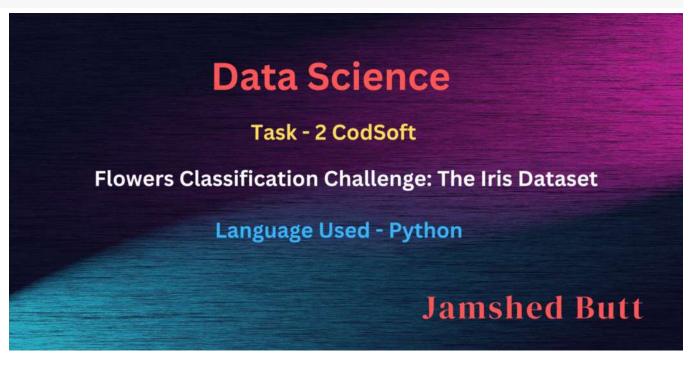
from IPython import display
display.Image("/content/Modern Minimal Gradient Background Technology Banner (1).gif")



Project Name ∜ Titanic Dataset ∜

AUTHOR: Jamshed Butt from Data Science



The aim of the Iris dataset is to facilitate research in pattern recognition, classification, and data analysis by providing measurements of iris flowers from three species, aiding in species differentiation.

Import Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import pylab
#Normalize Data
from sklearn.preprocessing import StandardScaler
#Conert Categorical to Numerical Value
from sklearn.preprocessing import LabelEncoder
#Columns Relationship for target value
from sklearn.feature_selection import mutual_info_classif,SelectKBest,f_classif
#Splitting Data
from \ sklearn.model\_selection \ import \ train\_test\_split, cross\_val\_score
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from \ sklearn.neighbors \ import \ KNeighbors Classifier
from \ sklearn.metrics \ import \ accuracy\_score, classification\_report, confusion\_matrix, roc\_curve, auc
from sklearn import metrics
```

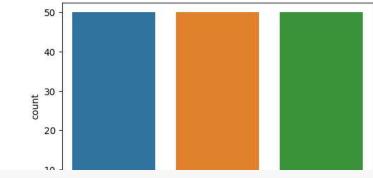
Load Dataset

```
df = pd.read_csv("/content/drive/MyDrive/Datasets/IRIS.csv")
df.head()
          sepal_length sepal_width petal_length petal_width
                                                                        species
      0
                    5.1
                                   3.5
                                                  1.4
                                                                 0.2 Iris-setosa
      1
                    4.9
                                   3.0
                                                  1.4
                                                                 0.2 Iris-setosa
      2
                    4.7
                                   3.2
                                                   1.3
                                                                 0.2 Iris-setosa
                    4.6
      3
                                   3.1
                                                   1.5
                                                                 0.2 Iris-setosa
                    5.0
                                                                 0.2 Iris-setosa
df.shape
     (150, 5)
df.info()
      <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 150 entries, 0 to 149
     Data columns (total 5 columns):
      # Column
                         Non-Null Count Dtype
      0 sepal_length 150 non-null
1 sepal_width 150 non-null
2 petal_length 150 non-null
                                             float64
                                             float64
                                             float64
      3 petal_width 150 non-null
4 species 150 non-null
                                             float64
                                             object
     dtypes: float64(4), object(1)
     memory usage: 6.0+ KB
df.isnull().sum()
     {\tt sepal\_length}
     sepal_width
     petal_length
                       0
     petal_width
                       0
     species
                        0
     dtype: int64
df.describe()
```

	sepal_length	sepal_width	petal_length	petal_width
cou	nt 150.000000	150.000000	150.000000	150.000000
mea	an 5.843333	3.054000	3.758667	1.198667
sto	0.828066	0.433594	1.764420	0.763161
mi	n 4.300000	2.000000	1.000000	0.100000
259	% 5.100000	2.800000	1.600000	0.300000
509	5.800000	3.000000	4.350000	1.300000
759	6.400000	3.300000	5.100000	1.800000
ma	x 7.900000	4.400000	6.900000	2.500000

Univariate Analysis

