Drive Mount and Dataset Unzip

HEALTH CARE

Predicting pneumonia from chest X-ray images

Dataset link: https://www.kaggle.com/tolgadincer/labeled-chest-xray-images

Google Drive link: https://drive.google.com/file/d/1xYceBz1JMSD4TDNQMQ2yMDYbe4oHZTIt/view?usp=sharing

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

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

```
# Unzip updated dataset from drive, with labelled test data
!mkdir dataset
%cd dataset
!unzip "/content/drive/MyDrive/archive.zip"
%cd ..
```

Common Cells for both Models

CONSTANTS, Helper Functions, Imports, Optimizer, Data Generator, Class Weights,Test Data Load

CONSTANTS

```
input_shape = (150,150,3)
target_size = (150,150)
epochs = 50
batch_size = 64
patience = 3
classes = ('normal', 'pneumonia')
train_dir = './dataset/chest_xray/train'
test_dir = './dataset/chest_xray/test'
```

Helper Functions

```
def plot_model_accuracy(H):
  plt.plot(H.history['accuracy'])
  plt.plot(H.history['val_accuracy'])
  plt.title('Model Auccary')
  plt.ylabel('Accuracy')
  plt.xlabel('Epoch')
  plt.legend(['Train Accuracy', 'Validation Accuracy'], loc='upper left', bbox_to_anchor=(1,1))
  plt.show()

def plot_model_loss(H):
  plt.plot(H.history['loss'])
  plt.plot(H.history['val_loss'])
  plt.title('Model Loss')
  plt.ylabel('Loss')
  plt.xlabel('Epoch')
  plt.legend(['Train Loss', 'Validation Loss'], loc='upper left', bbox_to_anchor=(1,1))
  plt.show()

def plot_model_lr(H):
  N = np.arange(0, len(H.epoch))
  plt.style.use('ggplot')
  plt.figure()
  plt.plot(N, H.history['accuracy'], label='train_accuracy')
  plt.plot(N, H.history['val_accuracy'], label='val_accuracy')
  plt.plot(N, H.history['loss'], label='train_loss')
  plt.plot(N, H.history['val_loss'], label='val_loss')
  plt.title('Training loss and accuracy')
  plt.xlabel('Epoch #')
  plt.ylabel('Loss/Accuracy')
  plt.legend()
  plt.show()

```

```
def load_data(data_dir):
  data = []
  labels = []
  class_dirs = os.listdir(data_dir)

  for direc in class_dirs:
    class_dir = os.path.join(data_dir, direc)
    for imagepath in tqdm(list(paths.list_images(class_dir))):
      image = cv2.imread(imagepath)
      image = cv2.resize(image, target_size)  # incase images not of same size
      data.append(image)
      labels.append(direc)
  # normalizing and converting to numpy array format
  data = np.array(data, dtype='float')/255.0
  labels = np.array(labels)
  return data, labels

def one_hot_encoding(pred):
  ohe = [0] * len(pred) # Equal to categories (i.e. 2)
  index = 0
  for i in range(len(pred)):
    if (pred[i] > pred[index]):
      index = i
  ohe[index] = 1
  return ohe

def get_title(pred, actual):
  if((pred == classes[0] and actual[0] == 1) or (pred == classes[1] and actual[1] == 1)):
    return pred + '(✓)'
  else:
    return pred + '(✕)'
```

Import Required Libraries

```
import os
import cv2
import numpy as np
import tensorflow
from imutils import paths
from sklearn.utils import class_weight
from sklearn.preprocessing import LabelBinarizer
from tqdm import tqdm
import matplotlib.pyplot as plt

from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from keras.preprocessing.image import ImageDataGenerator
from keras.layers import Dense, Dropout, GlobalAveragePooling2D
from tensorflow.keras.models import Sequential
```

SGD Optimizer (With Exponential Decay)

```
lr_schedule = keras.optimizers.schedules.ExponentialDecay(
    initial_learning_rate=1e-2,
    decay_steps=10000,
    decay_rate=0.9)
optimizer = keras.optimizers.SGD(learning_rate=lr_schedule)
```

Data Generator (Train, Validation, Test)

```
train_datagen = ImageDataGenerator(rescale = 1.0 / 255.0,
                                   validation_split = 0.2)

valid_datagen = ImageDataGenerator(rescale = 1.0 / 255.0,
                                   validation_split = 0.2)

test_datagen  = ImageDataGenerator(rescale = 1.0 / 255.0)
```

Flow from Directory (Train, Validation & Test)

```
train_dataset = train_datagen.flow_from_directory(directory = train_dir,
                                                  target_size = target_size,
                                                  class_mode = 'categorical',
                                                  subset = 'training',
                                                  batch_size = batch_size)
```

```
                                                    batch_size = batch_size)

valid_dataset = valid_datagen.flow_from_directory(directory = train_dir,
                                                  target_size = target_size,
                                                  class_mode = 'categorical',
                                                  subset = 'validation',
                                                  batch_size = batch_size)

test_dataset = test_datagen.flow_from_directory(directory = test_dir,
                                                target_size = target_size,
                                                class_mode = 'categorical',
                                                batch_size = batch_size)
```

```
Found 4187 images belonging to 2 classes.
Found 1045 images belonging to 2 classes.
Found 624 images belonging to 2 classes.
```

Evaluate Class Weights (To handle data imbalance)

```
train_class_weights = class_weight.compute_class_weight(
           'balanced',
            np.unique(train_dataset.classes),
            train_dataset.classes)

class_weights = { 0: train_class_weights[0], 1: train_class_weights[1] }
print('Class weights (imblanced classes):', class_weights)
```

```
Class weights (imblanced classes): {0: 1.938425925925926, 1: 0.6738010943031864}
```

