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Real time performance prediction in sports using machine learning algorithms

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Abstract: Predicting athletic performance is highly complex because it depends on many interacting factors. Conventional approaches – largely statistical analyses and expert judgement – tend to offer limited accuracy. To overcome these shortcomings, this study adopts machine-learning techniques to deliver real-time performance forecasts. First, we compiled athletes' demographic information and training records, then normalised and preprocessed the data. Drawing on extensive event-level datasets, we constructed a dynamic long short-term memory (LSTM) model that continuously captures and predicts athletes' competitive states. The model accurately anticipated swimmers' breathing patterns, with the predicted traces closely matching the observed values. It also estimated fatigue levels during the 08:00–12:00 time block: blood lactate concentrations rose from 1.2 mmol L^{-1} to 5.0 mmol L^{-1}, and subjective fatigue scores climbed from 2 to 8. Comprehensive experiments across multiple sports confirm the effectiveness of the proposed real-time performance-prediction framework.

Keywords: machine learning; competitive sports; real time performance prediction; LSTM; long short-term memory network; motion data analysis.

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1 Introduction

Sport performance has a decisive influence on competitive outcomes, so accurately forecasting athletes' competitive states is crucial for improving training and tactical decision-making. Traditional methods – rooted in expert judgement or fundamental statistical analyses – suffer from subjectivity and limited data-processing capacity. By contrast, machine-learning approaches can extract patterns from large-scale datasets, offering both higher accuracy and greater efficiency; they therefore hold considerable promise for sport science.

Athletes' performances depend on multiple interacting factors, including physical fitness, technical skill, environmental conditions, and psychological state. Li (2020) compared an improved adaptive back-propagation neural network with multiple linear regression and grey degree models, using partial Barcelona match data from the 2016–2017 season; the enhanced neural network produced the rolling prediction error. Li and Xu (2021) surveyed AI applications in basketball, including team and player analytics, result prediction, shot analysis, AI coaching, intelligent training systems, and injury prevention. Fuchs et al. (2021) built real-time performance models using decision trees and random forests, while Ristea et al. (2020) applied long short-term memory (LSTM) networks for rapid and accurate state prediction. Van Hooren et al. (2020) employed support vector machines to analyse physiological indices such as heart rate and blood oxygen saturation. Vaughan and Laborde (2021) fused convolutional and recurrent neural networks to predict tennis performance in real time. Morais et al. (2023) harnessed deep learning to assess movement trajectory, speed, and force. Despite progress, data quality still varies due to sensor placement, field conditions, weather, and other factors, and subjective bias may be introduced during data processing.

Recent work continues to refine machine-learning solutions. Faure et al. (2020) created a model that captures both individual and team-level basketball performance through in-depth motion-data analysis. Nikolaidis and Knechtle (2023) examined half-marathon performance trends, gender- and age-related differences, physiological correlates, and training loads. Furley (2023) integrated multiple algorithms into an efficient real-time prediction framework. Harris et al. (2023) demonstrated a moderate association between cardiac flow and exercise performance across diverse sports tasks, whereas Newman et al. (2023) highlighted how sports participation fosters life-skill transfer beyond the athletic domain. Addressing individual variability, Islamov (2021) proposed a personalised modelling algorithm that tailors predictions and training guidance to each athlete. Many of these studies, however, focus on single-sport contexts, so their generalisability warrants further investigation.

The present study explores machine-learning-based, in-exercise performance prediction across multiple sports. By continuously collecting data on movement trajectories, velocities, and forces, our model delivers real-time feedback to coaches and athletes. Such timely insights facilitate evidence-based adjustments to training, ultimately enhancing competitive performance.

2 Implementation of real time performance prediction under machine learning algorithms

2.1 Data collection and preprocessing

Research participants: This study recruited Chinese and provincial-level professional athletes as participants, totalling 180 individuals, comprising 112 males and 68 females. There are 6 outstanding athletes, 64 national first-level athletes, and 110 national second-level athletes. The average age of the study subjects is 20.51 ± 3.48.

Data collection: This paper uses various sensors and instruments to monitor the trajectory, speed, acceleration, strength, heart rate, blood oxygen saturation, and other parameters of athletes in real time, and models and predicts them later. Tables 1 and 2 present typical data collected, illustrating real-time data collection of athletes.

Table 1 Basic information of athletes

Athlete number	*Age*	*Height* (cm)	*Weight* (kg)	*Sports event*
1	20	180	75	Basketball
2	23	175	68	Soccer
3	24	178	73	Swimming
4	22	182	81	Track and field
5	24	170	62	Badminton
6	21	783	78	Tennis

Table 2 Athlete training data

Athlete number	*Training duration* (h)	*Exercise volume* (km)	*Average heart rate* (beats/minute)	*Maximum heart rate* (beats/minute)
1	3.5	15	140	160
2	4.0	20	145	165
3	3.0	12	135	155
4	4.5	25	150	170
5	4.0	20	140	160
6	3.0	18	142	167

When preprocessing the collected basic and training information of athletes, a series of data validation, cleaning, and conversion must also be carried out first (Hickman et al., 2022; Ranganathan, 2021). In the personal information form, age, height, weight, and other data can be verified, and any possible omissions or outliers can be identified and excluded. In addition, it is necessary to standardise or normalise height and weight to facilitate analysis and comparison. The training data of athletes is the same, and the authenticity of the data should be verified to eliminate any unreasonable data, such as training times and heart rates. Then, according to the physiological laws of the human body, the heart rate data should be converted accordingly. The corresponding standardised mathematical formula for data is as follows (Dupriest et al., 2023):

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

In equation (1), Z represents the standardised value; X represents the original numerical value (such as height or weight); μ is the average value of X, and σ is the standard deviation of X (Shi et al., 2020; Casquilho and Buescu, 2022). Normalise these data again, and the calculation formula is:

$$X_{normalised} = \frac{X - min(X)}{max(X) - min(X)} \tag{2}$$

Among them, $X_{normalised}$ represents the normalised value, while $min(X)$ and $max(X)$ represent the minimum and maximum values of X, respectively (Liu et al., 2020; Li et al., 2023). The resting heart rate of adults should be between 60–100 beats per minute, and the corresponding range of abnormal heart rate values should be checked using the following formula:

$$Maximum\,HeartRate(MHR) \approx 220 - \text{Age} \tag{3}$$

2.2 Building a Real-Time performance prediction model

Extended short-term memory network (LSTM) is an effective method for analysing temporal data and predicting game outcomes (Wang et al., 2020; Ma and Mao, 2020). Therefore, this paper employs the LSTM time series modelling method to construct a real-time performance prediction model, aiming to achieve accurate predictions and provide real-time display of competitive sports performance, as well as real-time training and tactical guidance for coaches and athletes. The LSTM unit constructed in this paper consists of four components: the input gate, the forget gate, the output gate, and the cell state (Chang et al., 2020; Huang et al., 2021). Here are these gates and their update formulas:

1 Forgetting gate:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{4}$$

In the formula, f_t is the output of the forget gate at the current moment, which determines which old information needs to be discarded; W_f is the forget gate weight matrix, connecting the previous hidden state h_{t-1} and the current input x_t; b_f is the forgetting gate bias term; σ represents the sigmoid activation function, with an output value range between (0,1), controlling the proportion of information retained (Zhang et al., 2021; Swamy et al., 2022).

2 Input gate:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{5}$$

$$\tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \tag{6}$$

Among them, i_t refers to the 'input gate' of the current time, used to determine what new information to store; $\tilde{C}_t$ is a candidate cell state for potential new stored content; W_i is the weight matrix of each unit and the weight matrix of each unit state; b_i and b_C respectively represent different bias terms; tanh is a hyperbolic orthogonal activation function that maps input data to the (–1,1) interval.

3 Cell state update:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{7}$$

C_t refers to the current unit state, which includes the process of forgetting old information and adding new information. $\odot$ is a unit level multiplication, which is a bitwise operation.

