Cricket Player Prediction Of Role In A Team Using ML Techniques

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***Abstract* – Cricket is one of the most popular sports in the world. In India, admiration for cricket is very huge for playing and as well as in viewing. When considering the aspect of players, who wanted to represent their country in this sport is also high. So, a need arises to find an easy way to filter out the players considering their skills and talent. Therefore, one of the simple ways to achieve the above is by proposing the best ML model. The fundamental intention of this model is to design a sophisticated prototype that assists cricket team selectors in making smart decisions regarding player selection. By analyzing player statistics like runs scored, wickets taken in different pitch conditions, and various other relevant factors, this model will provide valuable information to optimize team composition. Also comparing the performance of individuals in ODI and TEST conditions. At present country cricket board has a lot of options or choices because of the great talent and skill of the players. This model focuses on Indian players based on their category of role in the squad. It also makes the task easy for selectors to find the particular player for the required role for example consider batsmen there are different categories like Top Order, Middle Order, Wicketkeeper batsmen, etc. This model shows the compatibility of a particular player in the team based on statistics. The machine learning model that is developed shows the best-fit regression algorithm for players to be selected in ODI and TEST based on the required role needed for the team and also considers the individual player strengths for selecting them in the team. For predicting a player to be contoured in the ODI team algorithms like SVM and Decision Tree produce fewer error results whereas for predicting new players in the TEST team algorithms like LSTM and SVM produce fewer errors. So, the SVM model is the best regression technique for this kind of work.**

Keywords –Accuracy, Artificial Neural Network, Decision Tree, Gradient Boost, K-Nearest Neighbor, Mean Squared Error, R-squared error, Random Forest, Support Vector Machine.

I. INTRODUCTION

Cricket is generally referred to as the "gentleman's game." It is a sport celebrated for its complex nature and the critical role played by individuals in determining the overall team's success. In modern cricket strategic game plans have become data-driven. The selection of the perfect player for a match or tournament has becomes a difficult process. This machine learning model aims to transform and streamline this selection process by taking advantage of data or statistics of players. In this modern age, the application of ML algorithms spans a broad array of fields, comprising picture recognition, articulation processing, and forecasting of traffic jams. These algorithms are harnessed to address issues related to prediction and categorization. Among these, cricket, a never-ending fascination, stands out, with different tournaments like ICC WT20 and One-day World Cup, WTC, and different premier leagues such as IPL, Big Bash League, etc. Capturing the enthusiasts across the globe. The meticulous evaluation of both the batting and bowling abilities of players is also necessary to make a balanced team. For that, this model is a straightforward solution. It analyses each new player with modern existing players to easily understand their type or kind of game and provide them a role in the team according to their skills and talent. The concept of "Effective Runs" in cricket is a metric designed to assess a player's impact by considering their control in various game situations. While traditional statistics like runs scored and batting average provide insights into a player's performance, they don't always capture the context in which those runs were scored. If a lot of data like different conditions performance of each player is available along with the traditional data, then 'effective runs' metrics can be found and given as target value and a more efficient model can be developed. However, it is a very complex task because of more data requirements. So, sticking to the basic idea this model is developed. Data was gathered from open-source datasets of different first-class or international games, with weather, pitch, and control attributes.

There are different models or techniques of machine learning based on classification and prediction [1]. This model is a regressive (predictive) model so K-Nearest Neighbour (KNN), Support Vector Regression (SVM), Artificial Neural Networks (ANNs), decision tree, random forest, gradient boost, and long Short-term memory network (LSTM) can be employed for this kind of application. Logistic Regression, on the other hand, is well-suited for binary predictions like win or lose in a match. SVM can be used for dealing with both classification and regression tasks. [2],[3]. For the complicated patterns in the dataset, deep learning methods can be used such as artificial neural networks. One widely used algorithm is Random Forest, which combines multiple decision trees to provide robust and accurate forecasts for match outcomes and individual player performance [4]. Gradient Boost is mostly employed for peak accuracy and is responsible for predicting the upcoming match outcome and performance of each player. The decision Tree technique is protean for finding match results or player impact level in the game. Linear Regression is used for a consistent variable forecast which is always employed to predict players' impact metrics such as average score [5]. Therefore, this model will focus on the vigorous behavior of cricket, varying with the conditions and rival's strengths. It will explore machine learning algorithms and statistical techniques to predict player performance, ensuring that the selected player has the highest probability of achieving the greatest heights in their

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career and also contributing to the team's success in the forthcoming match. The section II of the paper is about the proposed model, datasets used for developing the model, different case inputs used in the model, and different preprocessing functions libraries used in the model are discussed briefly. The section III of the paper gives a clear idea about the ML algorithms used in the proposed model and its observations and comparison with other algorithms are discussed briefly.

