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RESEARCH ARTICLE

Prediction of IPL matches using Machine Learning while tackling ambiguity in results

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Abstract

Background/Objectives: The IPL (Indian Premier League) is one of the most viewed cricket matches in the world. With a perpetual increase in the popularity and advertising associated with it, forecasting the IPL matches is becoming a need for the advertisers and the sponsors. This paper is centered on the implementation of machine learning to foretell the winner of an IPL match. **Methods/Statistical analysis:** The cricket in the T-20 format is highly unpredictable - many features contribute to the result of a cricket match, and each attribute feature has a weighted impact on the outcome of a game. In this paper, first, a meaningful dataset through data mining was defined; next, essential features using various methods like feature engineering and Analytic Hierarchy Process were derived. Besides, a key issue on data symmetry and the inability of models to handle it was identified, which extends to all types of classification models that compare two or more classes using similar features for both the classes. This concept in the paper is termed as model ambiguity that occurs due to the model's asymmetric nature. Alongside, different machine learning classification algorithms like Naïve Bayes, SVM, k-Nearest Neighbor, Random Forest, Logistic Regression, ExtraTreesClassifier, XGBoost were adopted to train the models for predicting the winner. **Findings:** As per the investigation, tree-based classifiers provided better results with the derived model. The highest accuracy of 60.043% with Random Forest, with a standard deviation of 6.3% and an ambiguity of 1.4%, was observed. **Novelty/Applications:** Apart from reporting a more accurate result, the derived model has also solved the problem of multicollinearity and identified the issue of data symmetry (termed as model ambiguity). It can be leveraged by brands, sponsors, and advertisers to keep up their marketing strategies.

Keywords: The Indian Premier League; machine learning; analytic hierarchy process; winner prediction; IPL

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1 Introduction

The IPL (Indian Premier League) is a 20-20 cricket league in India where eight teams (representing eight cities in India) play against each other. This game is India's biggest cricket festival - the most celebrated and the most viewed, where the action is just not limited to the cricket field. The clatters, promotional events, cheerleaders, advertisements, fan clubs, interactions, and betting are celebrated along with the players and the matches.

The entire revenue cycle of the IPL revolves around advertising. IPL also utilizes television timeouts, and there are other humongous opportunities associated with advertising. Apart from national and global broadcasts, the matches are transmitted to regional channels in eight different languages. The brand value of the IPL was ₹475 billion (US$6.7 billion) in 2019 [(1)]. The IPL cricket league has proved to be a 'game-changer' for both cricket and the entire Indian advertising industry [(2)].

"Due to the saturated market, it is especially important for sports organizations to function with maximum efficiency and to make smart business decisions" [(3)]. One of the most common areas where Sports organizations use analytic is assessing an athlete's value to their brand and strategizing their marketing activities.

In this paper, models using machine learning to predict IPL matches' outcomes were developed. Figure 1 illustrates the entire process followed while conducting the research.

During the research, a multi-step approach was taken to gather and pre-process the historical data. Feature engineering [(4,5)] techniques were applied to derive more insights about the current dataset. Further, analysis of the essential features was done using selection techniques, and simultaneously best players were marked based on their performances. Optimized features from players' performance were then added to the team data. The issue of multicollinearity, which occurs when multiple features are highly linearly related was tackled. One of the main issues identified during the research was the symmetry in the dataset. The models returning different results for the same input fed in two configurations was observed. This concept in the paper is termed as model ambiguity, which occurs due to the model's inability to interpret data symmetry because of its asymmetric nature. The models were trained using multiple machine learning classification algorithms to develop a predictive model. The highest accuracy was observed with Random Forest, i.e., 60.043%, with a standard deviation of 6.3% and 1.4% ambiguity.

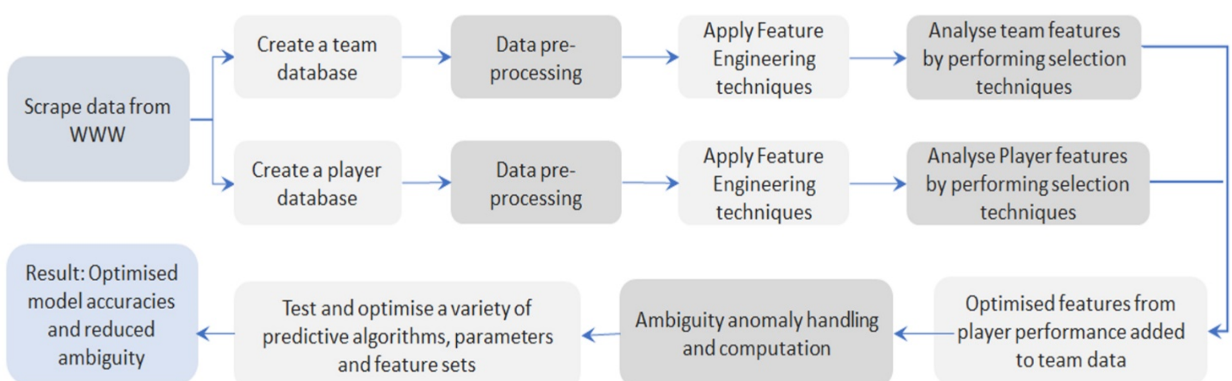


Fig 1. Complete process from data scrapping to creating optimised model accuracies with reduced ambiguity for predicting IPL matches' winner.

2 Related works

Many researchers have contributed towards predicting the results of cricket matches. Authors [(6)] proposed a paper on predicting the outcome of an IPL match, where they acquired the dataset available for all the 11 seasons from the archives of the IPL website [(7)] and applied the concept of Multivariate Linear Regression to calculate the strengths of a team using the data from the Player Points section of the official IPL website. Later for prediction, the scholars utilized various classifiers, namely Naive Bayes, Extreme Gradient Boosting, Support Vector Machine, Logistic Regression, Random Forests, and Multilayer perceptron. In another study, authors [(8)] adopted the Team Composition method to predict the outcome of an ODI match. They utilized the players' data career statistics (both recent and overall performance) to calculate the player's strength and aggregate to finalize the team strength. They also included other features like venue and toss. The model derived from their research gives the best result with the KNN algorithm.

Although not related to cricket match prediction, the authors conducted a study [9] to predict the performance of bowlers. They used Multilayer Perceptron and created a new feature using the data called CBR (Combined Bowling Rate) and calculating the harmonic mean of the Bowling Average, Bowling Economy, and Bowling Strike Rate. Authors [10] used the pressure Index of the team batting in the second innings to predict the match at different points of the chase; they devised a formula to calculate the pressure index at each point and used various methods to calculate the probability of a win based on the pressure index.

3 Material and Methods

3.1 Dataset

3.1.1 Dataset gathering

The historical dataset was obtained from various sources – Kaggle [11], ESPN Cricinfo [12] ,and iplt20 [7]. The performance data of individual players was scraped from the ESPN Cricinfo website by using Python Library Beautiful Soup [13] to calculate each player's strength and the team. This scrapped data demonstrates 26 features - including batting and bowling performances of the players. Additionally, match results data was obtained from Kaggle. This data displayed 18 features. The IPL winning point table yearly data was accumulated from the IPL website. This data demonstrated the point feature.

3.1.2 Pre-processing of data

3.1.2.1 Conversion of data format (Label Encoding).

Most of the Machine Learning algorithms work better with numerical values than the string values. Hence, all the string formats in the dataset were converted to the numerical formats utilizing the Label Encoding. The features that were converted: Team Names, Venue Names, Winning Team Name, Toss Winner Team Name.

3.1.2.2 Data cleaning and dealing with null values.

To produce accurate results, all the unnecessary features from the dataset were eliminated, for example – Umpire Name, Stadium Name, Date, Dl applied, Player of the match. The features that could result in data leakage, such as Win by Runs and Win by Wickets, were excluded. Further, all the match rows that were dismissed, drawn, or null were eradicated.

