```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
import matplotlib.pyplot as plt
# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

# import os
# for dirname, _, filenames in os.walk('/kaggle/input'):
#     for filename in filenames:
#         print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save &
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session


image_size = (256, 256)
batch_size = 1
train_ds = tf.keras.utils.image_dataset_from_directory(
  '/kaggle/input/garbage-classification/Garbage classification/Garbage classification',
  validation_split=0.2,
  subset="training",
  image_size=image_size,
  seed=123,
  batch_size=batch_size,
  color_mode="rgb"
)
val_ds = tf.keras.utils.image_dataset_from_directory(
  '/kaggle/input/garbage-classification/Garbage classification/Garbage classification',
  validation_split=0.2,
  subset="validation",
  image_size=image_size,
  seed=123,
  batch_size=batch_size,
  color_mode="rgb"
)
```

```
Found 2527 files belonging to 6 classes.
Using 2022 files for training.
Found 2527 files belonging to 6 classes.
Using 505 files for validation.
```

```
class_names = train_ds.class_names
num_classes = len(train_ds.class_names)
image_shape = image_size + (3,)
count = dict.fromkeys(class_names, 0)
for image, labels in train_ds:
    for i in range(batch_size):
        count[class_names[labels[0]]] += 1


plt.bar(range(len(count)), list(count.values()), align='center')
plt.xticks(range(len(count)), list(count.keys()))
```

```
([<matplotlib.axis.XTick at 0x7d8d70411750>,
  <matplotlib.axis.XTick at 0x7d8d704113d0>,
  <matplotlib.axis.XTick at 0x7d8d703f1f10>,
  <matplotlib.axis.XTick at 0x7d8d70381690>,
  <matplotlib.axis.XTick at 0x7d8d70381710>,
  <matplotlib.axis.XTick at 0x7d8d703813d0>],
 [Text(0, 0, 'cardboard'),
  Text(1, 0, 'glass'),
  Text(2, 0, 'metal'),
  Text(3, 0, 'paper'),
  Text(4, 0, 'plastic'),
  Text(5, 0, 'trash')])
```

```
plt.figure(figsize=(10,10))

for i, example in enumerate(train_ds.take(9)):
    image = example[0][0]
    label = example[1][0]

    ax = plt.subplot(3, 3, i+1)
    plt.imshow(image.numpy().astype("uint8"))
    plt.title(class_names[label])
    plt.axis("off")
```

Neural Network

```
model = Sequential([
    layers.Input(shape=image_shape),
    layers.Dense(128, activation='relu'),
    layers.Dropout(.2),
    layers.Dense(256, activation='relu'),
    layers.Dropout(.2),
    layers.Flatten(),
    layers.Dense(num_classes)
])



model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])


epochs=15
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/15
2023-04-22 22:03:20.388929: E tensorflow/core/grappler/optimizers/meta_optimizer.cc:954] layout failed: INVALID_ARGUMENT: Size of values
2022/2022 [==============================] - 85s 39ms/step - loss: 542.3392 - accuracy: 0.2834 - val_loss: 1.8292 - val_accuracy: 0.0574
Epoch 2/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.7465 - accuracy: 0.3294 - val_loss: 1.8465 - val_accuracy: 0.1723
Epoch 3/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.8629 - accuracy: 0.2982 - val_loss: 1.8199 - val_accuracy: 0.1743
Epoch 4/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.7995 - accuracy: 0.2794 - val_loss: 1.8029 - val_accuracy: 0.1762
Epoch 5/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.7466 - accuracy: 0.2621 - val_loss: 1.7660 - val_accuracy: 0.1822
Epoch 6/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.8256 - accuracy: 0.2463 - val_loss: 1.7435 - val_accuracy: 0.2475
Epoch 7/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.7273 - accuracy: 0.2730 - val_loss: 1.7201 - val_accuracy: 0.2653
Epoch 8/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.6699 - accuracy: 0.3205 - val_loss: 1.9330 - val_accuracy: 0.2812
Epoch 9/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.6018 - accuracy: 0.3398 - val_loss: 2.4155 - val_accuracy: 0.2752
Epoch 10/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.5030 - accuracy: 0.3961 - val_loss: 3.7635 - val_accuracy: 0.2792
Epoch 11/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.5932 - accuracy: 0.4085 - val_loss: 3.4495 - val_accuracy: 0.2792
Epoch 12/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.5424 - accuracy: 0.4095 - val_loss: 2.2216 - val_accuracy: 0.2772
Epoch 13/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.4318 - accuracy: 0.4426 - val_loss: 2.7552 - val_accuracy: 0.2970
Epoch 14/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.2871 - accuracy: 0.4679 - val_loss: 4.6169 - val_accuracy: 0.3188
Epoch 15/15
2022/2022 [==============================] - 78s 39ms/step - loss: 1.3463 - accuracy: 0.4703 - val_loss: 4.3838 - val_accuracy: 0.3188
```

