Abstract

Utilizing data spanning from 2013 to 2023 from a diverse range of sources, this research employs data scraping, cleaning, exploratory data analysis (EDA), and modeling to identify the optimal Men's and Women's Teams and Individual USA Olympic Artistic Gymnasts for the 2024 Olympic Games. The term "best" is defined as maximizing the total medal count in artistic gymnastics for the United States. The study integrates machine learning models, combinatorial optimization algorithms, and advanced data analysis techniques. Initial phases focus on predicting individual apparatus outcomes using binary classification, with evaluation based on key metrics such as accuracy, precision, recall, F1-Score, and F2-Score. During my investigation into team selection optimization, mixed-integer linear programming was a recurring theme. However, my research diverges from the norm as I embrace a novel approach that leverages Metaheuristics Algorithms, specifically Randomized Heuristic, Tabu Search, and Variable Neighborhood Search (VNS). Grounded in data analysis and algorithmic decision-making, the research strategically positions Team USA to maximize their medal count in the Paris 2024 Olympics.

1. Introduction

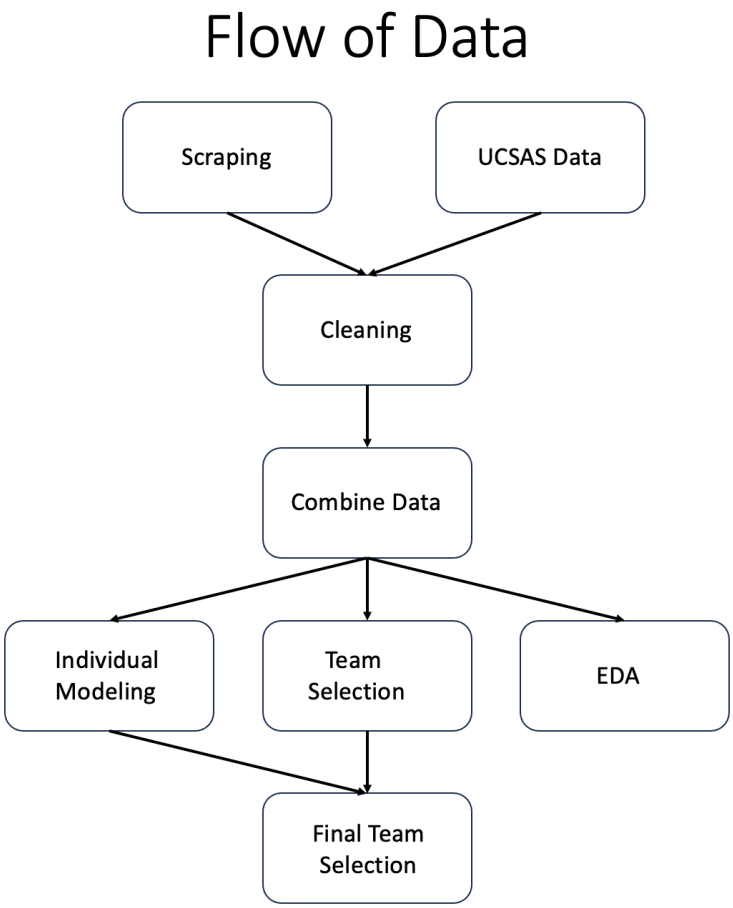
This research focuses on selecting the optimal Men's and Women's USA Olympic Artistic Gymnastics teams for the Paris 2024 Olympics, aiming to position Team USA for maximum medal count. The challenge involves identifying exceptional athletes for each team, considering both individual and team event success. Leveraging advanced analytics models, this study forecasts and compares medal counts, providing a data-driven foundation for strategic decision-making in the 2024 Olympic Games.

To determine the "best" gymnasts, baseline models for individual apparatus outcomes are established, with the ZeroR algorithm as a foundational benchmark. Various machine learning models, including Random Forest Classifier, AdaBoost Classifier, Support Vector Classifier (SVC), K Neighbors Classifier, Decision Tree Classifier, Gaussian Naïve Bayes, and Neural Networks, comprehensively assess individual gymnasts' performance and influencing factors.

Optimal team selection involves navigating complexities with optimization algorithms such as Randomized Heuristics, Stochastic Control, Tabu Search, Variable Neighborhood Search, and Brute Force. These algorithms play a pivotal role in optimizing team selection to maximize point totals.