Load Test Data

```
print('Loading test images:')
X_test, y_test = load_data(test_dir)
```

```
  3%|▌         | 6/234 [00:00<00:04, 50.42it/s]Loading test images:
100%|██████████| 234/234 [00:05<00:00, 45.10it/s]
100%|██████████| 390/390 [00:02<00:00, 146.21it/s]
```

Test Labels to One Hot Encoding

```
lb = LabelBinarizer()
y_test = lb.fit_transform(y_test)
y_test = np.hstack((1 - y_test, y_test))
```

Resnet50 (Base Model)

Resnet50 imagenet

```
from keras.applications.resnet50 import ResNet50
base_model = ResNet50(input_shape=input_shape, weights='imagenet', include_top=False)
```

Freezing Layers

```
for layer in base_model.layers:
    layer.trainable=False
```

Defining Layers

```
model_base=Sequential()
model_base.add(base_model)
model_base.add(GlobalAveragePooling2D())
model_base.add(Dense(64, activation='relu'))
model_base.add(Dropout(0.3))
model_base.add(Dense(2,activation='softmax'))
```

Model Summary

```
model_base.summary()
```

```
model_base.summary()
```

```
Model: "sequential_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Functional)        (None, 5, 5, 2048)        23587712
_________________________________________________________________
global_average_pooling2d_132 (None, 2048)              0
_________________________________________________________________
dense_278 (Dense)            (None, 64)                131136
_________________________________________________________________
dropout_19 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_279 (Dense)            (None, 2)                 130
=================================================================
Total params: 23,718,978
Trainable params: 131,266
Non-trainable params: 23,587,712
_________________________________________________________________
```

Model Compile with SGD Optimzer

```
model_base.compile(loss='categorical_crossentropy',
             optimizer=optimizer,
             metrics=['accuracy'])
```

Defining Callbacks

```
filepath = './best_base_weights.hdf5'

early_stopping = EarlyStopping(monitor = 'val_accuracy',
                              mode = 'max',
                              patience = patience,
                              verbose = 1)

checkpoint    = ModelCheckpoint(filepath,
                                monitor = 'val_accuracy',
                                mode='max',
                                save_best_only=True,
                                verbose = 1)

callback_list = [early_stopping, checkpoint]
```

Model Fitting

```
H_base = model_base.fit(train_dataset,
             validation_data=valid_dataset,
             epochs = epochs,
             callbacks = callback_list,
             class_weight = class_weights,
             verbose = 1)
```

```
Epoch 1/50
66/66 [==============================] - 53s 772ms/step - loss: 0.7648 - accuracy: 0.4847 - val_loss: 0.6941 - val_accuracy: 0.

Epoch 00001: val_accuracy improved from -inf to 0.43254, saving model to ./best_base_weights.hdf5
Epoch 2/50
66/66 [==============================] - 50s 752ms/step - loss: 0.6924 - accuracy: 0.4798 - val_loss: 0.6980 - val_accuracy: 0.

Epoch 00002: val_accuracy did not improve from 0.43254
Epoch 3/50
66/66 [==============================] - 49s 749ms/step - loss: 0.6926 - accuracy: 0.4645 - val_loss: 0.6770 - val_accuracy: 0.

Epoch 00003: val_accuracy improved from 0.43254 to 0.74258, saving model to ./best_base_weights.hdf5
Epoch 4/50
66/66 [==============================] - 50s 751ms/step - loss: 0.6884 - accuracy: 0.5729 - val_loss: 0.6878 - val_accuracy: 0.

Epoch 00004: val_accuracy improved from 0.74258 to 0.75694, saving model to ./best_base_weights.hdf5
Epoch 5/50
66/66 [==============================] - 50s 755ms/step - loss: 0.6869 - accuracy: 0.5367 - val_loss: 0.6707 - val_accuracy: 0.

Epoch 00005: val_accuracy did not improve from 0.75694
Epoch 6/50
66/66 [==============================] - 49s 749ms/step - loss: 0.6851 - accuracy: 0.5937 - val_loss: 0.7069 - val_accuracy: 0.

Epoch 00006: val_accuracy did not improve from 0.75694
Epoch 7/50
66/66 [==============================] - 49s 751ms/step - loss: 0.6788 - accuracy: 0.5087 - val_loss: 0.6742 - val_accuracy: 0.
```

```
Epoch 00007: val_accuracy improved from 0.75694 to 0.76364, saving model to ./best_base_weights.hdf5
Epoch 8/50
66/66 [==============================] - 49s 748ms/step - loss: 0.6872 - accuracy: 0.6037 - val_loss: 0.6725 - val_accuracy: 0.

Epoch 00008: val_accuracy improved from 0.76364 to 0.77703, saving model to ./best_base_weights.hdf5
Epoch 9/50
66/66 [==============================] - 50s 751ms/step - loss: 0.6851 - accuracy: 0.5900 - val_loss: 0.6675 - val_accuracy: 0.

Epoch 00009: val_accuracy did not improve from 0.77703
Epoch 10/50
66/66 [==============================] - 50s 753ms/step - loss: 0.6829 - accuracy: 0.5870 - val_loss: 0.6581 - val_accuracy: 0.

Epoch 00010: val_accuracy did not improve from 0.77703
Epoch 11/50
66/66 [==============================] - 50s 753ms/step - loss: 0.6865 - accuracy: 0.5698 - val_loss: 0.6794 - val_accuracy: 0.

Epoch 00011: val_accuracy did not improve from 0.77703
Epoch 00011: early stopping
```

