Predicting the Development Trend of University Sports Meeting Results Using LSTM Model

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ABSTRACT Result prediction is valuable in sports because it can help athletes improve performance and support the optimization of training efficiency. Similar time-series prediction methods are also important in engineering fields such as electromagnetic testing, antenna performance evaluation, and communication system monitoring, where trend forecasting can support resource allocation and process adjustment. As an important component of quality-oriented education, university sports meetings provide measurable data for evaluating students' physical fitness and improving physical education programs. Changes in sports meeting results can reflect long-term training effects and provide data support for teaching reform and training plan optimization. Long Short-Term Memory (LSTM), as a representative recurrent neural network, has advantages in processing long-sequence data and capturing nonlinear temporal dependencies. This study takes university sports meeting results as the research object and constructs an LSTM-based prediction model for result development trends. Experimental results show that the proposed model achieves higher prediction accuracy across different events than the ARIMA model and BP neural network. By analyzing the development trend of university sports meeting results, the model provides a scientific basis for optimizing training plans and event organization. The study also demonstrates the applicability of LSTM-based time-series prediction to engineering data analysis, including electromagnetic measurement sequences and antenna performance trend prediction.

INDEX TERMS lstm model, university sports meeting, time-series prediction, electromagnetic testing, antenna performance

I. INTRODUCTION

With the development of the times, the country has emphasized the concept of national fitness, leading to a period of rapid development in college physical education, a focus that ultimately supports the health and vitality of the workforce needed across major manufacturing sectors [1]. As a crucial component of quality-oriented education, organizing sports meetings is an indispensable basic link for all universities [2]. With the rapid advancement of science and technology and the fast development of the sports industry, data and information have experienced explosive growth. The development of contemporary sports, the improvement of sports competition results, and the enhancement of training levels increasingly rely on big data. Adjustments to training methods and content are made based on this data to improve sports performance most efficiently within a limited time [3,4].

Nowadays, the application of artificial intelligence algorithms has become increasingly widespread in the field of sports—ranging from large-scale international events like the Olympic Games to small-scale school sports meetings. In recent years, various prediction methods, such as grey prediction and statistical regression analysis, have been continuously introduced into sports events [5,6]. Predicting the results of important sports events has attracted growing attention from sports researchers in every country. Using scientific prediction methods to study sports competitions can help athletes win competitions. Therefore, guiding athletes' scientific training and improving sports performance through the relationship between prediction methods and relevant technical indicators is one of the important ways to enhance competitive levels in the era of big data [7-9].

At present, the Back Propagation (BP) neural network is a commonly used algorithm for predicting results in schools. Due to its strong fault tolerance, generalization ability, and nonlinear mapping capability, this type of algorithm has been effectively applied in various types of performance prediction [10]. However, such algorithms also have certain limitations in practical applications: they can only process individual inputs independently, and are prone to problems such as falling into local minima and slow convergence [11]. In performance prediction, various factors are often correlated with each other, and the foundation of early training has a certain impact on later competition results [12,13]. Therefore, the Recurrent Neural Network (RNN) model was proposed and widely applied. A typical representative of this type of model is the Long Short-Term Memory (LSTM) model, which mainly addresses issues such as gradient explosion and gradient vanishing during long-sequence training [14]. In simple terms, it is more important than general RNNs, as LSTM can achieve better performance in processing long sequences [15]. This study introduces the LSTM model for high-precision prediction of university sports meeting performance, aiming to construct a versatile technical support model for training optimization and management that is equally valuable for process control and efficiency enhancement in industrial settings.

Limitations related to data representativeness should be noted here. This study only uses sports meeting data from a single key university in a certain province during 2010-2023. Compared with higher-level competitions (such as inter-provincial university sports meetings or national youth sports events), the sample scope of school-level sports meeting data is relatively narrow, which may limit the representativeness and generalization ability of the research results. In future research, multi-university, multi-region data can be integrated to further improve the applicability of the model.

