Data Science Intern @Lets Grow More

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Task 1 : Iris Flower Classification ML Project | Dataset : [http://archive.ics.uci.edu/ml/datasets/Iris (http://archive.ics.uci.edu/ml/datasets/Iris)](http://archive.ics.uci.edu/ml/datasets/Iris)

--- Importing and Inspecting data

In [22]:
```
import pandas as pd
import numpy as np
import scipy.stats as st
import os
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import PolynomialFeatures
from sklearn import svm
from sklearn.metrics import classification_report
```

In [23]:
```
df=pd.read_csv('dataset.csv')
```

In [24]:
```
df
```

Out[24]:

	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 [25]:
```
df.head()
```

Out[25]:

	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

In [26]:
```
df.tail()
```

Out[26]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
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

In [27]:
```
df.describe()
```

Out[27]:

	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 [28]:
```
df.info
```

Out[28]:
```
<bound method DataFrame.info of       Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
0      1            5.1           3.5            1.4           0.2
1      2            4.9           3.0            1.4           0.2
2      3            4.7           3.2            1.3           0.2
3      4            4.6           3.1            1.5           0.2
4      5            5.0           3.6            1.4           0.2
..   ...            ...           ...            ...           ...
145  146            6.7           3.0            5.2           2.3
146  147            6.3           2.5            5.0           1.9
147  148            6.5           3.0            5.2           2.0
148  149            6.2           3.4            5.4           2.3
149  150            5.9           3.0            5.1           1.8

            Species
0       Iris-setosa
1       Iris-setosa
2       Iris-setosa
3       Iris-setosa
4       Iris-setosa
..              ...
145  Iris-virginica
146  Iris-virginica
147  Iris-virginica
148  Iris-virginica
149  Iris-virginica

[150 rows x 6 columns]>
```

In [29]:
```
df.shape
```

Out[29]:
```
(150, 6)
```

In [30]:
```
df["Species"].value_counts()
```

Out[30]:
```
Iris-virginica     50
Iris-versicolor    50
Iris-setosa        50
Name: Species, dtype: int64
```

In [31]:
```
df.Species.unique()
```

Out[31]:
```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

In [32]:
```
df.nunique()
```

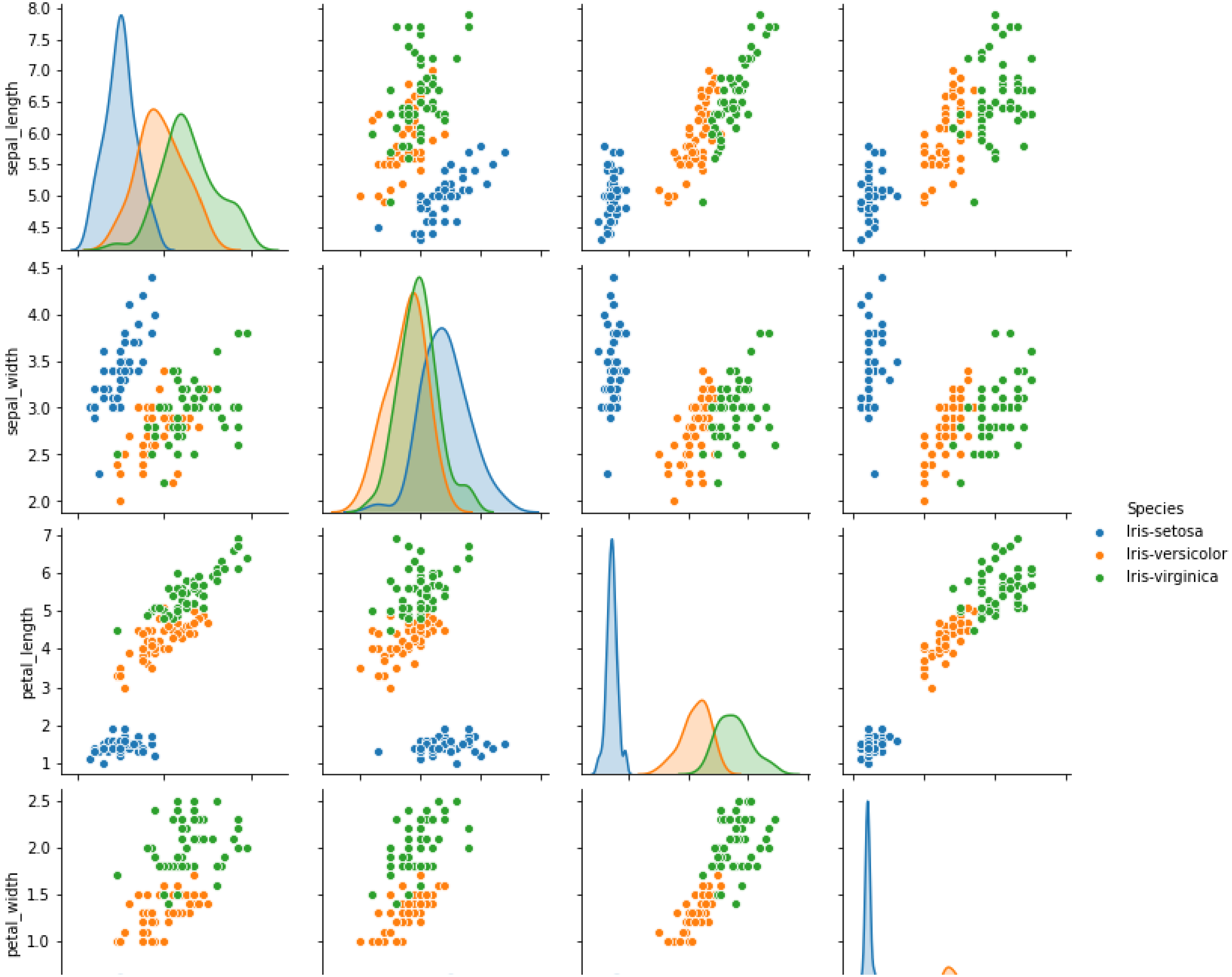
Out[32]:
```
Id               150
SepalLengthCm     35
SepalWidthCm      23
PetalLengthCm     43
PetalWidthCm      22
Species            3
dtype: int64
```

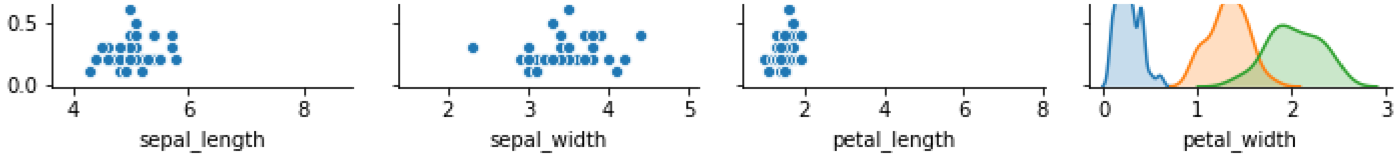
In [33]:
```
df = df.drop(columns = ['Id'])
df.info()
```

