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Prediction model of basketball players' playing time based on neural network

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Abstract

The purpose of this study is to predict the playing time of CBA league players through neural network model, and to explore the key factors affecting the playing time from the perspective of quantitative analysis, so as to provide data support for coaches to make decisions on arranging players to play. This paper selects 7340 items of average data of 367 players in CBA league in the regular season of 2021-2022 as the research object. In model training, other data indexes except playing time are used as input parameters, playing time is used as output variable, and automatic encoder is added to screen key data indexes, thus establishing playing time prediction model. The results show that five models and a total data model are established according to the players' positions on the field (point guard, shooting guard, small forward, power forward and center), and the highest value of the average error (MER) is 1.56 and the lowest value is 1.42. R2 is 0.785 at the highest and 0.726 at the lowest. The results show that the data indexes that affect playing time are position-specific, and the models established for different positions have high prediction ability for players' playing time. The average error of the total data model is the best, while the explanatory ability (R2) of the small forward model data is the best, which proves that each model can provide data support for coaches' decision-making.

Keywords

Neural network model; CBA;Data analysis; Playing time.

1. Introduction

Basketball is a fierce sport, and the decision of the coach in the game affects the outcome. Among them, it is one of the important decisions that coaches need to make to decide the athletes' playing time and the time allocation on the field, which involves many factors, such as players' technical performance, physical fitness and opponent lineup. With the progress of artificial intelligence technology, many new technologies and methods have emerged to lead the development of basketball. Zhang Mingxin pointed out in the coach's decision-making research that the basis of decision-making in the competition is an indispensable link to participate in the competition.[1]. Fang Xinfei proposed to establish an assistant decision support system for coaches, using data warehouse and data mining technology to provide decision-making help for coaches.[2]. It can be seen that most participating teams, including the national team, lack important auxiliary decision-making basis on the field. In order to solve this problem, Wang Zhe focused on the physical test data of CBA players, and analyzed the CBA players' season effectiveness through the multivariate logistic regression analysis model.[3]. Zhang Mingxin's research proves the importance of data analysis to the Guangdong men's basketball team by analyzing the successful cases driven by "all data"[4]. Shi Guangbin mentioned in his research that neural network model can learn and express complex patterns and nonlinear relationships in data.[5], which can deal with the nonlinear relationship in basketball data, is more powerful than the traditional model when dealing with highly complex data sets. Obviously, neural network model, as an artificial intelligence technology, shows

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unique and powerful application potential in basketball, and is widely used in the direction of team winning rate prediction.[6–8]. This paper aims to solve the specific decision-making problem of coaches in arranging players' playing time, and puts forward a prediction model based on neural network to predict players' playing time, which provides coaches with more data-supported decision-making methods.

2. Research objects and methods

2.1. Research objects

CBA League official website provided data of 367 players from 20 teams, including data of 20 basic technical indicators such as scoring and rebounding. The specific indicators are shown in Table 1. We take 20 technical indicators of 367 players from 20 teams, with a total of 7340 data as the research object.

Table 1:20 technical indicators of 1CBA players

Field number	break the rules	score	Total number of shots	Three-point total	Total number of free throws	backcourt rebounds	backboard	Three-point shooting percentage	line-ups
make holding attack	intercept in football and basketball	nut cap	Shooting hit count	Three-point hit number	Hit a free throw	Front rebound	make a penalty shot	shooting percentage	fault

2.2. Research method

2.2.1. Neural network model method

Neural network model processes a large number of historical competition data through multi-layer structure, and finds a prediction model that conforms to the relationship between the data. On the basketball court, the data index is as high as 20 items, and a large number of players can collect a lot of data, so it meets the requirements of neural network model. Based on the basic data dimension modeling, with the average data of players' scores, rebounds and assists as input values and playing time as output values, the prediction of basketball players' playing time is realized by establishing a neural network model, and the coach's rotation decision is optimized through the prediction value. Considering the different requirements of basketball position on technical ability, six models are established according to different position data as output variables. They are: point guard, shooting guard, small forward, power forward, center and all data models.

