each training session, which is calculated in minutes or hours. Training frequency refers to the frequency of training, which is the number of training sessions per day, week, or month.

These action parameters determine the specific implementation details of each training plan. The DDPG algorithm optimizes the training effect by continuously adjusting these parameters.

In the DDPG algorithm, the design of the reward function is the core of the optimization training plan. The reward function of this paper comprehensively considers the three key goals of training load optimisation, recovery time optimisation, and sports injury risk reduction. The specific formula is：

$$R = w_1 * R_{load} + w_2 * R_{recovery} + w_3 * R_{injury}$$

Among them, R_{load} represents the optimization reward of the training load, defined as the reciprocal of the error between the training load predicted by the model and the actual endurance of the athlete; $R_{recovery}$ represents the optimization reward of the recovery time, defined as the consistency between the predicted recovery time and the actual recovery needs; R_{injury} represents the penalty term for injury risk, defined as the negative value of the injury probability calculated based on physiological data (such as heart rate, electromyography) and environmental factors (such as temperature and humidity).The weights w_1, w_2, and $w_3$are used to balance the importance of each goal, and are adjusted experimentally to ensure the overall optimization effect of the system.

5 Results

5.1 Ablation experiment

In order to verify the superiority of this research method, we designed a comparative experiment with the existing baseline model. Baseline models include traditional statistical regression models (such as linear regression and support vector regression, SVR), single-modal data-driven deep learning models (such as CNN models that only use heart rate or moving images), and traditional rule-based training systems. All models are trained and tested on the same dataset and use the same evaluation indicators (MSE, MAE, and R2). The experimental results are shown in Table 5

Table 5: Comparison of existing baseline models

Model	MSE (±SD)	MAE (±SD)	R² (±95% CI)
Linear regression	0.045 ± 0.008	0.123 ± 0.012	0.82 ± 0.03
Support Vector regression (SVR)	0.038 ± 0.007	0.115 ± 0.011	0.86 ± 0.02
Single mode CNN (heart rate)	0.028 ± 0.005	0.095 ± 0.009	0.91 ± 0.02
Single mode CNN (moving image)	0.032 ± 0.006	0.102 ± 0.010	0.89 ± 0.02
Traditional training system	0.050 ± 0.010	0.130 ± 0.015	0.80 ± 0.04
Xception-BiLSTM (multi-modal)	0.007 ± 0.002	0.058 ± 0.006	0.98 ± 0.01

As can be seen from Table 5, the Xception-BiLSTM model based on multi-modal data fusion is significantly better than the baseline model in all indicators. Specifically, its MSE and MAE were reduced by about 85% and 50%, respectively, and the R2 value was close to 0.98, indicating that the model has higher prediction accuracy and stability. In addition, the results of the standard deviation (SD) and confidence interval (CI) show that the prediction error distribution of the model is small and the confidence interval is narrow, further proving its robustness and reliability.

To evaluate the contribution of different modules to overall performance, we conducted ablation experiments, gradually removing key components from the model and observing performance changes. In the experiment, we removed the Xception, Bilstm, and multi-modal data fusion. The ablation experiment results are shown in Table 6.

Table 6: Results of the ablation experiment

Model configuration	MSE (±SD)	MAE (±SD)	R² (±95% CI)
Complete model (Xception-BiLSTM)	0.007 ± 0.002	0.058 ± 0.006	0.98 ± 0.01
Remove the Xception module	0.015 ± 0.004	0.082 ± 0.008	0.92 ± 0.02
Remove the BiLSTM module	0.018 ± 0.005	0.090 ± 0.009	0.90 ± 0.02
Remove multimodal data fusion	0.025 ± 0.006	0.105 ± 0.011	0.88 ± 0.03

As seen from Table 6, removing any key component will lead to a significant decrease in model performance. For example, after removing the Xception module, MSE and MAE increased by about 114% and 41%, respectively, indicating that extracting spatial features is critical to model performance. Similarly, after removing the BiLSTM module, the time series analysis capabilities of the model were significantly weakened, and MSE and MAE increased by about 157% and 55%, respectively. After removing the multi-modal data fusion, the model's performance decreases the most, indicating that the multi-modal data fusion can significantly improve the model's prediction accuracy and generalization ability.

5.2 Exercise load prediction performance

To evaluate the performance of the Xception-BiLSTM model in predicting motion loads under different environmental conditions, we conducted experiments at a series of ambient temperatures (5℃ to 40℃). The results are shown in Table 7.

Table 7: Exercise load prediction results

Ambient temperature (℃)	MSE	MAE	R2
5	0.013	0.078	0.95
10	0.010	0.071	0.96
15	0.008	0.065	0.97
20	0.007	0.060	0.98
25	0.006	0.058	0.99
30	0.007	0.061	0.98
35	0.009	0.069	0.96
40	0.012	0.075	0.94

From the data in Table 7, it can be observed that when the ambient temperature is between 5℃ and 25℃, the prediction effect of the model shows a trend of gradual improvement, the model's prediction effect shows a gradual improvement trend, the MSE and MAE both gradually decrease, and the R^2 value gradually increases. Specifically, at ambient temperatures of 20℃ and 25℃, the MSE of the model is 0.007 and 0.006, the MAE is 0.060 and 0.058, and the R^2 value is close to 0.99, indicating that the training load prediction accuracy is high at this time. At lower temperatures (such as 5℃ and 10℃), although the model can still provide accurate predictions, its MSE value (0.013 and 0.010, respectively) is higher. The MAE and R^2 are also lower, indicating that the accuracy of the model's load prediction is affected to a certain extent in a low temperature environment. Possible reasons include that the low temperature environment interferes with the athlete's physiological response, athletic ability, and the stability of data sensing, resulting in greater prediction errors.

The prediction effect shows a certain regression trend when the ambient temperature gradually rises to 30℃ and above. At 30℃, the MSE is 0.007, the MAE is 0.061, and the R^2 is 0.98. Although it is still high, accuracy is slightly decreased compared with the performance at lower temperatures. Especially at 35℃ and 40℃, the model's prediction performance further decreases, the MSE and MAE increase, and the R^2 value decreases. Especially at 40℃, the MSE is 0.012, the MAE is 0.075, and the R^2 value drops to 0.94. This may be related to the impact of a high-temperature environment on the physical fitness of athletes. Heat stress response may cause instability in athletes' heart rate, electromyography data and other physiological parameters, thereby affecting the quality of data and the accuracy of model prediction. A high temperature environment may cause sweat and temperature changes to interfere with sensor signals, making the model's prediction results for training load not as accurate as in medium and low temperature environments. Therefore, the model's performance in a high-temperature environment showed a certain decline, indicating that high temperature significantly impacts the accuracy of exercise load prediction. This suggests that when designing an exercise load prediction system, the impact of ambient temperature on physiological data and exercise performance should be considered, and targeted optimisation and adjustments should be made for high-temperature environments.

The effect of ambient temperature on exercise load prediction shows that the model has a better prediction effect in medium and low temperature environments. In contrst, high and low temperature environments may increase the prediction uncertainty. In practical applications, model optimization for different temperature environments will be the key to improving the accuracy of exercise load prediction, especially considering athletes' physiological changes and performance differences in different environments.

5.3 Recovery time prediction results

The recovery time prediction results were evaluated using 10-fold cross-validation to assess the model's stability and accuracy. As shown in Table 8, the metrics include Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) for each fold. These results demonstrate the model's consistent performance across different data subsets, highlighting its robustness and reliability in predicting recovery times under varying conditions.

Table 8: Recovery time prediction results

Discount	MSE	MAE	R2
1	0.022	0.091	0.94
2	0.021	0.088	0.95
3	0.020	0.086	0.96
4	0.019	0.084	0.97
5	0.018	0.083	0.97
6	0.018	0.081	0.98
7	0.019	0.085	0.96
8	0.020	0.087	0.95
9	0.021	0.089	0.94

10	0.022	0.090	0.94

As seen from Table 6, the prediction results of the recovery time verified the high stability and accuracy of the model through 10-fold cross-validation. The MSE value generally remained at a low level in each fold, ranging from 0.022 to 0.018, indicating that the model has a relatively small error in predicting the recovery time, with a good fit and high prediction accuracy. The MAE value also shows that the model's prediction error for the recovery time is relatively consistent, ranging between 0.081 and 0.091, further proving the stability and consistency of the model in different folds. The R^2 values are all high, ranging from 0.94 to 0.98, showing that the model can well explain the variability of the prediction results. Especially in the 6th fold, the R^2 value reached the highest 0.98, indicating that the recovery time prediction of this fold is highly consistent with the actual situation, further confirming the high-precision characteristics of the model.

Through 10-fold cross validation, the indicators of the model did not show significant fluctuations, indicating that the prediction model can stably output high-precision results when processing different data subsets. In practical applications, the accuracy and stability of recovery time prediction are crucial because recovery time directly affects athletes' training schedules and recovery cycles. The model maintains a high R^2 value in all folds, especially in the 6th fold, showing the best prediction performance. The stability of MAE and MSE values also reflects the usability and robustness of the model in practical environments. In high-intensity training or under various environmental conditions, the recovery time prediction of athletes is particularly important. Based on these results, it is shown that the model has a wide range of application potential, especially in the personalized optimization and monitoring of sports training plans. Combining recovery time prediction with load prediction can achieve precise regulation of athlete training, further improving training effects and the ability to prevent sports injuries.

