Importing libraries for VGG16

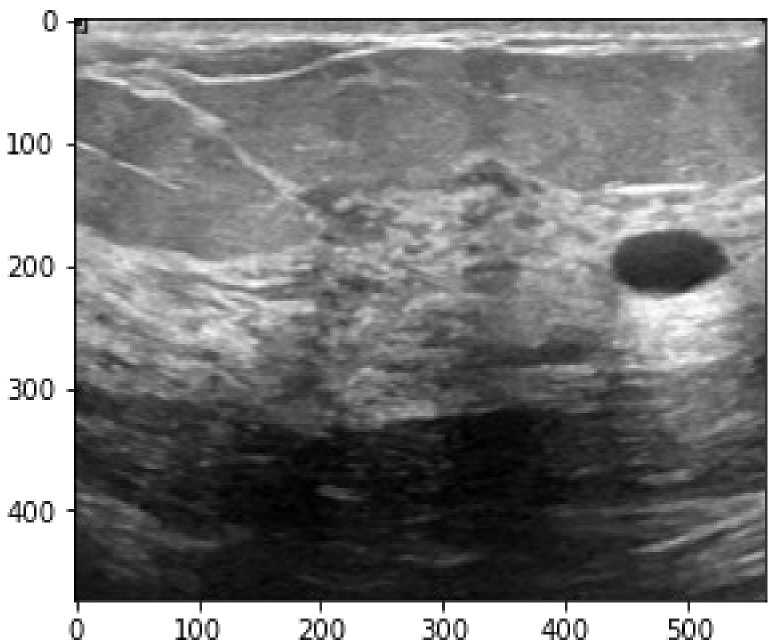
```
'''in this section we have imported various libraries nwhich we are
going to use in our model like
numpy, pandas, seaborn, matplotlib etc'''
import cv2 # this library is used to solve computer vision problems
import pickle # this is used for serializing and de-serializing Python
object structures
import seaborn as sns #imported for heat map
import matplotlib.image as mpimg # used for loading , rescaling, and
displaying images

import keras ## it is used for  for developing and evaluating deep
learning models
import tensorflow ## it is used for fast numerical computing

from tensorflow.keras.models import Model ##TensorFlow neural networks
by specifying the attributes, functions, and layers we want
from tensorflow.keras.utils import plot_model ##Converts a Keras model
to dot format and save to a file
from tensorflow.keras.models import Sequential # Used for implementing
simple layer-by-layer architectures without multiple inputs, multiple
outputs, or layer branches
from tensorflow.keras.applications import VGG16 #importing vgg19 model
from tensorflow.keras.callbacks import EarlyStopping #it is used to
specify an arbitrary large number of training epochs and stop training
once the model performance stops improving on a hold out validation
datase
from tensorflow.keras.preprocessing.image import ImageDataGenerator
#Generate batches of tensor image data with real-time data
augmentation
from tensorflow.keras.layers import
Input,Lambda,Dense,Flatten,Dropout,BatchNormalization,Activation

from sklearn.metrics import confusion_matrix,
classification_report,accuracy_score,recall_score,precision_score,f1_s
core # values
import os
import matplotlib.pyplot as plt
import numpy as np
```

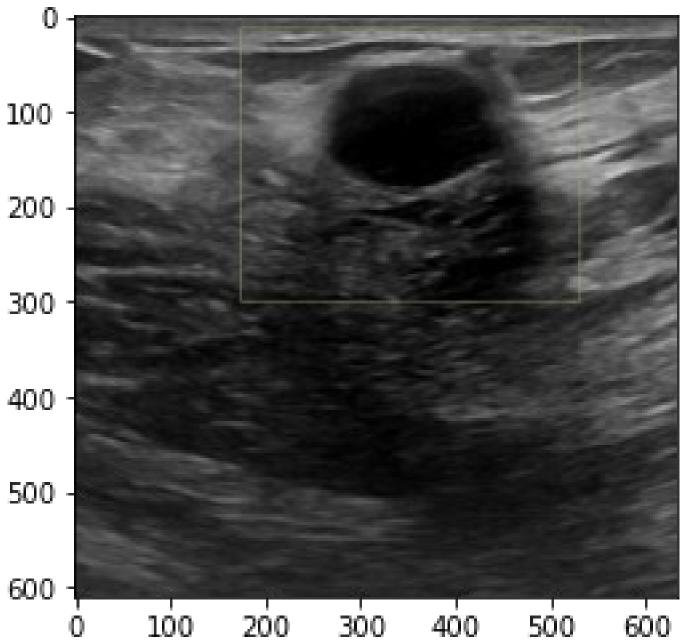
Defining data Paths

```
'''in this section we have imported our training,testing, validation
data from our local source in our laptop'''
train_path = r"C:\Users\Rahul Choubey\Documents\Dataset\Rishita
Dataset\archive (56)\Dataset_BUSI_with_GT\Train" # importing training
path
```

