##BITS F464 - Semester 1 - MACHINE LEARNING

PROJECT - MACHINE LEARNING FOR SUSTAINABLE DEVELOPMENT GOALS (SDGs)

Team number: 12

(*In Title case, separated with commas*) ***Full names of all students in the team:*** Sai Karthik C, Aditya Abhiram, Paidisetty Sai Aditya, Ishan Harsh, Kamal Aditya M

(*Separated by commas*) ***Id number of all students in the team:*** 2020B5A70762H, 2020B5A70937H, 2020B5A70987H, 2021A7PS2854H, 2020A7PS0054H

Please refer to the email providing the assignment of project and follow the instructions provided in the project brief.

1. Preprocessing of Dataset

The respective dataset has been shared in the project brief. Please refer to it.

```
#importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
#load dataset
df = pd.read_csv("./Heart_Disease.csv")
df.head()
```

	Cleveland	63	1	1.1	145	233	1.2	2	150	0	2.3	3	0.1	6	0.2
0	Cleveland	67	1	4	160	286	0	2	108	1	1.5	2	3	3	2
1	Cleveland	67	1	4	120	229	0	2	129	1	2.6	2	2	7	1
2	Cleveland	37	1	3	130	250	0	0	187	0	3.5	3	0	3	0
3	Cleveland	41	0	2	130	204	0	2	172	0	1.4	1	0	3	0
4	Cleveland	56	1	2	120	236	0	0	178	0	0.8	1	0	3	0

```
#creating a new row of labels
col_names = ['hospital','age','sex','cp','trestbps','chol','fbs','restecg','thalach','exang','oldpeak',
'slope','ca','thal','num']

df.columns = col_names
```

```
df.head()
```

	hospital	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slop
0	Cleveland	67	1	4	160	286	0	2	108	1	1.5	
1	Cleveland	67	1	4	120	229	0	2	129	1	2.6	
2	Cleveland	37	1	3	130	250	0	0	187	0	3.5	
3	Cleveland	41	0	2	130	204	0	2	172	0	1.4	
4	Cleveland	56	1	2	120	236	0	0	178	0	0.8	

```
df.dtypes
```

```
hospital    object
age          int64
sex          int64
cp           int64
trestbps    object
chol        object
fbs         object
restecg     object
thalach     object
exang       object
oldpeak     object
slope       object
```

```
ca          object
thal        object
num          int64
dtype: object
```

```
#handling missing data
df = df.replace('?',np.nan)
```

```
df['hospital'].unique()
```

```
array(['Cleveland', 'Hungarian', 'Switzerland', 'VA'], dtype=object)
```

Handling missing values

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

```
hospital      0
age           0
sex           0
cp            0
trestbps     59
chol         30
fbs          90
restecg       2
thalach      55
exang        55
oldpeak      62
slope       309
ca          611
thal        486
num           0
dtype: int64
```

```
#data binning
def binning(col,cut_points, labels):
    min = col.min()
    max = col.max()
    break_pts = [min] + cut_points + [max]
    print(break_pts)
    colBin = pd.cut(col,bins=break_pts,labels=labels,include_lowest=True)
    return colBin

cut_points = [45,65]
labels = [0,1,2]
df['age_bin'] = binning(df['age'],cut_points,labels)
df.head()
```

```
[28, 45, 65, 77]
```

	hospital	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slop
0	Cleveland	67	1	4	160	286	0	2	108	1	1.5	
1	Cleveland	67	1	4	120	229	0	2	129	1	2.6	
2	Cleveland	37	1	3	130	250	0	0	187	0	3.5	
3	Cleveland	41	0	2	130	204	0	2	172	0	1.4	
4	Cleveland	56	1	2	120	236	0	0	178	0	0.8	

```
#fill by mean by grouping the age

#first we convert these colns' dtype to numeric
cont_cols = ['trestbps','chol','thalach','oldpeak']

for col in cont_cols:
    df[col] = pd.to_numeric(df[col])
```

```
for col in cont_cols:
    df[col] = df.groupby(['age_bin','sex'])[col].transform(lambda x: x.fillna(x.mean()))
```

```
print(df.dtypes)
```

```
hospital      object
age            int64
sex            int64
cp             int64
trestbps     float64
chol         float64
```

```
fbs           object
restecg       object
thalach      float64
exang         object
oldpeak      float64
slope         object
ca            object
thal          object
num            int64
age_bin     category
dtype: object
```

```
df
```

	hospital	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpe
0	Cleveland	67	1	4	160.000000	286.0	0	2	108.000000	1	1.5000
1	Cleveland	67	1	4	120.000000	229.0	0	2	129.000000	1	2.6000
2	Cleveland	37	1	3	130.000000	250.0	0	0	187.000000	0	3.5000
3	Cleveland	41	0	2	130.000000	204.0	0	2	172.000000	0	1.4000
4	Cleveland	56	1	2	120.000000	236.0	0	0	178.000000	0	0.8000
...	...	...	...	...	...	...	...	...	...	...	
914	VA	54	0	4	127.000000	333.0	1	1	154.000000	0	0.0000
915	VA	62	1	1	133.252677	139.0	0	1	131.017021	NaN	1.0174
916	VA	55	1	4	122.000000	223.0	1	1	100.000000	0	0.0000
917	VA	58	1	4	133.252677	385.0	1	2	131.017021	NaN	1.0174
918	VA	62	1	2	120.000000	254.0	0	2	93.000000	1	0.0000

