LEKKALA GANESH MACHINE LEARNING INTERN IRIS FLOWER CLASSIFICATION ML PROJECT Description- This particular ML project is usually referred to as the "Hello World" of Machine Learning. The iris flowers dataset contains numeric attributes, and it is perfect for beginners to learn about supervised ML algorithms, mainly how to load and handle data. Also, since this is a small dataset, it can easily fit in memory without requiring special transformations or scaling capabilities. Data Set Link - http://archive.ics.uci.edu/ml/datasets/Iris **IMPORTING LIBRARIES** import pandas as pd import numpy as np import matplotlib .pyplot as plt import seaborn as sns %matplotlib inline columns = ['Sepal length' , 'Sepal width' , 'Petal length' , 'Petal width' , 'Species'] df = pd.read_csv('iris.data', names=columns) df.head() In [39]: Out[39]: Sepal length Sepal width Petal length Petal width Species 0.2 Iris-setosa 0 5.1 3.5 1.4 1 4.9 3.0 1.4 0.2 Iris-setosa 2 4.7 3.2 1.3 0.2 Iris-setosa 3.1 1.5 0.2 Iris-setosa 4.6 5.0 3.6 4 1.4 0.2 Iris-setosa df.shape (150, 5)Out[40]: df.isnull() In [41]: Sepal length Sepal width Petal length Petal width Species Out[41]: 0 False False False False False 1 False False False False False 2 False False False False False 3 False False False False False 4 False False False False False 145 False False False False False False 146 False False False False 147 False False False False False 148 False False False False False 149 False False False False False 150 rows × 5 columns In [42]: df.describe() Sepal length Sepal width Petal length Petal width 150.000000 150.000000 150.000000 150.000000 count 5.843333 3.054000 3.758667 1.198667 mean 0.433594 0.763161 0.828066 1.764420 std 4.300000 2.000000 1.000000 0.100000 min 2.800000 **25**% 5.100000 1.600000 0.300000 **50**% 5.800000 3.000000 4.350000 1.300000 **75**% 6.400000 3.300000 5.100000 1.800000 7.900000 4.400000 6.900000 2.500000 max VISUALISE THE WHOLE DATASET In [44]: sns.pairplot(df, hue='Species') <seaborn.axisgrid.PairGrid at 0x250e0875e80> Sepal length 4.5 4.0 Sepal width 3.5 2.5 2.0 Species Iris-setosa Iris-virginica Petal length 2.5 2.0 F 1.0 0.5 0.0 8 Petal length Petal width Sepal length df.columns Index(['Sepal length', 'Sepal width', 'Petal length', 'Petal width', Out[46]: 'Species'], dtype='object') In [47]: df.nunique() Sepal length 35 Out[47]: Sepal width 23 Petal length 43 Petal width 22 3 Species dtype: int64 df.Species.nunique() In [48]: Out[48]: 3 df.Species.value_counts() In [49]: Iris-setosa 50 Out[49]: Iris-versicolor 50 Iris-virginica 50 Name: Species, dtype: int64 df.max() In [50]: 7.9 Sepal length Out[50]: 4.4 Sepal width Petal length 6.9 Petal width 2.5 Species Iris-virginica dtype: object df.min() In [51]: Sepal length 4.3 Out[51]: Sepal width 2.0 Petal length 1.0 Petal width 0.1 Species Iris-setosa dtype: object DATA PREPROCESSING/CORRELATIONAL MATRIX In []: plt.figure(figsize=(10,7)) sns.heatmap(df.corr(), annot=True, cmap='seismic') plt.show() 1.0 Sepal length -0.11 0.87 0.82 0.8 - 0.6 Sepal width -0.11 -0.42 -0.36 0.4 Petal length - 0.2 0.87 -0.42 0.96 - 0.0 Petal width -0.2 0.82 -0.36 0.96 Petal length Sepal length Sepal width Petal width LABEL ENCODER In [76]: **from** sklearn.preprocessing **import** LabelEncoder le = LabelEncoder() In [81]: df['Species'] = le.fit_transform(df['Species']) df.head() Sepal length Sepal width Petal length Petal width Species Sprecies Out[81]: 3.5 0 5.1 1.4 0.2 0 1 4.9 3.0 1.4 0.2 0 0 2 4.7 3.2 1.3 0.2 0 0 3 4.6 3.1 1.5 0.2 0 0 5.0 3.6 0.2 0 0 1.4 In [82]: X = df.drop(columns=['Species']) Y = df['Species'] X[:5] Sepal length Sepal width Petal length Petal width Sprecies Out[82]: 5.1 3.5 1.4 0.2 0 1 4.9 3.0 1.4 0.2 0 2 4.7 3.2 1.3 0.2 0 4.6 3.1 1.5 0.2 0 5.0 3.6 4 1.4 0.2 0 SEPERATE FEATURES AND TARGET In [56]: data = df.values X = data[:,0:4]Y = data[:,4]CALCULATE AVERAGE OF EACH FEATURES FOR ALL CLASSES In [67]: Y_Data = np.array([np.average(X[:, i][Y==j].astype('float32')) for i in range (X.shape[1]) for j in (np.unique(Y))]) Y_Data_reshaped = Y_Data.reshape(4, 3) Y_Data_reshaped = np.swapaxes(Y_Data_reshaped, 0, 1) X_axis = np.arange(len(columns)-1) width = 0.25PLOT THE AVERAGE plt.bar(X_axis, Y_Data_reshaped[0], width, label = 'Setosa') plt.bar(X_axis+width, Y_Data_reshaped[1], width, label = 'Versicolour') plt.bar(X_axis+width*2, Y_Data_reshaped[2], width, label = 'Virginica') plt.xticks(X_axis, columns[:4]) plt.xlabel("Features") plt.ylabel("Value in cm.") plt.legend(bbox_to_anchor=(1.3,1)) plt.show() Setosa Versicolour 6 Virginica Value in cm. 2 1 Petal length Petal width Sepal length Sepal width Features MODEL TRAINING In [69]: 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) In [70]: from sklearn.svm import SVC svm = SVC()svm.fit(X_train, y_train) SVC() Out[70]: MODEL EVALUATION In [71]: predictions = svm.predict(X_test) from sklearn.metrics import accuracy_score accuracy_score(y_test, predictions) 0.95555555555556 Out[71]: **CLASSIFICATION REPORT** In [72]: from sklearn.metrics import classification_report print(classification_report(y_test, predictions)) recall f1-score support precision 1.00 Iris-setosa 1.00 1.00 11 Iris-versicolor 1.00 0.90 0.95 21 Iris-virginica 0.87 1.00 0.93 13 accuracy 0.96 45 0.96 0.97 0.96 45 macro avg weighted avg 0.96 0.96 0.96 45 **TESTING THE MODEL** In [73]: $X_{new} = np.array([[3, 2, 1, 0.2], [4.9, 2.2, 3.8, 1.1], [5.3, 2.5, 4.6, 1.9]])$ prediction = svm.predict(X_new) print("Prediction of Species: {}".format(prediction)) Prediction of Species: ['Iris-setosa' 'Iris-versicolor' 'Iris-virginica'] The model is predicting correctly because the setosa is shortest and virginica is the longest and versicolor is in between these two as we saw this in above graph. Save the model using pickle In [74]: **import** pickle with open('Model.pickle', 'wb') as f:

pickle.dump(svm, f)

with open('Model.pickle', 'rb') as f:

array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)

model = pickle.load(f)

LOAD THE MODEL

model.predict(X_new)

In [75]:

Out[75]: