

```
import numpy as np import pandas as pd import seaborn as sn
```

## # Iris Flower Classification using Scikit-learn library

```
In [128]: import numpy as np
import pandas as pd
import seaborn as sn
import matplotlib.pyplot as plt
```

```
In [129]: df=sn.load_dataset('iris')
df
```

Out[129]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

150 rows × 5 columns

from the above data consists of \*4 numeric attributes \*1 nominal attribute.

```
In [130]: df.head(10)
```

```
Out[130]:
```

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
5	5.4	3.9	1.7	0.4	setosa
6	4.6	3.4	1.4	0.3	setosa
7	5.0	3.4	1.5	0.2	setosa
8	4.4	2.9	1.4	0.2	setosa
9	4.9	3.1	1.5	0.1	setosa

```
In [131]: df.tail(10)
```

```
Out[131]:
```

	sepal_length	sepal_width	petal_length	petal_width	species
140	6.7	3.1	5.6	2.4	virginica
141	6.9	3.1	5.1	2.3	virginica
142	5.8	2.7	5.1	1.9	virginica
143	6.8	3.2	5.9	2.3	virginica
144	6.7	3.3	5.7	2.5	virginica
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

```
In [132]: df.drop_duplicates('species')
```

```
Out[132]:
```

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
50	7.0	3.2	4.7	1.4	versicolor
100	6.3	3.3	6.0	2.5	virginica

```
In [133]: df.isnull().sum()
```

```
Out[133]: sepal_length    0
sepal_width    0
petal_length    0
petal_width    0
species        0
dtype: int64
```

\*in the given data there is no null values.

\*let's visualize the data for more understanding.

```
In [134]: print(df)
```

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
..	...	...	...	...	...
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

[150 rows x 5 columns]

```
In [135]: #divide the data frmes based on their species data.
df1=df[df['species']=='setosa']
df2=df[df['species']=='versicolor']
df3=df[df['species']=='virginica']
```

```
In [136]: print(df1)
```

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
5	5.4	3.9	1.7	0.4	setosa
6	4.6	3.4	1.4	0.3	setosa
7	5.0	3.4	1.5	0.2	setosa
8	4.4	2.9	1.4	0.2	setosa
9	4.9	3.1	1.5	0.1	setosa
10	5.4	3.7	1.5	0.2	setosa
11	4.8	3.4	1.6	0.2	setosa
12	4.8	3.0	1.4	0.1	setosa
13	4.3	3.0	1.1	0.1	setosa
14	5.8	4.0	1.2	0.2	setosa
15	5.7	4.4	1.5	0.4	setosa
16	5.4	3.9	1.3	0.4	setosa
17	5.1	3.5	1.4	0.3	setosa
18	5.7	3.8	1.7	0.3	setosa
19	5.1	3.8	1.5	0.3	setosa
20	5.4	3.4	1.7	0.2	setosa
21	5.1	3.7	1.5	0.4	setosa
22	4.6	3.6	1.0	0.2	setosa
23	5.1	3.3	1.7	0.5	setosa
24	4.8	3.4	1.9	0.2	setosa
25	5.0	3.0	1.6	0.2	setosa
26	5.0	3.4	1.6	0.4	setosa
27	5.2	3.5	1.5	0.2	setosa
28	5.2	3.4	1.4	0.2	setosa
29	4.7	3.2	1.6	0.2	setosa
30	4.8	3.1	1.6	0.2	setosa
31	5.4	3.4	1.5	0.4	setosa
32	5.2	4.1	1.5	0.1	setosa
33	5.5	4.2	1.4	0.2	setosa
34	4.9	3.1	1.5	0.2	setosa
35	5.0	3.2	1.2	0.2	setosa
36	5.5	3.5	1.3	0.2	setosa
37	4.9	3.6	1.4	0.1	setosa
38	4.4	3.0	1.3	0.2	setosa
39	5.1	3.4	1.5	0.2	setosa
40	5.0	3.5	1.3	0.3	setosa
41	4.5	2.3	1.3	0.3	setosa
42	4.4	3.2	1.3	0.2	setosa
43	5.0	3.5	1.6	0.6	setosa
44	5.1	3.8	1.9	0.4	setosa
45	4.8	3.0	1.4	0.3	setosa
46	5.1	3.8	1.6	0.2	setosa
47	4.6	3.2	1.4	0.2	setosa
48	5.3	3.7	1.5	0.2	setosa
49	5.0	3.3	1.4	0.2	setosa

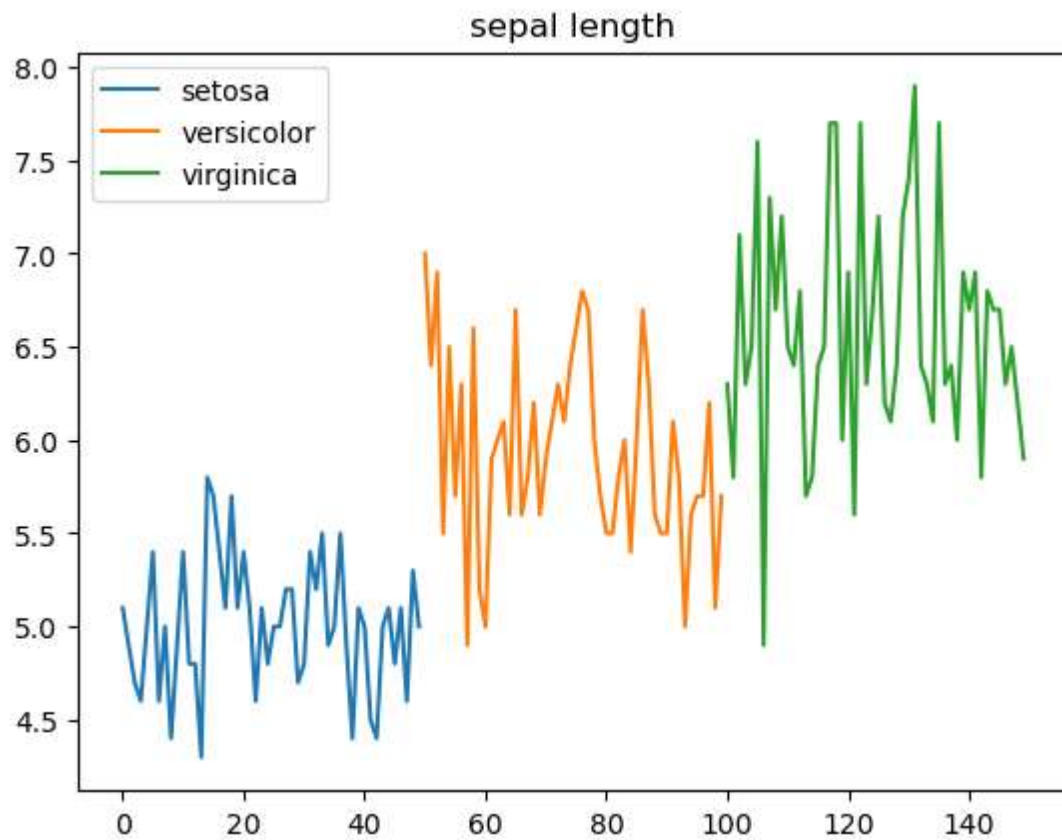
```
In [137]: print(df2)
```

	sepal_length	sepal_width	petal_length	petal_width	species
50	7.0	3.2	4.7	1.4	versicolor
51	6.4	3.2	4.5	1.5	versicolor
52	6.9	3.1	4.9	1.5	versicolor
53	5.5	2.3	4.0	1.3	versicolor
54	6.5	2.8	4.6	1.5	versicolor
55	5.7	2.8	4.5	1.3	versicolor
56	6.3	3.3	4.7	1.6	versicolor
57	4.9	2.4	3.3	1.0	versicolor
58	6.6	2.9	4.6	1.3	versicolor
59	5.2	2.7	3.9	1.4	versicolor
60	5.0	2.0	3.5	1.0	versicolor
61	5.9	3.0	4.2	1.5	versicolor
62	6.0	2.2	4.0	1.0	versicolor
63	6.1	2.9	4.7	1.4	versicolor
64	5.6	2.9	3.6	1.3	versicolor
65	6.7	3.1	4.4	1.4	versicolor
66	5.6	3.0	4.5	1.5	versicolor
67	5.8	2.7	4.1	1.0	versicolor
68	6.2	2.2	4.5	1.5	versicolor
69	5.6	2.5	3.9	1.1	versicolor
70	5.9	3.2	4.8	1.8	versicolor
71	6.1	2.8	4.0	1.3	versicolor
72	6.3	2.5	4.9	1.5	versicolor
73	6.1	2.8	4.7	1.2	versicolor
74	6.4	2.9	4.3	1.3	versicolor
75	6.6	3.0	4.4	1.4	versicolor
76	6.8	2.8	4.8	1.4	versicolor
77	6.7	3.0	5.0	1.7	versicolor
78	6.0	2.9	4.5	1.5	versicolor
79	5.7	2.6	3.5	1.0	versicolor
80	5.5	2.4	3.8	1.1	versicolor
81	5.5	2.4	3.7	1.0	versicolor
82	5.8	2.7	3.9	1.2	versicolor
83	6.0	2.7	5.1	1.6	versicolor
84	5.4	3.0	4.5	1.5	versicolor
85	6.0	3.4	4.5	1.6	versicolor
86	6.7	3.1	4.7	1.5	versicolor
87	6.3	2.3	4.4	1.3	versicolor
88	5.6	3.0	4.1	1.3	versicolor
89	5.5	2.5	4.0	1.3	versicolor
90	5.5	2.6	4.4	1.2	versicolor
91	6.1	3.0	4.6	1.4	versicolor
92	5.8	2.6	4.0	1.2	versicolor
93	5.0	2.3	3.3	1.0	versicolor
94	5.6	2.7	4.2	1.3	versicolor
95	5.7	3.0	4.2	1.2	versicolor
96	5.7	2.9	4.2	1.3	versicolor
97	6.2	2.9	4.3	1.3	versicolor
98	5.1	2.5	3.0	1.1	versicolor
99	5.7	2.8	4.1	1.3	versicolor

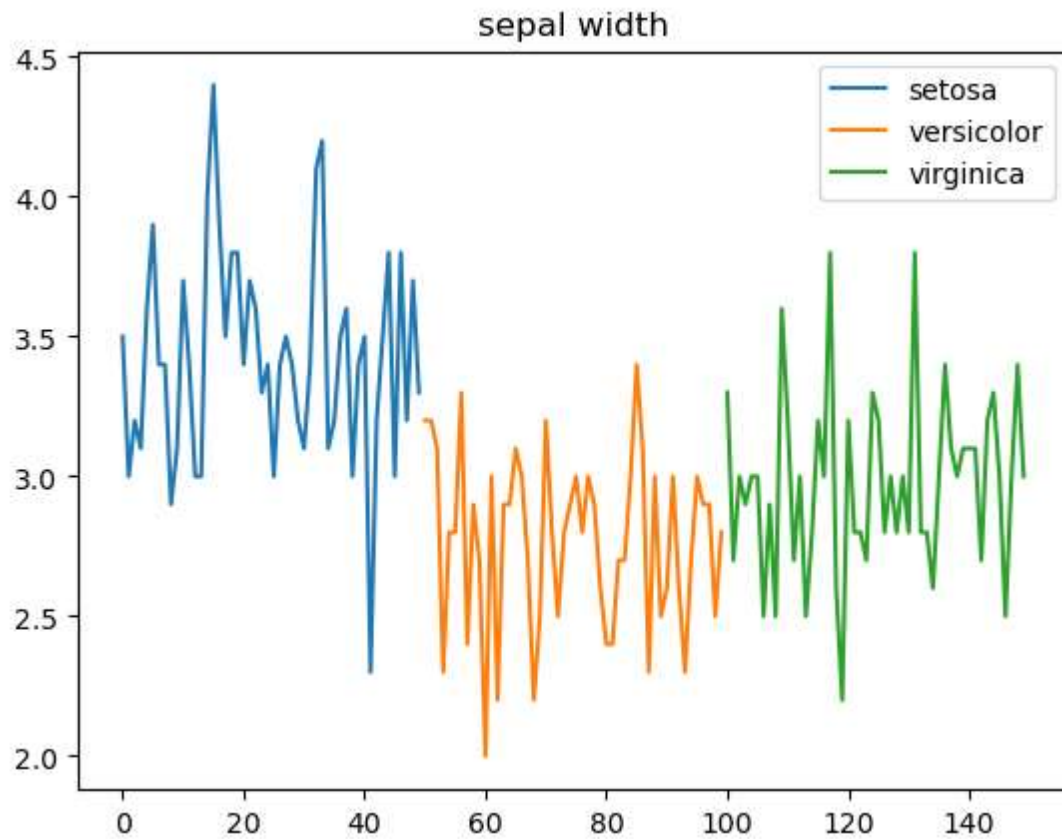
```
In [138]: print(df3)
```

	sepal_length	sepal_width	petal_length	petal_width	species
100	6.3	3.3	6.0	2.5	virginica
101	5.8	2.7	5.1	1.9	virginica
102	7.1	3.0	5.9	2.1	virginica
103	6.3	2.9	5.6	1.8	virginica
104	6.5	3.0	5.8	2.2	virginica
105	7.6	3.0	6.6	2.1	virginica
106	4.9	2.5	4.5	1.7	virginica
107	7.3	2.9	6.3	1.8	virginica
108	6.7	2.5	5.8	1.8	virginica
109	7.2	3.6	6.1	2.5	virginica
110	6.5	3.2	5.1	2.0	virginica
111	6.4	2.7	5.3	1.9	virginica
112	6.8	3.0	5.5	2.1	virginica
113	5.7	2.5	5.0	2.0	virginica
114	5.8	2.8	5.1	2.4	virginica
115	6.4	3.2	5.3	2.3	virginica
116	6.5	3.0	5.5	1.8	virginica
117	7.7	3.8	6.7	2.2	virginica
118	7.7	2.6	6.9	2.3	virginica
119	6.0	2.2	5.0	1.5	virginica
120	6.9	3.2	5.7	2.3	virginica
121	5.6	2.8	4.9	2.0	virginica
122	7.7	2.8	6.7	2.0	virginica
123	6.3	2.7	4.9	1.8	virginica
124	6.7	3.3	5.7	2.1	virginica
125	7.2	3.2	6.0	1.8	virginica
126	6.2	2.8	4.8	1.8	virginica
127	6.1	3.0	4.9	1.8	virginica
128	6.4	2.8	5.6	2.1	virginica
129	7.2	3.0	5.8	1.6	virginica
130	7.4	2.8	6.1	1.9	virginica
131	7.9	3.8	6.4	2.0	virginica
132	6.4	2.8	5.6	2.2	virginica
133	6.3	2.8	5.1	1.5	virginica
134	6.1	2.6	5.6	1.4	virginica
135	7.7	3.0	6.1	2.3	virginica
136	6.3	3.4	5.6	2.4	virginica
137	6.4	3.1	5.5	1.8	virginica
138	6.0	3.0	4.8	1.8	virginica
139	6.9	3.1	5.4	2.1	virginica
140	6.7	3.1	5.6	2.4	virginica
141	6.9	3.1	5.1	2.3	virginica
142	5.8	2.7	5.1	1.9	virginica
143	6.8	3.2	5.9	2.3	virginica
144	6.7	3.3	5.7	2.5	virginica
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

```
In [139]: #plt.plot(df1['sepal_length'])  
plt.plot(df1['sepal_length'],label='setosa')  
plt.plot(df2['sepal_length'],label='versicolor')  
plt.plot(df3['sepal_length'],label='virginica')  
plt.legend()  
plt.title('sepal length')  
plt.show()
```

