Data Science Intern at Let's Grow More LGMVIP

Beginner Level Task

Iris Flowers Classification ML Project

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Importing Libraries

```
# Importing Libraries
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
```

Connecting Google Drive with Google Colab

```
# Connecting Google Drive with Google Colab
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Importing Data Set from google drive

```
# Importing Data Set from google drive
import os
os.chdir('/content/drive/My Drive')
```

Reading Data set

```
# Reading Data set
data=pd.read_csv('iris_data.csv')
data.head()
```

	5.1	3.5	1.4	0.2	Iris-setosa
0	4.9	3.0	1.4	0.2	Iris-setosa
1	4.7	3.2	1.3	0.2	Iris-setosa
2	4.6	3.1	1.5	0.2	Iris-setosa
3	5.0	3.6	1.4	0.2	Iris-setosa
4	5.4	3.9	1.7	0.4	Iris-setosa

Giving Proper Heading to Columns

```
# Giving Proper Heading to Columns
data_header = ['SepalLength','SepalWidth','PetalLength','PetalWidth','Species']
data.to_csv('Iris.csv', header = data_header, index = False)
new_data = pd.read_csv('Iris.csv')
new_data.head()
```

	SepalLength	SepalWidth	PetalLength	PetalWidth	Species
0	4.9	3.0	1.4	0.2	Iris-setosa
1	4.7	3.2	1.3	0.2	Iris-setosa
2	4.6	3.1	1.5	0.2	Iris-setosa
3	5.0	3.6	1.4	0.2	Iris-setosa

Checking no. of rows and columns

```
# Checking no. of rows and columns
new_data.shape
```

```
(149, 5)
```

Checking datatypes in dataset

```
# Checking datatypes in dataset
new_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 149 entries, 0 to 148
Data columns (total 5 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   SepalLength  149 non-null    float64
 1   SepalWidth   149 non-null    float64
 2   PetalLength  149 non-null    float64
 3   PetalWidth   149 non-null    float64
 4   Species      149 non-null    object
dtypes: float64(4), object(1)
memory usage: 5.9+ KB
```

Describing the Dataset

```
# Describing Dataset
new_data.describe()
```

	SepalLength	SepalWidth	PetalLength	PetalWidth
count	149.000000	149.000000	149.000000	149.000000
mean	5.848322	3.051007	3.774497	1.205369
std	0.828594	0.433499	1.759651	0.761292
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.400000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

Checking null values in Dataset

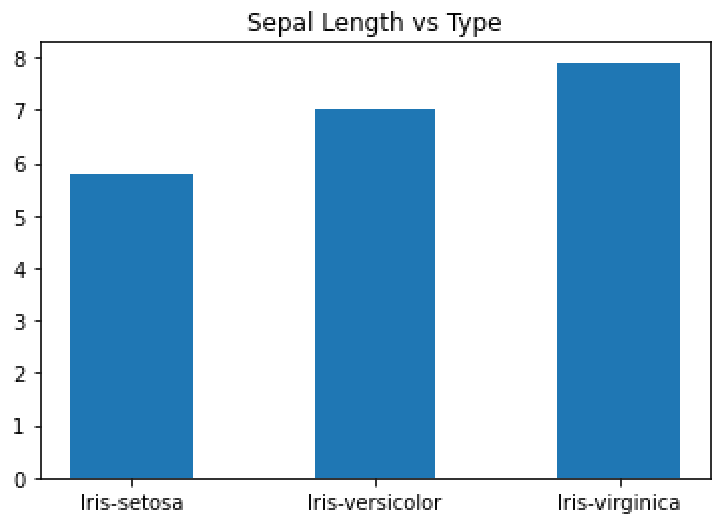
```
# Checking Null Values in DataSet
new_data.isnull().sum()
```

```
SepalLength    0
SepalWidth     0
PetalLength    0
PetalWidth     0
Species        0
dtype: int64
```

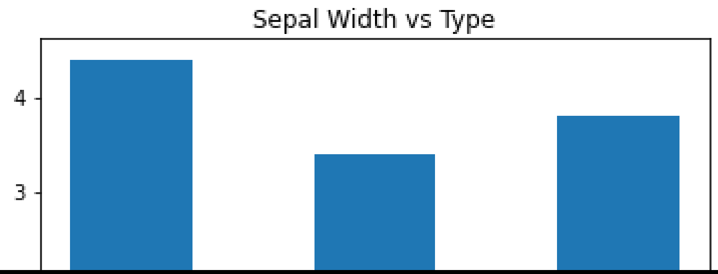
Data Visualization

Graphs of features vs Species

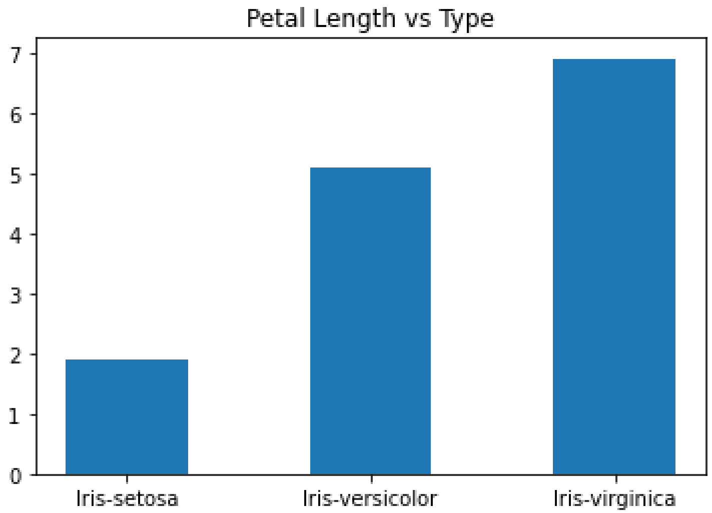
```
# Sepal Length vs Type
plt.bar(new_data['Species'],new_data['SepalLength'], width = 0.5)
plt.title("Sepal Length vs Type")
plt.show()
```



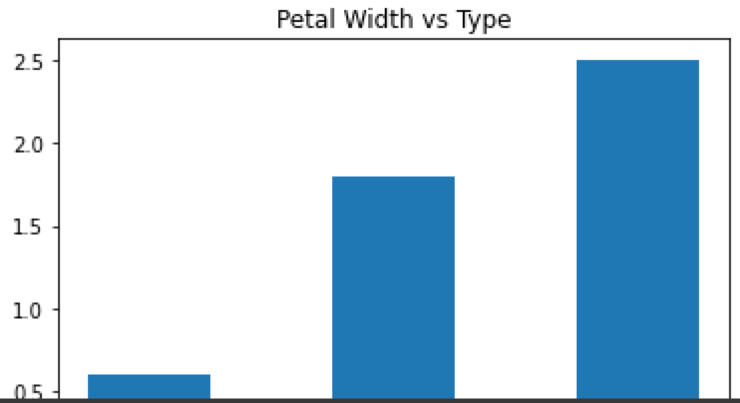

```
# Sepal Width vs Type
plt.bar(new_data['Species'],new_data['SepalWidth'], width = 0.5)
plt.title("Sepal Width vs Type")
plt.show()
```




```
# Petal Length vs Type
plt.bar(new_data['Species'],new_data['PetalLength'], width = 0.5)
plt.title("Petal Length vs Type")
plt.show()
```



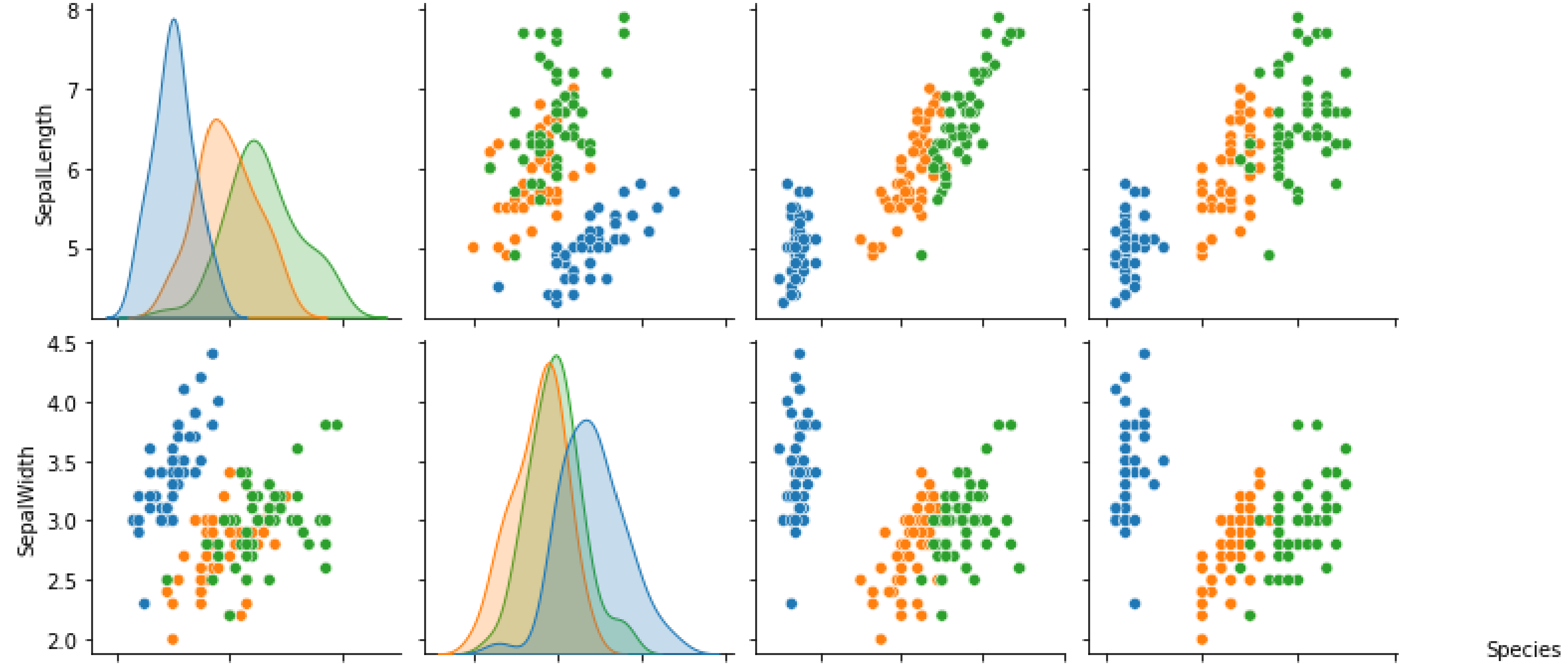

```
# Petal Width vs Type
plt.bar(new_data['Species'],new_data['PetalWidth'], width = 0.5)
plt.title("Petal Width vs Type")
plt.show()
```



Pair plot for Dataset

```
sns.pairplot(new_data,hue='Species')
```

```
<seaborn.axisgrid.PairGrid at 0x7f29b4f39ed0>
```



Splitting the Dataset

```python
x = new_data.drop(columns="Species")
y = new_data["Species"]
```

```python
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4, random_state = 1)
```

```python
x_train.head()
```

	SepalLength	SepalWidth	PetalLength	PetalWidth
12	4.3	3.0	1.1	0.1
2	4.6	3.1	1.5	0.2
97	5.1	2.5	3.0	1.1

```
1 x_test.head()
```

	SepalLength	SepalWidth	PetalLength	PetalWidth
145	6.3	2.5	5.0	1.9
89	5.5	2.6	4.4	1.2
54	5.7	2.8	4.5	1.3
77	6.0	2.9	4.5	1.5
84	6.0	3.4	4.5	1.6

```
1 y_train.head()
```

```
12          Iris-setosa
2           Iris-setosa
97      Iris-versicolor
112      Iris-virginica
103      Iris-virginica
Name: Species, dtype: object
```

```
1 y_test.head()
```

```
145      Iris-virginica
89      Iris-versicolor
54      Iris-versicolor
77      Iris-versicolor
84      Iris-versicolor
Name: Species, dtype: object
```

```
print("x_train: ", len(x_train))
print("x_test: ", len(x_test))
print("y_train: ", len(y_train))
print("y_test: ", len(y_test))
```

```
x_train:  89
x_test:  60
y_train:  89
y_test:  60
```

Building Model using Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, roc_auc_score
```

```
model = LogisticRegression()
model.fit(x_train, y_train)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (sta
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

```python
predict = model.predict(x_test)
print("Pridicted values on Test Data", predict)
```

```
Pridicted values on Test Data ['Iris-virginica' 'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor'
 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa'
 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa'
 'Iris-virginica' 'Iris-virginica' 'Iris-setosa' 'Iris-virginica'
 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa'
 'Iris-versicolor' 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-setosa'
 'Iris-virginica' 'Iris-virginica' 'Iris-setosa' 'Iris-virginica'
 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa'
 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor' 'Iris-virginica'
 'Iris-versicolor' 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor']
```

```python
y_test_pred = model.predict(x_test)
y_train_pred = model.predict(x_train)
```

```python
print("Training Accuracy : ", accuracy_score(y_train, y_train_pred))
print("Test Accuracy : ", accuracy_score(y_test, y_test_pred))
```

```
Training Accuracy :  0.9775280898876404
Test Accuracy :  0.95
```

Conclusion

Hence we conclude that we did Iris Flower Classification using Logistic Regression and we got Training Accuracy: 97% and Test Accuracy: 95%.