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About Features

All attributes are numeric variables and they are listed bellow:

squareMeters

numberOfRooms

hasYard

hasPool

floors : number of floors

cityCode : zip code

cityPartRange : the higher the range, the more exclusive the neighbourhood is

numPrevOwners : number of prevoious owners

made : year

isNewBuilt

hasStormProtector

basement : basement square meters

attic : attic square meteres

garage : garage size

hasStorageRoom

hasGuestRoom : number of guest rooms

price : price of a house

category : Luxury or Basic

Our task is to predict the 'category'

a dataset that contains 10,000 rows and 18 columns and it is classification.

libraries Importing

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import numpy as np
```

```python
from sklearn.model_selection import StratifiedShuffleSplit
from pandas.plotting import scatter_matrix
from sklearn.impute import SimpleImputer
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics.pairwise import rbf_kernel
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import FunctionTransformer
from sklearn.pipeline import make_pipeline
from sklearn import set_config
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn.metrics import roc_auc_score
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.linear_model import SGDClassifier
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.metrics import roc_curve
import matplotlib.patches as patches
```

Get the Data

```python
#reading the dataset and save it in dataFrame called "Traffic"

PHC = pd.read_csv(r"C:\Users\user\Downloads\ParisHousingClass.csv")
PHC
```

```
      squareMeters  numberOfRooms  hasYard  hasPool  floors  cityCode
\
0            75523              3        0        1      63      9373

1            80771             39        1        1      98     39381

2            55712             58        0        1      19     34457

3            32316             47        0        0       6     27939

4            70429             19        1        1      90     38045

...            ...            ...      ...      ...     ...       ...

9995          1726             89        0        1       5     73133

9996         44403             29        1        1      12     34606

9997         83841              3        0        0      69     80933

9998         59036             70        0        0      96     55856

9999          1440             84        0        0      49     18412


      cityPartRange  numPrevOwners  made  isNewBuilt
hasStormProtector  \
0                 3              8  2005           0
1
1                 8              6  2015           1
0
2                 6              8  2021           0
0
3                10              4  2012           0
1
4                 3              7  1990           1
0
...             ...            ...   ...         ...                ..
.
9995              7              6  2009           0
1
9996              9              4  1990           0
1
9997             10             10  2005           1
1
9998              1              3  2010           0
1
9999              6             10  1994           1
0

      basement  attic  garage  hasStorageRoom  hasGuestRoom      price
```

```
\
0           4313   9005     956                  0              7  7559081.5

1           3653   2436     128                  1              2  8085989.5

2           2937   8852     135                  1              9  5574642.1

3            659   7141     359                  0              3  3232561.2

4           8435   2429     292                  1              4  7055052.0

...          ...    ...     ...                ...            ...        ...

9995        9311   1698     218                  0              4   176425.9

9996        9061   1742     230                  0              0  4448474.0

9997        8304   7730     345                  1              9  8390030.5

9998        2590   6174     339                  1              4  5905107.0

9999        8485   2024     278                  1              6   146708.4


     category
0       Basic
1      Luxury
2       Basic
3      Luxury
4      Luxury
...       ...
9995    Basic
9996    Basic
9997    Basic
9998    Basic
9999    Basic

[10000 rows x 18 columns]

# get the top five rows by .head()
PHC.head()

   squareMeters  numberOfRooms  hasYard  hasPool  floors  cityCode  \
0         75523              3        0        1      63      9373
1         80771             39        1        1      98     39381
2         55712             58        0        1      19     34457
3         32316             47        0        0       6     27939
4         70429             19        1        1      90     38045

   cityPartRange  numPrevOwners  made  isNewBuilt
hasStormProtector  \
```

```
0              3              8  2005          0                  1

1              8              6  2015          1                  0

2              6              8  2021          0                  0

3             10              4  2012          0                  1

4              3              7  1990          1                  0


   basement  attic  garage  hasStorageRoom  hasGuestRoom      price
category
0      4313   9005     956               0             7  7559081.5
Basic
1      3653   2436     128               1             2  8085989.5
Luxury
2      2937   8852     135               1             9  5574642.1
Basic
3       659   7141     359               0             3  3232561.2
Luxury
4      8435   2429     292               1             4  7055052.0
Luxury

#summary of categorical attributes using the describe() method
PHC.describe()

       squareMeters  numberOfRooms       hasYard       hasPool
floors  \
count   10000.00000   10000.000000  10000.000000  10000.000000
10000.000000
mean    49870.13120      50.358400      0.508700      0.496800
50.276300
std     28774.37535      28.816696      0.499949      0.500015
28.889171
min        89.00000       1.000000      0.000000      0.000000
1.000000
25%     25098.50000      25.000000      0.000000      0.000000
25.000000
50%     50105.50000      50.000000      1.000000      0.000000
50.000000
75%     74609.75000      75.000000      1.000000      1.000000
76.000000
max     99999.00000     100.000000      1.000000      1.000000
100.000000

           cityCode  cityPartRange  numPrevOwners         made
isNewBuilt  \
count  10000.000000   10000.000000   10000.000000  10000.00000
10000.000000
```

```
mean   50225.486100       5.510100       5.521700   2005.48850
0.499100
std    29006.675799       2.872024       2.856667      9.30809
0.500024
min        3.000000       1.000000       1.000000   1990.00000
0.000000
25%    24693.750000       3.000000       3.000000   1997.00000
0.000000
50%    50693.000000       5.000000       5.000000   2005.50000
0.000000
75%    75683.250000       8.000000       8.000000   2014.00000
1.000000
max    99953.000000      10.000000      10.000000   2021.00000
1.000000

       hasStormProtector      basement        attic       garage  \
count       10000.000000  10000.000000  10000.00000  10000.00000
mean            0.499900   5033.103900   5028.01060    553.12120
std             0.500025   2876.729545   2894.33221    262.05017
min             0.000000      0.000000      1.00000    100.00000
25%             0.000000   2559.750000   2512.00000    327.75000
50%             0.000000   5092.500000   5045.00000    554.00000
75%             1.000000   7511.250000   7540.50000    777.25000
max             1.000000  10000.000000  10000.00000   1000.00000

       hasStorageRoom  hasGuestRoom         price
count    10000.000000   10000.00000  1.000000e+04
mean         0.503000       4.99460  4.993448e+06
std          0.500016       3.17641  2.877424e+06
min          0.000000       0.00000  1.031350e+04
25%          0.000000       2.00000  2.516402e+06
50%          1.000000       5.00000  5.016180e+06
75%          1.000000       8.00000  7.469092e+06
max          1.000000      10.00000  1.000677e+07

# get quick discription about the data by .info()

PHC.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 18 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   squareMeters       10000 non-null  int64
 1   numberOfRooms      10000 non-null  int64
 2   hasYard            10000 non-null  int64
 3   hasPool            10000 non-null  int64
 4   floors             10000 non-null  int64
 5   cityCode           10000 non-null  int64
```

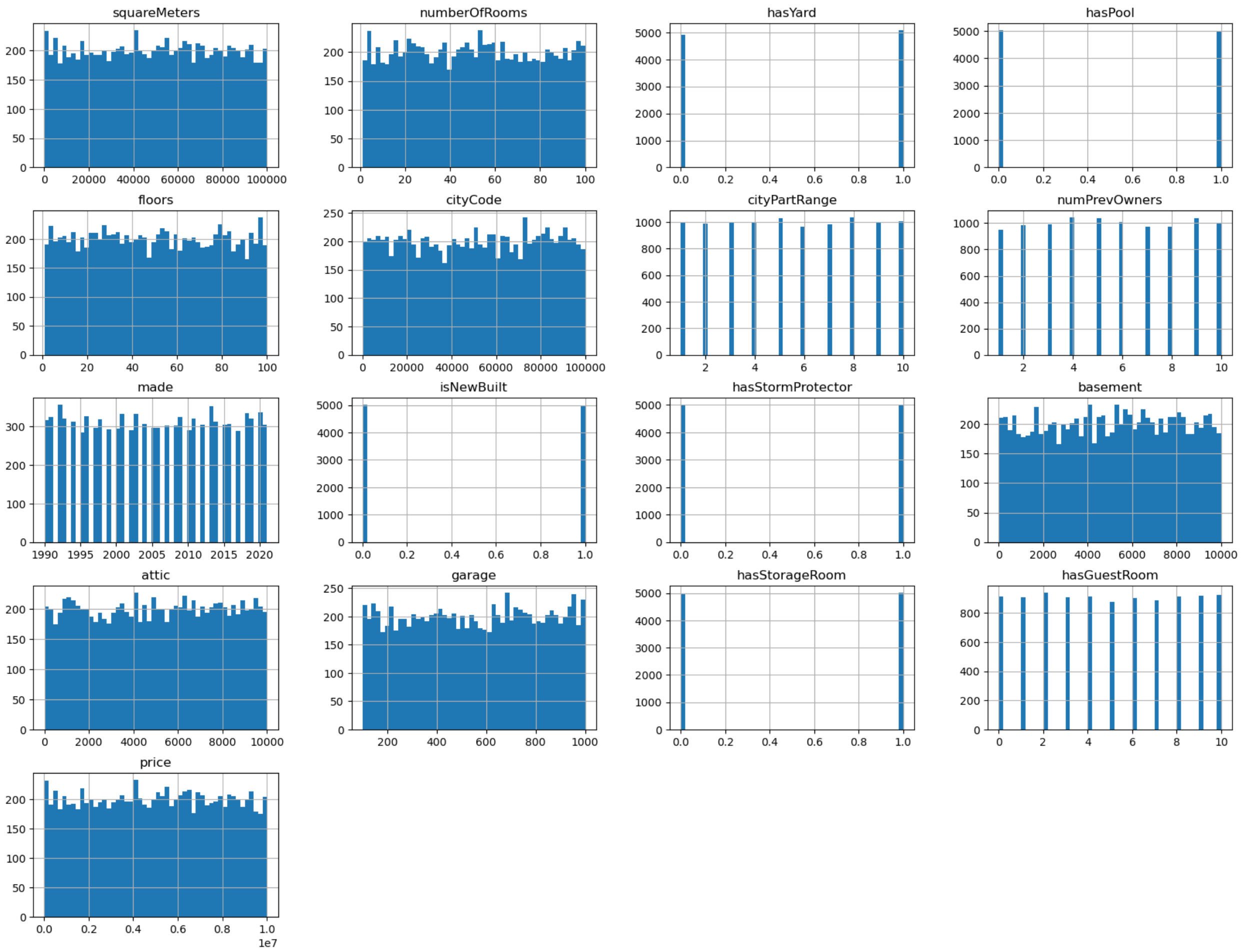
```
 6   cityPartRange      10000 non-null  int64
 7   numPrevOwners      10000 non-null  int64
 8   made               10000 non-null  int64
 9   isNewBuilt         10000 non-null  int64
 10  hasStormProtector  10000 non-null  int64
 11  basement           10000 non-null  int64
 12  attic              10000 non-null  int64
 13  garage             10000 non-null  int64
 14  hasStorageRoom     10000 non-null  int64
 15  hasGuestRoom       10000 non-null  int64
 16  price              10000 non-null  float64
 17  category           10000 non-null  object
dtypes: float64(1), int64(16), object(1)
memory usage: 1.4+ MB
```

```
#using .describe() with categorical attribues
PHC['category'].describe()
```

```
count     10000
unique        2
top       Basic
freq       7470
Name: category, dtype: object
```

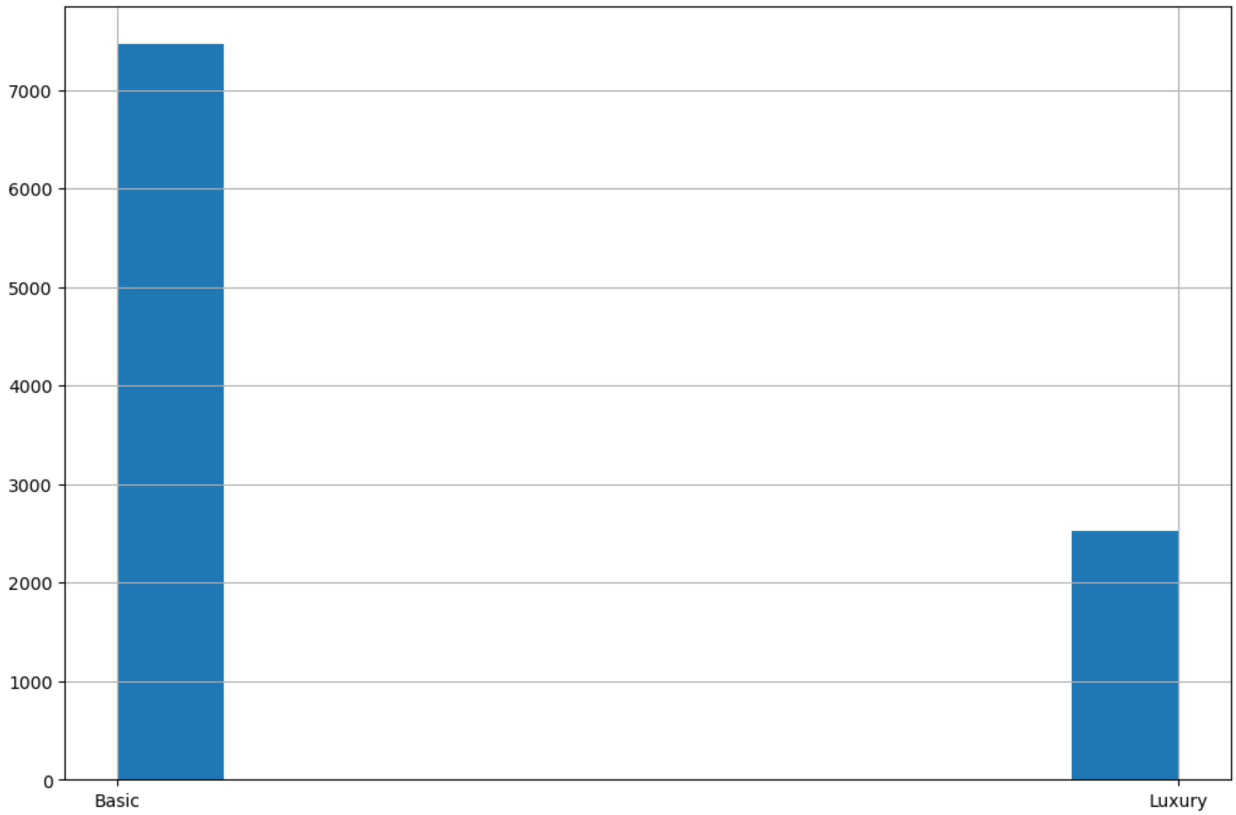
Data Visualization

```
PHC.hist(bins=50, figsize=(20,15))
plt.show()
```

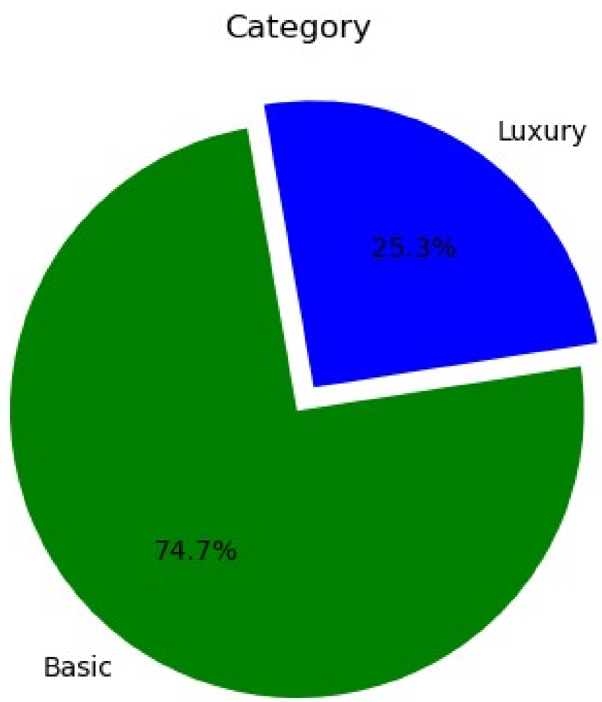



```python
#This displays a comparison between the two categories in the Category column:
PHC['category'].hist(figsize = (12,8))
plt.show
```

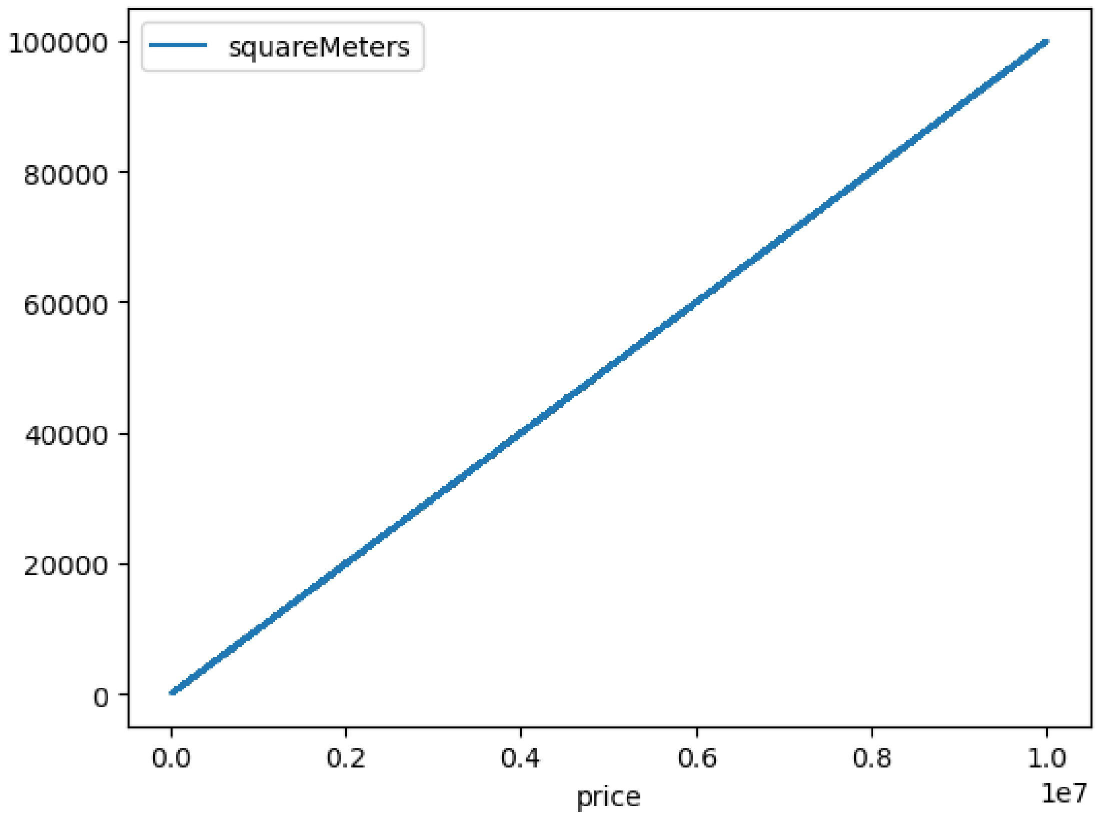
```
<function matplotlib.pyplot.show(close=None, block=None)>
```




```
#pie plot that shows the percentage of the two classes(Basic,Luxury)
in the "Category" column
x = PHC['category'].value_counts()
values = [x.Basic,x.Luxury]
Ans= ['Basic','Luxury']
plt.title('Category')
colors = ['green', 'blue']
plt.pie(values,labels = Ans,autopct = '%1.1f%%',startangle=100,explode
=(0,.1), colors=colors)
plt.show()
```




```
#the relationship between squareMeters and price columns:
PHC.plot(x="price", y="squareMeters")
plt.show()

#The larger the square meter, the higher the price
```

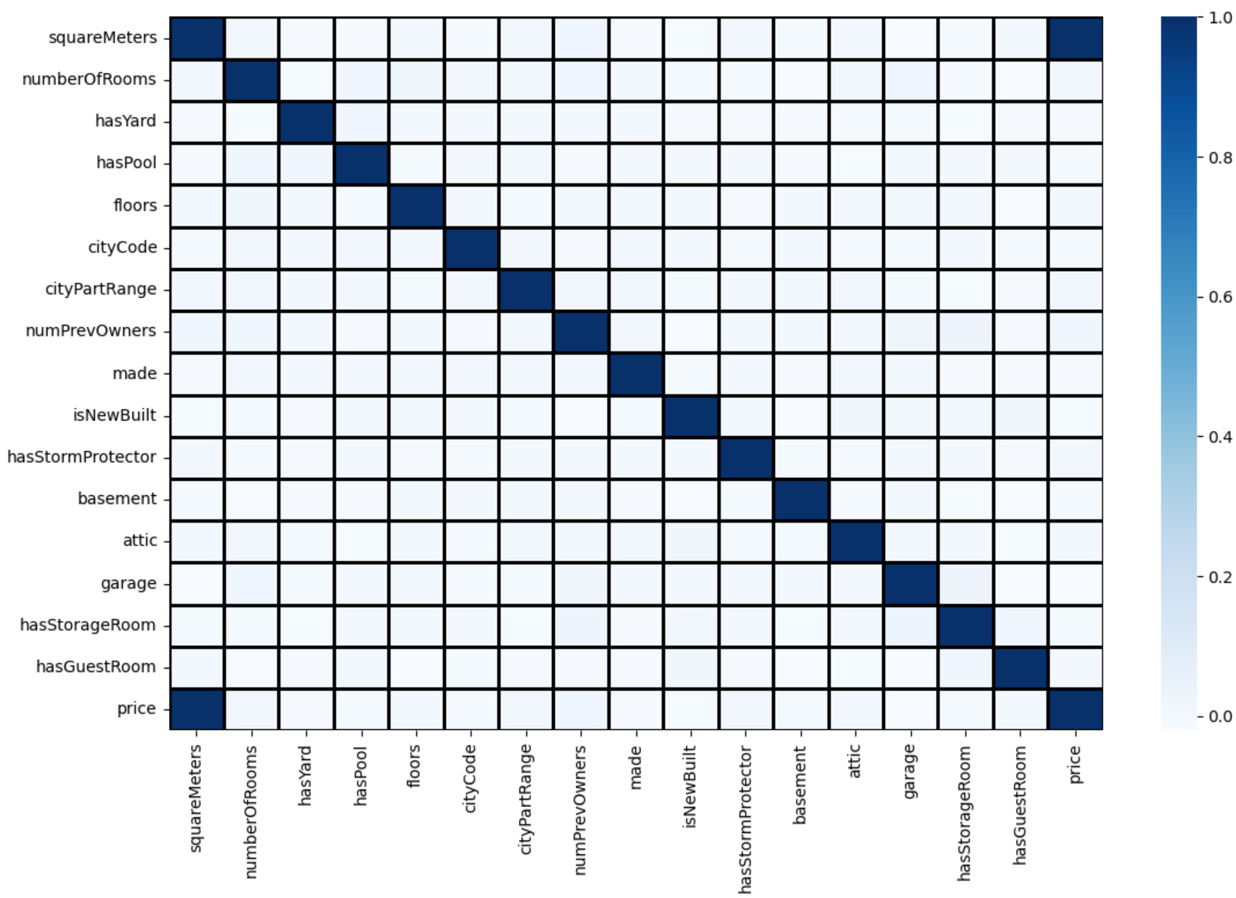


Looking for Correlations

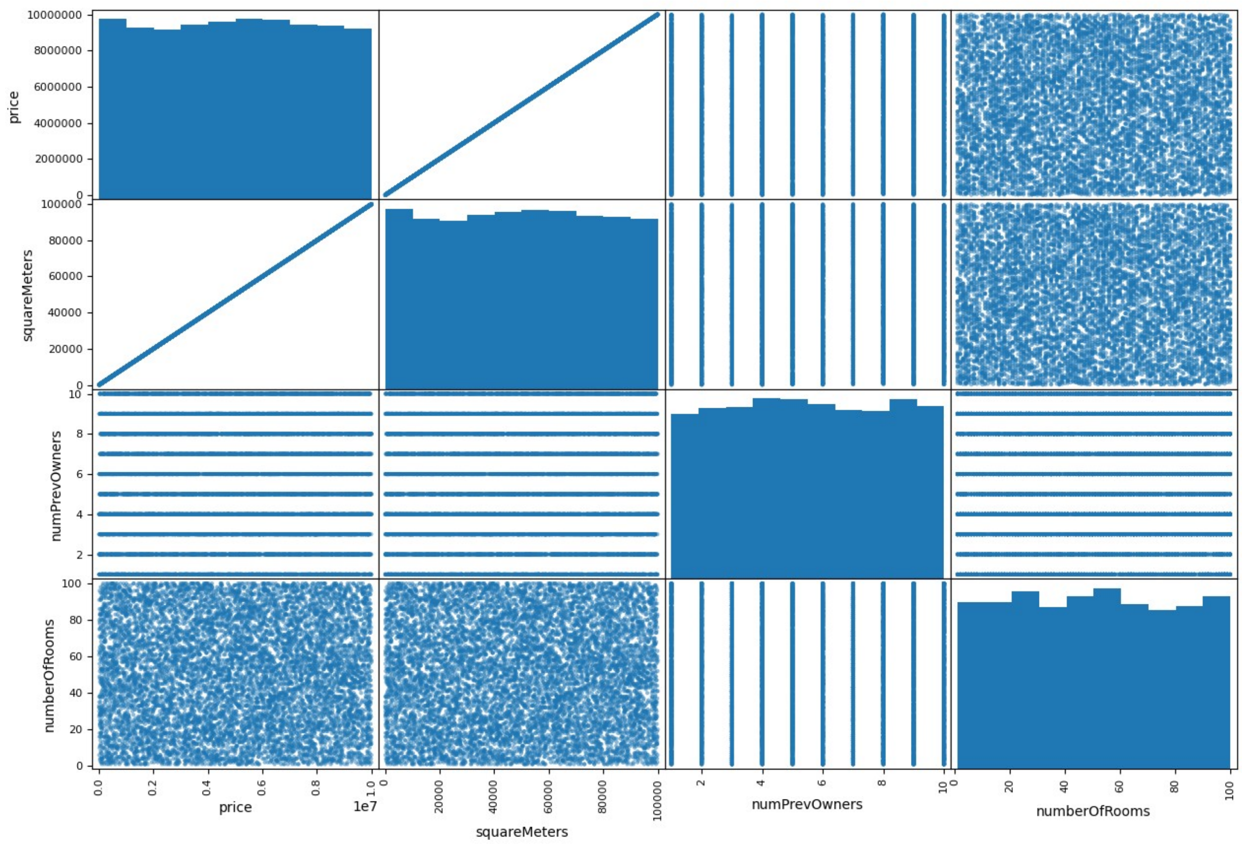
```
corr_matrix = PHC.corr()

# see the correlation between price and all columns
corr_matrix["price"].sort_values(ascending=False)
```

```
price                1.000000
squareMeters         0.999999
numPrevOwners        0.016619
numberOfRooms        0.009591
cityPartRange        0.008813
hasStormProtector    0.007496
floors               0.001654
attic               -0.000600
hasGuestRoom        -0.000644
cityCode            -0.001539
hasStorageRoom      -0.003485
basement            -0.003967
hasPool             -0.005070
hasYard             -0.006119
made                -0.007210
isNewBuilt          -0.010643
garage              -0.017229
Name: price, dtype: float64
```

```
import seaborn as sns
import matplotlib.pyplot as plt
Data = PHC.select_dtypes(np.number)
plt.figure(figsize=(13,8))
sns.heatmap(corr_matrix,cmap='Blues', linecolor='black', linewidths= 2
)
plt.show()
#The provided matrix illustrates the correlation among features, with
color intensity reflecting the correlation value.
#A Blue color indicates a strong  correlation between the two
features, whereas a bright color suggests a negative correlation.
```




```
attributes = ["price", "squareMeters",
"numPrevOwners","numberOfRooms"]
scatter_matrix(PHC[attributes], figsize=(15, 10))
plt.show()
```



Data Cleaning

checking if there are missing values

```
PHC.isnull().sum()
```

```
squareMeters         0
numberOfRooms        0
hasYard              0
hasPool              0
floors               0
cityCode             0
cityPartRange        0
numPrevOwners        0
made                 0
isNewBuilt           0
hasStormProtector    0
basement             0
attic                0
garage               0
hasStorageRoom       0
hasGuestRoom         0
```

```
price               0
category            0
dtype: int64
```

Create a Test Set and Trian Set

```
# to make this notebook's output identical at every run
np.random.seed(42)

import numpy as np

# For illustration only. Sklearn has train_test_split()
def split_train_test(data, test_ratio):
    shuffled_indices = np.random.permutation(len(data))
    test_set_size = int(len(data) * test_ratio)
    test_indices = shuffled_indices[:test_set_size]
    train_indices = shuffled_indices[test_set_size:]
    return data.iloc[train_indices], data.iloc[test_indices]

train_set, test_set = split_train_test(PHC, 0.2)
len(train_set)

8000

len(test_set)

2000

# make the data stratification by shuffle and split
from sklearn.model_selection import train_test_split

train_set, test_set = train_test_split(PHC, test_size=0.2,
random_state=42)
test_set.head()

      squareMeters  numberOfRooms  hasYard  hasPool  floors  cityCode
\
6252         79553              7        1        0      61     35059

4684         37047             79        1        1      87     57780

1731         85476             36        1        0      44     83386

4742         64209             30        1        1      55     53245

4521         64550             89        1        1      68      4708


      cityPartRange  numPrevOwners  made  isNewBuilt
hasStormProtector  \
6252              8              2  1996           1
```

```
1
4684                 3              3  2019          1
0
1731                 9              7  1992          0
1
4742                 5              5  1992          1
0
4521                 7              2  2019          0
0

      basement  attic  garage  hasStorageRoom  hasGuestRoom      price
\
6252      3372   7603     896               1             1  7964369.6

4684      5658   8216     160               0             5  3713548.9

1731      6698   6043     692               1             7  8553019.2

4742      9761   6148     525               1             0  6428666.2

4521      1945   8269     495               0            10  6465184.9


     category
6252   Luxury
4684   Luxury
1731    Basic
4742   Luxury
4521    Basic
```

We Handle Missing Data, Dealing with Categorical Data, Combining Data and Scaling Data.

```
PHC['totalNumOfRooms'] = PHC['numberOfRooms']
+PHC['hasGuestRoom']
PHC.drop(['hasGuestRoom','numberOfRooms'],axis = 1,inplace = True)

from sklearn.compose import make_column_selector,
make_column_transformer

num_attribs = PHC.select_dtypes(np.number)
cat_attribs = [['category']]
num_pipeline =
make_pipeline(SimpleImputer(strategy="median"),StandardScaler())
cat_pipeline =
make_pipeline( SimpleImputer(strategy="most_frequent"),OneHotEncoder(h
andle_unknown="ignore"))

preprocessing = ColumnTransformer([("cat", cat_pipeline,
make_column_selector(dtype_include=object)),("num", num_pipeline,
make_column_selector(dtype_include=np.number))])
```

```
PHC_prep = preprocessing.fit_transform(PHC)
##converting it to DataFrame
PHC_D = pd.DataFrame(PHC_prep,columns
=preprocessing.get_feature_names_out() )

PHC_D.shape

(10000, 18)

preprocessing.get_feature_names_out()

array(['cat__category_Basic', 'cat__category_Luxury',
'num__squareMeters',
       'num__hasYard', 'num__hasPool', 'num__floors', 'num__cityCode',
       'num__cityPartRange', 'num__numPrevOwners', 'num__made',
       'num__isNewBuilt', 'num__hasStormProtector', 'num__basement',
       'num__attic', 'num__garage', 'num__hasStorageRoom',
'num__price',
       'num__totalNumOfRooms'], dtype=object)

corr_matrix1 = PHC_D.select_dtypes(np.number).corr()
corr_matrix1[["cat__category_Basic",
"cat__category_Luxury"]].sort_values(by=["cat__category_Basic",
"cat__category_Luxury"], ascending=False)
```

	cat__category_Basic	cat__category_Luxury
cat__category_Basic	1.000000	-1.000000
num__basement	0.021868	-0.021868
num__squareMeters	0.017982	-0.017982
num__price	0.017663	-0.017663
num__hasStormProtector	0.011385	-0.011385
num__totalNumOfRooms	0.010871	-0.010871
num__cityPartRange	0.009496	-0.009496
num__numPrevOwners	0.007320	-0.007320
num__garage	0.005081	-0.005081
num__attic	0.003978	-0.003978
num__hasStorageRoom	-0.000189	0.000189
num__cityCode	-0.005574	0.005574
num__hasPool	-0.006025	0.006025
num__floors	-0.008273	0.008273
num__made	-0.008380	0.008380
num__hasYard	-0.567788	0.567788
num__isNewBuilt	-0.579797	0.579797
cat__category_Luxury	-1.000000	1.000000

```
#split into three partS train set, test set and validation set:
split = StratifiedShuffleSplit(n_splits=2, test_size=0.1,
random_state=42)
for train_index, test_index in split.split(PHC_D,
PHC_D[["cat__category_Basic", "cat__category_Luxury"]]):
```

```
    strat_train_set1 = PHC_D.iloc[train_index]
    strat_test_set = PHC_D.iloc[test_index]
print("train set size = "+str(len(strat_train_set1)))
print("test set size = "+str(len(strat_test_set)))
```

```
train set size = 9000
test set size = 1000
```

```
split = StratifiedShuffleSplit(n_splits=2, test_size=0.1,
random_state=42)
for train_index, test_index in split.split(strat_train_set1,
strat_train_set1[["cat__category_Basic", "cat__category_Luxury"]]):
    strat_train_set = strat_train_set1.iloc[train_index]
    strat_val_set = strat_train_set1.iloc[test_index]
print("train set size = "+str(len(strat_train_set)))
print("validation set size = "+str(len(strat_val_set)))
```

```
train set size = 8100
validation set size = 900
```

To ensure a nearly equal distribution of data among the test, training, and validation sets

```
strat_train_set[["cat__category_Basic",
"cat__category_Luxury"]].value_counts() / len(strat_train_set)
```

```
cat__category_Basic  cat__category_Luxury
1.0                  0.0                     0.747037
0.0                  1.0                     0.252963
dtype: float64
```

```
strat_test_set[["cat__category_Basic",
"cat__category_Luxury"]].value_counts() / len(strat_test_set)
```

```
cat__category_Basic  cat__category_Luxury
1.0                  0.0                     0.747
0.0                  1.0                     0.253
dtype: float64
```

```
strat_val_set[["cat__category_Basic",
"cat__category_Luxury"]].value_counts() / len(strat_val_set)
```

```
cat__category_Basic  cat__category_Luxury
1.0                  0.0                     0.746667
0.0                  1.0                     0.253333
dtype: float64
```

Seperate Labels

```
Data_train = strat_train_set.drop(["cat__category_Basic",
"cat__category_Luxury"],axis = 1)
```

```
Label_train = strat_train_set["cat__category_Basic"].copy()
Data_test = strat_test_set.drop(["cat__category_Basic",
"cat__category_Luxury"],axis = 1)
Label_test = strat_test_set["cat__category_Basic"].copy()
Data_val = strat_val_set.drop(["cat__category_Basic",
"cat__category_Luxury"],axis = 1)
Label_val = strat_val_set["cat__category_Basic"].copy()
```

```
!pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in c:\users\user\
anaconda3\lib\site-packages (0.11.0)
Requirement already satisfied: numpy>=1.17.3 in c:\users\user\
anaconda3\lib\site-packages (from imbalanced-learn) (1.21.5)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\user\
anaconda3\lib\site-packages (from imbalanced-learn) (2.2.0)
Requirement already satisfied: scipy>=1.5.0 in c:\users\user\
anaconda3\lib\site-packages (from imbalanced-learn) (1.9.1)
Requirement already satisfied: joblib>=1.1.1 in c:\users\user\
anaconda3\lib\site-packages (from imbalanced-learn) (1.3.2)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\user\
anaconda3\lib\site-packages (from imbalanced-learn) (1.3.2)
```

```
#we are going to use the SMOTE( ) to balance it because the data
imbalanced
#Explaining the functionality of SMOTE(): It enhances dataset balance
by creating additional instances in a proportionate manner
#This process involves generating new instances based on the existing
minority cases, where, in this particular dataset,
#the minority pertains to the Luxury category.

