

Momentum-Based Race Analysis and GRU-Based Predictive Modeling

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ABSTRACT

This study analyzes the data from the 2023 Wimbledon Men's Tennis Final, defines the concept of "momentum", and constructs a time - series prediction model based on the Gated Recurrent Unit (GRU). The objective is to develop a model capable of precisely capturing the point - by - point dynamic states during the match and presenting them in a visual format. Additionally, it validates the stochastic characteristics of the "momentum" phenomenon and evaluates its influence mechanism on the match trends.

KEYWORDS

Momentum; Correlation test; Machine learning; Binary logistic regression; GRU; Confusion matrix

1. INTRODUCTION

In sports, "momentum" is often referred to the mental and/or physical "boo-boos" that athletes benefit from. How to capitalize on this "momentum" is becoming a big challenge that coaches and athletes are eager to solve. In this paper, we aim to find the mystery of 'momentum' at the 2023 Wimbledon Gentlemen's final.

We were trying to develop a model that captures the flow of play as points occur and apply it to one or more of the matches. The objective of the model should identify which player is performing better at a given time in the match, as well as how much better they are performing. Provide a visualization based on your model to depict the match flow. We are inspired by the physical formulas as well as the definition of momentum to give the form of the expression for the scoring probability, and define the potential in a tennis match as the accumulation of the scoring probability with respect to time, which is the result of a combination of consideration of the temporal nature of momentum as well as the visualization effect. We then applied various machine learning models to compute the coefficients of the scoring probability expression and compared the advantages and disadvantages of the different models. We also selected the data of a game as the visualization target, and the results show that the momentum we defined is able to visualize the course of the game well.

Some tennis coaches are skeptical that "momentum" plays any role in the match. Instead, they postulate that swings in play and runs of success by one player are random. We first performed an autocorrelation test on the scoring time series, and the results showed that the scoring time series had strong autocorrelation, thus rejecting the claim that the scoring was random. Further, we tested the correlation between momentum as well as scoring using the Kendall's Tau method, and the results showed that the momentum we defined better reflected the game trend.

In order to help coaches find if there are indicators that can help determine when the flow of play is about to change from favoring one player to the other. We filtered the variables with high correlation with scoring probability through binary logistic regression: `distancerun`, whether or not they were serving last time whether or not scored, the number of sets won the number of points scored so far, and argued that their swing would lead to a swings in match trends. Further, we compared the line graphs of these key variables with the match trend and found that their swings were significantly correlated, further proving our idea. We paid special attention to these key variables during the analysis of the variables, thus providing recommendations for the PLAYER in terms of physical condition, mental condition, and match tactics. Next we built a GRU time series prediction model with the aim of predicting the match trend after a period of time, using the ReLU function as the activation function, Adam's algorithm for optimization, and ultimately the cross-entropy loss as the loss function.

So as to identify any factors that might need to be included in future models, we randomly took 6 matches as the test dataset to test the GRU model established in the previous problem, and calculated the accuracy, recall, precision and F1 score of the model's prediction through the method of confusion matrix analysis, and concluded that the model predicted well, and plotted the distribution of the internal weights of the GRU model, and concluded that the model fit was normal. which can generalizable the model to other matches.

2. DESCRIPTION OF THE PROBLEM AND ASSUMPTIONS

2.1. Restatement of the Problem

The match between Carlos Alcaraz and Novak Djokovic witnessed a clear change in momentum that challenged the traditional view of the role of 'momentum' in tennis. We want to accomplish the following task by analyzing data from the men's singles final at Wimbledon 2023:

- **Model Development:** Create a model that captures the flow of a match and apply it to one or more matches. The model should be able to determine which player is performing better at a given point in the match and provide a visualization depicting the flow of the match. The development process should specifically take into account the higher probability of the serving side winning the score in tennis.
- **Evaluating "Momentum":** Evaluate the tennis coach's skepticism about the role of "Momentum" in the game and the coach's suggestion that fluctuations in the game are random.
- **Predicting Match Changes:** Determine if there are indicators that point to a shift in the flow of a match from one player's favor to another. Develop models to predict these fluctuations using the data provided for at least one match, identifying relevant factors. Provide recommendations based on past momentum variances in light of history to guide players' strategies when playing new matches against different opponents.
- **Model Testing and Generalization:** Test the developed model in other matches and evaluate its predictive accuracy. Explore factors that may enhance the performance of the model and assess its ability to generalize to different conditions, such as women's matches, different tournaments, different court surfaces, and other sports such as table tennis.

2.2. Overview of Our Work

The flowchart is shown in the figure In addressing Problem 1 (Develop a model that captures the flow of play as points occur and apply it to one or more of the matches. The model should identify which player is performing better at a given time in the match, as well as how much better they are performing. Provide a visualization based on your model to depict the match flow).

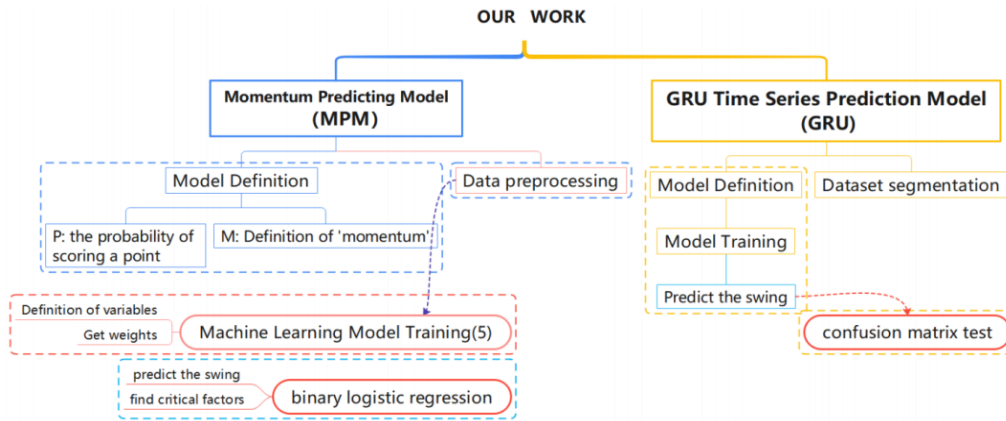


Figure 1. Workflow of Momentum-based Modeling and Analysis

We drew inspiration from physical formulas and the momentum concept to formulate the expression for scoring probability. The potential in a tennis match was defined as the accumulation of scoring probability over time, considering the temporal nature of momentum and visualization effects. Various machine learning models were employed to calculate coefficients for this expression, and their pros and cons were compared. Using a game dataset for visualization, the results demonstrated that our defined momentum effectively depicted the game’s progression.

