Reading and Importing Data #importing csv file import pandas as pd import numpy as np import seaborn as sns from sklearn.metrics import recall\_score from sklearn.metrics import precision\_score from sklearn.metrics import recall\_score from sklearn.metrics import classification\_report from sklearn.metrics import classification\_report, confusion\_matrix data = pd.read\_csv("diabetes.csv") In [2]: data.head() Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age Outcome Out[2]: 0 148 6 72 35 0 33.6 0.627 50 1 1 1 85 66 29 0 26.6 31 0 0.351 2 8 183 64 0 0 23.3 0.672 32 1 3 1 89 66 23 21 0 94 28.1 0.167 4 0 137 40 35 168 43.1 2.288 33 1 In [3]: data.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 768 entries, 0 to 767 Data columns (total 9 columns): Column Non-Null Count Dtype Pregnancies 768 non-null 0 int64 768 non-null 1 Glucose int64 768 non-null BloodPressure int64 SkinThickness 768 non-null int64 Insulin 768 non-null int64 5 768 non-null float64 BMIDiabetesPedigreeFunction 768 non-null 6 float64 7 768 non-null int64 Age Outcome 768 non-null int64 dtypes: float64(2), int64(7)memory usage: 54.1 KB data.shape Out[4]: (768, 9) data.describe() In [5]: Out[5]: **Pregnancies** Glucose BloodPressure SkinThickness Insulin DiabetesPedigreeFunction Outcome Age 768.000000 768.000000 768.000000 768.000000 768.000000 768.000000 768.000000 768.000000 count 768.000000 3.845052 120.894531 69.105469 20.536458 79.799479 31.992578 0.471876 33.240885 0.348958 mean std 3.369578 31.972618 19.355807 15.952218 115.244002 7.884160 0.331329 11.760232 0.476951 min 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.078000 21.000000 0.000000 25% 1.000000 99.000000 62.000000 0.000000 0.000000 27.300000 0.243750 24.000000 0.000000 3.000000 117.000000 72.000000 29.000000 0.000000 **50**% 23.000000 30.500000 32.000000 0.372500 6.000000 140.250000 32.000000 0.626250 41.000000 1.000000 **75**% 80.000000 127.250000 36.600000 17.000000 199.000000 122.000000 99.000000 846.000000 2.420000 81.000000 1.000000 max 67.100000 from matplotlib import pyplot import matplotlib.pyplot as plt data.plot(kind='density', subplots=True, layout=(3,3), sharex=False , figsize =(10,10)) plt.show() 0.150 0.030 Pregnancies<sub>0.0125</sub> Glucose 0.125 .025 0.0100 0.100 .020 0.0050 0.0050 Density BloodPressure 0.075 0.015 0.050 .010 0.0025 0.025 .005 0.000 0.000 0.000 20 Ó 100 100 10 -100 200 300 SkinThickness — ВМІ Insulin 0.025 0.05 .006 0.04 0.020 0.004 Density 0.015 0.03 0.02 0.010 .002 0.005 0.01 0.000 **0**.000 0.00 100 500 1000 -<u>5</u>0 150 -500 100 0.05 2.0 DiabetesPedigreeFunction — Age Outcome 1.5 0.04 0.03 0.02 Density 0.0 1.0 0.5 0.5 0.01 0.0 0.00 0.0 Data pre-processing data.isnull().sum() Out[7]: Pregnancies 0 Glucose BloodPressure 0 SkinThickness Insulin BMI DiabetesPedigreeFunction Age Outcome dtype: int64 features = data.columns cols = (data[features] == 0).sum() print(cols) Pregnancies 111 5 Glucose 35 BloodPressure 227 SkinThickness Insulin 374 BMI 11 DiabetesPedigreeFunction Age Outcome dtype: int64 data['Pregnancies']=data['Pregnancies'].replace(0, data['Pregnancies'].mean()) In [9]: data['Glucose']=data['Glucose'].replace(0, data['Glucose'].mean()) In [10]: data['BloodPressure']=data['BloodPressure'].replace(0, data['BloodPressure'].mean()) In [11]: data['SkinThickness']=data['SkinThickness'].replace(0,data['SkinThickness'].mean()) In [12]: data['Insulin']=data['Insulin'].replace(0, data['Insulin'].mean()) In [13]: In [14]: data['BMI']=data['BMI'].replace(0, data['BMI'].mean()) In [15]: features = data.columns cols = (data[features] == 0).sum() print(cols) Pregnancies Glucose 0 BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction 0 Age Outcome 500 dtype: int64 Visualisation data['Outcome'].value\_counts() In [16]: Out[16]: 0 268 Name: Outcome, dtype: int64 sns.countplot(data['Outcome'], label="Count") C:\Users\KIIT\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinte rpretation. warnings.warn( Out[17]: <AxesSubplot:xlabel='Outcome', ylabel='count'> 500 400 300 200 100 Outcome data.hist(figsize=(15,10)) In [18]: plt.show() BloodPressure Pregnancies Glucose 250 250 150 200 200 125 100 150 150 75 100 100 50 50 50 25 15 10 75 100 125 150 175 20 40 60 50 100 120 SkinThickness BMI Insulin 500 200 300 150 300 200 100 200 100 50 100 100 400 800 30 DiabetesPedigreeFunction Outcome Age 300 500 300 250 400 250 200 200 300 150 150 200 100 100 100 50 50 sns.pairplot(data) Out[19]: <seaborn.axisgrid.PairGrid at 0x1b06cb14910> 15.0 175 1.0 0.8 0.2 75 100 125 400 600 800 0.00 0.25 0.50 0.75 1.00 Co-Relation In [21]: corrmat = data.corr() top\_corr\_features = corrmat.index plt.figure(figsize=(20,20)) g=sns.heatmap(data[top\_corr\_features].corr(),annot=True,cmap= "RdYlGn") 0.25 0.046 -0.017 -0.01 0.53 0.25 Pregnancies · 0.4 0.27 Glucose 0.49 - 0.8 0.011 0.28 0.33 0.25 0.00037 BloodPressure 0.046 0.54 SkinThickness - 0.6 Insulin -0.017 0.4 0.011 0.039 - 0.4 0.28 0.54 0.026 0.31 BMI -0.01 0.14 0.00037 0.15 0.15 0.034 DiabetesPedigreeFunction - 0.2 0.53 0.27 0.33 0.026 0.034 Age 0.25 0.49 0.31 Outcome SkinThickness DiabetesPedigreeFunction Pregnancies Glucose BloodPressure Insulin Outcome data.corr() Age Outcome Out[22]: Pregnancies Glucose BloodPressure SkinThickness Insulin **BMI** DiabetesPedigreeFunction -0.010297 0.525261 0.247971 **Pregnancies** 1.000000 0.152568 0.253275 0.045776 -0.016738 0.097663 Glucose 0.152568 1.000000 0.219666 0.160766 0.396597 0.231478 0.137106 0.266600 0.492908 **BloodPressure** 0.000371 0.326740 0.162986 0.253275 0.219666 1.000000 0.134155 0.010926 0.281231 **SkinThickness** 0.045776 0.160766 0.240361 0.535703 0.154961 0.026423 0.175026 0.134155 1.000000 Insulin -0.016738 0.396597 0.010926 0.240361 1.000000 0.189856 BMI 0.097663 0.231478 0.281231 0.535703 0.189856 1.000000 DiabetesPedigreeFunction  $-0.010297 \quad 0.137106$ 0.000371 0.154961 0.157806 0.153508 1.000000 0.033561 0.173844 0.525261 0.266600 0.326740 0.026423 0.038652 0.025748 0.033561 1.000000 0.238356 Age 0.179185 0.312254 Outcome 0.247971 0.492908 0.162986 0.175026 0.173844 0.238356 1.000000 Training and Testing Data In [23]: from sklearn.model\_selection import train\_test\_split x = data.drop(['Outcome'], axis=1) y = data['Outcome'] x\_train , x\_test ,y\_train ,y\_test =train\_test\_split(x,y ,test\_size=0.4, random\_state = 0) In [24]: x\_train.shape In [25]: Out[25]: (460, 8) from sklearn.preprocessing import StandardScaler In [26]: sc = StandardScaler() x\_train = sc.fit\_transform(x\_train)  $x_{test} = sc.transform(x_{test})$ In [27]: x\_train Out[27]: array([[-0.46500509, 0.21706518, 0.39668828, ..., -0.61376354, -0.43821198, 0.0507091 ], [-1.13643605, -1.4276812 , 0.06850793, ..., -0.38506909, 0.16184365, -0.96347286],  $[-0.12928961, 0.67759417, -1.24421347, \ldots, -0.45653611,$ -0.54410415, 0.30425459],  $[-0.12928961, -0.96715221, -0.66989786, \ldots, -1.14261946,$ -0.95296558, -1.04798802], [ 2.22071875, -1.26320656, 0.06850793, ..., -0.37077569, -0.50586531, 0.13522426], [ 0.20642587, 0.41443475, 0.72486863, ..., -0.10026186,0.4942274 , 3.0087398 ]]) In [28]: x\_test Out[28]: array([[-1.13643605, 2.48681519, 0.2325981, ..., 1.45877993, 2.71208005, -0.96347286],  $[-0.80072057, -0.53951816, 0.06850793, \ldots, 0.12949343,$ -0.1999546 , -0.8789577 ], [-0.12928961, -1.55926091, -0.91603312, ..., 0.18666704, -0.23819344, -0.70992737],  $[ 0.54214135, 0.80917388, -0.09558225, \ldots, 0.12949343,$ 0.45598856, 1.40295171], [-1.13643605, 0.74338402, -1.40830365, ..., -0.4279493 , 0.27067727, -0.37186672], [ 0.54214135, 0.34864489, -0.25967242, ..., 0.38677469, 0.20596538, -0.37186672]]) unique\_classes = list(y\_train.unique()) In [29]: unique\_classes from sklearn.utils import class\_weight out\_dict = {} for classes in unique\_classes: out\_dict[classes] = y\_train.shape[0]/((y\_train.loc[y\_train == classes].shape[0]) \*len(unique\_classes)) out\_dict Out[29]: {1: 1.3939393939394, 0: 0.7796610169491526} **Using Logistic Regression** from sklearn.linear\_model import LogisticRegression In [30]:  $clf = LogisticRegression(class_weight=\{1: 1.3939393939394, 0: 0.7796610169491526\})$ clf.fit(x\_train, y\_train) Out[30]: LogisticRegression(class\_weight={0: 0.7796610169491526, 1: 1.3939393939393939}) y\_pred= clf.predict(x\_test) In [31]: from sklearn.metrics import accuracy\_score In [32]: accuracy\_score(y\_pred , y\_test) Out[32]: 0.7597402597402597 print(classification\_report(y\_test,y\_pred)) precision recall f1-score support 0 0.82 0.81 0.82 205 1 0.64 0.65 0.64 103 accuracy 0.76 308 0.73 0.73 0.73 308 macro avg weighted avg 0.76 0.76 0.76 Using Random Forest Regressor from sklearn.ensemble import RandomForestClassifier In [34]: clf = RandomForestClassifier(class\_weight={1: 1.393939393939394, 0: 0.7796610169491526}) clf.fit(x\_train, y\_train) predicted = clf.predict(x\_test) In [35]: accuracy\_score(predicted, y\_test) Out[35]: 0.7532467532467533 In [36]: print(classification\_report(y\_test, predicted)) recall f1-score support precision 0 0.77 0.90 0.83 205 0.70 0.56 1 0.47 103 0.75 308 accuracy 0.73 0.68 0.69 308 macro avg 0.75 0.75 0.74 308 weighted avg Using Decision Tree Classifier from sklearn.tree import DecisionTreeClassifier In [37]:  $clf = DecisionTreeClassifier(class_weight=\{1: 1.393939393939394, 0: 0.7796610169491526\})$ clf.fit(x\_train, y\_train) predicted = clf.predict(x\_test) In [38]: accuracy\_score(predicted, y\_test) Out[38]: 0.7305194805194806 print(classification\_report(y\_test, predicted)) In [39]: precision recall f1-score support 0 0.79 0.81 0.80 205 0.60 0.56 0.58 103 1 accuracy 0.73 308 0.70 0.69 308 macro avg 0.69 weighted avg 0.73 0.73 0.73 308