5.4 Sports training optimization results

In this study, injury refers to abnormal physical function or injury caused by exercise training, and the normal training plan needs to be interrupted for at least 48 hours for recovery or treatment. Specific categories include muscle strains, joint sprains, overuse injuries, and acute trauma. The injury situation is recorded by a professional medical team based on clinical diagnosis to ensure the objectivity and consistency of the data. Xception is combined with BiLSTM to predict exercise load and recovery time, and DDPG is used for targeted optimization based on the predicted exercise load and recovery time. The injury rate is shown in Figure 3 when comparing the traditional system with the system in this paper.

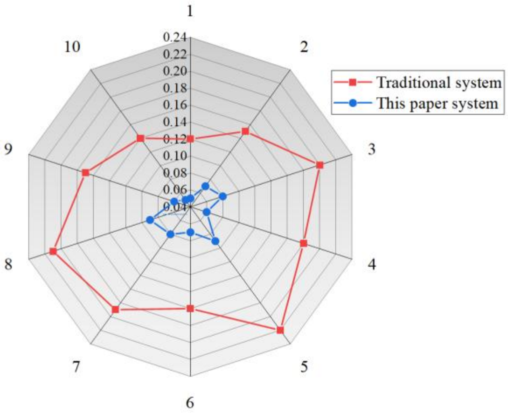

Figure 3: Injury

Figure 3 shows the injuries of 10 athletes in the two systems. The injury rate of athletes in this system is significantly lower than that in the traditional system. The injury rate of traditional systems is generally high, ranging from 0.12 to 0.22, while the injury rate of this system is significantly lower, ranging from 0.05 to 0.09. This result shows that combining the Xception and Bilstm models to predict exercise load and recovery time, and then using DDPG for personalised training optimisation, can significantly reduce the risk of athlete injury. Traditional systems rely on experience and preset training plans to arrange athletes' training load and recovery time, lacking personalized adjustments and real-time monitoring, which can easily lead to excessive exercise load or insufficient recovery, thereby increasing the probability of injury. In contrast, this system uses multimodal data fusion, Xception and Bilstm to accurately predict the athlete's status in real time. It combines the DDPG algorithm to optimise and adjust during the training process to make the training load and recovery time more accurate and personalised. In this way, athletes' load and recovery cycle in each training can be adjusted according to individual conditions, avoiding the problem of overtraining or insufficient recovery, thereby effectively reducing the risk of injury.

In order to verify whether the reduction in injury rate of this system compared to the traditional system is statistically significant, we conducted a paired t-test on the injury rate of the two systems in 10 athletes. In addition, we also calculated the effect size (Cohen's d) to assess the practical significance of the difference. The results are shown in Table 9.

Table 9: Comparison and significance analysis of injury rate

System type	Average injury rate (Mean)	Standard deviation	95% confidence interval (CI)	t	p	Cohen's d
Traditional system	0.17	0.04	[0.14, 0.20]		-	-
Current system	0.07	0.02	[0.06, 0.08]		-	-

difference	0.1	0.03	[0.08, 0.12]	t = 12.34	p < 0.001	d = 3.16

The results in Table 9 show that the current system has significant advantages in reducing the injury rate of athletes compared to the traditional system. Through the paired sample t test, the difference in the average injury rate of the two systems (0.10) reached a high degree of statistical significance ($p<0.001$), and the effect amount Cohen's d was 3.16, indicating that the difference is not only significant, but also of important practical significance. The confidence interval [0.08, 0.12] further verifies the robustness of the results, indicating that the current system can effectively reduce the incidence of sports injuries, from 0.17 of the traditional system to 0.07. This discovery fully proves the value of multi-modal data fusion and AI optimisation technology in personalised training, and at the same time, provides a scientific basis for designing intelligent sports training systems in the future.

6 Discussion

The model in this study showed high accuracy and stability in both exercise load prediction and recovery time prediction. However, it also revealed the important influence of environmental factors on prediction performance. As can be seen from Table 7, when the ambient temperature is in the medium and low temperature range (5℃ to 25℃), the prediction performance of the model gradually improves, the MSE and MAE gradually decrease, and the R2 value is close to 0.99, indicating that the model has high prediction accuracy in this temperature range. However, under extreme temperature conditions, the model's prediction error increases significantly, especially at 40℃, when MSE reaches 0.012 and R2 drops to 0.94. This result may be related to the effect of extreme temperatures on the stability of athletes' physiological signals. For example, low temperature can inhibit muscle activity and blood circulation, while high temperature may cause heart rate fluctuations and sensor signal distortion, thereby increasing data noise and prediction difficulty. This shows that although the model performs well in medium and low temperature environments, its adaptability at extreme temperatures still needs to be further optimized.