Load Base Model Weights (if required)

```
1 model_base.load_weights("best_base_weights.hdf5")
```

Resnet50 (Summary)

Test Loss/Accuracy, Training/Validation Graphs, Confusion Matrix, Classification Report & Visual Results

Evaluating Loss and AUC - Test Data

```
1 score = model_base.evaluate(test_dataset)
2 print('Test Loss: ', score[0])
3 print('Test Accuracy: ', score[1])
```

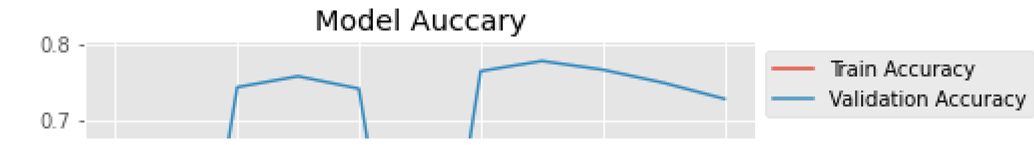
```
10/10 [==============================] - 6s 588ms/step - loss: 0.6780 - accuracy: 0.7244
Test Loss:  0.6780446767807007
Test Accuracy:  0.7243589758872986
```

Summarize Model Loss

```
1 plot_model_loss(H_base)
```

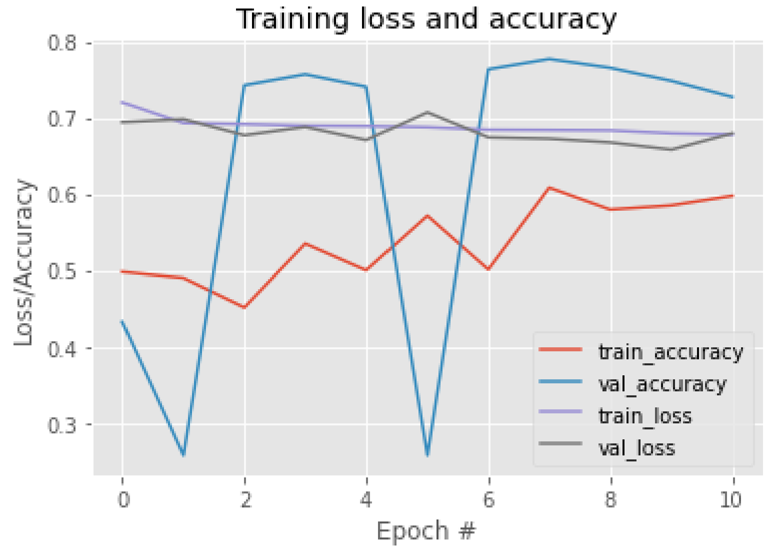
Summarize Model Accuracy

```
1 plot_model_accuracy(H_base)
```



Summarize Learning Curve (Accuracy and Loss)

```
plot_model_lr(H_base)
```



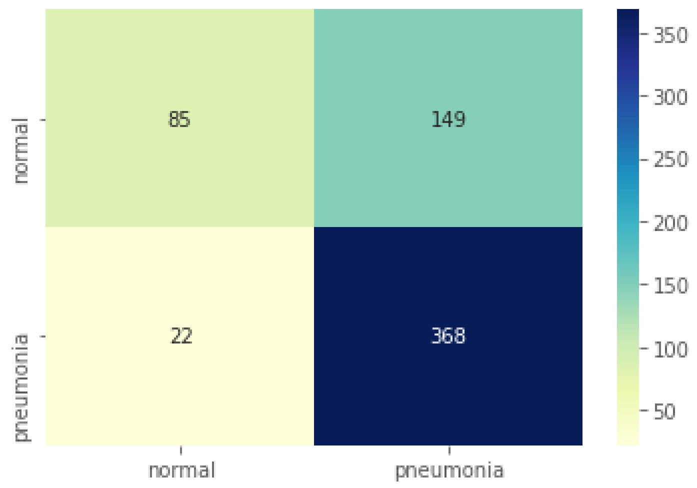
CONFUSION MATRIX

```
# Making prediction
y_pred = model_base.predict(X_test)
y_true = np.argmax(y_test, axis=-1)

# Plotting the confusion matrix
from sklearn.metrics import confusion_matrix
confusion_mtx = confusion_matrix(y_true, np.argmax(y_pred, axis=1))
confusion_mtx
```

```
array([[ 85, 149],
       [ 22, 368]])
```

```
import seaborn as sns
sns.heatmap(confusion_mtx, xticklabels=classes, yticklabels=classes, annot=True, fmt='d', cmap="YlGnBu")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7b8fd17898>
```



