

Final Project Submission

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Blog post URL:<https://github.com/nkbuddy/dsc-phase-4-project-Image-Classification-with-Deep-Learning> (<https://github.com/nkbuddy/dsc-phase-4-project-Image-Classification-with-Deep-Learning>)

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STEP 1: Define the Problem

Identifying whether or not they have pneumonia by Image-Based Deep Learning. Pneumonia is lungs with inflammatory, blackage of the bronchiole, and Alveoli with fluid. When interpreting the x-ray, the radiologist will look for white spots in the lungs (called infiltrates) that identify an infection.

Step 2: Gather the Data

This dataset contains thousands of validated Chest X-Ray images described. The images are split into a training set and a testing set of independent patients. Images are labeled as (disease)-(randomized patient ID)-(image number by this patient) and split into 2 directories: Pneumonia, and NORMAL. The dataset is from Mendeley Data. University of California San Diego, Guangzhou Women and Children's Medical Center. The three contributors are Daniel Kermay, Kang Zhang, Michael Goldbaum.

Step 3: Prepare Data for Consumption

3.1 Import Libraries

```
In [71]: import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
!pip3 install pillow
from keras.preprocessing.image import ImageDataGenerator, array_to_img
import os
from sklearn.metrics import confusion_matrix
from keras.utils.np_utils import to_categorical
from sklearn import preprocessing
from keras import models
from keras import layers
from keras import optimizers
import seaborn as sns
from pathlib import Path
```

Requirement already satisfied: pillow in /Users/alanchan/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages (7.2.0)

3.11 Load Data Modelling Libraries

```
In [72]: # Directory path
train_data_dir = '/Users/alanchan/Documents/Flatiron/dsc-phase-4-project/train_data'
test_data_dir = '/Users/alanchan/Documents/Flatiron/dsc-phase-4-project/test_data'
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

# Get all the data in the directory data/validation (132 images), and
test_generator = test_datagen.flow_from_directory(
    test_data_dir,
    target_size=(150, 150), batch_size = 20,
    class_mode = 'binary')

# Get all the data in the directory data/train (790 images), and reshape
train_generator = train_datagen.flow_from_directory(
    train_data_dir,
    target_size=(150, 150), batch_size = 20,
    class_mode = 'binary')

# Create the datasets
train_images, train_labels = next(train_generator)
test_images, test_labels = next(test_generator)
```

Found 624 images belonging to 2 classes.
Found 5232 images belonging to 2 classes.

```
In [73]: test_generator.n
```

```
Out[73]: 624
```

```
In [74]: train_generator.n
```

```
Out[74]: 5232
```

3.2 Meet and Greet Data

```
In [75]: normal_cases_dir = Path(train_data_dir+"/NORMAL")
pneumonia_cases_dir = Path(train_data_dir+"/PNEUMONIA")
normal_cases = normal_cases_dir.glob('*.jpeg')
pneumonia_cases = pneumonia_cases_dir.glob('*.jpeg')

# An empty list. We will insert the data into this list in (img_path,
train_data_df = []

# Go through all the normal cases. The label for these cases will be 0
for img in normal_cases:
    train_data_df.append((img,0))

# Go through all the pneumonia cases. The label for these cases will be 1
for img in pneumonia_cases:
    train_data_df.append((img, 1))

# Get a pandas dataframe from the data we have in our list
train_data_df = pd.DataFrame(train_data_df, columns=['image', 'label'])

# Shuffle the data
train_data_df = train_data_df.sample(frac=1.).reset_index(drop=True)

# How the dataframe looks like?
train_data_df.head()
```

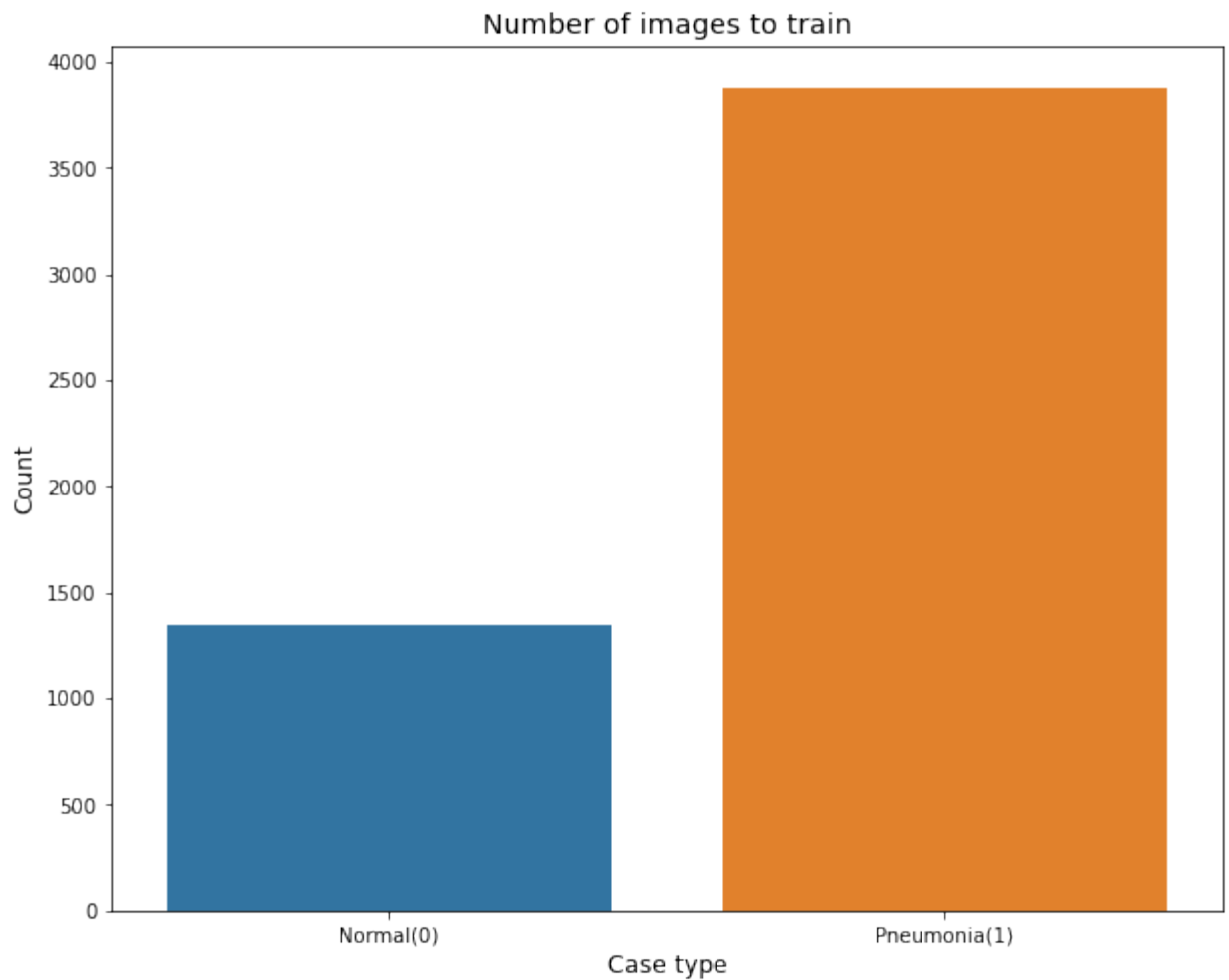
Out[75]:

