Importing Libraries

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
```

Loading Dataset

```
file_name =
("https://raw.githubusercontent.com/SUKHMAN-SINGH-1612/Data-Science-
Projects/refs/heads/main/E-Commerce%20Product%20Delivery
%20Prediction/E_Commerce.csv")
df = pd.read_csv(file_name)
df.head()
```

```
   ID Warehouse_block Mode_of_Shipment  Customer_care_calls
Customer_rating  \
0   1               D           Flight                    4
2
1   2               F           Flight                    4
5
2   3               A           Flight                    2
2
3   4               B           Flight                    3
3
4   5               C           Flight                    2
2

   Cost_of_the_Product  Prior_purchases Product_importance Gender  \
0                  177                3                 low      F
1                  216                2                 low      M
2                  183                4                 low      M
3                  176                4              medium      M
4                  184                3              medium      F

   Discount_offered  Weight_in_gms  Reached.on.Time_Y.N
0                44           1233                    1
1                59           3088                    1
2                48           3374                    1
3                10           1177                    1
4                46           2484                    1
```

Analysis of Data

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10999 entries, 0 to 10998
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   10999 non-null  int64
 1   Warehouse_block      10999 non-null  object
 2   Mode_of_Shipment     10999 non-null  object
 3   Customer_care_calls  10999 non-null  int64
 4   Customer_rating      10999 non-null  int64
 5   Cost_of_the_Product  10999 non-null  int64
 6   Prior_purchases      10999 non-null  int64
 7   Product_importance   10999 non-null  object
 8   Gender               10999 non-null  object
 9   Discount_offered     10999 non-null  int64
 10  Weight_in_gms        10999 non-null  int64
 11  Reached.on.Time_Y.N  10999 non-null  int64
dtypes: int64(8), object(4)
memory usage: 1.0+ MB
```

```
df.isnull().sum()
```

```
ID                     0
Warehouse_block        0
Mode_of_Shipment       0
Customer_care_calls    0
Customer_rating        0
Cost_of_the_Product    0
Prior_purchases        0
Product_importance     0
Gender                 0
Discount_offered       0
Weight_in_gms          0
Reached.on.Time_Y.N    0
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

