4 Final Project Submission

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- pace: Part time
- Scheduled project review data/time: January th, 2022, AM (Mountain Time)
- Course Instructor: Abhineet
- Blog post URL: https://github.com/lddrasler/Pneumonia-Detection-Tensor-Flow-and-Keras (https://github.com/lddrasler/Pneumonia-Detection-Tensor-Flow-and-Keras)
- GitHub repository: https://wordpress.com/post/callableleticia.blog/101 (https://wordpress.com/post/callableleticia.blog/101)

Importing Packages

In [1]:
```
import tensorflow as tf
import numpy as np
from tensorflow.keras.preprocessing import image_dataset_from_directory
import matplotlib.pyplot as plt
from tensorflow import keras
from tensorflow.keras import layers
```

Open the directories

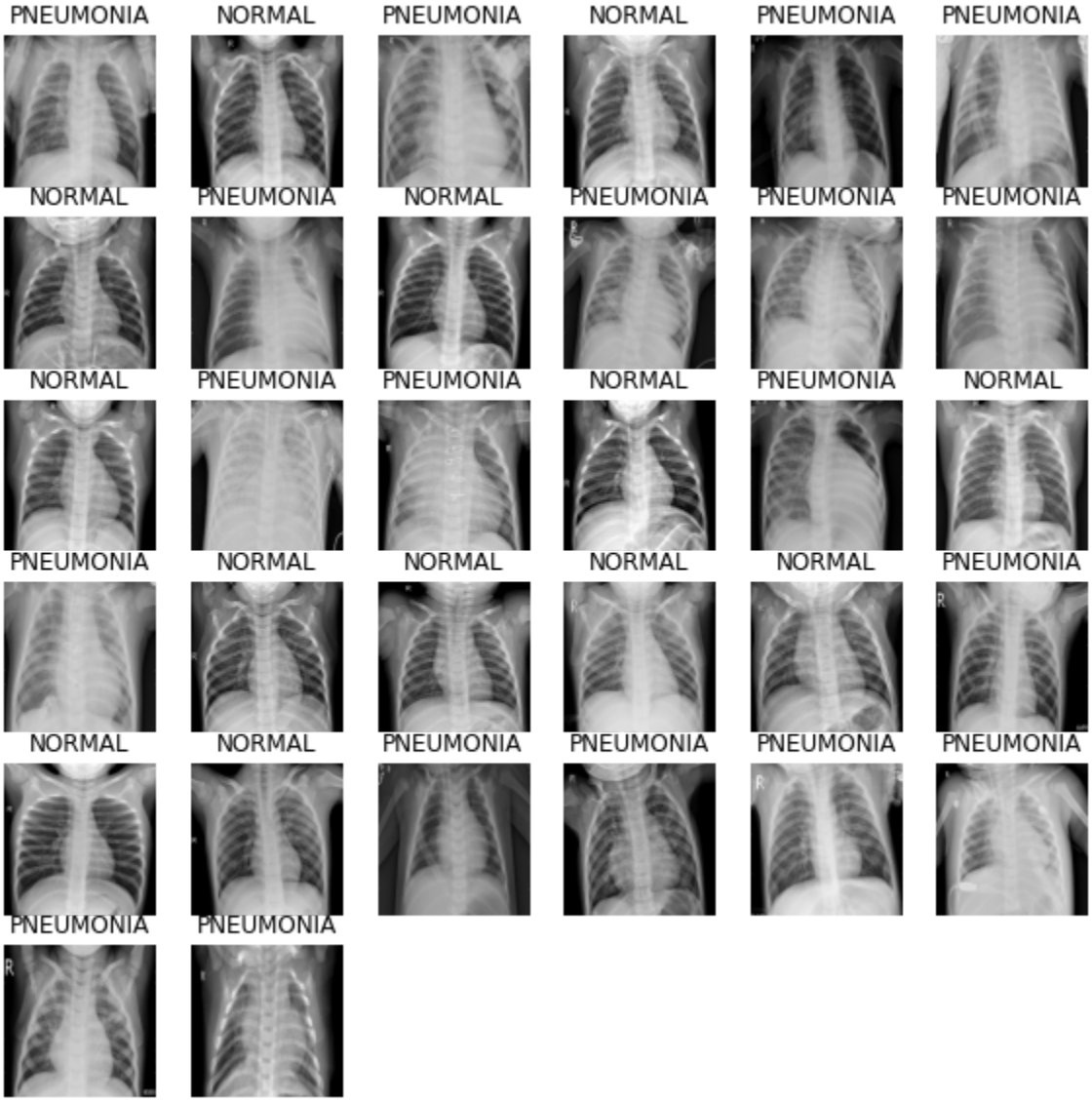
In [2]:
```
train_directory='chest_xray\\train'
val_directory='chest_xray\\val'
test_directory='chest_xray\\test'

# using image_dataset_from_directory
# to find out how many files and classes the dataset has

train_data=image_dataset_from_directory(train_directory,color_mode="grayscale")
val_data=image_dataset_from_directory(val_directory,color_mode="grayscale")
test_data=image_dataset_from_directory(test_directory,color_mode="grayscale")
```

```
Found 5216 files belonging to 2 classes.
Found 16 files belonging to 2 classes.
Found 624 files belonging to 2 classes.
```

Plotting random images from our train data file

In [3]:

```
plt.figure(figsize=(10, 10))
class_names = train_data.class_names
for images, labels in train_data.take(1):
    for i in range(len(images)):
        ax = plt.subplot(6, 6, i + 1)
        plt.imshow(images[i].numpy().astype("uint8"),cmap='gray')
        plt.title(class_names[labels[i]])
        plt.axis("off")
```



Baseline Fully Connected Neural Network

In [4]:

```
inputs = keras.Input(shape=(256, 256, 1))
x = layers.Rescaling(1./255)(inputs)
x = layers.Flatten()(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model_baseline = keras.Model(inputs=inputs, outputs=outputs)

model_baseline.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
              metrics=["accuracy"])
```

In [5]:

```
callbacks_baseline = [
 keras.callbacks.ModelCheckpoint(
 filepath="baseline_model.keras",
 save_best_only=True,
 monitor="val_loss")
]

history_baseline = model_baseline.fit(
 train_data,
 epochs=15,
 validation_data=val_data,
 callbacks=callbacks_baseline)
```

```
Epoch 1/15
163/163 [==============================] - 13s 75ms/step - loss: 3.7488 - accuracy:
0.7427 - val_loss: 2.0293 - val_accuracy: 0.8125
Epoch 2/15
163/163 [==============================] - 13s 75ms/step - loss: 1.9834 - accuracy:
0.8317 - val_loss: 11.4065 - val_accuracy: 0.5000
Epoch 3/15
163/163 [==============================] - 15s 86ms/step - loss: 1.5900 - accuracy:
0.8637 - val_loss: 1.6170 - val_accuracy: 0.7500
Epoch 4/15
163/163 [==============================] - 18s 104ms/step - loss: 1.5290 - accuracy:
0.8750 - val_loss: 4.5848 - val_accuracy: 0.6875
Epoch 5/15
163/163 [==============================] - 17s 101ms/step - loss: 1.2871 - accuracy:
0.8905 - val_loss: 0.3674 - val_accuracy: 0.8125
Epoch 6/15
163/163 [==============================] - 18s 105ms/step - loss: 1.2331 - accuracy:
0.9018 - val_loss: 0.1379 - val_accuracy: 0.8750
Epoch 7/15
163/163 [==============================] - 17s 101ms/step - loss: 1.1809 - accuracy:
0.9041 - val_loss: 1.0325 - val_accuracy: 0.9375
Epoch 8/15
163/163 [==============================] - 18s 103ms/step - loss: 1.1693 - accuracy:
0.9095 - val_loss: 9.1917 - val_accuracy: 0.5625
Epoch 9/15
163/163 [==============================] - 17s 102ms/step - loss: 1.1143 - accuracy:
0.9137 - val_loss: 9.8717 - val_accuracy: 0.5625
Epoch 10/15
163/163 [==============================] - 17s 102ms/step - loss: 1.0918 - accuracy:
0.9160 - val_loss: 1.2066 - val_accuracy: 0.9375
Epoch 11/15
163/163 [==============================] - 18s 104ms/step - loss: 1.0175 - accuracy:
0.9208 - val_loss: 0.8982 - val_accuracy: 0.9375
Epoch 12/15
163/163 [==============================] - 17s 101ms/step - loss: 0.9975 - accuracy:
0.9158 - val_loss: 0.8909 - val_accuracy: 0.8125
Epoch 13/15
163/163 [==============================] - 18s 106ms/step - loss: 1.0235 - accuracy:
0.9204 - val_loss: 0.9798 - val_accuracy: 0.9375
Epoch 14/15
163/163 [==============================] - 16s 97ms/step - loss: 1.0374 - accuracy:
0.9241 - val_loss: 1.1385 - val_accuracy: 0.9375
Epoch 15/15
163/163 [==============================] - 17s 99ms/step - loss: 0.9668 - accuracy:
0.9314 - val_loss: 12.6372 - val_accuracy: 0.5625
```

In [7]:
```
test_loss, test_acc = model_baseline.evaluate(test_data)
print(f"Test accuracy: {test_acc:.3f}")
```

```
20/20 [==============================] - 1s 41ms/step - loss: 14.1111 - accuracy: 0.6
426
Test accuracy: 0.643
```

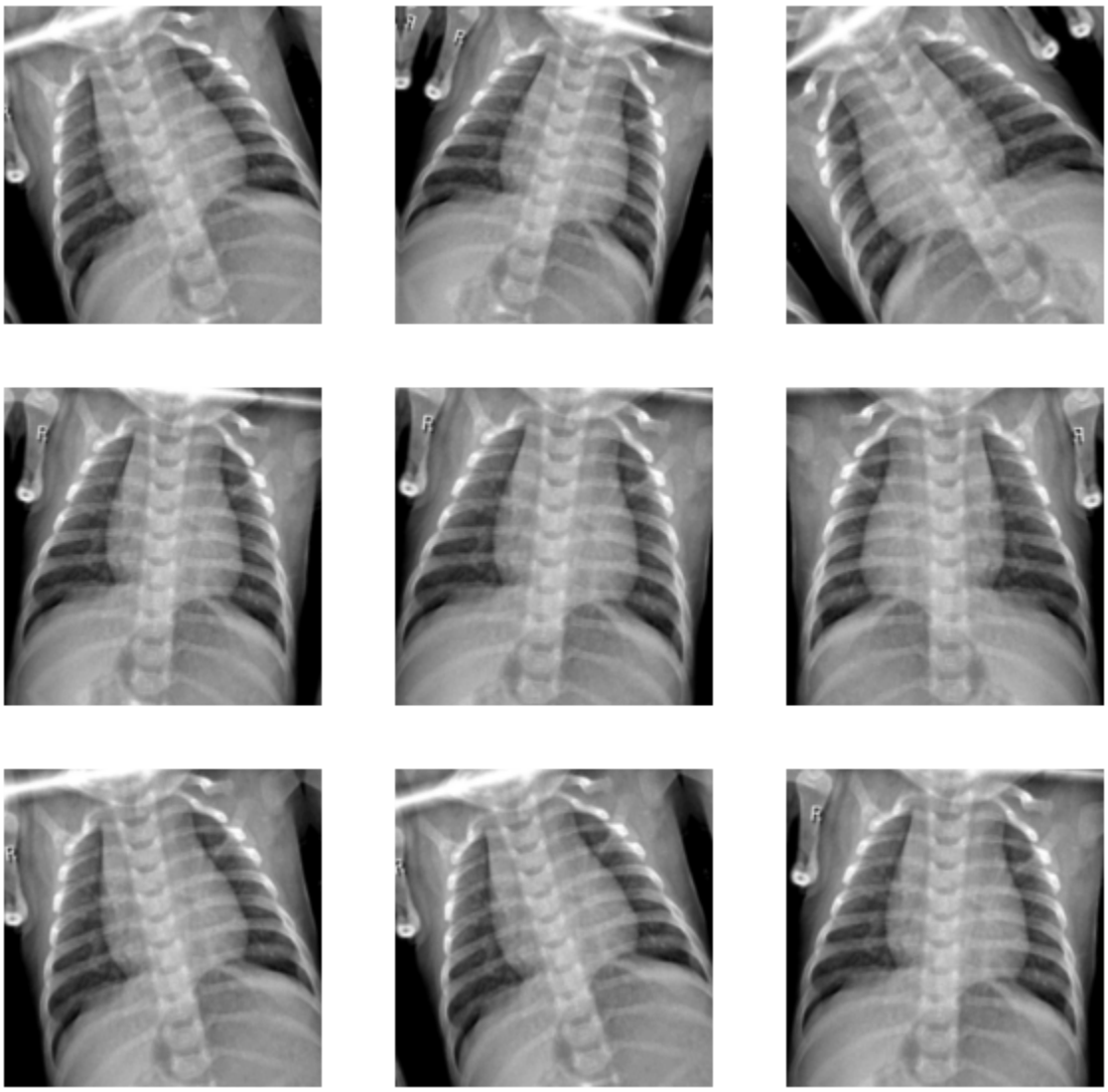
The simple Neural Network does not have a great performance because

Convoluntional Neural Network

In [8]:
```
# adding data augmentation to help the model not to overfit

data_augmentation = keras.Sequential(
 [
     layers.RandomFlip("horizontal"),
     layers.RandomRotation(0.1),
     layers.RandomZoom(0.1),
 ]
)
```

In [9]:

```
plt.figure(figsize=(10, 10))
for images, _ in train_data.take(1):
    for i in range(9):
        augmented_images = data_augmentation(images)
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(augmented_images[0].numpy().astype("uint8"),cmap='gray')
        plt.axis("off")
```



In [10]:

```
inputs = keras.Input(shape=(256, 256, 1))

# adding data_augmentation to prevent overfitting
x = data_augmentation(inputs)

# first convoluntional layer
x = layers.Rescaling(1./255)(x)
x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)

# second convoluntional layer
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)

# third convoluntional layer
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)

# fourth convoluntional layer
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)

# fifth convoluntional layer
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)

# flatten
x = layers.Flatten()(x)

# dropout to prevent overfitting

x = layers.Dropout(0.5)(x)
x = layers.Dense(512, activation="relu")(x)

outputs = layers.Dense(1, activation='sigmoid')(x)

model_3 = keras.Model(inputs=inputs, outputs=outputs)
model_3.compile(loss="binary_crossentropy",
                optimizer="rmsprop",
                metrics=["accuracy"])
```

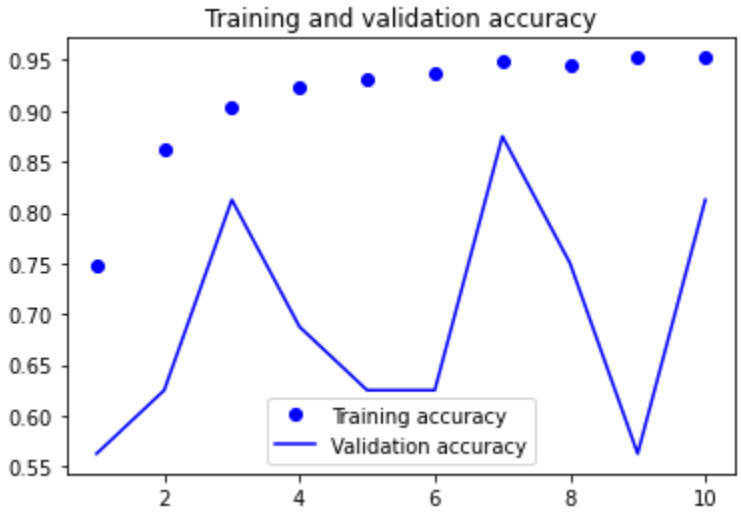
In [11]:
```
callbacks_3 = [
 keras.callbacks.ModelCheckpoint(
     filepath='x_ray_covn_model_NN.{epoch:02d}.hdf5',
     save_best_only=False,
     monitor="val_loss")
]
```

In [12]:
```
history_3 = model_3.fit(
 train_data,
 epochs=10,
 validation_data=val_data,
 callbacks=callbacks_3)
```

```
Epoch 1/10
163/163 [==============================] - 462s 3s/step - loss: 0.9677 - accuracy: 0.
7479 - val_loss: 0.8539 - val_accuracy: 0.5625
Epoch 2/10
163/163 [==============================] - 434s 3s/step - loss: 0.3636 - accuracy: 0.
8629 - val_loss: 2.7568 - val_accuracy: 0.6250
Epoch 3/10
163/163 [==============================] - 435s 3s/step - loss: 0.2650 - accuracy: 0.
9036 - val_loss: 0.5207 - val_accuracy: 0.8125
Epoch 4/10
163/163 [==============================] - 431s 3s/step - loss: 0.2111 - accuracy: 0.
9237 - val_loss: 0.6908 - val_accuracy: 0.6875
Epoch 5/10
163/163 [==============================] - 423s 3s/step - loss: 0.1896 - accuracy: 0.
9316 - val_loss: 0.5871 - val_accuracy: 0.6250
Epoch 6/10
163/163 [==============================] - 419s 3s/step - loss: 0.1688 - accuracy: 0.
9377 - val_loss: 1.6239 - val_accuracy: 0.6250
Epoch 7/10
163/163 [==============================] - 426s 3s/step - loss: 0.1478 - accuracy: 0.
9494 - val_loss: 0.3934 - val_accuracy: 0.8750
Epoch 8/10
163/163 [==============================] - 448s 3s/step - loss: 0.1542 - accuracy: 0.
9448 - val_loss: 0.4593 - val_accuracy: 0.7500
Epoch 9/10
163/163 [==============================] - 441s 3s/step - loss: 0.1421 - accuracy: 0.
9525 - val_loss: 0.6913 - val_accuracy: 0.5625
Epoch 10/10
163/163 [==============================] - 439s 3s/step - loss: 0.1499 - accuracy: 0.
9523 - val_loss: 0.4059 - val_accuracy: 0.8125
```

In [13]:

```
accuracy = history_3.history["accuracy"]
val_accuracy = history_3.history["val_accuracy"]
loss = history_3.history["loss"]
val_loss = history_3.history["val_loss"]
epochs = range(1, len(accuracy) + 1)

plt.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training and validation accuracy")
# plt.xlim([1, 25])
plt.legend()
plt.figure()
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.legend()
# plt.xlim([1, 25])

plt.show()
```



In [17]:

```
test_model_03 = keras.models.load_model("x_ray_covn_model_NN.24.hdf5")
test_loss, test_acc = test_model_03.evaluate(test_data)
print(f"Test accuracy: {test_acc:.3f}")
```

```
20/20 [==============================] - 21s 943ms/step - loss: 0.2494 - accuracy: 0.
9071
Test accuracy: 0.907
```

In [18]:
```
test_model_03.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 256, 256, 1)]     0

 sequential (Sequential)     (None, 256, 256, 1)       0

 rescaling_1 (Rescaling)     (None, 256, 256, 1)       0

 conv2d (Conv2D)             (None, 254, 254, 32)      320

 max_pooling2d (MaxPooling2D  (None, 127, 127, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 125, 125, 64)      18496

 max_pooling2d_1 (MaxPooling  (None, 62, 62, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 60, 60, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 30, 30, 128)      0
 2D)

 conv2d_3 (Conv2D)           (None, 28, 28, 256)       295168

 max_pooling2d_3 (MaxPooling  (None, 14, 14, 256)      0
 2D)

 conv2d_4 (Conv2D)           (None, 12, 12, 256)       590080

 flatten_1 (Flatten)         (None, 36864)             0

 dropout (Dropout)           (None, 36864)             0

 dense_1 (Dense)             (None, 512)               18874880

 dense_2 (Dense)             (None, 1)                 513

=================================================================
Total params: 19,853,313
Trainable params: 19,853,313
Non-trainable params: 0
_________________________________________________________________
```

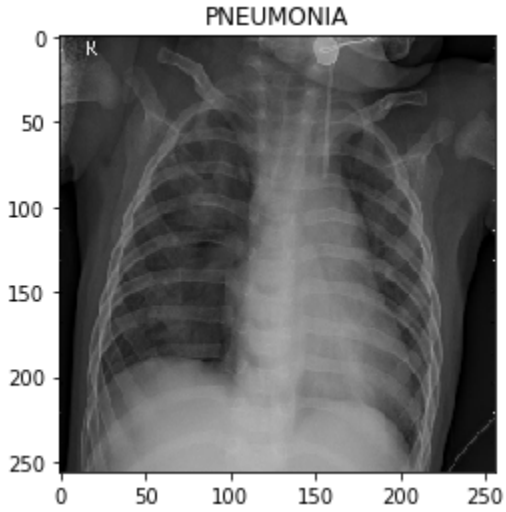
LIME PACKAGE

In [19]:
```
from lime import lime_image

explainer = lime_image.LimeImageExplainer()
```

In [20]:
```
data=image_dataset_from_directory(train_directory)
```

```
Found 5216 files belonging to 2 classes.
```

In [21]:
```
# from skimage.color import gray2rgb
data =list(train_data.take(1))
image = data[0][0][4].numpy().astype(np.uint8)
label=data[0][1][4].numpy()
class_names = train_data.class_names

from matplotlib import pyplot as plt
plt.imshow(image.reshape(256,256), interpolation='nearest',cmap='gray')
plt.title(class_names[label])
# plt.imshow(image_color, interpolation='nearest')
plt.show()
```



In [22]:
```
def reshape_img(image):
    return image.reshape(256,256)

def new_predict_fn(images):
    images=images[:,:,:,:1]
    return test_model_03.predict(images)

explanation = explainer.explain_instance(image.reshape(256,256),
                                         new_predict_fn,
                                         top_labels=2, hide_color=0,
                                         num_samples=1000)
```

```
100%                                                1000/1000 [01:06<00:00, 11.35it/s]
```

In [23]:
```
from skimage.segmentation import mark_boundaries

temp_1, mask_1 = explanation.get_image_and_mask(explanation.top_labels[0], positive_onl
                                                num_features=5, hide_rest=True)
temp_2, mask_2 = explanation.get_image_and_mask(explanation.top_labels[0], positive_onl
                                                num_features=10, hide_rest=False)

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,15))
ax1.imshow(mark_boundaries(temp_1.astype('uint8'), mask_1))
ax2.imshow(mark_boundaries(temp_2.astype('uint8'), mask_2))
ax1.axis('off')
ax2.axis('off')
```

Out[23]: (-0.5, 255.5, 255.5, -0.5)