```
plt.figure(figsize=(6,4))
sns.countplot(x="species",data=df)
plt.xlabel("Species",fontsize=14)
plt.show()
```



df["species"].value_counts()

Iris-setosa 50
Iris-versicolor 50
Iris-virginica 50
Name: species, dtype: int64

```
sns.set(rc={"figure.figsize":(6,4)})
sns.distplot(df["sepal_length"], kde=True, color="orange", bins=10)
```

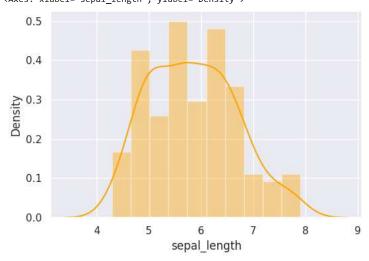
<ipython-input-9-e0a31f1805d9>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(df["sepal_length"], kde=True, color="orange", bins=10)
<Axes: xlabel='sepal_length', ylabel='Density'>



```
plt.figure(figsize=(6,4))
sns.scatterplot(x="sepal_length",y=df.index,data=df)
plt.show()
```

```
sns.set(rc={"figure.figsize":(6,4)})
sns.distplot(df["sepal_width"], kde=True, color="orange", bins=10)
```

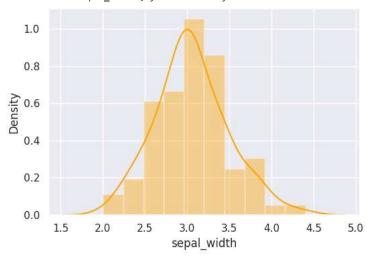
<ipython-input-11-5b24ae600e6a>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

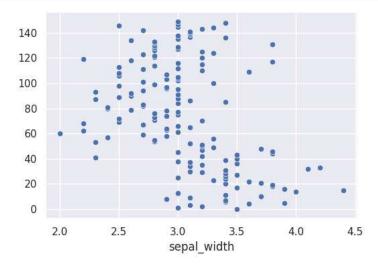
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(df["sepal_width"], kde=True, color="orange", bins=10)
<Axes: xlabel='sepal_width', ylabel='Density'>



```
plt.figure(figsize=(6,4))
sns.scatterplot(x="sepal_width",y=df.index,data=df)
plt.show()
```



```
sns.set(rc={"figure.figsize":(6,4)})
sns.distplot(df["petal_length"], kde=True, color="orange", bins=10)
```

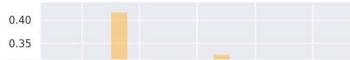
<ipython-input-13-53ed0085d8fc>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

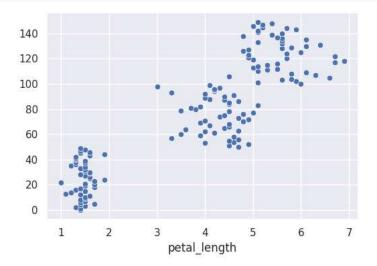
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(df["petal_length"], kde=True, color="orange", bins=10)
<Axes: xlabel='petal_length', ylabel='Density'>



plt.figure(figsize=(6,4))
sns.scatterplot(x="petal_length",y=df.index,data=df)
plt.show()



```
sns.set(rc={"figure.figsize":(6,4)})
sns.distplot(df["petal_width"], kde=True, color="orange", bins=10)
```

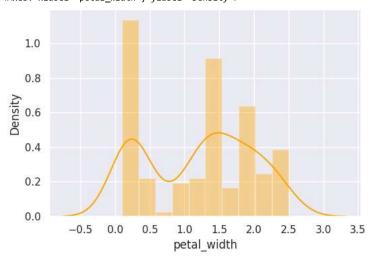
<ipython-input-15-6f7a78f94cf3>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

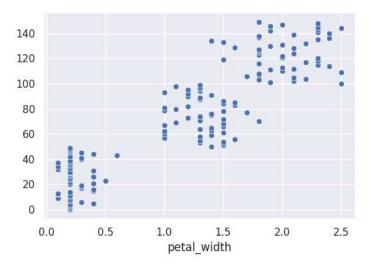
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see $\underline{\text{https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751}}$

sns.distplot(df["petal_width"], kde=True, color="orange", bins=10)
<Axes: xlabel='petal_width', ylabel='Density'>



```
plt.figure(figsize=(6,4))
sns.scatterplot(x="petal_width",y=df.index,data=df)
plt.show()
```



▼ EDA (Exploratory Data Analysis)

Removeing Duplicate

```
duplicate = df.duplicated()
print(duplicate.sum())

3

df.drop_duplicates(inplace=True)

df.duplicated().sum()
```

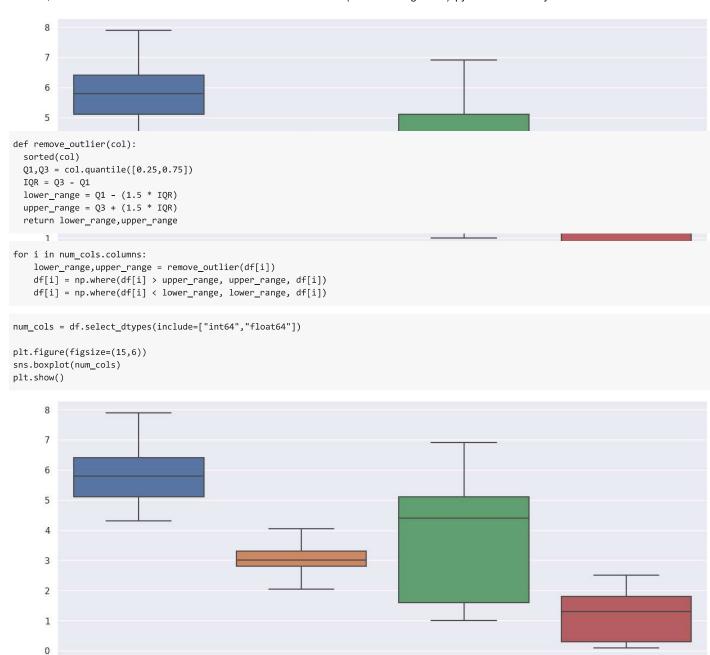
▼ Check NaN Value And Remove NaN Values

```
df.isnull().sum()

sepal_length  0
sepal_width  0
petal_length  0
petal_width  0
species  0
dtype: int64
```

▼ Removing Outlier

