

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list the files in the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets uploaded to S3
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside this notebook
```

```
import os
import shutil

def clean_kaggle_output_directory(output_dir):
    """
    Removes all files and subdirectories in the specified output directory.
    If the directory does not exist, it is created.
    """
    if os.path.exists(output_dir):
        # Remove everything in the output directory
        for filename in os.listdir(output_dir):
            file_path = os.path.join(output_dir, filename)
            try:
                if os.path.isfile(file_path) or os.path.islink(file_path):
                    os.unlink(file_path) # remove file or link
                elif os.path.isdir(file_path):
                    shutil.rmtree(file_path) # remove directory
            except Exception as e:
                print(f"Failed to delete {file_path}. Reason: {e}")
    else:
        os.makedirs(output_dir)
    print(f"Output directory '{output_dir}' is now clean and ready.")

# Example usage:
kaggle_output_dir = "/kaggle/working/" # adjust this path as needed
clean_kaggle_output_directory(kaggle_output_dir)
```

→ Output directory '/kaggle/working/' is now clean and ready.

```
import os

def count_images_in_dir(directory):
    """Count the number of image files in each subfolder of the given directory
    counts = {}
    for class_name in os.listdir(directory):
        class_path = os.path.join(directory, class_name)
        if os.path.isdir(class_path):
            # Count files that are images (assumes image files have common extensions)
            image_extensions = ('.png', '.jpg', '.jpeg', '.bmp', '.gif', '.tiff')
            num_images = sum(1 for fname in os.listdir(class_path)
                            if fname.lower().endswith(image_extensions))
            counts[class_name] = num_images
    return counts

# Define the base dataset directory.
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)'

# Count images for train and test sets.
for subset in ['train', 'test']:
    subset_dir = os.path.join(data_dir, subset)
    counts = count_images_in_dir(subset_dir)
    print(f"{subset.capitalize()} set:")
    for class_name, count in counts.items():
        print(f"  {class_name}: {count} images")
```

↳ Train set:
benign: 1440 images
malignant: 1440 images
Test set:
benign: 360 images
malignant: 360 images

✓ cycleGAN

train/malignant

```
import os
import glob
import time
import random
import zipfile
import itertools
```

```
import numpy as np
from PIL import Image

import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, Dataset
import torchvision.transforms as transforms
import torchvision.utils as vutils
import matplotlib.pyplot as plt

# -----
# 1. Setup & Reproducibility
# -----
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)
seed = 42
random.seed(seed)
np.random.seed(seed)
torch.manual_seed(seed)
if device.type == 'cuda':
    torch.cuda.manual_seed(seed)

# -----
# 2. Dataset Preparation
# -----
# Custom dataset for a single folder (assumes folder contains only images)
class SingleFolderDataset(Dataset):
    def __init__(self, folder, transform=None):
        self.folder = folder
        self.image_paths = glob.glob(os.path.join(folder, "*"))
        self.transform = transform
    def __len__(self):
        return len(self.image_paths)
    def __getitem__(self, idx):
        img = Image.open(self.image_paths[idx]).convert("RGB")
        if self.transform:
            img = self.transform(img)
        return img

# Define two transforms: Domain A is the original image; Domain B uses heavy au
transform_A = transforms.Compose([
    transforms.Resize((256, 256)),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])
transform_B = transforms.Compose([
    transforms.Resize((256, 256)),
```

```
transforms.ColorJitter(brightness=0.8, contrast=0.8, saturation=0.8, hue=0.
transforms.RandomHorizontalFlip(),
transforms.RandomRotation(20),
transforms.ToTensor(),
transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)))
])

# Set your dataset base path (adjust this path to point to your dataset)
dataset_base = "/kaggle/input/k-mean-clustering/segmented_data" # e.g., "/kaggle/input/k-mean-clustering/segmented_data"

# Then set the specific folder for malignant images:
malignant_folder = os.path.join(dataset_base, "train", "malignant")

# Create datasets for two domains using the same images
dataset_A = SingleFolderDataset(malignant_folder, transform=transform_A)
dataset_B = SingleFolderDataset(malignant_folder, transform=transform_B)

# DataLoaders (CycleGAN commonly uses batch_size=1)
batch_size = 1
loader_A = DataLoader(dataset_A, batch_size=batch_size, shuffle=True, num_workers=4)
loader_B = DataLoader(dataset_B, batch_size=batch_size, shuffle=True, num_workers=4)

# Create an iterator that zips the two dataloaders (unpaired training is assumed)
def dataloader_zip(loader_A, loader_B):
    return zip(loader_A, loader_B)
data_loader = dataloader_zip(loader_A, loader_B)

# -----
# 3. Define CycleGAN Networks
# -----
# Residual block used in the generator
class ResidualBlock(nn.Module):
    def __init__(self, dim):
        super(ResidualBlock, self).__init__()
        self.block = nn.Sequential(
            nn.ReflectionPad2d(1),
            nn.Conv2d(dim, dim, kernel_size=3),
            nn.InstanceNorm2d(dim),
            nn.ReLU(True),
            nn.ReflectionPad2d(1),
            nn.Conv2d(dim, dim, kernel_size=3),
            nn.InstanceNorm2d(dim)
        )
    def forward(self, x):
        return x + self.block(x)

# Generator network (ResNet-based)
```

```
class ResnetGenerator(nn.Module):
    def __init__(self, input_nc, output_nc, ngf=64, n_blocks=9):
        assert(n_blocks >= 0)
        super(ResnetGenerator, self).__init__()
        model = [
            nn.ReflectionPad2d(3),
            nn.Conv2d(input_nc, ngf, kernel_size=7),
            nn.InstanceNorm2d(ngf),
            nn.ReLU(True)
        ]
        # Downsampling
        n_downsampling = 2
        for i in range(n_downsampling):
            mult = 2 ** i
            model += [
                nn.Conv2d(ngf * mult, ngf * mult * 2, kernel_size=3, stride=2,
                nn.InstanceNorm2d(ngf * mult * 2),
                nn.ReLU(True))
            ]
        # Residual blocks
        mult = 2 ** n_downsampling
        for i in range(n_blocks):
            model += [ResidualBlock(ngf * mult)]
        # Upsampling
        for i in range(n_downsampling):
            mult = 2 ** (n_downsampling - i)
            model += [
                nn.ConvTranspose2d(ngf * mult, int(ngf * mult / 2), kernel_size=3,
                    padding=1, output_padding=1),
                nn.InstanceNorm2d(int(ngf * mult / 2)),
                nn.ReLU(True)
            ]
        model += [
            nn.ReflectionPad2d(3),
            nn.Conv2d(ngf, output_nc, kernel_size=7),
            nn.Tanh()
        ]
        self.model = nn.Sequential(*model)
    def forward(self, input):
        return self.model(input)

# PatchGAN Discriminator
class NLayerDiscriminator(nn.Module):
    def __init__(self, input_nc, ndf=64, n_layers=3):
        super(NLayerDiscriminator, self).__init__()
        kw = 4
        padw = 1
        sequence = [
```

```
        nn.Conv2d(input_nc, ndf, kernel_size=kw, stride=2, padding=padw),
        nn.LeakyReLU(0.2, True)
    ]
    nf_mult = 1
    for n in range(1, n_layers):
        nf_mult_prev = nf_mult
        nf_mult = min(2 ** n, 8)
        sequence += [
            nn.Conv2d(ndf * nf_mult_prev, ndf * nf_mult, kernel_size=kw, st
            nn.InstanceNorm2d(ndf * nf_mult),
            nn.LeakyReLU(0.2, True)
        ]
    nf_mult_prev = nf_mult
    nf_mult = min(2 ** n_layers, 8)
    sequence += [
        nn.Conv2d(ndf * nf_mult_prev, ndf * nf_mult, kernel_size=kw, stride=2, padding=padw),
        nn.InstanceNorm2d(ndf * nf_mult),
        nn.LeakyReLU(0.2, True)
    ]
    sequence += [nn.Conv2d(ndf * nf_mult, 1, kernel_size=kw, stride=1, padding=0)]
    self.model = nn.Sequential(*sequence)

def forward(self, input):
    return self.model(input)

# Instantiate networks and move to device
G_A2B = ResnetGenerator(3, 3, n_blocks=9).to(device) # maps domain A -> domain B
G_B2A = ResnetGenerator(3, 3, n_blocks=9).to(device) # maps domain B -> domain A
D_A = NLayerDiscriminator(3).to(device) # discriminates domain A
D_B = NLayerDiscriminator(3).to(device) # discriminates domain B

# -----
# 4. Losses & Optimizers
# -----
criterion_GAN = nn.MSELoss().to(device)
criterion_cycle = nn.L1Loss().to(device)
criterion_identity = nn.L1Loss().to(device)

lr = 0.0002
beta1 = 0.5
optimizer_G = optim.Adam(itertools.chain(G_A2B.parameters(), G_B2A.parameters()))
optimizer_D_A = optim.Adam(D_A.parameters(), lr=lr, betas=(beta1, 0.999))
optimizer_D_B = optim.Adam(D_B.parameters(), lr=lr, betas=(beta1, 0.999))

# -----
# 5. Training Loop for CycleGAN
# -----
num_epochs = 50
# Folder to save generated images per epoch
```

```
epoch_save_dir = "/kaggle/working/epoch_images"
os.makedirs(epoch_save_dir, exist_ok=True)

# Prepare fixed images for monitoring progress (one sample from each loader)
fixed_A = next(iter(loader_A)).to(device)
fixed_B = next(iter(loader_B)).to(device)

# CycleGAN uses PatchGAN so we create a "valid" map of labels.
def create_target_tensor(input_tensor, value):
    # Assuming the discriminator output is 30x30 (depends on image size and arc
    return torch.full((input_tensor.size(0), 1, 30, 30), value, device=device)

for epoch in range(1, num_epochs + 1):
    start_time = time.time()
    for i, (real_A, real_B) in enumerate(data_loader):
        real_A = real_A.to(device)
        real_B = real_B.to(device)
        valid = create_target_tensor(real_A, 1.0)
        fake = create_target_tensor(real_A, 0.0)

        # -----
        # Train Generators
        # -----
        optimizer_G.zero_grad()

        # Identity loss: G_B2A(real_A) should equal real_A and G_A2B(real_B) sh
        loss_id_A = criterion_identity(G_B2A(real_A), real_A)
        loss_id_B = criterion_identity(G_A2B(real_B), real_B)
        loss_identity = (loss_id_A + loss_id_B) * 0.5

        # GAN loss
        fake_B = G_A2B(real_A)
        loss_GAN_A2B = criterion_GAN(D_B(fake_B), valid)
        fake_A = G_B2A(real_B)
        loss_GAN_B2A = criterion_GAN(D_A(fake_A), valid)
        loss_GAN = (loss_GAN_A2B + loss_GAN_B2A) * 0.5

        # Cycle consistency loss: G_B2A(G_A2B(real_A)) should equal real_A, and
        rec_A = G_B2A(fake_B)
        loss_cycle_A = criterion_cycle(rec_A, real_A)
        rec_B = G_A2B(fake_A)
        loss_cycle_B = criterion_cycle(rec_B, real_B)
        loss_cycle = (loss_cycle_A + loss_cycle_B) * 10.0

        # Total generator loss
        loss_G = loss_identity + loss_GAN + loss_cycle
        loss_G.backward()
        optimizer_G.step()
```

```
# -----
# Train Discriminator A
# -----
optimizer_D_A.zero_grad()
loss_D_A_real = criterion_GAN(D_A(real_A), valid)
loss_D_A_fake = criterion_GAN(D_A(fake_A.detach()), fake)
loss_D_A = (loss_D_A_real + loss_D_A_fake) * 0.5
loss_D_A.backward()
optimizer_D_A.step()

# -----
# Train Discriminator B
# -----
optimizer_D_B.zero_grad()
loss_D_B_real = criterion_GAN(D_B(real_B), valid)
loss_D_B_fake = criterion_GAN(D_B(fake_B.detach()), fake)
loss_D_B = (loss_D_B_real + loss_D_B_fake) * 0.5
loss_D_B.backward()
optimizer_D_B.step()

elapsed = time.time() - start_time
print(f"Epoch [{epoch}/{num_epochs}] - Loss_G: {loss_G.item():.4f}, Loss_D_"

# Save generated images on fixed sample from domain A at the end of each epoch
with torch.no_grad():
    fake_B_fixed = G_A2B(fixed_A)
    epoch_image_path = os.path.join(epoch_save_dir, f"epoch_{epoch}.png")
    vutils.save_image(fake_B_fixed, epoch_image_path, normalize=True)

# -----
# 6. Generate 243 New Images & Zip Output
# -----
# Folder to store final generated images
final_output_dir = "/kaggle/working/final_output"
os.makedirs(final_output_dir, exist_ok=True)

# Randomly sample 243 indices from dataset_A (from malignant images)
num_new_images = 243
indices = random.sample(range(len(dataset_A)), num_new_images)

for idx in indices:
    # Get image from domain A and generate new image via G_A2B
    img = dataset_A[idx]
    img_tensor = img.unsqueeze(0).to(device) # add batch dimension
    with torch.no_grad():
        generated_img = G_A2B(img_tensor)
    save_filename = os.path.join(final_output_dir, f"generated_{idx}.png")
```

```
vutils.save_image(generated_img, save_filename, normalize=True)

# Create a zip file of the final generated images (for Kaggle output)
zip_filename = "/kaggle/working/generated_images.zip"
with zipfile.ZipFile(zip_filename, 'w') as zipf:
    for root, _, files in os.walk(final_output_dir):
        for file in files:
            zipf.write(os.path.join(root, file), arcname=file)
print(f"Zip file saved as: {zip_filename}")
```

→ Using device: cuda

```
Epoch [1/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 39
Epoch [2/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [3/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [4/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [5/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [6/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [7/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [8/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [9/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [10/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [11/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [12/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [13/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [14/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [15/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [16/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [17/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [18/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [19/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [20/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [21/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [22/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [23/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [24/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [25/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [26/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [27/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [28/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [29/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [30/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [31/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [32/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [33/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [34/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [35/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [36/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [37/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [38/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [39/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0.
Epoch [40/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
```

```
Epoch [41/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Epoch [42/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Epoch [43/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Epoch [44/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Epoch [45/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Epoch [46/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Epoch [47/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Epoch [48/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Epoch [49/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Epoch [50/50] - Loss_G: 4.6986, Loss_D_A: 0.1102, Loss_D_B: 0.0958, Time: 0
Zip file saved as: /kaggle/working/generated_images.zip
```

test/malignant

```
import os
import glob
import time
import random
import zipfile
import itertools
import numpy as np
from PIL import Image

import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, Dataset
import torchvision.transforms as transforms
import torchvision.utils as vutils
import matplotlib.pyplot as plt

# =====
# 1. Setup & Reproducibility
# =====
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

seed = 42
random.seed(seed)
np.random.seed(seed)
torch.manual_seed(seed)
if device.type == 'cuda':
    torch.cuda.manual_seed(seed)

# =====
# 2. Dataset Path & Cleaning Kaggle Output Directory
# =====
```

```
# Set your dataset base path (adjust this path to point to your dataset)
dataset_base = "/kaggle/input/k-mean-clustering/segmented_data" # Change to your dataset base path

# Use test/malignant folder for CycleGAN training
malignant_folder = os.path.join(dataset_base, "test", "malignant")
print("Malignant folder:", malignant_folder)

# Kaggle output directory for final results
kaggle_output_dir = "/kaggle/working/final-results"
os.makedirs(kaggle_output_dir, exist_ok=True)

def clean_directory(directory):
    if os.path.exists(directory):
        for filename in os.listdir(directory):
            file_path = os.path.join(directory, filename)
            try:
                if os.path.isfile(file_path) or os.path.islink(file_path):
                    os.unlink(file_path)
                elif os.path.isdir(file_path):
                    import shutil
                    shutil.rmtree(file_path)
            except Exception as e:
                print(f"Failed to delete {file_path}. Reason: {e}")
    else:
        os.makedirs(directory)
    print(f"Directory '{directory}' is now clean.")

# Clean the output directory before saving new results.
clean_directory(kaggle_output_dir)

# =====
# 3. Dataset Preparation & Transforms
# =====

# Custom dataset for a single folder
class SingleFolderDataset(Dataset):
    def __init__(self, folder, transform=None):
        self.folder = folder
        self.image_paths = glob.glob(os.path.join(folder, "*"))
        self.transform = transform

    def __len__(self):
        return len(self.image_paths)

    def __getitem__(self, idx):
        img = Image.open(self.image_paths[idx]).convert("RGB")
        if self.transform:
            img = self.transform(img)
        return img
```

```
# Domain A: Original images; Domain B: Strong augmentations
transform_A = transforms.Compose([
    transforms.Resize((256, 256)),
    transforms.ToTensor(),
    # Normalize to [-1, 1] for Tanh activation at output of generator
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])
transform_B = transforms.Compose([
    transforms.Resize((256, 256)),
    transforms.ColorJitter(brightness=0.8, contrast=0.8, saturation=0.8, hue=0.1),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(20),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])

# Create datasets using the same malignant folder for both domains
dataset_A = SingleFolderDataset(malignant_folder, transform=transform_A)
dataset_B = SingleFolderDataset(malignant_folder, transform=transform_B)

# DataLoaders (batch_size=1 is standard for CycleGAN)
batch_size = 1
loader_A = DataLoader(dataset_A, batch_size=batch_size, shuffle=True, num_workers=4)
loader_B = DataLoader(dataset_B, batch_size=batch_size, shuffle=True, num_workers=4)

# Create an iterator that zips the two loaders (unpaired training)
def dataloader_zip(loader_A, loader_B):
    return zip(loader_A, loader_B)
data_loader = dataloader_zip(loader_A, loader_B)

# =====
# 4. Define CycleGAN Networks
# =====
# Residual Block used in the generators
class ResidualBlock(nn.Module):
    def __init__(self, dim):
        super(ResidualBlock, self).__init__()
        self.block = nn.Sequential(
            nn.ReflectionPad2d(1),
            nn.Conv2d(dim, dim, kernel_size=3),
            nn.InstanceNorm2d(dim),
            nn.ReLU(True),
            nn.ReflectionPad2d(1),
            nn.Conv2d(dim, dim, kernel_size=3),
            nn.InstanceNorm2d(dim)
        )
    def forward(self, x):
```

```
    return x + self.block(x)

# Generator (ResNet-based)
class ResnetGenerator(nn.Module):
    def __init__(self, input_nc, output_nc, ngf=64, n_blocks=9):
        assert(n_blocks >= 0)
        super(ResnetGenerator, self).__init__()
        model = [
            nn.ReflectionPad2d(3),
            nn.Conv2d(input_nc, ngf, kernel_size=7),
            nn.InstanceNorm2d(ngf),
            nn.ReLU(True)
        ]
        # Downsampling
        n_downsampling = 2
        for i in range(n_downsampling):
            mult = 2 ** i
            model += [
                nn.Conv2d(ngf * mult, ngf * mult * 2, kernel_size=3, stride=2,
                nn.InstanceNorm2d(ngf * mult * 2),
                nn.ReLU(True))
            ]
        # Residual blocks
        mult = 2 ** n_downsampling
        for i in range(n_blocks):
            model += [ResidualBlock(ngf * mult)]
        # Upsampling
        for i in range(n_downsampling):
            mult = 2 ** (n_downsampling - i)
            model += [
                nn.ConvTranspose2d(ngf * mult, int(ngf * mult / 2), kernel_size=3,
                padding=1, output_padding=1),
                nn.InstanceNorm2d(int(ngf * mult / 2)),
                nn.ReLU(True))
            ]
        model += [
            nn.ReflectionPad2d(3),
            nn.Conv2d(ngf, output_nc, kernel_size=7),
            nn.Tanh()
        ]
        self.model = nn.Sequential(*model)
    def forward(self, input):
        return self.model(input)

# PatchGAN Discriminator
class NLayerDiscriminator(nn.Module):
    def __init__(self, input_nc, ndf=64, n_layers=3):
        super(NLayerDiscriminator, self).__init__()
```

```

kw = 4
padw = 1
sequence = [
    nn.Conv2d(input_nc, ndf, kernel_size=kw, stride=2, padding=padw),
    nn.LeakyReLU(0.2, True)
]
nf_mult = 1
for n in range(1, n_layers):
    nf_mult_prev = nf_mult
    nf_mult = min(2 ** n, 8)
    sequence += [
        nn.Conv2d(ndf * nf_mult_prev, ndf * nf_mult, kernel_size=kw, st
        nn.InstanceNorm2d(ndf * nf_mult),
        nn.LeakyReLU(0.2, True)
    ]
nf_mult_prev = nf_mult
nf_mult = min(2 ** n_layers, 8)
sequence += [
    nn.Conv2d(ndf * nf_mult_prev, ndf * nf_mult, kernel_size=kw, stride=2, padding=padw),
    nn.InstanceNorm2d(ndf * nf_mult),
    nn.LeakyReLU(0.2, True)
]
sequence += [nn.Conv2d(ndf * nf_mult, 1, kernel_size=kw, stride=1, padding=0)]
self.model = nn.Sequential(*sequence)

def forward(self, input):
    return self.model(input)

# Instantiate generators and discriminators
G_A2B = ResnetGenerator(3, 3, n_blocks=9).to(device) # Maps original -> augmented
G_B2A = ResnetGenerator(3, 3, n_blocks=9).to(device) # Maps augmented -> original
D_A = NLayerDiscriminator(3).to(device) # Discriminates domain A
D_B = NLayerDiscriminator(3).to(device) # Discriminates domain B

# =====
# 5. Define Loss Functions & Optimizers
# =====
criterion_GAN = nn.MSELoss().to(device)
criterion_cycle = nn.L1Loss().to(device)
criterion_identity = nn.L1Loss().to(device)

lr = 0.0002
beta1 = 0.5
optimizer_G = optim.Adam(itertools.chain(G_A2B.parameters(), G_B2A.parameters()))
optimizer_D_A = optim.Adam(D_A.parameters(), lr=lr, betas=(beta1, 0.999))
optimizer_D_B = optim.Adam(D_B.parameters(), lr=lr, betas=(beta1, 0.999))

# =====
# 6. Training Loop for CycleGAN

```

```
# =====
num_epochs = 50

# Folder to save per-epoch generated images (for monitoring progress)
epoch_save_dir = "/kaggle/working/epoch_images"
os.makedirs(epoch_save_dir, exist_ok=True)

# Use a fixed sample from domain A for visualization
fixed_A = next(iter(loader_A)).to(device)

# Helper function to create target tensors for PatchGAN
def create_target_tensor(input_tensor, value):
    # Adjust size as needed (e.g., 30x30 for a 256x256 input image using PatchGAN)
    return torch.full((input_tensor.size(0), 1, 30, 30), value, device=device)

print("Starting CycleGAN training...")
for epoch in range(1, num_epochs + 1):
    start_time = time.time()
    for i, (real_A, real_B) in enumerate(data_loader):
        real_A = real_A.to(device)
        real_B = real_B.to(device)
        valid = create_target_tensor(real_A, 1.0)
        fake = create_target_tensor(real_A, 0.0)

        # -----
        # Train Generators
        # -----
        optimizer_G.zero_grad()

        # Identity loss: generators should preserve color composition
        loss_id_A = criterion_identity(G_B2A(real_A), real_A)
        loss_id_B = criterion_identity(G_A2B(real_B), real_B)
        loss_identity = (loss_id_A + loss_id_B) * 0.5

        # GAN loss
        fake_B = G_A2B(real_A)
        loss_GAN_A2B = criterion_GAN(D_B(fake_B), valid)
        fake_A = G_B2A(real_B)
        loss_GAN_B2A = criterion_GAN(D_A(fake_A), valid)
        loss_GAN = (loss_GAN_A2B + loss_GAN_B2A) * 0.5

        # Cycle consistency loss: image should come back to original domain
        rec_A = G_B2A(fake_B)
        loss_cycle_A = criterion_cycle(rec_A, real_A)
        rec_B = G_A2B(fake_A)
        loss_cycle_B = criterion_cycle(rec_B, real_B)
        loss_cycle = (loss_cycle_A + loss_cycle_B) * 10.0
```

```
# Total generator loss
loss_G = loss_identity + loss_GAN + loss_cycle
loss_G.backward()
optimizer_G.step()

# -----
# Train Discriminator A
# -----
optimizer_D_A.zero_grad()
loss_D_A_real = criterion_GAN(D_A(real_A), valid)
loss_D_A_fake = criterion_GAN(D_A(fake_A.detach()), fake)
loss_D_A = (loss_D_A_real + loss_D_A_fake) * 0.5
loss_D_A.backward()
optimizer_D_A.step()

# -----
# Train Discriminator B
# -----
optimizer_D_B.zero_grad()
loss_D_B_real = criterion_GAN(D_B(real_B), valid)
loss_D_B_fake = criterion_GAN(D_B(fake_B.detach()), fake)
loss_D_B = (loss_D_B_real + loss_D_B_fake) * 0.5
loss_D_B.backward()
optimizer_D_B.step()

elapsed = time.time() - start_time
print(f"Epoch [{epoch}/{num_epochs}] - Loss_G: {loss_G.item():.4f}, Loss_D_"

# Save generated images from the fixed sample at end of each epoch
with torch.no_grad():
    fake_B_fixed = G_A2B(fixed_A)
epoch_image_path = os.path.join(epoch_save_dir, f"epoch_{epoch}.png")
vutils.save_image(fake_B_fixed, epoch_image_path, normalize=True)

# -----
# 7. Generate 60 New Images & Zip the Output
# -----
# Folder to store final generated images
final_output_dir = "/kaggle/working/final_output"
os.makedirs(final_output_dir, exist_ok=True)

# Randomly sample 60 indices from dataset_A (test/malignant images)
num_new_images = 60
indices = random.sample(range(len(dataset_A)), num_new_images)

for idx in indices:
    img = dataset_A[idx]
    img_tensor = img.unsqueeze(0).to(device) # add batch dimension
```

```
with torch.no_grad():
    generated_img = G_A2B(img_tensor)
    save_filename = os.path.join(final_output_dir, f"generated_{idx}.png")
    vutils.save_image(generated_img, save_filename, normalize=True)

# Zip the final generated images into Kaggle output directory
zip_filename = os.path.join(kaggle_output_dir, "generated_images.zip")
with zipfile.ZipFile(zip_filename, 'w') as zipf:
    for root, _, files in os.walk(final_output_dir):
        for file in files:
            file_path = os.path.join(root, file)
            zipf.write(file_path, arcname=file)
print(f"Zip file saved as: {zip_filename}")
```

→ Using device: cuda

Malignant folder: /kaggle/input/k-mean-clustering/segmented_data/test/malign
Directory '/kaggle/working/final-results' is now clean.

Starting CycleGAN training...

```
Epoch [1/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 99
Epoch [2/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [3/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [4/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [5/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [6/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [7/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [8/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [9/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [10/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [11/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [12/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [13/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [14/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [15/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [16/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [17/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [18/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [19/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [20/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [21/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [22/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [23/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [24/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [25/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [26/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [27/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [28/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [29/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [30/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [31/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [32/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0.
Epoch [33/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
```

```
Epoch [34/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [35/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [36/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [37/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [38/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [39/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [40/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [41/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [42/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [43/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [44/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [45/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [46/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [47/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [48/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [49/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Epoch [50/50] - Loss_G: 1.0705, Loss_D_A: 0.3349, Loss_D_B: 0.5647, Time: 0
Zip file saved as: /kaggle/working/final-results/generated_images.zip
```

▼ Restnet 50

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

# =====
# 1. Reproducibility & Device Setup
# =====
random.seed(42)
np.random.seed(42)
torch.manual_seed(42)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)
```

```
# =====
# 2. Data Preparation & Augmentation
# =====
# Adjust these paths as per your dataset structure.
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)'
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Data augmentation for training and simple transforms for testing.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                       [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                       [0.229, 0.224, 0.225])
])

# Load datasets using ImageFolder (ensure your folder names match)
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

# -----
# Visualization 1: Pie Chart of Class Distribution
# -----
def plot_class_distribution(dataset):
    class_names = dataset.classes
    class_counts = {class_name: 0 for class_name in class_names}
    for _, label in dataset.imgs:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())

    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%.1f%%', startangle=140)
    plt.title('Class Distribution')
    plt.show()

plot_class_distribution(train_dataset)
```

```
# Create DataLoaders
batch_size = 32
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size)

# =====
# 3. Model Initialization & Fine-Tuning
# =====
# Load pre-trained ResNet50 and modify the final layer for 2 classes.
model_ft = models.resnet50(pretrained=True)
num_ftrs = model_ft.fc.in_features
model_ft.fc = nn.Linear(num_ftrs, 2)
model_ft = model_ft.to(device)

criterion = nn.CrossEntropyLoss()
optimizer_ft = optim.Adam(model_ft.parameters(), lr=1e-4)
exp_lr_scheduler = lr_scheduler.StepLR(optimizer_ft, step_size=7, gamma=0.1)

# =====
# 4. Training Function
# =====
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    # Lists to store training history for visualization.
    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    for epoch in range(num_epochs):
        print('Epoch {}/{}'.format(epoch+1, num_epochs))
        print('-' * 10)

        # Each epoch has a training and validation phase.
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train() # Set to training mode.
                dataloader = train_loader
            else:
                model.eval() # Set to evaluation mode.
                dataloader = test_loader

            running_loss = 0.0
            running_corrects = 0
```

```
# Iterate over data.
for inputs, labels in tqdm(dataloader):
    inputs = inputs.to(device)
    labels = labels.to(device)

    optimizer.zero_grad()
    with torch.set_grad_enabled(phase == 'train'):
        outputs = model(inputs)
        _, preds = torch.max(outputs, 1)
        loss = criterion(outputs, labels)

    if phase == 'train':
        loss.backward()
        optimizer.step()

    running_loss += loss.item() * inputs.size(0)
    running_corrects += torch.sum(preds == labels.data)

if phase == 'train':
    scheduler.step()

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

print('{} Loss: {:.4f} Acc: {:.4f}'.format(phase, epoch_loss, epoch_acc))

if phase == 'train':
    train_loss_history.append(epoch_loss)
    train_acc_history.append(epoch_acc.item())
else:
    val_loss_history.append(epoch_loss)
    val_acc_history.append(epoch_acc.item())

# Deep copy the model if performance improves.
if phase == 'val' and epoch_acc > best_acc:
    best_acc = epoch_acc
    best_model_wts = copy.deepcopy(model.state_dict())

print()

time_elapsed = time.time() - since
print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60, time_elapsed % 60))
print('Best Val Acc: {:.4f}'.format(best_acc))

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
```

```
        'val_loss': val_loss_history,
        'val_acc': val_acc_history
    }
    return model, history

# Train the model (adjust the number of epochs as needed)
num_epochs = 25
model_ft, history = train_model(model_ft, criterion, optimizer_ft, exp_lr_sche

# -----
# Visualization 2: Accuracy & Loss Curves
# -----
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_curves(history)

# -----
# 5. Model Evaluation on Test Set
# -----
model_ft.eval()
all_preds = []
all_probs = [] # Store probabilities for the positive class (malignant)
all_labels = []

with torch.no_grad():
```

```
for inputs, labels in tqdm(test_loader):
    inputs = inputs.to(device)
    labels = labels.to(device)
    outputs = model_ft(inputs)
    probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Probability for
    _, preds = torch.max(outputs, 1)
    all_preds.extend(preds.cpu().numpy())
    all_probs.extend(probs.cpu().numpy())
    all_labels.extend(labels.cpu().numpy())

# -----
# Visualization 3: Classification Report
# -----
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

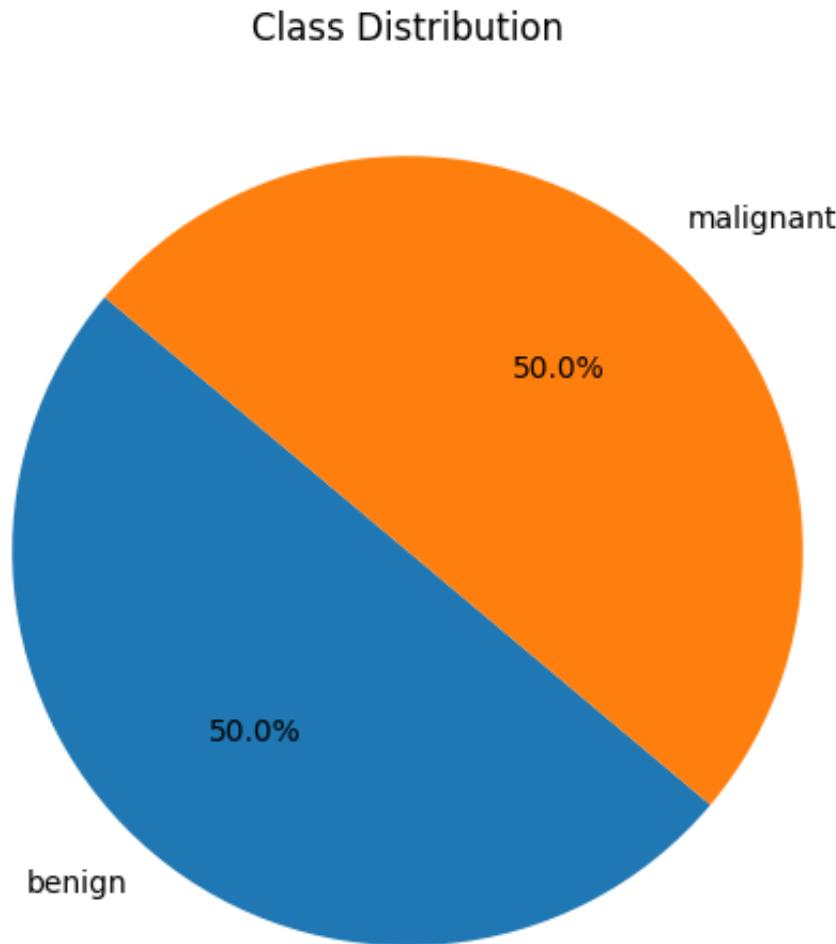
# -----
# Visualization 4: Confusion Matrix
# -----
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)

thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

# -----
# Visualization 5: ROC Curve and AUC
# -----
fpr, tpr, thresholds = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = {:.2f})'.f
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
```

```
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

→ Using device: cuda:0



```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: U
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: U
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet50-0676ba61.pth" to
100%|██████████| 97.8M/97.8M [00:01<00:00, 89.3MB/s]
Epoch 1/25
-----
100%|██████████| 90/90 [00:18<00:00, 4.96it/s]
train Loss: 0.3945 Acc: 0.8160
100%|██████████| 23/23 [00:01<00:00, 12.26it/s]
val Loss: 0.3377 Acc: 0.8389

Epoch 2/25
-----
100%|██████████| 80/80 [00:17<00:00, 5.00it/s]
```

```
100%|██████████| 23/23 [00:01<00:00, 12.58it/s]
train Loss: 0.3555 Acc: 0.8351
100%|██████████| 23/23 [00:01<00:00, 12.58it/s]
val Loss: 0.3427 Acc: 0.8306
```

Epoch 3/25

```
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]
train Loss: 0.3241 Acc: 0.8476
100%|██████████| 23/23 [00:02<00:00, 11.41it/s]
val Loss: 0.3274 Acc: 0.8333
```

Epoch 4/25

```
100%|██████████| 90/90 [00:17<00:00, 5.07it/s]
train Loss: 0.3137 Acc: 0.8601
100%|██████████| 23/23 [00:01<00:00, 12.90it/s]
val Loss: 0.3193 Acc: 0.8458
```

Epoch 5/25

```
100%|██████████| 90/90 [00:17<00:00, 5.07it/s]
train Loss: 0.3088 Acc: 0.8615
100%|██████████| 23/23 [00:01<00:00, 13.03it/s]
val Loss: 0.3285 Acc: 0.8458
```

Epoch 6/25

```
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]
train Loss: 0.2922 Acc: 0.8677
100%|██████████| 23/23 [00:01<00:00, 12.58it/s]
val Loss: 0.3788 Acc: 0.8292
```

Epoch 7/25

```
100%|██████████| 90/90 [00:17<00:00, 5.04it/s]
train Loss: 0.2905 Acc: 0.8708
100%|██████████| 23/23 [00:01<00:00, 12.78it/s]
val Loss: 0.2937 Acc: 0.8611
```

Epoch 8/25

```
100%|██████████| 90/90 [00:17<00:00, 5.06it/s]
train Loss: 0.2418 Acc: 0.8934
100%|██████████| 23/23 [00:01<00:00, 13.02it/s]
val Loss: 0.2864 Acc: 0.8653
```

Epoch 9/25

```
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]
train Loss: 0.2241 Acc: 0.8986
100%|██████████| 23/23 [00:01<00:00, 12.91it/s]
val Loss: 0.2936 Acc: 0.8667
```

10 / 25

```
Epoch 10/25
-----
100%|██████████| 90/90 [00:17<00:00, 5.07it/s]
train Loss: 0.2113 Acc: 0.9111
100%|██████████| 23/23 [00:01<00:00, 12.81it/s]
val Loss: 0.2860 Acc: 0.8792
```

Epoch 11/25

```
-----
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]
train Loss: 0.1952 Acc: 0.9188
100%|██████████| 23/23 [00:01<00:00, 12.92it/s]
val Loss: 0.3010 Acc: 0.8736
```

Epoch 12/25

```
-----
100%|██████████| 90/90 [00:17<00:00, 5.07it/s]
train Loss: 0.2062 Acc: 0.9122
100%|██████████| 23/23 [00:01<00:00, 12.91it/s]
val Loss: 0.3074 Acc: 0.8806
```

Epoch 13/25

```
-----
100%|██████████| 90/90 [00:17<00:00, 5.06it/s]
train Loss: 0.1941 Acc: 0.9125
100%|██████████| 23/23 [00:01<00:00, 12.98it/s]
val Loss: 0.3149 Acc: 0.8778
```

Epoch 14/25

```
-----
100%|██████████| 90/90 [00:17<00:00, 5.07it/s]
train Loss: 0.1908 Acc: 0.9153
100%|██████████| 23/23 [00:01<00:00, 12.98it/s]
val Loss: 0.3046 Acc: 0.8736
```

Epoch 15/25

```
-----
100%|██████████| 90/90 [00:17<00:00, 5.07it/s]
train Loss: 0.1675 Acc: 0.9299
100%|██████████| 23/23 [00:01<00:00, 13.08it/s]
val Loss: 0.3006 Acc: 0.8792
```

Epoch 16/25

```
-----
100%|██████████| 90/90 [00:17<00:00, 5.07it/s]
train Loss: 0.1834 Acc: 0.9219
100%|██████████| 23/23 [00:01<00:00, 12.66it/s]
val Loss: 0.2973 Acc: 0.8736
```

Epoch 17/25

```
-----
100%|██████████| 90/90 [00:17<00:00, 5.06it/s]
train Loss: 0.1720 Acc: 0.9247
100%|██████████| 23/23 [00:01<00:00, 12.97it/s]
```

```
val Loss: 0.3115 ACC: 0.8/64
```

Epoch 18/25

```
-----  
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]  
train Loss: 0.1722 Acc: 0.9219  
100%|██████████| 23/23 [00:01<00:00, 13.02it/s]  
val Loss: 0.3056 Acc: 0.8764
```

Epoch 19/25

```
-----  
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]  
train Loss: 0.1835 Acc: 0.9215  
100%|██████████| 23/23 [00:01<00:00, 13.04it/s]  
val Loss: 0.3128 Acc: 0.8750
```

Epoch 20/25

```
-----  
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]  
train Loss: 0.1712 Acc: 0.9247  
100%|██████████| 23/23 [00:01<00:00, 13.04it/s]  
val Loss: 0.3109 Acc: 0.8792
```

Epoch 21/25

```
-----  
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]  
train Loss: 0.1774 Acc: 0.9264  
100%|██████████| 23/23 [00:01<00:00, 12.15it/s]  
val Loss: 0.3109 Acc: 0.8750
```

Epoch 22/25

```
-----  
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]  
train Loss: 0.1714 Acc: 0.9233  
100%|██████████| 23/23 [00:01<00:00, 13.22it/s]  
val Loss: 0.3101 Acc: 0.8792
```

Epoch 23/25

```
-----  
100%|██████████| 90/90 [00:17<00:00, 5.07it/s]  
train Loss: 0.1672 Acc: 0.9267  
100%|██████████| 23/23 [00:01<00:00, 13.13it/s]  
val Loss: 0.3105 Acc: 0.8736
```

Epoch 24/25

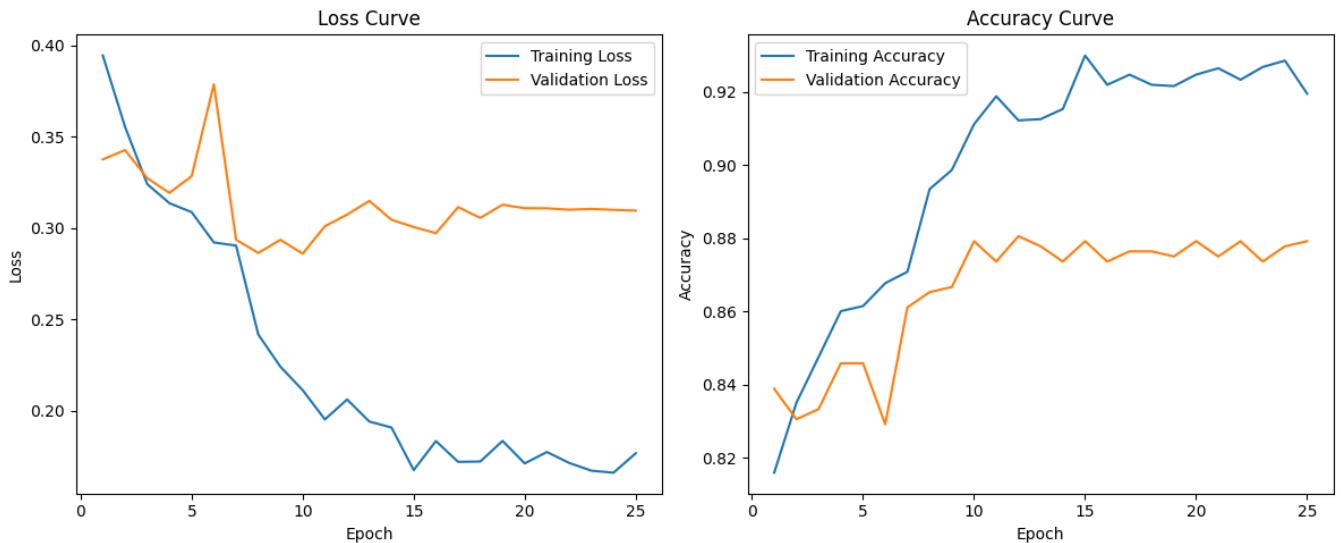
```
-----  
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]  
train Loss: 0.1661 Acc: 0.9285  
100%|██████████| 23/23 [00:01<00:00, 13.04it/s]  
val Loss: 0.3100 Acc: 0.8778
```

Epoch 25/25

```
-----  
100%|██████████| 90/90 [00:17<00:00, 5.08it/s]  
-----
```

```
train Loss: 0.1767 Acc: 0.9194
100% |██████████| 23/23 [00:01<00:00, 12.75it/s]
val Loss: 0.3096 Acc: 0.8792
```

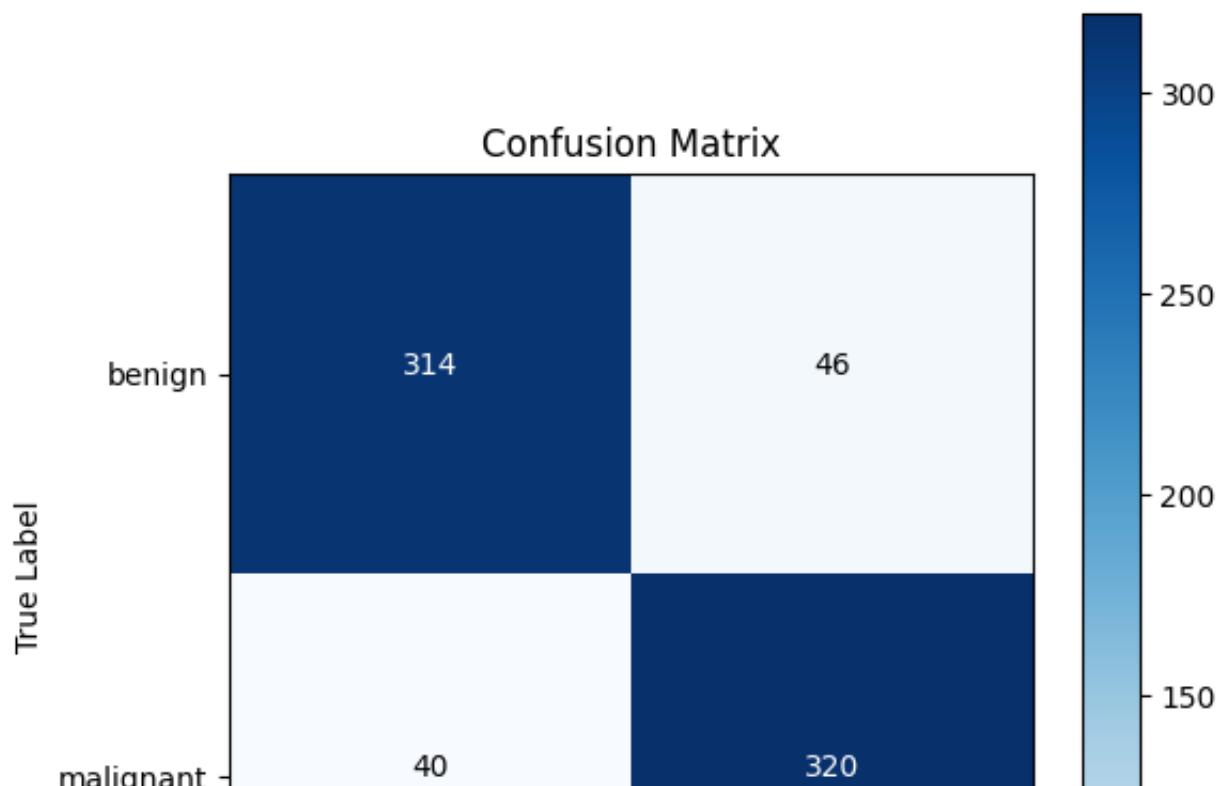
Training complete in 8m 10s
Best Val Acc: 0.8806

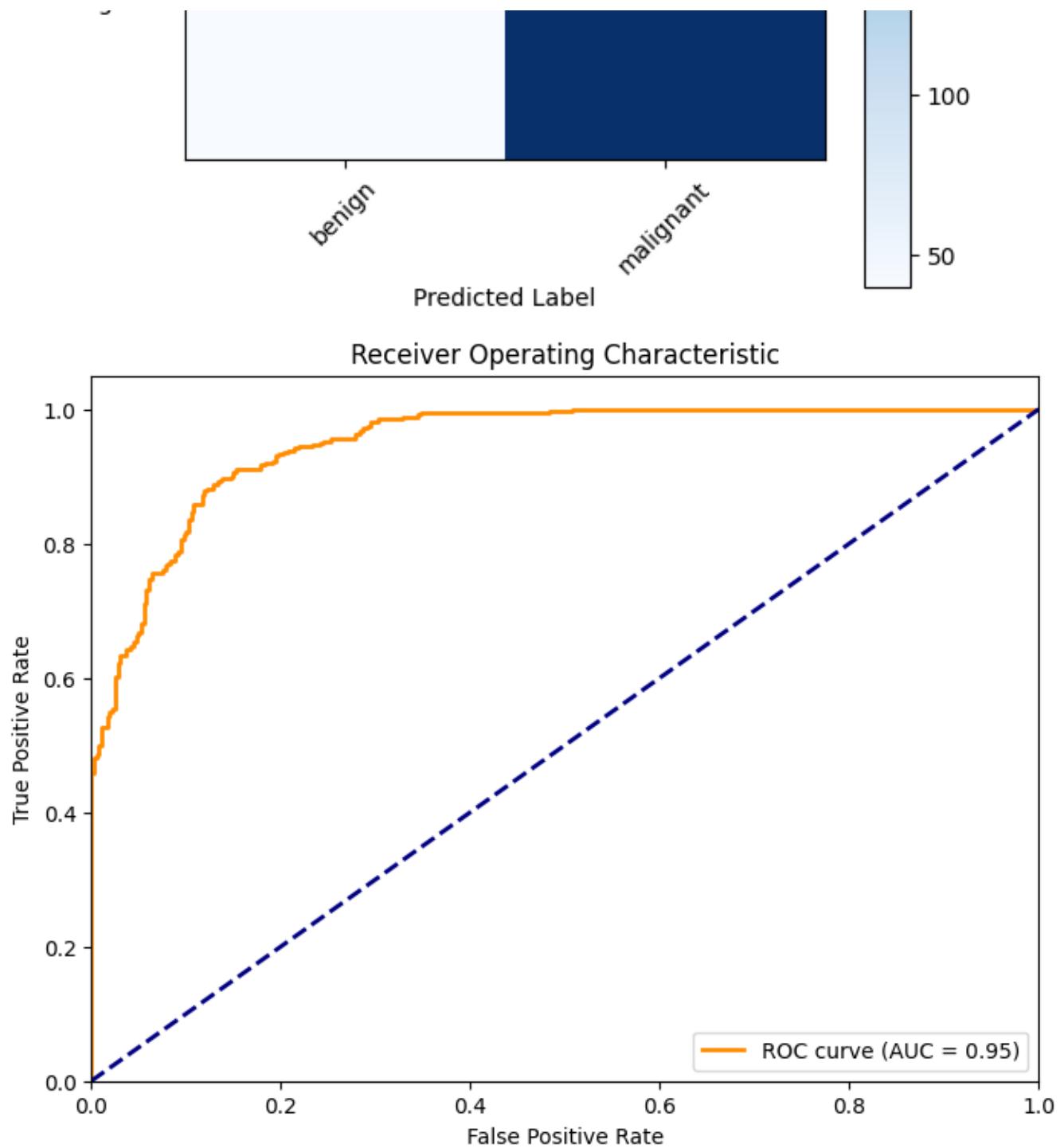


```
100% |██████████| 23/23 [00:01<00:00, 12.98it/s]
```

Classification Report:

	precision	recall	f1-score	support
benign	0.89	0.87	0.88	360
malignant	0.87	0.89	0.88	360
accuracy			0.88	720
macro avg	0.88	0.88	0.88	720
weighted avg	0.88	0.88	0.88	720





✓ Restnet50

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader, Subset
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from sklearn.model_selection import StratifiedKFold
from tqdm import tqdm

#####
# 1. Reproducibility & Device Setup
#####
random.seed(42)
np.random.seed(42)
torch.manual_seed(42)
torch.cuda.manual_seed_all(42)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Adjust these paths to your dataset location
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)'
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Data augmentation for training and simple transforms for testing.
```

```
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])

# Load datasets using ImageFolder (structure: train/benign, train/malignant)
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization: Class Distribution
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    # Works for ImageFolder datasets
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())
    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%1.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")

print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. Define Training Function for One Fold
#####
def train_model_fold(model, criterion, optimizer, scheduler,
                     train_loader, val_loader, num_epochs=25):
    ....
```

```
Train a model on a single fold using the provided train and validation load.
Returns the best model (state_dict loaded) and training history.
"""
since = time.time()
best_model_wts = copy.deepcopy(model.state_dict())
best_acc = 0.0

# Lists to store training history
train_loss_history = []
train_acc_history = []
val_loss_history = []
val_acc_history = []

for epoch in range(num_epochs):
    print(f"Epoch {epoch+1}/{num_epochs}")
    print('-' * 10)
    # Each epoch has training and validation phases
    for phase in ['train', 'val']:
        if phase == 'train':
            model.train()
            loader = train_loader
        else:
            model.eval()
            loader = val_loader

        running_loss = 0.0
        running_corrects = 0
        total_samples = 0

        for inputs, labels in tqdm(loader, desc=f"{phase}"):
            inputs = inputs.to(device)
            labels = labels.to(device)
            optimizer.zero_grad()

            with torch.set_grad_enabled(phase == 'train'):
                outputs = model(inputs)
                _, preds = torch.max(outputs, 1)
                loss = criterion(outputs, labels)

                if phase == 'train':
                    loss.backward()
                    optimizer.step()

            running_loss += loss.item() * inputs.size(0)
            running_corrects += torch.sum(preds == labels.data).item()
            total_samples += inputs.size(0)

        epoch_loss = running_loss / total_samples

        if phase == 'val':
            train_loss_history.append(running_loss)
            train_acc_history.append(running_corrects / total_samples)
            val_loss_history.append(epoch_loss)
            val_acc_history.append(running_corrects / total_samples)

            if epoch_loss < best_loss:
                best_loss = epoch_loss
                best_model_wts = copy.deepcopy(model.state_dict())
                best_acc = running_corrects / total_samples

    print(f"Epoch {epoch+1}/{num_epochs} completed. Best accuracy: {best_acc:.4f}.")
```

```
epoch_acc  = running_corrects / total_samples

print(f"{{phase.capitalize()}} Loss: {{epoch_loss:.4f}} Acc: {{epoch_acc:.4f}}")

if phase == 'train':
    train_loss_history.append(epoch_loss)
    train_acc_history.append(epoch_acc)
    scheduler.step() # Step the scheduler every epoch in training
else:
    val_loss_history.append(epoch_loss)
    val_acc_history.append(epoch_acc)
    # Deep copy model if improved on validation
    if epoch_acc > best_acc:
        best_acc = epoch_acc
        best_model_wts = copy.deepcopy(model.state_dict())

print()

time_elapsed = time.time() - since
print(f"Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s")
print(f"Best Val Acc: {best_acc:.4f}")

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

#####
# 5. K-Fold Cross Validation Training
#####
# Use StratifiedKFold on training dataset indices
num_folds = 5
batch_size = 32
skf = StratifiedKFold(n_splits=num_folds, shuffle=True, random_state=42)

# Extract targets from ImageFolder (list of labels)
targets = [s[1] for s in train_dataset.samples]

fold_histories = []
best_fold_model = None
best_fold_val_acc = 0.0

for fold, (train_idx, val_idx) in enumerate(skf.split(np.zeros(len(targets)), targets)):
    print(f"===== Fold {fold+1}/{num_folds} =====")
```

```
# Create subsets for current fold
from torch.utils.data import Subset
train_subset = Subset(train_dataset, train_idx)
val_subset = Subset(train_dataset, val_idx)

# Create DataLoaders for current fold
train_loader_fold = DataLoader(train_subset, batch_size=batch_size, shuffle=True)
val_loader_fold = DataLoader(val_subset, batch_size=batch_size, shuffle=False)

# Initialize a fresh pre-trained ResNet50 model with dropout in final layer
model_fold = models.resnet50(pretrained=True)
num_ftrs = model_fold.fc.in_features
model_fold.fc = nn.Sequential(
    nn.Dropout(p=0.5),
    nn.Linear(num_ftrs, 2)
)
model_fold = model_fold.to(device)

criterion = nn.CrossEntropyLoss()
optimizer_fold = optim.Adam(model_fold.parameters(), lr=1e-4)
scheduler_fold = lr_scheduler.StepLR(optimizer_fold, step_size=7, gamma=0.1)

# Train on current fold
model_fold, history = train_model_fold(model_fold, criterion, optimizer_fold,
                                         train_loader_fold, val_loader_fold,
                                         fold_histories.append(history))

# Record best fold based on highest validation accuracy from this fold's history
current_best = max(history['val_acc'])
print(f"Fold {fold+1} best Val Acc: {current_best:.4f}")
if current_best > best_fold_val_acc:
    best_fold_val_acc = current_best
    best_fold_model = model_fold # save the model from best fold

print(f"\nOverall Best Fold Val Acc: {best_fold_val_acc:.4f}")

#####
# 6. Plot Training Curves (from best fold)
#####
# Plot loss and accuracy curves for the best fold
best_history = fold_histories[np.argmax([max(h['val_acc'])]) for h in fold_histories]
epochs = range(1, len(best_history['train_loss']) + 1)
plt.figure(figsize=(12,5))

# Loss Curve
plt.subplot(1, 2, 1)
plt.plot(epochs, best_history['train_loss'], label='Train Loss')
plt.plot(epochs, best_history['val_loss'], label='Val Loss')
```

```
plt.title('Loss Curve (Best Fold)')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
# Accuracy Curve
plt.subplot(1, 2, 2)
plt.plot(epochs, best_history['train_acc'], label='Train Acc')
plt.plot(epochs, best_history['val_acc'], label='Val Acc')
plt.title('Accuracy Curve (Best Fold)')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.tight_layout()
plt.show()

#####
# 7. Final Evaluation on Test Set
#####
best_fold_model.eval()
all_preds = []
all_probs = [] # store probability for class "malignant" (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(DataLoader(test_dataset, batch_size=batch_size,
                                            desc="Testing")):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = best_fold_model(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # probability for
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

# -----
# Visualization: Classification Report
# -----
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

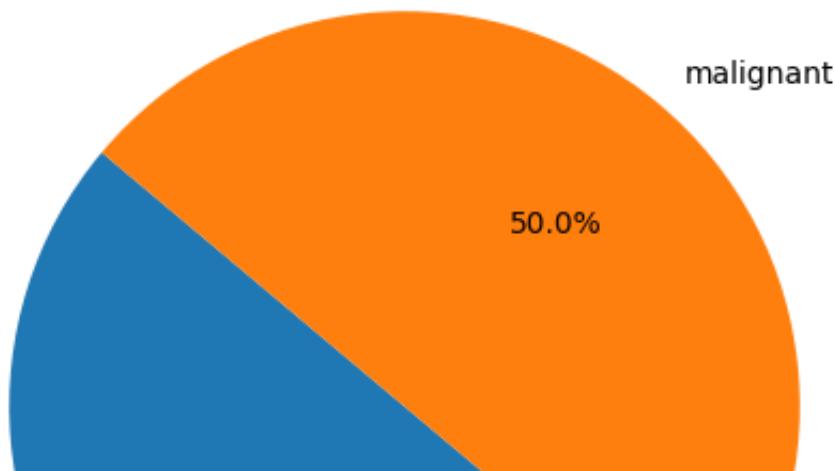
# -----
# Visualization: Confusion Matrix
# -----
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
```

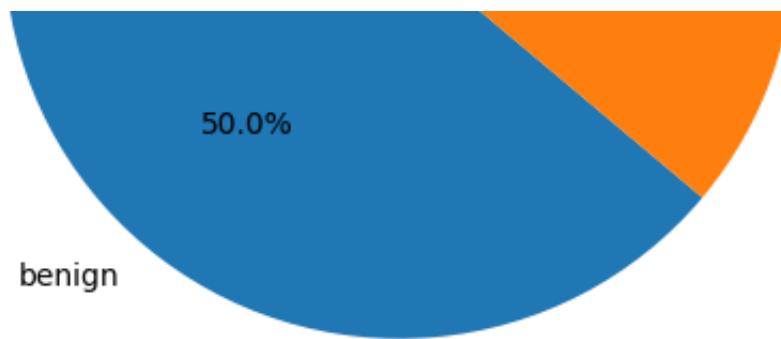
```
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
              horizontalalignment="center",
              color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

# -----
# Visualization: ROC Curve & AUC
# -----
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:0.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

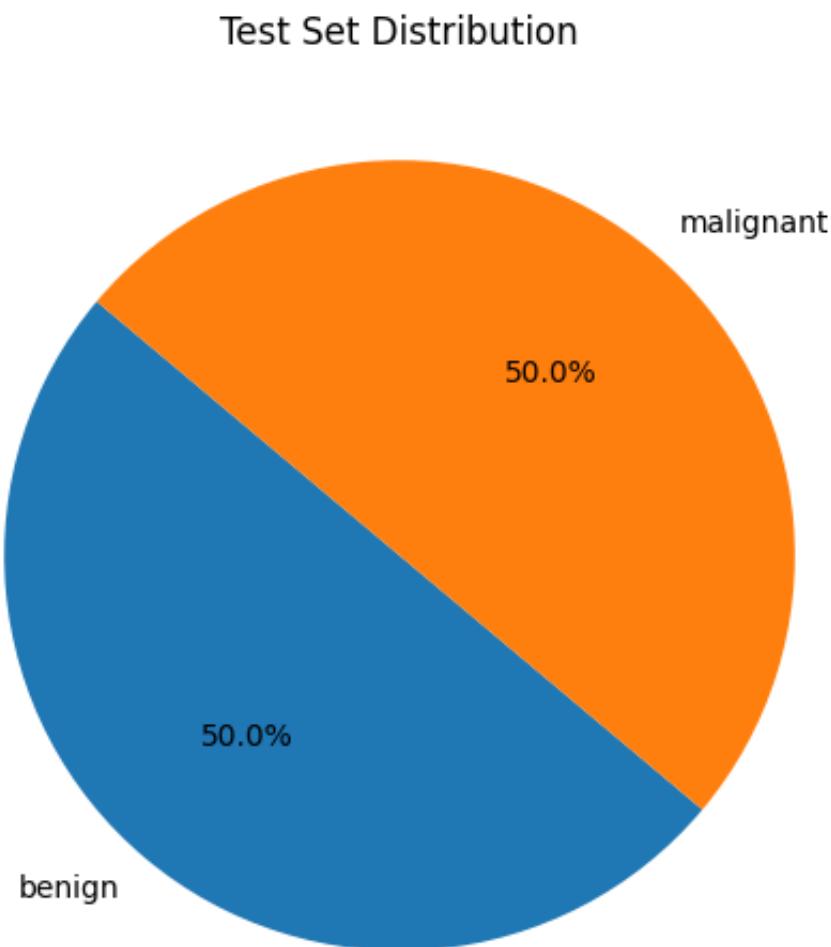
Using device: cuda:0
Train Set Distribution:

Train Set Distribution





Test Set Distribution:



```
===== Fold 1/5 =====
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: U
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: U
  warnings.warn(msg)
Epoch 1/25
-----
train: 100%|██████████| 72/72 [00:14<00:00,  5.05it/s]
Train Loss: 0.4095 Acc: 0.7904
val: 100%|██████████| 18/18 [00:01<00:00, 12.02it/s]
Val Loss: 0.3291 Acc: 0.8368
```

Epoch 2/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.06it/s]  
Train Loss: 0.3425 Acc: 0.8372  
val: 100%|██████████| 18/18 [00:01<00:00, 11.90it/s]  
Val Loss: 0.3575 Acc: 0.8229
```

Epoch 3/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]  
Train Loss: 0.3259 Acc: 0.8472  
val: 100%|██████████| 18/18 [00:01<00:00, 11.91it/s]  
Val Loss: 0.3601 Acc: 0.8264
```

Epoch 4/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.06it/s]  
Train Loss: 0.3050 Acc: 0.8633  
val: 100%|██████████| 18/18 [00:01<00:00, 11.86it/s]  
Val Loss: 0.4044 Acc: 0.8264
```

Epoch 5/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.06it/s]  
Train Loss: 0.2925 Acc: 0.8624  
val: 100%|██████████| 18/18 [00:01<00:00, 11.92it/s]  
Val Loss: 0.3403 Acc: 0.8403
```

Epoch 6/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]  
Train Loss: 0.2908 Acc: 0.8685  
val: 100%|██████████| 18/18 [00:01<00:00, 11.94it/s]  
Val Loss: 0.3638 Acc: 0.8247
```

Epoch 7/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]  
Train Loss: 0.2704 Acc: 0.8824  
val: 100%|██████████| 18/18 [00:01<00:00, 11.84it/s]  
Val Loss: 0.3603 Acc: 0.8316
```

Epoch 8/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2497 Acc: 0.8924  
val: 100%|██████████| 18/18 [00:01<00:00, 11.63it/s]  
Val Loss: 0.3093 Acc: 0.8542
```

Epoch 9/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.2195 Acc: 0.9028
```

```
val: 100%|██████████| 18/18 [00:01<00:00, 11.49it/s]
Val Loss: 0.3295 Acc: 0.8420
```

Epoch 10/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.2095 Acc: 0.9076
val: 100%|██████████| 18/18 [00:01<00:00, 11.50it/s]
Val Loss: 0.3342 Acc: 0.8594
```

Epoch 11/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1985 Acc: 0.9110
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]
Val Loss: 0.3288 Acc: 0.8472
```

Epoch 12/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1923 Acc: 0.9141
val: 100%|██████████| 18/18 [00:01<00:00, 11.73it/s]
Val Loss: 0.3891 Acc: 0.8507
```

Epoch 13/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1810 Acc: 0.9227
val: 100%|██████████| 18/18 [00:01<00:00, 11.95it/s]
Val Loss: 0.3812 Acc: 0.8455
```

Epoch 14/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1945 Acc: 0.9128
val: 100%|██████████| 18/18 [00:01<00:00, 11.84it/s]
Val Loss: 0.3647 Acc: 0.8472
```

Epoch 15/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.1772 Acc: 0.9245
val: 100%|██████████| 18/18 [00:01<00:00, 11.87it/s]
Val Loss: 0.3619 Acc: 0.8559
```

Epoch 16/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.1725 Acc: 0.9227
val: 100%|██████████| 18/18 [00:01<00:00, 11.83it/s]
Val Loss: 0.3821 Acc: 0.8472
```

Epoch 17/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1734 Acc: 0.9284
val: 100%|██████████| 18/18 [00:01<00:00, 12.10it/s]
Val Loss: 0.3691 Acc: 0.8490
```

Epoch 18/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.1735 Acc: 0.9214
val: 100%|██████████| 18/18 [00:01<00:00, 11.88it/s]
Val Loss: 0.3467 Acc: 0.8576
```

Epoch 19/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.1709 Acc: 0.9275
val: 100%|██████████| 18/18 [00:01<00:00, 11.95it/s]
Val Loss: 0.3730 Acc: 0.8455
```

Epoch 20/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.1553 Acc: 0.9323
val: 100%|██████████| 18/18 [00:01<00:00, 11.94it/s]
Val Loss: 0.3295 Acc: 0.8559
```

Epoch 21/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.1584 Acc: 0.9375
val: 100%|██████████| 18/18 [00:01<00:00, 11.73it/s]
Val Loss: 0.3659 Acc: 0.8542
```

Epoch 22/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.1765 Acc: 0.9214
val: 100%|██████████| 18/18 [00:01<00:00, 11.83it/s]
Val Loss: 0.3556 Acc: 0.8646
```

Epoch 23/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1687 Acc: 0.9280
val: 100%|██████████| 18/18 [00:01<00:00, 11.72it/s]
Val Loss: 0.3763 Acc: 0.8524
```

Epoch 24/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.1729 Acc: 0.9223
val: 100%|██████████| 18/18 [00:01<00:00, 11.98it/s]
Val Loss: 0.3769 Acc: 0.8646
```

Epoch 25/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.06it/s]  
Train Loss: 0.1648 Acc: 0.9301  
val: 100%|██████████| 18/18 [00:01<00:00, 12.06it/s]  
Val Loss: 0.3697 Acc: 0.8542
```

Training complete in 6m 35s

Best Val Acc: 0.8646

Fold 1 best Val Acc: 0.8646

```
===== Fold 2/5 =====
```

Epoch 1/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.4277 Acc: 0.7969  
val: 100%|██████████| 18/18 [00:01<00:00, 11.79it/s]  
Val Loss: 0.3378 Acc: 0.8420
```

Epoch 2/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]  
Train Loss: 0.3590 Acc: 0.8225  
val: 100%|██████████| 18/18 [00:01<00:00, 11.75it/s]  
Val Loss: 0.2944 Acc: 0.8559
```

Epoch 3/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.3273 Acc: 0.8429  
val: 100%|██████████| 18/18 [00:01<00:00, 11.76it/s]  
Val Loss: 0.3170 Acc: 0.8628
```

Epoch 4/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.3148 Acc: 0.8537  
val: 100%|██████████| 18/18 [00:01<00:00, 11.67it/s]  
Val Loss: 0.3864 Acc: 0.8594
```

Epoch 5/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]  
Train Loss: 0.3354 Acc: 0.8485  
val: 100%|██████████| 18/18 [00:01<00:00, 11.64it/s]  
Val Loss: 0.2915 Acc: 0.8576
```

Epoch 6/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.3064 Acc: 0.8529  
val: 100%|██████████| 18/18 [00:01<00:00, 11.36it/s]  
Val Loss: 0.2860 Acc: 0.8611
```

Epoch 7/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]  
Train Loss: 0.3015 Acc: 0.8663  
val: 100%|██████████| 18/18 [00:01<00:00, 11.79it/s]  
Val Loss: 0.2933 Acc: 0.8455
```

Epoch 8/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.2536 Acc: 0.8880  
val: 100%|██████████| 18/18 [00:01<00:00, 11.64it/s]  
Val Loss: 0.2483 Acc: 0.8802
```

Epoch 9/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2400 Acc: 0.8954  
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]  
Val Loss: 0.2693 Acc: 0.8594
```

Epoch 10/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2335 Acc: 0.8889  
val: 100%|██████████| 18/18 [00:01<00:00, 11.64it/s]  
Val Loss: 0.2922 Acc: 0.8663
```

Epoch 11/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.2138 Acc: 0.9067  
val: 100%|██████████| 18/18 [00:01<00:00, 11.69it/s]  
Val Loss: 0.2729 Acc: 0.8872
```

Epoch 12/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.1999 Acc: 0.9041  
val: 100%|██████████| 18/18 [00:01<00:00, 11.65it/s]  
Val Loss: 0.2843 Acc: 0.8767
```

Epoch 13/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2118 Acc: 0.9062  
val: 100%|██████████| 18/18 [00:01<00:00, 11.60it/s]  
Val Loss: 0.2603 Acc: 0.8767
```

Epoch 14/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.1983 Acc: 0.9141  
val: 100%|██████████| 18/18 [00:01<00:00, 11.68it/s]  
Val Loss: 0.2676 Acc: 0.8698
```

```
train 100%|██████████| 72/72 [00:14<00:00,  5.04it/s]
```

Epoch 15/25

```
train: 100%|██████████| 72/72 [00:14<00:00,  5.04it/s]
```

Train Loss: 0.1946 Acc: 0.9162

```
val: 100%|██████████| 18/18 [00:01<00:00, 11.75it/s]
```

Val Loss: 0.2593 Acc: 0.8802

Epoch 16/25

```
train: 100%|██████████| 72/72 [00:14<00:00,  5.05it/s]
```

Train Loss: 0.1879 Acc: 0.9188

```
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]
```

Val Loss: 0.2466 Acc: 0.8941

Epoch 17/25

```
train: 100%|██████████| 72/72 [00:14<00:00,  5.03it/s]
```

Train Loss: 0.1907 Acc: 0.9171

```
val: 100%|██████████| 18/18 [00:01<00:00, 11.79it/s]
```

Val Loss: 0.2489 Acc: 0.8906

Epoch 18/25

```
train: 100%|██████████| 72/72 [00:14<00:00,  5.04it/s]
```

Train Loss: 0.1864 Acc: 0.9149

```
val: 100%|██████████| 18/18 [00:01<00:00, 11.70it/s]
```

Val Loss: 0.2857 Acc: 0.8854

Epoch 19/25

```
train: 100%|██████████| 72/72 [00:14<00:00,  5.04it/s]
```

Train Loss: 0.1850 Acc: 0.9184

```
val: 100%|██████████| 18/18 [00:01<00:00, 11.82it/s]
```

Val Loss: 0.2712 Acc: 0.8819

Epoch 20/25

```
train: 100%|██████████| 72/72 [00:14<00:00,  5.04it/s]
```

Train Loss: 0.1878 Acc: 0.9132

```
val: 100%|██████████| 18/18 [00:01<00:00, 11.41it/s]
```

Val Loss: 0.2578 Acc: 0.8837

Epoch 21/25

```
train: 100%|██████████| 72/72 [00:14<00:00,  5.02it/s]
```

Train Loss: 0.1834 Acc: 0.9253

```
val: 100%|██████████| 18/18 [00:01<00:00, 11.67it/s]
```

Val Loss: 0.3214 Acc: 0.8733

Epoch 22/25

```
train: 100%|██████████| 72/72 [00:14<00:00,  5.03it/s]
```

Train Loss: 0.1894 Acc: 0.9115

```
train loss: 0.1950 Acc: 0.9093
val: 100%|██████████| 18/18 [00:01<00:00, 11.65it/s]
Val Loss: 0.2629 Acc: 0.8715
```

Epoch 23/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.1950 Acc: 0.9093
val: 100%|██████████| 18/18 [00:01<00:00, 11.58it/s]
Val Loss: 0.2766 Acc: 0.8802
```

Epoch 24/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1783 Acc: 0.9154
val: 100%|██████████| 18/18 [00:01<00:00, 11.69it/s]
Val Loss: 0.2825 Acc: 0.8802
```

Epoch 25/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1842 Acc: 0.9232
val: 100%|██████████| 18/18 [00:01<00:00, 11.40it/s]
Val Loss: 0.2746 Acc: 0.8715
```

Training complete in 6m 37s

Best Val Acc: 0.8941

Fold 2 best Val Acc: 0.8941

===== Fold 3/5 =====

Epoch 1/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.3991 Acc: 0.8047
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]
Val Loss: 0.3630 Acc: 0.8403
```

Epoch 2/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.3406 Acc: 0.8429
val: 100%|██████████| 18/18 [00:01<00:00, 11.53it/s]
Val Loss: 0.3788 Acc: 0.8212
```

Epoch 3/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.3220 Acc: 0.8451
val: 100%|██████████| 18/18 [00:01<00:00, 11.63it/s]
Val Loss: 0.3615 Acc: 0.8316
```

Epoch 4/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.3017 Acc: 0.8624
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]
```

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Val Loss: 0.3976 Acc: 0.8125
```

Epoch 5/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.2900 Acc: 0.8646
val: 100%|██████████| 18/18 [00:01<00:00, 11.41it/s]
Val Loss: 0.3652 Acc: 0.8177
```

Epoch 6/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.2935 Acc: 0.8694
val: 100%|██████████| 18/18 [00:01<00:00, 11.78it/s]
Val Loss: 0.4162 Acc: 0.8472
```

Epoch 7/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.2827 Acc: 0.8681
val: 100%|██████████| 18/18 [00:01<00:00, 11.79it/s]
Val Loss: 0.3378 Acc: 0.8420
```

Epoch 8/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.2457 Acc: 0.8867
val: 100%|██████████| 18/18 [00:01<00:00, 11.86it/s]
Val Loss: 0.3468 Acc: 0.8368
```

Epoch 9/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.2204 Acc: 0.9041
val: 100%|██████████| 18/18 [00:01<00:00, 11.88it/s]
Val Loss: 0.3229 Acc: 0.8594
```

Epoch 10/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.2197 Acc: 0.9045
val: 100%|██████████| 18/18 [00:01<00:00, 11.67it/s]
Val Loss: 0.3423 Acc: 0.8368
```

Epoch 11/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.2072 Acc: 0.9023
val: 100%|██████████| 18/18 [00:01<00:00, 11.80it/s]
Val Loss: 0.3326 Acc: 0.8542
```

Epoch 12/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
```

```
train: 100%|██████████| 12/12 [00:14<00:00, 5.04it/s]
Train Loss: 0.1942 Acc: 0.9119
val: 100%|██████████| 18/18 [00:01<00:00, 11.62it/s]
Val Loss: 0.3149 Acc: 0.8663
```

Epoch 13/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1898 Acc: 0.9123
val: 100%|██████████| 18/18 [00:01<00:00, 11.67it/s]
Val Loss: 0.3187 Acc: 0.8611
```

Epoch 14/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1881 Acc: 0.9128
val: 100%|██████████| 18/18 [00:01<00:00, 11.92it/s]
Val Loss: 0.3554 Acc: 0.8420
```

Epoch 15/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1748 Acc: 0.9197
val: 100%|██████████| 18/18 [00:01<00:00, 11.67it/s]
Val Loss: 0.3428 Acc: 0.8490
```

Epoch 16/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.1670 Acc: 0.9262
val: 100%|██████████| 18/18 [00:01<00:00, 11.83it/s]
Val Loss: 0.3202 Acc: 0.8507
```

Epoch 17/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1760 Acc: 0.9240
val: 100%|██████████| 18/18 [00:01<00:00, 11.44it/s]
Val Loss: 0.3096 Acc: 0.8854
```

Epoch 18/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1735 Acc: 0.9210
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]
Val Loss: 0.3409 Acc: 0.8594
```

Epoch 19/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1722 Acc: 0.9232
val: 100%|██████████| 18/18 [00:01<00:00, 11.80it/s]
Val Loss: 0.3186 Acc: 0.8490
```

Epoch 20/25

```
Epoch 20/25
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1632 Acc: 0.9306
val: 100%|██████████| 18/18 [00:01<00:00, 11.81it/s]
Val Loss: 0.3435 Acc: 0.8559
```

Epoch 21/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.1625 Acc: 0.9253
val: 100%|██████████| 18/18 [00:01<00:00, 11.53it/s]
Val Loss: 0.3305 Acc: 0.8576
```

Epoch 22/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.1730 Acc: 0.9214
val: 100%|██████████| 18/18 [00:01<00:00, 11.67it/s]
Val Loss: 0.3475 Acc: 0.8628
```

Epoch 23/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1709 Acc: 0.9240
val: 100%|██████████| 18/18 [00:01<00:00, 11.78it/s]
Val Loss: 0.3270 Acc: 0.8524
```

Epoch 24/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.1746 Acc: 0.9145
val: 100%|██████████| 18/18 [00:01<00:00, 11.78it/s]
Val Loss: 0.3495 Acc: 0.8507
```

Epoch 25/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.1908 Acc: 0.9110
val: 100%|██████████| 18/18 [00:01<00:00, 11.76it/s]
Val Loss: 0.3195 Acc: 0.8663
```

Training complete in 6m 37s

Best Val Acc: 0.8854

Fold 3 best Val Acc: 0.8854

===== Fold 4/5 =====

Epoch 1/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.4343 Acc: 0.7882
val: 100%|██████████| 18/18 [00:01<00:00, 11.74it/s]
Val Loss: 0.3172 Acc: 0.8524
```

Epoch 2/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.3561 Acc: 0.8255  
val: 100%|██████████| 18/18 [00:01<00:00, 11.59it/s]  
Val Loss: 0.3194 Acc: 0.8316
```

Epoch 3/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]  
Train Loss: 0.3590 Acc: 0.8338  
val: 100%|██████████| 18/18 [00:01<00:00, 11.77it/s]  
Val Loss: 0.3083 Acc: 0.8472
```

Epoch 4/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.3282 Acc: 0.8407  
val: 100%|██████████| 18/18 [00:01<00:00, 11.95it/s]  
Val Loss: 0.3154 Acc: 0.8455
```

Epoch 5/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.3115 Acc: 0.8581  
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]  
Val Loss: 0.3206 Acc: 0.8472
```

Epoch 6/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.2921 Acc: 0.8685  
val: 100%|██████████| 18/18 [00:01<00:00, 11.73it/s]  
Val Loss: 0.3066 Acc: 0.8698
```

Epoch 7/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2938 Acc: 0.8624  
val: 100%|██████████| 18/18 [00:01<00:00, 11.68it/s]  
Val Loss: 0.3042 Acc: 0.8681
```

Epoch 8/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2356 Acc: 0.8889  
val: 100%|██████████| 18/18 [00:01<00:00, 11.85it/s]  
Val Loss: 0.2948 Acc: 0.8542
```

Epoch 9/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2321 Acc: 0.8941  
val: 100%|██████████| 18/18 [00:01<00:00, 11.56it/s]  
Val Loss: 0.2939 Acc: 0.8490
```

Epoch 10/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.2202 Acc: 0.9006  
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]  
Val Loss: 0.2874 Acc: 0.8628
```

Epoch 11/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2135 Acc: 0.8980  
val: 100%|██████████| 18/18 [00:01<00:00, 11.58it/s]  
Val Loss: 0.2949 Acc: 0.8628
```

Epoch 12/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2004 Acc: 0.9102  
val: 100%|██████████| 18/18 [00:01<00:00, 11.59it/s]  
Val Loss: 0.2938 Acc: 0.8663
```

Epoch 13/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.1997 Acc: 0.9102  
val: 100%|██████████| 18/18 [00:01<00:00, 11.87it/s]  
Val Loss: 0.2951 Acc: 0.8542
```

Epoch 14/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]  
Train Loss: 0.1784 Acc: 0.9136  
val: 100%|██████████| 18/18 [00:01<00:00, 11.73it/s]  
Val Loss: 0.3222 Acc: 0.8646
```

Epoch 15/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.1899 Acc: 0.9158  
val: 100%|██████████| 18/18 [00:01<00:00, 11.80it/s]  
Val Loss: 0.3100 Acc: 0.8438
```

Epoch 16/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.1921 Acc: 0.9175  
val: 100%|██████████| 18/18 [00:01<00:00, 11.87it/s]  
Val Loss: 0.3110 Acc: 0.8542
```

Epoch 17/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]  
Train Loss: 0.1938 Acc: 0.9171
```

```
val: 100%|██████████| 18/18 [00:01<00:00, 11.90it/s]
Val Loss: 0.2737 Acc: 0.8785
```

Epoch 18/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.05it/s]
Train Loss: 0.1821 Acc: 0.9258
val: 100%|██████████| 18/18 [00:01<00:00, 11.99it/s]
Val Loss: 0.3003 Acc: 0.8750
```

Epoch 19/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.1864 Acc: 0.9110
val: 100%|██████████| 18/18 [00:01<00:00, 11.74it/s]
Val Loss: 0.2753 Acc: 0.8733
```

Epoch 20/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.1951 Acc: 0.9162
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]
Val Loss: 0.2610 Acc: 0.8733
```

Epoch 21/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.1760 Acc: 0.9206
val: 100%|██████████| 18/18 [00:01<00:00, 11.94it/s]
Val Loss: 0.3049 Acc: 0.8681
```

Epoch 22/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.06it/s]
Train Loss: 0.1759 Acc: 0.9236
val: 100%|██████████| 18/18 [00:01<00:00, 11.86it/s]
Val Loss: 0.3113 Acc: 0.8594
```

Epoch 23/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.1814 Acc: 0.9253
val: 100%|██████████| 18/18 [00:01<00:00, 11.68it/s]
Val Loss: 0.2865 Acc: 0.8663
```

Epoch 24/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.1807 Acc: 0.9214
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]
Val Loss: 0.2797 Acc: 0.8733
```

Epoch 25/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.1761 Acc: 0.9206
val: 100%|██████████| 18/18 [00:01<00:00, 11.90it/s]
Val Loss: 0.2881 Acc: 0.8663
```

Training complete in 6m 36s
Best Val Acc: 0.8785
Fold 4 best Val Acc: 0.8785
===== Fold 5/5 =====
Epoch 1/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.4270 Acc: 0.7995
val: 100%|██████████| 18/18 [00:01<00:00, 11.47it/s]
Val Loss: 0.3223 Acc: 0.8559
```

Epoch 2/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.3625 Acc: 0.8355
val: 100%|██████████| 18/18 [00:01<00:00, 11.74it/s]
Val Loss: 0.3315 Acc: 0.8403
```

Epoch 3/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.3434 Acc: 0.8490
val: 100%|██████████| 18/18 [00:01<00:00, 11.71it/s]
Val Loss: 0.3114 Acc: 0.8524
```

Epoch 4/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.3221 Acc: 0.8442
val: 100%|██████████| 18/18 [00:01<00:00, 11.75it/s]
Val Loss: 0.3303 Acc: 0.8264
```

Epoch 5/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.3056 Acc: 0.8563
val: 100%|██████████| 18/18 [00:01<00:00, 11.60it/s]
Val Loss: 0.3468 Acc: 0.8524
```

Epoch 6/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.2978 Acc: 0.8581
val: 100%|██████████| 18/18 [00:01<00:00, 11.51it/s]
Val Loss: 0.3267 Acc: 0.8594
```

Epoch 7/25

```
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
```

```
Train Loss: 0.2894 Acc: 0.8681
val: 100%|██████████| 18/18 [00:01<00:00, 11.64it/s]
Val Loss: 0.3000 Acc: 0.8785
```

Epoch 8/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.2574 Acc: 0.8850
val: 100%|██████████| 18/18 [00:01<00:00, 11.66it/s]
Val Loss: 0.2896 Acc: 0.8611
```

Epoch 9/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.2230 Acc: 0.8976
val: 100%|██████████| 18/18 [00:01<00:00, 11.62it/s]
Val Loss: 0.2886 Acc: 0.8819
```

Epoch 10/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.2139 Acc: 0.8997
val: 100%|██████████| 18/18 [00:01<00:00, 11.40it/s]
Val Loss: 0.2862 Acc: 0.8733
```

Epoch 11/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]
Train Loss: 0.2157 Acc: 0.9006
val: 100%|██████████| 18/18 [00:01<00:00, 11.64it/s]
Val Loss: 0.2863 Acc: 0.8802
```

Epoch 12/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.2104 Acc: 0.9041
val: 100%|██████████| 18/18 [00:01<00:00, 11.73it/s]
Val Loss: 0.3031 Acc: 0.8611
```

Epoch 13/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]
Train Loss: 0.2090 Acc: 0.9067
val: 100%|██████████| 18/18 [00:01<00:00, 11.77it/s]
Val Loss: 0.2900 Acc: 0.8906
```

Epoch 14/25

```
-----
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]
Train Loss: 0.2023 Acc: 0.9045
val: 100%|██████████| 18/18 [00:01<00:00, 11.67it/s]
Val Loss: 0.3200 Acc: 0.8681
```

Epoch 15/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.2044 Acc: 0.9106  
val: 100%|██████████| 18/18 [00:01<00:00, 11.65it/s]  
Val Loss: 0.2965 Acc: 0.8733
```

Epoch 16/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.1900 Acc: 0.9141  
val: 100%|██████████| 18/18 [00:01<00:00, 11.64it/s]  
Val Loss: 0.3003 Acc: 0.8715
```

Epoch 17/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]  
Train Loss: 0.1912 Acc: 0.9093  
val: 100%|██████████| 18/18 [00:01<00:00, 11.63it/s]  
Val Loss: 0.2964 Acc: 0.8767
```

Epoch 18/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.1731 Acc: 0.9253  
val: 100%|██████████| 18/18 [00:01<00:00, 11.45it/s]  
Val Loss: 0.2988 Acc: 0.8819
```

Epoch 19/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.1891 Acc: 0.9119  
val: 100%|██████████| 18/18 [00:01<00:00, 11.69it/s]  
Val Loss: 0.3043 Acc: 0.8698
```

Epoch 20/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.03it/s]  
Train Loss: 0.1867 Acc: 0.9162  
val: 100%|██████████| 18/18 [00:01<00:00, 11.85it/s]  
Val Loss: 0.3053 Acc: 0.8663
```

Epoch 21/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.1928 Acc: 0.9102  
val: 100%|██████████| 18/18 [00:01<00:00, 11.92it/s]  
Val Loss: 0.3081 Acc: 0.8750
```

Epoch 22/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.1736 Acc: 0.9193  
val: 100%|██████████| 18/18 [00:01<00:00, 11.70it/s]  
Val Loss: 0.3234 Acc: 0.8646
```

Epoch 23/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.1904 Acc: 0.9123  
val: 100%|██████████| 18/18 [00:01<00:00, 11.69it/s]  
Val Loss: 0.2954 Acc: 0.8819
```

Epoch 24/25

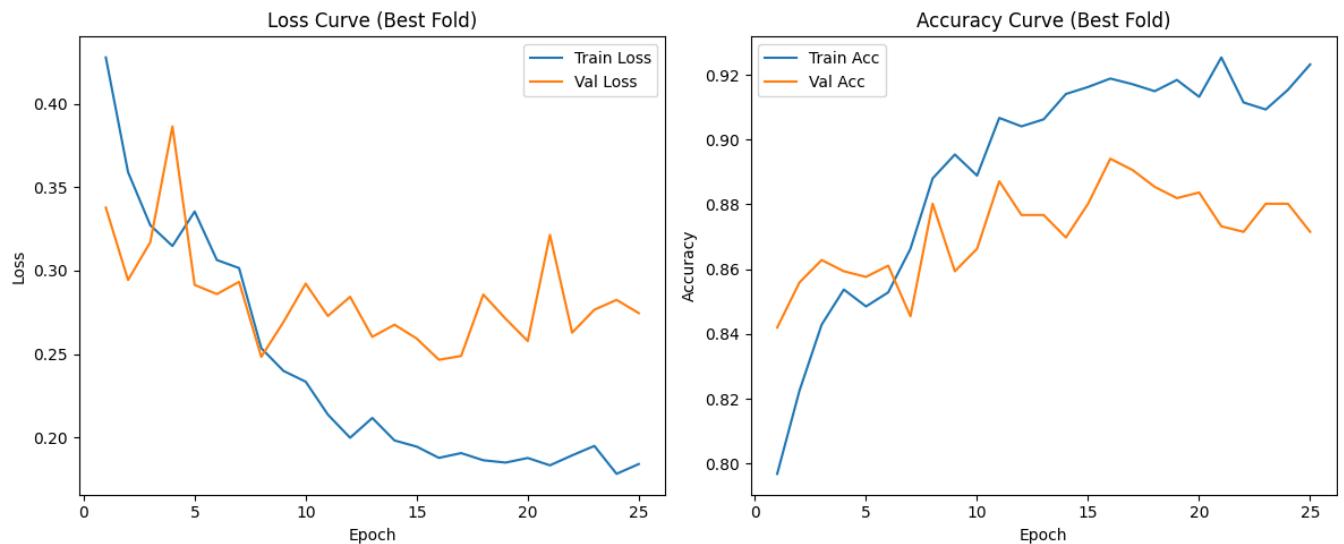
```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.02it/s]  
Train Loss: 0.1896 Acc: 0.9136  
val: 100%|██████████| 18/18 [00:01<00:00, 11.77it/s]  
Val Loss: 0.3165 Acc: 0.8767
```

Epoch 25/25

```
-----  
train: 100%|██████████| 72/72 [00:14<00:00, 5.04it/s]  
Train Loss: 0.1846 Acc: 0.9201  
val: 100%|██████████| 18/18 [00:01<00:00, 11.84it/s]  
Val Loss: 0.3150 Acc: 0.8663
```

Training complete in 6m 37s
Best Val Acc: 0.8906
Fold 5 best Val Acc: 0.8906

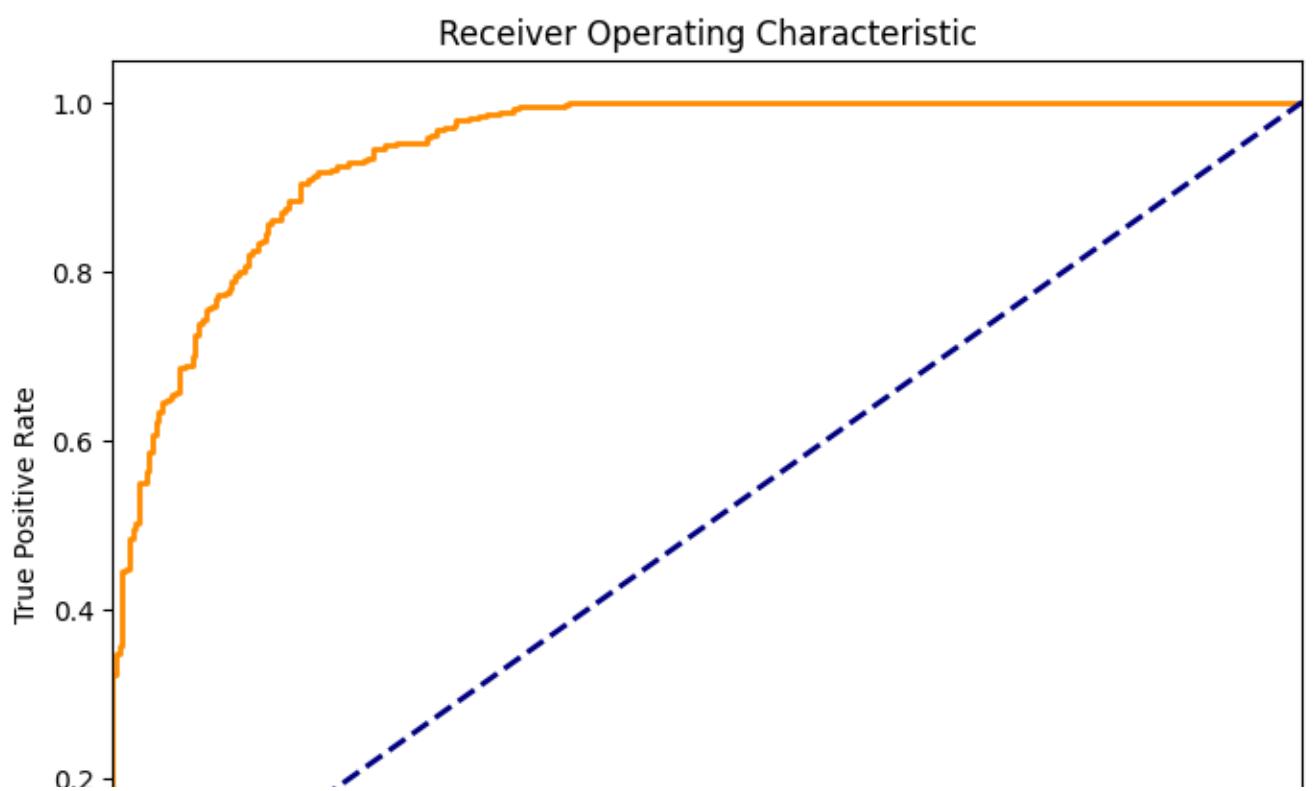
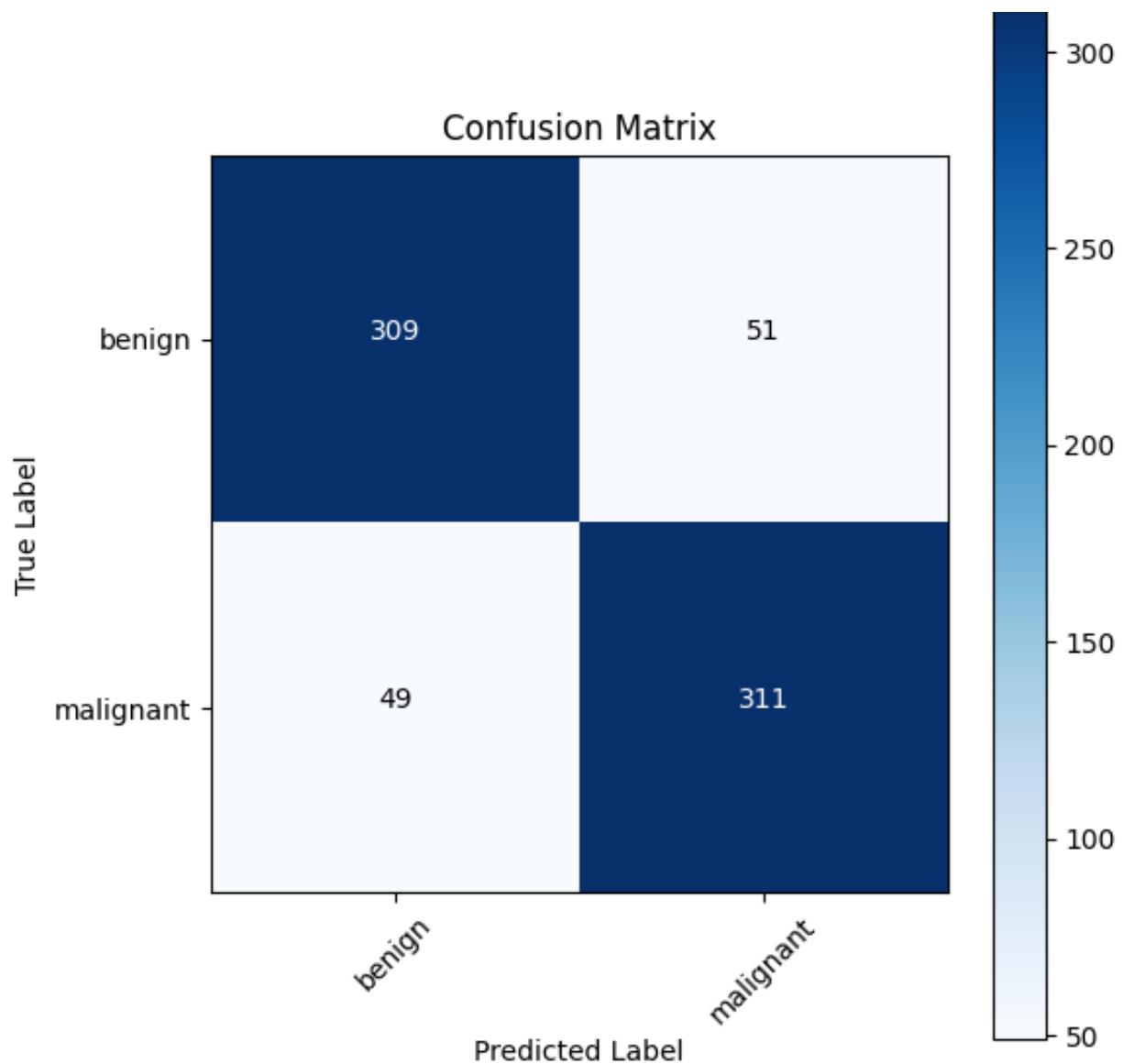
Overall Best Fold Val Acc: 0.8941

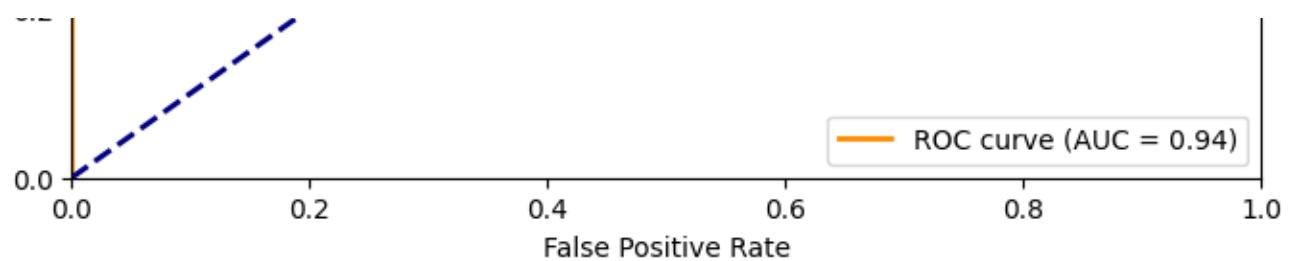


Testing: 100%|██████████| 23/23 [00:01<00:00, 12.77it/s]

Classification Report:

	precision	recall	f1-score	support
benign	0.86	0.86	0.86	360
malignant	0.86	0.86	0.86	360
accuracy			0.86	720
macro avg	0.86	0.86	0.86	720
weighted avg	0.86	0.86	0.86	720





✓ DenseNet201

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
```

```
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Update this path to your dataset directory
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)'
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Define strong augmentation for training and standard transforms for testing.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])

# Load datasets using ImageFolder
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
```

```
labels = list(class_counts.keys())
counts = list(class_counts.values())
plt.figure(figsize=(6,6))
plt.pie(counts, labels=labels, autopct='%.1f%%', startangle=140)
plt.title(title)
plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. DataLoaders
#####
# Create DataLoaders (adjust batch_size as needed)
batch_size = 16
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r

#####
# 5. Model Initialization & Fine-Tuning (DenseNet201)
#####
# Load DenseNet201 with pretrained ImageNet weights.
model_dense = models.densenet201(pretrained=True)
# DenseNet201's classifier is a single linear layer stored in model_dense.class
in_features = model_dense.classifier.in_features
# Replace classifier with dropout + linear layer for 2 classes.
model_dense.classifier = nn.Sequential(
    nn.Dropout(p=0.5),
    nn.Linear(in_features, 2)
)
model_dense = model_dense.to(device)

#####
# 6. Training Function
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    for epoch in range(num_epochs):
```

```
print(f"Epoch {epoch+1}/{num_epochs}")
print("-" * 10)
# Each epoch has a training and validation phase.
for phase in ['train', 'val']:
    if phase == 'train':
        model.train()
        dataloader = train_loader
    else:
        model.eval()
        dataloader = test_loader

    running_loss = 0.0
    running_corrects = 0
    total_samples = 0

    for inputs, labels in tqdm(dataloader, desc=phase):
        inputs = inputs.to(device)
        labels = labels.to(device)

        optimizer.zero_grad()
        with torch.set_grad_enabled(phase == 'train'):
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            loss = criterion(outputs, labels)

            if phase == 'train':
                loss.backward()
                optimizer.step()

            running_loss += loss.item() * inputs.size(0)
            running_corrects += torch.sum(preds == labels.data).item()
            total_samples += inputs.size(0)

    if phase == 'train':
        scheduler.step()

    epoch_loss = running_loss / total_samples
    epoch_acc = running_corrects / total_samples
    print(f"{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}")

    if phase == 'train':
        train_loss_history.append(epoch_loss)
        train_acc_history.append(epoch_acc)
    else:
        val_loss_history.append(epoch_loss)
        val_acc_history.append(epoch_acc)
        if epoch_acc > best_acc:
            best_acc = epoch_acc
```

```
best_model_wts = copy.deepcopy(model.state_dict())
print()

time_elapsed = time.time() - since
print(f"Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s")
print(f"Best Validation Acc: {best_acc:.4f}")

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_dense = optim.Adam(model_dense.parameters(), lr=1e-4)
scheduler_dense = lr_scheduler.StepLR(optimizer_dense, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####
num_epochs = 25
model_dense, history = train_model(model_dense, criterion, optimizer_dense, scheduler_dense, num_epochs)

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
```

```
plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
plt.title('Accuracy Curve')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()

plot_training_curves(history)

#####
# 10. Model Evaluation on Test Set
#####
model_dense.eval()
all_preds = []
all_probs = [] # Probabilities for malignant (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_dense(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Class 1 probability
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

#####
# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

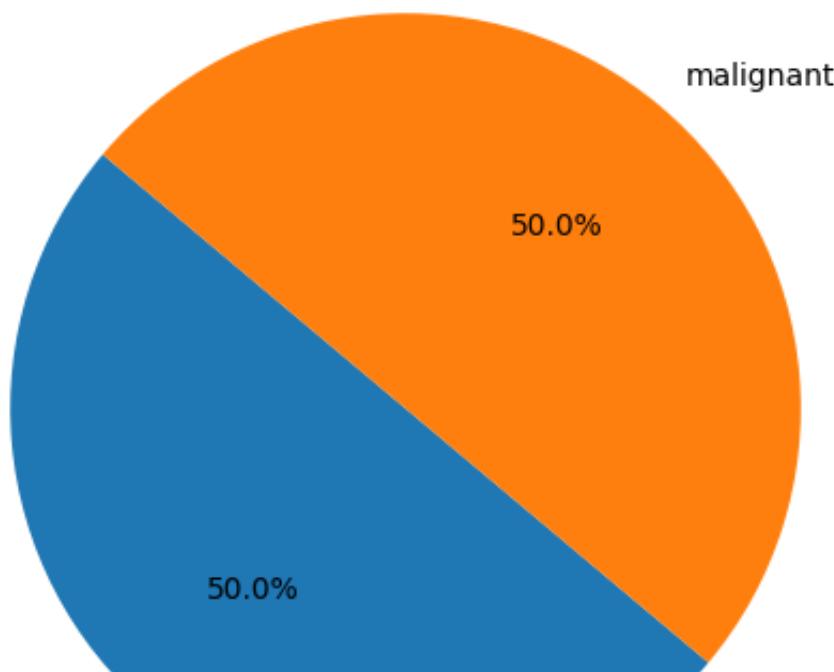
#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
```

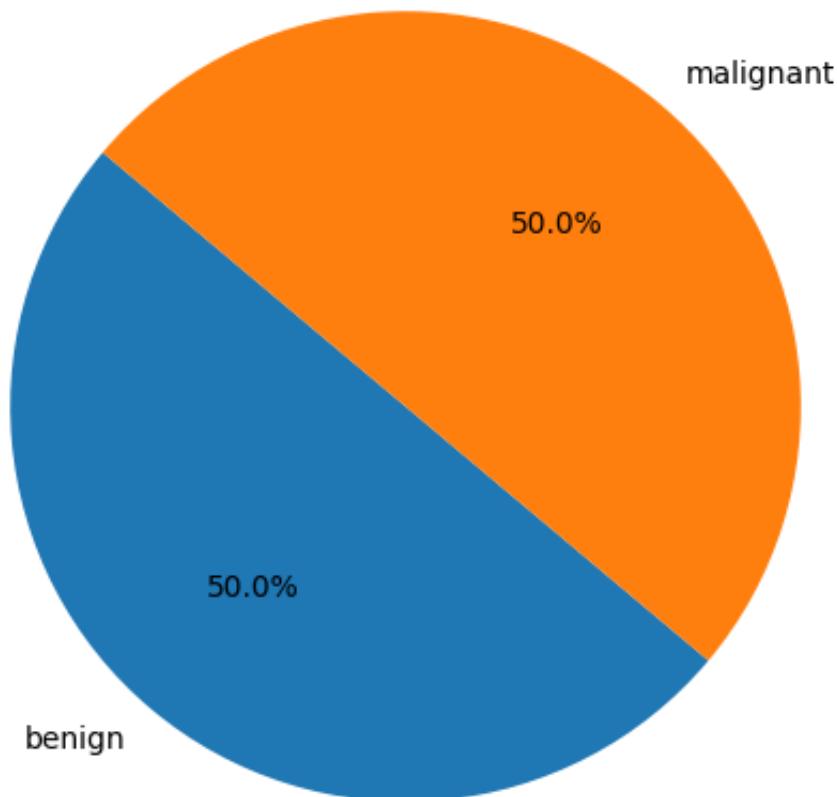
```
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
              horizontalalignment="center",
              color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####
# 13. Visualization 5: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

→ Using device: cuda:0
Train Set Distribution:

Train Set Distribution