Compiler

Automatic encoder is a kind of neural network structure with unsupervised learning. It can learn the compressed representation of input data, and choose the index that has the greatest influence on the target data on the basis of reconstructing the original data. This study mainly uses the feature learning and dimensionality reduction functions of the automatic encoder, which is used to learn 20 complex and multidimensional data and get effective features after centralized processing of all the data. At the same time, high-dimensional data can be mapped to low-dimensional space, while retaining most of the information.

2.2.2. Numerical analysis method

Standardized treatment

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In the obtained data, the index weights of different data sets are different. If these data are directly input into the model, the prediction effect of the model will be affected because of the different numerical values among the data. Therefore, we need to standardize the data.[9].

The specific calculation method is as follows:

$$x' = \frac{x-\bar{x}}{\sigma} \tag{1}$$

Where x is the data before standardization, the data after standardization, the average value of the data, and σ is the standard deviation of the data.$x'\bar{x}$

Model evaluation index

The two evaluation indexes selected in this study include Mean Squared Error, MSE) and determining coefficient (R-squared).

Mean square error, as shown in formula (2), is an index to measure the difference between the predicted value and the actual value of the model. In the field of data prediction, a lower MER usually means that the prediction of the model is more accurate.

The MSE formula is expressed as:

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

N represents the number of data samples, y is the real value, and it is the output value of the model, that is, the predicted value.$\hat{y}$

Determinant coefficient, as shown in Formula (4), R value is a commonly used index to measure the goodness of fit of the model, and it is usually used to evaluate the explanatory degree of the model to the variability. The closer its value is to 1, the stronger the explanatory ability of the model to the data, and a high R value usually means that the model can better capture the changing trend in the data.

The r formula is expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2} \tag{3}$$

Where n represents the number of data samples, y is the real value, and it is the output value of the model, that is, the predicted value.$\hat{y}$

Statistical analysis of influencing factors of playing time

Pearson correlation coefficient analysis and SPSS27.0 scatter analysis are mainly used in this study.

Pearson correlation coefficient is a method to measure the correlation strength between two variables, and its value ranges from 0 to 1. A value close to 1 indicates a strong positive correlation, while 0 indicates no linear correlation. Pearson heat map can be used to visually show the correlation strength between multiple variables, and the correlation coefficient can be expressed by the depth of color, so that it is convenient to observe which variables have strong correlation.

SPSS27.0 scatter function to draw the scatter distribution of playing time and score, rebound and assist data. Scatter chart shows the distribution trend between two variables, which helps us to judge the linear relationship between them.

3. Results and discussion

3.1. Modeling of Basketball Players' Playing Time Based on Neural Network

Neural network is based on multi-layer error information propagation to realize prediction. The basketball playing time prediction model studied in this paper adopts a three-layer structure, as shown in Figure 1.7340 data after standardization (standard deviation and mean value are

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shown in Table 2) are divided into five data sets according to position and all data are input into the model respectively.

Table 2:Average and standard deviation of data indicators

index	average value	standard deviation	index	average value	standard deviation
score	7.31	5.789	break the rules	1.69	.793
foreplate	.93	.810	Hit a shot	2.67	2.067
backboard	2.27	1.731	Shoot a shot	6.19	4.407
backboard	3.21	2.354	Three-point hit	.79	.826
make holding attack	1.76	1.802	Three-point shot	2.43	2.217
intercept in football and basketball	.71	.561	Hit a free throw	1.18	1.268
nut cap	.28	.437	Free throw shot	1.60	1.600
fault	1.24	.861	time	18.61	8.987

After inputting the data, it is planned to adopt 80% training and 20% testing, 70% training and 30% verification of the data, and set the error result of the training loss function to one thousandth, in which the learning rates of the automatic encoder and the neural network are set to 0.0002 and 0.0003, the batch size is 64, and the set number of training iterations is 1000. By training the model and learning the pattern and correlation of input data, the accurate prediction of playing time is realized.

In this paper, the final output mode of the model is set as loss function. The loss function is defined by nn.MSELoss (). Nn.MSELoss () is a loss function class in PyTorch, which is used to calculate the loss of Mean Squared Error. See formula (2) in 1.2.2 for the specific formula. In the training process, the mean square error loss between the predicted output of the model and the real label is calculated. Set the ordinate as the loss value and the abscissa as the training times, and output the results as shown in Figures 1, 2 and 3.

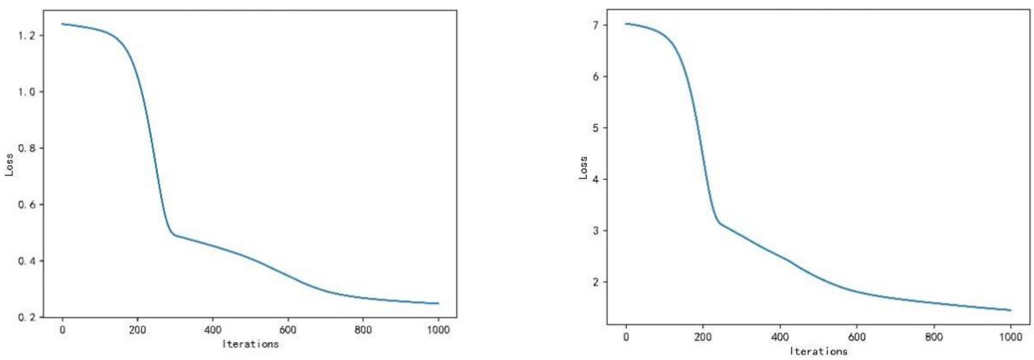

Figure 1:Point guard and total data loss result chart

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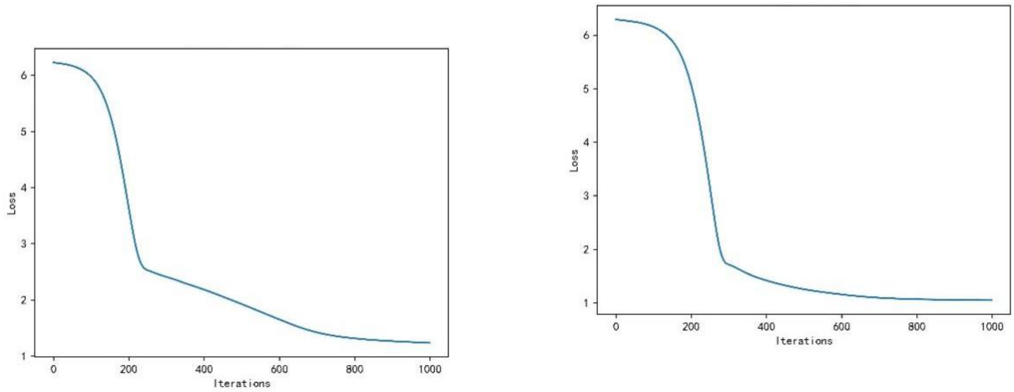

Figure 2:Loss Results of Ball Guard and Small Forward

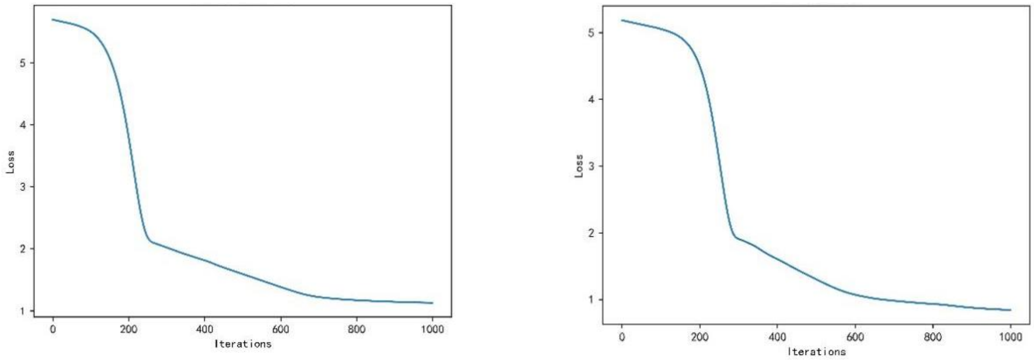

Figure 3:Loss Results of Power Forward and Center

As shown in the left figure of Figure 1, the total data loss function graph begins to decrease below the loss value of 2, and rapidly decreases to 0.5 in the training interval from 0 to 300 times, and then the inflection point appears at 300 times, and then the change rate decreases, and tends to be flat at 700 times. As shown in the right figure of Figure 1, the loss function diagram of the point guard begins to decrease from the loss value of 7, and then rapidly decreases to 3,200 in the training interval from 0 to 200, and then the change rate decreases, and tends to be flat after 600 trainings. As shown in the left figure of Figure 2, the loss function diagram of shooting guard begins to decrease from the loss value of 6.2, and rapidly decreases to 2.5 in the interval from 0 to 220 trainings, and then the change rate decreases after the inflection point appears in 220 trainings, and tends to be flat after 650 trainings. As shown in the right figure of Figure 2, the loss function diagram of small forward begins to decline below the loss value of 6.2, and rapidly drops to 1.5 in the training interval from 0 to 230, and then the inflection point appears in the training of 230, and then the change rate decreases, and it tends to be flat in the training of 800. As shown in the left figure of Figure 3, the power forward loss function graph begins to decline below the loss value of 5.7, and rapidly drops to 2,210 training sessions from 0 to 210, and then the change rate decreases, and tends to be flat after 600 training sessions. As shown in the right figure of Figure 3, the loss function diagram of the center starts to decline below the loss value of 5.1, and rapidly drops to 1.8 in the training interval from 0 to 220, and then the inflection point appears in the training of 220, and then the change rate decreases, and it tends to be flat in the training of 600.

3.2. Evaluation results of playing time prediction model

Models are established based on different positions, and the prediction results of the model are tested. The test results are shown in Table 3. For point guard playing time model, the mean square error of test samples is 1.48, R2 is 0.756, while for shooting guard playing time model,

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the mean square error of test samples is 1.43, R2 is 0.785, for small forward playing time model, the mean square error of test samples is 1.43, R2 is 0.785, and for power forward playing time model, the mean square error of test samples is 1.56, R2 is 0.731. The mean square error of the test sample is 1.48, R2 is 0.726, and the mean square error of the test sample is 1.42, R2 is 0.767 for the total data playing time model. The R2 comparison chart of each model is shown in Figure 4. By comparing the determination coefficient (r) of each model, we can observe that the explanatory power of the model is relatively high, among which the playing time models of shooting guard and small forward are the most outstanding, with the highest r value, indicating that these two models have the best effect in explaining the variation of playing time. However, the R of the power forward playing time model is slightly lower, indicating that its explanatory power is slightly inferior to other models.

Generally speaking, the predicted values of these models are very close to the actual values, which shows that the model fitting effect is good. These test results show that our model can accurately predict the playing time of basketball players in different positions, which has important reference value for team management and tactical arrangement.

Table 3 :The evaluation result chart of the player's playing time prediction model

Playing time prediction model	MSE	R2
point guard	1.48	0.756
shooting guard	1.43	0.785
small forward	1.43	0.785
power forward	1.56	0.731
centre	1.48	0.726
Total data	1.42	0.767

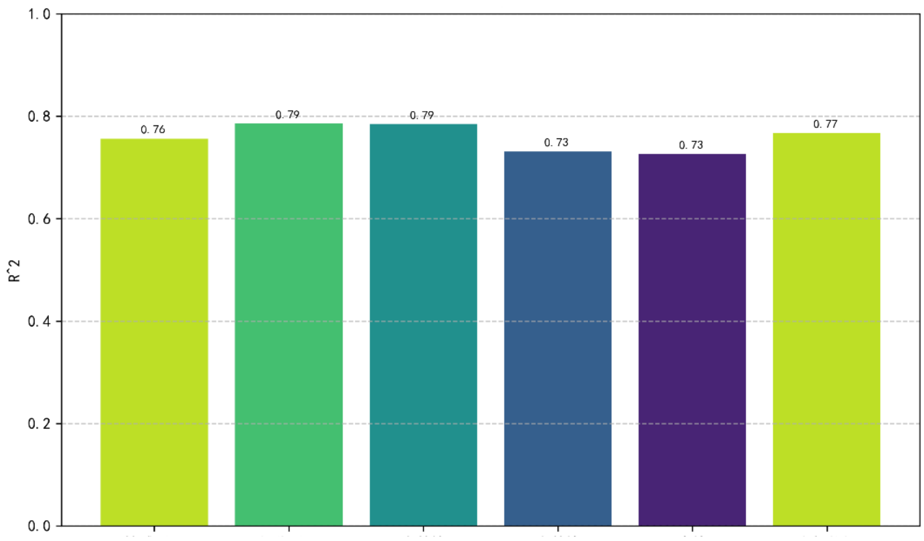

Figure 4:Comparison chart of model determination coefficient (R2)

