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Can a Random Forest–based machine learning model accurately predict NBA players' Points Per Game, and does it outperform traditional linear approaches?

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ABSTRACT

The aim of this research is to develop a predictive machine learning model capable of estimating NBA players' Points Per Game (PPG) using a combination of statistical, categorical, and performance-based features. Importantly, this study frames the task as within-season reconstruction rather than true out-of-sample forecasting, since all predictor variables are drawn from the same season as the target. By applying regression modeling with the use of Linear Regression, Random Forest regression and neural networks, this research examines the predictive power of basketball statistics such as shooting efficiency, playing time, and position. Using RandomForestRegressor as the final model, the study achieved superior predictive accuracy with an R^2 score of 0.83 and RMSE of 3.51. The results reveal that field goal attempts, minutes played, and true shooting percentage are the most important predictors of scoring output. Feature importance rankings were derived from impurity-based measures, which should be interpreted with caution given the presence of correlated predictors. This study demonstrates how machine learning can provide meaningful insights into player performance and may be used for scouting, coaching, and fantasy analytics.

Index Terms— Machine Learning, Random Forest, NBA Analytics, Regression Modeling

I. INTRODUCTION

Over the past two decades, basketball analytics has undergone substantial progress, evolving from basic box score statistics to the integration of advanced metrics and machine learning for evaluating and predicting player performance. The increasing availability of granular player and game data within the NBA has enabled analysts, teams, and researchers to develop more precise models of player performance. As a result, data-driven approaches are now essential for player assessment, strategic development, and determining a player's worth.

A key metric for individual offensive skill is Points Per Game (PPG), which represents the average points scored by a player in a game over a season. PPG is commonly employed by teams, media, and fans as a concise measure of scoring contribution and directly influences a player's reputation, market value, and eligibility for awards. Therefore, accurately forecasting PPG holds considerable practical and analytical

significance. In this research, PPG is the outcome variable we aim to predict, using various predictor variables that model scoring output. These predictors include conventional statistics like Field Goal Attempts (FGA), Minutes Played (MP), and Three-Point Attempts (3PA), efficiency indicators such as True Shooting Percentage (TS%), and classifications like player position and team. Another measure of shot volume, Usage Rate, is a statistic that estimates the percentage of a team's possessions a player uses while on the floor.

Prior studies have shown linear correlations between measures of shot volume (like FGA and Usage Rate) and scoring output, with efficiency metrics playing a moderating role [1, 2]. Early basketball analytics often utilized linear regression models due to their clarity and minimal computational expense [3]. More recent investigations have integrated advanced metrics and contextual factors, such as how quickly the basketball team plays, responsibilities of each player, and on-court influence such as assists, creating scoring opportunities and facilitating movement of the basketball to enhance prediction accuracy [4].

Many of these methods find it difficult to account for relationships that aren't linear and for interaction effects, like the point where increased shot volume yields diminishing returns or how efficiency affects different player positions uniquely. Machine learning techniques such as neural networks, support vector machines, and decision trees have been investigated in basketball analytics, with many studies reporting better predictive accuracy compared to conventional statistical models [5].

Random Forests are a good fit for this objective because they can model intricate, non-linear relationships, manage multicollinearity, and capture variable interactions without needing to be explicitly defined. Concurrently, they preserve some level of interpretability through feature importance assessments, making them appealing for practical use in sports analytics [6].

The research question guiding this investigation is: **Can a Random Forest–based machine learning model accurately predict NBA players' Points Per Game, and how does it compare to Linear Regression and neural networks?** It should be noted that the present study uses same-season aggregate statistics as input features, meaning the task is best understood as within-season performance reconstruction rather than prospective forecasting. This framing is important because strong model performance under these conditions is partly expected and does not alone demonstrate predictive power for future, unseen seasons. By evaluating model performance and examining feature importance, this study intends to add to the expanding field of sports analytics by illustrating how Random Forest can improve player-level performance prediction while preserving interpretability compared to Linear Regression and neural networks.