4 Output gate:

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{8}$$

$$h_t = o_t \odot \tanh\left(C_t\right) \tag{9}$$

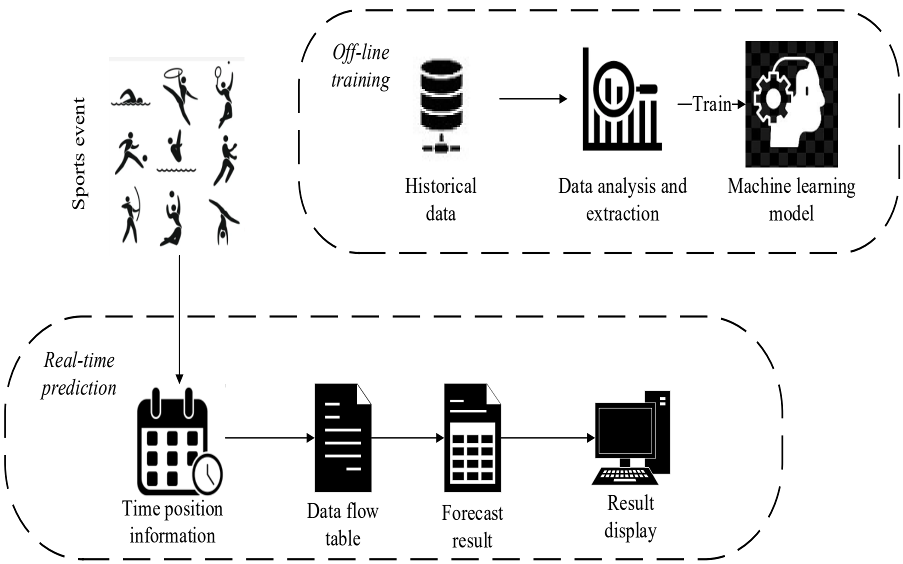
Among them, o_t is the output of the current output gate, which can determine the current hidden state based on the unit state of the input end. h_t represents the implicit state at the current moment, which is used as input for the next moment and is used in the final forecast result.

Through the operations described above, the LSTM's gates regulate each cell's state, generate the corresponding hidden states, and feed them into subsequent prediction layers (e.g., forecasting score differentials or individual athlete scores) (Du et al., 2020; Liu et al., 2022). After iterative training, the network integrates the temporal dynamics of multiple influencing variables, significantly enhancing its ability to predict future event outcomes (Chen et al., 2022; Gauch et al., 2021).

The proposed real-time prediction pipeline begins with an offline training phase: historical data are analysed, key features extracted, and a machine-learning model tailored to a specific sport is trained until it accurately reflects evolving performance patterns. During online inference, a streaming data table supplies live metrics – such as split times and positions – which the model converts into instantaneous predictions. Achieving both accuracy and low-latency feedback enables coaches and athletes to adjust tactics and training plans on the fly.

By seamlessly integrating offline processes (historical data ingestion, deep feature extraction, and model building) with online components (spatiotemporal data streams, dynamic tables, predictive outputs, and visual dashboards), the framework delivers true end-to-end, real-time performance prediction (Mahesh, 2020; Janiesch et al., 2021). Figure 1 illustrates the detailed workflow.

Figure 1 Real time performance prediction process



3 Real-time performance prediction experiment and machine learning algorithms in sports

3.1 Evaluation of respiratory movement prediction

This experiment primarily investigated the breathing patterns of swimmers, and based on these findings, a curve chart was established to predict the breathing movements of swimmers, as shown in Figure 2. Figure 2 illustrates the swimmer's breathing movement over 300 s. The first subchart displays the actual respiratory activity of athletes, while the second subchart shows the predictions made in this paper based on the constructed real-time performance prediction model (Zhao, 2024; Wang et al., 2023, 2024; Zhang et al., 2024, Zhang, 2024). Among them, the horizontal axis represents time (seconds), and the vertical axis represents respiratory movement amplitude (%). By comparing the model's predictions with measured data, it is possible to gain a better understanding of the breathing patterns of athletes and evaluate the model's effectiveness in complex sports environments. This is very helpful for optimising swimming training and improving the level of athletes.

The simulation of human respiratory activity resulted in two curves in Figure 2: measured values and predicted values. Both exhibit obvious respiratory cycle characteristics, but there is a consistent pattern between them and the actual values. At the same time, there are also prediction errors, which stem from the limited historical data, the model's predictive ability, and random noise. Although there is some margin of error, the overall trend is consistent with the actual situation, indicating that the model accurately reflects the dynamic process of human respiration. By comparing two sets of data, the predictive performance of the model can be evaluated, and further optimisation can be carried out to enable it to influence respiratory movements more accurately.

3.2 Sports data

In modern sports research, a comprehensive analysis of core physiological indicators and performance data of athletes can provide a better understanding of their physical condition and competitive potential. To optimise the training plan, prevent excessive fatigue, and enhance performance, this study continuously monitors key physiological parameters, including heart rate changes and blood oxygen saturation levels, in real-time. It combines precise measurements of speed, acceleration, and motion trajectory to construct a comprehensive model of training and competition performance. Figures 3 and 4 show the prediction results for athlete movements, with a total prediction time of 100 s. This result not only provides a more comprehensive understanding of the athlete's physical state, but also serves as a reference for personalised training and competition.

