

Exploring the dynamic performance of tennis matches: a comparison of momentum models based on neural networks and entropy weighting methods

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Abstract. The aim of this paper is to develop two models to evaluate the performance of players in tennis matches, which these studies refer to as "momentum models". This paper described the process of building a momentum model, which included the building and solving of two models based on Artificial Neural Network (ANN) and Information Entropy Weighting Method (EWM). In the ANN-based model, the authors first constructed a neural network structure that could perfectly handle a given dataset and prove its effectiveness through comparative experiments. Then, the authors interpreted and validated the output results for the model to reflect its ability to describe the momentum of the race. In the EWM-based model, the authors determined the weights of the features through the information entropy weighting method, which were used to calculate the momentum of the players in the match, and demonstrated the changes of the momentum through linear and scatter plots. Subsequently, the authors compared and analyzed the momentum with the score and comprehensively evaluated the player's performance by calculating the cumulative momentum. Finally, the authors evaluated the generalization performance of the model and found that the model showed good generalization ability under different training set sizes and different feature conditions. The results of the study showed that the authors' proposed model could effectively evaluate players' performance in tennis matches and have strong generalization ability.

Keywords: Tennis game, momentum model, artificial neural network, entropy weight method.

1. Introduction

In tennis, a player's performance often determines the winner of a match. However, how to accurately assess a player's performance in a match and predict the trend of the match is a complex and intriguing problem. To address this challenge, these studies proposed an initiative to build two different momentum models [1-2].

First, these studies constructed a model to evaluate the dynamic performance of players during a match using advanced artificial neural network (ANN) techniques. The ANN model learned from a large amount of match data and was able to accurately predict the performance of players at different moments in time. Through this approach, these studies could gain insights into the players' technical characteristics, game strategies, and psychological states, and provide valuable insights for coaches, players, and spectators [3].

Second, these studies built another momentum model by using the Entropy weight method (EWM) method. By comparing the historical performance and match data of different players, the EWM model was able to better capture the dynamics of the game and provide more accurate predictions. This approach provided us with a new perspective that helped us better understand the competitive relationship between players and the trend of the game.

Through the establishment of these two models, these studies were able to gain a deeper understanding of the key factors in a tennis match, and provide an important reference for improving the players' competitive level and the spectacle of the match. These studies invite you to join us in our journey of discovery to unravel the mystery of the tennis game [4-5]. This paper used a dataset from <https://www.comap.com/contests/mcm-icm>.

2. Establish Momentum Models

2.1. Establishment of models

2.1.1. The model based on ANN

The basic steps of the performance model based on Artificial Neural Network (ANN) are as follows:

First, Building the neural network. The network architecture proposed could handle the given dataset perfectly and shows an amazing performance with an accuracy of 92.7%.

Next, these studies are going to prove the validity of our model. As the form of our I/O was determined (39 input features & binary classification problem), the first and last Linear Layer and the Cross Entropy Loss function became essential.

Then, these studies make contrast experiment to prove that the Transformer Encoder Layer can improve performance of the model. These studies remove this layer and can see there are almost 10 percent accuracy descent which means the Transformer Encoder Layer make those contributions [6-7].

What's more, these studies also explored whether a more complex network architecture can make the performance better. These studies added two Linear Layer in both input Sequential and output Sequential and two more Transformer Encoder Layers, and then these studies run a test. There're close to 0.1% improvement in accuracy compared to our model, however the complexity of the network is doubled, which means a deadly risk of OVERFIT in a larger training dataset the model perhaps will be deployed to in the future. These studies believe the little improvement doesn't worth the risk.

Therefore, taking all the factors these studies mentioned above into account, these studies have chosen the model presented at the beginning of this section as our final model.

2.1.2. The model based on EWM

In information theory, entropy is a measure of uncertainty, and the degree of randomness and disorder can be judged according to the calculate entropy. If the information entropy of a certain index is smaller, it indicates that the degree of variation of the index value is greater, the more information it can provide, the more significant play in the comprehensive evaluation, and the greater its weight [8].