```
<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 [34]:
```
df.isnull().sum()
```
Out[34]:
```
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```
In [35]:
```
df = df.rename(columns = {'SepalLengthCm': 'sepal_length', 'PetalLengthCm': 'petal_length', 'SepalWidthCm': 'sepal_width
print(df)
```
```
     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
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 x 5 columns]
```
--- Visualizing the data

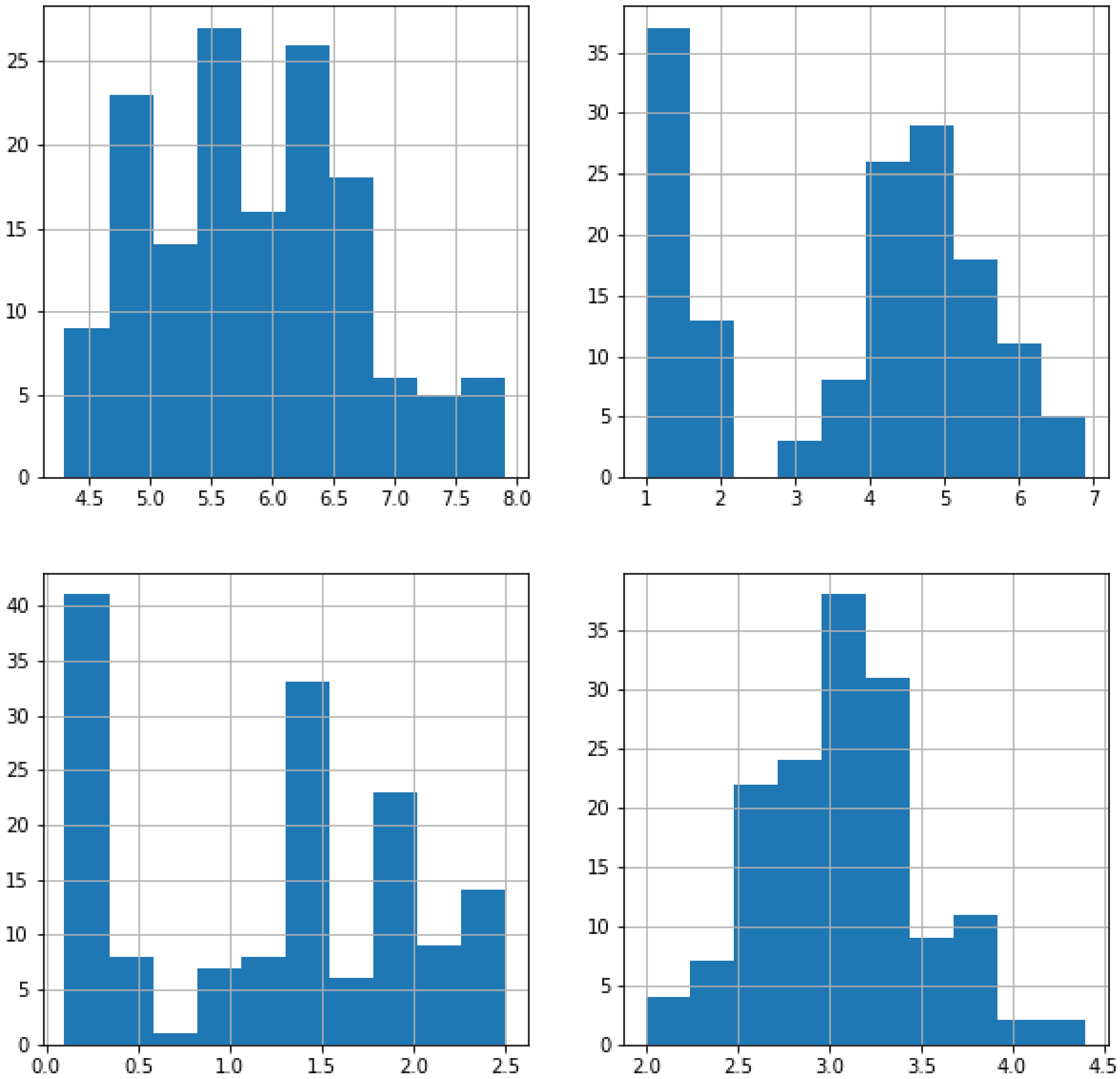
In [36]:
```
sns.pairplot(df, hue = "Species")
plt.show()
```




0.5
0.0
4
6
8
sepal_length
2
3
4
5
sepal_width
2
4
6
8
petal_length
0
1
2
3
petal_width

In [37]:

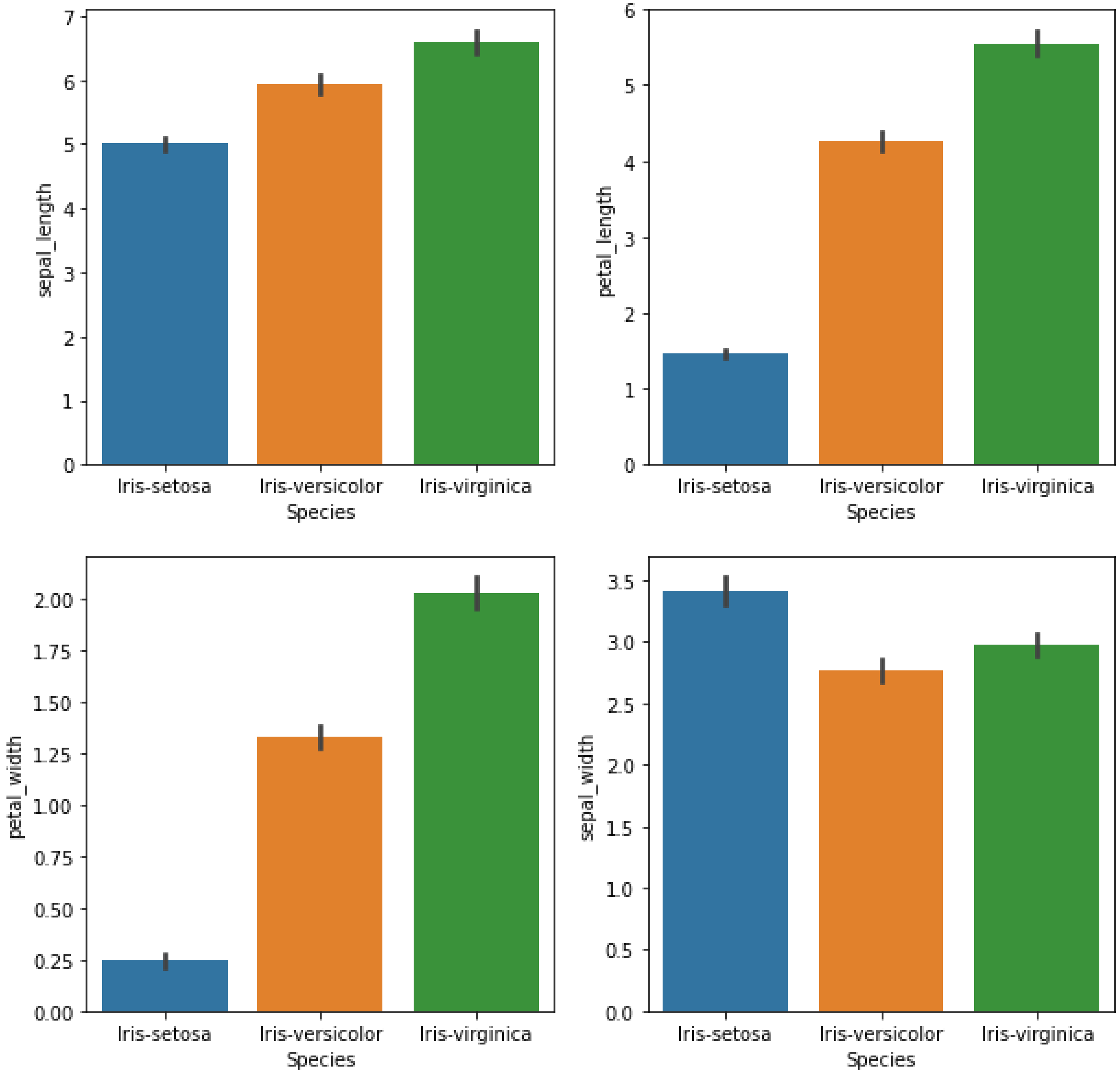
```
def histplots():
    fig,axes=plt.subplots(2,2,figsize=(10,10))
    df['sepal_length'].hist(ax=axes[0][0])
    df['petal_length'].hist(ax=axes[0][1])
    df['petal_width'].hist(ax=axes[1][0])
    df['sepal_width'].hist(ax=axes[1][1])
    plt.show()

