Task3Iris-Flower-Classification

August 4, 2024

1 CodSoft DataScience Internship

1.1 Task 3: IRIS FLOWER CLASSIFICATION

[1]:
```
# importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Loading Dataset

[2]:
```
df = pd.read_csv('IRIS.csv')
df.head()
```

[2]:

	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

Information of Dataset columns

[3]:
```
df.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
```

Calculating statical values

```
[4]: df.describe()
```

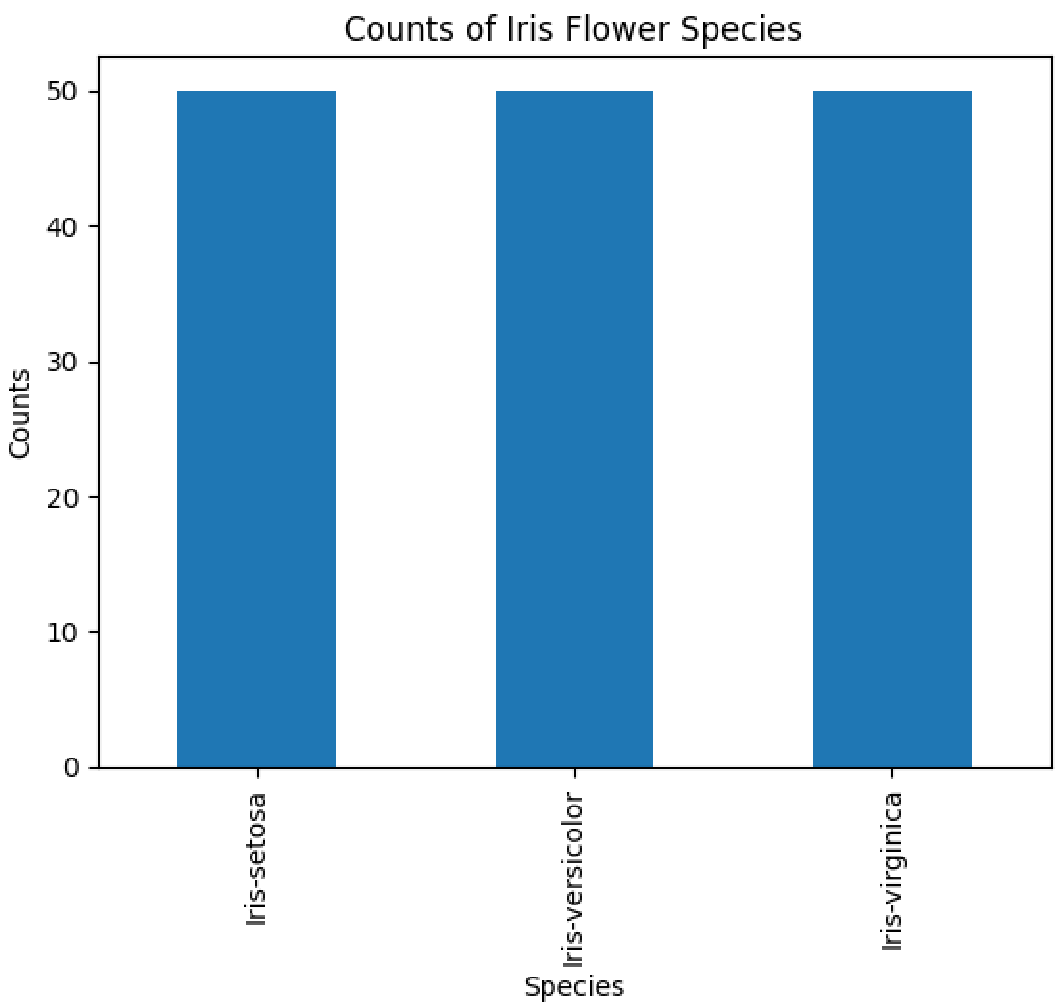
```
[4]:        sepal_length  sepal_width  petal_length  petal_width
     count    150.000000   150.000000    150.000000   150.000000
     mean       5.843333     3.054000      3.758667     1.198667
     std        0.828066     0.433594      1.764420     0.763161
     min        4.300000     2.000000      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
```

Checking null values in the dataset

```
[5]: df.isnull().sum()
```

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

```
[6]: df['species'].value_counts().plot(kind='bar')
     plt.xlabel('Species')
     plt.ylabel('Counts')
     plt.title('Counts of Iris Flower Species')
     plt.show()
```



[7]:
```
df.shape
```

[7]: (150, 5)

Data Wrangling / preprocessing Checking the species of flower using species column

[8]:
```
df['species'].unique()
```

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

We can see we have Three Species of the Iris Flower

We have to convert the categorical data into numerical processing

[9]:
```
df['species'] =df['species'].apply({'Iris-setosa':0,'Iris-versicolor':
↪1,'Iris-virginica':2,}.get)
```

[10]:
```
df.head(1)
```

[10]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	0

[11]:
```
df.tail(2)
```

[11]:

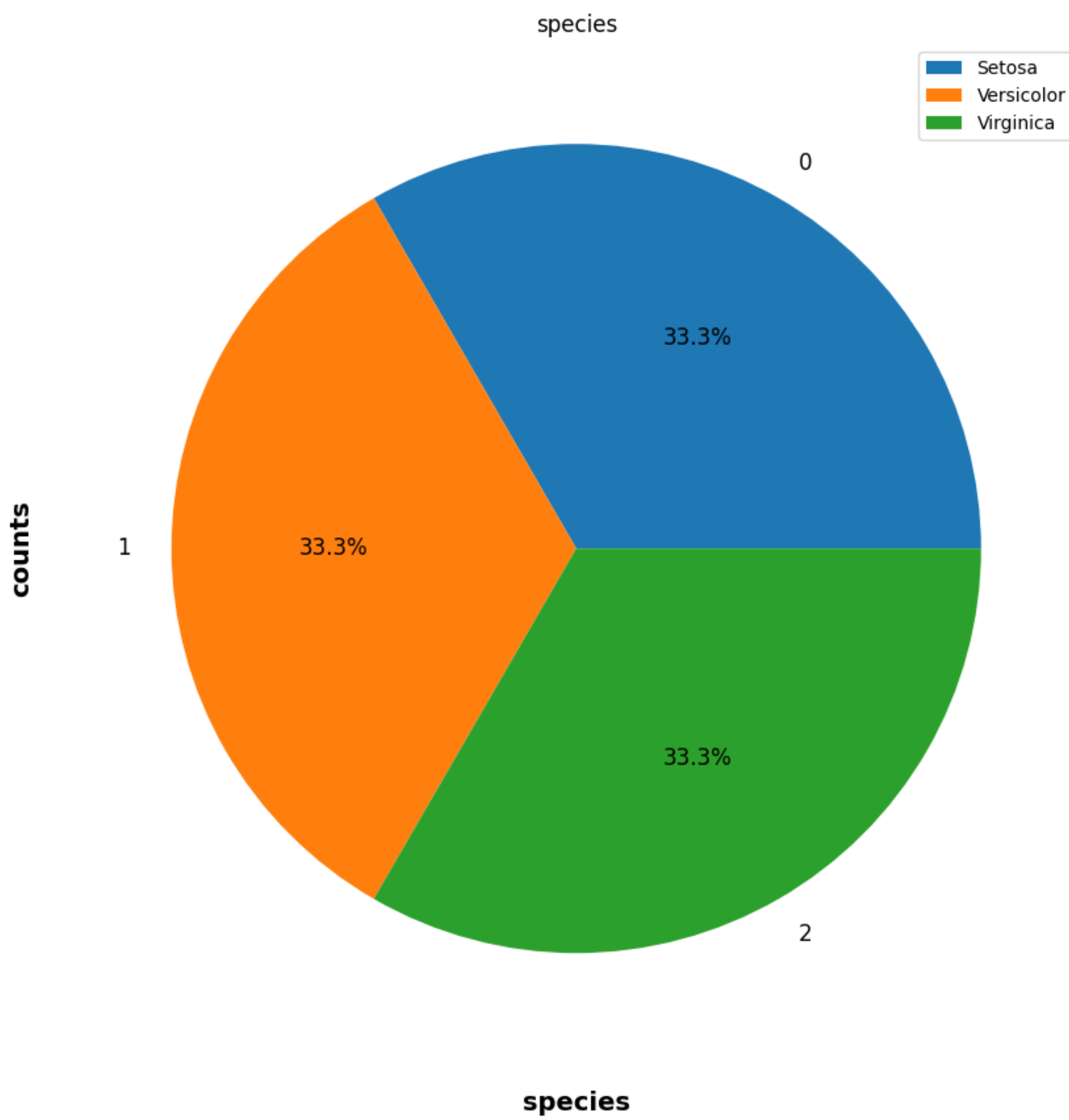
	sepal_length	sepal_width	petal_length	petal_width	species
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

[12]:
```
df.info()
```

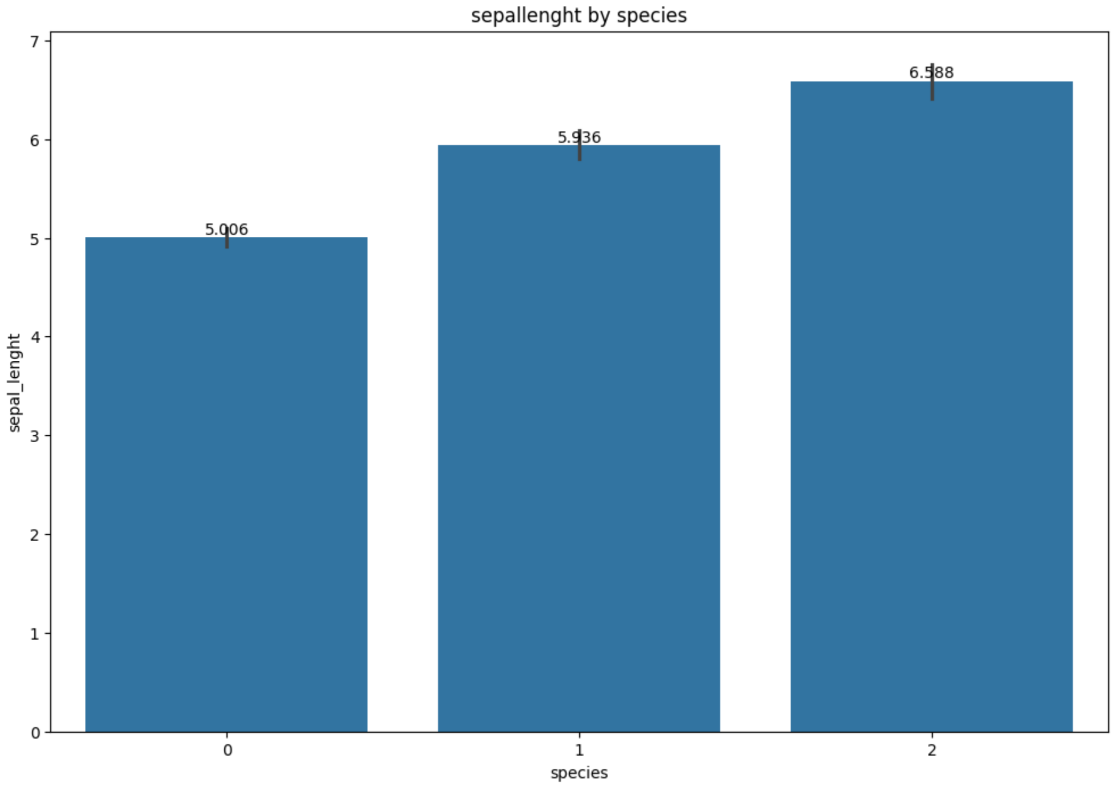
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    int64
dtypes: float64(4), int64(1)
memory usage: 6.0 KB
```

2 Data visualization

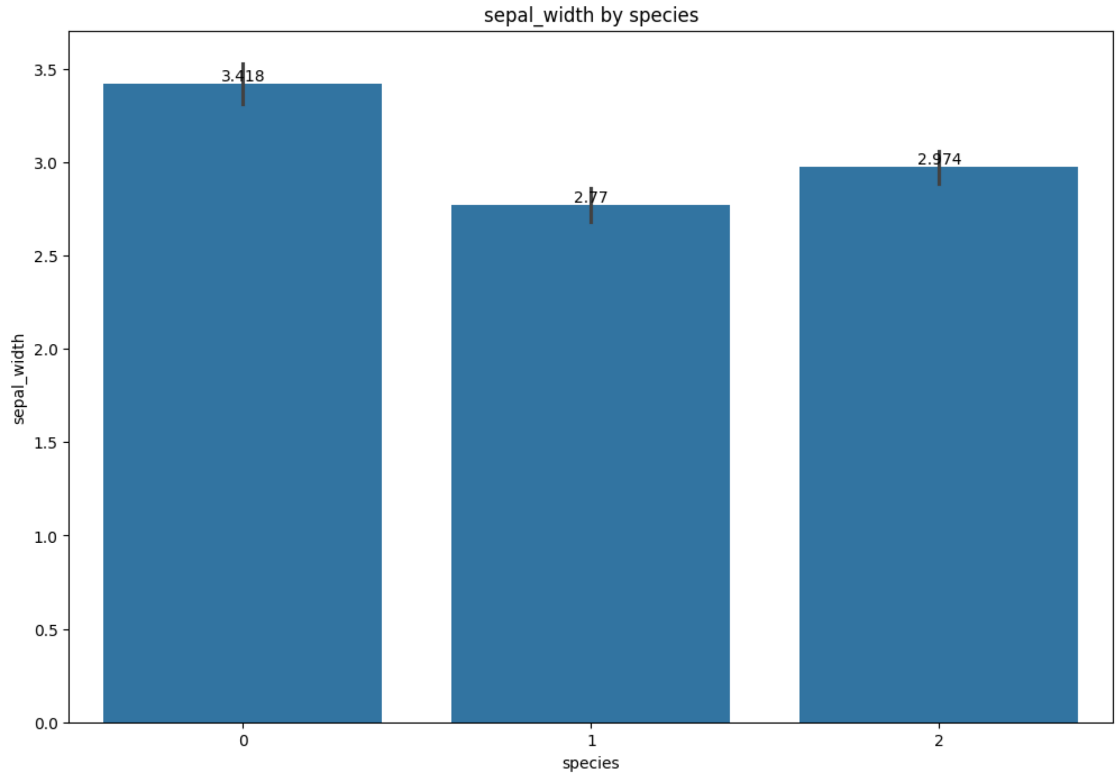
[13]:
```
plt.figure(figsize = (20, 10))
explode = (0,0,0.09)
count_iris = df['species'].value_counts()
count_iris.plot(kind = 'pie', fontsize = 12, autopct = '%.1f%%')
plt.title('species')
plt.xlabel('species', weight = "bold", color = "#000000", fontsize = 14,␣
 ↪labelpad = 20)
plt.ylabel('counts', weight = "bold", color = "#000000", fontsize = 14,␣
 ↪labelpad = 20)
plt.legend(labels  = ['Setosa','Versicolor','Virginica'])
plt.show()
```



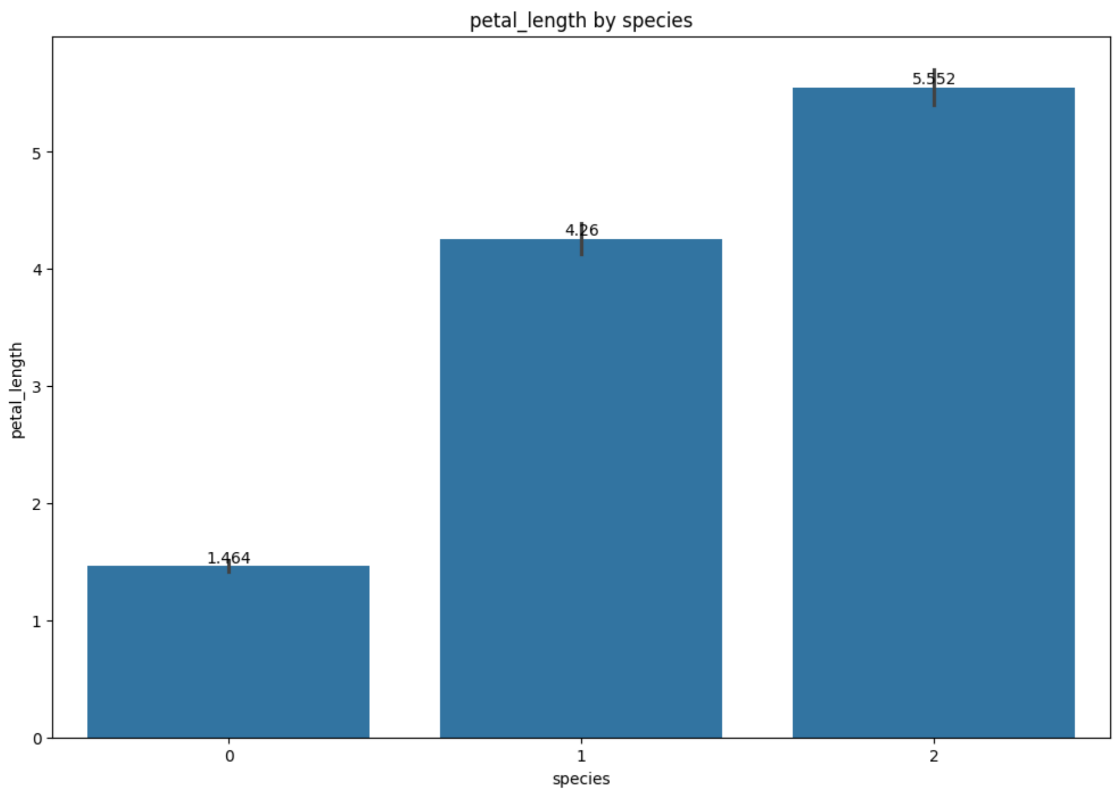
[14]:
```
plt.figure(figsize=(12,8))
ax=sns.barplot(x=df['species'],y=df['sepal_length'])
ax.bar_label(ax.containers[0], fontsize=10);
plt.title('sepallenght by species')
plt.xlabel('species')
plt.ylabel('sepal_lenght')
plt.show()
```



[15]:
```
plt.figure(figsize=(12,8))
ax=sns.barplot(x=df['species'],y=df['sepal_width'])
ax.bar_label(ax.containers[0], fontsize=10);
plt.title('sepal_width by species')
plt.xlabel('species')
plt.ylabel('sepal_width')
plt.show()
```



[16]:
```
plt.figure(figsize=(12,8))
ax=sns.barplot(x=df['species'],y=df['petal_length'])
ax.bar_label(ax.containers[0], fontsize=10);
plt.title('petal_length by species')
plt.xlabel('species')
plt.ylabel('petal_length')
plt.show()
```



[ ]:

[ ]:

[ ]:

[ ]:

Preparing Dataset for Model Development

Dividing data into dependent and independent variables

[17]:
```
x = df.drop(['species'],axis=1)
y = df['species']
x.head()
```

[17]:

	sepal_length	sepal_width	petal_length	petal_width
0	5.1	3.5	1.4	0.2
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	3.6	1.4	0.2

[18]:
```
y.head()
```

[18]:
```
0    0
1    0
2    0
3    0
4    0
Name: species, dtype: int64
```

Dividing data into training and testing sets for further processing

[19]:
```
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=4)
```

3 Model Development

3.0.1 1. DecisionTreeClassification

[20]:
```
from sklearn.tree import DecisionTreeClassifier
import sklearn.tree as tree
```

[21]:
```
Tree = DecisionTreeClassifier()
```

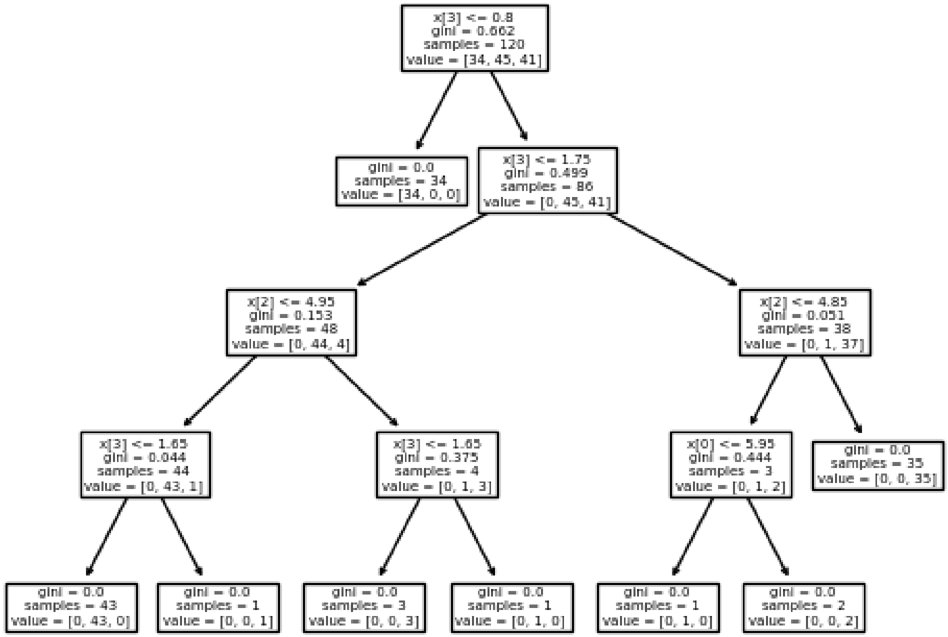
[22]:
```
# Trainin the data
Tree.fit(x_train,y_train)
```

[22]:
```
DecisionTreeClassifier()
```

[23]:
```
# Predicting the classification of flower
Classification1 = Tree.predict(x_test)
print(Classification1)
```

```
[2 0 2 2 2 1 2 0 0 2 0 0 0 1 2 0 1 0 0 2 0 2 1 0 0 0 0 0 0 2]
```

[24]:
```
tree.plot_tree(Tree)
plt.show()
```



Evaluation of Model

[25]:
```
from sklearn.metrics import confusion_matrix,accuracy_score
```

[26]:
```
accuracyScore = accuracy_score(y_test,Classification1)
conMatrix = confusion_matrix(y_test,Classification1)
```

[27]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,Classification1))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        16
           1       1.00      0.80      0.89         5
           2       0.90      1.00      0.95         9

    accuracy                           0.97        30
   macro avg       0.97      0.93      0.95        30
weighted avg       0.97      0.97      0.97        30
```

[28]:
```
conMatrix
```

[28]:
```
array([[16,  0,  0],
       [ 0,  4,  1],
       [ 0,  0,  9]])
```

[29]:
```
print('The accuracy of the model is {:.2f}%.'.format(accuracyScore*100))
```

```
The accuracy of the model is 96.67%.
```

3.0.2 2. LogisticRegression Classification Model

[30]:
```
from sklearn.linear_model import LogisticRegression
```

[31]:
```
regression = LogisticRegression(multi_class = 'multinomial',solver='lbfgs')
```

[32]:
```
regression.fit(x_train,y_train)
```

```
/home/suresh/.local/lib/python3.10/site-
packages/sklearn/linear_model/_logistic.py:469: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[32]:
```
LogisticRegression(multi_class='multinomial')
```

[33]:
```
Classification2 = regression.predict(x_test)
```

[34]:
```
Classification2
```

[34]:
```
array([2, 0, 2, 2, 2, 1, 2, 0, 0, 2, 0, 0, 0, 1, 2, 0, 1, 0, 0, 2, 0, 2,
       1, 0, 0, 0, 0, 0, 0, 2])
```

Evaluation using jaccard-score

[35]:
```
accuracy1 = accuracy_score(y_test,Classification1)
print('The Model is {:.2f}% accurate.'.format(accuracy1*100))
```

```
The Model is 96.67% accurate.
```

3.0.3 3. RandomForestClassifier Classification Model

[36]:
```
from sklearn.ensemble import RandomForestClassifier
forest = RandomForestClassifier()
```

[37]:
```
forest.fit(x_train,y_train)
```

[37]:
```
RandomForestClassifier()
```

[38]:
```
ClassPrediction = forest.predict(x_test)
```

[39]:
```
print(ClassPrediction)
```

```
[2 0 2 2 2 1 2 0 0 2 0 0 0 1 2 0 1 0 0 2 0 2 1 0 0 0 0 0 0 2]
```

Model evaluation

[40]:
```
accuracyScore3 = accuracy_score(y_test,ClassPrediction)
conMatrix3 = confusion_matrix(y_test,ClassPrediction)
```

[41]:
```
print(conMatrix3)
```

```
[[16  0  0]
 [ 0  4  1]
 [ 0  0  9]]
```

[42]:
```
print("The accuracy of the RandomRorestClassifier is {:.2f}%.".
 ↪format(accuracyScore3*100))
```

```
The accuracy of the RandomRorestClassifier is 96.67%.
```

3.0.4 4. KNeighbourClassifier

[47]:
```
from sklearn.neighbors import KNeighborsClassifier
neighbor = KNeighborsClassifier(n_neighbors = 4)
```

Fitting the data

[48]:
```
neighbor.fit(x_train,y_train)
```

[48]:
```
KNeighborsClassifier(n_neighbors=4)
```

[51]:
```
predict = neighbor.predict(x_test)
print(predict)
```

```
[2 0 2 2 2 1 2 0 0 2 0 0 0 1 2 0 1 0 0 2 0 2 1 0 0 0 0 0 0 2]
```

Evaluation of the model

[52]:
```
print(accuracy_score(y_test,predict))
```

```
0.9666666666666667
```

3.1 Conclusions

From the above classification machine learning algorithe we can see the all of the accuracy score is same. so we can use any of them to predict the classification of the new Data.

3.2 Author

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