Figure (1) and (2) in Figure 3 show the trends of heart rate and blood oxygen saturation over time, respectively. The velocity curve in Figure 4(1) shows the variation of velocity over time. The acceleration graph in Figure 4(2) illustrates the relationship between acceleration and time, and the variation in acceleration can reveal the pattern of variation in athletes' performance during the exercise process. The trajectory diagram in Figure 4(3) describes the athlete's movement trajectory using multiple points in two planes of the sports stadium, connecting the points with a black line to form a movement trajectory. During the calculation process, the starting and ending points can be marked in red circles, and a red dashed line can indicate the direction of the overall displacement. From the changes in motion trajectory, one can know the direction and amplitude of the motion.

Figure 2 Respiratory movement prediction (see online version for colours)

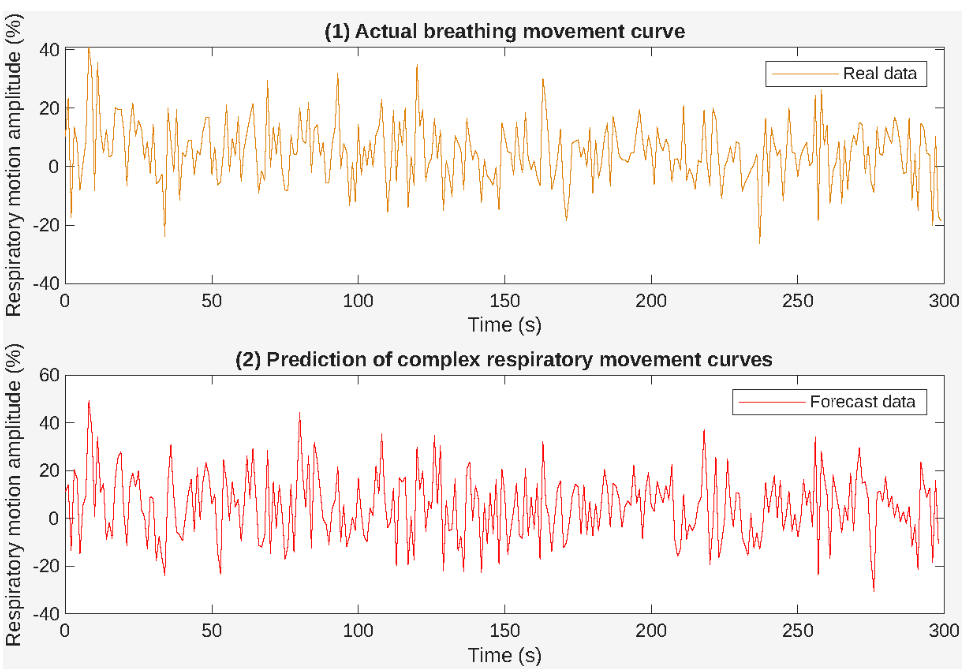


Figure 3 Heart rate and blood oxygen saturation curve (see online version for colours)

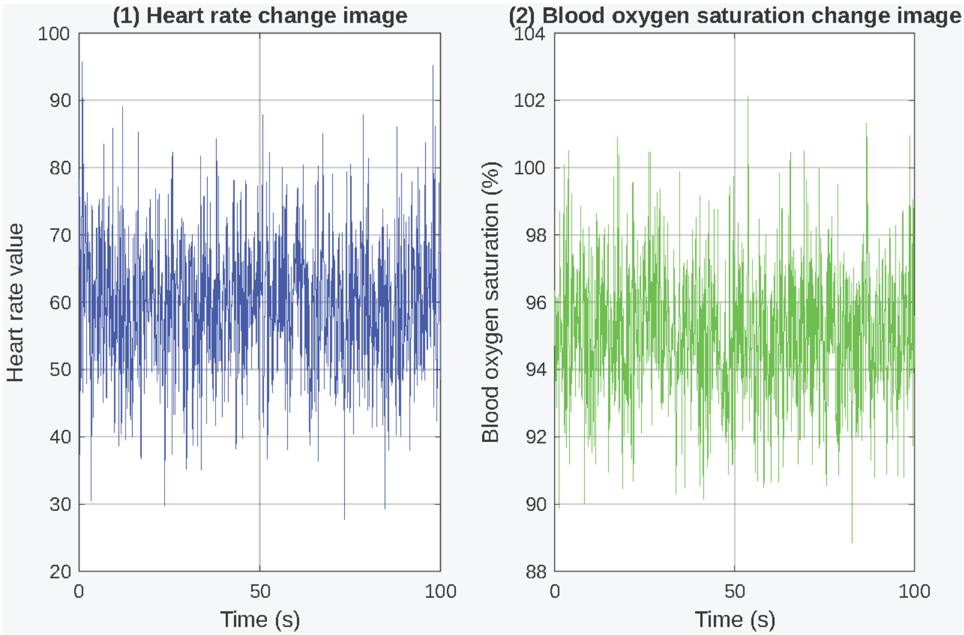
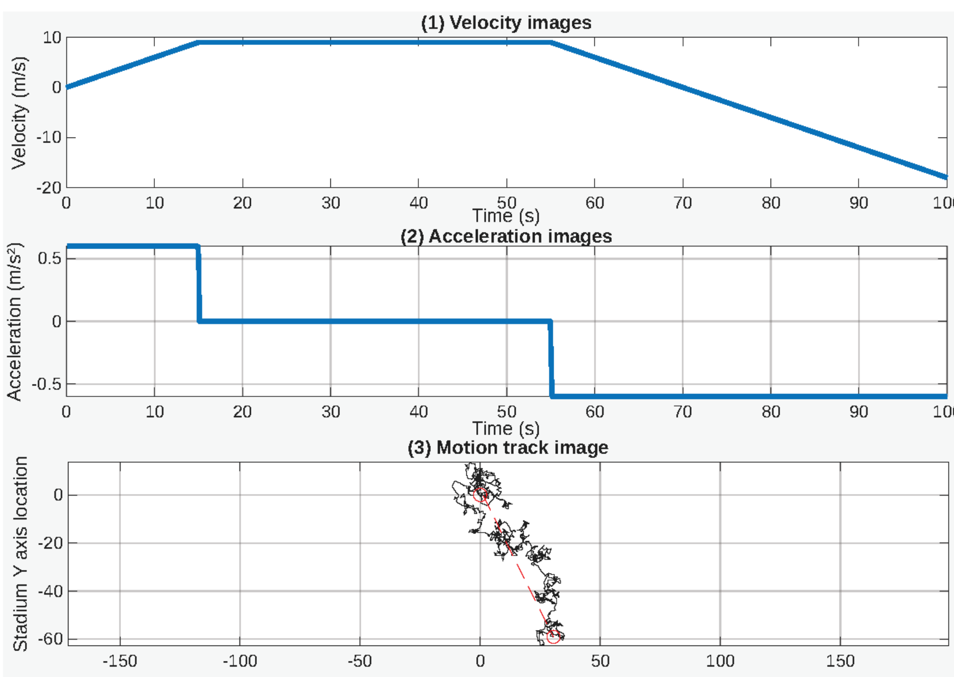


Figure 4 Velocity, acceleration, and motion trajectory (see online version for colours)



Through experiments, it was found that changes in heart rate exhibit certain regularity, whereas the trend of changes in blood oxygen saturation is relatively stable. From the heart rate chart, it is evident that there is a periodic oscillation in the heart rate. The measurement results of blood oxygen saturation show that it remains above 90%. Therefore, the values of heart rate and blood oxygen saturation obtained in this experiment can more accurately reflect physiological changes in the human body and be used for subsequent research and analysis.

3.3 Prediction of fatigue level

Fatigue is a common phenomenon in sports training and competitions. This study also conducted a predictive study on the fatigue level of athletes, using lactate content and subjective fatigue as evaluation indicators. By real-time monitoring the changes in indicators such as lactate levels and subjective fatigue of athletes during exercise, the degree of fatigue of athletes can be predicted. This paper employs the double Y-axis chart method, utilising the actual human lactate level (mmol/L) as the left Y-axis and subjective fatigue (rated on a scale of 1–10 points) as the right Y-axis for comparison. This paper selects four time periods, ranging from 8 to 12 on the horizontal coordinate axis, to clarify the correspondence between fatigue level and predicted values. The experimental results are presented in Figure 5. The research findings of this paper can help individuals gain a deeper understanding of how fatigue impacts the athletic level of athletes, and can also provide a theoretical basis for developing reasonable training plans and competition strategies.

The experimental data in Figure 5 show that from 8 to 12 o'clock, the lactate concentration in the athlete's body increased from 1.2 mmol/L to 5.0 mmol/L, and the corresponding subjective fatigue score increased from the initial 2–8 points. With the extension of training time, the lactate content in the body increases, and the subjective fatigue level of the body also rises, indicating that the body's fatigue level is gradually intensifying. This can enable coaches to be more precise and effectively control fatigue during training, thereby improving their athletes' competitive level. During training and competition, close attention should be paid to changes in indicators such as lactate content and fatigue level in the body, and training and competition plans should be adjusted promptly to prevent excessive fatigue and sports injuries.

Overall, with the increase of exercise load, the trend of changes in lactate concentration and subjective fatigue over time indicates a specific correlation between the two. The results of this study suggest that measuring lactate content and subjective fatigue levels in the body can serve as indicators for predicting the body's state of fatigue.

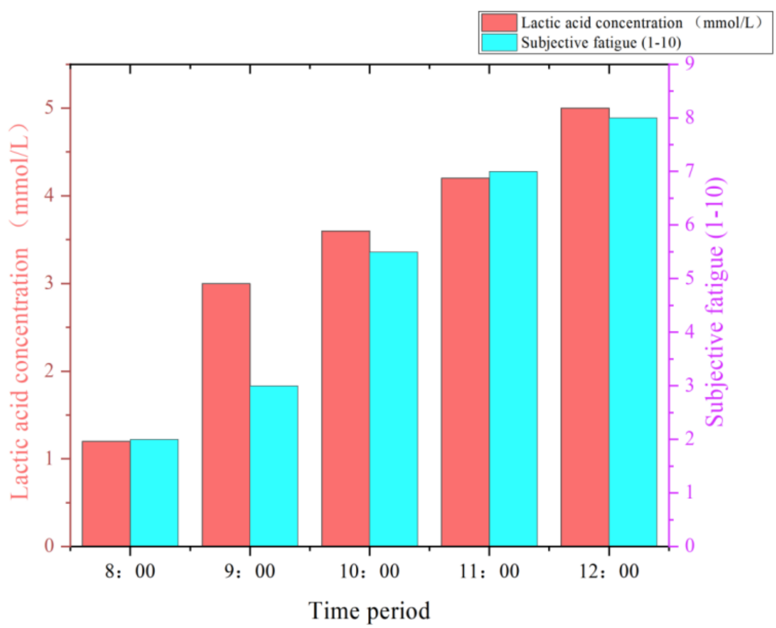
In sports, the mental state of athletes directly affects their performance in competitions. Anxiety levels, motivation levels, self-confidence, and attention levels all have a profound impact on an athlete's performance. This paper also collects relevant psychological data to better understand how the psychological state of athletes affects their performance. The data in Table 3 shows the changes in anxiety level, motivation level, self-confidence, and attention level of athletes. Based on the experimental results, targeted psychological training programs can be proposed for athletes to manage their mental state, which is of great significance for enhancing their competitive level.

Table 3 Psychological state assessment

Time period	*Anxiety level*	*Motivation level*	*Confidence level*	*Focus on the level*
8:00	45	65	70	55
9:00	52	62	72	62
10:00	57	54	68	65
11:00	60	48	65	71
12:00	64	43	60	72

As shown in Table 3, the anxiety level of athletes gradually increases from 8am to 12am. This indicates that as competition or training approaches, athletes can experience more anxiety and unease, which can hurt their performance. The gradual decline in motivation level indicates that athletes gradually lose their enthusiasm in competition or training, which affects their performance. At the same time, the decrease in athlete confidence indicates that athletes gradually lose confidence during competition or training, which in turn affects their performance. Contrary to other indicators, the athlete's concentration gradually increases, indicating that the athlete gradually improves their concentration during competition or practice, and changes in concentration have a specific effect on performance (Moyer et al., 2025; Chen et al., 2024; Tairan et al., 2024).

Figure 5 Fatigue level prediction (see online version for colours)



Through the above research, it has been found that changes in mentality during competitions and training can have a significant impact on athletes' performance. Therefore, targeted psychological training can help athletes overcome anxiety, improve motivation levels, enhance self-confidence, and maintain a moderate level of attention, which is beneficial for their performance in competition.

4 Conclusions

This paper integrates real-time data analysis to investigate the real-time performance prediction of athletes in sports using machine learning algorithms. By collecting data on athletes' physical fitness, training, and competition metrics, machine learning algorithms enable the real-time prediction of their athletic performance, thereby enhancing training effectiveness and competitive outcomes. Future research will build on this foundation to enhance the accuracy and reliability of the predictions, thereby providing more robust scientific support for the real-time assessment of athletic status during competitions.

Conflicts of interest

All authors declare that they have no conflicts of interest.

Authors Contribution

Yunpeng Jia conceived the research idea, designed the framework, and drafted the manuscript. Jing Liang contributed to data analysis, literature review, and manuscript revision. Both authors discussed the results and approved the final version of the manuscript.

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