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1 Question 1

Dataset URL: https://drive.google.com/drive/folders/1iPzZ5Vlg7XF5KPrxStY6o09zOIf1g54C?usp=sharing

[1]:
```
%%capture

!pip install numpy
!pip install pandas
!pip install seaborn
!pip install scikit-learn
!pip install opendatasets
!pip install kaggle
!pip install tensorflow
!pip install pillow
```

1.1 Question 1.1:

[2]:
```
# importing required libraries
import os
import pathlib
import random
import PIL
import PIL.Image
import numpy as np
import tensorflow as tf
```

[3]:
```
# Declaring image properties
import matplotlib.pyplot as plt

plt.rc('font', size=12)
plt.rc('axes', labelsize=14, titlesize=14)
plt.rc('legend', fontsize=12)
plt.rc('xtick', labelsize=10)
plt.rc('ytick', labelsize=10)
```

[4]:
```
# importing warnings package and filtering the warnings
import warnings
```

```
warnings.filterwarnings('ignore')
```

[5]:
```
# setting random seed for entire program
np.random.seed(22)
```

1.1.1 Take at least 100 images per class with at least 3 classes using your phone/camera.

[6]:
```
train_data_dir = pathlib.Path('Dataset/train')
```

[7]:
```
train_image_count = len(list(train_data_dir.glob('*/*.jpg')))
print(train_image_count)
```

```
900
```

[8]:
```
test_data_dir = pathlib.Path('Dataset/test')
test_image_count = len(list(test_data_dir.glob('*/*.jpg')))
print(test_image_count)
```

```
300
```

1.1.2 Display 5 examples from each class.

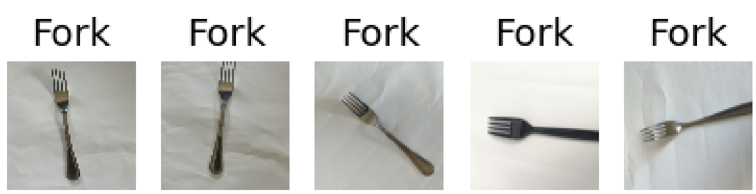
[9]:
```
def print_images_per_class(data_dir, class_name):
    data = list(data_dir.glob(class_name+'/*'))
    random_numbers = random.sample(range(1, len(data)), 5)

    plt.figure(figsize=(5, 5))

    for index_i, number in enumerate(random_numbers):
        ax = plt.subplot(1, 5, index_i+1)
        plt.imshow(PIL.Image.open(str(data[number])))
        plt.title(class_name)
        plt.axis("off")
```

[10]:
```
print("Images in training dataset")
print_images_per_class(train_data_dir, 'Cup')
print_images_per_class(train_data_dir, 'Knife')
print_images_per_class(train_data_dir, 'Fork')
print_images_per_class(train_data_dir, 'Spoon')
```

```
Images in training dataset
```



[11]:
```
print("Images in testing dataset")
print_images_per_class(test_data_dir, 'Cup')
print_images_per_class(test_data_dir, 'Knife')
print_images_per_class(test_data_dir, 'Fork')
print_images_per_class(test_data_dir, 'Spoon')
```

```
Images in testing dataset
```

1.2 Question 1.2

1.2.1 Split the images into a training set, a validation set, and a test set.

Out of 100% data, we have kept 60% training data, 15% validation data and 25% testing data.

