```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import math
import seaborn as sns
import cv2
import os
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from keras.utils.np_utils import to_categorical
from keras.models import Model  #Input
from keras.layers import Dense, Conv2D, BatchNormalization, GlobalAveragePooling2D, Input
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ModelCheckpoint, ReduceLROnPlateau
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications.resnet import ResNet50
from tensorflow.keras.utils import plot_model
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization, Input, Flatten

# Supress info, warnings and error messages
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'


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

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

```
disease_types = ['COVID', 'non-COVID']

train_dir = data_dir = '/content/drive/MyDrive/CT scan'

train_data = []

for index, sp in enumerate(disease_types):
    for file in os.listdir(os.path.join(train_dir, sp)):
        train_data.append([sp + "/" + file, index, sp])

train = pd.DataFrame(train_data, columns = ['File', 'ID','Disease Type'])
train
```

	File	ID	Disease Type
0	COVID/Covid (215).png	0	COVID
1	COVID/Covid (124).png	0	COVID
2	COVID/Covid (26).png	0	COVID
3	COVID/Covid (187).png	0	COVID
4	COVID/Covid (203).png	0	COVID
...	...	...	...
2476	non-COVID/Non-Covid (1132).png	1	non-COVID
2477	non-COVID/Non-Covid (1061).png	1	non-COVID
2478	non-COVID/Non-Covid (1174).png	1	non-COVID
2479	non-COVID/Non-Covid (1022).png	1	non-COVID
2480	non-COVID/Non-Covid (1028).png	1	non-COVID

2481 rows × 3 columns

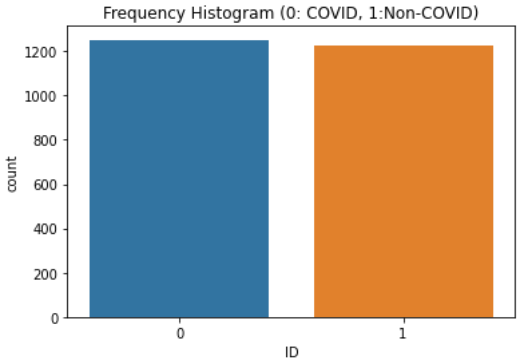
Then, the data are randomly shuffled to separate the training and test set, according to which the network will be trained and tested, respectively. The percentage of the training set corresponds to 80% of the data, while that of the test set, to the remaining 20% of the total data. In the pre-processing stage, the images are cropped to dimensions 224x224, categorized according to the class to which they belong and subjected to accidental alteration of some features, such as shift, inversion, focus, etc.

```
Seed = 40

train = train.sample(frac = 1, replace=False, random_state = Seed)

# Reset indices (row numbers)
train = train.reset_index(drop = True)
```

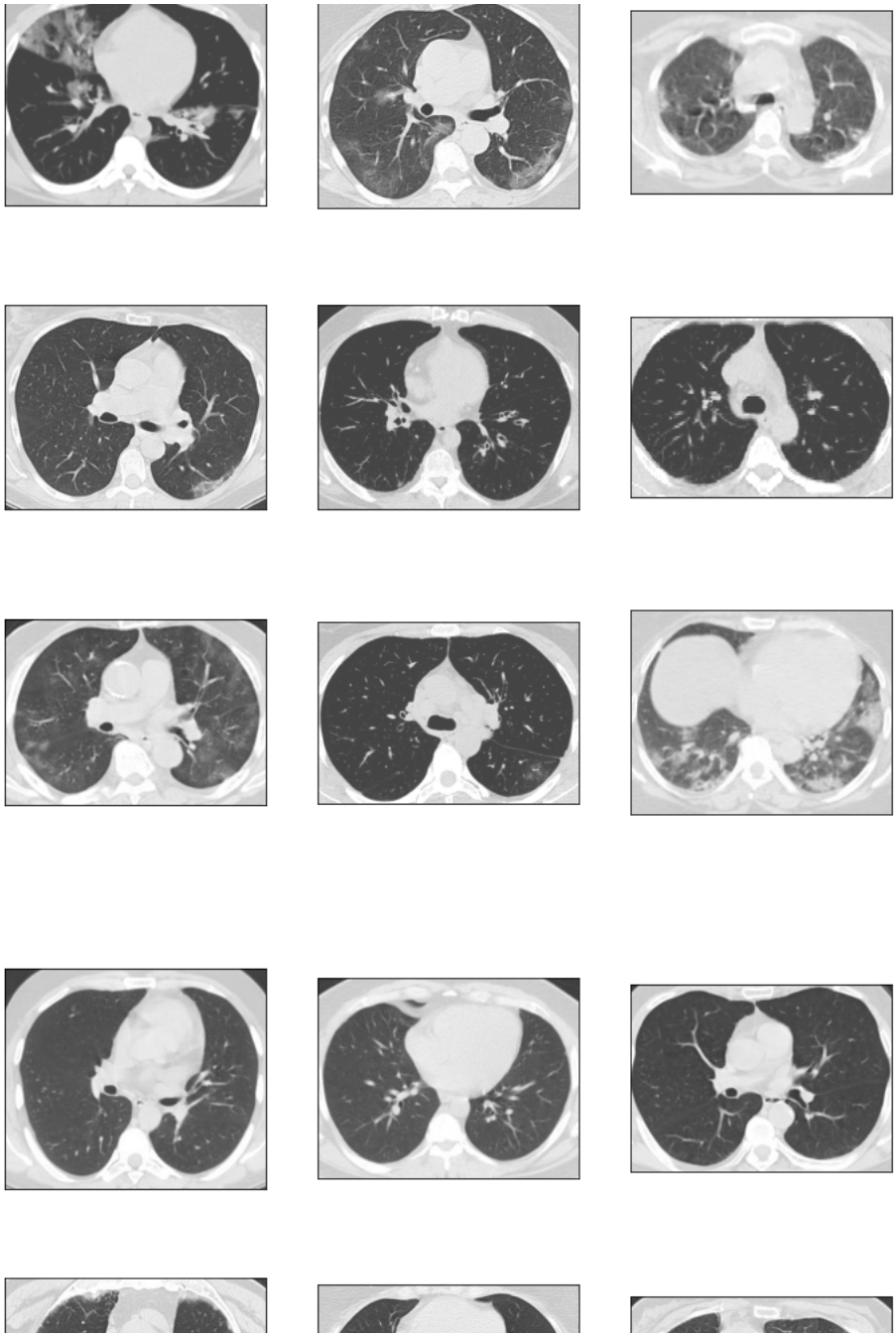
```
sns.countplot(x = "ID", data = train).set_title("Frequency Histogram (0: COVID, 1:Non-COVID)")
train
```

	File	ID	Disease Type
0	COVID/Covid (26).png	0	COVID
1	COVID/Covid (716).png	0	COVID
2	COVID/Covid (579).png	0	COVID
3	non-COVID/Non-Covid (266).png	1	non-COVID
4	COVID/Covid (852).png	0	COVID
...	...	...	...
2476	non-COVID/Non-Covid (543).png	1	non-COVID
2477	non-COVID/Non-Covid (164).png	1	non-COVID
2478	non-COVID/Non-Covid (990).png	1	non-COVID
2479	non-COVID/Non-Covid (723).png	1	non-COVID
2480	non-COVID/Non-Covid (100).png	1	non-COVID

2481 rows × 3 columns




```
def plot_defects(defect_types, rows, cols):
    fig, ax = plt.subplots(rows, cols, figsize=(12, 12))
    defect_files = train['File'][train['Disease Type'] == defect_types].values

    n = 0
    fig.suptitle(defect_types, fontsize = 22, color = "white")
    for i in range(rows):
        for j in range(cols):
            image_path = os.path.join(data_dir, defect_files[n])
            ax[i, j].set_xticks([])
            ax[i, j].set_yticks([])
            ax[i, j].imshow(cv2.imread(image_path))
            n += 1


plot_defects('COVID', 3, 3)
plot_defects('non-COVID', 3, 3)
```



```
IMAGE_SIZE = 224

# OpenCV Function to load colored image
def read_image(filepath):
    return cv2.imread(os.path.join(data_dir, filepath))

# OpenCV Function to resize an image
def resize_image(image, image_size):
    return cv2.resize(image.copy(), image_size, interpolation = cv2.INTER_AREA)
```

```
X_train = np.zeros((train.shape[0], IMAGE_SIZE, IMAGE_SIZE, 3))

for i, file in enumerate(train['File'].values):
    image = read_image(file)
    if image is not None:
        X_train[i] = resize_image(image, (IMAGE_SIZE, IMAGE_SIZE))

X_Train = X_train / 255.0   # Pixel normalization
print('Train Shape:', X_Train.shape)

Y_train = to_categorical(train['ID'].values, num_classes = 2)

print(Y_train)
```

```
     Train Shape: (2481, 224, 224, 3)
     [[1. 0.]
      [1. 0.]
      [1. 0.]
      ...
```

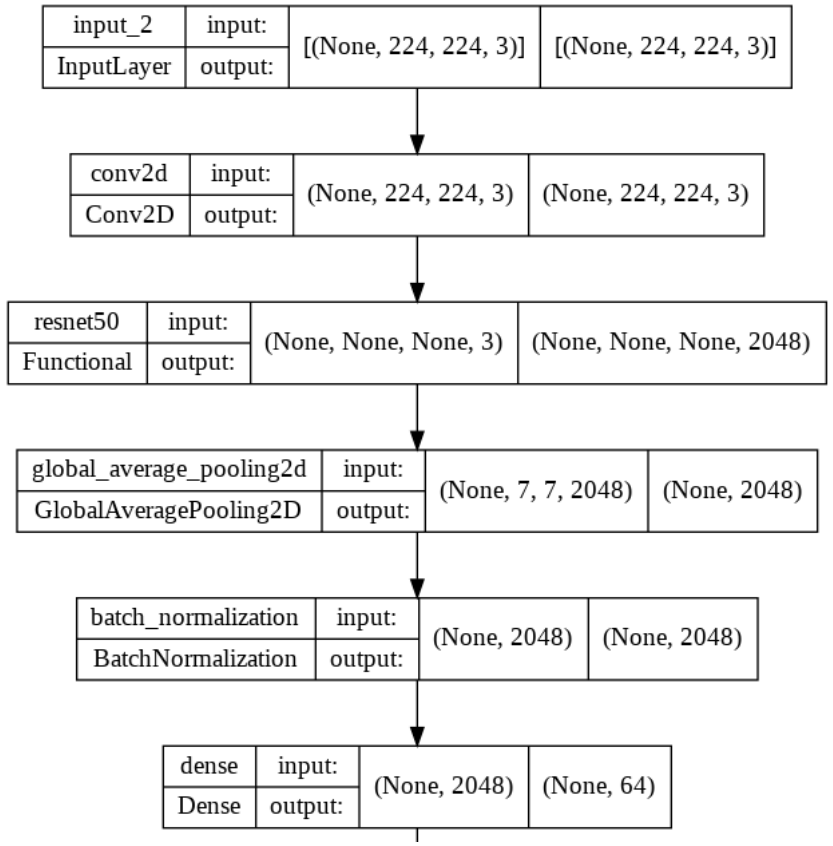
```
       [0. 1.]
       [0. 1.]
       [0. 1.]]
```

```
# Dataframe split to train and validation set (80% train and 20% validation)
X_train, X_val, Y_train, Y_val = train_test_split(X_Train,
                                                  Y_train,
                                                  test_size = 0.2, # Percent 20% of the data is using as test set
                                                  random_state = Seed)

print(f'X_train:', X_train.shape)
print(f'X_val:', X_val.shape)
print(f'Y_train:', Y_train.shape)
print(f'Y_val:', Y_val.shape)
```

```
     X_train: (1984, 224, 224, 3)
     X_val: (497, 224, 224, 3)
     Y_train: (1984, 2)
     Y_val: (497, 2)
```

```
# Architectural function for Resnet50
def build_resnet50(IMAGE_SIZE, channels):

    resnet50 = ResNet50(weights = 'imagenet', include_top = False)

    input = Input(shape = (IMAGE_SIZE, IMAGE_SIZE, channels))
    x = Conv2D(3, (3, 3), padding = 'same')(input)
    x = resnet50(x)
    x = GlobalAveragePooling2D()(x)
    x = BatchNormalization()(x)
    x = Dense(64, activation = 'relu')(x)
    x = BatchNormalization()(x)

    output = Dense(2, activation = 'softmax')(x)

    # model
    model = Model(input, output)

    optimizer = Adam(learning_rate = 0.003, beta_1 = 0.9, beta_2 = 0.999, epsilon = 0.1, decay = 0.0)
    model.compile(loss = 'categorical_crossentropy',  # minimize the negative multinomial log-likelihood also known as the cross-entropy.
                  optimizer = optimizer,
                  metrics = ['accuracy'])
    model.summary()

    return model


channels = 3

model = build_resnet50(IMAGE_SIZE, channels)
annealer = ReduceLROnPlateau(monitor = 'val_accuracy',  # Reduce learning rate when Validation accuracy remains constant
                             factor = 0.70,  # Rate by which the learning rate will decrease
                             patience = 5,   # number of epochs without improvement, after which the learning rate will decrease
                             verbose = 1,    # Display messages
                             min_lr = 1e-4   # lower limit on the learning rate.
                            )
checkpoint = ModelCheckpoint('model.h5', verbose = 1, save_best_only = True)  # Save neural network weights

# Generates batches of image data with data augmentation
datagen = ImageDataGenerator(rotation_range = 360, # Degree range for random rotations
                         width_shift_range = 0.2,   # Range for random horizontal shifts
                         height_shift_range = 0.2,  # Range for random vertical shifts
                         zoom_range = 0.2,          # Range for random zoom
                         horizontal_flip = True,    # Randomly flip inputs horizontally
                         vertical_flip = True)      # Randomly flip inputs vertically

datagen.fit(X_train)

plot_model(model, to_file = 'convnet.png', show_shapes = True, show_layer_names = True)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weig
94773248/94765736 [==============================] - 1s 0us/step
94781440/94765736 [==============================] - 1s 0us/step
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 224, 224, 3)]     0

 conv2d (Conv2D)             (None, 224, 224, 3)       84

 resnet50 (Functional)       (None, None, None, 2048)  23587712

 global_average_pooling2d (G  (None, 2048)             0
 lobalAveragePooling2D)

 batch_normalization (BatchN  (None, 2048)             8192
 ormalization)

 dense (Dense)               (None, 64)                131136

 batch_normalization_1 (Batc  (None, 64)               256
 hNormalization)

 dense_1 (Dense)             (None, 2)                 130

=================================================================
Total params: 23,727,510
Trainable params: 23,670,166
Non-trainable params: 57,344
_________________________________________________________________
```



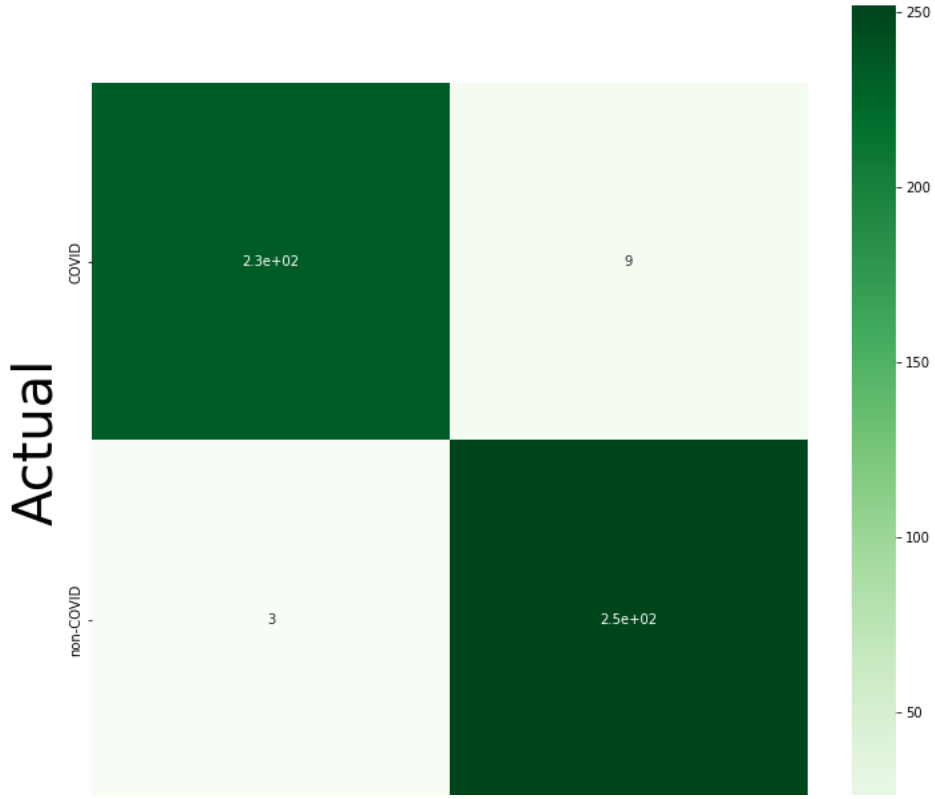

```
BATCH_SIZE = 32
EPOCHS = 50

# Fit of the model that includes the augmented images in terms of their characteristics
hist = model.fit(datagen.flow(X_train, Y_train, batch_size = BATCH_SIZE),
                 steps_per_epoch = X_train.shape[0] // BATCH_SIZE,
                 epochs = EPOCHS,
                 verbose = 1,
                 callbacks = [annealer, checkpoint],
                 validation_data = (X_val, Y_val))
```

```
Epoch 1/50
62/62 [==============================] - ETA: 0s - loss: 0.5884 - accuracy: 0.7369
Epoch 1: val_loss improved from inf to 1.97931, saving model to model.h5
62/62 [==============================] - 50s 517ms/step - loss: 0.5884 - accuracy: 0.7369 - val_loss: 1.9793 - val_accuracy: 0.4
Epoch 2/50
62/62 [==============================] - ETA: 0s - loss: 0.4038 - accuracy: 0.8327
Epoch 2: val_loss did not improve from 1.97931
62/62 [==============================] - 27s 439ms/step - loss: 0.4038 - accuracy: 0.8327 - val_loss: 4.5689 - val_accuracy: 0.4
Epoch 3/50
```

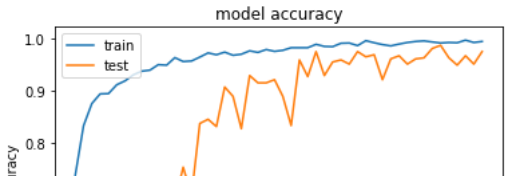
```
62/62 [==============================] - ETA: 0s - loss: 0.3291 - accuracy: 0.8755
Epoch 3: val_loss did not improve from 1.97931
62/62 [==============================] - 27s 439ms/step - loss: 0.3291 - accuracy: 0.8755 - val_loss: 14.0244 - val_accuracy: 0.4
Epoch 4/50
62/62 [==============================] - ETA: 0s - loss: 0.2664 - accuracy: 0.8942
Epoch 4: val_loss did not improve from 1.97931
62/62 [==============================] - 28s 445ms/step - loss: 0.2664 - accuracy: 0.8942 - val_loss: 19.4652 - val_accuracy: 0.4
Epoch 5/50
62/62 [==============================] - ETA: 0s - loss: 0.2630 - accuracy: 0.8947
Epoch 5: val_loss did not improve from 1.97931
62/62 [==============================] - 28s 445ms/step - loss: 0.2630 - accuracy: 0.8947 - val_loss: 7.3958 - val_accuracy: 0.4
Epoch 6/50
62/62 [==============================] - ETA: 0s - loss: 0.2097 - accuracy: 0.9118
Epoch 6: val_loss did not improve from 1.97931
62/62 [==============================] - 28s 441ms/step - loss: 0.2097 - accuracy: 0.9118 - val_loss: 3.9438 - val_accuracy: 0.5
Epoch 7/50
62/62 [==============================] - ETA: 0s - loss: 0.1971 - accuracy: 0.9194
Epoch 7: val_loss did not improve from 1.97931
62/62 [==============================] - 28s 445ms/step - loss: 0.1971 - accuracy: 0.9194 - val_loss: 3.7219 - val_accuracy: 0.4
Epoch 8/50
62/62 [==============================] - ETA: 0s - loss: 0.1693 - accuracy: 0.9309
Epoch 8: val_loss improved from 1.97931 to 1.65606, saving model to model.h5
62/62 [==============================] - 29s 465ms/step - loss: 0.1693 - accuracy: 0.9309 - val_loss: 1.6561 - val_accuracy: 0.4
Epoch 9/50
62/62 [==============================] - ETA: 0s - loss: 0.1531 - accuracy: 0.9380
Epoch 9: val_loss improved from 1.65606 to 0.96230, saving model to model.h5
62/62 [==============================] - 30s 480ms/step - loss: 0.1531 - accuracy: 0.9380 - val_loss: 0.9623 - val_accuracy: 0.5
Epoch 10/50
62/62 [==============================] - ETA: 0s - loss: 0.1475 - accuracy: 0.9400
Epoch 10: val_loss did not improve from 0.96230
62/62 [==============================] - 28s 443ms/step - loss: 0.1475 - accuracy: 0.9400 - val_loss: 1.4260 - val_accuracy: 0.4
Epoch 11/50
62/62 [==============================] - ETA: 0s - loss: 0.1344 - accuracy: 0.9506
Epoch 11: val_loss did not improve from 0.96230
62/62 [==============================] - 28s 445ms/step - loss: 0.1344 - accuracy: 0.9506 - val_loss: 1.8728 - val_accuracy: 0.4
Epoch 12/50
62/62 [==============================] - ETA: 0s - loss: 0.1258 - accuracy: 0.9496
Epoch 12: val_loss did not improve from 0.96230
62/62 [==============================] - 28s 446ms/step - loss: 0.1258 - accuracy: 0.9496 - val_loss: 2.1467 - val_accuracy: 0.4
Epoch 13/50
62/62 [==============================] - ETA: 0s - loss: 0.0939 - accuracy: 0.9642
Epoch 13: val_loss improved from 0.96230 to 0.69623, saving model to model.h5
62/62 [==============================] - 29s 469ms/step - loss: 0.0939 - accuracy: 0.9642 - val_loss: 0.6962 - val_accuracy: 0.6
Epoch 14/50
62/62 [==============================] - ETA: 0s - loss: 0.1032 - accuracy: 0.9567
Epoch 14: val_loss improved from 0.69623 to 0.54984, saving model to model.h5
```

```
Y_pred = model.predict(X_val)

Y_pred = np.argmax(Y_pred, axis = 1)
Y_true = np.argmax(Y_val, axis = 1)

cm = confusion_matrix(Y_true, Y_pred)
plt.figure(figsize = (12, 12))
ax = sns.heatmap(cm, cmap = plt.cm.Greens, annot = True, square = True, xticklabels = disease_types, yticklabels = disease_types)
ax.set_ylabel('Actual', fontsize = 40)
ax.set_xlabel('Predicted', fontsize = 40)


TP = cm[1][1]
print(f"True Positive: {TP}")


FN = cm[1][0]
print(f"False Negative: {FN}")

TN = cm[0][0]
print(f"True Negative: {TN}")

FP = cm[0][1]
print(f"False Positive: {FP}")

# Sensitivity, recall, or true positive rate
print(f"True Positive Rate: {TP / (TP + FN)}")

# Specificity or true negative rate
print(f"True Negative Rate: {TN / (TN + FP)}\n")

final_loss, final_accuracy = model.evaluate(X_val, Y_val)
print(f"\nFinal Loss: {final_loss}, Final Accuracy: {final_accuracy}")
```

```
True Positive: 252
False Negative: 3
True Negative: 233
False Positive: 9
True Positive Rate: 0.9882352941176471
True Negative Rate: 0.9628099173553719

16/16 [==============================] - 2s 98ms/step - loss: 0.0540 - accuracy: 0.9759

Final Loss: 0.05403857305645943, Final Accuracy: 0.9758551120758057
```

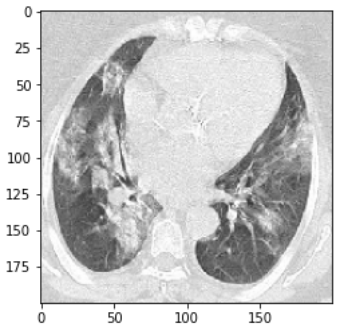



```
# Accuracy plot
plt.plot(hist.history['accuracy'])
plt.plot(hist.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc = 'upper left')
plt.show()

# Loss plot
plt.plot(hist.history['loss'])
plt.plot(hist.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc = 'upper left')
plt.show()
```




```
from keras.preprocessing import image

img = image.load_img('/content/drive/MyDrive/CT scan/COVID/Covid (1007).png', grayscale = False, target_size = (224, 224))
show_img = image.load_img('/content/drive/MyDrive/CT scan/COVID/Covid (1007).png', grayscale = False, target_size = (200, 200))
disease_class = ['Covid-19','Non Covid-19']
x = image.img_to_array(img)
x = np.expand_dims(x, axis = 0)
x /= 255

custom = model.predict(x)
print(custom[0])

plt.imshow(show_img)
plt.show()

a = custom[0]
ind = np.argmax(a)

print('Prediction:',disease_class[ind])
```

```
[1.000000e+00 4.365647e-11]
```



```
Prediction: Covid-19
```

Colab paid products - Cancel contracts here

✓ 0s completed at 4:08 PM