Vision Dataset (Pneumonia classification): LTI

```
from google.colab import drive
drive.mount('/content/drive')
    Mounted at /content/drive
from google.colab import files
files.upload()
#create a kaggle folder
! mkdir ~/.kaggle
#copy the Kaggle.json file into Kaggle folder
!cp kaggle.json ~/.kaggle/
#permission for ison to act
! chmod 600 ~/.kaggle/kaggle.json
! kaggle datasets download -d paultimothymooney/chest-xray-pneumonia
    Choose files No file chosen
                                   Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to e
    Saving kaggle.json to kaggle.json
    Downloading chest-xray-pneumonia.zip to /content
    100% 2.29G/2.29G [00:28<00:00, 40.5MB/s]
    100% 2.29G/2.29G [00:28<00:00, 85.1MB/s]
! unzip chest-xray-pneumonia.zip
    Streaming output truncated to the last 5000 lines.
      inflating: chest_xray/train/NORMAL/IM-0435-0001-0001.jpeg
      inflating: chest xray/train/NORMAL/IM-0435-0001.jpeg
      inflating: chest xray/train/NORMAL/IM-0437-0001-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0437-0001-0002.jpeg
      inflating: chest_xray/train/NORMAL/IM-0437-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0438-0001.jpeq
      inflating: chest_xray/train/NORMAL/IM-0439-0001-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0439-0001-0002.jpeg
      inflating: chest_xray/train/NORMAL/IM-0439-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0440-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0441-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0442-0001.jpeg
      inflating: chest xray/train/NORMAL/IM-0444-0001.jpeg
      inflating: chest xray/train/NORMAL/IM-0445-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0446-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0447-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0448-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0449-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0450-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0451-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0452-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0453-0001-0002.jpeg
      inflating: chest xray/train/NORMAL/IM-0453-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0455-0001.jpeg
      inflating: chest xray/train/NORMAL/IM-0456-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0457-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0458-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0459-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0460-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0461-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0463-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0464-0001.jpeg
      inflating: chest xray/train/NORMAL/IM-0465-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0466-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0467-0001-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0467-0001-0002.jpeg
      inflating: chest_xray/train/NORMAL/IM-0467-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0469-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0471-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0472-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0473-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0474-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0475-0001.jpeg
      inflating: chest xray/train/NORMAL/IM-0476-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0477-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0478-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0479-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0480-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0481-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0482-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0483-0001.jpeg
```

inflating: chest_xray/train/NORMAL/IM-0484-0001.jpeg

```
inflating: chest_xray/train/NORMAL/IM-0485-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0486-0001.jpeg
      inflating: chest xray/train/NORMAL/IM-0487-0001.jpeg
      inflating: chest_xray/train/NORMAL/IM-0488-0001.jpeg
      inflating: chest xray/train/NORMAL/IM-0489-0001.jpeg
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read csv)
import tensorflow as tf
from tensorflow.keras import models
from tensorflow.keras import layers
import matplotlib.pyplot as plt
import seaborn as sns
import keras
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification report, confusion matrix
from keras.callbacks import ReduceLROnPlateau
import pathlib
# Input data files are available in the "../input/" directory.
import os
for dirname, _, filenames in os.walk('/kaggle datasets download -d paultimothymooney/chest-xray-pneumonia'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
#to handle .DS Store 'hidden files'
train = 'chest_xray/chest_xray/train/NORMAL'
train P = 'chest xray/chest xray/train/PNEUMONIA'
test = 'chest_xray/chest_xray/test/NORMAL
test_P = 'chest_xray/chest_xray/test/PNEUMONIA'
val = 'chest xray/chest xray/val/NORMAL'
val P = 'chest xray/chest xray/val/PNEUMONIA'
train = pathlib.Path(train)
train P = pathlib.Path(train P)
test = pathlib.Path(test)
test_P = pathlib.Path(test_P)
val = pathlib.Path(val)
val_P = pathlib.Path(val_P)
# for item in train.glob("*"):
# print(item.name)
list_ds_N = tf.data.Dataset.list_files(str(train/'*.jpeg'))
list ds P = tf.data.Dataset.list files(str(train P/'*.jpeg'))
list_ds_test_N = tf.data.Dataset.list_files(str(test/'*.jpeg'))
list ds test P = tf.data.Dataset.list files(str(test P/'*.jpeg'))
list_ds_val_N = tf.data.Dataset.list_files(str(val/'*.jpeg'))
list ds val P = tf.data.Dataset.list files(str(val P/'*.jpeg'))
for f in list ds P.take(5):
 print(f.numpy())
    b'chest_xray/chest_xray/train/PNEUMONIA/person758_bacteria_2662.jpeg'
    b'chest_xray/chest_xray/train/PNEUMONIA/person1644_bacteria_4357.jpeg'
    b'chest_xray/chest_xray/train/PNEUMONIA/person803_bacteria_2710.jpeg
    b'chest_xray/chest_xray/train/PNEUMONIA/person700 bacteria 2599.jpeg
    b'chest_xray/chest_xray/train/PNEUMONIA/person292 virus 599.jpeg
list_ds = list_ds_N.concatenate(list_ds_P)
list_ds_test = list_ds_test_N.concatenate(list_ds_test_P)
list ds val = list ds val N.concatenate(list ds val P)
# Reads an image from a file, decodes it into a dense tensor, and resizes it
# to a fixed shape.
def parse image(filename):
 parts = tf.strings.split(file_path, '/')
 label = parts[-2]
 image = tf.io.read_file(filename)
 image = tf.io.decode_image(image, expand_animations = False)
 image = tf.image.convert_image_dtype(image, tf.float32)
 image = tf.image.resize(image, [150, 150])
 return image, label
def show(image, label):
 plt.figure()
```

```
plt.imshow( tf.squeeze(image))
plt.title(label.numpy().decode('utf-8'))
plt.axis('off')
```

