LetsGrowMore Task 1 Project Iris Flower for more detail refer the below links

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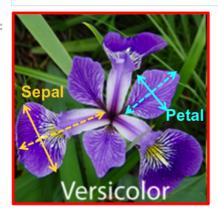
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IRIS FLOWER Classification using Machine Learning

DATASET TAKEN FROM KAGGLE

In [5]:
 from IPython.display import Image
 Image(filename='E:/LETSGROWMORE INTERN/BEGGINERS LEVEL/IRIS DATASET/image.png', width

Out[5]:







IMPORT LIBRARIES

import numpy as np # to calculate matrix problem we go for it
import pandas as pd # data processing where used for import dataset ect..
import matplotlib.pyplot as plt #used for visualzing the dataset

Importing dataset

```
In [9]:
           iris = pd.read_csv('E:/LETSGROWMORE INTERN/BEGGINERS LEVEL/IRIS DATASET/archive/IRIS
           print(iris)
               sepal_length sepal_width petal_length petal_width
                                                                                 species
          0
                         5.1
                                       3.5
                                                      1.4
                                                                    0.2
                                                                             Iris-setosa
                         4.9
                                       3.0
                                                      1.4
                                                                    0.2
                                                                             Iris-setosa
          1
          2
                         4.7
                                       3.2
                                                      1.3
                                                                    0.2
                                                                             Iris-setosa
          3
                                                                    0.2
                                                                             Iris-setosa
                         4.6
                                       3.1
                                                      1.5
          4
                                                                             Iris-setosa
                         5.0
                                       3.6
                                                      1.4
                                                                    0.2
                         . . .
                                                       . . .
                                                                    2.3 Iris-virginica
          145
                         6.7
                                       3.0
                                                      5.2
                                                                    1.9 Iris-virginica
          146
                                       2.5
                                                      5.0
                         6.3
                                                                    2.0 Iris-virginica
          147
                         6.5
                                       3.0
                                                      5.2
                                                                    2.3 Iris-virginica
          148
                         6.2
                                       3.4
                                                      5.4
                                                                    1.8 Iris-virginica
          149
                         5.9
                                       3.0
                                                      5.1
          [150 rows x 5 columns]
In [10]:
           iris.head() # viewing first 5 dataset headers means values
Out[10]:
             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
In [11]:
           iris.shape # num of rows and cols
Out[11]: (150, 5)
In [12]:
           #set rest of data atribute into feature variable
           features=iris[['sepal_length','sepal_width','petal_length','petal_width']]
In [13]:
           #display top 5 rows of features
           features.head()
Out[13]:
             sepal_length sepal_width petal_length petal_width
          0
                     5.1
                                                         0.2
                                 3.5
                                              1.4
          1
                     4.9
                                 3.0
                                             1.4
                                                         0.2
          2
                     4.7
                                 3.2
                                             1.3
                                                         0.2
          3
                     4.6
                                 3.1
                                             1.5
                                                         0.2
          4
                     5.0
                                             1.4
                                                         0.2
                                 3.6
In [35]:
           iris.describe(include='all')
                  sepal_length sepal_width petal_length petal_width
Out[35]:
                                                                     species
```

	sepal_length	sepal_width	petal_length	petal_width	species
count	150.000000	150.000000	150.000000	150.000000	150
unique	NaN	NaN	NaN	NaN	3
top	NaN	NaN	NaN	NaN	Iris-setosa
freq	NaN	NaN	NaN	NaN	50
mean	5.843333	3.054000	3.758667	1.198667	NaN
std	0.828066	0.433594	1.764420	0.763161	NaN
min	4.300000	2.000000	1.000000	0.100000	NaN
25%	5.100000	2.800000	1.600000	0.300000	NaN
50%	5.800000	3.000000	4.350000	1.300000	NaN
75%	6.400000	3.300000	5.100000	1.800000	NaN
max	7.900000	4.400000	6.900000	2.500000	NaN

In [36]: ir

iris.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):

#	Column	Non-Null Count	Dtype
0	sepal_length	150 non-null	float64
1	sepal_width	150 non-null	float64
2	petal_length	150 non-null	float64
3	petal_width	150 non-null	float64
4	species	150 non-null	object

dtypes: float64(4), object(1)

memory usage: 6.0+ KB

Finding Missing values and replacing

In [42]: iris.drop(columns="petal_width",inplace=False)

