1 Phase 4 Project - Image Classification

In this project, we will aim to use artificial neural networks to identify pneumonia by looking at x-ray images of patients' lungs.

1.1 Obtain

The data for this project comes from Kaggle. https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia (https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia)

We will download the images into the './data' folder, then use Keras' ImageDataGenerator to feed the images into our models.

In [1]:

```
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

executed in 5.66s, finished 11:33:34 2021-04-30

In [2]:

```
# Instantiate ImageDataGenerators for train, validation, and test data
train_data = ImageDataGenerator(rescale=1/255,
                                shear_range=0.2,
                                zoom_range=0.2,
                                horizontal_flip=True)
val_data = ImageDataGenerator(rescale=1/255)
test_data = ImageDataGenerator(rescale=1/255)

# Feed the data
train_generator = train_data.flow_from_directory('./data/train',
                                                 color_mode='rgb',
                                                 target_size=(224,224),
                                                 batch_size=32,
                                                 class_mode='binary')
val_generator = val_data.flow_from_directory('./data/val',
                                             color_mode='rgb',
                                             target_size=(224,224),
                                             batch_size=16,
                                             shuffle=False,
                                             class_mode='binary')
test_generator = test_data.flow_from_directory('./data/test',
                                               color_mode='rgb',
                                               target_size=(224,224),
                                               batch_size=32,
                                               shuffle=False,
                                               class_mode='binary')
```

executed in 732ms, finished 11:33:34 2021-04-30

```
Found 5216 images belonging to 2 classes.
Found 16 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
```

1.2 Scrub

There isn't much to be done for this dataset in terms of scrubbing. Each image is saved into folders based on what set it is part of (train, val, or test) and what its label is (normal or pneumonia). To go through the images and look for inconsistencies would require medical knowledge beyond my training.

1.3 Examine

In [3]:

```
import matplotlib.pyplot as plt
%matplotlib inline
```

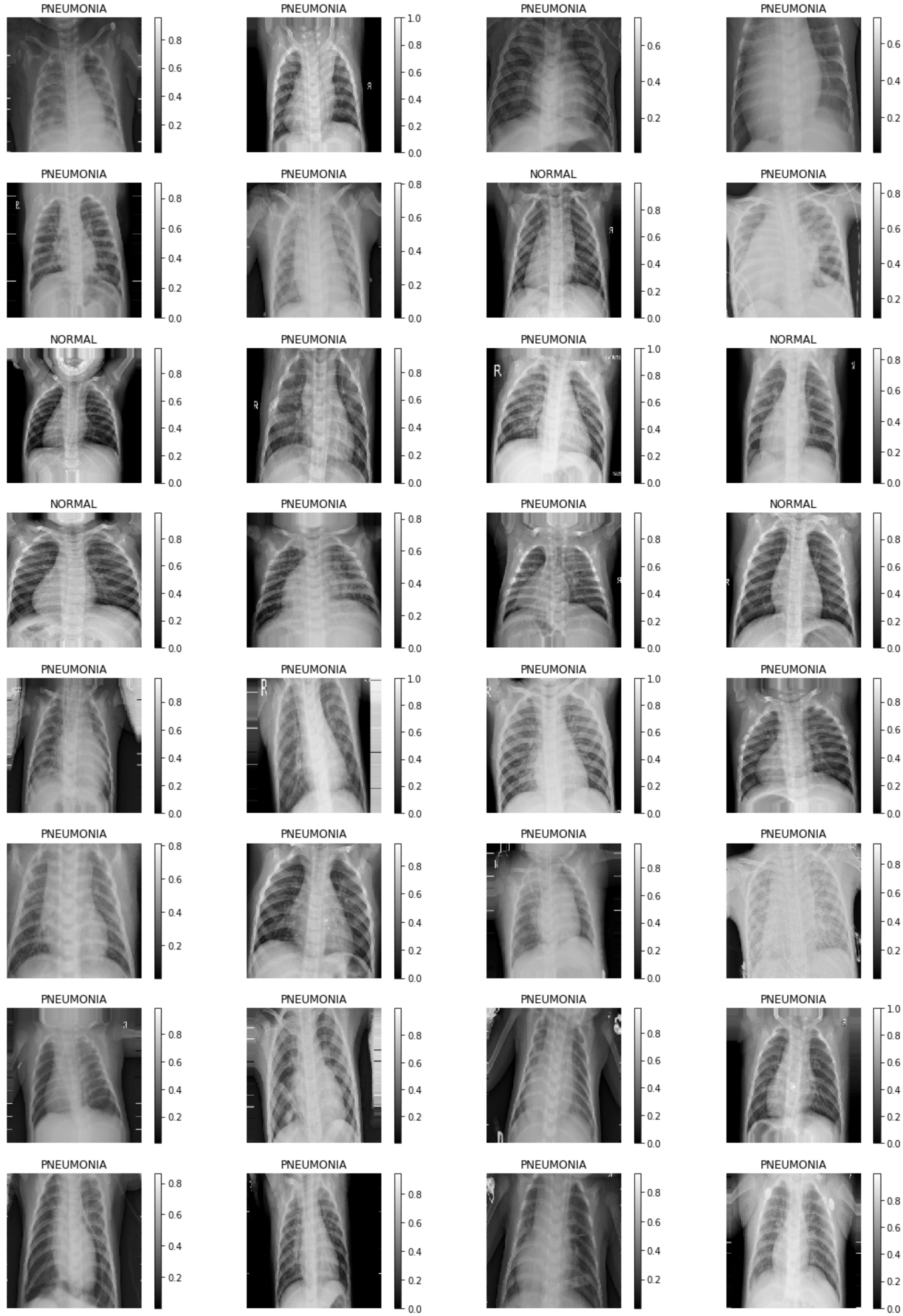
executed in 280ms, finished 11:33:35 2021-04-30

We'll use our train_generator to load up some images for us to look at.

In [4]:

```
img, labels = train_generator.next()

plt.figure(figsize=(15,20))
for i in range(len(img)):
    label = 'NORMAL'
    if labels[i] == 1:
        label = 'PNEUMONIA'
    plt.subplot(8,4,i+1)
    plt.title(label)
    plt.imshow(img[i], cmap='gray')
    plt.axis('off')
    plt.colorbar()
plt.tight_layout()
```

executed in 3.62s, finished 11:33:38 2021-04-30



Just at a first glance, the 'pneumonia' images appear to be a little fuzzier. The 'normal' images appear to have a more defined black area between the ribs. However, it's not something I would be comfortable trying to differentiate on my own, so let's try out some neural networks!

1.4 Model

In [5]:
```
from tensorflow.keras.models import *
from tensorflow.keras.layers import *
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping

from sklearn.metrics import confusion_matrix, classification_report
```
executed in 745ms, finished 11:33:39 2021-04-30

In [6]:
```
# Adding some callbacks to avoid training for too long
def init_callbacks():
    early_stopping = EarlyStopping(monitor='val_loss', patience=5)
    model_checkpoint = ModelCheckpoint('best_model.h5', monitor='val_loss',
                                       verbose=1, save_best_only=True,
                                       save_weights_only=True)

    callbacks = [early_stopping, model_checkpoint]
    return callbacks
```
executed in 15ms, finished 11:33:39 2021-04-30

1.4.1 Model 1

Let's start with a model with a single hidden layer. We'll use 128 nodes with 'relu' activation.

In [7]:
```
model_1 = Sequential()
model_1.add(Flatten(input_shape=(224,224,3)))
model_1.add(Dense(128, activation='relu'))
model_1.add(Dense(1, activation='sigmoid'))

model_1.compile(loss='binary_crossentropy',
               optimizer='adam',
               metrics=['accuracy'])
model_1.summary()
```
executed in 286ms, finished 11:33:39 2021-04-30

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
flatten (Flatten)            (None, 150528)            0         
_________________________________________________________________
dense (Dense)                (None, 128)               19267712  
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129       
=================================================================
Total params: 19,267,841
Trainable params: 19,267,841
Non-trainable params: 0
_________________________________________________________________
```

