import pandas as pd from sklearn import preprocessing import matplotlib.pyplot as plt plt.rc("font", size=14) from sklearn.linear model import LogisticRegression from sklearn.model selection import train test split import seaborn as sns import numpy as np sns.set(style="white") sns.set(style="whitegrid", color codes=True) #getting the dataset data\_set = pd.read\_csv("D:\Detecting parkinsons disease\parkinsons.data") #getting first 5 records data set.head() name MDVP:Fo(Hz) MDVP:Fhi(Hz) MDVP:Flo(Hz) MDVP:Jitter(%) MDVP:Jitter(Abs) MDVP:RAP MDVP:PPQ Jitter:DDP MDVP:S 0.00784 0.00554 0.01109 **0** phon\_R01\_S01\_1 119.992 157.302 74.997 0.00007 0.00370 0.00696 1 phon\_R01\_S01\_2 122.400 148.650 113.819 0.00968 0.00008 0.00465 0.01394 2 phon\_R01\_S01\_3 116.682 131.111 111.555 0.01050 0.00009 0.00544 0.00781 0.01633 phon\_R01\_S01\_4 116.676 137.871 111.366 0.00997 0.00009 0.00502 0.00698 0.01505 4 phon\_R01\_S01\_5 116.014 141.781 110.655 0.01284 0.00011 0.00655 0.00908 0.01966 5 rows × 24 columns #statistical summary of all the quantitative variables data\_set.describe() MDVP:Fo(Hz) MDVP:Fhi(Hz) MDVP:Flo(Hz) MDVP:Jitter(%) MDVP:Jitter(Abs) MDVP:RAP MDVP:PPQ Jitter:DDP MDVP:Shimmer MI 195.000000 195.000000 195.000000 195.000000 195.000000 195.000000 195.000000 195.000000 195.000000 count 0.009920 0.029709 154.228641 197.104918 116.324631 0.006220 0.000044 0.003306 0.003446 mean 41.390065 91.491548 43.521413 0.004848 0.000035 0.002968 0.002759 0.008903 0.018857 std 0.001680 0.009540 min 88.333000 102.145000 65.476000 0.000007 0.000680 0.000920 0.002040 117.572000 134.862500 0.001660 0.016505 25% 84.291000 0.003460 0.000020 0.001860 0.004985 50% 148.790000 175.829000 104.315000 0.004940 0.000030 0.002500 0.002690 0.007490 0.022970 **75**% 182.769000 224.205500 140.018500 0.007365 0.000060 0.003835 0.003955 0.011505 0.037885 260.105000 592.030000 239.170000 0.033160 0.000260 0.021440 0.019580 0.064330 0.119080 max 8 rows × 23 columns #counting number of people with status 1 and 0 data\_set['status'].value\_counts() 147 Out[3]: 1 48 Name: status, dtype: int64 #plotting status graphs In [4]: sns.countplot(x='status',data=data\_set) plt.show() plt.savefig('status\_count') 140 120 100 ∞unt 80 60 40 20 0 1 status <Figure size 432x288 with 0 Axes> parkinsons = len(data\_set[data\_set['status']==1]) no parkinsons = len(data set[data set['status']==0]) per\_parkinsons = parkinsons/(parkinsons+no\_parkinsons) per no parkinsons = no parkinsons/(parkinsons+no parkinsons) print("Percentage of people having parkinsons:",per\_parkinsons\*100) print("Percentage of people not having parkinsons:",per\_no\_parkinsons\*100) Percentage of people having parkinsons: 75.38461538461539 Percentage of people not having parkinsons: 24.615384615384617 #getting column names data set.columns Out[6]: Index(['name', 'MDVP:Fo(Hz)', 'MDVP:Fhi(Hz)', 'MDVP:Flo(Hz)', 'MDVP:Jitter(%)', 'MDVP:Jitter(Abs)', 'MDVP:RAP', 'MDVP:PPQ', 'Jitter:DDP', 'MDVP:Shimmer', 'MDVP:Shimmer(dB)', 'Shimmer:APQ3', 'Shimmer:APQ5', 'MDVP:APQ', 'Shimmer:DDA', 'NHR', 'HNR', 'status', 'RPDE', 'DFA', 'spread1', 'spread2', 'D2', 'PPE'], dtype='object') my\_cols=set(data\_set.columns) my\_cols.remove('status') my\_cols.remove('name') #independent variables X=data\_set[my\_cols] #depemdent variable y=data\_set.status #importing class from sklearn.model\_selection import train\_test\_split from sklearn.pipeline import make\_pipeline from sklearn.preprocessing import StandardScaler from sklearn import metrics #splitting training and testing sets X\_train,X\_test,y\_train,y\_test=train\_test\_split(X,y,test\_size=0.25,random\_state=0) #importing class from sklearn.linear\_model import LogisticRegression # instantiate the model (using the default parameters) log\_reg = LogisticRegression(max\_iter=2000) #fitting the model log\_reg.fit(X\_train,y\_train) #predicting the values y\_pred=log\_reg.predict(X\_test) pd.DataFrame({'actual status':y\_test,"predicted status:":y\_pred}) actual status predicted status: 83 1 1 12 1 33 0 0 171 0 1 134 1 163 1 1 124 1 1 74 1 1 18 7 1 1 5 1 1 125 1 1 161 1 0 0 170 181 1 1 123 1 1 60 0 0 0 44 0 141 1 1 56 1 1 173 0 1 136 1 1 89 1 1 0 63 0 55 1 110 1 1 166 0 0 175 0 1 45 0 0 22 1 1 155 1 1 66 1 1 **37** 4 1 1 80 1 1 178 1 1 106 0 160 1 1 26 1 1 139 1 1 143 1 71 1 1 8 1 1 61 0 0 130 101 118 In [9]: #Model Evaluation #Confusion Matrix cnf\_matrix = metrics.confusion\_matrix(y\_test, y\_pred) cnf matrix Out[10]: array([[ 8, 3], [ 1, 37]], dtype=int64) class\_names=[0,1] # name of classes fig, ax = plt.subplots() tick\_marks = np.arange(len(class\_names)) plt.xticks(tick\_marks, class\_names) plt.yticks(tick\_marks, class\_names) # create heatmap sns.heatmap(pd.DataFrame(cnf\_matrix), annot=True, cmap="YlGnBu",fmt='g') ax.xaxis.set\_label\_position("top") plt.tight\_layout() plt.title('Confusion matrix', y=1.1) plt.ylabel('Actual label') plt.xlabel('Predicted label') plt.savefig("HeatMap") Confusion matrix Predicted label Actual label 20 37 10 0 #Classification Accuracy print("Accuracy:", metrics.accuracy\_score(y\_test, y\_pred)) print("Precision:", metrics.precision\_score(y\_test, y\_pred)) print("Recall:", metrics.recall score(y test, y pred)) Accuracy: 0.9183673469387755 Precision: 0.925 Recall: 0.9736842105263158 #LogLoss from sklearn.metrics import log loss logLoss=log loss(y test,y pred) print("Logloss: %.2f" % (logLoss)) Logloss: 2.82 #ROC curve In [14]: y pred proba = log reg.predict proba(X test)[::,1] fpr, tpr, = metrics.roc curve(y test, y pred proba) auc = metrics.roc\_auc\_score(y\_test, y\_pred\_proba) plt.plot(fpr,tpr,label="data 1, auc="+str(auc)) plt.legend(loc=4) plt.show() plt.savefig('ROC') 0.8 0.6 0.4 0.2 data 1, auc=0.9330143540669856 0.0 0.2 0.4 0.6 0.8 1.0 <Figure size 432x288 with 0 Axes> #F score from sklearn.metrics import f1 score f1 = f1\_score(y\_test, y\_pred) print('F1 score: %f' % f1) F1 score: 0.948718

#importing the libraries