# Class Challenge: Image Classification of COVID-19 X-rays

# Task 2 [Total points: 30]

# Setup

- This assignment involves the following packages: 'matplotlib', 'numpy', and 'sklearn'.
- If you are using conda, use the following commands to install the above packages:

```
conda install matplotlib
conda install numpy
conda install -c anaconda scikit-learn
```

• If you are using pip, use use the following commands to install the above packages:

```
pip install matplotlib
pip install numpy
pip install sklearn
```

## Data

Please download the data using the following link: COVID-19.

• After downloading 'Covid\_Data\_GradientCrescent.zip', unzip the file and you should see the following data structure:

```
|--all
|-----train
|-----test
|--two
|-----train
|-----test
```

• Put the 'all' folder, the 'two' folder and this python notebook in the **same directory** so that the following code can correctly locate the data.

# [20 points] Multi-class Classification

### **Load Image Data**

```
In [1]:
         import os
         import tensorflow as tf
         import numpy as np
         import matplotlib.pyplot as plt
         from tensorflow.keras import layers, models
         from tensorflow.keras.preprocessing.image import ImageDataGenerator
         from tensorflow.keras.applications.xception import Xception
         from tensorflow.keras.applications.mobilenet v2 import MobileNetV2
         from keras.callbacks import ModelCheckpoint, EarlyStopping
         os.environ['OMP NUM THREADS'] = '1'
         os.environ['CUDA VISIBLE DEVICES'] = '-1'
         tf. version
Out[1]: '2.8.0'
In [3]:
         DATA LIST = os.listdir('all/train')
         DATASET PATH = 'all/train'
         TEST DIR = 'all/test'
         IMAGE SIZE
                     = (224, 224)
         NUM CLASSES = len(DATA LIST)
         BATCH SIZE
                       = 10 # try reducing batch size or freeze more Layers if your GPU runs out of memory
         NUM_EPOCHS
                       = 100
         LEARNING RATE = 0.0001 # start off with high rate first 0.001 and experiment with reducing it gradually
```

#### **Generate Training and Validation Batches**

Found 216 images belonging to 4 classes. Found 54 images belonging to 4 classes.

#### [10 points] Build Model

Hint: Starting from a pre-trained model typically helps performance on a new task, e.g. starting with weights obtained by training on ImageNet.

```
In [7]:
         #Model 1 using Xception pre-trained model -> 0.71-0.75 test acc
         base model = Xception(weights="imagenet", include top=False, input shape=train batches.image shape)
         model = models.Sequential([
             tf.keras.Model(inputs=base model.input, outputs=base model.output, name="xception"),
             layers.GlobalAveragePooling2D(),
             layers.Dense(256, activation='relu', name="dense1"),
             layers.Dropout(0.2, name="dropout1"),
             layers.Dense(4, activation="softmax", name="pred dense")
         1)
         model.get layer("xception").trainable=False
         #summary of model architecture
         model.summary()
         #compile the model
         model.compile(
             optimizer=tf.keras.optimizers.Adam(learning rate=LEARNING RATE),
             loss=tf.keras.losses.CategoricalCrossentropy(),
             metrics=['accuracy'],
```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
xception (Functional)	(None, 7, 7, 2048)	20861480
<pre>global_average_pooling2d_1 (GlobalAveragePooling2D)</pre>	(None, 2048)	0
dense1 (Dense)	(None, 256)	524544
dropout1 (Dropout)	(None, 256)	0
<pre>pred_dense (Dense)</pre>	(None, 4)	1028
Total params: 21,387,052 Trainable params: 525,572 Non-trainable params: 20,861,480		

```
In [6]:
```

```
#Model 2 using MobileNet V2 pre-trained model
base_model2 = MobileNetV2(weights="imagenet", include_top=False, input_shape=train_batches.image_shape)
model2 = models.Sequential([
    tf.keras.Model(inputs=base model2.input, outputs=base model2.output, name="mobilenet"),
    layers.Flatten(),
    layers.Dense(128, activation='relu', name="dense1"),
    layers.Dropout(0.35, name="dropout1"),
    layers.Dense(4, activation="softmax", name="pred dense")
1)
model2.get layer("mobilenet").trainable=False
#summary of model architecture
model2.summary()
#compile the model
model2.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=LEARNING_RATE),
    loss=tf.keras.losses.CategoricalCrossentropy(),
    metrics=['accuracy'],
```

Layer (type)	Output Shape	Param #
mobilenet (Functional)	(None, 7, 7, 1280)	2257984
flatten (Flatten)	(None, 62720)	0
dense1 (Dense)	(None, 128)	8028288
dropout1 (Dropout)	(None, 128)	0
pred_dense (Dense)	(None, 4)	516

-----

Total params: 10,286,788
Trainable params: 8,028,804
Non-trainable params: 2,257,984

\_\_\_\_\_

#### [5 points] Train Model

In [ ]:

```
22
6
/share/pkg.7/tensorflow/2.8.0/install/lib/SCC/../python3.8/site-packages/keras_preprocessing/image/image_data_generator.p
y:720: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit on any training data.
Fit it first by calling `.fit(numpy_data)`.
    warnings.warn('This ImageDataGenerator specifies '
/share/pkg.7/tensorflow/2.8.0/install/lib/SCC/../python3.8/site-packages/keras_preprocessing/image/image_data_generator.p
y:739: UserWarning: This ImageDataGenerator specifies `zca_whitening`, but it hasn't been fit on any training data. Fit i
t first by calling `.fit(numpy_data)`.
    warnings.warn('This ImageDataGenerator specifies '
Epoch 1/100
```

```
21/21 [===========] - 65s 3s/step - loss: 1.3526 - accuracy: 0.3398 - val loss: 1.1421 - val accuracy:
0.6600
Epoch 2/100
21/21 [============= ] - 61s 3s/step - loss: 1.1521 - accuracy: 0.5194 - val loss: 1.0134 - val accuracy:
0.5600
Epoch 3/100
21/21 [============ ] - 61s 3s/step - loss: 0.9892 - accuracy: 0.6262 - val loss: 0.9125 - val accuracy:
0.6400
Epoch 4/100
21/21 [============ ] - 62s 3s/step - loss: 0.9117 - accuracy: 0.6359 - val loss: 0.9360 - val accuracy:
0.5800
Epoch 5/100
21/21 [============= ] - 61s 3s/step - loss: 0.8298 - accuracy: 0.6893 - val loss: 0.8413 - val accuracy:
0.6400
Epoch 6/100
21/21 [============= ] - 61s 3s/step - loss: 0.8302 - accuracy: 0.6952 - val loss: 0.8635 - val accuracy:
0.6000
Epoch 7/100
21/21 [============ ] - 61s 3s/step - loss: 0.7421 - accuracy: 0.7282 - val loss: 0.8219 - val accuracy:
0.6200
Epoch 8/100
0.6400
Epoch 9/100
21/21 [============ ] - 61s 3s/step - loss: 0.7223 - accuracy: 0.7136 - val loss: 0.8548 - val accuracy:
0.6800
Epoch 10/100
21/21 [============= ] - 61s 3s/step - loss: 0.7074 - accuracy: 0.7330 - val loss: 0.7446 - val accuracy:
0.7000
Epoch 11/100
21/21 [============ ] - 61s 3s/step - loss: 0.7267 - accuracy: 0.7233 - val loss: 0.6911 - val accuracy:
0.6800
Epoch 12/100
21/21 [============= ] - 61s 3s/step - loss: 0.6907 - accuracy: 0.7136 - val loss: 0.6714 - val accuracy:
0.6200
Epoch 13/100
21/21 [=========== ] - 61s 3s/step - loss: 0.6666 - accuracy: 0.7379 - val_loss: 0.7875 - val_accuracy:
0.7000
Epoch 14/100
21/21 [============ ] - 61s 3s/step - loss: 0.6866 - accuracy: 0.6796 - val loss: 0.6636 - val accuracy:
0.7000
Epoch 15/100
21/21 [============= ] - 61s 3s/step - loss: 0.6727 - accuracy: 0.7427 - val loss: 0.7577 - val accuracy:
0.6400
Epoch 16/100
21/21 [============= ] - 61s 3s/step - loss: 0.6424 - accuracy: 0.7524 - val loss: 0.6571 - val accuracy:
0.7200
Epoch 17/100
21/21 [============ ] - 61s 3s/step - loss: 0.6232 - accuracy: 0.7621 - val loss: 0.7289 - val accuracy:
```

```
0.6600
Epoch 18/100
21/21 [============ ] - 61s 3s/step - loss: 0.6550 - accuracy: 0.6990 - val loss: 0.8193 - val accuracy:
0.6800
Epoch 19/100
21/21 [============ ] - 61s 3s/step - loss: 0.6322 - accuracy: 0.7379 - val loss: 0.6521 - val accuracy:
0.7200
Epoch 20/100
21/21 [============ ] - 61s 3s/step - loss: 0.5856 - accuracy: 0.7621 - val loss: 0.6879 - val accuracy:
0.7400
Epoch 21/100
21/21 [============= ] - 60s 3s/step - loss: 0.5983 - accuracy: 0.7718 - val loss: 0.6075 - val accuracy:
0.7400
Epoch 22/100
21/21 [============= ] - 61s 3s/step - loss: 0.5550 - accuracy: 0.7913 - val loss: 0.7843 - val accuracy:
0.6000
Epoch 23/100
21/21 [============= ] - 61s 3s/step - loss: 0.6556 - accuracy: 0.7233 - val loss: 0.6613 - val accuracy:
0.6600
Epoch 24/100
21/21 [============ ] - 61s 3s/step - loss: 0.5942 - accuracy: 0.7816 - val loss: 0.6673 - val accuracy:
0.6800
Epoch 25/100
21/21 [============ ] - 62s 3s/step - loss: 0.6042 - accuracy: 0.7524 - val loss: 0.6686 - val accuracy:
0.7800
Epoch 26/100
21/21 [============ ] - 61s 3s/step - loss: 0.6057 - accuracy: 0.7816 - val loss: 0.6486 - val accuracy:
0.7200
Epoch 27/100
21/21 [============= ] - 61s 3s/step - loss: 0.5447 - accuracy: 0.7864 - val loss: 0.7335 - val accuracy:
0.7000
Epoch 28/100
21/21 [============= ] - 61s 3s/step - loss: 0.6110 - accuracy: 0.6990 - val loss: 0.7353 - val accuracy:
0.6400
Epoch 29/100
21/21 [============ ] - 61s 3s/step - loss: 0.6508 - accuracy: 0.7524 - val_loss: 0.7340 - val_accuracy:
0.7000
Epoch 30/100
21/21 [============ ] - 60s 3s/step - loss: 0.5687 - accuracy: 0.7621 - val loss: 0.6032 - val accuracy:
0.7800
Epoch 31/100
21/21 [============ ] - 60s 3s/step - loss: 0.5228 - accuracy: 0.8058 - val loss: 0.6893 - val accuracy:
0.7400
Epoch 32/100
21/21 [============= ] - 61s 3s/step - loss: 0.6124 - accuracy: 0.7573 - val loss: 0.7036 - val accuracy:
0.6800
Epoch 33/100
21/21 [============= ] - 61s 3s/step - loss: 0.5942 - accuracy: 0.7379 - val loss: 0.7043 - val accuracy:
0.6600
```

```
Epoch 34/100
21/21 [============= ] - 60s 3s/step - loss: 0.5604 - accuracy: 0.7864 - val loss: 0.6697 - val accuracy:
0.7600
Epoch 35/100
21/21 [===========] - 61s 3s/step - loss: 0.6246 - accuracy: 0.7330 - val loss: 0.7918 - val accuracy:
0.5800
Epoch 36/100
21/21 [============ ] - 61s 3s/step - loss: 0.5866 - accuracy: 0.7670 - val loss: 0.6952 - val accuracy:
0.7200
Epoch 37/100
21/21 [============= ] - 63s 3s/step - loss: 0.5280 - accuracy: 0.8010 - val loss: 0.6916 - val accuracy:
0.7200
Epoch 38/100
21/21 [============= ] - 63s 3s/step - loss: 0.5322 - accuracy: 0.7816 - val loss: 0.6508 - val accuracy:
0.6600
Epoch 39/100
21/21 [============ ] - 62s 3s/step - loss: 0.5222 - accuracy: 0.7816 - val loss: 0.6160 - val accuracy:
0.6600
Epoch 40/100
21/21 [============ ] - 63s 3s/step - loss: 0.5074 - accuracy: 0.7816 - val loss: 0.8761 - val accuracy:
0.5400
Epoch 41/100
21/21 [============= ] - 62s 3s/step - loss: 0.4977 - accuracy: 0.8107 - val loss: 0.6851 - val accuracy:
0.7000
Epoch 42/100
21/21 [============ ] - 62s 3s/step - loss: 0.4911 - accuracy: 0.7961 - val loss: 0.7635 - val accuracy:
0.6000
Epoch 43/100
21/21 [============= ] - 62s 3s/step - loss: 0.5363 - accuracy: 0.7767 - val loss: 0.5931 - val accuracy:
0.7400
Epoch 44/100
21/21 [============= ] - 62s 3s/step - loss: 0.5064 - accuracy: 0.7913 - val loss: 0.5641 - val accuracy:
0.7400
Epoch 45/100
21/21 [============= ] - 62s 3s/step - loss: 0.5226 - accuracy: 0.8058 - val loss: 0.6501 - val accuracy:
0.7200
Epoch 46/100
21/21 [===========] - 64s 3s/step - loss: 0.4910 - accuracy: 0.7767 - val loss: 0.7196 - val accuracy:
0.7000
Epoch 47/100
21/21 [============= ] - 62s 3s/step - loss: 0.5630 - accuracy: 0.7427 - val loss: 0.6744 - val accuracy:
0.7600
Epoch 48/100
21/21 [============= ] - 62s 3s/step - loss: 0.4872 - accuracy: 0.7864 - val loss: 0.7298 - val accuracy:
0.6600
Epoch 49/100
21/21 [============= ] - 62s 3s/step - loss: 0.5342 - accuracy: 0.8058 - val loss: 0.6986 - val accuracy:
0.6800
Epoch 50/100
```

```
21/21 [============= ] - 62s 3s/step - loss: 0.5684 - accuracy: 0.7864 - val loss: 0.7218 - val accuracy:
0.6600
Epoch 51/100
21/21 [============ ] - 62s 3s/step - loss: 0.5600 - accuracy: 0.7718 - val loss: 0.8378 - val accuracy:
0.6400
Epoch 52/100
21/21 [============ ] - 62s 3s/step - loss: 0.5621 - accuracy: 0.7767 - val loss: 0.7358 - val accuracy:
0.7200
Epoch 53/100
21/21 [============ ] - 62s 3s/step - loss: 0.5310 - accuracy: 0.8000 - val loss: 0.7367 - val accuracy:
0.6400
Epoch 54/100
21/21 [============= ] - 61s 3s/step - loss: 0.4649 - accuracy: 0.8058 - val loss: 0.7826 - val accuracy:
0.6400
Epoch 55/100
0.7000
Epoch 56/100
21/21 [============= ] - 62s 3s/step - loss: 0.4390 - accuracy: 0.8447 - val loss: 0.7326 - val accuracy:
0.6400
Epoch 57/100
21/21 [============= ] - 62s 3s/step - loss: 0.4992 - accuracy: 0.8010 - val loss: 0.7567 - val accuracy:
0.6400
Epoch 58/100
21/21 [============= ] - 62s 3s/step - loss: 0.5020 - accuracy: 0.8107 - val loss: 0.7688 - val accuracy:
0.6200
Epoch 59/100
21/21 [============= ] - 62s 3s/step - loss: 0.5322 - accuracy: 0.7913 - val loss: 0.7087 - val accuracy:
0.7000
Epoch 60/100
21/21 [============= ] - 62s 3s/step - loss: 0.4967 - accuracy: 0.7864 - val loss: 0.7129 - val accuracy:
0.7400
Epoch 61/100
21/21 [============= ] - 64s 3s/step - loss: 0.5179 - accuracy: 0.8048 - val loss: 0.7799 - val accuracy:
0.6800
Epoch 62/100
21/21 [============ ] - 61s 3s/step - loss: 0.4746 - accuracy: 0.8107 - val loss: 0.4889 - val accuracy:
0.7600
Epoch 63/100
21/21 [============= ] - 62s 3s/step - loss: 0.4484 - accuracy: 0.8155 - val loss: 0.7426 - val accuracy:
0.6800
Epoch 64/100
21/21 [============ ] - 61s 3s/step - loss: 0.4519 - accuracy: 0.7913 - val loss: 0.7112 - val accuracy:
0.6800
Epoch 65/100
0.6400
Epoch 66/100
```

```
0.6600
Epoch 67/100
21/21 [============ ] - 63s 3s/step - loss: 0.4952 - accuracy: 0.7913 - val loss: 0.6824 - val accuracy:
0.6600
Epoch 68/100
21/21 [============= ] - 62s 3s/step - loss: 0.3717 - accuracy: 0.8689 - val loss: 0.5875 - val accuracy:
0.7000
Epoch 69/100
21/21 [============ ] - 63s 3s/step - loss: 0.4931 - accuracy: 0.8107 - val loss: 0.7239 - val accuracy:
0.6600
Epoch 70/100
0.7000
Epoch 71/100
0.6200
Epoch 72/100
0.7000
Epoch 73/100
21/21 [============= ] - 63s 3s/step - loss: 0.4541 - accuracy: 0.8107 - val loss: 0.5657 - val accuracy:
0.8000
Epoch 74/100
21/21 [============ ] - 63s 3s/step - loss: 0.5446 - accuracy: 0.7816 - val loss: 0.5738 - val accuracy:
0.7000
Epoch 75/100
21/21 [============= ] - 64s 3s/step - loss: 0.4689 - accuracy: 0.8252 - val loss: 0.6138 - val accuracy:
0.6600
Epoch 76/100
0.7000
Epoch 77/100
21/21 [============= ] - 63s 3s/step - loss: 0.4631 - accuracy: 0.8107 - val loss: 0.6436 - val accuracy:
0.7000
Epoch 78/100
21/21 [============ ] - 62s 3s/step - loss: 0.4148 - accuracy: 0.8398 - val loss: 0.6817 - val accuracy:
0.6600
Epoch 79/100
21/21 [============= ] - 62s 3s/step - loss: 0.4778 - accuracy: 0.8333 - val loss: 0.7577 - val accuracy:
0.6800
Epoch 80/100
21/21 [============ ] - 63s 3s/step - loss: 0.4908 - accuracy: 0.7913 - val loss: 0.6060 - val accuracy:
0.7600
Epoch 81/100
0.6600
Epoch 82/100
0.7000
```

```
Epoch 83/100
0.7000
Epoch 84/100
0.6800
Epoch 85/100
21/21 [============ ] - 63s 3s/step - loss: 0.4086 - accuracy: 0.8398 - val loss: 0.6204 - val accuracy:
0.6800
Epoch 86/100
0.6800
Epoch 87/100
0.6800
Epoch 88/100
21/21 [============= ] - 63s 3s/step - loss: 0.4535 - accuracy: 0.8155 - val loss: 0.7324 - val accuracy:
0.6600
Epoch 89/100
21/21 [============] - 62s 3s/step - loss: 0.3982 - accuracy: 0.8010 - val loss: 0.6595 - val accuracy:
0.7200
Epoch 90/100
21/21 [============= ] - 62s 3s/step - loss: 0.4041 - accuracy: 0.8301 - val loss: 0.5718 - val accuracy:
0.6800
Epoch 91/100
21/21 [============ ] - 63s 3s/step - loss: 0.4674 - accuracy: 0.8107 - val loss: 0.7876 - val accuracy:
0.7000
Epoch 92/100
21/21 [============= ] - 62s 3s/step - loss: 0.4593 - accuracy: 0.8058 - val loss: 0.6309 - val accuracy:
0.7000
Epoch 93/100
0.7200
Epoch 94/100
0.6800
Epoch 95/100
0.7000
Epoch 96/100
21/21 [============ ] - 61s 3s/step - loss: 0.5105 - accuracy: 0.8058 - val loss: 0.7199 - val accuracy:
0.6800
Epoch 97/100
21/21 [============= ] - 61s 3s/step - loss: 0.4073 - accuracy: 0.8447 - val loss: 0.6854 - val accuracy:
0.6600
Epoch 98/100
0.7200
Epoch 99/100
```

```
21/21 [=========== ] - 62s 3s/step - loss: 0.5036 - accuracy: 0.8058 - val_loss: 0.5611 - val_accuracy:
      0.8000
      Epoch 100/100
      21/21 [============ ] - 63s 3s/step - loss: 0.4692 - accuracy: 0.7961 - val loss: 0.6078 - val accuracy:
      0.7000
In [7]:
      #FIT MODEL2 - MobileNet V2
       print(len(train batches))
       print(len(valid batches))
       STEP SIZE TRAIN=train batches.n//train batches.batch size
       STEP SIZE VALID=valid batches.n//valid batches.batch size
      NUM EPOCHS=85
      history2 = model2.fit(train batches, steps per epoch=STEP SIZE TRAIN, validation data=valid batches,
                       validation steps=STEP SIZE VALID, epochs=NUM EPOCHS)
      22
      /share/pkg.7/tensorflow/2.8.0/install/lib/SCC/../python3.8/site-packages/keras preprocessing/image/image data generator.p
      y:720: UserWarning: This ImageDataGenerator specifies `featurewise center`, but it hasn't been fit on any training data.
      Fit it first by calling `.fit(numpy data)`.
       warnings.warn('This ImageDataGenerator specifies '
      /share/pkg.7/tensorflow/2.8.0/install/lib/SCC/../python3.8/site-packages/keras preprocessing/image/image data generator.p
      y:739: UserWarning: This ImageDataGenerator specifies `zca whitening`, but it hasn't been fit on any training data. Fit i
      t first by calling `.fit(numpy data)`.
       warnings.warn('This ImageDataGenerator specifies '
      Epoch 1/85
      cv: 0.5000
      Epoch 2/85
      21/21 [============ ] - 7s 316ms/step - loss: 1.4160 - accuracy: 0.4757 - val loss: 1.1339 - val accurac
      v: 0.5000
      Epoch 3/85
      21/21 [============ ] - 7s 308ms/step - loss: 1.0484 - accuracy: 0.5728 - val loss: 1.0165 - val accurac
      v: 0.5400
      Epoch 4/85
      y: 0.5600
      Epoch 5/85
      y: 0.7000
      Epoch 6/85
      v: 0.6600
      Epoch 7/85
```

```
v: 0.5600
Epoch 8/85
v: 0.6800
Epoch 9/85
21/21 [============= ] - 6s 302ms/step - loss: 0.7429 - accuracy: 0.6650 - val loss: 0.7631 - val accurac
y: 0.6400
Epoch 10/85
21/21 [============== ] - 7s 305ms/step - loss: 0.8323 - accuracy: 0.6165 - val loss: 0.6165 - val accurac
v: 0.7000
Epoch 11/85
v: 0.7000
Epoch 12/85
v: 0.7000
Epoch 13/85
21/21 [============= ] - 6s 304ms/step - loss: 0.7511 - accuracy: 0.7039 - val loss: 0.7487 - val accurac
v: 0.6600
Epoch 14/85
21/21 [===========] - 7s 319ms/step - loss: 0.7189 - accuracy: 0.7039 - val loss: 0.6840 - val accurac
v: 0.6400
Epoch 15/85
21/21 [============= ] - 6s 302ms/step - loss: 0.6588 - accuracy: 0.7039 - val loss: 0.5924 - val accurac
v: 0.6800
Epoch 16/85
v: 0.6600
Epoch 17/85
v: 0.6600
Epoch 18/85
v: 0.7200
Epoch 19/85
v: 0.7400
Epoch 20/85
21/21 [============= ] - 7s 298ms/step - loss: 0.6176 - accuracy: 0.7573 - val loss: 0.7331 - val accurac
y: 0.6600
Epoch 21/85
21/21 [============= ] - 6s 294ms/step - loss: 0.7350 - accuracy: 0.6845 - val loss: 0.5877 - val accurac
y: 0.7800
Epoch 22/85
v: 0.6200
Epoch 23/85
```

```
v: 0.6800
Epoch 24/85
21/21 [============= ] - 6s 304ms/step - loss: 0.5874 - accuracy: 0.7670 - val loss: 0.6742 - val accurac
v: 0.7000
Epoch 25/85
21/21 [============ ] - 7s 306ms/step - loss: 0.6517 - accuracy: 0.6942 - val loss: 0.7059 - val accurac
v: 0.6800
Epoch 26/85
21/21 [============= ] - 7s 303ms/step - loss: 0.6305 - accuracy: 0.7524 - val loss: 0.6063 - val accurac
v: 0.6600
Epoch 27/85
v: 0.6200
Epoch 28/85
v: 0.7400
Epoch 29/85
v: 0.7800
Epoch 30/85
21/21 [============ ] - 6s 298ms/step - loss: 0.6032 - accuracy: 0.7184 - val loss: 0.5960 - val accurac
v: 0.6800
Epoch 31/85
21/21 [============= ] - 7s 305ms/step - loss: 0.5921 - accuracy: 0.7573 - val loss: 0.6551 - val accurac
v: 0.6600
Epoch 32/85
v: 0.6600
Epoch 33/85
v: 0.6200
Epoch 34/85
v: 0.6400
Epoch 35/85
v: 0.7000
Epoch 36/85
21/21 [============= ] - 6s 292ms/step - loss: 0.5625 - accuracy: 0.7573 - val loss: 0.4894 - val accurac
y: 0.6800
Epoch 37/85
21/21 [============= ] - 6s 302ms/step - loss: 0.5994 - accuracy: 0.7573 - val loss: 0.6936 - val accurac
v: 0.7000
Epoch 38/85
v: 0.6800
Epoch 39/85
v: 0.7000
```

```
Epoch 40/85
v: 0.5800
Epoch 41/85
v: 0.6600
Epoch 42/85
21/21 [============== ] - 6s 300ms/step - loss: 0.5617 - accuracy: 0.8107 - val loss: 0.6964 - val accurac
v: 0.6200
Epoch 43/85
v: 0.7600
Epoch 44/85
v: 0.7000
Epoch 45/85
v: 0.7200
Epoch 46/85
v: 0.7200
Epoch 47/85
21/21 [============== ] - 6s 297ms/step - loss: 0.4564 - accuracy: 0.8058 - val loss: 0.7807 - val accurac
y: 0.6400
Epoch 48/85
21/21 [============= ] - 7s 311ms/step - loss: 0.5845 - accuracy: 0.7718 - val loss: 0.6363 - val accurac
y: 0.7400
Epoch 49/85
v: 0.7400
Epoch 50/85
v: 0.6800
Epoch 51/85
v: 0.7000
Epoch 52/85
21/21 [============ ] - 6s 298ms/step - loss: 0.4754 - accuracy: 0.7961 - val loss: 0.5898 - val accurac
v: 0.7200
Epoch 53/85
21/21 [============= ] - 7s 308ms/step - loss: 0.4551 - accuracy: 0.7913 - val loss: 0.7522 - val accurac
v: 0.6800
Epoch 54/85
21/21 [============== ] - 6s 299ms/step - loss: 0.3787 - accuracy: 0.8155 - val loss: 0.6327 - val accurac
v: 0.6400
Epoch 55/85
v: 0.7200
Epoch 56/85
```

```
v: 0.7400
Epoch 57/85
v: 0.6200
Epoch 58/85
v: 0.7000
Epoch 59/85
21/21 [============== ] - 6s 295ms/step - loss: 0.4230 - accuracy: 0.8155 - val loss: 0.6952 - val accurac
v: 0.7000
Epoch 60/85
v: 0.7600
Epoch 61/85
v: 0.6600
Epoch 62/85
21/21 [============= ] - 6s 303ms/step - loss: 0.4848 - accuracy: 0.7718 - val loss: 0.5780 - val accurac
v: 0.7000
Epoch 63/85
v: 0.6800
Epoch 64/85
21/21 [============== ] - 7s 296ms/step - loss: 0.4953 - accuracy: 0.7961 - val loss: 0.5970 - val accurac
v: 0.6400
Epoch 65/85
v: 0.7400
Epoch 66/85
v: 0.7200
Epoch 67/85
v: 0.6400
Epoch 68/85
v: 0.7400
Epoch 69/85
21/21 [============= ] - 7s 309ms/step - loss: 0.5625 - accuracy: 0.7913 - val loss: 0.6556 - val accurac
y: 0.6600
Epoch 70/85
21/21 [============= ] - 7s 310ms/step - loss: 0.4485 - accuracy: 0.7961 - val loss: 0.5324 - val accurac
y: 0.7000
Epoch 71/85
v: 0.7400
Epoch 72/85
```

```
y: 0.6600
Epoch 73/85
21/21 [============ ] - 6s 297ms/step - loss: 0.4846 - accuracy: 0.8107 - val loss: 0.4284 - val accurac
v: 0.7800
Epoch 74/85
21/21 [============= ] - 6s 300ms/step - loss: 0.4253 - accuracy: 0.7864 - val loss: 0.6919 - val accurac
v: 0.6800
Epoch 75/85
v: 0.6800
Epoch 76/85
v: 0.7200
Epoch 77/85
v: 0.7800
Epoch 78/85
v: 0.7400
Epoch 79/85
21/21 [============ ] - 6s 300ms/step - loss: 0.4804 - accuracy: 0.8058 - val loss: 0.7075 - val accurac
v: 0.7200
Epoch 80/85
21/21 [============= ] - 6s 302ms/step - loss: 0.4646 - accuracy: 0.7864 - val loss: 0.6573 - val accurac
y: 0.7000
Epoch 81/85
21/21 [============== ] - 7s 306ms/step - loss: 0.5263 - accuracy: 0.7864 - val loss: 0.6306 - val accurac
v: 0.7000
Epoch 82/85
v: 0.7000
Epoch 83/85
v: 0.7800
Epoch 84/85
v: 0.7000
Epoch 85/85
21/21 [============== ] - 6s 300ms/step - loss: 0.4208 - accuracy: 0.7961 - val loss: 0.5657 - val accurac
v: 0.7600
```

#### [5 points] Plot Accuracy and Loss During Training

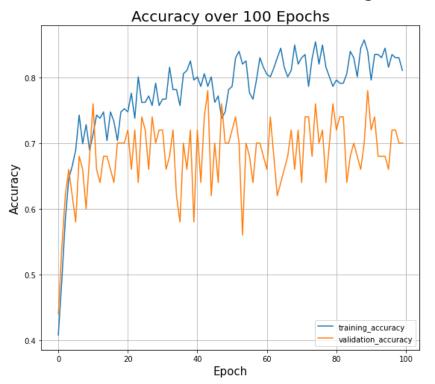
```
plt.figure(figsize=(20,8))
plt.suptitle("Model Using Pre-Trained Xception Model", fontsize=24)

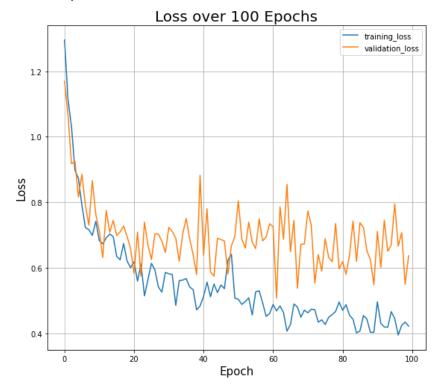
#plot the accuracies for the training and validation sets
plt.subplot(1, 2, 1)
```

```
plt.plot(history.history['accuracy'], label='training_accuracy')
plt.plot(history.history['val accuracy'], label = 'validation accuracy')
plt.title('Accuracy over %s Epochs' % NUM EPOCHS, fontsize=20)
plt.xlabel('Epoch', fontsize=15)
plt.ylabel('Accuracy', fontsize=15)
plt.grid()
plt.legend(loc='lower right')
#plot the loss for the training and validation sets
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='training loss')
plt.plot(history.history['val loss'], label = 'validation loss')
plt.title('Loss over %s Epochs' % NUM EPOCHS, fontsize=20)
plt.xlabel('Epoch', fontsize=15)
plt.ylabel('Loss', fontsize=15)
plt.grid()
plt.legend(loc='upper right')
```

Out[10]: <matplotlib.legend.Legend at 0x2b9ac7d62670>

## Model Using Pre-Trained Xception Model

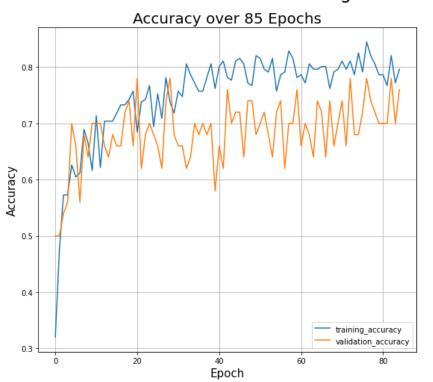


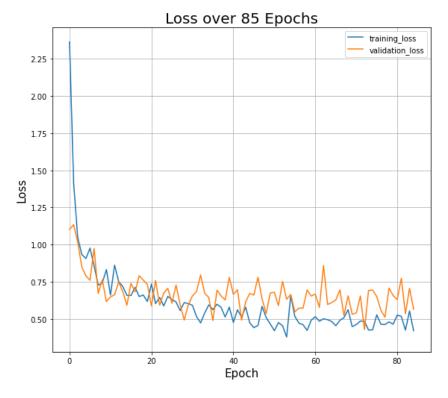


```
In [8]:
         plt.figure(figsize=(20,8))
         plt.suptitle("Model Using Pre-Trained MobileNet V2 Model", fontsize=24)
         #plot the accuracies for the training and validation sets
         plt.subplot(1, 2, 1)
         plt.plot(history2.history['accuracy'], label='training accuracy')
         plt.plot(history2.history['val accuracy'], label = 'validation accuracy')
         plt.title('Accuracy over %s Epochs' % NUM EPOCHS, fontsize=20)
         plt.xlabel('Epoch', fontsize=15)
         plt.ylabel('Accuracy', fontsize=15)
         plt.grid()
         plt.legend(loc='lower right')
         #plot the loss for the training and validation sets
         plt.subplot(1, 2, 2)
         plt.plot(history2.history['loss'], label='training loss')
         plt.plot(history2.history['val loss'], label = 'validation loss')
         plt.title('Loss over %s Epochs' % NUM EPOCHS, fontsize=20)
         plt.xlabel('Epoch', fontsize=15)
         plt.ylabel('Loss', fontsize=15)
         plt.grid()
         plt.legend(loc='upper right')
```

Out[8]: <matplotlib.legend.Legend at 0x2b927739ab80>

## Model Using Pre-Trained MobileNet V2 Model





### **Testing Model**

Test loss: 0.514977753162384 Test accuracy: 0.7777777910232544

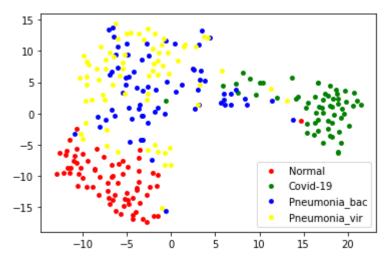
# [10 points] TSNE Plot

Test loss: 0.8865880966186523 Test accuracy: 0.6388888955116272

t-Distributed Stochastic Neighbor Embedding (t-SNE) is a widely used technique for dimensionality reduction that is particularly well suited for the visualization of high-dimensional datasets. After training is complete, extract features from a specific deep layer of your choice, use t-SNE to reduce the dimensionality of your extracted features to 2 dimensions and plot the resulting 2D features.

```
label = tsne_eval_generator.class_indices
classes = tsne eval generator.classes
fea_tsne = TSNE(learning_rate=50).fit_transform(features)
X,Y = zip(*fea tsne)
X Nor=[]
Y Nor=[]
X Cov=[]
Y_Cov=[]
X_Bac=[]
Y Bac=[]
X_Vir=[]
Y Vir=[]
for x,y,c in zip(X,Y,classes):
    if(label['covid']==c):
        X_Cov.append(x)
        Y Cov.append(y)
    elif(label['normal']==c):
        X Nor.append(x)
        Y Nor.append(y)
    elif(label['pneumonia_bac']==c):
        X Bac.append(x)
        Y_Bac.append(y)
    else:
        X Vir.append(x)
        Y Vir.append(y)
plt.scatter(X Nor, Y Nor, c='red', label='Normal', s=15)
plt.scatter(X Cov, Y Cov, c='green', label='Covid-19', s=15)
plt.scatter(X_Bac, Y_Bac, c='blue', label='Pneumonia_bac', s=15)
plt.scatter(X Vir, Y Vir, c='yellow', label='Pneumonia vir', s=15)
plt.legend()
plt.show()
```

Found 270 images belonging to 4 classes.



```
In [11]:
          #Model 2 - MobileNet V2
          from sklearn.manifold import TSNE
          intermediate layer model = models.Model(inputs=model2.input,
                                                   outputs=model2.get layer('dense1').output)
          tsne_eval_generator = test_datagen.flow_from_directory(DATASET_PATH,target_size=IMAGE_SIZE,
                                                             batch size=1, shuffle=False, seed=42, class mode="categorical")
          # raise NotImplementedError("Extract features from the tsne data generator and fit a t-SNE model for the features,"
                                       "and plot the resulting 2D features of the four classes.")
          features = intermediate layer model.predict(tsne eval generator)
          label = tsne eval generator.class indices
          classes = tsne eval generator.classes
          fea_tsne = TSNE(learning_rate=50).fit_transform(features)
          X,Y = zip(*fea tsne)
          X Nor=[]
          Y_Nor=[]
          X Cov=[]
          Y_Cov=[]
          X_Bac=[]
          Y_Bac=[]
```

```
X_Vir=[]
Y_Vir=[]
for x,y,c in zip(X,Y,classes):
    if(label['covid']==c):
        X Cov.append(x)
        Y Cov.append(y)
    elif(label['normal']==c):
        X Nor.append(x)
        Y_Nor.append(y)
    elif(label['pneumonia bac']==c):
        X Bac.append(x)
        Y_Bac.append(y)
    else:
        X Vir.append(x)
        Y_Vir.append(y)
plt.scatter(X_Nor, Y_Nor, c='red', label='Normal', s=15)
plt.scatter(X_Cov, Y_Cov, c='green', label='Covid-19', s=15)
plt.scatter(X Bac, Y Bac, c='blue', label='Pneumonia bac', s=15)
plt.scatter(X_Vir, Y_Vir, c='yellow', label='Pneumonia_vir', s=15)
plt.legend()
plt.show()
```

Found 270 images belonging to 4 classes.