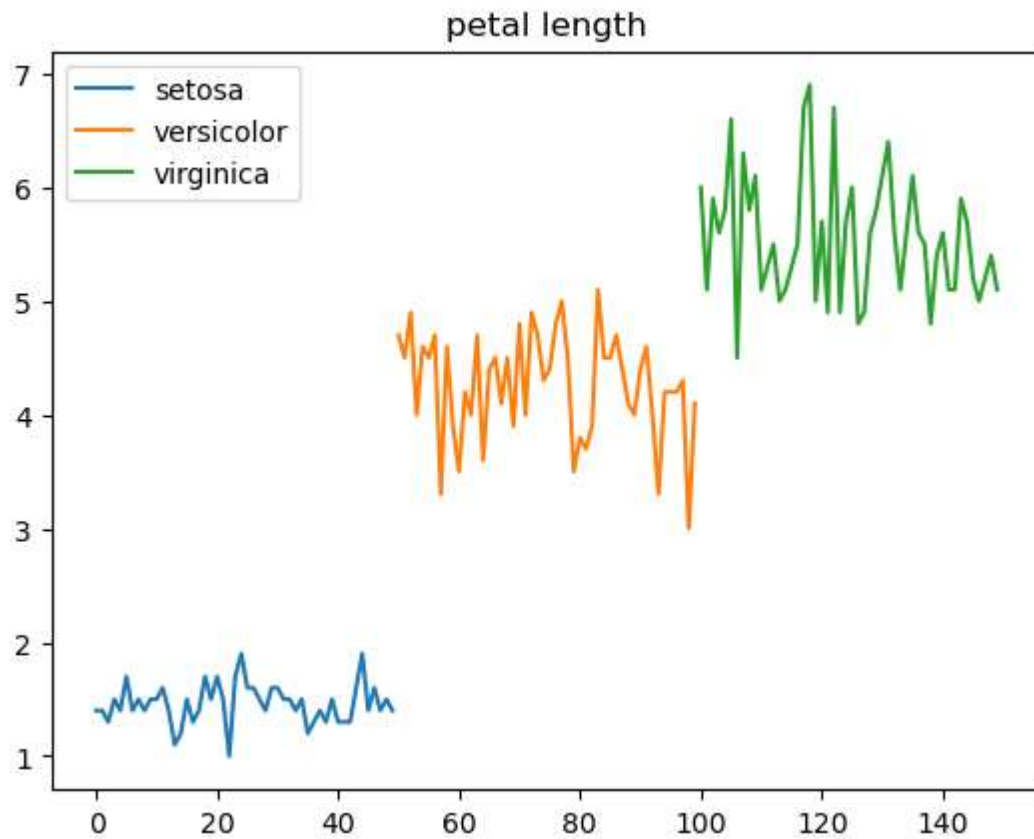


```
In [140]: plt.plot(df1['sepal_width'],label='setosa')
plt.plot(df2['sepal_width'],label='versicolor')
plt.plot(df3['sepal_width'],label='virginica')
plt.legend()
plt.title('sepal width')
plt.show()
```

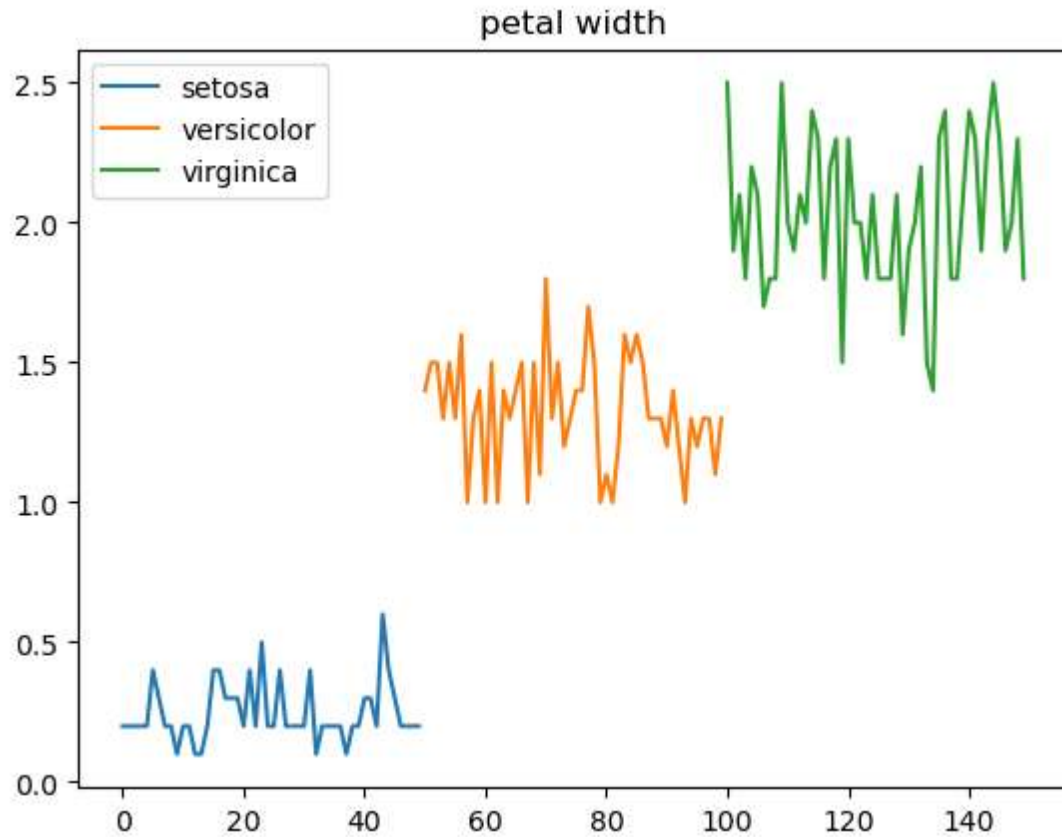




```
In [141]: plt.plot(df1['petal_length'],label='setosa')  
plt.plot(df2['petal_length'],label='versicolor')  
plt.plot(df3['petal_length'],label='virginica')  
plt.legend()  
plt.title('petal length')  
plt.show()
```

