

1 . EDA and Data Cleaning:

We've imported pandas toolkit for performing matplotlib.pyplot for plotting my data and numpy.

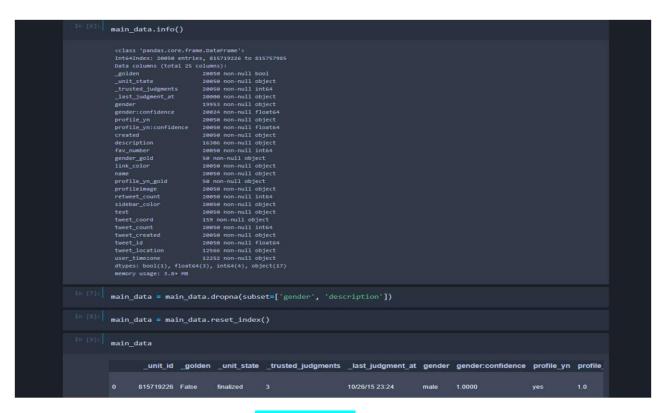
EDA(Exploratory Data Analysis),

- ☐ Imported pandas as pd
- ☐ Imported matplotlib.pylot as plt
- ☐ Imported numpy as np

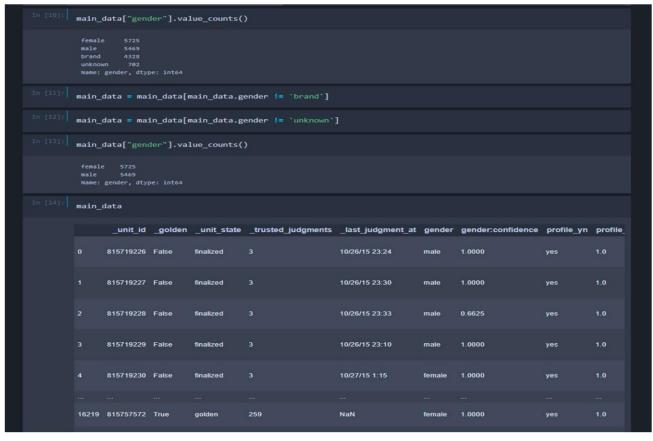
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
main_data = pd.read_csv("Information.csv", encoding="ISO-8859-1")
main_data = main_data.set_index("_unit_id")
main_data
          _golden _unit_state _trusted_judgments _last_judgment_at gender gender:confidence profile yn profile_yn:con
 unit id
815719226 False
                                                   10/26/15 23:24
                   finalized
                                                                              1.0000
                                                                                                           1.0
815719227 False
                   finalized
                                                   10/26/15 23:30
                                                                              1.0000
815719228 False
                                                   10/26/15 23:33
                                                                             0.6625
                   finalized
```

Imported the given "Information.csv" file using pd.read_csv() into main_data.

Then we've used .info() function to check for null values and then we've used .dropna() to drop null values in the required columns and as there will be variation in the index values we've used reset_index() to reset the index for the data set as shown below.



For further cleaning we've used .value_counts() function for the gender column so as to remove the genders other than male as female as shown in the figure.

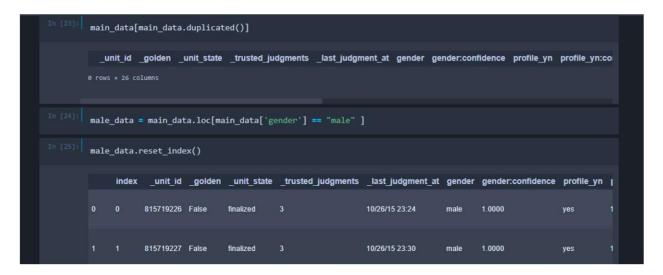


