IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 30 March 2024, accepted 13 May 2024, date of publication 21 May 2024, date of current version 31 May 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3403688

RESEARCH ARTICLE

A Spatiotemporal Deep Learning-Based Multisource Data Analytics Framework for Basketball Game

HAN LIN[1], MUREN BAO[2], AND CHENRAN KANG[3]

[1]School of Physical Education and Sport Science, Fujian Normal University, Fuzhou, Fujian 350117, China
[2]School of Physical Education, Inner Mongolia University, Hohhot 010021, China
[3]School of Physical Education, Inner Mongolia Normal University, Hohhot 010000, China

Corresponding author: Muren Bao (baomuren517518@163.com)

ABSTRACT Data analytics has been an important business demand for basketball game. Conventionally, it was implemented with use of statistical approaches, yet neglecting the perception of spatiotemporal characteristics data. To deal with the problem, we introduce deep learning to reveal potential spatiotemporal features from multisource data. Therefore, a spatiotemporal deep learning-based multisource data analytics framework for basketball game, is proposed in this paper. Firstly, advanced deep learning models under spatiotemporal characteristics are elaborated, and a back propagation-based convolution neural network structure is utilized to extract the spatiotemporal features. Then, a systematic data collection and preprocessing method under spatiotemporal characteristics is defined, and thus formulating the spatiotemporal deep learning-based data analytics framework. Furthermore, we conduct a case study to make empirical analysis for the proposed technical framework. The results show that the proposal can well make prediction for some key factors of basketball game, and that it can provide some predictive information for the game preparation from the technical dimension.

INDEX TERMS Spatiotemporal deep learning, data analytics, technical forecasting, convolution neural network.

I. INTRODUCTION

In basketball games, spatiotemporal characteristics are a very important factor, as the position of players on the court constantly changes over time, and the spatiotemporal environment of players in different positions can also affect their performance and decision-making [1]. Through deep learning methods, we can better understand and analyze these spatiotemporal features, and discover valuable information from them. In basketball games, time characteristics include the time points of the game, the remaining time of the game clock, etc. These time characteristics have an impact on the player's performance and game results [2]. For example, the scoring ability and defensive intensity at the end of the game may be influenced by time characteristics. Meanwhile, spatial features include the relative position of players and the distribution of areas on the field [3]. Players in different positions may have different roles and characteristics, and spatial characteristics can also affect the passing, attacking, and defensive strategies between players [4]. Therefore, combining spatiotemporal characteristics for basketball game data analysis can help us more comprehensively understand the dynamic changes of the game and the interactive relationships between players [5]. Through deep learning methods, we can use techniques such as neural networks to model and analyze a large amount of basketball game data, mining hidden patterns and associations within it.

In terms of time domain, deep learning methods can provide detailed time series analysis of the competition process [6]. By modeling and predicting the data during the game process, we can gain insight into the development trend of the game, analyze the team's offensive and defensive strategies, and provide targeted tactical suggestions for coaches and players [7], [8], [9]. In terms of airspace, deep learning

The associate editor coordinating the review of this manuscript and approving it for publication was Alberto Cano.

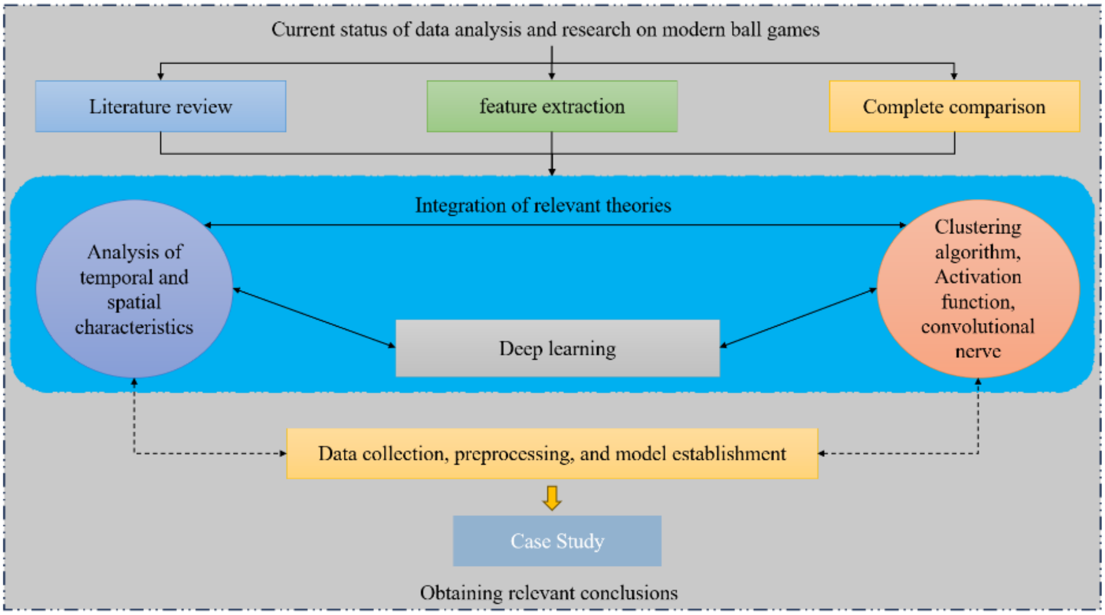

FIGURE 1. The technical roadmap for research work of this paper.

methods can observe and analyze the position and movement trajectory of players on the field from different perspectives. By analyzing player tracking data, we can reveal the collaborative relationships between players, the spatial layout in games, and the evolution of team tactics. This is of great significance for evaluating player performance, studying the effectiveness of different tactical systems, and discovering new tactical strategies. The main contributions of this article are:

1) The use of deep learning technology for backpropagation analysis of basketball game data under spatiotemporal characteristics has not been reflected in previous researches.

2) The use of deep learning methods to predict events in basketball matches, such as free throws, three-pointers, and long-distance passes, takes into account spatiotemporal characteristics and is relatively comprehensive, resulting in ideal results.

3) This method can capture the temporal nature of the game, such as changes in the player's position and movements, providing a more accurate basis for tactical decision-making.

Structure of the article is as follows. Chapter 1 introduces deep learning methods based on spatiotemporal features; The second chapter introduces and analyzes the relevant research of predecessors; The third chapter mainly completes the construction of basic theoretical knowledge, including spatio-temporal basketball data feature analysis, clustering algorithm, Activation function, Convolutional neural network and back-propagation method; Chapter 4 establishes a deep learning analysis model for basketball data feature analysis based on spatiotemporal features; Chapter 5 compares actual predictions; Finally, summarize and analyze. The research framework is shown in Figure 1.

II. LITERATURE REVIEW

Chen and Wang [10] have published research on deep learning based motion trajectory data analysis, exploring how to use deep learning models to identify athlete trajectories and actions during competitions. Their research helps us understand how to use deep learning methods to analyze sports data in basketball games. Wang et al. [11] research focuses on the fields of spatiotemporal data mining and pattern recognition, proposing a deep learning model based on temporal and spatial features for analyzing data in sports competitions. Their research findings provide us with ideas on how to integrate spatiotemporal features for data analysis. Li [12] have made great achievements in the field of basketball data analysis. By combining deep learning techniques with spatiotemporal features, they proposed a new data analysis method that can more accurately predict the performance and results of players in games. Their research findings provide new ideas and methods for basketball game data analysis based on spatiotemporal characteristics. Chhetri et al. [13] research focuses on the spatiotemporal analysis of athlete behavior characteristics and proposes a deep learning based action recognition method that can effectively extract key behavioral features from basketball game videos. Their research provides us with ideas and methods for in-depth analysis of basketball game data from the perspective of spatiotemporal characteristics. Liu et al. [14] research involves spatiotemporal analysis of player movement trajectories in basketball games. They attempted to combine deep learning techniques and spatiotemporal feature extraction methods to propose a novel trajectory prediction model that can be used to analyze player movement paths during games. These research findings provide important references for us to understand the spatiotemporal characteristics behind basketball game data.

