task1_template

December 3, 2020

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

2 Task 1 [Total points: 30]

2.1 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
```

2.2 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.

2.3 [20 points] Binary Classification: COVID-19 vs. Normal

[1]:
```
import os

import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import VGG16
```

```
import warnings
warnings.filterwarnings('ignore')

os.environ['OMP_NUM_THREADS'] = '1'
os.environ['CUDA_VISIBLE_DEVICES'] = '-1'
tf.__version__
```

[1]: '2.0.0'

Load Image Data

[2]:
```
DATA_LIST = os.listdir('two/train')
DATASET_PATH  = 'two/train'
TEST_DIR =  'two/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    = 40
LEARNING_RATE = 0.0005 # start off with high rate first 0.001 and experiment␣
 ↪with reducing it gradually
```

Generate Training and Validation Batches

[3]:
```
train_datagen = ImageDataGenerator(rescale=1./
 ↪255,rotation_range=50,featurewise_center = True,
                                   featurewise_std_normalization =␣
 ↪True,width_shift_range=0.2,
                                   height_shift_range=0.2,shear_range=0.
 ↪25,zoom_range=0.1,
                                   zca_whitening = True,channel_shift_range =␣
 ↪20,
                                   horizontal_flip = True,vertical_flip = True,
                                   validation_split = 0.2,fill_mode='constant')

train_batches = train_datagen.
 ↪flow_from_directory(DATASET_PATH,target_size=IMAGE_SIZE,
                                                  ␣
 ↪shuffle=True,batch_size=BATCH_SIZE,
                                                  subset = "training",seed=42,
                                                  class_mode="binary")

valid_batches = train_datagen.
 ↪flow_from_directory(DATASET_PATH,target_size=IMAGE_SIZE,
                                                  ␣
 ↪shuffle=True,batch_size=BATCH_SIZE,
                                                  subset = "validation",seed=42,
```

```
                                                   class_mode="binary")
```

```
Found 104 images belonging to 2 classes.
Found 26 images belonging to 2 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.

[4]:
```
vgg_16 = VGG16(weights = 'imagenet', include_top = False, \
              input_shape = (224,224,3), classes = NUM_CLASSES)

for layer in vgg_16.layers:
  layer.trainable = False

model = tf.keras.models.Sequential()

model.add(vgg_16)

model.add(tf.keras.layers.Flatten())

model.add(tf.keras.layers.Dropout(.25))

model.add(tf.keras.layers.Dense(256, activation = 'relu'))

model.add(tf.keras.layers.Dropout(.15))

model.add(tf.keras.layers.Dense(1, activation = 'sigmoid'))

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 7, 7, 512)         14714688
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dropout (Dropout)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 256)               6422784
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 257
=================================================================
Total params: 21,137,729
Trainable params: 6,423,041
```

```
Non-trainable params: 14,714,688
_________________________________________________________________
```

[5 points] Train Model

```
[5]: #FIT MODEL
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

OPTIMIZER = tf.keras.optimizers.Adam(learning_rate = LEARNING_RATE)

model.compile(optimizer = OPTIMIZER, \
                loss=tf.keras.losses.BinaryCrossentropy(), \
                metrics=['accuracy'])


history = model.fit(train_batches, steps_per_epoch = STEP_SIZE_TRAIN, \
                    epochs = NUM_EPOCHS, validation_data = valid_batches, \
                    validation_steps = STEP_SIZE_VALID)
```

```
11
3
Train for 10 steps, validate for 2 steps
Epoch 1/40
10/10 [==============================] - 34s 3s/step - loss: 1.9919 - accuracy:
0.5106 - val_loss: 0.5776 - val_accuracy: 0.5500
Epoch 2/40
10/10 [==============================] - 30s 3s/step - loss: 0.5644 - accuracy:
0.6702 - val_loss: 0.2974 - val_accuracy: 0.9000
Epoch 3/40
10/10 [==============================] - 31s 3s/step - loss: 0.4104 - accuracy:
0.8298 - val_loss: 0.2258 - val_accuracy: 0.9000
Epoch 4/40
10/10 [==============================] - 34s 3s/step - loss: 0.3020 - accuracy:
0.8723 - val_loss: 0.1001 - val_accuracy: 1.0000
Epoch 5/40
10/10 [==============================] - 30s 3s/step - loss: 0.1807 - accuracy:
0.9362 - val_loss: 0.1158 - val_accuracy: 1.0000
Epoch 6/40
10/10 [==============================] - 35s 3s/step - loss: 0.2187 - accuracy:
0.9362 - val_loss: 0.1816 - val_accuracy: 0.9500
Epoch 7/40
10/10 [==============================] - 33s 3s/step - loss: 0.2517 - accuracy:
0.8617 - val_loss: 0.1283 - val_accuracy: 0.9500
Epoch 8/40
```

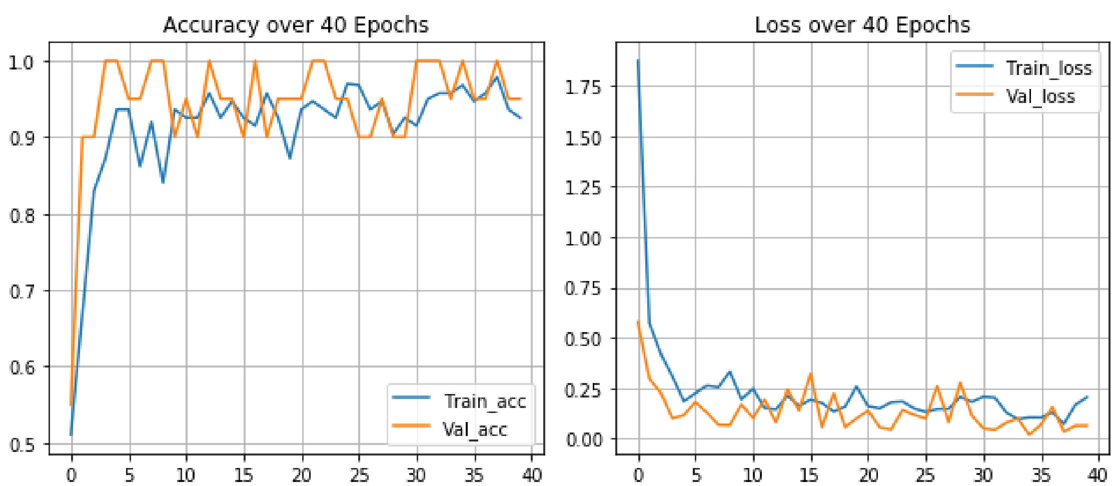
```
10/10 [==============================] - 37s 4s/step - loss: 0.2543 - accuracy:
0.9200 - val_loss: 0.0677 - val_accuracy: 1.0000
Epoch 9/40
10/10 [==============================] - 35s 3s/step - loss: 0.3167 - accuracy:
0.8404 - val_loss: 0.0665 - val_accuracy: 1.0000
Epoch 10/40
10/10 [==============================] - 35s 4s/step - loss: 0.1902 - accuracy:
0.9362 - val_loss: 0.1689 - val_accuracy: 0.9000
Epoch 11/40
10/10 [==============================] - 30s 3s/step - loss: 0.2416 - accuracy:
0.9255 - val_loss: 0.1015 - val_accuracy: 0.9500
Epoch 12/40
10/10 [==============================] - 36s 4s/step - loss: 0.1472 - accuracy:
0.9255 - val_loss: 0.1932 - val_accuracy: 0.9000
Epoch 13/40
10/10 [==============================] - 30s 3s/step - loss: 0.1458 - accuracy:
0.9574 - val_loss: 0.0797 - val_accuracy: 1.0000
Epoch 14/40
10/10 [==============================] - 33s 3s/step - loss: 0.2104 - accuracy:
0.9255 - val_loss: 0.2428 - val_accuracy: 0.9500
Epoch 15/40
10/10 [==============================] - 33s 3s/step - loss: 0.1537 - accuracy:
0.9468 - val_loss: 0.1379 - val_accuracy: 0.9500
Epoch 16/40
10/10 [==============================] - 32s 3s/step - loss: 0.1877 - accuracy:
0.9255 - val_loss: 0.3209 - val_accuracy: 0.9000
Epoch 17/40
10/10 [==============================] - 33s 3s/step - loss: 0.1685 - accuracy:
0.9149 - val_loss: 0.0568 - val_accuracy: 1.0000
Epoch 18/40
10/10 [==============================] - 34s 3s/step - loss: 0.1408 - accuracy:
0.9574 - val_loss: 0.2239 - val_accuracy: 0.9000
Epoch 19/40
10/10 [==============================] - 30s 3s/step - loss: 0.1508 - accuracy:
0.9255 - val_loss: 0.0565 - val_accuracy: 0.9500
Epoch 20/40
10/10 [==============================] - 31s 3s/step - loss: 0.2577 - accuracy:
0.8723 - val_loss: 0.0998 - val_accuracy: 0.9500
Epoch 21/40
10/10 [==============================] - 35s 3s/step - loss: 0.1569 - accuracy:
0.9362 - val_loss: 0.1380 - val_accuracy: 0.9500
Epoch 22/40
10/10 [==============================] - 34s 3s/step - loss: 0.1416 - accuracy:
0.9468 - val_loss: 0.0557 - val_accuracy: 1.0000
Epoch 23/40
10/10 [==============================] - 35s 3s/step - loss: 0.1932 - accuracy:
0.9362 - val_loss: 0.0459 - val_accuracy: 1.0000
Epoch 24/40
```

```
10/10 [==============================] - 33s 3s/step - loss: 0.1774 - accuracy:
0.9255 - val_loss: 0.1413 - val_accuracy: 0.9500
Epoch 25/40
10/10 [==============================] - 36s 4s/step - loss: 0.1489 - accuracy:
0.9700 - val_loss: 0.1175 - val_accuracy: 0.9500
Epoch 26/40
10/10 [==============================] - 36s 4s/step - loss: 0.1254 - accuracy:
0.9681 - val_loss: 0.0989 - val_accuracy: 0.9000
Epoch 27/40
10/10 [==============================] - 33s 3s/step - loss: 0.1386 - accuracy:
0.9362 - val_loss: 0.2596 - val_accuracy: 0.9000
Epoch 28/40
10/10 [==============================] - 35s 3s/step - loss: 0.1394 - accuracy:
0.9468 - val_loss: 0.0807 - val_accuracy: 0.9500
Epoch 29/40
10/10 [==============================] - 35s 3s/step - loss: 0.1966 - accuracy:
0.9043 - val_loss: 0.2770 - val_accuracy: 0.9000
Epoch 30/40
10/10 [==============================] - 33s 3s/step - loss: 0.1796 - accuracy:
0.9255 - val_loss: 0.1134 - val_accuracy: 0.9000
Epoch 31/40
10/10 [==============================] - 33s 3s/step - loss: 0.1980 - accuracy:
0.9149 - val_loss: 0.0511 - val_accuracy: 1.0000
Epoch 32/40
10/10 [==============================] - 37s 4s/step - loss: 0.2033 - accuracy:
0.9500 - val_loss: 0.0440 - val_accuracy: 1.0000
Epoch 33/40
10/10 [==============================] - 34s 3s/step - loss: 0.1226 - accuracy:
0.9574 - val_loss: 0.0788 - val_accuracy: 1.0000
Epoch 34/40
10/10 [==============================] - 35s 4s/step - loss: 0.0974 - accuracy:
0.9574 - val_loss: 0.0982 - val_accuracy: 0.9500
Epoch 35/40
10/10 [==============================] - 36s 4s/step - loss: 0.0997 - accuracy:
0.9681 - val_loss: 0.0192 - val_accuracy: 1.0000
Epoch 36/40
10/10 [==============================] - 35s 3s/step - loss: 0.0989 - accuracy:
0.9468 - val_loss: 0.0690 - val_accuracy: 0.9500
Epoch 37/40
10/10 [==============================] - 35s 4s/step - loss: 0.1235 - accuracy:
0.9574 - val_loss: 0.1556 - val_accuracy: 0.9500
Epoch 38/40
10/10 [==============================] - 35s 4s/step - loss: 0.0691 - accuracy:
0.9787 - val_loss: 0.0341 - val_accuracy: 1.0000
Epoch 39/40
10/10 [==============================] - 35s 4s/step - loss: 0.1626 - accuracy:
0.9362 - val_loss: 0.0638 - val_accuracy: 0.9500
Epoch 40/40
```

```
10/10 [==============================] - 35s 4s/step - loss: 0.1961 - accuracy:
0.9255 - val_loss: 0.0641 - val_accuracy: 0.9500
```

[5 points] Plot Accuracy and Loss During Training

[6]:
```python
import matplotlib.pyplot as plt

plt.figure(figsize = (9,4))

plt.subplot(1, 2, 1)
plt.grid()
plt.plot(history.history['accuracy'], label='Train_acc')
plt.plot(history.history['val_accuracy'], label = 'Val_acc')
plt.title("Accuracy over 40 Epochs")
plt.legend(loc='lower right')

plt.subplot(1, 2, 2)
plt.grid()
plt.plot(history.history['loss'], label='Train_loss')
plt.plot(history.history['val_loss'], label = 'Val_loss')
plt.title("Loss over 40 Epochs")
plt.legend(loc='upper right')

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

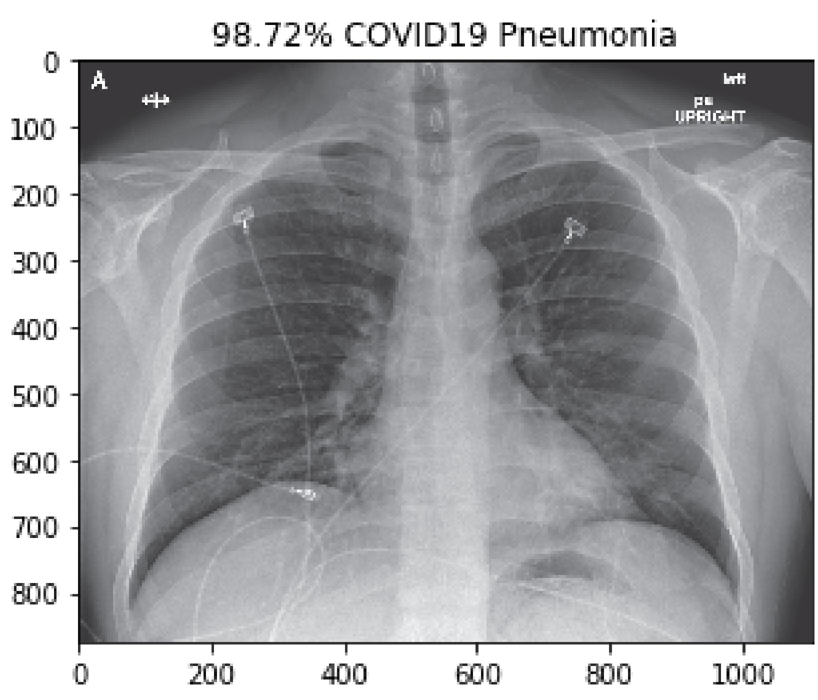


Plot Test Results

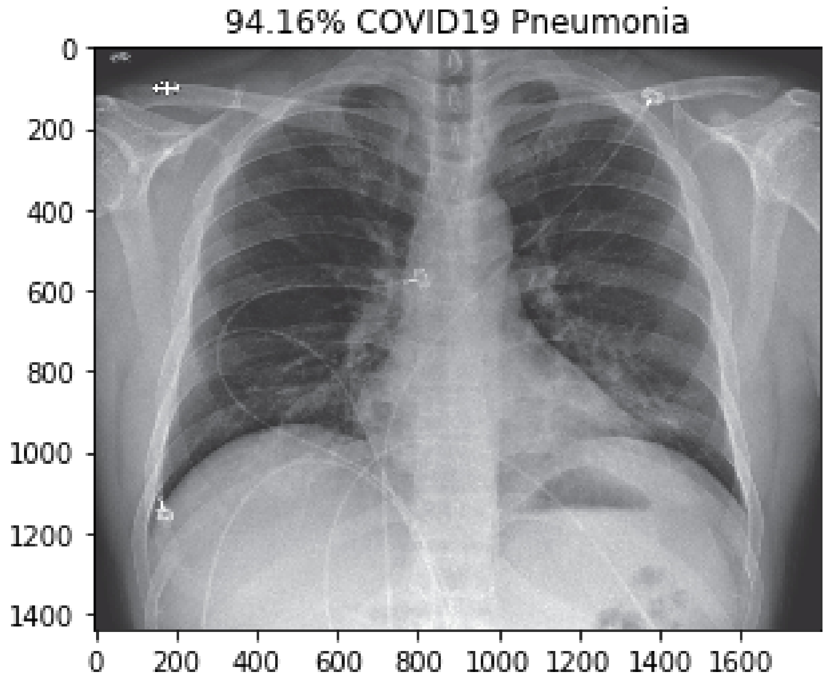
[7]:
```python
import matplotlib.image as mpimg

test_datagen = ImageDataGenerator(rescale=1. / 255)
```

```
eval_generator = test_datagen.
 ↪flow_from_directory(TEST_DIR,target_size=IMAGE_SIZE,
                                                              ␣
 ↪batch_size=1,shuffle=False,seed=42,class_mode="binary")
eval_generator.reset()
pred = model.predict_generator(eval_generator,18,verbose=1)
for index, probability in enumerate(pred):
    image_path = TEST_DIR + "/" +eval_generator.filenames[index]
    image = mpimg.imread(image_path)
    if image.ndim < 3:
        image = np.reshape(image,(image.shape[0],image.shape[1],1))
        image = np.concatenate([image, image, image], 2)
#         print(image.shape)

    pixels = np.array(image)
    plt.imshow(pixels)

    print(eval_generator.filenames[index])
    if probability > 0.5:
        plt.title("%.2f" % (probability[0]*100) + "% Normal")
    else:
        plt.title("%.2f" % ((1-probability[0])*100) + "% COVID19 Pneumonia")
    plt.show()
```

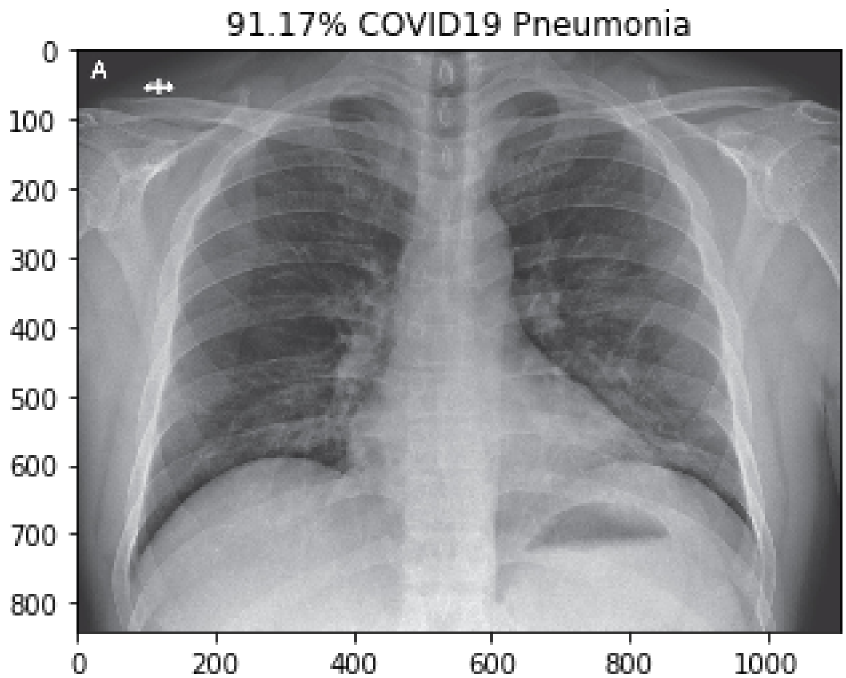
```
Found 18 images belonging to 2 classes.
18/18 [==============================] - 5s 286ms/step
covid\nejmoa2001191_f3-PA.jpeg
```



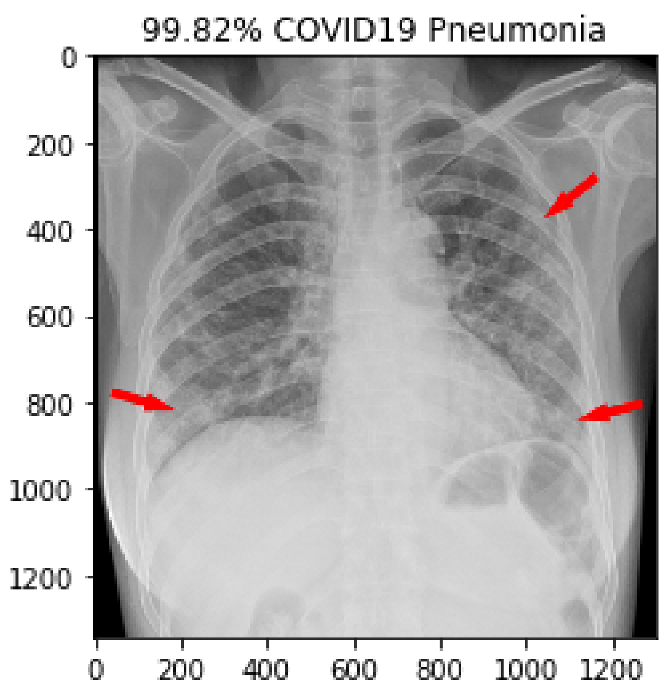
covid\nejmoa2001191_f4.jpeg



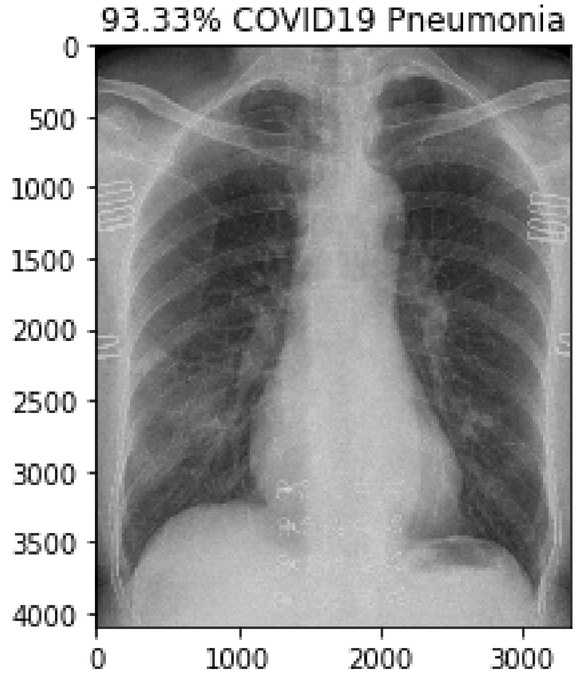
covid\nejmoa2001191_f5-PA.jpeg



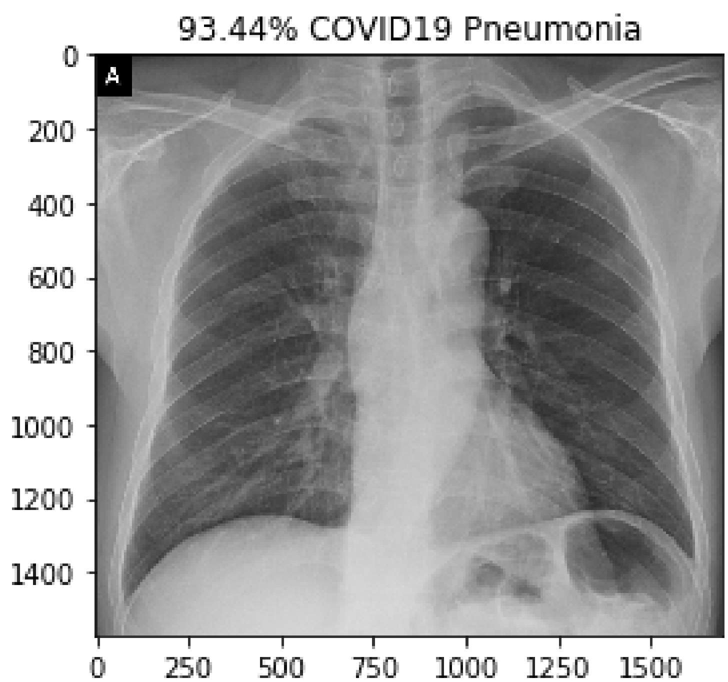
covid\radiol.2020200490.fig3.jpeg



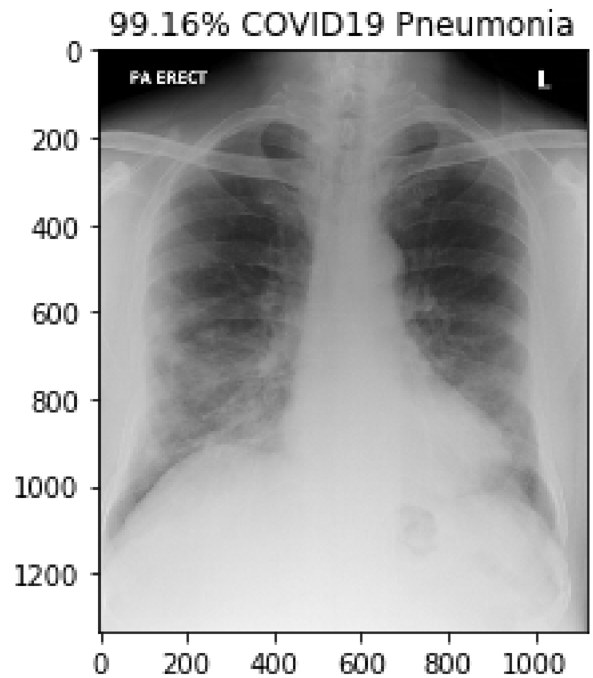
covid\ryct.2020200028.fig1a.jpeg



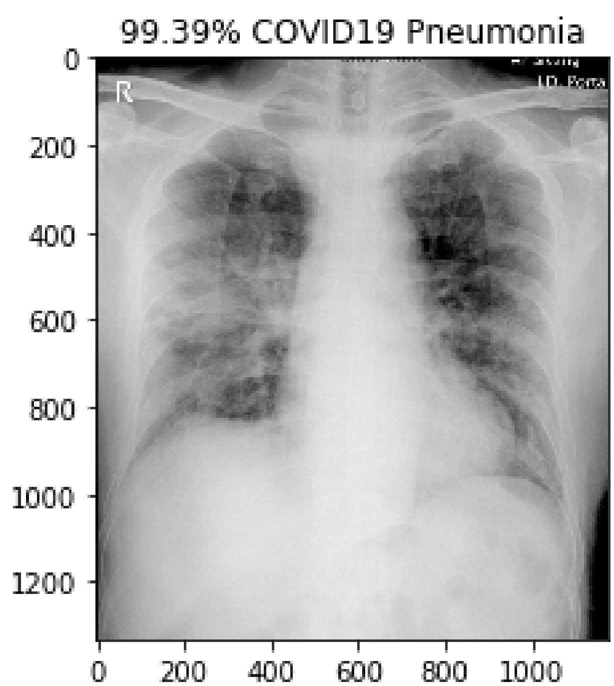
covid\ryct.2020200034.fig2.jpeg



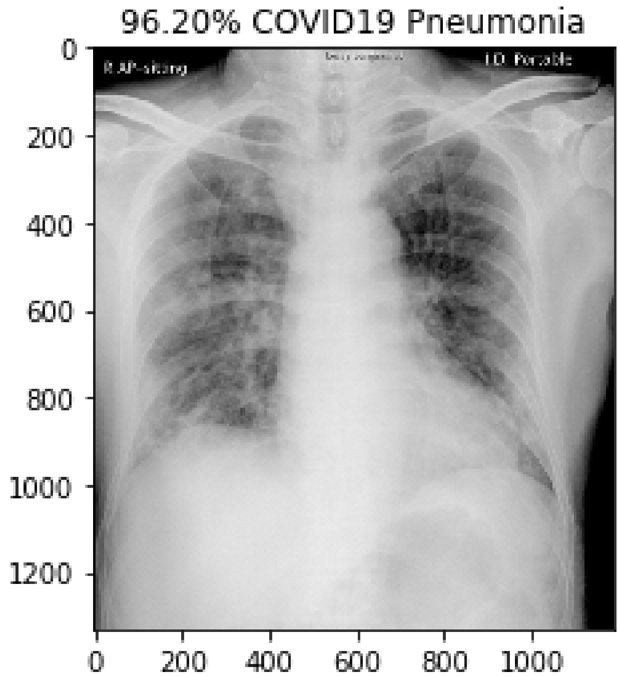
covid\ryct.2020200034.fig5-day0.jpeg



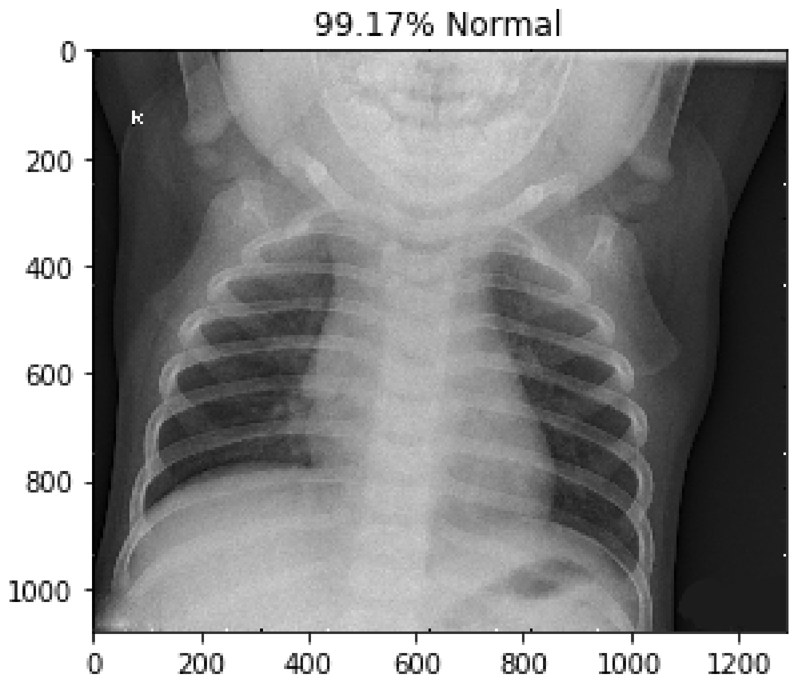
covid\ryct.2020200034.fig5-day4.jpeg



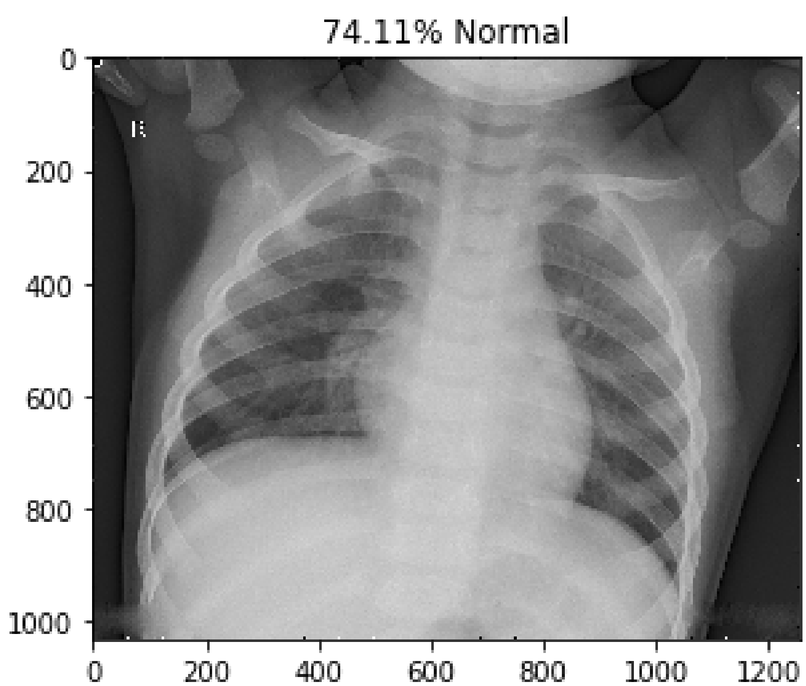
covid\ryct.2020200034.fig5-day7.jpeg



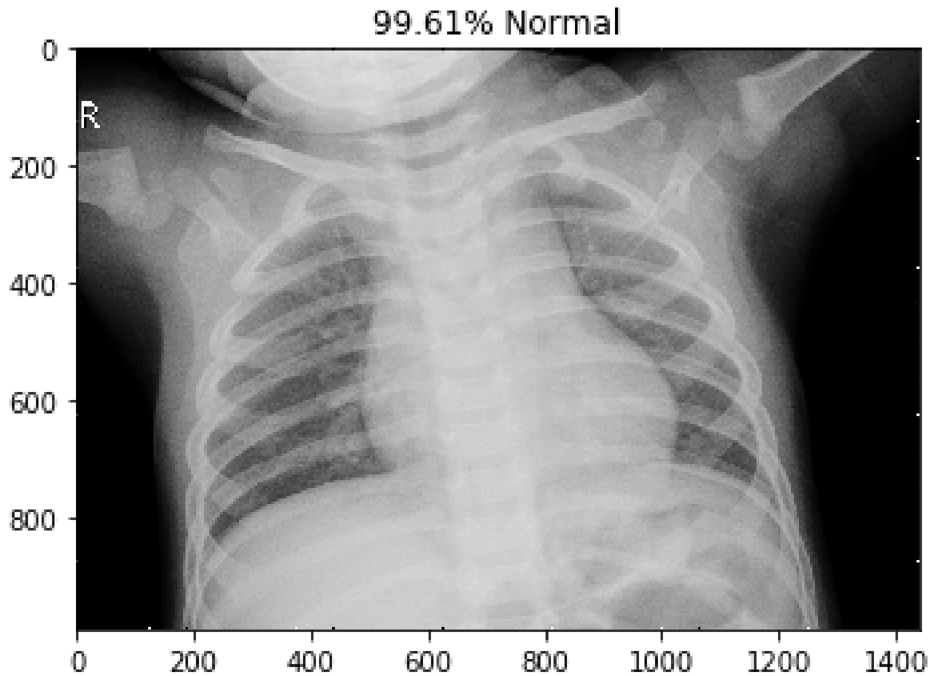
normal\NORMAL2-IM-1385-0001.jpeg



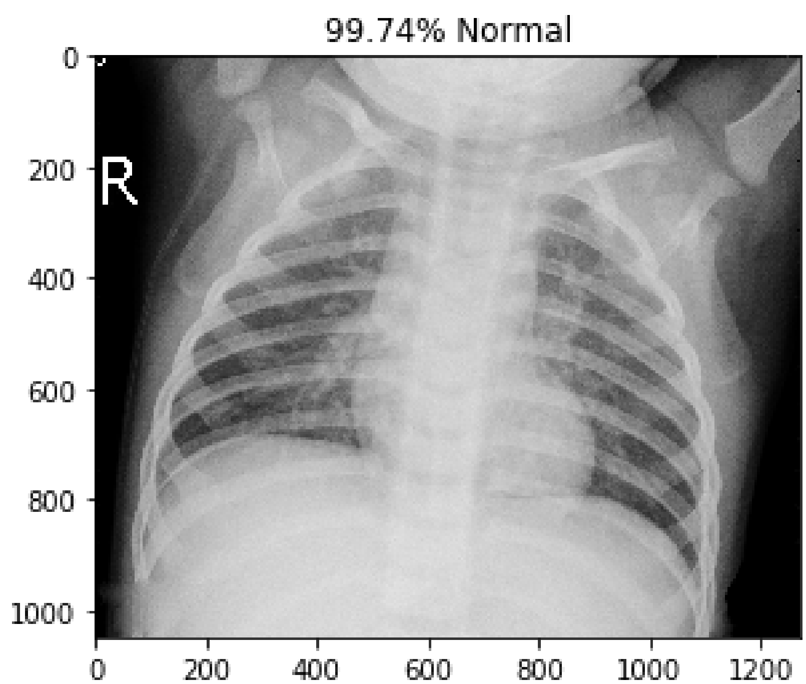
normal\NORMAL2-IM-1396-0001.jpeg



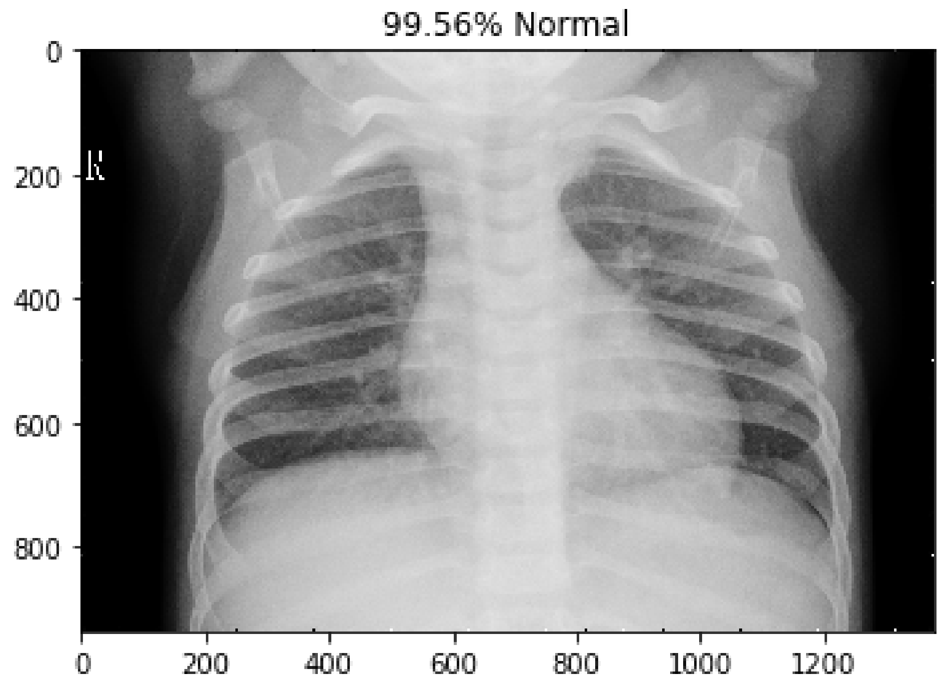
normal\NORMAL2-IM-1400-0001.jpeg



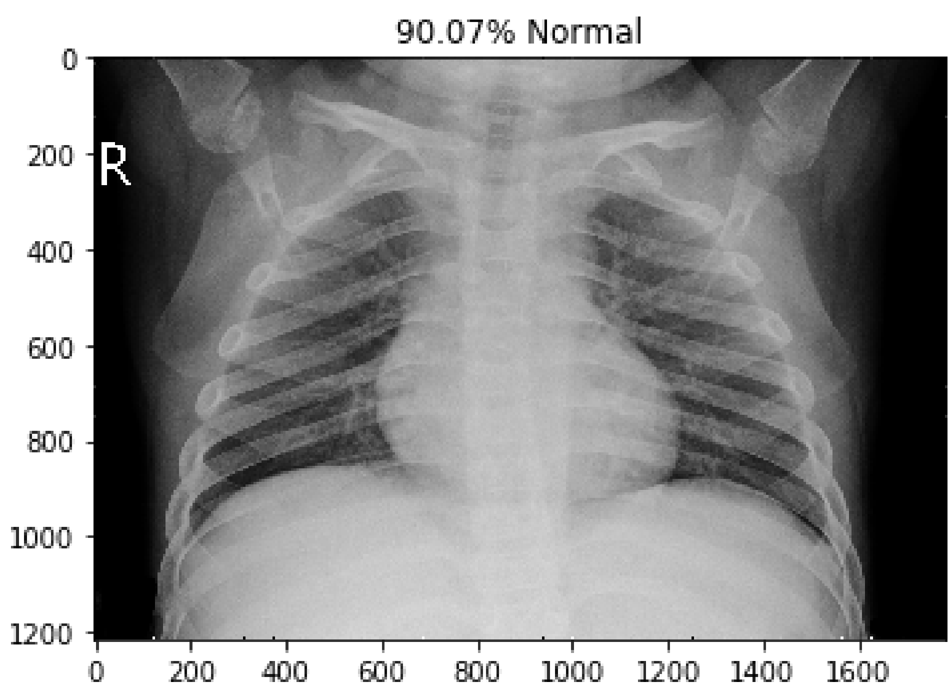
normal\NORMAL2-IM-1401-0001.jpeg



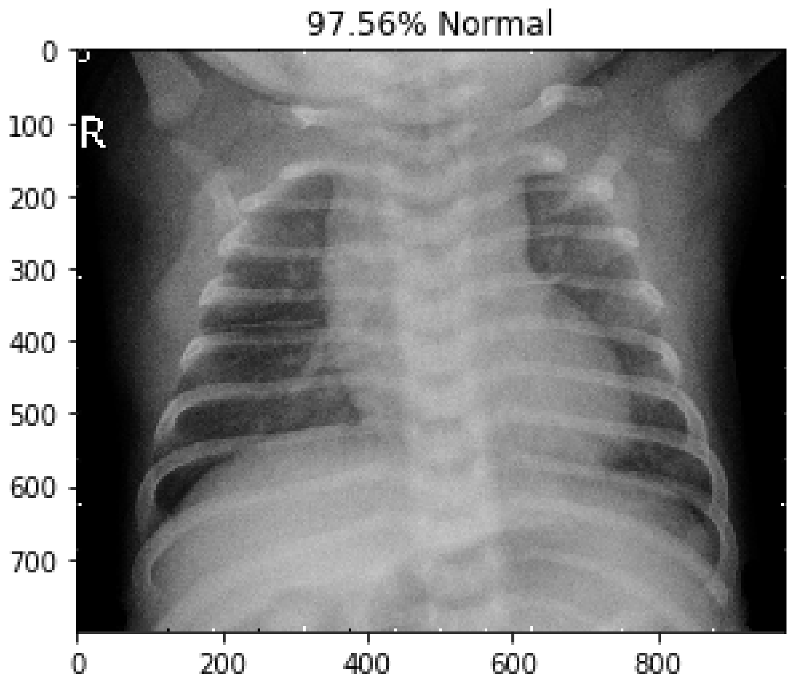
normal\NORMAL2-IM-1406-0001.jpeg



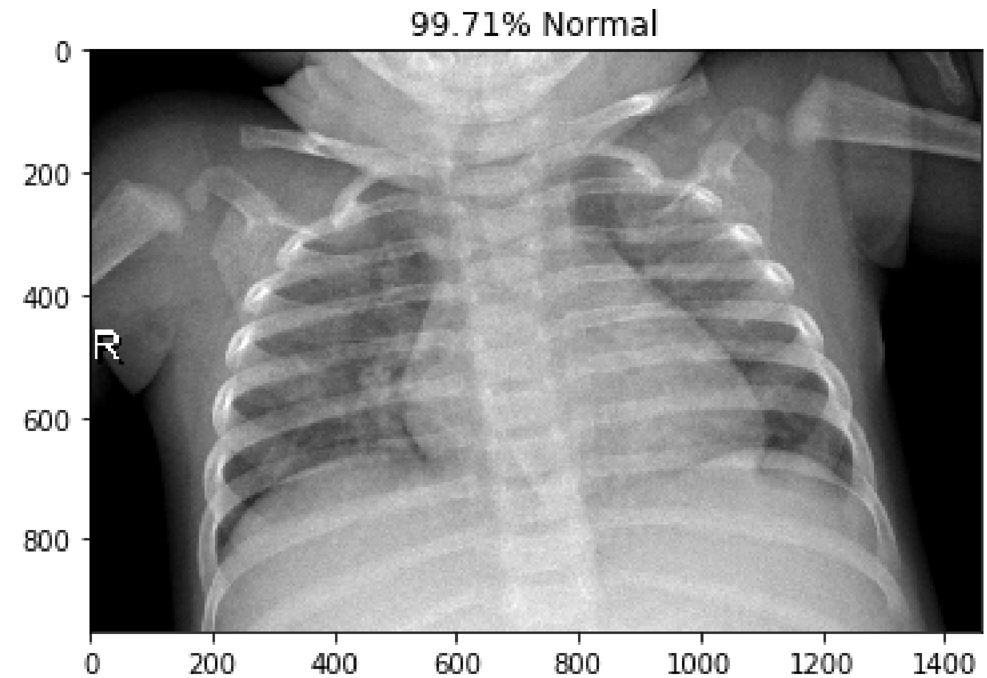
normal\NORMAL2-IM-1412-0001.jpeg



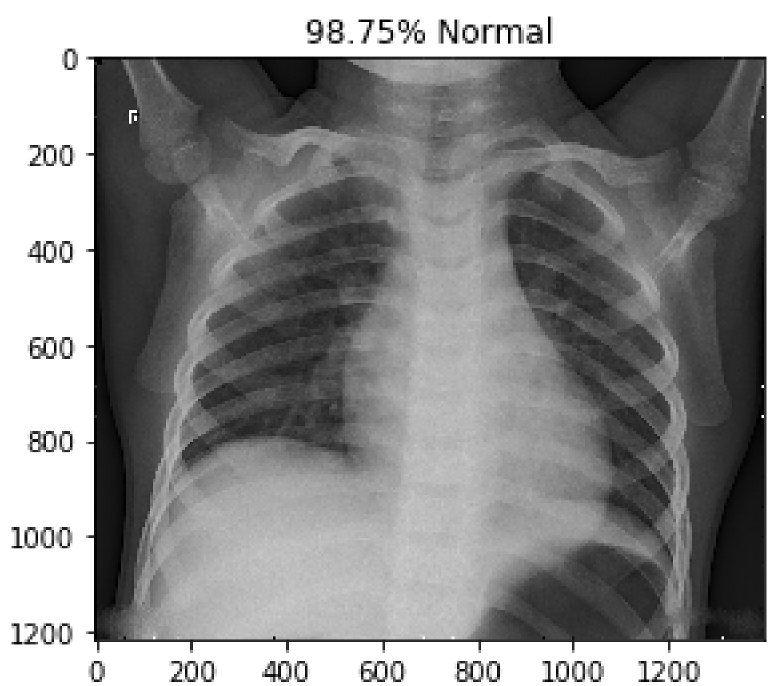
normal\NORMAL2-IM-1419-0001.jpeg



normal\NORMAL2-IM-1422-0001.jpeg



normal\NORMAL2-IM-1423-0001.jpeg

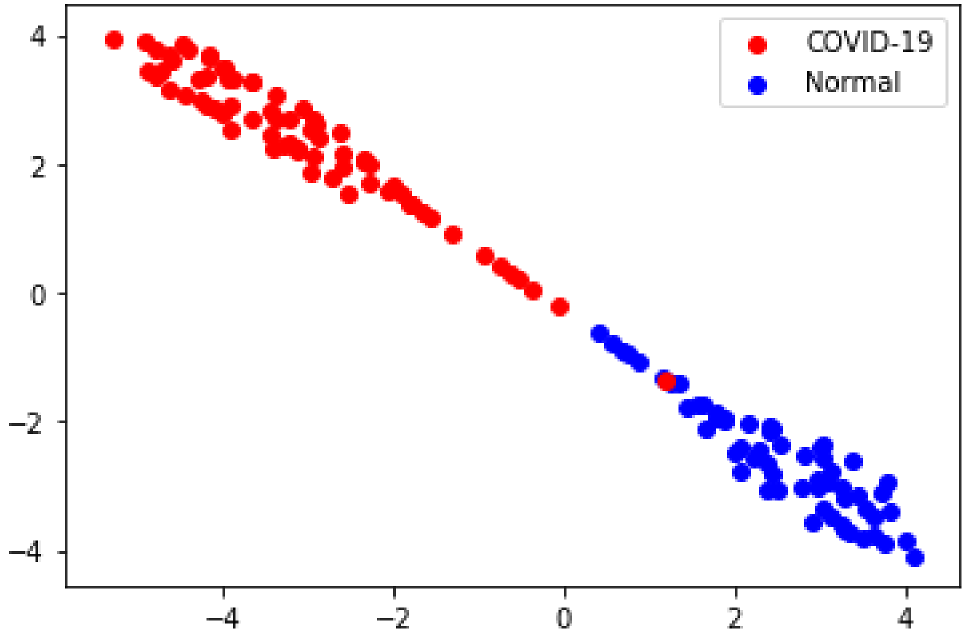


2.4 [10 points] TSNE Plot

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.

[8]:
```
from sklearn.manifold import TSNE

intermediate_layer_model = tf.keras.models.Model(inputs=model.input, \
                                      outputs=model.get_layer('dense').output)

tsne_data_generator = test_datagen.
 ↪flow_from_directory(DATASET_PATH,target_size=IMAGE_SIZE, \
                                                          ␣
 ↪batch_size=1,shuffle=False,seed=42,class_mode="binary")

features = intermediate_layer_model.predict_generator(tsne_data_generator)


labels = []

for i in range(len(tsne_data_generator)):
    labels.extend(tsne_data_generator.__getitem__(i)[1])

tsne = TSNE(perplexity = 50, learning_rate = 80).fit_transform(features)

for i in range(len(tsne)):
    if labels[i] == 1.0:
        # covid
        c = plt.scatter(tsne[:,0][i], tsne[:,1][i], color = 'red')
    else:
        # normal
        n = plt.scatter(tsne[:,0][i], tsne[:,1][i], color = 'blue')

plt.legend((c, n), ("COVID-19", "Normal"))

plt.show()
```

```
Found 130 images belonging to 2 classes.
```


COVID-19
Normal
4
2
0
−2
−4
−4
−2
0
2
4