Setup

Import TensorFlow and other necessary libraries:

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

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential

import pandas as pd
```

Import Data

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
import pathlib
data_dir = pathlib.Path('/content/drive/MyDrive/is-that-santa')
```

There are 1230 total images:

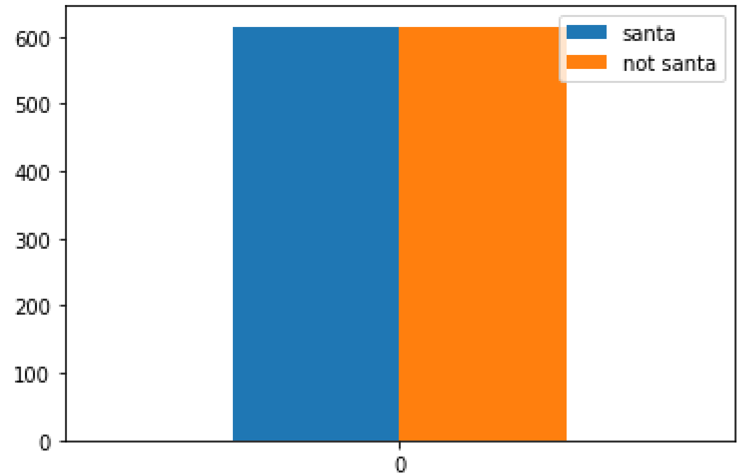
```
image_count = len(list(data_dir.glob('*/*.jpg')))
print(image_count)

santa_count = len(list(data_dir.glob('santa/*')))
print(santa_count)

notSanta_count = len(list(data_dir.glob('not-a-santa/*')))
print(notSanta_count)
```

```
1230
615
615
```

Target Distribution

```
# Distribution
df = pd.DataFrame([(santa_count, notSanta_count)], columns=('santa', 'not santa'))

df.plot.bar(rot=0)

# It's even so it doesn't really matter
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcede1a5730>
```



Here are some santas:

```
santa = list(data_dir.glob('santa/*'))
PIL.Image.open(str(santa[2]))
```


```
PIL.Image.open(str(santa[1]))
```

And some not santas:

```
notSanta = list(data_dir.glob('not-a-santa/*'))
PIL.Image.open(str(notSanta[0]))
```

```
PIL.Image.open(str(notSanta[1]))
```

Load data using a Keras utility

Load these images off disk using `tf.keras.utils.image_dataset_from_directory` utility.

Create a dataset

Define some parameters for the loader:

```
batch_size = 32
img_height = 180
img_width = 180
```

Train/Test Split

```
train_ds = tf.keras.utils.image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset="training",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

```
Found 1230 files belonging to 2 classes.
Using 984 files for training.
```

```
val_ds = tf.keras.utils.image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset="validation",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

```
Found 1230 files belonging to 2 classes.
Using 246 files for validation.
```

```
class_names = train_ds.class_names
print(class_names)
```

```
['not-a-santa', 'santa']
```

Visualize the data

Here are the first nine images from the training dataset:

```
import matplotlib.pyplot as plt

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

Configure the dataset for performance

Using `Dataset.cache` and `Dataset.prefetch`

```
AUTOTUNE = tf.data.AUTOTUNE

train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

Standardize the data

Standardize `[0, 255]` RGB values to be in the `[0, 1]` range by using `tf.keras.layers.Rescaling`:

```
normalization_layer = layers.Rescaling(1./255)
```

Apply to the dataset by calling `Dataset.map`:

```
normalized_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
image_batch, labels_batch = next(iter(normalized_ds))
first_image = image_batch[0]
```

A Basic Keras Sequential Model

Create the model

The Keras Sequential model consists of three convolution blocks (`tf.keras.layers.Conv2D`) with a max pooling layer (`tf.keras.layers.MaxPooling2D`) in each of them. There's a fully-connected layer (`tf.keras.layers.Dense`) with 128 units on top of it that is activated by a ReLU activation function (`'relu'`).

```
num_classes = len(class_names)

model = Sequential([
  layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
  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)
])
```

Compile the model

Using the `tf.keras.optimizers.Adam` optimizer and `tf.keras.losses.SparseCategoricalCrossentropy` loss function.

