ibimbing | JANUARY 2025

Portfolio Data Science

Iris Classification Machine Learning with Decision Tree

by Hanin Firginita Gilty

CASE STUDY

Create a simple machine learning (classification) program using the dataset provided by scikit-learn. Can be accessed at the following link:
https://scikit-learn.org/1.5/datasets/toy_dataset.html.

On these datasets, it is free to use any algorithm. You can learn the algorithm for classification at the following link:
https://www.geeksforgeeks.org/top-6-machine-learning-algorithms-for-classification/

ibimbing

ABOUT DATASET

The Iris dataset was used in R.A. Fisher's classic 1936 paper, The Use of Multiple Measurements in Taxonomic Problems, and can also be found on the UCI Machine Learning Repository.

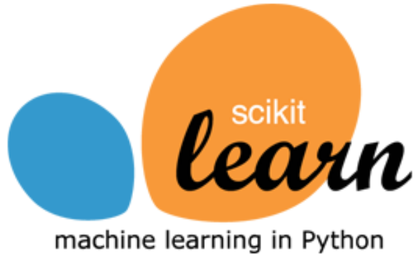
It includes three iris species with 50 samples each as well as some properties about each flower. One flower species is linearly separable from the other two, but the other two are not linearly separable from each other.

The columns in this dataset are:

- Id
- SepalLengthCm
- SepalWidthCm
- PetalLengthCm
- PetalWidthCm
- Species

ibimbing

TOOL USED



ibimbing

IMPORT LIBRARY

1. Import Libraries

```
[ ]  # Importing multiple library to read,analysed and visualized the dataset

     import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     %matplotlib inline
     import seaborn as sns
     from sklearn.preprocessing import LabelEncoder
     from sklearn.model_selection import train_test_split
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.metrics import classification_report, confusion_matrix
     from sklearn.tree import plot_tree
```

```
[ ]  # Loading dataset
     iris = sns.load_dataset('iris')
     iris.head()
```

	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

The Iris dataset contains measurements of 150 iris flowers, 50 from each of 3 species (setosa, versicolor, virginica). It includes 4 features: sepal length, sepal width, petal length, and petal width (all in cm).

ibimbing

EXPLORATORY DATA ANALYSIS

2. Exploratory Data Analysis

```
[ ] # DataFrame Information
    iris.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
```

```
[ ] # Desciribing Data
    iris.describe()
```

	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

```
[ ] # DataFrame Shape
    iris.shape
```

```
(150, 5)
```

```
[ ] # Checking Missing Value
    print("Checking Missing Value: ")
    iris.isnull().sum()
```

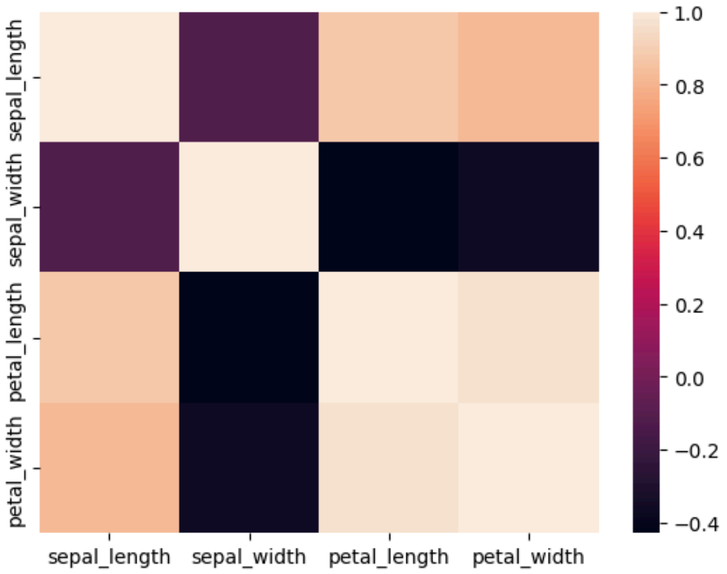
```
Checking Missing Value:
```

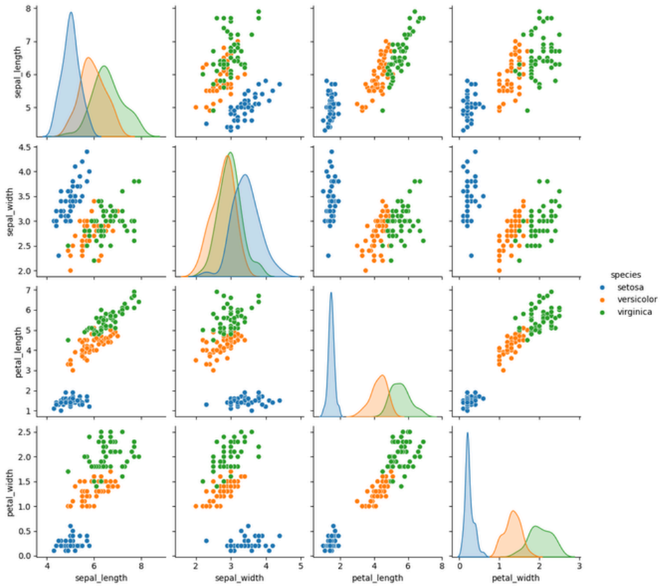
	0
sepal_length	0
sepal_width	0
petal_length	0
petal_width	0
species	0

dtype: int64

DATA VISUALIZATION USING VARIOUS ATTRIBUTES

Both visualizations indicate that petal length and petal width are the most important features for distinguishing between iris species, exhibiting strong correlations and clear separation in scatter plots.





PREDICTING TARGET VARIABLE

```
[ ] # Separating target varibale(y) & feature variables (x)
    target = iris['species']
    data = iris.copy()
    data = data.drop('species',axis =1)

    x = data # dependent variable

    target # independent variable
```

	species
0	setosa
1	setosa
2	setosa
3	setosa
4	setosa
...	...
145	virginica
146	virginica
147	virginica
148	virginica
149	virginica

150 rows × 1 columns

```
[ ] # Label encoding as target variable
    le = LabelEncoder()
    target = le.fit_transform(target)
    target
```

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

```
[ ] y = target
```

ibimbing

TRAINING TEST DATASET

```
[ ]  # Splitting the data - 80:20 ratio
     x_train,x_test,y_train,y_test = train_test_split ( x,y, test_size = 0.2, random_state = 40)
```

DECISION TREE CLASSIFIER

```
[ ] # Defining the decision tree alogritham
    model = DecisionTreeClassifier()
    model.fit(x_train,y_train)
    print('Decision Tree Classifier Created')
```

```
Decision Tree Classifier Created
```

```
[ ] # Predicting values from test data using confusion matrix and classification report.
    y_predt = model.predict(x_test)
    from sklearn.metrics import confusion_matrix
    print(confusion_matrix(y_test,y_predt))
```

```
[[ 8  0  0]
 [ 0 12  0]
 [ 0  0 10]]
```

```
[ ] print('Classification report: \n', classification_report(y_test,y_predt))
```

```
Classification report:
                precision    recall  f1-score   support

             0       1.00      1.00      1.00         8
             1       1.00      1.00      1.00        12
             2       1.00      1.00      1.00        10

      accuracy                           1.00        30
     macro avg       1.00      1.00      1.00        30
  weighted avg       1.00      1.00      1.00        30
```

```
[ ] model.feature_importances_
```

```
array([0.02919099, 0.        , 0.06433933, 0.90646968])
```

```
[ ] features = pd.DataFrame(model.feature_importances_,index = x.columns)
    features.head()
```

	0
sepal_length	0.029191
sepal_width	0.000000
petal_length	0.064339
petal_width	0.906470

```
[ ] model2 = DecisionTreeClassifier(criterion ='entropy',ccp_alpha=0.4)
```

```
[ ] model2.fit(x_train,y_train)
```

```
DecisionTreeClassifier(ccp_alpha=0.4, criterion='entropy')
```

```
[ ] y_predt2 = model2.predict(x_test)
    print(confusion_matrix(y_test,y_predt2))
```

```
[[ 8  0  0]
 [ 0 12  0]
 [ 0  0 10]]
```

```
[ ] print('Classification report: \n', classification_report(y_test,y_predt2))
```

```
Classification report:
                precision    recall  f1-score   support

             0       1.00      1.00      1.00         8
             1       1.00      1.00      1.00        12
             2       1.00      1.00      1.00        10

      accuracy                           1.00        30
     macro avg       1.00      1.00      1.00        30
  weighted avg       1.00      1.00      1.00        30
```

```
[ ] features2= pd.DataFrame(model2.feature_importances_,index = x.columns)
    features2.head()
```

	0
sepal_length	0.000000
sepal_width	0.000000
petal_length	0.694729
petal_width	0.305271

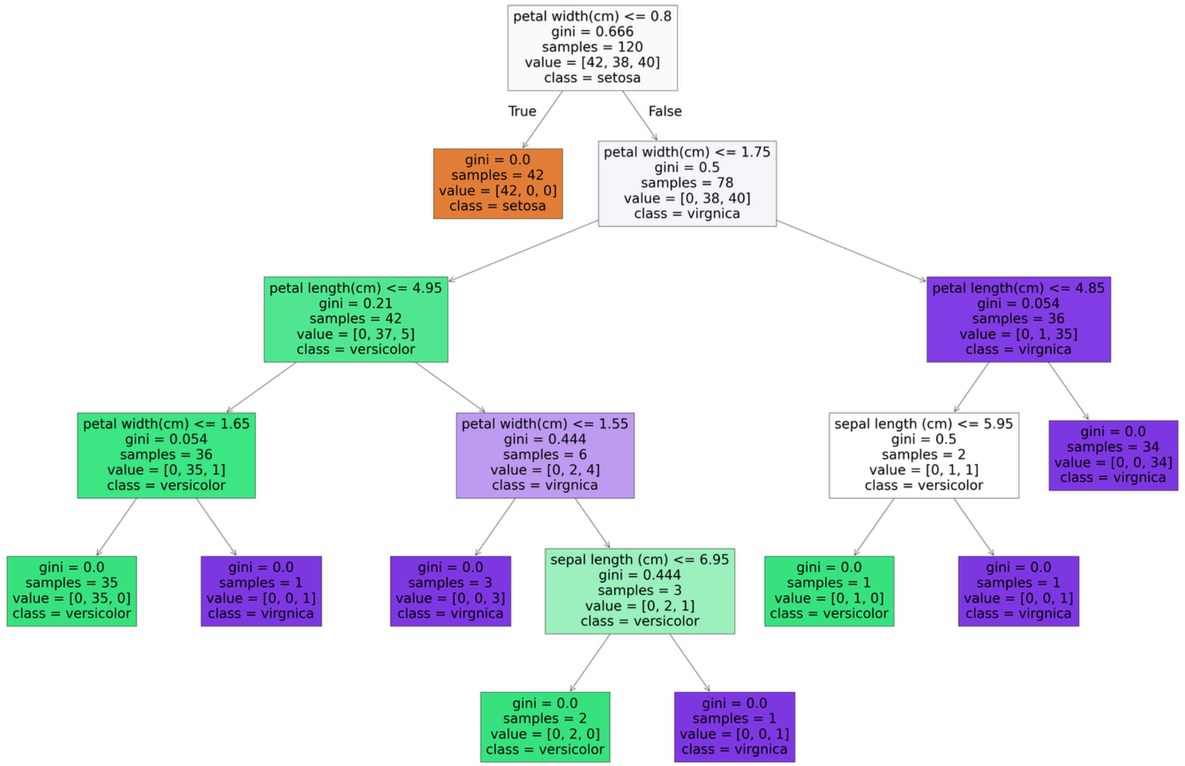
ibimbing

VISUALIZING THE TRAINED MODEL

```
[ ]  from sklearn import tree
     fn = ['sepal length (cm)','sepalwidth (cm)','petal length(cm)','petal width(cm)']
     cn =['setosa','versicolor','virgnica']
     fig = plt.figure (figsize =(60,40))
     tree.plot_tree(model,feature_names = fn,
                    class_names = cn ,
                    filled = True);
     # fig.savefig('imagename.png')
```

Decision Tree Visualization:

- Feature Names: 'sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)'
- Class Names: 'setosa', 'versicolor', 'virginica'
- The decision tree is visualized using tree.plot_tree



ibimbing

CHECKING MODEL ACCURACY

```
[ ]  # Model Accuracy
     import sklearn.metrics as sm
     print("Accuracy:",f"{sm.accuracy_score(y_test, y_predt)* 100:.2f}%")
```

```
Accuracy: 100.00%
```

Accuracy Score: The model achieved an accuracy score of 100%, which indicates that all predictions made by the decision tree classifier on the test dataset were correct.

ibimbing

Thank you