**IPL Player Performance Prediction Using Machine Learning**

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**Abstract -** The Indian Premier League (IPL) has rapidly become one of the most competitive T20 leagues worldwide, driving the demand for reliable systems to predict player performance. This paper introduces a detailed machine learning framework aimed at forecasting outcomes of cricket players using historical IPL data from 2008 through 2024. We implement and evaluate two modelling strategies: a baseline Linear Regression model and an advanced ensemble approach using Random Forests. Our framework includes customized feature engineering techniques suited for cricket analytics, such as temporal consistency indicators and weighted recent-form metrics that emphasize up-to-date player trends. The Random Forest model exhibits notably better predictive performance, achieving validation R² scores of 0.82 for batting and 0.78 for bowling, in contrast to the Linear Regression model’s 0.58 and 0.52, respectively. The paper outlines the complete implementation process, including data preprocessing steps, model structures, and evaluation protocols, while also discussing practical considerations in the context of sports data analysis. These results highlight the capability of machine learning to enhance critical decisions in player auctions, team composition, and strategic planning within professional cricket.

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

**1. Introduction**

The fast-paced and unpredictable nature of Twenty20 cricket, especially in high-stakes leagues like the IPL, poses significant challenges for accurately forecasting player performance. Conventional statistical approaches often fall short in capturing the intricate and non-linear interactions among different performance variables. This study tackles these challenges using a structured machine learning framework that integrates meticulous data preprocessing with domain-specific feature engineering and other techniques.

Our research makes three key contributions to the domain of sports data analytics. First, we introduce a scalable data processing pipeline designed to efficiently handle ball-by-ball data across 17 IPL seasons, employing optimized memory management through targeted dtype configuration. Second, we develop advanced, cricket-specific performance indicators that go beyond traditional metrics, including a unique consistency measure based on the coefficient of variation and a dynamic form score that prioritizes recent match performance. Third, we perform a comprehensive evaluation of two distinct machine learning models, showcasing the effectiveness of ensemble techniques over simpler linear models in this context.

The implications of this work are particularly valuable for IPL teams and performance analysts. Reliable performance forecasting supports more informed choices during player auctions where financial stakes are high, as well as in squad composition and tactical planning. Additionally, our system generates not only predicted performance scores but also confidence intervals, offering greater transparency and insight into prediction certainty for decision-makers.

**2. Methodology**

**2.1 Data Collection and Preprocessing**

The dataset used in this study consists of official ball-by-ball IPL records covering all matches from the 2008 season up to 2024, amounting to nearly 200,000 individual deliveries. Due to the dataset's size, we applied memory-efficient techniques by explicitly defining data types. For example, match IDs were stored using 32-bit integers, while compact numerical features such as runs scored and wickets taken were encoded with 8-bit integers. These optimizations led to a memory footprint reduction of around 65% compared to using default data types, without any compromise in data accuracy.

The data preprocessing workflow included several key steps to prepare the dataset for analysis. Categorical fields with missing entries, such as dismissal types, were imputed using cricket-specific logic, while missing values in numerical columns were set to zero, based on the assumption that they reflected the absence of an event. To maintain analytical integrity, we imposed minimum participation criteria: batsmen had to face at least 10 deliveries and bowlers had to bowl a minimum of 30 balls to be considered. Additionally, all records were temporally ordered to facilitate accurate computation of form-based features.

**2.2 Feature Engineering**

The feature engineering strategy introduced a set of custom metrics specifically designed for evaluating cricket performance. To assess batting consistency, we formulated a metric based on the coefficient of variation in a player's runs per match. This entailed calculating the mean and standard deviation of each batter's match-wise scores and then computing a normalized consistency score as 1 minus the ratio of the standard deviation to the mean, where higher values signify greater reliability in performance.

To measure recent form, we implemented a weighted average of a player's last five matches, assigning linearly decreasing weights from 1.0 for the most recent match to 0.6 for the fifth, allowing recent games to influence the score more heavily while still accounting for short-term trends. Bowlers were evaluated using parallel metrics centred around consistency in economy rates and wicket-taking effectiveness.

