FIFA 19: PLAYER POTENTIAL PREDICTOR & EXPLORATORY DATA ANALYSIS

INDERPREET SINGH TOOR

6TH OCTOBER, 2019

1. INTRODUCTION

1.1 BACKGROUND

FIFA is the biggest E-Sport Football Simulation game franchise in the world at the moment. The first FIFA game in its long annually recurring history was launched 26 years ago in 1993. It was the first Football simulation game to be officially licensed from FIFA, the world football governing body. FIFA has a mammoth community with millions of players battling out in various game modes every single day.

FIFA 19 which came out in September, 2018 sold over 4.3 million copies within a week of hitting the shelves. Till date FIFA 19 has sold around 25 million copies taking the numbers to near 300 million for the for all FIFA titles combined. FIFA 19 was the first title in FIFA game series to get the official exclusive license for UEFA Competitions which was previously held by Pro Evolution Soccer, a fierce competitor to FIFA.

FIFA 19 has various game modes either offline or online. Offline modes include the Kick-Off mode, The Journey and Career Mode. Online Mode includes Co-op mode and FIFA Ultimate Team mode.

Manager mode is the most realistic mode if we look at how football as a game is played and scheduled throughout the world. It behaves in mostly the same way as a Manager of a football club would in real life, although the game only cover a few aspects while in real life there are much more things to be covered by the Manager.

1.2 PROBLEM

Manger Mode let's you play the game as the Manager of a team whose job is to meet the objectives set by the board which are evaluated at the season's end. There is a limited budget, depending on the team you choose initially, for you to buy players and improve the team in general. While you always want the best players in your team, in reality good players are hard to get and cost lots of money and even if you have good players you are always in need of youngsters who can be a real superstars in near future.

Now finding these wonder kids is very difficult. Many times we don't actually know how much the player will grow in coming years. So, it's a risk investing in youth. Many times it pays off and sometimes it doesn't. In this scenario many gamers would definitely be delighted if they could somehow find out the actual potential of a youngster before actually buying him for a price which is justified. There are websites like www.sofifia.com which offer detail insights of a player including it's potential rating but when generic players start to popup midway through the Manager mode then there is absolutely no way to know the actual potential of a player.

This project aims to predict the potential of any youngster of age 23 or below and also explore the data of FIFA 19 and find out some interesting facts about the game like which club is the most economical in terms of player wages or which countries have the best forwards or which countries have the best youngsters.

2. DATA

2.1 DATA REQUIREMENTS

For this project we need information about players such as their name, nationality, age, club for which they play, their overall rating, their potential rating, which position they play on and their individual attributes like ball control, finishing, crossing, tackling, Goalkeeper diving, etc. which defines how good they are according to their playing positions. In addition to this we need their wage information for some exploratory analysis.

2.2 DATA SOURCE

Our required dataset of FIFA 19 game was downloaded from www.kaggle.com where a user by the name of Karan Gadiya scrapped the data from Sofifa website. Therefore, there was no need for us to scrap the data once again from www.sofifa.com.

The link from where the data set was download is given below:

- https://www.kaggle.com/karangadiya/fifa19

2.3 DATA CLEANING

Luckily for us most of the dataset was nicely formatted keeping aside one or two things. We didn't actually have to spend a lot of time in cleaning the data for our predictive modelling. Our model required information of U23 players so we selected those players using simple python functions, although we had to drop all rows which contained one or multiple null values since that would interfere with our predictive modelling.

During Exploratory data analysis we had to clean the column containing wages which had string values attached to it and change them into more suitable numeric values. After that we changed its type from integer for visualization purposes. We had to create new columns for different exploratory tasks which we will discuss in the methodology section.

3. METHODOLOGY

Our project cover two aspects:

a. We explore the dataset to find out interesting analysis about the FIFA 19 game.

b. We predict the potential of players using Machine Learning model.

3.1 EXPLORATORY DATA ANALYSIS

When we have such large dataset as that of FIFA 19 we get interesting insights from it. There are thousands of things we can explore we have the data of 652 clubs in total. We have chosen some of the most interesting questions like which are the most economical clubs and which clubs are the most lavish in terms of wager per player rating. We will also see players of which countries earn the best and which countries players take home the worst salaries in FIFA 19. Of course, there are many more questions which we will answer by analysing data. The dataset in FIFA 19 is one of the most realistic representation of the real world data so the findings from this data may be applied to real world of football in approximation.

Let's begin the exploratory analysis of FIFA 19 dataset.

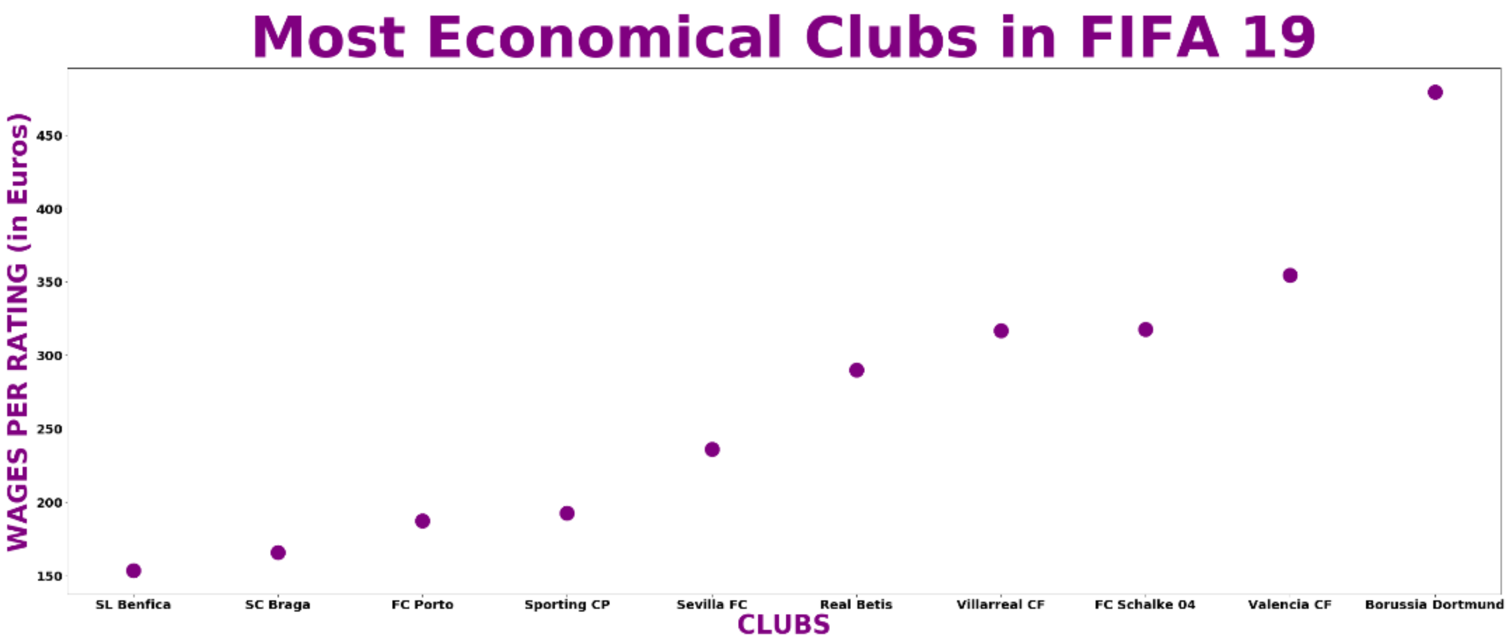
1. MOST ECONOMICAL AND LAVISH CLUBS OF FIFA 19

For this task we needed 3 parameters of a player, namely: Club, Overall and Wage. In order to find out the most economical and lavish clubs first we cleaned the wage parameter of players and converted the data type into more suitable integer type. We created a new column representing the wage per rating for each player. Then we grouped the dataset by clubs and performed the mean function to find out the average of all the needed columns. To have fair output we only considered clubs who had the average overall ratings of 74 or above as low average overall rated clubs will usually have very low income and it is very hard to differentiate the wage structure of a club. Moreover, we are interested in clubs which have highly rated players which will enable us to see the difference very clearly in the wage structure of the club.

Following are the top 10 clubs having the lowest average wage per rating in FIFA 19.

Club	Overall	Wage	Wage/Rating
SL Benfica	77.000000	12035.714286	153.393582
SC Braga	74.821429	12500.000000	165.480989
FC Porto	76.678571	14642.857143	187.229207
Sporting CP	76.133333	14866.666667	192.179671
Sevilla FC	75.200000	18533.333333	235.990927
Real Betis	75.185185	22925.925926	289.868549
Villarreal CF	74.343750	24718.750000	316.641462
FC Schalke 04	74.310345	24586.206897	317.488355
Valencia CF	74.696970	28121.212121	354.289470
Borussia Dortmund	75.333333	38121.212121	479.021540

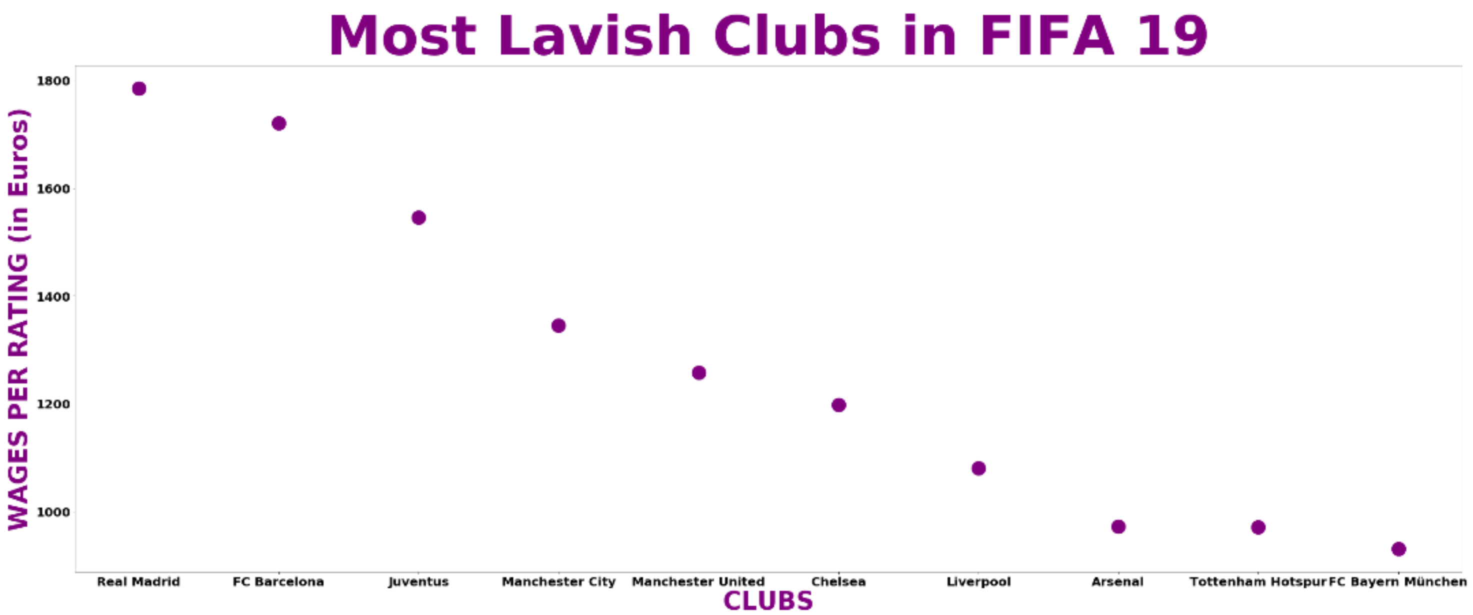
Interestingly we can observe from the figure below that top 4 clubs in this list are from Portugal with SL Benfica being the most economical club which signifies the great amount of talent in the Portuguese league when compared to wages offered to the players all over Europe. We have also seen on regular basis that clubs such as FC Porto are known to scout young talented players from South America and sell them for hefty amount to bigger and richer clubs all over the Europe. Following them we have 4 Spanish Clubs namely: Sevilla FC, Real Betis and Villareal CF, and two German clubs namely: FC Shalke 04 and Borussia Dortmund rounding off the top 10 list. Interesting stuff here is that Borussia Dortmund is considered a German Football Heavyweight.



Following are the top 10 most lavish clubs having the highest wage per rating ratio in FIFA 19.

Club	Overall	Wage	Wage/Rating
Real Madrid	78.242424	152030.303030	1784.575701
FC Barcelona	78.030303	146575.757576	1721.032363
Juventus	82.280000	131680.000000	1545.742373
Manchester City	76.727273	113363.636364	1344.513339
Manchester United	77.242424	102757.575758	1257.590944
Chelsea	76.787879	98454.545455	1197.114569
Liverpool	76.000000	87939.393939	1079.792716
Arsenal	75.181818	78424.242424	971.493917
Tottenham Hotspur	76.696970	79484.848485	970.461491
FC Bayern München	77.000000	78827.586207	930.688777

When we look at the graph there was absolutely no shadow of doubt that Real Madrid CF and FC Barcelona are the most lavish clubs considering their enormous budget and a demanding fans who only and only want the best players in the world. Italian giants Juventus are knocking on the door at the top having seen meteoric rise in this decade. So much so that in July 2018, they acquired the services of Cristiano Ronaldo making a statement that they are here to stay and want to win the Champions League. Following Juventus we have 6 English clubs with Manchester City leading the pack. Having 6 clubs in top 10 most lavish clubs list shows why the English Premier League is hottest property in terms of money matters. EPL has the world's expensive sponsorship deals giving clubs fast flowing cash to offer best wages possible.



2. COUNTRIES WITH HIGHEST AND LOWEST PLAYER WAGES IN FIFA 19

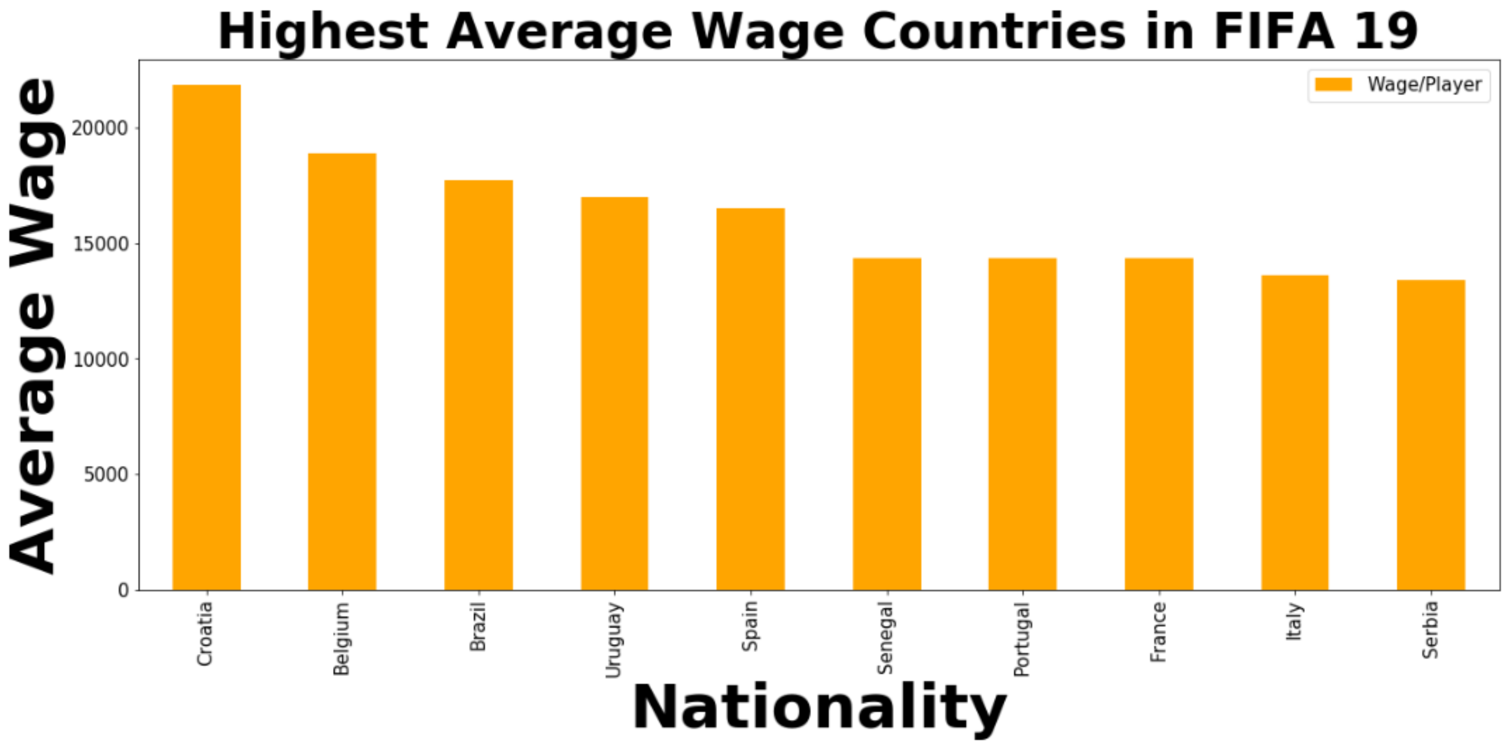
For this task we needed three player parameters, namely: Nationality, Age and Wage. In order to have fair comparison we filter the dataset for players having attained the age of 18 years and above and in order to have meaningful output we include only those countries which have 100 or above players satisfying the above criteria. We tweak the dataset first by grouping our dataset by countries and imposing sum function to calculate the cumulative sum of wages of all the players. Then we create a new column which is the result of cumulative wages of players divided by number of players of each country giving us the average wage of a player of a particular country.

The following are the top 10 countries with highest player wages in FIFA 19.

	Nationality	Wage	Count	Wage/Player
0	Croatia	2731000	125	21848.0
1	Belgium	4797000	254	18886.0
2	Brazil	14621000	824	17744.0
3	Uruguay	2534000	149	17007.0
4	Spain	17470000	1060	16481.0
5	Senegal	1867000	130	14362.0
6	Portugal	4607000	321	14352.0
7	France	12786000	893	14318.0
8	Italy	9441000	693	13623.0
9	Serbia	1689000	126	13405.0

Croatian players earn the most wages which might surprise a few but we all have seen how Croatia defeated big guns to reach the final of FIFA World Cup 18 which shows there is much quality in there having players such as Luka Modric, Evan Rakitic who are arguably the best players in their positions and clubs pay good amount for that. Belgium are another dark horse. Belgium currently have the best generation of footballer in their history at the moment. Players such as Eden Hazard, Kevin De Bruyne and Lukaku to name a few are world class talents earning extra-ordinary incomes. Looking at the top 10 we see 7 countries from Europe which shows how dominating European Football and European players are on world stage.

An interesting information we get is that England and Germany are missing from the list. We concluded this is because FIFA 19 includes 4 divisions of English football and 3 divisions of German football. Hence, this decreases the average income per player of both of these countries. We also that Senegal is the only African country which features in this list. Uruguay and Brazil from South America also feature high in this list only behind Croatia and Belgium.



The following are the top 10 countries with lowest player wages in FIFA 19.

	Nationality	Wage	Count	Wage/Player
0	Korea Republic	1019000	334	3051.0
1	China PR	1224000	391	3130.0
2	Australia	780000	227	3436.0
3	Japan	1648000	475	3469.0
4	Norway	1117000	322	3469.0
5	Sweden	1604000	383	4188.0
6	United States	1497000	347	4314.0
7	Saudi Arabia	1740000	340	5118.0
8	Republic of Ireland	1814000	351	5168.0
9	Chile	2018000	385	5242.0

Korean players earn the lowest in FIFA 19. We also observe that top 4 countries in this list play in Asian Zone which confirms that although Asian countries are emerging in world football they stay far behind the best. There are very few superstar players in Asia which play at the highest level in world football. The same is true for other countries in this list as although they might have some good players but majority of other players are nowhere near the top bundle and therefore, don't command big wages.

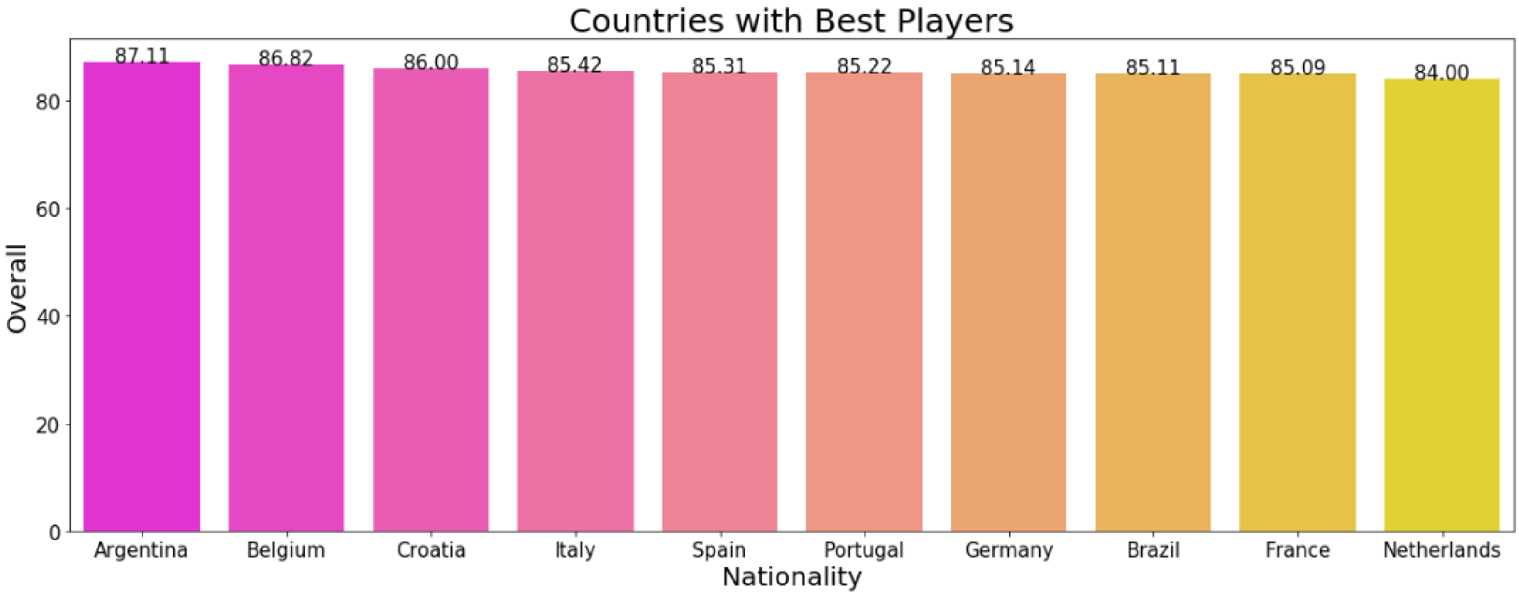
3. COUNTRIES WITH BEST RATED PLAYERS

In this task we required two player parameters, namely: Nationality and Overall. We first sort the values of our dataset by Overall in descending order with the highest rated players listed first. Then we select the first 100 players from the list and group them by their countries. Then we apply the mean function to calculate the average rating of players for each country. In order to have a meaningful result we examine only those countries which have 5 or more players in top 100 players list.

The following are the top 10 countries with best rated players in FIFA 19.

	Nationality	Age	Overall	Count
0	Argentina	28.888889	87.111111	9
1	Belgium	28.818182	86.818182	11
2	Croatia	31.200000	86.000000	5
3	Italy	30.250000	85.416667	12
4	Spain	28.827586	85.310345	29
5	Portugal	28.777778	85.222222	9
6	Germany	26.619048	85.142857	21
7	Brazil	28.321429	85.107143	28
8	France	26.409091	85.090909	22
9	Netherlands	27.833333	84.000000	6

Argentina have the best rated players in FIFA 19 closely followed by Belgium and Croatia. There are 8 nations from Europe and 2 nations from South America in this list.



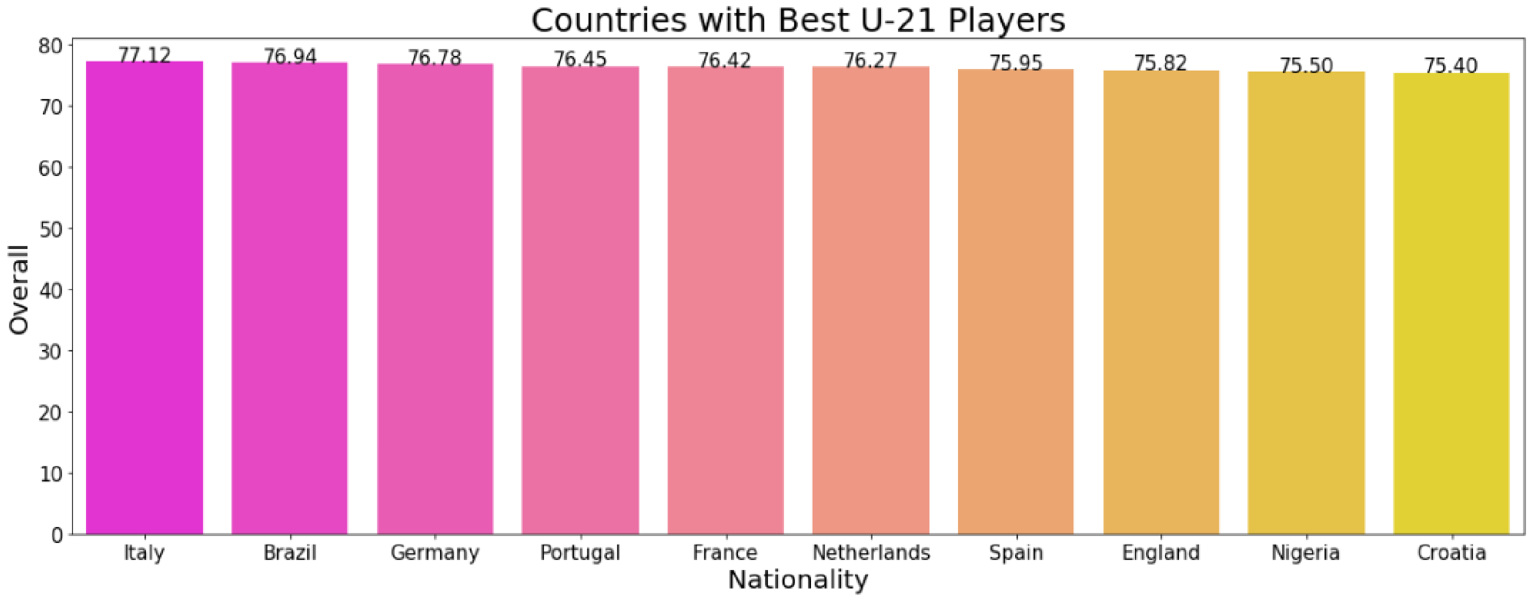
4. COUNTRIES WITH BEST U-21 PLAYERS

For this task we take four player parameters, namely: Nationality, Age, Overall and Potential. We first filter out the players aged 21 or below from our dataset. Then we sort our dataset by overall in descending order and select first 200 players. Then we group the dataset by countries and apply mean function to find the average rating of players for each country. In order to have a meaningful result we only select those countries which have at least 5 players in top 200 young players.

The following are the top 10 countries with the highest rated U-21 players in FIFA 19.

	Nationality	Age	Overall	Potential	Count
0	Italy	20.375000	77.125000	87.875000	8
1	Brazil	20.555556	76.944444	85.611111	18
2	Germany	20.666667	76.777778	84.555556	9
3	Portugal	20.545455	76.454545	84.363636	11
4	France	20.290323	76.419355	85.000000	31
5	Netherlands	20.181818	76.272727	84.545455	11
6	Spain	20.590909	75.954545	83.954545	22
7	England	20.058824	75.823529	85.352941	17
8	Nigeria	20.666667	75.500000	84.166667	6
9	Croatia	20.400000	75.400000	84.400000	5

Italy tops the list with average overall of ratings of above 77 and average potential of nearly 88. Brazil leads the packs among rest of the countries where stats are almost similar. We have 8 countries from Europe, 1 from South America and 1 from Africa.



3.2 PREDICTING PLAYER'S POTENTIAL USING MACHINE LEARNING

The main aim of this project was to predict the potential of a player based on its attributes. Our dataset features only U-23 or below aged players because it is only reasonable if we calculate potential of young players as aged players near the age of 27-28 years have already reached or nearing their potential best ratings.

A more useful result will be if we can predict player's potential based on its playing position. This way we have to only deal with player attributes which are position dominant. This way we can drastically reduce the number of required attributes for our prediction model. This will increase our calculation speed as well as it becomes easier for gamers to collect the data for a player they want to get into their team. So we specify the number of position specific attributes for each player must be exactly 5 plus three position neutral attributes, namely: Age, Overall and Potential, totalling to 8 player attributes.

Now we count the total number of possible U-23 players' positions in, which comes out to be staggering 27 in number. Naturally here we need to group similar positions so that our model doesn't become unnecessarily complicated and difficult to understand and implement. So we broadly categorize the 27 possible positions into following 8 different positional categories:

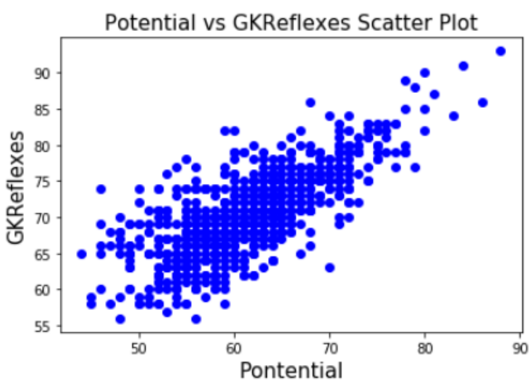
Goalkeepers, Centre Backs, Full Backs, Defensive Midfielders, Central Midfielders, Attacking Midfielders, Wingers/Wide Midfielders, Strikers/Centre Forwards.

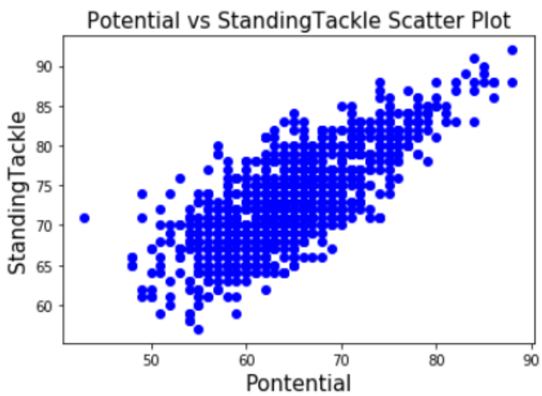
```
Total Unique Positions for U-23 Players are :  27
Number of U-23 Players per position :

 ST      933
CM      808
CB      805
GK      777
RM      514
LB      504
RB      501
LM      484
CAM     435
CDM     379
LW      220
RW      206
LCB     153
RCB     136
LCM     114
RCM     114
LDM      60
RDM      51
LS       50
RS       46
RWB      39
CF       39
LWB      24
RF        3
LF        2
RAM       1
LAM       1
Name: Position, dtype: int64
```

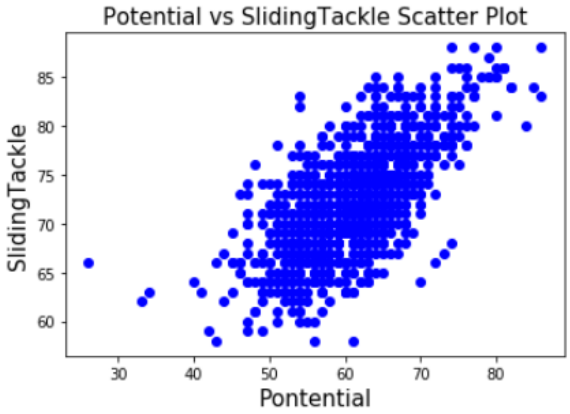
In order to pick the best machine learning model we need to take a look at our data and see what outcome we want. As the goal of this exercise is to predict the potential of a player which is numeric data it becomes evident that we don't need Classification and Clustering techniques here are we calculating raw numeric values. Hence, the best machine learning algorithm for this task will we Regression.

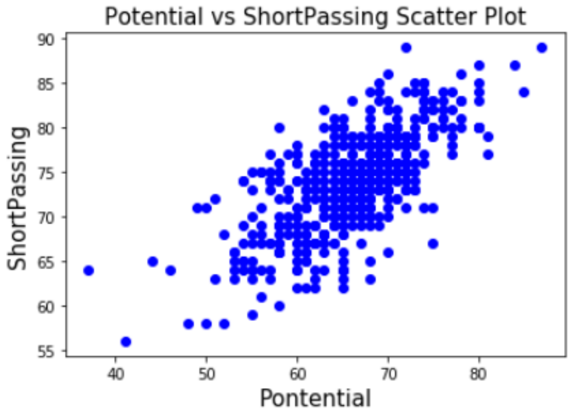
Now we need to see if our data is suitable for Linear or Non-Linear Regression. For this we draw scatter plot to understand which algorithm model to choose.

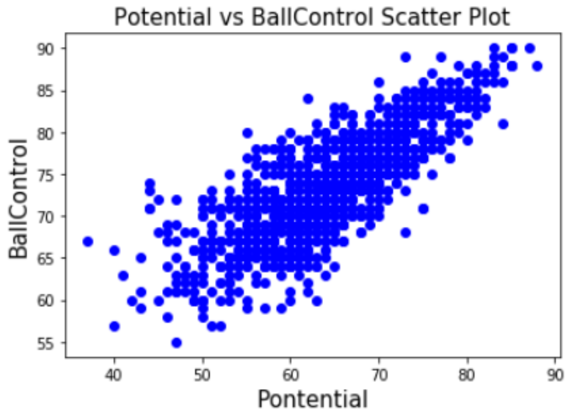
We take different player positional attributes and draw them against given player potential. We see that every plot we draw show linearly rising data points. This implies that we need to implement Multiple-Linear Regression model on our dataset.

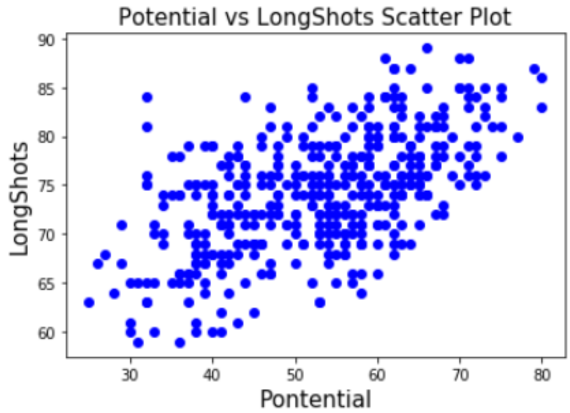


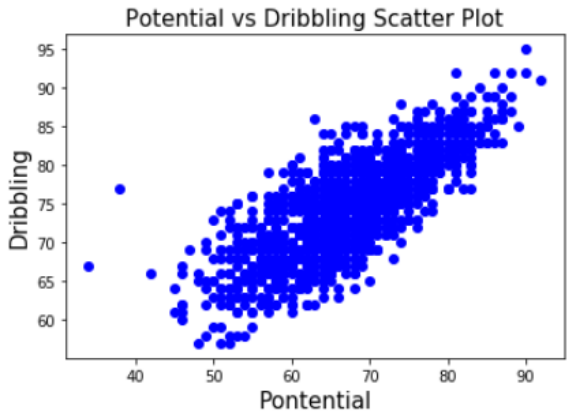


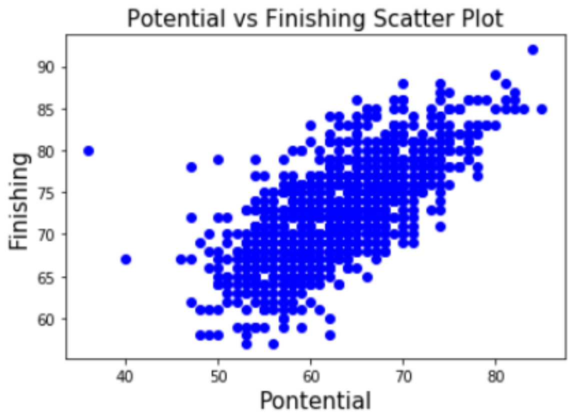












The observation made from these plots leads us to Linear Regression. Before applying the model we need to check which top 5 positional attributes we need for each of the 8 positional categories we created by combining the 27 positions. For this we use correlation function and check how much each attributes are correlated to each other. We are looking for attributes which are highly correlated with the Overall attribute of a player. Example of correlation function for Central Midfielders can be observed in the following table:

	Overall	Potential	Age	ShortPassing	Dribbling	LongPassing	BallControl	Reactions	LongShots	Positioning	Vision
Overall	1.000000	0.834110	0.520162	0.902613	0.892059	0.877915	0.932450	0.862242	0.789789	0.735269	0.882389
Potential	0.834110	1.000000	0.077495	0.780226	0.777160	0.743753	0.794351	0.718041	0.636238	0.606759	0.744623
Age	0.520162	0.077495	1.000000	0.439946	0.415846	0.448946	0.444802	0.431570	0.435619	0.386293	0.445438
ShortPassing	0.902613	0.780226	0.439946	1.000000	0.806246	0.911900	0.854745	0.749763	0.648502	0.613697	0.790396
Dribbling	0.892059	0.777160	0.415846	0.806246	1.000000	0.784324	0.913213	0.732539	0.716284	0.678266	0.807405
LongPassing	0.877915	0.743753	0.448946	0.911900	0.784324	1.000000	0.821499	0.695021	0.669036	0.587168	0.781241
BallControl	0.932450	0.794351	0.444802	0.854745	0.913213	0.821499	1.000000	0.774996	0.747401	0.669150	0.833600
Reactions	0.862242	0.718041	0.431570	0.749763	0.732539	0.695021	0.774996	1.000000	0.650577	0.651978	0.735407
LongShots	0.789789	0.636238	0.435619	0.648502	0.716284	0.669036	0.747401	0.650577	1.000000	0.635837	0.693486
Positioning	0.735269	0.606759	0.386293	0.613697	0.678266	0.587168	0.669150	0.651978	0.635837	1.000000	0.660153
Vision	0.882389	0.744623	0.445438	0.790396	0.807405	0.781241	0.833600	0.735407	0.693486	0.660153	1.000000

As we can see Dribbling, Short Passing, Long Passing, Ball Control and Vision are the top 5 attributes that co-relate with the Overall attribute of a player. Hence, we will use them as data for our model. Sometimes we need to replace some attributes with closely related other attributes to get the best results.

We use these positional attributes for each positional category:

S.No.	Position	Attributes
1	Goalkeeper	'GKDiving', 'GKHandling', 'GKKicking', 'GKPositioning', 'GKReflexes'
2	Centre Back	'HeadingAccuracy', 'Interceptions', 'Marking', 'StandingTackle', 'SlidingTackle'
3	Full Back	'Crossing', 'BallControl', 'Interceptions', 'StandingTackle', 'SlidingTackle'
4	Defensive Midfielder	'ShortPassing', 'LongPassing', 'BallControl', 'Composure', 'StandingTackle'
5	Central Midfielder	'ShortPassing', 'Dribbling', 'LongPassing', 'BallControl', 'Vision'
6	Attacking Midfielder	'Finishing', 'ShortPassing', 'Dribbling',' BallControl', 'LongShots'
7	Wide Midfielder / Winger	'Finishing', 'Crossing', 'ShortPassing', 'Dribbling', 'BallControl'
8	Striker / Centre Forward	'Finishing', 'Dribbling', 'BallControl', 'ShotPower', 'Positioning'

Now in order to have a quality model and avoid over fitting of model we split our datasets, one containing independent variable i.e. all player positional attributes and another containing the dependable variable i.e. player potential, using Train Test data split function from ‘SKLEARN’ library. We then fit the model on training set using Linear Regression Constructor. Once the model is fitted we are ready to predict the player potential using test dataset containing all the player’s positional attributes.

Now that we have the predicted results we calculate how well the model performs in comparison to the actual potential attribute data. For this we use Root Mean Squared Error (RMSE) and R-Squared evaluation techniques.

Root Mean Squared Error (RMSE) is used to measure the difference in the values predicted by a model and actual observed values. RMSE is the square root of the average of squared errors. The closer the RMSE value to zero, the better our model.

R-Squared is the proportion of variance of Dependant variable that is predictable from the Independent variable. R-Squared measures how close the data is to the fitted Regression Line. R-Squared value varies between 0% and 100%. Value closer to 0% indicates bad model fitting and data whereas value closer to 100% indicates great model fitting.

If the model is badly fitted, we can tweak and change some positional attributes to get a possibly good fitted model.

Let’s check the results section and evaluate our machine learning model.

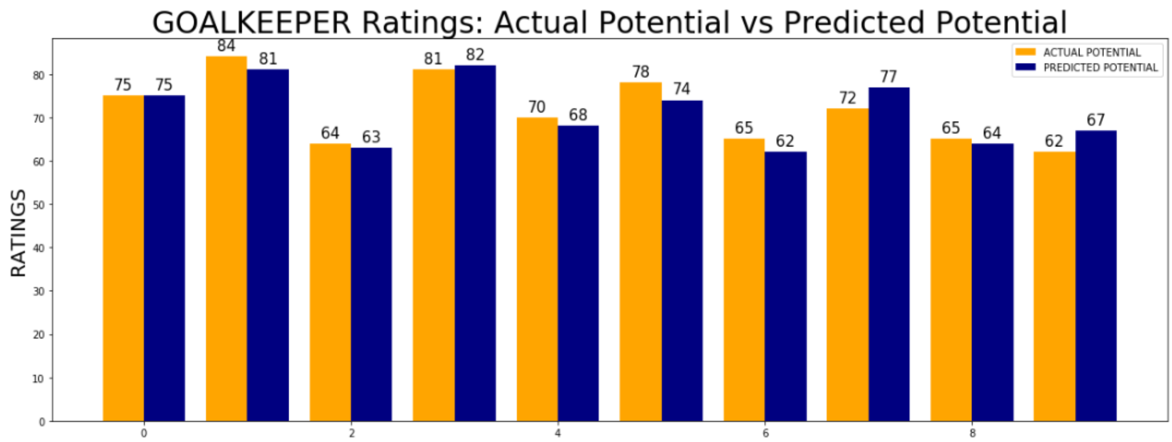
4. RESULTS

We performed Linear Regression model fitting for U-23 players to predict their potential according to their positional attributes. We broadly divided the positions into 8 positional categories:

Goalkeepers, Centre Backs, Full Backs, Defensive Midfielders, Central Midfielders, Attacking Midfielders, Wingers/Wide Midfielders, Strikers/Centre Forwards.

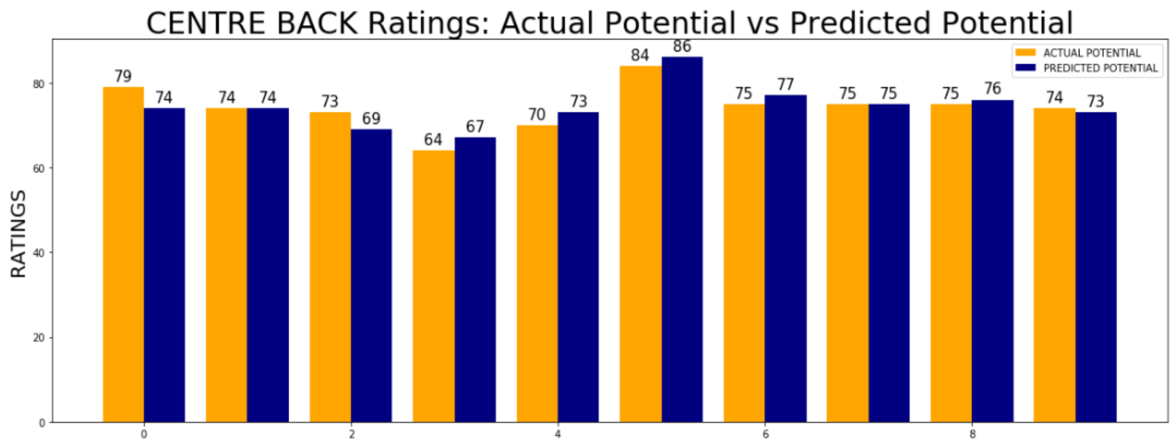
We will now look at the results of each of these positional categories.

A) GOALKEEPER



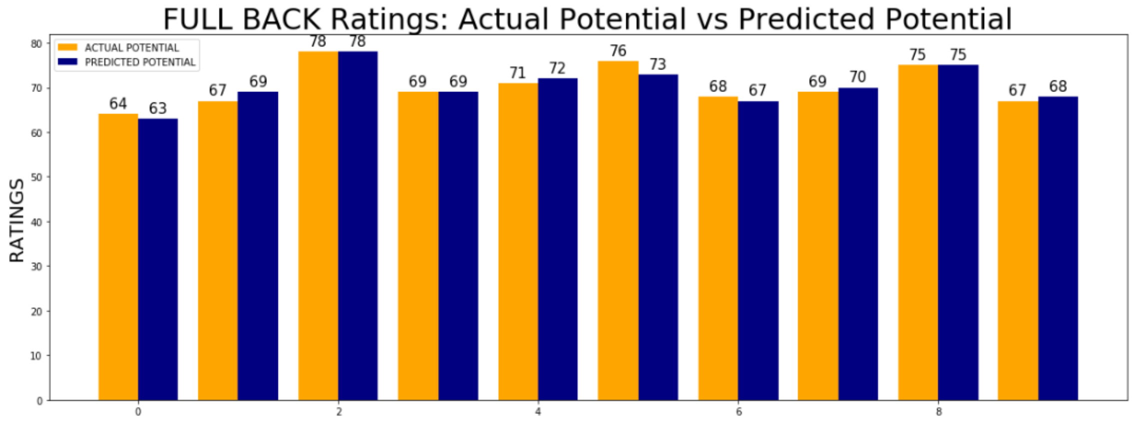
Root mean square error : 5.87618884550656
R2 score : 0.8563858464181078

B) CENTRE BACK



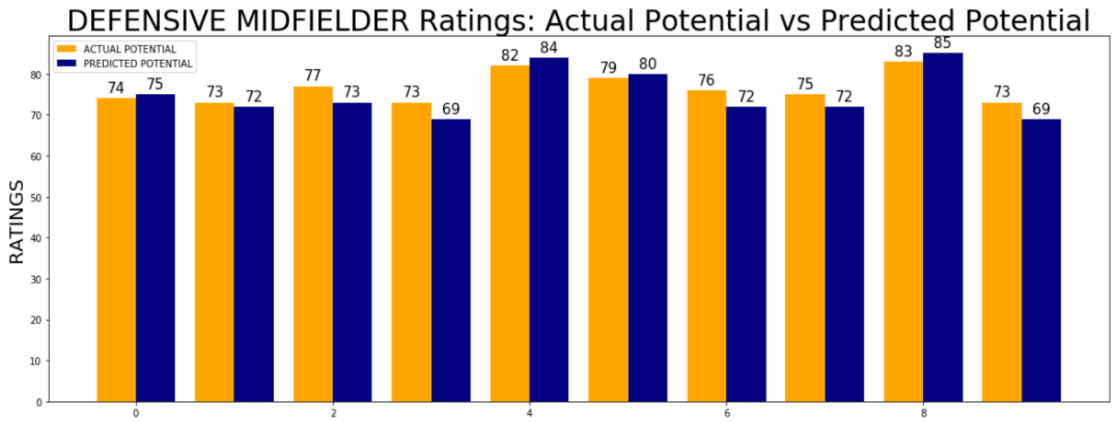
Root mean square error : 5.848133564732575
R2 score : 0.8169089318178537

C) FULL BACK



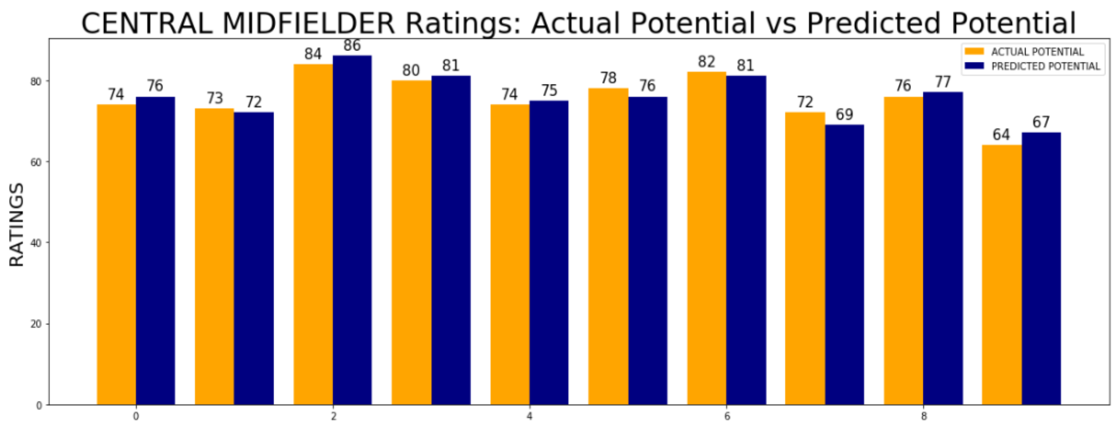
Root mean square error : 5.366467675209051
R2 score : 0.8348795817924303

D) DEFENSIVE MIDFIELDER



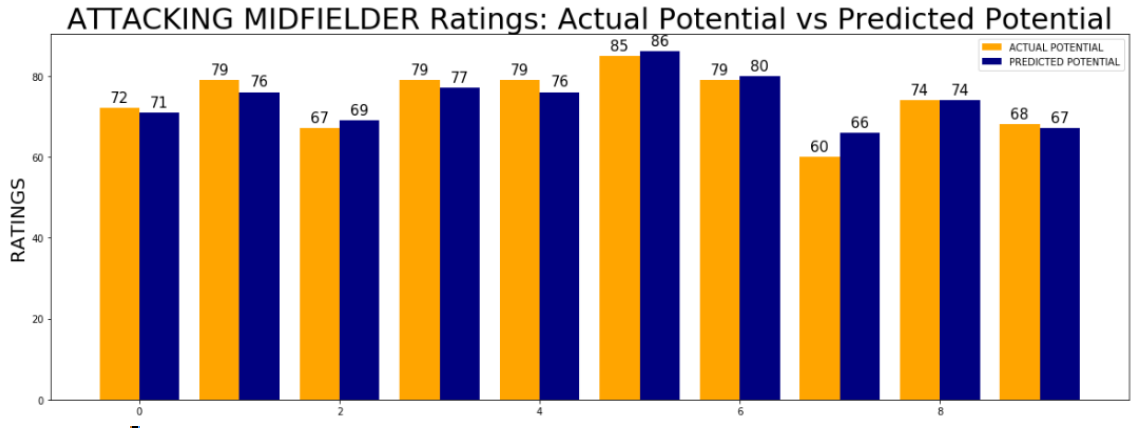
Root mean square error : 4.994911637192226
R2 score : 0.8284962894880246

E) CENTRAL MIDFIELDER



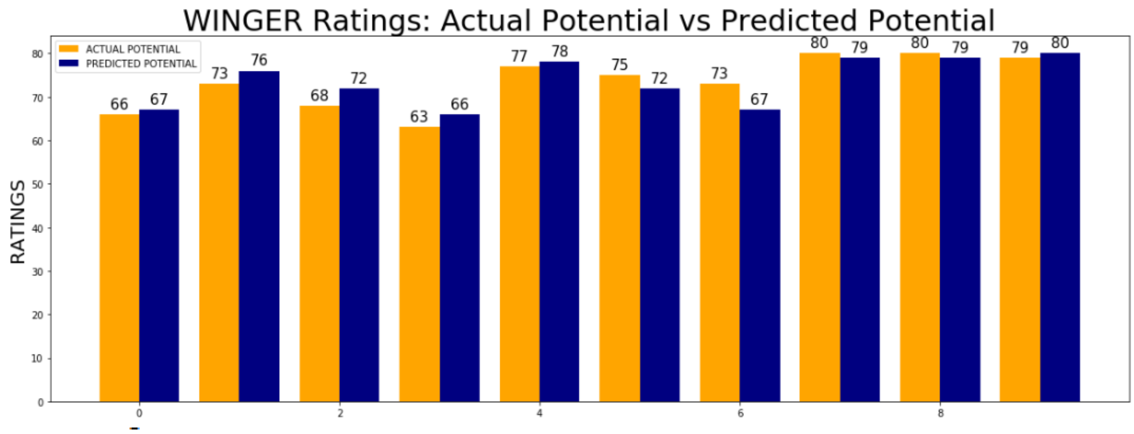
Root mean square error : 5.391572660427436
R2 score : 0.8760934603906961

F) ATTACKING MIDFIELDER



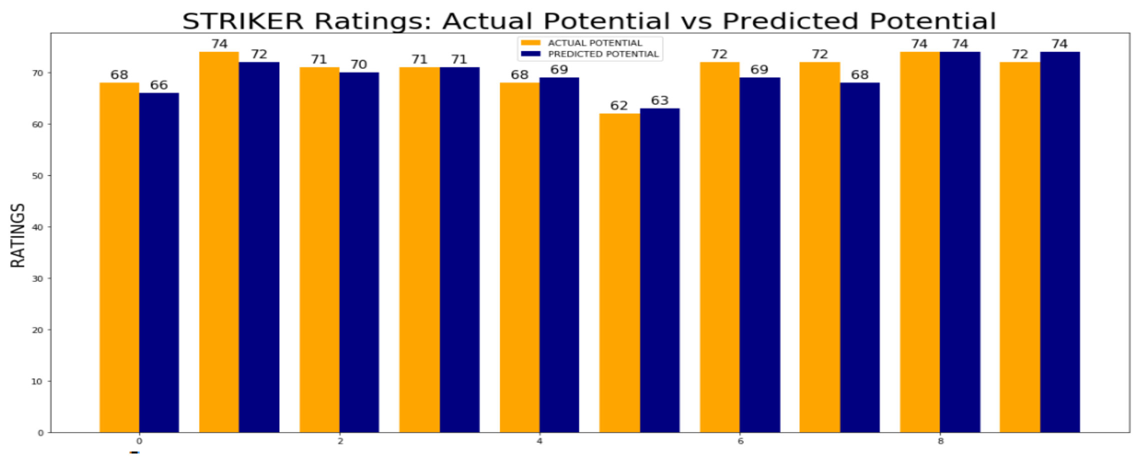

```
Mean Sqaured Error :  6.134280487990313
R2 Score :  0.8279643205361391
```

G) WIDE MIDFIELDER / WINGER




```
Mean Sqaured Error :  4.897028784707573
R2 Score :  0.8839914898259899
```

H) STRIKER / CENTRE FORWARD




```
Mean Sqaured Error :  4.602817840530803
R2 Score :  0.863141257248628
```

5. DISCUSSION

We started our project with the main aim to find out if we can predict a player's potential rating with accuracy. We divided 27 positions into 8 positional categories to best estimate the results for just 5 positional attributes for each player. Let's discuss the results for each positional category.

For Goalkeepers we predicted the potential attribute with 85.6% accuracy and RMSE of 5.87 which indicates our model is good fit and will work on any outside data with flying colours. The R^2 for Centre Backs give us 81.69% accuracy which is fine in all regards. We see similar trends in all of the positional categories with Central Midfielders with 87.60% and Wide Midfielders or Wingers with 88.39% having the best predicted accuracy in comparison to actual potential attribute.

We conclude from the given results that our model was generally a good fit for the given train and test data and the positional attributes we had chosen for each positional category were the right ones.

Looking at the trends we can observe that Ball Controls is the dominating positional attribute in 6 positional categories of Full Backs, Defensive Midfielders, Central Midfielders, Attacking Midfielders, Wingers/Wide Midfielders and Strikers/Centre Forwards. This shows how much fast-paced the modern game has become with players now playing quick passing game and in order to execute this style of play Managers prefer players who have excellent first touch and control of the ball. Short Passing becomes a necessity in the midfield and we can verify that by observing this attribute in Defensive Midfielders, Central Midfielders, Attacking Midfielders, Wingers/Wide Midfielders positional categories.

Players playing in the wide areas of the pitch need to provide service in the box for the forward players. In this scenario crossing the ball with accuracy and precision to the path of the man making the run becomes very important attribute to have. We can observe that Full Backs and Wide Midfielders/Wingers possess the crossing attribute when we are fitting the model. A bad or goof crossing attribute will affect the model fitting likewise for these particular positional categories.

In Football Goals wins you games. It's simple as that, but hard to execute at the highest level. For Goals to happen players playing upfront like the Strikers, Wingers and Attacking midfielders must have the skill and an eye to put the ball in the back of the net. That's why we have the evidence that Finishing is an important attribute of these positional categories.

We reaffirm our idea that right positional categories are very important aspect to consider if we are predicting the potential of a player using machine learning algorithm from the results. We can presume many of these attributes if we have in depth knowledge of the game. If not then we can always find the correlating among the attributes and fine tune our model fitting by picking the right attributes.

6. CONCLUSION

Football in today's world is more than just a game. For some it's a form of life. It brings joy, sadness and every possible emotion out of the fans. 3.5 Billion people watched the FIFA World Cup 2018 indicating how big this sport really is. Not everyone can become a football star. So fans try to mimic their favourite teams and choose to play E-Sports soccer emulation games like EA Sports' FIFA or Konami's Pro Evolution Soccer. Soccer emulation has become very realistic over the years. In FIFA 19 in particular we have Manager Mode lets you play as the Manager of your favourite team and allow you to imitate the regular football season in the game itself.

In order to have an edge over the AI that is powering the opposition teams in Manager mode it's always good to have the right kind of players in our team. Exploratory data analysis of FIFA 19 reveals some great insights about the game which is very essential for gamers. This information can be used for scouting purposes in the game which can greatly increase the chances of getting the best players for your team at the price you can afford to pay. You can also get youth players from countries which suit the criteria you set after looking at the graphs from the exploratory data analysis.

When it comes to young players, whether they are your youth setup or part of your senior team squad, it's very important to know if they can grow on to become the superstars in their prime. It's very difficult to judge just by looking at the attribute data available to exactly pinpoint a player's potential. For this we used machine learning model and predicted the player's potential with a very high degree of accuracy. This enables gamers to have an edge and future proof the club by getting the rights young players for their team.

Of course there are other aspects we would like to know such as what is the optimal position we should play a player or what is the right wage and money to be offered to players when signing them. These question can be answered using machine learning and will be part of future scope of this project.