Based on a diverse dataset spanning 2015 to 2023 from reputable platforms like Thegymter.net, Wikipedia.org, and the UConn Sports Analytics Symposium 2024, the study integrates machine learning models, optimization algorithms, and comprehensive data analysis. The goal is to provide Team USA with a strategic advantage to maximize their medal count in the Paris 2024 Olympics.

2. Data Collection and Preprocessing



2.1. Data Sources

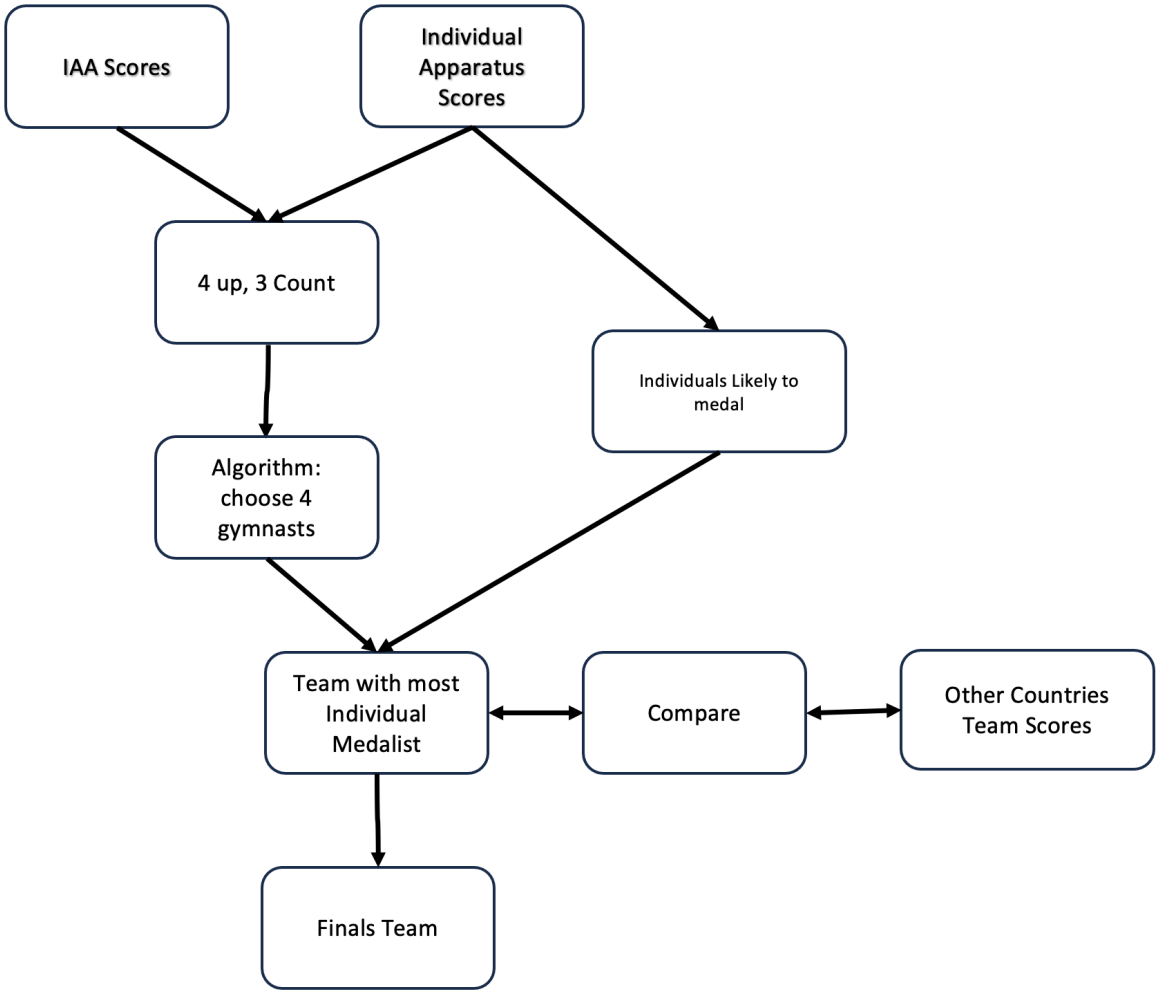
This research derives its data from reputable platforms such as Thegymter.net, UCSAS 2024 USOPC Data Challenge, and Wikipedia.org. The dataset spans from 2013 to 2023, focusing primarily on international competitions like world cups, world championships, and the Olympics. Key data includes individual scores, overall performances, event rankings, athlete details, and various scores (execution, difficulty, penalties). Due to time constraints, the primary emphasis in data collection lies on the years 2023 and 2022, resulting in a substantial dataset, albeit one that may not be as exhaustive as ideal.