The calculation steps of EWM are as follows:

Step 1. Construct a multi-attribute evaluation matrix A with n evaluation objects and k attribute evaluation indexes.

$$A = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix} \quad (1) \text{Step 2. Standardize the data } x_{ij} \text{ in the multi-attribute evaluation matrix } A \text{ using the deviation standardization method.}$$

$$y_{ij} = \frac{x_{ij} - \min(X_i)}{\max(X_i) - \min(X_i)} \quad (2)$$

Step 3. Calculate the proportion p_{ij} of the data at the i degree in the j th attribute component.

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^n y_{ij}} \quad (3)$$

Step 4. Calculate the entropy e_j of the j th attribute component.

$$e_j = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}) \quad (4)$$

Step 5. Calculate the coefficient of variation g_j of the j th attribute component.

$$g_j = 1 - e_j \quad (5)$$

Step 6. Calculate the weight coefficient w_j of the j th attribute component.

$$w_j = \frac{g_j}{\sum_{j=1}^k g_j} \quad (6)$$

Step 7. Calculate the comprehensive score s_i of the i th evaluation object.

$$s_i = \sum_{j=1}^k w_j x_{ij} \quad (7)$$

The above s_i is the momentum these studies need, and these studies can use it to reflect the performances of players in each moment.

To simplify the model calculation, these studies selected only 7 eigenvalues, which were shown in Table 1 below. And these studies intended to use the EWM to weight the features in a fixed window time to obtain momentum.

Table 1. Features in the performance model

Feature	Description
$feature_1$	The number of winning games in the current set
$feature_2$	The leading score of this game
$feature_3$	Whether player is the server
$feature_4$	The leading score of this match
$feature_5$	Whether scored by returning (no touch)
$feature_6$	Whether there is a double fault in this game
$feature_7$	The ratio of the number of net play times to the net play score

Then these studies defined the feature calculation function, which returned the values of the seven features in a fixed window time. The feature data of the two players was stored in separate files.

The processing of feature data was as follows:

Step 1. Observe the distribution of feature data and analyze the relationship of feature data

Step 2. Calculate the relationship between the feature variables

Step 3. Determine weight coefficient of each feature

Based on the calculation processions of entropy weight method, these studies processed the features of the two players respectively, and finally obtained the weight coefficient of each feature, which was used as the weight of our model. The coefficients were as follows in table 2.

Table 2. Weight coefficient of each of feature

Player1	Value	Player2	Value
$weight_1$	0.009973	$weight_1$	0.005880
$weight_2$	0.018697	$weight_2$	0.009896
$weight_3$	0.028571	$weight_3$	0.038377
$weight_4$	0.473300	$weight_4$	0.454092
$weight_5$	0.067742	$weight_5$	0.047788
$weight_6$	0.016110	$weight_6$	0.008725
$weight_7$	0.385608	$weight_7$	0.435242

2.2. Solution of Models

2.2.1. Solving in the model based on ANN

In the proposed neural network model, in order to complete the binary classification task, the last layer was composed of two neurons whose activation function was Sigmoid function. After training, the two neurons should output two values after a series of processing of the input features, and after comparing the two values, these studies used the category corresponding to the larger value as the category of model classification [9-10].

Given the definition of momentum in the problem, these studies thought that the output of the last two neurons in our model perfectly fits the definition of momentum.

These studies take the match described in the article as an example(2023-wimbledon-1701), the red line in Figure 1 is the "point_victor" column in the data. If the red line coincides with the coordinate 0, Alcaez wins at that point in time, and if it does not, Djokovic wins. The blue line represents the momentum difference between Djokovic and Alcaez based on our model and the definition of momentum. The green line is the cumulative momentum difference between Djokovic and Alcaez.

