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Data Analysis on Predicting the Top 12 Fantasy Football Players by Position

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Abstract. Fantasy football enthusiasts rely on rankings populated by their platform of choice to draft winning teams and make strategic roster decisions. This study presents a comprehensive analysis of player performance data to forecast the top 12 fantasy points performers per position for the upcoming season. Leveraging machine learning techniques and historical data, our model identifies key performance indicators and trends to inform player evaluations. Insights gleaned from positional trends, breakout candidates, risk assessment, and matchup analysis offer a competitive edge. By addressing limitations, ethical considerations, and avenues for future research, this study contributes to the advancement of fantasy sports analysis and enhances fan engagement with the NFL and other professional leagues.

1 Introduction

Fantasy football is a game where participants can manage the football lineups and play one on one. This started roughly 50 years ago using pencil and paper (Shipman, 2009). The process of fantasy football is to build our team through drafting, which is where participants select one player at a time until the roster is complete. Our main goal for this research is to determine the top 12 fantasy football players for each position for the upcoming season. For each position in fantasy football (Quarterback, Running Back, Wide Receiver, Tight End, Defense, and Kicker), they comprise a rank of each player, essentially predicting the total number of points scored by that player and creating a descending list of the totals. The points are determined by the player's real-life performance in the game. So, the player who is projected to score the most points that season would be the number one ranked player for that position. However, this ranking never ends up being accurate as at the end of the season we find that the actual ranking contains players that outperformed their projected totals by Yahoo or vice versa. Relying on their preseason rankings is not the best idea. It would be best to find a way to more accurately predict a ranking that can outperform competitors who are relying on Yahoo's predictions.

Fantasy football is important to investigate because there is real money on the line and it has become important to fans. It has gained revenue of billions of dollars in the past years (Becker & Sun, 2016). At the end of the day, fantasy football is mostly played to win money. Fantasy football can be played by everyone including individuals and companies. It can also have its own set of rules for points. There are huge fantasy football leagues that participants have played in such as Yahoo, Inc. and ESPN, Inc. If a person can give themselves a competitive edge over the competition, this would allow them to leverage this advantage to win more money. Fantasy football is easily manageable due to the lineup being changed weekly within a 17-game season for each team as well as most games being played on the same day. Rankings are created by fantasy experts based on historical data and statistics. These rankings are refined through a combination of domain knowledge and analytical methods.

For this research, there are two ideas that can be used to predict the players rankings. One of the ideas is to determine the features of importance. Using both domain knowledge as well as feature selection methods, there will need to uncover what important statistics play into a player's future success. This will also include information about health as well as pure football statistics. There are many factors that play into a player's performance such as their coaching staff, training staff, salary, and overall team. The other idea is to figure out a way to understand and interpret college player's statistics so that it can be used to assess their future success in the NFL.

The goal of this research is to use both domain knowledge, as well as feature selection methodologies to determine what statistics, both football and health, will give the best picture of a player's future success. A methodology will be established to predict the performance of each player based on various metrics for the upcoming season, which spans 17 games. These predictions will then be used to determine the top 12 fantasy football players in the 2024 season per position. Participants can then decide in what order they will draft their players in fantasy football based on rankings derived by our methodology.

2 Literature Review

2.1 Types of Fantasy Football Leagues

There are various types of fantasy football leagues such as draft, draft only, best ball, custom scoring, dynasty/keeper, guillotine, auction league, and superflex league (Smola, 2024). The most common type of league is draft league. This league is where participants create their new lineup (waiver wire and trades included) by drafting on a yearly basis to compete against their friends, company, etc (Smola, 2024). Drafting works on a random turn-based system where a participant can have first pick, second pick, etc. In round 2, the turns are opposite of round 1 where for example, the participant with the first pick will pick last. Round 3 repeats what was initially done in round 1. Another type of league is the draft only league which is similar to the regular draft league except there are no weekly roster moves, management, and trading involved (Smola, 2024). Participants have to solely rely on their draft picks. The best ball league is where winning participants are determined by the highest scoring players in the lineup, whether the players are on the fantasy team's starting lineup or on the bench (Smola, 2024). The custom scoring league is where the fantasy football league owner can set their own scoring rules for each position (Smola, 2024). For example, a quarterback throwing a touchdown pass can be set to be worth 6 points rather than 4 points. For the dynasty league, participating players retain their current roster for however many years the owner of the league sets (Smola, 2024). The Keeper league is very similar to the dynasty league except the participating players can retain a certain number of players from the previous season based on the set rules (Smola, 2024). The down side of the keeper league is that participants will be losing a draft pick to retain a player of their choosing. An emerging type of league is guillotine league. In this league, the participant with the overall lowest score is eliminated each week until there is only one fantasy player remaining (Smola, 2024). The eliminated participant's fantasy players would be placed back into the waiver pool for the remaining participants to pick from. The draft league is one way to create a team, but the auction league is completely opposite where participants will have to bid fictional dollars on players (Smola, 2024). Similar to real auctions, the highest bidder wins the player. Finally for the superflex league, there is a position in the fantasy lineup called "flex player" where participants can choose an extra running back, wide receiver, or tight end (Smola, 2024).

In the dynamic world of fantasy football, the scoring rule set serves as the guiding framework that transforms on-field actions into tangible fantasy points. Our scoring system is meticulously crafted to encapsulate the nuances of player performance across various positions, providing fantasy football enthusiasts with a comprehensive and engaging gameplay experience.

At the heart of our scoring rule set lies the composition of each team's starting lineup, carefully structured to encompass a diverse array of offensive and defensive talent. Quarterbacks (QB), the architects of on-field strategy, earn significant points for touchdown passes, with each successful throw garnering 6 points. Additionally, quarterbacks accrue 1 point for every 25 passing yards, while interceptions and fumbles result in a deduction of 2 points each. Notably, quarterbacks also receive 1 point for every 10 rushing yards gained, adding a dynamic dimension to their scoring potential.

Running backs (RB), wide receivers (WR), and tight ends (TE) collectively form the backbone of offensive production in fantasy football. These versatile players earn 6 points for every touchdown scored, whether through rushing or receiving. Moreover, the yardage gained by these players is duly rewarded, with 1 point awarded for every 10 rushing or receiving yards. Notably, catches by wide receivers and tight ends are valued at 1 point each, underscoring the importance of receptions in fantasy football scoring.

The flex position offers strategic flexibility to team managers, allowing them to deploy an additional running back, wide receiver, or tight end based on matchup advantages and roster depth. Points accrued by players in the flex position are calculated based on their respective scoring metrics, ensuring equitable scoring opportunities across all eligible positions.

In addition to offensive players, our scoring rule set also encompasses team defenses and kickers. Defenses earn points for defensive touchdowns, sacks, and interceptions, while kickers are rewarded for successful field goals and extra points converted.

In conclusion, our scoring rule set for fantasy football is designed to mirror the excitement and unpredictability of real-life NFL action. By meticulously defining the point allocation for each position and incorporating nuanced scoring metrics, we aim to provide fantasy football enthusiasts with an immersive and rewarding experience, fostering strategic decision-making and competitive gameplay.

2.2 NFL Data Science

The NFL players statistics are collected based on position and how the players perform against other teams, whether they are offensive players, defensive players, or special teams players on a weekly and yearly basis. Quarterback statistics are collected based on pass attempts, pass completion, yards (air or rushing), touchdowns (passing or rushing), interceptions, and fumbles (total amount and amount lost). Running back statistics are collected based on rushing attempts, yards (rushing or receiving), touchdowns (rushing or receiving), and fumbles. Wide receiver and tight end statistics are collected based on catches, yards, touchdowns, and fumbles. Whereas defense statistics are collected by team and individual players, fantasy football is collected only by team. In fantasy football, this statistic consists of yards allowed, touchdowns (allowed and returned), sacks, punt returns, kickoff returns, punt blocks, field goal blocks, and turnovers. Kicker statistics are collected based on field goals made, field goal attempts, yard ranges kicked, and blocked field goals.