2.2. Data Preprocessing Steps

The data preprocessing stage is crucial for ensuring dataset integrity and usability. In the 'Scraping' directory, web scraping code generates CSV files of raw data. The 'Cleaning' directory addresses tasks like filling/removing missing values and standardizing column names. The 'Combine Data' directory facilitates the integration of information from diverse competitions for each event, offering a comprehensive perspective. Acknowledging dataset imbalances, especially in the minority class, poses challenges. Therefore, Robust models for imbalanced datasets will be employed to ensure fair and accurate

representation across classes. These preprocessing steps transform raw data into a clean, structured, and uniform dataset for accurate and insightful analysis.

3. Methodology



3.1. Individual

3.1.1. Models

Various machine learning models were utilized to predict individual apparatus outcomes. Notable models include the Random Forest Classifier, AdaBoost Classifier, Support Vector Classifier (SVC), K-Neighbors Classifier, Decision Tree Classifier, Gaussian Naïve Bayes, and Neural Networks.

3.1.2. Hyperparameter Tuning

To optimize model performance, a Grid Search approach was employed for hyperparameter tuning. This systematic method explored predefined hyperparameter spaces to enhance model effectiveness.

3.1.3. Cross-validation Strategies

Holdout validation and k-folds cross-validation were employed. Holdout validation divided the dataset into training and validation sets, while k-folds cross-validation involved dividing samples into equal-sized folds for training and testing.

3.1.4. Base Model

The ZeroR classifier, a simple method predicting the majority class, served as a baseline for comparing other classification methods.

3.1.5. Confusion Matrix

Utilized for performance evaluation, the confusion matrix provided insights into accuracy, precision, F1-Score, and F2-Score, crucial for assessing model proficiency.

These comprehensive evaluation metrics provide a robust analysis of the individual machine learning models' performance in predicting gymnastics outcomes.

3.2. Team

In the process of team selection, two distinct datasets were employed. The initial dataset prioritized comprehensive all-around scores, while the second dataset focused on individual apparatus scores for USA gymnasts.

3.2.1. Qualification Round

The qualification round uses 4 up 3 counts, where four athletes will compete on each apparatus. The cumulative total of the three highest scores on each apparatus determines the advancing teams. Several algorithms were used with the same goal in mind; to get the three highest scores from four gymnasts.

3.2.1.1. Men's team selection

Tabu Search, Randomized Heuristic, and Variable Neighborhood Search algorithms were used, incorporating data from 2022 to 2023. In case of multiple entries, the maximum score was chosen, capturing each gymnast's optimal potential.

3.2.1.2. Women's team selection

Tabu Search, Randomized Heuristic, Variable Neighborhood Search, and Brute Force algorithms were used with datasets from 2022 to 2023. For multiple entries, the mean score was used for Team USA, ensuring reliability in assessing each gymnast's performance. In case of multiple entries for other countries, the maximum score was chosen, capturing each gymnast's optimal potential. While it may appear unfair, the forthcoming observation will demonstrate that Team USA simply outperforms all other countries by a

significant margin. (The maximum scores for Team USA were initially employed, establishing a significant lead of over 4.5 points ahead of the second-place contender.)

3.2.2. Finals

A 3 up 3 count structure in the finals involves three gymnasts per apparatus, with cumulative scores contributing to the final team score. Selection criteria were based on Individual All-Around (IAA) scores, concurrently considering the inclusion of potential individual medalists in the final roster.

4. Evaluation and Results

4.1. Individual Apparatus Evaluation and Results

This analysis draws upon historical data encompassing Men's and Women's international gymnastics competitions. The models for Women were trained on data spanning from 2013 to 2021, while the models for Men were trained on a more limited timeframe from 2018 to 2020, due to time constraints. The evaluation of the models involves the utilization of unseen data from the years 2022 and 2023 for inference.