```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: U
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: U
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/densenet201-c1103571.pth"
100%|██████████| 77.4M/77.4M [00:00<00:00, 179MB/s]
Epoch 1/25
-----
train: 100%|██████████| 180/180 [00:50<00:00,  3.57it/s]
Train Loss: 0.4721 Acc: 0.7722
val: 100%|██████████| 45/45 [00:04<00:00, 10.75it/s]
Val Loss: 0.3627 Acc: 0.8264

Epoch 2/25
-----
train: 100%|██████████| 180/180 [00:48<00:00,  3.67it/s]
Train Loss: 0.4065 Acc: 0.7927
```

```
train loss: 0.3533 Acc: 0.8251
val: 100%|████████| 45/45 [00:04<00:00, 10.50it/s]
Val Loss: 0.3531 Acc: 0.8250

Epoch 3/25
-----
train: 100%|████████| 180/180 [00:49<00:00, 3.65it/s]
Train Loss: 0.3913 Acc: 0.8122
val: 100%|████████| 45/45 [00:04<00:00, 10.57it/s]
Val Loss: 0.3578 Acc: 0.8472

Epoch 4/25
-----
train: 100%|████████| 180/180 [00:49<00:00, 3.65it/s]
Train Loss: 0.3843 Acc: 0.8226
val: 100%|████████| 45/45 [00:04<00:00, 10.60it/s]
Val Loss: 0.3176 Acc: 0.8431

Epoch 5/25
-----
train: 100%|████████| 180/180 [00:49<00:00, 3.66it/s]
Train Loss: 0.3772 Acc: 0.8219
val: 100%|████████| 45/45 [00:04<00:00, 10.64it/s]
Val Loss: 0.3416 Acc: 0.8556

Epoch 6/25
-----
train: 100%|████████| 180/180 [00:49<00:00, 3.66it/s]
Train Loss: 0.3541 Acc: 0.8396
val: 100%|████████| 45/45 [00:04<00:00, 10.57it/s]
Val Loss: 0.3711 Acc: 0.8319

Epoch 7/25
-----
train: 100%|████████| 180/180 [00:49<00:00, 3.64it/s]
Train Loss: 0.3402 Acc: 0.8326
val: 100%|████████| 45/45 [00:04<00:00, 10.61it/s]
Val Loss: 0.3398 Acc: 0.8222

Epoch 8/25
-----
train: 100%|████████| 180/180 [00:49<00:00, 3.65it/s]
Train Loss: 0.3158 Acc: 0.8542
val: 100%|████████| 45/45 [00:04<00:00, 10.60it/s]
Val Loss: 0.2949 Acc: 0.8556

Epoch 9/25
-----
train: 100%|████████| 180/180 [00:49<00:00, 3.66it/s]
Train Loss: 0.2842 Acc: 0.8684
val: 100%|████████| 45/45 [00:04<00:00, 10.63it/s]
Val Loss: 0.2986 Acc: 0.8556

Epoch 10/25
```

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.66it/s]  
Train Loss: 0.2882 Acc: 0.8688  
val: 100%|██████████| 45/45 [00:04<00:00, 10.61it/s]  
Val Loss: 0.2923 Acc: 0.8667
```

Epoch 11/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.66it/s]  
Train Loss: 0.2785 Acc: 0.8701  
val: 100%|██████████| 45/45 [00:04<00:00, 10.63it/s]  
Val Loss: 0.2886 Acc: 0.8667
```

Epoch 12/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.66it/s]  
Train Loss: 0.2649 Acc: 0.8753  
val: 100%|██████████| 45/45 [00:04<00:00, 10.61it/s]  
Val Loss: 0.2908 Acc: 0.8597
```

Epoch 13/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.65it/s]  
Train Loss: 0.2708 Acc: 0.8767  
val: 100%|██████████| 45/45 [00:04<00:00, 10.54it/s]  
Val Loss: 0.2967 Acc: 0.8597
```

Epoch 14/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.64it/s]  
Train Loss: 0.2522 Acc: 0.8788  
val: 100%|██████████| 45/45 [00:04<00:00, 10.50it/s]  
Val Loss: 0.3051 Acc: 0.8597
```

Epoch 15/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.65it/s]  
Train Loss: 0.2489 Acc: 0.8906  
val: 100%|██████████| 45/45 [00:04<00:00, 10.56it/s]  
Val Loss: 0.3068 Acc: 0.8597
```

Epoch 16/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.65it/s]  
Train Loss: 0.2489 Acc: 0.8840  
val: 100%|██████████| 45/45 [00:04<00:00, 10.55it/s]  
Val Loss: 0.3036 Acc: 0.8625
```

Epoch 17/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.64it/s]  
Train Loss: 0.2531 Acc: 0.8903  
val: 100%|██████████| 45/45 [00:04<00:00, 10.59it/s]  
Val Loss: 0.3009 Acc: 0.8625
```

Epoch 18/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.65it/s]  
Train Loss: 0.2572 Acc: 0.8812  
val: 100%|██████████| 45/45 [00:04<00:00, 10.58it/s]  
Val Loss: 0.3044 Acc: 0.8597
```

Epoch 19/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.65it/s]  
Train Loss: 0.2370 Acc: 0.8910  
val: 100%|██████████| 45/45 [00:04<00:00, 10.52it/s]  
Val Loss: 0.2977 Acc: 0.8611
```

Epoch 20/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.66it/s]  
Train Loss: 0.2530 Acc: 0.8823  
val: 100%|██████████| 45/45 [00:04<00:00, 10.58it/s]  
Val Loss: 0.3011 Acc: 0.8611
```

Epoch 21/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.65it/s]  
Train Loss: 0.2387 Acc: 0.8927  
val: 100%|██████████| 45/45 [00:04<00:00, 10.59it/s]  
Val Loss: 0.2962 Acc: 0.8569
```

Epoch 22/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.64it/s]  
Train Loss: 0.2463 Acc: 0.8910  
val: 100%|██████████| 45/45 [00:04<00:00, 10.38it/s]  
Val Loss: 0.2996 Acc: 0.8611
```

Epoch 23/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.65it/s]  
Train Loss: 0.2410 Acc: 0.8917  
val: 100%|██████████| 45/45 [00:04<00:00, 10.59it/s]  
Val Loss: 0.2998 Acc: 0.8597
```

Epoch 24/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.66it/s]  
Train Loss: 0.2513 Acc: 0.8823  
val: 100%|██████████| 45/45 [00:04<00:00, 10.60it/s]  
Val Loss: 0.2981 Acc: 0.8611
```

Epoch 25/25

```
-----  
train: 100%|██████████| 180/180 [00:49<00:00, 3.66it/s]  
Train Loss: 0.2451 Acc: 0.8931  
----- 100%|██████████| 45/45 500 04:00:00 10 60it/s
```

```
val: 100%|██████████| 45/45 [00:04<00:00, 10.60it/s]
Val Loss: 0.3003 Acc: 0.8639
```

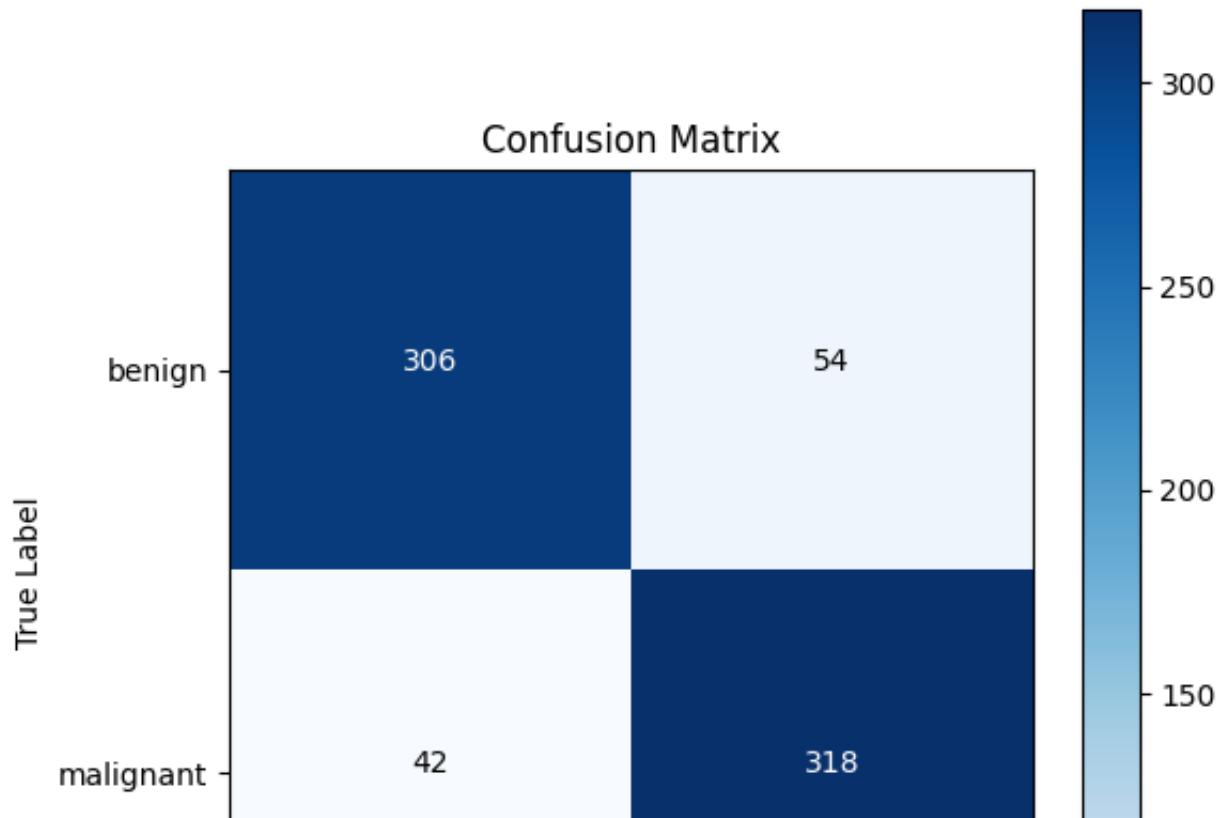
Training complete in 22m 20s
Best Validation Acc: 0.8667

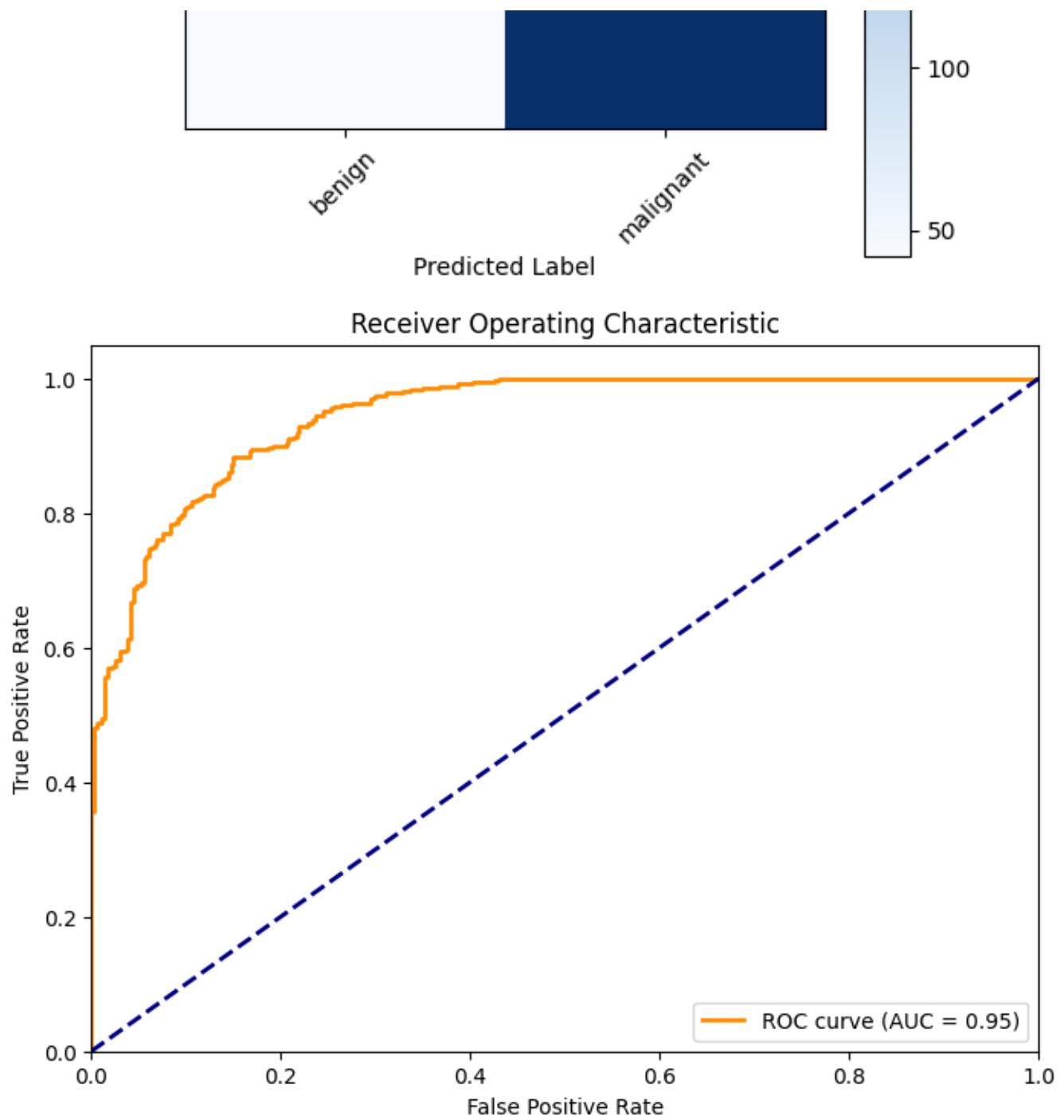


```
Testing: 100%|██████████| 45/45 [00:17<00:00, 2.54it/s]
```

Classification Report:

	precision	recall	f1-score	support
benign	0.88	0.85	0.86	360
malignant	0.85	0.88	0.87	360
accuracy			0.87	720
macro avg	0.87	0.87	0.87	720
weighted avg	0.87	0.87	0.87	720





✓ Xception via TIMM

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm
import timm # PyTorch Image Models

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Dataset folder structure:
# data/
#   train/
#     benign/
#     malignant/
#   test/
```

```
#      benign/
#      malignant/

data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)' #
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Define strong augmentations for training and standard transforms for testing.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])

test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])

# Load datasets using ImageFolder.
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())
    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")
```

```
#####
# 4. DataLoaders
#####
# Adjust batch_size as needed (lower if encountering memory issues)
batch_size = 16
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r

#####
# 5. Model Initialization & Fine-Tuning (Xception)
#####
# Using TIMM to create the Xception model. Ensure timm is installed (pip instal
model_xception = timm.create_model('xception', pretrained=True, num_classes=2)
model_xception = model_xception.to(device)

#####
# 6. Training Function
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    # History lists for visualization.
    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    # Optionally use AMP for mixed precision training to speed up training and
    scaler = torch.cuda.amp.GradScaler()

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        print("-" * 10)
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
                dataloader = train_loader
            else:
                model.eval()
                dataloader = test_loader

            running_loss = 0.0
            running_corrects = 0
            total_samples = 0
```

```
for inputs, labels in tqdm(dataloader, desc=phase):
    inputs = inputs.to(device)
    labels = labels.to(device)
    optimizer.zero_grad()

    with torch.set_grad_enabled(phase == 'train'):
        with torch.cuda.amp.autocast():
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            loss = criterion(outputs, labels)
        if phase == 'train':
            scaler.scale(loss).backward()
            scaler.step(optimizer)
            scaler.update()

        running_loss += loss.item() * inputs.size(0)
        running_corrects += torch.sum(preds == labels.data).item()
        total_samples += inputs.size(0)

    if phase == 'train':
        scheduler.step()

epoch_loss = running_loss / total_samples
epoch_acc = running_corrects / total_samples
print(f'{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

if phase == 'train':
    train_loss_history.append(epoch_loss)
    train_acc_history.append(epoch_acc)
else:
    val_loss_history.append(epoch_loss)
    val_acc_history.append(epoch_acc)
    if epoch_acc > best_acc:
        best_acc = epoch_acc
        best_model_wts = copy.deepcopy(model.state_dict())
print()

time_elapsed = time.time() - since
print(f'Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s')
print(f'Best Validation Acc: {best_acc:.4f}')

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
```

```
    return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_xception = optim.Adam(model_xception.parameters(), lr=1e-4)
scheduler_xception = lr_scheduler.StepLR(optimizer_xception, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####
num_epochs = 25
model_xception, history = train_model(model_xception, criterion, optimizer_xception, scheduler_xception, num_epochs)

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_curves(history)
```

```
#####
# 10. Model Evaluation on Test Set
#####
```

```
model_xception.eval()
all_preds = []
all_probs = [] # Probabilities for malignant (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_xception(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Probability for
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

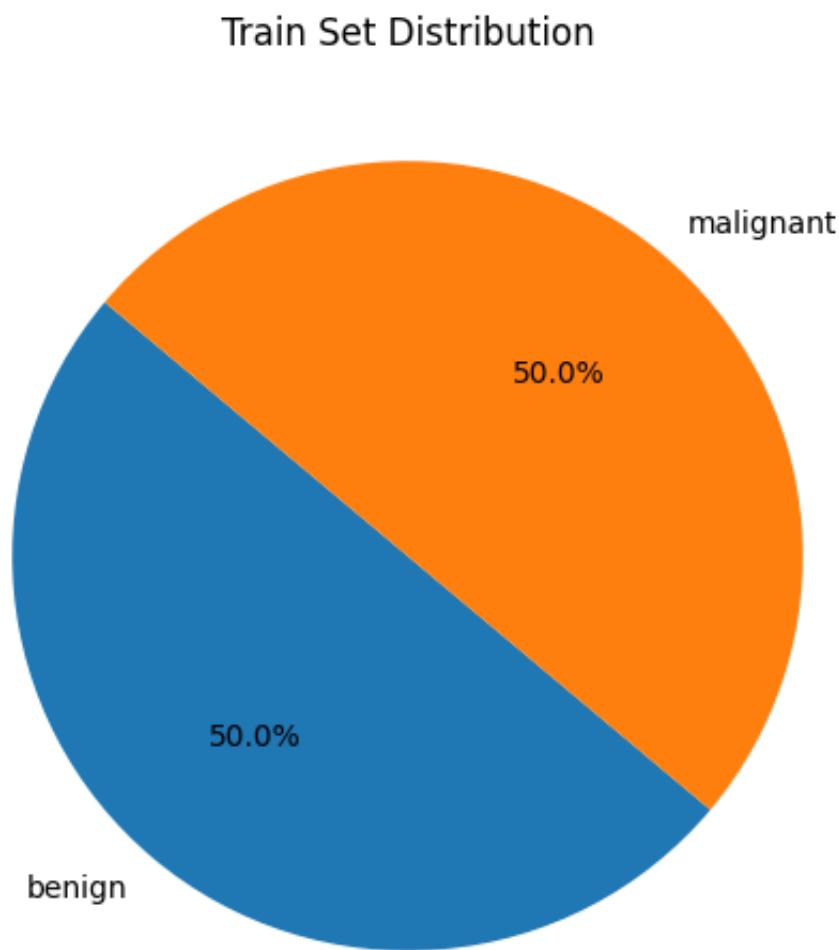
#####
# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####
# 13. Visualization 5: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
```

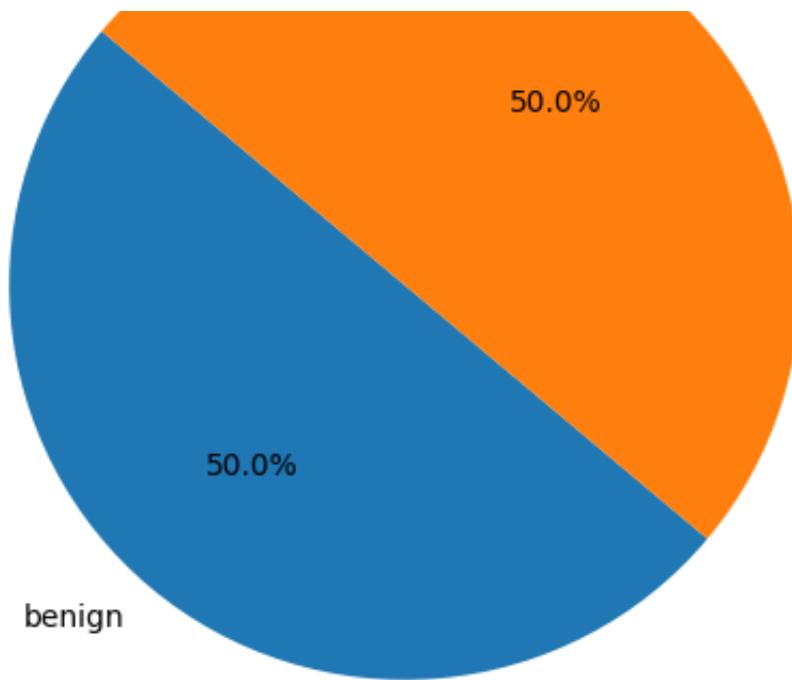
```
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

Using device: cuda:0
Train Set Distribution:



Test Set Distribution:





```
/usr/local/lib/python3.10/dist-packages/timm/models/_factory.py:117: UserWa
    model = create_fn(
Downloading: "https://github.com/rwightman/pytorch-image-models/releases/do
<ipython-input-4-b47122d1a503>:119: FutureWarning: `torch.cuda.amp.GradScal
    scaler = torch.cuda.amp.GradScaler()
Epoch 1/25
-----
train:  0%|          | 0/180 [00:00<?, ?it/s]<ipython-input-4-b47122d1a503
    with torch.cuda.amp.autocast():
train: 100%|██████████| 180/180 [00:20<00:00,  8.59it/s]
Train Loss: 0.4844 Acc: 0.7590
val: 100%|██████████| 45/45 [00:01<00:00, 23.20it/s]
Val Loss: 0.4368 Acc: 0.8111

Epoch 2/25
-----
train: 100%|██████████| 180/180 [00:19<00:00,  9.01it/s]
Train Loss: 0.4180 Acc: 0.8052
val: 100%|██████████| 45/45 [00:01<00:00, 23.85it/s]
Val Loss: 0.3652 Acc: 0.8389

Epoch 3/25
-----
train: 100%|██████████| 180/180 [00:19<00:00,  9.17it/s]
Train Loss: 0.3815 Acc: 0.8174
val: 100%|██████████| 45/45 [00:01<00:00, 23.93it/s]
Val Loss: 0.3434 Acc: 0.8375

Epoch 4/25
-----
train: 100%|██████████| 180/180 [00:19<00:00,  9.17it/s]
Train Loss: 0.3524 Acc: 0.8396
```

```
val: 100%|██████████| 45/45 [00:01<00:00, 23.85it/s]
Val Loss: 0.3292 Acc: 0.8639

Epoch 5/25
-----
train: 100%|██████████| 180/180 [00:19<00:00, 9.03it/s]
Train Loss: 0.3479 Acc: 0.8410
val: 100%|██████████| 45/45 [00:01<00:00, 23.75it/s]
Val Loss: 0.3472 Acc: 0.8444

Epoch 6/25
-----
train: 100%|██████████| 180/180 [00:19<00:00, 9.03it/s]
Train Loss: 0.3156 Acc: 0.8503
val: 100%|██████████| 45/45 [00:01<00:00, 23.82it/s]
Val Loss: 0.3487 Acc: 0.8514

Epoch 7/25
-----
train: 100%|██████████| 180/180 [00:19<00:00, 9.11it/s]
Train Loss: 0.3145 Acc: 0.8594
val: 100%|██████████| 45/45 [00:01<00:00, 23.89it/s]
Val Loss: 0.3721 Acc: 0.8542

Epoch 8/25
-----
train: 100%|██████████| 180/180 [00:19<00:00, 9.12it/s]
Train Loss: 0.2896 Acc: 0.8660
val: 100%|██████████| 45/45 [00:01<00:00, 23.82it/s]
Val Loss: 0.3350 Acc: 0.8708

Epoch 9/25
-----
train: 100%|██████████| 180/180 [00:19<00:00, 9.10it/s]
Train Loss: 0.2517 Acc: 0.8819
val: 100%|██████████| 45/45 [00:01<00:00, 23.86it/s]
Val Loss: 0.3272 Acc: 0.8625

Epoch 10/25
-----
train: 100%|██████████| 180/180 [00:19<00:00, 9.09it/s]
Train Loss: 0.2621 Acc: 0.8878
val: 100%|██████████| 45/45 [00:01<00:00, 24.02it/s]
Val Loss: 0.3221 Acc: 0.8708

Epoch 11/25
-----
train: 100%|██████████| 180/180 [00:19<00:00, 9.09it/s]
Train Loss: 0.2466 Acc: 0.8931
val: 100%|██████████| 45/45 [00:01<00:00, 23.84it/s]
Val Loss: 0.3329 Acc: 0.8694

Epoch 12/25
-----
```

```
train: 100%|██████████| 180/180 [00:19<00:00, 9.06it/s]
Train Loss: 0.2531 Acc: 0.8830
val: 100%|██████████| 45/45 [00:01<00:00, 23.79it/s]
Val Loss: 0.3401 Acc: 0.8583
```

Epoch 13/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.08it/s]
Train Loss: 0.2477 Acc: 0.8986
val: 100%|██████████| 45/45 [00:01<00:00, 23.80it/s]
Val Loss: 0.3403 Acc: 0.8653
```

Epoch 14/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.09it/s]
Train Loss: 0.2213 Acc: 0.9066
val: 100%|██████████| 45/45 [00:01<00:00, 23.80it/s]
Val Loss: 0.3334 Acc: 0.8750
```

Epoch 15/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.09it/s]
Train Loss: 0.2335 Acc: 0.8958
val: 100%|██████████| 45/45 [00:01<00:00, 23.57it/s]
Val Loss: 0.3317 Acc: 0.8792
```

Epoch 16/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.10it/s]
Train Loss: 0.2333 Acc: 0.8941
val: 100%|██████████| 45/45 [00:01<00:00, 23.78it/s]
Val Loss: 0.3403 Acc: 0.8736
```

Epoch 17/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.09it/s]
Train Loss: 0.2180 Acc: 0.9014
val: 100%|██████████| 45/45 [00:01<00:00, 23.52it/s]
Val Loss: 0.3375 Acc: 0.8708
```

Epoch 18/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.00it/s]
Train Loss: 0.2390 Acc: 0.8903
val: 100%|██████████| 45/45 [00:01<00:00, 23.86it/s]
Val Loss: 0.3253 Acc: 0.8736
```

Epoch 19/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.09it/s]
Train Loss: 0.2291 Acc: 0.9000
val: 100%|██████████| 45/45 [00:01<00:00, 24.01it/s]
Val Loss: 0.3313 Acc: 0.8708
```

Epoch 20/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.09it/s]  
Train Loss: 0.2281 Acc: 0.8958  
val: 100%|██████████| 45/45 [00:02<00:00, 22.02it/s]  
Val Loss: 0.3435 Acc: 0.8653
```

Epoch 21/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.01it/s]  
Train Loss: 0.2317 Acc: 0.8976  
val: 100%|██████████| 45/45 [00:01<00:00, 23.67it/s]  
Val Loss: 0.3391 Acc: 0.8708
```

Epoch 22/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.07it/s]  
Train Loss: 0.2239 Acc: 0.9049  
val: 100%|██████████| 45/45 [00:01<00:00, 23.92it/s]  
Val Loss: 0.3368 Acc: 0.8736
```

Epoch 23/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.07it/s]  
Train Loss: 0.2295 Acc: 0.8924  
val: 100%|██████████| 45/45 [00:01<00:00, 23.14it/s]  
Val Loss: 0.3313 Acc: 0.8667
```

Epoch 24/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.09it/s]  
Train Loss: 0.2242 Acc: 0.8958  
val: 100%|██████████| 45/45 [00:01<00:00, 23.89it/s]  
Val Loss: 0.3382 Acc: 0.8694
```

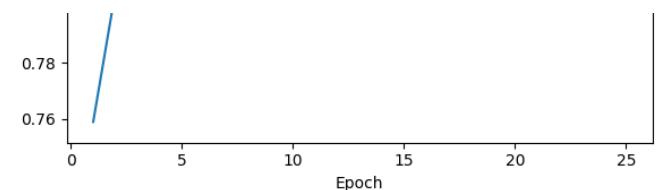
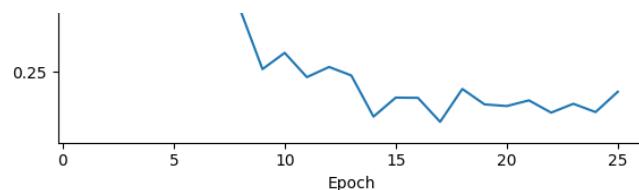
Epoch 25/25

```
-----  
train: 100%|██████████| 180/180 [00:19<00:00, 9.06it/s]  
Train Loss: 0.2372 Acc: 0.8955  
val: 100%|██████████| 45/45 [00:01<00:00, 23.75it/s]  
Val Loss: 0.3376 Acc: 0.8722
```

Training complete in 9m 5s

Best Validation Acc: 0.8792

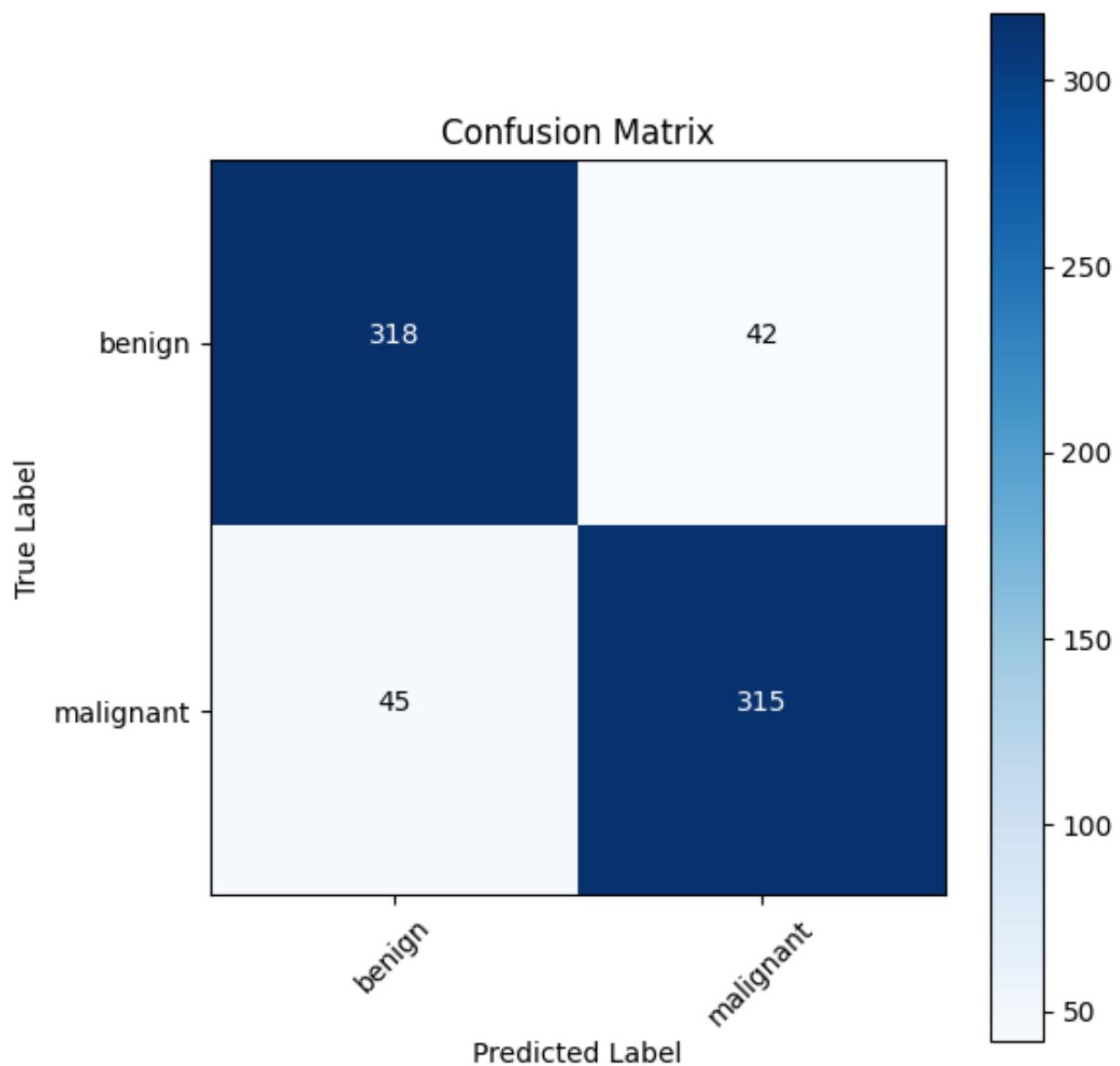




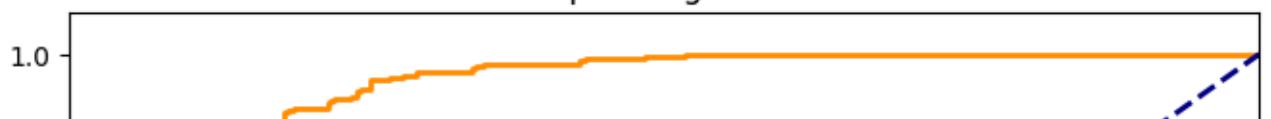
Testing: 100% |  | 45/45 [00:03<00:00, 12.78it/s]

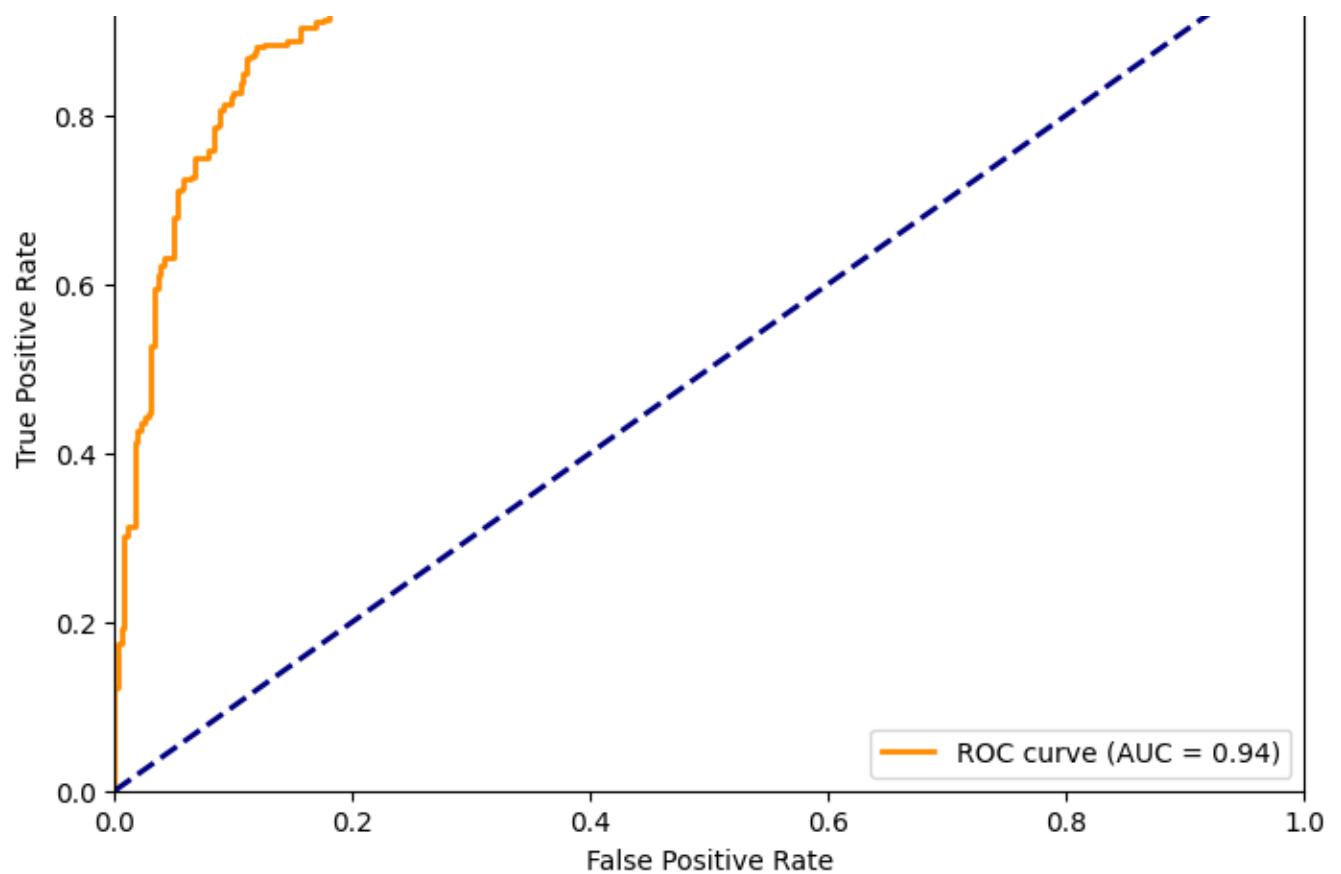
Classification Report:

	precision	recall	f1-score	support
benign	0.88	0.88	0.88	360
malignant	0.88	0.88	0.88	360
accuracy			0.88	720
macro avg	0.88	0.88	0.88	720
weighted avg	0.88	0.88	0.88	720



Receiver Operating Characteristic





✓ InceptionV3

```
import os
import random
import numpy as np
import torch
```

```
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Dataset directory structure:
# data/
#   ..train/
#     benign/
#     malignant/
#   test/
#     benign/
#     malignant/
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)' #
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# InceptionV3 expects 299x299 images.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(299),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
```

```
        std=[0.229, 0.224, 0.225])  
    ])  
test_transforms = transforms.Compose([  
    transforms.Resize(320),  
    transforms.CenterCrop(299),  
    transforms.ToTensor(),  
    transforms.Normalize(mean=[0.485, 0.456, 0.406],  
                        std=[0.229, 0.224, 0.225])  
)  
  
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)  
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)  
  
#####  
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)  
#####  
def plot_class_distribution(dataset, title="Class Distribution"):  
    class_names = dataset.classes  
    class_counts = {name: 0 for name in class_names}  
    for _, label in dataset.samples:  
        class_counts[class_names[label]] += 1  
    labels = list(class_counts.keys())  
    counts = list(class_counts.values())  
    plt.figure(figsize=(6,6))  
    plt.pie(counts, labels=labels, autopct='%1.1f%%', startangle=140)  
    plt.title(title)  
    plt.show()  
  
print("Train Set Distribution:")  
plot_class_distribution(train_dataset, "Train Set Distribution")  
print("Test Set Distribution:")  
plot_class_distribution(test_dataset, "Test Set Distribution")  
  
#####  
# 4. DataLoaders  
#####  
batch_size = 16 # Adjust if needed  
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r  
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r  
  
#####  
# 5. Model Initialization & Fine-Tuning (InceptionV3)  
#####  
# Using the new weights API. Note: When using pretrained weights, aux_logits m  
from torchvision.models import inception_v3, Inception_V3_Weights  
weights = Inception_V3_Weights.IMGNET1K_V1  
model_inception = inception_v3(weights=weights, aux_logits=True)  
# Replace the final fully connected layer. The default fc has in_features = 204
```

```
in_features = model_inception.fc.in_features
model_inception.fc = nn.Linear(in_features, 2)
model_inception = model_inception.to(device)

#####
# 6. Training Function
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        print("-" * 10)

        # Each epoch has training and validation phases.
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
                dataloader = train_loader
            else:
                model.eval()
                dataloader = test_loader

            running_loss = 0.0
            running_corrects = 0
            total_samples = 0

            for inputs, labels in tqdm(dataloader, desc=phase):
                inputs = inputs.to(device)
                labels = labels.to(device)
                optimizer.zero_grad()

                with torch.set_grad_enabled(phase == 'train'):
                    outputs = model(inputs)
                    # If outputs is a tuple (Inception returns (main, aux) when
                    if isinstance(outputs, tuple):
                        outputs = outputs[0]
                    _, preds = torch.max(outputs, 1)
                    loss = criterion(outputs, labels)

                    if phase == 'train':
```

```
        loss.backward()
        optimizer.step()

        running_loss += loss.item() * inputs.size(0)
        running_corrects += torch.sum(preds == labels.data).item()
        total_samples += inputs.size(0)

    if phase == 'train':
        scheduler.step()

    epoch_loss = running_loss / total_samples
    epoch_acc = running_corrects / total_samples
    print(f'{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

    if phase == 'train':
        train_loss_history.append(epoch_loss)
        train_acc_history.append(epoch_acc)
    else:
        val_loss_history.append(epoch_loss)
        val_acc_history.append(epoch_acc)
        if epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = copy.deepcopy(model.state_dict())
print()

time_elapsed = time.time() - since
print(f'Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s')
print(f'Best Validation Acc: {best_acc:.4f}')

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_inception = optim.Adam(model_inception.parameters(), lr=1e-4)
scheduler_inception = lr_scheduler.StepLR(optimizer_inception, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####

```

```
num_epochs = 25
model_inception, history = train_model(model_inception, criterion, optimizer_ir

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####

def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_curves(history)

#####
# 10. Model Evaluation on Test Set
#####

model_inception.eval()
all_preds = []
all_probs = [] # Probabilities for malignant (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_inception(inputs)
        # Use only the primary output
        if isinstance(outputs, tuple):
```

```
        outputs = outputs[0]
probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Probability for
_, preds = torch.max(outputs, 1)
all_preds.extend(preds.cpu().numpy())
all_probs.extend(probs.cpu().numpy())
all_labels.extend(labels.cpu().numpy())

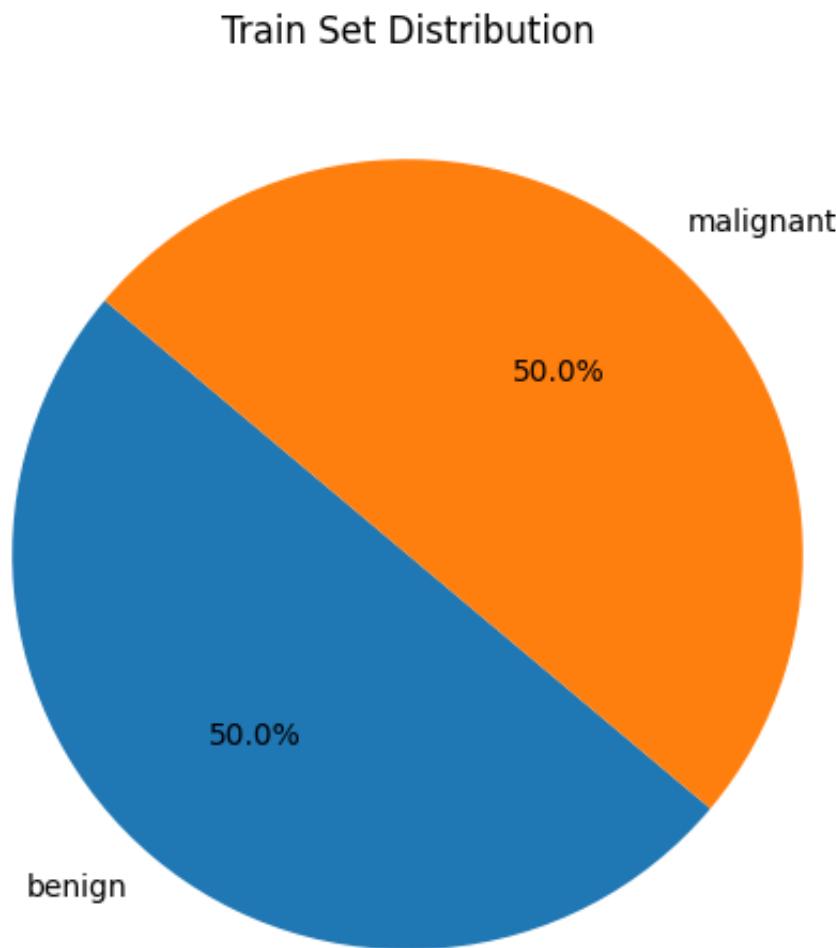
#####
# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

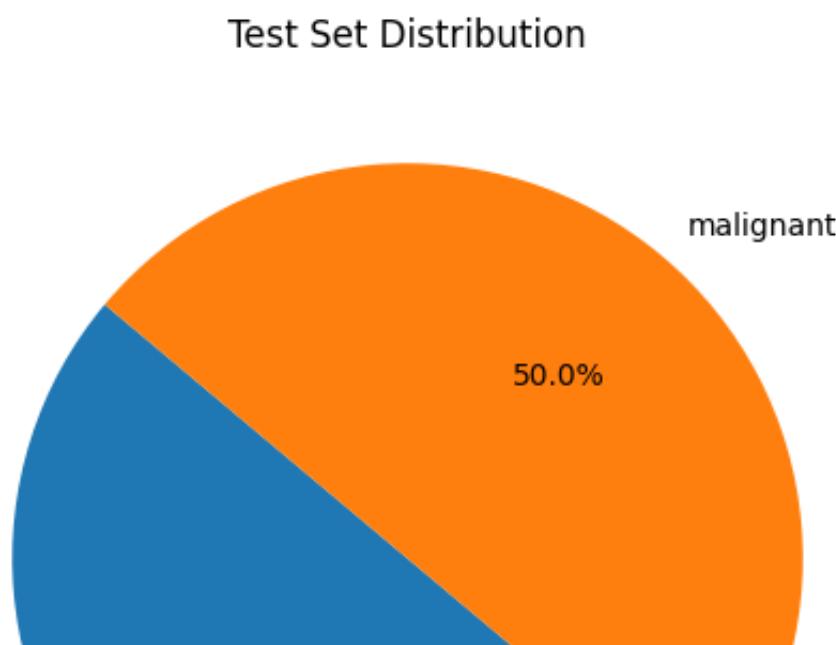
#####
# 13. Visualization 5: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
```

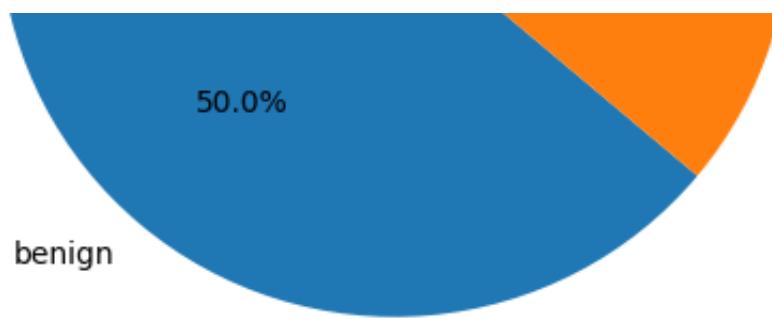
```
plt.show()
```

Using device: cuda:0
Train Set Distribution:



Test Set Distribution:





Downloading: "[Epoch 1/25](https://download.pytorch.org/models/inception_v3_google-0cc3c1100%|██████████| 104M/104M [00:00<00:00, 207MB/s]</p></div><div data-bbox=)

train: 100%|██████████| 180/180 [00:51<00:00, 3.49it/s]
Train Loss: 0.4772 Acc: 0.7646
val: 100%|██████████| 45/45 [00:03<00:00, 12.65it/s]
Val Loss: 0.4115 Acc: 0.8056

Epoch 2/25

train: 100%|██████████| 180/180 [00:50<00:00, 3.59it/s]
Train Loss: 0.4042 Acc: 0.8042
val: 100%|██████████| 45/45 [00:03<00:00, 12.51it/s]
Val Loss: 0.3682 Acc: 0.8319

Epoch 3/25

train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.3778 Acc: 0.8253
val: 100%|██████████| 45/45 [00:03<00:00, 12.64it/s]
Val Loss: 0.3391 Acc: 0.8458

Epoch 4/25

train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.3796 Acc: 0.8306
val: 100%|██████████| 45/45 [00:03<00:00, 12.63it/s]
Val Loss: 0.3929 Acc: 0.8208

Epoch 5/25

train: 100%|██████████| 180/180 [00:50<00:00, 3.57it/s]
Train Loss: 0.3526 Acc: 0.8365
val: 100%|██████████| 45/45 [00:03<00:00, 12.60it/s]
Val Loss: 0.3592 Acc: 0.8292

Epoch 6/25

train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.3550 Acc: 0.8358
val: 100%|██████████| 45/45 [00:03<00:00, 12.54it/s]

Val Loss: 0.3305 Acc: 0.8472

Epoch 7/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]  
Train Loss: 0.3481 Acc: 0.8413  
val: 100%|██████████| 45/45 [00:03<00:00, 12.51it/s]  
Val Loss: 0.3514 Acc: 0.8375
```

Epoch 8/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]  
Train Loss: 0.3019 Acc: 0.8580  
val: 100%|██████████| 45/45 [00:03<00:00, 12.61it/s]  
Val Loss: 0.3218 Acc: 0.8583
```

Epoch 9/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]  
Train Loss: 0.2890 Acc: 0.8663  
val: 100%|██████████| 45/45 [00:03<00:00, 12.62it/s]  
Val Loss: 0.3205 Acc: 0.8556
```

Epoch 10/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]  
Train Loss: 0.2776 Acc: 0.8726  
val: 100%|██████████| 45/45 [00:03<00:00, 12.63it/s]  
Val Loss: 0.3126 Acc: 0.8583
```

Epoch 11/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]  
Train Loss: 0.2693 Acc: 0.8743  
val: 100%|██████████| 45/45 [00:03<00:00, 12.67it/s]  
Val Loss: 0.3195 Acc: 0.8611
```

Epoch 12/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]  
Train Loss: 0.2594 Acc: 0.8896  
val: 100%|██████████| 45/45 [00:03<00:00, 12.63it/s]  
Val Loss: 0.3092 Acc: 0.8667
```

Epoch 13/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]  
Train Loss: 0.2650 Acc: 0.8809  
val: 100%|██████████| 45/45 [00:03<00:00, 12.62it/s]  
Val Loss: 0.3131 Acc: 0.8639
```

Epoch 14/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
```

```
Train Loss: 0.2505 Acc: 0.8906
val: 100%|██████████| 45/45 [00:03<00:00, 12.68it/s]
Val Loss: 0.3027 Acc: 0.8694
```

Epoch 15/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.2492 Acc: 0.8868
val: 100%|██████████| 45/45 [00:03<00:00, 12.59it/s]
Val Loss: 0.3036 Acc: 0.8667
```

Epoch 16/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.2468 Acc: 0.8872
val: 100%|██████████| 45/45 [00:03<00:00, 12.49it/s]
Val Loss: 0.3059 Acc: 0.8681
```

Epoch 17/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.2374 Acc: 0.8951
val: 100%|██████████| 45/45 [00:03<00:00, 12.41it/s]
Val Loss: 0.2991 Acc: 0.8681
```

Epoch 18/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.2275 Acc: 0.9017
val: 100%|██████████| 45/45 [00:03<00:00, 12.50it/s]
Val Loss: 0.3105 Acc: 0.8639
```

Epoch 19/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.2549 Acc: 0.8844
val: 100%|██████████| 45/45 [00:03<00:00, 12.58it/s]
Val Loss: 0.3056 Acc: 0.8681
```

Epoch 20/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.57it/s]
Train Loss: 0.2440 Acc: 0.8899
val: 100%|██████████| 45/45 [00:03<00:00, 12.11it/s]
Val Loss: 0.3047 Acc: 0.8694
```

Epoch 21/25

```
-----  
train: 100%|██████████| 180/180 [00:50<00:00, 3.59it/s]
Train Loss: 0.2409 Acc: 0.8951
val: 100%|██████████| 45/45 [00:03<00:00, 12.40it/s]
Val Loss: 0.3072 Acc: 0.8667
```

Epoch 22/25

```
-----
train: 100%|██████████| 180/180 [00:50<00:00, 3.57it/s]
Train Loss: 0.2343 Acc: 0.8955
val: 100%|██████████| 45/45 [00:03<00:00, 12.58it/s]
Val Loss: 0.3102 Acc: 0.8653
```

Epoch 23/25

```
-----
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.2375 Acc: 0.8986
val: 100%|██████████| 45/45 [00:03<00:00, 12.45it/s]
Val Loss: 0.3141 Acc: 0.8653
```

Epoch 24/25

```
-----
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.2397 Acc: 0.8948
val: 100%|██████████| 45/45 [00:03<00:00, 12.52it/s]
Val Loss: 0.3067 Acc: 0.8722
```

Epoch 25/25

```
-----
train: 100%|██████████| 180/180 [00:50<00:00, 3.58it/s]
Train Loss: 0.2329 Acc: 0.8993
val: 100%|██████████| 45/45 [00:03<00:00, 12.47it/s]
Val Loss: 0.3169 Acc: 0.8625
```

Training complete in 22m 29s

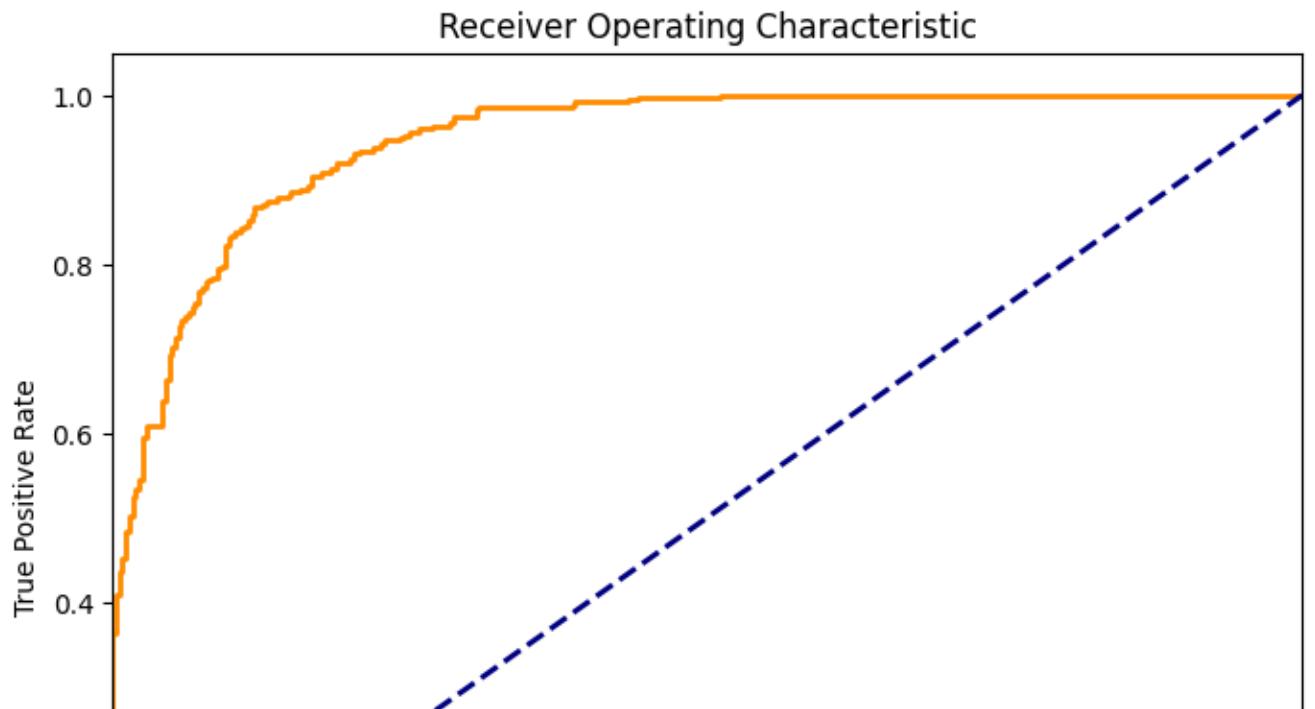
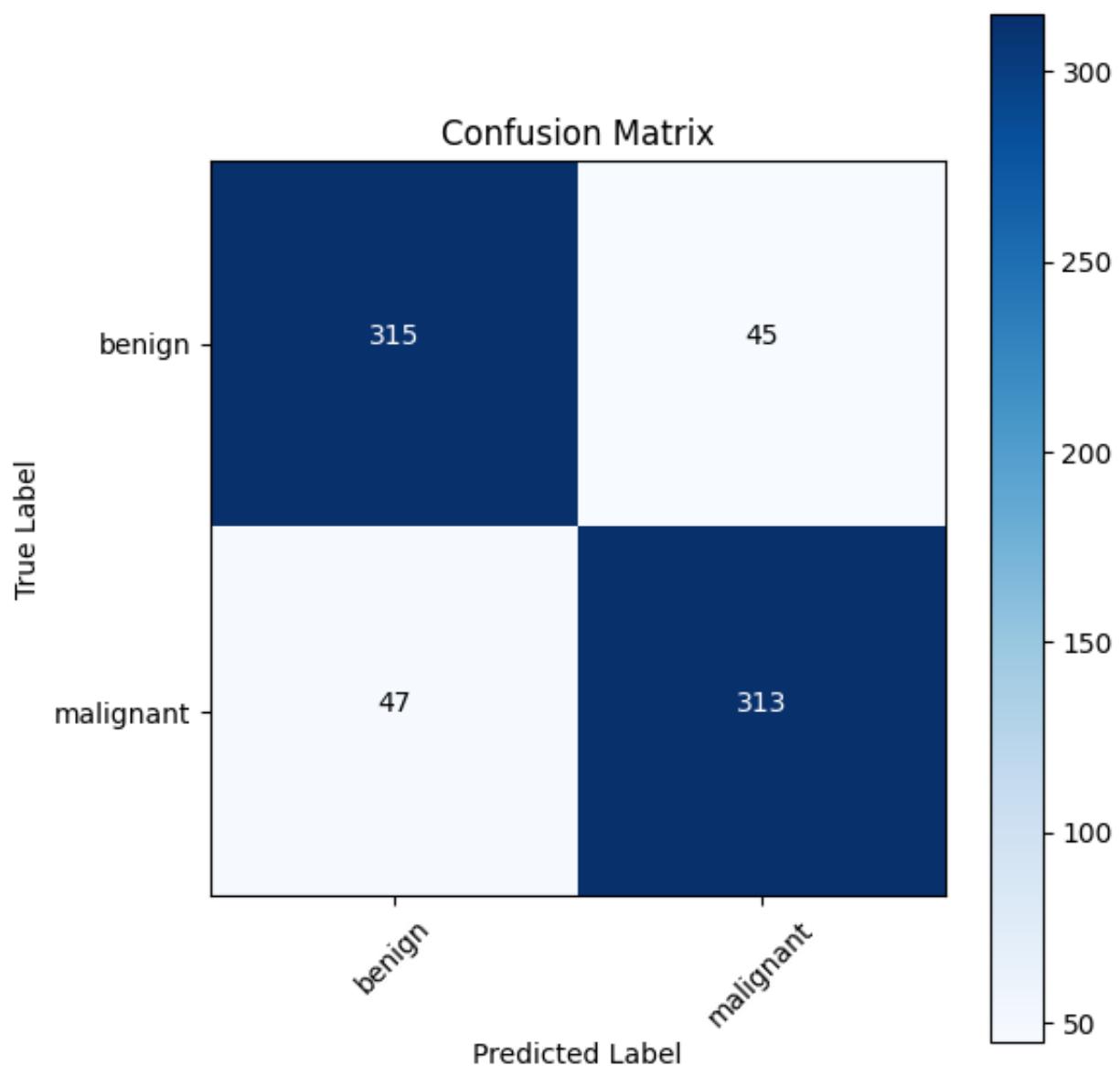
Best Validation Acc: 0.8722

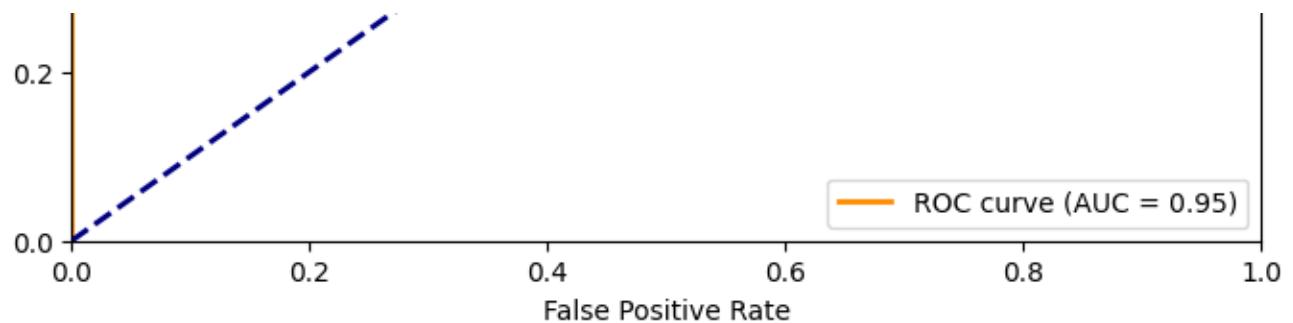


Testing: 100%|██████████| 45/45 [00:03<00:00, 12.51it/s]

Classification Report:

	precision	recall	f1-score	support
benign	0.87	0.88	0.87	360
malignant	0.87	0.87	0.87	360
accuracy			0.87	720
macro avg	0.87	0.87	0.87	720
weighted avg	0.87	0.87	0.87	720





✓ Ablation study (without segmentation)

Restnet 50

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

# =====
# 1. Reproducibility & Device Setup
```

```
# =====
random.seed(42)
np.random.seed(42)
torch.manual_seed(42)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

# =====
# 2. Data Preparation & Augmentation
# =====
# Adjust these paths as per your dataset structure.
data_dir = '/kaggle/input/k-mean-clustering/segmented_data'
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Data augmentation for training and simple transforms for testing.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
# Load datasets using ImageFolder (ensure your folder names match)
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

# -----
# Visualization 1: Pie Chart of Class Distribution
# -----
def plot_class_distribution(dataset):
    class_names = dataset.classes
    class_counts = {class_name: 0 for class_name in class_names}
    for _, label in dataset.imgs:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
```

```
counts = list(class_counts.values())

plt.figure(figsize=(6,6))
plt.pie(counts, labels=labels, autopct='%.1f%%', startangle=140)
plt.title('Class Distribution')
plt.show()

plot_class_distribution(train_dataset)

# Create DataLoaders
batch_size = 32
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

# =====
# 3. Model Initialization & Fine-Tuning
# =====
# Load pre-trained ResNet50 and modify the final layer for 2 classes.
model_ft = models.resnet50(pretrained=True)
num_ftrs = model_ft.fc.in_features
model_ft.fc = nn.Linear(num_ftrs, 2)
model_ft = model_ft.to(device)

criterion = nn.CrossEntropyLoss()
optimizer_ft = optim.Adam(model_ft.parameters(), lr=1e-4)
exp_lr_scheduler = lr_scheduler.StepLR(optimizer_ft, step_size=7, gamma=0.1)

# =====
# 4. Training Function
# =====
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    # Lists to store training history for visualization.
    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    for epoch in range(num_epochs):
        print('Epoch {}/{}'.format(epoch+1, num_epochs))
        print('-' * 10)

        # Each epoch has a training and validation phase.
        for phase in ['train', 'val']:
            if phase == 'train':
```

```
model.train() # Set to training mode.
dataloader = train_loader
else:
    model.eval() # Set to evaluation mode.
    dataloader = test_loader

running_loss = 0.0
running_corrects = 0

# Iterate over data.
for inputs, labels in tqdm(dataloader):
    inputs = inputs.to(device)
    labels = labels.to(device)

    optimizer.zero_grad()
    with torch.set_grad_enabled(phase == 'train'):
        outputs = model(inputs)
        _, preds = torch.max(outputs, 1)
        loss = criterion(outputs, labels)

        if phase == 'train':
            loss.backward()
            optimizer.step()

    running_loss += loss.item() * inputs.size(0)
    running_corrects += torch.sum(preds == labels.data)

if phase == 'train':
    scheduler.step()

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

print('{} Loss: {:.4f} Acc: {:.4f}'.format(phase, epoch_loss, epoch_acc))

if phase == 'train':
    train_loss_history.append(epoch_loss)
    train_acc_history.append(epoch_acc.item())
else:
    val_loss_history.append(epoch_loss)
    val_acc_history.append(epoch_acc.item())

# Deep copy the model if performance improves.
if phase == 'val' and epoch_acc > best_acc:
    best_acc = epoch_acc
    best_model_wts = copy.deepcopy(model.state_dict())

print()
```

```
time_elapsed = time.time() - since
print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60, time_elapsed % 60))
print('Best Val Acc: {:.4f}'.format(best_acc))

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

# Train the model (adjust the number of epochs as needed)
num_epochs = 25
model_ft, history = train_model(model_ft, criterion, optimizer_ft, exp_lr_sche

# -----
# Visualization 2: Accuracy & Loss Curves
# -----
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_curves(history)
```

```
# =====
# 5. Model Evaluation on Test Set
# =====
model_ft.eval()
all_preds = []
all_probs = [] # Store probabilities for the positive class (malignant)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_ft(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Probability for
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

# -----
# Visualization 3: Classification Report
# -----
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

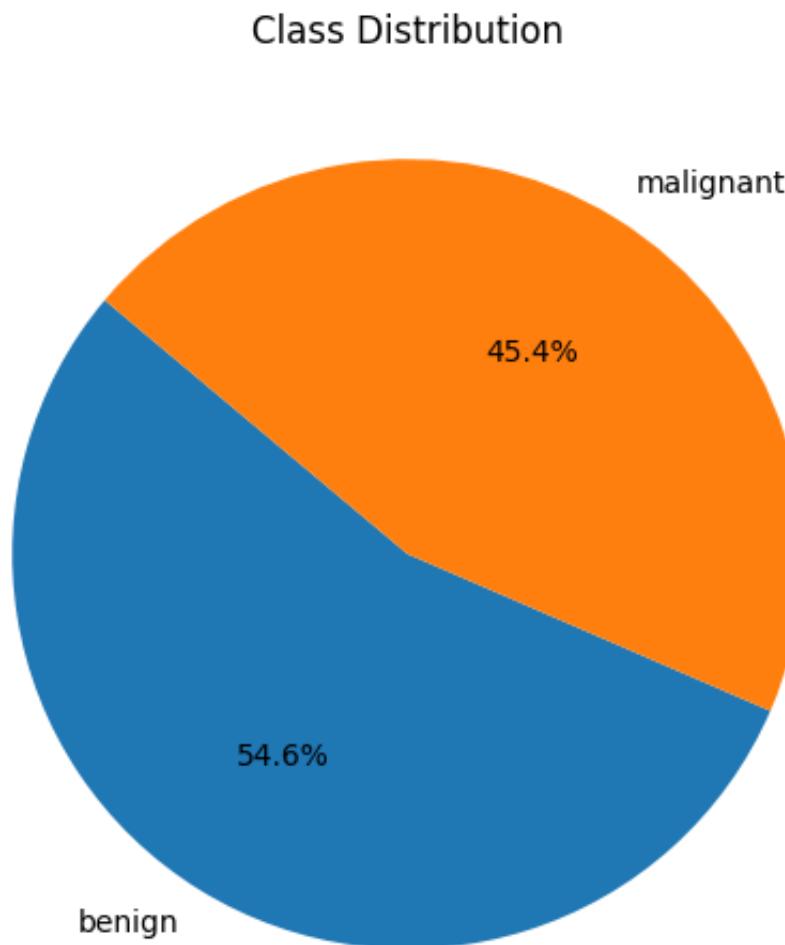
# -----
# Visualization 4: Confusion Matrix
# -----
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)

thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

# -----
```

```
# Visualization 5: ROC Curve and AUC
# -----
fpr, tpr, thresholds = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

→ Using device: cuda:0



```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarning: warnings.warn()
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarning: warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet50-0676ba61.pth" to 1000.0%
```

100% |██████████| 97.0M/97.0M [00:00<00:00, 214MB/s]

Epoch 1/25

100% |██████████| 83/83 [00:17<00:00, 4.76it/s]

train Loss: 0.4223 Acc: 0.7922

100% |██████████| 21/21 [00:01<00:00, 12.75it/s]

val Loss: 0.3996 Acc: 0.8227

Epoch 2/25

100% |██████████| 83/83 [00:16<00:00, 5.12it/s]

train Loss: 0.3746 Acc: 0.8271

100% |██████████| 21/21 [00:01<00:00, 13.13it/s]

val Loss: 0.3628 Acc: 0.8318

Epoch 3/25

100% |██████████| 83/83 [00:16<00:00, 5.14it/s]

train Loss: 0.3683 Acc: 0.8214

100% |██████████| 21/21 [00:01<00:00, 13.20it/s]

val Loss: 0.3574 Acc: 0.8212

Epoch 4/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]

train Loss: 0.3468 Acc: 0.8407

100% |██████████| 21/21 [00:01<00:00, 13.26it/s]

val Loss: 0.3589 Acc: 0.8136

Epoch 5/25

100% |██████████| 83/83 [00:16<00:00, 5.12it/s]

train Loss: 0.3100 Acc: 0.8570

100% |██████████| 21/21 [00:01<00:00, 13.16it/s]

val Loss: 0.3825 Acc: 0.8303

Epoch 6/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]

train Loss: 0.3220 Acc: 0.8506

100% |██████████| 21/21 [00:01<00:00, 13.32it/s]

val Loss: 0.3649 Acc: 0.8409

Epoch 7/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]

train Loss: 0.3055 Acc: 0.8567

100% |██████████| 21/21 [00:01<00:00, 13.13it/s]

val Loss: 0.3205 Acc: 0.8485

Epoch 8/25

100% |██████████| 83/83 [00:16<00:00, 5.10it/s]

train Loss: 0.2816 Acc: 0.8786

100% |██████████| 21/21 [00:01<00:00, 13.00it/s]

100% |██████████| 21/21 [00:01<00:00, 12.92it/s]
val Loss: 0.3049 Acc: 0.8576

Epoch 9/25

100% |██████████| 83/83 [00:16<00:00, 5.04it/s]
train Loss: 0.2467 Acc: 0.8878
100% |██████████| 21/21 [00:01<00:00, 13.10it/s]
val Loss: 0.3158 Acc: 0.8455

Epoch 10/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]
train Loss: 0.2443 Acc: 0.8859
100% |██████████| 21/21 [00:01<00:00, 13.11it/s]
val Loss: 0.3218 Acc: 0.8500

Epoch 11/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]
train Loss: 0.2254 Acc: 0.8991
100% |██████████| 21/21 [00:01<00:00, 13.05it/s]
val Loss: 0.3231 Acc: 0.8424

Epoch 12/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]
train Loss: 0.2352 Acc: 0.8847
100% |██████████| 21/21 [00:01<00:00, 13.22it/s]
val Loss: 0.3266 Acc: 0.8485

Epoch 13/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]
train Loss: 0.2155 Acc: 0.9056
100% |██████████| 21/21 [00:01<00:00, 13.15it/s]
val Loss: 0.3277 Acc: 0.8606

Epoch 14/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]
train Loss: 0.2003 Acc: 0.9086
100% |██████████| 21/21 [00:01<00:00, 13.30it/s]
val Loss: 0.3369 Acc: 0.8545

Epoch 15/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]
train Loss: 0.2043 Acc: 0.9018
100% |██████████| 21/21 [00:01<00:00, 13.32it/s]
val Loss: 0.3330 Acc: 0.8530

Epoch 16/25

100% |██████████| 83/83 [00:16<00:00, 5.13it/s]
train Loss: 0.2043 Acc: 0.9018
100% |██████████| 21/21 [00:01<00:00, 13.32it/s]
val Loss: 0.3330 Acc: 0.8530

```
100%|██████████| 83/83 [00:16<00:00, 5.14it/s]
train Loss: 0.1868 Acc: 0.9128
100%|██████████| 21/21 [00:01<00:00, 12.77it/s]
val Loss: 0.3315 Acc: 0.8561
```

Epoch 17/25

```
100%|██████████| 83/83 [00:16<00:00, 5.11it/s]
train Loss: 0.1978 Acc: 0.9120
100%|██████████| 21/21 [00:01<00:00, 13.26it/s]
val Loss: 0.3382 Acc: 0.8530
```

Epoch 18/25

```
100%|██████████| 83/83 [00:16<00:00, 5.14it/s]
train Loss: 0.1994 Acc: 0.9056
100%|██████████| 21/21 [00:01<00:00, 13.28it/s]
val Loss: 0.3334 Acc: 0.8545
```

Epoch 19/25

```
100%|██████████| 83/83 [00:16<00:00, 5.15it/s]
train Loss: 0.1953 Acc: 0.9041
100%|██████████| 21/21 [00:01<00:00, 13.24it/s]
val Loss: 0.3345 Acc: 0.8606
```

Epoch 20/25

```
100%|██████████| 83/83 [00:16<00:00, 5.13it/s]
train Loss: 0.1831 Acc: 0.9196
100%|██████████| 21/21 [00:01<00:00, 13.20it/s]
val Loss: 0.3493 Acc: 0.8576
```

Epoch 21/25

```
100%|██████████| 83/83 [00:16<00:00, 5.14it/s]
train Loss: 0.1860 Acc: 0.9143
100%|██████████| 21/21 [00:01<00:00, 13.27it/s]
val Loss: 0.3456 Acc: 0.8515
```

Epoch 22/25

```
100%|██████████| 83/83 [00:16<00:00, 5.14it/s]
train Loss: 0.1899 Acc: 0.9135
100%|██████████| 21/21 [00:01<00:00, 13.27it/s]
val Loss: 0.3389 Acc: 0.8530
```

Epoch 23/25

```
100%|██████████| 83/83 [00:16<00:00, 5.14it/s]
train Loss: 0.1840 Acc: 0.9196
100%|██████████| 21/21 [00:01<00:00, 13.16it/s]
val Loss: 0.3346 Acc: 0.8606
```

Epoch 24/25

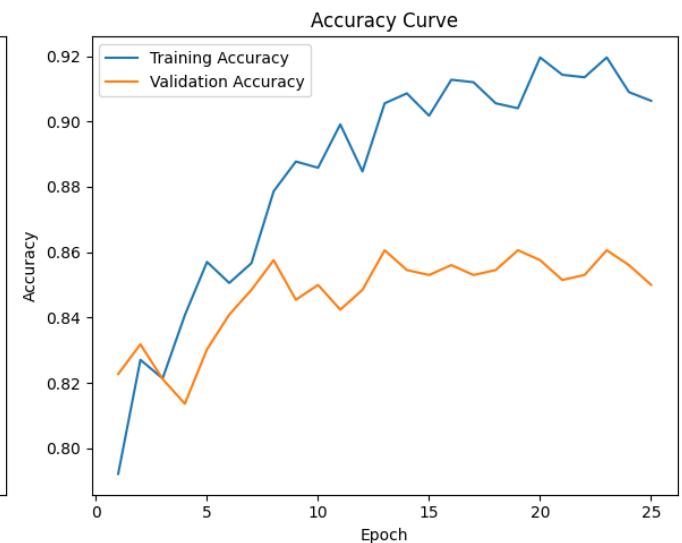
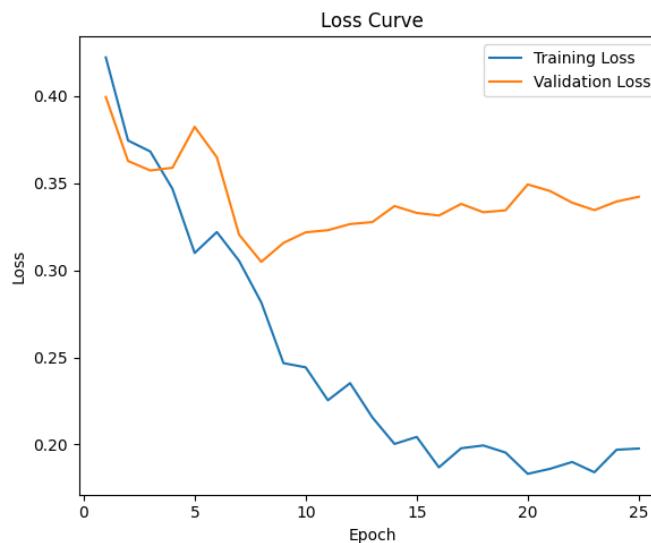
```
100%|██████████| 83/83 [00:16<00:00, 5.13it/s]
train Loss: 0.1969 Acc: 0.9090
100%|██████████| 21/21 [00:01<00:00, 13.24it/s]
val Loss: 0.3395 Acc: 0.8561
```

Epoch 25/25

```
100%|██████████| 83/83 [00:16<00:00, 5.14it/s]
train Loss: 0.1976 Acc: 0.9063
100%|██████████| 21/21 [00:01<00:00, 12.75it/s]
val Loss: 0.3423 Acc: 0.8500
```

Training complete in 7m 26s

Best Val Acc: 0.8606



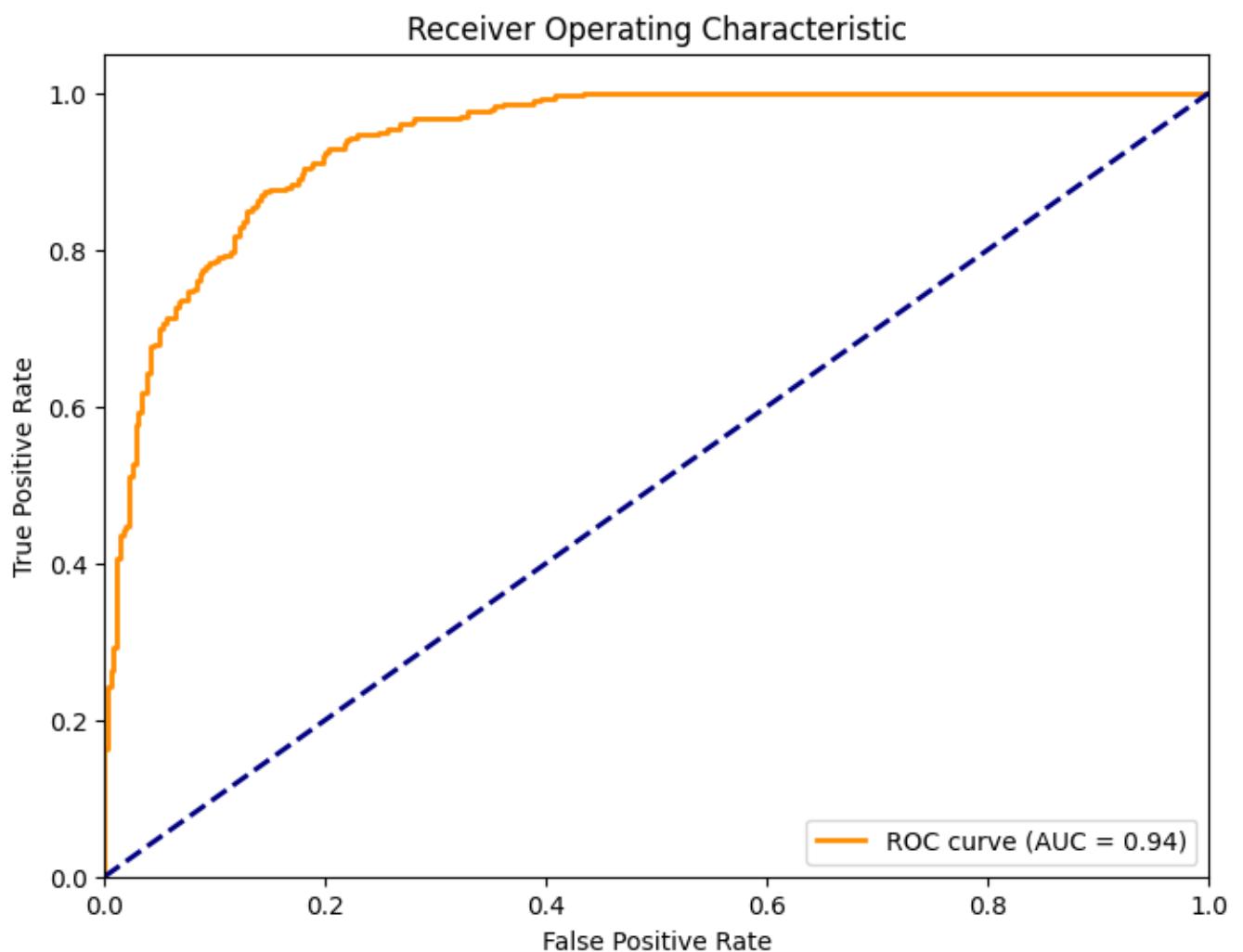
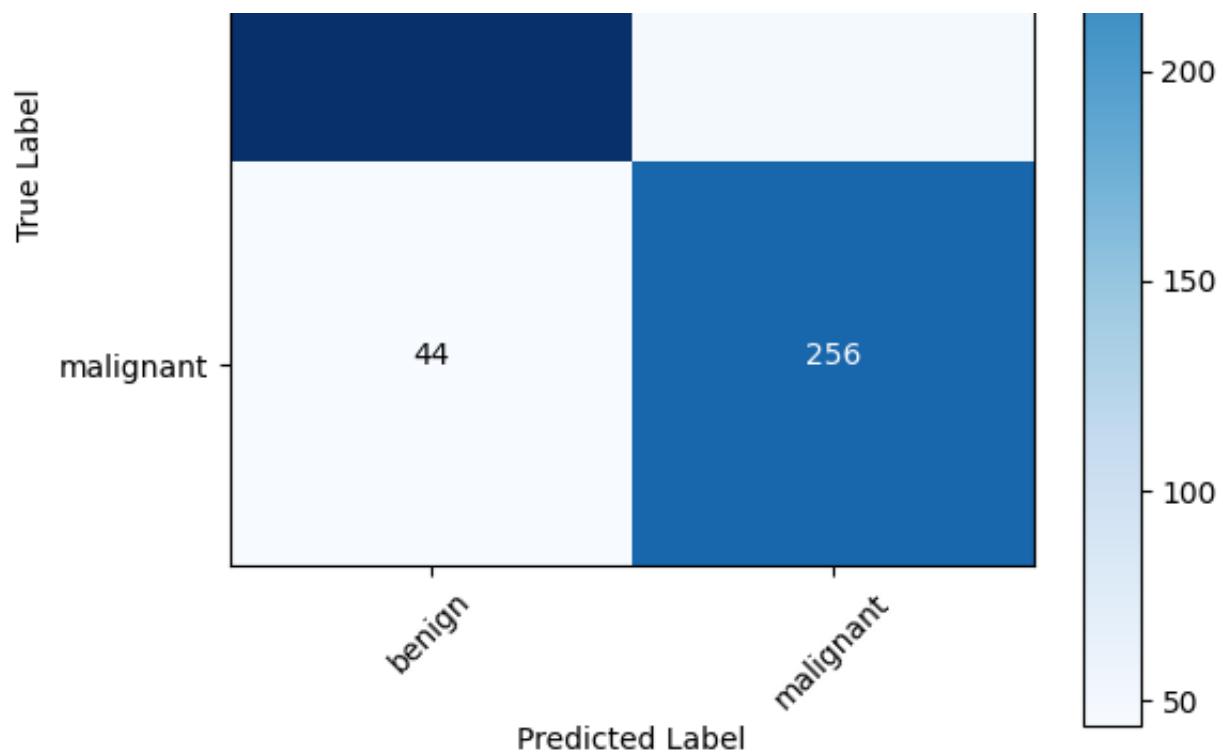
```
100%|██████████| 21/21 [00:01<00:00, 13.25it/s]
```

Classification Report:

	precision	recall	f1-score	support
benign	0.88	0.87	0.87	360
malignant	0.84	0.85	0.85	300
accuracy			0.86	660
macro avg	0.86	0.86	0.86	660
weighted avg	0.86	0.86	0.86	660

Confusion Matrix





DenseNet201

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
```

```
#####
# Update this path to your dataset directory
data_dir = '/kaggle/input/k-mean-clustering/segmented_data'
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Define strong augmentation for training and standard transforms for testing.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])

# Load datasets using ImageFolder
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())
    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%1.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")
```

```
#####
# 4. DataLoaders
#####
# Create DataLoaders (adjust batch_size as needed)
batch_size = 16
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r

#####
# 5. Model Initialization & Fine-Tuning (DenseNet201)
#####
# Load DenseNet201 with pretrained ImageNet weights.
model_dense = models.densenet201(pretrained=True)
# DenseNet201's classifier is a single linear layer stored in model_dense.class
in_features = model_dense.classifier.in_features
# Replace classifier with dropout + linear layer for 2 classes.
model_dense.classifier = nn.Sequential(
    nn.Dropout(p=0.5),
    nn.Linear(in_features, 2)
)
model_dense = model_dense.to(device)

#####
# 6. Training Function
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        print("-" * 10)
        # Each epoch has a training and validation phase.
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
                dataloader = train_loader
            else:
                model.eval()
                dataloader = test_loader

            running_loss = 0.0
```

```
running_corrects = 0
total_samples = 0

for inputs, labels in tqdm(dataloader, desc=phase):
    inputs = inputs.to(device)
    labels = labels.to(device)

    optimizer.zero_grad()
    with torch.set_grad_enabled(phase == 'train'):
        outputs = model(inputs)
        _, preds = torch.max(outputs, 1)
        loss = criterion(outputs, labels)

    if phase == 'train':
        loss.backward()
        optimizer.step()

    running_loss += loss.item() * inputs.size(0)
    running_corrects += torch.sum(preds == labels.data).item()
    total_samples += inputs.size(0)

if phase == 'train':
    scheduler.step()

epoch_loss = running_loss / total_samples
epoch_acc = running_corrects / total_samples
print(f'{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

if phase == 'train':
    train_loss_history.append(epoch_loss)
    train_acc_history.append(epoch_acc)
else:
    val_loss_history.append(epoch_loss)
    val_acc_history.append(epoch_acc)
    if epoch_acc > best_acc:
        best_acc = epoch_acc
        best_model_wts = copy.deepcopy(model.state_dict())
print()

time_elapsed = time.time() - since
print(f'Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s')
print(f'Best Validation Acc: {best_acc:.4f}')

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
```

```
        'val_acc': val_acc_history
    }
    return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_dense = optim.Adam(model_dense.parameters(), lr=1e-4)
scheduler_dense = lr_scheduler.StepLR(optimizer_dense, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####
num_epochs = 25
model_dense, history = train_model(model_dense, criterion, optimizer_dense, scheduler_dense, num_epochs)

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_curves(history)
```

```
#####
```

```
# 10. Model Evaluation on Test Set
#####
model_dense.eval()
all_preds = []
all_probs = [] # Probabilities for malignant (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_dense(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Class 1 probability
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

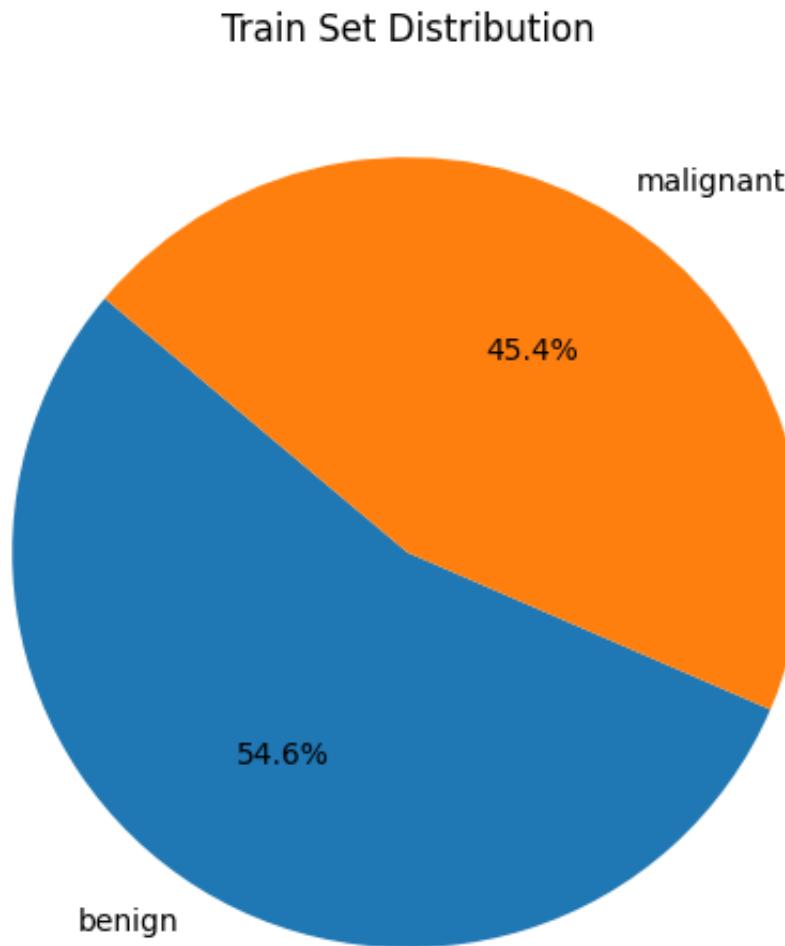
#####
# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.classes))

#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####
# 13. Visualization 5: ROC Curve & AUC
#####
```

```
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

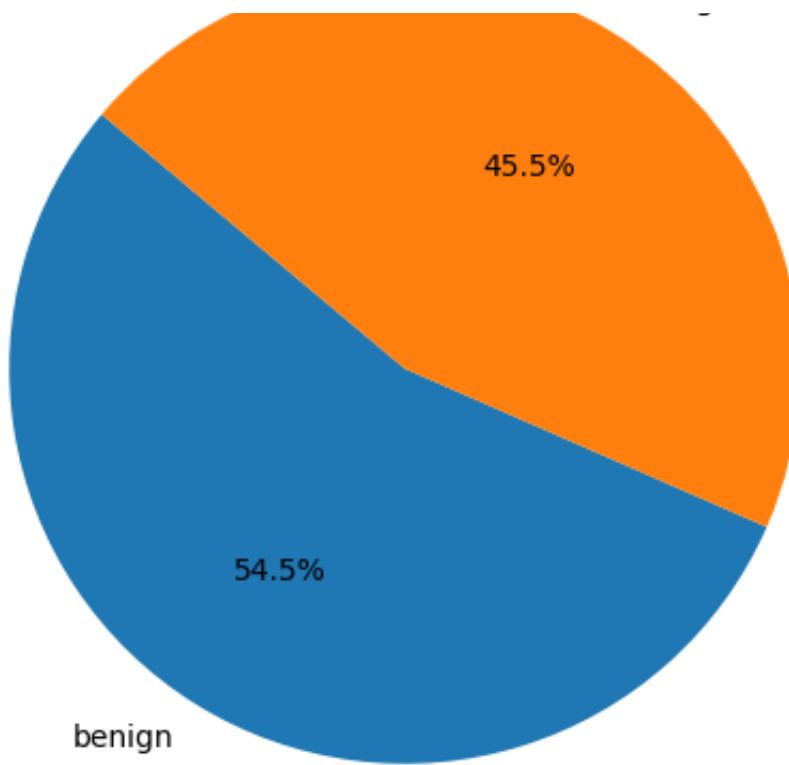
→ Using device: cuda:0
Train Set Distribution:



Test Set Distribution:

Test Set Distribution





```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: U
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: U
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/densenet201-c1103571.pth"
100%|██████████| 77.4M/77.4M [00:00<00:00, 222MB/s]
Epoch 1/25
-----
train: 100%|██████████| 165/165 [00:30<00:00,  5.50it/s]
Train Loss: 0.5082 Acc: 0.7516
val: 100%|██████████| 42/42 [00:02<00:00, 14.08it/s]
Val Loss: 0.3772 Acc: 0.8121

Epoch 2/25
-----
train: 100%|██████████| 165/165 [00:29<00:00,  5.54it/s]
Train Loss: 0.4339 Acc: 0.7952
val: 100%|██████████| 42/42 [00:02<00:00, 14.58it/s]
Val Loss: 0.3744 Acc: 0.8303

Epoch 3/25
-----
train: 100%|██████████| 165/165 [00:29<00:00,  5.51it/s]
Train Loss: 0.4199 Acc: 0.8002
val: 100%|██████████| 42/42 [00:02<00:00, 14.56it/s]
Val Loss: 0.3317 Acc: 0.8439

Epoch 4/25
-----
train: 100%|██████████| 165/165 [00:29<00:00,  5.56it/s]
```

```
Train Loss: 0.4053 Acc: 0.8074
val: 100%|██████████| 42/42 [00:02<00:00, 14.61it/s]
Val Loss: 0.3689 Acc: 0.8242
```

Epoch 5/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]
Train Loss: 0.3908 Acc: 0.8180
val: 100%|██████████| 42/42 [00:02<00:00, 14.48it/s]
Val Loss: 0.3660 Acc: 0.8136
```

Epoch 6/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.52it/s]
Train Loss: 0.3656 Acc: 0.8252
val: 100%|██████████| 42/42 [00:02<00:00, 14.47it/s]
Val Loss: 0.3651 Acc: 0.8439
```

Epoch 7/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]
Train Loss: 0.3830 Acc: 0.8210
val: 100%|██████████| 42/42 [00:02<00:00, 14.53it/s]
Val Loss: 0.3179 Acc: 0.8364
```

Epoch 8/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]
Train Loss: 0.3376 Acc: 0.8495
val: 100%|██████████| 42/42 [00:02<00:00, 14.17it/s]
Val Loss: 0.3061 Acc: 0.8515
```

Epoch 9/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]
Train Loss: 0.3167 Acc: 0.8593
val: 100%|██████████| 42/42 [00:02<00:00, 14.50it/s]
Val Loss: 0.3022 Acc: 0.8636
```

Epoch 10/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.54it/s]
Train Loss: 0.3049 Acc: 0.8699
val: 100%|██████████| 42/42 [00:02<00:00, 14.60it/s]
Val Loss: 0.3081 Acc: 0.8576
```

Epoch 11/25

```
-----  
train: 100%|██████████| 165/165 [00:30<00:00, 5.50it/s]
Train Loss: 0.2896 Acc: 0.8695
val: 100%|██████████| 42/42 [00:03<00:00, 13.94it/s]
Val Loss: 0.3025 Acc: 0.8621
```

Epoch 12/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.53it/s]  
Train Loss: 0.2764 Acc: 0.8760  
val: 100%|██████████| 42/42 [00:02<00:00, 14.55it/s]  
Val Loss: 0.3027 Acc: 0.8727
```

Epoch 13/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]  
Train Loss: 0.2757 Acc: 0.8779  
val: 100%|██████████| 42/42 [00:02<00:00, 14.54it/s]  
Val Loss: 0.3073 Acc: 0.8606
```

Epoch 14/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.54it/s]  
Train Loss: 0.2667 Acc: 0.8843  
val: 100%|██████████| 42/42 [00:02<00:00, 14.51it/s]  
Val Loss: 0.2979 Acc: 0.8727
```

Epoch 15/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.54it/s]  
Train Loss: 0.2778 Acc: 0.8756  
val: 100%|██████████| 42/42 [00:02<00:00, 14.54it/s]  
Val Loss: 0.2986 Acc: 0.8773
```

Epoch 16/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]  
Train Loss: 0.2654 Acc: 0.8752  
val: 100%|██████████| 42/42 [00:02<00:00, 14.54it/s]  
Val Loss: 0.3016 Acc: 0.8636
```

Epoch 17/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.56it/s]  
Train Loss: 0.2651 Acc: 0.8828  
val: 100%|██████████| 42/42 [00:02<00:00, 14.53it/s]  
Val Loss: 0.2992 Acc: 0.8758
```

Epoch 18/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.51it/s]  
Train Loss: 0.2560 Acc: 0.8859  
val: 100%|██████████| 42/42 [00:02<00:00, 14.53it/s]  
Val Loss: 0.2982 Acc: 0.8727
```

Epoch 19/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]  
Train Loss: 0.2585 Acc: 0.8847  
val: 100%|██████████| 42/42 [00:02<00:00, 14.51it/s]  
Val Loss: 0.2994 Acc: 0.8758
```

Epoch 20/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]  
Train Loss: 0.2578 Acc: 0.8859  
val: 100%|██████████| 42/42 [00:02<00:00, 14.53it/s]  
Val Loss: 0.2967 Acc: 0.8727
```

Epoch 21/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]  
Train Loss: 0.2609 Acc: 0.8805  
val: 100%|██████████| 42/42 [00:02<00:00, 14.55it/s]  
Val Loss: 0.2980 Acc: 0.8712
```

Epoch 22/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]  
Train Loss: 0.2725 Acc: 0.8768  
val: 100%|██████████| 42/42 [00:02<00:00, 14.54it/s]  
Val Loss: 0.2973 Acc: 0.8773
```

Epoch 23/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]  
Train Loss: 0.2518 Acc: 0.8832  
val: 100%|██████████| 42/42 [00:02<00:00, 14.58it/s]  
Val Loss: 0.2982 Acc: 0.8636
```

Epoch 24/25

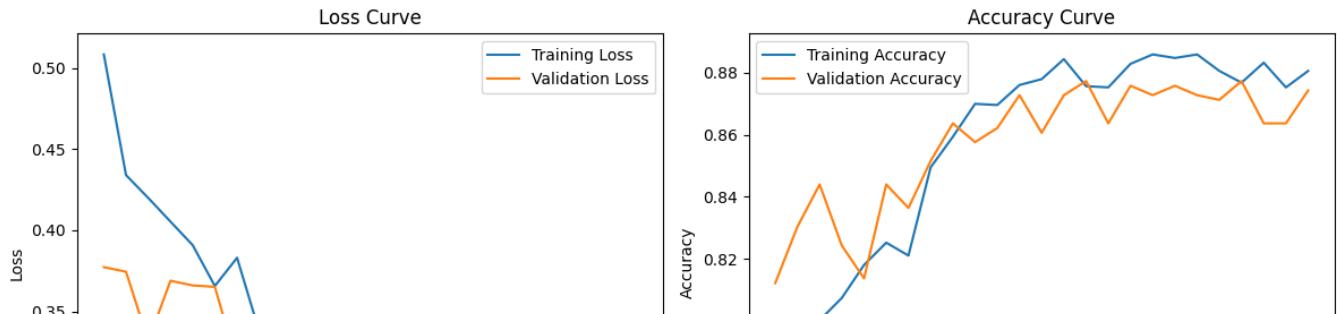
```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]  
Train Loss: 0.2653 Acc: 0.8752  
val: 100%|██████████| 42/42 [00:02<00:00, 14.66it/s]  
Val Loss: 0.2984 Acc: 0.8636
```

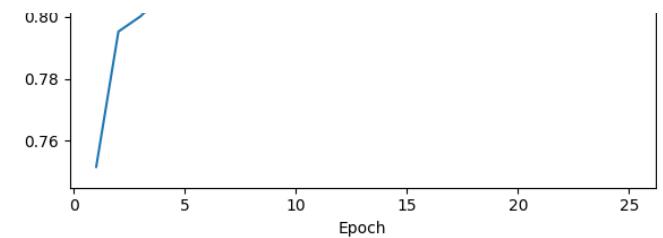
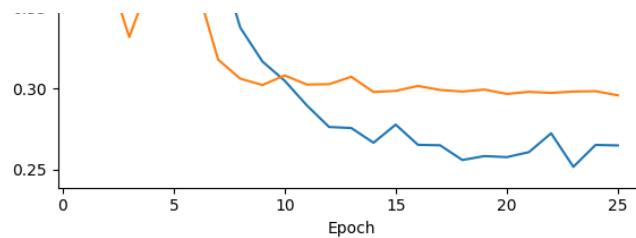
Epoch 25/25

```
-----  
train: 100%|██████████| 165/165 [00:29<00:00, 5.55it/s]  
Train Loss: 0.2650 Acc: 0.8805  
val: 100%|██████████| 42/42 [00:02<00:00, 14.51it/s]  
Val Loss: 0.2959 Acc: 0.8742
```

Training complete in 13m 38s

Best Validation Acc: 0.8773

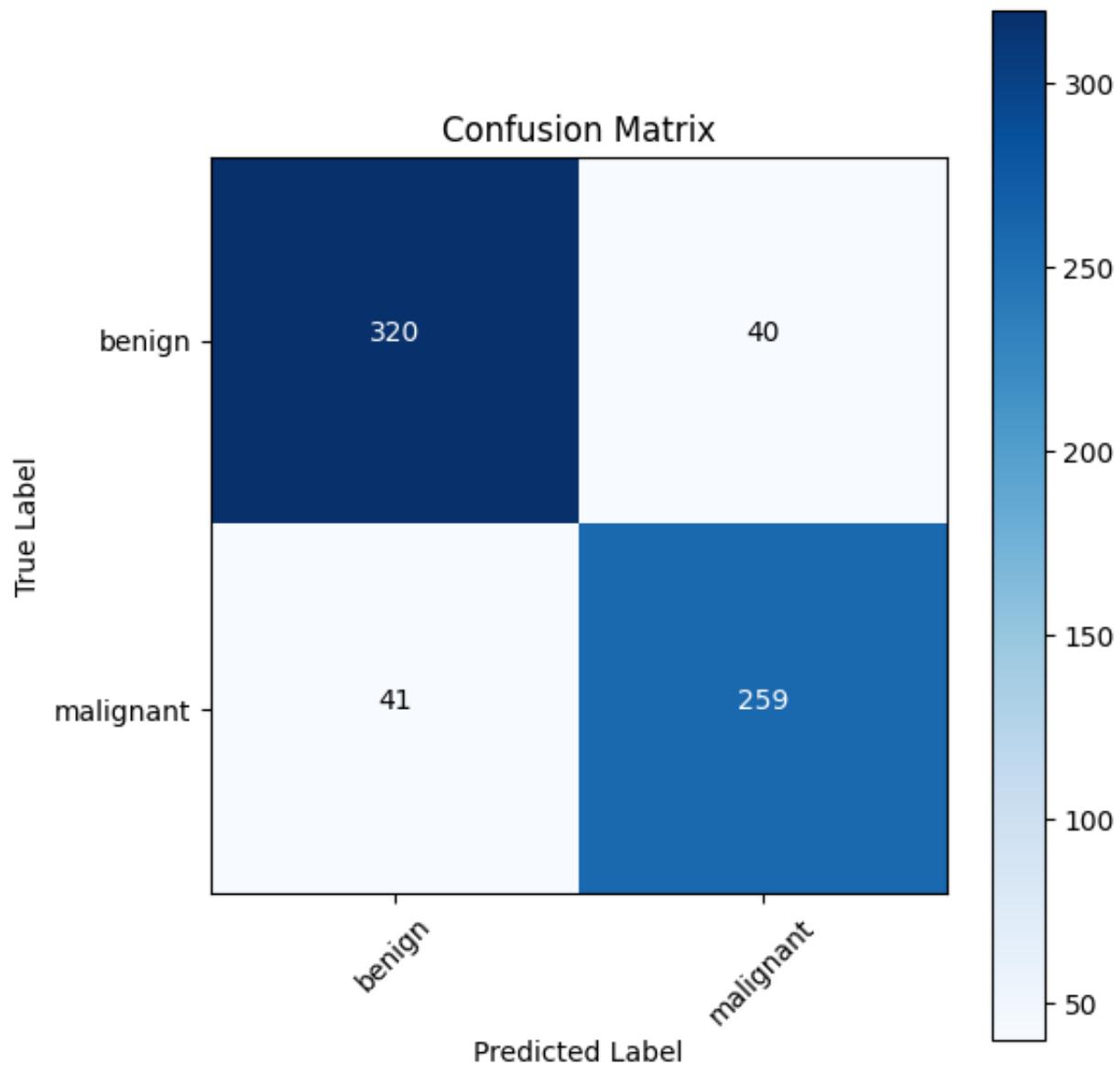




Testing: 100% | 42/42 [00:02<00:00, 14.62it/s]

