IRIS flower classification Using Machine Learning

Author: Krishna Sayanti Deb

Data Description:

```
The IRIS dataset consists of 3 types of IRIS flowers(Setosa,Versicolour,Virginica).The rows of the
dataset are sample where
the columns are the features.

Features:
1. sepal length in cm
2. sepal width in cm
3. petal length in cm
4. petal width in cm
5. class:
-- Iris Setosa
-- Iris Versicolour
-- Iris Virginica
```

Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

Importing Dataset

In [2]:
```
data = pd.read_csv(r'C:\Users\LENOVO\Desktop\Internship\CipherByte Technoligies\Task-1\Iris Flower - Iris
```

In [3]:
```
data
```

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

In [4]:
```
data.shape
```

Out[4]:
```
(150, 6)
```

In [5]:
```
#ID column in not important for analysing the data, so have to drop ID column

data = data.drop('Id', axis=1)
```

In [6]:
```
data
```

Out[6]:

	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
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 5 columns

Data Summarization

In [7]:
```
#shape
data.shape
```

Out[7]:
```
(150, 5)
```

In [8]:
```
#Checking null values

data.isnull().sum()
```

Out[8]:
```
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

In [9]:
```
#there is no null value in the dataset
```

In [10]:
```
#columns name
data.columns
```

Out[10]:
```
Index(['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

In [11]:
```
#Species value Counts
data.Species.value_counts()
```

Out[11]:
```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: Species, dtype: int64
```

In [12]:
```
#Information
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   SepalLengthCm  150 non-null    float64
 1   SepalWidthCm   150 non-null    float64
 2   PetalLengthCm  150 non-null    float64
 3   PetalWidthCm   150 non-null    float64
 4   Species        150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

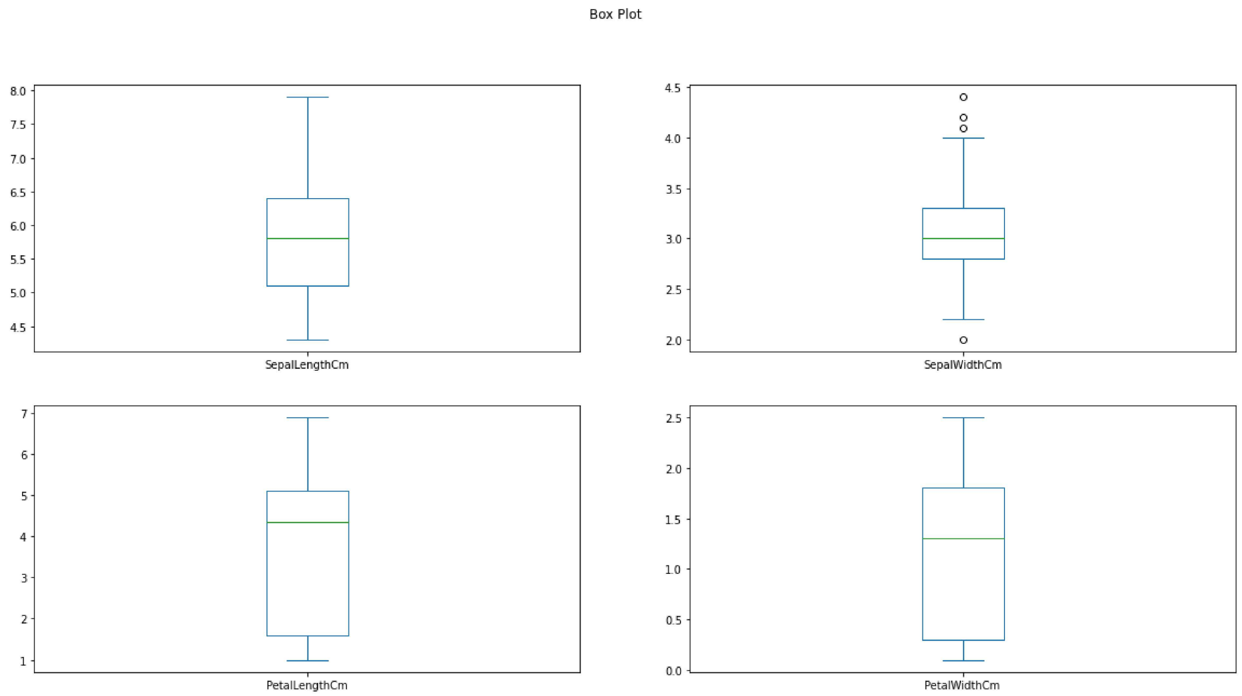
In [13]:
```
#Description
data.describe()
```

Out[13]:

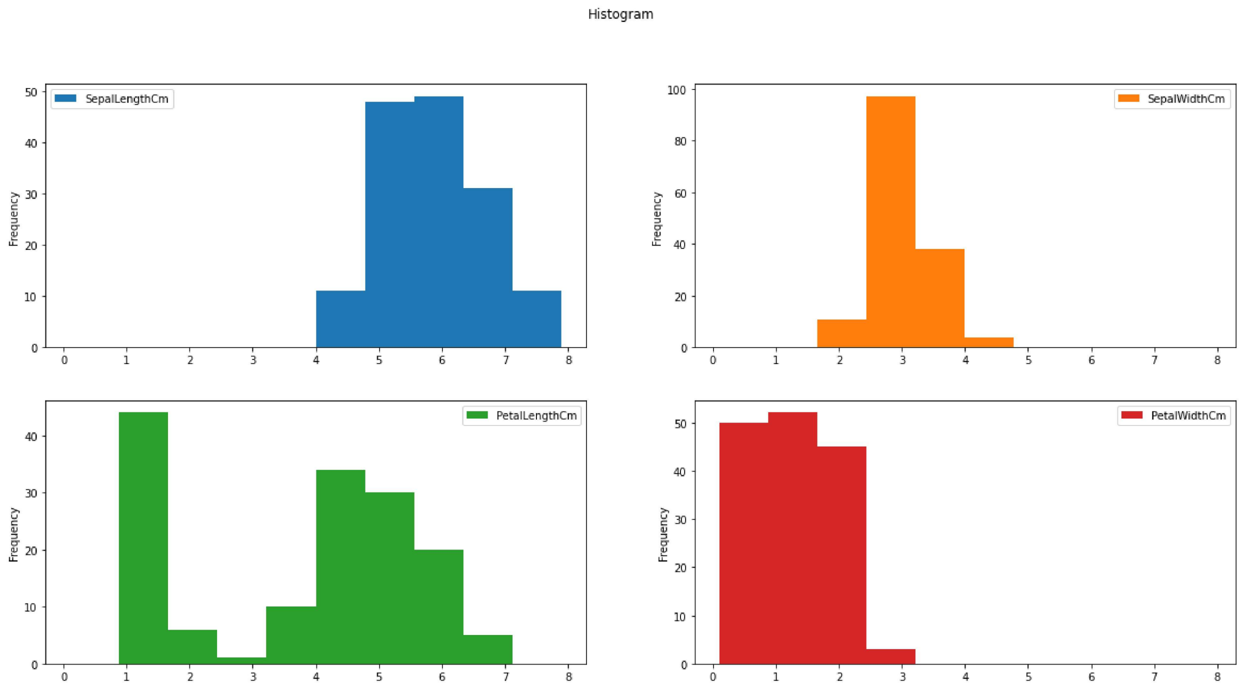
	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000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

Data Visualization

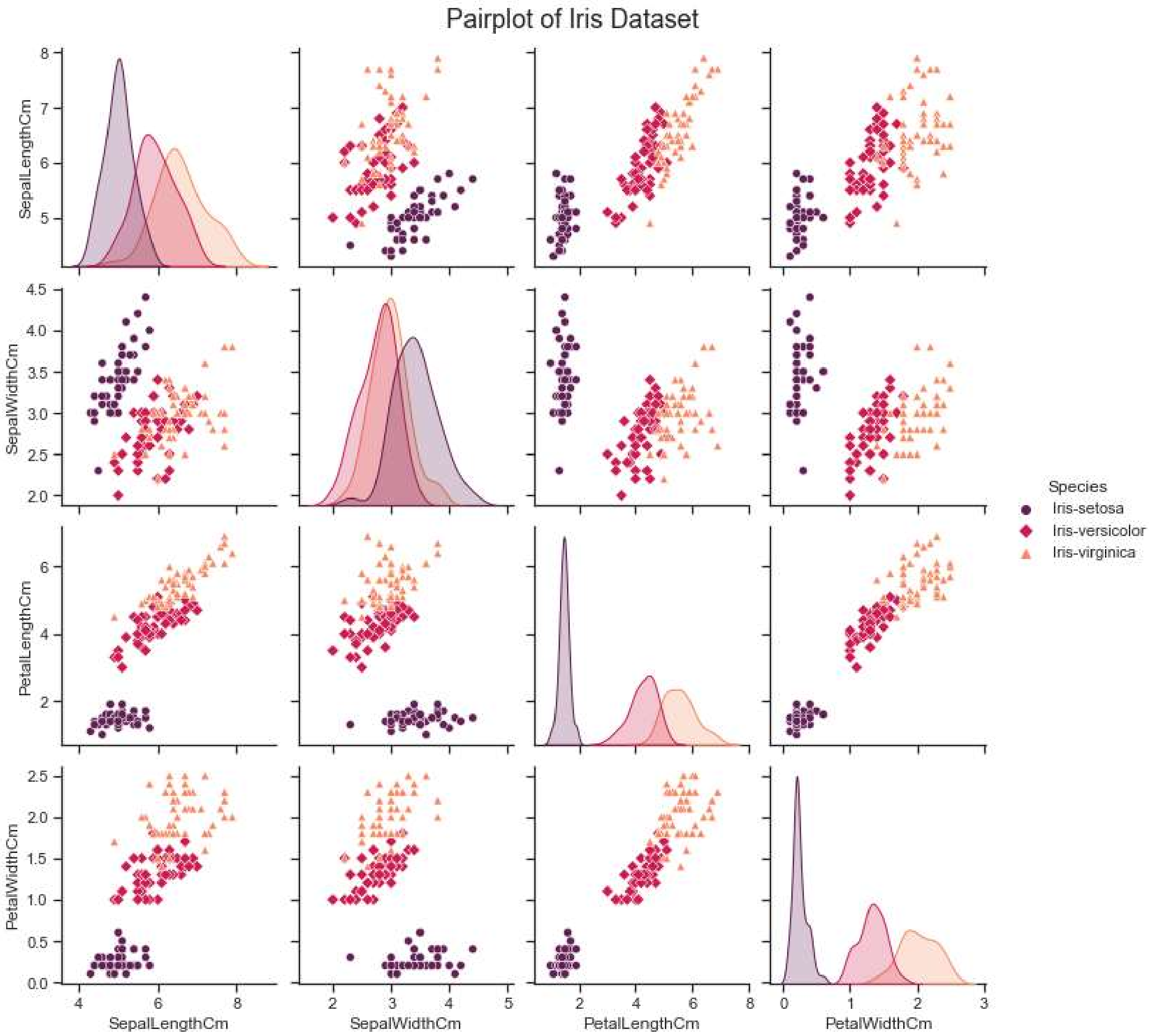
In [14]:
```
#boxplot
data.plot(kind = 'box', subplots = True, layout=(2,2), sharex=False, sharey= False, figsize=(20,10), tit