4.2. Model Performance Metrics

For each apparatus, the data was run through the various models (3.1.1.), and their accuracy, precision, F1-scores, and F2-scores were compared. Once the best model was selected, judged by its accuracy and F2-score, it was optimized using grid search for parameter tuning. From there the data was scrutinized with feature importance. Although the option of feature scaling was contemplated, the utilization of AdaBoost and Random Forest classifiers for binary classification demonstrated resilience to fluctuations in feature scales. As a result, explicit scaling was deemed unnecessary in the analytical process. The models underwent additional iterations to evaluate the potential for improvements.

In addition to accuracy, I also evaluated the classifiers based on the F2-score metric. The F2-score considers both precision and recall, with a higher weight given to recall. It measures the overall effectiveness of the classifier in selecting top gymnasts while minimizing false negatives.

The findings indicate that, across various gymnastics events, both the Random Forest and AdaBoost classifiers consistently demonstrated high accuracy. Moreover, both classifiers consistently attained elevated F2-scores, emphasizing their proficiency in accurately identifying top performers.

In summary, the Random Forest and AdaBoost classifiers consistently demonstrated high accuracy and F2-scores in the selection process for Team USA gymnasts. These findings highlight the effectiveness of these classifiers in accurately identifying the top gymnasts while minimizing false negatives. The results provide valuable insights for improving the selection process and ensuring the inclusion of the most deserving gymnasts in Team USA.

4.3. Individuals likely to Medal

The gymnasts identified in the preceding models are deemed probable contenders for securing medals on behalf of Team USA. It is essential to note that the models were designed with a primary focus on minimizing false negatives rather than false positives. Consequently, there exists a likelihood that certain gymnasts identified in the following list may not necessarily be destined to secure a medal.

4.3.1. Women

Apparatus	Gymnast
Balance Beam	Simone Biles
Balance Beam	Joscelyn Roberson
Vault	Simone Biles
Uneven Bars	Shilese Jones
Uneven Bars	Zoe Miller
IAA	Jordan Chiles
Floor	Simone Biles
Floor	Ashlee Sullivan

4.3.2. Men

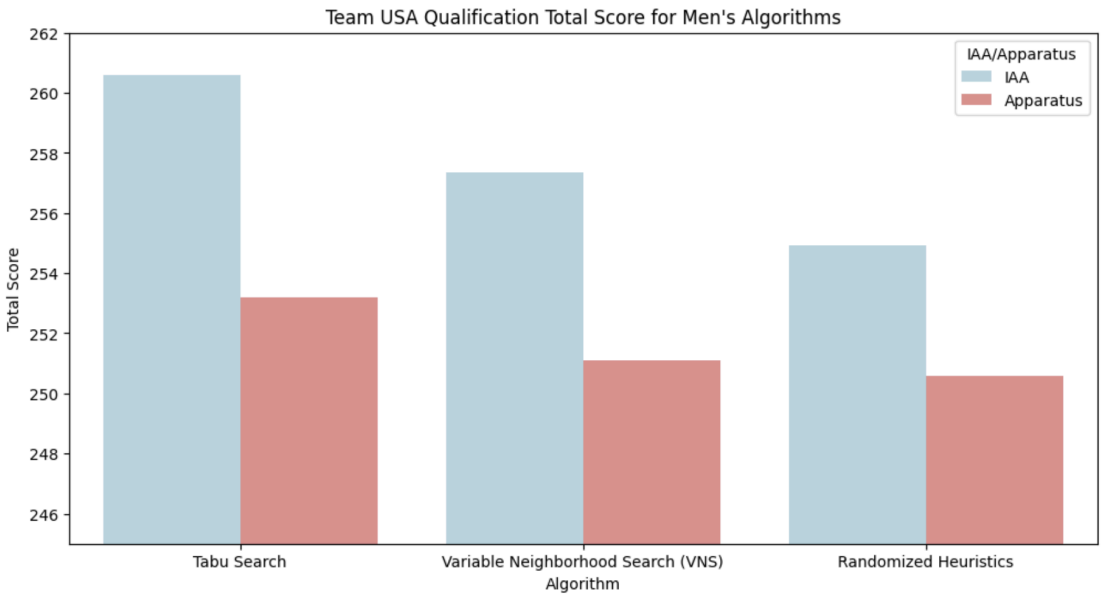
Apparatus	Gymnast
Parallel Bars	Yul Moldauer

4.4. Team Evaluation and Results

Initially, the algorithms were implemented with data sets containing all American women or men from the data scraped from international events. This resulted in optimized teams for the men and women. The implementation of individual event modeling led to the inclusion of gymnasts who were not part of the initially selected teams. This necessitated the adoption of different approaches for forming the Men's and Women's teams.

4.4.1. Men’s Team Evaluation and Results

The top-performing algorithms for men’s team selection were Tabu Search and Variable Neighborhood Search (VNS), consistently favoring Individual All-around (IAA) data sets. Tabu Search, particularly with IAA Scores, emerged as the highest-scoring algorithm.



(Note that the y-axis does not initiate at zero for improved visibility of nuances in high-scoring algorithmic predictions.)

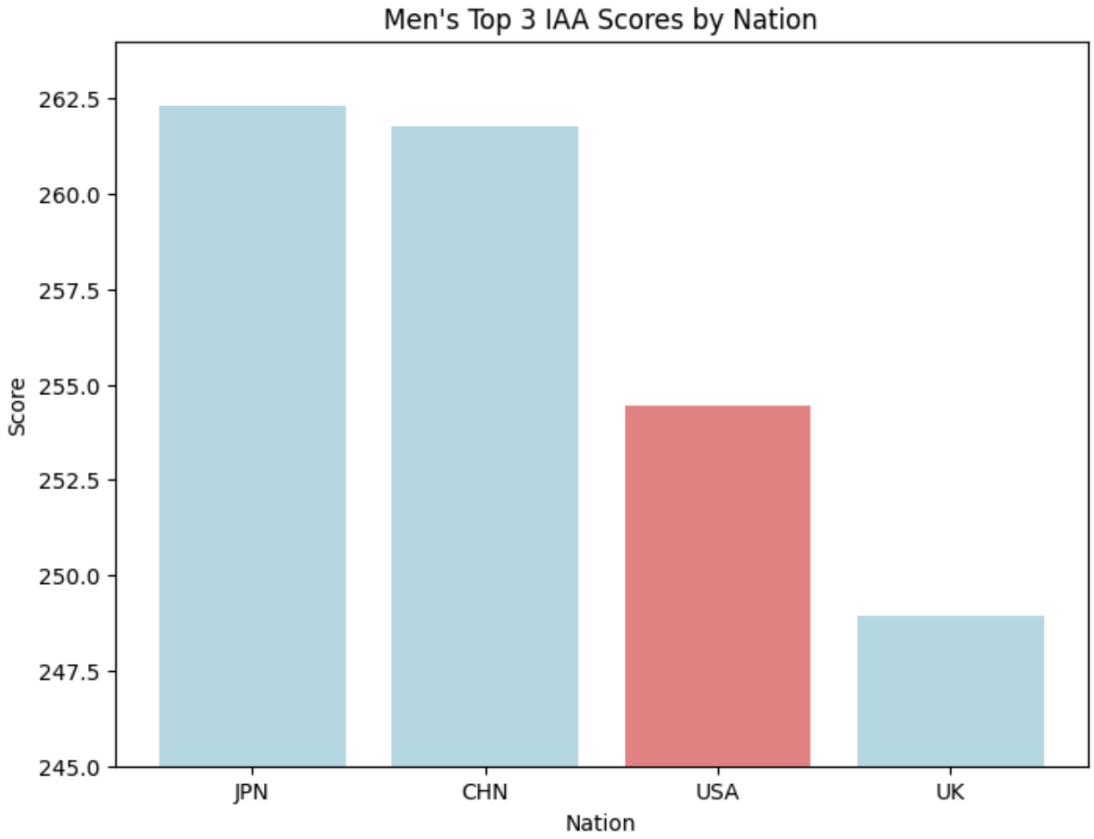
The initial phase involves evaluating the likelihood of Team USA securing a medal in the team competition and identifying the gymnasts pivotal to the team's success. Subsequent stages of analysis focus on pinpointing individual gymnasts with the highest probability of medaling in specific individual events. The investigation identified one gymnast expected to excel in individual apparatus events, and this gymnast was already included in our team selection.

The algorithms for team selection were extended to other nations showcasing convincing performance for team USA in the qualification round for the 2024 Olympics. This extension provides a valuable framework for predicting scores among top-performing nations, aiding in the selection of gymnasts for Team USA. The main goal was to optimize the individual medal potential of gymnasts while ensuring the overall success of the team.

