Notebook

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1 Image Classification with Deep Learning Project #4

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- Scheduled project review date/time: ***January, 2023***
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1.0.1 Overview:

- A radiology department at ”Be Well Healthcare Center’ is interested in decreasing the work load of its radiologists by hiring a data scientist to develop a machine learning model to screen chest x-ray images and automatically mark those with pneumonia.
- My goal is to build a Neural Network model to classify chest x-ray images as belonging to one of the two categoies: pneumonia and normal. My main purpose was to make predictions as accurately as possible while maximizing the number of True Positives (recall) and minimizing False Negatives, so that we catch as many people as possible with pneumonia (at the expense of marking some healthy people with pneumonia).

1.0.2 Data Understanding:

The data was obtained from Kaggle. 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.

For the analysis of chest x-ray images, all chest radiographs were initially screened for quality control by removing all low quality or unreadable scans. The diagnoses for the images were then graded by two expert physicians before being cleared for training the AI system. In order to account for any grading errors, the evaluation set was also checked by a third expert.

1.0.3 Modeling:

1. The data was re-split into training, test and val sets using different ratios: 80% for train, 10% for validation and 10% for the test set.
2. The data was pre-processed, specifically the images were re-scaled and standardized.
3. Several versions of neural networks were built, tuned and validated:

- Artificial Neural Network ANN
- Convolutional Neural Network CNN
- Transfer Learning with VGG16
- Transfer Learning with ResNest50V2

1.0.4 Evaluation:

4. Accuracy was used as the scoring metric for tuning hyperparameters and recall was used for evaluating model performance. Whilst we would prefer an overall higher accuracy, our focus is on recall as this metric is particularly important for patient safety and to minimize the legal risk.

[1]:
```
# Import required packages
import pandas as pd
import numpy as np
import seaborn as sns
import math

import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import seaborn as sns
%matplotlib inline

from tensorflow import keras
from keras import layers
from keras import models
from keras import optimizers
from keras import regularizers
from keras.models import Sequential
from keras.layers import Dense, Conv2D , MaxPool2D , Flatten , Dropout ,␣
↪BatchNormalization
from keras.regularizers import l2
from keras.optimizers import SGD
from keras.wrappers import scikit_learn
from keras.callbacks import EarlyStopping, ModelCheckpoint
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator

from sklearn.metrics import classification_report, accuracy_score,␣
↪confusion_matrix, ConfusionMatrixDisplay

import warnings
warnings.filterwarnings('ignore')

import os
```

[2]:
```
# Making sure we work on CPU
# You can set environment variables in the notebook using os.environ. Do the␣
↪following before initializing TensorFlow to limit TensorFlow to first GPU.
os.environ["CUDA_DEVICE_ORDER"]="PCI_BUS_ID"
os.environ["CUDA_VISIBLE_DEVICES"]="0"``

# You can double check that you have the correct devices visible to TF
from tensorflow.python.client import device_lib
print(device_lib.list_local_devices())
```

```
[name: "/device:CPU:0"
device_type: "CPU"
memory_limit: 268435456
locality {
}
incarnation: 5315553729275501727
, name: "/device:XLA_CPU:0"
device_type: "XLA_CPU"
memory_limit: 17179869184
locality {
}
incarnation: 9774807852142177369
physical_device_desc: "device: XLA_CPU device"
]
```

2 Data Visualization

[3]:
```
# specify the local directory of train, validation and test data:
train_dir = "Data/chest_xray/train/"
val_dir = "Data/chest_xray/val/"
test_dir ="Data/chest_xray/test/"
```

2.0.1 Display the first image with pneumonia from the train dataset:

[179]:
```
os.listdir("Data/chest_xray/train/PNEUMONIA")[0]
```

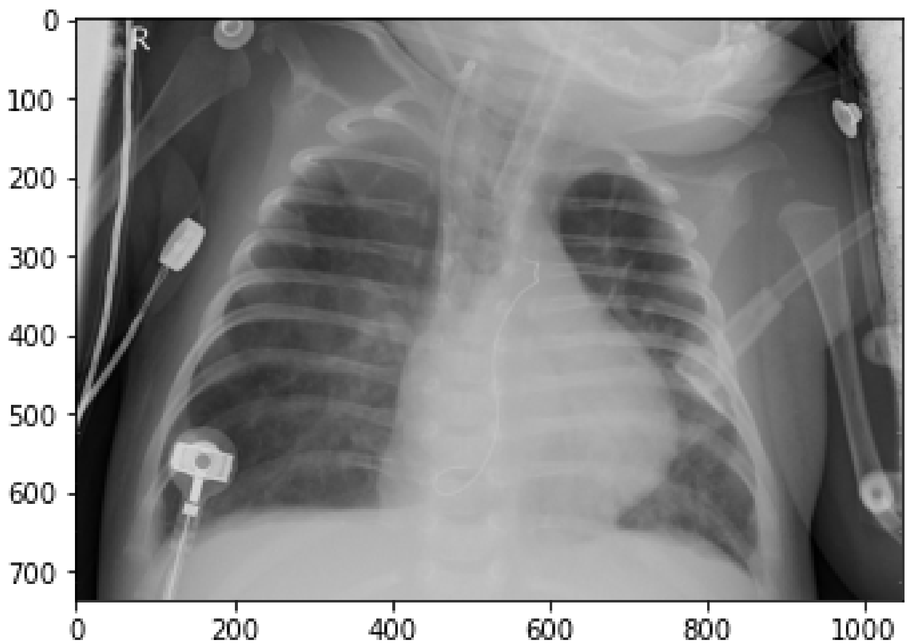
[179]:
```
'person63_bacteria_306.jpeg'
```

[256]:
```
filename = 'Data/chest_xray/train/PNEUMONIA/person63_bacteria_306.jpeg'
sample_img = image.load_img(filename)
img_array = image.img_to_array(sample_img)  # converts image into a numpy array

print(f"Image Shape: {img_array.shape}")  # width and height
print(f"Max pixel: {img_array.max()}")
print(f"Min pixel: {img_array.min()}")
print(f"Image: {img_array}")
```

```python
# Display the image
plt.imshow(sample_img, cmap='gray'); # plt.imshow(img_array.astype('uint8'))

# another way to open image:
# from PIL import Image
# img = Image.open(filename)
```

```
Image Shape: (736, 1048, 3)
Max pixel: 255.0
Min pixel: 0.0
Image: [[[210. 210. 210.]
  [208. 208. 208.]
  [206. 206. 206.]
  …
  [213. 213. 213.]
  [215. 215. 215.]
  [216. 216. 216.]]

 [[210. 210. 210.]
  [208. 208. 208.]
  [206. 206. 206.]
  …
  [213. 213. 213.]
  [216. 216. 216.]
  [217. 217. 217.]]

 [[210. 210. 210.]
  [208. 208. 208.]
  [205. 205. 205.]
  …
  [213. 213. 213.]
  [216. 216. 216.]
  [218. 218. 218.]]

 …

 [[ 16.  16.  16.]
  [ 15.  15.  15.]
  [ 14.  14.  14.]
  …
  [ 47.  47.  47.]
  [ 47.  47.  47.]
  [ 47.  47.  47.]]

 [[ 16.  16.  16.]
  [ 15.  15.  15.]
```

```
 [ 14.   14.   14.]
 …
 [ 46.   46.   46.]
 [ 46.   46.   46.]
 [ 46.   46.   46.]]

[[ 16.   16.   16.]
 [ 15.   15.   15.]
 [ 14.   14.   14.]
 …
 [ 46.   46.   46.]
 [ 46.   46.   46.]
 [ 46.   46.   46.]]]
```

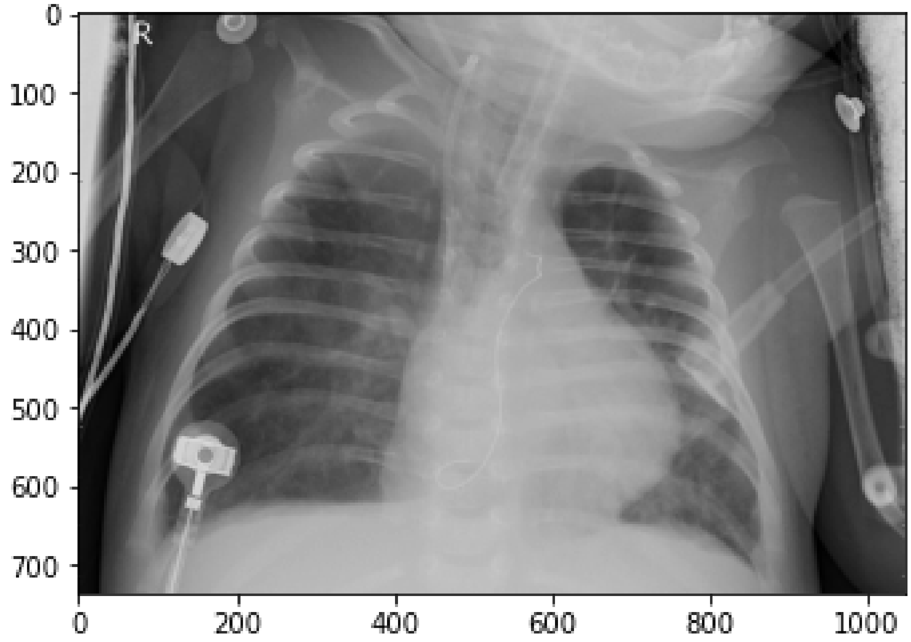


[257]:
```python
# show RGB for 48th row, 454th column
img_array[48][454]
```

[257]:
```
array([141., 141., 141.], dtype=float32)
```

[262]:
```python
# reduce the 3 dimensions (RGB) into one dimension (only R):
oneDim_image = img_array[:,:,0] #
plt.imshow(oneDim_image.astype('uint8'), cmap='gray')
# same image as above, there is no color contribution.
```

[262]:
```
<matplotlib.image.AxesImage at 0x7fcbb71a4d60>
```

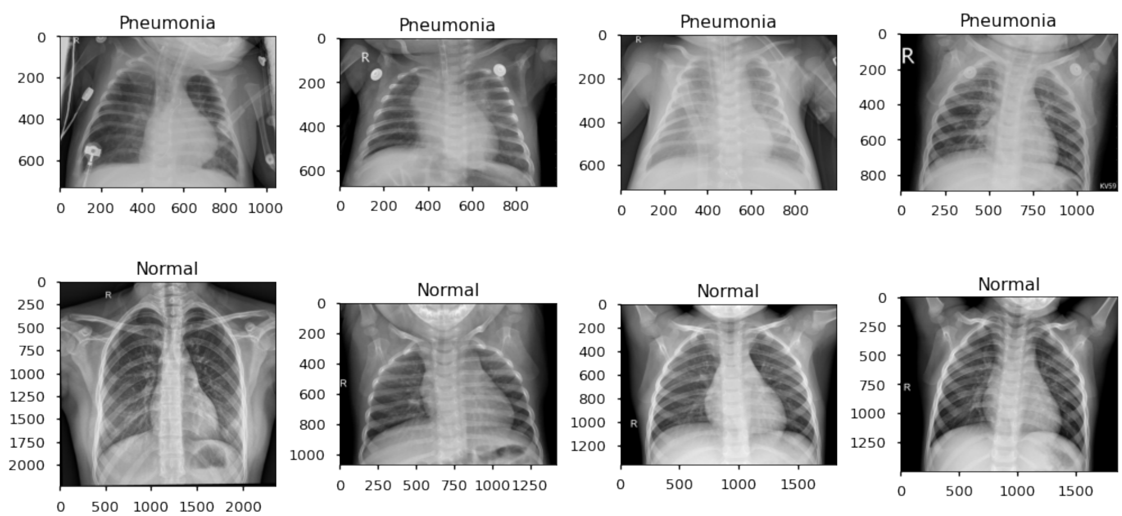


- The dimensions of the image are 1048 pixels width and 736 pixels height.
- Coded as RGB color mode although the raw image is grayscale and the pixels repeat.
- The maximum pixel value is 255 and the minimum is 0.

2.0.2 Visualize the first 4 normal and 4 pneumonia x-rays:

[185]:
```
# Specify the set of images inside pnemonia and normal
pneumonia = os.listdir("Data/chest_xray/train/PNEUMONIA")
normal = os.listdir("Data/chest_xray/train/NORMAL")

# Specify the location of the files = the directory
pneumonia_dir = "Data/chest_xray/train/PNEUMONIA"
normal_dir = "Data/chest_xray/train/NORMAL"

# Show the first four pictures from the train set of X-rays with and with/o␣
↪Pneumonia

with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(2, 4, figsize=(14,7))
    for i in range(4):
        # Combine the image directory with the specific jpeg to be able to␣
↪locate it
        # Read the image into an array.
        img_pneumonia = plt.imread(os.path.join(pneumonia_dir, pneumonia[i]))
        img_normal = plt.imread(os.path.join(normal_dir, normal[i]))
```

```
        # Display the image
        ax[0,i].imshow(img_pneumonia, cmap = 'gray')
        ax[1,i].imshow(img_normal, cmap = 'gray')

        # ax[0,i].set_axis_off()
        # ax[1,i].set_axis_off()

        ax[0,i].set_title("Pneumonia")
        ax[1,i].set_title("Normal")

plt.tight_layout()
plt.savefig('./images/RawImages', dpi=300, bbox_inches='tight')
```



- The normal chest X-ray (top panel) seem to depict more clear lungs without any areas of abnormal opacification.
- The chest X-ray (bottom panel) with pneumonia seem to depict less clear lungs with some areas of opacification/consolidation.

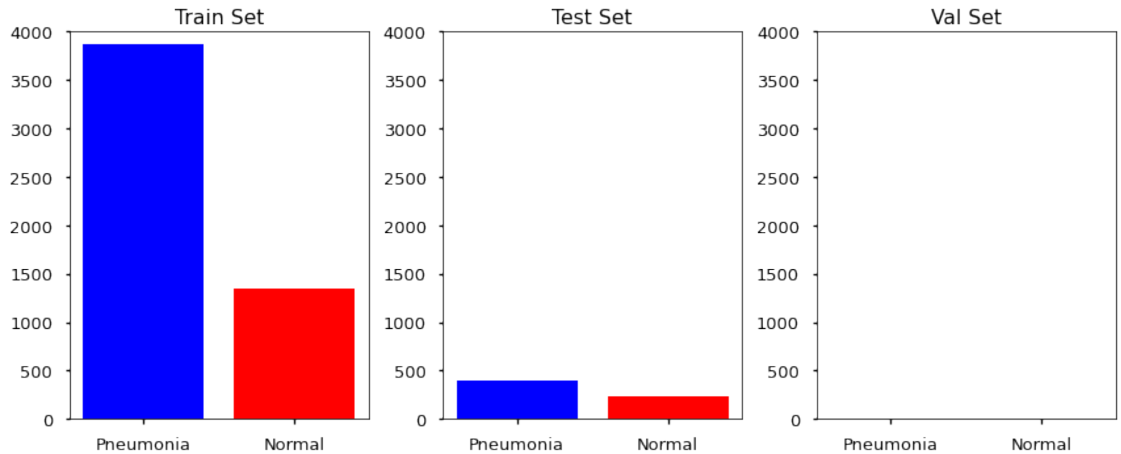
2.0.3 What is total number of normal and pneumonia images in the train-test-val sets?

[10]:
```
# Specify the set of images inside pnemonia and normal for train, test, val␣
↪sets:
num_pneumonia_train = (len(os.listdir("Data/chest_xray/train/PNEUMONIA")) )
num_normal_train = (len(os.listdir("Data/chest_xray/train/NORMAL")) )

num_pneumonia_test = (len(os.listdir("Data/chest_xray/test/PNEUMONIA")) )
num_normal_test = (len(os.listdir("Data/chest_xray/test/NORMAL")) )
```

```python
num_pneumonia_val = (len(os.listdir("Data/chest_xray/val/PNEUMONIA")) )
num_normal_val = (len(os.listdir("Data/chest_xray/val/NORMAL")))

with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12, 5))
    ax1.bar(x = ["Pneumonia","Normal"], height=[num_pneumonia_train, num_normal_train], color=["blue", "red"])
    ax1.set_title('Train Set')
    ax2.bar(x = ["Pneumonia","Normal"], height=[num_pneumonia_test, num_normal_test], color=["blue", "red"])
    ax2.set_title('Test Set')
    ax3.bar(x = ["Pneumonia","Normal"], height=[num_pneumonia_val, num_normal_val], color=["blue", "red"])
    ax3.set_title('Val Set')

    ax1.set_ylim([0, 4000])
    ax2.set_ylim([0, 4000])
    ax3.set_ylim([0, 4000])
    plt.tight_layout()

print(f"Train Pneumomia: {num_pneumonia_train}")
print(f"Train Normal: {num_normal_train}")
print("-------------------")
print(f"Test Pneumomia: {num_pneumonia_test}")
print(f"Test Normal: {num_normal_test}")
print("--------------------")
print(f"Val Pneumomia: {num_pneumonia_val}")
print(f"Val Normal: {num_normal_val}")
print("--------------------")

TrainTotal = num_pneumonia_train + num_normal_train
TestTotal = num_pneumonia_test + num_normal_test
ValTotal = num_pneumonia_val + num_normal_val
Total = TrainTotal + TestTotal + ValTotal
print(f"Train Images Percentage: {np.round((TrainTotal / Total),3) }")
print(f"Test Images Percentage: {np.round((TestTotal / Total),3) }")
print(f"Val Images Percentage: {np.round((ValTotal / Total),3) }")
```

```
Train Pneumomia: 3876
Train Normal: 1342
-------------------
Test Pneumomia: 390
Test Normal: 234
--------------------
Val Pneumomia: 9
Val Normal: 9
--------------------
```

```
Train Images Percentage: 0.89
Test Images Percentage: 0.106
Val Images Percentage: 0.003
```



- Number of images in the **validation** set appears too low with a total of 18 images and total percentage of **.3%**. We need to boost it to at about 10%.
- Number of images in the **test** set appears ideal with a total percentage of **10%**.
- Number of images in the **train** set is good with a total percentage of **89%**, but we will move some of the images from train to the validation set to boost the numbers in the val set. 80% is sufficient for the train set.

2.0.4 Change the size of the Train-Test-Val sets:

- Using splitfolders package (https://pypi.org/project/split-folders/)
- Split the data in the folder **“Data/INPUT”** with **“Pneumonia” and “Normal”** subfolders into the output folder **“Data/OUTPUT”** with **“train”,“test”,“val”** subfolders using the pre-specified percentages.

[11]:
```python
# !pip install split-folders
import splitfolders

# Change the size of Train, Test and Val sets with ratios: .81, .09, .1.
# To only split into training and validation set, set a tuple to `ratio`, i.e,␣
↪`(.8, .2)`.
splitfolders.ratio("Data/INPUT", output="Data/OUTPUT",
    seed=1337, ratio=(.81, .09, .1), group_prefix=None, move=False) # default␣
↪values
```

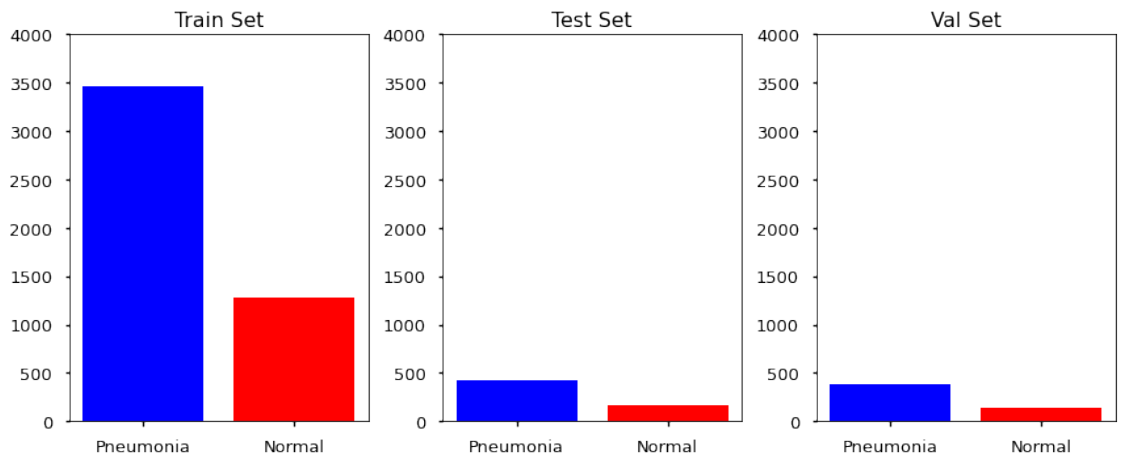
```
Copying files: 5856 files [00:08, 694.03 files/s]
```

2.0.5 What is total number of normal and pneumonia images in the NEW train-test-val sets?

[12]:
```
num_pneumonia_train = (len(os.listdir("Data/OUTPUT/train/PNEUMONIA")) )
num_normal_train = (len(os.listdir("Data/OUTPUT/train/NORMAL")) )

num_pneumonia_test = (len(os.listdir("Data/OUTPUT/test/PNEUMONIA")) )
num_normal_test = (len(os.listdir("Data/OUTPUT/test/NORMAL")) )

num_pneumonia_val = (len(os.listdir("Data/OUTPUT/val/PNEUMONIA")) )
num_normal_val = (len(os.listdir("Data/OUTPUT/val/NORMAL")))

with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12, 5))
    ax1.bar(x = ["Pneumonia","Normal"], height=[num_pneumonia_train,␣
 ↪num_normal_train], color=["blue", "red"])
    ax1.set_title('Train Set')
    ax2.bar(x = ["Pneumonia","Normal"], height=[num_pneumonia_test,␣
 ↪num_normal_test], color=["blue", "red"])
    ax2.set_title('Test Set')
    ax3.bar(x = ["Pneumonia","Normal"], height=[num_pneumonia_val,␣
 ↪num_normal_val], color=["blue", "red"])
    ax3.set_title('Val Set')

    ax1.set_ylim([0, 4000])
    ax2.set_ylim([0, 4000])
    ax3.set_ylim([0, 4000])
    plt.tight_layout()

print(f"Train Pneumomia: {num_pneumonia_train}")
print(f"Train Normal: {num_normal_train}")
print("--------------------")
print(f"Test Pneumomia: {num_pneumonia_test}")
print(f"Test Normal: {num_normal_test}")
print("---------------------")
print(f"Val Pneumomia: {num_pneumonia_val}")
print(f"Val Normal: {num_normal_val}")
print("---------------------")

TrainTotal = num_pneumonia_train + num_normal_train
TestTotal = num_pneumonia_test + num_normal_test
ValTotal = num_pneumonia_val + num_normal_val
Total = TrainTotal + TestTotal + ValTotal
print(f"Train Images Percentage: {np.round((TrainTotal / Total),3) }")
print(f"Test Images Percentage: {np.round((TestTotal / Total),3) }")
print(f"Val Images Percentage: {np.round((ValTotal / Total),3) }")
```

```
Train Pneumomia: 3461
```

```
Train Normal: 1282
-------------------
Test Pneumomia: 428
Test Normal: 159
--------------------
Val Pneumomia: 384
Val Normal: 142
--------------------
Train Images Percentage: 0.81
Test Images Percentage: 0.1
Val Images Percentage: 0.09
```



- New split looks much better with about 80% train, 10% test and 10% validation.

[13]:
```
# Specify the new location of the train, test and val images
train_dir = "Data/OUTPUT/train/"
test_dir ="Data/OUTPUT/test/"
val_dir = "Data/OUTPUT/val/"
```

3 Image Preprocessing:

3.1 Data Normalization:

- **Pixel Normalization**: For images, a common thing that is done is to make sure each pixel value is between 0 and 1. This can be done by dividing the entire matrix by 255.
- **Size Rescaling**: Since all of the images are different sizes, we need to rescale (standardize) them using a target width and height. We will use a size of 128x128. In general, the resolutions for training CNNs usually range between 64×64 and 256×256.
- **Reshaping into tensors**: Convolutional Neural Networks takes its input as **tensors**. We will use the output from flow_from_directory() directly to feed them into the CNNs.

- **Reshaping into vectors**: A multilayer perceptron (MLP) - fully connected atrificial Neural Network (ANN) takes its input as **vectors** (single-dimensional array), not matrices (2-D grid) or tensors (generalized matrix). So we need to reshape the images into a single 16384-dimensional vector (128x128) to feed them into the ANNs.

[14]:
```
print(f"Train Images Total#: {TrainTotal}")
print(f"Test Images Total#: {TestTotal}")
print(f"Val Images Total#: {ValTotal}")
```

```
Train Images Total#: 4743
Test Images Total#: 587
Val Images Total#: 526
```

3.1.1 Format the data using Keras ImageDataGenerator():

- Rescale pixel values to be between 0-1.
- Rescale the size to be 128 x 128
- Reformat the target data into 1s (pneumonia) and 0s (normal) # class_mode='binary'

[15]:
```
# For example, if you have 1000 images in your dataset and the batch size is␣
↪defined as 10.
# Then the "ImageDataGenerator" will produce 10 images in each iteration of the␣
↪training.
# We will use the size of the whole dataset since there are no computational␣
↪issues with ~5000 images.

# Each pixel is originally between 255 and 0, Rescale the data to be between 0␣
↪and 1.
train_datagen = ImageDataGenerator(rescale=1/255)
test_datagen = ImageDataGenerator(rescale=1/255)
val_datagen = ImageDataGenerator(rescale=1/255)

# Target Size: 128 x 128: The dimensions to which all images found will be␣
↪resized:

# get the data from the training directory
train_generator = train_datagen.flow_from_directory(train_dir,
                                                    target_size=(128, 128),
                                                    batch_size=4743, # default␣
↪is 32
                                                    class_mode='binary')

# get the data from the validation directory
test_generator = test_datagen.flow_from_directory(test_dir,
                                                  target_size=(128, 128),
                                                  batch_size=587,
                                                  class_mode='binary')
```

```
# get the data from the validation directory
val_generator = val_datagen.flow_from_directory(val_dir,
                                                target_size=(128, 128),
                                                batch_size=526,
                                                class_mode='binary')


print(train_generator.class_indices)
```

```
Found 4743 images belonging to 2 classes.
Found 587 images belonging to 2 classes.
Found 526 images belonging to 2 classes.
{'NORMAL': 0, 'PNEUMONIA': 1}
```

4743 divisors: 17, 31, 51, 93, 153,

[16]:
```
train_generator.image_shape, test_generator.image_shape, val_generator.
↪image_shape
```

[16]:
```
((128, 128, 3), (128, 128, 3), (128, 128, 3))
```

3.1.2 Create the transformed data sets:

Tensor for CNN:

[203]:
```
# tensors for CNN:
# next() returns the next item in the iterator = The first batch of the images,␣
↪in our case all images.
train_image, train_label = next(train_generator)
test_image, test_label = next(test_generator)
val_image, val_label = next(val_generator)
```

[18]:
```
print(train_image.shape)
print(train_label.shape)
```

```
(4743, 128, 128, 3)
(4743,)
```

[192]:
```
train_image[0].shape
```

[192]:
```
(128, 128, 3)
```

[199]:
```
# display the first image tensor
train_image[0]
```

[199]:
```
array([[[0.        , 0.        , 0.        ],
        [0.        , 0.        , 0.        ],
        [0.        , 0.        , 0.        ],
        …,
        [0.6117647 , 0.6117647 , 0.6117647 ],
```

```
 [0.8117648 , 0.8117648 , 0.8117648 ],
 [0.9960785 , 0.9960785 , 0.9960785 ]],

[[0.        , 0.        , 0.        ],
 [0.        , 0.        , 0.        ],
 [0.        , 0.        , 0.        ],
 …,
 [0.6039216 , 0.6039216 , 0.6039216 ],
 [0.83921576, 0.83921576, 0.83921576],
 [1.        , 1.        , 1.        ]],

[[0.        , 0.        , 0.        ],
 [0.        , 0.        , 0.        ],
 [0.        , 0.        , 0.        ],
 …,
 [0.5882353 , 0.5882353 , 0.5882353 ],
 [0.8078432 , 0.8078432 , 0.8078432 ],
 [0.9960785 , 0.9960785 , 0.9960785 ]],

…,

[[0.        , 0.        , 0.        ],
 [0.03529412, 0.03529412, 0.03529412],
 [0.07058824, 0.07058824, 0.07058824],
 …,
 [0.454902  , 0.454902  , 0.454902  ],
 [0.5137255 , 0.5137255 , 0.5137255 ],
 [0.77647066, 0.77647066, 0.77647066]],

[[0.        , 0.        , 0.        ],
 [0.03529412, 0.03529412, 0.03529412],
 [0.07843138, 0.07843138, 0.07843138],
 …,
 [0.41960788, 0.41960788, 0.41960788],
 [0.5137255 , 0.5137255 , 0.5137255 ],
 [0.75294125, 0.75294125, 0.75294125]],

[[0.        , 0.        , 0.        ],
 [0.02352941, 0.02352941, 0.02352941],
 [0.08235294, 0.08235294, 0.08235294],
 …,
 [0.427451  , 0.427451  , 0.427451  ],
 [0.53333336, 0.53333336, 0.53333336],
 [0.7686275 , 0.7686275 , 0.7686275 ]]], dtype=float32)
```

Vector of ANN:

- Reshape the transformed images into vectors to be able to use them in ANN

[20]:
```
# Reshape images
# train from (4743, 128, 128, 3) to (4743, 49152)

X_train = train_image.reshape(train_image.shape[0], -1)
X_test = test_image.reshape(test_image.shape[0], -1)
X_val = val_image.reshape(val_image.shape[0], -1)

print(X_train.shape)
print(X_test.shape)
print(X_val.shape)
```

```
(4743, 49152)
(587, 49152)
(526, 49152)
```

- Reshape the transformed labels:

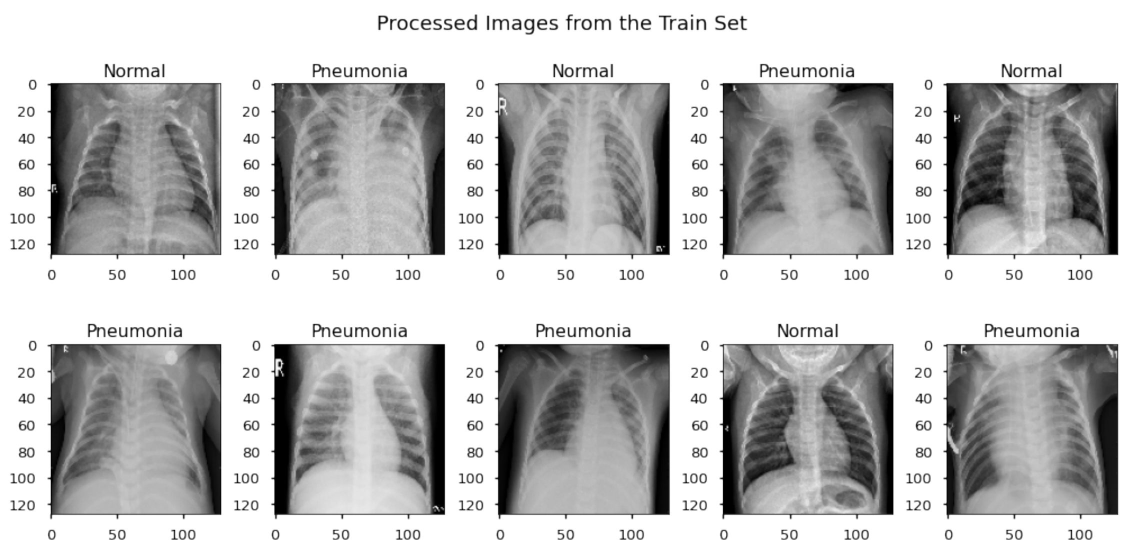
[21]:
```
'''
Reshape labels from (4743,) array([0., 1., 0., ..., 1., 1., 1.]
to (4743, 1)
array([[0.],
       [1.],
       [0.],
       ...,
       [1.],
       [1.],
       [1.]],:
'''
# Reshape labels

y_train = np.reshape(train_label, (4743,1))   # y_train2 = train_label.
 ↪reshape(train_label.shape[0], 1)
y_test = np.reshape(test_label, (587,1))
y_val = np.reshape(val_label, (526,1))

print(y_train.shape)
print(y_test.shape)
print(y_val.shape)
```

```
(4743, 1)
(587, 1)
(526, 1)
```

3.1.3 Visualize some of the transformed images from the training dataset:

- The images appear in a standardized way now:

[132]:
```python
plt.figure(figsize=(14,7))

with plt.style.context('seaborn-talk'):
    for i in range(10):
        ax = plt.subplot(2,5,i+1) # This is object oriented and different from␣
↪plt.subplots()
        plt.imshow(train_image[i])
        if train_label[i]==0:
            plt.title("Normal")
        else:
            plt.title("Pneumonia")
        # plt.axis('off')
plt.suptitle('Processed Images from the Train Set',fontsize=18)
plt.tight_layout()
plt.savefig('./images/ProcessedImages', dpi=300, bbox_inches='tight')
```



4 MODELING:

5 Baseline Artificial Neural Network:

- One input layer with 5 neurons wiht relu activation which works well with images.
- One output layer with 1 neuron for the binary classification (normal versus pneumonia).
- Input shape is a vector with 49152 rows (128 x 128 x 3)
- Using Adam optimizer ("Adaptive Moment Estimation") an adoptive learning rate optimizer which is widely used for training deep neural networks and in image processing. Adam combines the best properties of the AdaGrad and RMSProp algorithms to provide an optimization algorithm. Learning rate defaults to 0.001 but the contribution of gradients to updated weight varies over epochs, hence ADAPTIVE.

[23]:
```
# Size of the image vector:
128*128*3
```

[23]: 49152

[24]:
```
# specify the model:
model = models.Sequential()

# Add dense layers with relu activation
model.add(layers.Dense(5, activation='relu', input_shape = (49152,)))
# Add final layer with sigmoid activation
model.add(layers.Dense(1, activation='sigmoid'))  # because this is a binary␣
↪decision task

model.compile(loss = 'binary_crossentropy',  # because this is a binary␣
↪decision task
              optimizer = 'adam',
              metrics = ['accuracy'])  # [keras.metrics.Recall()
```

[25]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 5)                 245765
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 6
=================================================================
Total params: 245,771
Trainable params: 245,771
Non-trainable params: 0
_________________________________________________________________
```

[26]:
```
# Fit model, set epochs to 31 because 4743 is divisible to 31.
Baseline_ANN = model.fit(X_train, y_train, epochs = 100, batch_size = 31,␣
↪verbose =0,
                    validation_data = (X_val, y_val))
```

```
Epoch 1/100
153/153 [==============================] - 1s 8ms/step - loss: 0.8407 -
accuracy: 0.7116 - val_loss: 0.6671 - val_accuracy: 0.7300
Epoch 2/100
153/153 [==============================] - 0s 3ms/step - loss: 0.6551 -
accuracy: 0.7297 - val_loss: 0.6437 - val_accuracy: 0.7300
Epoch 3/100
153/153 [==============================] - 0s 3ms/step - loss: 0.6347 -
```

```
accuracy: 0.7297 - val_loss: 0.6262 - val_accuracy: 0.7300
Epoch 4/100
153/153 [==============================] - 0s 3ms/step - loss: 0.6194 -
accuracy: 0.7297 - val_loss: 0.6130 - val_accuracy: 0.7300
Epoch 5/100
153/153 [==============================] - 0s 3ms/step - loss: 0.6081 -
accuracy: 0.7297 - val_loss: 0.6036 - val_accuracy: 0.7300
Epoch 6/100
153/153 [==============================] - 0s 3ms/step - loss: 0.6000 -
accuracy: 0.7297 - val_loss: 0.5968 - val_accuracy: 0.7300
Epoch 7/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5944 -
accuracy: 0.7297 - val_loss: 0.5920 - val_accuracy: 0.7300
Epoch 8/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5906 -
accuracy: 0.7297 - val_loss: 0.5888 - val_accuracy: 0.7300
Epoch 9/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5879 -
accuracy: 0.7297 - val_loss: 0.5868 - val_accuracy: 0.7300
Epoch 10/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5863 -
accuracy: 0.7297 - val_loss: 0.5853 - val_accuracy: 0.7300
Epoch 11/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5852 -
accuracy: 0.7297 - val_loss: 0.5845 - val_accuracy: 0.7300
Epoch 12/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5845 -
accuracy: 0.7297 - val_loss: 0.5840 - val_accuracy: 0.7300
Epoch 13/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5841 -
accuracy: 0.7297 - val_loss: 0.5836 - val_accuracy: 0.7300
Epoch 14/100
153/153 [==============================] - 1s 5ms/step - loss: 0.5839 -
accuracy: 0.7297 - val_loss: 0.5835 - val_accuracy: 0.7300
Epoch 15/100
153/153 [==============================] - 1s 5ms/step - loss: 0.5838 -
accuracy: 0.7297 - val_loss: 0.5834 - val_accuracy: 0.7300
Epoch 16/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5837 -
accuracy: 0.7297 - val_loss: 0.5833 - val_accuracy: 0.7300
Epoch 17/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5833 - val_accuracy: 0.7300
Epoch 18/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 19/100
153/153 [==============================] - 1s 5ms/step - loss: 0.5836 -
```

```
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 20/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 21/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 22/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 23/100
153/153 [==============================] - 1s 5ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 24/100
153/153 [==============================] - 1s 5ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 25/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 26/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 27/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 28/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 29/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 30/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 31/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 32/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 33/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 34/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 35/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
```

```
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 36/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 37/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 38/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 39/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 40/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 41/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 42/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 43/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 44/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 45/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 46/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 47/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 48/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 49/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 50/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 51/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
```

```
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 52/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 53/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 54/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 55/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 56/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 57/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 58/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 59/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 60/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 61/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 62/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 63/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 64/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 65/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 66/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 67/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
```

```
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 68/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 69/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 70/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 71/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 72/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 73/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 74/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 75/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 76/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 77/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 78/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 79/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 80/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 81/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 82/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 83/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
```

```
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 84/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 85/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 86/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 87/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 88/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 89/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 90/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 91/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 92/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 93/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 94/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 95/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 96/100
153/153 [==============================] - 0s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 97/100
153/153 [==============================] - 1s 3ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 98/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 99/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
```

```
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
Epoch 100/100
153/153 [==============================] - 1s 4ms/step - loss: 0.5836 -
accuracy: 0.7297 - val_loss: 0.5832 - val_accuracy: 0.7300
```

5.0.1 Evaluate the model performance:

- A traditional Neural Network and CNN uses different data shapes as the input images. Vector for ANN and tensor for CNN.
- A traditional Neural Network and CNN also differ in how how accuracy metrics are reported: "accuracy" and "val_accuracy" for ANN versus "acc" and "val_acc" for CNN.
- Therefore, we need to specify the result from the model, Xtrain, Xtest, accuracy and valaccuracy for the function below to be generalizable:

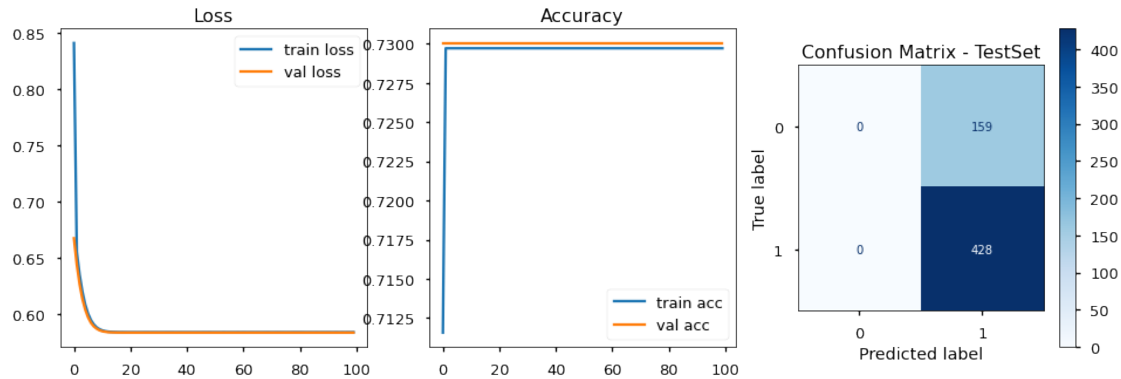
[27]:
```python
def visualize_model_performance(result, Xtrainname, Xtestname, accuracy,␣
↪valaccuracy):

    with plt.style.context('seaborn-talk'):

        # Diplay train and validation loss and accuracy:
        fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(16,5))
        ax1.plot(result.history['loss'])
        ax1.plot(result.history['val_loss'])
        ax1.set_title("Loss")
        ax1.legend(labels = ['train loss', 'val loss'])
        ax2.plot(result.history[accuracy])
        ax2.plot(result.history[valaccuracy])
        ax2.legend(labels = ['train acc', 'val acc'])
        ax2.set_title('Accuracy')

        # Output (probability) predictions for the test set
        y_hat_test = result.model.predict(Xtestname)
        y_pred = np.rint(y_hat_test).astype(np.int) # Round elements of the␣
↪array to the nearest integer.
        y_true = y_test.astype(np.int)

        # Generate a confusion matrix displaying the predictive accuracy of the␣
↪model on the test set:
        cm = confusion_matrix(y_true, y_pred) # normalize = 'true'
        disp = ConfusionMatrixDisplay(confusion_matrix=cm)
        disp.plot(cmap = "Blues", ax=ax3)
        ax3.set_title('Confusion Matrix - TestSet')

        # Print Classification Report displaying the performance of the model␣
↪on the test set using various metrics:
        print('Classification Report:')
        print(classification_report(y_true, y_pred))
        print('\n')
```

```
    # Print final train and test loss and accuracy:
    train_loss, train_acc = result.model.evaluate(Xtrainname, y_train);
    test_loss, test_acc = result.model.evaluate(Xtestname, y_test);
    print('--------------------------')
    print(f'Final Train Loss: {np.round(train_loss,4)}')
    print(f'Final Test Loss: {np.round(test_loss,4)}')
    print('--------------------------')
    print(f'Final Train Acc: {np.round(train_acc,4)}')
    print(f'Final Test Acc: {np.round(test_acc,4)}')
    print('\n')
```

[218]:
```
y_hat_test = Deeper_CNN.model.predict(test_image)
y_pred = np.rint(y_hat_test).astype(np.int) # Round elements of the array to␣
 ↪the nearest integer.
y_true = y_test.astype(np.int)
```

[28]:
```
visualize_model_performance(Baseline_ANN, X_train, X_test, "accuracy",␣
 ↪"val_accuracy")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       159
           1       0.73      1.00      0.84       428

    accuracy                           0.73       587
   macro avg       0.36      0.50      0.42       587
weighted avg       0.53      0.73      0.61       587



149/149 [==============================] - 0s 2ms/step - loss: 0.5836 -
accuracy: 0.7297
19/19 [==============================] - 0s 2ms/step - loss: 0.5841 - accuracy:
0.7291
--------------------------
Final Train Loss: 0.5836
Final Test Loss: 0.5841
--------------------------
Final Train Acc: 0.7297
Final Test Acc: 0.7291
```



- The extremely simple baseline ANN is basically predicting all x-rays as Pneumonia, which still leads to a 72% accuracy.

6 Bigger/Deeper Artificial Neural Network:

- Add an input layer with 128 meurons
- Add three hidden layers with 64, 32 and 10 neurons.
- Add the output layer with 1 neuron.

Early Stopping: Specify early stopping training for all the subsequent models so that once the model performance stops improving on a hold out validation dataset the training will stop. It helps with overfitting and it won't run for more epochs unnecessarily:

[29]:
```
# Patience number of 10: the number of epochs to wait before early stop if no␣
↪progress on the validation set.
early_stop = EarlyStopping(monitor='val_loss', patience=10,␣
↪restore_best_weights=True)
```

[30]:
```
model = models.Sequential()

# Add dense layers with relu activation
model.add(layers.Dense(128, activation='relu', input_shape = (49152,)))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(10, activation='relu'))

# Add final layer with sigmoid activation
model.add(layers.Dense(1, activation='sigmoid'))

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

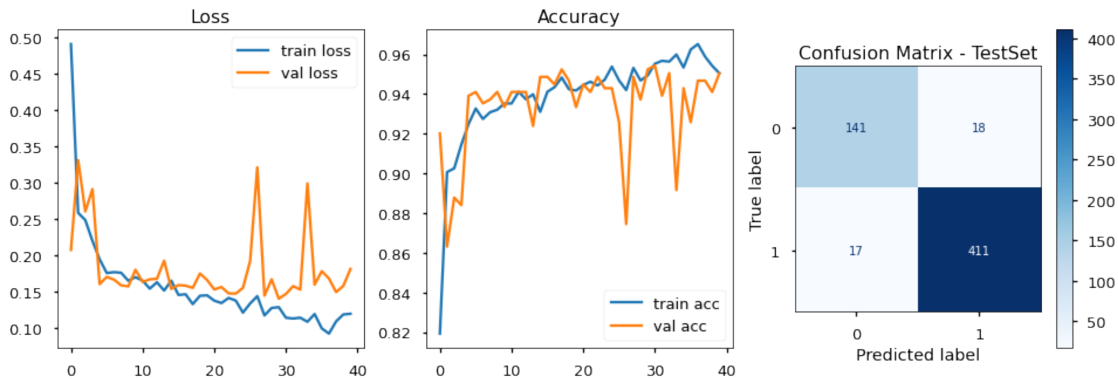
[31]:
```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_2 (Dense)              (None, 128)               6291584
_________________________________________________________________
dense_3 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_4 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_5 (Dense)              (None, 10)                330
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 11
=================================================================
Total params: 6,302,261
Trainable params: 6,302,261
Non-trainable params: 0
_________________________________________________________________
```

[32]:
```
Deeper_ANN = model.fit(X_train, y_train, epochs = 100, batch_size = 31, verbose␣
↪= 0,
                    validation_data = (X_val, y_val), callbacks = [early_stop])
```

[33]:
```
visualize_model_performance(Deeper_ANN, X_train, X_test, "accuracy",␣
↪"val_accuracy")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.89      0.89       159
           1       0.96      0.96      0.96       428

    accuracy                           0.94       587
   macro avg       0.93      0.92      0.92       587
weighted avg       0.94      0.94      0.94       587



149/149 [==============================] - 1s 4ms/step - loss: 0.0927 -
accuracy: 0.9646
19/19 [==============================] - 0s 4ms/step - loss: 0.1660 - accuracy:
0.9404
--------------------------
Final Train Loss: 0.0927
Final Test Loss: 0.166
--------------------------
Final Train Acc: 0.9646
Final Test Acc: 0.9404
```



- A Deeper ANN with 5 layers improves the performance extensively achieving an overall accuracy of 94% on the test set.
- Recall for pneumonia is 96%, that is predicting true pneumonia cases as pneumonia. 17 out of 428 pneumonia cases are mislabeled as normal.

7 Deeper ANN with Class Weights (due to class inbalance):

- Using the same number of layers / neurons as above but adding class weights to see if it would improve performance.

[34]:
```
pneumonia = os.listdir("Data/OUTPUT/train/PNEUMONIA")
normal = os.listdir("Data/OUTPUT/train/NORMAL")

weight_pneumonia = len(normal)/(len(normal) + len(pneumonia))
weight_normal = len(pneumonia)/(len(normal) + len(pneumonia))

print(len(pneumonia), len(normal))
print(f'Weight for class pneumonia: {np.round(weight_pneumonia, 2)}')
print(f'Weight for class normal: {np.round(weight_normal, 2)}')
```

```
3461 1282
Weight for class pneumonia: 0.27
Weight for class normal: 0.73
```

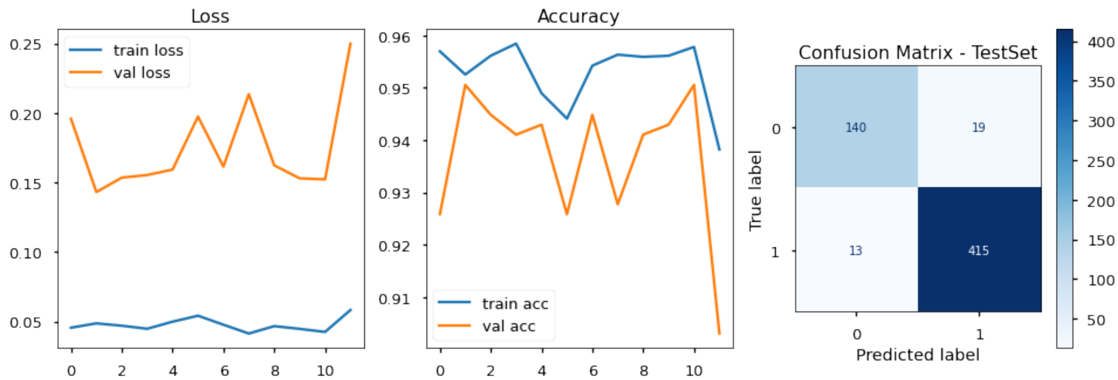
[35]:
```
weights_dict = {0:np.round(weight_normal, 2) , 1: np.round(weight_pneumonia, 2)}
weights_dict
```

[35]:
```
{0: 0.73, 1: 0.27}
```

```
[36]: Weighted_ANN = model.fit(X_train, y_train, epochs = 100, batch_size = 31,
      ↪verbose = 0,
                         validation_data = (X_val, y_val), class_weight =
      ↪weights_dict, callbacks = [early_stop])
```

```
[37]: visualize_model_performance(Weighted_ANN, X_train, X_test, "accuracy",
      ↪"val_accuracy")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.88      0.90       159
           1       0.96      0.97      0.96       428

    accuracy                           0.95       587
   macro avg       0.94      0.93      0.93       587
weighted avg       0.95      0.95      0.95       587



149/149 [==============================] - 1s 4ms/step - loss: 0.0881 -
accuracy: 0.9656
19/19 [==============================] - 0s 4ms/step - loss: 0.1633 - accuracy:
0.9455
--------------------------
Final Train Loss: 0.0881
Final Test Loss: 0.1633
--------------------------
Final Train Acc: 0.9656
Final Test Acc: 0.9455
```



- Using class weights for the Deeper ANN with 4 layers does not seem to improve overall

performance,
- But recall for pneumonia is now up to 97%. Only 13 out of 428 pneumonia cases are mislabeled as normal.

8 Baseline Convolutional Neural Network:

- Baseline model with 1 convolutional layer, 1 max pooling layer, and 1 fully connected layer
- Number of output filters in the convolutional layer is 8.
- Kernel Size is 3 x 3. If your images are smaller than 128×128 you may want to consider sticking with strictly 1×1 and 3×3 filters.
- A fully connected layer with 16 neurons. Neurons in this layer have full connectivity with all neurons in the preceding and succeeding layer as seen in regular FCNN. The FC layer helps to map the representation between the input and the output.
- An output layer with 1 neuron making the predictions.

[230]:
```
model = Sequential()

# 1st Convolution and Pooling
model.add(Conv2D(8, (3, 3), activation='relu', input_shape=(128, 128, 3)))
model.add(MaxPool2D(pool_size = (2, 2)))

# Flatten
model.add(Flatten())

# Include a fully-connected layer and an output layer
model.add(Dense(activation = 'relu', units = 8)) # inner layer
model.add(Dense(activation = 'sigmoid', units = 1)) # output layer

# Compile model
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =␣
↪['acc'])

model.summary()
```

```
Model: "sequential_16"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_23 (Conv2D)           (None, 126, 126, 8)       224
_________________________________________________________________
max_pooling2d_32 (MaxPooling (None, 63, 63, 8)         0
_________________________________________________________________
flatten_14 (Flatten)         (None, 31752)             0
_________________________________________________________________
dense_45 (Dense)             (None, 8)                 254024
_________________________________________________________________
dense_46 (Dense)             (None, 1)                 9
```

```
=================================================================
Total params: 254,257
Trainable params: 254,257
Non-trainable params: 0
_________________________________________________________________
```

[232]:

```
# Train the model
Baseline_CNN = model.fit(train_image, y_train, epochs = 100, batch_size=31,
                    validation_data = (val_image, y_val), callbacks =␣
 ↪[early_stop])
```

```
Epoch 1/100
153/153 [==============================] - 8s 52ms/step - loss: 0.5990 - acc:
0.7297 - val_loss: 0.5959 - val_acc: 0.7300
Epoch 2/100
153/153 [==============================] - 8s 50ms/step - loss: 0.5937 - acc:
0.7297 - val_loss: 0.5914 - val_acc: 0.7300
Epoch 3/100
153/153 [==============================] - 7s 46ms/step - loss: 0.5900 - acc:
0.7297 - val_loss: 0.5884 - val_acc: 0.7300
Epoch 4/100
153/153 [==============================] - 7s 47ms/step - loss: 0.5876 - acc:
0.7297 - val_loss: 0.5865 - val_acc: 0.7300
Epoch 5/100
153/153 [==============================] - 7s 46ms/step - loss: 0.5860 - acc:
0.7297 - val_loss: 0.5852 - val_acc: 0.7300
Epoch 6/100
153/153 [==============================] - 7s 47ms/step - loss: 0.5851 - acc:
0.7297 - val_loss: 0.5844 - val_acc: 0.7300
Epoch 7/100
153/153 [==============================] - 8s 52ms/step - loss: 0.5845 - acc:
0.7297 - val_loss: 0.5839 - val_acc: 0.7300
Epoch 8/100
153/153 [==============================] - 7s 47ms/step - loss: 0.5841 - acc:
0.7297 - val_loss: 0.5836 - val_acc: 0.7300
Epoch 9/100
153/153 [==============================] - 7s 46ms/step - loss: 0.5839 - acc:
0.7297 - val_loss: 0.5835 - val_acc: 0.7300
Epoch 10/100
153/153 [==============================] - 7s 47ms/step - loss: 0.5837 - acc:
0.7297 - val_loss: 0.5834 - val_acc: 0.7300
Epoch 11/100
153/153 [==============================] - 8s 52ms/step - loss: 0.5837 - acc:
0.7297 - val_loss: 0.5833 - val_acc: 0.7300
Epoch 12/100
153/153 [==============================] - 7s 49ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5833 - val_acc: 0.7300
Epoch 13/100
```

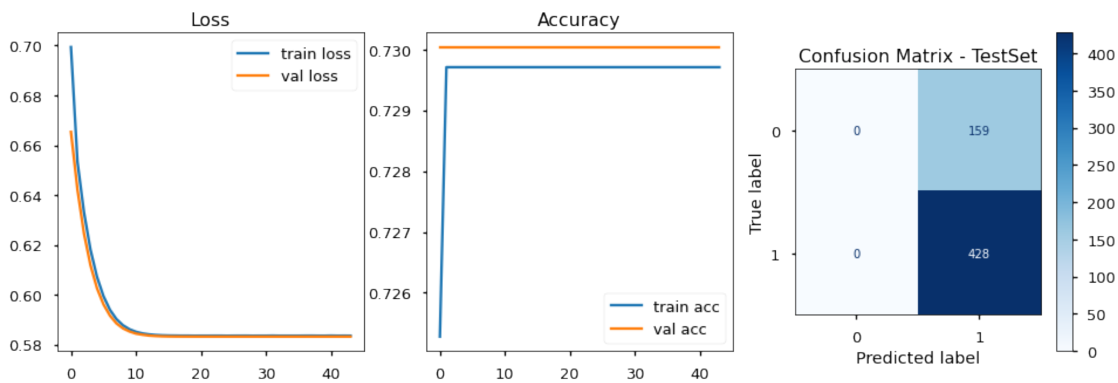
```
153/153 [==============================] - 8s 50ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 14/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 15/100
153/153 [==============================] - 8s 52ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 16/100
153/153 [==============================] - 7s 46ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 17/100
153/153 [==============================] - 8s 51ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 18/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 19/100
153/153 [==============================] - 9s 57ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 20/100
153/153 [==============================] - 8s 51ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 21/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 22/100
153/153 [==============================] - 7s 47ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 23/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 24/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 25/100
153/153 [==============================] - 8s 49ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 26/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 27/100
153/153 [==============================] - 7s 49ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 28/100
153/153 [==============================] - 8s 49ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 29/100
```

```
153/153 [==============================] - 8s 49ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 30/100
153/153 [==============================] - 7s 47ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 31/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 32/100
153/153 [==============================] - 7s 47ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 33/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 34/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 35/100
153/153 [==============================] - 7s 48ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 36/100
153/153 [==============================] - 7s 47ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
Epoch 37/100
153/153 [==============================] - 8s 51ms/step - loss: 0.5836 - acc:
0.7297 - val_loss: 0.5832 - val_acc: 0.7300
```

[139]:
```
visualize_model_performance(Baseline_CNN, train_image, test_image, "acc",
 ↪"val_acc")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       159
           1       0.73      1.00      0.84       428

    accuracy                           0.73       587
   macro avg       0.36      0.50      0.42       587
weighted avg       0.53      0.73      0.61       587



149/149 [==============================] - 2s 14ms/step - loss: 0.5836 - acc:
0.7297
19/19 [==============================] - 0s 13ms/step - loss: 0.5841 - acc:
0.7291
--------------------------
Final Train Loss: 0.5836
```

```
Final Test Loss: 0.5841
--------------------------
Final Train Acc: 0.7297
Final Test Acc: 0.7291
```



- The simple baseline CNN is predicting all x-rays as Pneumonia, which still leads to a 72% accuracy.

9 Deeper CNN:

- I will deepen the neural network to include more layers, filters and neurons to pull more features out of the images to improve the model.
- Layers early in the network architecture (i.e., closer to the actual input image) learn fewer convolutional filters while layers deeper in the network (i.e., closer to the output predictions) will learn more filters.

[41]:
```
model = Sequential()

# 1st Convolution and Pooling
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3))) 
 ↪#input_shape=(128, 128,1)
model.add(MaxPool2D(pool_size = (2, 2)))  # 32 is number of filters

# 2nd Convolution and Pooling
model.add(Conv2D(64, (3, 3), activation="relu"))
model.add(MaxPool2D(pool_size = (2, 2)))

# 3rd Convolution and Pooling
model.add(Conv2D(128, (3, 3), activation="relu"))
model.add(MaxPool2D(pool_size = (2, 2)))

# Flatten
```

```
model.add(Flatten())

# activation
model.add(Dense(activation = 'relu', units = 128)) # inner layer
model.add(Dense(activation = 'relu', units = 64)) # inner layer
model.add(Dense(activation = 'sigmoid', units = 1)) # output layer

# Compile model
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =␣
 ↪['acc'])

model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 126, 126, 32)      896
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 61, 61, 64)        18496
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 30, 30, 64)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 28, 28, 128)       73856
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 14, 14, 128)       0
_________________________________________________________________
flatten_1 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_9 (Dense)              (None, 128)               3211392
_________________________________________________________________
dense_10 (Dense)             (None, 64)                8256
_________________________________________________________________
dense_11 (Dense)             (None, 1)                 65
=================================================================
Total params: 3,312,961
Trainable params: 3,312,961
Non-trainable params: 0
_________________________________________________________________
```

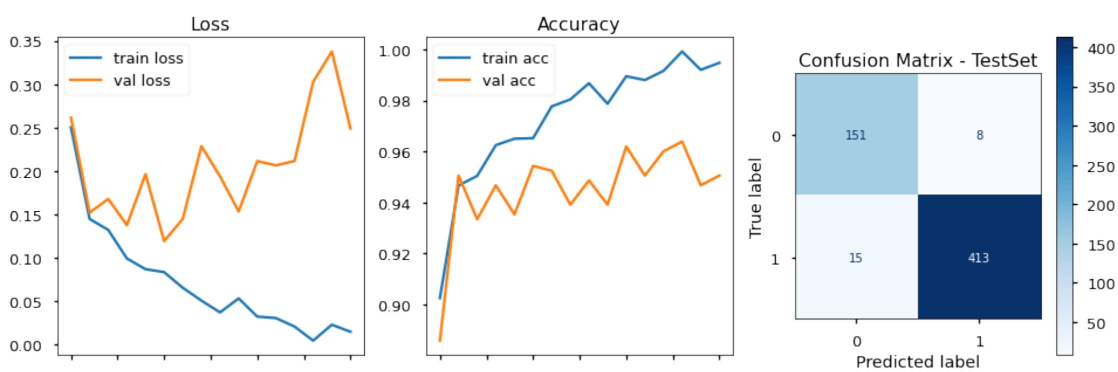
[42]:
```
Deeper_CNN = model.fit(train_image, y_train, epochs = 100, batch_size=31,
                     validation_data = (val_image, y_val), callbacks =␣
 ↪[early_stop])
```

```
Epoch 1/100
```

```
153/153 [==============================] - 47s 310ms/step - loss: 0.2503 - acc:
0.9026 - val_loss: 0.2615 - val_acc: 0.8859
Epoch 2/100
153/153 [==============================] - 49s 322ms/step - loss: 0.1446 - acc:
0.9467 - val_loss: 0.1519 - val_acc: 0.9506
Epoch 3/100
153/153 [==============================] - 47s 306ms/step - loss: 0.1320 - acc:
0.9505 - val_loss: 0.1677 - val_acc: 0.9335
Epoch 4/100
153/153 [==============================] - 47s 306ms/step - loss: 0.0990 - acc:
0.9625 - val_loss: 0.1374 - val_acc: 0.9468
Epoch 5/100
153/153 [==============================] - 47s 310ms/step - loss: 0.0867 - acc:
0.9650 - val_loss: 0.1963 - val_acc: 0.9354
Epoch 6/100
153/153 [==============================] - 47s 306ms/step - loss: 0.0832 - acc:
0.9652 - val_loss: 0.1190 - val_acc: 0.9544
Epoch 7/100
153/153 [==============================] - 45s 297ms/step - loss: 0.0652 - acc:
0.9777 - val_loss: 0.1447 - val_acc: 0.9525
Epoch 8/100
153/153 [==============================] - 45s 294ms/step - loss: 0.0504 - acc:
0.9804 - val_loss: 0.2285 - val_acc: 0.9392
Epoch 9/100
153/153 [==============================] - 45s 297ms/step - loss: 0.0368 - acc:
0.9867 - val_loss: 0.1937 - val_acc: 0.9487
Epoch 10/100
153/153 [==============================] - 45s 293ms/step - loss: 0.0529 - acc:
0.9787 - val_loss: 0.1532 - val_acc: 0.9392
Epoch 11/100
153/153 [==============================] - 45s 295ms/step - loss: 0.0319 - acc:
0.9895 - val_loss: 0.2114 - val_acc: 0.9620
Epoch 12/100
153/153 [==============================] - 47s 310ms/step - loss: 0.0302 - acc:
0.9880 - val_loss: 0.2064 - val_acc: 0.9506
Epoch 13/100
153/153 [==============================] - 45s 297ms/step - loss: 0.0204 - acc:
0.9916 - val_loss: 0.2115 - val_acc: 0.9601
Epoch 14/100
153/153 [==============================] - 46s 303ms/step - loss: 0.0042 - acc:
0.9992 - val_loss: 0.3029 - val_acc: 0.9639
Epoch 15/100
153/153 [==============================] - 47s 309ms/step - loss: 0.0226 - acc:
0.9920 - val_loss: 0.3378 - val_acc: 0.9468
Epoch 16/100
153/153 [==============================] - 48s 312ms/step - loss: 0.0145 - acc:
0.9947 - val_loss: 0.2489 - val_acc: 0.9506
```

[43]:
```
visualize_model_performance(Deeper_CNN, train_image, test_image, "acc",
    "val_acc")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.95      0.93       159
           1       0.98      0.96      0.97       428

    accuracy                           0.96       587
   macro avg       0.95      0.96      0.95       587
weighted avg       0.96      0.96      0.96       587



149/149 [==============================] - 11s 74ms/step - loss: 0.0516 - acc:
0.9821
19/19 [==============================] - 1s 71ms/step - loss: 0.1050 - acc:
0.9608
--------------------------
Final Train Loss: 0.0516
Final Test Loss: 0.105
--------------------------
Final Train Acc: 0.9821
Final Test Acc: 0.9608
```



- Using a deeper CNN overall accuracy is at 96% on the test set.
- Recall for pneumonia is high at 96%. Only 15 out of 428 pneumonia cases are mislabeled as normal.
- Recall for pneumonia is high at 95%. only 8 out of 159 was mislabeled.
- The model does not seem to overfit a much, but let’s still experiment with some regularization techniques:

10 CNN with dropout regularization:

- Dropout regularization helps prevent neural networks from overfitting. Dropout works by randomly disabling neurons and their corresponding connections. This prevents the network from relying too much on single neurons and forces all neurons to learn to generalize better.

[56]:
```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

[57]:
```
model = Sequential()

# 1st Convolution and Pooling and dropout
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3))) ␣
↪#input_shape=(128, 128,1)
model.add(MaxPool2D(pool_size = (2, 2)))
model.add(Dropout(0.4)) # regularization, turn off 40% of the neurons

# 2nd Convolution and Pooling
model.add(Conv2D(64, (3, 3), activation="relu"))
model.add(MaxPool2D(pool_size = (2, 2)))
model.add(Dropout(0.4)) # regularization

# 3rd Convolution and Pooling
model.add(Conv2D(128, (3, 3), activation="relu"))
model.add(MaxPool2D(pool_size = (2, 2)))
model.add(Dropout(0.4)) # regularization

# Flatten
model.add(Flatten())

model.add(Dense(activation = 'relu', units = 128)) # inner layer
model.add(Dropout(0.2)) # regularization
model.add(Dense(activation = 'relu', units = 64)) # inner layer
model.add(Dropout(0.2)) # regularization
model.add(Dense(activation = 'sigmoid', units = 1)) # output layer

model.save("Dropout_CNN")

# Compile model
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =␣
↪['acc'])

model.summary()
```

```
INFO:tensorflow:Assets written to: Dropout_CNN/assets
Model: "sequential_7"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
=================================================================
conv2d_14 (Conv2D)           (None, 126, 126, 32)      896
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 63, 63, 32)        0
_________________________________________________________________
dropout_10 (Dropout)         (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 61, 61, 64)        18496
_________________________________________________________________
max_pooling2d_15 (MaxPooling (None, 30, 30, 64)        0
_________________________________________________________________
dropout_11 (Dropout)         (None, 30, 30, 64)        0
_________________________________________________________________
conv2d_16 (Conv2D)           (None, 28, 28, 128)       73856
_________________________________________________________________
max_pooling2d_16 (MaxPooling (None, 14, 14, 128)       0
_________________________________________________________________
dropout_12 (Dropout)         (None, 14, 14, 128)       0
_________________________________________________________________
flatten_5 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_21 (Dense)             (None, 128)               3211392
_________________________________________________________________
dropout_13 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_22 (Dense)             (None, 64)                8256
_________________________________________________________________
dropout_14 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_23 (Dense)             (None, 1)                 65
=================================================================
Total params: 3,312,961
Trainable params: 3,312,961
Non-trainable params: 0
_________________________________________________________________
```

[61]:
```
Dropout_CNN = model.fit(train_image, y_train, epochs = 100, batch_size=31,
                    validation_data=(val_image, y_val), callbacks =
 ↪[early_stop] )
```

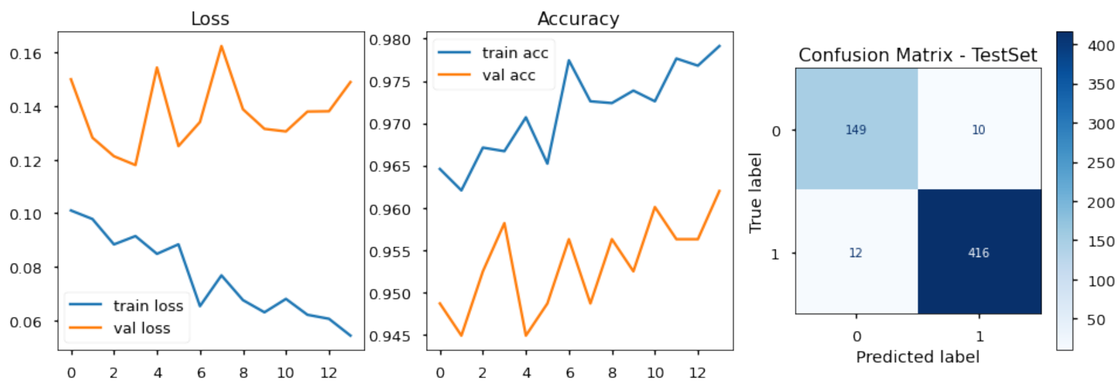
```
Epoch 1/100
153/153 [==============================] - 47s 308ms/step - loss: 0.1011 - acc:
0.9646 - val_loss: 0.1500 - val_acc: 0.9487
Epoch 2/100
153/153 [==============================] - 49s 320ms/step - loss: 0.0979 - acc:
0.9620 - val_loss: 0.1282 - val_acc: 0.9449
Epoch 3/100
153/153 [==============================] - 50s 329ms/step - loss: 0.0884 - acc:
```

```
0.9671 - val_loss: 0.1213 - val_acc: 0.9525
Epoch 4/100
153/153 [==============================] - 49s 317ms/step - loss: 0.0915 - acc:
0.9667 - val_loss: 0.1180 - val_acc: 0.9582
Epoch 5/100
153/153 [==============================] - 47s 310ms/step - loss: 0.0849 - acc:
0.9707 - val_loss: 0.1544 - val_acc: 0.9449
Epoch 6/100
153/153 [==============================] - 48s 315ms/step - loss: 0.0884 - acc:
0.9652 - val_loss: 0.1251 - val_acc: 0.9487
Epoch 7/100
153/153 [==============================] - 48s 311ms/step - loss: 0.0653 - acc:
0.9774 - val_loss: 0.1341 - val_acc: 0.9563
Epoch 8/100
153/153 [==============================] - 50s 324ms/step - loss: 0.0768 - acc:
0.9726 - val_loss: 0.1625 - val_acc: 0.9487
Epoch 9/100
153/153 [==============================] - 48s 315ms/step - loss: 0.0676 - acc:
0.9724 - val_loss: 0.1389 - val_acc: 0.9563
Epoch 10/100
153/153 [==============================] - 48s 313ms/step - loss: 0.0630 - acc:
0.9739 - val_loss: 0.1315 - val_acc: 0.9525
Epoch 11/100
153/153 [==============================] - 49s 317ms/step - loss: 0.0680 - acc:
0.9726 - val_loss: 0.1306 - val_acc: 0.9601
Epoch 12/100
153/153 [==============================] - 54s 350ms/step - loss: 0.0621 - acc:
0.9777 - val_loss: 0.1380 - val_acc: 0.9563
Epoch 13/100
153/153 [==============================] - 49s 320ms/step - loss: 0.0606 - acc:
0.9768 - val_loss: 0.1381 - val_acc: 0.9563
Epoch 14/100
153/153 [==============================] - 48s 315ms/step - loss: 0.0543 - acc:
0.9791 - val_loss: 0.1490 - val_acc: 0.9620
```

[62]:
```
visualize_model_performance(Dropout_CNN, train_image, test_image, "acc",␣
↪"val_acc")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.94      0.93       159
           1       0.98      0.97      0.97       428

    accuracy                           0.96       587
   macro avg       0.95      0.95      0.95       587
weighted avg       0.96      0.96      0.96       587
```

```
149/149 [==============================] - 9s 63ms/step - loss: 0.0585 - acc:
0.9812
19/19 [==============================] - 1s 62ms/step - loss: 0.1007 - acc:
0.9625
--------------------------
Final Train Loss: 0.0585
Final Test Loss: 0.1007
--------------------------
Final Train Acc: 0.9812
Final Test Acc: 0.9625
```



- Using a deeper CNN with dropout regularization the overall accuracy is slightly higher: 96.3% on the test set.
- Recall for pneumonia is also slightly highed with 97%. Only 12 out of 428 pneumonia cases are mislabeled as normal.
- For the predicting the normal x-rays, only 10 out of 159 was mislabeled.

11 CNN with dropout and class weights:

[66]:

```
Weighted_CNN = model.fit(train_image, y_train, epochs = 100, batch_size=31,
                     validation_data=(val_image, y_val),
                          callbacks = [early_stop], class_weight = weights_dict)
```

```
Epoch 1/100
153/153 [==============================] - 47s 309ms/step - loss: 0.0340 - acc:
0.9705 - val_loss: 0.1351 - val_acc: 0.9506
Epoch 2/100
153/153 [==============================] - 47s 310ms/step - loss: 0.0313 - acc:
0.9720 - val_loss: 0.1334 - val_acc: 0.9449
```

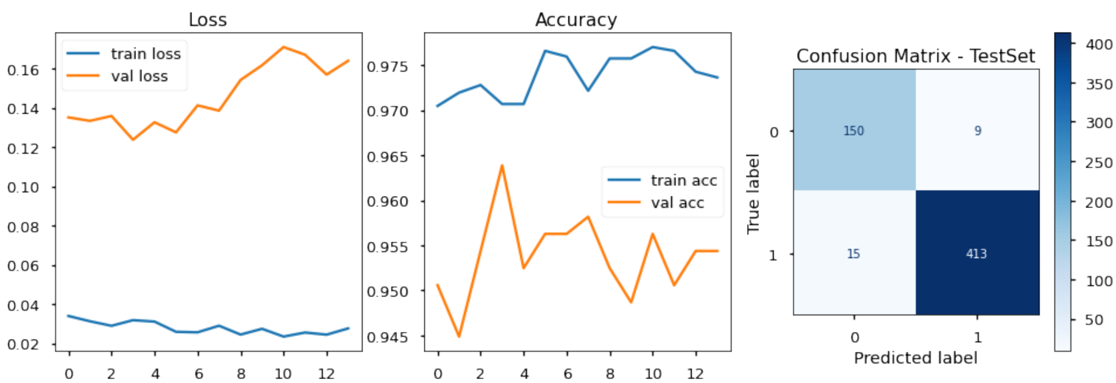
```
Epoch 3/100
153/153 [==============================] - 48s 311ms/step - loss: 0.0290 - acc:
0.9728 - val_loss: 0.1358 - val_acc: 0.9544
Epoch 4/100
153/153 [==============================] - 51s 335ms/step - loss: 0.0318 - acc:
0.9707 - val_loss: 0.1237 - val_acc: 0.9639
Epoch 5/100
153/153 [==============================] - 50s 326ms/step - loss: 0.0311 - acc:
0.9707 - val_loss: 0.1326 - val_acc: 0.9525
Epoch 6/100
153/153 [==============================] - 50s 324ms/step - loss: 0.0259 - acc:
0.9766 - val_loss: 0.1275 - val_acc: 0.9563
Epoch 7/100
153/153 [==============================] - 49s 321ms/step - loss: 0.0257 - acc:
0.9760 - val_loss: 0.1412 - val_acc: 0.9563
Epoch 8/100
153/153 [==============================] - 48s 312ms/step - loss: 0.0290 - acc:
0.9722 - val_loss: 0.1386 - val_acc: 0.9582
Epoch 9/100
153/153 [==============================] - 50s 324ms/step - loss: 0.0245 - acc:
0.9758 - val_loss: 0.1542 - val_acc: 0.9525
Epoch 10/100
153/153 [==============================] - 48s 314ms/step - loss: 0.0275 - acc:
0.9758 - val_loss: 0.1617 - val_acc: 0.9487
Epoch 11/100
153/153 [==============================] - 50s 325ms/step - loss: 0.0235 - acc:
0.9770 - val_loss: 0.1709 - val_acc: 0.9563
Epoch 12/100
153/153 [==============================] - 50s 325ms/step - loss: 0.0256 - acc:
0.9766 - val_loss: 0.1670 - val_acc: 0.9506
Epoch 13/100
153/153 [==============================] - 50s 325ms/step - loss: 0.0245 - acc:
0.9743 - val_loss: 0.1569 - val_acc: 0.9544
Epoch 14/100
153/153 [==============================] - 48s 317ms/step - loss: 0.0277 - acc:
0.9736 - val_loss: 0.1639 - val_acc: 0.9544
```

[67]:
```
visualize_model_performance(Weighted_CNN, train_image, test_image, "acc",␣
↪"val_acc")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.94      0.93       159
           1       0.98      0.96      0.97       428

    accuracy                           0.96       587
   macro avg       0.94      0.95      0.95       587
```

```
weighted avg       0.96      0.96      0.96       587
```

```
149/149 [==============================] - 10s 70ms/step - loss: 0.0496 - acc:
0.9827
19/19 [==============================] - 1s 71ms/step - loss: 0.1088 - acc:
0.9591
--------------------------
Final Train Loss: 0.0496
Final Test Loss: 0.1088
--------------------------
Final Train Acc: 0.9827
Final Test Acc: 0.9591
```



- Adding class weights does not change the results much, it even made the recall value for pneumonue a bit worse by increasing the weight for normal cases. Since we care about detecting true positives - pneumonia we will not use class weights.

12 CNN with L2 regularization:

- L2 regularization is also known as weight decay as it forces the weights to decay towards zero (but not exactly zero).
- L2 regularization combats overfitting by forcing weights to be small.

[51]:
```
model = Sequential()

# 1st Convolution and Pooling and dropout
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3),
 ↪kernel_regularizer=regularizers.l2(0.005)))
model.add(MaxPool2D(pool_size = (2, 2)))
```

```
# 2nd Convolution and Pooling
model.add(Conv2D(64, (3, 3), activation="relu", kernel_regularizer=regularizers.
 ↪l2(0.005))) # default is 0.01
model.add(MaxPool2D(pool_size = (2, 2)))

# 3rd Convolution and Pooling
model.add(Conv2D(128, (3, 3), activation="relu",␣
 ↪kernel_regularizer=regularizers.l2(0.005)))
model.add(MaxPool2D(pool_size = (2, 2)))

# Flatten
model.add(Flatten())

# Add dense layers
model.add(Dense(activation = 'relu', units = 128,␣
 ↪kernel_regularizer=regularizers.l2(0.005))) # inner layer
model.add(Dense(activation = 'relu', units = 64,␣
 ↪kernel_regularizer=regularizers.l2(0.005))) # inner layer
model.add(Dense(activation = 'sigmoid', units = 1)) # output layer

# Compile model
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =␣
 ↪['acc'])

model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_8 (Conv2D)            (None, 126, 126, 32)      896
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 61, 61, 64)        18496
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 30, 30, 64)        0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 28, 28, 128)       73856
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 14, 14, 128)       0
_________________________________________________________________
flatten_3 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_15 (Dense)             (None, 128)               3211392
_________________________________________________________________
dense_16 (Dense)             (None, 64)                8256
```

```
_________________________________________________________________
dense_17 (Dense)             (None, 1)                 65
=================================================================
Total params: 3,312,961
Trainable params: 3,312,961
Non-trainable params: 0
_________________________________________________________________
```

[52]:
```
L2_CNN = model.fit(train_image, y_train, epochs = 100, batch_size=31,
                    validation_data=(val_image, y_val), callbacks =␣
 ↪[early_stop])
```

```
Epoch 1/100
153/153 [==============================] - 44s 289ms/step - loss: 0.8820 - acc:
0.8433 - val_loss: 0.4094 - val_acc: 0.9259
Epoch 2/100
153/153 [==============================] - 44s 289ms/step - loss: 0.3960 - acc:
0.9220 - val_loss: 0.3745 - val_acc: 0.9202
Epoch 3/100
153/153 [==============================] - 44s 288ms/step - loss: 0.3257 - acc:
0.9336 - val_loss: 0.3021 - val_acc: 0.9316
Epoch 4/100
153/153 [==============================] - 44s 289ms/step - loss: 0.2809 - acc:
0.9471 - val_loss: 0.2779 - val_acc: 0.9354
Epoch 5/100
153/153 [==============================] - 44s 288ms/step - loss: 0.2723 - acc:
0.9416 - val_loss: 0.2409 - val_acc: 0.9506
Epoch 6/100
153/153 [==============================] - 44s 285ms/step - loss: 0.2642 - acc:
0.9422 - val_loss: 0.2445 - val_acc: 0.9487
Epoch 7/100
153/153 [==============================] - 44s 287ms/step - loss: 0.2408 - acc:
0.9479 - val_loss: 0.2464 - val_acc: 0.9468
Epoch 8/100
153/153 [==============================] - 44s 288ms/step - loss: 0.2373 - acc:
0.9492 - val_loss: 0.2286 - val_acc: 0.9506
Epoch 9/100
153/153 [==============================] - 44s 285ms/step - loss: 0.2215 - acc:
0.9517 - val_loss: 0.2312 - val_acc: 0.9392
Epoch 10/100
153/153 [==============================] - 44s 287ms/step - loss: 0.2108 - acc:
0.9528 - val_loss: 0.2058 - val_acc: 0.9525
Epoch 11/100
153/153 [==============================] - 44s 286ms/step - loss: 0.2199 - acc:
0.9486 - val_loss: 0.2167 - val_acc: 0.9468
Epoch 12/100
153/153 [==============================] - 44s 288ms/step - loss: 0.2127 - acc:
0.9549 - val_loss: 0.1986 - val_acc: 0.9525
```

```
Epoch 13/100
153/153 [==============================] - 45s 293ms/step - loss: 0.2044 - acc:
0.9532 - val_loss: 0.1941 - val_acc: 0.9544
Epoch 14/100
153/153 [==============================] - 44s 285ms/step - loss: 0.1889 - acc:
0.9591 - val_loss: 0.1868 - val_acc: 0.9582
Epoch 15/100
153/153 [==============================] - 44s 286ms/step - loss: 0.1846 - acc:
0.9608 - val_loss: 0.2108 - val_acc: 0.9449
Epoch 16/100
153/153 [==============================] - 44s 286ms/step - loss: 0.1805 - acc:
0.9591 - val_loss: 0.2039 - val_acc: 0.9506
Epoch 17/100
153/153 [==============================] - 44s 285ms/step - loss: 0.1875 - acc:
0.9549 - val_loss: 0.1962 - val_acc: 0.9468
Epoch 18/100
153/153 [==============================] - 44s 286ms/step - loss: 0.1763 - acc:
0.9606 - val_loss: 0.1788 - val_acc: 0.9601
Epoch 19/100
153/153 [==============================] - 44s 287ms/step - loss: 0.1756 - acc:
0.9599 - val_loss: 0.1826 - val_acc: 0.9601
Epoch 20/100
153/153 [==============================] - 44s 286ms/step - loss: 0.1705 - acc:
0.9629 - val_loss: 0.1854 - val_acc: 0.9563
Epoch 21/100
153/153 [==============================] - 44s 287ms/step - loss: 0.1676 - acc:
0.9614 - val_loss: 0.1947 - val_acc: 0.9411
Epoch 22/100
153/153 [==============================] - 43s 283ms/step - loss: 0.1732 - acc:
0.9604 - val_loss: 0.2181 - val_acc: 0.9354
Epoch 23/100
153/153 [==============================] - 43s 284ms/step - loss: 0.1604 - acc:
0.9646 - val_loss: 0.1890 - val_acc: 0.9525
Epoch 24/100
153/153 [==============================] - 44s 284ms/step - loss: 0.1647 - acc:
0.9610 - val_loss: 0.1747 - val_acc: 0.9601
Epoch 25/100
153/153 [==============================] - 44s 284ms/step - loss: 0.1648 - acc:
0.9631 - val_loss: 0.1820 - val_acc: 0.9506
Epoch 26/100
153/153 [==============================] - 43s 284ms/step - loss: 0.1556 - acc:
0.9673 - val_loss: 0.1907 - val_acc: 0.9525
Epoch 27/100
153/153 [==============================] - 43s 284ms/step - loss: 0.1656 - acc:
0.9629 - val_loss: 0.2437 - val_acc: 0.9297
Epoch 28/100
153/153 [==============================] - 44s 285ms/step - loss: 0.1602 - acc:
0.9614 - val_loss: 0.1787 - val_acc: 0.9506
```

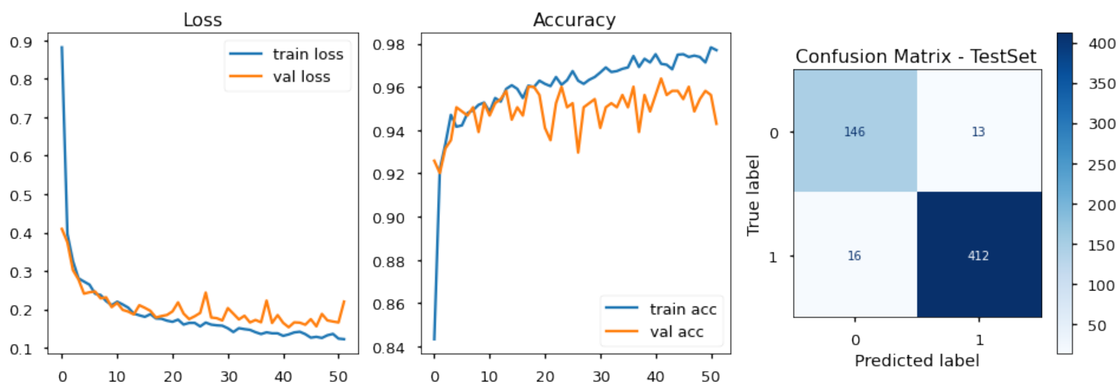
```
Epoch 29/100
153/153 [==============================] - 43s 283ms/step - loss: 0.1584 - acc:
0.9633 - val_loss: 0.1770 - val_acc: 0.9525
Epoch 30/100
153/153 [==============================] - 43s 283ms/step - loss: 0.1575 - acc:
0.9646 - val_loss: 0.1711 - val_acc: 0.9544
Epoch 31/100
153/153 [==============================] - 43s 283ms/step - loss: 0.1507 - acc:
0.9667 - val_loss: 0.2032 - val_acc: 0.9411
Epoch 32/100
153/153 [==============================] - 43s 284ms/step - loss: 0.1410 - acc:
0.9690 - val_loss: 0.1886 - val_acc: 0.9506
Epoch 33/100
153/153 [==============================] - 43s 281ms/step - loss: 0.1510 - acc:
0.9669 - val_loss: 0.1738 - val_acc: 0.9525
Epoch 34/100
153/153 [==============================] - 43s 282ms/step - loss: 0.1485 - acc:
0.9673 - val_loss: 0.1833 - val_acc: 0.9506
Epoch 35/100
153/153 [==============================] - 43s 284ms/step - loss: 0.1466 - acc:
0.9684 - val_loss: 0.1659 - val_acc: 0.9563
Epoch 36/100
153/153 [==============================] - 43s 279ms/step - loss: 0.1406 - acc:
0.9690 - val_loss: 0.1724 - val_acc: 0.9506
Epoch 37/100
153/153 [==============================] - 43s 281ms/step - loss: 0.1357 - acc:
0.9743 - val_loss: 0.1664 - val_acc: 0.9601
Epoch 38/100
153/153 [==============================] - 43s 280ms/step - loss: 0.1402 - acc:
0.9692 - val_loss: 0.2229 - val_acc: 0.9392
Epoch 39/100
153/153 [==============================] - 43s 281ms/step - loss: 0.1376 - acc:
0.9730 - val_loss: 0.1647 - val_acc: 0.9563
Epoch 40/100
153/153 [==============================] - 43s 283ms/step - loss: 0.1376 - acc:
0.9713 - val_loss: 0.1850 - val_acc: 0.9487
Epoch 41/100
153/153 [==============================] - 43s 281ms/step - loss: 0.1310 - acc:
0.9751 - val_loss: 0.1648 - val_acc: 0.9563
Epoch 42/100
153/153 [==============================] - 43s 280ms/step - loss: 0.1348 - acc:
0.9707 - val_loss: 0.1534 - val_acc: 0.9639
Epoch 43/100
153/153 [==============================] - 43s 280ms/step - loss: 0.1399 - acc:
0.9703 - val_loss: 0.1661 - val_acc: 0.9563
Epoch 44/100
153/153 [==============================] - 43s 279ms/step - loss: 0.1418 - acc:
0.9682 - val_loss: 0.1654 - val_acc: 0.9582
```

```
Epoch 45/100
153/153 [==============================] - 43s 280ms/step - loss: 0.1355 - acc:
0.9749 - val_loss: 0.1600 - val_acc: 0.9582
Epoch 46/100
153/153 [==============================] - 43s 281ms/step - loss: 0.1263 - acc:
0.9751 - val_loss: 0.1744 - val_acc: 0.9544
Epoch 47/100
153/153 [==============================] - 43s 281ms/step - loss: 0.1285 - acc:
0.9739 - val_loss: 0.1558 - val_acc: 0.9601
Epoch 48/100
153/153 [==============================] - 43s 279ms/step - loss: 0.1255 - acc:
0.9745 - val_loss: 0.1881 - val_acc: 0.9487
Epoch 49/100
153/153 [==============================] - 43s 279ms/step - loss: 0.1325 - acc:
0.9739 - val_loss: 0.1712 - val_acc: 0.9544
Epoch 50/100
153/153 [==============================] - 43s 278ms/step - loss: 0.1361 - acc:
0.9713 - val_loss: 0.1684 - val_acc: 0.9582
Epoch 51/100
153/153 [==============================] - 43s 279ms/step - loss: 0.1239 - acc:
0.9783 - val_loss: 0.1659 - val_acc: 0.9563
Epoch 52/100
153/153 [==============================] - 43s 279ms/step - loss: 0.1224 - acc:
0.9770 - val_loss: 0.2201 - val_acc: 0.9430
```

[53]:
```
visualize_model_performance(L2_CNN, train_image, test_image, "acc", "val_acc")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.92      0.91       159
           1       0.97      0.96      0.97       428

    accuracy                           0.95       587
   macro avg       0.94      0.94      0.94       587
weighted avg       0.95      0.95      0.95       587



149/149 [==============================] - 10s 65ms/step - loss: 0.1196 - acc:
0.9791
19/19 [==============================] - 1s 62ms/step - loss: 0.1803 - acc:
0.9506
--------------------------
Final Train Loss: 0.1196
Final Test Loss: 0.1803
--------------------------
Final Train Acc: 0.9791
```

```
Final Test Acc: 0.9506
```



- Using a deeper CNN with L2 regularization (instead of dropout) achieves similar but slightly worse results:
- The overall accuracy is: 95% on the test set.
- Recall for pneumonia is 96%. 16 out of 428 pneumonia cases are mislabeled as normal.
- 13 out of 159 normal cases were mislabeled.

13 CNN with dropout and L2 regularization:

[68]:
```
model = Sequential()

# 1st Convolution and Pooling and dropout
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3))) 
 ↪#input_shape=(128, 128,1)
model.add(MaxPool2D(pool_size = (2, 2)))
model.add(Dropout(0.4)) # regularization


# 2nd Convolution and Pooling
model.add(Conv2D(64, (3, 3), activation="relu", kernel_regularizer=regularizers.
 ↪l2(0.005))) # default is 0.01
model.add(MaxPool2D(pool_size = (2, 2)))
model.add(Dropout(0.4)) # regularization

# 3rd Convolution and Pooling
model.add(Conv2D(128, (3, 3), activation="relu",
 ↪kernel_regularizer=regularizers.l2(0.005)))
model.add(MaxPool2D(pool_size = (2, 2)))
model.add(Dropout(0.4)) # regularization
```

```
# Flatten
model.add(Flatten())

model.add(Dense(activation = 'relu', units = 128,␣
 ↪kernel_regularizer=regularizers.l2(0.005))) # inner layer
model.add(Dropout(0.2)) # regularization

model.add(Dense(activation = 'relu', units = 64,␣
 ↪kernel_regularizer=regularizers.l2(0.005))) # inner layer
model.add(Dropout(0.2)) # regularization

model.add(Dense(activation = 'sigmoid', units = 1)) # output layer

model.save("Dropout_L2_CNN")

# Compile model
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =␣
 ↪['acc'])

model.summary()
```

```
INFO:tensorflow:Assets written to: Dropout_L2_CNN/assets
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_17 (Conv2D)           (None, 126, 126, 32)      896
_________________________________________________________________
max_pooling2d_17 (MaxPooling (None, 63, 63, 32)        0
_________________________________________________________________
dropout_15 (Dropout)         (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_18 (Conv2D)           (None, 61, 61, 64)        18496
_________________________________________________________________
max_pooling2d_18 (MaxPooling (None, 30, 30, 64)        0
_________________________________________________________________
dropout_16 (Dropout)         (None, 30, 30, 64)        0
_________________________________________________________________
conv2d_19 (Conv2D)           (None, 28, 28, 128)       73856
_________________________________________________________________
max_pooling2d_19 (MaxPooling (None, 14, 14, 128)       0
_________________________________________________________________
dropout_17 (Dropout)         (None, 14, 14, 128)       0
_________________________________________________________________
flatten_6 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_24 (Dense)             (None, 128)               3211392
```

```
_________________________________________________________________
dropout_18 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_25 (Dense)             (None, 64)                8256
_________________________________________________________________
dropout_19 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_26 (Dense)             (None, 1)                 65
=================================================================
Total params: 3,312,961
Trainable params: 3,312,961
Non-trainable params: 0
_________________________________________________________________
```

[69]:

```
Dropout_L2_CNN = model.fit(train_image, y_train, epochs = 100, batch_size=31,
                    validation_data=(val_image, y_val), callbacks =
 ↪[early_stop])
```

```
Epoch 1/100
153/153 [==============================] - 48s 311ms/step - loss: 1.3092 - acc:
0.7563 - val_loss: 0.6555 - val_acc: 0.8441
Epoch 2/100
153/153 [==============================] - 51s 336ms/step - loss: 0.4962 - acc:
0.8805 - val_loss: 0.4205 - val_acc: 0.9163
Epoch 3/100
153/153 [==============================] - 52s 341ms/step - loss: 0.3728 - acc:
0.9125 - val_loss: 0.3564 - val_acc: 0.9259
Epoch 4/100
153/153 [==============================] - 52s 341ms/step - loss: 0.3416 - acc:
0.9203 - val_loss: 0.3686 - val_acc: 0.8954
Epoch 5/100
153/153 [==============================] - 49s 322ms/step - loss: 0.3091 - acc:
0.9226 - val_loss: 0.3544 - val_acc: 0.9049
Epoch 6/100
153/153 [==============================] - 49s 320ms/step - loss: 0.3170 - acc:
0.9222 - val_loss: 0.3184 - val_acc: 0.9240
Epoch 7/100
153/153 [==============================] - 49s 321ms/step - loss: 0.2886 - acc:
0.9315 - val_loss: 0.2854 - val_acc: 0.9354
Epoch 8/100
153/153 [==============================] - 49s 320ms/step - loss: 0.2853 - acc:
0.9275 - val_loss: 0.2733 - val_acc: 0.9411
Epoch 9/100
153/153 [==============================] - 49s 323ms/step - loss: 0.2565 - acc:
0.9393 - val_loss: 0.2499 - val_acc: 0.9468
Epoch 10/100
153/153 [==============================] - 49s 319ms/step - loss: 0.2703 - acc:
0.9338 - val_loss: 0.2507 - val_acc: 0.9373
```

```
Epoch 11/100
153/153 [==============================] - 49s 323ms/step - loss: 0.2534 - acc:
0.9399 - val_loss: 0.2740 - val_acc: 0.9278
Epoch 12/100
153/153 [==============================] - 49s 320ms/step - loss: 0.2500 - acc:
0.9418 - val_loss: 0.2349 - val_acc: 0.9430
Epoch 13/100
153/153 [==============================] - 49s 318ms/step - loss: 0.2437 - acc:
0.9420 - val_loss: 0.2188 - val_acc: 0.9487
Epoch 14/100
153/153 [==============================] - 49s 322ms/step - loss: 0.2435 - acc:
0.9408 - val_loss: 0.2322 - val_acc: 0.9430
Epoch 15/100
153/153 [==============================] - 49s 321ms/step - loss: 0.2321 - acc:
0.9448 - val_loss: 0.2231 - val_acc: 0.9525
Epoch 16/100
153/153 [==============================] - 52s 337ms/step - loss: 0.2391 - acc:
0.9458 - val_loss: 0.2164 - val_acc: 0.9487
Epoch 17/100
153/153 [==============================] - 54s 352ms/step - loss: 0.2202 - acc:
0.9496 - val_loss: 0.2497 - val_acc: 0.9449
Epoch 18/100
153/153 [==============================] - 49s 324ms/step - loss: 0.2510 - acc:
0.9420 - val_loss: 0.2442 - val_acc: 0.9354
Epoch 19/100
153/153 [==============================] - 49s 322ms/step - loss: 0.2369 - acc:
0.9405 - val_loss: 0.2755 - val_acc: 0.9316
Epoch 20/100
153/153 [==============================] - 48s 314ms/step - loss: 0.2375 - acc:
0.9439 - val_loss: 0.2384 - val_acc: 0.9373
Epoch 21/100
153/153 [==============================] - 48s 317ms/step - loss: 0.2221 - acc:
0.9502 - val_loss: 0.2548 - val_acc: 0.9278
Epoch 22/100
153/153 [==============================] - 51s 332ms/step - loss: 0.2353 - acc:
0.9386 - val_loss: 0.2186 - val_acc: 0.9468
Epoch 23/100
153/153 [==============================] - 53s 345ms/step - loss: 0.2247 - acc:
0.9490 - val_loss: 0.2284 - val_acc: 0.9411
Epoch 24/100
153/153 [==============================] - 51s 336ms/step - loss: 0.2134 - acc:
0.9528 - val_loss: 0.2637 - val_acc: 0.9278
Epoch 25/100
153/153 [==============================] - 52s 341ms/step - loss: 0.2249 - acc:
0.9483 - val_loss: 0.2147 - val_acc: 0.9449
Epoch 26/100
153/153 [==============================] - 50s 324ms/step - loss: 0.2245 - acc:
0.9467 - val_loss: 0.2064 - val_acc: 0.9506
```

```
Epoch 27/100
153/153 [==============================] - 49s 321ms/step - loss: 0.2350 - acc:
0.9454 - val_loss: 0.2577 - val_acc: 0.9335
Epoch 28/100
153/153 [==============================] - 52s 342ms/step - loss: 0.2270 - acc:
0.9502 - val_loss: 0.2323 - val_acc: 0.9449
Epoch 29/100
153/153 [==============================] - 51s 333ms/step - loss: 0.2157 - acc:
0.9511 - val_loss: 0.2037 - val_acc: 0.9487
Epoch 30/100
153/153 [==============================] - 50s 329ms/step - loss: 0.2265 - acc:
0.9437 - val_loss: 0.2326 - val_acc: 0.9373
Epoch 31/100
153/153 [==============================] - 50s 330ms/step - loss: 0.2161 - acc:
0.9481 - val_loss: 0.2324 - val_acc: 0.9449
Epoch 32/100
153/153 [==============================] - 50s 324ms/step - loss: 0.2135 - acc:
0.9507 - val_loss: 0.2066 - val_acc: 0.9506
Epoch 33/100
153/153 [==============================] - 48s 315ms/step - loss: 0.2191 - acc:
0.9517 - val_loss: 0.2018 - val_acc: 0.9468
Epoch 34/100
153/153 [==============================] - 50s 328ms/step - loss: 0.2006 - acc:
0.9524 - val_loss: 0.2178 - val_acc: 0.9525
Epoch 35/100
153/153 [==============================] - 50s 324ms/step - loss: 0.2298 - acc:
0.9445 - val_loss: 0.2303 - val_acc: 0.9449
Epoch 36/100
153/153 [==============================] - 54s 355ms/step - loss: 0.2195 - acc:
0.9483 - val_loss: 0.2206 - val_acc: 0.9525
Epoch 37/100
153/153 [==============================] - 52s 338ms/step - loss: 0.2139 - acc:
0.9502 - val_loss: 0.2221 - val_acc: 0.9582
Epoch 38/100
153/153 [==============================] - 51s 337ms/step - loss: 0.2045 - acc:
0.9519 - val_loss: 0.2260 - val_acc: 0.9392
Epoch 39/100
153/153 [==============================] - 52s 337ms/step - loss: 0.2090 - acc:
0.9502 - val_loss: 0.2115 - val_acc: 0.9468
Epoch 40/100
153/153 [==============================] - 53s 348ms/step - loss: 0.2045 - acc:
0.9519 - val_loss: 0.2028 - val_acc: 0.9468
Epoch 41/100
153/153 [==============================] - 49s 319ms/step - loss: 0.2071 - acc:
0.9532 - val_loss: 0.2047 - val_acc: 0.9411
Epoch 42/100
153/153 [==============================] - 50s 328ms/step - loss: 0.2027 - acc:
0.9549 - val_loss: 0.2193 - val_acc: 0.9525
```

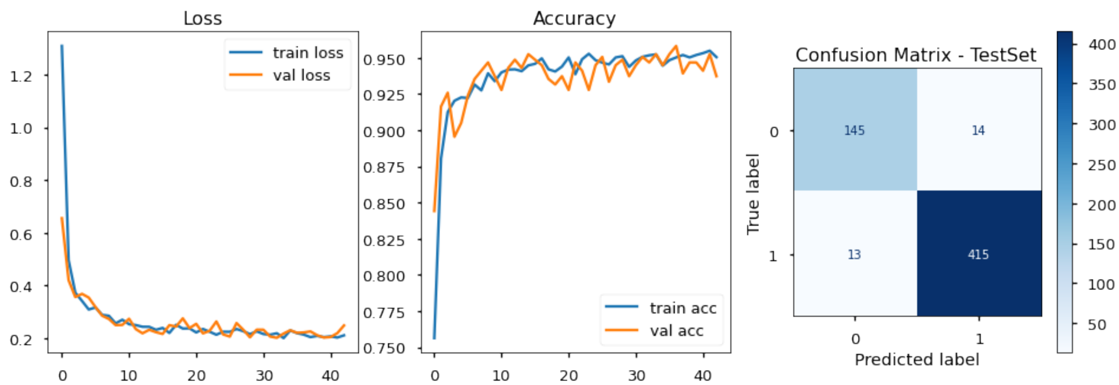
```
Epoch 43/100
153/153 [==============================] - 50s 329ms/step - loss: 0.2111 - acc:
0.9505 - val_loss: 0.2486 - val_acc: 0.9373
```

[70]:
```python
visualize_model_performance(Dropout_L2_CNN, train_image, test_image, "acc", "val_acc")
```

Classification Report:

	precision	recall	f1-score	support
0	0.92	0.91	0.91	159
1	0.97	0.97	0.97	428
accuracy			0.95	587
macro avg	0.94	0.94	0.94	587
weighted avg	0.95	0.95	0.95	587

```
149/149 [==============================] - 11s 71ms/step - loss: 0.1749 - acc:
0.9658
19/19 [==============================] - 1s 66ms/step - loss: 0.1975 - acc:
0.9540
--------------------------
Final Train Loss: 0.1749
Final Test Loss: 0.1975
--------------------------
Final Train Acc: 0.9658
Final Test Acc: 0.954
```



- Using a deeper CNN with dropout as well as L2 does not change results much: accuracy is a still high at 95% on the test set.

- Recall for pneumonia is also still high with 97%. 13 out of 428 pneumonia cases are mislabeled as normal.

14 CNN with dropout and lower learning rate:

- One of the key hyperparameters to set in order to train a neural network is the learning rate for gradient descent. This parameter scales the magnitude of our weight updates in order to minimize the network's loss function.
- If your learning rate is set too low, training will progress very slowly as you are making very tiny updates to the weights in your network. However, if your learning rate is set too high, it can cause undesirable divergent behavior in your loss function.

[71]:
```
model = keras.models.load_model("Dropout_CNN")
```

```
WARNING:tensorflow:No training configuration found in save file, so the model
was *not* compiled. Compile it manually.
```

[72]:
```
optm = optimizers.Adam(learning_rate=0.0005) # default is 0.001

model.compile(optimizer = optm, loss = 'binary_crossentropy', metrics = ['acc'])

LowLearnRate_CNN = model.fit(train_image, y_train, epochs = 100, batch_size=31,
                    validation_data=(val_image, y_val),
                         callbacks = [early_stop])
```

```
Epoch 1/100
153/153 [==============================] - 50s 326ms/step - loss: 0.5059 - acc:
0.7774 - val_loss: 0.3982 - val_acc: 0.8840
Epoch 2/100
153/153 [==============================] - 50s 324ms/step - loss: 0.2356 - acc:
0.9119 - val_loss: 0.2438 - val_acc: 0.9106
Epoch 3/100
153/153 [==============================] - 51s 331ms/step - loss: 0.1836 - acc:
0.9289 - val_loss: 0.2678 - val_acc: 0.9125
Epoch 4/100
153/153 [==============================] - 49s 323ms/step - loss: 0.1658 - acc:
0.9397 - val_loss: 0.1711 - val_acc: 0.9354
Epoch 5/100
153/153 [==============================] - 50s 330ms/step - loss: 0.1554 - acc:
0.9427 - val_loss: 0.1691 - val_acc: 0.9240
Epoch 6/100
153/153 [==============================] - 51s 334ms/step - loss: 0.1475 - acc:
0.9473 - val_loss: 0.1489 - val_acc: 0.9316
Epoch 7/100
153/153 [==============================] - 48s 316ms/step - loss: 0.1434 - acc:
0.9488 - val_loss: 0.1380 - val_acc: 0.9506
Epoch 8/100
153/153 [==============================] - 49s 322ms/step - loss: 0.1324 - acc:
```

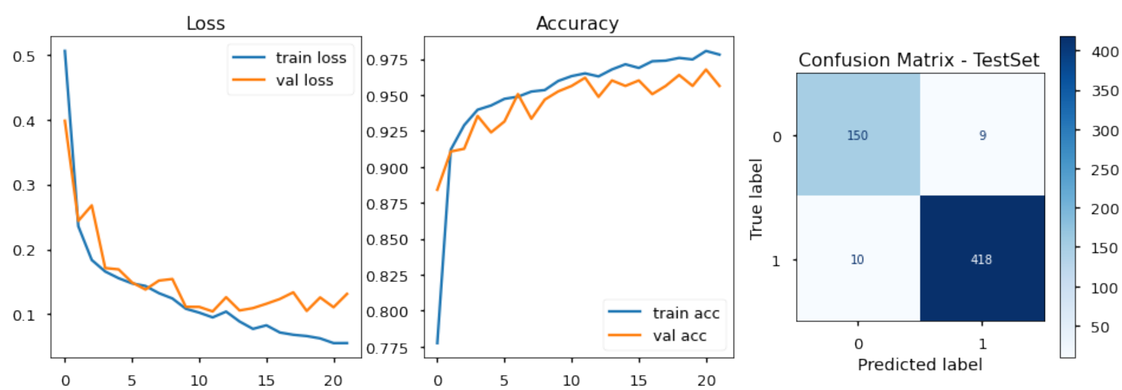
```
0.9524 - val_loss: 0.1518 - val_acc: 0.9335
Epoch 9/100
153/153 [==============================] - 53s 344ms/step - loss: 0.1242 - acc:
0.9534 - val_loss: 0.1542 - val_acc: 0.9468
Epoch 10/100
153/153 [==============================] - 48s 314ms/step - loss: 0.1084 - acc:
0.9597 - val_loss: 0.1113 - val_acc: 0.9525
Epoch 11/100
153/153 [==============================] - 48s 315ms/step - loss: 0.1023 - acc:
0.9631 - val_loss: 0.1112 - val_acc: 0.9563
Epoch 12/100
153/153 [==============================] - 51s 336ms/step - loss: 0.0950 - acc:
0.9650 - val_loss: 0.1042 - val_acc: 0.9620
Epoch 13/100
153/153 [==============================] - 49s 321ms/step - loss: 0.1039 - acc:
0.9629 - val_loss: 0.1261 - val_acc: 0.9487
Epoch 14/100
153/153 [==============================] - 48s 312ms/step - loss: 0.0887 - acc:
0.9677 - val_loss: 0.1057 - val_acc: 0.9601
Epoch 15/100
153/153 [==============================] - 49s 318ms/step - loss: 0.0773 - acc:
0.9713 - val_loss: 0.1093 - val_acc: 0.9563
Epoch 16/100
153/153 [==============================] - 48s 312ms/step - loss: 0.0828 - acc:
0.9688 - val_loss: 0.1161 - val_acc: 0.9601
Epoch 17/100
153/153 [==============================] - 48s 311ms/step - loss: 0.0717 - acc:
0.9734 - val_loss: 0.1234 - val_acc: 0.9506
Epoch 18/100
153/153 [==============================] - 48s 311ms/step - loss: 0.0682 - acc:
0.9739 - val_loss: 0.1337 - val_acc: 0.9563
Epoch 19/100
153/153 [==============================] - 50s 325ms/step - loss: 0.0662 - acc:
0.9758 - val_loss: 0.1050 - val_acc: 0.9639
Epoch 20/100
153/153 [==============================] - 47s 310ms/step - loss: 0.0626 - acc:
0.9747 - val_loss: 0.1258 - val_acc: 0.9563
Epoch 21/100
153/153 [==============================] - 47s 310ms/step - loss: 0.0554 - acc:
0.9806 - val_loss: 0.1107 - val_acc: 0.9677
Epoch 22/100
153/153 [==============================] - 49s 317ms/step - loss: 0.0554 - acc:
0.9781 - val_loss: 0.1313 - val_acc: 0.9563
```

[73]:
```
visualize_model_performance(LowLearnRate_CNN, train_image, test_image, "acc",
    "val_acc")
```

```
Classification Report:
```

```
              precision    recall  f1-score   support

           0       0.94      0.94      0.94       159
           1       0.98      0.98      0.98       428

    accuracy                           0.97       587
   macro avg       0.96      0.96      0.96       587
weighted avg       0.97      0.97      0.97       587
```

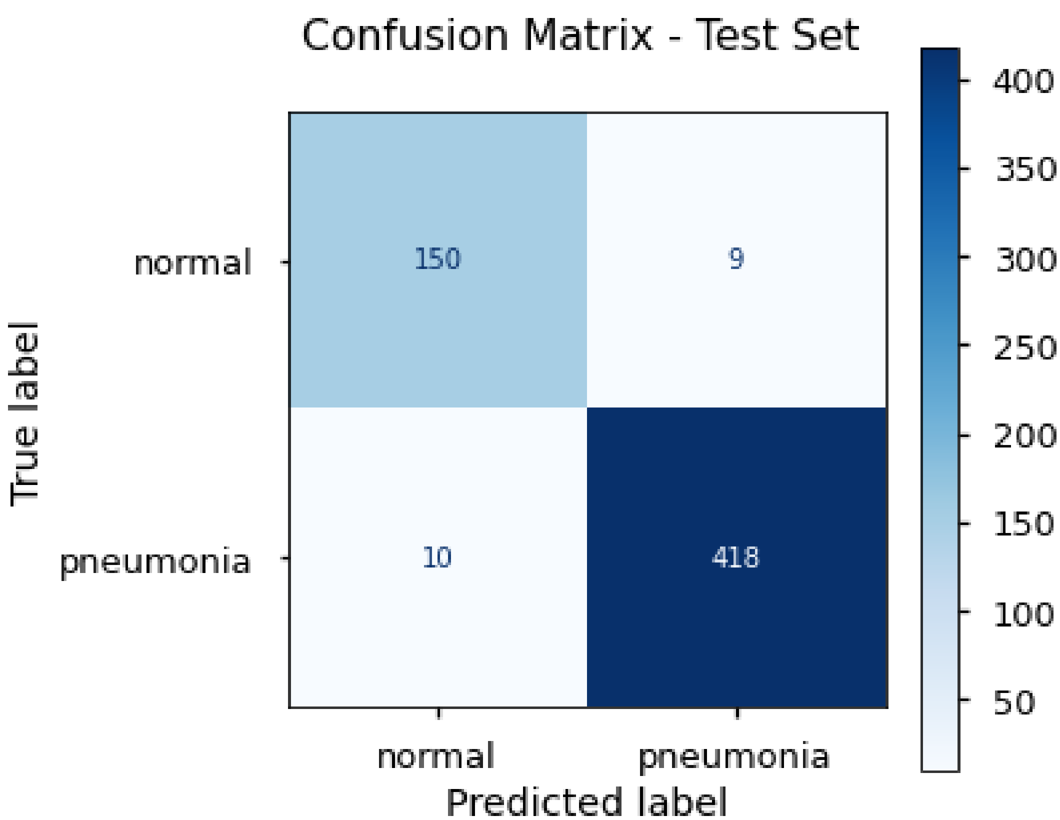
```
149/149 [==============================] - 10s 69ms/step - loss: 0.0757 - acc:
0.9743
19/19 [==============================] - 1s 65ms/step - loss: 0.1058 - acc:
0.9676
--------------------------
Final Train Loss: 0.0757
Final Test Loss: 0.1058
--------------------------
Final Train Acc: 0.9743
Final Test Acc: 0.9676
```



- Adding a lower learning rate to dropout regularization slightly improved the model:
- Accuracy is still high at 96.8% on the test set.
- Recall for pneumonia is higher with 98%.
- Recall for normal is higher with 94%.

[140]:
```
# Diplay seperately for the powerpoint:
with plt.style.context('seaborn-talk'):

    fig, ax1 = plt.subplots(figsize=(5,5))
```

```
    # Output (probability) predictions for the test set
    y_hat_test = LowLearnRate_CNN.model.predict(test_image)
    y_pred = np.rint(y_hat_test).astype(np.int) # Round elements of the array␣
 ↪to the nearest integer.
    y_true = y_test.astype(np.int)

    # Generate a confusion matrix displaying the predictive accuracy of the␣
 ↪model on the test set:
    cm = confusion_matrix(y_true, y_pred) # normalize = 'true'
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['normal',
                                                                        ␣
 ↪'pneumonia'])
    disp.plot(cmap = "Blues", ax=ax1)
    ax1.set_title('Confusion Matrix - Test Set \n')
plt.savefig('./images/CNN_confusionmatrix_cnn', dpi=300, bbox_inches='tight')
```



15 Transfer Learning with VGG16:

- Transfer learning (TL) focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. For example, knowledge gained while learning to recognize cars could apply when trying to recognize trucks. (Source: https://en.wikipedia.org/wiki/Transfer_learning)

- It is quite popular in deep learning where pre-trained models are used as the starting point on Computer Vision (CV) tasks. This way one can get the benefit of using complex models developed by others as start point and on top of it build more.

15.0.1 Adjustments to deafult VGG16:

- Use the weights as it was in original model, so we set weights = 'imagenet'
- Change the image size from the input layer so we can use the model on our images: (128, 128, 3)
- Remove the top layers by setting: include_top=False to include your own fully connected layers with adjusted neuron parameters.
- Add a final layer with a binary classification output.
- We will not train the default model layers. We will only train the final added layers. So, we will set properties for trainable = False.

15.0.2 The default VGG16 model:

[74]:
```
from tensorflow.keras.applications import VGG16
```

[75]:
```
# the default VGG16 model
model_vgg16=VGG16()
model_vgg16.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
```

```
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0

_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160

_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808

_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808

_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0

_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808

_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808

_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808

_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0

_________________________________________________________________
flatten (Flatten)            (None, 25088)             0

_________________________________________________________________
fc1 (Dense)                  (None, 4096)              102764544

_________________________________________________________________
fc2 (Dense)                  (None, 4096)              16781312

_________________________________________________________________
predictions (Dense)          (None, 1000)              4097000
=================================================================
Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0

_________________________________________________________________
```

15.0.3 Create the base VGG16 model:

[76]:
```
base_model = VGG16(include_top = False, weights = "imagenet", input_shape =
 ↪(128, 128, 3))
# all the layers intrainable - freeze the layers (except last ones we will be
 ↪adding)
base_model.trainable = False
base_model.summary()
```

```
Model: "vgg16"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         [(None, 128, 128, 3)]     0

_________________________________________________________________
block1_conv1 (Conv2D)        (None, 128, 128, 64)      1792
```

```
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 128, 128, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 64, 64, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 64, 64, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 64, 64, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 32, 32, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 32, 32, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 32, 32, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 32, 32, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 16, 16, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 16, 16, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 16, 16, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 8, 8, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 8, 8, 512)         2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 8, 8, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 8, 8, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 4, 4, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 0
Non-trainable params: 14,714,688
_________________________________________________________________
```

15.0.4 Create the full VGG16 model:

[77]:
```
model = Sequential()
model.add(base_model)
model.add(Flatten())

# Add the fully connected layers
```

```python
model.add(Dense(128, activation = "relu"))
model.add(Dropout(0.4)) # regularization
model.add(Dense(64, activation = "relu"))
model.add(Dropout(0.4)) # regularization
model.add(Dense(1, activation = "sigmoid"))

# You could freeze layers here too:
# for layer in base_model.layers[:-1]:  # or for layer in base_model.layers:
# layer.trainable = False

model.summary()
```

```
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Functional)           (None, 4, 4, 512)         14714688
_________________________________________________________________
flatten_7 (Flatten)          (None, 8192)              0
_________________________________________________________________
dense_27 (Dense)             (None, 128)               1048704
_________________________________________________________________
dropout_20 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_28 (Dense)             (None, 64)                8256
_________________________________________________________________
dropout_21 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_29 (Dense)             (None, 1)                 65
=================================================================
Total params: 15,771,713
Trainable params: 1,057,025
Non-trainable params: 14,714,688
_________________________________________________________________
```

[78]:
```python
# Compile model, select loss function and optimizer to use
model.compile(loss = 'binary_crossentropy',
              optimizer = 'adam',
              metrics = ['accuracy'])
```

[79]:
```python
# Fit model
VGG16 = model.fit(train_image, y_train, epochs = 100, batch_size=31,
                    validation_data=(val_image, y_val),
                        callbacks = [early_stop])
```

```
Epoch 1/100
153/153 [==============================] - 241s 2s/step - loss: 0.3194 -
```

```
accuracy: 0.8678 - val_loss: 0.1442 - val_accuracy: 0.9544
Epoch 2/100
153/153 [==============================] - 239s 2s/step - loss: 0.1745 -
accuracy: 0.9391 - val_loss: 0.1317 - val_accuracy: 0.9525
Epoch 3/100
153/153 [==============================] - 236s 2s/step - loss: 0.1573 -
accuracy: 0.9448 - val_loss: 0.1314 - val_accuracy: 0.9601
Epoch 4/100
153/153 [==============================] - 235s 2s/step - loss: 0.1391 -
accuracy: 0.9526 - val_loss: 0.1138 - val_accuracy: 0.9525
Epoch 5/100
153/153 [==============================] - 235s 2s/step - loss: 0.1275 -
accuracy: 0.9559 - val_loss: 0.1130 - val_accuracy: 0.9544
Epoch 6/100
153/153 [==============================] - 234s 2s/step - loss: 0.1241 -
accuracy: 0.9566 - val_loss: 0.1268 - val_accuracy: 0.9544
Epoch 7/100
153/153 [==============================] - 233s 2s/step - loss: 0.1137 -
accuracy: 0.9585 - val_loss: 0.1063 - val_accuracy: 0.9563
Epoch 8/100
153/153 [==============================] - 232s 2s/step - loss: 0.1162 -
accuracy: 0.9606 - val_loss: 0.1149 - val_accuracy: 0.9506
Epoch 9/100
153/153 [==============================] - 231s 2s/step - loss: 0.1047 -
accuracy: 0.9627 - val_loss: 0.1209 - val_accuracy: 0.9506
Epoch 10/100
153/153 [==============================] - 231s 2s/step - loss: 0.1051 -
accuracy: 0.9574 - val_loss: 0.1074 - val_accuracy: 0.9582
Epoch 11/100
153/153 [==============================] - 231s 2s/step - loss: 0.0897 -
accuracy: 0.9639 - val_loss: 0.1108 - val_accuracy: 0.9601
Epoch 12/100
153/153 [==============================] - 232s 2s/step - loss: 0.0880 -
accuracy: 0.9667 - val_loss: 0.1192 - val_accuracy: 0.9563
Epoch 13/100
153/153 [==============================] - 233s 2s/step - loss: 0.0926 -
accuracy: 0.9650 - val_loss: 0.1216 - val_accuracy: 0.9525
Epoch 14/100
153/153 [==============================] - 234s 2s/step - loss: 0.0893 -
accuracy: 0.9661 - val_loss: 0.1084 - val_accuracy: 0.9563
Epoch 15/100
153/153 [==============================] - 235s 2s/step - loss: 0.0846 -
accuracy: 0.9713 - val_loss: 0.1013 - val_accuracy: 0.9639
Epoch 16/100
153/153 [==============================] - 235s 2s/step - loss: 0.0880 -
accuracy: 0.9673 - val_loss: 0.1099 - val_accuracy: 0.9582
Epoch 17/100
153/153 [==============================] - 235s 2s/step - loss: 0.0779 -
```

```
accuracy: 0.9675 - val_loss: 0.1231 - val_accuracy: 0.9601
Epoch 18/100
153/153 [==============================] - 236s 2s/step - loss: 0.0668 -
accuracy: 0.9751 - val_loss: 0.1100 - val_accuracy: 0.9639
Epoch 19/100
153/153 [==============================] - 236s 2s/step - loss: 0.0723 -
accuracy: 0.9709 - val_loss: 0.0933 - val_accuracy: 0.9620
Epoch 20/100
153/153 [==============================] - 235s 2s/step - loss: 0.0792 -
accuracy: 0.9644 - val_loss: 0.1713 - val_accuracy: 0.9506
Epoch 21/100
153/153 [==============================] - 240s 2s/step - loss: 0.0760 -
accuracy: 0.9703 - val_loss: 0.1167 - val_accuracy: 0.9601
Epoch 22/100
153/153 [==============================] - 245s 2s/step - loss: 0.0521 -
accuracy: 0.9802 - val_loss: 0.1588 - val_accuracy: 0.9601
Epoch 23/100
153/153 [==============================] - 242s 2s/step - loss: 0.0633 -
accuracy: 0.9734 - val_loss: 0.1345 - val_accuracy: 0.9639
Epoch 24/100
153/153 [==============================] - 244s 2s/step - loss: 0.0641 -
accuracy: 0.9743 - val_loss: 0.1570 - val_accuracy: 0.9601
Epoch 25/100
153/153 [==============================] - 242s 2s/step - loss: 0.0652 -
accuracy: 0.9736 - val_loss: 0.1138 - val_accuracy: 0.9601
Epoch 26/100
153/153 [==============================] - 236s 2s/step - loss: 0.0727 -
accuracy: 0.9709 - val_loss: 0.1688 - val_accuracy: 0.9620
Epoch 27/100
153/153 [==============================] - 237s 2s/step - loss: 0.0616 -
accuracy: 0.9755 - val_loss: 0.1143 - val_accuracy: 0.9639
Epoch 28/100
153/153 [==============================] - 235s 2s/step - loss: 0.0635 -
accuracy: 0.9745 - val_loss: 0.1395 - val_accuracy: 0.9639
Epoch 29/100
153/153 [==============================] - 235s 2s/step - loss: 0.0539 -
accuracy: 0.9768 - val_loss: 0.1153 - val_accuracy: 0.9639
```

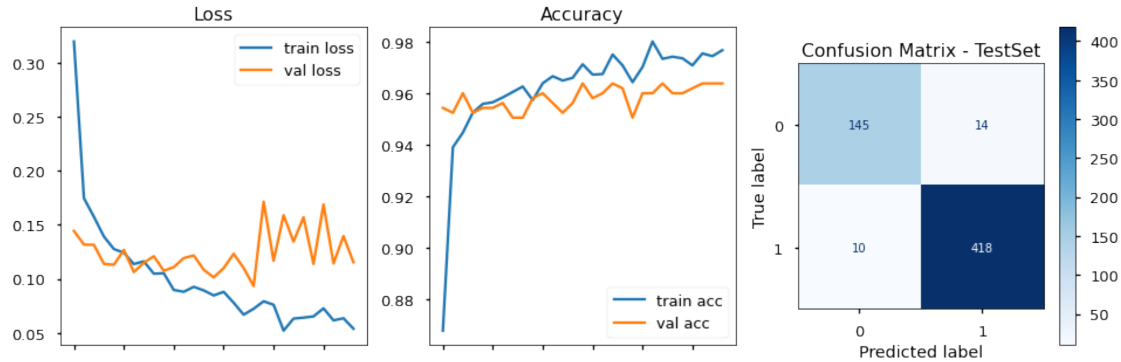
[80]:

```
visualize_model_performance(VGG16, train_image, test_image, "accuracy",
 ↪"val_accuracy")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.91      0.92       159
           1       0.97      0.98      0.97       428

    accuracy                           0.96       587
```

```
   macro avg       0.95      0.94      0.95       587
weighted avg       0.96      0.96      0.96       587
```

```
149/149 [==============================] - 210s 1s/step - loss: 0.0379 -
accuracy: 0.9871
19/19 [==============================] - 25s 1s/step - loss: 0.0960 - accuracy:
0.9591
--------------------------
Final Train Loss: 0.0379
Final Test Loss: 0.096
--------------------------
Final Train Acc: 0.9871
Final Test Acc: 0.9591
```



- Using transfer learning with VGG16 we get very similar results.
- Overall accuracy is 95.9% on the test set.
- Recall for pneumonia is high with 98%. Only 10 out of 428 pneumonia cases are mislabeled as normal.
- Recall for normal is slightly lower with 91%. 14 out of 159 was mislabeled.

16 Transfer Learning with RESNET50V2:

16.0.1 Default RESNET50V2:

[81]:
```python
from keras.applications.resnet_v2 import ResNet50V2
```

[82]:
```python
# the default VGG16 model
model_ResNet50V2=keras.applications.resnet_v2.ResNet50V2()
model_ResNet50V2.summary()
```

```
Model: "resnet50v2"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_3 (InputLayer)            [(None, 224, 224, 3) 0
__________________________________________________________________________________________________
conv1_pad (ZeroPadding2D)       (None, 230, 230, 3)  0           input_3[0][0]
__________________________________________________________________________________________________
conv1_conv (Conv2D)             (None, 112, 112, 64) 9472        conv1_pad[0][0]
__________________________________________________________________________________________________
pool1_pad (ZeroPadding2D)       (None, 114, 114, 64) 0
conv1_conv[0][0]
__________________________________________________________________________________________________
pool1_pool (MaxPooling2D)       (None, 56, 56, 64)   0           pool1_pad[0][0]
__________________________________________________________________________________________________
conv2_block1_preact_bn (BatchNo (None, 56, 56, 64)   256
pool1_pool[0][0]
__________________________________________________________________________________________________
conv2_block1_preact_relu (Activ (None, 56, 56, 64)   0
conv2_block1_preact_bn[0][0]
__________________________________________________________________________________________________
conv2_block1_1_conv (Conv2D)    (None, 56, 56, 64)   4096
conv2_block1_preact_relu[0][0]
__________________________________________________________________________________________________
conv2_block1_1_bn (BatchNormali (None, 56, 56, 64)   256
conv2_block1_1_conv[0][0]
__________________________________________________________________________________________________
conv2_block1_1_relu (Activation (None, 56, 56, 64)   0
conv2_block1_1_bn[0][0]
__________________________________________________________________________________________________
conv2_block1_2_pad (ZeroPadding (None, 58, 58, 64)   0
conv2_block1_1_relu[0][0]
__________________________________________________________________________________________________
conv2_block1_2_conv (Conv2D)    (None, 56, 56, 64)   36864
conv2_block1_2_pad[0][0]
```

```
________________________________________________________________________________
__________________
conv2_block1_2_bn (BatchNormali (None, 56, 56, 64)   256
conv2_block1_2_conv[0][0]
________________________________________________________________________________
__________________
conv2_block1_2_relu (Activation (None, 56, 56, 64)   0
conv2_block1_2_bn[0][0]
________________________________________________________________________________
__________________
conv2_block1_0_conv (Conv2D)    (None, 56, 56, 256)  16640
conv2_block1_preact_relu[0][0]
________________________________________________________________________________
__________________
conv2_block1_3_conv (Conv2D)    (None, 56, 56, 256)  16640
conv2_block1_2_relu[0][0]
________________________________________________________________________________
__________________
conv2_block1_out (Add)          (None, 56, 56, 256)  0
conv2_block1_0_conv[0][0]
conv2_block1_3_conv[0][0]
________________________________________________________________________________
__________________
conv2_block2_preact_bn (BatchNo (None, 56, 56, 256)  1024
conv2_block1_out[0][0]
________________________________________________________________________________
__________________
conv2_block2_preact_relu (Activ (None, 56, 56, 256)  0
conv2_block2_preact_bn[0][0]
________________________________________________________________________________
__________________
conv2_block2_1_conv (Conv2D)    (None, 56, 56, 64)   16384
conv2_block2_preact_relu[0][0]
________________________________________________________________________________
__________________
conv2_block2_1_bn (BatchNormali (None, 56, 56, 64)   256
conv2_block2_1_conv[0][0]
________________________________________________________________________________
__________________
conv2_block2_1_relu (Activation (None, 56, 56, 64)   0
conv2_block2_1_bn[0][0]
________________________________________________________________________________
__________________
conv2_block2_2_pad (ZeroPadding (None, 58, 58, 64)   0
conv2_block2_1_relu[0][0]
________________________________________________________________________________
__________________
conv2_block2_2_conv (Conv2D)    (None, 56, 56, 64)   36864
```

```
conv2_block2_2_pad[0][0]
________________________________________________________________________________
__________________
conv2_block2_2_bn (BatchNormali (None, 56, 56, 64)   256
conv2_block2_2_conv[0][0]
________________________________________________________________________________
__________________
conv2_block2_2_relu (Activation (None, 56, 56, 64)   0
conv2_block2_2_bn[0][0]
________________________________________________________________________________
__________________
conv2_block2_3_conv (Conv2D)    (None, 56, 56, 256)  16640
conv2_block2_2_relu[0][0]
________________________________________________________________________________
__________________
conv2_block2_out (Add)          (None, 56, 56, 256)  0
conv2_block1_out[0][0]
conv2_block2_3_conv[0][0]
________________________________________________________________________________
__________________
conv2_block3_preact_bn (BatchNo (None, 56, 56, 256)  1024
conv2_block2_out[0][0]
________________________________________________________________________________
__________________
conv2_block3_preact_relu (Activ (None, 56, 56, 256)  0
conv2_block3_preact_bn[0][0]
________________________________________________________________________________
__________________
conv2_block3_1_conv (Conv2D)    (None, 56, 56, 64)   16384
conv2_block3_preact_relu[0][0]
________________________________________________________________________________
__________________
conv2_block3_1_bn (BatchNormali (None, 56, 56, 64)   256
conv2_block3_1_conv[0][0]
________________________________________________________________________________
__________________
conv2_block3_1_relu (Activation (None, 56, 56, 64)   0
conv2_block3_1_bn[0][0]
________________________________________________________________________________
__________________
conv2_block3_2_pad (ZeroPadding (None, 58, 58, 64)   0
conv2_block3_1_relu[0][0]
________________________________________________________________________________
__________________
conv2_block3_2_conv (Conv2D)    (None, 28, 28, 64)   36864
conv2_block3_2_pad[0][0]
________________________________________________________________________________
__________________
```

```
conv2_block3_2_bn (BatchNormali (None, 28, 28, 64)   256
conv2_block3_2_conv[0][0]
__________________________________________________________________________________________________
conv2_block3_2_relu (Activation (None, 28, 28, 64)   0
conv2_block3_2_bn[0][0]
__________________________________________________________________________________________________
max_pooling2d_20 (MaxPooling2D) (None, 28, 28, 256)  0
conv2_block2_out[0][0]
__________________________________________________________________________________________________
conv2_block3_3_conv (Conv2D)    (None, 28, 28, 256)  16640
conv2_block3_2_relu[0][0]
__________________________________________________________________________________________________
conv2_block3_out (Add)          (None, 28, 28, 256)  0
max_pooling2d_20[0][0]
conv2_block3_3_conv[0][0]
__________________________________________________________________________________________________
conv3_block1_preact_bn (BatchNo (None, 28, 28, 256)  1024
conv2_block3_out[0][0]
__________________________________________________________________________________________________
conv3_block1_preact_relu (Activ (None, 28, 28, 256)  0
conv3_block1_preact_bn[0][0]
__________________________________________________________________________________________________
conv3_block1_1_conv (Conv2D)    (None, 28, 28, 128)  32768
conv3_block1_preact_relu[0][0]
__________________________________________________________________________________________________
conv3_block1_1_bn (BatchNormali (None, 28, 28, 128)  512
conv3_block1_1_conv[0][0]
__________________________________________________________________________________________________
conv3_block1_1_relu (Activation (None, 28, 28, 128)  0
conv3_block1_1_bn[0][0]
__________________________________________________________________________________________________
conv3_block1_2_pad (ZeroPadding (None, 30, 30, 128)  0
conv3_block1_1_relu[0][0]
__________________________________________________________________________________________________
conv3_block1_2_conv (Conv2D)    (None, 28, 28, 128)  147456
conv3_block1_2_pad[0][0]
__________________________________________________________________________________________________
```

```
__________________
conv3_block1_2_bn (BatchNormali (None, 28, 28, 128)  512
conv3_block1_2_conv[0][0]
________________________________________________________________________________
__________________
conv3_block1_2_relu (Activation (None, 28, 28, 128)  0
conv3_block1_2_bn[0][0]
________________________________________________________________________________
__________________
conv3_block1_0_conv (Conv2D)    (None, 28, 28, 512)  131584
conv3_block1_preact_relu[0][0]
________________________________________________________________________________
__________________
conv3_block1_3_conv (Conv2D)    (None, 28, 28, 512)  66048
conv3_block1_2_relu[0][0]
________________________________________________________________________________
__________________
conv3_block1_out (Add)          (None, 28, 28, 512)  0
conv3_block1_0_conv[0][0]
conv3_block1_3_conv[0][0]
________________________________________________________________________________
__________________
conv3_block2_preact_bn (BatchNo (None, 28, 28, 512)  2048
conv3_block1_out[0][0]
________________________________________________________________________________
__________________
conv3_block2_preact_relu (Activ (None, 28, 28, 512)  0
conv3_block2_preact_bn[0][0]
________________________________________________________________________________
__________________
conv3_block2_1_conv (Conv2D)    (None, 28, 28, 128)  65536
conv3_block2_preact_relu[0][0]
________________________________________________________________________________
__________________
conv3_block2_1_bn (BatchNormali (None, 28, 28, 128)  512
conv3_block2_1_conv[0][0]
________________________________________________________________________________
__________________
conv3_block2_1_relu (Activation (None, 28, 28, 128)  0
conv3_block2_1_bn[0][0]
________________________________________________________________________________
__________________
conv3_block2_2_pad (ZeroPadding (None, 30, 30, 128)  0
conv3_block2_1_relu[0][0]
________________________________________________________________________________
__________________
conv3_block2_2_conv (Conv2D)    (None, 28, 28, 128)  147456
conv3_block2_2_pad[0][0]
```

```
________________________________________________________________________________
__________________
conv3_block2_2_bn (BatchNormali (None, 28, 28, 128)  512
conv3_block2_2_conv[0][0]
________________________________________________________________________________
__________________
conv3_block2_2_relu (Activation (None, 28, 28, 128)  0
conv3_block2_2_bn[0][0]
________________________________________________________________________________
__________________
conv3_block2_3_conv (Conv2D)    (None, 28, 28, 512)  66048
conv3_block2_2_relu[0][0]
________________________________________________________________________________
__________________
conv3_block2_out (Add)          (None, 28, 28, 512)  0
conv3_block1_out[0][0]
conv3_block2_3_conv[0][0]
________________________________________________________________________________
__________________
conv3_block3_preact_bn (BatchNo (None, 28, 28, 512)  2048
conv3_block2_out[0][0]
________________________________________________________________________________
__________________
conv3_block3_preact_relu (Activ (None, 28, 28, 512)  0
conv3_block3_preact_bn[0][0]
________________________________________________________________________________
__________________
conv3_block3_1_conv (Conv2D)    (None, 28, 28, 128)  65536
conv3_block3_preact_relu[0][0]
________________________________________________________________________________
__________________
conv3_block3_1_bn (BatchNormali (None, 28, 28, 128)  512
conv3_block3_1_conv[0][0]
________________________________________________________________________________
__________________
conv3_block3_1_relu (Activation (None, 28, 28, 128)  0
conv3_block3_1_bn[0][0]
________________________________________________________________________________
__________________
conv3_block3_2_pad (ZeroPadding (None, 30, 30, 128)  0
conv3_block3_1_relu[0][0]
________________________________________________________________________________
__________________
conv3_block3_2_conv (Conv2D)    (None, 28, 28, 128)  147456
conv3_block3_2_pad[0][0]
________________________________________________________________________________
__________________
conv3_block3_2_bn (BatchNormali (None, 28, 28, 128)  512
```

```
conv3_block3_2_conv[0][0]
__________________________________________________________________________________
__________________
conv3_block3_2_relu (Activation (None, 28, 28, 128)  0
conv3_block3_2_bn[0][0]
__________________________________________________________________________________
__________________
conv3_block3_3_conv (Conv2D)    (None, 28, 28, 512)  66048
conv3_block3_2_relu[0][0]
__________________________________________________________________________________
__________________
conv3_block3_out (Add)          (None, 28, 28, 512)  0
conv3_block2_out[0][0]
conv3_block3_3_conv[0][0]
__________________________________________________________________________________
__________________
conv3_block4_preact_bn (BatchNo (None, 28, 28, 512)  2048
conv3_block3_out[0][0]
__________________________________________________________________________________
__________________
conv3_block4_preact_relu (Activ (None, 28, 28, 512)  0
conv3_block4_preact_bn[0][0]
__________________________________________________________________________________
__________________
conv3_block4_1_conv (Conv2D)    (None, 28, 28, 128)  65536
conv3_block4_preact_relu[0][0]
__________________________________________________________________________________
__________________
conv3_block4_1_bn (BatchNormali (None, 28, 28, 128)  512
conv3_block4_1_conv[0][0]
__________________________________________________________________________________
__________________
conv3_block4_1_relu (Activation (None, 28, 28, 128)  0
conv3_block4_1_bn[0][0]
__________________________________________________________________________________
__________________
conv3_block4_2_pad (ZeroPadding (None, 30, 30, 128)  0
conv3_block4_1_relu[0][0]
__________________________________________________________________________________
__________________
conv3_block4_2_conv (Conv2D)    (None, 14, 14, 128)  147456
conv3_block4_2_pad[0][0]
__________________________________________________________________________________
__________________
conv3_block4_2_bn (BatchNormali (None, 14, 14, 128)  512
conv3_block4_2_conv[0][0]
__________________________________________________________________________________
__________________
```

```
conv3_block4_2_relu (Activation (None, 14, 14, 128)  0
conv3_block4_2_bn[0][0]
________________________________________________________________________________
__________________
max_pooling2d_21 (MaxPooling2D) (None, 14, 14, 512)  0
conv3_block3_out[0][0]
________________________________________________________________________________
__________________
conv3_block4_3_conv (Conv2D)    (None, 14, 14, 512)  66048
conv3_block4_2_relu[0][0]
________________________________________________________________________________
__________________
conv3_block4_out (Add)          (None, 14, 14, 512)  0
max_pooling2d_21[0][0]
conv3_block4_3_conv[0][0]
________________________________________________________________________________
__________________
conv4_block1_preact_bn (BatchNo (None, 14, 14, 512)  2048
conv3_block4_out[0][0]
________________________________________________________________________________
__________________
conv4_block1_preact_relu (Activ (None, 14, 14, 512)  0
conv4_block1_preact_bn[0][0]
________________________________________________________________________________
__________________
conv4_block1_1_conv (Conv2D)    (None, 14, 14, 256)  131072
conv4_block1_preact_relu[0][0]
________________________________________________________________________________
__________________
conv4_block1_1_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block1_1_conv[0][0]
________________________________________________________________________________
__________________
conv4_block1_1_relu (Activation (None, 14, 14, 256)  0
conv4_block1_1_bn[0][0]
________________________________________________________________________________
__________________
conv4_block1_2_pad (ZeroPadding (None, 16, 16, 256)  0
conv4_block1_1_relu[0][0]
________________________________________________________________________________
__________________
conv4_block1_2_conv (Conv2D)    (None, 14, 14, 256)  589824
conv4_block1_2_pad[0][0]
________________________________________________________________________________
__________________
conv4_block1_2_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block1_2_conv[0][0]
________________________________________________________________________________
```

```
------------------
conv4_block1_2_relu (Activation (None, 14, 14, 256)  0
conv4_block1_2_bn[0][0]
________________________________________________________________________________
------------------
conv4_block1_0_conv (Conv2D)    (None, 14, 14, 1024) 525312
conv4_block1_preact_relu[0][0]
________________________________________________________________________________
------------------
conv4_block1_3_conv (Conv2D)    (None, 14, 14, 1024) 263168
conv4_block1_2_relu[0][0]
________________________________________________________________________________
------------------
conv4_block1_out (Add)          (None, 14, 14, 1024) 0
conv4_block1_0_conv[0][0]
conv4_block1_3_conv[0][0]
________________________________________________________________________________
------------------
conv4_block2_preact_bn (BatchNo (None, 14, 14, 1024) 4096
conv4_block1_out[0][0]
________________________________________________________________________________
------------------
conv4_block2_preact_relu (Activ (None, 14, 14, 1024) 0
conv4_block2_preact_bn[0][0]
________________________________________________________________________________
------------------
conv4_block2_1_conv (Conv2D)    (None, 14, 14, 256)  262144
conv4_block2_preact_relu[0][0]
________________________________________________________________________________
------------------
conv4_block2_1_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block2_1_conv[0][0]
________________________________________________________________________________
------------------
conv4_block2_1_relu (Activation (None, 14, 14, 256)  0
conv4_block2_1_bn[0][0]
________________________________________________________________________________
------------------
conv4_block2_2_pad (ZeroPadding (None, 16, 16, 256)  0
conv4_block2_1_relu[0][0]
________________________________________________________________________________
------------------
conv4_block2_2_conv (Conv2D)    (None, 14, 14, 256)  589824
conv4_block2_2_pad[0][0]
________________________________________________________________________________
------------------
conv4_block2_2_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block2_2_conv[0][0]
```

```
________________________________________________________________________________
__________________
conv4_block2_2_relu (Activation (None, 14, 14, 256)  0
conv4_block2_2_bn[0][0]
________________________________________________________________________________
__________________
conv4_block2_3_conv (Conv2D)    (None, 14, 14, 1024) 263168
conv4_block2_2_relu[0][0]
________________________________________________________________________________
__________________
conv4_block2_out (Add)          (None, 14, 14, 1024) 0
conv4_block1_out[0][0]
conv4_block2_3_conv[0][0]
________________________________________________________________________________
__________________
conv4_block3_preact_bn (BatchNo (None, 14, 14, 1024) 4096
conv4_block2_out[0][0]
________________________________________________________________________________
__________________
conv4_block3_preact_relu (Activ (None, 14, 14, 1024) 0
conv4_block3_preact_bn[0][0]
________________________________________________________________________________
__________________
conv4_block3_1_conv (Conv2D)    (None, 14, 14, 256)  262144
conv4_block3_preact_relu[0][0]
________________________________________________________________________________
__________________
conv4_block3_1_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block3_1_conv[0][0]
________________________________________________________________________________
__________________
conv4_block3_1_relu (Activation (None, 14, 14, 256)  0
conv4_block3_1_bn[0][0]
________________________________________________________________________________
__________________
conv4_block3_2_pad (ZeroPadding (None, 16, 16, 256)  0
conv4_block3_1_relu[0][0]
________________________________________________________________________________
__________________
conv4_block3_2_conv (Conv2D)    (None, 14, 14, 256)  589824
conv4_block3_2_pad[0][0]
________________________________________________________________________________
__________________
conv4_block3_2_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block3_2_conv[0][0]
________________________________________________________________________________
__________________
conv4_block3_2_relu (Activation (None, 14, 14, 256)  0
```

```
conv4_block3_2_bn[0][0]
__________________________________________________________________________________________________
conv4_block3_3_conv (Conv2D)    (None, 14, 14, 1024) 263168
conv4_block3_2_relu[0][0]
__________________________________________________________________________________________________
conv4_block3_out (Add)          (None, 14, 14, 1024) 0
conv4_block2_out[0][0]
conv4_block3_3_conv[0][0]
__________________________________________________________________________________________________
conv4_block4_preact_bn (BatchNo (None, 14, 14, 1024) 4096
conv4_block3_out[0][0]
__________________________________________________________________________________________________
conv4_block4_preact_relu (Activ (None, 14, 14, 1024) 0
conv4_block4_preact_bn[0][0]
__________________________________________________________________________________________________
conv4_block4_1_conv (Conv2D)    (None, 14, 14, 256)  262144
conv4_block4_preact_relu[0][0]
__________________________________________________________________________________________________
conv4_block4_1_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block4_1_conv[0][0]
__________________________________________________________________________________________________
conv4_block4_1_relu (Activation (None, 14, 14, 256)  0
conv4_block4_1_bn[0][0]
__________________________________________________________________________________________________
conv4_block4_2_pad (ZeroPadding (None, 16, 16, 256)  0
conv4_block4_1_relu[0][0]
__________________________________________________________________________________________________
conv4_block4_2_conv (Conv2D)    (None, 14, 14, 256)  589824
conv4_block4_2_pad[0][0]
__________________________________________________________________________________________________
conv4_block4_2_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block4_2_conv[0][0]
__________________________________________________________________________________________________
conv4_block4_2_relu (Activation (None, 14, 14, 256)  0
conv4_block4_2_bn[0][0]
__________________________________________________________________________________________________
```

```
conv4_block4_3_conv (Conv2D)    (None, 14, 14, 1024) 263168
conv4_block4_2_relu[0][0]
________________________________________________________________________________
__________________
conv4_block4_out (Add)          (None, 14, 14, 1024) 0
conv4_block3_out[0][0]
conv4_block4_3_conv[0][0]
________________________________________________________________________________
__________________
conv4_block5_preact_bn (BatchNo (None, 14, 14, 1024) 4096
conv4_block4_out[0][0]
________________________________________________________________________________
__________________
conv4_block5_preact_relu (Activ (None, 14, 14, 1024) 0
conv4_block5_preact_bn[0][0]
________________________________________________________________________________
__________________
conv4_block5_1_conv (Conv2D)    (None, 14, 14, 256)  262144
conv4_block5_preact_relu[0][0]
________________________________________________________________________________
__________________
conv4_block5_1_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block5_1_conv[0][0]
________________________________________________________________________________
__________________
conv4_block5_1_relu (Activation (None, 14, 14, 256)  0
conv4_block5_1_bn[0][0]
________________________________________________________________________________
__________________
conv4_block5_2_pad (ZeroPadding (None, 16, 16, 256)  0
conv4_block5_1_relu[0][0]
________________________________________________________________________________
__________________
conv4_block5_2_conv (Conv2D)    (None, 14, 14, 256)  589824
conv4_block5_2_pad[0][0]
________________________________________________________________________________
__________________
conv4_block5_2_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block5_2_conv[0][0]
________________________________________________________________________________
__________________
conv4_block5_2_relu (Activation (None, 14, 14, 256)  0
conv4_block5_2_bn[0][0]
________________________________________________________________________________
__________________
conv4_block5_3_conv (Conv2D)    (None, 14, 14, 1024) 263168
conv4_block5_2_relu[0][0]
________________________________________________________________________________
```

```
__________________
conv4_block5_out (Add)          (None, 14, 14, 1024) 0
conv4_block4_out[0][0]
conv4_block5_3_conv[0][0]
________________________________________________________________________________
__________________
conv4_block6_preact_bn (BatchNo (None, 14, 14, 1024) 4096
conv4_block5_out[0][0]
________________________________________________________________________________
__________________
conv4_block6_preact_relu (Activ (None, 14, 14, 1024) 0
conv4_block6_preact_bn[0][0]
________________________________________________________________________________
__________________
conv4_block6_1_conv (Conv2D)    (None, 14, 14, 256)  262144
conv4_block6_preact_relu[0][0]
________________________________________________________________________________
__________________
conv4_block6_1_bn (BatchNormali (None, 14, 14, 256)  1024
conv4_block6_1_conv[0][0]
________________________________________________________________________________
__________________
conv4_block6_1_relu (Activation (None, 14, 14, 256)  0
conv4_block6_1_bn[0][0]
________________________________________________________________________________
__________________
conv4_block6_2_pad (ZeroPadding (None, 16, 16, 256)  0
conv4_block6_1_relu[0][0]
________________________________________________________________________________
__________________
conv4_block6_2_conv (Conv2D)    (None, 7, 7, 256)    589824
conv4_block6_2_pad[0][0]
________________________________________________________________________________
__________________
conv4_block6_2_bn (BatchNormali (None, 7, 7, 256)    1024
conv4_block6_2_conv[0][0]
________________________________________________________________________________
__________________
conv4_block6_2_relu (Activation (None, 7, 7, 256)    0
conv4_block6_2_bn[0][0]
________________________________________________________________________________
__________________
max_pooling2d_22 (MaxPooling2D) (None, 7, 7, 1024)   0
conv4_block5_out[0][0]
________________________________________________________________________________
__________________
conv4_block6_3_conv (Conv2D)    (None, 7, 7, 1024)   263168
conv4_block6_2_relu[0][0]
```

```
____________________________________________________________________________
__________________
conv4_block6_out (Add)          (None, 7, 7, 1024)   0
max_pooling2d_22[0][0]
conv4_block6_3_conv[0][0]
____________________________________________________________________________
__________________
conv5_block1_preact_bn (BatchNo (None, 7, 7, 1024)   4096
conv4_block6_out[0][0]
____________________________________________________________________________
__________________
conv5_block1_preact_relu (Activ (None, 7, 7, 1024)   0
conv5_block1_preact_bn[0][0]
____________________________________________________________________________
__________________
conv5_block1_1_conv (Conv2D)    (None, 7, 7, 512)    524288
conv5_block1_preact_relu[0][0]
____________________________________________________________________________
__________________
conv5_block1_1_bn (BatchNormali (None, 7, 7, 512)    2048
conv5_block1_1_conv[0][0]
____________________________________________________________________________
__________________
conv5_block1_1_relu (Activation (None, 7, 7, 512)    0
conv5_block1_1_bn[0][0]
____________________________________________________________________________
__________________
conv5_block1_2_pad (ZeroPadding (None, 9, 9, 512)    0
conv5_block1_1_relu[0][0]
____________________________________________________________________________
__________________
conv5_block1_2_conv (Conv2D)    (None, 7, 7, 512)    2359296
conv5_block1_2_pad[0][0]
____________________________________________________________________________
__________________
conv5_block1_2_bn (BatchNormali (None, 7, 7, 512)    2048
conv5_block1_2_conv[0][0]
____________________________________________________________________________
__________________
conv5_block1_2_relu (Activation (None, 7, 7, 512)    0
conv5_block1_2_bn[0][0]
____________________________________________________________________________
__________________
conv5_block1_0_conv (Conv2D)    (None, 7, 7, 2048)   2099200
conv5_block1_preact_relu[0][0]
____________________________________________________________________________
__________________
conv5_block1_3_conv (Conv2D)    (None, 7, 7, 2048)   1050624
```

```
conv5_block1_2_relu[0][0]
________________________________________________________________________________
__________________
conv5_block1_out (Add)          (None, 7, 7, 2048)   0
conv5_block1_0_conv[0][0]
conv5_block1_3_conv[0][0]
________________________________________________________________________________
__________________
conv5_block2_preact_bn (BatchNo (None, 7, 7, 2048)   8192
conv5_block1_out[0][0]
________________________________________________________________________________
__________________
conv5_block2_preact_relu (Activ (None, 7, 7, 2048)   0
conv5_block2_preact_bn[0][0]
________________________________________________________________________________
__________________
conv5_block2_1_conv (Conv2D)    (None, 7, 7, 512)    1048576
conv5_block2_preact_relu[0][0]
________________________________________________________________________________
__________________
conv5_block2_1_bn (BatchNormali (None, 7, 7, 512)    2048
conv5_block2_1_conv[0][0]
________________________________________________________________________________
__________________
conv5_block2_1_relu (Activation (None, 7, 7, 512)    0
conv5_block2_1_bn[0][0]
________________________________________________________________________________
__________________
conv5_block2_2_pad (ZeroPadding (None, 9, 9, 512)    0
conv5_block2_1_relu[0][0]
________________________________________________________________________________
__________________
conv5_block2_2_conv (Conv2D)    (None, 7, 7, 512)    2359296
conv5_block2_2_pad[0][0]
________________________________________________________________________________
__________________
conv5_block2_2_bn (BatchNormali (None, 7, 7, 512)    2048
conv5_block2_2_conv[0][0]
________________________________________________________________________________
__________________
conv5_block2_2_relu (Activation (None, 7, 7, 512)    0
conv5_block2_2_bn[0][0]
________________________________________________________________________________
__________________
conv5_block2_3_conv (Conv2D)    (None, 7, 7, 2048)   1050624
conv5_block2_2_relu[0][0]
________________________________________________________________________________
__________________
```

```
conv5_block2_out (Add)          (None, 7, 7, 2048)   0
conv5_block1_out[0][0]
conv5_block2_3_conv[0][0]
________________________________________________________________________________
__________________
conv5_block3_preact_bn (BatchNo (None, 7, 7, 2048)   8192
conv5_block2_out[0][0]
________________________________________________________________________________
__________________
conv5_block3_preact_relu (Activ (None, 7, 7, 2048)   0
conv5_block3_preact_bn[0][0]
________________________________________________________________________________
__________________
conv5_block3_1_conv (Conv2D)    (None, 7, 7, 512)    1048576
conv5_block3_preact_relu[0][0]
________________________________________________________________________________
__________________
conv5_block3_1_bn (BatchNormali (None, 7, 7, 512)    2048
conv5_block3_1_conv[0][0]
________________________________________________________________________________
__________________
conv5_block3_1_relu (Activation (None, 7, 7, 512)    0
conv5_block3_1_bn[0][0]
________________________________________________________________________________
__________________
conv5_block3_2_pad (ZeroPadding (None, 9, 9, 512)    0
conv5_block3_1_relu[0][0]
________________________________________________________________________________
__________________
conv5_block3_2_conv (Conv2D)    (None, 7, 7, 512)    2359296
conv5_block3_2_pad[0][0]
________________________________________________________________________________
__________________
conv5_block3_2_bn (BatchNormali (None, 7, 7, 512)    2048
conv5_block3_2_conv[0][0]
________________________________________________________________________________
__________________
conv5_block3_2_relu (Activation (None, 7, 7, 512)    0
conv5_block3_2_bn[0][0]
________________________________________________________________________________
__________________
conv5_block3_3_conv (Conv2D)    (None, 7, 7, 2048)   1050624
conv5_block3_2_relu[0][0]
________________________________________________________________________________
__________________
conv5_block3_out (Add)          (None, 7, 7, 2048)   0
conv5_block2_out[0][0]
conv5_block3_3_conv[0][0]
```

```
------------------------------------------------------------------------------------------------------
post_bn (BatchNormalization)    (None, 7, 7, 2048)   8192
conv5_block3_out[0][0]

------------------------------------------------------------------------------------------------------
post_relu (Activation)          (None, 7, 7, 2048)   0           post_bn[0][0]

------------------------------------------------------------------------------------------------------
avg_pool (GlobalAveragePooling2 (None, 2048)         0           post_relu[0][0]

------------------------------------------------------------------------------------------------------
predictions (Dense)             (None, 1000)         2049000     avg_pool[0][0]
======================================================================================================
Total params: 25,613,800
Trainable params: 25,568,360
Non-trainable params: 45,440
------------------------------------------------------------------------------------------------------
```

16.0.2 Adjustments to default RESNET50:

- Use the weights as it was in original model, so we set weights = 'imagenet'
- Change the image size from the input layer so we can use the model on our images: (128, 128, 3)
- Remove the top layers by setting: include_top=False
- Add a final layer with a binary classification output.
- We will not train the default model layers. We will only train the final added layers. So, we will set properties for trainable = False.

[109]:
```
base_model = keras.applications.resnet_v2.ResNet50V2(weights = "imagenet",
                                              input_shape = (128, 128, 3),
                                              pooling = "max", include_top =
 ↪False,

                                              classes = 2)


base_model.trainable = False
base_model.summary()
```

```
Model: "resnet50v2"
------------------------------------------------------------------------------------------------------
Layer (type)                    Output Shape         Param #     Connected to
======================================================================================================
input_5 (InputLayer)            [(None, 128, 128, 3) 0
------------------------------------------------------------------------------------------------------
```

```
__________________
conv1_pad (ZeroPadding2D)       (None, 134, 134, 3)  0           input_5[0][0]
________________________________________________________________________________
__________________
conv1_conv (Conv2D)             (None, 64, 64, 64)   9472        conv1_pad[0][0]
________________________________________________________________________________
__________________
pool1_pad (ZeroPadding2D)       (None, 66, 66, 64)   0
conv1_conv[0][0]
________________________________________________________________________________
__________________
pool1_pool (MaxPooling2D)       (None, 32, 32, 64)   0           pool1_pad[0][0]
________________________________________________________________________________
__________________
conv2_block1_preact_bn (BatchNo (None, 32, 32, 64)   256
pool1_pool[0][0]
________________________________________________________________________________
__________________
conv2_block1_preact_relu (Activ (None, 32, 32, 64)   0
conv2_block1_preact_bn[0][0]
________________________________________________________________________________
__________________
conv2_block1_1_conv (Conv2D)    (None, 32, 32, 64)   4096
conv2_block1_preact_relu[0][0]
________________________________________________________________________________
__________________
conv2_block1_1_bn (BatchNormali (None, 32, 32, 64)   256
conv2_block1_1_conv[0][0]
________________________________________________________________________________
__________________
conv2_block1_1_relu (Activation (None, 32, 32, 64)   0
conv2_block1_1_bn[0][0]
________________________________________________________________________________
__________________
conv2_block1_2_pad (ZeroPadding (None, 34, 34, 64)   0
conv2_block1_1_relu[0][0]
________________________________________________________________________________
__________________
conv2_block1_2_conv (Conv2D)    (None, 32, 32, 64)   36864
conv2_block1_2_pad[0][0]
________________________________________________________________________________
__________________
conv2_block1_2_bn (BatchNormali (None, 32, 32, 64)   256
conv2_block1_2_conv[0][0]
________________________________________________________________________________
__________________
conv2_block1_2_relu (Activation (None, 32, 32, 64)   0
conv2_block1_2_bn[0][0]
```

```
--------------------------------------------------------------------------------
------------------
conv2_block1_0_conv (Conv2D)    (None, 32, 32, 256)  16640
conv2_block1_preact_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block1_3_conv (Conv2D)    (None, 32, 32, 256)  16640
conv2_block1_2_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block1_out (Add)          (None, 32, 32, 256)  0
conv2_block1_0_conv[0][0]
conv2_block1_3_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block2_preact_bn (BatchNo (None, 32, 32, 256)  1024
conv2_block1_out[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block2_preact_relu (Activ (None, 32, 32, 256)  0
conv2_block2_preact_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block2_1_conv (Conv2D)    (None, 32, 32, 64)   16384
conv2_block2_preact_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block2_1_bn (BatchNormali (None, 32, 32, 64)   256
conv2_block2_1_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block2_1_relu (Activation (None, 32, 32, 64)   0
conv2_block2_1_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block2_2_pad (ZeroPadding (None, 34, 34, 64)   0
conv2_block2_1_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block2_2_conv (Conv2D)    (None, 32, 32, 64)   36864
conv2_block2_2_pad[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block2_2_bn (BatchNormali (None, 32, 32, 64)   256
conv2_block2_2_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv2_block2_2_relu (Activation (None, 32, 32, 64)   0
```

```
conv2_block2_2_bn[0][0]
__________________________________________________________________________________________________
conv2_block2_3_conv (Conv2D)    (None, 32, 32, 256)  16640
conv2_block2_2_relu[0][0]
__________________________________________________________________________________________________
conv2_block2_out (Add)          (None, 32, 32, 256)  0
conv2_block1_out[0][0]
conv2_block2_3_conv[0][0]
__________________________________________________________________________________________________
conv2_block3_preact_bn (BatchNo (None, 32, 32, 256)  1024
conv2_block2_out[0][0]
__________________________________________________________________________________________________
conv2_block3_preact_relu (Activ (None, 32, 32, 256)  0
conv2_block3_preact_bn[0][0]
__________________________________________________________________________________________________
conv2_block3_1_conv (Conv2D)    (None, 32, 32, 64)   16384
conv2_block3_preact_relu[0][0]
__________________________________________________________________________________________________
conv2_block3_1_bn (BatchNormali (None, 32, 32, 64)   256
conv2_block3_1_conv[0][0]
__________________________________________________________________________________________________
conv2_block3_1_relu (Activation (None, 32, 32, 64)   0
conv2_block3_1_bn[0][0]
__________________________________________________________________________________________________
conv2_block3_2_pad (ZeroPadding (None, 34, 34, 64)   0
conv2_block3_1_relu[0][0]
__________________________________________________________________________________________________
conv2_block3_2_conv (Conv2D)    (None, 16, 16, 64)   36864
conv2_block3_2_pad[0][0]
__________________________________________________________________________________________________
conv2_block3_2_bn (BatchNormali (None, 16, 16, 64)   256
conv2_block3_2_conv[0][0]
__________________________________________________________________________________________________
conv2_block3_2_relu (Activation (None, 16, 16, 64)   0
conv2_block3_2_bn[0][0]
__________________________________________________________________________________________________
```

```
max_pooling2d_26 (MaxPooling2D) (None, 16, 16, 256)  0
conv2_block2_out[0][0]

__________________________________________________________________________________________________
conv2_block3_3_conv (Conv2D)    (None, 16, 16, 256)  16640
conv2_block3_2_relu[0][0]

__________________________________________________________________________________________________
conv2_block3_out (Add)          (None, 16, 16, 256)  0
max_pooling2d_26[0][0]
conv2_block3_3_conv[0][0]

__________________________________________________________________________________________________
conv3_block1_preact_bn (BatchNo (None, 16, 16, 256)  1024
conv2_block3_out[0][0]

__________________________________________________________________________________________________
conv3_block1_preact_relu (Activ (None, 16, 16, 256)  0
conv3_block1_preact_bn[0][0]

__________________________________________________________________________________________________
conv3_block1_1_conv (Conv2D)    (None, 16, 16, 128)  32768
conv3_block1_preact_relu[0][0]

__________________________________________________________________________________________________
conv3_block1_1_bn (BatchNormali (None, 16, 16, 128)  512
conv3_block1_1_conv[0][0]

__________________________________________________________________________________________________
conv3_block1_1_relu (Activation (None, 16, 16, 128)  0
conv3_block1_1_bn[0][0]

__________________________________________________________________________________________________
conv3_block1_2_pad (ZeroPadding (None, 18, 18, 128)  0
conv3_block1_1_relu[0][0]

__________________________________________________________________________________________________
conv3_block1_2_conv (Conv2D)    (None, 16, 16, 128)  147456
conv3_block1_2_pad[0][0]

__________________________________________________________________________________________________
conv3_block1_2_bn (BatchNormali (None, 16, 16, 128)  512
conv3_block1_2_conv[0][0]

__________________________________________________________________________________________________
conv3_block1_2_relu (Activation (None, 16, 16, 128)  0
conv3_block1_2_bn[0][0]

______________________________________________________________________________
```

```
------------------
conv3_block1_0_conv (Conv2D)    (None, 16, 16, 512)  131584
conv3_block1_preact_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block1_3_conv (Conv2D)    (None, 16, 16, 512)  66048
conv3_block1_2_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block1_out (Add)          (None, 16, 16, 512)  0
conv3_block1_0_conv[0][0]
conv3_block1_3_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_preact_bn (BatchNo (None, 16, 16, 512)  2048
conv3_block1_out[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_preact_relu (Activ (None, 16, 16, 512)  0
conv3_block2_preact_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_1_conv (Conv2D)    (None, 16, 16, 128)  65536
conv3_block2_preact_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_1_bn (BatchNormali (None, 16, 16, 128)  512
conv3_block2_1_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_1_relu (Activation (None, 16, 16, 128)  0
conv3_block2_1_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_2_pad (ZeroPadding (None, 18, 18, 128)  0
conv3_block2_1_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_2_conv (Conv2D)    (None, 16, 16, 128)  147456
conv3_block2_2_pad[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_2_bn (BatchNormali (None, 16, 16, 128)  512
conv3_block2_2_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_2_relu (Activation (None, 16, 16, 128)  0
conv3_block2_2_bn[0][0]
```

```
--------------------------------------------------------------------------------
------------------
conv3_block2_3_conv (Conv2D)    (None, 16, 16, 512)  66048
conv3_block2_2_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block2_out (Add)          (None, 16, 16, 512)  0
conv3_block1_out[0][0]
conv3_block2_3_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_preact_bn (BatchNo (None, 16, 16, 512)  2048
conv3_block2_out[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_preact_relu (Activ (None, 16, 16, 512)  0
conv3_block3_preact_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_1_conv (Conv2D)    (None, 16, 16, 128)  65536
conv3_block3_preact_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_1_bn (BatchNormali (None, 16, 16, 128)  512
conv3_block3_1_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_1_relu (Activation (None, 16, 16, 128)  0
conv3_block3_1_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_2_pad (ZeroPadding (None, 18, 18, 128)  0
conv3_block3_1_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_2_conv (Conv2D)    (None, 16, 16, 128)  147456
conv3_block3_2_pad[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_2_bn (BatchNormali (None, 16, 16, 128)  512
conv3_block3_2_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_2_relu (Activation (None, 16, 16, 128)  0
conv3_block3_2_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv3_block3_3_conv (Conv2D)    (None, 16, 16, 512)  66048
```

```
conv3_block3_2_relu[0][0]
__________________________________________________________________________________
__________________
conv3_block3_out (Add)          (None, 16, 16, 512)  0
conv3_block2_out[0][0]
conv3_block3_3_conv[0][0]
__________________________________________________________________________________
__________________
conv3_block4_preact_bn (BatchNo (None, 16, 16, 512)  2048
conv3_block3_out[0][0]
__________________________________________________________________________________
__________________
conv3_block4_preact_relu (Activ (None, 16, 16, 512)  0
conv3_block4_preact_bn[0][0]
__________________________________________________________________________________
__________________
conv3_block4_1_conv (Conv2D)    (None, 16, 16, 128)  65536
conv3_block4_preact_relu[0][0]
__________________________________________________________________________________
__________________
conv3_block4_1_bn (BatchNormali (None, 16, 16, 128)  512
conv3_block4_1_conv[0][0]
__________________________________________________________________________________
__________________
conv3_block4_1_relu (Activation (None, 16, 16, 128)  0
conv3_block4_1_bn[0][0]
__________________________________________________________________________________
__________________
conv3_block4_2_pad (ZeroPadding (None, 18, 18, 128)  0
conv3_block4_1_relu[0][0]
__________________________________________________________________________________
__________________
conv3_block4_2_conv (Conv2D)    (None, 8, 8, 128)    147456
conv3_block4_2_pad[0][0]
__________________________________________________________________________________
__________________
conv3_block4_2_bn (BatchNormali (None, 8, 8, 128)    512
conv3_block4_2_conv[0][0]
__________________________________________________________________________________
__________________
conv3_block4_2_relu (Activation (None, 8, 8, 128)    0
conv3_block4_2_bn[0][0]
__________________________________________________________________________________
__________________
max_pooling2d_27 (MaxPooling2D) (None, 8, 8, 512)    0
conv3_block3_out[0][0]
__________________________________________________________________________________
__________________
```

```
conv3_block4_3_conv (Conv2D)    (None, 8, 8, 512)    66048
conv3_block4_2_relu[0][0]

__________________________________________________________________________________________________
conv3_block4_out (Add)          (None, 8, 8, 512)    0
max_pooling2d_27[0][0]
conv3_block4_3_conv[0][0]

__________________________________________________________________________________________________
conv4_block1_preact_bn (BatchNo (None, 8, 8, 512)    2048
conv3_block4_out[0][0]

__________________________________________________________________________________________________
conv4_block1_preact_relu (Activ (None, 8, 8, 512)    0
conv4_block1_preact_bn[0][0]

__________________________________________________________________________________________________
conv4_block1_1_conv (Conv2D)    (None, 8, 8, 256)    131072
conv4_block1_preact_relu[0][0]

__________________________________________________________________________________________________
conv4_block1_1_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block1_1_conv[0][0]

__________________________________________________________________________________________________
conv4_block1_1_relu (Activation (None, 8, 8, 256)    0
conv4_block1_1_bn[0][0]

__________________________________________________________________________________________________
conv4_block1_2_pad (ZeroPadding (None, 10, 10, 256)  0
conv4_block1_1_relu[0][0]

__________________________________________________________________________________________________
conv4_block1_2_conv (Conv2D)    (None, 8, 8, 256)    589824
conv4_block1_2_pad[0][0]

__________________________________________________________________________________________________
conv4_block1_2_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block1_2_conv[0][0]

__________________________________________________________________________________________________
conv4_block1_2_relu (Activation (None, 8, 8, 256)    0
conv4_block1_2_bn[0][0]

__________________________________________________________________________________________________
conv4_block1_0_conv (Conv2D)    (None, 8, 8, 1024)   525312
conv4_block1_preact_relu[0][0]

__________________________________________________________________________________________________
```

```
------------------
conv4_block1_3_conv (Conv2D)    (None, 8, 8, 1024)   263168
conv4_block1_2_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block1_out (Add)          (None, 8, 8, 1024)   0
conv4_block1_0_conv[0][0]
conv4_block1_3_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_preact_bn (BatchNo (None, 8, 8, 1024)   4096
conv4_block1_out[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_preact_relu (Activ (None, 8, 8, 1024)   0
conv4_block2_preact_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_1_conv (Conv2D)    (None, 8, 8, 256)    262144
conv4_block2_preact_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_1_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block2_1_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_1_relu (Activation (None, 8, 8, 256)    0
conv4_block2_1_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_2_pad (ZeroPadding (None, 10, 10, 256)  0
conv4_block2_1_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_2_conv (Conv2D)    (None, 8, 8, 256)    589824
conv4_block2_2_pad[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_2_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block2_2_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_2_relu (Activation (None, 8, 8, 256)    0
conv4_block2_2_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block2_3_conv (Conv2D)    (None, 8, 8, 1024)   263168
conv4_block2_2_relu[0][0]
```

```
--------------------------------------------------------------------------------
------------------
conv4_block2_out (Add)          (None, 8, 8, 1024)   0
conv4_block1_out[0][0]
conv4_block2_3_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_preact_bn (BatchNo (None, 8, 8, 1024)   4096
conv4_block2_out[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_preact_relu (Activ (None, 8, 8, 1024)   0
conv4_block3_preact_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_1_conv (Conv2D)    (None, 8, 8, 256)    262144
conv4_block3_preact_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_1_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block3_1_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_1_relu (Activation (None, 8, 8, 256)    0
conv4_block3_1_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_2_pad (ZeroPadding (None, 10, 10, 256)  0
conv4_block3_1_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_2_conv (Conv2D)    (None, 8, 8, 256)    589824
conv4_block3_2_pad[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_2_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block3_2_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_2_relu (Activation (None, 8, 8, 256)    0
conv4_block3_2_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_3_conv (Conv2D)    (None, 8, 8, 1024)   263168
conv4_block3_2_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block3_out (Add)          (None, 8, 8, 1024)   0
```

```
conv4_block2_out[0][0]
conv4_block3_3_conv[0][0]
__________________________________________________________________________________________________
conv4_block4_preact_bn (BatchNo (None, 8, 8, 1024)   4096
conv4_block3_out[0][0]
__________________________________________________________________________________________________
conv4_block4_preact_relu (Activ (None, 8, 8, 1024)   0
conv4_block4_preact_bn[0][0]
__________________________________________________________________________________________________
conv4_block4_1_conv (Conv2D)    (None, 8, 8, 256)    262144
conv4_block4_preact_relu[0][0]
__________________________________________________________________________________________________
conv4_block4_1_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block4_1_conv[0][0]
__________________________________________________________________________________________________
conv4_block4_1_relu (Activation (None, 8, 8, 256)    0
conv4_block4_1_bn[0][0]
__________________________________________________________________________________________________
conv4_block4_2_pad (ZeroPadding (None, 10, 10, 256)  0
conv4_block4_1_relu[0][0]
__________________________________________________________________________________________________
conv4_block4_2_conv (Conv2D)    (None, 8, 8, 256)    589824
conv4_block4_2_pad[0][0]
__________________________________________________________________________________________________
conv4_block4_2_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block4_2_conv[0][0]
__________________________________________________________________________________________________
conv4_block4_2_relu (Activation (None, 8, 8, 256)    0
conv4_block4_2_bn[0][0]
__________________________________________________________________________________________________
conv4_block4_3_conv (Conv2D)    (None, 8, 8, 1024)   263168
conv4_block4_2_relu[0][0]
__________________________________________________________________________________________________
conv4_block4_out (Add)          (None, 8, 8, 1024)   0
conv4_block3_out[0][0]
conv4_block4_3_conv[0][0]
__________________________________________________________________________________________________
```

```
__________________
conv4_block5_preact_bn (BatchNo (None, 8, 8, 1024)   4096
conv4_block4_out[0][0]
________________________________________________________________________________
__________________
conv4_block5_preact_relu (Activ (None, 8, 8, 1024)   0
conv4_block5_preact_bn[0][0]
________________________________________________________________________________
__________________
conv4_block5_1_conv (Conv2D)    (None, 8, 8, 256)    262144
conv4_block5_preact_relu[0][0]
________________________________________________________________________________
__________________
conv4_block5_1_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block5_1_conv[0][0]
________________________________________________________________________________
__________________
conv4_block5_1_relu (Activation (None, 8, 8, 256)    0
conv4_block5_1_bn[0][0]
________________________________________________________________________________
__________________
conv4_block5_2_pad (ZeroPadding (None, 10, 10, 256)  0
conv4_block5_1_relu[0][0]
________________________________________________________________________________
__________________
conv4_block5_2_conv (Conv2D)    (None, 8, 8, 256)    589824
conv4_block5_2_pad[0][0]
________________________________________________________________________________
__________________
conv4_block5_2_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block5_2_conv[0][0]
________________________________________________________________________________
__________________
conv4_block5_2_relu (Activation (None, 8, 8, 256)    0
conv4_block5_2_bn[0][0]
________________________________________________________________________________
__________________
conv4_block5_3_conv (Conv2D)    (None, 8, 8, 1024)   263168
conv4_block5_2_relu[0][0]
________________________________________________________________________________
__________________
conv4_block5_out (Add)          (None, 8, 8, 1024)   0
conv4_block4_out[0][0]
conv4_block5_3_conv[0][0]
________________________________________________________________________________
__________________
conv4_block6_preact_bn (BatchNo (None, 8, 8, 1024)   4096
conv4_block5_out[0][0]
```

```
--------------------------------------------------------------------------------
------------------
conv4_block6_preact_relu (Activ (None, 8, 8, 1024)   0
conv4_block6_preact_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block6_1_conv (Conv2D)    (None, 8, 8, 256)    262144
conv4_block6_preact_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block6_1_bn (BatchNormali (None, 8, 8, 256)    1024
conv4_block6_1_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block6_1_relu (Activation (None, 8, 8, 256)    0
conv4_block6_1_bn[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block6_2_pad (ZeroPadding (None, 10, 10, 256)  0
conv4_block6_1_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block6_2_conv (Conv2D)    (None, 4, 4, 256)    589824
conv4_block6_2_pad[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block6_2_bn (BatchNormali (None, 4, 4, 256)    1024
conv4_block6_2_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block6_2_relu (Activation (None, 4, 4, 256)    0
conv4_block6_2_bn[0][0]
--------------------------------------------------------------------------------
------------------
max_pooling2d_28 (MaxPooling2D) (None, 4, 4, 1024)   0
conv4_block5_out[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block6_3_conv (Conv2D)    (None, 4, 4, 1024)   263168
conv4_block6_2_relu[0][0]
--------------------------------------------------------------------------------
------------------
conv4_block6_out (Add)          (None, 4, 4, 1024)   0
max_pooling2d_28[0][0]
conv4_block6_3_conv[0][0]
--------------------------------------------------------------------------------
------------------
conv5_block1_preact_bn (BatchNo (None, 4, 4, 1024)   4096
```

```
conv4_block6_out[0][0]
__________________________________________________________________________________________________
conv5_block1_preact_relu (Activ (None, 4, 4, 1024)   0
conv5_block1_preact_bn[0][0]
__________________________________________________________________________________________________
conv5_block1_1_conv (Conv2D)    (None, 4, 4, 512)    524288
conv5_block1_preact_relu[0][0]
__________________________________________________________________________________________________
conv5_block1_1_bn (BatchNormali (None, 4, 4, 512)    2048
conv5_block1_1_conv[0][0]
__________________________________________________________________________________________________
conv5_block1_1_relu (Activation (None, 4, 4, 512)    0
conv5_block1_1_bn[0][0]
__________________________________________________________________________________________________
conv5_block1_2_pad (ZeroPadding (None, 6, 6, 512)    0
conv5_block1_1_relu[0][0]
__________________________________________________________________________________________________
conv5_block1_2_conv (Conv2D)    (None, 4, 4, 512)    2359296
conv5_block1_2_pad[0][0]
__________________________________________________________________________________________________
conv5_block1_2_bn (BatchNormali (None, 4, 4, 512)    2048
conv5_block1_2_conv[0][0]
__________________________________________________________________________________________________
conv5_block1_2_relu (Activation (None, 4, 4, 512)    0
conv5_block1_2_bn[0][0]
__________________________________________________________________________________________________
conv5_block1_0_conv (Conv2D)    (None, 4, 4, 2048)   2099200
conv5_block1_preact_relu[0][0]
__________________________________________________________________________________________________
conv5_block1_3_conv (Conv2D)    (None, 4, 4, 2048)   1050624
conv5_block1_2_relu[0][0]
__________________________________________________________________________________________________
conv5_block1_out (Add)          (None, 4, 4, 2048)   0
conv5_block1_0_conv[0][0]
conv5_block1_3_conv[0][0]
__________________________________________________________________________________________________
```

```
conv5_block2_preact_bn (BatchNo (None, 4, 4, 2048)   8192
conv5_block1_out[0][0]
______________________________________________________________________________
__________________
conv5_block2_preact_relu (Activ (None, 4, 4, 2048)   0
conv5_block2_preact_bn[0][0]
______________________________________________________________________________
__________________
conv5_block2_1_conv (Conv2D)    (None, 4, 4, 512)    1048576
conv5_block2_preact_relu[0][0]
______________________________________________________________________________
__________________
conv5_block2_1_bn (BatchNormali (None, 4, 4, 512)    2048
conv5_block2_1_conv[0][0]
______________________________________________________________________________
__________________
conv5_block2_1_relu (Activation (None, 4, 4, 512)    0
conv5_block2_1_bn[0][0]
______________________________________________________________________________
__________________
conv5_block2_2_pad (ZeroPadding (None, 6, 6, 512)    0
conv5_block2_1_relu[0][0]
______________________________________________________________________________
__________________
conv5_block2_2_conv (Conv2D)    (None, 4, 4, 512)    2359296
conv5_block2_2_pad[0][0]
______________________________________________________________________________
__________________
conv5_block2_2_bn (BatchNormali (None, 4, 4, 512)    2048
conv5_block2_2_conv[0][0]
______________________________________________________________________________
__________________
conv5_block2_2_relu (Activation (None, 4, 4, 512)    0
conv5_block2_2_bn[0][0]
______________________________________________________________________________
__________________
conv5_block2_3_conv (Conv2D)    (None, 4, 4, 2048)   1050624
conv5_block2_2_relu[0][0]
______________________________________________________________________________
__________________
conv5_block2_out (Add)          (None, 4, 4, 2048)   0
conv5_block1_out[0][0]
conv5_block2_3_conv[0][0]
______________________________________________________________________________
__________________
conv5_block3_preact_bn (BatchNo (None, 4, 4, 2048)   8192
conv5_block2_out[0][0]
______________________________________________________________________________
```

```
__________________
conv5_block3_preact_relu (Activ (None, 4, 4, 2048)   0
conv5_block3_preact_bn[0][0]
________________________________________________________________________________
__________________
conv5_block3_1_conv (Conv2D)    (None, 4, 4, 512)    1048576
conv5_block3_preact_relu[0][0]
________________________________________________________________________________
__________________
conv5_block3_1_bn (BatchNormali (None, 4, 4, 512)    2048
conv5_block3_1_conv[0][0]
________________________________________________________________________________
__________________
conv5_block3_1_relu (Activation (None, 4, 4, 512)    0
conv5_block3_1_bn[0][0]
________________________________________________________________________________
__________________
conv5_block3_2_pad (ZeroPadding (None, 6, 6, 512)    0
conv5_block3_1_relu[0][0]
________________________________________________________________________________
__________________
conv5_block3_2_conv (Conv2D)    (None, 4, 4, 512)    2359296
conv5_block3_2_pad[0][0]
________________________________________________________________________________
__________________
conv5_block3_2_bn (BatchNormali (None, 4, 4, 512)    2048
conv5_block3_2_conv[0][0]
________________________________________________________________________________
__________________
conv5_block3_2_relu (Activation (None, 4, 4, 512)    0
conv5_block3_2_bn[0][0]
________________________________________________________________________________
__________________
conv5_block3_3_conv (Conv2D)    (None, 4, 4, 2048)   1050624
conv5_block3_2_relu[0][0]
________________________________________________________________________________
__________________
conv5_block3_out (Add)          (None, 4, 4, 2048)   0
conv5_block2_out[0][0]
conv5_block3_3_conv[0][0]
________________________________________________________________________________
__________________
post_bn (BatchNormalization)    (None, 4, 4, 2048)   8192
conv5_block3_out[0][0]
________________________________________________________________________________
__________________
post_relu (Activation)          (None, 4, 4, 2048)   0           post_bn[0][0]
________________________________________________________________________________
```

```
------------------
max_pool (GlobalMaxPooling2D)   (None, 2048)         0           post_relu[0][0]
================================================================================
==================
Total params: 23,564,800
Trainable params: 0
Non-trainable params: 23,564,800
--------------------------------------------------------------------------------
------------------
```

[114]:

```python
model = Sequential()
model.add(base_model)
model.add(Flatten())

# Add the fully connected layers
model.add(Dense(128, activation = "relu"))
model.add(Dropout(0.4)) # regularization
model.add(Dense(64, activation = "relu"))
model.add(Dropout(0.4)) # regularization
model.add(Dense(1, activation = "sigmoid"))

model.summary()
model.save("RESNET50V2");
```

```
Model: "sequential_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50v2 (Functional)      (None, 2048)              23564800
_________________________________________________________________
flatten_10 (Flatten)         (None, 2048)              0
_________________________________________________________________
dense_36 (Dense)             (None, 128)               262272
_________________________________________________________________
dropout_26 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_37 (Dense)             (None, 64)                8256
_________________________________________________________________
dropout_27 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_38 (Dense)             (None, 1)                 65
=================================================================
Total params: 23,835,393
Trainable params: 270,593
Non-trainable params: 23,564,800
_________________________________________________________________
INFO:tensorflow:Assets written to: RESNET50V2/assets
```

[116]:
```
# Compile model
model.compile(optimizer = "adam", loss = "binary_crossentropy", metrics =␣
 ↪["accuracy"])
```

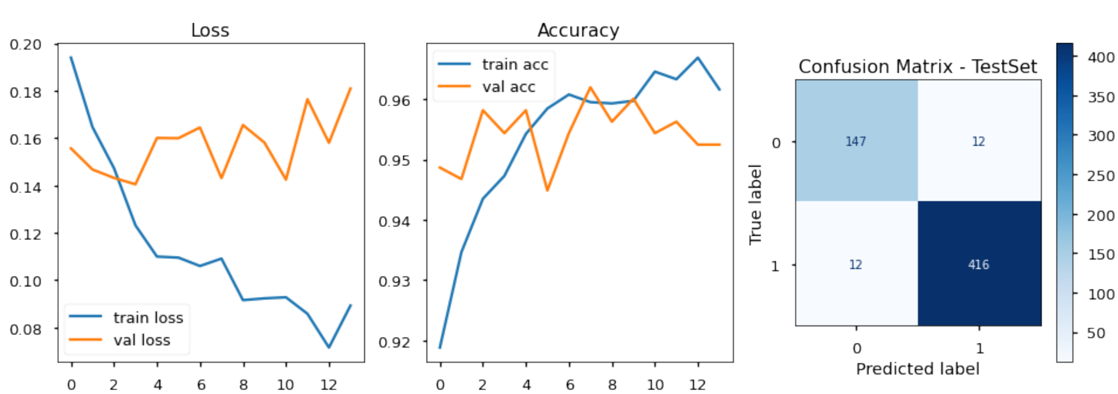
[119]:
```
# Fit model
RESNET50V2 = model.fit(train_image, y_train, epochs = 100, batch_size=31,
                    validation_data=(val_image, y_val),
                         callbacks = [early_stop])
```

```
Epoch 1/100
153/153 [==============================] - 81s 531ms/step - loss: 0.1940 -
accuracy: 0.9188 - val_loss: 0.1557 - val_accuracy: 0.9487
Epoch 2/100
153/153 [==============================] - 82s 534ms/step - loss: 0.1647 -
accuracy: 0.9346 - val_loss: 0.1468 - val_accuracy: 0.9468
Epoch 3/100
153/153 [==============================] - 82s 539ms/step - loss: 0.1474 -
accuracy: 0.9435 - val_loss: 0.1432 - val_accuracy: 0.9582
Epoch 4/100
153/153 [==============================] - 82s 536ms/step - loss: 0.1232 -
accuracy: 0.9473 - val_loss: 0.1405 - val_accuracy: 0.9544
Epoch 5/100
153/153 [==============================] - 82s 536ms/step - loss: 0.1100 -
accuracy: 0.9542 - val_loss: 0.1601 - val_accuracy: 0.9582
Epoch 6/100
153/153 [==============================] - 83s 541ms/step - loss: 0.1095 -
accuracy: 0.9585 - val_loss: 0.1600 - val_accuracy: 0.9449
Epoch 7/100
153/153 [==============================] - 82s 539ms/step - loss: 0.1060 -
accuracy: 0.9608 - val_loss: 0.1645 - val_accuracy: 0.9544
Epoch 8/100
153/153 [==============================] - 83s 541ms/step - loss: 0.1091 -
accuracy: 0.9595 - val_loss: 0.1431 - val_accuracy: 0.9620
Epoch 9/100
153/153 [==============================] - 84s 547ms/step - loss: 0.0916 -
accuracy: 0.9593 - val_loss: 0.1656 - val_accuracy: 0.9563
Epoch 10/100
153/153 [==============================] - 82s 538ms/step - loss: 0.0923 -
accuracy: 0.9597 - val_loss: 0.1581 - val_accuracy: 0.9601
Epoch 11/100
153/153 [==============================] - 82s 539ms/step - loss: 0.0928 -
accuracy: 0.9646 - val_loss: 0.1425 - val_accuracy: 0.9544
Epoch 12/100
153/153 [==============================] - 83s 541ms/step - loss: 0.0858 -
accuracy: 0.9633 - val_loss: 0.1765 - val_accuracy: 0.9563
Epoch 13/100
153/153 [==============================] - 84s 546ms/step - loss: 0.0716 -
```

```
accuracy: 0.9669 - val_loss: 0.1581 - val_accuracy: 0.9525
Epoch 14/100
153/153 [==============================] - 85s 552ms/step - loss: 0.0893 -
accuracy: 0.9616 - val_loss: 0.1810 - val_accuracy: 0.9525
```

[120]:
```
visualize_model_performance(RESNET50V2, train_image, test_image, "accuracy",
 ↪"val_accuracy")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.92      0.92       159
           1       0.97      0.97      0.97       428

    accuracy                           0.96       587
   macro avg       0.95      0.95      0.95       587
weighted avg       0.96      0.96      0.96       587



149/149 [==============================] - 70s 472ms/step - loss: 0.0731 -
accuracy: 0.9717
19/19 [==============================] - 8s 445ms/step - loss: 0.1048 -
accuracy: 0.9591
--------------------------
Final Train Loss: 0.0731
Final Test Loss: 0.1048
--------------------------
Final Train Acc: 0.9717
Final Test Acc: 0.9591
```



- Using transfet learning with RESNET5V2 we get similarly good results.

- Overall accuracy is 95.9% on the test set.
- Recall for pneumonia is high with 97%. Only 12 out of 428 pneumonia cases are mislabeled as normal.
- Recall for normal is at 92%. 12 out of 159 was mislabeled.

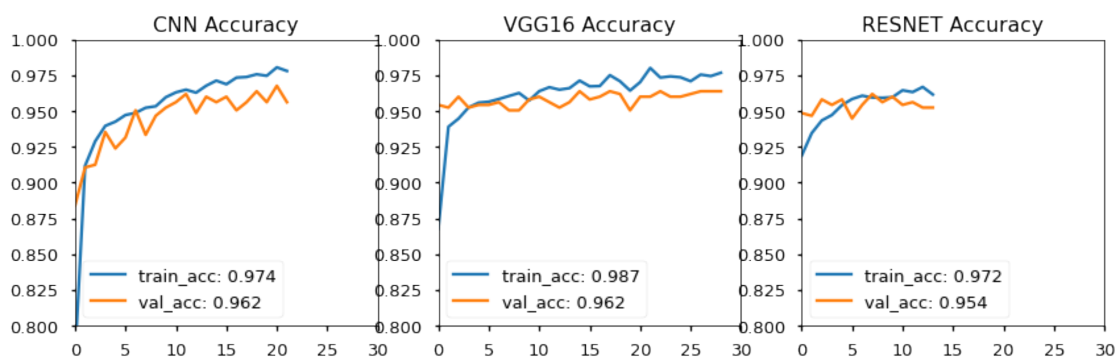
17 Best Performing Model?

[121]:
```
train_acc_LowLearnRate_CNN = np.round(LowLearnRate_CNN.model.
↪evaluate(train_image, y_train)[1],3)
val_acc_LowLearnRate_CNN = np.round(LowLearnRate_CNN.model.evaluate(val_image,␣
↪y_val)[1],3)

train_acc_VGG16 = np.round(VGG16.model.evaluate(train_image, y_train)[1],3)
val_acc_VGG16 = np.round(VGG16.model.evaluate(val_image, y_val)[1],3)

train_acc_RESNET50V2 = np.round(RESNET50V2.model.evaluate(train_image,␣
↪y_train)[1],3)
val_acc_RESNET50V2 = np.round(RESNET50V2.model.evaluate(val_image, y_val)[1],3)
```

```
149/149 [==============================] - 0s 3ms/step - loss: 0.0881 -
accuracy: 0.9656
17/17 [==============================] - 0s 4ms/step - loss: 0.1431 - accuracy:
0.9506
149/149 [==============================] - 9s 61ms/step - loss: 0.0757 - acc:
0.9743
17/17 [==============================] - 1s 59ms/step - loss: 0.1042 - acc:
0.9620
149/149 [==============================] - 202s 1s/step - loss: 0.0379 -
accuracy: 0.9871
17/17 [==============================] - 21s 1s/step - loss: 0.0933 - accuracy:
0.9620
149/149 [==============================] - 80s 535ms/step - loss: 0.0731 -
accuracy: 0.9717
17/17 [==============================] - 8s 453ms/step - loss: 0.1405 -
accuracy: 0.9544
```

[124]:
```
with plt.style.context('seaborn-talk'):
    fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(14,4))

    ax1.plot(LowLearnRate_CNN.history['acc'])
    ax1.plot(LowLearnRate_CNN.history['val_acc'])
    ax1.set_title('CNN Accuracy')
    ax1.legend(labels = [f'train_acc: {train_acc_LowLearnRate_CNN}', f'val_acc:␣
↪{val_acc_LowLearnRate_CNN}'])
    ax1.set_ylim([0.80, 1])
    ax1.set_xlim([0, 30])
```

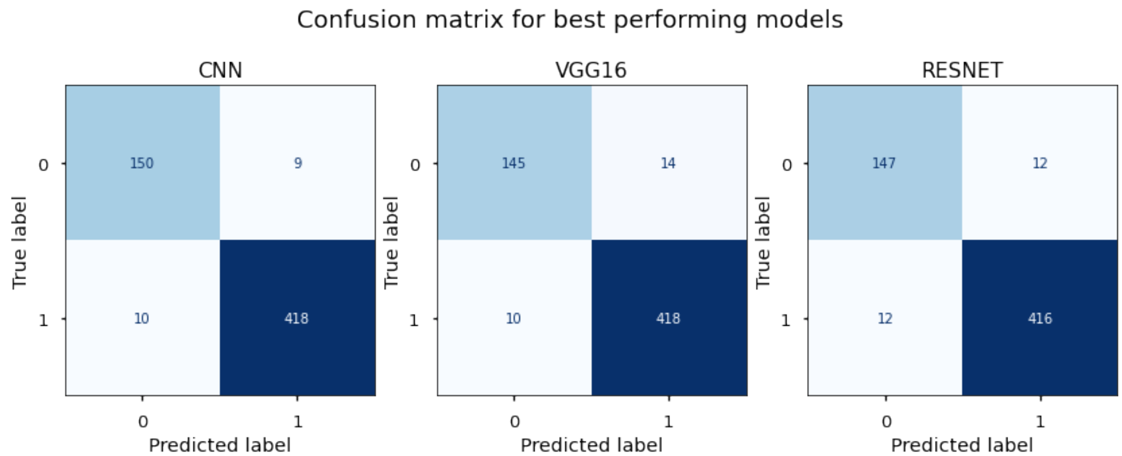
```
    ax2.plot(VGG16.history['accuracy'])
    ax2.plot(VGG16.history['val_accuracy'])
    ax2.set_title('VGG16 Accuracy')
    ax2.legend(labels = [f'train_acc: {train_acc_VGG16}', f'val_acc:␣
↪{val_acc_VGG16}'])
    ax2.set_ylim([0.80, 1])
    ax2.set_xlim([0, 30])

    ax3.plot(RESNET50V2.history['accuracy'])
    ax3.plot(RESNET50V2.history['val_accuracy'])
    ax3.set_title('RESNET Accuracy')
    ax3.legend(labels = [f'train_acc: {train_acc_RESNET50V2}', f'val_acc:␣
↪{val_acc_RESNET50V2}'])
    ax3.set_ylim([0.80, 1])
    ax3.set_xlim([0, 30])

plt.savefig('./images/CompareModels_train_val_acc', dpi=300,␣
↪bbox_inches='tight')
```



- All CNN models performed similarly well with no apparent signs of overfitting as seen by the loss and accuracy trends for the training and validation sets

[125]:
```
with plt.style.context('seaborn-talk'):

    fig, axs = plt.subplots(1, 3, figsize=(14,5))
    fig.suptitle("Confusion matrix for best performing models \n", fontsize=18)

    for ax, result, modelname in zip(axs.
↪ravel(),[LowLearnRate_CNN,VGG16,RESNET50V2],['CNN','VGG16', 'RESNET']):
        y_hat_test = result.model.predict(test_image)
        y_pred = np.rint(y_hat_test).astype(np.int)
        y_true = y_test.astype(np.int)
        cm = confusion_matrix(y_true, y_pred) # normalize = 'true'
```

```
        disp = ConfusionMatrixDisplay(confusion_matrix=cm)
        disp.plot(cmap = "Blues", ax=ax, colorbar =False)
        ax.set_title(modelname)
plt.savefig('./images/CompareModels_ConfusionMatrices', dpi=300,␣
 ↪bbox_inches='tight')
```



- All models reached overall accuracy levels of 95-96% and recall values of 97-98% for the pneumonia cases for the tets set.
- **CNN with dropout regularization and a lower learning rate** was chosen as the final model since it gave the best performance on test dataset by missing only 10 pneumonia-positive cases out of 428, and 9 out of 159 normal cases. It is also simpler than VGG or ResNet models.
- Using tuned CNN results on the test set were:
  - overall accuracy score of 97%,
  - recall score of 94% for class normal, and 98% for class pneumonia
  - f1 score of 94% for class normal, and 98% for class pneumonia

18 Visualize Intermediate Activations:

[91]:
```
best_model = keras.models.load_model("Dropout_CNN")
best_model.summary()
```

```
WARNING:tensorflow:No training configuration found in save file, so the model
was *not* compiled. Compile it manually.
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

```
conv2d_14 (Conv2D)           (None, 126, 126, 32)      896
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 63, 63, 32)        0
_________________________________________________________________
dropout_10 (Dropout)         (None, 63, 63, 32)        0
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 61, 61, 64)        18496
_________________________________________________________________
max_pooling2d_15 (MaxPooling (None, 30, 30, 64)        0
_________________________________________________________________
dropout_11 (Dropout)         (None, 30, 30, 64)        0
_________________________________________________________________
conv2d_16 (Conv2D)           (None, 28, 28, 128)       73856
_________________________________________________________________
max_pooling2d_16 (MaxPooling (None, 14, 14, 128)       0
_________________________________________________________________
dropout_12 (Dropout)         (None, 14, 14, 128)       0
_________________________________________________________________
flatten_5 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_21 (Dense)             (None, 128)               3211392
_________________________________________________________________
dropout_13 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_22 (Dense)             (None, 64)                8256
_________________________________________________________________
dropout_14 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_23 (Dense)             (None, 1)                 65
=================================================================
Total params: 3,312,961
Trainable params: 3,312,961
Non-trainable params: 0
_________________________________________________________________
```

18.0.1 Load a sample Image, Transform the Image to a Tensor and Visualize:

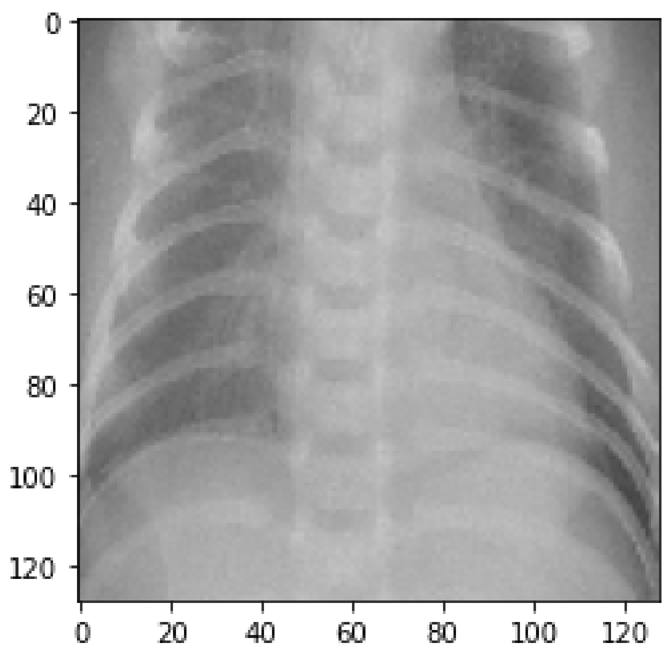
[92]:
```
os.listdir("Data/OUTPUT/train/PNEUMONIA")[0:15]
```

[92]:
```
['person63_bacteria_306.jpeg',
 'person1438_bacteria_3721.jpeg',
 'person478_virus_975.jpeg',
 'person661_bacteria_2553.jpeg',
 'person1214_bacteria_3166.jpeg',
 'person1353_virus_2333.jpeg',
 'person26_bacteria_122.jpeg',
 'person1619_bacteria_4261.jpeg',
```

```
 'person890_bacteria_2814.jpeg',
 'person147_bacteria_706.jpeg',
 'person1491_bacteria_3893.jpeg',
 'person69_bacteria_338.jpeg',
 'person100_bacteria_482.jpeg',
 'person321_bacteria_1489.jpeg',
 'person281_bacteria_1329.jpeg']
```

[93]:
```
filename = 'Data/chest_xray/train/PNEUMONIA/person69_bacteria_338.jpeg'
img = image.load_img(filename, target_size=(128, 128))
img_tensor = image.img_to_array(img)
img_tensor = np.expand_dims(img_tensor, axis=0)
img_tensor /= 255.

# Check tensor shape
print(img_tensor.shape)

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

```
(1, 128, 128, 3)
```



18.0.2 Plot Feature Maps:

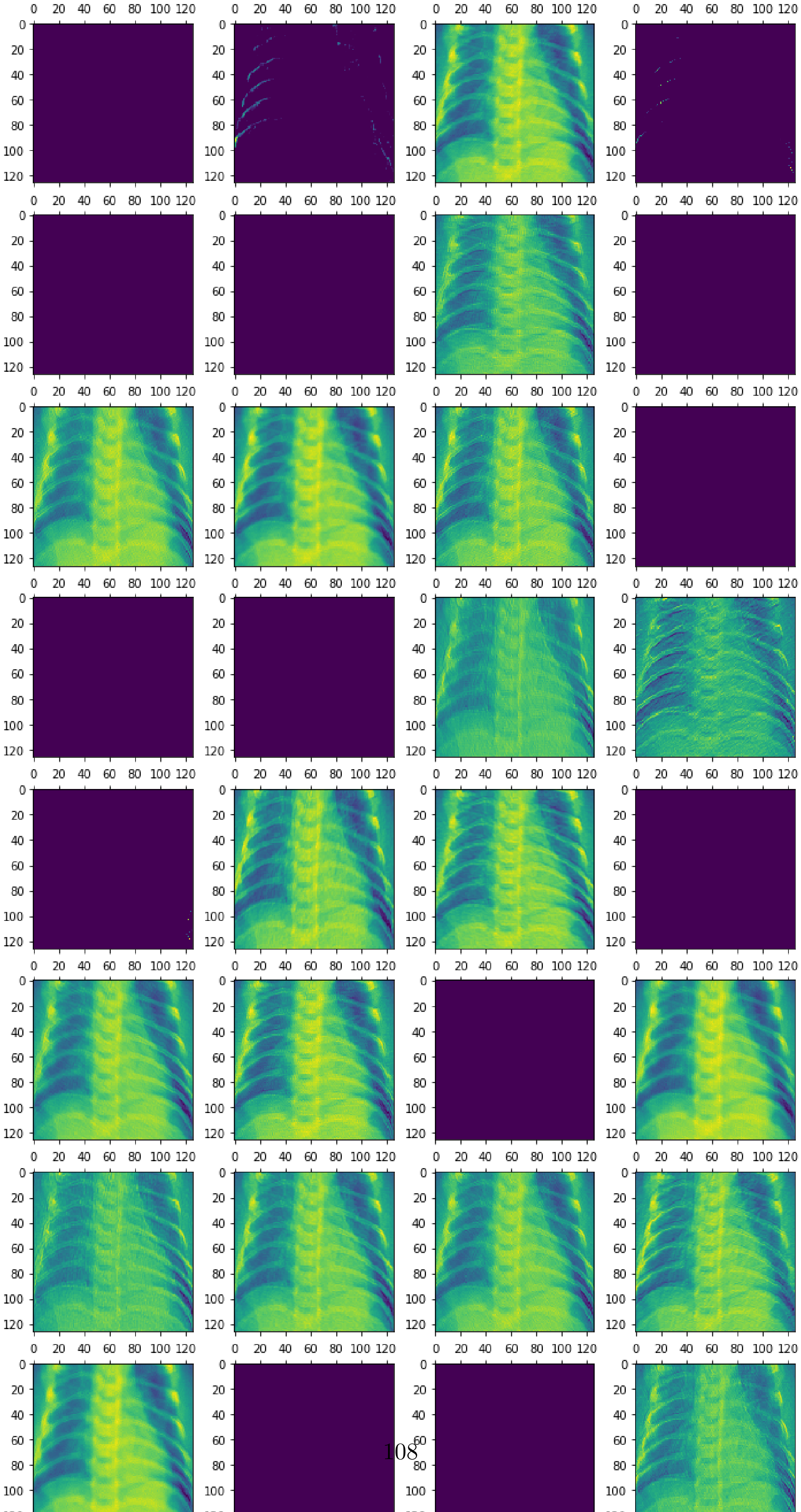
- The idea of visualizing a feature map for a specific input image would be to understand what features of the input are detected or preserved in the feature maps.
- Specifically, the models are comprised of small linear filters and the result of applying filters called activation maps / feature maps. Visualize all 32 of the channels / filters from the first activation function.
- We can also visualize a single channel / filter across each of the feature maps / activation layers. Representations learned by CNN architectures become increasingly more abstract with the depth of the layers.

18.0.3 Visualize all 32 of the channels from the first activation function.

- The initial three layers output feature maps that have 32 channels each.

[94]:
```
# Extract the feature maps, or layer outputs from each of the activation␣
↪functions in the model.
layer_outputs = [layer.output for layer in best_model.layers[:8]]

# Generate models that transform the image from its raw state to these feature␣
↪map
activation_model = models.Model(inputs=best_model.input, outputs=layer_outputs)

#  Take these transformations and visualize each channel for each feature map.␣
↪Returns an array for each activation layer
activations = activation_model.predict(img_tensor)
```

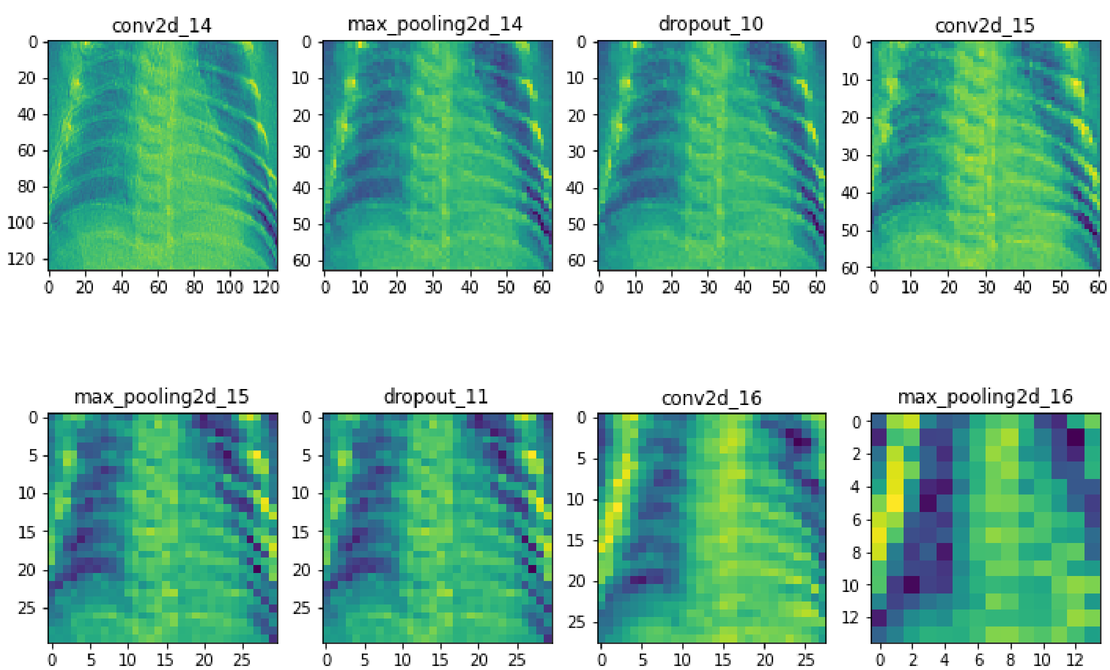
[95]:
```
# Visualize all 32 of the channels from the first activation function:

fig, axes = plt.subplots(8, 4, figsize=(12,24))
for i in range(32):
    row = i//4
    column = i%4
    ax = axes[row, column]
    first_layer_activation = activations[0] # first activation channel
    ax.matshow(first_layer_activation[0, :, :, i], cmap='viridis')
# In the case of the blank images displayed, this indicates that the patterns␣
↪were not present in the current image.
```



18.0.4 Visualize a single channel for each of the activation layers:

- Below is the visualization of the 25th channel for each of the activation layers. (Recall that there are more channels in later layers.)

[190]:
```
fig, axes = plt.subplots(2,4, figsize=(12,8))

layer_names = []
for layer in best_model.layers[:8]:  # layers until the 8th layer
    layer_names.append(layer.name)

for i in range(8):
    row = i//4
    column = i%4
    ax = axes[row, column]
    cur_layer = activations[i]
    ax.matshow(cur_layer[0, :, :,24])
    ax.xaxis.set_ticks_position('bottom')
    ax.set_title(layer_names[i])

plt.savefig('./images/ActivationChannels', dpi=300, bbox_inches='tight')
```



- Deeper layers are more abstract representations. This demonstrates how the representations

learned by CNN architectures become increasingly abstract with the depth of the layers.
- The expectation would be that the feature maps close to the input detect small or fine-grained detail, whereas feature maps close to the output of the model capture more general features.

18.0.5 Visualize each of the channels for each of feature maps of the convolutional layers:

- Code taken from https://github.com/learn-co-curriculum/dsc-visualizing-activation-functions-lab/tree/solution

[108]:
```
from keras import models
import math

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

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

activations = activation_model.predict(img_tensor)

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

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

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


iteration = 0
fig , axes = plt.subplots(nrows=n_rows, ncols=n_cols, figsize=(n_cols, n_rows*1.
 ↪5))

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

        ax = axes[row, column]

        channel_image = layer_activation[0,
                                         :, :,
                                         ch_idx]
```

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

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

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

fig.subplots_adjust(hspace=1.25)
plt.show()
```


conv2d_14
max_pooling2d_14
dropout_10
conv2d_15
max_pooling2d_15
dropout_11
conv2d_16
max_pooling2d_16

18.1 Recommendations

- Neural network may be used to aid the healthcare professional in stream-lining the diagnosing process when classifying x-ray images. This may allow for a quicker return time and greater patient satisfaction.
- Catching as many people with pneumonia as possible is particularly important for early intervention. Use of ANN for image classification might lead to more positive outcomes because the positive patients can begin treatment right away as opposed to waiting lenghty periods of time until they hear from the readings of the radiologist and interpretation of the doctor.
- Such process would also reduce any radiologist's/doctor's stress at having to look through a great deal of images. They could instead use their time to more rigorously go over the images that fall more into the grey zone based on the model predictions.
- Less time the doctors expend looking at images to arrive at a diagnosis, the more time they can allocate to dealing with more demanding and complex procedures.

18.2 Limitations and Next Steps

- We can use data augmentation methods to increase the size of the training data set which could improve model performance on unseen data.
- We can crop the images to exclude the electrodes and the R script from the display which negatively affect the image processing algorithm.
- We could address the class imbalance issue using oversampling techniques which could again improve performance.

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[141]:
```
! export PATH=/Library/TeX/texbin:$PATH
```

[143]:
```
! jupyter nbconvert --to PDF Notebook.ipynb
```

```
[NbConvertApp] Converting notebook Notebook.ipynb to PDF
[NbConvertApp] Writing 3410327 bytes to Notebook.pdf
```

[ ]:
```
```