histplots()
```



0 5 10 15 20 25
4.5 5.0 5.5 6.0 6.5 7.0 7.5 8.0
0 5 10 15 20 25 30 35
1 2 3 4 5 6 7
0 5 10 15 20 25 30 35 40
0.0 0.5 1.0 1.5 2.0 2.5
0 5 10 15 20 25 30 35
2.0 2.5 3.0 3.5 4.0 4.5

In [38]:

```
def barplots():
    fig,axes=plt.subplots(2,2,figsize=(10,10))
    sns.barplot(x=df.Species,y=df['sepal_length'],ax=axes[0][0])
    sns.barplot(x=df.Species,y=df['petal_length'],ax=axes[0][1])
    sns.barplot(x=df.Species,y=df['petal_width'],ax=axes[1][0])
    sns.barplot(x=df.Species,y=df['sepal_width'],ax=axes[1][1])
    plt.show()

barplots()
```



--- Correlation

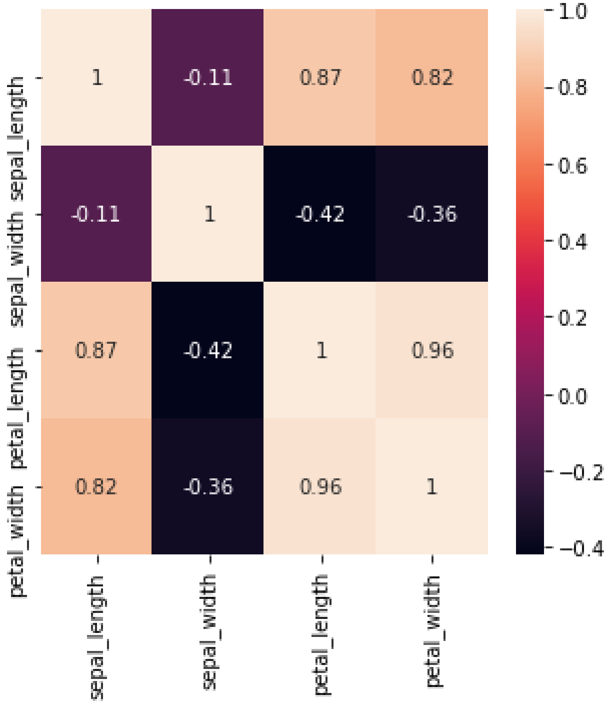
In [39]:
```
df.corr()
```

Out[39]:

	sepal_length	sepal_width	petal_length	petal_width
sepal_length	1.000000	-0.109369	0.871754	0.817954
sepal_width	-0.109369	1.000000	-0.420516	-0.356544
petal_length	0.871754	-0.420516	1.000000	0.962757
petal_width	0.817954	-0.356544	0.962757	1.000000

In [40]:
```
corr = df.corr()
fig, ax = plt.subplots(figsize=(5,5))
sns.heatmap(corr, annot=True, ax=ax)
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x25fa39166d0>



Setting integer location

In [43]:
```
X=df.iloc[:,:-1].values
```

In [44]:
```
X
```

```
       [4.8, 3.4, 1.9, 0.2],
       [5. , 3. , 1.6, 0.2],
       [5. , 3.4, 1.6, 0.4],
       [5.2, 3.5, 1.5, 0.2],
       [5.2, 3.4, 1.4, 0.2],
       [4.7, 3.2, 1.6, 0.2],
       [4.8, 3.1, 1.6, 0.2],
       [5.4, 3.4, 1.5, 0.4],

       [5.2, 4.1, 1.5, 0.1],
       [5.5, 4.2, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5. , 3.2, 1.2, 0.2],
       [5.5, 3.5, 1.3, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [4.4, 3. , 1.3, 0.2],
       [5.1, 3.4, 1.5, 0.2],
       [5. , 3.5, 1.3, 0.3],
       [4.5, 2.3, 1.3, 0.3],
       [4.4, 3.2, 1.3, 0.2],
```

In [45]:
```
Y=df.iloc[:,-1].values
```

In [46]:
```
Y
```

Out[46]:
```
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])
```

Applying LabelEncoder

In [47]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
Y = le.fit_transform(Y)
print(Y)
```

```
[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 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]
```

Splitting the data into training dataset and testing dataset

In [48]:
```
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=2)
```

In [49]:
```
X_train
```

```
       [5.4, 3.4, 1.7, 0.2],
       [6.7, 3.1, 5.6, 2.4],
       [6.3, 3.4, 5.6, 2.4],
       [7.6, 3. , 6.6, 2.1],
       [6. , 2.2, 5. , 1.5],
       [4.3, 3. , 1.1, 0.1],
       [4.8, 3.1, 1.6, 0.2],
       [5.8, 2.7, 5.1, 1.9],
       [5.7, 2.8, 4.1, 1.3],
       [5.2, 2.7, 3.9, 1.4],
       [7.7, 3. , 6.1, 2.3],
       [6.3, 2.7, 4.9, 1.8],
       [6.1, 2.8, 4. , 1.3],
       [5.1, 3.7, 1.5, 0.4],
       [5.7, 2.8, 4.5, 1.3],
       [5.4, 3.9, 1.3, 0.4],
       [5.8, 2.8, 5.1, 2.4],
       [5.8, 2.6, 4. , 1.2],
       [5.1, 2.5, 3. , 1.1],
       [5.7, 3.8, 1.7, 0.3]
```

In [51]:
```
y_train
```

Out[51]:
```
array([2, 0, 1, 2, 1, 0, 2, 1, 1, 2, 1, 1, 2, 1, 0, 2, 0, 1, 0, 0, 0, 2,
       2, 2, 0, 2, 2, 2, 2, 0, 0, 2, 1, 1, 2, 2, 1, 0, 1, 0, 2, 1, 1, 0,
       1, 1, 1, 2, 0, 1, 0, 1, 2, 0, 1, 0, 0, 0, 2, 2, 0, 0, 2, 2, 1, 2,
       1, 1, 2, 0, 2, 2, 2, 0, 2, 0, 0, 1, 2, 1, 2, 1, 1, 2, 1, 1, 1, 2,
       1, 2, 1, 0, 1, 1, 1, 1, 2, 1, 0, 0, 2, 1, 2, 0, 2, 0, 2, 2, 0, 1,
       0, 2, 1, 0, 2, 1, 0, 0, 1, 0], dtype=int64)
```

In [52]:
```
X_test
```

Out[52]:
```
array([[4.6, 3.4, 1.4, 0.3],
       [4.6, 3.1, 1.5, 0.2],
       [5.7, 2.5, 5. , 2. ],
       [4.8, 3. , 1.4, 0.1],
       [4.8, 3.4, 1.9, 0.2],
       [7.2, 3. , 5.8, 1.6],
       [5. , 3. , 1.6, 0.2],
       [6.7, 2.5, 5.8, 1.8],
       [6.4, 2.8, 5.6, 2.1],
       [4.8, 3. , 1.4, 0.3],
       [5.3, 3.7, 1.5, 0.2],
       [4.4, 3.2, 1.3, 0.2],
       [5. , 3.2, 1.2, 0.2],
       [5.4, 3.9, 1.7, 0.4],
       [6. , 3.4, 4.5, 1.6],
       [6.5, 2.8, 4.6, 1.5],
       [4.5, 2.3, 1.3, 0.3],
       [5.7, 2.9, 4.2, 1.3],
       [6.7, 3.3, 5.7, 2.5],
       [5.5, 2.5, 4. , 1.3],
       [6.7, 3. , 5. , 1.7],
       [6.4, 2.9, 4.3, 1.3],
       [6.4, 3.2, 5.3, 2.3],
       [5.6, 2.7, 4.2, 1.3],
       [6.3, 2.3, 4.4, 1.3],
       [4.7, 3.2, 1.6, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [6.1, 3. , 4.9, 1.8],
       [5.1, 3.8, 1.9, 0.4],
       [7.2, 3.2, 6. , 1.8]])
```

In [53]:
```
y_test
```

Out[53]:
```
array([0, 0, 2, 0, 0, 2, 0, 2, 2, 0, 0, 0, 0, 0, 1, 1, 0, 1, 2, 1, 1, 1,
       2, 1, 1, 0, 0, 2, 0, 2], dtype=int64)
```

In [54]:
```
len(X_train)
```
Out[54]:
```
120
```
In [56]:
```
len(y_train)
```
Out[56]:
```
120
```
In [57]:
```
len(X_test)
```
Out[57]:
```
30
```
In [58]:
```
len(y_test)
```
Out[58]:
```
30
```
--- supervised ML algorithms

Linear Regression

In [60]:
```
model = LinearRegression()