In [8]:
```
history_1 = model_1.fit(train_generator,
                        epochs=25,
                        validation_data=val_generator,
                        callbacks=init_callbacks())
```

executed in 21m 24s, finished 11:55:04 2021-04-30

```
Epoch 1/25
163/163 [==============================] - 85s 518ms/step - loss: 10.2409 - acc
uracy: 0.7107 - val_loss: 1.1253 - val_accuracy: 0.6250

Epoch 00001: val_loss improved from inf to 1.12532, saving model to best_model.
h5
Epoch 2/25
163/163 [==============================] - 83s 510ms/step - loss: 0.5110 - accu
racy: 0.8483 - val_loss: 1.3954 - val_accuracy: 0.6250

Epoch 00002: val_loss did not improve from 1.12532
Epoch 3/25
163/163 [==============================] - 79s 484ms/step - loss: 0.7264 - accu
racy: 0.8335 - val_loss: 0.4280 - val_accuracy: 0.8125

Epoch 00003: val_loss improved from 1.12532 to 0.42795, saving model to best_mo
del.h5
Epoch 4/25
163/163 [==============================] - 79s 483ms/step - loss: 0.5145 - accu
racy: 0.8560 - val_loss: 0.5614 - val_accuracy: 0.8125

Epoch 00004: val_loss did not improve from 0.42795
Epoch 5/25
163/163 [==============================] - 79s 484ms/step - loss: 0.4260 - accu
racy: 0.8654 - val_loss: 0.4773 - val_accuracy: 0.8750

Epoch 00005: val_loss did not improve from 0.42795
Epoch 6/25
163/163 [==============================] - 80s 488ms/step - loss: 0.3632 - accu
racy: 0.8713 - val_loss: 0.4110 - val_accuracy: 0.8125

Epoch 00006: val_loss improved from 0.42795 to 0.41102, saving model to best_mo
del.h5
Epoch 7/25
163/163 [==============================] - 80s 493ms/step - loss: 0.5262 - accu
racy: 0.8736 - val_loss: 0.5517 - val_accuracy: 0.8125

Epoch 00007: val_loss did not improve from 0.41102
Epoch 8/25
163/163 [==============================] - 81s 496ms/step - loss: 0.2719 - accu
racy: 0.8879 - val_loss: 1.7139 - val_accuracy: 0.5625

Epoch 00008: val_loss did not improve from 0.41102
Epoch 9/25
163/163 [==============================] - 81s 494ms/step - loss: 0.4088 - accu
racy: 0.8603 - val_loss: 0.4153 - val_accuracy: 0.8125

Epoch 00009: val_loss did not improve from 0.41102
Epoch 10/25
163/163 [==============================] - 80s 491ms/step - loss: 0.3270 - accu
```

```
racy: 0.8788 - val_loss: 0.4605 - val_accuracy: 0.8125

Epoch 00010: val_loss did not improve from 0.41102
Epoch 11/25
163/163 [==============================] - 80s 492ms/step - loss: 0.2860 - accu
racy: 0.9011 - val_loss: 0.3609 - val_accuracy: 0.8750

Epoch 00011: val_loss improved from 0.41102 to 0.36087, saving model to best_mo
del.h5
Epoch 12/25
163/163 [==============================] - 79s 485ms/step - loss: 0.2330 - accu
racy: 0.9082 - val_loss: 0.4875 - val_accuracy: 0.8125

Epoch 00012: val_loss did not improve from 0.36087
Epoch 13/25
163/163 [==============================] - 80s 492ms/step - loss: 0.2534 - accu
racy: 0.9000 - val_loss: 0.4168 - val_accuracy: 0.7500

Epoch 00013: val_loss did not improve from 0.36087
Epoch 14/25
163/163 [==============================] - 79s 487ms/step - loss: 0.2462 - accu
racy: 0.8994 - val_loss: 0.5039 - val_accuracy: 0.8125

Epoch 00014: val_loss did not improve from 0.36087
Epoch 15/25
163/163 [==============================] - 80s 488ms/step - loss: 0.2433 - accu
racy: 0.8950 - val_loss: 0.5235 - val_accuracy: 0.8125

Epoch 00015: val_loss did not improve from 0.36087
Epoch 16/25
163/163 [==============================] - 79s 486ms/step - loss: 0.2679 - accu
racy: 0.8914 - val_loss: 0.4259 - val_accuracy: 0.6875

Epoch 00016: val_loss did not improve from 0.36087
```

Because of our callbacks, the model stopped training early because the loss was not improving on the validation set.