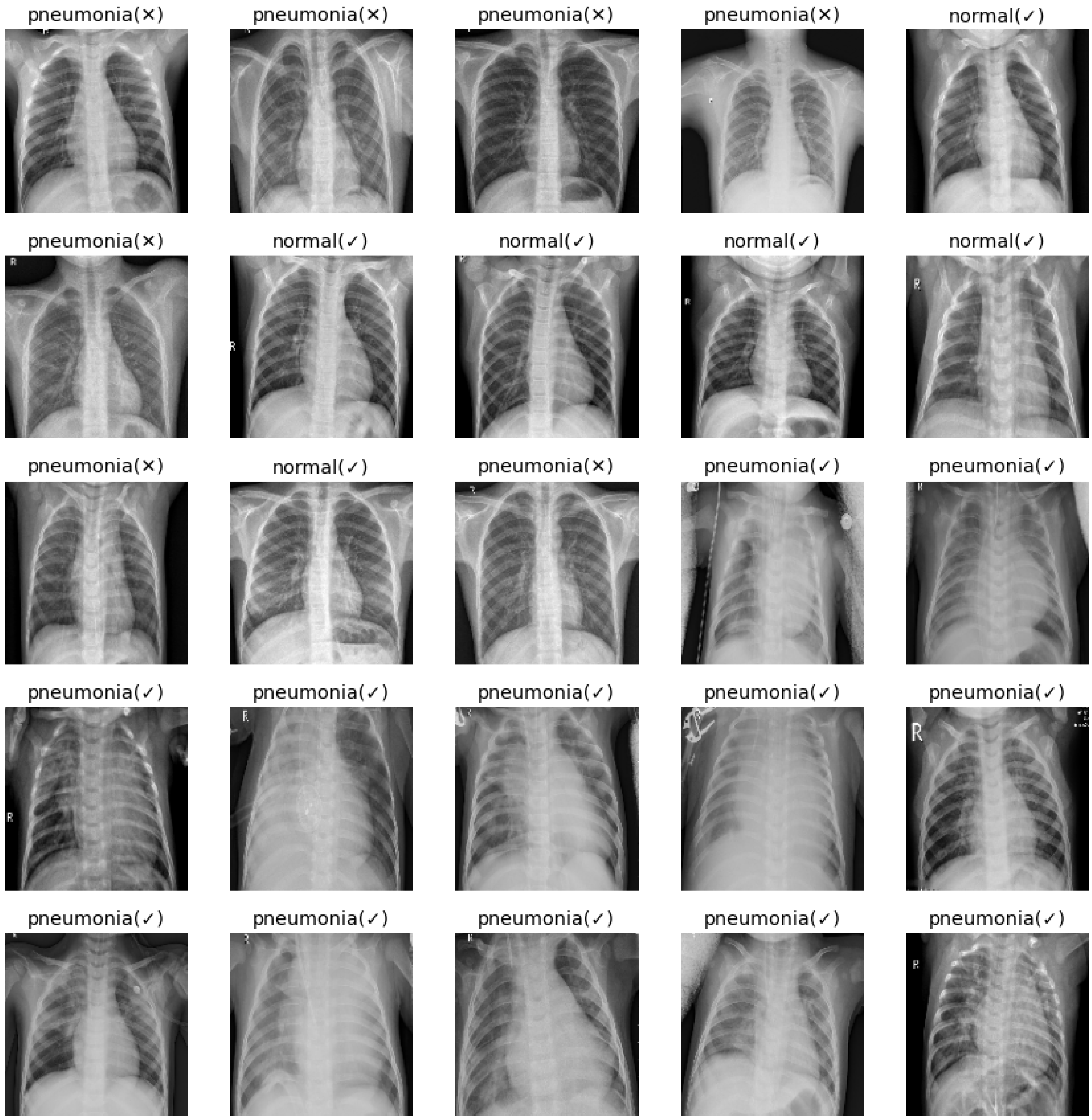
Classification Report (Precision, Recall, F1-score, Support)

```
from sklearn.metrics import classification_report
predictions = model_base.predict(X_test, batch_size=32)
print(classification_report(y_test.argmax(axis=1), predictions.argmax(axis=1), target_names=classes))
```

```
              precision    recall  f1-score   support

      normal       0.79      0.36      0.50       234
   pneumonia       0.71      0.94      0.81       390

    accuracy                           0.73       624
   macro avg       0.75      0.65      0.66       624
weighted avg       0.74      0.73      0.69       624
```

Visual Results

```
fig, ax = plt.subplots(nrows=5, ncols=5, sharex=True, sharey=True, figsize=(12,12))
num=0
for i in range(5):
    for j in range(5):
        img = X_test[num]
        ax[i][j].imshow(img)
        ohe = one_hot_encoding(y_pred[num])
        ax[i][j].set_title(get_title(classes[ohe.index(1)], y_test[num]))
        num += 18

ax[0][0].set_yticks([])
ax[0][0].set_xticks([])
plt.tight_layout()
plt.show()
```



Resnet50 + CBAM (Enhanced Model)

```
from keras.layers import GlobalAveragePooling2D, GlobalMaxPooling2D, Reshape, Dense, multiply, Permute, Concatenate, Conv2D, Add,
from keras import backend as K
from keras.activations import sigmoid

def attach_attention_module(net, attention_module):
  net = cbam_block(net)
  return net

def cbam_block(cbam_feature, ratio=8):
  cbam_feature = channel_attention(cbam_feature, ratio)
  cbam_feature = spatial_attention(cbam_feature)
  return cbam_feature
```

```
def channel_attention(input_feature, ratio=8):
  channel_axis = 1 if K.image_data_format() == "channels_first" else -1
  channel = input_feature.shape[channel_axis]

  shared_layer_one = Dense(channel//ratio,
               activation='relu',
               kernel_initializer='he_normal',
               use_bias=True,
               bias_initializer='zeros')
  shared_layer_two = Dense(channel,
               kernel_initializer='he_normal',
               use_bias=True,
               bias_initializer='zeros')

  avg_pool = GlobalAveragePooling2D()(input_feature)
  avg_pool = Reshape((1,1,channel))(avg_pool)
  assert avg_pool.shape[1:] == (1,1,channel)
  avg_pool = shared_layer_one(avg_pool)
  assert avg_pool.shape[1:] == (1,1,channel//ratio)
  avg_pool = shared_layer_two(avg_pool)
  assert avg_pool.shape[1:] == (1,1,channel)

  max_pool = GlobalMaxPooling2D()(input_feature)
  max_pool = Reshape((1,1,channel))(max_pool)
  assert max_pool.shape[1:] == (1,1,channel)
  max_pool = shared_layer_one(max_pool)
  assert max_pool.shape[1:] == (1,1,channel//ratio)
  max_pool = shared_layer_two(max_pool)
  assert max_pool.shape[1:] == (1,1,channel)

  cbam_feature = Add()([avg_pool,max_pool])
  cbam_feature = Activation('sigmoid')(cbam_feature)

  if K.image_data_format() == "channels_first":
    cbam_feature = Permute((3, 1, 2))(cbam_feature)

  return multiply([input_feature, cbam_feature])

def spatial_attention(input_feature):
  kernel_size = 7

  if K.image_data_format() == "channels_first":
    channel = input_feature.shape[1]
    cbam_feature = Permute((2,3,1))(input_feature)
  else:
    channel = input_feature.shape[-1]
    cbam_feature = input_feature

  avg_pool = Lambda(lambda x: K.mean(x, axis=3, keepdims=True))(cbam_feature)
  assert avg_pool.shape[-1] == 1
  max_pool = Lambda(lambda x: K.max(x, axis=3, keepdims=True))(cbam_feature)
  assert max_pool.shape[-1] == 1
  concat = Concatenate(axis=3)([avg_pool, max_pool])
  assert concat.shape[-1] == 2
  cbam_feature = Conv2D(filters = 1,
          kernel_size=kernel_size,
          strides=1,
          padding='same',
          activation='sigmoid',
          kernel_initializer='he_normal',
          use_bias=False)(concat)
  assert cbam_feature.shape[-1] == 1

  if K.image_data_format() == "channels_first":
    cbam_feature = Permute((3, 1, 2))(cbam_feature)

  return multiply([input_feature, cbam_feature])
```

```
import keras
from keras.layers import Dense, Conv2D, BatchNormalization, Activation
from keras.layers import AveragePooling2D, Input, Flatten
from keras.optimizers import Adam
from keras.callbacks import ModelCheckpoint, LearningRateScheduler
from keras.callbacks import ReduceLROnPlateau
from keras.preprocessing.image import ImageDataGenerator
from keras.regularizers import l2
from keras import backend as K
from keras.models import Model
```

```
def resnet_layer(inputs,
                 num_filters=16,
                 kernel_size=3,
                 strides=1,
                 activation='relu',
                 batch_normalization=True,
                 conv_first=True):

    conv = Conv2D(num_filters,
                  kernel_size=kernel_size,
                  strides=strides,
                  padding='same',
                  kernel_initializer='he_normal',
                  kernel_regularizer=l2(1e-4))

    x = inputs
    if conv_first:
        x = conv(x)
        if batch_normalization:
            x = BatchNormalization()(x)
        if activation is not None:
            x = Activation(activation)(x)
    else:
        if batch_normalization:
            x = BatchNormalization()(x)
        if activation is not None:
            x = Activation(activation)(x)
        x = conv(x)
    return x

def resnet_v1(input_shape, depth, attention_module='cbam_block'):
    if (depth - 2) % 6 != 0:
        raise ValueError('depth should be 6n+2 (eg 20, 32, 44 in [a])')
    # Start model definition.
    num_filters = 16
    num_res_blocks = int((depth - 2) / 6)

    inputs = Input(shape=input_shape)
    x = resnet_layer(inputs=inputs)
    # Instantiate the stack of residual units
    for stack in range(3):
        for res_block in range(num_res_blocks):
            strides = 1
            if stack > 0 and res_block == 0:  # first layer but not first stack
                strides = 2  # downsample
            y = resnet_layer(inputs=x,
                             num_filters=num_filters,
                             strides=strides)
            y = resnet_layer(inputs=y,
                             num_filters=num_filters,
                             activation=None)
            if stack > 0 and res_block == 0:  # first layer but not first stack
                # linear projection residual shortcut connection to match
                # changed dims
                x = resnet_layer(inputs=x,
                                 num_filters=num_filters,
                                 kernel_size=1,
                                 strides=strides,
                                 activation=None,
                                 batch_normalization=False)

            y = attach_attention_module(y, attention_module)
            x = keras.layers.add([x, y])
            x = Activation('relu')(x)
        num_filters *= 2

    # Add classifier on top.
    # v1 does not use BN after last shortcut connection-ReLU
    x = AveragePooling2D(pool_size=8)(x)
    x = Flatten()(x)
    x = Dense(1024, activation='relu')(x)
    x = BatchNormalization()(x)
    x = Dense(1024, activation='relu')(x)
    x = BatchNormalization()(x)
    x = Dropout(0.5)(x)
    outputs = Dense(2, activation='softmax')(x)

    # Instantiate model.
    model = Model(inputs=inputs, outputs=outputs)
```

```
    return model
```

Resnet 50 + CBAM (Enhanced Model)

```
# For ResNet, specify the depth (e.g. ResNet50: depth=50)
depth = 50
model_enhanced = resnet_v1(input_shape=input_shape, depth=depth, attention_module='cbam_block')
```

Model Summary

```
model_enhanced.summary()
```

```
Model: "model_14"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_29 (InputLayer)           [(None, 150, 150, 3) 0
__________________________________________________________________________________________________
conv2d_1050 (Conv2D)            (None, 150, 150, 16) 448         input_29[0][0]
__________________________________________________________________________________________________
batch_normalization_727 (BatchN (None, 150, 150, 16) 64          conv2d_1050[0][0]
__________________________________________________________________________________________________
activation_1041 (Activation)    (None, 150, 150, 16) 0           batch_normalization_727[0][0]
__________________________________________________________________________________________________
conv2d_1051 (Conv2D)            (None, 150, 150, 16) 2320        activation_1041[0][0]
__________________________________________________________________________________________________
batch_normalization_728 (BatchN (None, 150, 150, 16) 64          conv2d_1051[0][0]
__________________________________________________________________________________________________
activation_1042 (Activation)    (None, 150, 150, 16) 0           batch_normalization_728[0][0]
__________________________________________________________________________________________________
conv2d_1052 (Conv2D)            (None, 150, 150, 16) 2320        activation_1042[0][0]
__________________________________________________________________________________________________
batch_normalization_729 (BatchN (None, 150, 150, 16) 64          conv2d_1052[0][0]
__________________________________________________________________________________________________
global_average_pooling2d_349 (G (None, 16)           0           batch_normalization_729[0][0]
__________________________________________________________________________________________________
global_max_pooling2d_336 (Globa (None, 16)           0           batch_normalization_729[0][0]
__________________________________________________________________________________________________
reshape_672 (Reshape)           (None, 1, 1, 16)     0           global_average_pooling2d_349[0][0
__________________________________________________________________________________________________
reshape_673 (Reshape)           (None, 1, 1, 16)     0           global_max_pooling2d_336[0][0]
__________________________________________________________________________________________________
dense_738 (Dense)               (None, 1, 1, 2)      34          reshape_672[0][0]
                                                                 reshape_673[0][0]
__________________________________________________________________________________________________
dense_739 (Dense)               (None, 1, 1, 16)     48          dense_738[0][0]
                                                                 dense_738[1][0]
__________________________________________________________________________________________________
add_672 (Add)                   (None, 1, 1, 16)     0           dense_739[0][0]
                                                                 dense_739[1][0]
__________________________________________________________________________________________________
activation_1043 (Activation)    (None, 1, 1, 16)     0           add_672[0][0]
__________________________________________________________________________________________________
multiply_672 (Multiply)         (None, 150, 150, 16) 0           batch_normalization_729[0][0]
                                                                 activation_1043[0][0]
__________________________________________________________________________________________________
lambda_672 (Lambda)             (None, 150, 150, 1)  0           multiply_672[0][0]
__________________________________________________________________________________________________
lambda_673 (Lambda)             (None, 150, 150, 1)  0           multiply_672[0][0]
__________________________________________________________________________________________________
concatenate_336 (Concatenate)   (None, 150, 150, 2)  0           lambda_672[0][0]
                                                                 lambda_673[0][0]
__________________________________________________________________________________________________
conv2d_1053 (Conv2D)            (None, 150, 150, 1)  98          concatenate_336[0][0]
__________________________________________________________________________________________________
multiply_673 (Multiply)         (None, 150, 150, 16) 0           multiply_672[0][0]
                                                                 conv2d_1053[0][0]
__________________________________________________________________________________________________
add_673 (Add)                   (None, 150, 150, 16) 0           activation_1041[0][0]
                                                                 multiply_673[0][0]
__________________________________________________________________________________________________
activation_1044 (Activation)    (None, 150, 150, 16) 0           add_673[0][0]
```

Model Compile with SGD Optimizer

```
model_enhanced.compile(loss='binary_crossentropy',
              metrics=[tensorflow.keras.metrics.AUC(name = 'accuracy')],
              optimizer=optimizer)
```

Data Augmentation (Training Data)

```
train_augmented = ImageDataGenerator(rescale = 1.0 / 255.0,
                                     featurewise_center=False,
                                     samplewise_center=False,
                                     featurewise_std_normalization=False,
                                     samplewise_std_normalization=False,
                                     zca_whitening=False,
                                     rotation_range=20,
                                     width_shift_range=0.2,
                                     height_shift_range=0.2,
                                     shear_range=0.2,
                                     zoom_range=0.2,
                                     channel_shift_range=0.2,
                                     fill_mode='nearest',
                                     horizontal_flip=False,
                                     validation_split = 0.2)
```

Flow form Directory (Training & Validation Data)

```
train_augmented_dataset = train_augmented.flow_from_directory(directory = train_dir,
                                                              target_size = target_size,
                                                              class_mode = 'categorical',
                                                              subset = 'training',
                                                              batch_size = batch_size)
```

```
Found 4187 images belonging to 2 classes.
```

Defining Callbacks

```
filepath = './best_enhanced_weights.hdf5'

early_stopping = EarlyStopping(monitor = 'val_accuracy',
                               mode = 'max',
                               patience = patience,
                               verbose = 1)

checkpoint    = ModelCheckpoint(filepath,
                                monitor = 'val_accuracy',
                                mode='max',
                                save_best_only=True,
                                verbose = 1)

callback_list = [early_stopping, checkpoint]
```

```
# Fit the model on the batches generated by datagen.flow().
H_enhanced = model_enhanced.fit(train_augmented_dataset,
                                validation_data=valid_dataset,
                                class_weight = class_weights,
                                epochs=epochs,
                                verbose=1,
                                callbacks=callback_list)
```

```
Epoch 1/50
66/66 [==============================] - 116s 2s/step - loss: 1.0176 - accuracy: 0.7680 - val_loss: 1.0940 - val_accuracy: 0.55

Epoch 00001: val_accuracy improved from -inf to 0.55956, saving model to ./best_enhanced_weights.hdf5
Epoch 2/50
66/66 [==============================] - 98s 1s/step - loss: 0.7820 - accuracy: 0.8856 - val_loss: 0.9551 - val_accuracy: 0.799

Epoch 00002: val_accuracy improved from 0.55956 to 0.79963, saving model to ./best_enhanced_weights.hdf5
Epoch 3/50
66/66 [==============================] - 99s 1s/step - loss: 0.7573 - accuracy: 0.9036 - val_loss: 1.0167 - val_accuracy: 0.860

Epoch 00003: val_accuracy improved from 0.79963 to 0.86033, saving model to ./best_enhanced_weights.hdf5
Epoch 4/50
66/66 [==============================] - 99s 1s/step - loss: 0.7468 - accuracy: 0.9037 - val_loss: 1.0716 - val_accuracy: 0.840

Epoch 00004: val_accuracy did not improve from 0.86033
Epoch 5/50
66/66 [==============================] - 99s 1s/step - loss: 0.7034 - accuracy: 0.9251 - val_loss: 0.7838 - val_accuracy: 0.918

Epoch 00005: val_accuracy improved from 0.86033 to 0.91848, saving model to ./best_enhanced_weights.hdf5
Epoch 6/50
66/66 [==============================] - 99s 1s/step - loss: 0.7171 - accuracy: 0.9207 - val_loss: 1.0501 - val_accuracy: 0.829

Epoch 00006: val_accuracy did not improve from 0.91848
Epoch 7/50
66/66 [==============================] - 100s 2s/step - loss: 0.7023 - accuracy: 0.9223 - val_loss: 0.6844 - val_accuracy: 0.94
```

```
Epoch 00007: val_accuracy improved from 0.91848 to 0.94817, saving model to ./best_enhanced_weights.hdf5
Epoch 8/50
66/66 [==============================] - 99s 1s/step - loss: 0.7003 - accuracy: 0.9232 - val_loss: 0.5939 - val_accuracy: 0.970

Epoch 00008: val_accuracy improved from 0.94817 to 0.97035, saving model to ./best_enhanced_weights.hdf5
Epoch 9/50
66/66 [==============================] - 100s 1s/step - loss: 0.6764 - accuracy: 0.9389 - val_loss: 0.5968 - val_accuracy: 0.97

Epoch 00009: val_accuracy improved from 0.97035 to 0.97266, saving model to ./best_enhanced_weights.hdf5
Epoch 10/50
66/66 [==============================] - 100s 2s/step - loss: 0.6459 - accuracy: 0.9444 - val_loss: 1.4110 - val_accuracy: 0.68

Epoch 00010: val_accuracy did not improve from 0.97266
Epoch 11/50
66/66 [==============================] - 100s 1s/step - loss: 0.6592 - accuracy: 0.9463 - val_loss: 2.0835 - val_accuracy: 0.48

Epoch 00011: val_accuracy did not improve from 0.97266
Epoch 12/50
66/66 [==============================] - 99s 1s/step - loss: 0.6251 - accuracy: 0.9535 - val_loss: 0.8991 - val_accuracy: 0.885

Epoch 00012: val_accuracy did not improve from 0.97266
Epoch 00012: early stopping
```

Load Enhanced Model Weights (if required)

```
1 model_enhanced.load_weights("best_enhanced_weights.hdf5")
```

Resnet50 + CBAM (Summary)

Test Loss/Accuracy, Training/Validation Graphs, Confusion Matrix, Classification Report & Visual Results

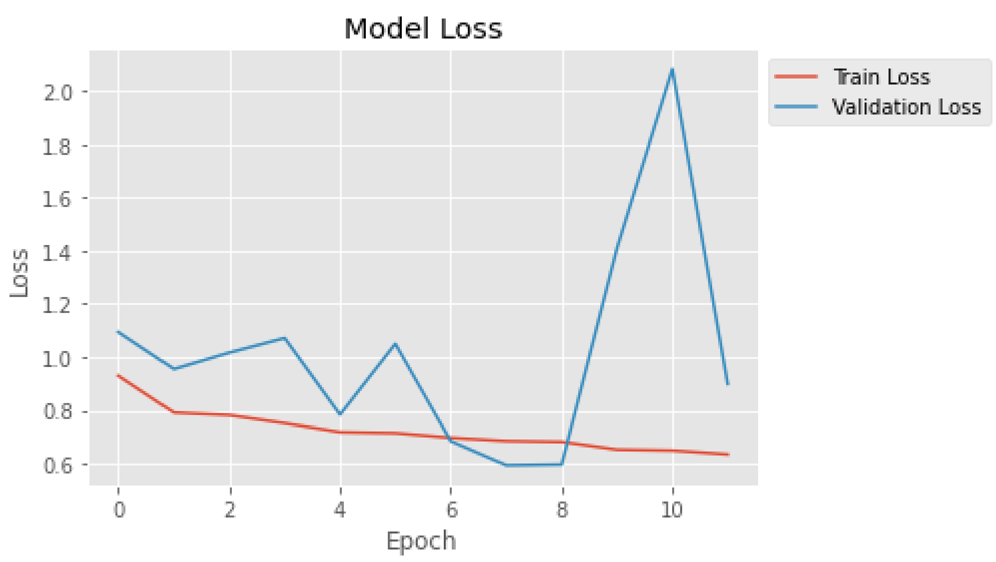
Evaluating Loss and AUC - Test Data

```
1 score = model_enhanced.evaluate(test_dataset)
2 print('Test Loss: ', score[0])
3 print('Test Accuracy: ', score[1])
```

```
10/10 [==============================] - 7s 633ms/step - loss: 0.6687 - accuracy: 0.9432
Test Loss:  0.6687048673629761
Test Accuracy:  0.9431834816932678
```

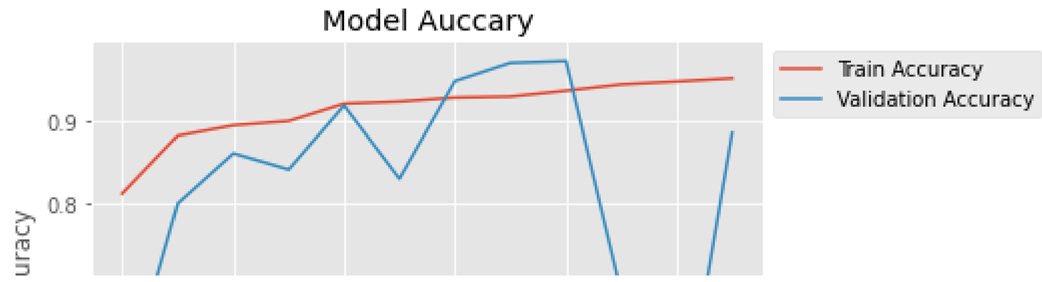
Summarize Model Loss

```
1 plot_model_loss(H_enhanced)
```



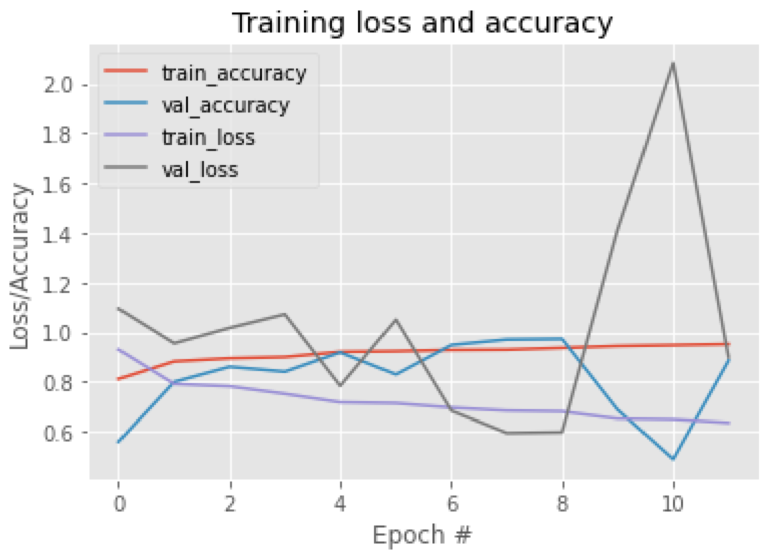
Summarie Model Accuracy

```
1 plot_model_accuracy(H_enhanced)
```



Summarize Learning Curve (Accuracy and Loss)


```
plot_model_lr(H_enhanced)
```



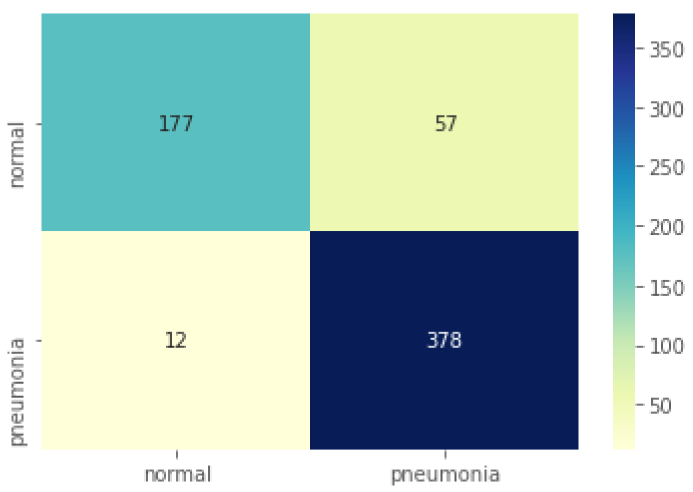
CONFUSION MATRIX

```
# Making prediction
y_pred_enhanced = model_enhanced.predict(X_test)
y_true = np.argmax(y_test, axis=-1)

# Plotting the confusion matrix
from sklearn.metrics import confusion_matrix
confusion_mtx = confusion_matrix(y_true, np.argmax(y_pred_enhanced, axis=1))
confusion_mtx
```

```
array([[177,  57],
       [ 12, 378]])
```

```
import seaborn as sns
sns.heatmap(confusion_mtx, xticklabels=classes, yticklabels=classes, annot=True, fmt='d', cmap="YlGnBu")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f79664fdc50>
```



Classification Report (Precision, Recall, F1-score, Support)

```
from sklearn.metrics import classification_report
predictions = model_enhanced.predict(X_test, batch_size=32)
print(classification_report(y_test.argmax(axis=1), predictions.argmax(axis=1), target_names=classes))
```

```
              precision    recall  f1-score   support

      normal       0.94      0.76      0.84       234
   pneumonia       0.87      0.97      0.92       390

    accuracy                           0.89       624
   macro avg       0.90      0.86      0.88       624
weighted avg       0.89      0.89      0.89       624
```

Visual Results

```
fig, ax = plt.subplots(nrows=5, ncols=5, sharex=True, sharey=True, figsize=(12,12))
num=0
for i in range(5):
    for j in range(5):
        img = X_test[num]
        ax[i][j].imshow(img)
        ohe = one_hot_encoding(y_pred_enhanced[num])
        ax[i][j].set_title(get_title(classes[ohe.index(1)], y_test[num]))
        num += 18

ax[0][0].set_yticks([])
ax[0][0].set_xticks([])
plt.tight_layout()
plt.show()
```