II. RESEARCH STATUS

International research on sports prediction has a long history and rich experience. Dating back to the 1960s, with the technological progress driven by wars, scientific and systematic prediction methods gradually began to be applied in competitive sports competitions. Over time, European and American countries have shifted from simply predicting competition results in the early stage to predicting the future development of individual athletes and even sports events. An increasing number of data mining technologies and related algorithms have been applied to the analysis and prediction of sports event data. Scholars have attempted to add more data features, reduce redundant features, and combine scientific models to significantly improve prediction accuracy [16]. Overall, countries around the world attach great importance to the application of machine learning algorithms in the sports field and have achieved breakthroughs to varying degrees [17,18]. As a type of machine learning algorithm, neural network algorithms provide broad development space for sports performance prediction and have unique advantages in data prediction and analysis [19]. Various types of performance prediction methods have been studied in the sports field, and their predictions for some large-scale events are relatively accurate. Domestic research mainly focuses on predicting athletes' competition results and rankings through data, as well as predicting the current level of college students' physical health. João Gustavo Claudino [20] and his team from the University of São Paulo used methods such as artificial intelligence and artificial neural networks to analyze and predict athletes' personal abilities. They applied artificial neural networks, decision tree classifiers, and support vector machines to predict the risk of sports injuries, and also used these technologies to predict competition results in sports such as football and basketball, achieving favorable outcomes; they further used AI to improve team sports. Adam Maszczyk, Artur Golas [21], and others predicted the performance of javelin athletes and found that neural network models had higher prediction accuracy compared with nonlinear regression models. The GM (1,1) model was used to predict the results of the men's 400m freestyle event at the next Olympic Games, boldly predicting that the result would break the Olympic record and verifying the credibility of the model. Neural network algorithms have also been successfully applied in NBA games: by collecting historical data of teams and players, and predicting whether a team can win based on the results of data analysis, the possibility of being defeated by weaker teams is avoided. Timely adjustments to the order of players' appearance are made to increase the chance of winning [22].

III. TECHNICAL ROUTE AND RELATED THEORIES

A. RESEARCH CONTENT

This study takes the sports meeting performance data of a university from 2010 to 2023 as the research object, with the main contents as follows:

- Data collection and preprocessing: Select performance data of 10 representative events, and conduct data cleaning, missing value handling, and outlier detection;
- Feature engineering: Perform normalization on the preprocessed data to eliminate the impact of dimensional differences, and divide input sequences and output sequences based on time windows to provide a data foundation for model training;
- Model construction: Build an LSTM prediction model based on the Keras framework, and determine the model's network structure and training parameters;
- Model verification and comparison: Adopt the 5-fold cross-validation method to verify the model's stability, and compare it with the ARIMA model and BP neural network simultaneously;
- Result analysis and application: Based on the model's prediction results, analyze the development trend of performance in each event of the university's sports meeting and put forward targeted training suggestions.

B. TECHNICAL ROUTE

The technical route of this study is shown in the figure below:

C. PRINCIPLES AND METHODS OF THE LSTM MODEL

Long Short-Term Memory (LSTM) is a special type of Recurrent Neural Network (RNN) designed for processing long-sequence data. It adopts special hidden units: while inheriting most of the characteristics of RNN models, it can

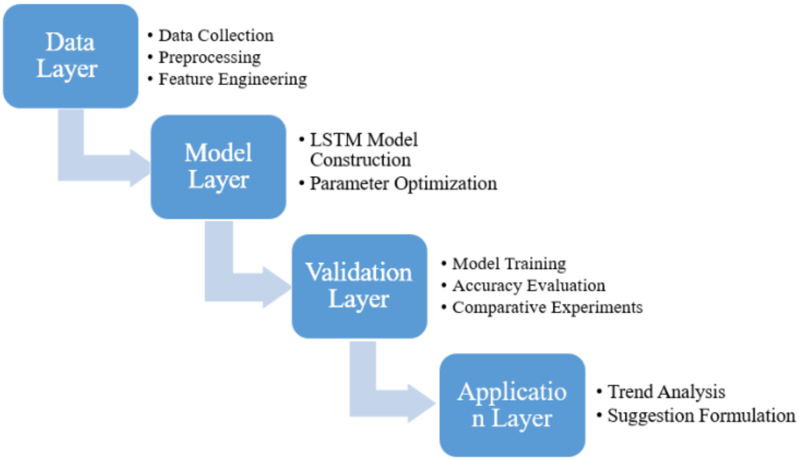

FIGURE 1. The technical route.

address the long-term dependency problem, avoid gradient vanishing, and possesses advantages such as high model accuracy, fast training speed, and strong parallel processing capability [10-12]. The basic structure of the current LSTM network is shown in Figure 2.