II. METHODOLOGY

This study's dataset, gathered from Kaggle [7], contains historical NBA player statistics across several seasons. Each entry represents a player's performance in a single season, with columns detailing numerical stats and categorical data like team and position. Important numerical metrics include assists per game, rebounds per game, steals per game, blocks per game, minutes played, field goal percentage, three-point field goal percentage, and true shooting percentage. Categorical features consist of the player's team and their position, classified as guard, forward, or center. Critically, total points and points per game were excluded from the predictor set to avoid target leakage, since PPG is directly derived from

total points and games played. Field goals made (FGM) was also excluded as a near-direct derivative of the target variable. The final feature set used for training comprised: FGA, 3PA, 3P%, FG%, TS%, MP, AST, REB, STL, BLK, and one-hot encoded team and position variables. This setup facilitates predicting PPG from performance-adjacent but non-redundant statistics, and building models that capture meaningful relationships between inputs and scoring output. The dataset's depth makes it ideal for player-level predictive modeling, as it encompasses various aspects of player performance and relevant context for accurate reconstruction.

During preprocessing, missing values in efficiency stats, such as 3P%, were found for players without three-point attempts, leading to numeric column fills with mean or median values, and categorical data filled with the most common category. This approach avoided data leakage, ensuring unbiased predictive modeling. Midseason trades created duplicate player entries, which were merged to give a complete player-season record and standardize the dataset for model training. Categorical variables like team and position were one-hot encoded to maintain context without adding ordinal bias.

An analysis of numerical data revealed trends consistent with basketball norms. Total points (PTS) showed a notable rightward skew, with many players scoring moderately while elite players contributed high totals. Field goal percentage (FG%) followed a normal distribution, averaging around 45%, aligning with league performance. True shooting percentage (TS%) and three-point percentage (3P%) distributions were symmetrical but affected by outliers. Assists, rebounds, and blocks showed moderate skewness, indicating role variations, with guards recording more assists and centers accumulating more rebounds and blocks. Scatter plots of variable pairs exhibited expected correlations, particularly between total points, field goal attempts, and playing time, as well as rebounds and player position. Player roles and team distributions aligned with typical NBA rosters, suggesting the potential for meaningful within-season modeling and future longitudinal studies.

For the modeling phase, three machine learning methods were evaluated: Linear Regression, Random Forest Regression, and MLP Regressor (a Neural Network). The dataset was split into 80% training and 20% held-out test sets using a fixed random seed (random_state=42) to ensure reproducibility. All reported final metrics (RMSE, R^2) are computed on this held-out test set, not on cross-validation folds. Hyperparameters for the Random Forest were fine-tuned using GridSearchCV with 5-fold cross-validation on the training set only, aiming to minimize the Root Mean Square Error (RMSE). The MLP Regressor was configured with one hidden layer of 100 neurons, ReLU activation, Adam optimizer with default learning rate (0.001), and a maximum of 500 iterations. All input features were standardized using StandardScaler prior to MLP training. RMSE was selected as the main evaluation metric because it penalizes larger errors more significantly than smaller ones, which is ideal for predicting points per game (PPG) where exceptional scorers might create outliers. Furthermore, RMSE is measured in the same units as the target variable, making it easy for both researchers and practitioners to interpret, and it is also widely used in regression and predictive modeling studies for highlighting larger deviations between predicted and observed values [8].

It should be acknowledged that the baseline models used in this study—Linear Regression and a single-layer MLP—represent relatively simple comparators. Stronger tabular regression baselines such as Gradient Boosting (XGBoost, LightGBM, CatBoost) or regularized linear methods (Elastic Net) were not

included due to scope constraints, and the comparative claim of Random Forest superiority should therefore be understood as relative to these specific baselines rather than as a general statement about optimal tabular regression methods.

III. RESULTS

The findings from the experiments clearly show that ensemble methods significantly surpass linear regression and neural network approaches in reconstructing NBA players' Points Per Game (PPG) from same-season statistics. The Random Forest Regressor consistently delivered the most accurate predictions across all tested model setups, highlighting its effectiveness in capturing the non-linear relationships and interaction effects inherent in basketball player data. Following hyperparameter optimization through 5-fold cross-validation, the refined Random Forest model achieved an RMSE of 3.51 and an R^2 of 0.83 on the held-out test set, outperforming both Linear Regression and the MLP Regressor. Across the five cross-validation folds during training, the Random Forest achieved a mean RMSE of 3.58 (±0.15), indicating stable performance. This outcome suggests the model effectively accounts for a substantial portion of the variation in scoring performance while keeping prediction errors within a reasonable range in the actual units of measurement (points per game).