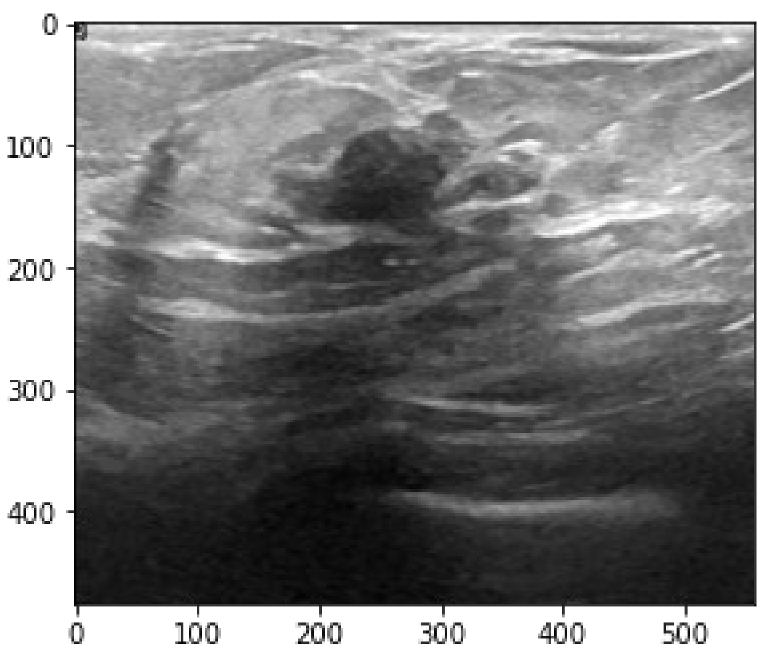
```
test_path = r"C:\Users\Rahul Choubey\Documents\Dataset\Rishita
Dataset\archive (56)\Dataset_BUSI_with_GT\Test" # importing testing
path
val_path = r"C:\Users\Rahul Choubey\Documents\Dataset\Rishita Dataset\
archive (56)\Dataset_BUSI_with_GT\Test" # importing validation path

'''in this section we showed two images of each categories of our
dataset '''
for folder in os.listdir(train_path):
    sub_path = train_path + "/" + folder # accessing the images in the
training folder
    print(folder) # print the folder name
    for i in range(2): # print 2 images of each folder
        temp_path = os.listdir(sub_path)[i] # defining the temporary
path
        temp_path = sub_path + "/" + temp_path
        img = mpimg.imread(temp_path) # function to read the path of
the image
        implot = plt.imshow(img)
        plt.show() #shows the image
```

