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A Machine Learning Approach to Forecasting Outcomes in Limited Overs Cricket

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Abstract

This study explores the application of machine learning techniques to forecasting outcomes in limited overs cricket matches, with a particular focus on One Day Internationals (ODIs). The research investigates how classification algorithms can be effectively utilized to analyze both contextual and dynamic factors that influence match results, including venue details, toss decisions, team strength, and historical performance records. By employing a structured methodology encompassing feature selection, data preprocessing, model training, and comparative performance evaluation, the study aims to demonstrate the feasibility and accuracy of predictive analytics in cricket. Two supervised learning approaches, Decision Trees and Multilayer Perceptron (MLP) neural networks, were implemented and tested on a curated dataset of over 3,900 ODI matches spanning nearly five decades. The models were assessed using established performance metrics such as Accuracy, Precision, Recall, F1 Score, and Average Precision, ensuring a comprehensive evaluation of predictive capability. The findings highlight that machine learning models can capture the nonlinear interactions among game-related variables and substantially improve forecasting accuracy compared to traditional statistical methods. Additionally, this work introduces a practical implementation through a custom-built application, CricAI, which enables users to input match-specific details and receive outcome predictions in real time. Beyond predictive performance, the study provides valuable insights into the key determinants of ODI outcomes, underscoring the importance of domain-specific feature engineering. By bridging theory with practical application, this research contributes to the growing field of sports analytics and demonstrates the potential of machine learning to enhance strategic planning, fan engagement, and decision-making in competitive cricket. Looking ahead, the framework can be extended to incorporate real-time, in-game data streams to enable dynamic outcome forecasting, paving the way for more adaptive and interactive sports analytics systems.

Keywords: Machine Learning in Sports, Sports Outcome Prediction, Supervised Learning Algorithms, Predictive Modeling in Cricket, Sports Data Analytics

INTRODUCTION

Cricket, one of the most popular sports globally, is a bat- and-ball game played between two teams of eleven players each. The game is structured in innings, during which one team bats with the aim of accumulating as many runs as possible, while the other team fields, attempting to limit scoring and dismiss batters. The batting phase concludes when the predefined number of legal deliveries (balls) has been bowled or when ten batters are dismissed. The outcome of the match is decided by the aggregate number of runs scored, making run generation and prevention central to the game's dynamics.

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Over the years, cricket has evolved into a sport rich in statis- tics and strategic complexity. Numerous variables such as pitch conditions, toss results, weather, venue, player performance trends, and team composition can significantly affect the out-come of a match. These complexities, coupled with cricket's inherently uncertain nature, make it a compelling candidate for predictive analytics. In recent times, the confluence of big data and machine learning has opened new possibilities for modeling and forecasting cricket match outcomes. These approaches not only offer intriguing insights for fans and bettors but also have practical value for coaches, analysts, and administrators seeking a competitive edge.

The global regulatory authority for cricket, the International Cricket Council (ICC), oversees the conduct of matches and maintains the official rules of the game. At the international level, the sport is contested in three primary formats: Test matches, One Day Internationals (ODIs), and Twenty20 (T20) matches. Each format varies in duration and strategic approach. Test cricket, often regarded as the purest form of the game, spans up to five days and allows each team two innings. It emphasizes endurance, technique, and long-term strategy. One Day Internationals restrict each team to a maximum of 50 overs (or 300 balls), typically concluding in a single day.

ODIs strike a balance between strategy and pace, making them ideal for analytical modeling. T20 cricket, the most condensed format, consists of 20 overs per team and is characterized by rapid scoring, aggressive play, and heightened spectator engagement.

This study focuses specifically on One Day Internationals. ODIs present an ideal use case for machine learning because they contain structured rules, a rich history of recorded data, and a well-defined set of outcomes. Given the wide range of factors that influence match results, accurate forecasting is a non-trivial task that necessitates sophisticated analytical tools. Predicting match outcomes requires careful consideration of both qualitative and quantitative variables, many of which interact in nonlinear ways.

In our research, we identify and select a curated set of features that have demonstrated empirical relevance in determining match outcomes, drawing upon established literature and prior empirical work. These features include team strength, venue details, previous head-to-head performance, toss outcome, player statistics, and contextual information such as match type (day or day-night). Using this multidimensional dataset, we train and evaluate two well-established supervised learning algorithms: Decision Trees and Multi- Layer Perceptron (MLP) neural networks. Both models are tasked with classifying match outcomes based on the provided inputs.

