A Prediction Model for Tennis Match Fluctuations Based on the BP Neural Network

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Abstract. Tennis is a global sport, with Wimbledon being one of the most historic and prestigious international tennis opens. The concept of "momentum" in tennis matches, defined as "strength or force gained by motion or by a series of events," plays a critical role in influencing the course of a match. This paper selects specific indicators combined with the scoring situations in matches for correlation analysis using Kendall's tau-b method. Reasonable indicators are chosen for classification through a backpropagation neural network to predict the match process and analyze fluctuations in the match flow, which are then visualized. The analysis identifies various turning points within the match proceedings. This model is a good way to analyze and predict fluctuations in tennis matches.This research is anticipated to contribute to the prediction of scores in sports events.

Keywords: Momentum, TOPSIS, Kendall's tau-b Correlation Analysis, BP Neural Network, Runs Test.

1. Introduction

Tennis is a sport celebrated globally[1], with the Wimbledon Championships heralded as one of the most historic and prestigious international tennis events[2]. The concept of "momentum" in tennis matches, defined as the strength or force acquired through motion or a sequence of events, significantly influences the dynamics of the game[3].

The research conducted by Walid Briki and colleagues discovered that psychological momentum is a dynamic phenomenon characterized by non-linearity and historical dependency[4]. Giovanni Angelini and his team introduced a new version of the Elo rating method, designed for predicting outcomes in tennis matches[5]. Nadav Goldschmied and his collaborators analyzed ice hockey and found that winning a fight does not increase the likelihood of winning the game, regardless of the score. Andrew E[6]. Evans and associates explored the connection between psychological momentum and performance within the context of golf competitions[7].

Addressing the issues identified, this paper proposes a predictive model based on the backpropagation (BP) neural network, incorporating various influential factors within matches. The model offers a visual representation of the direction and fluctuations of matches and predicts the flow of the competition. This research is expected to contribute to the prediction of outcomes in tennis tournaments.

2. The Construction and Solution of the Model

2.1. Notations

The primary notations used in this paper are listed in Table 1.

Table 1: Notations

Symbol	Description
m	The m-th match
s	The s-th set
g	The g-th game
p	The p-th point
A	Whether the set score is obtained
B	Whether the game score is obtained
C	Whether the point score is obtained
j	1layer 1
k	2layer 2
a	Whether it's an ace
D	Running distance
v	Serving speed
w	Serving direction
d	Serving depth
S	Whether the player serves during a game

2.2. Processing of Data

The data for this study were sourced from the official Wimbledon website, with match data from the second round of the men's singles at the 2023 Wimbledon Championships extracted using Python.

The process initiates with data encoding, followed by the utilization of interpolation to address missing values and the elimination of erroneous data. To accurately capture the fluctuations in athletes' performance throughout the match, a range of evaluation metrics has been established. In summary, the impact on players' "momentum" is categorized into three distinct aspects: psychological, serving and technique, and physical strength.Table 2 presents the selection of evaluation metrics and their corresponding calculation formulas.

Table 2: Evaluation indicators

Metric	Symbol	Calculation method
Number of games won in this set	X1	$X1_{s,j} = \sum B_{s,j}$
The number of points in this game	X2	$X2_{j,s,g,p} = \sum_{p=1}^{p-1} C_{j,s,g,p} - \sum_{p=1}^{p-1} C_{k,s,g,p}$
Server	X3	$X3_{j,s,g} = S_{j,s,g}$
Whether the previous point scored or not	X4	$X4_{j,s,g,p} = C_{j,s,g,p-1}$
The score lead in this match	X5	$X5_{j,s,g,p} = \sum_{s=1}^{s}\sum_{g=1}^{g}\sum_{p=1}^{p} C_{j,s,g,p} - \sum_{s=1}^{s}\sum_{g=1}^{g}\sum_{p=1}^{p} C_{k,s,g,p}$
Whether or not the round is scored	X6	$X6_{j,s,g,p} = C_{j,s,g,p}$
Ace	X7	$X7_{j,s,g,p} = a_{j,s,g,p}$
The quality of the serve	X8	$X8_{j,s,g,p} = v_{s,g,p} * w_{s,g,p} * d_{s,g,p}$

It is posited that the integration of existing data, especially through the examination of historical metrics, is crucial for predictive analysis. Observations indicate that turning points in matches are highly probable during instances of consecutive scoring, serving, changes in game and set scores, executing an ace, returning a winning shot, physical exhaustion, and serving errors. Consequently, these elements are collectively considered in the formulation of match predictions.The predictive indicators are shown in Table 3.