[12]:
```
batch_size = 32
img_height = 224
img_width = 224
```

[13]:
```
# Create the training dataset
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
```

```
    train_data_dir,
    validation_split=0.2,
    subset="training",
    seed=42,
    image_size=(img_height, img_width),
    batch_size=batch_size,
    shuffle=True,
)
```

```
Found 900 files belonging to 4 classes.
Using 720 files for training.
```

[14]:
```
# Create the validation dataset
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    train_data_dir,
    validation_split=0.2,
    subset="validation",
    seed=42,
    image_size=(img_height, img_width),
    batch_size=batch_size,
    shuffle=True,
)
```

```
Found 900 files belonging to 4 classes.
Using 180 files for validation.
```

[15]:
```
# Create the test dataset
test_ds = tf.keras.utils.image_dataset_from_directory(
    test_data_dir,
    validation_split=None,
    subset=None,
    seed=42,
    image_size=(img_height, img_width),
    batch_size=batch_size,
    shuffle=True,
)
```

```
Found 300 files belonging to 4 classes.
```

[16]:
```
class_names = train_ds.class_names
n_classes = len(class_names)
print(class_names)
```

```
['Cup', 'Fork', 'Knife', 'Spoon']
```

1.3 Question 1.3

1.3.1 Build the input pipeline, including the appropriate preprocessing operations, and add data augmentation.

[17]:
```
augmentation_pipeline = tf.keras.Sequential([
    tf.keras.layers.Resizing(height=180, width=180, crop_to_aspect_ratio=True),
    tf.keras.layers.experimental.preprocessing.RandomZoom(0.1),
    tf.keras.layers.experimental.preprocessing.RandomTranslation(0.1, 0.1),
    tf.keras.layers.experimental.preprocessing.RandomRotation(0.1),
    tf.keras.layers.experimental.preprocessing.
 ↪RandomFlip("horizontal_and_vertical"),
])
```

[18]:
```
# Apply data augmentation to the training dataset
train_ds = train_ds.map(lambda x, y: (augmentation_pipeline(x), y))
val_ds = val_ds.map(lambda x, y: (augmentation_pipeline(x), y))
test_ds = test_ds.map(lambda x, y: (augmentation_pipeline(x), y))

# Prefetch the dataset for improved performance
train_ds = train_ds.prefetch(buffer_size=tf.data.AUTOTUNE)
val_ds = val_ds.prefetch(buffer_size=tf.data.AUTOTUNE)
test_ds = test_ds.prefetch(buffer_size=tf.data.AUTOTUNE)
```

[19]:
```
plt.figure(figsize=(5, 5))
for images, labels in train_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")
```

[20]:
```
plt.figure(figsize=(5, 5))
for images, labels in val_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")
```

[21]:
```
plt.figure(figsize=(5, 5))
for images, labels in test_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"))
        plt.title(class_names[labels[i]])
        plt.axis("off")
```

1.4 Question 1.4

Note: Professor had asked us to explore the concept of "Pre-trained models for transfer learning" during lecture 23.

1.4.1 Fine-tune a pretrained model of your choice on this dataset (the one you created in part 3).

[22]:
```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
np.random.seed(42)
```

If you want to build an image classifier but you do not have enough training data, then it is often a good idea to reuse the lower layers of a pretrained model (include_top=False).

[23]:
```
base_model = tf.keras.applications.xception.Xception(weights="imagenet",␣
↪include_top=False)
avg = tf.keras.layers.GlobalAveragePooling2D()(base_model.output)
output = tf.keras.layers.Dense(n_classes, activation="softmax")(avg)
model = tf.keras.Model(inputs=base_model.input, outputs=output)
```

It's usually a good idea to freeze the weights of the pretrained layers.

[24]:
```
for layer in base_model.layers:
    layer.trainable = False
```

Here, we are using adam optimizer with learning rate 1e-2.

[25]:
```
optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)
model.compile(loss="sparse_categorical_crossentropy", optimizer=optimizer,␣
 ↪metrics=["accuracy"])
history = model.fit(train_ds, validation_data=val_ds, epochs=3)
```

```
Epoch 1/3
23/23 [==============================] - 27s 1s/step - loss: 89.0001 - accuracy:
0.3583 - val_loss: 20.1531 - val_accuracy: 0.4278
Epoch 2/3
23/23 [==============================] - 27s 1s/step - loss: 19.1552 - accuracy:
0.5083 - val_loss: 28.3133 - val_accuracy: 0.4611
Epoch 3/3
23/23 [==============================] - 27s 1s/step - loss: 13.0486 - accuracy:
0.5931 - val_loss: 9.1614 - val_accuracy: 0.6444
```

After training the model for a few epochs, its validation accuracy reached about 65% (for this dataset). This means that the top layers are now pretty well trained, so we are ready to unfreeze all the layers (or you could try unfreezing just the top ones) and continue training.

[26]:
```
for layer in base_model.layers[56:]:
    layer.trainable = True

optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)
model.compile(loss="sparse_categorical_crossentropy", optimizer=optimizer,␣
 ↪metrics=["accuracy"])
history = model.fit(train_ds, validation_data=val_ds, epochs=20)
```

```
Epoch 1/20
23/23 [==============================] - 58s 2s/step - loss: 1.4936 - accuracy:
0.4403 - val_loss: 165.1978 - val_accuracy: 0.2944
Epoch 2/20
23/23 [==============================] - 52s 2s/step - loss: 0.9660 - accuracy:
0.5611 - val_loss: 946.9922 - val_accuracy: 0.2611
Epoch 3/20
23/23 [==============================] - 52s 2s/step - loss: 0.7518 - accuracy:
0.6958 - val_loss: 114.8772 - val_accuracy: 0.3167
Epoch 4/20
23/23 [==============================] - 52s 2s/step - loss: 0.6370 - accuracy:
0.7083 - val_loss: 29.6834 - val_accuracy: 0.2056
Epoch 5/20
23/23 [==============================] - 52s 2s/step - loss: 0.6070 - accuracy:
0.7514 - val_loss: 8.2851 - val_accuracy: 0.3278
Epoch 6/20
```

```
23/23 [==============================] - 52s 2s/step - loss: 0.4763 - accuracy:
0.8028 - val_loss: 2.9939 - val_accuracy: 0.4444
Epoch 7/20
23/23 [==============================] - 52s 2s/step - loss: 0.3870 - accuracy:
0.8500 - val_loss: 2.8672 - val_accuracy: 0.4333
Epoch 8/20
23/23 [==============================] - 54s 2s/step - loss: 0.3641 - accuracy:
0.8403 - val_loss: 8.4773 - val_accuracy: 0.4056
Epoch 9/20
23/23 [==============================] - 53s 2s/step - loss: 0.3466 - accuracy:
0.8653 - val_loss: 7.2162 - val_accuracy: 0.2833
Epoch 10/20
23/23 [==============================] - 52s 2s/step - loss: 0.2690 - accuracy:
0.8917 - val_loss: 22.9106 - val_accuracy: 0.3056
Epoch 11/20
23/23 [==============================] - 52s 2s/step - loss: 0.2434 - accuracy:
0.9097 - val_loss: 6.1352 - val_accuracy: 0.3944
Epoch 12/20
23/23 [==============================] - 52s 2s/step - loss: 0.2760 - accuracy:
0.8986 - val_loss: 7.0398 - val_accuracy: 0.5722
Epoch 13/20
23/23 [==============================] - 51s 2s/step - loss: 0.2587 - accuracy:
0.9042 - val_loss: 16.5741 - val_accuracy: 0.3333
Epoch 14/20
23/23 [==============================] - 51s 2s/step - loss: 0.2144 - accuracy:
0.9153 - val_loss: 7.8407 - val_accuracy: 0.4944
Epoch 15/20
23/23 [==============================] - 51s 2s/step - loss: 0.1899 - accuracy:
0.9306 - val_loss: 6.7112 - val_accuracy: 0.5556
Epoch 16/20
23/23 [==============================] - 52s 2s/step - loss: 0.1935 - accuracy:
0.9375 - val_loss: 5.9818 - val_accuracy: 0.5833
Epoch 17/20
23/23 [==============================] - 52s 2s/step - loss: 0.1292 - accuracy:
0.9583 - val_loss: 6.0129 - val_accuracy: 0.4722
Epoch 18/20
23/23 [==============================] - 52s 2s/step - loss: 0.1406 - accuracy:
0.9514 - val_loss: 102.3793 - val_accuracy: 0.2667
Epoch 19/20
23/23 [==============================] - 52s 2s/step - loss: 0.1618 - accuracy:
0.9389 - val_loss: 4.7153 - val_accuracy: 0.5167
Epoch 20/20
23/23 [==============================] - 51s 2s/step - loss: 0.1344 - accuracy:
0.9528 - val_loss: 0.4144 - val_accuracy: 0.8833
```

[27]:
```
model_score = model.evaluate(test_ds)
```

```
10/10 [==============================] - 8s 675ms/step - loss: 0.3301 -
```

accuracy: 0.9200

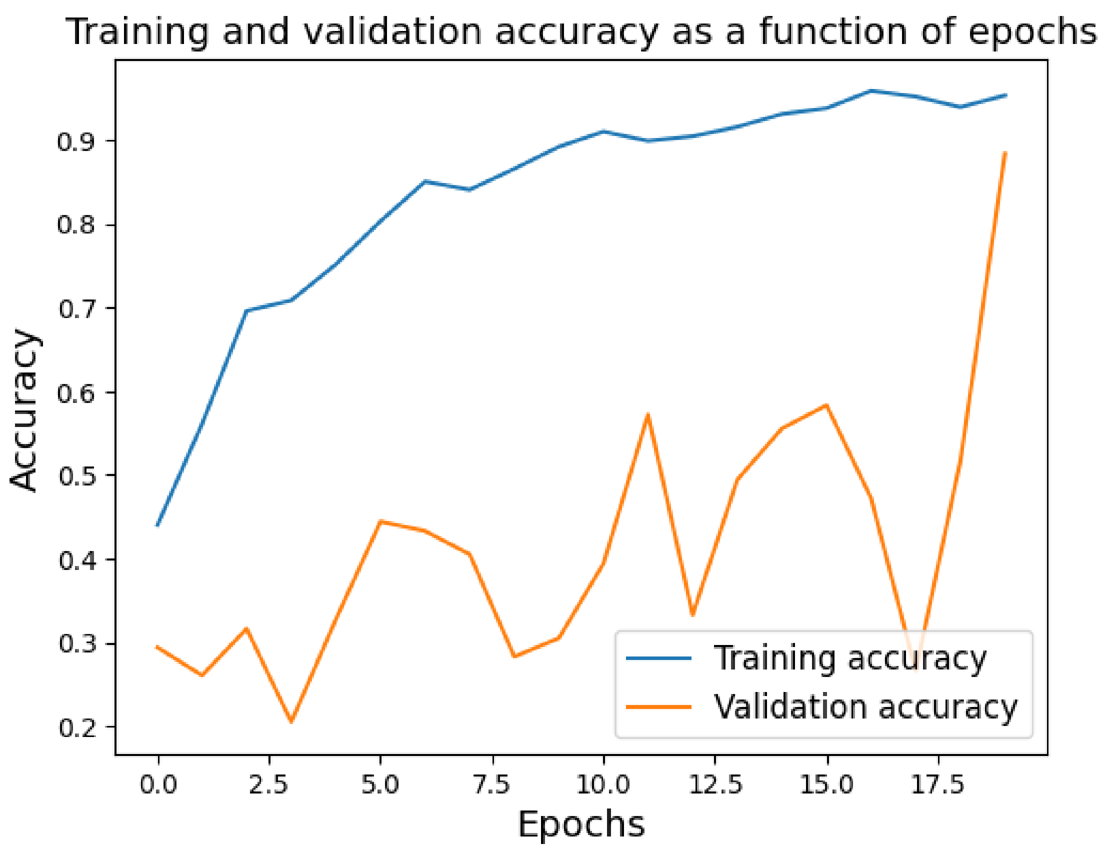
1.4.2 Report classification accuracy.

