In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report
```

In [4]:
```
data =pd.read_csv('Iris.csv')
```

In [5]:
```
data
```

Out[5]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

In [9]:
```
data.shape
```

Out[9]:
```
(150, 6)
```

In [11]:
```
data.head()
```

Out[11]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

In [13]:
```
data.describe()
```

Out[13]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

In [15]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             150 non-null    int64  
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object 
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

handling missing values

In [17]:
```
data.isnull().sum()
```

Out[17]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

handling categorical data

In [21]:
```
data.drop(columns='Id', inplace=True)
```

In [ ]:
```
# performing train test
```

In [63]:
```
if 'Id' in data.columns:
    data= df.drop(columns='Id')
le = LabelEncoder()
data['Species'] = le.fit_transform(data['Species'])
```

In [65]:
```
X = data.drop(columns='Species')
y = data['Species']
```

In [67]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [69]:
```
nn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)
```

Out[69]:
```
KNeighborsClassifier(n_neighbors=3)
```

In [71]:
```
y_pred = knn.predict(X_test)
```

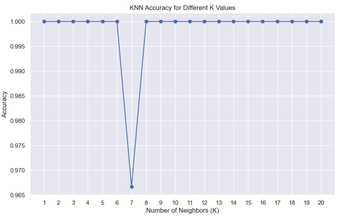
In [73]:
```
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred, target_names=le.classes_))
```

```
Accuracy: 1.0

Classification Report:
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       1.00      1.00      1.00         9
 Iris-virginica       1.00      1.00      1.00        11

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

for different k values

In [155]:
```
for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    accuracies.append(acc)
```

In [157]:
```
# Plotting the results
plt.figure(figsize=(10, 6))
plt.plot(k_values, accuracies, marker='o')
plt.title('KNN Accuracy for Different K Values')
plt.xlabel('Number of Neighbors (K)')
plt.ylabel('Accuracy')
plt.xticks(k_values)
plt.grid(True)
plt.show()
```



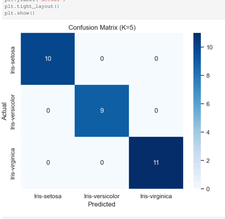
The plot shows how the classification accuracy changes with different values of K. Typically, lower values of K can lead to overfitting, while higher values can result in underfitting.

Evaluate model using accuracy, confusion matrix.

In [161]:
```
from sklearn.metrics import confusion_matrix, classification_report
best_k = 3
knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

In [163]:
```
accuracy = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred, target_names=le.classes_)
```

In [175]:
```
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=le.classes_, yticklabels=le.classes_)
plt.title(f'Confusion Matrix (k={best_k})')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.show()
```



In [121]:
```
accuracy , report
```

Out[121]:
```
(1.0,
 '              precision    recall  f1-score   support\n\n Iris-setosa       1.00      1.00      1.00        10\nIris-versicolor       1.00      1.00      1.00         9\n Iris-virginica       1.00      1.00      1.00        11\n\n       accuracy                           1.00        30\n      macro avg       1.00      1.00      1.00        30\n   weighted avg       1.00      1.00      1.00        30\n')
```

With K = 5, the model achieved: Accuracy: 100% Confusion Matrix: All predictions were correct for each class.

Classification Report: Precision, recall, and F1-score are all 1.00 across all classes.

Visualize decision boundaries.

In [180]:
```
# Use only the first two features
X = data.iloc[:, :2].values
y = data['Species'].values
```

In [182]:
```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

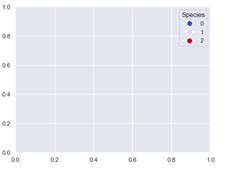
In [184]:
```
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

# Create mesh grid for decision boundaries
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                     np.arange(y_min, y_max, 0.01))
```

In [186]:
```
Z = knn.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
```

In [187]:
```
# Plot
plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.coolwarm)
scatter = plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.coolwarm, edgecolor='black')
plt.xlabel('SepalLengthCm')
plt.ylabel('SepalWidthCm')
plt.title('KNN Decision Boundaries (First Two Features)')
```

Out[187]:
```
Text(0.5, 1.0, 'KNN Decision Boundaries (First Two Features)')
```

In [110]:
```
species_names = le.classes_
class_ids = np.unique(y)
handles = [plt.Line2D([], [], marker='s', color='w', label=species_names[i],
                      markerfacecolor=plt.cm.coolwarm(i / 2), markersize=15) for i in class_ids]
plt.legend(handles=handles, title='Species')
plt.show()
```


Species
0
1
2
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0