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

Model summary

View layers

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_1 (Rescaling)     (None, 180, 180, 3)       0

 conv2d (Conv2D)             (None, 180, 180, 16)      448

 max_pooling2d (MaxPooling2D  (None, 90, 90, 16)       0
```

```
 )

 conv2d_1 (Conv2D)           (None, 90, 90, 32)        4640

 max_pooling2d_1 (MaxPooling  (None, 45, 45, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 45, 45, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 22, 22, 64)       0
 2D)

 flatten (Flatten)           (None, 30976)             0

 dense (Dense)               (None, 128)               3965056

 dense_1 (Dense)             (None, 2)                 258

=================================================================
Total params: 3,988,898
Trainable params: 3,988,898
Non-trainable params: 0
_________________________________________________________________
```

Train the model

Train the model for 10 epochs

```
epochs=10
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/10
31/31 [==============================] - 1s 27ms/step - loss: 0.0050 - accuracy: 0.9990 - val_loss: 0.5340 - val_accuracy: 0.9106
Epoch 2/10
31/31 [==============================] - 1s 24ms/step - loss: 0.0023 - accuracy: 1.0000 - val_loss: 0.4327 - val_accuracy: 0.9187
Epoch 3/10
31/31 [==============================] - 1s 24ms/step - loss: 0.0012 - accuracy: 1.0000 - val_loss: 0.5107 - val_accuracy: 0.9309
Epoch 4/10
```

```
31/31 [==============================] - 1s 24ms/step - loss: 8.1585e-04 - accuracy: 1.0000 - val_loss: 0.4780 - val_accuracy: 0.9187
Epoch 5/10
31/31 [==============================] - 1s 24ms/step - loss: 6.4522e-04 - accuracy: 1.0000 - val_loss: 0.5248 - val_accuracy: 0.9309
Epoch 6/10
31/31 [==============================] - 1s 24ms/step - loss: 4.1402e-04 - accuracy: 1.0000 - val_loss: 0.5143 - val_accuracy: 0.9268
Epoch 7/10
31/31 [==============================] - 1s 23ms/step - loss: 3.4308e-04 - accuracy: 1.0000 - val_loss: 0.5296 - val_accuracy: 0.9309
Epoch 8/10
31/31 [==============================] - 1s 23ms/step - loss: 2.8823e-04 - accuracy: 1.0000 - val_loss: 0.5407 - val_accuracy: 0.9309
Epoch 9/10
31/31 [==============================] - 1s 24ms/step - loss: 2.4241e-04 - accuracy: 1.0000 - val_loss: 0.5628 - val_accuracy: 0.9309
Epoch 10/10
31/31 [==============================] - 1s 24ms/step - loss: 2.1223e-04 - accuracy: 1.0000 - val_loss: 0.5710 - val_accuracy: 0.9309
```

Visualize training results

Create plots of the loss and accuracy on the training and validation sets:

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

print("final training accuracy: {:.2f}".format(acc[-1]))

print("final validation accuracy: {:.2f}".format(val_acc[-1]))

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

print("final training loss: {:.2f}".format(loss[-1]))
print("final validation loss: {:.2f}".format(val_loss[-1]))

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()
```

```
final training accuracy: 1.00
final validation accuracy: 0.93
final training loss: 0.00
final validation loss: 0.57
```