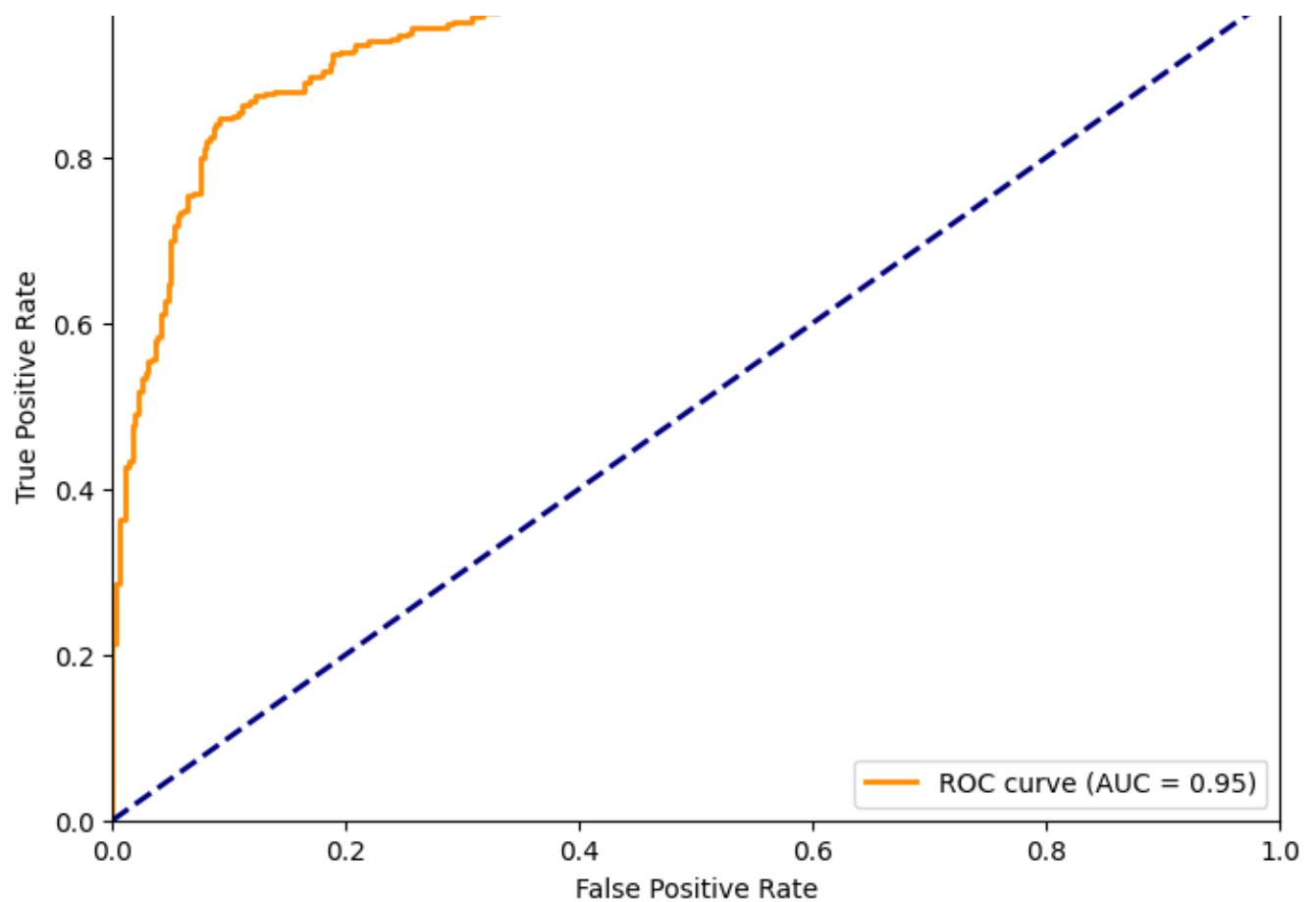
Classification Report:

	precision	recall	f1-score	support
benign	0.89	0.89	0.89	360
malignant	0.87	0.86	0.86	300
accuracy			0.88	660
macro avg	0.88	0.88	0.88	660
weighted avg	0.88	0.88	0.88	660



Receiver Operating Characteristic





Xception via TIMM

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
```

```
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm
import timm # PyTorch Image Models

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Dataset folder structure:
# data/
#   train/
#     benign/
#     malignant/
#   test/
#     benign/
#     malignant/

data_dir = '/kaggle/input/k-mean-clustering/segmented_data' # Update this path
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Define strong augmentations for training and standard transforms for testing.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),
    transforms.ToTensor(),
```

```
transforms.Normalize([0.485, 0.456, 0.406],
                   [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                       [0.229, 0.224, 0.225])
])

# Load datasets using ImageFolder.
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())
    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%1.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. DataLoaders
#####
# Adjust batch_size as needed (lower if encountering memory issues)
batch_size = 16
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r

#####
# 5. Model Initialization & Fine-Tuning (Xception)
#####
# Using TIMM to create the Xception model. Ensure timm is installed (pip instal
model_xception = timm.create_model('xception', pretrained=True, num_classes=2)
```

```
model_xception = model_xception.to(device)

#####
# 6. Training Function
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    # History lists for visualization.
    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    # Optionally use AMP for mixed precision training to speed up training and
    scaler = torch.cuda.amp.GradScaler()

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        print("-" * 10)
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
                dataloader = train_loader
            else:
                model.eval()
                dataloader = test_loader

            running_loss = 0.0
            running_corrects = 0
            total_samples = 0

            for inputs, labels in tqdm(dataloader, desc=phase):
                inputs = inputs.to(device)
                labels = labels.to(device)
                optimizer.zero_grad()

                with torch.set_grad_enabled(phase == 'train'):
                    with torch.cuda.amp.autocast():
                        outputs = model(inputs)
                        _, preds = torch.max(outputs, 1)
                        loss = criterion(outputs, labels)
                    if phase == 'train':
                        scaler.scale(loss).backward()
                        scaler.step(optimizer)
                        scaler.update()

            if phase == 'val':
                val_loss_history.append(running_loss / total_samples)
                val_acc_history.append((running_corrects / total_samples) * 100)
            else:
                train_loss_history.append(running_loss / total_samples)
                train_acc_history.append((running_corrects / total_samples) * 100)

            if phase == 'train':
                scheduler.step()

    return model, best_model_wts, best_acc
```

```
        running_loss += loss.item() * inputs.size(0)
        running_corrects += torch.sum(preds == labels.data).item()
        total_samples += inputs.size(0)

    if phase == 'train':
        scheduler.step()

    epoch_loss = running_loss / total_samples
    epoch_acc = running_corrects / total_samples
    print(f'{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

    if phase == 'train':
        train_loss_history.append(epoch_loss)
        train_acc_history.append(epoch_acc)
    else:
        val_loss_history.append(epoch_loss)
        val_acc_history.append(epoch_acc)
        if epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = copy.deepcopy(model.state_dict())
    print()

time_elapsed = time.time() - since
print(f'Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s')
print(f'Best Validation Acc: {best_acc:.4f}')

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_xception = optim.Adam(model_xception.parameters(), lr=1e-4)
scheduler_xception = lr_scheduler.StepLR(optimizer_xception, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####
num_epochs = 25
model_xception, history = train_model(model_xception, criterion, optimizer_xception, scheduler_xception, num_epochs, device)
```

```
#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_curves(history)

#####
# 10. Model Evaluation on Test Set
#####
model_xception.eval()
all_preds = []
all_probs = [] # Probabilities for malignant (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_xception(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Probability for
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
```

```
all_labels.extend(labels.cpu().numpy())

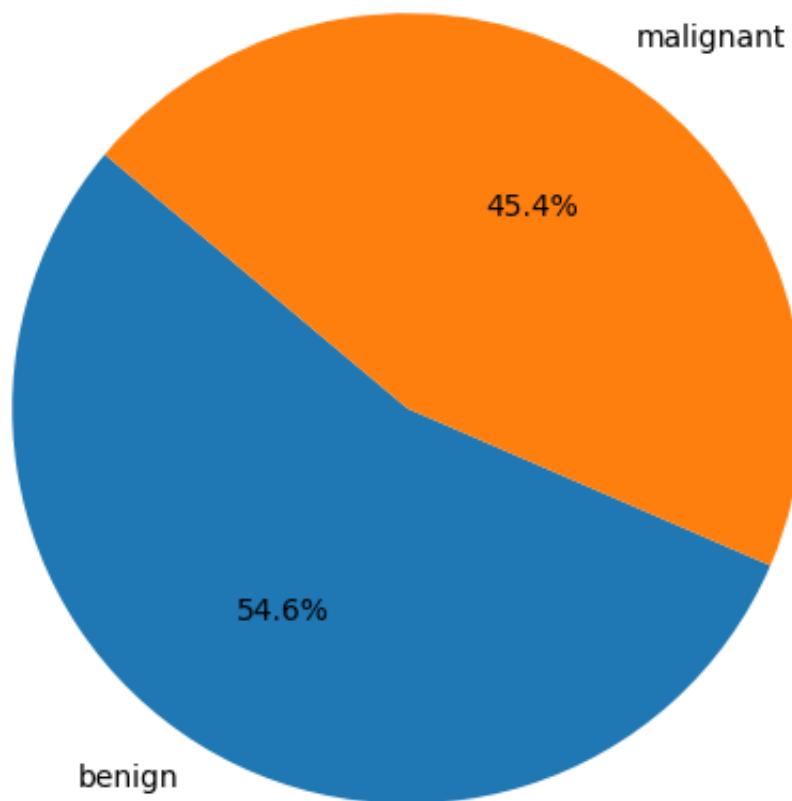
#####
# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####
# 13. Visualization 5: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

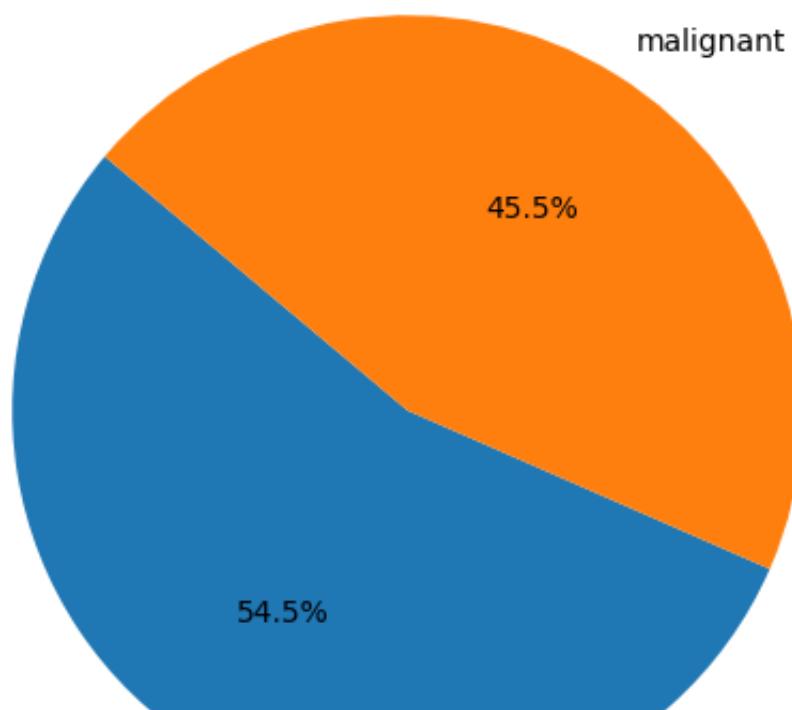
→ Using device: cuda:0
Train Set Distribution:

Train Set Distribution



Test Set Distribution:

Test Set Distribution





benign

```
/usr/local/lib/python3.10/dist-packages/timm/models/_factory.py:117: UserWa
    model = create_fn(
Downloading: "https://github.com/rwightman/pytorch-image-models/releases/do
<ipython-input-3-04627512dee3>:119: FutureWarning: `torch.cuda.amp.GradScal
    scaler = torch.cuda.amp.GradScaler()
Epoch 1/25
-----
train:  0% | 0/165 [00:00<?, ?it/s]<ipython-input-3-04627512dee3
    with torch.cuda.amp.autocast():
train: 100%|██████████| 165/165 [00:26<00:00,  6.31it/s]
Train Loss: 0.4901 Acc: 0.7490
val: 100%|██████████| 42/42 [00:02<00:00, 20.05it/s]
Val Loss: 0.4107 Acc: 0.7879

Epoch 2/25
-----
train: 100%|██████████| 165/165 [00:25<00:00,  6.36it/s]
Train Loss: 0.4177 Acc: 0.7952
val: 100%|██████████| 42/42 [00:02<00:00, 20.06it/s]
Val Loss: nan Acc: 0.8136

Epoch 3/25
-----
train: 100%|██████████| 165/165 [00:25<00:00,  6.37it/s]
Train Loss: 0.4136 Acc: 0.8062
val: 100%|██████████| 42/42 [00:02<00:00, 20.12it/s]
Val Loss: 0.3695 Acc: 0.8394

Epoch 4/25
-----
train: 100%|██████████| 165/165 [00:25<00:00,  6.36it/s]
Train Loss: 0.3669 Acc: 0.8286
val: 100%|██████████| 42/42 [00:02<00:00, 20.12it/s]
Val Loss: 0.3377 Acc: 0.8485

Epoch 5/25
-----
train: 100%|██████████| 165/165 [00:25<00:00,  6.36it/s]
Train Loss: 0.3615 Acc: 0.8309
val: 100%|██████████| 42/42 [00:02<00:00, 20.16it/s]
Val Loss: 0.3789 Acc: 0.8152

Epoch 6/25
-----
train: 100%|██████████| 165/165 [00:25<00:00,  6.35it/s]
Train Loss: 0.3395 Acc: 0.8464
val: 100%|██████████| 42/42 [00:02<00:00, 19.78it/s]
Val Loss: 0.3788 Acc: 0.8121
```

Epoch 7/25

```
-----  
train: 100%|██████████| 165/165 [00:26<00:00, 6.34it/s]  
Train Loss: 0.3336 Acc: 0.8366  
val: 100%|██████████| 42/42 [00:02<00:00, 20.09it/s]  
Val Loss: 0.3343 Acc: 0.8515
```

Epoch 8/25

```
-----  
train: 100%|██████████| 165/165 [00:25<00:00, 6.35it/s]  
Train Loss: 0.2932 Acc: 0.8756  
val: 100%|██████████| 42/42 [00:02<00:00, 20.05it/s]  
Val Loss: 0.3211 Acc: 0.8576
```

Epoch 9/25

```
-----  
train: 100%|██████████| 165/165 [00:26<00:00, 6.33it/s]  
Train Loss: 0.2828 Acc: 0.8752  
val: 100%|██████████| 42/42 [00:02<00:00, 19.70it/s]  
Val Loss: 0.3245 Acc: 0.8591
```

Epoch 10/25

```
-----  
train: 100%|██████████| 165/165 [00:26<00:00, 6.33it/s]  
Train Loss: 0.2582 Acc: 0.8836  
val: 100%|██████████| 42/42 [00:02<00:00, 19.39it/s]  
Val Loss: 0.3182 Acc: 0.8561
```

Epoch 11/25

```
-----  
train: 100%|██████████| 165/165 [00:26<00:00, 6.34it/s]  
Train Loss: 0.2496 Acc: 0.8915  
val: 100%|██████████| 42/42 [00:02<00:00, 20.06it/s]  
Val Loss: 0.3112 Acc: 0.8561
```

Epoch 12/25

```
-----  
train: 100%|██████████| 165/165 [00:26<00:00, 6.35it/s]  
Train Loss: 0.2600 Acc: 0.8866  
val: 100%|██████████| 42/42 [00:02<00:00, 19.86it/s]  
Val Loss: 0.3273 Acc: 0.8576
```

Epoch 13/25

```
-----  
train: 100%|██████████| 165/165 [00:26<00:00, 6.33it/s]  
Train Loss: 0.2478 Acc: 0.8889  
val: 100%|██████████| 42/42 [00:02<00:00, 17.69it/s]  
Val Loss: 0.3121 Acc: 0.8621
```

Epoch 14/25

```
-----  
train: 100%|██████████| 165/165 [00:26<00:00, 6.30it/s]  
Train Loss: 0.2443 Acc: 0.8904
```

```
val: 100%|██████████| 42/42 [00:02<00:00, 19.13it/s]
Val Loss: 0.3289 Acc: 0.8591

Epoch 15/25
-----
train: 100%|██████████| 165/165 [00:26<00:00, 6.33it/s]
Train Loss: 0.2400 Acc: 0.8900
val: 100%|██████████| 42/42 [00:02<00:00, 19.78it/s]
Val Loss: 0.3242 Acc: 0.8667

Epoch 16/25
-----
train: 100%|██████████| 165/165 [00:26<00:00, 6.34it/s]
Train Loss: 0.2373 Acc: 0.8942
val: 100%|██████████| 42/42 [00:02<00:00, 19.91it/s]
Val Loss: 0.3163 Acc: 0.8591

Epoch 17/25
-----
train: 100%|██████████| 165/165 [00:26<00:00, 6.34it/s]
Train Loss: 0.2485 Acc: 0.8881
val: 100%|██████████| 42/42 [00:02<00:00, 19.88it/s]
Val Loss: 0.3235 Acc: 0.8530

Epoch 18/25
-----
train: 100%|██████████| 165/165 [00:26<00:00, 6.33it/s]
Train Loss: 0.2358 Acc: 0.8953
val: 100%|██████████| 42/42 [00:02<00:00, 19.64it/s]
Val Loss: 0.3217 Acc: 0.8576

Epoch 19/25
-----
train: 100%|██████████| 165/165 [00:26<00:00, 6.33it/s]
Train Loss: 0.2348 Acc: 0.8991
val: 100%|██████████| 42/42 [00:02<00:00, 19.94it/s]
Val Loss: 0.3152 Acc: 0.8621

Epoch 20/25
-----
train: 100%|██████████| 165/165 [00:26<00:00, 6.33it/s]
Train Loss: 0.2296 Acc: 0.9033
val: 100%|██████████| 42/42 [00:02<00:00, 19.52it/s]
Val Loss: 0.3245 Acc: 0.8576

Epoch 21/25
-----
train: 100%|██████████| 165/165 [00:26<00:00, 6.33it/s]
Train Loss: 0.2255 Acc: 0.8980
val: 100%|██████████| 42/42 [00:02<00:00, 19.79it/s]
Val Loss: 0.3232 Acc: 0.8591

Epoch 22/25
-----
```

```
train: 100%|██████████| 165/165 [00:26<00:00, 6.34it/s]
Train Loss: 0.2348 Acc: 0.8976
val: 100%|██████████| 42/42 [00:02<00:00, 19.90it/s]
Val Loss: 0.3231 Acc: 0.8636
```

Epoch 23/25

```
train: 100%|██████████| 165/165 [00:26<00:00, 6.34it/s]
Train Loss: 0.2407 Acc: 0.8950
val: 100%|██████████| 42/42 [00:02<00:00, 19.78it/s]
Val Loss: 0.3237 Acc: 0.8606
```

Epoch 24/25

```
train: 100%|██████████| 165/165 [00:26<00:00, 6.31it/s]
Train Loss: 0.2314 Acc: 0.9006
val: 100%|██████████| 42/42 [00:02<00:00, 19.85it/s]
Val Loss: 0.3155 Acc: 0.8636
```

Epoch 25/25

```
train: 100%|██████████| 165/165 [00:26<00:00, 6.33it/s]
Train Loss: 0.2349 Acc: 0.8972
val: 100%|██████████| 42/42 [00:02<00:00, 19.81it/s]
Val Loss: 0.3168 Acc: 0.8576
```

Training complete in 11m 45s

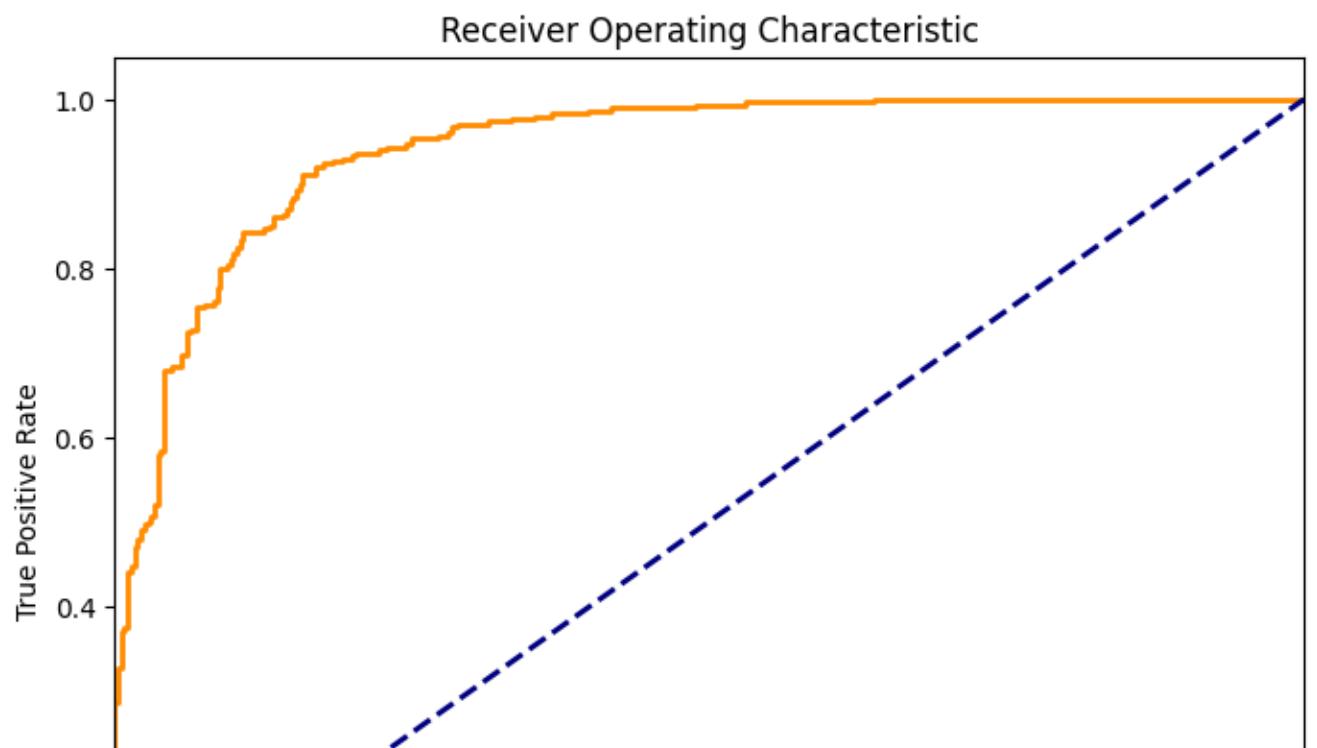
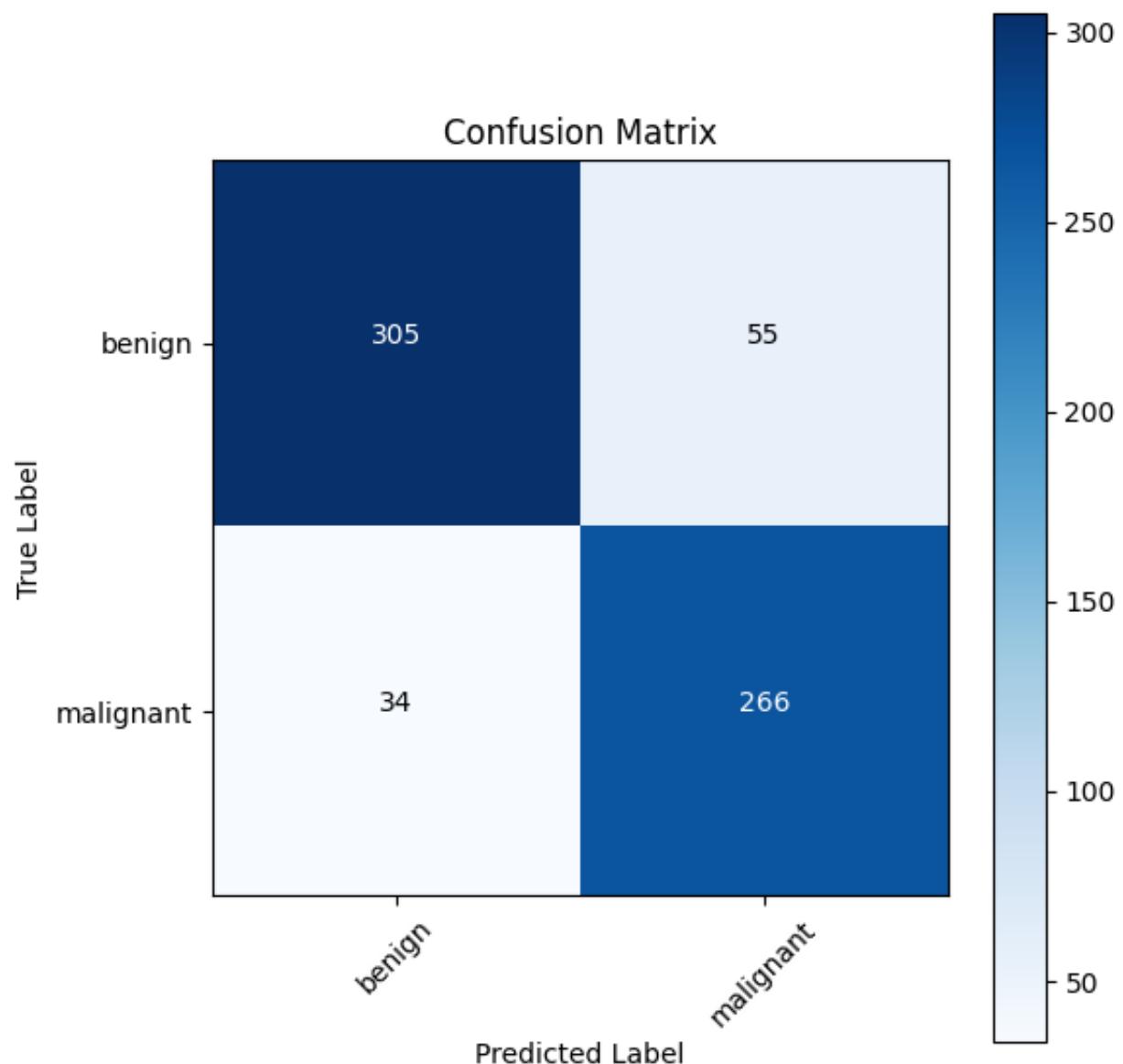
Best Validation Acc: 0.8667

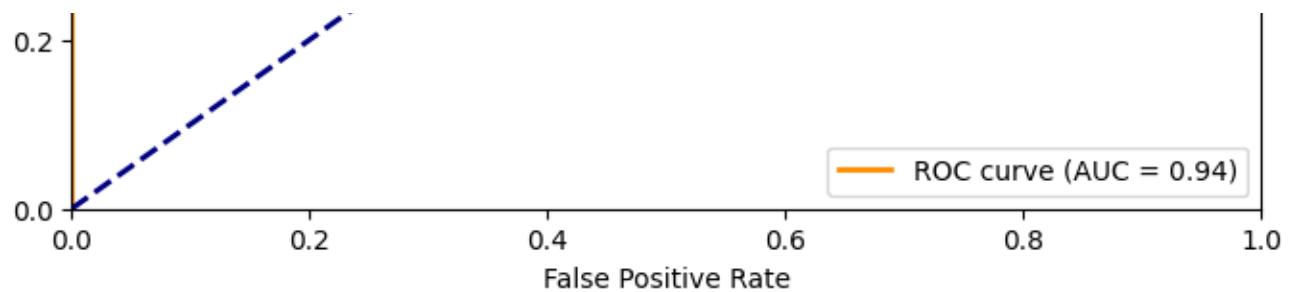


```
Testing: 100%|██████████| 42/42 [00:02<00:00, 18.81it/s]
```

Classification Report:

	precision	recall	f1-score	support
benign	0.90	0.85	0.87	360
malignant	0.83	0.89	0.86	300
accuracy			0.87	660
macro avg	0.86	0.87	0.86	660
weighted avg	0.87	0.87	0.87	660





InceptionV3

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
```

```
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Dataset directory structure:
# data/
#   ..train/
#     benign/
#     malignant/
#   test/
#     benign/
#     malignant/
data_dir = '/kaggle/input/k-mean-clustering/segmented_data' # Update as needed
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# InceptionV3 expects 299x299 images.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(299),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(320),
    transforms.CenterCrop(299),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])
])
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####
```

```
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())
    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. DataLoaders
#####
batch_size = 16 # Adjust if needed
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r

#####
# 5. Model Initialization & Fine-Tuning (InceptionV3)
#####
# Using the new weights API. Note: When using pretrained weights, aux_logits must
from torchvision.models import inception_v3, Inception_V3_Weights
weights = Inception_V3_Weights.IMAGENET1K_V1
model_inception = inception_v3(weights=weights, aux_logits=True)
# Replace the final fully connected layer. The default fc has in_features = 2048
in_features = model_inception.fc.in_features
model_inception.fc = nn.Linear(in_features, 2)
model_inception = model_inception.to(device)

#####
# 6. Training Function
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []
```

```
for epoch in range(num_epochs):
    print(f"Epoch {epoch+1}/{num_epochs}")
    print("-" * 10)

    # Each epoch has training and validation phases.
    for phase in ['train', 'val']:
        if phase == 'train':
            model.train()
            dataloader = train_loader
        else:
            model.eval()
            dataloader = test_loader

        running_loss = 0.0
        running_corrects = 0
        total_samples = 0

        for inputs, labels in tqdm(dataloader, desc=phase):
            inputs = inputs.to(device)
            labels = labels.to(device)
            optimizer.zero_grad()

            with torch.set_grad_enabled(phase == 'train'):
                outputs = model(inputs)
                # If outputs is a tuple (Inception returns (main, aux) when
                if isinstance(outputs, tuple):
                    outputs = outputs[0]
                _, preds = torch.max(outputs, 1)
                loss = criterion(outputs, labels)

                if phase == 'train':
                    loss.backward()
                    optimizer.step()

                running_loss += loss.item() * inputs.size(0)
                running_corrects += torch.sum(preds == labels.data).item()
                total_samples += inputs.size(0)

        if phase == 'train':
            scheduler.step()

        epoch_loss = running_loss / total_samples
        epoch_acc = running_corrects / total_samples
        print(f"{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}")

        if phase == 'train':
            train_loss_history.append(epoch_loss)
```

```
        train_acc_history.append(epoch_acc)
    else:
        val_loss_history.append(epoch_loss)
        val_acc_history.append(epoch_acc)
        if epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = copy.deepcopy(model.state_dict())
    print()

    time_elapsed = time.time() - since
    print(f"Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s")
    print(f"Best Validation Acc: {best_acc:.4f}")

    model.load_state_dict(best_model_wts)
    history = {
        'train_loss': train_loss_history,
        'train_acc': train_acc_history,
        'val_loss': val_loss_history,
        'val_acc': val_acc_history
    }
    return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_inception = optim.Adam(model_inception.parameters(), lr=1e-4)
scheduler_inception = lr_scheduler.StepLR(optimizer_inception, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####
num_epochs = 25
model_inception, history = train_model(model_inception, criterion, optimizer_inception, scheduler_inception, num_epochs)

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
```

```
plt.ylabel('Loss')
plt.legend()

# Accuracy Curve
plt.subplot(1, 2, 2)
plt.plot(epochs, history['train_acc'], label='Training Accuracy')
plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
plt.title('Accuracy Curve')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()

plot_training_curves(history)

#####
# 10. Model Evaluation on Test Set
#####
model_inception.eval()
all_preds = []
all_probs = [] # Probabilities for malignant (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_inception(inputs)
        # Use only the primary output
        if isinstance(outputs, tuple):
            outputs = outputs[0]
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Probability for
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

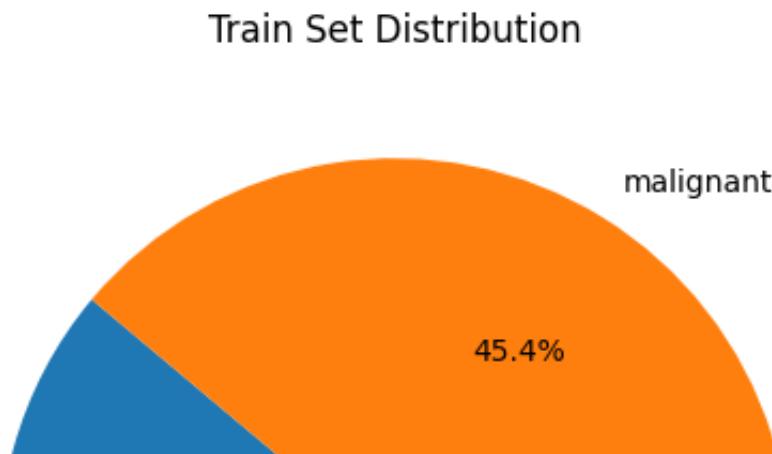
#####
# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

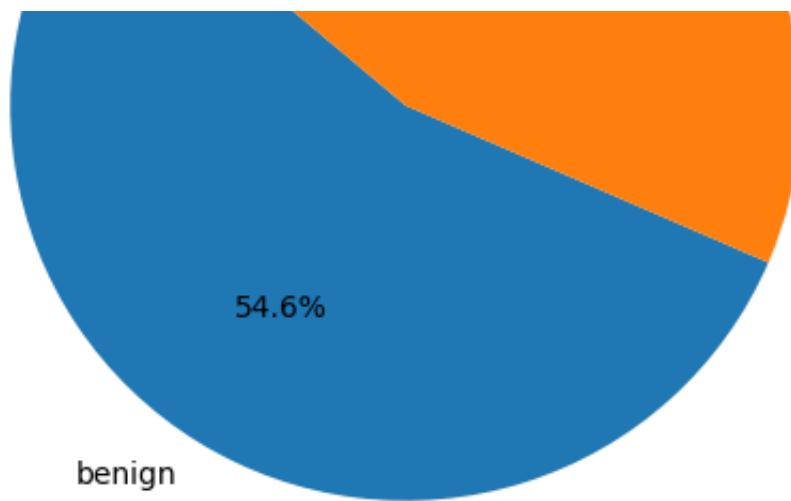
#####
# 12. Visualization 4: Confusion Matrix
#####
```

```
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####
# 13. Visualization 5: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:0.4f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

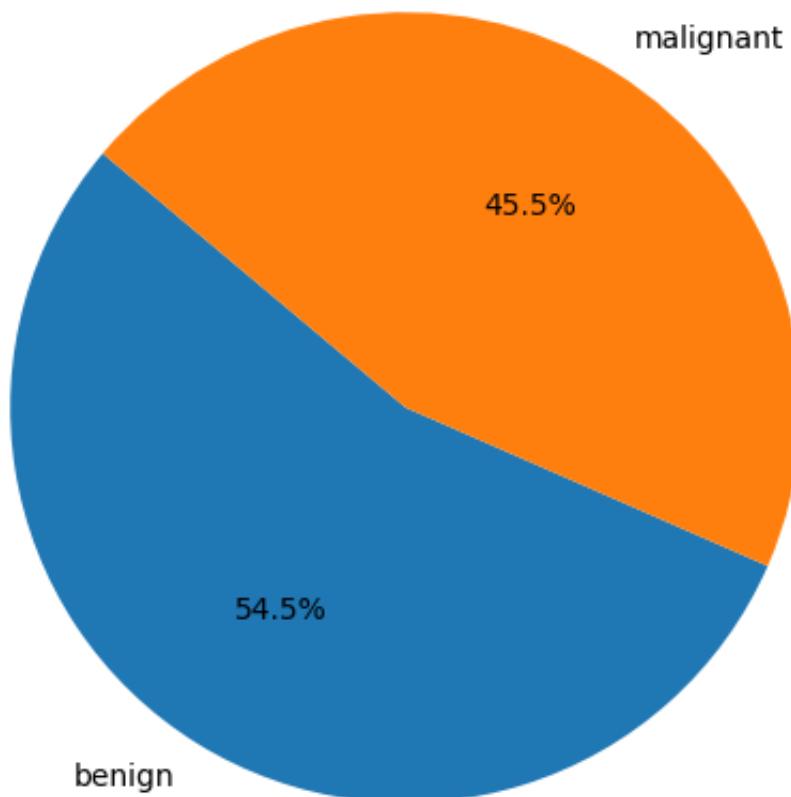
→ Using device: cuda:0
Train Set Distribution:





Test Set Distribution:

Test Set Distribution



```
Downloading: "https://download.pytorch.org/models/inception_v3_google-0cc3c
100% |██████████| 104M/104M [00:00<00:00, 168MB/s]
Epoch 1/25
-----
train: 100%|██████████| 165/165 [00:28<00:00,  5.72it/s]
Train Loss: 0.4995 Acc: 0.7596
test: 100%|██████████| 165/165 [00:02<00:00, 16.02it/s]
```

```
val: 100%|██████████| 42/42 [00:02<00:00, 10.72it/s]
Val Loss: 0.3934 Acc: 0.8121
```

Epoch 2/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.4326 Acc: 0.7990
val: 100%|██████████| 42/42 [00:02<00:00, 16.36it/s]
Val Loss: 0.3913 Acc: 0.8197
```

Epoch 3/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.4108 Acc: 0.8020
val: 100%|██████████| 42/42 [00:02<00:00, 17.61it/s]
Val Loss: 0.3547 Acc: 0.8364
```

Epoch 4/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.3895 Acc: 0.8142
val: 100%|██████████| 42/42 [00:02<00:00, 16.75it/s]
Val Loss: 0.4135 Acc: 0.8242
```

Epoch 5/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.3723 Acc: 0.8350
val: 100%|██████████| 42/42 [00:02<00:00, 17.52it/s]
Val Loss: 0.3798 Acc: 0.8439
```

Epoch 6/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.3768 Acc: 0.8237
val: 100%|██████████| 42/42 [00:02<00:00, 17.32it/s]
Val Loss: 0.3564 Acc: 0.8409
```

Epoch 7/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.3400 Acc: 0.8536
val: 100%|██████████| 42/42 [00:02<00:00, 16.87it/s]
Val Loss: 0.3472 Acc: 0.8424
```

Epoch 8/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.3174 Acc: 0.8593
val: 100%|██████████| 42/42 [00:02<00:00, 17.48it/s]
Val Loss: 0.3327 Acc: 0.8485
```

Epoch 9/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.3000 Acc: 0.8631
```

```
train: 100%|██████████| 165/165 [00:28<00:00, 5.73it/s]
Train Loss: 0.3029 Acc: 0.8578
val: 100%|██████████| 42/42 [00:02<00:00, 17.63it/s]
Val Loss: 0.3270 Acc: 0.8485
```

Epoch 10/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.73it/s]
Train Loss: 0.2835 Acc: 0.8684
val: 100%|██████████| 42/42 [00:02<00:00, 17.51it/s]
Val Loss: 0.3236 Acc: 0.8545
```

Epoch 11/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.2959 Acc: 0.8669
val: 100%|██████████| 42/42 [00:02<00:00, 17.51it/s]
Val Loss: 0.3238 Acc: 0.8530
```

Epoch 12/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.73it/s]
Train Loss: 0.2565 Acc: 0.8832
val: 100%|██████████| 42/42 [00:02<00:00, 17.36it/s]
Val Loss: 0.3214 Acc: 0.8682
```

Epoch 13/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.74it/s]
Train Loss: 0.2735 Acc: 0.8703
val: 100%|██████████| 42/42 [00:02<00:00, 16.80it/s]
Val Loss: 0.3220 Acc: 0.8591
```

Epoch 14/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.73it/s]
Train Loss: 0.2457 Acc: 0.8874
val: 100%|██████████| 42/42 [00:02<00:00, 17.48it/s]
Val Loss: 0.3441 Acc: 0.8545
```

Epoch 15/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.74it/s]
Train Loss: 0.2570 Acc: 0.8896
val: 100%|██████████| 42/42 [00:02<00:00, 17.50it/s]
Val Loss: 0.3439 Acc: 0.8576
```

Epoch 16/25

```
-----  
train: 100%|██████████| 165/165 [00:28<00:00, 5.76it/s]
Train Loss: 0.2601 Acc: 0.8900
val: 100%|██████████| 42/42 [00:02<00:00, 17.56it/s]
Val Loss: 0.3320 Acc: 0.8591
```

```
Epoch 1 / 25
-----
train: 100%|██████████| 165/165 [00:28<00:00, 5.76it/s]
Train Loss: 0.2717 Acc: 0.8779
val: 100%|██████████| 42/42 [00:02<00:00, 17.54it/s]
Val Loss: 0.3346 Acc: 0.8591
```

Epoch 18 / 25

```
-----
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.2544 Acc: 0.8862
val: 100%|██████████| 42/42 [00:02<00:00, 17.64it/s]
Val Loss: 0.3358 Acc: 0.8515
```

Epoch 19 / 25

```
-----
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.2478 Acc: 0.8938
val: 100%|██████████| 42/42 [00:02<00:00, 17.71it/s]
Val Loss: 0.3306 Acc: 0.8561
```

Epoch 20 / 25

```
-----
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.2487 Acc: 0.8889
val: 100%|██████████| 42/42 [00:02<00:00, 17.66it/s]
Val Loss: 0.3336 Acc: 0.8591
```

Epoch 21 / 25

```
-----
train: 100%|██████████| 165/165 [00:28<00:00, 5.74it/s]
Train Loss: 0.2587 Acc: 0.8836
val: 100%|██████████| 42/42 [00:02<00:00, 17.51it/s]
Val Loss: 0.3313 Acc: 0.8576
```

Epoch 22 / 25

```
-----
train: 100%|██████████| 165/165 [00:28<00:00, 5.74it/s]
Train Loss: 0.2531 Acc: 0.8938
val: 100%|██████████| 42/42 [00:02<00:00, 16.67it/s]
Val Loss: 0.3288 Acc: 0.8561
```

Epoch 23 / 25

```
-----
train: 100%|██████████| 165/165 [00:28<00:00, 5.76it/s]
Train Loss: 0.2358 Acc: 0.8953
val: 100%|██████████| 42/42 [00:02<00:00, 16.24it/s]
Val Loss: 0.3241 Acc: 0.8621
```

Epoch 24 / 25

```
-----
train: 100%|██████████| 165/165 [00:28<00:00, 5.75it/s]
Train Loss: 0.2487 Acc: 0.8885
val: 100%|██████████| 42/42 [00:02<00:00, 15.69it/s]
```

Val Loss: 0.3347 Acc: 0.8591

Epoch 25/25

train: 100%|██████████| 165/165 [00:28<00:00, 5.76it/s]

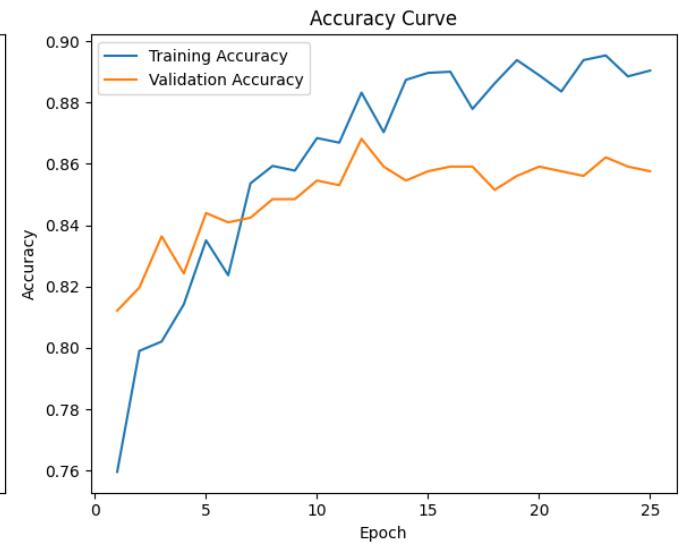
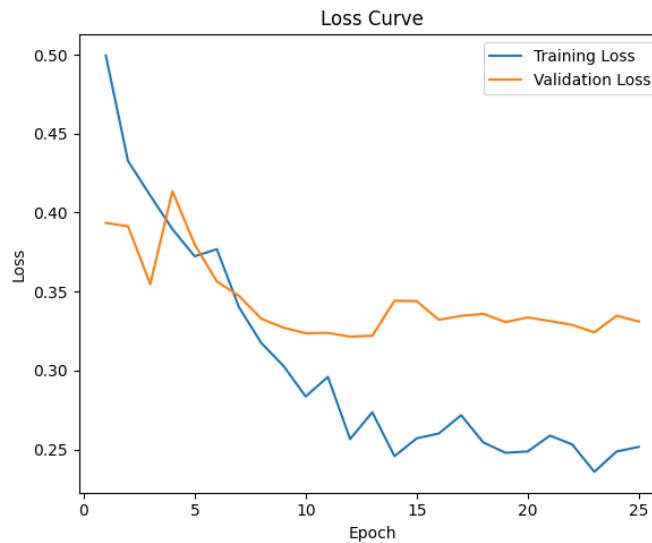
Train Loss: 0.2516 Acc: 0.8904

val: 100%|██████████| 42/42 [00:02<00:00, 17.11it/s]

Val Loss: 0.3310 Acc: 0.8576

Training complete in 12m 60s

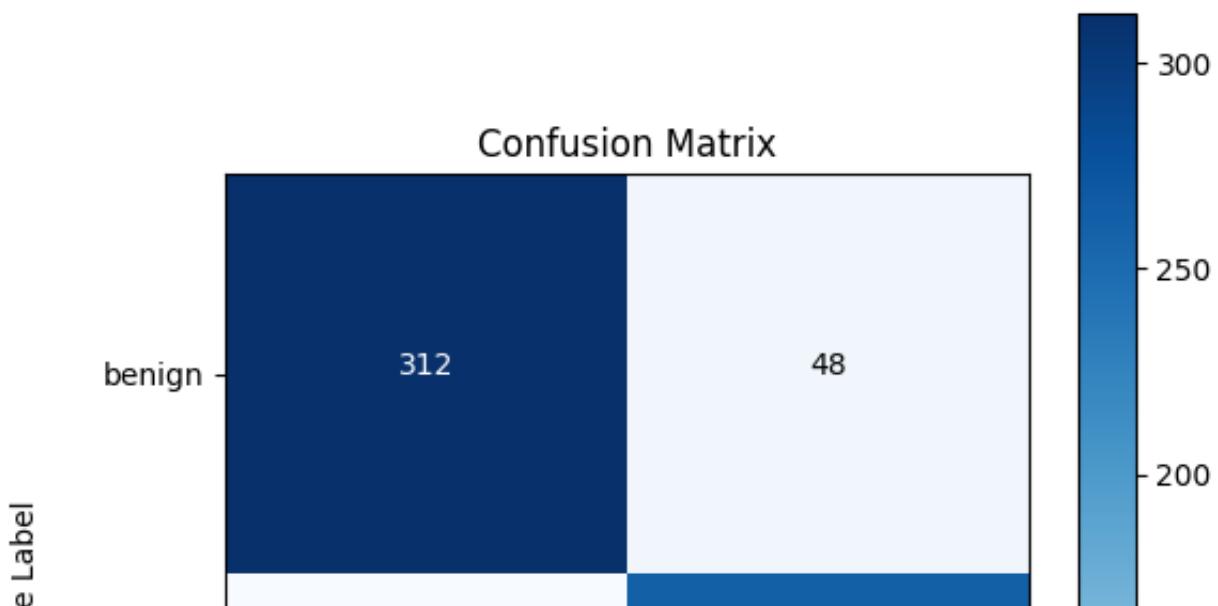
Best Validation Acc: 0.8682

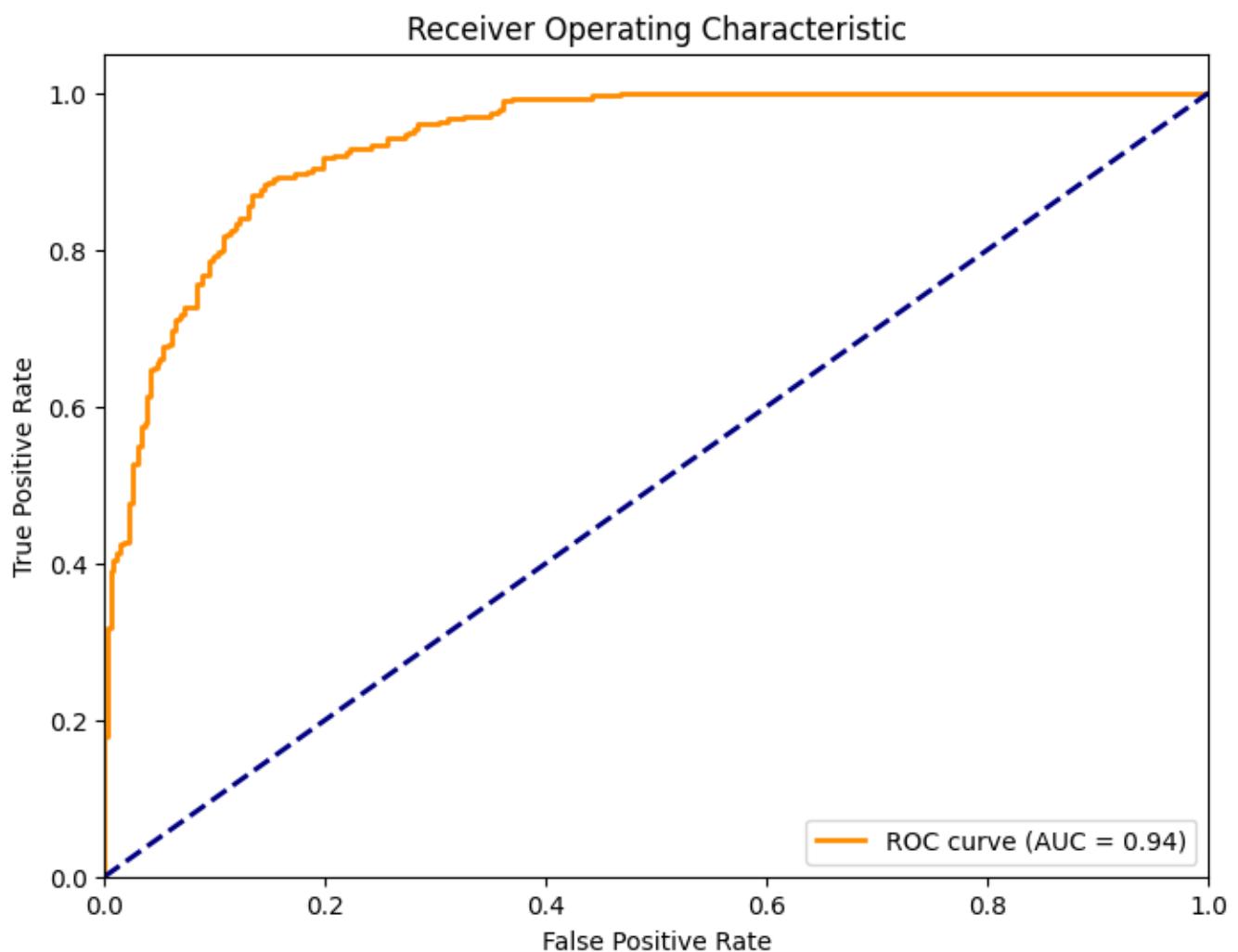
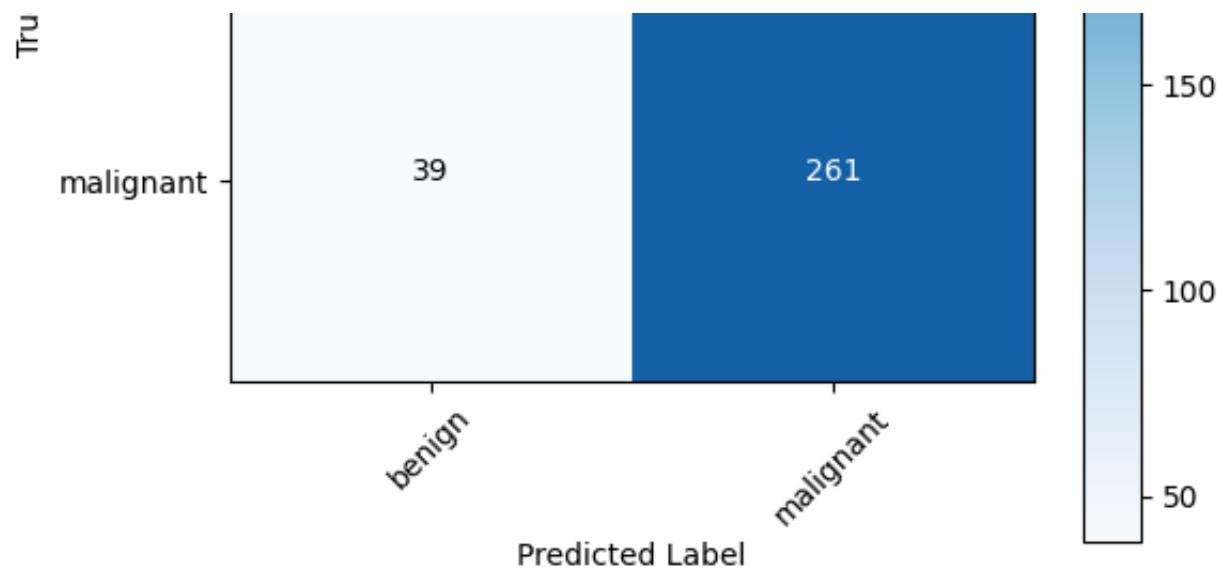


Testing: 100%|██████████| 42/42 [00:02<00:00, 16.81it/s]

Classification Report:

	precision	recall	f1-score	support
benign	0.89	0.87	0.88	360
malignant	0.84	0.87	0.86	300
accuracy			0.87	660
macro avg	0.87	0.87	0.87	660
weighted avg	0.87	0.87	0.87	660