	image	label
0	/Users/alanchan/Documents/Flatiron/dsc-phase-4...	1
1	/Users/alanchan/Documents/Flatiron/dsc-phase-4...	1
2	/Users/alanchan/Documents/Flatiron/dsc-phase-4...	1
3	/Users/alanchan/Documents/Flatiron/dsc-phase-4...	1
4	/Users/alanchan/Documents/Flatiron/dsc-phase-4...	1

```
In [76]: cases_count = train_data_df['label'].value_counts()
print(cases_count)

# Plot the results
plt.figure(figsize=(10,8))
sns.barplot(x=cases_count.index, y=cases_count.values)
plt.title('Number of images to train', fontsize=14)
plt.xlabel('Case type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xticks(range(len(cases_count.index)), ['Normal(0)', 'Pneumonia(1)'])
plt.show()
```

```
1    3883
0    1349
Name: label, dtype: int64
```



In [77]: `array_to_img(train_images[0])`

Out[77]:



In [78]: `train_images[0]`

Out[78]: `array([[0.29803923, 0.29803923, 0.29803923],`
 `[0.31764707, 0.31764707, 0.31764707],`
 `[0.3137255 , 0.3137255 , 0.3137255],`
 `...,`
 `[0.3529412 , 0.3529412 , 0.3529412],`
 `[0.27450982, 0.27450982, 0.27450982],`
 `[0.21960786, 0.21960786, 0.21960786]],`

 `[[0.30588236, 0.30588236, 0.30588236],`
 `[0.32941177, 0.32941177, 0.32941177],`
 `[0.32156864, 0.32156864, 0.32156864],`
 `...,`
 `[0.34509805, 0.34509805, 0.34509805],`
 `[0.24313727, 0.24313727, 0.24313727],`
 `[0.24705884, 0.24705884, 0.24705884]],`

 `[[0.28627452, 0.28627452, 0.28627452],`
 `[0.31764707, 0.31764707, 0.31764707],`
 `[0.34509805, 0.34509805, 0.34509805],`
 `...,`
 `[0.32941177, 0.32941177, 0.32941177],`
 `[0.22352943, 0.22352943, 0.22352943],`
 `[0.20784315, 0.20784315, 0.20784315]],`

 `...,`

 `[[0. , 0. , 0.],`
 `[0. , 0. , 0.],`
 `[0. , 0. , 0.],`
 `...,`
 `[0. , 0. , 0.],`
 `[0. , 0. , 0.],`
 `[0. , 0. , 0.]],`

 `[[0. , 0. , 0.],`

```

        [0.         , 0.         , 0.         ],
        [0.         , 0.         , 0.         ],
        ...,
        [0.         , 0.         , 0.         ],
        [0.         , 0.         , 0.         ],
        [0.         , 0.         , 0.         ]],
    [[ [0.         , 0.         , 0.         ],
        [0.         , 0.         , 0.         ],
        [0.         , 0.         , 0.         ],
        ...,
        [0.         , 0.         , 0.         ],
        [0.         , 0.         , 0.         ],
        [0.         , 0.         , 0.         ]]], dtype=float32)

```

```

In [79]: print(np.shape(train_images))
print(np.shape(train_labels))
print(np.shape(test_images))
print(np.shape(test_labels))

```

```

(20, 150, 150, 3)
(20,)
(20, 150, 150, 3)
(20,)

```

```

In [80]: train_generator.class_indices

```

```

Out[80]: {'NORMAL': 0, 'PNEUMONIA': 1}

```

Step 5: Model Data

```

In [81]: from keras.preprocessing.image import ImageDataGenerator
import datetime

```

```

original_start = datetime.datetime.now()
start = datetime.datetime.now()

```

```
In [53]: from keras import layers
from keras import models

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',
                        input_shape=(150, 150, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

```
In [54]: from keras import optimizers

model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=1e-4),
              metrics=['acc'])
```

5.11 Model Performance with Cross-Validation (CV)

```
In [55]: history = model.fit(train_generator,
                             steps_per_epoch=100,
                             epochs=30,
                             validation_data=test_generator,
                             validation_steps=20)
```

```
Epoch 1/30
100/100 [=====] - 65s 649ms/step - loss: 0.4
759 - acc: 0.7826 - val_loss: 0.6766 - val_acc: 0.6350
Epoch 2/30
100/100 [=====] - 66s 662ms/step - loss: 0.2
734 - acc: 0.8830 - val_loss: 0.4916 - val_acc: 0.7750
Epoch 3/30
100/100 [=====] - 60s 598ms/step - loss: 0.1
828 - acc: 0.9262 - val_loss: 0.4010 - val_acc: 0.8350
Epoch 4/30
100/100 [=====] - 63s 631ms/step - loss: 0.1
356 - acc: 0.9430 - val_loss: 0.5450 - val_acc: 0.8150
Epoch 5/30
100/100 [=====] - 57s 565ms/step - loss: 0.1
254 - acc: 0.9520 - val_loss: 0.2959 - val_acc: 0.9025
Epoch 6/30
```



