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The Rating of Basketball Players' Competitive Performance Based on RBF-EVA Method

Jian Jia, Shangqiu Engineering College, China
Hua Chen, Jiangsu Vocational College of Medicine, China*

ABSTRACT

Basketball, as an offensive and defensive game centered around high altitude, has become an international mass competitive sport. Traditional methods cannot comprehensively evaluate the future potential of players, nor can they simply add up individual competitive abilities to judge the overall competitive performance of a team. To address these issues, this article proposes a video-based RBF neural network competitive scoring method, which analyzes players' past sports behavior, captures every subtle difference in their abilities, and achieves objective evaluation of players' competitive performance. Through comparative experiments, the accuracy of the test results is improved by about 5% compared to conventional RBF methods. This indicates that the improved RBF neural network designed in this article has significantly better prediction performance than traditional convolutional neural networks. This study provides a new method for evaluating the competitive performance of basketball players and has important guiding significance for basketball training and skill enhancement.

KEYWORDS

Basketball, Competitive Performance, Mobile Operating Systems and Applications, Rating, RBF Neural Network

INTRODUCTION

As a collective, comprehensive, and three-dimensional offensive and defensive game, basketball, originates from the process of human labor and survival and is a reflection of social and cultural progress (Choi et al., 2023). With the development of modern society, basketball has become an international mass competitive sport that integrates technology, culture, education, and skills (Montgomery et al., 2010). However, when analysts and coaches are evaluating the competitive performance of basketball players, traditional statistical data cannot fully reflect every aspect of their potential impact on future teams, and the simple addition of individual competitive abilities cannot accurately evaluate the overall competitive performance of basketball teams (Sansone et al., 2023). To address the aforementioned issues, we propose a video-based radial basis function (RBF) neural network competitive performance scoring method. By watching a large number of basketball videos of basketball players, analysts using this method can capture every subtle difference in their abilities and use discriminators to distinguish sports performance, achieving objective evaluation of

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*Corresponding Author

players' competitive performances, and thus adjusting training intensity accordingly. However, in traditional RBF networks, most of the adjustments to the prediction models of basketball players' competitive behavior are based on subjective desires; these adjustments lack evaluation methods for the overall performance of basketball teams. To improve this issue, we propose three improvement methods based on the aforementioned challenges: the introduction of hidden layer neurons, network parameter adjustment, and hidden layer neuron deletion. Using these three methods will further improve the accuracy of basketball player competitive behavior prediction models. In this study, we used online learning models to predict the competitive behavior of basketball players and to verify the effectiveness of the improved RBF-EVA(Radial Basis Function Network - External Validation Approach) algorithm proposed in this article through comparative experiments with traditional prediction methods. The experimental results show that the improved RBF neural network that we designed for this paper has significantly better prediction performance than traditional convolutional neural networks. In summary, this study aims to improve the basketball player competitive behavior prediction model through a video-based RBF neural network competitive performance scoring method to provide more accurate and objective evaluation methods, and thus, provide strong support for the training and development of basketball players.

Combining the RBF neural network model with the EVA method, we established an RBF-EVA evaluation model to compensate for the shortcomings of traditional EVA methods in predicting player ability EVA and form a more scientific player ability evaluation method.

We applied the EVA method to the emerging industry of artificial intelligence, verified its applicability in the artificial intelligence industry, and further promoted and optimized the role of the EVA method in player ability assessment.

LITERATURE REVIEW

Since its introduction to China at the end of the Qing Dynasty, modern basketball has become increasingly popular owing to its characteristics of spatial confrontation, diverse content, comprehensive changes, fitness and intelligence, enlightenment education, and profession and commerce (Moreno-Pérez et al., 2023). Basketball has flourished with the progress of the times, and the overall level is constantly improving (Leukel, C., & Gollhofer, 2023). Today's basketball games have become a comprehensive confrontation between athletes' competitive abilities and a competition for overall team strength, with higher requirements for athletes' physical fitness and abilities (Jin et al., 2023). The evaluation of basketball players' competitive performances has always been a hot topic in the field of basketball research. Previous studies have mainly used traditional statistical data to evaluate the competitive performances of players, but this method cannot fully reflect the potential impact of players on the team and their abilities in various aspects (Suryadi et al., 2023). With the development of deep learning technology, video-based competitive performance scoring methods have gradually become the focus of research. The video-based competitive performance scoring method uses deep learning models to capture every subtle difference in a basketball player's ability by watching a large number of basketball videos, and it also uses discriminators to distinguish sports performance, thus achieving objective evaluation of the player's competitive performance. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are the most commonly used models that can effectively extract spatial and temporal features from videos (Hidayat et al., 2023). However, traditional CNN and RNN models have some problems, such as overfitting and long training time (Philipp et al., 2023). To improve these issues, researchers have proposed some new models. Among them, the attention mechanism-based model can automatically select important keyframes or time periods in the video to more accurately evaluate the athlete's competitive performance (Guimarães et al., 2023). Models based on residual networks can reduce information loss and improve model performance by jumping connections (Philipp et al., 2023). In addition to evaluating the competitive performance of individual players, some researchers also have focused on the evaluation methods of the overall competitive performance of basketball teams. For example, Dhia et al. (2023) applied image processing technology to extract the position information of a team and evaluate the overall competitive level of the team by analyzing its movement trajectory and passing route. In addition, Bonder and Shim (2023) used data mining technology to analyze game data and extract the factors that have the greatest impact on team wins and losses to help teams optimize tactics and improve overall competitive level.

RELATED MATERIALS AND METHODS

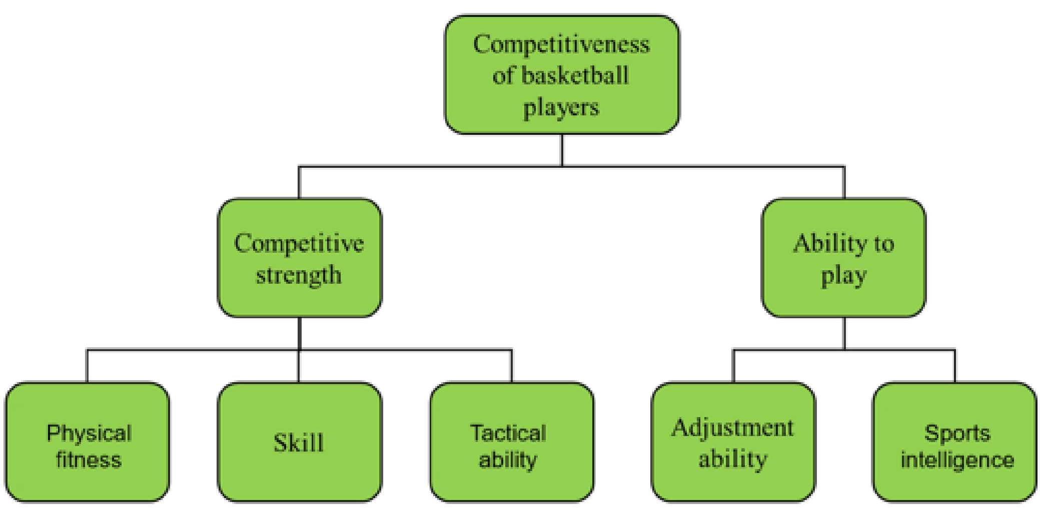
Competitive Ability of Basketball Players

Basketball is a skill-dominated sport in which players compete against each other on the same field. It has high technicality and on-the-spot performance. The competitive ability of basketball players can be divided into structural levels as shown in Figure 1.

The current domestic theoretical research on basketball players' athletic abilities is far from meeting the needs of technological development. Therefore, theoretical research on the content of basketball players' competitive abilities is particularly important. By studying the structure of basketball players' competitive abilities and its influencing factors, analysts and coaches are able to guide the teaching and training of basketball sports in a targeted manner, improve the overall level of basketball players' competitive abilities, and then improve the sports performance of athletes in the game(Čaušević et al., 2023).

The abilities that basketball players must have to participate in competitions and training include the content, structure, structural characteristics, structural relationships, and influencing factors of basketball players' athletic abilities that Pamuk et al. (2023) studied. Modern basketball is a collective, comprehensive, three-dimensional offensive and defensive confrontation designed for scoring by shooting at a target at a high altitude. The athletic abilities of basketball players refer to the skills that basketball players must have to participate in training and competitions. They include the content of the basketball player's competitive ability, the function of the basketball player's competitive ability, the structure of the basketball player's competitive ability, the structural characteristics of the competitive ability, the structural relationship of the competitive ability, and the factors that affect the basketball player's competitive ability. According to the basic principles of sports training,

Figure 1. The three-level structure of basketball players' competitive abilities



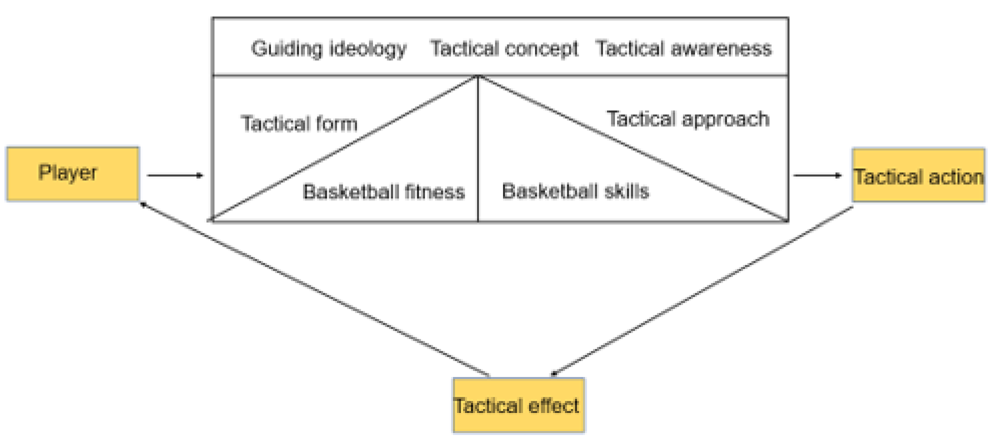
combined with the characteristics of basketball, the competitive abilities of general basketball players is mainly reflected in the ability to complete movements, such as physical fitness, skills, and tactical ability, as well as the athletes' psychological adjustment ability and sports intelligence. The ability requirements are relatively weak.

Physical fitness refers to the basic athletic ability of an athlete's body and is an important part of an athlete's competitive ability (Zhao et al., 2023). The physical development level of basketball players is determined by the development of body shape, physical function, and athletic quality. The general physical training of basketball players refers to the use of a variety of nonspecialized physical exercises to transform the athletes' physical shapes, improve physical health, improve physical function, and comprehensively develop sports quality.

Sports technique refers to the method of completing sports actions, which is an important determinant of the level of athletes' competitive abilities (Naik & Hashmi, 2023). Reasonable and correct sports techniques must meet the requirements of the sports rules of the project; these techniques are conducive to the full exertion of the physical and mental abilities of the athletes and help the athletes to obtain good competitive results. Basketball sports technology mainly includes offensive technology and defensive technology. Basketball skills are divided into basic skills (single skills), combined skills, position skills, and fuzzy position skills. In the process of learning basketball skills, fuzzy position skills, as a higher level of basketball skills, are based on basic skills, combination skills, and position skills, and are a higher-level skill among all basketball skills. Basic basketball skills are the foundation; only by paying attention to it can you gain an advantage in basketball competition.