▼ EfficientNetV2-L

```
import os
os.environ["PYT0RCH_CUDA_ALLOC_CONF"] = "expandable_segments:True"

import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader, Subset
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from sklearn.model_selection import StratifiedKFold
from tqdm import tqdm

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)
```

```
#####
# 2. Data Preparation & Augmentation
#####
# Adjust these paths to your dataset location
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)'
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Data augmentation for training and standard transforms for testing.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
# Load datasets using ImageFolder (expects subdirectories "benign" and "malignant")
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization: Dataset Class Distribution (Pie Chart)
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())

    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
```

```
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. DataLoaders
#####
batch_size = 8 # Reduced batch size to save GPU memory
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r

#####
# 5. Model Initialization & Fine-Tuning (EfficientNet_V2_L)
#####
from torchvision.models import efficientnet_v2_l, EfficientNet_V2_L_Weights
weights = EfficientNet_V2_L_Weights.IMGNET1K_V1
model_ft = efficientnet_v2_l(weights=weights)
num_ftrs = model_ft.classifier[1].in_features
model_ft.classifier = nn.Sequential(
    nn.Dropout(p=0.5),
    nn.Linear(num_ftrs, 2)
)
model_ft = model_ft.to(device)

#####
# 6. Training Function with Mixed Precision
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    # Initialize GradScaler for mixed precision training
    scaler = torch.cuda.amp.GradScaler()

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        print("-" * 10)

        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
                dataloader = train_loader
            else:
```

```
model.eval()
dataloader = test_loader

running_loss = 0.0
running_corrects = 0
total_samples = 0

for inputs, labels in tqdm(dataloader, desc=phase):
    inputs = inputs.to(device)
    labels = labels.to(device)
    optimizer.zero_grad()

    with torch.set_grad_enabled(phase == 'train'):
        with torch.cuda.amp.autocast():
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            loss = criterion(outputs, labels)

        if phase == 'train':
            scaler.scale(loss).backward()
            scaler.step(optimizer)
            scaler.update()

    running_loss += loss.item() * inputs.size(0)
    running_corrects += torch.sum(preds == labels.data).item()
    total_samples += inputs.size(0)

epoch_loss = running_loss / total_samples
epoch_acc = running_corrects / total_samples
print(f'{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

if phase == 'train':
    train_loss_history.append(epoch_loss)
    train_acc_history.append(epoch_acc)
    scheduler.step()
else:
    val_loss_history.append(epoch_loss)
    val_acc_history.append(epoch_acc)
    if epoch_acc > best_acc:
        best_acc = epoch_acc
        best_model_wts = copy.deepcopy(model.state_dict())
print()

time_elapsed = time.time() - since
print(f'Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s')
print(f'Best Validation Acc: {best_acc:.4f}')

model.load_state_dict(best_model_wts)
```

```
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

#####
# 7. K-Fold Cross Validation Training with EfficientNet_V2_L
#####
num_folds = 5
batch_size = 8 # Use the same small batch size here
skf = StratifiedKFold(n_splits=num_folds, shuffle=True, random_state=42)
targets = [s[1] for s in train_dataset.samples]

fold_histories = []
best_fold_model = None
best_fold_val_acc = 0.0

for fold, (train_idx, val_idx) in enumerate(skf.split(np.zeros(len(targets)), t
    print(f"===== Fold {fold+1}/{num_folds} =====")
    from torch.utils.data import Subset
    train_subset = Subset(train_dataset, train_idx)
    val_subset = Subset(train_dataset, val_idx)

    train_loader_fold = DataLoader(train_subset, batch_size=batch_size, shuffle=f
    val_loader_fold = DataLoader(val_subset, batch_size=batch_size, shuffle=f

    # Initialize a new EfficientNet_V2_L for the fold
    model_fold = efficientnet_v2_l(weights=weights)
    num_ftrs = model_fold.classifier[1].in_features
    model_fold.classifier = nn.Sequential(
        nn.Dropout(p=0.5),
        nn.Linear(num_ftrs, 2)
    )
    model_fold = model_fold.to(device)

    criterion = nn.CrossEntropyLoss()
    optimizer_fold = optim.Adam(model_fold.parameters(), lr=1e-4)
    scheduler_fold = lr_scheduler.StepLR(optimizer_fold, step_size=7, gamma=0.1

    # Train on current fold
    model_fold, history = train_model(model_fold, criterion, optimizer_fold, sc
    fold_histories.append(history)

    current_best = max(history['val_acc'])
    print(f"Fold {fold+1} best Val Acc: {current_best:.4f}")
```

```
if current_best > best_fold_val_acc:
    best_fold_val_acc = current_best
    best_fold_model = model_fold

# Clear GPU memory after each fold
del model_fold
torch.cuda.empty_cache()

print(f"\nOverall Best Fold Val Acc: {best_fold_val_acc:.4f}")

#####
# 8. Plot Training Curves (Best Fold)
#####
best_history = fold_histories[np.argmax([max(h['val_acc']) for h in fold_histories])]
epochs = range(1, len(best_history['train_loss']) + 1)
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(epochs, best_history['train_loss'], label='Train Loss')
plt.plot(epochs, best_history['val_loss'], label='Val Loss')
plt.title('Loss Curve (Best Fold)')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1,2,2)
plt.plot(epochs, best_history['train_acc'], label='Train Acc')
plt.plot(epochs, best_history['val_acc'], label='Val Acc')
plt.title('Accuracy Curve (Best Fold)')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.tight_layout()
plt.show()

#####
# 9. Final Evaluation on Test Set
#####
# Ensure the best_fold_model is available (reload if saved externally)
best_fold_model.eval()
all_preds = []
all_probs = [] # probabilities for malignant (class index 1)
all_labels = []

test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, num_workers=4)
with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = best_fold_model(inputs)
```

```
probs = nn.functional.softmax(outputs, dim=1)[:, 1]
_, preds = torch.max(outputs, 1)
all_preds.extend(preds.cpu().numpy())
all_probs.extend(probs.cpu().numpy())
all_labels.extend(labels.cpu().numpy())

#####
# 10. Visualization: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

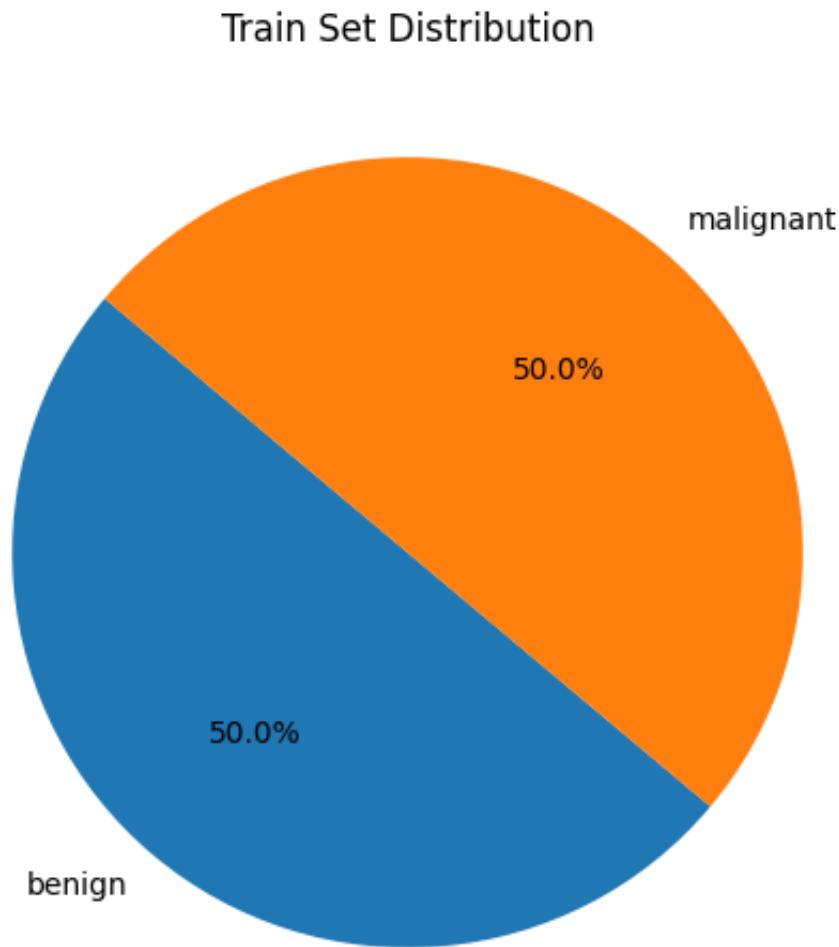
#####
# 11. Visualization: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
              horizontalalignment="center",
              color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####
# 12. Visualization: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])telegram web
telegram web

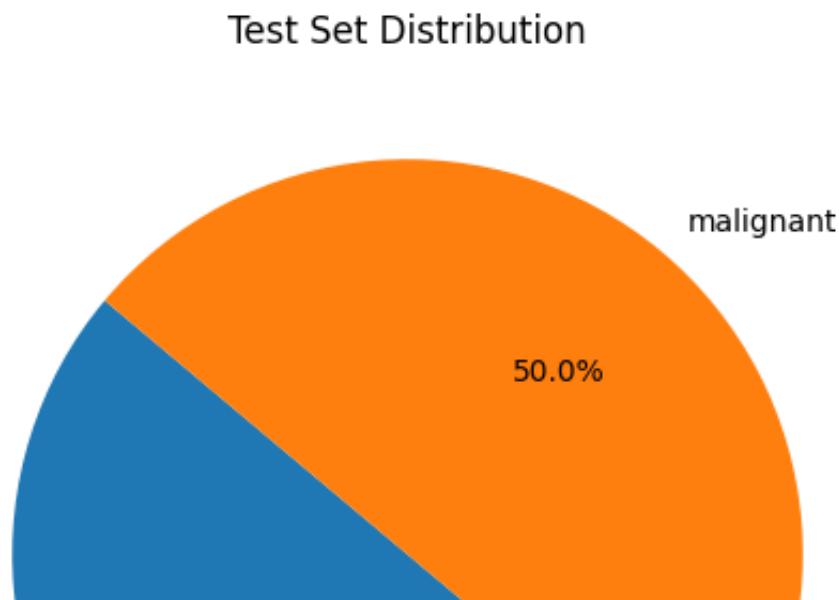
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
```

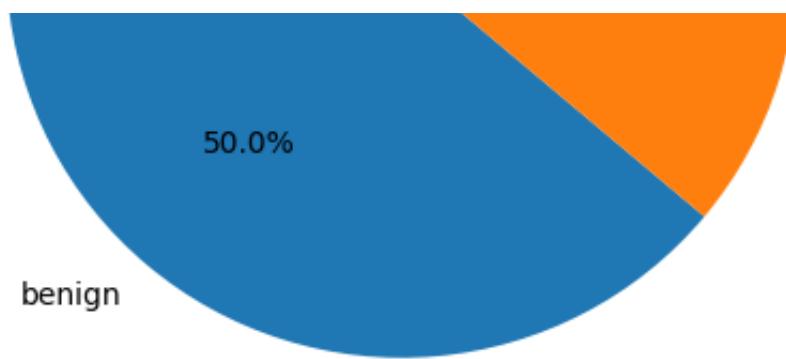
```
plt.legend(loc="lower right")
plt.show()
```

Using device: cuda:0
Train Set Distribution:



Test Set Distribution:





```
Downloading: "https://download.pytorch.org/models/efficientnet\_v2\_l-59c7131
100%|██████████| 455M/455M [00:08<00:00, 59.0MB/s]
=====
<ipython-input-1-ea2fae48a96a>:116: FutureWarning: `torch.cuda.amp.GradScal
    scaler = torch.cuda.amp.GradScaler()
Epoch 1/25
-----
train:  0%|          | 0/360 [00:00<?, ?it/s]<ipython-input-1-ea2fae48a96a
    with torch.cuda.amp.autocast():
train: 100%|██████████| 360/360 [01:53<00:00,  3.18it/s]
Train Loss: 0.5118 Acc: 0.7462
val: 100%|██████████| 90/90 [00:06<00:00, 13.31it/s]
Val Loss: 0.4095 Acc: 0.7986

Epoch 2/25
-----
train: 100%|██████████| 360/360 [01:50<00:00,  3.25it/s]
Train Loss: 0.4807 Acc: 0.7590
val: 100%|██████████| 90/90 [00:06<00:00, 13.16it/s]
Val Loss: 0.3361 Acc: 0.8361

Epoch 3/25
-----
train: 100%|██████████| 360/360 [01:50<00:00,  3.26it/s]
Train Loss: 0.4491 Acc: 0.7833
val: 100%|██████████| 90/90 [00:06<00:00, 13.28it/s]
Val Loss: 0.3494 Acc: 0.8250

Epoch 4/25
-----
train: 100%|██████████| 360/360 [01:51<00:00,  3.24it/s]
Train Loss: 0.4282 Acc: 0.7934
val: 100%|██████████| 90/90 [00:06<00:00, 13.16it/s]
Val Loss: 0.3463 Acc: 0.8486

Epoch 5/25
-----
train: 100%|██████████| 360/360 [01:50<00:00,  3.27it/s]
Train Loss: 0.4033 Acc: 0.8010
val: 100%|██████████| 90/90 [00:06<00:00, 13.34it/s]
Val Loss: 0.3218 Acc: 0.8625
```

Epoch 6/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]  
Train Loss: 0.3879 Acc: 0.8174  
val: 100%|██████████| 90/90 [00:06<00:00, 13.16it/s]  
Val Loss: 0.3714 Acc: 0.8181
```

Epoch 7/25

```
-----  
train: 100%|██████████| 360/360 [01:51<00:00, 3.24it/s]  
Train Loss: 0.3889 Acc: 0.8219  
val: 100%|██████████| 90/90 [00:06<00:00, 13.23it/s]  
Val Loss: 0.3172 Acc: 0.8569
```

Epoch 8/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]  
Train Loss: 0.3367 Acc: 0.8490  
val: 100%|██████████| 90/90 [00:06<00:00, 13.01it/s]  
Val Loss: 0.3267 Acc: 0.8583
```

Epoch 9/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]  
Train Loss: 0.3199 Acc: 0.8479  
val: 100%|██████████| 90/90 [00:06<00:00, 13.16it/s]  
Val Loss: 0.2957 Acc: 0.8639
```

Epoch 10/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]  
Train Loss: 0.3136 Acc: 0.8490  
val: 100%|██████████| 90/90 [00:06<00:00, 13.16it/s]  
Val Loss: 0.3017 Acc: 0.8667
```

Epoch 11/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]  
Train Loss: 0.3078 Acc: 0.8712  
val: 100%|██████████| 90/90 [00:06<00:00, 13.21it/s]  
Val Loss: 0.2846 Acc: 0.8778
```

Epoch 12/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]  
Train Loss: 0.2962 Acc: 0.8618  
val: 100%|██████████| 90/90 [00:06<00:00, 13.19it/s]  
Val Loss: 0.2936 Acc: 0.8694
```

Epoch 13/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]  
Train Loss: 0.2952 Acc: 0.8681
```

```
val: 100%|██████████| 90/90 [00:06<00:00, 13.21it/s]
Val Loss: 0.2841 Acc: 0.8736

Epoch 14/25
-----
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.2823 Acc: 0.8715
val: 100%|██████████| 90/90 [00:06<00:00, 13.26it/s]
Val Loss: 0.2801 Acc: 0.8750

Epoch 15/25
-----
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.2705 Acc: 0.8778
val: 100%|██████████| 90/90 [00:06<00:00, 13.28it/s]
Val Loss: 0.2819 Acc: 0.8681

Epoch 16/25
-----
train: 100%|██████████| 360/360 [01:50<00:00, 3.24it/s]
Train Loss: 0.2849 Acc: 0.8701
val: 100%|██████████| 90/90 [00:06<00:00, 13.09it/s]
Val Loss: 0.2860 Acc: 0.8736

Epoch 17/25
-----
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]
Train Loss: 0.2695 Acc: 0.8771
val: 100%|██████████| 90/90 [00:06<00:00, 13.14it/s]
Val Loss: 0.2826 Acc: 0.8722

Epoch 18/25
-----
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.2754 Acc: 0.8764
val: 100%|██████████| 90/90 [00:06<00:00, 13.35it/s]
Val Loss: 0.2876 Acc: 0.8681

Epoch 19/25
-----
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]
Train Loss: 0.2677 Acc: 0.8809
val: 100%|██████████| 90/90 [00:06<00:00, 13.26it/s]
Val Loss: 0.2872 Acc: 0.8694

Epoch 20/25
-----
train: 100%|██████████| 360/360 [01:51<00:00, 3.24it/s]
Train Loss: 0.2777 Acc: 0.8851
val: 100%|██████████| 90/90 [00:06<00:00, 13.18it/s]
Val Loss: 0.2881 Acc: 0.8653

Epoch 21/25
-----
```

```
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]
Train Loss: 0.2678 Acc: 0.8760
val: 100%|██████████| 90/90 [00:06<00:00, 13.19it/s]
Val Loss: 0.2923 Acc: 0.8611
```

Epoch 22/25

```
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.2709 Acc: 0.8781
val: 100%|██████████| 90/90 [00:06<00:00, 13.30it/s]
Val Loss: 0.2931 Acc: 0.8667
```

Epoch 23/25

```
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]
Train Loss: 0.2553 Acc: 0.8878
val: 100%|██████████| 90/90 [00:06<00:00, 13.28it/s]
Val Loss: 0.2874 Acc: 0.8653
```

Epoch 24/25

```
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.2594 Acc: 0.8778
val: 100%|██████████| 90/90 [00:06<00:00, 13.17it/s]
Val Loss: 0.3006 Acc: 0.8597
```

Epoch 25/25

```
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.2482 Acc: 0.8872
val: 100%|██████████| 90/90 [00:06<00:00, 13.18it/s]
Val Loss: 0.2851 Acc: 0.8750
```

Training complete in 49m 1s
Best Validation Acc: 0.8778
Fold 1 best Val Acc: 0.8778

===== Fold 2/5 =====

Epoch 1/25

```
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]
Train Loss: 0.5417 Acc: 0.7312
val: 100%|██████████| 90/90 [00:06<00:00, 13.24it/s]
Val Loss: 0.4154 Acc: 0.7917
```

Epoch 2/25

```
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.4797 Acc: 0.7632
val: 100%|██████████| 90/90 [00:06<00:00, 13.25it/s]
Val Loss: 0.3962 Acc: 0.8056
```

Epoch 3/25

```
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
```

```
Train Loss: 0.4594 Acc: 0.7729
val: 100%|██████████| 90/90 [00:06<00:00, 13.35it/s]
Val Loss: 0.3442 Acc: 0.8514
```

Epoch 4/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]
Train Loss: 0.4144 Acc: 0.8031
val: 100%|██████████| 90/90 [00:06<00:00, 13.15it/s]
Val Loss: 0.3527 Acc: 0.8333
```

Epoch 5/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.3979 Acc: 0.8243
val: 100%|██████████| 90/90 [00:06<00:00, 13.29it/s]
Val Loss: 0.3249 Acc: 0.8542
```

Epoch 6/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.4000 Acc: 0.8080
val: 100%|██████████| 90/90 [00:06<00:00, 13.22it/s]
Val Loss: 0.3461 Acc: 0.8444
```

Epoch 7/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]
Train Loss: 0.3779 Acc: 0.8212
val: 100%|██████████| 90/90 [00:06<00:00, 13.14it/s]
Val Loss: 0.3528 Acc: 0.8250
```

Epoch 8/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.3531 Acc: 0.8469
val: 100%|██████████| 90/90 [00:06<00:00, 13.21it/s]
Val Loss: 0.2941 Acc: 0.8569
```

Epoch 9/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.27it/s]
Train Loss: 0.3284 Acc: 0.8583
val: 100%|██████████| 90/90 [00:06<00:00, 13.29it/s]
Val Loss: 0.2878 Acc: 0.8542
```

Epoch 10/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]
Train Loss: 0.3128 Acc: 0.8576
val: 100%|██████████| 90/90 [00:06<00:00, 13.21it/s]
Val Loss: 0.2847 Acc: 0.8611
```

Epoch 11/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.27it/s]  
Train Loss: 0.3123 Acc: 0.8628  
val: 100%|██████████| 90/90 [00:06<00:00, 13.17it/s]  
Val Loss: 0.2924 Acc: 0.8639
```

Epoch 12/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]  
Train Loss: 0.2871 Acc: 0.8701  
val: 100%|██████████| 90/90 [00:06<00:00, 13.16it/s]  
Val Loss: 0.2872 Acc: 0.8764
```

Epoch 13/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]  
Train Loss: 0.2786 Acc: 0.8760  
val: 100%|██████████| 90/90 [00:06<00:00, 13.21it/s]  
Val Loss: 0.2976 Acc: 0.8639
```

Epoch 14/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]  
Train Loss: 0.2786 Acc: 0.8705  
val: 100%|██████████| 90/90 [00:06<00:00, 13.21it/s]  
Val Loss: 0.2908 Acc: 0.8708
```

Epoch 15/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.25it/s]  
Train Loss: 0.2748 Acc: 0.8729  
val: 100%|██████████| 90/90 [00:06<00:00, 13.13it/s]  
Val Loss: 0.2853 Acc: 0.8750
```

Epoch 16/25

```
-----  
train: 100%|██████████| 360/360 [01:50<00:00, 3.26it/s]  
Train Loss: 0.2623 Acc: 0.8823  
val: 100%|██████████| 90/90 [00:06<00:00, 13.23it/s]  
Val Loss: 0.2896 Acc: 0.8667
```

Epoch 17/25

```
-----  
train: 91%|██████████| 327/360 [01:40<00:09, 3.31it/s]
```

✓ EfficientNetV2-M

```
import os
```

```
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Update this path to your dataset directory
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)'
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Strong augmentation for training; standard normalization for testing.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
```

```
transforms.CenterCrop(224),
transforms.ToTensor(),
transforms.Normalize([0.485, 0.456, 0.406],
[0.229, 0.224, 0.225])
])

# Load datasets using ImageFolder
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####

def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())

    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%1.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. DataLoaders
#####

batch_size = 32 # Adjust batch size if needed for memory
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r

#####
# 5. Model Initialization & Fine-Tuning (EfficientNetV2-M)
#####

# We use EfficientNetV2-M (a smaller variant than V2-L) to help reduce memory
from torchvision.models import efficientnet_v2_m, EfficientNet_V2_M_Weights
weights = EfficientNet_V2_M_Weights.IMAGENET1K_V1 # or use DEFAULT for latest

model_ft = efficientnet_v2_m(weights=weights)
num_ftrs = model_ft.classifier[1].in_features
model_ft.classifier = nn.Sequential(
```

```
    nn.Dropout(p=0.5),
    nn.Linear(num_fts, 2)
)
model_ft = model_ft.to(device)

#####
# 6. Training Function
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    # Lists for training history
    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        print("-" * 10)

        # Each epoch: training and validation phases.
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
                dataloader = train_loader
            else:
                model.eval()
                dataloader = test_loader

            running_loss = 0.0
            running_corrects = 0
            total_samples = 0

            for inputs, labels in tqdm(dataloader, desc=phase):
                inputs = inputs.to(device)
                labels = labels.to(device)

                optimizer.zero_grad()
                with torch.set_grad_enabled(phase == 'train'):
                    outputs = model(inputs)
                    _, preds = torch.max(outputs, 1)
                    loss = criterion(outputs, labels)

                if phase == 'train':
                    loss.backward()

            if phase == 'train':
                scheduler.step()
```

```
        optimizer.step()

        running_loss += loss.item() * inputs.size(0)
        running_corrects += torch.sum(preds == labels.data).item()
        total_samples += inputs.size(0)

    if phase == 'train':
        scheduler.step()

    epoch_loss = running_loss / total_samples
    epoch_acc = running_corrects / total_samples

    print(f'{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

    if phase == 'train':
        train_loss_history.append(epoch_loss)
        train_acc_history.append(epoch_acc)
    else:
        val_loss_history.append(epoch_loss)
        val_acc_history.append(epoch_acc)
        if epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = copy.deepcopy(model.state_dict())

    print()

time_elapsed = time.time() - since
print(f'Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s')
print(f'Best Validation Acc: {best_acc:.4f}')

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

#####
# 7. Set Loss, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_ft = optim.Adam(model_ft.parameters(), lr=1e-4)
scheduler_ft = lr_scheduler.StepLR(optimizer_ft, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####
```

```
#####
num_epochs = 25
model_ft, history = train_model(model_ft, criterion, optimizer_ft, scheduler_ft

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_curves(history)

#####
# 10. Model Evaluation on Test Set
#####
model_ft.eval()
all_preds = []
all_probs = [] # Probabilities for the malignant class (index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_ft(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Class 1 probabil
```

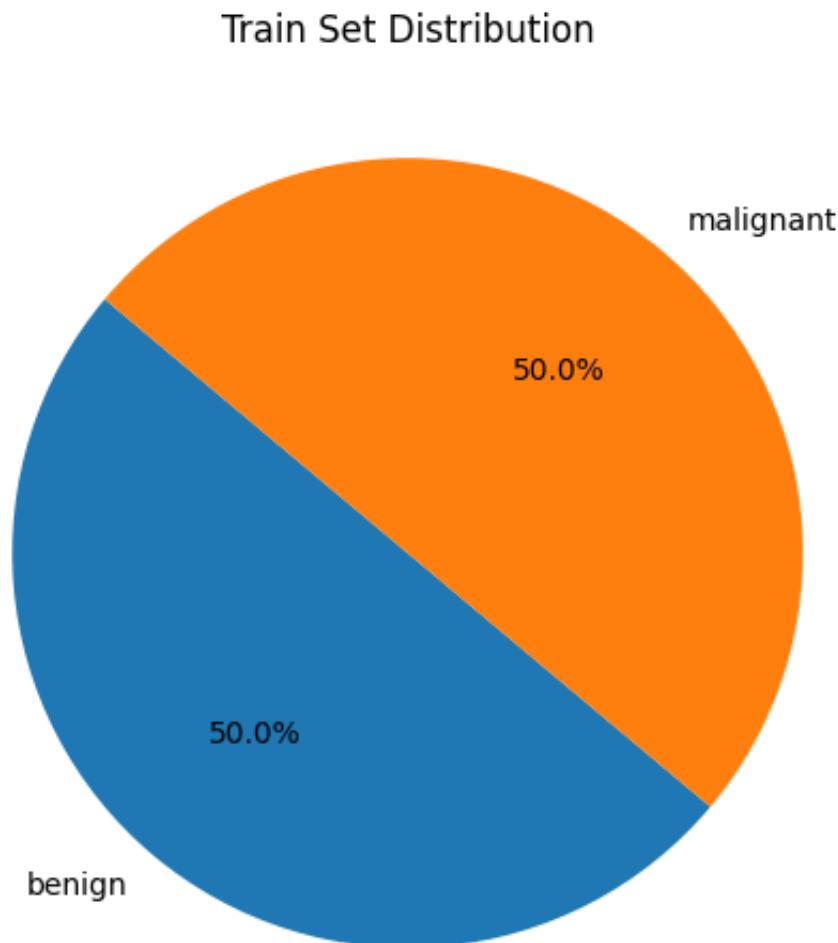
```
_, preds = torch.max(outputs, 1)
all_preds.extend(preds.cpu().numpy())
all_probs.extend(probs.cpu().numpy())
all_labels.extend(labels.cpu().numpy())

#####
# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.classes))

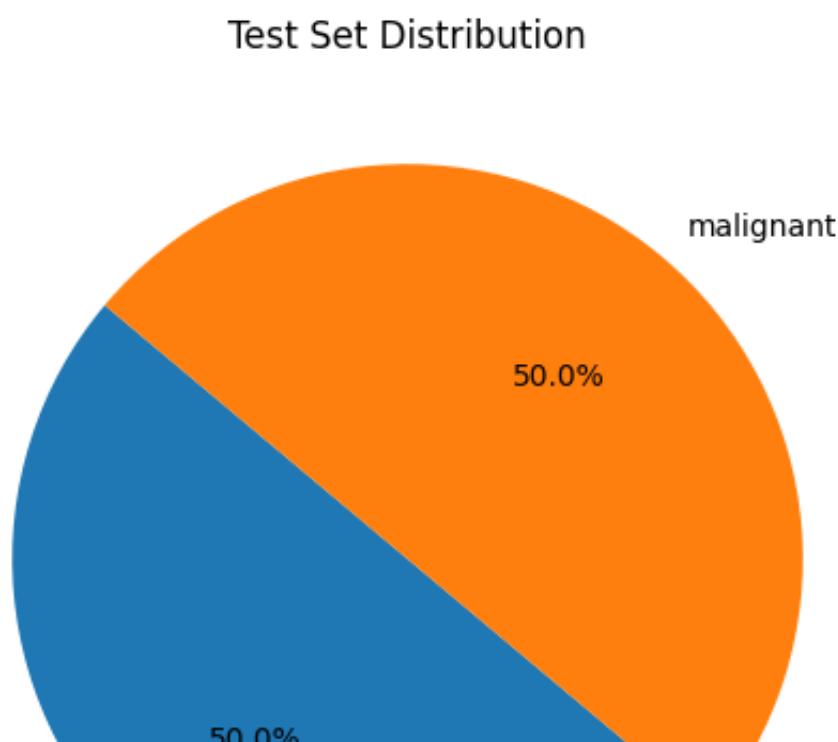
#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
              horizontalalignment="center",
              color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####
# 13. Visualization 5: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

Using device: cuda:0
Train Set Distribution:



Test Set Distribution:





Downloading: "https://download.pytorch.org/models/efficientnet_v2_m-dc08266
100%|██████████| 208M/208M [00:00<00:00, 221MB/s]

Epoch 1/25

```
-----  
train: 100%|██████████| 90/90 [00:40<00:00,  2.20it/s]  
Train Loss: 0.4959 Acc: 0.7427  
val: 100%|██████████| 23/23 [00:03<00:00,  7.55it/s]  
Val Loss: 0.4238 Acc: 0.8097
```

Epoch 2/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00,  2.29it/s]  
Train Loss: 0.3853 Acc: 0.8135  
val: 100%|██████████| 23/23 [00:03<00:00,  7.63it/s]  
Val Loss: 0.3470 Acc: 0.8375
```

Epoch 3/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00,  2.29it/s]  
Train Loss: 0.3727 Acc: 0.8212  
val: 100%|██████████| 23/23 [00:02<00:00,  7.74it/s]  
Val Loss: 0.3366 Acc: 0.8361
```

Epoch 4/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00,  2.29it/s]  
Train Loss: 0.3614 Acc: 0.8306  
val: 100%|██████████| 23/23 [00:02<00:00,  7.80it/s]  
Val Loss: 0.3214 Acc: 0.8611
```

Epoch 5/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00,  2.29it/s]  
Train Loss: 0.3296 Acc: 0.8458  
val: 100%|██████████| 23/23 [00:02<00:00,  7.71it/s]  
Val Loss: 0.3370 Acc: 0.8569
```

Epoch 6/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00,  2.29it/s]  
Train Loss: 0.3291 Acc: 0.8351  
val: 100%|██████████| 23/23 [00:02<00:00,  7.76it/s]  
Val Loss: 0.3648 Acc: 0.8431
```

Epoch 7/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2983 Acc: 0.8622  
val: 100%|██████████| 23/23 [00:02<00:00, 7.76it/s]  
Val Loss: 0.3493 Acc: 0.8403
```

Epoch 8/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.27it/s]  
Train Loss: 0.2856 Acc: 0.8701  
val: 100%|██████████| 23/23 [00:03<00:00, 7.26it/s]  
Val Loss: 0.3028 Acc: 0.8681
```

Epoch 9/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2596 Acc: 0.8740  
val: 100%|██████████| 23/23 [00:02<00:00, 7.76it/s]  
Val Loss: 0.3160 Acc: 0.8653
```

Epoch 10/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2692 Acc: 0.8760  
val: 100%|██████████| 23/23 [00:02<00:00, 7.78it/s]  
Val Loss: 0.3170 Acc: 0.8639
```

Epoch 11/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2657 Acc: 0.8740  
val: 100%|██████████| 23/23 [00:03<00:00, 7.52it/s]  
Val Loss: 0.3227 Acc: 0.8611
```

Epoch 12/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2336 Acc: 0.8920  
val: 100%|██████████| 23/23 [00:02<00:00, 7.75it/s]  
Val Loss: 0.3273 Acc: 0.8681
```

Epoch 13/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2314 Acc: 0.8917  
val: 100%|██████████| 23/23 [00:02<00:00, 7.81it/s]  
Val Loss: 0.3421 Acc: 0.8653
```

Epoch 14/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2437 Acc: 0.8882  
val: 100%|██████████| 23/23 [00:03<00:00, 7.57it/s]  
Val Loss: 0.3249 Acc: 0.8708
```

Epoch 15/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2262 Acc: 0.8990  
val: 100%|██████████| 23/23 [00:02<00:00, 7.78it/s]  
Val Loss: 0.3175 Acc: 0.8694
```

Epoch 16/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2333 Acc: 0.8899  
val: 100%|██████████| 23/23 [00:02<00:00, 7.75it/s]  
Val Loss: 0.3213 Acc: 0.8708
```

Epoch 17/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2325 Acc: 0.8899  
val: 100%|██████████| 23/23 [00:03<00:00, 7.53it/s]  
Val Loss: 0.3201 Acc: 0.8694
```

Epoch 18/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2143 Acc: 0.8969  
val: 100%|██████████| 23/23 [00:02<00:00, 7.80it/s]  
Val Loss: 0.3227 Acc: 0.8681
```

Epoch 19/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2245 Acc: 0.8931  
val: 100%|██████████| 23/23 [00:02<00:00, 7.78it/s]  
Val Loss: 0.3173 Acc: 0.8681
```

Epoch 20/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2141 Acc: 0.9052  
val: 100%|██████████| 23/23 [00:03<00:00, 7.52it/s]  
Val Loss: 0.3189 Acc: 0.8667
```

Epoch 21/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2221 Acc: 0.9035  
val: 100%|██████████| 23/23 [00:02<00:00, 7.73it/s]  
Val Loss: 0.3205 Acc: 0.8681
```

Epoch 22/25

```
-----  
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]  
Train Loss: 0.2083 Acc: 0.9052
```

```
val: 100%|██████████| 23/23 [00:02<00:00, 7.82it/s]
Val Loss: 0.3249 Acc: 0.8667
```

Epoch 23/25

```
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]
Train Loss: 0.2299 Acc: 0.9000
val: 100%|██████████| 23/23 [00:03<00:00, 7.55it/s]
Val Loss: 0.3275 Acc: 0.8653
```

Epoch 24/25

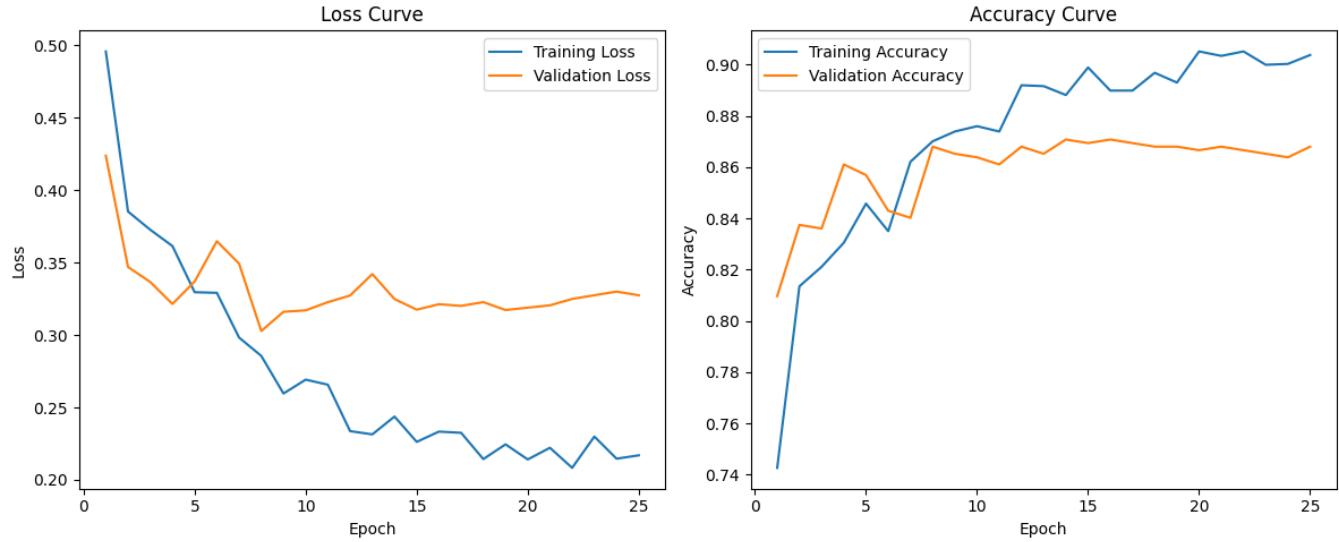
```
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]
Train Loss: 0.2146 Acc: 0.9003
val: 100%|██████████| 23/23 [00:02<00:00, 7.81it/s]
Val Loss: 0.3300 Acc: 0.8639
```

Epoch 25/25

```
train: 100%|██████████| 90/90 [00:39<00:00, 2.29it/s]
Train Loss: 0.2169 Acc: 0.9038
val: 100%|██████████| 23/23 [00:02<00:00, 7.72it/s]
Val Loss: 0.3275 Acc: 0.8681
```

Training complete in 17m 39s

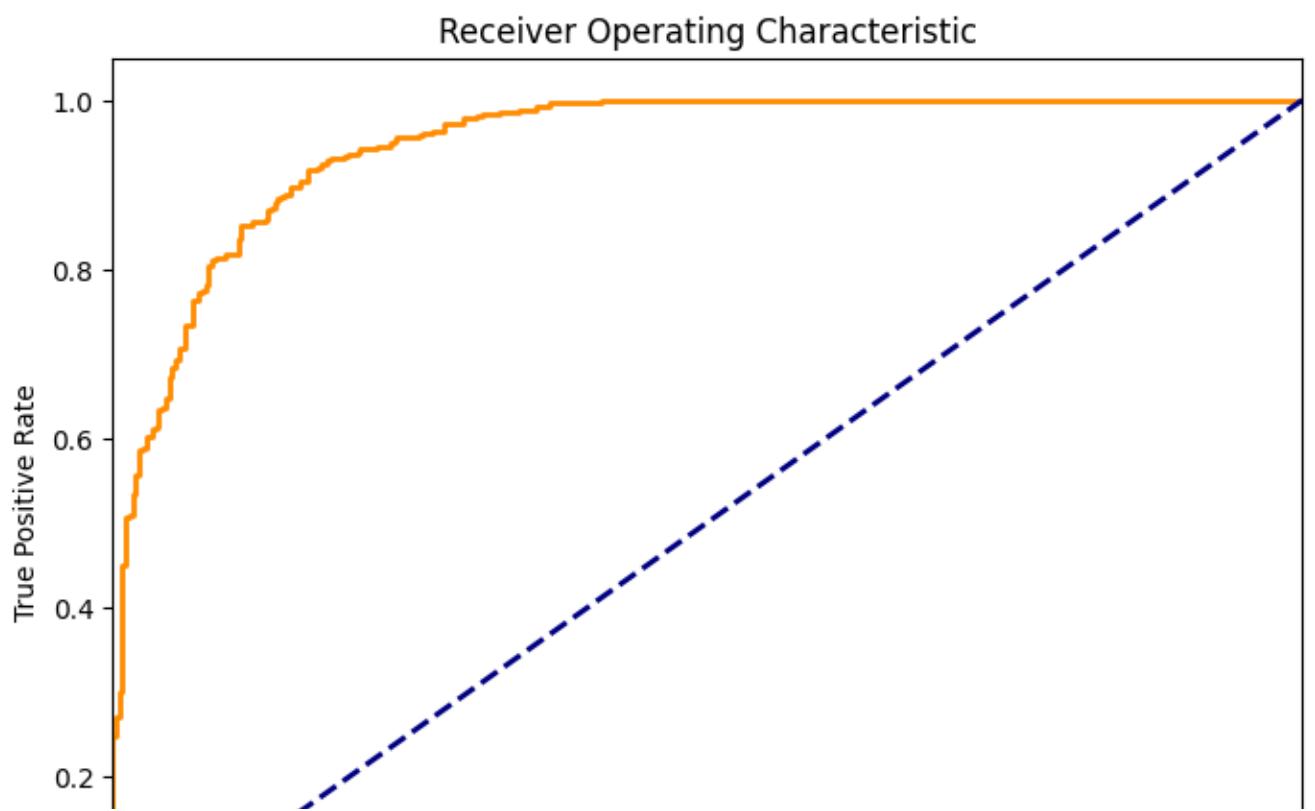
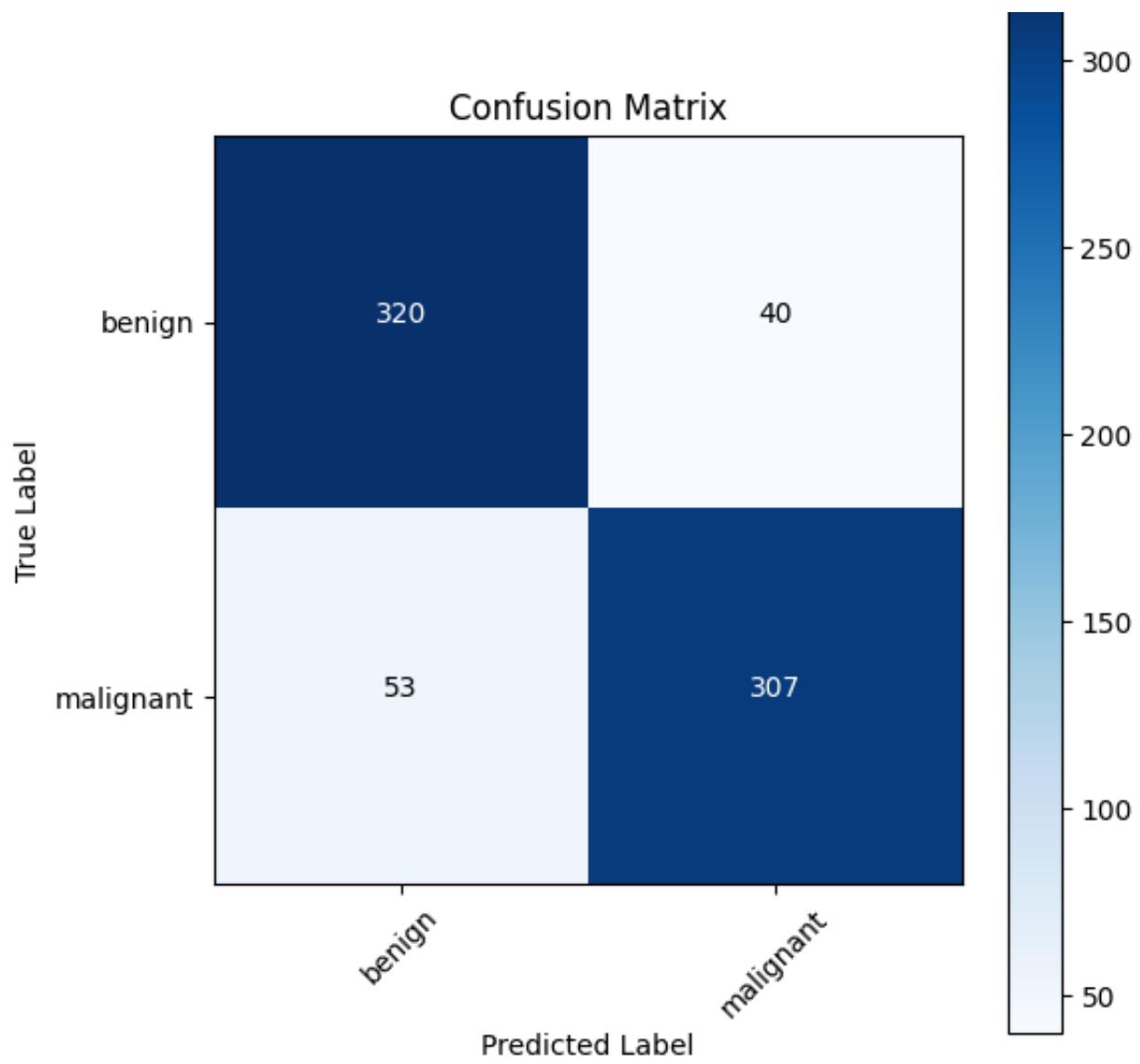
Best Validation Acc: 0.8708

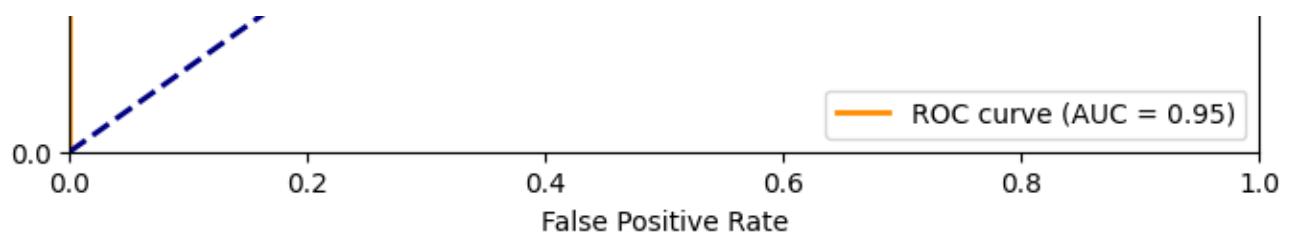


```
Testing: 100%|██████████| 23/23 [00:02<00:00, 7.88it/s]
```

Classification Report:

	precision	recall	f1-score	support
benign	0.86	0.89	0.87	360
malignant	0.88	0.85	0.87	360
accuracy			0.87	720
macro avg	0.87	0.87	0.87	720
weighted avg	0.87	0.87	0.87	720





✓ ConvNeXt_Base

```
# Set environment variable to help avoid fragmentation issues
import os
os.environ["PYTORCH_CUDA_ALLOC_CONF"] = "expandable_segments:True"

import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

# Clear GPU cache before starting
torch.cuda.empty_cache()
```

```
#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)' #
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])

train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
```

```
    class_counts[class_names[label]] += 1
labels = list(class_counts.keys())
counts = list(class_counts.values())
plt.figure(figsize=(6,6))
plt.pie(counts, labels=labels, autopct='%.1f%%', startangle=140)
plt.title(title)
plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. DataLoaders
#####
# To further conserve memory, we use a smaller batch size and fewer workers.
batch_size = 8 # Try reducing to 8 if 16/32 cause memory issues
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r

#####
# 5. Model Initialization & Fine-Tuning (ConvNeXt-Base)
#####
from torchvision.models import convnext_base, ConvNeXt_Base_Weights
weights = ConvNeXt_Base_Weights.IMAGENET1K_V1
model_convnext = convnext_base(weights=weights)
# The original classifier is a Sequential with (LayerNorm, Flatten, Linear)
# We rebuild it to flatten first, then apply LayerNorm, dropout, and a final Li
in_features = model_convnext.classifier[2].in_features
model_convnext.classifier = nn.Sequential(
    nn.Flatten(),
    nn.LayerNorm(in_features, eps=1e-6),
    nn.Dropout(p=0.5),
    nn.Linear(in_features, 2)
)
model_convnext = model_convnext.to(device)

#####
# 6. Training Function with Mixed Precision (AMP)
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    train_loss_history = []
    train_acc_history = []
```

```
val_loss_history = []
val_acc_history = []

scaler = torch.cuda.amp.GradScaler() # For mixed precision training

for epoch in range(num_epochs):
    print(f"Epoch {epoch+1}/{num_epochs}")
    print("-" * 10)
    for phase in ['train', 'val']:
        if phase == 'train':
            model.train()
            dataloader = train_loader
        else:
            model.eval()
            dataloader = test_loader

        running_loss = 0.0
        running_corrects = 0
        total_samples = 0

        for inputs, labels in tqdm(dataloader, desc=phase):
            inputs = inputs.to(device)
            labels = labels.to(device)
            optimizer.zero_grad()

            with torch.set_grad_enabled(phase == 'train'):
                with torch.cuda.amp.autocast():
                    outputs = model(inputs)
                    _, preds = torch.max(outputs, 1)
                    loss = criterion(outputs, labels)

                if phase == 'train':
                    scaler.scale(loss).backward()
                    scaler.step(optimizer)
                    scaler.update()

                running_loss += loss.item() * inputs.size(0)
                running_corrects += torch.sum(preds == labels.data).item()
                total_samples += inputs.size(0)

        if phase == 'train':
            scheduler.step()

        epoch_loss = running_loss / total_samples
        epoch_acc = running_corrects / total_samples
        print(f"{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}")

        if phase == 'train':
```

```
        train_loss_history.append(epoch_loss)
        train_acc_history.append(epoch_acc)
    else:
        val_loss_history.append(epoch_loss)
        val_acc_history.append(epoch_acc)
        if epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = copy.deepcopy(model.state_dict())
    print()

time_elapsed = time.time() - since
print(f"Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s")
print(f"Best Validation Acc: {best_acc:.4f}")

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_convnext = optim.Adam(model_convnext.parameters(), lr=1e-4)
scheduler_convnext = lr_scheduler.StepLR(optimizer_convnext, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####
num_epochs = 25
model_convnext, history = train_model(model_convnext, criterion, optimizer_convnext, num_epochs)

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
```

```
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Accuracy Curve
plt.subplot(1, 2, 2)
plt.plot(epochs, history['train_acc'], label='Training Accuracy')
plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
plt.title('Accuracy Curve')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()

plot_training_curves(history)

#####
# 10. Model Evaluation on Test Set
#####
model_convnext.eval()
all_preds = []
all_probs = [] # Probabilities for malignant (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_convnext(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Probability for
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

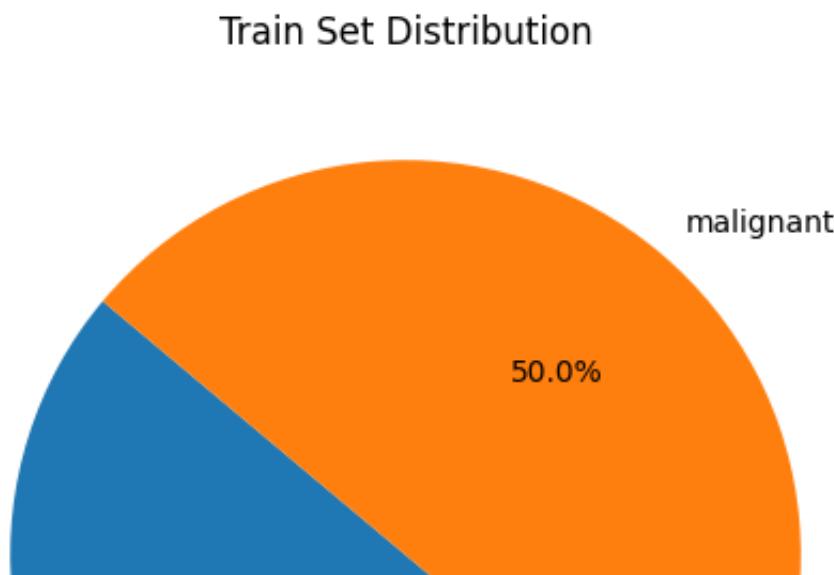
#####
# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

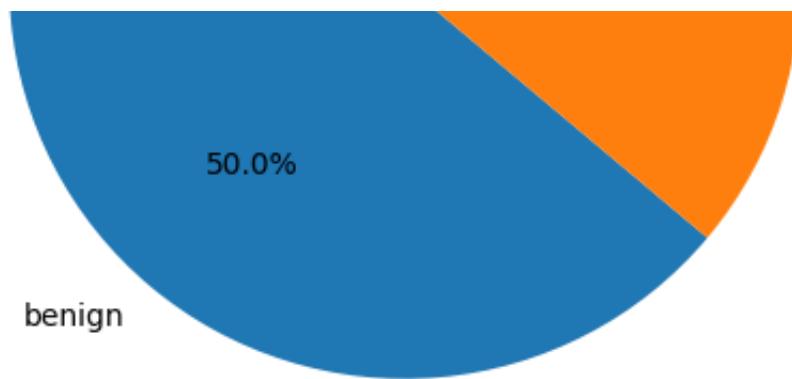
#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
```

```
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
              horizontalalignment="center",
              color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()
```

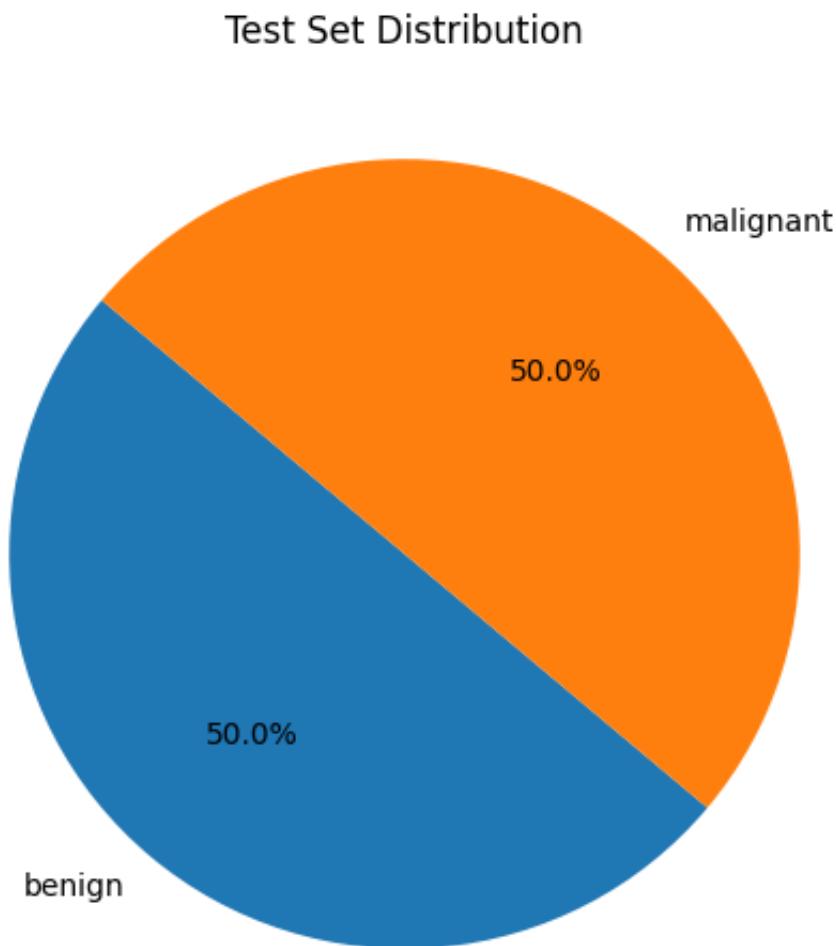
```
#####
# 13. Visualization 5: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:0.4f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

→ Using device: cuda:0
Train Set Distribution:





Test Set Distribution:



```
Downloading: "https://download.pytorch.org/models/convnext_base-6075fbad.pt"
100%|██████████| 338M/338M [00:01<00:00, 200MB/s]
<ipython-input-1-8cd3d416f9b1>:121: FutureWarning: `torch.cuda.amp.GradScal
    scaler = torch.cuda.amp.GradScaler() # For mixed precision training
Epoch 1/25
-----
train:  0%|          | 0/360 [00:00<?, ?it/s]<ipython-input-1-8cd3d416f9b1
    with torch.cuda.amp.autocast():
train: 100%|██████████| 360/360 [00:45<00:00,  7.90it/s]
Train Loss: 0.5214 Acc: 0.7507
```

```
val: 100%|██████████| 90/90 [00:04<00:00, 20.42it/s]
Val Loss: 0.3741 Acc: 0.8236

Epoch 2/25
-----
train: 100%|██████████| 360/360 [00:44<00:00, 8.05it/s]
Train Loss: 0.4070 Acc: 0.8017
val: 100%|██████████| 90/90 [00:03<00:00, 28.13it/s]
Val Loss: 0.4124 Acc: 0.7958

Epoch 3/25
-----
train: 100%|██████████| 360/360 [00:45<00:00, 7.94it/s]
Train Loss: 0.3844 Acc: 0.8135
val: 100%|██████████| 90/90 [00:03<00:00, 27.72it/s]
Val Loss: 0.2939 Acc: 0.8611

Epoch 4/25
-----
train: 100%|██████████| 360/360 [00:45<00:00, 7.89it/s]
Train Loss: 0.3478 Acc: 0.8340
val: 100%|██████████| 90/90 [00:03<00:00, 27.68it/s]
Val Loss: 0.3186 Acc: 0.8528

Epoch 5/25
-----
train: 100%|██████████| 360/360 [00:45<00:00, 7.84it/s]
Train Loss: 0.3225 Acc: 0.8469
val: 100%|██████████| 90/90 [00:03<00:00, 27.42it/s]
Val Loss: 0.3240 Acc: 0.8597

Epoch 6/25
-----
train: 100%|██████████| 360/360 [00:45<00:00, 7.83it/s]
Train Loss: 0.3043 Acc: 0.8594
val: 100%|██████████| 90/90 [00:03<00:00, 27.30it/s]
Val Loss: 0.2922 Acc: 0.8806

Epoch 7/25
-----
train: 100%|██████████| 360/360 [00:46<00:00, 7.78it/s]
Train Loss: 0.3030 Acc: 0.8566
val: 100%|██████████| 90/90 [00:03<00:00, 27.17it/s]
Val Loss: 0.3341 Acc: 0.8528

Epoch 8/25
-----
train: 100%|██████████| 360/360 [00:46<00:00, 7.81it/s]
Train Loss: 0.2525 Acc: 0.8882
val: 100%|██████████| 90/90 [00:03<00:00, 27.17it/s]
Val Loss: 0.2698 Acc: 0.8847

Epoch 9/25
-----
```

```
train: 100%|██████████| 360/360 [00:46<00:00, 7.80it/s]
Train Loss: 0.2247 Acc: 0.8976
val: 100%|██████████| 90/90 [00:03<00:00, 27.09it/s]
Val Loss: 0.2739 Acc: 0.8819
```

Epoch 10/25

```
train: 100%|██████████| 360/360 [00:46<00:00, 7.81it/s]
Train Loss: 0.2130 Acc: 0.9028
val: 100%|██████████| 90/90 [00:03<00:00, 26.94it/s]
Val Loss: 0.2665 Acc: 0.8861
```

Epoch 11/25

```
train: 100%|██████████| 360/360 [00:46<00:00, 7.80it/s]
Train Loss: 0.2118 Acc: 0.9115
val: 100%|██████████| 90/90 [00:03<00:00, 27.06it/s]
Val Loss: 0.2702 Acc: 0.8833
```

Epoch 12/25

```
train: 100%|██████████| 360/360 [00:46<00:00, 7.79it/s]
Train Loss: 0.1950 Acc: 0.9111
val: 100%|██████████| 90/90 [00:03<00:00, 27.03it/s]
Val Loss: 0.2707 Acc: 0.8819
```

Epoch 13/25

```
train: 100%|██████████| 360/360 [00:46<00:00, 7.79it/s]
Train Loss: 0.1941 Acc: 0.9125
val: 100%|██████████| 90/90 [00:03<00:00, 26.77it/s]
Val Loss: 0.2759 Acc: 0.8917
```

Epoch 14/25

```
train: 100%|██████████| 360/360 [00:46<00:00, 7.72it/s]
Train Loss: 0.1716 Acc: 0.9285
val: 100%|██████████| 90/90 [00:03<00:00, 26.87it/s]
Val Loss: 0.2880 Acc: 0.8833
```

Epoch 15/25

```
train: 100%|██████████| 360/360 [00:46<00:00, 7.78it/s]
Train Loss: 0.1619 Acc: 0.9267
val: 100%|██████████| 90/90 [00:03<00:00, 26.89it/s]
Val Loss: 0.2928 Acc: 0.8806
```

Epoch 16/25

```
train: 100%|██████████| 360/360 [00:46<00:00, 7.78it/s]
Train Loss: 0.1805 Acc: 0.9142
val: 100%|██████████| 90/90 [00:03<00:00, 27.01it/s]
Val Loss: 0.2914 Acc: 0.8833
```

Epoch 17/25

```
-----  
train: 100%|██████████| 360/360 [00:46<00:00, 7.78it/s]  
Train Loss: 0.1665 Acc: 0.9198  
val: 100%|██████████| 90/90 [00:03<00:00, 26.10it/s]  
Val Loss: 0.2913 Acc: 0.8861
```

Epoch 18/25

```
-----  
train: 100%|██████████| 360/360 [00:46<00:00, 7.78it/s]  
Train Loss: 0.1660 Acc: 0.9247  
val: 100%|██████████| 90/90 [00:03<00:00, 26.96it/s]  
Val Loss: 0.2919 Acc: 0.8875
```

Epoch 19/25

```
-----  
train: 100%|██████████| 360/360 [00:46<00:00, 7.78it/s]  
Train Loss: 0.1675 Acc: 0.9253  
val: 100%|██████████| 90/90 [00:03<00:00, 27.06it/s]  
Val Loss: 0.2896 Acc: 0.8889
```

Epoch 20/25

```
-----  
train: 100%|██████████| 360/360 [00:46<00:00, 7.80it/s]  
Train Loss: 0.1607 Acc: 0.9281  
val: 100%|██████████| 90/90 [00:03<00:00, 27.01it/s]  
Val Loss: 0.2931 Acc: 0.8861
```

Epoch 21/25

```
-----  
train: 100%|██████████| 360/360 [00:46<00:00, 7.75it/s]  
Train Loss: 0.1637 Acc: 0.9260  
val: 100%|██████████| 90/90 [00:03<00:00, 26.98it/s]  
Val Loss: 0.2942 Acc: 0.8889
```

Epoch 22/25

```
-----  
train: 100%|██████████| 360/360 [00:46<00:00, 7.80it/s]  
Train Loss: 0.1605 Acc: 0.9257  
val: 100%|██████████| 90/90 [00:03<00:00, 27.27it/s]  
Val Loss: 0.2942 Acc: 0.8889
```

Epoch 23/25

```
-----  
train: 100%|██████████| 360/360 [00:46<00:00, 7.82it/s]  
Train Loss: 0.1661 Acc: 0.9236  
val: 100%|██████████| 90/90 [00:03<00:00, 27.11it/s]  
Val Loss: 0.2941 Acc: 0.8903
```

Epoch 24/25

```
-----  
train: 100%|██████████| 360/360 [00:46<00:00, 7.79it/s]  
Train Loss: 0.1566 Acc: 0.9292  
val: 100%|██████████| 90/90 [00:03<00:00, 26.98it/s]
```

```
Val Loss: 0.2945 Acc: 0.8903
Epoch 25/25
-----
train: 100%|██████████| 360/360 [00:46<00:00, 7.80it/s]
Train Loss: 0.1686 Acc: 0.9316
val: 100%|██████████| 90/90 [00:03<00:00, 27.08it/s]
Val Loss: 0.2945 Acc: 0.8903
```

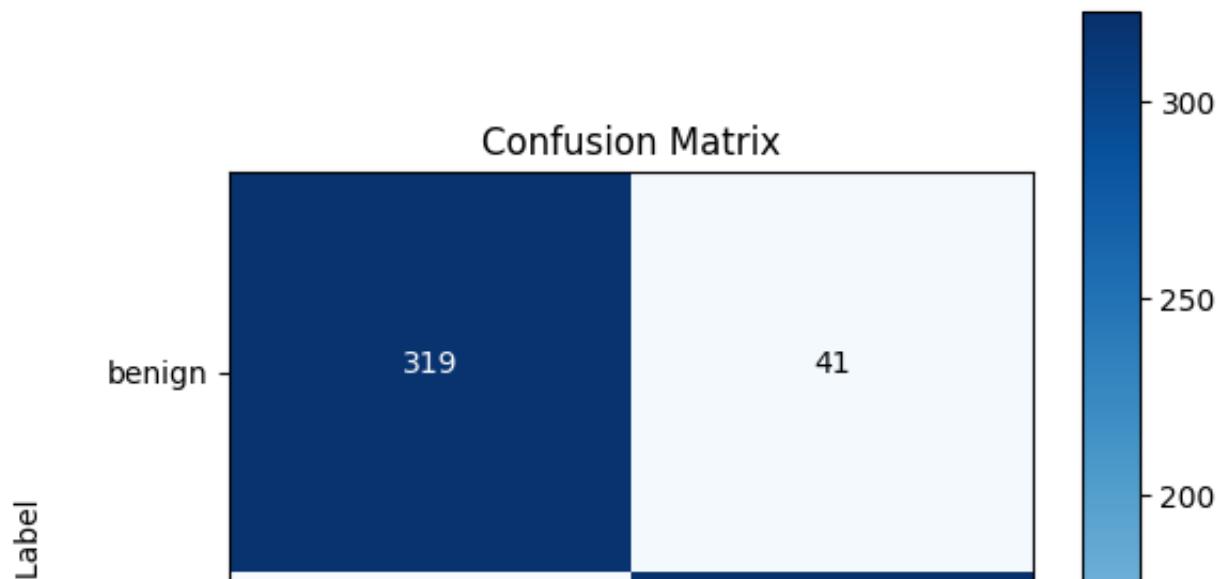
Training complete in 20m 36s
 Best Validation Acc: 0.8917

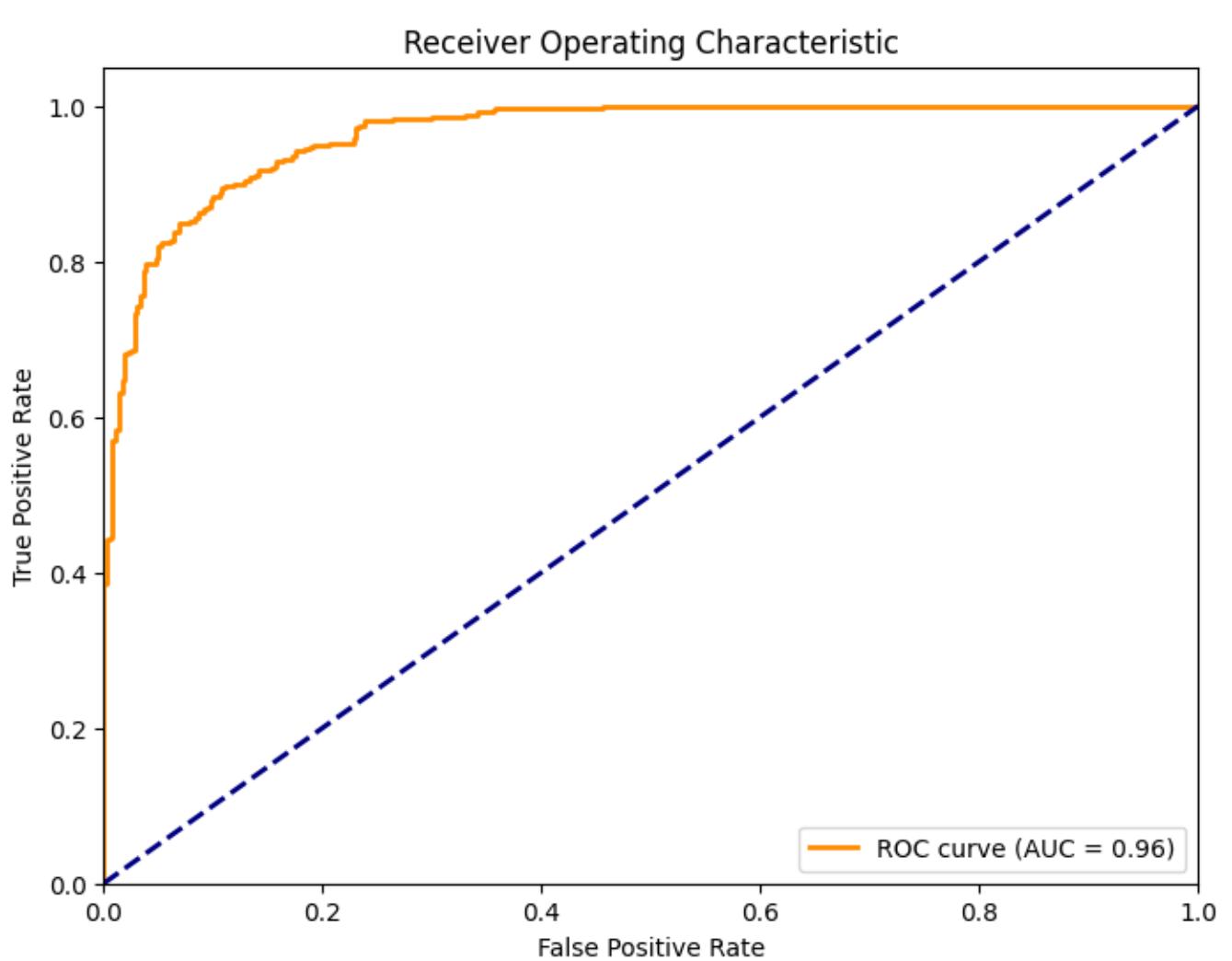
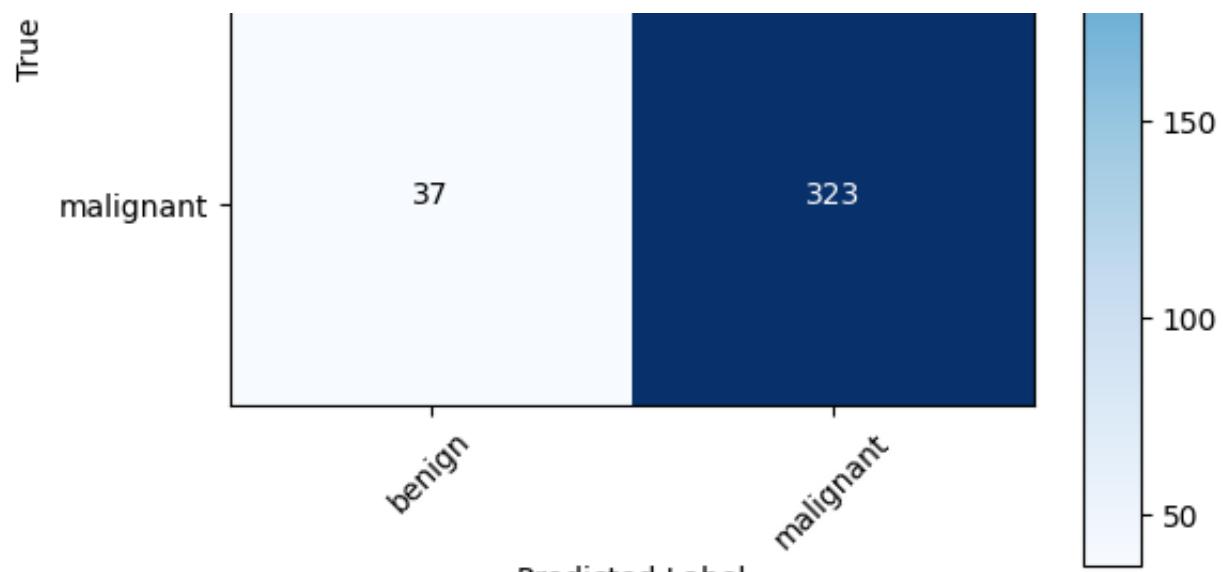


Testing: 100%|██████████| 90/90 [00:08<00:00, 10.12it/s]

Classification Report:

	precision	recall	f1-score	support
benign	0.90	0.89	0.89	360
malignant	0.89	0.90	0.89	360
accuracy			0.89	720
macro avg	0.89	0.89	0.89	720
weighted avg	0.89	0.89	0.89	720





with k-fold & hyper-parameter

```
#####
# 1. Environment Setup, Imports & Reproducibility
#####

import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader, Subset
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from tqdm import tqdm
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from sklearn.model_selection import StratifiedKFold

# Set environment variable to help avoid fragmentation issues
os.environ["PYTORCH_CUDA_ALLOC_CONF"] = "expandable_segments:True"

# Clear GPU cache before starting
torch.cuda.empty_cache()

# Set the random seed for reproducibility
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

# Choose device (GPU if available)
```

```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Update the data_dir path as needed.
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)'
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Define transforms (with augmentation for training)
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                      [0.229, 0.224, 0.225])
])
# Create datasets
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization: Class Distribution (Pie Chart)
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())
    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%.1f%%', startangle=140)
    plt.title(title)
    plt.show()
```

```
print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. Hyperparameter Tuning with K-Fold Cross Validation Setup
#####
# Hyperparameter grid (adjust these as needed)
param_grid = {
    "lr": [1e-4, 1e-3],
    "dropout": [0.3, 0.5]
}

# Define number of folds for cross validation
num_folds = 5
skf = StratifiedKFold(n_splits=num_folds, shuffle=True, random_state=SEED)

# Set batch size and number of epochs for CV training
batch_size = 8
num_epochs = 25

#####
# 5. Helper Functions: Model Builder & Training Function
#####
def build_model(dropout, device):
    """
    Build a ConvNeXt-Base model with the specified dropout probability.
    """
    from torchvision.models import convnext_base, ConvNeXt_Base_Weights
    weights = ConvNeXt_Base_Weights.IMGNET1K_V1
    model = convnext_base(weights=weights)
    in_features = model.classifier[2].in_features
    model.classifier = nn.Sequential(
        nn.Flatten(),
        nn.LayerNorm(in_features, eps=1e-6),
        nn.Dropout(p=dropout),
        nn.Linear(in_features, 2)
    )
    return model.to(device)

def train_model(model, criterion, optimizer, scheduler, train_loader, val_loader):
    """
    Train the model using mixed precision with an optional validation phase.
    If val_loader is provided, the function will evaluate after each epoch and
    """
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
```

```
best_acc = 0.0

train_loss_history = []
train_acc_history = []
val_loss_history = []
val_acc_history = []

scaler = torch.cuda.amp.GradScaler() # For mixed precision training

for epoch in range(num_epochs):
    print(f"Epoch {epoch+1}/{num_epochs}")
    print("-" * 10)

    # ----- Training Phase -----
    model.train()
    running_loss = 0.0
    running_corrects = 0
    total_samples = 0
    for inputs, labels in tqdm(train_loader, desc="Training", leave=False):
        inputs = inputs.to(device)
        labels = labels.to(device)
        optimizer.zero_grad()

        with torch.cuda.amp.autocast():
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            loss = criterion(outputs, labels)

            scaler.scale(loss).backward()
            scaler.step(optimizer)
            scaler.update()

        running_loss += loss.item() * inputs.size(0)
        running_corrects += torch.sum(preds == labels.data).item()
        total_samples += inputs.size(0)

    epoch_loss = running_loss / total_samples
    epoch_acc = running_corrects / total_samples
    train_loss_history.append(epoch_loss)
    train_acc_history.append(epoch_acc)
    print(f"Train Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}")

    # ----- Validation Phase (if provided) -----
    if val_loader is not None:
        model.eval()
        val_running_loss = 0.0
        val_running_corrects = 0
        val_total = 0
```

```
        for inputs, labels in tqdm(val_loader, desc="Validation", leave=False):
            inputs = inputs.to(device)
            labels = labels.to(device)
            with torch.no_grad():
                with torch.cuda.amp.autocast():
                    outputs = model(inputs)
                    _, preds = torch.max(outputs, 1)
                    loss = criterion(outputs, labels)
                    val_running_loss += loss.item() * inputs.size(0)
                    val_running_corrects += torch.sum(preds == labels.data).item()
                    val_total += inputs.size(0)
            val_loss = val_running_loss / val_total
            val_acc = val_running_corrects / val_total
            val_loss_history.append(val_loss)
            val_acc_history.append(val_acc)
            print(f"Val Loss: {val_loss:.4f} Acc: {val_acc:.4f}")

        if val_acc > best_acc:
            best_acc = val_acc
            best_model_wts = copy.deepcopy(model.state_dict())
    else:
        # If no validation loader is provided, use training metrics.
        best_acc = epoch_acc

    scheduler.step()
    print()

time_elapsed = time.time() - since
print(f"Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s")
if val_loader is not None:
    print(f"Best Val Acc: {best_acc:.4f}")
else:
    print(f"Final Train Acc: {best_acc:.4f}")
model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, best_acc, history

#####
# 6. Hyperparameter Search with K-Fold Cross Validation
#####
best_cv_acc = 0.0
best_params = {}
```

```
# Loop over each combination of hyperparameters in the grid
for lr in param_grid["lr"]:
    for dropout in param_grid["dropout"]:
        cv_scores = []
        print(f"\nEvaluating hyperparameters: lr = {lr}, dropout = {dropout}")
        # Use stratified splits based on dataset targets
        for fold, (train_idx, val_idx) in enumerate(skf.split(np.zeros(len(traj)), traj["diagnosis"])):
            print(f"\n--- Fold {fold+1}/{num_folds} ---")
            # Create subsets for training and validation for this fold
            train_subset = Subset(train_dataset, train_idx)
            val_subset = Subset(train_dataset, val_idx)
            train_loader_cv = DataLoader(train_subset, batch_size=batch_size, shuffle=True)
            val_loader_cv = DataLoader(val_subset, batch_size=batch_size, shuffle=True)

            # Build a new model instance for each fold with the current hyperparameters
            model_cv = build_model(dropout, device)
            criterion_cv = nn.CrossEntropyLoss()
            optimizer_cv = optim.Adam(model_cv.parameters(), lr=lr)
            scheduler_cv = lr_scheduler.StepLR(optimizer_cv, step_size=7, gamma=0.1)

            # Train the model on the current fold
            model_cv, best_val_acc, _ = train_model(model_cv, criterion_cv, optimizer_cv, scheduler_cv, train_loader_cv, val_loader_cv)
            cv_scores.append(best_val_acc)
            print(f"Fold {fold+1} Val Acc: {best_val_acc:.4f}")

        avg_cv_acc = sum(cv_scores) / len(cv_scores)
        print(f"\nAverage CV Acc for lr = {lr}, dropout = {dropout}: {avg_cv_acc:.4f}")
        # Update best hyperparameters if this combination is superior
        if avg_cv_acc > best_cv_acc:
            best_cv_acc = avg_cv_acc
            best_params = {"lr": lr, "dropout": dropout}

print("\n====")
print("Hyperparameter Tuning Complete!")
print(f"Best CV Accuracy: {best_cv_acc:.4f}")
print(f"Best Hyperparameters: lr = {best_params['lr']}, dropout = {best_params['dropout']}")
print("====\n")

#####
# 7. Final Training on Full Training Set with Best Hyperparameters
#####
print("Training final model on full training set using best hyperparameters...")

# Build final model with the best dropout setting
final_model = build_model(best_params["dropout"], device)
criterion_final = nn.CrossEntropyLoss()
optimizer_final = optim.Adam(final_model.parameters(), lr=best_params["lr"])
```

```
scheduler_final = lr_scheduler.StepLR(optimizer_final, step_size=7, gamma=0.1)

# Create a DataLoader for the full training set
full_train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)

# (Here we do not provide a validation loader so training metrics will be reported on the full training set)
final_model, _, full_history = train_model(final_model, criterion_final, optimizer_final, full_train_loader, val_loader=None, num_epochs=10, device=device)

#####
# 8. Evaluate the Final Model on the Test Set
#####
final_model.eval()
all_preds = []
all_probs = [] # Probabilities for class index 1 (assumed positive/malignant)
all_labels = []

test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, num_workers=4)
with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing Final Model"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = final_model(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Probability for class 1
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

#####
# 9. Final Visualizations: Training Curves, Classification Report, Confusion Matrix
#####
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    if history['val_loss']:
        plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
```

```
plt.plot(epochs, history['train_acc'], label='Training Accuracy')
if history['val_acc']:
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
plt.title('Accuracy Curve')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()

# Plot training curves from final training (if available)
plot_training_curves(full_history)

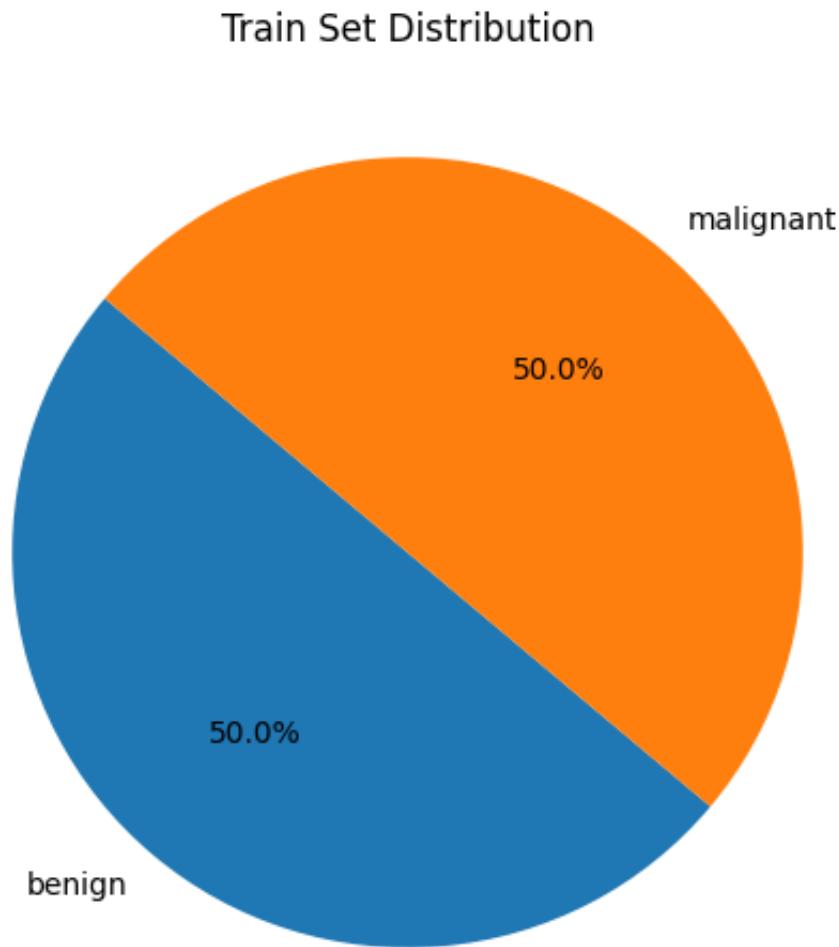
# Classification Report
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.classes))

# Confusion Matrix
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

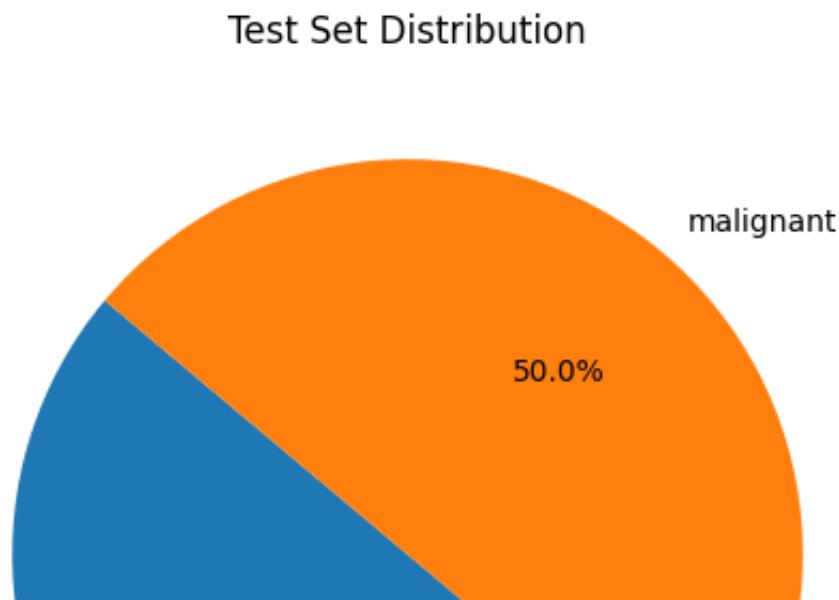
# ROC Curve & AUC
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
```

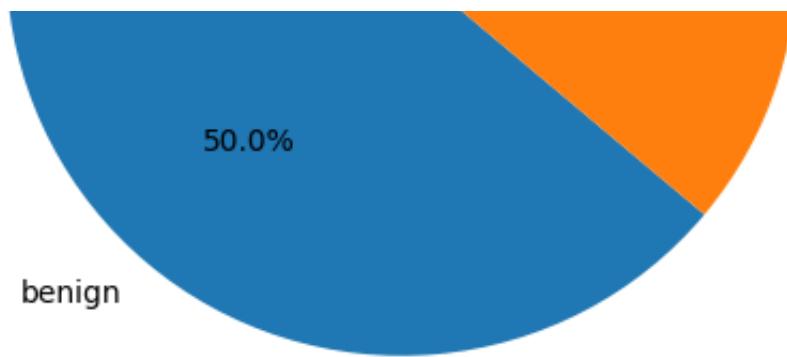
```
plt.legend(loc="lower right")
plt.show()
```

Using device: cuda:0
Train Set Distribution:



Test Set Distribution:





```
Evaluating hyperparameters: lr = 0.0001, dropout = 0.3
```

```
--- Fold 1/5 ---
```

```
Downloading: "https://download.pytorch.org/models/convnex\_base-6075fbad.pt"  
100%|██████████| 338M/338M [00:01<00:00, 193MB/s]
```

```
<ipython-input-1-30989d096fdb>:139: FutureWarning: `torch.cuda.amp.GradScal  
scaler = torch.cuda.amp.GradScaler() # For mixed precision training
```

```
Epoch 1/25
```

```
-----  
Training: 0% | 0/288 [00:00<?, ?it/s]<ipython-input-1-30989d096  
with torch.cuda.amp.autocast():
```

```
Train Loss: 0.4829 Acc: 0.7635
```

```
Validation: 0% | 0/72 [00:00<?, ?it/s]<ipython-input-1-30989d09  
with torch.cuda.amp.autocast():
```

```
Val Loss: 0.4197 Acc: 0.7917
```

```
Epoch 2/25
```

```
-----  
Train Loss: 0.3887 Acc: 0.8108
```

```
Val Loss: 0.3732 Acc: 0.8108
```

```
Epoch 3/25
```

```
-----  
Train Loss: 0.3653 Acc: 0.8325
```

```
Val Loss: 0.4250 Acc: 0.7917
```

```
Epoch 4/25
```

```
-----  
Train Loss: 0.3454 Acc: 0.8390
```

```
Val Loss: 0.3565 Acc: 0.8160
```

```
Epoch 5/25
```

```
-----  
Train Loss: 0.3169 Acc: 0.8633
```

```
Val Loss: 0.3616 Acc: 0.8264
```

```
Epoch 6/25
```

```
-----  
Train Loss: 0.3179 Acc: 0.8498
```

```
Val Loss: 0.3722 Acc: 0.8264
```

Epoch 7/25

Train Loss: 0.2920 Acc: 0.8685
Val Loss: 0.3879 Acc: 0.8351

Epoch 8/25

Train Loss: 0.2270 Acc: 0.8976
Val Loss: 0.3386 Acc: 0.8576

Epoch 9/25

Train Loss: 0.2133 Acc: 0.9036
Val Loss: 0.3511 Acc: 0.8576

Epoch 10/25

Train Loss: 0.1844 Acc: 0.9175
Val Loss: 0.3283 Acc: 0.8542

Epoch 11/25

Train Loss: 0.1942 Acc: 0.9080
Val Loss: 0.3624 Acc: 0.8472

Epoch 12/25

Train Loss: 0.1702 Acc: 0.9188
Val Loss: 0.3539 Acc: 0.8594

Epoch 13/25

Train Loss: 0.1766 Acc: 0.9132
Val Loss: 0.4022 Acc: 0.8420

Epoch 14/25

Train Loss: 0.1584 Acc: 0.9310
Val Loss: 0.4032 Acc: 0.8542

Epoch 15/25

Train Loss: 0.1591 Acc: 0.9280
Val Loss: 0.3712 Acc: 0.8594

Epoch 16/25

Train Loss: 0.1583 Acc: 0.9262
Val Loss: 0.3402 Acc: 0.8628

Epoch 17/25

Training: 36% |  | 105/288 [00:14<00:24, 7.46it/s]

✓ Grad-CAM++

```
import torch
import torch.nn.functional as
import numpy as np
import matplotlib.pyplot as plt

#####
# Grad-CAM++ Implementation
#####
class GradCAMPlusPlus:
    """
    Grad-CAM++ class for generating visual explanations using the Grad-CAM++ method.
    """

    def __init__(self, model: torch.nn.Module, target_layer: torch.nn.Module):
        """
        Initialize the GradCAMPlusPlus object.

        Args:
            model (torch.nn.Module): The model to inspect.
            target_layer (torch.nn.Module): The target convolutional layer to inspect.
        """

        self.model = model
        self.target_layer = target_layer
        self.gradients = None
        self.activations = None
        self.hook_handles = []
        self._register_hooks()

    def _register_hooks(self):
        def forward_hook(module, input, output):
            self.activations = output.detach()

        def backward_hook(module, grad_in, grad_out):
            # grad_out[0] corresponds to the gradients of the output
            self.gradients = grad_out[0].detach()

        self.hook_handles.append(self.target_layer.register_forward_hook(forward_hook))
        self.hook_handles.append(self.target_layer.register_backward_hook(backward_hook))

    def remove_hooks(self):
        """
        Remove the forward and backward hooks.
        """


```

```
"""
for handle in self.hook_handles:
    handle.remove()

def generate_cam(self, input_tensor: torch.Tensor, target_class: int) -> np.
"""
Generate Grad-CAM++ heatmap for the given input and target class.

Args:
    input_tensor (torch.Tensor): Input image tensor of shape (1, C, H,
    target_class (int): Class index for which to generate the heatmap.

Returns:
    np.ndarray: Upsampled heatmap (H x W) with values in [0, 1].
"""
# Forward pass
output = self.model(input_tensor)

# Zero gradients and create a one-hot vector for the target class
self.model.zero_grad()
one_hot = torch.zeros_like(output)
one_hot[0, target_class] = 1

# Backward pass to get gradients of target class score with respect to
output.backward(gradient=one_hot, retain_graph=True)

# Retrieve the saved gradients and activations
gradients = self.gradients # shape: (1, C, h, w)
activations = self.activations # shape: (1, C, h, w)
eps = 1e-8

# Compute the squared and cubed gradients
grad_squared = gradients ** 2
grad_cubed = gradients ** 3

# Sum the squared gradients over spatial dimensions (i,j)
global_sum_grad_squared = torch.sum(grad_squared, dim=(2, 3), keepdim=True)
global_sum_activations_grad_cubed = torch.sum(activations * grad_cubed, dim=(2, 3), keepdim=True)

# Compute denominator for alpha coefficients
denominator = 2 * global_sum_grad_squared + global_sum_activations_grad_cubed

# Calculate alpha coefficients for each pixel (channel-wise)
alphas = grad_squared / (denominator + eps)

# Compute weights by summing the product of alphas and ReLU of gradient
weights = torch.sum(alphas * F.relu(gradients), dim=(2, 3), keepdim=True)
```

```
# Weighted combination of forward activation maps
cam = torch.sum(weights * activations, dim=1, keepdim=True)
cam = F.relu(cam)

# Normalize the CAM to [0,1]
cam_min = cam.view(cam.size(0), -1).min(dim=1, keepdim=True)[0].unsqueeze(1)
cam_max = cam.view(cam.size(0), -1).max(dim=1, keepdim=True)[0].unsqueeze(1)
cam = (cam - cam_min) / (cam_max - cam_min + eps)

# Upsample to the input image size
cam = F.interpolate(cam, size=input_tensor.shape[2:], mode='bilinear',)

return cam[0, 0].cpu().numpy()
```

```
#####
# Helper Functions for Visualization
#####
def denormalize(img_tensor: torch.Tensor, mean=[0.485, 0.456, 0.406],
                std=[0.229, 0.224, 0.225]) -> np.ndarray:
    """
    Denormalize an image tensor and convert to numpy array.
    
```

Args:

```
    img_tensor (torch.Tensor): Tensor of shape (C, H, W).
    mean (list): Mean used for normalization.
    std (list): Standard deviation used for normalization.
```

Returns:

```
    np.ndarray: Denormalized image in H x W x C format with values in [0,1]
    """
    img = img_tensor.clone().detach().cpu().numpy().transpose(1, 2, 0)
    img = std * img + mean
    img = np.clip(img, 0, 1)
    return img
```

```
def overlay_heatmap(image: np.ndarray, heatmap: np.ndarray, alpha: float = 0.4,
                     colormap: str = 'jet') -> np.ndarray:
    """
    Overlay a heatmap on an image.
    
```

Args:

```
    image (np.ndarray): Original image array in [0,1].
    heatmap (np.ndarray): Heatmap array in [0,1].
    alpha (float): Transparency factor for heatmap overlay.
    colormap (str): Colormap to use.
```

Returns:

```
    np.ndarray: Image with heatmap overlay.
```

.....

```
cmap = plt.get_cmap(colormap)
heatmap_color = cmap(heatmap)
heatmap_color = heatmap_color[..., :3] # discard alpha channel if present
overlaid_img = heatmap_color * alpha + image * (1 - alpha)
overlaid_img = np.clip(overlaid_img, 0, 1)
return overlaid_img
```

```
def visualize_gradcam_per_class(model: torch.nn.Module, gradcam: GradCAMPlusPlus,
                                  dataset, num_samples: int = 3, device: str = 'cpu'):
    ....
```

Visualize Grad-CAM++ results row-wise, where each row corresponds to a class.

For each class, `num_samples` images are selected from the dataset, the Grad-CAM++ heatmap is computed, and the resulting overlay is displayed.

Args:

```
    model (torch.nn.Module): The trained model.
    gradcam (GradCAMPlusPlus): Initialized GradCAM++ object.
    dataset: Dataset (e.g., torchvision.datasets.ImageFolder) with .classes
    num_samples (int): Number of images per class to visualize.
    device (str): Device to perform computations ('cpu' or 'cuda').
    ....
```

Dictionary to hold overlays per class

```
class_to_overlays = {cls_idx: [] for cls_idx in range(len(dataset.classes))}
```

```
# Loop through dataset and collect overlays until reaching num_samples per class
for idx in range(len(dataset)):
    ....
```

```
    img, label = dataset[idx]
    if len(class_to_overlays[label]) < num_samples:
        input_tensor = img.unsqueeze(0).to(device)
        # Compute Grad-CAM++ heatmap for the true class (can be adjusted to target other classes)
        heatmap = gradcam.generate_cam(input_tensor, target_class=label)
        orig_img = denormalize(img)
        overlay_img = overlay_heatmap(orig_img, heatmap)
        class_to_overlays[label].append(overlay_img)
    if all(len(v) >= num_samples for v in class_to_overlays.values()):
        break
```

Plot images row-wise (one row per class)

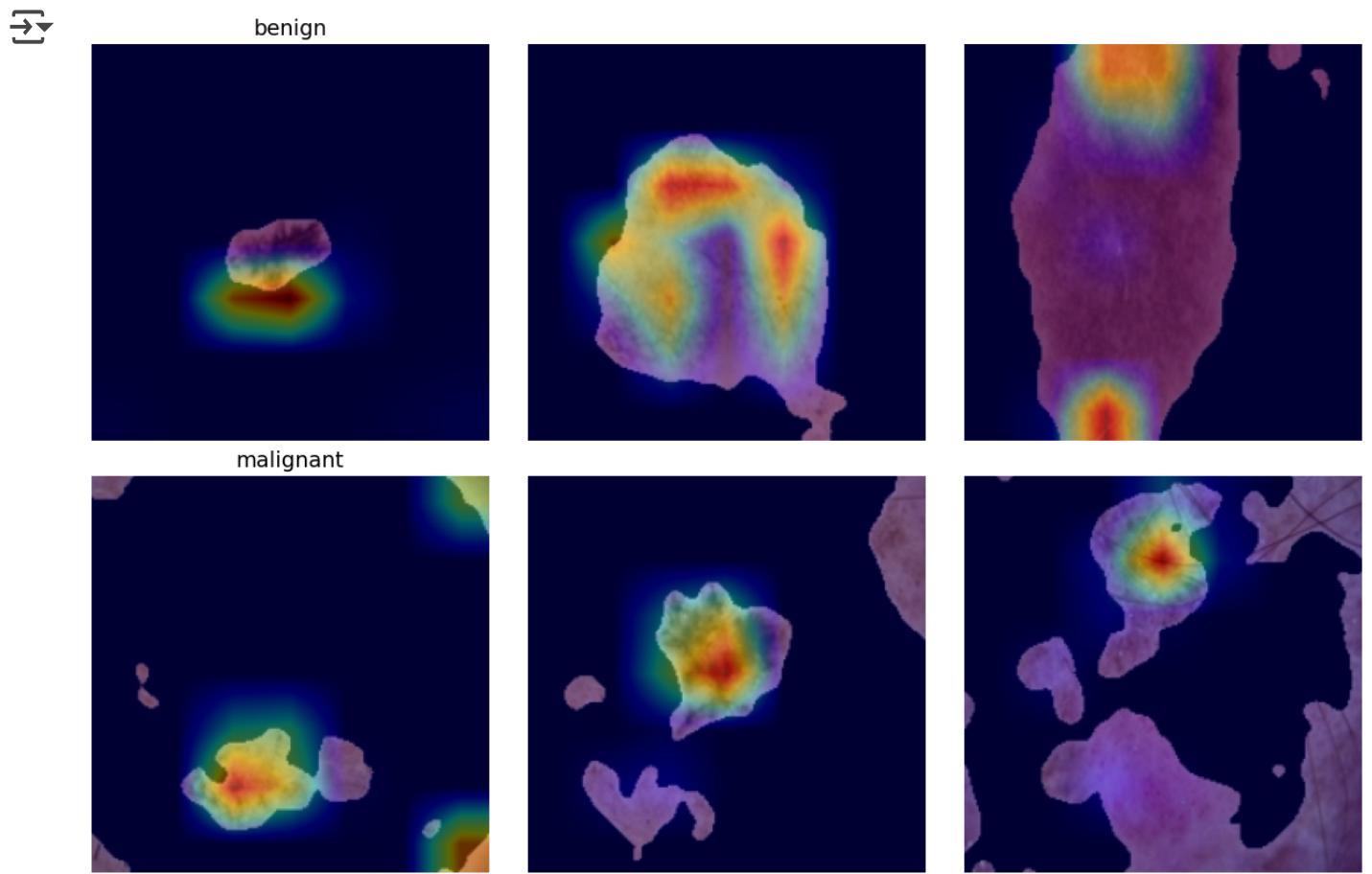
```
num_classes = len(dataset.classes)
fig, axes = plt.subplots(num_classes, num_samples, figsize=(num_samples * 4, num_classes * 4))
for cls_idx, overlays in class_to_overlays.items():
    for j, overlay_img in enumerate(overlays):
        ax = axes[cls_idx, j] if num_classes > 1 else axes[j]
        ax.imshow(overlay_img)
        ax.axis('off')
        if j == 0:
```

```
        ax.set_title(dataset.classes[cls_idx], fontsize=14)
        plt.tight_layout()
        plt.show()

#####
# Integration and Visualization
#####
# Set the target layer for Grad-CAM++.
# Here, we choose the last layer in the features block of ConvNeXt-Base.
# (Adjust the layer selection if needed.)
target_layer = model_convnext.features[-1]
gradcam_pp = GradCAMPlusPlus(model_convnext, target_layer)

# Visualize Grad-CAM++ outputs for the test dataset.
# This will display rows of images (with heatmap overlays) per class.
visualize_gradcam_per_class(model_convnext, gradcam_pp, test_dataset, num_sampl

# Remove hooks if no longer needed.
gradcam_pp.remove_hooks()
```



✓ Swin Transformer-B

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Dataset folder structure:
# data/
#   train/
#     benign/
#     malignant/
#   test/
#     benign/
#     malignant/

data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)' #
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# Define strong augmentations for training and standard normalization for testi
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
```

```
transforms.RandomHorizontalFlip(p=0.5),
transforms.RandomRotation(10),
transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.
transforms.ToTensor(),
transforms.Normalize([0.485, 0.456, 0.406],
[0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
transforms.Resize(256),
transforms.CenterCrop(224),
transforms.ToTensor(),
transforms.Normalize([0.485, 0.456, 0.406],
[0.229, 0.224, 0.225])
])

# Load datasets using ImageFolder
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())

    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%1.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. DataLoaders
#####
# Create DataLoaders (adjust batch_size as needed)
batch_size = 16
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r
```

```
#####
# 5. Model Initialization & Fine-Tuning (Swin Transformer-B)
#####
# Use the pretrained Swin Transformer-B from torchvision.
from torchvision.models import swin_b, Swin_B_Weights
weights = Swin_B_Weights.IMAGENET1K_V1
model_swin = swin_b(weights=weights)

# Replace the classifier head with a dropout and a Linear layer for 2 classes.
# The Swin Transformer in torchvision uses 'model_swin.head' as its classifier.
num_features = model_swin.head.in_features
model_swin.head = nn.Sequential(
    nn.Dropout(p=0.5),
    nn.Linear(num_features, 2)
)
model_swin = model_swin.to(device)

#####
# 6. Training Function
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    # Use mixed precision training to reduce memory and speed up computations.
    scaler = torch.cuda.amp.GradScaler()

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        print("-" * 10)

        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
                dataloader = train_loader
            else:
                model.eval()
                dataloader = test_loader

            running_loss = 0.0
            running_corrects = 0
            total_samples = 0
```

```
for inputs, labels in tqdm(dataloader, desc=phase):
    inputs = inputs.to(device)
    labels = labels.to(device)
    optimizer.zero_grad()

    with torch.set_grad_enabled(phase == 'train'):
        with torch.cuda.amp.autocast():
            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)
            loss = criterion(outputs, labels)

        if phase == 'train':
            scaler.scale(loss).backward()
            scaler.step(optimizer)
            scaler.update()

        running_loss += loss.item() * inputs.size(0)
        running_corrects += torch.sum(preds == labels.data).item()
        total_samples += inputs.size(0)

    if phase == 'train':
        scheduler.step()

    epoch_loss = running_loss / total_samples
    epoch_acc = running_corrects / total_samples
    print(f'{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

    if phase == 'train':
        train_loss_history.append(epoch_loss)
        train_acc_history.append(epoch_acc)
    else:
        val_loss_history.append(epoch_loss)
        val_acc_history.append(epoch_acc)
        if epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = copy.deepcopy(model.state_dict())
print()

time_elapsed = time.time() - since
print(f"Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s")
print(f"Best Validation Acc: {best_acc:.4f}")

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
```

```
        'val_acc': val_acc_history
    }
    return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_swin = optim.Adam(model_swin.parameters(), lr=1e-4)
scheduler_swin = lr_scheduler.StepLR(optimizer_swin, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####
num_epochs = 25
model_swin, history = train_model(model_swin, criterion, optimizer_swin, scheduler_swin, num_epochs)

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####
def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_curves(history)
```

```
#####
```

```
# 10. Model Evaluation on Test Set
#####
model_swin.eval()
all_preds = []
all_probs = [] # Probabilities for the malignant class (index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_swin(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Class 1 probability
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

#####

# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

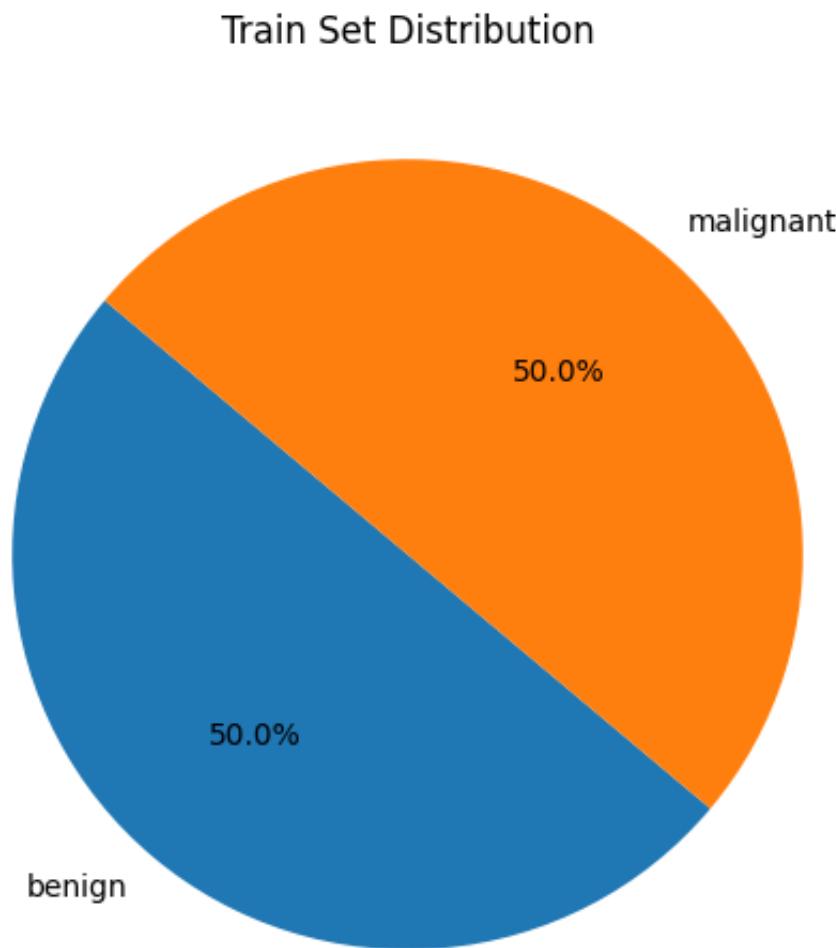
#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####

# 13. Visualization 5: ROC Curve & AUC
#####
```

```
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

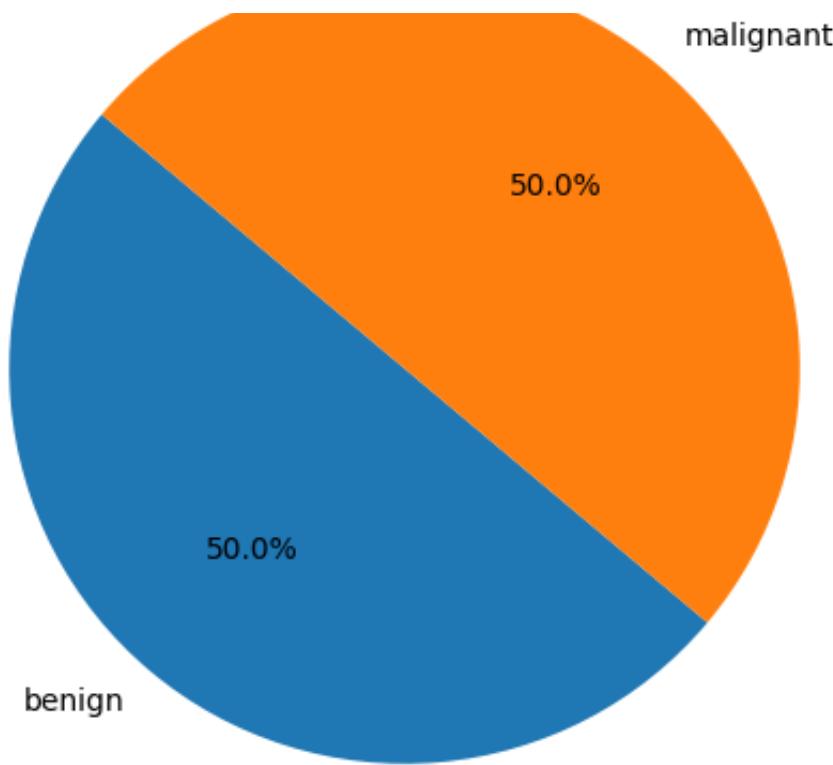
→ Using device: cuda:0
Train Set Distribution:



Test Set Distribution:

Test Set Distribution