plt.show()
```



In [15]:
```
#histogram
data.plot(kind = 'hist', subplots = True, layout=(2,2), sharex=False, sharey= False, figsize=(20,10), ti
plt.show()
```



In [16]:
```
sns.set_theme(style='ticks')
fig=sns.pairplot(data, hue = "Species", markers= ['o','D','^'],palette='rocket')
fig.fig.suptitle('Pairplot of Iris Dataset', y=1.02, fontsize = 18)
plt.show()
```



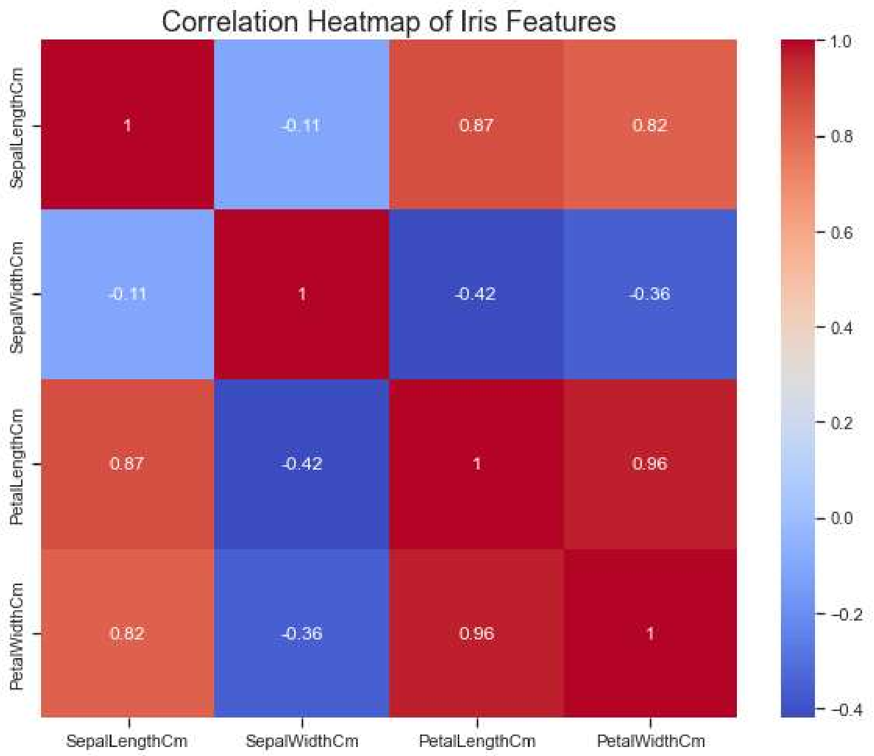

