In [ ]:
```
from google.colab import drive
drive.mount('/content/MyDrive/')
```

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

DESCRIPTION

Artificial Intelligence has evolved a lot and is currently able to solve problems that are very complex and require human specialization. One such area is healthcare.

A lot of research happens every day to use deep learning for the betterment of humanity, and one such is healthcare.

Objective:

To build a model using a convolutional neural network that can classify lung infection in a person using medical imagery

Dataset Description:

The dataset contains three different classes, including healthy, type 1 disease, and type 2 disease.

```
Train folder: This folder has images for training the model, which is divided
into subfolders having the same name as the class.

Test folder: This folder has images for testing the model, which is divided in
to subfolders having the same name as the class.
```

Following operations should be performed using Keras or PyTorch or Torch vision-

```
Import the necessary libraries

Plot the sample images for all the classes

Plot the distribution of images across the classes

Build a data augmentation for train data to create new data with translation,
rescale and flip, and rotation transformations. Rescale the image at 48x48

Build a data augmentation for test data to create new data and rescale the ima
ge at 48x48

Read images directly from the train folder and test folder using the appropria
te function
```

In [ ]:
```
import os
import time
import cv2
from google.colab.patches import cv2_imshow
import pickle
import random as rnd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
import tensorflow as tf
import tensorflow.keras as keras
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import confusion_matrix
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.applications import MobileNet
from tensorflow.keras.applications.mobilenet import preprocess_input
from tensorflow.keras.layers import Dense, Activation, Conv2D, MaxPooling
2D, Flatten, Dropout, BatchNormalization, GlobalAveragePooling2D
from tensorflow.keras.preprocessing import image_dataset_from_directory
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import tensorflow.keras.layers as tfl
from tensorflow.keras.layers.experimental.preprocessing import RandomFli
p, RandomRotation
```

In [ ]:
```
def preprocess(image_path, train, image_size):
    image = cv2.imread(image_path)
    image = cv2.resize(image, (image_size, image_size))
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = image/255
    return image
```

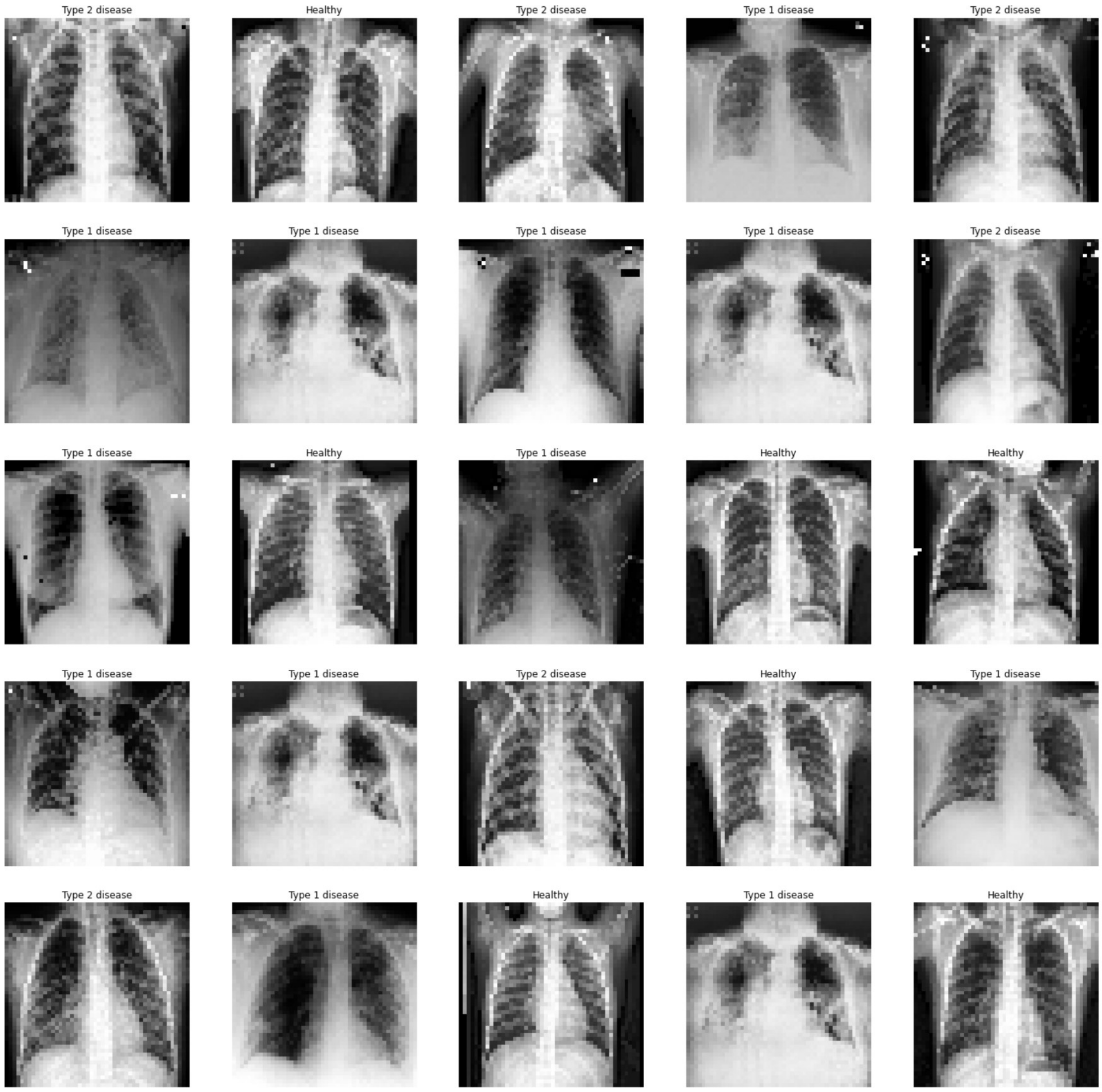
In [ ]:
```
def get_data(data_dir, train=True, image_size=48):
    data = []
    labels = []
    if train:
        path = os.path.join(data_dir, 'train')
    else:
        path = os.path.join(data_dir, 'test')
    for folder in os.listdir(path):
        if folder == ".DS_Store":
            continue
        image_dir = os.path.join(path, folder)
        for image in os.listdir(image_dir):
            if image == ".DS_Store":
                continue
            image_path = os.path.join(image_dir, image)

            image = preprocess(image_path, train, image_size)
            data.append(image)
            labels.append([folder])
    if train:
        datagen = ImageDataGenerator(
            rotation_range = 20,
            shear_range = 0.1,
            zoom_range = 0.1,
            horizontal_flip = False,)
        datagen.fit(data)
    return np.array(data), np.array(labels)
```

In [ ]:
```
train_images, train_labels = get_data('/content/MyDrive/MyDrive/Adv Deep Learning Image Recognition/Dataset_Detection_of_Lung_Infection/data')
test_images, test_labels = get_data('/content/MyDrive/MyDrive/Adv Deep Learning Image Recognition/Dataset_Detection_of_Lung_Infection/data', train=False)
print(train_images.shape)
print(test_images.shape)
```

