Data Set

```
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6.5,3.0,5.2,2.0,Iris-virginica
6.2,3.4,5.4,2.3,Iris-virginica
5.9,3.0,5.1,1.8,Iris-virginica
```

Code

```
# DataFlair Iris Classification
# Import Packages
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd



columns = ['Sepal length', 'Sepal width', 'Petal length', 'Petal width',
'Class_labels'] # As per the iris dataset information



# Load the data
df = pd.read_csv('iris.data', names=columns)
```

```
df.head()



# Some basic statistical analysis about the data
df.describe()



# Visualize the whole dataset
sns.pairplot(df, hue='Class_labels')



# Seperate features and target
data = df.values
X = data[:,0:4]
Y = data[:,4]



# Calculate avarage of each features for all classes
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 = 0.25



# Plot the avarage
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()



# Split the data to train and test dataset.
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)



# Support vector machine algorithm
from sklearn.svm import SVC
svn = SVC()
svn.fit(X_train, y_train)
```

```python
# Predict from the test dataset
predictions = svn.predict(X_test)
```

```python
# Calculate the accuracy
from sklearn.metrics import accuracy_score
accuracy_score(y_test, predictions)
```

```python
# A detailed classification report
from sklearn.metrics import classification_report
print(classification_report(y_test, predictions))
```

```python
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 of the species from the input vector
prediction = svn.predict(X_new)
print("Prediction of Species: {}".format(prediction))
```

```python
# Save the model
import pickle
with open('SVM.pickle', 'wb') as f:
    pickle.dump(svn, f)
```

```python
# Load the model
with open('SVM.pickle', 'rb') as f:
    model = pickle.load(f)
```

```python
model.predict(X_new)
```

Screenshots

This code is executed in a 'Google Colaboratory' notebook and the screenshots are given below.

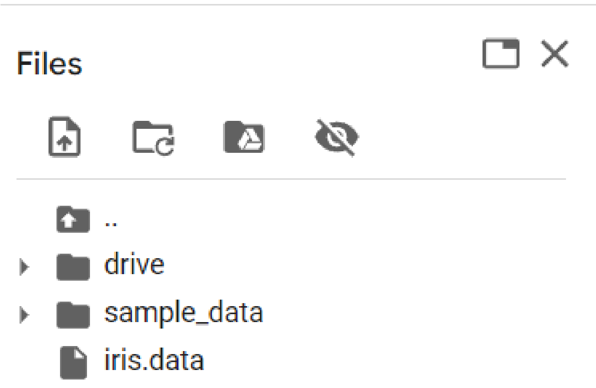
DataFlair Iris Flower Classification

```
[2]  import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     import pandas as pd
     %matplotlib inline
```

Connect G drive

```
[5]  from google.colab import drive
     drive.mount('/content/drive')

     Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```



Load the data

```
columns = ['Sepal length', 'Sepal width', 'Petal length', 'Petal width', 'Class_labels']
df = pd.read_csv('iris.data', names=columns)
df.head()
```

	Sepal length	Sepal width	Petal length	Petal width	Class_labels
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

Statistical analysis about the data

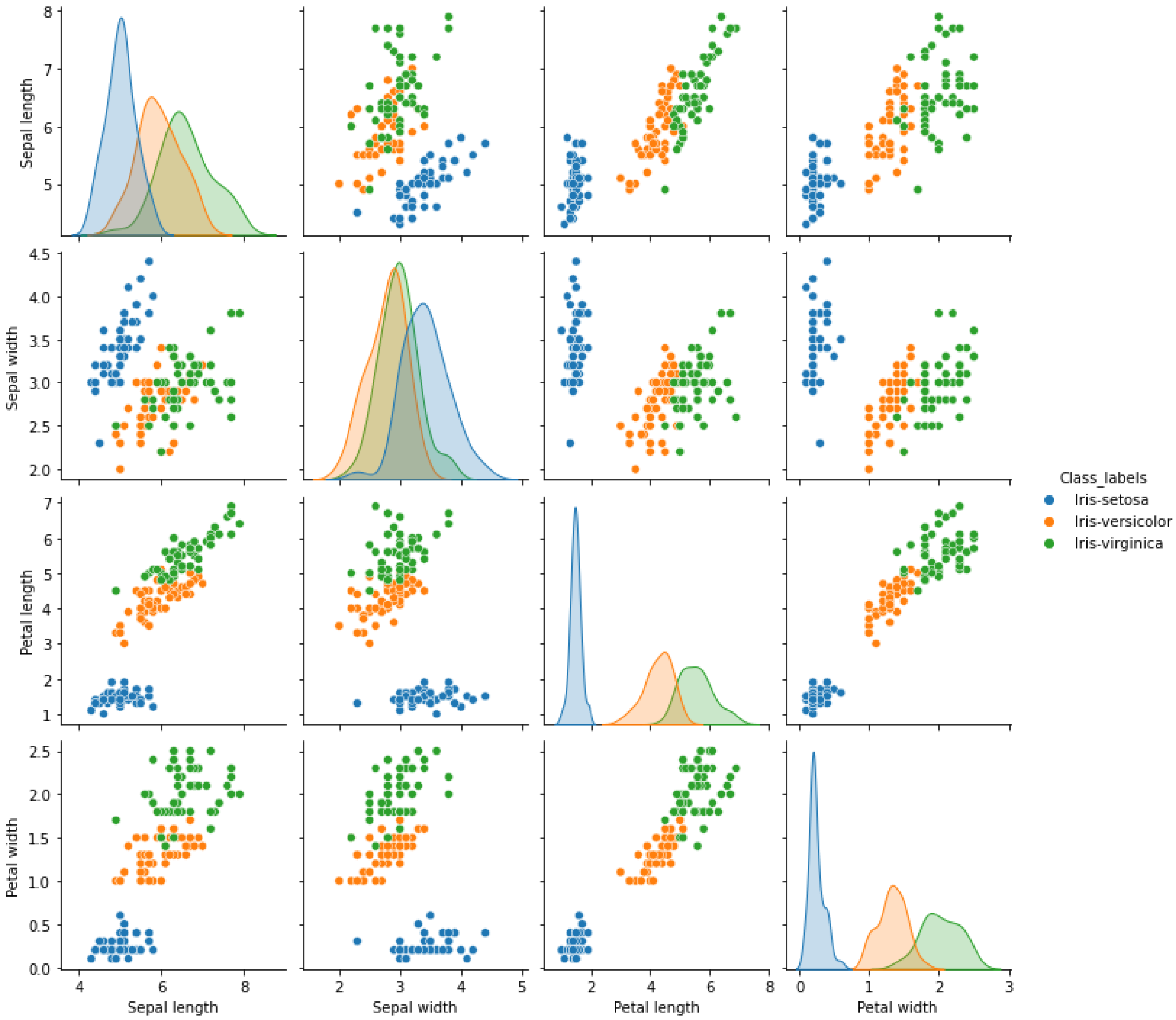
```
df.describe()
```

	Sepal length	Sepal width	Petal length	Petal width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

Visualize the dataset

```
sns.pairplot(df, hue='Class_labels')
```

```
<seaborn.axisgrid.PairGrid at 0x7f9201513190>
```



Separating features and target

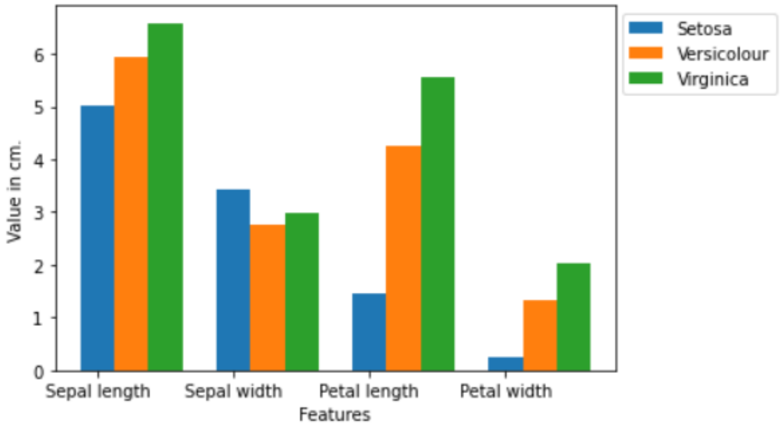
```
[9]  data = df.values
     X = data[:,0:4]
     Y = data[:,4]
```

Calculating average of each feature (for all classes)

```
[10] 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 = 0.25
```

Plotting 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()
```



Split the data to train and test dataset.

```
[12] 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)
```

Support vector machine algorithm

```
[13] from sklearn.svm import SVC
     svn = SVC()
     svn.fit(X_train, y_train)

     SVC()
```

This is formatted as code and then accuracy is calculated

```
predictions = svn.predict(X_test)

from sklearn.metrics import accuracy_score
accuracy_score(y_test, predictions)

0.9666666666666667
```

Detailed classification report

```
[15] from sklearn.metrics import classification_report
     print(classification_report(y_test, predictions))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        11
Iris-versicolor       1.00      0.89      0.94         9
 Iris-virginica       0.91      1.00      0.95        10

       accuracy                           0.97        30
      macro avg       0.97      0.96      0.96        30
   weighted avg       0.97      0.97      0.97        30
```

Prediction of the species from the input vector

```
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 = svn.predict(X_new)
print("Prediction of Species: {}".format(prediction))
```

```
Prediction of Species: ['Iris-setosa' 'Iris-versicolor' 'Iris-virginica']
```

Saving and loading the model

```
import pickle
with open('SVM.pickle', 'wb') as f:
    pickle.dump(svn, f)

with open('SVM.pickle', 'rb') as f:
    model = pickle.load(f)
model.predict(X_new)
```

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