The LSTM model consists of an input gate, a forget gate, an output gate, and a cell state.

The forget gate is responsible for determining which information to discard from the cell state, with its expression given by:

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

Among them, b_f is the bias term of the forget gate, W_f is the weight matrix of the forget gate, and σ is the sigmoid activation function. When f_t is close to 1, the information in the cell state is retained; when f_t is close to 0, the information in the cell state is discarded.

The input gate is responsible for determining which new information is stored in the cell state, with its expression given by:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{2}$$

$$\widetilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \tag{3}$$

Among them, W_i and W_C are the weight matrices of the input gate and the candidate cell state, respectively; b_i and b_C are the corresponding bias terms, respectively.

Cell State Update: Combine the results of the forget gate and the input gate to update the cell state C_t. The calculation formula is as follows:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \tag{4}$$

Output Gate: Determines the output value based on the cell state and is responsible for deciding the hidden state at the current moment. The calculation formula is as follows:

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{5}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{6}$$

Among them, W_o is the weight matrix of the output gate, and b_o is the bias term of the output gate.

D. MODEL EVALUATION METRICS

To objectively evaluate the prediction performance of the LSTM model, the calculation formulas for each metric are as follows:

1) Mean Absolute Error (MAE)

Mean Absolute Error (MAE) measures the average absolute deviation between predicted values and actual values, with the calculation formula given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

Among them, n is the number of samples, y_i is the actual value of the i-th sample, and $\hat{y}_i$ is the predicted value of the i-th sample.

2) Mean Squared Error (MSE)

Mean Squared Error (MSE) measures the average squared deviation between predicted values and actual values, with the calculation formula given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{8}$$

3) Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) is the square root of MSE, which facilitates intuitive understanding of the error magnitude. Its calculation formula is given by:

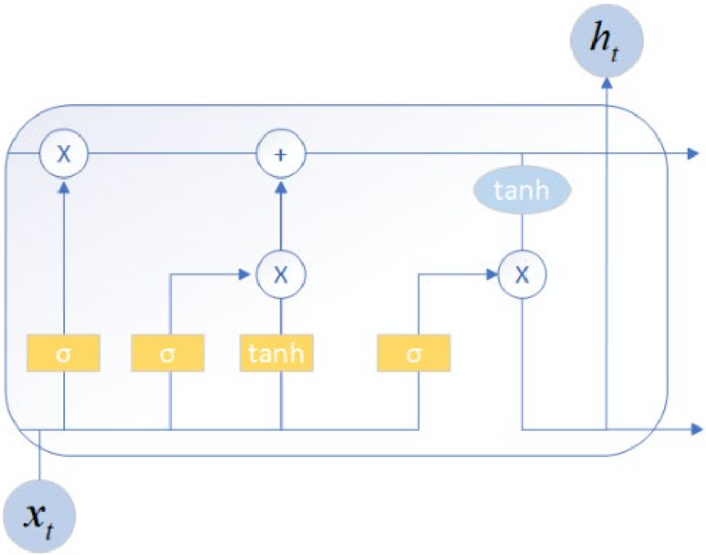

FIGURE 2. The basic structure of the current LSTM network.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{9}$$

Note: MSE and RMSE are both included as evaluation metrics because although they are mathematically related, RMSE has the same unit as the original data, which is more intuitive for readers to understand the actual error range of the model. For example, in the Men's 100m event, RMSE is 0.28 seconds, which directly reflects the average error magnitude in time units, while MSE (0.08) is a squared value and is more sensitive to large errors, helping to identify extreme deviations in the model's prediction results. Therefore, the combination of MSE and RMSE can provide a more comprehensive evaluation of the model's performance.

4) Coefficient of Determination (R^2)

Coefficient of Determination (R^2) measures the goodness of fit of the model to the data, with a value range of ($-\infty$, 1]. Its calculation formula is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{10}$$

Among them, $\bar{y}$ is the average value of the actual values.

IV. RESEARCH DATA AND PREPROCESSING

A. DATA SOURCE

The data in this study is derived from the official performance records of the spring sports meeting (2010–2023) of a key university in a certain province (hereinafter referred to as "the university"). Ten representative events with a large number of participants and complete data records were selected as the research objects. The specific event categories and data time periods are shown in Table 1.

TABLE 1. Classification of Research Events and Data Time Periods

Event Category	Specific Event	Data Time Period	Sample Size (Participants per Year)
Track and Field	Men's 100m	2010–2023	30–45 people/year
Track and Field	Women's 100m	2010–2023	25–38 people/year
Track and Field	Men's 1500m	2010–2023	20–32 people/year
Track and Field	Women's 800m	2010–2023	18–28 people/year
Ball Sports	Men's Basketball (Points per Game)	2010–2023	12 teams/year (12 people per team)
Ball Sports	Women's Volleyball (Points per Game)	2010–2023	10 teams/year (10 people per team)
Physical Fitness	Men's Standing Long Jump	2010–2023	40–55 people/year
Physical Fitness	Women's Standing Long Jump	2010–2023	35–48 people/year
Physical Fitness	Men's Pull-Ups (Number of Repetitions)	2010–2023	25–38 people/year
Physical Fitness	Women's Sit-Ups (Number of Repetitions in 30 Seconds)	2010–2023	30–42 people/year

Note: After sorting, data from years with fewer than 10 participants was excluded to ensure sample validity.

B. DATA PREPROCESSING

The original performance data has issues such as missing values, outliers, and inconsistent dimensions, which require data preprocessing.

1) Data Cleaning

The core of data cleaning is handling missing values. After inspecting the original data, it was found that missing values mainly occur in the following two scenarios: For individual events in some years, no performance records were kept due to insufficient participants (e.g., only 8 teams participated in the women's volleyball event in 2012, so points per game were not recorded); Performance records of individual athletes were missing due to recording errors (e.g., the results of 2 athletes in the men's 100m event in 2018 were not entered into the system).

To address the above missing values, the following methods were adopted in this study:

1) For event-level missing values, linear interpolation based on historical data only (excluding future data after the missing point) was used for imputation. Specifically, if the data of year t is missing, the data of year $t-1$ and $t-2$ are used for linear interpolation to avoid data leakage. This method ensures that the imputation process only relies on available historical information, which is consistent with the time sequence logic of the prediction task and avoids overestimating the model's predictive ability.

2) For athlete-level missing values, the average performance of the event in that year was used for imputation.

After data cleaning, there were no missing values in the performance data of the 10 events from 2010 to 2023.

2) Outlier Detection and Handling

Outliers refer to observed values that differ significantly from most other data points. Their causes may include athlete violations, recording errors, etc.

This study used the box plot method for outlier detection, with the specific steps as follows:

1) Calculate the quartiles (Q1, Q2, Q3) of the performance data for each event in each year, where Q1 is the lower quartile (25th percentile) and Q3 is the upper quartile (75th percentile).

2) Calculate the interquartile range (IQR = Q3 - Q1) and determine the criteria for identifying outliers: values less than Q1 - 1.5×IQR or greater than Q3 + 1.5×IQR are defined as outliers.

3) For the detected outliers, the trimmed mean (excluding the top 5% and bottom 5% of data) of the event in that year was used for replacement instead of the median. The trimmed mean can reduce the impact of extreme values while retaining the overall distribution characteristics of the data, avoiding artificial compression of the data distribution towards the center and more accurately reflecting the real performance level of athletes in that year.

Taking the performance data of the men's 100m event as an example, the results of outlier detection are shown in Table 2:

TABLE 2. Outlier Detection and Handling Results for the Men's 100m Event (Unit: Seconds)

Year	Original Data (Partial)	Q1	Q3	IQR	Out lier	Processed Data
2013	10.8, 11.2, 15.6, 11.5	11.0	11.6	0.6	15.6	11.3
2017	10.5, 10.9, 9.8, 11.2	10.6	11.1	0.5	9.8	10.9
2021	10.3, 10.7, 12.1, 10.8	10.5	10.9	0.4	12.1	10.7

3) Data Normalization

Due to significant differences in the units and value ranges of performance data across different events, direct input of such data into the model would cause the model to be overly sensitive to features with larger values, thereby affecting training effectiveness. Therefore, it is necessary to perform normalization on the data. For events where lower values indicate better performance (e.g., time-based events such as Men's 100m and Men's 1500m), the reversed Min-Max normalization method is used to ensure that normalized values consistently reflect better performance moving towards 1. For events where higher values indicate better performance (e.g., Men's Pull-Ups, Women's Standing Long Jump), the standard Min-Max normalization method is used.