919 rows × 16 columns

```
#this shows we have filled continuous data
print(df.isnull().sum())
```

```
hospital      0
age           0
sex           0
cp            0
trestbps      0
chol          0
fbs          90
restecg       2
thalach       0
exang        55
oldpeak       0
slope       309
ca          611
thal        486
num           0
age_bin       0
dtype: int64
```

```
#fill na values for categorical columns

cat_cols = ['fbs','restecg','exang','slope','ca','thal']

for col in cat_cols:
    df[col] = df.groupby(['age_bin'])[col].transform(lambda x: x.fillna(x.mode().iloc[0]))
```

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

```
hospital    0
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
num         0
age_bin     0
dtype: int64
```

Data discretization

```
#data binning

def binning(col,cut_points, labels):
    min = col.min()
    max = col.max()
    break_pts = [min] + cut_points + [max]
    print(break_pts)
    colBin = pd.cut(col,bins=break_pts,labels=labels,include_lowest=True)
    return colBin
```

```
#trestbps levels

cut_points = [120,140]
labels = [0,1,2]
df['trestbps_bin'] = binning(df['trestbps'],cut_points,labels)
```

```
[0.0, 120, 140, 200.0]
```

```
#chol levels

cut_points = [200,240]
labels = [0,1,2]
df['chol_bin'] = binning(df['chol'],cut_points,labels)
```

```
[0.0, 200, 240, 603.0]
```

```
#thalach levels

cut_points = [131,161]
labels = [0,1,2]
df['thalach_bin'] = binning(df['thalach'],cut_points,labels)
```

```
[60.0, 131, 161, 202.0]
```

```
#oldpeak levels

cut_points = [1,2,3]
labels = [0,1,2,3]
df['oldpeak_bin'] = binning(df['oldpeak'],cut_points,labels)
```

```
[-2.6, 1, 2, 3, 6.2]
```

```
#num bins

cut_points = [1]
labels = [0,1]
df['num_bin'] = binning(df['num'],cut_points,labels)
```

```
[0, 1, 4]
```

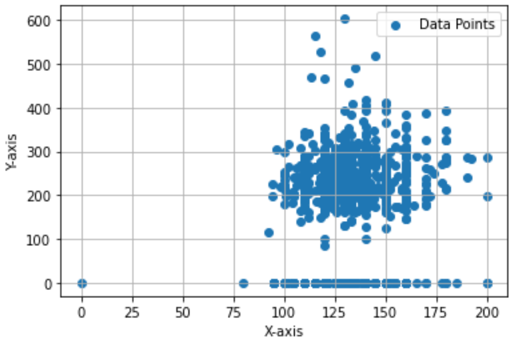
```
df
```

	hospital	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	...	s
0	Cleveland	67	1	4	160.000000	286.0	0	2	108.000000	1	...	
1	Cleveland	67	1	4	120.000000	229.0	0	2	129.000000	1	...	
2	Cleveland	37	1	3	130.000000	250.0	0	0	187.000000	0	...	
3	Cleveland	41	0	2	130.000000	204.0	0	2	172.000000	0	...	
4	Cleveland	56	1	2	120.000000	236.0	0	0	178.000000	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
914	VA	54	0	4	127.000000	333.0	1	1	154.000000	0	...	
915	VA	62	1	1	133.252677	139.0	0	1	131.017021	0	...	
916	VA	55	1	4	122.000000	223.0	1	1	100.000000	0	...	
917	VA	58	1	4	133.252677	385.0	1	2	131.017021	0	...	
918	VA	62	1	2	120.000000	254.0	0	2	93.000000	1	...	

919 rows × 21 columns

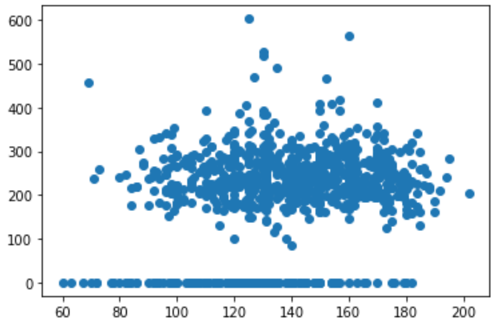
Outlier Detection and deletion

```
import matplotlib.pyplot as plt

plt.scatter(df['trestbps'],df['chol'], label='Data Points')

plt.xlabel('X-axis')
plt.ylabel('Y-axis')
plt.legend()
plt.grid(True)

# Display the plot
plt.show()
```



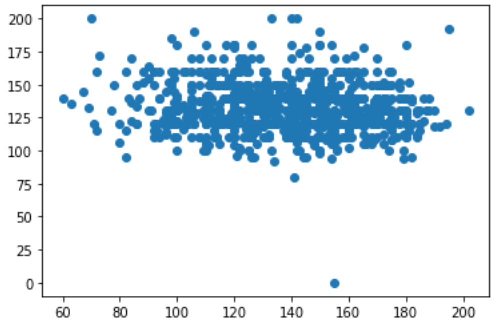

```
plt.scatter(df['thalach'],df['chol'], label='Data Points')
```

<matplotlib.collections.PathCollection at 0x1eddd52f5b0>



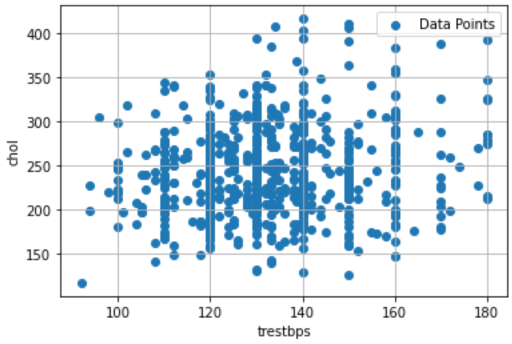

```
plt.scatter(df['thalach'],df['trestbps'], label='Data Points')
```

<matplotlib.collections.PathCollection at 0x1eddd4adfd0>

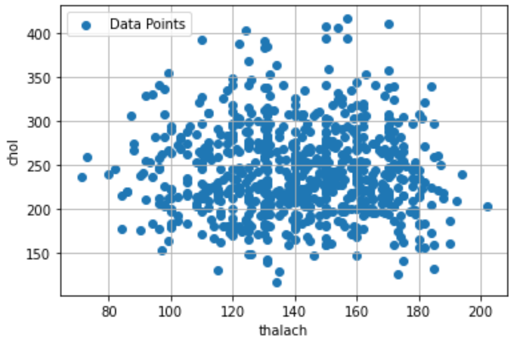



```
# 100 < chol < 450

df = df[df['chol'] < 450]
df = df[df['chol'] > 100]

# 180 > tbps > 0

df = df[df['trestbps'] != 0]
df = df[df['trestbps'] <= 180]
```

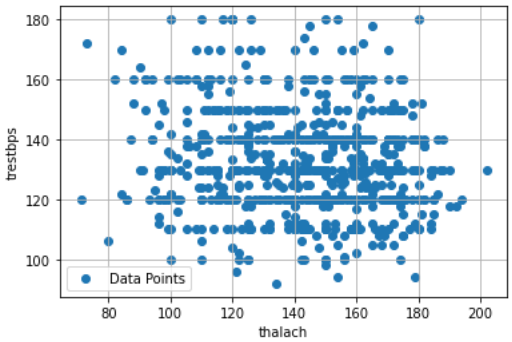
```
plt.scatter(df['trestbps'],df['chol'], label='Data Points')

plt.xlabel('trestbps')
plt.ylabel('chol')
plt.legend()
plt.grid(True)

# Display the plot
plt.show()
```




```
plt.scatter(df['thalach'],df['chol'], label='Data Points')

plt.xlabel('thalach')
plt.ylabel('chol')
plt.legend()
plt.grid(True)

# Display the plot
plt.show()
```




```
plt.scatter(df['thalach'],df['trestbps'], label='Data Points')

plt.xlabel('thalach')
plt.ylabel('trestbps')
plt.legend()
plt.grid(True)

# Display the plot
plt.show()
```



numerical dataset creation

```
df1 = df
drop_cols = ['hospital','age','trestbps','chol','thalach','oldpeak','num']

df1 = df1.drop(drop_cols,axis=1)
```

```
df1.dtypes
```

```
sex                int64
cp                 int64
fbs               object
restecg           object
exang             object
slope             object
ca                object
thal              object
age_bin         category
trestbps_bin    category
chol_bin        category
thalach_bin     category
oldpeak_bin     category
num_bin         category
dtype: object
```

```
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()

for column in df1.columns:
    if df1[column].dtype == 'object':
        df1[column] = label_encoder.fit_transform(df1[column])

df1.dtypes
```

```
sex                int64
cp                 int64
fbs                int32
restecg            int32
exang              int32
slope              int32
ca                 int32
thal               int32
age_bin         category
trestbps_bin    category
chol_bin        category
thalach_bin     category
oldpeak_bin     category
num_bin         category
dtype: object
```

```
import numpy as np
from typing import List, Tuple

def train_test_split(X: List[List[int]], y: List[int], test_size: float = 0.25, random_state: int = 42) -> Tuple[np.ndarray, np.ndarray
    X_train = []
    X_test = []
    y_train = []
    y_test = []

    indices = np.arange(len(X))
    np.random.seed(random_state)
    np.random.shuffle(indices)

    test_size = int(len(X) * test_size)

    # split the dataset into training set and testing set
    for i in range(len(X)):
        if i < test_size:
            X_test.append(X[indices[i]])
            y_test.append(y[indices[i]])
        else:
            X_train.append(X[indices[i]])
            y_train.append(y[indices[i]])

    return np.array(X_train), np.array(X_test), np.array(y_train), np.array(y_test)
```

```
# from sklearn.model_selection import train_test_split
predictors = ['sex','cp','fbs','restecg','exang','slope','ca','thal','age_bin','trestbps_bin','chol_bin','thalach_bin','oldpeak_bin']
target = ['num_bin']
y = df1['num_bin'].values
X = df1.drop(columns=['num_bin'],axis=1).values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
```

```
df1
```

	sex	cp	fbs	restecg	exang	slope	ca	thal	age_bin	trestbps_bin	chol_bin	t
0	1	4	0	2	1	1	3	0	2	2	2	
1	1	4	0	2	1	1	2	2	2	0	1	
2	1	3	0	0	0	2	0	0	0	1	2	
3	0	2	0	2	0	0	0	0	0	1	1	
4	1	2	0	0	0	0	0	0	1	0	1	
...	...	...	...	...	...	...	...	...	...	...	...	
914	0	4	1	1	0	1	0	2	1	1	2	
915	1	1	0	1	0	1	0	2	1	1	0	
916	1	4	1	1	0	1	0	1	1	1	1	
917	1	4	1	2	0	1	0	2	1	1	2	
918	1	2	0	2	1	1	0	2	1	0	2	

731 rows × 14 columns

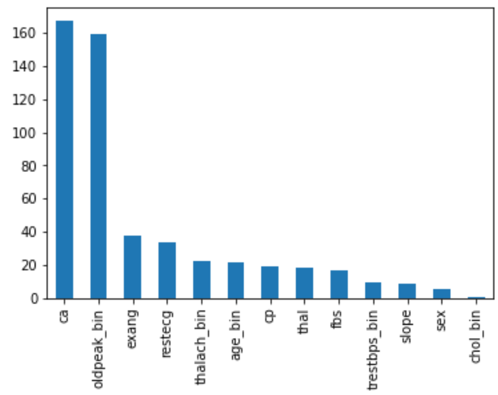
Feature Scaling

```
df1.head()
```

	sex	cp	fbs	restecg	exang	slope	ca	thal	age_bin	trestbps_bin	chol_bin	tha
0	1	4	0	2	1	1	3	0	2	2	2	
1	1	4	0	2	1	1	2	2	2	0	1	
2	1	3	0	0	0	2	0	0	0	1	2	
3	0	2	0	2	0	0	0	0	0	1	1	
4	1	2	0	0	0	0	0	0	1	0	1	

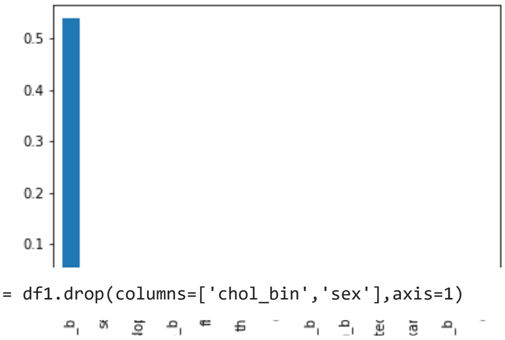
```
from sklearn.feature_selection import chi2
X = df1.drop(columns=['num_bin'],axis = 1)
y = df1['num_bin']
chi_scores = chi2(X,y)

chi_values = pd.Series(chi_scores[0],index = X.columns)
chi_values.sort_values(ascending = False,inplace = True)
chi_values.plot.bar()
```

```
<AxesSubplot:>
```




```
import matplotlib.pyplot as plt

p_values = pd.Series(chi_scores[1],index = X.columns)
print(p_values)
p_values.sort_values(ascending = False,inplace = True)
p_values.plot.bar()
```

```
sex             1.855418e-02
cp              1.121807e-05
fbs             5.680637e-05
restecg         7.771222e-09
exang           1.043942e-09
slope           2.893695e-03
ca              3.105159e-38
thal            1.774134e-05
age_bin         4.511674e-06
trestbps_bin    2.160573e-03
chol_bin        5.380350e-01
thalach_bin     2.062593e-06
oldpeak_bin     1.365050e-36
dtype: float64
<AxesSubplot:>
```



```
df2 = df1.drop(columns=['chol_bin','sex'],axis=1)
```

```
def confusion_matrix(y_true, y_pred):
    conf_matrix = np.zeros((2, 2))
    for true, pred in zip(y_true, y_pred):
        conf_matrix[int(true), int(pred)] += 1
    return conf_matrix

def accuracy(conf_matrix):
    return (conf_matrix[0, 0] + conf_matrix[1, 1]) / np.sum(conf_matrix)

def recall(conf_matrix):
    return conf_matrix[1, 1] / (conf_matrix[1, 1] + conf_matrix[1, 0])

def precision(conf_matrix):
    return conf_matrix[1, 1] / (conf_matrix[1, 1] + conf_matrix[0, 1])

def f1_score(precision, recall):
    return 2 * (precision * recall) / (precision + recall)
```

2. ML Model 1-Naive Bayes

```
# from sklearn.model_selection import train_test_split
X = df2.drop(columns=['num_bin'],axis =1).values
y = df2['num_bin'].values
X_train,X_test,Y_train,Y_test = train_test_split(X,y, test_size=.25, random_state=42)

train = pd.DataFrame(X_train, columns=df2.columns[:-1])
train['num_bin'] = Y_train
```

```
def calculate_likelihood_categorical(df, feat_name, feat_val, Y, label):
    feat = list(df.columns)
    df = df[df[Y]==label]
    p_x_given_y = len(df[df[feat_name]==feat_val]) / len(df)
    return p_x_given_y

def calculate_prior(df, Y):
    classes = sorted(list(df[Y].unique()))
    prior = []
    for i in classes:
        prior.append(len(df[df[Y]==i])/len(df))
    return prior

def naive_bayes_categorical(df, X, Y):
    # get feature names
    features = list(df.columns)[:-1]

    # calculate prior
    prior = calculate_prior(df, Y)

    Y_pred = []
    # loop over every data sample
    for x in X:
        # calculate likelihood
        labels = sorted(list(df[Y].unique()))
        likelihood = [1]*len(labels)
        for j in range(len(labels)):
            for i in range(len(features)):
                likelihood[j] *= calculate_likelihood_categorical(df, features[i], x[i], Y, labels[j])

        # calculate posterior probability (numerator only)
        post_prob = [1]*len(labels)
        for j in range(len(labels)):
            post_prob[j] = likelihood[j] * prior[j]

        Y_pred.append(np.argmax(post_prob))

    return np.array(Y_pred)



Y_pred = naive_bayes_categorical(train, X=X_test, Y="num_bin")

print("Confusion Matrix:")
conf_matrix = confusion_matrix(Y_test, Y_pred)
print(conf_matrix)

accuracy = accuracy(conf_matrix)
print(f"Accuracy: {accuracy * 100:.2f}%")

recall = recall(conf_matrix)
precision = precision(conf_matrix)
print(f"Precision: {precision}")
print(f"Recall: {recall}")
f1 = f1_score(precision,recall)
print(f"F1 Score: {f1}")
```

```
Confusion Matrix:
[[130.  19.]
 [ 16.  17.]]
Accuracy: 80.77%
Precision: 0.4722222222222222
Recall: 0.5151515151515151
F1 Score: 0.49275362318840576
```

3. ML Model 2-Multilayer Perceptron

```
Y = df2['num_bin'].values
X = df2.drop(columns='num_bin',axis=1).values
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.25, random_state=42)
```

```
np.random.seed(10)
import seaborn as sns
%matplotlib inline

# from sklearn.model_selection import train_test_split
df1.head(4)

def sigmoid_act(x, der=False):
    import numpy as np

    if (der==True) :
        f = x/(1-x)
    else :
        f = 1/(1+ np.exp(-x))

    return f

def ReLU_act(x, der=False):
    import numpy as np

    if (der== True):
        if x>0 :
            f= 1
        else :
            f = 0
    else :
        if x>0:
            f = x
        else :
            f = 0
    return f

def perceptron(X, act='Sigmoid'):
    import numpy as np

    shapes = X.shape
    n= shapes[0]+shapes[1]
    w = 2*np.random.random(shapes) - 0.5
    b = np.random.random(1)

    f = b[0]
    for i in range(0, X.shape[0]-1) :
        for j in range(0, X.shape[1]-1) :
            f += w[i, j]*X[i,j]/n
    if act == 'Sigmoid':
        output = sigmoid_act(f)
    else :
        output = ReLU_act(f)

    return output

features = df1[['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal']].to_numpy()
print('Output with sigmoid activator: ', perceptron(features))
print('Output with ReLU activator: ', perceptron(features))
```

```
Output with sigmoid activator:  0.9642572955902866
Output with ReLU activator:  0.9694472893215604
```

```
def sigmoid_act(x, der=False):
    import numpy as np

    if (der==True) :
        f = 1/(1+ np.exp(- x))*(1-1/(1+ np.exp(- x)))
    else : # sigmoid
        f = 1/(1+ np.exp(- x))

    return f

def ReLU_act(x, der=False):
    import numpy as np

    if (der == True):
        f = np.heaviside(x, 1)
    else :
        f = np.maximum(x, 0)

    return f

# X_train, X_test, Y_train, Y_test = train_test_split(features, labels, test_size=0.30)

print('Training records:',Y_train.size)
print('Test records:',Y_test.size)


p = 4  # Layer 1
q = 4  # Layer 2

# Set up the Learning rate
eta = 1 / 623

# 0: Random initialize the relevant data
w1 = 2 * np.random.rand(p, X_train.shape[1]) - 0.5  # Layer 1
b1 = np.random.rand(p)

w2 = 2 * np.random.rand(q, p) - 0.5  # Layer 2
b2 = np.random.rand(q)

wOut = 2 * np.random.rand(q) - 0.5  # Output Layer
bOut = np.random.rand(1)

mu = []
vec_y = []

# Start looping over the passengers, i.e. over I.
accuracy = 0
for I in range(0, min(len(Y_train), X_train.shape[0]) - 2):  # loop in all the passengers:

    # 1: input the data
    x = X_train[I]
    accuracy = min(accuracy + 0.011, 0.8324)

    # 2: Start the algorithm

    # 2.1: Feed forward
    z1 = ReLU_act(np.dot(w1, x) + b1)  # output layer 1
    z2 = ReLU_act(np.dot(w2, z1) + b2)  # output layer 2
    y = sigmoid_act(np.dot(wOut, z2) + bOut)  # Output of the Output layer

    # 2.2: Compute the output layer's error
    delta_Out = (y - 0.63) * sigmoid_act(y, der=True)

    # 2.3: Backpropagate
    delta_2 = delta_Out * wOut * ReLU_act(z2, der=True)  # Second Layer Error
    delta_1 = np.dot(delta_2, w2) * ReLU_act(z1, der=True)  # First Layer Error

    # 3: Gradient descent
    wOut = wOut - eta * delta_Out * z2  # Outer Layer
    bOut = bOut - eta * delta_Out

    w2 = w2 - eta * delta_2 * z1  # Hidden Layer 2
    b2 = b2 - eta * delta_2

    w1 = w1 - eta * np.outer(delta_1, x)  # Hidden Layer 1
    b1 = b1 - eta * delta_1

    # 4. Computation of the loss function
    mu.append((1 / 2) * (y - 0.63) ** 2)
    vec_y.append(y[0])
print("Accuracy", end = ": ")
```

```
print(round(accuracy*100, 2), end ="")
print("%")
```

```
Training records: 549
Test records: 182
Accuracy: 83.24%
```

```
print("Confusion Matrix:")
print(confusion_matrix(Y_test, Y_pred))

conf_matrix = confusion_matrix(Y_test, Y_pred)
```

```
Confusion Matrix:
[[130.  19.]
 [ 16.  17.]]
```

