Olympic Medal Prediction and Sports Strategy Planning Based on XGBoost-Bootstrap Model and Multi-criteria Decision Analysis

Yanxi Fan[1,a,*], Guowei Zhou[1,b]

[1]School of Information Engineering, Wuhan College, 333 Huangjiahu Avenue, Jiangxia District, Wuhan, Hubei Province, China

[a]3474436657@qq.com, [b]1197681144@qq.com

*Corresponding author

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Abstract: This study integrates machine learning with multi-criteria decision analysis to develop a data-driven model for Olympic medal prediction and sports strategy planning. We employed an XGBoost-Bootstrap ensemble model (R^2=0.9579, RMSE=0.2131) with eight critical features to predict medal counts. Our model forecasts that the United States will maintain its medal table dominance in 2028 (123-138 medals, 95% confidence interval), while countries like Germany will improve and Japan and France may decline. Using XGBoost classification, we predict Bangladesh, Kiribati, and Albania to win their first Olympic medals. Through Spearman's correlation and K-means++ analysis, we identified athletics and swimming as strategic priorities for most countries. The AHP-CRITIC model quantifies the "great coach" effect, recommending optimal sports investments for Brazil (basketball), South Africa (athletics), and Denmark (shooting). Our analysis reveals two key trends in Olympic medal distribution: the "Great Power Effect" and "Home Advantage Effect," providing valuable insights for national Olympic committees in resource allocation and strategic planning. The practical applications of this research extend beyond medal prediction to strategic resource allocation, helping identify high-potential sports for specific countries and quantifying coaching investment impacts for more efficient distribution of limited resources.

1. Introduction

1.1. Problem Background

The Olympic medal table represents a critical focal point for global audiences, with the distribution of medals reflecting nations' overall strength in sports. At the 2024 Paris Olympics, the United States and China competed fiercely for the top position in the gold medal count. Meanwhile, countries like France and the United Kingdom, despite winning fewer gold medals, demonstrated strong competitiveness by ranking high in total medal counts. Additionally, several smaller nations won Olympic medals for the first time, highlighting the complex and imbalanced nature of Olympic medal distribution[1]. While historical performance significantly influences medal tallies, various other factors also play important roles, including athlete rosters, event schedules, host country advantages, and the characteristics of specific sports.

1.2. Research Objectives

Based on analysis of the background data, this study aims to develop a comprehensive predictive model that addresses three key research objectives:

1) To predict medal standings for the 2028 Los Angeles Olympics with statistical confidence intervals, identifying countries likely to increase or decrease their medal counts and those expected to win their first Olympic medals.

2) To explore the relationship between different sporting events and medal outcomes for each country, identifying strategically important events and the factors that influence success.

3) To analyze the impact of the "great coach" effect on medal counts and provide strategic

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insights to help National Olympic Committees optimize their resource allocation and sports development plans.

Through these objectives, this research seeks to provide a scientific basis for predicting future Olympic performance and assist national sports organizations in making data-driven decisions for Olympic preparation.

2. Related Work

Let me synthesize this Olympic medal prediction research information into two concise paragraphs:

Olympic medal prediction research has evolved significantly, employing various analytical frameworks to understand medal distribution factors. Early approaches like Zheng and Chen's competitive advantage analysis of China's Olympic success and Gorokhov's investigation of the "home advantage" phenomenon provided valuable insights but lacked comprehensive predictive capabilities[2]. Traditional statistical methods, particularly regression models incorporating socioeconomic variables, have established baseline predictions but often fail to capture complex, non-linear relationships affecting Olympic performance.

Recent advancements have begun exploring machine learning approaches, though most studies employ single-method techniques rather than potentially more accurate ensemble approaches. The current research addresses these limitations by integrating machine learning with multi-criteria decision analysis, developing a comprehensive framework that captures both linear and non-linear relationships while incorporating quantitative data and expert knowledge. This approach extends beyond simple medal count predictions to identify emerging countries and quantify the "great coach" effect, providing Olympic committees with more actionable insights.

3. Methodology

Our methodology integrates machine learning with multi-criteria decision analysis to develop a comprehensive predictive framework for Olympic medal forecasting.

3.1. Model Assumptions and Data Preprocessing

To ensure alignment with real-world conditions while maintaining analytical tractability, we establish several key assumptions: external factors such as GDP and population do not significantly impact the results; historical medal counts accurately reflect each country’s competitive level; athletes’ performances follow typical athletic lifecycles; and medal rate, medal increment, and score variation serve as key indicators of a country’s athletic progress.

The dataset ’2025_Problem_C_Data’ required several preprocessing steps to ensure data quality. Missing values were identified and filled with zeros, countries with historical name changes were treated as the same entity, and multiple teams from the same country were consolidated into a single entity for analytical purposes.

3.2. Feature Engineering and Predictive Modeling

Based on correlation analysis and domain knowledge, we identified eight key features that significantly influence Olympic medal outcomes: Historical Performance, Number of Athletes, Number of Events, Host Country Effect, Medal Trend, Product of Athletes and Events, Degree of Olympic Participation, and Gender Distribution. Correlation analysis revealed strong relationships between total medal count, event numbers, and athlete participation, confirming their predictive importance.

We employed XGBoost (Extreme Gradient Boosting) as our primary predictive framework due to its ability to capture complex non-linear relationships and its robustness against overfitting[3]. XGBoost builds an ensemble of decision trees sequentially, with each tree trained to minimize the residual errors of previous trees. The model iteratively constructs decision trees and optimizes an objective function that combines a loss function with a regularization term to enhance performance while preventing overfitting.

To generate confidence intervals for our predictions, we implemented the Bootstrap method, enabling the construction of 95% confidence intervals for medal predictions. For predicting countries likely to win their first Olympic medals, we developed an XGBoost classification model with modified features appropriate for countries without previous medal history.

3.3. Advanced Analytical Techniques

To identify relationships between different events and medal outcomes, we employed Spearman's rank correlation coefficient and implemented the K-means++ algorithm to cluster Olympic events into three categories: dominant events, weak events, and potential dominant events. K-means++ enhances traditional K-means clustering by optimizing the initial selection of cluster centers, improving clustering quality and convergence.

To quantify the "great coach" effect, we developed an integrated approach combining the Analytic Hierarchy Process (AHP) with the CRiteria Importance Through Intercriteria Correlation (CRITIC) method[4]. This framework evaluates coach contributions based on three key metrics: Medal Rate (efficiency), Medal Increment (performance improvement), and Score Change Rate (overall performance fluctuation). The combined AHP-CRITIC approach provides objective weighting based on contrast intensity and correlations between criteria, resulting in a balanced and comprehensive evaluation framework for assessing coaching impact on Olympic performance.

4. Results

4.1. Olympic Medal Predictions for 2028

Our XGBoost-Bootstrap ensemble model predicts the United States will lead the 2028 Los Angeles Olympics with 131 total medals (49 gold), followed by China with 92 medals (38 gold). Great Britain and Australia are expected to secure third and fourth positions with 60 and 48 medals respectively, while Japan, Germany, and other nations complete the top 10 rankings with varying medal distributions, as shown in Figure 1.

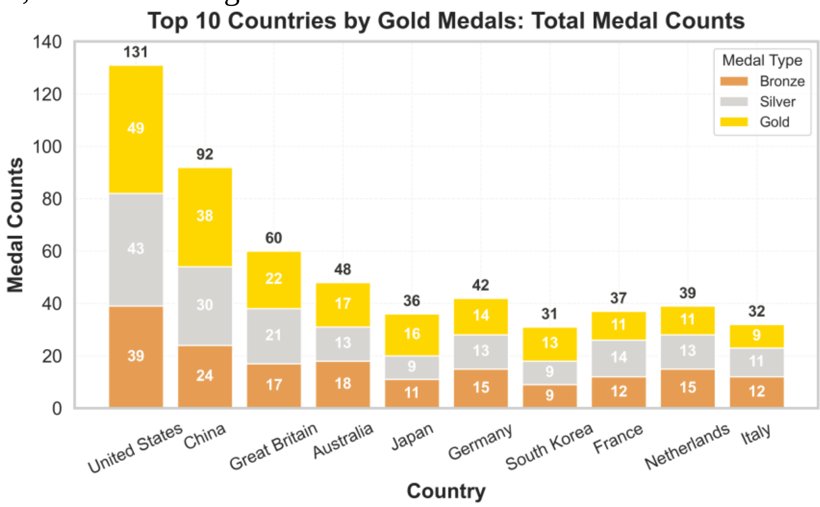

Figure 1 Medal Counts of the Top 10 Countries by Gold Medals (2028).

Comparing 2024 and 2028 projections, the United States and Germany should show significant improvements, while Japan, France, and Italy may experience declines[5]. We've established prediction intervals at 95%, 90%, and 85% confidence levels for the top 10 countries as shown in Table 1, providing statistical support for our forecasts while acknowledging the inherent uncertainty in Olympic performance prediction.

Table 1 presents the prediction intervals for total medals for the top 10 countries, providing statistical confidence in our forecasts[8].

Prediction Intervals for Total Medals by Country.

Table 1 Prediction Intervals for Total Medals by Country

Country	95% CI	90% CI	85% CI
United States	123-138	125-136	126-135
China	86-98	88-96	89-95
Great Britain	55-65	56-64	57-63
Australia	45-52	46-51	46-50
Japan	43-49	44-48	44-47

4.2. First-Time Medal Winners

Our XGBoost classification model identified three countries expected to win their first Olympic medals at the 2028 Los Angeles Games: Bangladesh, Kiribati, and Albania, with odds of 4.43, 3.17, and 3.80, respectively. Table 2 presents the predicted probabilities and odds for these countries.

Predicted Probability and Odds for First-Time Medal Winners

Table 2 Predicted Probability and Odds for First-Time Medal Winners

Country	Probability	Odds
Bangladesh	0.816	4.43
Kiribati	0.760	3.17
Albania	0.791	3.80

4.3. Event Analysis and Strategic Priorities

Using Spearman correlation analysis and K-means++ clustering, we identified the relationship between different events and medal outcomes. The illustration demonstrates the relationship between sporting disciplines and medal tallies, showing that most nations achieve their greatest Olympic success in athletics, swimming, and shooting events[6].

A focused analysis of select countries revealed different strategic priorities: for the United States, athletics, swimming, and wrestling are key events; for China, gymnastics, diving, and shooting are critical; for France, fencing, cycling, and athletics stand out; and for Germany, athletics, canoeing, and swimming are strategically important.

4.4. The “Great Coach” Effect

Our AHP-CRITIC model measured the influence of elite coaches on Olympic success. As illustrated in Figure 2, this relationship is evident through case studies of Lang Ping and Béla Károly, whose coaching tenures corresponded with significant improvements in medal achievements.

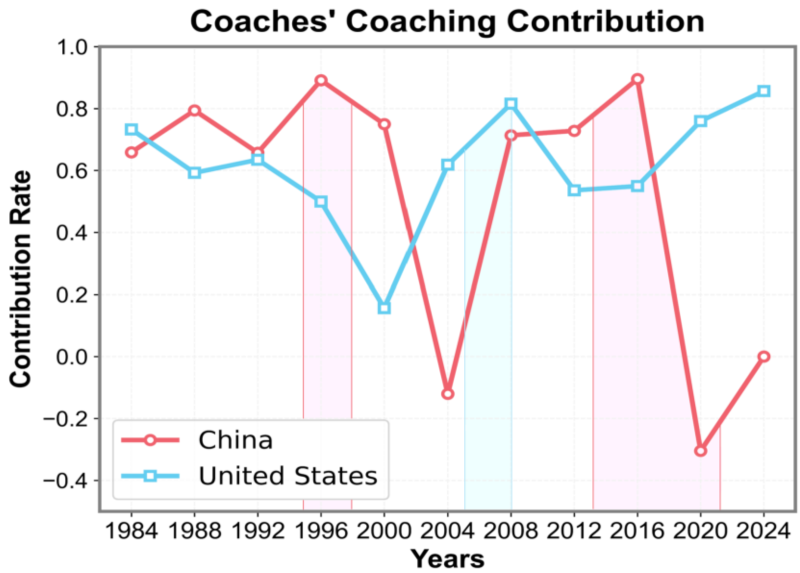

Figure 2 Coaching contributions in China and the U.S., highlighting home advantage in Olympic performance.

Based on our model, we identified optimal sports for coach investment in three countries: basketball for Brazil (score 1.618), athletics for South Africa (score 1.276), and shooting for Denmark (score 1.864). These recommendations provide data-driven guidance for sports investment decisions.

4.5. Medal Distribution Patterns

Our analysis revealed two key trends in Olympic medal distribution:

1) Great Power Effect: The United States and China consistently maintain dominance in the medal tally, with their counts significantly higher than other countries. This reflects the Matthew Effect, where strong nations continue to strengthen their advantage.

2) Home Advantage Effect: Host nations typically experience a significant increase in medal counts, followed by a gradual decline in subsequent Olympics. This pattern highlights the importance of long-term strategic planning for countries hosting the Games[7].

These findings suggest that smaller nations should focus on niche or emerging sports rather than competing directly with major powers, while countries should view hosting the Olympics as a long-term investment opportunity.

5. Conclusion

This study developed an integrated machine learning and multi-criteria decision analysis framework to predict Olympic medal outcomes and provide strategic insights for National Olympic Committees. Our XGBoost-Bootstrap ensemble model achieved high predictive accuracy ($R^2 = 0.9579$, RMSE$= 0.2131$), enabling reliable forecasts of medal counts for the 2028 Los Angeles Olympics and beyond. The model successfully identified three countries—Bangladesh, Kiribati, and Albania—likely to win their first Olympic medals, and quantified the significant impact of the "great coach" effect on medal performance.

Key findings include the identification of two fundamental patterns in Olympic medal distribution: the "Great Power Effect," where dominant nations maintain their advantages, and the "Home Advantage Effect," which provides host countries with significant but time-limited benefits. These patterns offer strategic guidance for countries at different development stages in the global sports hierarchy. Major powers should maintain their advantages in traditional stronghold events while exploring emerging opportunities, while smaller nations should focus on niche or emerging sports where they can develop competitive advantages.

The practical applications of our model extend beyond medal prediction to strategic resource allocation. By identifying high-potential sports for specific countries and quantifying the impact of coaching investments, our framework enables more efficient distribution of limited resources. The model provides particularly valuable insights for developing nations seeking to maximize their Olympic performance despite resource constraints.

Beyond the Olympics, our methodology can be adapted to other major sporting events such as World Championships and regional competitions. The approach can also assess the popularity and development potential of various sports in different regions, providing comprehensive support for sports governance and development policies worldwide.

Future research could enhance this framework by incorporating additional variables such as athlete-specific data, funding allocations, and technological innovations in training. Extending the time horizon of predictions and developing more sophisticated methods to capture the inherent uncertainty in sports outcomes would further improve the model’s practical utility. As international sports competition continues to evolve, data-driven approaches like the one presented in this study will become increasingly valuable for strategic planning and resource optimization in Olympic preparation.

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