3.3. Analysis results of influencing factors of playing time

3.3.1. SPSS analysis results of influencing factors of playing time

In this study, three scatter charts were created in SPSS software, with scores, rebounds and assists as abscissa and playing time as ordinate, labeled as Figure 5, Figure 6 and Figure 7. Through the distribution of these scatter charts, we can observe the relationship between the three data and playing time.

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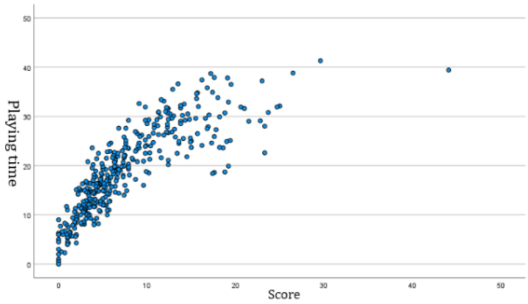

Figure 5:Scatter plot of the relationship between score and playing time

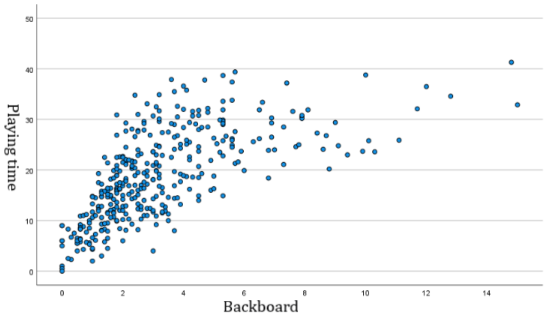

Figure 6:Scatter chart of the relationship between rebound and playing time

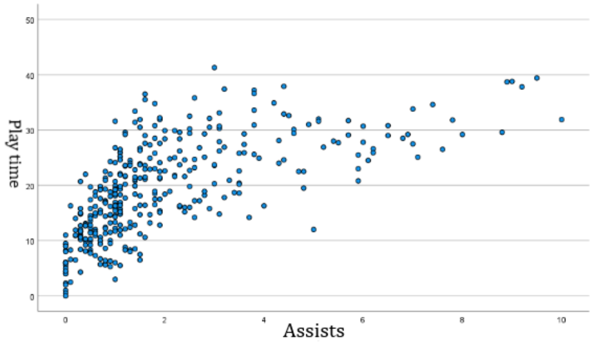

Figure 7:Scatter plot of the relationship between assists and playing time

As can be seen from the scatter chart, the average scores, rebounds and assists increase with the increase of playing time, which indicates that the performance of players is affected by playing time to some extent. However, in the higher playing time interval (20-40 minutes), the data showed a trend of great fluctuation and dispersion, which indicated that the relationship between player performance and playing time was complex, not linear but nonlinear, indicating that many factors needed to work together.

3.3.2. Pearson coefficient analysis results of playing time influencing factors

In this study, the horizontal axis and vertical axis of Pearson's heat map (as shown in Figures 8, 9 and 10) contain many data indicators related to basketball performance. In order to analyze the correlation between playing time and other data, we only need to pay attention to the "playing time" in the horizontal or vertical axis of the chart. By observing the color depth of the item "playing time", we can intuitively understand the correlation between playing time and every other indicator. For example, if "playing time" and "scoring" are in dark colors, it can be inferred that there is a high correlation between playing time and scoring, suggesting that the longer a player plays, the more chances he will score. By observing the colors corresponding to other indicators, we can analyze the correlation between playing time and other statistics such as rebounds and assists.

