==================> Capstone Project <====================

Problem Statement

CT Scan Images Classification

Data Overview

This dataset contains 1252 Ct scans that are positive for SARS-CoV-2 infection (COVID-19) and 1230 CT scans for patients no-infected by SARS-CoV-2 scans in total. These data have been collected from real parients in hospitals from Sao Paulo, Brazil. The aim of this dataset is to encourage the resarch and development of artificial intelligence methods which are able to identify if a person is infected by SARS-CoV-2 through the analysis of his/her CT scans.

✈️ Steps To Complete This Capstone Project

1- Download the Data from this Link.
https://drive.google.com/drive/folders/1WOeodRmv1Mw5Cswuip3nUIi6ViQWKpo_?usp=sharing

2- the images are in differnet sizes so you have to take a fixed size on which you have to work.

3- Do data augmentation on it, mention at least 5args inside it.

4- Train Model on it you only have to use resnet from resnet you can pick any layer model like - ResNet-18, ResNet-34, ResNet-50, ResNet-101, ResNet-110, ResNet-152, ResNet-164, ResNet-1202.

And mention early stopping and modelcheckpoint while training.

5- Do Prediction and mention multiple performance metrics.

1. **Import** the Rquired **Libraries**

In [17]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
#%matplotlib inline
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
from tensorflow.keras.layers import Input
from keras.layers import Dense, Conv2D, BatchNormalization, GlobalAveragePooling2D
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ModelCheckpoint, ReduceLROnPlateau
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.utils import plot_model

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

print("All Libraries are Imported Succesfully")
```

```
All Libraries are Imported Succesfully
```

2. Load the Dataset

In [2]:
```
disease_types = ['Covid', 'Non-Covid']

train_dir = data_dir = '/content/drive/MyDrive/Colab Notebooks/Capstone Project/Datase
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
```

Out[2]:

	File	ID	Disease Type
0	Covid/Covid (726).png	0	Covid
1	Covid/Covid (810).png	0	Covid
2	Covid/Covid (727).png	0	Covid
3	Covid/Covid (757).png	0	Covid
4	Covid/Covid (742).png	0	Covid
...	...	...	...
2476	Non-Covid/Non-Covid (671).png	1	Non-Covid
2477	Non-Covid/Non-Covid (733).png	1	Non-Covid
2478	Non-Covid/Non-Covid (727).png	1	Non-Covid
2479	Non-Covid/Non-Covid (695).png	1	Non-Covid
2480	Non-Covid/Non-Covid (775).png	1	Non-Covid

2481 rows × 3 columns

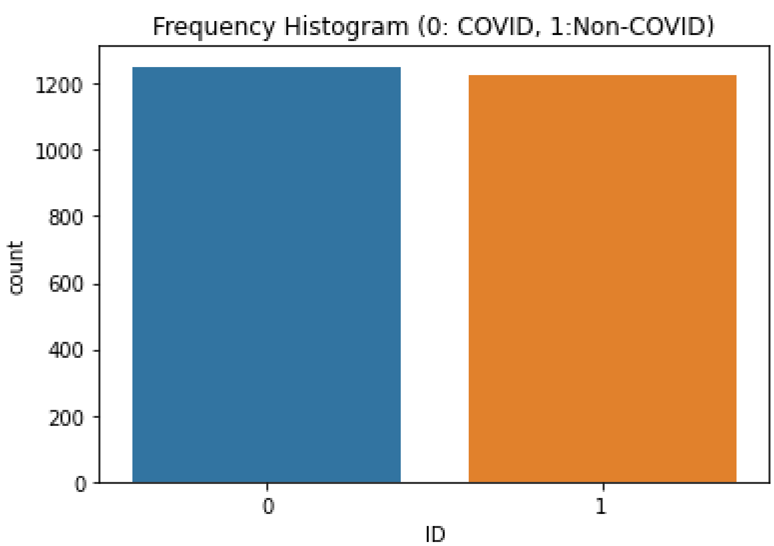
Setting Up the Dataset and adding column for the Histogram

In [3]:
```
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-
train
```

Out[3]:

	File	ID	Disease Type
0	Covid/Covid (727).png	0	Covid
1	Covid/Covid (277).png	0	Covid
2	Covid/Covid (29).png	0	Covid
3	Non-Covid/Non-Covid (540).png	1	Non-Covid
4	Covid/Covid (1203).png	0	Covid
...	...	...	...
2476	Non-Covid/Non-Covid (254).png	1	Non-Covid
2477	Non-Covid/Non-Covid (802).png	1	Non-Covid
2478	Non-Covid/Non-Covid (1052).png	1	Non-Covid
2479	Non-Covid/Non-Covid (1034).png	1	Non-Covid
2480	Non-Covid/Non-Covid (87).png	1	Non-Covid

2481 rows × 3 columns

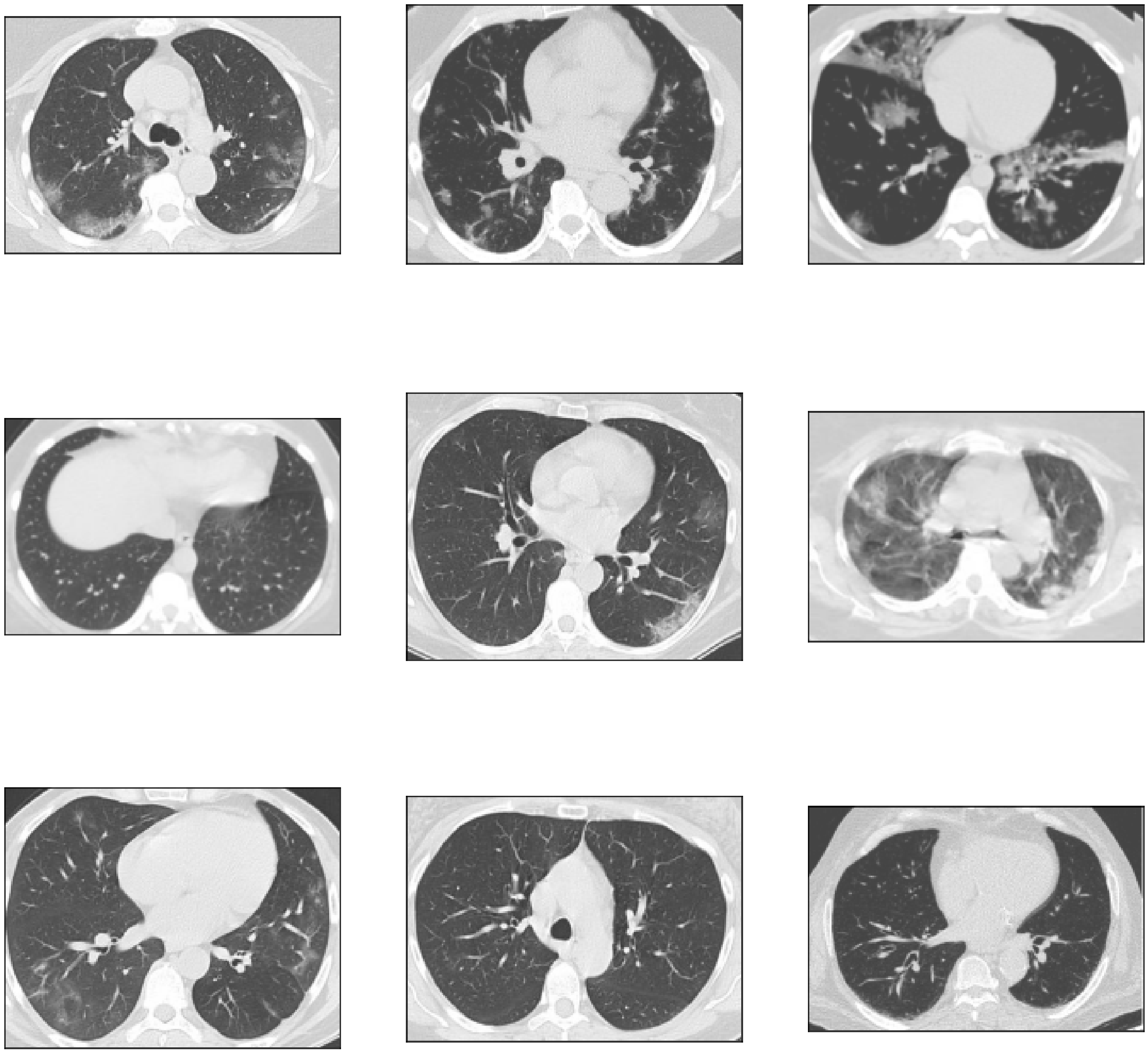


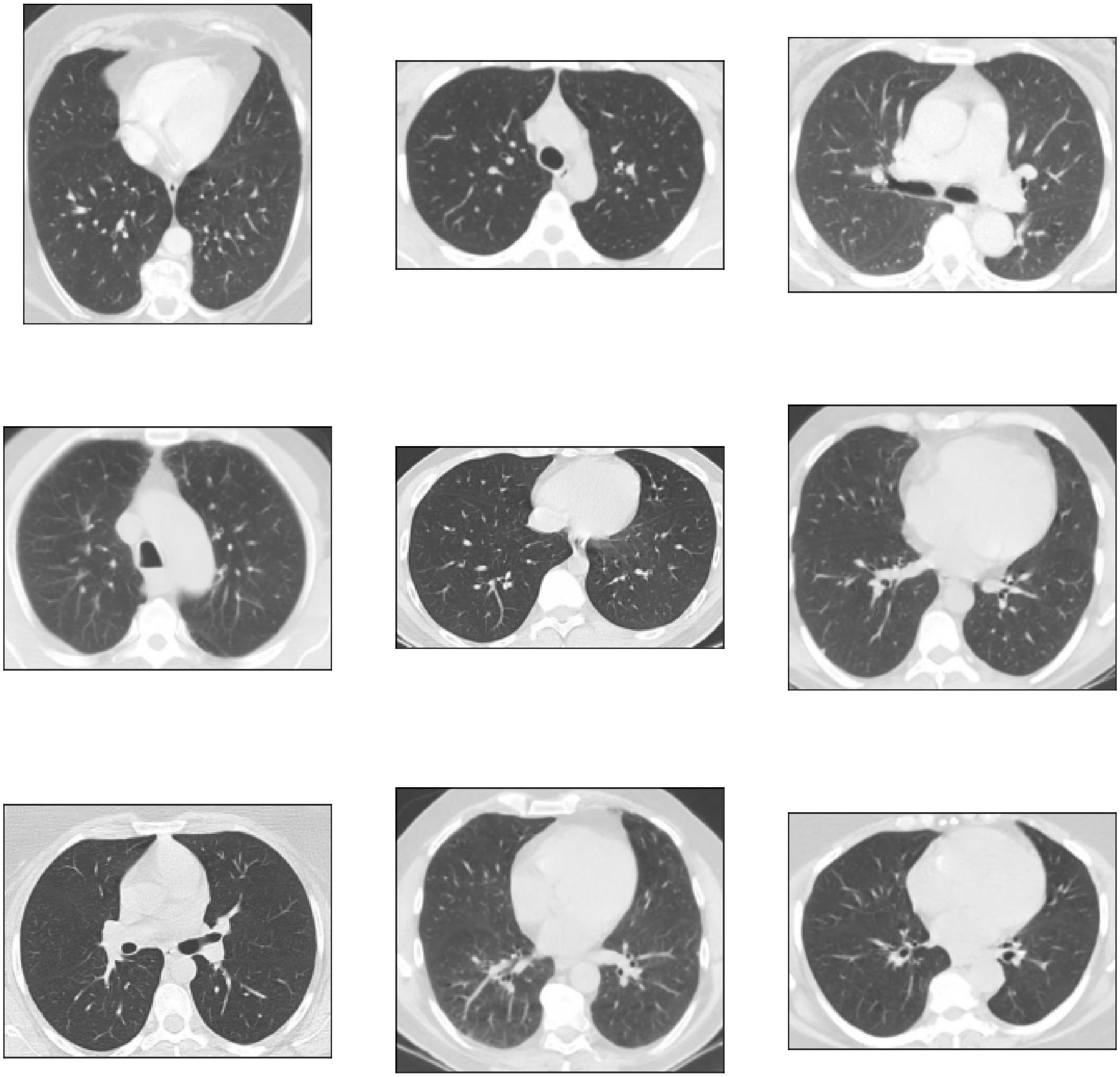
Observation :

1. We have total 2481 Images in our dataset.
2. Positive are 1250 CT scan images.
3. Negatice are 1230 CT scan images.

Ploting the Images

In [4]:
```
from collections.abc import ValuesView
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 = n+1

plot_defects('Covid', 3, 3)
plot_defects('Non-Covid', 3, 3)
```





3. Resizing the Images

In [5]:
```
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)
```

Observations :

Here I am resizing all the images to one size so that my model can train perfectly and do right predictions.

In [6]:
```
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.]]
```

4. Spliting the Dataset into Train and Test

In [7]:
```
# 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 th
                                                  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)
```

5. Building Model ResNet50

In [8]:
```
# Architectural function for DenseNet-169
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.
    model.compile(loss = 'categorical_crossentropy',  # minimize the negative multinom
                  optimizer = optimizer,
                  metrics = ['accuracy'])
    model.summary()

    return model
```

Observations :

1- Here I am training my model from ResNet50.

2- I am using Imagenet for wights.

3- For my model input size is 224.

4- Conv2d layer, Global Average Pooling, Batch Normalization these parameters i am using here.

5- My loss will be the Categorical Crossentropy

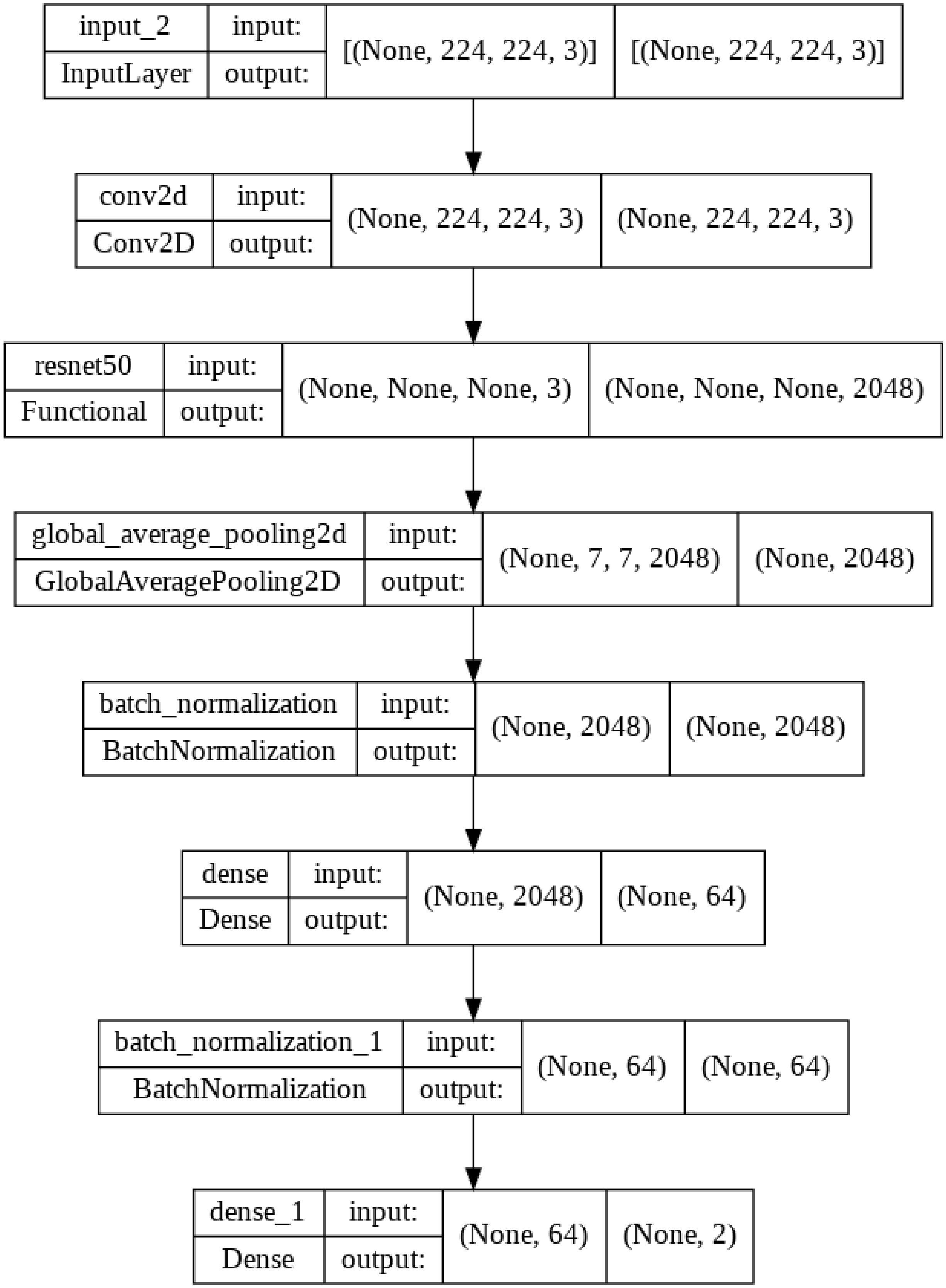
Data Augmentation

In [9]:

```
channels = 3

model = build_ResNet50(IMAGE_SIZE, channels)
annealer = ReduceLROnPlateau(monitor = 'val_accuracy',  # Reduce learning rate when Va
                             factor = 0.70,  # Rate by which the learning rate will de
                             patience = 5,   # number of epochs without improvement, a
                             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 m

# 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 shift
                        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
```

```
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
_________________________________________________________________
```

Out[9]:



6. Training the Model

In [10]:
```
BATCH_SIZE = 8
EPOCHS = 50
```

```
# Fit of the model that includes the augmented images in terms of their characteristic
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
248/248 [==============================] - ETA: 0s - loss: 0.6146 - accuracy: 0.7359
Epoch 1: val_loss improved from inf to 4.68321, saving model to model.h5
248/248 [==============================] - 59s 150ms/step - loss: 0.6146 - accuracy:
0.7359 - val_loss: 4.6832 - val_accuracy: 0.4869 - lr: 0.0030
Epoch 2/50
248/248 [==============================] - ETA: 0s - loss: 0.4294 - accuracy: 0.8059
Epoch 2: val_loss improved from 4.68321 to 2.25375, saving model to model.h5
248/248 [==============================] - 35s 141ms/step - loss: 0.4294 - accuracy:
0.8059 - val_loss: 2.2537 - val_accuracy: 0.4869 - lr: 0.0030
Epoch 3/50
248/248 [==============================] - ETA: 0s - loss: 0.3833 - accuracy: 0.8372
Epoch 3: val_loss improved from 2.25375 to 1.27102, saving model to model.h5
248/248 [==============================] - 34s 136ms/step - loss: 0.3833 - accuracy:
0.8372 - val_loss: 1.2710 - val_accuracy: 0.5151 - lr: 0.0030
Epoch 4/50
248/248 [==============================] - ETA: 0s - loss: 0.3738 - accuracy: 0.8372
Epoch 4: val_loss improved from 1.27102 to 0.45459, saving model to model.h5
248/248 [==============================] - 34s 136ms/step - loss: 0.3738 - accuracy:
0.8372 - val_loss: 0.4546 - val_accuracy: 0.7767 - lr: 0.0030
Epoch 5/50
248/248 [==============================] - ETA: 0s - loss: 0.3320 - accuracy: 0.8609
Epoch 5: val_loss did not improve from 0.45459
248/248 [==============================] - 32s 129ms/step - loss: 0.3320 - accuracy:
0.8609 - val_loss: 0.9704 - val_accuracy: 0.6640 - lr: 0.0030
Epoch 6/50
248/248 [==============================] - ETA: 0s - loss: 0.3438 - accuracy: 0.8644
Epoch 6: val_loss improved from 0.45459 to 0.23998, saving model to model.h5
248/248 [==============================] - 34s 136ms/step - loss: 0.3438 - accuracy:
0.8644 - val_loss: 0.2400 - val_accuracy: 0.9135 - lr: 0.0030
Epoch 7/50
248/248 [==============================] - ETA: 0s - loss: 0.3126 - accuracy: 0.8679
Epoch 7: val_loss did not improve from 0.23998
248/248 [==============================] - 36s 145ms/step - loss: 0.3126 - accuracy:
0.8679 - val_loss: 0.2536 - val_accuracy: 0.9135 - lr: 0.0030
Epoch 8/50
248/248 [==============================] - ETA: 0s - loss: 0.2937 - accuracy: 0.8780
Epoch 8: val_loss did not improve from 0.23998
248/248 [==============================] - 32s 130ms/step - loss: 0.2937 - accuracy:
0.8780 - val_loss: 1.0396 - val_accuracy: 0.5272 - lr: 0.0030
Epoch 9/50
248/248 [==============================] - ETA: 0s - loss: 0.2849 - accuracy: 0.8790
Epoch 9: val_loss did not improve from 0.23998
248/248 [==============================] - 32s 130ms/step - loss: 0.2849 - accuracy:
0.8790 - val_loss: 0.4024 - val_accuracy: 0.8652 - lr: 0.0030
Epoch 10/50
248/248 [==============================] - ETA: 0s - loss: 0.2936 - accuracy: 0.8745
Epoch 10: val_loss did not improve from 0.23998
248/248 [==============================] - 32s 130ms/step - loss: 0.2936 - accuracy:
0.8745 - val_loss: 0.4092 - val_accuracy: 0.8913 - lr: 0.0030
Epoch 11/50
248/248 [==============================] - ETA: 0s - loss: 0.2811 - accuracy: 0.8831
Epoch 11: ReduceLROnPlateau reducing learning rate to 0.002100000018253922.

Epoch 11: val_loss improved from 0.23998 to 0.23202, saving model to model.h5
248/248 [==============================] - 34s 136ms/step - loss: 0.2811 - accuracy:
0.8831 - val_loss: 0.2320 - val_accuracy: 0.9095 - lr: 0.0030
Epoch 12/50
248/248 [==============================] - ETA: 0s - loss: 0.2719 - accuracy: 0.8997
Epoch 12: val_loss did not improve from 0.23202
```

```
248/248 [==============================] - 32s 129ms/step - loss: 0.2719 - accuracy:
0.8997 - val_loss: 0.4670 - val_accuracy: 0.8129 - lr: 0.0021
Epoch 13/50
248/248 [==============================] - ETA: 0s - loss: 0.1982 - accuracy: 0.9214
Epoch 13: val_loss did not improve from 0.23202
248/248 [==============================] - 32s 129ms/step - loss: 0.1982 - accuracy:
0.9214 - val_loss: 0.2339 - val_accuracy: 0.9135 - lr: 0.0021
Epoch 14/50
248/248 [==============================] - ETA: 0s - loss: 0.2265 - accuracy: 0.9098
Epoch 14: val_loss did not improve from 0.23202
248/248 [==============================] - 32s 129ms/step - loss: 0.2265 - accuracy:
0.9098 - val_loss: 1.1749 - val_accuracy: 0.6016 - lr: 0.0021
Epoch 15/50
248/248 [==============================] - ETA: 0s - loss: 0.2348 - accuracy: 0.9032
Epoch 15: val_loss did not improve from 0.23202
248/248 [==============================] - 32s 129ms/step - loss: 0.2348 - accuracy:
0.9032 - val_loss: 0.3384 - val_accuracy: 0.8390 - lr: 0.0021
Epoch 16/50
248/248 [==============================] - ETA: 0s - loss: 0.2498 - accuracy: 0.9042
Epoch 16: val_loss improved from 0.23202 to 0.21326, saving model to model.h5
248/248 [==============================] - 34s 136ms/step - loss: 0.2498 - accuracy:
0.9042 - val_loss: 0.2133 - val_accuracy: 0.9175 - lr: 0.0021
Epoch 17/50
248/248 [==============================] - ETA: 0s - loss: 0.2184 - accuracy: 0.9153
Epoch 17: val_loss improved from 0.21326 to 0.20781, saving model to model.h5
248/248 [==============================] - 34s 137ms/step - loss: 0.2184 - accuracy:
0.9153 - val_loss: 0.2078 - val_accuracy: 0.9155 - lr: 0.0021
Epoch 18/50
248/248 [==============================] - ETA: 0s - loss: 0.2023 - accuracy: 0.9249
Epoch 18: val_loss did not improve from 0.20781
248/248 [==============================] - 32s 130ms/step - loss: 0.2023 - accuracy:
0.9249 - val_loss: 0.3145 - val_accuracy: 0.9235 - lr: 0.0021
Epoch 19/50
248/248 [==============================] - ETA: 0s - loss: 0.1843 - accuracy: 0.9355
Epoch 19: val_loss did not improve from 0.20781
248/248 [==============================] - 32s 130ms/step - loss: 0.1843 - accuracy:
0.9355 - val_loss: 0.4504 - val_accuracy: 0.8632 - lr: 0.0021
Epoch 20/50
248/248 [==============================] - ETA: 0s - loss: 0.2048 - accuracy: 0.9214
Epoch 20: val_loss improved from 0.20781 to 0.16727, saving model to model.h5
248/248 [==============================] - 34s 136ms/step - loss: 0.2048 - accuracy:
0.9214 - val_loss: 0.1673 - val_accuracy: 0.9356 - lr: 0.0021
Epoch 21/50
248/248 [==============================] - ETA: 0s - loss: 0.1690 - accuracy: 0.9385
Epoch 21: val_loss did not improve from 0.16727
248/248 [==============================] - 32s 130ms/step - loss: 0.1690 - accuracy:
0.9385 - val_loss: 0.2404 - val_accuracy: 0.9095 - lr: 0.0021
Epoch 22/50
248/248 [==============================] - ETA: 0s - loss: 0.1932 - accuracy: 0.9274
Epoch 22: val_loss did not improve from 0.16727
248/248 [==============================] - 32s 130ms/step - loss: 0.1932 - accuracy:
0.9274 - val_loss: 0.2293 - val_accuracy: 0.9296 - lr: 0.0021
Epoch 23/50
248/248 [==============================] - ETA: 0s - loss: 0.1779 - accuracy: 0.9345
Epoch 23: val_loss did not improve from 0.16727
248/248 [==============================] - 32s 130ms/step - loss: 0.1779 - accuracy:
0.9345 - val_loss: 0.1698 - val_accuracy: 0.9276 - lr: 0.0021
Epoch 24/50
248/248 [==============================] - ETA: 0s - loss: 0.1943 - accuracy: 0.9254
Epoch 24: val_loss did not improve from 0.16727
```

```
248/248 [==============================] - 33s 131ms/step - loss: 0.1943 - accuracy:
0.9254 - val_loss: 0.2686 - val_accuracy: 0.9034 - lr: 0.0021
Epoch 25/50
248/248 [==============================] - ETA: 0s - loss: 0.1745 - accuracy: 0.9294
Epoch 25: ReduceLROnPlateau reducing learning rate to 0.0014699999475851653.

Epoch 25: val_loss did not improve from 0.16727
248/248 [==============================] - 32s 129ms/step - loss: 0.1745 - accuracy:
0.9294 - val_loss: 0.6511 - val_accuracy: 0.8270 - lr: 0.0021
Epoch 26/50
248/248 [==============================] - ETA: 0s - loss: 0.1599 - accuracy: 0.9435
Epoch 26: val_loss did not improve from 0.16727
248/248 [==============================] - 32s 130ms/step - loss: 0.1599 - accuracy:
0.9435 - val_loss: 0.2603 - val_accuracy: 0.8994 - lr: 0.0015
Epoch 27/50
248/248 [==============================] - ETA: 0s - loss: 0.1245 - accuracy: 0.9572
Epoch 27: val_loss improved from 0.16727 to 0.09714, saving model to model.h5
248/248 [==============================] - 34s 136ms/step - loss: 0.1245 - accuracy:
0.9572 - val_loss: 0.0971 - val_accuracy: 0.9718 - lr: 0.0015
Epoch 28/50
248/248 [==============================] - ETA: 0s - loss: 0.1117 - accuracy: 0.9688
Epoch 28: val_loss did not improve from 0.09714
248/248 [==============================] - 32s 130ms/step - loss: 0.1117 - accuracy:
0.9688 - val_loss: 0.6843 - val_accuracy: 0.7746 - lr: 0.0015
Epoch 29/50
248/248 [==============================] - ETA: 0s - loss: 0.1471 - accuracy: 0.9516
Epoch 29: val_loss improved from 0.09714 to 0.08412, saving model to model.h5
248/248 [==============================] - 34s 136ms/step - loss: 0.1471 - accuracy:
0.9516 - val_loss: 0.0841 - val_accuracy: 0.9678 - lr: 0.0015
Epoch 30/50
248/248 [==============================] - ETA: 0s - loss: 0.1386 - accuracy: 0.9486
Epoch 30: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 129ms/step - loss: 0.1386 - accuracy:
0.9486 - val_loss: 0.8945 - val_accuracy: 0.7002 - lr: 0.0015
Epoch 31/50
248/248 [==============================] - ETA: 0s - loss: 0.1260 - accuracy: 0.9567
Epoch 31: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 130ms/step - loss: 0.1260 - accuracy:
0.9567 - val_loss: 0.3168 - val_accuracy: 0.9155 - lr: 0.0015
Epoch 32/50
248/248 [==============================] - ETA: 0s - loss: 0.1174 - accuracy: 0.9627
Epoch 32: ReduceLROnPlateau reducing learning rate to 0.0010289999307133257.

Epoch 32: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 130ms/step - loss: 0.1174 - accuracy:
0.9627 - val_loss: 0.5649 - val_accuracy: 0.8008 - lr: 0.0015
Epoch 33/50
248/248 [==============================] - ETA: 0s - loss: 0.1015 - accuracy: 0.9622
Epoch 33: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 130ms/step - loss: 0.1015 - accuracy:
0.9622 - val_loss: 0.0888 - val_accuracy: 0.9678 - lr: 0.0010
Epoch 34/50
248/248 [==============================] - ETA: 0s - loss: 0.0831 - accuracy: 0.9698
Epoch 34: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 130ms/step - loss: 0.0831 - accuracy:
0.9698 - val_loss: 0.9765 - val_accuracy: 0.6821 - lr: 0.0010
Epoch 35/50
248/248 [==============================] - ETA: 0s - loss: 0.0927 - accuracy: 0.9693
Epoch 35: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 131ms/step - loss: 0.0927 - accuracy:
```

```
0.9693 - val_loss: 0.1176 - val_accuracy: 0.9618 - lr: 0.0010
Epoch 36/50
248/248 [==============================] - ETA: 0s - loss: 0.1296 - accuracy: 0.9572
Epoch 36: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 130ms/step - loss: 0.1296 - accuracy:
0.9572 - val_loss: 0.2019 - val_accuracy: 0.9396 - lr: 0.0010
Epoch 37/50
248/248 [==============================] - ETA: 0s - loss: 0.0985 - accuracy: 0.9642
Epoch 37: ReduceLROnPlateau reducing learning rate to 0.0007202999433502554.

Epoch 37: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 130ms/step - loss: 0.0985 - accuracy:
0.9642 - val_loss: 0.1179 - val_accuracy: 0.9557 - lr: 0.0010
Epoch 38/50
248/248 [==============================] - ETA: 0s - loss: 0.1108 - accuracy: 0.9642
Epoch 38: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 131ms/step - loss: 0.1108 - accuracy:
0.9642 - val_loss: 0.0998 - val_accuracy: 0.9557 - lr: 7.2030e-04
Epoch 39/50
248/248 [==============================] - ETA: 0s - loss: 0.0815 - accuracy: 0.9748
Epoch 39: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 130ms/step - loss: 0.0815 - accuracy:
0.9748 - val_loss: 0.1044 - val_accuracy: 0.9638 - lr: 7.2030e-04
Epoch 40/50
248/248 [==============================] - ETA: 0s - loss: 0.0810 - accuracy: 0.9743
Epoch 40: val_loss did not improve from 0.08412
248/248 [==============================] - 33s 134ms/step - loss: 0.0810 - accuracy:
0.9743 - val_loss: 0.1339 - val_accuracy: 0.9517 - lr: 7.2030e-04
Epoch 41/50
248/248 [==============================] - ETA: 0s - loss: 0.1033 - accuracy: 0.9698
Epoch 41: val_loss did not improve from 0.08412
248/248 [==============================] - 32s 130ms/step - loss: 0.1033 - accuracy:
0.9698 - val_loss: 0.2593 - val_accuracy: 0.9095 - lr: 7.2030e-04
Epoch 42/50
248/248 [==============================] - ETA: 0s - loss: 0.0917 - accuracy: 0.9698
Epoch 42: val_loss improved from 0.08412 to 0.07990, saving model to model.h5
248/248 [==============================] - 34s 135ms/step - loss: 0.0917 - accuracy:
0.9698 - val_loss: 0.0799 - val_accuracy: 0.9759 - lr: 7.2030e-04
Epoch 43/50
248/248 [==============================] - ETA: 0s - loss: 0.0856 - accuracy: 0.9698
Epoch 43: val_loss did not improve from 0.07990
248/248 [==============================] - 32s 130ms/step - loss: 0.0856 - accuracy:
0.9698 - val_loss: 0.1937 - val_accuracy: 0.9256 - lr: 7.2030e-04
Epoch 44/50
248/248 [==============================] - ETA: 0s - loss: 0.0894 - accuracy: 0.9708
Epoch 44: val_loss did not improve from 0.07990
248/248 [==============================] - 33s 135ms/step - loss: 0.0894 - accuracy:
0.9708 - val_loss: 0.0804 - val_accuracy: 0.9759 - lr: 7.2030e-04
Epoch 45/50
248/248 [==============================] - ETA: 0s - loss: 0.0874 - accuracy: 0.9662
Epoch 45: val_loss did not improve from 0.07990
248/248 [==============================] - 32s 130ms/step - loss: 0.0874 - accuracy:
0.9662 - val_loss: 0.1187 - val_accuracy: 0.9577 - lr: 7.2030e-04
Epoch 46/50
248/248 [==============================] - ETA: 0s - loss: 0.0865 - accuracy: 0.9698
Epoch 46: val_loss did not improve from 0.07990
248/248 [==============================] - 32s 131ms/step - loss: 0.0865 - accuracy:
0.9698 - val_loss: 0.0895 - val_accuracy: 0.9698 - lr: 7.2030e-04
Epoch 47/50
248/248 [==============================] - ETA: 0s - loss: 0.0794 - accuracy: 0.9748
```

```
Epoch 47: ReduceLROnPlateau reducing learning rate to 0.0005042099684942513.

Epoch 47: val_loss did not improve from 0.07990
248/248 [==============================] - 32s 130ms/step - loss: 0.0794 - accuracy:
0.9748 - val_loss: 0.1044 - val_accuracy: 0.9678 - lr: 7.2030e-04
Epoch 48/50
248/248 [==============================] - ETA: 0s - loss: 0.0703 - accuracy: 0.9788
Epoch 48: val_loss did not improve from 0.07990
248/248 [==============================] - 32s 130ms/step - loss: 0.0703 - accuracy:
0.9788 - val_loss: 0.0800 - val_accuracy: 0.9759 - lr: 5.0421e-04
Epoch 49/50
248/248 [==============================] - ETA: 0s - loss: 0.0636 - accuracy: 0.9819
Epoch 49: val_loss did not improve from 0.07990
248/248 [==============================] - 32s 129ms/step - loss: 0.0636 - accuracy:
0.9819 - val_loss: 0.2078 - val_accuracy: 0.9215 - lr: 5.0421e-04
Epoch 50/50
248/248 [==============================] - ETA: 0s - loss: 0.0610 - accuracy: 0.9798
Epoch 50: val_loss did not improve from 0.07990
248/248 [==============================] - 32s 130ms/step - loss: 0.0610 - accuracy:
0.9798 - val_loss: 0.0809 - val_accuracy: 0.9799 - lr: 5.0421e-04
```

Observations :

1- My **final Accuracy** is **0.9798**.

1. **final Loss** is **0.0610**.
2. **Val_loss** is **0.0809**.
3. **Val_accuracy** is **0.9790**.

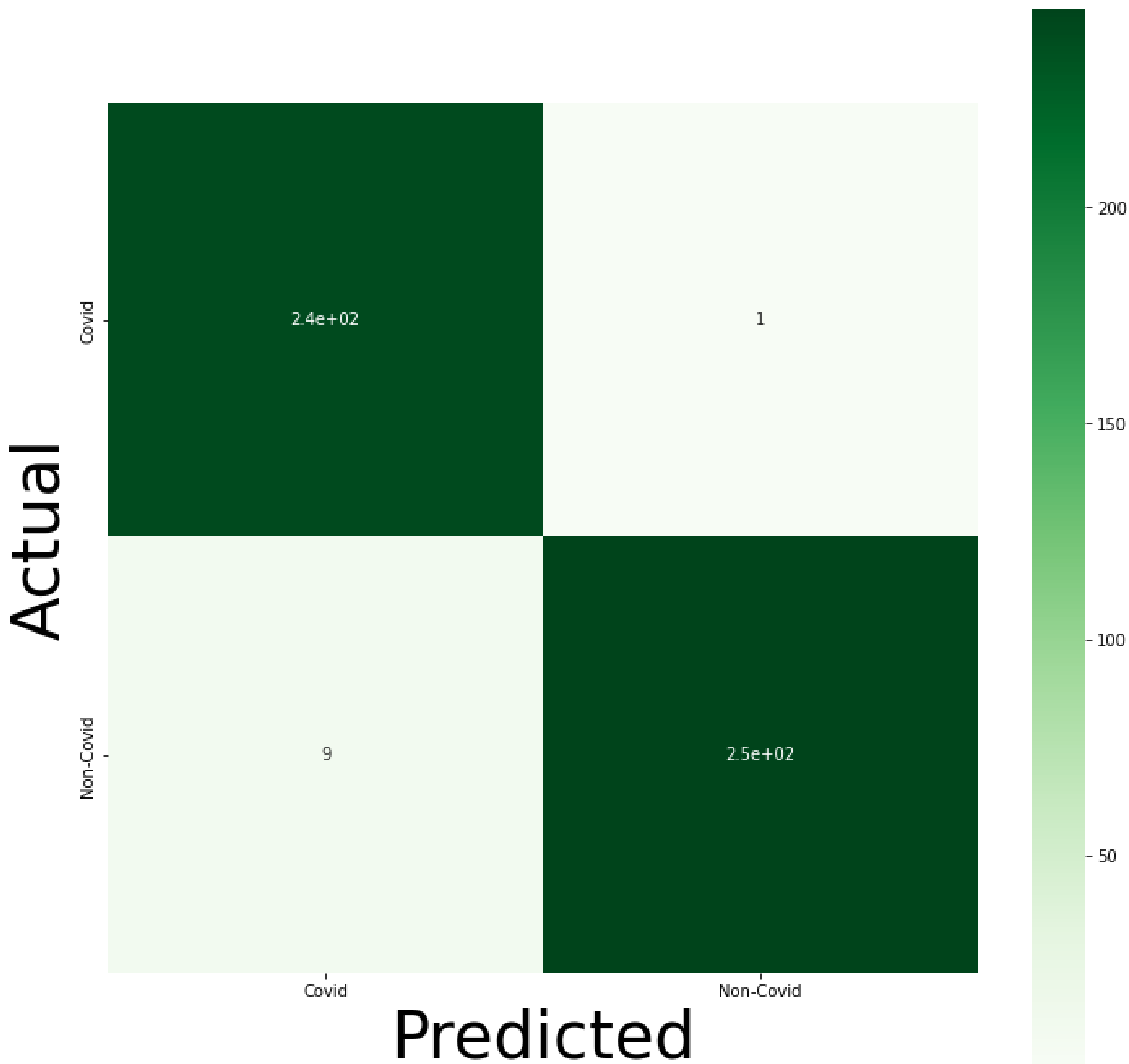
Checking the Accuracy

In [11]:

```
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 =
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: 246
False Negative: 9
True Negative: 241
False Positive: 1
True Positive Rate: 0.9647058823529412
True Negative Rate: 0.9958677685950413

16/16 [==============================] - 2s 103ms/step - loss: 0.0809 - accuracy: 0.9
799

