day47-knn-hyperparameter-tuning

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Day47 KNN(clf) Hyperparameter Tuning By: Loga Aswin

[42]:
```
#importing library
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

Data Pre-processing :

[43]:
```
df = pd.read_csv("/content/IRIS.csv")
df
```

[43]:

	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]

[44]:
```
df.shape
```

[44]: (150, 5)

[45]:
```
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
```

[58]:
```
df.isnull().sum()
```

[58]:
```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
```

[46]:
```
df.species.unique()
```

[46]:
```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

[47]:
```
df.species.value_counts()
```

[47]:
```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: species, dtype: int64
```

[48]:
```
df['species'] = df['species'].replace({'Iris-setosa':1, 'Iris-versicolor':2,␣
↪'Iris-virginica':3})
```

[49]:
```
df.head()
```

[49]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	1
1	4.9	3.0	1.4	0.2	1
2	4.7	3.2	1.3	0.2	1
3	4.6	3.1	1.5	0.2	1
4	5.0	3.6	1.4	0.2	1

[50]:
```
df.tail()
```

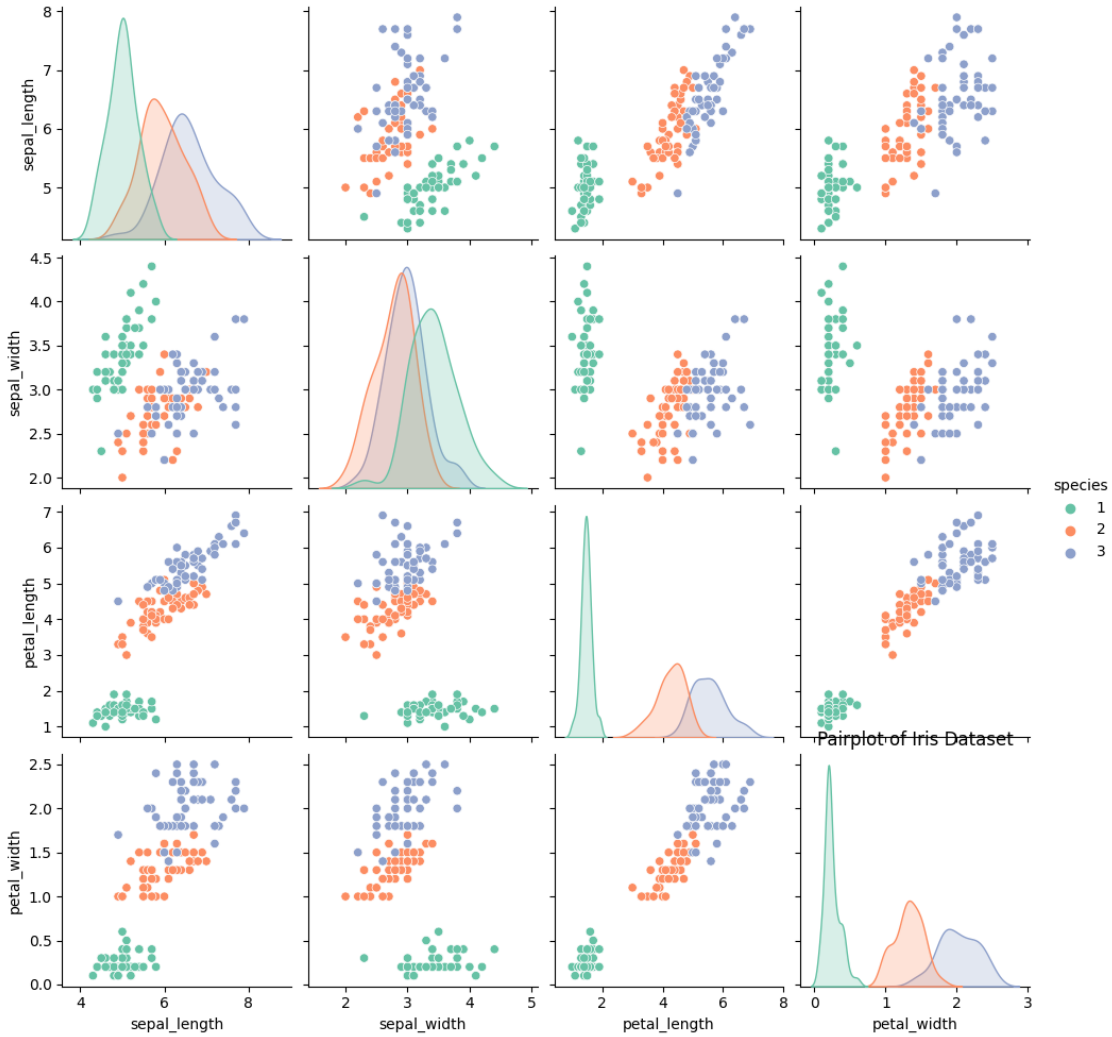
[50]:

	sepal_length	sepal_width	petal_length	petal_width	species
145	6.7	3.0	5.2	2.3	3
146	6.3	2.5	5.0	1.9	3
147	6.5	3.0	5.2	2.0	3
148	6.2	3.4	5.4	2.3	3

149	5.9	3.0	5.1	1.8	3

Exploratory Data Analysis (EDA) :

[51]:
```
sns.pairplot(df, hue='species', palette='Set2')
plt.title('Pairplot of Iris Dataset')
plt.show()
```



[52]:
```
X = df.drop('species', axis=1)
Y = df['species']
```

Splitting data into train and test:

[53]:
```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.20,␣
↪random_state = 0)
```

Create and Train KNN Classifier :

[54]:
```
from sklearn.neighbors import KNeighborsClassifier

# Initialize KNN classifier
knn = KNeighborsClassifier()

# Fit the model
knn.fit(X_train, y_train)

# Make predictions on the test set
y_pred = knn.predict(X_test)
```

[55]:
```
pd.DataFrame({'Actual':y_test, 'Predicted':y_pred})
```

[55]:

	Actual	Predicted
114	3	3
62	2	2
33	1	1
107	3	3
7	1	1
100	3	3
40	1	1
86	2	2
76	2	2
71	2	2
134	3	3
51	2	2
73	2	2
54	2	2
63	2	3
37	1	1
78	2	2
90	2	2
45	1	1
16	1	1
121	3	3
66	2	2
24	1	1
8	1	1
126	3	3
22	1	1
44	1	1
97	2	2

```
93        2          2
26        1          1
```

Model Evaluation Metrics:

[56]:
```
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪accuracy_score

accuracy = accuracy_score(y_test, y_pred)
print(accuracy)

matrix = confusion_matrix(y_test, y_pred)
matrix

report = classification_report(y_test, y_pred)
print(report)
```

```
0.9666666666666667
              precision    recall  f1-score   support

           1       1.00      1.00      1.00        11
           2       1.00      0.92      0.96        13
           3       0.86      1.00      0.92         6

    accuracy                           0.97        30
   macro avg       0.95      0.97      0.96        30
weighted avg       0.97      0.97      0.97        30
```

Hyperparameter Tuning :

[57]:
```
from sklearn.datasets import make_blobs
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import GridSearchCV

# dataset
X, y = make_blobs(n_samples=1000, centers=2, n_features=100, cluster_std=20)

# KNN model
model = KNeighborsClassifier()

# Define hyperparameters grid
param_grid = {
    'n_neighbors': range(1, 21, 2),
    'weights': ['uniform', 'distance'],
    'metric': ['euclidean', 'manhattan', 'minkowski']
}
```

```python
# Define cv stratergy
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

# Perform GridSearchCV
grid_search = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1,␣
 ↪cv=cv, scoring='accuracy', error_score=0)
grid_result = grid_search.fit(X, y)

# Get best model
best_model = grid_result.best_estimator_

# predictions
y_pred = best_model.predict(X)

# accuracy
accuracy = accuracy_score(y, y_pred)
print("Accuracy: %.2f" % accuracy)

# confusion matrix
conf_matrix = confusion_matrix(y, y_pred)
print("Confusion Matrix:\n", conf_matrix)

# classification report
class_report = classification_report(y, y_pred)
print("Classification Report:\n", class_report)
```

```
Accuracy: 0.98
Confusion Matrix:
 [[493   7]
 [  9 491]]
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.98       500
           1       0.99      0.98      0.98       500

    accuracy                           0.98      1000
   macro avg       0.98      0.98      0.98      1000
weighted avg       0.98      0.98      0.98      1000
```