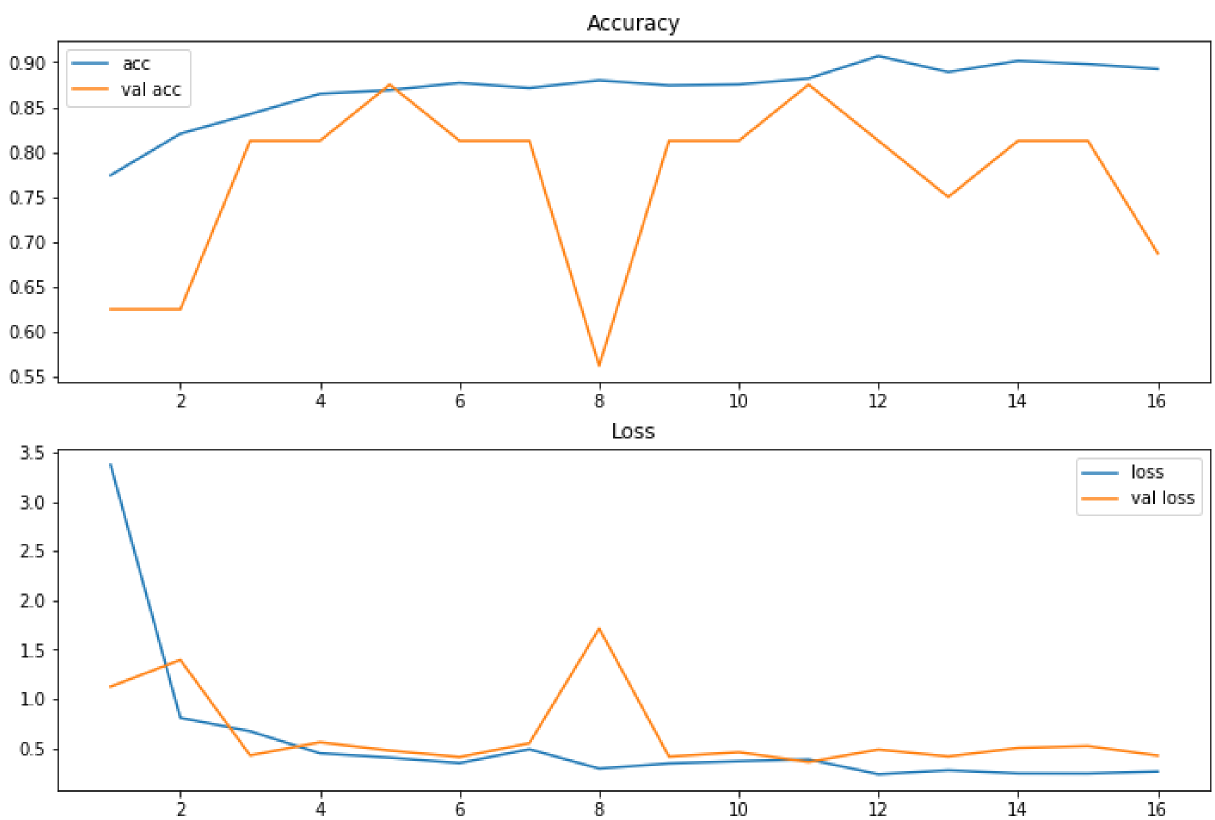
Let's make a quick function to plot out the model's performance across epochs.

In [9]:
```
def plot_model(hist):
    '''
    input: fitted model
    output: plots of accuracy and loss
    '''
    x = range(1,len(hist.history['loss'])+1)
    fig,ax = plt.subplots(2,1,figsize=(12,8))
    ax[0].plot(x, hist.history['accuracy'], label='acc')
    ax[0].plot(x, hist.history['val_accuracy'], label='val acc')
    ax[0].legend()
    ax[0].set_title('Accuracy')
    ax[1].plot(x, hist.history['loss'], label='loss')
    ax[1].plot(x, hist.history['val_loss'], label='val loss')
    ax[1].legend()
    ax[1].set_title('Loss')
    plt.show()
```

executed in 13ms, finished 11:55:04 2021-04-30

In [10]:
```
plot_model(history_1)
```

executed in 266ms, finished 11:55:04 2021-04-30



Those lines really started diverging quickly. Let's load up the best weights and check our performance on the test set.