Some discrepancies between accuracies and losses

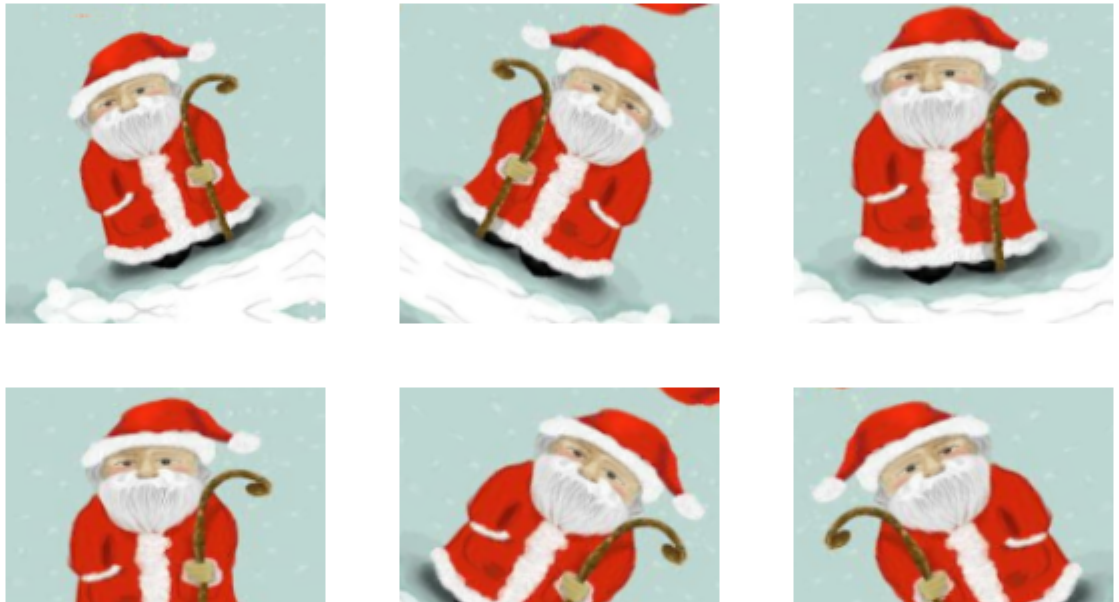
Data augmentation to handle Overfitting (Adjusted CNN)

Generate additional data through transformations using `tf.keras.layers.RandomFlip`, `tf.keras.layers.RandomRotation`, and `tf.keras.layers.RandomZoom`.

```
data_augmentation = keras.Sequential(
  [
    layers.RandomFlip("horizontal",
                      input_shape=(img_height,
                                  img_width,
                                  3)),
    layers.RandomRotation(0.1),
    layers.RandomZoom(0.1),
  ]
)
```

Augmentation Examples:

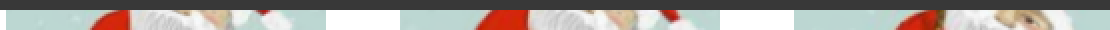
```
plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
  for i in range(9):
    augmented_images = data_augmentation(images)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")
```



Dropout

Dropout Regularization

Create a new neural network with `tf.keras.layers.Dropout`



```
model = Sequential([
  data_augmentation,
  layers.Rescaling(1./255),
  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.Dropout(0.2),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes, name="outputs")
])
```

Compile and train the model

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

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential_1 (Sequential)   (None, 180, 180, 3)       0

 rescaling_2 (Rescaling)     (None, 180, 180, 3)       0

 conv2d_3 (Conv2D)           (None, 180, 180, 16)      448

 max_pooling2d_3 (MaxPooling  (None, 90, 90, 16)       0
 2D)

 conv2d_4 (Conv2D)           (None, 90, 90, 32)        4640

 max_pooling2d_4 (MaxPooling  (None, 45, 45, 32)       0
 2D)

 conv2d_5 (Conv2D)           (None, 45, 45, 64)        18496

 max_pooling2d_5 (MaxPooling  (None, 22, 22, 64)       0
 2D)

 dropout (Dropout)           (None, 22, 22, 64)        0

 flatten_1 (Flatten)         (None, 30976)             0

 dense_2 (Dense)             (None, 128)               3965056

 outputs (Dense)             (None, 2)                 258

=================================================================
Total params: 3,988,898
Trainable params: 3,988,898
Non-trainable params: 0
_________________________________________________________________
```

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

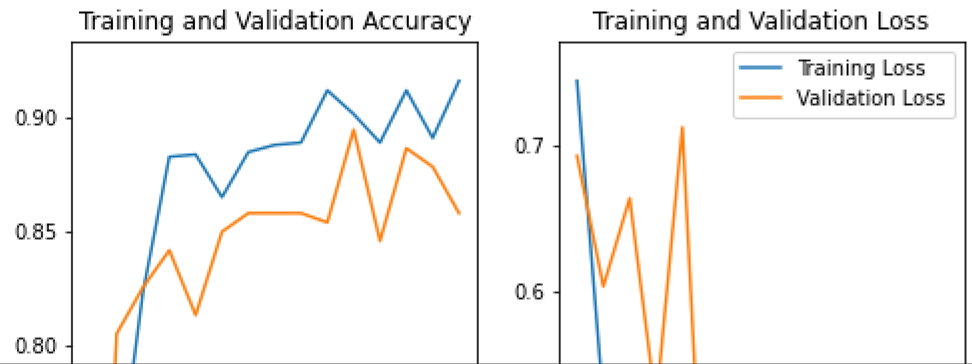
```
Epoch 1/15
31/31 [==============================] - 2s 49ms/step - loss: 0.7438 - accuracy: 0.6348 - val_loss: 0.6925 - val_accuracy: 0.5691
Epoch 2/15
31/31 [==============================] - 1s 41ms/step - loss: 0.5240 - accuracy: 0.7357 - val_loss: 0.6032 - val_accuracy: 0.8049
Epoch 3/15
31/31 [==============================] - 1s 41ms/step - loss: 0.3898 - accuracy: 0.8231 - val_loss: 0.6636 - val_accuracy: 0.8252
Epoch 4/15
31/31 [==============================] - 1s 41ms/step - loss: 0.2965 - accuracy: 0.8824 - val_loss: 0.5220 - val_accuracy: 0.8415
Epoch 5/15
31/31 [==============================] - 1s 41ms/step - loss: 0.2682 - accuracy: 0.8835 - val_loss: 0.7121 - val_accuracy: 0.8130
Epoch 6/15
31/31 [==============================] - 1s 41ms/step - loss: 0.3198 - accuracy: 0.8647 - val_loss: 0.3597 - val_accuracy: 0.8496
Epoch 7/15
31/31 [==============================] - 1s 40ms/step - loss: 0.2789 - accuracy: 0.8845 - val_loss: 0.3815 - val_accuracy: 0.8577
Epoch 8/15
31/31 [==============================] - 1s 41ms/step - loss: 0.2620 - accuracy: 0.8876 - val_loss: 0.4204 - val_accuracy: 0.8577
Epoch 9/15
31/31 [==============================] - 1s 40ms/step - loss: 0.2385 - accuracy: 0.8887 - val_loss: 0.3997 - val_accuracy: 0.8577
Epoch 10/15
31/31 [==============================] - 1s 40ms/step - loss: 0.2143 - accuracy: 0.9116 - val_loss: 0.4487 - val_accuracy: 0.8537
Epoch 11/15
31/31 [==============================] - 1s 42ms/step - loss: 0.2326 - accuracy: 0.9011 - val_loss: 0.3641 - val_accuracy: 0.8943
Epoch 12/15
31/31 [==============================] - 1s 41ms/step - loss: 0.2230 - accuracy: 0.8887 - val_loss: 0.4186 - val_accuracy: 0.8455
Epoch 13/15
31/31 [==============================] - 1s 41ms/step - loss: 0.2256 - accuracy: 0.9116 - val_loss: 0.2996 - val_accuracy: 0.8862
Epoch 14/15
31/31 [==============================] - 1s 41ms/step - loss: 0.2465 - accuracy: 0.8907 - val_loss: 0.3222 - val_accuracy: 0.8780
Epoch 15/15
31/31 [==============================] - 1s 40ms/step - loss: 0.2030 - accuracy: 0.9157 - val_loss: 0.4090 - val_accuracy: 0.8577
```

Visualize training results

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

```
print("final training accuracy: {:.2f}".format(acc[-1]))
print("final validation accuracy: {:.2f}".format(val_acc[-1]))

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

print("final training loss: {:.2f}".format(loss[-1]))
print("final validation loss: {:.2f}".format(val_loss[-1]))

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()
```

```
final training accuracy: 0.92
final validation accuracy: 0.86
final training loss: 0.20
final validation loss: 0.41
```



Model Transfer

Data Pre-processing

```
BATCH_SIZE = 32
IMG_SIZE = (180, 180)

train_dataset = train_ds

validation_dataset = val_ds
```

Rescale pixels

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

Create Base Model from MobileNet V2

```
IMG_SHAPE = IMG_SIZE + (3,)
base_model = tf.keras.applications.MobileNetV2(input_shape=IMG_SHAPE,
```

```
                                               include_top=False,
                                               weights='imagenet')
```

```
WARNING:tensorflow:`input_shape` is undefined or non-square, or `rows` is not in [96, 128, 160, 192, 224]. Weights for input shape (224, 224) will be lo
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_224_
9406464/9406464 [==============================] - 0s 0us/step
```

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

```
(32, 6, 6, 1280)
```

Freeze convolutional base

```
base_model.trainable = False
```

```
# Summary of Architecture
base_model.summary()
```

```
 block_7_add (Add)              (None, 12, 12, 64)   0           ['block_6_project_BN[0][0]',
                                                                  'block_7_project_BN[0][0]']

 block_8_expand (Conv2D)        (None, 12, 12, 384)  24576       ['block_7_add[0][0]']

 block_8_expand_BN (BatchNormal  (None, 12, 12, 384)  1536       ['block_8_expand[0][0]']
 ization)

 block_8_expand_relu (ReLU)     (None, 12, 12, 384)  0           ['block_8_expand_BN[0][0]']

 block_8_depthwise (DepthwiseCo  (None, 12, 12, 384)  3456       ['block_8_expand_relu[0][0]']
 nv2D)

 block_8_depthwise_BN (BatchNor  (None, 12, 12, 384)  1536       ['block_8_depthwise[0][0]']
 malization)

 block_8_depthwise_relu (ReLU)  (None, 12, 12, 384)  0           ['block_8_depthwise_BN[0][0]']

 block_8_project (Conv2D)       (None, 12, 12, 64)   24576       ['block_8_depthwise_relu[0][0]']

 block_8_project_BN (BatchNorma  (None, 12, 12, 64)  256         ['block_8_project[0][0]']
```

```
lization)

block_8_add (Add)              (None, 12, 12, 64)   0           ['block_7_add[0][0]',
                                                                 'block_8_project_BN[0][0]']

block_9_expand (Conv2D)        (None, 12, 12, 384)  24576       ['block_8_add[0][0]']

block_9_expand_BN (BatchNormal  (None, 12, 12, 384)  1536       ['block_9_expand[0][0]']
ization)

block_9_expand_relu (ReLU)     (None, 12, 12, 384)  0           ['block_9_expand_BN[0][0]']

block_9_depthwise (DepthwiseCo  (None, 12, 12, 384)  3456       ['block_9_expand_relu[0][0]']
nv2D)

block_9_depthwise_BN (BatchNor  (None, 12, 12, 384)  1536       ['block_9_depthwise[0][0]']
malization)

block_9_depthwise_relu (ReLU)  (None, 12, 12, 384)  0           ['block_9_depthwise_BN[0][0]']

block_9_project (Conv2D)       (None, 12, 12, 64)   24576       ['block_9_depthwise_relu[0][0]']

block_9_project_BN (BatchNorma  (None, 12, 12, 64)  256         ['block_9_project[0][0]']
lization)