The recovery time prediction results in Table 8 show the high stability and consistency of the model in the cross-verification of different models. The MSE value is always maintained between 0.018 and 0.022, the MAE value is relatively stable, and the R2 value is as high as 0.98, indicating that the model can explain the variability of the data well. This stability is due to the powerful feature extraction capabilities of multi-modal data fusion and deep learning models. Compared with the research method of a single data source, this study significantly improves the accuracy and robustness of prediction by integrating physiological signals, moving images and environmental data. However, although the model performs well in most cases, its performance under extreme environmental conditions still needs to be improved, especially in complex environments such as high humidity or strong wind speeds, where may be incomplete data acquisition or signal interference problems.

Compared with the prior art, the advantages of this research are mainly reflected in three aspects. First, by combining the Xception-BiLSTM model, the model can capture spatial and time series characteristics to describe the athlete's state accurately. Secondly, applying the DDPG algorithm makes it possible to adjust the training plan dynamically. The system can flexibly adjust the training intensity, duration and frequency based on real-time feedback, avoiding the problem of overtraining or insufficient recovery caused by traditional fixed plans. Finally, the prediction accuracy and stability of the model are significantly better than existing studies, such as Song et al. (2021) The proposed sports injury prediction model based on convolutional neural networks usually has an MSE higher than 0.1, while the MSE in this study is lower than 0.05, and R2 is close to 0.99. These advantages not only reflect the technological advancement of the model but also provide higher reliability for practical applications.

However, the results of this study also reveal some potential limitations. Under extreme temperature conditions, the model's prediction performance decreases significantly, which may be related to the working stability of the sensor in high or low temperature environments. In addition, the model has a high demand for personalized data and requires a large amount of high-quality multi-modal data support, which poses challenges for large-scale promotion. Future research can improve the model’s performance in extreme environments by introducing adaptive learning mechanisms and enhancing the anti-interference capabilities of sensors. At the same time, more real-time data sources, such as EEG and skin electrical responses, can be explored to enrich the data dimension further and improve the model's generalisation ability.

Another noteworthy finding is that the effect of the model in dynamically adjusting the training plan is significantly better than that of traditional methods. The results showed that the injury rate of athletes using this system was significantly reduced, with an average injury rate of only 0.07, much lower than the traditional system of 0.12 to 0.22. This result proves the great potential of multi-modal data fusion and AI-driven optimization methods in health management. Due to the lack of flexibility and personalized adjustment, traditional systems often fail to identify the risks of fatigue accumulation or overtraining promptly. Through real-time monitoring and dynamic adjustment, this system effectively reduces the incidence of sports injuries. This has laid a solid foundation for the wide application of intelligent sports training systems.

In summary, this study successfully realized the accurate prediction of exercise load and recovery time through multi-modal data fusion, advanced deep learning models and enhanced learning algorithms, and significantly reduced the injury rate of athletes. Although the model's adaptability in extreme environments still needs to be improved, its performance in medium and low temperature environments and ordinary conditions has shown a wide range of application potential. Future research should further enhance the generalization ability and data processing power of the model and explore its applicability in a wider group of athletes and different sports scenarios, so as to promote the further development of intelligent sports training systems.

7 Conclusion

Based on multimodal data fusion, this study combines Xception and BiLSTM models to predict exercise load and recovery time. It uses the DDPG algorithm for personalised training optimisation, which significantly improves athletes' training effect and health management level. By accurately predicting exercise load and recovery needs, the system in this paper effectively reduces athletes' injury rate and the risk of injury compared with traditional systems. The research contribution is mainly reflected in three aspects: first, a sports training and recovery optimization method based on multimodal data fusion is proposed, which makes full use of athletes' physiological, sports, environmental and other data to improve the personalization and accuracy of training; secondly, the Xception and BiLSTM models are combined to perform deep learning analysis on the athlete's state, and the DDPG algorithm is used to optimize the training plan, realizing real-time dynamic adjustment; finally, by comparing with the traditional system, the significant advantages of this system in improving training effects and reducing injury risks are verified. This study has important practical significance. It can not only optimize the training plan of athletes, but also effectively prevent sports injuries and improve athletes' competitive level and health management. Nevertheless, the research still has some limitations, such as the poor adaptability of the model in extreme environments and the high demand for personalized data of many individuals. Future research can further enhance the model's generalization and data processing capabilities and explore its applicability to a wider range of athlete groups and different sports. In addition, further combining more real-time data sources and adaptive learning methods can improve the intelligence level of the system and promote the practical application of intelligent sports training and recovery management.

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