Assignment 2 - Regression and Classification

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Stefan Dimitrov Velev, 0MI3400521, Big Data Technologies

Faculty of Mathematics and Informatics, Sofia University

[86]:
```python
# Import required Python libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from matplotlib.colors import ListedColormap
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.neighbors import KNeighborsClassifier
```

0.0.1 Task 1: Regression

a. Find a linear regression model that relates the living area to the selling price.

If you did any data cleaning step(s), describe what you did and explain why.

[87]:
```python
# Read the given CSV file
df = pd.read_csv('./data/data_assignment2.csv', delimiter=',')
```

[88]:
```python
df.head()
```

[88]:

	ID	Living_area	Rooms	Land_size	Biarea	Age	Selling_price
0	1	104	5.0	271.0	25.0	33	4600000
1	2	99	5.0	1506.0	6.0	88	4450000
2	3	133	6.0	486.0	NaN	44	4900000
3	4	175	7.0	728.0	NaN	14	6625000
4	5	118	6.0	1506.0	NaN	29	4600000

[89]:
```python
print("The number of rows in the data frame is:", len(df))
```

```
The number of rows in the data frame is: 56
```

[90]:
```
# Remove the unnecessary columns in the data frame
df = df[['ID', 'Living_area', 'Selling_price']]
```

[91]:
```
df.head()
```

[91]:

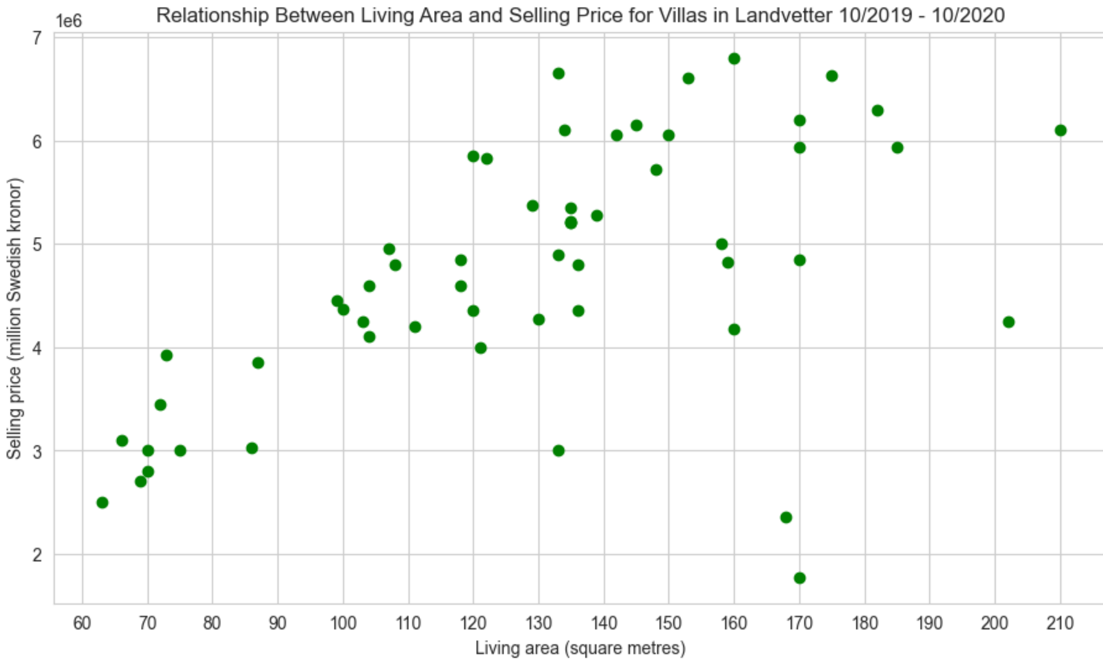
	ID	Living_area	Selling_price
0	1	104	4600000
1	2	99	4450000
2	3	133	4900000
3	4	175	6625000
4	5	118	4600000

[92]:
```
# Remove rows with missing values (if there are any)
df = df.dropna()
```

[93]:
```
print("The number of rows in the data frame is:", len(df))
```

```
The number of rows in the data frame is: 56
```

[94]:
```
# Draw scatter plot of the data
plt.figure(figsize=(11, 6))
plt.scatter(df['Living_area'], df['Selling_price'], color='green')
plt.xticks(range(60, 220, 10))
plt.xlabel('Living area (square metres)')
plt.ylabel('Selling price (million Swedish kronor)')

plt.title('Relationship Between Living Area and Selling Price for Villas in␣
↪Landvetter 10/2019 - 10/2020')
plt.show()
```



[95]:
```
# Observe some statistics related to the data
df.describe()
```

[95]:

	ID	Living_area	Selling_price
count	56.000000	56.000000	5.600000e+01
mean	28.500000	128.678571	4.713125e+06
std	16.309506	36.006619	1.241117e+06
min	1.000000	63.000000	1.775000e+06
25%	14.750000	104.000000	4.075000e+06
50%	28.500000	133.000000	4.812500e+06
75%	42.250000	154.250000	5.831250e+06
max	56.000000	210.000000	6.800000e+06

[96]:
```
# Find the two outliers with relatively large living areas but low selling␣
↪prices for a villa
min_price_outliers = df.nsmallest(n= 2, columns = 'Selling_price')
print(min_price_outliers)
```

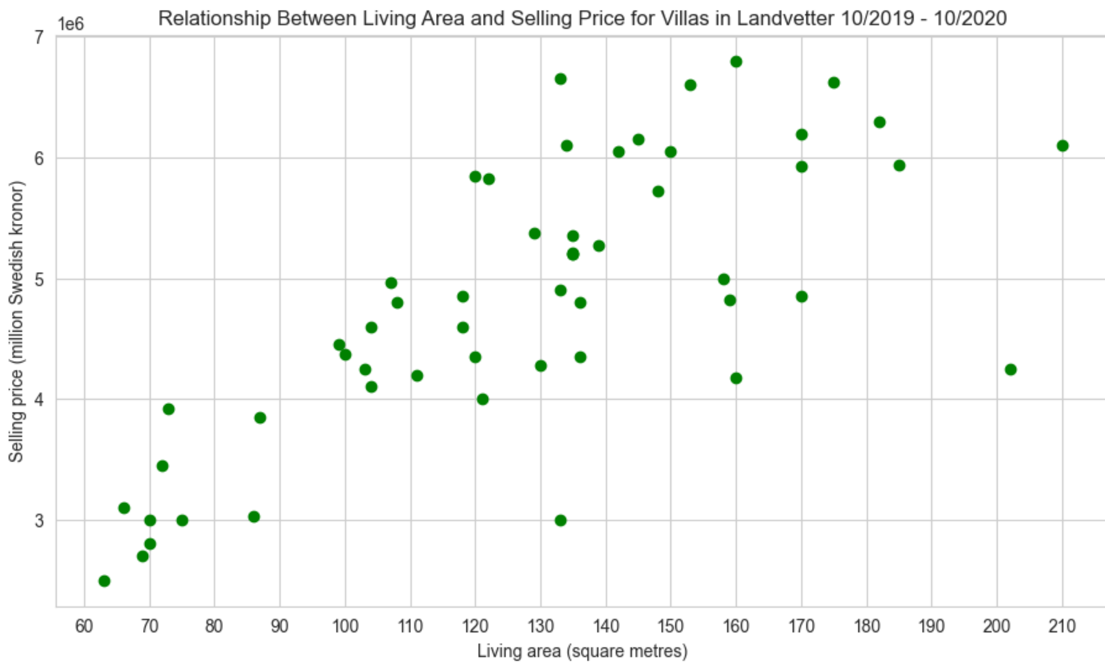
```
    ID  Living_area  Selling_price
40  41          170        1775000
45  46          168        2360000
```

[97]:
```
# Remove the outliers from the df (as these are special cases which will change␣
↪the regression line if left)
df = df.drop(min_price_outliers.index)
```

[98]:
```
print("The number of rows in the data frame is:", len(df))
```

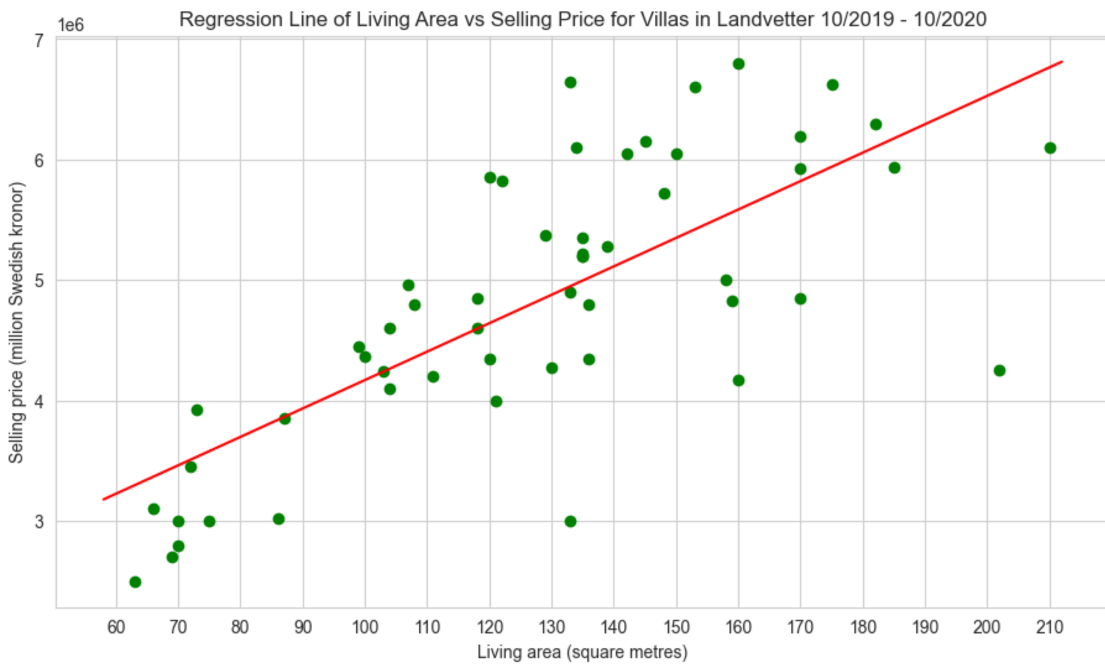
```
The number of rows in the data frame is: 54
```

[99]:
```
# Draw scatter plot of the data
plt.figure(figsize=(11, 6))
plt.scatter(df['Living_area'], df['Selling_price'], color='green')
plt.xticks(range(60, 220, 10))
plt.xlabel('Living area (square metres)')
plt.ylabel('Selling price (million Swedish kronor)')

plt.title('Relationship Between Living Area and Selling Price for Villas in␣
↪Landvetter 10/2019 - 10/2020')
plt.show()
```



[100]:
```
# Construct a linear regression model and visualise the regression line
model = LinearRegression()
model.fit(df['Living_area'].values[:, np.newaxis], df['Selling_price'])
xfit = np.array([58, 212])
yfit = model.predict(xfit[:, np.newaxis])

plt.figure(figsize=(11, 6))
plt.scatter(df['Living_area'], df['Selling_price'], color='green')
plt.plot(xfit, yfit, color='red')
```

```
plt.xticks(range(60, 220, 10))
plt.xlabel('Living area (square metres)')
plt.ylabel('Selling price (million Swedish kronor)')

plt.title('Regression Line of Living Area vs Selling Price for Villas in␣
 ↪Landvetter 10/2019 - 10/2020')
plt.show()
```



b. What are the values of the slope and intercept of the regression line?

[101]:
```
# Find the values of the slope and the intercept with the help of the␣
 ↪constructed model
print('The value of the slope (gradient) is:', model.coef_[0])
print('The value of the intercept is:', model.intercept_)
```

```
The value of the slope (gradient) is: 23597.794749444976
The value of the intercept is: 1809821.2159409611
```

c. Use this model to predict the selling price of houses which have living area 100 m2, 150 m2 and 200 m2.

[102]:
```
# Predict the selling price of the villas by using the constructed model
living_area_list = [100, 150, 200]
for current_living_area in living_area_list:
    print(f'The predicted selling price of a villa with a living area of␣
 ↪{current_living_area} m2 is {model.predict(np.
 ↪array([[current_living_area]]))[0]:.2f} Swedish kronor.')
```

```
The predicted selling price of a villa with a living area of 100 m2 is
4169600.69 Swedish kronor.
The predicted selling price of a villa with a living area of 150 m2 is
5349490.43 Swedish kronor.
The predicted selling price of a villa with a living area of 200 m2 is
6529380.17 Swedish kronor.
```

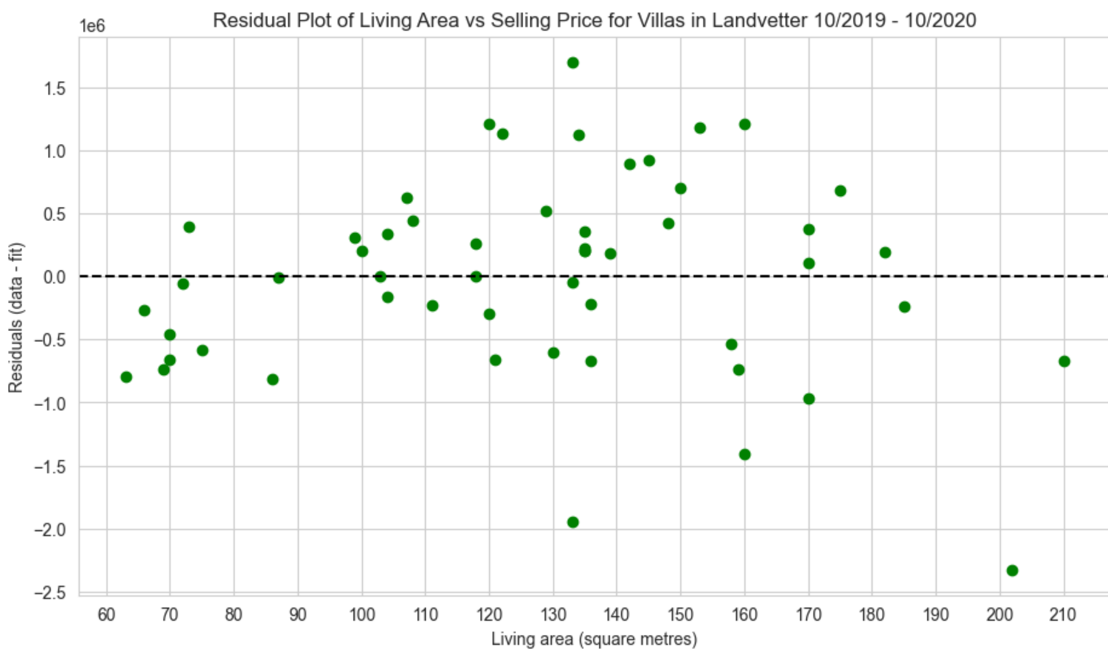
d. Draw a residual plot.

[103]:
```python
# Find correlation (quantifies the strength of a linear trend) using Numpy
y_pred = model.predict(df['Living_area'].values[:, np.newaxis])
correlation_matrix = np.corrcoef(df['Selling_price'], y_pred)
print(f'The correlation R between the actual selling prices and the predicted␣
↪selling prices with the model is {correlation_matrix[0, 1]:.2f}.')
```

```
The correlation R between the actual selling prices and the predicted selling
prices with the model is 0.73.
```

[104]:
```python
# Calculate the residuals by finding the difference between observed and␣
↪expected (based on the model fit)
residuals = df['Selling_price'] - y_pred
```

[105]:
```python
# Draw a residual plot
plt.figure(figsize=(11, 6))
plt.scatter(df['Living_area'], residuals, color='green')
plt.axhline(0, color='black', linestyle='--')

plt.xticks(range(60, 220, 10))
plt.xlabel('Living area (square metres)')
plt.ylabel('Residuals (data - fit)')

plt.title('Residual Plot of Living Area vs Selling Price for Villas in␣
↪Landvetter 10/2019 - 10/2020')
plt.show()
```



0.0.2 Task 2: Classification

a. Use a confusion matrix to evaluate the use of logistic regression to classify the iris data set.

[106]:
```
# Load Iris data set
iris = load_iris()
x_iris = iris.data[:, :2]
y_iris = iris.target
print('Feature names:', iris.feature_names)
print('Target names:', iris.target_names)
```

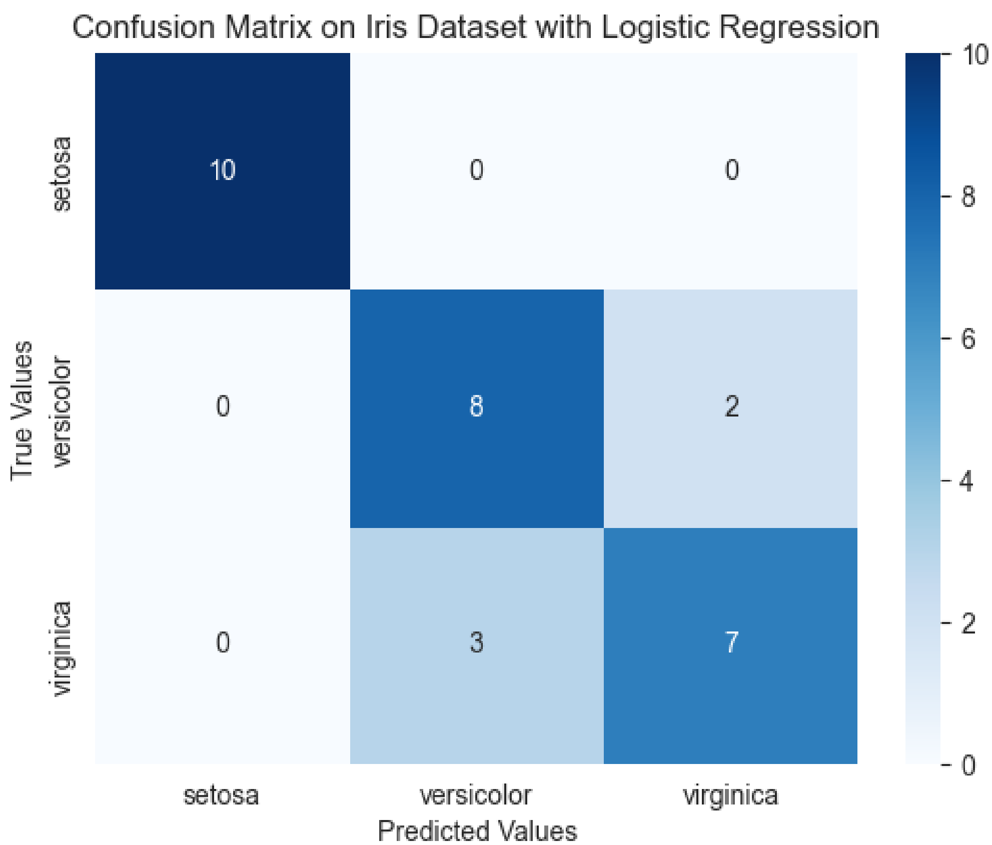
```
Feature names: ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)',
'petal width (cm)']
Target names: ['setosa' 'versicolor' 'virginica']
```

[107]:
```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(x_iris, y_iris, test_size=0.
↪2)
```

[108]:
```
# Construct a logistic regression model
model_iris_logistic = LogisticRegression(max_iter=200)
model_iris_logistic.fit(X_train, y_train)
y_pred = model_iris_logistic.predict(X_test)
```

[109]:
```
# Construct a confusion matrix to evaluate the use of the logistic regression␣
↪model
```

```
conf_matrix_logistic_regression = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix_logistic_regression, annot=True, fmt='d', cmap='Blues',
 ↪xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Confusion Matrix on Iris Dataset with Logistic Regression')
plt.show()
```

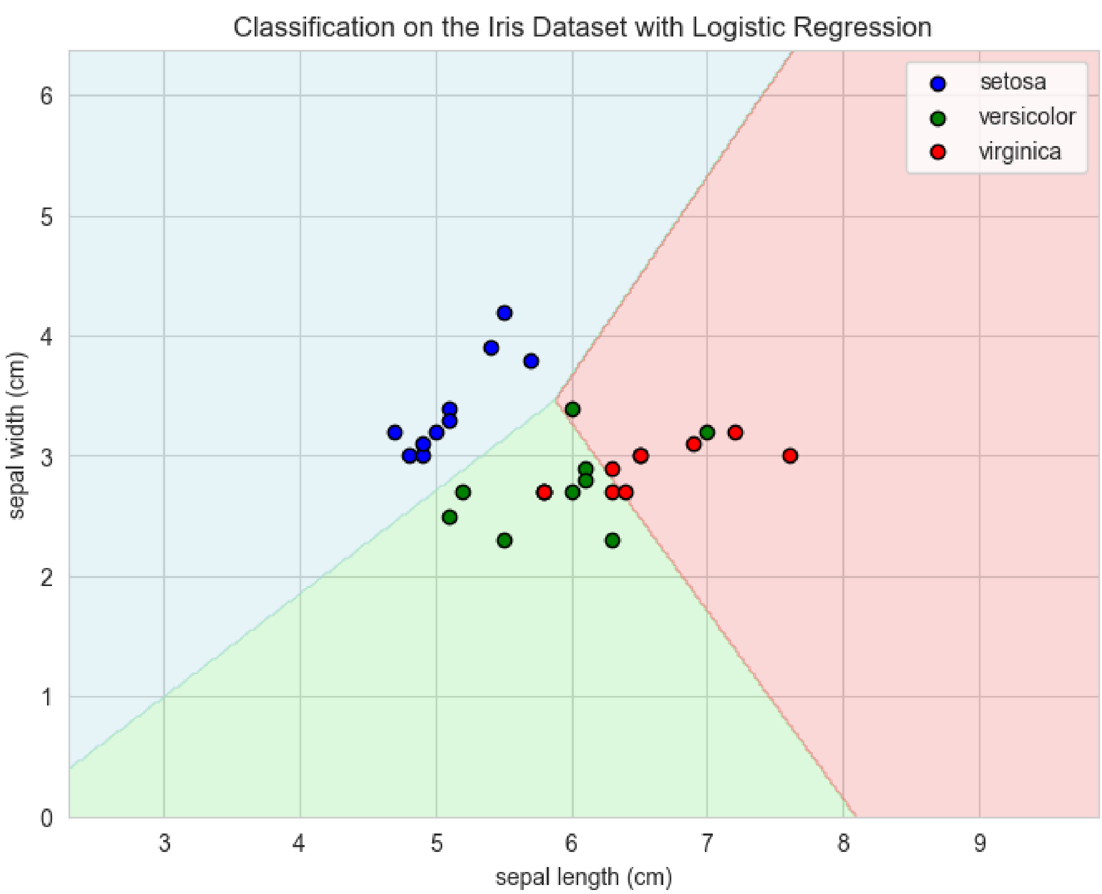


[110]:
```
# Find the accuracy (the number of correct predictions divided by the total
 ↪number of predictions) of the logistic regression model
accuracy_logistic_regression = accuracy_score(y_test, y_pred)
print(f'The accuracy of the logistic regression model on the Iris dataset is
 ↪{accuracy_logistic_regression:.2f}')
```

```
The accuracy of the logistic regression model on the Iris dataset is 0.83
```

[111]:
```
h = 0.02
x_min, x_max = X_train[:, 0].min() - 2, X_train[:, 0].max() + 2
y_min, y_max = X_train[:, 1].min() - 2, X_train[:, 1].max() + 2
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
```

```
Z = model_iris_logistic.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

cmap_light = ListedColormap(["lightblue", "lightgreen", "lightcoral"])
cmap_bold = ListedColormap(["blue", "green", "red"])

plt.figure(figsize=(8, 6))
plt.contourf(xx, yy, Z, cmap=cmap_light, alpha=0.3)

for i, color in enumerate(cmap_bold.colors):
    idx = y_test == i
    plt.scatter(X_test[idx, 0], X_test[idx, 1], c=color, edgecolor="k",␣
 ↪label=iris.target_names[i])

plt.xlabel(iris.feature_names[0])
plt.ylabel(iris.feature_names[1])
plt.title('Classification on the Iris Dataset with Logistic Regression')

plt.legend()
plt.show()
```



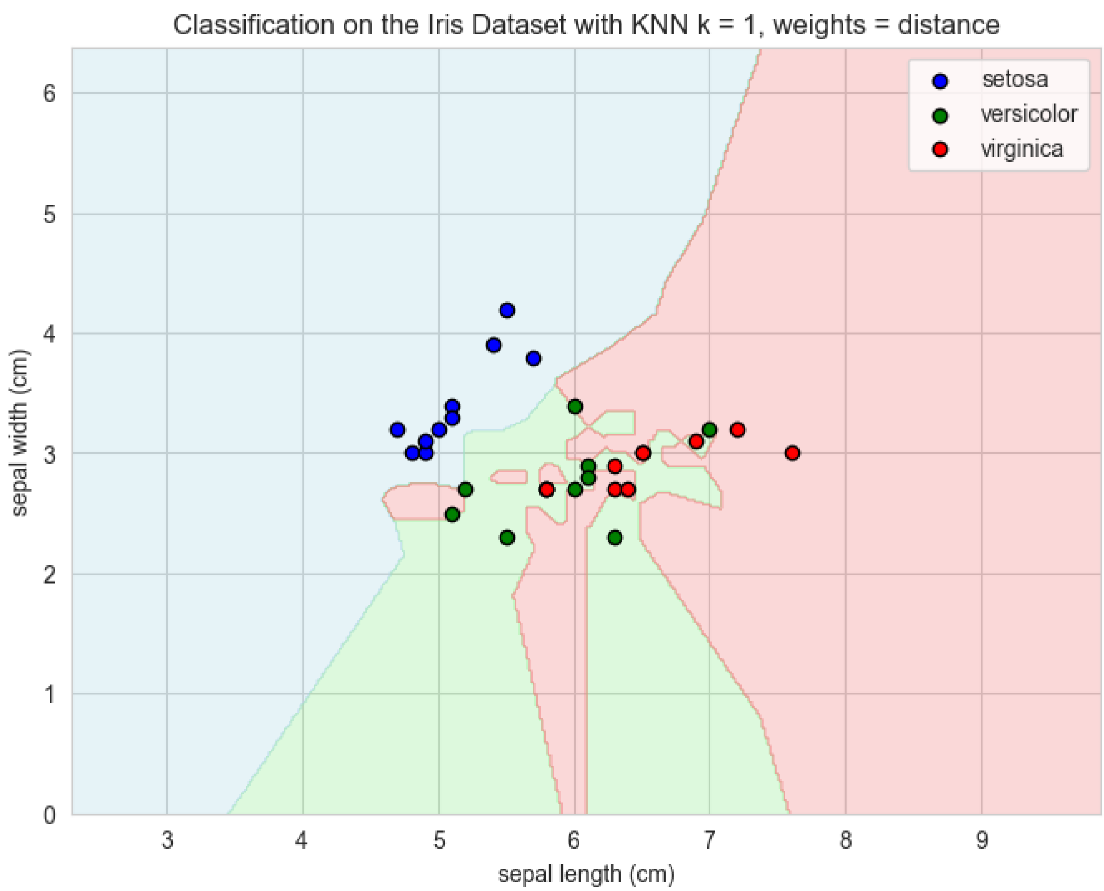
b. Use k-nearest neighbours to classify the iris dataset with some different values for k, and with uniform and distance-based weights. What will happen when k grows larger for the different cases? Why?

[112]:
```
def knn_classifier(neighbours, weights, plot = True):
    model_iris_knn = KNeighborsClassifier(n_neighbors=neighbours,␣
 ↪weights=weights)

    if plot == False:
        model_iris_knn.fit(X_train, y_train)
        y_pred = model_iris_knn.predict(x_iris)
        accuracy_knn = accuracy_score(y_iris, y_pred)
        return accuracy_knn

    model_iris_knn.fit(X_train, y_train)
    y_pred = model_iris_knn.predict(X_test)
    accuracy_knn = accuracy_score(y_test, y_pred)
    print(f'The accuracy of the KNN model with k = {neighbours}, w =␣
 ↪"{weights}" on the Iris dataset is {accuracy_knn:.2f}')

    h = 0.02
    x_min, x_max = X_train[:, 0].min() - 2, X_train[:, 0].max() + 2
    y_min, y_max = X_train[:, 1].min() - 2, X_train[:, 1].max() + 2
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))

    Z = model_iris_knn.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    cmap_light = ListedColormap(["lightblue", "lightgreen", "lightcoral"])
    cmap_bold = ListedColormap(["blue", "green", "red"])

    plt.figure(figsize=(8, 6))
    plt.contourf(xx, yy, Z, cmap=cmap_light, alpha=0.3)

    for i, color in enumerate(cmap_bold.colors):
        idx = y_test == i
        plt.scatter(X_test[idx, 0], X_test[idx, 1], c=color, edgecolor="k",␣
 ↪label=iris.target_names[i])

    plt.xlabel(iris.feature_names[0])
    plt.ylabel(iris.feature_names[1])
    plt.title(f'Classification on the Iris Dataset with KNN k = {neighbours},␣
 ↪weights = {weights}')

    plt.legend()
```

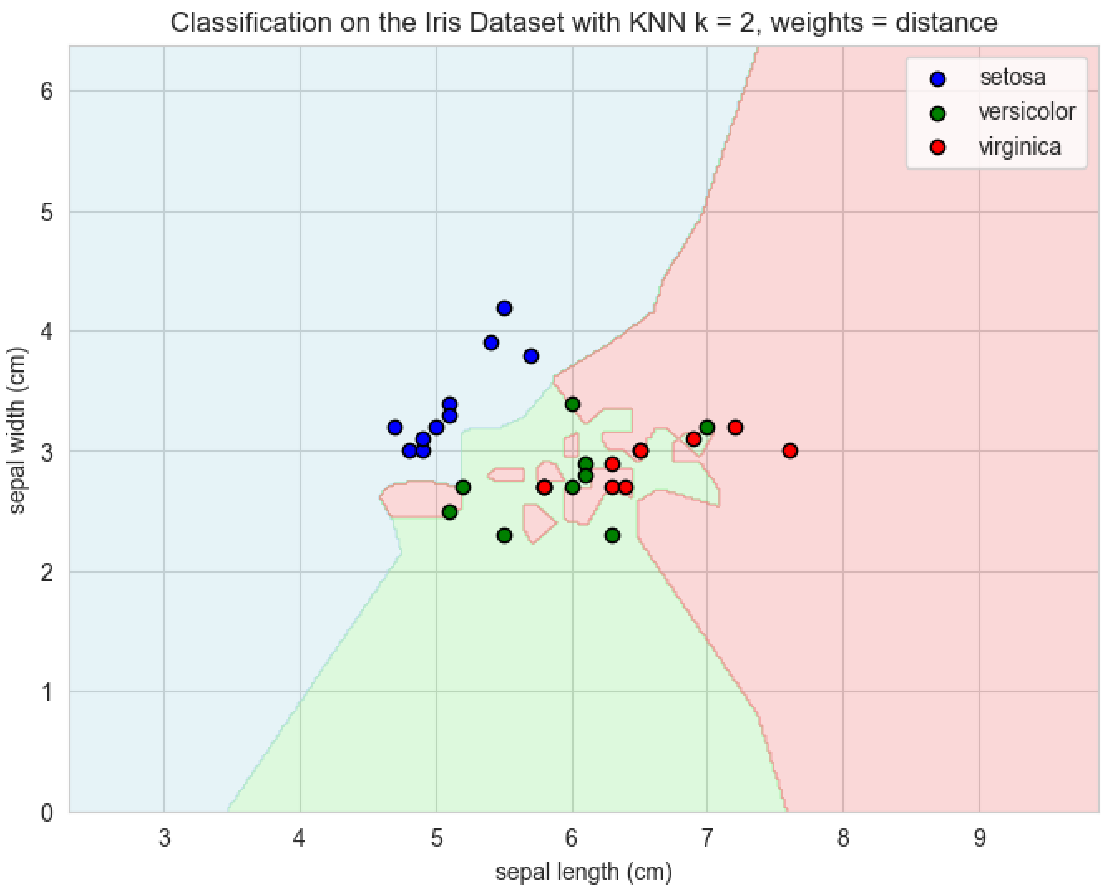
```
    plt.show()

    return accuracy_knn
```

[113]:
```
accuracy_list_knn_distance = []
for i in range(1, 16):
    accuracy_list_knn_distance.append(knn_classifier(i, 'distance'))
print(accuracy_list_knn_distance)
accuracy_series_knn_distance = pd.Series(accuracy_list_knn_distance)
```

