
CAPSTONE PROJECT

IRIS FLOWER CLASSIFICATION

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OUTLINE

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PROBLEM STATEMENT

The Iris flower dataset consists of three species: setosa, versicolor, and virginica. These species can be distinguished based on their measurements. Now, imagine that you have the measurements of Iris flowers categorized by their respective species. Your objective is to train a machine learning model that can learn from these measurements and accurately classify the Iris flowers into their respective species. Use the Iris dataset to develop a model that can classify iris flowers into different species based on their sepal and petal measurements. This dataset is widely used for introductory classification tasks.

PROPOSED SOLUTION

1. Import Necessary Libraries
2. Load and Explore the Dataset
3. Data Preprocessing
 - Handle missing values
 - Outlier detection and treatment
 - Feature scaling
4. Split the Data
5. Model Selection and Training
6. Model Evaluation
 - Evaluate the trained models on the test set using metrics like accuracy, and confusion matrix.
 - Choose the best-performing model based on the evaluation metrics.
7. Model Deployment
 - If required, deploy the chosen model for real-time predictions.

SYSTEM APPROACH

The "System Approach" section outlines the overall strategy and methodology for developing and implementing the Iris flower classification. Here's a suggested structure for this section:

- Data Acquisition and Preprocessing
- Data Splitting
- Model Selection and Training
- Model Evaluation
- Deployment Environment

ALGORITHM & DEPLOYMENT

1. Algorithm

The Iris dataset is a classic example of a multi-class classification problem. Given its relatively small size and clear separation between classes, several algorithms can achieve high accuracy. Here are some popular choices:

- Logistic Regression
- Training
- Testing
- Accuracy
- Confusion Matrix

2. Deployment

once you've trained and evaluated your model, the next step is deployment. This involves making the model accessible for use in applications.

- Web application
- API
- Mobile application
- Cloud platform

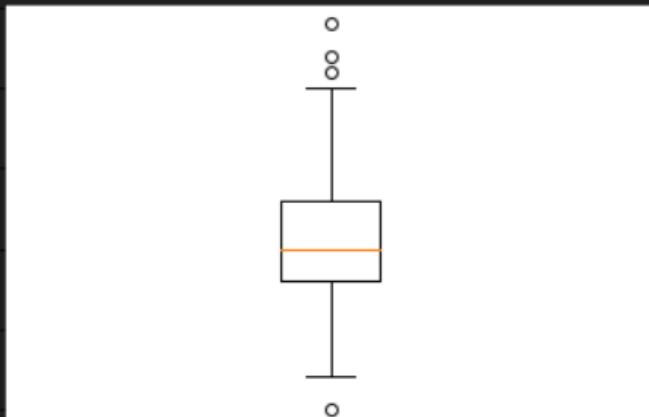
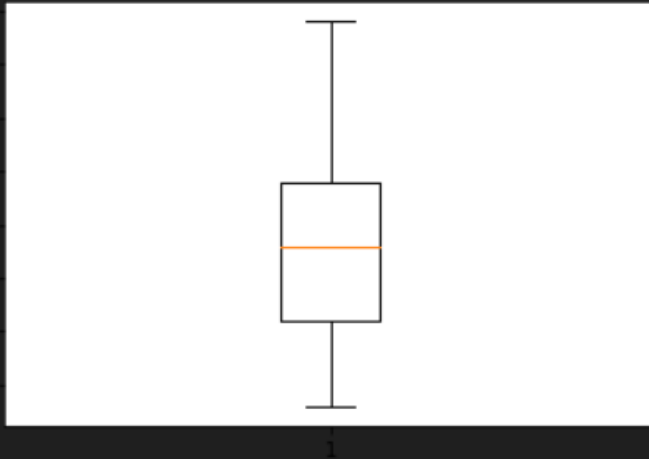
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
iris=pd.read_csv("/content/irisdata.csv")
print(iris)
```

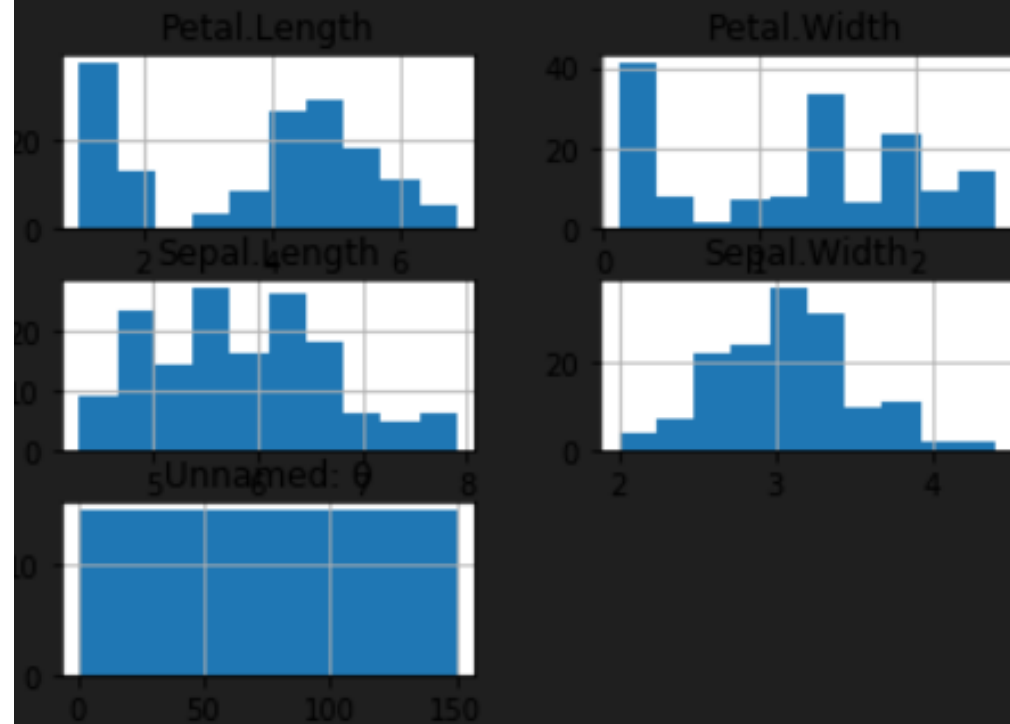
	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
..
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	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]
```

```
import matplotlib.pyplot as plt
plt.figure(1)
plt.boxplot([iris['Sepal.Length']])
plt.figure(2)
plt.boxplot([iris['Sepal.Width']])
plt.show()
```

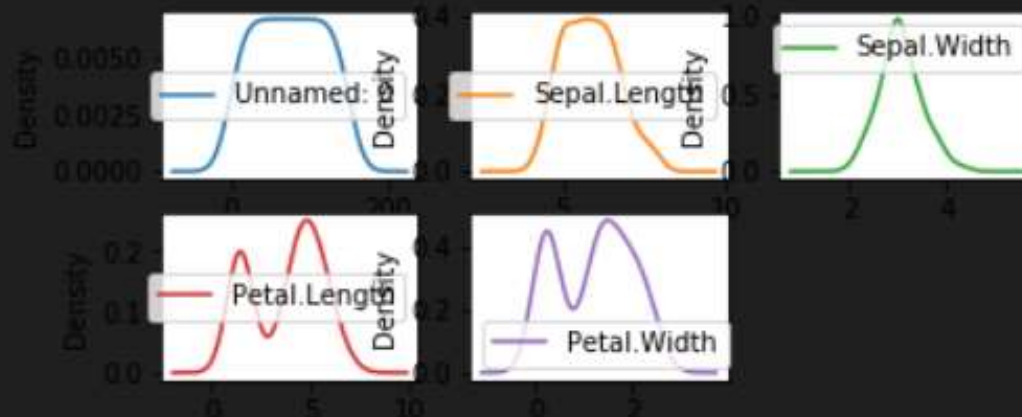



```
iris.hist()  
plt.show()
```



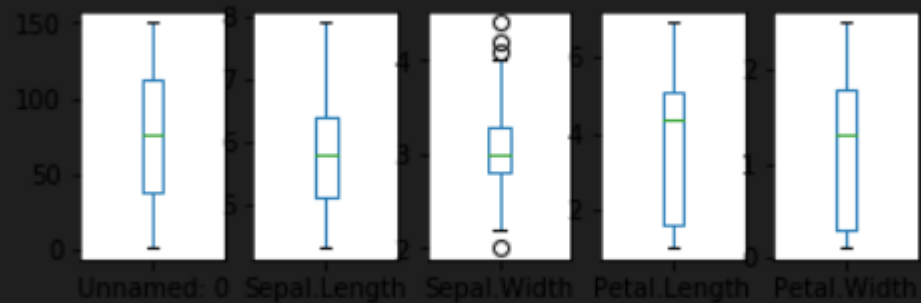
```
iris.plot(kind='density',subplots = True, layout =(3,3),sharex = False)
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000002900CD2EA48>,  
      <matplotlib.axes._subplots.AxesSubplot object at 0x000002900CDA7048>,  
      <matplotlib.axes._subplots.AxesSubplot object at 0x000002900CDD9E88>],  
      [<matplotlib.axes._subplots.AxesSubplot object at 0x000002900CE0F0C8>,  
      <matplotlib.axes._subplots.AxesSubplot object at 0x000002900CE43A88>,  
      <matplotlib.axes._subplots.AxesSubplot object at 0x000002900CE7D488>],  
      [<matplotlib.axes._subplots.AxesSubplot object at 0x000002900CEB6448>,  
      <matplotlib.axes._subplots.AxesSubplot object at 0x000002900CEF4E48>,  
      <matplotlib.axes._subplots.AxesSubplot object at 0x000002900CEFC248>]],  
      dtype=object)
```