3.1.3 Class imbalance

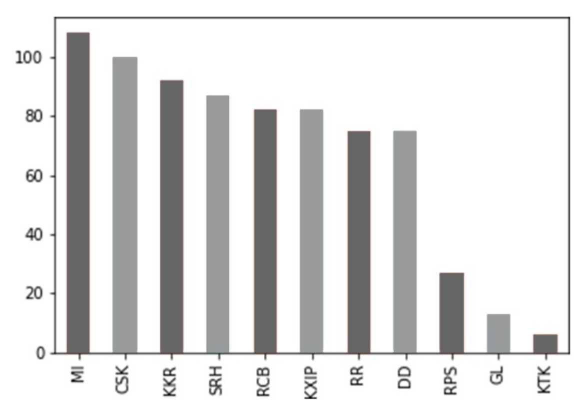


Fig 2. Historical data of the number of times each participating team has won a match during the IPL

Class Imbalance is a problem in machine learning where the class distribution is highly imbalanced [14,15]. Predicting the results using the team's name was not feasible as it can cause a massive Class Imbalance between the groups. For example – MI (Mumbai Indians) winning more than 100 matches whereas KTK (Kochi Tuskers Kerala) wining less than 10 matches is a Class Imbalance problem. Refer to Figure 2. Hence, to rule out the class imbalance, the model was designed to predict the winner based on the essential features instead of the Team names, declaring either Team 1 or Team 2 as a winner. Moreover, the number of times Team 1 won is more than Team 2 was noticed. Further, to resolve this issue and balance the Team 1 winning and Team 2 winning in the label column, few values of column Team 1 were interchanged with column Team 2.

3.1.4 Assumptions

A few assumptions to make the model accurate and robust were followed. The owners changed the names of few teams due to legal actions or due to the change in the ownership; however, the players and team dynamics did not change. The name Delhi Capitals was changed to Delhi Daredevils, Deccan Chargers to Sunrisers Hyderabad, and Pune Warriors to Rising Pune Supergiant. In these cases, the same team irrespective of the change in the name was taken. Moreover, the data of only 11 players for a team based on the highest number of matches they have played during the IPL was considered.

Refer Table 1 for the features extracted from the gathered and pre-processed data.

Table 1. Final features extracted from gathered data

Player	Mat	Inns	NO	Runs
HS	Ave	BF	SR	100
50	4's	6's	Overs	Mdns
Wkts	Econ	Ct	St	
		a. Features extracted from ESPN Cricinfo		
Team	Won	Lost		
Tied	Pts			
		b. Features extracted from IPL T20		
Season	City	Team_1	Team_2	
Toss_Winner	Toss_Decision	Winner		
		c. Features extracted from IPL T20		

3.2 Feature engineering

3.2.1 Base features

3.2.1.1 Features from the processed data:.

From the gathered and processed data, following three meaningful features were extracted.

1. City 2. Toss Winner 3. Toss Decision

Since the algorithms do not interpret string values, label encoding on the above three features was done, as follows:

1. City: If the match is played on the home ground of Team 1, the city value is taken as zero. If the match is played on the home ground of Team 2, then the city's value is taken as 1, and if the match is played in some other city, then the city value is taken as 2.

2. Toss Winner: If the Toss is won by Team 1, the Toss Winner value is taken as zero. If the Toss is won by Team 2, the Toss Winner value is taken as 1.

3. Toss Decision: If the Toss winner chooses to Bat, the value of the Toss Decision is taken as zero, and if the Toss winner chooses to Bowl, then the value of the Toss Decision is taken as 1.

For Base Feature Distribution, refer to Figure 3 .

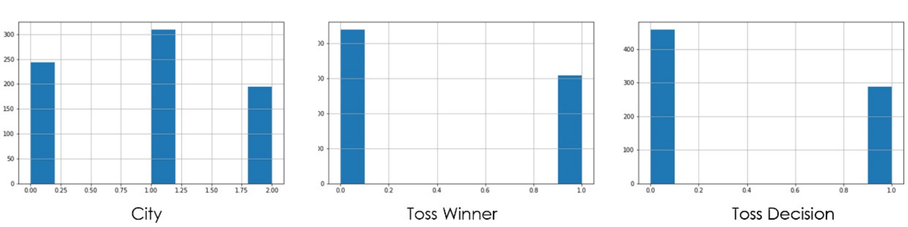


Fig 3. Feature distribution of base features

3.2.1.2 Dream 11 strength calculation.

In the first approach, the Dream11 points table was referred to derive the formula. For the definitions of point system and their notations, refer to Appendix A (a, b, c, d).

3.2.1.2.1 Batting Score of a player

. **Input:** Players p ∈ P, Career Statistics of player p: φ(p)
Output: Batsmen Score of all the players: φBatsman Score

1. for all players p ∈ P do
2. φ ← φ(p)
3. u ← (1* ΦRuns_Scored) +(1*Φnum_4s) + (2*Φnum_6s) + (8*Φfifties) + (16*Φhundreds) - (2*Φfduck)
4. if Φbat_strike_rate < =50:
   v ← -6
   else if Φbat_strike_rate > 50 and Φbat_strike_rate < =60:
   v ← -4
   else if Φbat_strike_rate > 60 and Φbat_strike_rate < = 70:
   v ← -2
   endif
5. w ← v * Φbat_strike_rate* Φbat_innings
6. y ← u + w
7. φBatsman Score ← y
8. end for

3.2.1.2.2 Bowling Score of a player

. **Input:** Players p ∈ P, Career Statistics of player p: φ(p)
Output: Bowling Score of all the players: φBowling_Score

1. for all players p ∈ P do
2. φ ← φ(p)
3. u ← (25*Φwickets) + (8*Φctchs) + (12*Φstmp) + (8*Φ4_wicket_haul) + (16*Φ5_wicket_haul) + (8*Φmaidens)
4. if Φbowl_economy < = 6 and Φbowl_economy > 5:
   v ← 2
   else if Φbowl_economy > 4 and Φbowl_economy < = 5:
   v ← 4
   else if Φbowl_economy < = 4:
   v ← 6
   else if Φbowl_economy > = 9 and Φbowl_economy < 10:
   v ← -2
   else if Φbowl_economy >= 10 and Φbowl_economy < 11 :
   v ← -4
   else if Φbowl_economy >= 11:
   v ← -6
   endif
5. w ← v * Φbowl_economy* Φbowl_innings
6. y ← u + w
7. φBowling_Score ← y
8. end for

3.2.1.2.3 Total Score of a player

. **Input:** Players p ∈ P, φBowling_Score, φBatsman_Score
Output: Total Strength← φ Total _Strength, φBatsman_Strength, φBowling_Strength

1. for all players p ∈ P, φBowling_Score, φBatting_Score do

2. φ Total_Strength ← (φBowling_Score + φBatting_Score) / φtot_matches
3. φBatsman_Strength ← φBatting_Score / φBat_innings
4. φBowling_Strength ←φBowling_Score/ φBowl_innings
5. endfor

3.2.1.2.4 Team Strength

. **Input:** Top 11 Players p ∈ P, φ Total _Strength, φBatsman_Strength, φBowling_Strength
Output: Team Strength: φTeam _Strength

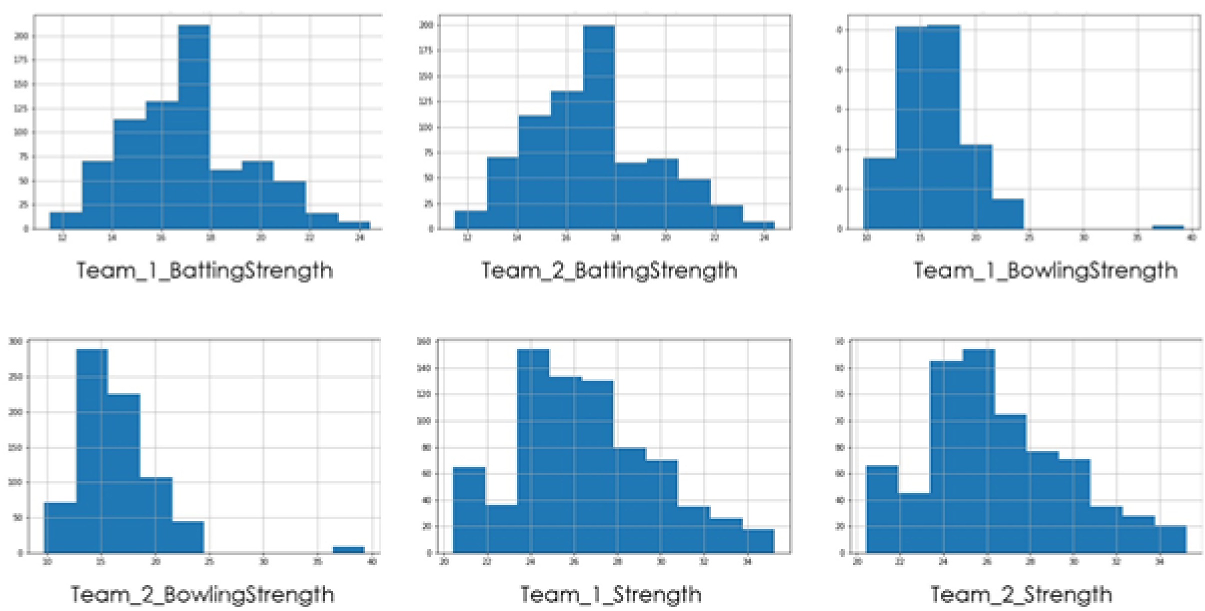
1. for all players p ∈ P , φTotal_Strength do
2. φTeam _Strength ← ($\sum \varphi$ *Total _Strength* / φmax_matches)
3. φTeam_Batting_Strength ← ($\sum$ φ *Batsman _Strength* / φmax_matches)
4. φTeam _Bowling_Strength ← ($\sum$ φ *Bowling _Strength* / φmax_matches)
5. endfor