The men's team selection process began by the algorithms choosing four athletes— Khoi Young, Asher Hong, Fred Richard, and Yul Moldauer—for the qualification round, yielding a combined score of approximately 260.579, which should pass the qualifying rounds to the finals. The only gymnast with the potential to medal in individual events is Moldauer, who is already selected for the team. From here we have a space for Colt Walker, who boasted the second highest IAA score among Americans at 85.00. The team of Walker, Moldauer, and Richards could potentially score 254.992 in the final round. These scores were then compared with other top

Olympic-qualified countries, including Japan, China, the United Kingdom, Switzerland, and Germany.

(Germany and Switzerland scores were below 245, and not in the following chart)

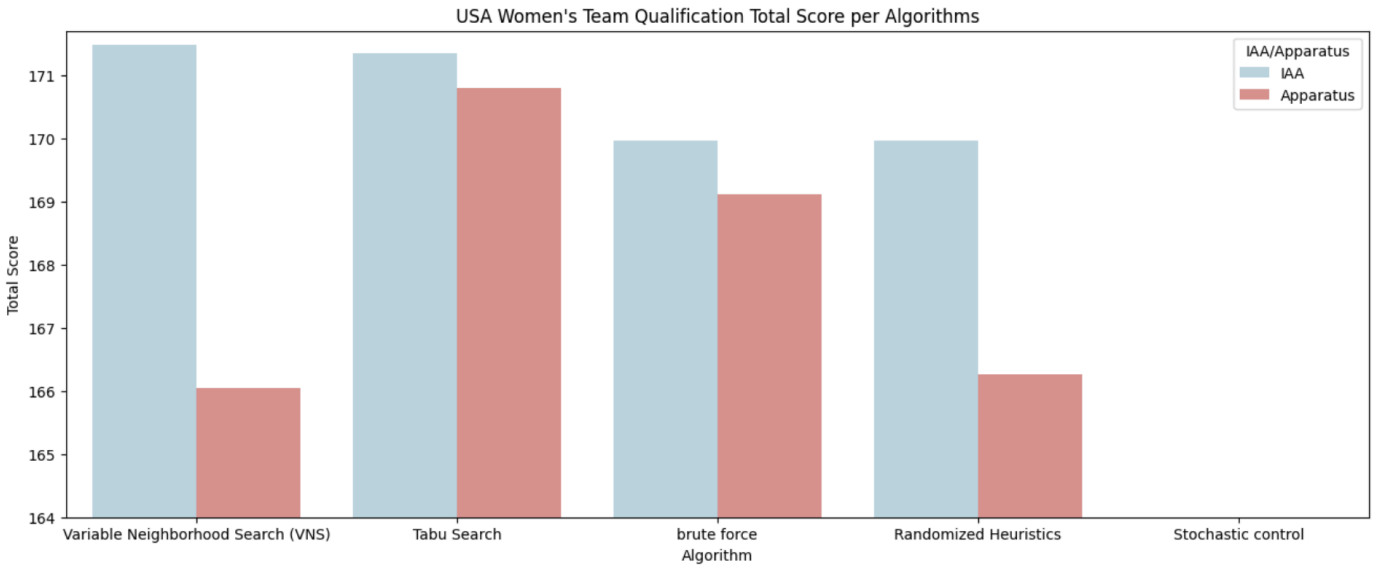


(Note that the y-axis does not begin at zero to emphasize variations in the upper range of scores.)

Above we can see that Team USA should potentially medal in the 2024 Olympics.

4.4.2. Women's Team Evaluation and Results

The comparative evaluation of diverse algorithms across the IAA and Apparatus data sets provided nuanced insights into their respective performances in finding the highest scoring USA team. Tabu Search and Variable Neighborhood Search (VNS) algorithms demonstrated the highest scores, with the advantage leaning towards data sets using IAA scores. Specifically, the VNS algorithm stood out as the top-performer.



(Note that the y-axis does not initiate at zero to provide a more detailed view of the performance distinctions between the algorithms.)

