1. Import Libraries/Dataset (0 mark)
   A. Import the required libraries and the dataset (use Google Drive if required).
   B. Check the GPU available (recommended- use free GPU provided by Google Colab).

How do Deep Learning Networks distinguish between healthy and unhealthy lungs? Most deep neural network applied to the task of pneumonia diagnosis have been adapted from natural image classification. Since natural image classification models have a large number of parameters as well as high hardware requirements, which makes them prone to overfitting and harder to deploy in mobile settings (Fourcade & Khonsari, 2019).

Convolutional Neural Networks are a common form of deep networks for classification tasks. CNNs have extensive learning capacity and can infer the nature of an input image without any prior knowledge, which makes them a suitable method for image classification (Toraman, Alakus, & Turkoglu, 2020). CNNs make use of the following three properties:

1. First: units in each layer receive inputs from the previous units which are located in a small neighborhood. This way, elementary features such as edges and corners can be extracted. Then these features will be combined in next layers to detect higher order features.
2. Second: important property is the concept of shared weights, which means similar feature detectors are used for the entire image.
3. Third: CNNs usually have several sub-sampling layers. These layers are based on the fact that the precise location of the features are not only beneficial, but also harmful, because this information tends to vary for different instances (Yadav & Jadhav, 2019).

In [23]:
```python
#libraries
import numpy as np
import pandas as pd
import random

# folder
import os

# Imports packages to view data
import cv2
from glob import glob
import matplotlib.pyplot as plt
from PIL import Image
from google.colab.patches import cv2_imshow
from prettytable import PrettyTable

# visu
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
plt.rc('image', cmap='gray')

# sklearn
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

#tensorflow and keras
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Activation, Dense, Flatten, BatchNormalization, Conv2D, MaxPool2D
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.metrics import categorical_crossentropy
from tensorflow.keras import layers
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.layers import Activation, Dropout, Flatten, Dense
from tensorflow.keras import backend as K
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau, ModelCheckpoint
from tensorflow.keras.regularizers import l2

#google drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", for
ce_remount=True).
```

In [2]:
```python
print(tf.__version__)
```

```
2.7.0
```

In [40]:
```python
train_data_dir = "/content/drive/My Drive/Colab Notebooks/chest_xray/train"
val_data_dir = "/content/drive/My Drive/Colab Notebooks/chest_xray/val"
test_data_dir = "/content/drive/My Drive/Colab Notebooks/chest_xray/test"
```

In [4]:
```python
!ls "/content/drive/My Drive/Colab Notebooks/chest_xray"
```

```
test  train  val
```

Exploratory Data Analysis

1. Data Visualization and augmentation (1 mark)
   A. Plot at least two samples from each class of the dataset (use matplotlib/seaborn/any other library).

In [41]:
```python
# Set up folders for normal cases and pneumonia cases wihtin our train data
train_n = train_data_dir + '/NORMAL/'
train_p = train_data_dir + '/PNEUMONIA/'

# Random normal picture from train set
print(f"Normal X-Rays From Validation Set: {len(os.listdir(train_n))} ")
print(f"PNEUMONIA X-Rays From Validation Set: {len(os.listdir(train_p))} ")
```

```
Normal X-Rays From Validation Set: 1342
PNEUMONIA X-Rays From Validation Set: 3876
```

In [14]:
```python
## Select 10 normal pictures
norm_pic = os.listdir(train_n)[25:35] # for 10 images only we are showing
norm_pic
```

Out[14]:
```
['IM-0546-0001.jpeg',
 'IM-0534-0001.jpeg',
 'IM-0539-0001-0001.jpeg',
 'IM-0533-0001-0002.jpeg',
 'IM-0545-0001-0001.jpeg',
 'IM-0542-0001.jpeg',
 'IM-0551-0001-0001.jpeg',
 'IM-0548-0001.jpeg',
 'IM-0535-0001.jpeg',
 'IM-0545-0001-0002.jpeg']
```

In [15]:
```python
norm_pic_address = [train_n + pic for pic in norm_pic]
norm_pic_address
```

Out[15]:
```
['/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0546-0001.jpeg',
 '/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0534-0001.jpeg',
 '/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0539-0001-0001.jpeg',
 '/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0533-0001-0002.jpeg',
 '/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0545-0001-0001.jpeg',
 '/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0542-0001.jpeg',
 '/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0551-0001-0001.jpeg',
 '/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0548-0001.jpeg',
 '/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0535-0001.jpeg',
 '/content/drive/My Drive/Colab Notebooks/chest_xray/train/NORMAL/IM-0545-0001-0002.jpeg']
```

In [13]:
```python
print(f"Pneumonia X-Rays From Validation Set: {len(os.listdir(train_p))} ")
```

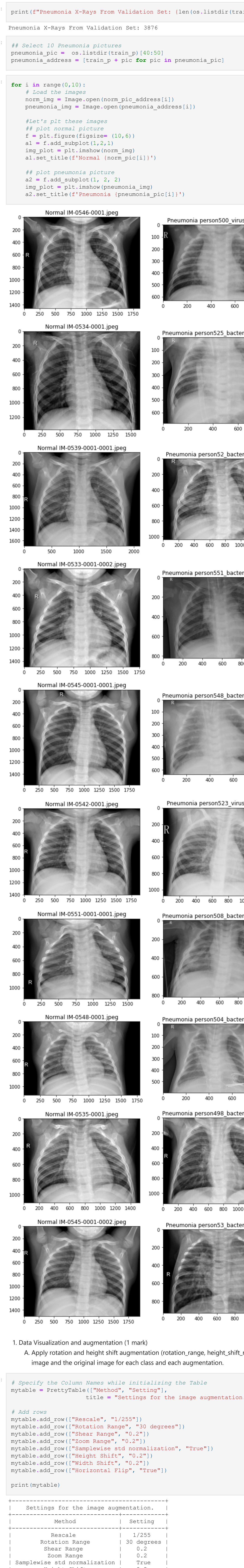
```
Pneumonia X-Rays From Validation Set: 3876
```

In [16]:
```python
## Select 10 Pneumonia pictures
pneumonia_pic =  os.listdir(train_p)[40:50]
pneumonia_address = [train_p + pic for pic in pneumonia_pic]
```

In [17]:
```python
for i in range(0,10):
    # Load the images
    norm_img = Image.open(norm_pic_address[i])
    pneumonia_img = Image.open(pneumonia_address[i])

    #Let's plt these images
    ## plot normal picture
    f = plt.figure(figsize= (10,6))
    a1 = f.add_subplot(1,2,1)
    img_plot = plt.imshow(norm_img)
    a1.set_title(f'Normal {norm_pic[i]}')

    ## plot pneumonia picture
    a2 = f.add_subplot(1, 2, 2)
    img_plot = plt.imshow(pneumonia_img)
    a2.set_title(f'Pneumonia {pneumonia_pic[i]}')
```



1. Data Visualization and augmentation (1 mark)
   A. Apply rotation and height shift augmentation (rotation_range, height_shift_range)to the dataset separately. Print the augmented image and the original image for each class and each augmentation.

In [24]:
```python
# Specify the Column Names while initializing the Table
mytable = PrettyTable(["Method", "Setting"],
                      title = "Settings for the image augmentation.")

# Add rows
mytable.add_row(["Rescale", "1/255"])
mytable.add_row(["Rotation Range", "30 degrees"])
mytable.add_row(["Shear Range", "0.2"])
mytable.add_row(["Zoom Range", "0.2"])
mytable.add_row(["Samplewise std normalization", "True"])
mytable.add_row(["Height Shift", "0.2"])
mytable.add_row(["Width Shift", "0.2"])
mytable.add_row(["Horizontal Flip", "True"])

print(mytable)
```

```
+-------------------------------------------+
|    Settings for the image augmentation.   |
+------------------------------+------------+
|            Method            |  Setting   |
+------------------------------+------------+
|           Rescale            |   1/255    |
|        Rotation Range        | 30 degrees |
|         Shear Range          |    0.2     |
|          Zoom Range          |    0.2     |
| Samplewise std normalization |    True    |
|         Height Shift         |    0.2     |
|         Width Shift          |    0.2     |
|       Horizontal Flip        |    True    |
+------------------------------+------------+
```

Create a data augmentor

data_augmentor = ImageDataGenerator(samplewise_center=True, # set each sample mean to 0

rescale=1./255, # rescale

rotation_range = 30, # randomly rotate images in the range (degrees, 0 to 180)

shear_range=0.2, # Randomly shear image

zoom_range = 0.2, # Randomly zoom image

samplewise_std_normalization=True, # divide each input by its std

validation_split=0.2,

height_shift_range = 0.2, # randomly shift images horizontally (fraction of total height)

width_shift_range = 0.2, # randomly shift images horizontally (fraction of total width)

horizontal_flip = True) # randomly flip images

In [25]:
```python
data_augmentor = ImageDataGenerator(samplewise_center=True,
                                    rescale=1./255,
                                    shear_range=0.2,
                                    zoom_range = 0.2,
                                    samplewise_std_normalization=True,
                                    validation_split=0.2)

# Set hyperparameters
target_size = (128,128)
target_dims = (128, 128, 3) # add channel for RGB
n_batch_size = 32
```

1. Data Visualization and augmentation (1 mark)
   A. Bring the train and test data in the required format

In [28]:
```python
# Create datasets
train_generator = data_augmentor.flow_from_directory(train_data_dir,  target_size=target_size, subset='training
val_generator = data_augmentor.flow_from_directory(train_data_dir, target_size=target_size,subset='validation',
test_generator = data_augmentor.flow_from_directory(test_data_dir, target_size=target_size,batch_size= 1,class_
```

```
Found 4173 images belonging to 2 classes.
Found 1043 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
```

1. Data Visualization and augmentation (1 mark)
   A. Print the shapes of train and test data

In [38]:
```python
train_generator.image_shape
```

Out[38]:
```
(128, 128, 3)
```

In [39]:
```python
test_generator.image_shape
```

Out[39]:
```
(128, 128, 3)
```

1. Model Building (0.2*5 = 1 mark)

The Architecture Our architecture for the CNN has been inspired by the article from Stephan and colleagues (2019) and Yadav and Sjadav (2019). Their neural network architectures were specifically designed for pneumonia image classification tasks. The proposed architecture consists of the convolution, max-pooling, and classification layers combined together. We will now dive into each component and why we chose them.

1. Model Building (0.2*5 = 1 mark)
   A. Sequential Model layers- Use AT LEAST 3 hidden layers with appropriate input for each. Choose the best number for hidden units and give reasons.
   B. Add L2 regularization to all the layers.
   C. Add one layer of dropout at the appropriate position and give reasons.
   D. Choose the appropriate activation function for all the layers.

In [30]:
```python
def initialize_model(name):
    model = Sequential(name=name)
    model.add(layers.Conv2D(32, (3, 3), activation="relu", input_shape=target_dims, padding='same'))
    model.add(layers.MaxPool2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(layers.Conv2D(64, (3, 3), activation="relu", padding='same'))
    model.add(layers.MaxPool2D(pool_size=(2, 2)))
    model.add(Dropout(0.1))

    model.add(layers.Conv2D(128, (3, 3), activation="relu", padding='same'))
    model.add(layers.MaxPool2D(pool_size=(3, 3)))
    model.add(Dropout(0.1))

    model.add(layers.Flatten())
    model.add(layers.Dense(64, activation='relu'))
    model.add(Dropout(0.2))
    model.add(layers.Dense(1, activation='sigmoid'))

    return model
```

Dropout Dropout is used to prevent overfitting by temporarily “dropping” a neuron during training time at each iteration with probability p. Which means that all the inputs and outputs to this neuron will be disabled at the current iteration. The dropped-out neurons are resampled with probability p at every training step, so a dropped out neuron at one step can be active at the next one. The hyperparameter p is called the dropout-rate and we set it to 0.5, corresponding to 50% of the neurons being dropped out which is proposed as the best option for X-ray image classification (yadav & Jadhav, 2019).

1. Model Building (0.2*5 = 1 mark)
   A. Print the model summary.

In [31]:
```python
model = initialize_model(name="basemodel")
model.summary()
```

```
Model: "basemodel"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 128, 128, 32)      896

 max_pooling2d (MaxPooling2D  (None, 64, 64, 32)       0
 )

 dropout (Dropout)           (None, 64, 64, 32)        0

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

 max_pooling2d_1 (MaxPooling  (None, 32, 32, 64)       0
 2D)

 dropout_1 (Dropout)         (None, 32, 32, 64)        0

 conv2d_2 (Conv2D)           (None, 32, 32, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 10, 10, 128)      0
 2D)

 dropout_2 (Dropout)         (None, 10, 10, 128)       0

 flatten (Flatten)           (None, 12800)             0

 dense (Dense)               (None, 64)                819264

 dropout_3 (Dropout)         (None, 64)                0

 dense_1 (Dense)             (None, 1)                 65

=================================================================
Total params: 912,577
Trainable params: 912,577
Non-trainable params: 0
_________________________________________________________________
```

1. Model Compilation (0.25 mark)
   A. Compile the model with the appropriate loss function.
   B. Use an appropriate optimizer. Give reasons for the choice of learning rate and its value.
   C. Use accuracy as a metric.

In [32]:
```python
def compile_model(model):
    model.compile(optimizer="adam",loss='binary_crossentropy',metrics="binary_accuracy")
    return model
```

Regularization

In order to prevent our model to overtrain we implement the following regularization measures.

In [34]:
```python
model_baseline = initialize_model(name="baseline")
history_baseline = compile_model(model_baseline)
callback = [EarlyStopping(patience=5, monitor='val_accuracy', restore_best_weights=True),
            ReduceLROnPlateau(monitor = 'val_loss', patience = 2, factor=0.3, verbose=1),
            ModelCheckpoint("xray_model_v2.h5",save_best_only=True)]
```

1. Model Training (0.5 + 0.25 = 0.75 mark)
   A. Train the model for an appropriate number of epochs. Print the train and validation accuracy and loss for each epoch. Use the appropriate batch size.
   B. Plot the loss and accuracy history graphs for both train and validation set. Print the total time taken for training.

In [35]:
```python
history_baseline = model_baseline.fit(train_generator,
                                      batch_size=n_batch_size,
                                      epochs=1,
                                      validation_data=val_generator,shuffle=True,
                                      callbacks=callback) #,class_weight=class_weights)
```

```
131/131 [==============================] - ETA: 0s - loss: 0.3407 - binary_accuracy: 0.8531WARNING:tensorflow:E
arly stopping conditioned on metric `val_accuracy` which is not available. Available metrics are: loss,binary_a
ccuracy,val_loss,val_binary_accuracy
131/131 [==============================] - 1430s 11s/step - loss: 0.3407 - binary_accuracy: 0.8531 - val_loss:
0.2502 - val_binary_accuracy: 0.8945 - lr: 0.0010
```

1. Model Evaluation (0.5 + 0.5 = 1 mark)
   A. Print the final train and validation loss and accuracy. Print confusion matrix and classification report for the validation dataset. Analyse and report the best and worst performing class.
   B. Print the two most incorrectly classified images for each class in the test dataset.

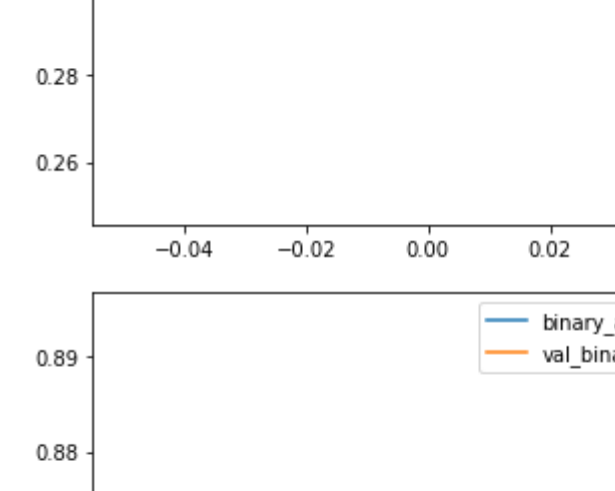
In [36]:
```python
scores = model_baseline.evaluate(val_generator)
scores
```

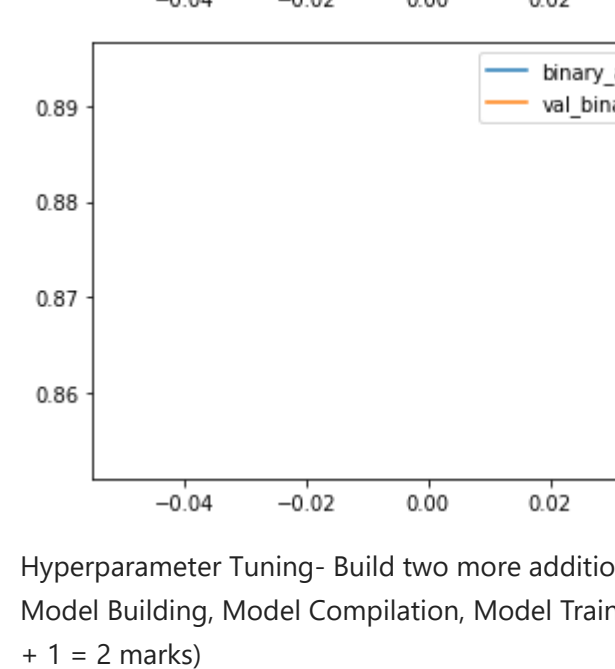
```
33/33 [==============================] - 27s 819ms/step - loss: 0.2688 - binary_accuracy: 0.8840
```

Out[36]:
```
[0.26881924271583557, 0.8839884996414185]
```

Evaluate our model by looking at a graph

In [42]:
```python
history_frame = pd.DataFrame(history_baseline.history)
history_frame.loc[:, ['loss', 'val_loss']].plot()
history_frame.loc[:, ['binary_accuracy', 'val_binary_accuracy']].plot();
```





Hyperparameter Tuning- Build two more additional models by changing the following hyperparameters ONE at a time. Write the code for Model Building, Model Compilation, Model Training and Model Evaluation as given in the instructions above for each additional model. (1 + 1 = 2 marks)

1. Optimiser: Use a different optimizer with the appropriate LR value.
2. Network Depth: Change the number of hidden layers and hidden units for each layer. Write a comparison between each model and give reasons for the difference in results.