block_9_add (Add)              (None, 12, 12, 64)   0           ['block_8_add[0][0]',
                                                                 'block_9_project_BN[0][0]']

block_10_expand (Conv2D)       (None, 12, 12, 384)  24576       ['block_9_add[0][0]']

block_10_expand_BN (BatchNorma  (None, 12, 12, 384)  1536       ['block_10_expand[0][0]']
lization)

block_10_expand_relu (ReLU)    (None, 12, 12, 384)  0           ['block_10_expand_BN[0][0]']

block_10_depthwise (DepthwiseC  (None, 12, 12, 384)  3456       ['block_10_expand_relu[0][0]']
onv2D)
```

Add a Classification Head

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

```
(32, 1280)
```

Convert features into a single prediction per image

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

```
(32, 1)
```

Build Model

```
inputs = tf.keras.Input(shape=(180, 180, 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)
```

Compile Model

```
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, 180, 180, 3)]     0
```

```
 sequential_1 (Sequential)   (None, 180, 180, 3)       0

 tf.math.truediv (TFOpLambda  (None, 180, 180, 3)      0
 )

 tf.math.subtract (TFOpLambd  (None, 180, 180, 3)      0
 a)

 mobilenetv2_1.00_224 (Funct  (None, 6, 6, 1280)       2257984
 ional)

 global_average_pooling2d (G  (None, 1280)             0
 lobalAveragePooling2D)

 dropout_1 (Dropout)         (None, 1280)              0

 dense_3 (Dense)             (None, 1)                 1281

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

Train the Model

```
initial_epochs = 10

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

```
8/8 [==============================] - 3s 72ms/step - loss: 0.7739 - accuracy: 0.5610
```

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

```
initial loss: 0.77
initial accuracy: 0.56
```

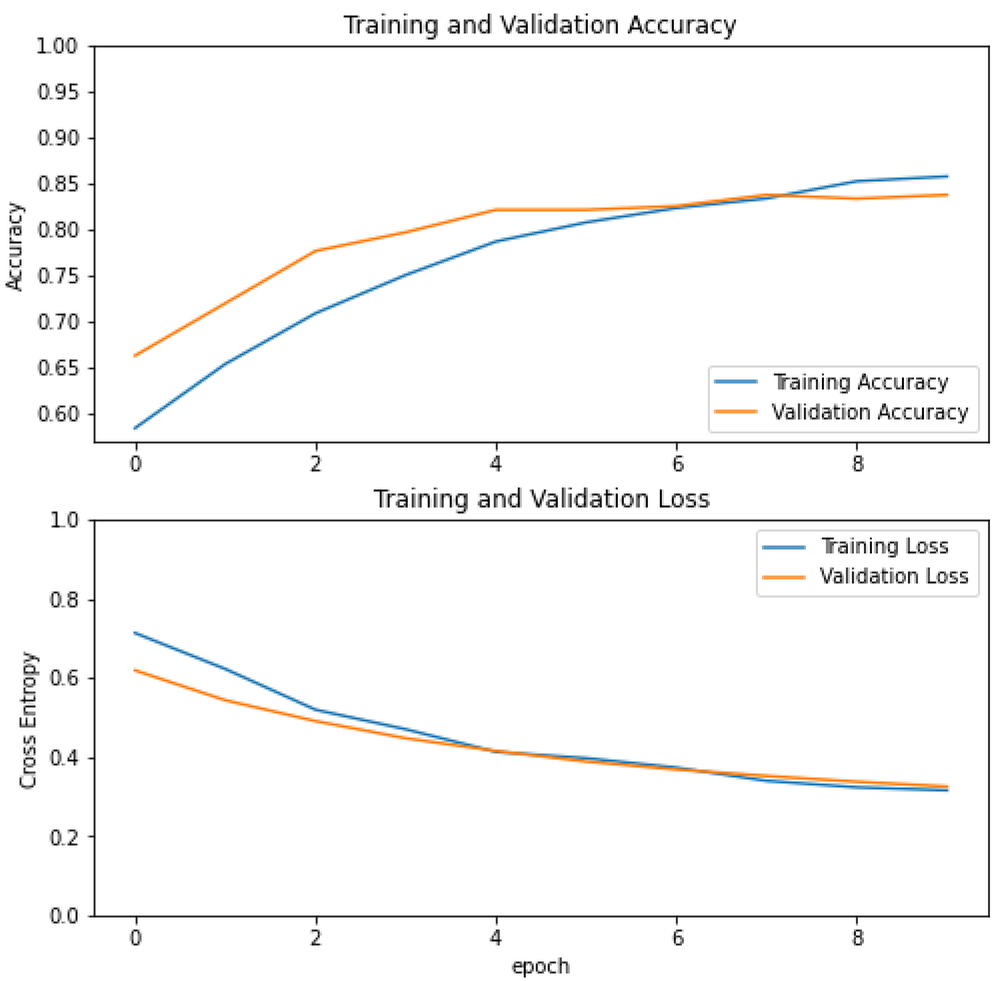
```
history = model.fit(train_dataset,
                    epochs=initial_epochs,
                    validation_data=validation_dataset)
```

