Pneumonia Image Classification

Business Understanding:

In this image classification project, I am utilizing neural networks - primarily convolutional neural networks - to create a model that can identify whether or not a patient has pneumonia by analyzing their lung x-rays.

There are two types of pneumonia - bacterial and viral. The image classification system will have to be able to pick out both, while not necessarily knowing which one is which, as the types of pneumonia are not labeled in the dataset.

Data Understanding:

The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (Pneumonia/Normal). There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).

Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. All chest X-ray imaging was performed as part of patients' routine clinical care.

Due to the relatively small amount of validation data (16 images), as well as test data, I will create my own validation data instead of using the provided split.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import keras
from keras.models import Sequential
from keras.layers import Dense, Conv2D, BatchNormalization, MaxPooling2D, D
ropout, Flatten
from sklearn.preprocessing import StandardScaler, LabelBinarizer
import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'
import tensorflow as tf
from keras import models
from keras import layers
import pathlib
import PIL
import seaborn as sns
import time
import scipy
import numpy as np
from PIL import Image
from scipy import ndimage
from sklearn.model_selection import train_test_split, cross_val_score
from keras.preprocessing.image import ImageDataGenerator, array_to_img, img
_to_array, load_img
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import numpy as np
import seaborn as sns
from tensorflow.keras.models import Sequential
from tensorflow.keras.regularizers import l2
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.wrappers import scikit_learn
from tensorflow.keras.callbacks import EarlyStopping
import shutil
import random
import glob
import os
import sys
import itertools
import warnings
import statistics
```

Define Scoring Metric

For the purposes of this analysis, I think a custom scoring metric is necessary.

My reasoning is this:

- False negatives could cause patients with pneumonia to not recieve further testing. This would be the worst possibility, out of the options.
- False positives would cost more due to testing people who did not actually have pneumonia, or could cause people without pneumonia to needlessly worry about their health. This is also costly, but not as costly as mis-diagnosing an individual with pneumonia.

Thus, I want to minimize false negatives while keeping false positives to an appropriate level.

According to [https://towardsdatascience.com/performance-metrics-confusion-matrix-precision-recall-and-f1-score-a8fe076a2262 (https://towardsdatascience.com/performance-metrics-confusion-matrix-precision-recall-and-f1-score-a8fe076a2262)](https://towardsdatascience.com/performance-metrics-confusion-matrix-precision-recall-and-f1-score-a8fe076a2262), the F1 score gives the same weightage to recall and precision, BUT there is a weighted F1 score in which we can give different weightage to recall and precision. As discussed in the previous section, different problems give different weightage to recall and precision.

F_B = (1+B^2) *[(Precision* Recall) / ((B^2 * Precision) + Recall)]

Beta represents how many times recall is more important than precision. If the recall is twice as important as precision, the value of Beta is 2.

Thus, for the purpose of this project, my Weighted F1 score will be:

F_B = (1+3^2) *[(Precision* Recall) / ((3^2 * Precision) + Recall)]

Check Data

In [2]:
```
train_norm_size = len(os.listdir('re-split_data/train/normal'))
train_pneum_size = len(os.listdir('re-split_data/train/pneumonia'))
test_norm_size = len(os.listdir('re-split_data/test/normal'))
test_pneum_size = len(os.listdir('re-split_data/test/pneumonia'))
valid_norm_size = len(os.listdir('re-split_data/validation/normal'))
valid_pneum_size = len(os.listdir('re-split_data/validation/pneumonia'))


train_size = train_norm_size + train_pneum_size -1
test_size = test_norm_size + test_pneum_size -1
validation_size = valid_norm_size + valid_pneum_size

print(f' There are {train_size} images in the training set, {test_size} in
the test set, and {validation_size} in the validation set')

print(f'train norm is {train_norm_size}')
print(f'train pneum is {train_pneum_size}')
print(f'test norm: {test_norm_size}')
print(f'test pneum: {test_pneum_size}')
print(f'valid norm: {valid_norm_size}')
print(f'valid pneum: {valid_pneum_size}')
```

```
 There are 3272 images in the training set, 1752 in the test set, and 816 i
n the validation set
train norm is 883
train pneum is 2390
test norm: 473
test pneum: 1280
valid norm: 220
valid pneum: 596
```

Add Functions

In [3]:

```
# Define Result Saving Initial Function
dfcols = ['Model', 'RW Score', 'F1', 'Recall', 'Precision', 'Accuracy']
model_summary = pd.DataFrame(columns=dfcols)


def save_result(cf, model_name):
            global model_summary
            accuracy  = np.trace(cf) / float(np.sum(cf))
            recall = cf[1,1] / sum(cf[:,1])
            precision    = cf[1,1] / sum(cf[1,:])
            f1_score  = 2*precision*recall / (precision + recall)
            beta = 9 # 3^2
            rw_score = (1+beta) * ((precision * recall) / ((beta * precisio
n) + recall))

            #cv_std = statistics.stdev([cv1, cv2, cv3, cv4, cv5])
            #cv_avg = (cv1 + cv2 + cv3 + cv4 + cv5) / 5
            results_columns = ['Model', 'RW Score', 'F1', 'Recall', 'Precis
ion', 'Accuracy']
            row = [(model_name, rw_score, f1_score, recall, precision, accu
racy)]
            res = pd.DataFrame(columns = results_columns, data = row)
            yeep = [model_summary, res]
            model_summary = pd.concat(yeep)
            model_summary = model_summary.sort_values('Accuracy', ascending
= False)
            model_summary = model_summary.drop_duplicates()
            return model_summary.round(3)
```

In [4]:

```
# 1. Confusion Matrix
# SOURCE: The origin of this confusion matrix code was found on medium, '
# from https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30f
ea
def make_confusion_matrix(cf,
                          group_names=None,
                          categories='auto',
                          count=True,
                          percent=True,
                          cbar=True,
                          xyticks=True,
                          xyplotlabels=True,
                          sum_stats=True,
                          figsize=None,
                          cmap='Blues',
                          title=None):
    # CODE TO GENERATE TEXT INSIDE EACH SQUARE
    blanks = ['' for i in range(cf.size)]

    if group_names and len(group_names)==cf.size:
        group_labels = ["{}\n".format(value) for value in group_names]
    else:
        group_labels = blanks

    if count:
        group_counts = ["{0:0.0f}\n".format(value) for value in cf.flatten
()]
    else:
        group_counts = blanks

    if percent:
        group_percentages = ["{0:.2%}".format(value) for value in cf.flatte
n()/np.sum(cf)]
    else:
        group_percentages = blanks

    box_labels = [f"{v1}{v2}{v3}".strip() for v1, v2, v3 in zip(group_label
s,group_counts,group_percentages)]
    box_labels = np.asarray(box_labels).reshape(cf.shape[0],cf.shape[1])


    # CODE TO GENERATE SUMMARY STATISTICS & TEXT FOR SUMMARY STATS
    if sum_stats:
        #Accuracy is sum of diagonal divided by total observations
        accuracy  = np.trace(cf) / float(np.sum(cf))

        #if it is a binary confusion matrix, show some more stats
        if len(cf)==2:
            #Metrics for Binary Confusion Matrices
            recall = cf[1,1] / sum(cf[:,1])
            precision    = cf[1,1] / sum(cf[1,:])
            f1_score  = 2*precision*recall / (precision + recall)
            beta = 9
            rw_score = (1+beta) * ((precision * recall) / ((beta * precisio
n) + recall))
```

```
            stats_text = "\n\nAccuracy={:0.3f}\nPrecision={:0.3f}\nRecall=
{:0.3f}\nF1 Score={:0.3f}\nRW Score={:0.3f}".format(
                accuracy,precision,recall,f1_score, rw_score)
        else:
            stats_text = "\n\nAccuracy={:0.3f}".format(accuracy)
    else:
        stats_text = ""


    # SET FIGURE PARAMETERS ACCORDING TO OTHER ARGUMENTS
    if figsize==None:
        #Get default figure size if not set
        figsize = plt.rcParams.get('figure.figsize')

    if xyticks==False:
        #Do not show categories if xyticks is False
        categories=False


    # MAKE THE HEATMAP VISUALIZATION
    plt.figure(figsize=figsize)
    sns.heatmap(cf,annot=box_labels,fmt="",cmap=cmap,cbar=cbar,xticklabels=
categories,yticklabels=categories)

    if xyplotlabels:
        plt.ylabel('True label')
        plt.xlabel('Predicted label' + stats_text)
    else:
        plt.xlabel(stats_text)

    if title:
        plt.title(title)
```

Re-Splitting (Hide)

Check re-aggregated images

Due to the issues with the given train/test split, i re-aggregated the images. From here, I will train/test split the data myself.

In [5]:
```
'''
folder = 're-split_data/NORMAL'
path = folder
p = os.listdir(path)
pf = pd.DataFrame(p)
norm_tot = len(pf)

folder = 're-split_data/PNEUMONIA'
path = folder
p = os.listdir(path)
pf = pd.DataFrame(p)
pneum_tot = len(pf)
pneum_weight = len(pf) / 5863
norm_weight = 1 - pneum_weight

print(f' There are {len(pf[0])} images in the pneumonia folder')
print(f' there are {1576 + len(pf[0])} total images in the dataset')
print(f' The weight of pneumonia is {round(pneum_weight,2)}')
print(f' The weight of normal is {round(norm_weight,2)}')

'''
```

Out[5]:
```
"\nfolder = 're-split_data/NORMAL'\npath = folder\np = os.listdir(path)\npf
= pd.DataFrame(p)\nnorm_tot = len(pf)\n\nfolder = 're-split_data/PNEUMONIA
'\npath = folder\np = os.listdir(path)\npf = pd.DataFrame(p)\npneum_tot = l
en(pf)\npneum_weight = len(pf) / 5863\nnorm_weight = 1 - pneum_weight\n\npr
int(f' There are {len(pf[0])} images in the pneumonia folder')\nprint(f' th
ere are {1576 + len(pf[0])} total images in the dataset')\nprint(f' The wei
ght of pneumonia is {round(pneum_weight,2)}')\nprint(f' The weight of norma
l is {round(norm_weight,2)}')\n\n"
```

From here, there is some code which I used to re-split the data.

In [6]:
```
# define test and train split percentages
'''
norm_train = norm_tot * .7
norm_test = norm_tot * .3
pneum_train = pneum_tot * .7
pneum_test = pneum_tot * .3
'''

'''
pf = os.listdir('re-split_data/NORMAL')
rand_norm_files = random.sample(pf, int(norm_train))
for file in rand_norm_files:
    shutil.copy('re-split_data/NORMAL/' + file, 're-split_data/train/normal
')
'''
```

Out[6]:
```
"\npf = os.listdir('re-split_data/NORMAL')\nrand_norm_files = random.sample
(pf, int(norm_train))\nfor file in rand_norm_files:\n    shutil.copy('re-sp
lit_data/NORMAL/' + file, 're-split_data/train/normal')\n"
```

In [7]:
```
'''
p1 = os.listdir('re-split_data/train/normal')
p1 = pd.DataFrame(p1)

p2 = os.listdir('re-split_data/NORMAL')
p2 = pd.DataFrame(p2)

tester_files = pd.concat([p1[0],p2[0]]).drop_duplicates(keep=False)
'''
```

Out[7]:
```
"\np1 = os.listdir('re-split_data/train/normal')\np1 = pd.DataFrame(p1)\n\n
p2 = os.listdir('re-split_data/NORMAL')\np2 = pd.DataFrame(p2)\n\ntester_fi
les = pd.concat([p1[0],p2[0]]).drop_duplicates(keep=False)\n"
```

In [8]:
```
#for file in tester_files:
    #shutil.copy('re-split_data/NORMAL/' + file, 're-split_data/test/normal
')
```

In [9]:
```
'''
# The pneumonia files
pf = os.listdir('re-split_data/PNEUMONIA')

rand_Pfiles = random.sample(pf, int(pneum_train))

for file in rand_Pfiles:
    shutil.copy('re-split_data/PNEUMONIA/' + file, 're-split_data/train/pne
umonia')

p3 = os.listdir('re-split_data/train/pneumonia')
p3 = pd.DataFrame(p3)

p4 = os.listdir('re-split_data/PNEUMONIA')
p4 = pd.DataFrame(p4)

tester_p =  pd.concat([p3[0],p4[0]]).drop_duplicates(keep=False)

for file in tester_p:
    shutil.copy('re-split_data/PNEUMONIA/' + file, 're-split_data/test/pneu
monia')
'''
```

Out[9]:
```
"\n# The pneumonia files\npf = os.listdir('re-split_data/PNEUMONIA')\n\nran
d_Pfiles = random.sample(pf, int(pneum_train))\n\nfor file in rand_Pfiles:\
n    shutil.copy('re-split_data/PNEUMONIA/' + file, 're-split_data/train/pn
eumonia')\n\np3 = os.listdir('re-split_data/train/pneumonia')\np3 = pd.Data
Frame(p3)\n\np4 = os.listdir('re-split_data/PNEUMONIA')\np4 = pd.DataFrame
(p4)\n\ntester_p =  pd.concat([p3[0],p4[0]]).drop_duplicates(keep=False)\n\
nfor file in tester_p:\n    shutil.copy('re-split_data/PNEUMONIA/' + file,
're-split_data/test/pneumonia')\n"
```

Validation Files

Make a validation set from the train set

In [10]:
```
'''
pf = os.listdir('re-split_data/train/normal')
norm_tot = len(pf)
pf1 = os.listdir('re-split_data/train/pneumonia')
pneum_tot = len(pf1)

print(f' There are {norm_tot} images in the normal training folder and {pne
um_tot} in the pneumonia training folder')
'''
```

Out[10]:
```
"\npf = os.listdir('re-split_data/train/normal')\nnorm_tot = len(pf)\npf1 =
os.listdir('re-split_data/train/pneumonia')\npneum_tot = len(pf1)\n\nprint
(f' There are {norm_tot} images in the normal training folder and {pneum_to
t} in the pneumonia training folder')\n"
```

In [11]:
```
'''
pf2 = os.listdir('re-split_data/validation/normal')
valid_norm_tot = len(pf2)
pf3 = os.listdir('re-split_data/validation/pneumonia')
valid_pneum_tot = len(pf3)

rand_sample_valid_norm = random.sample(pf2, 110)
rand_sample_valid_pneum = random.sample(pf3, 298)

for file in rand_sample_valid_norm:
    shutil.move('re-split_data/validation/normal/' + file, 're-split_data/t
rain/normal')

for file in rand_sample_valid_pneum:
    shutil.move('re-split_data/validation/pneumonia/' + file, 're-split_dat
a/train/pneumonia')

'''
```

Out[11]:
```
"\npf2 = os.listdir('re-split_data/validation/normal')\nvalid_norm_tot = le
n(pf2)\npf3 = os.listdir('re-split_data/validation/pneumonia')\nvalid_pneum
_tot = len(pf3)\n\nrand_sample_valid_norm = random.sample(pf2, 110)\nrand_s
ample_valid_pneum = random.sample(pf3, 298)\n\nfor file in rand_sample_vali
d_norm:\n    shutil.move('re-split_data/validation/normal/' + file, 're-spl
it_data/train/normal')\n\nfor file in rand_sample_valid_pneum:\n    shutil.
move('re-split_data/validation/pneumonia/' + file, 're-split_data/train/pne
umonia')\n    \n"
```

Generate Test and Train Images

In [12]:
```
# get all the data in the directory split/test , and reshape them
train_generator = ImageDataGenerator(rescale=1./255).flow_from_directory('r
e-split_data/train',
        target_size=(64, 64), batch_size = train_size)

test_generator =ImageDataGenerator(rescale=1./255).flow_from_directory('re-
split_data/test',
        target_size=(64, 64), batch_size = test_size, shuffle= False)

valid_generator =ImageDataGenerator(rescale=1./255).flow_from_directory('re
-split_data/validation',
        target_size=(64, 64), batch_size = validation_size)
```

```
Found 3272 images belonging to 2 classes.
Found 1752 images belonging to 2 classes.
Found 816 images belonging to 2 classes.
```

In [13]:
```
# create the data sets
train_images, train_labels = next(train_generator)
test_images, test_labels = next(test_generator)
valid_images, valid_labels = next(valid_generator)
```

In [185]:
```
train_labels2 = pd.DataFrame(train_labels)
train_labels2
```

Out[185]:

	0	1
0	0.0	1.0
1	0.0	1.0
2	0.0	1.0
3	0.0	1.0
4	0.0	1.0
...	...	...
3267	0.0	1.0
3268	0.0	1.0
3269	0.0	1.0
3270	0.0	1.0
3271	0.0	1.0

3272 rows × 2 columns

In [186]:
```
train_labels2[0].sum()
```

Out[186]:
```
882.0
```

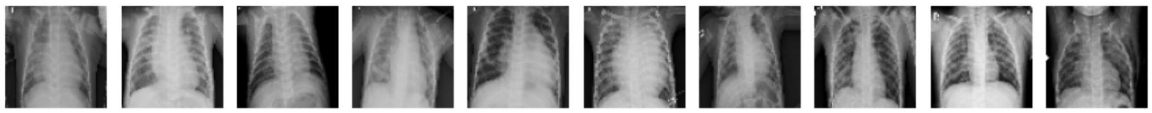
In [187]:
```
train_labels2[1].sum()
```

Out[187]:
```
2390.0
```

This shows us that if column '0' equals 1, it is a NORMAL label.

In [14]:
```
def show_images(images):
    fig, axes = plt.subplots(1, 10, figsize=(12,12))
    axes = axes.flatten()
    for img, ax in zip(images, axes):
        ax.imshow(img)
        ax.axis('off')
    plt.tight_layout()
    plt.show()
```

In [15]:
```
show_images(train_images)
```



In [16]:
```
train_img = train_images.reshape(train_images.shape[0], -1)
test_img = test_images.reshape(test_images.shape[0], -1)
valid_img = valid_images.reshape(valid_images.shape[0], -1)

print(train_img.shape)
print(test_img.shape)
print(valid_img.shape)
```

```
(3272, 12288)
(1752, 12288)
(816, 12288)
```

In [17]:
```
train_y = np.reshape(train_labels[:,0], (train_size,1))
test_y = np.reshape(test_labels[:,0], (test_size,1))
valid_y = np.reshape(valid_labels[:,0], (validation_size,1))

print(train_y.shape)
print(test_y.shape)
print(valid_y.shape)
```

```
(3272, 1)
(1752, 1)
(816, 1)
```

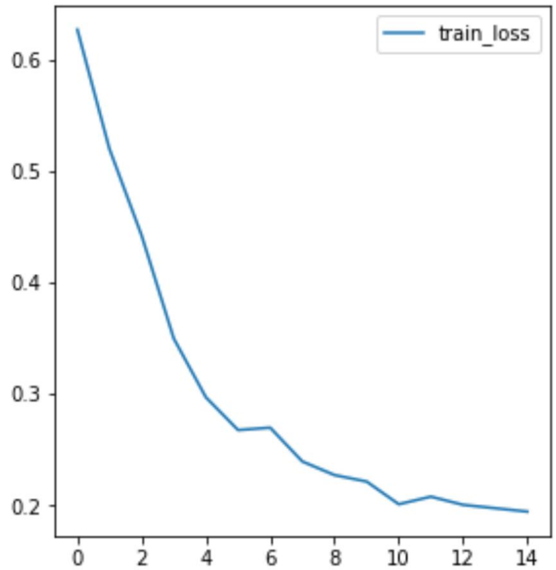
Baseline Model

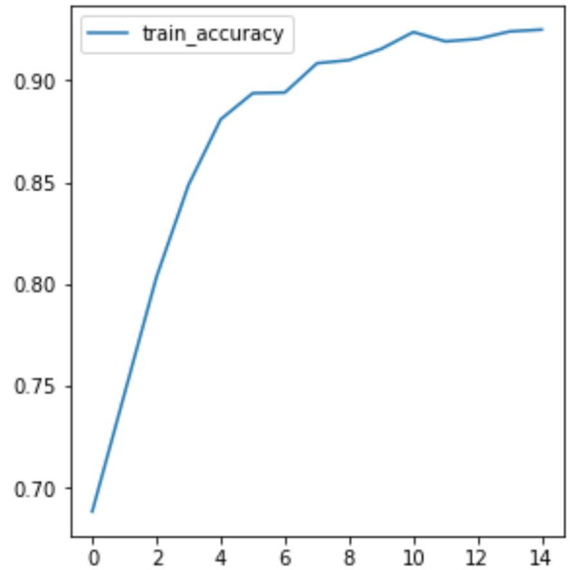
In [18]:
```
# Build a baseline fully connected model
model = models.Sequential()
model.add(layers.Dense(20, activation='relu', input_shape=(12288,))) # 2 hi
dden layers
model.add(layers.Dense(7, activation='relu'))
model.add(layers.Dense(5, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

In [19]:
```
model.compile(optimizer='sgd',
              loss='binary_crossentropy',
              metrics=['accuracy'])

baseline = model.fit(train_img, train_y,epochs=15, batch_size=32)

train_loss = baseline.history['loss']
train_acc = baseline.history['accuracy']

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 5))
sns.lineplot(x=baseline.epoch, y=train_loss, ax=ax1, label='train_loss')
sns.lineplot(x=baseline.epoch, y=train_acc, ax=ax2, label='train_accuracy')
```

```
Epoch 1/15
103/103 [==============================] - 8s 75ms/step - loss: 0.6268 - ac
curacy: 0.6886
Epoch 2/15
103/103 [==============================] - 9s 86ms/step - loss: 0.5197 - ac
curacy: 0.7460
Epoch 3/15
103/103 [==============================] - 8s 80ms/step - loss: 0.4422 - ac
curacy: 0.8035
Epoch 4/15
103/103 [==============================] - 8s 77ms/step - loss: 0.3498 - ac
curacy: 0.8487
Epoch 5/15
103/103 [==============================] - 8s 77ms/step - loss: 0.2971 - ac
curacy: 0.8808
Epoch 6/15
103/103 [==============================] - 8s 78ms/step - loss: 0.2677 - ac
curacy: 0.8936
Epoch 7/15
103/103 [==============================] - 8s 78ms/step - loss: 0.2699 - ac
curacy: 0.8939
Epoch 8/15
103/103 [==============================] - 8s 76ms/step - loss: 0.2395 - ac
curacy: 0.9083
Epoch 9/15
103/103 [==============================] - 8s 79ms/step - loss: 0.2274 - ac
curacy: 0.9098
Epoch 10/15
103/103 [==============================] - 8s 79ms/step - loss: 0.2215 - ac
curacy: 0.9153
Epoch 11/15
103/103 [==============================] - 8s 79ms/step - loss: 0.2012 - ac
curacy: 0.9236
Epoch 12/15
103/103 [==============================] - 8s 82ms/step - loss: 0.2080 - ac
curacy: 0.9190
Epoch 13/15
103/103 [==============================] - 8s 76ms/step - loss: 0.2007 - ac
curacy: 0.9202
Epoch 14/15
103/103 [==============================] - 8s 78ms/step - loss: 0.1976 - ac
curacy: 0.9239
Epoch 15/15
103/103 [==============================] - 8s 80ms/step - loss: 0.1946 - ac
curacy: 0.9248
```

Out[19]:
```
<AxesSubplot:>
```





SkLearn Version for Cross-Validation

In [20]:
```
# Build function that builds the model so we can evaluate in sklearn
def build_model():
    model.add(layers.Dense(20, activation='relu', input_shape=(12288,))) # 
2 hidden layers
    model.add(layers.Dense(7, activation='relu'))
    model.add(layers.Dense(5, activation='relu'))
    model.add(layers.Dense(1, activation='sigmoid'))

    model.compile(optimizer='sgd',
              loss='binary_crossentropy',
              metrics=['accuracy'])

    return model
```

In [21]:
```
keras_model = scikit_learn.KerasClassifier(build_model,
                                          epochs=15,
                                          batch_size=32,
                                          verbose=2)
```

Results

In [22]:
```
results_train = model.evaluate(train_img, train_y)
```

```
103/103 [==============================] - 8s 74ms/step - loss: 0.1566 - ac
curacy: 0.9428
```

In [23]:
```
results_test = model.evaluate(test_img, test_y)
```

```
55/55 [==============================] - 4s 74ms/step - loss: 0.1946 - accu
racy: 0.9229
```

In [24]:
```
predictions = model.predict(x = test_img, verbose=0)
```

In [25]:
```
pred_check = np.round(predictions)
```

In [26]:
```
pred_check = pred_check[:]
pred_check = pred_check.flatten()
pred_check
```

Out[26]:
```
array([0., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

In [27]:
```
test_check = test_labels[:,0]
test_check
```

Out[27]:
```
array([1., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

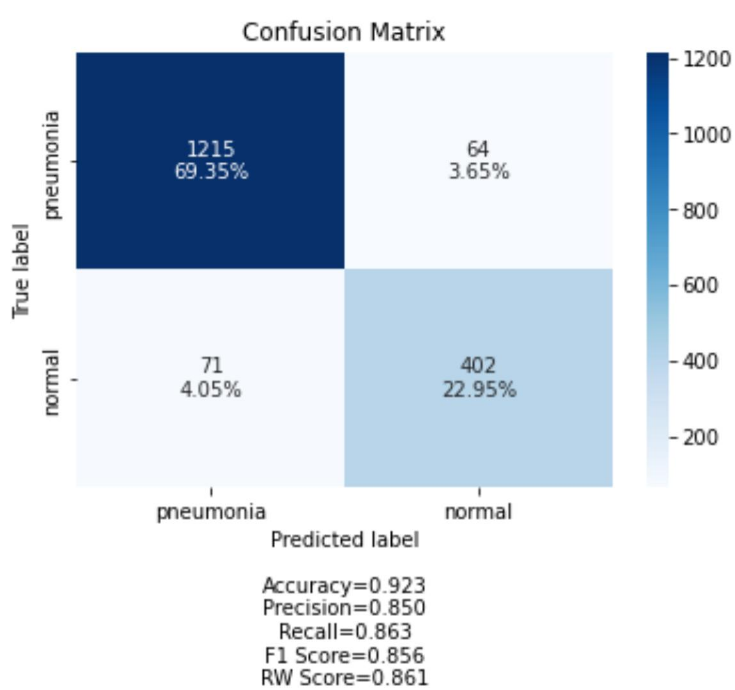
In [28]:
```
cm = confusion_matrix(y_true=test_check, y_pred=pred_check)
```

In [29]:
```
save_result(cm, 'baseline_model')
```

Out[29]:

	Model	RW Score	F1	Recall	Precision	Accuracy
0	baseline_model	0.861	0.856	0.863	0.85	0.923

In [30]:
```
cm_plot_labels = ['pneumonia', 'normal']
make_confusion_matrix(cm, categories = cm_plot_labels, title='Confusion Mat
rix')
```



Convolutional Neural Network (CNN) #1

In [31]:
```
model = models.Sequential()

model.add(layers.Conv2D(32, (3, 3), activation='relu',
                        input_shape=(64 ,64,  3)))
model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Conv2D(32, (4, 4), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

In [32]:
```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d (Conv2D)              (None, 62, 62, 32)        896       

max_pooling2d (MaxPooling2D) (None, 31, 31, 32)        0         

conv2d_1 (Conv2D)            (None, 28, 28, 32)        16416     
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 32)        0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 12, 12, 64)        18496     

max_pooling2d_2 (MaxPooling2 (None, 6, 6, 64)          0         

flatten (Flatten)            (None, 2304)              0         
_________________________________________________________________
dense_4 (Dense)              (None, 64)                147520    
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 65        
=================================================================
Total params: 183,393
Trainable params: 183,393
Non-trainable params: 0
_________________________________________________________________
```

In [33]:
```
model.compile(loss='binary_crossentropy',
              optimizer="sgd",
              metrics=['accuracy'])
```

Train Initial Simple CNN

In [34]:
```
cnn_1 = model.fit(train_images,
                    train_y,
                    epochs=25,
                    validation_data=(valid_images, valid_y),
                    validation_steps = validation_size)
```

```
Epoch 1/25
103/103 [==============================] - 16s 154ms/step - loss: 0.5929 -
accuracy: 0.7304 - val_loss: 0.5820 - val_accuracy: 0.7304
Epoch 2/25
103/103 [==============================] - 16s 153ms/step - loss: 0.5725 -
accuracy: 0.7304 - val_loss: 0.5572 - val_accuracy: 0.7304
Epoch 3/25
103/103 [==============================] - 16s 152ms/step - loss: 0.5404 -
accuracy: 0.7304 - val_loss: 0.4996 - val_accuracy: 0.7304
Epoch 4/25
103/103 [==============================] - 15s 145ms/step - loss: 0.4832 -
accuracy: 0.7781 - val_loss: 0.3968 - val_accuracy: 0.8542
Epoch 5/25
103/103 [==============================] - 15s 149ms/step - loss: 0.4038 -
accuracy: 0.8188 - val_loss: 0.3631 - val_accuracy: 0.8076
Epoch 6/25
103/103 [==============================] - 16s 158ms/step - loss: 0.3394 -
accuracy: 0.8579 - val_loss: 0.4914 - val_accuracy: 0.7647
Epoch 7/25
103/103 [==============================] - 17s 166ms/step - loss: 0.2759 -
accuracy: 0.8854 - val_loss: 0.2383 - val_accuracy: 0.8971
Epoch 8/25
103/103 [==============================] - 16s 155ms/step - loss: 0.2504 -
accuracy: 0.8973 - val_loss: 0.5562 - val_accuracy: 0.7843
Epoch 9/25
103/103 [==============================] - 16s 157ms/step - loss: 0.2413 -
accuracy: 0.8985 - val_loss: 0.2822 - val_accuracy: 0.8664
Epoch 10/25
103/103 [==============================] - 15s 150ms/step - loss: 0.2091 -
accuracy: 0.9181 - val_loss: 0.2163 - val_accuracy: 0.9093
Epoch 11/25
103/103 [==============================] - 16s 156ms/step - loss: 0.2051 -
accuracy: 0.9169 - val_loss: 0.2437 - val_accuracy: 0.8958
Epoch 12/25
103/103 [==============================] - 15s 142ms/step - loss: 0.1978 -
accuracy: 0.9233 - val_loss: 0.3334 - val_accuracy: 0.8468
Epoch 13/25
103/103 [==============================] - 16s 153ms/step - loss: 0.1923 -
accuracy: 0.9224 - val_loss: 0.1677 - val_accuracy: 0.9314
Epoch 14/25
103/103 [==============================] - 15s 148ms/step - loss: 0.1823 -
accuracy: 0.9328 - val_loss: 0.1644 - val_accuracy: 0.9449
Epoch 15/25
103/103 [==============================] - 15s 147ms/step - loss: 0.1831 -
accuracy: 0.9273 - val_loss: 0.1661 - val_accuracy: 0.9326
Epoch 16/25
103/103 [==============================] - 13s 131ms/step - loss: 0.1773 -
accuracy: 0.9318 - val_loss: 0.2322 - val_accuracy: 0.9069
Epoch 17/25
103/103 [==============================] - 16s 156ms/step - loss: 0.1789 -
accuracy: 0.9288 - val_loss: 0.1497 - val_accuracy: 0.9461
Epoch 18/25
103/103 [==============================] - 17s 168ms/step - loss: 0.1710 -
accuracy: 0.9373 - val_loss: 0.1440 - val_accuracy: 0.9461
Epoch 19/25
103/103 [==============================] - 17s 162ms/step - loss: 0.1703 -
```

```
accuracy: 0.9346 - val_loss: 0.4063 - val_accuracy: 0.8554
Epoch 20/25
103/103 [==============================] - 16s 160ms/step - loss: 0.1666 -
accuracy: 0.9383 - val_loss: 0.1440 - val_accuracy: 0.9498
Epoch 21/25
103/103 [==============================] - 16s 158ms/step - loss: 0.1648 -
accuracy: 0.9370 - val_loss: 0.1507 - val_accuracy: 0.9510
Epoch 22/25
103/103 [==============================] - 16s 156ms/step - loss: 0.1582 -
accuracy: 0.9389 - val_loss: 0.1352 - val_accuracy: 0.9571
Epoch 23/25
103/103 [==============================] - 16s 152ms/step - loss: 0.1535 -
accuracy: 0.9419 - val_loss: 0.1313 - val_accuracy: 0.9510
Epoch 24/25
103/103 [==============================] - 16s 156ms/step - loss: 0.1573 -
accuracy: 0.9407 - val_loss: 0.1347 - val_accuracy: 0.9510
Epoch 25/25
103/103 [==============================] - 15s 144ms/step - loss: 0.1509 -
accuracy: 0.9425 - val_loss: 0.1316 - val_accuracy: 0.9608
```

In [35]:
```python
results_train = model.evaluate(train_images, train_y)
```

```
103/103 [==============================] - 4s 40ms/step - loss: 0.1364 - ac
curacy: 0.9474
```

In [36]:
```python
results_test = model.evaluate(test_images, test_y)
```

```
55/55 [==============================] - 2s 35ms/step - loss: 0.1803 - accu
racy: 0.9309
```

Prediction for Confusion Matrix

In [37]:
```python
predictions = model.predict(x = test_images, steps = 10, verbose=0)
```

In [38]:
```python
pred_check = np.round(predictions)
```

In [39]:
```python
pred_check = pred_check[:]
pred_check = pred_check.flatten()
pred_check
```

Out[39]:
```
array([0., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

In [40]:
```python
test_check = test_labels[:,0]
test_check
```

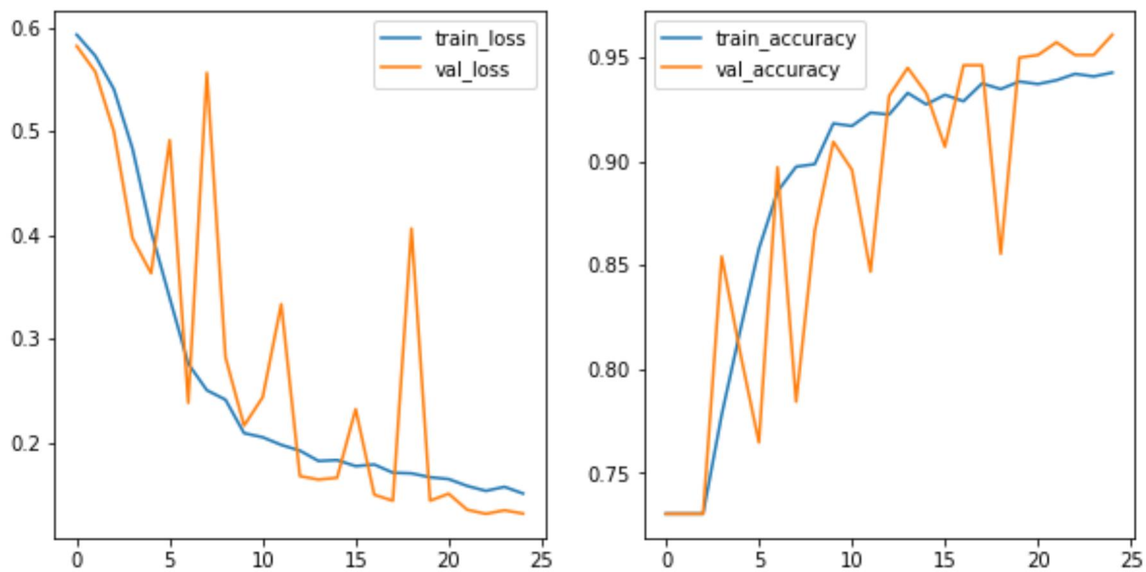
Out[40]:
```
array([1., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

In [41]:
```python
cm = confusion_matrix(y_true=test_check, y_pred=pred_check)
```

CNN #1 Results

In [42]:
```
train_loss = cnn_1.history['loss']
train_acc = cnn_1.history['accuracy']
val_loss = cnn_1.history['val_loss']
val_acc = cnn_1.history['val_accuracy']

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 5))
sns.lineplot(x=cnn_1.epoch, y=train_loss, ax=ax1, label='train_loss')
sns.lineplot(x=cnn_1.epoch, y=train_acc, ax=ax2, label='train_accuracy')
sns.lineplot(x=cnn_1.epoch, y=val_loss, ax=ax1, label='val_loss')
sns.lineplot(x=cnn_1.epoch, y=val_acc, ax=ax2, label='val_accuracy')
```

Out[42]: <AxesSubplot:>



In [43]:
```
def build_cnn():
    model = models.Sequential()
    model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(64
,64,  3)))
    model.add(layers.MaxPooling2D((2, 2)))

    model.add(layers.Conv2D(32, (4, 4), activation='relu'))
    model.add(layers.MaxPooling2D((2, 2)))

    model.add(layers.Conv2D(64, (3, 3), activation='relu'))
    model.add(layers.MaxPooling2D((2, 2)))

    model.add(layers.Flatten())
    model.add(layers.Dense(64, activation='relu'))
    model.add(layers.Dense(1, activation='sigmoid'))        #Last layer mus
t be 1 for binary classification

    model.compile(loss='binary_crossentropy',
              optimizer="sgd",
              metrics=['accuracy'])

    return model
```

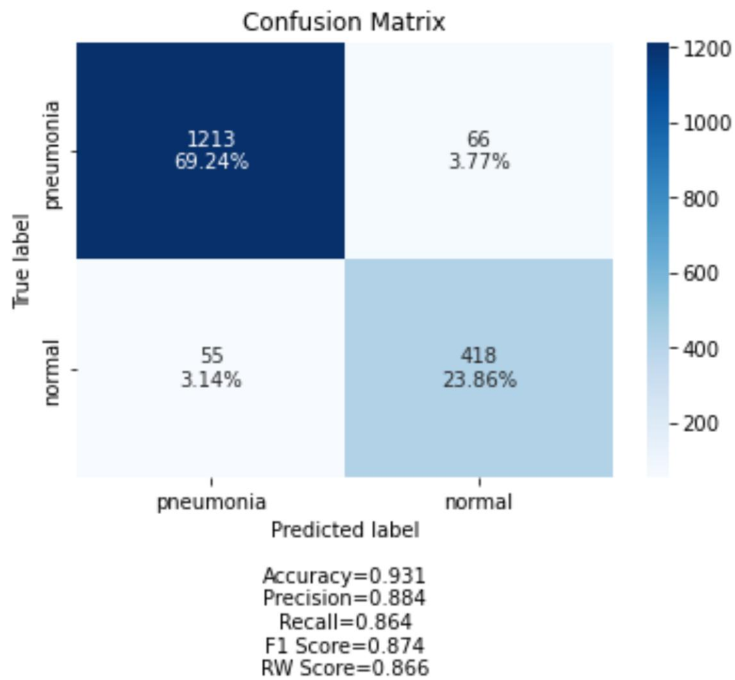
In [44]:
```
keras_model2 = scikit_learn.KerasClassifier(build_cnn,
                                            epochs=25,
                                            validation_data=(valid_images,
valid_y),
                                            validation_steps = validation_s
ize)
```

In [45]:
```
save_result(cm,'CNN #1')
```

Out[45]:

	Model	RW Score	F1	Recall	Precision	Accuracy
0	CNN #1	0.866	0.874	0.864	0.884	0.931
0	baseline_model	0.861	0.856	0.863	0.850	0.923

In [46]:
```
cm_plot_labels = ['pneumonia', 'normal']
make_confusion_matrix(cm, categories = cm_plot_labels, title='Confusion Matrix')
```



CNN Model 2

For this model, I added another round of Conv2D and MaxPooling layers, and changed the optimizer to "adam"

In [47]:

```
model2 = models.Sequential()

model2.add(layers.Conv2D(32, (3, 3), activation='relu',
                        input_shape=(64 ,64,  3)))
model2.add(layers.MaxPooling2D((2, 2)))

model2.add(layers.Conv2D(32, (4, 4), activation='relu'))
model2.add(layers.MaxPooling2D((2, 2)))

model2.add(layers.Conv2D(64, (3, 3), activation='relu'))
model2.add(layers.MaxPooling2D((2, 2)))

model2.add(layers.Conv2D(96, (3, 3), activation='relu'))
model2.add(layers.MaxPooling2D((2, 2)))

model2.add(layers.Flatten())
model2.add(layers.Dense(64, activation='relu'))
model2.add(layers.Dense(1, activation='sigmoid'))

model2.compile(loss='binary_crossentropy',
              optimizer="adam",
              metrics=['accuracy'])
```

In [48]:
```
history2 = model2.fit(train_images,
                     train_y,
                     epochs=50,
                     validation_data=(valid_images, valid_y),
                     validation_steps = validation_size)
```

```
Epoch 1/50
103/103 [==============================] - 14s 128ms/step - loss: 0.5128 -
accuracy: 0.7549 - val_loss: 0.4897 - val_accuracy: 0.7402
Epoch 2/50
103/103 [==============================] - 13s 127ms/step - loss: 0.2891 -
accuracy: 0.8811 - val_loss: 0.1954 - val_accuracy: 0.9167
Epoch 3/50
103/103 [==============================] - 11s 111ms/step - loss: 0.2183 -
accuracy: 0.9141 - val_loss: 0.1449 - val_accuracy: 0.9436
Epoch 4/50
103/103 [==============================] - 11s 112ms/step - loss: 0.1590 -
accuracy: 0.9377 - val_loss: 0.1154 - val_accuracy: 0.9596
Epoch 5/50
103/103 [==============================] - 13s 127ms/step - loss: 0.1350 -
accuracy: 0.9542 - val_loss: 0.1255 - val_accuracy: 0.9632
Epoch 6/50
103/103 [==============================] - 13s 127ms/step - loss: 0.1303 -
accuracy: 0.9514 - val_loss: 0.1058 - val_accuracy: 0.9620
Epoch 7/50
103/103 [==============================] - 13s 128ms/step - loss: 0.1109 -
accuracy: 0.9603 - val_loss: 0.0941 - val_accuracy: 0.9657
Epoch 8/50
103/103 [==============================] - 13s 123ms/step - loss: 0.0982 -
accuracy: 0.9633 - val_loss: 0.0930 - val_accuracy: 0.9669
Epoch 9/50
103/103 [==============================] - 13s 126ms/step - loss: 0.0900 -
accuracy: 0.9649 - val_loss: 0.1270 - val_accuracy: 0.9559
Epoch 10/50
103/103 [==============================] - 12s 118ms/step - loss: 0.0804 -
accuracy: 0.9710 - val_loss: 0.1081 - val_accuracy: 0.9694
Epoch 11/50
103/103 [==============================] - 13s 127ms/step - loss: 0.0830 -
accuracy: 0.9676 - val_loss: 0.1210 - val_accuracy: 0.9596
Epoch 12/50
103/103 [==============================] - 13s 125ms/step - loss: 0.0628 -
accuracy: 0.9759 - val_loss: 0.1048 - val_accuracy: 0.9608
Epoch 13/50
103/103 [==============================] - 12s 116ms/step - loss: 0.0595 -
accuracy: 0.9780 - val_loss: 0.0923 - val_accuracy: 0.9706
Epoch 14/50
103/103 [==============================] - 12s 120ms/step - loss: 0.0524 -
accuracy: 0.9780 - val_loss: 0.0915 - val_accuracy: 0.9706
Epoch 15/50
103/103 [==============================] - 13s 126ms/step - loss: 0.0428 -
accuracy: 0.9850 - val_loss: 0.1108 - val_accuracy: 0.9669
Epoch 16/50
103/103 [==============================] - 12s 120ms/step - loss: 0.0328 -
accuracy: 0.9887 - val_loss: 0.1095 - val_accuracy: 0.9620
Epoch 17/50
103/103 [==============================] - 13s 127ms/step - loss: 0.0237 -
accuracy: 0.9948 - val_loss: 0.1209 - val_accuracy: 0.9681
Epoch 18/50
103/103 [==============================] - 12s 121ms/step - loss: 0.0216 -
accuracy: 0.9924 - val_loss: 0.1031 - val_accuracy: 0.9694
Epoch 19/50
103/103 [==============================] - 13s 130ms/step - loss: 0.0180 -
```

```
accuracy: 0.9951 - val_loss: 0.1614 - val_accuracy: 0.9645
Epoch 20/50
103/103 [==============================] - 13s 131ms/step - loss: 0.0218 -
accuracy: 0.9930 - val_loss: 0.1682 - val_accuracy: 0.9547
Epoch 21/50
103/103 [==============================] - 13s 121ms/step - loss: 0.0177 -
accuracy: 0.9948 - val_loss: 0.1314 - val_accuracy: 0.9706
Epoch 22/50
103/103 [==============================] - 13s 124ms/step - loss: 0.0095 -
accuracy: 0.9969 - val_loss: 0.1246 - val_accuracy: 0.9632
Epoch 23/50
103/103 [==============================] - 13s 128ms/step - loss: 0.0040 -
accuracy: 0.9997 - val_loss: 0.1466 - val_accuracy: 0.9645
Epoch 24/50
103/103 [==============================] - 13s 124ms/step - loss: 0.0015 -
accuracy: 1.0000 - val_loss: 0.1398 - val_accuracy: 0.9694
Epoch 25/50
103/103 [==============================] - 12s 120ms/step - loss: 8.9061e-0
4 - accuracy: 1.0000 - val_loss: 0.1498 - val_accuracy: 0.9681
Epoch 26/50
103/103 [==============================] - 13s 125ms/step - loss: 4.8710e-0
4 - accuracy: 1.0000 - val_loss: 0.1469 - val_accuracy: 0.9681
Epoch 27/50
103/103 [==============================] - 12s 120ms/step - loss: 3.5925e-0
4 - accuracy: 1.0000 - val_loss: 0.1533 - val_accuracy: 0.9706
Epoch 28/50
103/103 [==============================] - 13s 130ms/step - loss: 2.8403e-0
4 - accuracy: 1.0000 - val_loss: 0.1576 - val_accuracy: 0.9681
Epoch 29/50
103/103 [==============================] - 13s 123ms/step - loss: 2.3593e-0
4 - accuracy: 1.0000 - val_loss: 0.1601 - val_accuracy: 0.9694
Epoch 30/50
103/103 [==============================] - 13s 125ms/step - loss: 2.1481e-0
4 - accuracy: 1.0000 - val_loss: 0.1632 - val_accuracy: 0.9657
Epoch 31/50
103/103 [==============================] - 13s 127ms/step - loss: 1.8072e-0
4 - accuracy: 1.0000 - val_loss: 0.1642 - val_accuracy: 0.9706
Epoch 32/50
103/103 [==============================] - 12s 121ms/step - loss: 1.6162e-0
4 - accuracy: 1.0000 - val_loss: 0.1667 - val_accuracy: 0.9694
Epoch 33/50
103/103 [==============================] - 13s 128ms/step - loss: 1.4522e-0
4 - accuracy: 1.0000 - val_loss: 0.1682 - val_accuracy: 0.9706
Epoch 34/50
103/103 [==============================] - 13s 124ms/step - loss: 1.2853e-0
4 - accuracy: 1.0000 - val_loss: 0.1708 - val_accuracy: 0.9706
Epoch 35/50
103/103 [==============================] - 13s 126ms/step - loss: 1.1495e-0
4 - accuracy: 1.0000 - val_loss: 0.1711 - val_accuracy: 0.9718
Epoch 36/50
103/103 [==============================] - 13s 129ms/step - loss: 1.0194e-0
4 - accuracy: 1.0000 - val_loss: 0.1735 - val_accuracy: 0.9718
Epoch 37/50
103/103 [==============================] - 13s 122ms/step - loss: 9.1947e-0
5 - accuracy: 1.0000 - val_loss: 0.1751 - val_accuracy: 0.9730
Epoch 38/50
```

```
103/103 [==============================] - 13s 124ms/step - loss: 8.5983e-0
5 - accuracy: 1.0000 - val_loss: 0.1767 - val_accuracy: 0.9706
Epoch 39/50
103/103 [==============================] - 13s 126ms/step - loss: 7.7741e-0
5 - accuracy: 1.0000 - val_loss: 0.1787 - val_accuracy: 0.9706
Epoch 40/50
103/103 [==============================] - 13s 124ms/step - loss: 6.9789e-0
5 - accuracy: 1.0000 - val_loss: 0.1803 - val_accuracy: 0.9706
Epoch 41/50
103/103 [==============================] - 12s 118ms/step - loss: 6.4773e-0
5 - accuracy: 1.0000 - val_loss: 0.1813 - val_accuracy: 0.9718
Epoch 42/50
103/103 [==============================] - 13s 125ms/step - loss: 6.0882e-0
5 - accuracy: 1.0000 - val_loss: 0.1824 - val_accuracy: 0.9718
Epoch 43/50
103/103 [==============================] - 12s 117ms/step - loss: 5.4448e-0
5 - accuracy: 1.0000 - val_loss: 0.1838 - val_accuracy: 0.9730
Epoch 44/50
103/103 [==============================] - 12s 120ms/step - loss: 5.1299e-0
5 - accuracy: 1.0000 - val_loss: 0.1859 - val_accuracy: 0.9718
Epoch 45/50
103/103 [==============================] - 12s 120ms/step - loss: 4.7310e-0
5 - accuracy: 1.0000 - val_loss: 0.1869 - val_accuracy: 0.9730
Epoch 46/50
103/103 [==============================] - 12s 117ms/step - loss: 4.2243e-0
5 - accuracy: 1.0000 - val_loss: 0.1897 - val_accuracy: 0.9706
Epoch 47/50
103/103 [==============================] - 13s 127ms/step - loss: 3.8696e-0
5 - accuracy: 1.0000 - val_loss: 0.1904 - val_accuracy: 0.9706
Epoch 48/50
103/103 [==============================] - 13s 121ms/step - loss: 3.6505e-0
5 - accuracy: 1.0000 - val_loss: 0.1923 - val_accuracy: 0.9730
Epoch 49/50
103/103 [==============================] - 12s 119ms/step - loss: 3.2550e-0
5 - accuracy: 1.0000 - val_loss: 0.1926 - val_accuracy: 0.9730
Epoch 50/50
103/103 [==============================] - 12s 119ms/step - loss: 3.0552e-0
5 - accuracy: 1.0000 - val_loss: 0.1947 - val_accuracy: 0.9706
```

In [49]:
```
results_train = model2.evaluate(train_images, train_y)
```

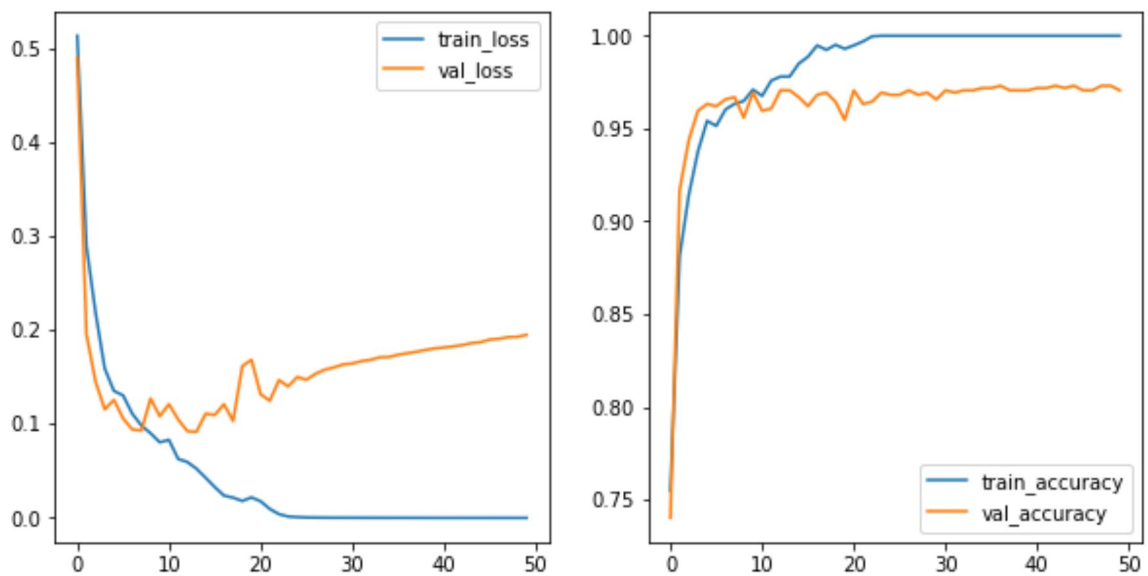
```
103/103 [==============================] - 1s 10ms/step - loss: 2.7606e-05
- accuracy: 1.0000
```

In [50]:
```
results_test = model2.evaluate(test_images, test_y)
```

```
55/55 [==============================] - 1s 10ms/step - loss: 0.3585 - accu
racy: 0.9515
```

In [51]:
```
train_loss = history2.history['loss']
train_acc = history2.history['accuracy']
val_loss = history2.history['val_loss']
val_acc = history2.history['val_accuracy']

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 5))
sns.lineplot(x=history2.epoch, y=train_loss, ax=ax1, label='train_loss')
sns.lineplot(x=history2.epoch, y=train_acc, ax=ax2, label='train_accuracy')
sns.lineplot(x=history2.epoch, y=val_loss, ax=ax1, label='val_loss')
sns.lineplot(x=history2.epoch, y=val_acc, ax=ax2, label='val_accuracy')
```

Out[51]: <AxesSubplot:>



In [52]:
```
def build_cnn2():
    model2 = models.Sequential()
    model2.add(layers.Conv2D(32, (3, 3), activation='relu',
                            input_shape=(64 ,64,  3)))
    model2.add(layers.MaxPooling2D((2, 2)))

    model2.add(layers.Conv2D(32, (4, 4), activation='relu'))
    model2.add(layers.MaxPooling2D((2, 2)))

    model2.add(layers.Conv2D(64, (3, 3), activation='relu'))
    model2.add(layers.MaxPooling2D((2, 2)))

    model2.add(layers.Conv2D(96, (3, 3), activation='relu'))
    model2.add(layers.MaxPooling2D((2, 2)))

    model2.add(layers.Flatten())
    model2.add(layers.Dense(64, activation='relu'))
    model2.add(layers.Dense(1, activation='sigmoid'))

    model2.compile(loss='binary_crossentropy',
              optimizer="Adam",
              metrics=['accuracy'])

    return model2
```

In [53]:
```
keras_model3 = scikit_learn.KerasClassifier(build_cnn2,
                                            epochs=50,
                                            validation_data=(valid_images,
valid_y),
                                            validation_steps = validation_s
ize)
```

Prediction for Confusion Matrix

In [54]:
```
predictions = model2.predict(x = test_images, steps = 10, verbose=0)
```

In [55]:
```
pred_check = np.round(predictions)
```

In [56]:
```
pred_check = pred_check[:]
pred_check = pred_check.flatten()
pred_check
```

Out[56]:
```
array([1., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

