From Stats to Scores: Analyzing NBA Game Outcomes with Random Forest and QDA

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1. Introduction

For this project, we conducted an in-depth analysis of the 2023-24 NBA Dataset provided to us. The NBA Dataset is an organization by a team of game statistics for each match during the 2023-24 season. Our objective was to test different models to predict the outcome of each game based on historical data. The dataset included 21 possible predictors, including minutes played, points scored, field goals (made, attempted, and percentage), three-point field goals (made, attempted, and percentage), free throws (made, attempted, and percentage), rebounds, assists, steals, blocks, etc.

We used feature engineering before testing our models with Quantitative Discriminant Analysis (QDA) and Random Forest. With our selected features, Random Forest performed the best with a testing accuracy of 78%. In this paper, we provide a detailed breakdown of our analysis, including data preprocessing, experimental setup, and results and analysis.

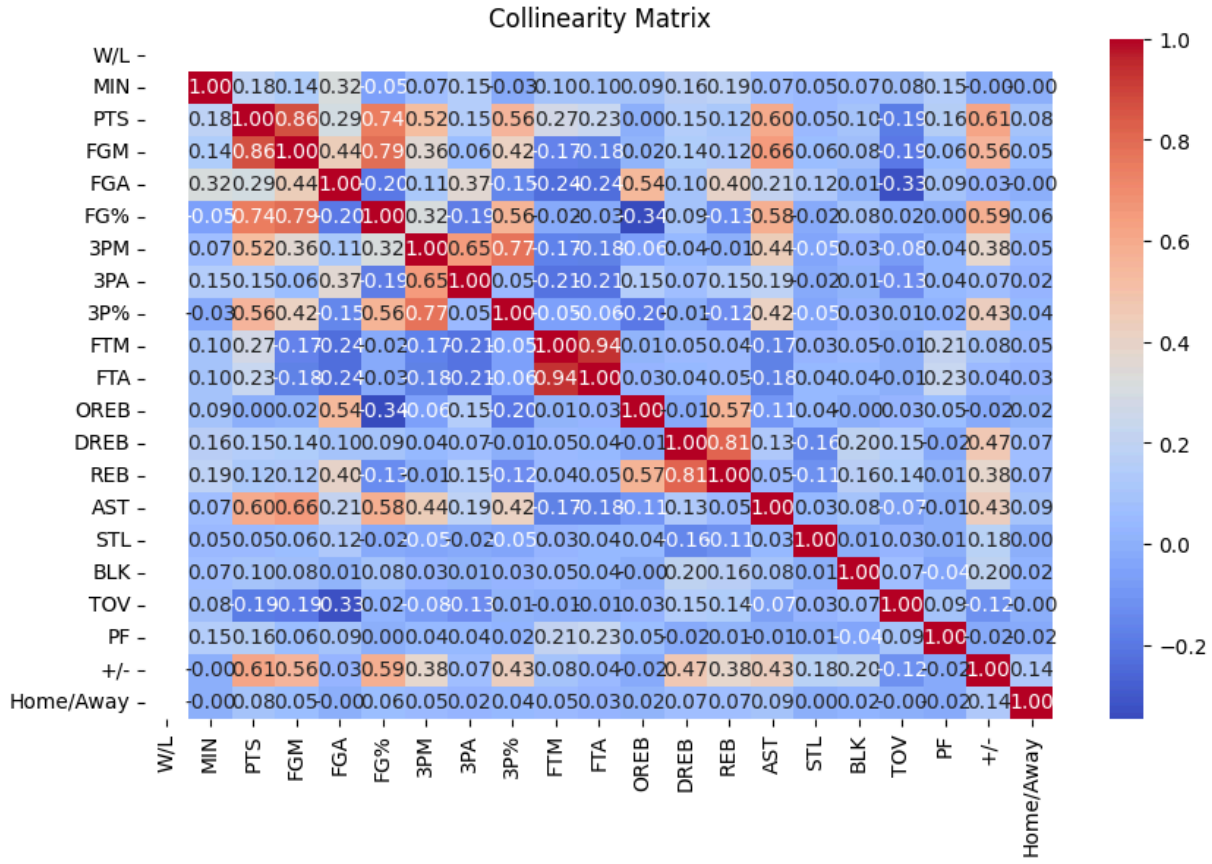
2. Exploratory Data Analysis

2.1 Dataset Description

The dataset contains a total of 2,460 entries split between 24 columns. There are 3 categorical variables and 21 numerical variables. The target column, the W/L column, is categorical. Since we are predicting wins or losses, regression models will only work as they are designed for

continuous numerical variables. As a result, we chose to use classification models during our analysis. Both QDA and Random Forest are suitable for our data. Random Forest is able to handle both categorical and numerical variables making it a good choice for our model. Although QDA uses numerical data, we are able to preprocess our data to convert categorical columns into numerical, and its ability to capture nonlinear relationships between features makes it a good fit for our data where interactions between statistics are more complex.

2.2 Collinearity Matrix



We created a heatmap to display the correlations between the numerical variables in the data. In it, we observe a strong positive correlation between OREB and REB and between FGM and PTS. We also can see moderate positive correlations between FG% and PTS, FG% and FGM,

FGM and FG%, and 3P% and 3PM. These correlations are natural because the more offense rebounds a team has, the more total rebounds they will have. The same applies to any field goal, points, and three-point statistics as they all depend on points scored during the game. In order to get rid of collinear predictors, we made sure to use a step-by-step variable selection, leaving us with all significant predictors.

2.3 Observation Split

