RESEARCH ON PHYSICAL FITNESS TRAINING OF FOOTBALL PLAYERS BASED ON IMPROVED LSTM NEURAL NETWORK TO IMPROVE PHYSICAL ENERGY SAVING AND HEALTH

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ABSTRACT

In order to ensure that the physical function of football players adapts to the development of modern football level, and avoid the phenomenon of inability to adapt to the intensity of modern football games due to lack of physical fitness. Aiming at the physical training of football players, this paper proposes an improved long-short-term memory network (W-LSTM) model for the optimization and prediction of physical training. The model effectively combines the global feature extraction ability of LSTM for time series data and the preprocessing ability of the extracted data, which reduces the loss of feature information and achieves high prediction accuracy. The front door is added on the basis of LSTM, which combines training and physical function to reduce the impact of fluctuations in data outliers on the prediction results, effectively improving the accuracy of physical training optimization and prediction, and using body shape, exercise tolerance, exercise intensity and fitness level as input values to conduct comparative experiments on the three models of W-LSTM, LM-BP and ARIMA. The study found that W-LSTM has a lower mean square error (0.011) and a higher correlation coefficient (0.985), indicating that the model proposed in this paper is significantly better than other existing comparison models in terms of the accuracy of prediction results.

KEYWORDS

W-LSTM; Football; Athlete; Physical fitness; Prediction model

PAPER INDEX

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1. INTRODUCTION

With the increasing level of football around the world, the competition is intensifying, and the level of scientific training is also increasing. The daily training experience of football players around the world shows that athletes in different periods and regions follow some almost the same training principles in terms of training content and training methods, and have some similar or even common characteristics [1]. However, with the diversification of the world football level and training process, this lack of training content and training methods for individual characteristics has been unable to adapt to the inevitable laws of football development, and will inevitably hinder the improvement of athletes' competitive ability and regional football level [2]. Therefore, while we carry out the overall general training of football players, it is absolutely necessary to carry out individualized training for players, and it is also in line with the general law of the development of world football.

The physical training of football players is a time series problem for improving physical energy and health. For the prediction problem of time series, long-short term memory neural network [3] (long-short term memory, LSTM) has been widely used in speech recognition [4], network Flow prediction [5], pre-drilling logging curve prediction[6], power and image prediction [7-8], toxic gas law prediction[9] and other fields. Mao et al. proposed an LSTM model for image caption generation as early as 2015, pioneering the application of this research field in image caption generation. Peng et al. [10] used LSTM for the prediction of generated sentences, using dual LSTM layers to tune the parameters to improve the accuracy of sentence generation. In 2017, some scholars proposed a new time-varying parallel recurrent neural network for the generation of sports health image captions, which can obtain dynamic visual and textual representations at each time step, thus solving existing methods. The problem that currently generated words do not match the obtained image features in [11]. In addition, some scholars have applied the attention mechanism to the prediction of physical education innovation indicators, and found that the attention model can effectively improve the prediction accuracy of the innovation direction of physical education [12]. Kyunghyun et al. [13-14] proposed another gating mechanism of Gated Recurrent Unit (GRU), which is different from LSTM. The goal is to make each recurrent unit adaptively capture the dependencies of different time scales. Chung et al. [15] also conducted a specific study on GRU. However, this idea is also difficult to process data in combination with abnormal fluctuations and large fluctuations of data.

Physical fitness is one of the five basic elements of football players' competitive ability, and it is the physical ability necessary for football players to perform their technical and tactical skills normally and achieve excellent sports performance [16]. Physical fitness plays a pivotal role in a competitive football game. However, each athlete's upper limit of physical fitness and reserves are not the same, so it is difficult to excavate the limit of each athlete if the traditional unified training method is used [17]. In this regard, this study addresses the importance of physical fitness training using the LSTM model. However, the traditional long-term memory neural network model has the problem of premature saturation. Therefore, considering the

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improvement of the standard LSTM model, a new W-LSTM model is proposed to input physical fitness data and physical function data to train the model to reduce the number of different athletes. The influence of physical fitness and physical fitness on the prediction results, so as to provide a suitable numerical basis for the training of different athletes.

