DATA BEGINNER LEVEL ANALYTICS INTERMEDIATE LEVEL **LGM VIRTUAL INTERNSHIP PROGRAM 2021** • ADVANCE LEVEL Beginner Level Task... Task-1 Iris Flowers Classification ML Project: 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. Dataset: http://archive.ics.uci.edu/ml/datasets/Iris Name Madhav Pandey 1. Importing some important libraries and Packages import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns import missingno as msno print("Necessary packages included successfully!") Necessary packages included successfully! 2.Importing the dataset df = pd.read_csv('Iris.csv') sepal_length sepal_width petal_length petal_width Out[17]: species 5.1 3.5 1.4 0.2 Iris-setosa 4.9 3.0 1.4 0.2 Iris-setosa 2 4.7 3.2 1.3 Iris-setosa 4.6 3.1 1.5 Iris-setosa 4 5.0 3.6 1.4 0.2 Iris-setosa 145 2.3 Iris-virginica 6.7 3.0 5.2 146 6.3 2.5 5.0 1.9 Iris-virginica 147 2.0 Iris-virginica 6.5 3.0 5.2 148 2.3 Iris-virginica 3.0 5.1 149 5.9 1.8 Iris-virginica 150 rows × 5 columns 3. Data Exploration In [18]: r,c = df.shapeprint("Number of rows = ",r) print("Number of columns = ",c) Number of rows = 150Number of columns = 5In [19]: df.head() sepal_length sepal_width petal_length petal_width species Out[19]: 0 3.5 5.1 1.4 0.2 Iris-setosa 4.9 3.0 1.4 0.2 Iris-setosa 2 4.7 3.2 1.3 0.2 Iris-setosa 4.6 3.1 1.5 0.2 Iris-setosa 5.0 3.6 1.4 0.2 Iris-setosa In [20]: # to display stats about data df.describe() sepal_length sepal_width petal_length petal_width Out[20]: 150.000000 150.000000 150.000000 150.000000 count 3.054000 5.843333 3.758667 1.198667 mean 1.764420 0.828066 0.433594 0.763161 std 4.300000 2.000000 1.000000 0.100000 min **25**% 5.100000 2.800000 1.600000 0.300000 **50**% 5.800000 3.000000 4.350000 1.300000 6.400000 3.300000 5.100000 1.800000 **75**% max 7.900000 4.400000 6.900000 2.500000 In [21]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 150 entries, 0 to 149 Data columns (total 5 columns): # Column Non-Null Count Dtype sepal_length 150 non-null 0 float64 sepal_width 150 non-null float64 petal_length 150 non-null float64 petal_width 150 non-null float64 4 species 150 non-null object dtypes: float64(4), object(1) memory usage: 6.0+ KB 4. Checking Missing Values In [22]: print("Are there any missing values in the dataset ?", df.isnull().values.any()) Are there any missing values in the dataset ? False In [23]: msno.bar(df,figsize=(10,6),color='lightpink') plt.show() 150 1.0 150 8.0 120 0.6 90 0.4 60 0.2 30 0.0 0 5. Statistical Analysis In [24]: df.describe(include='all').T Out[24]: std min 25% 50% 75% count unique mean max top freq sepal_length 150.0 NaN NaN NaN sepal_width 150.0 NaN NaN NaN 3.054 0.433594 2.0 2.8 3.0 3.3 petal_length 150.0 3.758667 1.0 1.6 4.35 NaN petal_width 150.0 NaN 1.198667 0.763161 0.1 0.3 1.3 species 150 3 Iris-setosa NaN Nan Nan Nan Nan Nan In [26]: df['species'].unique() array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object) 6. Parametric Visualization g=sns.relplot(x='sepal_length', y='sepal_width', data=df, hue='species', style='species') g.fig.set_size_inches(18,8) plt.show() 4.5 4.0 species Iris-setosa Iris-versicolor 2.5 2.0 7.5 8.0 4.5 5.0 5.5 6.0 6.5 7.0 sepal_length In [28]: sns.pairplot(df, hue='species') plt.show() 4.5 2.5 2.0 species Iris-setosa Iris-versicolor Iris-virginica 2.5 petal width 0.5 sepal_length sepal_width petal_length petal_width plt.figure(figsize=(18,10)) plt.subplot(3,2,1)sns.boxplot(x='species',y='petal_length',data=df) plt.subplot(2,2,2) sns.boxplot(x='species', y='petal_width', data=df) plt.subplot(2,2,3)sns.boxplot(x='species', y='sepal_length', data=df) plt.subplot(2,2,4)sns.boxplot(x='species', y='sepal_width', data=df) plt.show() 2.5 2.0 petal width Iris-setosa Iris-versicolor Iris-virginica species 0.5 0.0 Iris-setosa Iris-versicolor Iris-virginica 4.5 8.0 7.5 4.0 7.0 sepal width sepal length 5.5 2.5 5.0 4.5 2.0 Iris-setosa Iris-versicolor Iris-virginica Iris-setosa Iris-versicolor Iris-virginica species species plt.figure(figsize=(18,10)) plt.subplot(2,2,1)sns.violinplot(x='species',y='petal_length',data=df) plt.subplot(2,2,2) sns.violinplot(x='species', y='petal_width', data=df) plt.subplot(2,2,3) sns.violinplot(x='species', y='sepal_length', data=df) plt.subplot(2,2,4)sns.violinplot(x='species', y='sepal_width', data=df) plt.show() 2.5 2.0 petal width 0.5 0.0 Iris-versicolor Iris-virginica Iris-versicolor Iris-virginica Iris-setosa Iris-setosa species species 4.5 4.0 sepal width 2.5 2.0 Iris-setosa Iris-versicolor Iris-virginica Iris-setosa Iris-versicolor Iris-virginica species species plt.figure(figsize=(18,7)) sns.boxplot(data=df).set_title("Normal distribution of Iris features\n", size=20) plt.show() Normal distribution of Iris features sepal_length sepal_width petal_length petal_width plt.figure(figsize=(18,7)) sns.violinplot(data=df).set_title("Variance of Iris features\n", size=20) plt.show() Variance of Iris features

