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Research on Momentum prediction algorithm for athletes based on the CNN-LSTM Model

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Abstract. Momentum has been widely recognized as a psychological factor affecting athletes' performance during sports events. Quantifying the momentum of both athletes in a match and predicting its future trends and reversals can provide effective information for coaches to make tactical decisions during a match. In this paper, taking the Wimbledon dataset as an example, the quantitative model of momentum is firstly constructed by the rank-sum-ratio evaluation method based on EWMA. Subsequently, this paper introduces the CNN network to process the data input based on the traditional LSTM network, takes the output data of the CNN network as the input layer of the LSTM network, and constructs a CNN-LSTM model to predict the change of momentum of athletes in the match, and the reversal time of momentum of athletes of both sides points. Through the model comparison analysis, this paper found that the prediction accuracy of the CNN-LSTM in different time periods is up to 85%, surpassing the LSTM network by 10%. This paper helps coaches and athletes to identify the future trend of momentum in the course of the match so that they can make reasonable tactical arrangements to achieve better performance in sports events.

Keywords: Sports events, Momentum, Prediction Model, CNN-LSTM.

1. Introduction

The relationship between momentum and athlete performance has piqued the curiosity of coaches and sports psychologists since the late 1970s [1]. Momentum can be understood as a power or force acquired through a series of events [2]. In sports competitions, a team or player may feel that they have momentum in these special moments after experiencing special events such as match points, winning streaks, etc [3]. Exploring when the momentum of both athletes will change as the game progresses is not only conducive to the correct adjustment of the athletes' mentality to cope with the game but also enables the coaches to make timely strategic adjustments to ensure that the athletes' performance is better.

With the advent of information technology innovation and the era of big data, a large number of machine learning models have been created to provide effective help for the planning and prediction of sports events [4-5]. Among them, the LSTM (Long Short-Term Memory) model is widely used for its excellent performance in time series problem processing [6]. Currently, scholars have conducted related research on momentum prediction using machine learning models: Li et al. used logistic regression model to predict momentum fluctuations and visualized momentum by BP neural network [7], On the other hand, Lin et al. used the XGBoost machine learning technique to construct the model, combined with the particle swarm optimization algorithm to fine-tune the parameters, and investigated the key aspects affecting momentum [8].

However, few scholars have focused on the temporal nature of momentum in the game, capturing the changes in momentum sequences in the time dimension. In summary, this paper will introduce a CNN (Convolutional Neural Networks) model based on the LSTM model to sample the raw data, i.e., it ensures that the model can deal with the local features of the sequences and captures the long-term dependencies in the time series data.

2. Overview of work

2.1. Data proceeding

The dataset for this paper is derived from Wimbledon 2023 men's matches after the first 2 rounds. A total of 31 matches were recorded in the dataset, which includes details of the scoring of the match such as whether each point was a winning shot, serve errors, net shots, and other scoring details such as distance run, serve speed, number of hits, etc. of the athletes' hitting process. In order to accurately and multidimensionally assess a player's performance in a specific time period and to take into account the player's psychological condition, this paper selects features from player 1's perspective. In this paper, six-dimensional features are selected, and each feature represents a different meaning.

Table 1 Explanation of feature selection

	feature 1	feature 2	feature 3
Name	point difference in game	point difference in set	great performance
	feature 4	feature 5	feature 6
Name	poor performance	opponent serves to win	missed chances to win

Based on the six feature indicators in Table 1 Explanation of feature selection, this paper adopts the rank-sum ratio comprehensive evaluation model based on Exponential Weighted Moving Average, establishes an evaluation model for each game, comprehensively calculates the performance score of each score of athlete in a game, and calculates the respective momentum of the athletes of both sides by using formula 1.

$$mom_{ij} = \frac{ps_{ij}}{\sum_{i=1}^{2} ps_{ij}} \quad (i = 1,2) \tag{1}$$

where ps_{ij} is the performance score of athlete i at the jth score and mom_{ij} is the momentum of athlete i at the jth score. When $\Delta mom_{ij} < 0$, it means that the momentum of athlete i at the jth score is reversed.

