Iris Flower Classification using KNN

Objective

- The aim is to classify iris flowers among three species from measurements of sepals and petals' length and width.The central goal here is to design a model using KNN Classifier that makes useful classifications for new flowers or, in other words, one which exhibits good generalization.
- The iris data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant.

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Importing essential Libraries

In [1]:

```
import numpy as np
import pandas as pd
from sklearn import datasets
import seaborn as sns
from math import sqrt
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score,recall_score,confusion_matrix,classification_r
eport,r2_score,mean_squared_error
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import StratifiedKFold
kFold = StratifiedKFold(n_splits=5)
```

Loading Dataset

In [2]:

```
iris = datasets.load_iris()

##Converting to pandas dataframe
df = pd.DataFrame(iris.data, columns=iris.feature_names)
df['species'] = pd.Series(iris.target)
```

In [3]:

```
# concise summary of a DataFrame

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 (cm) 150 non-null float64
 1 sepal width (cm) 150 non-null float64
 2 petal length (cm) 150 non-null float64
 3 petal width (cm) 150 non-null float64
 4 species 150 non-null int64
dtypes: float64(4), int64(1)
memory usage: 6.0 KB
```

In [4]:

```
# statistical details

df.describe()
```

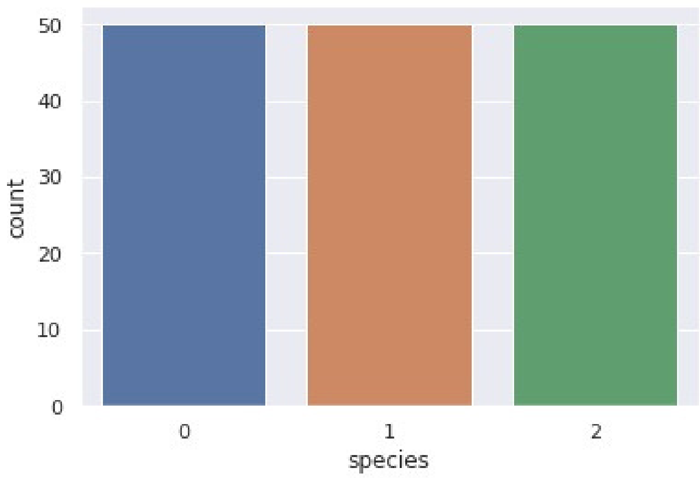
Out[4]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	species
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.057333	3.758000	1.199333	1.000000
std	0.828066	0.435866	1.765298	0.762238	0.819232
min	4.300000	2.000000	1.000000	0.100000	0.000000
25%	5.100000	2.800000	1.600000	0.300000	0.000000
50%	5.800000	3.000000	4.350000	1.300000	1.000000
75%	6.400000	3.300000	5.100000	1.800000	2.000000
max	7.900000	4.400000	6.900000	2.500000	2.000000

In [5]:

```
# Finding and visualizing number of Instances available for each target class.

print(df.species.value_counts())
sns.set_theme(style="darkgrid")
ax = sns.countplot(x="species", data=df)
```

```
2 50
1 50
0 50
Name: species, dtype: int64
```