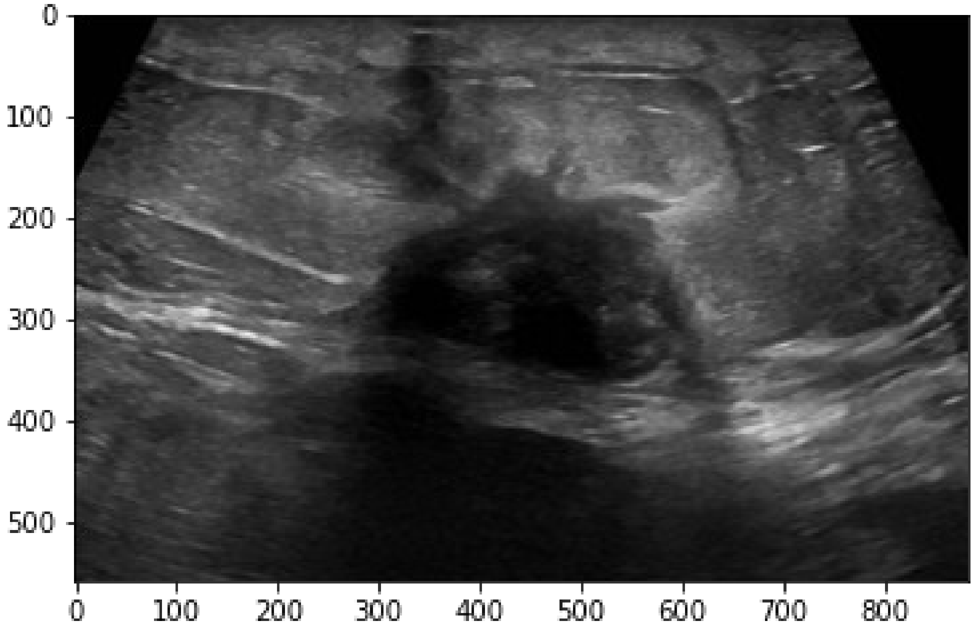
```
benign
```




0
100
200
300
400
500
600
0
100
200
300
400
500
600

malignant


0
100
200
300
400
0
100
200
300
400
500



Converting image to pixels

```
'''in this section we have converted our image to pixels '''
#function to convert image to pixels
def imagearray(path,size):
    data = []
    for folder in os.listdir(path): # list directory
        sub_path = path+"/"+folder # declaring sub path which includes
the folder and the image path


        for img in os.listdir(sub_path):
            image_path = sub_path+"/"+img # defining image path
            img_arr = cv2.imread(image_path) # function to read the
image path
            img_arr = cv2.resize(img_arr,size) # resizing th eimage
array
            data.append(img_arr) # append the data with image array
    return data  # return the data value

''''in this section we have declared the size of the image to resize
in 250*250 size'''
#declaring the size
size = (250,250)

'''in this section we have converted our image into image array of
training,testing,validation'''
train = imagearray(train_path,size) # defining the train image array
test = imagearray(test_path,size) # defining the test image array
val = imagearray(val_path,size) # defining the validation image array
```

Normalization

```
'''in this section we have normalized our images into numpy array of
each training, testing, validation data'''
#converting images into numpy array
x_train = np.array(train) # converting training data into numpy array
x_test = np.array(test) # converting testing data into numpy array
x_val = np.array(val) # converting validation data into numpy array

x_train = x_train/255 # setting the numpy array size in 255 for
training data
x_test = x_test/255 # setting the numpy array size in 255 for testing
data
x_val = x_val/255 # setting the numpy array size in 255 for validation
data
```

Defining Target Variables

```
'''in this section we have defined the target variables which we have
to predict in our model'''
#function to define target variables
def data_class(data_path,size,class_mode):
    datagen = ImageDataGenerator(rescale = 1./255) # rescaling the
image in 255 array size
    classes = datagen.flow_from_directory(data_path,
                                           target_size = size,
                                           batch_size = 32,
                                           class_mode = class_mode) #
defining the target variables with some parameters
    return classes # return the class value

'''in this section we have to split our data into
train_class,test_class,validation_class'''
train_class = data_class(train_path,size,"sparse") # defining the
train class
test_class = data_class(test_path,size,"sparse") # defining the test
class
val_class = data_class(val_path,size,"sparse") # defining the
validation class
```

```
Found 497 images belonging to 2 classes.
Found 148 images belonging to 2 classes.
Found 148 images belonging to 2 classes.
```

```
'''in this section we have declared target variables of training,
testing, validation'''
y_train = train_class.classes # defining the dependent training class
y_test = test_class.classes # defining the dependent testing class
y_val = val_class.classes # defining the dependent validation class
```

```
train_class.classes # checking the 0 and 1 number of values in
training data
```

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

```
train_class.class_indices # checking the 2 categories of
classification in training data
```

```
{'benign': 0, 'malignant': 1}
```

```
'''in this section we have printed the shape of the y_train and
y_test'''
print("y_train_shape",y_train.shape,"y_test_shape",y_test.shape)
# printing the shape of the training and the testing dependent data
```

```
y_train_shape (497,) y_test_shape (148,)
```