```
100/100 [=====] - 60s 597ms/step - loss: 0.1
101 - acc: 0.9550 - val_loss: 0.3988 - val_acc: 0.8625
Epoch 7/30
100/100 [=====] - 62s 622ms/step - loss: 0.1
089 - acc: 0.9608 - val_loss: 0.4621 - val_acc: 0.8425
Epoch 8/30
100/100 [=====] - 70s 701ms/step - loss: 0.1
009 - acc: 0.9600 - val_loss: 0.2553 - val_acc: 0.9050
Epoch 9/30
100/100 [=====] - 57s 569ms/step - loss: 0.0
967 - acc: 0.9629 - val_loss: 0.4378 - val_acc: 0.8625
Epoch 10/30
100/100 [=====] - 59s 593ms/step - loss: 0.0
853 - acc: 0.9675 - val_loss: 0.5711 - val_acc: 0.8175
Epoch 11/30
100/100 [=====] - 60s 599ms/step - loss: 0.0
749 - acc: 0.9740 - val_loss: 0.4771 - val_acc: 0.8625
Epoch 12/30
100/100 [=====] - 58s 578ms/step - loss: 0.0
777 - acc: 0.9729 - val_loss: 0.3259 - val_acc: 0.9025
Epoch 13/30
100/100 [=====] - 61s 610ms/step - loss: 0.0
748 - acc: 0.9730 - val_loss: 0.7767 - val_acc: 0.8225
Epoch 14/30
100/100 [=====] - 57s 566ms/step - loss: 0.0
633 - acc: 0.9790 - val_loss: 0.8548 - val_acc: 0.7875
Epoch 15/30
100/100 [=====] - 2990s 30s/step - loss: 0.0
641 - acc: 0.9780 - val_loss: 0.4359 - val_acc: 0.8675
Epoch 16/30
100/100 [=====] - 1046s 10s/step - loss: 0.0
532 - acc: 0.9785 - val_loss: 0.4271 - val_acc: 0.8725
Epoch 17/30
100/100 [=====] - 43s 431ms/step - loss: 0.0
517 - acc: 0.9800 - val_loss: 0.6364 - val_acc: 0.8575
Epoch 18/30
100/100 [=====] - 42s 424ms/step - loss: 0.0
585 - acc: 0.9790 - val_loss: 0.8103 - val_acc: 0.8300
Epoch 19/30
100/100 [=====] - 44s 437ms/step - loss: 0.0
541 - acc: 0.9814 - val_loss: 0.9306 - val_acc: 0.8025
Epoch 20/30
100/100 [=====] - 43s 434ms/step - loss: 0.0
486 - acc: 0.9824 - val_loss: 0.7183 - val_acc: 0.8450
Epoch 21/30
100/100 [=====] - 44s 442ms/step - loss: 0.0
508 - acc: 0.9820 - val_loss: 0.5527 - val_acc: 0.8525
Epoch 22/30
100/100 [=====] - 45s 452ms/step - loss: 0.0
429 - acc: 0.9850 - val_loss: 0.6475 - val_acc: 0.8450
```

```
Epoch 23/30
100/100 [=====] - 46s 461ms/step - loss: 0.0
439 - acc: 0.9864 - val_loss: 0.4564 - val_acc: 0.8775
Epoch 24/30
100/100 [=====] - 47s 469ms/step - loss: 0.0
436 - acc: 0.9859 - val_loss: 0.6697 - val_acc: 0.8450
Epoch 25/30
100/100 [=====] - 48s 478ms/step - loss: 0.0
458 - acc: 0.9819 - val_loss: 0.6479 - val_acc: 0.8375
Epoch 26/30
100/100 [=====] - 48s 479ms/step - loss: 0.0
455 - acc: 0.9829 - val_loss: 0.3320 - val_acc: 0.9150
Epoch 27/30
100/100 [=====] - 51s 507ms/step - loss: 0.0
400 - acc: 0.9854 - val_loss: 0.6081 - val_acc: 0.8750
Epoch 28/30
100/100 [=====] - 47s 471ms/step - loss: 0.0
411 - acc: 0.9845 - val_loss: 0.3200 - val_acc: 0.9225
Epoch 29/30
100/100 [=====] - 52s 519ms/step - loss: 0.0
344 - acc: 0.9865 - val_loss: 0.4055 - val_acc: 0.9075
Epoch 30/30
100/100 [=====] - 53s 528ms/step - loss: 0.0
391 - acc: 0.9865 - val_loss: 0.5085 - val_acc: 0.8775
```

Step 6: Validate and Implement

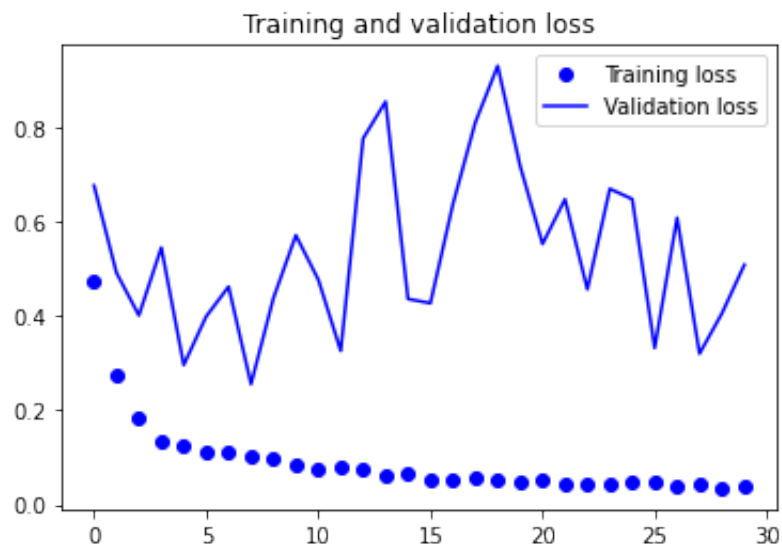
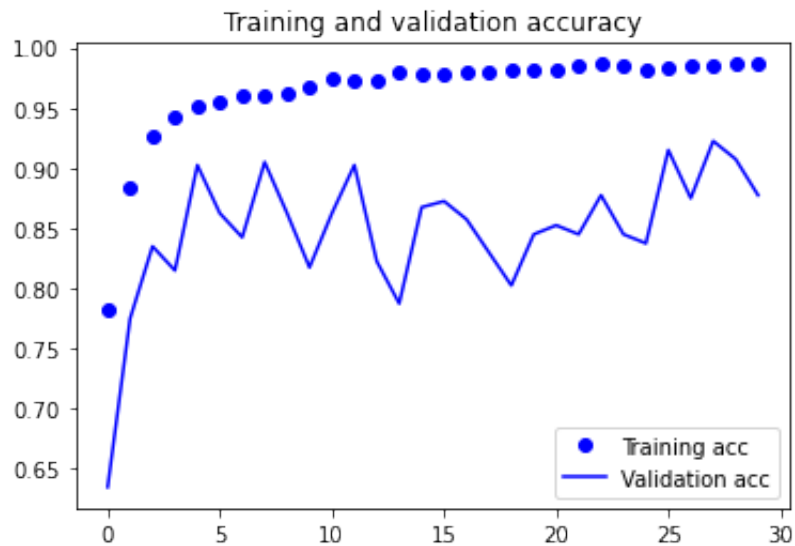
In [56]:

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

acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```



```
In [57]: end = datetime.datetime.now()
elapsed = end - start
print('Training took a total of {}'.format(elapsed))
test_loss, test_acc = model.evaluate(test_generator, steps=20)
print('test acc:', test_acc)
```

Training took a total of 1:32:45.973435

```
In [ ]: model.save('image_classifier.model1')
```

WARNING:tensorflow:From /Users/alanchan/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/tensorflow/python/training/tracking/tracking.py:111: Model.state_updates (from tensorflow.python.keras.engine.training) is deprecated and will be removed in a future version.
Instructions for updating:
This property should not be used in TensorFlow 2.0, as updates are applied automatically.

WARNING:tensorflow:From /Users/alanchan/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/tensorflow/python/training/tracking/tracking.py:111: Layer.updates (from tensorflow.python.keras.engine.base_layer) is deprecated and will be removed in a future version.
Instructions for updating:
This property should not be used in TensorFlow 2.0, as updates are applied automatically.

INFO:tensorflow:Assets written to: image_classifier.model1/assets

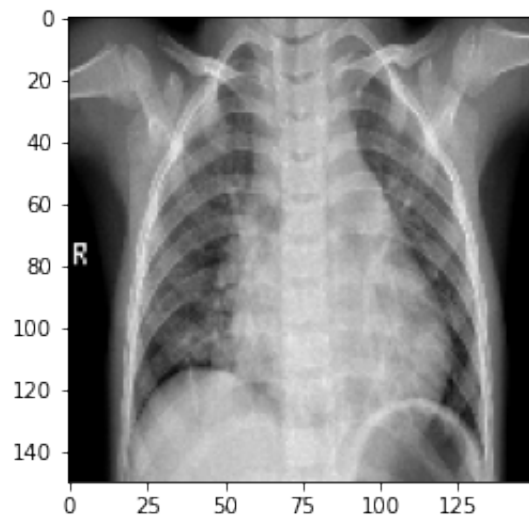
```
In [ ]: from keras.models import load_model
model = load_model('image_classifier.model1')
model.summary()
```

Model: "sequential_10"

Layer (type)	Output Shape	Param #
=====		
conv2d_4 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_4 (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_5 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_5 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_6 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_6 (MaxPooling2D)	(None, 17, 17, 128)	0
conv2d_7 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_7 (MaxPooling2D)	(None, 7, 7, 128)	0
flatten_2 (Flatten)	(None, 6272)	0
dense_29 (Dense)	(None, 512)	3211776
dense_30 (Dense)	(None, 1)	513
=====		
Total params: 3,453,121		
Trainable params: 3,453,121		
Non-trainable params: 0		

```
In [ ]: from keras.preprocessing import image
import matplotlib.image as mpimg
import matplotlib.pyplot as plt
%matplotlib inline

filename = 'data/chest_xray/test/PNEUMONIA/BACTERIA-40699-0002.jpeg'
img = image.load_img(filename, target_size=(150, 150))
plt.imshow(img)
plt.show()
```



```
In [ ]: import numpy as np

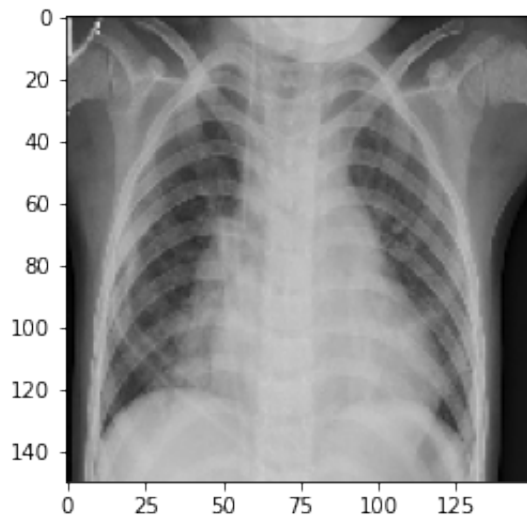
img_tensor = image.img_to_array(img)
img_tensor = np.expand_dims(img_tensor, axis=0)

# Follow the Original Model Preprocessing
img_tensor /= 255.

# Check tensor shape
print(img_tensor.shape)

# Preview an image
plt.imshow(img_tensor[0])
plt.show()
```

(1, 150, 150, 3)



```
In [ ]: from keras import models
import math

# Extract model layer outputs
layer_outputs = [layer.output for layer in model.layers[:8]]

# Create a model for displaying the feature maps
activation_model = models.Model(inputs=model.input, outputs=layer_outputs)

activations = activation_model.predict(img_tensor)

# Extract Layer Names for Labelling
layer_names = []
for layer in model.layers[:8]:
    layer_names.append(layer.name)

total_features = sum([a.shape[-1] for a in activations])
```

```

total_features

n_cols = 16
n_rows = math.ceil(total_features / n_cols)

iteration = 0
fig, axes = plt.subplots(nrows=n_rows, ncols=n_cols, figsize=(n_cols,

for layer_n, layer_activation in enumerate(activations):
    n_channels = layer_activation.shape[-1]
    for ch_idx in range(n_channels):
        row = iteration // n_cols
        column = iteration % n_cols

        ax = axes[row, column]

        channel_image = layer_activation[0,
                                         :, :,
                                         ch_idx]
        # Post-process the feature to make it visually palatable
        channel_image -= channel_image.mean()
        channel_image /= channel_image.std()
        channel_image *= 64
        channel_image += 128
        channel_image = np.clip(channel_image, 0, 255).astype('uint8')

        ax.imshow(channel_image, aspect='auto', cmap='viridis')
        ax.get_xaxis().set_ticks([])
        ax.get_yaxis().set_ticks([])

        if ch_idx == 0:
            ax.set_title(layer_names[layer_n], fontsize=10)
            iteration += 1

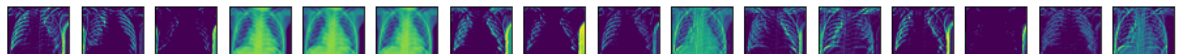
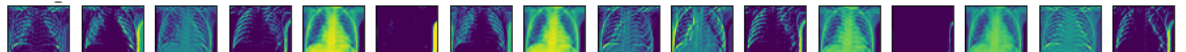
fig.subplots_adjust(hspace=1.25)
plt.savefig('Intermediate_Activations_Visualized.pdf')
plt.show()

```

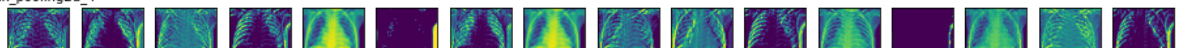
<ipython-input-150-938022819771>:40: RuntimeWarning: invalid value encountered in true_divide

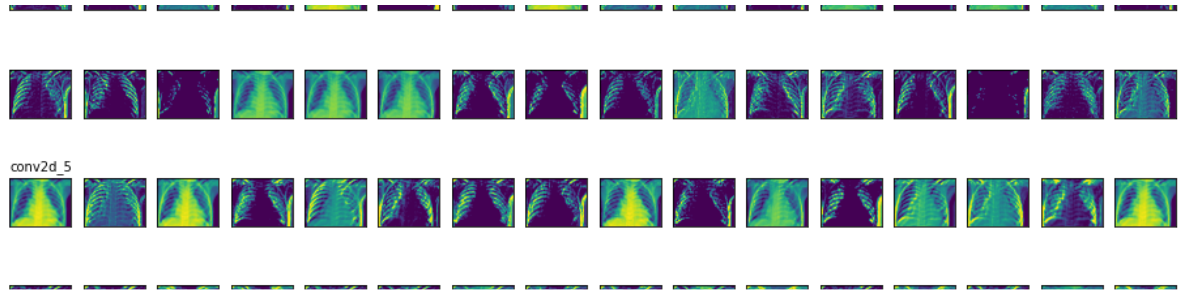
```
channel_image /= channel_image.std()
```

conv2d_4



max_pooling2d_4





5.12 Tune Model

5.121 second model

```
In [82]: from tensorflow.keras import datasets
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense # creates densely connected
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Conv2D # convolution layer
from tensorflow.keras.layers import MaxPooling2D # max pooling layer
```

```
In [92]: model = Sequential()
# define 3x3 filter window sizes. Create 32 filters.
model.add(Conv2D(filters=32,
                  kernel_size=(3, 3),
                  activation='relu',
                  input_shape=(150, 150, 3)))

# max pool in 2x2 window
model.add(MaxPooling2D(pool_size=(2, 2)))
# define 3x3 filter window sizes. Create 64 filters.
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))

# transition to dense fully-connected part of network
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

```
In [94]: model.compile(loss='binary_crossentropy',
                      optimizer=optimizers.RMSprop(lr=1e-4),
                      metrics=['acc'])
```