To facilitate real-world application of our findings, we developed a user-friendly desktop application named CricAI. This software allows users to input match-specific parameters and receive predicted outcomes based on trained models. CricAI is designed to serve as a decision-support tool for teams, analysts, broadcasters, and enthusiasts seeking to better understand and anticipate game results. Its real-time predictions can aid in pre-match preparation, in-game decision- making, and post-match analysis.

An important methodological decision was the exclusion of unsupervised learning approaches such as clustering. While clustering is useful for pattern discovery in unlabeled data, it does not align with our objective of predicting known categorical outcomes (e.g., win or loss). Our focus remains firmly within the domain of supervised learning, where historical data is labeled with match results, enabling direct model training and evaluation.

APPROACH FOR ANALYSIS

Data Acquisition and Preparation

The dataset utilized in this research was collected using a custom-developed web scraping script, which was configured to send a request every second in compliance with ethical scraping standards as shown in Table 1. The primary source for the match data was the publicly available cricket archive.

Table 1. Sample Odi dataset format with match details and outcomes

Match Id	Team 1	Team 2	Winner	Margin	Ground
ODI #1	Australia	England	Australia	5 wickets	Melbourne
ODI #2	England	Australia	England	6 wickets	Manchester
ODI #3	England	Australia	Australia	5 wickets	Lord’s

The dataset encompasses records of One Day International (ODI) cricket matches played from January 5, 1971, to October 29, 2017, totaling 3933 matches. During preprocessing, entries corresponding to matches with inconclusive outcomes—such as those that ended in ties, no results, or were abandoned due to weather interruptions—were excluded. Additionally, matches involving composite teams (e.g., World XI, Asia XI, Africa XI) were removed to maintain consistency and relevance.

To enhance the learning capacity of our models and reduce potential bias due to team ordering, the dataset was synthetically doubled by swapping the positions of the competing teams. For instance, a match recorded as Team A vs Team B was mirrored as Team B vs Team A, with features adjusted accordingly as shown in Figure 1 and 2.

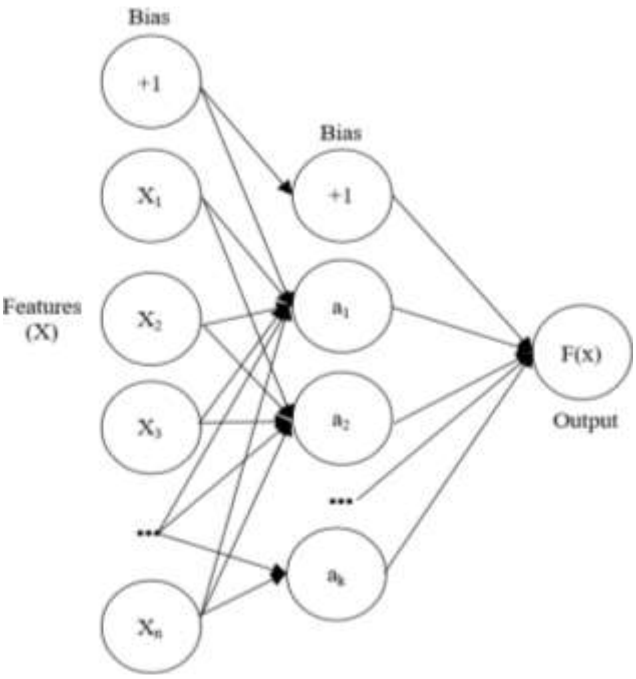

Figure 1. Architecture of Multilayer Perceptron (MLP) Neural Network

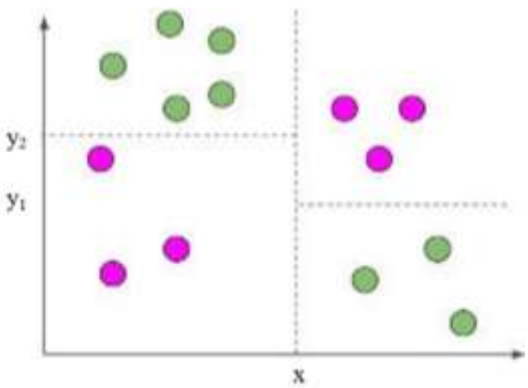

Figure 2. Decision Tree Classifier Structure for ODI Match Outcome Prediction

To make the data suitable for input to classification algorithms, categorical encoding was performed. Specifically, dummy variables were created to represent categorical features, ensuring that the input format conformed to the expectations of scikit-learn classifiers.