```
main data.info()
                         11194 non-null bool
11194 non-null object
 __trusted_judgments
_last_judgment_at
 gender:confidence
profile_yn
profile_yn:confidence
created
                        11194 non-null float64
11194 non-null object
gender_gold
link_color
                         11194 non-null object
11194 non-null object
profile_yn_gold
profileimage
retweet_count
sidebar_color
                        11194 non-null object
11194 non-null object
                        73 non-null object
11194 non-null int64
tweet_location
user_timezone 7776 non-null object dtypes: bool(1), float64(3), int64(5), object(17)
           _unit_id _trusted_judgments gender:confidence profile_yn:confidence fav_number retweet_count tweet_count
                                                                                  11194.000000 11194.000000 1.119400e+04
                                      11194.000000
0.918876
count 1.119400e+04 11194.000000
                                                               11194,000000
mean 8.157297e+08 3.709577
                                                                0.994986
                                                                                                                         3.058215e+04 (
                                 0.162631
0.320600
                                         0.320600
1.000000
1.0000
                                                                                         13729.554831 1.634918
                                                                0.040760
                                                                                                                          7.285694e+04 4
min 8.157192e+08 3.000000
                                                                                        0.000000
                                                                                                         0.000000
                                                                                                                          1.000000e+00 (
                                                                                         217.000000 0.000000
25% 8.157239e+08 3.000000
                                                                1.000000
                                                                                                                          2.824500e+03 (
50% 8.157301e+08 3.000000 1.000000 1.000000 1408.500000 0.0000000
                                                                                                                         1.027250e+04 (
75% 8.157349e+08 3.000000
                                           1.000000
                                                                 1.000000
                                                                                          5613.250000 0.000000
                                                                                                                          3.127625e+04 (
                                  1.000000
max 8.157580e+08 274.000000
                                                                 1.000000
                                                                                         341621.000000 153.000000
                                                                                                                         2.680199e+06 (
```

```
main_data.columns
 _unit_id _golden _trusted_judgments gender:confidence profile_yn:confidence fav_number retweet_cou
                                                                 0.009249
0.00
                1.000000 0.216284 0.216015
                                                   -0.010097
                                                                                        0.008180
                                                                                                     0.009449
                0.216284 1.000000 0.998882
                                                                      0.005003
                                                                                                     -0.001470
gender:confidence -0.010097 0.013999 0.014247
                                                    1.000000
                                                                                          -0.051640
                                                                                                     -0.000374
profile_yn:confidence 0.009249 0.004995 0.005003
                                                    0.251552
                                                                     1.000000
                                                                                          0.002145
                                                                                                     0.003393
                0.008180 0.008804 0.008729
                                                    -0.051640
                                                                     0.002145
                                                                                         1.000000
                                                                                                     0.018456
                0.009449 -0.001425 -0.001470
                                                    -0.000374
                                                                     0.003393
retweet_count
                                                                                         0.018456
                                                                                                     1.000000
                0.001812 -0.012300 -0.012336
0.852216 -0.000971 -0.000912
```

Once the data was clean we've separated the male and the female data by using .loc[] and scanning through gender column.

Separating Male data from main data:



Separating Female data from main data:

In [26]:	fema	le_data	a = main_c	lata.loc[main_data['gender'] == "femal	le"]				j
In [27]:	<pre>female_data = female_data.reset_index()</pre>										
In [28]:	fema	le_data	a								
		index	_unit_id	_golden	_unit_state	_trusted_judgments	_last_judgment_at	gender	gender:confidence	profile_yn	ı
	0	4	815719230	False	finalized	3	10/27/15 1:15	female	1.0000	yes	
			815719231	False	finalized	3	10/27/15 1:47	female	1.0000	yes	
	2	8	815719234	False	finalized	3	10/27/15 1:52	female	1.0000	yes	1

2 . Questions asked on data set:

I. What are the most common emotions/words used by Males and Females?

Ans. Most common word used by Males is 'the'.

Most common word used by Females is 'and'.

Description for I'st question:

As we separated the male and female data sets we used .str.split(expand=True).stack().value_counts() function to split count and stack up the max counter value and saved it into a list for both male and female data sets as the max counter value is stacked up arr[0] gives us the most used emotion or word used by male as well as female

```
In [32]: arr = male_data["text"].str.split(expand=True).stack().value_counts()
In [33]: arr_f = female_data["text"].str.split(expand=True).stack().value_counts()
In [34]: arr
```

```
the 2755
and 2229
to 1695
a 1468
I 1397
MBM.CDM/DECJ 1
Gene_Lbyt
avert_Dri_Dri_ 1
dust_ 1258, dtype: int4