```
Epoch 1/10
31/31 [==============================] - 6s 98ms/step - loss: 0.7136 - accuracy: 0.5838 - val_loss: 0.6191 - val_accuracy: 0.6626
Epoch 2/10
31/31 [==============================] - 3s 90ms/step - loss: 0.6226 - accuracy: 0.6535 - val_loss: 0.5436 - val_accuracy: 0.7195
Epoch 3/10
31/31 [==============================] - 3s 91ms/step - loss: 0.5195 - accuracy: 0.7086 - val_loss: 0.4908 - val_accuracy: 0.7764
Epoch 4/10
31/31 [==============================] - 2s 55ms/step - loss: 0.4700 - accuracy: 0.7503 - val_loss: 0.4474 - val_accuracy: 0.7967
Epoch 5/10
31/31 [==============================] - 2s 55ms/step - loss: 0.4128 - accuracy: 0.7867 - val_loss: 0.4153 - val_accuracy: 0.8211
Epoch 6/10
31/31 [==============================] - 2s 55ms/step - loss: 0.3969 - accuracy: 0.8075 - val_loss: 0.3884 - val_accuracy: 0.8211
Epoch 7/10
31/31 [==============================] - 2s 55ms/step - loss: 0.3730 - accuracy: 0.8231 - val_loss: 0.3684 - val_accuracy: 0.8252
Epoch 8/10
31/31 [==============================] - 2s 55ms/step - loss: 0.3396 - accuracy: 0.8335 - val_loss: 0.3520 - val_accuracy: 0.8374
Epoch 9/10
31/31 [==============================] - 2s 55ms/step - loss: 0.3232 - accuracy: 0.8522 - val_loss: 0.3374 - val_accuracy: 0.8333
Epoch 10/10
31/31 [==============================] - 2s 54ms/step - loss: 0.3156 - accuracy: 0.8574 - val_loss: 0.3252 - val_accuracy: 0.8374
```

Visualize the Training Results

```
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()),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()
```




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

print("final training accuracy: {:.2f}".format(acc[-1]))
print("final validation accuracy: {:.2f}".format(val_acc[-1]))

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

```
print("final training loss: {:.2f}".format(loss[-1]))
print("final validation loss: {:.2f}".format(val_loss[-1]))
```

```
final training accuracy: 0.86
final validation accuracy: 0.84
final training loss: 0.32
final validation loss: 0.33
```

Fine tuning

Unfreeze Model

