```
# Importing required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model selection import train test split
# Import pickle Package
import pickle
1st model - Linear Regression
# Importing the boston.csv dataset
df1 = pd.read csv("Bosto housing.csv")
df1.drop('Unnamed: 0',axis=1,inplace=True)
df1.head()
      rm lstat indus ptratio medv
0
  6.575
         4.98 2.31
                          15.3 24.0
1 6.421 9.14 7.07
                          17.8 21.6
  7.185 4.03
                 7.07
                          17.8 34.7
3 6.998 2.94
                 2.18
                          18.7 33.4
  7.147
          5.33
                 2.18
                          18.7 36.2
# independent & dependent data
X = df1.iloc[:, :-1].values
y = df1.iloc[:, -1].values
# splitting data into trainig & testing data
X train, X test, y train, y test = train test split(X, y,
test size=0.20, random state=42)
# Creating a linear regression model using the linear regression
module from the sklearn library
from sklearn.linear model import LinearRegression
reg = LinearRegression()
reg.fit(X_train,y_train)
LinearRegression()
# Save the LR Model to file in the current working directory
Pkl Filename = "Pickle reg Model.pkl"
with open(Pkl Filename, 'wb') as file:
   pickle.dump(reg, file)
```

## 2nd model - Logistic Regression # Importing the Diabetes.csv dataset df2 = pd.read\_csv("diabetes.csv") df2.head()

	preg	plas	pres	skin	insu	mass	pedi	age	class
0	6	148	72	35	0	33.6	0.627	50	tested_positive
1	1	85	66	29	0	26.6	0.351		tested_negative
2	8	183	64	0	0	23.3	0.672	32	tested_positive
3	1	89	66	23	94	28.1	0.167	21	tested_negative
4	0	137	40	35	168	43.1	2.288	33	tested_positive

This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective is to predict based on diagnostic measurements whether a patient has diabetes.

Several constraints were placed on the selection of these instances from a larger database. In particular, all patients here are females at least 21 years old of Pima Indian heritage.

Number of Instances: 768

Number of Attributes: 8 plus class

## **Attributes:**

Pregnancies: Number of times pregnant

Glucose: Plasma glucose concentration a 2 hours in an oral glucose tolerance test

BloodPressure: Diastolic blood pressure (mm Hg)

SkinThickness: Triceps skin fold thickness (mm)

Insulin: 2-Hour serum insulin (mu U/ml)

BMI: Body mass index (weight in kg/(height in m) $^2$ )

DiabetesPedigreeFunction: Diabetes pedigree function

Age: Age (years)

Outcome: Class variable (0 or 1)

# Assigning the predictor variables to 'x' and response variable to 'y'

```
x = df2.drop('class',axis=1)
y = df2['class']
```

# Using the standard scaler function for scaling the data.

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X = sc.fit transform(x)
```

```
# Splitting the dataset into train and test data.
from sklearn.model selection import train test split
x train,x test,y train,y test =
train_test_split(X,y,test_size=0.3,random_state=30)
# Using the linear model module of sklearn to build a Logistic
Regression model.
from sklearn.linear model import LogisticRegression
logReg = LogisticRegression()
logReg.fit(x_train,y_train)
LogisticRegression()
# Save the LogisticReg Model to file in the current working directory
Pkl Filename = "Pickle LogReg Model.pkl"
with open(Pkl Filename, 'wb') as file:
    pickle.dump(logReg, file)
3rd model - KNN Classifier
# Importing the Iris dataset
df3 = pd.read csv("Iris.csv")
df3.drop('Id',axis=1,inplace =True)
df3.head()
   SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm
Species
             5.1
                            3.5
                                           1.4
                                                          0.2
                                                              Iris-
0
setosa
             4.9
                           3.0
                                           1.4
                                                          0.2
1
                                                              Iris-
setosa
             4.7
                           3.2
                                           1.3
                                                          0.2 Iris-
setosa
             4.6
                           3.1
                                           1.5
                                                          0.2 Iris-
setosa
             5.0
                            3.6
                                           1.4
                                                          0.2 Iris-
setosa
# Assigning the predictor variables to 'x' and response variable to
^{\mathsf{I}}V^{\mathsf{I}}
X = df3.iloc[:,:-1]
Y = df3.iloc[:,-1]
X train,X test,Y train,Y test = train test split(X,Y,test size =
0.2, random_state = 0)
# Building a KNN Classifier using sklearn library.
```

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n neighbors=7)
knn.fit(X_train, Y_train)
KNeighborsClassifier(n neighbors=7)
# Save the KNN Model to file in the current working directory
Pkl Filename = "Pickle knn Model.pkl"
with open(Pkl Filename, 'wb') as file:
    pickle.dump(knn, file)
4th Model - Decision Trees
# Importing the dataset
df4 = pd.read csv("German Credit Data.csv")
df4
                  duration credit_history
    checkin acc
                                             amount savings_acc \
0
            A11
                         6
                                       A34
                                               1169
                                                             A65
                        48
                                       A32
                                               5951
1
            A12
                                                             A61
2
            A14
                        12
                                       A34
                                               2096
                                                             A61
3
            A11
                        42
                                       A32
                                               7882
                                                             A61
4
            A11
                        24
                                       A33
                                               4870
                                                             A61
995
            A14
                        12
                                       A32
                                               1736
                                                             A61
                        30
996
            A11
                                       A32
                                               3857
                                                             A61
                        12
997
            A14
                                       A32
                                                804
                                                             A61
998
            A11
                        45
                                       A32
                                               1845
                                                             A61
999
            A12
                        45
                                       A34
                                               4576
                                                             A62
    present emp since inst rate personal status
                                                     residing since
                                                                       age
\
0
                   A75
                                 4
                                                A93
                                                                   4
                                                                       67
1
                   A73
                                 2
                                                A92
                                                                   2
                                                                        22
2
                                 2
                   A74
                                                                   3
                                                                        49
                                                A93
                                 2
3
                   A74
                                                A93
                                                                   4
                                                                        45
                                 3
4
                   A73
                                                A93
                                                                   4
                                                                        53
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                   . . .
                               . . .
                                                . . .
                                                                  . . .
                                                                       . . .
995
                   A74
                                                A92
                                                                        31
                                 3
                                                                   4
996
                   A73
                                 4
                                                A91
                                                                   4
                                                                        40
997
                   A75
                                 4
                                                A93
                                                                   4
                                                                        38
```

```
998
                  A73
                               4
                                             A93
                                                                    23
999
                  A71
                               3
                                             A93
                                                                4
                                                                    27
    inst plans num credits
                             job status
0
          A143
                          2 A173
1
          A143
                          1
                            A173
                                        1
2
          A143
                          1
                            A172
                                        0
3
                                        0
          A143
                          1
                            A173
4
                                        1
          A143
                          2 A173
          . . .
                             . . .
. .
                        . . .
                                       . . .
995
                            A172
          A143
                          1
                                        0
996
         A143
                          1 A174
                                        0
997
         A143
                                        0
                          1 A173
                                        1
998
         A143
                          1 A173
999
          A143
                          1 A173
                                        0
[1000 rows x 14 columns]
# Select the categorical columns and use Label Encoder for encoding
the categorical values to numerical.
cat cols = df4.select dtypes(include = ['object']).copy()
cat cols.columns
from sklearn.preprocessing import LabelEncoder
for i in cat cols.columns:
    df4[i] = LabelEncoder().fit transform(df4[i])
# Splitting predictor and response variables
X = df4.drop(columns = ['status'],axis = 1)
v = df4.status
# splitting the dataset into train and test datasets
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size =
0.2, random state = 42)
# Building a decision tree model
# Importing decisiontree classifier and gridsearchev modules from
sklearn
from sklearn.model selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
# configuring the gridsearch again to print all the evaluation metrics
tree_para = {'criterion':['gini','entropy'],'max_depth':np.arange(2,
11)}
grid search cv = GridSearchCV(DecisionTreeClassifier(random state =
```

```
42), tree para, cv = 10, scoring='roc auc')
grid_search_cv.fit(X_train,y_train)
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(random state=42),
             param grid={'criterion': ['gini', 'entropy'],
                          'max_depth': array([ 2, 3, 4, 5, 6, 7,
8, 9, 10])},
             scoring='roc auc')
# Save the DT Model to file in the current working directory
Pkl Filename = "Pickle deciTree Model.pkl"
with open(Pkl Filename, 'wb') as file:
    pickle.dump(grid search cv, file)
5th Model - Multi Layer Perceptron (NN)
# importing the wine dataset
df5 = pd.read csv("wine.csv")
df5.head()
   Class Alcohol
                   Malic acid
                                 Ash
                                      Alcalinity of ash
                                                          Magnesium
0
            14.23
                          1.71
                                2.43
       1
                                                    15.6
                                                                127
1
       1
            13.20
                         1.78
                                2.14
                                                    11.2
                                                                100
2
       1
            13.16
                         2.36
                                2.67
                                                    18.6
                                                                101
3
            14.37
       1
                         1.95
                               2.50
                                                    16.8
                                                                113
4
       1
            13.24
                         2.59 2.87
                                                   21.0
                                                                118
   Total phenols Flavanoids
                              Nonflavanoid phenols Proanthocyanins
0
            2.80
                        3.06
                                               0.28
                                                                 2.29
                                               0.26
1
            2.65
                        2.76
                                                                 1.28
2
            2.80
                        3.24
                                               0.30
                                                                 2.81
3
            3.85
                        3.49
                                               0.24
                                                                 2.18
4
            2.80
                        2.69
                                               0.39
                                                                 1.82
   Color intensity
                     Hue
                          OD280/OD315 of diluted wines
                                                          Proline
0
                                                   3.92
              5.64
                    1.04
                                                              1065
1
              4.38
                    1.05
                                                   3.40
                                                              1050
2
                                                    3.17
              5.68
                    1.03
                                                              1185
3
              7.80
                    0.86
                                                   3.45
                                                              1480
              4.32 1.04
                                                   2.93
                                                               735
```

## Title of Database: Wine recognition data

These data are the results of a chemical analysis of wines grown in the same region in Italy but derived from three different cultivars. The analysis determined the quantities of 13 constituents found in each of the three types of wines.

## The 13 attributes are

1) Alcohol

```
2) Malic acid
3) Ash
4) Alcalinity of ash
5) Magnesium
6) Total phenols
7) Flavanoids
8) Nonflavanoid phenols
9) Proanthocyanins
10)Color intensity
11)Hue
12)OD280/OD315 of diluted wines
13)Proline
Number of Instances
class 1 59
class 2 71
class 3 48
#Convert variable to categorical.
df5.Class=df5.Class.astype('category')
#Splitting the predictor & response variables
X = df5.drop(columns = ['Class'],axis =1)
v = df5.Class
from sklearn.preprocessing import StandardScaler
X = StandardScaler().fit_transform(X)
# Spliting of the dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X,y,
test size=0.3, random state = 42)
# Importing Multi-Layer Perceptron Classifier model
from sklearn.neural network import MLPClassifier
#Create a MLP Classifier with 3 layers
```

model = MLPClassifier(hidden\_layer\_sizes=(13,13,13),
activation='relu', max iter=500,learning rate init=0.5)