

```
import matplotlib.pyplot as plt
import numpy as np
import os
import tensorflow as tf
```

```
_URL = 'https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip'
```

```
path_to_zip = tf.keras.utils.get_file('cats_and_dogs.zip', origin=_URL, extract=True)
PATH = os.path.join(os.path.dirname(path_to_zip), 'cats_and_dogs_filtered')
```

```
train_dir = os.path.join(PATH, 'train')
validation_dir = os.path.join(PATH, 'validation')
```

```
BATCH_SIZE = 32
IMG_SIZE = (160, 160)
```

```
train_dataset = tf.keras.utils.image_dataset_from_directory(train_dir, shuffle=True, batch_s
```

↳ Downloading data from https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip
68606236/68606236 [=====] - 0s 0us/step
Found 2000 files belonging to 2 classes.



```
validation_dataset = tf.keras.utils.image_dataset_from_directory(validation_dir,
                                                                    shuffle=True,
                                                                    batch_size=BATCH_SIZE,
                                                                    image_size=IMG_SIZE)
```

Found 1000 files belonging to 2 classes.

```
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")
```

dogs



dogs



cats



dogs



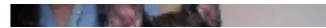
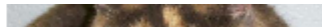
dogs



dogs



```
val_batches = tf.data.experimental.cardinality(validation_dataset)
test_dataset = validation_dataset.take(val_batches // 5)
validation_dataset = validation_dataset.skip(val_batches // 5)
```



```
print('Number of validation batches: %d' % tf.data.experimental.cardinality(validation_dataset))
print('Number of test batches: %d' % tf.data.experimental.cardinality(test_dataset))
```

```
Number of validation batches: 26
Number of test batches: 6
```

