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In the Name of Allah, the Most Beneficent, the Most Merciful

==

```
*----------------------------------------------------------AUTHOR_DETAILS ------------------------------------------------------------------*
|                                                                                                                                           |
|        Project Title  = Developing a Pneumonia Disease Prediction System (from X-ray Images) using CNN-based Deep Neural Networks        |
|                                                                                                                                           |
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|                                                                                                                                           |
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|                                                                                                                                           |
|        Version        = 1.0                                                                                                              |
|                                                                                                                                           |
*-------------------------------------------------------------------------------------------------------------------------------------------*
```

------------------- PROJECT PURPOSE --------------------

The main purpose of this Project is to demonstrate CNN-based Deep Neural Network can be used for the development and evaluation of Pneumonia Disease Prediction System (from X-ray Images).

For this purpose, In sha Allah, I will treat Pneumonia Disease Prediction Problem as a Binary Classificaiton Problem i.e. the main goal is to discriminate between two Classses: (1) Normal and (2) Pneumonia and evaluation of Pneumonia Classification from an Image.

For this purpose, Insha Allah, I will execute the Machine Learning Cycle

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Pneumonia Disease Prediction System- Machine Learning Cycle

Machine Learning Cycle

Four phases of a Machine Learning Cycle are

Training Phase

- **Build the Model using Training Data**

Testing Phase

- **Evaluate the performance of Model using Testing Data**

Application Phase

- **Deploy the Model in Real-world , to make prediction on Real-time unseen Data**

Feedback Phase

- **Take Feedback form the Users and Domain Experts to improve the Model**

Steps – Executing Machine Learning Cycle

Step 01: Import Libraries

Step 02: Load Training Data, Testing Data and Validation Data

Step 2.1: Load Training Data

Step 2.2: Load Testing Data

Step 2.3: Load Validation Data

Step 03: Understand and Pre-process Training Data, Testing Data and Validation Data

Step 3.1: Understand Training Data

Step 3.2: Understand Testing Data

Step 3.3: Understand Validation Data

Step 3.4: Pre-process Training Data

Step 3.4.1: Resize X-ray Images in Training Data

Step 3.4.2: Convert Resized X-ray Images in Training Data into Grayscale

Step 3.5: Pre-process Testing Data

Step 3.5.1: Resize X-ray Images in Testing Data

Step 3.5.2: Convert Resized X-ray Images in Testing Data into Grayscale

Step 3.6: Pre-process Validation Data

Step 3.6.1: Resize X-ray Images in Validation Data

Step 3.6.2: Convert Resized X-ray Images in Validation Data into Grayscale

Step 04: Represent Training Data, Testing Data and Validation Data in Machine Understandable Format

Step 4.1: Represent Training Data into Machine Understandable Format

Step 4.1.1: Convert Resized Grayscale X-ray Images in Training Data into Numpy Array

Step 4.1.2: Nomalize Numpy Array of Grayscale X-ray Images in Training Data

Step 4.2: Represent Testing Data into Machine Understandable Format

Step 4.2.1: Convert Resized Grayscale X-ray Images in Testing Data into Numpy Array

Step 4.2.2: Nomalize Numpy Array of Grayscale X-ray Images in Testing Data

Step 4.3: Represent Validation Data into Machine Understandable Format

Step 4.3.1: Convert Resized Grayscale X-ray Images in Validation Data into Numpy Array

Step 4.3.1: Nomalize Numpy Array of Grayscale X-ray Images in Validation Data

Step 05: Execute the Training Phase

Step 5.1: Create CNN Model Architecture

Step 5.2: Hyperparameters Settings

Step 5.3: Create CNN Model Object

Step 5.4: Initialize Optimizer and Loss Function

Step 5.5: Evaluation Measure

Step 5.6: Calculate Epoch Elapsed Time

Step 5.7: Train Model

Step 5.8: Save Model

Step 06: Execute the Testing Phase

Step 6.1: Load Saved Model (Saved in Step 5.8)

Step 6.2: Make Predictions on Testing Data

Step 6.3: Evaluate Performance of Trained Model on Test Data

Step 6.3.1: Calculate Accuracy

Step 6.3.2: Draw Confusion Matrix

Step 6.3.3: Print Classification Report

Step 07: Execute the Application Phase

Step 7.1: Take Input (X-ray Image) from User

Step 7.2: Convert User Input (X-ray Image) into Feature Vector (Exactly Same as Feature Vectors of Training Data, Testing Data and Validation Data)

Step 7.3: Make Prediction on Unseen Data

Step 7.3.1: Load the Model (Saved in Step 5.8)

Step 7.3.2: Apply Model on Feature Vector of Unseen Data

Step 7.3.3: Return Prediction to the User

Step 08: Execute the Feedback Phase

Step 09: Improve Model Based on Feedback

Step 1: Import Libraries

```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import seaborn as sns
import keras
import pandas as pd
import numpy as np
from keras.models import Model, Sequential,load_model
from keras.layers import Dense, Conv2D , MaxPool2D , Flatten , Dropout , BatchNormalization
from keras.preprocessing.image import ImageDataGenerator
from keras.optimizers import Adam, RMSprop,SGD
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
import cv2
import os
import itertools


# Mount Your Google Drive with Google Colab
from google.colab import drive
drive.mount('/content/drive')
```

```
    Mounted at /content/drive
```

Step 02: Load Training Data, Testing Data and Validation Data

Step 2.1: Load Training Data

```
'''
    /*---------------------------- LOAD_DATASET ----------------
    | Function  : load_dataset()
    | Purpose   : Reads Dataset(X-ray Images) in .jpeg file format
    | Arguments :
    |       dataset_dir : Path to dataset file
    |
    | Return    :
```

```
    .
    |       dataset    : Dataset in dataframe format
    *------------------------------------------------------------*/
'''

labels = ['normal', 'pneumonia']
def load_dataset(dataset_dir):
  dataset = []
  for label in labels:
    path = os.path.join(dataset_dir, label)
    classes = labels.index(label)
    for data in os.listdir(path):
      try:
        image_array = cv2.imread(os.path.join(path, data))
        dataset.append([image_array, classes])
      except Exception as e:
        print(e)
  return dataset

training_data = load_dataset('/content/drive/MyDrive/Binary Class Pneumonia Classification/Sample Data/Training_Data')
```

Step 2.2: Load Testing Data

```
testing_data = load_dataset('/content/drive/MyDrive/Binary Class Pneumonia Classification/Sample Data/Testing_Data')
```

Step 2.3: Load Validation Data

```
validation_data = load_dataset('/content/drive/MyDrive/Binary Class Pneumonia Classification/Sample Data/Validation_Data')
```

Step 3: Understand and Pre-process Training Data, Testing Data and Validation Data

Step 3.1: Understand Training Data

```
normal=0
pneumonia = 0
print("Main Characteristics of Training Data")
print ("=====================================\n")
print("Total Instances (X-ray Images)                 = ",len(training_data))
for images in training_data:
    if(images[1] == 0):
      normal = normal+1
    else:
      pneumonia = pneumonia+1
print("Total Instances (X-ray Images) With Disease    = ",pneumonia)
print("Total Instances (X-ray Images) Without Disease = ",normal)
```

```
Main Characteristics of Training Data
=====================================

Total Instances (X-ray Images)                 =  72
Total Instances (X-ray Images) With Disease    =  36
Total Instances (X-ray Images) Without Disease =  36
```

Step 3.2: Understand Testing Data

```
normal=0
pneumonia = 0
print("Main Characteristics of Testing Data")
```

```
print ("===================================\n")
print("Total Instances (X-ray Images)                 = ",len(testing_data))
for images in testing_data:
    if(images[1] == 0):
      normal = normal+1
    else:
      pneumonia = pneumonia+1
print("Total Instances (X-ray Images) With Disease    = ",pneumonia)
print("Total Instances (X-ray Images) Without Disease = ",normal)
```

```
Main Characteristics of Testing Data
===================================

Total Instances (X-ray Images)                 =  20
Total Instances (X-ray Images) With Disease    =  10
Total Instances (X-ray Images) Without Disease =  10
```

Step 3.3: Understand Validation Data

```
normal=0
pneumonia = 0
print("Main Characteristics of Validation Data")
print ("=======================================\n")
print("Total Instances (X-ray Images)                 = ",len(validation_data))
for images in validation_data:
    if(images[1] == 0):
      normal = normal+1
    else:
      pneumonia = pneumonia+1
print("Total Instances (X-ray Images) With Disease    = ",pneumonia)
print("Total Instances (X-ray Images) Without Disease = ",normal)
```

```
Main Characteristics of Validation Data
```

```
=======================================

Total Instances (X-ray Images)                 =  8
Total Instances (X-ray Images) With Disease    =  4
Total Instances (X-ray Images) Without Disease =  4
```

Step 3.4: Pre-process Training Data

Step 3.4.1 Resize X-ray Images in Training Data

```
'''
    /*---------------------------- DISPLAY_IMAGE ----------------
    | Function  : display_image()
    | Purpose   : To Display X-Ray Images
    | Arguments :
    |       original_image : Path to dataset file
    |
    | Return    :
    |       dataset    : Dataset in dataframe format
    *-----------------------------------------------------------*/
'''

def display_image(original_image, preprocessed_image, title1 , title2 ):
  plt.figure(figsize=(10,10))

  plt.subplot(1,2,1)
  plt.imshow(original_image[0][0], cmap='gray')
  plt.tick_params(axis='both', which='both', top=False, bottom=False, left=False, right=False, labelbottom=False, labeltop=False, lal
  plt.title(title1)

  plt.figure(figsize=(10,10))
  plt.subplot(1,2,2)
  plt.imshow(preprocessed_image[0][0], cmap='gray')
  plt.tick_params(axis='both', which='both', top=False, bottom=False, left=False, right=False, labelbottom=False, labeltop=False, lal
  plt.title(title2)
```

```
'''
    /*---------------------------- DATA_RESIZING ------------------------
    | Function  : resize()
    |
    | Purpose   : Resize Resolution of Original Image into Desired Resolution:
    | Arguments :
    |      original_image: Original Image to be Resized
    | Return    :
    |       resized_image: Resized Image
    *-----------------------------------------------------------=-----*/
'''
def resize(dataset_dir,width,height):
  image_dimension=(width,height)
  labels = ['normal', 'pneumonia']
  resized_image = []
  for label in labels:
        path = os.path.join(dataset_dir, label)
        classes = labels.index(label)
        for image in os.listdir(path):
          original_image = cv2.imread(os.path.join(path, image))
          resized_array = cv2.resize(original_image, image_dimension) # Reshaping images to preferred size
          resized_image.append([resized_array, classes])

  return np.array(resized_image) # Convert Image into numpy array form
```

```
image_width = 224
image_height = 224
resized_training_data = resize('/content/drive/MyDrive/Binary Class Pneumonia Classification/Sample Data/Training_Data',image_width,
```

```
display_image(training_data,resized_training_data,'Original Image',"Resized Image")
```

Original Image

Resized Image

Step 3.4.2: Convert Resized X-ray Images in Training Data into Grayscale

```
'''
    /*---------------------------- RGB to GRAY -------------------------
    | Function  : to_grayscale()
    |
    | Purpose   : Convert Images in RGB into Grayscale Images
    | Arguments :
    |     resized_image: Resized Image
    | Return    :
```

```
    |       grayscale_image: Converted Image into Grayscale
    *---------------------------------------------------------------=-----*/
'''
def to_grayscale(resized_image):
  image_dimension=(224,224)
  labels = ['normal', 'pneumonia']
  grayscale_image = []
  for label in labels:
        path = os.path.join(resized_image, label)
        classes = labels.index(label)
        for image in os.listdir(path):
          original_image = cv2.imread(os.path.join(path, image))
          resized_array = cv2.resize(original_image, image_dimension)
          grayscale_array = cv2.cvtColor(resized_array,cv2.COLOR_RGB2GRAY)
          grayscale_image.append([grayscale_array, classes])

  return np.array(grayscale_image)


grayscale_training_data = to_grayscale('/content/drive/MyDrive/Binary Class Pneumonia Classification/Sample Data/Training_Data')


display_image(training_data,grayscale_training_data,'Original Image',"Grayscale Image")
```

Original Image

Grayscale Image

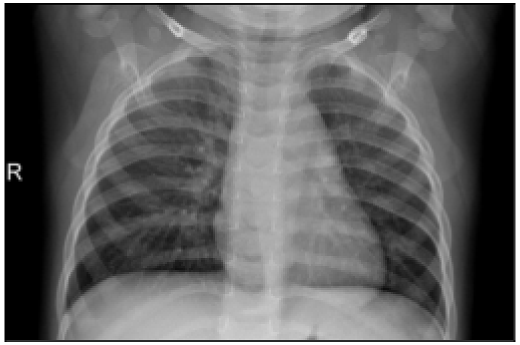
Step 3.5: Pre-process Testing Data

Step 3.5.1 Resize X-ray Images in Testing Data

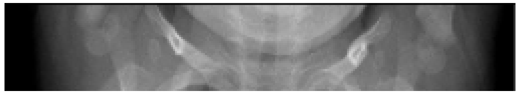
```
resized_testing_data = resize('/content/drive/MyDrive/Binary Class Pneumonia Classification/Sample Data/Testing_Data',image_width,ima
```

```
display_image(testing_data,resized_testing_data,'Original Image',"Resized Image")
```

Original Image



Resized Image

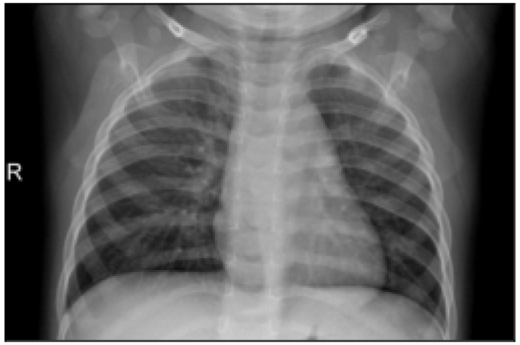


Step 3.5.2: Convert Resized X-ray Images in Training Data into Grayscale

```
grayscale_testing_data = to_grayscale('/content/drive/MyDrive/Binary Class Pneumonia Classification/Sample Data/Testing_Data')
```

```
display_image(testing_data,grayscale_testing_data,'Original Image',"Grayscale Image")
```

Original Image



Grayscale Image

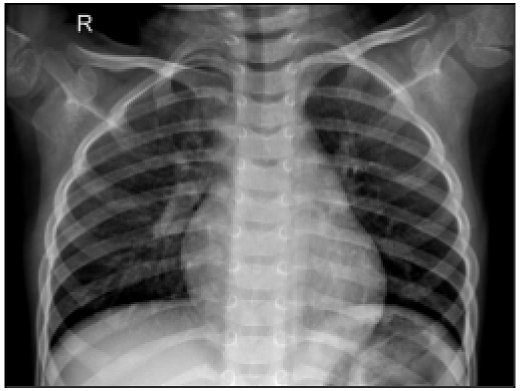
Step 3.6: Pre-process Validation Data

Step 3.6.1 Resize X-ray Images in validation Data

```
resized_validation_data = resize('/content/drive/MyDrive/Binary Class Pneumonia Classification/Sample Data/Validation_Data',image_wi
```

```
display_image(validation_data,resized_validation_data,'Original Image',"Resized Image")
```

Original Image

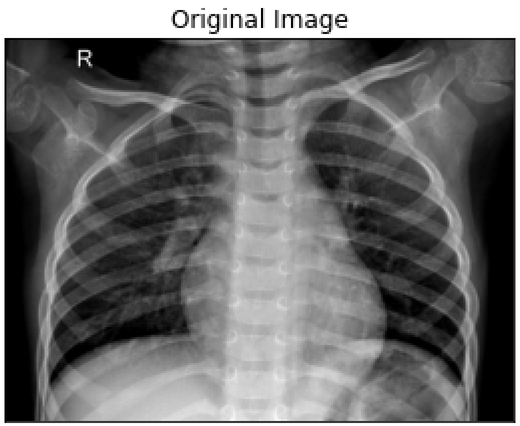


Resized Image

Step 3.5.2: Convert Resized X-ray Images in Training Data into Grayscale

```
grayscale_validation_data = to_grayscale('/content/drive/MyDrive/Binary Class Pneumonia Classification/Sample Data/Validation_Data')
```

```
display_image(validation_data,grayscale_validation_data,'Original Image',"Grayscale Image")
```



Step 4: Represent Training Data, Testing Data and Validation Data in Machine Understandable Format

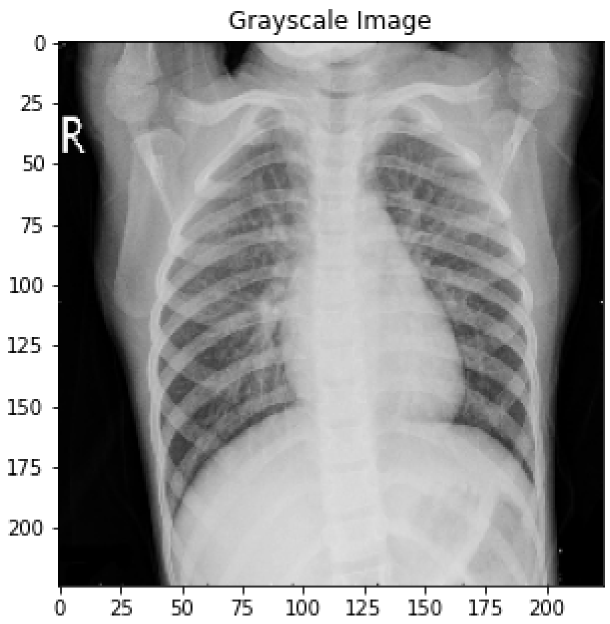
Step 4.1: Represent Training Data Into Machine Understandable Format

Step 4.1.1: Convert Resized Grayscale X-ray Images in Training Data into Numpy Array

```
def display(image,title):

  plt.figure(figsize=(5,5))
  plt.imshow(image[0][0], cmap='gray')
  plt.title(title)


training_data_array = np.asarray(grayscale_training_data)
print("Grayscale X-ray Image of Training Data")
print("=======================================")
display(grayscale_training_data,"Grayscale Image")
print("Grayscale X-ray Image of Training Data into Numpy Array Form")
```

```
print("Grayscale X-ray Image of Training Data into Numpy Array Form")
print("==============================================================")
print(training_data_array[0][0])
```

```
Grayscale X-ray Image of Training Data
=======================================
Grayscale X-ray Image of Training Data into Numpy Array Form
==============================================================
[[141   3   3 ...  17   5   0]
 [  1   1 124 ...  15   4   0]
 [222   3   2 ...  15   1   0]
 ...
 [  3   3   3 ...   0   0   3]
 [  3   3   3 ...   0   1   3]
 [  9   3   3 ...   0   2   3]]
```



Step 4.1.2: Nomalize Numpy Array of Grayscale X-ray Images in Training Data

```
'''
    /*-----------------------------------------------SPLIT -------------------------------------
    | Function  : split()
```

```
    | Function  : split()
    | Purpose   : Split Training, Testing, Validation Data Into Feature Vector and Labels:
    |
    | Arguments :
    |       image_array: Numpy array of Image
    | Return    :
    |       input_feature_vector,output_labels: Splitted dataset into Feature Vector and Output Labels
    *-------------------------------------------------------------------------------------------------*/
'''

def split(image_array):
  input_feature_vector = []
  output_labels = []

  for feature, label in image_array:
    input_feature_vector.append(feature)
    output_labels.append(label)
  return input_feature_vector,output_labels



'''
    /*----------------------------------------- DATA_NORMALIZATION -----------------------------------
    | Function  : data_normalization()
    | Purpose   : perform a grayscale normalization to reduce the effect of illumination's differences:
    |
    | Arguments :
    |       feature: Feature Vector to be Normalize
    | Return    :
    |       feature: Normalized Feature Vector
    *---------------------------------------------------------------------------------------------------*/
'''

def data_normalization(input_feature_vector):
  # Normalize the data
  input_feature_vector = np.array(input_feature_vector)
  input_feature_vector = input_feature_vector.astype('float32')
  input_feature_vector= input_feature_vector/ 255
  return input_feature_vector
```

```
    return input_feature_vector


print("Data Trainnig Data in Numpy Array into Input Feature Vector and Output Labels")
print("==============================================================================")
input_training_data,output_training_label = split(training_data_array)
print("Training Data After Split")
print("========================")
print("\nFeature Vector of Trainig Data")
print("================================")
print(input_training_data)

print("\nOutput Labels of Training Data")
print("===============================\n")
print (output_training_label)
```

```
        [33, 33, 37, ..., 62, 65, 59],
        [33, 35, 34, ..., 57, 62, 60],
        ...,
        [33, 40, 53, ..., 63, 61, 62],
        [38, 50, 54, ..., 68, 66, 61],
        [35, 36, 48, ..., 70, 58, 54]], dtype=uint8), array([[22, 24, 25, ..., 30, 31, 31],
        [22, 23, 26, ..., 33, 30, 31],
        [22, 24, 27, ..., 35, 31, 32],
        ...,
        [10, 10, 11, ...,  8, 10, 10],
        [10, 10, 11, ...,  8,  9, 10],
        [10, 10, 11, ...,  8,  9, 10]], dtype=uint8), array([[18, 20, 22, ..., 12,  8,  8],
        [20, 22, 23, ..., 13,  9,  8],
        [20, 19, 21, ..., 13,  9,  8],
        ...,
        [ 0,  0,  0, ...,  6, 12, 10],
        [ 0,  0,  0, ...,  9, 10, 11],
        [ 0,  0,  0, ...,  9, 10, 10]], dtype=uint8), array([[  6,   9,  13, ...,   0,   0,   0],
        [  6,   9,  13, ...,   0,   0,   0],
        [  6,   8,  13, ...,   0,   0,   0],
        ...,
        [195,   4,   0, ...,   0,   4, 195],
        [  1,   1,   0, ...,   0,   1,   1],
        [  0,   0,   0, ...,   0,   0,   0]], dtype=uint8), array([[ 42,  47,  45, ...,  26,  35,  31],
```

```
        [ 45,  45,  47, ...,  30,  36,  32],
        [ 40,  48,  49, ...,  45,  37,  33],
        ...,
        [ 25,  41,  44, ...,  37,  40,  40],
        [ 29,  41,  43, ...,  33,  32, 135],
        [ 30,  36,  41, ...,  28, 109,  54]], dtype=uint8), array([[12, 12, 12, ...,  5,  2,  0],
        [12, 12, 12, ...,  9,  4,  1],
        [12, 12, 12, ...,  9,  5,  0],
        ...,
        [37, 36, 35, ..., 17, 17, 17],
        [37, 35, 34, ..., 16, 17, 17],
        [36, 34, 31, ..., 16, 17, 17]], dtype=uint8), array([[ 32,  30,  32, ...,   3,   3,   4],
        [ 33,  32,  34, ...,   1,   1,   3],
        [ 36,  35,  35, ...,   0,   1,   2],
        ...,
        [  2,   2,   0, ..., 108, 143, 153],
        [  2,   2,   0, ..., 101, 141, 162],
        [  2,   2,   0, ..., 115, 138, 154]], dtype=uint8), array([[0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        ...,
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0]], dtype=uint8), array([[49, 60, 70, ..., 46, 42, 36],
        [61, 74, 80, ..., 44, 46, 41],
        [79, 73, 67, ..., 47, 46, 45],
        ...,
        [ 6,  4,  2, ...,  3,  4, 10],
        [ 7,  3,  2, ...,  4,  6,  7],
        [ 9,  4,  2, ...,  4,  7, 11]], dtype=uint8)]

Output Labels of Training Data
================================
```

```
print("Normalization of Feature Vecotrs of Training Data")
print("==================================================\n")

normalized_training_data = data_normalization(input_training_data)
print(normalized_training_data)
```

```
Normalization of Feature Vecotrs of Training Data
=================================================

[[[0.5529412  0.01176471 0.01176471 ... 0.06666667 0.01960784 0.        ]
  [0.00392157 0.00392157 0.4862745  ... 0.05882353 0.01568628 0.        ]
  [0.87058824 0.01176471 0.00784314 ... 0.05882353 0.00392157 0.        ]
  ...
  [0.01176471 0.01176471 0.01176471 ... 0.         0.         0.01176471]
  [0.01176471 0.01176471 0.01176471 ... 0.         0.00392157 0.01176471]
  [0.03529412 0.01176471 0.01176471 ... 0.         0.00784314 0.01176471]]

 [[0.2901961  0.00392157 0.6313726  ... 0.2784314  0.29411766 0.30980393]
  [0.01176471 0.         0.00392157 ... 0.2901961  0.26666668 0.38431373]
  [0.12941177 0.01176471 0.         ... 0.29803923 0.3254902  0.44705883]
  ...
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.00784314 0.         0.         ... 0.         0.         0.        ]
  [0.00784314 0.         0.         ... 0.         0.         0.        ]]

 [[0.25490198 0.29803923 0.30588236 ... 0.23529412 0.23529412 0.21568628]
  [0.2509804  0.2784314  0.29803923 ... 0.23137255 0.22352941 0.21176471]
  [0.2509804  0.28627452 0.29803923 ... 0.23137255 0.20784314 0.19607843]
  ...
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]]

 ...

 [[0.1254902  0.11764706 0.1254902  ... 0.01176471 0.01176471 0.01568628]
  [0.12941177 0.1254902  0.13333334 ... 0.00392157 0.00392157 0.01176471]
  [0.14117648 0.13725491 0.13725491 ... 0.         0.00392157 0.00784314]
  ...
  [0.00784314 0.00784314 0.         ... 0.42352942 0.56078434 0.6       ]
  [0.00784314 0.00784314 0.         ... 0.39607844 0.5529412  0.63529414]
  [0.00784314 0.00784314 0.         ... 0.4509804  0.5411765  0.6039216 ]]

 [[0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
```

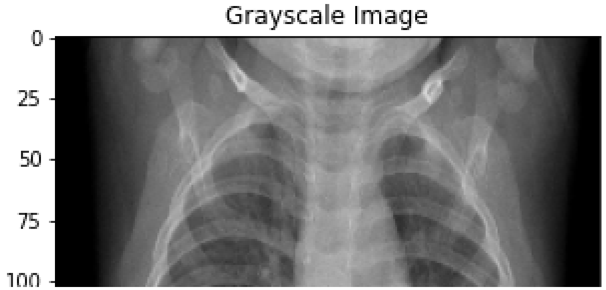
```
  ...
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]]

 [[0.19215687 0.23529412 0.27450982 ... 0.18039216 0.16470589 0.14117648]
  [0.23921569 0.2901961  0.3137255  ... 0.17254902 0.18039216 0.16078432]
  [0.30980393 0.28627452 0.2627451  ... 0.18431373 0.18039216 0.1764706 ]
  ...
  [0.02352941 0.01568628 0.00784314 ... 0.01176471 0.01568628 0.03921569]
  [0.02745098 0.01176471 0.00784314 ... 0.01568628 0.02352941 0.02745098]
  [0.03529412 0.01568628 0.00784314 ... 0.01568628 0.02745098 0.04313726]]]
```

Step 4.2: Represent Testing Data Into Machine Understandable Format

Step 4.2.1: Convert Resized Grayscale X-ray Images in Testing Data into Numpy Array

```
testing_data_array = np.asarray(grayscale_testing_data)
print("Grayscale X-ray Image of testing Data")
print("=====================================")
display(grayscale_testing_data,"Grayscale Image")
print("Grayscale X-ray Image of testing Data into Numpy Array Form")
print("=========================================================")
print(testing_data_array[0][0])
```

```
Grayscale X-ray Image of testing Data
=======================================
Grayscale X-ray Image of testing Data into Numpy Array Form
===========================================================
[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```



Step 4.2.2: Nomalize Numpy Array of Grayscale X-ray Images in Testing Data

```
print("Testing Data in Numpy Array into Input Feature Vector and Output Labels")
print("=======================================================================")
input_testing_data,output_testing_label = split(testing_data_array)
print("Testing Data After Split")
print("=========================")
print("\nFeature Vector of Testing Data")
print("================================")
print(input_testing_data)

print("\nOutput Labels of Testing Data")
print("================================\n")
print (output_testing_label)
```

```
       [159, 252,   8, ...,   0,   0, 157]], dtype=uint8), array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
```

```
...,
[0, 0, 0, ..., 0, 0, 0],
[0, 0, 0, ..., 0, 0, 0],
[0, 0, 0, ..., 0, 0, 0]], dtype=uint8), array([[156, 163, 168, ..., 159, 246, 122],
[156, 163, 164, ..., 159, 137, 127],
[156, 163, 162, ..., 159,  50, 116],
...,
[ 41, 119, 102, ...,   0,   0,   2],
[  1, 213, 132, ...,   0,   0,   0],
[  8,  10,   7, ...,   0,   0,   0]], dtype=uint8), array([[  1,   3,   3, ..., 250,  35,   4],
[  1,   3,   3, ...,   9, 253,   1],
[  0,   1,   2, ...,  12, 113,  13],
...,
[ 91,  39, 176, ...,   0,   0,   0],
[  7, 232, 250, ...,   0,   1,   1],
[157, 248,   5, ...,   0,   2, 158]], dtype=uint8), array([[ 20,  24,  28, ...,  17,  19,  23],
[ 21,  24,  30, ...,  16,  18,  21],
[ 21,  29,  31, ...,  14,  16,  19],
...,
[138, 145, 150, ...,  17,  21,  20],
[139, 145, 151, ...,  17,  16,  20],
[143, 149, 151, ...,  17,  17,  24]], dtype=uint8), array([[  7,  12,  16, ...,   6, 248,   7],
[  6,  11,  15, ...,   3,   0,   0],
[  6,   8,  13, ...,   9, 250,   4],
...,
[  0,   0,   1, ...,   0,   0,   1],
[  6, 246, 252, ...,   0,   0,   1],
[  1,  10,   7, ...,   0,   0,   1]], dtype=uint8), array([[173, 171, 167, ..., 132, 132, 137],
[176, 164, 160, ..., 132, 124, 137],
[170, 169, 157, ..., 128, 118, 138],
...,
[ 65,  93, 117, ...,  18,  18,  18],
[ 67,  98, 120, ...,  18,  18,  18],
[ 68, 103, 122, ...,  18,  18,  18]], dtype=uint8), array([[ 59,  73,  74, ..., 133, 241,  84],
[ 62,  77,  73, ..., 100,  87,  78],
[ 58,  69,  87, ..., 108,  31,  84],
...,
[  0,   0,   0, ...,   0,   0,   0],
[  2, 117, 254, ...,   0,   0,   0],
[  9,   0,   0, ...,   0,   0,   0]], dtype=uint8), array([[  0,   0,   0, ..., 197,  95,   6],
[  0,   0,   0, ...,  13,  22,   2],
[  0,   0,   0, ..., 219, 249,   9],
```

```
        ...,
        [ 45,  72, 104, ...,   0,   0,   0],
        [  4, 249, 245, ...,   0,   0,   7],
        [159,  18,   0, ...,   0,   0, 158]], dtype=uint8), array([[127, 129, 130, ..., 115, 112, 113],
        [147, 135, 132, ..., 113, 117, 126],
        [141, 142, 136, ..., 254,  39, 122],
        ...,
        [ 20,  45,  63, ..., 250,  70,   1],
        [ 20,  42,  62, ...,   4,   1,   0],
        [ 22,  47,  65, ...,   0,   0,   0]], dtype=uint8)]

Output Labels of Testing Data
================================

[0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1]
```

```
print("Normalization of Feature Vecotrs of Testing Data")
print("================================================\n")

normalized_testing_data = data_normalization(input_testing_data)
print(normalized_testing_data)
```

```
Normalization of Feature Vecotrs of Testing Data
================================================

[[[0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  ...
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]]

 [[0.         0.         0.         ... 0.17254902 0.13725491 0.06666667]
  [0.         0.         0.         ... 0.17254902 0.1254902  0.09019608]
  [0.         0.         0.         ... 0.1764706  0.1254902  0.05490196]
  ...
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]]
```

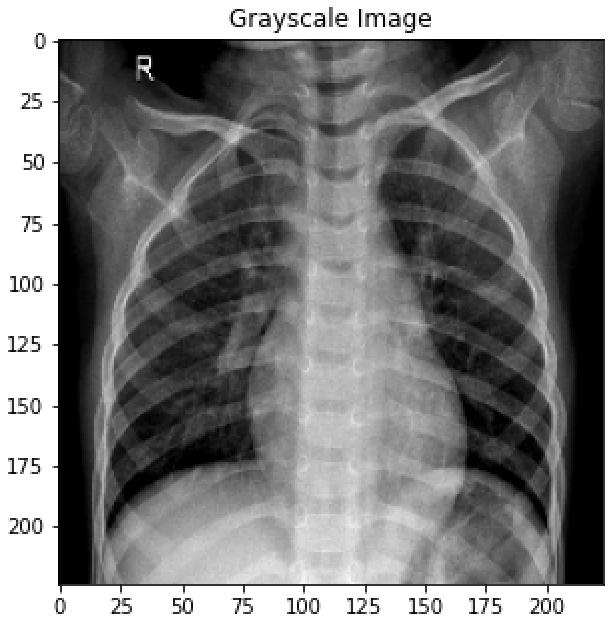
```
  [[0.3372549  0.38039216 0.39607844 ... 0.16862746 0.11372549 0.01176471]
   [0.3529412  0.3764706  0.39215687 ... 0.17254902 0.10588235 0.00784314]
   [0.36078432 0.39607844 0.4        ... 0.16862746 0.09411765 0.        ]
   ...
   [0.         0.         0.         ... 0.         0.         0.        ]
   [0.         0.         0.         ... 0.         0.         0.        ]
   [0.         0.         0.         ... 0.         0.         0.        ]]

  ...

  [[0.23137255 0.28627452 0.2901961  ... 0.52156866 0.94509804 0.32941177]
   [0.24313726 0.3019608  0.28627452 ... 0.39215687 0.34117648 0.30588236]
   [0.22745098 0.27058825 0.34117648 ... 0.42352942 0.12156863 0.32941177]
   ...
   [0.         0.         0.         ... 0.         0.         0.        ]
   [0.00784314 0.45882353 0.99607843 ... 0.         0.         0.        ]
   [0.03529412 0.         0.         ... 0.         0.         0.        ]]

  [[0.         0.         0.         ... 0.77254903 0.37254903 0.02352941]
   [0.         0.         0.         ... 0.05098039 0.08627451 0.00784314]
   [0.         0.         0.         ... 0.85882354 0.9764706  0.03529412]
   ...
   [0.1764706  0.28235295 0.40784314 ... 0.         0.         0.        ]
   [0.01568628 0.9764706  0.9607843  ... 0.         0.         0.02745098]
   [0.62352943 0.07058824 0.         ... 0.         0.         0.61960787]]

  [[0.49803922 0.5058824  0.50980395 ... 0.4509804  0.4392157  0.44313726]
   [0.5764706  0.5294118  0.5176471  ... 0.44313726 0.45882353 0.49411765]
   [0.5529412  0.5568628  0.53333336 ... 0.99607843 0.15294118 0.47843137]
   ...
   [0.07843138 0.1764706  0.24705882 ... 0.98039216 0.27450982 0.00392157]
   [0.07843138 0.16470589 0.24313726 ... 0.01568628 0.00392157 0.        ]
   [0.08627451 0.18431373 0.25490198 ... 0.         0.         0.        ]]]
```

Step 4.3: Represent Validation Data Into Machine Understandable Format

Step 4.3.1: Convert Resized Grayscale X-ray Images in Validation Data into Numpy Array

```
validation_data_array = np.asarray(grayscale_validation_data)
print("Grayscale X-ray Image of Validation Data")
print("=========================================")
display(grayscale_validation_data,"Grayscale Image")
print("Grayscale X-ray Image of Validation Data into Numpy Array Form")
print("==============================================================")
print(validation_data_array[0][0])
```

```
Grayscale X-ray Image of Validation Data
=========================================
Grayscale X-ray Image of Validation Data into Numpy Array Form
==============================================================
[[ 8 14 24 ... 64 60 61]
 [11 14 32 ... 69 68 65]
 [11 11 33 ... 70 69 57]
 ...
 [ 0  0  0 ...  0  0  0]
 [ 0  0  0 ...  0  0  0]
 [ 0  0  0 ...  0  0  0]]
```



Step 4.3.2: Nomalize Numpy Array of Grayscale X-ray Images in Validation Data

```
print("Validation Data in Numpy Array into Input Feature Vector and Output Labels")
print("===========================================================================")
input_validation_data,output_validation_label = split(validation_data_array)
print("Validation Data After Split")
print("===========================")
print("\nFeature Vector of Validation Data")
print("=================================")
print(input_validation_data)

print("\nOutput Labels of Validation Data")
print("================================\n")
print (output_validation_label)
```

```
Validation Data After Split
===========================

Feature Vector of Validation Data
===================================
[array([[ 8, 14, 24, ..., 64, 60, 61],
       [11, 14, 32, ..., 69, 68, 65],
       [11, 11, 33, ..., 70, 69, 57],
       ...,
       [ 0,  0,  0, ...,  0,  0,  0],
       [ 0,  0,  0, ...,  0,  0,  0],
       [ 0,  0,  0, ...,  0,  0,  0]], dtype=uint8), array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [2, 3, 3, ..., 0, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]], dtype=uint8), array([[ 77,   1,  89, ...,  15,  16,  15],
       [  1,   2,   1, ...,  15,  15,  16],
       [152,   1,   1, ...,  14,  15,  15],
       ...,
       [ 34,  38,  33, ...,  30,  29,  18],
       [ 51,  33,  36, ...,  31,  28,  30],
       [ 67,  33,  32, ...,  29,  27,  28]], dtype=uint8), array([[149,   4, 183, ..., 173,   2,   2],
```

```
        [  0,   1,   0, ...,   7,   2,   0],
        [112,   0,  70, ...,   5,   3,   1],
        ...,
        [  0,   0,   0, ...,   8,   8,   6],
        [  2,   0,   0, ...,   1,   2,   0],
        [  3,   0,   0, ..., 172,   2,   0]], dtype=uint8), array([[ 0,  0,  0, ..., 40, 31, 26],
        [ 0,  0,  0, ..., 38, 31, 23],
        [ 0,  0,  0, ..., 36, 31, 23],
        ...,
        [ 1,  1,  1, ...,  2,  2,  2],
        [ 1,  1,  1, ...,  2,  2,  2],
        [ 1,  1,  1, ...,  2,  2,  2]], dtype=uint8), array([[0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        ...,
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0]], dtype=uint8), array([[ 0,  0,  0, ...,  6,  6,  6],
        [ 0,  0,  0, ...,  6,  6,  6],
        [ 0,  0,  0, ...,  6,  6,  6],
        ...,
        [ 3,  8,  4, ..., 12, 14,  7],
        [ 1,  7,  4, ..., 11,  9,  3],
        [ 6,  2,  4, ..., 12,  5, 13]], dtype=uint8), array([[65, 67, 67, ..., 98, 93, 96],
        [61, 60, 59, ..., 95, 94, 93],
        [55, 55, 55, ..., 95, 92, 92],
        ...,
        [14, 37, 45, ..., 11,  8,  8],
        [19, 40, 51, ...,  8,  7, 11],
        [25, 41, 52, ...,  7,  9,  9]], dtype=uint8)]

Output Labels of Validation Data
==================================

[0, 0, 0, 0, 1, 1, 1, 1]
```

```
print("Normalization of Feature Vecotrs of Validation Data")
print("===================================================\n")

normalized_validation_data = data_normalization(input_validation_data)
print(normalized_validation_data)
```

```
Normalization of Feature Vecotrs of Validation Data
==================================================

[[[0.03137255 0.05490196 0.09411765 ... 0.2509804  0.23529412 0.23921569]
  [0.04313726 0.05490196 0.1254902  ... 0.27058825 0.26666668 0.25490198]
  [0.04313726 0.04313726 0.12941177 ... 0.27450982 0.27058825 0.22352941]
  ...
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]]

 [[0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.00784314 0.01176471 0.01176471 ... 0.         0.         0.        ]
  ...
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]]

 [[0.3019608  0.00392157 0.34901962 ... 0.05882353 0.0627451  0.05882353]
  [0.00392157 0.00784314 0.00392157 ... 0.05882353 0.05882353 0.0627451 ]
  [0.59607846 0.00392157 0.00392157 ... 0.05490196 0.05882353 0.05882353]
  ...
  [0.13333334 0.14901961 0.12941177 ... 0.11764706 0.11372549 0.07058824]
  [0.2        0.12941177 0.14117648 ... 0.12156863 0.10980392 0.11764706]
  [0.2627451  0.12941177 0.1254902  ... 0.11372549 0.10588235 0.10980392]]

 ...

 [[0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  ...
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]
  [0.         0.         0.         ... 0.         0.         0.        ]]

 [[0.         0.         0.         ... 0.02352941 0.02352941 0.02352941]
  [0.         0.         0.         ... 0.02352941 0.02352941 0.02352941]
  [0.         0.         0.         ... 0.02352941 0.02352941 0.02352941]
  ...
```

```
  [0.01176471 0.03137255 0.01568628 ... 0.04705882 0.05490196 0.02745098]
  [0.00392157 0.02745098 0.01568628 ... 0.04313726 0.03529412 0.01176471]
  [0.02352941 0.00784314 0.01568628 ... 0.04705882 0.01960784 0.05098039]]

 [[0.25490198 0.2627451  0.2627451  ... 0.38431373 0.3647059  0.3764706 ]
  [0.23921569 0.23529412 0.23137255 ... 0.37254903 0.36862746 0.3647059 ]
  [0.21568628 0.21568628 0.21568628 ... 0.37254903 0.36078432 0.36078432]
  ...
  [0.05490196 0.14509805 0.1764706  ... 0.04313726 0.03137255 0.03137255]
  [0.07450981 0.15686275 0.2        ... 0.03137255 0.02745098 0.04313726]
  [0.09803922 0.16078432 0.20392157 ... 0.02745098 0.03529412 0.03529412]]]
```

```
# resize data for deep learning
image_width = 224
image_height = 224
input_training_data = normalized_training_data.reshape(-1, image_width, image_height, 1)
output_training_label = np.array(output_training_label)

input_testing_data = normalized_testing_data.reshape(-1, image_width, image_height, 1)
output_testing_label = np.array(output_testing_label)

input_validation_data = normalized_validation_data.reshape(-1, image_width, image_height, 1)
output_validation_label = np.array(output_validation_label)
```

Step 05: Execute the Training Phase

Step 5.1:Create CNN Model Architecture

```
'''
    /*---------------------------- CREATE CNN MODEL -------------
    | Function  : create_model()
```

```
      | Purpose   : To Create CNN Model Architecture using Keras Library
      |
      | Arguments :
      |       input_dimension: Dimension of Input Images
      |       hidden_layer_activation: activation of hidden layer (relu/tanh/sigmoid)
      |       output_layer_activation: activation of output layer (sigmoid/softmax)
      |       output_unit: Number of unit in output layer
      | Return    :
      |       model: built CNN model
      *----------------------------------------------------------------*/
    '''

    def create_model(input_dimension,hidden_layer_activation,output_layer_activation,output_unit):
      model = Sequential()
      model.add(Conv2D(32 , (3,3) , strides = 1 , padding = 'same' , activation = hidden_layer_activation , input_shape = input_dimensio
      model.add(BatchNormalization())
      model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
      model.add(Conv2D(64 , (3,3) , strides = 1 , padding = 'same' , activation = hidden_layer_activation))
      model.add(Dropout(0.1))
      model.add(BatchNormalization())
      model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
      model.add(Conv2D(64 , (3,3) , strides = 1 , padding = 'same' , activation = hidden_layer_activation))
      model.add(BatchNormalization())
      model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
      model.add(Conv2D(128 , (3,3) , strides = 1 , padding = 'same' , activation = hidden_layer_activation))
      model.add(Dropout(0.2))
      model.add(BatchNormalization())
      model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
      model.add(Conv2D(256 , (3,3) , strides = 1 , padding = 'same' , activation = hidden_layer_activation))
      model.add(Dropout(0.2))
      model.add(BatchNormalization())
      model.add(MaxPool2D((2,2) , strides = 2 , padding = 'same'))
      model.add(Flatten())
      model.add(Dense(units = 128 , activation = hidden_layer_activation))
      model.add(Dropout(0.2))
      model.add(Dense(output_unit , activation = output_layer_activation))

      return model
```

Step 5.2: Hyperparameters Settings

```
'''
/*---------------- INITIALIZE_PARAMETERS ------------------
'''
input_dimension            = (image_width,image_height,1)
hidden_layer_activation    = 'relu'
output_layer_activation    = 'sigmoid'
output_unit                = 1
number_of_epochs           = 15
learning_rate              = 1e-4
```

Step 5.3: Create Model Object

```
model = create_model(input_dimension,hidden_layer_activation,output_layer_activation,output_unit)
```

Step 5.4: Initialize Optimizer and Loss Function

```
model.compile(optimizer = Adam(lr=learning_rate) , loss = 'binary_crossentropy' , metrics = ['accuracy'])
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_5 (Conv2D)            (None, 224, 224, 32)      320
_________________________________________________________________
```

```
batch_normalization_5 (Batch (None, 224, 224, 32)      128
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 112, 112, 32)      0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 112, 112, 64)      18496
_________________________________________________________________
dropout_4 (Dropout)          (None, 112, 112, 64)      0
_________________________________________________________________
batch_normalization_6 (Batch (None, 112, 112, 64)      256
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 56, 56, 64)        0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 56, 56, 64)        36928
_________________________________________________________________
batch_normalization_7 (Batch (None, 56, 56, 64)        256
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 28, 28, 64)        0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 28, 28, 128)       73856
_________________________________________________________________
dropout_5 (Dropout)          (None, 28, 28, 128)       0
_________________________________________________________________
batch_normalization_8 (Batch (None, 28, 28, 128)       512
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 14, 14, 128)       0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 14, 14, 256)       295168
_________________________________________________________________
dropout_6 (Dropout)          (None, 14, 14, 256)       0
_________________________________________________________________
batch_normalization_9 (Batch (None, 14, 14, 256)       1024
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 7, 7, 256)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 12544)             0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               1605760
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
```

```
Total params: 2,032,833
Trainable params: 2,031,745
Non-trainable params: 1,088
_________________________________________________________________
```

Step 5.5: Evaluation Measure

```
'''
    /*---------------------------- CALCULATE_ACCURACY -------------
    | Function  : calculate_accuracy()
    | Purpose   : Calculate accuracy score
    | Arguments :
    |       X_test : Feature vector of test Data
    |       Y_test : Actual Output Labels
    | Return    :
    |       accuracy   : Accuracy score
    *-------------------------------------------------------------*/
'''

def calculate_accuracy(X_test, Y_test):

  pred=model.predict(X_test)
  y_pred=np.argmax(pred,axis=1)

  loss, accuracy = model.evaluate(X_test, Y_test, verbose = 0)
  return accuracy
```

Step 5.6: Calculate Epoch Elapsed Time

```
'''
    /*---------------------------- EPOCH_TIME_CALCULATION -------------
    | Function  : epoch_time()
```

```
    | Purpose   : Calculate time elapsed in each epoch
    | Arguments :
    |       start_time   : Time when an epoch's execution starts
    |       end_time     : Time when an epoch's execution end
    | Return    :
    |       elapsed_mins : Time consumed by one epoch in minutes
    |       elapsed_secs : Time consumed by one epoch in seconds
    *---------------------------------------------------------*/
'''
def epoch_time(start_time, end_time):
    elapsed_time = end_time - start_time                   # Time elapsed by one epoch
    elapsed_mins = int(elapsed_time / 60)                  # Convert time in minutes
    elapsed_secs = int(elapsed_time - (elapsed_mins * 60)) # Convert time in seconds
    return elapsed_mins, elapsed_secs
```

Step 5.7: Train Model

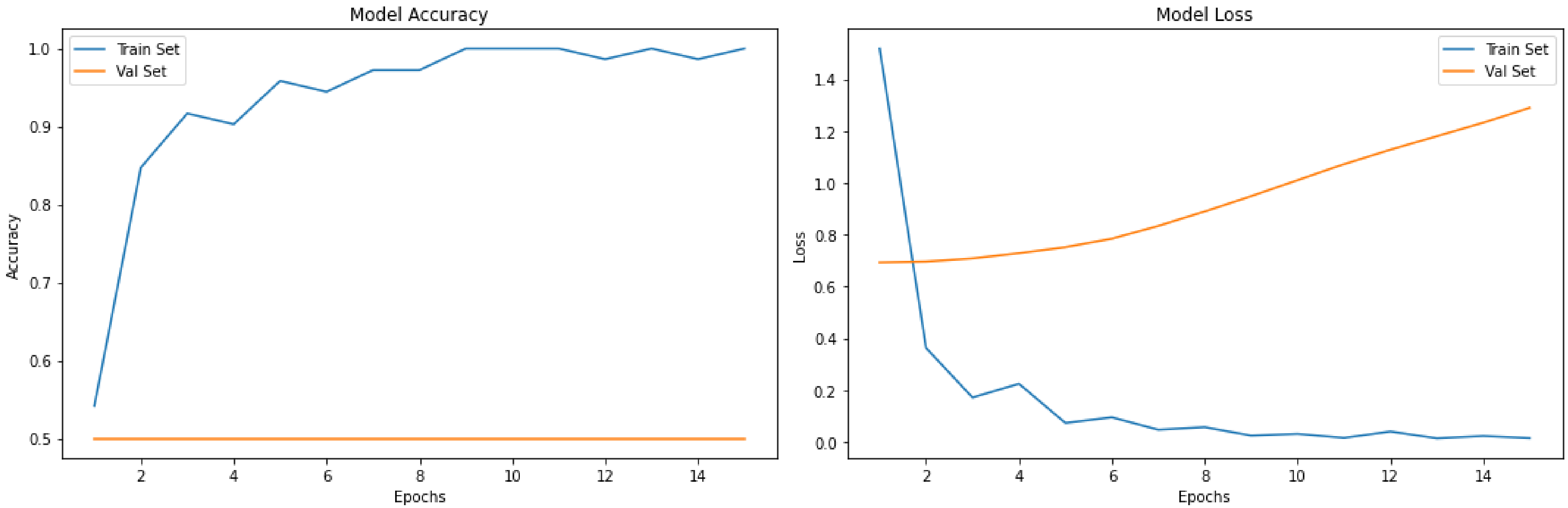
```
history = model.fit(input_training_data,output_training_label,epochs=number_of_epochs,validation_data=(input_validation_data,output_
```

```
Epoch 1/15
3/3 [==============================] - 6s 2s/step - loss: 1.5192 - accuracy: 0.5417 - val_loss: 0.6921 - val_accuracy: 0.5000
Epoch 2/15
3/3 [==============================] - 6s 2s/step - loss: 0.3624 - accuracy: 0.8472 - val_loss: 0.6957 - val_accuracy: 0.5000
Epoch 3/15
3/3 [==============================] - 6s 2s/step - loss: 0.1709 - accuracy: 0.9167 - val_loss: 0.7080 - val_accuracy: 0.5000
Epoch 4/15
3/3 [==============================] - 6s 2s/step - loss: 0.2242 - accuracy: 0.9028 - val_loss: 0.7283 - val_accuracy: 0.5000
Epoch 5/15
3/3 [==============================] - 6s 2s/step - loss: 0.0726 - accuracy: 0.9583 - val_loss: 0.7517 - val_accuracy: 0.5000
Epoch 6/15
3/3 [==============================] - 6s 2s/step - loss: 0.0945 - accuracy: 0.9444 - val_loss: 0.7843 - val_accuracy: 0.5000
Epoch 7/15
3/3 [==============================] - 6s 2s/step - loss: 0.0467 - accuracy: 0.9722 - val_loss: 0.8337 - val_accuracy: 0.5000
Epoch 8/15
3/3 [==============================] - 6s 2s/step - loss: 0.0566 - accuracy: 0.9722 - val_loss: 0.8896 - val_accuracy: 0.5000
Epoch 9/15
```

```
3/3 [==============================] - 6s 2s/step - loss: 0.0240 - accuracy: 1.0000 - val_loss: 0.9484 - val_accuracy: 0.5000
Epoch 10/15
3/3 [==============================] - 6s 2s/step - loss: 0.0306 - accuracy: 1.0000 - val_loss: 1.0104 - val_accuracy: 0.5000
Epoch 11/15
3/3 [==============================] - 6s 2s/step - loss: 0.0150 - accuracy: 1.0000 - val_loss: 1.0722 - val_accuracy: 0.5000
Epoch 12/15
3/3 [==============================] - 6s 2s/step - loss: 0.0397 - accuracy: 0.9861 - val_loss: 1.1280 - val_accuracy: 0.5000
Epoch 13/15
3/3 [==============================] - 6s 2s/step - loss: 0.0134 - accuracy: 1.0000 - val_loss: 1.1802 - val_accuracy: 0.5000
Epoch 14/15
3/3 [==============================] - 6s 2s/step - loss: 0.0222 - accuracy: 0.9861 - val_loss: 1.2324 - val_accuracy: 0.5000
Epoch 15/15
3/3 [==============================] - 6s 2s/step - loss: 0.0141 - accuracy: 1.0000 - val_loss: 1.2898 - val_accuracy: 0.5000
```

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs_range = range(1, len(history.epoch) + 1)

plt.figure(figsize=(15,5))

plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Train Set')
plt.plot(epochs_range, val_acc, label='Val Set')
plt.legend(loc="best")
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Model Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Train Set')
plt.plot(epochs_range, val_loss, label='Val Set')
plt.legend(loc="best")
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Model Loss')

plt.tight_layout()
```

```
plt.tight_layout()
plt.show()
```



Step 5.8: Save Model

```
'''
    /*--------------------------- SAVE_MODEL -------------
    | Function  : save_model()
    | Purpose   : Save a trained model on your hard disk
    | Arguments :
    |       drive_path: Path to the directory where the trained model will be saved
    |       model: model to be saved
    | Return    :
    |       Trained model will be saved on hard disk
    *----------------------------------------------------------*/
'''
```

```
'''
def save_model(drive_path,model):
  model.save(drive_path+'/Pneumonia Disease Prediction model.h5')


save_model('/content/drive/MyDrive/Binary Class Pneumonia Classification/Trained Model',model)
```

Step 06: Execute the Testing Phase

Step 6.1: Load Saved Model (Saved in Step 5.8)

```
'''
    /*---------------------------------- LOAD_MODEL ----------------------------------
    | Function  : load()
    | Purpose   : Load Saved Model from the Hard disk
    | Arguments :
    |       drive_path: Path to the directory where the trained model have been saved
    |
    | Return    :
    |       Trained model will be loaded from the hard disk
    *---------------------------------------------------------------------------------*/

'''
def load(drive_path):
  model=load_model(drive_path+'/Pneumonia Disease Prediction model.h5')
  return model


model = load('/content/drive/MyDrive/Binary Class Pneumonia Classification/Trained Model')
```

Step 6.2: Make Predictions on Testing Data

```
print("Model Predictions on Test Data")
print("==============================\n")

predictions=model.predict(input_testing_data)
predicted_output=np.argmax(predictions,axis=1)
print(predicted_output)
```

```
Model Predictions on Test Data
==============================

[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

Step 6.3: Evaluate Performance of Trained Model on Test Data

Step 6.3.1: Calculate Accuracy

```
accuracy = calculate_accuracy(input_testing_data,output_testing_label)
print("\nEvaluation on Test data= ", accuracy * 100)
```

```
Evaluation on Test data=  50.0
```

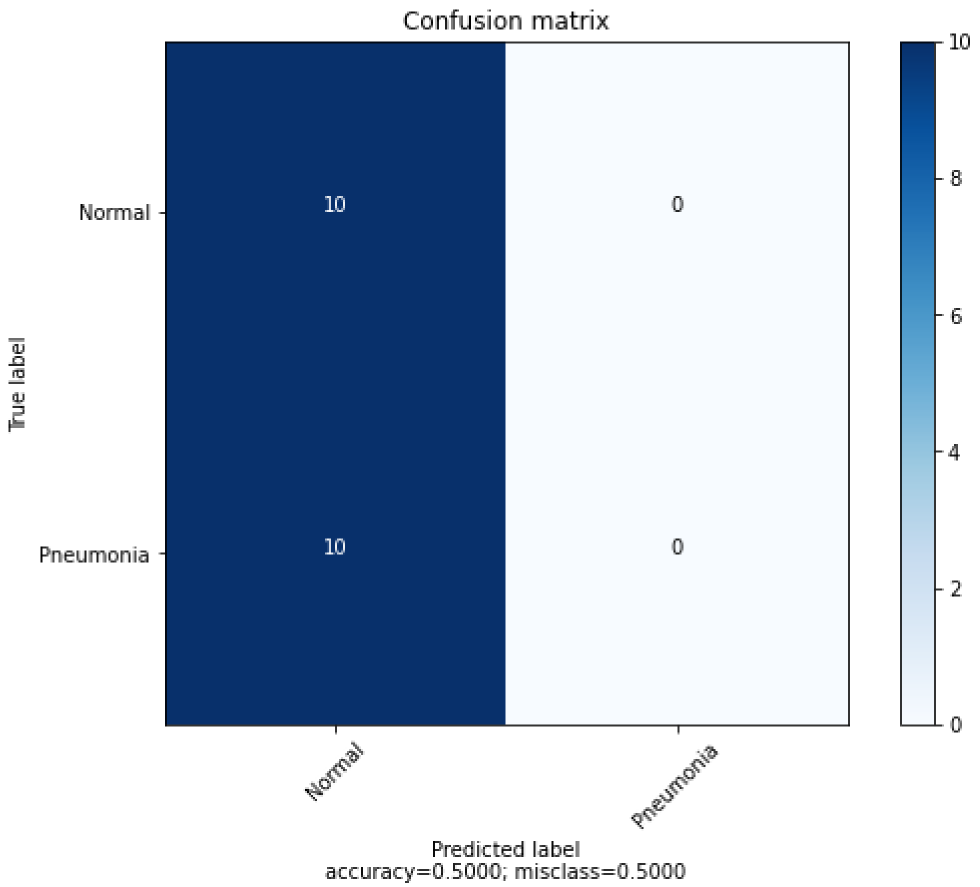
Step 6.3.2: Draw Confusion Matrix

```
"""
    given a sklearn confusion matrix (cm), make a nice plot

    Arguments
```

```
    ---------
    cm:           confusion matrix from sklearn.metrics.confusion_matrix

    target_names: given classification classes such as [0, 1, 2]
                  the class names, for example: ['high', 'medium', 'low']

    title:        the text to display at the top of the matrix

    cmap:         the gradient of the values displayed from matplotlib.pyplot.cm
                  see http://matplotlib.org/examples/color/colormaps_reference.html
                  plt.get_cmap('jet') or plt.cm.Blues

    normalize:    If False, plot the raw numbers
                  If True, plot the proportions

    Usage
    -----
    plot_confusion_matrix(cm           = cm,                  # confusion matrix created by
                                                              # sklearn.metrics.confusion_matrix
                          normalize    = True,                # show proportions
                          target_names = y_labels_vals,       # list of names of the classes
                          title        = best_estimator_name) # title of graph

    Citiation
    ---------
    http://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html

    """

def plot_confusion_matrix(cm,
                          target_names,
                          title='Confusion matrix',
                          cmap=None,
                          normalize=True):

    accuracy = np.trace(cm) / float(np.sum(cm))
    misclass = 1 - accuracy
```

```
    if cmap is None:
        cmap = plt.get_cmap('Blues')

    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()

    if target_names is not None:
        tick_marks = np.arange(len(target_names))
        plt.xticks(tick_marks, target_names, rotation=45)
        plt.yticks(tick_marks, target_names)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]


    thresh = cm.max() / 1.5 if normalize else cm.max() / 2
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        if normalize:
            plt.text(j, i, "{:0.4f}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")
        else:
            plt.text(j, i, "{:,}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")


    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accuracy, misclass))
    plt.show()


confusion_mtx = confusion_matrix(output_testing_label, predicted_output)
cm_plot_labels = ['Normal','Pneumonia']
cm = plot_confusion_matrix(confusion_mtx, target_names = cm_plot_labels, normalize=False)
```

```
cm = plot_confusion_matrix(confusion_mtx, target_names = cm_plot_labels, normalize=False)
```



Step 6.3.3: Print Classification Report

```
print(classification_report(output_testing_label,predicted_output))
```

```
              precision    recall  f1-score   support

           0       0.50      1.00      0.67        10
           1       0.00      0.00      0.00        10

    accuracy                           0.50        20
```

```
   macro avg       0.25      0.50      0.33        20
weighted avg       0.25      0.50      0.33        20

/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarning: Precision and F-score a
  _warn_prf(average, modifier, msg_start, len(result))
```

Step 7: Execute the Application Phase

Step 7.1: Take Input (X-ray Image) from User

```
file_path = '/content/drive/MyDrive/Binary Class Pneumonia Classification/Data for Application Phase/pneumonia.jpeg'
input_image = cv2.imread(file_path)
```

Step 7.2: Convert User Input (X-ray Image) into Feature Vector (Exactly Same as Feature Vectors of Training Data, Testing Data and Validation Data)

```
image = cv2.cvtColor(input_image, cv2.COLOR_RGB2GRAY)
image = cv2.resize(image, (image_width, image_height))

image = np.array(image)
image = image.astype('float32')
image= image/ 255
image = image.reshape(-1, image_width, image_height, 1)
```

Step 7.3: Make Prediction on Unseen Data

Step 7.3.1: Load Saved Model

```
model = load('/content/drive/MyDrive/Binary Class Pneumonia Classification/Trained Model')
```

Step 7.3.2: Apply Model on Feature Vector of Unseen Data

```
image = np.expand_dims(image, axis=-1)
prediction = (model.predict(image) > 0.5).astype("int32")
```

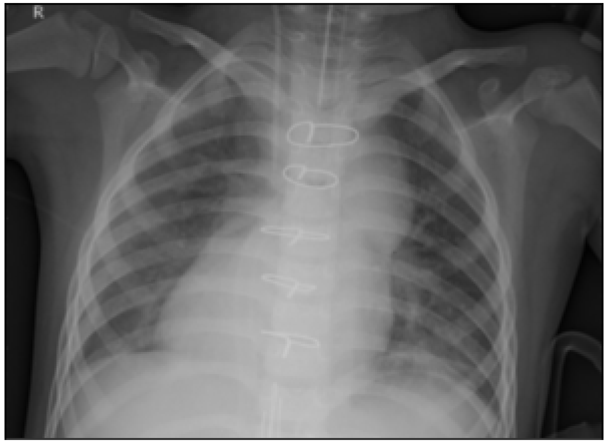
```
WARNING:tensorflow:5 out of the last 7 calls to <function Model.make_predict_function.<locals>.predict_function at 0x7ff76979a3
```

Step 7.3.3: Return Prediction to the User

```
if prediction == 0:
  print('\033[1m',"\n\nTrained Model Prediction")
  print('\033[1m',"+","="*30,"+")
  print('\033[1m',"|"," "*30,"|\n           Class : Normal       \n","|                                |")
  print('\033[1m',"+","="*30,"+")
  plt.imshow(input_image, cmap = 'gray', interpolation = 'bicubic')
  plt.xticks([]), plt.yticks([])  # to hide tick values on X and Y axis
  plt.show()

else:
  print('\033[1m',"\n\nTrained Model Prediction")
  print('\033[1m',"+","="*30,"+")
  print('\033[1m',"|"," "*30,"|\n           Class : Pneumonia       \n","|                                |")
  print('\033[1m',"+","="*30,"+")
  plt.imshow(input_image, cmap = 'gray', interpolation = 'bicubic')
```

```
plt.xticks([]), plt.yticks([])  # to hide tick values on X and Y axis
plt.show()
```

```
Trained Model Prediction
 + ============================== +
 |                                |
          Class : Pneumonia
 |                                |
 + ============================== +
```



Step 8: Execute the Feedback Phase

A Two Step Process

- Step 1: After sometime , take Feedback from
  - Domain Experts and Users on deployed Gender Prediction System
- Step 2: Make a List of Possible Improvements based on Feedback received

Step 9: Improve Model based on Feedback

- There is Always Room for Improvement 😊
- Based on Feedback form Domain Experts and Users
  - Improve your Model