from imblearn.over_sampling import SMOTE
from collections import Counter

before0 = Counter(Label_test)
before1 = Counter(Label_train)
before2 = Counter(Label_val)
print("Before: \nTest "+str(before0)+" \nTrain  "+str(before1)+" \
nValidation  "+str(before2))
```

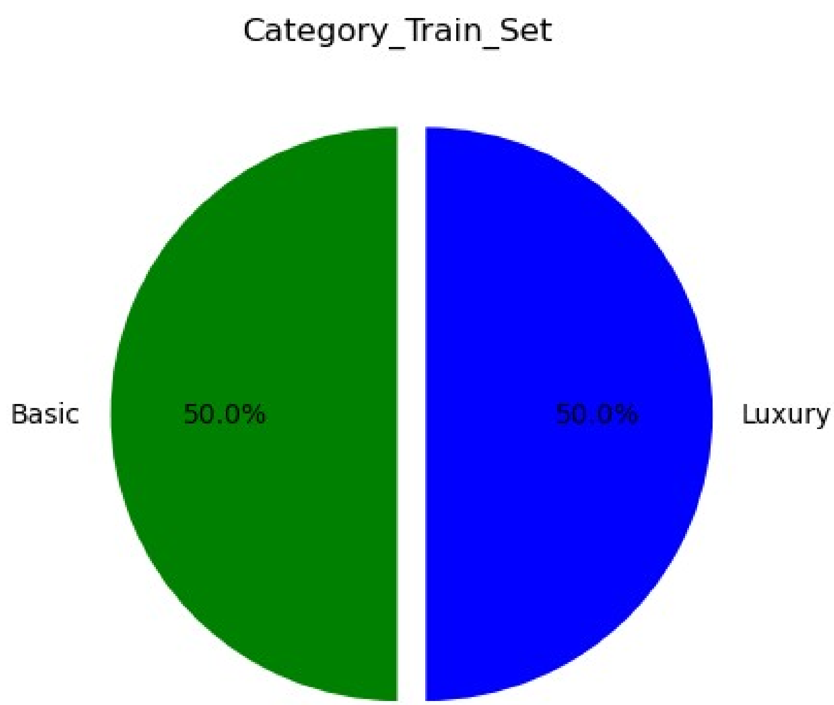
```
Before:
Test Counter({1.0: 747, 0.0: 253})
Train  Counter({1.0: 6051, 0.0: 2049})
Validation  Counter({1.0: 672, 0.0: 228})
```

```
sm = SMOTE(random_state = 2)
Data_train_b, Label_train_b = sm.fit_resample(Data_train, Label_train)
Data_test_b, Label_test_b = sm.fit_resample(Data_test, Label_test)
Data_val_b, Label_val_b = sm.fit_resample(Data_val, Label_val)
```

```
#the percentage of Bsic to Luxury after balancing
after0 = Counter(Label_test_b)
after1 = Counter(Label_train_b)
after2 = Counter(Label_val_b)
print("After: \nTest "+str(after0)+" \nTrain "+str(after1)+" \
nValidation "+str(after2))
```

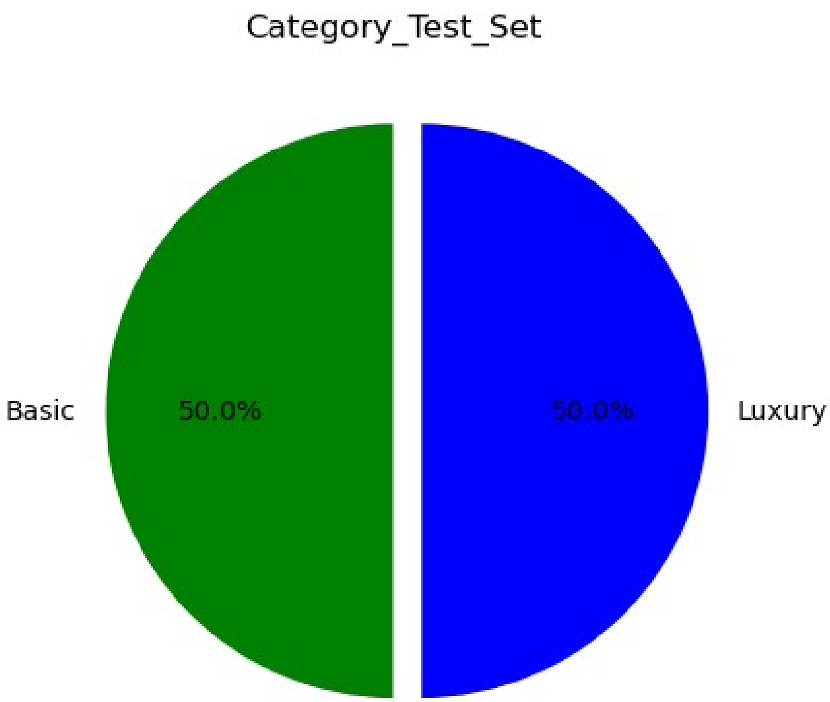
```
After:
Test Counter({0.0: 747, 1.0: 747})
Train Counter({1.0: 6051, 0.0: 6051})
Validation Counter({1.0: 672, 0.0: 672})
```

```
x_1 = Label_train_b.value_counts()
values_1 = [x_1[1.0],x_1[0]]
Ans_1= ['Basic','Luxury']
plt.title('Category_Train_Set')
colors = ['green', 'blue']
plt.pie(values_1,labels = Ans_1,autopct = '%1.1f%
%',startangle=90,explode =(0,.1), colors=colors)
plt.show()
```

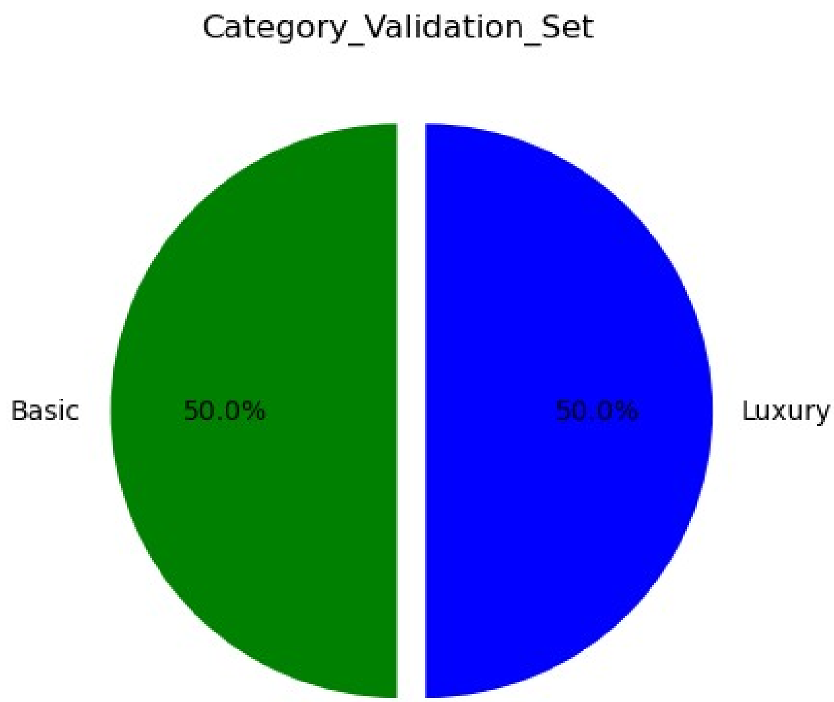



```
x_2= Label_test_b.value_counts()
values1 = [x_2[1.0],x_2[0]]
Ans_1= ['Basic','Luxury']
plt.title('Category_Test_Set')
```

```
colors = ['green', 'blue']
plt.pie(values_1,labels = Ans_1,autopct = '%1.1f%
%',startangle=90,explode =(0,.1), colors=colors)
plt.show()
```




```
x_3= Label_val_b.value_counts()
values1 = [x_3[1.0],x_3[0]]
Ans_1= ['Basic','Luxury']
plt.title('Category_Validation_Set')
colors = ['green', 'blue']
plt.pie(values_1,labels = Ans_1,autopct = '%1.1f%
%',startangle=90,explode =(0,.1), colors=colors)
plt.show()
```



Classification

in this part we did train the following models :

1.Logistic regression

2.LinearSVC model

3.Decision Tree

4.Random Forest Classifier

5.K-Nearest Neighbor Classifier

6.Binary classifier model

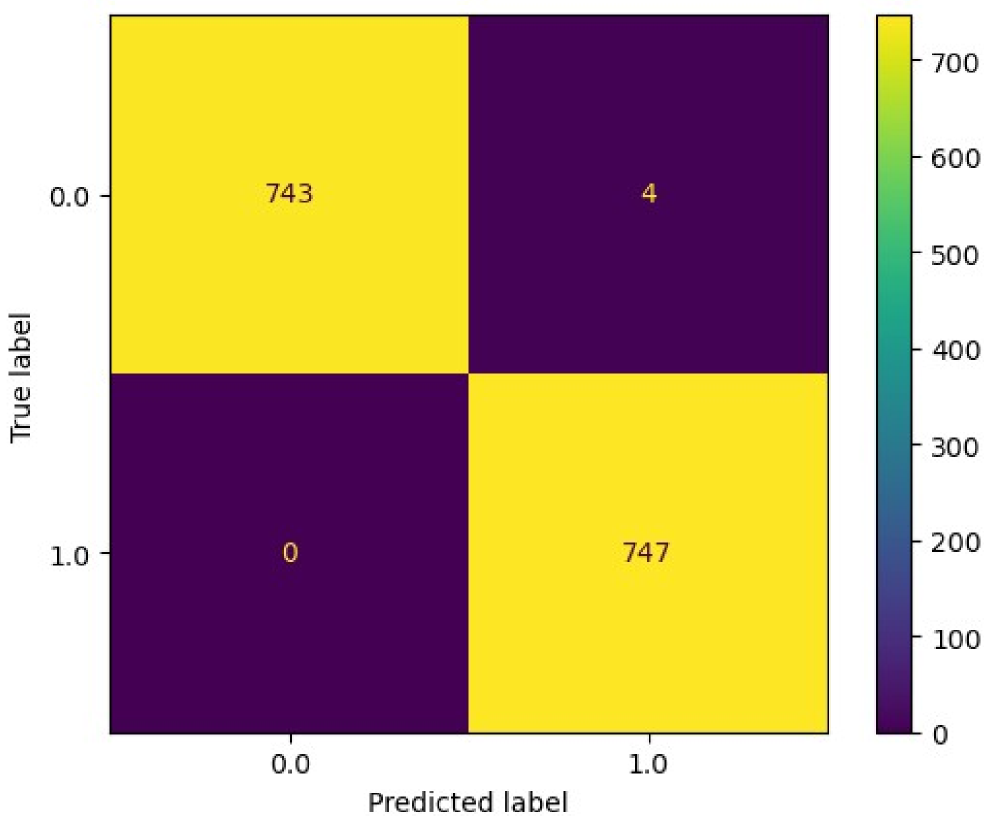
Logisric regression

```
log_clf =
LogisticRegression(random_state=42,penalty='l1',solver='liblinear')
LR = log_clf.fit(Data_train_b, Label_train_b)
score_train = cross_val_score(LR,Data_train_b, Label_train_b,
cv=3,scoring='accuracy')
score_test = cross_val_score(LR,Data_test_b, Label_test_b,
```

```
cv=3,scoring='accuracy')
print("Train Score "+ str(score_train))
print("Test Score "+ str(score_test))
```

```
Train Score [0.99776896 1.         0.99876054]
Test Score [0.99598394 0.99799197 0.99799197]
```

```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import ConfusionMatrixDisplay

y_pred=cross_val_predict(log_clf, Data_test_b, Label_test_b, cv=3)
ConfusionMatrixDisplay.from_predictions(Label_test_b,y_pred)
plt.show()
```



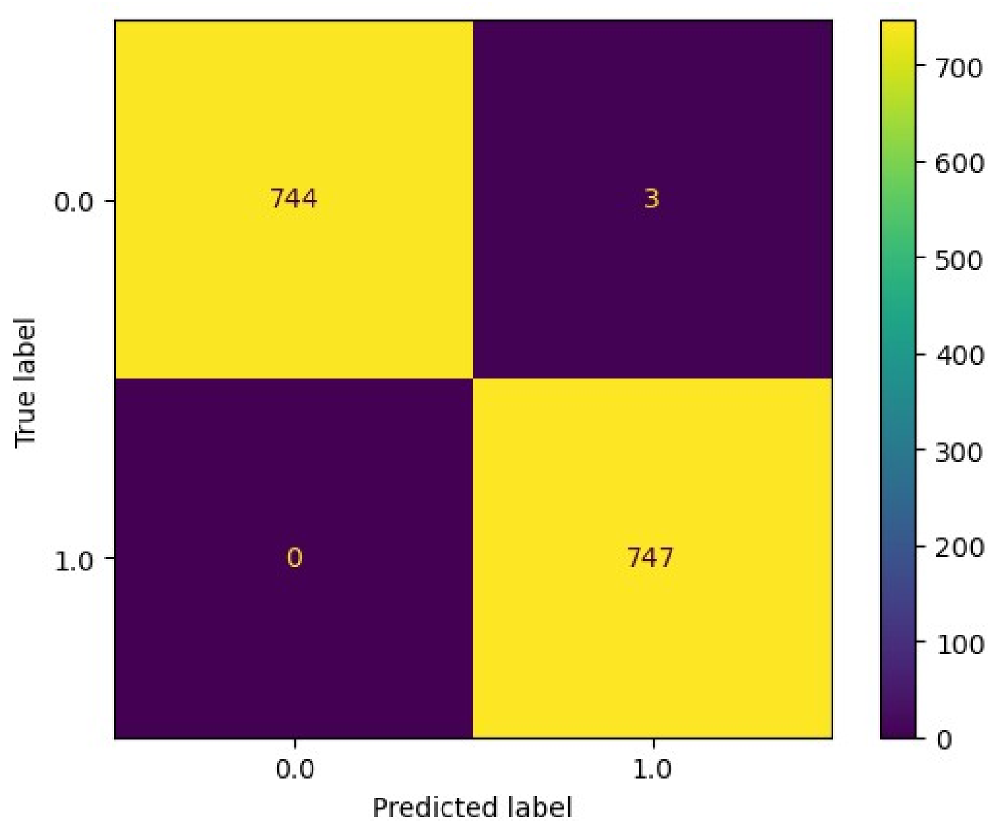
SVC model

```
svm_clf = SVC(random_state=42)
svc = svm_clf.fit(Data_train_b, Label_train_b)
score_train1 = cross_val_score(svc,Data_train_b, Label_train_b,
cv=3,scoring='accuracy')
score_test1 = cross_val_score(svc,Data_test_b, Label_test_b,
cv=3,scoring='accuracy')
```

```
print("Train Score: "+ str(score_train1))
print("Test Score: "+ str(score_test1))
```

```
Train Score: [0.99776896 1.         0.99876054]
Test Score: [0.99799197 0.99799197 0.99799197]
```

```
y_pred1=cross_val_predict(svm_clf, Data_test_b, Label_test_b, cv=3)
ConfusionMatrixDisplay.from_predictions(Label_test_b,y_pred1)
plt.show()
```

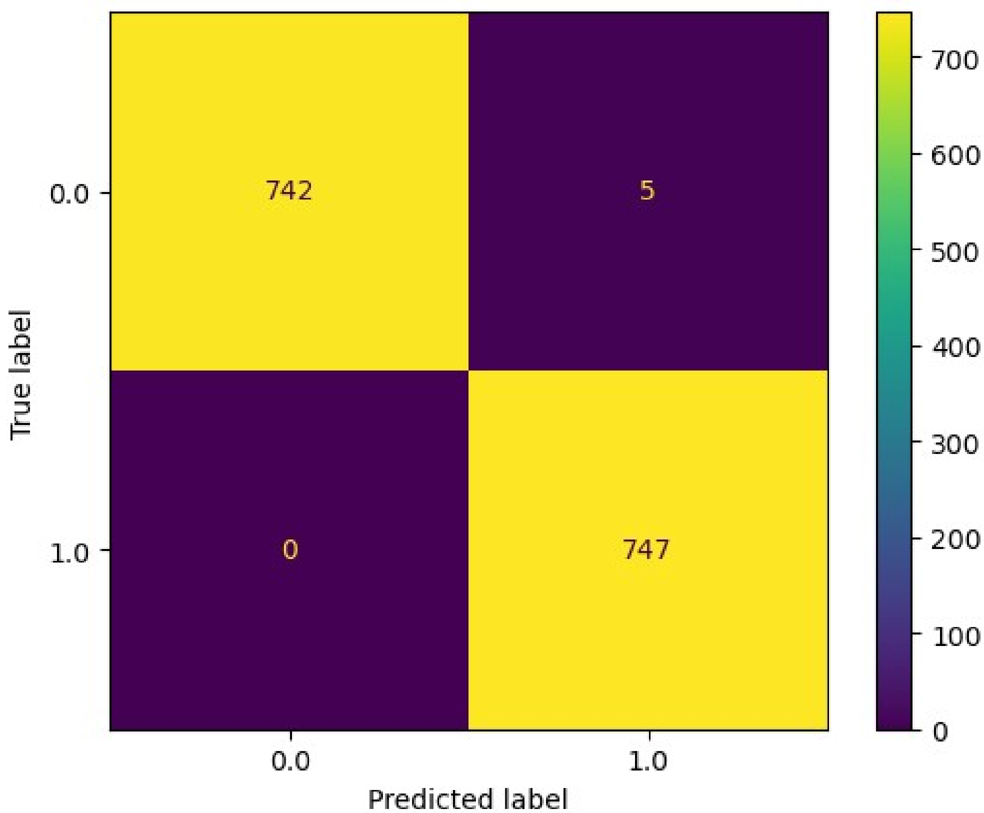


Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
tree_clf = DecisionTreeClassifier(max_depth=2, random_state=42)

score_train2 = cross_val_score(tree_clf,Data_train_b, Label_train_b,
cv=3,scoring='accuracy')
score_test2 = cross_val_score(tree_clf,Data_test_b, Label_test_b,
cv=3,scoring='accuracy')
print("Train Score: "+ str(score_train1))
print("Test Score: "+ str(score_test1))
```

```
Train Score: [0.99776896 1.         0.99876054]
Test Score: [0.99799197 0.99799197 0.99799197]
```

```
y_pred2=cross_val_predict(tree_clf, Data_test_b, Label_test_b, cv=3)
ConfusionMatrixDisplay.from_predictions(Label_test_b,y_pred2)
plt.show()
```

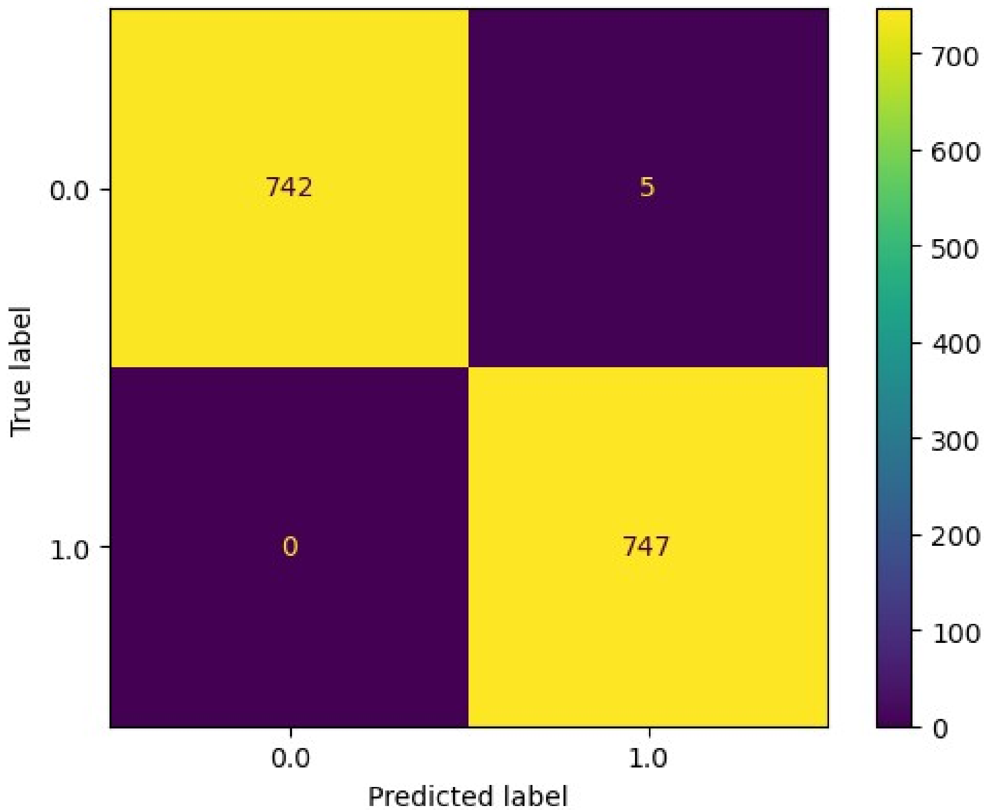


RandomForest Classifier

```
from sklearn.ensemble import RandomForestClassifier

rnd_clf = RandomForestClassifier(n_estimators=500, max_leaf_nodes=16,
                                 n_jobs=-1, random_state=42)
score_train3 = cross_val_score(svc,Data_train_b, Label_train_b,
cv=3,scoring='accuracy')
score_test3 = cross_val_score(svc,Data_test_b, Label_test_b,
cv=3,scoring='accuracy')
print("Train Score: "+ str(score_train1))
print("Test Score: "+ str(score_test1))
```

```
Train Score: [0.99776896 1.         0.99876054]
Test Score: [0.99799197 0.99799197 0.99799197]
```

```
y_pred3=cross_val_predict(rnd_clf, Data_test_b, Label_test_b, cv=3)
ConfusionMatrixDisplay.from_predictions(Label_test_b,y_pred3)
plt.show()
```

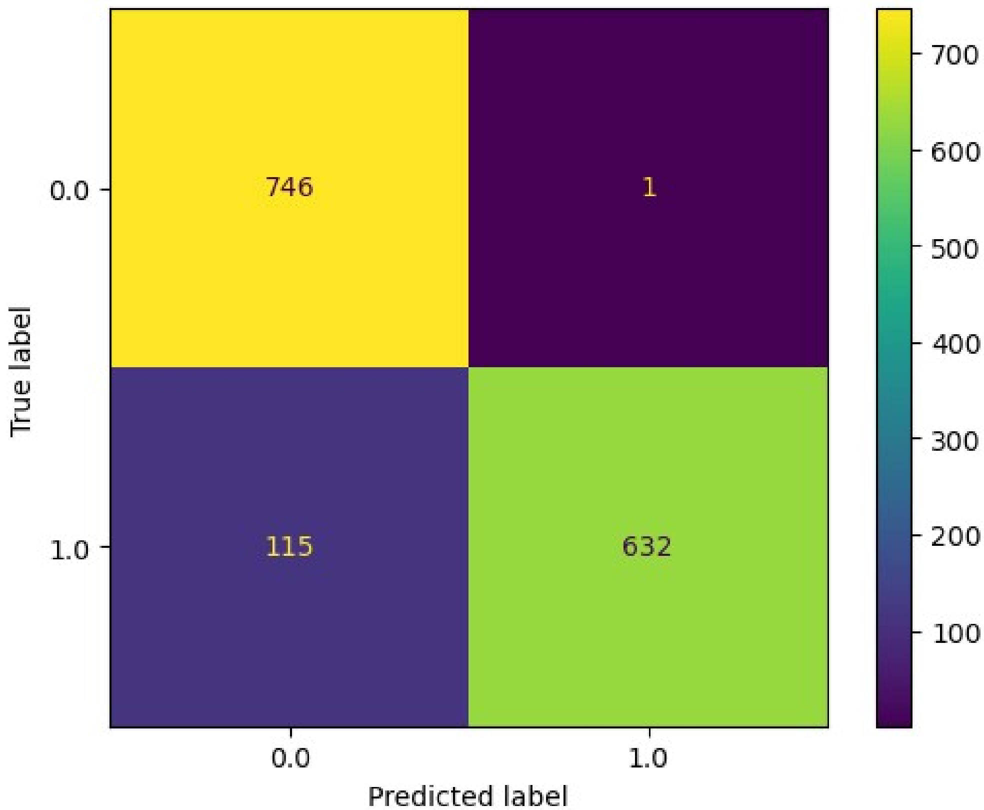


K-Nearest Neighbors (KNN)

```
knn_clf = KNeighborsClassifier()
knn = knn_clf.fit(Data_train_b, Label_train_b)
score_train4 = cross_val_score(knn,Data_train_b, Label_train_b,
cv=3,scoring='accuracy')
score_test4 = cross_val_score(knn,Data_test_b, Label_test_b,
cv=3,scoring='accuracy')
print("Train Score: "+ str(score_train4))
print("Test Score: "+ str(score_test4))
```

```
Train Score: [0.98116014 0.98140803 0.979177  ]
Test Score: [0.92971888 0.93373494 0.90361446]
```

```
y_pred4=cross_val_predict(knn, Data_test_b, Label_test_b, cv=3)
ConfusionMatrixDisplay.from_predictions(Label_test_b,y_pred4)
plt.show()
```



Binary Classifier

```
Label_train_1 = (Label_train_b==1)
Label_test_1 = (Label_test_b==1)
sgd_clf = SGDClassifier(random_state=42)
sgd_clf.fit(Data_train_b, Label_train_1)
```

```
SGDClassifier(random_state=42)
```

```
some_data = Data_train_b.iloc[0]
sgd_clf.predict([some_data])
```

```
C:\Users\user\anaconda3\lib\site-packages\sklearn\base.py:465:
UserWarning: X does not have valid feature names, but SGDClassifier
was fitted with feature names
  warnings.warn(
```

```
array([ True])
```

```
cross_val_score(sgd_clf,Data_train_b,Label_train_1, cv=3,
scoring="accuracy")
```

```
array([0.99776896, 0.99950421, 0.99876054])
```

```
p = { 'logistic_regression' : {'model':
LogisticRegression(random_state=42,penalty='l1',solver='liblinear'),
```

```
                                          'params': {'C':
[1,5,10,3,7,2] , 'tol':[.0001,.001,.00001,0.01],
                                                     'max_iter':
[50,100,200,800,1000]}},
      'RFC' :{'model': RandomForestClassifier(n_estimators=500,
max_leaf_nodes=16,
                                 n_jobs=-1, random_state=42),
                        'params' :  {'n_estimators': [100, 200,
300],'max_depth': [None, 5, 10]}},

                  'svm': {'model': svm.SVC(random_state=42),
                         'params' : {'C': [0, 1,10,20],'kernel':
['poly','linear'],'degree':[2,3]}},

                  'binary_classifier':{'model':
SGDClassifier(random_state=42),
                         'params' : {'max_iter':
[100,200,800,1000],'tol':[.0001,.001,.00001]}},

                  'knn' : {'model': KNeighborsClassifier(),
                          'params': {'n_neighbors': [1,10,20] }}
               }
table = []
for name, mp in p.items():
    clf =  GridSearchCV(mp['model'], mp['params'], cv=3)
    clf.fit(Data_train_b , Label_train_b)
    table.append({
        'model': name,
        'best_score': clf.best_score_,
        'best_params': clf.best_params_
    })

table =
pd.DataFrame(table,columns=['model','best_score','best_params'])
table
```

```
C:\Users\user\anaconda3\lib\site-packages\sklearn\model_selection\
_validation.py:425: FitFailedWarning:
12 fits failed out of a total of 48.
The score on these train-test partitions for these parameters will be
set to nan.
If these failures are not expected, you can try to debug them by
setting error_score='raise'.

Below are more details about the failures:
----------------------------------------------------------------------
----------
12 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\user\anaconda3\lib\site-packages\sklearn\
```

```
model_selection\_validation.py", line 729, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\user\anaconda3\lib\site-packages\sklearn\base.py",
line 1145, in wrapper
    estimator._validate_params()
  File "C:\Users\user\anaconda3\lib\site-packages\sklearn\base.py",
line 638, in _validate_params
    validate_parameter_constraints(
  File "C:\Users\user\anaconda3\lib\site-packages\sklearn\utils\
_param_validation.py", line 96, in validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'C'
parameter of SVC must be a float in the range (0.0, inf). Got 0
instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\Users\user\anaconda3\lib\site-packages\sklearn\model_selection\
_search.py:979: UserWarning: One or more of the test scores are non-
finite: [       nan        nan        nan        nan 0.83548174
0.99843001
 0.99851264 0.99843001 0.83548174 0.99843001 0.9989258  0.99843001
 0.83556437 0.99843001 0.99884317 0.99843001]
  warnings.warn(

                 model  best_score
best_params
0  logistic_regression    0.998926   {'C': 5, 'max_iter': 50, 'tol':
0.0001}
1                  RFC    0.999008  {'max_depth': None,
'n_estimators': 100}
2                  svm    0.998926  {'C': 10, 'degree': 3, 'kernel':
'poly'}
3    binary_classifier    0.998678          {'max_iter': 100, 'tol':
0.001}
4                  knn    0.988597
{'n_neighbors': 1}
```

```
#the model with the highest accuracy
table.iloc[0]
```

```
model                              logistic_regression
best_score                                    0.998926
best_params    {'C': 5, 'max_iter': 50, 'tol': 0.0001}
Name: 0, dtype: object
```

```
voting_clf = VotingClassifier(estimators=[('lr',log_clf),
('svc',svm_clf),('knn',knn_clf)],voting = 'hard')
voting_clf.fit(Data_train_b, Label_train_b)
```

```
VotingClassifier(estimators=[('lr',
                              LogisticRegression(penalty='l1',
random_state=42,
                                                 solver='liblinear')),
                             ('svc', SVC(random_state=42)),
                             ('knn', KNeighborsClassifier())])
```

```
for clf in (log_clf,svm_clf,knn_clf,voting_clf):
    clf.fit(Data_train_b, Label_train_b)
    label_pred = clf.predict(Data_test_b)

print(clf.__class__.__name__,accuracy_score(Label_test_b,label_pred))
```

```
LogisticRegression 0.9966532797858099
SVC 0.9966532797858099
KNeighborsClassifier 0.9859437751004017
VotingClassifier 0.9966532797858099
```

the Hyper Parameters of the Best Model

```
params = { 'logistic_regression' : {'model':
LogisticRegression(random_state=42,penalty='l1',solver='liblinear'),
                                    'params': {'C':
[1,5,10,3,7,2] , 'tol':[.0001,.001,.00001,0.01],
                                               'max_iter':
[50,100,200,800,1000]}}}

items = params.items()
for name1, mp1 in items:
    gs = GridSearchCV(log_clf, mp1['params'],cv = 3)
gs.fit(Data_train_b,Label_train_b)
print("Model Name: "+name1)
print("Best Score: "+ str(gs.best_score_))
print("Best Parameters: "+ str(gs.best_params_))
```

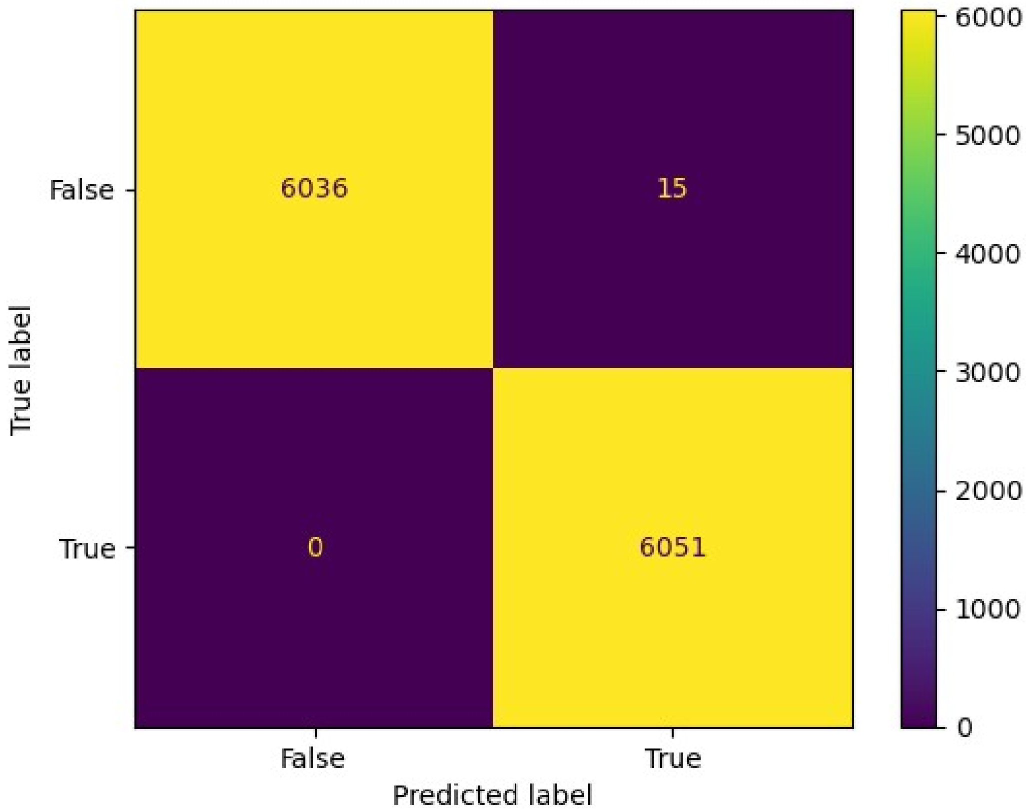
```
Model Name: logistic_regression
Best Score: 0.9989257973888614
Best Parameters: {'C': 5, 'max_iter': 50, 'tol': 0.0001}
```

```
end_mod = gs.best_estimator_

#the best model on the test data and the accuracy of the model
pred1 = end_mod.predict(Data_test_b)
pred2 = end_mod.predict(Data_val_b)
print("Test set accuracy:"+str(accuracy_score(Label_test_b,pred1)))
print("Validation set
accuracy:"+str(accuracy_score(Label_val_b,pred2)))
```

```
Test set accuracy:0.9966532797858099
Validation set accuracy:0.9985119047619048
```

confusion matrix

```
#confusion matrix to observe (TN,FP,FN,TP) and as we can see the
performance is good on the diagonal
from sklearn.metrics import ConfusionMatrixDisplay
ConfusionMatrixDisplay.from_predictions(Label_train_1, label_scores_2)
plt.show()
```



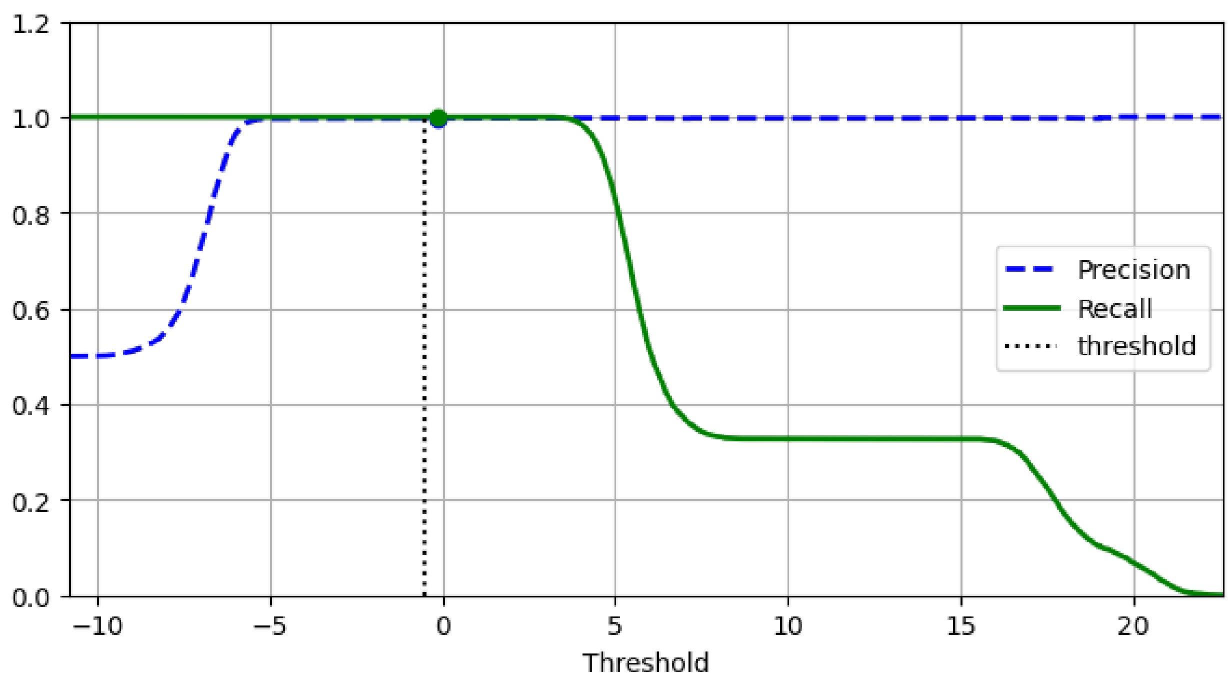
Precision, Recall, F1 score

```
#calculate precesion, recall and f1 score
print(precision_score(Label_train_1,label_scores_2))
print(recall_score(Label_train_1,label_scores_2))
print(f1_score(Label_train_1,label_scores_2))
```

```
0.9975272007912958
1.0
0.9987620698192622
```

```
# assuming that threshold = -0.5:
threshold = -0.5
label_scores = cross_val_predict(log_clf, Data_train_b, Label_train_1,
cv=3,method="decision_function")
label_scores_2 = (label_scores>threshold)
precisions, recalls, thresholds =
```

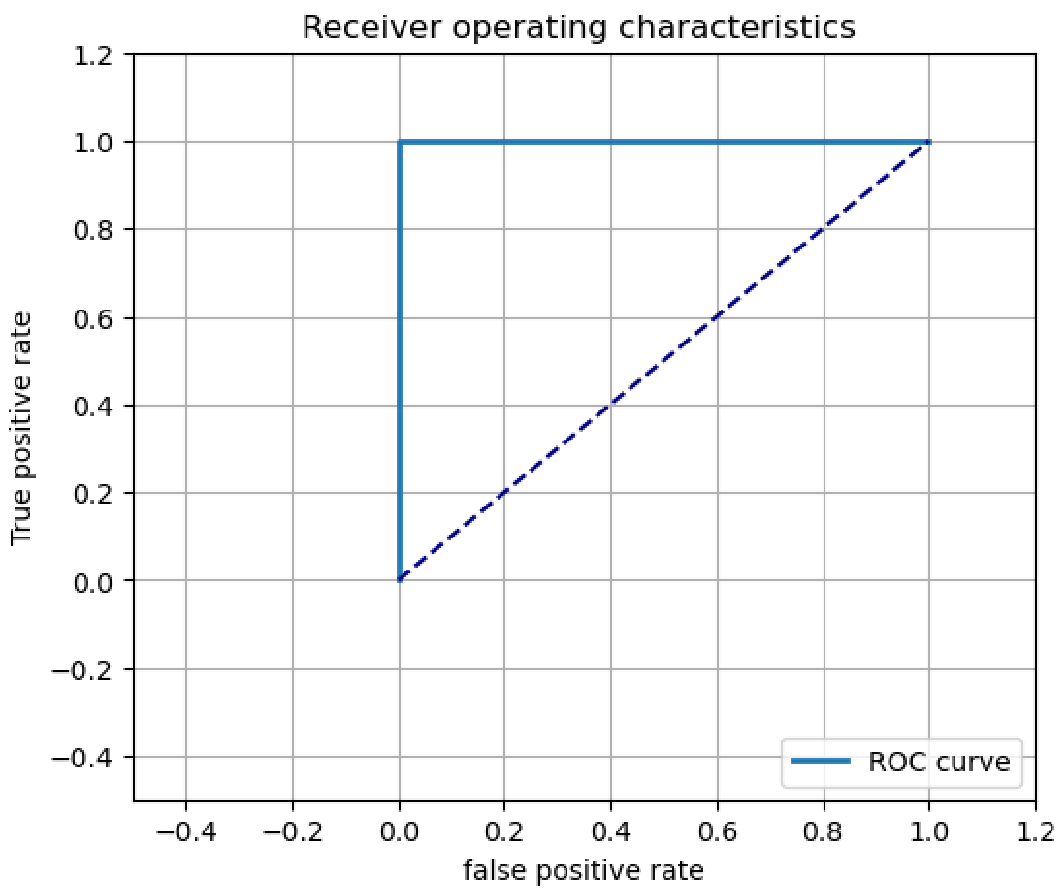
```
precision_recall_curve(Label_train_1,label_scores)

##plotting precision vs recall relation
threshold =-0.5
plt.figure(figsize=(8, 4))
plt.plot(thresholds, precisions[:-1], "b--", label="Precision",
linewidth=2)
plt.plot(thresholds, recalls[:-1], "g-", label="Recall", linewidth=2)
plt.vlines(threshold, 0, 1.0, "k", "dotted", label="threshold")

idx = (thresholds >= threshold).argmax()  # first index ≥ threshold
plt.plot(thresholds[idx], precisions[idx], "bo")
plt.plot(thresholds[idx], recalls[idx], "go")
plt.grid()
plt.xlabel("Threshold")
plt.legend(loc="center right")
plt.axis([thresholds.min(),thresholds.max(),0 , 1.2])

plt.show()
```



The ROC Curve

```
fpr,tpr,thresholds=roc_curve(Label_train_1,label_scores)
plt.figure(figsize=(6, 5))
plt.plot(fpr, tpr, linewidth=2, label='ROC curve')
plt.plot([0,1], [0,1],color='navy',linestyle='--')
plt.ylim([-0.5, 1.2])
plt.xlim([-0.5, 1.2])
plt.xlabel('false positive rate')
```

```
plt.ylabel('True positive rate')
plt.title('Receiver operating characteristics ')
plt.grid()
plt.legend(loc="lower right")
plt.show()
```



Neural Network

we already have read the data and prepared it then we import needed libararies and build the Model

```
import tensorflow as tf
from tensorflow import keras

len(Data_train)

8100

#one input layer, 4 middle layers and output layer.
```

```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(240,activation="relu",input_dim = 16))
model.add(tf.keras.layers.Dense(120, activation="relu"))
model.add(tf.keras.layers.Dense(60, activation="relu"))
model.add(tf.keras.layers.Dense(30, activation="relu"))
model.add(tf.keras.layers.Dense(15, activation="relu"))
model.add(tf.keras.layers.Dense(1, activation="softmax"))

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 240)               4080

 dense_1 (Dense)             (None, 120)               28920

 dense_2 (Dense)             (None, 60)                7260

 dense_3 (Dense)             (None, 30)                1830

 dense_4 (Dense)             (None, 15)                465

 dense_5 (Dense)             (None, 1)                 16

=================================================================
Total params: 42,571
Trainable params: 42,571
Non-trainable params: 0
_________________________________________________________________
```

```
model.layers
```

```
[<keras.layers.core.dense.Dense at 0x1ef63274100>,
 <keras.layers.core.dense.Dense at 0x1ef63274760>,
 <keras.layers.core.dense.Dense at 0x1ef51b7ec70>,
 <keras.layers.core.dense.Dense at 0x1ef63585c40>,
 <keras.layers.core.dense.Dense at 0x1ef635857f0>,
 <keras.layers.core.dense.Dense at 0x1ef63585ee0>]
```

```
keras.utils.plot_model(model,'My_model.png',show_shapes=True,dpi=60,ra
nkdir='LR')
```

```
You must install pydot (`pip install pydot`) and install graphviz (see
instructions at https://graphviz.gitlab.io/download/) for plot_model
to work.
```

```
hidden_0 = model.layers[0]
hidden_1 = model.layers[1]
hidden_2 = model.layers[2]
hidden_3 = model.layers[3]

print(hidden_0.name)
print(hidden_1.name)
print(hidden_2.name)
print(hidden_3.name)

dense
dense_1
dense_2
dense_3

#we bulid the model and compile them

checkpoint=keras.callbacks.ModelCheckpoint('Bm.h5',save_best_only=True
)
early_stopping=keras.callbacks.EarlyStopping(patience=20,restore_best_
weights=True)
model.compile(loss="binary_crossentropy",optimizer="sgd",
metrics=["accuracy"])

#train the model
history = model.fit(Data_train, Label_train,
epochs=25,callbacks=[cp,es], validation_data=(Data_val, Label_val))

Epoch 1/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0047
- accuracy: 0.7470 - val_loss: 0.0097 - val_accuracy: 0.7467
Epoch 2/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0046
- accuracy: 0.7470 - val_loss: 0.0096 - val_accuracy: 0.7467
Epoch 3/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0046
- accuracy: 0.7470 - val_loss: 0.0097 - val_accuracy: 0.7467
Epoch 4/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0044
- accuracy: 0.7470 - val_loss: 0.0097 - val_accuracy: 0.7467
Epoch 5/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0044
- accuracy: 0.7470 - val_loss: 0.0097 - val_accuracy: 0.7467
Epoch 6/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0043
- accuracy: 0.7470 - val_loss: 0.0098 - val_accuracy: 0.7467
Epoch 7/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0042
- accuracy: 0.7470 - val_loss: 0.0097 - val_accuracy: 0.7467
Epoch 8/25
```

```
254/254 [==============================] - 1s 4ms/step - loss: 0.0042
- accuracy: 0.7470 - val_loss: 0.0098 - val_accuracy: 0.7467
Epoch 9/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0041
- accuracy: 0.7470 - val_loss: 0.0098 - val_accuracy: 0.7467
Epoch 10/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0041
- accuracy: 0.7470 - val_loss: 0.0099 - val_accuracy: 0.7467
Epoch 11/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0040
- accuracy: 0.7470 - val_loss: 0.0098 - val_accuracy: 0.7467
Epoch 12/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0039
- accuracy: 0.7470 - val_loss: 0.0098 - val_accuracy: 0.7467
Epoch 13/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0039
- accuracy: 0.7470 - val_loss: 0.0098 - val_accuracy: 0.7467
Epoch 14/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0038
- accuracy: 0.7470 - val_loss: 0.0098 - val_accuracy: 0.7467
Epoch 15/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0038
- accuracy: 0.7470 - val_loss: 0.0099 - val_accuracy: 0.7467
Epoch 16/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0038
- accuracy: 0.7470 - val_loss: 0.0099 - val_accuracy: 0.7467
Epoch 17/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0037
- accuracy: 0.7470 - val_loss: 0.0099 - val_accuracy: 0.7467
Epoch 18/25
254/254 [==============================] - 1s 5ms/step - loss: 0.0037
- accuracy: 0.7470 - val_loss: 0.0099 - val_accuracy: 0.7467
Epoch 19/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0036
- accuracy: 0.7470 - val_loss: 0.0099 - val_accuracy: 0.7467
Epoch 20/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0036
- accuracy: 0.7470 - val_loss: 0.0099 - val_accuracy: 0.7467
Epoch 21/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0035
- accuracy: 0.7470 - val_loss: 0.0099 - val_accuracy: 0.7467
Epoch 22/25
254/254 [==============================] - 1s 4ms/step - loss: 0.0035
- accuracy: 0.7470 - val_loss: 0.0100 - val_accuracy: 0.7467
```

```python
history.params
```

```
{'verbose': 1, 'epochs': 25, 'steps': 254}
```

```python
print(history.epoch)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,
20, 21]
```

Evaluating the model

```
print(model.evaluate(Data_test,Label_test))
print(model.evaluate(Data_val,Label_val))
```

```
32/32 [==============================] - 0s 3ms/step - loss: 0.0162 -
accuracy: 0.7470
[0.01622191071510315, 0.746999979019165]
29/29 [==============================] - 0s 4ms/step - loss: 0.0096 -
accuracy: 0.7467
[0.009633174166083336, 0.746666669845581]
```

Binary Neural Network:

```
Label_val_binary=(Label_val==1).astype(np.float64)
Label_train_binary=(Label_train==1).astype(np.float64)
Label_test_binary=(Label_test==1).astype(np.float64)

tf.keras.backend.clear_session()
tf.random.set_seed(42)
model1 = tf.keras.Sequential()
model1.add(tf.keras.layers.Dense(240,activation="relu",input_dim =
16))
model1.add(tf.keras.layers.Dense(120, activation="relu"))
model1.add(tf.keras.layers.Dense(60, activation="relu"))
model1.add(tf.keras.layers.Dense(30, activation="relu"))
model1.add(tf.keras.layers.Dense(15, activation="relu"))

model1.add(keras.layers.Dense(1,activation='sigmoid'))

model1.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense (Dense)               (None, 240)               4080      

 dense_1 (Dense)             (None, 120)               28920     

 dense_2 (Dense)             (None, 60)                7260      

 dense_3 (Dense)             (None, 30)                1830      

 dense_4 (Dense)             (None, 15)                465       

 dense_5 (Dense)             (None, 1)                 16        
```

```
=================================================================
Total params: 42,571
Trainable params: 42,571
Non-trainable params: 0
_________________________________________________________________
```

```
checkpoint_Binary=keras.callbacks.ModelCheckpoint('model1.h5',save_bes
t_only=True)
model1.compile(loss=
'binary_crossentropy' ,optimizer=tf.keras.optimizers.RMSprop(learning_
rate=0.01,clipnorm=10,momentum=.9),
              metrics=['accuracy'])

history1 = model1.fit(Data_train,Label_train_binary,
epochs=40,callbacks=[checkpoint_Binary,es],validation_data=(Data_val,
Label_val_binary))
```

```
Epoch 1/40
254/254 [==============================] - 3s 6ms/step - loss: 0.0095
- accuracy: 0.9989 - val_loss: 0.0093 - val_accuracy: 0.9989
Epoch 2/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0095
- accuracy: 0.9989 - val_loss: 0.0102 - val_accuracy: 0.9989
Epoch 3/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0098
- accuracy: 0.9989 - val_loss: 0.0089 - val_accuracy: 0.9989
Epoch 4/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0093
- accuracy: 0.9989 - val_loss: 0.0104 - val_accuracy: 0.9989
Epoch 5/40
254/254 [==============================] - 1s 5ms/step - loss: 0.0096
- accuracy: 0.9989 - val_loss: 0.0094 - val_accuracy: 0.9989
Epoch 6/40
254/254 [==============================] - 1s 5ms/step - loss: 0.0100
- accuracy: 0.9989 - val_loss: 0.0092 - val_accuracy: 0.9989
Epoch 7/40
254/254 [==============================] - 1s 5ms/step - loss: 0.0090
- accuracy: 0.9989 - val_loss: 0.0099 - val_accuracy: 0.9989
Epoch 8/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0101
- accuracy: 0.9989 - val_loss: 0.0092 - val_accuracy: 0.9989
Epoch 9/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0089
- accuracy: 0.9989 - val_loss: 0.0092 - val_accuracy: 0.9989
Epoch 10/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0092
- accuracy: 0.9989 - val_loss: 0.0089 - val_accuracy: 0.9989
Epoch 11/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0103
```

```
- accuracy: 0.9989 - val_loss: 0.0098 - val_accuracy: 0.9989
Epoch 12/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0097
- accuracy: 0.9989 - val_loss: 0.0092 - val_accuracy: 0.9989
Epoch 13/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0103
- accuracy: 0.9989 - val_loss: 0.0092 - val_accuracy: 0.9989
Epoch 14/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0094
- accuracy: 0.9989 - val_loss: 0.0090 - val_accuracy: 0.9989
Epoch 15/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0094
- accuracy: 0.9989 - val_loss: 0.0091 - val_accuracy: 0.9989
Epoch 16/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0090
- accuracy: 0.9989 - val_loss: 0.0089 - val_accuracy: 0.9989
Epoch 17/40
254/254 [==============================] - 1s 5ms/step - loss: 0.0092
- accuracy: 0.9989 - val_loss: 0.0090 - val_accuracy: 0.9989
Epoch 18/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0091
- accuracy: 0.9989 - val_loss: 0.0089 - val_accuracy: 0.9989
Epoch 19/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0094
- accuracy: 0.9989 - val_loss: 0.0090 - val_accuracy: 0.9989
Epoch 20/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0092
- accuracy: 0.9989 - val_loss: 0.0098 - val_accuracy: 0.9989
Epoch 21/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0096
- accuracy: 0.9989 - val_loss: 0.0099 - val_accuracy: 0.9989
Epoch 22/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0103
- accuracy: 0.9989 - val_loss: 0.0092 - val_accuracy: 0.9989
Epoch 23/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0088
- accuracy: 0.9989 - val_loss: 0.0094 - val_accuracy: 0.9989
Epoch 24/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0098
- accuracy: 0.9989 - val_loss: 0.0091 - val_accuracy: 0.9989
Epoch 25/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0090
- accuracy: 0.9989 - val_loss: 0.0089 - val_accuracy: 0.9989
Epoch 26/40
254/254 [==============================] - 1s 5ms/step - loss: 0.0093
- accuracy: 0.9989 - val_loss: 0.0095 - val_accuracy: 0.9989
Epoch 27/40
254/254 [==============================] - 1s 5ms/step - loss: 0.0092
- accuracy: 0.9989 - val_loss: 0.0101 - val_accuracy: 0.9989
```

```
Epoch 28/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0104
- accuracy: 0.9989 - val_loss: 0.0096 - val_accuracy: 0.9989
Epoch 29/40
254/254 [==============================] - 1s 4ms/step - loss: 0.0096
- accuracy: 0.9989 - val_loss: 0.0095 - val_accuracy: 0.9989
Epoch 30/40
254/254 [==============================] - 1s 5ms/step - loss: 0.0098
- accuracy: 0.9989 - val_loss: 0.0089 - val_accuracy: 0.9989
```

```
print(model1.evaluate(Data_test,Label_test_binary))
print(model1.evaluate(Data_val,Label_val_binary))
```

```
32/32 [==============================] - 0s 3ms/step - loss: 0.0156 -
accuracy: 0.9980
[0.01564858667552471, 0.9980000257492065]
29/29 [==============================] - 0s 3ms/step - loss: 0.0089 -
accuracy: 0.9989
[0.008852272294461727, 0.9988889098167419]
```

The aaccuracy befor using Binary Neural Network is 0.75 and after using Binary Neural Network, we obtained 0.998 which is better than befor 0.75

```
model.predict(Data_test)
```

```
32/32 [==============================] - 0s 3ms/step
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 ####  Save Classifier
model.save("my_keras_model.h5")
```

Fine-Tuning Neural Network Hyperparameters

```
!pip install keras-tuner
```

```
Collecting keras-tuner
  Downloading keras_tuner-1.4.6-py3-none-any.whl (128 kB)
     ------------------------------------ 128.9/128.9 kB 841.6 kB/s
eta 0:00:00
Requirement already satisfied: requests in c:\users\user\anaconda3\
lib\site-packages (from keras-tuner) (2.28.1)
Requirement already satisfied: keras in c:\users\user\anaconda3\lib\
site-packages (from keras-tuner) (2.11.0)
Requirement already satisfied: packaging in c:\users\user\anaconda3\
lib\site-packages (from keras-tuner) (21.3)
Collecting kt-legacy
  Downloading kt_legacy-1.0.5-py3-none-any.whl (9.6 kB)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\users\
user\anaconda3\lib\site-packages (from packaging->keras-tuner) (3.0.9)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\user\
anaconda3\lib\site-packages (from requests->keras-tuner) (2022.9.14)
Requirement already satisfied: idna<4,>=2.5 in c:\users\user\
anaconda3\lib\site-packages (from requests->keras-tuner) (3.3)
Requirement already satisfied: charset-normalizer<3,>=2 in c:\users\
user\anaconda3\lib\site-packages (from requests->keras-tuner) (2.0.4)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\users\user\
anaconda3\lib\site-packages (from requests->keras-tuner) (1.26.11)
Installing collected packages: kt-legacy, keras-tuner
Successfully installed keras-tuner-1.4.6 kt-legacy-1.0.5
```

```
import keras_tuner as kt
```

```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
def model_builder(hp):
  model=keras.Sequential()
  hp_unit1=hp.Int('u1',min_value=8,max_value=240)
  model.add(keras.layers.Dense(units= hp_unit1,input_dim=16))
  hp_unit2=hp.Int('u2',min_value=120,max_value=240)
  model.add(keras.layers.Dense(units= hp_unit2))
  hp_unit3=hp.Int('u3',min_value=60,max_value=120)
  model.add(keras.layers.Dense(units= hp_unit3))
  hp_unit4=hp.Int('u4',min_value=30,max_value=60)
  model.add(keras.layers.Dense(units= hp_unit4))
  hp_unit5=hp.Int('u5',min_value=15,max_value=30)
  model.add(keras.layers.Dense(units= hp_unit5))
  model.add(keras.layers.Dense(1,activation='sigmoid'))
  l_rate=hp.Choice('learning_rate',values=[.01,.001,.0001])
  cnorm=hp.Choice('clipnorm',values=[10,20,30])
  model.compile(loss=
'binary_crossentropy' ,optimizer=tf.keras.optimizers.RMSprop(learning_
```

```
rate= l_rate,clipnorm=cnorm,momentum=.9),
                       metrics=['accuracy'])
  return model

es2=tf.keras.callbacks.EarlyStopping(monitor='val_accuracy',patience=2
0)

tuner=kt.Hyperband(model_builder,objective='val_accuracy',max_epochs=1
5)
tuner.search(Data_train,Label_train_binary,
epochs=70,validation_data=(Data_val,
Label_val_binary),callbacks=[es2])

Reloading Tuner from .\untitled_project\tuner0.json

best_params =tuner.get_best_hyperparameters(num_trials=1)[0]
print("First Layer : "+str( best_params.get('u1'))+"\nSecond layer: "+
str(best_params.get('u2'))+"\nThird layer:"
+str(best_params.get('u3'))+"\nForth layer:"
+str(best_params.get('u4'))+"\nThe optimal learing rate is:
"+str(best_params.get('learning_rate')))

First Layer : 235
Second layer: 237
Third layer:68
Forth layer:31
The optimal learing rate is: 0.001

final_model=tuner.hypermodel.build(best_params)
mod=final_model.fit(Data_train,Label_train_binary,epochs=40,validation
_data=(Data_val,Label_val_binary),callbacks=[checkpoint_Binary,es2])

Epoch 1/40
254/254 [==============================] - 2s 3ms/step - loss: 0.1042
- accuracy: 0.9851 - val_loss: 0.0344 - val_accuracy: 0.9978
Epoch 2/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0890
- accuracy: 0.9951 - val_loss: 0.0307 - val_accuracy: 0.9967
Epoch 3/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0638
- accuracy: 0.9942 - val_loss: 0.0112 - val_accuracy: 0.9989
Epoch 4/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0317
- accuracy: 0.9983 - val_loss: 0.0215 - val_accuracy: 0.9989
Epoch 5/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0309
- accuracy: 0.9980 - val_loss: 0.0182 - val_accuracy: 0.9989
Epoch 6/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0297
- accuracy: 0.9980 - val_loss: 0.0156 - val_accuracy: 0.9978
Epoch 7/40
```

```
254/254 [==============================] - 1s 3ms/step - loss: 0.0402
- accuracy: 0.9972 - val_loss: 0.0228 - val_accuracy: 0.9989
Epoch 8/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0342
- accuracy: 0.9980 - val_loss: 0.0801 - val_accuracy: 0.9700
Epoch 9/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0301
- accuracy: 0.9984 - val_loss: 0.0165 - val_accuracy: 0.9989
Epoch 10/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0276
- accuracy: 0.9981 - val_loss: 0.0111 - val_accuracy: 0.9989
Epoch 11/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0248
- accuracy: 0.9981 - val_loss: 0.0106 - val_accuracy: 0.9989
Epoch 12/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0271
- accuracy: 0.9981 - val_loss: 0.0183 - val_accuracy: 0.9989
Epoch 13/40
254/254 [==============================] - 0s 2ms/step - loss: 0.0256
- accuracy: 0.9989 - val_loss: 0.0102 - val_accuracy: 0.9989
Epoch 14/40
254/254 [==============================] - 1s 2ms/step - loss: 0.0306
- accuracy: 0.9975 - val_loss: 0.0140 - val_accuracy: 0.9989
Epoch 15/40
254/254 [==============================] - 1s 2ms/step - loss: 0.0245
- accuracy: 0.9975 - val_loss: 0.0104 - val_accuracy: 0.9989
Epoch 16/40
254/254 [==============================] - 1s 2ms/step - loss: 0.0272
- accuracy: 0.9979 - val_loss: 0.0188 - val_accuracy: 0.9989
Epoch 17/40
254/254 [==============================] - 0s 2ms/step - loss: 0.0288
- accuracy: 0.9986 - val_loss: 0.0108 - val_accuracy: 0.9989
Epoch 18/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0288
- accuracy: 0.9986 - val_loss: 0.0144 - val_accuracy: 0.9989
Epoch 19/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0240
- accuracy: 0.9986 - val_loss: 0.0172 - val_accuracy: 0.9989
Epoch 20/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0358
- accuracy: 0.9985 - val_loss: 0.0161 - val_accuracy: 0.9989
Epoch 21/40
254/254 [==============================] - 1s 3ms/step - loss: 0.0238
- accuracy: 0.9974 - val_loss: 0.0133 - val_accuracy: 0.9978
Epoch 22/40
254/254 [==============================] - 1s 2ms/step - loss: 0.0227
- accuracy: 0.9983 - val_loss: 0.0124 - val_accuracy: 0.9989
Epoch 23/40
```

```
254/254 [==============================] - 1s 2ms/step - loss: 0.0248
- accuracy: 0.9981 - val_loss: 0.0227 - val_accuracy: 0.9989
```