

missxmuyi

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CONTEXT

To apply for a master's degree is a very expensive and intensive work. With this kernel, students will guess their capacities and they will decide whetherto apply for a master's degree or not. So, basically this set is about the Graduate Admissions data i.e. Given a set of standardized scores like GRE, TOEFL, SOP standard scores, LOR standard scores. All those folks who are preparing for Master's, might point out this question, from where did you get SOP & LOR scores. This project aimed to assist prospective students in making informed decisions by providing them with insights into their potential for admission, it's worth considering that universities might utilize internal rating systems to standardize these scores and enhance their predictive accuracy.

```
[1]: #Used for Data Processing and Analysis
import pandas as pd
#Used for Mathematical Computations
import numpy as np
#Used for data visualizations
import matplotlib.pyplot as plt
#used for data Statistical visualizations
import seaborn as sns
#For calculate accuracy score from data
from sklearn.metrics import accuracy_score, confusion_matrix
```

```
[2]: # Load the dataset using Pandas
graduate_ad=pd.read_csv(r"C:\Python310\practice23\machine learning1\New_
↪folder\Admission_Predict_Ver1.1.csv")
```

```
[3]: #Extract first rows from datasets
graduate_ad.head()
```

```
[3]:   Serial No.  GRE Score  TOEFL Score  University Rating  SOP  LOR  CGPA  \
0         1      337      118              4  4.5  4.5  9.65
1         2      324      107              4  4.0  4.5  8.87
2         3      316      104              3  3.0  3.5  8.00
3         4      322      110              3  3.5  2.5  8.67
4         5      314      103              2  2.0  3.0  8.21
```

Research Chance of Admit

0	1	0.92
1	1	0.76
2	1	0.72
3	1	0.80
4	0	0.65

```
[4]: #Extract last five rows from datasets
graduate_ad.tail()
```

```
[4]:      Serial No.  GRE Score  TOEFL Score  University Rating  SOP  LOR  CGPA  \
495      496      332      108           5  4.5  4.0  9.02
496      497      337      117           5  5.0  5.0  9.87
497      498      330      120           5  4.5  5.0  9.56
498      499      312      103           4  4.0  5.0  8.43
499      500      327      113           4  4.5  4.5  9.04
```

	Research	Chance of Admit
495	1	0.87
496	1	0.96
497	1	0.93
498	0	0.73
499	0	0.84

```
[5]: #Total number of rows and columns
graduate_ad.shape
```

```
[5]: (500, 9)
```

```
[6]: #Information about the dataset like total no.of. rows,total no.of_
      ↪columns,datatypes of each columns and memory management
graduate_ad.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Serial No.            500 non-null   int64
1   GRE Score              500 non-null   int64
2   TOEFL Score            500 non-null   int64
3   University Rating      500 non-null   int64
4   SOP                    500 non-null   float64
5   LOR                    500 non-null   float64
6   CGPA                   500 non-null   float64
7   Research               500 non-null   int64
8   Chance of Admit        500 non-null   float64
dtypes: float64(4), int64(5)
```

memory usage: 35.3 KB

```
[7]: #Checking for any empty/null values present in dataset
graduate_ad.isnull().sum()
```

```
[7]: Serial No.      0
GRE Score      0
TOEFL Score    0
University Rating 0
SOP            0
LOR            0
CGPA           0
Research       0
Chance of Admit 0
dtype: int64
```

```
[8]: #Statistical measures of a dataframe
graduate_ad.describe()
```

```
[8]:
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP \
count	500.000000	500.000000	500.000000	500.000000	500.000000
mean	250.500000	316.472000	107.192000	3.114000	3.374000
std	144.481833	11.295148	6.081868	1.143512	0.991004
min	1.000000	290.000000	92.000000	1.000000	1.000000
25%	125.750000	308.000000	103.000000	2.000000	2.500000
50%	250.500000	317.000000	107.000000	3.000000	3.500000
75%	375.250000	325.000000	112.000000	4.000000	4.000000
max	500.000000	340.000000	120.000000	5.000000	5.000000

	LOR	CGPA	Research	Chance of Admit
count	500.000000	500.000000	500.000000	500.000000
mean	3.48400	8.576440	0.560000	0.72174
std	0.92545	0.604813	0.496884	0.14114
min	1.00000	6.800000	0.000000	0.34000
25%	3.00000	8.127500	0.000000	0.63000
50%	3.50000	8.560000	1.000000	0.72000
75%	4.00000	9.040000	1.000000	0.82000
max	5.00000	9.920000	1.000000	0.97000

```
[9]: graduate_ad.columns
```

```
[9]: Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP',
        'LOR ', 'CGPA', 'Research', 'Chance of Admit '],
        dtype='object')
```

PREPROCESSING THE DATASETS