```
num_cols = df.select_dtypes(include=["int64","float64"])
plt.figure(figsize=(15,6))
sns.boxplot(num_cols)
plt.show()
```



▼ Bivariate Analysis

sepal_length

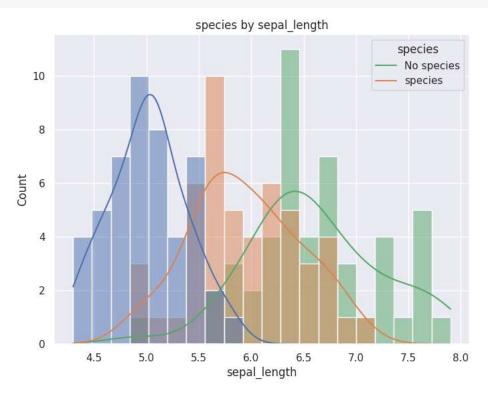
```
df.info()
     <class 'pandas.core.frame.DataFrame'>
     Int64Index: 147 entries, 0 to 149
     Data columns (total 5 columns):
     # Column
                     Non-Null Count Dtype
     0 sepal_length 147 non-null
                                       float64
         sepal_width 147 non-null
                                       float64
         petal_length 147 non-null
                                       float64
         petal_width 147 non-null
                                        float64
                       147 non-null
                                       object
          species
     dtypes: float64(4), object(1)
     memory usage: 6.9+ KB
plt.figure(figsize=(8, 6))
\verb|sns.histplot(data=df, x='sepal\_length', hue='species', kde=True, bins=20)|\\
plt.title('species by sepal_length')
plt.xlabel('sepal_length')
plt.ylabel('Count')
```

petal_length

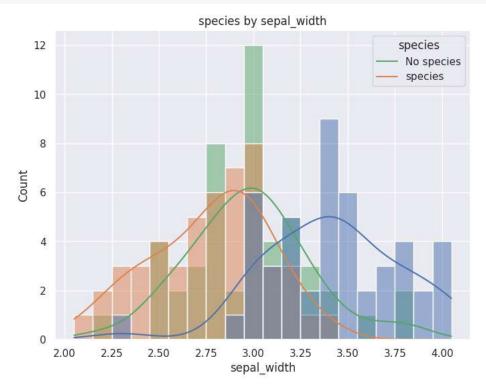
sepal_width

petal_width

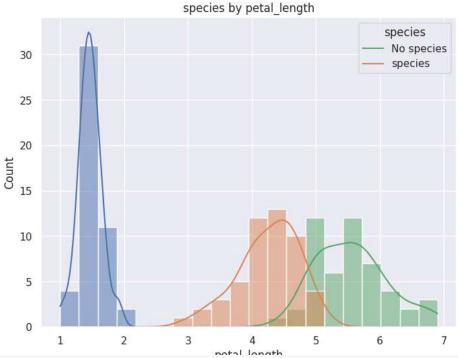
```
plt.legend(title='species', loc='upper right', labels=['No species', 'species'])
plt.show()
```



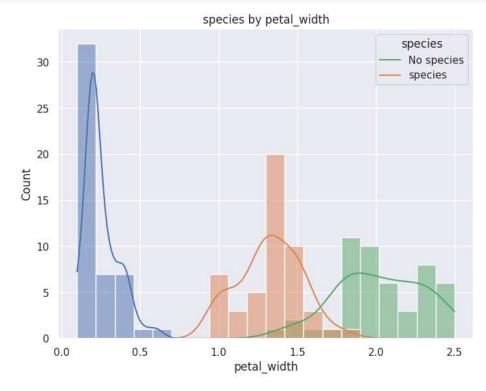
```
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x='sepal_width', hue='species', kde=True, bins=20)
plt.title('species by sepal_width')
plt.xlabel('sepal_width')
plt.ylabel('Count')
plt.legend(title='species', loc='upper right', labels=['No species', 'species'])
plt.show()
```



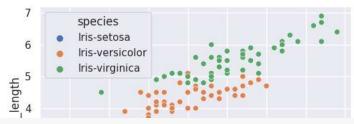
```
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x='petal_length', hue='species', kde=True, bins=20)
plt.title('species by petal_length')
plt.xlabel('petal_length')
plt.ylabel('Count')
plt.legend(title='species', loc='upper right', labels=['No species', 'species'])
plt.show()
```



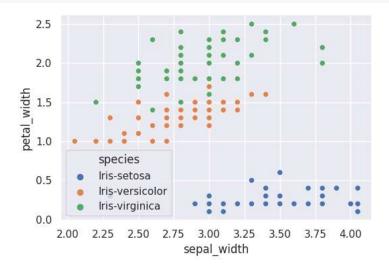
```
plt.figure(figsize=(8, 6))
sns.histplot(data=df, x='petal_width', hue='species', kde=True, bins=20)
plt.title('species by petal_width')
plt.xlabel('petal_width')
plt.ylabel('Count')
plt.legend(title='species', loc='upper right', labels=['No species', 'species'])
plt.show()
```



sns.scatterplot(x="sepal_length",y="petal_length",data=df,hue="species")
plt.show()

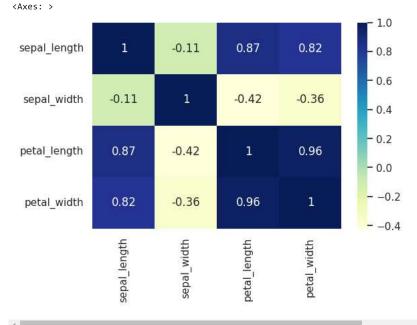


sns.scatterplot(x="sepal_width",y="petal_width",data=df,hue="species")
plt.show()

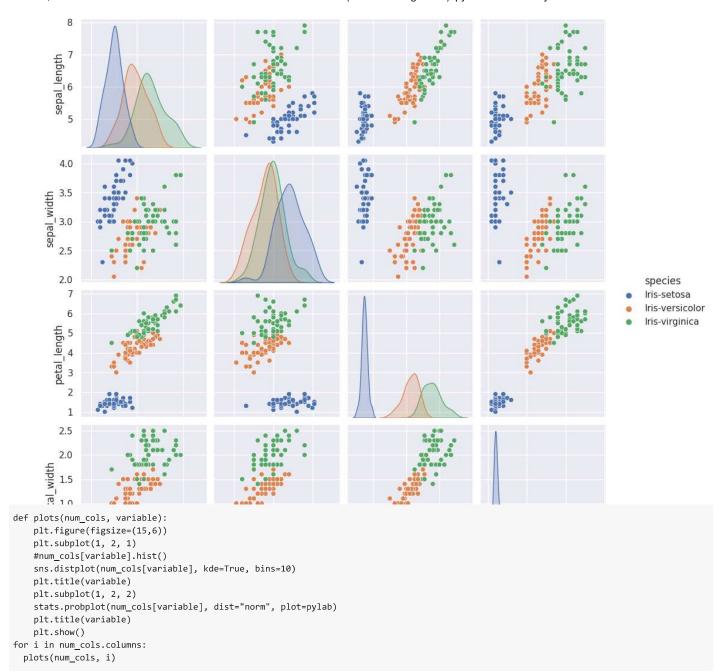


sns.heatmap(df.corr(), cmap="YlGnBu", annot=True)

<ipython-input-32-1f8db7c938a8>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve sns.heatmap(df.corr(), cmap="YlGnBu", annot=True)



sns.pairplot(df,hue="species")
plt.show()



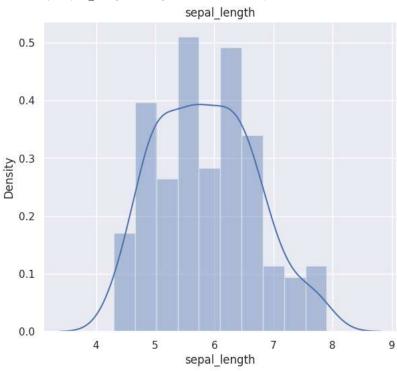
<ipython-input-33-d3397ca1f647>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(num_cols[variable], kde=True, bins=10)

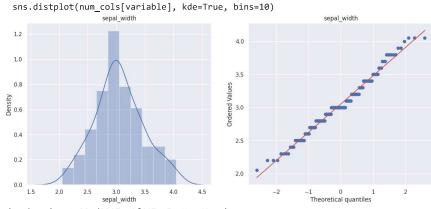


<ipython-input-33-d3397ca1f647>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

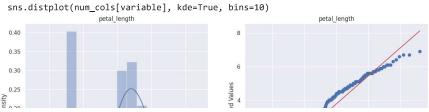


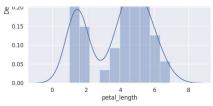
<ipython-input-33-d3397ca1f647>:5: UserWarning:

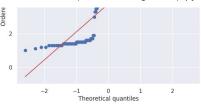
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see $\underline{\text{https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751}}$





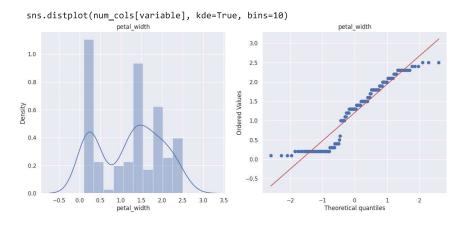


<ipython-input-33-d3397ca1f647>:5: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see $\underline{\text{https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751}}$



▼ Feature Engineering

▼ Mutual Information

X = df.iloc[:,:4]
Y = df["species"]

X.head()

	sepal_length	sepal_width	petal_length	petal_width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

mi_score = mutual_info_classif(X,Y)
mi_score = pd.Series(mi_score)

 $mi_score.index = X.columns$

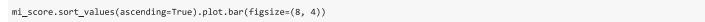
mi_score.sort_values(ascending=True)

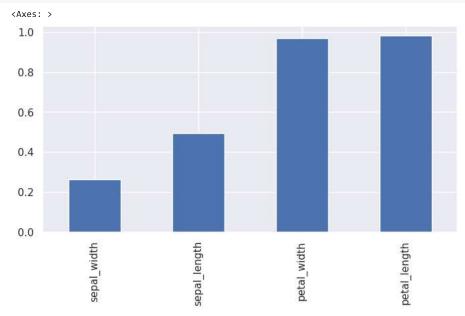
 sepal_width
 0.264381

 sepal_length
 0.493026

 petal_width
 0.970660

```
petal_length   0.981816
dtype: float64
```





▼ Spliting Data into Train and Test

```
train_data,test_data,train_label,test_label = train_test_split(X,Y,test_size=0.2,random_state=0)

print("train_data : ",train_data.shape)
print("train_label : ",train_label.shape)
print("test_data : ",test_data.shape)
print("test_label : ",test_label.shape)

train_data : (117, 4)
train_label : (117,)
test_data : (30, 4)
test_label : (30,)
```

▼ Normalizing Data

```
sc = StandardScaler()
train_data_sc = sc.fit_transform(train_data)
test_data_sc = sc.fit_transform(test_data)

train_data_sc
```

```
, 0.1320/591, 0.96381606,
0.621/66
                                          0.//148954],
[-0.10570022, 2.25537267, -1.51014241, -1.36810811],
[\ 0.621766\ ,\ 0.36799778,\ 0.84874823,\ 1.4401138\ ],
[-0.95441081, 1.78352895, -1.33754066, -1.23438326],
[-1.43938829, 0.36799778, -1.28000674, -1.36810811],
[ 0.37927726, -0.57568967, 0.56107864, 0.77148954],
[ 0.621766 , 0.36799778, 0.38847688, 0.37031498],
                                          1.4401138 ],
  2.1979428 , -0.10384595, 1.30901957,
[-0.10570022, -0.81161153, 0.73368039,
                                          0.90521439],
                                          0.37031498],
[-0.5906777 , -0.10384595, 0.38847688,
[-0.34818896, -0.10384595,
                            0.38847688,
                                          0.37031498],
[ 0.01554415, -0.10384595, 0.73368039,
                                          0.77148954],
[-0.46943333, -1.51937712, -0.07179446, -0.29830929],
[ 0.25803289, -0.57568967, 0.10080729, 0.10286527],
[ 0.621766 , -0.57568967, 1.02134998, 1.1726641 ], [-0.10570022, -0.81161153, 0.04327337, -0.03085958],
[\ 2.1979428\ ,\ 1.78352895,\ 1.65422308,\ 1.30638895],
\hbox{\tt [-0.5906777 , 0.8398415 , -1.22247282, -1.36810811],}
  \hbox{\tt 0.98549911, -0.10384595, 0.79121431, 1.4401138 ],}\\
  0.621766 , -0.33976781, 0.27340905,
                                          0.102865271.
[-0.22694459, -1.0475334 , -0.1868623 , -0.29830929],
[-1.07565518, -0.10384595, -1.28000674, -1.36810811],
[ \ 0.13678852, \ -0.81161153, \ \ 0.73368039, \ \ 0.50403983],
  1.22798785, 0.13207591, 0.90628214, 1.1726641 ],
[ 1.22798785, 0.13207591, 0.73368039, 1.4401138 ],
[-1.68187702, -1.75529898, -1.45260849, -1.23438326],
[-1.07565518, -2.34510364, -0.1868623 , -0.29830929],
[-0.46943333, -1.0475334 , 0.33094296, -0.03085958],
[ 0.50052163, -1.28345526, 0.61861255, 0.37031498],
[-0.46943333, -1.28345526, 0.10080729, 0.10286527],
[-1.80312139, -0.10384595, -1.45260849, -1.36810811],
```

Model

▼ Logistic Regression

```
model_lr = LogisticRegression().fit(train_data_sc,train_label)
y_pred_1 = model_lr.predict(test_data_sc)
y_pred_1
                     array(['Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-virginica',
                                               'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor', 'Iris-versicolor',
                                               'Iris-versicolor', 'Iris-setosa', 'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa', 'Iris-versicolor', 'Iris-setosa', 'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa', 'Iris-versicolor', 'Iris-vers
                                               'Iris-versicolor', 'Iris-virginica'], dtype=object)
 accuracy_score(y_pred_1,test_label)
                    1.0
 confusion_matrix(y_pred_1,test_label)
                     array([[11, 0, 0],
                                                 [ 0, 10,
                                                                                    0],
                                                [0, 0, 9]])
print(classification_report(y_pred_1,test_label))
                                                                                      precision
                                                                                                                                        recall f1-score
                                                                                                                                                                                                                  support
                                   Iris-setosa
                                                                                                         1.00
                                                                                                                                                1.00
                                                                                                                                                                                       1.00
                                                                                                                                                                                                                                     11
                     Iris-versicolor
                                                                                                         1.00
                                                                                                                                                1.00
                                                                                                                                                                                       1.00
                                                                                                                                                                                                                                     10
                        Iris-virginica
                                                                                                         1.00
                                                                                                                                                1.00
                                                                                                                                                                                       1.00
                                                                                                                                                                                                                                         9
                                                                                                                                                                                       1.00
                                                                                                                                                                                                                                      30
                                               accuracy
                                           macro avg
                                                                                                         1.00
                                                                                                                                                1.00
                                                                                                                                                                                       1.00
                                weighted avg
                                                                                                         1.00
                                                                                                                                                                                       1.00
                                                                                                                                                                                                                                      30
```

Random Forest Model

```
model_rf = RandomForestClassifier().fit(train_data_sc,train_label)
```

```
y_pred_2 = model_rf.predict(test_data_sc)
print("Train Data Accuracy :",(model_rf.score(train_data_sc,train_label)))
print("Test Data Accuracy :",(accuracy_score(y_pred_2,test_label)))
     Train Data Accuracy : 1.0
     Test Data Accuracy : 0.9666666666666667
confusion_matrix(y_pred_2,test_label)
     array([[11, 0, 0],
            [ 0, 10, 1],
[ 0, 0, 8]])
print(classification_report(y_pred_2,test_label))
                     precision
                                  recall f1-score support
                                    1.00
        Iris-setosa
                          1.00
                                              1.00
                                                          11
     Iris-versicolor
                          1.00
                                    0.91
                                              0.95
                                                          11
      Iris-virginica
                          0.89
                                    1.00
                                              0.94
                                                           8
            accuracy
                                               0.97
                                                           30
           macro avg
                         0.96
                                    0.97
                                              0.96
                                                           30
                          0.97
                                              0.97
        weighted avg
                                    0.97
                                                          30
```

KNN Model

```
model_knn = KNeighborsClassifier(n_neighbors=3).fit(train_data_sc,train_label)
y_pred_3 = model_knn.predict(test_data_sc)
print("Test Data Accuracy :",(accuracy_score(y_pred_3,test_label)))
     Test Data Accuracy : 0.9666666666666667
confusion_matrix(y_pred_3,test_label)
     array([[11, 0, 0],
            [ 0, 9, 0],
[ 0, 1, 9]])
print(classification_report(y_pred_3,test_label))
                      precision
                                  recall f1-score
                                                      support
         Iris-setosa
                           1.00
                                     1.00
                                               1.00
                                                           11
     Iris-versicolor
                           0.90
                                     1.00
                                               0.95
      Iris-virginica
                                               0.95
                                                           10
                           1.00
                                     0.90
            accuracy
                                               0.97
                                                           30
                           0.97
                                     0.97
                                               0.96
           macro avg
                                                           30
        weighted avg
                           0.97
                                     0.97
                                               0.97
                                                           30
```

✓ Connected to Python 3 Google Compute Engine backend