IRIS DATASET ANAYLSIS

The dataset is taken from https://www.kaggle.com/uciml/iris

IMPORTING THE LIBRARIES

In [1]:
```
import numpy as np
import pandas as pd
```

In [44]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import datasets
import seaborn as sns
```

LOAD THE DATASET

In [91]:
```
iris = pd.read_csv("C:/Users/HP/Desktop/coursera/project/iris_dataset/iris.csv")
```

EDA

In [34]:
```
iris.columns
```

Out[34]:
```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
```

```
       'Species'],
      dtype='object')
```

In [35]:
```
iris
```

Out[35]:

	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 [36]:
```
iris.describe()
```

Out[36]:

	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

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
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 [37]:
```
iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
Id               150 non-null int64
SepalLengthCm    150 non-null float64
SepalWidthCm     150 non-null float64
PetalLengthCm    150 non-null float64
PetalWidthCm     150 non-null float64
Species          150 non-null object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

In [38]:
```
iris.isnull().sum()
```

Out[38]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

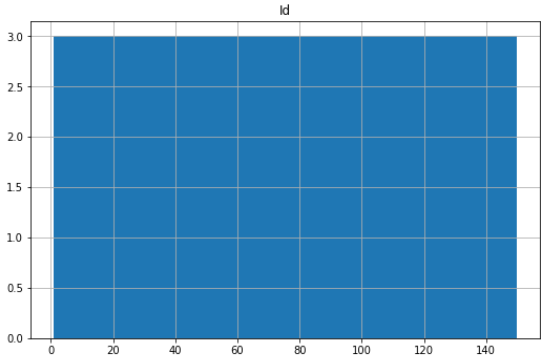
In [40]:
```
iris['Species'].unique()
```

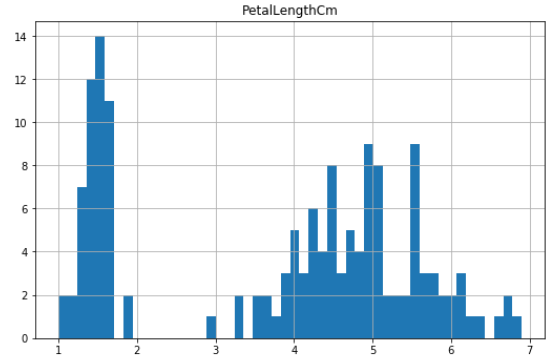
Out[40]:
```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=objec
t)
```

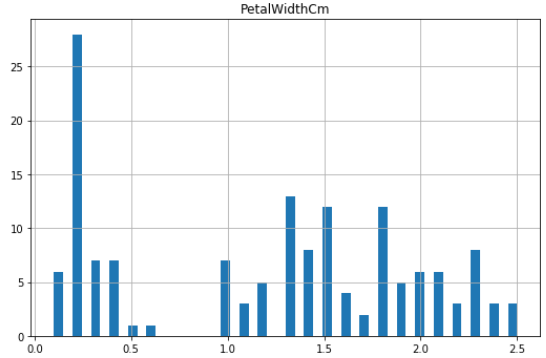
PLOT FEW GRAPHS

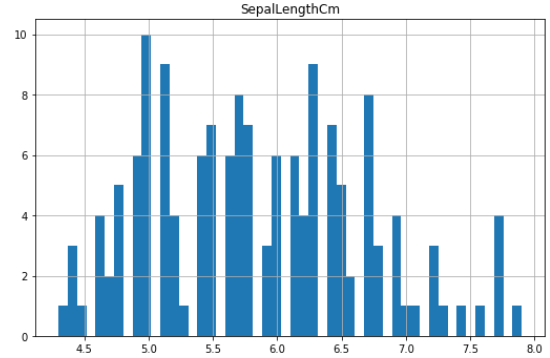
In [42]:
```
iris.hist(bins=50,figsize=(20,20))
```

