# X-Ray Diagnostics: Pediatric Pneumonia

This notebook will develop a model to classify pediatric chest x-rays with convolutional neural networks.

## Importing Downloaded Data

Importing Necessary Python Libraries

```
In [1]: import os, shutil
```

- 1. Splitting Original Directories into Train/Test/Validation Directories
- 2. Loading Directory Paths & Contents into Variables

```
In [2]:
         # Loading Directory Paths into Variables
         original_normal = 'ORIGINAL_DATA/NORMAL'
         original_pneumonia = 'ORIGINAL_DATA/PNEUMONIA'
         new_dir = 'data/'
         train_folder = os.path.join(new_dir, 'train')
         train_normal = os.path.join(train_folder, 'normal')
         train_pneumonia = os.path.join(train_folder, 'pneumonia')
         test_folder = os.path.join(new_dir, 'test')
         test_normal = os.path.join(test_folder, 'normal')
         test_pneumonia = os.path.join(test_folder, 'pneumonia')
         val_folder = os.path.join(new_dir, 'validation')
         val_normal = os.path.join(val_folder, 'normal')
         val_pneumonia = os.path.join(val_folder, 'pneumonia')
         # Creating Split Directories
         os.mkdir(new_dir)
         os.mkdir(test_folder)
         os.mkdir(test_normal)
         os.mkdir(test_pneumonia)
         os.mkdir(train_folder)
         os.mkdir(train_normal)
         os.mkdir(train_pneumonia)
         os.mkdir(val_folder)
         os.mkdir(val_normal)
         os.mkdir(val_pneumonia)
```

```
1583 images in NORMAL directory
        4273 images in PNEUMONIA directory
        # Copying Raw Data into Split Directories
In [4]:
         # train normal
         imgs = imgs_normal[:1200]
         for img in imgs:
             origin = os.path.join(original_normal, img)
             destination = os.path.join(train normal, img)
             shutil.copyfile(origin, destination)
         # test normal
         imgs = imgs_normal[1200:1383]
         for img in imgs:
             origin = os.path.join(original_normal, img)
             destination = os.path.join(test_normal, img)
             shutil.copyfile(origin, destination)
         # validation normal
         imgs = imgs normal[1383:]
         for img in imgs:
             origin = os.path.join(original_normal, img)
             destination = os.path.join(val_normal, img)
             shutil.copyfile(origin, destination)
         # train pneumonia
         imgs = imgs_pneumonia[:3900]
         for img in imgs:
             origin = os.path.join(original_pneumonia, img)
             destination = os.path.join(train_pneumonia, img)
             shutil.copyfile(origin, destination)
         # test pneumonia
         imgs = imgs_pneumonia[3900:4073]
         for img in imgs:
             origin = os.path.join(original_pneumonia, img)
             destination = os.path.join(test_pneumonia, img)
             shutil.copyfile(origin, destination)
         # validation pneumonia
         imgs = imgs_pneumonia[4073:]
         for img in imgs:
             origin = os.path.join(original_pneumonia, img)
             destination = os.path.join(val_pneumonia, img)
             shutil.copyfile(origin, destination)
        ## CELL INTENDED TO RE-ESTABLISH VARIABLES ##
In [5]:
         ## FROM DEAD/RESTARTED KERNELS ##
         # Loading Directory Paths into Variables
         train_folder = 'data/train'
         train_normal = 'data/train/normal'
         train_pneumonia = 'data/train/pneumonia'
         test_folder = 'data/test'
         test_normal = 'data/test/normal'
         test_pneumonia = 'data/test/pneumonia'
         val_folder = 'data/validation'
         val_normal = 'data/validation/normal'
         val_pneumonia = 'data/validation/pneumonia'
```

original\_pneumonia) if file.endswith('.jpeg')]
print(len(imgs\_pneumonia), 'images in PNEUMONIA directory')

```
In [6]: # Number of Images in Each Directory

a1 = len(os.listdir(train_normal))
a2 = len(os.listdir(train_pneumonia))
a = a1 + a2
b1 = len(os.listdir(test_normal))
b2 = len(os.listdir(test_pneumonia))
b = b1 + b2
c1 = len(os.listdir(val_normal))
c2 = len(os.listdir(val_pneumonia))
c = c1 + c2

print(a, 'images in train directory')
print(b, 'images in test directory')
print(c, 'images in validation directory')
5100 images in train directory
```

# **Preprocessing Data**

Importing Necessary Python Libraries

356 images in test directory 400 images in validation directory

Preprocess Part A

```
# flow_from_directory Variables
In [8]:
         targetimagesize_ = (150, 150)
         trainbatchsize_ = a
         testbatchsize_ = b
         valbatchsize_ = c
         # Reshape Data in train Directory
         train_generator = ImageDataGenerator(
             rescale=1./255).flow_from_directory(
             train_folder,
             target_size = targetimagesize_,
             batch_size = trainbatchsize_)
         # Reshape Data in test Directory
         test_generator = ImageDataGenerator(
             rescale=1./255).flow_from_directory(
             test_folder,
             target_size = targetimagesize_,
             batch_size = testbatchsize_)
         # Reshape Data in validation Directory
         val_generator = ImageDataGenerator(
             rescale=1./255).flow_from_directory(
             val_folder,
             target_size = targetimagesize_,
             batch_size = valbatchsize_)
```

```
Found 5100 images belonging to 2 classes.
         Found 356 images belonging to 2 classes.
         Found 400 images belonging to 2 classes.
         # Load Dataset into Variables
 In [9]:
          train_images, train_labels = next(train_generator)
          test_images, test_labels = next(test_generator)
          val_images, val_labels = next(val_generator)
          # Exploring Final Datasets
In [10]:
          m_train = train_images.shape[0]
          m_test = test_images.shape[0]
          m_val = val_images.shape[0]
          print ("Number of training samples: " + str(m_train))
          print ("Number of testing samples: " + str(m_test))
          print ("Number of validation samples: " + str(m_val))
          print ("train_images shape: " + str(train_images.shape))
          print ("train_labels shape: " + str(train_labels.shape))
          print ("test_images shape: " + str(test_images.shape))
          print ("test_labels shape: " + str(test_labels.shape))
          print ("val_images shape: " + str(val_images.shape))
          print ("val_labels shape: " + str(val_labels.shape))
         Number of training samples: 5100
         Number of testing samples: 356
         Number of validation samples: 400
         train_images shape: (5100, 150, 150, 3)
         train_labels shape: (5100, 2)
         test_images shape: (356, 150, 150, 3)
         test_labels shape: (356, 2)
         val_images shape: (400, 150, 150, 3)
         val_labels shape: (400, 2)
         Preprocess Part B
In [11]:
          # Reshaping into 2-D Array
          train_img = train_images.reshape(train_images.shape[0], -1)
          test_img = test_images.reshape(test_images.shape[0], -1)
          val_img = val_images.reshape(val_images.shape[0], -1)
          print(train_img.shape)
          print(test_img.shape)
          print(val_img.shape)
          (5100, 67500)
         (356, 67500)
         (400, 67500)
         # Loading y Variables as 2-D Array
In [12]:
          train_y = np.reshape(train_labels[:,0], (trainbatchsize_,1))
          test_y = np.reshape(test_labels[:,0], (testbatchsize_,1))
          val_y = np.reshape(val_labels[:,0], (valbatchsize_,1))
          input_shape_ = train_img.shape[1]
```

## Modeling

Importing Necessary Python Libraries

```
In [13]: # Importing Python Libraries to Fit Models
from keras.models import Sequential
from keras.layers import (
```

```
Conv2D, Dense, Flatten, MaxPooling2D)
from keras import optimizers

# Importing Python Libraries for Analysis
import datetime
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import (
    classification_report, roc_curve, auc,
    confusion_matrix)

%matplotlib inline
np.random.seed(123)
```

#### **Baseline Model**

```
In [14]:
     # Building the Model
     def Build_Baseline():
        model = Sequential()
        model.add(Dense(20, activation='relu',
                     input_shape=(input_shape_,)))
        model.add(Dense(7, activation='relu'))
        model.add(Dense(5, activation='relu'))
        model.add(Dense(1, activation='sigmoid'))
        # Compile model
        model.compile(optimizer='sgd',
                loss='binary crossentropy',
                metrics=['acc'])
        return model
     # Timer Start
In [15]:
     start = datetime.datetime.now()
     base = Build_Baseline()
In [16]:
     basehist = base.fit(train_img,
                 train_y,
                 epochs=50,
                 batch_size=32,
                 validation_data=(val_img, val_y))
     Epoch 1/50
     0.5014 - val_acc: 0.7825
     Epoch 2/50
     3702 - val_acc: 0.5200
     Epoch 3/50
     2888 - val_acc: 0.8700
     Epoch 4/50
     8482 - val_acc: 0.6125
     Epoch 5/50
     160/160 [============] - 1s 8ms/step - loss: 0.1877 - acc: 0.9286 - val_loss: 0.
     4494 - val_acc: 0.8100
     Epoch 6/50
     5184 - val_acc: 0.7875
     Epoch 7/50
     5070 - val_acc: 0.8000
     Epoch 8/50
     2193 - val_acc: 0.9025
```

```
Epoch 9/50
4827 - val_acc: 0.7850
Epoch 10/50
3105 - val acc: 0.8750
Epoch 11/50
4740 - val_acc: 0.7925
Epoch 12/50
3565 - val acc: 0.8500
Epoch 13/50
4667 - val_acc: 0.8000
Epoch 14/50
3021 - val_acc: 0.8775
Epoch 15/50
3877 - val_acc: 0.8475
Epoch 16/50
2056 - val_acc: 0.9125
Epoch 17/50
2109 - val acc: 0.9075
Epoch 18/50
4235 - val acc: 0.8200
Epoch 19/50
2334 - val_acc: 0.9075
Epoch 20/50
2266 - val_acc: 0.9050
Epoch 21/50
2035 - val_acc: 0.9300
Epoch 22/50
2167 - val acc: 0.9150
Epoch 23/50
2256 - val_acc: 0.9125
Epoch 24/50
2837 - val acc: 0.8850
Epoch 25/50
2191 - val_acc: 0.9025
Epoch 26/50
2172 - val_acc: 0.9125
Epoch 27/50
2213 - val acc: 0.9125
Epoch 28/50
2329 - val_acc: 0.8950
Epoch 29/50
2848 - val_acc: 0.8900
Epoch 30/50
2428 - val_acc: 0.9000
Epoch 31/50
```

5362 - val\_acc: 0.7850

Epoch 32/50

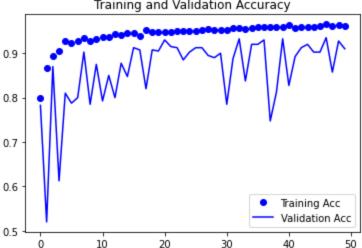
```
3199 - val_acc: 0.8875
   Epoch 33/50
   1935 - val_acc: 0.9325
   Epoch 34/50
   3693 - val_acc: 0.8375
   Epoch 35/50
   2020 - val acc: 0.9200
   Epoch 36/50
   2087 - val_acc: 0.9200
   Epoch 37/50
   1816 - val_acc: 0.9300
   Epoch 38/50
   7579 - val_acc: 0.7475
   Epoch 39/50
   4557 - val_acc: 0.8125
   Epoch 40/50
   1809 - val acc: 0.9325
   Epoch 41/50
   4450 - val_acc: 0.8275
   Epoch 42/50
   2581 - val_acc: 0.8925
   Epoch 43/50
   2369 - val_acc: 0.9125
   Epoch 44/50
   1993 - val_acc: 0.9200
   Epoch 45/50
   2287 - val_acc: 0.9025
   Epoch 46/50
   2337 - val_acc: 0.9025
   Epoch 47/50
   1786 - val_acc: 0.9350
   Epoch 48/50
   3447 - val_acc: 0.8575
   Epoch 49/50
   160/160 [==============] - 1s 8ms/step - loss: 0.0976 - acc: 0.9643 - val_loss: 0.
   1913 - val_acc: 0.9275
   Epoch 50/50
   2143 - val_acc: 0.9100
In [17]: | # Timer End
   end = datetime.datetime.now()
   elapsed = end - start
   print('Training Elapsed Time: {}'.format(elapsed))
```

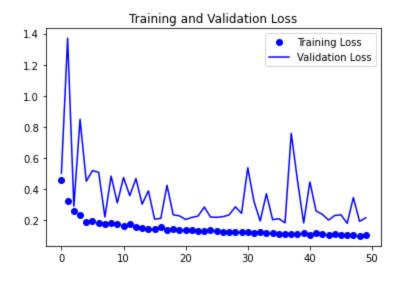
Training Elapsed Time: 0:01:09.876972

### **Baseline Model Analysis**

```
In [124... # Loading Variables for Analysis
    results_train = base.evaluate(train_img, train_y)
```

```
results_test = base.evaluate(test_img, test_y)
        pred_y = base.predict(test_img).ravel()
        fpr_, tpr_, thresholds_ = roc_curve(test_y, pred_y)
        auc_ = auc(fpr_, tpr_)
        In [125...
        # Evaluation Results
        print ('Train Results:', results_train)
        print ('Test Results:', results_test)
        Train Results: [0.11654186993837357, 0.9537255167961121]
        Test Results: [0.25213193893432617, 0.9044944047927856]
        acc = basehist.history['acc']
In [126...
        val_acc = basehist.history['val_acc']
        loss = basehist.history['loss']
        val_loss = basehist.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()
                   Training and Validation Accuracy
```



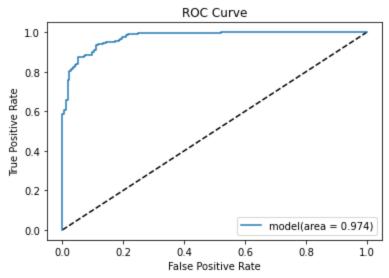


```
In [127...
          pred_y = (base.predict(test_img).ravel() > 0.5).astype(int)
In [128...
          # Confusion Matrix
          cm = confusion_matrix(test_y, pred_y)
          f = sns.heatmap(cm, annot=True, cmap='Greens',
                            xticklabels='PN', yticklabels='PN')
          plt.show()
          # Classification Report
          print(classification_report(test_y, pred_y))
                                                          - 160
                                                          - 140
                    1.6e+02
                                          11
          α.
                                                          - 120
                                                          - 100
                                                          - 80
                                                         - 60
                      23
                                        1.6e+02
          z^{-1}
                                                         - 40
                                                         - 20
                                          Ń
                      P
                         precision
                                       recall f1-score
                                                           support
                    0.0
                              0.88
                                         0.94
                                                    0.91
                                                               173
                   1.0
                              0.94
                                         0.87
                                                    0.90
                                                               183
                                                    0.90
                                                               356
              accuracy
             macro avg
                              0.91
                                         0.91
                                                    0.90
                                                                356
          weighted avg
                              0.91
                                         0.90
                                                    0.90
                                                               356
In [129...
          print('False Normal Rate:', (11/b2)*100)
          False Normal Rate: 6.358381502890173
In [130...
          plt.figure(1)
          plt.plot([0, 1], [0, 1], 'k--')
          plt.plot(fpr_, tpr_,
                    label='model(area = {:.3f})'.format(auc_))
           plt.xlabel('False Positive Rate')
```

plt.ylabel('True Positive Rate')

plt.title('ROC Curve')
plt.legend(loc='best')

plt.show()



```
In [131...
           auc_
          0.9736567800625414
Out[131...
In [134...
           pred_y = (base.predict(test_img).ravel() > 0.95).astype(int)
In [135...
           # Confusion Matrix
           cm = confusion_matrix(test_y, pred_y)
           f = sns.heatmap(cm, annot=True, cmap='cubehelix',
                            xticklabels='PN', yticklabels='PN')
           plt.show()
           # Classification Report
           print(classification_report(test_y, pred_y))
                                                         - 160
                                                          - 140
                    1.7e+02
                                                          - 120
                                                          100
                                                          80
                                                          60
          z
                                                          40
                      ė
                                          N
                         precision
                                       recall f1-score
                                                           support
                    0.0
                              0.71
                                         0.99
                                                    0.82
                                                                173
                    1.0
                              0.98
                                         0.61
                                                    0.75
                                                                183
              accuracy
                                                    0.79
                                                                356
             macro avg
                              0.84
                                         0.80
                                                    0.79
                                                                356
          weighted avg
                              0.85
                                         0.79
                                                    0.79
                                                                356
```

```
False Normal Rate: 1.1560693641618496

In [59]: base.save('XRAY_Baseline_Model.h5')
```

print('False Normal Rate:', (2/b2)\*100)

In [136...

#### **CNN Model**

```
# Building the Model
In [26]:
     def Build_CNN():
       model = Sequential()
       model.add(Conv2D(32, (3, 3), activation='relu',
                input_shape=(150 ,150, 3)))
       model.add(MaxPooling2D((2, 2)))
       model.add(Conv2D(32, (4, 4), activation='relu'))
       model.add(MaxPooling2D((2, 2)))
       model.add(Conv2D(64, (3, 3), activation='relu'))
       model.add(MaxPooling2D((2, 2)))
       model.add(Flatten())
       model.add(Dense(64, activation='relu'))
       model.add(Dense(1, activation='sigmoid'))
       # Compile model
       model.compile(optimizer='sgd',
              loss='binary_crossentropy',
              metrics=['acc'])
       return model
In [27]:
     # Timer Start
     start = datetime.datetime.now()
     cnn = Build_CNN()
In [29]:
     history = cnn.fit(train_images,
               train_y,
               epochs=50,
               batch_size=32,
               validation_data=(val_images, val_y))
    Epoch 1/50
    0.5916 - val acc: 0.6425
    Epoch 2/50
    0.3607 - val_acc: 0.8500
    Epoch 3/50
    0.3012 - val_acc: 0.8650
    Epoch 4/50
    0.2674 - val_acc: 0.8825
    Epoch 5/50
    0.7132 - val_acc: 0.6750
    Epoch 6/50
    0.2129 - val acc: 0.9150
    Epoch 7/50
    0.1949 - val acc: 0.9175
    Epoch 8/50
    0.3333 - val_acc: 0.8625
    Epoch 9/50
    0.1715 - val_acc: 0.9325
    Epoch 10/50
    0.1695 - val_acc: 0.9450
    Epoch 11/50
```

```
0.1835 - val_acc: 0.9250
Epoch 12/50
0.2253 - val acc: 0.9175
Epoch 13/50
0.1566 - val_acc: 0.9375
Epoch 14/50
0.2095 - val acc: 0.9175
Epoch 15/50
0.1643 - val_acc: 0.9450
Epoch 16/50
0.2025 - val_acc: 0.9225
Epoch 17/50
0.1763 - val_acc: 0.9425
Epoch 18/50
0.1336 - val_acc: 0.9525
Epoch 19/50
0.1328 - val_acc: 0.9625
Epoch 20/50
0.1662 - val_acc: 0.9400
Epoch 21/50
0.1287 - val_acc: 0.9600
Epoch 22/50
0.1561 - val acc: 0.9550
Epoch 23/50
0.1499 - val_acc: 0.9475
Epoch 24/50
0.1307 - val_acc: 0.9625
Epoch 25/50
0.1397 - val_acc: 0.9550
Epoch 26/50
0.1732 - val_acc: 0.9350
Epoch 27/50
0.1148 - val acc: 0.9625
Epoch 28/50
0.2118 - val_acc: 0.9200
Epoch 29/50
0.1289 - val_acc: 0.9550
Epoch 30/50
0.1178 - val_acc: 0.9700
Epoch 31/50
0.1282 - val_acc: 0.9575
Epoch 32/50
0.1449 - val_acc: 0.9600
Epoch 33/50
0.1240 - val_acc: 0.9650
Epoch 34/50
```

0.3962 - val\_acc: 0.8800

```
Epoch 35/50
0.1303 - val acc: 0.9575
Epoch 36/50
0.1437 - val_acc: 0.9550
Epoch 37/50
0.1247 - val_acc: 0.9550
Epoch 38/50
0.1289 - val_acc: 0.9550
Epoch 39/50
0.1221 - val acc: 0.9575
Epoch 40/50
0.2873 - val_acc: 0.9000
Epoch 41/50
0.1403 - val_acc: 0.9475
Epoch 42/50
0.1375 - val_acc: 0.9575
Epoch 43/50
0.1390 - val_acc: 0.9550
Epoch 44/50
0.1328 - val acc: 0.9625
Epoch 45/50
0.1209 - val_acc: 0.9600
Epoch 46/50
0.1782 - val_acc: 0.9500
Epoch 47/50
0.2284 - val_acc: 0.9350
Epoch 48/50
0.1670 - val_acc: 0.9550
Epoch 49/50
0.1363 - val_acc: 0.9650
Epoch 50/50
0.1306 - val_acc: 0.9575
# Timer End
end = datetime.datetime.now()
elapsed = end - start
print('Training Elapsed Time: {}'.format(elapsed))
```

Training Elapsed Time: 1:26:36.105971

### **CNN Model Analysis**

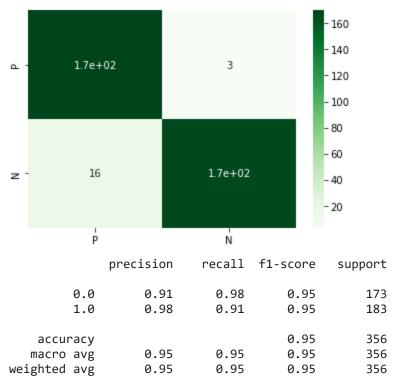
In [30]:

```
In [138...
           print ('Train Results:', results_train)
           print ('Test Results:', results_test)
          Train Results: [0.019027573987841606, 0.9950980544090271]
          Test Results: [0.1540239155292511, 0.9466292262077332]
In [139...
           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()
                         Training and validation accuracy
          1.00
          0.95
          0.90
          0.85
          0.80
          0.75
          0.70
                                                     Training acc
                                                     Validation acc
          0.65
                         10
                                   20
                                            30
                                                      40
                                                               50
                0
                          Training and validation loss
                                                    Training loss
          0.7
                                                    Validation loss
          0.6
          0.5
          0.4
          0.3
          0.2
          0.1
                0
                        10
                                  20
                                           30
                                                     40
           pred_y = (cnn.predict(test_images).ravel() > 0.5).astype(int)
In [140...
           # Confusion Matrix
In [141...
           cm = confusion_matrix(test_y, pred_y)
           f = sns.heatmap(cm, annot=True, cmap='Greens',
                            xticklabels='PN', yticklabels='PN')
```

# Results

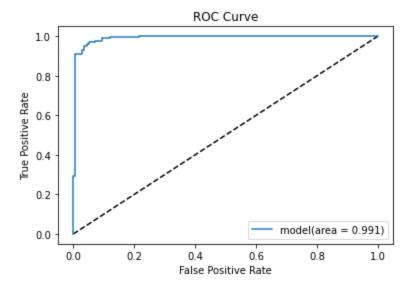
```
plt.show()

# Classification Report
print(classification_report(test_y, pred_y))
```



```
In [142... print('False Normal Rate:', (3/b2)*100)
```

False Normal Rate: 1.7341040462427744



```
In [144... auc_
```

Out[144... 0.9909030607410215

```
pred_y = (cnn.predict(test_images).ravel() > auc_).astype(int)
In [145...
           # Confusion Matrix
In [146...
           cm = confusion_matrix(test_y, pred_y)
           f = sns.heatmap(cm, annot=True, cmap='cubehelix',
                            xticklabels='PN', yticklabels='PN')
           plt.show()
           # Classification Report
           print(classification_report(test_y, pred_y))
                                                          - 160
                                                          - 140
                    1.7e+02
                                           1
                                                          - 120
                                                          - 100
                                                          - 80
                                                          60
                      61
                                        1.2e+02
          Z
                                                           40
                                                           20
                      þ
                                           Ν
                         precision
                                       recall f1-score
                                                            support
                              0.74
                                         0.99
                                                    0.85
                    0.0
                                                                173
                    1.0
                                                    0.80
                              0.99
                                         0.67
                                                                183
                                                    0.83
                                                                356
              accuracy
                                         0.83
             macro avg
                              0.87
                                                    0.82
                                                                356
          weighted avg
                                         0.83
                                                    0.82
                                                                356
                              0.87
           print('False Normal Rate:', (1/b2)*100)
In [147...
```

False Normal Rate: 0.5780346820809248

In [58]: cnn.save('XRAY\_CNN\_Model.h5')

### Image Classification Process (CNN)

Importing Necessary Libraries

```
In [60]: from keras.models import load_model
    from keras.preprocessing import image
    from keras import models
    import math
    import numpy as np
    import matplotlib.image as mpimg
    import matplotlib.pyplot as plt
    %matplotlib inline
```

Open/Load a Model

```
In [148... model = load_model('XRAY_CNN_Model.h5')
    model.summary()
```

Model: "sequential\_2"

Layer (type)	Output	Shape	2		Param	#
		=====	====:		======	====
conv2d_3 (Conv2D)	(None,	148,	148,	32)	896	

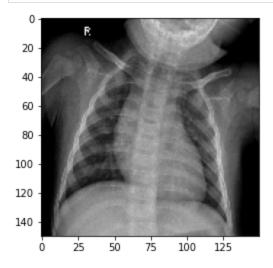
max_pooling2d_3 (MaxPooling2	(None,	74, 74, 32)	0
conv2d_4 (Conv2D)	(None,	71, 71, 32)	16416
max_pooling2d_4 (MaxPooling2	(None,	35, 35, 32)	0
conv2d_5 (Conv2D)	(None,	33, 33, 64)	18496
max_pooling2d_5 (MaxPooling2	(None,	16, 16, 64)	0
flatten_1 (Flatten)	(None,	16384)	0
dense_6 (Dense)	(None,	64)	1048640
dense_7 (Dense)	(None,	1)	65
Total params: 1,084,513		=============	========

Total params: 1,084,513 Trainable params: 1,084,513 Non-trainable params: 0

Open/Load Sample Test Image

```
open, zoda sampre rest image
```

```
In [149... filename = 'data/test/normal/NORMAL-7725506-0001.jpeg'
  img = image.load_img(filename, target_size=(150, 150))
  plt.imshow(img)
  plt.show()
```



View Image as Tensor

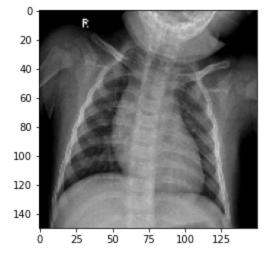
```
img_tensor = image.img_to_array(img)
img_tensor = np.expand_dims(img_tensor, axis=0)

# 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)



Visualization of Activation Layers

```
In [151...
          # Extract model layer outputs
          layer_outputs = [
              layer.output for layer in model.layers[:6]]
          # 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[:6]:
              layer_names.append(layer.name)
          total_features = sum([a.shape[-1] for a in activations])
          total_features
          n_{cols} = 12
          n_rows = math.ceil(total_features / n_cols)
          iteration = 0
          fig , axes = plt.subplots(nrows=n_rows, ncols=n_cols,
                                     figsize=(n_cols, n_rows*1.5))
          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]
                  channel_image -= channel_image.mean()
                  channel_image /= channel_image.std()
                  channel_image *= 32
                  channel_image += 64
                  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-151-2441043dfcd8>:40: RuntimeWarning: invalid value encountered in true_divide
  channel_image /= channel_image.std()
   conv2d 3
                                                                 max_pooling2d_3
max_pooling2d_4
```