We chose to use a 70-30 split for the data using 70% for the training dataset and 30% for the testing dataset. We found one missing variable in the dataset in the FT% column that led to the removal of one entry. This comes out to 1721 training entries and 738 testing entries.

3. Data Preprocessing

Before we could train our models, we needed to take the necessary steps to prepare our data. We chose to make new features from the existing data, creating rolling averages for each game statistic. After finding the averages, we also constructed a separate dataset featuring the differences between the rolling averages. This was followed by selecting the significant variables that we would use to train the models and assigning weights to certain game statistics. When training our models we decided to assign higher weights to game statistics based on how recently they occurred previous to the match being considered.

3.1 Data Cleaning

Before we could do any feature engineering or analysis, we first had to clean our dataset to make sure it would work for the methods we were using. First, we checked for missing data and

removed any rows that contained NA variables. Next, we converted the Win/Loss column to binary variables using 1 to represent a win and 0 to represent a loss. Similarly, we created a new column of binary variables to signify whether or not the match was a home or an away game for the corresponding team. For this column, 1 represents a home game and 0 represents an away game. Each of these steps was crucial to preventing errors when doing our analysis and ensuring our results would not be skewed in any way by the dataset.

3.2 Rolling Averages

In order to predict the outcome of the game, it is best to only look at data from before the match we are trying to predict. For this reason, we chose to use the rolling averages for each game statistic in our analysis. The rolling averages represent the average of each statistic from all of their season games prior to the match date.

3.3 Differences

After creating the rolling averages, we created a separate dataset of the differences in the averaged game statistics. Taking the difference in the rolling averages between the team and their opponent allowed us to compare the performances of both teams leading up to the game. Rather than analyzing each team's averages separately, this information highlights the strengths and weaknesses of each team relative to their opponent. Using the differences in our analysis allows our model to take into account the interplay between the recent trends of both team improving its ability to recognize key factors that affect the outcome of a match.

4. Experimental Setup

We evaluated the models through two main approaches: Quadratic Discriminant Analysis (QDA) and Random Forest.

- **QDA**: We decided to use QDA to leverage its ability to create flexible decision boundaries by assuming a joint normal probability distribution for each class. We trained the model on the training dataset and evaluated its performance on the test set using accuracy, a confusion matrix, and a classification report.
- **Random Forest**: Random forest is a method that constructs estimates from random subsets of the data based upon the majority vote of the trees for classification. We split the dataset into 70% training and 30% testing subsets and evaluated the model using accuracy and classification metrics.

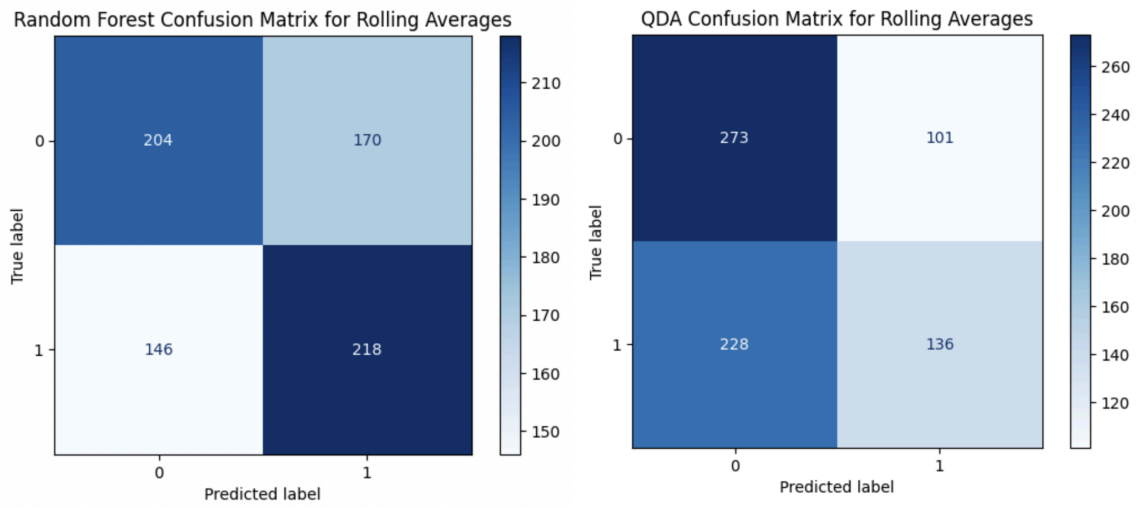
5. Results and Analysis

To evaluate the effectiveness of our predictive models, we have implemented and compared two approaches: QDA and Random Forest. We assessed these models through three different datasets that are derived from our feature engineering process: rolling averages, weighted rolling averages, and difference-based rolling averages.

5.1 Rolling Averages

The first dataset we tested focused on rolling averages of the game statistics from the game. This approach has aimed to capture trends in team performances by averaging all of the metrics from the previous games up to the games that are ready to be predicted.

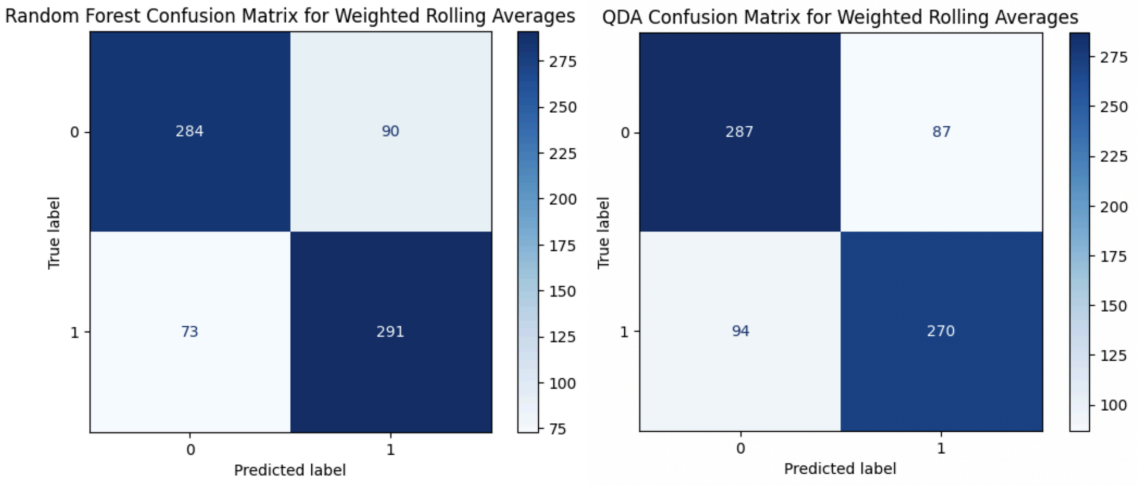
- Random Forest has achieved an accuracy of approximately 59%. This is only slightly outperforming the guessing and has suggested that simple rolling averages from the dataset itself are not sufficiently enough to account for the complexity of the game
- QDA has resulted in a similar accuracy of around 57% in which it slightly underperformed compared to the random forest. This might be cause that QDA is more effective for datasets that contain Gaussian distribution. The inherent non-linearity and interactions in basketball would perhaps make it less suitable.



5.2 Weighted Rolling Averages

To improve the prediction from the random forests, we have developed weighted rolling averages. This average will prioritize more recent games by assigning a higher weight to their statistics. This adjustment has quickly demonstrated the fact that recent performance is more indicative of the team's winning probability compared to the older games which are less applicable.

- Random forests have performed significantly better with this dataset with an accuracy of around 78%. This improvement from the original 59% has demonstrated its prediction power.
- QDA on the other hand has also shown improvement from 57% to 75%. However, it did not surpass the prediction accuracy for Random Forest once again.

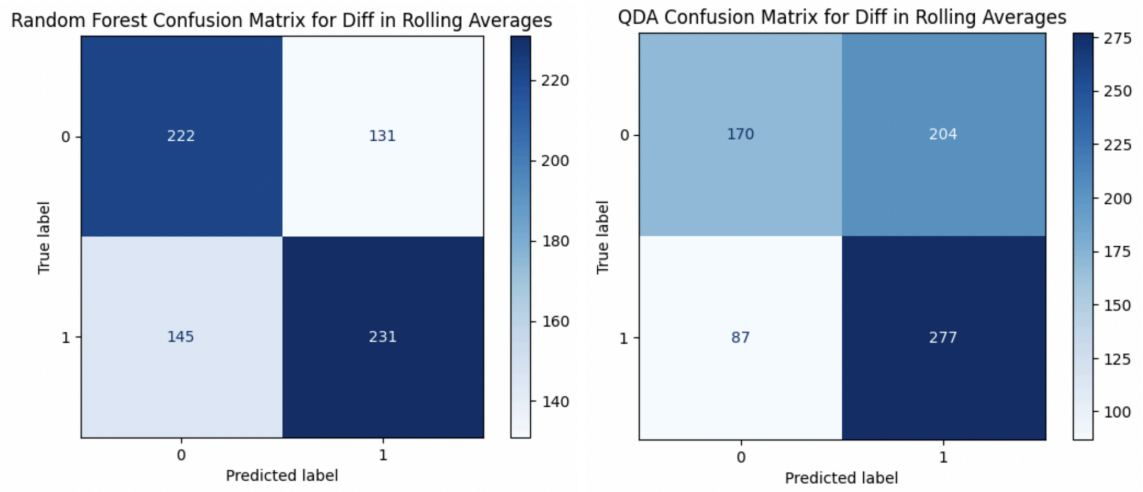


5.3 Difference-Based Rolling Averages

We continue to explore the dataset using differences in rolling averages. This approach will account for the relative performances of a team compared to its opponent by taking the differences between their respective rolling averages. By focusing more on the interplay between teams, we hope to find out whether or not the performance of the team compared to each other will matter in their success.