Innings Feature Engineering: The match margin information was used to infer the winning team's innings. Matches won by wickets implied a second-innings victory, while wins by runs indicated success in the first innings. This logic was used to generate a new feature, *Winner Innings*, and subsequently, the innings played by each team were determined by cross-referencing this feature with the winning team column. Venue-Based Feature Engineering: Venue-related features were constructed using the ground information available in the scraped dataset. By mapping match locations and host countries, we identified home and away statuses for both participating teams, enriching the feature set with contextual match environment details.

The final dataset was stored in a CSV format and partitioned into training and testing sets as follows:

- Training Set: 5620 matches
- Testing Set: 1874 matches

Multilayer Perceptron (MLP) Networks

The Multilayer Perceptron (MLP) is a class of feedforward artificial neural networks trained using supervised learning. An MLP models the mapping between an input vector $X = [x_1, x_2, ..., x_m]$ and an output target vector y, effectively learning a function f: $\mathrm{R}^n \rightarrow \mathrm{R}^t$, where n is the number of features and t denotes the number of output classes.

The architecture of an MLP consists of an input layer, one or more hidden layers, and an output layer. Each neuron computes a weighted sum of its inputs and applies a nonlinear activation function. This combination allows the network to learn complex, non-linear relationships in the data.

The model used in our implementation is MLPClassifier from the scikit-learn library, which employs the backpropagation algorithm in conjunction with gradient descent to optimize weights. The loss function used is cross-entropy, making the model suitable for probabilistic multi-class classification tasks. The function predict_proba returns class probabilities, which enhances interpretability.

Advantages of MLP:

- Capable of approximating non-linear decision boundaries.
- Learns continuously using backpropagation, refining its weights with each training iteration.
- Supports partial fitting, enabling online learning scenarios.

Limitations of MLP:

- Highly sensitive to the scale of input features, necessitating careful normalization.
- Functions as a black-box model, making it difficult to interpret learned patterns.
- Requires careful tuning of hyperparameters such as the number of hidden layers, neurons per layer, learning rate, and number of epochs.

Decision Tree Classifiers

Decision Trees are interpretable models used for supervised learning tasks such as classification and regression. They recursively partition the dataset into subsets based on feature values, forming a tree-like structure composed of internal decision nodes and terminal leaf nodes. Each decision node applies a condition based on a feature and a threshold, directing data flow down the appropriate branch.

For a given input dataset $\{x_i \in \mathrm{R}^n, y_i\}^{l}_{i=1}$, w+here x_i represents the feature vector and y_i the corresponding target label, the tree construction process involves identifying splits that minimize node impurity. Suppose Q is the data at a node m, and $\theta = (j, t_m)$ is a candidate split on feature j at threshold t_m, the split divides Q into:

$$Q_{\text{left}}(\theta) = \{(x, y) \mid x_j \leq t_m\},\ Q_{\text{right}}(\theta) = Q \setminus Q_{\text{left}}(\theta)$$

The impurity of a split is measured using an impurity function $H()$ (e.g., Gini impurity or entropy), and the best split θ^* minimizes the weighted average impurity:

$$G(Q, \theta) = \frac{n_{left}}{N_m} H\left(Q_{left}\right) + \frac{n_{right}}{N_m} H\left(Q_{right}\right), \qquad \theta^* = \arg\min_{\theta} G(Q, \theta)$$

Splitting continues recursively until stopping conditions are met, such as reaching a maximum depth or a minimum number of samples at a node.

Advantages of Decision Trees:
- Easy to understand, visualize, and explain through logical rules.
- Can handle both categorical and numerical features.
- Suitable for multi-output problems and missing value scenarios.

Limitations of Decision Trees:
- Prone to overfitting, especially with deep or complex trees.
- Sensitive to small changes in the training data, which may lead to significant structural variations.
- Class imbalance can lead to biased trees if not handled appropriately.

RESULTS AND OBSERVATIONS

Performance Evaluation Metrics

To assess the efficacy and reliability of our machine learning classifiers, it is essential to utilize well-established performance metrics. These evaluation indices offer a quantitative basis to compare different models and determine their predictive capabilities. A performance measure is a consolidated statistical value that reflects how accurately a model is able to learn from historical data and generalize to new, unseen instances.

In this study, we have applied a range of evaluation criteria to compare the performance of the Multilayer Perceptron (MLP) and Decision Tree classifiers. The key metrics considered in our comparative analysis include Accuracy, Precision, Recall, F1 Score, and Average Precision Score. Each of these measures serves a distinct purpose and helps us understand specific aspects of the model's strengths and limitations.

Accuracy Score: Accuracy is one of the most commonly used metrics for classification tasks. It indicates the proportion of correct predictions out of the total number of predictions made. Mathematically, it is defined as the ratio of correctly predicted samples to the total samples in the test set.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}$$

Although widely used, accuracy may not always be the best performance indicator—especially in cases of imbalanced datasets where the class distribution is skewed. For this reason, we also include other precision-based measures for a more granular performance evaluation.

Precision Score: Precision quantifies the model's ability to return only relevant results. It is defined as the ratio of true positive predictions to the sum of true positives and false positives:

$$Precision = \frac{T_p}{T_p + F_p}$$

Here, T_p refers to the number of true positive cases (correctly predicted positive samples), and F_p refers to the number of false positive cases (incorrectly predicted positive samples). A high precision score indicates that the model is effective in minimizing the number of irrelevant or incorrect positive predictions. Precision is particularly important in scenarios where false positives carry a high cost.

Recall Score: Also known as sensitivity or true positive rate, recall measures the model's ability to identify all relevant instances within a dataset. It is calculated as:

$$Recall = \frac{T_p}{T_p + F_n}$$

In this expression, F_n denotes false negatives, i.e., relevant instances that the model failed to identify. A high recall score means the classifier is successful in capturing most of the true positives and is less likely to miss important results.

F1 Score: The F1 Score provides a harmonic mean of the precision and recall scores. It is especially useful in cases where there is a trade-off between precision and recall, offering a balanced view by equally weighting both metrics:

$$F1 = 2\frac{Precision\ recall}{Precision\ recall}$$

A high F1 score indicates that the classifier maintains a good balance between identifying all relevant samples (recall) and being precise about the positive predictions it makes. This metric is particularly valuable in domains where both false positives and false negatives carry significant implications.

Average Precision Score (AP): Average Precision is a summarizing metric derived from the precision-recall curve. It captures the area under the curve (AUC) by computing the weighted mean of precision values at different recall levels. The formal expression is given as:

$$AP = \sum{}_k (R_k \vdash R_{k-1}).P_k$$

Here, P_k and R_k are the precision and recall at the k^{th} threshold. The AP metric offers a single-number evaluation that reflects both the completeness and relevancy of the classifier's predictions across all classification thresholds. It is widely adopted in ranking tasks and multi-class classification systems, where it is crucial to assess how well the classifier performs at different confidence thresholds shown in Table 2.

Why Multiple Metrics?: Using a combination of the above metrics ensures a holistic evaluation of classifier performance. For instance, while accuracy might show an optimistic picture on balanced datasets, it could be misleading when the data is skewed toward a particular class. In contrast, precision and recall offer deeper insights into the model's ability to correctly classify the minority class. The F1 Score balances these two, and Average Precision adds an aggregate probabilistic view. By analyzing all of these metrics together, we can make a more informed judgment about the overall reliability and robustness of the models used in this study shown in Table 3.

Comparative Analysis

Accuracy Score

Observation: We selected 3 teams: India, Australia and Pakistan randomly and separated the match records of these 3 teams to obtain the performance measure for them separately as shown in Figures 3-8.