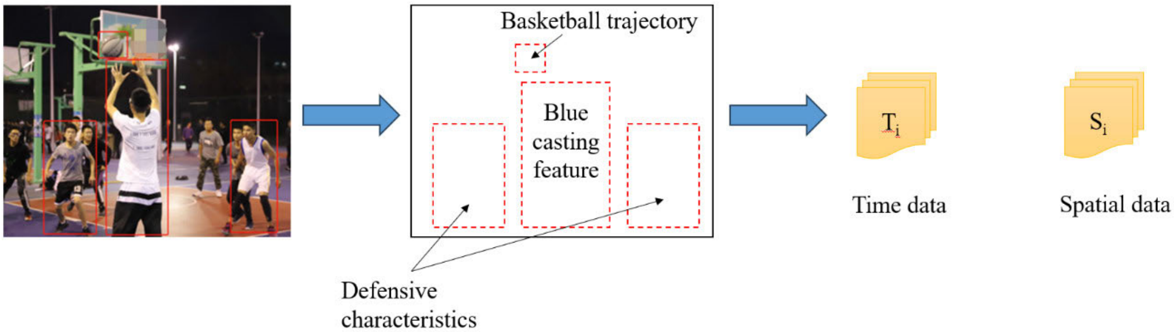

FIGURE 2. Schematic diagram of spatiotemporal characteristics of basketball matches.

By analyzing game videos and player position data, researchers can train deep learning models to recognize and classify different basketball movements, such as shooting, passing, defense, etc. At the same time, they can also analyze the collaborative behavior and tactical choices among players. These analyses can help teams better understand the key moments and strategies in the game. Some research findings have explored the spatial dynamics and tactical evolution in basketball games [15]. By analyzing the spatial position and movement trajectory of players in the game, researchers can use deep learning algorithms to construct more accurate spatial models.

The research of these scholars in the fields of deep learning and spatiotemporal data analysis provides us with valuable reference and inspiration, which can help us better understand and apply basketball game data analysis methods based on spatiotemporal feature perspectives. In my research, I will also draw on their achievements and explore how to use deep learning methods to analyze the spatiotemporal features in basketball game data, in order to obtain more in-depth research results and conclusions.

III. METHODOLOGY

A. SPATIOTEMPORAL DATA ANALYSIS

Spatiotemporal features are perceptual factors that cannot be separated from any kind of motion [16]. Analyzing basketball game data from the perspective of spatiotemporal characteristics is a very interesting research field. In basketball games, spatiotemporal characteristics are a very important factor, as the position of players on the court constantly changes over time, and the spatiotemporal environment of players in different positions can also affect their performance and decision-making. Through deep learning methods, we can better understand and analyze these spatiotemporal features, and discover valuable information from them, as shown in Figure 2. The following is a brief description of these two aspects:

1) Time characteristics: The time characteristics of a basketball game include the time of a single game and the time nodes in the game process, such as the front and back half of a half game. The analysis of time characteristics can help us identify the rhythm, changes, and trends of the game, determine the timing of the match's strength and weakness, and analyze the team's performance at different time periods.

2) Spatial characteristics: The spatial characteristics of basketball games are mainly manifested in the position and spatial layout on the court. By conducting data statistics and analysis on the performance of players in different positions, the team's offensive and defensive strategies, as well as the roles and characteristics of players in each position, can be revealed. In addition, the analysis of spatial characteristics can also explore the scoring efficiency, rebound competition, and assist allocation of teams in different positions.

1) SPATIOTEMPORAL FEATURES

Technology is the foundation of tactics, and completing good technical actions can reduce attack time [17]. Short term technical application can also improve the rhythm of attack, and technical completion time refers to the technical actions made by athletes within a certain period of time [18]. In basketball games, time characteristics include the time points of the game, the remaining time of the game clock, etc. These time characteristics have an impact on the player's performance and game results. For example, the scoring ability and defensive intensity at the end of the game may be influenced by time characteristics. Meanwhile, spatial features include the relative position of players and the distribution of areas on the field [19]. Players in different positions may have different roles and characteristics, and spatial characteristics can also affect the passing, attacking, and defensive strategies between players. Therefore, combining spatiotemporal characteristics for basketball game data analysis can help us more comprehensively understand the dynamic changes of the game and the interactive relationships between players.

In basketball games, athletes need to use time to make the right decisions. For example, after receiving the ball, they need to quickly judge whether there is a scoring opportunity [20]. By using deep learning models to predict the performance of players under different spatiotemporal characteristics, optimize game tactics and training plans, and even provide real-time data support and suggestions [21]. Through this approach, we can better utilize spatiotemporal characteristics to interpret basketball game data, providing strong support for improving team competitiveness and player performance.

The manifestation of spatial ability includes the ability to adapt in time and space, including takeoff, running without the ball, using technology in space, and controlling the range of basketball movement. The combination of spatial ability and basketball awareness enables athletes to more effectively utilize time and space to complete various movements and techniques. In shooting techniques, spatial characteristics can be divided into high ground space, moving space, jumping to maximum height or distance stage, and falling space. Athletes need to choose the best shooting space according to different situations and the position of defensive players in the game, which requires them to have good aerial skills, excellent aerial balance, explosive power, and adversarial ability. Through the coordination of aerial skills and techniques, athletes can complete precise shooting actions from high altitude or in motion during competitions, and effectively control the spatial range of shooting, improving the chances of scoring.

2) CLUSTERING ALGORITHM

Using clustering algorithms to partition and classify different entities such as players, teams, and matches, in order to reveal the information hidden behind the data. For example, clustering algorithms can be used to classify players based on indicators such as scoring ability, rebounding ability, and assist ability, in order to identify different levels and types of player groups. At the same time, the game can also be clustered according to spatiotemporal characteristics such as offensive style, defensive characteristics, and score trends, helping coaches and analysts better understand the evolution patterns and key nodes of the game [22]. It is expected to define classes C_p and C_q each containing p and q sample points, where d_{ij} is the distance between sample points x_i and x_j, and D is the distance between the two classes.

Single Linkage: D_{pq} is the minimum distance between sample points between classes. It is denoted as $D_{pq}= min\{d_{ij}| x_i \in C_p, x_j \in C_q\}$, and clustering results are easily affected by extreme values. Two classes with low similarity may merge into a single class due to the close distance between extreme sample points, resulting in a more loose cluster.

Complete Linkage: D_{pq} is the maximum distance between sample points between classes. It is denoted as $D_{pq}= max\{d_{ij}| x_i \in C_p, x_j \in C_q\}$, and the deficiency of fully connected classes is opposite to that of single connected classes. Two similar classes may not be able to be combined due to the extreme distance between sample points.

Average Linkage: D is the average distance between sample points in two categories, which has been calculated multiple times. The calculation formula is as follows [23].

$$D_{pq} = \frac{1}{p+q} \sum\nolimits_{x_i \in C_p} \sum\nolimits_{x_j \in C_q} d_{ij} \tag{1}$$

Core distance: The distance between sample point x and its k nearest neighbor, expressed as *corek(x)*:

$$core_k(x) = d(x, N_k(x)) \tag{2}$$

Mutual reachable distance: A new measure of distance between points, where the reachable distance between points a and b is the maximum of the three distances: the core distance of a, the core distance of b, and the straight line distance between points a and b [24]. It is represented as follows:

$$d_{mreach-k}(a, b) = max\{core_k(a), core_k(b), d(a, b)\} \tag{3}$$

In the fields of data mining and machine learning, the difference between dense and sparse regions can have an impact on clustering accuracy. The core distance refers to the farthest distance from a point to its k nearest neighboring points, while the reachable distance between two sample points refers to the reachable distance. The above formula indicates that the core distance of dense regions is relatively low, and the mutual reachable distance is also small. After transformation, it still remains concentrated. The core distance and mutual reachable distance of sparse regions are relatively large, and the gap with dense regions becomes larger, which is beneficial for improving clustering accuracy. Transforming the core distance and mutual accessibility distance of densely populated areas can help maintain their concentration, which helps maintain clustering accuracy.