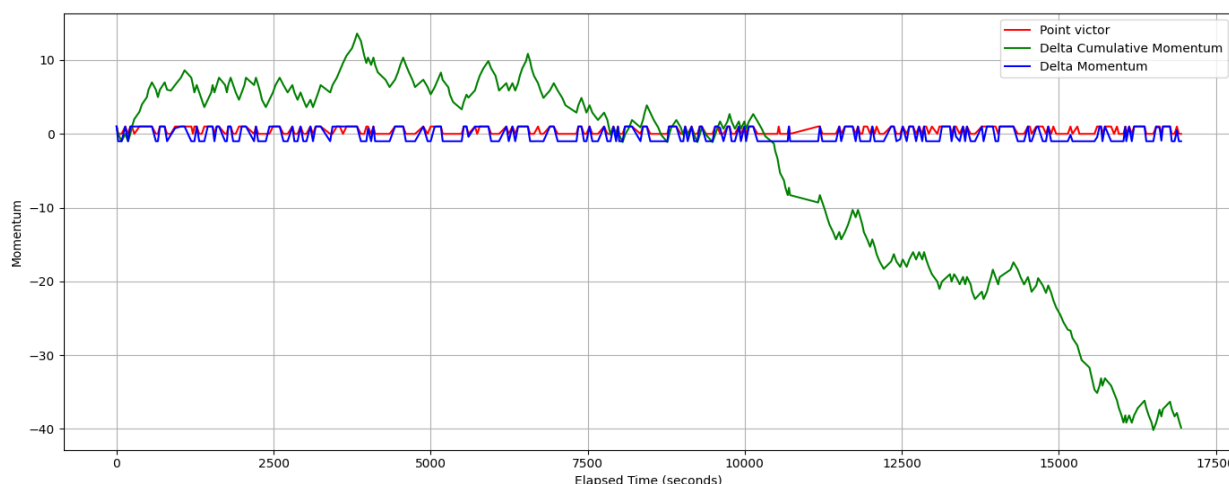


Figure 1. Relationship of game results and momentum

Through the red and blue lines, these studies could find that the momentum these studies calculated could better match the actual situation of the race. When the blue line is positive and the red line is one, the momentum difference between Djokovic and Alcaez is greater than 0. In other words, when Djokovic has stronger momentum, Djokovic is the "point_victor".

Through the green line, these studies could intuitively see that Djokovic's momentum gradually loses to Alcaez as the game progressing, resulting in Alcaez's final comeback victory.

And these studies could get more specific information by looking at the following data analysis in Figure 2 and Figure 3.

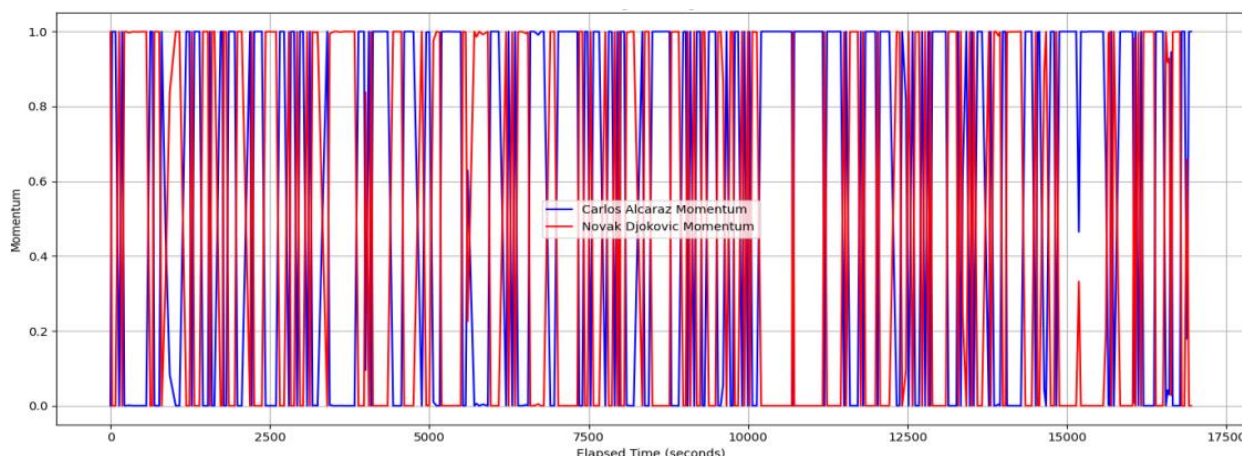


Figure 2. Momentum changes of two players in the match

Figure 3 described momentum changes of two players in the match. By comparing the changes of momentum and scores, these studies found that momentum roughly described two players' score conditions. When a player has more momentum than another, he is always able to score. Therefore, these studies thought that the momentum we calculate can reflect the players' performances during the match, and the greater momentum he has, the better he performs.