2.2. Our Work

To portray the trend and transformation of momentum in the process of competition, this paper first establishes a rank-sum ratio evaluation method based on the exponential smoothing method for portraying the change of momentum based on the performance indexes of athletes in the process of competition. After obtaining the momentum sequence, this paper uses 80% of the data as the training set and 20% of the data as the test set, firstly, the training data are extracted by CNN to extract the local features as the input data of LSTM, and then the LSTM is used to extract the long-distance features of these extracted local features for the training of the model. In the test, 5, 10, and 20 steps of time length are selected for prediction to compare the prediction performance of the model in different time lengths. The specific flow Figure 1 is shown.

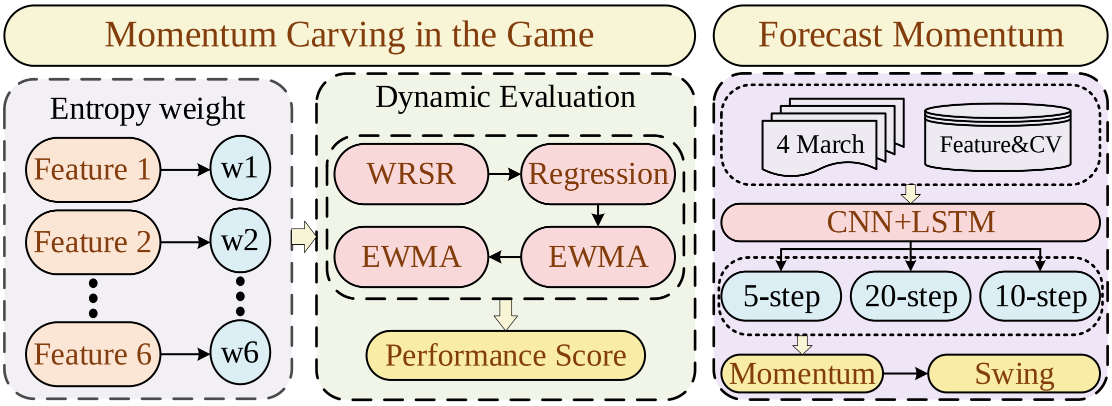

Figure 1 Analysis flow

3. Principles of Model Architecture

3.1. Modeling of LSTM

LSTM refers to Long Short-Term Memory Network, which is a temporal recurrent neural network suitable for processing and predicting important events with relatively long intervals and delays in a time series [9]. In this paper, LSTM can especially predict momentum, i.e., memorizing and forgetting different information during the prediction process. The specific operation structure of LSTM is shown in Figure 2 below.

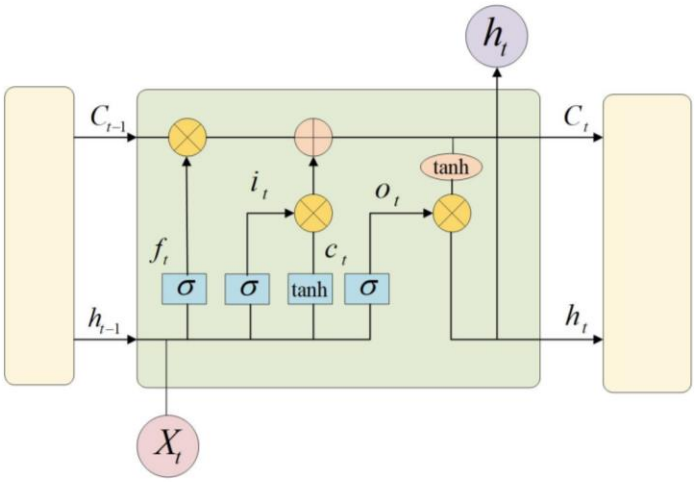

Figure 2 The working structure of LSTM

In this paper, we use the momentum change as the signal value of LSTM, which controls the transmission and processing of information through three gates: from left to right, these represent the Oblivion Gate, the Input Gate, and the Output Gate. The three gates contain a total of three sigmoid functions and two hyperbolic tangent functions. In summary, the LSTM passes two state values h and c at a time, where the state value c_t retains part of the information passed in at time $t-1$ and the filtered information passed in at time t. The state value c_t is used for the input predictions h and c.