2. W-LSTM RELATED MODEL THEORY

2.1. DATA PREPROCESSING

Since the athlete's physique is affected by training and physical function, the following definitions are made: define t as the number of training days: xi represents the physical fitness data of the i-th day, then the input data is $Xi = \{ x1, x2......xt\}$, $X2 = \{ x2, x3......xt + 1\}$, and so on, until the last day; the physical energy fluctuation is calculated using the formula $\Delta pi = pi - pi - 1$, when i = 1, assuming that the data of the previous day is 0, then Δw1 = w1, the input format for physical fitness is $\Delta Pi = \{\Delta p1, \Delta p2.....\Delta pt\}$, $\Delta P2 = \{ \Delta p2, \Delta p3, ...\Delta pt + 1\}$, and so on until the last day.

2.2. DEFINITION OF THE MODEL

The input to the LSTM model consists of trained and physical performance data, i.e. using the data from the previous t days as input to predict physical performance on day t + 1 [18]. LSTM is a special RNN structure, which was proposed by Hochreiter et al. [19] in 1997 to decide when and how to update the hidden state of RNN. Due to its unique design structure, LSTM can solve the gradient very well. Disappearance problem, it is especially suitable for dealing with timing problems. Standard LSTM units include forget, input, and output gates [20]. On the basis of LSTM, W-LSTM processes its input information accordingly, and takes training and physical function data as data input, and it also includes pre-gate, forget gate and output gate [21] (Fig. 1), therefore, it can process more information than a standard LSTM, and its input in this study contains training and physical performance information.

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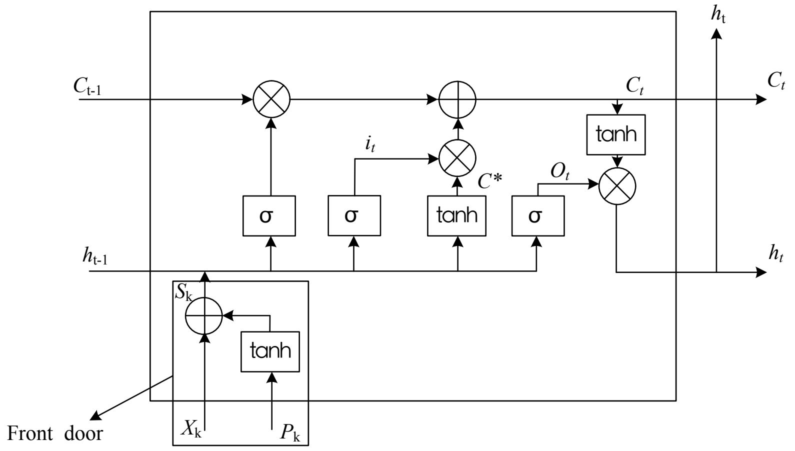

Figure 1. W-LSTM structure

Front gate, which combines body function information and function change information to form combined information:

$$s_k = W_x \times X_i + b_x + \tanh(\quad _P \times P_i \quad _p \tag{1}$$

Among them, X_i is the body function used to analyze the law of physical changes, P_i is the function fluctuation information extracted from the physical energy information as input alone to strengthen the model's processing of physical energy fluctuations, $\{Wx, Wp, bx, bp\}$ are network parameters [22]. The output result of the tanh activation function is between [-1, 1]. The closer the output value is to -1, the greater the negative fluctuation; the closer the output value is to 1, the greater the positive fluctuation. The larger the data fluctuation, the greater the impact on the training of the W-LSTM model. On the contrary, when the fluctuation is 0, the input fluctuation data has no effect on the training of the model. At this time, the W-LSTM model is equivalent to the standard LSTM [23].