```
[10]: X=graduate_ad.drop(['Serial No.','Chance of Admit '],axis=1)
```

```
[11]: print(X)
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
0	337	118	4	4.5	4.5	9.65	1
1	324	107	4	4.0	4.5	8.87	1
2	316	104	3	3.0	3.5	8.00	1
3	322	110	3	3.5	2.5	8.67	1
4	314	103	2	2.0	3.0	8.21	0
..
495	332	108	5	4.5	4.0	9.02	1
496	337	117	5	5.0	5.0	9.87	1
497	330	120	5	4.5	5.0	9.56	1
498	312	103	4	4.0	5.0	8.43	0
499	327	113	4	4.5	4.5	9.04	0

[500 rows x 7 columns]

```
[12]: y=graduate_ad['Chance of Admit ']  
y
```

```
[12]: 0    0.92  
1    0.76  
2    0.72  
3    0.80  
4    0.65  
  
...  
495  0.87  
496  0.96  
497  0.93  
498  0.73  
499  0.84
```

Name: Chance of Admit , Length: 500, dtype: float64

SPLITTING DATASET INTO TRAINING AND TEST DATA

```
[13]: from sklearn.model_selection import train_test_split
```

```
[14]: X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.  
↪20,random_state=42)
```

```
[15]: X_train,X_test,y_train,y_test
```

```
[15]: (  GRE Score  TOEFL Score  University Rating  SOP  LOR  CGPA  Research  
249      321      111           3  3.5  4.0  8.83         1  
433      316      111           4  4.0  5.0  8.54         0  
19       303      102           3  3.5  3.0  8.50         0  
322      314      107           2  2.5  4.0  8.27         0  
332      308      106           3  3.5  2.5  8.21         1
```

..
106	329	111		4	4.5	4.5	9.18	1
270	306	105		2	2.5	3.0	8.22	1
348	302	99		1	2.0	2.0	7.25	0
435	309	105		2	2.5	4.0	7.68	0
102	314	106		2	4.0	3.5	8.25	0

[400 rows x 7 columns],

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
361	334	116	4	4.0	3.5	9.54	1
73	314	108	4	4.5	4.0	9.04	1
374	315	105	2	2.0	2.5	7.65	0
155	312	109	3	3.0	3.0	8.69	0
104	326	112	3	3.5	3.0	9.05	1
..
347	299	94	1	1.0	1.0	7.34	0
86	315	106	3	4.5	3.5	8.42	0
75	329	114	2	2.0	4.0	8.56	1
438	318	110	1	2.5	3.5	8.54	1
15	314	105	3	3.5	2.5	8.30	0

[100 rows x 7 columns],

249	0.77
433	0.71
19	0.62
322	0.72
332	0.75
...	
106	0.87
270	0.72
348	0.57
435	0.55
102	0.62

Name: Chance of Admit , Length: 400, dtype: float64,

361	0.93
73	0.84
374	0.39
155	0.77
104	0.74
...	
347	0.42
86	0.72
75	0.72
438	0.67
15	0.54

Name: Chance of Admit , Length: 100, dtype: float64)

```
[16]: print(X_train.shape,X_test.shape,X.shape)
```

```
(400, 7) (100, 7) (500, 7)
```

```
[17]: y_train=[1 if value>0.8 else 0 for value in y_train]
y_test=[1 if value>0.8 else 0 for value in y_test]
y_train=np.array(y_train)
y_test=np.array(y_test)
```

```
[18]: print(y_train)
```

```
[0 0 0 0 0 0 0 1 0 0 0 1 1 1 0 0 0 1 0 0 0 1 0 0 0 0 0 1 1 0 0 0 1 0 1 0 1
 1 0 0 0 0 0 0 1 0 1 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
 0 1 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 1 0 0 0 0 0 0 0 0
 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 1 0 1 1 0 0 0 0 0 0 1 0
 0 0 1 0 0 0 1 0 0 1 1 1 1 0 0 0 1 0 1 1 0 0 0 1 0 0 1 0 0 1 1 0 0 0 0 0 1
 0 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 1 0 0 0 0 0 1 0 0 0 1 0 1 0 1 0 1 0 1
 1 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 1 1
 1 1 0 1 0 1 1 0 0 0 1 0 1 0 1 1 0 1 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0
 0 1 1 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 1 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 1 1 1 1 0 0 1 0 1 0 0 0 1 0
 1 1 1 1 0 0 0 0 0 0 1 1 1 0 1 0 0 0 1 0 1 1 0 1 1 1 0 0 0 0]
```

```
[19]: print(y_test)
```

```
[1 1 0 0 0 1 0 0 0 1 0 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 1 0 0 0
 1 0 0 1 0 0 1 1 0 1 1 0 1 1 0 0 0 1 0 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0
 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0]
```

STANDARDSCALER:

The StandardScaler is a preprocessing technique commonly used in machine learning to transform numerical features in a dataset. It is used to standardize the scale of the features, making them have a mean of 0 and a standard deviation of 1.

```
[20]: from sklearn.preprocessing import StandardScaler
```

```
[21]: SC=StandardScaler()
```

```
[22]: X_train=SC.fit_transform(X_train)
X_test=SC.fit_transform(X_test)
```

```
[23]: print(X_train)
```

```
[[ 0.38998634  0.6024183 -0.09829757 ...  0.56498381  0.4150183
   0.89543386]
 [-0.06640493  0.6024183  0.7754586 ...  1.65149114 -0.06785154
  -1.11677706]
 [-1.25302222 -0.87691722 -0.09829757 ... -0.52152352 -0.13445427
```

```

-1.11677706]
...
[-1.34430047 -1.37002906 -1.8458099 ... -1.60803084 -2.2157898
-1.11677706]
[-0.7053527 -0.38380538 -0.97205374 ... 0.56498381 -1.49981038
-1.11677706]
[-0.24896144 -0.21943477 -0.97205374 ... 0.02173015 -0.55072138
-1.11677706]]

```

[24]: X_test

```

[24]: array([[ 1.48887961e+00,  1.56082934e+00,  7.76121546e-01,
        6.25913605e-01,  0.00000000e+00,  1.58648736e+00,
        8.50962943e-01],
       [-1.16381425e-01,  2.29631609e-01,  7.76121546e-01,
        1.12267043e+00,  5.31494003e-01,  7.77715255e-01,
        8.50962943e-01],
       [-3.61183733e-02, -2.69567541e-01, -9.87791059e-01,
       -1.36111371e+00, -1.06298801e+00, -1.47067119e+00,
       -1.17513930e+00],
       [-2.76907529e-01,  3.96031326e-01, -1.05834756e-01,
       -3.67600054e-01, -5.31494003e-01,  2.11574782e-01,
       -1.17513930e+00],
       [ 8.46775196e-01,  8.95230476e-01, -1.05834756e-01,
        1.29156776e-01, -5.31494003e-01,  7.93890697e-01,
        8.50962943e-01],
       [ 1.08756435e+00,  7.28830760e-01,  7.76121546e-01,
        1.12267043e+00,  5.31494003e-01,  1.08504865e+00,
        8.50962943e-01],
       [-2.04269467e+00, -1.10156613e+00, -1.86974736e+00,
       -1.85787054e+00, -1.59448201e+00, -1.61625017e+00,
       -1.17513930e+00],
       [-1.15980110e+00, -1.03167824e-01,  7.76121546e-01,
       -8.64356883e-01, -5.31494003e-01, -1.44284943e-01,
       -1.17513930e+00],
       [ 2.04670782e-01,  3.96031326e-01, -1.05834756e-01,
        1.29156776e-01,  5.31494003e-01,  1.06887321e+00,
        8.50962943e-01],
       [ 3.65196886e-01,  8.95230476e-01,  7.76121546e-01,
       -3.67600054e-01,  1.06298801e+00,  4.86557297e-01,
        8.50962943e-01],
       [ 6.05986041e-01,  2.29631609e-01, -1.05834756e-01,
        1.29156776e-01, -5.31494003e-01,  6.59958036e-02,
       -1.17513930e+00],
       [ 4.41446785e-02,  3.96031326e-01, -1.05834756e-01,
        1.29156776e-01, -5.31494003e-01,  3.24802877e-01,
       -1.17513930e+00],