Data Visualization and augmentation

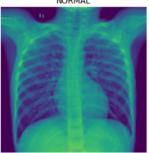
Plot at least two samples from each class of the dataset

Ploting sample data from training data set

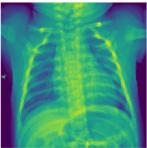
```
print('Ploting sample dataset from Training data')
file_path = next(iter(list_ds))
image, label = parse_image(file_path)
show(image, label)
print("-----")
file_path = next(iter(list_ds))
image, label = parse_image(file_path)
show(image, label)
```

Ploting sample dataset from Training data

NORMAL



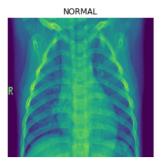
NORMAL



Ploting sample data from testing data set

```
print('Ploting sample dataset from Testing data')
file_path = next(iter(list_ds_test))
image, label = parse_image(file_path)
show(image, label)
print("-----")
file_path = next(iter(list_ds_test))
image, label = parse_image(file_path)
show(image, label)
```

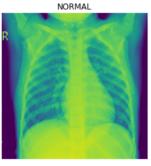
Ploting sample dataset from Testing data



Ploting sample data from validation data set

```
print('Ploting sample dataset from validation data')
file_path = next(iter(list_ds_val))
image, label = parse_image(file_path)
show(image, label)
print("-----")
file_path = next(iter(list_ds_val))
image, label = parse_image(file_path)
show(image, label)
```

Ploting sample dataset from validation data



NORMAL

Bringing the train and test data in the required format.

```
# Reading and Parsing the dataset
images_ds = list_ds.map(parse_image)
images_ds_test = list_ds_test.map(parse_image)
images_ds_val = list_ds_val.map(parse_image)
```

Apply rotation and height shift augmentatio

```
# defining rotate and shift function
import scipy.ndimage as ndimage
def random_rotate_image(image):
   image = ndimage.rotate(image, np.random.uniform(-30,30), reshape=False)
   return image

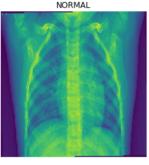
def random_shift_image(image):
   image = ndimage.shift(image, shift = 0.080)
   return image
```

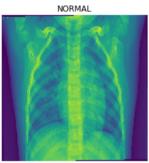
Ploting sample data post rotation and height shift on training data

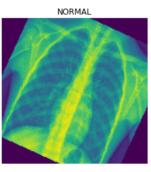
```
print('Ploting sample dataset from Training data post rotation')
image, label = next(iter(images ds))
image = random_rotate_image(image)
show(image, label)
print('Ploting sample dataset from Training data')
show(image, label)
print("----")
print('Ploting sample dataset from Training data post rotation')
image, label = next(iter(images_ds))
image = random rotate image(image)
show(image, label)
print('Ploting sample dataset from Training data')
show(image, label)
    Ploting sample dataset from Training data post rotation
    Ploting sample dataset from Training data
    Ploting sample dataset from Training data post rotation
    Ploting sample dataset from Training data
              NORMAL
              NORMAL
              NORMAL
               NORMAL
```