B. DEEP LEARNING

1) ACTIVATION FUNCTION

Activation Function is a crucial component that determines the nonlinear fitting ability of neural networks, which is mainly divided into linear Activation function and nonlinear Activation function: the linear Activation function, that is, the function is equal to x, and information is transferred directly in the neural network; The commonly used nonlinear Activation function, such as *Sigmaid*, *Tanh*, *ReLU*, etc., divide the information nonlinearly, transfer the data of the specified range and proportion, control the mapping of input to output, and make the neural network approach the complex function, otherwise the multi-layer neural network is meaningless [25].

The *Sigmaid* Activation function, which smoothly maps data between 0 and 1, is shown in the following formula.

$$Sigmoid(x) = \frac{1}{1+e^{-x}} \tag{4}$$

The *Tanh* Activation function is shown in the following formula. The *Tanh* function smoothly maps the data between -1 and 1, and its trend is roughly the same as that of the *Sigmoid* function. The Activation function is centered on 0, which distinguishes negative values from positive values, and the Rate of convergence is faster.

$$tanh(x) = \frac{1-e^{-2x}}{1+e^{-2x}} \tag{5}$$

TABLE 1. Comparative analysis of activation function.

Activation function	sigmoid	Tanh	ReLU	SoftPlus
RMSE	22.36	12.3	8.37	16.8

Because the curve of *Tanh* function is similar to that of *Sigmoid* function, it cannot solve the problem of Vanishing gradient problem caused by neuron saturation, nor can it be used for back propagation in neural networks. In the actual process of building neural network models, the *Tanh* function is usually preferred. For the analysis of basketball game data, we need to consider the complexity and diversity of the data, especially the changing patterns of spatiotemporal characteristics. In this context, selecting the appropriate activation function can help neural networks better learn the spatiotemporal features of data and improve the accuracy of prediction and analysis.

ReLu is the corrected linear unit, as shown in the following equation. When $x < 0$, the output is 0, and when $x > 0$, the output is x.

$$ReLU(x) = max(0, x) \tag{6}$$

Compared with *Sigmaid* and Tanh functions, *ReLU* Activation function can converge faster, and the rate of change will not decrease when $x > 0$, which will not cause the Vanishing gradient problem problem caused by neuron saturation. Therefore, *ReLU* Activation function can use areas greater than 0 for back propagation. Due to the fact that information does not need to be calculated and transmitted when $x < 0$, neural networks using *ReLU* functions have higher training efficiency. But the *ReLU* function also has the problem of gradient vanishing at $x < 0$.

The *Softplus* function is shown in the following equation. The *Softplus* function can be seen as a smooth version of *ReLU*, and its advantages and disadvantages are similar to *ReLU* [26].

$$SoftPlus(x) = log(1 + e^x) \tag{7}$$

For the needs of basketball game data analysis and prediction, Root-mean-square deviation RMSE was used to evaluate the selection of Activation function in the above LSTM. The results are shown in Table 1.

It can be seen from the experimental results that *ReLU* function has the best effect for this experiment. This paper selects *ReLU* function as the Activation function of the basketball game data analysis and prediction model.

2) CONVOLUTION NEURAL NETWORK

Deep learning is a machine learning technique that improves the learning ability of a network by constructing a deep structure composed of multiple neural network layers. The limited number of layers and learning ability of shallow networks limit their ability to process complex features and large sample data. The commonly used artificial neural network structure in deep learning is Convolutional Neural Network (CNN). Convolutional layers extract local features of input data through convolution operations, such as edge detection of images [27]. After the convolution operation, use the ReLU activation function to determine which convolution kernel best represents the feature in that region. This can be achieved by learning the weight values between each neuron. The operational process of CNN is shown as Figure 3.

Convolutional neural networks have shown outstanding performance in the field of image recognition. By applying convolutional neural networks to basketball game data, we can convert game information into image data, thereby achieving automatic analysis and prediction of games. In basketball games, spatiotemporal features such as player position, movement, and ball position have a significant impact on the game results [28]. Convolutional neural networks can effectively extract features from these data, helping us better understand the game process.

The commonly used methods for spatial autocorrelation include Moran's I, Geary's C, Join count, Getis, etc. Each of these methods has its own scope of use and limitations. The Moran's I statistics of spatial autocorrelation can be expressed as follows [29].

$$I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}z_iz_j}{\sum_{i=1}^{n} z_i^2} \tag{8}$$

where z_i is the deviation between the attribute of element i and its average value (xi-X), $w_{i,j}$ is the spatial weight between elements i and j, n is equal to the total number of elements, and S is the aggregation of all spatial weights:

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} \tag{9}$$

The statistical scores are calculated in the following form:

$$z_I = \frac{I - E[I]}{\sqrt{v[I]}} \tag{10}$$

Among,

$$E[I] = -1/(n-1) \tag{11}$$
$$V[I] = E[I^2] - E[I]^2 \tag{12}$$

By processing and analyzing basketball game data, combined with the feature extraction ability of convolutional neural networks, we can achieve in-depth analysis of player behavior, offensive and defensive strategies, and other aspects in the game, providing more valuable reference and guidance for coaches and players. This basketball game data analysis method based on spatiotemporal characteristics will provide

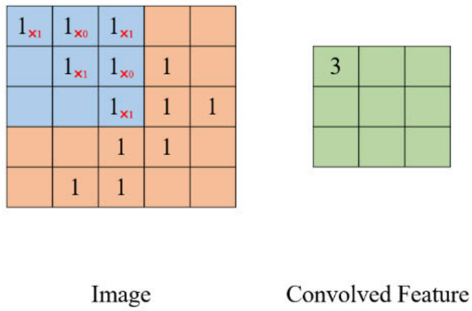

FIGURE 3. Convolutional layer calculation process.

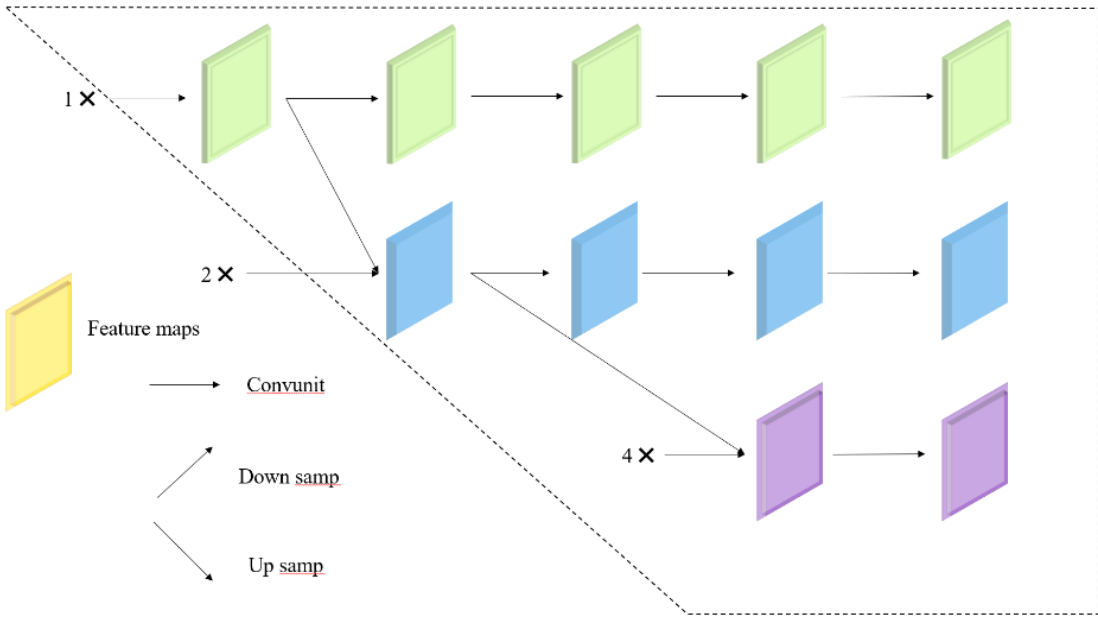

FIGURE 4. Neural network results.

new ideas and methods for the development and technological improvement of basketball. The network structure for target recognition usually adopts a Convolutional Neural Network (CNN) structure, which includes convolutional layers, pooling layers, and fully connected layers. This network structure can extract features such as shape and texture of objects, and recognize targets through classifiers [30]. For different datasets and targets, adjusting network layers, convolution kernel size, and network parameters can adapt to different target recognition tasks.In action recognition, due to the need to consider temporal changes and temporal information, Recurrent Neural Network (RNN) or its variants are often used, such as Long Short Term Memory (LSTM) or Gated Recurrent Unit (GRU). These network structures can model and recognize action sequences, where information from the feedforward process is retained and transmitted to subsequent time steps, resulting in better temporal representations. In addition to differences in network structure, parameter settings may also vary depending on the requirements of the task. For example, the number of batch data (batch size) sent to the network for training at once can affect the accuracy of gradient estimation and computational efficiency. A larger batch size may result in more stable gradient updates, but it also consumes more memory and computing resources. The number of iterations (or training cycles) used in the gradient update process can affect the network's ability to learn and generalize data. If there are too few iterations, the network may not be able to fully learn the features of the data, while if there are too many iterations, it may lead to overfitting of the training data. The results of the neural network are shown in Figure 4.

3) BACK PROPAGATION

Backpropagation is a commonly used optimization method in deep learning, used to train neural networks to reduce errors between predicted and target values. In the basketball game data analysis method based on spatiotemporal characteristics, we need to use deep learning methods to process complex

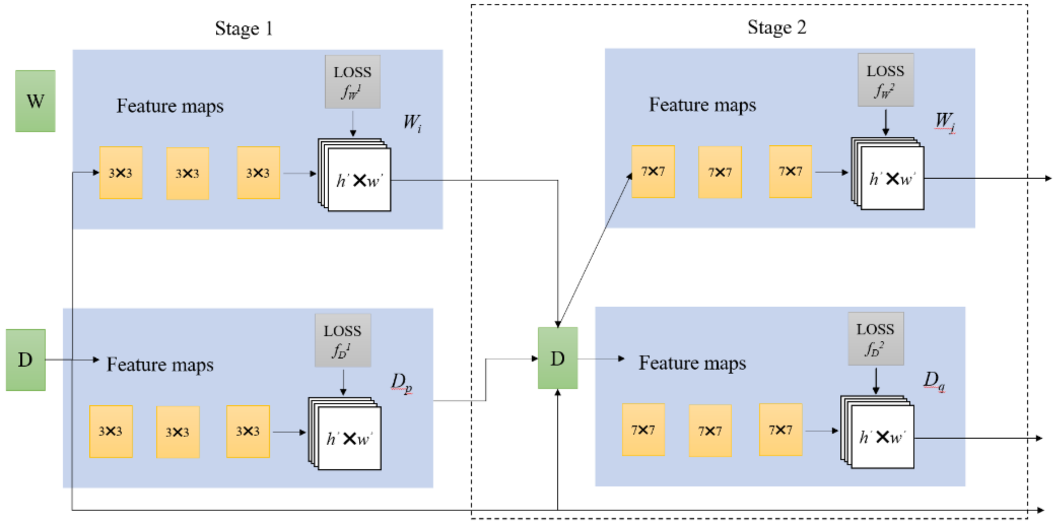

FIGURE 5. Reflection algorithm structure.

spatiotemporal data, in order to better understand the laws and trends of basketball games. Calculate the weighted input for each layer [31]:

$$z_i = \sum_j W_{ij} \cdot x_j + b_i \tag{13}$$

Among, W_{ij} is the weight between the j neuron in the i layer and the j neuron in the previous layer, x_j is the output of the j neuron in the previous layer, and b_i is the bias in the i layer. The weighted input is brought into the Activation function, and the above steps are repeated until the output layer is reached to obtain the prediction results of the network.

In neural networks, backpropagation calculates gradients and backpropagates to each layer of the network to update network parameters and minimize the loss function. For the research of basketball game data analysis, we can use player position, action, time and other information as inputs, extract spatiotemporal features through deep learning networks, and achieve the analysis and prediction of game data. According to the Chain rule, calculate the gradient of the output of the previous layer:

$$\frac{\partial L}{\partial x_j} = \sum_i \frac{\partial L}{\partial z_i} \cdot \frac{\partial z_i}{\partial x_j} \tag{14}$$

The above is a brief description and calculation formula of Backpropagation in Convolutional neural network. Backpropagation iteratively adjusts network parameters by calculating gradients, thereby improving the accuracy of the network in training data. Perform backpropagation, and the average pooling method is to average the pooling window, which can effectively preserve background features.

C. DATA COLLECTION UNDER SPATIOTEMPORAL CHARACTERISTICS

Basketball game data comes from a wide range of sources, including player trajectories, ball position and speed, scoring and rebounding statistics, as well as other indicators such as shooting percentage, block count, etc. Collecting basketball data under spatiotemporal characteristics requires the use of various sensors, devices, and technologies, as well as real-time data collection and processing. This means investing a significant amount of resources and technology to establish a data collection system and ensuring the accuracy and completeness of the data. Privacy is an important issue to consider.

When collecting player position data, it is necessary to protect the personal privacy of the players, take appropriate data protection and anonymization measures, ensure the security of the data, and not cause undue impact on the players. Basketball games involve a wide range of data types, from positional data to statistical data, as well as tactical and physical indicators, and so on. There are complex correlations and interactions between these data, which require high requirements for data collection and processing. When collecting basketball data under spatiotemporal characteristics, it is necessary to consider the privacy rights of players and spectators, and comply with relevant ethical norms. Ensuring the accuracy of data requires the use of high-quality sensors and equipment, as well as calibration and validation. Sensors and equipment should have good accuracy and stability, and calibration and verification are required to eliminate errors and deviations, ensuring the accuracy and reliability of data.

At the same time, the real-time nature of data is also crucial for real-time analysis and decision-making. The collected data needs to be analyzed and applied to extract valuable information and insights. This may involve complex data processing algorithms, model development, and machine learning technologies, with a high demand for data analysts and domain experts. Basketball data collection under spatiotemporal characteristics is a method that uses time and space as references to collect and analyze various data in basketball games. This data collection method can be used to evaluate player performance, tactical analysis, and game trend prediction. Here are some indicators and methods that may be used for basketball data collection under spatiotemporal characteristics:

1) Location data: Use sensors, cameras, or GPS devices to track players' position and movement trajectory on the field, and collect the position coordinates and motion path data of each player.

2) Action data: Through image analysis and recognition techniques, players' action data can be captured, such as shooting, passing, dribbling, etc., to analyze their technical level and action status.

3) Statistical data: Record the scores, rebounds, assists, steals, blocks, and other statistical data during the game, which can reflect the overall performance of players and teams, as well as the progress of the game.

4) Time data: Record the occurrence time of each event, including scoring time, pause time, game duration, etc., which can help analyze the rhythm and changes of the game.

5) Distance data: Using distance measuring devices or sensors to measure the distance between players can analyze the team's defensive and offensive strategies, as well as the cooperation between players.

By collecting and analyzing the above data, coaches and analysts can better understand the dynamics and complexity of basketball games, optimize tactical strategies, improve player performance, and predict game trends.

D. DATA PREPROCESSING BASED ON SPATIOTEMPORAL DEEP LEARNING

For data uploaded from electronic devices, there may be some step data uploaded under various abnormal circumstances. For example, using a wiggler to simulate, or directly tampering with the internal data of the pedometer, etc. The existence of these abnormal data is not only inconsistent with the platform's purpose of predicting motion data, but also has an impact on the accuracy of the model. The prerequisite for further processing the suspected abnormal data through screening [32].

If an athlete has a low duration of data for a certain basketball game, but their entire season is not very low, it can be considered that there are abnormal situations, which may be disguised using programs or data. Assuming an athlete's basketball game data is $v = (v_0, v_1, \ldots v_n)$. Among, v_i represents the data of the number of shots taken by a user in a basketball game by an athlete, assuming the function $l(v)$ [33]:

$$l_{0/1}(v_i) = \begin{cases} 1, & \mathit{if}\ v_i > 0; \\ 0, & \mathit{otherwise} \end{cases} \tag{15}$$

This function can indicate whether an athlete made a shot in a certain basketball game, or it can add a correction to the formula to prevent some error data, namely:

$$l_{0/1}(v_i) = \begin{cases} 1, & \mathit{if}\ v_i > \epsilon; \\ 0, & \mathit{otherwise} \end{cases} \tag{16}$$

where ϵ represented as a small positive integer, the data on the number of shots taken by an athlete in a basketball game can be expressed as:

$$D(x) = \sum\nolimits_{i=0}^{n} l(v_i) \tag{17}$$

After separating the movement styles of motion data, it is necessary to establish a model to analyze and predict the user's movement step data before monitoring their movement. Considering that the basketball game process may be related to a person's sports habits and sports conditions before the sports time point, and may also be affected by weather factors, so for the relevant data that can be obtained at present, a model based on Multiple time dimensions historical data can be established for analysis and prediction, and a model based on environmental data can also be established for analysis and prediction [34]. Considering the possibility of obtaining more information about users in the future, it is possible to support adding predictive models and using a certain model to fuse the analysis results of different features.

Analysis and prediction based on Multiple time dimensions historical data: establish models to analyze the hourly sports data and sports data of some venues. After obtaining prediction results for hourly data, they can be combined with input features of different game data to achieve higher prediction accuracy. The prediction results can be used for data monitoring and anomaly detection.

E. FORMULATION OF DATA ANALYTICS FRAMEWORK

We establish a basketball game data analysis model based on spatiotemporal features and implement it using deep learning methods. First, we need to collect an original data set of basketball games, including various statistical data in the game, such as scores, assists, rebounds, steals, etc. In addition [35], it is necessary to record the player's position data during the game, such as the player's coordinate positions at different time points and other feature data on the field. Next, we can use these data as input and use deep learning methods to construct an analytical model. One possible method is to use Convolutional neural network to extract image features, and then use Recurrent neural network to process time series data [36]. Through this network structure, the model can learn the position and action information of players at different time points, as well as the changes in the situation on the field.

In order to further improve the accuracy and generalization ability of the model, we can introduce attention mechanisms to focus on important events or critical moments in the competition. By weighting and focusing on data at critical moments, the model can more accurately capture the spatiotemporal characteristics of the competition. In addition, to enable the model to predict game results or provide valuable insights, we can add appropriate output layers. For example, you can use the full connection layer to predict the difference in scores or the outcome of the game, or use the Generative adversarial network to generate scenario conversion and tactical recommendations. Finally, in order to train and optimize the model, we can use a series of basketball game datasets, including historical game data, team and player data, tactical data, etc. By iterating repeatedly, adjusting model parameters and using appropriate Loss function, we can gradually improve the performance of the model.

Ensure the collection of raw data sets for basketball games, including various statistical data and player position data. These data can include statistical data such as scores, assists, rebounds, steals, as well as player position coordinates and other related characteristic data during the game. Through this deep learning network structure, the model can learn the position and action information of players at different time points, as well as the changes in the situation on the field. This allows you to analyze the spatiotemporal characteristics of basketball games, such as player movement patterns, changes in tactics and strategies, etc., in order to draw some insights and conclusions. Main structure of the proposed algorithm is shown as Figure 5, and its pseudocode is shown in Algorithm 1.

Algorithm 1 Spatiotemporal Deep Learning-Based Data Analytics Framework

Input: i, j data training frequency x and overall size n;
for all $x_i = 1$ to n, $x_j = 1$ to n do
for all $w_{ij} = 1$ to n **do**
Complete clustering analysis of data
while $D_{pq} = 0$
for $p = 1$: n
Update weights to complete positive and negative feedback
end for
If Data classification meets threshold requirements
Caculate the *E[I] and V[I]* based on Eq(11) and Eq(12)
Else
Eliminate non compliant data
end if
if $E[I]$ or $V[I]$ pre feedback results after data training is 0
Select different clustering results at the same time for further analysis
else
Output phased calculation results
end if
end for

IV. EXPERIMENTAL ANALYSIS

The research is based on official game public data and videos from the Chinese Basketball Association, which are game data recorded and organized by professional statisticians. This includes data on each player's score, rebounds, assists, blocks, steals, as well as the team's score, shooting percentage, rebounds, assists, and other data. When studying the basketball field, the data source was selected as the data generated by the 10 regular rotation players of the Los Angeles Lakers in the 2019-2020 NBA season in 82 regular games. These data sources are from the well-known foreign data website www.basketball reference. com, which includes data provided by sportsradar, a world-famous sports data analysis company. These data include the data that players cooperate with each other to complete an attack in the form of pick and roll, assist, screen, backboard pass, etc. Compared with domestic CBA league data, NBA data is more abundant, which meets your requirements for data form in research.

A. PREDICTION ANALYSIS OF FREE THROW

The use of deep learning methods for free throw prediction analysis requires the collection of a large amount of basketball game data, including player's free throw hit rate, game time, score, and other information. Then, we can input these data into deep learning models for training and prediction. In the aspect of Feature engineering, we can consider the following space-time characteristics: players' historical free throw hit rate: consider each player's free throw hit rate in the past games, which can be used as an important feature to predict their free throw hit rate in the current game; Game time and score: Game time and score are important factors that affect players' free throw performance. At the end of the game and with tight scores, players' free throw percentage may be affected by greater pressure. A player's physical condition is an important spatiotemporal characteristic. As the game progresses, players may become fatigued, which may affect their free throw performance.

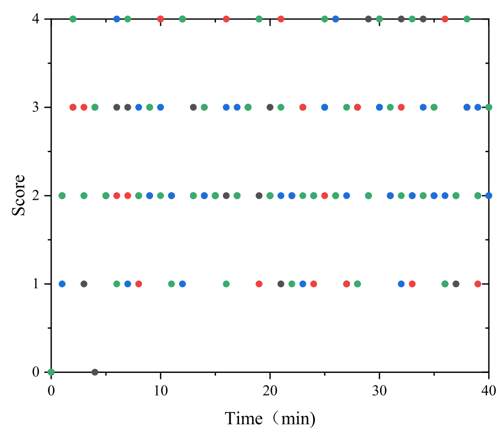

FIGURE 6. Data clustering analysis.

Regarding the amount of data, generally speaking, larger datasets can provide better training performance and predictive ability. Next, we can use deep learning models to train and predict free throw hit rates. Convolutional neural networks are used to extract spatial features. By training and adjusting the model, the predictive performance of the model is gradually optimized, and a model that performs well in predicting free throws is obtained. During the model training process, known free throw data is used for supervised learning, and the model parameters are adjusted to accurately predict the free throw hit rate to the greatest extent possible. The performance of deep learning models is influenced by the quality and quantity of data. In order to ensure the accuracy and reliability of the model's training and prediction results, it is necessary to ensure that there is sufficient data, which is accurate and comprehensive. By comprehensively considering the accuracy and comprehensiveness of data, as well as adopting techniques such as data augmentation, the performance and predictive ability of the model can be further improved. The clustering results are shown in Figure 6, and the prediction results are shown in Figure 7. The R-squared comparative analysis results are shown in Table 2 below.

TABLE 2. R-squared comparative analysis results.

EPOCH	RNN	CNN	MRNN	B-CNN	THIS
1	0.77	0.79	0.75	0.8	0.84
2	0.78	0.8	0.76	0.81	0.85
3	0.75	0.77	0.73	0.78	0.82
4	0.77	0.79	0.75	0.8	0.84
5	0.74	0.76	0.72	0.77	0.81
6	0.76	0.78	0.74	0.79	0.83
7	0.78	0.8	0.76	0.77	0.85
8	0.8	0.82	0.78	0.76	0.87

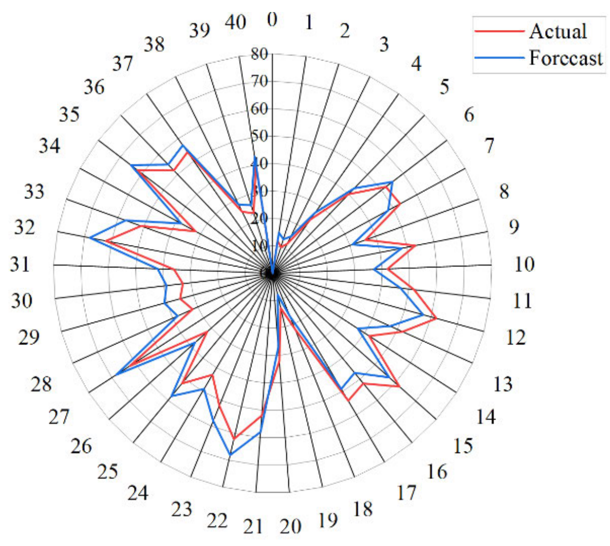

FIGURE 7. Comparison of free throw prediction results.

From the graph, we can see that the clustering results of the data obtained this time are basically concentrated around 2 points. Except for scoring 0 at time 0, there is basically no situation where the score is 0 at other competition times. This is in line with the actual competition situation, and the number of clusters for 1 point and 3 points is basically the same, which also proves that the authenticity of this data is guaranteed. On the other hand, we found that when only predicting free throws, the probability of free throws predicted by deep learning is higher than the actual value within 0-6 minutes after the start of the game, but not much, around 3%. However, when the time is 7-12 minutes, the predicted value is 6% lower than the actual value. This indicates that after deep learning, the model believes that the probability of free throws occurring during this time period is relatively low, The predicted value is always 3% -6% higher than the actual value within 13-40 minutes, indicating that the model believes that the probability of team members committing fouls is constantly increasing over time, which is in line with the actual situation. At present, the data we have obtained is based on predictions made for a certain game, which may deviate from the actual value, but the deviation is controlled at around 3% -6%, which is acceptable.

B. TRIPLE PREDICTION ANALYSIS

In order to predict and analyze the three-point shooting score, we first collected relevant data of basketball games, such as player's three-point shooting data, shooting position, shooting angle, game time, etc. These data are obtained through observation of competition videos, statistician records, or sensor devices. Before conducting data analysis, it is necessary to perform reasonable feature engineering processing on the collected data. For predicting the score of a three-point shot, spatiotemporal characteristics such as shooting position and angle can be used as key indicators. After considering additional features such as the player's historical three-point shooting rate and pre match training status to complete feature engineering, deep learning models can be used to predict three-point ball scores. Input feature information such as shooting position and angle, and extract spatial features through multi-layer convolution and pooling operations. Then, the extracted features can be input into the fully connected layer for classification and score prediction, as shown in the following Figure 8. The comparative analysis results of MAPE are shown in Table 3 below.

From the graph, we can see that there is a significant difference between the predicted three-point shot and the predicted free throw results. Both the actual and predicted results believe that the probability of a three-point shot occurring in the early stages of the game is relatively small. This is obtained by analyzing the psychological, sports speed, shooting posture, and other data of the team members. Around 9 minutes after the game, both the actual and predicted values suddenly increased, and the increase was significant, That is to say, around the 9th minute of the game, the prediction model assumes that team members will make more three-point pitches. In fact, this is also the case. However, unlike the actual value, there was a partial decrease in the actual value in the final stage of the game, which means that the three-point pitches that occurred in the final stage of the game will decrease. This may be related to team members' habits and the division of the field, but the predicted value did

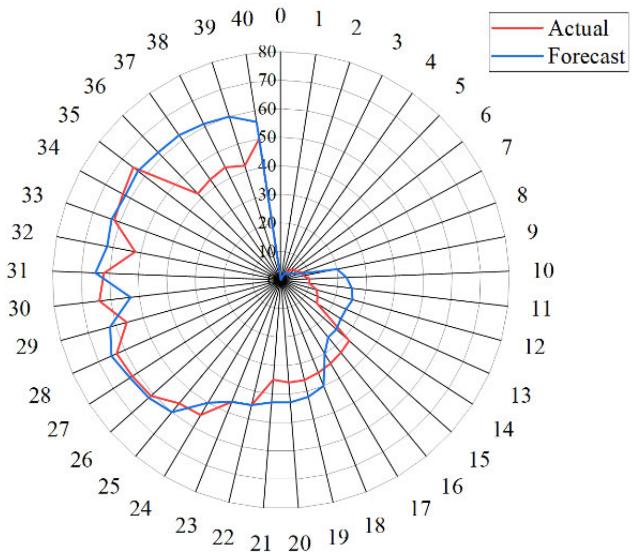

FIGURE 8. Comparative analysis of three point ball prediction.

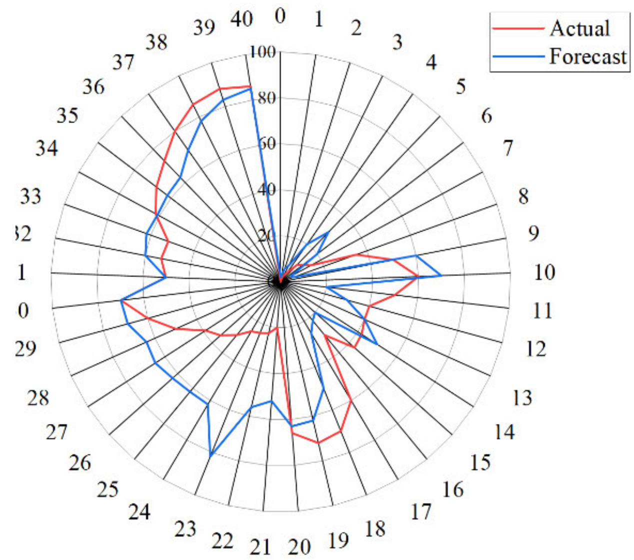

FIGURE 9. Analysis of long range pass prediction results.

TABLE 3. MAPE comparative analysis results.

EPOCH	RNN	CNN	MRNN	B-CNN	THIS
1	70	69	82	77	62
2	70	76	88	74	67
3	68	72	89	74	64
4	70	67	79	73	66
5	71	66	83	71	64
6	70	71	82	74	65
7	72	66	81	78	62
8	71	71	89	76	69

TABLE 4. RMSE comparative analysis results.

EPOCH	RNN	CNN	MRNN	B-CNN	THIS
1	80	72	76	82	82
2	80	79	82	79	87
3	78	75	83	79	84
4	80	70	73	78	86
5	81	69	77	76	84
6	74	74	76	79	85
7	72	69	75	83	82
8	73	74	83	81	89

not significantly decrease, It always maintains a high value, around 60%, indicating that the prediction model always believes that the probability of a three-point ball will remain stable over time, which is a significant difference between the prediction model and the actual situation.

C. PREDICTIVE ANALYSIS OF LONG RANGE PASSING

We continue to use the above data and the deep learning data analysis model provided by this study to predict and compare long-distance passing in basketball matches, and the results are shown in the following Figure 9. The RMSE comparative analysis results are shown in Table 4.

From the graph, we can see that the probability of long-distance passing suddenly increases in the last few minutes of the first quarter of the game, and remains high in the second quarter and continues to exceed the upper limit in the last few minutes of the second quarter. However, at the beginning of the third quarter, the actual value will fall back to a lower level and continue to rise until the end of the third quarter, and the probability of long-distance passing remains high in the fourth quarter; But the difference between the predicted value and the actual value lies in that the predicted value continues to rise after the start of the game, but suddenly rises after a rapid decline in the last few minutes of the first quarter, with a maximum deviation of 29% from the actual value.

In the later second quarter of the game, the actual value is relatively consistent with the predicted value, but in the third quarter of the game, the predicted value believes that there will be no high probability of long-distance passing events, which is related to the flow layer management in deep learning, The subsequent fourth section basically conforms to the trend of actual value changes. From it, we can see that the difference between the predicted value and the actual value in Section III is the largest. This may be the learning deviation of the stream layer management, or the mismatch between the Activation function and the competition in Section III, or it may be that these data cannot represent all the competitions and need more data support. In short, this issue will continue to be addressed in future research.

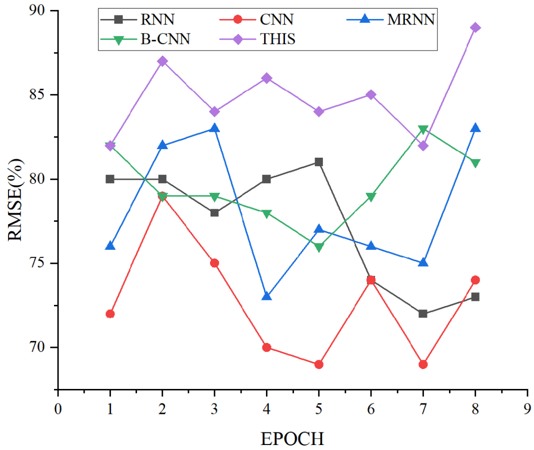

FIGURE 10. Comparison of RMSE for different methods.

Comparison of RMSE results for different methods is shown in Figure 10. The RMSE of RNN consistently fluctuates between 70% and 81%, with no significant trend. The RMSE of CNN decreased from 69% to 70% and then remained fluctuating between 70% and 75%. The RMSE of MRNN fluctuates from 73% to 83% without any significant trend. The RMSE of B-CNN fluctuates from 76% to 83% without any significant trend. The RMSE of THE algorithm fluctuates from 82% to 89% without any significant trend. When the number of iterations is 1, the CNN algorithm exhibits the lowest RMSE value (72%), which means that the difference between its predicted results and actual values is small. When the number of iterations is 8, the B-CNN algorithm exhibits the highest RMSE value (89%), indicating a significant difference between its predicted results and actual values. When the number of iterations is 6, the RNN algorithm and MRNN algorithm show lower RMSE values of 74% and 76%, respectively. Overall, there are differences in the performance of different algorithms at different iterations, and the method proposed in this study is more stable and robust.

V. CONCLUSION

The study conducted basketball game data analysis from the perspective of spatiotemporal characteristics, and explored key factors and patterns in basketball games through deep learning methods. After collecting and organizing a large amount of basketball game data, we used deep learning models to model and analyze these data. The aim of this study is to provide a new approach to understanding the key factors and patterns in basketball games, thereby providing useful advice and guidance for coaches and teams to make tactical and technical decisions.

We have found that time is a crucial characteristic in basketball games. By comparing data from different time periods, we observe that there is usually a significant difference in team performance compared to the middle stage at the beginning and end of the game. This indicates that teams need to adopt different strategies and tactics at different times of the game to improve their chances of winning. The spatial characteristics also have a significant impact on the results of basketball games. We observe that different positions and regions play different roles in the competition. For example, by analyzing the scoring situation of players and teams in different positions, we found that some positions are easier to score than others, so the team can strengthen the arrangement of these positions in attack. Our research also found that the spatiotemporal characteristics in basketball games are closely related to the team's victory or defeat. Through the analysis of deep learning models, we can predict the probability of a team winning under different spatiotemporal characteristics. This is very useful for coaches and teams to make tactical and strategic decisions, as they can adjust and optimize the game based on these predicted results.

This study provides a new perspective on basketball games through a basketball game data analysis method based on spatiotemporal characteristics, combined with deep learning models. Our research has identified key spatiotemporal features in basketball games and revealed the relationship between these features and team outcomes. This is of great significance for coaches and teams to make tactical and technical decisions, which can help them improve the team's competitiveness and win rate. I hope that the results of this study can inspire researchers and practitioners in the field of basketball game data analysis, and provide useful references and support for the development of basketball games.

REFERENCES

[1] J. Yang, F. Lin, C. Chakraborty, K. Yu, Z. Guo, A.-T. Nguyen, and J. J. P. C. Rodrigues, "A parallel intelligence-driven resource scheduling scheme for digital twins-based intelligent vehicular systems," *IEEE Trans. Intell. Vehicles*, vol. 8, no. 4, pp. 1–16, Jun. 2023.

[2] Z. Guo, Q. Zhang, F. Ding, X. Zhu, and K. Yu, "A novel fake news detection model for context of mixed languages through multiscale transformer," *IEEE Trans. Computat. Social Syst.*, vol. 23, no. 8, pp. 1–11, May 2024, doi: 10.1109/tcss.2023.3298480.

[3] Q. Li, L. Liu, Z. Guo, P. Vijayakumar, F. Taghizadeh-Hesary, and K. Yu, "Smart assessment and forecasting framework for healthy development index in urban cities," *Cities*, vol. 131, Dec. 2022, Art. no. 103971.

[4] Z. Guo, K. Yu, Z. Lv, K. R. Choo, P. Shi, and J. J. P. C. Rodrigues, "Deep federated learning enhanced secure POI microservices for cyber-physical systems," *IEEE Wireless Commun.*, vol. 29, no. 2, pp. 22–29, Apr. 2022.

[5] J. Huang, F. Yang, C. Chakraborty, Z. Guo, H. Zhang, L. Zhen, and K. Yu, "Opportunistic capacity based resource allocation for 6G wireless systems with network slicing," *Future Gener. Comput. Syst.*, vol. 140, pp. 390–401, Mar. 2023.

[6] Z. Guo, K. Yu, A. Jolfaei, A. K. Bashir, A. O. Almagrabi, and N. Kumar, "Fuzzy detection system for rumors through explainable adaptive learning," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 12, pp. 3650–3664, Dec. 2021.

[7] X. Zhu, F. Ma, F. Ding, Z. Guo, J. Yang, and K. Yu, "A low-latency edge computation offloading scheme for trust evaluation in finance-level artificial Intelligence of Things," *IEEE Internet Things J.*, vol. 11, no. 1, pp. 114–124, Jan. 2024.

[8] Z. Guo, Y. Shen, S. Wan, W.-L. Shang, and K. Yu, "Hybrid intelligence-driven medical image recognition for remote patient diagnosis in Internet of Medical things," *IEEE J. Biomed. Health Informat.*, vol. 26, no. 12, pp. 5817–5828, Dec. 2022.

[9] D. Meng, Y. Xiao, Z. Guo, A. Jolfaei, L. Qin, X. Lu, and Q. Xiang, "A data-driven intelligent planning model for UAVs routing networks in mobile Internet of Things," *Comput. Commun.*, vol. 179, pp. 231–241, Nov. 2021.

[10] L. Chen and W. Wang, "Analysis of technical features in basketball video based on deep learning algorithm," *Signal Process., Image Commun.*, vol. 83, Apr. 2020, Art. no. 115786.
[11] H. Wang, F. Zhang, X. Xie, and M. Guo, "DKN: Deep knowledge-aware network for news recommendation," in *Proc. World Wide Web Conf. World Wide Web*, 2018, pp. 1835–1844.
[12] P. Li, "An application of knowledge graph for enterprise risk prediction," in *Proc. Int. Conf. Comput. Eng. Netw.*, 2022, pp. 1029–1038.
[13] T. R. Chhetri, A. Kurteva, J. G. Adigun, and A. Fensel, "Knowledge graph based hard drive failure prediction," *Sensors*, vol. 22, no. 3, p. 985, Jan. 2022.
[14] W. Liu, C. C. Yan, J. Liu, and H. Ma, "Deep learning based basketball video analysis for intelligent arena application," *Multimedia Tools Appl.*, vol. 76, no. 23, pp. 24983–25001, Dec. 2017.
[15] Y. Wang, M. Sun, and L. Liu, "Basketball shooting angle calculation and analysis by deeply-learned vision model," *Future Gener. Comput. Syst.*, vol. 125, pp. 949–953, Dec. 2021.
[16] S. Klassen, J. Weed, and D. Evans, "Semi-supervised machine learning approaches for predicting the chronology of archaeological sites: A case study of temples from medieval angkor, Cambodia," *PLoS ONE*, vol. 13, no. 11, Nov. 2018, Art. no. e0205649.
[17] J. Wu, X. Xu, X. Liao, Z. Li, S. Zhang, and Y. Huang, "Intelligent diagnosis method of data center precision air conditioning fault based on knowledge graph," *Electronics*, vol. 12, no. 3, p. 498, Jan. 2023.
[18] L. Ma, X. Wu, Y. Kuang, Y. Tang, and D. Xiang, "Knowledge graph-based approach to trace the full life cycle information of decommissioned electromechanical products," in *Proc. IEEE 18th Int. Conf. Autom. Sci. Eng. (CASE)*, Aug. 2022, pp. 2028–2033.
[19] X. Li, C.-H. Chen, P. Zheng, Z. Wang, Z. Jiang, and Z. Jiang, "A knowledge graph-aided concept–knowledge approach for evolutionary smart product–service system development," *J. Mech. Des.*, vol. 142, no. 10, Oct. 2020, Art. no. 101403.
[20] T. Yang, C. Jiang, and P. Li, "Video analysis and system construction of basketball game by lightweight deep learning under the Internet of Things," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–14, Mar. 2022.
[21] J. Luettin, S. Monka, C. Henson, and L. Halilaj, "A survey on knowledge graph-based methods for automated driving," in *Knowledge Graphs and Semantic Web*. Cham, Switzerland: Springer, 2022, pp. 16–31.
[22] E. E. Kosasih, F. Margaroli, S. Gelli, A. Aziz, N. Wildgoose, and A. Brintrup, "Towards knowledge graph reasoning for supply chain risk management using graph neural networks," *Int. J. Prod. Res.*, vol. 1, pp. 1–17, Jul. 2022.
[23] B. Fakhar, H. Rashidy Kanan, and A. Behrad, "Event detection in soccer videos using unsupervised learning of spatio-temporal features based on pooled spatial pyramid model," *Multimedia Tools Appl.*, vol. 78, no. 12, pp. 16995–17025, Jun. 2019.
[24] D. Yuan, K. Zhou, and C. Yang, "Architecture and application of traffic safety management knowledge graph based on Neo4j," *Sustainability*, vol. 15, no. 12, p. 9786, Jun. 2023.
[25] K. Kurniawan, A. Ekelhart, E. Kiesling, G. Quirchmayr, and A. M. Tjoa, "KRYSTAL: Knowledge graph-based framework for tactical attack discovery in audit data," *Comput. Secur.*, vol. 121, Oct. 2022, Art. no. 102828.
[26] L. Wu, Z. Yang, Q. Wang, M. Jian, B. Zhao, J. Yan, and C. W. Chen, "Fusing motion patterns and key visual information for semantic event recognition in basketball videos," *Neurocomputing*, vol. 413, pp. 217–229, Nov. 2020.
[27] L. Halilaj, I. Dindorkar, J. Lüttin, and S. Rothermel, "A knowledge graph-based approach for situation comprehension in driving scenarios," in *Proc. 18th Int. Conf.*, 2021, pp. 699–716.
[28] Y. Song, "Construction of event knowledge graph based on semantic analysis," *Tehnicki vjesnik*, vol. 28, no. 5, pp. 1640–1646, 2021.
[29] P.-Y. Hsu, C.-T. Chen, C. Chou, and S.-H. Huang, "Explainable mutual fund recommendation system developed based on knowledge graph embeddings," *Int. J. Speech Technol.*, vol. 52, no. 9, pp. 10779–10804, Jul. 2022.
[30] M. U. Haque, M. M. Kholoosi, and M. A. Babar, "Kgsecconfig: A knowledge graph based approach for secured container orchestrator configuration," in *Proc. IEEE Int. Conf. Softw. Anal.*, 2022, pp. 420–431.
[31] B. Ma and M. Ji, "Motion feature retrieval in basketball match video based on multisource motion feature fusion," *Adv. Math. Phys.*, vol. 2022, pp. 1–10, Jan. 2022.
[32] X. Shen, X. Li, B. Zhou, Y. Jiang, and J. Bao, "Dynamic knowledge modeling and fusion method for custom apparel production process based on knowledge graph," *Adv. Eng. Informat.*, vol. 55, Jan. 2023, Art. no. 101880.
[33] L. Zhang, "Behaviour detection and recognition of college basketball players based on multimodal sequence matching and deep neural networks," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–11, May 2022.
[34] C. Ma, J. Fan, J. Yao, and T. Zhang, "NPU RGBD dataset and a feature-enhanced LSTM-DGCN method for action recognition of basketball players," *Appl. Sci.*, vol. 11, no. 10, p. 4426, May 2021.
[35] J. Chen, W. Wang, K. Yu, X. Hu, M. Cai, and M. Guizani, "Node connection strength matrix-based graph convolution network for traffic flow prediction," *IEEE Trans. Veh. Technol.*, vol. 72, no. 9, pp. 1–13, Sep. 2023.
[36] W. Yan, X. Jiang, and P. Liu, "A review of basketball shooting analysis based on artificial intelligence," *IEEE Access*, vol. 11, pp. 87344–87365, 2023.

HAN LIN was born in Xianyou, Fujiang, China, in 2009. He received the master's degree from Wuhan Institute of Physical Education. He is currently working with the College of Sports Science, Fujian Normal University. His main research interests include sports teaching and basketball training.

MUREN BAO received the bachelor's degree from Shenyang Sport University, in 2003, and the master's degree from Inner Mongolia University, in 2014. He is currently working with Inner Mongolia University. He has presided more than a provincial and ministerial project of Inner Mongolia and participated in many provincial projects. He has published one SCI article and 12 other national articles. His research interests include smart education, educational data mining, and physical education informatics.

CHENRAN KANG received the bachelor's degree from Tianjin Institute of Physical Education, in 2005, and the master's degree from Inner Mongolia Normal University, in 2012. She is currently working with Inner Mongolia Normal University. She has published several provincial-level journals and presided more than and participated in a number of school-level projects. Her research interests include smart education and educational big data.