Transfer Learning with MobileNetV2

February 17, 2024

1 Transfer Learning with MobileNetV2

[1]:
```
# Note

# A pre-trained model is a network that's already been trained on a large␣
 ↪dataset and saved.
# The pre-trained model (MobileNetV2) that we'll be using here has been␣
 ↪pre-trained on ImageNet, a dataset
# containing over 14 million images and 1000 classes.
```

[2]:
```
### v1.1
```

[3]:
```
# Importing the necessary packages

import matplotlib.pyplot as plt
import numpy as np
import os
import tensorflow as tf
import tensorflow.keras.layers as tfl

from tensorflow.keras.preprocessing import image_dataset_from_directory
from tensorflow.keras.layers.experimental.preprocessing import RandomFlip,␣
 ↪RandomRotation
```

1.0.1 Creating the dataset

[4]:
```
BATCH_SIZE = 32
IMG_SIZE = (160, 160)
directory = "dataset/"
train_dataset = image_dataset_from_directory(directory,
                                             shuffle=True,
                                             batch_size=BATCH_SIZE,
                                             image_size=IMG_SIZE,
                                             validation_split=0.2,
                                             subset='training',
```

```
                                                      seed=42)
validation_dataset = image_dataset_from_directory(directory,
                                                      shuffle=True,
                                                      batch_size=BATCH_SIZE,
                                                      image_size=IMG_SIZE,
                                                      validation_split=0.2,
                                                      subset='validation',
                                                      seed=42)

# The original dataset has some mislabelled images in it as well.

# Note 1

# 'image_size' means all images from the disk will be resized to 160 x 160␣
 ↪pixels before being used in training or validation
# datasets.
# The 'image_size' of train_dataset is same as 'image_size' of␣
 ↪validation_dataset which is same 'image_size' of test/real world
# dataset on which the model runs. This is because CNNs require a fixed input␣
 ↪size and also whatever the model is being
# trained on, it should be validated and tested on similar kind of data.

# shuffle = True ensures that if the minibatches created from the dataset have␣
 ↪indices 0,1,2,3,4,....n, then during first epoch,
# the order of minibatches maybe 0,1,2,3....n, but during the second epoch,␣
 ↪this order may change.
# Similarly during validation also this order may change.

# setting 'seed=42' ensures that same images are assigned to the training set␣
 ↪and the same images are assigned to the
# validation set each time we run the loading_dataset code, given the same␣
 ↪dataset and split ratio.

# For seed = x, the training set consists of a set A of images and the␣
 ↪validation set consists of a set B of images.
# A and B are non overlapping sets. For seed = y, the training set consists of␣
 ↪a set A' of images and the validation set
# consists of a set B' of images. A' and B' are non overlapping sets as well.

# The same 'validation_split' value must be set for both 'train_dataset' and␣
 ↪'validation_dataset'.
# If we set validation_split=0.2, it means that 20% of the dataset will be used␣
 ↪for validation, and the remaining 80% will be
# used for training.

# Note 2
```

```
# When we call image_dataset_from_directory and provide the path to the␣
↪top-level directory ("dataset/" in this example),
# the function automatically scans the subdirectories (dogs and cats) and␣
↪assigns labels to the images based on these
# subdirectory names. In this case, all images in the dogs directory are␣
↪labeled as "dogs", and all images in the cats
# directory are labeled as "cats".

# This method of organizing and labeling data is very common because it␣
↪simplifies the process of preparing datasets for
# training machine learning models.
```

```
Found 327 files belonging to 2 classes.
Using 262 files for training.
Found 327 files belonging to 2 classes.
Using 65 files for validation.
```

[5]:
```
# The MobileNetV2 and other pre-trained models are very flexible and accept the␣
↪input images in different sizes and not just in
# the size (160,160). This is because they have the GlobalAveragePooling2D␣
↪layers before the fully connected layers.

# The GlobalAveragePooling2D layers convert each layer into a single value␣
↪making the output size of the pooling layer
# independent of the input image's dimensions. This allows the model to adapt␣
↪to different input sizes and feed the
# result into fully connected layers, which do require fixed-size inputs.
```

[6]:
```
class_names = train_dataset.class_names

plt.figure(figsize=(10, 10))
for images, labels in train_dataset.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")

# When we specify .take(1), it means we are creating a new dataset that␣
↪contains only the first mini-batch of our
# training dataset.
```

1.0.2 Preprocessing and Augmentation

[7]:
```
AUTOTUNE = tf.data.experimental.AUTOTUNE
train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)

# Using prefetch() prevents a memory bottleneck that can occur when reading␣
↪from disk. It sets aside some data and
# keeps it ready for when it's needed, by creating a source dataset from your␣
↪input data, applying a transformation to
# preprocess it, then iterating over the dataset one element at a time. Because␣
↪the iteration is streaming,
```

```
# the data doesn't need to fit into memory.


# Initial Loading: A batch of data is loaded into memory and processed (e.g.,␣
↪decoded, resized, augmented).
# Training: The model begins training on the currently loaded batch.
# Prefetching: While the model is training, the next batch(es) of data are␣
↪loaded and prepared in the background.
# The buffer_size determines how many of these batches are prepared in advance.
```

[8]:
```
def data_augmenter():
    '''
    Create a Sequential model composed of 2 layers
    Returns:
        tf.keras.Sequential
    '''
    data_augmentation = tf.keras.Sequential()
    data_augmentation.add(RandomFlip('horizontal'))
    data_augmentation.add(RandomRotation(0.2))

    return data_augmentation

# Note

# We can directly pass a list of layers to the tf.keras.Sequential()␣
↪constructor.
# Alternatively, we can start with an empty tf.keras.Sequential() model and␣
↪then add layers one by one using the .add() method.

# RandomFlip('horizontal') - Flip along the horizontal axis.
# The RandomFlip('horizontal') layer in TensorFlow's Keras API will either flip␣
↪an image along the horizontal axis or
# leave it unchanged

# RandomRotation(0.2) - Each image will be rotated by a random angle within the␣
↪range of -72 to +72 degrees (0.2*360 = 72)

# Data augmentation doesn't directly increase the number of images in our␣
↪dataset.
# This means that each epoch can see slightly different versions of each image,␣
↪thereby effectively increasing the diversity of
# the training data without physically increasing the dataset size.
# This also means that the weights see different versions of the same image and␣
↪still classify them correctly.
```

[9]:
```
augmenter = data_augmenter()

assert(augmenter.layers[0].name.startswith('random_flip')), "First layer must␣
↪be RandomFlip"
assert augmenter.layers[0].mode == 'horizontal', "RadomFlip parameter must be␣
↪horizontal"
assert(augmenter.layers[1].name.startswith('random_rotation')), "Second layer␣
↪must be RandomRotation"
assert augmenter.layers[1].factor == 0.2, "Rotation factor must be 0.2"
assert len(augmenter.layers) == 2, "The model must have only 2 layers"

print('\033[92mAll tests passed!')
```

```
All tests passed!
```

[10]:
```
data_augmentation = data_augmenter()

for image, _ in train_dataset.take(1):
    plt.figure(figsize=(10, 10))
    first_image = image[0]
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        augmented_image = data_augmentation(tf.expand_dims(first_image, 0))
        plt.imshow(augmented_image[0] / 255)
        plt.axis('off')

# train_dataset.take(1) takes the first minibatch. first_image is the first␣
↪image in the first minibatch

# tf.expand_dims(first_image, 0) adds an extra dimension to first_image,␣
↪converting it from a 3D tensor of
# shape [height, width, channels] to a 4D tensor of shape [1, height, width,␣
↪channels]. This is necessary because
# the data augmentation layers expect a batch of images as input, even if the␣
↪batch contains only one image.

# The same image undergoes 2 random transformations 9 times and as a result we␣
↪get 9 variations of the same image.
```

[11]:
```
# Points to remember

# When calling image_data_set_from_directory(), specify the train/val subsets and match the seeds to prevent overlap
# Use prefetch() to prevent memory bottlenecks when reading from disk
# Give your model more to learn from with simple data augmentations like rotation and flipping.
# When using a pretrained model, it's best to reuse the weights it was trained on.
```

[12]:
```
preprocess_input = tf.keras.applications.mobilenet_v2.preprocess_input
```

```
# This is the input preprocessing layer of the pre-trained mobilenet_v2 model.␣
↪Before we use the pre-trained model on our data,
# it is important to preprocess the data using the same preprocessing layer of␣
↪the pre-trained mobilenet_v2 model.
# This is because the weights of the pre-trained model have been trained only␣
↪to process certain kinds of input data and
# it is essential for our data to be in that format.
```

1.0.3 Using MobileNetV2 for Transfer Learning

[13]:
```
# MobileNetV2 was trained on ImageNet and is optimized to run on mobile and␣
↪other low-power applications.
# It's 155 layers deep and very efficient for object detection and image␣
↪segmentation tasks, as well as classification tasks.

# Traditional convolutions are often very resource-intensive, and depthwise␣
↪separable convolutions are able to reduce the
# number of trainable parameters and operations and also speed up convolutions.
```

[14]:
```
IMG_SHAPE = IMG_SIZE + (3,)
# We know IMG_SIZE = (160,160). The tuples are being added.
# Resultant IMG_SHAPE = (160,160,3)
base_model = tf.keras.applications.MobileNetV2(input_shape=IMG_SHAPE,
                                               include_top=True,
                                               weights='imagenet')

# By weights = 'imagenet', it means the weights of MobileNetV2 which have been␣
↪trained on the imagenet data.
# include_top=True means the fully-connected output layers that were used for␣
↪classification on the
# original dataset (in this case, ImageNet) will be present.
# This is useful when you want to use the model for classification tasks␣
↪involving the same number of classes as the
# original dataset (1000 classes for ImageNet).
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applicatio
ns/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_160.h5
14540800/14536120 [==============================] - 0s 0us/step
```

[ ]:
```
base_model.summary()
```

[16]:
```
# Note the last 2 layers here. They are the so called top layers, and they are␣
↪responsible of the classification in the model.

nb_layers = len(base_model.layers)
```

```
print(base_model.layers[nb_layers - 2].name)
print(base_model.layers[nb_layers - 1].name)
```

```
global_average_pooling2d
predictions
```

[17]:
```
image_batch, label_batch = next(iter(train_dataset))
# next(iter(train_dataset)) retrieves the next minibatch

feature_batch = base_model(image_batch)
print(feature_batch.shape)
```

```
(32, 1000)
```

[18]:
```
#Shows the different label probabilities in one tensor
label_batch

# label_batch contains the labels corresponding to each image in image_batch.
 ↪The shape of label_batch is
# typically (batch_size,), with each entry being the label index for each image.
```

[18]:
```
<tf.Tensor: shape=(32,), dtype=int32, numpy=
array([1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0,
       0, 0, 1, 0, 1, 1, 1, 1, 0, 0], dtype=int32)>
```

[19]:
```
base_model.trainable = False
# The above line of code means that we are not further training the pre-trained
 ↪weights based on our data
image_var = tf.Variable(preprocess_input(image_batch))
# The preprocess_input doesn't automatically convert the image_batch into a
 ↪tensor. We have to do it manually.
# The above step is not necessary. It isn't necessary to convert into a tensor.
 ↪The base_model will automatically take care of
# it.
pred = base_model(image_var)

tf.keras.applications.mobilenet_v2.decode_predictions(pred.numpy(), top=2)

# The predictions returned by the base model below follow this format:

# First the class number, then a human-readable label, and last the probability
 ↪of the image belonging to that class.
# There are two of these returned for each image in the batch - these the top
 ↪two probabilities returned for that image.
```

```
Downloading data from https://storage.googleapis.com/download.tensorflow.org/dat
a/imagenet_class_index.json
```

```
40960/35363 [==================================] - 0s 0us/step
```

[19]:
```
[[('n02489166', 'proboscis_monkey', 0.10329965),
  ('n02102177', 'Welsh_springer_spaniel', 0.07883611)],
 [('n02125311', 'cougar', 0.1654676), ('n02389026', 'sorrel', 0.10764261)],
 [('n02437312', 'Arabian_camel', 0.2923283),
  ('n02437616', 'llama', 0.27713484)],
 [('n03944341', 'pinwheel', 0.31154886), ('n03047690', 'clog', 0.052500293)],
 [('n02454379', 'armadillo', 0.73107153),
  ('n01990800', 'isopod', 0.038719974)],
 [('n02437312', 'Arabian_camel', 0.25663644),
  ('n02422106', 'hartebeest', 0.12122728)],
 [('n02437616', 'llama', 0.6612557),
  ('n02090721', 'Irish_wolfhound', 0.23782855)],
 [('n02133161', 'American_black_bear', 0.82735676),
  ('n02134418', 'sloth_bear', 0.02925945)],
 [('n01518878', 'ostrich', 0.9267562),
  ('n02002724', 'black_stork', 0.0017766367)],
 [('n01518878', 'ostrich', 0.94954586),
  ('n02018795', 'bustard', 0.0028661634)],
 [('n02437616', 'llama', 0.8699833), ('n02412080', 'ram', 0.076757126)],
 [('n02415577', 'bighorn', 0.2429446), ('n02412080', 'ram', 0.160565)],
 [('n02437616', 'llama', 0.9473245), ('n02480495', 'orangutan', 0.0076571796)],
 [('n09428293', 'seashore', 0.48092392), ('n09421951', 'sandbar', 0.26179993)],
 [('n02437312', 'Arabian_camel', 0.95963204),
  ('n02504458', 'African_elephant', 0.0009881927)],
 [('n02509815', 'lesser_panda', 0.9096807),
  ('n02443114', 'polecat', 0.014759211)],
 [('n01518878', 'ostrich', 0.74165), ('n02002724', 'black_stork', 0.07205889)],
 [('n02437312', 'Arabian_camel', 0.49920738),
  ('n02412080', 'ram', 0.11842591)],
 [('n01518878', 'ostrich', 0.87967354),
  ('n02018795', 'bustard', 0.0077298395)],
 [('n02437616', 'llama', 0.82569915),
  ('n02437312', 'Arabian_camel', 0.010480011)],
 [('n01518878', 'ostrich', 0.9612779), ('n02410509', 'bison', 0.0013086519)],
 [('n02437616', 'llama', 0.636178), ('n02412080', 'ram', 0.058401026)],
 [('n02437616', 'llama', 0.5928003), ('n02417914', 'ibex', 0.039721698)],
 [('n02437616', 'llama', 0.83541703), ('n02104029', 'kuvasz', 0.048998024)],
 [('n03042490', 'cliff_dwelling', 0.3091509),
  ('n04208210', 'shovel', 0.06726616)],
 [('n02093647', 'Bedlington_terrier', 0.4338772),
  ('n02113799', 'standard_poodle', 0.4069308)],
 [('n02133161', 'American_black_bear', 0.97880507),
  ('n02132136', 'brown_bear', 0.0055297976)],
 [('n01518878', 'ostrich', 0.83605814), ('n02018795', 'bustard', 0.004823002)],
 [('n02133161', 'American_black_bear', 0.9362426),
```

```
 ('n02134418', 'sloth_bear', 0.007733786)],
[('n03240683', 'drilling_platform', 0.04555222),
 ('n04146614', 'school_bus', 0.033719867)],
[('n02437616', 'llama', 0.9278842),
 ('n02098286', 'West_Highland_white_terrier', 0.0057286685)],
[('n02437616', 'llama', 0.94477594), ('n02423022', 'gazelle', 0.0054335156)]]
```

[20]:
```
# here's a whole lot of labels here, some of them hilariously wrong, but none␣
↪of them say "alpaca."

# This is because MobileNet pretrained over ImageNet doesn't have the correct␣
↪labels for alpacas, so when you use the
# full model, all you get is a bunch of incorrectly classified images.
```

1.0.4 Freezing of weights

[21]:
```
def alpaca_model(image_shape=IMG_SIZE, data_augmentation=data_augmenter()):
    ''' Define a tf.keras model for binary classification out of the␣
↪MobileNetV2 model
    Arguments:
        image_shape -- Image width and height
        data_augmentation -- data augmentation function
    Returns:
    Returns:
        tf.keras.model
    '''


    input_shape = image_shape + (3,)


    base_model = tf.keras.applications.MobileNetV2(input_shape=input_shape,
                                                   include_top=False, # <==␣
↪Important!!!!
                                                   weights='imagenet') # From␣
↪imageNet

    # freeze the base model by making it non trainable
    base_model.trainable = False

    # create the input layer (Same as the imageNetv2 input size)
    inputs = tf.keras.Input(shape=input_shape)

    # apply data augmentation to the inputs
    x = data_augmenter()(inputs)
```

```
    # Data augmentation doesn't directly increase the number of images in our␣
↪dataset.
    # This means that each epoch can see slightly different versions of each␣
↪image, thereby effectively increasing the
    # diversity of the training data without physically increasing the dataset␣
↪size.
    # This also means that the weights see different versions of the same image␣
↪and still classify them correctly.

    # data preprocessing using the same weights the model was trained on
    x = preprocess_input(x)

    # set training to False to avoid keeping track of statistics in the batch␣
↪norm layer
    x = base_model(x, training=False)
    # By setting 'training = False', the batch statistics will not be␣
↪influenced by the test set during inference and will be
    # influenced only by the training set.
    # The BN layers will use the moving averages of mean and variance that were␣
↪computed during training,
    # rather than calculating them anew based on the current batch of test␣
↪data, unaffected by the variability in test data.

    # Another reason why batch statistics should be influenced only by training␣
↪set and not by test set is that the
    # training set minibatch is large whereas it can be only 1 test case that␣
↪we are predicting and we shouldn't allow such a
    # small sized test case to influence the batch statistics.  If we allow,␣
↪then a single outlier test case will change the
    # batch statistics.

    # add the new Binary classification layers
    # use global avg pooling to summarize the info in each channel
    x = tfl.GlobalAveragePooling2D()(x)
    # If the input to GlobalAveragePooling2D layer is a tensor of shape␣
↪(batch_size, height, width, channels), the output shape
    # after GlobalAveragePooling2D will be (batch_size, channels)

    # Since we used 'GlobalAveragePooling2D', we don't need to flatten.

    # include dropout with probability of 0.2 to avoid overfitting
    x = tfl.Dropout(rate=0.2)(x)
    # Note - Dropout is applied only during the training phase. Even during␣
↪validation/testing, dropout is not applied.
```

```
    # use a prediction layer with one neuron (as a binary classifier only needs␣
↪one)
    outputs = tfl.Dense(units=1, activation='linear')(x)

    model = tf.keras.Model(inputs, outputs)

    return model
```

Create your new model using the data_augmentation function defined earlier.

[22]:
```
model2 = alpaca_model(IMG_SIZE, data_augmentation)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applicatio
ns/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_160_no_top.h
5
9412608/9406464 [==============================] - 0s 0us/step
```

[23]:
```
from test_utils import summary, comparator

alpaca_summary = [['InputLayer', [(None, 160, 160, 3)], 0],
                    ['Sequential', (None, 160, 160, 3), 0],
                    ['TensorFlowOpLayer', [(None, 160, 160, 3)], 0],
                    ['TensorFlowOpLayer', [(None, 160, 160, 3)], 0],
                    ['Functional', (None, 5, 5, 1280), 2257984],
                    ['GlobalAveragePooling2D', (None, 1280), 0],
                    ['Dropout', (None, 1280), 0, 0.2],
                    ['Dense', (None, 1), 1281, 'linear']] #linear is the␣
↪default activation

comparator(summary(model2), alpaca_summary)

for layer in summary(model2):
    print(layer)
```

```
All tests passed!
['InputLayer', [(None, 160, 160, 3)], 0]
['Sequential', (None, 160, 160, 3), 0]
['TensorFlowOpLayer', [(None, 160, 160, 3)], 0]
['TensorFlowOpLayer', [(None, 160, 160, 3)], 0]
['Functional', (None, 5, 5, 1280), 2257984]
['GlobalAveragePooling2D', (None, 1280), 0]
['Dropout', (None, 1280), 0, 0.2]
['Dense', (None, 1), 1281, 'linear']
```

[24]:
```
base_learning_rate = 0.001
model2.compile(optimizer=tf.keras.optimizers.Adam(lr=base_learning_rate),
               loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
```

```
              metrics=['accuracy'])

# Note
# If 'from_logits' = True, the function will internally apply a sigmoid␣
↪activation to the logits before calculating the
# binary crossentropy loss. This is useful and numerically stable when the␣
↪model's final layer outputs raw logits,
# which are not constrained to [0, 1].
```

[25]:
```
initial_epochs = 5
history = model2.fit(train_dataset, validation_data=validation_dataset,␣
↪epochs=initial_epochs)
```

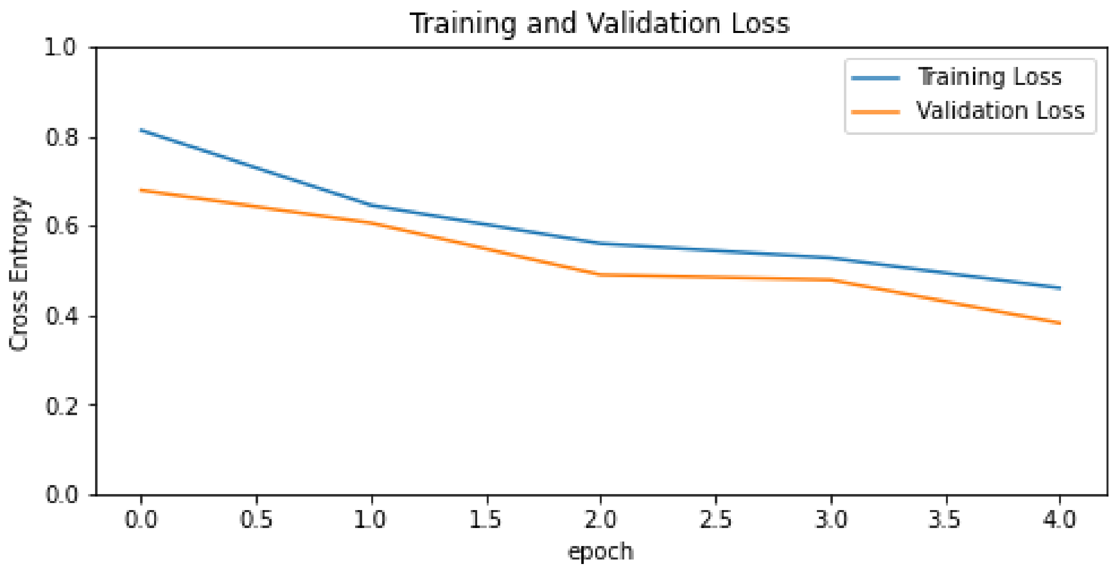
```
Epoch 1/5
9/9 [==============================] - 9s 946ms/step - loss: 0.8131 - accuracy:
0.5000 - val_loss: 0.6789 - val_accuracy: 0.5538
Epoch 2/5
9/9 [==============================] - 7s 792ms/step - loss: 0.6457 - accuracy:
0.6069 - val_loss: 0.6061 - val_accuracy: 0.5846
Epoch 3/5
9/9 [==============================] - 7s 823ms/step - loss: 0.5597 - accuracy:
0.6947 - val_loss: 0.4900 - val_accuracy: 0.6000
Epoch 4/5
9/9 [==============================] - 7s 799ms/step - loss: 0.5279 - accuracy:
0.7099 - val_loss: 0.4787 - val_accuracy: 0.6154
Epoch 5/5
9/9 [==============================] - 7s 811ms/step - loss: 0.4603 - accuracy:
0.7252 - val_loss: 0.3820 - val_accuracy: 0.6923
```

[26]:
```
# Note

# Yes, TensorFlow's Keras API provides flexibility in how you can fit (train)␣
↪your model, allowing for different types of
# input data.

# Method 1

# model.fit(x=inputs, y=outputs, epochs=100)

# Method 2

# model.fit(train_dataset, epochs=100)

# In both the above cases, there is no validation.

# Method 3
```

```
# model.fit(train_dataset, validation_data=validation_dataset, epochs=100)

# In above case, there is validation
```

[27]:
```
# Note

# The validation accuracy can sometime be higher than the training accuracy due␣
↪to following reasons

# 1) If there is strong regularization like dropout, then the model may not␣
↪perform well on the training set but may perform
# better on the validation dataset because during validation dropout is not␣
↪applied allowing the full capacity of the model to
# be used.

# 2) Small Dataset Size: If the training dataset is small, the model might not␣
↪have enough data to learn effectively,
# leading to lower training accuracy. However, if the validation set, by␣
↪chance, happens to contain examples that are
# easier for the model to classify, then better validation accuracy.
```

[28]:
```
acc = [0.] + history.history['accuracy']
val_acc = [0.] + history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

plt.figure(figsize=(8, 8))
plt.subplot(2, 1, 1)
plt.plot(acc, label='Training Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.ylabel('Accuracy')
plt.ylim([min(plt.ylim()),1])
plt.title('Training and Validation Accuracy')

plt.subplot(2, 1, 2)
plt.plot(loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.ylabel('Cross Entropy')
plt.ylim([0,1.0])
plt.title('Training and Validation Loss')
plt.xlabel('epoch')
plt.show()
```



[29]:
```
class_names
```

[29]: ['alpaca', 'not alpaca']

The results are ok, but could be better. Next, try some fine-tuning.

1.0.5 Fine-tuning the Model

[30]:
```
# Note

# For fine tuning a pre-trained model, we must use small learning rate to train␣
↪the later layers on our data because the
```

```
# weights have already been learnt and it is quite close to the minima. So if␣
↪learning rate is high, the optimizer may diverge.
# We need to use small learning rate because the weights are not learning for␣
↪the first time but they are in the final stages of
# learning.
```

[31]:
```
# Note

# When the network is in its earlier stages, it trains on low-level features,␣
↪like edges. In the later layers,
# more complex, high-level features like wispy hair or pointy ears begin to␣
↪emerge. For transfer learning,
# the low-level features can be kept the same, as they have common features for␣
↪most images. When you add new data,
# you generally want the high-level features to adapt to it, which is rather␣
↪like letting the network learn to
# detect features more related to your data, such as soft fur or big teeth.

# To achieve this, just unfreeze the final layers and re-run the optimizer with␣
↪a smaller learning rate,
# while keeping all the other layers frozen.
```

[32]:
```
base_model = model2.layers[4]
# To understand the above line of code, see the model2 layers in the code cell␣
↪below.
# The MobileNetV2 model is model2.layers[4]
base_model.trainable = True
# The above line of code makes all the layers of MobileNetV2 model trainable
# Let's take a look to see how many layers are in the base model
print("Number of layers in the base model: ", len(base_model.layers))

# Fine-tune from this layer onwards
fine_tune_at = 120

# Freeze all the layers before the `fine_tune_at` layer
for layer in base_model.layers[:fine_tune_at]:
    layer.trainable = False

# Define a BinaryCrossentropy loss function. Use from_logits=True
loss_function=tf.keras.losses.BinaryCrossentropy(from_logits=True)
# Define an Adam optimizer with a learning rate of 0.1 * base_learning_rate
optimizer = tf.keras.optimizers.Adam(lr=0.1*base_learning_rate)
# Use accuracy as evaluation metric
metrics=['accuracy']
```

```
model2.compile(loss=loss_function,
              optimizer = optimizer,
              metrics=metrics)

# Note

# So even if we set 1 layer as trainable, then it is required to compile the␣
 ↪model and define the optimizer,
# the loss function and metrics.
```

```
Number of layers in the base model:  155
```

[34]:
```
for i, layer in enumerate(model2.layers):
    print(i, layer.name)
```

```
0 input_3
1 sequential_3
2 tf_op_layer_RealDiv
3 tf_op_layer_Sub
4 mobilenetv2_1.00_160
5 global_average_pooling2d_1
6 dropout
7 dense
```

[35]:
```
assert type(loss_function) == tf.python.keras.losses.BinaryCrossentropy, "Not␣
 ↪the correct layer"
assert loss_function.from_logits, "Use from_logits=True"
assert type(optimizer) == tf.keras.optimizers.Adam, "This is not an Adam␣
 ↪optimizer"
assert optimizer.lr == base_learning_rate / 10, "Wrong learning rate"
assert metrics[0] == 'accuracy', "Wrong metric"

print('\033[92mAll tests passed!')
```

```
All tests passed!
```

[38]:
```
fine_tune_epochs = 5
total_epochs =  initial_epochs + fine_tune_epochs

history_fine = model2.fit(train_dataset,
                         epochs=total_epochs,
                         initial_epoch=history.epoch[-1],
                         validation_data=validation_dataset)

# When we specify the 'initial_epoch' parameter, the epoch number starts from␣
 ↪'initial_epoch' + 1 and goes upto
# total_epochs (inclusive)
```

```
Epoch 5/10
9/9 [==============================] - 9s 945ms/step - loss: 0.1523 - accuracy:
0.9389 - val_loss: 0.0681 - val_accuracy: 0.9846
Epoch 6/10
9/9 [==============================] - 8s 943ms/step - loss: 0.1167 - accuracy:
0.9618 - val_loss: 0.0632 - val_accuracy: 0.9538
Epoch 7/10
9/9 [==============================] - 9s 957ms/step - loss: 0.1259 - accuracy:
0.9389 - val_loss: 0.1120 - val_accuracy: 0.9692
Epoch 8/10
9/9 [==============================] - 8s 923ms/step - loss: 0.1065 - accuracy:
0.9504 - val_loss: 0.0918 - val_accuracy: 0.9846
Epoch 9/10
9/9 [==============================] - 8s 923ms/step - loss: 0.1056 - accuracy:
0.9695 - val_loss: 0.2592 - val_accuracy: 0.8769
Epoch 10/10
9/9 [==============================] - 8s 936ms/step - loss: 0.1282 - accuracy:
0.9389 - val_loss: 0.1030 - val_accuracy: 0.9231
```

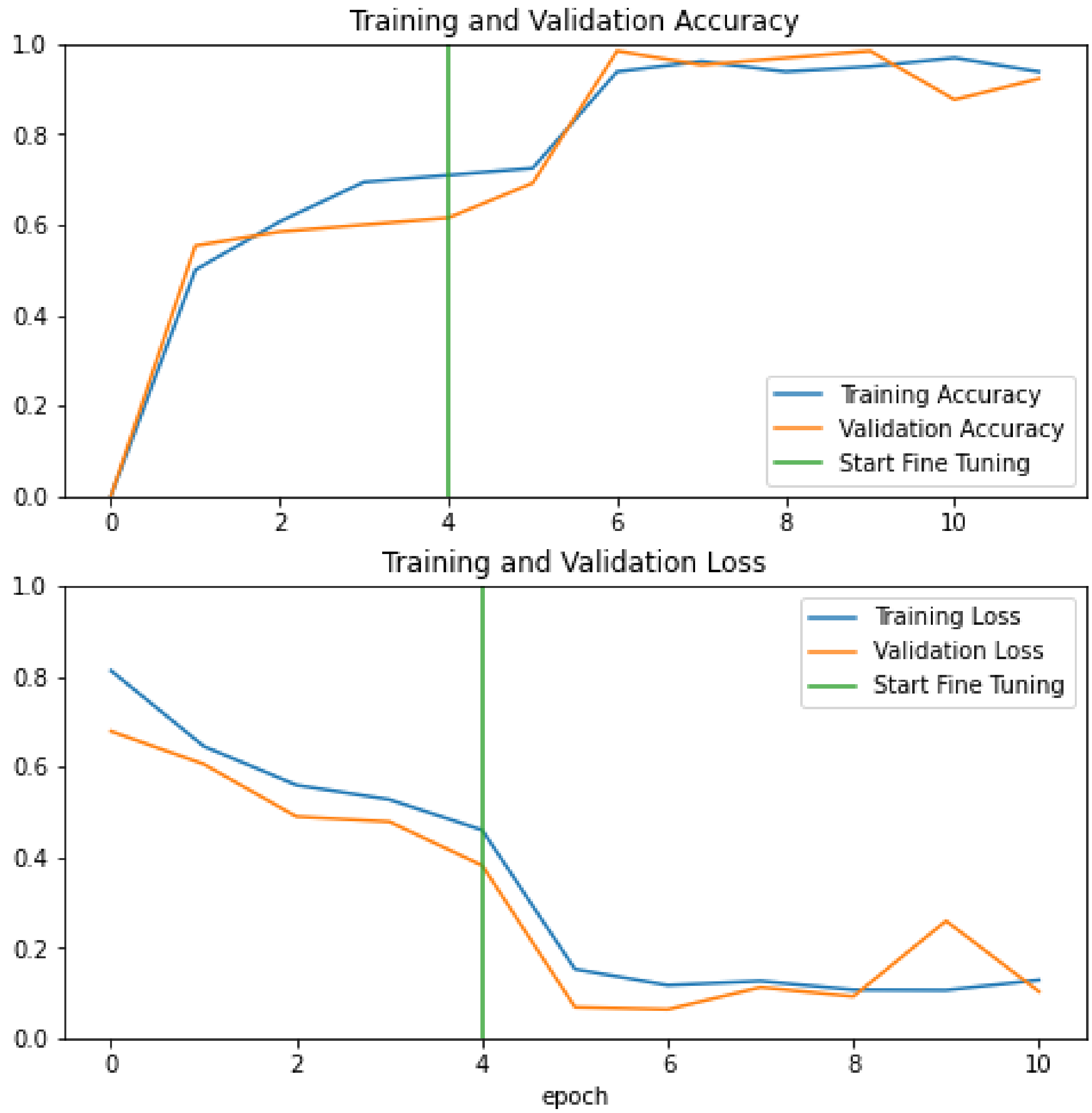
[37]:
```
print(history.epoch)
```

```
[0, 1, 2, 3, 4]
```

[39]:
```
acc += history_fine.history['accuracy']
val_acc += history_fine.history['val_accuracy']

loss += history_fine.history['loss']
val_loss += history_fine.history['val_loss']
```

[40]:
```
plt.figure(figsize=(8, 8))
plt.subplot(2, 1, 1)
plt.plot(acc, label='Training Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.ylim([0, 1])
plt.plot([initial_epochs-1,initial_epochs-1],
          plt.ylim(), label='Start Fine Tuning')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(2, 1, 2)
plt.plot(loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.ylim([0, 1.0])
plt.plot([initial_epochs-1,initial_epochs-1],
         plt.ylim(), label='Start Fine Tuning')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
```

```
plt.xlabel('epoch')
plt.show()
```



[ ]:
```
# Note

# The entire model was initially trained for 5 epochs with all the weights of␣
↪MobileNetV2 freezed.
# Then the entire model (already trained for 5 epochs) was trained for 5 more␣
↪epochs with only the first 120 layer weights of
# MobileNetV2 freezed and later layer weights trainable.
```

```
[ ]: # Note

# How fine tuning also helps batch normalization layers?

# Earlier when we freezed the BN layer parameters, the batch statistics (moving␣
 ↪average of mean and variance) were based on the
# imageNet dataset. The batch normalized version of imageNet dataset is of␣
 ↪distribution A whereas the
# batch normalized version of the test dataset is of distribution B. A and B␣
 ↪are different. The distribution B inputs are not
# familiar to the BN layer weights and hence these weights don't predict␣
 ↪efficiently.

# Now we unfreeze the BN layer parameters. Now the saved batch statistics␣
 ↪(moving average of mean and variance) in memory are
# based on the custom training dataset and also based on previously imageNet␣
 ↪dataset. if more fine-tuning is done,
# then the batch statistics (moving average of mean and variance) will be more␣
 ↪influenced by the moving average of custom
# training dataset. The batch normalized version of the custom training dataset␣
 ↪is of say distribution x.
# The batch normalized version of the test dataset is of say distribution y . x␣
 ↪and y are pretty close (if proper
# fine-tuning is done). The BN layer weights see a familiar distribution and␣
 ↪they predict efficiently.

# The new moving averages is found by considering the earlier moving average of␣
 ↪the imageNet and the moving average of the
# current custom training dataset.
```

```
[ ]: # Note

# To adapt the classifier to new data: Delete the top layer, add a new␣
 ↪classification layer, and train only on that layer.
# Fine-tune the final layers of your model to capture high-level details near␣
 ↪the end of the network and
# potentially improve accuracy.
```