Classification of All-Rounders in the Game of ODI Cricket: Machine Learning Approach

Player classification in the game of cricket is very important, as it helps the coach and the captain of the team to identify each player's role in the team and assign responsibilities accordingly. The objective of this study is to classify all-rounders into one of the four categories in one day international (ODI) Cricket format and to accurately predict the new all-rounders'. This study was conducted using a collection of 177 players and ten player-related performance indicators. The prediction was conducted using three machine learning classifiers, namely Naive Bayes (NB), k-nearest neighbours (kNN), and Random Forest (RF). According to the experimental outcomes, RF indicates significantly better prediction accuracy of 99.4%, than its counter parts.

Keywords: *Team sport, machine learning, cricket, ODI, player classification.*

Introduction

Cricket is considered as a bat and ball team game. The game has basically three formats, namely, the test cricket, one-day-international cricket (ODI), and T20. Test cricket, the longest format is regarded by experts of the game as the ultimate test of playing skills. An ODI cricket game is played for 300 legal deliveries (balls) per side, and the shortest format, T20 is played for 120 legal deliveries (balls) per side. A typical cricket team comprises of 11 players and the team batting first is identified by the outcome of tossing a coin. In the game of cricket, there are three major disciplines: batting, bowling, and the fielding. When selecting 11 players for a team, it is necessary to balancing the team by selecting players to represent each of the above three departments.

A player who excels in bowling the cricket ball is considered as a bowler, while a player with higher potential of hitting the cricket ball is considered as a batsman. An all-rounder is a regular performer with bat and the ball. According to Bailey (1989), an all-rounder is a player who is able to grasp a position in his team for either his batting or his bowling ability. Though fielding is an integral part in the game, batting and bowling skills are given higher priorities than fielding. A genuine all-rounder is a special all-rounder who is equally capable of batting and bowling, most importantly this player can bat as a quality batsman and bowl as s quality bowler. Majority of all-rounders in the game of cricket dominate either batting or bowling skills, therefore they are named as batting all-rounders or as bowling all-rounders.

Identification of all-rounders is very vital for the success of a team. Classifying an all-rounder as genuine, batting, or a bowling is even beneficial for cricket selection panels, coaches, and players. A review at the literature provides evidences of such studies. Using Indian Premier League (IPL) data, Silkia et al. (2011) classified all-rounders into four groups, namely performer,

batting all-rounder, bowling all-rounder, and under-performer. According to their results, the Naïve Bayes algorithm has given a classification accuracy of 66.7%. In an attempt to rank all-rounders in test cricket, Tan and Ramachandran (2010) utilized both batting and bowling statistics to devise a mathematical formula. In another study, Stevenson and Brewer (2019) derived a Bayesian parametric model to predict how international cricketers' abilities change between innings in a game. Furthermore, Christie (2012) researched physical requirements of fast bowlers and stated the necessity of physiological demands to evaluate bowlers' performances. Saikia et al. (2016) developed a performance measurement using a combination of batting and bowling statistics to quantify all-rounder's performance. Wickramasinghe (2014) introduced an algorithm to predict batsman's performance using a hierarchical linear model. This multi-level model used player-level and team-level performance indicators to predict the player's performance.

Selecting a team against a given opposition team is not an easy task, as various aspects including the strengths and the weaknesses of both teams are required to consider. Bandulasiri et al. (2016) identified a typical ODI game as a mixture of batting, bowling, and decision-making. Presence of a quality all-rounder in a team is an asset to a team, as it brings huge flexibility in the composition of the team. A good all-rounder makes the captain's job easy as the player can play a dual role, whenever the captain requires (Van Staden, 2008). Though the impact of all-rounders towards the success of a team is enormous, there is no underline criteria to identify them.

The existence of prior research work in identifying all-rounders in the game of cricket is handful. According to the knowledge of the author, there is no existing study regarding classification of all-rounders in ODI format. Our objective of this study is to device a method to categorize all-rounders in the ODI format of cricket. We use several machine learning techniques to classify an all-rounder as a genuine all-rounder, batting all-rounder, bowling all-rounder, and as an average all-rounder.