The calculation formulas are as follows:

1) For events with lower values = better performance (time-based events):

$$x' = \frac{x_{\max} - x}{x_{\max} - x_{\min}} \tag{11a}$$

Among them, x represents the original data, $x_{\min}$ is the minimum value of the performance data for the event, $x_{\max}$ is the maximum value of the performance data for the event, and x' denotes the normalized data.

2) For events with higher values = better performance (quantity/distance-based events):

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{11b}$$

Among them, the parameters are the same as above.

Taking the Men's 1500m (Unit: Seconds) and Women's Standing Long Jump (Unit: Meters) events as examples, the comparison of data before and after normalization is shown in Table 3:

TABLE 3. Comparison of Data Before and After Normalization

Event	Year	Original Data	Minimum Value	Maximum Value	Normalized Data (x')
Men's 1500m	2010	258.5	245.2	270.8	(258.5-245.2)/(270.8-245.2) = 0.52
Men's 1500m	2015	250.3	245.2	270.8	(250.3-245.2)/(270.8-245.2) = 0.20
Men's 1500m	2023	248.1	245.2	270.8	(248.1-245.2)/(270.8-245.2) = 0.11
Women's Standing Long Jump	2010	2.15	2.00	2.45	(2.15-2.00)/(2.45-2.00)
Women's Standing Long Jump	2015	2.28	2.00	2.45	(2.28-2.00)/(2.45-2.00)
Women's Standing Long Jump	2023	2.35	2.00	2.45	(2.35-2.00)/(2.45-2.00)

4) Construction of Sequential Data

This study adopts the sliding time window method to construct sequential data, with the specific steps as follows:

1) Determine the time window size T: The time window size indicates that the performance data of the previous T years is used to predict the performance of the T+1-th year. Through experimental verification (testing the model accuracy when T=3, T=4, and T=5 respectively), this study finally determines T=4, meaning the performance of the 5th year is predicted using the performance data of the previous 4 years.

2) Divide the input sequence (X) and output sequence (Y): Taking the Men's 100m event as an example, the performance data from 2010 to 2013 is used as the input sequence X1, and the performance data in 2014 is used as the output sequence Y1; the performance data from 2011 to 2014 is used as the input sequence X2, and the performance data in 2015 is used as the output sequence Y2, and so on until all samples are constructed.

3) Split the training set and test set: The constructed sequential data is split into a training set and a test set at a ratio of 7:3. The training set is used for model parameter learning, and the test set is used for evaluating the model's prediction accuracy.

After normalization, all model training and evaluation are based on normalized data. When calculating the evaluation metrics (MAE, MSE, RMSE, R^2) reported in Table 6, the predicted values and actual values are first de-normalized using the inverse of the corresponding normalization formula (11a or 11b) to restore them to the original data units (e.g., seconds, meters). This ensures that the evaluation metrics have practical physical meaning and can truly reflect the model's prediction error in real scenarios. Taking the Men's 100m event as an example, the results of sequential data construction are shown in Table 4:

TABLE 4. Results of Sequential Data Construction for the Men's 100m Event (After Normalization)

No.	Input Sequence	Output Sequence (Performance of the 5th Year)	Dataset Type
1	[0.62, 0.58, 0.55, 0.51]	0.48	Training Set
2	[0.58, 0.55, 0.51, 0.48]	0.45	Training Set
3	[0.55, 0.51, 0.48, 0.45]	0.42	Training Set
4	[0.51, 0.48, 0.45, 0.42]	0.39	Training Set
5	[0.48, 0.45, 0.42, 0.39]	0.36	Test Set
6	[0.45, 0.42, 0.39, 0.36]	0.33	Test Set

V. LSTM MODEL CONSTRUCTION AND TRAINING

A. MODEL CONSTRUCTION ENVIRONMENT

The LSTM model in this study is implemented based on the Python programming language, with the specific development environment as follows:

- Operating System: Windows 10 Professional (64-bit);
- Hardware Configuration: CPU is Intel Core i7-12700H, GPU is NVIDIA GeForce RTX 3060 (6GB video memory), and memory is 16GB;

B. MODEL STRUCTURE DESIGN

Based on the Keras framework, the LSTM model constructed in this paper adopts a four-layer structure of "Input Layer - Hidden Layer - Fully Connected Layer - Output Layer". The specific structural parameters are shown in Table 5:

TABLE 5. Structure and Parameter Settings of Each Layer of the Model

Layer Level	Layer Type	Core Parameters & Configuration	Function Description
Input Layer	Input Sequence	Dimension: (None, 4, 1); None: Batch size (dynamically adjustable); 4: Time window (performance of previous 4 years)	Receives historical performance sequence data and provides input data source for the model
Hidden Layers	1st LSTM Layer	Number of neurons: 64; Activation function: tanh; Return sequences: return_sequences=True	Extracts primary temporal features of the input sequence and outputs the complete sequence for further processing by the next LSTM layer
Hidden Layers	Dropout Layer	Dropout rate: 0.2	Randomly drops 20% of neurons to reduce the risk of model overfitting and enhance generalization ability
Hidden Layers	2nd LSTM Layer	Number of neurons: 32; Activation function: tanh; Return sequences: return_sequences=False	Deeply integrates the sequence features output by the first layer, outputs the hidden state of the last time step, and condenses key information
Fully Connected Layer	Dense Layer	Number of neurons: 16; Activation function: ReLU	Performs nonlinear transformation and dimension reduction on the features extracted by LSTM to enhance the expressive ability of features
Output Layer	Dense Layer	Number of neurons: 1; Activation function: None (linear output)	Outputs continuous prediction results, corresponding to the regression prediction task of university sports meeting performance

C. MODEL TRAINING PARAMETER SETTINGS

The selection of model training parameters directly affects the model's convergence speed and prediction accuracy.

After multiple rounds of experimental debugging, the final training parameters are determined as follows:

- Optimizer: The Adam optimizer is adopted, with a learning rate set to 0.001;
- Loss Function: Mean Squared Error (MSE) is used as the loss function, which is consistent with the model evaluation metrics;
- Evaluation Metrics: During the model compilation process, in addition to MSE, Mean Absolute Error (MAE) is also added as an evaluation metric;
- Batch Size: Set to 32, meaning 32 samples are input for each training iteration to balance training speed and memory usage;
- Epochs: Set to 100, and an Early Stopping mechanism is used to prevent overfitting;
- Ratio of Training Set to Validation Set: The training set is divided into a training subset and a validation subset at a ratio of 8:2. This ratio is determined based on multiple experiments to balance the model's training adequacy and validation reliability.

D. MODEL TRAINING PROCESS

The model training process mainly includes four steps: data loading, model compilation, model training, and model saving. The specific workflow is as follows:

1) Data Loading: The preprocessed sequential data is read using the Pandas library, and the input sequence X is converted into the 3D array format required by the LSTM model, i.e., (n, 4, 1), where n is the number of samples;

2) Model Compilation: The model is compiled using Keras' model.compile() function, with the optimizer, loss function, and evaluation metrics configured;

3) Model Training: Model training is performed using the model.fit() function. The training set and validation set data are input, and the batch size, number of epochs, and Early Stopping mechanism are set;

4) Model Saving: After training is completed, the model.save() function is used to save the optimal model for subsequent prediction and comparative experiments.

VI. MODEL PREDICTION RESULTS AND ANALYSIS

A. EVALUATION OF MODEL PREDICTION ACCURACY

In this study, 10 events are selected as the research objects, and the trained LSTM model is used for prediction respectively. The results are shown in Table 6.