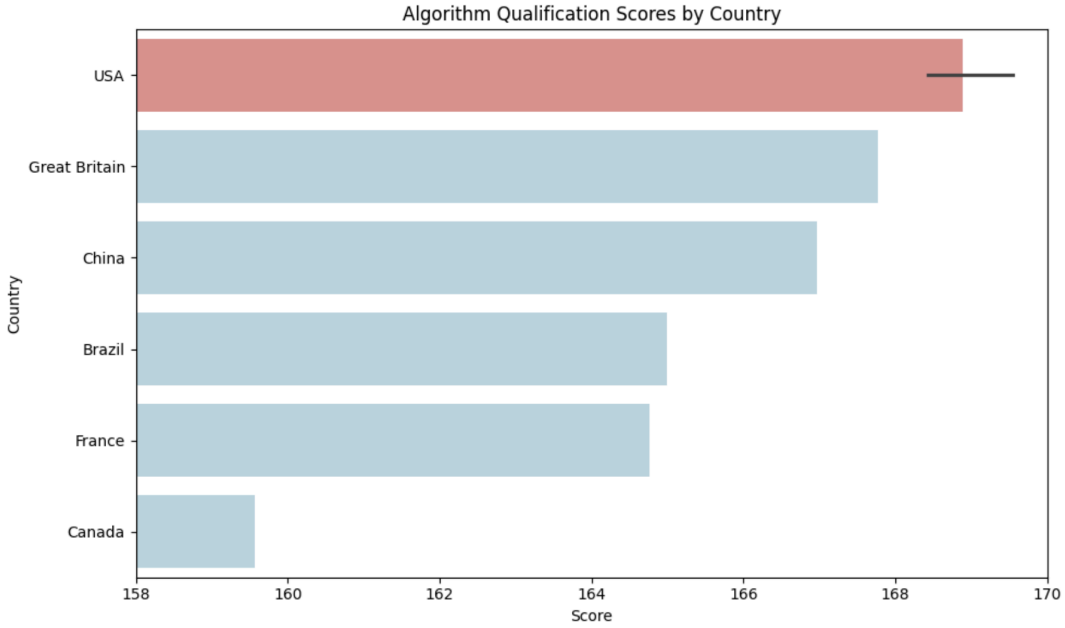
The initial step involves determining the likelihood of Team USA medaling in the team competition and identifying the gymnasts for the team. Subsequent stages include identifying individual gymnasts most likely to medal on specific apparatus. Analysis revealed several gymnasts likely to medal on individual apparatus, some of whom may not align with the predicted Team USA lineup.

The team selection algorithms were applied to other countries that performed well in team qualification for the 2024 Olympics, providing a guideline for estimating the scores of top-performing nations. This information assisted in the selection of gymnasts for Team USA, enhancing the potential for individual medals while ensuring the overall success of the team.\

The initially optimized women's team was examined with the goal of achieving a medal. Further data exploration and modeling were conducted due to the consideration of both the team's likelihood of winning a medal and the potential for six different women to possibly earn individual medals. To maximize medals, the women's team should include Simone Biles, predicted to win three individual medals, as well as four of the five remaining women predicted to potentially medal.

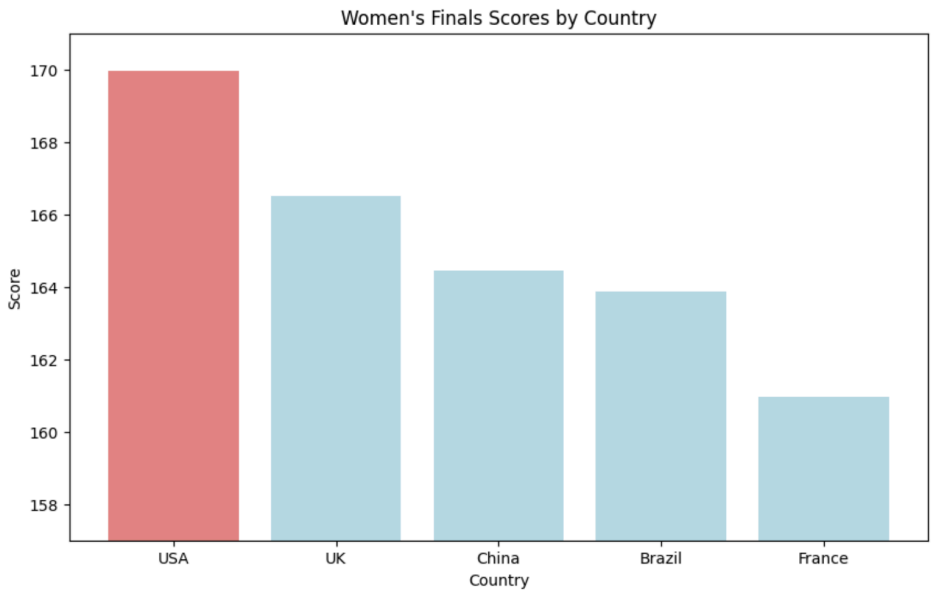
The algorithms were employed to select four gymnasts from the six potential medalists for qualifying. Team scores were compared with those of other top countries: Great Britain, China, Brazil, France, and Canada. In multiple scenarios, Simone Biles and Shilese Jones were consistently chosen, with Jordan Chiles being selected seven times. The graph below illustrates Team

USA is likely to pass the qualifying round easily, regardless of which two of the remaining three gymnasts are chosen. Consequently, Team USA should consist of Simone Biles, Shilese Jones, and Jordan Chiles, who should also compete in the final round, along with any two of Ashlee Sullivan, Joscelyn Roberson, or Zoe Miller. In the chart below the error bar for Team USA illustrates the range of scores associated with different team compositions.



(Note: x-axis does not commence at zero for a more detailed representation of differences in performance among nations.)

The Women's Team is predicted to have a phenomenal 2024 Olympics with a potential gold medal in the team competition. Below is a graph showing their predicted score in the finals compared to other top nations. The significance is heightened when considering that the scores for the listed countries represent the top scores of each gymnast from the past two years, while Team USA's scores are derived from the mean values of their performances.



(Note that the y-axis does not begin at zero for a closer examination of score differences among top countries.)

5. Conclusion

5.1. Findings

The exhaustive exploration of data scraping, cleaning, exploratory data analysis (EDA), and modeling has unveiled significant insights into the performance dynamics of both Men's and Women's USA Olympic Artistic Gymnastics teams for the upcoming 2024 Paris Olympics. My operational definition of "best," emphasizing the maximization of the total medal count, has guided a meticulous investigation across individual apparatus outcomes, team compositions, and strategic positioning for Team USA.

In terms of individual events, a diverse collection of machine learning models, encompassing Random Forest Classifier, AdaBoost Classifier, Support Vector Classifier, among others, showcased nuanced performances across various gymnastic disciplines. Results underscored the effectiveness of the Random Forest and AdaBoost classifiers, consistently displaying high accuracy and F2-scores, affirming their robustness in the intricate process of selecting top-performing gymnasts. These models demonstrated both reliability in identifying winners and adaptability to handle inherent imbalances within gymnastics datasets.

On the men's side, the optimization algorithms, including Tabu Search, Randomized Heuristic, and Variable Neighborhood Search, contributed valuable insights into the complexities of team composition. Results indicated that Tabu Search and Variable Neighborhood Search (VNS) algorithms, particularly when utilizing Individual All-Around (IAA) scores, emerged as the highest-scoring algorithms. These findings provide a comprehensive understanding of the intricate decision-making

processes involved in the selection of gymnasts for the Men's Team USA.

Meanwhile, the evaluation of the Women's Team revealed a potential gymnastics powerhouse for the 2024 Olympics, projecting an impressive total of eight medals. This includes both individual accolades and team achievements. The combination of individual gymnast predictions and team dynamics highlighted the multidimensional nature of gymnastics performance, showcasing the prowess of athletes like Simone Biles, Shilese Jones, and Jordan Chiles, among others.

5.2. Limitations

It is imperative to acknowledge the inherent constraints and limitations that accompany the study. This section aims to transparently specify the boundaries and potential sources of bias within the analysis, providing a nuanced perspective on the scope and applicability of the findings.

This study does not consider the impact of injuries, or the physical toll associated with participating in numerous events within a condensed time frame. Omitting these factors may limit the comprehensive understanding of athletes' capabilities, as injuries and physical fatigue can significantly influence performance outcomes.

The complexity of team sports, such as gymnastics, extends beyond individual performances. This analysis does not account for the dynamics of team cohesion, which plays a crucial role in team-based events.

The study employed historical data for Men's and Women's gymnastics, with Women's models trained on a dataset spanning from 2013 to 2021 and Men's models trained on a dataset from 2018 to 2020. Including data from the 2016 and 2020 Olympics provided a comprehensive testing ground. However, the discrepancy, resulting from time constraints, in the time span of data collection for Men's and Women's models should not introduce bias, but is noteworthy to mention.

5.3. Future Research

Conducting a more fine-grained analysis of individual features that contribute to gymnastic performance could refine the models. Investigating specific skills, techniques, or routine components and their impact on outcomes could lead to more targeted and actionable insights for athletes and coaches. Having a data set not only with the athlete’s name, scores, penalties, and dates, but also which skills were performed and at what point in their performance, as well as noting combinations of skills and in which order.