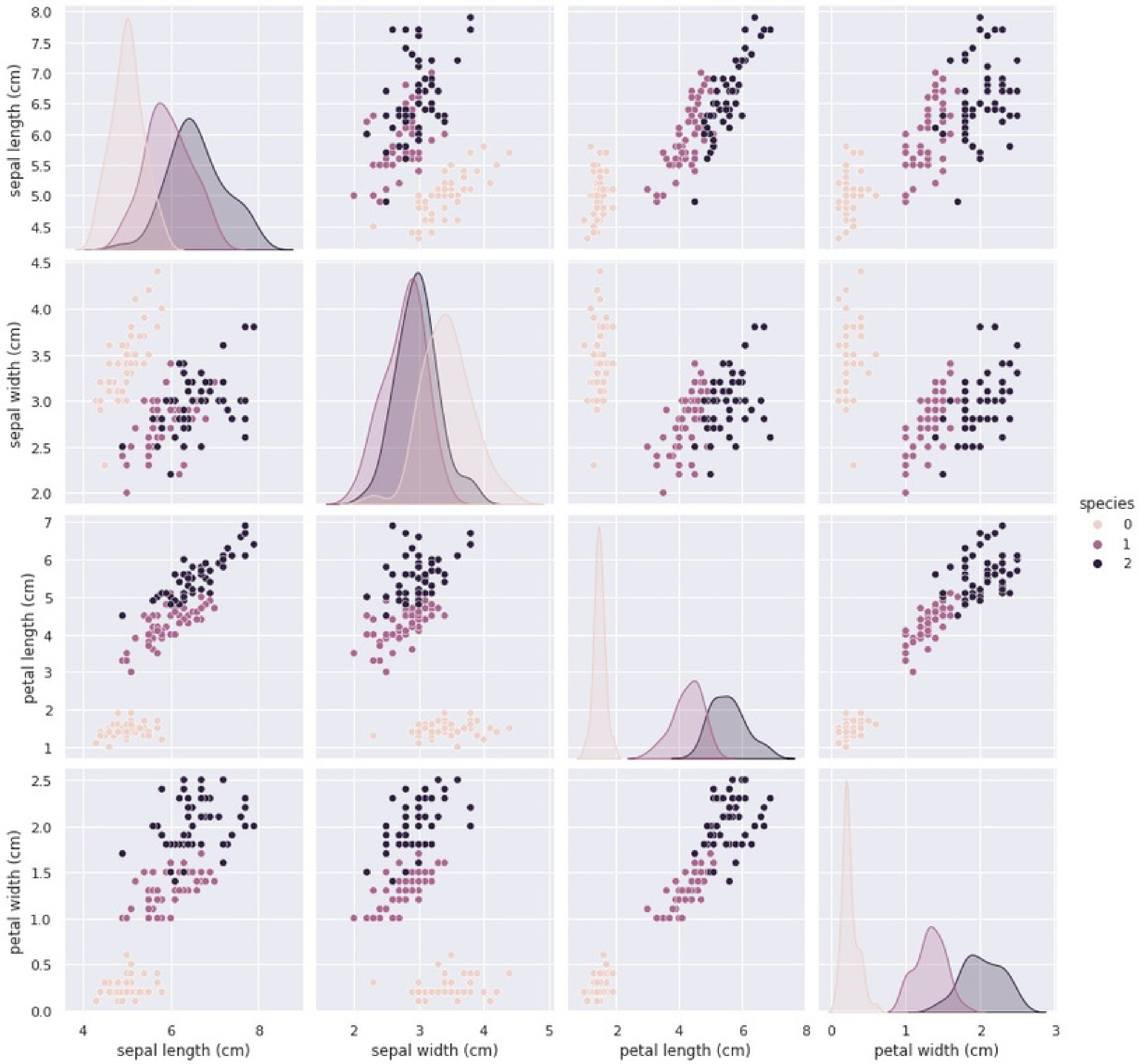


Data Visuaization

In [6]:

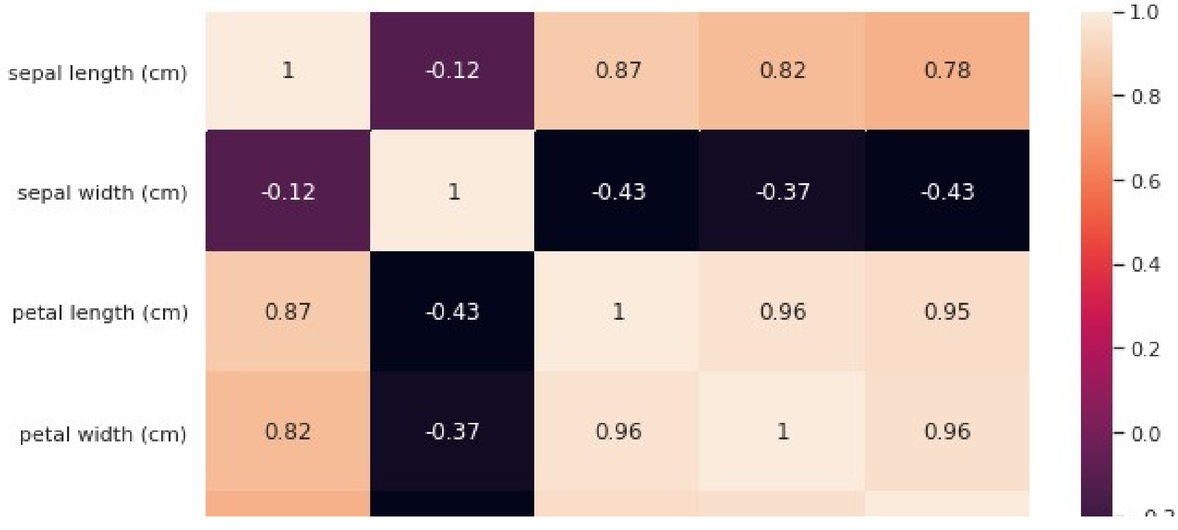
```
# Plotting pairwise relationships in a dataset.
```

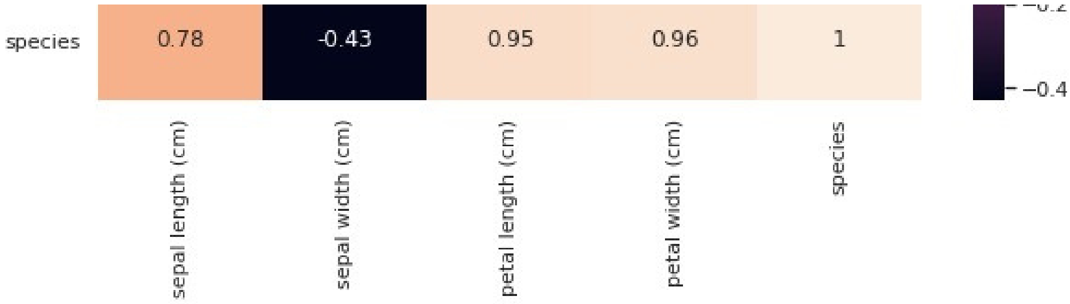
```
sns.pairplot(df,hue="species",height=3,aspect=1
) plt.show()
```



In [7]:

```
## heatmap to find correlation between attributes.

plt.figure(figsize=(10,6))
sns.heatmap(df.corr(),annot=True)
plt.show()
```





Feature Scaling and Data Splitting

In [8]:

```
# removing target class from dataset

y=df['species']
X= df.drop('species',axis=1)
```

In [9]:

```
# Dataset splitting

X_train, X_test, y_train, y_test = train_test_split(X, y ,test_size=0.3,random_state=10)
```

In [10]:

```
# Using Standard scaler for feature scaling

scaler = StandardScaler()
scaler.fit(X_train)
X_train                                    =
scaler.transform(X_train)  X_test  =
scaler.transform(X_test)
```

KNN Classifier

We will be using KNN CLassifier for this classification problem and will be using Euclidean distance to select nearest Neighbors. Euclidean distance is given by:-

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

Self-Define function

- We will develope our own function to create a KNN CLassfier.

USING Sk-Learn Library

- We will use KNeighborsClassifier from scikit-learn and will use gridSearch cv to find the best value of k.

Self Defined Function

Shuffling the data, to avoid overFitting problem

In [11]:

```
shuffle_index = np.random.permutation(df.shape[0])
df = df.iloc[shuffle_index]
df.head(5)
```

Out[11]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	species
116	6.5	3.0	5.5	1.8	2
63	6.1	2.9	4.7	1.4	1
10	5.4	3.7	1.5	0.2	0
20	5.4	3.4	1.7	0.2	0
141	6.9	3.1	5.1	2.3	2

Splitting the dataset in to 70% for training and 30% for testing the model.

