In [1]: import pandas as pd import numpy as np from sklearn.neural network import MLPClassifier from sklearn.datasets import load_digits from sklearn.model_selection import StratifiedShuffleSplit # Load the data into a pandas DataFrame df = pd.read_csv('hw1CIS400.csv', header=None, names=['id','diagnosis','radius_mean','texture_mean','perimeter_mean','area_mean','smoothness_mean','compactness_mean','d # Display the first 5 rows of the DataFrame In [2]: df.head() Out[2]: id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean concave ... radius_worst texture_worst perimeter_worst NaN 0 data NaN NaN NaN NaN NaN NaN NaN NaN ... NaN NaN NaN concave points_mean ... texture_worst perimeter_worst id diagnosis radius_mean 1 texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean area_worst 0.1471 ... 2 842302 M 17.99 10.38 122.8 1001 0.1184 0.2776 0.3001 17.33 184.6 2019 842517 M 20.57 17.77 132.9 1326 0.08474 0.07864 0.0869 0.07017 ... 23.41 158.8 1956 0.1279 ... **4** 84300903 M 19.69 21.25 130 1203 0.1096 0.1599 0.1974 25.53 152.5 1709 5 rows × 33 columns Out[2]: id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean concave ... radius_worst texture_worst perimeter_worst 0 data NaN NaN ... NaN points_mean ... texture_worst perimeter_worst 1 id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean area_worst 842302 M 17.99 10.38 122.8 1001 0.1184 0.2776 0.3001 0.1471 ... 2019 17.33 184.6 0.07017 ... 842517 M 20.57 17.77 132.9 1326 0.08474 0.07864 0.0869 23.41 158.8 1956 **4** 84300903 М 19.69 21.25 130 1203 0.1096 0.1599 0.1974 0.1279 ... 25.53 152.5 1709 $5 \text{ rows} \times 33 \text{ columns}$ In [3]: df.columns Out[3]: Index(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean', 'concave', 'points_mean', 'symmetry_mean', 'fractal_dimension_mean', 'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se', 'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_se', 'fractal_dimension_se', 'radius_worst', 'texture_worst', 'perimeter_worst', 'area_worst', 'smoothness_worst', 'compactness_worst', 'concavity_worst', 'concave points_worst', 'symmetry_worst', 'fractal_dimension_worst'], dtype='object') Out[3]: Index(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean', 'concave', 'points_mean', 'symmetry_mean', 'fractal_dimension_mean', 'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se', 'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_se', 'fractal_dimension_se', 'radius_worst', 'texture_worst', 'perimeter_worst', 'area_worst', 'smoothness_worst', 'compactness_worst', 'concavity_worst', 'concave points_worst', 'symmetry_worst', 'fractal_dimension_worst'], dtvpe='object') In [4]: df = df.iloc[1:]In [5]: df.head() Out[5]: id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean concave ... radius_worst texture_worst perimeter_worst points_mean ... texture_worst perimeter_worst id diagnosis radius_mean texture_mean perimeter_mean 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1203 0.1096 0.1599 0.1974 0.1279 ... 25.53 152.5 1709 77.58 0.1425 0.2839 0.1052 ... 567.7 **5** 84348301 M 11.42 20.38 386.1 0.2414 26.5 98.87 $5 \text{ rows} \times 33 \text{ columns}$ In [6]: df = df.iloc[1:]In [7]: df Out[7]: id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean concave ... radius_worst texture_worst perimeter_worst a 842302 2 M 17.99 10.38 122.8 1001 0.1184 0.2776 0.3001 0.1471 ... 17.33 184.6 2019 0.07017 ... 842517 M 20.57 17.77 132.9 1326 0.08474 0.07864 0.0869 23.41 158.8 1956 **4** 84300903 19.69 0.1096 0.1599 152.5 M 21.25 130 1203 0.1974 0.1279 ... 25.53 1709 **5** 84348301 567.7 M 11.42 20.38 77.58 386.1 0.1425 0.2839 0.2414 0.1052 ... 26.5 98.87 **6** 84358402 M 20.29 14.34 135.1 1297 0.1003 0.1328 0.198 0.1043 ... 16.67 152.2 1575 ••• ••• ••• ••• • • • • • • 566 926424 M 21.56 22.39 142 1479 0.111 0.1159 0.2439 0.1389 ... 26.4 166.1 2027 567 926682 M 20.13 28.25 131.2 1261 0.0978 0.1034 0.144 0.09791 ... 38.25 155 1731 126.7 568 926954 M 16.6 28.08 108.3 858.1 0.08455 0.1023 0.09251 0.05302 ... 34.12 1124 0.277 569 927241 M 20.6 29.33 140.1 1265 0.1178 0.3514 0.152 ... 39.42 184.6 1821 0 ... 570 В 7.76 24.54 47.92 181 0.05263 0.04362 59.16 268.6 92751 0 30.37 569 rows × 33 columns Out[7]: id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean concave ... radius_worst texture_worst perimeter_worst area_mean smoothness_mean compactness_mean concavity_mean concave ... 842302 M 17.99 10.38 122.8 1001 0.1184 0.2776 0.3001 0.1471 ... 17.33 184.6 2019 2 0.08474 842517 M 20.57 17.77 132.9 1326 0.07864 0.0869 0.07017 ... 23.41 158.8 1956 3 152.5 **4** 84300903 M 19.69 21.25 130 1203 0.1096 0.1599 0.1974 0.1279 ... 25.53 1709 **5** 84348301 M 11.42 20.38 77.58 386.1 0.1425 0.2839 0.2414 0.1052 ... 26.5 98.87 567.7 **6** 84358402 M 20.29 14.34 135.1 1297 0.1003 0.1328 0.198 0.1043 ... 16.67 152.2 1575 926424 21.56 22.39 142 1479 0.111 0.1159 0.2439 0.1389 ... 26.4 166.1 2027 566 M 567 926682 20.13 28.25 1261 0.0978 0.1034 0.144 0.09791 ... 38.25 155 1731 М 131.2 568 926954 M 16.6 28.08 108.3 858.1 0.08455 0.1023 0.09251 0.05302 ... 34.12 126.7 1124 569 927241 M 20.6 29.33 140.1 1265 0.1178 0.277 0.3514 0.152 ... 39.42 184.6 1821 В 181 0 ... 59.16 268.6 570 92751 7.76 24.54 47.92 0.05263 0.04362 0 30.37 569 rows × 33 columns df.isnull().sum() Out[8]: id diagnosis radius_mean texture mean perimeter mean area_mean smoothness_mean compactness_mean concavity_mean concave points_mean symmetry_mean fractal_dimension_mean radius_se texture_se perimeter_se area_se smoothness_se compactness_se concavity_se concave points_se symmetry_se fractal_dimension_se radius_worst texture_worst perimeter_worst area_worst smoothness_worst compactness worst concavity_worst concave points_worst symmetry_worst 569 fractal_dimension_worst dtype: int64 Out[8]: id 0 diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean concave points_mean symmetry_mean fractal_dimension_mean radius_se texture_se perimeter_se area_se smoothness_se compactness_se concavity_se concave points_se symmetry_se fractal_dimension_se radius_worst texture_worst perimeter_worst area_worst smoothness_worst compactness_worst concavity_worst concave points_worst symmetry_worst fractal dimension worst 569 dtype: int64 In [9]: df = df.drop(columns=['fractal dimension worst']) In [10]: df Out[10]: id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean concave ... fractal_dimension_se radius_worst texture_wo 842302 M 17.99 10.38 122.8 1001 0.1184 0.2776 0.3001 0.1471 ... 25.38 17.33 18 2 842517 M 20.57 17.77 132.9 1326 0.08474 0.07864 0.0869 0.07017 ... 24.99 23.41 15 3 **4** 84300903 M 19.69 21.25 130 1203 0.1096 0.1599 0.1974 0.1279 ... 23.57 25.53 15 **5** 84348301 11.42 20.38 77.58 386.1 0.1425 0.2839 0.2414 0.1052 ... 14.91 26.5 98 0.1003 **6** 84358402 M 20.29 14.34 135.1 1297 0.1328 0.198 0.1043 ... 22.54 16.67 15 926424 22.39 142 1479 0.111 0.1159 0.2439 0.1389 ... 16 566 M 21.56 25.45 26.4 926682 20.13 28.25 131.2 1261 0.0978 0.1034 0.09791 ... 23.69 38.25 567 M 0.144 0.05302 ... 568 926954 M 16.6 28.08 108.3 858.1 0.08455 0.1023 0.09251 18.98 34.12 12 569 927241 M 20.6 29.33 140.1 1265 0.1178 0.277 0.3514 0.152 ... 25.74 39.42 18 570 92751 В 7.76 24.54 47.92 181 0.05263 0.04362 0 0 ... 9.456 30.37 59 569 rows × 32 columns Out[10]: id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean concave ... fractal_dimension_se radius_worst texture_wo 0.1471 ... 842302 M 17.99 10.38 122.8 1001 0.1184 0.2776 0.3001 25.38 17.33 18 2 0.07017 ... 842517 20.57 17.77 132.9 1326 0.08474 0.07864 0.0869 24.99 23.41 15 **4** 84300903 M 19.69 21.25 130 1203 0.1096 0.1599 0.1974 0.1279 ... 23.57 25.53 15 0.1052 ... **5** 84348301 M 11.42 20.38 77.58 386.1 0.1425 0.2839 0.2414 14.91 26.5 98 **6** 84358402 0.1003 0.1043 ... 15 M 20.29 14.34 135.1 1297 0.1328 0.198 22.54 16.67 926424 22.39 1479 0.1159 16 566 21.56 142 0.111 0.2439 0.1389 ... 25.45 26.4 926682 28.25 131.2 0.0978 0.1034 0.144 0.09791 23.69 38.25 926954 16.6 28.08 108.3 0.08455 0.1023 0.09251 0.05302 ... 18.98 34.12 12 568 M 858.1 0.277 927241 20.6 29.33 140.1 0.1178 0.3514 0.152 ... 25.74 39.42 18 569 1265 570 92751 В 7.76 24.54 47.92 181 0.05263 0.04362 0 ... 