In [57]:
```
test_check = test_labels[:,0]
test_check
```

Out[57]:
```
array([1., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

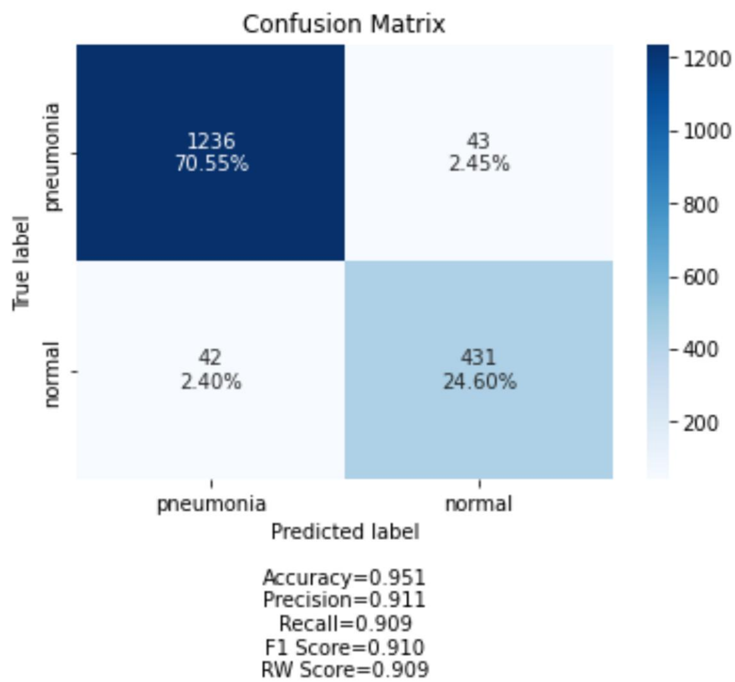
In [58]:
```
cm = confusion_matrix(y_true=test_check, y_pred=pred_check)
```

In [59]:
```
save_result(cm, 'CNN #2', )
```

Out[59]:

	Model	RW Score	F1	Recall	Precision	Accuracy
0	CNN #2	0.909	0.910	0.909	0.911	0.951
0	CNN #1	0.866	0.874	0.864	0.884	0.931
0	baseline_model	0.861	0.856	0.863	0.850	0.923

In [60]:
```
cm_plot_labels = ['pneumonia', 'normal']
make_confusion_matrix(cm, categories = cm_plot_labels, title='Confusion Mat
rix')
```



CNN Model 3

For this model, I add two layers of batch normalization and a 10% dropout. Also added one more layer of Conv2D and MaxPooling.

In [61]:
```
model3 = models.Sequential()

model3.add(layers.Conv2D(32, (3, 3), activation='relu',input_shape=(64 ,64,
3)))
model3.add(layers.MaxPooling2D((2, 2)))

model3.add(layers.Conv2D(32, (4, 4), activation='relu'))
model3.add(BatchNormalization())
model3.add(layers.MaxPooling2D((2, 2)))

model3.add(layers.Conv2D(64, (3, 3), activation='relu'))
model3.add(layers.MaxPooling2D((2, 2)))

model3.add(layers.Conv2D(128, (3, 3), activation='relu'))
model3.add(BatchNormalization())
model3.add(layers.MaxPooling2D((2, 2)))



model3.add(layers.Flatten())
model3.add(layers.Dense(64, activation='relu'))
model3.add(Dropout(0.1))
model3.add(layers.Dense(1, activation='sigmoid'))

model3.compile(loss='binary_crossentropy',
              optimizer="adam",
              metrics=['accuracy'])
```

In [62]:
```
model3.summary()
```

```
Model: "sequential_3"

Layer (type)                Output Shape              Param #
=================================================================
conv2d_7 (Conv2D)           (None, 62, 62, 32)        896

_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 31, 31, 32)       0

_________________________________________________________________
conv2d_8 (Conv2D)           (None, 28, 28, 32)        16416

batch_normalization (BatchNo (None, 28, 28, 32)       128

max_pooling2d_8 (MaxPooling2 (None, 14, 14, 32)       0

_________________________________________________________________
conv2d_9 (Conv2D)           (None, 12, 12, 64)        18496

_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 6, 6, 64)         0

conv2d_10 (Conv2D)          (None, 4, 4, 128)         73856

batch_normalization_1 (Batch (None, 4, 4, 128)        512

_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 2, 2, 128)        0

_________________________________________________________________
flatten_2 (Flatten)         (None, 512)               0

dense_8 (Dense)             (None, 64)                32832

dropout (Dropout)           (None, 64)                0

_________________________________________________________________
dense_9 (Dense)             (None, 1)                 65
=================================================================
Total params: 143,201
Trainable params: 142,881
Non-trainable params: 320
```

In [63]:
```
print(f'trainsize {train_size}, validation size {validation_size}')
```

```
trainsize 3272, validation size 816
```

In [64]:
```
history3 = model3.fit(train_images,  #Make sure that your dataset can generate at least `steps_per_epoch * epochs` batches
                    train_y,  #Integer or None. Number of samples per gradient update. default to 32. Do not specify the batch_size if your data is in the form of datasets, generators, or keras.utils.Sequence instances (since they generate batches).
                    #steps_per_epoch = 100,  #The steps per epoch determines how many steps are done before the model is updated.
                    epochs=50,                       # Integer. Number of epochs to train the model. An epoch is an iteration over the entire x and y data provided (unless the steps_per_epoch flag is set to something other than None). Note that in conjunction with initial_epoch, epochs is to be understood as "final epoch". The model is not trained for a number of iterations given by epochs, but merely until the epoch of index epochs is reached.
                    validation_data=(valid_images, valid_y),
                    validation_steps = validation_size)
```

```
Epoch 1/50
103/103 [==============================] - 15s 141ms/step - loss: 0.2536 -
accuracy: 0.9028 - val_loss: 0.5468 - val_accuracy: 0.7243
Epoch 2/50
103/103 [==============================] - 14s 136ms/step - loss: 0.1478 -
accuracy: 0.9450 - val_loss: 1.0107 - val_accuracy: 0.3039
Epoch 3/50
103/103 [==============================] - 15s 147ms/step - loss: 0.1218 -
accuracy: 0.9578 - val_loss: 0.6858 - val_accuracy: 0.6054
Epoch 4/50
103/103 [==============================] - 15s 144ms/step - loss: 0.1183 -
accuracy: 0.9575 - val_loss: 0.7674 - val_accuracy: 0.4657
Epoch 5/50
103/103 [==============================] - 14s 140ms/step - loss: 0.1005 -
accuracy: 0.9639 - val_loss: 0.2213 - val_accuracy: 0.9142
Epoch 6/50
103/103 [==============================] - 14s 140ms/step - loss: 0.0940 -
accuracy: 0.9667 - val_loss: 4.6814 - val_accuracy: 0.7304
Epoch 7/50
103/103 [==============================] - 15s 145ms/step - loss: 0.0842 -
accuracy: 0.9688 - val_loss: 1.0449 - val_accuracy: 0.5012
Epoch 8/50
103/103 [==============================] - 15s 143ms/step - loss: 0.0659 -
accuracy: 0.9765 - val_loss: 0.1416 - val_accuracy: 0.9498
Epoch 9/50
103/103 [==============================] - 14s 139ms/step - loss: 0.0521 -
accuracy: 0.9832 - val_loss: 0.3669 - val_accuracy: 0.8971
Epoch 10/50
103/103 [==============================] - 14s 132ms/step - loss: 0.0434 -
accuracy: 0.9853 - val_loss: 0.2769 - val_accuracy: 0.8934
Epoch 11/50
103/103 [==============================] - 15s 141ms/step - loss: 0.0301 -
accuracy: 0.9884 - val_loss: 0.2698 - val_accuracy: 0.9179
Epoch 12/50
103/103 [==============================] - 15s 142ms/step - loss: 0.0366 -
accuracy: 0.9875 - val_loss: 0.5107 - val_accuracy: 0.8064
Epoch 13/50
103/103 [==============================] - 13s 131ms/step - loss: 0.0436 -
accuracy: 0.9841 - val_loss: 0.3394 - val_accuracy: 0.9044
Epoch 14/50
103/103 [==============================] - 14s 135ms/step - loss: 0.0266 -
accuracy: 0.9917 - val_loss: 0.1878 - val_accuracy: 0.9583
Epoch 15/50
103/103 [==============================] - 13s 130ms/step - loss: 0.0174 -
accuracy: 0.9939 - val_loss: 0.1614 - val_accuracy: 0.9596
Epoch 16/50
103/103 [==============================] - 14s 135ms/step - loss: 0.0151 -
accuracy: 0.9942 - val_loss: 0.6765 - val_accuracy: 0.8529
Epoch 17/50
103/103 [==============================] - 14s 134ms/step - loss: 0.0049 -
accuracy: 0.9988 - val_loss: 0.4380 - val_accuracy: 0.9375
Epoch 18/50
103/103 [==============================] - 13s 125ms/step - loss: 0.0026 -
accuracy: 0.9991 - val_loss: 0.2337 - val_accuracy: 0.9436
Epoch 19/50
103/103 [==============================] - 14s 135ms/step - loss: 4.0530e-0
```

```
4 - accuracy: 1.0000 - val_loss: 0.2085 - val_accuracy: 0.9596
Epoch 20/50
103/103 [==============================] - 13s 130ms/step - loss: 2.4430e-0
4 - accuracy: 1.0000 - val_loss: 0.2149 - val_accuracy: 0.9620
Epoch 21/50
103/103 [==============================] - 15s 141ms/step - loss: 2.3692e-0
4 - accuracy: 1.0000 - val_loss: 0.2286 - val_accuracy: 0.9596
Epoch 22/50
103/103 [==============================] - 14s 141ms/step - loss: 1.5958e-0
4 - accuracy: 1.0000 - val_loss: 0.2406 - val_accuracy: 0.9596
Epoch 23/50
103/103 [==============================] - 15s 147ms/step - loss: 1.1811e-0
4 - accuracy: 1.0000 - val_loss: 0.2444 - val_accuracy: 0.9620
Epoch 24/50
103/103 [==============================] - 15s 145ms/step - loss: 1.3527e-0
4 - accuracy: 1.0000 - val_loss: 0.2453 - val_accuracy: 0.9645
Epoch 25/50
103/103 [==============================] - 14s 138ms/step - loss: 1.9100e-0
4 - accuracy: 1.0000 - val_loss: 0.2621 - val_accuracy: 0.9596
Epoch 26/50
103/103 [==============================] - 15s 142ms/step - loss: 1.3688e-0
4 - accuracy: 1.0000 - val_loss: 0.2512 - val_accuracy: 0.9632
Epoch 27/50
103/103 [==============================] - 14s 132ms/step - loss: 7.1218e-0
5 - accuracy: 1.0000 - val_loss: 0.2486 - val_accuracy: 0.9669
Epoch 28/50
103/103 [==============================] - 15s 141ms/step - loss: 5.1461e-0
5 - accuracy: 1.0000 - val_loss: 0.2525 - val_accuracy: 0.9620
Epoch 29/50
103/103 [==============================] - 15s 142ms/step - loss: 3.2336e-0
5 - accuracy: 1.0000 - val_loss: 0.2549 - val_accuracy: 0.9657
Epoch 30/50
103/103 [==============================] - 14s 132ms/step - loss: 4.9241e-0
5 - accuracy: 1.0000 - val_loss: 0.2531 - val_accuracy: 0.9645
Epoch 31/50
103/103 [==============================] - 15s 143ms/step - loss: 3.5341e-0
5 - accuracy: 1.0000 - val_loss: 0.2625 - val_accuracy: 0.9657
Epoch 32/50
103/103 [==============================] - 14s 136ms/step - loss: 2.4727e-0
5 - accuracy: 1.0000 - val_loss: 0.2690 - val_accuracy: 0.9645
Epoch 33/50
103/103 [==============================] - 14s 139ms/step - loss: 7.7267e-0
5 - accuracy: 1.0000 - val_loss: 0.2643 - val_accuracy: 0.9632
Epoch 34/50
103/103 [==============================] - 15s 141ms/step - loss: 3.2048e-0
5 - accuracy: 1.0000 - val_loss: 0.2674 - val_accuracy: 0.9657
Epoch 35/50
103/103 [==============================] - 14s 132ms/step - loss: 2.9231e-0
5 - accuracy: 1.0000 - val_loss: 0.2649 - val_accuracy: 0.9657
Epoch 36/50
103/103 [==============================] - 14s 139ms/step - loss: 1.5808e-0
5 - accuracy: 1.0000 - val_loss: 0.2709 - val_accuracy: 0.9632
Epoch 37/50
103/103 [==============================] - 15s 142ms/step - loss: 1.7154e-0
5 - accuracy: 1.0000 - val_loss: 0.2751 - val_accuracy: 0.9645
Epoch 38/50
```

```
103/103 [==============================] - 14s 140ms/step - loss: 4.2814e-0
5 - accuracy: 1.0000 - val_loss: 0.2856 - val_accuracy: 0.9632
Epoch 39/50
103/103 [==============================] - 15s 143ms/step - loss: 1.5362e-0
5 - accuracy: 1.0000 - val_loss: 0.2826 - val_accuracy: 0.9632
Epoch 40/50
103/103 [==============================] - 17s 168ms/step - loss: 1.2962e-0
5 - accuracy: 1.0000 - val_loss: 0.2853 - val_accuracy: 0.9645
Epoch 41/50
103/103 [==============================] - 17s 165ms/step - loss: 1.5056e-0
5 - accuracy: 1.0000 - val_loss: 0.2838 - val_accuracy: 0.9632
Epoch 42/50
103/103 [==============================] - 17s 162ms/step - loss: 1.6323e-0
5 - accuracy: 1.0000 - val_loss: 0.2876 - val_accuracy: 0.9645
Epoch 43/50
103/103 [==============================] - 16s 160ms/step - loss: 1.5799e-0
5 - accuracy: 1.0000 - val_loss: 0.2908 - val_accuracy: 0.9620
Epoch 44/50
103/103 [==============================] - 17s 167ms/step - loss: 1.0369e-0
5 - accuracy: 1.0000 - val_loss: 0.2947 - val_accuracy: 0.9632
Epoch 45/50
103/103 [==============================] - 17s 166ms/step - loss: 1.9991e-0
5 - accuracy: 1.0000 - val_loss: 0.2951 - val_accuracy: 0.9645
Epoch 46/50
103/103 [==============================] - 16s 157ms/step - loss: 1.0660e-0
5 - accuracy: 1.0000 - val_loss: 0.3021 - val_accuracy: 0.9620
Epoch 47/50
103/103 [==============================] - 17s 165ms/step - loss: 6.8248e-0
6 - accuracy: 1.0000 - val_loss: 0.2995 - val_accuracy: 0.9632
Epoch 48/50
103/103 [==============================] - 17s 162ms/step - loss: 1.3242e-0
5 - accuracy: 1.0000 - val_loss: 0.3077 - val_accuracy: 0.9620
Epoch 49/50
103/103 [==============================] - 16s 155ms/step - loss: 6.2434e-0
6 - accuracy: 1.0000 - val_loss: 0.3027 - val_accuracy: 0.9632
Epoch 50/50
103/103 [==============================] - 17s 165ms/step - loss: 7.8112e-0
6 - accuracy: 1.0000 - val_loss: 0.3017 - val_accuracy: 0.9632
```

In [65]:
```
results_train = model3.evaluate(train_images, train_y)
```

```
103/103 [==============================] - 1s 13ms/step - loss: 1.2746e-06
- accuracy: 1.0000
```

In [66]:
```
results_test = model3.evaluate(test_images, test_y)
```

```
55/55 [==============================] - 1s 13ms/step - loss: 0.4020 - accu
racy: 0.9475
```

In [67]:
```
results_train
```

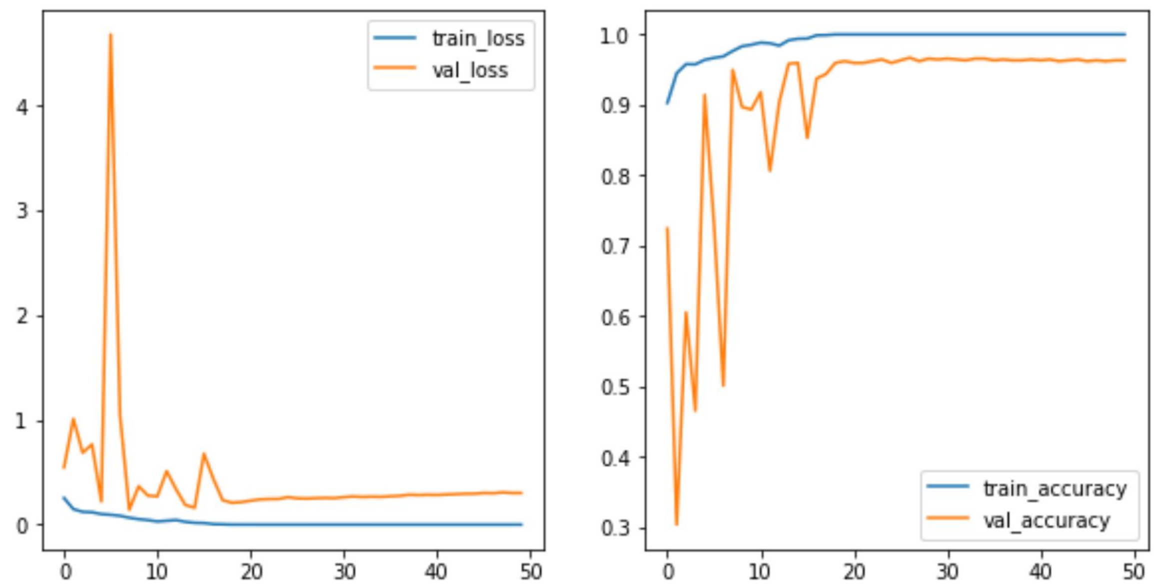
Out[67]:
```
[1.2745512094625155e-06, 1.0]
```

In [68]:
```
results_test
```

Out[68]: [0.4019615948200226, 0.9474886059761047]

In [69]:
```
train_loss = history3.history['loss']
train_acc = history3.history['accuracy']
val_loss = history3.history['val_loss']
val_acc = history3.history['val_accuracy']

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 5))
sns.lineplot(x=history3.epoch, y=train_loss, ax=ax1, label='train_loss')
sns.lineplot(x=history3.epoch, y=train_acc, ax=ax2, label='train_accuracy')
sns.lineplot(x=history3.epoch, y=val_loss, ax=ax1, label='val_loss')
sns.lineplot(x=history3.epoch, y=val_acc, ax=ax2, label='val_accuracy')
```

Out[69]: <AxesSubplot:>



In [70]:
```
#model3.save('models/model_3.h5')
```

In [71]:
```
def build_cnn3():
    model3 = models.Sequential()

    model3.add(layers.Conv2D(32, (3, 3), activation='relu',input_shape=(64
,64,  3)))
    model3.add(layers.MaxPooling2D((2, 2)))

    model3.add(layers.Conv2D(32, (4, 4), activation='relu'))
    model3.add(BatchNormalization())
    model3.add(layers.MaxPooling2D((2, 2)))

    model3.add(layers.Conv2D(64, (3, 3), activation='relu'))
    model3.add(layers.MaxPooling2D((2, 2)))

    model3.add(layers.Conv2D(128, (3, 3), activation='relu'))
    model3.add(BatchNormalization())
    model3.add(layers.MaxPooling2D((2, 2)))


    model3.add(layers.Flatten())
    model3.add(layers.Dense(64, activation='relu'))
    model3.add(Dropout(0.1))
    model3.add(layers.Dense(1, activation='sigmoid'))

    model3.compile(loss='binary_crossentropy',
              optimizer="adam",
              metrics=['accuracy'])

    return model3
```

In [72]:
```
keras_model4 = scikit_learn.KerasClassifier(build_cnn3,
                                            epochs=50,
# Integer. Number of epochs to train the model. An epoch is an iteration ov
er the entire x and y data provided (unless the steps_per_epoch flag is set
to something other than None). Note that in conjunction with initial_epoch,
epochs is to be understood as "final epoch". The model is not trained for a
number of iterations given by epochs, but merely until the epoch of index e
pochs is reached.
                    validation_data=(valid_images, valid_y),
                    validation_steps = validation_size)
```

Prediction for Confusion Matrix

In [73]:
```
predictions = model3.predict(x = test_images, steps = 10, verbose=0)
```

In [74]:
```
pred_check = np.round(predictions)
```

In [75]:
```
pred_check = pred_check[:]
pred_check = pred_check.flatten()
pred_check
```

Out[75]:
```
array([1., 1., 1., ..., 0., 1., 0.], dtype=float32)
```

In [76]:
```
test_check = test_labels[:,0]
test_check
```

Out[76]:
```
array([1., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

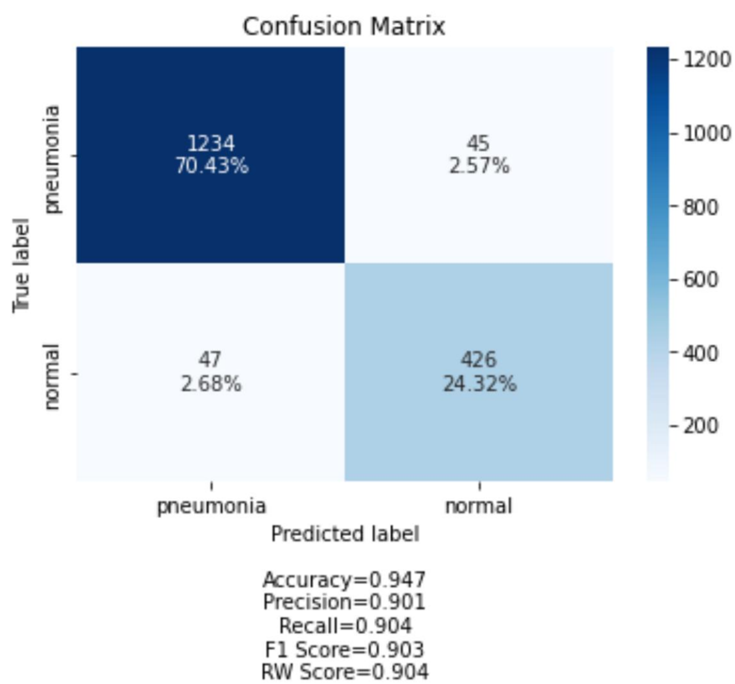
In [77]:
```
cm = confusion_matrix(y_true=test_check, y_pred=pred_check)
```

In [78]:
```
save_result(cm, 'CNN #3')
```

Out[78]:

	Model	RW Score	F1	Recall	Precision	Accuracy
0	CNN #2	0.909	0.910	0.909	0.911	0.951
0	CNN #3	0.904	0.903	0.904	0.901	0.947
0	CNN #1	0.866	0.874	0.864	0.884	0.931
0	baseline_model	0.861	0.856	0.863	0.850	0.923

In [79]:
```
cm_plot_labels = ['pneumonia', 'normal']
make_confusion_matrix(cm, categories = cm_plot_labels, title='Confusion Mat
rix')
```



CNN Model 4

For this model, I will add weights

In [80]:
```
neg = len(os.listdir('re-split_data/train/normal'))
pos = len(os.listdir('re-split_data/train/pneumonia'))
total = neg + pos
```

In [81]:
```
# Scaling by total/2 helps keep the loss to a similar magnitude.
# The sum of the weights of all examples stays the same.
weight_for_0 = (1 / neg) * (total / 2.0)
weight_for_1 = (1 / pos) * (total / 2.0)

class_weight = {0: weight_for_0, 1: weight_for_1} #

print('Weight for class 0: {:.2f}'.format(weight_for_0))
print('Weight for class 1: {:.2f}'.format(weight_for_1))

#Weight for class 0: 0.50 --- This is from https://www.tensorflow.org/tutor
ials/structured_data/imbalanced_data
#Weight for class 1: 289.44
```

```
Weight for class 0: 1.85
Weight for class 1: 0.68
```

In [82]:
```
model4 = models.Sequential()

model4.add(layers.Conv2D(32, (3, 3), activation='relu',input_shape=(64 ,64,
3)))
model4.add(layers.MaxPooling2D((2, 2)))

model4.add(layers.Conv2D(32, (4, 4), activation='relu'))
model4.add(BatchNormalization())
model4.add(layers.MaxPooling2D((2, 2)))

model4.add(layers.Conv2D(64, (3, 3), activation='relu'))
model4.add(layers.MaxPooling2D((2, 2)))

model4.add(layers.Conv2D(128, (3, 3), activation='relu'))
model4.add(BatchNormalization())
model4.add(layers.MaxPooling2D((2, 2)))


model4.add(layers.Flatten())
model4.add(layers.Dense(64, activation='relu'))
model4.add(Dropout(0.1))
model4.add(layers.Dense(1, activation='sigmoid'))

model4.compile(loss='binary_crossentropy',
              optimizer="adam",
              metrics=['accuracy'])
```

In [83]:
```
history4 = model4.fit(train_images,
                    train_y,
                    epochs=50,
                    validation_data=(valid_images, valid_y),
                    validation_steps = validation_size,
                    class_weight=class_weight)
```

```
Epoch 1/50
103/103 [==============================] - 17s 163ms/step - loss: 0.2515 -
accuracy: 0.8994 - val_loss: 0.5301 - val_accuracy: 0.7966
Epoch 2/50
103/103 [==============================] - 17s 164ms/step - loss: 0.1641 -
accuracy: 0.9389 - val_loss: 1.4481 - val_accuracy: 0.2696
Epoch 3/50
103/103 [==============================] - 17s 165ms/step - loss: 0.1399 -
accuracy: 0.9453 - val_loss: 0.3075 - val_accuracy: 0.8370
Epoch 4/50
103/103 [==============================] - 18s 172ms/step - loss: 0.1224 -
accuracy: 0.9514 - val_loss: 0.3145 - val_accuracy: 0.8934
Epoch 5/50
103/103 [==============================] - 20s 192ms/step - loss: 0.1022 -
accuracy: 0.9597 - val_loss: 0.2012 - val_accuracy: 0.9179
Epoch 6/50
103/103 [==============================] - 17s 162ms/step - loss: 0.1019 -
accuracy: 0.9612 - val_loss: 0.1865 - val_accuracy: 0.9375
Epoch 7/50
103/103 [==============================] - 17s 164ms/step - loss: 0.0882 -
accuracy: 0.9685 - val_loss: 2.7809 - val_accuracy: 0.3125
Epoch 8/50
103/103 [==============================] - 17s 166ms/step - loss: 0.0869 -
accuracy: 0.9658 - val_loss: 0.2949 - val_accuracy: 0.8701
Epoch 9/50
103/103 [==============================] - 17s 161ms/step - loss: 0.0675 -
accuracy: 0.9774 - val_loss: 2.1309 - val_accuracy: 0.7328
Epoch 10/50
103/103 [==============================] - 18s 172ms/step - loss: 0.0562 -
accuracy: 0.9798 - val_loss: 2.9822 - val_accuracy: 0.7304
Epoch 11/50
103/103 [==============================] - 16s 156ms/step - loss: 0.0654 -
accuracy: 0.9762 - val_loss: 0.1526 - val_accuracy: 0.9534
Epoch 12/50
103/103 [==============================] - 17s 162ms/step - loss: 0.0508 -
accuracy: 0.9807 - val_loss: 0.3456 - val_accuracy: 0.8542
Epoch 13/50
103/103 [==============================] - 17s 162ms/step - loss: 0.0583 -
accuracy: 0.9780 - val_loss: 0.2764 - val_accuracy: 0.8860
Epoch 14/50
103/103 [==============================] - 17s 161ms/step - loss: 0.0473 -
accuracy: 0.9804 - val_loss: 0.7378 - val_accuracy: 0.6838
Epoch 15/50
103/103 [==============================] - 18s 175ms/step - loss: 0.0302 -
accuracy: 0.9887 - val_loss: 0.1075 - val_accuracy: 0.9657
Epoch 16/50
103/103 [==============================] - 17s 163ms/step - loss: 0.0396 -
accuracy: 0.9859 - val_loss: 0.5260 - val_accuracy: 0.8186
Epoch 17/50
103/103 [==============================] - 17s 165ms/step - loss: 0.0391 -
accuracy: 0.9850 - val_loss: 0.1430 - val_accuracy: 0.9534
Epoch 18/50
103/103 [==============================] - 16s 157ms/step - loss: 0.0255 -
accuracy: 0.9890 - val_loss: 0.5616 - val_accuracy: 0.7794
Epoch 19/50
103/103 [==============================] - 17s 166ms/step - loss: 0.0180 -
```

```
accuracy: 0.9930 - val_loss: 2.5463 - val_accuracy: 0.7328
Epoch 20/50
103/103 [==============================] - 17s 165ms/step - loss: 0.0559 -
accuracy: 0.9786 - val_loss: 1.8068 - val_accuracy: 0.4547
Epoch 21/50
103/103 [==============================] - 18s 175ms/step - loss: 0.0505 -
accuracy: 0.9814 - val_loss: 0.2521 - val_accuracy: 0.9081
Epoch 22/50
103/103 [==============================] - 18s 171ms/step - loss: 0.0203 -
accuracy: 0.9921 - val_loss: 0.1832 - val_accuracy: 0.9473
Epoch 23/50
103/103 [==============================] - 17s 168ms/step - loss: 0.0263 -
accuracy: 0.9911 - val_loss: 0.1444 - val_accuracy: 0.9657
Epoch 24/50
103/103 [==============================] - 17s 166ms/step - loss: 0.0346 -
accuracy: 0.9862 - val_loss: 7.7792 - val_accuracy: 0.7304
Epoch 25/50
103/103 [==============================] - 16s 160ms/step - loss: 0.0474 -
accuracy: 0.9823 - val_loss: 0.2823 - val_accuracy: 0.9142
Epoch 26/50
103/103 [==============================] - 17s 162ms/step - loss: 0.0296 -
accuracy: 0.9887 - val_loss: 1.2618 - val_accuracy: 0.5723
Epoch 27/50
103/103 [==============================] - 17s 162ms/step - loss: 0.0205 -
accuracy: 0.9921 - val_loss: 0.1313 - val_accuracy: 0.9559
Epoch 28/50
103/103 [==============================] - 17s 165ms/step - loss: 0.0187 -
accuracy: 0.9927 - val_loss: 0.5204 - val_accuracy: 0.9020
Epoch 29/50
103/103 [==============================] - 17s 165ms/step - loss: 0.0382 -
accuracy: 0.9859 - val_loss: 0.3172 - val_accuracy: 0.9265
Epoch 30/50
103/103 [==============================] - 17s 161ms/step - loss: 0.0128 -
accuracy: 0.9945 - val_loss: 0.2207 - val_accuracy: 0.9375
Epoch 31/50
103/103 [==============================] - 17s 166ms/step - loss: 0.0119 -
accuracy: 0.9957 - val_loss: 0.2333 - val_accuracy: 0.9510
Epoch 32/50
103/103 [==============================] - 16s 159ms/step - loss: 0.0024 -
accuracy: 0.9994 - val_loss: 0.1631 - val_accuracy: 0.9694
Epoch 33/50
103/103 [==============================] - 17s 160ms/step - loss: 9.0149e-0
4 - accuracy: 1.0000 - val_loss: 0.1756 - val_accuracy: 0.9632
Epoch 34/50
103/103 [==============================] - 17s 164ms/step - loss: 5.8622e-0
4 - accuracy: 1.0000 - val_loss: 0.1803 - val_accuracy: 0.9645
Epoch 35/50
103/103 [==============================] - 17s 167ms/step - loss: 5.2858e-0
4 - accuracy: 1.0000 - val_loss: 0.1902 - val_accuracy: 0.9669
Epoch 36/50
103/103 [==============================] - 20s 191ms/step - loss: 3.5744e-0
4 - accuracy: 1.0000 - val_loss: 0.2028 - val_accuracy: 0.9608
Epoch 37/50
103/103 [==============================] - 22s 214ms/step - loss: 3.1089e-0
4 - accuracy: 1.0000 - val_loss: 0.2226 - val_accuracy: 0.9620
Epoch 38/50
```

```
103/103 [==============================] - 20s 193ms/step - loss: 2.7348e-0
4 - accuracy: 1.0000 - val_loss: 0.2254 - val_accuracy: 0.9571
Epoch 39/50
103/103 [==============================] - 21s 201ms/step - loss: 4.3576e-0
4 - accuracy: 1.0000 - val_loss: 0.2243 - val_accuracy: 0.9620
Epoch 40/50
103/103 [==============================] - 22s 213ms/step - loss: 4.4421e-0
4 - accuracy: 1.0000 - val_loss: 0.3107 - val_accuracy: 0.9632
Epoch 41/50
103/103 [==============================] - 22s 215ms/step - loss: 1.7506e-0
4 - accuracy: 1.0000 - val_loss: 0.2245 - val_accuracy: 0.9608
Epoch 42/50
103/103 [==============================] - 21s 206ms/step - loss: 6.9722e-0
5 - accuracy: 1.0000 - val_loss: 0.2263 - val_accuracy: 0.9657
Epoch 43/50
103/103 [==============================] - 21s 204ms/step - loss: 6.6471e-0
5 - accuracy: 1.0000 - val_loss: 0.2320 - val_accuracy: 0.9632
Epoch 44/50
103/103 [==============================] - 16s 159ms/step - loss: 5.8709e-0
5 - accuracy: 1.0000 - val_loss: 0.2294 - val_accuracy: 0.9669
Epoch 45/50
103/103 [==============================] - 18s 177ms/step - loss: 7.3191e-0
5 - accuracy: 1.0000 - val_loss: 0.2306 - val_accuracy: 0.9620
Epoch 46/50
103/103 [==============================] - 18s 170ms/step - loss: 8.5655e-0
5 - accuracy: 1.0000 - val_loss: 0.2369 - val_accuracy: 0.9645
Epoch 47/50
103/103 [==============================] - 17s 163ms/step - loss: 5.0351e-0
5 - accuracy: 1.0000 - val_loss: 0.2387 - val_accuracy: 0.9645
Epoch 48/50
103/103 [==============================] - 17s 166ms/step - loss: 2.1512e-0
5 - accuracy: 1.0000 - val_loss: 0.2393 - val_accuracy: 0.9645
Epoch 49/50
103/103 [==============================] - 18s 171ms/step - loss: 3.0723e-0
5 - accuracy: 1.0000 - val_loss: 0.2411 - val_accuracy: 0.9657
Epoch 50/50
103/103 [==============================] - 17s 162ms/step - loss: 3.5136e-0
5 - accuracy: 1.0000 - val_loss: 0.2465 - val_accuracy: 0.9632
```

In [84]:
```
results_train = model4.evaluate(train_images, train_y)
```

```
103/103 [==============================] - 1s 12ms/step - loss: 8.2286e-06
- accuracy: 1.0000
```

In [85]:
```
results_test = model4.evaluate(test_images, test_y)
```

```
55/55 [==============================] - 1s 12ms/step - loss: 0.3108 - accu
racy: 0.9566
```

In [86]:
```
results_train
```

Out[86]:
```
[8.228609658544883e-06, 1.0]
```

In [87]:

```
results_test
```

Out[87]:

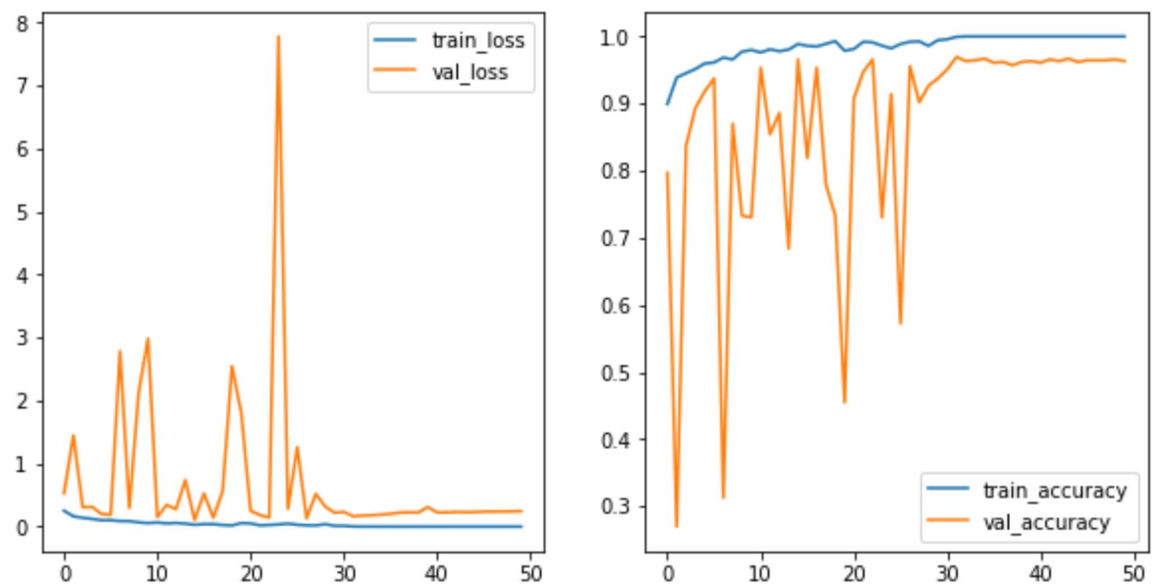
```
[0.3107980787754059, 0.956620991230011]
```

In [88]:

```
train_loss = history4.history['loss']
train_acc = history4.history['accuracy']
val_loss = history4.history['val_loss']
val_acc = history4.history['val_accuracy']

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 5))
sns.lineplot(x=history4.epoch, y=train_loss, ax=ax1, label='train_loss')
sns.lineplot(x=history4.epoch, y=train_acc, ax=ax2, label='train_accuracy')
sns.lineplot(x=history4.epoch, y=val_loss, ax=ax1, label='val_loss')
sns.lineplot(x=history4.epoch, y=val_acc, ax=ax2, label='val_accuracy')
```

Out[88]:

```
<AxesSubplot:>
```



In [89]:
```
def build_cnn5():
    model4 = models.Sequential()

    model4.add(layers.Conv2D(32, (3, 3), activation='relu',input_shape=(64
,64,  3)))
    model4.add(layers.MaxPooling2D((2, 2)))

    model4.add(layers.Conv2D(32, (4, 4), activation='relu'))
    model4.add(BatchNormalization())
    model4.add(layers.MaxPooling2D((2, 2)))

    model4.add(layers.Conv2D(64, (3, 3), activation='relu'))
    model4.add(layers.MaxPooling2D((2, 2)))

    model4.add(layers.Conv2D(128, (3, 3), activation='relu'))
    model4.add(BatchNormalization())
    model4.add(layers.MaxPooling2D((2, 2)))


    model4.add(layers.Flatten())
    model4.add(layers.Dense(64, activation='relu'))
    model4.add(Dropout(0.1))
    model4.add(layers.Dense(1, activation='sigmoid'))

    model4.compile(loss='binary_crossentropy',
              optimizer="adam",
              metrics=['accuracy'])

    return model4
```

In [90]:
```
keras_model5 = scikit_learn.KerasClassifier(build_cnn5,
                                            epochs=50,
                                            validation_data=(valid_images,
valid_y),
                                            validation_steps = validation_s
ize,
                                            class_weight = class_weight)
```

In [91]:
```
predictions = model4.predict(x = test_images, steps = 10, verbose=0)
```

In [92]:
```
pred_check = np.round(predictions)
```

In [93]:
```
pred_check = pred_check[:]
pred_check = pred_check.flatten()
pred_check
```

Out[93]:
```
array([1., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

In [94]:
```
test_check = test_labels[:,0]
test_check
```

Out[94]:
```
array([1., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

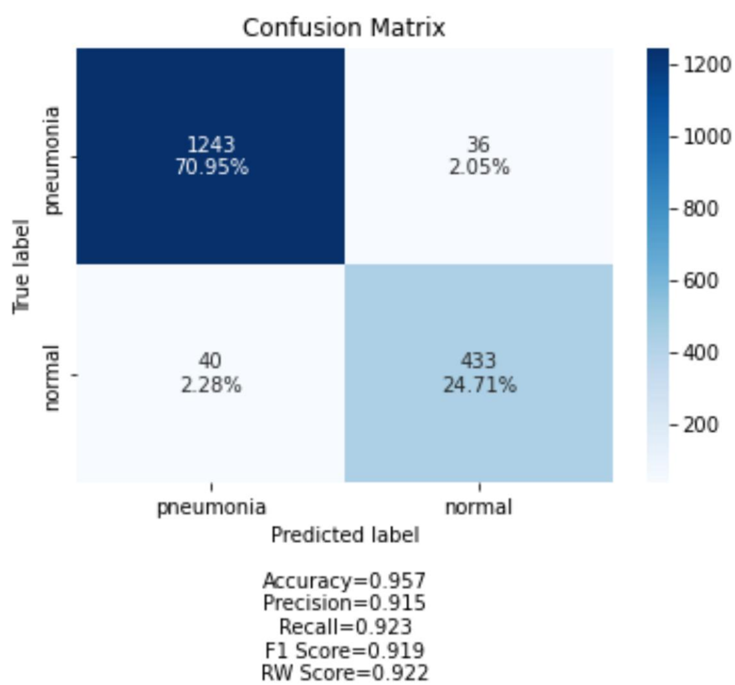
In [95]:
```
cm = confusion_matrix(y_true=test_check, y_pred=pred_check)
```

In [96]:
```
save_result(cm, 'CNN #4')
```

Out[96]:

	Model	RW Score	F1	Recall	Precision	Accuracy
0	CNN #4	0.922	0.919	0.923	0.915	0.957
0	CNN #2	0.909	0.910	0.909	0.911	0.951
0	CNN #3	0.904	0.903	0.904	0.901	0.947
0	CNN #1	0.866	0.874	0.864	0.884	0.931
0	baseline_model	0.861	0.856	0.863	0.850	0.923

In [97]:
```
cm_plot_labels = ['pneumonia', 'normal']
make_confusion_matrix(cm, categories = cm_plot_labels, title='Confusion Mat
rix')
```



CNN Model 5: Model 3 with added layer

After observing how the first five models ran, CNN #2 was the best model due to low standard deviation for the cross validation and high test and train accuracy. I will try adding dropout to help the little bit of overtraining that is occuring

In [98]:

```
model6 = models.Sequential()

model6.add(layers.Conv2D(32, (3, 3), activation='relu',input_shape=(64 ,64,
3)))
model6.add(layers.MaxPooling2D((2, 2)))

model6.add(layers.Conv2D(32, (4, 4), activation='relu'))
model6.add(BatchNormalization())
model6.add(layers.MaxPooling2D((2, 2)))

model6.add(layers.Conv2D(64, (3, 3), activation='relu'))
model6.add(BatchNormalization())
model6.add(layers.MaxPooling2D((2, 2)))

model6.add(layers.Conv2D(96, (3, 3), activation='relu', padding='same'))  #
new
model6.add(BatchNormalization())                                         # n
ew
model6.add(Dropout(0.1))                                                 # n
ew
model6.add(layers.MaxPooling2D((2, 2)))
# new

model6.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
model6.add(BatchNormalization())
model6.add(layers.MaxPooling2D((2, 2)))


model6.add(layers.Flatten())
model6.add(layers.Dense(64, activation='relu'))
model6.add(Dropout(0.1))
model6.add(layers.Dense(1, activation='sigmoid'))

model6.compile(loss='binary_crossentropy',
              optimizer="adam",
              metrics=['accuracy'])
```

In [99]:
```
history6 = model6.fit(train_images,
                    train_y,
                    epochs=50,
                    validation_data=(valid_images, valid_y),
                    validation_steps = validation_size,
                    class_weight = class_weight)
```

```
Epoch 1/50
103/103 [==============================] - 15s 144ms/step - loss: 0.2241 -
accuracy: 0.9034 - val_loss: 1.0929 - val_accuracy: 0.7304
Epoch 2/50
103/103 [==============================] - 15s 145ms/step - loss: 0.1518 -
accuracy: 0.9410 - val_loss: 1.4036 - val_accuracy: 0.7304
Epoch 3/50
103/103 [==============================] - 15s 143ms/step - loss: 0.1426 -
accuracy: 0.9447 - val_loss: 1.3484 - val_accuracy: 0.7353
Epoch 4/50
103/103 [==============================] - 15s 143ms/step - loss: 0.1083 -
accuracy: 0.9581 - val_loss: 0.4689 - val_accuracy: 0.7267
Epoch 5/50
103/103 [==============================] - 16s 155ms/step - loss: 0.1084 -
accuracy: 0.9560 - val_loss: 0.4136 - val_accuracy: 0.8199
Epoch 6/50
103/103 [==============================] - 17s 167ms/step - loss: 0.1033 -
accuracy: 0.9581 - val_loss: 0.2618 - val_accuracy: 0.8983
Epoch 7/50
103/103 [==============================] - 16s 156ms/step - loss: 0.0957 -
accuracy: 0.9630 - val_loss: 0.3147 - val_accuracy: 0.8725
Epoch 8/50
103/103 [==============================] - 15s 146ms/step - loss: 0.0869 -
accuracy: 0.9667 - val_loss: 0.3895 - val_accuracy: 0.8248
Epoch 9/50
103/103 [==============================] - 15s 150ms/step - loss: 0.0791 -
accuracy: 0.9664 - val_loss: 0.5231 - val_accuracy: 0.7904
Epoch 10/50
103/103 [==============================] - 16s 154ms/step - loss: 0.0799 -
accuracy: 0.9694 - val_loss: 2.0211 - val_accuracy: 0.7316
Epoch 11/50
103/103 [==============================] - 15s 148ms/step - loss: 0.0606 -
accuracy: 0.9731 - val_loss: 0.1677 - val_accuracy: 0.9436
Epoch 12/50
103/103 [==============================] - 15s 145ms/step - loss: 0.0552 -
accuracy: 0.9783 - val_loss: 0.7018 - val_accuracy: 0.7966
Epoch 13/50
103/103 [==============================] - 15s 150ms/step - loss: 0.0453 -
accuracy: 0.9801 - val_loss: 0.7240 - val_accuracy: 0.7892
Epoch 14/50
103/103 [==============================] - 14s 141ms/step - loss: 0.0389 -
accuracy: 0.9847 - val_loss: 0.6096 - val_accuracy: 0.8346
Epoch 15/50
103/103 [==============================] - 15s 145ms/step - loss: 0.0579 -
accuracy: 0.9780 - val_loss: 1.1437 - val_accuracy: 0.7316
Epoch 16/50
103/103 [==============================] - 15s 147ms/step - loss: 0.0628 -
accuracy: 0.9737 - val_loss: 3.5257 - val_accuracy: 0.7341
Epoch 17/50
103/103 [==============================] - 17s 169ms/step - loss: 0.0552 -
accuracy: 0.9780 - val_loss: 0.2381 - val_accuracy: 0.9179
Epoch 18/50
103/103 [==============================] - 16s 154ms/step - loss: 0.0580 -
accuracy: 0.9768 - val_loss: 1.5093 - val_accuracy: 0.7304
Epoch 19/50
103/103 [==============================] - 16s 154ms/step - loss: 0.0677 -
```

```
accuracy: 0.9752 - val_loss: 5.9237 - val_accuracy: 0.7304
Epoch 20/50
103/103 [==============================] - 16s 151ms/step - loss: 0.0545 -
accuracy: 0.9765 - val_loss: 0.8913 - val_accuracy: 0.7745
Epoch 21/50
103/103 [==============================] - 15s 146ms/step - loss: 0.0839 -
accuracy: 0.9673 - val_loss: 1.2214 - val_accuracy: 0.7721
Epoch 22/50
103/103 [==============================] - 16s 152ms/step - loss: 0.0431 -
accuracy: 0.9844 - val_loss: 0.1675 - val_accuracy: 0.9571
Epoch 23/50
103/103 [==============================] - 16s 154ms/step - loss: 0.0323 -
accuracy: 0.9862 - val_loss: 0.5166 - val_accuracy: 0.8762
Epoch 24/50
103/103 [==============================] - 16s 154ms/step - loss: 0.0354 -
accuracy: 0.9850 - val_loss: 0.6751 - val_accuracy: 0.8787
Epoch 25/50
103/103 [==============================] - 16s 151ms/step - loss: 0.0300 -
accuracy: 0.9875 - val_loss: 0.2796 - val_accuracy: 0.9338
Epoch 26/50
103/103 [==============================] - 16s 155ms/step - loss: 0.0232 -
accuracy: 0.9890 - val_loss: 0.7921 - val_accuracy: 0.8689
Epoch 27/50
103/103 [==============================] - 16s 157ms/step - loss: 0.0404 -
accuracy: 0.9884 - val_loss: 0.1049 - val_accuracy: 0.9632
Epoch 28/50
103/103 [==============================] - 15s 148ms/step - loss: 0.0170 -
accuracy: 0.9930 - val_loss: 0.2773 - val_accuracy: 0.9485
Epoch 29/50
103/103 [==============================] - 16s 161ms/step - loss: 0.0086 -
accuracy: 0.9969 - val_loss: 0.4706 - val_accuracy: 0.9154
Epoch 30/50
103/103 [==============================] - 16s 154ms/step - loss: 0.0217 -
accuracy: 0.9933 - val_loss: 0.1458 - val_accuracy: 0.9571
Epoch 31/50
103/103 [==============================] - 16s 151ms/step - loss: 0.0254 -
accuracy: 0.9896 - val_loss: 0.2570 - val_accuracy: 0.9473
Epoch 32/50
103/103 [==============================] - 15s 147ms/step - loss: 0.0238 -
accuracy: 0.9914 - val_loss: 0.3531 - val_accuracy: 0.9130
Epoch 33/50
103/103 [==============================] - 16s 152ms/step - loss: 0.0080 -
accuracy: 0.9969 - val_loss: 0.1255 - val_accuracy: 0.9706
Epoch 34/50
103/103 [==============================] - 16s 154ms/step - loss: 0.0030 -
accuracy: 0.9994 - val_loss: 0.1689 - val_accuracy: 0.9583
Epoch 35/50
103/103 [==============================] - 15s 144ms/step - loss: 0.0048 -
accuracy: 0.9976 - val_loss: 0.2054 - val_accuracy: 0.9473
Epoch 36/50
103/103 [==============================] - 16s 152ms/step - loss: 0.0078 -
accuracy: 0.9966 - val_loss: 0.2838 - val_accuracy: 0.9118
Epoch 37/50
103/103 [==============================] - 17s 167ms/step - loss: 0.0464 -
accuracy: 0.9826 - val_loss: 0.1300 - val_accuracy: 0.9461
Epoch 38/50
```

```
103/103 [==============================] - 17s 163ms/step - loss: 0.0125 -
accuracy: 0.9948 - val_loss: 0.1358 - val_accuracy: 0.9645
Epoch 39/50
103/103 [==============================] - 16s 152ms/step - loss: 0.0137 -
accuracy: 0.9954 - val_loss: 0.4000 - val_accuracy: 0.9081
Epoch 40/50
103/103 [==============================] - 16s 158ms/step - loss: 0.0092 -
accuracy: 0.9966 - val_loss: 1.0111 - val_accuracy: 0.7047
Epoch 41/50
103/103 [==============================] - 16s 154ms/step - loss: 0.0082 -
accuracy: 0.9966 - val_loss: 0.1587 - val_accuracy: 0.9596
Epoch 42/50
103/103 [==============================] - 16s 153ms/step - loss: 0.0063 -
accuracy: 0.9979 - val_loss: 1.1864 - val_accuracy: 0.8578
Epoch 43/50
103/103 [==============================] - 15s 145ms/step - loss: 0.0167 -
accuracy: 0.9936 - val_loss: 0.2773 - val_accuracy: 0.9583
Epoch 44/50
103/103 [==============================] - 16s 155ms/step - loss: 0.0563 -
accuracy: 0.9795 - val_loss: 0.1572 - val_accuracy: 0.9547
Epoch 45/50
103/103 [==============================] - 16s 151ms/step - loss: 0.0167 -
accuracy: 0.9917 - val_loss: 0.6077 - val_accuracy: 0.9093
Epoch 46/50
103/103 [==============================] - 16s 153ms/step - loss: 0.0139 -
accuracy: 0.9957 - val_loss: 2.9611 - val_accuracy: 0.7426
Epoch 47/50
103/103 [==============================] - 16s 154ms/step - loss: 0.0190 -
accuracy: 0.9948 - val_loss: 0.2072 - val_accuracy: 0.9461
Epoch 48/50
103/103 [==============================] - 16s 158ms/step - loss: 0.0080 -
accuracy: 0.9969 - val_loss: 0.1592 - val_accuracy: 0.9669
Epoch 49/50
103/103 [==============================] - 16s 159ms/step - loss: 0.0028 -
accuracy: 0.9988 - val_loss: 0.1479 - val_accuracy: 0.9596
Epoch 50/50
103/103 [==============================] - 16s 153ms/step - loss: 0.0103 -
accuracy: 0.9963 - val_loss: 0.4236 - val_accuracy: 0.9179
```

In [100]:

```
results_train = model6.evaluate(train_images, train_y)
```

```
103/103 [==============================] - 1s 12ms/step - loss: 0.2668 - ac
curacy: 0.9364
```

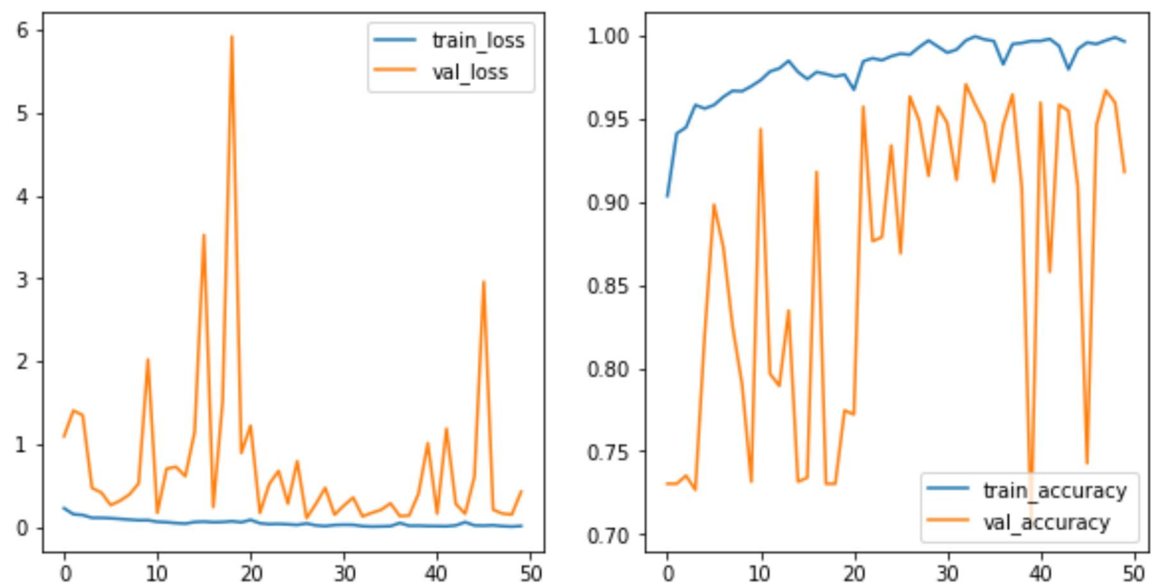
In [101]:

```
results_test = model6.evaluate(test_images, test_y)
```

```
55/55 [==============================] - 1s 12ms/step - loss: 0.4768 - accu
racy: 0.9138
```

In [102]:
```
train_loss = history6.history['loss']
train_acc = history6.history['accuracy']
val_loss = history6.history['val_loss']
val_acc = history6.history['val_accuracy']

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 5))
sns.lineplot(x=history6.epoch, y=train_loss, ax=ax1, label='train_loss')
sns.lineplot(x=history6.epoch, y=train_acc, ax=ax2, label='train_accuracy')
sns.lineplot(x=history6.epoch, y=val_loss, ax=ax1, label='val_loss')
sns.lineplot(x=history6.epoch, y=val_acc, ax=ax2, label='val_accuracy')
```

Out[102]: <AxesSubplot:>



In [103]:
```
def build_cnn6():
    model6 = models.Sequential()

    model6.add(layers.Conv2D(32, (3, 3), activation='relu',input_shape=(64
,64,  3)))
    model6.add(layers.MaxPooling2D((2, 2)))

    model6.add(layers.Conv2D(32, (4, 4), activation='relu'))
    model6.add(BatchNormalization())
    model6.add(layers.MaxPooling2D((2, 2)))

    model6.add(layers.Conv2D(64, (3, 3), activation='relu'))
    model6.add(BatchNormalization())
    model6.add(layers.MaxPooling2D((2, 2)))

    model6.add(layers.Conv2D(96, (3, 3), activation='relu', padding='same
'))  # new
    model6.add(BatchNormalization())
# new
    model6.add(Dropout(0.1))
# new
    model6.add(layers.MaxPooling2D((2, 2)))
# new

    model6.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same
'))
    model6.add(BatchNormalization())
    model6.add(layers.MaxPooling2D((2, 2)))


    model6.add(layers.Flatten())
    model6.add(layers.Dense(64, activation='relu'))
    model6.add(Dropout(0.1))
    model6.add(layers.Dense(1, activation='sigmoid'))

    model6.compile(loss='binary_crossentropy',
              optimizer="adam",
              metrics=['accuracy'])

    return model6
```

In [104]:
```
keras_model6 = scikit_learn.KerasClassifier(build_cnn6,
                                            epochs=50,
                                            validation_data=(valid_images,
valid_y),
                                            validation_steps = validation_s
ize,
                                            class_weight = class_weight)
```

Prediction for Confusion Matrix

In [105]:
```
predictions = model6.predict(x = test_images, steps = 10, verbose=0)
```

In [106]:
```
pred_check = np.round(predictions)
```

In [107]:
```
pred_check = pred_check[:]
pred_check = pred_check.flatten()
pred_check
```

Out[107]:
```
array([0., 1., 0., ..., 0., 0., 0.], dtype=float32)
```

In [108]:
```
test_check = test_labels[:,0]
test_check
```

Out[108]:
```
array([1., 1., 1., ..., 0., 0., 0.], dtype=float32)
```

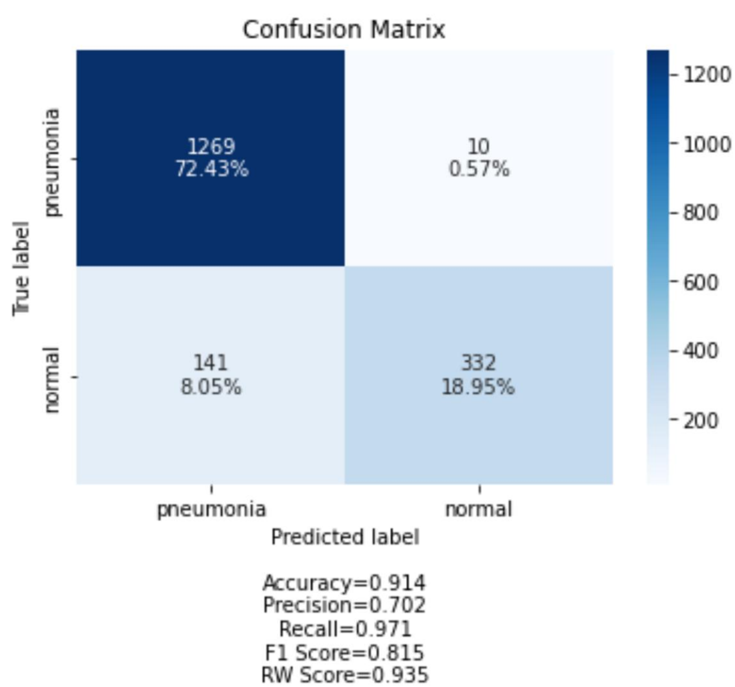
In [109]:
```
cm = confusion_matrix(y_true=test_check, y_pred=pred_check)
```

In [110]:
```
save_result(cm, 'CNN #6')
```

Out[110]:

	Model	RW Score	F1	Recall	Precision	Accuracy
0	CNN #4	0.922	0.919	0.923	0.915	0.957
0	CNN #2	0.909	0.910	0.909	0.911	0.951
0	CNN #3	0.904	0.903	0.904	0.901	0.947
0	CNN #1	0.866	0.874	0.864	0.884	0.931
0	baseline_model	0.861	0.856	0.863	0.850	0.923
0	CNN #6	0.935	0.815	0.971	0.702	0.914

In [111]:
```
cm_plot_labels = ['pneumonia', 'normal']
make_confusion_matrix(cm, categories = cm_plot_labels, title='Confusion Mat
rix')
```



VGG Model

In [237]:
```
train_path = 're-split_data/train'
valid_path = 're-split_data/validation'
test_path = 're-split_data/test'
```

In [238]:
```
train_batches2 = ImageDataGenerator(preprocessing_function=tf.keras.applica
tions.vgg16.preprocess_input) \
    .flow_from_directory(directory=train_path, target_size=(224, 224), batc
h_size=32)
valid_batches2 = ImageDataGenerator(preprocessing_function=tf.keras.applica
tions.vgg16.preprocess_input) \
    .flow_from_directory(directory=valid_path, target_size=(224, 224),  bat
ch_size=32)
test_batches2 = ImageDataGenerator(preprocessing_function=tf.keras.applicat
ions.vgg16.preprocess_input) \
    .flow_from_directory(directory=test_path, target_size=(224, 224),  batc
h_size=32, shuffle=False)
```

```
Found 3272 images belonging to 2 classes.
Found 816 images belonging to 2 classes.
Found 1752 images belonging to 2 classes.
```

In [239]:
```
# create the data sets
train_images2, train_labels2 = next(train_batches2)
test_images2, test_labels2 = next(test_batches2)
valid_images2, valid_labels2 = next(valid_batches2)

train_img2 = train_images2.reshape(train_images2.shape[0], -1)
test_img2 = test_images2.reshape(test_images2.shape[0], -1)
valid_img2 = valid_images2.reshape(valid_images2.shape[0], -1)

print(train_img2.shape)
print(test_img2.shape)
print(valid_img2.shape)
```

```
(32, 150528)
(32, 150528)
(32, 150528)
```

In [240]:
```
train_y2 = np.reshape(train_labels2[:,0], (32,1))
test_y2 = np.reshape(test_labels2[:,0], (32,1))
valid_y2 = np.reshape(valid_labels2[:,0], (32,1))
print(train_y2.shape)
print(test_y2.shape)
print(valid_y2.shape)
```

```
(32, 1)
(32, 1)
(32, 1)
```

In [241]:
```
# get all the data in the directory split/test , and reshape them
'''
train_generator = ImageDataGenerator(rescale=1./255).flow_from_directory('r
e-split_data/train',
        target_size=(64, 64), batch_size = train_size)

test_generator =ImageDataGenerator(rescale=1./255).flow_from_directory('re-
split_data/test',
        target_size=(64, 64), batch_size = test_size, shuffle= False)

valid_generator =ImageDataGenerator(rescale=1./255).flow_from_directory('re
-split_data/validation',
        target_size=(64, 64), batch_size = validation_size)
'''
```

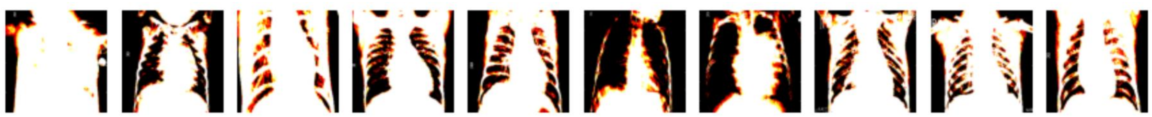
Out[241]:
```
"\ntrain_generator = ImageDataGenerator(rescale=1./255).flow_from_directory
('re-split_data/train',\n        target_size=(64, 64), batch_size = train_s
ize) \n\ntest_generator =ImageDataGenerator(rescale=1./255).flow_from_direc
tory('re-split_data/test',\n        target_size=(64, 64), batch_size = test
_size, shuffle= False) \n\nvalid_generator =ImageDataGenerator(rescale=1./2
55).flow_from_directory('re-split_data/validation',\n        target_size=(6
4, 64), batch_size = validation_size)\n"
```

In [242]:
```
# create the data sets
'''
train_images2, train_labels2 = next(train_generator)
test_images2, test_labels2 = next(test_generator)
valid_images2, valid_labels2 = next(valid_generator)
'''
```

Out[242]:
```
'\ntrain_images2, train_labels2 = next(train_generator)\ntest_images2, test
_labels2 = next(test_generator)\nvalid_images2, valid_labels2 = next(valid_
generator)\n'
```

In [243]:
```
show_images(train_images2)
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



In [244]:
```
'''
train_img2 = train_images2.reshape(train_images2.shape[0], -1)
test_img2 = test_images2.reshape(test_images2.shape[0], -1)
valid_img2 = valid_images2.reshape(valid_images2.shape[0], -1)

print(train_img2.shape)
print(test_img2.shape)
print(valid_img2.shape)
'''
```

Out[244]:
```
'\ntrain_img2 = train_images2.reshape(train_images2.shape[0], -1)\ntest_img2 = test_images2.reshape(test_images2.shape[0], -1)\nvalid_img2 = valid_images2.reshape(valid_images2.shape[0], -1)\n\nprint(train_img2.shape)\nprint(test_img2.shape)\nprint(valid_img2.shape)\n'
```

In [245]:
```
'''
train_y2 = np.reshape(train_labels2[:,0], (train_size,1))
test_y2 = np.reshape(test_labels2[:,0], (test_size,1))
valid_y2 = np.reshape(valid_labels2[:,0], (validation_size,1))

print(train_y2.shape)
print(test_y2.shape)
print(valid_y2.shape)
'''
```

Out[245]:
```
'\ntrain_y2 = np.reshape(train_labels2[:,0], (train_size,1))\ntest_y2 = np.reshape(test_labels2[:,0], (test_size,1))\nvalid_y2 = np.reshape(valid_labels2[:,0], (validation_size,1))\n\nprint(train_y2.shape)\nprint(test_y2.shape)\nprint(valid_y2.shape)\n'
```

In [246]:
```
vgg16_model = tf.keras.applications.vgg16.VGG16()
```

vgg16_model.summary()

In [247]:
```
# create new model of type sequential, then iterate over each of layers in vgg model (save last),
#  add layers to sequential.
#model_VGG = Sequential()
#for layer in vgg16_model.layers[:-1]:
   # model_VGG.add(layer)
```

In [248]:
```
#for layer in model_VGG.layers:
   # layer.trainable = False
```

In [249]:
```
#model_VGG.add(Dense(units=2, activation='sigmoid'))
```

In [250]:
```
#model_VGG.compile(optimizer=Adam(learning_rate=0.001), loss='binary_crossentropy', metrics=['accuracy'])
```

In [251]:
```
#vgg_hist = model_VGG.fit(x=train_batches,
 #                        steps_per_epoch = len(train_batches),
 #                        validation_data=valid_batches,
  #                       validation_steps = len(valid_batches),
 #                        epochs=7)
```

In [252]:
```
#os.mkdir('models')
```

In [253]:
```
#model_VGG.save('models/VGG_model.h5')
```

In [254]:
```
# load model
from tensorflow.keras.models import load_model
new_model = load_model('models/VGG_model.h5')
```

In [255]:
```
model_VGG = new_model
```

In [256]:
```
test_images2, test_labels2= next(test_batches2)
```

In [257]:
```
predictions = model_VGG.predict(x=test_batches2, steps=len(test_batches2), verbose = 0)
```

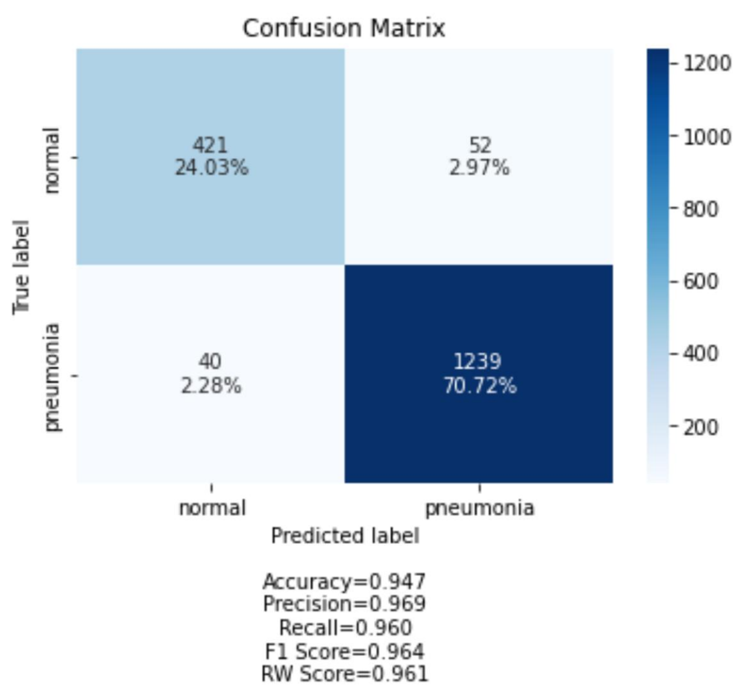
In [258]:
```
y_pred = np.argmax(predictions, axis = 1)
```

In [259]:
```
y_true = test_batches2.classes
```

In [260]:
```
# Confusion Matrix
cm = confusion_matrix(y_true = y_true, y_pred = y_pred)
cm
```

Out[260]:
```
array([[ 421,   52],
       [  40, 1239]], dtype=int64)
```

In [261]:
```
cm_plot_labels = ['normal', 'pneumonia']
make_confusion_matrix(cm, categories=cm_plot_labels, title='Confusion Matrix')
```



In [262]:
```
# Sanity Check

tp = cm[1,1]
fn = cm[0,1]
recall = tp / (tp + fn)
recall
```

Out[262]:
```
0.959721146398141
```

Expaining The Final Model With LIME

In [263]:
```
import lime
from lime import lime_image
```

In [264]:
```
explainer = lime_image.LimeImageExplainer()
```

Here, I am checking the labels and predictions of various images, then viewing the decision-making weights using LIME Explinations.

An explanation is a local linear approximation of the models behavior. While the model may be complex globally, it is simple(r) to approximate it around the vicinity of a particular insance (github.com/marcotcr/lime)

In [265]:
```
from skimage.segmentation import mark_boundaries
```

In [266]:
```
def check_label(train_images_num):
    img1 = train_images[train_images_num]
    img = train_labels[train_images_num][0]
    if img == 0:
        return 'pneumonia'
    else:
        return 'normal'
```

In [268]:
```
check_label(0)
```

Out[268]:
```
'pneumonia'
```

In [271]:
```
img = train_images[3].reshape(1,64, 64, 3)
pred = model4.predict(img)
pred = np.round(pred)
pred
```

Out[271]:
```
array([[0.]], dtype=float32)
```

In [273]:
```
img = train_images[20].reshape(1,64,64,3)
pred = model4.predict(img)
pred
```

Out[273]:
```
array([[6.1722814e-11]], dtype=float32)
```

In [274]:
```
def check_prediction(train_images_num):
    img = train_images[train_images_num].reshape(1,64,64,3)
    pred = model4.predict(img)
    if pred[0][0] < 0.5:
        return 'pneumonia'
    else:
        return 'normal'
```

In [275]:
```python
def plot_image_preds(train_images_num):
    img = train_images[train_images_num].reshape(1,64,64,3)
    pred = model4.predict(img)
    f, ax = plt.subplots(figsize=(10,8))
    plt.imshow(img[0])
    plt.title('Prediction: ' + check_prediction(train_images_num) + '\n' + 
'Label: ' + check_label(train_images_num), fontsize=20)
    plt.show()
```

In [276]:
```python
def plot_explanation(exp):
    temp, mask = exp.get_image_and_mask(exp.top_labels[0], positive_only=Tr
ue, hide_rest=False)
    f, ax = plt.subplots(figsize=(8, 8))
    plt.title('Explanation for classification', fontsize=20)
    plt.imshow(mark_boundaries(temp / 2 + 0.5, mask))
```

In [277]:
```python
# Plots the positive and negative explanations for the label

def plot_pos_neg_explanation(exp):
    temp, mask = exp.get_image_and_mask(exp.top_labels[0], positive_only=Fa
lse, hide_rest=False)
    f, ax = plt.subplots(figsize=(8, 8))
    plt.title('Explanation for classification ', fontsize=20)
    plt.imshow(mark_boundaries(temp / 2 + 0.5, mask))
```

In [278]:
```python
#Plots explanation with minimum weights

def plot_with_weights(exp, mw): # mw is the minimum weight
    temp, mask = exp.get_image_and_mask(exp.top_labels[0], positive_only=Fa
lse, hide_rest=False, min_weight = mw)
    f, ax = plt.subplots(figsize=(8, 8))
    plt.title('Explanation - with weights - for classification ', fontsize=
18)
    plt.imshow(mark_boundaries(temp / 2 + 0.5, mask))
```

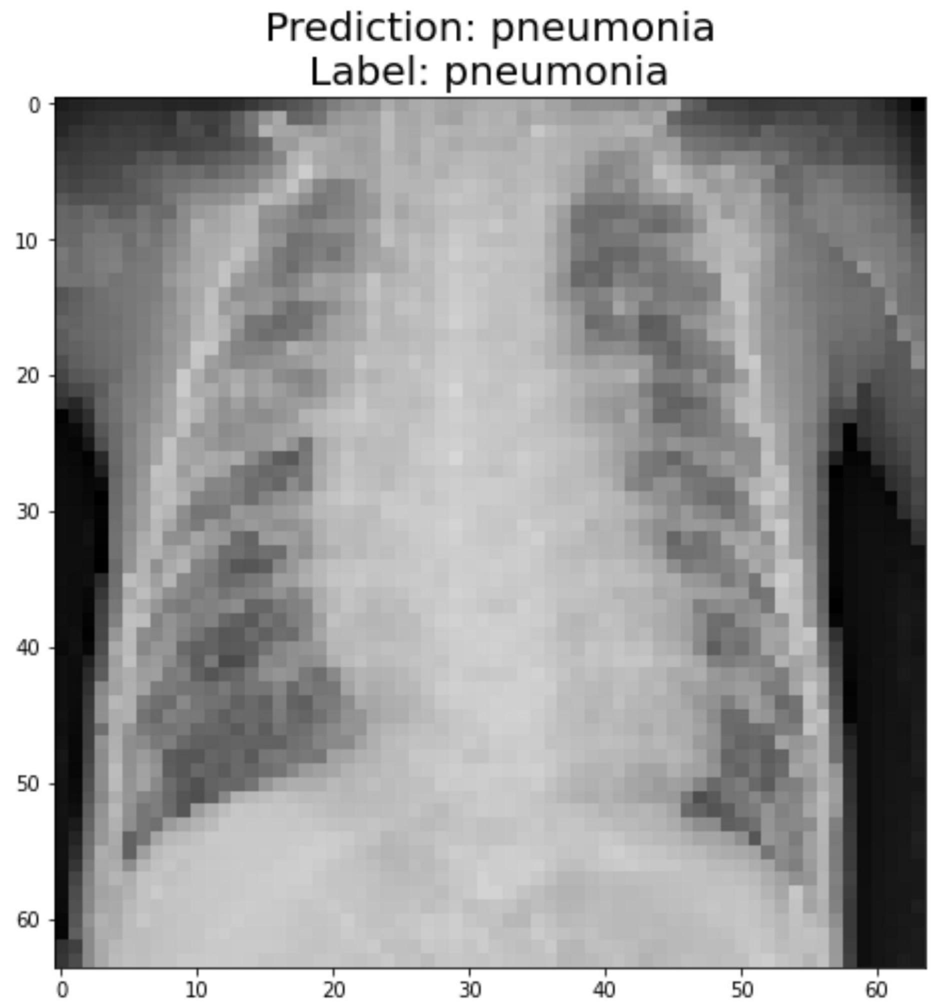
In [279]:
```python
# Plots the heatmap of the explanation

def plot_explanation_heatmap(exp):
    ind =  exp.top_labels[0]
    #Map each explanation weight to the corresponding superpixel
    dict_heatmap = dict(exp.local_exp[ind])
    heatmap = np.vectorize(dict_heatmap.get)(exp.segments)
    f, ax = plt.subplots(figsize=(8, 8))
    #Plot. The visualization makes more sense if a symmetrical colorbar is 
used.
    plt.imshow(heatmap, cmap = 'RdBu', vmin  = -heatmap.max(), vmax = heatm
ap.max())
    plt.title('Heatmap for classification ', fontsize=20)
    plt.colorbar()
```

In [285]:
```
# Hide color is the color for a superpixel turned OFF. Alternatively, if it
is NONE, the superpixel will be replaced by the average of its pixels
explanation1 = explainer.explain_instance(train_images[1].astype("double"),
model4.predict, top_labels=2, hide_color=0, num_samples=10000)
```

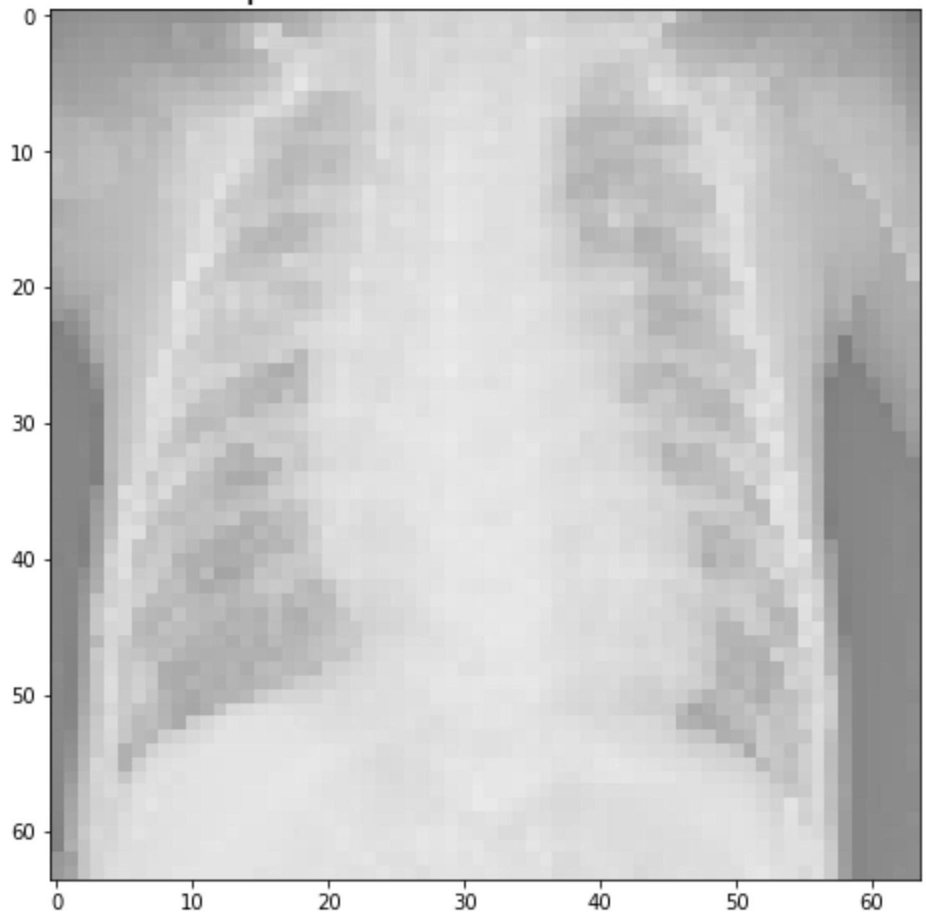
```
100%|██████████| 10000/10000 [00:45<00:00, 221.94it/s]
```

In [286]:

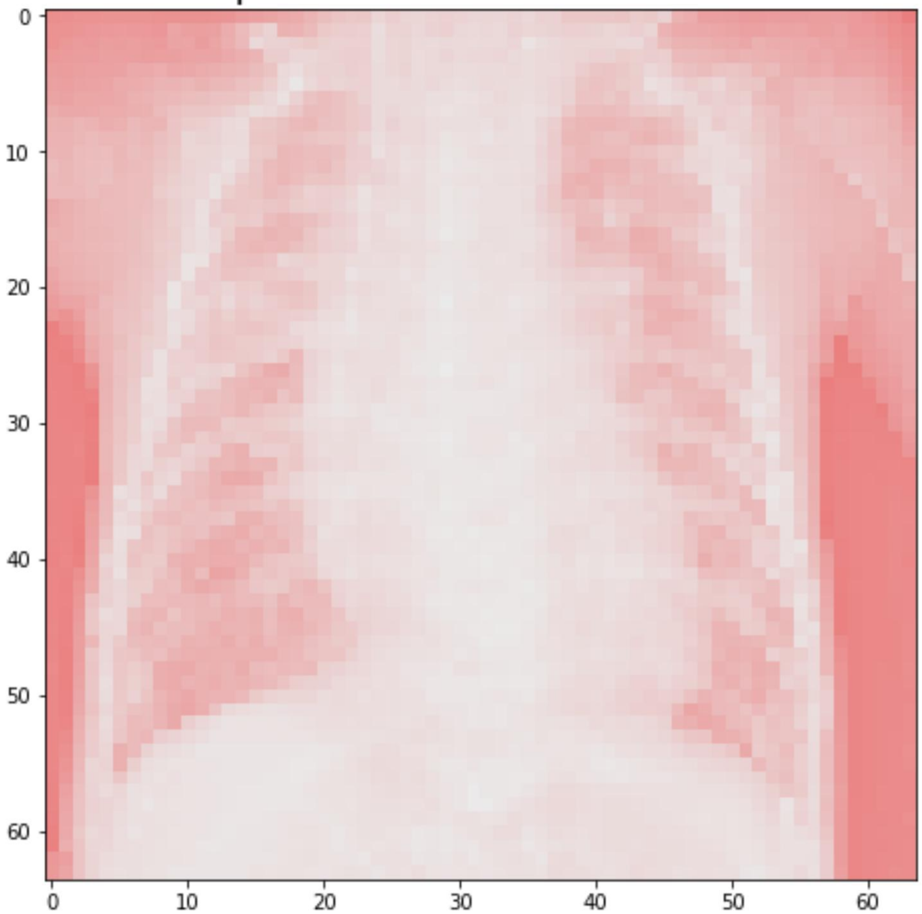
```
plot_image_preds(1)
plot_explanation(explanation1)
plot_pos_neg_explanation(explanation1)
plot_with_weights(explanation1, 0.5)
plot_explanation_heatmap(explanation1)
```


Prediction: pneumonia
Label: pneumonia
0
10
20
30
40
50
60
0
10
20
30
40
50
60

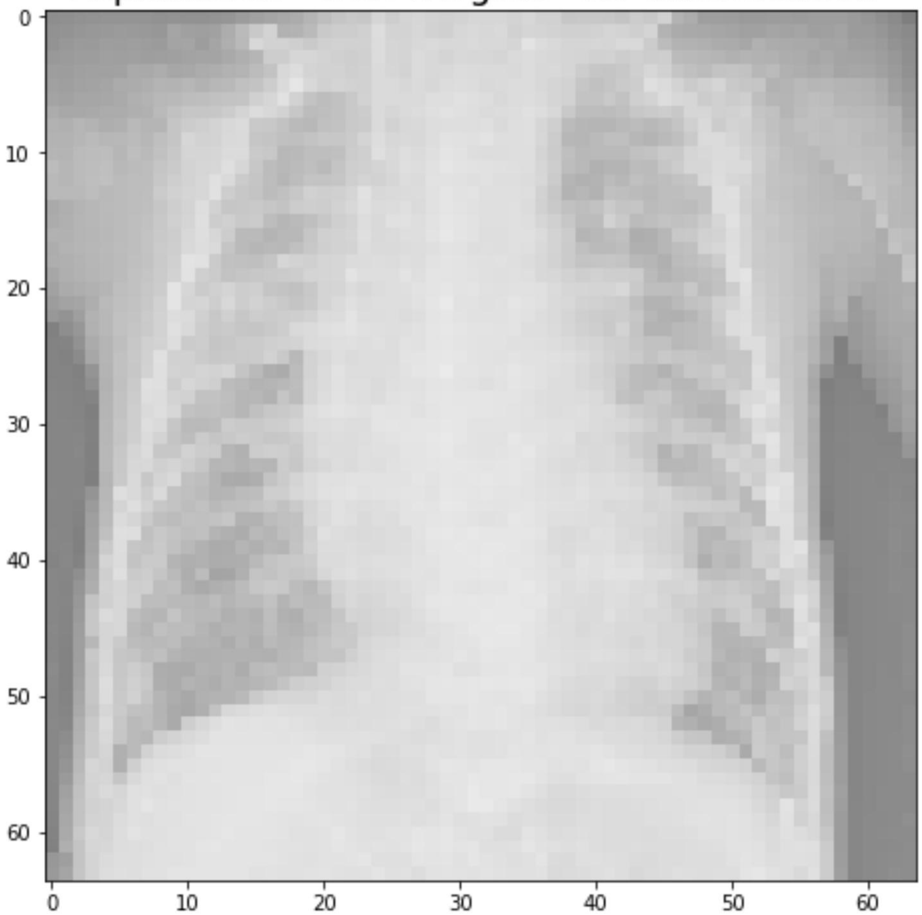
Explanation for classification



Explanation for classification



Explanation - with weights - for classification



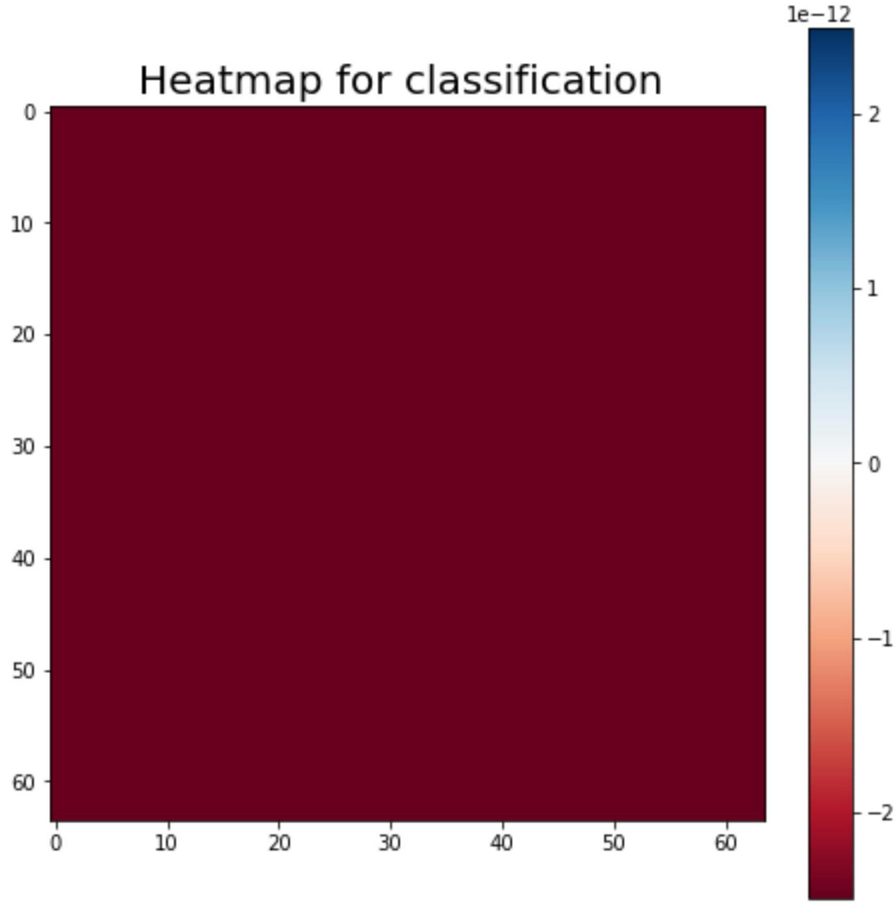
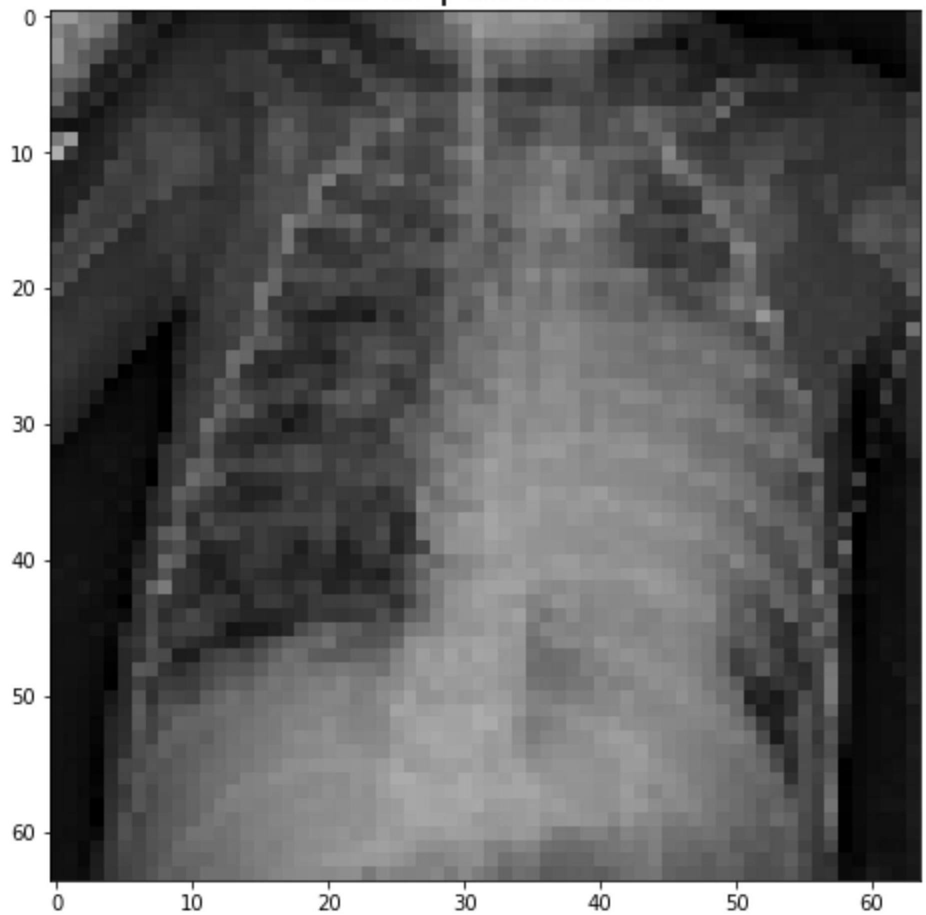


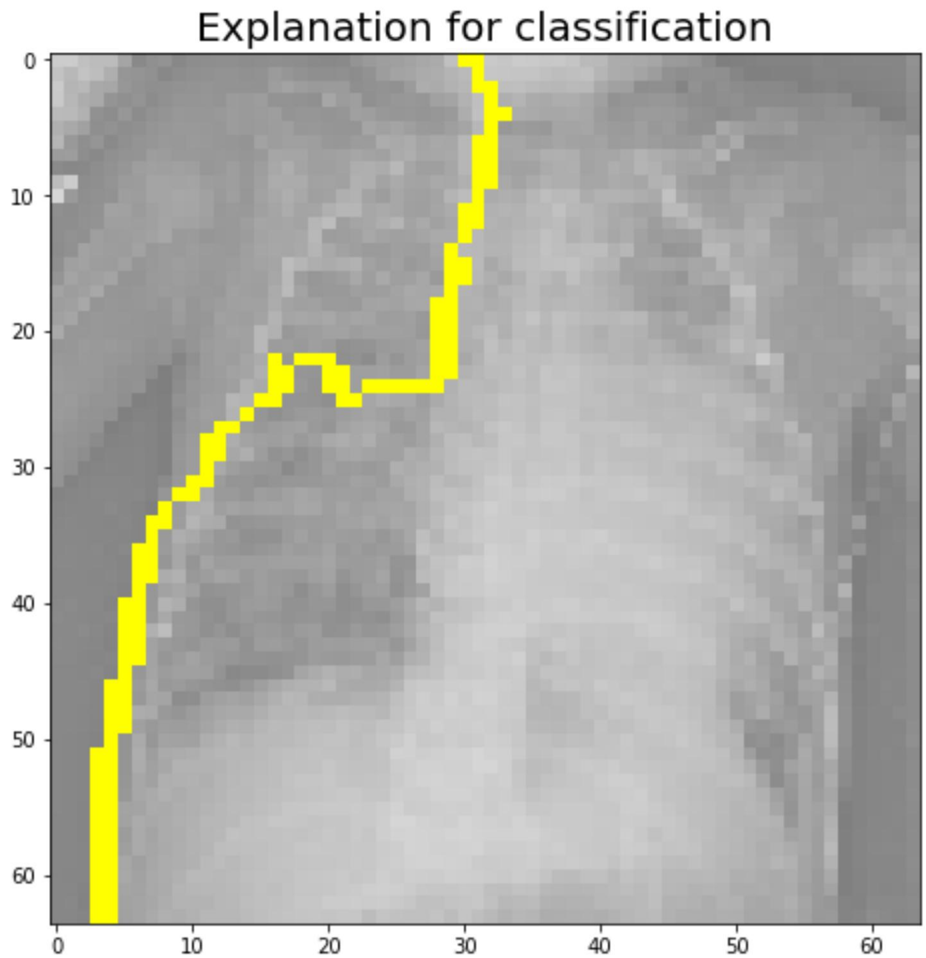
Image 2

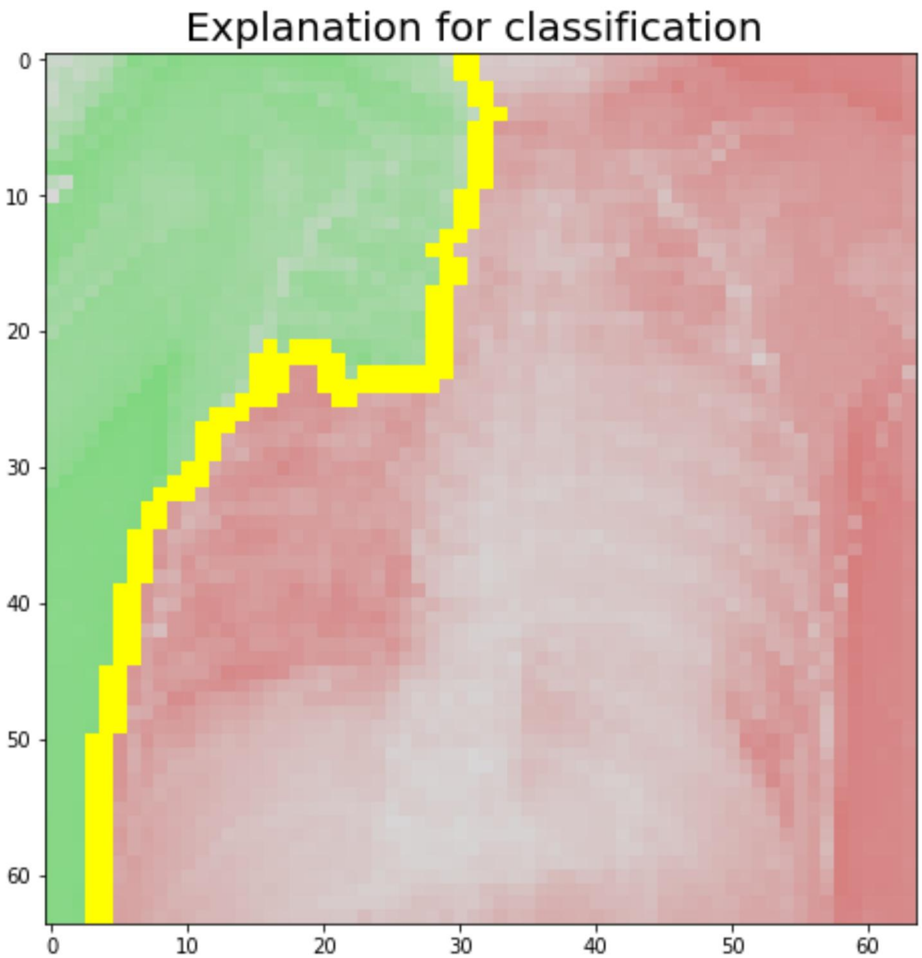
In [ ]:
```
# Hide color is the color for a superpixel turned OFF. Alternatively, if it is NONE, the superpixel will be replaced by the average of its pixels
explanation2 = explainer.explain_instance(train_images[12].astype("double"), model4.predict, top_labels = 2, hide_color=0, num_samples=10000)
```

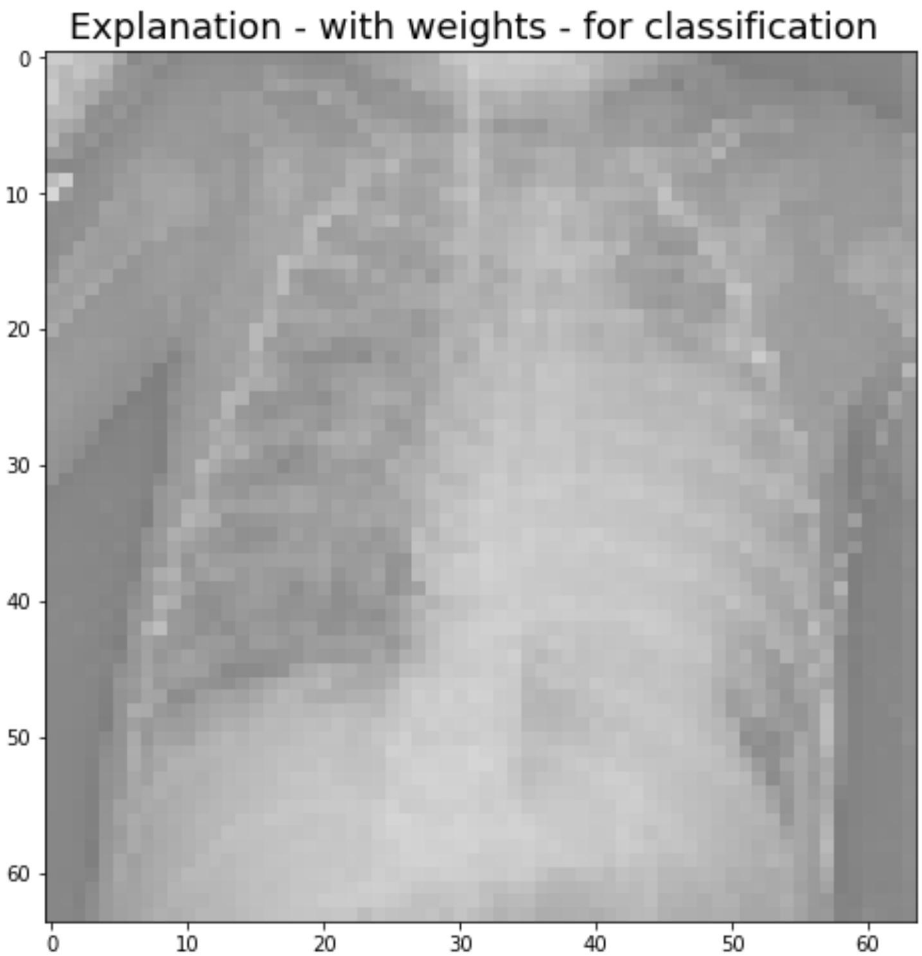
In [ ]:
```
plot_image_preds(12)
plot_explanation(explanation2)
plot_pos_neg_explanation(explanation2)
plot_with_weights(explanation2, 0.2)
plot_explanation_heatmap(explanation2)
```

Prediction: pneumonia
Label: pneumonia




Explanation for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60


Explanation for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60


Explanation - with weights - for classification
0
10
20
30
40
50
60

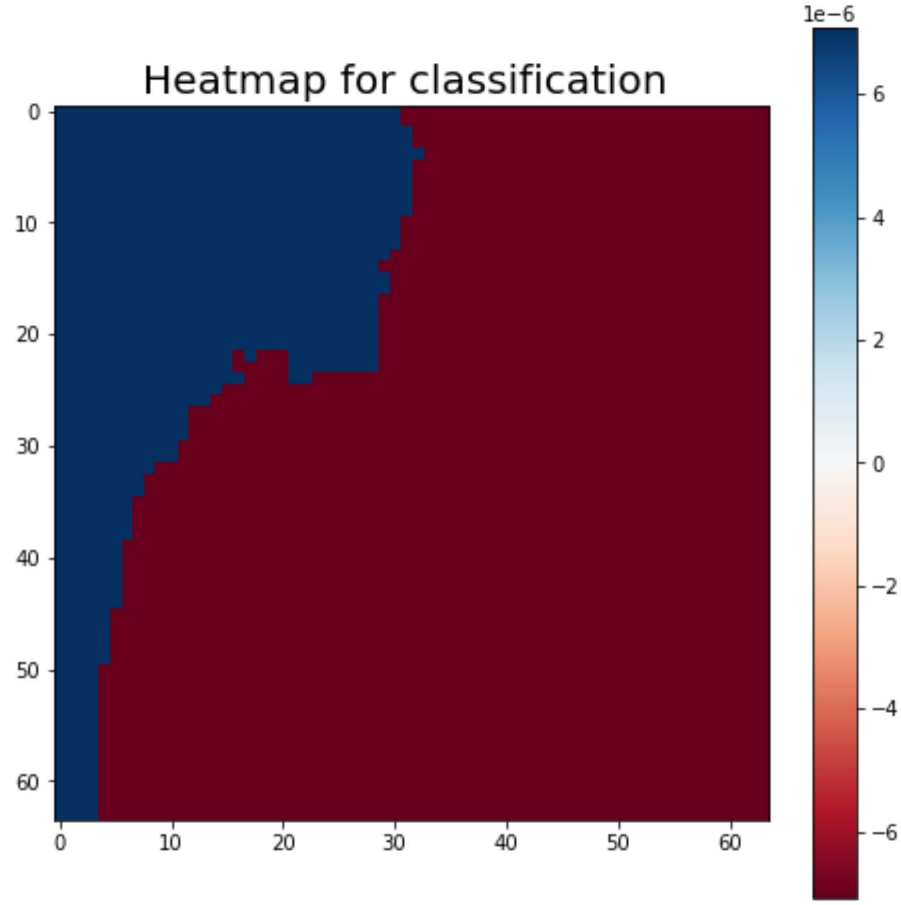
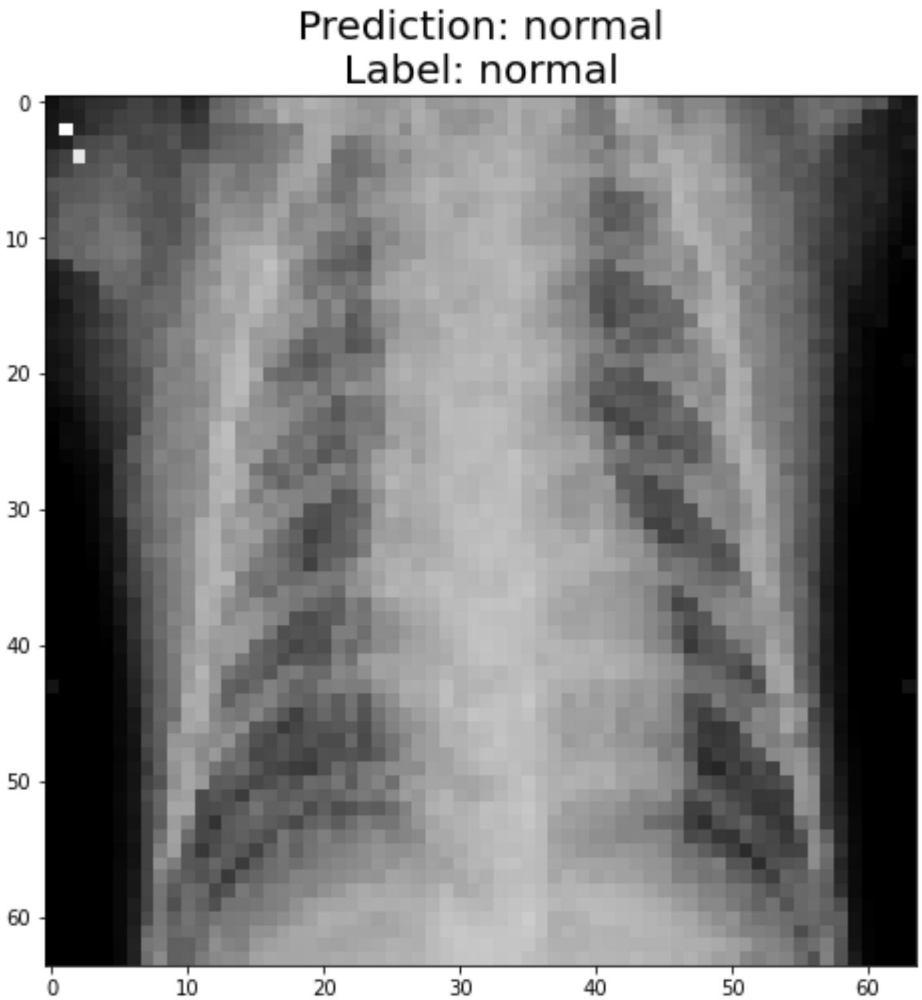


Image 3: A Positive Image

The first one I find

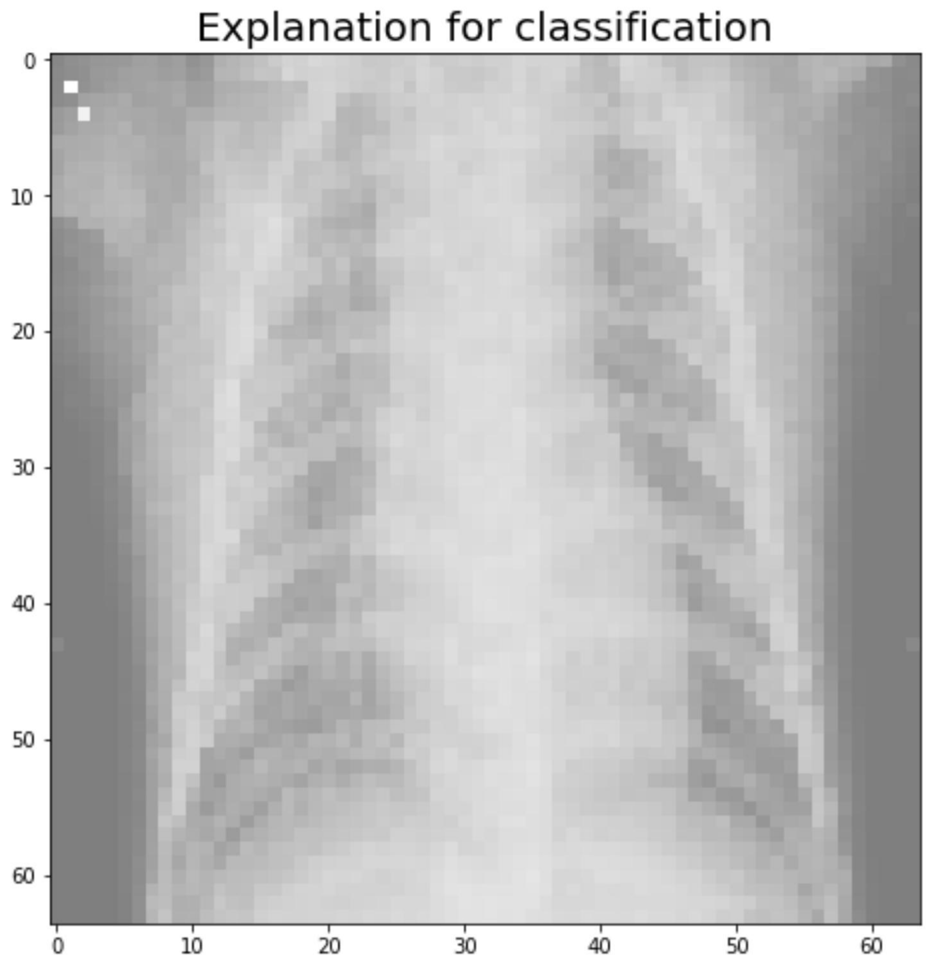
In [ ]:
```python
plot_image_preds(723)
```



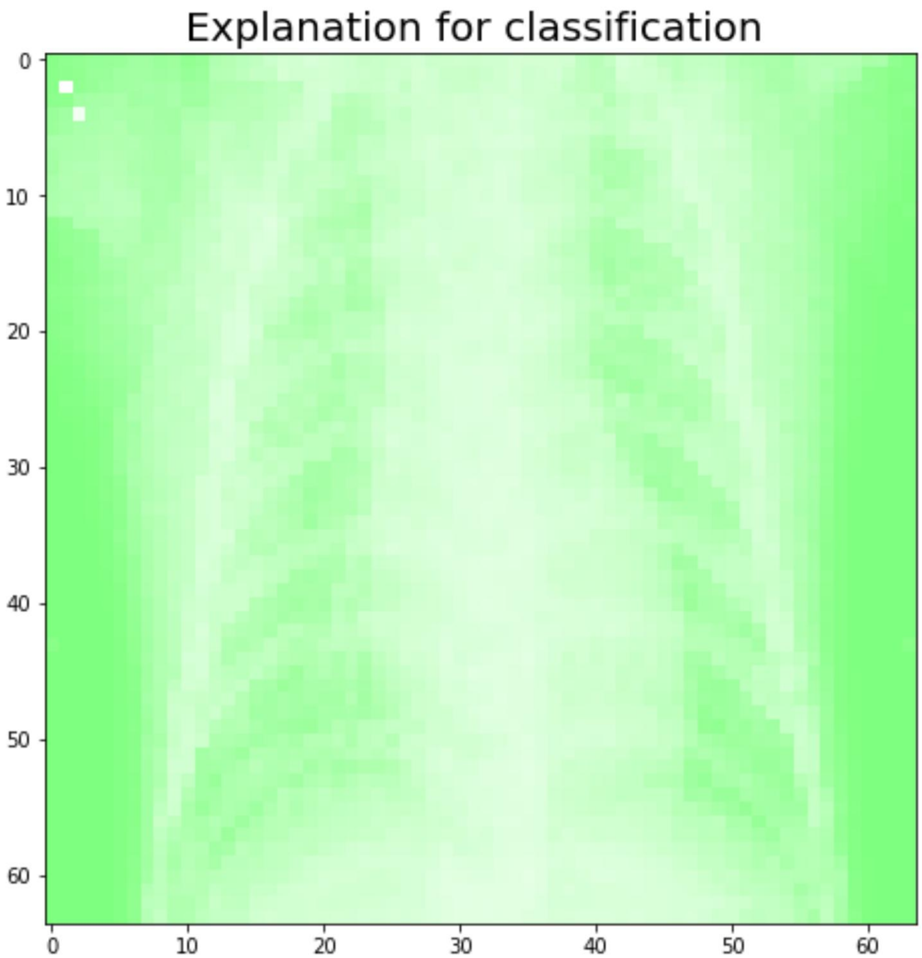
In [ ]:
```python
explanation3 = explainer.explain_instance(train_images[723].astype("double"), model4.predict, top_labels = 2, hide_color=0, num_samples=10000)
```

```
100%|██████████| 10000/10000 [00:44<00:00, 225.18it/s]
```

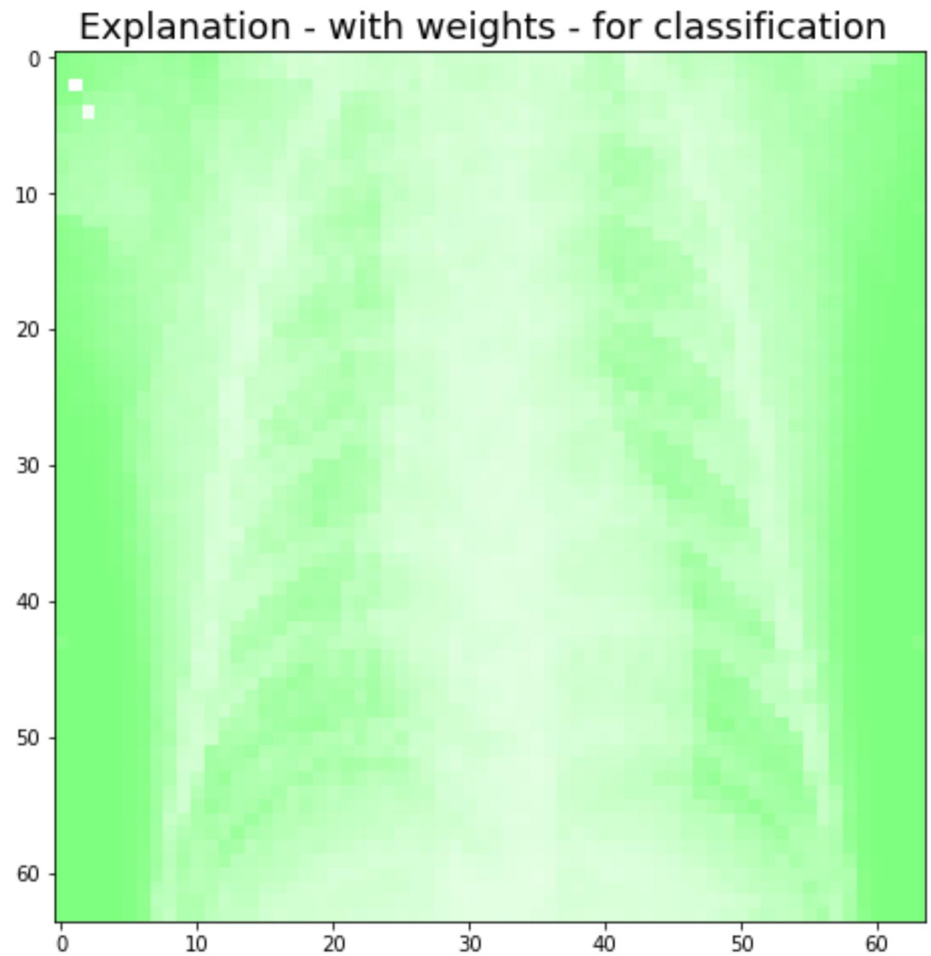
In [ ]:
```
plot_explanation(explanation3)
plot_pos_neg_explanation(explanation3)
plot_with_weights(explanation3, 0.2)
plot_explanation_heatmap(explanation3)
```



Explanation for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60



Explanation for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60


Explanation - with weights - for classification
0
10
20
30
40
50
60
0 10 20 30 40 50 60

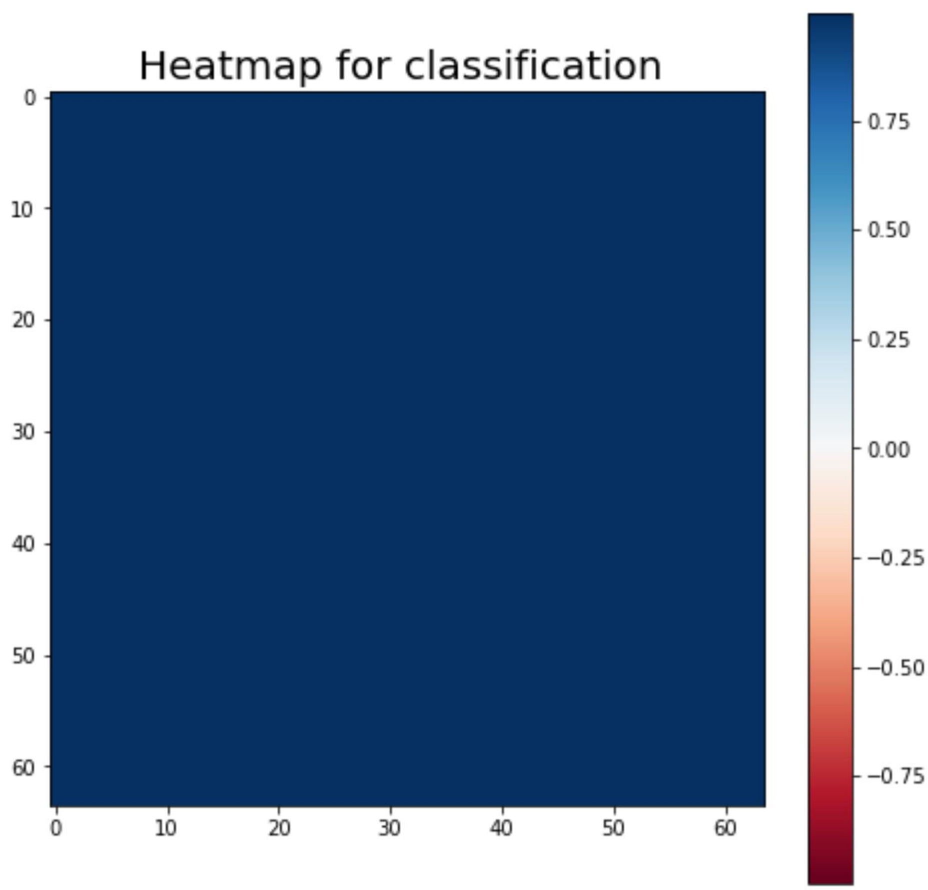
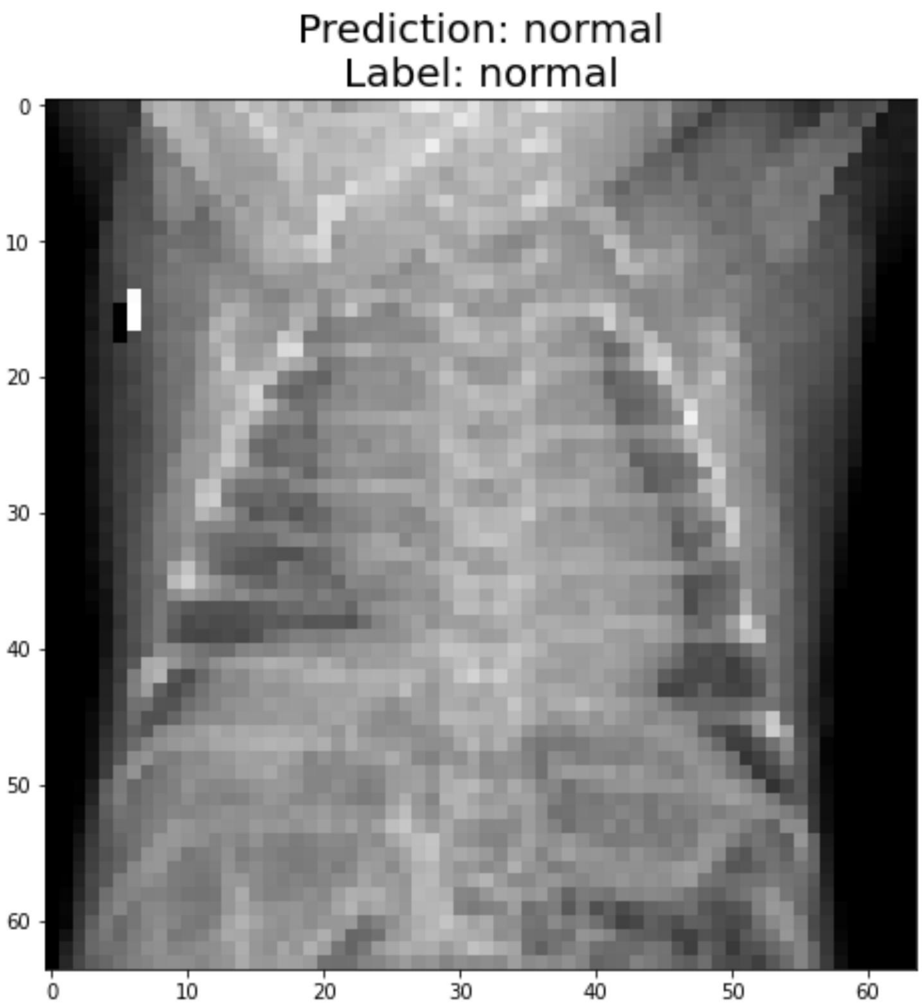

Heatmap for classification
0
10
20
30
40
50
60
0 10 20 30 40 50 60
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

Image 4

In [ ]:
```
explanation4 = explainer.explain_instance(train_images[804].astype("double"), model4.predict, top_labels = 2, hide_color=0, num_samples=10000)
```

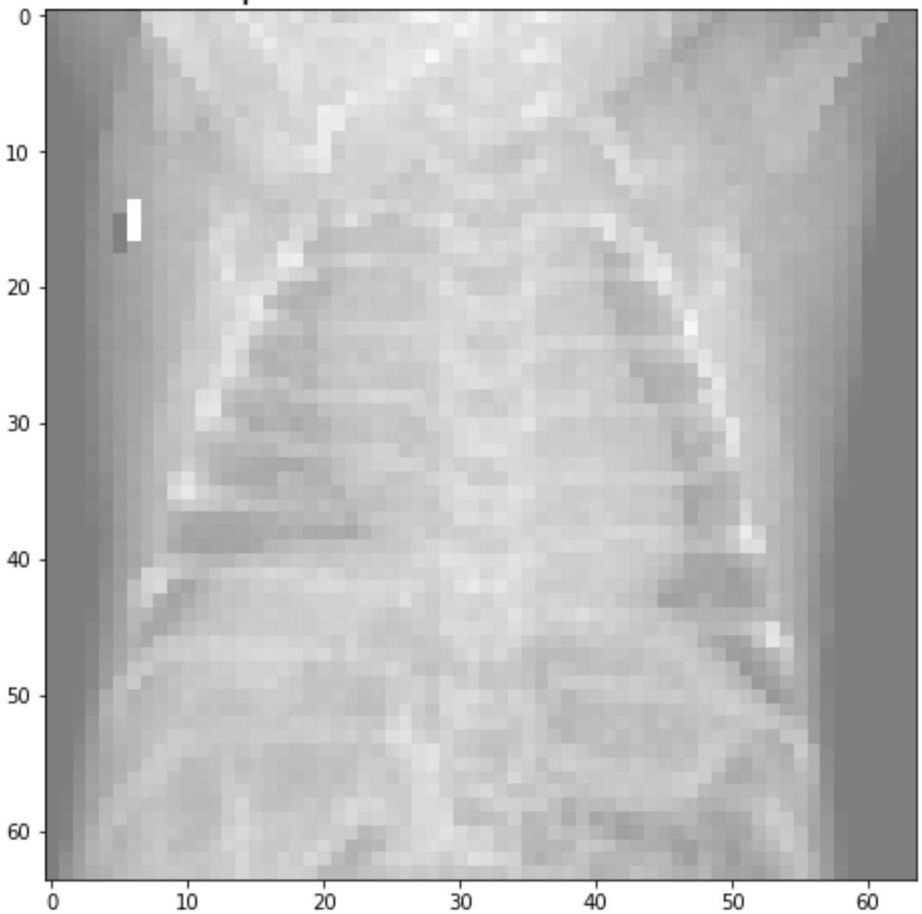
```
100%|██████████| 10000/10000 [00:44<00:00, 223.34it/s]
```

In [ ]:
```
plot_image_preds(804)
```

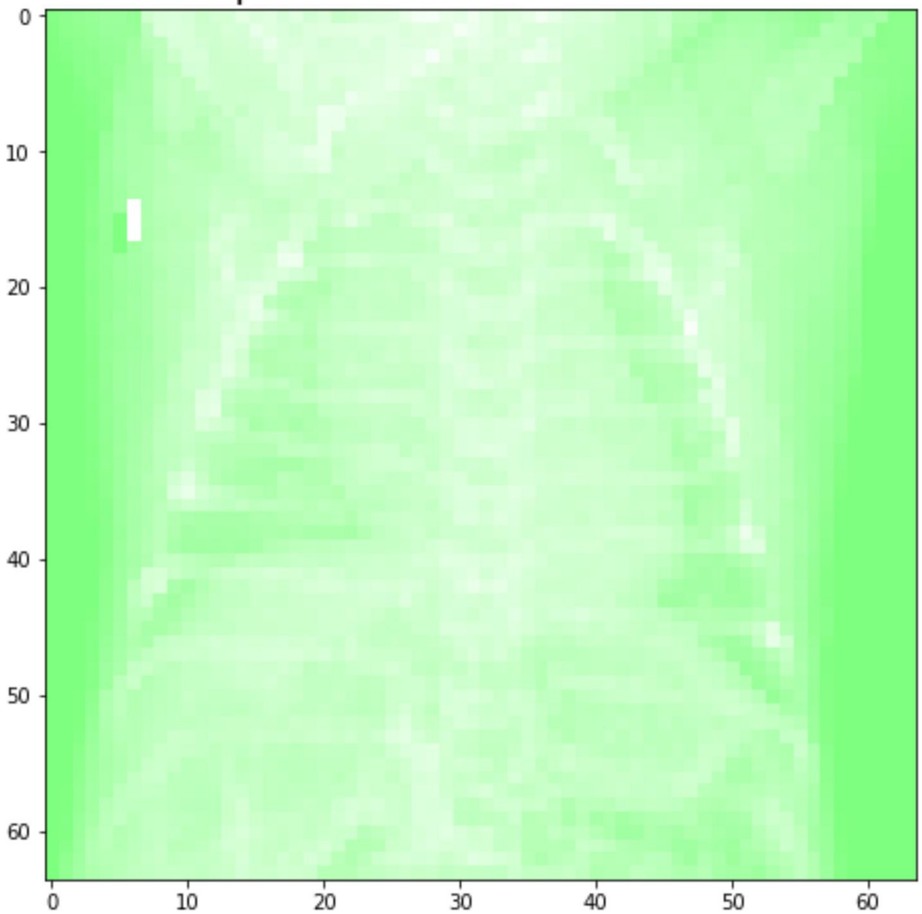


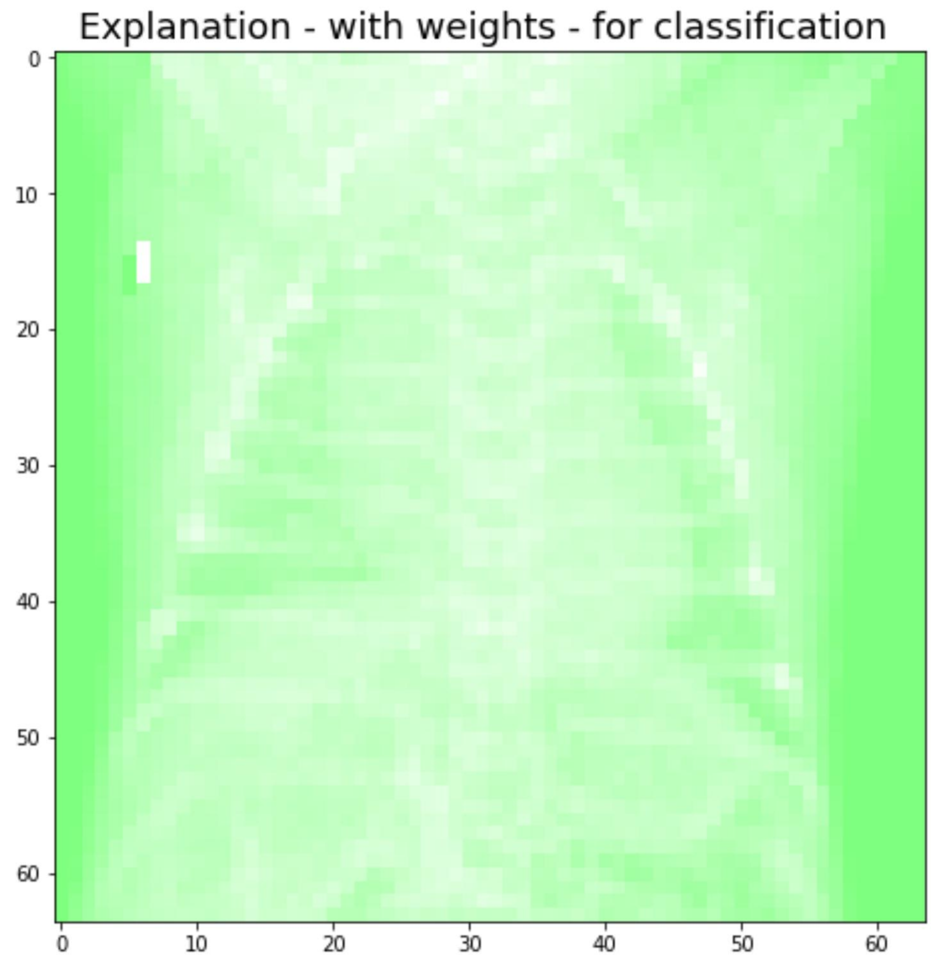
In [ ]:
```
plot_explanation(explanation4)
plot_pos_neg_explanation(explanation4)
plot_with_weights(explanation4, 0.2)
plot_explanation_heatmap(explanation4)
```

Explanation for classification



Explanation for classification




Explanation - with weights - for classification

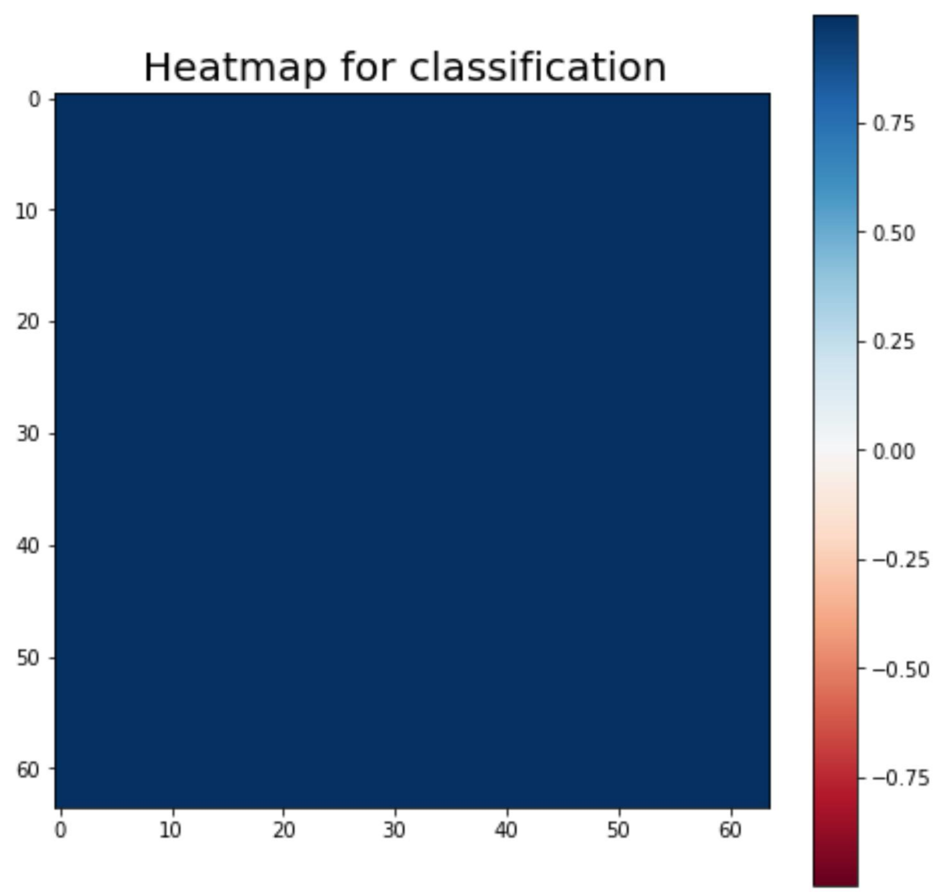
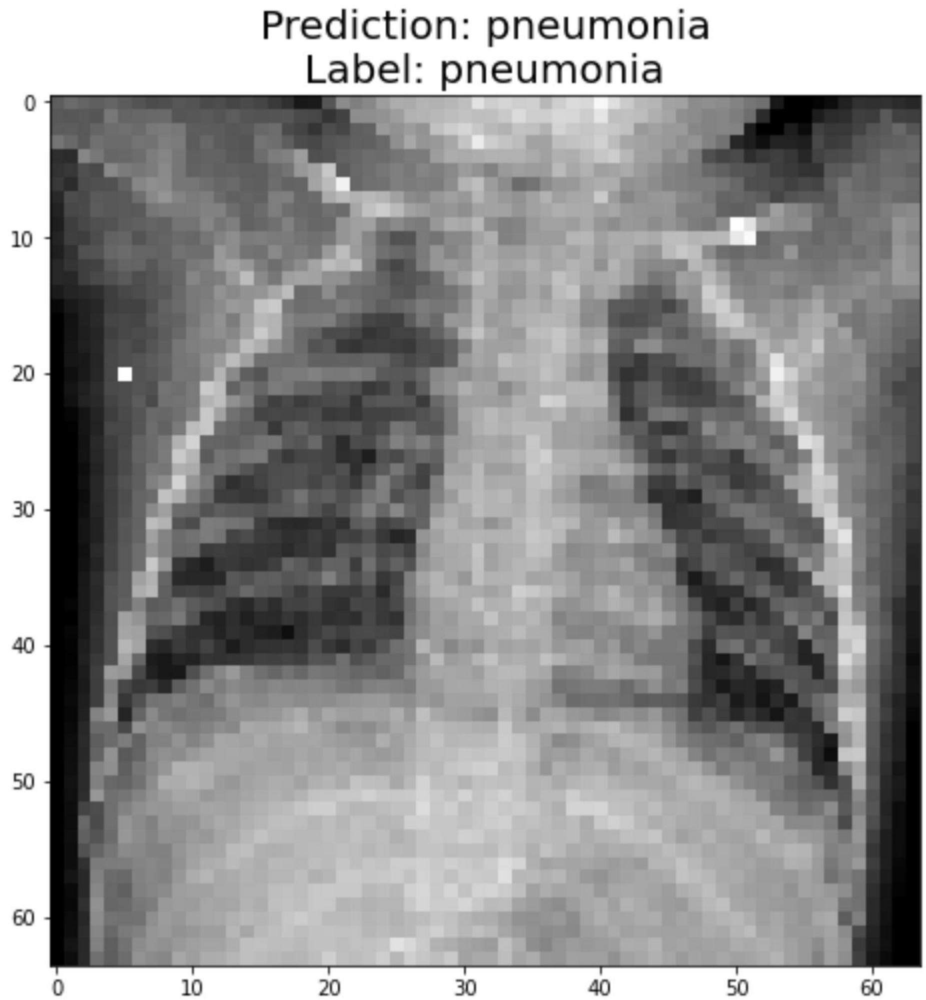

Heatmap for classification

Image 5

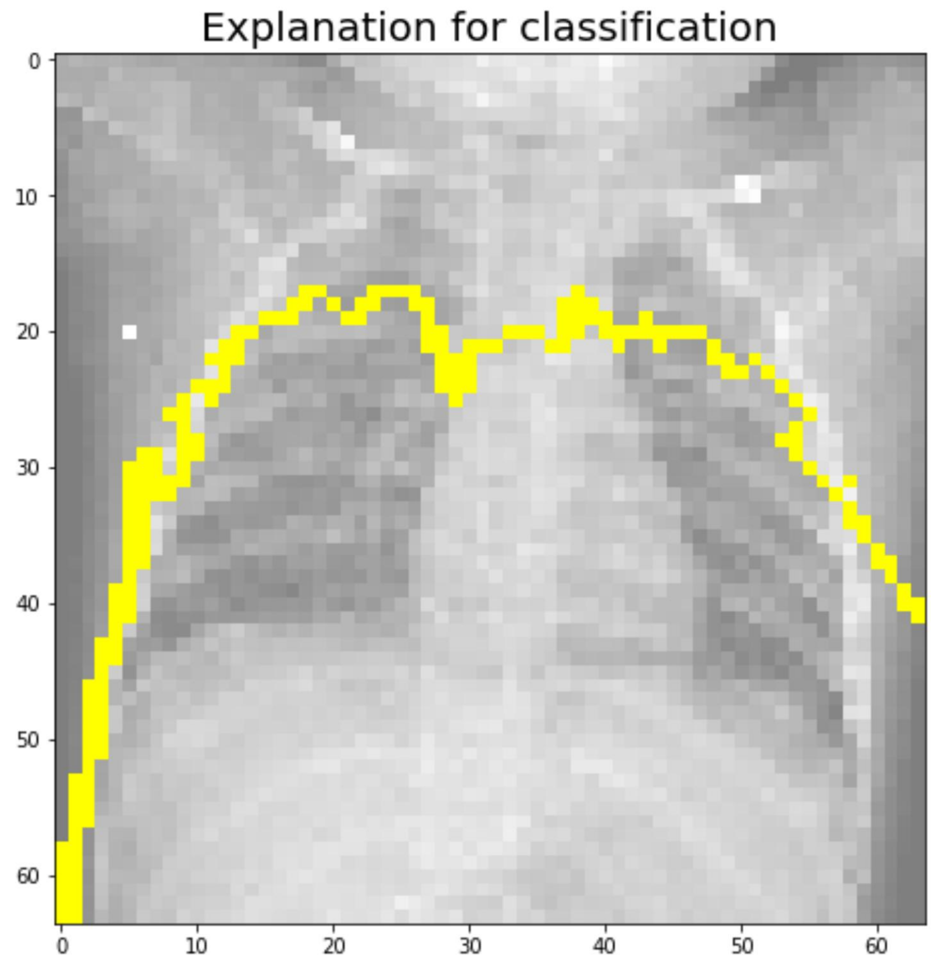
In [ ]:
```
plot_image_preds(233)
```

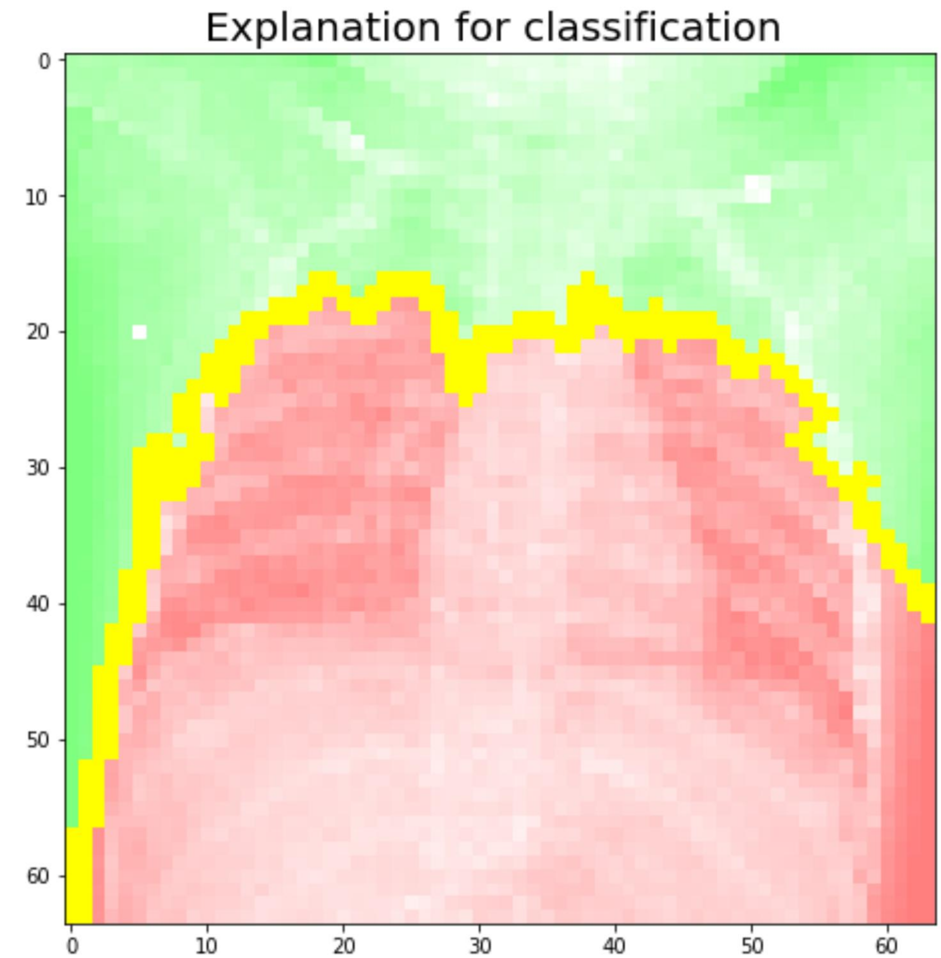


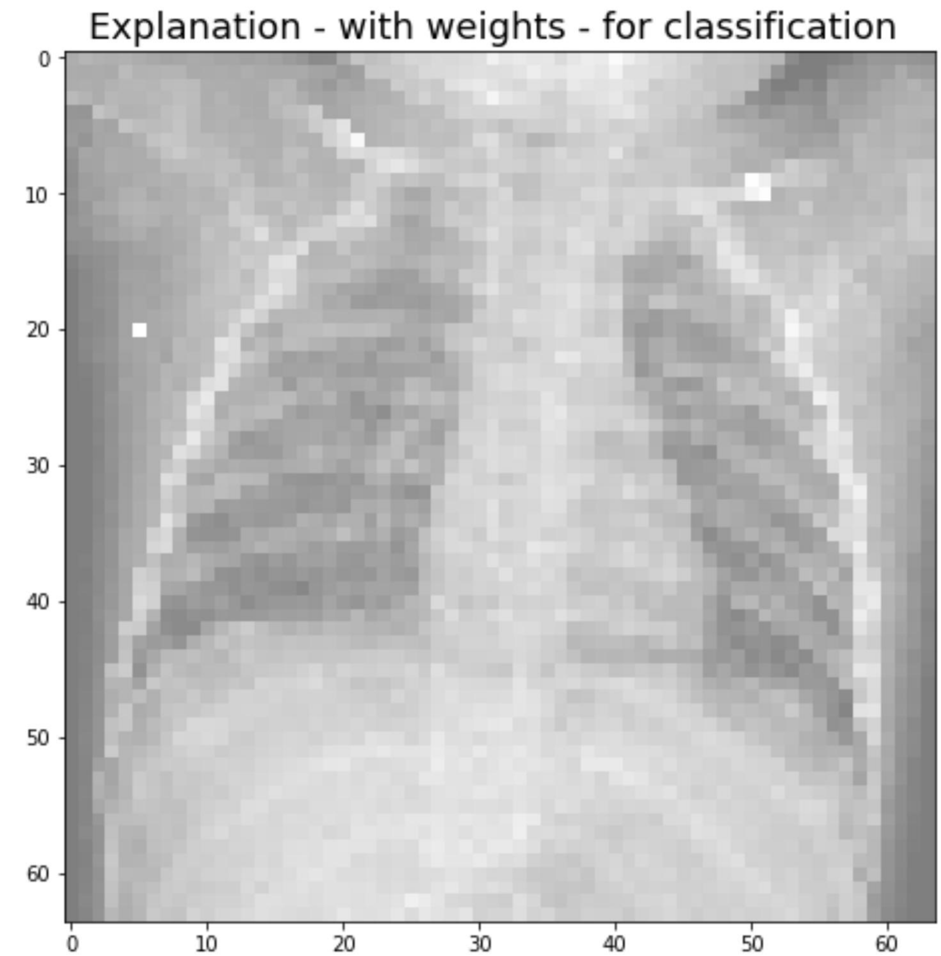
In [ ]:
```
explanation5 = explainer.explain_instance(train_images[233].astype("doubl
e"), model4.predict, top_labels = 2, hide_color=0, num_samples=10000)
```

```
100%|██████████| 10000/10000 [00:42<00:00, 235.76it/s]
```

In [ ]:
```
plot_explanation(explanation5)
plot_pos_neg_explanation(explanation5)
plot_with_weights(explanation5, 0.2)
plot_explanation_heatmap(explanation5)
```




Explanation for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60


Explanation - with weights - for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60

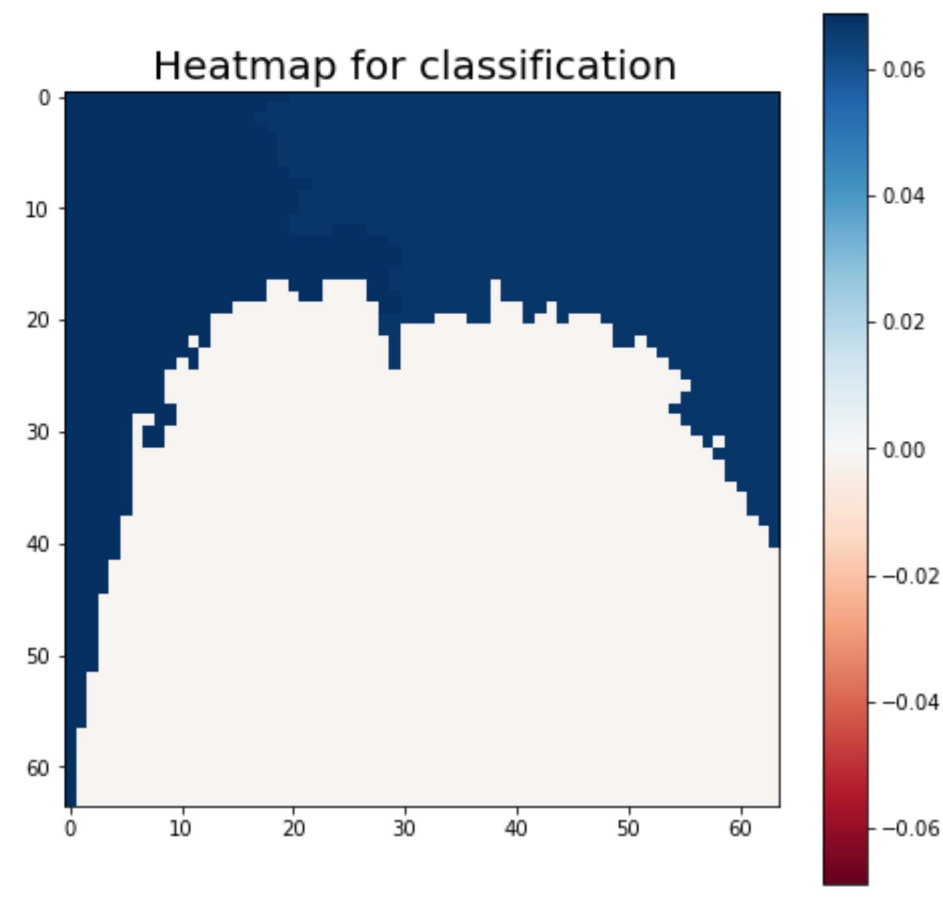
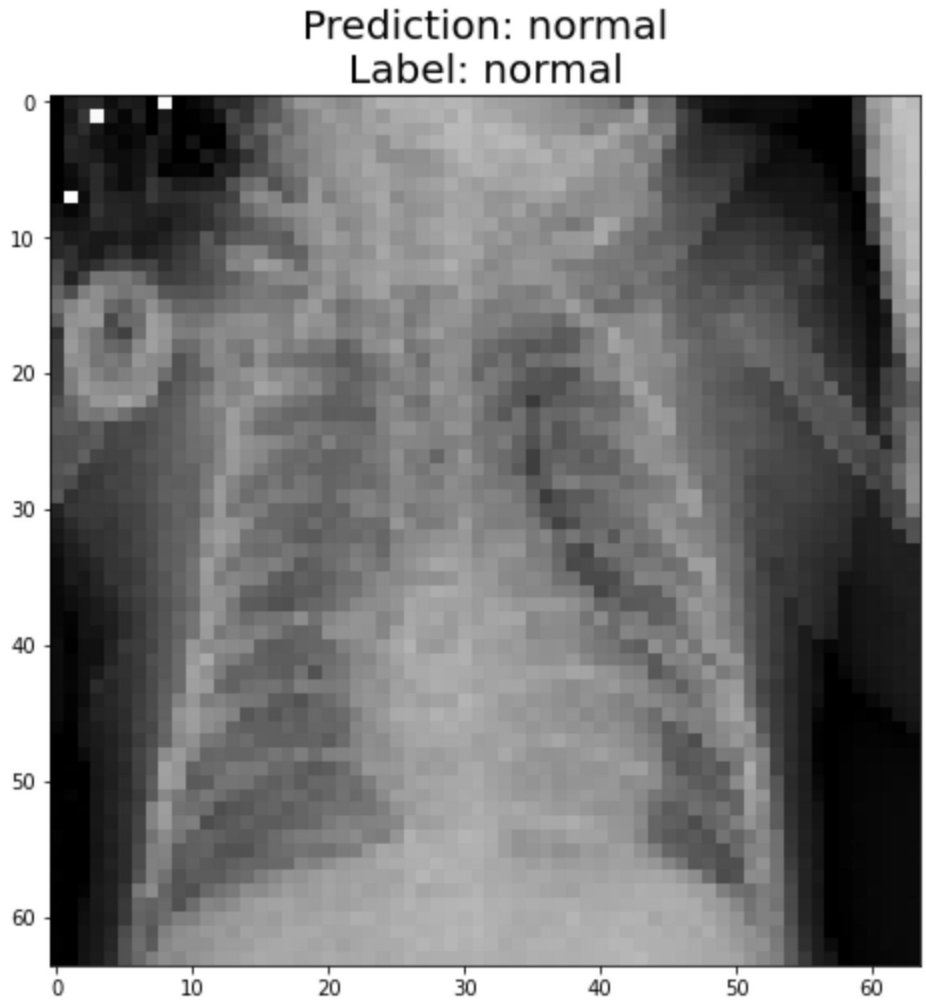

Heatmap for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06

Image 6

In [ ]:
```
plot_image_preds(414)
```

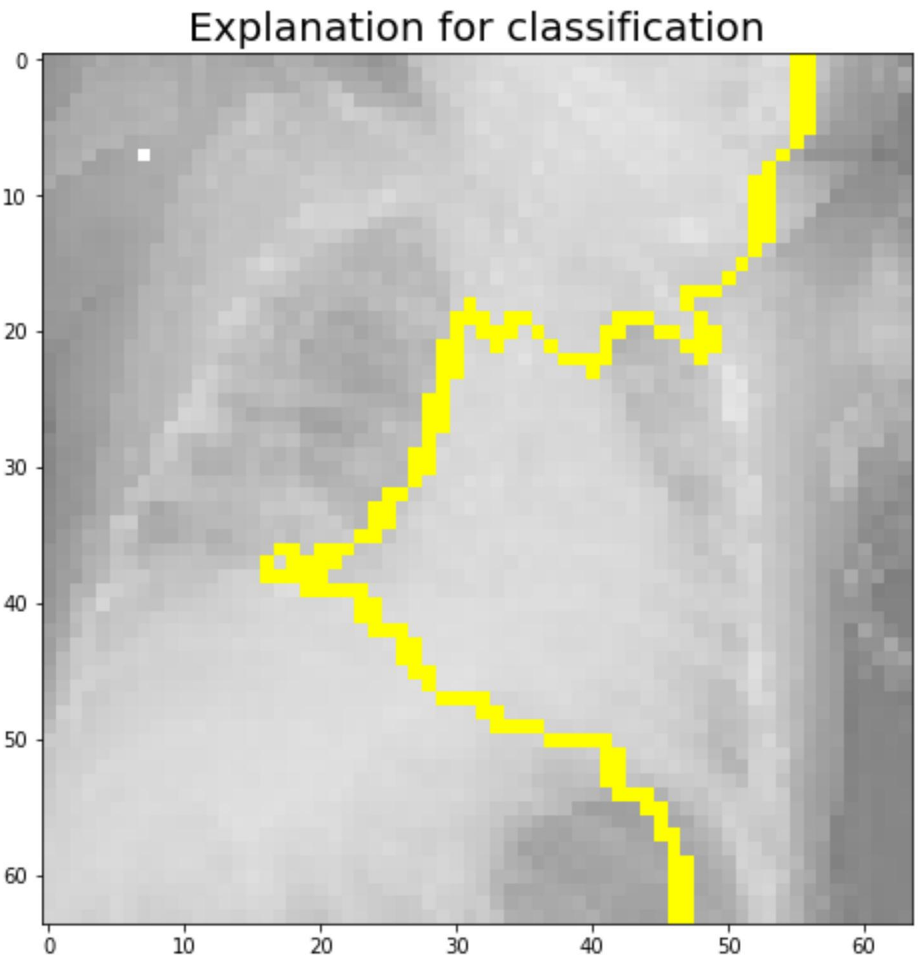


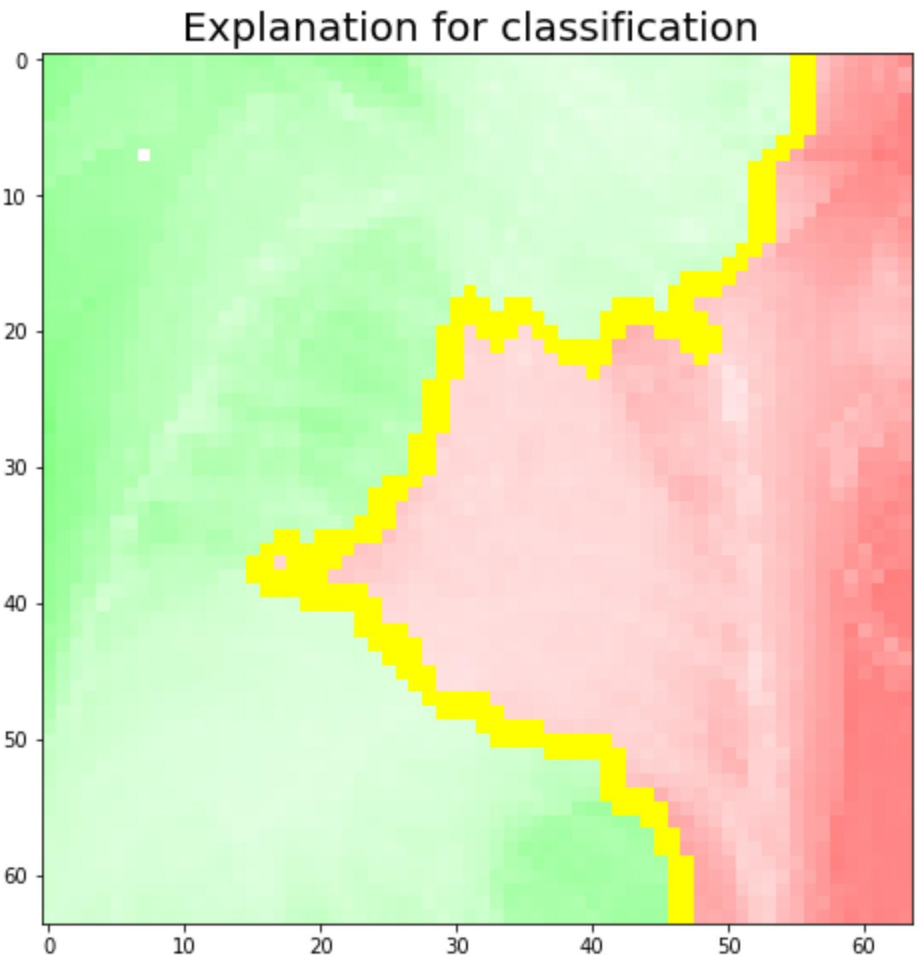
In [ ]:
```
# Image 123 is pneumonia
explanation6 = explainer.explain_instance(train_images[123].astype("double"), model4.predict, top_labels = 2, hide_color=0, num_samples=10000)
```

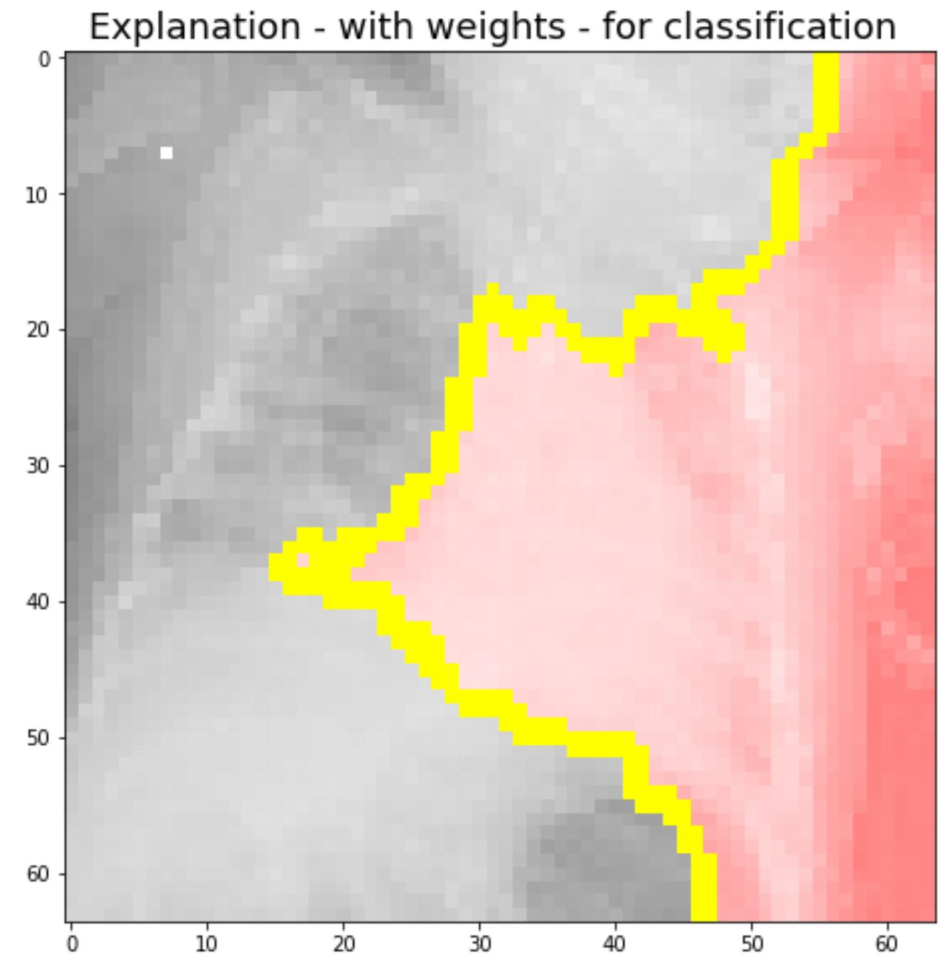
```
100%|██████████| 10000/10000 [00:41<00:00, 240.08it/s]
```

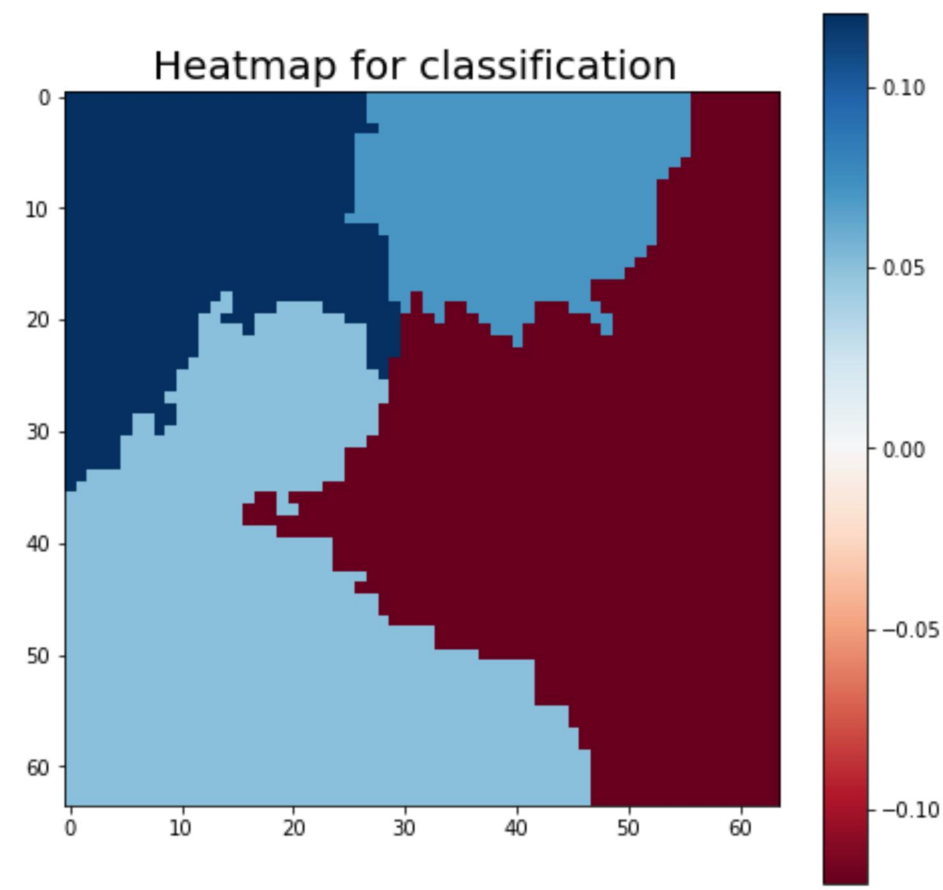
In [ ]:

```
plot_explanation(explanation6)
plot_pos_neg_explanation(explanation6)
plot_with_weights(explanation6, 0.2)
plot_explanation_heatmap(explanation6)
```


Explanation for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60


Explanation for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60


Explanation - with weights - for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60


Heatmap for classification
0
10
20
30
40
50
60
0
10
20
30
40
50
60
0.10
0.05
0.00
−0.05
−0.10

Conclusion

The VGG Model had the best F-beta score, making it the best model for this project.

Final Results

The final result included 1,239 true positives, 421 true negatives, 40 false negatives, and 52 false positives.

The final recall-weighted F-score (or, F-beta score) was .961.

The total accuracy was 94.7 percent.

Recall is the number of true positives divided by the total number of elements that actually belong to the positive class -i.e., true positives plus false negatives.

- Recall equaled .960.
- Precision equaled .969.
- The F1 Score equaled .964.

In product terms, this means that we could expect the model to correctly pick if an individual has pneumonia based on their x-ray 91.4 percent of the time. Further, it has a much higher false positive rate than false negative, as it was designed to.

If I could further this project, I would attempt further data augmentation. The data augmentation I attempted did not improve the performance of the model, although that portion of the model was cut out for brevity, along with numerous other versions of the CNNs.

Thank you.