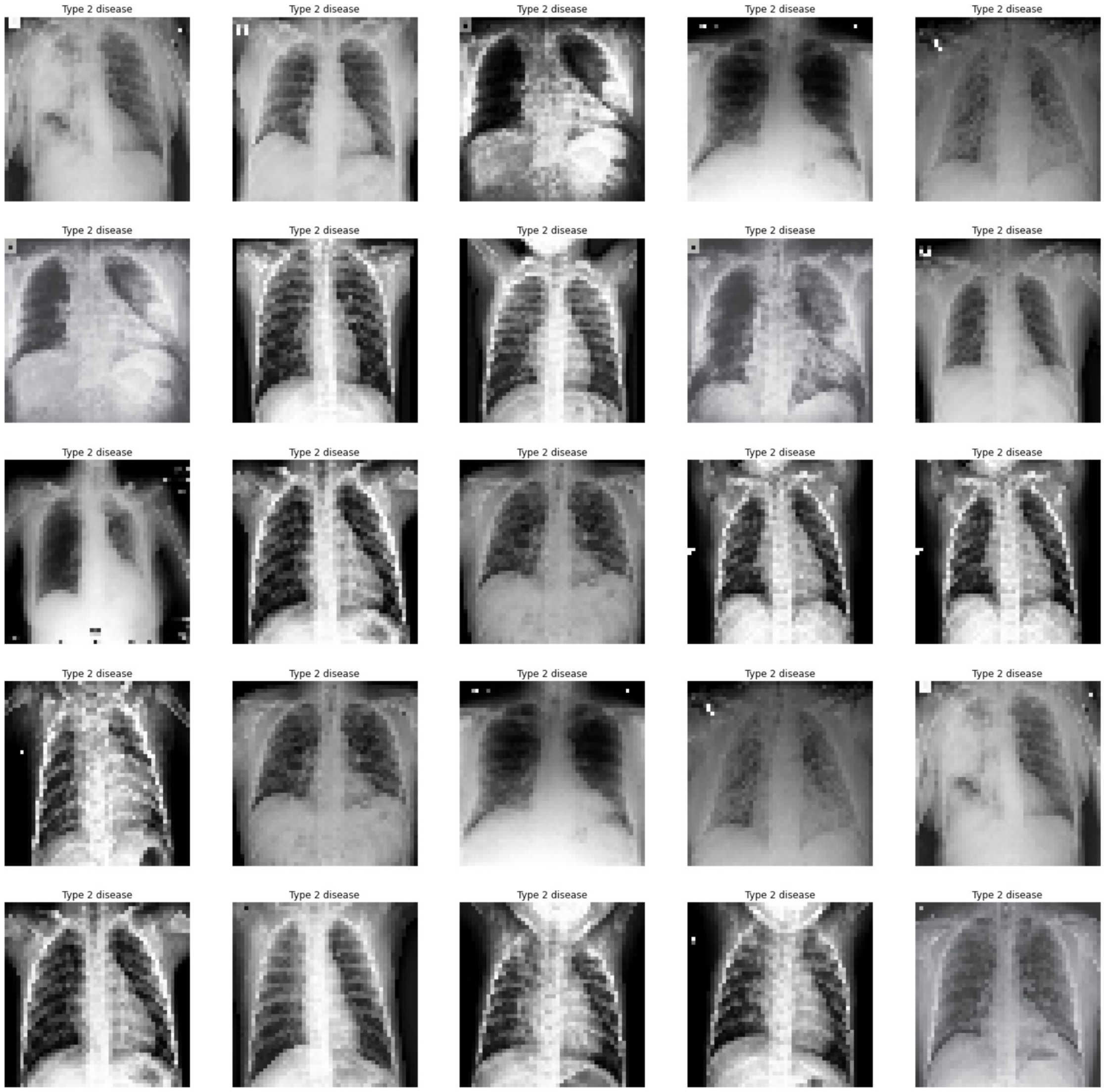
```
(251, 48, 48, 3)
(66, 48, 48, 3)
```

In [ ]:
```
def show_rnd_images(images, labels):
    fig, ax = plt.subplots(5, 5, figsize=(25,25))
    for i in range(5):
        for j in range(5):
            rnd_int = rnd.randint(0, len(images)-1)
            ax[i,j].imshow(images[rnd_int],cmap='gray')
            ax[i,j].axis("off")
            ax[i,j].title.set_text(labels[rnd_int][0])
    plt.show()
```

In [ ]:
```
show_rnd_images(train_images, train_labels)
```



In [ ]:
```
# Show test Images
show_rnd_images(test_images, train_labels)
```




In [ ]:
```
train_images, train_labels = get_data('/content/MyDrive/MyDrive/Adv Deep
Learning Image Recognition/Dataset_Detection_of_Lung_Infection/data')
test_images, test_labels = get_data('/content/MyDrive/MyDrive/Adv Deep Le
arning Image Recognition/Dataset_Detection_of_Lung_Infection/data', train
=False)
print(train_images.shape)
print(test_images.shape)
```

```
(251, 48, 48, 3)
(66, 48, 48, 3)
```

In [ ]:
```
# Change healthy to Healthy label in Test labels
train_labels[train_labels == ["Healthy"]] = ['Healthy']
test_labels[test_labels == ["Healthy"]] = ['Healthy']
```

In [ ]:
```
from sklearn.preprocessing import OneHotEncoder
enc = OneHotEncoder()
train_labels = enc.fit_transform(train_labels).toarray()
test_labels = enc.transform(test_labels).toarray()
```

In [ ]:
```
model = Sequential()

model.add(Conv2D(64, (3, 3), input_shape=train_images.shape[1:], padding=
'same'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2), padding='same'))

model.add(Conv2D(16, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2), padding='same'))

model.add(Flatten())

model.add(Dropout(0.5))
model.add(Dense(64))
model.add(Activation('relu'))

model.add(Dropout(0.5))
model.add(Dense(3))
model.add(Activation('sigmoid'))

early_stop = EarlyStopping(patience=3, monitor='val_loss', restore_best_w
eights=True)

model.compile(loss='categorical_crossentropy',optimizer='adam', metrics=
[keras.metrics.AUC(from_logits=True)])
```

In [ ]:
```
model.summary()
```

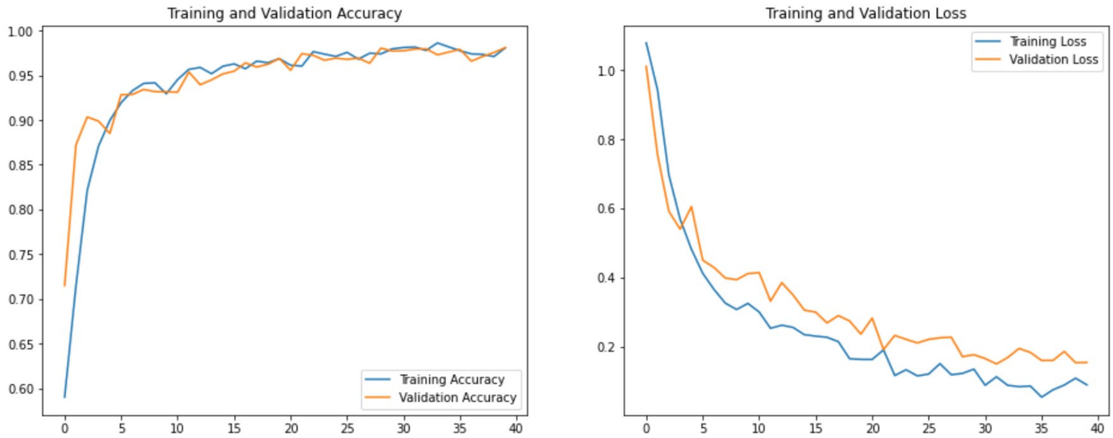
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 48, 48, 64)        1792      
                                                                 
 activation (Activation)     (None, 48, 48, 64)        0         
                                                                 
 max_pooling2d (MaxPooling2D  (None, 24, 24, 64)       0         
 )                                                               
                                                                 
 conv2d_1 (Conv2D)           (None, 24, 24, 16)        9232      
                                                                 
 activation_1 (Activation)   (None, 24, 24, 16)        0         
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 12, 12, 16)       0         
 2D)                                                             
                                                                 