In [95]:

```
history = model.fit(train_generator,
                    steps_per_epoch=100,
                    epochs=30,
                    validation_data=test_generator,
                    validation_steps=20)
```

```
Epoch 1/30
100/100 [=====] - 39s 393ms/step - loss: 0.4
147 - acc: 0.8243 - val_loss: 0.4925 - val_acc: 0.7300
Epoch 2/30
100/100 [=====] - 40s 396ms/step - loss: 0.2
075 - acc: 0.9232 - val_loss: 0.4527 - val_acc: 0.8150
Epoch 3/30
100/100 [=====] - 43s 426ms/step - loss: 0.1
516 - acc: 0.9440 - val_loss: 0.5359 - val_acc: 0.7900
Epoch 4/30
100/100 [=====] - 58s 583ms/step - loss: 0.1
134 - acc: 0.9500 - val_loss: 0.4319 - val_acc: 0.8175
Epoch 5/30
100/100 [=====] - 45s 455ms/step - loss: 0.1
159 - acc: 0.9578 - val_loss: 0.3331 - val_acc: 0.8750
Epoch 6/30
100/100 [=====] - 49s 486ms/step - loss: 0.1
065 - acc: 0.9575 - val_loss: 0.6600 - val_acc: 0.7875
Epoch 7/30
100/100 [=====] - 43s 426ms/step - loss: 0.0
934 - acc: 0.9645 - val_loss: 0.6169 - val_acc: 0.8025
Epoch 8/30
100/100 [=====] - 42s 424ms/step - loss: 0.0
894 - acc: 0.9675 - val_loss: 0.5253 - val_acc: 0.8425
Epoch 9/30
100/100 [=====] - 48s 481ms/step - loss: 0.0
768 - acc: 0.9709 - val_loss: 0.5749 - val_acc: 0.8300
Epoch 10/30
100/100 [=====] - 42s 416ms/step - loss: 0.0
660 - acc: 0.9755 - val_loss: 0.7017 - val_acc: 0.8050
Epoch 11/30
100/100 [=====] - 42s 416ms/step - loss: 0.0
594 - acc: 0.9749 - val_loss: 0.5039 - val_acc: 0.8325
Epoch 12/30
100/100 [=====] - 41s 412ms/step - loss: 0.0
708 - acc: 0.9735 - val_loss: 0.5393 - val_acc: 0.8400
Epoch 13/30
100/100 [=====] - 41s 406ms/step - loss: 0.0
601 - acc: 0.9775 - val_loss: 0.7039 - val_acc: 0.8275
Epoch 14/30
100/100 [=====] - 41s 415ms/step - loss: 0.0
642 - acc: 0.9745 - val_loss: 0.2670 - val_acc: 0.9200
Epoch 15/30
100/100 [=====] - 42s 416ms/step - loss: 0.0
```

```
535 - acc: 0.9784 - val_loss: 0.4371 - val_acc: 0.8825
Epoch 16/30
100/100 [=====] - 41s 407ms/step - loss: 0.0
557 - acc: 0.9794 - val_loss: 0.4159 - val_acc: 0.8725
Epoch 17/30
100/100 [=====] - 40s 404ms/step - loss: 0.0
523 - acc: 0.9825 - val_loss: 0.5341 - val_acc: 0.8625
Epoch 18/30
100/100 [=====] - 42s 419ms/step - loss: 0.0
555 - acc: 0.9805 - val_loss: 0.8293 - val_acc: 0.8100
Epoch 19/30
100/100 [=====] - 44s 436ms/step - loss: 0.0
407 - acc: 0.9895 - val_loss: 0.5649 - val_acc: 0.8700
Epoch 20/30
100/100 [=====] - 44s 437ms/step - loss: 0.0
568 - acc: 0.9805 - val_loss: 0.5231 - val_acc: 0.8600
Epoch 21/30
100/100 [=====] - 41s 414ms/step - loss: 0.0
433 - acc: 0.9885 - val_loss: 0.4733 - val_acc: 0.8875
Epoch 22/30
100/100 [=====] - 42s 418ms/step - loss: 0.0
412 - acc: 0.9845 - val_loss: 0.8575 - val_acc: 0.7950
Epoch 23/30
100/100 [=====] - 45s 451ms/step - loss: 0.0
347 - acc: 0.9895 - val_loss: 0.6119 - val_acc: 0.8450
Epoch 24/30
100/100 [=====] - 42s 420ms/step - loss: 0.0
403 - acc: 0.9865 - val_loss: 0.5185 - val_acc: 0.8775
Epoch 25/30
100/100 [=====] - 42s 421ms/step - loss: 0.0
312 - acc: 0.9900 - val_loss: 0.9348 - val_acc: 0.8125
Epoch 26/30
100/100 [=====] - 43s 431ms/step - loss: 0.0
323 - acc: 0.9890 - val_loss: 0.7235 - val_acc: 0.8450
Epoch 27/30
100/100 [=====] - 43s 426ms/step - loss: 0.0
429 - acc: 0.9824 - val_loss: 0.7158 - val_acc: 0.8375
Epoch 28/30
100/100 [=====] - 42s 423ms/step - loss: 0.0
311 - acc: 0.9875 - val_loss: 0.7071 - val_acc: 0.8450
Epoch 29/30
100/100 [=====] - 43s 426ms/step - loss: 0.0
227 - acc: 0.9925 - val_loss: 0.8110 - val_acc: 0.8350
Epoch 30/30
100/100 [=====] - 41s 409ms/step - loss: 0.0
172 - acc: 0.9945 - val_loss: 1.1031 - val_acc: 0.8175
```

In []:

```
test_loss, test_acc = model.evaluate(test_generator, steps=20)
print('test acc:', test_acc)
```

5.122 third model

In [98]: `from keras.layers import Dense, Conv2D , MaxPool2D , Flatten , Dropout`

```
In [102]: model = Sequential()
model.add(Conv2D(32 , (3,3) , strides = 1 , padding = 'same' , activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model.add(Conv2D(64 , (3,3) , strides = 1 , padding = 'same' , activation='relu'))
model.add(Dropout(0.1))
model.add(BatchNormalization())
model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model.add(Conv2D(64 , (3,3) , strides = 1 , padding = 'same' , activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model.add(Conv2D(128 , (3,3) , strides = 1 , padding = 'same' , activation='relu'))
model.add(Dropout(0.2))
model.add(BatchNormalization())
model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model.add(Conv2D(256 , (3,3) , strides = 1 , padding = 'same' , activation='relu'))
model.add(Dropout(0.2))
model.add(BatchNormalization())
model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
model.add(Flatten())
model.add(Dense(units = 128 , activation = 'relu'))
model.add(Dropout(0.2))
model.add(Dense(units = 1 , activation = 'sigmoid'))
```

```
In [103]: model.compile(loss='binary_crossentropy',
                        optimizer=optimizers.RMSprop(lr=1e-4),
                        metrics=['acc'])
```

```
In [104]: history = model.fit(train_generator,
                             steps_per_epoch=100,
                             epochs=30,
                             validation_data=test_generator,
                             validation_steps=20)
```

Epoch 1/30

```
100/100 [=====] - 62s 615ms/step - loss: 0.2731 - acc: 0.9040 - val_loss: 0.7065 - val_acc: 0.4200
```

```
Epoch 2/30
100/100 [=====] - 75s 747ms/step - loss: 0.1
231 - acc: 0.9560 - val_loss: 0.8417 - val_acc: 0.6500
Epoch 3/30
100/100 [=====] - 79s 792ms/step - loss: 0.1
034 - acc: 0.9568 - val_loss: 1.8571 - val_acc: 0.6075
Epoch 4/30
100/100 [=====] - 74s 741ms/step - loss: 0.0
905 - acc: 0.9695 - val_loss: 2.8763 - val_acc: 0.6175
Epoch 5/30
100/100 [=====] - 81s 809ms/step - loss: 0.0
792 - acc: 0.9754 - val_loss: 2.5143 - val_acc: 0.6100
Epoch 6/30
100/100 [=====] - 78s 779ms/step - loss: 0.0
722 - acc: 0.9775 - val_loss: 0.6081 - val_acc: 0.8025
Epoch 7/30
100/100 [=====] - 63s 633ms/step - loss: 0.0
681 - acc: 0.9779 - val_loss: 1.9347 - val_acc: 0.7050
Epoch 8/30
100/100 [=====] - 64s 639ms/step - loss: 0.0
601 - acc: 0.9794 - val_loss: 0.8764 - val_acc: 0.7725
Epoch 9/30
100/100 [=====] - 66s 658ms/step - loss: 0.0
653 - acc: 0.9795 - val_loss: 0.4569 - val_acc: 0.8700
Epoch 10/30
100/100 [=====] - 63s 630ms/step - loss: 0.0
514 - acc: 0.9824 - val_loss: 2.1285 - val_acc: 0.7075
Epoch 11/30
100/100 [=====] - 65s 653ms/step - loss: 0.0
522 - acc: 0.9839 - val_loss: 0.3798 - val_acc: 0.8900
Epoch 12/30
100/100 [=====] - 62s 618ms/step - loss: 0.0
378 - acc: 0.9880 - val_loss: 0.3395 - val_acc: 0.8975
Epoch 13/30
100/100 [=====] - 62s 623ms/step - loss: 0.0
459 - acc: 0.9890 - val_loss: 1.2502 - val_acc: 0.7800
Epoch 14/30
100/100 [=====] - 60s 604ms/step - loss: 0.0
292 - acc: 0.9900 - val_loss: 0.6929 - val_acc: 0.8525
Epoch 15/30
100/100 [=====] - 62s 617ms/step - loss: 0.0
360 - acc: 0.9885 - val_loss: 0.2378 - val_acc: 0.9225
Epoch 16/30
100/100 [=====] - 59s 591ms/step - loss: 0.0
269 - acc: 0.9910 - val_loss: 1.4877 - val_acc: 0.7875
Epoch 17/30
100/100 [=====] - 67s 670ms/step - loss: 0.0
178 - acc: 0.9915 - val_loss: 3.1016 - val_acc: 0.6775
Epoch 18/30
100/100 [=====] - 70s 697ms/step - loss: 0.0
```

```

205 - acc: 0.9940 - val_loss: 1.1261 - val_acc: 0.8375
Epoch 19/30
100/100 [=====] - 65s 653ms/step - loss: 0.0
216 - acc: 0.9935 - val_loss: 1.8571 - val_acc: 0.7675
Epoch 20/30
100/100 [=====] - 62s 619ms/step - loss: 0.0
285 - acc: 0.9915 - val_loss: 0.4933 - val_acc: 0.8975
Epoch 21/30
100/100 [=====] - 59s 593ms/step - loss: 0.0
373 - acc: 0.9925 - val_loss: 0.3121 - val_acc: 0.9100
Epoch 22/30
100/100 [=====] - 59s 591ms/step - loss: 0.0
272 - acc: 0.9925 - val_loss: 0.3410 - val_acc: 0.9150
Epoch 23/30
100/100 [=====] - 67s 670ms/step - loss: 0.0
185 - acc: 0.9925 - val_loss: 1.1054 - val_acc: 0.8200
Epoch 24/30
100/100 [=====] - 67s 667ms/step - loss: 0.0
294 - acc: 0.9920 - val_loss: 1.8069 - val_acc: 0.7675
Epoch 25/30
100/100 [=====] - 71s 714ms/step - loss: 0.0
228 - acc: 0.9935 - val_loss: 0.5513 - val_acc: 0.8850
Epoch 26/30
100/100 [=====] - 68s 681ms/step - loss: 0.0
190 - acc: 0.9950 - val_loss: 1.7847 - val_acc: 0.7850
Epoch 27/30
100/100 [=====] - 68s 684ms/step - loss: 0.0
109 - acc: 0.9980 - val_loss: 2.2121 - val_acc: 0.7575
Epoch 28/30
100/100 [=====] - 64s 644ms/step - loss: 0.0
135 - acc: 0.9970 - val_loss: 0.4390 - val_acc: 0.9075
Epoch 29/30
100/100 [=====] - 61s 606ms/step - loss: 0.0
178 - acc: 0.9955 - val_loss: 1.7067 - val_acc: 0.7975
Epoch 30/30
100/100 [=====] - 62s 617ms/step - loss: 0.0
214 - acc: 0.9925 - val_loss: 0.7148 - val_acc: 0.8775

```

```

In [105]: test_loss, test_acc = model.evaluate(test_generator, steps=20)
          print('test acc:', test_acc)

```

```

20/20 [=====] - 5s 235ms/step - loss: 0.7710
- acc: 0.8625
test acc: 0.862500011920929

```

Step6: Validate and Implement

```
In [111]: val_generator = test_datagen.flow_from_directory(
            test_data_dir,
            target_size=(150,150),batch_size = 500)

# Create the datasets
val_images, val_labels = next(val_generator)
```

Found 624 images belonging to 2 classes.

```
In [119]: np.shape(val_images)
```

```
Out[119]: (500, 150, 150, 3)
```

```
In [124]: preds = model.predict_classes(val_images)
           preds = preds.reshape(1,-1)[0]

# Original labels
orig_test_labels = np.argmax(val_labels, axis=-1)

print(orig_test_labels.shape)
print(preds.shape)
print(val_labels.shape)
```

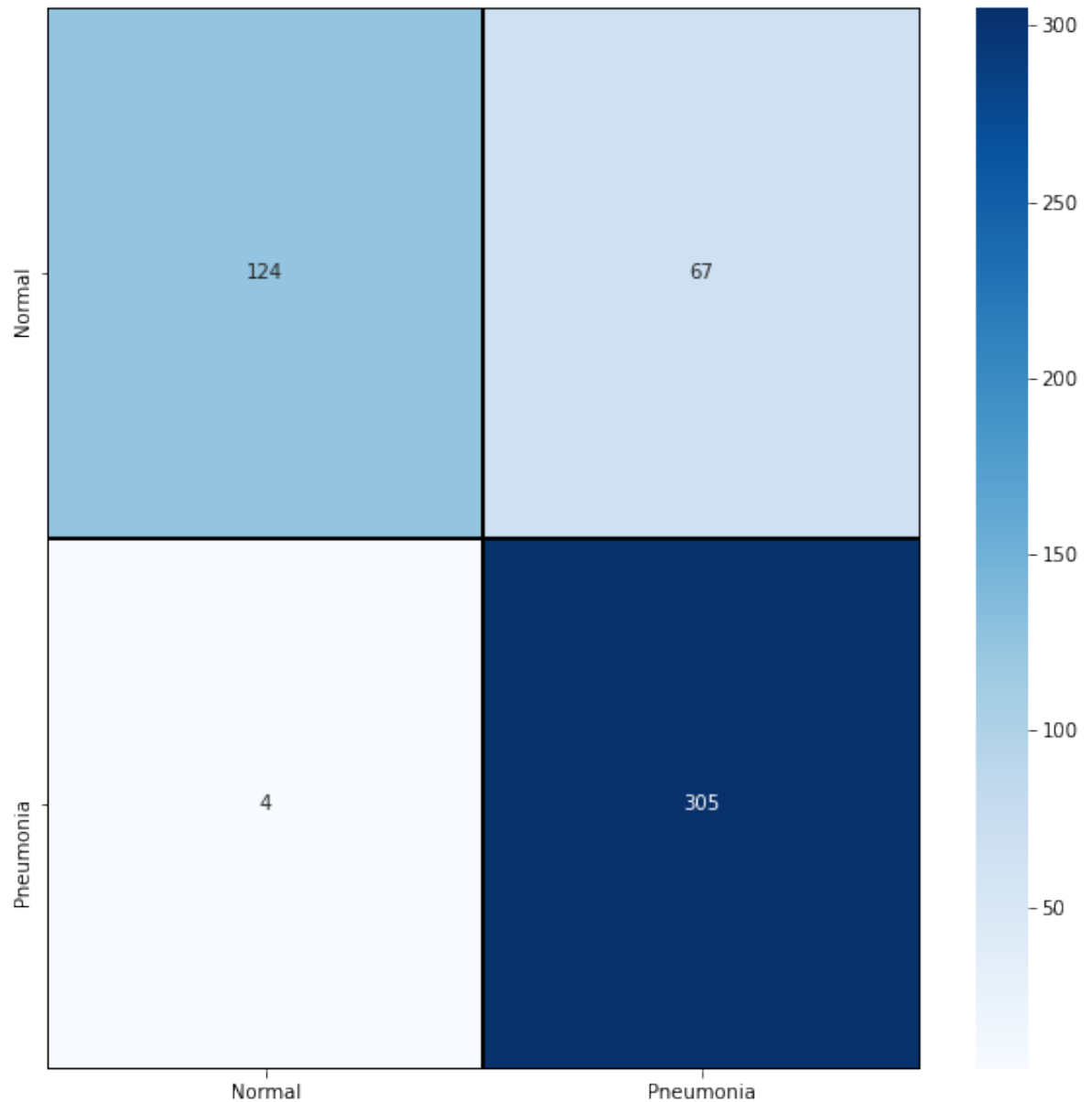
```
(500,)
(500,)
(500, 2)
```

```
In [125]: np.sum(preds)
```

```
Out[125]: 372
```

In [137]:

```
cm = confusion_matrix(orig_test_labels, preds)
cm = pd.DataFrame(cm, index = ['Normal', 'Pneumonia'], columns = ['N
plt.figure(figsize = (10,10))
sns.heatmap(cm,cmap= "Blues", linecolor = 'black', linewidth = 1, an
```




```
In [142]: correct = np.nonzero(preds == val_labels)[0]
incorrect = np.nonzero(preds != val_labels)[0]

<ipython-input-142-39fca69a639f>:1: DeprecationWarning: elementwise c
omparison failed; this will raise an error in the future.
    correct = np.nonzero(preds == val_labels)[0]
<ipython-input-142-39fca69a639f>:2: DeprecationWarning: elementwise c
omparison failed; this will raise an error in the future.
    incorrect = np.nonzero(preds != val_labels)[0]
```

```
In [147]: preds[0]
```

```
Out[147]: 1
```

```
In [148]: orig_test_labels[0]
```

```
Out[148]: 1
```

```
In [155]: TP = []
TN = []
FP = []
FN = []
for i in range(len(preds)):
    if preds[i] == orig_test_labels[i] == 1:
        TP.append(i)
    elif preds[i] == orig_test_labels[i] == 0:
        TN.append(i)
    elif preds[i] == 1 and orig_test_labels[i] == 0:
        FN.append(i)
    elif preds[i] == 0 and orig_test_labels[i] == 1:
        FP.append(i)
```

```
In [162]: print(len(TP))
print(len(TN))
print(len(FN))
print(len(FP))
```

```
305
124
67
4
```

```
In [176]: i = 0
for c in TP[:3]:
    plt.subplot(1,3,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.imshow(val_images[c], cmap="gray", interpolation='none')
    plt.title("Predicted Class {},Actual Class {}".format("PNEUMONIA",
    plt.tight_layout()
    i += 1
```

Predicted Class PNEUMONIA,Actual Class PNEUMONIA,Predicted Class PNEUMONIA,Actual Class PNEUMONIA,Predicted Class PNEUMONIA,Actual Class NORMAL



```
In [178]: i = 0
for c in TN[:3]:
    plt.subplot(1,3,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.imshow(val_images[c], cmap="gray", interpolation='none')
    plt.title("Predicted Class {},Actual Class {}".format("PNEUMONIA",
    plt.tight_layout()
    i += 1
```

Predicted Class PNEUMONIA,Actual Class PNEUMONIA,Predicted Class PNEUMONIA,Actual Class PNEUMONIA,Predicted Class PNEUMONIA,Actual Class NORMAL



```
In [179]: i = 0
for c in FP[:3]:
    plt.subplot(1,3,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.imshow(val_images[c], cmap="gray", interpolation='none')
    plt.title("Predicted Class {},Actual Class {}".format("PNEUMONIA",
    plt.tight_layout()
    i += 1
```

Predicted Class PNEUMONIA,Actual Class PNEUMONIA,Predicted Class PNEUMONIA,Actual Class PNEUMONIA,Predicted Class PNEUMONIA,Actual Class NORMAL



```
In [180]: i = 0
for c in FN[:3]:
    plt.subplot(1,3,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.imshow(val_images[c], cmap="gray", interpolation='none')
    plt.title("Predicted Class {},Actual Class {}".format("PNEUMONIA",
    plt.tight_layout()
    i += 1
```

Predicted Class PNEUMONIA,Actual Class PNEUMONIA,Predicted Class PNEUMONIA,Actual Class PNEUMONIA,Predicted Class PNEUMONIA,Actual Class NORMAL



Step 7: Optimize and Strategize

We see that our accuracy on our test data is 86.5%. This may indicate overfitting. Our recall is greater than our precision, indicating that almost all pneumonia images are correctly identified but some normal images are falsely identified. We should aim to increase our precision.

Type *Markdown* and LaTeX: α^2