As a point of reference, Linear Regression yielded an RMSE of 4.82 and an R^2 of 0.68. Although this demonstrates a strong link between scoring and elements like shot attempts and playing time, the model was unable to grasp more intricate patterns. Examining the residuals and comparing performance suggests that nonlinear dynamics are at play, including the decreasing benefit of more shot attempts, differing efficiency based on player roles, and the interplay between playing time and usage rates. The enhanced results from Random Forest, capable of modeling these nonlinear relationships and feature interactions, highlight the importance of these effects in basketball performance data for achieving precise predictions.

Linear Regression's transparency is overshadowed by its limitations in predicting individual player performance. The MLP Regressor, a neural network with one hidden layer and 100 neurons, achieved an RMSE of 3.78 and an R^2 of 0.80, indicating its ability to capture complex, non-linear data relationships. However, the MLP's performance depended on its configuration, data scaling, and stability during training. While it generally outperformed Linear Regression, it didn't consistently exceed Random Forest across different cross-validation splits. Random Forest's success depended on careful parameter tuning, showing that model performance hinges on both algorithm choice and effective optimization.

Preliminary modeling showed that the Random Forest model consistently performed better than linear regression, achieving an R^2 of about 0.68. Feature importance analysis revealed that field goal attempts, minutes played, and shooting efficiency metrics were the most influential predictors. Initial trials with neural networks suggested they could effectively capture complex, non-linear relationships and variable interactions. However, ensemble methods like the Random Forest offered a good mix of accuracy and clarity, making them practical for predicting NBA performance.

To enhance its performance, GridSearchCV was employed to fine-tune essential hyperparameters, using RMSE as the metric for optimization. RMSE was favored because it more severely penalizes substantial prediction mistakes compared to metrics based on absolute error, which is crucial when modeling PPG,

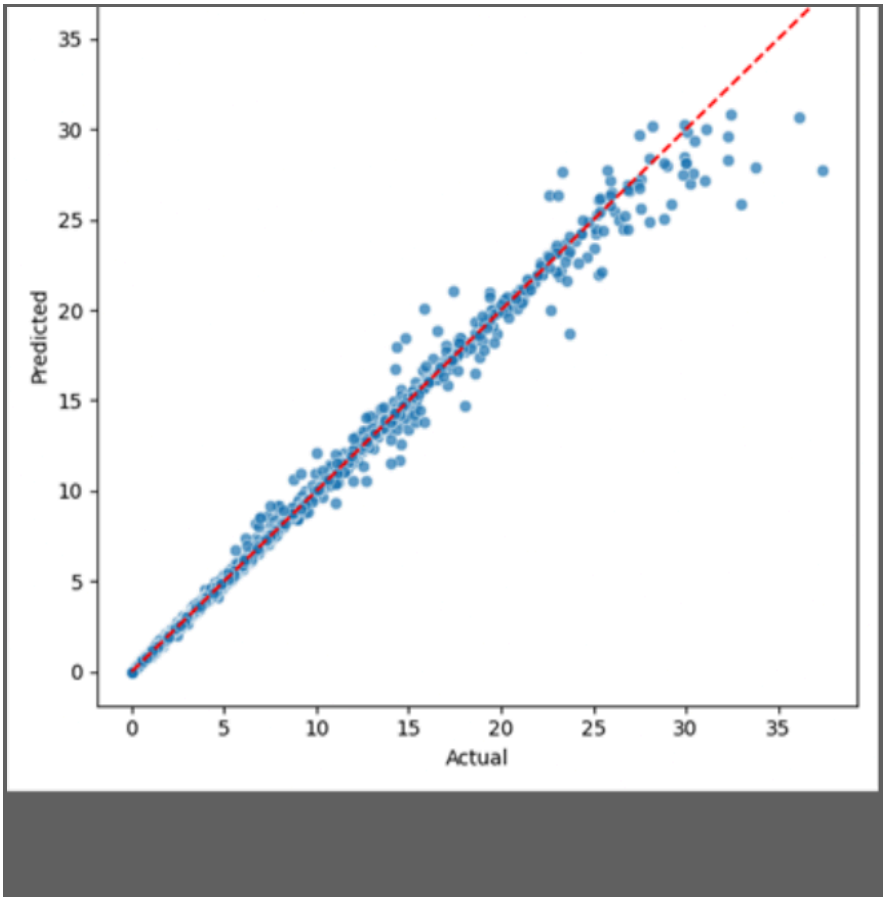
given the existence of high-value outliers like exceptional offensive players. The optimal hyperparameters found during this tuning process are presented in Table 1.