Forget gate is the historical state information that controls whether to "forget" [24].

$$f_f = \sigma \quad \times h_{t-} + \quad _f \times s_k + \quad _f \tag{2}$$

Among them, h_{t-1} is the hidden state of the previous sequence, and S_k is the input sequence of this time. Define W_f as the weighted matrix of h_{t-1}, U_f as the weighted matrix of S_k, and b_f as the bias.

The Input gate is responsible for supplementing the current input to the latest "memory". It consists of two parts: first, the Sigmoid layer outputs it; second, a Tanh layer creates a new candidate value vector, which will be added into the state. Define {Wt,Ut,bt}{Wa,Ua,ba} as the network parameters of the input gate, then

$$i_t = \sigma(w_t \times h_{t-1} + U_i \times s_i + b_t) \tag{3}$$

$$C^* = \tanh(w_a \times h_{t-1} + U_a \times s_k + b_a) \tag{4}$$

Then update the cell state:

https://doi.org/10.17993/3ctecno.2023.v12n1e43.127-140

$$C_t = C_{t-1} \times f_t + i_i \times C^* \tag{5}$$

The output gate controls how much "memory" can be used in the update of the next layer of the network. Define $\{Wo, Uo, bo\}$ as the network parameters of the output gate, and the calculation of the output gate can be expressed by formula 6:

$$O_t = \sigma(w_o \times s_k + U_o \times h_{t-1} + b_o) \tag{6}$$

After calculating O_t, it is necessary to use the Tanh function to suppress the memory value to [-1, 1], so the output formula of the final output gate is:

$$h_t = O_t \times \tanh(C_t) \tag{7}$$

The historical information output by the last W-LSTM layer passes through a prediction layer and outputs the result y:

$$y = W \times h_t + b \tag{8}$$

2.3. TRAINING PROCESS

The training process of W-LSTM is as follows: Calculate the output value of the W-LSTM cell according to the forward calculation formulas (1) ~ (8) [25]; Backpropagate in two directions according to time and network level to calculate the error term; according to the corresponding, calculate the gradient of each weight, and update the weight; repeat (1) to (3) to obtain a set of optimal parameters and keep them. To prevent overfitting during training, this study uses the Dropout regularization technique [26], which was proposed by Prof. Hinton's team in 2014. Dropout provides a clever way to increase the generalization ability of a network model by reducing weight connections.

3. TEST AND RESULT ANALYSIS

3.1. EXPERIMENT SETUP INSTRUCTIONS

In this section, the proposed W-LSTM model will be evaluated experimentally. The experimental environment is: INTEL Corei5 CPU, 2.80GHz; 4G memory. The experimental data is the daily training data of a football team in Xi'an from April 2022 to May 2022. Each comparative experiment was run 10 times, and the average value was taken.

Three comparison models are set up:

(1) W-LSTM model, input historical function information and physical fitness fluctuation information to train the model to make predictions.

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(2) The BP neural network improved by the LM algorithm only takes the historical functional information as input, and uses the physical fitness information of the previous n days to predict the physical fitness situation of the n+1th day.

(3) The ARIMA model regards the data sequence generated by physical fitness over time as a random sequence, and uses a certain mathematical model to approximately describe this sequence.

At the same time, in order to test the universality of the W-LSTM model, the three models were compared using four data of body shape, exercise tolerance, exercise intensity and fitness level.

3.2. SIMULATION COMPARISON TEST

This summary uses the W-LSTM model, the BP neural network improved by the LM algorithm and the ARIMA model to conduct experiments, and the mean square error (MSE) and the coefficient of determination (R2) are used to determine the accuracy of the prediction results.

$$MSE:$$

$$MSE = \frac{\sum (\text{Y\_actual} - Y\text{\_predict})^2}{n} \tag{9}$$

$$R^2:$$

$$R^2 = 1 - \frac{\sum (\text{Y\_actual} - Y\text{\_predict})^2}{\sum (\text{Y\_actual} - Y\text{\_mean})^2} \tag{10}$$

MSE and R2 are commonly used indicators to evaluate the accuracy of the model. MSE is a measure that reflects the degree of difference between the estimator and the estimated value. The smaller the MSE, the higher the accuracy of the model; the larger the R2, the greater the difference between the independent variable and the dependent variable. The higher the degree of explanation, the higher the percentage of changes caused by independent variables in the total change, and the denser the observation points are near the regression line, which means the higher the model fit. Where n represents the total sample, Y_actual represents the real data, Y_predict represents the prediction result, and Y_mean represents the average value of the real data.