The formulae for the process of operation of each gate are as follows:

Forget gate

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2}$$

$$cf = \sigma(c_{t-1} \cdot f_t) \tag{3}$$

Input gate

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$i_h = \tanh(W_h \cdot [h_{t-1}, x_t] + b_h) \tag{5}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot i_h \tag{6}$$

Output gate

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{8}$$

3.2. Modeling of CNN-LSTM

Based on the fact that a single LSTM may suffer from instability and gradient vanishing phenomenon, this paper combines CNN for modeling based on the above LSTM model. High-dimensional features are extracted by the short-sequence feature abstraction ability of CNN, and then LSTM synthesizes the short-sequence high-dimensional features for time series prediction, which makes the feature extraction process hierarchical and thus improves the expressive ability of the model [10].

The multi-feature sequence classification CNN-LSTM model is mainly composed of the signal input layer, CNN convolutional layer, pooling layer, LSTM layer, and classification output layer, the structure is shown in Figure 3:

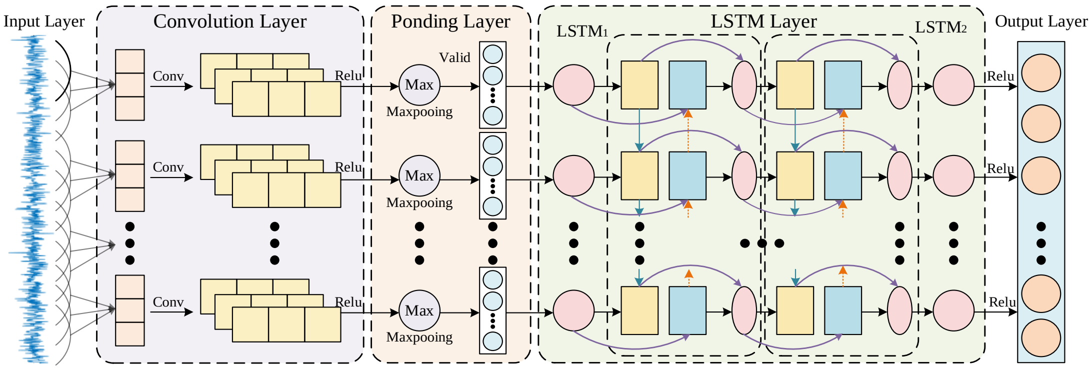

Figure 3 Schematic of CNN-LSTM model structure

The modeling process is specified as follows:

Step1 The input signal is normalized and fed into a CNN convolutional layer to adaptively extract features using a wide convolutional kernel:

$$c = f(X \otimes W + b) \tag{9}$$

Where $\otimes$ is the convolution operation and W is is the weight vector of the convolution kernel.

Step 2 The extracted features undergo a pooling operation in the maximum pooling layer to reduce the data dimensionality and retain the main feature information.

Step 3 The downscaled feature data is then used as the feature input to the LSTM layer to train the neural network and automatically learn the sequence features.

Step 4 The Adam algorithm is utilized to back-propagate the training error and gradually update the model parameters layer by layer.

Step 5 Signal features are output using Sigmoid activation functions for the task of predicting multi-feature input sequences.

