import numpy as np import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

df=pd.read_csv('/content/heart_disease.csv')

df.head()

₹		age	sex	chest	resting_blood_pressure	serum_cholestoral	fasting_blood_sugar	resting_electrocardiographic_results	maximum_heart_
	0	70	1	4	130	322	0	2	
	1	67	0	3	115	564	0	2	
	2	57	1	2	124	261	0	0	
	3	64	1	4	128	263	0	0	
	4	74	0	2	120	269	0	2	
	4 =								•

df.info()

RangeIndex: 270 entries, 0 to 269 Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype				
0	age	270 non-null	int64				
1	sex	270 non-null	int64				
2	chest	270 non-null	int64				
3	resting_blood_pressure	270 non-null	int64				
4	serum_cholestoral	270 non-null	int64				
5	fasting_blood_sugar	270 non-null	int64				
6	resting_electrocardiographic_results	270 non-null	int64				
7	maximum_heart_rate_achieved	270 non-null	int64				
8	exercise_induced_angina	270 non-null	int64				
9	oldpeak	270 non-null	float64				
10	slope	270 non-null	int64				
11	number_of_major_vessels	270 non-null	int64				
12	thal	270 non-null	int64				
13	result	270 non-null	int64				
11							

dtypes: float64(1), int64(13) memory usage: 29.7 KB

df.describe()



	age	sex	chest	resting_blood_pressure	${\tt serum_cholestoral}$	fasting_blood_sugar	$resting_electrocardiographic_r$
count	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.
mean	54.433333	0.677778	3.174074	131.344444	249.659259	0.148148	1.0
std	9.109067	0.468195	0.950090	17.861608	51.686237	0.355906	0.!
min	29.000000	0.000000	1.000000	94.000000	126.000000	0.000000	0.0
25%	48.000000	0.000000	3.000000	120.000000	213.000000	0.000000	0.0
50%	55.000000	1.000000	3.000000	130.000000	245.000000	0.000000	2.0
75%	61.000000	1.000000	4.000000	140.000000	280.000000	0.000000	2.1
max	77.000000	1.000000	4.000000	200.000000	564.000000	1.000000	2.0

from sklearn.preprocessing import StandardScaler scaler=StandardScaler()#creating

cool_names=df.columns scaled_df=scaler.fit_transform(df)#applying scaling scaled_df=pd.DataFrame(scaled_df,columns=cool_names) scaled_df.head()

а	ge sex	chest	resting_blood_pressure	${\tt serum_cholestoral}$	<pre>fasting_blood_sugar</pre>	resting_electrocardiographic_results
1 .7120	0.689500	0.870928	-0.075410	1.402212	-0.417029	0.981664
1 1.3821	-1.450327	-0.183559	-0.916759	6.093004	-0.417029	0.981664
0.2822	0.689500	-1.238045	-0.411950	0.219823	-0.417029	-1.026285
3 1.0521	0.689500	0.870928	-0.187590	0.258589	-0.417029	-1.026285
4 2.1520	32 -1.450327	-1.238045	-0.636310	0.374890	-0.417029	0.981664
	 1.71209 1.38214 0.28229 1.05218 	1 1.382140 -1.450327 2 0.282294 0.689500 3 1.052186 0.689500	0 1.712094 0.689500 0.870928 1 1.382140 -1.450327 -0.183559 2 0.282294 0.689500 -1.238045 3 1.052186 0.689500 0.870928	0 1.712094 0.689500 0.870928 -0.075410 1 1.382140 -1.450327 -0.183559 -0.916759 2 0.282294 0.689500 -1.238045 -0.411950 3 1.052186 0.689500 0.870928 -0.187590	0 1.712094 0.689500 0.870928 -0.075410 1.402212 1 1.382140 -1.450327 -0.183559 -0.916759 6.093004 2 0.282294 0.689500 -1.238045 -0.411950 0.219823 3 1.052186 0.689500 0.870928 -0.187590 0.258589	0 1.712094 0.689500 0.870928 -0.075410 1.402212 -0.417029 1 1.382140 -1.450327 -0.183559 -0.916759 6.093004 -0.417029 2 0.282294 0.689500 -1.238045 -0.411950 0.219823 -0.417029 3 1.052186 0.689500 0.870928 -0.187590 0.258589 -0.417029

#separating dependent and independent columns
x=scaled_df.drop(columns='result')
y=scaled_df['result']
y=y.astype('int')

#using naive bays algorithm

from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
from sklearn.model_selection import train_test_split

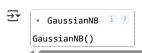
#Data splitting between train and test sets
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=4)

x_train.shape,x_test.shape,y_train.shape,y_test.shape

((216, 13), (54, 13), (216,), (54,))

#creating object of NB algorithm
nb=GaussianNB()

#training model
nb.fit(x_train,y_train)



#prediction on y (target column)
y_pred=nb.predict(x_test) #prediction on test data
y_pred_train=nb.predict(x_train) #prediction on train data

y_pred

y_pred_train

```
array([0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1,
```

#checking performance of algorithm on training data
print(classification_report(y_train,y_pred_train))

_	precision		recall	f1-score	support	
	0	0.90	0.90	0.90	124	
	1	0.87	0.86	0.86	92	

```
accuracy 0.88 216
macro avg 0.88 0.88 0.88 216
weighted avg 0.88 0.88 0.88 216
```

#checking performance of algorithm on training data
print(classification_report(y_test,y_pred))

_		precision	recall	f1-score	support
	0 1	0.69 0.82	0.85 0.64	0.76 0.72	26 28
	accuracy macro avg weighted avg	0.75 0.76	0.74 0.74	0.74 0.74 0.74	54 54 54

#training accuracy =88%
#testing accuracy=75%

#as traianing accuracy is greater than testing accuracy , by reasonable amount we can consider this algorithm is overfitting

training_accuracy=accuracy_score(y_train,y_pred_train)
testing_accuracy=accuracy_score(y_test,y_pred)
print(f'Training accuracy is {training_accuracy}')
print(f'Testing accuracy is {testing_accuracy}')

Training accuracy is 0.8842592592592593
Testing accuracy is 0.7407407407407407

#confusion matrix
confusion_matrix(y_test,y_pred)

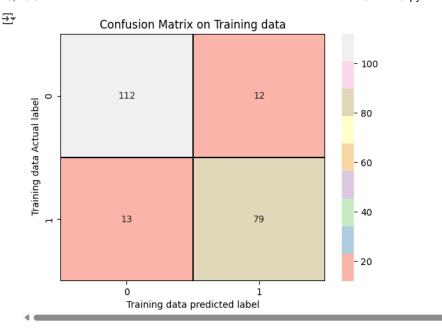
#confusion matrix
confusion_matrix(y_train,y_pred_train)

```
⇒ array([[112, 12],
[ 13, 79]])
```

cm2=confusion_matrix(y_test,y_pred)

cm1=confusion_matrix(y_train,y_pred_train)

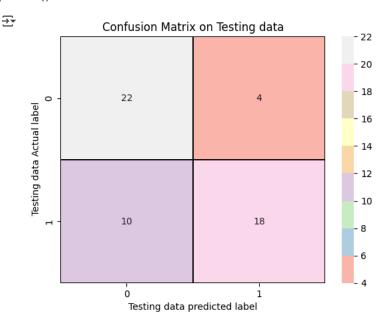
```
#plotting confusion matrix
sns.heatmap(cm1,annot=True,cmap='Pastel1',linewidths=0.3,linecolor='black',fmt='d')
plt.xlabel('Training data predicted label')
plt.ylabel('Training data Actual label')
plt.title('Confusion Matrix on Training data')
plt.show()
```



```
#0 indicates no heart disease
```

#1 indicates heart

```
#plotting confusion matrix
sns.heatmap(cm2,annot=True,cmap='Pastel1',linewidths=0.3,linecolor='black',fmt='d')
plt.xlabel('Testing data predicted label')
plt.ylabel(' Testing data Actual label')
plt.title('Confusion Matrix on Testing data')
plt.show()
```



```
#false nagative = 1 0 = 10
#false positive = 0 1 =4
#true nagative = 0 0 =22
#true positive = 1 1 =18 ;;; first take y axis then x axis

#conclusion
#for confusion matrix 2
#false nagative = 1 0 = 10
#false positive = 0 1 =4
#true nagative = 0 0 =22
#true positive = 1 1 =18 ;

#for confusion matrix 2
#false nagative = 1 0 = 12 (TP)
#false positive = 0 1 = 13 (TP)
```

```
#raise positive = 0 1 =13 (Fr)
#true nagative = 0 0 =112 (TN)
#true positive = 1 1 =79; (TP)
```

Start coding or generate with AT