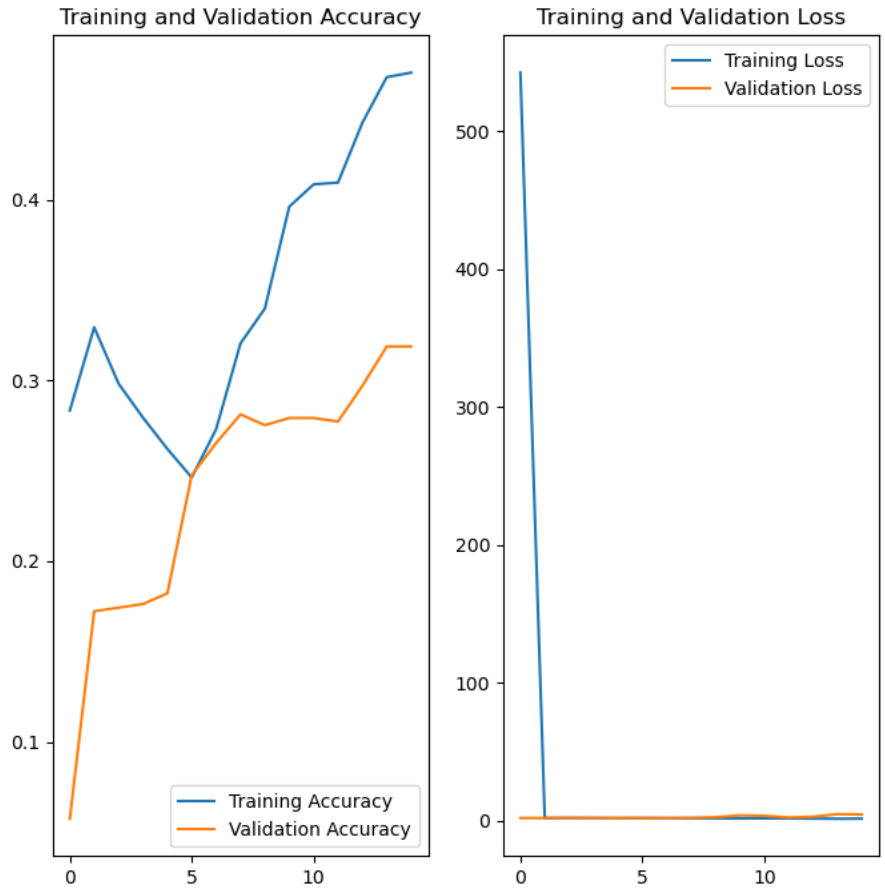
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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

epochs_range = range(epochs)

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

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



Convolutional Neural Network

```
model = Sequential([
  layers.Rescaling(1./255, input_shape=image_shape),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])
```

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])


model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 256, 256, 3)       0

 conv2d (Conv2D)             (None, 256, 256, 16)      448

 max_pooling2d (MaxPooling2D  (None, 128, 128, 16)     0
 )

 conv2d_1 (Conv2D)           (None, 128, 128, 32)      4640

 max_pooling2d_1 (MaxPooling  (None, 64, 64, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 64, 64, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 32, 32, 64)       0
 2D)

 flatten_1 (Flatten)         (None, 65536)             0

 dense_3 (Dense)             (None, 128)               8388736

 dense_4 (Dense)             (None, 6)                 774

=================================================================
Total params: 8,413,094
Trainable params: 8,413,094
Non-trainable params: 0
_________________________________________________________________
```