TABLE 6. Prediction Accuracy Metrics of the LSTM Model for Each Event

Event	MAE	MSE	RMSE	R^2
Men's 100m (Seconds)	0.25	0.08	0.28	0.92
Women's 100m (Seconds)	0.31	0.12	0.35	0.89
Men's 1500m (Seconds)	1.24	1.85	1.36	0.87
Women's 800m (Seconds)	0.98	1.12	1.06	0.88
Men's Basketball (Points per Game)	1.56	3.21	1.79	0.86
Women's Volleyball (Points per Game)	1.32	2.58	1.61	0.85
Men's Standing Long Jump (Meters)	0.03	0.0012	0.035	0.91
Women's Standing Long Jump (Meters)	0.04	0.0018	0.042	0.89
Men's Pull-Ups (Number of Repetitions)	0.45	0.28	0.53	0.90
Women's Sit-Ups (Number of Repetitions)	0.62	0.45	0.67	0.88

As can be seen from the data in Table 6, the LSTM model exhibits slight differences in prediction performance across the 10 events:

- Events with Optimal Accuracy: Men's Standing Long Jump (MAE = 0.03 meters, R^2 = 0.91) and Men's 100m (MAE = 0.25 seconds, R^2 = 0.92). The performance data of these events has relatively small volatility, making it easier for the model to capture patterns;
- Overall Performance: The R^2 value of all events is greater than 0.85, and the MAE is controlled between 0.03 and 1.56. This indicates that the LSTM model can effectively fit the time-series characteristics of university sports meeting performance, and the prediction results have high reliability.

B. COMPARATIVE EXPERIMENT WITH TRADITIONAL MODELS

The ARIMA model (a traditional time-series method) and the BP neural network (a shallow machine learning method) were selected as comparative models, and prediction experiments were conducted on the same dataset. The results are shown in Table 7. The LSTM model fully demonstrates its ability to handle long-term dependencies and nonlinear features.

TABLE 7. Comparison of Average Prediction Accuracy Metrics of the Three Models Across 10 Events

Model	Average MAE	Average MSE	Average RMSE	Average R^2
LSTM Model	0.73	0.98	0.92	0.89
ARIMA Model	1.25	2.36	1.54	0.72
BP Neural Network	0.98	1.62	1.27	0.80

C. ANALYSIS OF THE DEVELOPMENT TREND OF UNIVERSITY SPORTS MEETING PERFORMANCE

Based on the prediction results of the LSTM model and combined with the historical data from 2010 to 2023, the development trend of performance was analyzed from the perspective of event categories:

- Track and Field Events: Showing an overall "steady improvement" trend. For example, in the 100m sprint, the speed has increased significantly.
- Ball Sports Events: Showing a "fluctuating upward" trend, with significant differences between team events. For instance, in the men's basketball event, the average points per game have increased relatively significantly, while the points increase in the women's volleyball event is relatively small.
- Physical Fitness Events: Showing a "polarization" trend. Among them, strength events (pull-ups/sit-ups) have improved relatively slowly, which may be due to insufficient attention paid by students to these events.

VII. CONCLUSIONS

This study employed the LSTM model to predict university sports meeting performance and drew conclusions regarding the model's efficacy, findings that offer significant methodological insight for predictive applications across other complex data environments, including optimization challenges:

1. The LSTM-based prediction model shows high accuracy and can effectively capture the long-term dependencies and nonlinear characteristics of performance data.

2. The overall performance of the university's sports meeting shows an upward trend. Among all events, track and field sprint events have the most significant improvement, while strength events have improved relatively slowly.

3. It is predicted that from 2024 to 2026, the performance will further show an upward trend, but the gap between different events will gradually widen.

This study has certain limitations. First, the data is only from a single university, which may limit the generalization ability of the model. Future research can expand the data source to multiple universities in different regions to improve the model's adaptability. Second, the current model only uses historical performance data as input features, and future studies can incorporate more influencing factors such as students' physical fitness test data, training time, and weather conditions during competitions to further improve prediction accuracy. In addition, the application of the model in other fields proposed in the original manuscript requires more specific scenario verification and parameter adjustment, which can be explored in subsequent cross-field research.

This study provides a reliable model for predicting the development of university sports meeting performance. In the future, we can continue to explore the collaborative application of LSTM with other models to further optimize prediction performance.

AUTHOR CONTRIBUTIONS

Conceptualization –Runqi Li and Hong Guo; methodology – Runqi Li and Hong Guo; investigation – Runqi Li and Hong Guo; writing-original draft preparation – Runqi Li and Hong Guo. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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