In [33]: In [30]: In [31]: In [32]: sepal_length sepal_width petal_length petal_width 7. Attribute Correlation In [34]: plt.figure(figsize=(16,8)) sns.heatmap(df.corr(), annot=True, fmt='f', cmap='gist_heat').set_title('Correaltion of attributes\n', size=20) plt.show() Correaltion of attributes

-1.0 1.000000 -0.109369 0.871754 0.817954 - 0.8 - 0.6 -0.109369 1.000000 -0.420516 -0.356544 - 0.4 - 0.2 0.871754 -0.420516 1.000000 0.962757 - 0.0 -0.2-0.356544 0.817954 0.962757 1.000000 sepal_width sepal_length petal_length petal_width In [35]: X = df.iloc[:,0:4].valuesfrom sklearn.preprocessing import LabelEncoder le = LabelEncoder() $y = le.fit_transform(y)$ 8. Metric In [36]: from sklearn.metrics import make_scorer, accuracy_score, precision_score from sklearn.metrics import classification_report from sklearn.metrics import confusion_matrix from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score print("All necessary metrics included!") All necessary metrics included! 9.Model Selection In [37]: from sklearn.model_selection import KFold,train_test_split,cross_val_score from sklearn.ensemble import RandomForestClassifier from sklearn.linear_model import LogisticRegression from sklearn.linear_model import SGDClassifier from sklearn.tree import DecisionTreeClassifier from sklearn.neighbors import KNeighborsClassifier from sklearn.svm import SVC, LinearSVC from sklearn.naive_bayes import GaussianNB X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0) print("All Machine Learning packages included!") All Machine Learning packages included! 10.Random Forest Rule In [38]: rf = RandomForestClassifier(n_estimators=100) rf.fit(X_train,y_train) y_pred = rf.predict(X_test) acc_rf = round(accuracy_score(y_test,y_pred)*100,2) rf_acc = round(rf.score(X_train,y_train)*100,2) cm = confusion_matrix(y_test,y_pred) acc = accuracy_score(y_test,y_pred) prec = precision_score(y_test, y_pred, average='micro') recall = recall_score(y_test,y_pred,average='micro') f1 = f1_score(y_test,y_pred,average='micro') print("Confusion matrix of Random Forest\n", cm) print("Accuracy of Random Forest = ",acc) print("Precision of Random Forest = ",prec) print("Recall of Random Forest = ",recall) print("f1 score of Random Forest = ",f1) Confusion matrix of Random Forest [[11 0 0] [0 13 0] [0 0 6]] Accuracy of Random Forest = 1.0Precision of Random Forest = 1.0Recall of Random Forest = 1.0f1 score of Random Forest = 1.0 11.Logistic Regression Rule In [39]: lg = LogisticRegression(solver='lbfgs', max_iter=400) lg.fit(X_train,y_train) y_pred = lg.predict(X_test) acc_lg = round(accuracy_score(y_test, y_pred)*100, 2) lg_acc = round(lg.score(X_train,y_train)*100,2) cm = confusion_matrix(y_test,y_pred) acc = accuracy_score(y_test,y_pred) prec = precision_score(y_test, y_pred, average='micro') recall = recall_score(y_test,y_pred,average='micro') f1 = f1_score(y_test,y_pred,average='micro') print("Confusion matrix of Logistic Regression\n",cm) print("Accuracy of Logistic Regression = ",acc) print("Precision of Logistic Regression = ",prec) print("Recall of Logistic Regression = ",recall) print("f1 score of Logistic Regression = ",f1) Confusion matrix of Logistic Regression [[11 0 0] [0 13 0] [0 0 6]] Accuracy of Logistic Regression = 1.0 Precision of Logistic Regression = 1.0 Recall of Logistic Regression = 1.0 f1 score of Logistic Regression = 1.0 12.K Nearest Neighbours Rule In [40]: knn = KNeighborsClassifier(n_neighbors=3) knn.fit(X_train,y_train) y_pred = knn.predict(X_test) acc_knn = round(accuracy_score(y_test,y_pred)*100,2) knn_acc = round(knn.score(X_train,y_train)*100,2) cm = confusion_matrix(y_test,y_pred) acc = accuracy_score(y_test,y_pred) prec = precision_score(y_test, y_pred, average='micro') recall = recall_score(y_test, y_pred, average='micro') f1 = f1_score(y_test,y_pred,average='micro') print("Confusion matrix of K Nearest Neighbour\n",cm) print("Accuracy of K Nearest Neighbour = ",acc) print("Precision of K Nearest Neighbour = ",prec) print("Recall of K Nearest Neighbour = ", recall) print("f1 score of K Nearest Neighbour = ",f1) Confusion matrix of K Nearest Neighbour [[11 0 0] [0 12 1] [0 0 6]] Accuracy of K Nearest Neighbour = 0.9666666666666667 Precision of K Nearest Neighbour = 0.9666666666666667 f1 score of K Nearest Neighbour = 0.9666666666666667 13. KNN plt.figure(figsize=(20,7))

 $a_{index} = list(range(1,50))$

for i in list(range(1,50)):

model.fit(X_train,y_train)

plt.plot(a_index, a, marker="*")

14. Gaussian Naive Bayes rule

cm = confusion_matrix(y_test,y_pred) acc = accuracy_score(y_test,y_pred)

Confusion matrix of K Nearest Neighbour

acc_gauss = round(accuracy_score(y_test,y_pred)*100,2) gauss_acc = round(gauss.score(X_train,y_train)*100,2)

prec = precision_score(y_test,y_pred,average='micro') recall = recall_score(y_test,y_pred,average='micro')

print("Confusion matrix of K Nearest Neighbour\n",cm)

Accuracy of K Nearest Neighbour = 0.9666666666666667 f1 score of K Nearest Neighbour = 0.9666666666666667

acc_lsvc = round(accuracy_score(y_test,y_pred)*100,2) lsvc_acc = round(lsvc.score(X_train,y_train)*100,2)

prec = precision_score(y_test,y_pred,average='micro') recall = recall_score(y_test,y_pred,average='micro')

print("Confusion matrix of K Nearest Neighbour\n",cm)

acc_dt = round(accuracy_score(y_test, y_pred)*100, 2) dt_acc = round(dt.score(X_train,y_train)*100,2)

prec = precision_score(y_test,y_pred,average='micro') recall = recall_score(y_test,y_pred,average='micro')

print("Confusion matrix of K Nearest Neighbour\n",cm)