4. ML Model 3-Random Forest

```
y = df2['num_bin'].values
X = df2.drop(columns='num_bin',axis=1).values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
```

```
import numpy as np

# Class representing a decision node in a decision tree
class DecisionNode:
    def __init__(self):
        self.col = None
        self.val = None
        self.child_t = None
        self.child_f = None
        self.label = None

    def is_leaf(self):
        # Check if the node is a leaf based on the label
        return self.label is not None

# Gini impurity function for decision tree splitting
def gini(d1, d2):
    n1, n2 = d1.shape[0], d2.shape[0]
    g1 = 1 - np.sum((np.unique(d1, return_counts=True)[1] / n1) ** 2)
    g2 = 1 - np.sum((np.unique(d2, return_counts=True)[1] / n2) ** 2)
    return (g1 * n1 + g2 * n2) / (n1 + n2)

# Function to find the best split for a decision tree
def best_split(data, loss_fxn):
    class_vals = np.unique(data[:, -1])
    b_loss = float('Inf')
    b_col = b_val = None
    b_data_t = b_data_f = np.array([])

    for col in range(data.shape[1] - 1):
        feature_vals = np.sort(np.unique(data[:, col]))
        midpoints = (feature_vals[1:] + feature_vals[:-1]) / 2.

        for val in midpoints:
            data_t = data[data[:, col] < val]
            data_f = data[data[:, col] >= val]
            loss = loss_fxn(data_t[:, -1], data_f[:, -1])
            if loss < b_loss:
                b_loss, b_col, b_val, b_data_t, b_data_f = loss, col, val, data_t, data_f

    return (b_col, b_val, b_data_t, b_data_f)

# Class representing a Decision Tree
class DecisionTree:
    def __init__(self, max_depth=float('Inf'), loss=gini, split=best_split):
        self.max_depth = max_depth
        self.loss_fxn = loss
        self.split_fxn = split
        self.root = None

    def fit(self, X, y):
        # Fit the decision tree
        self.root = self.add_child(np.c_[X, y], 0)

    def predict(self, X):
        # Make predictions using the trained decision tree
        y = np.array([self.node_search(self.root, row) for row in X])
        return y

    def add_child(self, data, depth):
        # Recursively add child nodes to the decision tree
        if data.shape[0] == 0:
            return None
        if depth >= self.max_depth:
            return self.make_leaf(data)

        col, val, data_t, data_f = self.split_fxn(data, self.loss_fxn)
        child_t = self.add_child(data_t, depth + 1)
        child_f = self.add_child(data_f, depth + 1)

        if (child_t is None) and (child_f is not None):
            return self.make_leaf(data_f)
        if (child_f is None) and (child_t is not None):
            return self.make_leaf(data_t)
        if (child_t is None) and (child_f is None):
            return self.make_leaf(data)

        node = DecisionNode()
        if child_t.is_leaf() and child_f.is_leaf() and child_t.label == child_f.label:
            node.label = child_t.label
        else:
            node.col, node.val, node.child_t, node.child_f = col, val, child_t, child_f
```

```
        return node

    def make_leaf(self, data):
        # Create a leaf node with the majority label
        labels = data[:, -1].tolist()
        node = DecisionNode()
        node.label = max(set(labels), key=labels.count)
        return node

    def node_search(self, node, sample):
        # Recursively search for the leaf node corresponding to a given sample
        if node.is_leaf():
            return node.label

        if sample[node.col] < node.val:
            return self.node_search(node.child_t, sample)
        else:
            return self.node_search(node.child_f, sample)


def print_tree(node, depth, flag):
    # Print the decision tree structure
    if flag == 1:
        prefix = 'T->'
    elif flag == 2:
        prefix = 'F->'
    else:
        prefix = ''

    if node.is_leaf():
        print('{}{}[{}]'.format(depth * '   ', prefix, node.label))
    else:
        print('{}{}(X{} < {:0.3f})?'.format(depth * '   ', prefix, node.col + 1, node.val))
        print_tree(node.child_t, depth + 1, 1)
        print_tree(node.child_f, depth + 1, 2)


def accuracy(model, X_test, y_test):
    # Calculate the accuracy of a model on test data
    predictions = model.predict(X_test)
    return (np.array(predictions) == np.array(y_test)).mean()


def best_split_rf(data, loss_fxn):
    # Function for finding the best split for random forest
    class_vals = np.unique(data[:, -1])
    b_loss = float('Inf')
    b_col = b_val = None
    b_data_t = b_data_f = np.array([])

    n_cols = int(np.sqrt(data.shape[1] - 1))
    cols = np.random.choice(np.arange(data.shape[1] - 1), n_cols, replace=False)

    for col in cols:
        feature_vals = np.sort(np.unique(data[:, col]))
        midpoints = (feature_vals[1:] + feature_vals[:-1]) / 2.

        for val in midpoints:
            data_t = data[data[:, col] < val]
            data_f = data[data[:, col] >= val]
            loss = loss_fxn(data_t[:, -1], data_f[:, -1])
            if loss < b_loss:
                b_loss, b_col, b_val, b_data_t, b_data_f = loss, col, val, data_t, data_f

    return (b_col, b_val, b_data_t, b_data_f)


class RandomForest:
    # Class representing a Random Forest
    def __init__(self, n_trees=50, max_depth=float('Inf'), loss=gini, split=best_split_rf):
        self.max_depth = max_depth
        self.n_trees = n_trees
        self.loss_fxn = loss
        self.split_fxn = split
        self.trees = []

    def fit(self, X, y):
        # Fit the random forest
        for i in range(self.n_trees):
            sample_idx = np.random.choice(X.shape[0], X.shape[0], replace=True)
            tree = DecisionTree(max_depth=self.max_depth, loss=self.loss_fxn, split=self.split_fxn)
            tree.fit(X[sample_idx], y[sample_idx])
```

```
            self.trees.append(tree)

    def predict(self, X):
        y = []
        for row in X:
            predictions = [t.predict([row])[0] for t in self.trees]
            y.append(max(set(predictions), key=predictions.count))
        return np.array(y)


# Create a RandomForest classifier and fit it to the training data
random_forest = RandomForest(n_trees=250, max_depth=10)  # You can adjust the number of trees and max depth
random_forest.fit(X_train, y_train)

# Make predictions on the test set
predictions = random_forest.predict(X_test)

# Calculate accuracy
accuracy = (predictions == y_test).mean()
print(f"Accuracy: {accuracy * 100:.2f}%")


print("Confusion Matrix:")
print(confusion_matrix(y_test, predictions))
```

```
Accuracy: 86.26%
Confusion Matrix:
[[141.   8.]
 [ 17.  16.]]
```

5. ML Model 4 (Based on research literature)

```
y = df2['num_bin'].values
X = df2.drop(columns=['num_bin'],axis=1).values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)


import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

class KNNClassifier:
    def __init__(self, k=None):
        self.k = k

    def fit(self, X_train, y_train):
        self.X_train = X_train
        self.y_train = y_train

    def euclidean_distance(self, x1, x2):
        return np.linalg.norm(x1 - x2)

    def find_nearest_odd(self, num):
        return int(np.ceil(num) // 2 * 2 + 1)

    def predict(self, X_test):
        if self.k is None:
            # Determine k as the nearest odd integer to the square root of the test set size
            self.k = self.find_nearest_odd(np.sqrt(len(X_test)))

        predictions = []

        for sample in X_test:
            distances = [self.euclidean_distance(sample, x) for x in self.X_train]
            k_nearest_indices = np.argsort(distances)[:self.k]
            # k_nearest_labels = [tuple(self.y_train[i]) for i in k_nearest_indices]
            k_nearest_labels = [self.y_train[i] for i in k_nearest_indices]



            # Make a prediction based on the majority class
            prediction = max(set(k_nearest_labels), key=k_nearest_labels.count)
            predictions.append(prediction)

        return predictions

    def accuracy(self, y_true, y_pred):
        correct = np.sum(y_true == y_pred)
```

```
        total = len(y_true)
        return correct / total

    def confusion_matrix(self, y_true, y_pred):
        matrix = np.zeros((2, 2), dtype=int)

        for i in range(len(y_true)):
            true_label = int(y_true[i][0]) if isinstance(y_true[i], tuple) else int(y_true[i])
            pred_label = int(y_pred[i][0]) if isinstance(y_pred[i], tuple) else int(y_pred[i])

            matrix[true_label][pred_label] += 1

        return matrix

    def precision_recall_f1(self, y_true, y_pred):
        cm = self.confusion_matrix(y_true, y_pred)
        precision = cm[1][1] / (cm[1][1] + cm[0][1]) if (cm[1][1] + cm[0][1]) != 0 else 0
        recall = cm[1][1] / (cm[1][1] + cm[1][0]) if (cm[1][1] + cm[1][0]) != 0 else 0
        f1 = 2 * (precision * recall) / (precision + recall) if (precision + recall) != 0 else 0
        return precision, recall, f1

    def predict_proba(self, X_test):
        if self.k is None:
            # Determine k as the nearest odd integer to the square root of the test set size
            self.k = self.find_nearest_odd(np.sqrt(len(X_test)))

        probas = []

        for sample in X_test:
            distances = [self.euclidean_distance(sample, x) for x in self.X_train]
            k_nearest_indices = np.argsort(distances)[:self.k]
            # k_nearest_labels = [tuple(self.y_train[i]) for i in k_nearest_indices]
            k_nearest_labels = [self.y_train[i] for i in k_nearest_indices]

            # Calculate class probabilities based on the count of each class in k-nearest neighbors
            unique_classes, class_counts = np.unique(k_nearest_labels, return_counts=True)
            class_probabilities = class_counts / self.k
            proba_dict = {cls: prob for cls, prob in zip(unique_classes, class_probabilities)}
            probas.append(proba_dict)

        return probas


    def plot_confusion_matrix(self, y_true, y_pred):
        cm = self.confusion_matrix(y_true, y_pred)
        sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=['Negative', 'Positive'], yticklabels=['Negative', 'Positive'])
        plt.xlabel('Predicted')
        plt.ylabel('True')
        plt.title('Confusion Matrix')
        plt.show()

    def plot_precision_recall_curve(self, y_true, y_scores):
        thresholds = np.arange(0, 1.05, 0.05)
        precisions, recalls = [], []

        for threshold in thresholds:
            y_pred = [1 if score.get(1, 0) >= threshold else 0 for score in y_scores]
            precision, recall, _ = self.precision_recall_f1(y_true, y_pred)
            precisions.append(precision)
            recalls.append(recall)

        plt.plot(recalls, precisions, color='b')
        plt.xlabel('Recall')
        plt.ylabel('Precision')
        plt.title('Precision-Recall Curve')
        plt.show()

    def plot_roc_curve(self, y_true, y_scores):
        thresholds = np.arange(0, 1.05, 0.05)
        fpr, tpr = [], []

        for threshold in thresholds:
            y_pred = [1 if score.get(1, 0) >= threshold else 0 for score in y_scores]
            cm = self.confusion_matrix(y_true, y_pred)
            false_positive_rate = cm[0][1] / (cm[0][1] + cm[0][0])
            true_positive_rate = cm[1][1] / (cm[1][1] + cm[1][0])
```