9.456 30.37 59 0 569 rows × 32 columns In [11]: df.isnull().sum() Out[11]: id 0 0 diagnosis radius_mean texture_mean perimeter_mean area_mean 0 smoothness_mean 0 compactness_mean concavity_mean 0 concave points_mean symmetry_mean 0 fractal_dimension_mean radius_se texture_se perimeter_se area_se smoothness_se compactness_se concavity_se concave points_se 0 symmetry_se fractal_dimension_se 0 radius_worst 0 texture_worst 0 perimeter_worst area_worst smoothness_worst compactness_worst concavity_worst 0 concave points_worst symmetry_worst 0 dtype: int64 Out[11]: id 0 diagnosis 0 0 radius_mean 0 texture_mean 0 perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean concave points_mean 0 symmetry_mean fractal_dimension_mean radius_se texture_se perimeter_se area_se smoothness_se compactness_se concavity_se concave points_se symmetry_se fractal_dimension_se radius_worst texture_worst perimeter_worst area_worst smoothness_worst compactness_worst concavity_worst 0 concave points_worst 0 symmetry_worst dtype: int64 In [12]: # Determine the class distribution class_distribution = df['diagnosis'].value_counts() # Determine the minority class minority_class = class_distribution.idxmin() # Upsample the minority class df_minority_upsampled = df[df['diagnosis'] == minority_class].sample(n=class_distribution[minority_class], replace=True) # Concatenate the upsampled minority class with the original data frame df_balanced = pd.concat([df, df_minority_upsampled]) # Shuffle the rows of the balanced data frame df_balanced = df_balanced.sample(frac=1) # Split the data frame into training and testing sets training_set = df_balanced[:int(0.7 * df_balanced.shape[0])] testing_set = df_balanced[int(0.7 * df_balanced.shape[0]):] In [13]: # Check the class distribution class counts = df['diagnosis'].value counts() # Print the class distribution print(class_counts) 357 Μ 212 Name: diagnosis, dtype: int64 357 M 212 Name: diagnosis, dtype: int64 In [16]: # Load the data digits = load_digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [17]: # Split the data into training and test sets, ensuring balance sss = StratifiedShuffleSplit(n splits=1, test size=0.3, random state=0) train_index, test_index = next(sss.split(x, y)) x_train, x_test = x[train_index], x[test_index] y_train, y_test = y[train_index], y[test_index] In [18]: # Train the model mlp = MLPClassifier(hidden layer sizes=(x train.shape[1] * 2,), activation='logistic', solver='adam', max iter=500) mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) Test accuracy: 0.9814814814814815 Test accuracy: 0.9814814814814815 In [19]: # Load the data digits = load digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [20]: # Split the data into training and test sets, ensuring balance sss1 = StratifiedShuffleSplit(n splits=1, test size=0.3, random state=10) train_index, test_index = next(sss.split(x, y)) x train, x test = x[train index], x[test index]y_train, y_test = y[train_index], y[test_index] In [21]: # Train the model mlp = MLPClassifier(hidden_layer_sizes=(x_train.shape[1] * 2,), activation='logistic', solver='adam', max_iter=500) mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x test, y test) print('Test accuracy:', accuracy) Test accuracy: 0.9796296296296296 Test accuracy: 0.9796296296296296 In [22]: # Load the data digits = load_digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [23]: # Split the data into training and test sets, ensuring balance sss2 = StratifiedShuffleSplit(n_splits=1, test_size=0.3, random_state=20) train_index, test_index = next(sss.split(x, y)) x_train, x_test = x[train_index], x[test_index] y_train, y_test = y[train_index], y[test_index] In [24]: # Train the model $mlp = MLPClassifier(hidden_layer_sizes=(x_train.shape[1] * 2,), activation='logistic', solver='adam', max_iter=500)$ mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) In [25]: # Load the data digits = load digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [26]: # Split the data into training and test sets, ensuring balance sss3 = StratifiedShuffleSplit(n_splits=1, test_size=0.3, random_state=30) train_index, test_index = next(sss.split(x, y)) x_train, x_test = x[train_index], x[test_index] y_train, y_test = y[train_index], y[test_index] In [27]: # Train the model $mlp = MLPClassifier(hidden_layer_sizes=(x_train.shape[1] * 2,), activation='logistic', solver='adam', max_iter=500)$ mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) Test accuracy: 0.9796296296296 Test accuracy: 0.9796296296296296 In [28]: # Load the data digits = load_digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [29]: # Split the data into training and test sets, ensuring balance sss4 = StratifiedShuffleSplit(n_splits=1, test_size=0.3, random_state=40) train_index, test_index = next(sss.split(x, y)) x_train, x_test = x[train_index], x[test_index] y_train, y_test = y[train_index], y[test_index] In [30]: # Train the model mlp = MLPClassifier(hidden_layer_sizes=(x_train.shape[1] * 2,), activation='logistic', solver='adam', max_iter=500) mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) Test accuracy: 0.9814814814814815 Test accuracy: 0.9814814814814815 In [31]: # Load the data digits = load digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [32]: # Split the data into training and test sets, ensuring balance sss5 = StratifiedShuffleSplit(n_splits=1, test_size=0.3, random_state=55) train_index, test_index = next(sss.split(x, y)) x train, x test = x[train index], x[test index]y_train, y_test = y[train_index], y[test_index] In [33]: # Train the model $mlp = MLPClassifier(hidden_layer_sizes=(x_train_shape[1] * 2,), activation='logistic', solver='adam', max_iter=500)$ mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) Test accuracy: 0.9814814814814815 Test accuracy: 0.9814814814814815 In [34]: # Load the data digits = load_digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [37]: # Split the data into training and test sets, ensuring balance sss6 = StratifiedShuffleSplit(n_splits=1, test_size=0.3, random_state=63) train index, test index = next(sss.split(x, y)) x_train, x_test = x[train_index], x[test_index] y_train, y_test = y[train_index], y[test_index] In [38]: # Train the model mlp = MLPClassifier(hidden_layer_sizes=(x_train.shape[1] * 2,), activation='logistic', solver='adam', max_iter=500) mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) Test accuracy: 0.9814814814814815 Test accuracy: 0.9814814814814815 In [39]: # Load the data digits = load_digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [40]: # Split the data into training and test sets, ensuring balance sss7 = StratifiedShuffleSplit(n_splits=1, test_size=0.3, random_state=78) train_index, test_index = next(sss.split(x, y)) x_train, x_test = x[train_index], x[test_index] y_train, y_test = y[train_index], y[test_index] In [41]: # Train the model $mlp = MLPClassifier(hidden_layer_sizes=(x_train_shape[1] * 2,), activation='logistic', solver='adam', max_iter=500)$ mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) In [42]: # Load the data digits = load digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [43]: # Split the data into training and test sets, ensuring balance sss8 = StratifiedShuffleSplit(n_splits=1, test_size=0.3, random_state=13) train_index, test_index = next(sss.split(x, y)) x_train, x_test = x[train_index], x[test_index] y_train, y_test = y[train_index], y[test_index] In [44]: # Train the model $mlp = MLPClassifier(hidden_layer_sizes=(x_train.shape[1] * 2,), activation='logistic', solver='adam', max_iter=500)$ mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) Test accuracy: 0.9851851851852 Test accuracy: 0.9851851851852 In [45]: # Load the data digits = load_digits() x = digits.images.reshape(digits.images.shape[0], -1) y = digits.target In [46]: # Split the data into training and test sets, ensuring balance sss9 = StratifiedShuffleSplit(n_splits=1, test_size=0.3, random_state=33) train_index, test_index = next(sss.split(x, y)) x_train, x_test = x[train_index], x[test_index] y_train, y_test = y[train_index], y[test_index] In [47]: # Train the model $mlp = MLPClassifier(hidden_layer_sizes=(x_train_shape[1] * 2,), activation='logistic', solver='adam', max_iter=500)$ mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) Test accuracy: 0.9796296296296 Test accuracy: 0.9796296296296 In [48]: # Load the data digits = load_digits() x = digits.images.reshape(digits.images.shape[0], -1)y = digits.target In [51]: # Split the data into training and test sets, ensuring balance sss10 = StratifiedShuffleSplit(n_splits=1, test_size=0.3, random_state=102) train_index, test_index = next(sss.split(x, y)) x_train, x_test = x[train_index], x[test_index] y_train, y_test = y[train_index], y[test_index] In [52]: # Train the model $mlp = MLPClassifier(hidden_layer_sizes=(x_train.shape[1] * 2,), activation='logistic', solver='adam', max_iter=500)$ mlp.fit(x_train, y_train) # Evaluate the model accuracy = mlp.score(x_test, y_test) print('Test accuracy:', accuracy) Test accuracy: 0.9814814814814815 Test accuracy: 0.9814814814814815 In []: