Iris Classification - rubangino.in

Overview

This notebook has Iris Classification project, which includes the development of four different machine learning models of Logistic Regression, K-nearest classifier, Support Vector Classification, and Naive Bayes Classification to classify the Iris flowers into different species. This project involves the selection and training of a model, testing its performance, and deploying it with a Streamlit front-end. Among the four models, Logistic Regression was chosen to predict the Iris Dataset. The trained model is saved as a `model.pkl` file for an easy integration into the application.

Github project link: [https://github.com/Ruban2205/Iris_Classification (https://github.com/Ruban2205/Iris_Classification)](https://github.com/Ruban2205/Iris_Classification)

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Importing the Libraries 📝

In [2]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import pearsonr

import warnings
warnings.filterwarnings('ignore')
```

Loading the Dataset 🔃

In [3]:

```python
data_frame = pd.read_csv("Dataset/Iris.csv")
data_frame
```

Out[3]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

Data preprocessing 🗃️

In [4]:
```python
# To check the Statistics of Data
data_frame.describe()
```

Out[4]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

In [5]:
```python
# To check the DataTypes

data_frame.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             150 non-null    int64  
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object 
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

In [6]:
```python
# To Check if the dataset has null values.

# If more than 15% of null value is present in the particular column. DROP the Column.
# If it is less than 15% use Imputations techniques like Mean, Median and Mode.

data_frame.isna().sum()
```

Out[6]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

In [7]:
```python
# Check if the Duplicate rows exists.
# If any duplicated row is found. Then remove the entire row.

data_frame.duplicated().sum()
```

Out[7]:
```
0
```

In [8]:
```
# Drop the ID Column since, We don't need the column.
# Use Normalisation methods - StandardScalar, MinmaxScalar

data_frame.drop(columns=["Id"], inplace=True)
data_frame.head()
```

Out[8]:

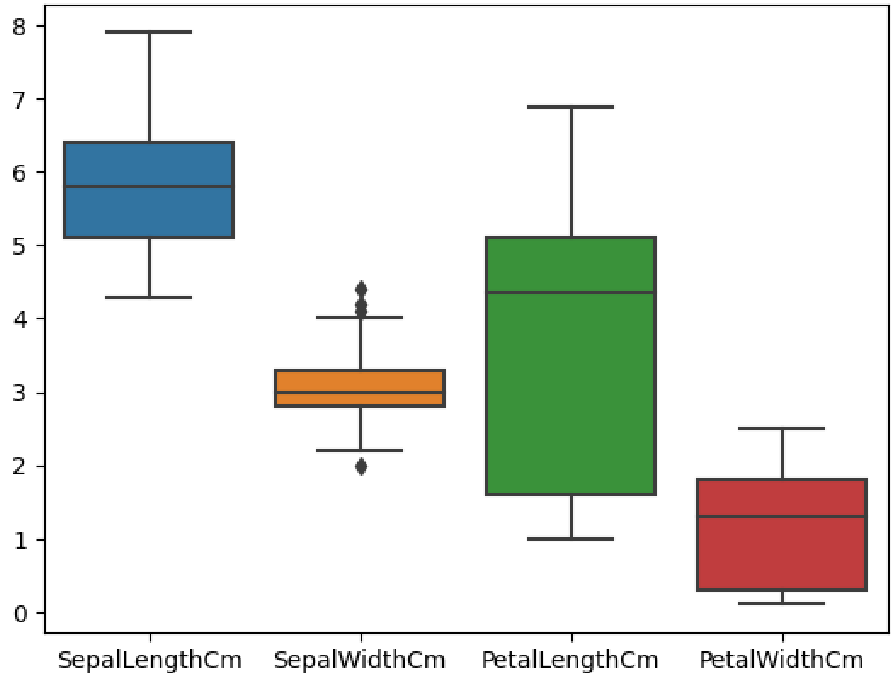
	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [9]:
```
# Scaling the Features.

# In this dataset the Inputs are Sepal length, Sepal Width, Petal length, and Petal Width
# The Outputs = Species

# X => Inputs -> SepalLenghtCm, SepalWidthCm, PetalLengthCm, PetalWidthCm
# Y => Ouput -> Species

features = ["SepalLengthCm", "SepalWidthCm", "PetalLengthCm", "PetalWidthCm"]
x = data_frame[features].values #Input
y = data_frame["Species"].values #Output
```

Box plot 📊

In [10]:
```
# Plotting the data to find outliers

sns.boxplot(data=data_frame)
```

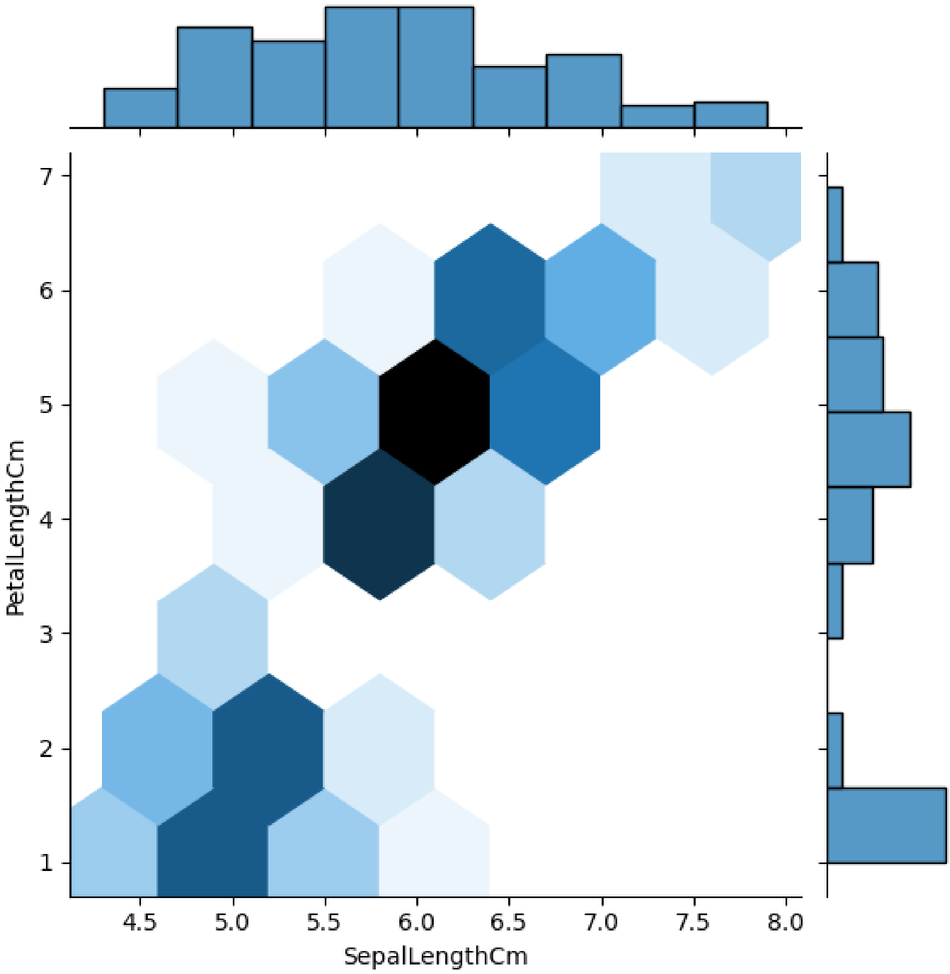
Out[10]: <AxesSubplot:>



Joint Plot

In [11]:
```
sns.jointplot(x=data_frame['SepalLengthCm'], y=data_frame['PetalLengthCm'], data=data_frame,
```

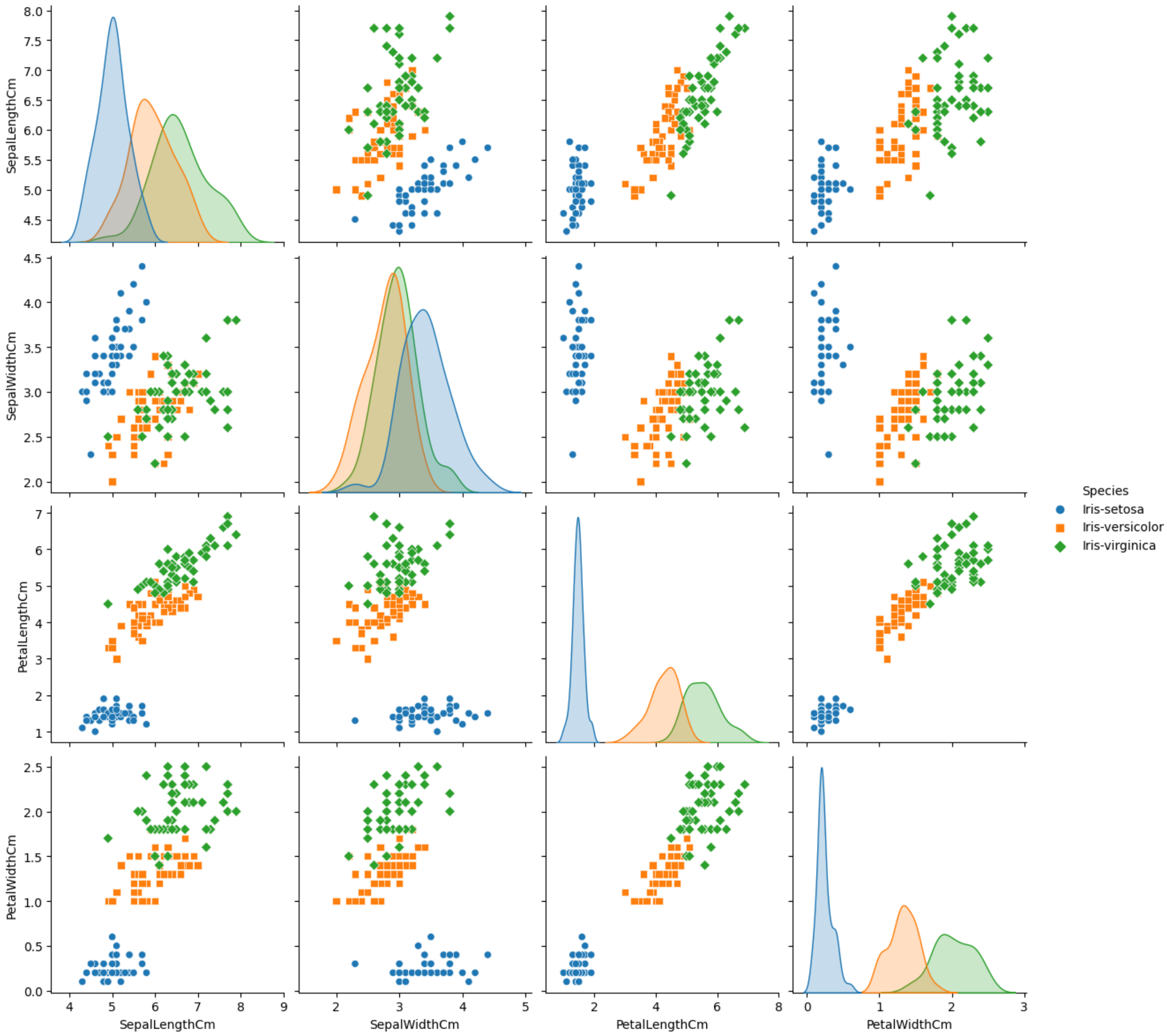
Out[11]: <seaborn.axisgrid.JointGrid at 0x1aaacb1dcc8>



Pair plot 📈

In [12]:
```python
# Pair plot - to find the outliers

sns.pairplot(data_frame, hue="Species", size=3, markers=["o", "s", "D"])
```

Out[12]: <seaborn.axisgrid.PairGrid at 0x1aaaca869c8>



Feature Scaling ⚖️

In [13]:
```python
# Seperate the data set into Train and Test

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=0)
```

Label Encoder 🏷️

In [14]:
```python
# Label Encoder
# A technique is used in Machine Learning to convert categorical variables into numerical fo

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
le.fit(y)
```

Out[14]: LabelEncoder()

In [15]:
```
# dir(le)

le.classes_
```
Out[15]:
```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

In [16]:
```
# Use mapping method to add the index to decode the output.

mapping = dict(zip(le.classes_, range(len(le.classes_))))
mapping
```
Out[16]:
```
{'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica': 2}
```

In [17]:
```
y = le.transform(y)
```

Standard Scaler

In [18]:
```
# Standard Scaler - To make all attribute values in a similar range (Normalization)
# Removes the mean and scales each feature/variable to unit variance.

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train)
```
Out[18]:
```
StandardScaler()
```

In [19]:
```
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Model Training

In [20]:
```
# Model Training  Libraries
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

Logistic Regression

In [21]:
```
# Fitting the values in Logistic Regression model

model = LogisticRegression()
model.fit(X_train_scaled, y_train)
```
Out[21]:
```
LogisticRegression()
```

In [22]:
```
model_prediction = model.predict(X_test_scaled)
```

In [23]:
```
accuracy_score(model_prediction, y_test)
```
Out[23]:
```
1.0
```

K-Nearest Neighbors

In [24]:
```
# Fitting the models in K-Nearest Neighbors (KNN)

classi = KNeighborsClassifier(n_neighbors=3)
classi.fit(X_train_scaled, y_train)
```
Out[24]:
```
KNeighborsClassifier(n_neighbors=3)
```

In [25]:
```
classi_pred = classi.predict(X_test_scaled)
```

In [26]:
```
accuracy_score(y_test, classi_pred)
```

Out[26]:
```
0.9666666666666667
```

Support Vector Classifier (SVC) 📈

In [27]:
```
# Fitting the models in support Vector Classifier (SVC)

from sklearn.svm import SVC

svc = SVC()
svc.fit(X_train_scaled, y_train)
```

Out[27]:
```
SVC()
```

In [28]:
```
svc_pred = svc.predict(X_test_scaled)
```

In [29]:
```
accuracy_score(y_test, svc_pred)
```

Out[29]:
```
1.0
```

Naive Bayes 📈

In [30]:
```
# Fitting the models in Naive Bayes

from sklearn.naive_bayes import GaussianNB

naive_b = GaussianNB()
naive_b.fit(X_train_scaled, y_train)
```

Out[30]:
```
GaussianNB()
```

In [31]:
```
naive_b_pred = naive_b.predict(X_test_scaled)
```

In [32]:
```
accuracy_score(y_test, naive_b_pred)
```

Out[32]:
```
0.9666666666666667
```

Model Evaluation ✅

In [33]:
```
# Confusion Matrix

confusion_matrix(y_test, model_prediction)
```

Out[33]:
```
array([[11,  0,  0],
       [ 0, 13,  0],
       [ 0,  0,  6]], dtype=int64)
```

In [34]:
```
confusion_matrix(y_test, classi_pred)
```

Out[34]:
```
array([[11,  0,  0],
       [ 0, 13,  0],
       [ 0,  1,  5]], dtype=int64)
```

In [35]:
```
confusion_matrix(y_test, svc_pred)
```

Out[35]:
```
array([[11,  0,  0],
       [ 0, 13,  0],
       [ 0,  0,  6]], dtype=int64)
```

In [36]:
```
confusion_matrix(y_test, naive_b_pred)
```
Out[36]:
```
array([[11,  0,  0],
       [ 0, 13,  0],
       [ 0,  1,  5]], dtype=int64)
```

Combining all the model scores 📒

In [37]:
```
# All Model Scores

results = pd.DataFrame({
    'Model' : ['Logistic Regression', 'SVM', 'KNN', 'Naive Bayes'],
    'Score' : [1.0, 1.0, 0.96, 0.96]
})

results_df = results.sort_values(by="Score", ascending=False)
results_df = results_df.set_index('Score')
results_df.head(9)
```
Out[37]:

Score	Model
1.00	Logistic Regression
1.00	SVM
0.96	KNN
0.96	Naive Bayes

Entire Model Prediction 📖

In [38]:
```
# Model Prediction

model_prediction
```
Out[38]:
```
array(['Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-virginica', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa'], dtype=object)
```

In [39]:
```
classi_pred
```
Out[39]:
```
array(['Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa'], dtype=object)
```

In [40]:
```
svc_pred
```

Out[40]:
```
array(['Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-virginica', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa'], dtype=object)
```

In [41]:
```
naive_b_pred
```

Out[41]:
```
array(['Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa'], dtype='<U15')
```

Model Building and Deployment 🌐

Overall model deployment flow

1. Data Collection
2. Data Preparation
3. Model building and Evaluation

---

4. Save model as pkl file
5. Load model using fastapi and deploy in localhost
6. Build and simple ui using streamlit and using post method access the model.

---

7. Build the front-end in react

---

8. Host frontend and backend in internet

In [42]:
```
#### To save the model in a pkl file

import pickle as pkl

pkl.dump(model, open('model.pkl', 'wb'))
pkl.dump(scaler, open('scaler.pkl', 'wb'))
```

In [43]:
```
# 2, 3, 4, 5

# load the scalar.pkl
with open('scaler.pkl', 'rb') as scaler_file:
    data = pkl.load(scaler_file)
```

In [44]:
```
type(data)
```

Out[44]:
```
sklearn.preprocessing._data.StandardScaler
```

In [45]:
```python
# Normalize using standard scalar
sample_input = np.array([2.0, 5.8, 2.8, 4.2]).reshape(-1,4)
processdata = data.transform(sample_input)
```

In [46]:
```python
processdata
```

Out[46]:
```
array([[-4.58247406,  6.38606206, -0.57151125,  3.83969158]])
```

In [50]:
```python
# Load the model.pkl

with open('model.pkl', 'rb') as model_file:
    model_data = pkl.load(model_file)

# Find ypred
model_predict = model_data.predict(processdata)

# Print the predicted class with decoded catergory label
model_predict
```

Out[50]:
```
array(['Iris-setosa'], dtype=object)
```

In [ ]:
```python
# Below code is to get the library informations.
# Run all the code block inorder to get the Correct informations.

# !pip install session_info
# import session_info
# session_info.show()
```


Acknowledgments

I would like to acknowledge the creators of the Iris Dataset and the developers of the python libraries and tools that help to make this project possible.

The Dataset that I have used in this notebook has taken from Kaggle.

Iris Dataset link: https://www.kaggle.com/datasets/uciml/iris (https://www.kaggle.com/datasets/uciml/iris)

Contact Information

For any inquiries, feedback, or collaboration opportunities regarding the Iris Classification IPYNB file. Please feel free to reach out to me throught the following channels:

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I'm open to discussions, questions, and suggestions related to Iris_Classification, Python programming, Machine Learning, Full stack Development and Data analysis. Don't hesitate to connect with me and start a conversation. Let's explore the fascinating world of Technology together!

Looking forward to connecting with you and sharing insights on the World of Technology!