```
df.describe()
```

```
                ID  Customer_care_calls  Customer_rating
Cost_of_the_Product  \
count  10999.00000         10999.000000     10999.000000
10999.000000
mean    5500.00000             4.054459         2.990545
210.196836
std     3175.28214             1.141490         1.413603
48.063272
min        1.00000             2.000000         1.000000
```

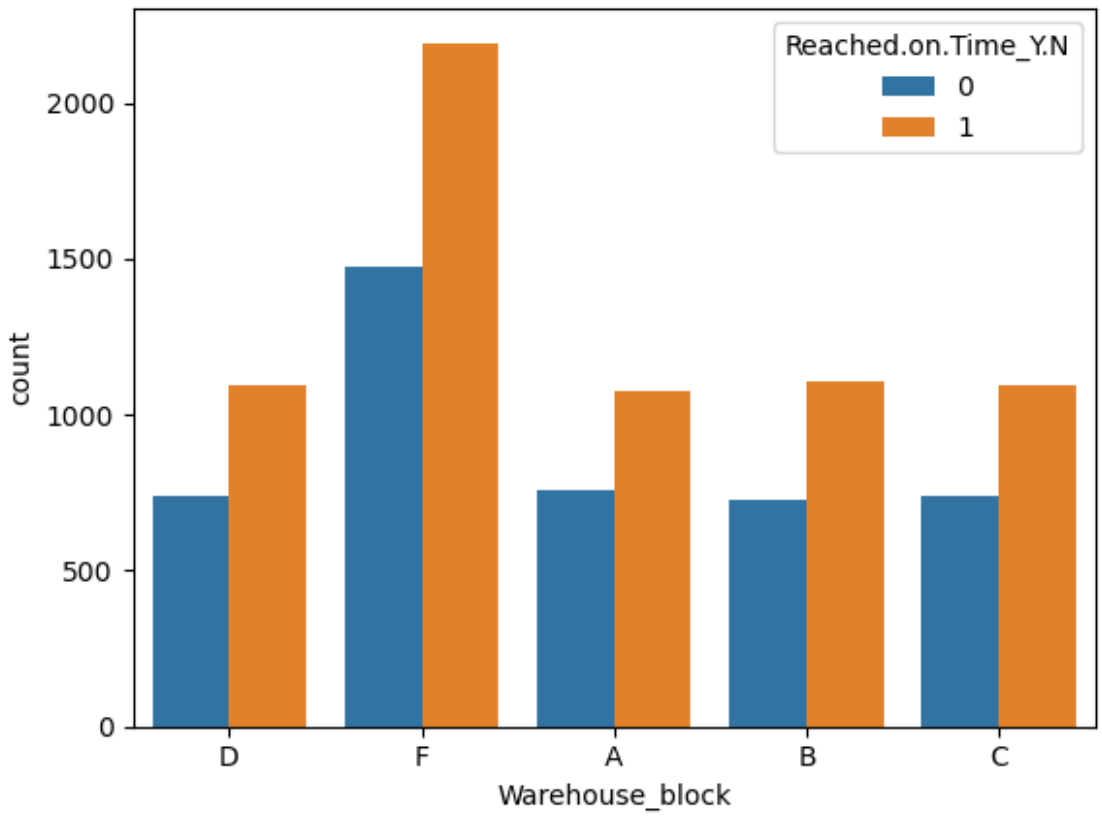
```
96.000000
25%     2750.50000              3.000000          2.000000
169.000000
50%     5500.00000              4.000000          3.000000
214.000000
75%     8249.50000              5.000000          4.000000
251.000000
max    10999.00000              7.000000          5.000000
310.000000

       Prior_purchases  Discount_offered  Weight_in_gms
Reached.on.Time_Y.N
count     10999.000000      10999.000000   10999.000000
10999.000000
mean          3.567597         13.373216    3634.016729
0.596691
std           1.522860         16.205527    1635.377251
0.490584
min           2.000000          1.000000    1001.000000
0.000000
25%           3.000000          4.000000    1839.500000
0.000000
50%           3.000000          7.000000    4149.000000
1.000000
75%           4.000000         10.000000    5050.000000
1.000000
max          10.000000         65.000000    7846.000000
1.000000
```

EDA

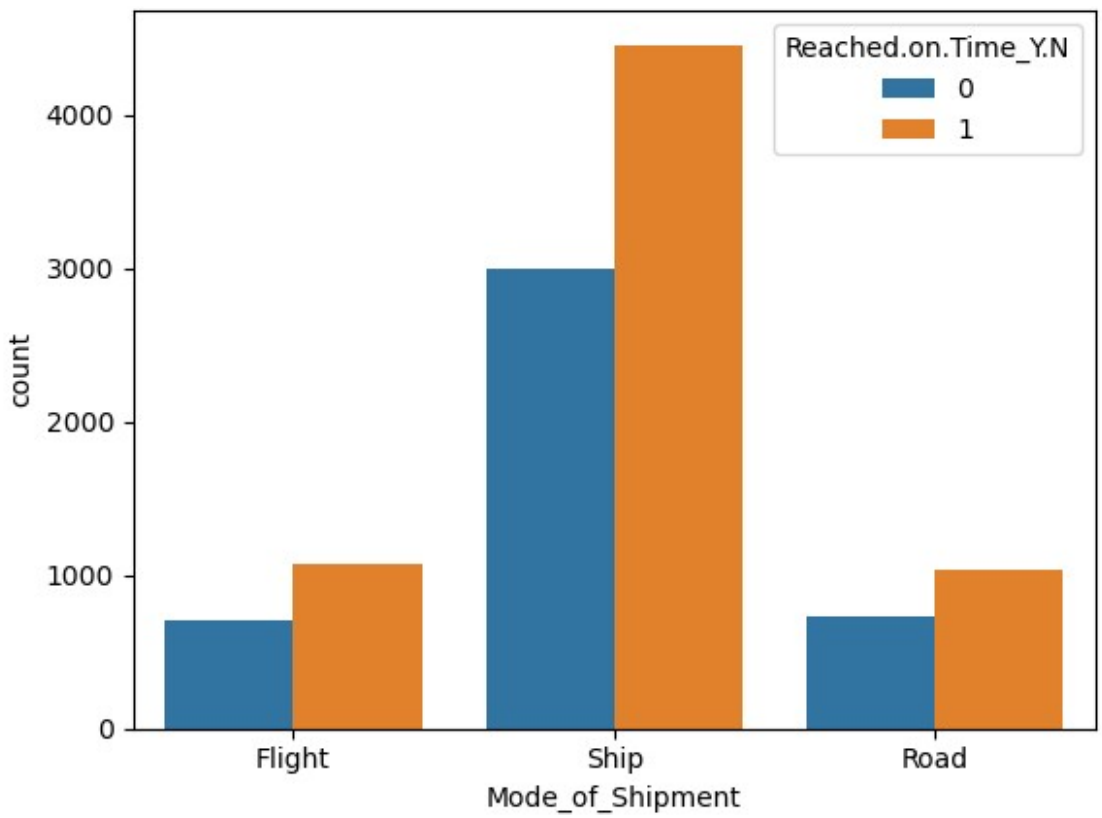
```
sns.countplot(x = 'Warehouse_block', hue = 'Reached.on.Time_Y.N',data
= df)

<Axes: xlabel='Warehouse_block', ylabel='count'>
```



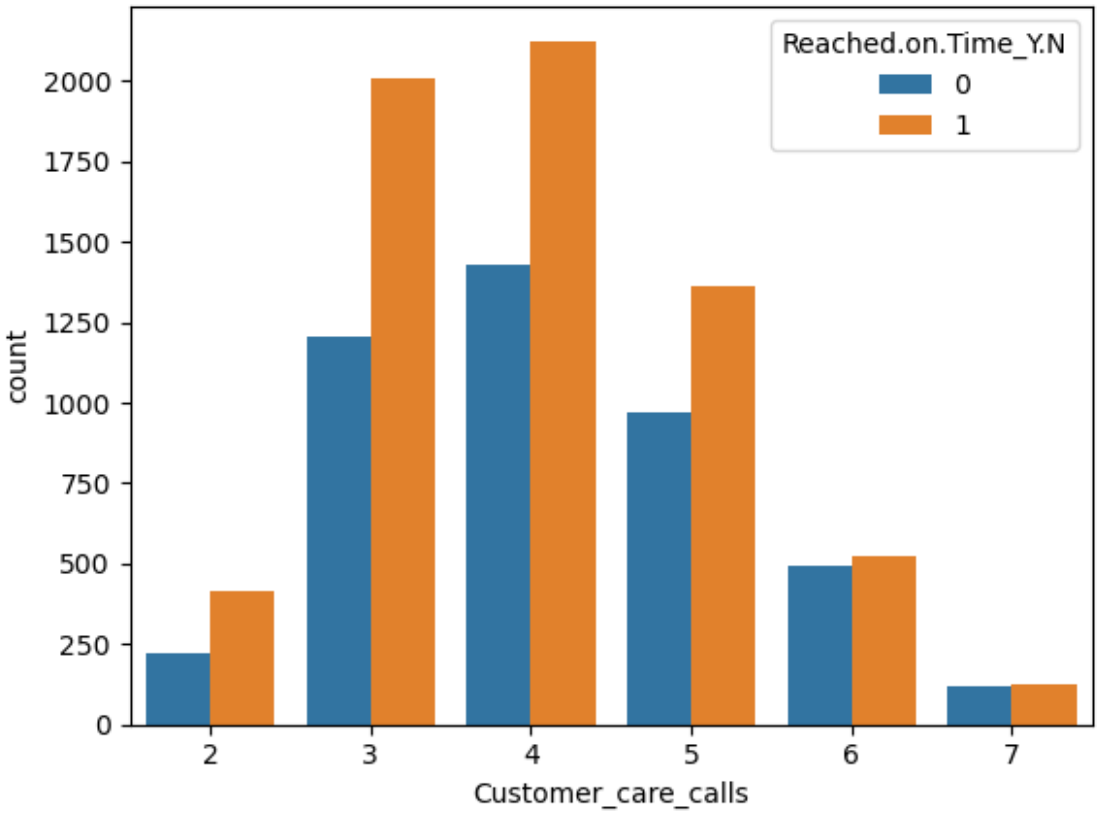

```
sns.countplot(x = 'Mode_of_Shipment', hue = 'Reached.on.Time_Y.N',data
= df)
```

```
<Axes: xlabel='Mode_of_Shipment', ylabel='count'>
```



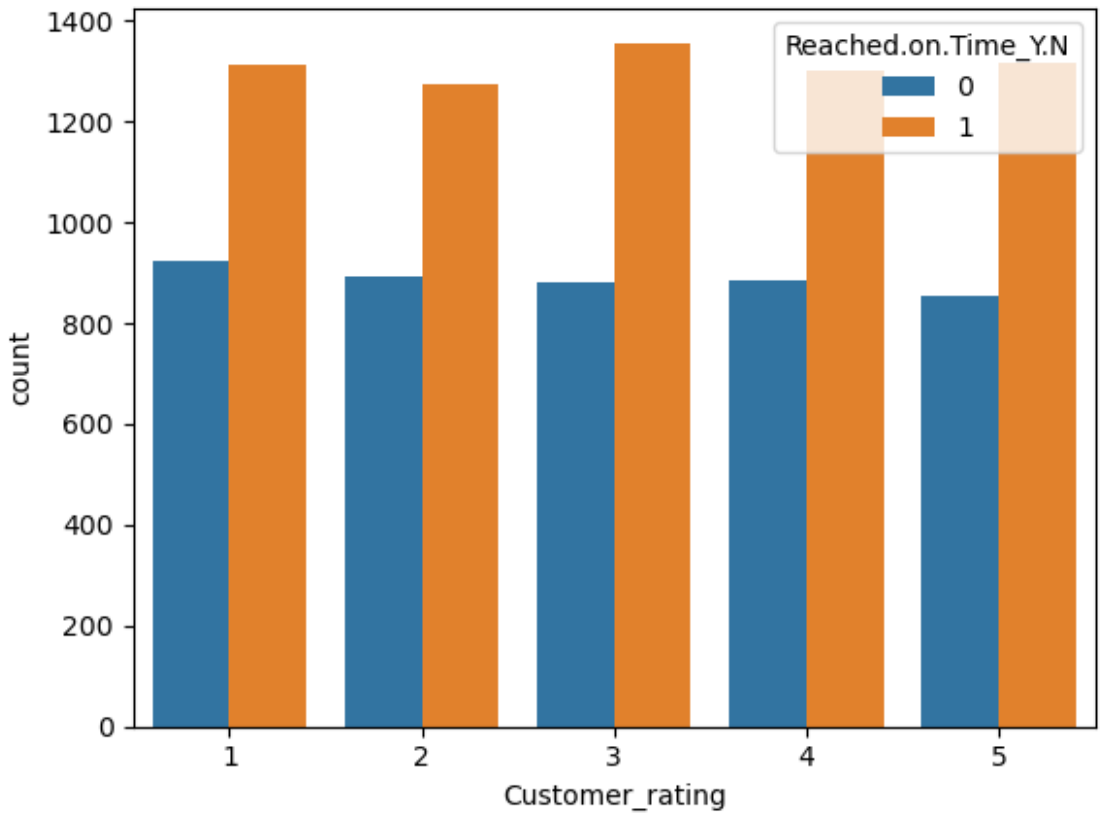

```
sns.countplot(x = 'Customer_care_calls',hue =
'Reached.on.Time_Y.N',data = df)
```

```
<Axes: xlabel='Customer_care_calls', ylabel='count'>
```



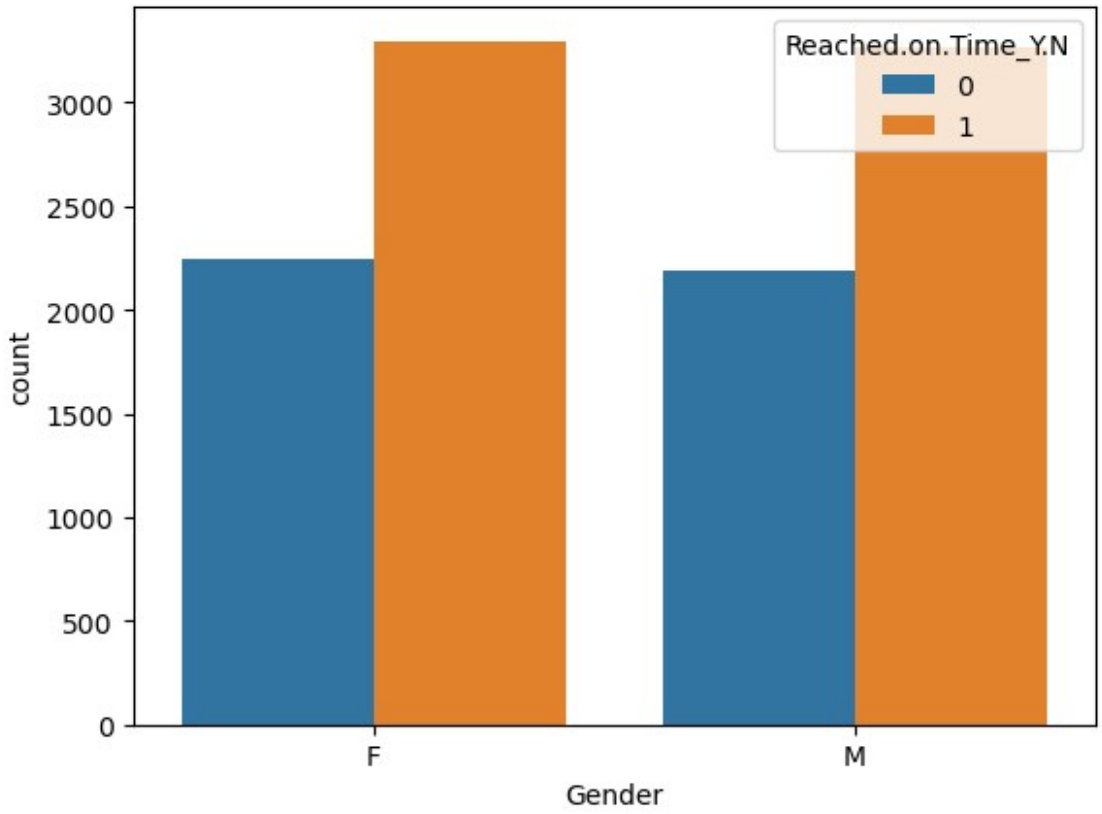

```
sns.countplot(x ='Customer_rating', hue = 'Reached.on.Time_Y.N',data = df)
```

```
<Axes: xlabel='Customer_rating', ylabel='count'>
```



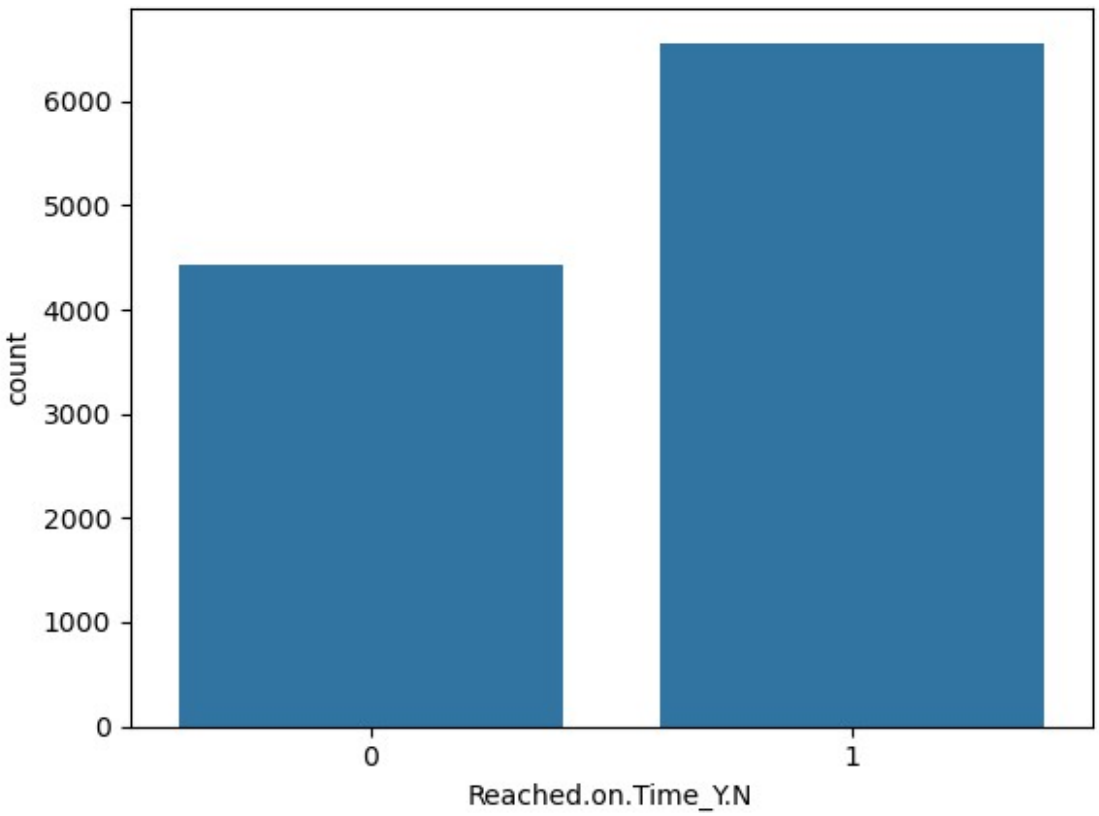

```
sns.countplot(x ='Gender', hue = 'Reached.on.Time_Y.N',data = df)
```

```
<Axes: xlabel='Gender', ylabel='count'>
```




```
sns.countplot(x = 'Reached.on.Time_Y.N', data = df)
```

```
<Axes: xlabel='Reached.on.Time_Y.N', ylabel='count'>
```



Converting categorical column into numerical column.

```
from sklearn.preprocessing import LabelEncoder
LE = LabelEncoder()
for column in df.columns:
    df[column] = LE.fit_transform(df[column])

final_res = []

X = df.drop(['Reached.on.Time_Y.N'],axis =1)
y = df['Reached.on.Time_Y.N']

# splitting the data as train and test
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(X,y,test_size =
0.2,random_state = 42)
print(x_train.shape,x_test.shape,y_train.shape,y_test.shape)
```

```
(8799, 11) (2200, 11) (8799,) (2200,)
```

Modelling

```
from sklearn.linear_model import LogisticRegression
LR = LogisticRegression()
LR.fit(x_train,y_train)
```

```
LogisticRegression()

y_pred = LR.predict(x_test)

from sklearn.metrics import accuracy_score
acc_LR = accuracy_score(y_test,y_pred)
acc_LR
final_res.append(acc_LR)

from sklearn.ensemble import RandomForestClassifier
RDC = RandomForestClassifier()
RDC.fit(x_train,y_train)

RandomForestClassifier()

y_pred1 = RDC.predict(x_test)

acc_RDC = accuracy_score(y_test,y_pred1)
acc_RDC
final_res.append(acc_RDC)

from sklearn.tree import DecisionTreeClassifier
DTC = DecisionTreeClassifier()
DTC.fit(x_train,y_train)

DecisionTreeClassifier()

y_pred2 = DTC.predict(x_test)

acc_DTC = accuracy_score(y_test,y_pred2)
acc_DTC
final_res.append(acc_DTC)

from sklearn.neighbors import KNeighborsClassifier
KNN = KNeighborsClassifier()
KNN.fit(x_train,y_train)

KNeighborsClassifier()

y_pred3 = KNN.predict(x_test)

acc_KNN = accuracy_score(y_test,y_pred3)
acc_KNN
final_res.append(acc_KNN)

from sklearn.svm import SVC
SV = SVC()
SV.fit(x_train,y_train)

SVC()

y_pred4 = SV.predict(x_test)
```

```
acc_SV = accuracy_score(y_test,y_pred4)
acc_SV
final_res.append(acc_SV)
```

```
from sklearn.ensemble import GradientBoostingClassifier
GBC = GradientBoostingClassifier()
GBC.fit(x_train,y_train)
```

```
GradientBoostingClassifier()
```

```
y_pred5 = GBC.predict(x_test)
```

```
acc_GBC = accuracy_score(y_test,y_pred5)
acc_GBC
final_res.append(acc_GBC)
```

```
from xgboost import XGBClassifier
XG = XGBClassifier()
XG.fit(x_train,y_train)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1,
colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1,
grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=0.300000012, max_bin=256,
max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0,
min_child_weight=1,
              missing=nan, monotone_constraints='()',
n_estimators=100,
              n_jobs=0, num_parallel_tree=1, predictor='auto',
random_state=0,
              reg_alpha=0, reg_lambda=1, ...)
```

```
y_pred6 = XG.predict(x_test)
```

```
acc_XG = accuracy_score(y_test,y_pred6)
acc_XG
final_res.append(acc_XG)
```

Conclusion

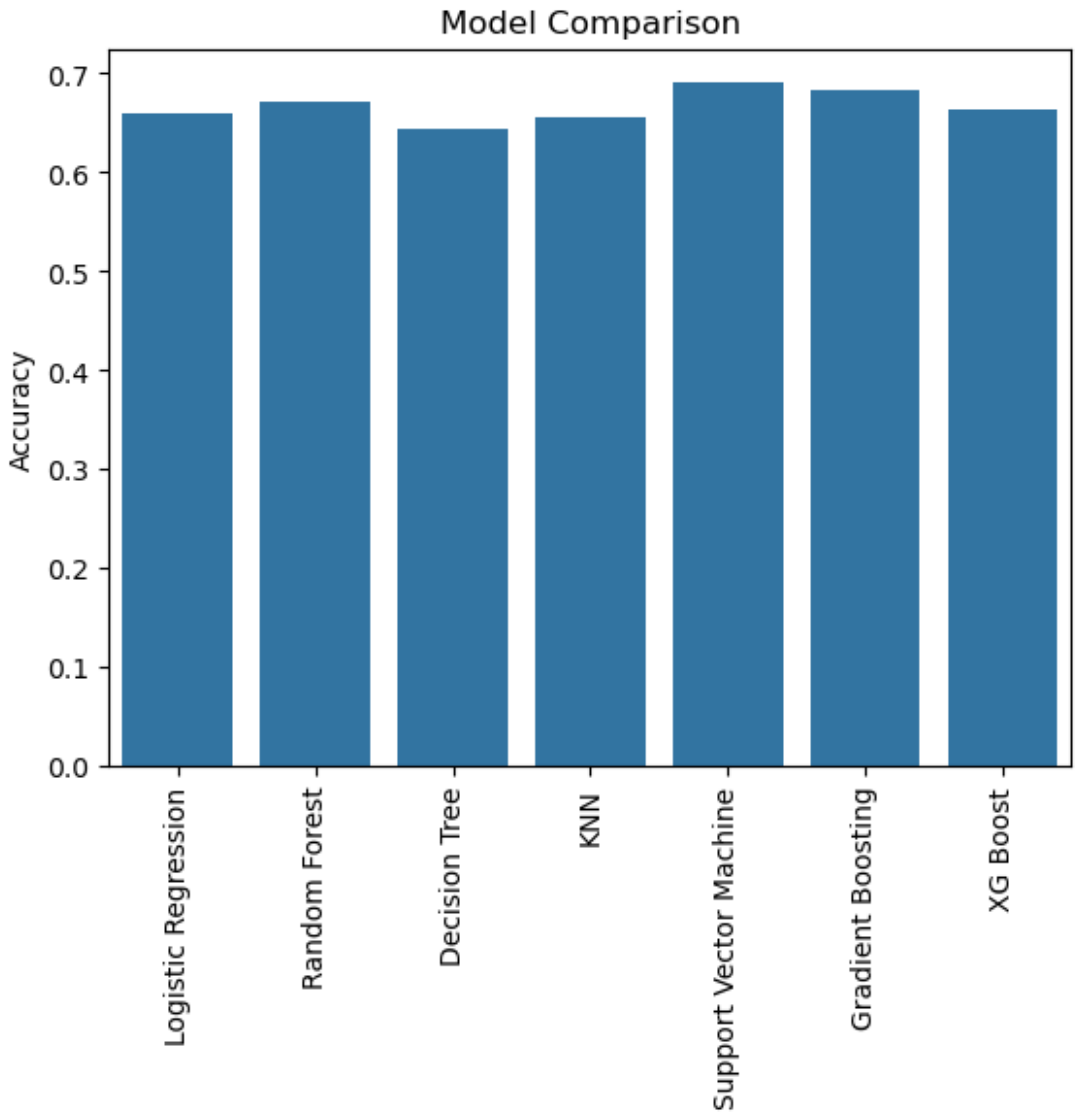
```
final = np.array(final_res)
result = final.reshape(-1,1)
column = ['Accuracy_score']
Index = ['Logistic Regression','Random Forest','Decision
Tree','KNN','Support Vector Machine','Gradient Boosting','XG Boost']
```

```
final_result = pd.DataFrame(result,columns = column,index = Index)
final_result
```

	Accuracy_score
Logistic Regression	0.659091
Random Forest	0.670455
Decision Tree	0.643636
KNN	0.655455
Support Vector Machine	0.690455
Gradient Boosting	0.683636
XG Boost	0.664091

```
models = ['Logistic Regression','Random Forest','Decision
Tree','KNN','Support Vector Machine','Gradient Boosting','XG Boost']
accuracy = [accuracy_score(y_test, y_pred), accuracy_score(y_test,
y_pred1), accuracy_score(y_test, y_pred2), accuracy_score(y_test,
y_pred3),accuracy_score(y_test, y_pred4),accuracy_score(y_test,
y_pred5),accuracy_score(y_test, y_pred6)]
sns.barplot(x=models, y=accuracy).set_title('Model Comparison')
plt.xticks(rotation=90)
plt.ylabel('Accuracy')
```

```
Text(0, 0.5, 'Accuracy')
```



Support Vector Machine is giving the good accuracy Score of 0.690, so Support Vector Machine is the best model for E-Commerce Product Delivery Prediction