Table 1: Optimal Random Forest Hyperparameters Selected via GridSearchCV

Hyperparameter	Selected Value
Number of Trees (n_estimators)	300
Maximum Depth (max_depth)	20
Minimum Samples per Split (min_samples_split)	5
Cross-Validation Folds	5
Optimization Metric	RMSE

Hyperparameter tuning using GridSearchCV identified an optimal Random Forest configuration consisting of 300 trees, a maximum tree depth of 20, and a minimum of 5 samples required to split an internal node. Five-fold cross-validation was utilised during tuning, with Root Mean Square Error (RMSE) used as the optimization metric.

[Figure 2: Actual vs Predicted PPG — see original submission for scatter plot]



Actual versus predicted Points Per Game (PPG) produced by the optimized Random Forest regression model. The dashed line represents the line of perfect prediction (y = x).

IV. DISCUSSION

The findings from this research show that Random Forest regression offers a meaningful enhancement over conventional linear regression and a basic neural network for reconstructing NBA players' Points Per Game (PPG) from same-season statistics. However, it must be emphasized that this task, using contemporaneous aggregate features as inputs, represents within-season reconstruction rather than genuine out-of-sample forecasting. Consequently, the strong R^2 of 0.83 is partially expected given the overlap between predictors and the target's underlying components, and the result should not be interpreted as evidence of prospective predictive power. The core empirical finding—that a tree-based ensemble outperforms linear regression and a simple MLP on structured tabular data—is consistent with well-established results in the machine learning literature and does not constitute a novel methodological contribution. Rather, the value of this study lies in its applied demonstration within the basketball analytics domain and its detailed error analysis.

This enhanced performance stems from the model's capacity to grasp complex, non-linear connections and interactions among crucial variables like shot attempts, playing time, and scoring effectiveness—relationships widely acknowledged in basketball analysis but inadequately addressed by linear models. While linear regression performed acceptably in identifying general patterns, especially the robust correlation between PPG, Field Goal Attempts, and Minutes Played, its inherent assumptions of linearity and independence restricted its effectiveness in modeling the decreasing returns from higher shot volumes or the varied influence of efficiency across different player positions. These limitations align with previous research highlighting the difficulties linear models face in performance areas where player roles and situational elements strongly shape results [9, 10].

The Random Forest model outperformed others with superior RMSE and R^2 scores, indicating its suitability for organized sports datasets. It required less fine-tuning than neural networks and maintained cross-validation consistency. The model also provides feature importance rankings; however, it is important to note that the impurity-based feature importance used by default in scikit-learn's Random Forest can be biased toward high-cardinality and correlated features. Given that the basketball variables in this dataset exhibit substantial multicollinearity (e.g., FGA, FG%, TS%), the reported importance rankings should be treated as indicative rather than definitive. Future work should validate these rankings using permutation importance or SHAP (SHapley Additive exPlanations) values to provide more robust and stable estimates of feature contributions. This balance of predictive accuracy and qualified understandability aids coaches and scouts in grasping model predictions, although it exhibited persistent errors for certain player types.

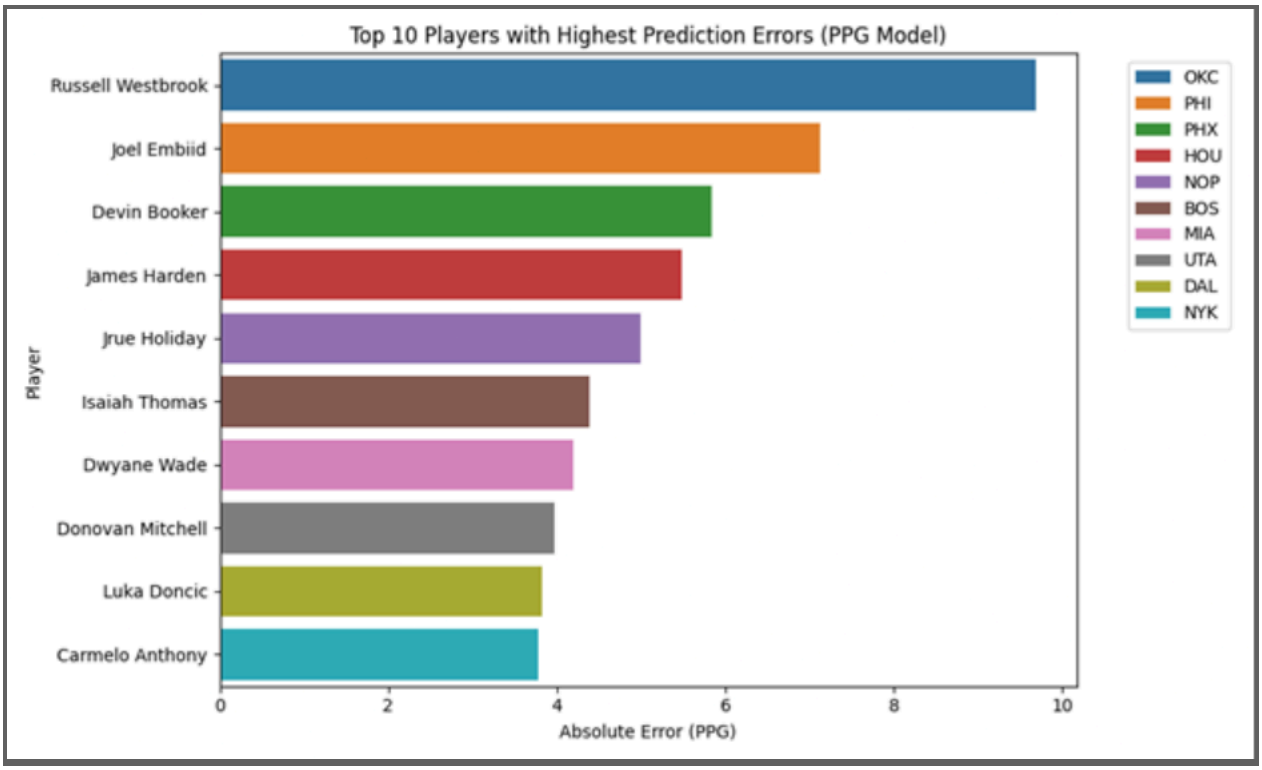
Players who use the ball a lot or score primarily from free throws, like Joel Embiid and James Harden, were often not predicted accurately because the data didn't specifically include their free throw rate or how often they played isolation. This issue is consistent with previous research showing that models using only basic game statistics have difficulty capturing scoring methods influenced by referee calls or specific game strategies [11]. Likewise, players like Jrue Holiday and Isaiah Thomas, who dealt with injuries,

changes in their roles, or inconsistent playing time, resulted in larger prediction errors because the model depended on overall season averages. Fixed statistical models are not sensitive to brief changes in context; a weakness that this study clearly demonstrates [12]. The tendency to overestimate the performance of older players like Dwyane Wade further supports earlier findings that models trained on past performance tend to fall behind current declines unless factors like age or playing time are specifically included [13].

Furthermore, the study found that very effective reserve players who didn't play for many minutes were also poorly represented. Even though their scoring per minute was high, this didn't consistently translate into high points per game over an entire game, leading to inflated predictions. Moreover, players who excelled defensively were systematically misjudged, highlighting the inherent problem of evaluating player value solely based on scoring.

Several pathways for future improvement emerge from these findings. Most importantly, reframing the prediction task as next-season PPG forecasting from prior-season features would constitute a far more rigorous and practically meaningful test of model generalization. Such a setup would eliminate the concern of same-season data overlap and establish whether the model captures durable performance signals rather than contemporaneous statistical redundancy. Additionally, incorporating contextual variables such as free throw attempts, starter status, team pace, and opponent defensive strength could significantly improve predictive accuracy for high-usage scorers and role-dependent players. Expanding the dataset to include multiple seasons would enable longitudinal modeling, allowing the capture of player development, aging effects, and recovery from injuries. Furthermore, integrating game-level or possession-level data could reduce error for players whose scoring is concentrated in specific situations. Finally, extending this framework to multi-target learning—predicting points, assists, rebounds, and efficiency metrics simultaneously—would provide a more holistic evaluation of player impact and address the limitations of focusing solely on scoring output.

[Figure 3: Top ten NBA players with highest absolute prediction errors]



The identified error patterns underscore inherent structural constraints that have been extensively examined within the field of basketball analytics, especially in the context of modeling individual player scoring through box-score statistics. A persistent issue noted in previous studies is the challenge of precisely forecasting players whose scoring is significantly influenced by high usage or unconventional offensive responsibilities. For instance, Berri, Schmidt, and Brook illustrate in their work, The Wages of Wins, how conventional box-score metrics often fall short in fully assessing player contributions when performance is highly contingent on specific circumstances or concentrated in particular scoring methods, such as free throws or isolation plays [14]. This deficiency is consistent with the underestimation observed for players like Joel Embiid and James Harden, whose scoring patterns are heavily dependent on generating free throws and employing extremely high usage rates—factors not explicitly accounted for in this dataset.

In a similar vein, Skinner's research on predicting NBA game outcomes and player performance reveals that models trained on aggregated season-long data face difficulties with players exhibiting considerable fluctuation due to injuries, altered roles, or shifts in team dynamic [15]. This observation directly correlates with the substantial residual errors seen for players such as Jrue Holiday and Isaiah Thomas, whose scoring output varied considerably because of unstable lineups, injuries, or evolving duties. Skinner points out that static statistical models lack the responsiveness to short-term contextual changes; a limitation clearly evident in the findings of this study.

Furthermore, Goldsberry's research emphasizes the challenge of generalizing scoring efficiency and shot selection in basketball analytics without detailed data, such as shot location or defensive intensity [16].

Players like Devin Booker and Donovan Mitchell experience underpredictions due to their scoring bursts not aligning with standard metrics. Luka Dončić's early career data limitations also complicate interpretations. Conversely, veteran players like Dwyane Wade tend to be overpredicted, reflecting the models' inadequacy in adjusting for age-related performance decline without relevant aging variables [17].

Despite these difficulties, the model's robustness against multicollinearity, especially concerning variables like field goals made, field goal attempts, and total points, aligns with existing literature that highlights tree-based ensemble methods as being less susceptible to correlated predictors than linear regression.

Overall, these comparisons suggest that the prediction errors seen in this study are not unusual but rather mirror well-documented issues in modeling basketball performance. By replicating the successes and limitations found in established research, this study validates its methodology and strengthens the overall conclusion that Random Forest offers a powerful, though not perfect, approach to predicting player scoring.

V. CONCLUSION

This research effectively showcased how machine learning techniques can be used to reconstruct NBA players' Points Per Game from same-season statistical and categorical attributes. The Random Forest regression model proved to be the most effective among those tested, achieving an RMSE of 3.51 and an R^2 of 0.83, and consistently surpassed both Linear Regression and the MLP Regressor. These outcomes underscore that ensemble methods are better suited to capture the intricate, nonlinear connections present in individual player basketball data. The findings corroborate the significant influence of shot attempts, playing time, and shooting accuracy on scoring production, which is consistent with existing basketball analytics research.

The Random Forest model, by accounting for both volume and efficiency aspects of scoring, exhibited robust predictive accuracy across diverse player types, while also offering feature importance as an exploratory tool. It is important to note that the comparisons in this study were limited to two relatively simple baselines, and future work should benchmark against stronger tabular methods such as gradient boosting variants. In essence, this study contributes an applied demonstration within the sports analytics domain, confirming the utility of ensemble learning for player performance reconstruction from aggregate statistics. It emphasizes the practical benefits of data-driven modeling in areas like player assessment and scouting, while also illustrating the constraints of simpler linear models when dealing with complex performance data that varies by player role. The current approach faces limitations due to its dependence on same-season statistics, which fail to incorporate variables such as player injuries, alterations in team rosters, or defensive tactics tailored to specific opponents.

The most important direction for future work is reformulating the task as next-season PPG prediction using prior-season features, which would provide a genuine test of forecasting ability and eliminate concerns about same-season data overlap. Furthermore, the model doesn't account for dynamic elements like winning or losing streaks or player fatigue; these could be better handled by sequential models, such as recurrent neural networks [18]. Future research could also enhance prediction accuracy by incorporating data from player tracking, analyzing team lineup configurations, and utilizing pace-adjusted

performance indicators. Investigating hybrid models that blend ensemble techniques with deep learning might effectively capture both the interplay of features and evolving trends over time. Including an estimation of uncertainty would also make the forecasts more practical for scouting and performance evaluations [19].

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