VGG19 Model

```
'''in this section we have initiated the vgg19 model that we have to
apply on our dataset'''
#initializing the model
vgg = VGG16(input_shape = (250,250,3),weights = "imagenet",
include_top = False)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58892288/58889256 [==============================] - 10s 0us/step
58900480/58889256 [==============================] - 10s 0us/step
```

```
for layer in vgg.layers:
    layer.trainable = False # making the trainable layer in vgg 19 as
false.
```

```
x = Flatten()(vgg.output)  # Flatten the image array of the
independent images
prediction = Dense(3,activation = "softmax")(x) # using the activation
function as softmax
```

```
'''in this section we have printed the summary of the resnet model'''
#summary of the model
model = Model(inputs = vgg.input, outputs = prediction) # summary of
the model with predicted values
model.summary() # function to show the summary
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 250, 250, 3)]     0

 block1_conv1 (Conv2D)       (None, 250, 250, 64)      1792

 block1_conv2 (Conv2D)       (None, 250, 250, 64)      36928

 block1_pool (MaxPooling2D)  (None, 125, 125, 64)      0

 block2_conv1 (Conv2D)       (None, 125, 125, 128)     73856
```

```
 block2_conv2 (Conv2D)       (None, 125, 125, 128)     147584

 block2_pool (MaxPooling2D)  (None, 62, 62, 128)       0

 block3_conv1 (Conv2D)       (None, 62, 62, 256)       295168

 block3_conv2 (Conv2D)       (None, 62, 62, 256)       590080

 block3_conv3 (Conv2D)       (None, 62, 62, 256)       590080

 block3_pool (MaxPooling2D)  (None, 31, 31, 256)       0

 block4_conv1 (Conv2D)       (None, 31, 31, 512)       1180160

 block4_conv2 (Conv2D)       (None, 31, 31, 512)       2359808

 block4_conv3 (Conv2D)       (None, 31, 31, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 15, 15, 512)       0

 block5_conv1 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_conv2 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_conv3 (Conv2D)       (None, 15, 15, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 3)                 75267

=================================================================
Total params: 14,789,955
Trainable params: 75,267
Non-trainable params: 14,714,688
_________________________________________________________________
```

```
'''in this section we have defined the early stopping'''
#initializing the earlystop
early_stop = EarlyStopping(mode = "min",verbose = 1, patience = 5) #
defining the early stop

'''in this section we have compiled the resnet model on our dataset'''
#compiling the model
model.compile(loss = "sparse_categorical_crossentropy",
             optimizer = "adam",
             metrics = ["accuracy"]) # function to compile the with
adam optimizer with accuracy matrix
```

```python
'''in this section we have fitted our resnet model on training data of
our dataset'''
#fitting the model
history = model.fit(x_train,y_train,
         epochs = 10,
          validation_data = (x_val,y_val)
          ,callbacks = [early_stop],
         batch_size = 20,
         shuffle = True,steps_per_epoch = 5)
```

```
Epoch 1/10
5/5 [==============================] - 17s 4s/step - loss: 1.1307 -
accuracy: 0.4300 - val_loss: 1.0798 - val_accuracy: 0.3243
Epoch 2/10
5/5 [==============================] - 16s 4s/step - loss: 0.8469 -
accuracy: 0.5500 - val_loss: 0.8410 - val_accuracy: 0.6757
Epoch 3/10
5/5 [==============================] - 16s 4s/step - loss: 0.4054 -
accuracy: 0.8000 - val_loss: 0.5127 - val_accuracy: 0.7568
Epoch 4/10
5/5 [==============================] - 16s 4s/step - loss: 0.4451 -
accuracy: 0.8200 - val_loss: 0.5348 - val_accuracy: 0.7568
Epoch 5/10
5/5 [==============================] - 16s 4s/step - loss: 0.4751 -
accuracy: 0.7938 - val_loss: 0.4918 - val_accuracy: 0.7568
Epoch 6/10
5/5 [==============================] - 16s 4s/step - loss: 0.3791 -
accuracy: 0.8100 - val_loss: 0.4478 - val_accuracy: 0.7905
Epoch 7/10
5/5 [==============================] - 17s 4s/step - loss: 0.2836 -
accuracy: 0.9400 - val_loss: 0.3752 - val_accuracy: 0.8514
Epoch 8/10
5/5 [==============================] - 19s 4s/step - loss: 0.2328 -
accuracy: 0.9100 - val_loss: 0.3731 - val_accuracy: 0.8311
Epoch 9/10
5/5 [==============================] - 18s 4s/step - loss: 0.2672 -
accuracy: 0.9100 - val_loss: 0.3452 - val_accuracy: 0.8311
Epoch 10/10
5/5 [==============================] - 17s 4s/step - loss: 0.2800 -
accuracy: 0.8763 - val_loss: 0.3252 - val_accuracy: 0.8784
```

```python
'''in this section we have evaluated the training accuracy of the
resnet model'''
model.evaluate(x_train,y_train,batch_size = 32) # evaluate model
showing training accuracy and loss
```

```
16/16 [==============================] - 33s 2s/step - loss: 0.2095 -
accuracy: 0.9356

[0.209457665681839, 0.9356136918067932]
```

```python
'''in this section we have evaluated the testing accuracy of the
resnet model'''
model.evaluate(x_test, y_test,batch_size = 32)# evaluate model showing
val accuracy and loss
```

```
5/5 [==============================] - 10s 2s/step - loss: 0.3252 -
accuracy: 0.8784
```