[28]:
```
print("For Pretrained Model : ")
print("loss :", model_score[0], "\t Accuracy : ", model_score[1])
```

```
For Pretrained Model :
loss : 0.33012694120407104       Accuracy :  0.9200000166893005
```

[29]:
```
# Plot the training and validation accuracy
plt.plot(history.history['accuracy'], label='Training accuracy')
plt.plot(history.history['val_accuracy'], label='Validation accuracy')
plt.title('Training and validation accuracy as a function of epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

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



[30]:
```
X_test, y_test = next(iter(test_ds))
```

[31]:
```
y_pred = tf.convert_to_tensor(np.argmax(model.predict(X_test), axis=1))
```

```
1/1 [==============================] - 1s 1s/step
```

1.4.3 Give a few examples of correct/incorrect classification (show a few images that were correctly/incorrectly classified).

[32]:
```
plt.figure(figsize=(10, 5))
for index in range(18):
    plt.subplot(3, 6, index + 1)
    plt.imshow((X_test[index] + 1).numpy().astype("uint8"))  # rescale to 0-1␣
 ↪for imshow()
    plt.title(f"Class: {class_names[y_pred[index]]}")
    plt.axis("off")

plt.show()
```

1.5 Question 1.5

1.5.1 Train from scratch (without pretraining) a deep neural network that contains convolutional layers on this dataset (the one you created in part 3).

[33]:
```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
np.random.seed(42)
```

```
scratch_model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, kernel_size=3, padding="same",␣
 ↪activation="relu", kernel_initializer="he_normal"),
    tf.keras.layers.Conv2D(64, kernel_size=3, padding="same",␣
 ↪activation="relu", kernel_initializer="he_normal"),
    tf.keras.layers.MaxPool2D(),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dropout(0.25),
    tf.keras.layers.Dense(128, activation="relu",␣
 ↪kernel_initializer="he_normal"),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(10, activation="softmax")
])
scratch_model.compile(loss="sparse_categorical_crossentropy",␣
 ↪optimizer="nadam", metrics=["accuracy"])
```

[34]:
```
scratch_model_history = scratch_model.fit(train_ds, validation_data=val_ds,␣
 ↪epochs=25)
```

```
Epoch 1/25
23/23 [==============================] - 51s 2s/step - loss: 5336.1646 -
accuracy: 0.1889 - val_loss: 2.2920 - val_accuracy: 0.2667
Epoch 2/25
23/23 [==============================] - 49s 2s/step - loss: 59.4611 - accuracy:
0.2361 - val_loss: 2.2689 - val_accuracy: 0.2667
Epoch 3/25
23/23 [==============================] - 48s 2s/step - loss: 2.2575 - accuracy:
0.2458 - val_loss: 2.2451 - val_accuracy: 0.2667
Epoch 4/25
23/23 [==============================] - 48s 2s/step - loss: 2.2337 - accuracy:
0.2458 - val_loss: 2.2216 - val_accuracy: 0.2667
Epoch 5/25
23/23 [==============================] - 48s 2s/step - loss: 2.2107 - accuracy:
0.2306 - val_loss: 2.1986 - val_accuracy: 0.2056
Epoch 6/25
23/23 [==============================] - 48s 2s/step - loss: 2.1876 - accuracy:
0.2250 - val_loss: 2.1761 - val_accuracy: 0.2667
Epoch 7/25
23/23 [==============================] - 48s 2s/step - loss: 2.1667 - accuracy:
0.2417 - val_loss: 2.1543 - val_accuracy: 0.2667
Epoch 8/25
23/23 [==============================] - 48s 2s/step - loss: 2.1438 - accuracy:
0.2319 - val_loss: 2.1331 - val_accuracy: 0.2056
Epoch 9/25
23/23 [==============================] - 48s 2s/step - loss: 2.1229 - accuracy:
0.2611 - val_loss: 2.1124 - val_accuracy: 0.2056
Epoch 10/25
```

```
23/23 [==============================] - 48s 2s/step - loss: 2.1023 - accuracy:
0.2611 - val_loss: 2.0923 - val_accuracy: 0.2056
Epoch 11/25
23/23 [==============================] - 48s 2s/step - loss: 2.0824 - accuracy:
0.2611 - val_loss: 2.0728 - val_accuracy: 0.2056
Epoch 12/25
23/23 [==============================] - 48s 2s/step - loss: 2.0631 - accuracy:
0.2611 - val_loss: 2.0538 - val_accuracy: 0.2056
Epoch 13/25
23/23 [==============================] - 48s 2s/step - loss: 2.0444 - accuracy:
0.2611 - val_loss: 2.0353 - val_accuracy: 0.2056
Epoch 14/25
23/23 [==============================] - 48s 2s/step - loss: 2.0262 - accuracy:
0.2611 - val_loss: 2.0175 - val_accuracy: 0.2056
Epoch 15/25
23/23 [==============================] - 48s 2s/step - loss: 2.0086 - accuracy:
0.2611 - val_loss: 2.0002 - val_accuracy: 0.2056
Epoch 16/25
23/23 [==============================] - 48s 2s/step - loss: 1.9915 - accuracy:
0.2611 - val_loss: 1.9835 - val_accuracy: 0.2056
Epoch 17/25
23/23 [==============================] - 48s 2s/step - loss: 1.9750 - accuracy:
0.2611 - val_loss: 1.9672 - val_accuracy: 0.2056
Epoch 18/25
23/23 [==============================] - 48s 2s/step - loss: 1.9589 - accuracy:
0.2611 - val_loss: 1.9515 - val_accuracy: 0.2056
Epoch 19/25
23/23 [==============================] - 48s 2s/step - loss: 1.9434 - accuracy:
0.2611 - val_loss: 1.9362 - val_accuracy: 0.2056
Epoch 20/25
23/23 [==============================] - 48s 2s/step - loss: 1.9283 - accuracy:
0.2611 - val_loss: 1.9215 - val_accuracy: 0.2056
Epoch 21/25
23/23 [==============================] - 48s 2s/step - loss: 1.9138 - accuracy:
0.2611 - val_loss: 1.9073 - val_accuracy: 0.2056
Epoch 22/25
23/23 [==============================] - 48s 2s/step - loss: 1.8997 - accuracy:
0.2611 - val_loss: 1.8935 - val_accuracy: 0.2056
Epoch 23/25
23/23 [==============================] - 48s 2s/step - loss: 1.8860 - accuracy:
0.2611 - val_loss: 1.8801 - val_accuracy: 0.2056
Epoch 24/25
23/23 [==============================] - 48s 2s/step - loss: 1.8728 - accuracy:
0.2611 - val_loss: 1.8672 - val_accuracy: 0.2056
Epoch 25/25
23/23 [==============================] - 48s 2s/step - loss: 1.8600 - accuracy:
0.2611 - val_loss: 1.8547 - val_accuracy: 0.2056
```

[35]:
```
scratch_model_score = scratch_model.evaluate(test_ds)
```

```
10/10 [==============================] - 4s 323ms/step - loss: 1.8536 -
accuracy: 0.2500
```

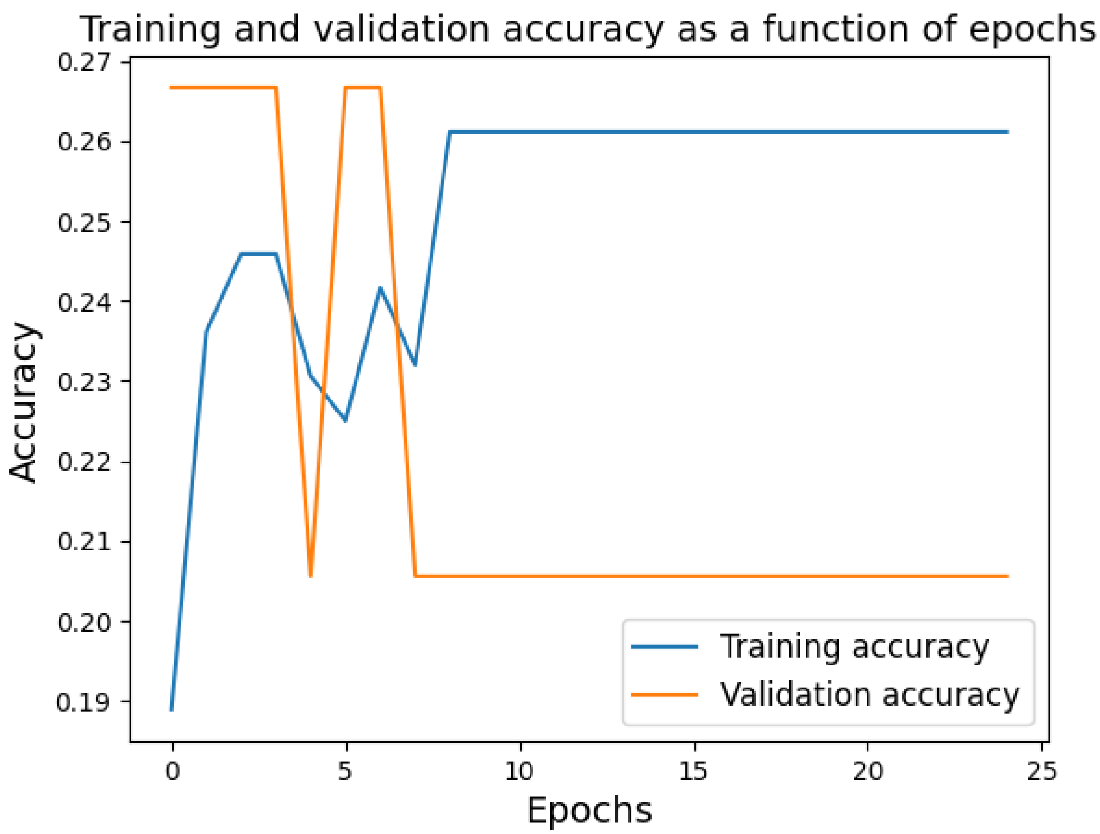
1.5.2 Report classification accuracy.

[36]:
```
print("For Pretrained Model : ")
print("loss :", scratch_model_score[0], "\t Accuracy : ",␣
 ↪scratch_model_score[1])
```

```
For Pretrained Model :
loss : 1.8536077737808228        Accuracy :  0.25
```

[37]:
```
# Plot the training and validation accuracy
plt.plot(scratch_model_history.history['accuracy'], label='Training accuracy')
plt.plot(scratch_model_history.history['val_accuracy'], label='Validation␣
 ↪accuracy')
plt.title('Training and validation accuracy as a function of epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

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



[38]:
```
X_test, y_test = next(iter(test_ds))
```

[39]:
```
y_pred = tf.convert_to_tensor(np.argmax(model.predict(X_test), axis=1))
```

```
1/1 [==============================] - 1s 861ms/step
```

1.5.3 Give a few examples of correct/incorrect classification (show a few images that were correctly/incorrectly classified).

[40]:
```
plt.figure(figsize=(10, 5))
for index in range(18):
    plt.subplot(3, 6, index + 1)
    plt.imshow((X_test[index] + 1).numpy().astype("uint8"))  # rescale to 0-1␣
 ↪for imshow()
    plt.title(f"Class: {class_names[y_pred[index]]}")
    plt.axis("off")

plt.show()
```

1.6 Observations:

1. The main difference observed when we computed the evaluation criteria between the fine-tuned pretrained model and the model developed from scratch is that the fine-tuned model gave higher accuracy for similar epochs compared to the model developed from scratch.
2. After 8 epochs, we see that there is no change in the accuracy for the model developed from scratch, thus either parameter fine-tuning is required or some change in the architecture is required.