```
epochs=15
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/15
2022/2022 [==============================] - 25s 8ms/step - loss: 1.7200 - accuracy: 0.2591 - val_loss: 1.5816 - val_accuracy: 0.3366
Epoch 2/15
2022/2022 [==============================] - 14s 7ms/step - loss: 1.5269 - accuracy: 0.3813 - val_loss: 1.5331 - val_accuracy: 0.3564
Epoch 3/15
2022/2022 [==============================] - 15s 7ms/step - loss: 1.2378 - accuracy: 0.5178 - val_loss: 1.5599 - val_accuracy: 0.3584
Epoch 4/15
2022/2022 [==============================] - 16s 8ms/step - loss: 0.8047 - accuracy: 0.7018 - val_loss: 1.9094 - val_accuracy: 0.4198
Epoch 5/15
2022/2022 [==============================] - 15s 7ms/step - loss: 0.4572 - accuracy: 0.8432 - val_loss: 2.5062 - val_accuracy: 0.3881
Epoch 6/15
2022/2022 [==============================] - 15s 7ms/step - loss: 0.2998 - accuracy: 0.9105 - val_loss: 3.5812 - val_accuracy: 0.4238
Epoch 7/15
2022/2022 [==============================] - 15s 7ms/step - loss: 0.1926 - accuracy: 0.9357 - val_loss: 4.2626 - val_accuracy: 0.4059
Epoch 8/15
2022/2022 [==============================] - 15s 7ms/step - loss: 0.1566 - accuracy: 0.9575 - val_loss: 5.0650 - val_accuracy: 0.4198
Epoch 9/15
2022/2022 [==============================] - 15s 7ms/step - loss: 0.1156 - accuracy: 0.9674 - val_loss: 5.8556 - val_accuracy: 0.3683
Epoch 10/15
2022/2022 [==============================] - 15s 7ms/step - loss: 0.1141 - accuracy: 0.9683 - val_loss: 5.5162 - val_accuracy: 0.4000
Epoch 11/15
2022/2022 [==============================] - 15s 7ms/step - loss: 0.0589 - accuracy: 0.9871 - val_loss: 6.2815 - val_accuracy: 0.4020
Epoch 12/15
2022/2022 [==============================] - 14s 7ms/step - loss: 0.0412 - accuracy: 0.9901 - val_loss: 8.1907 - val_accuracy: 0.3743
Epoch 13/15
2022/2022 [==============================] - 14s 7ms/step - loss: 0.0563 - accuracy: 0.9866 - val_loss: 7.3596 - val_accuracy: 0.4198
Epoch 14/15
2022/2022 [==============================] - 15s 7ms/step - loss: 0.0627 - accuracy: 0.9847 - val_loss: 7.6886 - val_accuracy: 0.3703
Epoch 15/15
2022/2022 [==============================] - 15s 7ms/step - loss: 0.0836 - accuracy: 0.9812 - val_loss: 7.3248 - val_accuracy: 0.4099
```

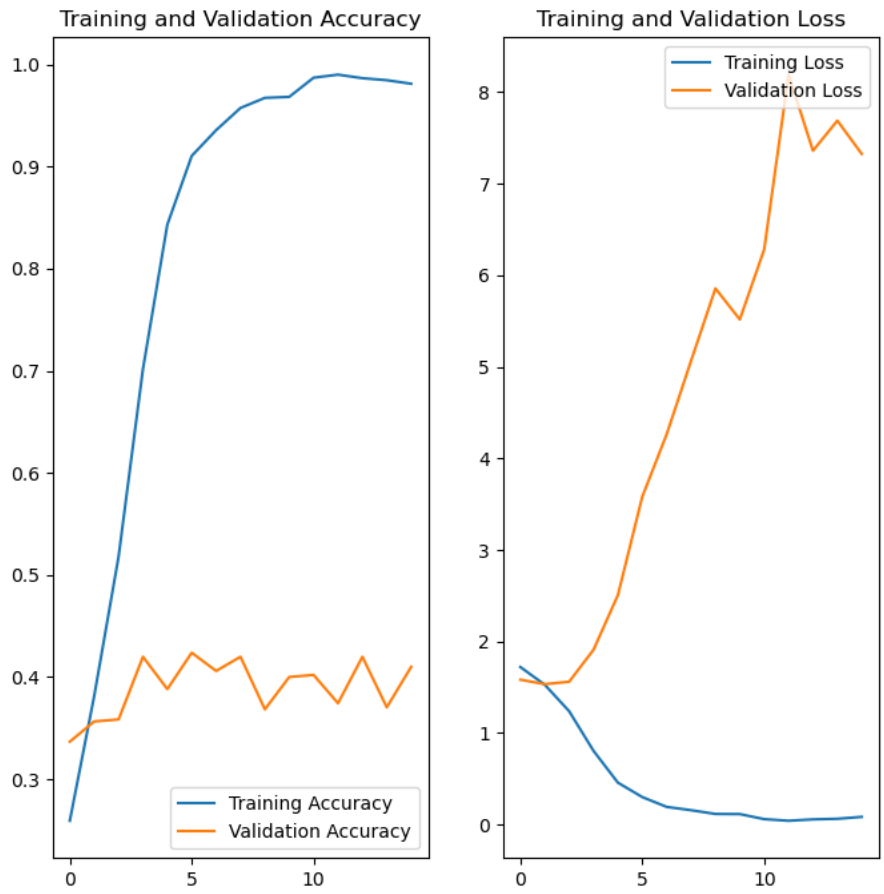
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
```