3.2.1.2.5 Cumulative Team Strength

. For a particular year, Team Strength represents the previous year's performance, whereas the Cumulative Team Strength signifies the mean of the Team Strength of all the last years. For example – for the Mumbai Indians in 2016, the Strength will be the 2015 strength, and Cumulative Strength will be the mean of the Strength from 2008 to 2015. From this section, eight significant features were collected, mentioned below:

1. **Team_1_BattingStrength**	2. **Team_2_BattingStrength**
3. **Team_1_BowlingStrength**	4. **Team_2_BowlingStrength**
5. **Team_1_Strength**	6. **Team_2_Strength**
7. **Team_1_CumulativeStrength**	8. **Team_2_CumulativeStrength**

For Dream 11 strength feature distribution, refer to Figure 4.



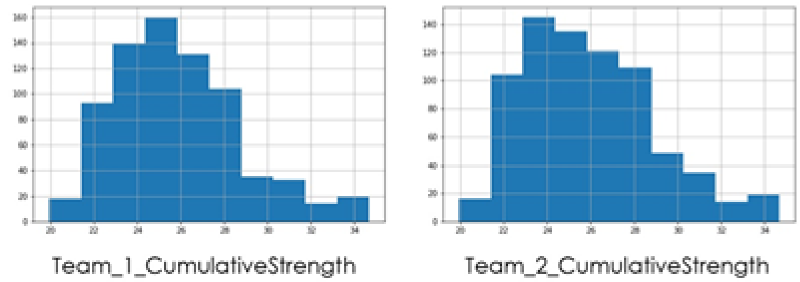


Fig 4. Feature distribution of Dream 11 strength features

3.2.1.3 Analytic hierarchy process for strength calculation

. Different measures highlight different aspects of a player's ability, which makes some features essential compared to others. For example, the strike rate is a necessary feature for a game - especially T20. In T20, the number of overs is less, which makes this feature more crucial as it adds to the team's ability to score maximum runs. The features were weighted according to their relative importance over other measures (features) in the research. The Analytic Hierarchy Process (AHP) was adopted to determine these weights for each player to calculate their bowling and batting features. Besides, we calculated the weights for each team based on their past performance.

The Analytic Hierarchy Process is a method for decision-making in complex conditions in which many variables or criteria are considered in prioritizing and selecting options [16]. AHP generates a weight for each evaluation criterion. The higher the weight for a corresponding criterion, the more important is the corresponding criterion (Refer to Appendix B). Finally, the AHP combines the criteria weights and the options amounts, thus determining a global score for each option and a consequent ranking. The global score for a given option is a weighted sum of the scores it obtained with respect to all the criteria [17].

3.2.1.3.1 Batting AHP

. Priority Order: The attributes were arranged in their decreasing order of importance based on the knowledge and experience from the T20 cricket matches, as below:

Batting Average > Innings > Strike Rate > 50's > 100's > 0's

Subsequently, a matrix was created to compare the importance of each attribute. Refer to Table 2.

Table 2. Criteria weights for Batting

Batting	Average	INN	SR	50's	100's	0's
Average	1	2	3	5	6	7
INN	0.5	1	2	4	5	6
SR	0.333333	0.5	1	3	4	5
50's	0.2	0.25	0.333333	1	2	3
100's	0.166667	0.2	0.25	0.5	1	2
0's	0.142857	0.166667	0.2	0.333333	0.5	1

Finally, from each attributed, weights were noted: Batting Average: 0. 3887, Innings: 0. 2601, Strike Rate: 0. 1754, Fifties: 0. 0834, Centuries: 0. 0550, Zeros: 0. 0373. Using these values the Batting strength through AHP was calculated.

$$AHP\ bat = 0.3887 * \text{Average} + 0.2600 * \text{Innings} \ + 0.1754 * \text{Strike Rate} + 0.0834 * 50's \ + 0.0550 * 100's - 0.0373 * 0's$$

3.2.1.3.2 Bowling AHP

. Priority Order: The attributes were arranged in their decreasing order of importance based on the knowledge and experience from the T20 cricket matches, as below:

Overs > Economy > Wickets > Bowling Average > Bowling Strike Rate > 4W Haul

Subsequently, a matrix was created to compare the importance of each attribute. Refer to Table 3.

Finally, the weights for each attributes were noted: Overs: 0.4174, Economy: 0.2634, Wickets: 0.1602, Bowling Average: 0.0975, Bowling Strike Rate: 0.067862, 4-Wickets Haul: 0.0615. Using these values the Bowling strength through AHP was calculated.

AHP bowl = 0.387509 * Overs + 0.281308 * Economy + 0.158765 * Wickets + 0.073609 * Bowling Average + 0.067862 * Bowling Strike Rate + 0.030947 * 4W Haul

Table 3. Criteria weights for Bowling

Bowling	Overs	Economy	Wickets	Bowling Avg	Bowling strike rate	4W Haul
Overs	1	2	4	6	6	7
Economy	0.5	1	4	5	5	6
Wickets	0.25	0.25	1	4	4	6
Bowling Avg	0.166666	0.2	0.25	1	1	5
Bowling SR	0.166666	0.2	0.25	1	1	4
4W Haul	0.142857	0.166666	0.166666	0.2	0.25	1

From this section, four essential features were formed, mentioned below:

1. **Team_1_AHP_Bat**	2. **Team_2_AHP_Bat**
3. **Team_1_AHP_Ball**	4. **Team_2_AHP_Ball**
5. **Team_1_AHP_BatBall**	6. **Team_2_AHP_BatBall**

For AHP Strength Feature Distribution, refer to Figure 5 .

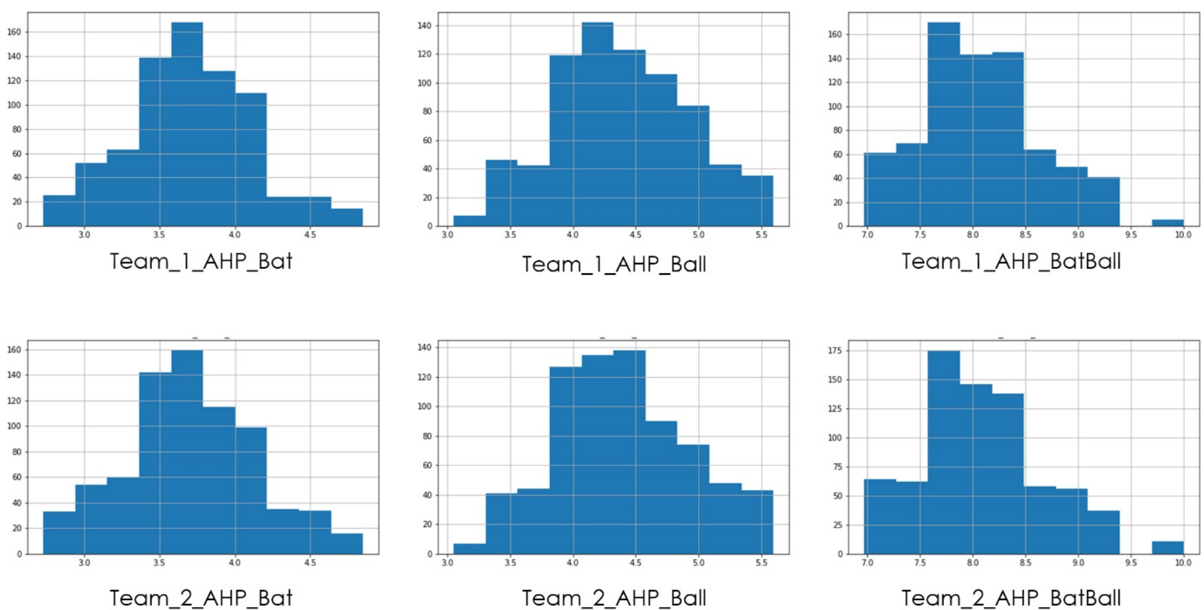


Fig 5. Feature distribution of AHP Strength features

3.2.1.4 Rank calculation using AHP

. Using the AHP, the coefficient for the win rate of each team against the other were derived. Assumption: KTK (Kochi Tuskers Kerala) and GL(Gujrat Lions) Teams were dropped while calculating the weights, as they never played against each other.

