import pandas as pd import numpy as np # For mathematical calculations import seaborn as sns # For data visualization import matplotlib.pyplot as plt import seaborn as sn # For plotting graphs import io %matplotlib inline import warnings # To ignore any warnings warnings.filterwarnings("ignore") filepath2 = r"C:\Users\91623\OneDrive\Desktop\projects\hill and valley\hill.csv" df= pd.read csv(filepath2) print(df) V5 V2 V3 V1 V4 V6 V7 \ 0 39.02 36.49 38.20 38.85 39.38 39.74 37.02 1.83 1.71 1.77 1.77 1.68 1.78 2 68177.69 66138.42 72981.88 74304.33 67549.66 69367.34 69169.41 3 44889.06 39191.86 40728.46 38576.36 45876.06 47034.00 46611.43 5.40 5.28 5.38 5.27 4 5.70 5.61 6.00 . 1207 13.00 12.87 13.27 13.04 13.19 12.53 14.31 48.55 50.43 50.09 50.11 49.67 48.95 1208 48.66 1209 10160.65 9048.63 8994.94 9514.39 9814.74 10195.24 10031.47 1210 34.81 35.07 34.98 32.37 34.16 34.03 33.31 1211 8489.43 7672.98 9132.14 7985.73 8226.85 8554.28 V10 ... V94 \ V8 V9 V92 V93 0 39.53 38.81 38.79 36.62 36.92 38.80 . . . 1 1.70 1.75 1.78 1.80 1.79 1.77 . . . 2 73268.61 74465.84 72503.37 73438.88 71053.35 71112.62 . . . 38466.15 ... 3 37668.32 40980.89 42625.67 40684.20 46960.73 5.38 5.34 5.87 ... 5.17 5.67 5.60 . . . 13.33 13.63 14.55 ... 12.48 12.15 13.15 1207 48.61 ... 1208 48.65 48.63 46.93 49.61 47.16 1209 10202.28 9152.99 9591.75 . . . 9068.11 9191.80 9275.04 1210 32.48 35.63 32.48 32.76 35.03 . . . 8635.14 1211 8967.24 8544.37 8609.73 9209.48 . . . 8496.33 V95 V96 V97 V98 V99 V100 Class 0 38.52 38.07 36.73 39.46 37.50 39.10 1.75 1.69 1 1.74 1.74 1.80 1.78 1 74916.48 72571.58 66348.97 71063.72 67404.27 74920.24 2 1 3 44546.80 45410.53 47139.44 43095.68 40888.34 39615.19 4 5.94 5.73 5.22 5.30 5.73 5.91 0 1207 12.35 13.58 13.86 12.88 13.87 13.51 1 1208 48.17 47.94 49.81 49.89 47.43 47.77 1209 9848.18 9074.17 9601.74 10366.24 8997.60 9305.77 1 1210 31.91 33.85 35.28 32.49 32.83 34.82 1 1211 8724.01 8219.99 8550.86 8679.43 8389.31 8712.80 [1212 rows x 101 columns] df.head() **V7 V9** V10 ... V93 V94 V1 V2 **V3 V4 V5** V6 **V8** V92 **V95** 0 39.02 36.49 38.20 38.85 39.38 39.74 37.02 39.53 38.81 38.79 ... 36.62 36.92 38.80 38.52 1 1.83 1.71 1.77 1.77 1.68 1.78 1.80 1.70 1.75 1.78 ... 1.80 1.79 1.77 1.74 **2** 68177.69 66138.42 72981.88 74304.33 67549.66 69367.34 69169.41 73268.61 74465.84 72503.37 ... 73438.88 71053.35 71112.62 74916.48 **3** 44889.06 39191.86 40728.46 38576.36 45876.06 47034.00 46611.43 37668.32 40980.89 38466.15 ... 42625.67 40684.20 46960.73 44546.80 5.87 ... 5.70 5.40 5.28 5.38 5.27 5.61 6.00 5.38 5.34 5.17 5.67 5.60 5.94  $5 \text{ rows} \times 101 \text{ columns}$ In [4]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 1212 entries, 0 to 1211 Columns: 101 entries, V1 to Class dtypes: float64(100), int64(1) memory usage: 956.5 KB df.dropna() **V6 V7** V9 **V2 V3 V4 V**5 **V8** V10 ... V92 **V93** V94 ۷1 0 39.02 36.49 38.20 38.85 39.38 39.74 37.02 39.53 38.81 38.79 36.62 36.92 38.80 3 1 1.83 1.71 1.77 1.77 1.68 1.78 1.80 1.70 1.75 1.78 1.80 1.79 1.77 **2** 68177.69 66138.42 72981.88 74304.33 67549.66 69367.34 69169.41 73268.61 74465.84 72503.37 73438.88 71053.35 71112.62 7491 44889.06 39191.86 40728.46 38576.36 45876.06 47034.00 46611.43 37668.32 40980.89 38466.15 42625.67 40684.20 46960.73 4454 4 5.70 5.40 5.28 5.38 5.27 5.61 6.00 5.38 5.34 5.87 5.17 5.67 5.60 ••• 13.27 13.04 1207 13.00 12.87 13.19 12.53 14.31 13.33 13.63 14.55 12.48 12.15 13.15 1 1208 48.66 50.11 48.55 50.43 50.09 49.67 48.95 48.65 48.63 48.61 46.93 49.61 47.16 4 **1209** 10160.65 9048.63 8994.94 9514.39 9814.74 10195.24 10031.47 10202.28 9152.99 9591.75 9068.11 9191.80 9275.04 984 1210 34.81 35.07 34.98 32.37 34.16 34.03 33.31 32.48 35.63 32.48 32.76 35.03 32.89 3 1211 8489.43 7672.98 9132.14 7985.73 8226.85 8554.28 8838.87 8967.24 8635.14 8544.37 8609.73 9209.48 8496.33 872 1212 rows × 101 columns y=df['Class'] x = df.drop(['Class'], axis = 1)Х V10 ... **V1 V2 V3 V4 V**5 **V6 V7 V8** V9 V91 V92 V93 39.38 3 0 39.02 38.20 38.85 39.74 37.02 39.53 38.81 37.57 36.92 36.49 38.79 36.62 1.80 1 1.83 1.71 1.77 1.77 1.68 1.78 1.80 1.70 1.75 1.78 1.79 1.71 72503.37 ... 69384.71 **2** 68177.69 66138.42 72981.88 74304.33 67549.66 69367.34 69169.41 73268.61 74465.84 73438.88 71053.35 44889.06 39191.86 40728.46 38576.36 45876.06 47034.00 46611.43 37668.32 40980.89 38466.15 47653.60 42625.67 40684.20 4696 6.00 4 5.70 5.40 5.28 5.38 5.27 5.61 5.38 5.34 5.87 5.52 5.17 5.67 13.27 1207 13.00 12.87 13.04 13.19 12.53 14.31 13.33 13.63 14.55 ... 12.89 12.48 12.15 1 1208 48.66 50.11 48.55 50.43 50.09 49.67 48.95 48.65 48.63 48.61 47.45 46.93 49.61 4 10202.28 10413.41 9814.74 10195.24 9068.11 927 **1209** 10160.65 9048.63 8994.94 9514.39 10031.47 9152.99 9591.75 9191.80 1210 34.81 35.07 34.98 32.37 34.16 34.03 33.31 32.48 35.63 32.48 33.18 32.76 35.03 3 9132.14 7985.73 8554.28 8838.87 8609.73 1211 8489.43 7672.98 8226.85 8967.24 8635.14 8544.37 ... 7747.70 9209.48 849 1212 rows × 100 columns from sklearn.preprocessing import StandardScaler ss=StandardScaler() x=StandardScaler().fit(x).transform(x) Х Out[15]: array([[-0.45248681, -0.45361784, -0.45100881, ..., -0.45609618, -0.45164274, -0.45545496], [-0.45455665, -0.45556372, -0.45302369, ..., -0.45821768,-0.45362255, -0.45755405], [ 3.33983504, 3.24466709, 3.58338069, ..., 3.5427869, 3.27907378, 3.74616847], [ 0.11084204, 0.0505953, 0.04437307, ..., 0.12533312,0.04456025, 0.06450317], [-0.45272112, -0.45369729, -0.45118691, ..., -0.45648861, -0.45190136, -0.45569511], [ 0.01782872, -0.02636986, 0.05196137, ..., 0.03036056, 0.01087365, 0.03123129]]) 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=2529) x train.shape, x test.shape, y train.shape, y test.shape Out[16]: ((848, 100), (364, 100), (848,), (364,)) In [17]: from sklearn.linear\_model import LogisticRegression lr=LogisticRegression() lr.fit(x train, y train) y pred = lr.predict(x test) from sklearn.metrics import confusion matrix ,classification report print(confusion\_matrix(y\_test,y\_pred)) print(classification\_report(y\_test,y\_pred)) [[176 4] [ 92 92]] precision recall f1-score support 0.66 0.98 0 0.79 180 0.96 0.50 0.66 184 0.74 364 accuracy 0.81 0.81 0.74 macro avq 0.72 364 0.74 0.72 364 weighted avg In [18]: **from** sklearn.ensemble **import** RandomForestClassifier rfc=RandomForestClassifier() rfc.fit(x train, y train) rfc pred=rfc.predict(x test) print(confusion matrix(y test, rfc pred)) print(classification report(y test,rfc pred)) [[105 75] [ 71 113]] precision recall f1-score support 0.59 0.60 0.58 180 0.60 0.61 0.61 184 0.60 364 accuracy 0.60 0.60 macro avg 0.60 364 weighted avg 0.60 0.60 0.60 364 In [19]: **from** sklearn **import** tree clf = tree.DecisionTreeClassifier() clf.fit(x\_train,y\_train) clf\_pred=clf.predict(x\_test) print(confusion\_matrix(y\_test,clf\_pred)) print(classification\_report(y\_test,clf\_pred)) [[100 80] [ 92 92]] precision recall f1-score support 0.52 0.56 0.54 180 0.53 0.50 0.52 184 0.53 364 accuracy 0.53 0.53 macro avg 0.53 364 weighted avg 0.53 0.53 0.53 364 In [20]: **from** sklearn.svm **import** SVC svC=SVC() svC.fit(x\_train,y\_train) svC\_pred=svC.predict(x\_test)  $\textbf{from} \ \texttt{sklearn.metrics} \ \textbf{import} \ \texttt{confusion\_matrix} \ \textbf{,} \texttt{classification\_report}$ print(confusion\_matrix(y\_test,svC\_pred)) print(classification\_report(y\_test,svC\_pred)) [[162 18] [159 25]] precision recall f1-score support 0.50 0.90 0.65 0.58 0.14 0.22 184 0.51 364 accuracy macro avq 0.54 0.52 0.43 364 weighted avg 0.54 0.51 0.43 364 from sklearn.naive\_bayes import GaussianNB gnb = GaussianNB() gnb.fit(x\_train,y\_train) gnb\_pred=gnb.predict(x\_test) print(confusion\_matrix(y\_test,gnb\_pred)) print(classification\_report(y\_test,gnb\_pred)) [[121 59] [102 82]] precision recall f1-score support 0 0.54 0.67 0.60 180 0.58 0.45 0.50 184 0.56 364 accuracy 0.56 0.56 0.55 364 macro avg weighted avg 0.56 0.56 0.55 364