In [11]:
```
model_1.save_weights('last_model.h5')
model_1.evaluate(test_generator)
```
executed in 5.03s, finished 11:55:09 2021-04-30

```
20/20 [==============================] - 4s 205ms/step - loss: 0.3286 - accurac
y: 0.8526
```

Out[11]:
```
[0.32862070202827454, 0.8525640964508057]
```

In [12]:
```
model_1.load_weights('best_model.h5')
model_1.evaluate(test_generator)
```
executed in 4.95s, finished 11:55:14 2021-04-30

```
20/20 [==============================] - 4s 202ms/step - loss: 0.3138 - accurac
y: 0.8590
```

Out[12]:
```
[0.3138106167316437, 0.8589743375778198]
```

In [13]:
```
predictions = model_1.predict(test_generator)
y_pred = (predictions > 0.5).astype('int')

y_true = test_generator.classes
```
executed in 4.91s, finished 11:55:19 2021-04-30

In [14]:
```
print(classification_report(y_true, y_pred))
print(confusion_matrix(y_true, y_pred))
```
executed in 14ms, finished 11:55:19 2021-04-30

```
              precision    recall  f1-score   support

           0       0.84      0.77      0.80       234
           1       0.87      0.91      0.89       390

    accuracy                           0.86       624
   macro avg       0.85      0.84      0.85       624
weighted avg       0.86      0.86      0.86       624

[[181  53]
 [ 35 355]]
```

Our base model gets us 86% accuracy with a 91% recall on positive cases. This is a good start. Let's see if we can improve our model.

1.4.2 Model 2 - Deeper

For the next model, we'll try going a little deeper with three hidden layers.

In [15]:

```
model_2 = Sequential()
model_2.add(Flatten(input_shape=(224,224,3)))
model_2.add(Dense(64, activation='relu'))
model_2.add(Dense(64, activation='relu'))
model_2.add(Dense(64, activation='relu'))
model_2.add(Dense(1, activation='sigmoid'))

model_2.compile(loss='binary_crossentropy',
                optimizer='adam',
                metrics=['accuracy'])
model_2.summary()
```

executed in 109ms, finished 11:55:19 2021-04-30

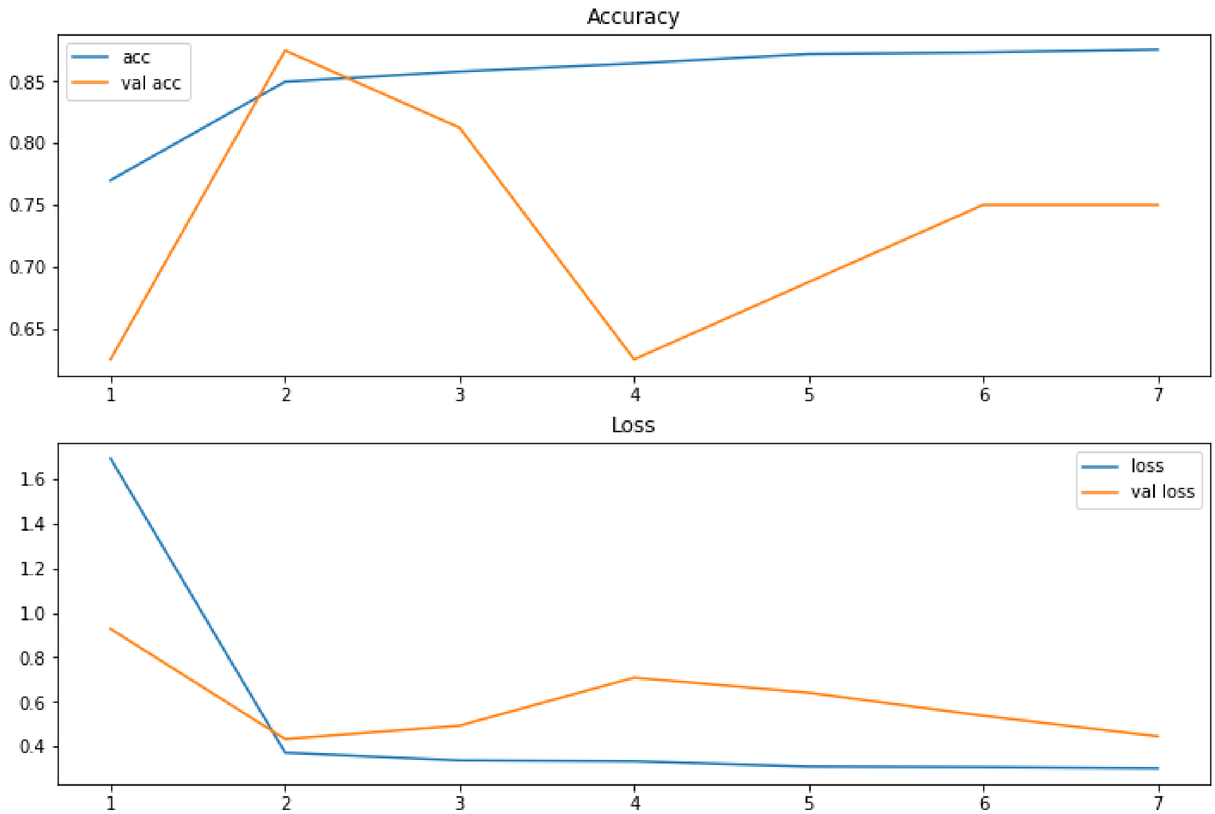
```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_1 (Flatten)          (None, 150528)            0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                9633856
_________________________________________________________________
dense_3 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_4 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 65
=================================================================
Total params: 9,642,241
Trainable params: 9,642,241
Non-trainable params: 0
_________________________________________________________________
```

In [16]:
```
history_2 = model_2.fit(train_generator,
                        epochs=25,
                        validation_data=val_generator,
                        callbacks=init_callbacks())
```

executed in 8m 58s, finished 12:04:18 2021-04-30

```
Epoch 1/25
163/163 [==============================] - 76s 466ms/step - loss: 3.8824 - accu
racy: 0.6885 - val_loss: 0.9281 - val_accuracy: 0.6250

Epoch 00001: val_loss improved from inf to 0.92809, saving model to best_model.
h5
Epoch 2/25
163/163 [==============================] - 76s 468ms/step - loss: 0.3942 - accu
racy: 0.8427 - val_loss: 0.4331 - val_accuracy: 0.8750

Epoch 00002: val_loss improved from 0.92809 to 0.43315, saving model to best_mo
del.h5
Epoch 3/25
163/163 [==============================] - 77s 470ms/step - loss: 0.3546 - accu
racy: 0.8508 - val_loss: 0.4934 - val_accuracy: 0.8125

Epoch 00003: val_loss did not improve from 0.43315
Epoch 4/25
163/163 [==============================] - 77s 472ms/step - loss: 0.3205 - accu
racy: 0.8655 - val_loss: 0.7093 - val_accuracy: 0.6250

Epoch 00004: val_loss did not improve from 0.43315
Epoch 5/25
163/163 [==============================] - 77s 470ms/step - loss: 0.2888 - accu
racy: 0.8773 - val_loss: 0.6411 - val_accuracy: 0.6875

Epoch 00005: val_loss did not improve from 0.43315
Epoch 6/25
163/163 [==============================] - 78s 476ms/step - loss: 0.3037 - accu
racy: 0.8755 - val_loss: 0.5380 - val_accuracy: 0.7500

Epoch 00006: val_loss did not improve from 0.43315
Epoch 7/25
163/163 [==============================] - 77s 475ms/step - loss: 0.2961 - accu
racy: 0.8761 - val_loss: 0.4452 - val_accuracy: 0.7500

Epoch 00007: val_loss did not improve from 0.43315
```

In [17]:
```
plot_model(history_2)
```
executed in 253ms, finished 12:04:18 2021-04-30



In [18]:
```
model_2.save_weights('last_model.h5')
model_2.evaluate(test_generator)
```
executed in 4.92s, finished 12:04:23 2021-04-30

```
20/20 [==============================] - 4s 201ms/step - loss: 0.3249 - accurac
y: 0.8542
```

Out[18]:
```
[0.32494595646858215, 0.8541666865348816]
```

In [19]:
```
model_2.load_weights('best_model.h5')
model_2.evaluate(test_generator)
```
executed in 4.86s, finished 12:04:28 2021-04-30

```
20/20 [==============================] - 4s 200ms/step - loss: 0.3420 - accurac
y: 0.8413
```

Out[19]:
```
[0.3419956564903259, 0.8413461446762085]
```

In [20]:
```
y_pred = model_2.predict(test_generator)
y_pred = (y_pred > 0.5).astype('int32')

print(classification_report(y_true, y_pred))
print(confusion_matrix(y_true, y_pred))
```
executed in 4.76s, finished 12:04:32 2021-04-30

```
              precision    recall  f1-score   support

           0       0.82      0.74      0.78       234
           1       0.85      0.90      0.88       390

    accuracy                           0.84       624
   macro avg       0.84      0.82      0.83       624
weighted avg       0.84      0.84      0.84       624

[[174  60]
 [ 39 351]]
```

1.4.3 Model 3 - Convolutional Neural Network

Convolutional neural networks have a reputation for being effective at image classification, so let's see if we can use the power of CNNs to improve our performance.

In [21]:
```
model_3 = Sequential()
model_3.add(Conv2D(128, kernel_size=3, activation='relu',
                   input_shape=(224,224,3)))
model_3.add(Conv2D(64, kernel_size=3, activation='relu'))
model_3.add(Conv2D(32, kernel_size=3, activation='relu'))
model_3.add(Flatten())
model_3.add(Dense(1, activation='sigmoid'))

model_3.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
model_3.summary()
```

executed in 91ms, finished 12:04:32 2021-04-30

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 222, 222, 128)     3584
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 220, 220, 64)      73792
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 218, 218, 32)      18464
_________________________________________________________________
flatten_2 (Flatten)          (None, 1520768)           0
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 1520769
=================================================================
Total params: 1,616,609
Trainable params: 1,616,609
Non-trainable params: 0
_________________________________________________________________
```

Convolutional Neural Networks take much more time to train, so I'm going to train this one in Google Colab and then load the weights after it's completed.

In [22]:
```
model_3 = tf.keras.models.load_model('cnn/content/cnn')
```

executed in 379ms, finished 12:04:33 2021-04-30

In [23]:
```
model_3.evaluate(test_generator)
```

executed in 19.2s, finished 12:04:52 2021-04-30

```
20/20 [==============================] - 19s 907ms/step - loss: 0.5595 - accura
cy: 0.7804
```

Out[23]:
```
[0.5594589710235596, 0.7804487347602844]
```

In [24]:
```
y_pred = model_3.predict(test_generator)
y_pred = (y_pred > 0.5).astype('int')

print(classification_report(y_true, y_pred))
print(confusion_matrix(y_true, y_pred, normalize='true'))
```

executed in 19.9s, finished 12:05:12 2021-04-30

```
              precision    recall  f1-score   support

           0       0.90      0.47      0.61       234
           1       0.75      0.97      0.85       390

    accuracy                           0.78       624
   macro avg       0.83      0.72      0.73       624
weighted avg       0.81      0.78      0.76       624

[[0.46581197 0.53418803]
 [0.03076923 0.96923077]]
```

1.4.4 Model 4 - More Complex CNN

This model will add MaxPooling2D layers for downsampling and Dropout layers to help reduce overfitting.

In [25]:
```
model_4 = Sequential()
model_4.add(Conv2D(32, kernel_size=(3,3), activation='relu',
                   input_shape=(224,224,3)))
model_4.add(Conv2D(64, kernel_size=(3,3), activation='relu'))
model_4.add(MaxPooling2D(pool_size=(2,2)))
model_4.add(Dropout(0.25))
model_4.add(Conv2D(128, kernel_size=(3,3), activation='relu'))
model_4.add(MaxPooling2D())
model_4.add(Dropout(0.25))
model_4.add(Flatten())
model_4.add(Dense(64, activation='relu'))
model_4.add(Dropout(0.5))
model_4.add(Dense(1, activation='sigmoid'))

model_4.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])

model_4.summary()
```

executed in 203ms, finished 12:05:12 2021-04-30

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 222, 222, 32)      896
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 220, 220, 64)      18496
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 110, 110, 64)      0
_________________________________________________________________
dropout (Dropout)            (None, 110, 110, 64)      0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 108, 108, 128)     73856
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 54, 54, 128)       0
_________________________________________________________________
dropout_1 (Dropout)          (None, 54, 54, 128)       0
_________________________________________________________________
flatten_3 (Flatten)          (None, 373248)            0
_________________________________________________________________
dense_7 (Dense)              (None, 64)                23887936
_________________________________________________________________
dropout_2 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 65
=================================================================
Total params: 23,981,249
Trainable params: 23,981,249
Non-trainable params: 0
_________________________________________________________________
```

With 23.9 million trainable parameters, we're going to train this one in Colab again.

In [26]:
```
model_4 = tf.keras.models.load_model('cnn2/content/cnn2')
```
executed in 1.43s, finished 12:05:14 2021-04-30

In [27]:
```
model_4.evaluate(test_generator)
```
executed in 10.9s, finished 12:05:24 2021-04-30

```
20/20 [==============================] - 10s 491ms/step - loss: 0.5111 - accura
cy: 0.8157
```

Out[27]:
```
[0.5110576152801514, 0.8157051205635071]
```

In [28]:
```
y_pred = model_4.predict(test_generator)
y_pred = (y_pred > 0.5).astype('int32')

print(classification_report(y_true, y_pred))
print(confusion_matrix(y_true, y_pred, normalize='true'))
```
executed in 10.7s, finished 12:05:35 2021-04-30

```
              precision    recall  f1-score   support

           0       0.98      0.52      0.68       234
           1       0.78      0.99      0.87       390

    accuracy                           0.82       624
   macro avg       0.88      0.76      0.78       624
weighted avg       0.85      0.82      0.80       624

[[0.52136752 0.47863248]
 [0.00769231 0.99230769]]
```

This model achieves 99% recall with 82% accuracy. It's not our most accurate model, but I think the boost in recall makes up for it. With our model identifying 99% of patients with pneumonia, a few false positives is an acceptable compromise.

1.5 iNterpret

Let's quickly compare our models.

In [29]:
```
def get_preds(model):
    '''returns a models predictions for the test set'''
    y_pred = model.predict(test_generator)
    y_pred = (y_pred > 0.5).astype('int')
    return y_pred
```
executed in 14ms, finished 12:05:35 2021-04-30

In [30]:

```
models = [model_1, model_2, model_3, model_4]
for i in range(4):
    print(f'Model {i+1}:')
    y_pred = get_preds(models[i])
    print(classification_report(y_true, y_pred))
    print()
    print(confusion_matrix(y_true, y_pred))
    print()
```

executed in 39.9s, finished 12:06:15 2021-04-30

```
Model 1:
              precision    recall  f1-score   support

           0       0.84      0.77      0.80       234
           1       0.87      0.91      0.89       390

    accuracy                           0.86       624
   macro avg       0.85      0.84      0.85       624
weighted avg       0.86      0.86      0.86       624


[[181  53]
 [ 35 355]]

Model 2:
              precision    recall  f1-score   support

           0       0.82      0.74      0.78       234
           1       0.85      0.90      0.88       390

    accuracy                           0.84       624
   macro avg       0.84      0.82      0.83       624
weighted avg       0.84      0.84      0.84       624


[[174  60]
 [ 39 351]]

Model 3:
              precision    recall  f1-score   support

           0       0.90      0.47      0.61       234
           1       0.75      0.97      0.85       390

    accuracy                           0.78       624
   macro avg       0.83      0.72      0.73       624
weighted avg       0.81      0.78      0.76       624


[[109 125]
 [ 12 378]]

Model 4:
              precision    recall  f1-score   support
```

```
           0       0.98      0.52      0.68       234
           1       0.78      0.99      0.87       390

    accuracy                           0.82       624
   macro avg       0.88      0.76      0.78       624
weighted avg       0.85      0.82      0.80       624


[[122 112]
 [  3 387]]
```

With class support of 234 negative to 390 positive, we would be getting ~50% accuracy with random guesses and ~60% accuracy with all-majority-class predictions. So every model has learned something and shows improved performance over random guessing.

With the problem at hand, we want a model that shows high recall on positive cases (predictions identify positive cases) and high precision on negative cases (negative predictions are true). We got a big jump on those metrics when we moved to the convolutional neural network, although the overall accuracy did take a bit of a hit. However, with our more complex CNN, we were able to improve accuracy to 82% with 99% positive recall and 98% negative precision.

2 Conclusion

We were able to get good results using Convolutional Neural Networks. While the accuracy was a bit lower than that of the more traditional neural networks, it did improve the positive recall significantly.

2.1 Recommendations

If pursuing this topic to further improve results, I would make the following recommendations.

1. More Data - The dataset used here is only a portion of a larger dataset. While the larger dataset does not necessarily guarantee better performance, more data will help to reduce overfitting because of increased variance in the training data. A larger dataset should also give a statistically stronger representation of real-world implementation.
2. Pretrained Models - There are a number of pretrained models out there which may be effective for this problem. Many of them are included with Keras. We did not explore any of those models in this notebook, but some research into those models may find some that improve performance without the work of constructing your own models.
3. Address Class Imbalance - When constructing these models, I did not address the issue of class imbalance. While I think the results are satisfactory, addressing the issue of class imbalance early (perhaps by constructing a custom loss function) might improve performance.

2.2 Future Work

Given more time with this data, I'd like to explore some of the popular CNN architectures. Whether or not they improve performance, I would like to get a look into the structure of these models to get a better idea of how convolutional neural networks accomplish their tasks.

In [ ]:

```

```