For Problem 2 (whether “momentum” plays any role in the match), an autocorrelation test on the scoring time series revealed strong autocorrelation, refuting the randomness claim. We tested the correlation between our defined momentum and scoring using Kendall’s Tau method, determining that our momentum better reflected the game trend.

In addressing Question 3 (if there are indicators that can help determine when the flow of play is about to change from favoring one player to the other), variables with high correlation with scoring probability were filtered through binary logistic regression, including distance run, previous serve, scoring status, sets won, and points scored so far. We argued that fluctuations in these variables would impact match trends. Comparison of line graphs for these key variables with the match trend showed significant correlations, reinforcing our hypothesis. Special attention was given to these variables during analysis, providing recommendations for the PLAYER in terms of physical condition, mental state, and match tactics.

Subsequently, we developed a GRU time series prediction model for Problem 4. Using the ReLU function as the activation function, Adam’s algorithm for optimization, and cross-entropy loss, the model aimed to predict match trends over time.

In evaluating Problem 4 (Test the model on one or more of the other matches. How well it predict the swings in the match? If the model performs poorly at times, we would identify any factors that might need to be included in future models) a test dataset of 6 matches was randomly selected to assess the GRU model.

Performance metrics, including accuracy, recall, precision, and F1 score, were calculated using confusion matrix analysis. The conclusion was that the model performed well. The distribution of internal weights in the GRU model was plotted, affirming a normal fit. In summary, our model exhibits good applicability due to its predictive accuracy and the generalizability of the dataset to other sporting events.

3. ASSUMPTIONS AND NOTATIONS

3.1. Assumptions

We have made several assumptions in our model to make it more applicable in complex real-world environments:

Match Environment Assumptions: It is assumed that the match environment is fair and consistent, and that there are no external factors that could have an abnormal effect on the overall trend of the match.

Player Condition Assumptions: It is assumed that the physical condition of the players during the game is stable and that there are no unknown physical conditions or other factors that could significantly affect their performance.

3.2. Notations

Table 1. Notation Table

Symbol	Description
x1	Number of sets ahead of opponent
x2	Number of games ahead of opponent in current set
x3	Points ahead of opponent in the current game
x4	Consecutive points won
x5	Indicates a server. Served and scored in the last point indicates the break point
x6	Previous point was a break point and scored
x7	Running distance in the previous three points
x8	Hit an untouchable winning serve
x9	Hit an untouchable winning shot
x10	Missed both serves and lost the point
x11	Made an unforced error
x12	Indicates that this is the i-th set in this game
x13	Indicates that this is the j-th game in the match
i	Indicates that this is the k-th point in the game
j	Indicates that it is the a-th player
k	
a	

4. QUESTION 1: DEFINITION OF MOMENTUM AND ITS VISUALIZATION IN MATCHES

4.1. Definition of Momentum

Inspired by the principles of physics and the definitions of momentum in dictionaries, we have observed a mathematical concept in tennis matches similar to acceleration. This concept is determined by the real-time conditions of players in the match and can probabilistically reflect the trend of the match in the next moment. Unlike momentum itself, which is not independent of the previous state at a specific moment, the velocity in momentum is the cumulative result of acceleration over time. Therefore, by accumulating the previously mentioned concept similar to acceleration over time, we have derived a concept similar to momentum that propels the progress of a tennis match. This concept reflects the comprehensive situation at a specific moment in a match and the trend of the match.

In summary, considering the temporal nature of momentum in a tennis match and the fact that the accumulation of real-time scoring probabilities can reduce its image jitter and thus visualize the progress of the match, we give the definition of momentum in tennis:

$$M_{i, j, k}^a = \sum_j \sum_k p_{i, j, k}^a \quad (1)$$

Where $p_{i, j, k}^a$ is the probability of player a winning points in the i -th set, the j -th game, and the k -th point, and we use the real-time state of the player to compute it

$$p_{i, j, k}^a = \sum_{n=1}^{13} w_n x_n \quad (2)$$

Our reasons for choosing these variables are given below.

4.2. Data Cleaning

We aim to clean up some data that may have a minimal impact on the results to reduce the scale of variables to be considered, thereby highlighting significant determining factors. To achieve this goal, we have ultimately decided not to consider the following variables:

- (a) Variables with relatively small differences between players: ‘set no’, ‘game no’, ‘point no’.
- (b) Variables that can be represented by other variables: The impact on the player’s endurance brought by ‘elapsed time’ and ‘rally count’ can be directly presented by the variable ‘p distance run’. Therefore, we replace these two variables with the player’s running distance. Additionally, ‘set no’, ‘game no’, and ‘point no’ are to some extent reflected in the player’s cumulative score, so we do not consider these variables.
- (c) Variables significantly correlated with player-specific tactics: ‘speed mph’, ‘serve width’, ‘serve depth’, ‘return depth’ are significantly correlated with player-specific tactics, meaning different things for different players. Therefore, their relationship with momentum is uncertain. We temporarily exclude them but will reconsider these variables when providing suggestions for players.

4.3. Parameter Determination

Now that we have determined the factors that influence the probability $p_{i, j, k}^a$ of whether this ball scores or not, i.e., x_n the next most important thing is to determine the magnitude of the influence of each different factor x_n on the probability P , i.e., w_n . Due to the large size of the dataset and the high completeness and accuracy of the dataset, this satisfies the prerequisites for using machine learning methods to determine the weights w_n , in addition to the fact that machine learning methods have a number of advantages over some traditional methods of determining the weights. Firstly, machine learning models automatically learn the weights of features through training data without manually defining the rules, which enables the models to extract useful feature information from the data and also makes the determination of weights more accurate. Secondly, machine learning models are able to adapt to complex non-linear relationships, which is important for dealing with complex problems in the real world, for example, deep learning models such as neural networks can learn complex feature representations. In addition, the laws learned by machine learning models through training data usually have some generalisation ability, i.e., they can make reasonable predictions even for unseen data, which allows the models to perform well in the face of new samples. Finally, machine

learning models are usually able to handle large-scale datasets more efficiently because they are able to learn generalised laws from a large number of samples. Taking all these considerations into account, we finally chose the following five machine learning methods.

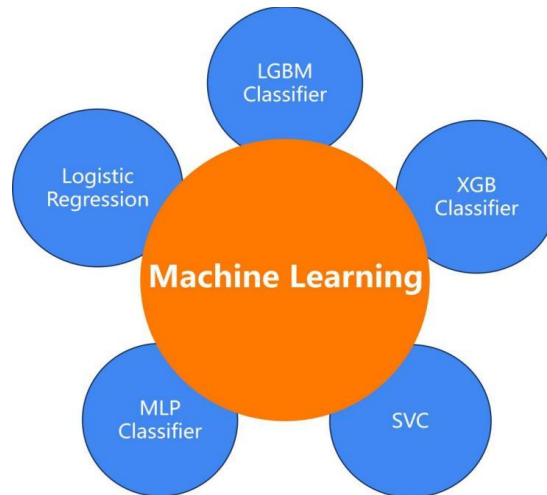


Figure 2. The machine learning models we use [1, 2]

LightGBM (LGBM) is a decision tree model based on the gradient boosting framework, which handles large-scale data in an efficient way. It uses histogram-based learning methods with faster training speed and lower memory footprint. Advantages: High performance, high efficiency, supports large-scale data. Scenarios: Large-scale datasets, problems with high performance requirements.

XGBoost (eXtreme Gradient Boosting) is a gradient boosting tree model that improves performance by integrating multiple decision trees, and it includes regularisation terms to provide control over overfitting. Benefits: High performance, some control over overfitting. Scenarios: Various data types, multiple problem types.

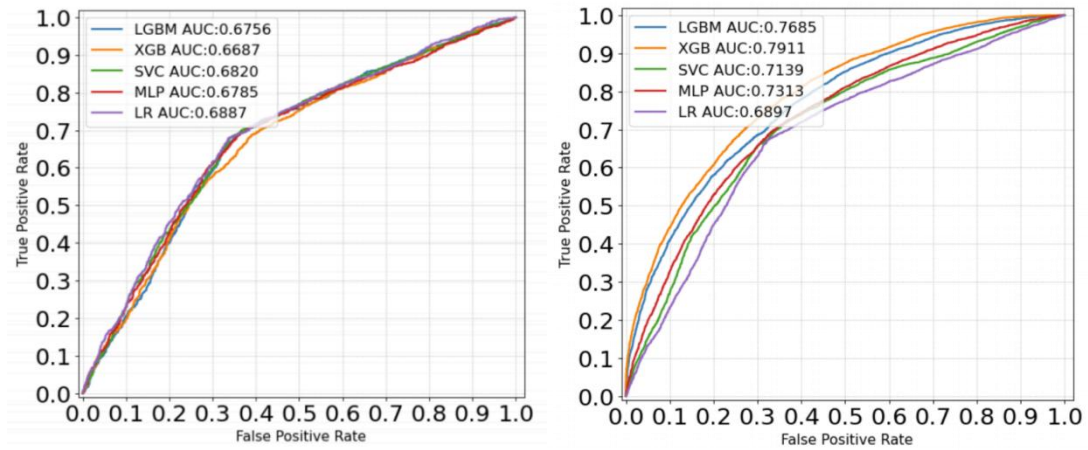
Support Vector Machine (SVM) is a supervised learning algorithm mainly used for classification and regression tasks, SVM separates different classes by finding decision boundaries (hyperplanes) in the data. Advantages: Effective in high-dimensional spaces, insensitive to feature scaling. Scenarios: Binary classification problems, high-dimensional data.

Multi-Layer Perceptron (MLP) is an artificial neural network consisting of multiple layers of neurons, which can be used to solve complex non-linear relationships for a variety of problems. Strengths: Capable of capturing complex non-linear relationships. Scenarios: Complex pattern recognition problems, image recognition, natural language processing, etc.

Logistic Regression (LR) is a linear model for binary classification problems that uses a logistic function (sigmoid function) to map the linear output to $[0, 1]$, which is used to estimate the probability that a sample belongs to a certain category. Advantages: Simple, easy to understand, does not require large amounts of data. Scenarios: binary classification problems, situations that require a simple model.

The next step to complete is to train the above five models separately, we will use 80 percent of the dataset as the training dataset, and the remaining 20 percent as the test dataset, and give the accuracy of the predicted data on the test dataset.

Based on the provided model evaluation metrics, the performance of each model can be briefly analysed.



(a) False Positive Rate 1

(b) False Positive Rate 2

Figure 3. Model Testing

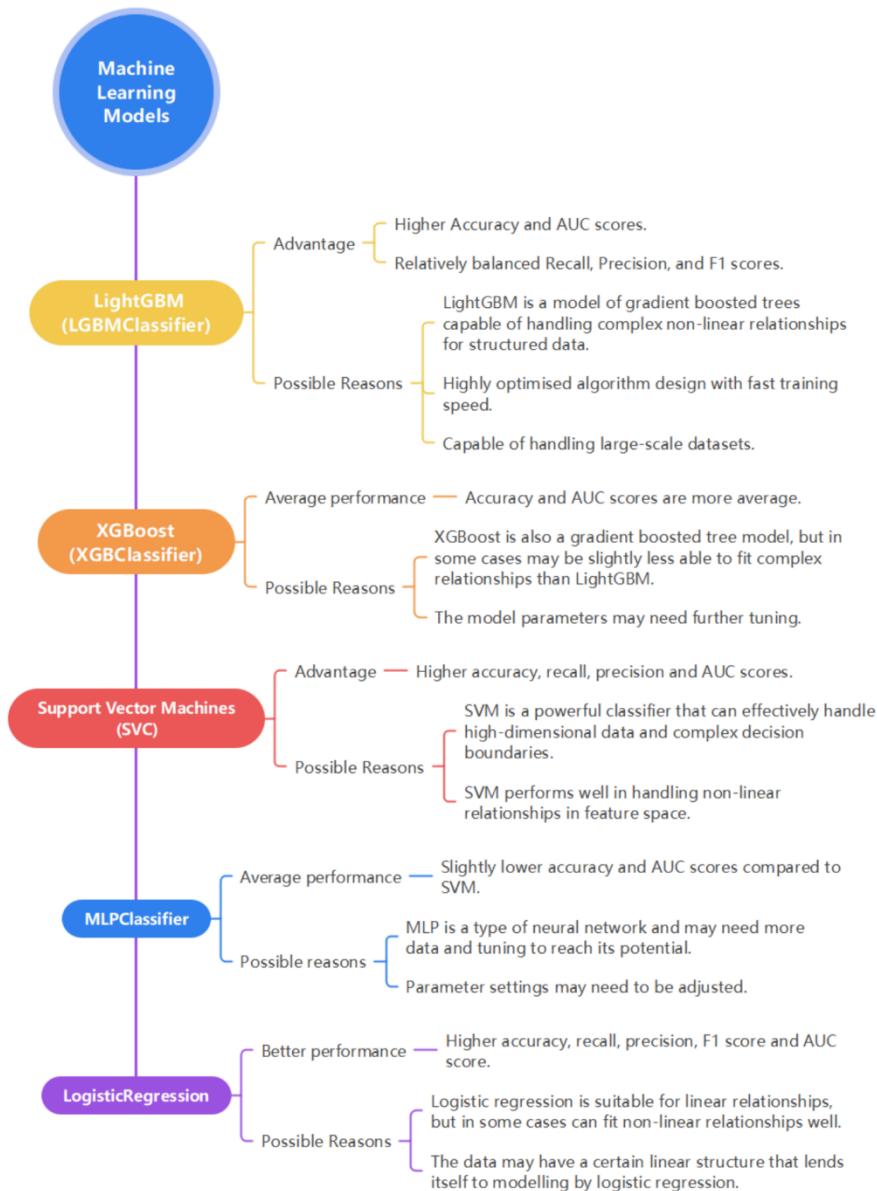


Figure 4. Analysis of the machine learning models we used

Combining the above analyses, we decided to use the LightGBM model with better performance, and the weights w_1 w_{13} determined using this model are shown in the following figure.

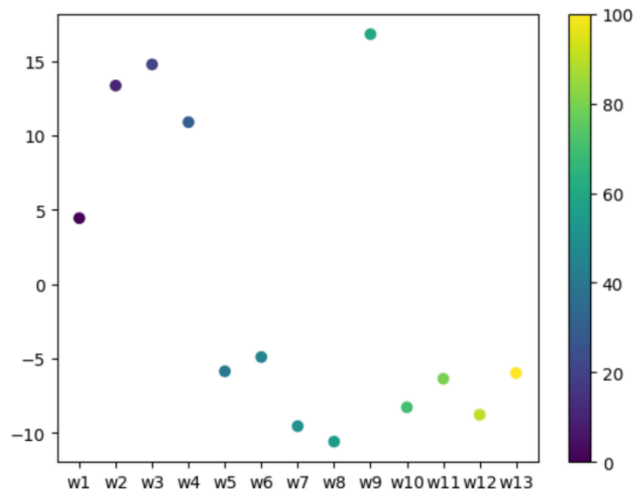


Figure 5. Analysis of the machine learning models we used

Further using this model, the probability visualisation image of whether a score is scored at the next moment under the current score situation is given for one of the matches as shown below, and further optimisation can be done by adjusting the model parameters, performing feature engineering, and trying the integration methods to improve the model performance.

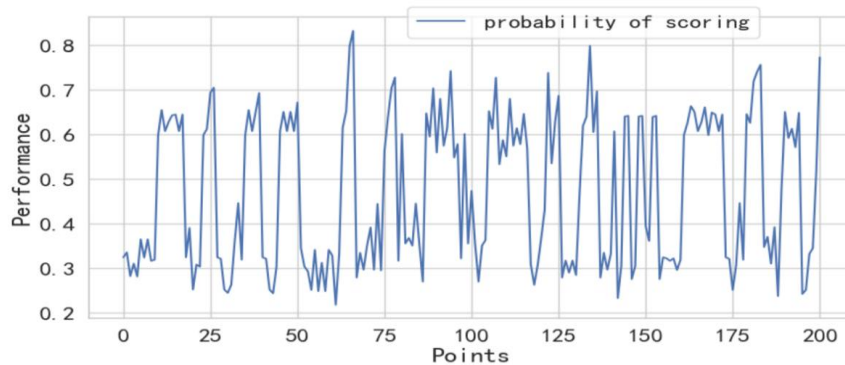


Figure 6. Probability of scoring in match 2023-wimbledon-1301

4.4. Visualization of the Race Using Momentum

As Figure 5 shows, the score probability image is too volatile to visualize the course of the game. Therefore, we choose to visualize the course of the game by accumulating it about time to get the momentum M and obtain a relatively stable line graph.

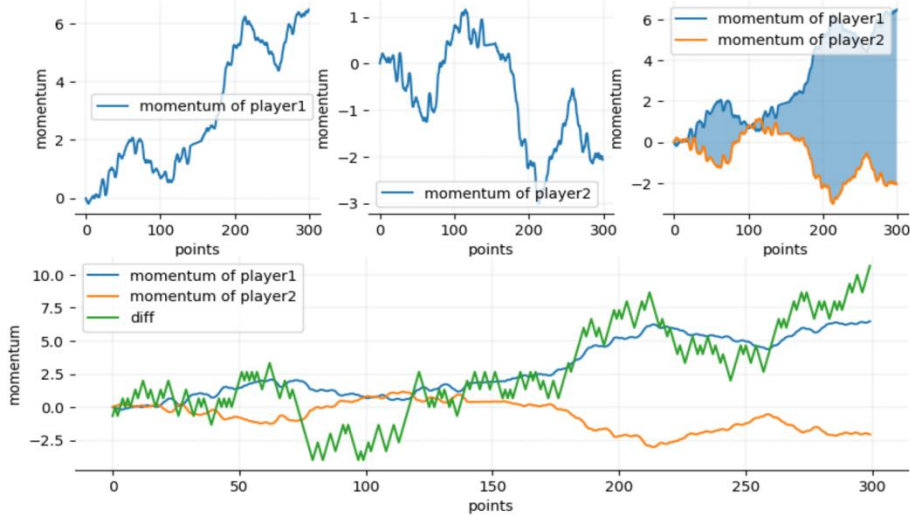


Figure 7. M in match 2023-wimbledon-1301

According to Figure 6 we can see the momentum trend of the two players in match 2023-wimbledon-1301 and the difference in their momentum, which matches what we can see from the scores of the match: in the first set player1 was ahead, player2 tied it up in the next set, but then player1 won two more sets in a row by a large margin to win the match.

5. NEGATING THE RANDOMNESS OF THE SCORE AND TESTING ITS CORRELATION WITH MOMENTUM

5.1. Disproving the Randomness of Scores Based on the Auto-correlation Test

The time series autocorrelation test is a method used for its intrinsic correlation, especially the correlation of the presence or absence of lagged terms in the data. The basic idea is to detect patterns of autocorrelation in the data by calculating the correlation coefficients of the time series at different lag orders.

We first assume that there is no autocorrelation in the data. Subsequently, the correlation coefficients at different lag orders are calculated:

$$\gamma_{t_0} = \frac{n}{n - t_0} \cdot \frac{\sum_{t=t_0+1}^n (Y_t - \bar{Y})(Y_{t-t_0} - \bar{Y})}{\sum_{t=1}^n (Y_t - \bar{Y})^2} \quad (3)$$

We selected the score data from match 2023-wimbledon-1301 and took the lag coefficients from 1 to 20 to test the correlation, and the results showed that the correlation remained above 60percent even at a lag order of 20, and the significance was consistently less than 0.05. We therefore rejected the original hypothesis that the scores were not random.

5.2. Testing the Correlation Between Momentum and Score Based on Kendall's Tau-a Method

We selected race 2023-wimbledon-1301 and plotted the scores of each of the two middle runners against their change in momentum, from which we see a similar trend between the two. We conducted a correlation test based on Kendall's Tau method to further determine the correlation between the two, thus completely rejecting the claim that the scores are randomized.

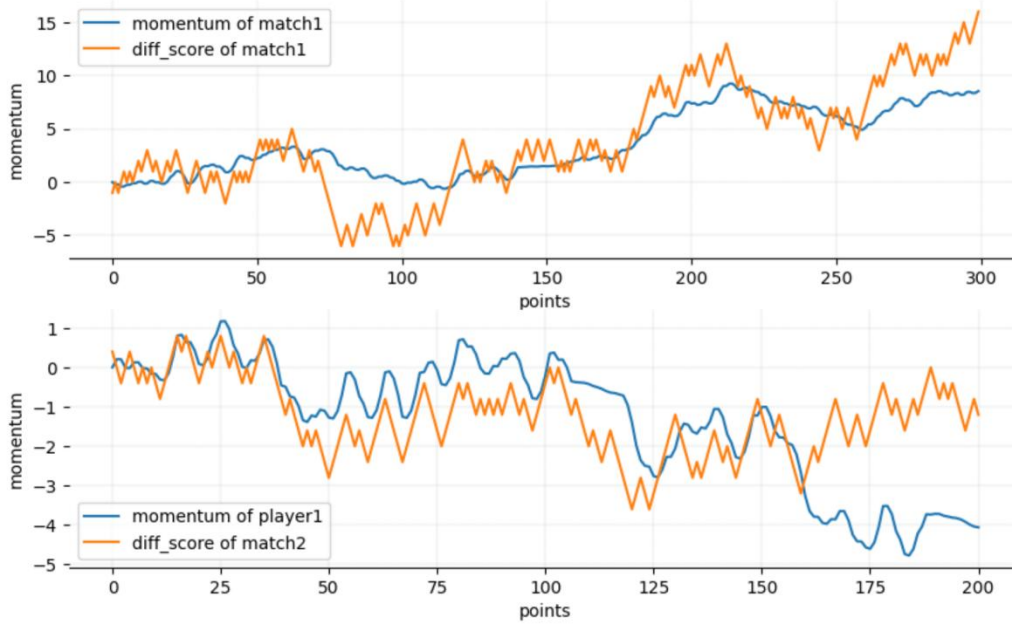


Figure 8. The scores of the two players in match 2023-wimbledon-1301 with their momentum trends

Kendall's Tau is a nonparametric statistical method for measuring the correlation between two variables. It is a rank correlation coefficient that is primarily used to assess the relationship between the ranks of two variables without requiring the data to satisfy assumptions such as normal distribution.

The calculation of Kendall's Tau involves ranking two variables. Ranking is the process of arranging the data from smallest to largest and representing each observation with the corresponding rank value. Tau can then be calculated by comparing the rankings of the two variables. The formula for calculating Kendall's Tau is as follows:

$$\tau = \frac{\text{Number of concordant pairs} - \text{Number of discordant pairs}}{\text{Total number of pairs}} \quad (4)$$

Where:

- Concordant pairs are pairs of observations in which the ranking relationship is consistent in both variables.
- Discordant pairs are pairs of observations whose rankings are inconsistent between the two variables.
- Total number of pairs is the number of all possible pairs.

After calculating Tau, its value ranges from -1 to 1, where:

When $\tau = 1$, it means that the two variables are perfectly positively correlated.

When $\tau = -1$, the two variables are completely negatively correlated.

When $\tau = 0$, there is no linear correlation between the two variables.

Finally we get $\tau = 0.687$, which shows that the score has a strong correlation with the potential, i.e., we can predict the trend of the score by the variable x_n .

6. EXPLORING KEY FACTORS TO PREDICT THE GAME

6.1. Identify the Key Factors that Can Indicate the Turn of the Game through Binary Logistic Regression

In Problem 1, we defined that the momentum and the probability of scoring at the next moment are expressed by the variable x_n . In Problem 2, we determined that momentum can better reflect the trend of the game. Therefore, we can identify the variables with higher weights to determine which swings in the variables will lead to swings in the game's trend. We accomplished this with binary logistic regression.

Binary logistic regression is a statistical model used to deal with binary classification problems.

In this model, we try to develop a probabilistic model of the relationship between input and output variables. The linear combinations are mapped to probabilities by means of a sigmoid function. For a linear combination of input variables, denoted as

$$z = w_0 + w_1x_1 + w_2x_2 + \dots + w_nx_n \quad (5)$$

Then, by means of the sigmoid function z maps to a probability between (0, 1):

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad (6)$$

Subsequently, a set of parameters is found by the maximum likelihood method that maximizes the probability of the observed data under a given model. And using the log loss function:

$$\mathbf{LogLoss} = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (7)$$

Where:

- N is the number of samples.
- y_i is the actual label of sample i (1 for positive class and 0 for negative class).
- \hat{y}_i is the model's response to the sample i predicted probability. to evaluate how close the model's predicted probability for each sample is to the actual label: when the model's predictions are close to the actual label, the value of the loss function is smaller.

Through the above tests, we found that the variables that have a greater impact on the probability of scoring are: running distance (x_9), cumulative scoring in previous matches ($x_1x_2x_3$), whether or not they are serving this time (x_5), whether or not they were serving last time & whether or not they scored on the court (x_6). Surprisingly, some of the variables that we had originally given high expectations did not have the expected weights: for example, consecutive points (x_4) and whether or not they were break points (x_7). Among the variables with higher weights, the variable whether or not the current time was a server (x_5) always showed regular fluctuations, so its effect on momentum was not considered.

We selected the match trends of match 2023-wimbledon-1301 and match 2023-wimbledon-1301 and detected the turning points in them, and found that the key variables mentioned above ($x_1x_2x_3x_6x_9$) did have large swings in these turning points, which further validated our conclusion that the swings in match trends can be predicted by the swings in these key variables.

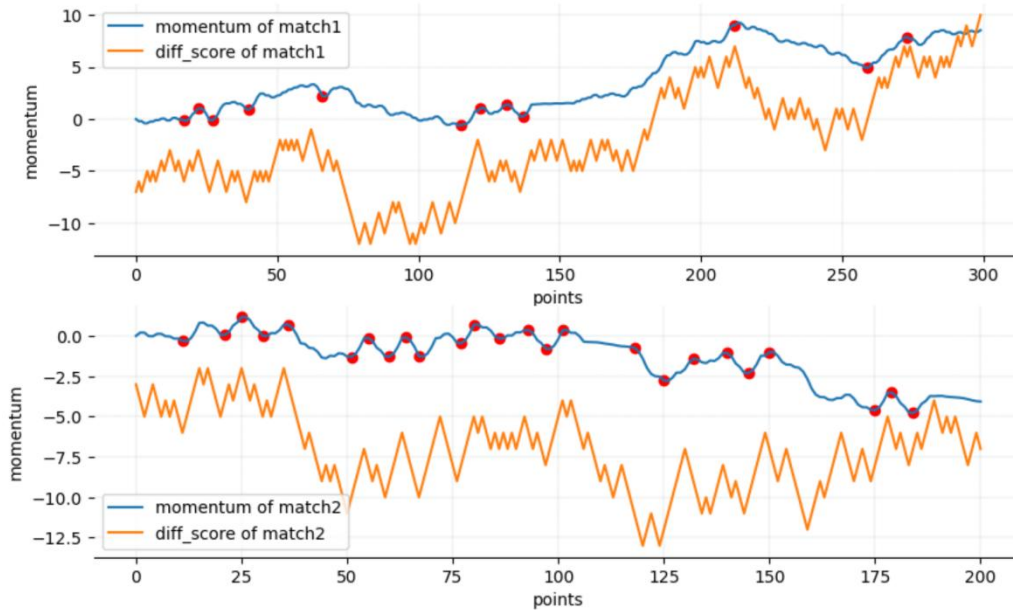


Figure 9. The turning point in two game

6.2. Suggestions for Players

Through our analysis, we concluded that the above key variables affect the match trend through the following aspects:

- Physical Functions: The swing in running distances significantly affects the trend of the game, with PLAYERS who run significantly more distances having a higher probability of falling behind in the following game.
- Psychological factors: serving errors and not serving but scoring a point have an impact on the trend of the match that goes far beyond whether the ball is scored or not, suggesting that psychological factors play an important role in the match. In addition, since the cumulative score may have a greater reflection on the player's level of play, we cannot be sure whether its effect on the match trend is through psychological effects, and therefore it is not considered for the time being.

In summary, we highly recommend that players consider how to minimize physical exertion and conduct mental resistance training in their daily training to avoid being unable to stop a disadvantage when the first signs of it are revealed

In addition, some variables related to the player's individualized playing style should also be considered, such as 'speed mph', 'serve width', serve depth The coach should study the opponent's style of play based on such variables, and then give a specific strategy.

6.3. Predictions for Games Based on GRU

By real-time monitoring the condition of the field we can get the value of the independent variable x_i at each moment, and according to the previously established model we have realised to determine the probability of scoring at the next moment according to the value of the current influencing factor x_i , and to get the momentum of the athlete at the current moment by adding up the probability of scoring at all the previous moments, but there are some shortcomings in this model. Firstly, we must know the value of the influencing factor x_i when calculating the size of the momentum at the current moment, which makes it difficult for coaches to collect information when predicting the trend of the game, and at the same time, the model can not accurately predict the game after a certain period of time, which makes the model not very suitable for the application of the real game scenarios.

We would like to find a model that can predict the trend of the game after a period of time based on the performance of the current athlete over a period of time, such as predicting whether the athlete will win the game in the end. Based on the above statements, it is easy to see that the model we want is essentially a time series prediction model.

In summary, we decided to use the Gated Recurrent Unit (GRU) model to predict whether or not a player will win the game based on the trend of all previous scores of the player at the current moment in a game, which is more convenient to apply to real games and also has a better prediction ability.

Compared to other traditional time series prediction models, deep learning models are able to automatically learn the representation of the input data without the need to manually extract features, which helps the models to better adapt to the complex structure and hierarchical features of the data, alleviates the dependence on specialised domain knowledge, and also facilitates quick predictions in matches with a short period of time. In addition the deep learning model introduces a nonlinear transformation through the activation function, which enables it to capture and represent complex nonlinear relationships, which provides a better fit to the complex trends in score changes during a match.

Compared to other methods in deep learning GRU [3, 4], which like Long Short-Term Memory Networks (LSTMs) focuses on solving the problem of gradient vanishing in traditional RNNs, GRU's gating structure makes it better able to capture and handle long-term dependencies, and therefore works better when dealing with sequential data that contains dependencies over long time spans. In addition, compared to LSTM, the GRU model has a simpler structure and contains fewer parameters, which helps to reduce the computational burden of the model, reduce the risk of overfitting, and improve the training efficiency.

The structure of the Gated Recurrent Unit (GRU) model contains hidden states, update gates, reset gates, new candidate hidden states, and final hidden state update, and the corresponding structure schematic and parameter calculation formula are as follows.

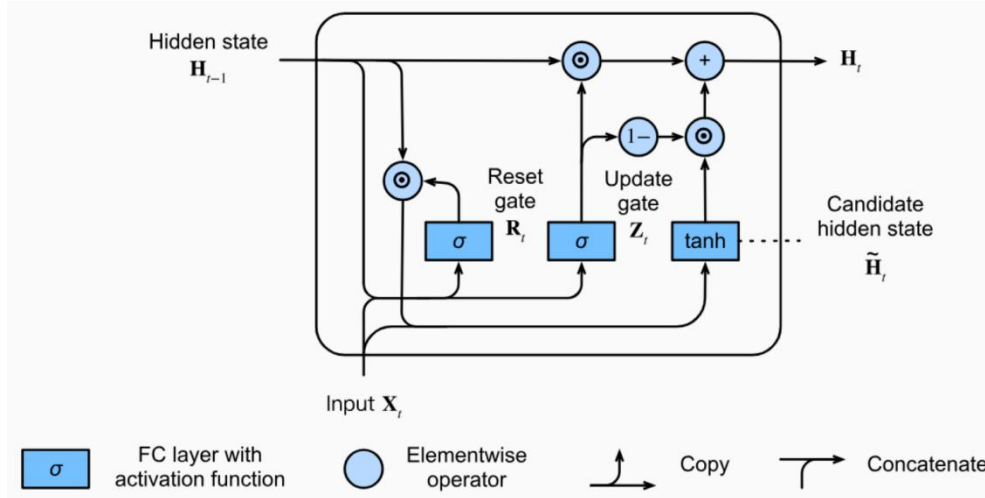


Figure 10. GRU layer structure

$$R_t = \sigma(X_t W_{xr} + H_{t-1} W_{hr} + b_r), \quad Z_t = \sigma(X_t W_{xz} + H_{t-1} W_{hz} + b_z),$$

$$H_t = \tanh(X_t W_{xh} + (R_t \odot H_{t-1}) W_{hh} + b_h), \quad H_t = Z_t \odot H_{t-1} + (1 - Z_t) \odot H_t \quad (8)$$

In order to prevent the problem of gradient vanishing and gradient explosion of the model, we adopt ReLU function as the activation function, and at the same time, we use Adaptive Moment Estimation (Adam) to optimise the function, Adam uses the adaptive learning rate mechanism to adjust the learning rate for each parameter, which can help to accelerate the convergence, and at the same time,

in order to solve the problem of the gradient estimation biased towards zero at the initial stage, the Adam introduces a bias correction mechanism to improve the stability of the algorithm. The cross-entropy loss during model training is as follows.

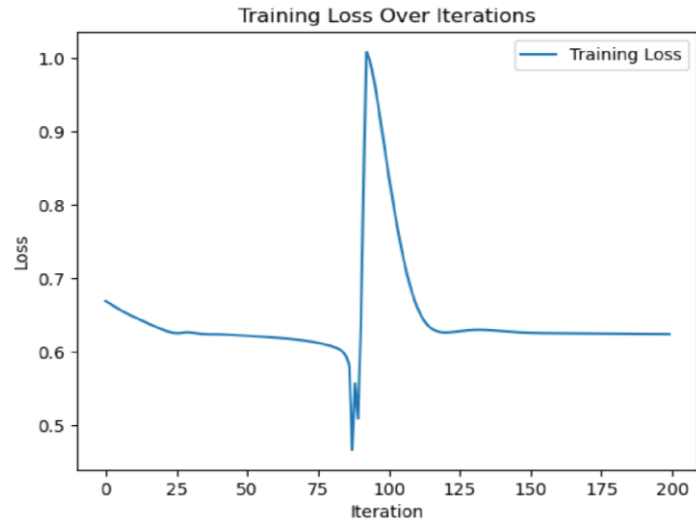


Figure 11. Training loss over iterations

From the figure, it can be seen that the model has a low loss rate on most of the training sets, and only on a small number of datasets there is a significant increase.

7. GENERALIZATION OF PREDICTIVE MODELS

7.1. Adaptability of Predictive Models to Other Data

For the detection of the above GRU model, firstly, we randomly select six games of all the matches as the test dataset, and use the scoring trends of the first two thirds of these six games as the inputs of the model to predict whether the final player scores or not. Finally, the predicted and actual results are plotted into a confusion matrix for analysis, and the confusion matrix is as follows.

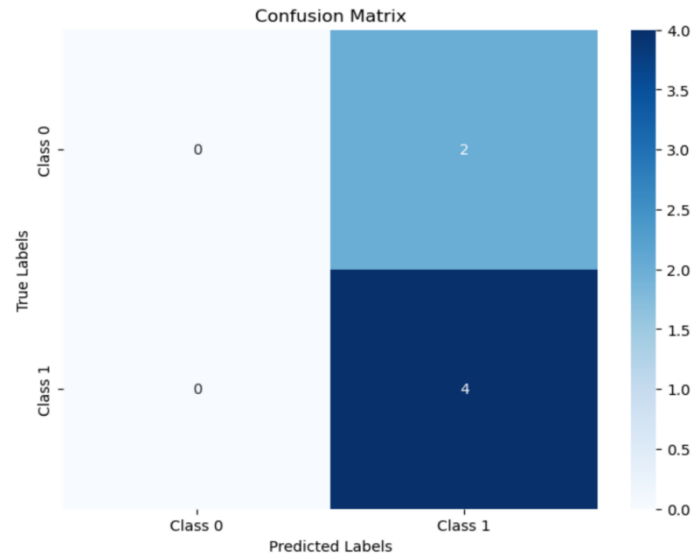


Figure 12. Confusion Matrix

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$\mathbf{Recall} = \frac{TP}{TP + FN} \quad (10)$$

$$\mathbf{Precision} = \frac{TP}{TP + FP} \quad (11)$$

$$\mathbf{F1} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (12)$$

It can be concluded that the prediction accuracy of the model is 66.67%, the recall rate is 100%, the precision rate is 66.67%, and the F1 score is 0.8, which shows that the model's prediction is still relatively accurate.

The following figure shows the weight distribution within the model at the end of training, from which it can be seen that the model fits well and there is no gradient disappearance or gradient explosion.

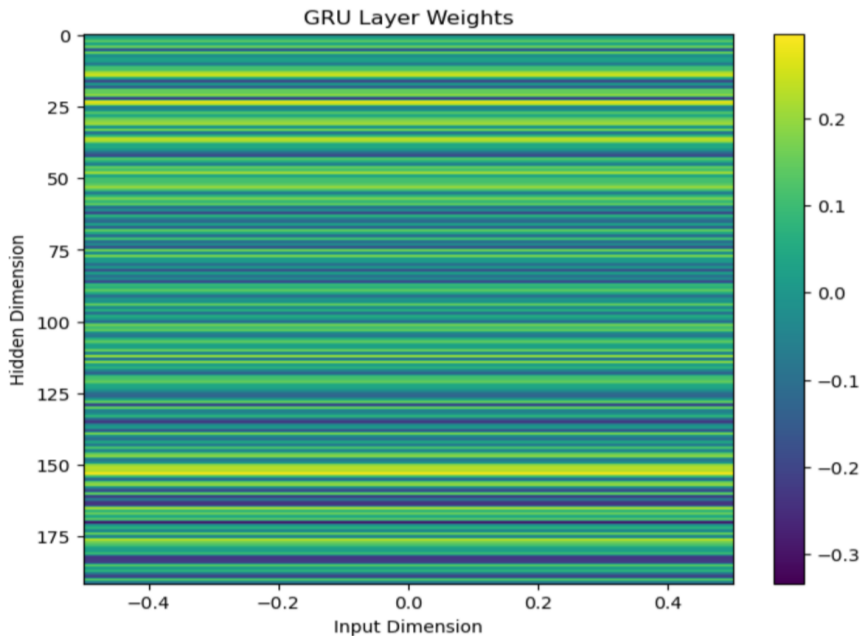


Figure 13. GRU Layer Weights

7.2. Generalization of the Model to Other Races

As discussed above, our model is able to predict the results of the men's singles match of the Australian Open more accurately, and shows good generalization and prediction ability in this aspect. The Australian Open, as one of the Grand Slam tournaments, is the most prestigious tournament in professional tennis, and the richness and representativeness of the data can prove the generalizability of our model. At the same time, our momentum indicators include physical factors such as running distance (x9), psychological factors such as double fault, and technical factors such as ace shot, which are three important factors affecting the performance of tennis competitions, and these factors are often found in other competitive sports, so it also reflects that our model has a better adaptability to different scenarios. model has a better adaptation to different scenarios of sports competitions.

8. SENSITIVITY ANALYSIS

Based on the final training results of the GRU model, the magnitude of the various weights in the model can be plotted as follows, where a larger weight indicates a higher sensitivity of the corresponding variable and vice versa a lower sensitivity.

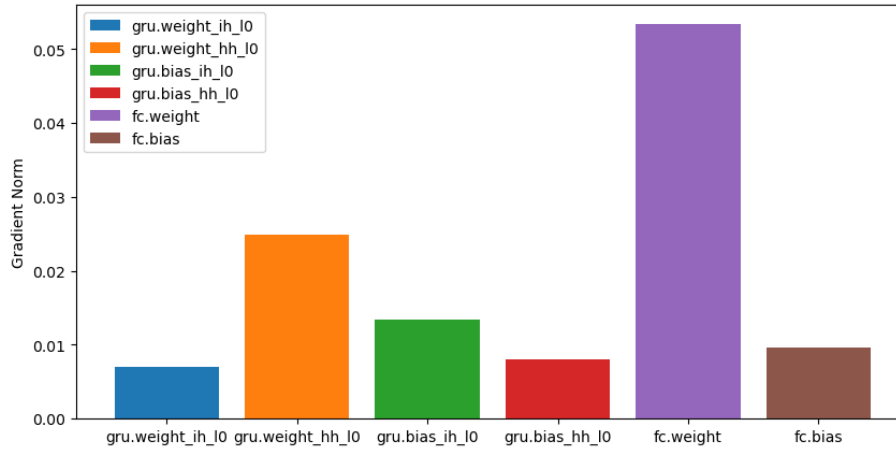


Figure 14. Data handling

9. MODEL EVALUATION

For the whole problem we have developed two models, the first one is a momentum predicting model and the second one is a GUR time series prediction model.

Momentum predicting model:

- Advantages: accurate prediction, can predict the momentum of the athlete at that moment more accurately.
- Disadvantages: unable to predict the trend of the game after a period of time, and more difficult to collect information. So it is not suitable for application in the real game process.

GRU time series prediction model:

- Advantages: it is possible to predict whether the athlete will win the race based on the existing time trend of the race.

10.MEMO

Hello Coach, based on our modelling, we have come up with some constructive conclusions and have made some recommendations for your consideration based on the conclusions.

Our model analyses the following most influential factors: 1. distance run 2. serve whether to score 3. cumulative scoring situation.

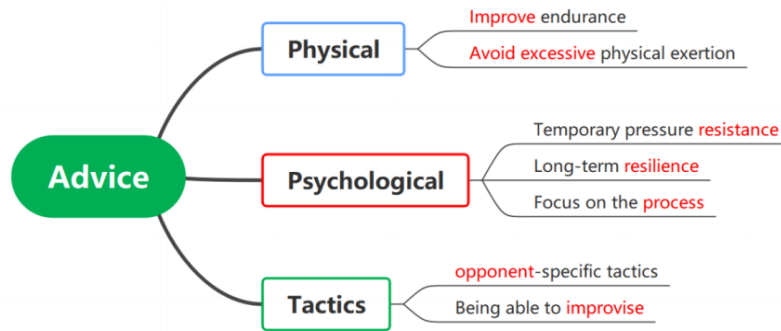


Figure 15. Our recommendations

On the physical side, it is recommended that players focus on endurance and fitness in their training. Endurance training can include long-distance running, aerobic exercise and persistence training to improve players’ staying power and endurance. There should also be a focus on avoiding unnecessary physical exertion, for example by optimizing running routes, controlling tempo and using intervals wisely to maximize physical savings. Through these physical drills and techniques, players can better cope with the physical challenges of the game and improve their game performance.

On the mental side, players are advised to focus on developing temporary resilience and long-term toughness. Temporary resilience involves the ability to cope with pressure and challenges during a game and can be improved through mental training, relaxation techniques and focus training. Long-term resilience, on the other hand, involves maintaining a stable mental state throughout a season or career and coping with setbacks and stress, which can be strengthened through counseling, self-regulation and mental preparation. Additionally, focusing on the process of the game is crucial; players need to learn to concentrate, control their emotions, and stay focused during the game, which can be achieved through focus training and mental conditioning. Through these mental aspects of training and skills, players can improve their mental fitness and better face the challenges in the game.

In terms of tactics, players are advised to designate specific tactics for different opponents and to know how to improvise during the game. Designating specific tactics for opponents requires coaches and players to analyze the characteristics and weaknesses of the opponents, formulate targeted tactical plans, and practice and adjust them in training. At the same time, players also need to have the ability to improvise during the game, and make flexible tactical adjustments at any time according to the game situation and the performance of the opponent, which needs to be improved through simulated matches, tactical training and analysis of the game video. Through these tactical training and skills, players can better cope with different opponents and game situations, and improve the flexibility and adaptability of the game.

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