II. PROPOSED MODEL

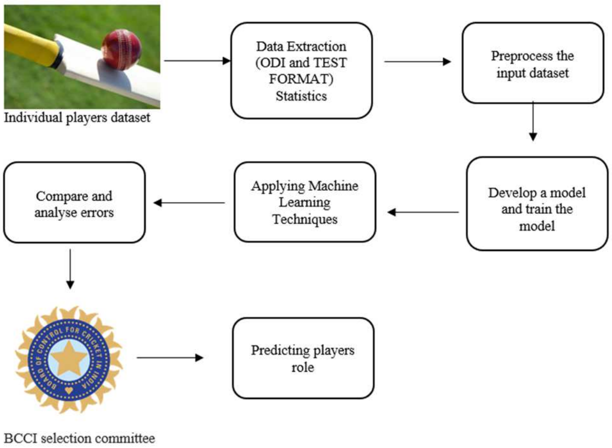

Fig 1. Block Diagram of the proposed model

The dataset is collected from cricinfo.com of players based on particular roles like batsmen, bowlers, all-rounders, and wicketkeepers along with their suitable statistics. The data collected is of ODI format stats of all capped Indian players (not retired) up to September 2023. To get an efficient regression model considering the present time situations (data of present active Indian capped players was only collected) is important. If all players of cricket including retired ones and all the other country players are considered then accurate selection would be missed because of wrong playing conditions. For example, in retired player statistics they would not be a good choice for predicting the present-day players, and for other country players, their stats will be good to consider in their conditions but not in Indian conditions.

Input in this model is of two different types:

I. Overall stats ODI format
II. Overall stats TEST format

Above mentioned types help to find the most accurate results for different conditions like ODI and TEST games. It also makes selectors work easy and also shows an ideal way to filter as there will be some players who can perform well in ODI and may not perform TEST or vice versa is also possible. When considering the first case i.e., overall stats there are three different files with the first type of categorization like batsmen, bowlers, and all-rounders [6],[7]. Each category contains players with sub-categories like batsmen (Top order, Middle Order, Lower Order or WK batsmen), bowlers (Spinners or Pacers), and Allrounders (Bat-spin or Bat-pace) along with cricket statistics like Batting average, bowling average, runs, economy, strike rate, wickets, best figures, 100s, 50s, no of 4s, 6s and no of balls bowled etc. The second and third cases also contain the same data but with different conditions of the game. The data for each role are considered separately because of their feature combinations. To get a high accuracy value and fewer errors there is a need to impute the missing data and outliers should be removed along with that need to use scaling methods which remove irrelevant or redundant features that might negatively impact performance as shown in Fig.1. For preprocessing, using methods like PCA (Principal component analysis) which is used for dimensionality reduction, Label Encoding which is used for converting categorical data into numerical data. Standardscaler which is used to maintain all the data in the same standard parameters. PCA can be done by transforming the original feature space system into a completely new coordinate system where the features are linearly unrelated. PCA attains this variation by identifying the directions, and axes, of maximum difference in the data and projecting it onto these axes. There are 5 steps involved in PCA which are:
Standardization
Computation of Covariance Matrix
Eigenvalue Decomposition
Principal Component Selection and Projection.

There are also Preprocessing Methods that were performed to make this proposed model more accurate and efficient. The following are the few methods that can be followed:
Data cleaning which removes any photocopied entries, incompatibilities, or missing values from the dataset. Next, Data transformation helps in converting category variables (player roles) into numerical representations using techniques like encoding. Next, Feature scaling is used to normalize numerical features to ensure they are on an equivalent scale, and also prevents influence by certain features during model training. Finally, Feature selection is used to search, find, and select relevant features that are most predictive of player performance using techniques such as correlation analysis. Fine-tuning methods are used to optimize model parameters, prevent overfitting, and improve performance. A few such techniques are as follows: Hyperparameter tuning optimizes the parameters of ML models (e.g., DT, RF, and ANN) using techniques like grid search or random search to maximize predictive performance. Next, Cross-validation is helpful to validate model performance using techniques like k-fold cross-validation to ensure general applicability and prevent overfitting. Next, Model selection is used to investigate different ML algorithms and architectures to find the most suitable model for predicting player performance based on the dataset.

Finally, Transfer learning explores the potential of using pre-trained models or knowledge from related tasks (e.g., cricket player performance prediction in other formats) to improve model performance. The next step in the process is to create a model for library functions like pandas, sklearn, numpy, and matplotlib, etc., which are used. Mainly library sklearn has a wide range of advantages for each ML technique and also many sub-functions in sklearn are needed for calling ML techniques that work on regression as well as classification. After creating a model next step is to fit the model and then to train and test the model from sklearn. model_selection library by importing the train_test_split function for each role separately calculating metrics and then comparing and observing the results to conclude the best fit and highly efficient technique.

III. REGRESSION FRAMEWORK AND OBSERVATIONS

After completing all the needed preprocessing work like imputation, outliers, and PCA steps which are used to reduce the errors of all the models. After fitting the model next step is to train and test the model. For training and testing, two important parameters assist in it. Those are the test size and random state. In this model, the proposed test size is 0.25 which means 75% of the data is used for training the model whereas the remaining 25% of data is used for testing the model. To get a consistent output, there is a need for a random state to be declared. In this model, the used random state is 0 or 42. The techniques used in this model are mentioned below with descriptions and comments of output received in each one:

A. KNN algorithm

This is called as K-nearest Neighbor algorithm. It is a supervised algorithm that is used for both clustering and prediction [8]. The primary objective of KNN is to predict the new data point based on the accessibility of existing data points [9]. The bowler category in both cases has a minimal error when compared to other categories such as batsmen and all-rounders. Accuracy of classifying the allrounder category was achieved highest when compared to the batsmen and bowler category in both the formats ODI and TEST. A new bowler can be effectively predicted by using this algorithm.

B. SVM algorithm

It is known as the Support Vector Machines algorithm. It is one of the supervised learning techniques which is used for both clustering and regression [10]. It is used to find out the hyperplane which is used to separate the data in classes. The data points on the margin are called support vectors [11]. In the case of the ODI format, bowlers have achieved minimal errors when compared to others whereas in the TEST format, the batsmen category got fewer errors. In the ODI format all-rounder has the greatest errors. Allrounders in TEST format cannot be predicted using this algorithm because there is only one bat-pace class in it. For SVR to work there should be at least more than 2 classes each for a category. Considering classifying accuracy bowlers have the highest of 88.89% among the other roles.

C. Random Forest (RF) algorithm

The main advantage of this algorithm is it reduces the problem of overfitting. It is a highly efficient technique when it comes to classification [12]. Random forest is a group learning algorithm because it works on building a multitude of decision trees. Each tree in the forest is a random subset of training data and features in the data which brings multiplicity [13],[14]. Out of three sections and two scenarios bowler role is easily predicted because of more differentiating sub-classes. Whereas the allrounder role has more errors because of the fewer no of current players in India who can bat as well as the ball. So, there is a huge opportunity for allrounders in the coming years of Indian cricket.

D. Decision Tree algorithm

It is a machine learning technique that works on the periodic splitting of data into subsets based on the values of different attributes which eventually leads to a tree-like shape of decision [15]. It is an interpretable and multiskilled algorithm used in machine learning for both classification and regression. It has achieved the highest testing accuracy of 75% for the role of batsmen. Like random forest and gradient boost algorithm, it is also highly efficient in clustering.

TABLE I. FOR BATSMEN ROLE IN ODI FORMAT PREDICTIONS

For Batsmen Role	Training Accuracy (%)	Testing Accuracy (%)	RMSE	MSE	MAE	R Squared Error
KNN	54.55	37.50	0.92	0.84	0.69	-0.38
SVM	35.71	40	0.54	0.29	0.49	0.47
RF	93	75	0.60	0.36	0.48	0.40
DT	95	75	0.54	0.29	0.49	0.47
GB	93	75	0.69	0.48	0.40	0.22
ANN	72.73	62.50	0.78	0.62	0.61	-0.01
LSTM	54.55	62.50	0.75	0.56	0.63	0.08

TABLE II. FOR BOWLER ROLE IN ODI FORMAT PREDICTIONS

For Bowler Role	Training Accuracy (%)	Testing Accuracy (%)	RMSE	MSE	MAE	R Squared Error
KNN	69.23	88.89	0.41	0.17	0.22	-0.69
SVM	75	83.33	0.38	0.14	0.23	-0.03
RF	97	77.78	0.38	0.15	0.33	-0.48
DT	88	55.56	0.38	0.14	0.23	-0.03
GB	97	77.78	0.48	0.24	0.39	-1.38
ANN	84.62	77.78	0.54	0.29	0.36	-1.99
LSTM	76.92	88.89	0.39	0.15	0.35	-0.57

TABLE III. FOR ALLROUNDER'S ROLE IN ODI FORMAT PREDICTIONS

For All-rounder Role	Training Accuracy (%)	Testing Accuracy (%)	RMSE	MSE	MAE	R Squared Error
KNN	75	50	0.43	0.19	0.38	0
SVM	83.33	50	1.36	1.84	1.33	-6.38
RF	90	25	0.69	0.47	0.64	-1.52
DT	78.78	25	0.87	0.75	0.75	-3.00
GB	90	25	0.87	0.75	0.75	-3.00
ANN	100	25	1.11	1.22	1.00	-5.53
LSTM	50	50	0.51	0.26	0.50	-0.40

E. Gradient Boost (GB) algorithm

It is also a grouped learning technique like RF and DT which is used to merge the forecast of multiple weak learners, typically decision trees, to produce the best predictive model. One of the famous executions of gradient boost is the Gradient Boosting Machine. It is sometimes also called as XGBoost technique [16]. The results of this method are similar to DT and RF. It is also an efficient classification method.

F. ANN algorithm

An artificial neural network (ANN) is a computational technique influenced by the biological neural networks present in the human brain. It contains associated nodes or neurons assembled into sheets [17]. These networks are very useful in machine learning to figure out patterns make assumptions and solve wide varieties of tasks by varying the weights of links. It is a complex algorithm as it takes more execution time similar to the LSTM algorithm. As it has to go through the required number of epochs [18]. It can easily find out testing and training log losses and Fig 2 also can plot the graph between training and validation loss.

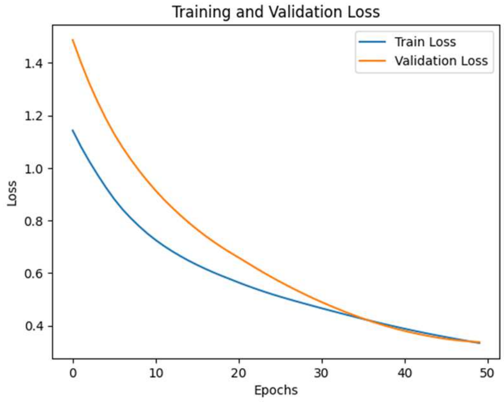

Fig.2. Training loss vs Validation loss (for one role) by ANN

G. LSTM algorithm

It is called Long Short-Term Memory. It is a type of recurrent neural network. It is a class of ANN formulated for succession data. LSTMs are generally more efficient in apprehending long-term dependencies and patterns in consecutive data, making them well-designed for operations such as time series forecasts, speech recognition, and natural language processing. It takes more execution time than the ANN algorithm as it is a larger picture of it. It is not very efficient for instant results. It is also useful for finding the log losses of test and train results as shown in Fig 3. With the help of this kind of algorithm plotting graphs for concluding can be easily achieved.

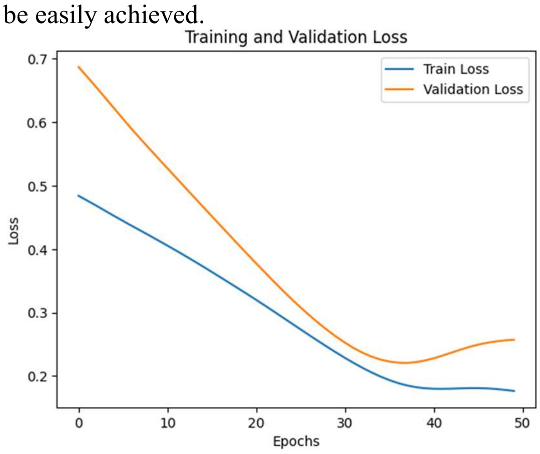

Fig.3. Training loss vs Validation loss (for one role) by LSTM

For the results, it can be observed that raw data is taken from online cricketing websites like Cricinfo. Data is taken from two popular cricketing formats ODI and TEST. These are again divided into 3 categories roles batsmen, bowlers, and all-rounders based on the features of stats they achieved in the present. Players considered are active players to achieve the results in current conditions. Tables (I, II & III) represent the results of the prediction and classification of ODI conditions whereas tables (IV, V & VI) represent the results of the prediction and classification of TEST conditions.