Competitive tactics refer to the tactics and actions taken during a game to overcome an opponent or to achieve a desired outcome of the game (Liang, 2023). Basketball tactics are divided into offensive tactics and defensive tactics. Offensive tactics include basic coordination of tactics such as fast break, offensive man-to-man, or offensive zone defense. Defensive tactics are divided into basic coordination of tactics such as fast break defense or man-to-man and zone defenses. Basketball tactics are an important part of the competitive ability of basketball players, including basic basketball tactics, basketball fixed tactics, and basketball variation tactics (Figure 2). Basketball competitive tactics are a means to exert collective strength and individual roles in basketball games. Their purpose is to organize the team members organically, ensure the overall combat effectiveness of the team to the greatest extent, give full play to their own strengths, restrict the opponent, master the initiative of the game, and compete to win the game.

Figure 2. Schematic diagram of basketball tactical application mechanism



Main Manifestations of Lack of Basketball Competitive Ability

A lack of basketball competitive ability can be due to many factors. One factor is the lack of physical performance. Basketball is a collective confrontation project. The use of skills and tactics is completed under the condition of physical confrontation. Participating in this sport well requires physical fitness. The lack of specialized physical fitness is manifested in insufficient strength, poor endurance, and poor physical resistance during competitions. The lack of special physical fitness, on one hand, is easy to make players injured in competition. Because of lack of strength and poor endurance, fatigue occurs earlier and lasts for a long time. When competing in confrontational sports in a fatigued state, athletes can become injured easily. On the other hand, the value of participating in this sport cannot be well obtained. Because the physical confrontation ability is not strong, comprehending the essence of the sport is impossible.

The second factor is the lack of skills. For example, insufficient mastery, inaccuracy, and unreasonable use of basketball techniques. The specific manifestations in the competition are poor technical timeliness, poor stability, and poor rationality. Poor timeliness is the difference in technology selection and application timing. For example, when a team breaks through with the ball, the opponent has already paid attention to the defensive breakthrough and chooses a position far away from the ball-holder. The ball-holder must use a fake shot to distract the opponent and then try to break through the opponent. When they use fake shots to distract opponents, they often choose to make breakthroughs before they reach the right position, and thus, they cannot form an effective attack. Poor stability means that technical actions have not formed a stable dynamic stereotype. Take free throws as an example. In sports, when the physical condition is good, the shooting rate will be relatively high. Once fatigue occurs, the movement will be deformed, and the shooting rate will drop significantly. Poor rationality means that the technical mastery is inaccurate and unreasonable.

The third factor is the lack of tactical ability. Basketball has a few tactical routines, and sometimes, the tactical application is lacking and inappropriate. The specific manifestations are weak coordination ability, poor adaptability, and poor execution ability in competition. The lack of coordination ability means that there is no tacit understanding with the companions, and there is little or no cooperation. During confrontation, there are too many solo battles, which is very unfavorable to the cultivation of collective consciousness and team spirit; poor adaptability means that corresponding tactics cannot be adopted in time according to the changes in the situation on the field. For example, when the opponent adopts an expanded zone defense, its attack is mainly based on breakthroughs. When the opponent switches to a smaller zone defense, its own offense will change to focus on shooting. In reality, this transformation of some players is not timely. Poor execution ability means that the on-court classmates cannot well execute the tactics arranged by the off-court guidance or the tactics that the partners agree to adopt.

The fourth factor is the lack of mental intelligence. Some players have poor basketball awareness, have weak special will, and do not follow rules in confrontation. The specific performance is that when the judgment, observation, and imagination are not strong in the competition, decisiveness, tenacity, and self-control are poor. Poor judgment means poor analysis and decision-making ability, such as inaccurate judgment on the flight path, flight speed, rotation, and rebound direction of the ball; all these inabilities are not good for stealing, grabbing, and catching the ball. Poor observation ability means not being able to gain insight in time to make changes in the field, and as a result, the corresponding strategies are naturally not timely. Lack of imagination means lack of creativity. Poor decisiveness means indecision; that is, not making decisions quickly and reasonably and easily making mistakes. Poor tenacity means not having a tenacious demeanor, being easy to rattle. Poor self-control is when players are not able to control their emotions well and are not calm when encountering problems. They are unstable in their own performance, indicating that the mastery of professional theory is not good.

RBF Radial Neural Network Prediction Model

Players are often measured by their stats, such as points and rebounds per game; however, these metrics don't reflect every aspect a coach may want to use to assess a player's potential impact on a future team. More importantly, these metrics are based on subjective evaluations of individuals (Charamis et al., 2023). At the same time, the assessment of the overall basketball team's competitive performance cannot simply be measured by the individual's competitive ability. To solve these problems, we propose a video-based RBF neural network competitive performance rating method. By watching a large number of basketball videos of a basketball player to capture every nuance of his or her ability, the coach can distinguish the sports performance through the discriminator. This method can realize the objective evaluation of the player's competitive performance so that the training intensity can be adjusted in a targeted manner. Assuming that the RBF neural network has only one hidden unit, we can express the training sample of the RBF neural network as {Xn, dn}, where the sample input is as shown in equation (1):

$$X_n = [x_{n1}, x_{n2}, \cdots x_{nM}]^T \tag{1}$$

The center of the radial basis function φ can be calculated using the formula shown in equation (2):

$$t_i = [t_{i1}, t_{i2}, \cdots t_{iM}] \tag{2}$$

When the network input training sample is Xn, the actual output of the network can be calculated by the formula shown in equation (3):

$$Y(X_n) = \sum_{i=1}^{t} w_i \varphi(X, t_i) \tag{3}$$

At present, in the field of RBF neural network, there are many RBF functions; some of the most commonly used are Gaussian function, inversion sigmoid function, and multi-quadratic function. The formula expressions are shown in equations (4)–(6):

$$\varphi(X, t_i) = \exp\left(-\frac{\left\|X - t_i\right\|^2}{2\sigma^2}\right) \tag{4}$$

$$\varphi(X, t_i) = \frac{1}{1 + \exp\left(\frac{\left\|X - t_i\right\|^2}{\delta^2}\right)} \tag{5}$$

$$\varphi(r) = \frac{1}{\sqrt{\left(r^2 + \delta^2\right)}} \tag{6}$$

The RBF neural network prediction process is divided into four steps. These steps are specifically analyzed as follows.

The first step is data normalization. The purpose of data normalization is to convert all data into values in the [0, 1] interval, making subsequent calculations more convenient. The data normalization formula is shown in equation (7):

$$X = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{7}$$

In equation (7), xmax represents the maximum value in the experimental data, xmin represents the minimum value in the experimental data, and X represents the normalized data value.

The second step is network structure setting. During the setting process of the RBF network structure, parameters such as the number of input and output layer neurons in the network and the sliding window value in the network are set based on the actual experimental needs. In this regard, in this paper, we will use the functions that come with the MATLAB software toolbox to build the RBF neural network. The specific expression formula is shown in equation (8):

$$net = netrbf(P, I, spread) \tag{8}$$

In equation (8), P represents the input vector matrix, I represents the training output vector, spread represents the distribution density value of the radial basis function, which will default to 1.0.

The third step is network training and testing. Use MATLAB software to simulate and test the RBF network that has been set up. Adjust the spread according to the test process and test results to obtain the optimal spread value.

The fourth step is error analysis and evaluation. Calculate the prediction error of the RBF neural network and evaluate the applicability of the method according to the calculation results.

Construction of Basketball Players' Competitive Performance Prediction Model RBF-EVA

Currently, the learning algorithms of RBF neural network are divided into two categories: offline learning and online learning (Wang & Shi, 2023). For this paper, we selected the online learning model to predict the competitive behavior of basketball players. However, in the traditional RBF network, most of the adjustments, including the number of network layers, weights, etc., are based on their subjective wishes, and there is a lack of methods for judging the overall athletic performance of the basketball team. In this regard, to address the above problems, we improved the basketball player's competitive behavior prediction model from three aspects: introducing new hidden layer neurons, adjusting network parameters, and deleting hidden layer neurons. The specific analysis is as follows:

For each input x_i, calculate the RBF kernel function as shown in equations (9)–(13):

$$\varphi_k(x_i) = \exp\left(-\frac{1}{\sigma_k^2}\left\|x_i - c_k\right\|^2\right), k = 1, \cdots, K \tag{9}$$

$$\hat{y}_i = f(x_i) = w_0 + \sum_{k=1}^{k} w_k \varphi_k(x_i) \tag{10}$$

$$d_i = \min_{1 \le k \le K} \left\| x_i - c_k \right\| \tag{11}$$

$$\delta_i = \max\left\{ \gamma\delta_{\max}, \delta_{\min} \right\} \tag{12}$$

$$e_{rms}^i = \sqrt{\sum_{j=i-(M-1)}^{i} \frac{\left\| y_j - \hat{y}_j \right\|^2}{M}} \tag{13}$$

In the formula, d represents the closest Euclidean distance to x, δ_{max} represents the maximum distance between input data, δ_{min} represents the minimum distance between input data, $0<\gamma<1$ is an attenuation coefficient, M represents the RMS sliding window width, and e_{rms} represents the root mean square of the output error after the ith sample is entered.

If we assume that |ei| > ε, di > δ and e_{rms} > εi are satisfied at the same time, and at this time, a new hidden layer neuron is added to the network, and K = K + 1, then the hidden layer neuron parameters are for the formulas shown in equations (14)–(16):

$$w_{K+1} = e_i \tag{14}$$

$$c_{K+1} = x_i \tag{15}$$

$$\sigma_{K+1} = kd_i \tag{16}$$

In equations (14) – (16), k represents the overlap factor that acts to determine the response width of neurons in the hidden layer.

The network parameters are updated by the formula shown in equation (17):

$$P_i = \left[I_{zxz} - K_i B_i^T \right] P_{i-1} + q_0 I_{zxz} \tag{17}$$

In equation (17), *B* represents the parameter state displayed by the ith sample after entering the network.

Now calculate the output of all hidden nodes. The specific normalized output vector formula is shown in equation (18):

$$r_{kj}^i = \frac{\left\| o_{k,j}^i \right\|}{\left\| o_{j,\max}^i \right\|}, k = 1,2,\cdots,K \tag{18}$$

If < ε2 are all established, then the kth hidden node can be deleted.

Prediction of Competitive Performance of Receivers

If we assume that the output shown in the predictor is a passing action, the predictor will then make a prediction for the pick of the opponent. When a basketball player is passing the ball, the player will select the teammate with the best conditions to catch the ball before passing it. In the process of selecting teammates, the player with the ball should not only consider the possible scoring advantage of the receiver but also the distance between passes. The smaller the distance between the player holding the ball and the player receiving the ball, the less likely the pass may be disrupted by the opponent and vice versa. In this regard, if we assume that there are k teammates in the field of vision of the player holding the ball, the favorable degree of teammate i's catching the ball is calculated as shown in equation (19):

$$\widehat{w_i} = w_1 \times U_{APF_i} + w_2 \times \frac{1}{d_{ci}^2}, where \quad w_1 + w_2 = 1 \tag{19}$$

In equation (19), U_{APFi} represents the information amount of the artificial potential energy field of teammate i; w1 and w2 represent the factor weights of teammate i and player c, respectively. Through this formula, the player with the best conditions for catching the ball in the court can be obtained and pass the ball to his or her teammates.

RESULTS AND ANALYSIS

Analysis of Experimental Results

To give the scientificity of the prediction method of the basketball player's competitive behavior proposed above, we proved the method experimentally. The whole experimental process consists of two parts: the training of the neural network and the prediction of the competitive behavior of the players holding the ball. In this experiment, the traditional RBF neural network (RBFNN) prediction method and the improved RBF-EVA algorithm proposed in this paper are compared with the basketball game videos of seven regular NBA seasons. For the rating of a single player, the traditional method is used first to rate the player's competitive performance, and then the method designed in this paper is used to rate the player's performance in real time. The results of the rating are compared with the traditional method.

Then, according to the designed algorithm, the overall competitive performance of the basketball team is evaluated in real time, and the analysis results are compared with the actual game results to analyze the effectiveness of the algorithm.

The performance of the RBFNN mainly depends on the structure of the network, especially the number of hidden layer nodes. The smaller the neural network, the better (Horvat et al., 2023). However, an overly complex network structure will lead to overfitting and fail to achieve good generalization performance. For this paper we used L1 and L2 regularization with sparse model ability to select the number of hidden layer nodes of the network structure and combined the idea of fuzzy control to properly scale the input data to improve the generalization ability. The introduction of a simulated annealing algorithm with global optimization ability effectively reduces the number of training times and saves time. The comparison chart of RBF training error drop is shown in Figure 3. The performance of the algorithm is compared with other algorithms, and the results are shown in Figure 4.

The test results in Figure 4 show that the prediction effect of the improved RBFNN designed in this paper is significantly better than that of the traditional convolutional neural network.

Figure 3. Comparison of estimation error changes (RBF training error drop)

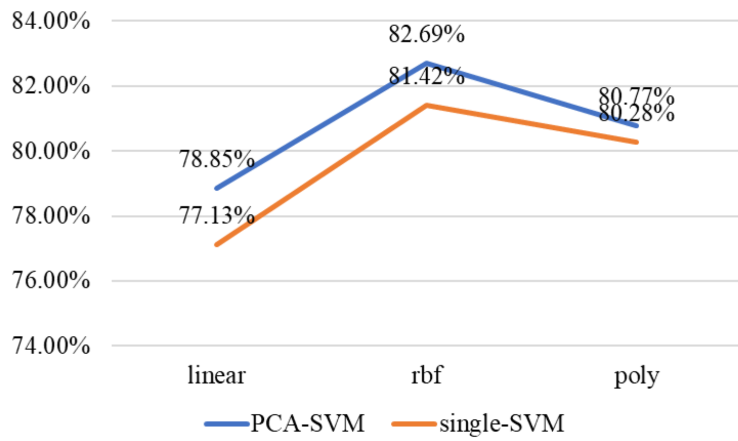
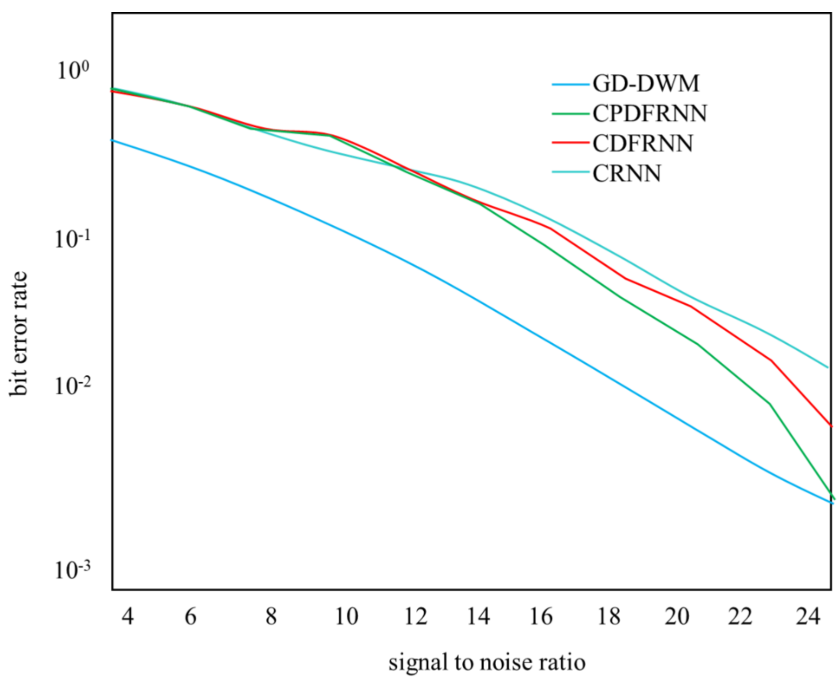


Figure 4. Comparison of estimation error changes by type of algorithm



Dynamic visualization of how the evaluation model changes over time is validated in the competitive performance ratings of individual basketball players. To do this, four pairs of basketball players are randomly selected, each representing the same position, and the proposed model evaluates each player over time. Figures 5 and 6 respectively show the competitive performances of two players with different competitive performances in the same position. Figure 5 represents the real-time rating of the player with the worst competitive performance, and Figure 6 represents the real-time rating of the player with the best competitive performance. It can be seen from these figures that the model can

Figure 5. Prediction of the worst player in the no. 1 position from competitive performance

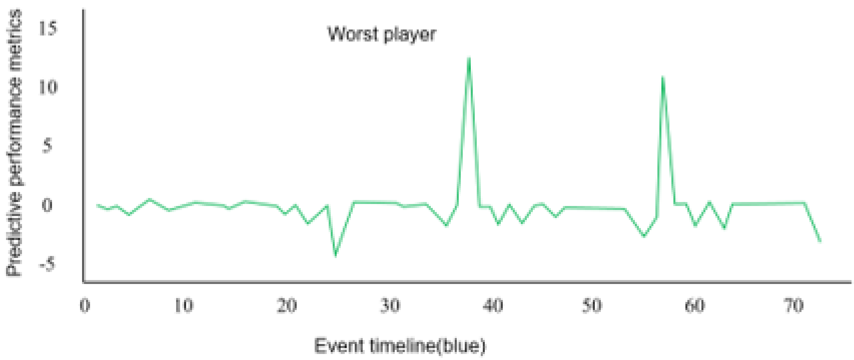
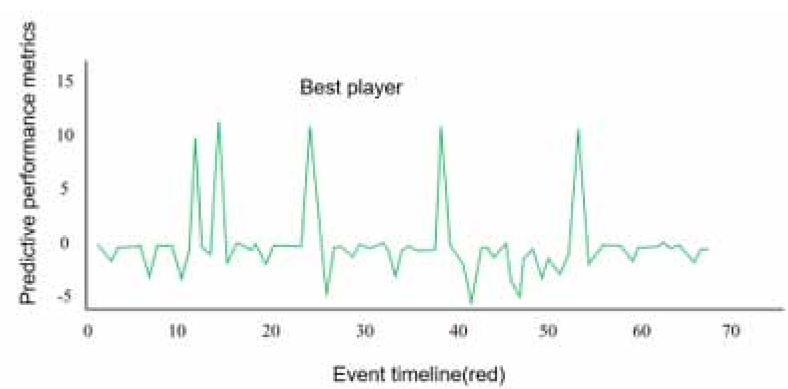


Figure 6. Prediction of the best player in the no. 1 position from competitive performance



effectively distinguish the best and worst players by rating the players' competitive performances in the same positions. For the evaluation of the players, the traditional method is used for identification.

The traditional RBFNN prediction method and the improved RBF algorithm proposed in this paper are tested and compared with the video of the NBA's seven regular season basketball games. The specific experimental results are shown in Figure 7.

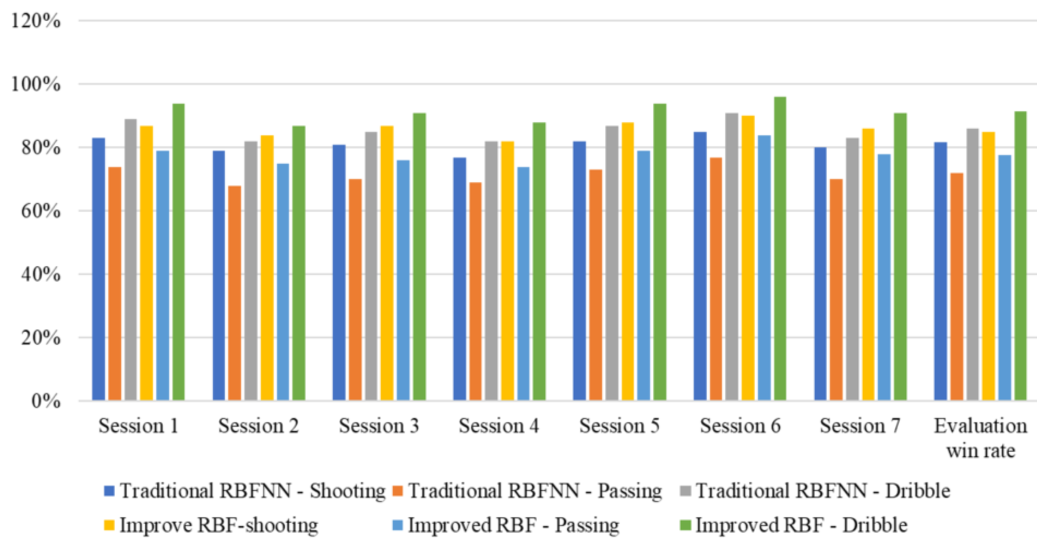
Figure 7 shows that when predicting the three behaviors of basketball players (shooting, passing, and dribbling), the average correct rate of the traditional RBFNN prediction method is 81.6%, 72.1%, and 86.1%, respectively. When the improved RBF algorithm in this paper was used, its average prediction accuracy is 80.0%, 77.7%, and 91.6%.

Therefore, these results reveal that the improved algorithm proposed in this paper is more accurate than the traditional algorithm. The reason for obtaining the above results is that the online prediction method introduced in this paper can update the basketball players' competitive behavior prediction data according to the results, and then adjust and change with the development of the basketball game during the calculation process. Thus, the online prediction method developed in this paper shows strong generalization ability and is able to accurately rate the overall team's competitive performance.

Analysis of RBF-EVA Evaluation Method

The main advantages of the RBF-EVA evaluation method are:

Figure 7. Prediction results of traditional RBFNN and improved RBF (changed to grouped histogram)



Comprehensiveness: The RBF-EVA evaluation method can comprehensively capture every subtle difference in a player's ability by introducing video-based competitive performance scoring (Goka et al., 2023). Compared with traditional statistical data, this method can better reflect the potential impact of players on the team and the comprehensive situation of various abilities.

Objectivity: The RBF-EVA evaluation method uses deep learning models to objectively evaluate the competitive performance of athletes (Chessa et al., 2023). By using discriminators to distinguish motion performance, the RBF-EVA evaluation method enables the interference of subjective factors to be reduced, and the objectivity of evaluation results is improved.

Accuracy: The RBF-EVA evaluation method can more accurately evaluate players' competitive performance by analyzing basketball game videos (Martonosi et al., 2023). This method can capture the actual performance of players in the competition, avoiding the potential shortcomings of traditional statistical data.

Real-time performance: The RBF-EVA evaluation method can evaluate athletes' competitive performances in real time. Through comparative experiments and the application of deep learning models, this method can provide timely evaluation results during matches, providing reference for coaches and teams to make adjustments.

In addition to its application in the evaluation of basketball players' competitive performances, the RBF-EVA evaluation method also has some related applications in other fields, such as football player evaluation. Similar to basketball player evaluation, the RBF-EVA evaluation method can be applied to the evaluation of football players' competitive performances. By analyzing football game videos, the RBF-EVA method can be used to evaluate players' skills, tactics, and overall performances in the game; this method also helps coaches and teams with decision-making.

Although the RBF-EVA evaluation method has some advantages, it also has some limitations. The following are some common limitations and corresponding countermeasures:

Data dependency: The RBF-EVA evaluation method requires a large amount of competition video data for training and evaluation. If the data volume is insufficient or the data quality is poor, it may affect the accuracy of the evaluation results. To address this issue, measures can be taken to increase data collection channels and improve data quality, such as introducing professional camera equipment and using multi angle recording.

Subjective factors: Although the RBF-EVA method reduces the interference of subjective factors through deep learning models, there is still a certain degree of subjective judgment—for example, whether the athlete's movements are accurate and meet tactical requirements. To reduce the impact of subjective factors, independent evaluations by multiple evaluators can be added and a comprehensive analysis of the results can be conducted (Facchinetti et al., 2023).

Insufficient contextual consideration: The RBF-EVA evaluation method is mainly based on video analysis and may not fully consider specific contextual factors of the competition, such as the competition environment and opponent strength. To comprehensively evaluate the performance of athletes, other data sources, such as statistical data and tactical analysis, can be combined to comprehensively consider contextual factors.

Explanatory and interpretable: Deep learning models play an important role in RBF-EVA evaluation methods, but these models are often considered black boxes and lack interpretability. This limitation may lead to difficulty understanding the specific reasons for the evaluation results. To improve interpretability, some interpretive machine learning methods can be used, such as attention mechanisms and feature importance analysis, to better understand the evaluation results.

Applicability limitations: The RBF-EVA evaluation method is currently mainly applied to the evaluation of basketball players' competitive performances, and further research and exploration are needed in other fields. For applications in different fields, adjusting and optimizing the model according to specific circumstances to ensure the applicability of the evaluation method are necessary.

Overall, the RBF-EVA evaluation method needs to fully consider these limitations in practical applications and take corresponding measures to improve the accuracy and reliability of the evaluation results. In addition, continuous research and improvement are also key to addressing limitations to promote the application and development of this method in different fields.

CONCLUSION

The popularity of basketball on a global scale is constantly increasing. More and more people are becoming exposed to basketball and participating in basketball games. Especially in Asia and Africa, the popularity and influence of basketball are constantly expanding. At present, the theoretical research on the athletic ability of basketball players in China is far from meeting the needs of technological development. Therefore, theoretical research on the connotation of basketball players' competitive ability is particularly important. Studying the structure and influencing factors of basketball players' competitive abilities provides targeted guidance for basketball teaching and training, thus improving the overall level of basketball players' competitive abilities, and ultimately, improving their performances in competitions. We introduced an online prediction method, using the RBF-EVA method to predict players' competitive abilities and update the predicted data of basketball players' competitive behavior in a timely manner based on the results. Then, the score changes with the development of the basketball game during the calculation process. The results show that the accuracy of this method is about 5% higher than that of traditional methods. In summary, the video-based RBFNN competitive performance scoring method proposed in this study has high accuracy and objectivity in evaluating basketball players' competitive performances. The application of this method can help coaches comprehensively evaluate the potential impact and various abilities of players and adjust training intensity accordingly, thereby improving the overall competitive level of the team.

Although this competitive scoring method provides new ideas and methods for evaluating basketball players' competitive performances, there are still some problems. First, the quantity and quality of sample data limit the accuracy and generalization ability of the model. Second, the complexity and long training time of the model limit its practical feasibility. In addition, the evaluation methods for the overall competitive performance of basketball teams still need further research and improvement. Future research should focus on increasing the quantity and quality of sample data, improving the accuracy and practicality of the model, and further exploring methods for evaluating the overall competitive performance of basketball teams to promote the development and progress of the basketball field.

DATA AVAILABILITY

The figures used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

We declare that we have no conflicts of interest.

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REFERENCES

Bonder, I. J., & Shim, A. L. (2023). In-season training model for national association of intercollegiate athletics female basketball players using "Microdosed" programming. *Strength and Conditioning Journal*, *45*(4), 395–410. doi:10.1519/SSC.0000000000000741

Čaušević, D., Čović, N., Abazović, E., Rani, B., Manolache, G. M., Ciocan, C. V., Zaharia, G., & Alexe, D. I. (2023). Predictors of speed and agility in youth male basketball players. *Applied Sciences (Basel, Switzerland)*, *13*(13), 7796. doi:10.3390/app13137796

Charamis, E., Marmarinos, C., & Ntzoufras, I. (2023). Estimating team possessions in high-level European basketball competition. *International Journal of Sports Science & Coaching*, *18*(1), 220–230. doi:10.1177/17479541211070788

Chessa, A., D'Urso, P., De Giovanni, L., Vitale, V., & Gebbia, A. (2023). Complex networks for community detection of basketball players. *Annals of Operations Research*, *325*(1), 363–389. doi:10.1007/s10479-022-04647-x

Choi, T., Cho, K., & Sung, Y. (2023). Approaches that use domain-specific expertise: Behavioral-cloning-based advantage actor-critic in basketball games. *Mathematics*, *11*(5), 1110. doi:10.3390/math11051110

Dhia, Z., Suryadi, D., Samodra, Y. T. J., Mashud, , Mardiyyaningsih, A. N., Saputra, E., Németh, Z., Syam, A., Dewintha, R., & Fazarudin, . (2023). Assessing the influence of playing method on the outcome of basketball shooting ability. *Physical Culture*. *Recreation and Rehabilitation*, *2*(1), 37–43. doi:10.15561/physcult.2023.0106

Facchinetti, T., Metulini, R., & Zuccolotto, P. (2023). Filtering active moments in basketball games using data from players tracking systems. *Annals of Operations Research*, *325*(1), 521–538. doi:10.1007/s10479-021-04391-8

Goka, R., Moroto, Y., Maeda, K., Ogawa, T., & Haseyama, M. (2023). Prediction of shooting events in soccer videos using complete bipartite graphs and players' spatial-temporal relations. *Sensors (Basel)*, *23*(9), 4506. doi:10.3390/s23094506 PMID:37177712

Guimarães, E., Baxter-Jones, A. D. G., Williams, A. M., Tavares, F., Janeira, M. A., & Maia, J. (2023). The effects of body size and training environment on the physical performance of adolescent basketball players: The INEX study. *Annals of Human Biology*, *50*(1), 26–34. doi:10.1080/03014460.2023.2169759 PMID:36650927

Hidayat, R., Fahmi, A., & Jalil, R. (2023). The Effect Of Right And Left Side Dribble Lay Up On The Students' Lay Up Ability Of Basketball Extracurricular Program. J*UARA*. *Jurnal Olahraga*, *8*(1), 44–51. doi:10.33222/juara.v8i1.2585

Horvat, T., Job, J., Logozar, R., & Livada, Č. (2023). A data-driven machine learning algorithm for predicting the outcomes of NBA games. *Symmetry*, *15*(4), 798. doi:10.3390/sym15040798

Jin, P., Ge, Z., & Fan, T. (2023). Research on visual search behaviors of basketball players at different levels of sports expertise. *Scientific Reports*, *13*(1), 1406. doi:10.1038/s41598-023-28754-2 PMID:36697486

Leukel, C., & Gollhofer, A. (2023). Applying augmented feedback in basketball training facilitates improvements in jumping performance. *European Journal of Sport Science*, *23*(3), 338–344. doi:10.1080/17461391.2022.2041732 PMID:35143734

Liang, X. (2023). A video images-aware knowledge extraction method for intelligent healthcare management of basketball players. *Mathematical Biosciences and Engineering*, *20*(2), 1919–1937. doi:10.3934/mbe.2023088 PMID:36899515

Lucia, S., Digno, M., Madinabeitia, I., & Di Russo, F. (2023). Testing a multicomponent training designed to improve sprint, agility and decision-making in elite basketball players. *Brain Sciences*, *13*(7), 984. doi:10.3390/brainsci13070984 PMID:37508916

Martonosi, S. E., Gonzalez, M., & Oshiro, N. (2023). Predicting elite NBA lineups using individual player order statistics. *Journal of Quantitative Analysis in Sports*, *19*(2), 51–71. doi:10.1515/jqas-2022-0039

Montgomery, P. G., Pyne, D. B., & Minahan, C. L. (2010). The physical and physiological demands of basketball training and competition. *International Journal of Sports Physiology and Performance*, *5*(1), 75–86. doi:10.1123/ijspp.5.1.75 PMID:20308698

Moreno-Pérez, V., Ruiz, J., Vazquez-Guerrero, J., Rodas, G., & Del Coso, J. (2023). Training and competition injury epidemiology in professional basketball players: A prospective observational study. *The Physician and Sportsmedicine*, *51*(2), 121–128. doi:10.1080/00913847.2021.2000325 PMID:34727823

Naik, B. T., & Hashmi, M. F. (2023). LSTM-BEND: Predicting the trajectories of basketball. *IEEE Sensors Letters*, *7*(4), 1–4. doi:10.1109/LSENS.2023.3253863

Pamuk, Ö., Makaracı, Y., Ceylan, L., Küçük, H., Kızılet, T., Ceylan, T., & Kaya, E. (2023). Associations between force-time related single-leg counter movement jump variables, agility, and linear sprint in competitive youth male basketball players. *Children (Basel, Switzerland)*, *10*(3), 427. doi:10.3390/children10030427 PMID:36979986

Philipp, N. M., Cabarkapa, D., Eserhaut, D. A., Yu, D., & Fry, A. C. (2023). Repeat sprint fatigue and altered neuromuscular performance in recreationally trained basketball players. *PLoS One*, *18*(7), e0288736. doi:10.1371/journal.pone.0288736 PMID:37459308

Sansone, P., Gasperi, L., Makivic, B., Gomez-Ruano, M. A., Tessitore, A., & Conte, D. (2023). An ecological investigation of average and peak external load intensities of basketball skills and game-based training drills. *Biology of Sport*, *40*(3), 649–656. doi:10.5114/biolsport.2023.119291 PMID:37398975

Suryadi, D., Suganda, M. A., Samodra, Y. T. J., Wati, I. D. P., Rubiyatno, R., Haïdara, Y., Wahyudi, I., & Saputra, E. (2023). Eye-hand coordination and agility with basketball lay-up skills: A correlation study in students. *JUMORA: Jurnal Moderasi Olahraga*, *3*(1), 60–71. doi:10.53863/mor.v3i1.681

Wang, T., & Shi, C. (2023). Basketball motion video target tracking algorithm based on improved gray neural network. *Neural Computing & Applications*, *35*(6), 4267–4282. doi:10.1007/s00521-022-07026-6

Zhao, K., Du, C., & Tan, G. (2023). Enhancing basketball game outcome prediction through fused graph convolutional networks and random forest algorithm. *Entropy (Basel, Switzerland)*, *25*(5), 765. doi:10.3390/e25050765 PMID:37238520

Jian Jia is a teacher at Shangqiu Engineering College.

Hua Chen is a teacher at Jiangsu Vocational College of Medicine.