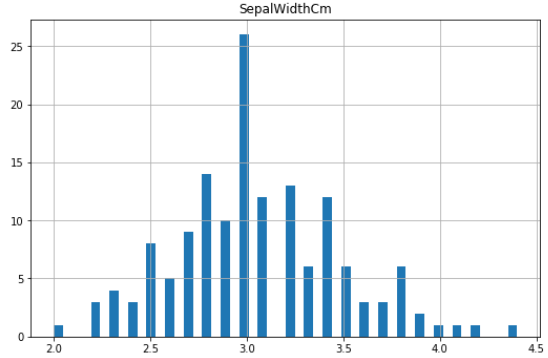
Out[42]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x0000012EFFFD
7C88>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012EFFE1
4648>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x0000012EFFDD
2F08>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012EFFDC
2AC8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x0000012E806C
F248>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000012E806E
EF88>]],
      dtype=object)
```





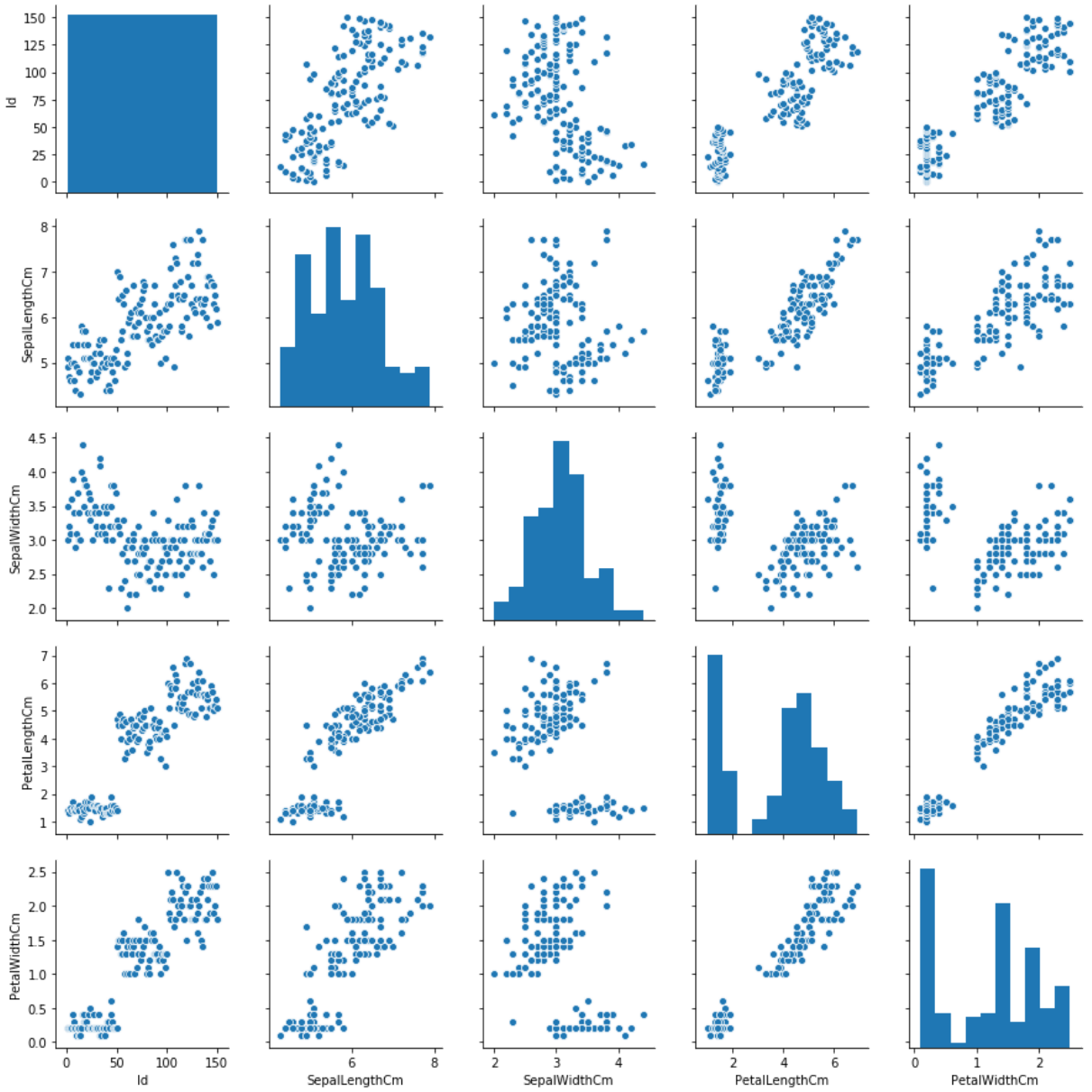






In [45]:
```
sns.pairplot(iris)
```

Out[45]:
```
<seaborn.axisgrid.PairGrid at 0x12e80b9cfc8>
```



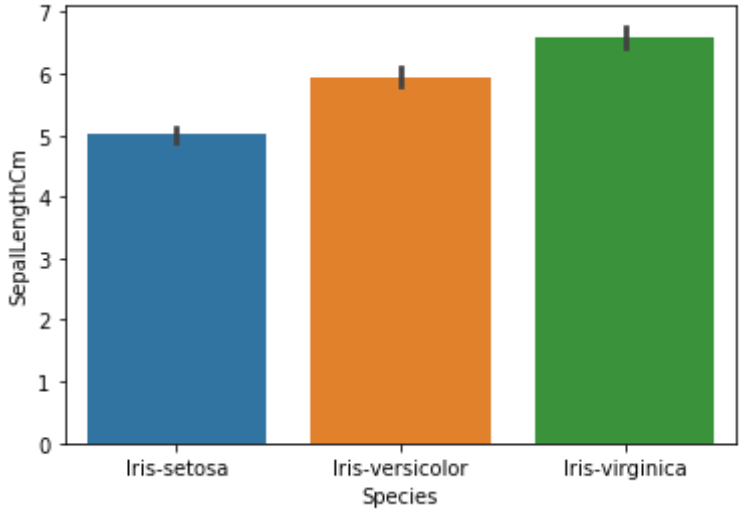
In [46]:
```
iris.columns
```

Out[46]:
```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWi
```

```
dthCm',
       'Species'],
      dtype='object')
```

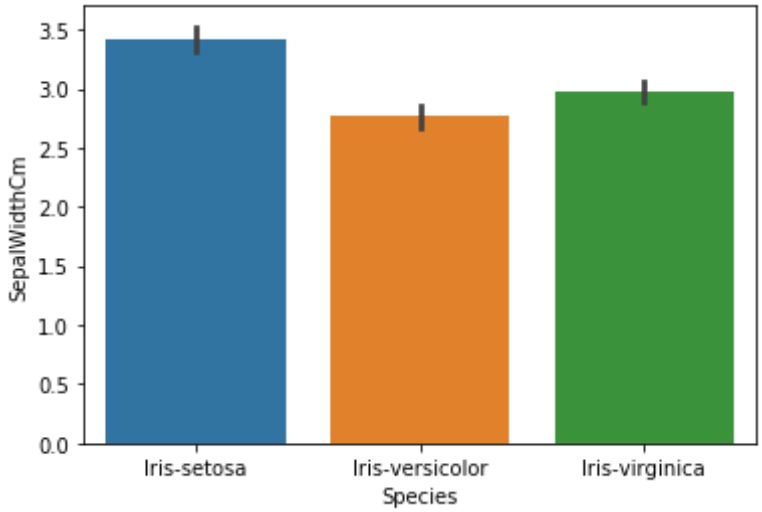
In [49]:
```
sns.barplot(x='Species',y='SepalLengthCm',data=iris)
```

Out[49]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x12e81fc80c8>
```



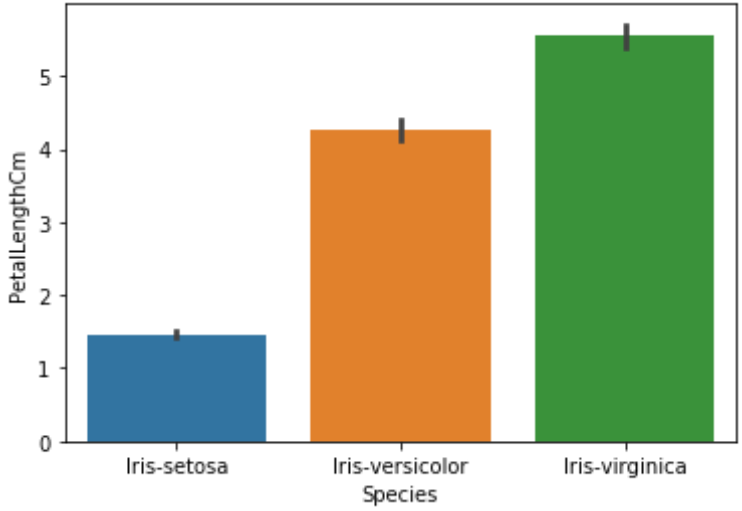
In [50]:
```
sns.barplot(x='Species',y='SepalWidthCm',data=iris)
```

Out[50]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x12e823863c8>
```



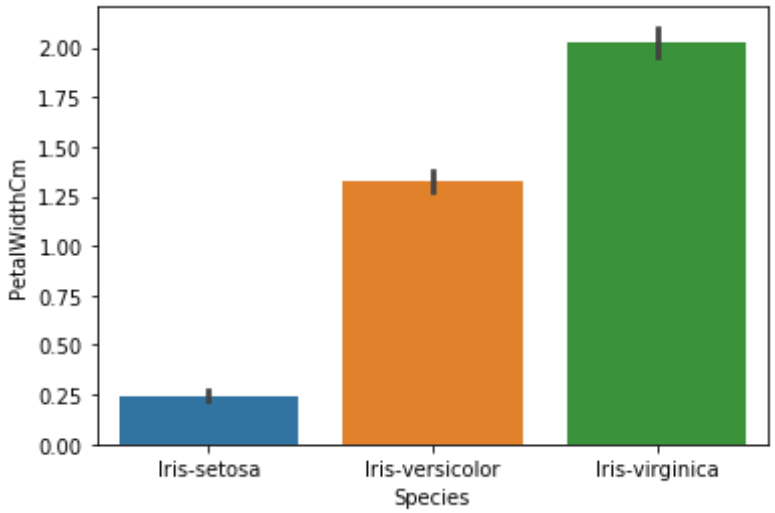
In [51]:
```
sns.barplot(x='Species',y='PetalLengthCm',data=iris)
```

Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x12e833b6b88>



In [52]:
```
sns.barplot(x='Species',y='PetalWidthCm',data=iris)
```

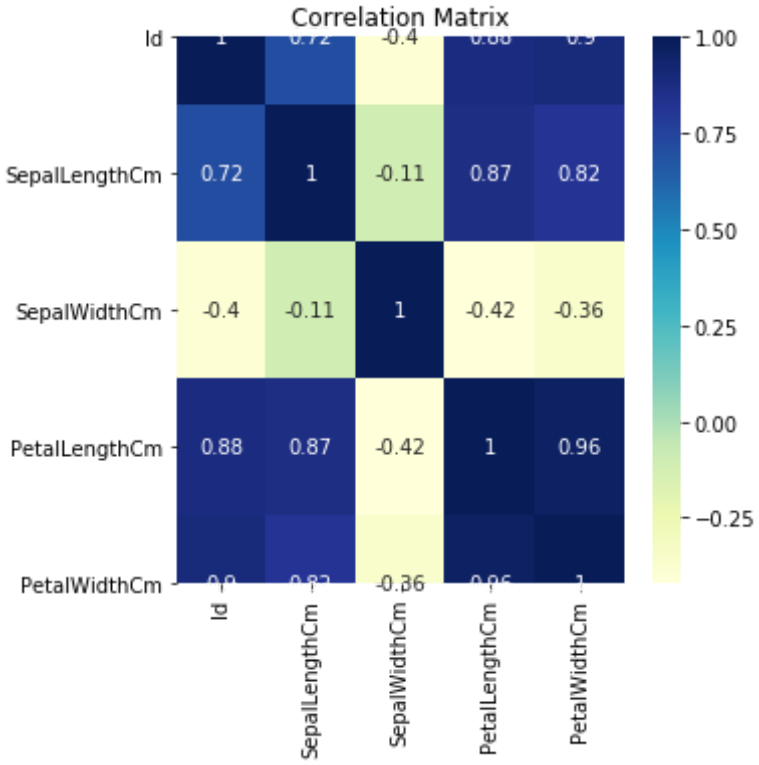
Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x12e83414248>



CORRELATION MATRIX

In [54]:
```
corr = iris.corr()
plt.figure(figsize=(5, 5))
plt.title('Correlation Matrix')
sns.heatmap(corr, cmap='YlGnBu', annot=True)
```

Out[54]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x12e8345e4c8>
```



ONE HOT ENCODING

In [64]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder =LabelEncoder()
iris['Species'] = label_encoder.fit_transform(iris['Species'])
```

SPLITTING THE DATASET INTO FEATURES AND LABELS

In [65]:
```
x=iris.drop('Species',axis=1)
y=iris['Species']
```

In [66]:
```
x
```

Out[66]:

	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

150 rows × 5 columns

In [77]:
```
x = iris.iloc[:, [0, 1, 2, 3]].values
```

In [78]:
```
x
```

Out[78]:
```
array([[  1. ,   5.1,   3.5,   1.4],
       [  2. ,   4.9,   3. ,   1.4],
       [  3. ,   4.7,   3.2,   1.3],
       [  4. ,   4.6,   3.1,   1.5],
       [  5. ,   5. ,   3.6,   1.4],
       [  6. ,   5.4,   3.9,   1.7],
       [  7. ,   4.6,   3.4,   1.4],
       [  8. ,   5. ,   3.4,   1.5],
       [  9. ,   4.4,   2.9,   1.4],
       [ 10. ,   4.9,   3.1,   1.5],
```

```
[ 11. ,   5.4,   3.7,   1.5],
[ 12. ,   4.8,   3.4,   1.6],
[ 13. ,   4.8,   3. ,   1.4],
[ 14. ,   4.3,   3. ,   1.1],
[ 15. ,   5.8,   4. ,   1.2],
[ 16. ,   5.7,   4.4,   1.5],
[ 17. ,   5.4,   3.9,   1.3],
[ 18. ,   5.1,   3.5,   1.4],
[ 19. ,   5.7,   3.8,   1.7],
[ 20. ,   5.1,   3.8,   1.5],
[ 21. ,   5.4,   3.4,   1.7],
[ 22. ,   5.1,   3.7,   1.5],
[ 23. ,   4.6,   3.6,   1. ],
[ 24. ,   5.1,   3.3,   1.7],
[ 25. ,   4.8,   3.4,   1.9],
[ 26. ,   5. ,   3. ,   1.6],
[ 27. ,   5. ,   3.4,   1.6],
[ 28. ,   5.2,   3.5,   1.5],
[ 29. ,   5.2,   3.4,   1.4],
[ 30. ,   4.7,   3.2,   1.6],
[ 31. ,   4.8,   3.1,   1.6],
[ 32. ,   5.4,   3.4,   1.5],
[ 33. ,   5.2,   4.1,   1.5],
[ 34. ,   5.5,   4.2,   1.4],
[ 35. ,   4.9,   3.1,   1.5],
[ 36. ,   5. ,   3.2,   1.2],
[ 37. ,   5.5,   3.5,   1.3],
[ 38. ,   4.9,   3.1,   1.5],
[ 39. ,   4.4,   3. ,   1.3],
[ 40. ,   5.1,   3.4,   1.5],
[ 41. ,   5. ,   3.5,   1.3],
[ 42. ,   4.5,   2.3,   1.3],
[ 43. ,   4.4,   3.2,   1.3],
[ 44. ,   5. ,   3.5,   1.6],
[ 45. ,   5.1,   3.8,   1.9],
[ 46. ,   4.8,   3. ,   1.4],
[ 47. ,   5.1,   3.8,   1.6],
[ 48. ,   4.6,   3.2,   1.4],
[ 49. ,   5.3,   3.7,   1.5],
```

```
[ 50. ,   5. ,   3.3,   1.4],
[ 51. ,   7. ,   3.2,   4.7],
[ 52. ,   6.4,   3.2,   4.5],
[ 53. ,   6.9,   3.1,   4.9],
[ 54. ,   5.5,   2.3,   4. ],
[ 55. ,   6.5,   2.8,   4.6],
[ 56. ,   5.7,   2.8,   4.5],
[ 57. ,   6.3,   3.3,   4.7],
[ 58. ,   4.9,   2.4,   3.3],
[ 59. ,   6.6,   2.9,   4.6],
[ 60. ,   5.2,   2.7,   3.9],
[ 61. ,   5. ,   2. ,   3.5],
[ 62. ,   5.9,   3. ,   4.2],
[ 63. ,   6. ,   2.2,   4. ],
[ 64. ,   6.1,   2.9,   4.7],
[ 65. ,   5.6,   2.9,   3.6],
[ 66. ,   6.7,   3.1,   4.4],
[ 67. ,   5.6,   3. ,   4.5],
[ 68. ,   5.8,   2.7,   4.1],
[ 69. ,   6.2,   2.2,   4.5],
[ 70. ,   5.6,   2.5,   3.9],
[ 71. ,   5.9,   3.2,   4.8],
[ 72. ,   6.1,   2.8,   4. ],
[ 73. ,   6.3,   2.5,   4.9],
[ 74. ,   6.1,   2.8,   4.7],
[ 75. ,   6.4,   2.9,   4.3],
[ 76. ,   6.6,   3. ,   4.4],
[ 77. ,   6.8,   2.8,   4.8],
[ 78. ,   6.7,   3. ,   5. ],
[ 79. ,   6. ,   2.9,   4.5],
[ 80. ,   5.7,   2.6,   3.5],
[ 81. ,   5.5,   2.4,   3.8],
[ 82. ,   5.5,   2.4,   3.7],
[ 83. ,   5.8,   2.7,   3.9],
[ 84. ,   6. ,   2.7,   5.1],
[ 85. ,   5.4,   3. ,   4.5],
[ 86. ,   6. ,   3.4,   4.5],
[ 87. ,   6.7,   3.1,   4.7],
[ 88. ,   6.3,   2.3,   4.4],
```

```
[ 89. ,   5.6,   3. ,   4.1],
[ 90. ,   5.5,   2.5,   4. ],
[ 91. ,   5.5,   2.6,   4.4],
[ 92. ,   6.1,   3. ,   4.6],
[ 93. ,   5.8,   2.6,   4. ],
[ 94. ,   5. ,   2.3,   3.3],
[ 95. ,   5.6,   2.7,   4.2],
[ 96. ,   5.7,   3. ,   4.2],
[ 97. ,   5.7,   2.9,   4.2],
[ 98. ,   6.2,   2.9,   4.3],
[ 99. ,   5.1,   2.5,   3. ],
[100. ,   5.7,   2.8,   4.1],
[101. ,   6.3,   3.3,   6. ],
[102. ,   5.8,   2.7,   5.1],
[103. ,   7.1,   3. ,   5.9],
[104. ,   6.3,   2.9,   5.6],
[105. ,   6.5,   3. ,   5.8],
[106. ,   7.6,   3. ,   6.6],
[107. ,   4.9,   2.5,   4.5],
[108. ,   7.3,   2.9,   6.3],
[109. ,   6.7,   2.5,   5.8],
[110. ,   7.2,   3.6,   6.1],
[111. ,   6.5,   3.2,   5.1],
[112. ,   6.4,   2.7,   5.3],
[113. ,   6.8,   3. ,   5.5],
[114. ,   5.7,   2.5,   5. ],
[115. ,   5.8,   2.8,   5.1],
[116. ,   6.4,   3.2,   5.3],
[117. ,   6.5,   3. ,   5.5],
[118. ,   7.7,   3.8,   6.7],
[119. ,   7.7,   2.6,   6.9],
[120. ,   6. ,   2.2,   5. ],
[121. ,   6.9,   3.2,   5.7],
[122. ,   5.6,   2.8,   4.9],
[123. ,   7.7,   2.8,   6.7],
[124. ,   6.3,   2.7,   4.9],
[125. ,   6.7,   3.3,   5.7],
[126. ,   7.2,   3.2,   6. ],
[127. ,   6.2,   2.8,   4.8],
```