When observing the results of Table I it can be inferred that SVM and Decision Tree algorithms produced the least error when compared to remaining models for predicting the role of a new batsman in the ODI team. From Table II it can be inferred that the SVM algorithm produced the least error values for predicting the role of new bowlers in the ODI team. From Table III it can be inferred that the KNN algorithm achieved the least error values for predicting a new allrounder for the ODI team when compared to all the used models.

IV. COMPARISONS AND INFERENCES

TABLE IV. PREDICTED ERRORS FOR BATSMEN ROLE IN TEST FORMAT

FOR Batsmen Role	Training Accuracy (%)	Testing Accuracy (%)	RMSE	MSE	MAE	R Squared Error
KNN	50	71.43	0.71	0.50	0.57	-1.45
SVM	41.67	80	0.48	0.23	0.32	-0.46
RF	91	45	0.84	0.71	0.76	-2.49
DT	95	44.4	0.85	0.71	0.71	-2.50
GB	95	44.4	1.03	1.07	0.92	-4.23
ANN	80	42.86	0.66	0.44	0.58	-1.14
LSTM	50	57.14	0.51	0.26	0.43	-0.26

TABLE V. PREDICTED ERRORS FOR BOWLERS' ROLE IN TEST FORMAT

For Bowler Role	Training Accuracy (%)	Testing Accuracy (%)	RMSE	MSE	MAE	R Squared Error
KNN	85.71	80	0.5	0.25	0.5	-0.56
SVM	88.89	66.67	0.51	0.26	0.38	-0.16
RF	95	80	0.42	0.18	0.36	-0.13
DT	91	60	0.63	0.4	0.42	-1.50
GB	91	60	0.43	0.19	0.32	-0.18
ANN	97	80	0.4	0.16	0.35	0.0
LSTM	85.71	80	0.37	0.14	0.35	0.13

TABLE VI. PREDICTED ERRORS FOR ALLROUNDER ROLE IN TEST FORMAT

FOR All-rounder Role	Training Accuracy (%)	Testing Accuracy (%)	RMSE	MSE	MAE	R Squared Error
KNN	100	50	0.71	0.5	0.5	-1.0
SVM	-	-	-	-	-	-
RF	97	50	0.82	0.67	0.67	-2.00
DT	97	50	0.82	0.67	0.67	-2.00
GB	93	25	0.87	0.75	0.75	-3.00
ANN	-	-	-	-	-	-
LSTM	-	-	-	-	-	-

From Table IV it can be inferred that SVM and LSTM algorithms achieved the least error in predicting a new batsman for the TEST team. Table V shows that LSTM and ANN had the least accurate errors for predicting a new bowler in the TEST team. From Table VI it can observed that KNN shows the least error for predicting a new allrounder player in the TEST team. It also observed that SVM, ANN, and LSTM rows are empty it is because, in the current data of active players of TEST, there are very few or less than two bat pace allrounders so this technique can be performed for less than two classes. So, it shows a fault in the code whereas the same code was successfully executed for the allrounder role in the ODI team list.

V. CONCLUSION AND FUTURE SCOPE

From all the case I results it can be observed that for predicting new players to be contoured in the ODI team algorithms like SVM, KNN, and Decision Tree produce good results whereas when compared in point of classification Decision tree, random forest, and gradient boost has achieved more accuracy. From all the case II results it can be observed that for predicting new players to be contoured in TEST team algorithms like LSTM, ANN, SVM, and KNN produce good results whereas when compared in point of classification same algorithm of regressions has achieved more accuracy. Therefore, it can be concluded that for the ODI player role to be predicted in the team SVM and KNN algorithms are the best fit. For the TEST player role to be predicted in the team LSTM and ANN algorithm is the best fit. But if consider the execution time for ANN and LSTM they will take more time than the remaining techniques because of the iterative epoch approach.

This idea can be taken to the next level by taking the data of each game in different pitch conditions, performance against different categories of bowlers (for batsmen role) or performance against the best batsmen (for bowler role), etc. for the upcoming match taking the opposition data like weakness of their batsmen and their bowler's record against the best batsmen in world and performance of them. The basic thought of making this model is to make the job easy for the selectors to filter the players. As first-class career stats are not easily available. If it possibly gets them then the job of assigning roles to new players becomes easier and the results of it are highly efficient and dependable. It is a hybrid model of classification and regression. Firstly, data clustering is done next updated data regression is performed.

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