Table 3: Predictive metrics

Metric	Calculation method
Score of the game(SoG)	
Score of the set(Sos)	
Score of the previous game(SopG)	$SopG_{j,s,g,p} = C_{j,s,g,p-1}$
Previous ace(Pa)	$ace_{j,s,g,p} = a_{j,s,g,p-1}$
Category of untouchable shot(CouS)	
Stamina	$Stam_{j,s,g,p} = 700 - \sum_{p=1}^{p-1} D_{j,s,g}$
Distance covered in the previous game(DipG)	
Service fault(Sf)	
Stroke count in the previous game(SipG)	
Frequency of sequential scoring(FosS)	
Server	$Server_{j,s,g} = S_{j,s,g}$

2.3. A Comprehensive Evaluation Model Based on TOPSIS and Entropy Weight Method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a widely used method for comprehensive evaluation that effectively utilizes the information from original data, precisely reflecting the differences between various evaluation schemes[8].

The Entropy Weight Method, an objective weighting approach, draws on the concept of information entropy. It calculates the information entropy of indicators to determine their weights based on the degree of relative change and its impact on the overall system, assigning weights according to the variance in indicator values. Indicators with greater degrees of change are assigned higher weights.

The integration of the Entropy Weight Method with TOPSIS allows for considering the weights of various indicators while providing a comprehensive evaluation across multiple criteria. This evaluation model offers a clear and intuitive way to observe the performance of players at different times.

It is proposed that momentum is defined as the level of a player's performance at a specific moment. A higher composite score at any point indicates superior performance, thereby suggesting increased momentum. Charting the composite scores and point outcomes for two competitors in the same match facilitates a visualization of the match's progression. This enables an assessment of performance levels and momentum through comparison of the players' composite scores. The concept is illustrated in the figures provided, with Figure 1 representing Group 1701 and Figure 2 representing Group 1401.

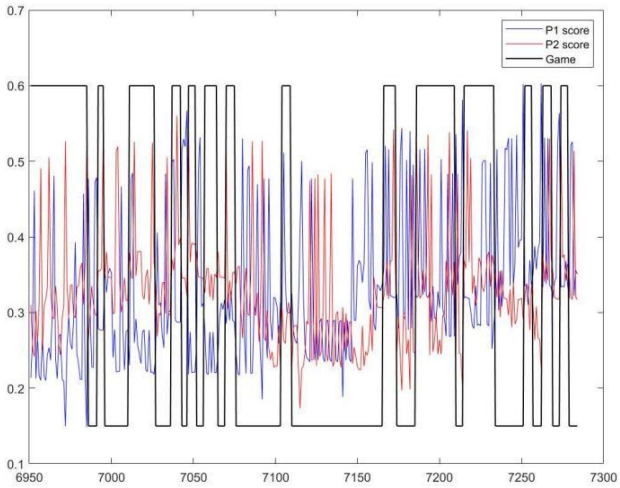


Figure 1. Comparison of player performance in the 1701

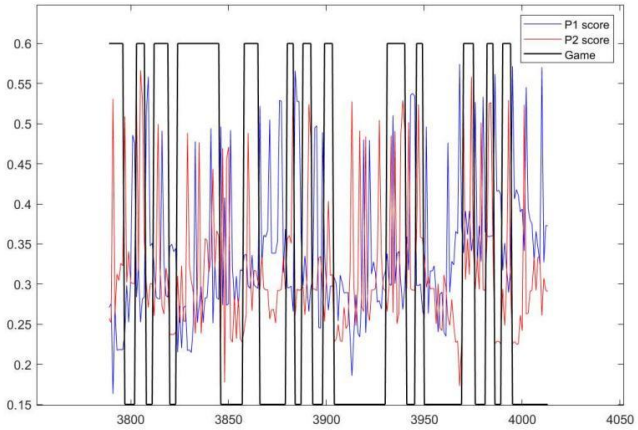


Figure 2. Comparison of player performance in the 1701 group

Figure 3 is a diagram correlating the scoring outcomes of the first 200 points (represented by solid circles) with the levels of momentum (depicted by hollow circles).Figure 3 demonstrates a high correlation between momentum and match scoring, indicating that the definition of momentum proposed in this paper is accurate.