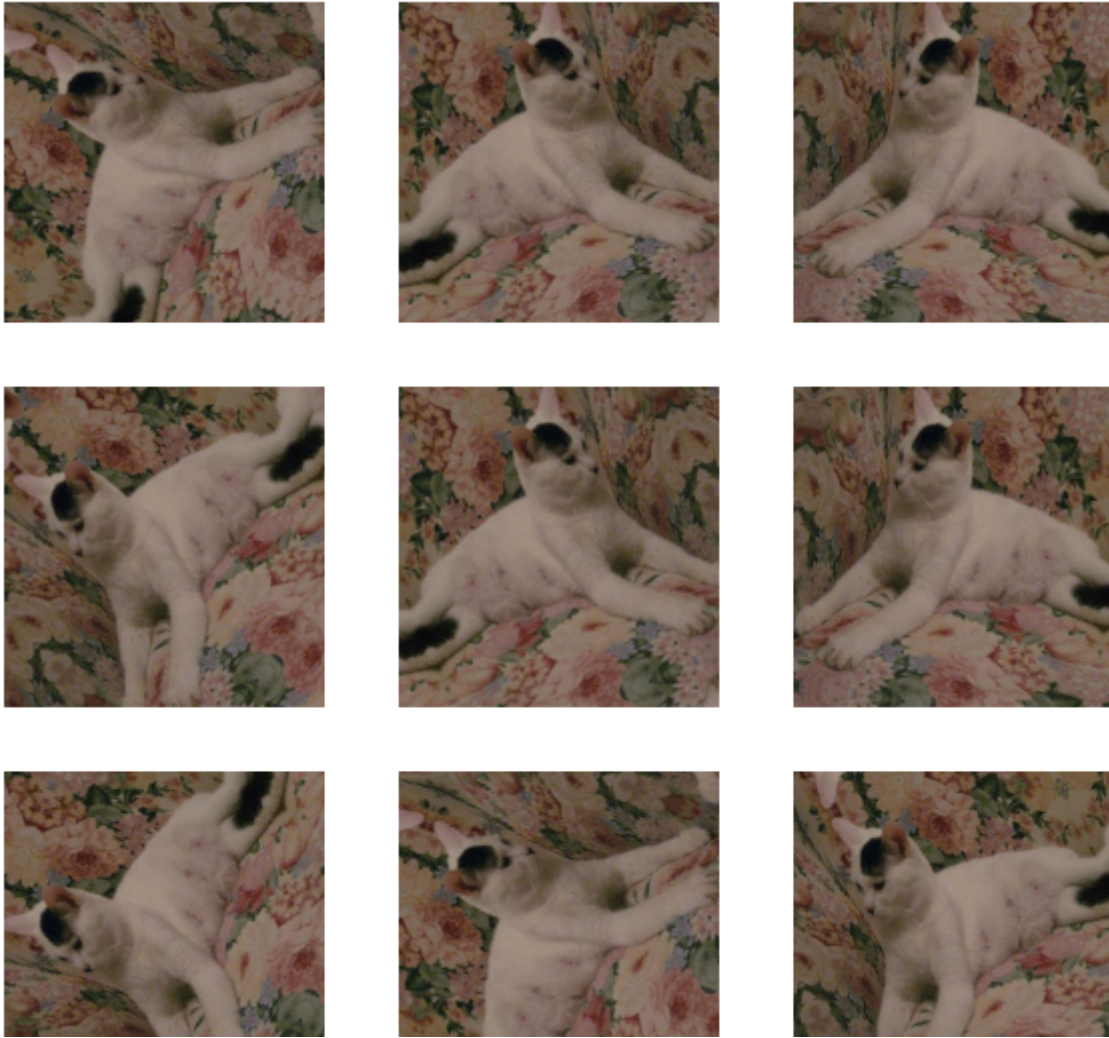


```
AUTOTUNE = tf.data.AUTOTUNE
```

```
train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)
validation_dataset = validation_dataset.prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.prefetch(buffer_size=AUTOTUNE)
```

```
data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip('horizontal'),
    tf.keras.layers.RandomRotation(0.2),
])
```

```
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')
```



```
preprocess_input = tf.keras.applications.mobilenet_v2.preprocess_input
```

```
rescale = tf.keras.layers.Rescaling(1./127.5, offset=-1)
```

```
# Create the base model from the pre-trained model MobileNet V2
```

```
IMG_SHAPE = IMG_SIZE + (3,)
```

```
base_model = tf.keras.applications.MobileNetV2(input_shape=IMG_SHAPE,
                                                include_top=False,
                                                weights='imagenet')
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet\_v2\_1.0\_128/mobilenet\_v2\_1.0\_128\_quant\_2019\_08\_27\_tf.tgz
9406464/9406464 [=====] - 0s 0us/step
```



```
image_batch, label_batch = next(iter(train_dataset))
```

```
feature_batch = base_model(image_batch)
```

```
print(feature_batch.shape)
```

```
(32, 5, 5, 1280)
```

```
base_model.trainable = False
```

```
# Let's take a look at the base model architecture
```

B

```
base_model.summary()
```

```
Model: "mobilenetv2_1.00_160"
```

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 160, 160, 3)]	0	[]
Conv1 (Conv2D)	(None, 80, 80, 32)	864	['input_1[0][0]']
bn_Conv1 (BatchNormalization)	(None, 80, 80, 32)	128	['Conv1[0][0]']
Conv1_relu (ReLU)	(None, 80, 80, 32)	0	['bn_Conv1[0][0]']
expanded_conv_depthwise (DepthwiseConv2D)	(None, 80, 80, 32)	288	['Conv1_relu[0][0]']
expanded_conv_depthwise_BN (BatchNormalization)	(None, 80, 80, 32)	128	['expanded_conv_depthwise[0][0]']
expanded_conv_depthwise_relu (ReLU)	(None, 80, 80, 32)	0	['expanded_conv_depthwise_BN[0][0]']
expanded_conv_project (Conv2D)	(None, 80, 80, 16)	512	['expanded_conv_depthwise_relu[0][0]']
expanded_conv_project_BN (BatchNormalization)	(None, 80, 80, 16)	64	['expanded_conv_project[0][0]']
block_1_expand (Conv2D)	(None, 80, 80, 96)	1536	['expanded_conv_project_BN[0][0]']
block_1_expand_BN (BatchNormalization)	(None, 80, 80, 96)	384	['block_1_expand[0][0]']
block_1_expand_relu (ReLU)	(None, 80, 80, 96)	0	['block_1_expand_BN[0][0]']
block_1_pad (ZeroPadding2D)	(None, 81, 81, 96)	0	['block_1_expand_relu[0][0]']
block_1_depthwise (DepthwiseConv2D)	(None, 40, 40, 96)	864	['block_1_pad[0][0]']
block_1_depthwise_BN (BatchNormalization)	(None, 40, 40, 96)	384	['block_1_depthwise[0][0]']
block_1_depthwise_relu (ReLU)	(None, 40, 40, 96)	0	['block_1_depthwise_BN[0][0]']
block_1_project (Conv2D)	(None, 40, 40, 24)	2304	['block_1_depthwise_relu[0][0]']
block_1_project_BN (BatchNormalization)	(None, 40, 40, 24)	96	['block_1_project[0][0]']
block_2_expand (Conv2D)	(None, 40, 40, 144)	3456	['block_1_project_BN[0][0]']
block_2_expand_BN (BatchNormalization)	(None, 40, 40, 144)	576	['block_2_expand[0][0]']
block_2_expand_relu (ReLU)	(None, 40, 40, 144)	0	['block_2_expand_BN[0][0]']

```
global_average_layer = tf.keras.layers.GlobalAveragePooling2D()
feature_batch_average = global_average_layer(feature_batch)
print(feature_batch_average.shape)
```

```
(32, 1280)
```

```
prediction_layer = tf.keras.layers.Dense(1)
prediction_batch = prediction_layer(feature_batch_average)
print(prediction_batch.shape)
```

```
(32, 1)
```

```
inputs = tf.keras.Input(shape=(160, 160, 3))
x = data_augmentation(inputs)
x = preprocess_input(x)
x = base_model(x, training=False)
x = global_average_layer(x)
x = tf.keras.layers.Dropout(0.2)(x)
outputs = prediction_layer(x)
model = tf.keras.Model(inputs, outputs)
```

```
base_learning_rate = 0.0001
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=base_learning_rate),
              loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "model"
```

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	[(None, 160, 160, 3)]	0
sequential (Sequential)	(None, 160, 160, 3)	0
tf.math.truediv (TFOpLambda)	(None, 160, 160, 3)	0
tf.math.subtract (TFOpLambda)	(None, 160, 160, 3)	0
mobilenetv2_1.00_160 (Functional)	(None, 5, 5, 1280)	2257984
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dropout (Dropout)	(None, 1280)	0
dense (Dense)	(None, 1)	1281

```
=====
```

```
Total params: 2,259,265
Trainable params: 1,281
Non-trainable params: 2,257,984
```

```
len(model.trainable_variables)
```

```
2
```

```
initial_epochs = 10
```

```
loss0, accuracy0 = model.evaluate(validation_dataset)
```

```
26/26 [=====] - 24s 742ms/step - loss: 0.9479 - accuracy: 0
```



```
print("initial loss: {:.2f}".format(loss0))
```

```
print("initial accuracy: {:.2f}".format(accuracy0))
```

```
initial loss: 0.95
```

```
initial accuracy: 0.33
```

```
history = model.fit(train_dataset,
                    epochs=initial_epochs,
                    validation_data=validation_dataset)
```

```
Epoch 1/10
```

```
63/63 [=====] - 69s 1s/step - loss: 0.7938 - accuracy: 0.505
```

```
Epoch 2/10
```

```
63/63 [=====] - 63s 994ms/step - loss: 0.5820 - accuracy: 0
```

```
Epoch 3/10
```

```
63/63 [=====] - 61s 961ms/step - loss: 0.4624 - accuracy: 0
```

```
Epoch 4/10
```

```
63/63 [=====] - 58s 914ms/step - loss: 0.3716 - accuracy: 0
```

```
Epoch 5/10
```

```
63/63 [=====] - 58s 924ms/step - loss: 0.3060 - accuracy: 0
```

```
Epoch 6/10
```

```
63/63 [=====] - 60s 949ms/step - loss: 0.2852 - accuracy: 0
```

```
Epoch 7/10
```

```
63/63 [=====] - 59s 931ms/step - loss: 0.2608 - accuracy: 0
```

```
Epoch 8/10
```

```
63/63 [=====] - 58s 926ms/step - loss: 0.2427 - accuracy: 0
```

```
Epoch 9/10
```

```
63/63 [=====] - 60s 950ms/step - loss: 0.2235 - accuracy: 0
```

```
Epoch 10/10
```

```
63/63 [=====] - 58s 923ms/step - loss: 0.2120 - accuracy: 0
```



```
acc = history.history['accuracy']
```

```
val_acc = history.history['val_accuracy']
```