model.fit(X_train,y_train)
```
Out[60]:
```
LinearRegression()
```

In [61]:
```
y_pred = model.predict(X_test)

sc_lr = round(model.score(X_test, y_test) * 100 , 2)

print("Accuracy: ", str(sc_lr) , " %" )
```

```
Accuracy:  93.71  %
```

Logistic Regression

In [63]:
```
model2 = LogisticRegression()

model2.fit(X_train,y_train)
```

Out[63]:
```
LogisticRegression()
```

In [64]:
```
sc_logr = round(model2.score(X_test, y_test) * 100,2)

print("Accuracy: ", str(sc_logr) ,  " %")
```

```
Accuracy:  96.67  %
```

Naive Bayes

In [65]:
```
nb = GaussianNB()

nb.fit(X_train,y_train)
```

Out[65]:
```
GaussianNB()
```

In [67]:
```
y_pred_nb = nb.predict(X_test)

score_nb = round(accuracy_score(y_pred_nb,y_test)*100,2)
```

In [68]:
```
print("Accuracy: "+str(score_nb)+" %")

print(classification_report(y_test, y_pred_nb))
```

```
Accuracy: 96.67 %
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       1.00      0.88      0.93         8
           2       0.89      1.00      0.94         8

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

KNN Classifier

In [69]:
```
model3 = KNeighborsClassifier()

model3.fit(X_train,y_train)
```

Out[69]:
```
KNeighborsClassifier()
```

In [71]:
```
sc_knn = round(model3.score(X_test, y_test) * 100,2)

print("Accuracy: ", str(sc_knn) , " %")
```

```
Accuracy:  100.0  %
```

Decision Tree Classifier

In [72]:
```
model4 = DecisionTreeClassifier()

model4.fit(X_train, y_train)
```

Out[72]:
```
DecisionTreeClassifier()
```

In [75]:
```
sc_knn = round(model3.score(X_test, y_test) * 100,2)

print("Accuracy: ", str(sc_knn) , " %")
```

```
Accuracy:  100.0  %
```

SVM

In [76]:
```
sv = svm.SVC(kernel='linear')

sv.fit(X_train, y_train)
```

Out[76]:
```
SVC(kernel='linear')
```

In [77]:
```
y_pred_svm = sv.predict(X_test)

sc_svm = round(accuracy_score(y_pred_svm,y_test)*100,2)
```