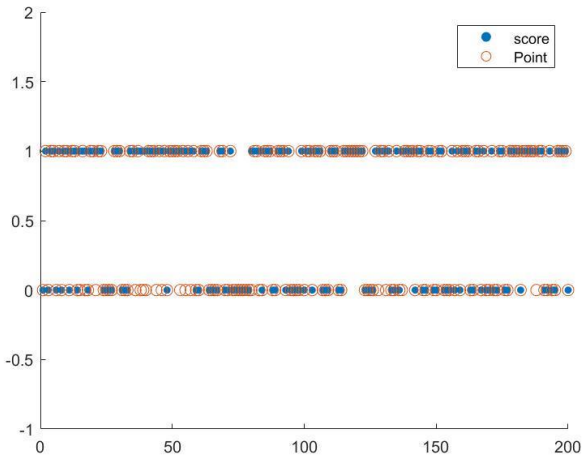


Figure 3. Comparison of momentum and scores

2.4. A predictive model for match progression using BP neural network-based classification

2.4.1 Selection of Indicator Data

It is hypothesized that the dynamics of a match can be accurately depicted through variations in the score. To ascertain the validity of the selected indicators, a correlation analysis is performed, linking these indicators with the match scoring data. Recognizing that certain datasets deviate from a normal distribution, Kendall's tau-b correlation analysis method is utilized to assess the data pertaining to Player 1[9].The results are illustrated in Figure 4.

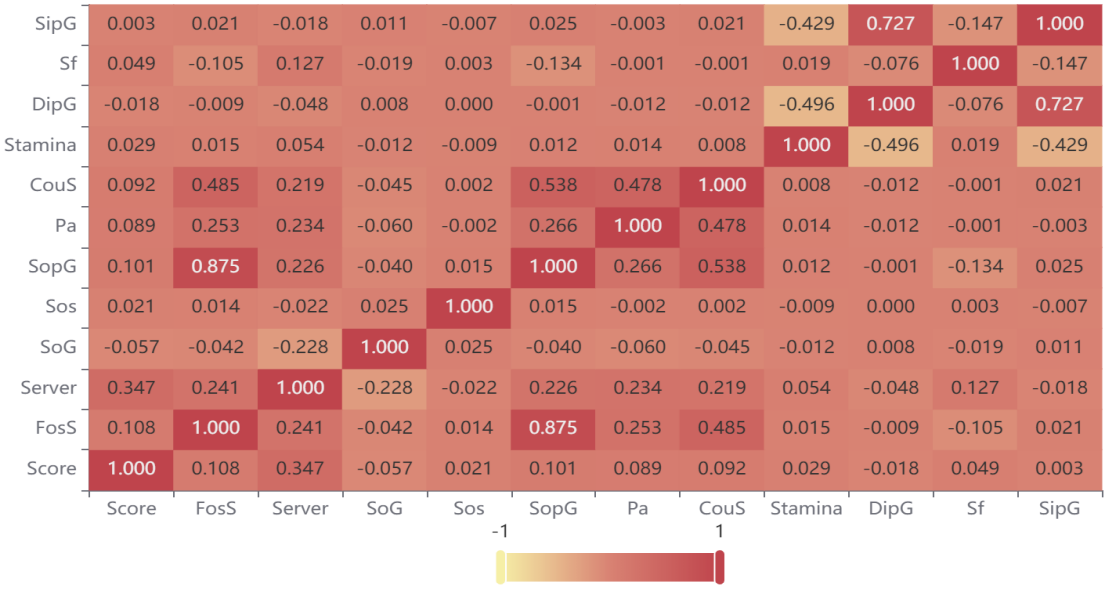


Figure 4. Correlation coefficient heat map of predictor indicators and scores

As illustrated in Figure 4, there is a significant correlation between the selected indicators and the progression of matches, demonstrating the rationality of the indicator selection in this study. The figure clearly delineates the relationship between these indicators and fluctuations in performance, as well as critical moments within the matches, validating the effectiveness of the methodological approach for indicator selection. This not only emphasizes their importance in the analysis and prediction of match outcomes but also proves the selection to be judicious. Hence, the choice of indicators is shown to be reasonable, providing a reliable basis for the analysis and prediction of sports competitions within an academic context.

2.4.2 An Introduction to the BP Neural Network

Based on neuroscience, artificial neural networks serve as an abstract model that mimics the human brain[10]. The learning and memorization of input-output patterns by backpropagation networks are achieved without the necessity for understanding the underlying mathematical equations. Through the application of the steepest descent method and backpropagation, adjustments are made to weights and thresholds to minimize errors, a process characterized by the propagation of signals forward and the correction of errors backward. Its logic diagram is depicted in Figure 5, illustrating the methodological framework. This approach ensures the effective adaptation of the network to perform tasks by continuously refining its performance, as errors encountered during the forward propagation are meticulously corrected in the subsequent backward phase.

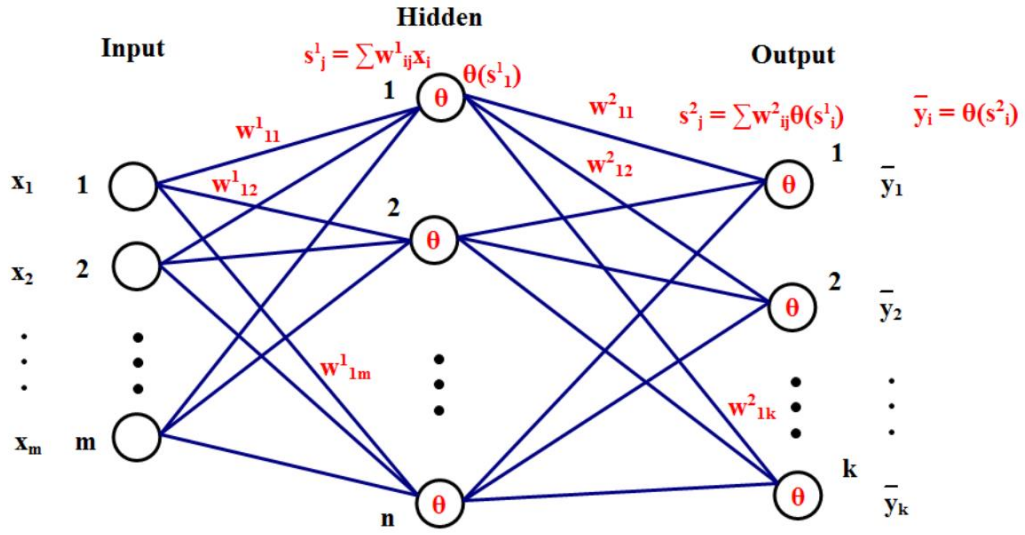


Figure 5. Schematic diagram of a neural network

Data from twenty matches were selected for analysis, and this data underwent normalization.Eighteen out of the twenty matches were allocated as the training set, while the remaining two were utilized as the test set.

Initially, the dependent and independent variables are defined as follows:

It is assumed that the input layer contains n neurons, the hidden layer is comprised of p neurons, and the output layer consists of q neurons.

Vector of the input layer: $x = (x_1, x_2, \ldots, x_n)$

Input vector for the hidden layer: $hi = (hi_1, hi_2, \ldots, hi_p)$

Output vector of the output layer: $yo = (yo_1, yo_2, \ldots, yo_q)$

Output vector of expected values: $d_o = (d_1, d_2, \ldots, d_q)$

Weight matrix connecting the input layer to the hidden layer: w_{hi}

Weight matrix connecting the hidden layer to the output layer: w_{oh}

The initialization of the network's w_{hi} and w_{oh} matrices is governed by the value range of the activation function. The maximum number of training iterations, denoted as M, along with the learning precision value, ε, are established. The activation function f(x) is selected, employing the widely used non-linear activation function, the ReLu function:

$$\text{ReLu(x)=max(0,1)} \tag{1}$$

Upon selecting sample data as input, the resulting outputs from hidden layer hi_h and output layer yo_o are obtained:

$$hi_h(k) = \sum_{i=0}^{n} w_{hi} x_i(k), h = 1,2,3,\cdots, p \tag{2}$$

$$yo_o(k) = f(\sum_{h=0}^{p} w_{oh} ho_h(k)), o = 1,2,3,\cdots, q \tag{3}$$

The error is calculated by comparing the network's actual output values with the expected output values d_o:

$$e = \frac{1}{2} \sum_{o=1}^{q} (d_o(k) - yo_o(k))^2 \tag{4}$$

The partial derivatives $\delta_o(k)$ and $\delta_h(k)$ of the error function, with respect to the neurons in the output and hidden layers respectively, are calculated:

$$\delta_o(k) = (d_o(k) - yo_o(k))yo_o'(k) \tag{5}$$

$$\delta_h(k) = (\sum_{o=1}^{q} \delta_o(k) w_{ho}) f'(hi_h(k)) \tag{6}$$

Subsequently, the error signals are utilized to modify the connection weights across the layers. Specifically, the weights from the hidden layer to the output layer are denoted as w_{oh}^{N+1}, and those from the input layer to the hidden layer as w_{hi}^{N+1}:

$$w_{hi}^{N+1} = w_{hi}^{N} + \mu\delta_h(k)x_i(k) \tag{7}$$

$$w_{oh}^{N+1} = w_{oh}^{N} + \mu\delta_o(k)ho_h(k) \tag{8}$$

Compute the overall error E:

$$E = \frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}(d_o(k) - y_o(k))^2 \tag{9}$$

3. Results

Through training and testing, a prediction of the match progression in the finals was made. The confusion matrix of the predicted values versus the true values is shown in Figure 6. It can be concluded that the probability of correctly predicting points with a true value of 1 is 78%, and the probability of correctly predicting points with a true value of 0 is 69.5%. This indicates that the model has essentially predicted the match progression, and that a change in "momentum" occurs when turning points in the match are reached.

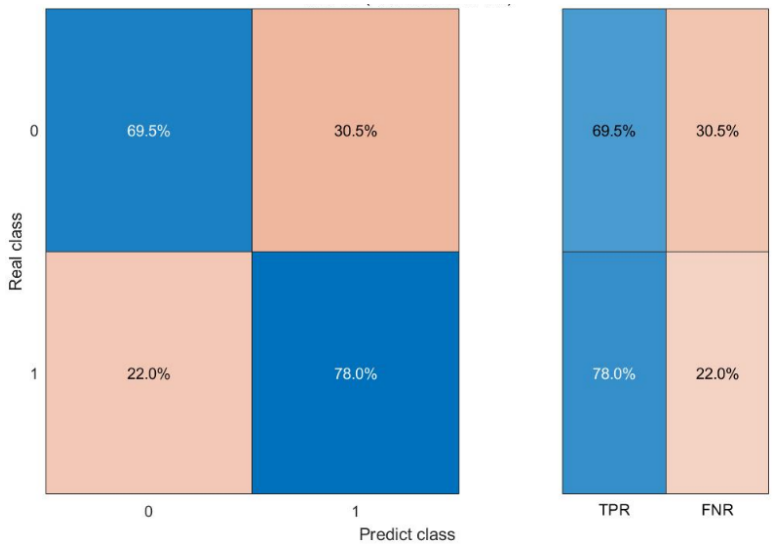


Figure 6. Prediction of the match flow of the Grand Final

Figure 7 displays the performance of the training set, where, following 1000 iterations, the minimum classification error was reduced to 0.23, resulting in an accuracy rate of 0.77.Figure 8 displays the ROC curve of the prediction set for the model, showing an AUC of 0.76. With 0.5 < AUC < 1, it is evident that the model's predictive capability surpasses that of random guessing, signifying its substantial predictive merit.

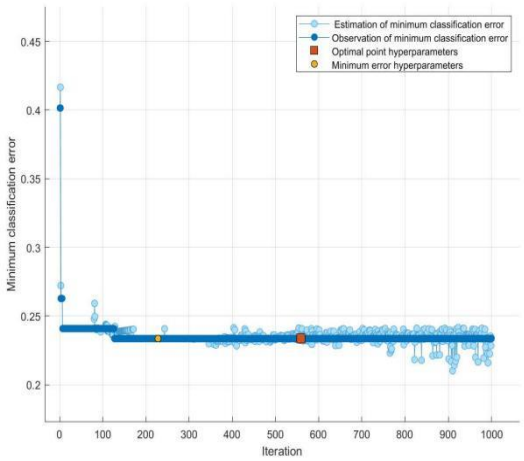


Figure 7. Neural network iteration performance graph

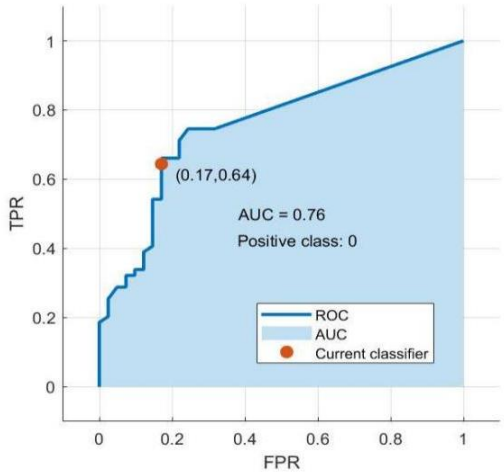


Figure 8.ROC plot of the prediction set

To enhance the persuasive power of the findings, the runs test methodology was utilized to assess the randomness inherent in the observed fluctuations[10].

Observing the momentum change figure obtained from the previous analysis, it was found that each inflection point corresponds to a fluctuation in the match. Therefore, inflection points are defined as match fluctuation points. The `ischange` function in MATLAB was used to identify these inflection points and plot the fluctuation graph. Figure 9 represents the match fluctuation graph:

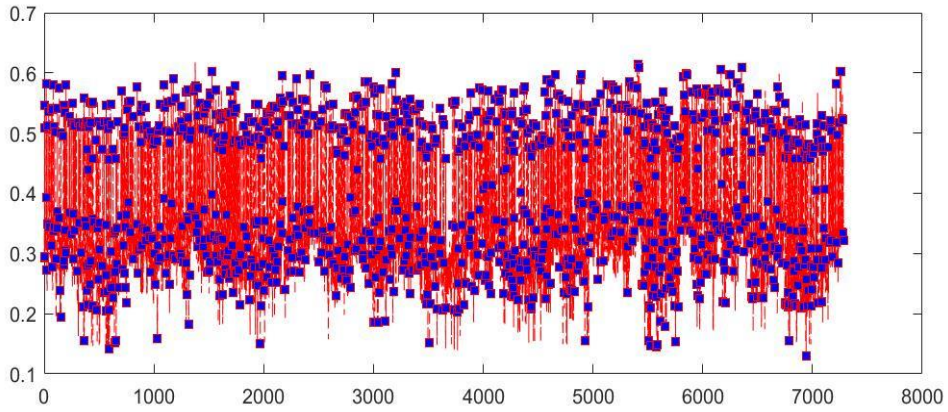


Figure 9. Chart of match swings

Definition of a Run: In the context of a mutation point sequence, a consecutive series of mutation points or non-mutation points is defined as a "run."

Compute the actual number of runs: Calculate the total number of runs, denoted as N, in the context of the match statistics.

Calculate the theoretical number of runs:

Let the total number of points be n, with n_1 representing the number of mutation points and n_2 representing the number of non-mutation points, $n = n_1 + n_2$.

The expected number of runs E[N] and the variance Var[N]:

$$E[N] = \frac{2n_1 n_2}{n} + 1 \tag{10}$$

$$Var[N] = \frac{2n_1 n_2 (2n_1 n_2 - n)}{n^2 (n-1)} \tag{11}$$

Calculate the test statistic Z:

$$Z = \frac{N - E[N]}{\sqrt{Var[N]}} \tag{12}$$

Through calculation, we obtained the test statistic Z=2.239, which is greater than 1.96 (typically considered significant at a 5% significance level when the absolute value of Z exceeds 1.96). Additionally, P=0.025, which is less than 0.05.As shown in Table 4:

Table 4: Predictive metrics Results of Run Test

Name	Sample Size	z	P
Mutation Status	7284	2.239	0.025**

Note: ***, **, and * respectively represent significance levels at 1%, 5%, and 10%.

From Table 4, it can be inferred that the number of runs is atypical, indicating that the mutation point data is non-random, thereby supporting the presence of momentum, which contradicts the coach's perspective.

4. Conclusions

Set against the backdrop of the Wimbledon Championships, this study conducts a comprehensive investigation into the momentum within tennis matches. An evaluation model that combines the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and the entropy weight method was established to analyze the data and visualize the competition process. Specific indicators, in conjunction with scoring situations in matches, were selected for correlation analysis employing Kendall's tau-b method. Furthermore, a predictive model utilizing the backpropagation (BP) neural network was developed, enabling the visualization of tennis match processes and facilitating an analysis and prediction of the dynamics of these matches. It is anticipated that the findings of this study will contribute to the future analysis of momentum within tennis competitions and enhance the predictive accuracy of match outcomes.

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