 flatten (Flatten)           (None, 2304)              0         
                                                                 
 dropout (Dropout)           (None, 2304)              0         
                                                                 
 dense (Dense)               (None, 64)                147520    
                                                                 
 activation_2 (Activation)   (None, 64)                0         
                                                                 
 dropout_1 (Dropout)         (None, 64)                0         
                                                                 
 dense_1 (Dense)             (None, 3)                 195       
                                                                 
 activation_3 (Activation)   (None, 3)                 0         
                                                                 
=================================================================
Total params: 158,739
Trainable params: 158,739
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:
```
history = model.fit(train_images, train_labels,
                    validation_data=(test_images, test_labels),
                    epochs=40)
```

```
Epoch 1/40
8/8 [==============================] - 2s 196ms/step - loss: 1.0783 - au
c: 0.5904 - val_loss: 1.0101 - val_auc: 0.7150
Epoch 2/40
8/8 [==============================] - 1s 161ms/step - loss: 0.9426 - au
c: 0.7145 - val_loss: 0.7552 - val_auc: 0.8722
Epoch 3/40
8/8 [==============================] - 1s 158ms/step - loss: 0.6970 - au
c: 0.8215 - val_loss: 0.5915 - val_auc: 0.9034
Epoch 4/40
8/8 [==============================] - 1s 157ms/step - loss: 0.5687 - au
c: 0.8709 - val_loss: 0.5398 - val_auc: 0.8988
Epoch 5/40
8/8 [==============================] - 2s 197ms/step - loss: 0.4817 - au
c: 0.8996 - val_loss: 0.6049 - val_auc: 0.8850
Epoch 6/40
8/8 [==============================] - 3s 329ms/step - loss: 0.4122 - au
c: 0.9194 - val_loss: 0.4500 - val_auc: 0.9284
Epoch 7/40
8/8 [==============================] - 2s 317ms/step - loss: 0.3654 - au
c: 0.9328 - val_loss: 0.4290 - val_auc: 0.9286
Epoch 8/40
8/8 [==============================] - 3s 360ms/step - loss: 0.3258 - au
c: 0.9409 - val_loss: 0.3984 - val_auc: 0.9342
Epoch 9/40
8/8 [==============================] - 3s 353ms/step - loss: 0.3075 - au
c: 0.9416 - val_loss: 0.3937 - val_auc: 0.9317
Epoch 10/40
8/8 [==============================] - 2s 308ms/step - loss: 0.3251 - au
c: 0.9294 - val_loss: 0.4112 - val_auc: 0.9315
Epoch 11/40
8/8 [==============================] - 2s 267ms/step - loss: 0.3000 - au
c: 0.9452 - val_loss: 0.4141 - val_auc: 0.9312
Epoch 12/40
8/8 [==============================] - 3s 350ms/step - loss: 0.2532 - au
c: 0.9566 - val_loss: 0.3317 - val_auc: 0.9536
Epoch 13/40
8/8 [==============================] - 2s 232ms/step - loss: 0.2620 - au
c: 0.9588 - val_loss: 0.3852 - val_auc: 0.9395
Epoch 14/40
8/8 [==============================] - 1s 158ms/step - loss: 0.2555 - au
c: 0.9518 - val_loss: 0.3493 - val_auc: 0.9449
Epoch 15/40
8/8 [==============================] - 1s 154ms/step - loss: 0.2346 - au
c: 0.9601 - val_loss: 0.3055 - val_auc: 0.9515
Epoch 16/40
8/8 [==============================] - 1s 157ms/step - loss: 0.2304 - au
c: 0.9627 - val_loss: 0.2998 - val_auc: 0.9546
Epoch 17/40
8/8 [==============================] - 1s 158ms/step - loss: 0.2271 - au
c: 0.9573 - val_loss: 0.2686 - val_auc: 0.9638
Epoch 18/40
8/8 [==============================] - 1s 159ms/step - loss: 0.2146 - au
c: 0.9658 - val_loss: 0.2898 - val_auc: 0.9593
Epoch 19/40
8/8 [==============================] - 1s 159ms/step - loss: 0.1651 - au
c: 0.9640 - val_loss: 0.2743 - val_auc: 0.9624
Epoch 20/40
8/8 [==============================] - 1s 158ms/step - loss: 0.1632 - au
c: 0.9686 - val_loss: 0.2361 - val_auc: 0.9688
```

```
Epoch 21/40
8/8 [==============================] - 1s 160ms/step - loss: 0.1630 - au
c: 0.9613 - val_loss: 0.2827 - val_auc: 0.9557
Epoch 22/40
8/8 [==============================] - 1s 156ms/step - loss: 0.1907 - au
c: 0.9603 - val_loss: 0.1916 - val_auc: 0.9742
Epoch 23/40
8/8 [==============================] - 1s 155ms/step - loss: 0.1166 - au
c: 0.9764 - val_loss: 0.2326 - val_auc: 0.9723
Epoch 24/40
8/8 [==============================] - 1s 155ms/step - loss: 0.1332 - au
c: 0.9736 - val_loss: 0.2213 - val_auc: 0.9669
Epoch 25/40
8/8 [==============================] - 1s 155ms/step - loss: 0.1155 - au
c: 0.9711 - val_loss: 0.2108 - val_auc: 0.9692
Epoch 26/40
8/8 [==============================] - 1s 155ms/step - loss: 0.1209 - au
c: 0.9756 - val_loss: 0.2212 - val_auc: 0.9679
Epoch 27/40
8/8 [==============================] - 1s 157ms/step - loss: 0.1508 - au
c: 0.9680 - val_loss: 0.2256 - val_auc: 0.9692
Epoch 28/40
8/8 [==============================] - 1s 156ms/step - loss: 0.1188 - au
c: 0.9747 - val_loss: 0.2273 - val_auc: 0.9635
Epoch 29/40
8/8 [==============================] - 1s 155ms/step - loss: 0.1227 - au
c: 0.9740 - val_loss: 0.1711 - val_auc: 0.9803
Epoch 30/40
8/8 [==============================] - 1s 154ms/step - loss: 0.1350 - au
c: 0.9795 - val_loss: 0.1767 - val_auc: 0.9772
Epoch 31/40
8/8 [==============================] - 1s 155ms/step - loss: 0.0883 - au
c: 0.9810 - val_loss: 0.1657 - val_auc: 0.9774
Epoch 32/40
8/8 [==============================] - 1s 156ms/step - loss: 0.1129 - au
c: 0.9815 - val_loss: 0.1500 - val_auc: 0.9793
Epoch 33/40
8/8 [==============================] - 1s 157ms/step - loss: 0.0881 - au
c: 0.9778 - val_loss: 0.1688 - val_auc: 0.9795
Epoch 34/40
8/8 [==============================] - 1s 156ms/step - loss: 0.0844 - au
c: 0.9862 - val_loss: 0.1948 - val_auc: 0.9729
Epoch 35/40
8/8 [==============================] - 1s 156ms/step - loss: 0.0862 - au
c: 0.9817 - val_loss: 0.1833 - val_auc: 0.9760
Epoch 36/40
8/8 [==============================] - 1s 158ms/step - loss: 0.0540 - au
c: 0.9774 - val_loss: 0.1601 - val_auc: 0.9789
Epoch 37/40
8/8 [==============================] - 1s 160ms/step - loss: 0.0751 - au
c: 0.9740 - val_loss: 0.1601 - val_auc: 0.9658
Epoch 38/40
8/8 [==============================] - 1s 157ms/step - loss: 0.0890 - au
c: 0.9734 - val_loss: 0.1862 - val_auc: 0.9711
Epoch 39/40
8/8 [==============================] - 1s 156ms/step - loss: 0.1088 - au
c: 0.9709 - val_loss: 0.1537 - val_auc: 0.9754
Epoch 40/40
8/8 [==============================] - 1s 156ms/step - loss: 0.0897 - au
c: 0.9807 - val_loss: 0.1543 - val_auc: 0.9808
```

In [ ]:
```
plt.figure(figsize=(16, 6))
plt.subplot(1, 2, 1)
plt.plot(history.history['auc'], label='Training Accuracy')
plt.plot(history.history['val_auc'], label='Validation Accuracy')
plt.legend()
plt.title('Training and Validation Accuracy')

# ________________ Graph 2 -------------------------

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend()
plt.title('Training and Validation Loss')
plt.show()
```




In [ ]:
```
def prediction(images):
    y_pred = []
    for i in model.predict(images).argmax(axis=1):
        tmp = [0., 0., 0.]
        tmp[i] = 1.
        y_pred.append(tmp)
    y_pred = enc.inverse_transform(y_pred)
    return y_pred
```

In [ ]:
```
y_pred = prediction(test_images)
```

```
3/3 [==============================] - 0s 21ms/step
```

In [ ]:
```
y_true = enc.inverse_transform(test_labels)
```

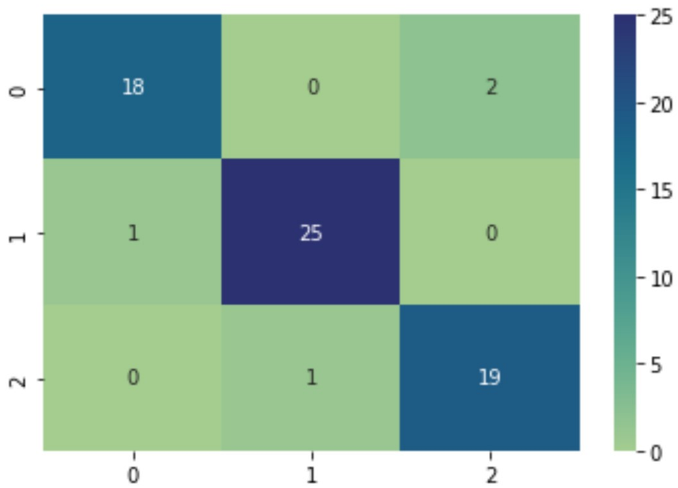
In [ ]:
```
from sklearn.metrics import accuracy_score, confusion_matrix,classificati
on_report
print(accuracy_score(y_true, y_pred))
print(classification_report(y_true, y_pred))
confusion_matrix(y_true, y_pred)
```

```
0.9393939393939394
                precision    recall  f1-score   support

       Healthy       0.95      0.90      0.92        20
Type 1 disease       0.96      0.96      0.96        26
Type 2 disease       0.90      0.95      0.93        20

      accuracy                           0.94        66
     macro avg       0.94      0.94      0.94        66
  weighted avg       0.94      0.94      0.94        66
```

Out[ ]:
```
array([[18,  0,  2],
       [ 1, 25,  0],
       [ 0,  1, 19]])
```

In [ ]:
```
sns.heatmap(confusion_matrix(y_true, y_pred),annot=True,fmt='d',cmap= "cr
est")
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6a12d85310>




In [ ]:
```
model.evaluate(test_images, test_labels, batch_size=16)
```

```
5/5 [==============================] - 0s 17ms/step - loss: 0.1543 - au
c: 0.9808
```

Out[ ]: [0.15426717698574066, 0.9808310270309448]

In [ ]:
```
model.save("Lung Detection model.h5")
```

In [ ]:
```
# Loading the .h5 model that we had saved in the previous step:
my_xray_cnnmodel = keras.models.load_model("/content/Lung Detection mode
l.h5")

# Defining an image path from the "pred" folder:
image_path = '/content/MyDrive/MyDrive/Adv Deep Learning Image Recognitio
n/Dataset_Detection_of_Lung_Infection/data/test/Healthy/0107.jpeg'

# Preprocessing the image to 150x150x3 size and predicting the label:
image = tf.keras.preprocessing.image.load_img(image_path,target_size=(48,
48,3))
input_arr = tf.keras.preprocessing.image.img_to_array(image)
input_arr = np.array([input_arr])
predictions = my_xray_cnnmodel.predict(input_arr)

classes = ['Healthy', 'Type 1 disease', 'Type 2 disease']

actual = ''

for class_name in classes:
    if class_name in image_path:
        actual = class_name

pred = classes[np.argmax(predictions, axis=1)[0]]

# Finally we are displaying the predicted outcome:
plt.figure(figsize=[8,5])
plt.imshow(image, cmap='gray')
#plt.title("Actual:"+actual+" /Predicted:"+pred, size=15)
plt.title(f"Actual:{actual} /Predicted:{pred}")
plt.axis('off')
plt.show()
```

```
1/1 [==============================] - 0s 132ms/step
```

Actual:Healthy /Predicted:Healthy

In [ ]:
```
actual
```

Out[ ]:
```
''
```

# Transfer learning using DenseNet121:

```
Prepare data for the pre-trained mobile net model, with color mode as RGB

Create an instance of a mobile net pre-trained model

Add dense layer, dropout layer, batch normalization layer on the pre-trained m
odel

Create a final output layer with a SoftMax activation function

Change the batch size activation function and optimize as rmsprop and observe
if the accuracy increases

Take the loss function as categorical cross-entropy

Use early stopping with the patience of two epoch and call back function for p
reventing overfitting

Try with ten numbers epoch

Train the model using a generator and test the accuracy of the test data at ev
ery epoch

 Plot the training and validation accuracy, and the loss

 Observe the precision, recall the F1-score for all classes for both grayscale

and color models, and determine if the model’s classes are good
```

In [ ]:
```
#import necessary librabry
import numpy as np
import pandas as pd
import cv2
from google.colab.patches import cv2_imshow
import os
import seaborn as sns
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

In [ ]:
```
#defining the base, train and validation directory path
train_dir = os.path.join('/content/MyDrive/MyDrive/Adv Deep Learning Imag
e Recognition/Dataset_Detection_of_Lung_Infection/data/train')
test_dir = os.path.join('/content/MyDrive/MyDrive/Adv Deep Learning Image
Recognition/Dataset_Detection_of_Lung_Infection/data/test')
```

In [ ]:
```
#defining the damage and whole , train nand validation directory
train_Healthy_dir = os.path.join(train_dir, 'Healthy')
train_T1_dir = os.path.join(train_dir, 'Type 1 disease')
train_T2_dri = os.path.join(train_dir, 'Type 2 disease')
test_Healthy_dir = os.path.join(test_dir, 'Healthy')
test_T1_dir = os.path.join(test_dir, 'Type 1 disease')
test_T2_dri = os.path.join(test_dir, 'Type 2 disease')
```

In [ ]:
```
#data augmentation
train_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)
```

In [ ]:
```
train_generator = train_datagen.flow_from_directory(
        train_dir,
        target_size=(224, 224),
        batch_size=15,
        class_mode='categorical')

validation_generator = test_datagen.flow_from_directory(
        test_dir,
        target_size=(224, 224),
        batch_size=15,
        class_mode='categorical')
```

```
Found 251 images belonging to 3 classes.
Found 66 images belonging to 3 classes.
```

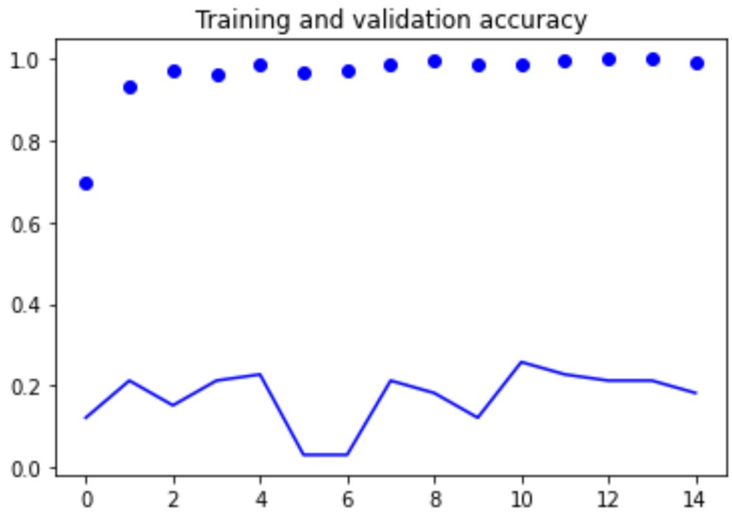
In [ ]:
```
from tensorflow.keras import Model
from tensorflow.keras.applications import DenseNet121

base_model = DenseNet121(input_shape = (224, 224, 3),  include_top = Fals
e, weights = 'imagenet')

x=   tf.keras.layers.Flatten()(base_model.output)
x=   tf.keras.layers.Dense(512, activation='relu')(x)
x=   tf.keras.layers.Dropout(0.5)(x)
x=   tf.keras.layers.Dense(64, activation='relu')(x)
x=   tf.keras.layers.Dense(3, activation='softmax')(x)

model1= Model(base_model.input, x)

model1.compile(loss='categorical_crossentropy',
              optimizer=Adam(lr=1e-4),
              metrics=['Accuracy','Precision','Recall'])

#training the model
history = model1.fit(
      train_generator,
      epochs=15,
      validation_data=validation_generator,
      verbose=2)
```