Priority Order: The priority order through AHP with the dataset of the matches played for win/loss for each team against each team was calculated. For example, the Team CSK (Chennai Super Kings) and MI (Mumbai Indians) played 27 matches against each other, and according to the dataset, MI won 16, and CSK won the rest 11 games. In this instance, in the MI row, the input will be 16/11 = 1.454545, and in the CSK row, it will be reciprocal, which is 11/16 or 1/1.4545454 = 0.6875. Refer to Table 4.

Table 4. Criteria weights for rank

Rank	CSK	DD	KKR	KXIP	MI	RCB	RPS	RR	SRH
CSK	1	2.5	1.857143	1.333333	0.6875	2.142857	2	2	2.142857
DD	0.4	1	0.769231	0.642857	1	0.571429	1.25	0.72727	1
KKR	0.538462	1.3	1	2.125	0.315789	1.4	3.5	1	1.888889
KXIP	0.75	1.555556	0.470588	1	0.846154	1	1	0.9	0.846154
MI	1.454545	1	3.166667	1.181818	1	1.777778	1.4	1	1.181818
RCB	0.466667	1.75	0.714286	1	0.5625	1	3.5	0.7	0.785714
RPS	0.5	0.8	0.285714	1	0.714286	0.285714	1	0.25	0.666667
RR	0.5	1.375	1	1.111111	1	1.428571	4	1	1.5
SRH	0.466667	1	0.529412	1.181818	0.846154	1.272727	1.5	0.66666	1

Further, the yearly ranks of each team based on the win ratios was noted and the ranks were derived using AHP. Refer to Table 5.

Table 5. Ranks of teams derived from AHP

Teams	RPS	DD	SRH	GL	KTK	RCB	KXIP	RR	KKR	MI	CSK
Coefficients	0.6043	0.8090	0.9042	1	1	1	0.9397	1.272	1.277	1.5188	1.6931
Ranks	9	8	7	5	5	5	6	4	3	2	1

For the KTK and GL, the mean value which is 1 as the coefficients was taken and two features were formed from this section, as below:

1. Team_1_Rank 2. Team_2_Rank

For AHP Rank Feature Distribution, refer to Figure 6 .

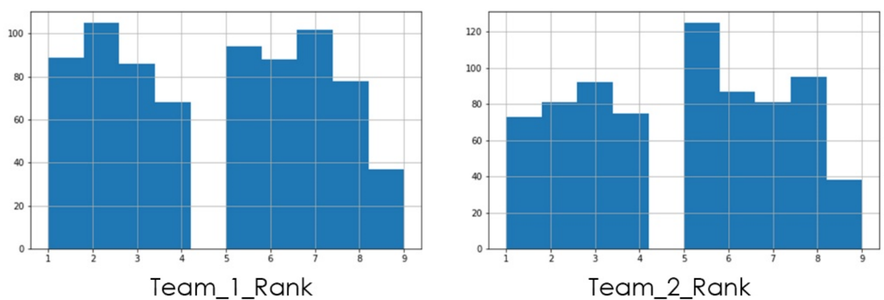


Fig 6. Feature distribution of AHP Rank features

3.2.1.5 Win rate

. For a cricket match, the win rate almost determines the overall performance of a team. A team is continuously winning the matches against other teams is a sign that the team's form is good and the probability of the team winning the upcoming matches is higher. On the other hand, a losing team reflects that it is not in good form and may even lose games further.

As next steps, the entire IPL match list played every year by each team from 2008 to 2019 was crawled. If the two teams played against each other for the first time, the win rate was reset to 0 for both the teams. Subsequently, all the played matches were checked and the winners for such occurrences were noted. This helped in defining a ratio for each team. For a match, the past win rate ratio of the team was considered as below:

Φwin_rate(Match R) = Total Number of wins till match R-1/ Total Number of matches played till R-1

Two important features from this section were derived, as below:

1. Team_1_Win_Rate 2. Team_2_Win_Rate

For Win Rate Feature Distribution, refer to Figure 7.

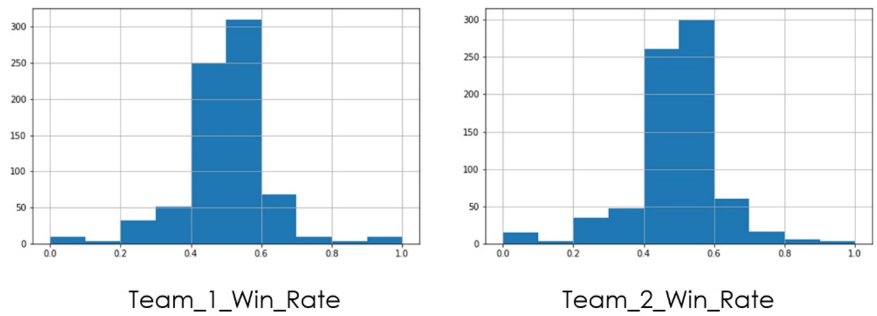


Fig 7. Feature Distribution of Win rate features

3.2.1.6 Team Points

. The IPL is a league tournament based on a point system. Every year, two teams play against each other twice before entering the semi-final match, if not eliminated. The point table comprises teams, match won/lost/tied, and net run rate. Teams' ranking was done according to the teams' points, and past performance features were fed to the model for predicting the results. Four significant features were formed from this section as below:

1. **Team_1_Point**	2. **Team_1_Cumulative Point**
3. **Team_2_Point**	4. **Team_2_Cumulative Point**

For a particular year, Team Point represents the previous year's performance, whereas the Cumulative Team Point represents the mean of the strengths of all the previous years.

For Team Point Feature Distribution, refer to Figure 8.

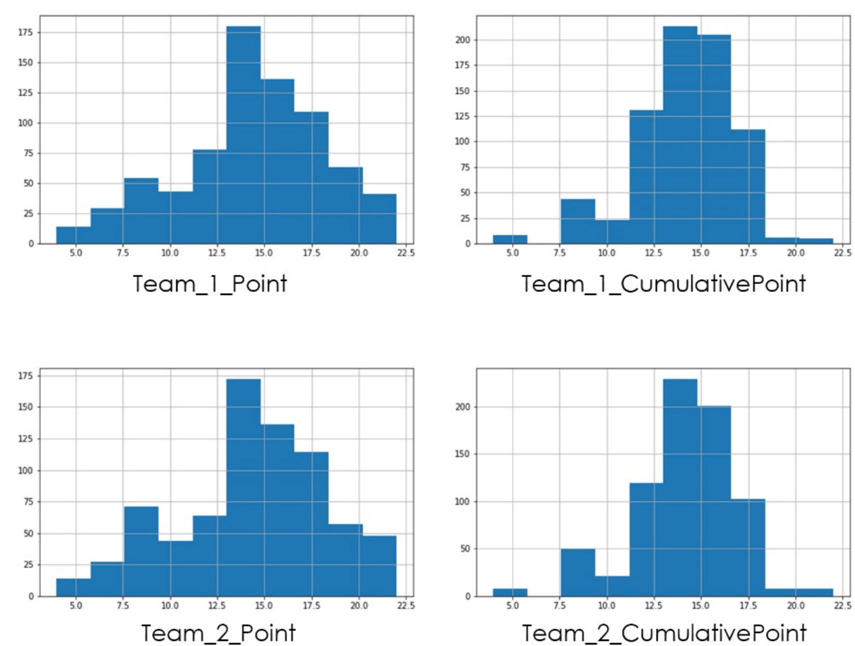


Fig 8. Feature Distribution of Team Point features

3.2.2 Intersection Features

3.2.2.1 Consistency

. The consistency of a team adds more weightage to its current performance than the overall performance. Therefore, 80 percent weightage was allotted to the current performance of a team and 20 percent weightage to their overall performance.

$$\text{Team 1 Consistency} = (\text{Team 1 Strength} * 0.8 + \text{Team 1 Cumulative Team Strength} * 0.2)/2$$
$$\text{Team 2 Consistency} = (\text{Team 2 Strength} * 0.8 + \text{Team 2 Cumulative Team Strength} * 0.2)/2$$

Two features were formed from this section, mentioned below:

1. Team_1_Consistency 2. Team_2_Consistency

For Consistency Feature Distribution, refer to Figure 9.

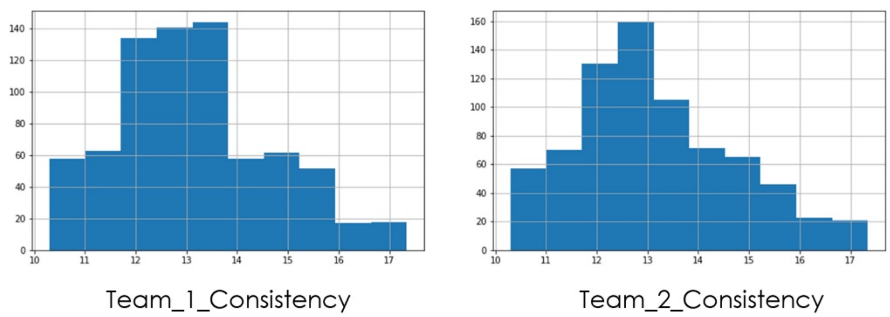


Fig 9. Feature Distribution of Consistency features

3.2.2.2 Win rate strength

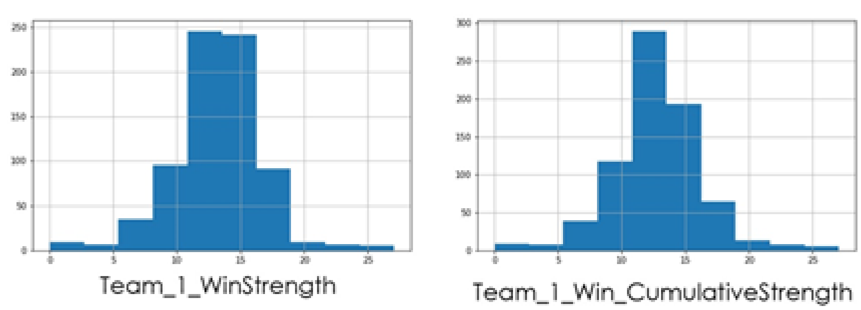
. The individual strength of a team represents how strong a team is by considering the stats. However, various other factors impact the winning of a team - for example - playing a team's sequence, performance as a team, and sentiments of the audience. This information was captured by multiplying the strength with the previous win rate of the team.

$$\text{Team 1 Win Strength} = \text{Team 1 Win Rate} * \text{Team 1 Strength}$$
$$\text{Team 2 Win Strength} = \text{Team 2 Win Rate} * \text{Team 2 Strength}$$
$$\text{Team 1 Win Cumulative Strength} = \text{Team 1 Win Rate} " \text{Team 1 Cumulative Strength}$$
$$\text{Team 2 Win Cumulative Strength} = \text{Team 2 Win Rate} " \text{Team 2 Cumulative Strength}$$

Four features were derived from this section, mentioned below:

1. **Team_1_WinStrength**	2. **Team_1_WinStrength**
3. **Team_2_Win_Cumulative Strength**	4. **Team_2_Win_Cumulative Strength**

For Win Strength Feature Distribution, refer to Figure 10.



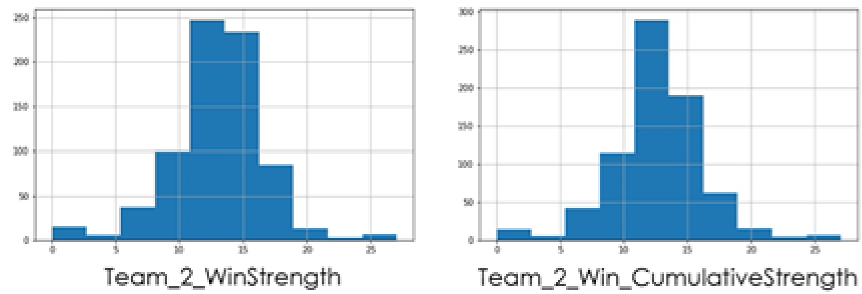


Fig 10. Feature Distribution of Win Strength features

3.2.3 Transformation Features

With all the formulated Base and Intersection features, Transformed features were developed. These features were created by subtracting two base features or intersection features from the same category. For example, Team1_Team_Strength is subtracted from the Team2_Team_Strength to create a new feature.

Since many new features based was created on base and intersection features for the model, multicollinearity [18] could occur. Multicollinearity occurs when multiple features in a model are highly linearly related, which means one variable can be predicted quite accurately using the other variable. The problem with multicollinearity is that it causes the model to overfit. To deal with multicollinearity in the derived model, all the base and intersection features that were used to create the new features were dropped.

3.2.4 Addressing the Symmetry in Data

As per the primary assumption, every team's performance is independent of the opposition team, toss decision, home-field advantage, and progress into the series. This allowed to make independent team features that will be present in both TEAM1 and TEAM2. The features generated can be broadly bucketed into Match and Team Features. As there are similar features for both TEAM1 and TEAM2, symmetry in the dataset was observed (Refer to Table 6).

Table 6. Example of a row from the dataset

Team1	Team 2	Team1_Strength	Team2_Strength	Winner	Team1
CSK	MI	X	Y	1	CSK

It is apparent to a human that while switching TEAM1 with TEAM2, the results will be the same. However, a machine learning model is asymmetric in nature and is neither capable of identifying the symmetry of features nor has a way to input the information about the symmetry of features. Hence, this information was entered to the model by generating a symmetric duplicate for every row in the training set (Refer to Table 7).

Table 7. Mirroring the row from the dataset

Team1	Team2	Team1_Strength	Team2_Strength	Winner
CSK	MI	X	Y	1
MI	CSK	Y	X	0

The below steps were taken to the train and test sets:

1. The original dataset is split using train_test_split from sklearn [19] library into training and test sets. The data was split such that 90% of data are in training set and 10% of data are in testing set.
2. The training set is then mirrored as shown above and append to the original training set which increases in training set size
3. The test set is also mirrored but the test sets were not appended to create two test sets

3.2.5 Model Ambiguity

The mirroring of the rows only tells the model about the existence of a symmetric scenario, but the model will still interpret the mirrored rows as new training set rows completely unrelated to the original rows. This asymmetric nature of the model leads to ambiguity in the results in certain rows (Refer to Table 8).

Table 8. Example of a match result and its mirrored data

Test Set	Team1	Team2	Winner	Prediction	Team
1	KKR	KXIP	1	1	KKR
2	KXIP	KKR	0	1	KXIP

The model was tested for a given match in two configurations. The model interprets both the cases as two different test cases. As a result, sometimes, the model returns different predictions for the same case. Such an occurrence is called Model Ambiguity. Note: This occurrence is not an incorrect prediction, as the prediction will be counted correct in either test set 1 accuracy or test set 2 accuracy.

To tackle this phenomenon of Model Ambiguity, the model was evaluated using five parameters apart from just training and test accuracy:

- Training Accuracy: % of correct predictions in mirrored and merged train set
- Test 1 Accuracy: % of correct prediction in the original test set
- Test 2 Accuracy: % of correct prediction in the mirrored test set
- Real Test Accuracy: % of correct prediction after discrediting the scores for ambiguous rows
- Ambiguity: % of rows in which ambiguity is observed

The objective of hyperparameter tuning was to maximize real test accuracy by driving down the ambiguity while evaluating the overfitting of the model using training accuracy and test 1 & 2 accuracies.

3.3 Data set split

Changing the random state in dataset the accuracy differs a lot was noted. This change occurs because the training and testing dataset is randomly split based on the state in which the data was put. To prevent such a scenario and to make the model robust RepeatedStratifiedKFold [20] was used. 10 folds and 2 iterations were selected to give a total of 20 folds. RepeatedStratifiedKFold was preferred over StratifiedKFold [20] as dataset is small, and RepeatedStratifiedKFold gives more fold with larger validation set.

Constant: Random State = 827 throughout the project was taken

The model was evaluated using accuracy and Standard Deviation, Cohen Kappa [21], Skewness [22,23] and Kurtosis [22,23]. To check or visualize the performance of the multi - class classification problem, AUC (Area Under The Curve) ROC (Receiver Operating Characteristics) curves were plotted. These curves are one of the most important evaluation metrics for checking any classification model's performance [24].

4 Results and Discussions

8 Supervised algorithms to train the derived model were selected:

4.1 Model implementation using Naïve Bayes

The Real test accuracy of 58.233 % with a standard deviation of 5.5 % and ambiguity of 3.0% were derived (Refer to Table 9).

Table 9. Best results from Naïve Bayes

Ambiguity	Real Test Accuracy	Train Accuracy	Cohen Kappa score
3.008 ± 2.5 %	58.233 ± 5.5 %	60.757 ± 0.9 %	0. 1891

The Area under the Curve is 0.63. The ROC curve was plotted with the best result using Naïve Bayes. The distribution of Real Test Accuracy was done to derive Skewness and Kurtosis of the Real Test Accuracy (Refer to Figure 11).

- Kurtosis of the Real Test Accuracy is -0.7954
- Skewness of the Real Test Accuracy: -0.2357

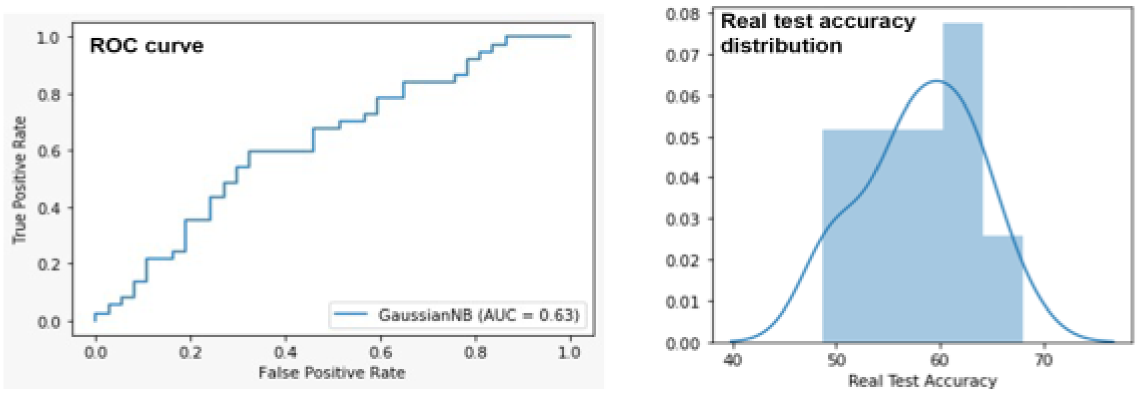


Fig 11. ROC curve and real test accuracy distribution with Naïve Bayes

4.2 Model implementation using logistic regression

The model was tuned with over 1232 combinations. Refer to Appendix C (a). The best results derived: Real Test Accuracy of 57.78% with a standard deviation of 5.8% and ambiguity of 2.2 % (Refer Table 10).

Table 10. Best result with hyperparameters using logistic regression

penalty	l2
solver	liblinear
max_iter	400
tol	1
C	2
Ambiguity	2.199455± 1.4 %
Real Test Accuracy	57.77618± 5.8 %
Train Accuracy	61.11655± 3.2 %
Cohen Kappa score	0.1351

Further, the ROC curve with the best result was made and AUC value of 0.57 was derived. The Real test accuracy distribution was plotted for deriving the Kurtosis and Skewness. Refer Figure 12.

- Kurtosis of the Real Test Accuracy: 0.5892
- Skewness of the Real Test Accuracy: 1.4699

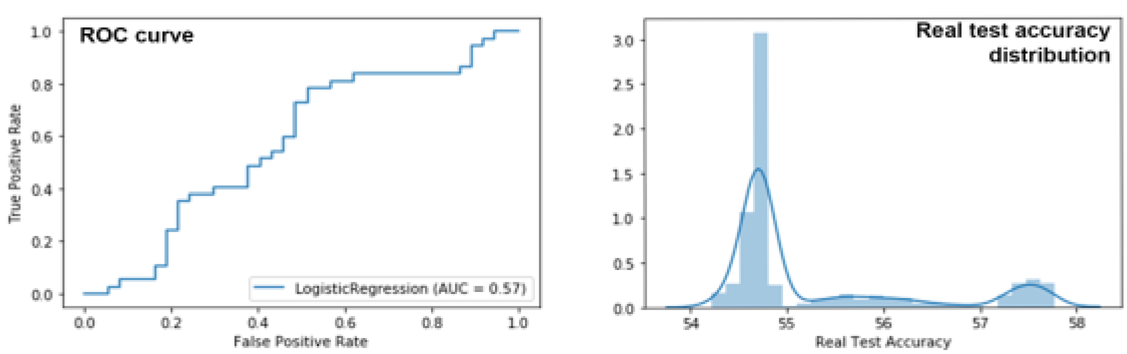


Fig 12. ROC Curve and Real test accuracy distribution with Logistic Regression

4.3 Model implementation using support vector machines

The model was tuned with over 25 combinations. Refer to Appendix C (b). Real test accuracy of 58.416% with a standard deviation of 5.69% and ambiguity of 0.24% was derived (Refer to Table 11).

Table 11. Best result with hyperparameters using support vector machines

c	0.1
Gamma	0.001
Kernal	rbf
Ambiguity	0.24 ± 0.3%
Real Test Accuracy	58.416% ± 5.69%
Train Accuracy	61.13 ± 4.2%
Cohen Kappa score	0.1921

The Area under the Curve is 0.72. The ROC curve was plotted with the best result from Support Vector Machines. The distribution of Real Test Accuracy was done to derive Skewness and Kurtosis of the Real Test Accuracy (Refer to Figure 13).

- Kurtosis of the Real Test Accuracy is 1.6979
- Skewness of the Real Test Accuracy: 0.4171

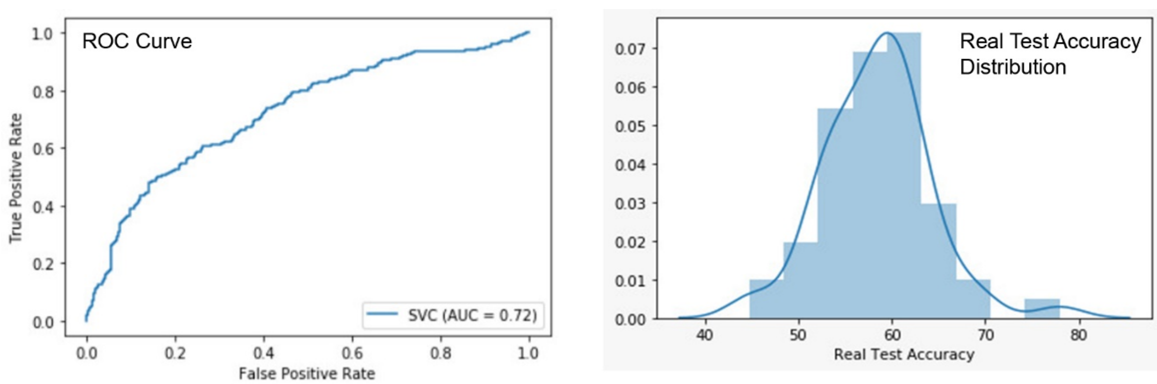


Fig 13. ROC Curve and Real test accuracy distribution with SVM

4.4 Model implementation using k- Nearest neighbours

The model was tuned with over 300 combinations. Refer to Appendix C (c). Real test accuracy of 53.472% with a standard deviation of 5.2% and ambiguity of 1.90% was derived (Refer to Table 12).

Table 12. Best result with hyperparameters using Knn

n_neighbors	15
weights	uniform
metrics	manhattan
Leaf-size	20
Ambiguity	1.900 ± 1.1%
Real Test Accuracy	53.472% ± 5.2%
Train Accuracy	62.043 ± 4.8 %
Cohen Kappa score	0.1634

The Area under the Curve is 0.81. The ROC curve was plotted with the best result using Knn. The distribution of Real Test Accuracy was done to derive Skewness and Kurtosis of the Real Test Accuracy (Refer to Figure 14).

- Kurtosis of the Real Test Accuracy is 0.0502
- Skewness of the Real Test Accuracy: -0.3635

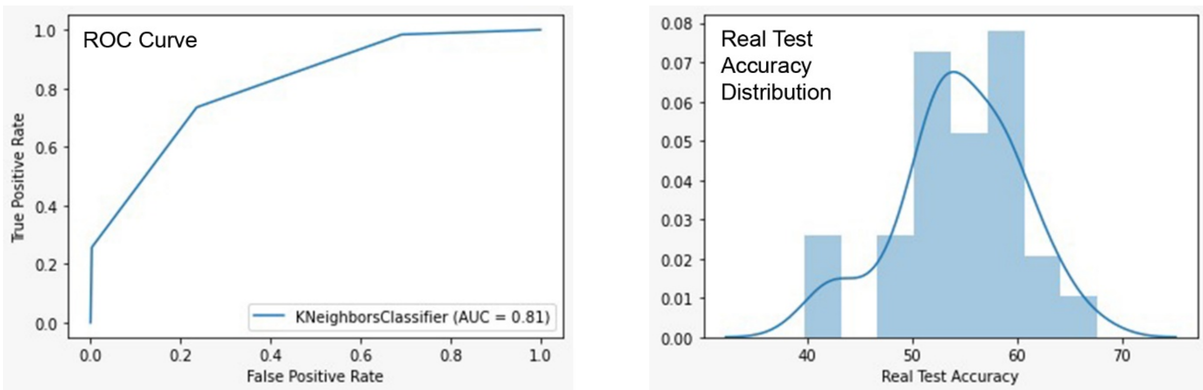


Fig 14. ROC curve and real test accuracy distribution with KNN

4.5 Model Implementation using ADABOOST

The model was tuned with over 56 combinations. Refer to Appendix C (d). The best result with the corresponding hyper-parameters were derived - Real test accuracy is 60.035% with a standard deviation of 6.2% and ambiguity of 5.4% (Refer to Table 13).

Table 13. Best result with hyper parameters using ADABOOST

learning_rate	0.01
n_estimators	150
Ambiguity	0.402 ± 0.9 %
Real Test Accuracy	60.035 ± 6.2 %
Train Accuracy	62.127 ± 0.9 %
Cohen Kappa score	0.194

Further the ROC curve with the best result was made and the AUC value of 0.62 was derived. The Real test accuracy distribution with ADABOOST was plotted for deriving the Kurtosis and Skewness (Refer Figure 15).

- Kurtosis of the Real Test Accuracy: -0.6021
- Skewness of the Real Test Accuracy: -0.4677

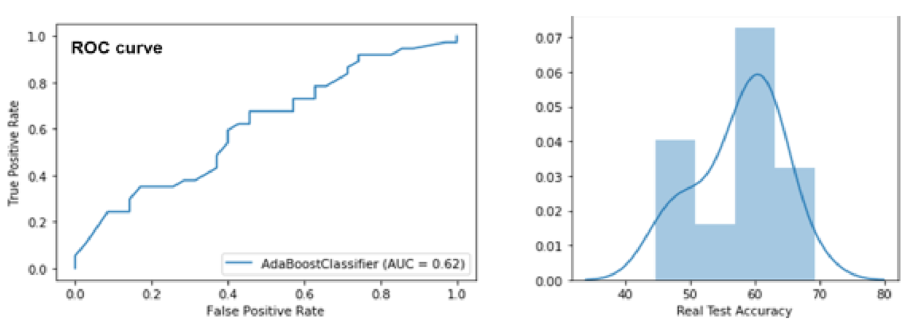


Fig 15. ROC curve and real test accuracy distribution for AdaBoostClassifier

4.6 Model Implementation using XGBOOST

The model was tuned with over 3600 combinations. Refer to Appendix C (e). The best result with the corresponding hyper-parameters were derived - Real test accuracy is 55.42 % with a standard deviation of 5.9% and ambiguity of 7% (Refer to Table 14).

Table 14. Best result with hyperparameters using XGBOOST

learning_rate	0.05
max_depth	4
min_child_weight	1
gamma	0
colsample_bytree	0.3
n_estimators	100
Ambiguity	7.098 ± 2.9 %
Real Test Accuracy	55.42 ± 5.9 %
Train Accuracy	78.079 ± 0.9 %
Cohen Kappa	0.228

Further the ROC curve with the best result was made and the AUC value of 0.62 was derived. The Real test accuracy distribution with XGBOOST was plotted for deriving the Kurtosis and Skewness (Refer Figure 16).

- Kurtosis of the Real Test Accuracy is -0.8633
- Skewness of the Real Test Accuracies: 0.0456

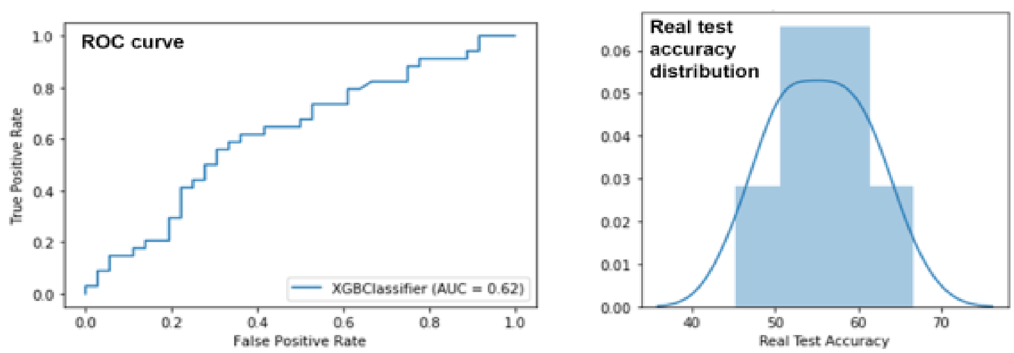


Fig 16. ROC Curve and Real test accuracy distribution for XGBOOST

4.7 Model implementation using ExtraTreesClassifiers

The model was tuned with over 320 combinations. Refer to Appendix C (f). The best results derived: Real Test Accuracy of 59.506 % with a standard deviation of 5.9% and ambiguity of 4.3% (Refer to Table 15).

Table 15. Best result with hyperparameters Extra TreesClassifier

n_estimators	2100
max_depth	12
max_features	log2
min_sample_leaf	12
Ambiguity	4.286 ± 2.0 %
Real Test Accuracy	59.506 ± 5.9 %
Train Accuracy	74.71 ± 0.5 %
Cohen Kappa	0.1864

Further the ROC curve with the best result was made and the AUC value of 0.64 was derived. The Real test accuracy distribution with ExtraTreesClassifiers was plotted for deriving the Kurtosis and Skewness (Refer to Figure 17).

- Kurtosis of the Real Test Accuracy is -0.2121
- Skewness of the Real Test Accuracies: 0.5902

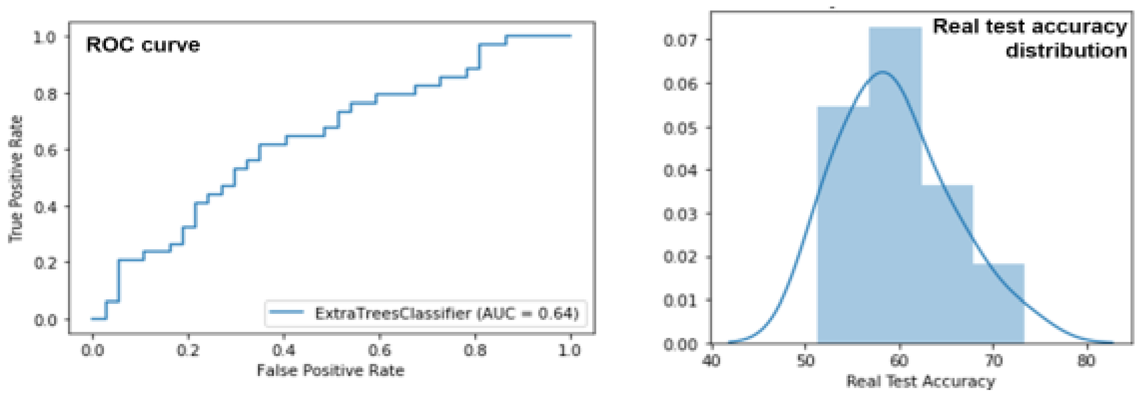


Fig 17. ROC Curve and Real test accuracy distribution for Extra TreesClassifier

4.8 Model Implementation using Random Forest Classifier

The model was tuned with over 1200 combinations[25]. Refer to Appendix C (g). The best result with the corresponding hyper-parameters were derived - Real test accuracy is 60.043 % with a standard deviation of 6.3% and ambiguity of 1.4% (Refer to Table 16).

Table 16. Best result with hyperparameters using Random Forest Classifier

max_features	0.5
bootstrap	True
max_depth	3
min_samples_leaf	4
min_samples_split	2
colsample_bytree	0.3
n_estimators	1200
Ambiguity	1.404 ± 1.4 %
Real Test Accuracy	60.043 ± 6.3 %
Train Accuracy	65.978 ± 0.7 %
Cohen Kappa	0.1785

Further, the ROC curve with the best result was made and the AUC value of 0.62 was derived. The Real test accuracy distribution with Random Forest Classifier was plotted for deriving the Kurtosis and Skewness (Refer to Figure 18).

- Kurtosis of the Real Test Accuracy is -0.8606
- Skewness of the Real Test Accuracies: -0.2491

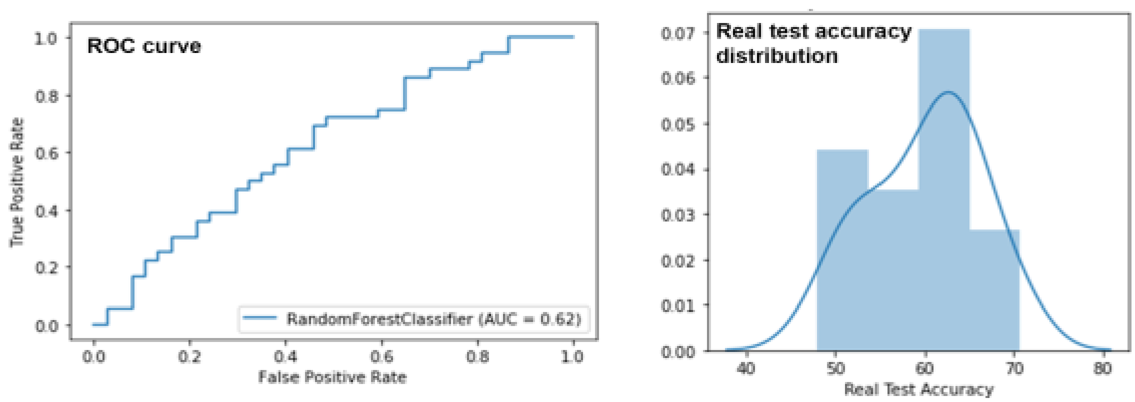


Fig 18. ROC Curve and real test accuracy distribution for Random Forest Classifier

5 Conclusion and Future Works

The research focused on predicting the winner for an IPL match using machine learning and utilizing the available historical data of IPL from season 2008-2019. In the process, various Data Science methods were adopted to conduct the study, including data mining, visualization, preparation of database, feature engineering, applying the Analytic hierarchical process, creating prediction models, and training classification techniques.

The IPL dataset was gathered and pre-processed. The missing values were removed, and variables were encoded into the numerical format to make the dataset uniform. The essential features were then derived from data using the domain knowledge to extract raw data features via data mining techniques, and the results were derived from the model. Since the dataset that is available for IPL is limited and small, multiple levels of features were created to make sure that the derived model is not underfit. Almost every feature that can affect the result of a match was derived. Further, the problem of multicollinearity was solved and the issue of data symmetry was identified (termed as model ambiguity). Several machine learning models were applied to the selected features to predict the IPL match results. The best results were concluded using the tree-based classifiers. The highest accuracy of 60.043% with Random Forest with a standard deviation of 6.3% and an ambiguity of 1.4% was observed (Refer to Table 17).

Table 17. Accuracies from various algorithms with their ambiguity and Cohen KappaScore

Algorithm	Accuracy	Cohen Kappa	Ambiguity
Naïve Bayes	58.23 ± 5.5 %	0.19	3.00 %
Adaboost	60.03 ± 6.2 %	0.19	0.40%
Logistic Regression	57.77± 5.8 %	0.13	2.20%
Support Vector Machines	58.42% ± 5.69%	0.19	0.24%
Knn	53.47% ± 5.2%	0.16	1.90%
XGBoost	55.42 ± 5.9 %	0.23	7.10 %
Extra Trees Classifier	59.51 ± 5.9 %	0.19	4.30%
Random Forest Classifier	60.04 ± 6.3 %	0.18	1.40%

In this research, the player's series-wise performance rather than their match-wise performance was taken while calculating the player's strength. For a more thorough approach to further develop this research, match wise data can be considered. The research can also be further enhanced by adding other factors like comparing players' performances at a particular stadium.

Appendices

Appendix A: Dream 11 Point Tables
a. Score Point Table:

Notation	Type of Points	Weight
φMatches	Being a part of the starting XI	4
φRuns_Scored	Every run scored	1
Φctchs	Total catches taken	8
Φfifties	Total number of 50s scored	8
Φhundreds	Total number of 100s scored	16
Φnum_4s	Total number of 4s scored	1
Φnum_6s	Total number of 6s scored	2
φstmp	Stumping/ Run Out (direct)	12
Φr_out	Run Out (Thrower/Catcher)	8/4
Φfduck	Dismissal for a Duck (only for batsmen, wicket-keepers and all-rounders)	-2
Φbat_innings	Number of times a player has batted in a match	
Φbowl_innings	Number of times a player has bowled in a match	
Φwickets	Number of wickets taken by a bowler in the season	25
Φmaidens	Number of times a bowler has bowled an over without conceding any runs	8
Φ4_wicket_houl	Number of times a player has taken 4 wickets in a single match	8
Φ5_wicket_houl	Number of times a player has taken 5 wickets in a single match	16
Φbowl_economy	Bowling economy of a player	
Φbat_strike_rate	Batting Strike Rate of a player	
Φmax_matches	Maximum matches played by a team	

b. Bonus Points

Type of Points	Weight
Every boundary hit	1
Every six-hit	2
Half-Century (50 runs scored by a batsman in a single inning)	8
Century (100 runs scored by a batsman in a single inning)	16
Maiden Over	8
4 wickets	8
5 wickets	16

c. Economy Rate

Type of Points	Weight
Minimum overs bowled by a player to be applicable	2 overs
Between 6 and 5 runs per over	2
Between 4.99 and 4 runs per over	4
Below 4 runs per over	6
Between 9 and 10 runs per over	-2
Between 10.01 and 11 runs per over	-4
Above 11 runs per over	-6

d. Strike Rate

Type of Points	Weight
Minimum balls faced by a player to be applicable	10 balls
Between 60 and 70 runs per 100 balls	-2

Continued on next page

Table 19 continued

Between 50 and 59.99 runs per 100 balls	-4
Below 50 runs per 100 balls	-6

Appendix B: Analytical Hierarchy Process Scale Table

The Fundamental Scale For Pairwise Comparisons		
Intensity of Importance	**Definition**	**Explanation**
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one element over another
5	Strong importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another, its dominance is demonstrated in practice

Appendix C: Hyperparameters used for training our model

a. Hyperparameters for Logistic Regression

penalty	l2, l1
solver	liblinear
max_iter	100, 200, 300, 400, 600, 900, 1200, 1500, 1800, 2100
tol	0.0001, 0.00001, 0.0005, 0.001, 0.1, 0.5, 1
C	1.0, 1.5, 2, 1.25, 1.75, 3, 4, 5, 7, 9 ,12

b. Hyperparameters for Support Vector Machines

Kernel	rbf
Gamma	1, 0.1, 0.01, 0.001, 0.0001
C	0.1, 1, 10, 100, 1000

Hyperparameters for Knn

n-neighbors	1, 3, 5,6, 8, 10,12, 14, 15, 18
Weights	uniform, distance
Metric	euclidean, manhattan, hamming
Leaf_Size	10, 15,20, 25,30

c. Hyperparameters for Adaboost

learning_rate	0. 005 ,0.01 ,0.02, 0.05,0.15, 0.5, 0.1,1
n_estimators	10,20,50,100,200,800,1000

d. Hyperparameters for XGboost

learning_rate	0.05, 0.10,0.15, 0.25
n_estimators	50,100,200,500,700,1000
max_depth	4,5,6,7,8
gamma	0,0.1, 0.2,0.3
min_child_weight	1,3
colsample_bytree	0.3, 0.4, 0.7

e. Hyperparameters for ExtraTreeClassifier

n_estimators	100,200,600,900,1200,1500,1800,2100
max_depth	3,4,5,12,15
max_features	Sqrt, log2
min_sample_leaf	3,5,8,12

f. Hyperparameters for RandomForestClassifier

bootstrap	True, False
max_depth	3,4,5,6,7
max_features	0.5, 'sqrt','log2'
min_samples_leaf	2, 4
min_samples_split	2, 5
criterion	Gini, entropy
n_estimators	800,1000,1200,1600,2000

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