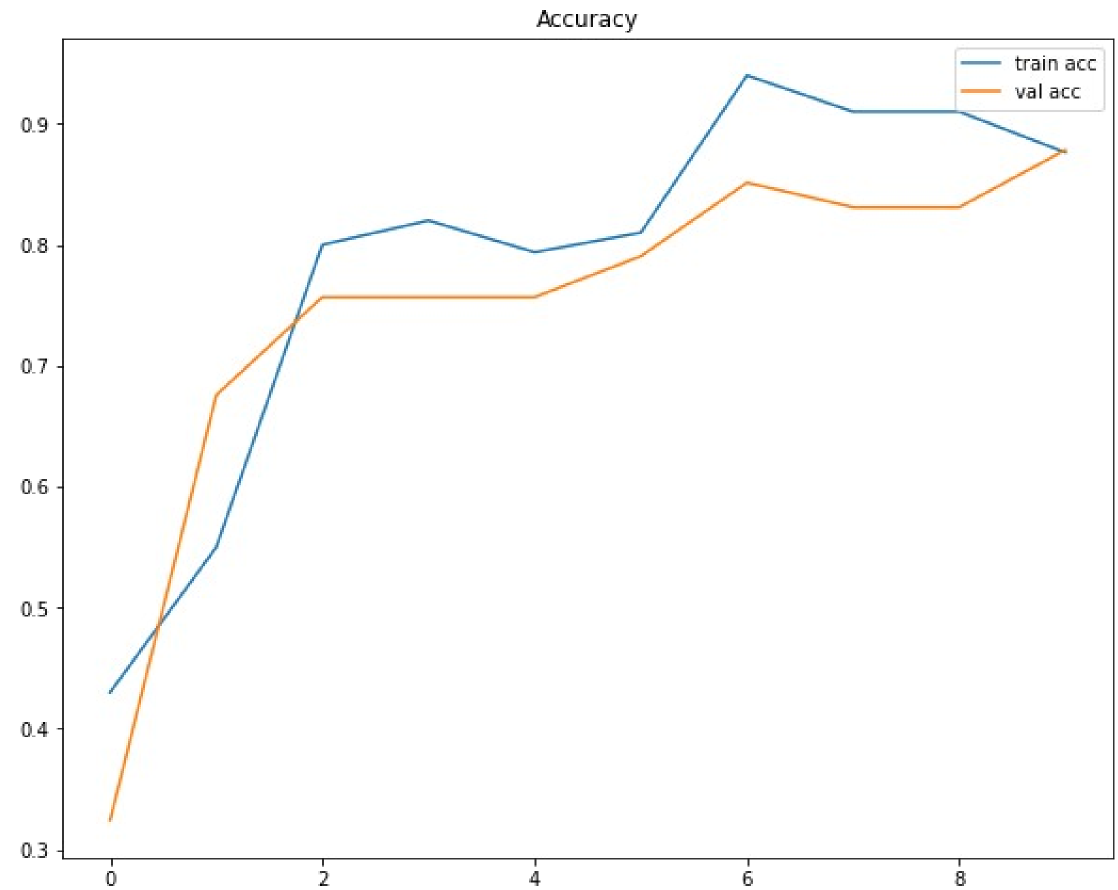
```
[0.32519692182540894, 0.8783783912658691]
```

```python
'''in this section we have evaluated the validation accuracy of the
resnet model'''
model.evaluate(x_val, y_val,batch_size = 32)# evaluate model showing
testing accuracy and loss
```

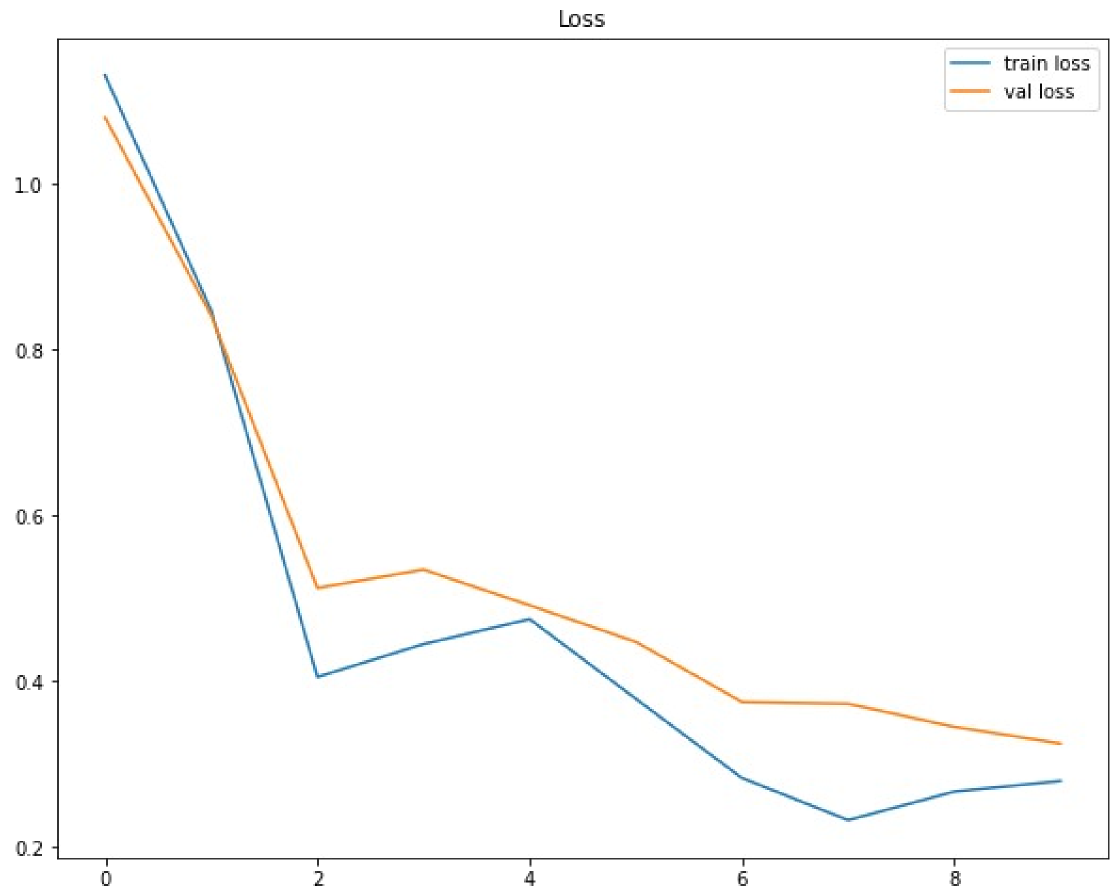
```
5/5 [==============================] - 10s 2s/step - loss: 0.3252 -
accuracy: 0.8784
```

```
[0.32519692182540894, 0.8783783912658691]
```

```python
'''in this section we have plotted the roc curve of the testing
data'''
plt.figure(figsize = (10,8))
plt.plot(history.history['accuracy'],label = 'train acc')
plt.plot(history.history['val_accuracy'],label = 'val acc')
plt.legend()
plt.title('Accuracy')
plt.show()
```




```
'''in this section we have plotted the roc curve of the training
data'''
plt.figure(figsize = (10,8))
plt.plot(history.history['loss'],label = 'train loss')
plt.plot(history.history['val_loss'],label = 'val loss')
plt.legend()
plt.title('Loss')
plt.show()
```

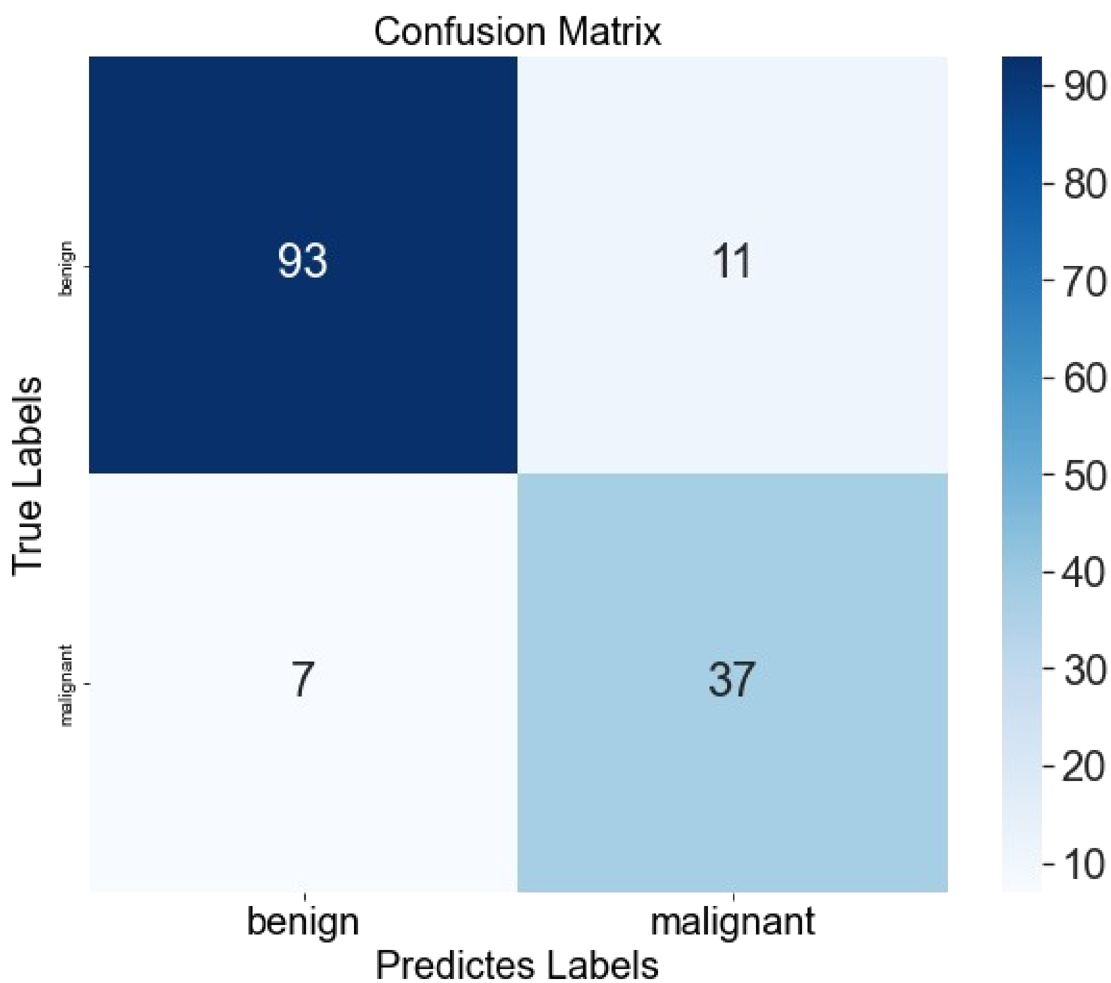



```
'''in this section we have predicted the x_test that how much it is
matching same value with y_test'''
#Making prediction
y_pred=model.predict(x_test)
y_pred=np.argmax(y_pred,axis=1)

'''in this section we have plotted the classification report of
testing data'''
print(classification_report(y_pred,y_test))

import warnings
warnings.simplefilter("ignore", UserWarning)
```

```
              precision    recall  f1-score   support

           0       0.93      0.89      0.91       104
           1       0.77      0.84      0.80        44

    accuracy                           0.88       148
   macro avg       0.85      0.87      0.86       148
weighted avg       0.88      0.88      0.88       148
```

```python
'''in this section we have plotted the confusion matrix of the testing data'''
cm = confusion_matrix(y_pred,y_test)

plt.figure(figsize = (10,8))
ax = plt.subplot()
sns.set(font_scale = 2.0)
sns.heatmap(cm,annot = True,fmt = 'g',cmap = "Blues", ax = ax);

# Labels, title and ticks
ax.set_xlabel("Predictes Labels", fontsize = 20); ax.set_ylabel('True Labels', fontsize = 20);
ax.set_title("Confusion Matrix", fontsize = 20);
ax.xaxis.set_ticklabels(["benign","malignant"], fontsize = 20);
ax.yaxis.set_ticklabels(["benign","malignant"])
```

```
[Text(0, 0.5, 'benign'), Text(0, 1.5, 'malignant')]
```




```python
'''in this section we have plotted the roc of the testing data'''
def plot_roc(model, x_test, y_test):
```

```
    # calculate the fpr and tpr for all thresholds of the 
classification
    probabilities = model.predict_proba(np.array(x_test))
    predictions = probabilities[:, 1]
    fpr, tpr, threshold = metrics.roc_curve(y_test, predictions)
    roc_auc = metrics.auc(fpr, tpr)

    plt.title('rahul')
    plt.plot(fpr, tpr, 'b', label='AUC = %0.2f' % roc_auc)
    plt.legend(loc='lower right')
    plt.plot([0, 1], [0, 1], 'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()

'''in this section we have printed the f1 score, precision ,recall'''
print("F1 score is: ",f1_score(y_test,y_pred,average = "micro"))
print("Recall value is: ",recall_score(y_test,y_pred,average = 
"weighted"))

import warnings
warnings.simplefilter("ignore", UserWarning)
print("Precision Score is: ",precision_score(y_test,y_pred,average = 
"micro"))
```

```
F1 score is:  0.8783783783783784
Recall value is:  0.8783783783783784
Precision Score is:  0.8783783783783784
```

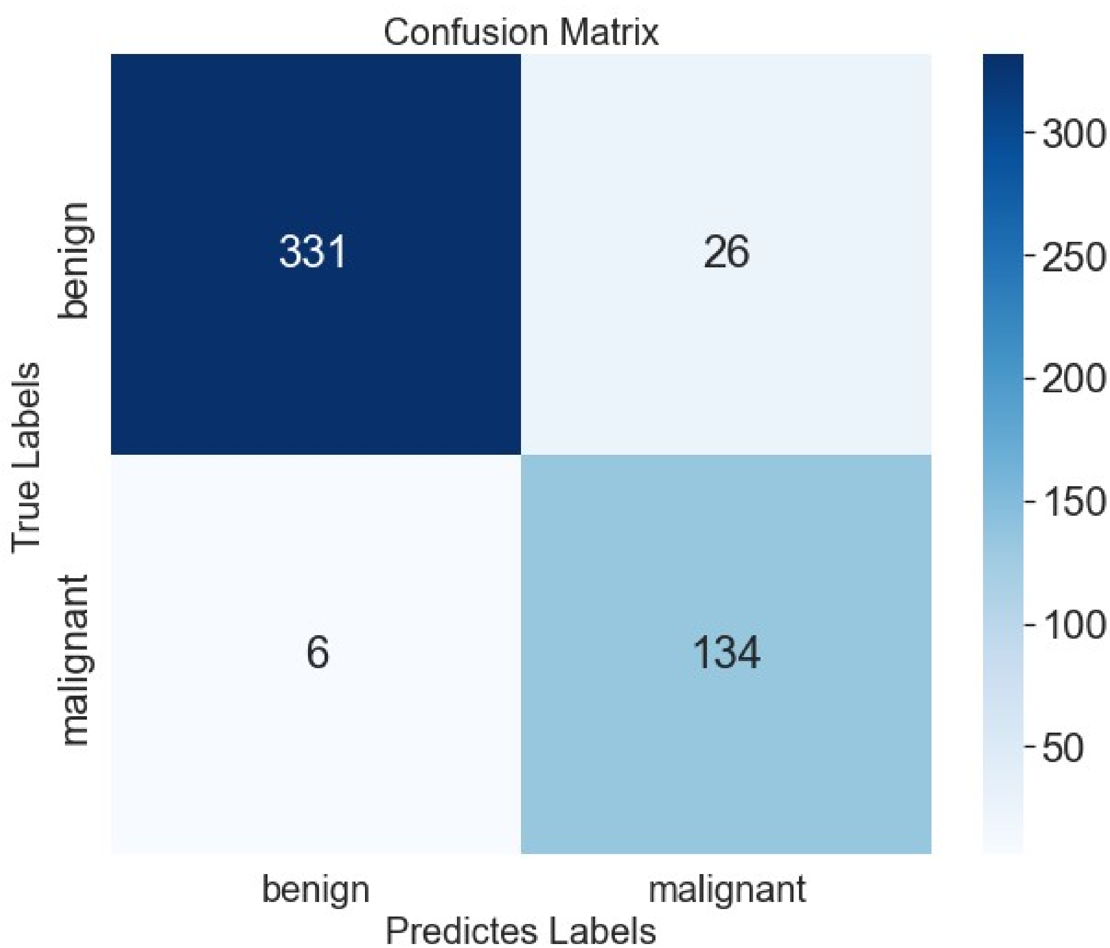
```
'''in this section we have predicted the x_train'''
#Making training prediction
y_pred_train=model.predict(x_train)
y_pred_train=np.argmax(y_pred_train,axis=1)

'''in this section we have plotted the classification report of the 
training data'''
print(classification_report(y_pred_train,y_train))

import warnings
warnings.simplefilter("ignore", UserWarning)
```

```
              precision    recall  f1-score   support

           0       0.98      0.93      0.95       357
           1       0.84      0.96      0.89       140

    accuracy                           0.94       497
   macro avg       0.91      0.94      0.92       497
```

```
weighted avg       0.94      0.94      0.94       497
```

```
'''in this section we have plotted the confusion matrix of training data'''
cm = confusion_matrix(y_pred_train,y_train)

plt.figure(figsize = (10,8))
ax = plt.subplot()
sns.set(font_scale = 2.0)
sns.heatmap(cm,annot = True,fmt = 'g',cmap = "Blues", ax = ax);

# Labels, title and ticks
ax.set_xlabel("Predictes Labels", fontsize = 20); ax.set_ylabel('True Labels', fontsize = 20);
ax.set_title("Confusion Matrix", fontsize = 20);
ax.xaxis.set_ticklabels(["benign","malignant"], fontsize = 20);
ax.yaxis.set_ticklabels(["benign","malignant"])
```

```
[Text(0, 0.5, 'benign'), Text(0, 1.5, 'malignant')]
```



```
'''in this section we have plotted the f1_score, precision ,recall
values of training data'''
print("F1 score is: ",f1_score(y_train,y_pred_train,average =
"micro"))
print("Recall value is: ",recall_score(y_train,y_pred_train,average =
"weighted"))

import warnings
warnings.simplefilter("ignore", UserWarning)
print("Precision Score is:
",precision_score(y_train,y_pred_train,average = "micro"))
```

```
F1 score is:  0.9356136820925554
Recall value is:  0.9356136820925554
Precision Score is:  0.9356136820925554
```