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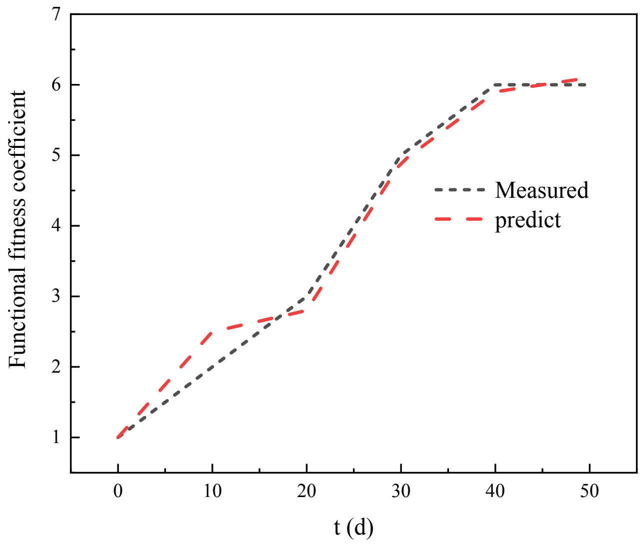

Figure 2. W-LSTM prediction results

By modeling and predicting the physical function sequence, Figures 2 and 3 are the comparison between the prediction results obtained by the W-LSTM model and the ARIMA model and the actual data. Obviously, for the W-LSTM model, the experimental value and the predicted value are extremely coincident and very close, which shows that the W-LSTM model proposed in this study has better prediction results.

By observing the data in Figure 3, it is found that the experimental results of the ARIMA model deviate significantly from other models, the coincidence rate between the experimental values and the predicted values is low, and R2 is even less than 0, which means that the predicted results have nothing to do with the original data. The ARIMA model performs well when dealing with stationary time series. When the data is not stationary, a stationary sequence needs to be obtained through a certain processing method. The physical function data used in this experiment has continuous invariance and mutation, that is, continuous invariance within a period of time. Change, the initial stage gradually increases, this characteristic leads to the loss of too much information when the data is differentiated, resulting in an extremely poor prediction effect of the ARIMA model and a large deviation.

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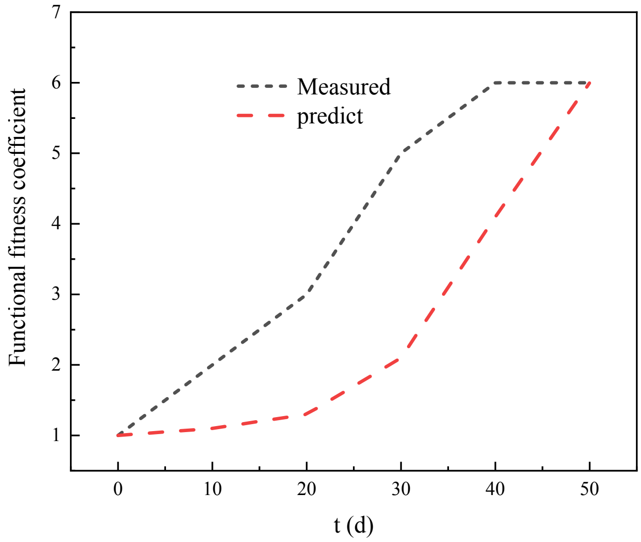

Figure 3. ARIMA model prediction results

After the training, the input data is used for prediction, and the MSE of the W-LSTM model and the BP neural network improved by the LM algorithm changes as the prediction progresses, as shown in Figure 4. The MSE of the W-LSTM model is 0.032, the MSE of the LM-BP model is 0.059, and the MSE of the ARIMA model is 0.923. The MSE of the W-LSTM model is smaller than other models, and the model has the highest accuracy; while R is larger than other models, which means that the fitting degree of the W-LSTM model is higher than that of other models. In general, the MSE trends of the two models are roughly the same, and the MSE of the W-LSTM model is generally smaller than the MSE of the BP neural network improved by the LM algorithm [27].