Besides, according to the changes of cumulative momentum and the data of this match, these studies also found a link between them. When the red line is higher than the blue line, Djokovic performs approximately better than Alcaez. After the blue line exceeds the red line, Djokovic's

advantage is no longer obvious, on the contrary, Alcaraz appears to be more advantageous. Since Alcaraz eventually wins the match and his cumulative momentum is greater at the end, he performs better in this match. Based on the above analysis, these studies could similarly think that momentum was a good indicator to measure a player's performance.

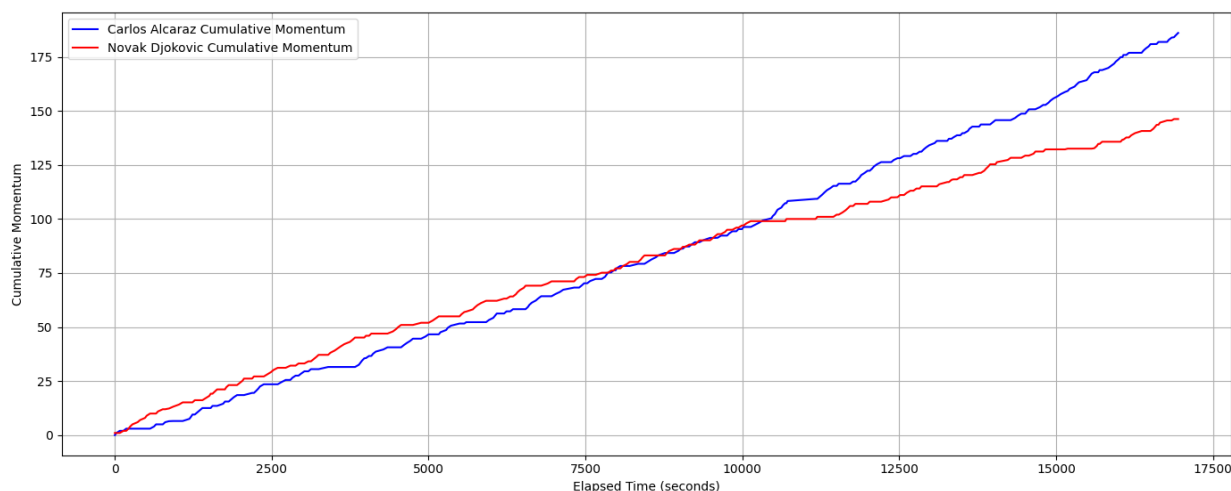


Figure 3. Cumulative momentum changes of two players in the match

2.2.2. Solving in the model based on EWM

These studies used the weight coefficient calculated on EWM to weight the eigenvalues and calculate the momentum of the two players at any moment in this match. Then, these studies drew a line chart and a scatter chart of the two players' momentum in this match, as shown in figure 4 and figure 5.