In [12]:

```
train_size = int(df.shape[0]*0.7)
train_df = df.iloc[:train_size,:]
test_df = df.iloc[train_size:,:]
train = train_df.values
test = test_df.values
y_true = test[:,-1]
```

In [13]:

```
# Defining function to find Euclidean Distance

def euclidean_distance(x_test, x_train):
 distance = 0
 for i in range(len(x_test)-1):
   distance   +=   (x_test[i]-x_train[i])**2
return sqrt(distance)
```

In [14]:

```
# Defining function to find neighbors

def get_neighbors(x_test, x_train, num_neighbors):
 distances = []
 data = []
 for i in x_train:
        distances.append(euclidean_distance(x_test,i))
data.append(i)
 distances = np.array(distances)
 data = np.array(data)
 sort_indexes = distances.argsort()          #argsort() function returns indices b
y sorting distances data in ascending order
data = data[sort_indexes]
                                             #modifying our data based on sorted i
ndices, so that we can get the nearest neightbours
return data[:num_neighbors]
```

In [15]:

```
# Function working as a model to predict.

def prediction(x_test, x_train, num_neighbors):
 classes = []
 neighbors = get_neighbors(x_test, x_train, num_neighbors)
 for i in neighbors:
 classes.append(i[-1])
 predicted = max(classes, key=classes.count)          #taking the most repeated c
lass
 return predicted
```

In [16]:

```
# Function to find Accuracy pf model
```

```
def accuracy(y_true, y_pred):
 num_correct = 0
 for i in range(len(y_true)):
 if y_true[i]==y_pred[i]:
 num_correct+=1
  accuracy  =  num_correct/len(y_true)
return accuracy
```

Evaluation

In [17]:

```
y_pred = []
for i in test:
 y_pred.append(prediction(i, train, 10))
y_pred
```

Out[17]:

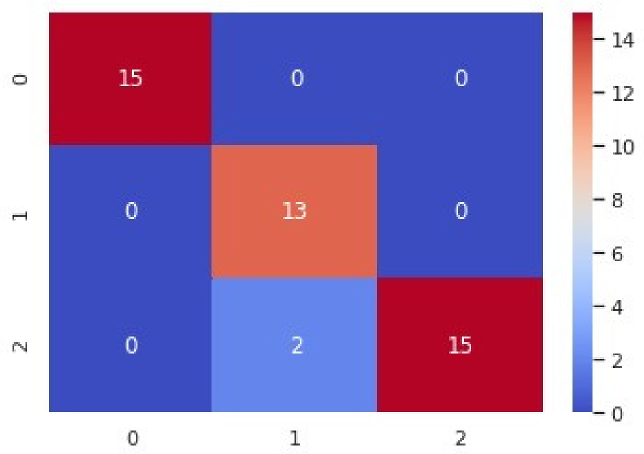
```
[2.0,
 2.0,
 1.0,
 0.0,
 2.0,
 1.0,
 0.0,
 1.0,
 0.0,
 2.0,
 1.0,
 1.0,
 0.0,
 0.0,
 1.0,
 2.0,
 2.0,
 1.0,
 0.0,
 0.0,
 0.0,
 1.0,
 0.0,
 1.0,
 0.0,
 1.0,
 2.0,
 1.0,
 2.0,
 1.0,
 2.0,
 0.0,
 1.0,
 2.0,
 2.0,
 0.0,
 0.0,
 1.0,
 0.0,
 2.0,
 2.0,
 2.0,
 2.0,
 0.0,
 1.0]
```

In [18]:

```
acc = accuracy(y_true, y_pred)
print("*******"*10)
print("Accuracy of the model is : ",acc)
```

```
rmse = sqrt(mean_squared_error(y_true, y_pred))
print("RMSE value = %.2f"%rmse)
print("R2 Score= %.2f"%r2_score(y_true, y_pred))
print("*******"*10)
# Confusion Matrix

cm=confusion_matrix(y_true, y_pred)
print("Confusion matrix of classifier : \n",cm)
print("\n")
sns.heatmap(cm, annot=True,cmap ='coolwarm')
print("*******"*10)
# Classification report of our model.
t=["Iris-setosa","Iris-versicolor","Iris-virginica"]
print(classification_report(y_true, y_pred,target_names=t))
print("*******"*10)
```

```
**********************************************************************
Accuracy of the model is : 0.9555555555555556
RMSE value = 0.21
R2 Score= 0.94
**********************************************************************
Confusion matrix of classifier :
[[15  0  0]
 [ 0 13  0]
 [ 0  2 15]]


**********************************************************************
 precision recall f1-score support
 Iris-setosa 1.00 1.00 1.00 15
Iris-versicolor 0.87 1.00 0.93 13
 Iris-virginica 1.00 0.88 0.94 17

 accuracy 0.96 45
 macro avg 0.96 0.96 0.96 45
 weighted avg 0.96 0.96 0.96 45

**********************************************************************
```



We got Test Accuracy of 95.56% by defining our function. It shows our model is working well good on this dataset.

