```
In [2]: import tensorflow as tf
        # Download pre-trained InceptionV3 model
        inceptionv3 = tf.keras.applications.InceptionV3(weights='imagenet')
In [3]: | # Load the pre-trained inceptionv3 model
        import tensorflow as tf
        # Load pre-trained InceptionV3 model without top classification layer
        inceptionv3 = tf.keras.applications.InceptionV3(weights='imagenet', include_top=False)
        # Remove the last layer from the model
        inceptionv3 = tf.keras.Model(inputs=inceptionv3.input, outputs=inceptionv3.layers[-1].output)
In [4]: |inceptionv3
Out[4]: <keras.engine.functional.Functional at 0x1c28c713430>
In [5]: | # Define the input size of the VGG16 model
        input size = (224, 224)
        # Specify the path to the PASCAL VOC 2007 dataset
        data = 'C:\\Users\\Admin\\Downloads\\VOCdevkit\\VOC2007'
In [ ]:
```

```
In [6]: import os
    import numpy as np
    from tensorflow.keras.applications.inception_v3 import InceptionV3, preprocess_input
    from tensorflow.keras.preprocessing.image import load_img, img_to_array

In [7]: # Specify the path to the training image folder
    train_image_folder = os.path.join(data, 'JPEGImages')
    train_image_folder

Out[7]: 'C:\\Users\\Admin\\Downloads\\VOCdevkit\\VOC2007\\JPEGImages'
In [8]: # Get the list of image filenames in the training set
    train_image_filenames = os.listdir(train_image_folder)
```

```
In [9]: # Load and preprocess the images in the PASCAL VOC 2007 training set
def preprocess_image(image_path):
    img = load_img(image_path, target_size=input_size)
    img = img_to_array(img)
    img = preprocess_input(img)
    return img

# Process each image in the training set and extract features
training_features = []
for filename in train_image_filenames:
    image_path = os.path.join(train_image_folder, filename)
    img = preprocess_image(image_path)
    features = inceptionv3.predict(tf.expand_dims(img, axis=0))
    training_features.append(features)

# Concatenate the extracted features into a single array
training_features = tf.concat(training_features, axis=0)
```

```
1/1 [======= ] - 1s 1s/step
1/1 [======= ] - 0s 81ms/step
1/1 [======= ] - 0s 92ms/step
1/1 [======= ] - 0s 82ms/step
1/1 [======= ] - 0s 81ms/step
1/1 [======= ] - 0s 103ms/step
1/1 [======= ] - 0s 62ms/step
1/1 [======= ] - 0s 83ms/step
1/1 [======= ] - 0s 76ms/step
1/1 [======= ] - 0s 78ms/step
1/1 [======= ] - 0s 99ms/step
1/1 [======= ] - 0s 82ms/step
1/1 [======= ] - 0s 81ms/step
1/1 [======= ] - 0s 61ms/step
1/1 [======= ] - 0s 61ms/step
1/1 [======= ] - 0s 60ms/step
1/1 [======= ] - 0s 62ms/step
```

```
In [10]: # Save the features to a NumPy array
         np.save('features.npy', training_features)
In [11]: # Specify the path to the annotations folder
         annotation_folder = os.path.join(data, 'Annotations')
In [12]: # Get the list of XML annotation filenames
         annotation filenames = os.listdir(annotation folder)
In [13]: # Process each XML annotation file and extract the label names
         import xml.etree.ElementTree as ET
         label names = []
         for filename in annotation filenames:
             annotation_path = os.path.join(annotation_folder, filename)
             tree = ET.parse(annotation path)
             root = tree.getroot()
             for obj in root.findall('object'):
                 class name = obj.find('name').text
                 label_names.append(class_name)
         # Get unique label names
         unique label names = list(set(label names))
```

```
In [24]: # Create a dictionary to map unique label names to label indices
         class_to_label = {label_name: label_index for label_index, label_name in enumerate(unique_label_names)}
         # Process each XML annotation file again and extract the labels
         labels = []
         labels_bin = []
         for filename in annotation filenames:
             labels=[]
             annotation_path = os.path.join(annotation_folder, filename)
             tree = ET.parse(annotation path)
             root = tree.getroot()
             for obj in root.findall('object'):
                 class name = obj.find('name').text
                 label = class_to_label[class_name]
                 labels.append(label)
             #test.append(labels)
             labels bin.append(labels)
         print(labels_bin)
In [14]: | from sklearn.svm import SVC
         from sklearn.model selection import train test split
         from sklearn.metrics import accuracy score, confusion matrix
         import numpy as np
         # Load the features and labels
         features = np.load('features.npy')
         labels = np.load('labels.npy')
         # Split the data into training and validation sets
         X train, X val, y train, y val = train test split(features, labels, test size=0.2, random state=42)
```

```
In []:
In [15]: len(X_train), len(X_val), len(y_train), len(y_val)
Out[15]: (3961, 991, 3961, 991)
```

```
In [34]:
         # Get the number of classes from the training labels
         num_classes = len(np.unique(y_train_2d))
         # Create a list to store the SVM classifiers
         svm_classifiers = []
         # Train binary SVM classifiers for each class
         for class_label in range(num_classes):
             # Create an SVM classifier object
             svm_classifier = svm.SVC(kernel='linear')
             # Prepare binary labels for the current class
             binary_train_labels = (y_train_2d == class_label)
             binary_val_labels = (y_val_2d == class_label)
             # Train the SVM classifier
             svm_classifier.fit(X_train_2d, binary_train_labels)
             # Predict on the validation set
             val predictions = svm classifier.predict(X val 2d)
             # Calculate accuracy
             accuracy = accuracy score(binary val labels, val predictions)
             print(f"Accuracy for class {class label}: {accuracy}")
             # Store the trained classifier
             svm classifiers.append(svm classifier)
```

```
Accuracy for class 0: 0.9525731584258325
Accuracy for class 1: 0.9919273461150353
Accuracy for class 2: 0.9576185671039354
Accuracy for class 3: 0.941473259334006
Accuracy for class 4: 0.9818365287588294
Accuracy for class 5: 0.9757820383451059
Accuracy for class 6: 0.9162462159434914
Accuracy for class 7: 0.9626639757820383
Accuracy for class 8: 0.9828456104944501
Accuracy for class 9: 0.9889001009081736
Accuracy for class 10: 0.992936427850656
Accuracy for class 11: 0.9727547931382442
Accuracy for class 12: 0.987891019172553
Accuracy for class 13: 0.9889001009081736
Accuracy for class 14: 0.9899091826437941
Accuracy for class 15: 0.887991927346115
Accuracy for class 16: 0.987891019172553
Accuracy for class 17: 0.9899091826437941
Accuracy for class 18: 0.9828456104944501
Accuracy for class 19: 0.9868819374369324
```

```
In [35]:
# Calculate confusion matrix
val_predictions_all = []
for classifier in svm_classifiers:
    val_predictions_all.append(classifier.decision_function(X_val_2d))
val_predictions_all = np.column_stack(val_predictions_all)
confusion_matrix = np.argmax(val_predictions_all, axis=1)

# Print confusion matrix
print("Confusion Matrix:")
print(confusion_matrix)
```

Confusion Matrix:

| In []: | |
|---------|--|
| | |