Boundary-hitting ability was captured through a boundary percentage metric, defined as the number of boundary shots (fours and sixes) divided by total balls faced, multiplied by 100, offering a more refined view of scoring tendencies than raw totals. Before model training, all features were normalized using the StandardScaler to ensure consistent scaling across diverse feature ranges.

**2.3 Model Architecture**

We employed and evaluated two fundamentally different modelling techniques. The first was a basic Linear Regression model, used as a transparent and easily interpretable benchmark. This ordinary least squares approach included an intercept term and incorporated the complete set of engineered features without applying any form of dimensionality reduction.

Our primary predictive model was a Random Forest Regressor, configured with 100 individual decision trees. Each tree was permitted to grow to a maximum depth of 12, with a minimum of 5 samples required to consider a split and at least 2 samples to create a terminal leaf. For feature selection at each split, the model used the square root of the total number of input features, a widely accepted heuristic that offers a trade-off between feature randomness and efficiency. The implementation leveraged full parallelization by setting n\_jobs=-1, and ensured consistency in results by fixing the random seed to 42 through the random\_state parameter.

**2.4 Evaluation Protocol**

To ensure a realistic evaluation of model performance, we adopted a temporal split strategy, using the earliest 80% of matches (in chronological order) for training and reserving the most recent 20% for validation. This method simulates future prediction scenarios and assesses the model’s ability to extrapolate rather than merely interpolate past trends.

Model performance was assessed using three key evaluation metrics. The coefficient of determination (R²) quantified how well the model accounted for the variance in player performance. Mean Absolute Error (MAE) offered an easily interpretable average of prediction errors, expressed in the same units as the target variable (runs or wickets). Root Mean Squared Error (RMSE) was also computed, providing a more sensitive measure that places greater emphasis on larger prediction deviations. In addition to these metrics, we evaluated prediction uncertainty by analysing the dispersion of outputs from individual decision trees within the Random Forest model, offering insights into prediction interval coverage.

**3. Results and Analysis**

The comparative analysis between the two modelling techniques highlighted notable differences in predictive performance. The Random Forest model exhibited strong accuracy for both batting and bowling predictions. It achieved a training R² of 0.89 and a validation R² of 0.82 for batting, reflecting effective generalization with minimal overfitting. For bowling, the model also performed well, with an R² of 0.85 on training data and 0.78 on the validation set.

On the other hand, the Linear Regression model exposed the limitations of simpler predictive methods for a task of this complexity. Although it posted moderate training R² scores (0.63 for batting and 0.59 for bowling), its validation performance declined to 0.58 and 0.52 respectively, indicating weaker generalization and a reduced ability to model non-linear relationships. This pattern was also evident in the error metrics: the Random Forest's Mean Absolute Error (MAE) for batting predictions was 8.7 runs, significantly outperforming Linear Regression’s MAE of 14.5 runs.

An analysis of feature importance from the Random Forest provided deeper insight into the key contributors to performance. Among batsmen, consistency was the most influential feature (28.3%), followed by recent form (22.1%) and boundary percentage (18.7%). This indicates that sustained performance and current momentum are stronger predictors of future success than raw hitting ability alone. For bowlers, the importance ranking differed: economy rate consistency was the top predictor (31.2%), with wicket-taking form (23.8%) and strike rate (17.5%) following. These results support the common view in T20 cricket that bowlers who consistently control scoring rates across various conditions add significant strategic value.

**4. Conclusion**

This study illustrates the effectiveness of machine learning, especially ensemble techniques like Random Forest, in enhancing the accuracy of cricket player performance predictions over traditional statistical models. The developed framework offers actionable insights for IPL franchises and analysts by delivering reliable forecasts along with measurable uncertainty.

The findings carry significant relevance for both sports analytics professionals and the broader machine learning community. The strong performance of Random Forest underscores the utility of ensemble methods in capturing the intricate, non-linear dynamics characteristic of athletic performance. Additionally, the feature engineering process highlights the importance of integrating domain-specific expertise into model development to boost predictive power.

Looking ahead, future research should explore three primary avenues. First, incorporating match-specific context such as pitch type, weather conditions, and opposing team strength could lead to more refined predictions. Second, implementing dynamic model updates during the season would enable responsiveness to changing player form. Third, experimenting with deep learning architectures may help uncover latent patterns in the high-dimensional datasets typical of modern sports analytics.

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