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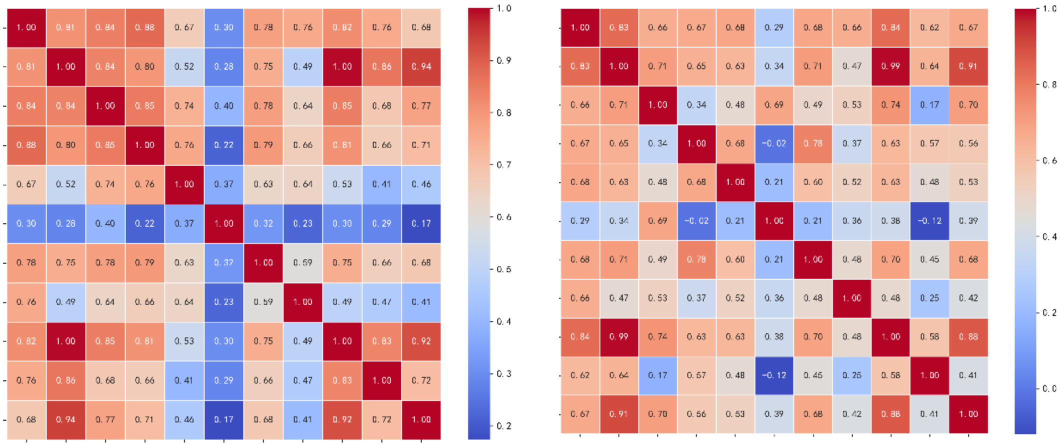

Figure 8:Point guard and all data Pearson heat map

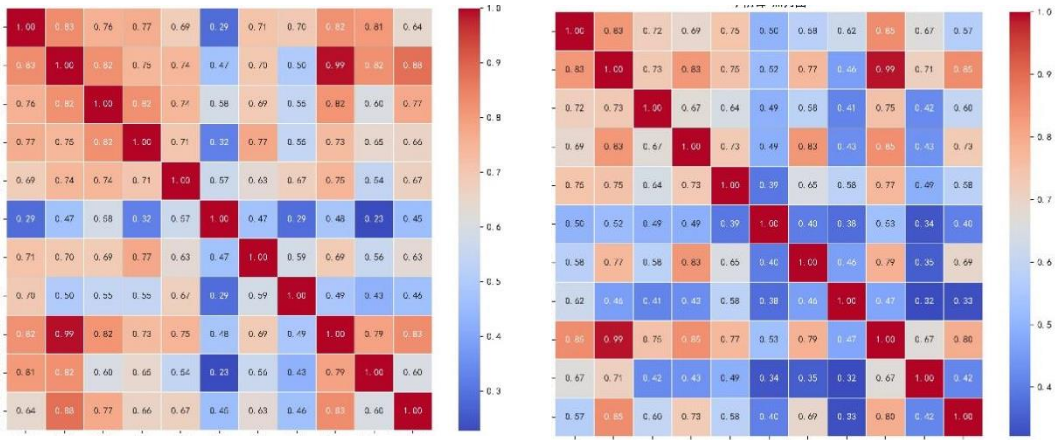

Figure 9:Pearson heat map of shooting guard and small forward

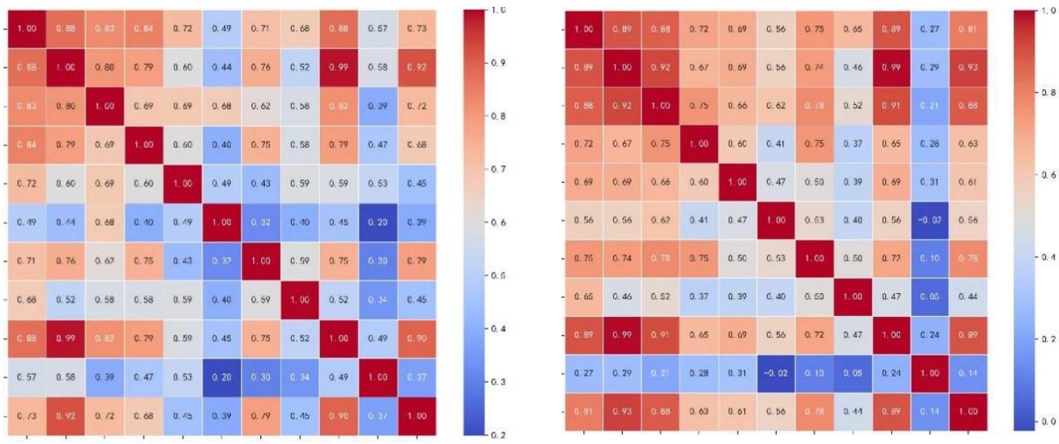

Figure 10:Pearson heat map of power forward and center

The left figure of Figure 8 shows that the correlation between playing time of point guards and scores, rebounds, assists and shooting percentage is above 0.8, and the lowest correlation is blocked shot of 0.30. The display on the right of Figure 8 shows that all the data are integrated, and the scores and shooting percentage are related to the high playing time, and the lowest correlation is the blocked shot; The left figure of Figure 9 shows that there are three items related to high playing time among shooting guards: scoring, shooting percentage and three-point shooting percentage; The display on the right of Figure 9shows that the small forward is

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scoring and shooting percentage, but other data are relatively average and have no particularly low values; The left figure of Figure 10shows that the high correlation area between power forward and playing time is the same as that of point guard, and the low correlation area is three-point shooting percentage. The right figure of Figure 10 shows that the center is relatively scoring and shooting percentage. The specific values of the correlation between playing time and each index are shown in Table 4.

Table 4 :Pearson correlation coefficient between players' playing time and technical data in each position

engineering data	point guard	shooting guard	small forward	power forward	centre	All data
score	0.81	0.83	0.83	0.88	0.89	0.83
backboard	0.84	0.76	0.72	0.83	0.88	0.66
make holding attack	0.88	0.77	0.69	0.84	0.72	0.67
intercept in football and basketball	0.67	0.69	0.75	0.72	0.69	0.68
nut cap	0.30	0.29	0.50	0.49	0.56	0.29
fault	0.78	0.71	0.58	0.71	0.75	0.68
break the rules	0.76	0.70	0.62	0.68	0.65	0.66
shooting percentage	0.82	0.82	0.85	0.88	0.89	0.84
Three-point hit rate	0.76	0.81	0.67	0.57	0.27	0.62
Free throw percentage	0.68	0.64	0.57	0.73	0.81	0.67

According to the results in Table 4, the responsibilities of basketball players in different positions are different. Point guards not only need to ensure the score and shooting percentage, but also need to organize and connect teams, so the correlation between score, shooting percentage and assists and playing time is high. Point guards are usually relatively short in height and it is difficult to complete the blocking technique, so the blocking data has a low impact on playing time. The shooting guard focuses on scoring and shooting percentage, and the correlation coefficient between three-point shooting percentage and playing time is high, which indicates that shooting guards may have higher requirements for long-range shooting. The duties of the small forward are relatively comprehensive, and all the data are relatively average in performance, with no particularly prominent or low data. Power forward and center belong to inside players, and the correlation coefficient between rebounding and blocking data is high, which shows their advantages in inside defense and rebounding. Power forward usually has a certain coordination responsibility at a position far from the basket, so the correlation coefficient of assists is also high. Generally speaking, no matter where you are, you can get more playing time if you show higher scoring ability, so the scoring and hit rate in each position are highly correlated with playing time. However, the correlation between the free-throw percentage and playing time in each position is low, which shows that the coach has low requirements for the free-throw percentage, and even if the free-throw percentage is low,

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players can still get playing time. This also confirms the phenomenon that China's free throw percentage is low in international competitions.

To sum up, increasing playing time will promote the performance of athletes, but this trend is not always stable. Therefore, coaches and team managers need to plan and arrange playing time reasonably to improve the individual performance of players and the tactical benefits of the whole team.

3.4. Discuss

This study collected rich game data of Chinese Basketball Association (CBA) league, which recorded the wonderful performance of the players on the field in detail. Through in-depth analysis of these performance data, we can not only predict the results of the competition, but also dig out the key elements to win the competition. This research method has been widely used in many team sports such as football and rugby, and has achieved remarkable results.[10,11]. In basketball, a high-speed and strategic sport, every data contains the secret of the team's victory or defeat. Whether it is shooting percentage, rebounding control, the number of assists, or defensive statistics such as steals and blocks, it is the cornerstone of building a game result prediction model. In the field of professional basketball data analysis, although the domestic research results are not as deep and extensive as those of foreign countries, the gap is gradually narrowing with the improvement of the understanding of the importance of data. The leading position of data research in foreign countries is partly attributed to the early recognition of the value of data analysis and its application in actual combat many years ago. As mentioned by Ley and others, the Oakland baseball team has successfully introduced data analysts with the help of statistical analysis methods since 2002, creating a new chapter in sports data analysis. It is particularly noteworthy that the data processing and analysis of American Men's Basketball Professional League (NBA) is famous for its rich and diverse data sources and fine index system. Mikołajec and other researchers selected the most critical items from 52 different game indicators through deep mining of NBA game data, including winning percentage (Win%), Offensive EFF, score per game in the third quarter (3rd Quarter PPG), winning percentage on the spot (Win% CG), average fouls (Avg Fouls) and average steals (AVG Fouls).[11]. This study draws lessons from the international advanced data analysis experience, combined with the specific reality of CBA league, and explores a data analysis model suitable for the development of domestic basketball.

In this study, we have constructed five neural network models for different basketball positions. These models show high performance in playing time prediction, and the mean square error (MSE) between the prediction results and the actual data is minimal, which fully proves the effectiveness and accuracy of using neural network technology in basketball data analysis. Both this study and previous literature show that the playing time of players in basketball matches is influenced by many factors.[12,13,11]. These factors not only include players' statistical performance, such as scoring, rebounding, assists, etc., but also involve players' tactical understanding and execution ability, physical fitness and game tactics arranged by coaches. At present, it is becoming a mainstream trend to use machine learning and neural network technology to assist sports decision-making, which reflects the frontier trend of combining modern science and technology with traditional sports.[14–16]. Similar methods have been widely used in football, tennis, skiing and other sports fields, and remarkable results have been achieved.[17–20].

The data set of this study focuses on CBA league, which limits the breadth and diversity of data. Future work undoubtedly needs to broaden the horizons of data collection and include more diverse and extensive information sources. In addition, in order to serve athletes of different levels more accurately, the follow-up research should be devoted to developing more universal neural network models and continuously expanding the scale and depth of data samples, so as

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to continuously refine and improve the existing models. Through the continuous iteration and evolution of the existing research, we are expected to further reveal the hidden complex laws in basketball, and open up a new road for basketball technology-assisted training and game analysis. This can not only promote the development of basketball science, but also provide valuable reference and inspiration for data analysis and technological innovation of other sports.

4. Conclusions and suggestions

In this study, the possibility and accuracy of using neural network model to predict CBA players' playing time are deeply explored. By establishing models of different positions to predict the playing time of players in each position, through the analysis of the loss function result diagram, all six models have a sharp decline interval and an inflection point. The sharp decline interval shows that the model learns the characteristics of data quickly in the early stage and can fit these characteristics well, while the inflection point shows that when the iteration is carried out for a certain number of times, the loss value decreases slowly and tends to be stable gradually, and the model approaches the optimal solution and has obtained the local minimum solution. Finally, the accuracy of the six neural network models in predicting the playing time of CBA players is over 98%, which shows that the models can accurately predict the playing time of basketball players in different positions, and the predicted results are highly fitted with the actual values.

At the same time, the influencing factors of playing time data are analyzed by SPSS scatter plot and Pearson heat map. It shows that the characteristic factors with high correlation of playing time are specific in different positions. This discovery reveals the uniqueness of different positions in basketball, and also highlights the importance of customized modeling. This achievement not only proves the effectiveness of nonlinear analysis method in predicting playing time with neural network model, but also verifies the necessity of location-based modeling. It is expected that changing the model will become a powerful tool for basketball coaches to make decisions on players' rotation.

In a word, the methodology and results of this study provide a new idea for the data analysis of CBA league matches, and a new perspective and solution for the data analysis of other sports events and the management of athletes. Looking forward to the future, we will continue to deepen the application of neural network model in sports field, and strive to optimize the selection of model parameters and data preprocessing process, so as to further improve the accuracy and practicability of the model and contribute more innovation and value to the field of sports data analysis.

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