```

[5.25722989e-01, -6.02366975e-01, 7.76121546e-01,
 -3.67600054e-01, -1.06298801e+00, -8.72179836e-01,
 8.50962943e-01],
 [1.97045792e+00, 1.39442963e+00, 1.65807785e+00,
 1.12267043e+00, 1.06298801e+00, 1.44090838e+00,
 8.50962943e-01],
 [6.86249093e-01, 5.62431043e-01, -1.05834756e-01,
 1.29156776e-01, -5.31494003e-01, 1.06887321e+00,
 8.50962943e-01],
 [-1.56111636e+00, -1.60076528e+00, -9.87791059e-01,
 -1.85787054e+00, -1.59448201e+00, -1.22803956e+00,
 -1.17513930e+00],
 [1.32835351e+00, 2.29631609e-01, 1.65807785e+00,
 1.12267043e+00, 5.31494003e-01, 7.45364370e-01,
 8.50962943e-01],
 [-1.24006415e+00, -1.60076528e+00, -9.87791059e-01,
 -3.67600054e-01, -5.31494003e-01, -7.42776300e-01,
 8.50962943e-01],
 [-1.40059025e+00, -9.35166408e-01, -9.87791059e-01,
 -1.85787054e+00, -1.59448201e+00, -1.13098691e+00,
 -1.17513930e+00],
 [-1.48085331e+00, -9.35166408e-01, -1.05834756e-01,
 -1.36111371e+00, 5.31494003e-01, -1.43832031e+00,
 8.50962943e-01],
 [-6.78222787e-01, -2.69567541e-01, -9.87791059e-01,
 -8.64356883e-01, 1.06298801e+00, -7.10425416e-01,
 8.50962943e-01],
 [-1.48085331e+00, -1.26796584e+00, 7.76121546e-01,
 -3.67600054e-01, 0.00000000e+00, -1.21186412e+00,
 -1.17513930e+00],
 [-3.57170580e-01, -7.68766692e-01, -1.05834756e-01,
 1.12267043e+00, 5.31494003e-01, 1.30697572e-01,
 8.50962943e-01],
 [9.27038248e-01, 3.96031326e-01, -1.05834756e-01,
 1.29156776e-01, 5.31494003e-01, 3.40978319e-01,
 8.50962943e-01],
 [9.27038248e-01, 8.95230476e-01, -1.05834756e-01,
 -3.67600054e-01, -5.31494003e-01, 2.60101108e-01,
 8.50962943e-01],
 [-1.15980110e+00, -7.68766692e-01, -1.05834756e-01,
 -8.64356883e-01, -1.59448201e+00, -6.94249974e-01,
 8.50962943e-01],
 [1.16782740e+00, 2.22642821e+00, 1.65807785e+00,
 1.12267043e+00, 1.59448201e+00, 1.61883824e+00,
 8.50962943e-01],
 [1.00730130e+00, 5.62431043e-01, 7.76121546e-01,
 1.61942726e+00, 5.31494003e-01, 9.39469675e-01,

8.50962943e-01],
 [-2.76907529e-01, -2.69567541e-01, -9.87791059e-01,
 -8.64356883e-01, -5.31494003e-01, -7.10425416e-01,
 -1.17513930e+00],
 [-2.76907529e-01, 6.32318924e-02, 7.76121546e-01,
 1.12267043e+00, 5.31494003e-01, 1.46873014e-01,
 8.50962943e-01],
 [-1.24006415e+00, -9.35166408e-01, -1.05834756e-01,
 1.29156776e-01, -1.06298801e+00, -1.09863603e+00,
 -1.17513930e+00],
 [2.84933834e-01, 5.62431043e-01, -1.05834756e-01,
 -3.67600054e-01, -1.06298801e+00, 3.73329203e-01,
 -1.17513930e+00],
 [-8.38748891e-01, -4.35967258e-01, -9.87791059e-01,
 -8.64356883e-01, -2.12597601e+00, -1.24421500e+00,
 -1.17513930e+00],
 [6.05986041e-01, 1.06163019e+00, 7.76121546e-01,
 6.25913605e-01, 1.06298801e+00, 1.08504865e+00,
 8.50962943e-01],
 [4.41446785e-02, -4.35967258e-01, -1.05834756e-01,
 -3.67600054e-01, 0.00000000e+00, -9.04530720e-01,
 8.50962943e-01],
 [2.84933834e-01, 2.29631609e-01, -1.05834756e-01,
 -3.67600054e-01, 0.00000000e+00, -3.10568488e-02,
 8.50962943e-01],
 [-1.24006415e+00, -1.43436556e+00, -1.86974736e+00,
 -1.36111371e+00, -1.06298801e+00, -8.72179836e-01,
 -1.17513930e+00],
 [1.32835351e+00, 1.89362878e+00, 1.65807785e+00,
 1.61942726e+00, 1.59448201e+00, 1.74824178e+00,
 8.50962943e-01],
 [-1.15980110e+00, -4.35967258e-01, -1.05834756e-01,
 1.29156776e-01, 5.31494003e-01, -7.10425416e-01,
 8.50962943e-01],
 [-3.61183733e-02, 6.32318924e-02, -9.87791059e-01,
 6.25913605e-01, -5.31494003e-01, -9.57586170e-02,
 8.50962943e-01],
 [1.97045792e+00, 1.06163019e+00, 7.76121546e-01,
 1.61942726e+00, 1.59448201e+00, 1.90999620e+00,
 8.50962943e-01],
 [-1.15980110e+00, -1.60076528e+00, -9.87791059e-01,
 -3.67600054e-01, -5.31494003e-01, -1.09863603e+00,
 8.50962943e-01],
 [-3.57170580e-01, -9.35166408e-01, -9.87791059e-01,
 -8.64356883e-01, 0.00000000e+00, -3.54565690e-01,
 8.50962943e-01],
 [9.27038248e-01, 1.06163019e+00, 7.76121546e-01,