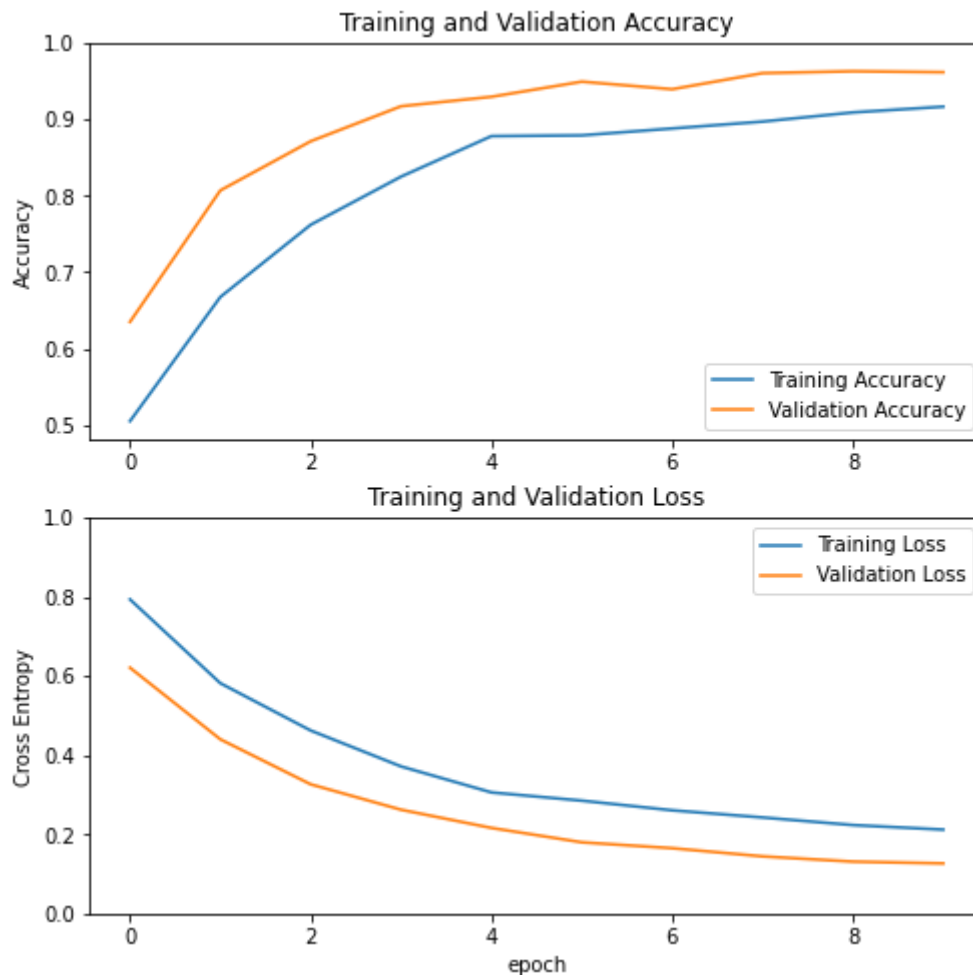
```
loss = history.history['loss']
```

```
val_loss = history.history['val_loss']
```

B


```
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()
```



```
base_model.trainable = True
```

```
# 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
```

B

```
fine_tune_at = 100
```

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

```
Number of layers in the base model: 154
```

```
model.compile(loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
              optimizer = tf.keras.optimizers.RMSprop(learning_rate=base_learning_rate/10)
              metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "model"
```

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	[(None, 160, 160, 3)]	0
sequential (Sequential)	(None, 160, 160, 3)	0
tf.math.truediv (TFOpLambda)	(None, 160, 160, 3)	0
tf.math.subtract (TFOpLambda)	(None, 160, 160, 3)	0
mobilenetv2_1.00_160 (Functional)	(None, 5, 5, 1280)	2257984
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dropout (Dropout)	(None, 1280)	0
dense (Dense)	(None, 1)	1281
=====		
Total params: 2,259,265		
Trainable params: 1,862,721		
Non-trainable params: 396,544		
=====		

```
len(model.trainable_variables)
```

```
56
```

```
fine_tune_epochs = 10
total_epochs = initial_epochs + fine_tune_epochs
history_fine = model.fit(train_dataset, epochs=total_epochs, initial_epoch=history.epoch[-1])
```

```
Epoch 10/20
```

```
63/63 [=====] - 86s 1s/step - loss: 0.0625 - accuracy: 0.97
```

```
Epoch 11/20
```

B


```

63/63 [=====] - 87s 1s/step - loss: 0.0453 - accuracy: 0.982
Epoch 12/20
63/63 [=====] - 85s 1s/step - loss: 0.0432 - accuracy: 0.983
Epoch 13/20
63/63 [=====] - 86s 1s/step - loss: 0.0569 - accuracy: 0.978
Epoch 14/20
63/63 [=====] - 86s 1s/step - loss: 0.0504 - accuracy: 0.981
Epoch 15/20
63/63 [=====] - 85s 1s/step - loss: 0.0542 - accuracy: 0.975
Epoch 16/20
63/63 [=====] - 85s 1s/step - loss: 0.0396 - accuracy: 0.986
Epoch 17/20
63/63 [=====] - 84s 1s/step - loss: 0.0398 - accuracy: 0.985
Epoch 18/20
63/63 [=====] - 85s 1s/step - loss: 0.0338 - accuracy: 0.988
Epoch 19/20
63/63 [=====] - 87s 1s/step - loss: 0.0319 - accuracy: 0.988
Epoch 20/20
63/63 [=====] - 83s 1s/step - loss: 0.0419 - accuracy: 0.982

```



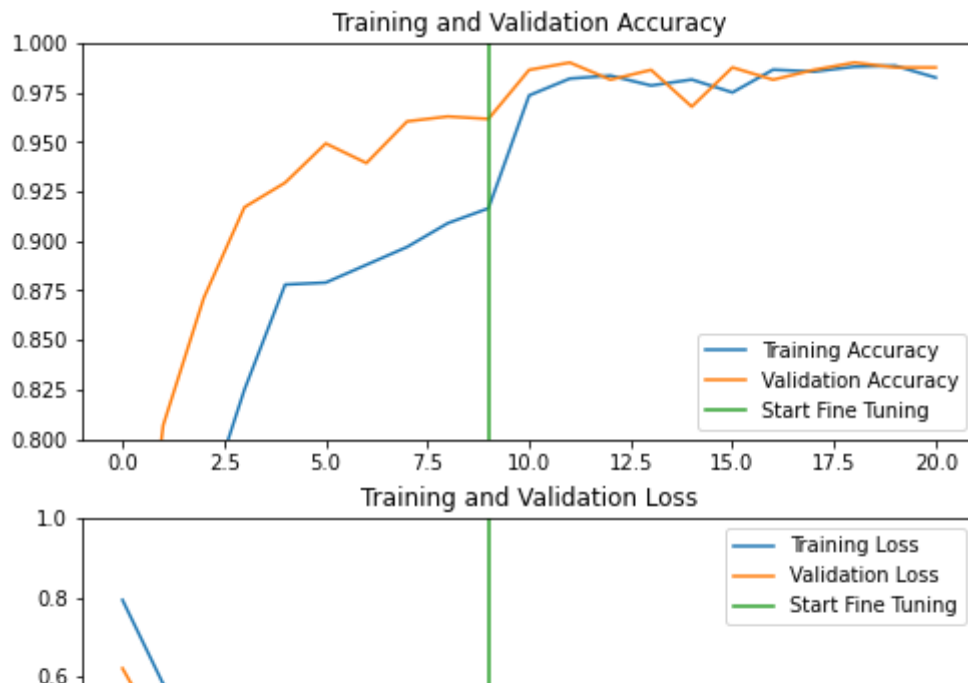
```

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

loss += history_fine.history['loss']
val_loss += history_fine.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.ylim([0.8, 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()

```



```
base_model.trainable = True
```

```
# 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 = 100
```

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

```
Number of layers in the base model: 154
```

```
model.compile(loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
              optimizer = tf.keras.optimizers.RMSprop(learning_rate=base_learning_rate/10)
              metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "model"
```

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 160, 160, 3)]	0
sequential (Sequential)	(None, 160, 160, 3)	0
tf.math.truediv (TFOpLambda)	(None, 160, 160, 3)	0
tf.math.subtract (TFOpLambda)	(None, 160, 160, 3)	0
mobilenetv2_1.00_160 (Func	(None, 5, 5, 1280)	2257984

B

```
ional)
```

```
global_average_pooling2d (GlobalAveragePooling2D) 0
```

```
dropout (Dropout) (None, 1280) 0
```

```
dense (Dense) (None, 1) 1281
```

```
=====
Total params: 2,259,265
Trainable params: 1,862,721
Non-trainable params: 396,544
=====
```

```
len(model.trainable_variables)
```

```
56
```

```
fine_tune_epochs = 10
```

```
total_epochs = initial_epochs + fine_tune_epochs
```

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

```
Epoch 10/20
```

```
63/63 [=====] - 93s 1s/step - loss: 0.0285 - accuracy: 0.989
```

```
Epoch 11/20
```

```
63/63 [=====] - 83s 1s/step - loss: 0.0344 - accuracy: 0.989
```

```
Epoch 12/20
```

```
63/63 [=====] - 86s 1s/step - loss: 0.0313 - accuracy: 0.988
```

```
Epoch 13/20
```

```
63/63 [=====] - 84s 1s/step - loss: 0.0326 - accuracy: 0.988
```

```
Epoch 14/20
```

```
63/63 [=====] - 84s 1s/step - loss: 0.0244 - accuracy: 0.990
```

```
Epoch 15/20
```

```
63/63 [=====] - 86s 1s/step - loss: 0.0254 - accuracy: 0.990
```

```
Epoch 16/20
```

```
63/63 [=====] - 88s 1s/step - loss: 0.0261 - accuracy: 0.989
```

```
Epoch 17/20
```

```
63/63 [=====] - 84s 1s/step - loss: 0.0323 - accuracy: 0.987
```

```
Epoch 18/20
```

```
63/63 [=====] - 83s 1s/step - loss: 0.0237 - accuracy: 0.989
```

```
Epoch 19/20
```

```
63/63 [=====] - 87s 1s/step - loss: 0.0184 - accuracy: 0.993
```

```
Epoch 20/20
```

```
63/63 [=====] - 84s 1s/step - loss: 0.0153 - accuracy: 0.994
```



```
acc += history_fine.history['accuracy']
```

```
val_acc += history_fine.history['val_accuracy']
```

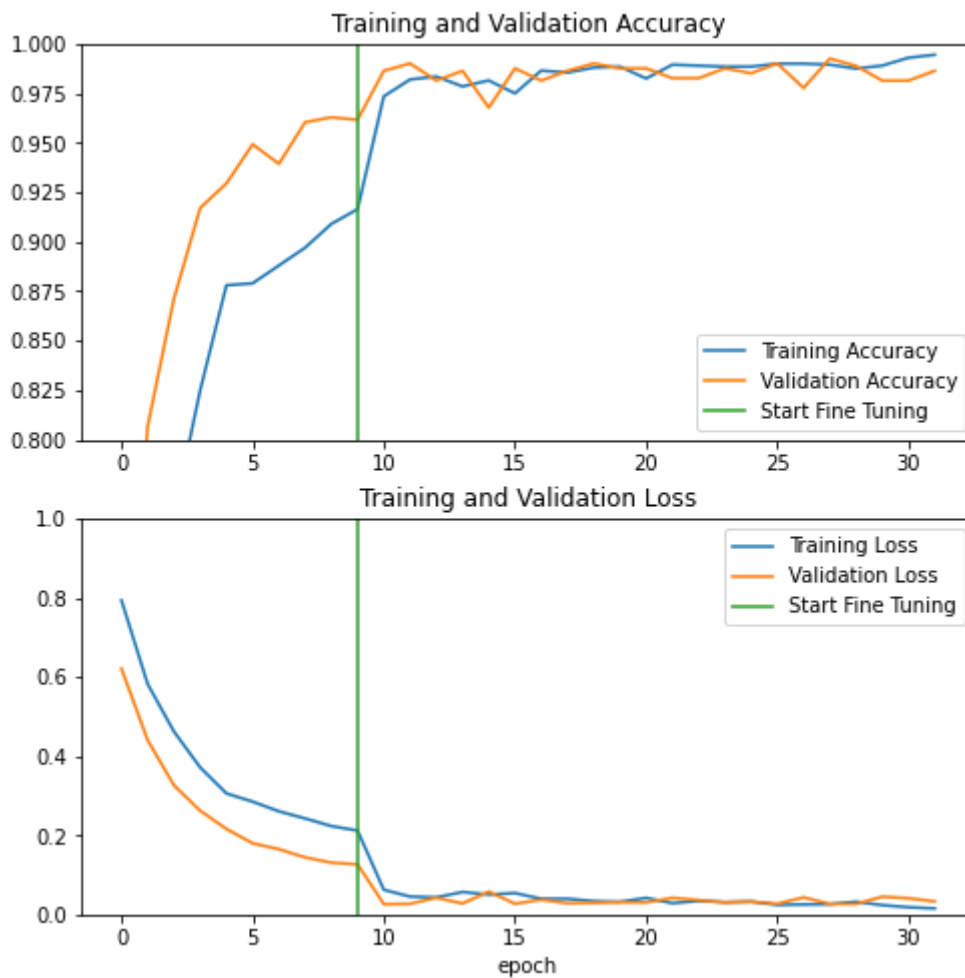
```
loss += history_fine.history['loss']
```

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

B

```
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([0.8, 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()
```



```
loss, accuracy = model.evaluate(test_dataset)
print('Test accuracy :', accuracy)
```

6/6 [=====] - 6s 856ms/step - loss: 0.0223 - accuracy: 0.994

Test accuracy : 0.9947916865348816



```
# Retrieve a batch of images from the test set
image_batch, label_batch = test_dataset.as_numpy_iterator().next()
predictions = model.predict_on_batch(image_batch).flatten()

# Apply a sigmoid since our model returns logits
predictions = tf.nn.sigmoid(predictions)
predictions = tf.where(predictions < 0.5, 0, 1)

print('Predictions:\n', predictions.numpy())
print('Labels:\n', label_batch)

plt.figure(figsize=(10, 10))
for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(image_batch[i].astype("uint8"))
    plt.title(class_names[predictions[i]])
    plt.axis("off")
```

Predictions:
[0 1 1 0 1 0 0 1 0 1 1 1 0 0 1 0 0 1 0 0 0 0 1 1 1 1 1 0]
Labels:
[0 1 1 0 1 0 0 1 0 1 1 1 0 0 1 0 0 1 0 0 0 0 1 1 1 1 1 0]



✓ 4s completed at 8:48 PM

● ✕