- With this dataset, the Random Forest model has achieved an accuracy of 62%, a drop compared to weighted rolling but a rise compared to the rolling average.

- QDA achieved an accuracy of 59%, once again underperforming Random Forest. However, compared to the rolling averages, it has slightly improved from 57% but it is still hard to say whether or not 2% is a huge increase.



5.4 Comparison of Models

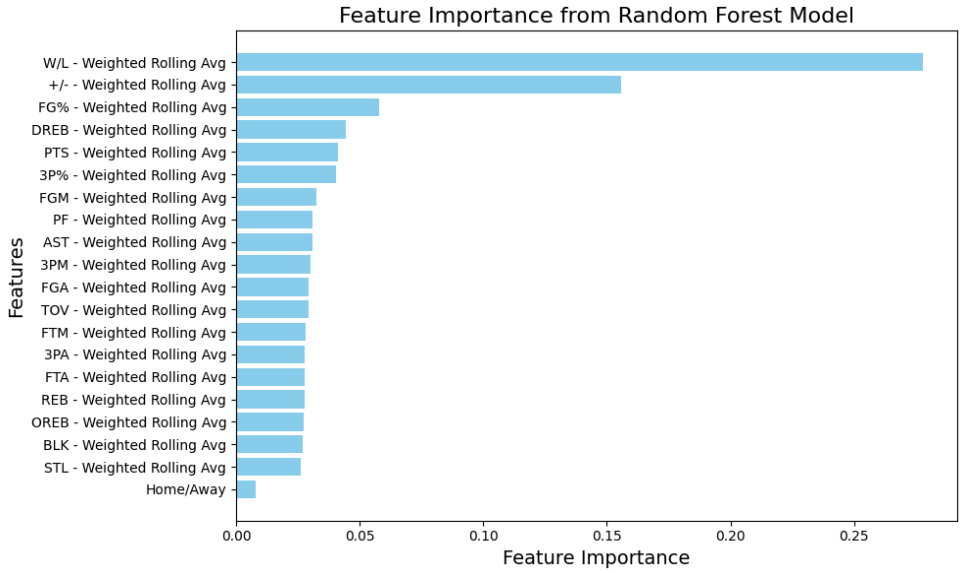
From our analysis, we can see the Random Forest model has been consistently outperforming QDA through all three datasets which makes sense because it has more versatility and the ability to model complex relationships in data.

Dataset	**Random Forest Accuracy**	**QDA Accuracy**
Rolling Averages	59%	57%
Weighted Rolling Averages	78%	75%
Difference-Based Rolling Avg	62%	59%

It is also important to note that by weighing the data, we can see the change of accuracy significantly. This could be because of the constant change in rosters in the NBA team.

5.5 Feature Importance

Lastly, to conclude our research, we have performed feature importance through forward selection in which W/L - Weighted Rolling Avg, DREB - Weighted Rolling Avg, and 3PA - Weighted Rolling Avg were the most significant variables that influenced the dataset.



Comparing this to the feature importance from the full random forest model we notice that the weighted rolling average of W/L remains the top predictor of which team wins the match. The second and third predictors from the chart, +/- and FG% are not selected when using forward selection, most likely because of multicollinearity.

6. Conclusion

6.1 Model Limitations

From our models, we found that the weighted rolling average of wins/losses, defensive rebounds, and three-point average influenced the winner of an NBA match the most, with the weighted rolling average of wins/losses being the most influential out of the three. This conclusion is not surprising as it's natural that a team with more wins leading up to a game will win that match. Because of the limited dataset from only one season, we still would not have a great way to predict, for example, a game in 2025 between Indiana and Washington.

6.2 Unexpected Discoveries

In all of our different datasets, we kept the home (1) and away (0) columns, yet as a predictor it was never significant. This goes against the common belief that the home team has an advantage. Perhaps, the advantage that a team has playing at home does not outweigh the teams' statistics often enough to produce significant results.