This study brings novelty for the cricket literature in many ways. According to the author's point of view, this is one of the first studies conducted to classify all-rounders in ODI version of the game using machine learning techniques. Furthermore, the selected player-related performance indicators and the used machine learning techniques are unique for this study. Findings of this study can benefit the entire cricket community and cricket industry as always prediction in sports brings an economical value to the industry(Gakis et al., 2016).

The rest of the manuscript is organized as follows. Next section will discuss about the data selection procedure and descriptive statistics about the collected data. In the methodology section, three machine learning techniques are discussed. Then, in the following section findings of this study are illustrated. Finally, the discussion and conclusion section will discuss further about the conducted study and concludes the manuscript.

Data Collection and Player- Selection Criteria

Data for this study was collected using a publically available website, under the following criteria. Players who have played more than 50 ODI games with an aggregate score of over 500 runs, were selected. Furthermore, it was essential for each player to have at least a half-century under their name, and collected more than 25 ODI wickets. Under the above criteria, a total of 177 players were selected and ten player related performance indicators (features) were recorded. Table 1 summarises these ten features and their descriptive statistics.

Table 1. *Descriptive Statistics of Dataset*

Variable	Description	Mean	SD
Matches:	The number of games each player has played	146.64	83.12
Runs:	Number of accumulated runs a player has scored in his career	2,972.79	2,859.03
HS:	Highest score a player has scored in his career	101.25	36.97
BatAv:	Batting average of a player	26.04	9.12
NumCen:	Number of times a player has scored 100 runs or more in a game	2.96	6.00
NumWkts:	Number of accumulated wickets a player has taken in this career	115.79	86.05
BesstB:	Best bowling figures as a bowler	4.51	0.98
BowAv:	Bowling average of the bowler	35.04	6.64
NFiveWkts:	Number of times a bowler has taken 5 or more wickets in a game	0.99	1.58
NCatches:	Number of catches a player has caught in his career	47.32	30.83

Saikia and Bhattacharjee (2011) classified all-rounders based on median value of both batting average and bowling averages. In this collected data, the distributions of both batting and bowling follow Gaussian distributions. Therefore, in this study we use the mean values of both batting and bowling averages to classify all-rounders according to the scheme summarised in table 2. Figure 1 illustrates the joint distribution of batting and bowling averages, and the four categories of players.

Based on the table 2 and figure 1, we classify each all-rounder into one of the four categories: genuine all-rounder *(G)*, batting all-rounder *(B)*, bowling all-rounder *(Bw)*, and average all-rounder *(A)*.
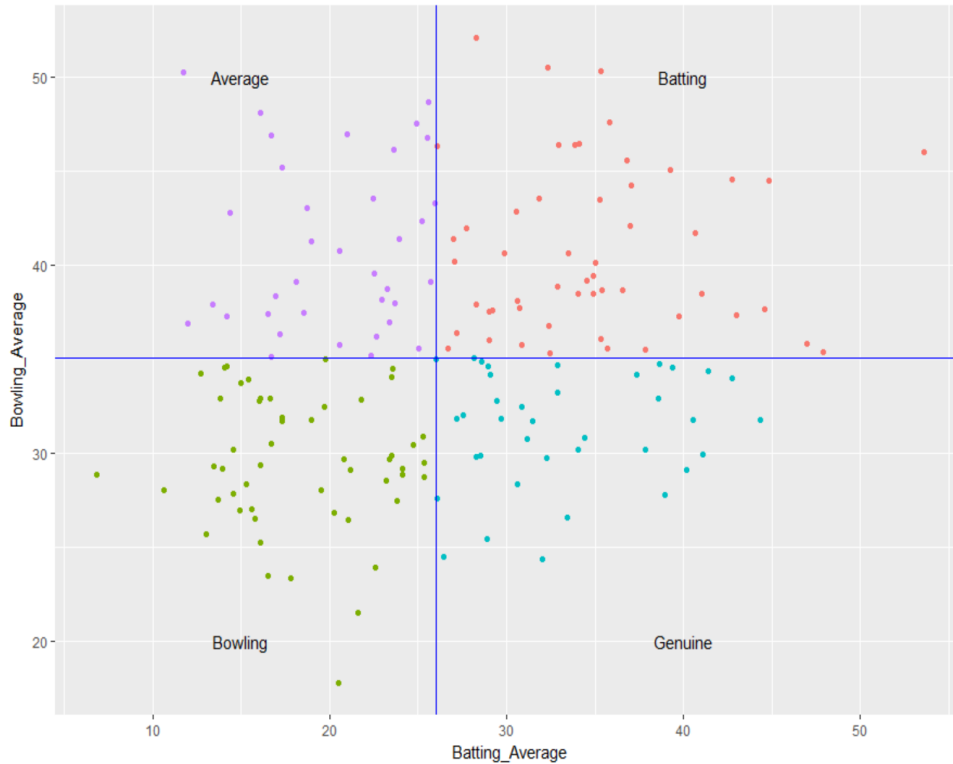
Figure 1. *Joint Distributions of Batting Averages and Bowling Averages*

Table 2. *Classification Criteria of All-Rounders*

Category of the all-rounder (Type)	Criteria	
	Batting Average	**Bowling Average**
Genuine (G)	> 26.04	< 35.04
Batting (B)	> 26.04	> 35.04
Bowling (Bw)	< 26.04	> 35.04
Average (A)	< 26.04	> 35.04

The class variable of the data set is named as *Type,* which represents each of the four classifications.

Methodology

In this study, we use three machine learning techniques, NB, kNN, and RF to classify all-rounders into one of the four groups. Regression analysis is one of the alternative conventional statistical procedures for an analysis like this. The number of data appoints used in regression analysis is higher, proportional to the number of involved features (Allision, 1999; Bai and Pan, 2009). Furthermore, some of the machine learning algorithms such as NB is

4

considered as a better performer with smaller datasets (Hand, 1992; Kuncheva, 2006). Under the previously stated constraints, we opt to use these three machine learning approaches to analyse these data.

Naïve Bayes (NB)

The NB classifier is considered as one of the simplest and accurate data classifying algorithms. The base of this classifier is the well-known Bayes theorem, used in probability theory. The simplicity, the accuracy, and the robustness of NB has made NB a popular classifying techniques with various applications (Arar & Ayan, 2017). As the literature indicates, NB is one of the top performing classifiers used in data mining (Wu et al., 2008).

Let $X = (x_1, x_2, ..., x_n)$ be a n-dimensional random vector (features) from domain D_X and $Y = (y_1, y_2, ..., y_m)$ be a m-dimensional vector (classes) from domain D_Y. In this study, $n = 10$ is the number of factors and $x_1, x_2, ..., x_{10}$, the first column of the table 1. Similarly, here $m = 4$ and $Y = (y_1, y_2, y_3, y_4)$; $y_1 = Genuine\ all-rounder$, $y_2 = Batting\ all-rounder$, $y_3 = Bowling\ all-rounder$, $y_4 = Average\ all-rounder$. Our aim is to estimate the value of Y by maximizing $P(Y = y \mid X = x)$. NB assumes that features are independent of each other for a given class. Therefore,

$$P(X_1 = x_1, X_2 = x_2, ..., X_n = x_n \mid Y = y)$$
$$= P(X_1 = x_1 \mid Y = y).P(X_2 = x_2 \mid Y = y)....P(X_n = x_n \mid Y = y)$$
$$= \prod_{i=1}^{n} P(X_i = x_i \mid Y = y).$$

According to the Bayes theorem, we have $P(y \mid X) = \dfrac{P(X \mid y)P(y)}{P(X)}$.

Then we can write $P(y \mid X)$ as follows.

$$P(y \mid X) = \frac{P(X = x, Y = y)}{P(X = x)}$$
$$= \frac{P(Y = y)P(X = x \mid Y = y)}{P(X = x)}$$
$$= \frac{P(Y = y)\prod_{i=1}^{n} P(X_i = x_i \mid Y = y)}{\prod_{i=1}^{n} P(X_i = x_i)}$$
$$\propto P(Y = y)\prod_{i=1}^{n} P(X_i = x_i \mid Y = y)$$

Therefore, our aim is to find y, that maximize the above expression. In another words, we need to find y, which is $\arg\max_y P(Y - y)P(Y = y)\prod_{i=1}^{n} P(X_i = x_i \mid Y = y)$.

1 *k-nearest neighbours algorithm (kNN)*
2
3   The kNN can be considered as one of the most simplest machine learning
4 classifiers, which is based on distance matric. Applications of kNN can be
5 found in text categorization (Elnahrawy, 2002), ranking models (Xiubo et al.,
6 2008), and object recognition (Bajramovic et al., 2006). If a novel data point is
7 given, kNN attempts to identify the correct category of the novel point, using
8 the characteristics of the neighbouring data points. The main trait of the data
9 points is going to be the distance from novel data point to each of the other data
10 points. When considering the distance metric, Euclidian is the most commonly
11 used one though other metrics such as Manhattan Distance, Mahalanobis
12 Distance and Chebychev Distances are also used in practice. Table 3 shows
13 some other popular distance matrices used in data classification.
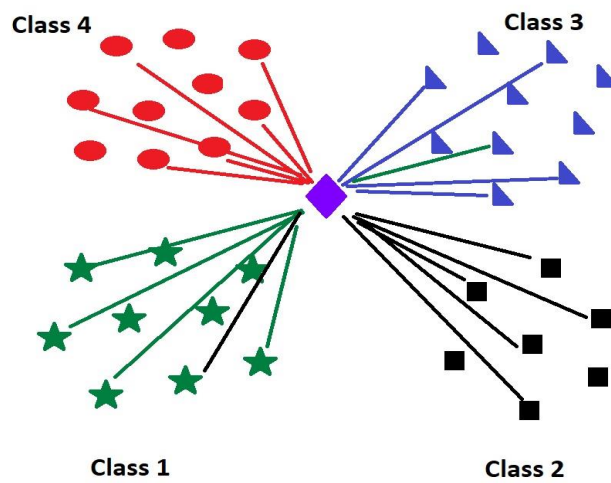
14
15 **Figure 2.** kNN Classifier
16
17   Let $\{x_i, y_i\}; i = 1, 2, ..., n$ be the training sample in which x_i represents the
18 feature value and $y_i \in \{c_1, c_2, ..., c_M\}$ represents the M categories (class value).
19 Furthermore, let X be a novel data point. The kNN algorithm can be
20 summarised as follows.
21
22 • Calculating the distance from this novel point X to all other points in the
23   dataset.
24 • Sort the distances from each point to the novel point and select the k
25   (usually an odd number to prevent tie situations) smallest distances, i.e.,
26   nearest k neighbours $y_{i1}, y_{i2}, ..., y_{ik}$.
27 • Then for each of the above k nearest neighbours, it records the
28   corresponding class (labels) $c_j; j = 1, 2, .., M$ and calculate the following
29   conditional probability.

$$P\left(c_x = c_j \mid X = x\right) = \frac{1}{k}\sum_{i=1}^{k} I_{c_i}(x);$$

$$\text{where } I_{c_i}(x) = \begin{cases} 1; x \in c_i \\ 0; x \notin c_i \end{cases}$$

- The class c_j that has the highest probability is assigned to the novel data point, as the category of the data point.

Table 3. *Popular Distance Metrics*

Name	Distance Matric
Euclidean	$\sqrt{\sum_{i=1}^{n}\left(x_i - y_i\right)^2}$
Manhattan	$\sum_{i=1}^{n} \mid x_i - y_i \mid$
Chebyshev	$\max\left(\mid x_i - y_i \mid\right)$
Minkowski	$\sqrt[p]{\sum_{i=1}^{n}\left(x_i - y_i\right)^p}$

Random Forest (RF)

RF algorithm extends the idea of decision trees by aggregating higher number of decision trees to reduce the variance of the novel decision tree (Couronné, 2018). Each tree is built upon a collection of random variables (features) and a collection of such random trees is called a Random Forest. Dues to the higher classification accuracy, RF is considered as one of the most successful classification algorithms in modern-times (Breiman, 2001; Biau and Scornet, 2016). Furthermore, the performance of this classification algorithm is significant for unbalanced and missing data (Shah et al., 2014), compared to its counterparts. RF has been studied by many researchers both in theoretically and experimentally since its introduction in 2001 (Bernard et al., 2007; Breiman, 2001; Geurts, 2006; Rodriguez, 2006) . Further studies have been conducted to improve the classification accuracy of RF by clever selection of the associated parameters of RF (Bernard et al., 2007).
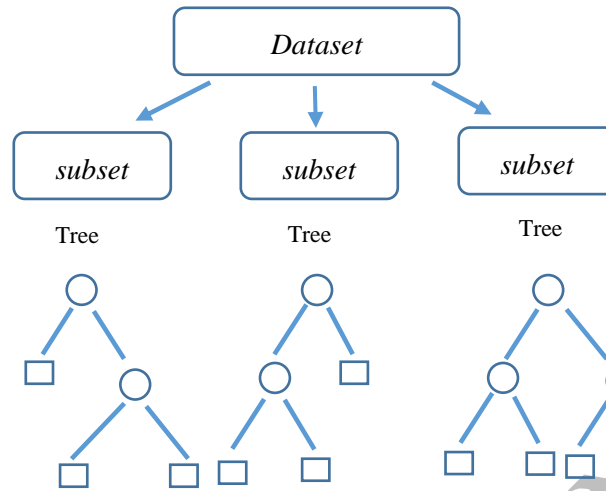
Figure 3. *Random Forest Classifier*

A handful of applications of machine learning algorithms in the context of cricket can be seen in the literature. Using kNN and NB classifiers, Kumar and Roy (2018) forecasted final score of an ODI score after the completion of the fifth over of the game. NB and RF were two of the machine learning techniques Passi and Pandey (2018) used in their study to predict the individual player's performance in the game of cricket. Using English T20 county cricket data from 2009 to 2014, Kampakis and Thomas (2015) developed a machine learning model to predict the outcome of the T20 cricket game.

Findings

All the experimental outcomes were tested under the k-fold cross-validation, which is used to generalize the findings of the study to any given independent sample as discussed in the literature (Burman, 1998; Kohavi 1995). We executed all of the three machine learning classifiers with the collected data and according to the experimental outcomes, NB classifier reached a maximum of 60.7% prediction accuracy. Furthermore, the maximum prediction accuracy using kNN was 55.08%. In order to see how the prediction accuracy changes with the selection of distance matric with kNN algorithm, we measured the prediction of accuracies with respect to the various distance matrices. Table 3, summarises the percentage of prediction accuracy for each of the selected distance metric and the value k used in kNN.

**Table 4.** *Distance Metric, K value, and Percentage of Prediction Accuracy*

Distance Metric	K	Percentage of Accuracy
Euclidian	3	47.55%
	5	49.36%
	7	46.77%
Manhattan	3	49.81%
	5	51.98%
	7	54.83%
Chebyshev	3	49.88%
	5	52.38%
	7	55.08%
Minkowski ,p=3	3	43.38%
	5	50.99%
	7	50.12%

With RF, an initial accuracy rate of 93.34% was recorded, which is the highest among the three classifiers we used. Further investigation was conducted to optimize the prediction accuracy, by varying the associated parameters of RF.

Important Parameters used in RF

Among the various parameters used with RF, the following important parameters were changed to see a better prediction rate.

n_estimators: This represents the number of trees in the RF.

max_features: This represents the maximum number of features when the RF selects the split point.

min_samples_leaf: This represents how many minimum number of data points in the end node.
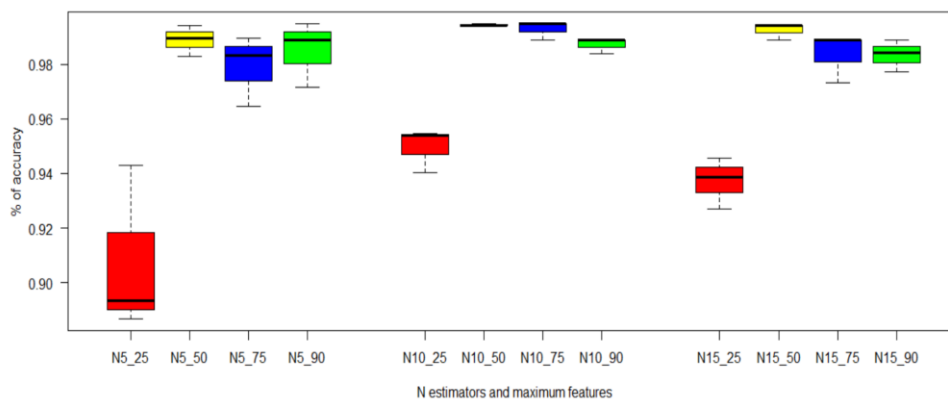
Figure 4. *Change of Prediction Accuracy with Different Parameters*

1   Values of n_estimators, max_features, and min_samples_leaf were varied
2   from $\{5, 10, 15\}$, $\{0.25, 0.50, 0.75, 0.90\}$, and $\{1, 2, 3\}$. The obtained
3   corresponding values of the percentages of prediction accuracies are displayed
4   by the figure 4.
5   After searching for better parameterization, we investigated the associated
6   errors with the RF Regression model. Both Mean Absolute Error (MAE) and
7   Mean Squared Error (MSE) were recorded for the model with previously
8   identified parameters. Figures 6 & 7 display the variation of both MAE and
9   MSE for each values of parameters. As the experimental outcomes indicated,
10   RF reached a maximum prediction accuracy of 99.4% with the selection of
11   *n_estimators=*10, *max_features=* 0.50, *min_samples_leaf=* 2, and
12   *n_estimators=*10, *max_features=0.75*, *min_samples_leaf=1*.
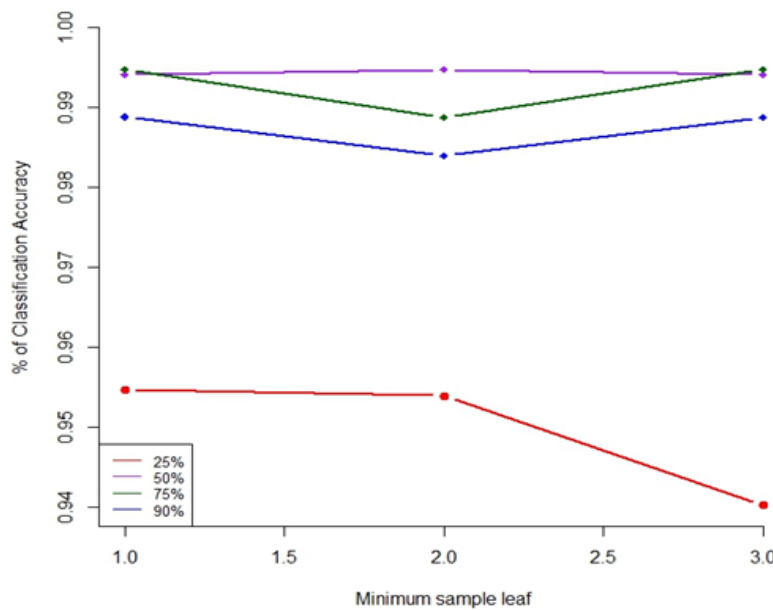

13
14   **Figure 5.** *Prediction Accuracy, max_features and min_samples_leaf for*
15   *n_estimators=10*
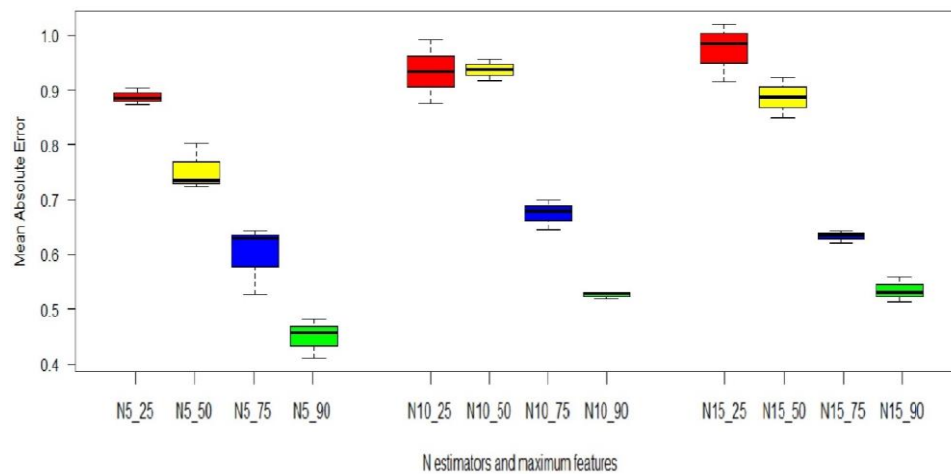

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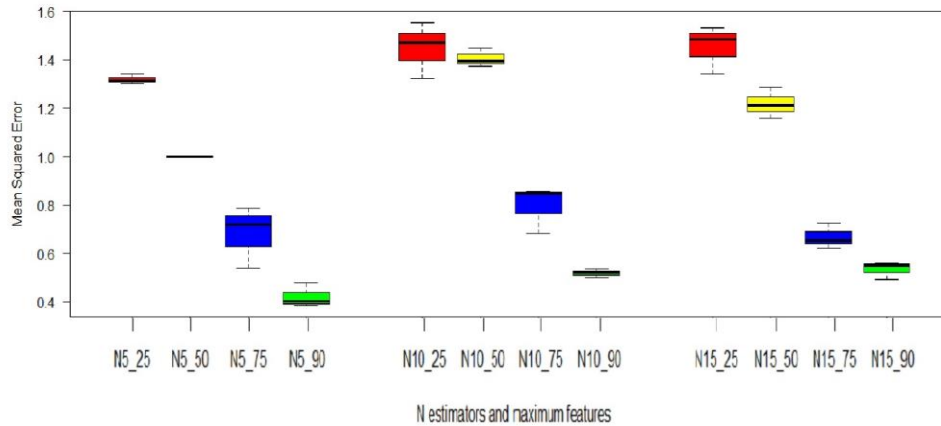17   **Figure 6.** *Parameters of Random Forest vs Mean Absolute Error*

Figure 7. *Parameters of Random Forest vs Mean Square Error*

Discussion and Conclusion

In this manuscript, we discussed how to categorize all-rounders in the game of ODI cricket. Using a collection of 177 players from all the ODI playing countries, ten player-related predictors, together with three machine learning techniques, we investigated how to categorize all-rounders into one of the four categories. In this study, we utilized three machine learning techniques, namely Random Forest (RF), k-nearest neighbours (kNN), and Naïve Bayes (NB) to predict the appropriate category each of the all-rounder should belong.

After initial execution of the above three algorithms, the prediction accuracies for kNN, NB, and RF were 50.08%, 59.00%, and 93.34% respectively. Further improvement of the prediction accuracy was able to achieve with the proper selection of the parameters. By changing the distance metric with kNN and the *k* value, we were able to improve the prediction accuracy up to 55.08%. Similarly, NB was improved up to 60.7%. According to the figures 4-7, it is clear that RF has improved to the highest prediction accuracy of 99.4%, with the selection of appropriate values for the parameters. This can be reached with two different parameter settings. i.e., when *n_estimators is* 10, *max_features* is 0.50, *min_samples_leaf* is 2, and *n_estimators* is 10, *max_features* is 0.75, *min_samples_leaf* is 1. In addition to the prediction accuracy, an investigation was conducted to find out the relative errors involved with these processes. According to the findings, these errors became minimum when *n_estimators* is 10, *max_features* is 0.75 and *min_samples_leaf* is 1 respectively and the values were 0.68 and 0.86 respectively.

In summary, our experimental results indicated that RF algorithm outperformed both kNN and NB by huge margins. The findings of this

study benefit the officials of the game of cricket and the players in many ways. Player selection committees, coaches of teams, and even the players can utilize these outcomes to identify appropriate all-rounders. It would be important to include additional performance indicators, including statistics about the opposition teams that the players play against for future studies.

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