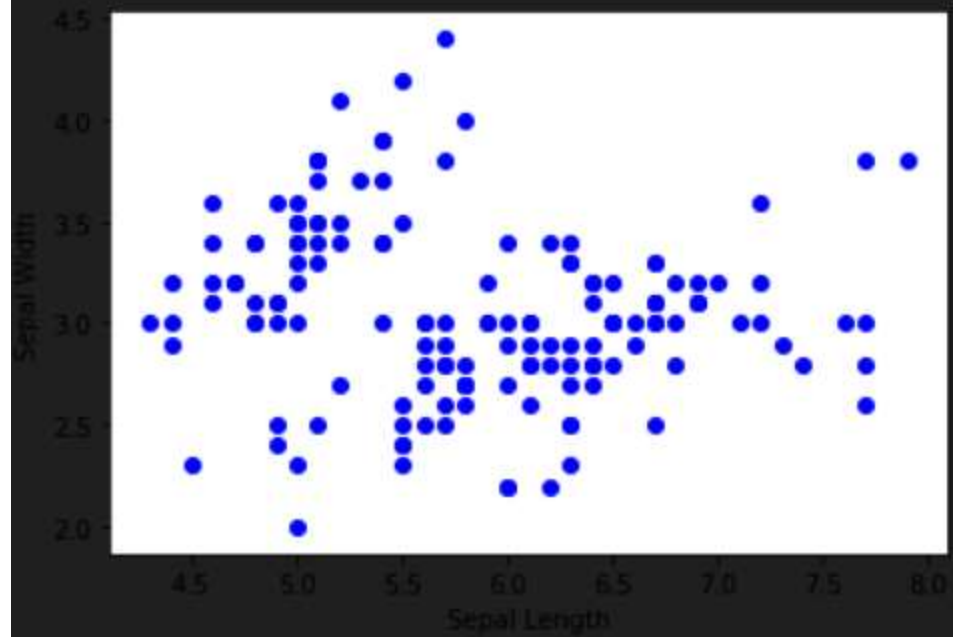


```
iris.plot(kind='box',subplots = True, layout =(2,5),sharex = False)
```

```
Unnamed: 0      AxesSubplot(0.125,0.536818;0.133621x0.343182)  
Sepal.Length    AxesSubplot(0.285345,0.536818;0.133621x0.343182)  
Sepal.Width      AxesSubplot(0.44569,0.536818;0.133621x0.343182)  
Petal.Length     AxesSubplot(0.606034,0.536818;0.133621x0.343182)  
Petal.Width      AxesSubplot(0.766379,0.536818;0.133621x0.343182)  
dtype: object
```



```
plt.xlabel("Sepal Length")  
plt.ylabel("Sepal Width")  
plt.scatter(X,Y,color='b')  
plt.show()
```



```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier
```

```
train, test = train_test_split(iris, test_size = 0.25)
print(train.shape)
print(test.shape)
```

```
(112, 6)
(38, 6)
```

```
train_X = train[['Sepal.Length', 'Sepal.Width', 'Petal.Length',
| | | | | 'Petal.Width']]
train_y = train.Species

test_X = test[['Sepal.Length', 'Sepal.Width', 'Petal.Length',
| | | | | 'Petal.Width']]
test_y = test.Species
```

```
train_X.head()
```

```
train_x.head()
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width
99	5.7	2.8	4.1	1.3
22	4.6	3.6	1.0	0.2
86	6.7	3.1	4.7	1.5
50	7.0	3.2	4.7	1.4
33	5.5	4.2	1.4	0.2

```
test_y.head()
```

```
90    versicolor
92    versicolor
147   virginica
16     setosa
82    versicolor
Name: Species, dtype: object
```

OUTPUT – ACCURACY AND CONFUSION MATRIX

```
model = LogisticRegression()  
model.fit(train_X, train_y)  
prediction = model.predict(test_X)  
print('Accuracy:', metrics.accuracy_score(prediction, test_y))
```

Accuracy: 0.9210526315789473

```
#Confusion matrix  
from sklearn.metrics import confusion_matrix  
confusion_mat = confusion_matrix(test_y, prediction)  
print("Confusion matrix: \n", confusion_mat)
```

Confusion matrix:

```
[[11  0  0]  
 [ 0 15  3]  
 [ 0  0  9]]
```

RESULT

Typically, when applying various machine learning algorithms to the Iris dataset, you can expect high accuracy rates. This is due to the dataset's relatively simple nature with clear separation between the three Iris species.

Accuracy: Often above 90%, frequently reaching 95-98% or even higher.

Confusion Matrix: Generally, a diagonal matrix with high values on the diagonal, suggesting correct classifications.

CONCLUSION

- The Iris flower classification project has been a successful exploration of machine learning concepts. The ability to accurately predict Iris species based on their measurements highlights the potential of these techniques for various applications. As we move forward, applying these learnings to more complex datasets will be crucial for developing robust and scalable machine learning solutions.

FUTURE SCOPE

The Iris dataset has served as a valuable stepping stone for many machine learning practitioners,
its simplicity limits its potential for groundbreaking resources.

1. Expand the dataset.
2. Advanced Machine Learning Techniques.
3. Real world applications.
4. Edge Computing.

REFERENCES

- The Iris dataset is a classic dataset often used as a starting point for machine learning projects. While it might not have extensive research dedicated solely to it, there are numerous resources available that cover the fundamentals of machine learning and classification, which can be applied to the Iris dataset.

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