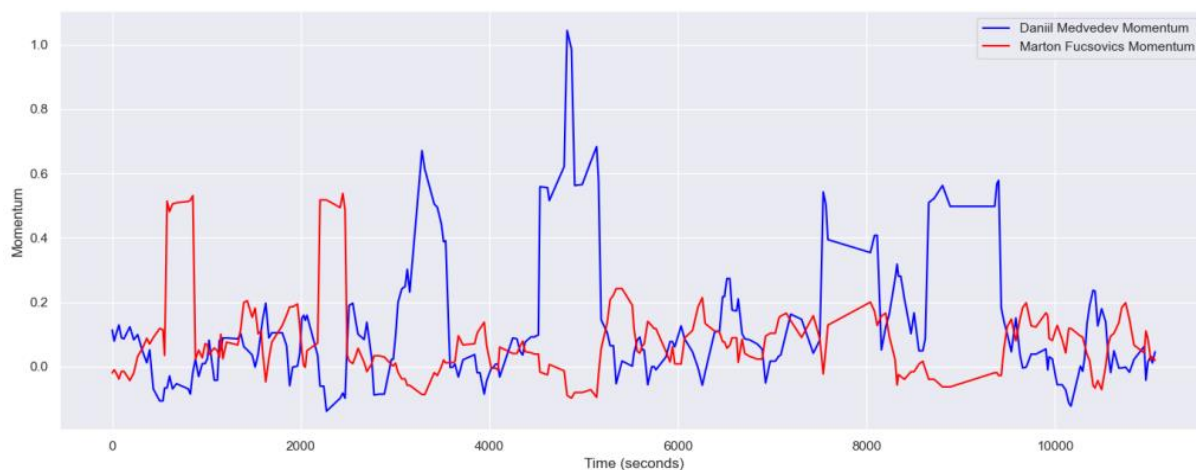


Figure 4. Line chart of the two players' momentum

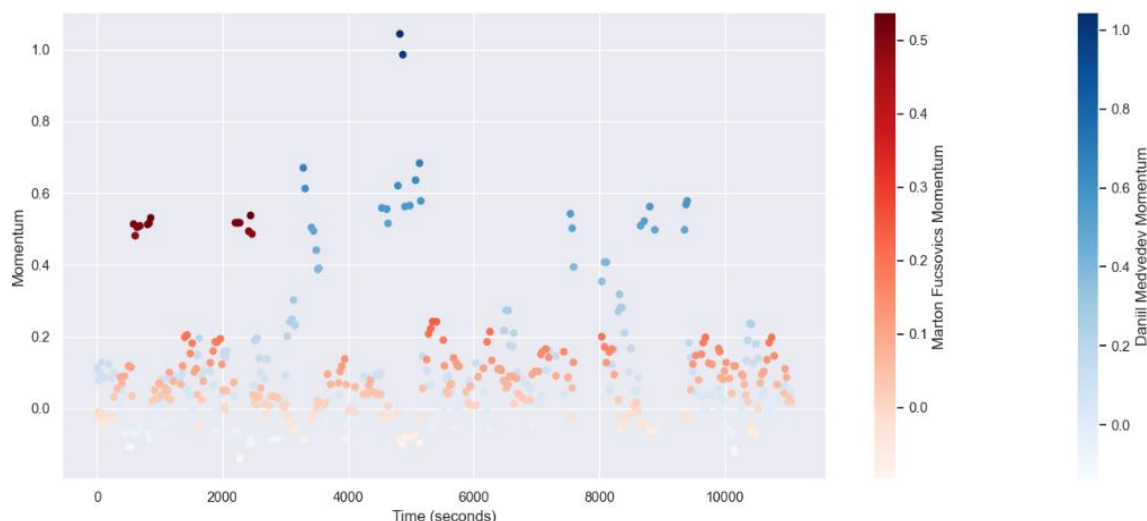


Figure 5. Scatter chart of the two players' momentum

Comparing momentum and scores, these studies found that when a player had a greater momentum at certain moment, he usually got a score. What these studies found testify that momentum could describe players' performances in matches.

However, it was not authoritative enough to judge a player's performance by his score situation alone. These studies also needed to evaluate a player's performance by considering multiple aspects of the player. And evaluating a player's performance required us to look at the whole course of the match, so these studies also needed to calculate the cumulative momentum of the two players.

Based on the above considerations, these studies calculated the cumulative momentum, which was the sum of the momentum from the start of the match to the current moment. After that, these studies drew a line chart and a scatter chat of the cumulative momentum respectively, as shown in figure 6 and figure 7.

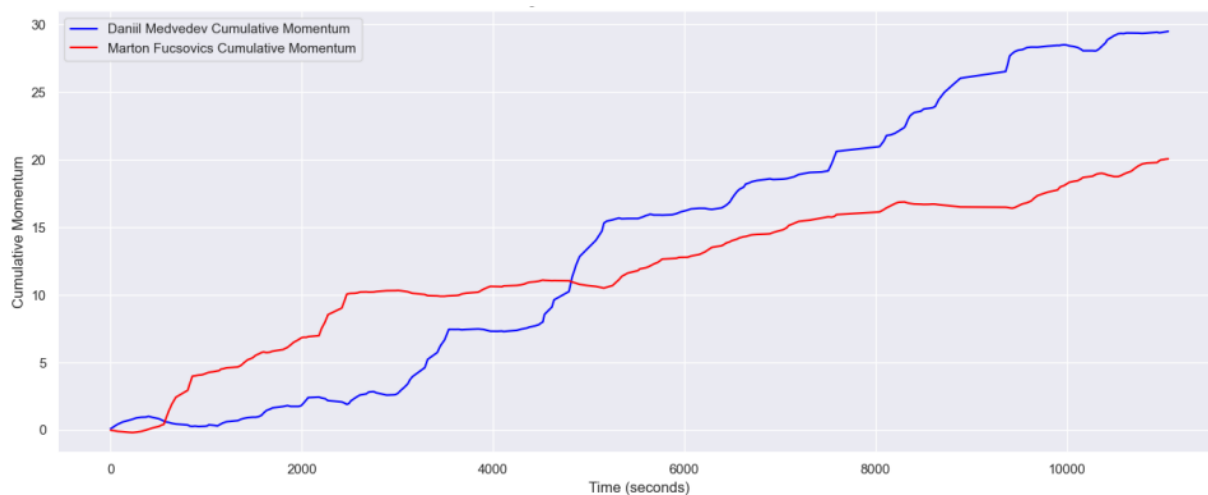


Figure 6. Line chart of the cumulative momentum

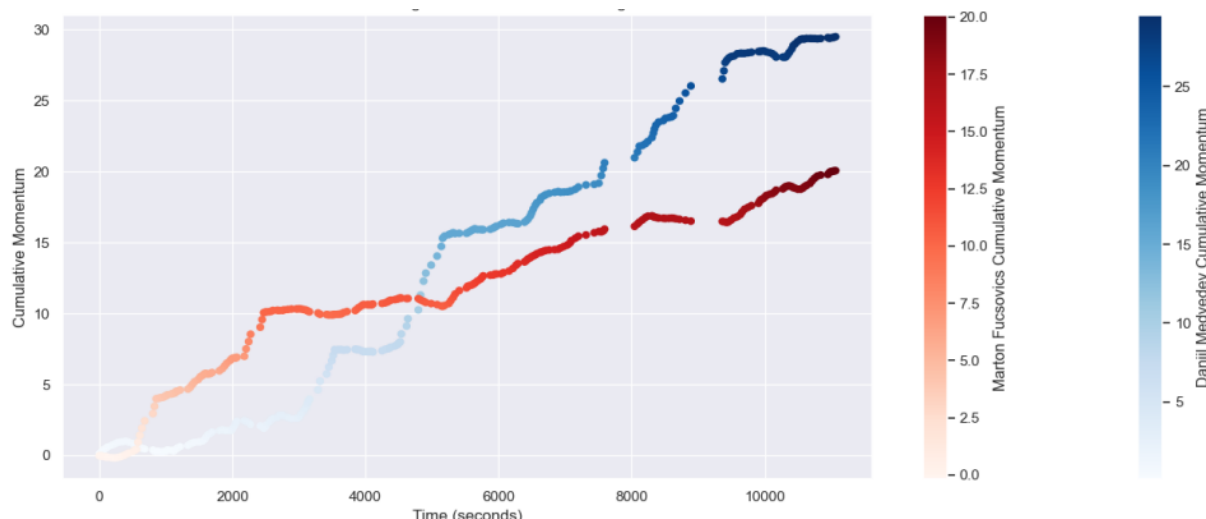


Figure 7. Scatter chart of the cumulative momentum

After considering multiple aspects of a player, these studies found that when a player's cumulative momentum exceeded that of his opponent, he tended to have an advantage in the match. Therefore, these studies thought that the current momentum and cumulative momentum calculated by our model could evaluate the performances of players well.

3. Generalization Performance

3.1. Generalization performance on small-scale dataset

To prove our model's generalization performance, these studies first tested it on the datasets that had smaller scale. These studies tried to use first 10 to 90 percent of the data set as the training set, and these studies found something irrational in the accuracy data, these studies analyzed and found that those data which is close to the final of the game(2023-wimbledon-1701) had more uncertainty. These studies then used the last 10 to 90 percent as our training set and designed comparative experiments to explore further.



Figure 8. Model generalization under different training set sizes

These studies found that the accuracy rate was better in the case of fewer training sets than in the case of more training sets, but the accuracy reached an astonishing 94.4% after using the last 80% data for training. These studies guessed that the final and semi-final matches had more uncertain factors than the preliminary matches. As described in the title, an unexpected dark horse victory. These studies could assume that the uncertainty of matches increases as the match progressing (from

the trial match to the final match). It would explain why the model performs worse in the latter part of the prediction.

Through the trend of accuracy, these studies could infer that when the model obtains at least 20% of the data, it could already obtain an almost stable accuracy of about 93%. It proved that the generalization of our model was pretty strong, and only about 1500 records could accurately judge the outcomes of a new round of matches.

3.2. Generalization performance on fewer feature

At the same time, these studies also changed the features in the model to observe the influence of each feature on prediction accuracy. The models with different features and their accuracy were shown in table 3.

Table 3. Models with different features and their Accuracy

Model	Accuracy
The model which has all features	92.38%
The model which removes the features about how to score	80.58%
The model which removes the specific performances of players	89.64%
The model which removes the information in previous games	92.72%
The model which removes who is the server	87.85%

Comparing the outcomes above, these studies get several conclusions as follows:

- (1) These features about how to score has a great boost to our model.
- (2) Model can learn less information from these features about the specific performances of players.
- (3) These features about the information in previous games can improve the stability of our model and assist the model to better determine the trend of current match.
- (4) The features about who is the server are pretty important in our model, and it can manifest the importance of service order in tennis matches.

To sum up, our future model must contain the features about how to score, the specific performances of players and who is server.

4. Conclusion

In this paper, these studies used both Artificial Neural Networks (ANN) and Entropy weight method (EWM) methods to build momentum models to assess player performance in tennis matches. By comparing the results of these two models, these studies found that they were both effective in predicting player performance and provided useful information to understand the trend of the match. In future research, these models can be further improved to increase their accuracy and usefulness.

References

- [1] Yang Jing. Research on Special Physical Training for tennis [C]// China Intelligent Engineering Research Society, China Bandy Association, Guangdong Physical Association. Proceedings of the 10th China Physical Training Science Conference (I). Guizhou Medical University; 2023: 5.
- [2] Pang Liang, Zhang Kun. Investigation and analysis on the influence of coach timeout effect on the outcome of basketball game [J]. Journal of Minnan Normal University (Natural Science Edition), 2016, 29 (01):103 - 109.
- [3] Li Zhenhui, Zhang Yushan. Prediction of NBA Games using long short-term memory Network [J]. Journal of Computer Applications, 2019, 41 (S2): 98 - 102.
- [4] “Artificial Neural Network——ANN (BP network).” [Online]. Available: https://blog.csdn.net/winner_liuhuan/article/details/125074137.
- [5] Hu Yixiang, Zhang Zhongxiang, Ma Qianyuan et al. The normal cloud model based on entropy weight method and the economic development of jiangsu province of toughness evaluation [J]. Journal of modern business, 2023 (12): 49 - 52.

- [6] Tan Wentao, Long Qiusheng, Li Zhilan. Research review of Badminton Match result prediction Model based on support vector machine [C]// Chinese Society of Sport Science. Abstract Collection of the 13th National Sports Science Conference -- Special Report (Sports Statistics Branch). [Publisher unknown], 2023: 3.
- [7] C.Y. Huang. Research on tennis match performance prediction model based on BP neural network [D]. Fujian Normal University, 2022.
- [8] Hong Yefei. A preliminary study on the use of ($\pm S$ - departure method) to predict competition scores [J]. New Course Introduction, 2015, (12): 29.
- [9] Zhu Wenfu. An attempted study on the prediction model of sports competition results [J]. Journal of Chongqing Gongshang University (Natural Science Edition), 2011, 28 (03): 318 - 321.
- [10] YANG Yongxiang. Prediction in sports [J]. Teaching and Learning of High School Mathematics, 2003, (09): 41 - 42.