```
base_model.trainable = True
```

```
# 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
```

Recompile Model

```
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, 180, 180, 3)]     0

 sequential_1 (Sequential)   (None, 180, 180, 3)       0

 tf.math.truediv (TFOpLambda  (None, 180, 180, 3)      0
 )

 tf.math.subtract (TFOpLambd  (None, 180, 180, 3)      0
 a)

 mobilenetv2_1.00_224 (Funct  (None, 6, 6, 1280)       2257984
 ional)

 global_average_pooling2d (G  (None, 1280)             0
 lobalAveragePooling2D)

 dropout_1 (Dropout)         (None, 1280)              0

 dense_3 (Dense)             (None, 1)                 1281

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

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

```
56
```

Retrain Model

```
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
31/31 [==============================] - 8s 97ms/step - loss: 0.2038 - accuracy: 0.9074 - val_loss: 0.1998 - val_accuracy: 0.9228
Epoch 11/20
31/31 [==============================] - 2s 67ms/step - loss: 0.1646 - accuracy: 0.9313 - val_loss: 0.1825 - val_accuracy: 0.9309
Epoch 12/20
31/31 [==============================] - 2s 69ms/step - loss: 0.1357 - accuracy: 0.9448 - val_loss: 0.1690 - val_accuracy: 0.9268
Epoch 13/20
31/31 [==============================] - 2s 81ms/step - loss: 0.1300 - accuracy: 0.9542 - val_loss: 0.1524 - val_accuracy: 0.9350
Epoch 14/20
31/31 [==============================] - 2s 73ms/step - loss: 0.1023 - accuracy: 0.9646 - val_loss: 0.1392 - val_accuracy: 0.9431
Epoch 15/20
31/31 [==============================] - 2s 68ms/step - loss: 0.0843 - accuracy: 0.9677 - val_loss: 0.1379 - val_accuracy: 0.9472
Epoch 16/20
31/31 [==============================] - 3s 92ms/step - loss: 0.0871 - accuracy: 0.9709 - val_loss: 0.1247 - val_accuracy: 0.9593
Epoch 17/20
31/31 [==============================] - 2s 77ms/step - loss: 0.0823 - accuracy: 0.9677 - val_loss: 0.1255 - val_accuracy: 0.9553
Epoch 18/20
31/31 [==============================] - 2s 68ms/step - loss: 0.0681 - accuracy: 0.9750 - val_loss: 0.1215 - val_accuracy: 0.9675
Epoch 19/20
31/31 [==============================] - 2s 68ms/step - loss: 0.0598 - accuracy: 0.9729 - val_loss: 0.1158 - val_accuracy: 0.9675
Epoch 20/20
31/31 [==============================] - 2s 67ms/step - loss: 0.0601 - accuracy: 0.9719 - val_loss: 0.1125 - val_accuracy: 0.9593
```

Visualize the Results

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

print("final training accuracy: {:.2f}".format(acc[-1]))
print("final validation accuracy: {:.2f}".format(val_acc[-1]))

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

print("final training loss: {:.2f}".format(loss[-1]))
print("final validation loss: {:.2f}".format(val_loss[-1]))
```

```
final training accuracy: 0.97
final validation accuracy: 0.96
```

```
final training loss: 0.06
final validation loss: 0.11
```

```
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()
```

Conclusions

I had 4 main approaches (4 models) that I worked with in this notebook. They were all sequential models and there was a regular CNN, a CNN with data augmentation, a model transfer, and model transfer with tuning.

The first CNN did amazingly well with the train set and managed to perfectly identify santa/not-santa. Even the validation accuracy of .93 was really impressive, but that tells me that this data was probably really easy to seperate.

The second CNN with data augmentation did worse when I ran it but the accuracy and loss graphs were much closer together than the first model. This could hopefully imply it could better generalize to other data it has yet to see.

The first model transfer did even poorer that the second CNN with its validation accuracy just trailing behind the second CNN. However, this was without any tuning.

The tuned model transfer did fantastic, even better than the first CNN when considering the validation accuracy of .96.

I assume these models did so well because the test data mostly consists of people or things that look like people. Given data that isn't similar to what I was using, I think the models would do significantly worse.