1.12267043e+00, 1.06298801e+00, 8.90943349e-01,
 8.50962943e-01],
 [1.97045792e+00, 1.22802991e+00, 1.65807785e+00,
 6.25913605e-01, 5.31494003e-01, 1.68354001e+00,
 8.50962943e-01],
 [-1.15980110e+00, -1.26796584e+00, -9.87791059e-01,
 -3.67600054e-01, -1.59448201e+00, -5.48670995e-01,
 -1.17513930e+00],
 [1.72966877e+00, 1.89362878e+00, 7.76121546e-01,
 1.12267043e+00, 1.06298801e+00, 1.76441722e+00,
 8.50962943e-01],
 [9.27038248e-01, 7.28830760e-01, 7.76121546e-01,
 6.25913605e-01, 1.06298801e+00, 7.13013486e-01,
 8.50962943e-01],
 [9.27038248e-01, -1.03167824e-01, 7.76121546e-01,
 6.25913605e-01, 1.06298801e+00, 3.08627435e-01,
 8.50962943e-01],
 [1.00730130e+00, 1.56082934e+00, 1.65807785e+00,
 1.61942726e+00, 1.59448201e+00, 1.52178559e+00,
 8.50962943e-01],
 [4.45459937e-01, 7.28830760e-01, 1.65807785e+00,
 1.61942726e+00, 1.59448201e+00, 1.44090838e+00,
 8.50962943e-01],
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```

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-1.17513930e+00]])

```

```

[25]: #Importing LogisticRegression model
from sklearn.linear_model import LogisticRegression

```

MODEL TRAINING AND EVALUATION

```

[26]: logr=LogisticRegression()
logr.fit(X_train,y_train)
y_pred1=logr.predict(X_test)
print(accuracy_score(y_pred1,y_test))

```

0.96

```

[27]: matrix=confusion_matrix(y_pred1,y_test)

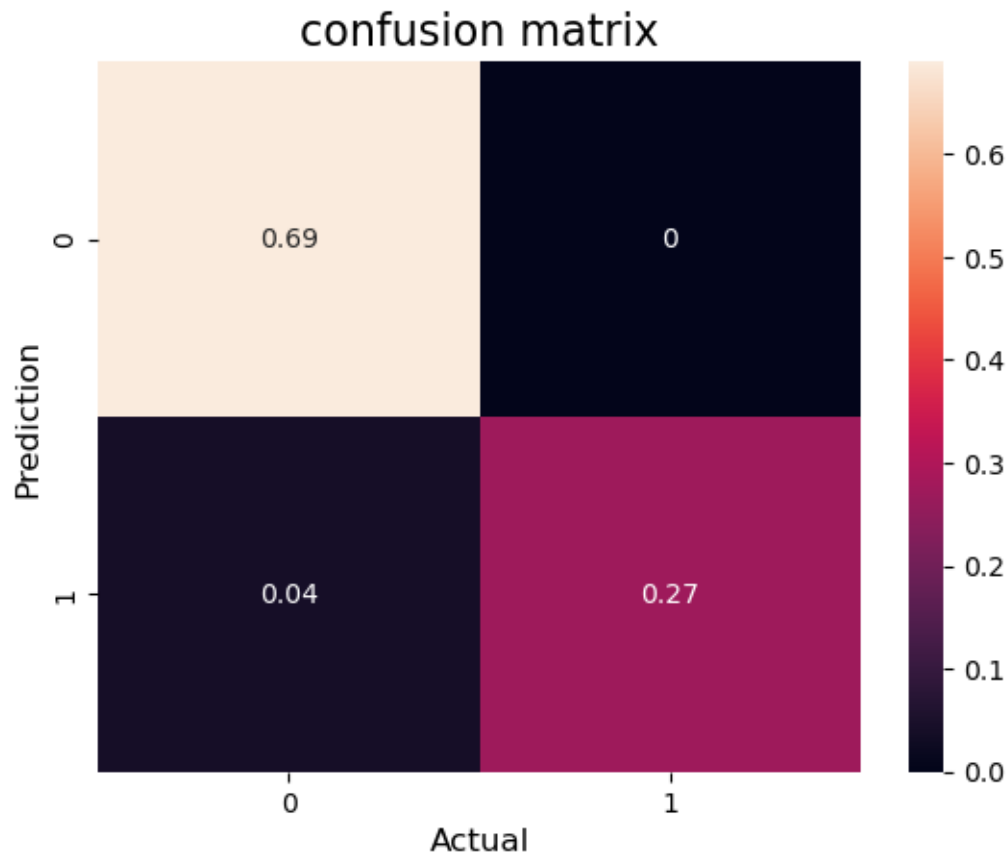
```

```

[28]: sns.heatmap(matrix/np.sum(matrix),
                  fmt='g',
                  annot= True)
plt.ylabel('Prediction', fontsize = 12)

```

```
plt.xlabel('Actual', fontsize = 12)
plt.title('confusion matrix',fontsize=16)
plt.show()
```



```
[29]: #Importing SupportVectorClassifier model
from sklearn import svm
```

MODEL TRAINING AND EVALUATION

```
[30]: svm=svm.SVC()
svm.fit(X_train,y_train)
y_pred2=svm.predict(X_test)
print(accuracy_score(y_pred2,y_test))
```

0.97

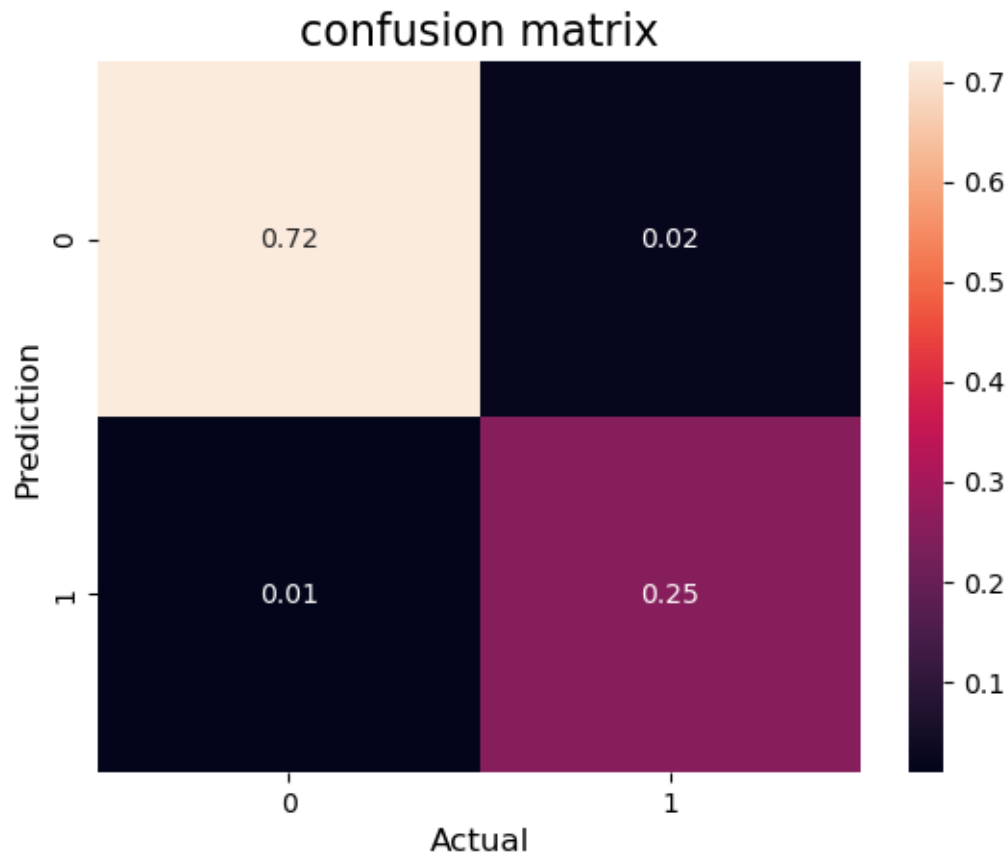
```
[31]: matrix=confusion_matrix(y_pred2,y_test)
```

```
[32]: sns.heatmap(matrix/np.sum(matrix),
                  fmt='g',
```

```

        annot= True)
plt.ylabel('Prediction', fontsize = 12)
plt.xlabel('Actual', fontsize = 12)
plt.title('confusion matrix',fontsize=16)
plt.show()

```



```

[33]: ##Importing KNN model
      from sklearn.neighbors import KNeighborsClassifier

```

MODEL TRAINING AND EVALUATION

```

[34]: knn=KNeighborsClassifier()
      knn.fit(X_train,y_train)
      y_pred3=knn.predict(X_test)
      print(accuracy_score(y_pred3,y_test))

```

0.97

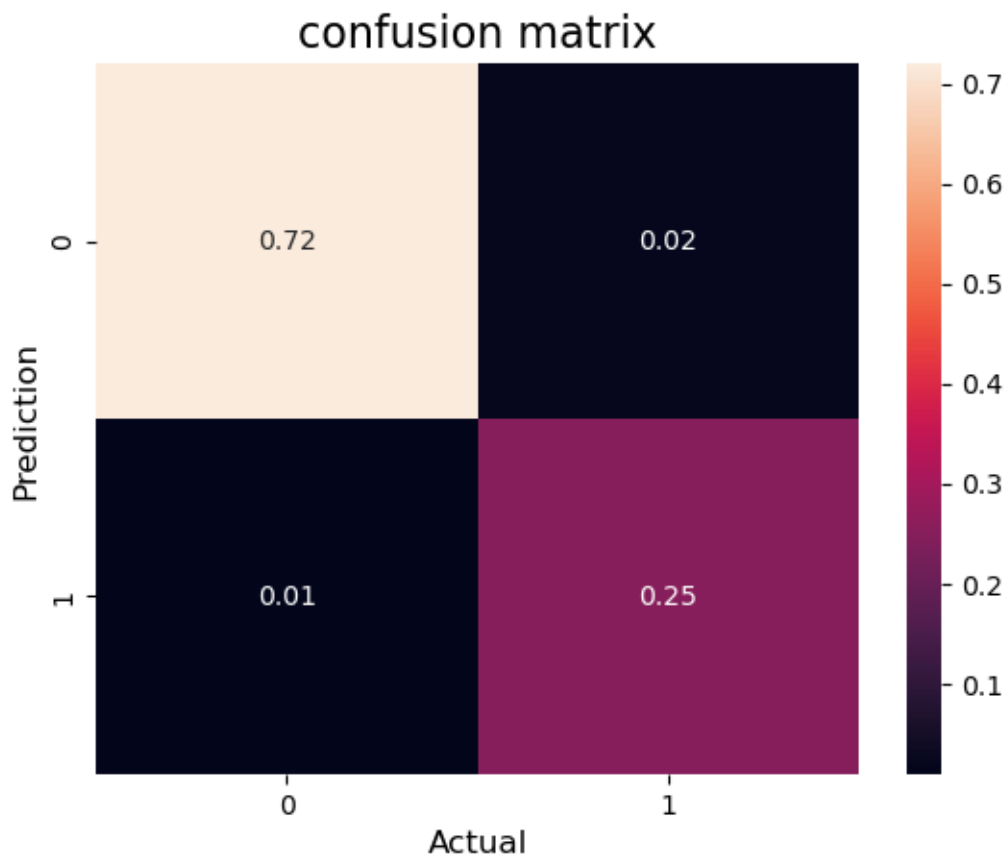
C:\Users\Varshini\anaconda3\lib\site-packages\sklearn\neighbors_classification.py:228: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode`

typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `axis` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to True or False to avoid this warning.

```
mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

```
[35]: matrix=confusion_matrix(y_pred3,y_test)
```

```
[36]: sns.heatmap(matrix/np.sum(matrix),
                fmt='g',
                annot= True)
plt.ylabel('Prediction', fontsize = 12)
plt.xlabel('Actual', fontsize = 12)
plt.title('confusion matrix',fontsize=16)
plt.show()
```



```
[37]: #Importing RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier
```

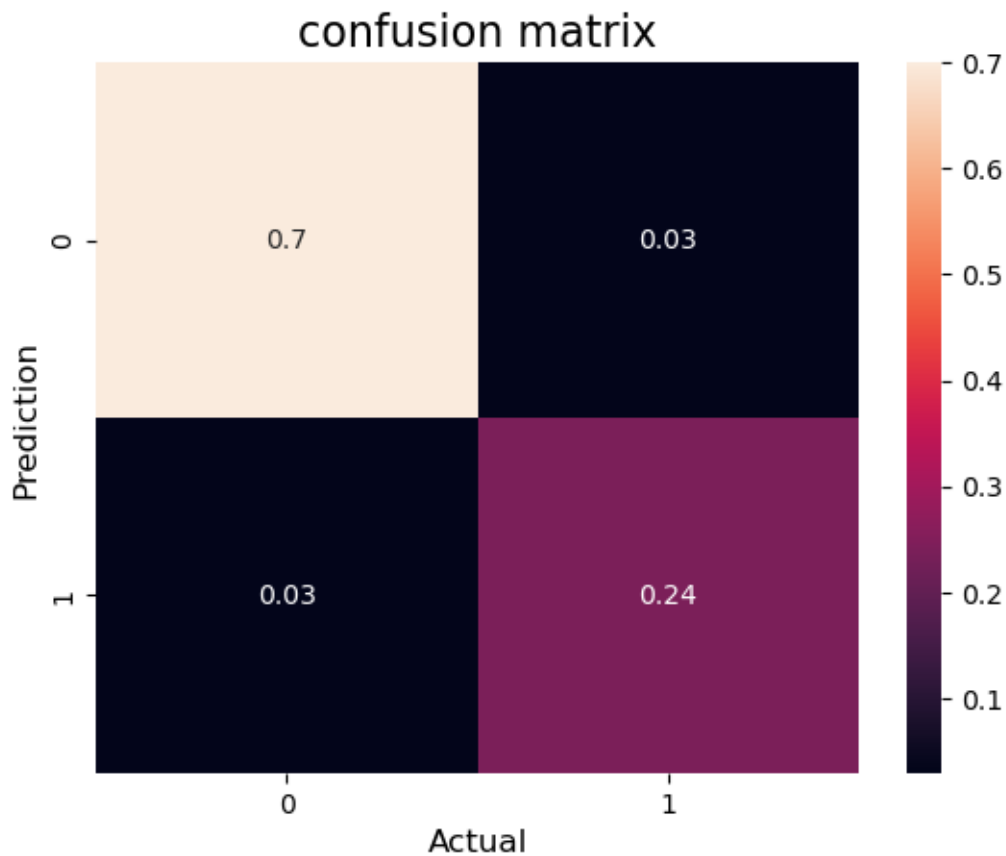
MODEL TRAINING AND EVALUATION


```
[38]: RDF=RandomForestClassifier()
      RDF.fit(X_train,y_train)
      y_pred4=RDF.predict(X_test)
      print(accuracy_score(y_pred4,y_test))
```