4. Analysis of results

In this paper, four matches (1301, 1401, 1501, 1601, and 1701) of the winner of this tournament, Carlos Alcaraz, are selected for prediction analysis of his momentum. In this paper, 80% of the data (698 entries) are used as training In this paper, 80% of the data (698 entries) are used as training data to put into the model for training and to see how well the training data fit. The development language used in this paper is Python 3.10.6, the framework is Pytorch 1.12.1, the GPU is NVIDIA GeForce RTX 3070 Laptop GPU, and the CPU is AMD Ryzen 7 5800H.

To compare the performance of different models for predicting momentum, the ARIMA model, SVR model, and LSTM model in addition to CNN-LSTM are selected for comparative analysis in this paper.

4.1. Training of models

When building a CNN-LSTM network, the first step is to determine the number of hidden layers. The number of hidden layers has a large impact on the training of the network, this paper determines the number of hidden layers according to the following formula [11].

$$h = \sqrt{m + n} + a \tag{10}$$

Where h is the number of nodes in the hidden layer, m is the number of nodes in the input layer, n is the number of nodes in the output layer, a is an adjustment constant between 1 and 10, and the final number of hidden layers in this paper is determined to be 5 layers. In this paper, the gradient descent in the model uses the Adam training algorithm to avoid the algorithm function falling into the local optimum, after much training, it found that when the iteration to 300 times when the model loss function is close to the convergence state, so the number of times the model training are set to 300 times.

The results of the model fitting were compared using the Root Mean Square Error (RMSE), which is a measure of the square root of the mean of the squared differences between the predicted and true values and is calculated as shown in Formula 11.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - y_i')^2}{N}} \tag{11}$$

Where y_i is the true value of momentum at the ith moment, and y_i' is the predicted value of momentum at the ith moment. the smaller the $RMSE$ value is, the better the result of model training.

Besides, The training result momentum is transformed into inversion of momentum, and the prediction result is measured by $Accuracy$ and F_β. F_β is calculated as follows:

$$F_\beta = (1 + \beta^2) \cdot \frac{precision \cdot recall}{\beta^2 \cdot precision + recall} \tag{12}$$

In this problem, $recall$ represents the positive cases that are predicted to be positive and account for all the samples that are positive cases, for the players' moment, the importance of $recall$ is greater than $precision$, so when calculating F_β, this paper takes $\beta = 2$, denoted as F_2, which represents that $recall$ is weighted more heavily than $precision$ [12]. The training results are shown in Table 2 is shown:

Table 2 Parameters of the degree of training fit

	ARIMA	SVR	LSTM	CNN-LSTM
$RMSE$	0.2672	0.1734	0.1649	**0.0680**
$Accuracy$	0.7835	0.8293	0.8316	**0.9519**
F_2	0.8246	0.8612	0.8671	**0.9682**

Observing Table 2, it can be seen that the $RMSE$ of the CNN-LSTM model is the smallest, and the smaller the RMSE is, the better the fit between the training data and the real data is. The closer the $Accuracy$ and F_2 are to 1, the higher the accuracy and precision of the model. Compared with other models, the Accuracy and F_2 of CNN-LSTM are the largest and close to 1. The box plots of the four training models and the fit of CNN-LSTM are shown in Figure 4:

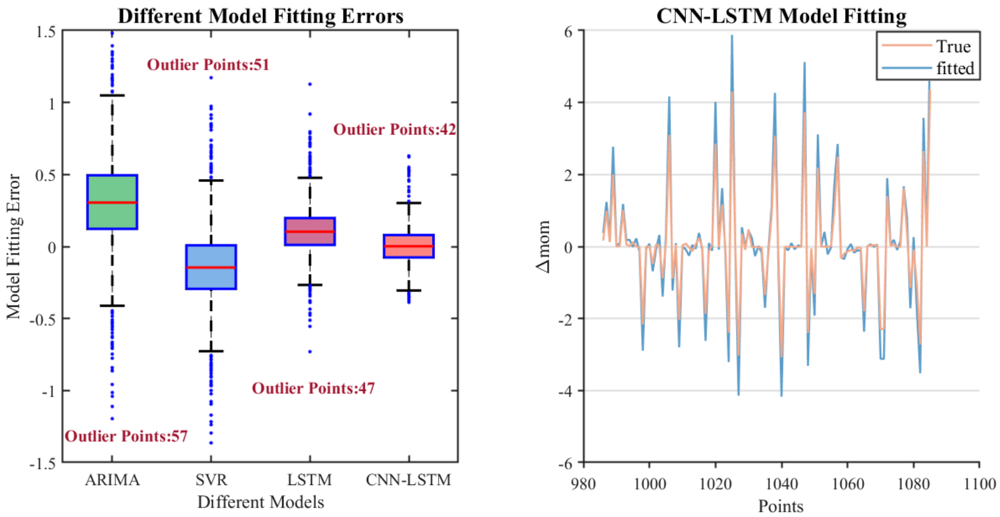

Figure 4 Box lines and fitted plots of the model

Observing Figure 4 shows that the mean line in the box of CNN-LSTM is closest to 0 and the box is flatter than the other models, which indicates that the error is minimized when predicting with this model, observing the fitting graph shows that the trend of the true and fitted values of CNN-LSTM are generally the same, which indicates that the CNN-LSTM model has a high degree of fit when it is trained with the CNN-LSTM model.

4.2. Testing of models

After model training, the model was tested with 20% of the test data. In real-world environments, coaches and athletes not only need to make adjustments to the trend of momentum changes in the short term, but also the trend of momentum in the long term is an important factor in decision-making for the whole game. To observe the performance of the model in dealing with data of different time lengths, this paper predicts the data of 5, 10, and 20 steps backward respectively. The prediction steps for 5 steps are as follows:

Step 1 Take 1 to i data in the test set for training.

Step 2 Prediction of $i+1st$ to $i+5th$ data.

Step 3 Put in the $i+1st$ data to update the model.

Step 4 Continue to predict the $i+2nd$ to $i+6th$ data. The prediction result momentum is transformed into inversion of momentum to calculate $Accuracy$ and F_2, and the results are obtained as shown in Table 3:

Table 3 Model Test Result

	5step		10step		20step	
	$Accuracy$	F_2	$Accuracy$	F_2	$Accuracy$	F_2
ARIMA	0.7665	0.8014	0.7335	0.7768	0.6826	0.7300
SVR	0.8144	0.8562	0.7814	0.8321	0.7665	0.8166
LSTM	0.8174	0.8470	0.8144	0.8586	0.7814	0.8370
CNN-LSTM	0.9432	0.9584	0.9129	0.9281	0.8623	0.9001

And calculate the $RMSE$ of the model based on the results of the predicted momentum, the prediction results of the four models are shown in Figure 5:

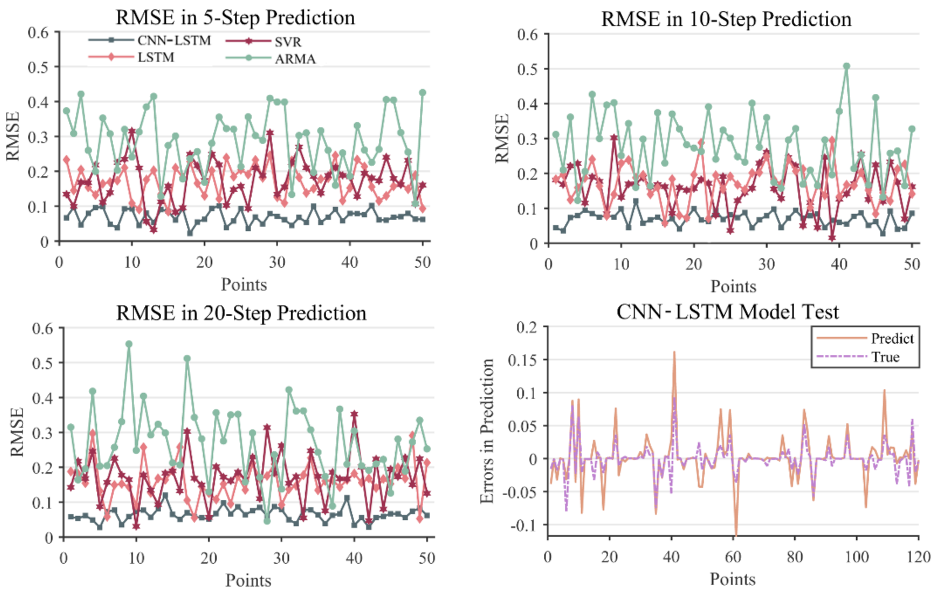

Figure 5 The RMSE and prediction of the 4 models

Observing Table, it can be seen that among these four models, the $Accuracy$ and F_2 of CNN-LSTM at 5 steps, 10 steps, and 20 steps are higher than the other three models and closer to 1. The $RMSE$ of each model in 5, 10, and 20-step prediction is taken as the mean of the RMSE of 5, 10, and 20-step prediction respectively. Observing Fig.5, it can be seen that the $RMSE$ of CNN-LSTM in 5, 10, and 20-step prediction is lower than other models, and the predicted values coincide with the real values in a general trend, which indicates that the prediction accuracy with CNN-LSTM is higher.

5. Comparison of previous studies

In this paper, we pioneered the use of a CNN-LSTM model to predict an athlete's momentum sequence as well as momentum reversal during a race. The model predicts 5, 10, and 20 steps with 94.32%, 91.29%, and 86.23% accuracy, respectively, which is at least 8.63% more accurate than the 77.6% accuracy obtained by Yu et al. using the LightGBM model [13], and more accurate than the weighted LSTM used by Hua et al. with 87.06% accuracy at 5 and 10 steps [14].

6. Discussion

6.1. Advantages and disadvantages

In this paper, when dealing with the prediction of momentum sequences of athletes in a game, we innovatively take into account the temporal order of the sequences and use LSTM neural networks to capture the correlation of momentum sequences in the temporal order of the whole game. In addition, this paper also combines the local perception and parallel computing characteristics of CNN networks to improve the running speed and prediction accuracy of the model and alleviate the phenomenon of gradient disappearance caused by the training process of LSTM networks.

However, there are still some shortcomings in the study of this paper.The time-series nature of LSTM can lead to the weight of the previous period's data decreasing with the growth of the time series, which is prone to the possibility of forgetting the past data.

6.2. Conclusion

Momentum, as an important factor that is difficult to quantify and affects the process of the game, has gradually stepped into the vision of coaches as well as athletes. In this paper, after selecting the performance scores of the athletes, this paper uses RSR based on EWMA to get the performance scores of the athletes and calculate the corresponding momentum, and then uses the CNN-LSTM model to predict the sequence of momentum and the inversion of momentum, and found that the RMSE of CNN-LSTM is smaller than that of ARIMA, SVR and LSTM model in the prediction of the test data in the 5, 10 and 20 steps, and in the accuracy of predicting momentum reversal, $Accuracy$ and F_2 are greater than 85% and 90%, respectively, in different step sizes, and the prediction performance is greater than that of the remaining three types of models in different step sizes. Therefore, the prediction of momentum sequences and momentum reversals using CNN-LSTM can achieve excellent performance. This study can help coaches and athletes identify the future trend of momentum during the game process so that they can make reasonable tactical arrangements to achieve better performance in sports events.

6.3. Outlook

Because of the possibility of forgetting the past data when training LSTM models for long time series, we will introduce the Attention mechanism or Transformer model in future research to further improve the progress of the model. In addition, in future research, we can also focus on the momentum prediction of different events, and select the corresponding score features to train the model for different events, to assist in the training of more sports events.

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