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

epochs_range = range(epochs)

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

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



Transfer Learning

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

Base Model

```
# Create the base model from the pre-trained model MobileNet V2
base_model = tf.keras.applications.MobileNetV2(input_shape=image_shape,
                                               include_top=False,
                                               weights='imagenet')
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf
9406464/9406464 [==============================] - 0s 0us/step
```

```
image_batch, label_batch = next(iter(train_ds))
feature_batch = base_model(image_batch)
print(feature_batch.shape)
```

```
(1, 8, 8, 1280)
```

```
base_model.trainable = False
```

Feature Extraction

Data Augmentation

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

Adding Classifiaction Head

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

```
(1, 1280)
```

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

```
(1, 1)
```

```
inputs = tf.keras.Input(shape=image_shape)
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_3 (InputLayer)        [(None, 256, 256, 3)]     0

 sequential_2 (Sequential)   (None, 256, 256, 3)       0

 tf.math.truediv (TFOpLambda  (None, 256, 256, 3)      0
 )

 tf.math.subtract (TFOpLambd  (None, 256, 256, 3)      0
 a)

 mobilenetv2_1.00_224 (Funct  (None, 8, 8, 1280)       2257984
 ional)

 global_average_pooling2d (G  (None, 1280)             0
```

```
 lobalAveragePooling2D)

 dropout_2 (Dropout)         (None, 1280)              0

 dense_5 (Dense)             (None, 1)                 1281

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

```
initial_epochs = 10

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

```
505/505 [==============================] - 6s 9ms/step - loss: -0.2249 - accuracy: 0.2317
```

```
print("initial loss: {:.2f}".format(loss0))
print("initial accuracy: {:.2f}".format(accuracy0))
```

```
initial loss: -0.22
initial accuracy: 0.23
```

```
history = model.fit(train_ds,
                    epochs=initial_epochs,
                    validation_data=val_ds)
```