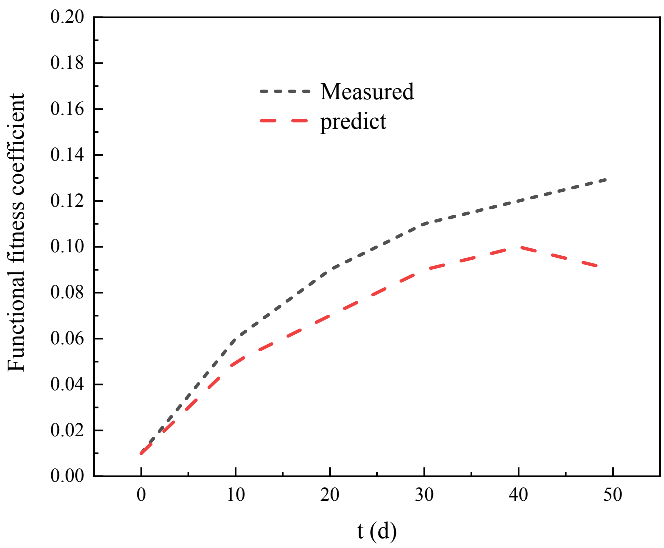

Figure 4. W-LSTM model and BP neural network improved by LM algorithm

Changes in MSE

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The input data fluctuates greatly at one-third of the total data, and at this time, the MSE of both models has a short-term increase, while the MSE fluctuation of the W-LSTM model is smaller than that of the BP neural network improved by the LM algorithm. This shows that the W-LSTM model has a better effect on handling large fluctuations in data. In order to verify the universality of the W-LSTM model, four kinds of data of body shape, exercise tolerance, exercise intensity and health level are used as input to carry out comparative experiments on the three models. The experimental results are shown in Table 1. The table shows the evaluation index of the prediction results of the three models on the four factors respectively. It can be seen that W-LSTM has better results than other models, and it shows that the W-LSTM model has good universality [28-29].

Table 1. MSE and R^2comparison

MSE				
Model	Body shape	Exercise tolerance	Exercise intensity	Fitness level
W-LSTM	0.074	0.031	0.137	0.011
LM-BP	0.163	0.048	0.238	0.017
ARIMA	3.244	-0.891	4.618	0.9048
R^2				
W-LSTM	0.985	0.867	0.904	0.935
LM-BP	0.967	0.793	0.833	0.919
ARIMA	0.317	-2.442	-2.191	-2.771

It can be seen from the above experiments that the W-LSTM model has higher accuracy, better fitting degree and good universality. On the whole, W-LSTM is a good prediction model for the physical fitness prediction problem of football players.

4. CONCLUSION

This paper proposes a physical fitness prediction method for football players based on the W-LSTM network model. The model is mainly constructed by LSTM, which can effectively extract the local and global features of influencing factors. After data analysis and variable reordering based on the maximum information coefficient method, making the data distribution more regular and easy to train. The research compares the prediction results of W-LSTM, LM-BP, and ARIMA models. The experimental results show that: (1) the prediction accuracy of W-LSTM is significantly better than other methods LM-BP and ARIMA models; (2) W-LSTM has lower MSE and higher R2 compared to the other two models, the correlation coefficient of its body shape reaches 0.985; (3) The LSTM is improved to become W-LSTM, and it is of practical value to apply it to the physical fitness prediction of football players.

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5. CONFLICT OF INTEREST

The authors declared that there is no conflict of interest.

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