Using SKLearn Library

In [19]:

```
knn_clf = KNeighborsClassifier()
param_grid = {'n_neighbors' : [1,2,3,4,5,7,8,9,10,11,12]}
grid_search = GridSearchCV (knn_clf, param_grid, cv=kFold,scoring = 'recall_weighted', r
eturn_train_score=True)
grid_search.fit(X_train, y_train)
```

Out[19]:

```
GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None, shuffle=False),
 error_score=nan,
 estimator=KNeighborsClassifier(algorithm='auto', leaf_size=30,
 metric='minkowski',
 metric_params=None, n_jobs=None,
 n_neighbors=5, p=2,
 weights='uniform'),
 iid='deprecated', n_jobs=None,
 param_grid={'n_neighbors': [1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12]},
 pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
 scoring='recall_weighted', verbose=0)
```

In [20]:

```
grid_search.best_params_
#grid_search.best_score_
```

Out[20]:

```
{'n_neighbors': 11}
```

In [21]:

```
knnclassifier = KNeighborsClassifier(n_neighbors=11)
knnclassifier.fit(X_train, y_train)
y_pred = knnclassifier.predict(X_test)
```

Evaluation

In [22]:

```
knn_train_accuracy = accuracy_score(y_train, knnclassifier.predict(X_train))
knn_test_accuracy = accuracy_score(y_test, knnclassifier.predict(X_test))
```

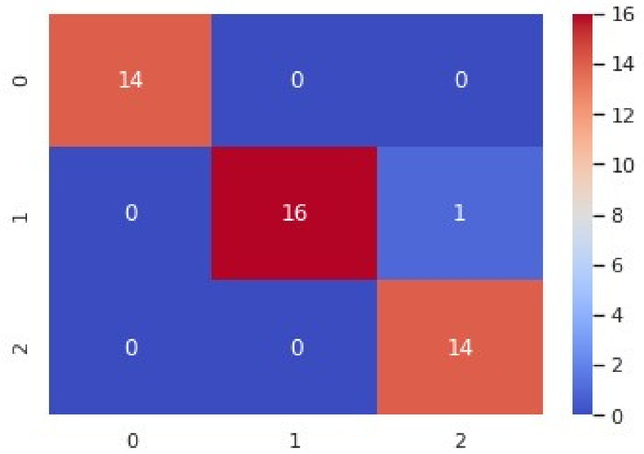
In [23]:

```
# Confusion Matrix

cm=confusion_matrix(y_test, y_pred)
print("Confusion matrix of classifier : \n",cm)
print("\n")
sns.heatmap(cm, annot=True,cmap ='coolwarm')
```

```
Confusion matrix of classifier :
[[14  0  0]
 [ 0 16  1]
 [ 0  0 14]]
```

Out[23]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff96a09c710>
```



In [24]:

```
# Classification report of our model.

t=["Iris-setosa","Iris-versicolor","Iris-virginica"]
print(classification_report(y_test, y_pred,target_names=t))
```

```
 precision recall f1-score support

 Iris-setosa 1.00 1.00 1.00 14
Iris-versicolor 1.00 0.94 0.97 17
 Iris-virginica 0.93 1.00 0.97 14

 accuracy 0.98 45
 macro avg 0.98 0.98 0.98 45
 weighted avg 0.98 0.98 0.98 45
```

In [25]:

```
rmse = sqrt(mean_squared_error(y_test, y_pred))
print("RMSE value = %.2f"%rmse)
print("R2 Score= %.2f"%r2_score(y_test, y_pred))
#print('Train Accuracy score:',knn_train_accuracy)
print('Test Accuracy score: ',knn_test_accuracy)
```

```
RMSE value = 0.15
R2 Score= 0.96
Test Accuracy score: 0.9777777777777777
```

We got test Accuracy of 97.78% on the iris Dataset using sklearn library using KNN Classifier with number of neighbors=11.

Thank you