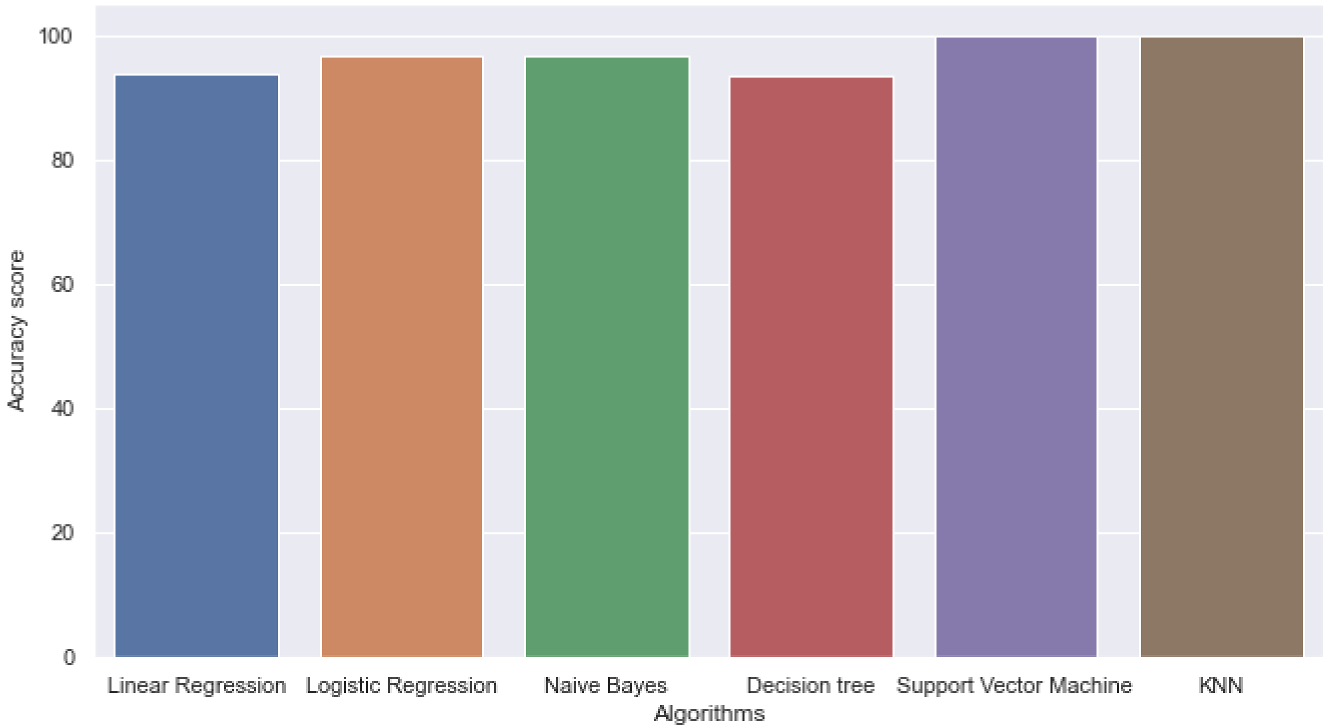
In [78]:
```
print("Accuracy: "+ str(sc_svm) +" %")

print(classification_report(y_test, y_pred_svm))
```

```
Accuracy: 100.0 %
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       1.00      1.00      1.00         8
           2       1.00      1.00      1.00         8

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

--- comparison Between all the classifier

In [79]:
```
scores_plt = [sc_lr , sc_logr , score_nb, sc_dt, sc_svm, sc_knn]
algorithms = ["Linear Regression","Logistic Regression","Naive Bayes","Decision tree","Support Vector Machine", "KNN"]
sns.set(rc={'figure.figsize':(11,6)})
plt.xlabel("Algorithms")
plt.ylabel("Accuracy score")

sns.barplot(algorithms,scores_plt)
```

Out[79]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x25fa356a250>
```



In [ ]:

```

```