Introduction

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INTRODUCTION

Breast cancer is one of the leading causes of cancer-related deaths among women globally. Early detection is critical in improving survival rates and treatment outcomes. Magnetic Resonance Imaging (MRI) has emerged as a highly effective tool for detecting and characterising breast tumours due to its superior imaging capabilities, providing detailed insights into soft tissue structures.

In this project, we focus on developing a predictive model for **Breast Cancer Prediction** using an **MRI dataset**. The goal is to design an automated system that accurately identifies and classifies breast tumours as either benign or malignant based on MRI scans. Leveraging the power of **Machine Learning (ML)** and **Convolutional Neural Networks (CNNs)**, the system aims to assist radiologists in making faster and more precise diagnoses.

DATA EXPLORATION

Data exploration is the first step of data analysis used to explore and visualize data to uncover insights from the start or identify areas or patterns to dig into more. Using interactive dashboards and point-and-click data exploration, users can better understand the bigger picture and get to insights faster.Data exploration is the initial step in data analysis and is used to understand a dataset before working with it.
METHODS:
Exploratory data analysis (EDA)

LOADING THE DATASET:

```
import os
import matplotlib.pyplot as plt
from PIL import Image
from torchvision import transforms
from torchvision.datasets import ImageFolder
from torch.utils.data import DataLoader
import cv2


# Define the path to your dataset
data_dir = "breast_cancer_dataset"

# Check the directory structure
train_dir = os.path.join(data_dir, 'train')
val_dir = os.path.join(data_dir, 'val')
test_dir = os.path.join(data_dir, 'test')
```

```
# Print the classes available in the train directory
print("Classes in training set:")
print(os.listdir(train_dir))

print("\nClasses in val set:")
print(os.listdir(val_dir))

print("\nClasses in test set:")
print(os.listdir(test_dir))
```

Classes in training set:
['Benign', 'Malignant']

Classes in val set:
['Benign', 'Malignant']

Classes in test set:
['Benign', 'Malignant']

ANALYSING THE DATASET:

```
import matplotlib.pyplot as plt
from PIL import Image

def count_images(directory):

    class_counts = {}
    for class_name in os.listdir(directory):
        class_path = os.path.join(directory, class_name)
        if os.path.isdir(class_path):
            class_counts[class_name] = len(os.listdir(class_path))
    return class_counts

# Count images in the training set
train_class_counts = count_images(train_dir)
print("Number of images in each class (train):", train_class_counts)
```

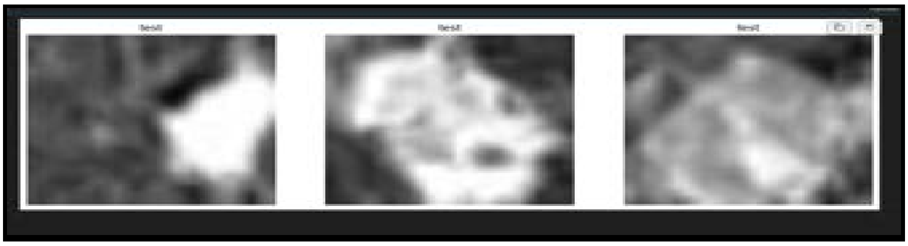
Number of images in each class (train): {'Benign': 61, 'Malignant': 105}

DISPLAYING SAMPLE OF IMAGES :

```
import os
import random
```

```python
import torch
import torchvision.transforms as transforms
from torchvision.datasets import ImageFolder
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt

# Define the path to your dataset
data_dir = 'breast_cancer_dataset'  # Use a raw string for Windows path

# Define the transformation for the images
transform = transforms.Compose([
    transforms.Resize((224, 224)),  # Resize images to 224x224
    transforms.ToTensor(),           # Convert images to PyTorch
tensors
])

# Load the dataset
dataset = ImageFolder(root=data_dir, transform=transform)
class_names = dataset.classes  # Get class names

# Create a DataLoader
dataloader = DataLoader(dataset, batch_size=32, shuffle=True)

def display_random_images(dataset, class_names, num_images=3):
    # Get a random sample of images for each class
    for class_index, class_name in enumerate(class_names):
        # Filter images belonging to the current class
        class_images = [dataset[i][0] for i in range(len(dataset)) if
dataset[i][1] == class_index]

        # Randomly select a few images
        if len(class_images) > 0:
            selected_images = random.sample(class_images,
min(num_images, len(class_images)))
            plt.figure(figsize=(15, 5))
            for i in range(len(selected_images)):
                plt.subplot(1, len(selected_images), i + 1)
                plt.imshow(selected_images[i].permute(1, 2, 0).numpy())
# Convert from CxHxW to HxWxC
                plt.title(class_name)
                plt.axis('off')
            plt.show()
```

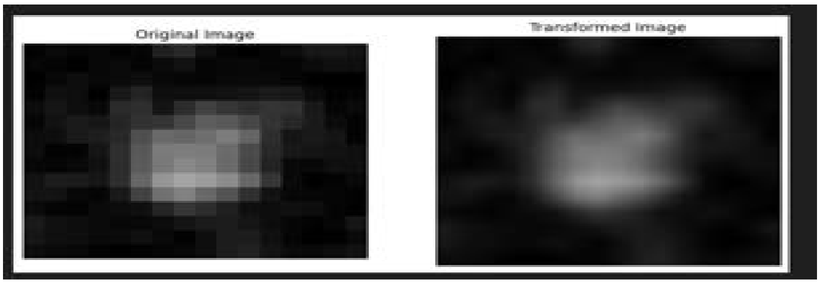
```
# Display random images from each class
display_random_images(dataset, class_names)
```



DATA TRANSFORMATION:

```
import torchvision.transforms as transforms
import torch

# Define transformations
transform = transforms.Compose([
   transforms.Resize((224, 224)),  # Resizing to 224x224 pixels
   transforms.ToTensor(),  # Converting to PyTorch tensor

   # Normalization- process of scaling pixel intensity values to a common range
   transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])  # Normalize
with ImageNet values
])
import torch
from PIL import Image
import torchvision.transforms as transforms
import matplotlib.pyplot as plt

def show_image_transformation(image_path):
   """
   Load an image from a path, apply transformation, and display both original and
transformed images.

   Args:
      image_path (str): Path to the image file.
   """
   # Load the image
   image = Image.open(image_path).convert("RGB")

   # Define the transformation (example: resize, convert to tensor, normalize)
   transform = transforms.Compose([
      transforms.Resize((128, 128)),  # Resize to 128x128
```

```python
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5])
    ])

    # Apply the transformation
    transformed_image = transform(image)

    # Unnormalize for visualization
    unnormalize = transforms.Normalize(
        mean=[-0.5 / 0.5, -0.5 / 0.5, -0.5 / 0.5],
        std=[1 / 0.5, 1 / 0.5, 1 / 0.5]
    )
    unnormalized_image = unnormalize(transformed_image)

    # Convert tensor to numpy array for visualization
    original_image_np = transforms.ToTensor()(image).permute(1, 2, 0).numpy()
    transformed_image_np = unnormalized_image.permute(1, 2, 0).numpy().clip(0, 1)

    # Plot both images
    fig, axs = plt.subplots(1, 2, figsize=(10, 5))
    axs[0].imshow(original_image_np)
    axs[0].set_title("Original Image")
    axs[0].axis("off")

    axs[1].imshow(transformed_image_np)
    axs[1].set_title("Transformed Image")
    axs[1].axis("off")

    plt.show()

# Usage example
image_path = input("test\Benign\BreaDM-Be-1810\SUB1\p-030.jpg ")
show_image_transformation(image_path)
```



DATA AUGMENTATION:

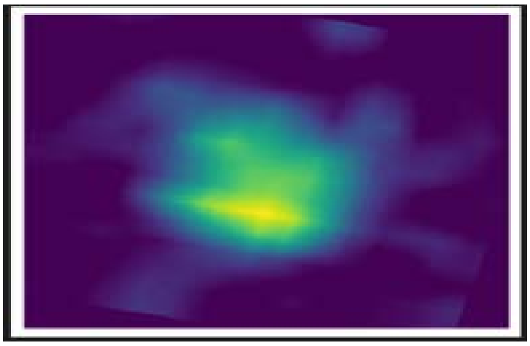
Data augmentation is a machine learning technique that can improve the performance of convolutional neural networks (CNNs) by increasing the size and diversity of training data.Data augmentation has been widely implemented in research for a range of computer vision tasks, from image classification to object detection. As such, there is a wealth of research on how augmented images improve the performance of state-of-the-art convolutional neural networks (CNNs) in image processing.Data augmentation is often used when data is imbalanced, but it can also be used to make data imbalanced to bias a model towards a certain case. However, augmentation can lead to overfitting in cases with very few data samples.

```
# Define data augmentation with additional techniques
augmentation_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.RandomHorizontalFlip(),  # Randomly flip the image horizontally
    transforms.RandomRotation(10),  # Random rotation
    transforms.RandomCrop(224, padding=4),  # Random crop with padding
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.2),  # Random
color jitter
    transforms.RandomGrayscale(p=0.1),  # Randomly convert image to grayscale with a
probability of 0.1
    transforms.RandomPerspective(distortion_scale=0.5, p=0.5),  # Random perspective
transformation
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])
```

TECHNIQUES FOR DATA AUGMENTATION:
Mirroring and random cropping =>methods of data augmentation(main thing have to do)Augmenting images by colour shifting
VISUALISING AUGMENTED IMAGE:

```
import torch
import torchvision.transforms as transforms
from PIL import Image
import matplotlib.pyplot as plt

# Load an example image (replace 'path_to_image.jpg' with the path to
your image)
image_path = 'test\Benign\BreaDM-Be-1810\SUB1\p-030.jpg '
image = Image.open(image_path)

# Define the augmentation transforms
```

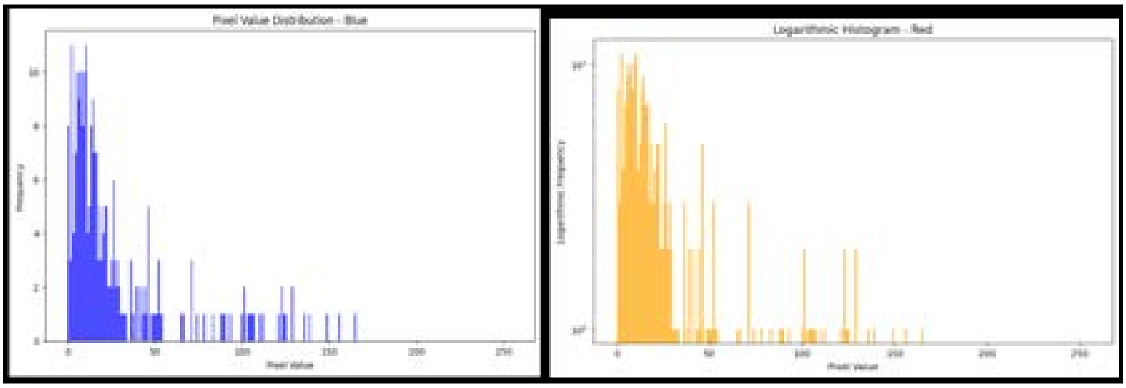
```
transform = transforms.Compose([
    transforms.Resize((256, 256)),          # Resize to 256x256
    transforms.RandomHorizontalFlip(),       # Randomly flip image
horizontally
    transforms.RandomRotation(30),           # Randomly rotate by up to
30 degrees
    transforms.ColorJitter(brightness=0.5, contrast=0.5,
saturation=0.5), # Random brightness, contrast, saturation
    transforms.RandomAffine(15),             # Random affine
transformation
])

# Apply the transformations to the image
augmented_image = transform(image)

# Convert the image to a format suitable for displaying
plt.imshow(augmented_image)
plt.axis('off')  # Turn off axis
plt.show()
```



Histogram of pixel values:

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

# Image path
image_path ='test\Benign\BreaDM-Be-1810\SUB1\p-030.jpg'

# Check if the file exists
if not os.path.exists(image_path):
    print(f"Error: The file at {image_path} does not exist.")
else:
```

```
    # Load the image and convert it to grayscale
    try:
        image = Image.open(image_path).convert('L')

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

        # Flatten the image array to 1D
        image_flat = image_array.flatten()

        # Plot basic histogram with color
        plt.figure(figsize=(10, 6))
        plt.hist(image_flat, bins=256, range=(0, 255), color='blue',
alpha=0.7)
        plt.title('Pixel Value Distribution - Blue')
        plt.xlabel('Pixel Value')
        plt.ylabel('Frequency')
        plt.show()

        # Cumulative Histogram
        plt.figure(figsize=(10, 6))
        plt.hist(image_flat, bins=256, range=(0, 255), color='green',
alpha=0.7, cumulative=True)
        plt.title('Cumulative Histogram - Green')
        plt.xlabel('Pixel Value')
        plt.ylabel('Cumulative Frequency')
        plt.show()

        # Logarithmic Histogram
        plt.figure(figsize=(10, 6))
        plt.hist(image_flat, bins=256, range=(0, 255), color='orange',
alpha=0.7, log=True)
        plt.title('Logarithmic Histogram - Red')
        plt.xlabel('Pixel Value')
        plt.ylabel('Logarithmic Frequency')
        plt.show()

    except OSError as e:
        print(f"Error opening the image: {e}")
```

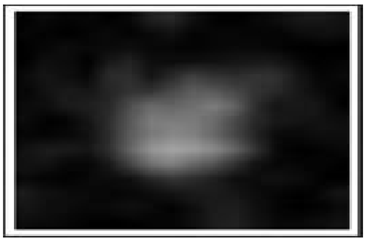


SETTING UP DATALOADERS:

Creating Dataset with updated transformation:

```
import torch
from torchvision import transforms
from torch.utils.data import DataLoader, Dataset
from PIL import Image
import matplotlib.pyplot as plt

# Define the transformation for a single image (resize to 224x224)
transform = transforms.Compose([
    transforms.Resize((224, 224)),        # Resize to 224x224
    transforms.ToTensor(),                # Convert to tensor
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224,
0.225])  # Normalize
])

# Define a custom dataset for a single image
class SingleImageDataset(Dataset):
    def __init__(self, image_path, transform=None):
        self.image_path = image_path
        self.transform = transform

    def __len__(self):
        return 1  # Only one image

    def __getitem__(self, idx):
        image = Image.open(self.image_path).convert("RGB")  # Load and
convert image to RGB
        if self.transform:
            image = self.transform(image)
        return image

# Load a single image and apply transformations
```

```
image_path ='test\Benign\BreaDM-Be-1810\SUB1\p-030.jpg'  # Replace with
the path to your image
dataset = SingleImageDataset(image_path=image_path, transform=transform)

# Create a DataLoader for the single image dataset
dataloader = DataLoader(dataset, batch_size=1, shuffle=False)

# Display the transformed image
for img in dataloader:
    img = img.squeeze(0)  # Remove the batch dimension
    img = img.permute(1, 2, 0)  # Rearrange dimensions for displaying

    # Unnormalize for display
    img = img * torch.tensor([0.229, 0.224, 0.225]) +
torch.tensor([0.485, 0.456, 0.406])
    img = img.clamp(0, 1)  # Clamp values to range [0, 1]

    plt.imshow(img)
    plt.axis('off')
    plt.show()
    break
```

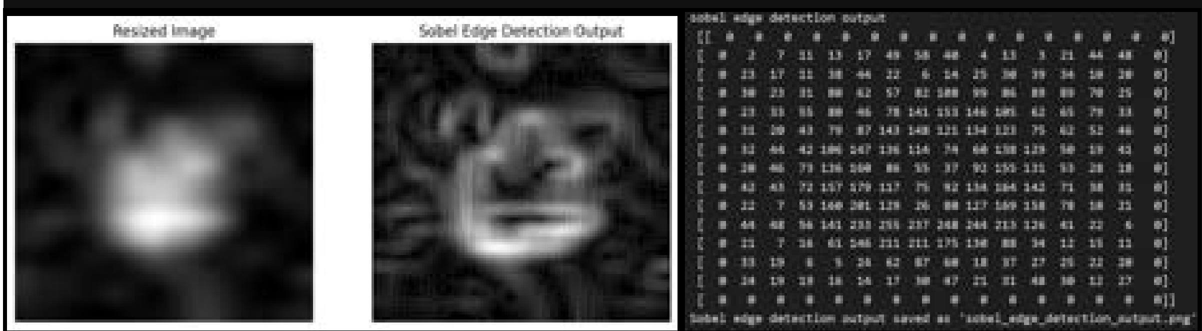


SOBEL OPERATOR:(resizing the image)

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

# Define Sobel kernels
sobel_x = np.array([[-1, 0, 1],
                    [-2, 0, 2],
                    [-1, 0, 1]])

sobel_y = np.array([[-1, -2, -1],
                    [ 0,  0,  0],
                    [ 1,  2,  1]])
```

```
# Function to apply convolution between image and kernel
def apply_convolution(image, kernel):
    height, width = image.shape
    output_image = np.zeros((height, width))

    # Apply convolution
    for i in range(1, height-1):
        for j in range(1, width-1):
            region = image[i-1:i+2, j-1:j+2]  # 3x3 region around the
pixel
            output_image[i, j] = np.sum(region * kernel)

    return output_image

# Function to compute gradient magnitude from Sobel outputs
def compute_gradient_magnitude(sobel_x_output, sobel_y_output):
    return np.sqrt(sobel_x_output**2 + sobel_y_output**2)

# Function to normalize the image for display
def normalize_image(image):
    image_min = np.min(image)
    image_max = np.max(image)
    normalized_image = (image - image_min) / (image_max - image_min) *
255
    return normalized_image.astype(np.uint8)

# Load your image (replace 'your_image.jpg' with the path to your image
file)
input_image_path = 'test\Benign\BreaDM-Be-1810\SUB1\p-030.jpg'  # Change
this to your image path
image = Image.open(input_image_path).convert('L')  # Convert to
grayscale

# Resize the image to a width of 225 pixels
new_width = 225
aspect_ratio = image.height / image.width
new_height = int(new_width * aspect_ratio)
image_resized = image.resize((new_width, new_height))

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

# Apply Sobel operators
```

```
sobel_x_output = apply_convolution(image_array, sobel_x)
sobel_y_output = apply_convolution(image_array, sobel_y)

# Calculate gradient magnitude (Sobel magnitude)
sobel_magnitude = compute_gradient_magnitude(sobel_x_output,
sobel_y_output)

# Normalize the output image for better visualization
normalized_output = normalize_image(sobel_magnitude)

# Convert to PIL Image
output_image = Image.fromarray(normalized_output)

# Save the output image
output_image.save('sobel_edge_detection_output.png')
print("Sobel edge detection output saved as
'sobel_edge_detection_output.png'")

# Display the original resized and the output image using matplotlib
plt.figure(figsize=(10, 5))

# Display original resized image
plt.subplot(1, 2, 1)
plt.title("Resized Image")
plt.imshow(image_array, cmap='gray')
plt.axis('off')  # Hide axes

# Display Sobel output image
plt.subplot(1, 2, 2)
plt.title("Sobel Edge Detection Output")
plt.imshow(normalized_output, cmap='gray')
plt.axis('off')  # Hide axes

plt.show()  # Show the figure with both images
```

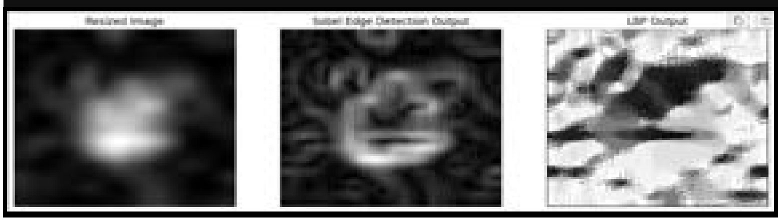


LOCAL BINARY PATTERN:

```
import numpy as np
from PIL import Image
import matplotlib.pyplot as plt
# Define Sobel kernels
sobel_x = np.array([[-1, 0, 1],
                    [-2, 0, 2],
                    [-1, 0, 1]])
sobel_y = np.array([[-1, -2, -1],
                    [ 0,  0,  0],
                    [ 1,  2,  1]])
# Function to apply convolution between image and kernel
def apply_convolution(image, kernel):
    height, width = image.shape
    output_image = np.zeros((height, width))
      # Apply convolution
    for i in range(1, height-1):
        for j in range(1, width-1):
            region = image[i-1:i+2, j-1:j+2]  # 3x3 region around the
pixel
            output_image[i, j] = np.sum(region * kernel)

    return output_image

# Function to compute gradient magnitude from Sobel outputs
def compute_gradient_magnitude(sobel_x_output, sobel_y_output):
    return np.sqrt(sobel_x_output**2 + sobel_y_output**2)
# Function to normalize the image for display
def normalize_image(image):
    image_min = np.min(image)
    image_max = np.max(image)
    normalized_image = (image - image_min) / (image_max - image_min) *
255
    return normalized_image.astype(np.uint8)
# Function to compute Local Binary Pattern (LBP)
def compute_lbp(image):
    height, width = image.shape
    lbp_image = np.zeros((height, width), dtype=np.uint8)

    for i in range(1, height-1):
        for j in range(1, width-1):
```

```
            center_pixel = image[i, j]
            binary_string = ''
# Clockwise comparison of the 8 neighbors starting from the top-left
            binary_string += '1' if image[i-1, j-1] >= center_pixel else
'0'
            binary_string += '1' if image[i-1, j] >= center_pixel else
'0'
            binary_string += '1' if image[i-1, j+1] >= center_pixel else
'0'
            binary_string += '1' if image[i, j+1] >= center_pixel else
'0'
            binary_string += '1' if image[i+1, j+1] >= center_pixel else
'0'
            binary_string += '1' if image[i+1, j] >= center_pixel else
'0'
            binary_string += '1' if image[i+1, j-1] >= center_pixel else
'0'
            binary_string += '1' if image[i, j-1] >= center_pixel else
'0'

# Convert binary string to decimal and assign to the LBP image
            lbp_image[i, j] = int(binary_string, 2)

    return lbp_image
# Load your image
input_image_path = 'test\Benign\BreaDM-Be-1810\SUB1\p-030.jpg'  # Change
this to your image path
image = Image.open(input_image_path).convert('L')  # Convert to
grayscale
# Resize the image to a width of 225 pixels
new_width = 225
aspect_ratio = image.height / image.width
new_height = int(new_width * aspect_ratio)
image_resized = image.resize((new_width, new_height))
# Convert the resized image to a NumPy array
image_array = np.array(image_resized)
# Apply Sobel operators
sobel_x_output = apply_convolution(image_array, sobel_x)
sobel_y_output = apply_convolution(image_array, sobel_y)
# Calculate gradient magnitude (Sobel magnitude)
sobel_magnitude = compute_gradient_magnitude(sobel_x_output,
sobel_y_output)
# Normalize the Sobel output image for better visualization
```

```
normalized_sobel_output = normalize_image(sobel_magnitude)
# Compute Local Binary Pattern (LBP)
lbp_image = compute_lbp(image_array)
# Normalize the LBP output for better visualization
normalized_lbp_output = normalize_image(lbp_image)
# Convert to PIL Image
sobel_output_image = Image.fromarray(normalized_sobel_output)
lbp_output_image = Image.fromarray(normalized_lbp_output)
# Save the Sobel and LBP output images
sobel_output_image.save('sobel_edge_detection_output.png')
lbp_output_image.save('lbp_output.png')
print("Sobel and LBP outputs saved as 'sobel_edge_detection_output.png'
and 'lbp_output.png'")
# Display the original resized, Sobel output, and LBP output images
using matplotlib
plt.figure(figsize=(15, 5))
# Display original resized image
plt.subplot(1, 3, 1)
plt.title("Resized Image")
plt.imshow(image_array, cmap='gray')
plt.axis('off')  # Hide axes
# Display Sobel output image
plt.subplot(1, 3, 2)
plt.title("Sobel Edge Detection Output")
plt.imshow(normalized_sobel_output, cmap='gray')
plt.axis('off')  # Hide axes
# Display LBP output image
plt.subplot(1, 3, 3)
plt.title("LBP Output")
plt.imshow(normalized_lbp_output, cmap='gray')
plt.axis('off')  # Hide axes

plt.show()  # Show the figure with all images
```



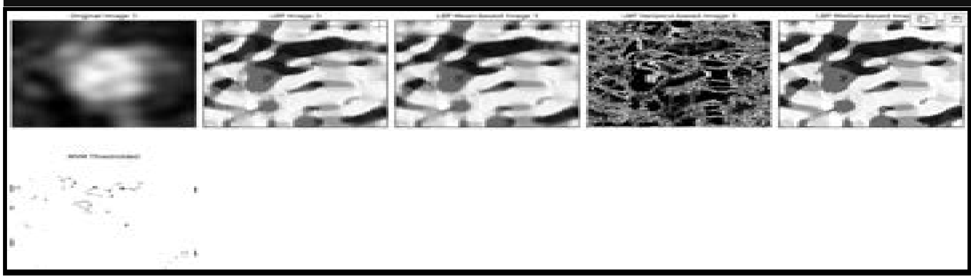
MVM-LBP IMAGES ON 5 IMAGES:
LBP Mean based, LBP Variance based, LBP Median based, MVM Thresholded:

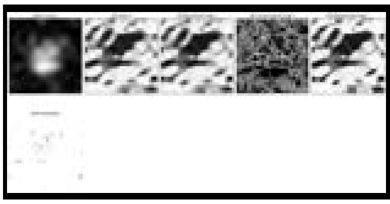
```
import numpy as np
from PIL import Image
```

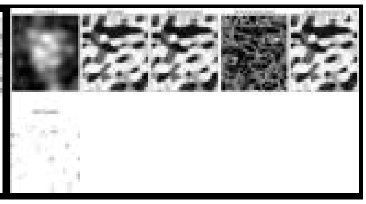
```
import matplotlib.pyplot as plt
from scipy.ndimage import generic_filter
import os
# Function to normalize the image for display
def normalize_image(image):
    image_min = np.min(image)
    image_max = np.max(image)
    normalized_image = ((image - image_min) / (image_max - image_min) *
255).astype(np.uint8)
    return normalized_image
# Function to compute Local Binary Pattern (LBP)
def compute_lbp(image, radius=1, neighbors=8):
    height, width = image.shape
    lbp_image = np.zeros((height, width), dtype=np.uint8)
       for i in range(radius, height - radius):
        for j in range(radius, width - radius):
            center_pixel = image[i, j]
            binary_string = ''
            offsets = [(dy, dx) for dy in range(-radius, radius+1) for
dx in range(-radius, radius+1) if dy != 0 or dx != 0]
            for dy, dx in offsets[:neighbors]:  # Take only specified
neighbors
                binary_string += '1' if image[i + dy, j + dx] >=
center_pixel else '0'
            lbp_image[i, j] = int(binary_string, 2)
       return lbp_image
# Define functions to compute local mean, variance, and median
def local_mean(image, size=3):
    return generic_filter(image, np.mean, size=size)
def local_variance(image, size=3):
    return generic_filter(image, np.var, size=size)
def local_median(image, size=3):
    return generic_filter(image, np.median, size=size)
# Apply MVM threshold using the formula
def apply_mvm_threshold(mean_image, variance_image, median_image):
    threshold = (mean_image + np.sqrt(variance_image) + median_image) /
3
    binary_image = (mean_image > threshold) * 255  # Apply threshold to
the mean image (or change as desired)
    return binary_image.astype(np.uint8)
# List of image paths (replace these with paths to your images)
image_paths = [
    'test/Benign/BreaDM-Be-1810/SUB1/p-030.jpg',
```

```python
    'test/Benign/BreaDM-Be-1810/SUB2/p-030.jpg',
    'test/Benign/BreaDM-Be-1810/SUB3/p-030.jpg',
    'test/Benign/BreaDM-Be-1810/SUB5/p-030.jpg',
    'test/Benign/BreaDM-Be-1810/SUB6/p-030.jpg'
]
# Directory to save output images
output_dir = "output_images"
os.makedirs(output_dir, exist_ok=True)
# Process each image in the list
for idx, image_path in enumerate(image_paths, start=1):
    # Load and resize image using Lanczos filter for high quality
    image = Image.open(image_path).convert('L')
    new_width = 225
    aspect_ratio = image.height / image.width
    new_height = int(new_width * aspect_ratio)
    image_resized = image.resize((new_width, new_height), Image.LANCZOS)
    image_array = np.array(image_resized)
   # Compute LBP image
    lbp_image = compute_lbp(image_array, radius=1, neighbors=8)
    # Apply mean, variance, and median transformations to LBP image
    lbp_mean_based = local_mean(lbp_image, size=3)
    lbp_variance_based = local_variance(lbp_image, size=3)
    lbp_median_based = local_median(lbp_image, size=3)
   # Normalize for better display
    lbp_mean_based = normalize_image(lbp_mean_based)
    lbp_variance_based = normalize_image(lbp_variance_based)
    lbp_median_based = normalize_image(lbp_median_based)
   # Apply MVM threshold using the formula
    mvm_thresholded = apply_mvm_threshold(lbp_mean_based,
lbp_variance_based, lbp_median_based)
    # Display the images
    plt.figure(figsize=(20, 10))

    # Display original resized image
    plt.subplot(2, 5, 1)
    plt.title(f"Original Image {idx}")
    plt.imshow(image_array, cmap='gray')
    plt.axis('off')
    # Display LBP image
    plt.subplot(2, 5, 2)
    plt.title(f"LBP Image {idx}")
    plt.imshow(lbp_image, cmap='gray')
    plt.axis('off')
```

```
    # Display LBP mean-based image
    plt.subplot(2, 5, 3)
    plt.title(f"LBP Mean-based Image {idx}")
    plt.imshow(lbp_mean_based, cmap='gray')
    plt.axis('off')
    # Display LBP variance-based image
    plt.subplot(2, 5, 4)
    plt.title(f"LBP Variance-based Image {idx}")
    plt.imshow(lbp_variance_based, cmap='gray')
    plt.axis('off')
    # Display LBP median-based image
    plt.subplot(2, 5, 5)
    plt.title(f"LBP Median-based Image {idx}")
    plt.imshow(lbp_median_based, cmap='gray')
    plt.axis('off')
    # Display MVM thresholded image
    plt.subplot(2, 5, 6)
    plt.title("MVM Thresholded")
    plt.imshow(mvm_thresholded, cmap='gray')
    plt.axis('off')
    plt.tight_layout()
    plt.show()
```







GLMC FOR TEXTURE EXTRACTION:

The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.

```
import numpy as np
from PIL import Image
import matplotlib.pyplot as plt
from scipy.ndimage import generic_filter
```

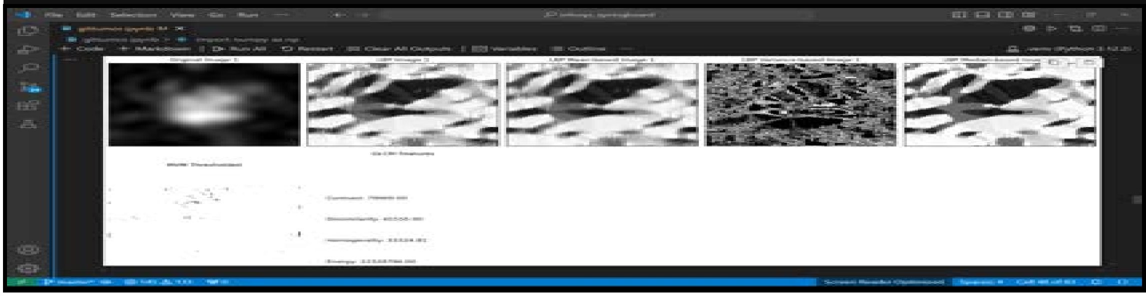
```
import os

# Function to normalize the image for display
def normalize_image(image):
    image_min = np.min(image)
    image_max = np.max(image)
    normalized_image = ((image - image_min) / (image_max - image_min) *
255).astype(np.uint8)
    return normalized_image

# Function to compute Local Binary Pattern (LBP)
def compute_lbp(image, radius=1, neighbors=8):
    height, width = image.shape
    lbp_image = np.zeros((height, width), dtype=np.uint8)

    for i in range(radius, height - radius):
        for j in range(radius, width - radius):
            center_pixel = image[i, j]
            binary_string = ''
            offsets = [(dy, dx) for dy in range(-radius, radius+1) for
dx in range(-radius, radius+1) if dy != 0 or dx != 0]
            for dy, dx in offsets[:neighbors]:  # Take only specified
neighbors
                binary_string += '1' if image[i + dy, j + dx] >=
center_pixel else '0'
            lbp_image[i, j] = int(binary_string, 2)

    return lbp_image

# Define functions to compute local mean, variance, and median
def local_mean(image, size=3):
    return generic_filter(image, np.mean, size=size)

def local_variance(image, size=3):
    return generic_filter(image, np.var, size=size)

def local_median(image, size=3):
    return generic_filter(image, np.median, size=size)

# Apply MVM threshold using the formula
def apply_mvm_threshold(mean_image, variance_image, median_image):
    threshold = (mean_image + np.sqrt(variance_image) + median_image) /
3
```

```
    binary_image = (mean_image > threshold) * 255
    return binary_image.astype(np.uint8)

# Function to compute GLCM manually
def compute_glcm(image, distance=1, angle=0):
    """Compute GLCM for a single distance and angle."""
    max_gray = 256  # Assuming 8-bit image
    glcm = np.zeros((max_gray, max_gray), dtype=np.int32)

    dx = int(np.round(np.cos(angle) * distance))
    dy = int(np.round(np.sin(angle) * distance))

    for i in range(image.shape[0] - dy):
        for j in range(image.shape[1] - dx):
            row = image[i, j]
            col = image[i + dy, j + dx]
            glcm[row, col] += 1

    return glcm

# Functions to compute GLCM properties
def contrast(glcm):
    i, j = np.ogrid[0:glcm.shape[0], 0:glcm.shape[1]]
    return np.sum(glcm * (i - j) ** 2)

def dissimilarity(glcm):
    i, j = np.ogrid[0:glcm.shape[0], 0:glcm.shape[1]]
    return np.sum(glcm * np.abs(i - j))

def homogeneity(glcm):
    i, j = np.ogrid[0:glcm.shape[0], 0:glcm.shape[1]]
    return np.sum(glcm / (1.0 + (i - j) ** 2))

def energy(glcm):
    return np.sum(glcm ** 2)

# List of image paths (replace these with paths to your images)
image_paths = [
    'test/Benign/BreaDM-Be-1810/SUB1/p-030.jpg',
    'test/Benign/BreaDM-Be-1810/SUB2/p-030.jpg',
    'test/Benign/BreaDM-Be-1810/SUB3/p-030.jpg',
    'test/Benign/BreaDM-Be-1810/SUB5/p-030.jpg',
    'test/Benign/BreaDM-Be-1810/SUB6/p-030.jpg'
```

```
]

# Directory to save output images
output_dir = "output_images"
os.makedirs(output_dir, exist_ok=True)

# Process each image in the list
for idx, image_path in enumerate(image_paths, start=1):
    # Load and resize image
    image = Image.open(image_path).convert('L')
    new_size = (225, 225)
    image_resized = image.resize(new_size, Image.LANCZOS)
    image_array = np.array(image_resized)

    # Compute LBP image
    lbp_image = compute_lbp(image_array, radius=1, neighbors=8)

    # Apply mean, variance, and median transformations to LBP image
    lbp_mean_based = local_mean(lbp_image, size=3)
    lbp_variance_based = local_variance(lbp_image, size=3)
    lbp_median_based = local_median(lbp_image, size=3)

    # Normalize for better display
    lbp_mean_based = normalize_image(lbp_mean_based)
    lbp_variance_based = normalize_image(lbp_variance_based)
    lbp_median_based = normalize_image(lbp_median_based)

    # Apply MVM threshold
    mvm_thresholded = apply_mvm_threshold(lbp_mean_based,
lbp_variance_based, lbp_median_based)

    # Compute GLCM and its properties
    glcm = compute_glcm(image_array, distance=1, angle=0)
    contrast_value = contrast(glcm)
    dissimilarity_value = dissimilarity(glcm)
    homogeneity_value = homogeneity(glcm)
    energy_value = energy(glcm)

    # Display the images and GLCM features
    plt.figure(figsize=(20, 10))

    # Display original resized image
    plt.subplot(2, 5, 1)
```

```
    plt.title(f"Original Image {idx}")
    plt.imshow(image_array, cmap='gray')
    plt.axis('off')

    # Display LBP image
    plt.subplot(2, 5, 2)
    plt.title(f"LBP Image {idx}")
    plt.imshow(lbp_image, cmap='gray')
    plt.axis('off')

    # Display LBP mean-based image
    plt.subplot(2, 5, 3)
    plt.title(f"LBP Mean-based Image {idx}")
    plt.imshow(lbp_mean_based, cmap='gray')
    plt.axis('off')

    # Display LBP variance-based image
    plt.subplot(2, 5, 4)
    plt.title(f"LBP Variance-based Image {idx}")
    plt.imshow(lbp_variance_based, cmap='gray')
    plt.axis('off')

    # Display LBP median-based image
    plt.subplot(2, 5, 5)
    plt.title(f"LBP Median-based Image {idx}")
    plt.imshow(lbp_median_based, cmap='gray')
    plt.axis('off')

    # Display MVM thresholded image
    plt.subplot(2, 5, 6)
    plt.title("MVM Thresholded")
    plt.imshow(mvm_thresholded, cmap='gray')
    plt.axis('off')

    # Display GLCM features
    plt.subplot(2, 5, 7)
    plt.title("GLCM Features")
    plt.text(0.1, 0.6, f"Contrast: {contrast_value:.2f}", fontsize=12)
    plt.text(0.1, 0.4, f"Dissimilarity: {dissimilarity_value:.2f}",
fontsize=12)
    plt.text(0.1, 0.2, f"Homogeneity: {homogeneity_value:.2f}",
fontsize=12)
    plt.text(0.1, 0.0, f"Energy: {energy_value:.2f}", fontsize=12)
```

```
    plt.axis('off')

    plt.tight_layout()
    plt.show()
```



LOADING VGG16 MODEL

```
class CustomVGG16(nn.Module):
    def __init__(self, num_classes=2):
        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
        self.classifier = nn.Sequential(
            nn.Linear(512 * 7 * 7, 4096), # Adjust input size for VGG16's avgpool output
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(4096, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(4096, num_classes)
        )

    def forward(self, x):
        # Pass through feature layers
        x = self.features(x)

        # Pass through avgpool layer
        x = self.avgpool(x)

        # Reshape the output to a 2D tensor (batch_size, 512*7*7)
        x = torch.flatten(x, 1)  # Flatten from (batch_size, 512, 7, 7) to (batch_size, 512*7*7)

        # Pass through the custom classifier
```

```
        x = self.classifier(x)

        return x
 model=CustomVGG16(num_classes=2)
print(model)
```

Early Stopping function:

```
import numpy as np
import torch

class EarlyStopping:
    def __init__(self, patience=7, verbose=False, delta=0, path='checkpoint.pt', trace_func=print):
        """
        Args:
            patience (int): How long to wait after last time validation loss improved.
                            Default: 7
            verbose (bool): If True, prints a message for each validation loss improvement.
                            Default: False
            delta (float): Minimum change in the monitored quantity to qualify as an improvement.
                            Default: 0
            path (str): Path for the checkpoint to save the best model.
                            Default: 'checkpoint.pt'
            trace_func (function): Function to print trace messages.
                            Default: print
        """
        self.patience = patience
        self.verbose = verbose
        self.counter = 0
        self.best_score = None
        self.early_stop = False
        self.val_loss_min = np.Inf  # Set to infinity to ensure the first comparison
        self.delta = delta
        self.path = path
        self.trace_func = trace_func

    def __call__(self, val_loss, model):
        """Check if early stopping condition is met and save the model if there's improvement."""
        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
```

Train dataset using pretrained vgg16 model:
VGG16 (AUC,CONFUSION_MATRIX):

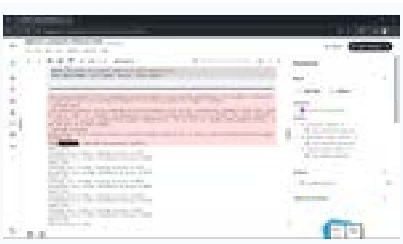
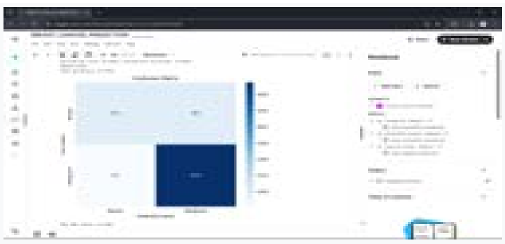
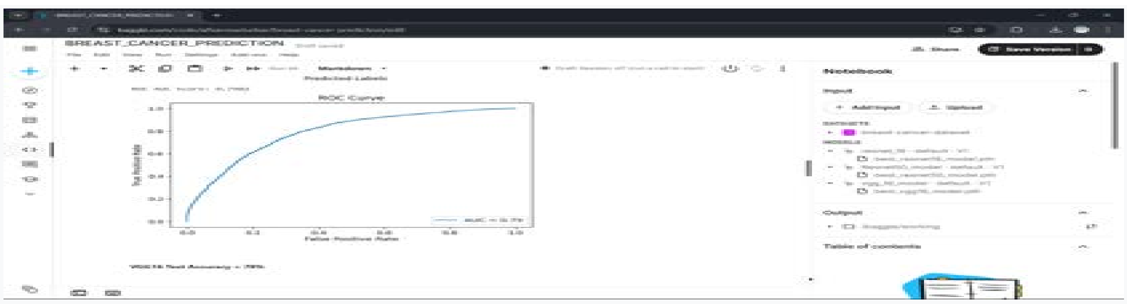
```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, models, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_auc_score, roc_curve
import seaborn as sns

# Helper functions
def plot_auc(y_true, y_scores):
    """Plot the ROC AUC curve."""
    auc_score = roc_auc_score(y_true, y_scores)
    print(f"ROC AUC Score: {auc_score:.4f}")
    fpr, tpr, _ = roc_curve(y_true, y_scores)
    plt.figure()
    plt.plot(fpr, tpr, label=f"AUC = {auc_score:.2f}")
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend(loc='lower right')
    plt.show()

def plot_confusion_matrix(y_true, y_pred, classes):
    """Plot the confusion matrix."""
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=classes, yticklabels=classes)
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Confusion Matrix')
    plt.show()

# Model creation function
def create_vgg16_model(num_classes):
    model = models.vgg16(pretrained=True)
```

```
    # Freeze the convolutional layers
    for param in model.features.parameters():
        param.requires_grad = False

    # Modify the classifier to match the number of classes
    model.classifier[6] = nn.Linear(model.classifier[6].in_features, num_classes)

    return model

# Training function
def train_vgg16(model, train_loader, val_loader, criterion, optimizer, device, num_epochs=10,
patience=5):
    model = model.to(device)
    best_accuracy = 0.0
    best_model_wts = model.state_dict()
    early_stop_counter = 0

    for epoch in range(num_epochs):
        print(f"Epoch {epoch + 1}/{num_epochs}")

        # Training phase
        model.train()
        running_loss = 0.0
        running_corrects = 0

        for inputs, labels in train_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            # Zero the parameter gradients
            optimizer.zero_grad()

            # Forward pass
            outputs = model(inputs)
            loss = criterion(outputs, labels)

            # Backward pass and optimization
            loss.backward()
            optimizer.step()

            # Track statistics
            running_loss += loss.item() * inputs.size(0)
            _, preds = torch.max(outputs, 1)
            running_corrects += torch.sum(preds == labels.data)

        epoch_loss = running_loss / len(train_loader.dataset)
        epoch_acc = running_corrects.double() / len(train_loader.dataset)

        print(f"Training Loss: {epoch_loss:.4f}, Training Accuracy: {epoch_acc:.4f}")
```

```
  # Validation phase
        model.eval()
        val_running_loss = 0.0
        val_running_corrects = 0

        with torch.no_grad():
            for inputs, labels in val_loader:
                inputs, labels = inputs.to(device), labels.to(device)

                # Forward pass
                outputs = model(inputs)
                loss = criterion(outputs, labels)

                # Track statistics
                val_running_loss += loss.item() * inputs.size(0)
                _, preds = torch.max(outputs, 1)
                val_running_corrects += torch.sum(preds == labels.data)

        val_loss = val_running_loss / len(val_loader.dataset)
        val_acc = val_running_corrects.double() / len(val_loader.dataset)

        print(f"Validation Loss: {val_loss:.4f}, Validation Accuracy: {val_acc:.4f}")

        # Save the model if it has the best accuracy so far
        if val_acc > best_accuracy:
            best_accuracy = val_acc
            best_model_wts = model.state_dict()
            early_stop_counter = 0  # Reset counter when validation improves
        else:
            early_stop_counter += 1

        if early_stop_counter >= patience:
            print("Early stopping triggered.")
            break

    # Load the best model weights
    model.load_state_dict(best_model_wts)
    torch.save(model.state_dict(), 'best_vgg16_model.pth')
    print(f"Best Validation Accuracy: {best_accuracy:.4f}")

# Testing function
def test_vgg16(model, test_loader, device, class_names):
    """Test the model and plot metrics."""
    model.eval()
    test_corrects = 0
    all_labels = []
    all_preds = []
    all_probs = []

    with torch.no_grad():
```

```
        for inputs, labels in test_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            probs = torch.softmax(outputs, dim=1)[:, 1]  # Assuming binary classification

            test_corrects += torch.sum(preds == labels.data)
            all_labels.extend(labels.cpu().numpy())
            all_preds.extend(preds.cpu().numpy())
            all_probs.extend(probs.cpu().numpy())

    test_acc = test_corrects.double() / len(test_loader.dataset)
    print(f"Test Accuracy: {test_acc:.4f}")

    # Plot the confusion matrix
    plot_confusion_matrix(all_labels, all_preds, class_names)

    # Plot the ROC AUC curve
    plot_auc(all_labels, all_probs)

# Main workflow
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
img_size = 224

train_dir = '/kaggle/input/breast-cancer-dataset/clasification-roi/train'
val_dir = '/kaggle/input/breast-cancer-dataset/clasification-roi/val'
test_dir = '/kaggle/input/breast-cancer-dataset/clasification-roi/test'

data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(img_size),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'val': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(img_size),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'test': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(img_size),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}
```

```
train_dataset = datasets.ImageFolder(train_dir, transform=data_transforms['train'])
val_dataset = datasets.ImageFolder(val_dir, transform=data_transforms['val'])
test_dataset = datasets.ImageFolder(test_dir, transform=data_transforms['test'])

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)

num_classes = len(train_dataset.classes)
class_names = train_dataset.classes
model = create_vgg16_model(num_classes)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.classifier.parameters(), lr=0.0001)

train_vgg16(model, train_loader, val_loader, criterion, optimizer, device, num_epochs=50,
patience=5)
model.load_state_dict(torch.load('best_vgg16_model.pth'))
test_vgg16(model, test_loader, device, class_names)
```

Resnet50 (AUC,CONFUSION_MATRIX):

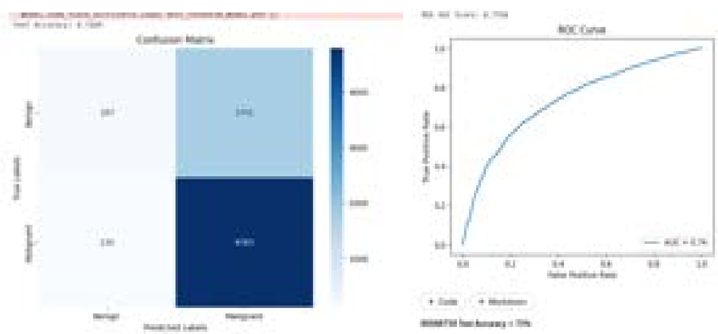
```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, models, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_auc_score, roc_curve
import seaborn as sns

# Helper functions (same as provided)
def plot_auc(y_true, y_scores):
    """Plot the ROC AUC curve."""
    auc_score = roc_auc_score(y_true, y_scores)
    print(f"ROC AUC Score: {auc_score:.4f}")
```

```
    fpr, tpr, _ = roc_curve(y_true, y_scores)
    plt.figure()
    plt.plot(fpr, tpr, label=f"AUC = {auc_score:.2f}")
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend(loc='lower right')
    plt.show()

def plot_confusion_matrix(y_true, y_pred, classes):
    """Plot the confusion matrix."""
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=classes, yticklabels=classes)
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Confusion Matrix')
    plt.show()

# Model creation function for ResNet-50
def create_resnet50_model(num_classes):
    model = models.resnet50(pretrained=True)

    # Freeze the convolutional layers
    for param in model.parameters():
        param.requires_grad = False

    # Replace the fully connected layer to match the number of classes
    model.fc = nn.Linear(model.fc.in_features, num_classes)

    return model

# Training function
def train_resnet50(model, train_loader, val_loader, criterion, optimizer, device, num_epochs=10,
patience=5):
    model = model.to(device)
    best_accuracy = 0.0
    best_model_wts = model.state_dict()
    early_stop_counter = 0

    for epoch in range(num_epochs):
        print(f"Epoch {epoch + 1}/{num_epochs}")

        # Training phase
        model.train()
        running_loss = 0.0
        running_corrects = 0

        for inputs, labels in train_loader:
            inputs, labels = inputs.to(device), labels.to(device)
```

```
        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        # Backward pass and optimization
        loss.backward()
        optimizer.step()

        # Track statistics
        running_loss += loss.item() * inputs.size(0)
        _, preds = torch.max(outputs, 1)
        running_corrects += torch.sum(preds == labels.data)

    epoch_loss = running_loss / len(train_loader.dataset)
    epoch_acc = running_corrects.double() / len(train_loader.dataset)

    print(f"Training Loss: {epoch_loss:.4f}, Training Accuracy: {epoch_acc:.4f}")

    # Validation phase
    model.eval()
    val_running_loss = 0.0
    val_running_corrects = 0

    with torch.no_grad():
        for inputs, labels in val_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            # Forward pass
            outputs = model(inputs)
            loss = criterion(outputs, labels)

            # Track statistics
            val_running_loss += loss.item() * inputs.size(0)
            _, preds = torch.max(outputs, 1)
            val_running_corrects += torch.sum(preds == labels.data)

    val_loss = val_running_loss / len(val_loader.dataset)
    val_acc = val_running_corrects.double() / len(val_loader.dataset)

    print(f"Validation Loss: {val_loss:.4f}, Validation Accuracy: {val_acc:.4f}")

    # Save the model if it has the best accuracy so far
    if val_acc > best_accuracy:
        best_accuracy = val_acc
        best_model_wts = model.state_dict()
        early_stop_counter = 0  # Reset counter when validation improves
```

```
        else:
            early_stop_counter += 1

        if early_stop_counter >= patience:
            print("Early stopping triggered.")
            break

    # Load the best model weights
    model.load_state_dict(best_model_wts)
    torch.save(model.state_dict(), 'best_resnet50_model.pth')
    print(f"Best Validation Accuracy: {best_accuracy:.4f}")

# Testing function
def test_resnet50(model, test_loader, device, class_names):
    """Test the model and plot metrics."""
    model.eval()
    test_corrects = 0
    all_labels = []
    all_preds = []
    all_probs = []

    with torch.no_grad():
        for inputs, labels in test_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            probs = torch.softmax(outputs, dim=1)[:, 1]  # Assuming binary classification

            test_corrects += torch.sum(preds == labels.data)
            all_labels.extend(labels.cpu().numpy())
            all_preds.extend(preds.cpu().numpy())
            all_probs.extend(probs.cpu().numpy())

    test_acc = test_corrects.double() / len(test_loader.dataset)
    print(f"Test Accuracy: {test_acc:.4f}")

    # Plot the confusion matrix
    plot_confusion_matrix(all_labels, all_preds, class_names)

    # Plot the ROC AUC curve
    plot_auc(all_labels, all_probs)

# Main workflow
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
img_size = 224

train_dir = '/kaggle/input/breast-cancer-dataset/clasification-roi/train'
val_dir = '/kaggle/input/breast-cancer-dataset/clasification-roi/val'
test_dir = '/kaggle/input/breast-cancer-dataset/clasification-roi/test'
```

```
data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(img_size),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'val': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(img_size),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'test': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(img_size),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}

train_dataset = datasets.ImageFolder(train_dir, transform=data_transforms['train'])
val_dataset = datasets.ImageFolder(val_dir, transform=data_transforms['val'])
test_dataset = datasets.ImageFolder(test_dir, transform=data_transforms['test'])

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)

num_classes = len(train_dataset.classes)
class_names = train_dataset.classes
model = create_resnet50_model(num_classes)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.fc.parameters(), lr=0.0001)

train_resnet50(model, train_loader, val_loader, criterion, optimizer, device, num_epochs=50,
patience=5)
model.load_state_dict(torch.load('best_resnet50_model.pth'))
test_resnet50(model, test_loader, device, class_names)
```



Resnet18 (AUC,CONFUSION_MATRIX):

```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, models, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_auc_score, roc_curve
import seaborn as sns

# Helper functions (same as provided)
def plot_auc(y_true, y_scores):
    """Plot the ROC AUC curve."""
    auc_score = roc_auc_score(y_true, y_scores)
    print(f"ROC AUC Score: {auc_score:.4f}")
    fpr, tpr, _ = roc_curve(y_true, y_scores)
    plt.figure()
    plt.plot(fpr, tpr, label=f"AUC = {auc_score:.2f}")
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend(loc='lower right')
    plt.show()

def plot_confusion_matrix(y_true, y_pred, classes):
    """Plot the confusion matrix."""
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=classes, yticklabels=classes)
    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Confusion Matrix')
    plt.show()

# Model creation function for ResNet-18
def create_resnet18_model(num_classes):
    model = models.resnet18(pretrained=True)

    # Freeze the convolutional layers
    for param in model.parameters():
        param.requires_grad = False

    # Replace the fully connected layer to match the number of classes
    model.fc = nn.Linear(model.fc.in_features, num_classes)

    return model

# Training function
```

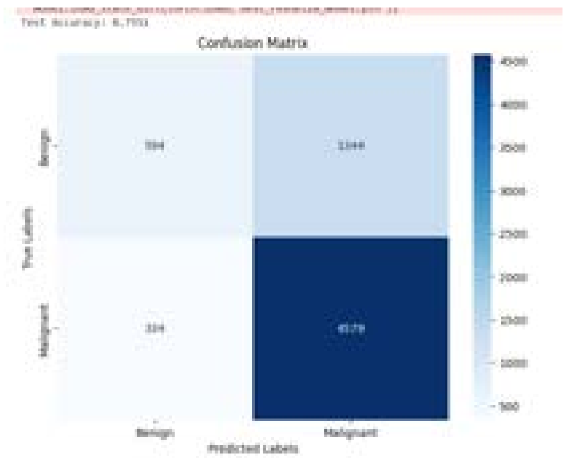
```
def train_resnet18(model, train_loader, val_loader, criterion, optimizer, device, num_epochs=10,
patience=5):
    model = model.to(device)
    best_accuracy = 0.0
    best_model_wts = model.state_dict()
    early_stop_counter = 0

    for epoch in range(num_epochs):
        print(f"Epoch {epoch + 1}/{num_epochs}")

        # Training phase
        model.train()
        running_loss = 0.0
        running_corrects = 0

        for inputs, labels in train_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            # Zero the parameter gradients
            optimizer.zero_grad()

            # Forward pass
            outputs = model(inputs)
            loss = criterion(outputs, labels)

            # Backward pass and optimization
            loss.backward()
            optimizer.step()

            # Track statistics
            running_loss += loss.item() * inputs.size(0)
            _, preds = torch.max(outputs, 1)
            running_corrects += torch.sum(preds == labels.data)

        epoch_loss = running_loss / len(train_loader.dataset)
        epoch_acc = running_corrects.double() / len(train_loader.dataset)

        print(f"Training Loss: {epoch_loss:.4f}, Training Accuracy: {epoch_acc:.4f}")

        # Validation phase
        model.eval()
        val_running_loss = 0.0
        val_running_corrects = 0

        with torch.no_grad():
            for inputs, labels in val_loader:
                inputs, labels = inputs.to(device), labels.to(device)

                # Forward pass
                outputs = model(inputs)
```

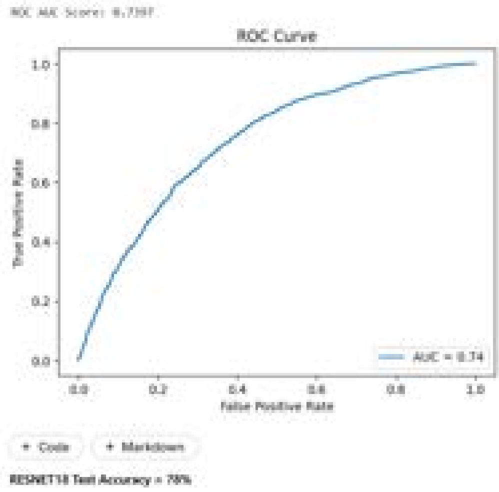
```
            loss = criterion(outputs, labels)

            # Track statistics
            val_running_loss += loss.item() * inputs.size(0)
            _, preds = torch.max(outputs, 1)
            val_running_corrects += torch.sum(preds == labels.data)

        val_loss = val_running_loss / len(val_loader.dataset)
        val_acc = val_running_corrects.double() / len(val_loader.dataset)

        print(f"Validation Loss: {val_loss:.4f}, Validation Accuracy: {val_acc:.4f}")

        # Save the model if it has the best accuracy so far
        if val_acc > best_accuracy:
            best_accuracy = val_acc
            best_model_wts = model.state_dict()
            early_stop_counter = 0  # Reset counter when validation improves
        else:
            early_stop_counter += 1

        if early_stop_counter >= patience:
            print("Early stopping triggered.")
            break

    # Load the best model weights
    model.load_state_dict(best_model_wts)
    torch.save(model.state_dict(), 'best_resnet18_model.pth')
    print(f"Best Validation Accuracy: {best_accuracy:.4f}")

# Testing function
def test_resnet18(model, test_loader, device, class_names):
    """Test the model and plot metrics."""
    model.eval()
    test_corrects = 0
    all_labels = []
    all_preds = []
    all_probs = []

    with torch.no_grad():
        for inputs, labels in test_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            probs = torch.softmax(outputs, dim=1)[:, 1]  # Assuming binary classification

            test_corrects += torch.sum(preds == labels.data)
            all_labels.extend(labels.cpu().numpy())
            all_preds.extend(preds.cpu().numpy())
            all_probs.extend(probs.cpu().numpy())
```

```
    test_acc = test_corrects.double() / len(test_loader.dataset)
    print(f"Test Accuracy: {test_acc:.4f}")

    # Plot the confusion matrix
    plot_confusion_matrix(all_labels, all_preds, class_names)

    # Plot the ROC AUC curve
    plot_auc(all_labels, all_probs)

# Main workflow
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
img_size = 224

train_dir = '/kaggle/input/breast-cancer-dataset/clasification-roi/train'
val_dir = '/kaggle/input/breast-cancer-dataset/clasification-roi/val'
test_dir = '/kaggle/input/breast-cancer-dataset/clasification-roi/test'

data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(img_size),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'val': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(img_size),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
    'test': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(img_size),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
    ]),
}

train_dataset = datasets.ImageFolder(train_dir, transform=data_transforms['train'])
val_dataset = datasets.ImageFolder(val_dir, transform=data_transforms['val'])
test_dataset = datasets.ImageFolder(test_dir, transform=data_transforms['test'])

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)

num_classes = len(train_dataset.classes)
class_names = train_dataset.classes
model = create_resnet18_model(num_classes)
```

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.fc.parameters(), lr=0.0001)

train_resnet18(model, train_loader, val_loader, criterion, optimizer, device, num_epochs=50, patience=5)
model.load_state_dict(torch.load('best_resnet18_model.pth'))
test_resnet18(model, test_loader, device, class_names)



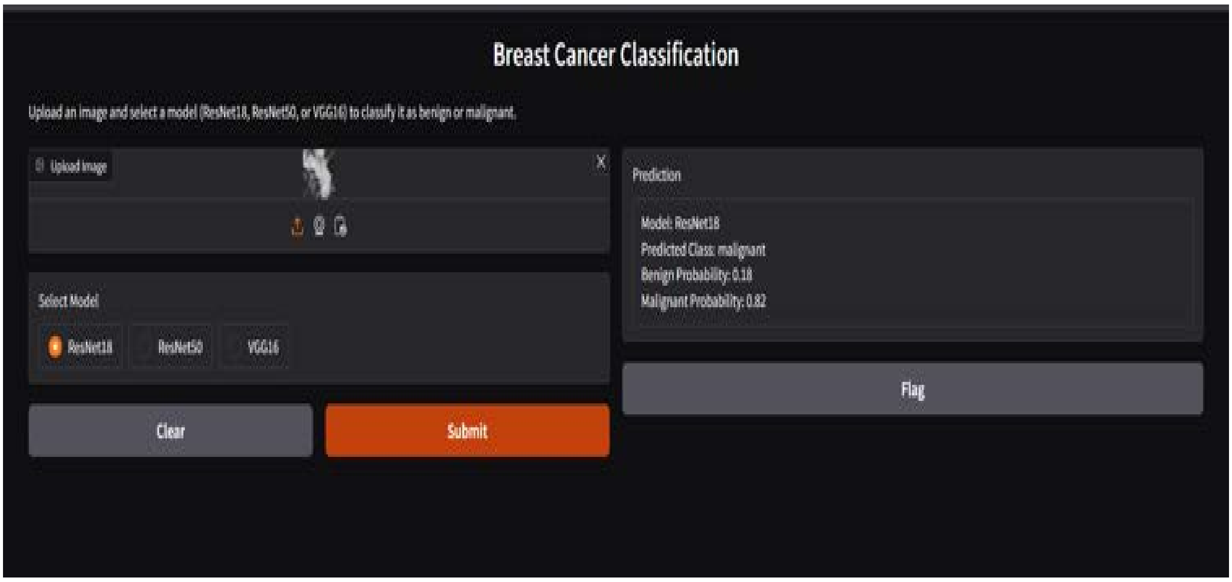


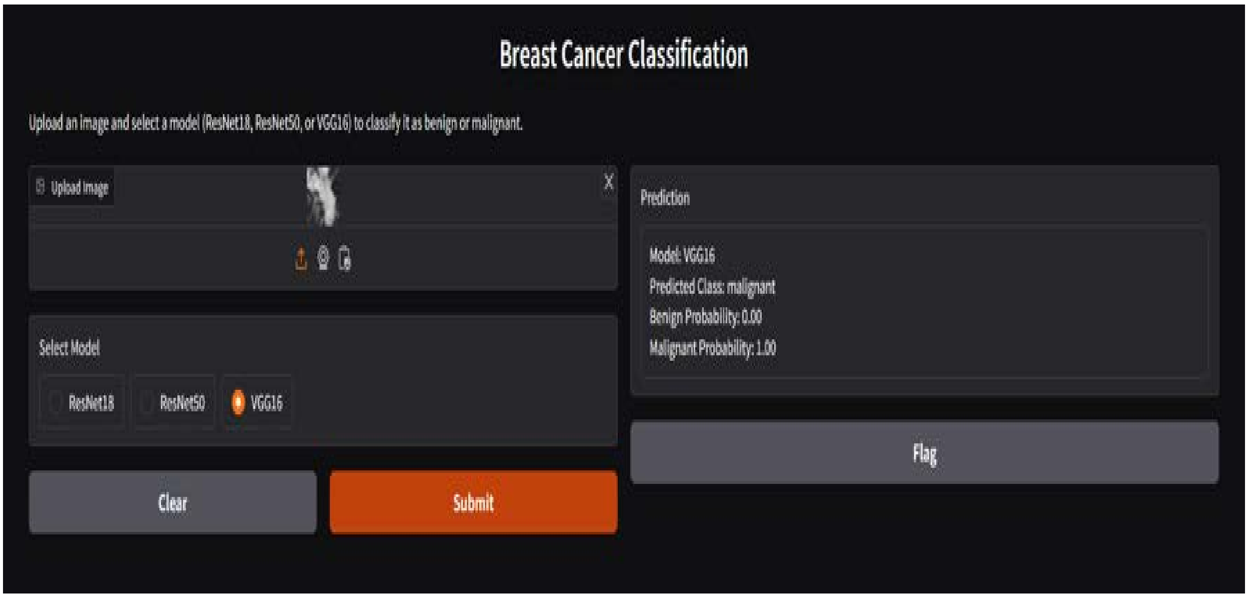
Using gradio library on all three models(resnet50,resnet18,vgg16):

```
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
```

```python
# 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/input/resnet_18/pytorch/default/1/best_resnet18_model.pth",
        "ResNet50": "/kaggle/input/resnet50_model/pytorch/default/1/best_resnet50_model.pth",
        "VGG16": "/kaggle/input/vgg_16_model/pytorch/default/1/best_vgg16_model.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"Model: {model_name}\n"
        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.Radio(["ResNet18", "ResNet50", "VGG16"], label="Select Model")
    ],
    outputs=gr.Textbox(label="Prediction"),
    title="Breast Cancer Classification",
    description="Upload an image and select a model (ResNet18, ResNet50, or VGG16) to classify it as benign or malignant."
)

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





VGG16 IS THE BEST ACCURACY MODEL WITH 78 PERCENT

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