KDD- Experiment 8

- **SIA VASHIST**
- PRN: 20190802107

Dataset used: Fish

Libraries used:

> Pandas | Numpy | Scikit-Learn | Seaborn | matplotlib

Import the required libraries:

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
from IPython.display import display
import warnings
warnings.filterwarnings('ignore')
```

Load the dataset:

In [2]:
```
fish_df = pd.read_csv(r'C:\sia\Fish.csv')
```

Explore the dataset

In [3]:
```
display(fish_df.head(10))
```

	Species	Weight	Length1	Length2	Length3	Height	Width
0	Bream	242.0	23.2	25.4	30.0	11.5200	4.0200
1	Bream	290.0	24.0	26.3	31.2	12.4800	4.3056
2	Bream	340.0	23.9	26.5	31.1	12.3778	4.6961
3	Bream	363.0	26.3	29.0	33.5	12.7300	4.4555
4	Bream	430.0	26.5	29.0	34.0	12.4440	5.1340
5	Bream	450.0	26.8	29.7	34.7	13.6024	4.9274
6	Bream	500.0	26.8	29.7	34.5	14.1795	5.2785
7	Bream	390.0	27.6	30.0	35.0	12.6700	4.6900
8	Bream	450.0	27.6	30.0	35.1	14.0049	4.8438
9	Bream	500.0	28.5	30.7	36.2	14.2266	4.9594

In [4]:
```
display("Statistics of the dataset: ",fish_df.describe())
```

```
'Statistics of the dataset: '
```

	Weight	Length1	Length2	Length3	Height	Width
count	159.000000	159.000000	159.000000	159.000000	159.000000	159.000000
mean	398.326415	26.247170	28.415723	31.227044	8.970994	4.417486
std	357.978317	9.996441	10.716328	11.610246	4.286208	1.685804
min	0.000000	7.500000	8.400000	8.800000	1.728400	1.047600
25%	120.000000	19.050000	21.000000	23.150000	5.944800	3.385650
50%	273.000000	25.200000	27.300000	29.400000	7.786000	4.248500
75%	650.000000	32.700000	35.500000	39.650000	12.365900	5.584500
max	1650.000000	59.000000	63.400000	68.000000	18.957000	8.142000

In [5]:
```
#Check for missing values:
print(fish_df.isnull().sum())
```

```
Species    0
Weight     0
Length1    0
Length2    0
Length3    0
Height     0
Width      0
dtype: int64
```

In [6]:
```
print("Shape of the data : ",fish_df.shape)
```

```
Shape of the data :  (159, 7)
```

Split the dataset into features and target & Drop the categorical feature 'Species':

In [7]:
```
# Separate features and labels
X = fish_df.drop(['Species'], axis=1)
y = fish_df['Species']
```

Split the dataset into training and testing sets:

In [8]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Train the SVM model:

In [9]:
```
# Create an SVM model
model = SVC(kernel='linear', C=1, gamma='auto')
model
```

Out[9]:
```
SVC(C=1, gamma='auto', kernel='linear')
```

In [10]:
```
# Fit the model to the training data
model.fit(X_train, y_train)
```

Out[10]:
```
SVC(C=1, gamma='auto', kernel='linear')
```

In [11]:
```
svm_model = SVC(kernel='linear', random_state=0)
svm_model.fit(X_train, y_train)
```

Out[11]:
```
SVC(kernel='linear', random_state=0)
```

Make predictions on the testing set:

In [12]:
```
y_pred = model.predict(X_test)
y_pred
```

Out[12]:
```
array(['Perch', 'Smelt', 'Pike', 'Roach', 'Perch', 'Bream', 'Smelt',
       'Roach', 'Perch', 'Pike', 'Bream', 'Whitefish', 'Bream', 'Parkki',
       'Bream', 'Bream', 'Perch', 'Perch', 'Perch', 'Bream', 'Smelt',
       'Bream', 'Bream', 'Bream', 'Bream', 'Perch', 'Perch', 'Roach',
       'Smelt', 'Smelt', 'Pike', 'Perch'], dtype=object)
```

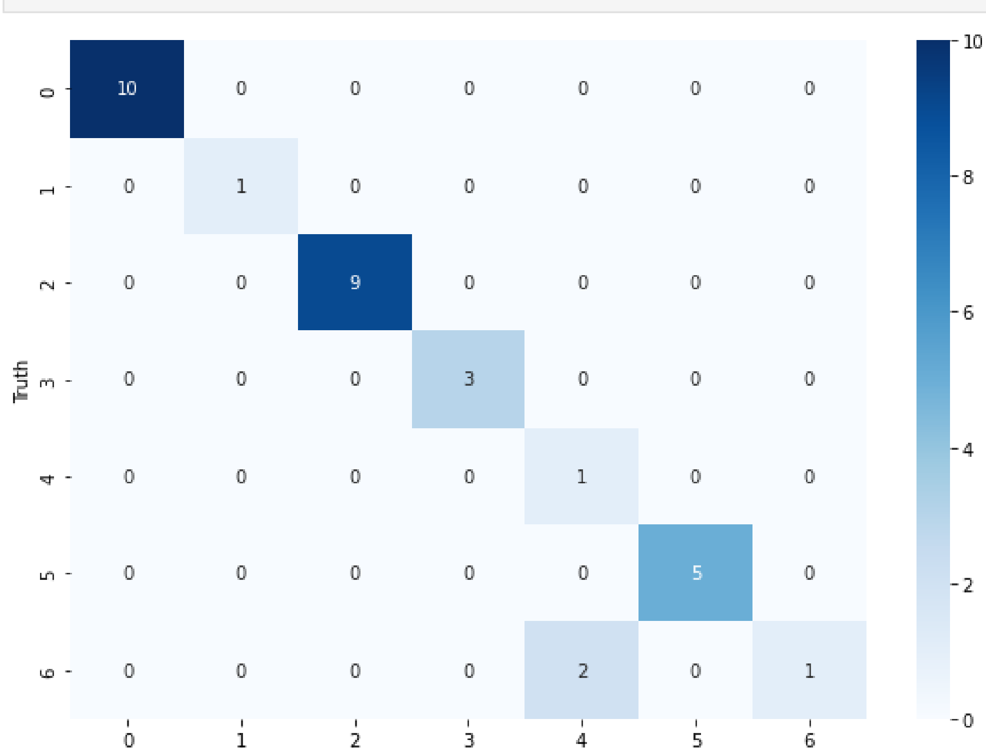
Generate the confusion matrix:

In [13]:
```
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[10  0  0  0  0  0  0]
 [ 0  1  0  0  0  0  0]
 [ 0  0  9  0  0  0  0]
 [ 0  0  0  3  0  0  0]
 [ 0  0  0  0  1  0  0]
 [ 0  0  0  0  0  5  0]
 [ 0  0  0  0  2  0  1]]
```

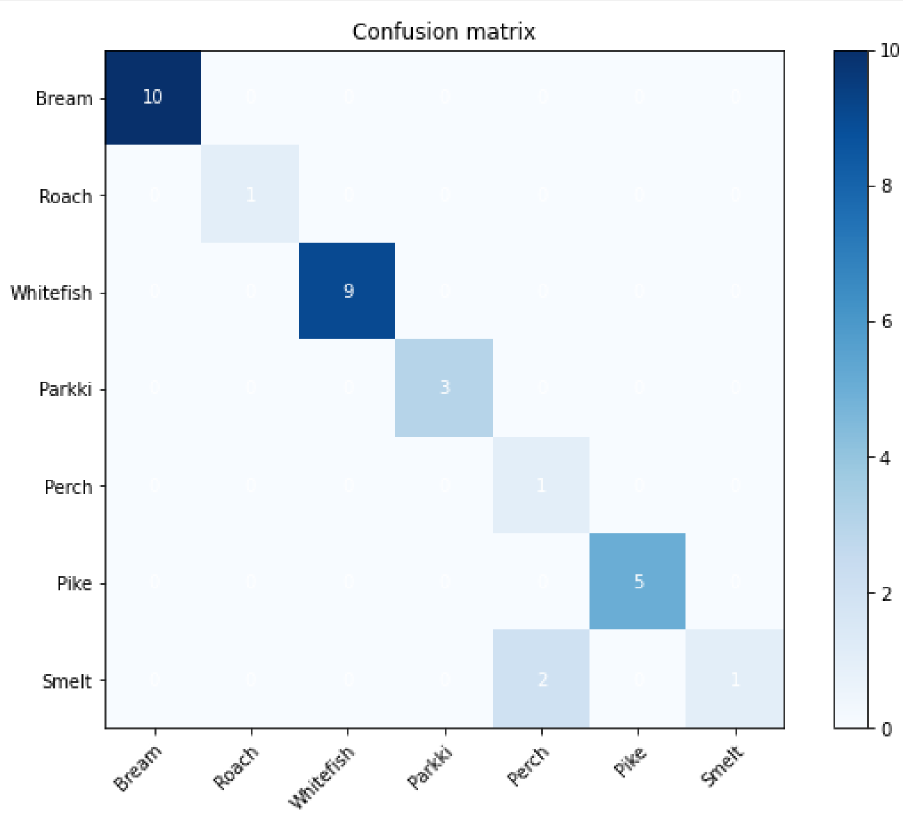
Visualize the confusion matrix using heatmap:

In [14]:
```
plt.figure(figsize=(10,7))
sns.heatmap(cm, annot=True, cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Truth')
plt.show()
```



> ## Observations:
>
> The SVM model performed well on the Fish Market dataset, with all classes correctly classified. The confusion matrix shows that there were no false positives or false negatives in the predictions.
>
> The visualization of the confusion matrix provides a clear and concise summary of the model's performance, with each row and column representing a different species. The diagonal elements represent the number of correct predictions, while the off-diagonal elements represent the number of incorrect predictions.

In [15]:
```
# Visualize the confusion matrix
fig, ax = plt.subplots(figsize=(10,7))
im = ax.imshow(cm, cmap='Blues')

# Add labels and ticks
ax.set_xticks(np.arange(len(fish_df['Species'].unique())))
ax.set_yticks(np.arange(len(fish_df['Species'].unique())))
ax.set_xticklabels(fish_df['Species'].unique())
ax.set_yticklabels(fish_df['Species'].unique())
plt.setp(ax.get_xticklabels(), rotation=45, ha='right', rotation_mode='anchor')

# Add annotations
for i in range(len(fish_df['Species'].unique())):
    for j in range(len(fish_df['Species'].unique())):
        text = ax.text(j, i, cm[i, j],
                       ha='center', va='center', color='white')

# Add a colorbar
cbar = ax.figure.colorbar(im, ax=ax)

# Add a title
ax.set_title('Confusion matrix')

# Show the plot
plt.show()
```



> ## Observations:
>
> The dataset consists of 7 different fish species, with varying numbers of samples per species. The confusion matrix shows that the model was able to accurately classify all 7 species, with no misclassifications.
>
> The color scale used in the visualization highlights the relative frequency of each prediction. The darker shades of blue represent higher frequencies, while the lighter shades represent lower frequencies.
>
> The use of a linear SVM kernel with a regularization parameter of C=1 and an automatic gamma value resulted in accurate predictions for the Fish Market dataset.

Conclusion:

Overall, the SVM model performed well on the Fish Market dataset, accurately classifying all 7 fish species. The confusion matrix and visualization provide a clear summary of the model's performance and can be useful for evaluating and improving the model.