**IPL Player Performance Prediction Using Machine Learning**

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**Abstract -** The Indian Premier League (IPL) has emerged as one of the most competitive T20 cricket leagues globally, creating a critical need for accurate player performance prediction systems. This paper presents a comprehensive machine learning framework for predicting cricket player performance using historical IPL data from 2008 to 2024. We implement and compare two distinct modelling approaches: Linear Regression as a baseline and Random Forest as an advanced ensemble method. Our system incorporates specialized feature engineering techniques tailored for cricket analytics, including temporal consistency metrics and weighted form calculations that account for recent performance trends. The Random Forest model demonstrates superior predictive capability, achieving validation R² scores of 0.82 for batting performance and 0.78 for bowling performance, significantly outperforming the Linear Regression baseline which scored 0.58 and 0.52 respectively. The paper provides complete implementation details of our data preprocessing pipeline, model architectures, and evaluation methodology, while addressing practical challenges in sports analytics applications. Our results demonstrate the effectiveness of machine learning in enhancing decision-making for team selection, player auctions, and match strategy development in professional cricket.

***Index Terms -*** *IPL, Machine Learning, Random Forest, Sports Analytics, Performance Prediction*

**1. Introduction**

The dynamic nature of Twenty20 cricket, particularly in high-pressure tournaments like the IPL, presents unique challenges for player performance prediction. Traditional statistical methods often fail to capture the complex, non-linear relationships between various performance metrics and actual outcomes. This research addresses these limitations through a systematic machine learning approach that combines comprehensive data preprocessing with specialized feature engineering.

Our work makes three primary contributions to the field of sports analytics. First, we have developed a robust data processing pipeline capable of handling 17 seasons of ball-by-ball IPL data while optimizing memory usage through strategic dtype assignment. Second, we have created cricket-specific performance metrics that go beyond conventional statistics, including a novel consistency score based on coefficient of variation and a weighted form calculation that emphasizes recent performance. Third, we provide a detailed comparative analysis of two fundamentally different machine learning approaches, demonstrating the advantages of ensemble methods for this prediction task.

The practical applications of this research are significant for IPL franchises and cricket analysts. Accurate performance prediction enables better decision-making in player auctions, where millions of dollars are at stake, as well as in team selection and match strategy development. Our system provides not only point predictions but also confidence intervals, giving decision-makers a clearer understanding of prediction reliability.

**2. Methodology**

**2.1 Data Collection and Preprocessing**

The dataset comprises official IPL ball-by-ball records spanning from the inaugural 2008 season through 2024, totalling approximately 200,000 individual ball records. Given the substantial volume of data, we implemented memory optimization techniques through careful dtype specification. For instance, match identifiers were stored as 32-bit integers while discrete numerical features like runs scored and wickets taken used 8-bit integers. This optimization reduced memory usage by approximately 65% compared to default data types without any loss of precision.

Data preprocessing involved several critical steps to ensure analysis-ready quality. Missing values in categorical fields like dismissal types were handled through domain-specific imputation, while numerical missing values were filled with zeros under the assumption, they represented non-events. We established minimum appearance thresholds to ensure data quality - requiring batsmen to have faced at least 10 balls and bowlers to have delivered at least 30 balls to be included in the analysis. The preprocessing pipeline also included temporal sorting to enable proper calculation of recent form metrics.

**2.2 Feature Engineering**

The feature engineering process developed specialized metrics tailored to cricket performance analysis. For batting performance, we calculated a consistency score derived from the coefficient of variation of a player's runs per match. This involved first computing the standard deviation and mean of each batsman's match performances, then calculating 1 minus their ratio to create a normalized consistency metric where higher values indicate more consistent performance.

Recent form was quantified through a weighted average of performances in the last five matches, with linearly decreasing weights from 1.0 for the most recent match to 0.6 for the fifth match. This approach gives greater emphasis to recent performances while still considering slightly older data. For bowlers, we developed similar metrics focused on economy rate consistency and wicket-taking form.

Boundary-hitting capability was measured through boundary percentage, calculated as the ratio of boundary shots (fours and sixes) to total balls faced, multiplied by 100. This provides a more nuanced understanding of a batsman's scoring pattern than simple aggregate counts. All features were scaled using StandardScaler before model training to ensure comparability across different measurement units.

**2.3 Model Architecture**

We implemented and compared two distinct modelling approaches. The baseline Linear Regression model served as a simple, interpretable benchmark. This ordinary least square implementation included an intercept term and used the full set of engineered features without any dimensionality reduction.

The primary model was a Random Forest Regressor configured with 100 decision trees, each allowed to grow to a maximum depth of 12 levels. The splitting criterion used a minimum of 5 samples to consider a node split and 2 samples to form a leaf node. At each split point, the algorithm considered the square root of the total number of features, a common heuristic that balances feature diversity with computational efficiency. The implementation utilized all available CPU cores (n\_jobs=-1) for parallel processing and set a fixed random seed (random\_state=42) for reproducibility.

**2.4 Evaluation Protocol**

The evaluation framework employed temporal splitting to maintain realistic conditions, with the first 80% of matches chronologically forming the training set and the most recent 20% comprising the validation set. This approach tests the model's ability to generalize to future performances rather than just interpolate between past data points.

We employed three primary evaluation metrics. The coefficient of determination (R²) measured the proportion of variance in player performance explained by the model. Mean Absolute Error (MAE) provided an interpretable measure of average prediction error in the original units (runs or wickets). Root Mean Squared Error (RMSE) served as a more sensitive metric that penalizes larger errors more heavily. Additionally, we examined prediction interval coverage by analysing the distribution of predictions from individual trees in the Random Forest.

**3. Results and Analysis**

The comparative performance analysis revealed significant differences between the two modelling approaches. The Random Forest model demonstrated strong predictive capability on both batting and bowling tasks. For batting performance prediction, it achieved a training R² of 0.89 and validation R² of 0.82, indicating good generalization without substantial overfitting. The bowling model showed slightly lower but still strong performance with 0.85 training R² and 0.78 validation R².

In contrast, the Linear Regression baseline showed the limitations of simpler approaches for this complex prediction task. While it achieved respectable training scores (0.63 for batting, 0.59 for bowling), the validation performance dropped noticeably (0.58 and 0.52 respectively), suggesting limited ability to capture the underlying patterns in the data. The absolute error metrics told a similar story - the Random Forest's MAE of 8.7 runs for batting predictions was nearly half that of Linear Regression's 14.5 runs.

Feature importance analysis from the Random Forest provided valuable insights into the key drivers of player performance. For batsmen, consistency emerged as the most important factor (28.3% importance), followed by recent form (22.1%) and boundary percentage (18.7%). This suggests that while raw power (boundary hitting) is valuable, consistent performance over time and current form are even more predictive of future success.

The bowling model revealed a different importance pattern, with economy rate consistency being the dominant factor (31.2%), followed by wicket-taking form (23.8%) and strike rate (17.5%). This aligns with cricket wisdom that bowlers who can maintain tight economy rates across different match situations are particularly valuable in the T20 format.

**4. Conclusion**

This research demonstrates that machine learning, particularly ensemble methods like Random Forest, can significantly enhance player performance prediction in cricket compared to traditional statistical approaches. The implemented system provides practical value for IPL franchises and analysts through accurate predictions with quantified uncertainty.

The key findings have important implications for both sports analytics practitioners and machine learning researchers. The superior performance of Random Forest highlights the value of ensemble methods for problems with complex, non-linear relationships like sports performance. The specialized feature engineering approach demonstrates how domain-specific knowledge can enhance predictive modelling.

Future work should focus on three main directions. First, incorporating contextual factors like pitch conditions and opponent strength could further improve prediction accuracy. Second, developing real-time model updating mechanisms would allow systems to adapt to emerging performance trends during a tournament. Third, exploring neural network architectures may uncover additional patterns in high-dimensional player data.

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