```
#explanation
From the above diagram it is clear that--
1. Sepal Length is more dependent on Sepal width and vice versa
2. Petal Length is more dependent on Sepal width
3. Petal width is more dependent on Sepal Length
```

In [17]:
```
data.corr()
```

Out[17]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
SepalLengthCm	1.000000	-0.109369	0.871754	0.817954
SepalWidthCm	-0.109369	1.000000	-0.420516	-0.356544
PetalLengthCm	0.871754	-0.420516	1.000000	0.962757
PetalWidthCm	0.817954	-0.356544	0.962757	1.000000

In [35]:
```
#heatmap
plt.figure(figsize=(10,8))
sns.heatmap(data.corr(),annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap of Iris Features' , fontsize = 18)
plt.show()
```



Data Preprocessing

In [19]:
```
x = data.values[:, :4]
y = data.values[:,4]
```

In [20]:
```
x
```

Out[20]:
```
array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3.0, 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5.0, 3.6, 1.4, 0.2],
       [5.4, 3.9, 1.7, 0.4],
       [4.6, 3.4, 1.4, 0.3],
       [5.0, 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3.0, 1.4, 0.1],
       [4.3, 3.0, 1.1, 0.1],
       [5.8, 4.0, 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [5.7, 3.8, 1.7, 0.3],
```

In [21]:
```
y
#Transform y into label encoding and built the model
```

Out[21]:
```
array(['Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica'], dtype=object)
```

Transform categorical data to numeric data

In [22]:
```
from sklearn.preprocessing import LabelEncoder
```

In [23]:
```
le = LabelEncoder()
```

In [24]:
```
y = le.fit_transform(y)
```

In [25]:
```
y
```

Out[25]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

Creating a Validation Dataset

In [26]:
```
#import train_test_split

from sklearn.model_selection import train_test_split
```

In [27]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2, random_state=123)
```

Model Selection

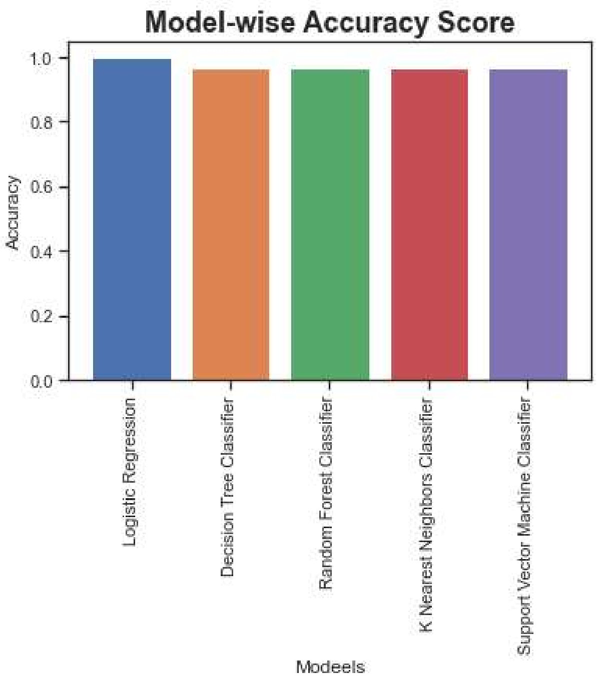
```
As the IRIS-Flower dataset contains Target column so it is a supervised data.
So to classify this dataset we have to use supervised classification model such as Logistic Regression,
Decision Tree,
Random Forest, Support Vector Machine, K Nearest Neighbour.
```

Model Building

In [28]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

In [39]:
```
#models
models = [
    ("Logistic Regression", LogisticRegression()),
    ("Decision Tree Classifier", DecisionTreeClassifier()),
    ("Random Forest Classifier", RandomForestClassifier()),
    ("K Nearest Neighbors Classifier", KNeighborsClassifier()),
    ("Support Vector Machine Classifier", SVC())
]

#train models

results = []

for name,model in models:
    model.fit(x_train,y_train)
    y_pred = model.predict(x_test)
    accuracy = accuracy_score(y_test, y_pred)
    results.append((name,accuracy))

#print result

print("Model Performance:")
for name,accuracy in results:
    print(f'{name}: {accuracy}')

    #prepare a bar chart
    plt.bar(name,accuracy)
    plt.xticks(rotation= 90)
    plt.xlabel("Modeels")
    plt.ylabel("Accuracy")
    plt.title("Model-wise Accuracy Score", fontsize=18, fontweight= 'bold')
```

```
Model Performance:
Logistic Regression: 1.0
Decision Tree Classifier: 0.9666666666666667
Random Forest Classifier: 0.9666666666666667
K Nearest Neighbors Classifier: 0.9666666666666667
Support Vector Machine Classifier: 0.9666666666666667
```




```
Inferences:
From the above accuracy score it is clearly vissible that Logistic Regression classifier is the based
suitable model to
classify IRIS-Flower dataset.
```

Model Testing

In [40]:
```
#show Y pred y test
y_test
```

Out[40]:
```
array([1, 2, 2, 1, 0, 2, 1, 0, 0, 1, 2, 0, 1, 2, 2, 2, 0, 0, 1, 0, 0, 2,
       0, 2, 0, 0, 0, 2, 2, 0])
```

In [41]:
```
#map labeled column (y_test,y_pred)
def map_label(label):
    if label == 0:
        return "Iris-setosa"
    elif label == 1:
        return "Iris-versicolor"
    elif label == 2:
        return "Iris-virginica"
    else:
        return "Unknown"


mapped_y_pred = list(map(map_label,y_pred))
mapped_y_test = list(map(map_label,y_test))
```

In [42]:
```
#tally y_test and y_pred value
df = pd.DataFrame({"y_test":mapped_y_test, "y_pred":mapped_y_pred})
```

In [43]:
```
df
```

Out[43]:

	y_test	y_pred
0	Iris-versicolor	Iris-versicolor
1	Iris-virginica	Iris-virginica
2	Iris-virginica	Iris-virginica
3	Iris-versicolor	Iris-versicolor
4	Iris-setosa	Iris-setosa
5	Iris-virginica	Iris-versicolor
6	Iris-versicolor	Iris-versicolor
7	Iris-setosa	Iris-setosa
8	Iris-setosa	Iris-setosa
9	Iris-versicolor	Iris-versicolor
10	Iris-virginica	Iris-virginica
11	Iris-setosa	Iris-setosa
12	Iris-versicolor	Iris-versicolor
13	Iris-virginica	Iris-virginica
14	Iris-virginica	Iris-virginica
15	Iris-virginica	Iris-virginica
16	Iris-setosa	Iris-setosa
17	Iris-setosa	Iris-setosa
18	Iris-versicolor	Iris-versicolor
19	Iris-setosa	Iris-setosa
20	Iris-setosa	Iris-setosa
21	Iris-virginica	Iris-virginica
22	Iris-setosa	Iris-setosa
23	Iris-virginica	Iris-virginica
24	Iris-setosa	Iris-setosa
25	Iris-setosa	Iris-setosa
26	Iris-setosa	Iris-setosa
27	Iris-virginica	Iris-virginica
28	Iris-virginica	Iris-virginica
29	Iris-setosa	Iris-setosa

```
-------------------------------------------------------End------------------------------------------------------------------
```