In (35): arr_f

In (35): arr_f.index[0]
```

```
In [39]: arr_f.index[0]
```

II. What gender makes more typos in their tweets?

Ans. The gender with more typos in their tweets is Male.

Description for II'nd question:

We've taken temp variable and appended the data from text column into the temp variable for male and female so that the data is stored in single variable as a list. Then we've imported nltk toolkit and downloaded punkt function. Then by creating a function we've joined the lists into a string by using .join() inbuilt function for both male and female data. By using .word_tokenize() we've separated the words from to string to a list to recheck the most common words we've imported counter from collections counter to count through the list. Then we had to install the spellchecker toolkit to the python by using "pip install -U pyspellchecker" in the command promt at the specified location in the figure. Then we've imported SpellChecker from spellchecker. Then we've separated the wrongly spelt word by using .unkown() function and created a separate list for both male and female. Then by using the len() function we've found the number of typos done by both male and female.

```
for x in male_data["text"]:
    temp.append(x)

print(temp)

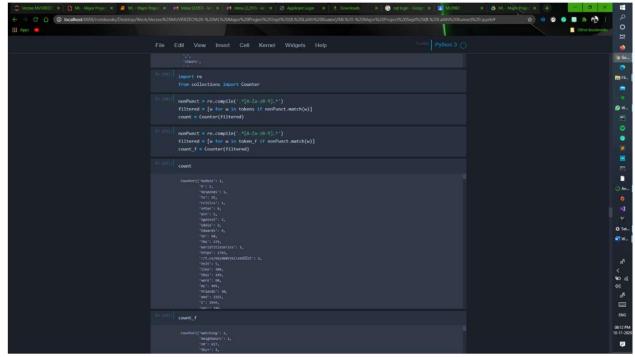
['Roobie E Responds To Critics After Min Against Eddie Edwards In The MoorldTitleSeries https://conNsymBinVyKZ, '\xs90IIt felt like they we re my friends and it was living the story with them.xs90/wsd https://conlampGOVYHNO Merctired #ZAMI https://coolcacAMPOFE, 'i absolutely ador e when louis starts the songs it hits me hard but if feels good, 'Hit @Ordenspieth . Looking the turl - do you use @ETTIT'] bon't ty pically see an advanced user on the @PmcATOURI https://conHSBOUMSFERC.', 'Gals Bingo Clubs bought for #EZAMIS THE US' Sargest High Street bin go operator, Gals, is being taken over by Vaxido, https://contraves.blu03' "@ECOLORIZ-yiPd Ditto - Title High Edwards and retweet stuff - lesst it sucks less than Facebook hala FP, 'YALL UMRAD SIGNT Meth THE CHORNIS CAME ON, A TEAR ROLLED DOOM MIS FACE https://contraves.org/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/pubm.com/p
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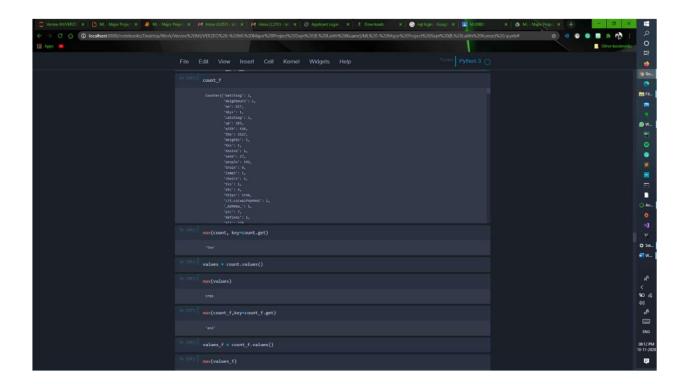
Converting the text column into List:



Tokenizing the converted string:

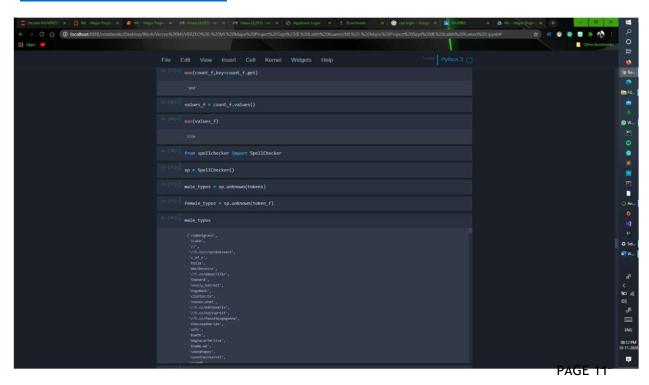
Using Counter to count max repeated words:



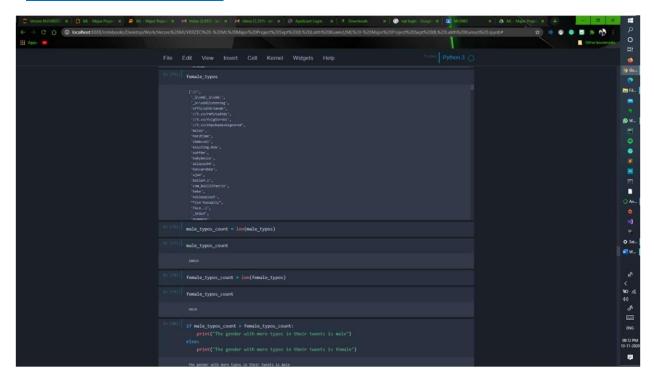


Installing pyspellchecker to pc:

Checking miss spelt words:



Counting miss spelt words:

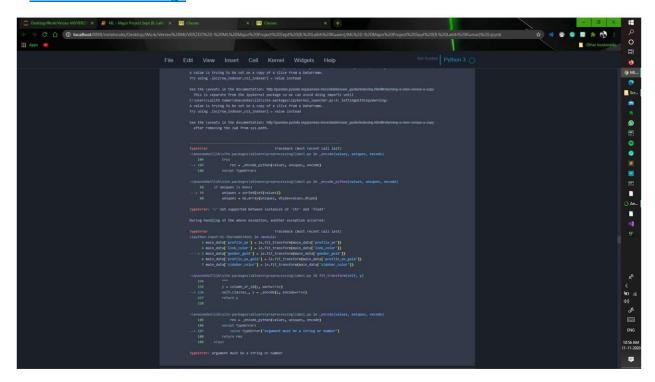


3 . Feature selection and Feature engineering:

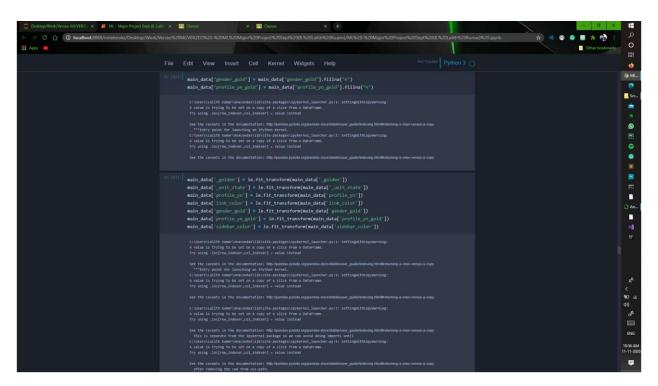
For splitting the data all the independent data from which the predictions are to be made are stored in X and the dependent variable is stored in Y. By importing the LableEncoder from sklearn.preprocessing we've encoded the columns containing string into a specific code depending upon the data. We've faced type error issue as there were some null values which we couldn't delete from data. By using .fillna() function we've filled all the null values with a character and then encoded the resultant data.

By importing train_test_split from sklearn.model_selection we've set the training and testing data of both independent and dependent variable i.e., X and Y.

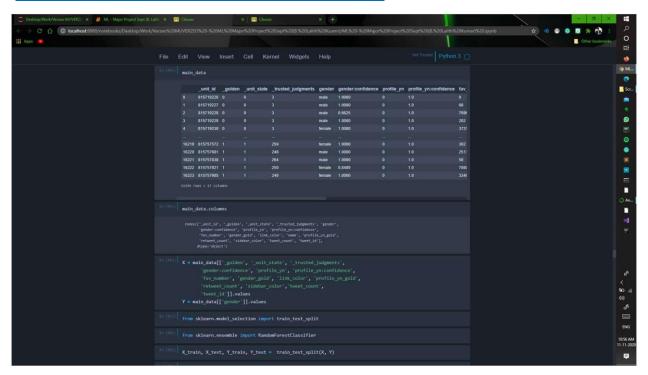
Error while encoding:



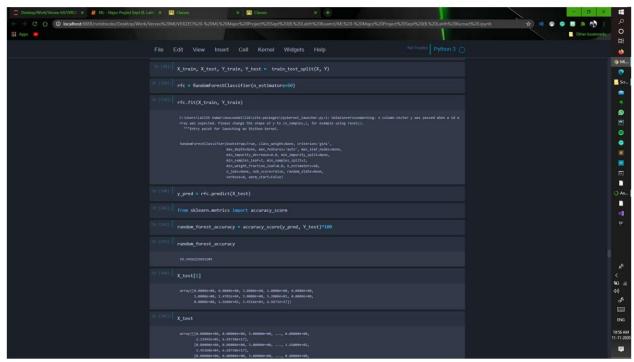
Error rectification while encoding:



Splitting data for training and testing purposes:



Calling Random Forest Algorithm:



4 . Ensemble Machine Learning Modelling:

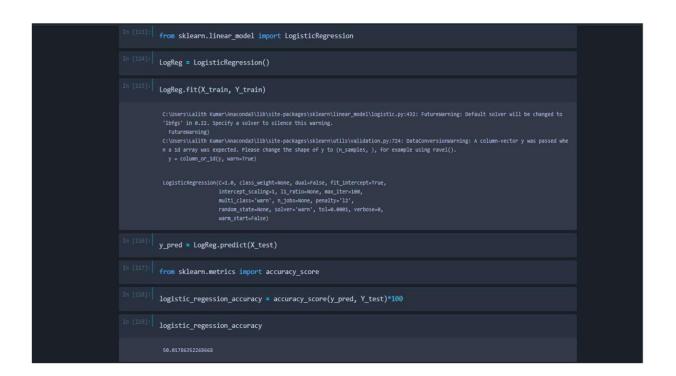
1. Random Forest Algorithm -

We've imported RandomForestClassifier from sklearn.ensemble. We've fitted the X_train and Y_train to the random forest classifier and by using .predict() we've predicted the values for X_test.

By importing accuracy_scores from sklearn.metrics we've found the accuracy of predicted value i.e. y_pred and test value i.e. Y_test. As shown in the above figure.

2.Logistic Regression -

We've imported LogisticRegression from sklearn.linear_model. We've fitted the X_train and Y_train to the and by using .predict() we've predicted the values for X_test. By importing accuracy_scores from sklearn.metrics we've found the accuracy of predicted value i.e. y_pred and test value i.e. Y_test. As shown in the figure.



3.SVM Algorithm -

We've imported sym from sklearn. We've fitted the X train and Y train to the random forest classifier and by using predict()) we've predicted the values for X test. By importing accuracy_scores from sklearn.metrics we've found the accuracy of predicted value i.e. y pred and test value i.e. Y test. As shown in the figure.



X train and Y train to the and by using .predict() we've predicted the values for X test. By importing accuracy scores from sklearn.metrics we've found the accuracy of predicted value i.e. y pred and test value i.e. Y test. As shown in the figure.

KNN ALGORITHM
In [124]: from sklearn.neighbors import KNeighborsClassifier
In [125]: knn=KNeighborsClassifier(n_neighbors=60)
In [126]: knn.fit(X_train,Y_train)
C:\Users\Lalith Kumar\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: DataConversionWarning: A column-vector y was passed when a 1d a rray was expected. Please change the shape of y to (n_samples,), for example using ravel(). """Entry point for launching an IPython kernel. KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski', metric_params=None, n_jobs=None, n_neighbors=60, p=2, weights='uniform')
<pre>1n (127): y_pred=knn.predict(X_test)</pre>
In [128]: from sklearn.metrics import accuracy_score
accuracy_score(y_pred,Y_test)
0.548410146480886

5. Accuracy Results:

- **☐** *Random Forests 59.34*
- ☐ Logistic Regression 50.01
- **☐** *SVM Algorithm* − *50.80*
- **☐** *KNN algorithm* **−** *54.84*

Additional Functions Performed:

☐ Plotted Heatmap by importing seaborn



☐ In Random Forest calculated the accuracy for all the Estimators in the range of 1 to 100, plotted the graph for all the accuracies and found the average of 100 accuracies.

```
temps()

for i in range(1,100):

    rfc = RandomforestClassifier(n_estimators=1)
    rfc.fit(X_train,Y_train)
    y_pred=rfc.predict(X_test)
    temp[i]=accuracy_score(y_pred,Y_test)*100

c:\Users\tallth zumar\tascores(y_pred,Y_test)*100

c:\Users\taslth zumar\tascores(y_pred,Y_test)*100

c:\Users\taslth zumar\tascores(y_pred,Y_test)*100

c:\Users\taslth zumar\tascores(y_pred,Y_test)*100

c:\Users\taslth zumar\tascores(y_pred,Y_test)*100

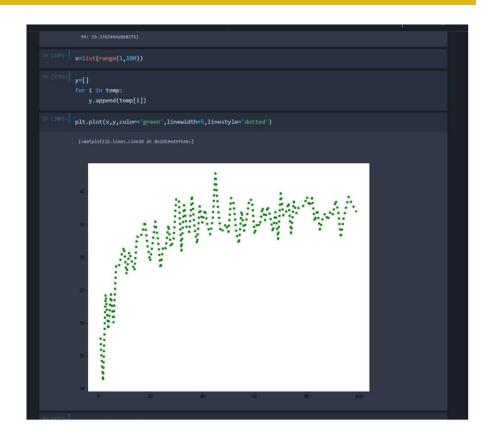
c:\Users\taslth zumar\tascores(y_pred,Y_test)*100

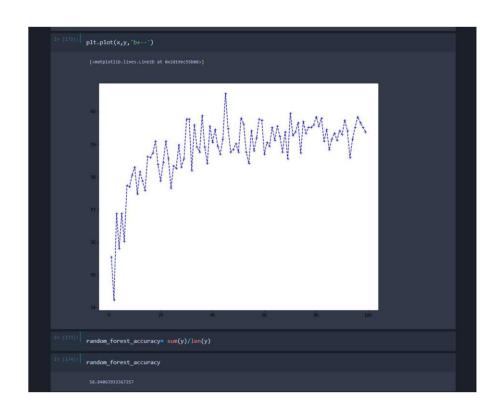
c:\Users\tascores(y_pred,Y_test)*100

c:\Users\taslth zumar\tascores(y_pred,Y_test)*100

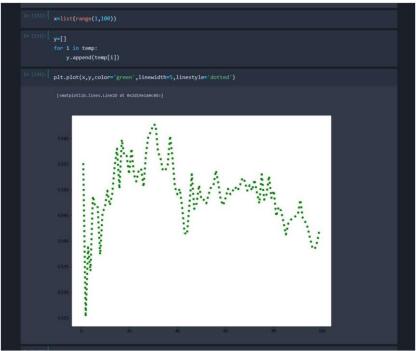
c:\Users\tascores(y_pred,Y_test)*100

c:\Users\tascores(y_pred,
```

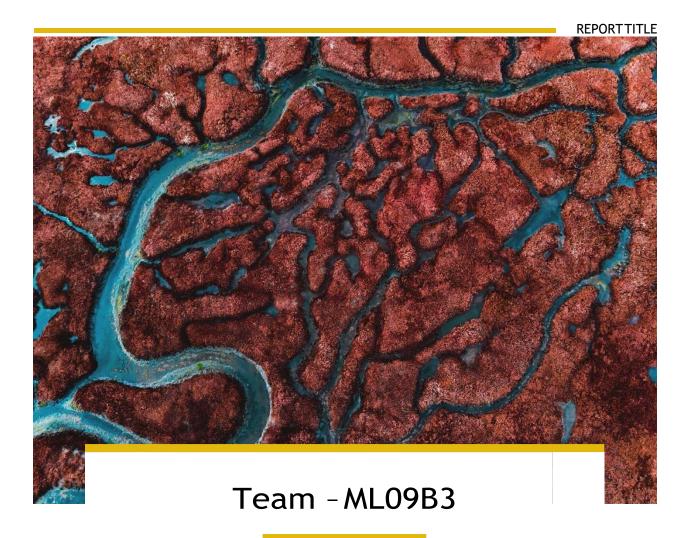




☐ In KNN Algorithm calculated the accuracy for all the Neighbours in the range of 1 to 100, plotted the graph for all the accuracies and found the average of 100 accuracies.







- **B.** Lalith Kumar
- ♣ Niti Goel
- **4** Aswin CA
- Himani Thakkar
- Aishwary Krishna Singh
- Sreeja Samanthapuri
- Utkarsh Soni
- Ruchita Singh
- Santosh Reddy
- Mohammad Abdul Saleem
- Jay Chandra