Final Loss: 0.08092107623815536, Final Accuracy: 0.9798792600631714
```



Observations :

1- **True Positive: 246**

2- False Negative: 9

3- **True Negative: 241**

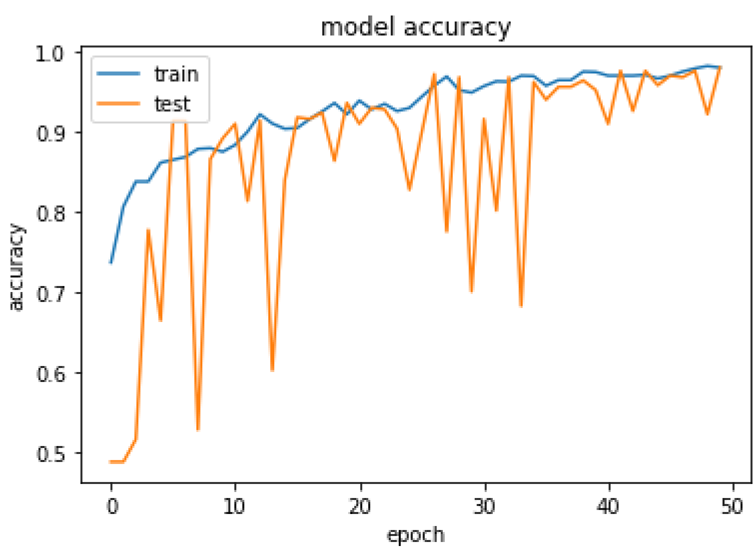
4- False Positive: 1

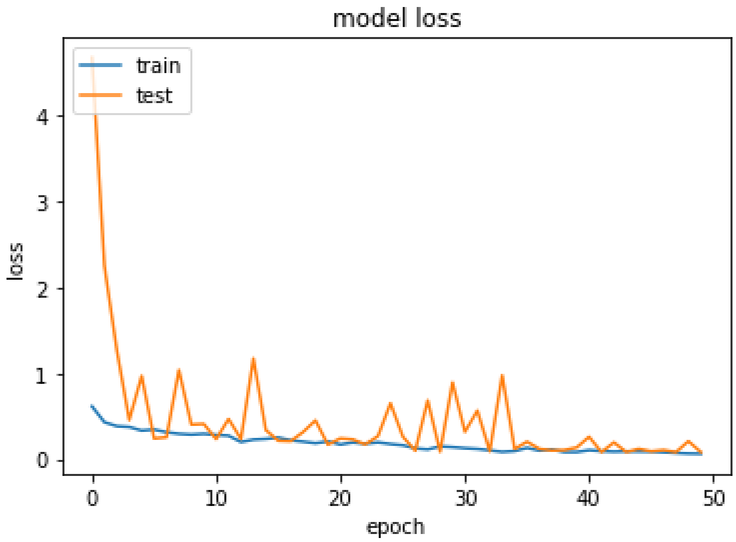
5- **True Positive Rate: 0.9647058823529412**

6- **True Negative Rate: 0.9958677685950413**

7. Comparing the Model Acccuracy

In [12]:
```
# 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()
```



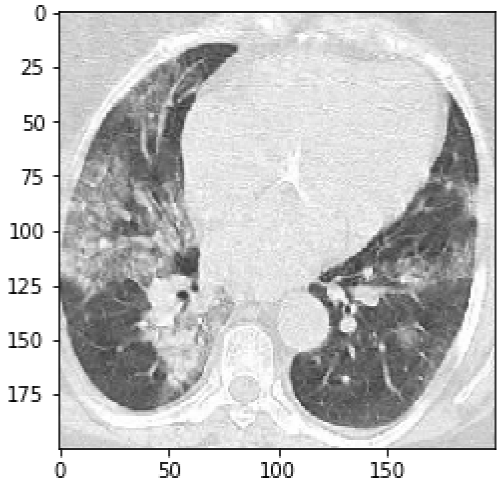


8. Predicting the Images

Test 1

In [15]:
```
from keras.preprocessing import image

img = image.load_img('/content/drive/MyDrive/Colab Notebooks/Capstone Project/Dataset/
show_img = image.load_img('/content/drive/MyDrive/Colab Notebooks/Capstone Project/Dat
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])
```

```
[9.99899626e-01 1.00384554e-04]
```



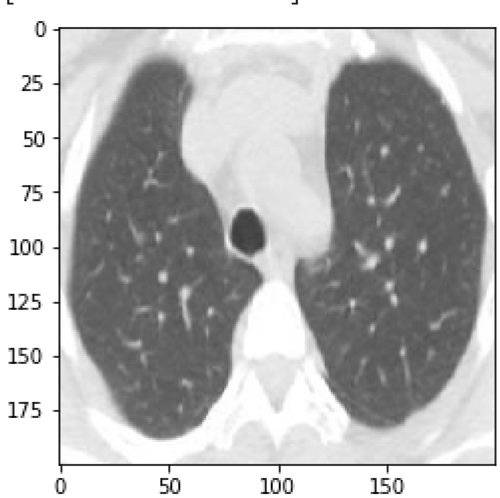
```
Prediction: Covid-19
```

Test 2

In [14]:

```
from keras.preprocessing import image

img = image.load_img('/content/drive/MyDrive/Colab Notebooks/Capstone Project/Dataset/
show_img = image.load_img('/content/drive/MyDrive/Colab Notebooks/Capstone Project/Dat
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])
```

```
[0.0328724 0.9671277]
```

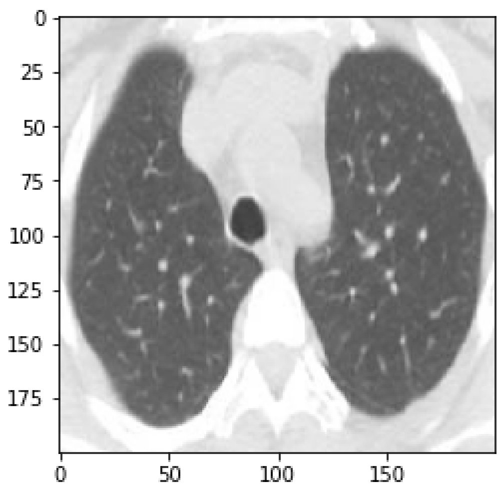


```
Prediction: Non Covid-19
```

Test 3

In [16]:
```
from keras.preprocessing import image

img = image.load_img('/content/drive/MyDrive/Colab Notebooks/Capstone Project/Dataset/
show_img = image.load_img('/content/drive/MyDrive/Colab Notebooks/Capstone Project/Dat
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])
```

```
[4.2860906e-04 9.9957138e-01]
```




```
Prediction: Non Covid-19
```

As we can see all the points are predected correctly.

The **Capstone Project** has been **completed Succesfully.**