## Exercise-2

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1) Import libraries.

```
[]: import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import Xception
from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, Dropout
from tensorflow.keras.models import Sequential
import matplotlib.pyplot as plt
```

2) Load and preprocess data.

```
[]: # Load and preprocess data
     train_datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)
     test_datagen = ImageDataGenerator(rescale=1./255)
     train_generator = train_datagen.flow_from_directory(
         r'images\train',
         target_size=(299, 299), # Xception requires input images to be at least_
      4299x299
         batch size=32,
         class_mode='binary', # or 'categorical' if more than two classes
         subset='training'
     validation_generator = train_datagen.flow_from_directory(
         r'images\train',
         target_size=(299, 299),
         batch_size=32,
         class_mode='binary',
         subset='validation'
```

Found 80 images belonging to 2 classes. Found 20 images belonging to 2 classes.

3) Define graph function.

```
[]: # Define function to plot performance metrics
     def plot_performance(history, title):
         plt.figure(figsize=(12, 6))
         # Plot training & validation accuracy values
         plt.subplot(1, 2, 1)
         plt.plot(history.history['accuracy'])
         plt.plot(history.history['val_accuracy'])
         plt.title('Model Accuracy ' + title)
         plt.ylabel('Accuracy')
         plt.xlabel('Epoch')
         plt.legend(['Train', 'Validation'], loc='upper left')
         # Plot training & validation loss values
         plt.subplot(1, 2, 2)
         plt.plot(history.history['loss'])
         plt.plot(history.history['val_loss'])
         plt.title('Model Loss ' + title)
         plt.ylabel('Loss')
         plt.xlabel('Epoch')
         plt.legend(['Train', 'Validation'], loc='upper left')
         plt.tight_layout()
         plt.show()
```

4) Define and Train model.

```
[]: # Define the Xception model
     base_model = Xception(weights='imagenet', include_top=False, input_shape=(299, __
      ⇒299, 3))
     # Freeze the convolutional base
     base_model.trainable = False
     # Add classification head
     model = Sequential([
         base_model,
         GlobalAveragePooling2D(),
         Dense(512, activation='relu'), # Add a fully connected layer with 512
      \hookrightarrowunits and ReLU activation
         Dropout(0.5), # Add a dropout layer with dropout rate of 0.5 to reduce
      →overfitting
         Dense(256, activation='relu'), # Add another fully connected layer with_
      →256 units and ReLU activation
         Dropout(0.5), # Add another dropout layer
         Dense(1, activation='sigmoid') # Final output layer for binary

⊔
      \hookrightarrow classification
```

Model: "sequential\_6"

Layer (type)	Output Shape	Param #
xception (Functional)	(None, 10, 10, 2048)	20861480
<pre>global_average_pooling2d_6   (GlobalAveragePooling2D)</pre>	(None, 2048)	0

Layer (type)	Output Shape	Param #
xception (Functional)	(None, 10, 10, 2048)	20861480
<pre>global_average_pooling2d_6   (GlobalAveragePooling2D)</pre>	(None, 2048)	0
dense_18 (Dense)	(None, 512)	1049088
dropout_12 (Dropout)	(None, 512)	0
dense_19 (Dense)	(None, 256)	131328
dropout_13 (Dropout)	(None, 256)	0
dense_20 (Dense)	(None, 1)	257

Total params: 22042153 (84.08 MB)
Trainable params: 1180673 (4.50 MB)
Non-trainable params: 20861480 (79.58 MB)

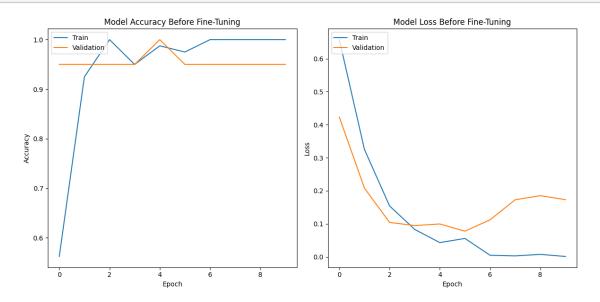
\_\_\_\_\_\_

Epoch 1/10

0.5625 - val\_loss: 0.4231 - val\_accuracy: 0.9500

```
Epoch 2/10
  0.9250 - val_loss: 0.2081 - val_accuracy: 0.9500
  Epoch 3/10
  1.0000 - val_loss: 0.1043 - val_accuracy: 0.9500
  Epoch 4/10
  0.9500 - val_loss: 0.0948 - val_accuracy: 0.9500
  Epoch 5/10
  0.9875 - val_loss: 0.0996 - val_accuracy: 1.0000
  Epoch 6/10
  0.9750 - val_loss: 0.0777 - val_accuracy: 0.9500
  Epoch 7/10
  1.0000 - val_loss: 0.1121 - val_accuracy: 0.9500
  Epoch 8/10
  1.0000 - val_loss: 0.1729 - val_accuracy: 0.9500
  Epoch 9/10
  1.0000 - val_loss: 0.1852 - val_accuracy: 0.9500
  Epoch 10/10
  1.0000 - val_loss: 0.1733 - val_accuracy: 0.9500
   5) Evaluate the model.
[]: # Evaluate the model
  test_generator = test_datagen.flow_from_directory(
    r'images\test',
    target_size=(299, 299),
    batch_size=32,
    class_mode='binary'
  test_loss, test_acc = model.evaluate(test_generator)
  print('Test accuracy:', test_acc)
  Found 10 images belonging to 2 classes.
  1.0000
  1.0000
  Test accuracy: 1.0
   6) Plot model performance.
```

### []: plot\_performance(history, 'Before Fine-Tuning')



#### 7) Fine-tune the model.

```
[]: # Unfreeze some layers of the base model
   base_model.trainable = True
   # It's important to recompile the model after unfreezing the base model
   model.compile(optimizer=tf.keras.optimizers.Adam(1e-5), # Lower learning rate_
    ⇔for fine-tuning
            loss='binary crossentropy',
            metrics=['accuracy'])
   history_fine = model.fit(train_generator, epochs=5,__
    →validation_data=validation_generator)
  Epoch 1/5
  0.9875 - val_loss: 0.1676 - val_accuracy: 0.9500
  1.0000 - val_loss: 0.1651 - val_accuracy: 0.9500
  Epoch 3/5
  1.0000 - val_loss: 0.1627 - val_accuracy: 0.9500
  Epoch 4/5
  1.0000 - val_loss: 0.1619 - val_accuracy: 0.9500
  Epoch 5/5
```

8) Evaluate Fine-tuned model.

Found 10 images belonging to 2 classes.

9) Plot model performance

### []: plot\_performance(history\_fine, 'After Fine-Tuning')