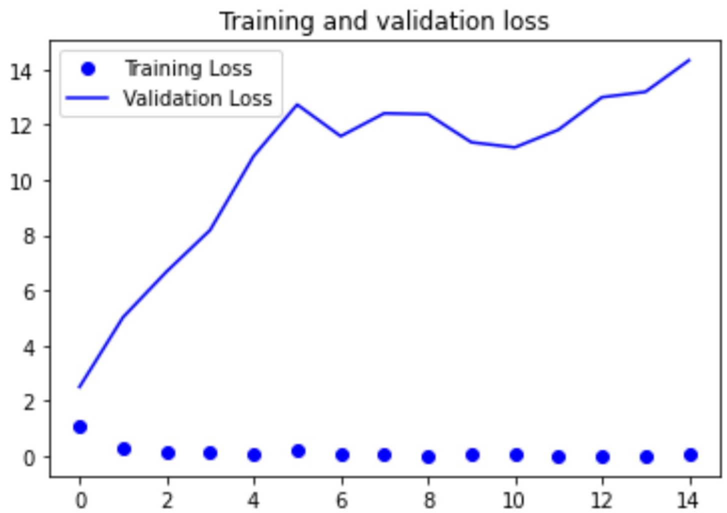
```
/usr/local/lib/python3.8/dist-packages/keras/optimizers/optimizer_v2/ada
m.py:110: UserWarning: The `lr` argument is deprecated, use `learning_ra
te` instead.
  super(Adam, self).__init__(name, **kwargs)
```

```
Epoch 1/15
17/17 - 274s - loss: 1.1153 - Accuracy: 0.6972 - precision: 0.7049 - rec
all: 0.6853 - val_loss: 2.4994 - val_Accuracy: 0.1212 - val_precision:
0.0968 - val_recall: 0.0909 - 274s/epoch - 16s/step
Epoch 2/15
17/17 - 236s - loss: 0.3150 - Accuracy: 0.9323 - precision: 0.9360 - rec
all: 0.9323 - val_loss: 5.0268 - val_Accuracy: 0.2121 - val_precision:
0.2031 - val_recall: 0.1970 - 236s/epoch - 14s/step
Epoch 3/15
17/17 - 220s - loss: 0.1372 - Accuracy: 0.9721 - precision: 0.9721 - rec
all: 0.9721 - val_loss: 6.6807 - val_Accuracy: 0.1515 - val_precision:
0.1515 - val_recall: 0.1515 - 220s/epoch - 13s/step
Epoch 4/15
17/17 - 219s - loss: 0.1759 - Accuracy: 0.9602 - precision: 0.9602 - rec
all: 0.9602 - val_loss: 8.1865 - val_Accuracy: 0.2121 - val_precision:
0.2121 - val_recall: 0.2121 - 219s/epoch - 13s/step
Epoch 5/15
17/17 - 215s - loss: 0.0627 - Accuracy: 0.9880 - precision: 0.9880 - rec
all: 0.9841 - val_loss: 10.8670 - val_Accuracy: 0.2273 - val_precision:
0.2273 - val_recall: 0.2273 - 215s/epoch - 13s/step
Epoch 6/15
17/17 - 225s - loss: 0.2290 - Accuracy: 0.9681 - precision: 0.9681 - rec
all: 0.9681 - val_loss: 12.7354 - val_Accuracy: 0.0303 - val_precision:
0.0303 - val_recall: 0.0303 - 225s/epoch - 13s/step
Epoch 7/15
17/17 - 216s - loss: 0.0815 - Accuracy: 0.9721 - precision: 0.9721 - rec
all: 0.9721 - val_loss: 11.5891 - val_Accuracy: 0.0303 - val_precision:
0.0303 - val_recall: 0.0303 - 216s/epoch - 13s/step
Epoch 8/15
17/17 - 214s - loss: 0.0409 - Accuracy: 0.9880 - precision: 0.9880 - rec
all: 0.9880 - val_loss: 12.4189 - val_Accuracy: 0.2121 - val_precision:
0.2154 - val_recall: 0.2121 - 214s/epoch - 13s/step
Epoch 9/15
17/17 - 219s - loss: 0.0099 - Accuracy: 0.9960 - precision: 0.9960 - rec
all: 0.9960 - val_loss: 12.3850 - val_Accuracy: 0.1818 - val_precision:
0.1818 - val_recall: 0.1818 - 219s/epoch - 13s/step
Epoch 10/15
17/17 - 213s - loss: 0.0551 - Accuracy: 0.9880 - precision: 0.9880 - rec
all: 0.9880 - val_loss: 11.3696 - val_Accuracy: 0.1212 - val_precision:
0.1212 - val_recall: 0.1212 - 213s/epoch - 13s/step
Epoch 11/15
17/17 - 218s - loss: 0.0349 - Accuracy: 0.9880 - precision: 0.9880 - rec
all: 0.9880 - val_loss: 11.1813 - val_Accuracy: 0.2576 - val_precision:
0.2576 - val_recall: 0.2576 - 218s/epoch - 13s/step
Epoch 12/15
17/17 - 213s - loss: 0.0055 - Accuracy: 0.9960 - precision: 0.9960 - rec
all: 0.9960 - val_loss: 11.8196 - val_Accuracy: 0.2273 - val_precision:
0.2273 - val_recall: 0.2273 - 213s/epoch - 13s/step
Epoch 13/15
17/17 - 212s - loss: 0.0025 - Accuracy: 1.0000 - precision: 1.0000 - rec
all: 1.0000 - val_loss: 13.0010 - val_Accuracy: 0.2121 - val_precision:
0.2121 - val_recall: 0.2121 - 212s/epoch - 12s/step
Epoch 14/15
17/17 - 214s - loss: 9.2716e-04 - Accuracy: 1.0000 - precision: 1.0000 -
recall: 1.0000 - val_loss: 13.1961 - val_Accuracy: 0.2121 - val_precisio
n: 0.2121 - val_recall: 0.2121 - 214s/epoch - 13s/step
Epoch 15/15
17/17 - 219s - loss: 0.0314 - Accuracy: 0.9920 - precision: 0.9920 - rec
all: 0.9920 - val_loss: 14.3393 - val_Accuracy: 0.1818 - val_precision:
0.1818 - val_recall: 0.1818 - 219s/epoch - 13s/step
```

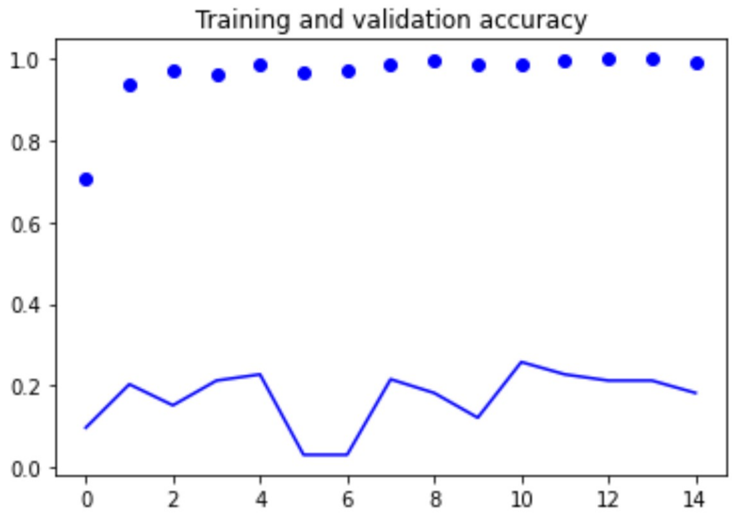
In [ ]:
```
#weights saving
model1.save("mobile_net classifier.h5")
```

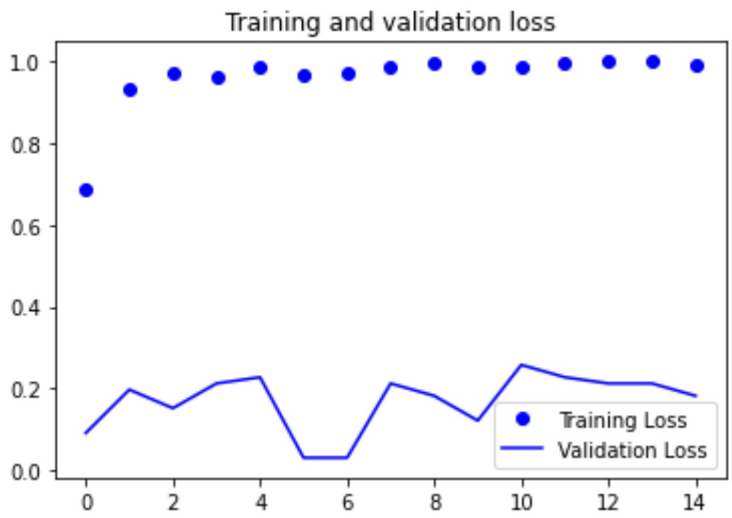
In [ ]:
```
import matplotlib.pyplot as plt
acc = history.history['Accuracy']
val_acc = history.history['val_Accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training Loss')
plt.plot(epochs, val_loss, 'b', label='Validation Loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```



In [ ]:
```
import matplotlib.pyplot as plt
acc = history.history['precision']
val_acc = history.history['val_precision']
loss = history.history['recall']
val_loss = history.history['val_recall']

epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training Loss')
plt.plot(epochs, val_loss, 'b', label='Validation Loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```



In [ ]:
```
def get_data_224(data_dir, train=True, image_size=224):
    data = []
    labels = []
    if train:
        path = os.path.join(data_dir, 'train')
    else:
        path = os.path.join(data_dir, 'test')
    for folder in os.listdir(path):
        if folder == ".DS_Store":
            continue
        image_dir = os.path.join(path, folder)
        for image in os.listdir(image_dir):
            if image == ".DS_Store":
                continue
            image_path = os.path.join(image_dir, image)

            image = preprocess(image_path, train, image_size)
            data.append(image)
            labels.append([folder])
    if train:
        datagen = ImageDataGenerator(
            rotation_range = 20,
            shear_range = 0.1,
            zoom_range = 0.1,
            horizontal_flip = False,)
        datagen.fit(data)
    return np.array(data), np.array(labels)
```

In [ ]:
```
train_images, train_labels2 = get_data_224('/content/MyDrive/MyDrive/Adv Deep Learning Image Recognition/Dataset_Detection_of_Lung_Infection/data')
test_images, test_labels2 = get_data_224('/content/MyDrive/MyDrive/Adv Deep Learning Image Recognition/Dataset_Detection_of_Lung_Infection/data', train=False)
print(train_images.shape)
print(test_images.shape)
```

```
(251, 224, 224, 3)
(66, 224, 224, 3)
```

In [ ]:
```
# Change healthy to Healthy label in Test labels
test_labels2[test_labels2 == ["healthy"]] = ['Healthy']
```

In [ ]:
```
from sklearn.preprocessing import OneHotEncoder
enc = OneHotEncoder()
train_labels = enc.fit_transform(train_labels2).toarray()
test_labels = enc.transform(test_labels2).toarray()
```

In [ ]:
```
def prediction_m(images):
    y_pred = []
    for i in model1.predict(images).argmax(axis=1):
        tmp = [0., 0., 0.]
        tmp[i] = 1.
        y_pred.append(tmp)
    y_pred = enc.inverse_transform(y_pred)
    return y_pred
```

In [ ]:
```
y_pred_m = prediction_m(test_images)
```

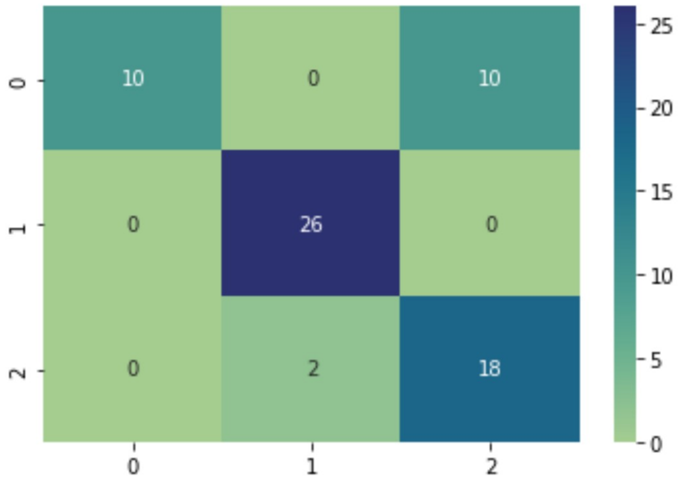
```
3/3 [==============================] - 12s 2s/step
```

In [ ]:
```
y_true_m = enc.inverse_transform(test_labels)
```

In [ ]:
```
print(accuracy_score(y_true_m, y_pred_m))
print(classification_report(y_true_m, y_pred_m))
confusion_matrix(y_true_m, y_pred_m)

sns.heatmap(confusion_matrix(y_true_m, y_pred_m),annot=True,fmt='d',cmap=
"crest")
```

```
0.8181818181818182
                precision    recall  f1-score   support

       Healthy       1.00      0.50      0.67        20
Type 1 disease       0.93      1.00      0.96        26
Type 2 disease       0.64      0.90      0.75        20

      accuracy                           0.82        66
     macro avg       0.86      0.80      0.79        66
  weighted avg       0.86      0.82      0.81        66
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2958111520>



In [ ]:
```
# Loading the .h5 model that we had saved in the previous step:
my_xray_cnnmodel = tf.keras.models.load_model("/content/mobile_net classi
fier.h5")

# Defining an image path from the "pred" folder:
image_path = '/content/MyDrive/MyDrive/Adv Deep Learning Image Recognitio
n/Dataset_Detection_of_Lung_Infection/data/test/Type 2 disease/0110.jpeg'

# Preprocessing the image to 150x150x3 size and predicting the label:
image = tf.keras.preprocessing.image.load_img(image_path,target_size=(22
4,224,3))
input_arr = tf.keras.preprocessing.image.img_to_array(image)
input_arr = np.array([input_arr])
predictions = my_xray_cnnmodel.predict(input_arr)

classes = ['Healthy', 'Type 1 disease', 'Type 2 disease']

actual = ''

for class_name in classes:
    if class_name in image_path:
        actual = class_name

pred = classes[np.argmax(predictions, axis=1)[0]]

# Finally we are displaying the predicted outcome:
plt.figure(figsize=[8,5])
plt.imshow(image)
plt.title("Actual:"+actual+" /Predicted:"+pred, size=15)
plt.axis('off')
plt.show()
```

```
1/1 [==============================] - 2s 2s/step
```

Actual:Type 2 disease /Predicted:Type 2 disease

# Transfer Learning using MObile Net:

```
Prepare the dataset for the transfer learning algorithm using Densenet121 with
the image size as 224x224x3

Freeze the top layers of the pre-trained model

Add a dense layer at the end of the pre-trained model followed by a dropout la
yer and try various combinations to get an accuracy

Add the final output layer with a SoftMax activation function

Take loss function as categorical cross-entropy

Take Adam as an optimizer

Use early stopping to prevent overfitting

Try with 15 number of epoch and batch size with seven, also try various values
to see the impact on results

Train the model using the generator and test the accuracy of the test data at
every epoch

 Plot the training and validation accuracy, and the loss

Observe the precision, recall the F1-score for all classes for both grayscale
and color models, and determine if the model’s classes are good
```

Final step:

```
Compare all the models on the basis of accuracy, precision, recall, and f1-sco
re
```

In [ ]:

```
from tensorflow.keras import Model
from tensorflow.keras.applications import MobileNetV2
IMG_SHAPE = (224,224,3)
base_model_1 = tf.keras.applications.MobileNetV2(input_shape=IMG_SHAPE,
                                                 include_top=False,
                                                 weights='imagenet')
```

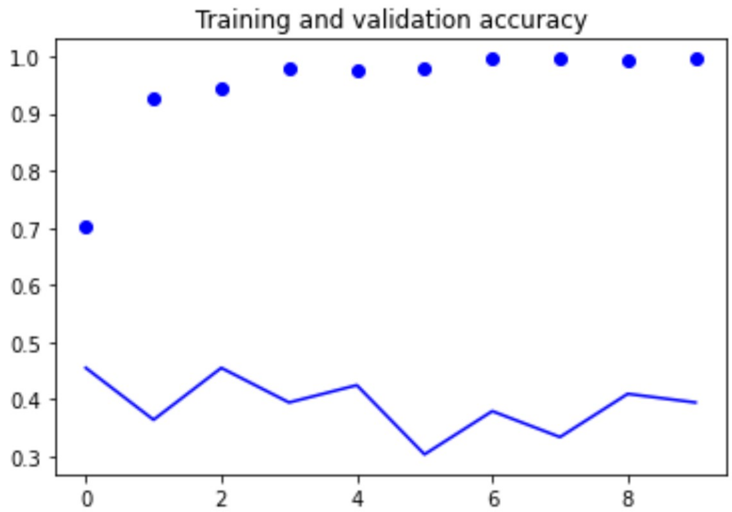
In [ ]:
```
x=   tf.keras.layers.Flatten()(base_model_1.output)
x=   tf.keras.layers.Dense(512, activation='relu')(x)
x=   tf.keras.layers.Dropout(0.5)(x)
x=   tf.keras.layers.Dense(64, activation='relu')(x)
x=   tf.keras.layers.Dense(3, activation='softmax')(x)

model2= Model(base_model_1.input, x)

model2.compile(loss='categorical_crossentropy',
              optimizer=Adam(lr=1e-4),
              metrics=['Accuracy','Precision','Recall'])

#training the model
history = model2.fit(
      train_generator,
      epochs=10,
      validation_data=validation_generator,
      verbose=2)
```

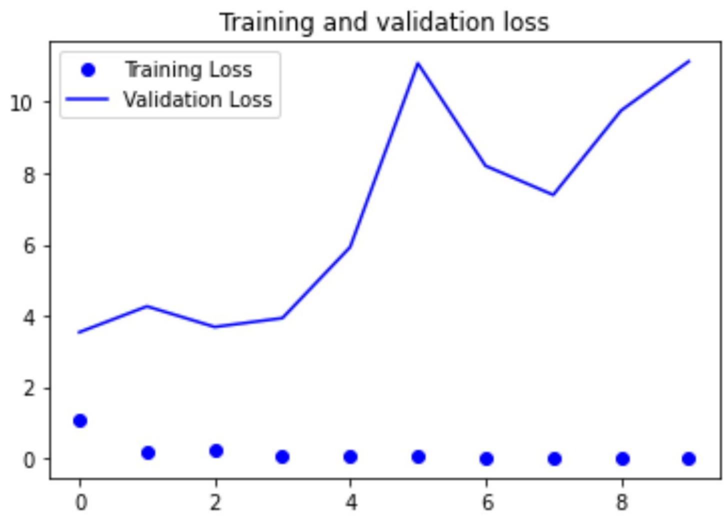
```
/usr/local/lib/python3.8/dist-packages/keras/optimizers/optimizer_v2/ada
m.py:110: UserWarning: The `lr` argument is deprecated, use `learning_ra
te` instead.
  super(Adam, self).__init__(name, **kwargs)

Epoch 1/10
17/17 - 73s - loss: 1.0551 - Accuracy: 0.7012 - precision: 0.7114 - reca
ll: 0.6972 - val_loss: 3.5342 - val_Accuracy: 0.4545 - val_precision: 0.
4462 - val_recall: 0.4394 - 73s/epoch - 4s/step
Epoch 2/10
17/17 - 64s - loss: 0.1884 - Accuracy: 0.9283 - precision: 0.9283 - reca
ll: 0.9283 - val_loss: 4.2614 - val_Accuracy: 0.3636 - val_precision: 0.
3636 - val_recall: 0.3636 - 64s/epoch - 4s/step
Epoch 3/10
17/17 - 69s - loss: 0.2139 - Accuracy: 0.9442 - precision: 0.9438 - reca
ll: 0.9363 - val_loss: 3.6835 - val_Accuracy: 0.4545 - val_precision: 0.
4615 - val_recall: 0.4545 - 69s/epoch - 4s/step
Epoch 4/10
17/17 - 67s - loss: 0.0635 - Accuracy: 0.9801 - precision: 0.9801 - reca
ll: 0.9801 - val_loss: 3.9313 - val_Accuracy: 0.3939 - val_precision: 0.
4062 - val_recall: 0.3939 - 67s/epoch - 4s/step
Epoch 5/10
17/17 - 66s - loss: 0.0457 - Accuracy: 0.9761 - precision: 0.9761 - reca
ll: 0.9761 - val_loss: 5.9249 - val_Accuracy: 0.4242 - val_precision: 0.
4242 - val_recall: 0.4242 - 66s/epoch - 4s/step
Epoch 6/10
17/17 - 67s - loss: 0.0514 - Accuracy: 0.9801 - precision: 0.9801 - reca
ll: 0.9801 - val_loss: 11.0870 - val_Accuracy: 0.3030 - val_precision:
0.3030 - val_recall: 0.3030 - 67s/epoch - 4s/step
Epoch 7/10
17/17 - 65s - loss: 0.0094 - Accuracy: 0.9960 - precision: 0.9960 - reca
ll: 0.9960 - val_loss: 8.2081 - val_Accuracy: 0.3788 - val_precision: 0.
3788 - val_recall: 0.3788 - 65s/epoch - 4s/step
Epoch 8/10
17/17 - 68s - loss: 0.0192 - Accuracy: 0.9960 - precision: 0.9960 - reca
ll: 0.9960 - val_loss: 7.3915 - val_Accuracy: 0.3333 - val_precision: 0.
3438 - val_recall: 0.3333 - 68s/epoch - 4s/step
Epoch 9/10
17/17 - 66s - loss: 0.0147 - Accuracy: 0.9920 - precision: 0.9920 - reca
ll: 0.9920 - val_loss: 9.7579 - val_Accuracy: 0.4091 - val_precision: 0.
4091 - val_recall: 0.4091 - 66s/epoch - 4s/step
Epoch 10/10
17/17 - 66s - loss: 0.0132 - Accuracy: 0.9960 - precision: 0.9960 - reca
ll: 0.9960 - val_loss: 11.1401 - val_Accuracy: 0.3939 - val_precision:
0.4000 - val_recall: 0.3939 - 66s/epoch - 4s/step
```

In [ ]:

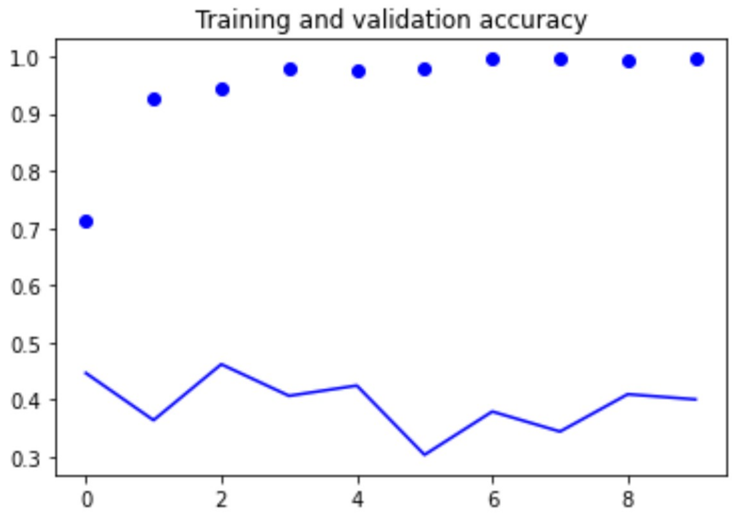
```
#weights saving
model2.save("Densenet121_classifier_m.h5")
```

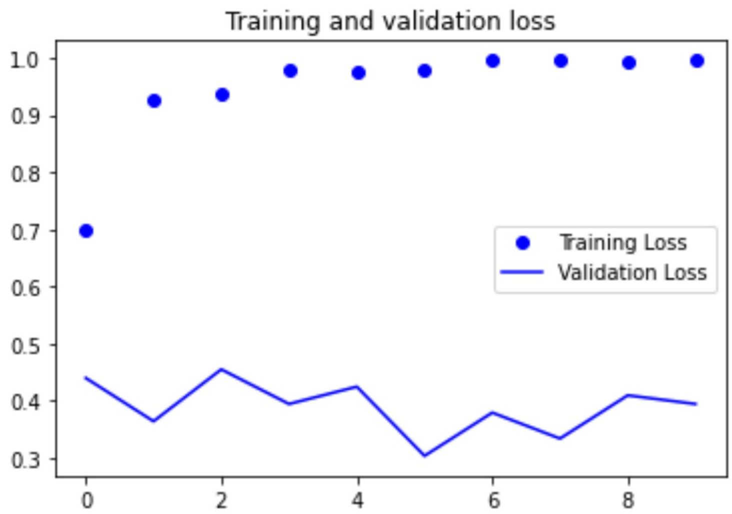
In [ ]:
```
import matplotlib.pyplot as plt
acc = history.history['Accuracy']
val_acc = history.history['val_Accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training Loss')
plt.plot(epochs, val_loss, 'b', label='Validation Loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```



In [ ]:
```
import matplotlib.pyplot as plt
acc = history.history['precision']
val_acc = history.history['val_precision']
loss = history.history['recall']
val_loss = history.history['val_recall']

epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training Loss')
plt.plot(epochs, val_loss, 'b', label='Validation Loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```



In [ ]:
```
def prediction_m2(images):
    y_pred = []
    for i in model2.predict(images).argmax(axis=1):
        tmp = [0., 0., 0.]
        tmp[i] = 1.
        y_pred.append(tmp)
    y_pred = enc.inverse_transform(y_pred)
    return y_pred
```

In [ ]:
```
y_pred_m2 = prediction_m2(test_images)
```

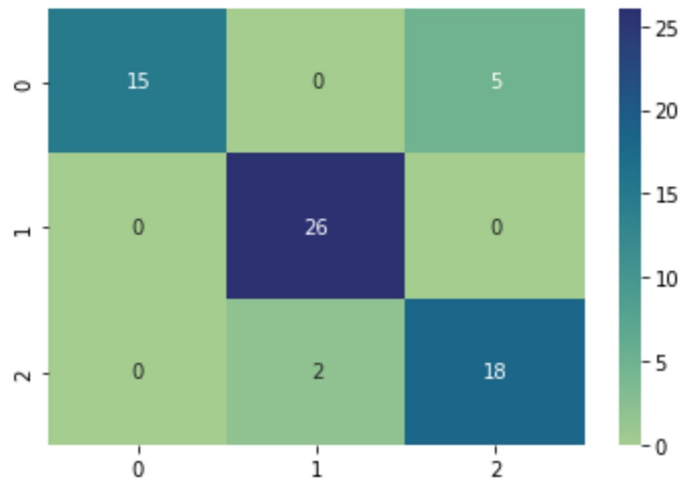
```
3/3 [==============================] - 2s 580ms/step
```

In [ ]:
```
y_true_m2 = enc.inverse_transform(test_labels)
```

In [ ]:
```
print(accuracy_score(y_true_m, y_pred_m))
print(classification_report(y_true_m, y_pred_m))
confusion_matrix(y_true_m, y_pred_m)

sns.heatmap(confusion_matrix(y_true_m, y_pred_m),annot=True,fmt='d',cmap=
"crest")
```

```
0.8939393939393939
                precision    recall  f1-score   support

       Healthy       1.00      0.75      0.86        20
Type 1 disease       0.93      1.00      0.96        26
Type 2 disease       0.78      0.90      0.84        20

      accuracy                           0.89        66
     macro avg       0.90      0.88      0.89        66
  weighted avg       0.91      0.89      0.89        66
```

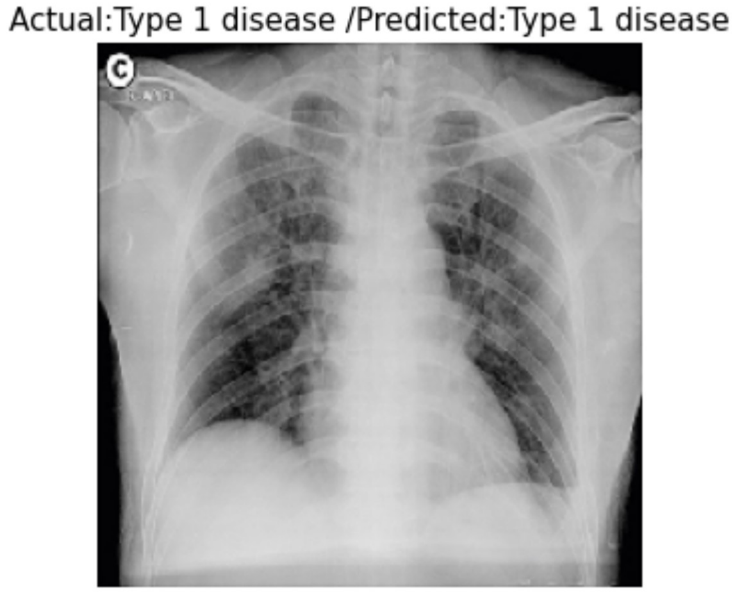
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f29580fc2e0>



In [ ]:
```
# Loading the .h5 model that we had saved in the previous step:
my_xray_cnnmodel = tf.keras.models.load_model("/content/Densenet121_class
ifier_m.h5")

# Defining an image path from the "pred" folder:
image_path = '/content/MyDrive/MyDrive/Adv Deep Learning Image Recognitio
n/Dataset_Detection_of_Lung_Infection/data/test/Type 1 disease/0120.jpg'

# Preprocessing the image to 150x150x3 size and predicting the label:
image = tf.keras.preprocessing.image.load_img(image_path,target_size=(22
4,224,3))
input_arr = tf.keras.preprocessing.image.img_to_array(image)
input_arr = np.array([input_arr])
predictions = my_xray_cnnmodel.predict(input_arr)

classes = ['Healthy', 'Type 1 disease', 'Type 2 disease']

actual = ''

for class_name in classes:
    if class_name in image_path:
        actual = class_name

pred = classes[np.argmax(predictions, axis=1)[0]]

# Finally we are displaying the predicted outcome:
plt.figure(figsize=[8,5])
plt.imshow(image)
plt.title("Actual:"+actual+" /Predicted:"+pred, size=15)
plt.axis('off')
plt.show()
```

```
WARNING:tensorflow:5 out of the last 12 calls to <function Model.make_pr
edict_function.<locals>.predict_function at 0x7f2960f185e0> triggered t
f.function retracing. Tracing is expensive and the excessive number of t
racings could be due to (1) creating @tf.function repeatedly in a loop,
(2) passing tensors with different shapes, (3) passing Python objects in
stead of tensors. For (1), please define your @tf.function outside of th
e loop. For (2), @tf.function has reduce_retracing=True option that can
avoid unnecessary retracing. For (3), please refer to https://www.tensor
flow.org/guide/function#controlling_retracing and https://www.tensorflo
w.org/api_docs/python/tf/function for  more details.
```

```
1/1 [==============================] - 1s 942ms/step
```




In [ ]: