Research on Tennis Match Outcome Prediction Based on Multi-Algorithm Integration and Bayesian Analysis

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Abstract. The intense competition in the men's singles final of the 2023 Wimbledon Championships highlighted the dynamic and unpredictable nature of tennis matches. Inspired by this observation, this study aims to quantify and analyze momentum shifts in tennis matches and explore their impact on match outcomes. We compare multiple machines learning algorithms, including MLP, Logistic Regression, XGBoost, and Naive Bayes, ultimately selecting the XGBoost model for its superior ability to handle nonlinear relationships and high-dimensional data. Furthermore, we optimize the XGBoost model with a Genetic Algorithm (GA) to better capture match dynamics and employ LightGBM to predict fluctuations during matches. Additionally, Bayesian Change Point Analysis is used to detect key fluctuation points. Through data preprocessing, feature extraction (covering technical, tactical, psychological, and physical factors), and model training and validation, our findings reveal that momentum plays a significant role in determining match outcomes. This study presents a novel analytical framework, offering new perspectives and methods for understanding and predicting tennis match results.

Keywords: GA-XGBoost, LightGBM, Bayesian Change Point Analysis, Machine Learning, Tennis Momentum Prediction.

1. Introduction

The concept of “momentum” in sports, defined as the strength or force gained by motion or a series of events, remains an elusive and debated phenomenon. While athletes or teams often subjectively perceive momentum during a game, its objective quantification and impact on performance have been a topic of ongoing research. Some scholars argue that momentum is largely a psychological construct [1], while others have attempted to develop statistical models to capture its presence in competition dynamics [2]. However, defining momentum in a measurable manner and assessing its influence on match outcomes remains a challenge.

Previous studies have sought to predict match outcomes using statistical and machine learning approaches. Del Corral & Prieto-Rodríguez (2010) applied Brier Scores to predict Grand Slam results based on ranking differences, but their models were limited by a small dataset and failed to consider in-game fluctuations [3]. Rosker & Majcen Rosker (2021) used a random forest model to analyze tennis players’ visual behaviors during serve returns, but their research was constrained by sample diversity [4]. More recently, Almarashi et al. (2024) employed time series models for player ranking prediction, effectively capturing temporal trends but potentially overlooking nonlinear dependencies in match dynamics [5].

Addressing these limitations, our research focuses on the 2023 Wimbledon Men's Singles final and employs advanced mathematical and statistical techniques to analyze momentum shifts. By comparing multiple machine learning algorithms, we select XGBoost for its ability to process complex data structures. Further optimization through a genetic algorithm, combined with LightGBM for predictive modeling and Bayesian Change Point Analysis, allows us to capture dynamic momentum fluctuations more effectively. Special emphasis is placed on identifying critical moments within the match and evaluating their impact on player performance and the final outcome. By delving into the nuances of momentum, this study aims to offer novel insights and methodologies for understanding and predicting the results of sports competitions.

2. Methods

2.1. Selection of Model

When predicting tennis matches, it is necessary to weigh the adaptability and limitations of the models: ARIMA is suitable for linear smooth sequences but does not handle nonlinear dynamics well [6]; logistic regression reveals the probability of winning or losing a single feature; XGBoost integrates multi-factors and provides an in-depth analysis; MLP neural networks are good at complex nonlinear problems but have weak explanatory power [6]; and Parker's Bayes ignores correlation and leads to limited prediction in strongly correlated data. Based on this, machine learning algorithms are found to be more suitable for prediction, and a comparison of machine learning algorithms is carried out in the following steps:

Step1. Data Splitting: Use 5-fold cross-validation to divide the original dataset into five exclusive parts [7], taking one part as the validation set and combining the remaining four as the training set for each iteration.

Step2. Model Training: Train the model using the training set; apply the trained model to predict on the validation set; calculate various evaluation metrics, including Accuracy, Recall, Precision, F1, AUC.

Step3. Results Comparison: After completing all the 5 iterations, the average value of each index of each algorithm in the 5 times of cross-validation is calculated, so as to compare and analyze the performance of each algorithm.

2.2. Development of GA-XGBoost Model to Capture Match Dynamics

The XGBoost algorithm is favored for dataset analysis and prediction due to its superior ensemble learning and ability to manage nonlinear, high-dimensional data [8]. However, optimizing its many hyperparameters requires precision. Traditional tuning methods may not fully explore the search space, risking suboptimal results. Genetic algorithms offer a solution by globally optimizing through natural selection-like processes, using crossover and mutation to iteratively approach the optimal hyperparameter set.

Moreover, combining 5-fold cross-validation maintains objective evaluation of model generalizability while ensuring that the XGBoost model optimized through Genetic Algorithms demonstrates stable predictive performance across different data subsets, thus maintaining high accuracy when facing new samples.

2.2.1. Genetic Algorithm

Genetic Algorithm (GA) is an evolutionary computation technique inspired by the principles of natural selection and genetics[9]. It employs operations such as selection, crossover, and mutation to evolve populations of potential solutions iteratively. Through a fitness-based evaluation process, GA achieves robust optimization and adaptability, making it a powerful method for solving complex problems.

2.2.2. XGBoost Model

XGBoost is a Boosting-type tree integration model, extended on the basis of gradient boosting decision tree GBDT [10], capable of multi-threaded parallel computation, and iteratively generating new trees, which can combine multiple weak learners with lower classification performance into a strong learner with higher accuracy. XGBoost employs the XGBoost sampling of fields[8], and introduces regular terms into the loss function, thus preventing the model from overfitting. XGBoost samples the fields, introduces the regular term into the loss function, thus preventing the model from overfitting and reducing the computation amount of the model, and introduces a genetic algorithm to search for the optimal hyperparameter combinations.

2.3. LightGBM Model

LightGBM is a novel GBDT (Gradient Boosted Decision Tree) algorithm proposed by *Ke* in 2017 *(Ke et al., 2017)*. GBDT has the functional characteristics of Gradient Boosting and Decision Tree, and has the advantages of good training effect and not easy to overfit.

LightGBM is favored for its efficient handling of large-scale data and complex non-linear relationships [11]. In the context of predicting momentum in tennis matches, momentum's changes involve interactions between multiple variables and exhibit time dependence. LightGBM can reduce computation costs through its unique histogram optimization technique. This process is illustrated in Figure 1, which provides a visual representation of the histogram-based decision tree algorithm. Its distinctive leaf-wise decision tree growth strategy effectively explores the model space and reduces the risk of overfitting when dealing with high-dimensional features containing eight interacting indicators. Additionally, LightGBM offers a range of regularization methods and flexible parameter tuning options to further enhance model generalization performance.

One of LightGBM's characteristics is the use of a histogram-based decision tree algorithm. This algorithm discretizes continuous feature values into k bins and generates histograms with a width of k. During sample traversal, it uses the discretized values as indices. After traversal, the histograms accumulate the necessary statistics, and then, through the discrete values of the histogram, it finds the optimal split point.

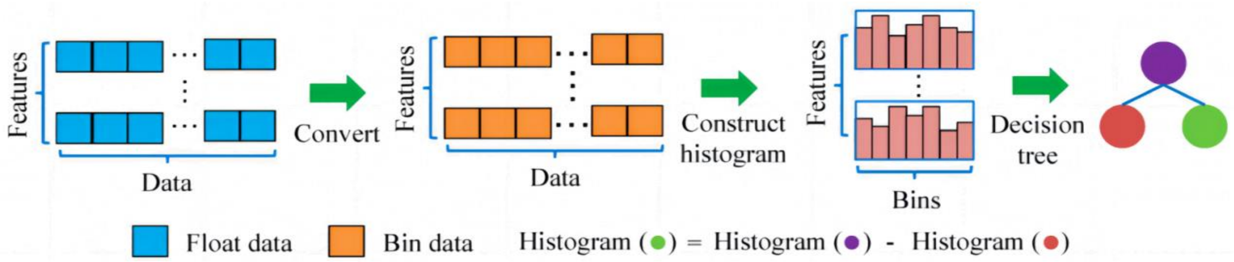


Figure 1. Histogram-Based Decision Tree Algorithm

Another feature of LightGBM is the adoption of a more efficient leaf-wise growth strategy, specifically, a leaf-wise strategy with depth constraints (leaf-wise direction). Before splitting, this strategy first traverses all leaves in the tree and identifies the leaf with the highest gain for splitting, allowing it to split again and repeat the process. Empirical evidence has shown that under the same number of splits, the leaf-wise approach achieves higher accuracy and adds a maximum depth limit on leaves to prevent overfitting. This growth strategy is visually represented in Figure 2, where the white and black dots represent leaves with maximum and non-maximum split gains, respectively. The leaf-wise direction of growth is illustrated in Figure 2 below, where white and black dots represent leaves with maximum and non-maximum split gains, respectively:

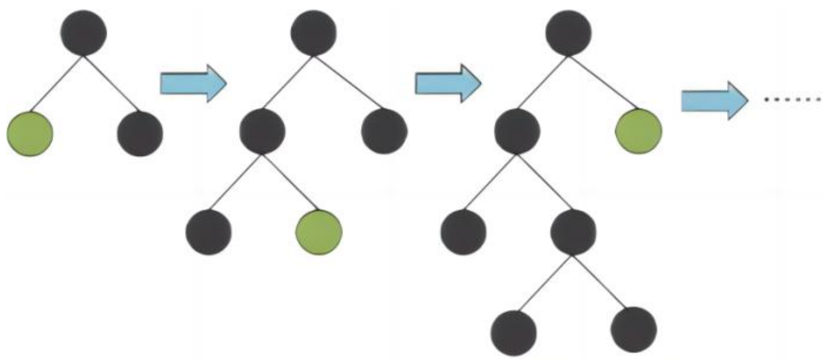


Figure 2. Schematic Diagram of Leaf-Wise Tree Growth

2.4. Bayesian Change Point Analysis

Bayesian Change Point Analysis is particularly suitable for analyzing fluctuations in momentum during tennis matches, as it quantifies uncertainty and integrates historical data and experiential judgment, providing a probabilistic explanation for changes in momentum. The flexibility of this method allows it to adapt to various data distributions and update in real-time to reflect new situations in the match. Its posterior analysis offers deep insights for formulating and adjusting match strategies, making it a powerful tool for decision-making in fast-paced tennis matches.

The steps for detecting fluctuation points during a match through Bayesian Change Point Analysis are as follows:

Time series data might change at certain points, dividing the time series[6] into segments with different distributions.

- Basic assumption: Times series data $y_1,\cdots,y_T$ might change at certain points, dividing the times series into segments with different distributions.
- Model definition: Let P (τ|y) donate the posterior probability of a change point τ given data y, with the goal to estimate P(τ|y) and thereby determine the location of change points:

$$\mathrm{P}(\tau \mid y)=\frac{P(y \mid \tau)P(\tau)}{P(y)}d \tag{1}$$

Where, $\mathrm{P}(\tau)$ is the prior probability of the variable point and $\mathrm{P}(y)$ is the marginal probability of the data y.

- Likelihood estimation: For each hypothesized change point location τ, calculate the likelihood of the data before and after τ. Given data follows a normal distribution, the likelihood $\mathrm{P}(y|\tau)$ can be calculated as follows:

$$\mathrm{P}(y \mid \tau)=\prod_{i=1}^{\tau} P(y_i \mid \theta_1)\prod_{i=\tau+1}^{\tau} P(y_i \mid \theta_2) \tag{2}$$

Where θ_1 and θ_2 are parameters before and after the change point, such as mean and variance, are considered.

- Posterior probability calculation: Calculate the posterior probability for each potential τ and identify those τ with significant posterior probabilities as potential change points.

3. Results

3.1. Data Pre-processing

The dataset used in this paper covers every point detailed record after the first two rounds of the 2023 Wimbledon men's singles, involving a wide range of information on match scoring, serving techniques, and more(https://www.mathmodels.org/Problems/2024/MCM-C/data_dictionary.csv).

1) Data Pre-processing

Given the large and diverse dataset, to ensure computational accuracy, during the preliminary data inspection, we discovered missing values in the attached data for serve width, serve depth, serve speed, and return depth. Therefore, it is necessary to impute the missing values:

For categorical data such as serve width, serve depth, and return depth, imputation with the mode is utilized.

For the numerical feature of serve speed, missing values in the selected numerical columns are filled using a median strategy. The specific implementation is as follows:

$$\begin{cases} \mathrm{x}_{i,\ j} & if\ X_{i,j} \text{ is not missing} \\ median(X_j) & if\ X_{i,j} \text{ is missing} \end{cases} \tag{3}$$

Finally, based on reasonable speculation and logical judgment related to other relevant indicators, we will further adjust the imputed outliers according to scoring rules for rational correction.

2) Data Standardization

Due to the dataset containing various types of measurements (such as time, distance, and speed), it is necessary to standardize and normalize the data.

Part1. Data Normalization

For continuous numerical features like "p_distance_run" and "speed_mph", we employ linear normalization to adjust their scales. This process aims to ensure that all features fall within the same standard interval (typically [0, 1]), preventing imbalanced impacts during comparison and modeling caused by the natural scale differences among various features. Thus, regardless of their original numerical ranges, all features can be fairly and effectively considered and applied within the mathematical model.

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{4}$$

Through this method, all features will be scaled to the same range between 0 and 1, allowing them to be fairly compared and calculated within the mathematical model.

Part2. Processing of Scoring Data

When analyzing scoring data in tennis matches, converting the number of points won from 1 to 9 into standard scoring rules is essential: 0 is converted to 0 points, 1 to 15 points, 2 to 30 points, and 3 to 40 points. Any score beyond 3 is considered as deuce, with each additional point representing an advantage. This conversion allows the data to intuitively reflect the progress of the match and aligns with traditional scoring methods.

3.2. Extraction of Data Features

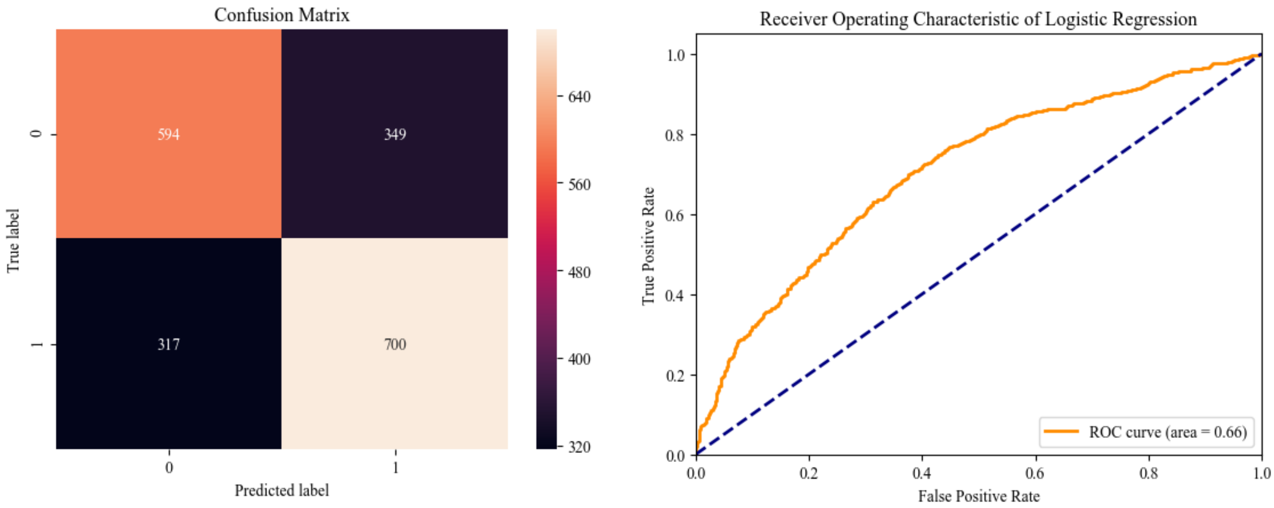
In our deep dive into tennis performance, we consulted relevant literature and discovered in a particular study that the key factors affecting tennis match outcomes were systematically divided into four core dimensions: technical, tactical, psychological, and physical[12]. These indicators were carefully selected based on their relevance and measurability, and they are presented in Table 1:

Table 1. Selection of indicators

Indicator	Symbol	Indicator	Symbol
Number of games won in current set	x_1	Whether scoring directly from a shot	x_7
Lead score in the current game	x_2	Occurrence of unforced errors	x_8
Server of the point	x_3	Ratio of net play scoring	x_9
Whether leading the opponent	x_4	Ratio of serve points opportunities to actual scores	x_{10}
Number of sets won in the match	x_5	Total running distance within the point	x_{11}
Whether scoring directly from serve	x_6	Speed of serve	x_{12}

To systematically explore the proposed indicators' impact on whether a player can win a certain point in a match and their significance, we employed a binary logistic regression analysis method for a detailed study [13].

The results are shown in the Figure 3 below:



(a) Confusion Matrix of the Model (b) ROC Curve of the Model

Figure 3. Projected Results

The left graph, Figure 3(a), is a confusion matrix, which visualizes the relationship between the predicted results of the model and the actual observations; the right graph, Figure 3(b), is the ROC curve, the higher the AUC value, the stronger the performance of the model. the results show that the AUC value of the logistic regression model reaches 0.66, F_1has a value of 0.67 and the ACC has a value of 0.61, indicating that the model has a certain predictive effect.

3.3. Results of Selection of Model

The Table 2 shows the ACC, Recall, Precision, F1 and AUC scores of the four models:

Table 2. Indicator scores for the four models

MODEL	ACC	RECALL	PRECISION	F1	AUC
MLP	0.62	0.66	0.67	0.67	0.75
LOGISTIC REGRESSION	0.61	0.64	0.64	0.67	0.71
XGBOOST	0.67	0.69	0.72	0.69	0.79
NAIVE BAYES	0.65	0.64	0.66	0.65	0.7

Across both training and testing sets, the XGBoost model demonstrates the best AUC value, followed by MLP and Logistic Regression models, while the Naive Bayes model shows the lowest AUC value. This concludes that the XGBoost model performs best in this tennis match prediction task.

The XGBoost model is chosen for predicting tennis match outcomes primarily due to its strong handling of nonlinear relationships and high-dimensional data. In tennis competitions, the elements deciding the final victory are diverse and intertwined, presenting a complex nonlinear dependency pattern. By integrating and optimizing multiple decision trees, the XGBoost algorithm can deeply mine and capture this complexity, automatically identifying key indicators significantly impacting match outcomes through its built-in feature importance evaluation mechanism. Therefore, for comprehensive analysis of multifactorial interactions, revealing core influencing variables, and enhancing prediction accuracy, we chose XGBoost as the ideal tool for constructing the predictive model.

3.4. Result of Development of GA-XGBoost Model to Capture Match Dynamics

The results indicate that when using the XGBoost algorithm with a four-fold cross-validation (K=4), an average performance metric of 0.803 was achieved across the different subsets.

The improvement in model metrics before and after optimization is evident, as illustrated in Table 3:

Table 3. Comparison of Indicators

INDICATORS	ACC	RECALL	PRECISION	F1	AUC
BEFORE	0.67	0.69	0.72	0.69	0.79
AFTER	0.76	0.73	0.74	0.71	0.81

To further validate the model, we conducted a real-time performance visualization of the classic match in the 2023 Wimbledon men's singles final, where 20-year-old Spanish rising star Carlos Alcaraz defeated 36-year-old Novak Djokovic. The model achieved an accuracy of 0.73 in its predictions. Through precise data analysis and dynamic simulation, our model not only captured the intensity of each point but also provided a highly accurate foresight of potential score changes at crucial moments for the players. This real-time performance prediction is visually demonstrated in Figure 4.

Figure 4. Real-time Performance Prediction

We visualized the p_1 players' performance, with curves of different colors representing datasets from different sets. It is noticeable that the score probabilities for certain datasets peak during specific time intervals while dropping in others. For instance, the score probability for Set 1 reached its peak between approximately 100 and 200 points, whereas the score probability for Set 3 peaked between around 150 and 250 points. This might reflect changes in the players' performance during the match or adjustments in their opponents' strategies. Furthermore, despite variations in the trends of each curve, they all to some extent reflected the players' scoring situations. For example, the score probability for Set 4 remained consistently high for most of the time, suggesting that the player exhibited relative stability throughout the match.

3.5. The Role of Momentum

One dictionary definition of momentum is “strength or force gained by motion or by a series of events. In the realm of tennis research, the concept of momentum is often understood as the "strength" or "force" accumulated by athletes or teams through a series of consecutive points, successful tactical execution, and psychological advantages. While there is some debate in academic discussions, some scholars firmly believe that momentum significantly influences game outcomes, while others argue that fluctuations in scoring during a match are more indicative of random behavior. For example, attempts have been made to quantify momentum as an indicator called "score momentum" in models proposed by Clark (2008) and in research by Taylor & Francis (2014) regarding dynamic changes in point differentials.

Specifically, it is defined as follows:

$$M(t) = \omega_1 \cdot P(t) + \omega_2 \cdot \Delta S(t) \quad (5)$$

Where M(t) represents the momentum at time point t, P(t) is the player's scoring probability at time point t, and ΔS(t) is the point differential within a specific time window before time point. ω_1 and ω_2 represent the weights of the two components.

To further explore and quantify the impact of momentum effects in tennis matches, we selected eight representative indicators to comprehensively assess the evolution of momentum. We continued to use the GA-XGBoost model and employed these eight indicators to classify point victors. The results are shown in Table 4:

Table 4. Selection of indicators

Indicator	Symbol	Indicator	Symbol
Lead score in the current game	x_1	Ratio of net play scoring	x_5
Winning the current point	x_2	Ratio of serve point opportunities to actual scores	x_6
Scoring conditions	x_3	Speed of serve	x_7
Error occurrences	x_4	Running distance for the current score	x_8

Continuing to use the GA-XGBoost model and employing the eight indicators representing momentum to classify point victors, the results are presented in Figure 5:

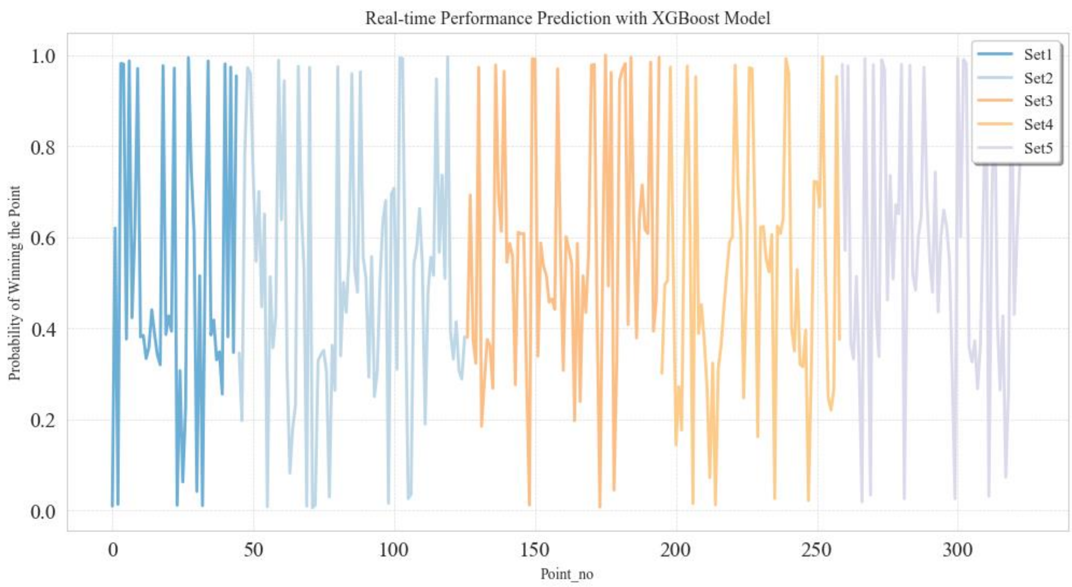


Figure 5. Real-time Performance Prediction

Table 5. Selection of indicators

ACC	RECALL	PRECISION	F1	AUC
0.80	0.76	0.85	0.79	0.88

From Figure 5, it can be observed that the curves exhibit a certain degree of fluctuation, indicating that the scoring situation of players in tennis matches is not static but varies with the progress of the game. This fluctuation may be influenced by various factors, including the players' states, opponent strategies, and match conditions. Furthermore, despite different trends in each curve, an overall pattern is evident. For instance, at certain time intervals, some datasets exhibit higher score probabilities, while at other times, they are lower. This may reflect changes in player performance during the match or adjustments in the opponent's strategies. Additionally, although the trends of the curves vary, they all to some extent reflect the players' scoring situations. This implies that momentum can be classified and used to predict scores for each point, contradicting the assertion made by the tennis coach.

As shown in Table 5, the performance metrics of the model, including accuracy (ACC), recall, precision, F1 score, and area under the curve (AUC), demonstrate the effectiveness of the selected indicators in predicting tennis match outcomes. These metrics provide a quantitative assessment of the model's ability to capture the dynamics of the game.

The Figure 6 shows the weight distribution of various indicators obtained by the GA-XGBoost model. Notably, the score situation carries the highest weight, followed by errors and running distance. Hence, these indicators can evaluate which events or behaviors in the game are strongly correlated with the match outcome. This indicates that momentum indeed has an impact on the outcome of the game and is not purely random.

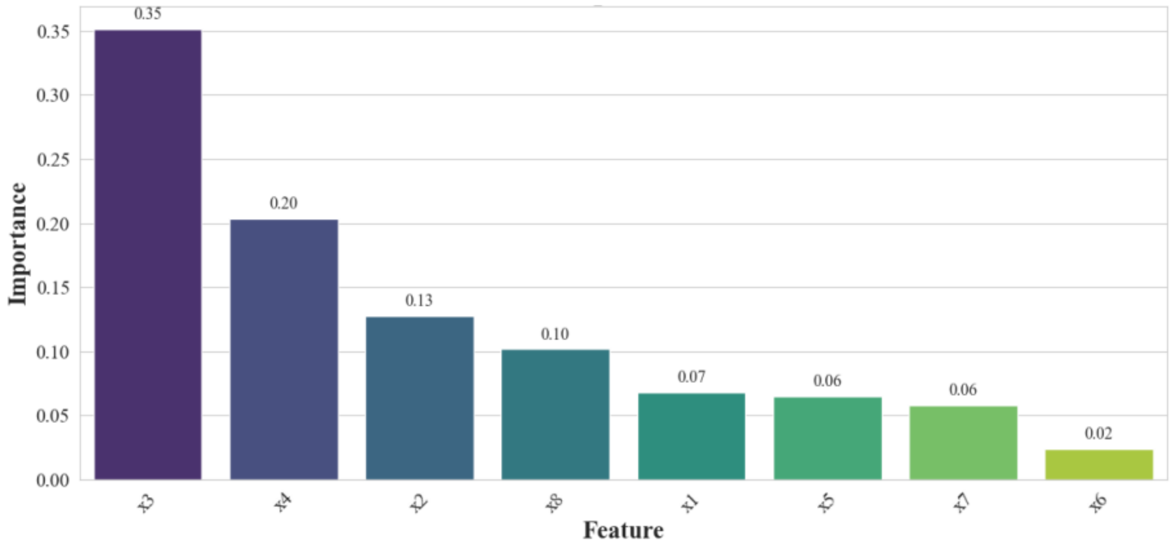


Figure 6. Feature Importance Scores

3.6. LightGBM Prediction of Match Fluctuations

3.6.1. Prediction of Match Fluctuations

Since we have confirmed that momentum significantly affects score changes during the course of a game, we can predict when the game's momentum will shift from favoring one player to another.

Firstly, we standardized these eight indicators, transforming the raw data into standardized scores with a mean of 0 and a standard deviation of 1. Based on the standardized values of each indicator and their corresponding weight coefficients, we used a weighted summation method to calculate the player's momentum score. This can be expressed as follows:

$$M(t) = \sum_{i=1, i\neq 4}^{8} \omega_i s_i - \omega_4 s_4 \tag{6}$$

Where ω_i represents the weight of the i-th indicator, and s_i represents the score of the i-th indicator.

Next, we predict fluctuations in momentum based on its changes over time in the match.

To validate the reliability of the LightGBM model, we use metrics such as MSE, RMSE, and SMAPE for model accuracy measurement. After parameter optimization, the results for each metric on the training and validation sets are presented in Table 6:

Table 6. Model Accuracy Test Results

	MSE	RMSE	MAE	R^2	SMAPE
TRAINING SET	0.0007	0.0089	0.0039	0.9910	1.5572.
TESTING SET	0.0005	0.0075	0.0046	0.9929	1.7914

Based on the metric data, we can easily conclude that the model results fit the real data well. This conclusion is also supported by the observed values in comparison with the predicted values in Figure 7:

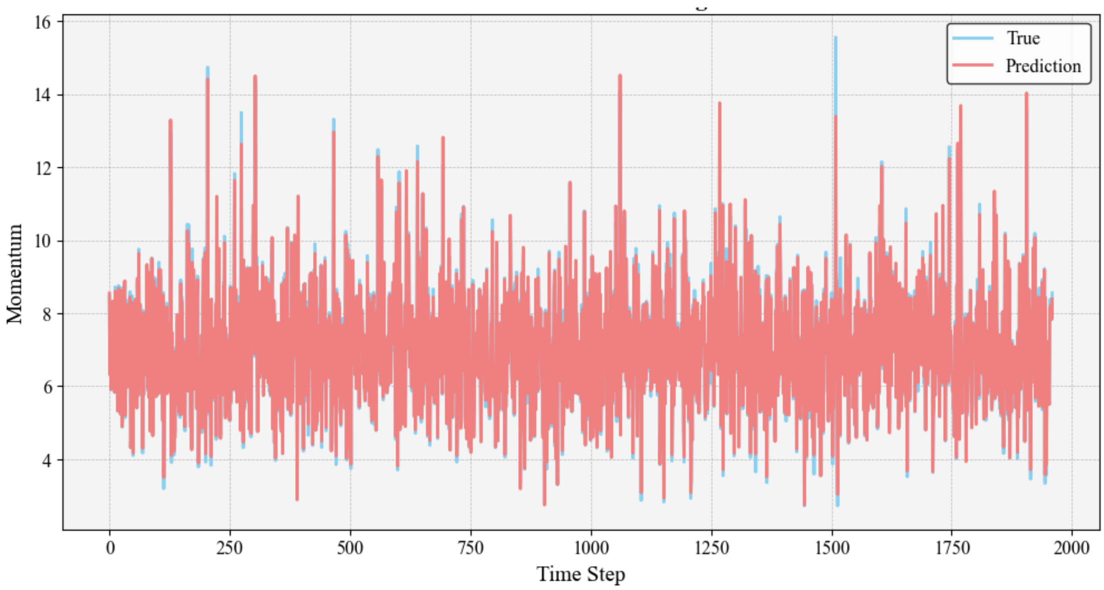


Figure 7. Momentum Prediction with LightGBM

3.6.2. Most Relevant Factors

In exploring the correlation between eight indicators and momentum to determine which factors are most related to the fluctuations in competitions, we utilize the Pearson correlation coefficient or Spearman's rank correlation coefficient to measure the magnitude of the correlation between two variables.

First, we need to assess whether the data conforms to a normal distribution. Given the large volume of data selected from the dataset, the Kolmogorov-Smirnov (K-S) test is employed:

Original hypothesis H_0: the two data distributions are consistent, or the data conforms to a theoretical distribution.

The K-S statistic D, is defined as follows:

$$D = \max | f(x) - g(x) | \tag{7}$$

If the observed value D > D (n, α), then the null hypothesis is rejected; otherwise, it is accepted.

The final results, as shown in Figure 8 and Figure 9, indicate that the data conforms to a normal distribution, hence the Pearson correlation coefficient is chosen. The results of Pearson's correlation coefficient analysis are as follows:

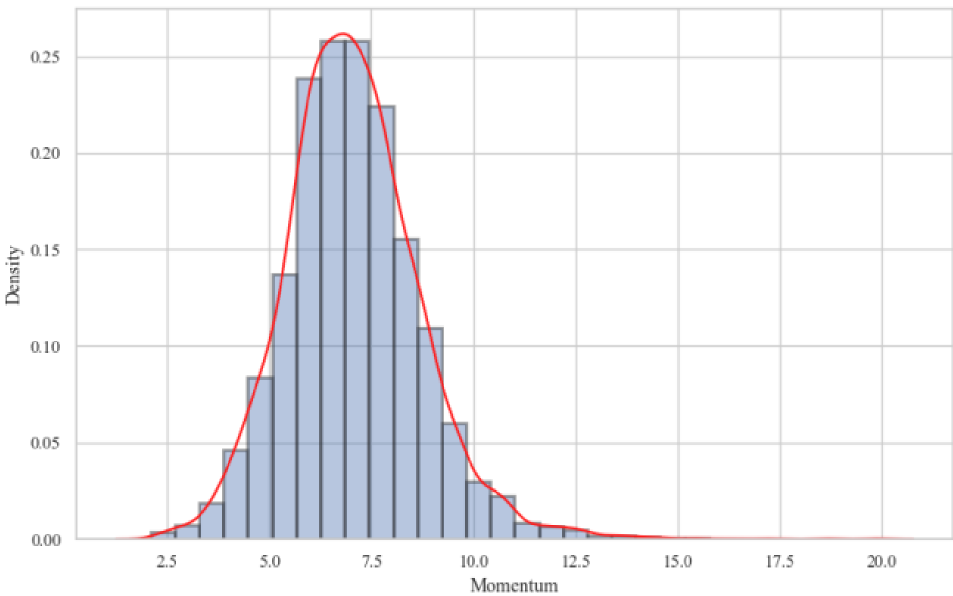


Figure 8. K-S test Results

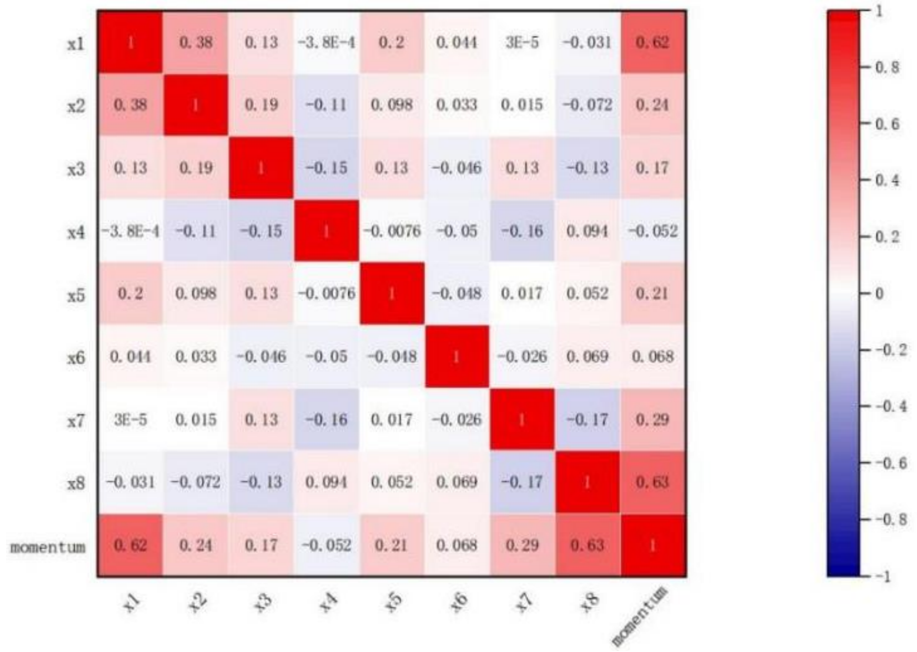


Figure 9. Correlation between Indicators

3.7. Bayesian Detection of Fluctuation Points

When advising a player on participating in a new match against another, we utilize Bayesian Change Point Analysis to conduct a deep granular analysis of the player's historical match data. The identified "change points" represent moments or conditions in the match where a performance decline may occur [11].

The detected change points in a match are illustrated in Figure 10:

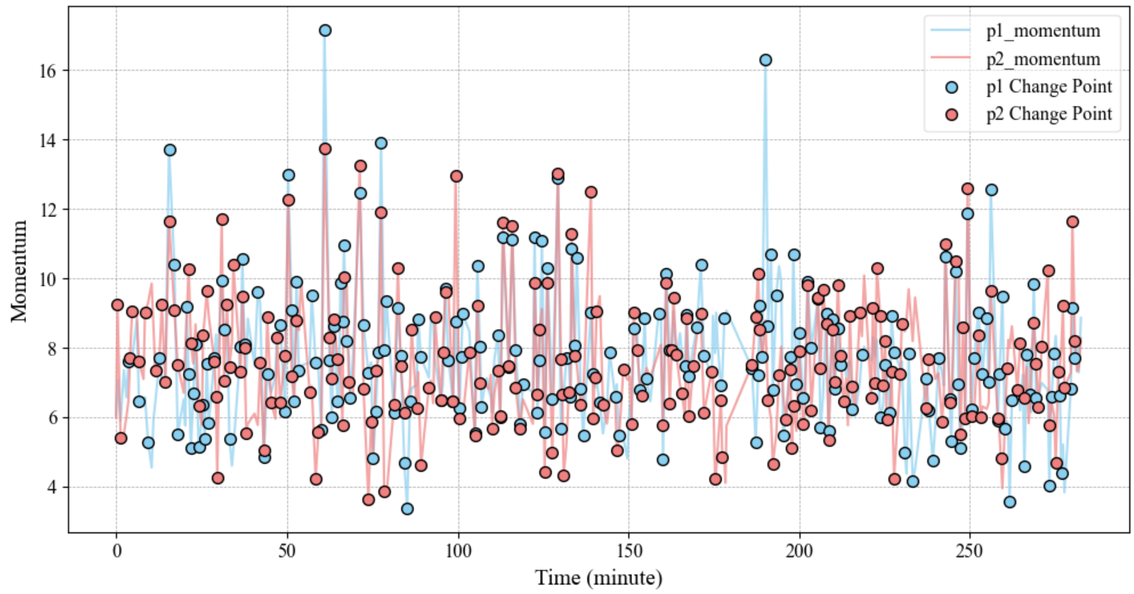


Figure 10. Momentum Changes Over Time

These "change points" changes indicate conditions under which a player may show instability. Each player has their characteristics and vulnerabilities; by analyzing match data and integrating selected indicators, reasons for instability might stem from technical skills, match strategy, mental adjustment capabilities, and physical condition. Each match is unique, with unpredictable situations, and facing different opponents may require different strategies. Before the occurrence of identified "change points," analyzing the opponent's dynamic transition patterns in past matches to adjust strategies dynamically can provide a greater advantage.

1) Technical Level

The analysis identifies key indicators (e.g., x3, x4) affecting fluctuation pointsn [2], providing insights into performance stability and suggesting strategies for optimizing key shot types and adapting tactics during critical phases of matches.

2) Mental Adjustment Capability

Indicators such as x1 and x2 highlight the importance of psychological conditioning. Our research emphasizes the development of mental resilience and timely psychological guidance as key contributions to addressing performance fluctuations.

3) Physical Condition

Indicators (e.g., x7, x8) reveal the impact of physical decline after long rallies. We propose targeted fitness enhancement strategies and game management approaches to mitigate fatigue and maintain performance consistency.

4) Match Strategy

Key indicators (e.g., x5, x6) underscore the role of strategic adjustments during matches. Our contribution lies in identifying methods to predict and address fluctuation points, optimizing playing styles, and managing match pace effectively.

4. Conclusion

This study integrates multiple algorithms and Bayesian analysis for tennis match prediction. XGBoost outperforms others in handling tennis data complexity. The GA-XGBoost model enhanced by genetic algorithm captures match dynamics well. Feature extraction reveals key influencing factors, and momentum's impact is confirmed. LightGBM predicts fluctuations accurately, and Bayesian analysis offers insights for strategies. Overall, it provides a novel framework for understanding and predicting tennis matches, beneficial for future research and practical applications.

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