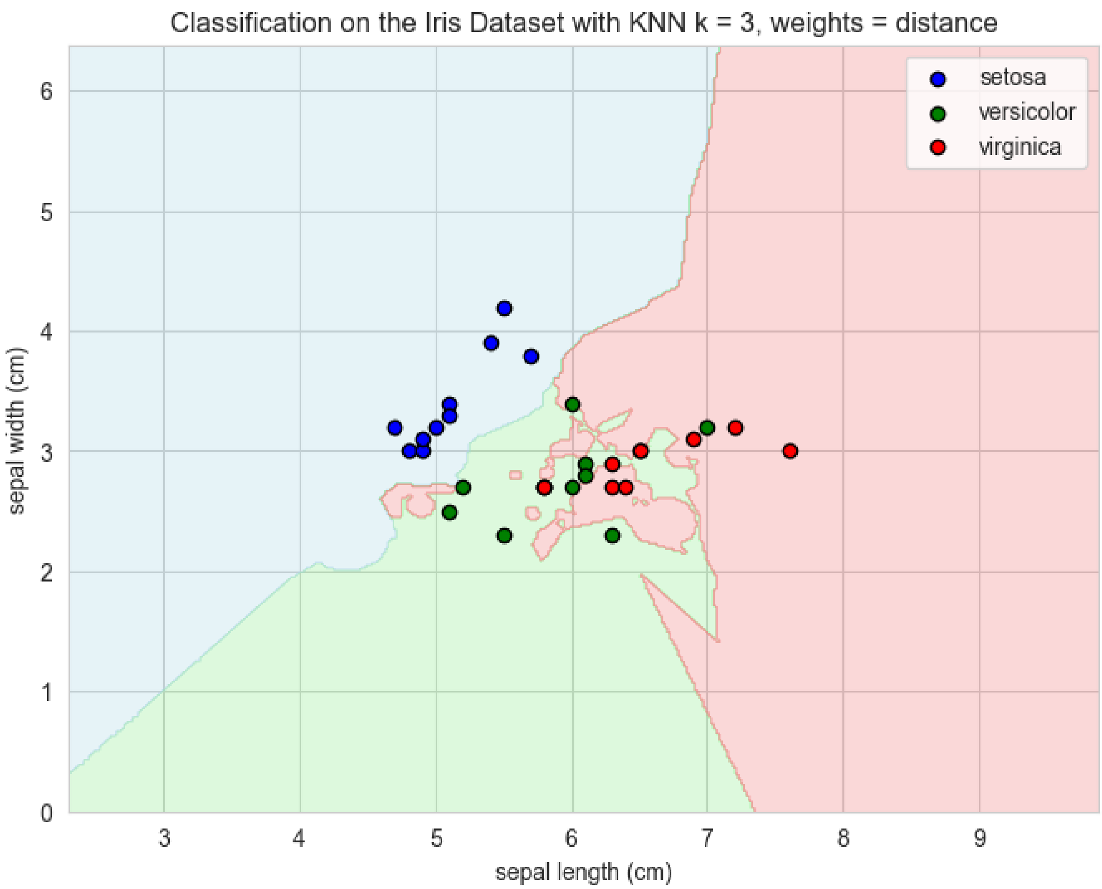
```
The accuracy of the KNN model with k = 1, w = "distance" on the Iris dataset is
0.77
```



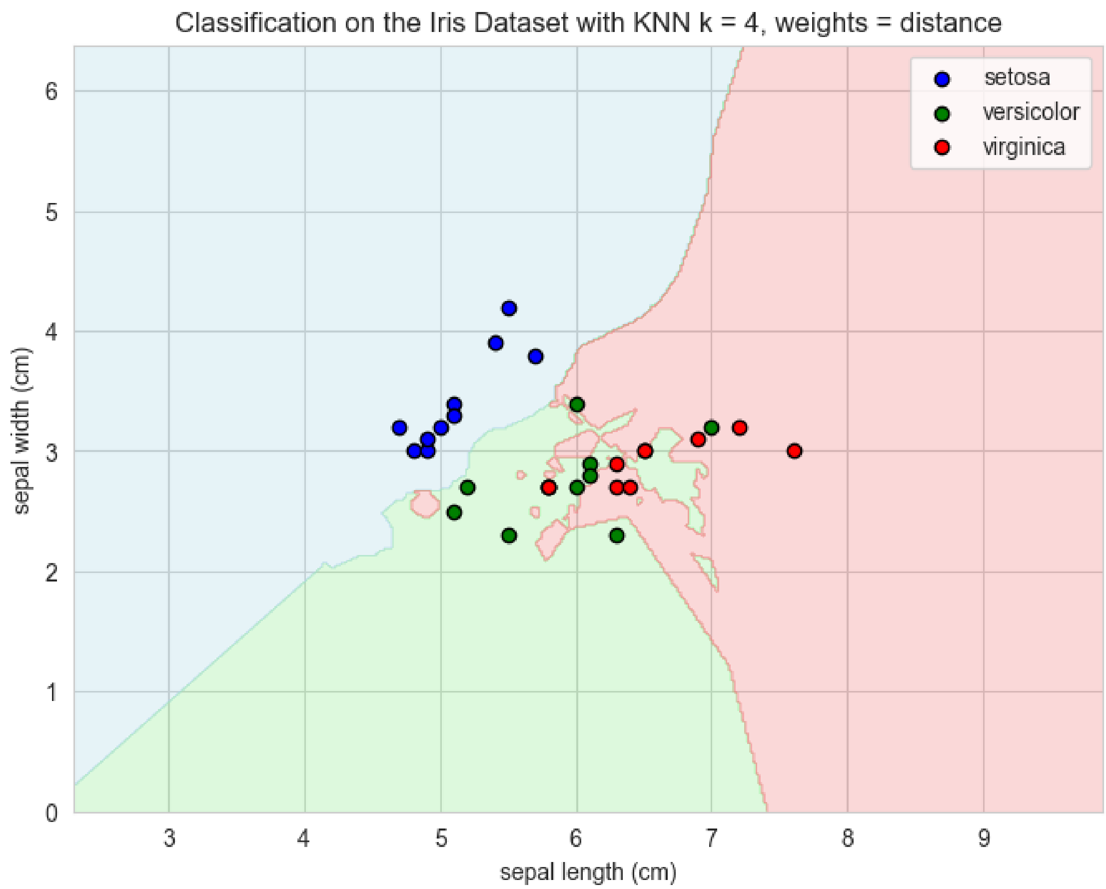

```
The accuracy of the KNN model with k = 2, w = "distance" on the Iris dataset is
0.77
```



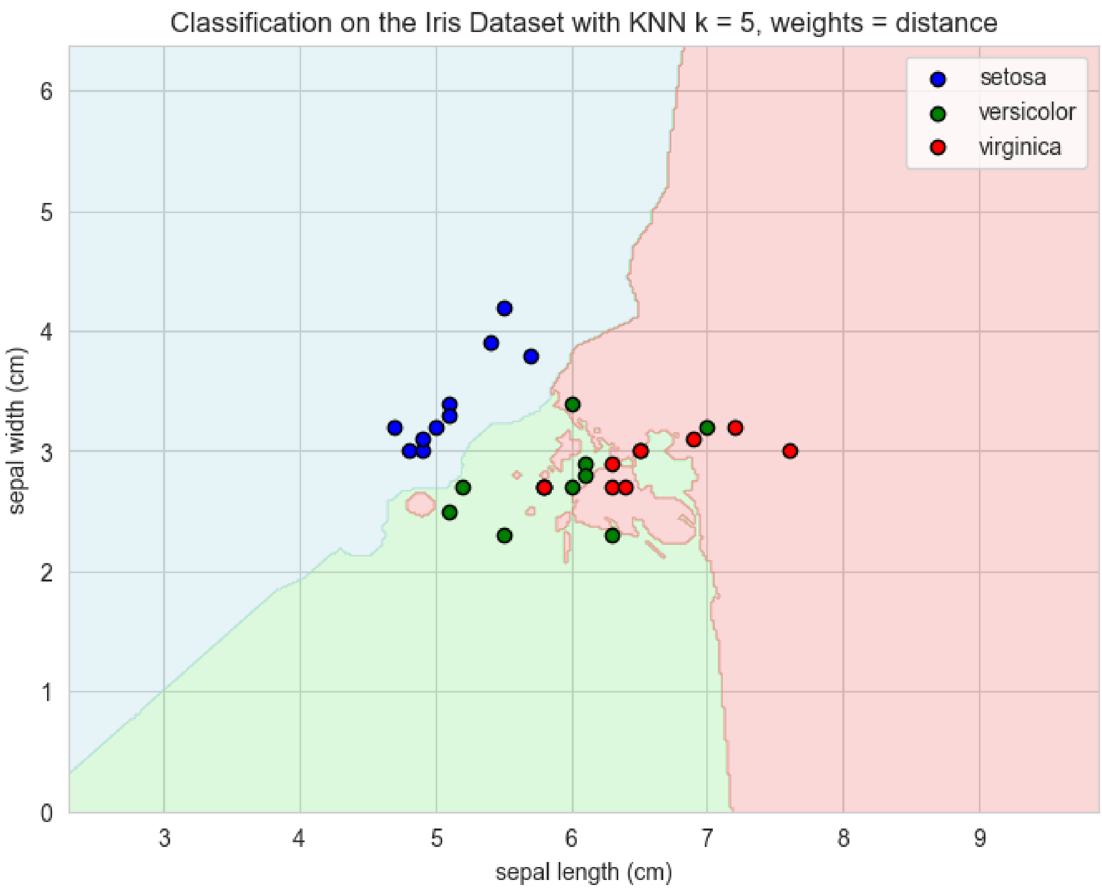

```
The accuracy of the KNN model with k = 3, w = "distance" on the Iris dataset is
0.80
```



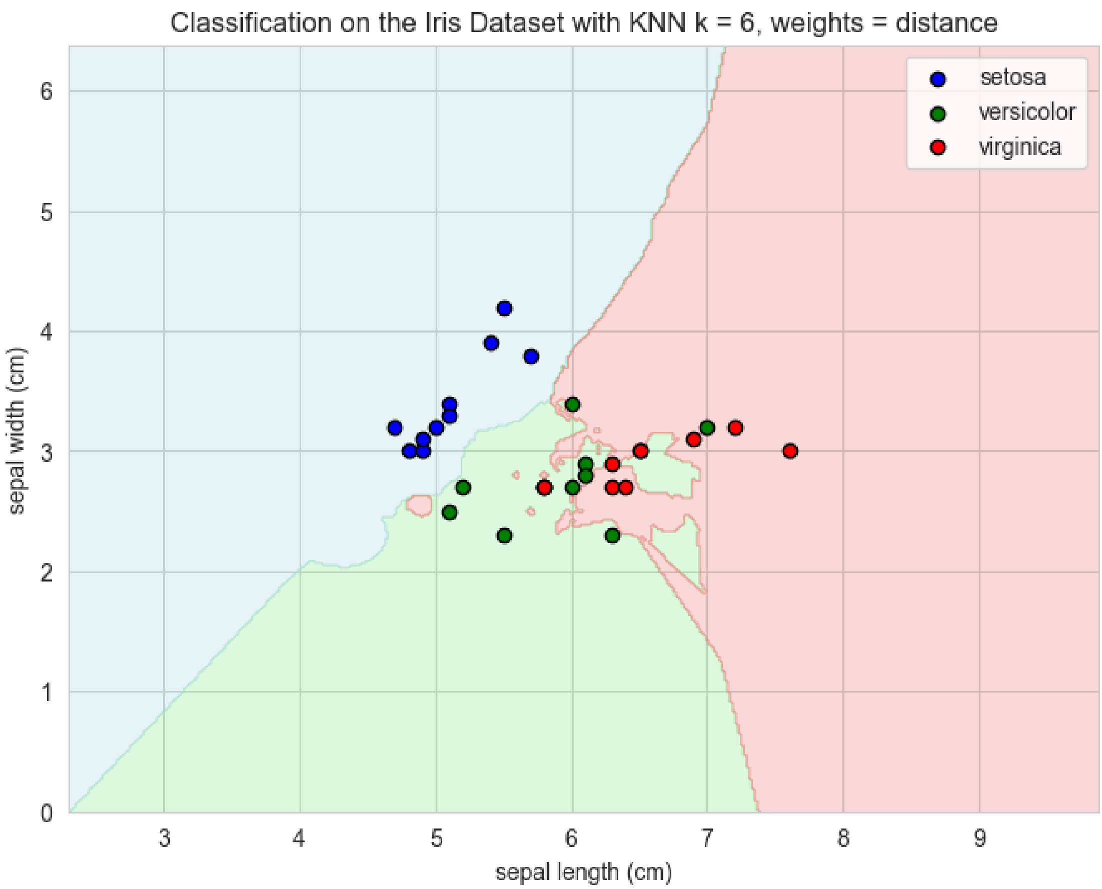
The accuracy of the KNN model with k = 4, w = "distance" on the Iris dataset is 0.80



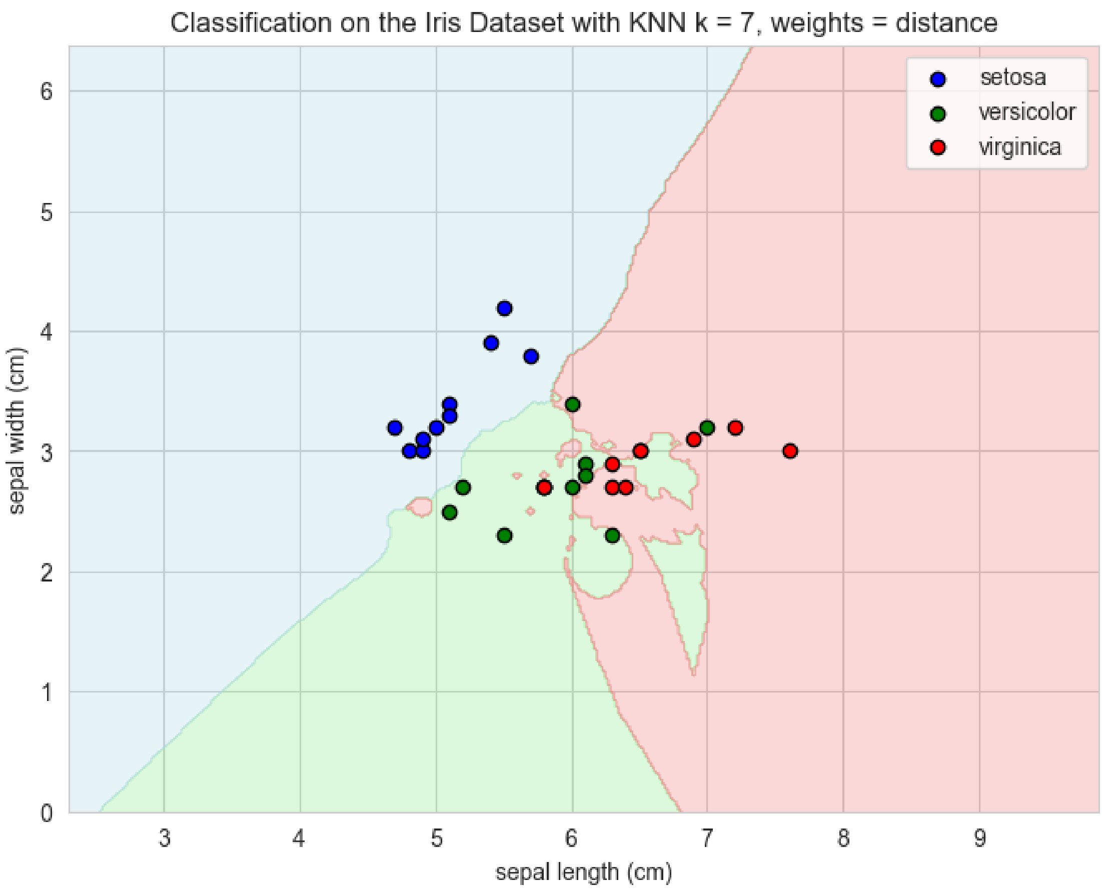

```
The accuracy of the KNN model with k = 5, w = "distance" on the Iris dataset is
0.83
```



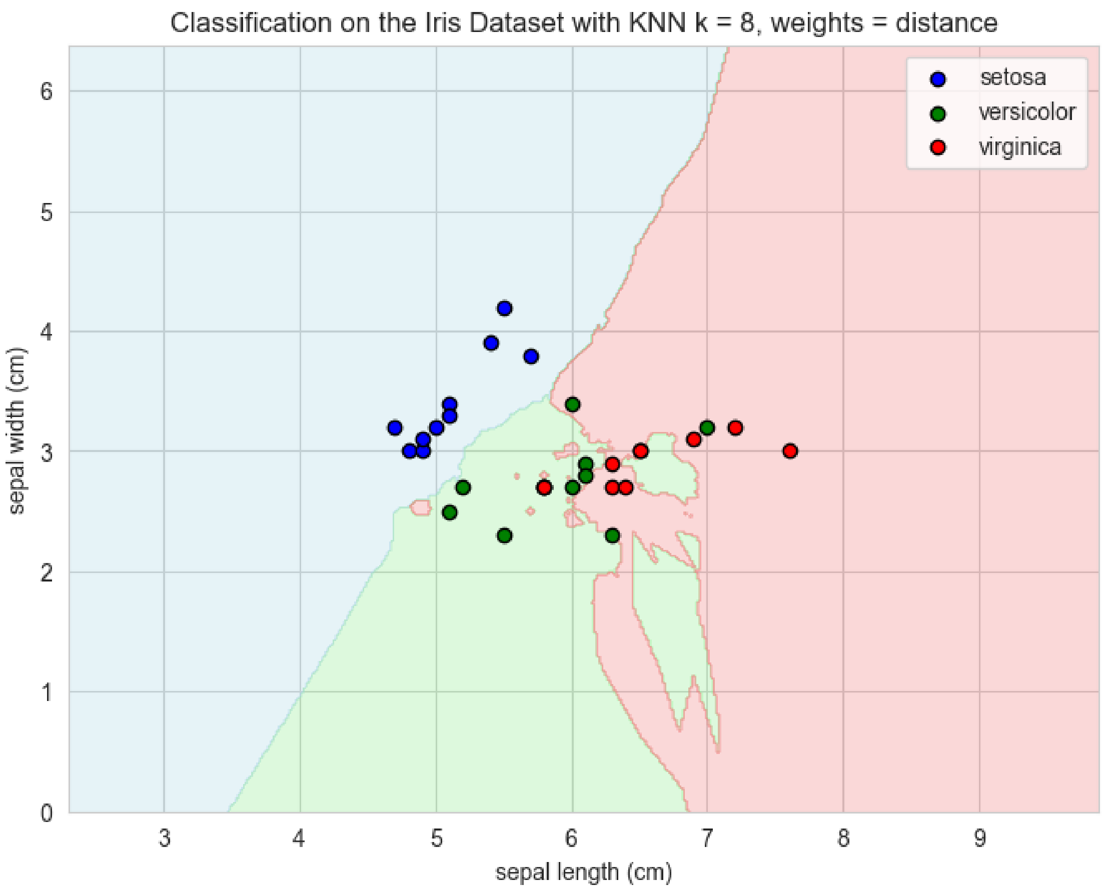

```
The accuracy of the KNN model with k = 6, w = "distance" on the Iris dataset is
0.83
```



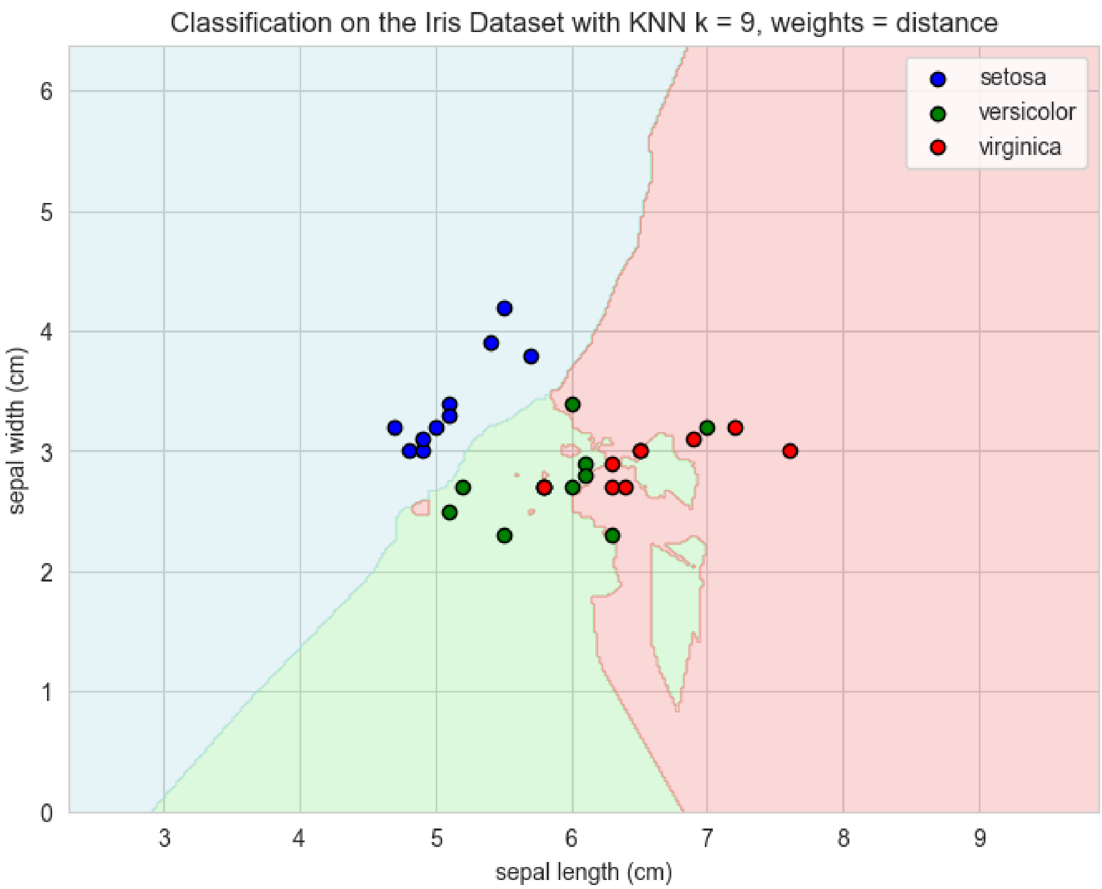

```
The accuracy of the KNN model with k = 7, w = "distance" on the Iris dataset is
0.83
```



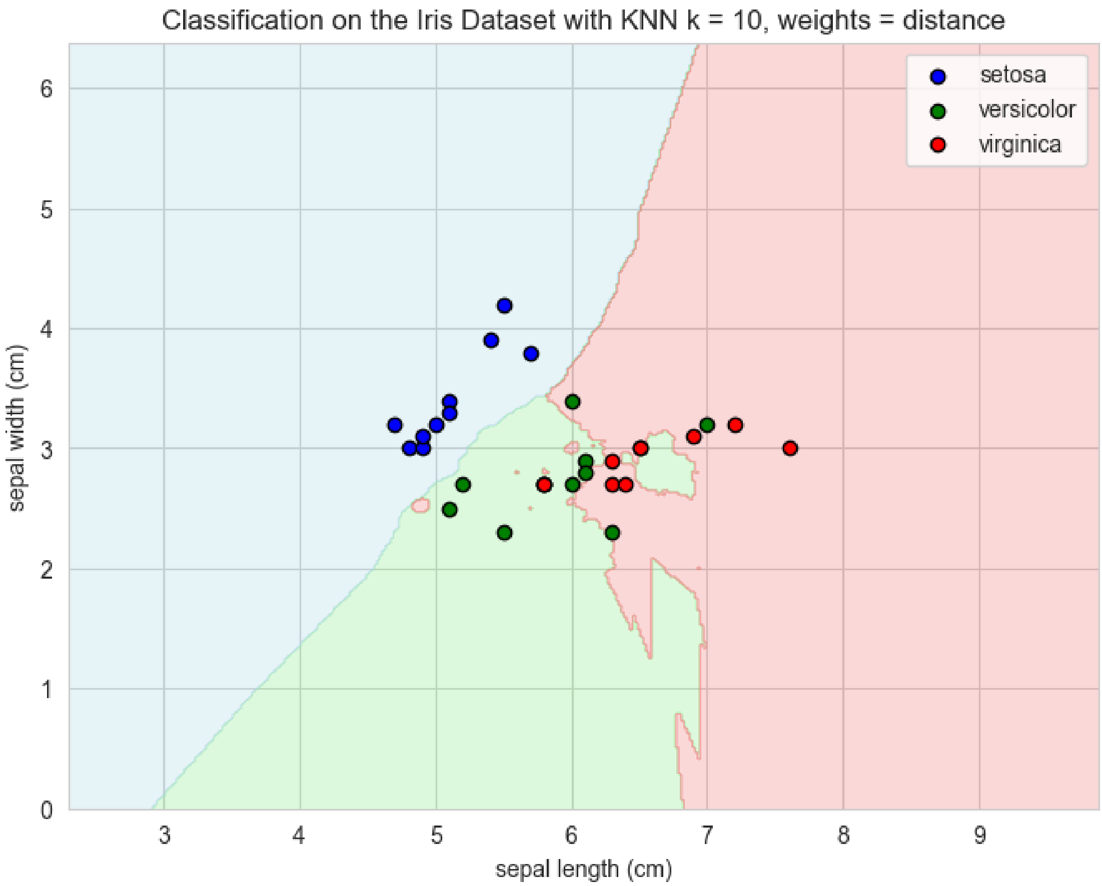
The accuracy of the KNN model with k = 8, w = "distance" on the Iris dataset is 0.83



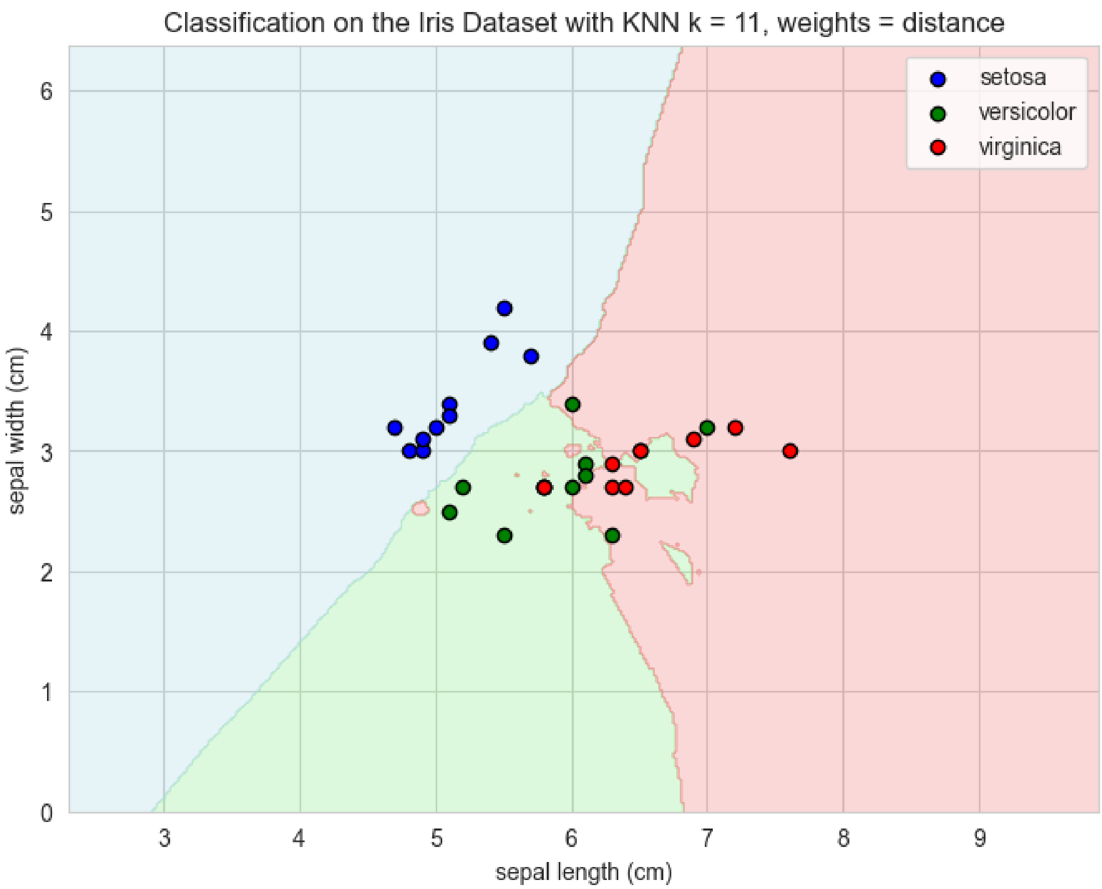

```
The accuracy of the KNN model with k = 9, w = "distance" on the Iris dataset is
0.80
```



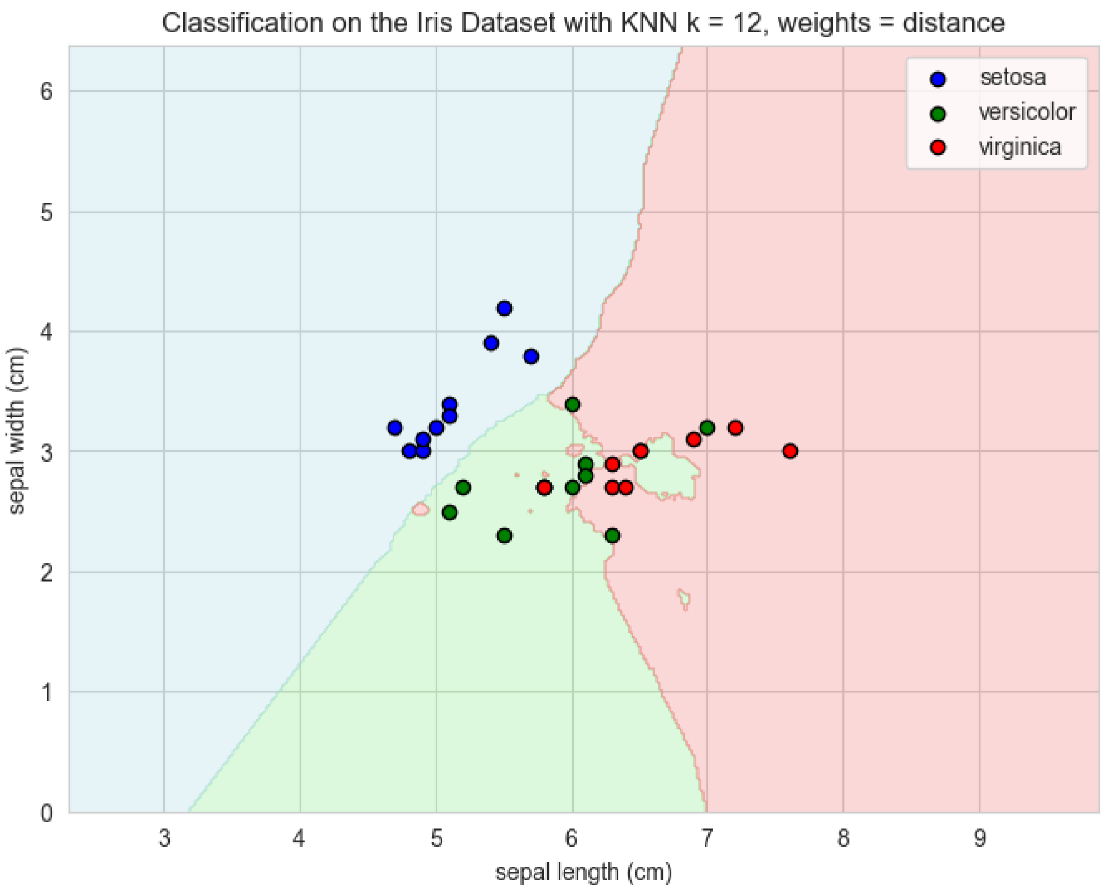

```
The accuracy of the KNN model with k = 10, w = "distance" on the Iris dataset is
0.80
```



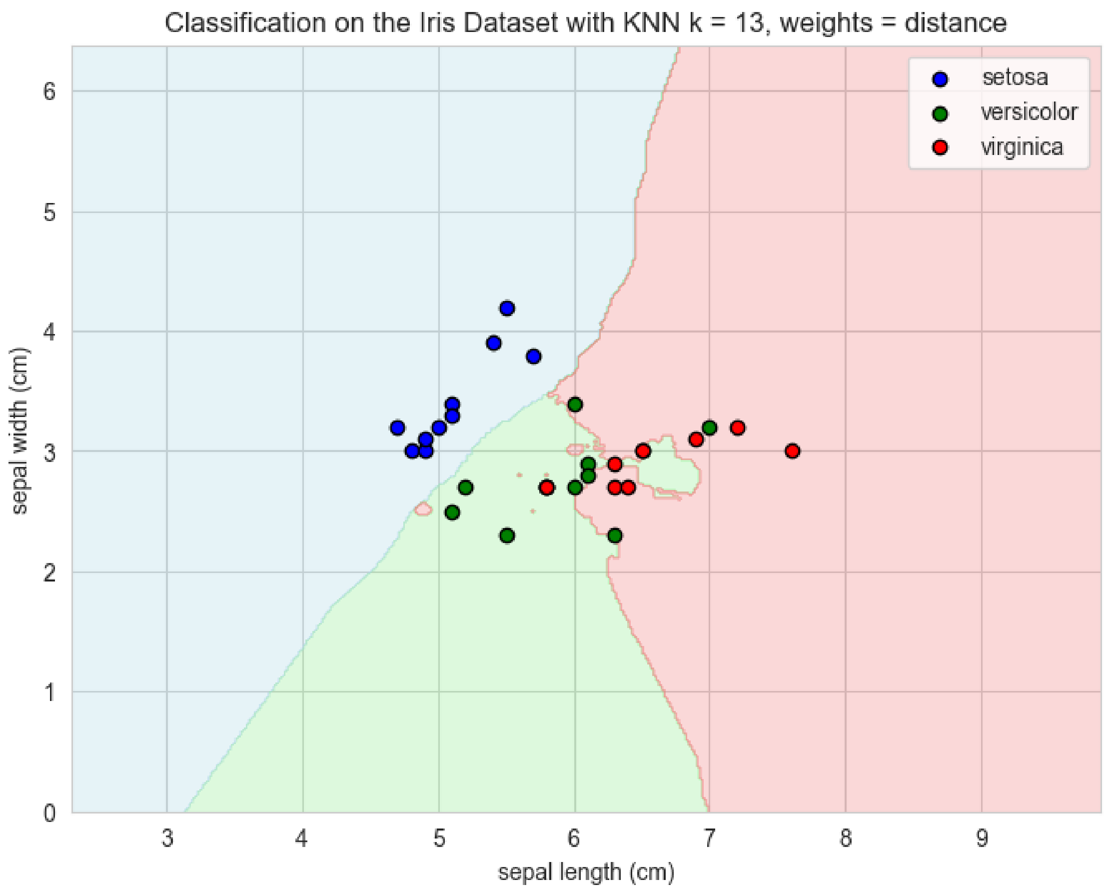

```
The accuracy of the KNN model with k = 11, w = "distance" on the Iris dataset is
0.80
```



