MAJOR PROJECT

NAME

P SASI KUMAR

SUB

TEACHNOOK DATASCIENCE
MAJOR PROJECT

TOPICS

TAKE ANY DATASET OF YOUR CHOICE ,PERFORM EDA(EXPLORATORY DATA ANALYSIS) AND APPLY A SUITABLE CLASSIFIER,REGRESSOR OR CLUSTERER AND CALCULATE THE ACCURACY OF THE MODEL.

SUBMITTED TO

TEACHNOOK
IIT BHUVANESHWAR

okilzhgni

July 28, 2023

[ ]:
```
#IRIS FLOWER DATASET - Logistic Regression
#dataset - IRIS FLOWER DATASET
#datset - https://raw.githubusercontent.com/ameenmanna8824/DATASETS/main/IRIS.
 ↪csv
```

[ ]:
```
#1.Take tha data and create dataframe
import pandas as pd
df = pd.read_csv('https://raw.githubusercontent.com/ameenmanna8824/DATASETS/
 ↪main/IRIS.csv')
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]

[ ]:
```
#2.step no 2 not required
```

[ ]:
```
fsize = df.groupby('species',sort = False).size()
fsize
```

[ ]:
```
species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
dtype: int64
```

[ ]:
```
#3.Step no 3 not required
#We cannot apply visualisation for CLASSIFICATION MODEL
```

[ ]:
```
#4.Divide the data into input and output
```

[ ]:
```
#input - sepal length,sepal width, petal length,petal width
#output - species
```

[ ]:
```
x = df.iloc[:,:4].values
y = df.iloc[:,4].values
```

[ ]:
```
#5.Train and Test variables
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,random_state =0)
#Random_state is used to avoid duplicates
```

[ ]:
```
#6.Normalisation or Scaling
#here step no 6 is not required because our inputs are already scaled
```

[ ]:
```
#7.Apply a classifier regressor or clusterer
from sklearn.linear_model import LogisticRegression
model = LogisticRegression
```

[ ]:
```
#8.Fit the model
from sklearn.linear_model import LogisticRegression

# Initialize the model
model = LogisticRegression()

# Fit the model to the training data
model.fit(x_train, y_train)
```

[ ]:
```
#10.predict the output
y_pred = model.predict(x_test) #using the input testing values , we predict the␣
 ↪output.
y_pred
```

[ ]:
```
array(['Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-virginica', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
       'Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
```

```
        'Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
        'Iris-virginica'], dtype=object)
```

[ ]:
```
y_test #Actual oupit
```

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

[ ]:
```
#10.Accuracy
from sklearn.metrics import accuracy_score
accuracy_score(y_pred,y_test)*100
```

[ ]:
```
97.36842105263158
```

[ ]:
```
#INDIVIDUAL PREDICTION
model.predict([[5.1,3.1,1.4,0.2]])
```

[ ]:
```
array(['Iris-setosa'], dtype=object)
```

[ ]:
```
model.predict([[5.7,2.8,4.5,1.3]])
```

[ ]:
```
array(['Iris-versicolor'], dtype=object)
```

[ ]:
```
model.predict([[7.7,3.8,6.7,2.2]])
```

[ ]:
```
array(['Iris-virginica'], dtype=object)
```

[ ]:
```
#Custom values
model.predict([[6.8,3.3,7.9,4.5]])
```

[ ]:
```
array(['Iris-virginica'], dtype=object)
```

[ ]:
```
#EXPLORATORY DATA ANALYSIS(EDA) - PRE MACHINE LEARNING
#EDA -  WE FIND DIFFERENT INSIGHTS and WE COME TO CONCLUSIONS using our DATA
```

[ ]:
```
#Dataset:https://raw.githubusercontent.com/ameenmanna8824/DATASETS/main/IRIS.csv
```

[ ]:
```
#import pandas as pd
#df = pd.read_csv('https://raw.githubusercontent.com/ameenmanna8824/DATASETS/
 ↪main/IRIS.csv')
#df
```

[ ]:
```
import pandas as pd
df = pd.read_csv('https://raw.githubusercontent.com/ameenmanna8824/DATASETS/
 ↪main/IRIS.csv')
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]

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

[ ]:

	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

[ ]:
```
df.size
```

[ ]:
```
750
```

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

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

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

[ ]:
```
<bound method DataFrame.info of      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]>
```