0.94

```
[39]: matrix=confusion_matrix(y_pred4,y_test)
```

```
[40]: sns.heatmap(matrix/np.sum(matrix),
                  fmt='g',
                  annot= True)
plt.ylabel('Prediction', fontsize = 12)
plt.xlabel('Actual', fontsize = 12)
plt.title('confusion matrix',fontsize=16)
plt.show()
```



```
[41]: final_output=pd.DataFrame({'Model':['LR','SVC','KNN','RDF'],'ACCURACY_SCORE':
      ↳[accuracy_score(y_pred1,y_test),
```

```

↪ accuracy_score(y_pred2,y_test),
↪ accuracy_score(y_pred3,y_test),
↪ accuracy_score(y_pred4,y_test)]]})

```

```
[42]: final_output
```

```

[42]:   Model  ACCURACY_SCORE
0    LR          0.96
1    SVC          0.97
2    KNN          0.97
3    RDF          0.94

```

ACCURACY BARPLOT

Accuracy is a common metric used in machine learning and statistics to measure the performance of a classification model. It provides a straightforward way to understand how well the model is predicting the correct classes compared to the total number of instances

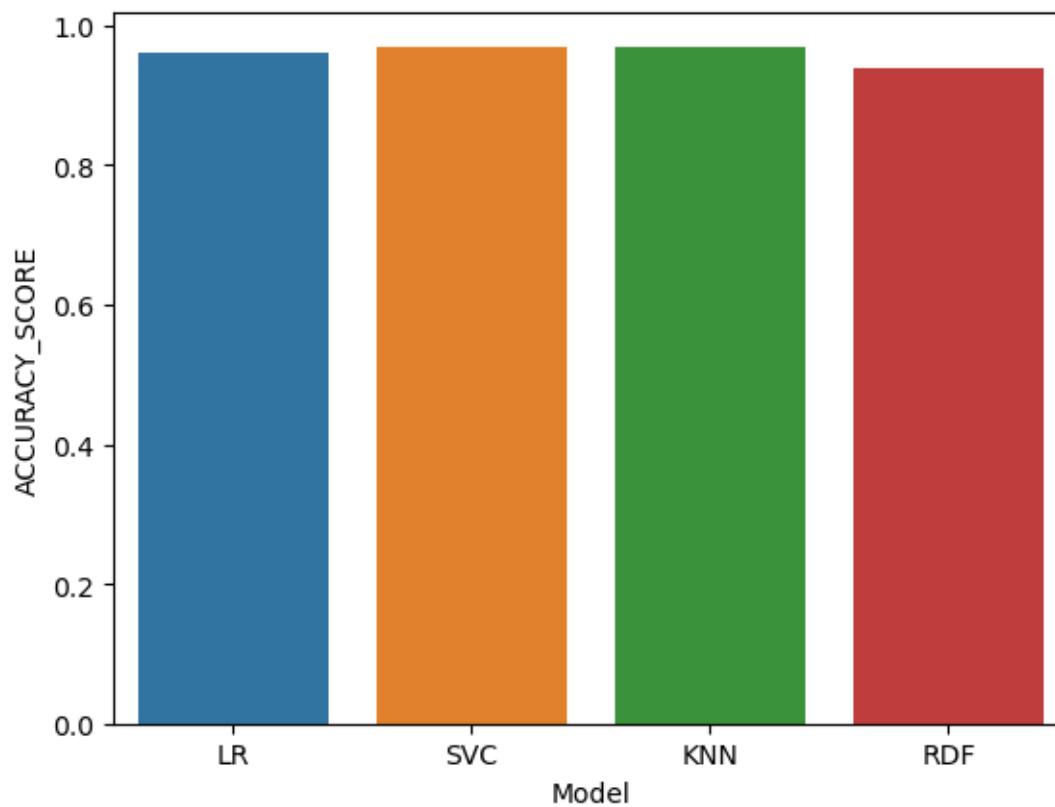
```
[43]: sns.barplot(final_output['Model'],final_output['ACCURACY_SCORE'])
```

```

C:\Users\Varshini\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
    warnings.warn(

```

```
[43]: <AxesSubplot:xlabel='Model', ylabel='ACCURACY_SCORE'>
```



Hence, SVM and KNearestNeighbours has more accuracy than other models, while comparing to the confusion matrix it has less **FN** values according to the classification model.