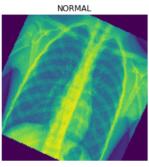
print('Ploting sample dataset from Testing data post rotation')

```
03/04/2023, 00:14
   image, label = next(iter(images_ds_test))
   image = random_rotate_image(image)
   show(image, label)
   print('Ploting sample dataset from test data')
   show(image, label)
   print("----")
   print('Ploting sample dataset from Testing data post rotation')
   image, label = next(iter(images_ds_test))
   image = random_rotate_image(image)
   show(image, label)
   print('Ploting sample dataset from test data')
   show(image, label)
   Ploting sample dataset from Testing data post rotation
       Ploting sample dataset from test data
       Ploting sample dataset from Testing data post rotation
       Ploting sample dataset from test data
                 NORMAL
```









```
print('Ploting sample dataset from validation data post rotation')
image, label = next(iter(images_ds_val))
image = random_rotate_image(image)
show(image, label)
print('Ploting sample dataset from validation data')
show(image, label)
```

```
print("------")
print('Ploting sample dataset from validation data post rotation')

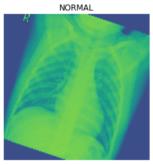
image, label = next(iter(images_ds_val))
image = random_rotate_image(image)
show(image, label)

print('Ploting sample dataset from validation data')
show(image, label)

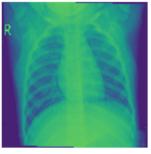
Ploting sample dataset from validation data post rotation
Ploting sample dataset from validation data

Ploting sample dataset from validation data post rotation
Ploting sample dataset from validation data post rotation
Ploting sample dataset from validation data post rotation
Ploting sample dataset from validation data
```

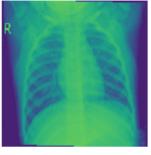




NORMAL



NORMAL



```
# def tf_random_rotate_image(image, label):
# im_shape = image.shape
# [image,] = tf.py_function(random_rotate_image, [image], [tf.float32])
# image.set_shape(im_shape)
# return image, label

# rot_ds = images_ds.map(tf_random_rotate_image)
# rot_ds_test = images_ds_test.map(tf_random_rotate_image)
# rot_ds_val = images_ds_val.map(tf_random_rotate_image)
```

```
# image, label = next(iter(rot_ds_test))
# plt.figure(figsize = (5,5))
# plt.imshow(tf.squeeze(image), cmap='gray')
# plt.title(label)

# image, label = next(iter(rot_ds_val))
# plt.figure(figsize = (5,5))
# plt.imshow(tf.squeeze(image), cmap='gray')
# plt.title(label)
```

Print the shapes of train and test data.

```
image, label = next(iter(images ds))
print('shape of the training data', len(list_ds), image.shape[0])
print("----
image, label = next(iter(images_ds_test))
print('shape of the testing data', len(list_ds_test), image.shape[0])
print("-----
image, label = next(iter(images_ds_val))
print('shape of the validation data', len(list_ds_val), image.shape[0])
    shape of the training data 5216 150
    shape of the testing data 624 150
    shape of the validation data 16 150
labels = ['PNEUMONIA', 'NORMAL']
img size = 150
def get_training_data(data_dir):
   data = []
    for label in labels:
       path = os.path.join(data dir, label)
       class num = labels.index(label)
        for img in os.listdir(path):
           try:
               img_arr = cv2.imread(os.path.join(path, img), cv2.IMREAD_GRAYSCALE)
                resized_arr = cv2.resize(img_arr, (img_size, img_size)) # Reshaping images to preferred size
               data.append([resized arr, class num])
            except Exception as e:
               print(e)
    return np.arrav(data)
train = get_training_data('chest_xray/chest_xray/train/')
test = get_training_data('chest_xray/chest_xray/test/')
val = get_training_data('chest_xray/chest_xray/val/')
    OpenCV(4.1.2) /io/opencv/modules/imgproc/src/resize.cpp:3720: error: (-215:Assertion failed) !ssize.empty() in function '
    OpenCV(4.1.2) /io/opencv/modules/imgproc/src/resize.cpp:3720: error: (-215:Assertion failed) !ssize.empty() in function '
    /usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:15: VisibleDeprecationWarning: Creating an ndarray from rage
      from ipykernel import kernelapp as app
    OpenCV(4.1.2) /io/opencv/modules/imgproc/src/resize.cpp:3720: error: (-215:Assertion failed) !ssize.empty() in function '
    OpenCV(4.1.2) /io/opencv/modules/imgproc/src/resize.cpp:3720: error: (-215:Assertion failed) !ssize.empty() in function '
x train = []
y_train = []
x val = []
y_val = []
x_test = []
y_test = []
for feature, label in train:
    x train.append(feature)
   y_train.append(label)
for feature, label in test:
    x_test.append(feature)
   y_test.append(label)
```

```
for feature, label in val:
    x_val.append(feature)
    y_val.append(label)
# Normalize the data
x_{train} = np.array(x_{train}) / 255
x_val = np.array(x_val) / 255
x test = np.array(x test) / 255
# y_train = np.array(y_train)
# y_val = np.array(y_val)
# y_test = np.array(y_test)
y train = tf.keras.utils.to categorical(y train)
y_test = tf.keras.utils.to_categorical(y test)
y_val = tf.keras.utils.to_categorical(y_val)
Xtrain = x_train.reshape((5216, 150*150))
Xtest = x_{test.reshape((624, 150*150))}
Xval = x_val.reshape((16, 150*150))
```

Model building

```
# Create a model object
from keras.layers import Dropout
tf.keras.backend.clear_session() #clear old tf seesion and models
dnnModel = models.Sequential()
# Layer 1 = input layer
# specify the input size in the first layer.
dnnModel.add(layers.Dense(50, activation='relu', input_shape= (150*150,), kernel_regularizer='12'))
# Layer 2 = hidden layer
dnnModel.add(layers.Dense(60, activation='relu', kernel_regularizer='12'))
# dropout in hidden layers with weight constraint
dnnModel.add(Dropout(0.2))
# Layer 3 = hidden layer
dnnModel.add(layers.Dense(30, activation='relu', kernel_regularizer='12'))
# Layer 4 = output layer
dnnModel.add(layers.Dense(2, activation='softmax', kernel_regularizer='12'))
dnnModel.summarv()
    Model: "sequential"
```

Layer (type)	Output	-	Param #
dense (Dense)	(None,		1125050
dense_1 (Dense)	(None,	60)	3060
dropout (Dropout)	(None,	60)	0
dense_2 (Dense)	(None,	30)	1830
dense_3 (Dense)	(None,	2)	62
Total params: 1,130,002 Trainable params: 1,130,002 Non-trainable params: 0	=====		=======

Model Compilation

```
dnnModel.compile( optimizer = 'adam', loss = 'binary crossentropy', metrics=['accuracy', 'mse'] )
```

Model Training

h = dnnModel.fit(Xtrain, y train, batch size=64, validation data = (Xtest, y test), epochs=200)

import datetime

t1 = datetime.datetime.now()

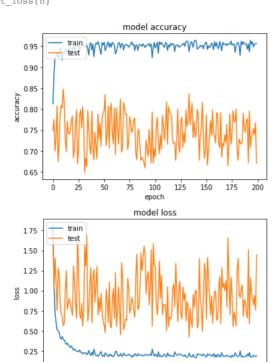
```
t2 = datetime.datetime.now()
    Epoch 1/200
    82/82 [=====
                                  ======] - 3s 29ms/step - loss: 1.8098 - accuracy: 0.8127 - mse: 0.1363 - val_loss: 1.5892
    Epoch 2/200
                                           - 2s 26ms/step - loss: 1.0375 - accuracy: 0.8854 - mse: 0.0845 - val loss: 1.0381
    82/82 [=
    Epoch 3/200
    82/82 [====
                                           - 2s 26ms/step - loss: 0.7184 - accuracy: 0.9218 - mse: 0.0572 - val loss: 1.4043
    Epoch 4/200
    82/82 [====
                                       ===1 - 2s 27ms/step - loss: 0.6008 - accuracy: 0.9260 - mse: 0.0547 - val loss: 1.1106
    Epoch 5/200
    82/82 [====
                                              4s 43ms/step - loss: 0.5104 - accuracy: 0.9363 - mse: 0.0466 - val loss: 0.7531
    Epoch 6/200
    82/82
                                             3s 38ms/step - loss: 0.4986 - accuracy: 0.9277 - mse: 0.0543 - val_loss: 1.2790
    Epoch 7/200
    82/82
                                              2s 26ms/step - loss: 0.4843 - accuracy: 0.9225 - mse: 0.0571 - val loss: 1.1906
    Epoch 8/200
    82/82
                                             2s 27ms/step - loss: 0.4118 - accuracy: 0.9459 - mse: 0.0422 - val loss: 0.8347
    Epoch 9/200
    82/82
                                           - 2s 27ms/step - loss: 0.3971 - accuracy: 0.9421 - mse: 0.0447 - val loss: 0.7081
    Epoch 10/200
    82/82
                                   ======1 - 2s 26ms/step - loss: 0.4300 - accuracy: 0.9172 - mse: 0.0609 - val loss: 0.6804
          [=====
    Epoch
          11/200
    82/82
                                            - 2s 28ms/step - loss: 0.3918 - accuracy: 0.9327 - mse: 0.0503 - val_loss: 0.5622
    Epoch
          12/200
    82/82 [====
                                              2s 25ms/step - loss: 0.3839 - accuracy: 0.9317 - mse: 0.0514 - val loss: 0.5947
    Epoch
          13/200
    82/82
                                              2s 26ms/step - loss: 0.3582 - accuracy: 0.9383 - mse: 0.0479 - val loss: 1.0117
    Epoch 14/200
    82/82 [====
                                             2s 27ms/step - loss: 0.3313 - accuracy: 0.9434 - mse: 0.0431 - val loss: 1.2462
    Epoch 15/200
    82/82 [=====
                                             2s 24ms/step - loss: 0.3463 - accuracy: 0.9344 - mse: 0.0500 - val loss: 0.7679
    Epoch 16/200
    82/82
                                              2s 27ms/step - loss: 0.3237 - accuracy: 0.9369 - mse: 0.0472 - val loss: 0.8396
    Epoch 17/200
    82/82
                                              2s 25ms/step - loss: 0.3030 - accuracy: 0.9465 - mse: 0.0417 - val loss: 0.9019
    Epoch 18/200
    82/82 [====
                                           - 2s 26ms/step - loss: 0.2930 - accuracy: 0.9408 - mse: 0.0436 - val loss: 0.8371
          19/200
    Epoch
    82/82
                                           - 2s 26ms/step - loss: 0.3135 - accuracy: 0.9293 - mse: 0.0505 - val loss: 0.7632
    Epoch 20/200
    82/82 [=====
                                           - 2s 26ms/step - loss: 0.2828 - accuracy: 0.9438 - mse: 0.0426 - val loss: 0.6930
    Epoch 21/200
    82/82 [=====
                                           - 2s 26ms/step - loss: 0.2593 - accuracy: 0.9492 - mse: 0.0381 - val loss: 1.3076
    Epoch 22/200
    82/82 [=====
                                              2s 25ms/step - loss: 0.2734 - accuracy: 0.9402 - mse: 0.0440 - val loss: 1.1349
    Epoch 23/200
    82/82 [==
                                              2s 26ms/step - loss: 0.2576 - accuracy: 0.9461 - mse: 0.0404 - val loss: 0.8486
    Epoch 24/200
    82/82 [===
                                         =1 - 2s 25ms/step - loss: 0.2480 - accuracy: 0.9503 - mse: 0.0382 - val loss: 0.6571
    Epoch 25/200
    82/82 [=====
                                              2s 26ms/step - loss: 0.2430 - accuracy: 0.9500 - mse: 0.0390 - val loss: 1.7212
    Epoch 26/200
    82/82 [====
                                           - 2s 25ms/step - loss: 0.2386 - accuracy: 0.9498 - mse: 0.0390 - val loss: 1.2329
    Epoch 27/200
    82/82
                                              2s 24ms/step - loss: 0.2618 - accuracy: 0.9398 - mse: 0.0462 - val loss: 0.7149
    Epoch 28/200
    82/82 [=====
                                       ===] - 1s 18ms/step - loss: 0.2331 - accuracy: 0.9486 - mse: 0.0388 - val loss: 0.6511
    Epoch 29/200
                          ========] - 1s 18ms/step - loss: 0.2281 - accuracy: 0.9532 - mse: 0.0376 - val loss: 0.8447
```

summarize history for accuracy and loss

```
print('time taken by the model', t2-t1)
    time taken by the model 0:06:26.746463
# summarize history for accuracy
def plot acc(history):
 plt.plot(history.history['accuracy'])
 plt.plot(history.history['val_accuracy'])
 plt.title('model accuracy')
 plt.ylabel('accuracy')
 plt.xlabel('epoch')
 plt.legend(['train', 'test'], loc='upper left')
 plt.show()
# summarize history for loss
def plot loss(history):
 plt.plot(history.history['loss'])
 plt.plot(history.history['val_loss'])
 plt.title('model loss')
```

```
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

plot_acc(h)
plot_loss(h)
```



Model Evaluation

50

100 125 150 175

epoch

```
#prediction
result = dnnModel.predict(Xval)
print(result.shape)
result = pd.DataFrame(result)
result.columns = ['proba1', 'proba2']
result['output'] = result['probal'].apply(lambda x : 1 if x >= 0.50 else 0)
result.head()
    WARNING:tensorflow:5 out of the last 13 calls to <function Model.make predict
    (16, 2)
         proba1
                 proba2 output
       0.998612
                0.001388
     1 0.996382 0.003618
     2 0.997664 0.002336
     3 0.995824 0.004176
     4 0.998222 0.001778
yval = pd.DataFrame(y_val)
yval.columns = ['trueval1',
                            'trueval2']
yval = yval[['trueval1']]
yval.head()
```

trueval1

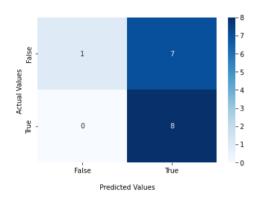
Model confusion matrix report

```
import seaborn as sns
from sklearn.metrics import confusion_matrix
cf_matrix = confusion_matrix(yval['truevall'], result['output'])
ax = sns.heatmap(cf_matrix, annot=True, cmap='Blues')
ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');

## Ticket labels - List must be in alphabetical order
ax.xaxis.set_ticklabels(['False','True'])
ax.yaxis.set_ticklabels(['False','True'])

## Display the visualization of the Confusion Matrix.
plt.show()
```

Seaborn Confusion Matrix with labels



Model classification report

```
from sklearn.metrics import classification report
target_names = ['class pneumonia', 'class normal']
print(classification_report(yval['trueval1'], result['output'], target_names=target_names))
                     precision
                                 recall f1-score
                                                    support
    class pneumonia
                          1.00
                                   0.12
                                              0.22
                                                           8
       class normal
                                    1.00
                                              0.70
           accuracy
                                              0.56
                                                          16
                          0.77
                                    0.56
          macro ava
                                              0.46
                                                          16
       weighted avg
                          0.77
                                    0.56
                                              0.46
                                                          16
```

Hyperparameter Tuning

1. Optimiser: Use a different optimizer with the appropriate LR value.

```
# learning rate schedule
def step_decay(epoch):
    initial_lrate = 0.1
    drop = 0.5
    epochs_drop = 10.0
    lrate = initial_lrate * math.pow(drop, math.floor((1+epoch)/epochs_drop))
    return lrate
```

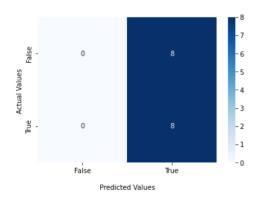
03/04/2023.00:14

```
# Create a model object
from keras.layers import Dropout
from keras.callbacks import LearningRateScheduler
import math
import random
import numpy as np
tf.keras.backend.clear_session() #clear old tf seesion and models
dnnModel = models.Sequential()
# Layer 1 = input layer
# specify the input size in the first layer.
dnnModel.add(layers.Dense(50, activation='relu', input_shape= (150*150,), kernel_regularizer='12'))
# Layer 2 = hidden layer
dnnModel.add(layers.Dense(60, activation='relu', kernel_regularizer='12'))
# dropout in hidden layers with weight constraint
dnnModel.add(Dropout(0.2))
# Layer 3 = hidden layer
dnnModel.add(layers.Dense(30, activation='relu', kernel regularizer='12'))
# Layer 4 = output layer
dnnModel.add(layers.Dense(2, activation='softmax', kernel_regularizer='12'))
dnnModel.summary()
# learning schedule callback
lrate = LearningRateScheduler(step_decay)
callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=50)
# Configure the model for training, by using appropriate optimizers and regularizations
# Available optimizer: adam, rmsprop, adagrad, sgd
# loss: objective that the model will try to minimize.
# Available loss: categorical crossentropy, binary crossentropy, mean squared error
# metrics: List of metrics to be evaluated by the model during training and testing.
dnnModel.compile(optimizer = tf.keras.optimizers.SGD(learning_rate=0.0, momentum=0.9), loss = 'binary_crossentropy', metrics=[
h = dnnModel.fit( Xtrain, y_train, batch_size=64, validation_data = (Xtest, y_test), epochs=50, callbacks=[callback, lrate])
```

```
DL_Pneumonia_Dataset.ipynb - Colaboratory
    Epocn 4//50
    22/82 [=========================== ] - 1s 17ms/step - loss: 0.5701 - accuracy: 0.7429 - mse: 0.2132 - val loss: 0.6951
    Epoch 48/50
                           =========] - 1s 17ms/step - loss: 0.5700 - accuracy: 0.7429 - mse: 0.2136 - val loss: 0.6954
    82/82 [====
    Epoch 49/50
    82/82 [====
                          ========= ] - 1s 17ms/step - loss: 0.5700 - accuracy: 0.7429 - mse: 0.2137 - val loss: 0.6952
    Epoch 50/50
    82/82 [====
                            ========] - 1s 17ms/step - loss: 0.5700 - accuracy: 0.7429 - mse: 0.2134 - val loss: 0.6951
#prediction
result = dnnModel.predict(Xval)
print(result.shape)
result = pd.DataFrame(result)
result.columns = ['proba1', 'proba2']
result['output'] = result['probal'].apply(lambda x : 1 if x >= 0.50 else 0)
result.head()
    (16, 2)
        proba1
                proba2 output
     0 0.892996 0.107004
     1 0.892996 0.107004
     2 0.892996 0.107004
     3 0.892996 0.107004
     4 0.892996 0.107004
```

```
import seaborn as sns
from sklearn.metrics import confusion_matrix
cf_matrix = confusion_matrix(yval['trueval1'], result['output'])
ax = sns.heatmap(cf matrix, annot=True, cmap='Blues')
ax.set_title('Seaborn Confusion Matrix with labels\n\n');
ax.set xlabel('\nPredicted Values')
ax.set_ylabel('Actual Values ');
## Ticket labels - List must be in alphabetical order
ax.xaxis.set_ticklabels(['False','True'])
ax.yaxis.set_ticklabels(['False','True'])
## Display the visualization of the Confusion Matrix.
plt.show()
```

Seaborn Confusion Matrix with labels



from sklearn.metrics import classification report

target_names = ['class pneumonia', 'class normal'] print(classification_report(yval['trueval1'], result['output'], target_names=target_names))

	precision	recall	f1-score	support
class pneumonia class normal	0.00	0.00	0.00	8
accuracy macro avg	0.25	0.50	0.50	16 16
weighted avg	0.25	0.50	0.33	16

 $/usr/local/lib/python 3.7/dist-packages/sklearn/metrics/_classification.py: 1308: \ Undefined Metric Warning: \ Precision \ and \ F-starting and \ F-starting are the starting and \ F-starting are the starting are the starting and \ F-starting are the starting are the starting$ _warn_prf(average, modifier, msg_start, len(result)) /usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1308: UndefinedMetricWarning: Precision and F-s _warn_prf(average, modifier, msg_start, len(result))

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1308: UndefinedMetricWarning: Precision and F-s _warn_prf(average, modifier, msg_start, len(result))

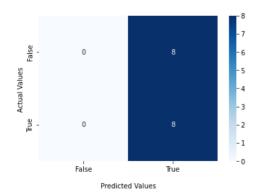
```
# Create a model object
from keras.layers import Dropout
from keras.callbacks import LearningRateScheduler
import math
import random
import numpy as np
tf.keras.backend.clear session() #clear old tf seesion and models
dnnModel = models.Sequential()
# Layer 1 = input layer
# specify the input size in the first layer.
dnnModel.add(layers.Dense(50, activation='relu', input_shape= (150*150,), kernel reqularizer='12'))
# Layer 2 = hidden layer
dnnModel.add(layers.Dense(80, activation='relu', kernel_regularizer='12'))
# dropout in hidden layers with weight constraint
dnnModel.add(Dropout(0.2))
# Layer 3 = hidden layer
dnnModel.add(layers.Dense(60, activation='relu', kernel_regularizer='12'))
# dropout in hidden layers with weight constraint
dnnModel.add(Dropout(0.2))
# Layer 4 = hidden layer
dnnModel.add(layers.Dense(30, activation='relu', kernel regularizer='12'))
# Layer 5 = hidden layer
dnnModel.add(layers.Dense(10, activation='relu', kernel_regularizer='12'))
# Laver 6 = output laver
dnnModel.add(layers.Dense(2, activation='softmax', kernel_regularizer='12'))
dnnModel.summary()
# learning schedule callback
lrate = LearningRateScheduler(step_decay)
callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=50)
# Configure the model for training, by using appropriate optimizers and regularizations
# Available optimizer: adam, rmsprop, adagrad, sgd
# loss: objective that the model will try to minimize.
# Available loss: categorical_crossentropy, binary_crossentropy, mean_squared_error
# metrics: List of metrics to be evaluated by the model during training and testing.
dnnModel.compile(optimizer = tf.keras.optimizers.SGD(learning_rate=0.0, momentum=0.9), loss = 'binary_crossentropy', metrics=[
h = dnnModel.fit( Xtrain, y_train, batch_size=64, validation_data = (Xtest, y_test), epochs=50, callbacks=[callback, lrate])
```

```
82/82 |=====
    Epoch 43/50
    82/82 [============ ] - 2s 26ms/step - loss: 0.5700 - accuracy: 0.7429 - mse: 0.2134 - val loss: 0.6948
    Epoch 44/50
    82/82 [====
                            =======] - 2s 24ms/step - loss: 0.5700 - accuracy: 0.7429 - mse: 0.2132 - val loss: 0.6948
    Epoch 45/50
    82/82 [======
                    ==========] - 2s 26ms/step - loss: 0.5700 - accuracy: 0.7429 - mse: 0.2137 - val_loss: 0.6950
    Epoch 46/50
                                  ===] - 2s 27ms/step - loss: 0.5700 - accuracy: 0.7429 - mse: 0.2134 - val loss: 0.6948
    82/82 [==
    Epoch 47/50
    82/82 [====
                           ======== 1 - 2s 24ms/step - loss: 0.5701 - accuracy: 0.7429 - mse: 0.2142 - val loss: 0.6954
    Epoch 48/50
    82/82 [====
                              ======1 - 2s 25ms/step - loss: 0.5701 - accuracy: 0.7429 - mse: 0.2134 - val loss: 0.6953
    Epoch 49/50
    82/82 [====
                        =========] - 2s 23ms/step - loss: 0.5700 - accuracy: 0.7429 - mse: 0.2136 - val_loss: 0.6949
    Epoch 50/50
    82/82 [====
                      ========1 - 2s 24ms/step - loss: 0.5700 - accuracy: 0.7429 - mse: 0.2132 - val loss: 0.6947
#prediction
result = dnnModel.predict(Xval)
print(result.shape)
result = pd.DataFrame(result)
result.columns = ['proba1', 'proba2']
result['output'] = result['proba1'].apply(lambda x : 1 if x >= 0.50 else 0)
result.head()
    (16, 2)
       proba1
               proba2 output
    0 0.892324 0.107676
                           1
      0.892324 0.107676
```

2 0.892324 0.107676 **3** 0.892324 0.107676 4 0.892324 0.107676

```
import seaborn as sns
from sklearn.metrics import confusion_matrix
cf matrix = confusion matrix(yval['trueval1'], result['output'])
ax = sns.heatmap(cf_matrix, annot=True, cmap='Blues')
ax.set title('Seaborn Confusion Matrix with labels\n\n');
ax.set_xlabel('\nPredicted Values')
ax.set ylabel('Actual Values ');
## Ticket labels - List must be in alphabetical order
ax.xaxis.set ticklabels(['False','True'])
ax.yaxis.set ticklabels(['False','True'])
## Display the visualization of the Confusion Matrix.
plt.show()
```

Seaborn Confusion Matrix with labels



```
from sklearn.metrics import classification report
```

```
target_names = ['class pneumonia', 'class normal']
print(classification report(yval['trueval1'], result['output'], target names=target names))
```

	precision	recall	f1-score	support
class pneumonia	0.00	0.00	0.00	8
class normal	0.50	1.00	0.67	8

accuracy			0.50	16
macro avg	0.25	0.50	0.33	16
weighted avg	0.25	0.50	0.33	16

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1308: UndefinedMetricWarning: Precision and F-s _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1308: UndefinedMetricWarning: Precision and F-s _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1308: UndefinedMetricWarning: Precision and F-s _warn_prf(average, modifier, msg_start, len(result))

Description on function used in model building

Problem Statement: Classification

Output: Binary output

Final activation function: Sigmoid

Loss Funciton: Binary cross entropy/ categorial_crossentropy

ReLU — This results in a numerical value greater than 0

Sigmoid — This results in a value between 0 and 1 which we can infer to be how confident it is of it being in the class

Binary Cross Entropy — Cross entropy quantifies the difference between two probability distribution. Our model predicts a model distribution of $\{p, 1-p\}$ (binary distribution) for each of the classes. We use binary cross-entropy to compare these with the true distributions $\{y, 1-y\}$ for each class and sum up their results

Conclusion:

Adam optimization has performed better with training accuracy of 95.63% than Stochastic Gradient Descent (SGD) model with accuracy of 74.0%