'Score':[acc_knn,acc_lg,acc_rf,acc_gauss,acc_lsvc,acc_dt],

ax = sns.barplot(x='Model', y='Accuracy_score', data=res)

'Accuracy_score':[knn_acc,lg_acc,rf_acc,gauss_acc,lsvc_acc,dt_acc]

ax.text(i,v+1,str(v),horizontalalignment='center',size=15,color='indigo')

96.67

Logistic Regression

'Model':['KNN','Logistic Regression','Random Forest','Naive Bayes','Support Vector Regression','Decision Tree'],

100.0

Random Forest

100.0

Decision Tree

95.83

Support Vector Regression

95.0

Naive Bayes

Model

f1 = f1_score(y_test,y_pred,average='micro')

print("Accuracy of K Nearest Neighbour = ",acc) print("Precision of K Nearest Neighbour = ",prec) print("Recall of K Nearest Neighbour = ",recall) print("f1 score of K Nearest Neighbour = ",f1)

14. Linear Support Vector Classifier Rule

f1 = f1_score(y_test,y_pred,average='micro')

print("Accuracy of K Nearest Neighbour = ",acc) print("Precision of K Nearest Neighbour = ",prec) print("Recall of K Nearest Neighbour = ",recall) print("f1 score of K Nearest Neighbour = ",f1)

lsvc = LinearSVC(max_iter=4000)

cm = confusion_matrix(y_test,y_pred) acc = accuracy_score(y_test,y_pred)

Confusion matrix of K Nearest Neighbour

Accuracy of K Nearest Neighbour = 1.0Precision of K Nearest Neighbour = 1.0 Recall of K Nearest Neighbour = 1.0 f1 score of K Nearest Neighbour = 1.0

15. Decision Tree Classifier Rule

cm = confusion_matrix(y_test,y_pred) acc = accuracy_score(y_test,y_pred)

Confusion matrix of K Nearest Neighbour

Accuracy of K Nearest Neighbour = 1.0 Precision of K Nearest Neighbour = 1.0 Recall of K Nearest Neighbour = 1.0 f1 score of K Nearest Neighbour = 1.0

17. Model Scorer Rule

plt.figure(figsize=(20,8))

labels = (res['Accuracy_score']) for i, v in enumerate(labels):

95.0

THANK YOU SO MUCH!

res = pd.DataFrame(

dt = DecisionTreeClassifier()

dt.fit(X_train,y_train) y_pred = dt.predict(X_test)

lsvc.fit(X_train,y_train) y_pred = lsvc.predict(X_test)

f1 = f1_score(y_test,y_pred,average='micro')

print("Accuracy of K Nearest Neighbour = ",acc) print("Precision of K Nearest Neighbour = ",prec) print("Recall of K Nearest Neighbour = ", recall) print("f1 score of K Nearest Neighbour = ",f1)

gauss = GaussianNB()

[[11 0 0] [0 13 0] [0 1 5]]

[[11 0 0] [0 13 0] [0 0 6]]

[[11 0 0] [0 13 0] [0 0 6]]

gauss.fit(X_train,y_train) y_pred = gauss.predict(X_test)

prediction = model.predict(X_test)

model = KNeighborsClassifier(n_neighbors=i)

pecify a dtype explicitly to silence this warning.

a = a.append(pd.Series(accuracy_score(y_test, prediction)))

C:\Users\DELL\AppData\Local\Temp/ipykernel_7556/1961719357.py:3: DeprecationWarning: The default dtype for empty Series will be 'object' instead of 'float64' in a future version. S

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49

a = pd.Series() x = range(1, 50)

plt.xticks(x) plt.show()

a = pd.Series()

1.00

0.92

0.90

0.88

In [42]:

In [43]:

In [44]:

In [45]:

res

100

80

40

20

In []: