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Phase4 Project

X-Ray Diagnostics: Pediatric Pneumonia

The development of a classification model to diagnose pediatric chest x-rays as "normal" or "pneumonia" with convolutional neural networks is detailed in the notebook below.

I. Importing Downloaded Data (https://data.mendeley.com/datasets/rscbjbr9sj/3)

The data (https://data.mendeley.com/datasets/rscbjbr9sj/3) (peditric chest x-rays) was manually downloaded from Mendeley (https://data.mendeley.com/). The original data was previously sectioned into training and testing directories each containing images sorted into normal and pneumonia directories. The data was recombined into an overall directory (still depicting normal and pneumonia directory titles) so that it can be resplit as desired into training/testing/validation directories.

A. Importing Necessary Python Libraries

In [1]:
```
import os, shutil
```
executed in 19ms, finished 12:51:55 2021-06-05

B. Sorting the Data

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

In [2]:
```
%%script echo Skipped Cell
# 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)
```
executed in 33ms, finished 12:51:56 2021-06-05

```
Skipped Cell
```

In [3]:

```
## CELL INTENDED TO RE-ESTABLISH VARIABLES ##
## FROM DEAD/RESTARTED KERNELS ##

# Loading Directory Paths into Variables
original_normal = 'ORIGINAL_DATA/NORMAL'
original_pneumonia = 'ORIGINAL_DATA/PNEUMONIA'

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'
```

executed in 8ms, finished 12:51:57 2021-06-05

In [4]:

```
# Exploring Raw Source Data

# Number of Images in NORMAL Directory
imgs_normal = [file for file in os.listdir(
    original_normal) if file.endswith('.jpeg')]
print(len(imgs_normal), 'images in NORMAL directory')

# Number of Images in PNEUMONIA Directory
imgs_pneumonia = [file for file in os.listdir(
    original_pneumonia) if file.endswith('.jpeg')]
print(len(imgs_pneumonia), 'images in PNEUMONIA directory')
```

executed in 26ms, finished 12:51:58 2021-06-05

```
1583 images in NORMAL directory
4273 images in PNEUMONIA directory
```

In [5]:
```
%%script echo Skipped Cell
# Copying Raw Data into Split Directories

# 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)
```

executed in 27ms, finished 12:51:58 2021-06-05

```
Skipped Cell
```

Verifying Data in Split Directories

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')
```

executed in 22ms, finished 12:52:00 2021-06-05

```
5100 images in train directory
356 images in test directory
400 images in validation directory
```

II. Preprocessing Data

Although the data has been previously sorted and organized into the directories according to their "normal" or "pneumonia" labels, the images themselves are rescaled and reshaped in order to help reduce the time needed to train the model.

A. Importing Necessary Python Libraries

In [7]:
```
import scipy
import numpy as np
from PIL import Image
from scipy import ndimage
from keras.preprocessing.image import (
    ImageDataGenerator, array_to_img,
    img_to_array, load_img)
```

executed in 3.21s, finished 12:52:05 2021-06-05

B. Resizing and Reshaping Data

In [8]:
```
# flow_from_directory Variables
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_)
```

executed in 297ms, finished 12:52:05 2021-06-05

```
Found 5100 images belonging to 2 classes.
Found 356 images belonging to 2 classes.
Found 400 images belonging to 2 classes.
```

In [9]:
```
# Load Dataset into Variables
train_images, train_labels = next(train_generator)
test_images, test_labels = next(test_generator)
val_images, val_labels = next(val_generator)
```

executed in 58.7s, finished 12:53:04 2021-06-05

In [10]:
```
# Exploring Final Datasets
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))
```

executed in 14ms, finished 12:53:04 2021-06-05

```
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)
```

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)
```

executed in 13ms, finished 12:53:04 2021-06-05

```
(5100, 67500)
(356, 67500)
(400, 67500)
```

In [12]:
```
# Loading y Variables as 2-D Array

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]
```

executed in 14ms, finished 12:53:04 2021-06-05

III. Modeling

A. 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
```

executed in 1.24s, finished 12:53:05 2021-06-05

B. Baseline Model

1. Building the 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
```

executed in 13ms, finished 12:53:05 2021-06-05

In [15]:
```
# Timer Start
start = datetime.datetime.now()
```

executed in 15ms, finished 12:53:05 2021-06-05

In [16]:

```
base = Build_Baseline()
basehist = base.fit(train_img,
                    train_y,
                    epochs=50,
                    batch_size=32,
                    validation_data=(val_img, val_y))
```

executed in 1m 4.19s, finished 12:54:09 2021-06-05

```
Epoch 1/50
160/160 [==============================] - 1s 8ms/step - loss: 0.5361 - acc: 0.7590 - val_loss: 0.7159 - val_acc: 0.5000
Epoch 2/50
160/160 [==============================] - 1s 8ms/step - loss: 0.3773 - acc: 0.8178 - val_loss: 0.6063 - val_acc: 0.6575
Epoch 3/50
160/160 [==============================] - 1s 8ms/step - loss: 0.2826 - acc: 0.8886 - val_loss: 0.3099 - val_acc: 0.8625
Epoch 4/50
160/160 [==============================] - 1s 8ms/step - loss: 0.2386 - acc: 0.8976 - val_loss: 0.3263 - val_acc: 0.8550
Epoch 5/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1940 - acc: 0.9243 - val_loss: 0.3606 - val_acc: 0.8300
Epoch 6/50
160/160 [==============================] - 1s 8ms/step - loss: 0.2130 - acc: 0.9206 - val_loss: 0.4830 - val_acc: 0.7875
Epoch 7/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1864 - acc: 0.9273 - val_loss: 0.3722 - val_acc: 0.8350
Epoch 8/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1767 - acc: 0.9306 - val_loss: 0.4390 - val_acc: 0.8025
Epoch 9/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1737 - acc: 0.9325 - val_loss: 0.9133 - val_acc: 0.6700
Epoch 10/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1681 - acc: 0.9369 - val_loss: 0.2313 - val_acc: 0.9000
Epoch 11/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1695 - acc: 0.9345 - val_loss: 0.3454 - val_acc: 0.8650
Epoch 12/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1572 - acc: 0.9427 - val_loss: 0.2513 - val_acc: 0.9025
Epoch 13/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1583 - acc: 0.9410 - val_loss: 0.2684 - val_acc: 0.8925
Epoch 14/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1484 - acc: 0.9467 - val_loss: 0.2086 - val_acc: 0.9200
Epoch 15/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1507 - acc: 0.9429 - val_loss: 0.2609 - val_acc: 0.8900
Epoch 16/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1481 - acc: 0.9400 - val_loss: 0.2355 - val_acc: 0.9000
Epoch 17/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1510 - acc: 0.9437 - val_loss: 0.3260 - val_acc: 0.8750
Epoch 18/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1453 - acc: 0.9439 - val_loss: 0.2122 - val_acc: 0.9125
Epoch 19/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1436 - acc: 0.9471 - val_loss: 0.2028 - val_acc: 0.9125
Epoch 20/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1449 - acc: 0.9453 - val_loss: 0.3621 - val_acc: 0.8575
Epoch 21/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1379 - acc: 0.9500 - val_loss: 0.3660 - val_acc: 0.8650
Epoch 22/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1410 - acc: 0.9459 - val_loss: 0.2090 - val_acc: 0.9075
Epoch 23/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1372 - acc: 0.9494 - val_loss: 0.2434 - val_acc: 0.8900
Epoch 24/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1352 - acc: 0.9514 - val_loss: 0.3621 - val_acc: 0.8575
Epoch 25/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1354 - acc: 0.9506 - val_loss: 0.1966 - val_acc: 0.9200
Epoch 26/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1326 - acc: 0.9480 - val_loss: 0.2653 - val_acc: 0.8925
Epoch 27/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1353 - acc: 0.9486 - val_loss: 0.2405 - val_acc: 0.9000
Epoch 28/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1263 - acc: 0.9557 - val_loss: 0.2315 - val_acc: 0.9125
Epoch 29/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1295 - acc: 0.9539 - val_loss: 0.1905 - val_acc: 0.9200
Epoch 30/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1334 - acc: 0.9496 - val_loss: 0.1910 - val_acc: 0.9200
Epoch 31/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1313 - acc: 0.9514 - val_loss: 0.6114 - val_acc: 0.7675
Epoch 32/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1268 - acc: 0.9533 - val_loss: 0.1998 - val_acc: 0.9200
Epoch 33/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1287 - acc: 0.9545 - val_loss: 0.2108 - val_acc: 0.9125
Epoch 34/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1266 - acc: 0.9520 - val_loss: 0.1962 - val_acc: 0.9200
Epoch 35/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1304 - acc: 0.9531 - val_loss: 0.1918 - val_acc: 0.9225
Epoch 36/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1239 - acc: 0.9551 - val_loss: 0.2299 - val_acc: 0.9050
Epoch 37/50
```

```
160/160 [==============================] - 1s 8ms/step - loss: 0.1225 - acc: 0.9537 - val_loss: 0.1918 - val_acc: 0.9250
Epoch 38/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1152 - acc: 0.9590 - val_loss: 0.2613 - val_acc: 0.8925
Epoch 39/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1189 - acc: 0.9545 - val_loss: 0.1962 - val_acc: 0.9200
Epoch 40/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1191 - acc: 0.9545 - val_loss: 0.2009 - val_acc: 0.9250
Epoch 41/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1202 - acc: 0.9555 - val_loss: 0.1848 - val_acc: 0.9250
Epoch 42/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1197 - acc: 0.9531 - val_loss: 0.1895 - val_acc: 0.9250
Epoch 43/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1174 - acc: 0.9555 - val_loss: 0.1815 - val_acc: 0.9250
Epoch 44/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1288 - acc: 0.9510 - val_loss: 0.1984 - val_acc: 0.9250
Epoch 45/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1143 - acc: 0.9576 - val_loss: 0.2000 - val_acc: 0.9150
Epoch 46/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1179 - acc: 0.9553 - val_loss: 0.3960 - val_acc: 0.8600
Epoch 47/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1171 - acc: 0.9571 - val_loss: 0.4166 - val_acc: 0.8450
Epoch 48/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1209 - acc: 0.9545 - val_loss: 0.3602 - val_acc: 0.8000
Epoch 49/50
160/160 [==============================] - 1s 8ms/step - loss: 0.1154 - acc: 0.9582 - val_loss: 0.1950 - val_acc: 0.9250
Epoch 50/50
160/160 [==============================] - 1s 7ms/step - loss: 0.1133 - acc: 0.9586 - val_loss: 0.1999 - val_acc: 0.9250
```

In [17]:

```
# Timer End
end = datetime.datetime.now()
elapsed = end - start
print('Training Elapsed Time: {}'.format(elapsed))
```

executed in 14ms, finished 12:54:09 2021-06-05

```
Training Elapsed Time: 0:01:04.207171
```

2. Analyzing the Model

In [18]:

```
# 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_)
```

executed in 895ms, finished 12:54:10 2021-06-05

```
160/160 [==============================] - 1s 4ms/step - loss: 0.1189 - acc: 0.9567
12/12 [==============================] - 0s 2ms/step - loss: 0.1967 - acc: 0.9213
```

In [19]:

```
# Evaluation Results
print ('Train Results:', results_train)
print ('Test Results:', results_test)
```

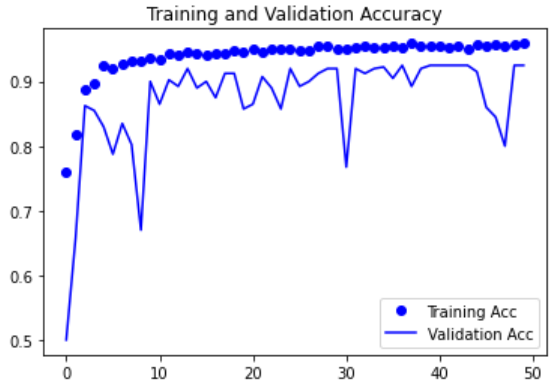
executed in 14ms, finished 12:54:10 2021-06-05

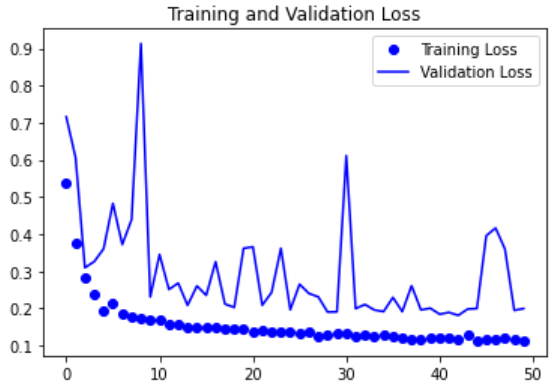
```
Train Results: [0.11892931163311005, 0.9566666483879089]
Test Results: [0.1967228651046753, 0.9213483333587646]
```

In [20]:

```
acc = basehist.history['acc']
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()
```

executed in 391ms, finished 12:54:11 2021-06-05





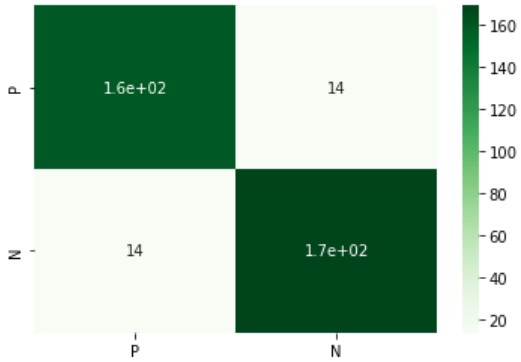
In [21]:

```
# Predicting Normal/Pneumonia of Test Group-
# Determining Diagnosis @ Halfway Point
# of Logistic Regression Curve
pred_y = (base.predict(test_img).ravel() > 0.5).astype(int)
```

executed in 203ms, finished 12:54:11 2021-06-05

In [22]:
```
# 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))
```

executed in 189ms, finished 12:54:11 2021-06-05



	precision	recall	f1-score	support
0.0	0.92	0.92	0.92	173
1.0	0.92	0.92	0.92	183
accuracy			0.92	356
macro avg	0.92	0.92	0.92	356
weighted avg	0.92	0.92	0.92	356

In [23]:
```
print('False Normal Rate:', (11/b2)*100)
```

executed in 14ms, finished 12:54:11 2021-06-05

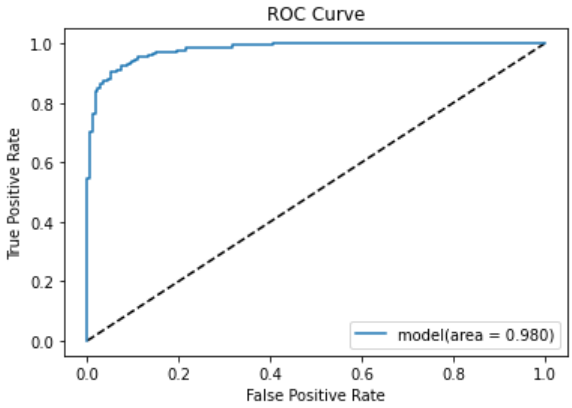
```
False Normal Rate: 6.358381502890173
```

3. Optimizing the Model

Reducing the rate at which the model predicts "Normal" when actual values are "Pneumonia" to prevent misdiagnosis.

In [24]:
```
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()
```

executed in 173ms, finished 12:54:11 2021-06-05



In [25]:
```
auc_
```

executed in 13ms, finished 12:54:11 2021-06-05

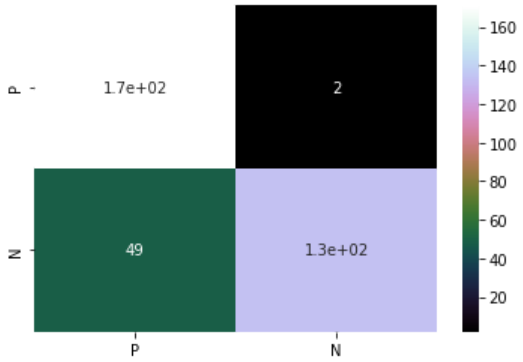
Out[25]:
```
0.9796898196405446
```

In [26]:
```
# Rescaling Normal/Pneumonia Diagnosis using AUC Value
pred_y = (base.predict(test_img).ravel() > auc_).astype(int)
```

executed in 79ms, finished 12:54:11 2021-06-05

In [27]:
```
# 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))
```

executed in 174ms, finished 12:54:12 2021-06-05




```
              precision    recall  f1-score   support

         0.0       0.78      0.99      0.87       173
         1.0       0.99      0.73      0.84       183

    accuracy                           0.86       356
   macro avg       0.88      0.86      0.86       356
weighted avg       0.88      0.86      0.85       356
```

In [28]:
```
print('False Normal Rate:', (2/b2)*100)
```

executed in 15ms, finished 12:54:12 2021-06-05

```
False Normal Rate: 1.1560693641618496
```

4. Saving the Model

In [29]:
```
base.save('XRAY_Baseline_Model.h5')
```

executed in 62ms, finished 12:54:12 2021-06-05

CNN Model

1. Building the Model

In [30]:

```
# Building the Model

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
```

executed in 14ms, finished 12:54:12 2021-06-05

In [31]:

```
# Timer Start
start = datetime.datetime.now()
```

executed in 13ms, finished 12:54:12 2021-06-05

In [32]:

```
cnn = Build_CNN()
history = cnn.fit(train_images,
                  train_y,
                  epochs=50,
                  batch_size=32,
                  validation_data=(val_images, val_y))
```

executed in 51m 31s, finished 13:45:43 2021-06-05

```
Epoch 1/50
160/160 [==============================] - 61s 380ms/step - loss: 0.5130 - acc: 0.7708 - val_loss: 0.5581 - val_acc: 0.6950
Epoch 2/50
160/160 [==============================] - 58s 365ms/step - loss: 0.3733 - acc: 0.8410 - val_loss: 0.3906 - val_acc: 0.8300
Epoch 3/50
160/160 [==============================] - 59s 368ms/step - loss: 0.2646 - acc: 0.8937 - val_loss: 0.3256 - val_acc: 0.8625
Epoch 4/50
160/160 [==============================] - 60s 374ms/step - loss: 0.2054 - acc: 0.9218 - val_loss: 0.3241 - val_acc: 0.8750
Epoch 5/50
160/160 [==============================] - 60s 377ms/step - loss: 0.1907 - acc: 0.9259 - val_loss: 0.3654 - val_acc: 0.8450
Epoch 6/50
160/160 [==============================] - 61s 379ms/step - loss: 0.1656 - acc: 0.9378 - val_loss: 0.2482 - val_acc: 0.9075
Epoch 7/50
160/160 [==============================] - 61s 383ms/step - loss: 0.1582 - acc: 0.9418 - val_loss: 0.2230 - val_acc: 0.9100
Epoch 8/50
160/160 [==============================] - 60s 377ms/step - loss: 0.1436 - acc: 0.9465 - val_loss: 0.2370 - val_acc: 0.9000
Epoch 9/50
160/160 [==============================] - 61s 382ms/step - loss: 0.1386 - acc: 0.9484 - val_loss: 0.2672 - val_acc: 0.8950
Epoch 10/50
160/160 [==============================] - 63s 394ms/step - loss: 0.1287 - acc: 0.9537 - val_loss: 0.1682 - val_acc: 0.9350
Epoch 11/50
160/160 [==============================] - 63s 397ms/step - loss: 0.1262 - acc: 0.9553 - val_loss: 0.1628 - val_acc: 0.9400
Epoch 12/50
160/160 [==============================] - 62s 385ms/step - loss: 0.1171 - acc: 0.9588 - val_loss: 0.1727 - val_acc: 0.9350
Epoch 13/50
160/160 [==============================] - 62s 387ms/step - loss: 0.1143 - acc: 0.9584 - val_loss: 0.1567 - val_acc: 0.9450
Epoch 14/50
160/160 [==============================] - 62s 387ms/step - loss: 0.1097 - acc: 0.9606 - val_loss: 0.1726 - val_acc: 0.9400
Epoch 15/50
160/160 [==============================] - 61s 382ms/step - loss: 0.1047 - acc: 0.9627 - val_loss: 0.1469 - val_acc: 0.9525
Epoch 16/50
160/160 [==============================] - 62s 386ms/step - loss: 0.1049 - acc: 0.9606 - val_loss: 0.2974 - val_acc: 0.8900
Epoch 17/50
160/160 [==============================] - 62s 389ms/step - loss: 0.0969 - acc: 0.9639 - val_loss: 0.2013 - val_acc: 0.9375
Epoch 18/50
160/160 [==============================] - 63s 394ms/step - loss: 0.0951 - acc: 0.9661 - val_loss: 0.1658 - val_acc: 0.9450
Epoch 19/50
160/160 [==============================] - 64s 397ms/step - loss: 0.0905 - acc: 0.9680 - val_loss: 0.1398 - val_acc: 0.9500
Epoch 20/50
160/160 [==============================] - 63s 391ms/step - loss: 0.0878 - acc: 0.9680 - val_loss: 0.1511 - val_acc: 0.9500
Epoch 21/50
160/160 [==============================] - 61s 384ms/step - loss: 0.0839 - acc: 0.9698 - val_loss: 0.1331 - val_acc: 0.9575
Epoch 22/50
160/160 [==============================] - 62s 388ms/step - loss: 0.0840 - acc: 0.9690 - val_loss: 0.1448 - val_acc: 0.9525
Epoch 23/50
160/160 [==============================] - 62s 386ms/step - loss: 0.0815 - acc: 0.9716 - val_loss: 0.2096 - val_acc: 0.9250
Epoch 24/50
160/160 [==============================] - 62s 385ms/step - loss: 0.0774 - acc: 0.9731 - val_loss: 0.2647 - val_acc: 0.8950
Epoch 25/50
160/160 [==============================] - 61s 380ms/step - loss: 0.0762 - acc: 0.9720 - val_loss: 0.1574 - val_acc: 0.9525
Epoch 26/50
160/160 [==============================] - 61s 380ms/step - loss: 0.0734 - acc: 0.9749 - val_loss: 0.1541 - val_acc: 0.9525
Epoch 27/50
160/160 [==============================] - 61s 380ms/step - loss: 0.0714 - acc: 0.9747 - val_loss: 0.1467 - val_acc: 0.9525
Epoch 28/50
160/160 [==============================] - 63s 392ms/step - loss: 0.0652 - acc: 0.9751 - val_loss: 0.1208 - val_acc: 0.9525
Epoch 29/50
160/160 [==============================] - 62s 386ms/step - loss: 0.0671 - acc: 0.9749 - val_loss: 0.1404 - val_acc: 0.9575
Epoch 30/50
160/160 [==============================] - 61s 380ms/step - loss: 0.0648 - acc: 0.9769 - val_loss: 0.1654 - val_acc: 0.9475
Epoch 31/50
160/160 [==============================] - 61s 382ms/step - loss: 0.0617 - acc: 0.9776 - val_loss: 0.3617 - val_acc: 0.8850
Epoch 32/50
160/160 [==============================] - 60s 375ms/step - loss: 0.0612 - acc: 0.9782 - val_loss: 0.1366 - val_acc: 0.9625
Epoch 33/50
160/160 [==============================] - 61s 383ms/step - loss: 0.0569 - acc: 0.9776 - val_loss: 0.1175 - val_acc: 0.9700
Epoch 34/50
160/160 [==============================] - 62s 386ms/step - loss: 0.0556 - acc: 0.9794 - val_loss: 0.1394 - val_acc: 0.9550
Epoch 35/50
160/160 [==============================] - 61s 380ms/step - loss: 0.0532 - acc: 0.9810 - val_loss: 0.1220 - val_acc: 0.9575
Epoch 36/50
160/160 [==============================] - 61s 381ms/step - loss: 0.0517 - acc: 0.9820 - val_loss: 0.1267 - val_acc: 0.9650
Epoch 37/50
160/160 [==============================] - 61s 381ms/step - loss: 0.0486 - acc: 0.9839 - val_loss: 0.1236 - val_acc: 0.9600
```

```
Epoch 38/50
160/160 [==============================] - 60s 372ms/step - loss: 0.0487 - acc: 0.9847 - val_loss: 0.1825 - val_acc: 0.9400
Epoch 39/50
160/160 [==============================] - 61s 379ms/step - loss: 0.0455 - acc: 0.9837 - val_loss: 0.1354 - val_acc: 0.9600
Epoch 40/50
160/160 [==============================] - 61s 382ms/step - loss: 0.0427 - acc: 0.9851 - val_loss: 0.1359 - val_acc: 0.9575
Epoch 41/50
160/160 [==============================] - 63s 391ms/step - loss: 0.0416 - acc: 0.9859 - val_loss: 0.1225 - val_acc: 0.9650
Epoch 42/50
160/160 [==============================] - 62s 384ms/step - loss: 0.0436 - acc: 0.9847 - val_loss: 0.1474 - val_acc: 0.9600
Epoch 43/50
160/160 [==============================] - 61s 380ms/step - loss: 0.0405 - acc: 0.9851 - val_loss: 0.1441 - val_acc: 0.9575
Epoch 44/50
160/160 [==============================] - 62s 387ms/step - loss: 0.0442 - acc: 0.9857 - val_loss: 0.2112 - val_acc: 0.9300
Epoch 45/50
160/160 [==============================] - 62s 389ms/step - loss: 0.0389 - acc: 0.9855 - val_loss: 0.1222 - val_acc: 0.9675
Epoch 46/50
160/160 [==============================] - 60s 374ms/step - loss: 0.0335 - acc: 0.9882 - val_loss: 0.1219 - val_acc: 0.9650
Epoch 47/50
160/160 [==============================] - 62s 385ms/step - loss: 0.0303 - acc: 0.9906 - val_loss: 0.1308 - val_acc: 0.9625
Epoch 48/50
160/160 [==============================] - 62s 385ms/step - loss: 0.0307 - acc: 0.9900 - val_loss: 0.1489 - val_acc: 0.9550
Epoch 49/50
160/160 [==============================] - 65s 406ms/step - loss: 0.0325 - acc: 0.9882 - val_loss: 0.2357 - val_acc: 0.9100
Epoch 50/50
160/160 [==============================] - 64s 399ms/step - loss: 0.0333 - acc: 0.9880 - val_loss: 0.1913 - val_acc: 0.9450
```

In [33]:

```python
# Timer End
end = datetime.datetime.now()
elapsed = end - start
print('Training Elapsed Time: {}'.format(elapsed))
```

executed in 32ms, finished 13:45:43 2021-06-05

```
Training Elapsed Time: 0:51:30.924207
```

2. Analyzing the Model

In [34]:

```python
# Loading Variables for Analysis

results_train = cnn.evaluate(train_images, train_y)
results_test = cnn.evaluate(test_images, test_y)

pred_y = cnn.predict(test_images).ravel()

fpr_, tpr_, thresholds_ = roc_curve(test_y, pred_y)
auc_ = auc(fpr_, tpr_)
```

executed in 12.3s, finished 13:45:55 2021-06-05

```
160/160 [==============================] - 11s 66ms/step - loss: 0.0378 - acc: 0.9845
12/12 [==============================] - 1s 59ms/step - loss: 0.2865 - acc: 0.9213
```

In [35]:

```python
# Results
print ('Train Results:', results_train)
print ('Test Results:', results_test)
```

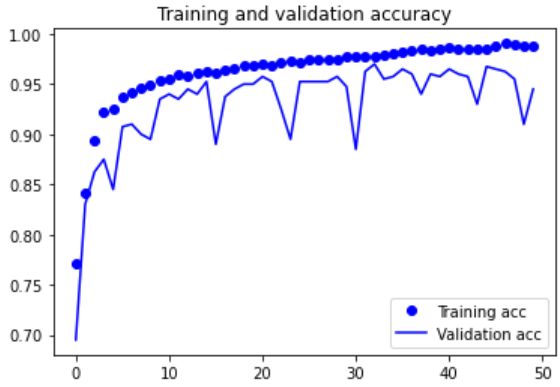
executed in 13ms, finished 13:45:55 2021-06-05

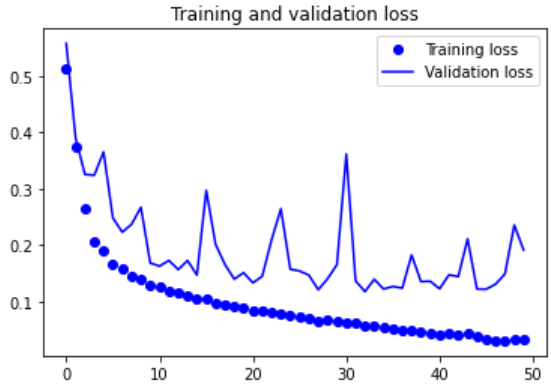
```
Train Results: [0.037786077708005905, 0.9845098257064819]
Test Results: [0.2864915132522583, 0.9213483333587646]
```

In [36]:

```
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()
```

executed in 350ms, finished 13:45:55 2021-06-05





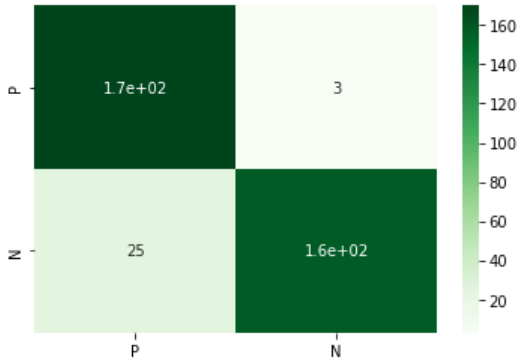
In [37]:

```
# Predicting Normal/Pneumonia of Test Group-
# Determining Diagnosis @ Halfway Point
# of Logistic Regression Curve
pred_y = (cnn.predict(test_images).ravel() > 0.5).astype(int)
```

executed in 754ms, finished 13:45:56 2021-06-05

In [38]:
```
# 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))
```

executed in 219ms, finished 13:45:56 2021-06-05



	precision	recall	f1-score	support
0.0	0.87	0.98	0.92	173
1.0	0.98	0.86	0.92	183
accuracy			0.92	356
macro avg	0.93	0.92	0.92	356
weighted avg	0.93	0.92	0.92	356

In [39]:
```
print('False Normal Rate:', (3/b2)*100)
```

executed in 12ms, finished 13:45:56 2021-06-05

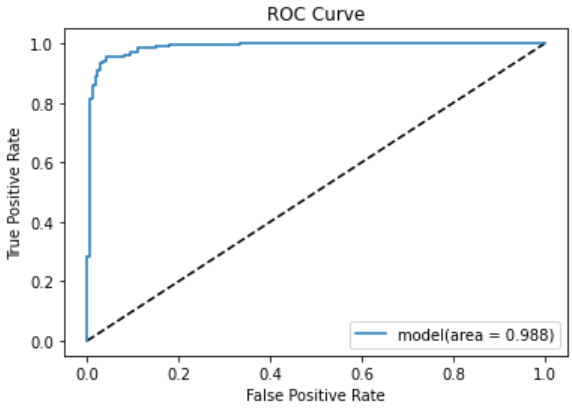
```
False Normal Rate: 1.7341040462427744
```

3. Optimizing the Model

Reducing the rate at which the model predicts "Normal" when actual values are "Pneumonia" to prevent misdiagnosis.

In [40]:
```
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()
```

executed in 173ms, finished 13:45:56 2021-06-05



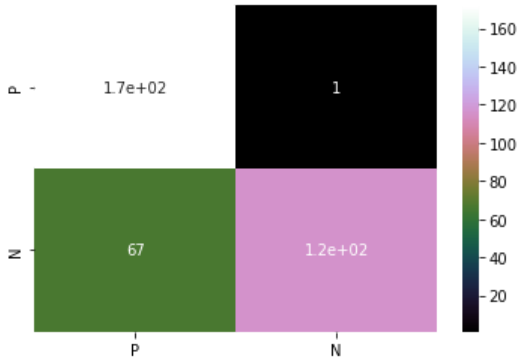
In [41]:
```
auc_
```

executed in 15ms, finished 13:45:57 2021-06-05

Out[41]:
```
0.9875864683028523
```

In [42]:
```
# Rescaling Normal/Pneumonia Diagnosis using AUC Value
pred_y = (cnn.predict(test_images).ravel() > auc_).astype(int)
```
executed in 762ms, finished 13:45:57 2021-06-05

In [43]:
```
# 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))
```
executed in 188ms, finished 13:45:57 2021-06-05



	precision	recall	f1-score	support
0.0	0.72	0.99	0.83	173
1.0	0.99	0.63	0.77	183
accuracy			0.81	356
macro avg	0.86	0.81	0.80	356
weighted avg	0.86	0.81	0.80	356

In [44]:
```
print('False Normal Rate:', (1/b2)*100)
```
executed in 15ms, finished 13:45:57 2021-06-05

```
False Normal Rate: 0.5780346820809248
```

4. Saving the Model

In [45]:
```
cnn.save('XRAY_CNN_Model.h5')
```
executed in 45ms, finished 13:45:58 2021-06-05

IV. Visualizing Model's Classification Process

A. Importing Necessary Python Libraries

In [46]:
```
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
```
executed in 15ms, finished 13:45:58 2021-06-05

B. Breaking Down the Process

1. Loading the CNN Model to Visualize

In [47]:
```
model = load_model('XRAY_CNN_Model.h5')
model.summary()
```

executed in 107ms, finished 13:45:58 2021-06-05

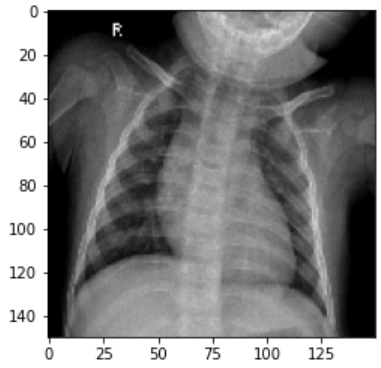
```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 148, 148, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 71, 71, 32)        16416
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 35, 35, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 33, 33, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 16384)             0
_________________________________________________________________
dense_4 (Dense)              (None, 64)                1048640
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 65
=================================================================
Total params: 1,084,513
Trainable params: 1,084,513
Non-trainable params: 0
_________________________________________________________________
```

2. Sample Test Image

Choosing and viewing the sample test image to be observed in the process.

In [48]:
```
filename = 'data/test/normal/NORMAL-7725506-0001.jpeg'
img = image.load_img(filename, target_size=(150, 150))
plt.imshow(img)
plt.show()
```

executed in 173ms, finished 13:45:58 2021-06-05



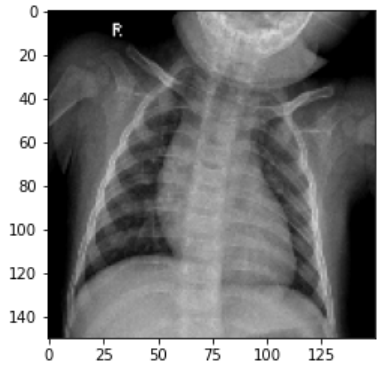
Viewing the Image as Tensor

In [49]:

```
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()
```

executed in 157ms, finished 13:45:58 2021-06-05

```
(1, 150, 150, 3)
```



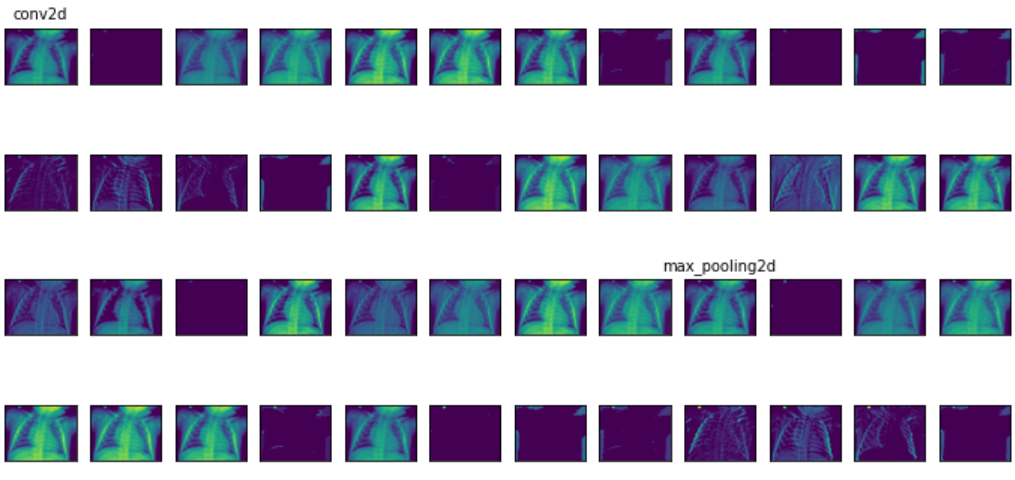
Visualizing the Image Processed through the Activation Layers

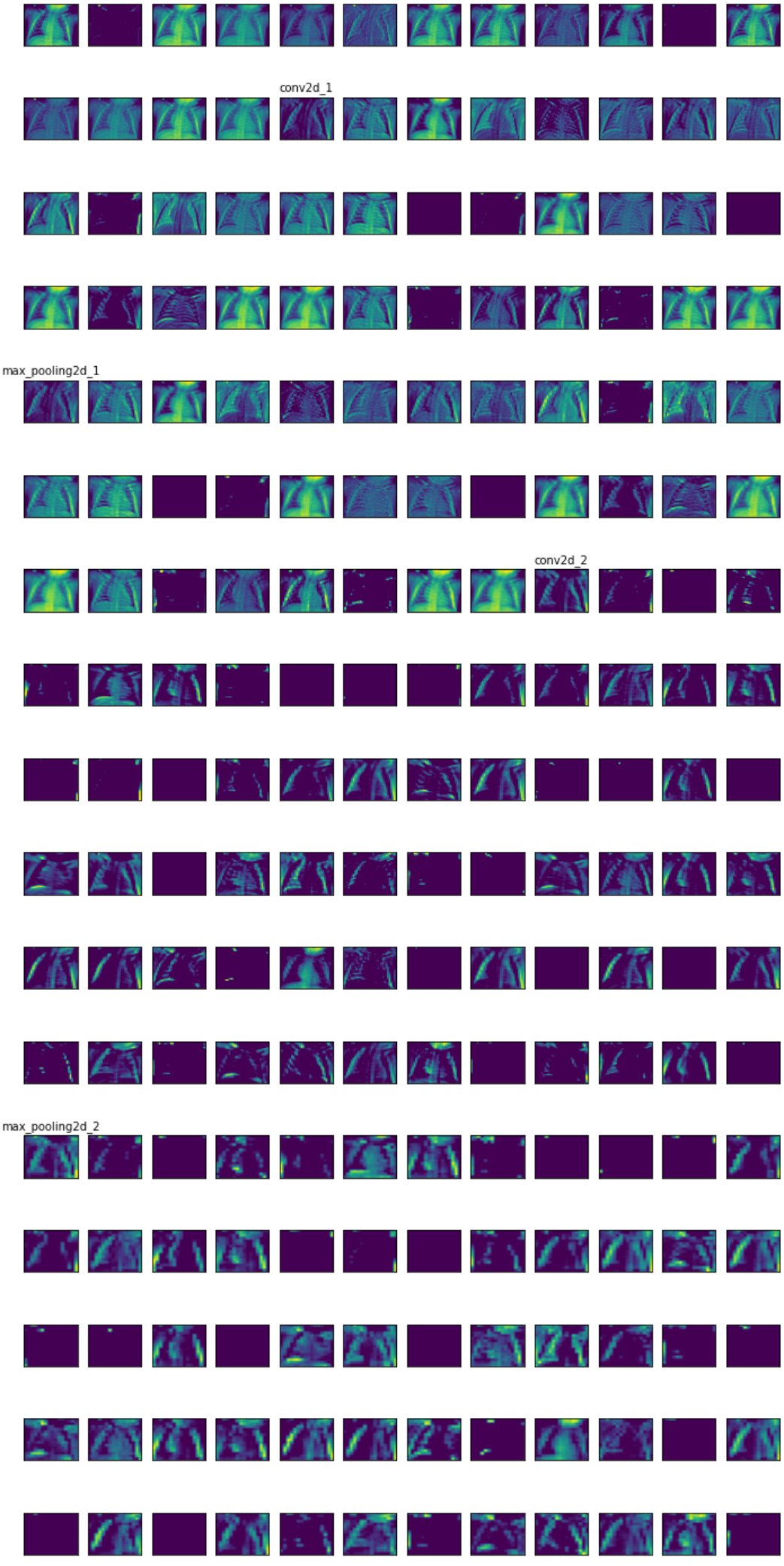
In [50]:

```
# 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()
```

executed in 9.44s, finished 13:46:07 2021-06-05

```
<ipython-input-50-2441043dfcd8>:40: RuntimeWarning: invalid value encountered in true_divide
  channel_image /= channel_image.std()
```




conv2d_1
max_pooling2d_1
conv2d_2
max_pooling2d_2