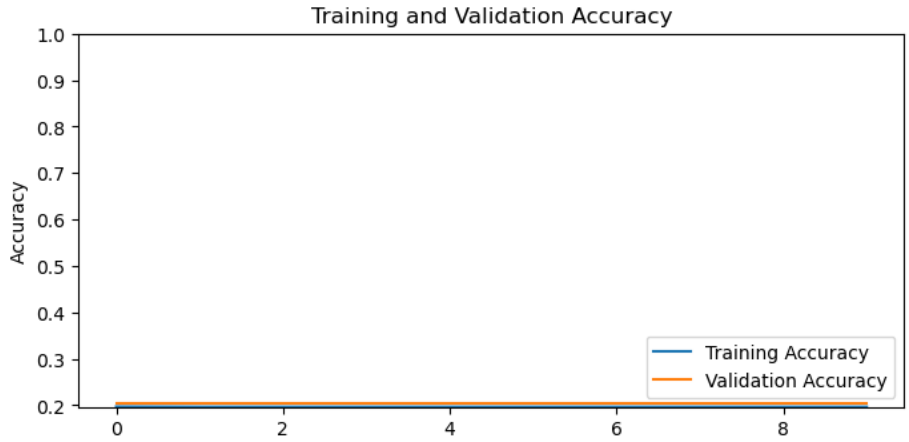
```
Epoch 1/10
2022/2022 [==============================] - 35s 15ms/step - loss: -21.1117 - accuracy: 0.1973 - val_loss: -39.1773 - val_accuracy: 0.20
Epoch 2/10
2022/2022 [==============================] - 30s 15ms/step - loss: -61.1551 - accuracy: 0.1968 - val_loss: -77.5614 - val_accuracy: 0.20
Epoch 3/10
2022/2022 [==============================] - 30s 15ms/step - loss: -102.3228 - accuracy: 0.1968 - val_loss: -116.0098 - val_accuracy: 0.
Epoch 4/10
2022/2022 [==============================] - 30s 15ms/step - loss: -142.5291 - accuracy: 0.1968 - val_loss: -154.5656 - val_accuracy: 0.
Epoch 5/10
2022/2022 [==============================] - 30s 15ms/step - loss: -183.1707 - accuracy: 0.1968 - val_loss: -193.0489 - val_accuracy: 0.
Epoch 6/10
2022/2022 [==============================] - 30s 15ms/step - loss: -223.3655 - accuracy: 0.1968 - val_loss: -231.4556 - val_accuracy: 0.
Epoch 7/10
2022/2022 [==============================] - 30s 15ms/step - loss: -264.3979 - accuracy: 0.1968 - val_loss: -269.9103 - val_accuracy: 0.
Epoch 8/10
2022/2022 [==============================] - 30s 15ms/step - loss: -304.4212 - accuracy: 0.1968 - val_loss: -308.3747 - val_accuracy: 0.
Epoch 9/10
2022/2022 [==============================] - 30s 15ms/step - loss: -344.6414 - accuracy: 0.1968 - val_loss: -346.7709 - val_accuracy: 0.
Epoch 10/10
2022/2022 [==============================] - 30s 15ms/step - loss: -384.1013 - accuracy: 0.1968 - val_loss: -385.1770 - val_accuracy: 0.
```

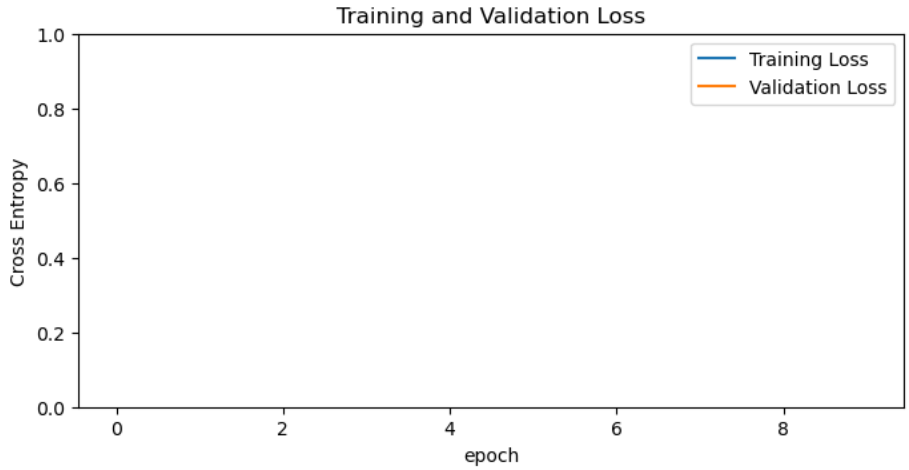
```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

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()),max(plt.ylim())])
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([min(plt.ylim()),1.0])
plt.title('Training and Validation Loss')
plt.xlabel('epoch')
plt.show()
```