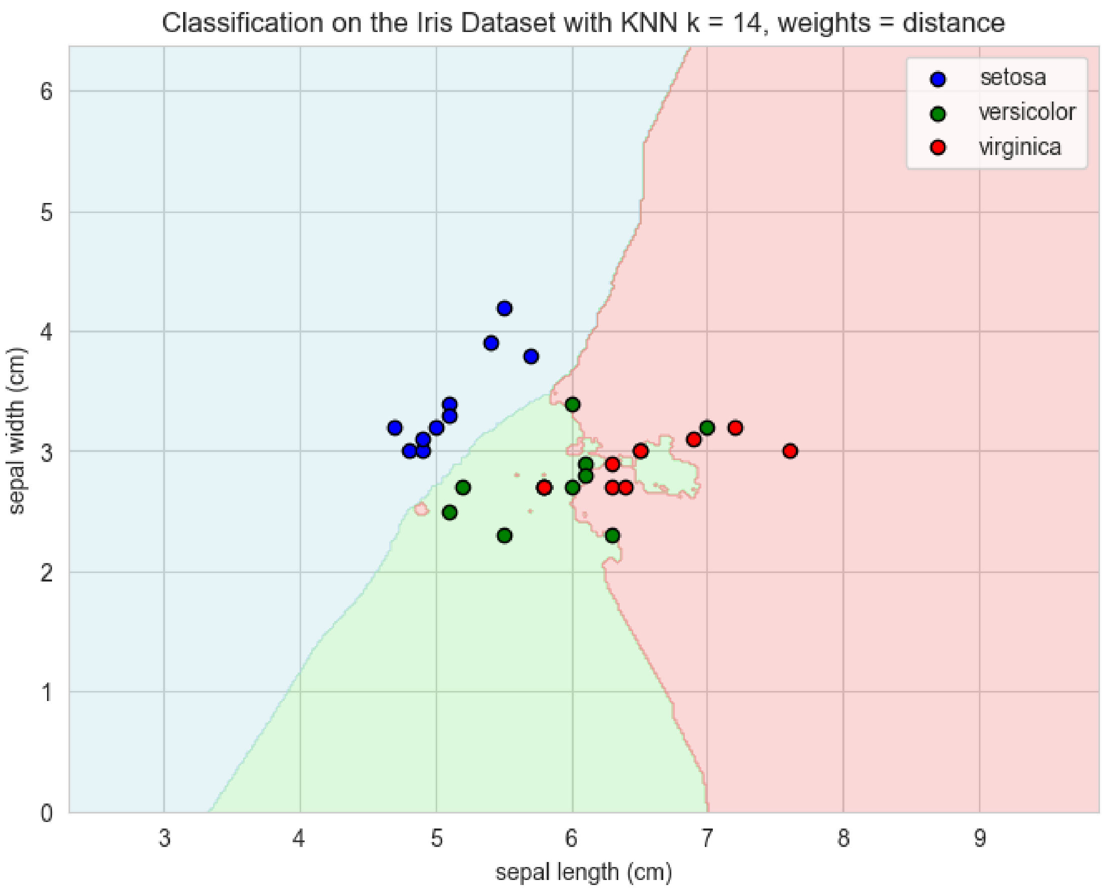

```
The accuracy of the KNN model with k = 12, w = "distance" on the Iris dataset is
0.80
```



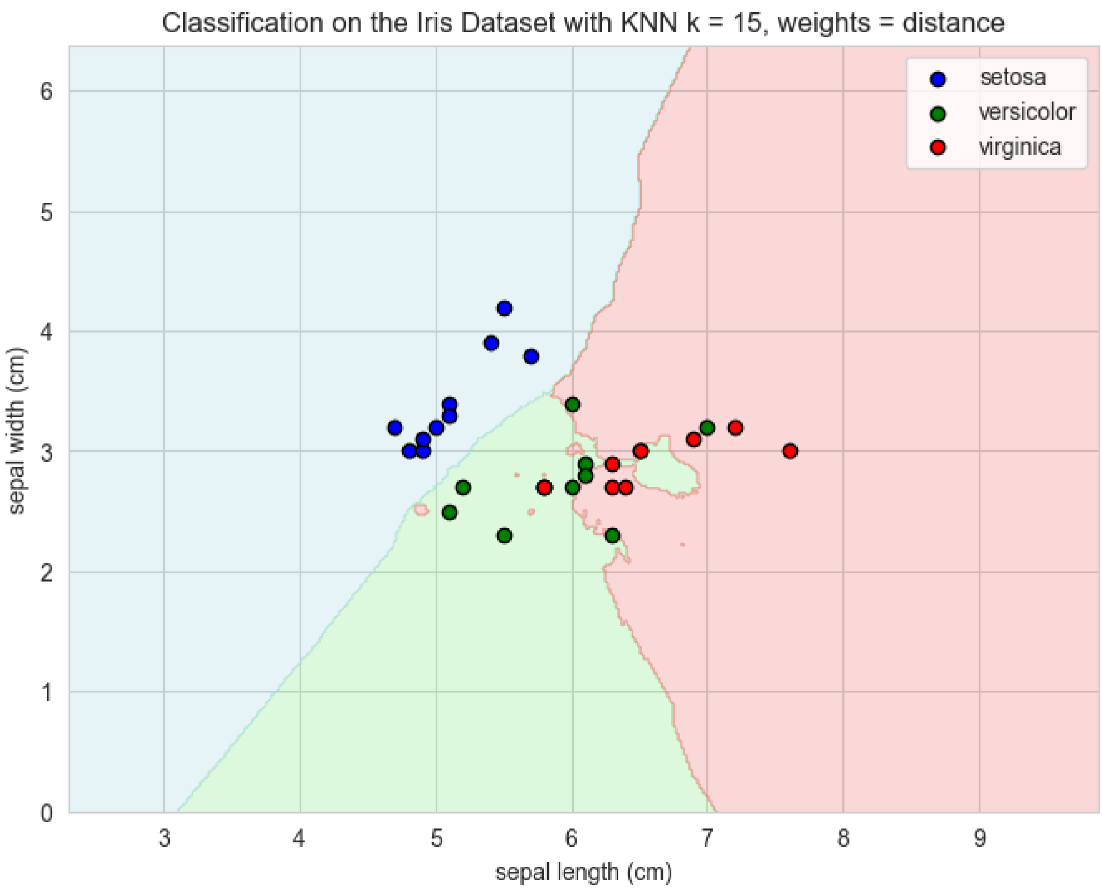

```
The accuracy of the KNN model with k = 13, w = "distance" on the Iris dataset is
0.80
```




```
The accuracy of the KNN model with k = 14, w = "distance" on the Iris dataset is
0.80
```




```
The accuracy of the KNN model with k = 15, w = "distance" on the Iris dataset is
0.83
```

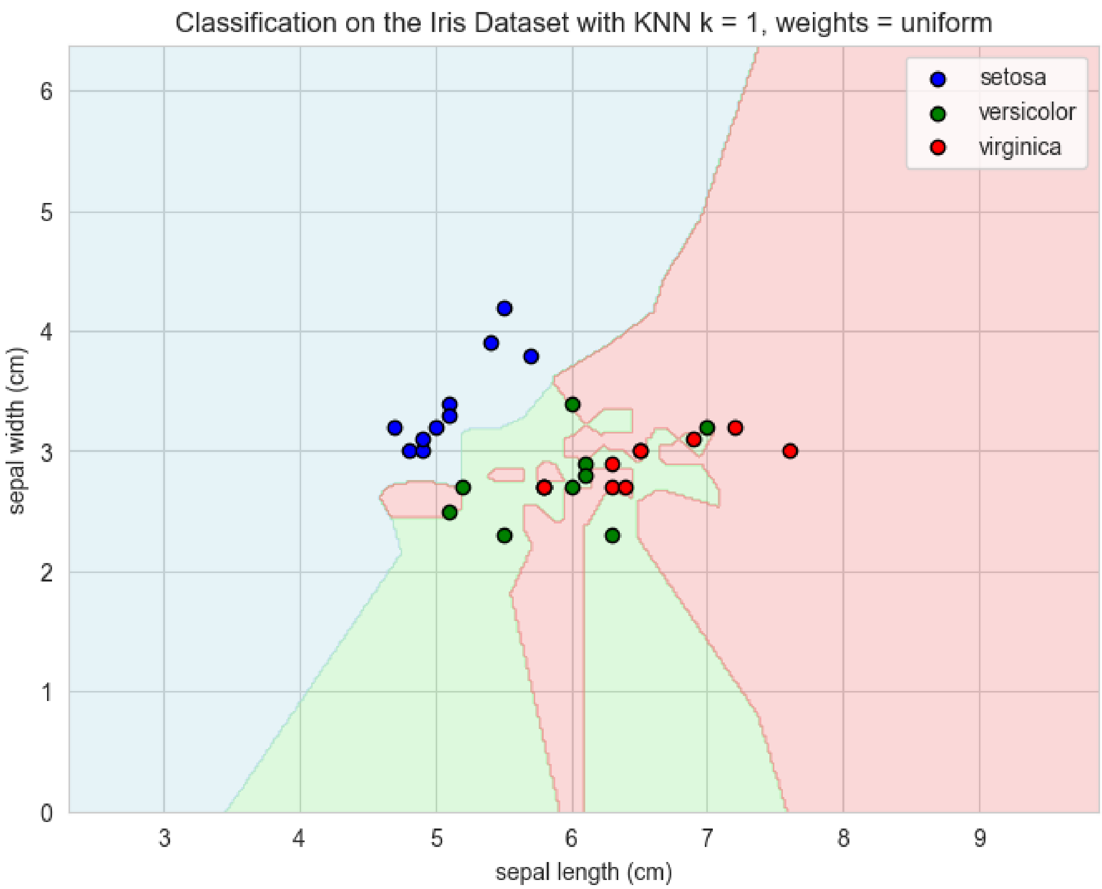



```
[0.7666666666666667, 0.7666666666666667, 0.8, 0.8, 0.8333333333333334,
0.8333333333333334, 0.8333333333333334, 0.8333333333333334, 0.8, 0.8, 0.8, 0.8,
0.8, 0.8, 0.8333333333333334]
```

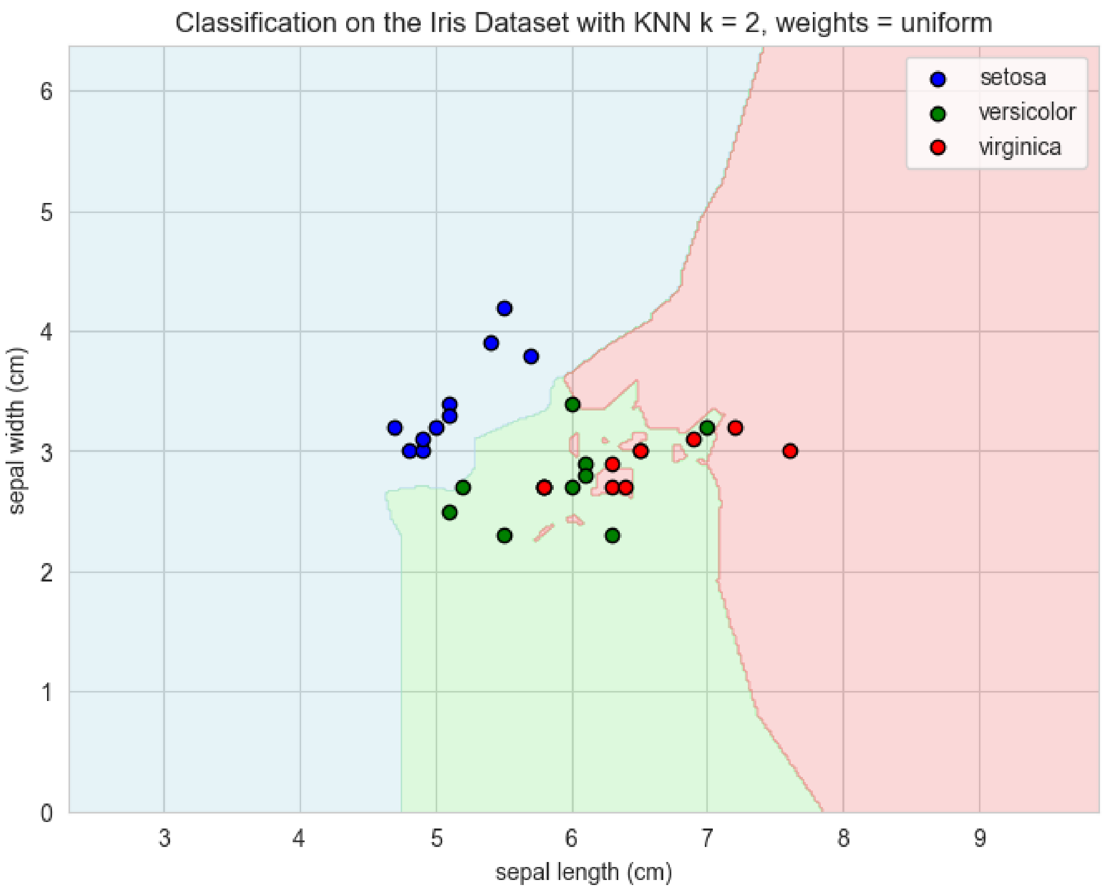
[114]:

```
accuracy_list_knn_uniform = []
for i in range(1, 16):
    accuracy_list_knn_uniform.append(knn_classifier(i, 'uniform'))
print(accuracy_list_knn_uniform)
accuracy_series_knn_uniform = pd.Series(accuracy_list_knn_uniform)
```

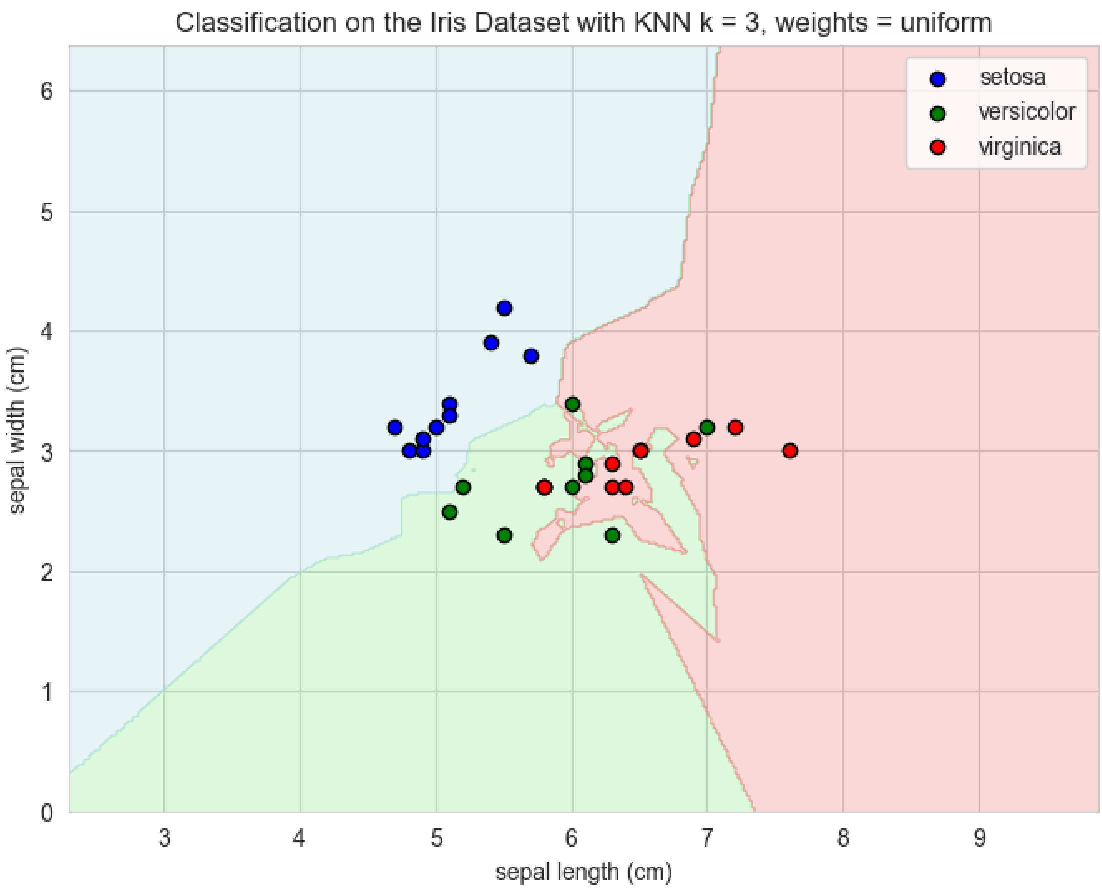
```
The accuracy of the KNN model with k = 1, w = "uniform" on the Iris dataset is
0.77
```



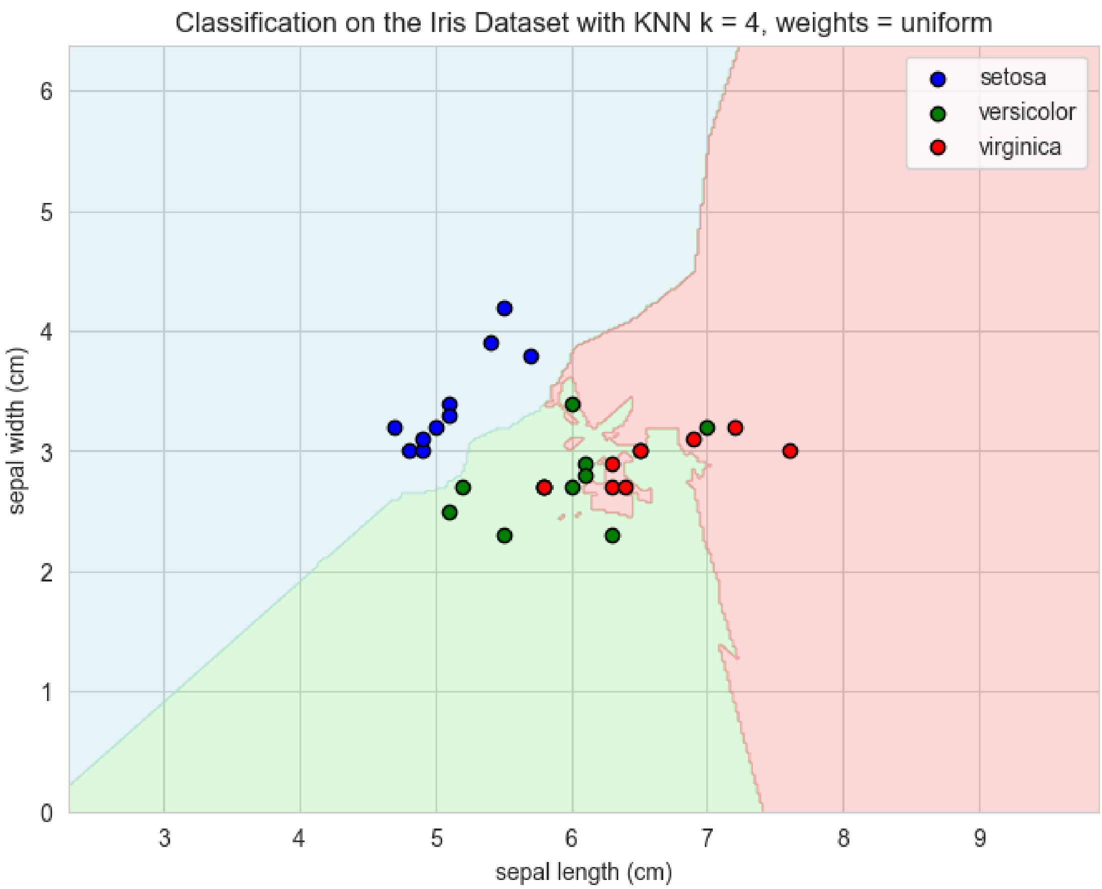
The accuracy of the KNN model with k = 2, w = "uniform" on the Iris dataset is 0.80



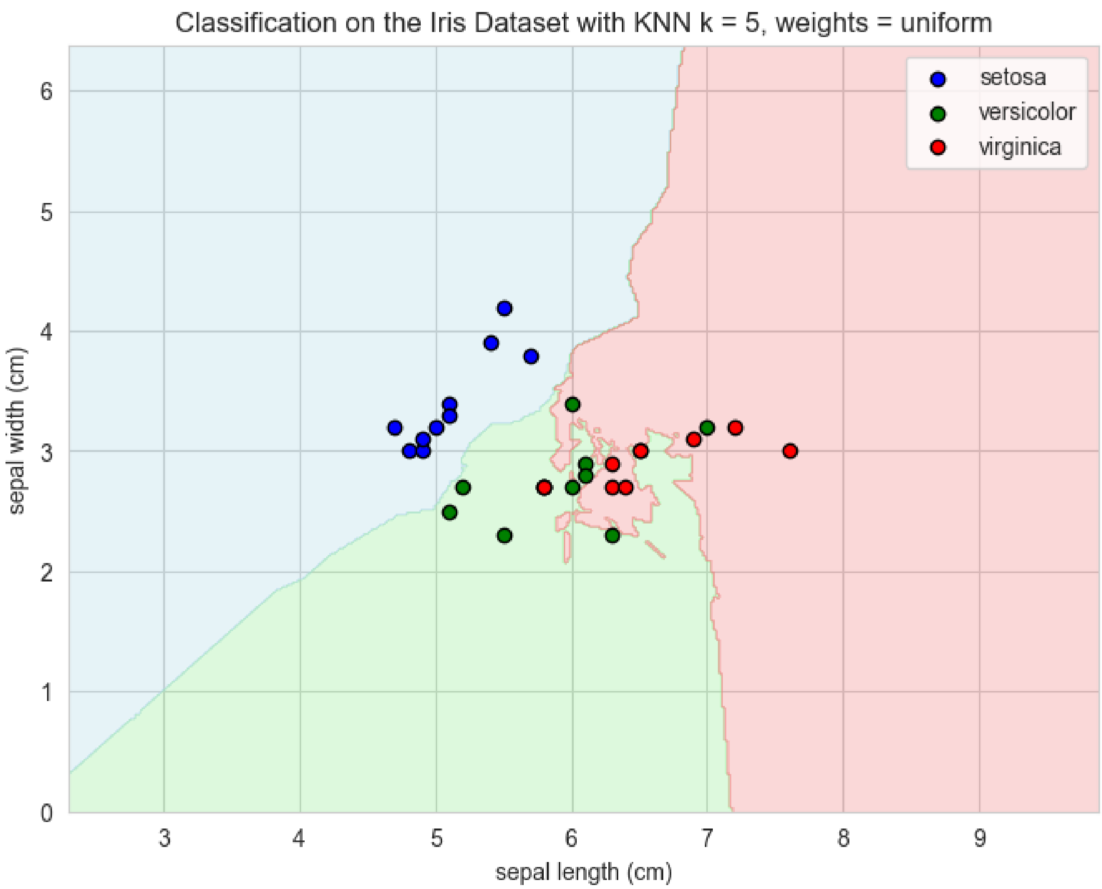
The accuracy of the KNN model with k = 3, w = "uniform" on the Iris dataset is 0.77



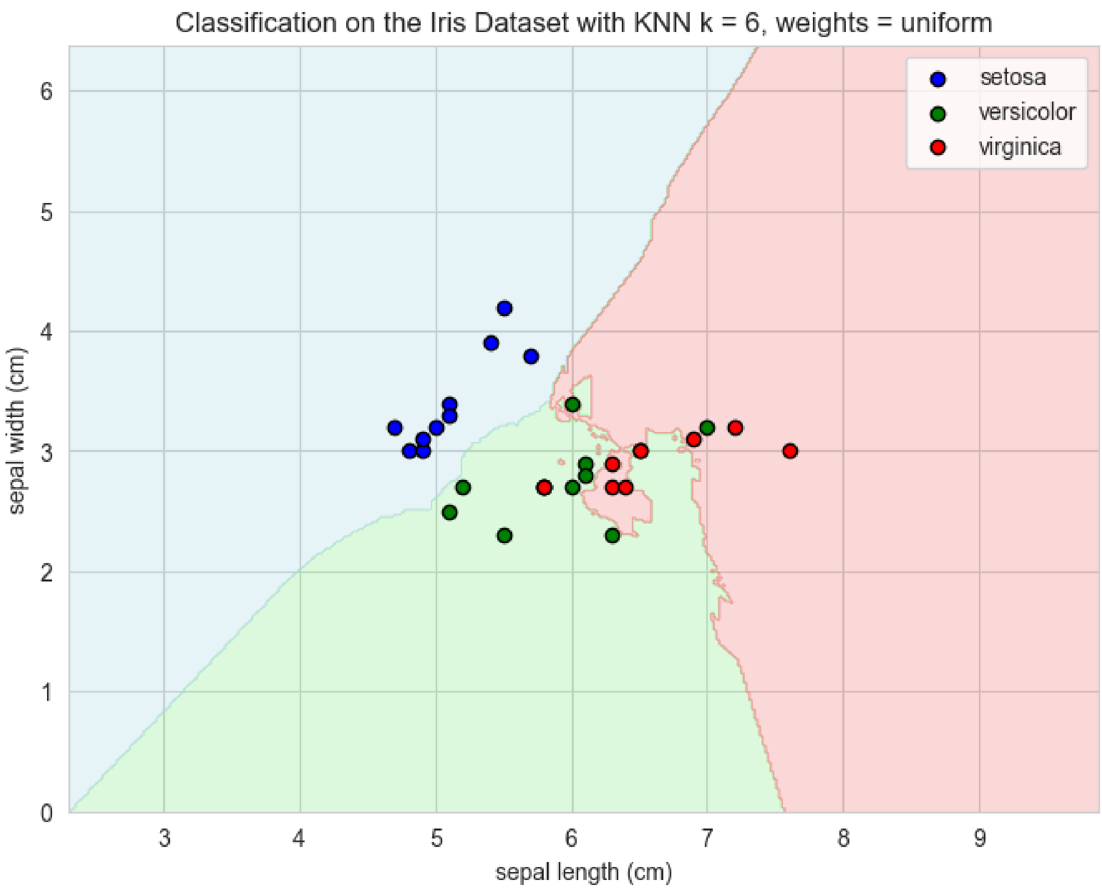

```
The accuracy of the KNN model with k = 4, w = "uniform" on the Iris dataset is
0.80
```



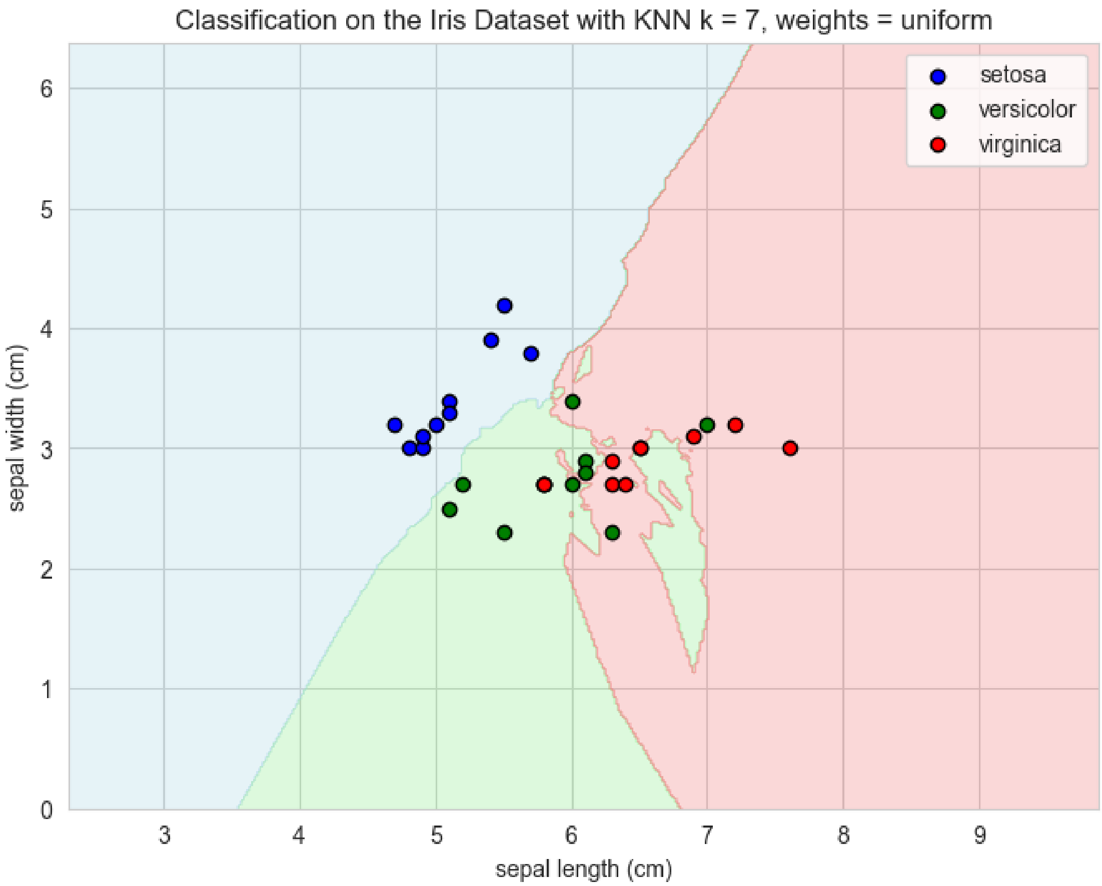

```
The accuracy of the KNN model with k = 5, w = "uniform" on the Iris dataset is
0.80
```



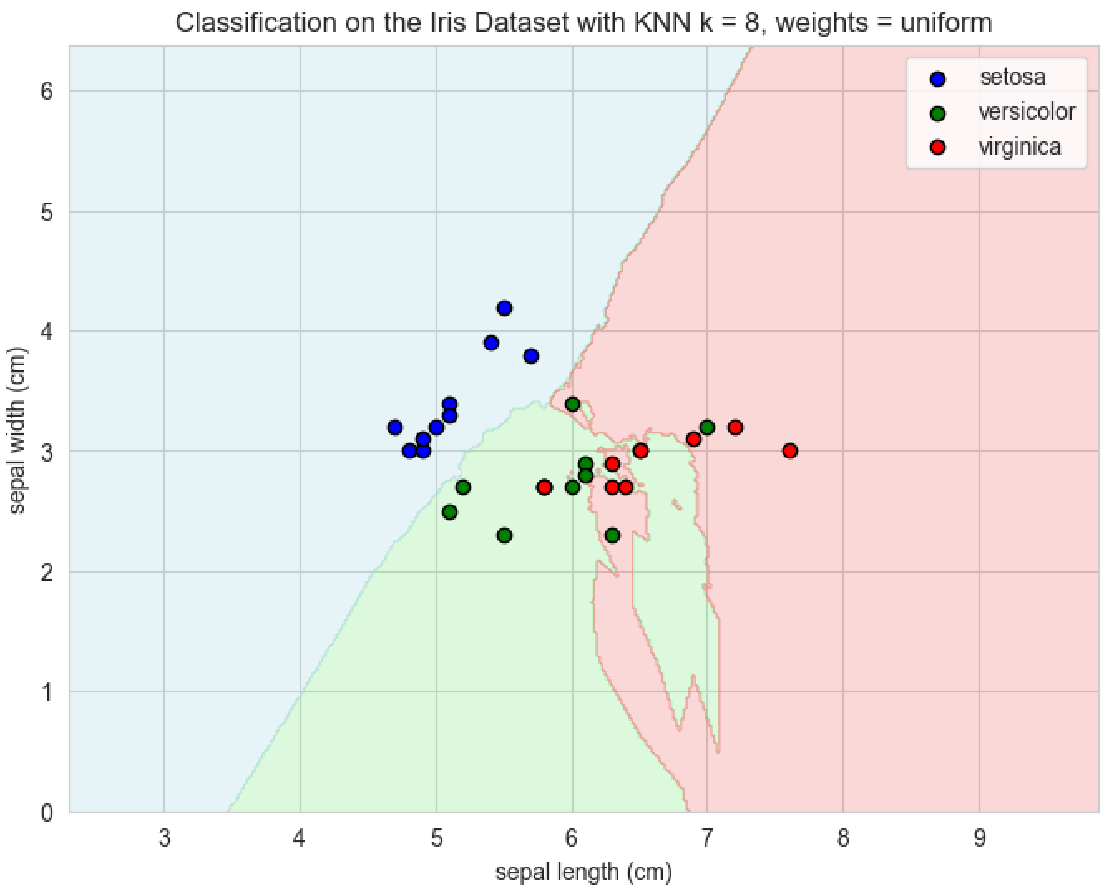

```
The accuracy of the KNN model with k = 6, w = "uniform" on the Iris dataset is
0.80
```



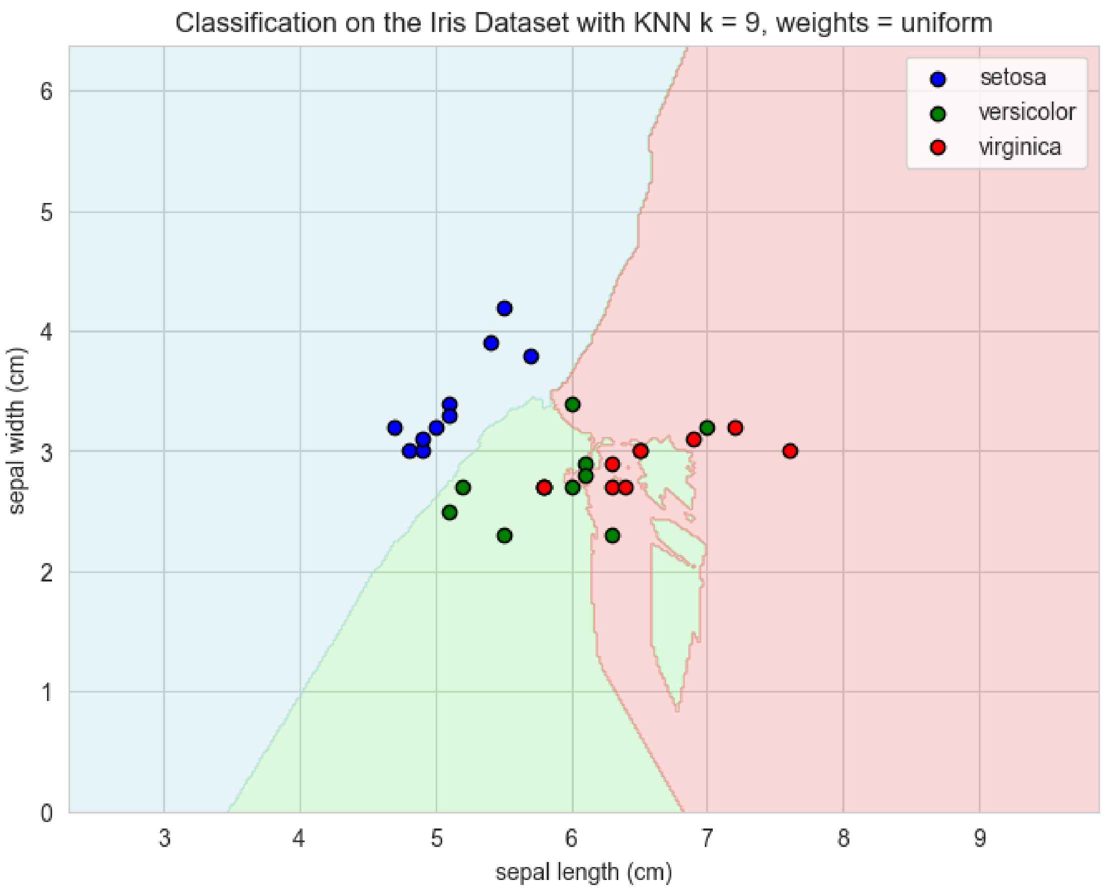

```
The accuracy of the KNN model with k = 7, w = "uniform" on the Iris dataset is
0.77
```



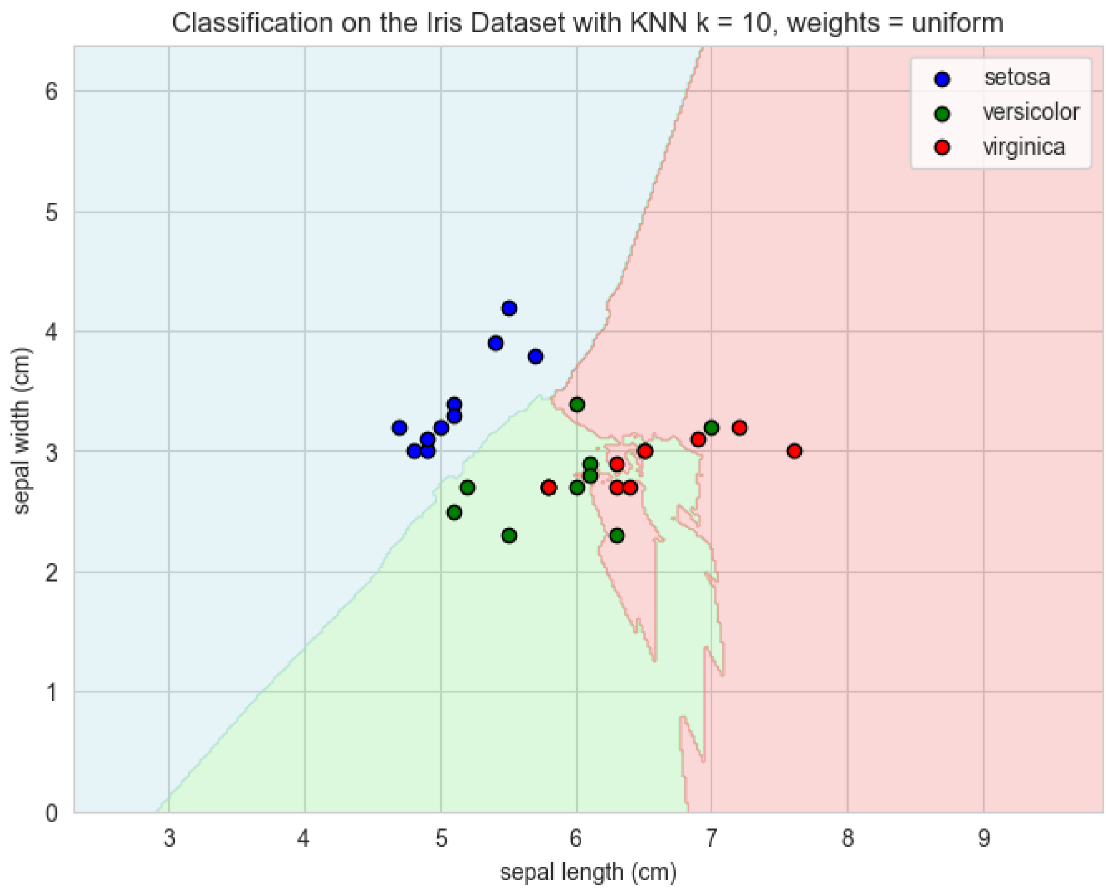

```
The accuracy of the KNN model with k = 8, w = "uniform" on the Iris dataset is
0.73
```



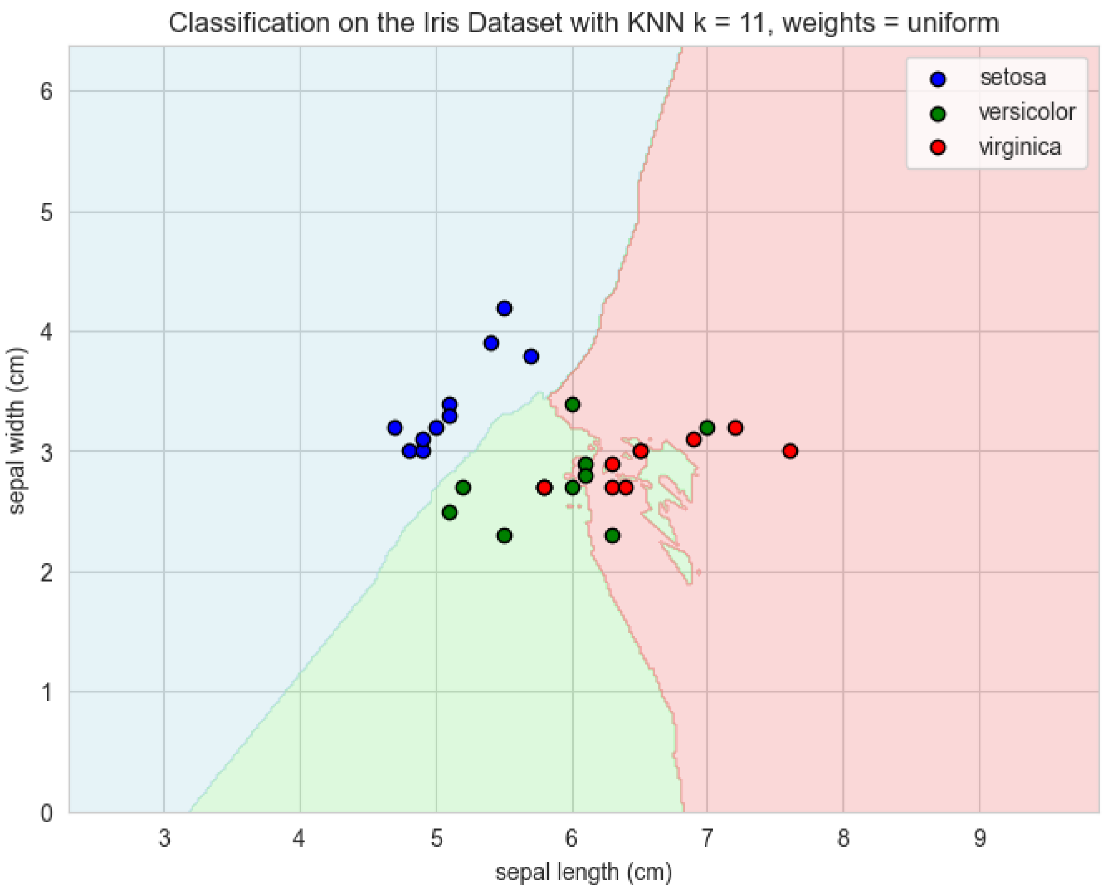

```
The accuracy of the KNN model with k = 9, w = "uniform" on the Iris dataset is
0.73
```



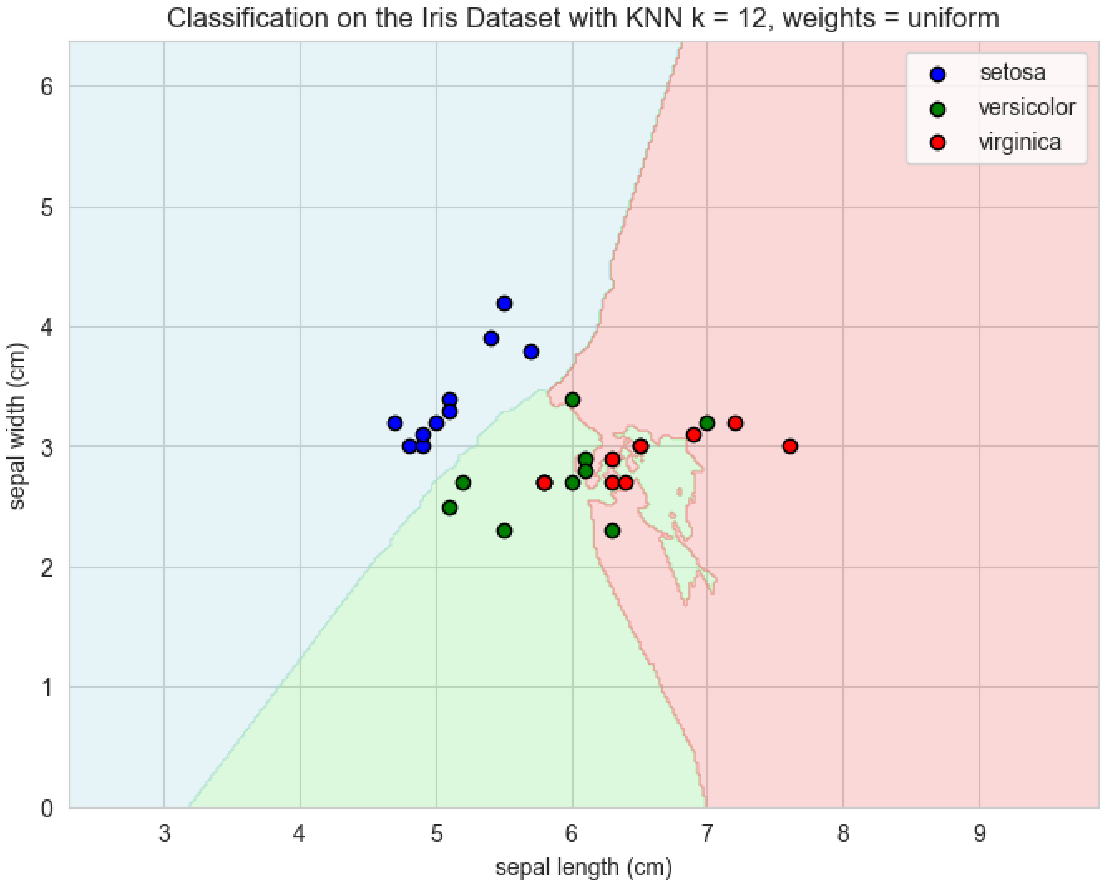
The accuracy of the KNN model with k = 10, w = "uniform" on the Iris dataset is 0.63



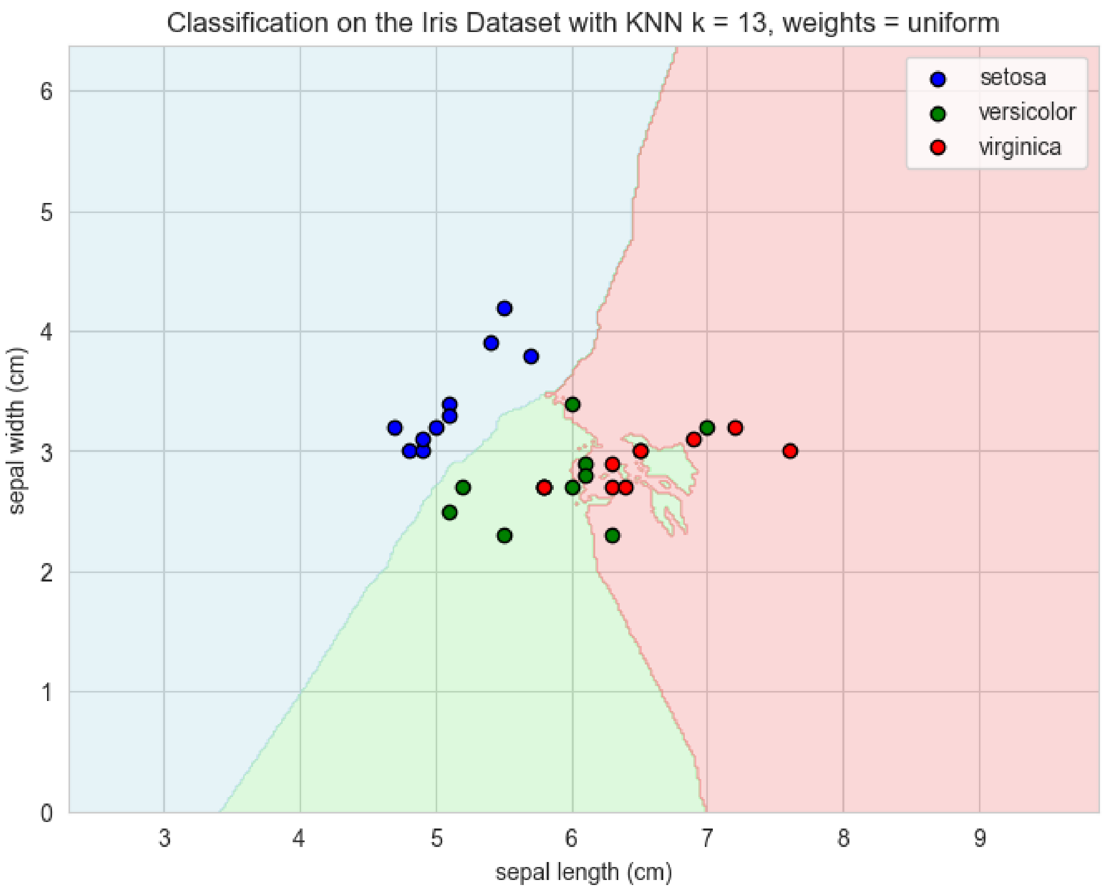
The accuracy of the KNN model with k = 11, w = "uniform" on the Iris dataset is 0.70



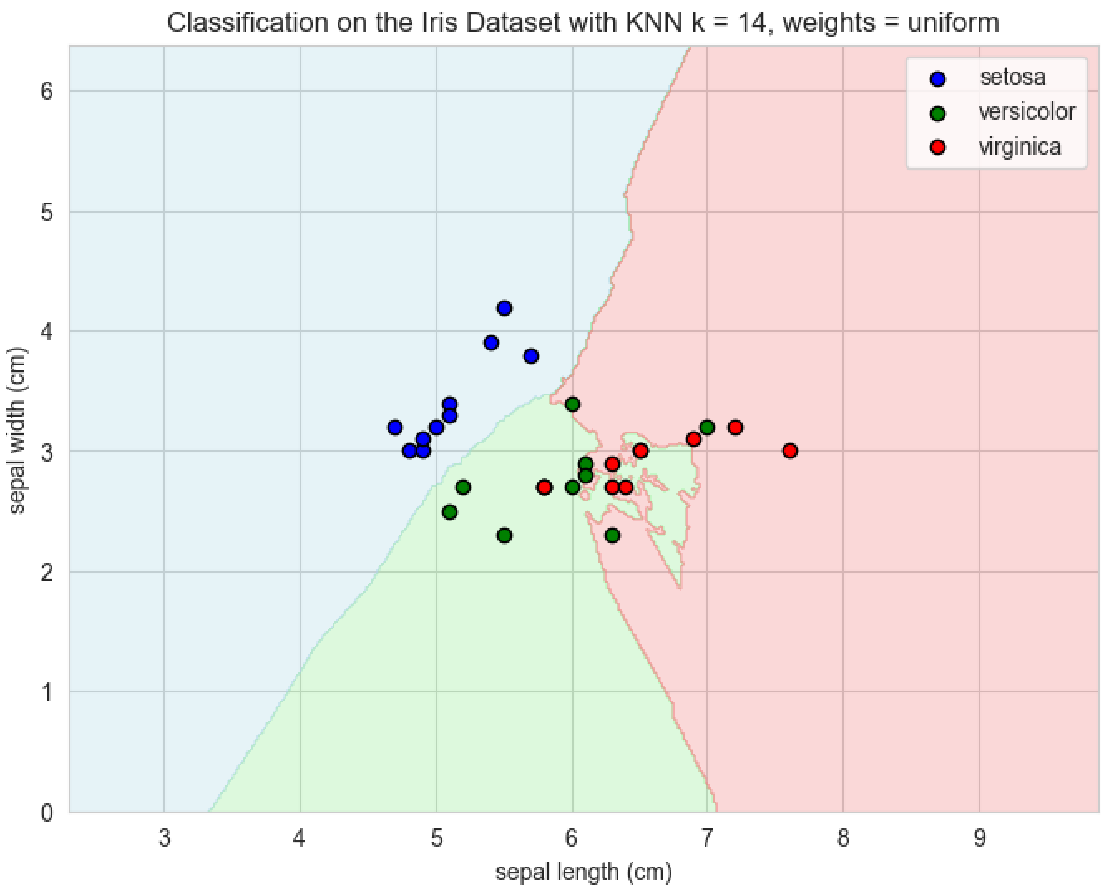

```
The accuracy of the KNN model with k = 12, w = "uniform" on the Iris dataset is
0.67
```



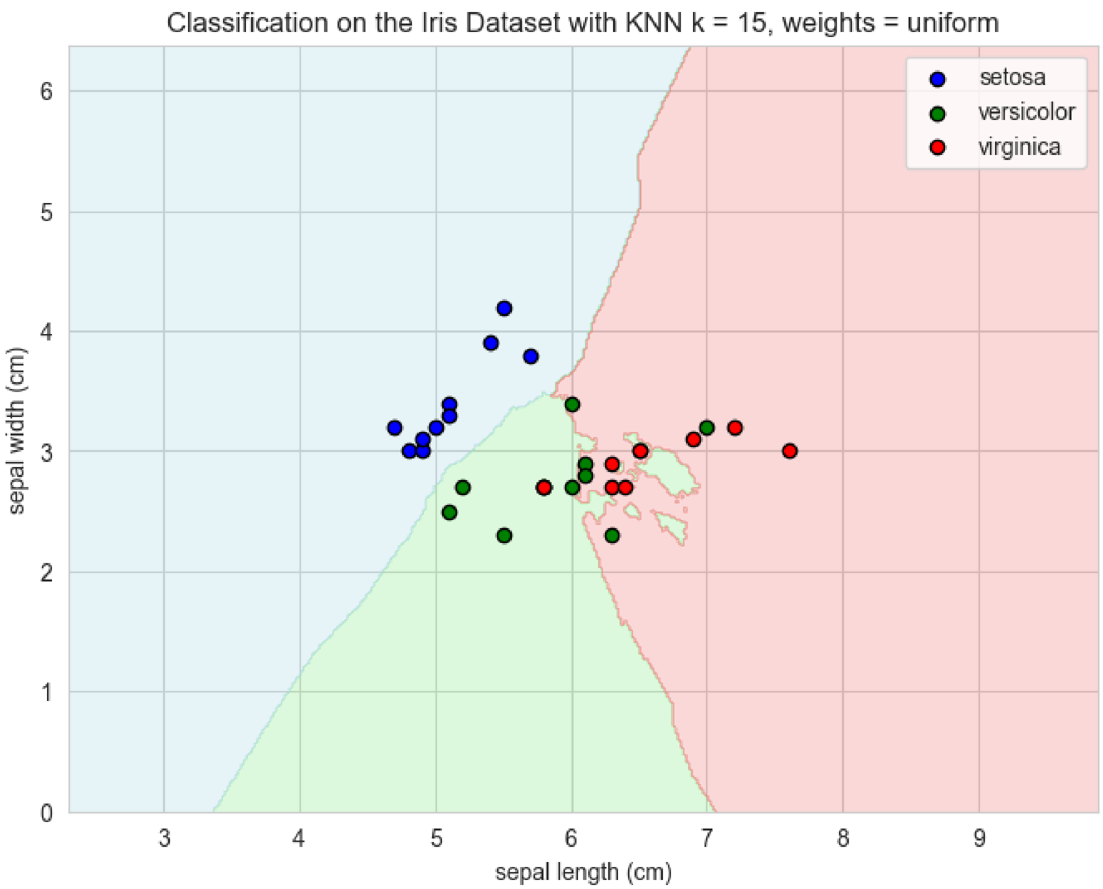
The accuracy of the KNN model with k = 13, w = "uniform" on the Iris dataset is 0.73




```
The accuracy of the KNN model with k = 14, w = "uniform" on the Iris dataset is
0.70
```




```
The accuracy of the KNN model with k = 15, w = "uniform" on the Iris dataset is
0.70
```



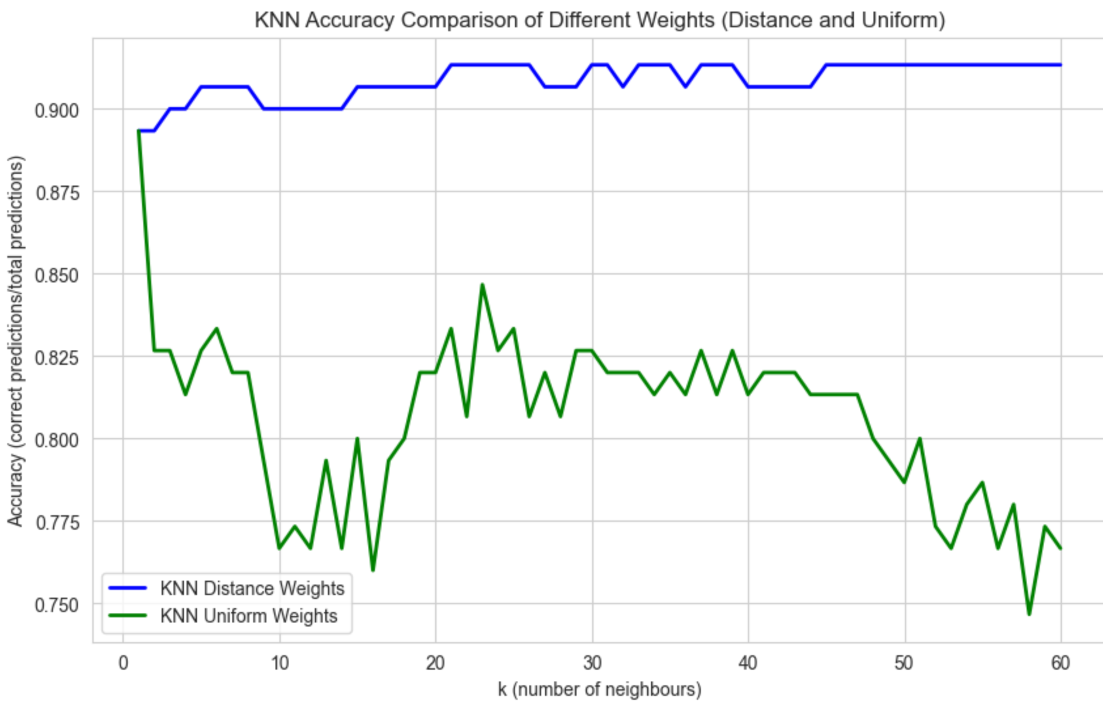

```
[0.7666666666666667, 0.8, 0.7666666666666667, 0.8, 0.8, 0.8, 0.7666666666666667,
0.7333333333333333, 0.7333333333333333, 0.6333333333333333, 0.7,
0.6666666666666666, 0.7333333333333333, 0.7, 0.7]
```

[115]:
```
accuracy_list_knn_distance = []
for i in range(1, 61):
    accuracy_list_knn_distance.append(knn_classifier(i, 'distance', plot=False))
accuracy_series_knn_distance = pd.Series(accuracy_list_knn_distance)
```

[116]:
```
accuracy_list_knn_uniform = []
for i in range(1, 61):
    accuracy_list_knn_uniform.append(knn_classifier(i, 'uniform', plot=False))
accuracy_series_knn_uniform = pd.Series(accuracy_list_knn_uniform)
```

[117]:
```
accuracy_series_knn_distance.index = range(1, len(accuracy_list_knn_distance) +␣
 ↪1)
accuracy_series_knn_uniform.index = range(1, len(accuracy_list_knn_uniform) + 1)

plt.figure(figsize=(10, 6))
```

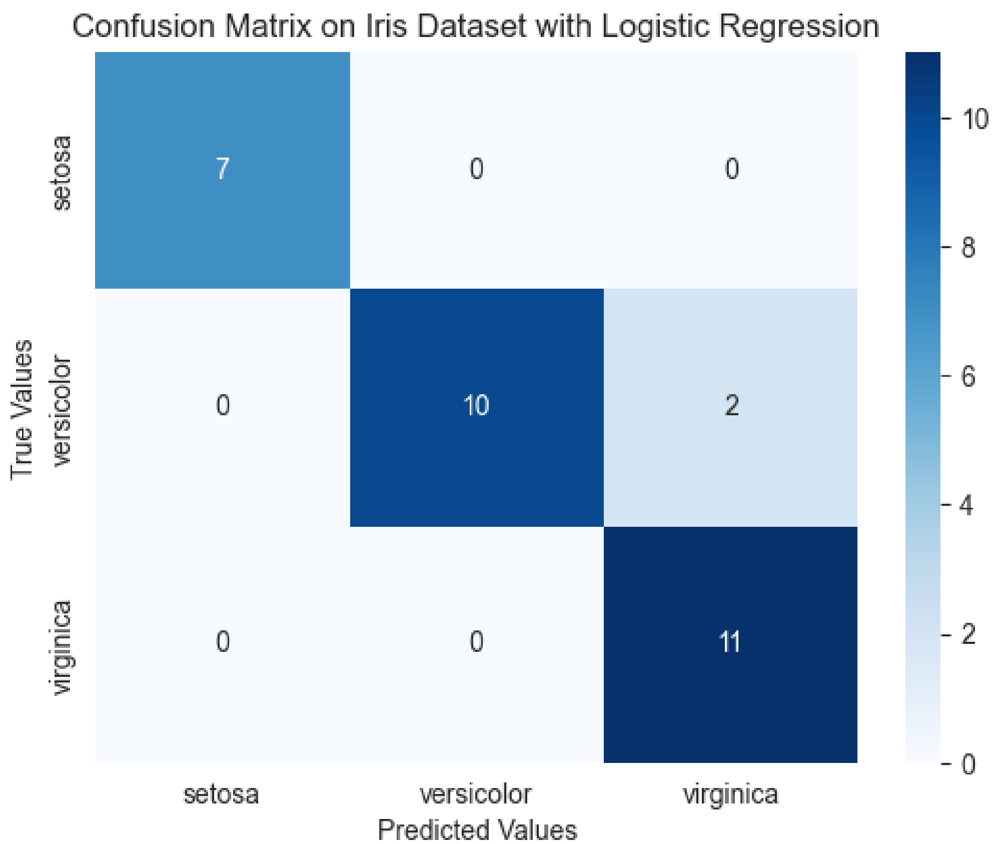
```
plt.plot(accuracy_series_knn_distance.index, accuracy_series_knn_distance,
         label='KNN Distance Weights', color='blue', linewidth=2)

plt.plot(accuracy_series_knn_uniform.index, accuracy_series_knn_uniform,
         label='KNN Uniform Weights', color='green', linewidth=2)

plt.xlabel('k (number of neighbours)')
plt.ylabel('Accuracy (correct predictions/total predictions)')
plt.title('KNN Accuracy Comparison of Different Weights (Distance and Uniform)')

plt.legend()

plt.show()
```



c. Compare the classification models for the iris data set that are generated by k-nearest neighbours (for the different settings from question b) and by logistic regression. Calculate confusion matrices for these models and discuss the performance of the various models.

[138]:
```
x_iris = iris.data
y_iris = iris.target

X_train, X_test, y_train, y_test = train_test_split(x_iris, y_iris, test_size=0.
 ↪2)
```

```
model_iris_logistic = LogisticRegression(max_iter=200)
model_iris_logistic.fit(X_train, y_train)
y_pred = model_iris_logistic.predict(X_test)

conf_matrix_logistic_regression = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix_logistic_regression, annot=True, fmt='d', cmap='Blues',␣
↪xticklabels=iris.target_names,
            yticklabels=iris.target_names)
plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Confusion Matrix on Iris Dataset with Logistic Regression')
plt.show()
accuracy_logistic_regression = accuracy_score(y_test, y_pred)
print(f'The accuracy of the logistic regression model on the Iris dataset is␣
↪{accuracy_logistic_regression:.2f}')
```




```
The accuracy of the logistic regression model on the Iris dataset is 0.93
```

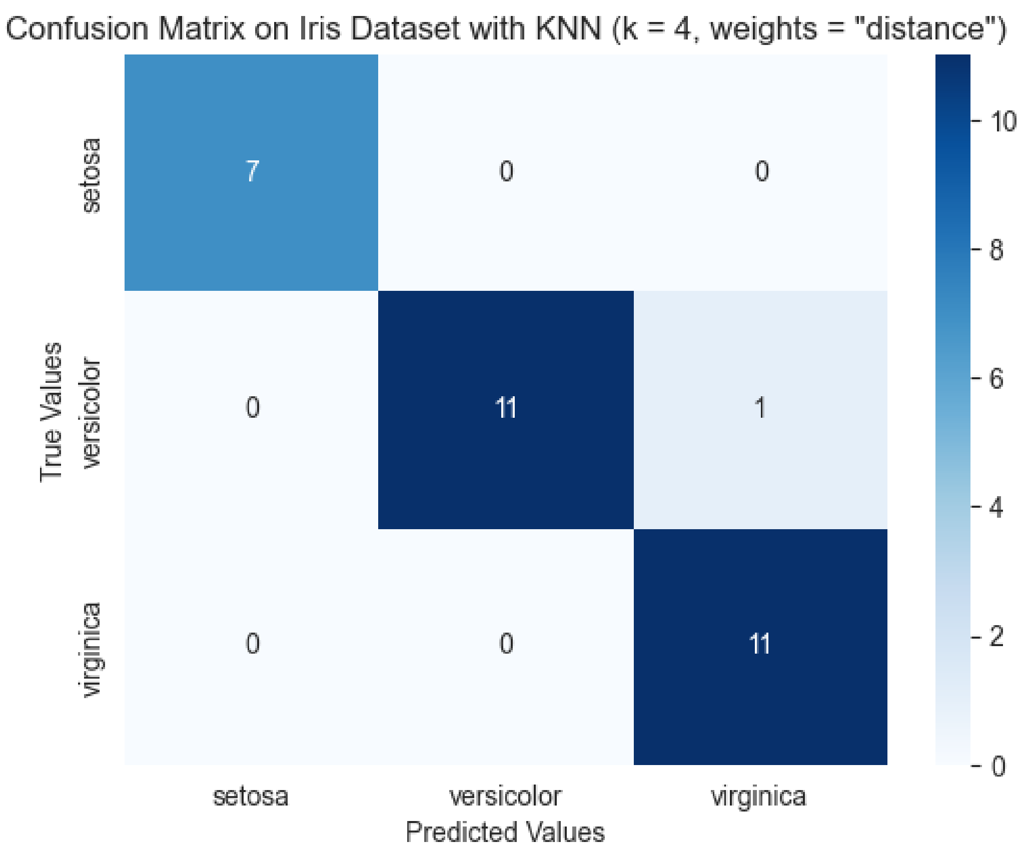
[139]:
```
cv_scores_logistic_regression = cross_val_score(model_iris_logistic, x_iris,␣
↪y_iris, cv=5)
```

```
print(f"Average accuracy of linear regression model with 5-fold cross␣
 ↪validation: {np.mean(cv_scores_logistic_regression):.2f}")
```

```
Average accuracy of linear regression model with 5-fold cross validation: 0.97
```

[142]:

```
model_iris_knn = KNeighborsClassifier(n_neighbors=4, weights='distance')
model_iris_knn.fit(X_train, y_train)
y_pred = model_iris_knn.predict(X_test)

conf_matrix_knn = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix_knn, annot=True, fmt='d', cmap='Blues',␣
 ↪xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted Values')
plt.ylabel('True Values')
plt.title('Confusion Matrix on Iris Dataset with KNN (k = 4, weights =␣
 ↪"distance")')
plt.show()

accuracy_knn = accuracy_score(y_test, y_pred)
print(f'The accuracy of the KNN model with k = 4, weights = "distance" on the␣
 ↪Iris dataset is {accuracy_knn:.2f}')
```



```
The accuracy of the KNN model with k = 4, weights = "distance" on the Iris
dataset is 0.97
```

[141]:
```
cv_scores_knn = cross_val_score(model_iris_knn, x_iris, y_iris, cv=5)
print(f"Average accuracy of KNN model with 5-fold cross validation: {np.
 ↪mean(cv_scores_knn):.2f}")
```

```
Average accuracy of KNN model with 5-fold cross validation: 0.97
```