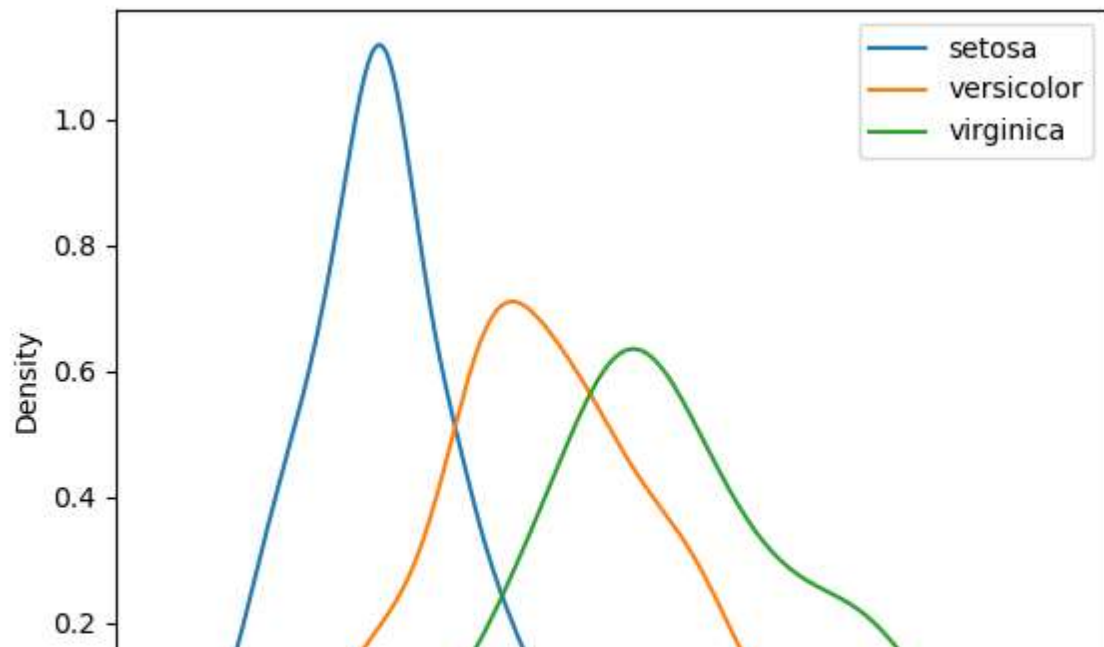


```
In [142]: plt.plot(df1['petal_width'],label='setosa')
plt.plot(df2['petal_width'],label='versicolor')
plt.plot(df3['petal_width'],label='virginica')
plt.legend()
plt.title('petal width')
plt.show()
```

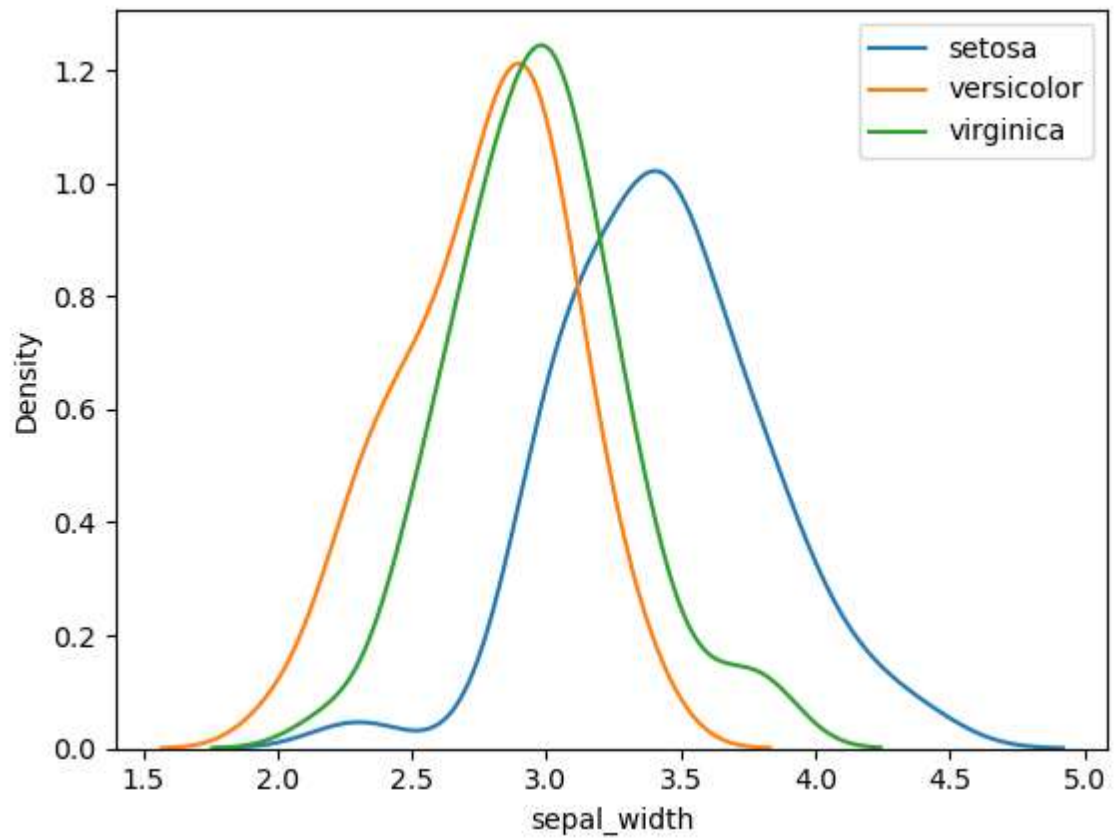


\*\*\*from the above four graphs we can understand that setosa leaves are small compared to versicolor where as it is smaller than virginica.

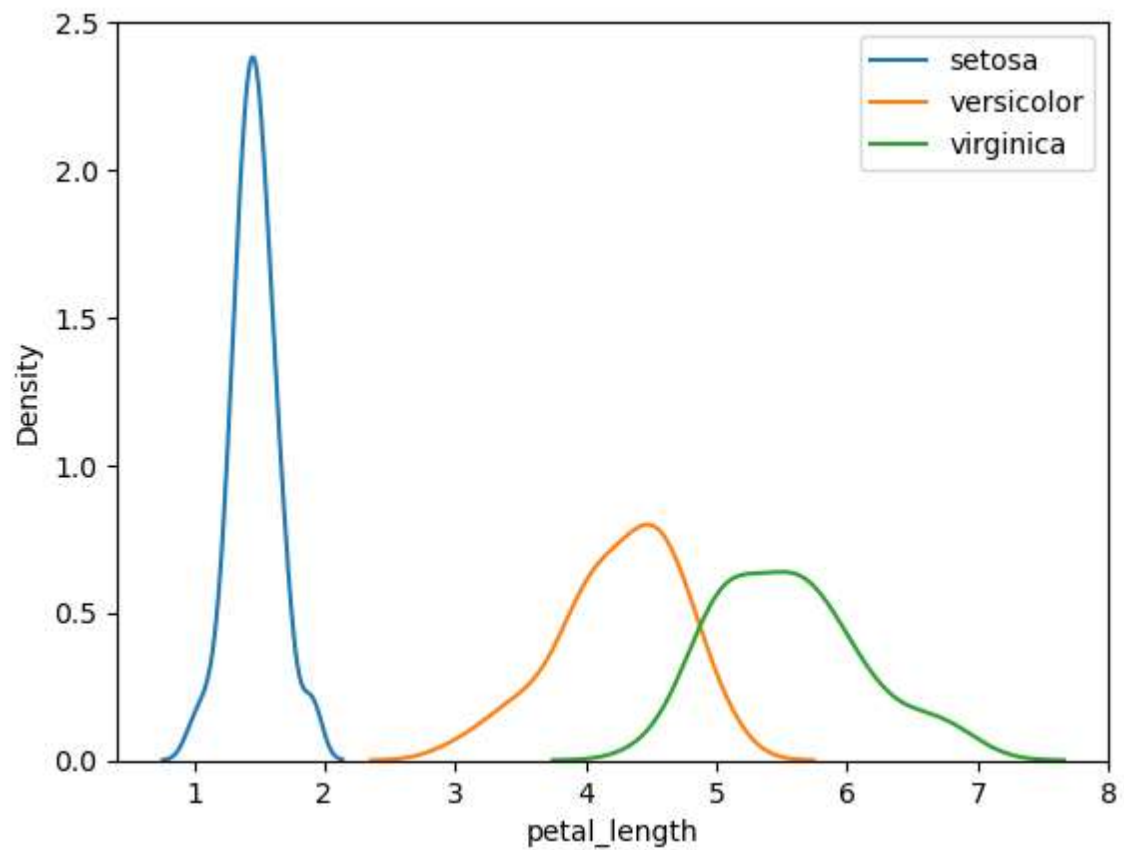
```
In [143]: sn.kdeplot(df1['sepal_length'],label='setosa')
sn.kdeplot(df2['sepal_length'],label='versicolor')
sn.kdeplot(df3['sepal_length'],label='virginica')
plt.legend()
plt.show()
```



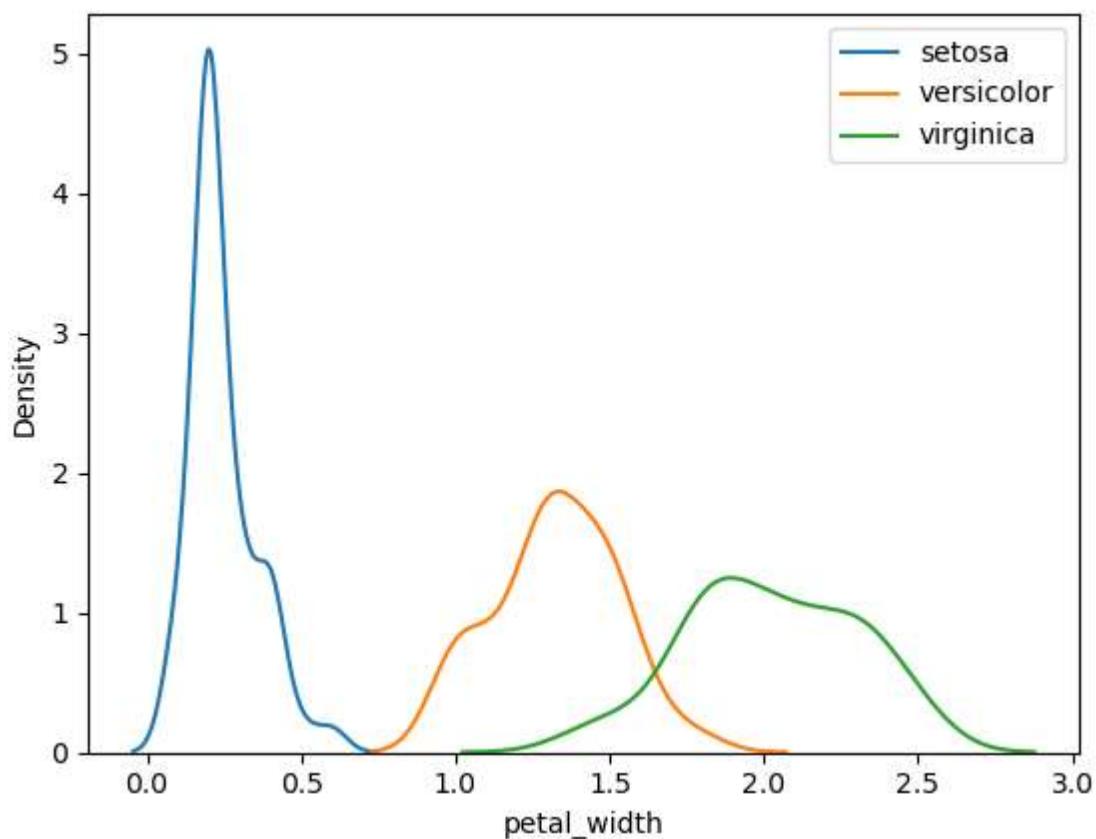
```
In [144]: sn.kdeplot(df1['sepal_width'],label='setosa')  
sn.kdeplot(df2['sepal_width'],label='versicolor')  
sn.kdeplot(df3['sepal_width'],label='virginica')  
plt.legend()  
plt.show()
```



```
In [145]: sn.kdeplot(df1['petal_length'],label='setosa')  
sn.kdeplot(df2['petal_length'],label='versicolor')  
sn.kdeplot(df3['petal_length'],label='virginica')  
plt.legend()  
plt.show()
```



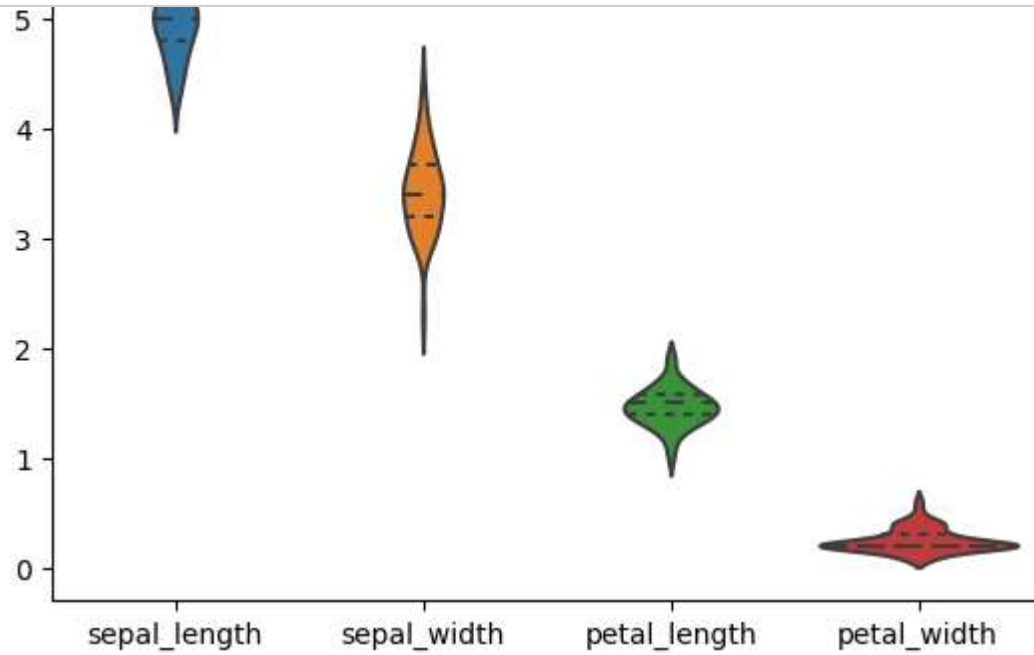
```
In [146]: sn.kdeplot(df1['petal_width'],label='setosa')
sn.kdeplot(df2['petal_width'],label='versicolor')
sn.kdeplot(df3['petal_width'],label='virginica')
plt.legend()
plt.show()
```



if we observe carefully , out of 4 graphs in 3, though setosa has high density but low scale.

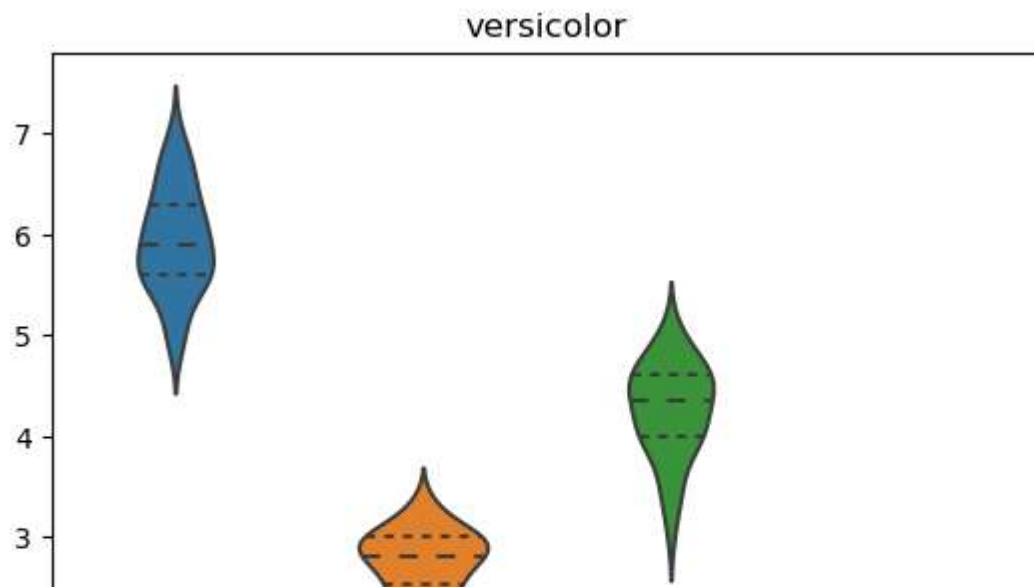
\*\*\*\*visualizing with violin plots

```
In [147]: sn.violinplot(df1,inner='quartile')  
plt.title('setosa')
```

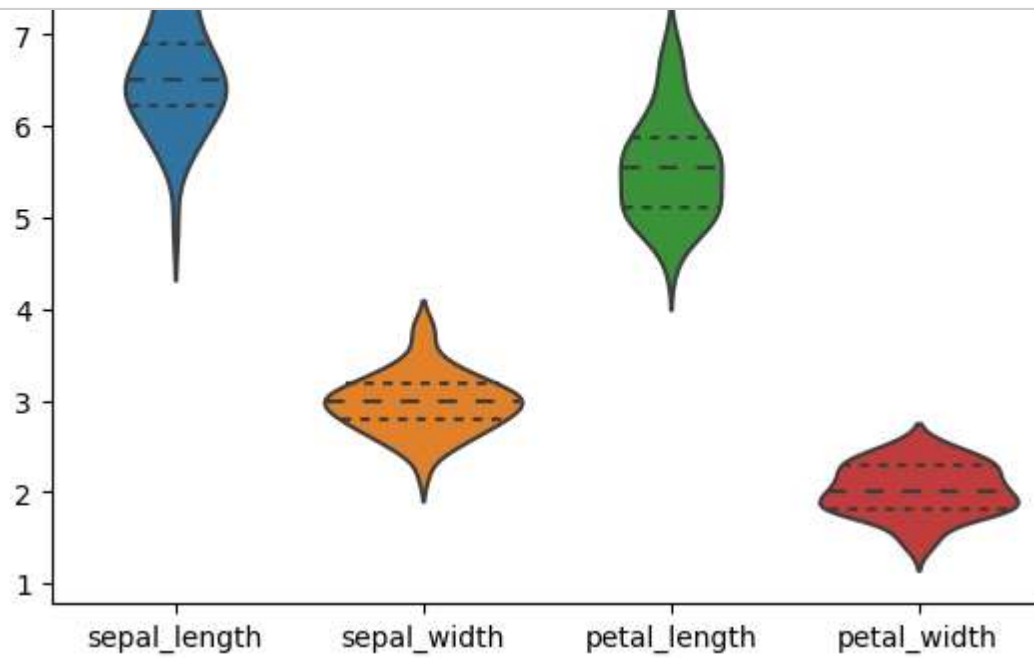


```
In [148]: sn.violinplot(df2,inner='quartile')  
plt.title('versicolor')
```

Out[148]: Text(0.5, 1.0, 'versicolor')



```
In [149]: sn.violinplot(df3,inner='quartile')  
plt.title('virginica')
```

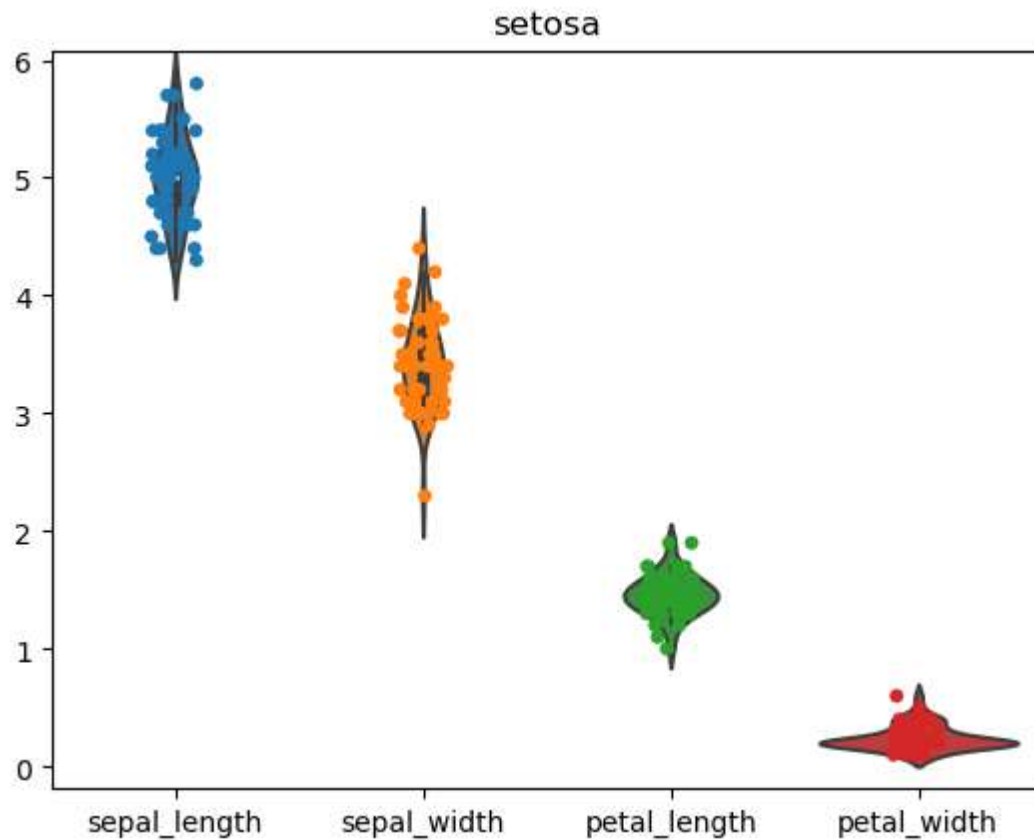


\*\*\*let's see the sinaplot(combination of both strip chart as well as violinplot)



```
In [150]: sn.violinplot(df1)
sn.stripplot(df1)
plt.title('setosa')
plt.figure(figsize=(10,10))
```

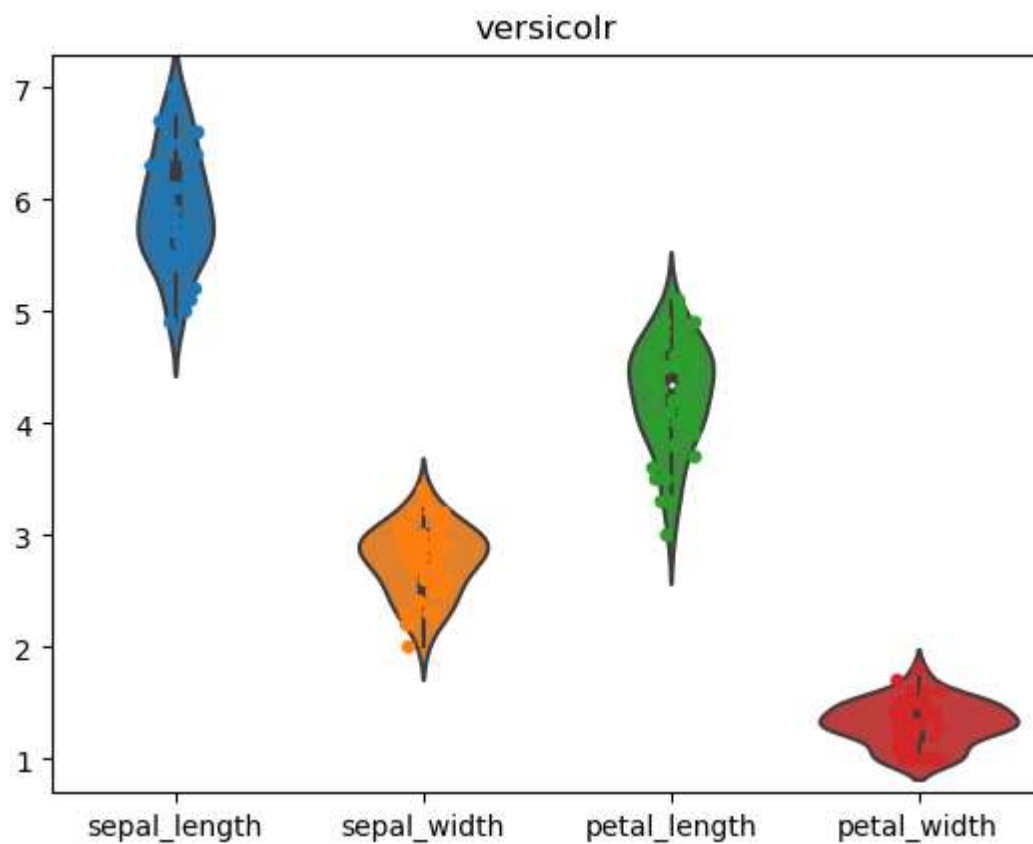
Out[150]: <Figure size 1000x1000 with 0 Axes>



<Figure size 1000x1000 with 0 Axes>

```
In [151]: sn.violinplot(df2)
sn.stripplot(df2)
plt.title('versicolr')
plt.figure(figsize=(10,10))
```

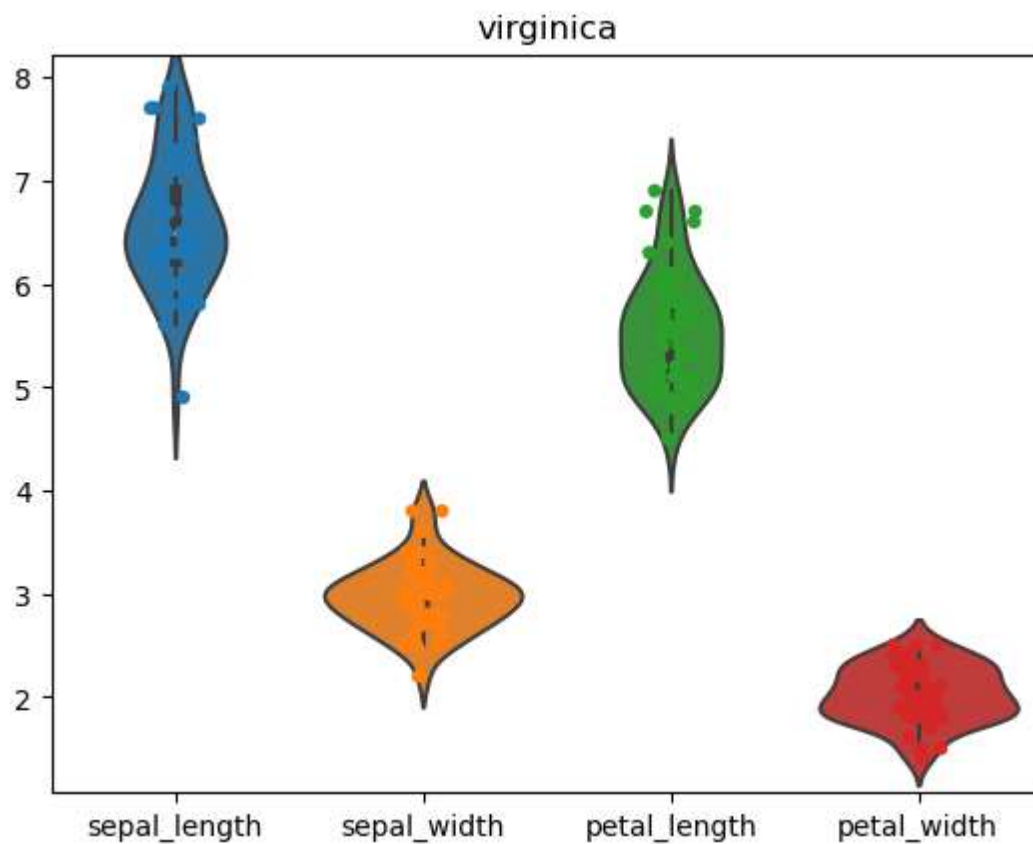
Out[151]: <Figure size 1000x1000 with 0 Axes>



<Figure size 1000x1000 with 0 Axes>

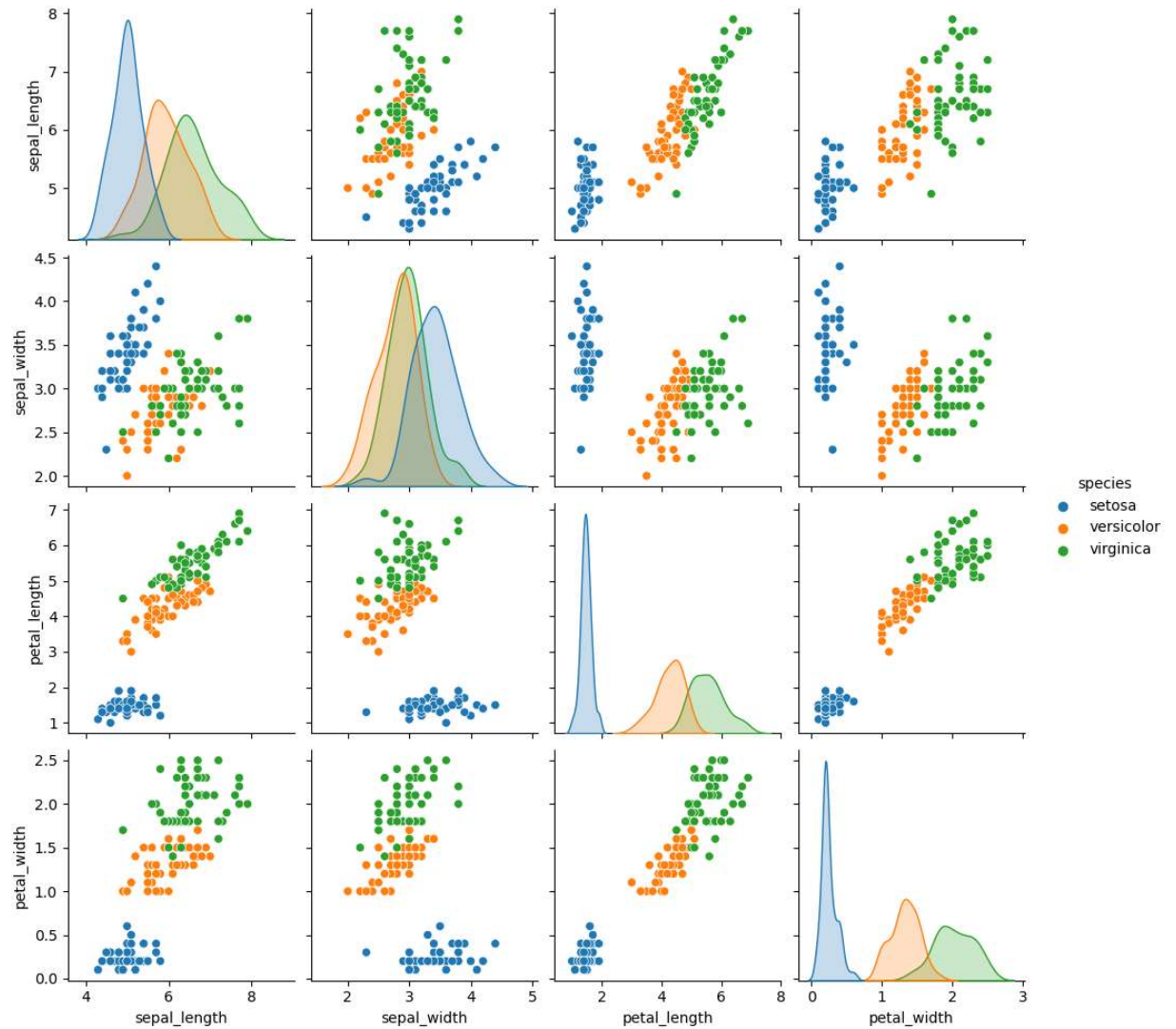
```
In [152]: sn.violinplot(df3)
sn.stripplot(df3)
plt.title('virginica')
plt.figure(figsize=(10,10))
```

Out[152]: <Figure size 1000x1000 with 0 Axes>



<Figure size 1000x1000 with 0 Axes>

```
In [153]: sn.pairplot(df,hue='species')
plt.show()
```



```
In [154]: from sklearn import metrics
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

```
In [155]: df.describe()
```

```
Out[155]:
```

	sepal_length	sepal_width	petal_length	petal_width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.057333	3.758000	1.199333
std	0.828066	0.435866	1.765298	0.762238
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

```
In [156]: x1=df.iloc[:,3]
print(x1.head())
```

	sepal_length	sepal_width	petal_length
0	5.1	3.5	1.4
1	4.9	3.0	1.4
2	4.7	3.2	1.3
3	4.6	3.1	1.5
4	5.0	3.6	1.4

```
In [157]: y1=df.iloc[:,4]
print(y1.head())
```

0	setosa
1	setosa
2	setosa
3	setosa
4	setosa

Name: species, dtype: object

```
In [158]: x1_train,x1_test,y1_train,y1_test=train_test_split(x1,y1)
```

```
In [159]: print(x1_train,x1_test,y1_train,y1_test)
```

	sepal_length	sepal_width	petal_length
127	6.1	3.0	4.9
45	4.8	3.0	1.4
9	4.9	3.1	1.5
25	5.0	3.0	1.6
30	4.8	3.1	1.6
..	...	...	...
122	7.7	2.8	6.7
35	5.0	3.2	1.2
12	4.8	3.0	1.4
5	5.4	3.9	1.7
11	4.8	3.4	1.6

[112 rows x 3 columns]	sepal_length	sepal_width	petal_length
0	5.1	3.5	1.4
146	6.3	2.5	5.0
87	6.3	2.3	4.4
136	6.3	3.4	5.6
120	6.9	3.2	5.7
53	5.5	2.3	4.0
101	5.8	2.7	5.1
55	5.7	2.8	4.5
52	6.9	3.1	4.9
139	6.9	3.1	5.4
78	6.0	2.9	4.5
90	5.5	2.6	4.4
125	7.2	3.2	6.0
21	5.1	3.7	1.5
137	6.4	3.1	5.5
135	7.7	3.0	6.1
22	4.6	3.6	1.0
145	6.7	3.0	5.2
61	5.9	3.0	4.2
60	5.0	2.0	3.5
41	4.5	2.3	1.3
99	5.7	2.8	4.1
142	5.8	2.7	5.1
111	6.4	2.7	5.3
84	5.4	3.0	4.5
47	4.6	3.2	1.4
132	6.4	2.8	5.6
69	5.6	2.5	3.9
115	6.4	3.2	5.3
106	4.9	2.5	4.5
148	6.2	3.4	5.4
56	6.3	3.3	4.7
43	5.0	3.5	1.6
67	5.8	2.7	4.1
126	6.2	2.8	4.8
68	6.2	2.2	4.5
91	6.1	3.0	4.6
54	6.5	2.8	4.6
45	setosa		127 virginica
9	setosa		
25	setosa		
30	setosa		
...			

```
122    virginica
35      setosa
12      setosa
5       setosa
11      setosa
Name: species, Length: 112, dtype: object 0      setosa
146    virginica
87     versicolor
136    virginica
120    virginica
53     versicolor
101    virginica
55     versicolor
52     versicolor
139    virginica
78     versicolor
90     versicolor
125    virginica
21      setosa
137    virginica
135    virginica
22      setosa
145    virginica
61     versicolor
60     versicolor
41      setosa
99     versicolor
142    virginica
111    virginica
84     versicolor
47      setosa
132    virginica
69     versicolor
115    virginica
106    virginica
148    virginica
56     versicolor
43      setosa
67     versicolor
126    virginica
68     versicolor
91     versicolor
54     versicolor
Name: species, dtype: object
```

\*\*\*\*try the DECISION TREE CLASSIFIER

```
In [160]: model=DecisionTreeClassifier()
```

```
In [161]: print(model)
```

```
DecisionTreeClassifier()
```



```
In [162]: model.fit(x1_train,y1_train)
```

```
Out[162]: ▾ DecisionTreeClassifier  
DecisionTreeClassifier()
```

```
In [163]: predictions=model.predict(x1_test)  
accuracy=accuracy_score(y1_test,predictions)
```

```
In [164]: print("Accuracy of the data is ",accuracy)
```

Accuracy of the data is 0.8947368421052632

\*\*\*\*Let's try the logistic Regression

```
In [165]: model2=LogisticRegression()  
model2.fit(x1_train,y1_train)
```

```
Out[165]: ▾ LogisticRegression  
LogisticRegression()
```

```
In [166]: pre2=model.predict(x1_test)  
a1=accuracy_score(y1_test,pre2)
```

```
In [167]: print("Accuracy of the data is",a1*100)
```

Accuracy of the data is 89.47368421052632

\*\*\*we created 2 ML Models ,trained them and observed their accuracy

**hence we have completed the task.**