Fine Tuning

```
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_3 (InputLayer)        [(None, 256, 256, 3)]     0

 sequential_2 (Sequential)   (None, 256, 256, 3)       0

 tf.math.truediv (TFOpLambda  (None, 256, 256, 3)      0
 )

 tf.math.subtract (TFOpLambd  (None, 256, 256, 3)      0
 a)

 mobilenetv2_1.00_224 (Funct  (None, 8, 8, 1280)       2257984
 ional)
```

```
 global_average_pooling2d (G  (None, 1280)            0
 lobalAveragePooling2D)

 dropout_2 (Dropout)         (None, 1280)            0

 dense_5 (Dense)             (None, 1)               1281

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

```
fine_tune_epochs = 10
total_epochs =  initial_epochs + fine_tune_epochs

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

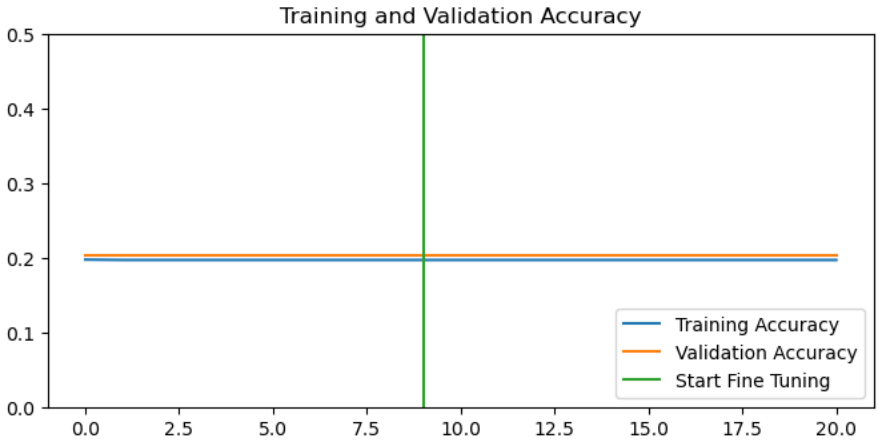
```
Epoch 10/20
2022/2022 [==============================] - 55s 22ms/step - loss: -6343.2456 - accuracy: 0.1968 - val_loss: -6687.9141 - val_accuracy:
Epoch 11/20
2022/2022 [==============================] - 44s 22ms/step - loss: -6887.1162 - accuracy: 0.1968 - val_loss: -6748.1274 - val_accuracy:
Epoch 12/20
2022/2022 [==============================] - 44s 22ms/step - loss: -7047.5200 - accuracy: 0.1968 - val_loss: -7014.0615 - val_accuracy:
Epoch 13/20
2022/2022 [==============================] - 44s 22ms/step - loss: -7208.3350 - accuracy: 0.1968 - val_loss: -7154.0527 - val_accuracy:
Epoch 14/20
2022/2022 [==============================] - 44s 22ms/step - loss: -7354.4229 - accuracy: 0.1968 - val_loss: -7254.2358 - val_accuracy:
Epoch 15/20
2022/2022 [==============================] - 44s 22ms/step - loss: -7507.6934 - accuracy: 0.1968 - val_loss: -7436.2754 - val_accuracy:
Epoch 16/20
2022/2022 [==============================] - 44s 22ms/step - loss: -7667.2451 - accuracy: 0.1968 - val_loss: -7540.5107 - val_accuracy:
Epoch 17/20
2022/2022 [==============================] - 44s 22ms/step - loss: -7819.6914 - accuracy: 0.1968 - val_loss: -7678.7139 - val_accuracy:
Epoch 18/20
2022/2022 [==============================] - 44s 22ms/step - loss: -7972.3208 - accuracy: 0.1968 - val_loss: -7847.5215 - val_accuracy:
Epoch 19/20
2022/2022 [==============================] - 44s 22ms/step - loss: -8113.9160 - accuracy: 0.1968 - val_loss: -7954.1084 - val_accuracy:
Epoch 20/20
2022/2022 [==============================] - 44s 22ms/step - loss: -8250.7617 - accuracy: 0.1968 - val_loss: -8135.7822 - val_accuracy:
```

```
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, .5])
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()
```


Training and Validation Accuracy
0.5
0.4
0.3
0.2
0.1
0.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Training Accuracy
Validation Accuracy
Start Fine Tuning


Training and Validation Loss
1.0
0.8
0.6
0.4
0.2
Training Loss
Validation Loss
Start Fine Tuning

Analyisis