```
       [128. ,   6.1,   3. ,   4.9],
       [129. ,   6.4,   2.8,   5.6],
       [130. ,   7.2,   3. ,   5.8],
       [131. ,   7.4,   2.8,   6.1],
       [132. ,   7.9,   3.8,   6.4],
       [133. ,   6.4,   2.8,   5.6],
       [134. ,   6.3,   2.8,   5.1],
       [135. ,   6.1,   2.6,   5.6],
       [136. ,   7.7,   3. ,   6.1],
       [137. ,   6.3,   3.4,   5.6],
       [138. ,   6.4,   3.1,   5.5],
       [139. ,   6. ,   3. ,   4.8],
       [140. ,   6.9,   3.1,   5.4],
       [141. ,   6.7,   3.1,   5.6],
       [142. ,   6.9,   3.1,   5.1],
       [143. ,   5.8,   2.7,   5.1],
       [144. ,   6.8,   3.2,   5.9],
       [145. ,   6.7,   3.3,   5.7],
       [146. ,   6.7,   3. ,   5.2],
       [147. ,   6.3,   2.5,   5. ],
       [148. ,   6.5,   3. ,   5.2],
       [149. ,   6.2,   3.4,   5.4],
       [150. ,   5.9,   3. ,   5.1]])
```

In [67]:
```
y
```

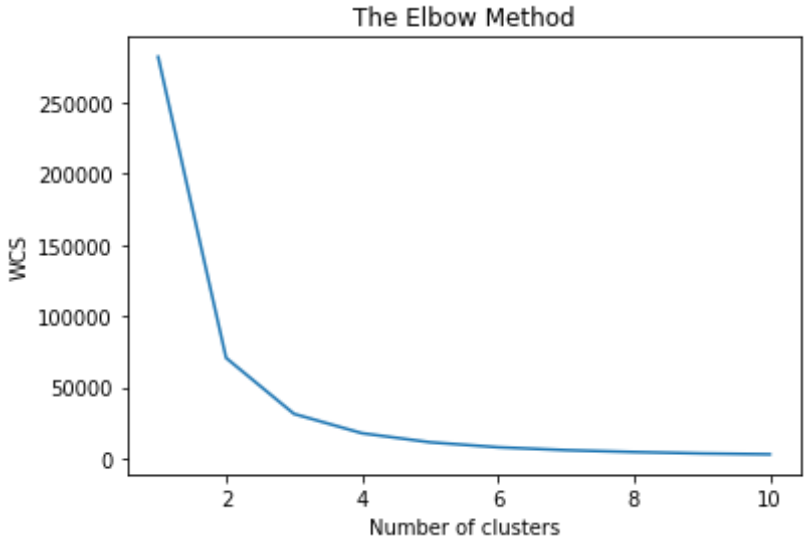
Out[67]:
```
0      0
1      0
2      0
3      0
4      0
      ..
145    2
146    2
147    2
148    2
149    2
Name: Species, Length: 150, dtype: int32
```

K MEANS CLUSTERING

In [79]:
```
from sklearn.cluster import KMeans
wcs = []
```

In [80]:
```
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++',
                    max_iter = 300, n_init = 10, random_state = 0)
    kmeans.fit(x)
    wcs.append(kmeans.inertia_)
```

In [81]:
```
plt.plot(range(1, 11), wcs)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCS') # Within cluster sum of squares
plt.show()
```

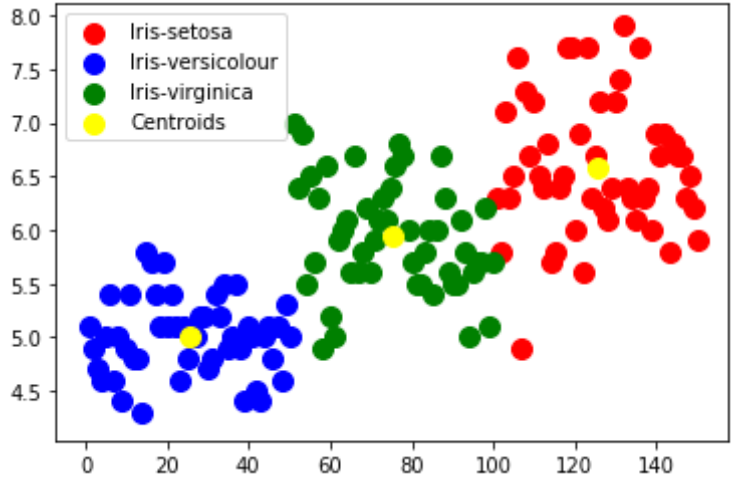


In [82]:
```
kmeans = KMeans(n_clusters = 3, init = 'k-means++',
                max_iter = 300, n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(x)
```

In [83]:
```
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1],
            s = 100, c = 'red', label = 'Iris-setosa')
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1],
            s = 100, c = 'blue', label = 'Iris-versicolour')
plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1],
            s = 100, c = 'green', label = 'Iris-virginica')

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1
],
            s = 100, c = 'yellow', label = 'Centroids')

plt.legend()
plt.show()
```



TRAIN TEST SPLIT

In [84]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.5)
```

MODEL

In [85]:
```
from sklearn import tree
classifier=tree.DecisionTreeClassifier()
```

In [86]:
```
from sklearn import neighbors
classifier=neighbors.KNeighborsClassifier()
```

In [87]:
```
classifier.fit(x_train,y_train)
```

Out[87]:
```
KNeighborsClassifier()
```

In [88]:
```
predictions=classifier.predict(x_test)
```

In [89]:
```
from sklearn.metrics import accuracy_score
print(accuracy_score(y_test,predictions))
```

```
0.9866666666666667
```

In [ ]:
```

```