NFL statistics are very important because it determines the outcome of a player and team performance. There are many factors that come into performances such as the team's coaches, training staff, and injuries. NFL statistics can outline a player or team strengths and weaknesses (Khanacademy, n.d.). For example, a team's defense can be ranked 32nd for allowing the most amount of yards per game. It allows teams to have a comprehensive view of their opponents.

2.3 Feature Selection

In constructing our predictive models, we underwent a thorough process of feature selection to encapsulate the intricate dynamics of player performance in fantasy football. Drawing from a rich dataset comprising fifty distinct statistics for each player, our models embraced an extensive array of season-to-date features. The term "season-to-date" signifies the computation of a rolling average for each statistic up to, but excluding, the current week's game. This methodology facilitated the incorporation of past performance metrics as predictors of future player performance. Noteworthy statistics integrated into the model encompass passing yards, passing touchdowns, interceptions thrown, rushing yards, receptions, and fumbles lost. (Porter, *Predictive Analytics for Fantasy Football: Predicting Player Performance Across the NFL* 2018) In tandem with season-to-date features, we incorporated game-specific characteristics to augment predictive accuracy. Binary indicator variables were devised to capture pivotal attributes of each game, including whether the player competed at home or away. We recognized the potential influence of home-field advantage on player performance, thus deeming it essential for inclusion in our models. (Porter, *Predictive Analytics for Fantasy Football: Predicting Player Performance Across the NFL* 2018) Moreover, dummy variables were formulated to account for the offensive inclination of the player's team, acknowledging that team strategies and dynamics can significantly impact individual player performance. Lastly, dummy variables for the player's opponent were integrated into the model, reflecting the caliber of the opposing team, which in turn can influence player scoring potential. (Baak, *Fantasy Football*

Profitability: Using Machine Learning to Construct Optimal Teams and See Consistent Returns 2021)

Through meticulous feature selection, our objective was to fashion models that adeptly capture the multifaceted nature of fantasy football performance, encompassing both player-specific metrics and contextual game characteristics. By amalgamating a diverse range of predictors, our models strive to furnish robust and actionable insights for fantasy football aficionados, facilitating informed decision-making in draft selections and lineup management. (Lutz, *Fantasy Football Prediction* 2015)

2.4 Applying Football Analysis to Fantasy Football

Fantasy football analytics is a burgeoning field that integrates various methodologies to predict player performance and guide strategic decision-making within the realm of fantasy sports. This review synthesizes key studies from diverse perspectives to offer a comprehensive understanding of the methodologies and insights shaping fantasy football analytics.

David et al. (2011) conducted a seminal study exploring the application of committees of artificial neural networks to predict NFL outcomes. By leveraging ensemble methods, the researchers demonstrated notable improvements in prediction accuracy, highlighting the efficacy of sophisticated modeling techniques in fantasy football analysis. Their findings underscore the importance of employing advanced computational methods to enhance predictive capabilities in fantasy football analytics.

Shipman (2009) delved into the theoretical underpinnings of fantasy sports, presenting the model of blending real and virtual elements in gaming experiences. This theoretical framework elucidates the psychological and engagement mechanisms driving fantasy football participation, offering valuable insights into the motivations and behaviors of fantasy sports enthusiasts. Shipman's work enriches our understanding of the complex interplay between real-world sports events and virtual gaming experiences in fantasy football.

Stathole (2020) delved into the relationship between NFL draft selection and fantasy rookie success. Through empirical analysis of draft data and rookie performance metrics, Stathole uncovered patterns that shed light on the predictive power of draft outcomes in fantasy football contexts. This study offers valuable insights into the role of draft strategies and player evaluations in shaping fantasy football rosters, providing actionable information for fantasy football enthusiasts seeking to maximize their team's success.

Shih (2019a) provided practical insights into fantasy football analytics using machine learning techniques. Through a Medium article, Shih demonstrated the application of machine learning algorithms to analyze player data and predict fantasy football outcomes. By leveraging advanced computational methods, Shih's work offers valuable resources for enthusiasts interested in harnessing data-driven approaches to enhance their strategic decision-making processes in fantasy football leagues.

Jdashbrock (2023) provided an introductory overview of time series analysis in sports, offering insights into the application of temporal data analysis techniques in understanding sports dynamics. This resource contributes to the growing body of literature on data-driven approaches in sports analytics, laying the groundwork for further exploration of time series methodologies in the context of fantasy football analytics.

In addition to empirical studies and practical applications, the GitHub project "Predicting fantasy football points using machine learning" (n.d.) offers a hands-on approach to predictive modeling in fantasy football. This project enables enthusiasts to experiment with machine learning algorithms and player data by providing access to code and datasets, fostering a deeper understanding of data-driven approaches in fantasy football analytics.

These studies contribute to a nuanced understanding of fantasy football analytics, encompassing theoretical frameworks, empirical investigations, and practical applications of advanced methodologies. By synthesizing insights from diverse sources, fantasy football enthusiasts can leverage various tools and perspectives to enhance their strategic decision-making processes and maximize success in the dynamic realm of fantasy sports.

By applying advanced statistical analysis methodologies, we will achieve superior accuracy in predicting the rankings of the top 12 players by position for the upcoming NFL season compared to Yahoo's predictions.

3 Methods

3.1 Data

Data for this study were obtained from the Pro Football Reference website spanning the years 2009 to 2023. We focused on player statistics for quarterbacks, running backs, wide receivers, tight ends, kickers, and team defenses. The final dataset comprised projected fantasy player data for the top 12 players at each position, excluding team defenses.

We curated the data to ensure accuracy and consistency across all player positions. Specifically, we extracted key performance metrics such as passing yards, touchdowns, rushing yards, receptions, field goal success rates, and defensive statistics. By encompassing a comprehensive range of player positions, we aimed to capture the diverse dynamics of fantasy football scoring systems and player contributions.

3.2 Model Architecture

Our project comprises two main components aimed at providing accurate projections and rankings for fantasy football enthusiasts. In the estimation piece, we focus on predicting each player's projected points for the upcoming season. To ensure precision and reliability, we curated a comprehensive dataset encompassing key performance metrics for players across all positions. This dataset includes crucial statistics such as passing yards, touchdowns, rushing yards, receptions, field goal success rates, and defensive contributions.

In our analysis, we leveraged a diverse ensemble of machine learning algorithms tailored to the unique characteristics of different player positions. Specifically, we utilized five distinct algorithms: ridge regression, Bayesian ridge regression, elastic net regularization, random forest, and gradient boosting. Each algorithm was intricately calibrated to account for the nuances and dynamics specific to quarterbacks, running backs, wide receivers, tight ends, and place kickers.

To train and assess the performance of our models, we employed rigorous cross-validation techniques, partitioning the dataset into randomly selected training sets (80%) and test sets (20%). This approach ensured the robustness and generalizability of our models by evaluating their predictive accuracy on unseen data. The primary evaluation metric used to gauge the effectiveness of our models was the root mean squared error (RMSE), providing a comprehensive measure of accuracy and predictive precision.

Ultimately, our models were deployed to generate raw projections for the top 12 fantasy players at each position. These projections serve as valuable insights for fantasy football enthusiasts, empowering them with reliable estimates for player performance in the upcoming season.

Following the estimation piece, we transition to the ranking component, where we deploy advanced data science methods to refine and prioritize player projections. This stage involves accounting for various tangible and intangible factors to determine the final rankings of players.

By integrating additional data sources and applying sophisticated analytical techniques, we aim to augment the raw projections generated in the estimation piece. Factors such as player injury history, team dynamics, schedule strength, and potential breakout performances are meticulously considered to refine the initial projections.

Through this iterative process, we derive a comprehensive ranking system that goes beyond mere statistical projections. Our data-driven approach allows us to capture the holistic impact of players on fantasy football outcomes, providing users with nuanced insights for draft selections and lineup management.

4 Results

The objective of this research was to identify key features that can be used to accurately predict the fantasy points of NFL players for the upcoming season, with the goal of outperforming Yahoo’s Fantasy experts' projections. Through this research, we aimed to accept or reject the hypothesis that integrating advanced statistical indicators and machine learning models can significantly improve the accuracy of fantasy football player performance predictions.

While we cannot definitively confirm our hypothesis until the season concludes, our preliminary analysis indicates that integrating advanced features with traditional fantasy point predictions shows potential for enhancing the accuracy of player rankings. Our model, particularly the Random Forest Regressor, demonstrated robust and reliable predictions in preliminary tests. This model resulted in a more nuanced ranking system when combined with additional weighted features. Integrating features such as offensive contributions, playoff performance, touchdowns, strength of schedule, and playing conditions provided a comprehensive view of each player's potential fantasy value.

Risk factors such as injuries, age, and workload significantly impact player performance. These factors should be carefully considered when making predictions. Additionally, it is crucial to ensure the model remains adaptable to team dynamics and game strategy changes to maintain prediction accuracy.

Beyond the upcoming season, factors contributing to the long-term fantasy value of players include their durability, role stability, and growth potential. Dynasty league managers can evaluate player longevity and sustainability by considering these factors in their strategies.

Team dynamics, such as offensive schemes, quarterback play, and offensive line performance, significantly influence the fantasy production of individual players. Analyzing these dynamics, along with matchup factors like opposing defenses and game scripts, can provide a more comprehensive view of player performance and enhance predictive models.

4.1 Model Selection and Evaluation

To predict the fantasy points, we experimented with several machine learning models: Ridge Regression, Lasso Regression, Random Forest Regressor, and Gradient Boosting Regressor. Each model was evaluated based on its mean squared error (MSE) and R-squared (R2) values.

After evaluating the performance of each model, the Random Forest Regressor with hyper-tuned parameters was selected as the final model due to its balance of accuracy and robustness.

Table 1. This table shows the comparison of the performances for each of the different models.

Model	Mean Squared Error	R-Squared
Ridge Regression	2.54	0.9997
Lasso Regression	2.51	0.9997
Random Forest Regressor	53.85	0.9936
Gradient Boosting Regressor	42.71	0.9949

4.2 Integration of New Features and Final Predictions

We then integrated the projected fantasy points from the Random Forest model with additional weighted features to derive new predictions. This weighted approach allowed us to refine the player rankings by considering both the projected points and additional influential factors.

4.3 Rankings per Position

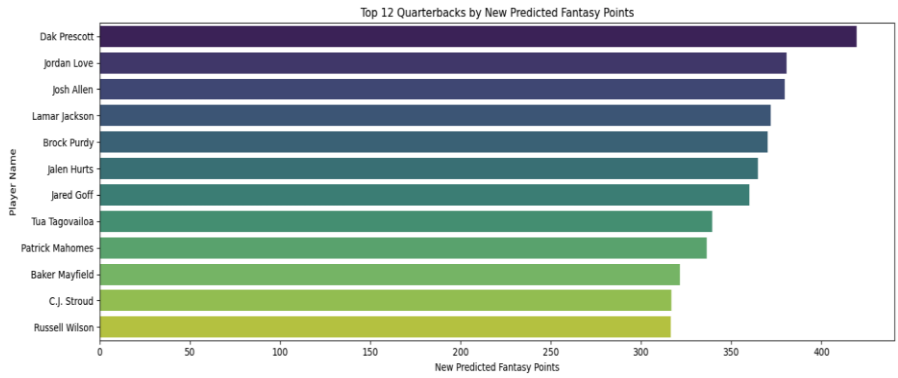

Fig 1. This shows a figure consisting of the top 12 quarterbacks by the new predicted fantasy points. The darker the color, the higher the ranking based on the projected fantasy points.

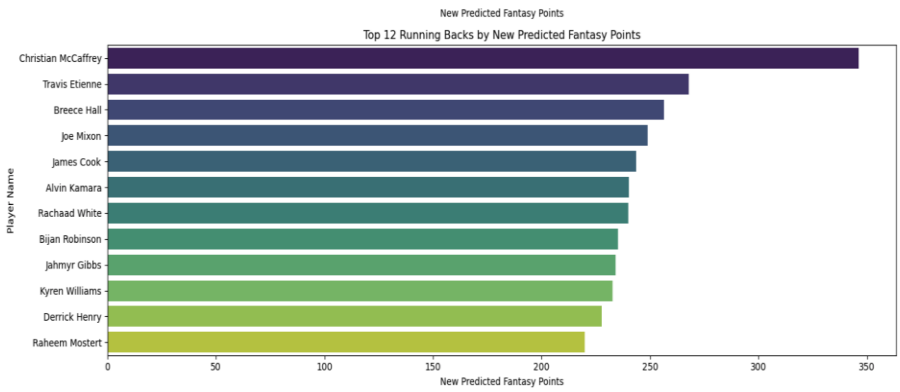

Fig 2. This figure consists of the top 12 running backs based on the newly predicted fantasy points. The darker the color, the higher the ranking based on the projected fantasy points.

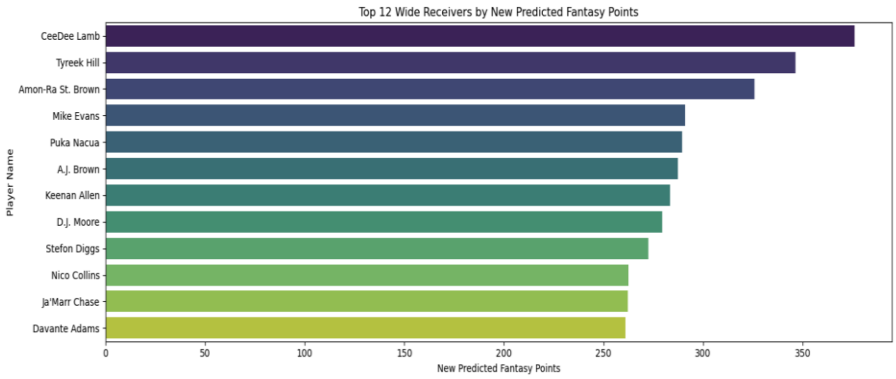

Fig 3. This shows a figure consisting of the top 12 wide receivers by the new predicted fantasy points. The darker the color, the higher the ranking based on the projected fantasy points.

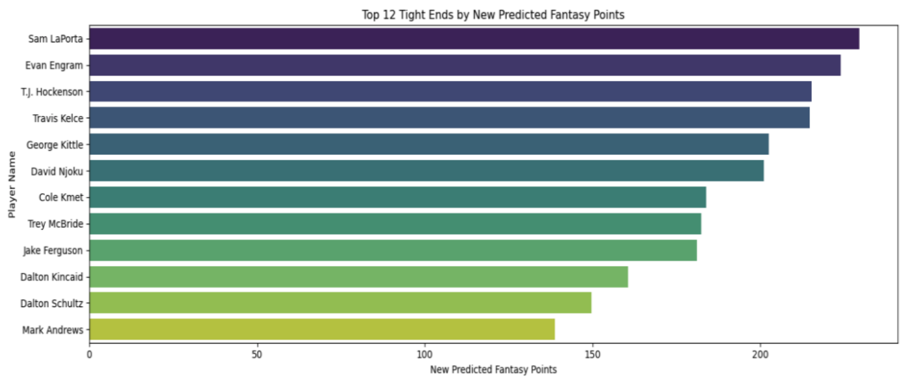

Fig 4. This shows a figure consisting of the top 12 tight ends by the new predicted fantasy points. The darker the color, the higher the ranking based on the projected fantasy points.

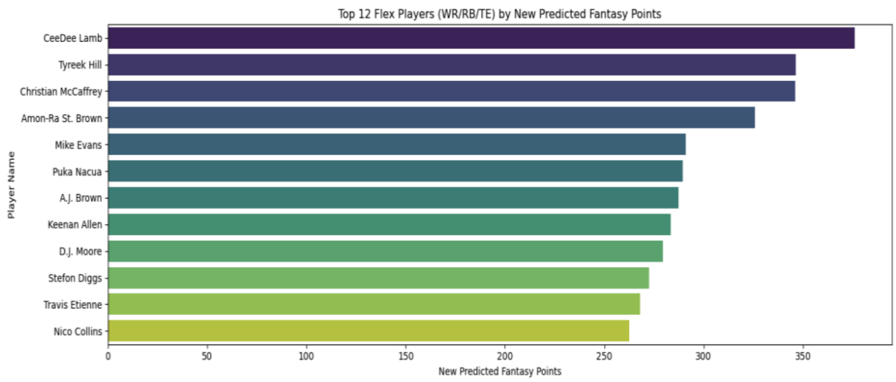

Fig 5. This shows a figure consisting of the top 12 flex (wide receiver, running back, and tight end) players by the new predicted fantasy points. The darker the color, the higher the ranking based on the projected fantasy points.

5 Discussion

5.1 Interpretation of Results

Based on the results, the best draft team is Dak Prescott at quarterback, Christian McCaffrey at running back, CeeDee Lamb and Tyreek Hill at wide receiver or flex, and Sam LaPorta at tight end.

5.2 Implications

These findings are significant for fantasy football enthusiasts and analysts. Users can make more informed decisions when drafting and managing their fantasy football teams by employing a multifaceted approach that considers both projected points and contextual factors. This approach not only improves the accuracy of player evaluations but also enhances strategic planning for both drafts and in-season management.

5.3 Limitations

The primary limitation of this research is the inherent variability and unpredictability of sports performance. Player injuries, sudden changes in team dynamics, and unanticipated external factors can significantly impact performance and are challenging to predict accurately. Another challenge encountered was ensuring the model's adaptability to these dynamic conditions. Although historical data provides a strong foundation, it may not fully capture the complexities of future performances. Additionally, the effectiveness of the model in real-world applications remains to be validated at the end of the season when actual player performances can be compared to the predictions.

5.4 Ethics

The ethical considerations in this research primarily involve the accuracy and fairness of the predictions. Ensuring that the models do not disproportionately favor certain players or teams over others is crucial. Additionally, transparency in how predictions are made is important for maintaining trust among users.

5.5 Future Research

Future work could involve integrating real-time data and improving models through advanced techniques like deep learning and reinforcement learning. Future research could delve deeper into other influential factors such as injury histories, age, workload, and other risk factors that impact the reliability and consistency of player performance. Additionally, exploring long-term player value and how it affects dynasty league management could provide further insights. Analyzing team dynamics and matchup factors could also enhance the predictive model's accuracy.

6 Conclusion

The research suggests that integrating advanced features with machine learning models has the potential to enhance the accuracy of fantasy football player performance predictions. By employing a Random Forest model and incorporating additional weighted features, we developed a comprehensive and nuanced ranking system that shows promise as an accurate ranking methodology. These preliminary findings offer valuable insights for fantasy football enthusiasts and analysts, enabling more informed decision-making and strategic planning. While using historical data, factors such as age, injury history, and team dynamics appear to play crucial roles in predicting player performance. Future evaluations will determine the model's effectiveness compared to traditional methods, providing a solid foundation for more sophisticated fantasy football prediction models.

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