# Breast Cancer Tumor Detection Using MRI Dataset

Email: - 2k22.cse.2213298@gmail.com

Name: - Aryan Katiyar

**[Infosys Springboard 5.0]**

# CODE→ // TASKS PERFORMED :-

//1. COUNT OF BENIGN AND MALIGNANT IMAGES FROM THE TEST DATASET

// 2. DATA AUGMENTATION PERFORMED ON TEST DATASET

// 3. RANDOM CROP AND NORMALIZATION PERFORMED ON TRAIN AND VALIDATION DATASET

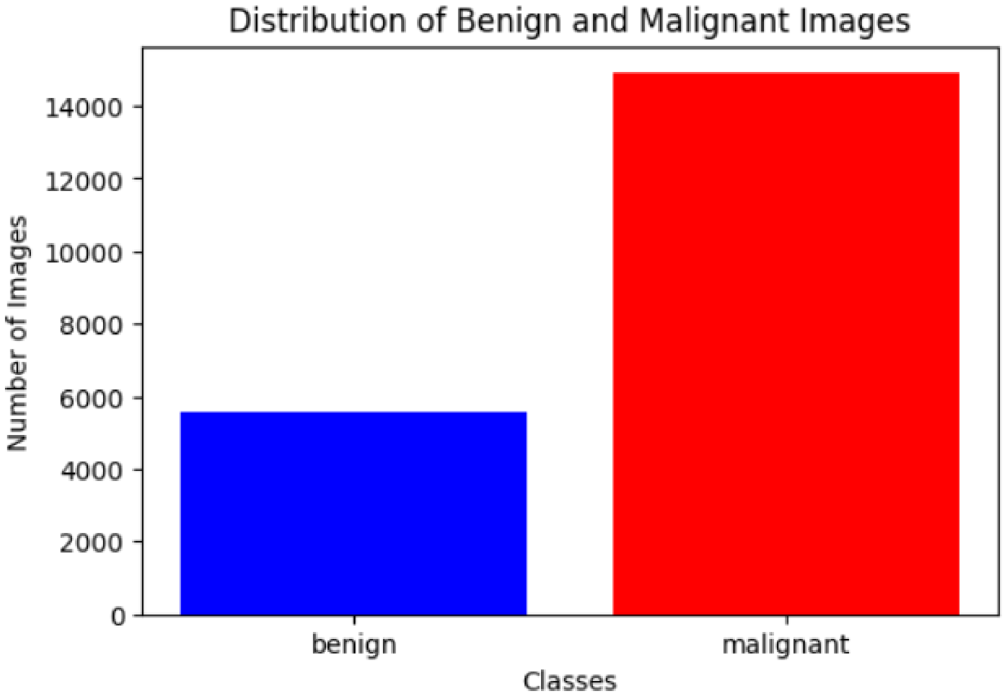
```
import matplotlib.pyplot as plt
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
from collections import Counter
import numpy as np
import torch

# Define transformations for the training set (with data augmentation)
train_transform = transforms.Compose([
    transforms.RandomResizedCrop(224),          # Randomly crop the
image and resize to 224x224
    transforms.RandomHorizontalFlip(),          # Randomly flip the
images horizontally
    transforms.RandomVerticalFlip(),            # Randomly flip the
images vertically
    transforms.RandomRotation(20),              # Rotate the images by
up to 20 degrees
    transforms.ColorJitter(brightness=0.2, contrast=0.2,
saturation=0.2),  # Add random color jitter
    transforms.RandomAffine(degrees=0, translate=(0.1, 0.1)),  #
Randomly translate the image
    transforms.RandomPerspective(distortion_scale=0.5, p=0.5),  #
Random perspective transformation
    transforms.ToTensor(),                  # Convert the image to a
PyTorch tensor
    transforms.GaussianBlur(kernel_size=(5, 9), sigma=(0.1, 5)), #
Apply Gaussian blur with random kernel
    transforms.RandomErasing(p=0.5, scale=(0.02, 0.2)),         #
Randomly erase a portion of the image (applied to tensor)
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224,
0.225])  # Normalize based on ImageNet
])
```

```
# Define transformations for test and validation sets (only resize and
normalization)
test_val_transform = transforms.Compose([
    transforms.Resize((224, 224)),       # Resize the image to 224x224
    transforms.ToTensor(),               # Convert the image to a
PyTorch tensor
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224,
0.225])  # Normalize based on ImageNet
])

# Path to subfolders
data_dir_train = '/content/drive/MyDrive/Tumor_Trace/clasification-
roi/train'
data_dir_test = '/content/drive/MyDrive/Tumor_Trace/clasification-
roi/test'
data_dir_val = '/content/drive/MyDrive/Tumor_Trace/clasification-
roi/val'

# Load the datasets using ImageFolder
train_dataset = datasets.ImageFolder(root=data_dir_train,
transform=train_transform)
test_dataset = datasets.ImageFolder(root=data_dir_test,
transform=test_val_transform)
val_dataset = datasets.ImageFolder(root=data_dir_val,
transform=test_val_transform)

# Count the total number of images in each class for the training
dataset
class_counts = Counter(train_dataset.targets)

benign_count = class_counts[train_dataset.class_to_idx['Benign']]
malignant_count = class_counts[train_dataset.class_to_idx['Malignant']]

# Print the counts
print(f"Total Benign Images: {benign_count}")
print(f"Total Malignant Images: {malignant_count}")

# Plotting the graph between total number of benign and malignant
images
plt.figure(figsize=(6, 4))
plt.bar(['benign', 'malignant'], [benign_count, malignant_count],
color=['blue', 'red'])
plt.title('Distribution of Benign and Malignant Images')
plt.xlabel('Classes')
plt.ylabel('Number of Images')
plt.show()
```

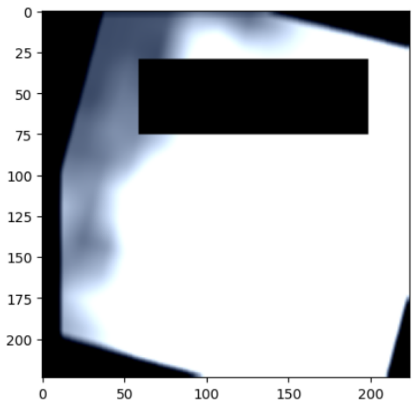
```python
# Visualizing some augmented images from the training dataset
def imshow(img):
    img = img / 2 + 0.5  # unnormalize the image (after normalization
in transform)
    np_img = img.numpy()
    plt.imshow(np.transpose(np_img, (1, 2, 0)))  # convert from tensor
to image
    plt.show()

# Create DataLoader for augmented image visualization (from training
dataset)
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)

# Get a batch of images from the train dataloader
data_iter = iter(train_loader)
images, labels = next(data_iter)

# Show a few augmented images from training set
print("Augmented Images from Training Set:")
for i in range(5):  # Display first 5 images from the batch
    imshow(images[i])

# Create DataLoader for test and validation datasets (no augmentation,
only resize and normalization)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
val_loader = DataLoader(val_dataset, batch_size=32, shuffle=False)
```

OUTPUT→

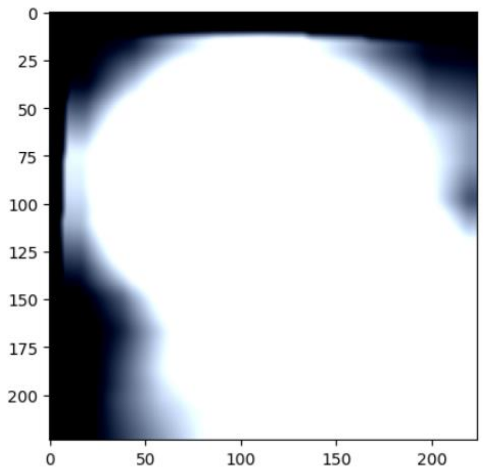
```
Total Benign Images: 5559
Total Malignant Images: 14895
```



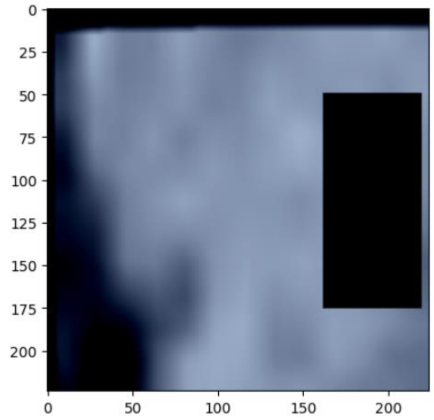

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



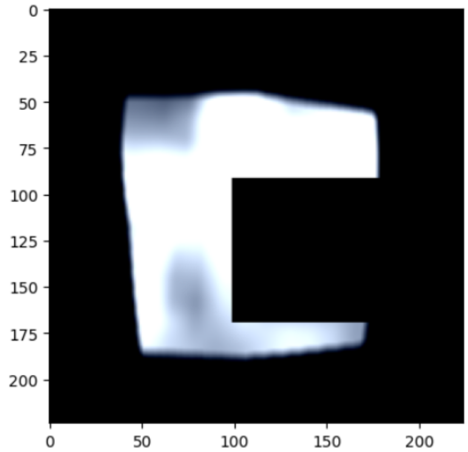

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Augmented Images from Training Set:
```



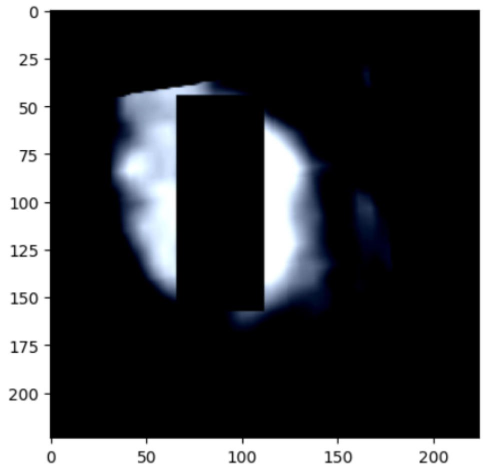
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).




WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



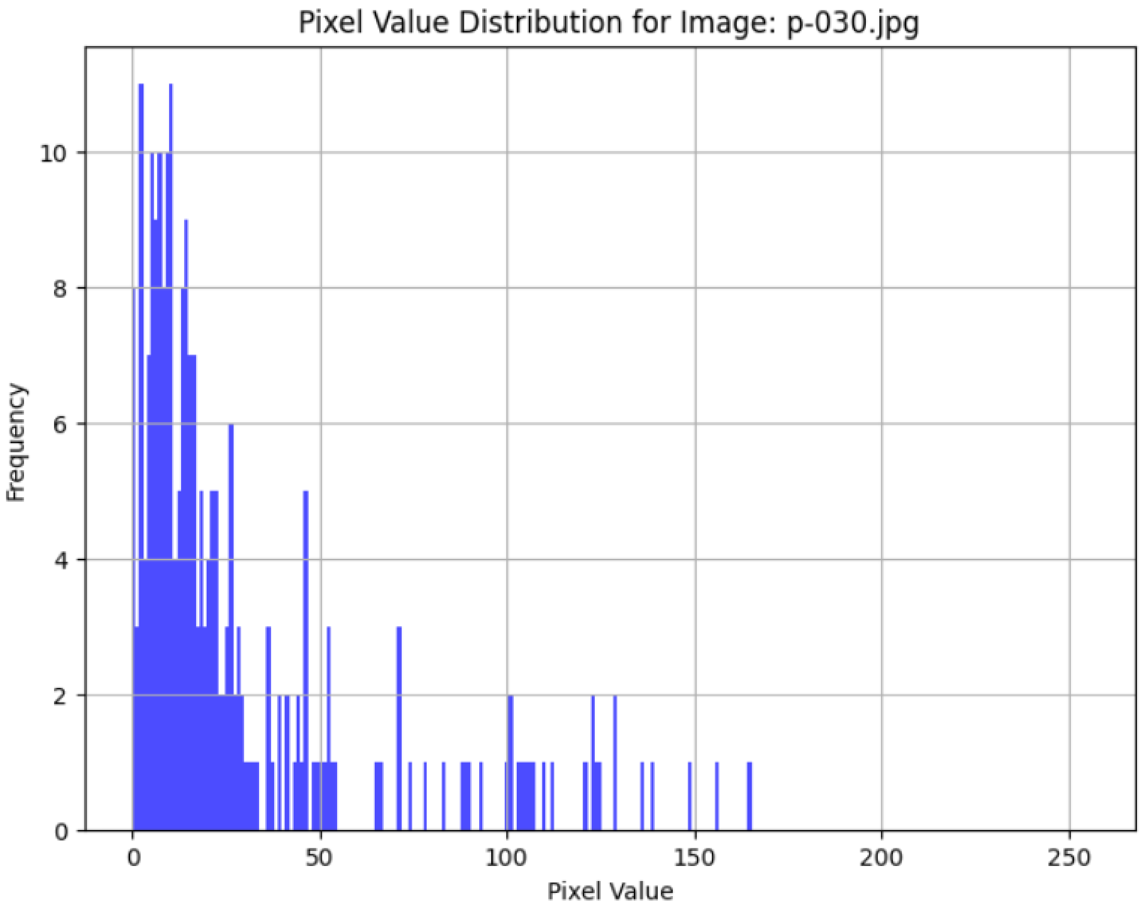

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



# CODE→ frequency Vs input value

```
import os
import matplotlib.pyplot as plt
import numpy as np
from PIL import Image

# Define the path to the specific image
image_path = '/content/drive/MyDrive/Tumor_Trace/clasification-roi/test/Benign/BreaDM-Be-1810/SUB1/p-030.jpg'  # Ensure this path is correct

# Load the image
image = Image.open(image_path).convert('L')  # Ensure grayscale conversion

# Convert the image to a NumPy array
image_array = np.array(image)

# Flatten the image into a 1D array for easier plotting
flat_image_array = image_array.flatten()

# Plotting the histogram of pixel values
plt.figure(figsize=(8, 6))
plt.hist(flat_image_array, bins=256, range=(0, 255), color='blue', alpha=0.7)
plt.title(f'Pixel Value Distribution for Image: {os.path.basename(image_path)}')
plt.xlabel('Pixel Value')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()

# Print the most frequent pixel values
unique, counts = np.unique(flat_image_array, return_counts=True)
frequencies = np.asarray((unique, counts)).T
print(frequencies)
```

OUTPUT→


Pixel Value Distribution for Image: p-030.jpg
Frequency
0
2
4
6
8
10
0
50
100
150
200
250
Pixel Value

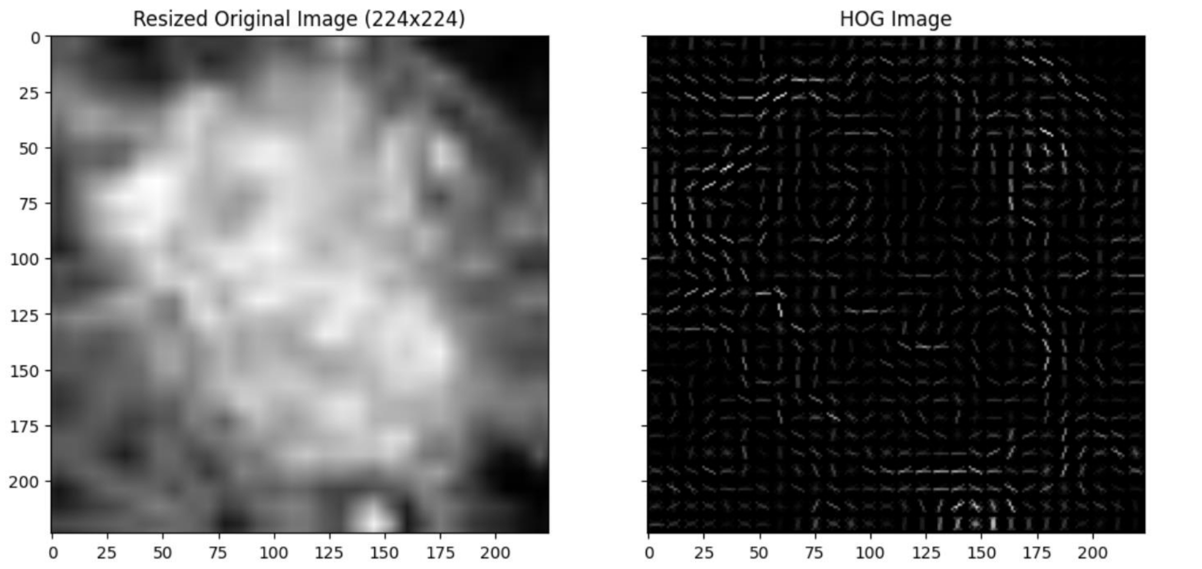
# HOG IMPLEMENTATION PERFORMED

# Code:-

```
import matplotlib.pyplot as plt

from skimage.feature import hog

from skimage.io import imread

from skimage.color import rgb2gray

from skimage.transform import resize



# Read image

image = imread('/kaggle/input/bctumor/test/Malignant/BreaDM-Ma-
1916/SUB7/p-039.jpg')



# Resize image to 224x224

image_resized = resize(image, (224, 224))



# Convert image to grayscale if it has multiple channels (e.g., RGB)

if len(image_resized.shape) > 2:

    image_resized = rgb2gray(image_resized)



# Compute HOG features and HOG image

hog_features, hog_image = hog(image_resized,

                              orientations=9,

                              pixels_per_cell=(8, 8),

                              cells_per_block=(2, 2),
```

```
                                block_norm='L2-Hys',

                                visualize=True)


# Visualize the original and HOG images

fig, ax = plt.subplots(1, 2, figsize=(12, 6), sharex=True, sharey=True)


ax[0].imshow(image_resized, cmap='gray')

ax[0].set_title('Resized Original Image (224x224)')


ax[1].imshow(hog_image, cmap='gray')

ax[1].set_title('HOG Image')


plt.show()
```

**Output:-**



# Convolution Performed:-

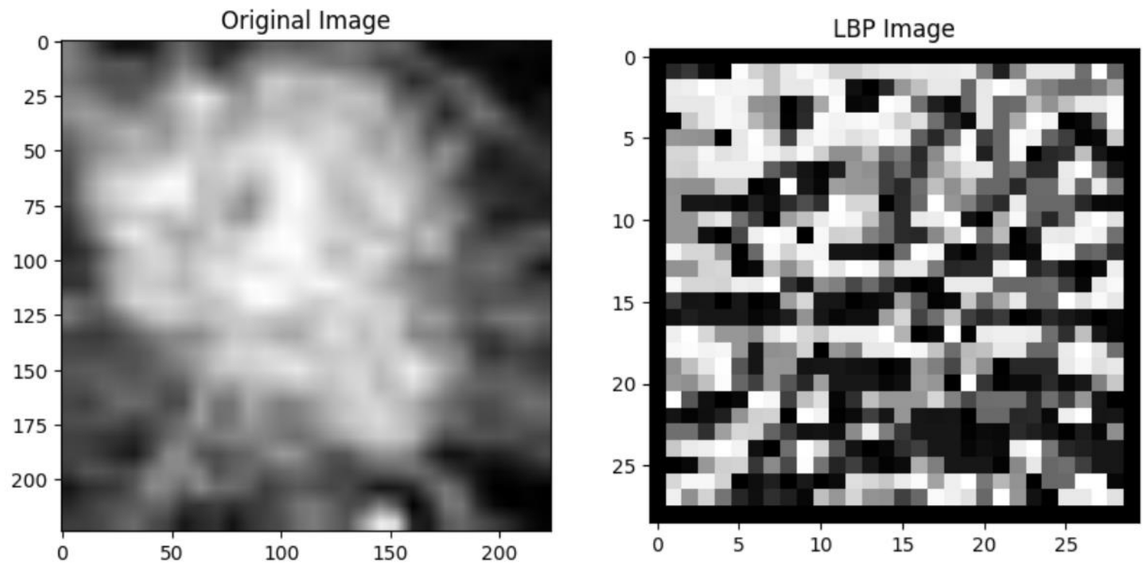
# Code:-

```
import cv2

import numpy as np

import matplotlib.pyplot as plt



def calculate_lbp(gray_image):

    """

    Function to calculate the Local Binary Pattern (LBP) of a grayscale
image.



    == Input ==

    gray_image: A grayscale image as a 2D NumPy array



    == Output ==

    img_lbp: LBP image of the same size

    """



    # Initialize the output LBP image with zeros

    img_lbp = np.zeros_like(gray_image)



    # Define the 3x3 neighborhood size

    neighboor = 3



    # Loop through each pixel (excluding the border pixels)
```

```
    for ih in range(1, gray_image.shape[0] - 1):
        for iw in range(1, gray_image.shape[1] - 1):
            # Extract the 3x3 block of pixels centered at (ih, iw)
            block = gray_image[ih-1:ih+2, iw-1:iw+2]

            # Get the center pixel value
            center = block[1, 1]

            # Perform binary comparison and compute LBP value
            binary_pattern = (block >= center).astype(np.uint8)
            binary_pattern[1, 1] = 0  # Ignore the center pixel itself

            # Flatten and convert the binary pattern to a decimal value
            lbp_value = binary_pattern.flatten()
            lbp_value = np.delete(lbp_value, 4)  # Remove center pixel
value
            lbp_decimal = np.sum(lbp_value * (2**np.arange(8)))

            # Store the LBP value in the output image
            img_lbp[ih, iw] = lbp_decimal

    return img_lbp


# Load a sample image and convert it to grayscale
```

```
image = cv2.imread('/kaggle/input/bctumor/test/Malignant/BreaDM-Ma-1916/SUB7/p-038.jpg')  # Replace with the path to your image

gray_image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)



# Resize the image to 224x224 pixels

image = cv2.resize(image, (224, 224))



# Calculate the LBP of the image

lbp_image = calculate_lbp(gray_image)



# Display the original and LBP images

plt.figure(figsize=(10, 5))



# Original color image

plt.subplot(1, 2, 1)

plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))  # Convert BGR to RGB for correct color display

plt.title('Original Image')



# LBP image (grayscale)

plt.subplot(1, 2, 2)

plt.imshow(lbp_image, cmap='gray')

plt.title('LBP Image')



plt.show()
```

# Output:-



Original Image
LBP Image
0 25 50 75 100 125 150 175 200
0 50 100 150 200
0 5 10 15 20 25
0 5 10 15 20 25

# Mean,Median,Varience based LBP

# is performed with histogtogram output

## code:-

```
import numpy as np

import matplotlib.pyplot as plt

from PIL import Image


def mean_based_lbp(image_path):

    image = Image.open(image_path).convert('L').resize((224, 224))

    img_array = np.array(image)

    rows, cols = img_array.shape

    lbp_image = np.zeros((rows, cols), dtype=np.uint8)


    for i in range(1, rows - 1):

        for j in range(1, cols - 1):

            neighborhood = img_array[i-1:i+2, j-1:j+2]

            center_pixel = img_array[i, j]

            mean_value = (np.sum(neighborhood) - center_pixel) / 8

            surrounding_pixels = np.delete(neighborhood.flatten(), 4)

            binary_pattern = (surrounding_pixels >=
mean_value).astype(int)

            lbp_image[i, j] = (binary_pattern * (2 **
np.arange(8))).sum()
```

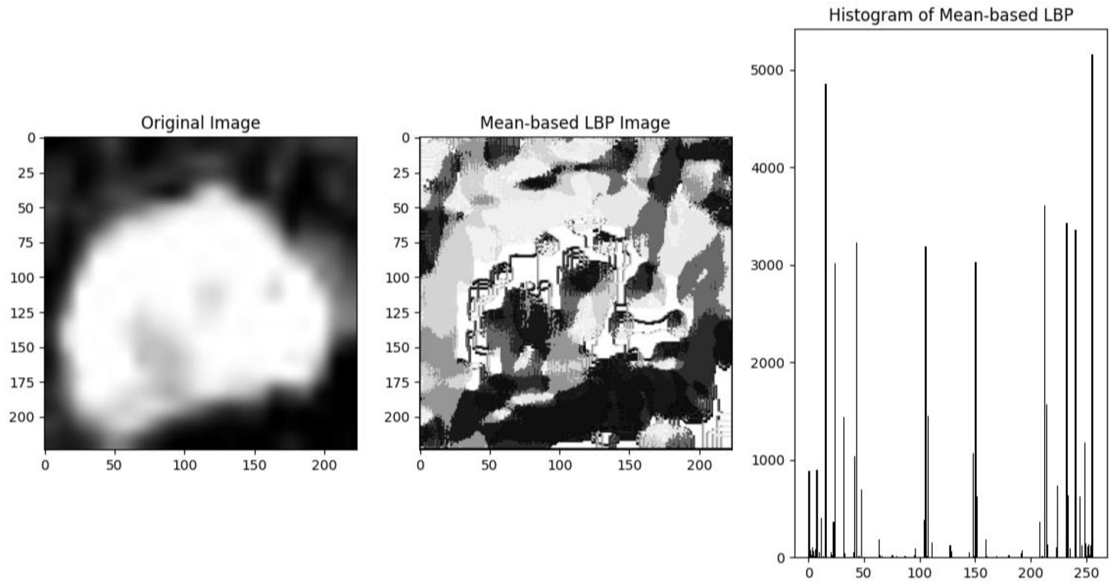
```
    lbp_image_normalized = (lbp_image / lbp_image.max()) * 255


    plt.figure(figsize=(14, 7))

    plt.subplot(1, 3, 1)

    plt.imshow(img_array, cmap='gray')

    plt.title('Original Image')

    plt.subplot(1, 3, 2)

    plt.imshow(lbp_image_normalized, cmap='gray')

    plt.title('Mean-based LBP Image')

    plt.subplot(1, 3, 3)

    plt.hist(lbp_image_normalized.ravel(), bins=256, range=(0, 256),
color='black')

    plt.title('Histogram of Mean-based LBP')

    plt.show()


def median_based_lbp(image_path):

    image = Image.open(image_path).convert('L').resize((224, 224))

    img_array = np.array(image)

    rows, cols = img_array.shape

    lbp_image = np.zeros((rows, cols), dtype=np.uint8)


    for i in range(1, rows - 1):

        for j in range(1, cols - 1):

            neighborhood = img_array[i-1:i+2, j-1:j+2]

            center_pixel = img_array[i, j]
```

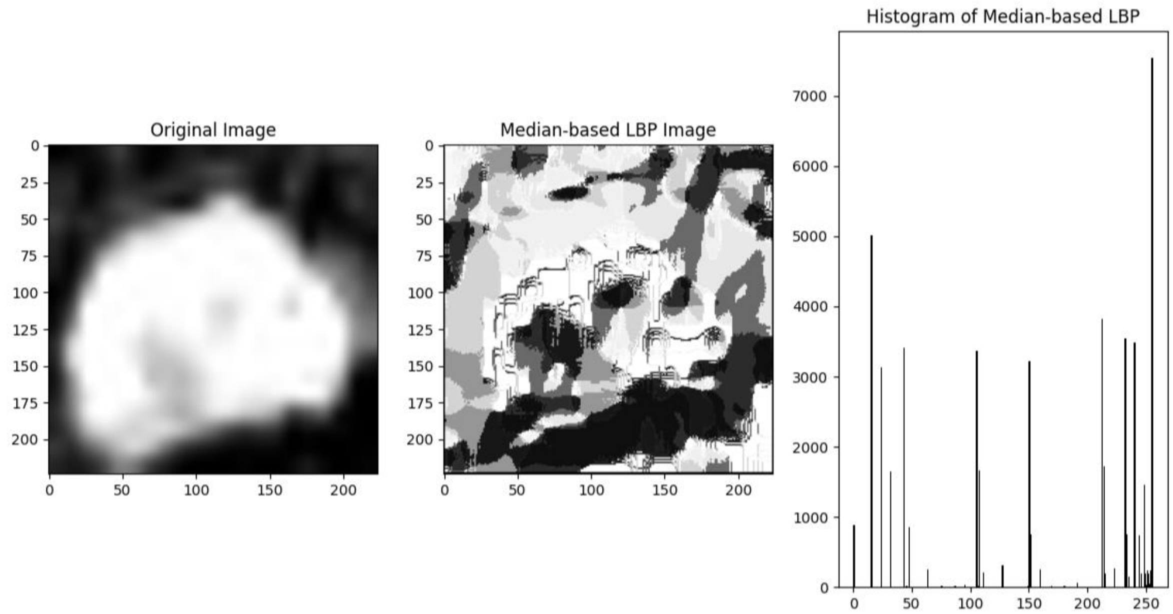
```
            median_value = np.median(np.delete(neighborhood.flatten(),
4))

            surrounding_pixels = np.delete(neighborhood.flatten(), 4)

            binary_pattern = (surrounding_pixels >=
median_value).astype(int)

            lbp_image[i, j] = (binary_pattern * (2 **
np.arange(8))).sum()



    lbp_image_normalized = (lbp_image / lbp_image.max()) * 255



    plt.figure(figsize=(14, 7))

    plt.subplot(1, 3, 1)

    plt.imshow(img_array, cmap='gray')

    plt.title('Original Image')

    plt.subplot(1, 3, 2)

    plt.imshow(lbp_image_normalized, cmap='gray')

    plt.title('Median-based LBP Image')

    plt.subplot(1, 3, 3)

    plt.hist(lbp_image_normalized.ravel(), bins=256, range=(0, 256),
color='black')

    plt.title('Histogram of Median-based LBP')

    plt.show()



def variance_based_lbp(image_path):

    image = Image.open(image_path).convert('L').resize((224, 224))

    img_array = np.array(image)

    rows, cols = img_array.shape
```

```
    lbp_image = np.zeros((rows, cols), dtype=np.uint8)

    for i in range(1, rows - 1):
        for j in range(1, cols - 1):
            neighborhood = img_array[i-1:i+2, j-1:j+2]
            center_pixel = img_array[i, j]
            variance_value = np.var(np.delete(neighborhood.flatten(),
4))
            surrounding_pixels = np.delete(neighborhood.flatten(), 4)
            binary_pattern = (surrounding_pixels >=
variance_value).astype(int)
            lbp_image[i, j] = (binary_pattern * (2 **
np.arange(8))).sum()

    lbp_image_normalized = (lbp_image / lbp_image.max()) * 255

    plt.figure(figsize=(14, 7))
    plt.subplot(1, 3, 1)
    plt.imshow(img_array, cmap='gray')
    plt.title('Original Image')
    plt.subplot(1, 3, 2)
    plt.imshow(lbp_image_normalized, cmap='gray')
    plt.title('Variance-based LBP Image')
    plt.subplot(1, 3, 3)
    plt.hist(lbp_image_normalized.ravel(), bins=256, range=(0, 256),
color='black')
```

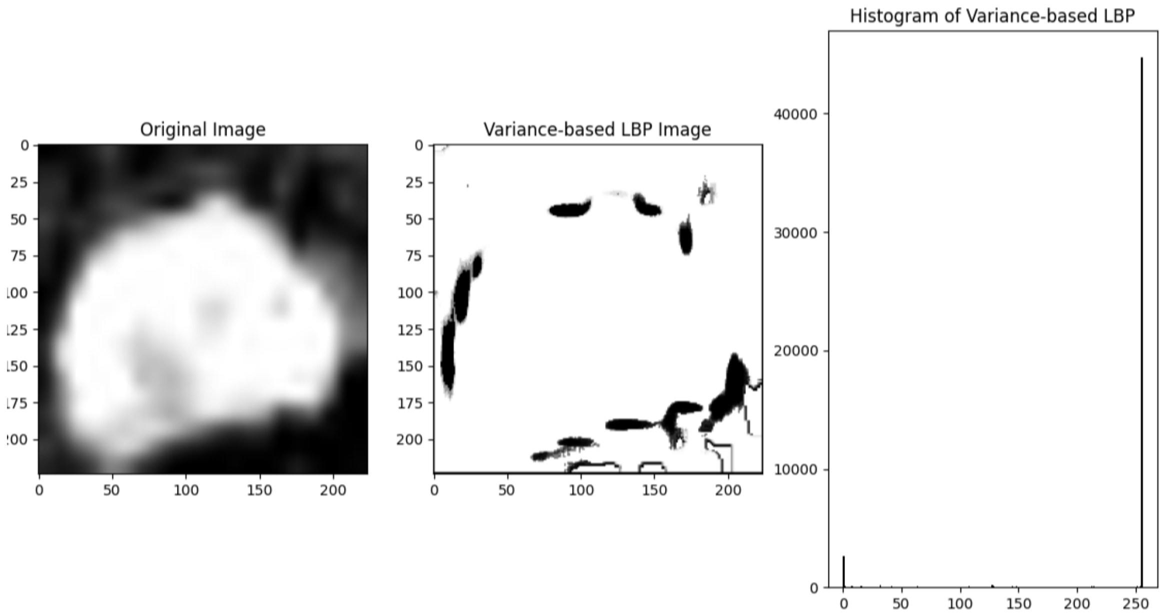
```
    plt.title('Histogram of Variance-based LBP')

    plt.show()



# Example usage
image_path = '/kaggle/input/bctumor/train/Malignant/BreaDM-Ma-
2127/SUB7/p-049.jpg'

mean_based_lbp(image_path)

median_based_lbp(image_path)

variance_based_lbp(image_path)
```

## **Output:-**





Original Image
Median-based LBP Image
Histogram of Median-based LBP

Original Image
Variance-based LBP Image
Histogram of Variance-based LBP

# Now we will observe the mean median and variance based on 5 images

# Code:-

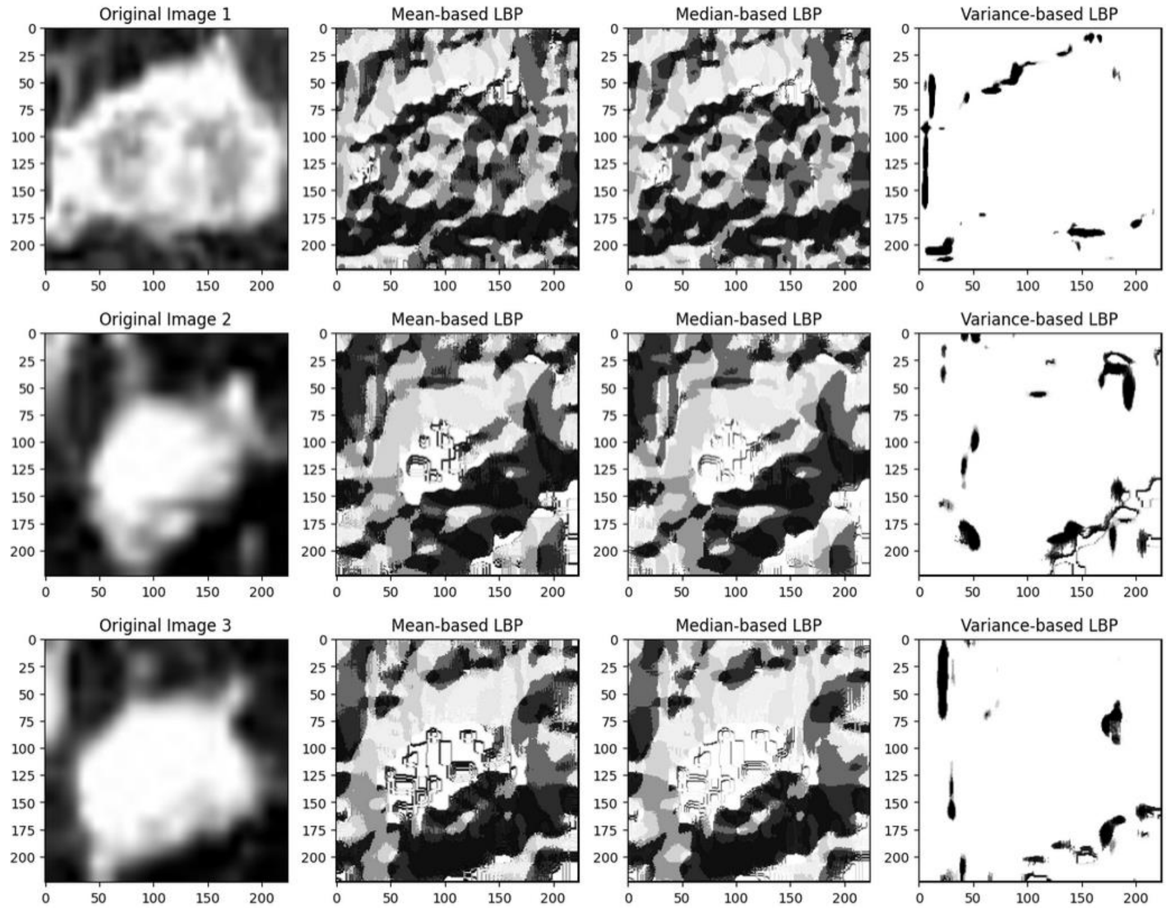
```
import numpy as np

import matplotlib.pyplot as plt

from PIL import Image



def mean_based_lbp(img_array):

    rows, cols = img_array.shape

    lbp_image = np.zeros((rows, cols), dtype=np.uint8)



    for i in range(1, rows - 1):

        for j in range(1, cols - 1):

            neighborhood = img_array[i-1:i+2, j-1:j+2]

            center_pixel = img_array[i, j]

            mean_value = (np.sum(neighborhood) - center_pixel) / 8

            surrounding_pixels = np.delete(neighborhood.flatten(), 4)

            binary_pattern = (surrounding_pixels >=
mean_value).astype(int)

            lbp_image[i, j] = (binary_pattern * (2 **
np.arange(8))).sum()



    return (lbp_image / lbp_image.max()) * 255
```

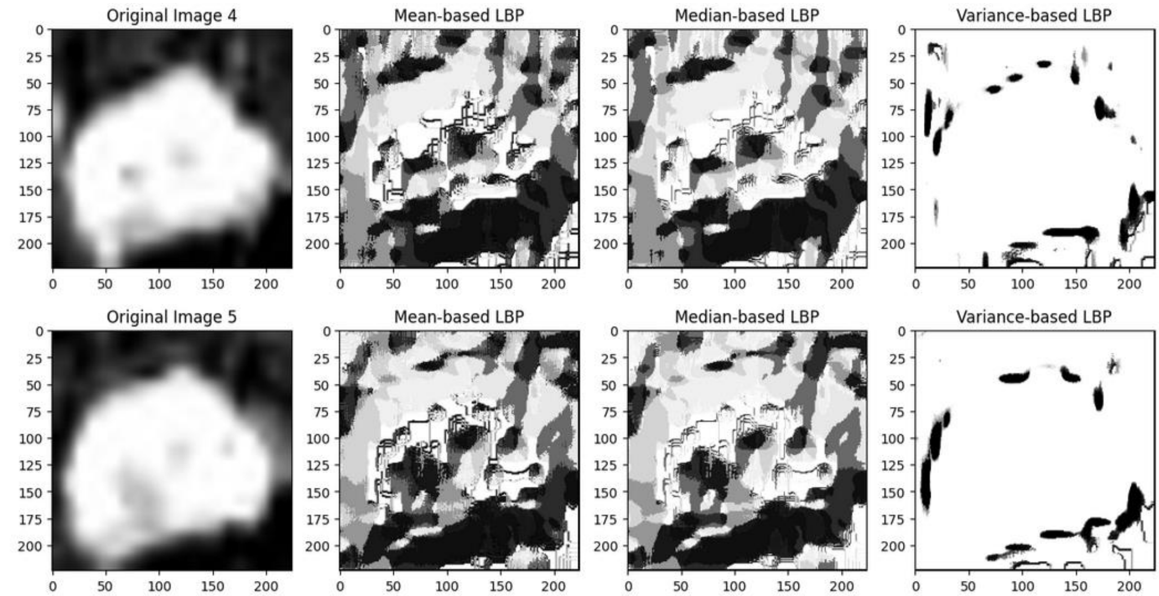
```
def median_based_lbp(img_array):

    rows, cols = img_array.shape

    lbp_image = np.zeros((rows, cols), dtype=np.uint8)



    for i in range(1, rows - 1):

        for j in range(1, cols - 1):

            neighborhood = img_array[i-1:i+2, j-1:j+2]

            center_pixel = img_array[i, j]

            median_value = np.median(np.delete(neighborhood.flatten(),
4))

            surrounding_pixels = np.delete(neighborhood.flatten(), 4)

            binary_pattern = (surrounding_pixels >=
median_value).astype(int)

            lbp_image[i, j] = (binary_pattern * (2 **
np.arange(8))).sum()



    return (lbp_image / lbp_image.max()) * 255



def variance_based_lbp(img_array):

    rows, cols = img_array.shape

    lbp_image = np.zeros((rows, cols), dtype=np.uint8)



    for i in range(1, rows - 1):

        for j in range(1, cols - 1):

            neighborhood = img_array[i-1:i+2, j-1:j+2]

            center_pixel = img_array[i, j]
```

```
            variance_value = np.var(np.delete(neighborhood.flatten(),
4))

            surrounding_pixels = np.delete(neighborhood.flatten(), 4)

            binary_pattern = (surrounding_pixels >=
variance_value).astype(int)

            lbp_image[i, j] = (binary_pattern * (2 **
np.arange(8))).sum()


    return (lbp_image / lbp_image.max()) * 255


# List of image paths

image_paths = [

    '/kaggle/input/bctumor/train/Malignant/BreaDM-Ma-2127/SUB7/p-
049.jpg',

    '/kaggle/input/bctumor/train/Malignant/BreaDM-Ma-1815/SUB3/p-
047.jpg',

    '/kaggle/input/bctumor/train/Malignant/BreaDM-Ma-1815/SUB3/p-
048.jpg',

    '/kaggle/input/bctumor/train/Malignant/BreaDM-Ma-1815/SUB3/p-
049.jpg',

    '/kaggle/input/bctumor/train/Malignant/BreaDM-Ma-1815/SUB3/p-
050.jpg'

]


# Processing and displaying all images

for idx, image_path in enumerate(image_paths):

    image = Image.open(image_path).convert('L').resize((224, 224))

    img_array = np.array(image)

```

```
    mean_lbp = mean_based_lbp(img_array)

    median_lbp = median_based_lbp(img_array)

    variance_lbp = variance_based_lbp(img_array)


    plt.figure(figsize=(15, 5))


    plt.subplot(1, 4, 1)

    plt.imshow(img_array, cmap='gray')

    plt.title(f'Original Image {idx+1}')


    plt.subplot(1, 4, 2)

    plt.imshow(mean_lbp, cmap='gray')

    plt.title('Mean-based LBP')


    plt.subplot(1, 4, 3)

    plt.imshow(median_lbp, cmap='gray')

    plt.title('Median-based LBP')


    plt.subplot(1, 4, 4)

    plt.imshow(variance_lbp, cmap='gray')

    plt.title('Variance-based LBP')


    plt.show()
```

## Output:-


Original Image 1
Mean-based LBP
Median-based LBP
Variance-based LBP
Original Image 2
Mean-based LBP
Median-based LBP
Variance-based LBP
Original Image 3
Mean-based LBP
Median-based LBP
Variance-based LBP
0 25 50 75 100 125 150 175 200
0 50 100 150 200


Original Image 4
Mean-based LBP
Median-based LBP
Variance-based LBP
Original Image 5
Mean-based LBP
Median-based LBP
Variance-based LBP
0 25 50 75 100 125 150 175 200
0 50 100 150 200

# GLCM Matrix Calculation:-

```
import numpy as np


def calculate_horizontal_glcm(matrix, distance=1):


    max_gray_level = np.max(matrix) + 1

    glcm = np.zeros((max_gray_level, max_gray_level), dtype=int)


    rows, cols = matrix.shape


    for i in range(rows):

        for j in range(cols - distance):

            current_pixel = matrix[i, j]

            neighbor_pixel = matrix[i, j + distance]




            glcm[current_pixel, neighbor_pixel] += 1


    return glcm


# Example input matrix

input_matrix = np.array([

    [0, 1, 2, 3],

    [1, 0, 3, 2],

    [2, 3, 0, 1],
```

```
    [3, 2, 1, 0]
])

# Calculate the horizontal GLCM for the given input matrix
glcm_matrix = calculate_horizontal_glcm(input_matrix, distance=1)
print("Horizontal GLCM Matrix:\n", glcm_matrix)
```

## output:-

```
Horizontal GLCM Matrix:
 [[0 2 0 1]
 [2 0 1 0]
 [0 1 0 2]
 [1 0 2 0]]
```

# Now we will start the model training part

# Loading vgg16 model

```
import torch

import torchvision.models as models

vgg16 = models.vgg16(pretrained=True)

vgg16.eval()

print(vgg16)
```

```
/opt/conda/lib/python3.10/site-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weights' instead.
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weight
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.cache/torch/hub/checkpoints/vgg16-397923af.pth
100%|██████████| 528M/528M [00:10<00:00, 54.4MB/s]
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
```

# Implementing a Custom_Vgg16 function

# Code:-

```
import torch

import torch.nn as nn

from torchvision import models



class CustomVGG16(nn.Module):

    def __init__(self, num_classes=2):

        # Initialize the parent class

        super(CustomVGG16, self).__init__()



        # Load the pre-trained VGG16 model

        vgg16 = models.vgg16(pretrained=True)
```

```
        # Extract the features and avgpool layers
        self.features = vgg16.features
        self.avgpool = vgg16.avgpool

        # Define a new classifier using nn.Sequential
        self.classifier = nn.Sequential(
            nn.Linear(512 * 7 * 7, 4096),  # First linear layer
            nn.ReLU(),                     # ReLU activation
            nn.Dropout(),                  # Dropout layer
            nn.Linear(4096, 4096),         # Second linear layer
            nn.ReLU(),                     # ReLU activation
            nn.Dropout(),                  # Dropout layer
            nn.Linear(4096, num_classes)   # Final linear layer for
binary classification
        )

    def forward(self, x):
        # Pass the input through the features layer
        x = self.features(x)

        # Use the avgpool layer and reshape the output to a 2D tensor
        x = self.avgpool(x)
        x = torch.flatten(x, 1)  # Flatten the tensor (batch_size,
num_features)

        # Pass the reshaped output to the custom classifier
```

```
        x = self.classifier(x)


        return x


# Example of creating an instance of CustomVGG16

model = CustomVGG16(num_classes=2)
```

# Now, we will implement early stopping function

# Code:-

```
import numpy as np

import torch



class EarlyStopping:

    def __init__(self, patience=7, verbose=False, delta=0,
path='checkpoint.pt', trace_func=print):

        """

        Early stops the training if validation loss doesn't improve
after a given patience.



        Parameters:

        - patience (int): How long to wait after the last time
validation loss improved.

        - verbose (bool): If True, prints a message for each validation
loss improvement.

        - delta (float): Minimum change in the monitored quantity to
qualify as an improvement.

        - path (str): Path for saving the model checkpoint.

        - trace_func (function): Function to print messages; can be set
to print/logging.

        """

        self.patience = patience

        self.verbose = verbose

        self.delta = delta

        self.path = path
```

```
        self.trace_func = trace_func

        self.counter = 0

        self.best_score = None

        self.early_stop = False

        self.val_loss_min = np.Inf


    def __call__(self, val_loss, model):

        """

        Call this function to check if the validation loss has
improved.

        If not improved, increment the counter. If improved, reset
counter and save model.



        Parameters:

        - val_loss (float): Current validation loss.

        - model (torch.nn.Module): Model to save if validation loss
decreases.

        """

        score = -val_loss

        if self.best_score is None:

            self.best_score = score

            self.save_checkpoint(val_loss, model)

        elif score < self.best_score + self.delta:

            self.counter += 1

            self.trace_func(f'EarlyStopping counter: {self.counter} out
of {self.patience}')

            if self.counter >= self.patience:
```

```
                self.early_stop = True

        else:

            self.best_score = score

            self.save_checkpoint(val_loss, model)

            self.counter = 0


    def save_checkpoint(self, val_loss, model):

        """Saves model when validation loss decreases."""

        if self.verbose:

            self.trace_func(f'Validation loss decreased 
({self.val_loss_min:.6f} --> {val_loss:.6f}). Saving model ...')

        torch.save(model.state_dict(), self.path)

        self.val_loss_min = val_loss
```

## Now we will transform our images to make input in the model

```
_test_transforms = transforms.Compose([
    transforms.Resize(224),                         # Resize the image to 256x256
    transforms.CenterCrop(224),                     # Center crop to 224x224
    transforms.ToTensor(),                          # Convert to tensor
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]) # Normalize with ImageNet mean and std
])
```

## #Loading the Dataset

```
from torchvision import datasets, transforms
from torch.utils.data import DataLoader

# Define transformations (resize and normalization only, no augmentation)
transform = transforms.Compose([
    transforms.Resize((224, 224)),          # Resize the image to 224x224
    transforms.ToTensor(),                  # Convert the image to a PyTorch tensor
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])  # Normalize based on ImageNet
])

# Replace BreastCancerDataset with ImageFolder for loading datasets
train_dir = '/kaggle/input/bctumor/train'
val_dir = '/kaggle/input/bctumor/val'
test_dir = '/kaggle/input/bctumor/test'

# Load datasets using ImageFolder
train_dataset = datasets.ImageFolder(root=train_dir, transform=transform)
val_dataset = datasets.ImageFolder(root=val_dir, transform=transform)
test_dataset = datasets.ImageFolder(root=test_dir, transform=transform)

# Create DataLoaders for each dataset
```

```
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=32, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Now your datasets are ready for use
```

# // training vgg16 model

```
import torch

import torch.nn.functional as F

from tqdm import tqdm

import torch.optim as optim

from tqdm import tqdm


device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

model = model.to(device)
```

# # Train Function

```
import torch
from tqdm import tqdm
import torch.nn as nn
import torch.nn.functional as F

epoch = 0
total_epochs = 50
loader = train_loader  # Ensure this is a DataLoader instance for
training data
criterion = nn.CrossEntropyLoss()
l2_decay = 0.01
lr = 0.01  # Learning rate
```

```
def train(epoch, model, total_epochs, loader, criterion, l2_decay):
    learning_rate = max(lr * (0.1 ** (epoch // 10)), 1e-5)
    optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate,
momentum=0.9, weight_decay=l2_decay)
    # Rest of the code...



    model.train()

    correct = 0
    for data, label in tqdm(loader, desc=f'Epoch
{epoch+1}/{total_epochs}', unit='batch'):
        #data = data.float().cuda()

        #label = label.long().cuda()
        data = data.float().to(device)
        label = label.long().to(device)

        output = model(data)
        optimizer.zero_grad()
        loss = F.nll_loss(F.log_softmax(output, dim=1), label)
        loss.backward()
        optimizer.step()

        pred = output.data.max(1)[1]
        correct += pred.eq(label.data.view_as(pred)).cpu().sum()

    print(f'train accuracy: {100. * correct / len(loader.dataset)}%')
```

# #Validation Function

```
import torch
import numpy as np
from sklearn import metrics
from sklearn.metrics import roc_curve, auc as compute_auc
import torch.nn.functional as F

def validation(model, val_loader):
    model.eval()  # Set model to evaluation mode
    test_loss = 0
    correct = 0
    all_predictions = []  # Store all predictions
    all_targets = []      # Store all targets
    possibilities = None  # Store probabilities for AUC
```

```
    for data, target in val_loader:
        if torch.cuda.is_available():
            data, target = data.cuda(), target.cuda()

        val_output = model(data)

        # Calculate test loss
        test_loss += F.nll_loss(F.log_softmax(val_output, dim=1),
target, reduction='sum').item()

        # Get predictions and accumulate them
        pred = val_output.data.max(1)[1]
        all_predictions.extend(pred.cpu().numpy())  # Collect all
predictions
        all_targets.extend(target.cpu().numpy())    # Collect all
target labels

        # Calculate probabilities for AUC
        possibility = F.softmax(val_output,
dim=1).cpu().detach().numpy()
        if possibilities is None:
            possibilities = possibility
        else:
            possibilities = np.concatenate((possibilities,
possibility), axis=0)

        # Calculate the number of correct predictions
        correct += pred.eq(target.data.view_as(pred)).cpu().sum()

    # Compute confusion matrix
    cm = metrics.confusion_matrix(all_targets, all_predictions)

    # One-hot encode the labels for AUC computation
    num_classes = val_output.shape[1]
    label_onehot =
np.eye(num_classes)[np.array(all_targets).astype(int)]

    # Compute ROC curve and AUC
    fpr, tpr, thresholds = roc_curve(label_onehot.ravel(),
possibilities.ravel())
    auc_value = compute_auc(fpr, tpr)  # Use renamed function here

    # Average test loss per sample
    test_loss /= len(val_loader.dataset)

    # Calculate sensitivity and specificity
    specificity = 1 - fpr[1] if len(fpr) > 1 else 0
```

```
    sensitivity = tpr[1] if len(tpr) > 1 else 0

    print('Specificity: {:.4f}, Sensitivity: {:.4f}, AUC: 
{:.4f}'.format(specificity, sensitivity, auc_value))
    print('\nTest set: Average loss: {:.4f}, Accuracy: 
{:.2f}%\n'.format(test_loss, 100. * correct / len(val_loader.dataset)))

    return test_loss, 100. * correct / len(val_loader.dataset), cm, 
auc_value
```

## Now, Initiallizing the parameters and loading custom Vgg16

```python
total_epochs = 50

lr = 0.01

momentum = 0.9

no_cuda = False

num_classes=2

log_interval = 10

l2_decay = 0.01

model = CustomVGG16(num_classes=num_classes)

model = model.to(device)

CustomVGG16(num_classes=num_classes)
```

```
/opt/conda/lib/python3.10/site-packages/torchvision/models/_utils.py:208: 
UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be 
removed in the future, please use 'weights' instead.
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/torchvision/models/_utils.py:223: 
UserWarning: Arguments other than a weight enum or `None` for 'weights' are 
deprecated since 0.13 and may be removed in the future. The current 
behavior is equivalent to passing `weights=VGG16_Weights.IMAGENET1K_V1`. 
You can also use `weights=VGG16_Weights.DEFAULT` to get the most up-to-date 
weights.
  warnings.warn(msg)
CustomVGG16(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, 
ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 
1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, 
ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 
1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 
1))
```

```
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU()
    (2): Dropout(p=0.5, inplace=False)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU()
    (5): Dropout(p=0.5, inplace=False)
    (6): Linear(in_features=4096, out_features=2, bias=True)
  )
)
```

---

---

# Now training the model

```
# please make sure you are using variables that match your own
environment.
```

```
# model training on Validation

model.to(device)  # here device is cuda
best_accuracy = 0
early_stop = EarlyStopping(patience=20, verbose=True)
project_name = 'tumor_classfication'
model_name = 'vgg16'

# we will be using epochs. epochs will be defined in another code
block.

for epoch in range(1, total_epochs + 1):

      #train(epoch, model)#train(epoch, total_epochs, train_loader,
criterion, l2_decay, lr)

    train(epoch, model, total_epochs, train_loader, criterion,
l2_decay)

    with torch.no_grad():

        test_loss,_,_, auc = validation(model , val_loader)

        #accuracy, test_loss, auc_value = test(model, test_loader)
        #print(f"Test Accuracy: {accuracy:.2f}%, Loss: {test_loss:.4f},
AUC: {auc_value:.4f}")


    # making sure that the model can run on multiple GPUs

    dict = model.module.state_dict() if isinstance(model,
nn.parallel.DistributedDataParallel) else model.state_dict()

    model_save_dir = os.path.join('model', project_name, model_name)

    if not os.path.exists(model_save_dir):

        os.makedirs(model_save_dir)

    early_stop(test_loss, model)

    if auc > best_accuracy:

        best_accuracy = auc

        #torch.save(os.path.join(model_save_dir,
f'{model_name}_{epoch}.pth'), _use_new_zipfile_serialization=False)
        torch.save(dict, os.path.join(model_save_dir,
f'{model_name}_{epoch}.pth'), _use_new_zipfile_serialization=False)
```

```
    if early_stop.early_stop:

        print("Early stopping")

        break
```

```
Epoch 2/50: 100%|██████████| 639/639 [04:50<00:00,  2.20batch/s]
train accuracy: 84.44259643554688%
Specificity: 1.0000, Sensitivity: 0.0101, AUC: 0.9192

Test set: Average loss: 0.3461, Accuracy: 81.30%

Validation loss decreased (inf --> 0.346125). Saving model ...
Epoch 3/50: 100%|██████████| 639/639 [03:17<00:00,  3.24batch/s]
train accuracy: 90.40814208984375%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8745

Test set: Average loss: 0.4374, Accuracy: 76.57%

EarlyStopping counter: 1 out of 20
Epoch 4/50: 100%|██████████| 639/639 [03:16<00:00,  3.25batch/s]
train accuracy: 90.92198944091797%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8659

Test set: Average loss: 0.4618, Accuracy: 76.02%

EarlyStopping counter: 2 out of 20
Epoch 5/50: 100%|██████████| 639/639 [03:20<00:00,  3.19batch/s]
train accuracy: 92.33140563964844%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8730

Test set: Average loss: 0.4737, Accuracy: 76.72%

EarlyStopping counter: 3 out of 20
Epoch 6/50: 100%|██████████| 639/639 [03:21<00:00,  3.18batch/s]
train accuracy: 92.71312713623047%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.9151

Test set: Average loss: 0.3882, Accuracy: 82.00%

EarlyStopping counter: 4 out of 20
Epoch 7/50: 100%|██████████| 639/639 [03:16<00:00,  3.25batch/s]
train accuracy: 93.69677734375%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8963

Test set: Average loss: 0.4005, Accuracy: 79.14%

EarlyStopping counter: 5 out of 20
Epoch 8/50: 100%|██████████| 639/639 [03:17<00:00,  3.24batch/s]
train accuracy: 94.07360076904297%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8835

Test set: Average loss: 0.4601, Accuracy: 78.48%

EarlyStopping counter: 6 out of 20
Epoch 9/50: 100%|██████████| 639/639 [03:17<00:00,  3.23batch/s]
```

```
train accuracy: 94.42595672607422%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8978

Test set: Average loss: 0.4009, Accuracy: 80.19%

EarlyStopping counter: 7 out of 20
Epoch 10/50: 100%|██████████| 639/639 [03:18<00:00,  3.23batch/s]
train accuracy: 94.48468017578125%
Specificity: 1.0000, Sensitivity: 0.1217, AUC: 0.9204

Test set: Average loss: 0.5308, Accuracy: 82.25%

EarlyStopping counter: 8 out of 20
Epoch 11/50: 100%|██████████| 639/639 [03:17<00:00,  3.23batch/s]
train accuracy: 98.82059478759766%
Specificity: 1.0000, Sensitivity: 0.0804, AUC: 0.9286

Test set: Average loss: 0.4507, Accuracy: 83.61%

EarlyStopping counter: 9 out of 20
Epoch 12/50: 100%|██████████| 639/639 [03:17<00:00,  3.24batch/s]
train accuracy: 99.47636413574219%
Specificity: 1.0000, Sensitivity: 0.1111, AUC: 0.9336

Test set: Average loss: 0.4754, Accuracy: 84.26%

EarlyStopping counter: 10 out of 20
Epoch 13/50: 100%|██████████| 639/639 [03:16<00:00,  3.25batch/s]
train accuracy: 99.65743255615234%
Specificity: 1.0000, Sensitivity: 0.0870, AUC: 0.9251

Test set: Average loss: 0.4974, Accuracy: 83.11%

EarlyStopping counter: 11 out of 20
Epoch 14/50: 100%|██████████| 639/639 [03:16<00:00,  3.25batch/s]
train accuracy: 99.75531005859375%
Specificity: 1.0000, Sensitivity: 0.1212, AUC: 0.9164

Test set: Average loss: 0.5832, Accuracy: 82.35%

EarlyStopping counter: 12 out of 20
Epoch 15/50: 100%|██████████| 639/639 [03:17<00:00,  3.24batch/s]
train accuracy: 99.76020050048828%
Specificity: 1.0000, Sensitivity: 0.1202, AUC: 0.9276

Test set: Average loss: 0.5303, Accuracy: 83.51%

EarlyStopping counter: 13 out of 20
Epoch 16/50: 100%|██████████| 639/639 [03:19<00:00,  3.20batch/s]
train accuracy: 99.75041961669922%
Specificity: 1.0000, Sensitivity: 0.1347, AUC: 0.9261

Test set: Average loss: 0.5683, Accuracy: 83.01%

EarlyStopping counter: 14 out of 20
Epoch 17/50: 100%|██████████| 639/639 [03:18<00:00,  3.22batch/s]
train accuracy: 99.72105407714844%
Specificity: 1.0000, Sensitivity: 0.0679, AUC: 0.8993

Test set: Average loss: 0.6361, Accuracy: 80.19%
```

```
EarlyStopping counter: 15 out of 20
Epoch 18/50: 100%|██████████| 639/639 [03:16<00:00,  3.26batch/s]
train accuracy: 99.7944564819336%
Specificity: 1.0000, Sensitivity: 0.1166, AUC: 0.9221

Test set: Average loss: 0.5539, Accuracy: 83.06%

EarlyStopping counter: 16 out of 20
Epoch 19/50: 100%|██████████| 639/639 [03:15<00:00,  3.27batch/s]
train accuracy: 99.77488708496094%
Specificity: 1.0000, Sensitivity: 0.1187, AUC: 0.9176

Test set: Average loss: 0.6069, Accuracy: 82.30%

EarlyStopping counter: 17 out of 20
Epoch 20/50: 100%|██████████| 639/639 [03:17<00:00,  3.24batch/s]
train accuracy: 99.76020050048828%
Specificity: 1.0000, Sensitivity: 0.0744, AUC: 0.9182

Test set: Average loss: 0.5491, Accuracy: 83.16%

EarlyStopping counter: 18 out of 20
Epoch 21/50: 100%|██████████| 639/639 [03:17<00:00,  3.24batch/s]
train accuracy: 99.9363784790039%
Specificity: 1.0000, Sensitivity: 0.1071, AUC: 0.9180

Test set: Average loss: 0.5881, Accuracy: 82.05%

EarlyStopping counter: 19 out of 20
Epoch 22/50: 100%|██████████| 639/639 [03:17<00:00,  3.24batch/s]
train accuracy: 99.97063446044922%
Specificity: 1.0000, Sensitivity: 0.1131, AUC: 0.9181

Test set: Average loss: 0.6001, Accuracy: 82.20%

EarlyStopping counter: 20 out of 20
Early stopping
```

# **#Test Function**

```python
from sklearn.metrics import roc_auc_score, roc_curve,
classification_report, confusion_matrix
import torch
import numpy as np
import torch.nn.functional as F

def test(model, test_loader):
    """
    Function to evaluate the model on the test dataset.

    Parameters:
    - model (torch.nn.Module): The trained model.
    - test_loader (DataLoader): DataLoader for the test dataset.

    Returns:
    - accuracy (float): Test accuracy in percentage.
    - test_loss (float): Average test loss.
    - auc_value (float): AUC score.
    """
    model.eval()  # Set model to evaluation mode
    test_loss = 0
    correct = 0
    possibilities = None
    all_predictions = []
    all_targets = []

    # Iterate through the test DataLoader
    for data, target in test_loader:
        data, target = data.to(device), target.to(device)
        test_output = model(data)  # Forward pass

        # Compute loss
        test_loss += F.nll_loss(F.log_softmax(test_output, dim=1),
target, reduction='sum').item()

        # Get predictions
        pred = test_output.data.max(1)[1]
        all_predictions.extend(pred.cpu().numpy())
        all_targets.extend(target.cpu().numpy())

        # Get probabilities for AUC calculation
        possibility = F.softmax(test_output, dim=1).cpu().data.numpy()
        if possibilities is None:
            possibilities = possibility
        else:
            possibilities = np.concatenate((possibilities,
possibility), axis=0)
```

```
        # Count correct predictions
        correct += pred.eq(target.data.view_as(pred)).sum().item()

    # Convert all predictions and targets to numpy arrays
    all_predictions = np.array(all_predictions)
    all_targets = np.array(all_targets)

    # Classification metrics
    print(classification_report(all_targets, all_predictions,
target_names=['benign', 'malignant'], digits=4))

    # Confusion matrix
    cm = confusion_matrix(all_targets, all_predictions)
    print("Confusion Matrix:\n", cm)

    # AUC score
    num_classes = possibilities.shape[1]
    label_onehot = np.eye(num_classes)[all_targets]
    fpr, tpr, _ = roc_curve(label_onehot.ravel(),
possibilities.ravel())
    auc_value = roc_auc_score(label_onehot, possibilities,
average="macro")

    # Average loss and accuracy
    test_loss /= len(test_loader.dataset)
    accuracy = 100. * correct / len(test_loader.dataset)
    print('Specificity: {:.4f}, Sensitivity: {:.4f}, AUC:
{:.4f}'.format(1 - fpr[0], tpr[0], auc_value))
    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{}
({:.2f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset), accuracy))

    return accuracy, test_loss, auc_value, fpr, tpr, cm
```

# **Output:-**

```
test(model, test_loader)
```

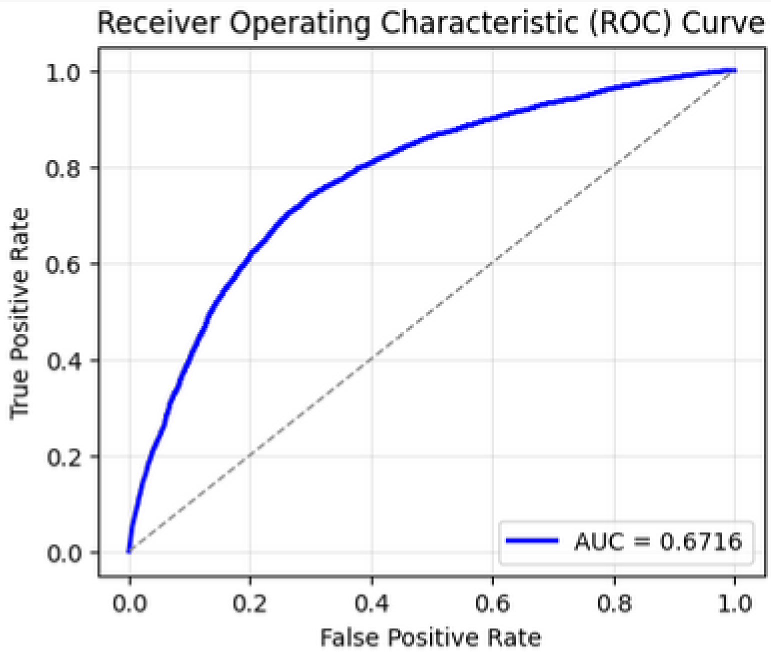
```
              precision    recall  f1-score   support

      benign     0.5010    0.3695    0.4253      1938
   malignant     0.7746    0.8549    0.8128      4913

    accuracy                         0.7176      6851
   macro avg     0.6378    0.6122    0.6190      6851
weighted avg     0.6972    0.7176    0.7032      6851

Confusion Matrix:
 [[ 716 1222]
 [ 713 4200]]
Specificity: 1.0000, Sensitivity: 0.0000, AUC: 0.6716

Test set: Average loss: 1.7644, Accuracy: 4916/6851 (71.76%)

(71.75594803678295,
 1.7643584101601721,
 0.6716401243347351,
 array([0.        , 0.00525471, 0.00919574, ..., 0.98963655, 0.98963655,
        1.        ]),
 array([0.        , 0.0507955 , 0.0719603 , ..., 0.99985404, 1.        ,
        1.        ]),
 array([[ 716, 1222],
        [ 713, 4200]]))
```

```
test_accuracy, test_loss, test_auc, fpr, tpr, cm = test(model, test_loader)
```


```
              precision    recall  f1-score   support

      benign     0.5010    0.3695    0.4253      1938
   malignant     0.7746    0.8549    0.8128      4913

    accuracy                         0.7176      6851
   macro avg     0.6378    0.6122    0.6190      6851
weighted avg     0.6972    0.7176    0.7032      6851

Confusion Matrix:
 [[ 716 1222]
 [ 713 4200]]
Specificity: 1.0000, Sensitivity: 0.0000, AUC: 0.6716

Test set: Average loss: 1.7644, Accuracy: 4916/6851 (71.76%)
```

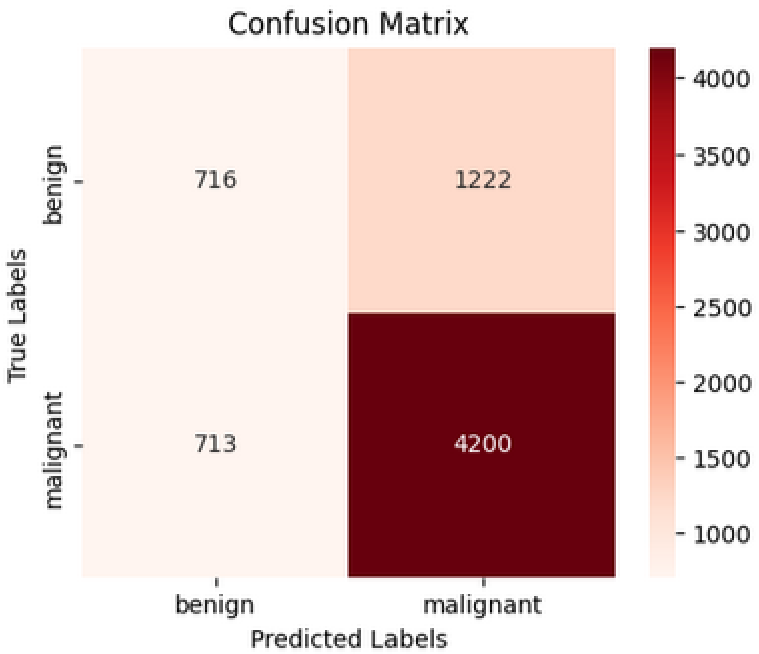
# #plotting graph and confusion Matrix

```
import matplotlib.pyplot as plt

def plot_auc(fpr, tpr, auc_value):
    plt.figure(figsize=(5, 4))
    plt.plot(fpr, tpr, color='blue', lw=2, label=f'AUC =
{auc_value:.4f}')
    plt.plot([0, 1], [0, 1], color='gray', linestyle='--', lw=1)   #
Diagonal line
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc='lower right')
    plt.grid(alpha=0.3)
    plt.show()

plot_auc(fpr, tpr, test_auc)
```



# #Plotting Confusion Matrix

```
import seaborn as sns
def plot_confusion_matrix(cm, class_names):
    plt.figure(figsize=(5, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Reds',
xticklabels=class_names, yticklabels=class_names)
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Confusion Matrix')
    plt.show()

plot_confusion_matrix(cm, class_names=['benign', 'malignant'])
```



# #Implementing Resnet18

```
import torch
import torch.nn as nn
import torchvision.models as models

# ResNet18 class that inherits from nn.Module
class Resnet18(nn.Module):
    def __init__(self, num_classes=2):
        super(Resnet18, self).__init__()

        # Load the pretrained ResNet18 model
        model_resnet18 = models.resnet18(pretrained=True)

        # Extract layers from pretrained model
        self.conv1 = model_resnet18.conv1       # initial convolutional
layer
        self.bn1 = model_resnet18.bn1           # batch normalization
layer
        self.relu = model_resnet18.relu         # ReLU activation
function
        self.maxpool = model_resnet18.maxpool   # max pooling layer

        # ResNet blocks for feature extraction
        self.layer1 = model_resnet18.layer1
        self.layer2 = model_resnet18.layer2
        self.layer3 = model_resnet18.layer3
        self.layer4 = model_resnet18.layer4     # deeper layers for
increasing depth of the network

        # Average pooling layer
        self.avgpool = model_resnet18.avgpool

        # Replace the fully connected layer for custom number of
classes
        self._features = model_resnet18.fc.in_features
        self.fc = nn.Linear(self._features, num_classes)

    def forward(self, x):
        x = self.conv1(x)                       # apply convolutional
layer
        x = self.bn1(x)                         # apply batch
normalization
        x = self.relu(x)                        # apply ReLU activation
        x = self.maxpool(x)                     # apply max pooling
        x = self.layer1(x)                      # pass through ResNet
layer 1
```

```
        x = self.layer2(x)                          # pass through ResNet
layer 2
        x = self.layer3(x)                          # pass through ResNet
layer 3
        x = self.layer4(x)                          # pass through ResNet
layer 4
        x = self.avgpool(x)                         # apply average pooling
        x = x.view(x.size(0), -1)                   # flatten for the fully
connected layer
        x = self.fc(x)                              # apply fully connected
layer for output
        return x

# Print the model architecture
if __name__ == "__main__":
    model1 = Resnet18(num_classes=2)
    #print(model1)
```

# Now Training Resnet18

```
import torch.nn as nn
total_epochs = 50
lr = 0.01
momentum = 0.9
no_cuda = False
num_classes=2
log_interval = 10
l2_decay = 0.01
model = Resnet18(num_classes=num_classes)
model = model.to(device)
criterion = nn.CrossEntropyLoss()
```

```
from torchvision.models import resnet18

# Initialize ResNet18 model
model = resnet18(pretrained=True)  # Load a pre-trained ResNet18
num_ftrs = model.fc.in_features    # Get the number of input features
to the fully connected layer
model.fc = nn.Linear(num_ftrs, num_classes)  # Replace the fully
connected layer for your specific task
model = model.to(device)

# Loss function
criterion = nn.CrossEntropyLoss()

# Early stopping setup (implement EarlyStopping in your environment)
early_stop = EarlyStopping(patience=20, verbose=True)

# Project and model names
project_name = 'tumor_classification'
model_name = 'ResNet18'

best_accuracy = 0
model_save_dir = os.path.join('model', project_name, model_name)
os.makedirs(model_save_dir, exist_ok=True)

# Training loop
for epoch in range(1, total_epochs + 1):
    train(epoch, model, total_epochs, train_loader, criterion,
l2_decay)
    with torch.no_grad():
        test_loss, accuracy, cm, auc = validation(model, val_loader)
```

```
    # Save the model if it achieves the best AUC
    model_dict = model.state_dict()
    if auc > best_accuracy:
        best_accuracy = auc
        torch.save(model_dict, os.path.join(model_save_dir,
f'{model_name}_{epoch}.pth'))
    early_stop(test_loss, model)
    if early_stop.early_stop:
        print("Early stopping")
        break
```

## **Output :-**

```
Epoch 2/50: 100%|██████████| 639/639 [01:18<00:00,  8.10batch/s]
train accuracy: 87.0558853149414%
Specificity: 1.0000, Sensitivity: 0.0010, AUC: 0.8515

Test set: Average loss: 0.6394, Accuracy: 73.25%

Validation loss decreased (inf --> 0.639401). Saving model ...
Epoch 3/50: 100%|██████████| 639/639 [01:19<00:00,  8.05batch/s]
train accuracy: 94.05403137207031%
Specificity: 1.0000, Sensitivity: 0.0111, AUC: 0.9451

Test set: Average loss: 0.3697, Accuracy: 87.38%

Validation loss decreased (0.639401 --> 0.369708). Saving model ...
Epoch 4/50: 100%|██████████| 639/639 [01:20<00:00,  7.98batch/s]
train accuracy: 95.8255844116211%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.9266

Test set: Average loss: 0.4239, Accuracy: 84.62%

EarlyStopping counter: 1 out of 20
Epoch 5/50: 100%|██████████| 639/639 [01:17<00:00,  8.29batch/s]
train accuracy: 96.45198822021484%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8545

Test set: Average loss: 0.5771, Accuracy: 77.68%

EarlyStopping counter: 2 out of 20
Epoch 6/50: 100%|██████████| 639/639 [01:14<00:00,  8.52batch/s]
train accuracy: 97.27904510498047%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8505

Test set: Average loss: 0.5468, Accuracy: 76.87%

EarlyStopping counter: 3 out of 20
Epoch 7/50: 100%|██████████| 639/639 [01:18<00:00,  8.17batch/s]
train accuracy: 97.2398910522461%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.9143

Test set: Average loss: 0.4178, Accuracy: 81.75%

EarlyStopping counter: 4 out of 20
Epoch 8/50: 100%|██████████| 639/639 [01:19<00:00,  8.05batch/s]
```

```
train accuracy: 97.53841400146484%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8669

Test set: Average loss: 0.5115, Accuracy: 78.33%

EarlyStopping counter: 5 out of 20
Epoch 9/50: 100%|██████████| 639/639 [01:20<00:00,  7.95batch/s]
train accuracy: 97.72438049316406%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9117

Test set: Average loss: 0.4347, Accuracy: 83.86%

EarlyStopping counter: 6 out of 20
Epoch 10/50: 100%|██████████| 639/639 [01:20<00:00,  7.93batch/s]
train accuracy: 97.54820251464844%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.9003

Test set: Average loss: 0.5119, Accuracy: 82.35%

EarlyStopping counter: 7 out of 20
Epoch 11/50: 100%|██████████| 639/639 [01:21<00:00,  7.85batch/s]
train accuracy: 99.73573303222656%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9021

Test set: Average loss: 0.4736, Accuracy: 82.96%

EarlyStopping counter: 8 out of 20
Epoch 12/50: 100%|██████████| 639/639 [01:17<00:00,  8.28batch/s]
train accuracy: 99.91680908203125%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9088

Test set: Average loss: 0.4493, Accuracy: 84.11%

EarlyStopping counter: 9 out of 20
Epoch 13/50: 100%|██████████| 639/639 [01:16<00:00,  8.33batch/s]
train accuracy: 99.96084594726562%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9180

Test set: Average loss: 0.4122, Accuracy: 85.17%

EarlyStopping counter: 10 out of 20
Epoch 14/50: 100%|██████████| 639/639 [01:16<00:00,  8.32batch/s]
train accuracy: 99.98042297363281%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.8931

Test set: Average loss: 0.4911, Accuracy: 83.06%

EarlyStopping counter: 11 out of 20
Epoch 15/50: 100%|██████████| 639/639 [01:13<00:00,  8.64batch/s]
train accuracy: 99.99510955810547%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.8958

Test set: Average loss: 0.4745, Accuracy: 82.55%

EarlyStopping counter: 12 out of 20
Epoch 16/50: 100%|██████████| 639/639 [01:14<00:00,  8.60batch/s]
train accuracy: 99.9902114868164%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9164

Test set: Average loss: 0.4133, Accuracy: 85.52%
```

```
EarlyStopping counter: 13 out of 20
Epoch 17/50: 100%|██████████| 639/639 [01:14<00:00,  8.60batch/s]
train accuracy: 100.0%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9111

Test set: Average loss: 0.4263, Accuracy: 84.26%

EarlyStopping counter: 14 out of 20
Epoch 18/50: 100%|██████████| 639/639 [01:14<00:00,  8.57batch/s]
train accuracy: 99.99510955810547%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9035

Test set: Average loss: 0.4541, Accuracy: 84.06%

EarlyStopping counter: 15 out of 20
Epoch 19/50: 100%|██████████| 639/639 [01:17<00:00,  8.29batch/s]
train accuracy: 99.9902114868164%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9151

Test set: Average loss: 0.4163, Accuracy: 85.37%

EarlyStopping counter: 16 out of 20
Epoch 20/50: 100%|██████████| 639/639 [01:17<00:00,  8.21batch/s]
train accuracy: 99.9902114868164%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9044

Test set: Average loss: 0.4416, Accuracy: 84.16%

EarlyStopping counter: 17 out of 20
Epoch 21/50: 100%|██████████| 639/639 [01:18<00:00,  8.14batch/s]
train accuracy: 100.0%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9131

Test set: Average loss: 0.4198, Accuracy: 84.97%

EarlyStopping counter: 18 out of 20
Epoch 22/50: 100%|██████████| 639/639 [01:20<00:00,  7.96batch/s]
train accuracy: 100.0%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9098

Test set: Average loss: 0.4310, Accuracy: 84.77%

EarlyStopping counter: 19 out of 20
Epoch 23/50: 100%|██████████| 639/639 [01:18<00:00,  8.16batch/s]
train accuracy: 99.99510955810547%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.9183

Test set: Average loss: 0.4066, Accuracy: 85.72%

EarlyStopping counter: 20 out of 20
Early stopping
```

# Resnet18 Testing

```
from sklearn.metrics import roc_auc_score, roc_curve,
classification_report, confusion_matrix
import torch
import numpy as np
import torch.nn.functional as F

def test(model, test_loader):
    """
    Function to evaluate the model on the test dataset.

    Parameters:
    - model (torch.nn.Module): The trained model.
    - test_loader (DataLoader): DataLoader for the test dataset.

    Returns:
    - accuracy (float): Test accuracy in percentage.
    - test_loss (float): Average test loss.
    - auc_value (float): AUC score.
    """
    model.eval()  # Set model to evaluation mode
    test_loss = 0
    correct = 0
    possibilities = None
    all_predictions = []
    all_targets = []

    # Iterate through the test DataLoader
    for data, target in test_loader:
        data, target = data.to(device), target.to(device)
        test_output = model(data)  # Forward pass

        # Compute loss
        test_loss += F.nll_loss(F.log_softmax(test_output, dim=1),
target, reduction='sum').item()

        # Get predictions
        pred = test_output.data.max(1)[1]
        all_predictions.extend(pred.cpu().numpy())
        all_targets.extend(target.cpu().numpy())

        # Get probabilities for AUC calculation
        possibility = F.softmax(test_output, dim=1).cpu().data.numpy()
        if possibilities is None:
            possibilities = possibility
        else:
```

```
            possibilities = np.concatenate((possibilities, 
possibility), axis=0)

        # Count correct predictions
        correct += pred.eq(target.data.view_as(pred)).sum().item()

    # Convert all predictions and targets to numpy arrays
    all_predictions = np.array(all_predictions)
    all_targets = np.array(all_targets)

    # Classification metrics
    print(classification_report(all_targets, all_predictions, 
target_names=['benign', 'malignant'], digits=4))

    # Confusion matrix
    cm = confusion_matrix(all_targets, all_predictions)
    print("Confusion Matrix:\n", cm)

    # AUC score
    num_classes = possibilities.shape[1]
    label_onehot = np.eye(num_classes)[all_targets]
    fpr, tpr, _ = roc_curve(label_onehot.ravel(), 
possibilities.ravel())
    auc_value = roc_auc_score(label_onehot, possibilities, 
average="macro")

    # Average loss and accuracy
    test_loss /= len(test_loader.dataset)
    accuracy = 100. * correct / len(test_loader.dataset)
    print('Specificity: {:.4f}, Sensitivity: {:.4f}, AUC: 
{:.4f}'.format(1 - fpr[0], tpr[0], auc_value))
    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} 
({:.2f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset), accuracy))

    return accuracy, test_loss, auc_value, fpr, tpr
```

## Output:-

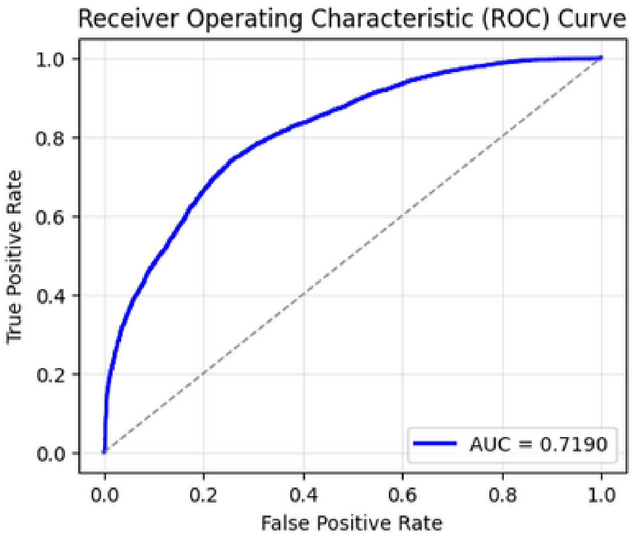
```
test_accuracy, test_loss, test_auc, fpr, tpr = test(model, test_loader)
```

```
              precision    recall  f1-score   support

      benign     0.6200    0.2147    0.3189      1938
   malignant     0.7537    0.9481    0.8398      4913

    accuracy                         0.7406      6851
   macro avg     0.6868    0.5814    0.5794      6851
weighted avg     0.7159    0.7406    0.6925      6851

Confusion Matrix:
 [[ 416 1522]
 [ 255 4658]]
Specificity: 1.0000, Sensitivity: 0.0000, AUC: 0.7190

Test set: Average loss: 0.8269, Accuracy: 5074/6851 (74.06%)
```

---

# NOW Plotting graph for the same model :-

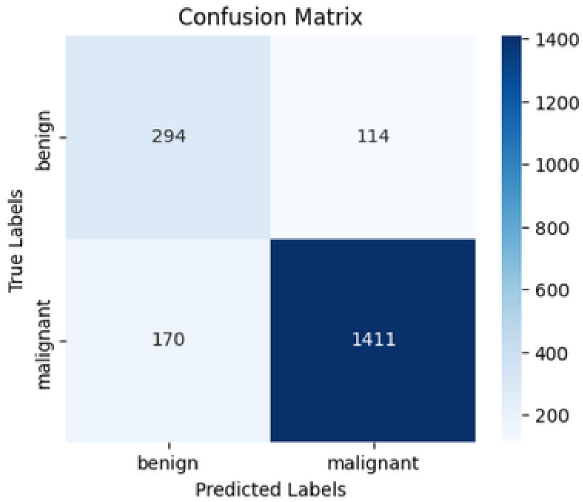
```python
import matplotlib.pyplot as plt

def plot_auc(fpr, tpr, auc_value):
    plt.figure(figsize=(5, 4))
    plt.plot(fpr, tpr, color='blue', lw=2, label=f'AUC = {auc_value:.4f}')
    plt.plot([0, 1], [0, 1], color='gray', linestyle='--', lw=1)  # Diagonal line
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc='lower right')
    plt.grid(alpha=0.3)
    plt.show()
plot_auc(fpr, tpr, test_auc)
```




---

# Now we will plot the confusion matrix

```python
import seaborn as sns

def plot_confusion_matrix(cm, class_names):
    plt.figure(figsize=(5, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Confusion Matrix')
    plt.show()
plot_confusion_matrix(cm, class_names=['benign', 'malignant'])
```



# NOW we will implement resnet 50 as same as resnet18

```
import torch
import torch.nn as nn
import torchvision.models as models

class resnet50(nn.Module):
    def __init__(self, num_classes=2):
        super(resnet50, self).__init__()

        # Load the pretrained ResNet50 model
        model_resnet50 = models.resnet50(pretrained=True)

        # Extract layers from the pretrained model
        self.conv1 = model_resnet50.conv1        # initial
convolutional layer
        self.bn1 = model_resnet50.bn1            # batch normalization
layer
        self.relu = model_resnet50.relu          # ReLU activation
function
        self.maxpool = model_resnet50.maxpool    # max pooling layer

        # ResNet blocks for feature extraction
        self.layer1 = model_resnet50.layer1
        self.layer2 = model_resnet50.layer2
        self.layer3 = model_resnet50.layer3
        self.layer4 = model_resnet50.layer4      # deeper layers for
increasing depth of the network

        # Average pooling layer
        self.avgpool = model_resnet50.avgpool

        # Replace the fully connected layer for custom number of
classes
        self._features = model_resnet50.fc.in_features
        self.fc = nn.Linear(self._features, num_classes)

    def forward(self, x):
        x = self.conv1(x)                        # apply convolutional
layer
        x = self.bn1(x)                          # apply batch
normalization
        x = self.relu(x)                         # apply ReLU
activation
        x = self.maxpool(x)                      # apply max pooling
```

```
        x = self.layer1(x)                        # pass through ResNet
layer 1
        x = self.layer2(x)                        # pass through ResNet
layer 2
        x = self.layer3(x)                        # pass through ResNet
layer 3
        x = self.layer4(x)                        # pass through ResNet
layer 4
        x = self.avgpool(x)                       # apply average
pooling
        x = x.view(x.size(0), -1)                 # flatten for the
fully connected layer
        x = self.fc(x)                            # apply fully
connected layer for output
        return x

# Print the model architecture
if __name__ == "__main__":
    model2 = resnet50(num_classes=2)
    #print(model2)
```

# /// Initializing the parameters and training the model

```
import torch.nn as nn
total_epochs = 50
lr = 0.01
momentum = 0.9
no_cuda = False
num_classes=2
log_interval = 10
l2_decay = 0.01
model = resnet50(num_classes=num_classes)
model = model.to(device)
criterion = nn.CrossEntropyLoss()
```

```
from torchvision.models import resnet50

# Initialize ResNet50 model
model = resnet50(pretrained=True)  # Load a pre-trained ResNet50
```

```
num_ftrs = model.fc.in_features    # Get the number of input features
to the fully connected layer
model.fc = nn.Linear(num_ftrs, num_classes)  # Replace the fully
connected layer for your specific task
model = model.to(device)

# Loss function
criterion = nn.CrossEntropyLoss()

# Early stopping setup (implement EarlyStopping in your environment)
early_stop = EarlyStopping(patience=20, verbose=True)

# Project and model names
project_name = 'tumor_classification'
model_name = 'ResNet50'

best_accuracy = 0
model_save_dir = os.path.join('model', project_name, model_name)
os.makedirs(model_save_dir, exist_ok=True)

# Training loop
for epoch in range(1, total_epochs + 1):
    train(epoch, model, total_epochs, train_loader, criterion,
l2_decay)
    with torch.no_grad():
        test_loss, accuracy, cm, auc = validation(model, val_loader)
    # Save the model if it achieves the best AUC
    model_dict = model.state_dict()
    if auc > best_accuracy:
        best_accuracy = auc
        torch.save(model_dict, os.path.join(model_save_dir,
f'{model_name}_{epoch}.pth'))
    early_stop(test_loss, model)
    if early_stop.early_stop:
        print("Early stopping")
        break
# Save the model at the final epoch if early stopping is triggered
final_model_save_path = os.path.join(model_save_dir,
f'{model_name}_final_epoch.pth')
torch.save(model.state_dict(), final_model_save_path,
_use_new_zipfile_serialization=False)
print(f"Final model saved at:
{os.path.abspath(final_model_save_path)}")
```

# Output :-

```
Epoch 2/50: 100%|██████████| 639/639 [02:36<00:00,  4.08batch/s]
train accuracy: 86.9139633178711%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8513

Test set: Average loss: 0.5529, Accuracy: 75.11%

Validation loss decreased (inf --> 0.552876). Saving model ...
Epoch 3/50: 100%|██████████| 639/639 [02:35<00:00,  4.11batch/s]
train accuracy: 91.6952133178711%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8775

Test set: Average loss: 0.4440, Accuracy: 78.73%

Validation loss decreased (0.552876 --> 0.443954). Saving model ...
Epoch 4/50: 100%|██████████| 639/639 [02:31<00:00,  4.22batch/s]
train accuracy: 91.53372192382812%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8421

Test set: Average loss: 0.5380, Accuracy: 76.07%

EarlyStopping counter: 1 out of 20
Epoch 5/50: 100%|██████████| 639/639 [02:28<00:00,  4.29batch/s]
train accuracy: 92.8354721069336%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.9130

Test set: Average loss: 0.3709, Accuracy: 81.50%

Validation loss decreased (0.443954 --> 0.370907). Saving model ...
Epoch 6/50: 100%|██████████| 639/639 [02:28<00:00,  4.29batch/s]
train accuracy: 93.51570892333984%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.6146

Test set: Average loss: 1.0713, Accuracy: 59.63%

EarlyStopping counter: 1 out of 20
Epoch 7/50: 100%|██████████| 639/639 [02:27<00:00,  4.34batch/s]
train accuracy: 94.16168975830078%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8875

Test set: Average loss: 0.5882, Accuracy: 79.39%

EarlyStopping counter: 2 out of 20
Epoch 8/50: 100%|██████████| 639/639 [02:27<00:00,  4.33batch/s]
train accuracy: 93.98062133789062%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8523

Test set: Average loss: 0.5926, Accuracy: 76.57%

EarlyStopping counter: 3 out of 20
Epoch 9/50: 100%|██████████| 639/639 [02:26<00:00,  4.35batch/s]
train accuracy: 94.79788208007812%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.9166

Test set: Average loss: 0.4207, Accuracy: 83.86%

EarlyStopping counter: 4 out of 20
```

```
Epoch 10/50: 100%|██████████| 639/639 [02:26<00:00,  4.36batch/s]
train accuracy: 94.91533660888672%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.7946

Test set: Average loss: 0.7814, Accuracy: 73.20%

EarlyStopping counter: 5 out of 20
Epoch 11/50: 100%|██████████| 639/639 [02:26<00:00,  4.37batch/s]
train accuracy: 98.99187469482422%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8335

Test set: Average loss: 0.6837, Accuracy: 74.26%

EarlyStopping counter: 6 out of 20
Epoch 12/50: 100%|██████████| 639/639 [02:27<00:00,  4.35batch/s]
train accuracy: 99.68679809570312%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8461

Test set: Average loss: 0.6570, Accuracy: 76.12%

EarlyStopping counter: 7 out of 20
Epoch 13/50: 100%|██████████| 639/639 [02:26<00:00,  4.35batch/s]
train accuracy: 99.82872009277344%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8291

Test set: Average loss: 0.7117, Accuracy: 74.51%

EarlyStopping counter: 8 out of 20
Epoch 14/50: 100%|██████████| 639/639 [02:29<00:00,  4.28batch/s]
train accuracy: 99.85318756103516%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8142

Test set: Average loss: 0.7894, Accuracy: 72.10%

EarlyStopping counter: 9 out of 20
Epoch 15/50: 100%|██████████| 639/639 [02:32<00:00,  4.19batch/s]
train accuracy: 99.89723205566406%
Specificity: 0.9995, Sensitivity: 0.0000, AUC: 0.8332

Test set: Average loss: 0.7160, Accuracy: 75.31%

EarlyStopping counter: 10 out of 20
Epoch 16/50: 100%|██████████| 639/639 [02:33<00:00,  4.16batch/s]
train accuracy: 99.90702056884766%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8394

Test set: Average loss: 0.6747, Accuracy: 75.92%

EarlyStopping counter: 11 out of 20
Epoch 17/50: 100%|██████████| 639/639 [02:28<00:00,  4.30batch/s]
train accuracy: 99.9363784790039%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8091

Test set: Average loss: 0.8079, Accuracy: 71.24%

EarlyStopping counter: 12 out of 20
Epoch 18/50: 100%|██████████| 639/639 [02:27<00:00,  4.33batch/s]
train accuracy: 99.91191101074219%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8396

Test set: Average loss: 0.6782, Accuracy: 76.52%
```

```
EarlyStopping counter: 13 out of 20
Epoch 19/50: 100%|██████████| 639/639 [02:27<00:00,  4.33batch/s]
train accuracy: 99.91680908203125%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.7977

Test set: Average loss: 0.8371, Accuracy: 70.04%

EarlyStopping counter: 14 out of 20
Epoch 20/50: 100%|██████████| 639/639 [02:27<00:00,  4.32batch/s]
train accuracy: 99.81403350830078%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8087

Test set: Average loss: 0.7207, Accuracy: 71.54%

EarlyStopping counter: 15 out of 20
Epoch 21/50: 100%|██████████| 639/639 [02:27<00:00,  4.34batch/s]
train accuracy: 99.9461669921875%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8558

Test set: Average loss: 0.6294, Accuracy: 75.52%

EarlyStopping counter: 16 out of 20
Epoch 22/50: 100%|██████████| 639/639 [02:28<00:00,  4.32batch/s]
train accuracy: 99.97553253173828%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8248

Test set: Average loss: 0.7349, Accuracy: 72.95%

EarlyStopping counter: 17 out of 20
Epoch 23/50: 100%|██████████| 639/639 [02:30<00:00,  4.26batch/s]
train accuracy: 99.97553253173828%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8447

Test set: Average loss: 0.6761, Accuracy: 75.01%

EarlyStopping counter: 18 out of 20
Epoch 24/50: 100%|██████████| 639/639 [02:27<00:00,  4.33batch/s]
train accuracy: 99.9559555053711%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8383

Test set: Average loss: 0.6953, Accuracy: 75.31%

EarlyStopping counter: 19 out of 20
Epoch 25/50: 100%|██████████| 639/639 [02:29<00:00,  4.28batch/s]
train accuracy: 99.96574401855469%
Specificity: 1.0000, Sensitivity: 0.0005, AUC: 0.8217

Test set: Average loss: 0.7503, Accuracy: 72.90%

EarlyStopping counter: 20 out of 20
Early stopping
Final model saved at:
/kaggle/working/model/tumor_classification/ResNet50/ResNet50_final_epoch.pt
h
```

# // ImplementingTesting Function

```
from sklearn.metrics import roc_auc_score, roc_curve,
classification_report, confusion_matrix
import torch
import numpy as np
import torch.nn.functional as F

def test(model, test_loader):
    """
    Function to evaluate the model on the test dataset.

    Parameters:
    - model (torch.nn.Module): The trained model.
    - test_loader (DataLoader): DataLoader for the test dataset.

    Returns:
    - accuracy (float): Test accuracy in percentage.
    - test_loss (float): Average test loss.
    - auc_value (float): AUC score.
    """
    model.eval()  # Set model to evaluation mode
    test_loss = 0
    correct = 0
    possibilities = None
    all_predictions = []
    all_targets = []

    # Iterate through the test DataLoader
    for data, target in test_loader:
        data, target = data.to(device), target.to(device)
        test_output = model(data)  # Forward pass

        # Compute loss
        test_loss += F.nll_loss(F.log_softmax(test_output, dim=1),
target, reduction='sum').item()

        # Get predictions
        pred = test_output.data.max(1)[1]
        all_predictions.extend(pred.cpu().numpy())
        all_targets.extend(target.cpu().numpy())

        # Get probabilities for AUC calculation
        possibility = F.softmax(test_output, dim=1).cpu().data.numpy()
        if possibilities is None:
            possibilities = possibility
        else:
```

```
            possibilities = np.concatenate((possibilities, 
possibility), axis=0)

        # Count correct predictions
        correct += pred.eq(target.data.view_as(pred)).sum().item()

    # Convert all predictions and targets to numpy arrays
    all_predictions = np.array(all_predictions)
    all_targets = np.array(all_targets)

    # Classification metrics
    print(classification_report(all_targets, all_predictions, 
target_names=['benign', 'malignant'], digits=4))

    # Confusion matrix
    cm = confusion_matrix(all_targets, all_predictions)
    print("Confusion Matrix:\n", cm)

    # AUC score
    num_classes = possibilities.shape[1]
    label_onehot = np.eye(num_classes)[all_targets]
    fpr, tpr, _ = roc_curve(label_onehot.ravel(), 
possibilities.ravel())
    auc_value = roc_auc_score(label_onehot, possibilities, 
average="macro")

    # Average loss and accuracy
    test_loss /= len(test_loader.dataset)
    accuracy = 100. * correct / len(test_loader.dataset)
    print('Specificity: {:.4f}, Sensitivity: {:.4f}, AUC: 
{:.4f}'.format(1 - fpr[0], tpr[0], auc_value))
    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} 
({:.2f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset), accuracy))

    return test_loss, accuracy, cm, auc_value
```

# Output:-

resnet50 testing

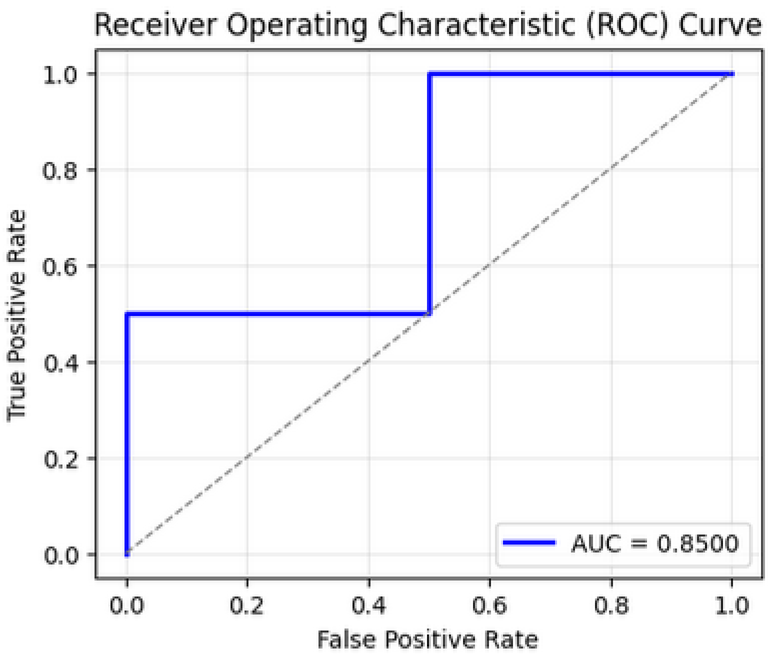
```
[ ] test_accuracy, test_loss, test_auc, fpr = test(model, test_loader)
```

```
              precision    recall  f1-score   support

      benign     0.5520    0.3617    0.4370      1938
   malignant     0.7784    0.8842    0.8279      4913

    accuracy                         0.7364      6851
   macro avg     0.6652    0.6229    0.6325      6851
weighted avg     0.7143    0.7364    0.7173      6851

Confusion Matrix:
 [[ 701 1237]
 [ 569 4344]]
Specificity: 1.0000, Sensitivity: 0.0000, AUC: 0.7018

Test set: Average loss: 0.8197, Accuracy: 5045/6851 (73.64%)
```

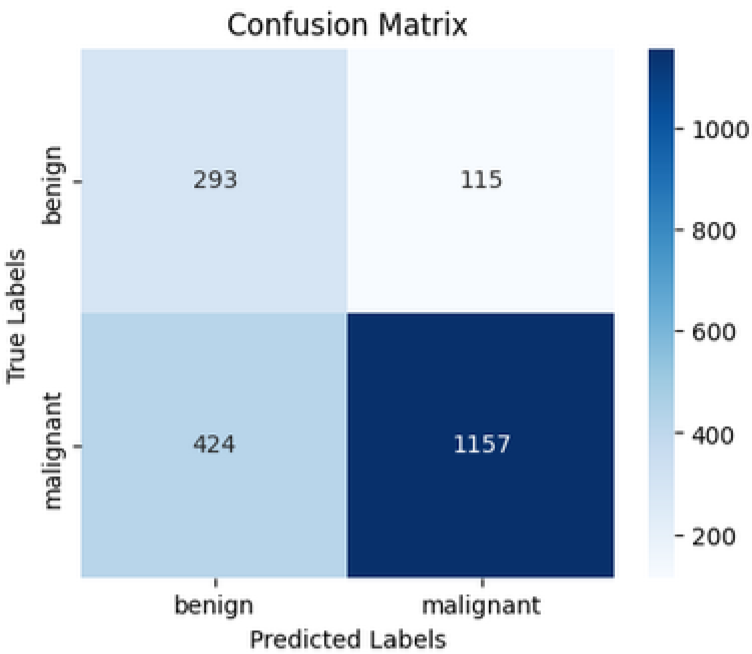
---

# Now plotting graph and confusion matrix

```
import matplotlib.pyplot as plt

def plot_auc(fpr, tpr, auc_value):
    plt.figure(figsize=(5, 4))
    plt.plot(fpr, tpr, color='blue', lw=2, label=f'AUC =
{auc_value:.4f}')
    plt.plot([0, 1], [0, 1], color='gray', linestyle='--', lw=1)   #
Diagonal line
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc='lower right')
    plt.grid(alpha=0.3)
    plt.show()
plot_auc(fpr, tpr, test_auc)
```




```
import seaborn as sns

def plot_confusion_matrix(cm, class_names):
    plt.figure(figsize=(5, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=class_names, yticklabels=class_names)
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Confusion Matrix')
    plt.show()
plot_confusion_matrix(cm, class_names=['benign', 'malignant'])
```



Confusion Matrix
True Labels
benign
malignant
293
115
424
1157
benign
malignant
Predicted Labels
1000
800
600
400
200

# NOW with all the code we will implement Gradio for UI for our Models

```
[ ] pip install gradio

Collecting gradio
  Downloading gradio-5.6.0-py3-none-any.whl.metadata (16 kB)
Requirement already satisfied: aiofiles<24.0,>=22.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (22.1.0)
Requirement already satisfied: anyio<5.0,>=3.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (4.4.0)
Collecting fastapi<1.0,>=0.115.2 (from gradio)
  Downloading fastapi-0.115.5-py3-none-any.whl.metadata (27 kB)
Collecting ffmpy (from gradio)
  Downloading ffmpy-0.4.0-py3-none-any.whl.metadata (2.9 kB)
Collecting gradio-client==1.4.3 (from gradio)
  Downloading gradio_client-1.4.3-py3-none-any.whl.metadata (7.1 kB)
Requirement already satisfied: httpx>=0.24.1 in /opt/conda/lib/python3.10/site-packages (from gradio) (0.27.0)
Requirement already satisfied: huggingface-hub>=0.25.1 in /opt/conda/lib/python3.10/site-packages (from gradio) (0.25.1)
Requirement already satisfied: jinja2<4.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (3.1.4)
Requirement already satisfied: markupsafe~=2.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (2.1.5)
Requirement already satisfied: numpy<3.0,>=1.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (1.26.4)
Requirement already satisfied: orjson~=3.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (3.10.4)
Requirement already satisfied: packaging in /opt/conda/lib/python3.10/site-packages (from gradio) (21.3)
Requirement already satisfied: pandas<3.0,>=1.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (2.2.2)
Requirement already satisfied: pillow<12.0,>=8.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (10.3.0)
Requirement already satisfied: pydantic>=2.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (2.9.2)
Requirement already satisfied: pydub in /opt/conda/lib/python3.10/site-packages (from gradio) (0.25.1)
Collecting python-multipart==0.0.12 (from gradio)
  Downloading python_multipart-0.0.12-py3-none-any.whl.metadata (1.9 kB)
Requirement already satisfied: pyyaml<7.0,>=5.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (6.0.2)
Collecting ruff>=0.2.2 (from gradio)
  Downloading ruff-0.8.0-py3-none-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (25 kB)
Collecting safehttpx<1.0,>=0.1.1 (from gradio)
  Downloading safehttpx-0.1.1-py3-none-any.whl.metadata (4.1 kB)
Collecting semantic-version~=2.0 (from gradio)
  Downloading semantic_version-2.10.0-py2.py3-none-any.whl.metadata (9.7 kB)
Collecting starlette<1.0,>=0.40.0 (from gradio)
  Downloading starlette-0.41.3-py3-none-any.whl.metadata (6.0 kB)
Collecting tomlkit==0.12.0 (from gradio)
  Downloading tomlkit-0.12.0-py3-none-any.whl.metadata (2.7 kB)
Requirement already satisfied: typer<1.0,>=0.12 in /opt/conda/lib/python3.10/site-packages (from gradio) (0.12.3)
Requirement already satisfied: typing-extensions~=4.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (4.12.2)
Requirement already satisfied: uvicorn>=0.14.0 in /opt/conda/lib/python3.10/site-packages (from gradio) (0.30.1)
Requirement already satisfied: fsspec in /opt/conda/lib/python3.10/site-packages (from gradio-client==1.4.3->gradio) (2024.6.1)
Requirement already satisfied: websockets<13.0,>=10.0 in /opt/conda/lib/python3.10/site-packages (from gradio-client==1.4.3->gradio) (12.0)
Requirement already satisfied: idna>=2.8 in /opt/conda/lib/python3.10/site-packages (from anyio<5.0,>=3.0->gradio) (3.7)
Requirement already satisfied: sniffio>=1.1 in /opt/conda/lib/python3.10/site-packages (from anyio<5.0,>=3.0->gradio) (1.3.1)
Requirement already satisfied: exceptiongroup>=1.0.2 in /opt/conda/lib/python3.10/site-packages (from anyio<5.0,>=3.0->gradio) (1.2.0)
```

# Code:-

```
import gradio as gr
from PIL import Image
import torch
import torch.nn as nn
from torchvision import models, transforms

# Load your trained model dynamically
def load_model(model_name, model_path):
    if model_name == "ResNet18":
        model = models.resnet18(pretrained=False)  # Use
pretrained=False for your custom-trained models
        model.fc = nn.Linear(model.fc.in_features, 2)  # Binary
classification
    elif model_name == "ResNet50":
        model = models.resnet50(pretrained=False)
        model.fc = nn.Linear(model.fc.in_features, 2)  # Binary
classification
    elif model_name == "VGG16":
        model = models.vgg16(pretrained=False)
        model.classifier[6] =
nn.Linear(model.classifier[6].in_features, 2)  # Binary classification
```

```
    else:
        raise ValueError("Invalid model name.")

    # Load your trained model weights
    model.load_state_dict(torch.load(model_path,
map_location=torch.device('cpu')))
    model.eval()
    return model

# Preprocessing function for input images
def preprocess_image(image):
    transform = transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224,
0.225])
    ])
    return transform(image).unsqueeze(0)  # Add batch dimension

# Prediction function
def predict(image, model_name):
    image = Image.fromarray(image)  # Convert numpy array to PIL image
    input_tensor = preprocess_image(image)

    # Map model names to weight file paths
    model_paths = {
        "ResNet18":
"/kaggle/working/model/tumor_classification/ResNet18/ResNet18_final_epo
ch.pth",
        "ResNet50":
"/kaggle/working/model/tumor_classification/ResNet50/ResNet50_final_epo
ch.pth",
        "VGG16":
"/kaggle/working/model/tumor_classfication/vgg16/vgg16_final_epoch.pth"
    }

    model_path = model_paths[model_name]
    model = load_model(model_name, model_path)

    with torch.no_grad():
        outputs = model(input_tensor)
        probabilities = torch.softmax(outputs, dim=1)[0]

        # Extract class names and their respective probabilities
        benign_prob = probabilities[0].item()
        malignant_prob = probabilities[1].item()
        predicted_idx = probabilities.argmax().item()
```

```
        predicted_class = class_names[predicted_idx]

    # Create a response string
    response = (
        f"Predicted Class: {predicted_class}\n"
        f"Benign Probability: {benign_prob:.2f}\n"
        f"Malignant Probability: {malignant_prob:.2f}"
    )
    return response

# Define global variables
class_names = ["benign", "malignant"]  # Binary classes

# Define the Gradio interface
interface = gr.Interface(
    fn=predict,
    inputs=[
        gr.Image(type="numpy", label="Upload Image"),
        gr.Dropdown(choices=["ResNet18","VGG16", "ResNet50"],
label="Select Model")
    ],
    outputs=gr.Textbox(label="Prediction"),
    title="Breast Cancer Classification",
    description="Upload an image and select a model to classify it as
benign or malignant.",

)

# Launch the Gradio app
interface.launch()
```

## [https://b489701ac1bf2e4c34.gradio.live](https://b489701ac1bf2e4c34.gradio.live)