[ ]:
```
df.sample(6)
```

[ ]:
```
     sepal_length  sepal_width  petal_length  petal_width         species
92            5.8          2.6           4.0          1.2  Iris-versicolor
71            6.1          2.8           4.0          1.3  Iris-versicolor
37            4.9          3.1           1.5          0.1      Iris-setosa
59            5.2          2.7           3.9          1.4  Iris-versicolor
21            5.1          3.7           1.5          0.4      Iris-setosa
82            5.8          2.7           3.9          1.2  Iris-versicolor
```

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

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

[ ]:
```
df.describe(include='all')
```

[ ]:
```
        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
```

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

```
<ipython-input-33-2f6f6606aa2c>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
```

```
to silence this warning.
  df.corr()
```

[ ]:

	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

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

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

[ ]:
```
df_setosa = df.loc[df['species']=='setosa']
df_setosa.describe()
```

[ ]:

	sepal_length	sepal_width	petal_length	petal_width
count	0.0	0.0	0.0	0.0
mean	NaN	NaN	NaN	NaN
std	NaN	NaN	NaN	NaN
min	NaN	NaN	NaN	NaN
25%	NaN	NaN	NaN	NaN
50%	NaN	NaN	NaN	NaN
75%	NaN	NaN	NaN	NaN
max	NaN	NaN	NaN	NaN

[ ]:
```
#Slice row indexes from 25 to 43 and column indexes 0 and 1
#var.iloc[row slicing,column slicing]
df.iloc[40:64,2:5]
```

[ ]:

	petal_length	petal_width	species
40	1.3	0.3	Iris-setosa
41	1.3	0.3	Iris-setosa
42	1.3	0.2	Iris-setosa
43	1.6	0.6	Iris-setosa
44	1.9	0.4	Iris-setosa
45	1.4	0.3	Iris-setosa
46	1.6	0.2	Iris-setosa
47	1.4	0.2	Iris-setosa
48	1.5	0.2	Iris-setosa
49	1.4	0.2	Iris-setosa
50	4.7	1.4	Iris-versicolor

```
51          4.5          1.5  Iris-versicolor
52          4.9          1.5  Iris-versicolor
53          4.0          1.3  Iris-versicolor
54          4.6          1.5  Iris-versicolor
55          4.5          1.3  Iris-versicolor
56          4.7          1.6  Iris-versicolor
57          3.3          1.0  Iris-versicolor
58          4.6          1.3  Iris-versicolor
59          3.9          1.4  Iris-versicolor
60          3.5          1.0  Iris-versicolor
61          4.2          1.5  Iris-versicolor
62          4.0          1.0  Iris-versicolor
63          4.7          1.4  Iris-versicolor
```

1 New Section

[ ]:
```
#Let us consider the column species
#Now I want to know the exact count of the unique flower names
df['species'].nunique()
```

[ ]:
```
3
```

[ ]:
```
#Now I want the unique fruit names
fname = df['species'].unique()
fname
```

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

[ ]:
```
#Now I want to find out the exact count of each and every flower
#Iris-setosa       - 50
#Iris-versicolor   - 50
#Iris-virginica    - 50
fsize = df.groupby('species',sort = False).size()
fsize
#By default ,.groupby sets the values in Alphabetical order
```

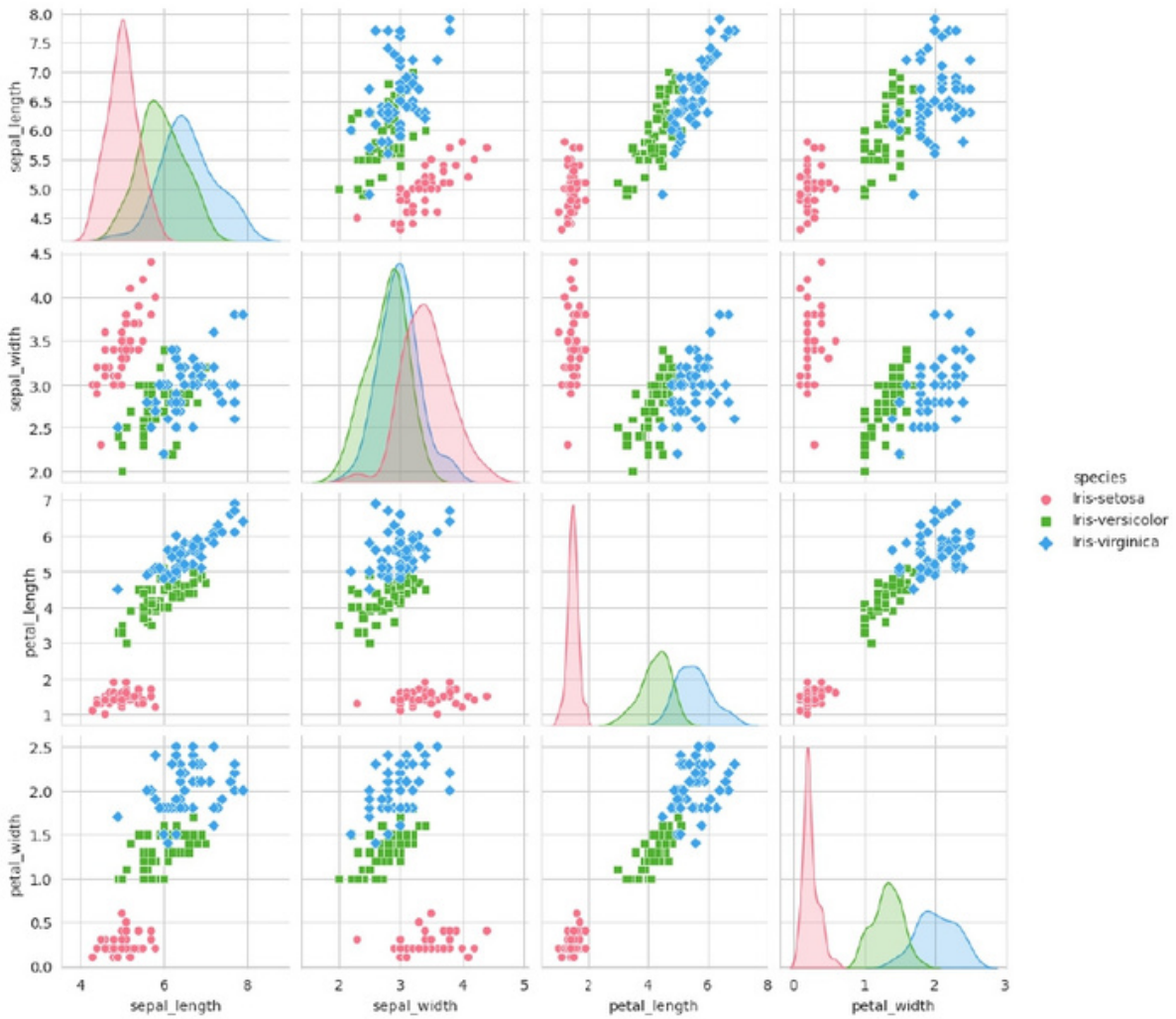
[ ]:
```
species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
dtype: int64
```

[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.close()
```

```
sns.set_style('whitegrid')
sns.pairplot(df, hue="species", markers=["o", "s", "D"], palette="husl")
```

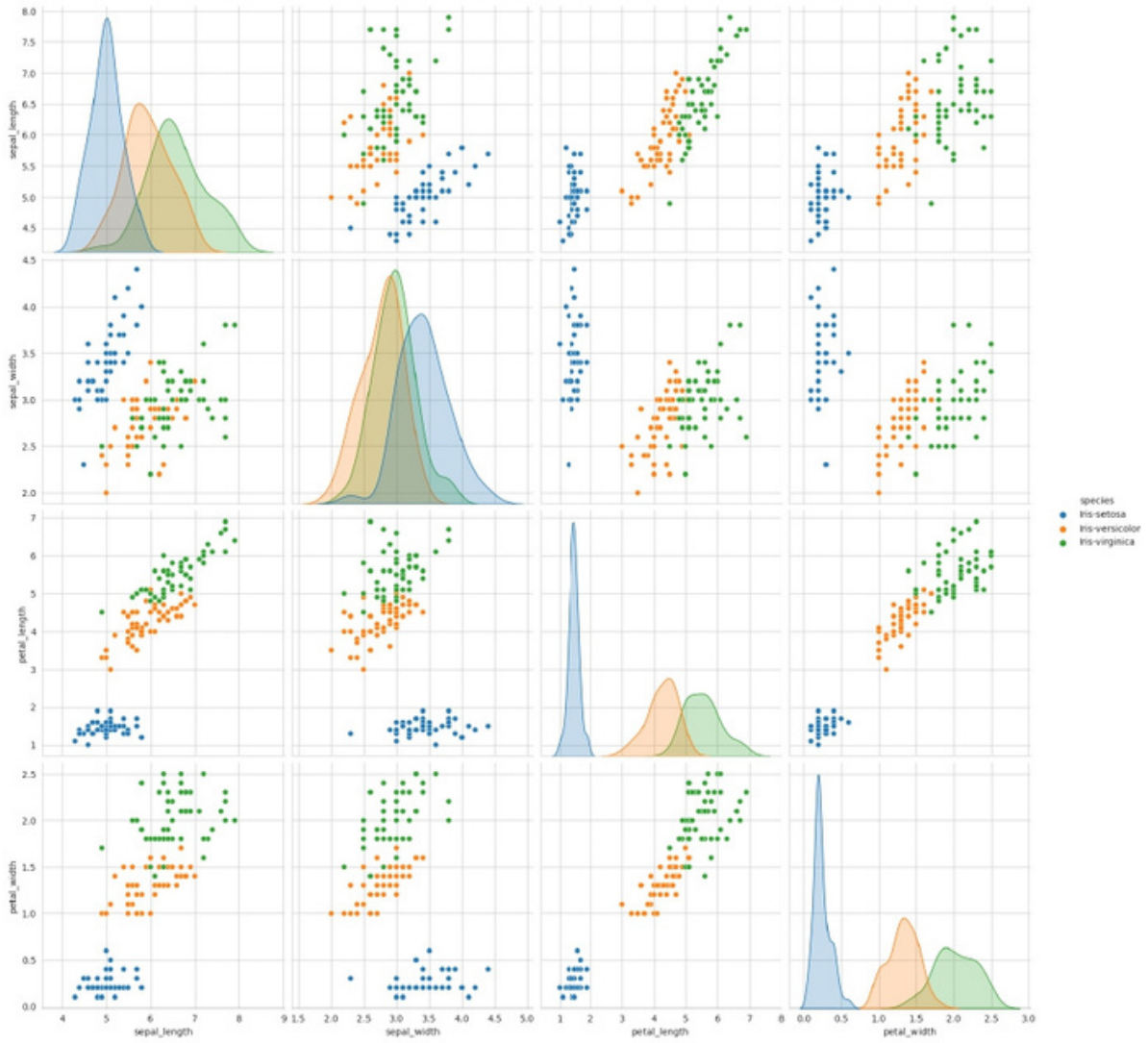
[ ]: <seaborn.axisgrid.PairGrid at 0x7d7f089cedd0>



[ ]:
```
plt.close()
sns.set_style('whitegrid')
sns.pairplot(df, hue='species', size=4)
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/axisgrid.py:2095: UserWarning:
The `size` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

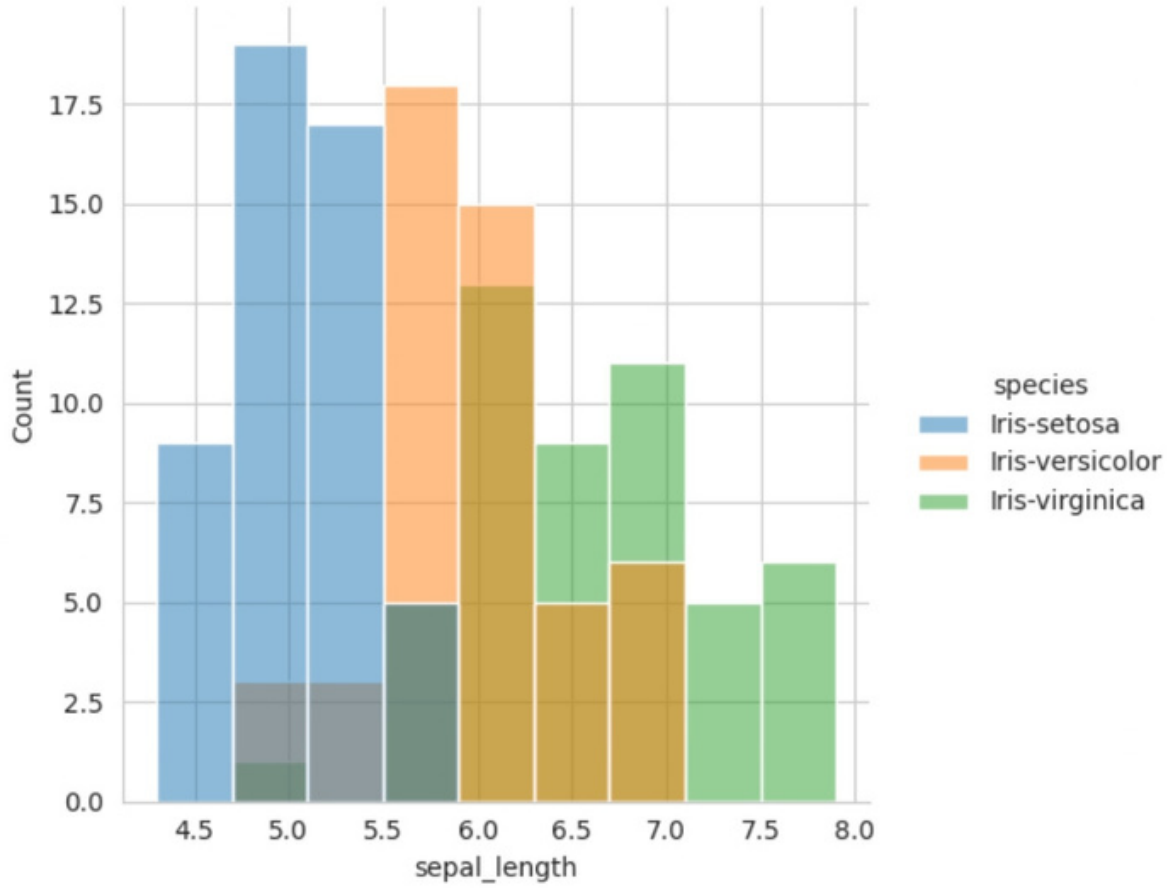
[ ]: <seaborn.axisgrid.PairGrid at 0x7d7ec061f880>



[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

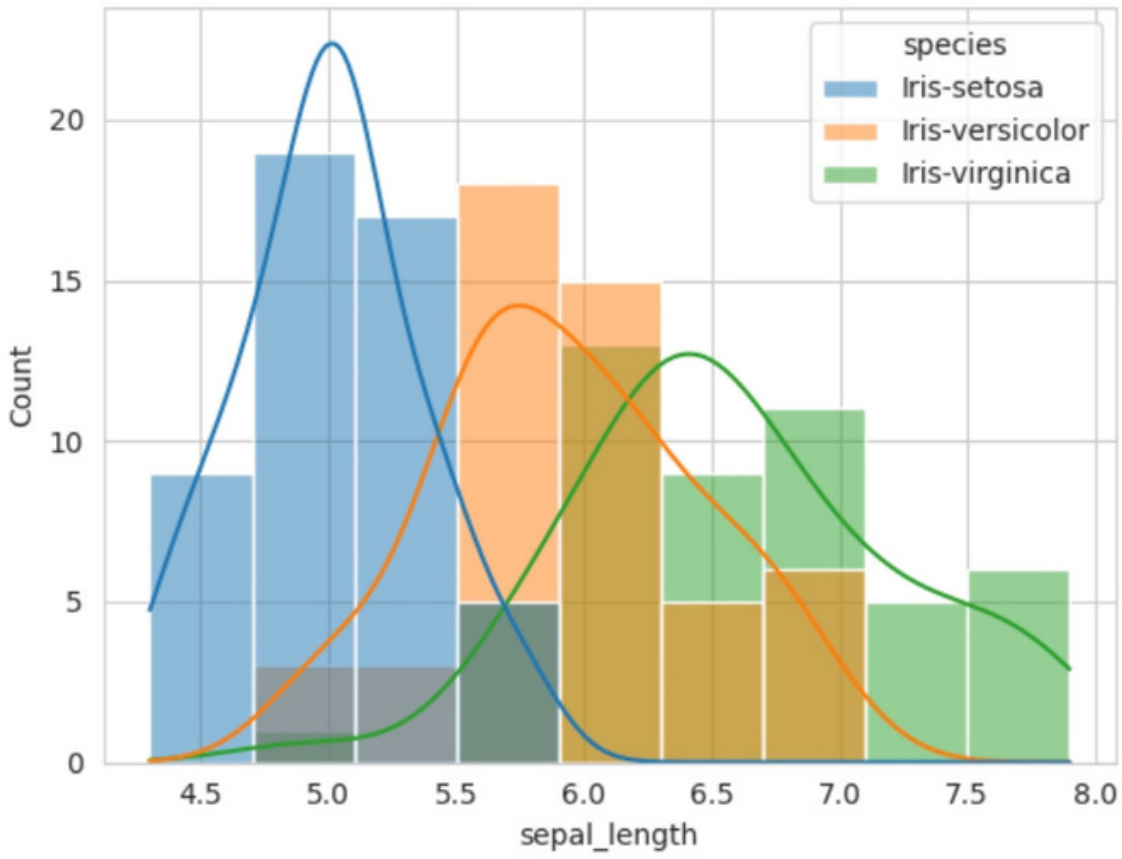
[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Use displot (figure-level function) to plot histograms
sns.displot(df, x='sepal_length', hue='species', height=5)
plt.show()
```



[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Use histplot (axes-level function) to plot histograms
sns.histplot(data=df, x='sepal_length', hue='species', kde=True)
plt.show()
```



[ ]:
```
sns.displot(df, x="petal_length", hue="species", height=5)
plt.show()
```