Out[42]:		sepal_length	sepal_width	petal_length	species
	0	5.1	3.5	1.4	Iris-setosa
	1	4.9	3.0	1.4	Iris-setosa
	2	4.7	3.2	1.3	Iris-setosa
	3	4.6	3.1	1.5	Iris-setosa
	4	5.0	3.6	1.4	Iris-setosa
	•••	•••	•••	•••	•••
	145	6.7	3.0	5.2	Iris-virginica
	146	6.3	2.5	5.0	Iris-virginica
	147	6.5	3.0	5.2	Iris-virginica
	148	6.2	3.4	5.4	Iris-virginica

	sepal_length	sepal_width	petal_length	species	
149	5.9	3.0	5.1	Iris-virginica	

150 rows × 4 columns

```
In [43]: iris.isnull().sum()

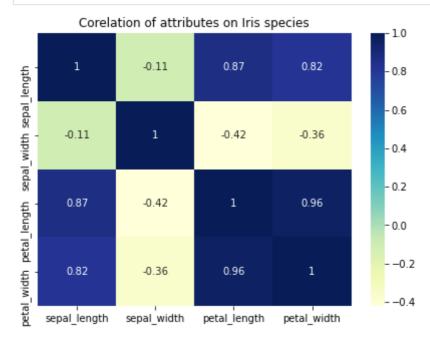
Out[43]: sepal_length  0
    sepal_width  0
    petal_length  0
    petal_width  0
    species  0
    dtype: int64
```

DATA VISUALIZATION

```
In [44]: #CORRELATION iris.corr()
```

Out[44]:		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

```
import seaborn as sns
plt.subplots(figsize = (7,5))
sns.heatmap(iris.corr(),annot=True,cmap="YlGnBu").set_title("Corelation of attribute
plt.show()
```



Target Finding for test and train dataset even for predicting

```
In [18]:
          #set species column as target column
          target=iris['species']
          print(target)
                   Iris-setosa
         1
                   Iris-setosa
         2
                   Iris-setosa
                   Iris-setosa
         3
                   Iris-setosa
                Iris-virginica
         145
                Iris-virginica
         146
         147
                Iris-virginica
         148
                Iris-virginica
         149
                Iris-virginica
         Name: species, Length: 150, dtype: object
In [19]:
          #checking unique value counts
          target.value_counts()
Out[19]: Iris-setosa
                             50
         Iris-versicolor
                             50
         Iris-virginica
                             50
         Name: species, dtype: int64
```

LABLE ENCODING

```
In [22]: #Label encoder from sklearn for label encoding
    from sklearn.preprocessing import LabelEncoder

In [23]: #coverting text value into numerical value
    target=pd.Series(LabelEncoder().fit_transform(target))

In [24]: #check unique value counts
    target.value_counts()

Out[24]: 0     50
     1     50
     2     50
     dtype: int64
```

TEST TRAIN SPLIT

```
In [25]: #import for the sake of split 25% for test
from sklearn.model_selection import train_test_split

In [26]: #split data for train and test
    x_train,x_test,y_train,y_test=train_test_split(features,target)

In [27]: #printing data Lengths/number of rows/data
    print(len(x_train))
    print(len(y_train))
```

```
print(len(x_test))
print(len(y_test))

112
112
38
38
```

PREDICTION USING NAIVE BAYES ALGORITHM

Naive Bayes is a classification algorithm for binary (two-class) and multi-class classification problems. The technique is easiest to understand when described using binary or categorical input values. This is a very strong assumption that is most unlikely in real data, the attributes do not interact.

```
In [28]:
        #import naive bayes classifier from sklearn package
        from sklearn.naive bayes import GaussianNB
In [29]:
        #created a object for the classifier
        bc=GaussianNB()
In [30]:
        #train usinge train data
        bc.fit(x_train,y_train)
Out[30]: GaussianNB()
In [50]:
        #predict target data for test feature data and save into pred variable
        pred=bc.predict(x_test)
        print(pred)
        1]
```

CLASSIFICATION REPORT ON IRIS FLOWER DATSET

```
In [32]:
          #importing classification report function
          from sklearn.metrics import classification report
In [33]:
          print(classification_report(pred,y_test))
                      precision recall f1-score
                                                     support
                   0
                           1.00
                                     1.00
                                               1.00
                                                          12
                   1
                           1.00
                                     1.00
                                               1.00
                                                          12
                   2
                           1.00
                                     1.00
                                               1.00
                                                          14
             accuracy
                                               1.00
                                                          38
                         1.00
                                     1.00
                                               1.00
                                                          38
            macro avg
         weighted avg
                           1.00
                                     1.00
                                               1.00
                                                          38
```

ACCURACY SCORE 100

Thank you