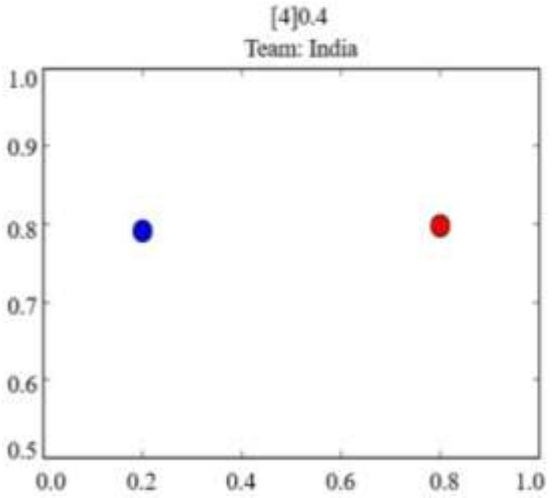

Figure 3. P = 0.791, R = 0.797

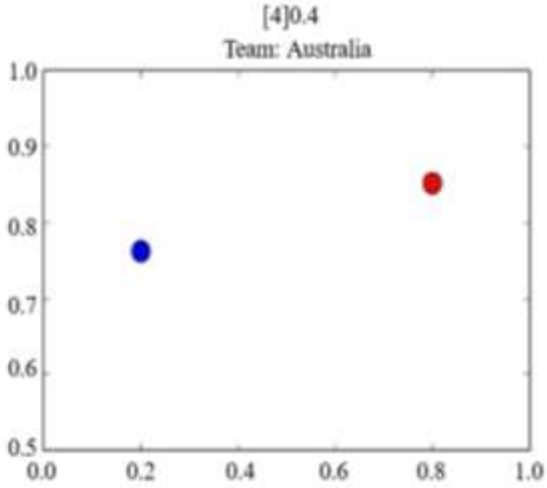

Figure 4. P = 0.760, R = 0.850,

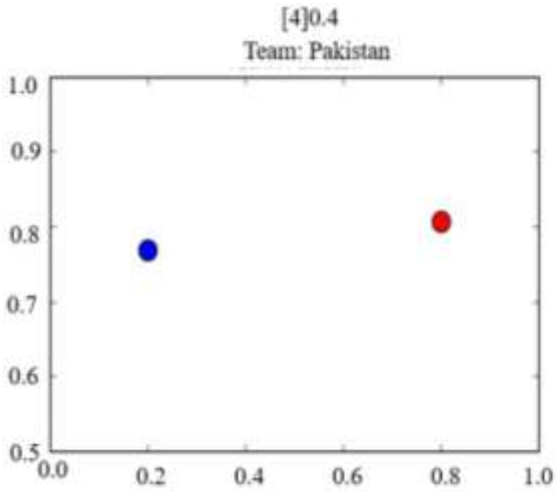

Figure 5. P = 0.767, R = 0.806

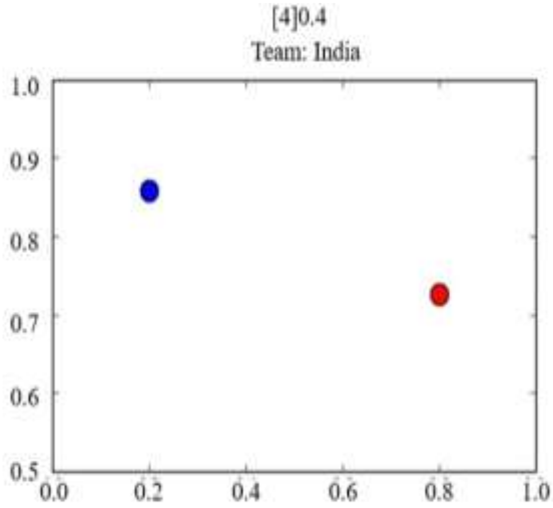

Figure 6. P = 0.859, R = 0.726

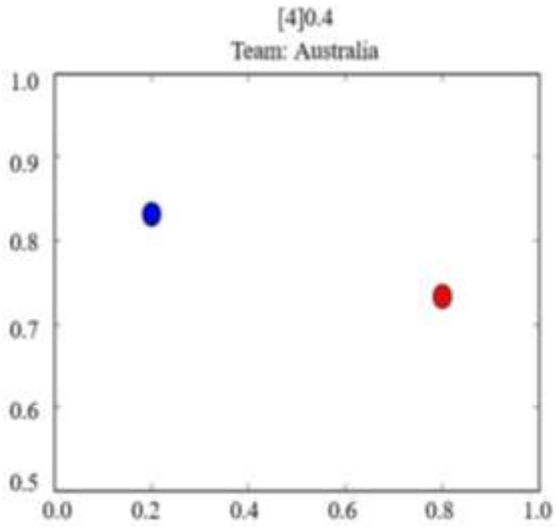

Figure 7. P = 0.830, R = 0.733

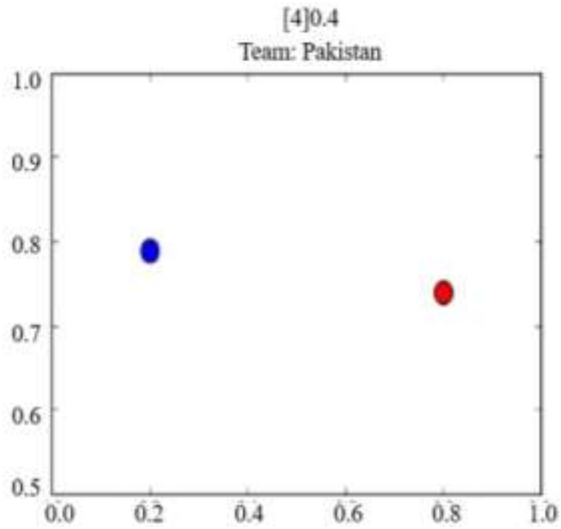

Figure 8. P = 0.789, R = 0.739

Table 2. Accuracy Score observations

Accuracy Score	MLP Classifier	Decision Tree Classifier
	0.574	0.551

Table 3. Accuracy Score observations by Team

Team name	Training dataset size	Testing dataset size
India	1320	440
Australia	1288	430
Pakistan	1281	427

RELATED WORK

The integration of machine learning techniques into sports analytics has gained considerable momentum in recent years. However, when it comes to the game of cricket—despite its data-rich nature and strategic depth—machine learning applications remain relatively underexplored in comparison to other sports like football or baseball. This limited body of research is partially due to the sport's unique structure, complex game rules, and regional concentration of popularity. Unlike games with fixed durations and consistent structures, cricket presents challenges in standardizing data for predictive modeling, thereby demanding specialized analytical approaches [1,2].

Most of the existing analytical work related to cricket adopts statistical or probabilistic modeling techniques, with relatively fewer studies exploring data-driven machine learning frameworks. Traditional statistical modeling has long been the dominant methodology for analyzing game dynamics, forecasting scores and identifying performance trends. While these models have provided foundational insights, they often fall short when it comes to capturing the nonlinear patterns and high-dimensional relationships present in real-world match data—challenges that machine learning algorithms are inherently well-suited to address.

A notable contribution in this space comes from Bailey and Clarke [3], who developed a predictive model aimed at fore- casting the result of an ongoing One Day International (ODI) cricket match. Their work introduced the WASP (Winning and Score Predictor) model, which employs principles of dynamic programming to estimate the likely outcomes of in-progress matches based on the current match state. WASP, developed by Dr. Scott Brooker and Dr. Seamus Hogan at the University of Canterbury, became one of the earliest publicly recognized analytical tools applied to live cricket.

Table 4. Comparative Performance metrics of Decision Tree and Multilayer Perception Classifiers

Classifier	Performance Measure	India	Australia	Pakistan
Multilayer Perceptron Classifier	Recall_Score	0.797	0.85	0.806
	Precision_Score	0.791	0.76	0.767
	F1_Score	0.794	0.803	0.786
	Average_P_Score	0.744	0.744	0.724
Decision Tree Classifier	Recall_Score	0.726	0.733	0.739
	Precision_Score	0.859	0.83	0.789
	F1_Score	0.787	0.779	0.763
	Average_P_Score	0.785	0.779	0.719

In more recent efforts, Neeraj Pathak and Hardik Wadhwa [4] explored outcome prediction using several machine learning classification models, including Support Vector Machines (SVM), Random Forests, and Naive Bayes classifiers. Their study evaluated the performance of these algorithms in terms of accuracy, highlighting the strengths and weaknesses of each classifier in the context of cricket match data. Similarly, Preeti Satao and her team [5] adopted unsupervised learning approaches, specifically clustering techniques, to identify patterns in cricket match data and estimate score outcomes based on grouped feature similarities.

Multilayer Perception & Decision classifier based on match data extracted from ESPN Cricinfo

Several researchers have also examined the statistical rele- vance of contextual game attributes. For example, Shah and Shah conducted in- depth studies on how factors such as home-ground advantage, day versus day-night match settings, and prior head-to-head performance influence match outcomes [6,7]. Their findings suggest that venue, match format, and team history are among the most significant predictors when forecasting game results, reaffirm- ing the need to incorporate such domain-specific attributes into predictive models.

Another line of research was carried out by Bandulasiri and Kapadia et al. focused on team composition and relative team strength as predictors of match outcome [8,9]. By using supervised learning algorithms, they demonstrated that carefully curated team-related features—such as player skill distributions, recent form, and lineup balance—can significantly improve the accuracy of match predictions. Their work reinforced the idea that data-driven features derived from actual team compositions offer a meaningful advantage in model performance.

In addition, analyzed a variety of factors contributing to match outcomes in limited- overs cricket [10]. Their analysis emphasized that match conditions, pitch reports, toss decisions, and team statistics each play a critical role in determining the likelihood of a team's victory. They highlighted the complexity of integrating qualitative and quantitative variables into a single cohesive model—an area where hybrid machine learning approaches could offer substantial improvements.

Despite these valuable contributions, the cricket analytics landscape still lacks a comprehensive, unified framework that leverages the full potential of modern machine learning techniques. Most studies are limited either by narrow feature selection, small datasets, or a reliance on traditional algorithms that may not scale well to large and dynamic datasets. Furthermore, little emphasis has been placed on developing end-to-end tools or applications that can serve as real-time decision support systems for coaches, analysts, or broadcasters.

Our work aims to fill this gap by implementing and comparing two well-established supervised classification techniques—Multilayer Perceptron (MLP) Networks and Decision Trees—while also developing a user-friendly software interface to apply these models in practice. By combining comprehensive feature engineering, rigorous evaluation metrics, and practical implementation through the CricAI desktop application, this study contributes both methodologically and applicationally to the growing field of cricket analytics.

CONCLUSION

This study presents a data-driven approach for predicting the outcomes of One Day International (ODI) cricket matches using two widely adopted supervised machine learning techniques—Multilayer Perceptron (MLP) Networks and Decision Trees. We conducted a detailed comparative evaluation of these models based on multiple performance metrics, including Accuracy, Precision, Recall, F1 Score, and Average Precision. The classifiers were trained using historical pre-match data, and the predictions were assessed using a thoroughly processed and labeled dataset that covered a wide span of matches from 1971 to 2017.

One of the key insights from this analysis is that pre-game attributes, when carefully selected and engineered, can be effectively used to forecast match results. This includes con- textual features such as venue, toss decision, historical team performance, and innings-related indicators. The combination of such domain-specific variables with robust machine learning models offers a practical and scalable solution for predictive sports analytics in cricket.

Key Contributions

The primary contributions of this work are outlined as follows:

- *Empirical Comparison of Algorithms:* We conducted a systematic comparative analysis of two distinct super- vised learning algorithms applied to the same cricket dataset. This allowed us to assess their relative strengths, weaknesses, and suitability for predicting match out- comes.
- *Feature-Driven Analysis of Outcome Determinants:* Our study highlights and quantifies the importance of multiple pre-match features in influencing the final result of ODI games. By integrating these features, we enhance the predictive power of the models.
- *Software Implementation:* We designed and developed a user-friendly desktop application, CricAI, that encapsulates the trained models and enables users—ranging from analysts to casual fans—to forecast match results by inputting relevant pre-game data.

Future Scope

While the current work lays a foundational framework, several avenues for future enhancement exist:

- *Temporal Relevance of Historical Data:* The dataset spans nearly five decades of cricket history. However, the evolution of game formats, strategies, rules, and player fitness over time may reduce the relevance of older matches in modern predictions. In future work, we aim to apply temporal weighting techniques or consider a rolling window of recent matches to improve model relevance.
- *Team Composition and Player-Centric Metrics:* Our current analysis primarily focuses on team-level at- tributes. Expanding the feature set to include player- specific statistics such as batting averages, bowling economy, recent form, and injury status could lead to more granular and accurate predictions. Machine learning models like ensemble techniques or neural architectures with attention mechanisms may be employed for better con- textual modeling.
- *Extension to Other Sports Domains:* The methodology proposed in this study is not limited to cricket. It can be adapted for use in similar structured sports like football, hockey, and baseball, where historical and contextual data play a crucial role in outcome forecasting.
- Real-Time In-Game Predictions: While this work focuses on pre-match predictions, real-time forecasting of match outcomes using in-game data (e.g., current run rate, wickets, and overs remaining) is a promising direction. Integrating streaming data processing with dynamic ma- chine learning models would enable this transition.

In conclusion, this research demonstrates that machine learning holds considerable promise in the field of sports analytics. With continued advancements in data availability, computational tools, and model architectures, predictive systems like the one proposed here can provide meaningful insights, enhance strategic planning, and enrich the viewer experience in cricket and beyond.

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