```
Downloading: "https://download.pytorch.org/models/swin_b-68c6b09e.pth" to /
100%|██████████| 335M/335M [00:01<00:00, 200MB/s]
<ipython-input-1-04b50f1985b7>:128: FutureWarning: `torch.cuda.amp.GradScal
    scaler = torch.cuda.amp.GradScaler()
Epoch 1/25
-----
train:  0% | 0/180 [00:00<?, ?it/s]<ipython-input-1-04b50f1985b7
    with torch.cuda.amp.autocast():
train: 100%|██████████| 180/180 [00:46<00:00,  3.87it/s]
Train Loss: 0.4950 Acc: 0.7552
val: 100%|██████████| 45/45 [00:03<00:00, 11.27it/s]
Val Loss: 0.3439 Acc: 0.8431

Epoch 2/25
-----
train: 100%|██████████| 180/180 [00:47<00:00,  3.78it/s]
Train Loss: 0.4075 Acc: 0.8038
val: 100%|██████████| 45/45 [00:04<00:00, 10.41it/s]
Val Loss: 0.3758 Acc: 0.8194

Epoch 3/25
-----
train: 100%|██████████| 180/180 [00:48<00:00,  3.72it/s]
Train Loss: 0.3711 Acc: 0.8174
val: 100%|██████████| 45/45 [00:04<00:00, 10.74it/s]
Val Loss: 0.3142 Acc: 0.8444

Epoch 4/25
-----
train: 100%|██████████| 180/180 [00:48<00:00,  3.74it/s]
```

```
Train Loss: 0.3817 Acc: 0.8177
val: 100%|██████████| 45/45 [00:04<00:00, 10.71it/s]
Val Loss: 0.3643 Acc: 0.8250
```

Epoch 5/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.73it/s]
Train Loss: 0.3451 Acc: 0.8458
val: 100%|██████████| 45/45 [00:04<00:00, 10.79it/s]
Val Loss: 0.3096 Acc: 0.8500
```

Epoch 6/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]
Train Loss: 0.3326 Acc: 0.8399
val: 100%|██████████| 45/45 [00:04<00:00, 10.63it/s]
Val Loss: 0.3057 Acc: 0.8444
```

Epoch 7/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]
Train Loss: 0.3258 Acc: 0.8438
val: 100%|██████████| 45/45 [00:04<00:00, 10.74it/s]
Val Loss: 0.2833 Acc: 0.8597
```

Epoch 8/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.73it/s]
Train Loss: 0.2821 Acc: 0.8646
val: 100%|██████████| 45/45 [00:04<00:00, 10.76it/s]
Val Loss: 0.2672 Acc: 0.8736
```

Epoch 9/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]
Train Loss: 0.2642 Acc: 0.8753
val: 100%|██████████| 45/45 [00:04<00:00, 10.78it/s]
Val Loss: 0.2714 Acc: 0.8681
```

Epoch 10/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]
Train Loss: 0.2562 Acc: 0.8795
val: 100%|██████████| 45/45 [00:04<00:00, 10.74it/s]
Val Loss: 0.2591 Acc: 0.8750
```

Epoch 11/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.73it/s]
Train Loss: 0.2529 Acc: 0.8781
val: 100%|██████████| 45/45 [00:04<00:00, 10.73it/s]
Val Loss: 0.2663 Acc: 0.8736
```

Epoch 12/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2438 Acc: 0.8833  
val: 100%|██████████| 45/45 [00:04<00:00, 10.72it/s]  
Val Loss: 0.2656 Acc: 0.8792
```

Epoch 13/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.73it/s]  
Train Loss: 0.2358 Acc: 0.8868  
val: 100%|██████████| 45/45 [00:04<00:00, 10.70it/s]  
Val Loss: 0.2519 Acc: 0.8806
```

Epoch 14/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2366 Acc: 0.8892  
val: 100%|██████████| 45/45 [00:04<00:00, 10.78it/s]  
Val Loss: 0.2583 Acc: 0.8792
```

Epoch 15/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2219 Acc: 0.8948  
val: 100%|██████████| 45/45 [00:04<00:00, 10.72it/s]  
Val Loss: 0.2588 Acc: 0.8778
```

Epoch 16/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2264 Acc: 0.9014  
val: 100%|██████████| 45/45 [00:04<00:00, 10.76it/s]  
Val Loss: 0.2579 Acc: 0.8736
```

Epoch 17/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2186 Acc: 0.8965  
val: 100%|██████████| 45/45 [00:04<00:00, 10.71it/s]  
Val Loss: 0.2605 Acc: 0.8750
```

Epoch 18/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2198 Acc: 0.8990  
val: 100%|██████████| 45/45 [00:04<00:00, 10.72it/s]  
Val Loss: 0.2636 Acc: 0.8736
```

Epoch 19/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2254 Acc: 0.8920  
val: 100%|██████████| 45/45 [00:04<00:00, 10.73it/s]  
Val Loss: 0.2617 Acc: 0.8708
```

Epoch 20/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2166 Acc: 0.8948  
val: 100%|██████████| 45/45 [00:04<00:00, 10.77it/s]  
Val Loss: 0.2631 Acc: 0.8736
```

Epoch 21/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2191 Acc: 0.9014  
val: 100%|██████████| 45/45 [00:04<00:00, 10.79it/s]  
Val Loss: 0.2641 Acc: 0.8750
```

Epoch 22/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2166 Acc: 0.9052  
val: 100%|██████████| 45/45 [00:04<00:00, 10.75it/s]  
Val Loss: 0.2641 Acc: 0.8750
```

Epoch 23/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.73it/s]  
Train Loss: 0.2227 Acc: 0.8990  
val: 100%|██████████| 45/45 [00:04<00:00, 10.63it/s]  
Val Loss: 0.2640 Acc: 0.8764
```

Epoch 24/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.74it/s]  
Train Loss: 0.2200 Acc: 0.8993  
val: 100%|██████████| 45/45 [00:04<00:00, 10.72it/s]  
Val Loss: 0.2637 Acc: 0.8764
```

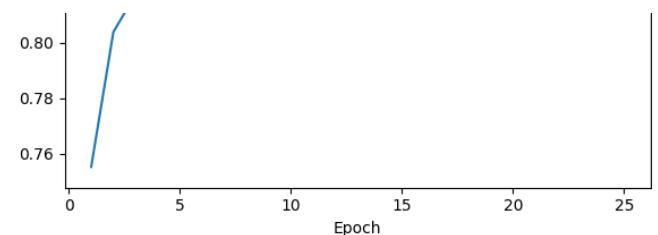
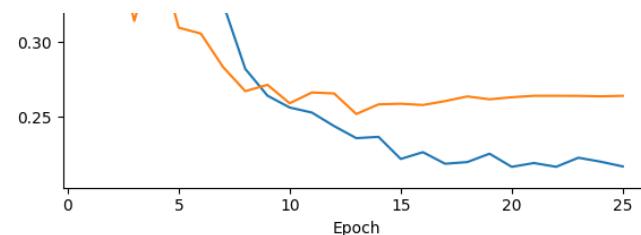
Epoch 25/25

```
-----  
train: 100%|██████████| 180/180 [00:48<00:00, 3.75it/s]  
Train Loss: 0.2168 Acc: 0.8993  
val: 100%|██████████| 45/45 [00:04<00:00, 10.80it/s]  
Val Loss: 0.2640 Acc: 0.8764
```

Training complete in 21m 47s

Best Validation Acc: 0.8806

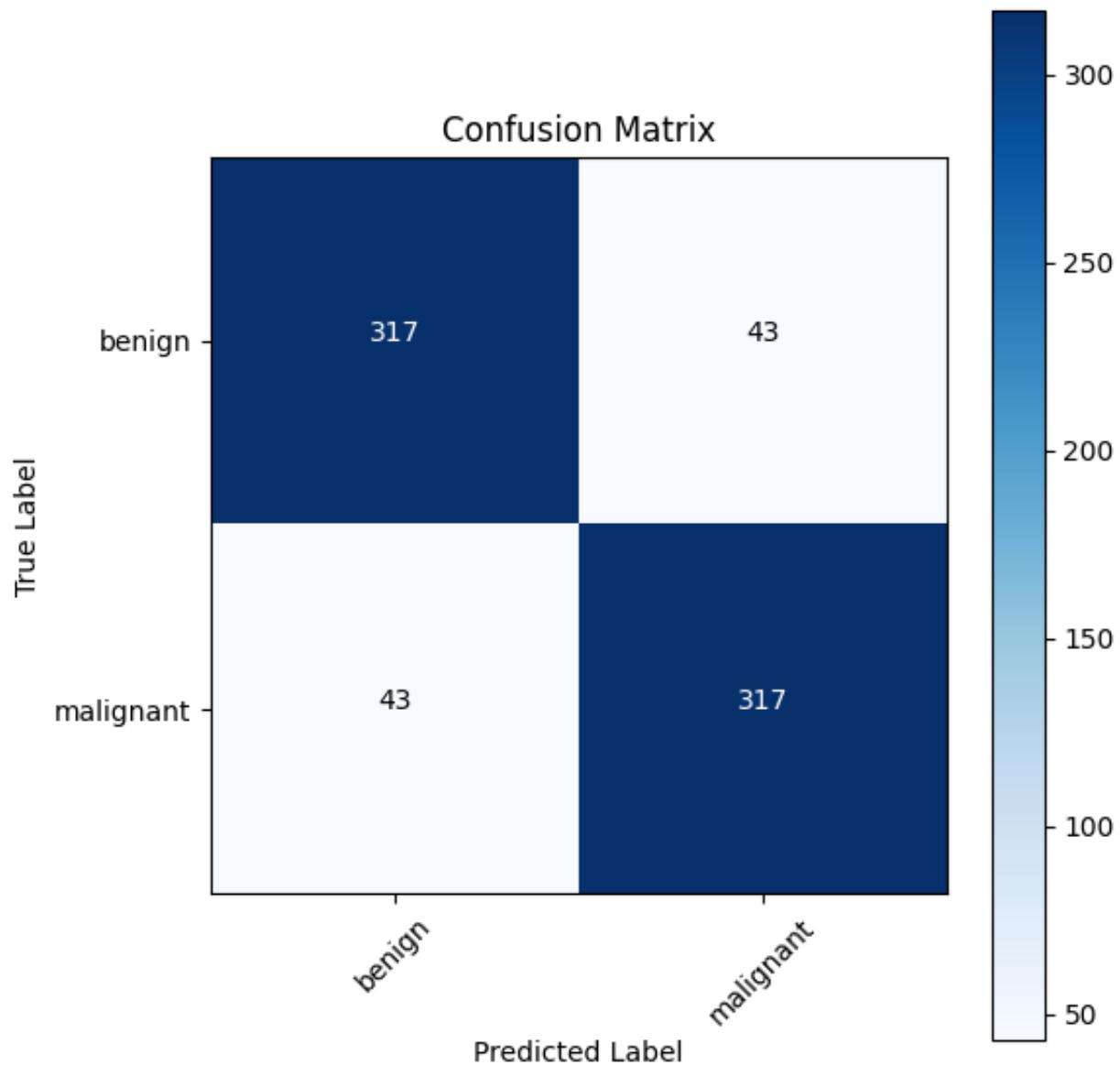




Testing: 100% |████████| 45/45 [00:09<00:00, 4.67it/s]

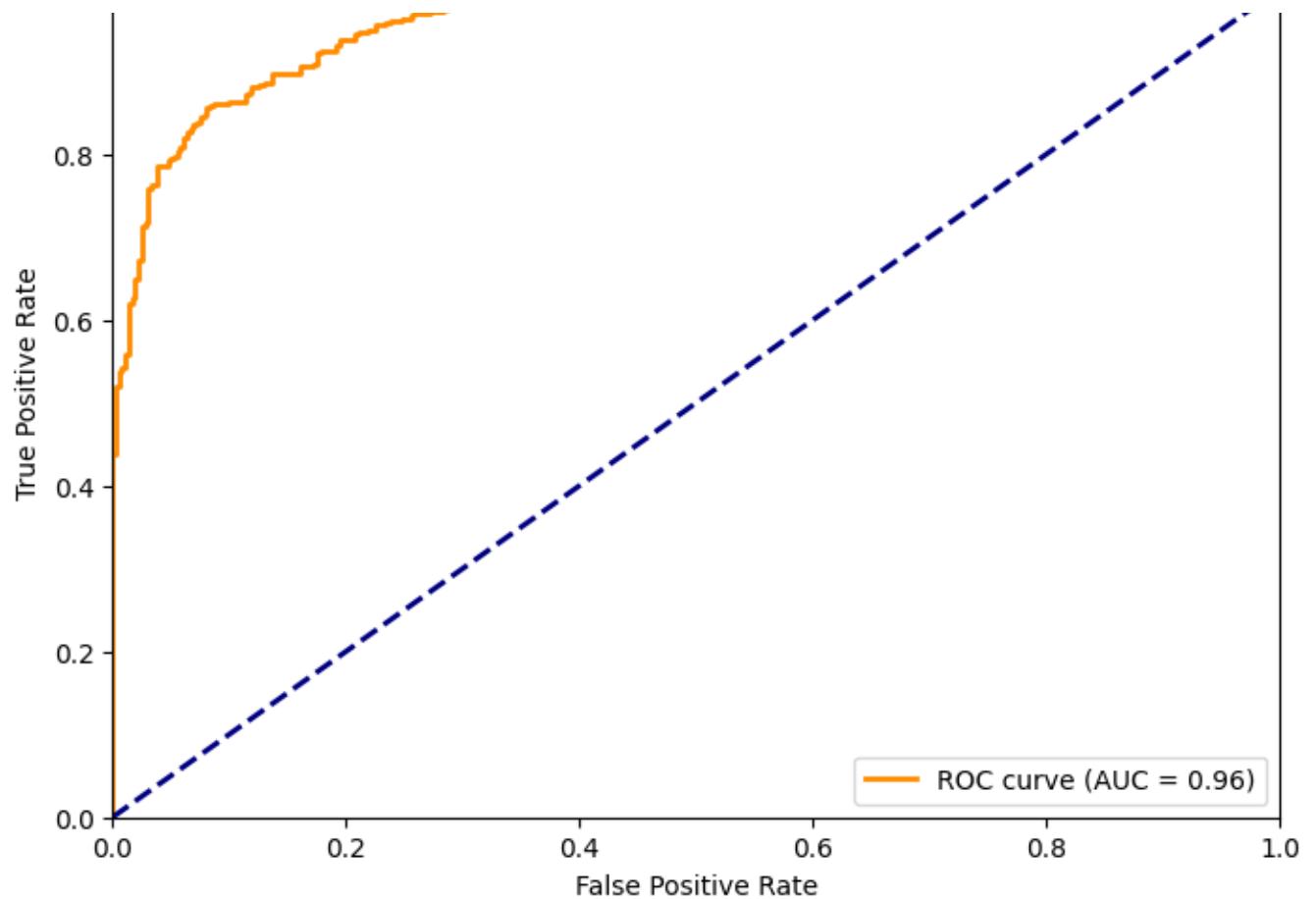
Classification Report:

	precision	recall	f1-score	support
benign	0.88	0.88	0.88	360
malignant	0.88	0.88	0.88	360
accuracy			0.88	720
macro avg	0.88	0.88	0.88	720
weighted avg	0.88	0.88	0.88	720



Receiver Operating Characteristic





✓ Vision Transformer ViT model (vit_base_patch16_224)

```
import os
import random
import numpy as np
```

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm
import timm # for Vision Transformer

#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Dataset directory structure:
# data/
#   train/
#     benign/
#     malignant/
#   test/
#     benign/
#     malignant/
data_dir = '/kaggle/input/k-means-cyclegan/k-means segmented_data(cycleGAN)' #
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# ViT typically uses 224x224 images.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.
```

```
transforms.ToTensor(),
transforms.Normalize([0.485, 0.456, 0.406],
[0.229, 0.224, 0.225])
])
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
[0.229, 0.224, 0.225])
])

# Load datasets using ImageFolder
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####
def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())
    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%1.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. DataLoaders
#####
batch_size = 16 # Adjust based on GPU memory
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, r
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, r

#####
# 5. Model Initialization & Fine-Tuning (Vision Transformer)
#####
# We use TIMM to create a ViT model (vit_base_patch16_224) pretrained on ImageN
model_vit = timm.create_model('vit_base_patch16_224', pretrained=True, num_clas
```

```
model_vit = model_vit.to(device)

#####
# 6. Training Function
#####
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    # Lists to store history
    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    # Optionally, enable mixed precision training for memory and speed (if available)
    scaler = torch.cuda.amp.GradScaler()

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        print("-" * 10)

        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
                dataloader = train_loader
            else:
                model.eval()
                dataloader = test_loader

            running_loss = 0.0
            running_corrects = 0
            total_samples = 0

            for inputs, labels in tqdm(dataloader, desc=phase):
                inputs = inputs.to(device)
                labels = labels.to(device)
                optimizer.zero_grad()

                with torch.set_grad_enabled(phase == 'train'):
                    with torch.cuda.amp.autocast():
                        outputs = model(inputs)
                        _, preds = torch.max(outputs, 1)
                        loss = criterion(outputs, labels)

                if phase == 'train':
                    scaler.scale(loss).backward()
```

```
        scaler.step(optimizer)
        scaler.update()

        running_loss += loss.item() * inputs.size(0)
        running_corrects += torch.sum(preds == labels.data).item()
        total_samples += inputs.size(0)

    if phase == 'train':
        scheduler.step()

    epoch_loss = running_loss / total_samples
    epoch_acc = running_corrects / total_samples
    print(f'{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

    if phase == 'train':
        train_loss_history.append(epoch_loss)
        train_acc_history.append(epoch_acc)
    else:
        val_loss_history.append(epoch_loss)
        val_acc_history.append(epoch_acc)
        if epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = copy.deepcopy(model.state_dict())
print()

time_elapsed = time.time() - since
print(f'Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s')
print(f'Best Validation Acc: {best_acc:.4f}')

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer_vit = optim.Adam(model_vit.parameters(), lr=1e-4)
scheduler_vit = lr_scheduler.StepLR(optimizer_vit, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####

```

```
num_epochs = 25
model_vit, history = train_model(model_vit, criterion, optimizer_vit, scheduler

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####

def plot_training_curves(history):
    epochs = range(1, len(history['train_loss']) + 1)
    plt.figure(figsize=(12,5))

    # Loss Curve
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history['train_loss'], label='Training Loss')
    plt.plot(epochs, history['val_loss'], label='Validation Loss')
    plt.title('Loss Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()

    # Accuracy Curve
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history['train_acc'], label='Training Accuracy')
    plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
    plt.title('Accuracy Curve')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.tight_layout()
    plt.show()

plot_training_curves(history)

#####
# 10. Model Evaluation on Test Set
#####

model_vit.eval()
all_preds = []
all_probs = [] # Probabilities for malignant (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model_vit(inputs)
        _, preds = torch.max(outputs, 1)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Class 1 probabil
```

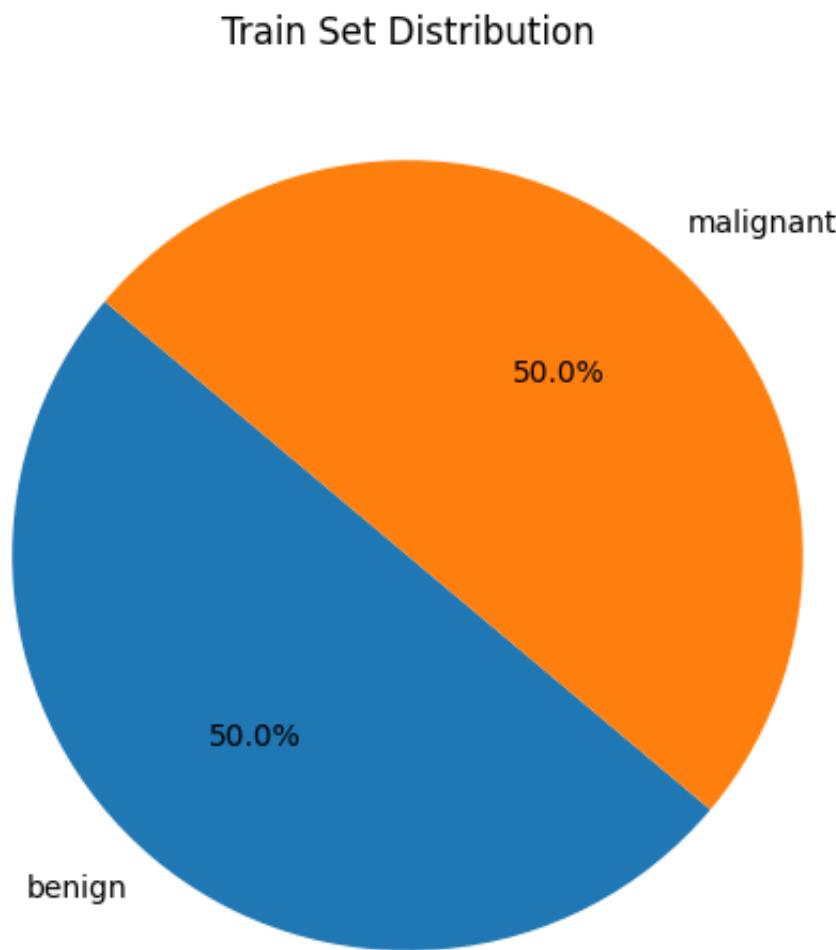
```
all_preds.extend(preds.cpu().numpy())
all_probs.extend(probs.cpu().numpy())
all_labels.extend(labels.cpu().numpy())

#####
# 11. Visualization 3: Classification Report
#####
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.c

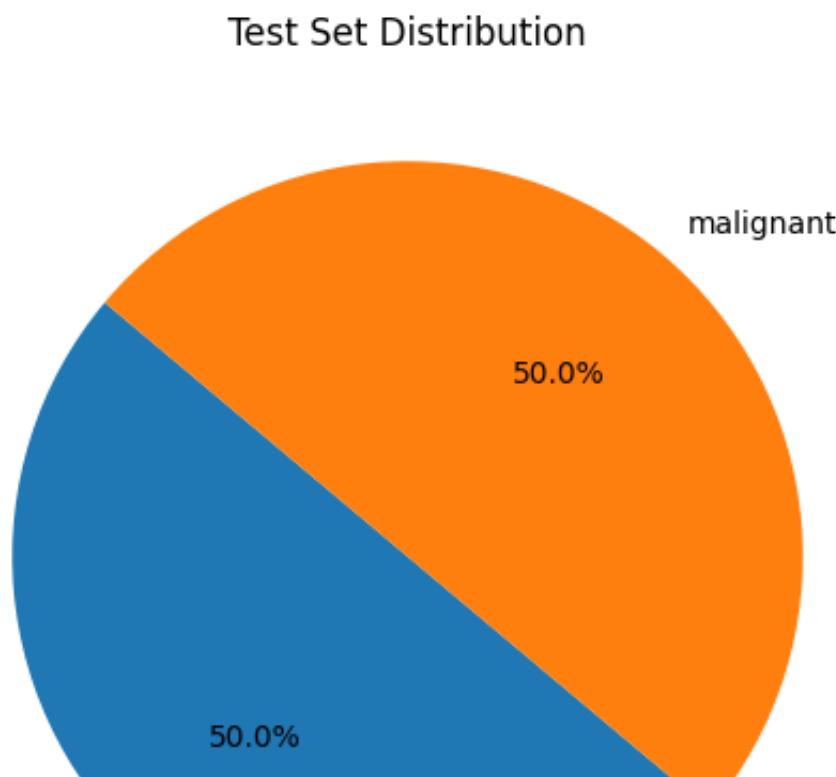
#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####
# 13. Visualization 5: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

Using device: cuda:0
Train Set Distribution:



Test Set Distribution:





```
model.safetensors:  0%|          | 0.00/346M [00:00<?, ?B/s]
<ipython-input-7-6b0779b64c9e>:117: FutureWarning: `torch.cuda.amp.GradScal
    scaler = torch.cuda.amp.GradScaler()
Epoch 1/25
-----
train:  0%|          | 0/180 [00:00<?, ?it/s]<ipython-input-7-6b0779b64c9e
    with torch.cuda.amp.autocast():
train: 100%|██████████| 180/180 [00:30<00:00,  5.96it/s]
Train Loss: 0.6272 Acc: 0.6573
val: 100%|██████████| 45/45 [00:02<00:00, 18.55it/s]
Val Loss: 0.4467 Acc: 0.8000

Epoch 2/25
-----
train: 100%|██████████| 180/180 [00:28<00:00,  6.27it/s]
Train Loss: 0.4559 Acc: 0.7840
val: 100%|██████████| 45/45 [00:02<00:00, 19.22it/s]
Val Loss: 0.4190 Acc: 0.8125

Epoch 3/25
-----
train: 100%|██████████| 180/180 [00:28<00:00,  6.27it/s]
Train Loss: 0.4364 Acc: 0.7816
val: 100%|██████████| 45/45 [00:02<00:00, 18.76it/s]
Val Loss: 0.3838 Acc: 0.8264

Epoch 4/25
-----
train: 100%|██████████| 180/180 [00:29<00:00,  6.15it/s]
Train Loss: 0.4063 Acc: 0.8073
val: 100%|██████████| 45/45 [00:02<00:00, 18.61it/s]
Val Loss: 0.4203 Acc: 0.8056

Epoch 5/25
-----
train: 100%|██████████| 180/180 [00:28<00:00,  6.23it/s]
Train Loss: 0.4094 Acc: 0.8017
val: 100%|██████████| 45/45 [00:02<00:00, 18.90it/s]
Val Loss: 0.3722 Acc: 0.8292

Epoch 6/25
-----
train: 100%|██████████| 180/180 [00:28<00:00,  6.25it/s]
Train Loss: 0.3949 Acc: 0.8125
val: 100%|██████████| 45/45 [00:02<00:00, 18.09it/s]
Val Loss: 0.4359 Acc: 0.7986
```

Epoch 7/25

```
-----  
train: 100%|██████████| 180/180 [00:28<00:00, 6.21it/s]  
Train Loss: 0.3973 Acc: 0.8063  
val: 100%|██████████| 45/45 [00:02<00:00, 18.31it/s]  
Val Loss: 0.4346 Acc: 0.8028
```

Epoch 8/25

```
-----  
train: 100%|██████████| 180/180 [00:28<00:00, 6.22it/s]  
Train Loss: 0.3397 Acc: 0.8337  
val: 100%|██████████| 45/45 [00:02<00:00, 18.02it/s]  
Val Loss: 0.3328 Acc: 0.8444
```

Epoch 9/25

```
-----  
train: 100%|██████████| 180/180 [00:28<00:00, 6.24it/s]  
Train Loss: 0.3228 Acc: 0.8479  
val: 100%|██████████| 45/45 [00:02<00:00, 18.57it/s]  
Val Loss: 0.3244 Acc: 0.8528
```

Epoch 10/25

```
-----  
train: 100%|██████████| 180/180 [00:28<00:00, 6.25it/s]  
Train Loss: 0.3070 Acc: 0.8514  
val: 100%|██████████| 45/45 [00:02<00:00, 18.61it/s]  
Val Loss: 0.2977 Acc: 0.8569
```

Epoch 11/25

```
-----  
train: 100%|██████████| 180/180 [00:28<00:00, 6.25it/s]  
Train Loss: 0.2983 Acc: 0.8608  
val: 100%|██████████| 45/45 [00:02<00:00, 18.68it/s]  
Val Loss: 0.2984 Acc: 0.8681
```

Epoch 12/25

```
-----  
train: 100%|██████████| 180/180 [00:28<00:00, 6.23it/s]  
Train Loss: 0.2948 Acc: 0.8601  
val: 100%|██████████| 45/45 [00:02<00:00, 18.67it/s]  
Val Loss: 0.2962 Acc: 0.8639
```

Epoch 13/25

```
-----  
train: 100%|██████████| 180/180 [00:29<00:00, 6.20it/s]  
Train Loss: 0.2952 Acc: 0.8667  
val: 100%|██████████| 45/45 [00:02<00:00, 18.44it/s]  
Val Loss: 0.3068 Acc: 0.8653
```

Epoch 14/25

```
-----  
train: 100%|██████████| 180/180 [00:29<00:00, 6.19it/s]  
Train Loss: 0.2944 Acc: 0.8608
```

```
val: 100%|██████████| 45/45 [00:02<00:00, 18.56it/s]
Val Loss: 0.3096 Acc: 0.8708

Epoch 15/25
-----
train: 100%|██████████| 180/180 [00:29<00:00, 6.20it/s]
Train Loss: 0.2651 Acc: 0.8747
val: 100%|██████████| 45/45 [00:02<00:00, 18.74it/s]
Val Loss: 0.3006 Acc: 0.8681

Epoch 16/25
-----
train: 100%|██████████| 180/180 [00:28<00:00, 6.21it/s]
Train Loss: 0.2738 Acc: 0.8747
val: 100%|██████████| 45/45 [00:02<00:00, 18.72it/s]
Val Loss: 0.2991 Acc: 0.8736

Epoch 17/25
-----
train: 100%|██████████| 180/180 [00:29<00:00, 6.21it/s]
Train Loss: 0.2693 Acc: 0.8747
val: 100%|██████████| 45/45 [00:02<00:00, 18.56it/s]
Val Loss: 0.2930 Acc: 0.8736

Epoch 18/25
-----
train: 100%|██████████| 180/180 [00:29<00:00, 6.20it/s]
Train Loss: 0.2726 Acc: 0.8750
val: 100%|██████████| 45/45 [00:02<00:00, 18.65it/s]
Val Loss: 0.2924 Acc: 0.8750

Epoch 19/25
-----
train: 100%|██████████| 180/180 [00:29<00:00, 6.20it/s]
Train Loss: 0.2683 Acc: 0.8757
val: 100%|██████████| 45/45 [00:02<00:00, 18.62it/s]
Val Loss: 0.2907 Acc: 0.8708

Epoch 20/25
-----
train: 100%|██████████| 180/180 [00:28<00:00, 6.21it/s]
Train Loss: 0.2593 Acc: 0.8816
val: 100%|██████████| 45/45 [00:02<00:00, 18.58it/s]
Val Loss: 0.2899 Acc: 0.8736

Epoch 21/25
-----
train: 100%|██████████| 180/180 [00:28<00:00, 6.21it/s]
Train Loss: 0.2623 Acc: 0.8733
val: 100%|██████████| 45/45 [00:02<00:00, 18.63it/s]
Val Loss: 0.2887 Acc: 0.8764

Epoch 22/25
-----
```

```
train: 100%|██████████| 180/180 [00:28<00:00, 6.22it/s]
Train Loss: 0.2565 Acc: 0.8809
val: 100%|██████████| 45/45 [00:02<00:00, 18.78it/s]
Val Loss: 0.2890 Acc: 0.8750
```

Epoch 23/25

```
train: 100%|██████████| 180/180 [00:29<00:00, 6.21it/s]
Train Loss: 0.2623 Acc: 0.8733
val: 100%|██████████| 45/45 [00:02<00:00, 18.65it/s]
Val Loss: 0.2889 Acc: 0.8764
```

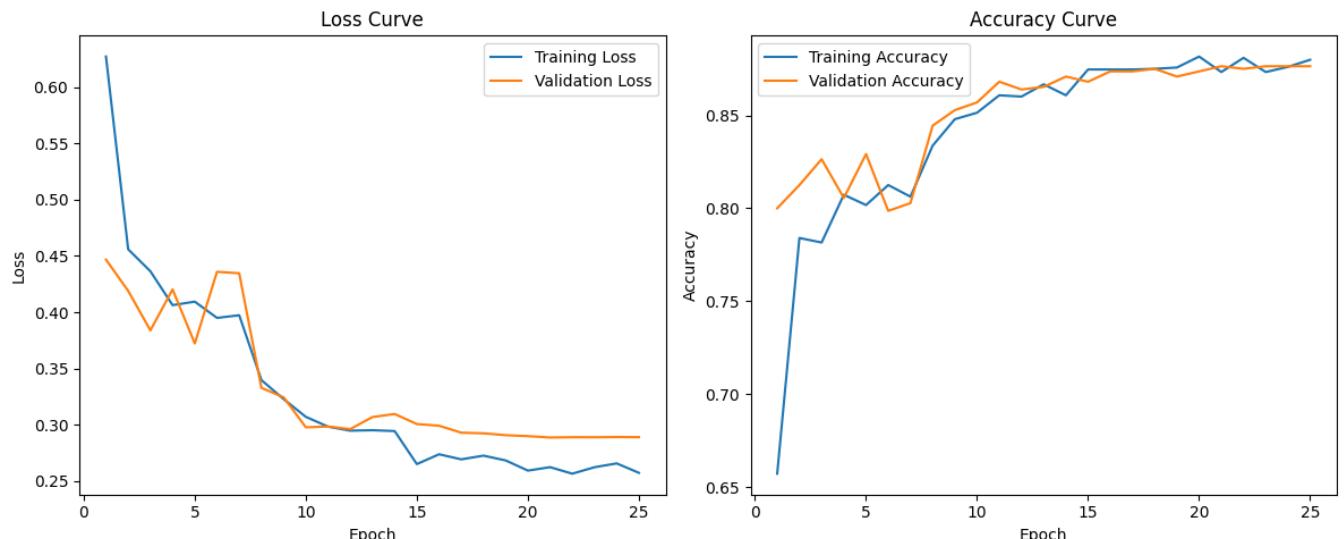
Epoch 24/25

```
train: 100%|██████████| 180/180 [00:29<00:00, 6.20it/s]
Train Loss: 0.2657 Acc: 0.8760
val: 100%|██████████| 45/45 [00:02<00:00, 18.61it/s]
Val Loss: 0.2891 Acc: 0.8764
```

Epoch 25/25

```
train: 100%|██████████| 180/180 [00:29<00:00, 6.19it/s]
Train Loss: 0.2573 Acc: 0.8799
val: 100%|██████████| 45/45 [00:02<00:00, 18.71it/s]
Val Loss: 0.2890 Acc: 0.8764
```

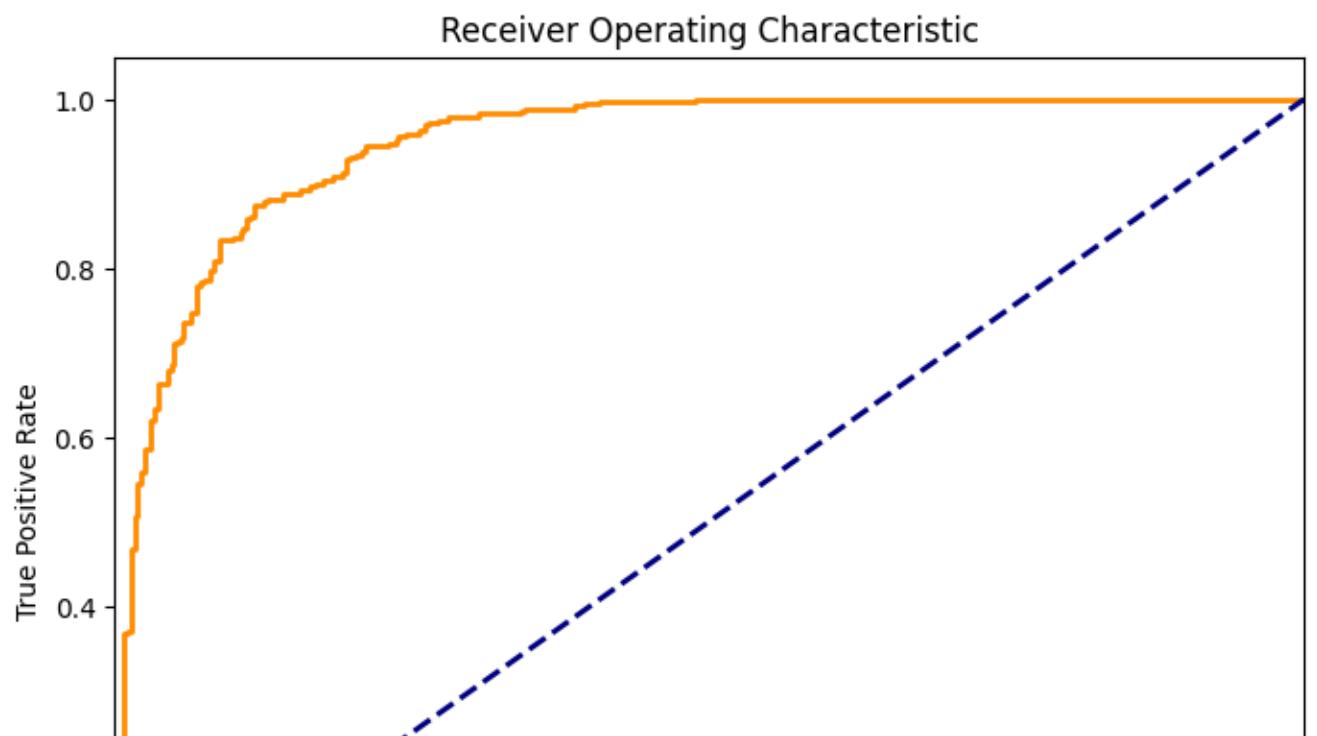
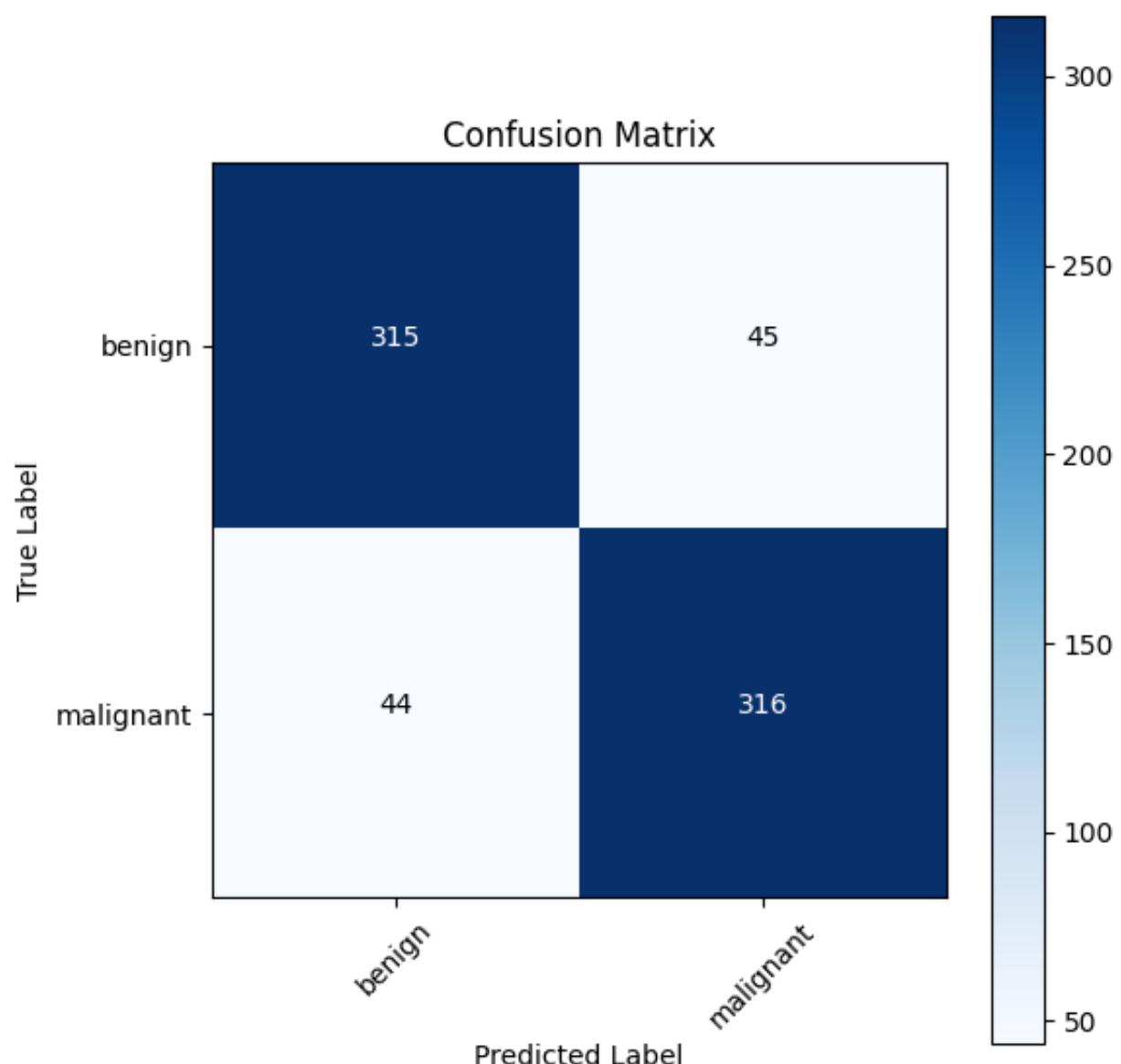
Training complete in 13m 6s
Best Validation Acc: 0.8764

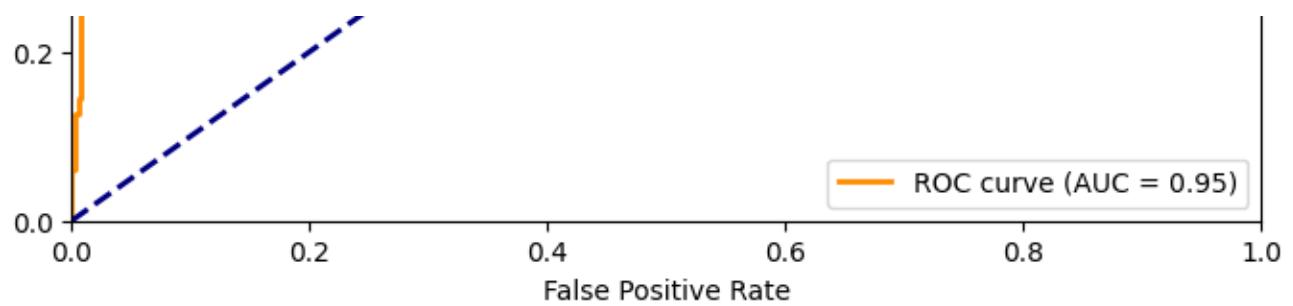


Testing: 100%|██████████| 45/45 [00:09<00:00, 4.89it/s]

Classification Report:

	precision	recall	f1-score	support
benign	0.88	0.88	0.88	360
malignant	0.88	0.88	0.88	360
accuracy			0.88	720
macro avg	0.88	0.88	0.88	720
weighted avg	0.88	0.88	0.88	720





✓ A custom hybrid CNN–ViT model

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt
import time
import copy
from sklearn.metrics import classification_report, confusion_matrix, roc_curve,
from tqdm import tqdm

# Optionally, set environment variable to reduce fragmentation
os.environ["PYTORCH_CUDA_ALLOC_CONF"] = "expandable_segments:True"
torch.cuda.empty_cache()
```

```
#####
# 1. Reproducibility & Device Setup
#####
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

#####
# 2. Data Preparation & Augmentation
#####
# Dataset folder structure:
# data/
#   train/
#     benign/
#     malignant/
#   test/
#     benign/
#     malignant/
data_dir = '/kaggle/input/k-means-cyclegan/k-means' segmented_data(cycleGAN) # 
train_dir = os.path.join(data_dir, 'train')
test_dir = os.path.join(data_dir, 'test')

# We'll use strong augmentation for training.
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])
])
# Testing transforms: resize and center crop.
test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])
])
```

```
train_dataset = datasets.ImageFolder(train_dir, transform=train_transforms)
test_dataset = datasets.ImageFolder(test_dir, transform=test_transforms)

#####
# 3. Visualization 1: Dataset Class Distribution (Pie Chart)
#####

def plot_class_distribution(dataset, title="Class Distribution"):
    class_names = dataset.classes
    class_counts = {name: 0 for name in class_names}
    for _, label in dataset.samples:
        class_counts[class_names[label]] += 1
    labels = list(class_counts.keys())
    counts = list(class_counts.values())
    plt.figure(figsize=(6,6))
    plt.pie(counts, labels=labels, autopct='%1.1f%%', startangle=140)
    plt.title(title)
    plt.show()

print("Train Set Distribution:")
plot_class_distribution(train_dataset, "Train Set Distribution")
print("Test Set Distribution:")
plot_class_distribution(test_dataset, "Test Set Distribution")

#####
# 4. DataLoaders
#####

batch_size = 16 # Adjust as needed
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, num_workers=4)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, num_workers=4)

#####
# 5. Hybrid CNN-ViT Model Definition
#####

# This custom model uses a pretrained ResNet50 as a CNN backbone to extract spatial features.
# The feature map is flattened to a sequence of tokens, projected to a lower dimension,
# a learnable [CLS] token and positional embeddings are added,
# and the tokens are passed through a Transformer encoder.
# The [CLS] token output is then used for classification.

class HybridCNNViT(nn.Module):
    def __init__(self, num_classes=2, hidden_dim=768, num_transformer_layers=6, patch_size=16):
        super(HybridCNNViT, self).__init__()
        # Pretrained CNN Backbone (ResNet50 without avgpool and fc)
        cnn = models.resnet50(pretrained=True)
        self.cnn_backbone = nn.Sequential(*list(cnn.children())[:-2])
        # For 224x224 input, ResNet50 produces (batch, 2048, 7, 7)
        self.num_patches = 7 * 7 # 49 patches
        self.patch_dim = 2048
        # Project each patch to the hidden dimension expected by the transformer
        self.patch_to_token = nn.Linear(2048, hidden_dim)
```

```
    self.linear_projection = nn.Linear(self.patch_dim, hidden_dim)
    # Class token
    self.cls_token = nn.Parameter(torch.zeros(1, 1, hidden_dim))
    # Positional embedding for patches + class token
    self.pos_embedding = nn.Parameter(torch.zeros(1, self.num_patches + 1, hidden_dim))
    # Transformer encoder
    encoder_layer = nn.TransformerEncoderLayer(d_model=hidden_dim, nhead=num_heads)
    self.transformer_encoder = nn.TransformerEncoder(encoder_layer, num_layers)
    # Classification head
    self.fc = nn.Linear(hidden_dim, num_classes)
    self.dropout = nn.Dropout(0.5)
    self._init_weights()

def _init_weights(self):
    nn.init.trunc_normal_(self.pos_embedding, std=0.02)
    nn.init.trunc_normal_(self.cls_token, std=0.02)
    nn.init.xavier_uniform_(self.fc.weight)
    nn.init.zeros_(self.fc.bias)

def forward(self, x):
    # x: (batch, 3, 224, 224)
    features = self.cnn_backbone(x)  # shape: (batch, 2048, 7, 7)
    batch_size = features.size(0)
    # Flatten spatial dimensions: (batch, 2048, 49) -> (batch, 49, 2048)
    features = features.flatten(2).transpose(1, 2)
    # Project to hidden dimension: (batch, 49, hidden_dim)
    tokens = self.linear_projection(features)
    # Prepare class token and concatenate: (batch, 1, hidden_dim)
    cls_tokens = self.cls_token.expand(batch_size, -1, -1)
    tokens = torch.cat((cls_tokens, tokens), dim=1)  # (batch, 50, hidden_dim)
    # Add positional embeddings
    tokens = tokens + self.pos_embedding
    # Permute for transformer: (sequence, batch, d_model)
    tokens = tokens.transpose(0, 1)
    # Transformer Encoder
    transformer_out = self.transformer_encoder(tokens)
    # Use the output of the class token (first token)
    cls_output = transformer_out[0]
    cls_output = self.dropout(cls_output)
    logits = self.fc(cls_output)
    return logits

# Initialize the model
model = HybridCNNViT(num_classes=2, hidden_dim=768, num_transformer_layers=6, num_heads=12)
model = model.to(device)

#####
# 6. Training Function
#####
```

```
def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    since = time.time()
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    # Mixed precision training (optional but helps with memory/speed)
    scaler = torch.cuda.amp.GradScaler()

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        print("-" * 10)
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
                dataloader = train_loader
            else:
                model.eval()
                dataloader = test_loader

            running_loss = 0.0
            running_corrects = 0
            total_samples = 0

            for inputs, labels in tqdm(dataloader, desc=phase):
                inputs = inputs.to(device)
                labels = labels.to(device)
                optimizer.zero_grad()

                with torch.set_grad_enabled(phase == 'train'):
                    with torch.cuda.amp.autocast():
                        outputs = model(inputs)
                        _, preds = torch.max(outputs, 1)
                        loss = criterion(outputs, labels)

                    if phase == 'train':
                        scaler.scale(loss).backward()
                        scaler.step(optimizer)
                        scaler.update()

                running_loss += loss.item() * inputs.size(0)
                running_corrects += torch.sum(preds == labels.data).item()
                total_samples += inputs.size(0)
```

```
    if phase == 'train':
        scheduler.step()

        epoch_loss = running_loss / total_samples
        epoch_acc = running_corrects / total_samples
        print(f'{phase.capitalize()} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}')

    if phase == 'train':
        train_loss_history.append(epoch_loss)
        train_acc_history.append(epoch_acc)
    else:
        val_loss_history.append(epoch_loss)
        val_acc_history.append(epoch_acc)
        if epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = copy.deepcopy(model.state_dict())
    print()

time_elapsed = time.time() - since
print(f'Training complete in {time_elapsed//60:.0f}m {time_elapsed%60:.0f}s')
print(f'Best Validation Acc: {best_acc:.4f}')

model.load_state_dict(best_model_wts)
history = {
    'train_loss': train_loss_history,
    'train_acc': train_acc_history,
    'val_loss': val_loss_history,
    'val_acc': val_acc_history
}
return model, history

#####
# 7. Set Loss Function, Optimizer, and Scheduler
#####
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=1e-4)
scheduler = lr_scheduler.StepLR(optimizer, step_size=7, gamma=0.1)

#####
# 8. Train the Model
#####
num_epochs = 25
model, history = train_model(model, criterion, optimizer, scheduler, num_epochs)

#####
# 9. Visualization 2: Training Curves (Accuracy & Loss)
#####
def plot_training_curves(history):
```

```
epochs = range(1, len(history['train_loss']) + 1)
plt.figure(figsize=(12,5))

# Loss Curve
plt.subplot(1, 2, 1)
plt.plot(epochs, history['train_loss'], label='Training Loss')
plt.plot(epochs, history['val_loss'], label='Validation Loss')
plt.title('Loss Curve')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Accuracy Curve
plt.subplot(1, 2, 2)
plt.plot(epochs, history['train_acc'], label='Training Accuracy')
plt.plot(epochs, history['val_acc'], label='Validation Accuracy')
plt.title('Accuracy Curve')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()

plot_training_curves(history)

#####
# 10. Model Evaluation on Test Set
#####
model.eval()
all_preds = []
all_probs = [] # Probabilities for malignant (class index 1)
all_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_loader, desc="Testing"):
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model(inputs)
        probs = nn.functional.softmax(outputs, dim=1)[:, 1] # Class 1 probability
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())
        all_probs.extend(probs.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

#####
# 11. Visualization 3: Classification Report
#####
#
```

```
print("Classification Report:")
print(classification_report(all_labels, all_preds, target_names=train_dataset.classes))

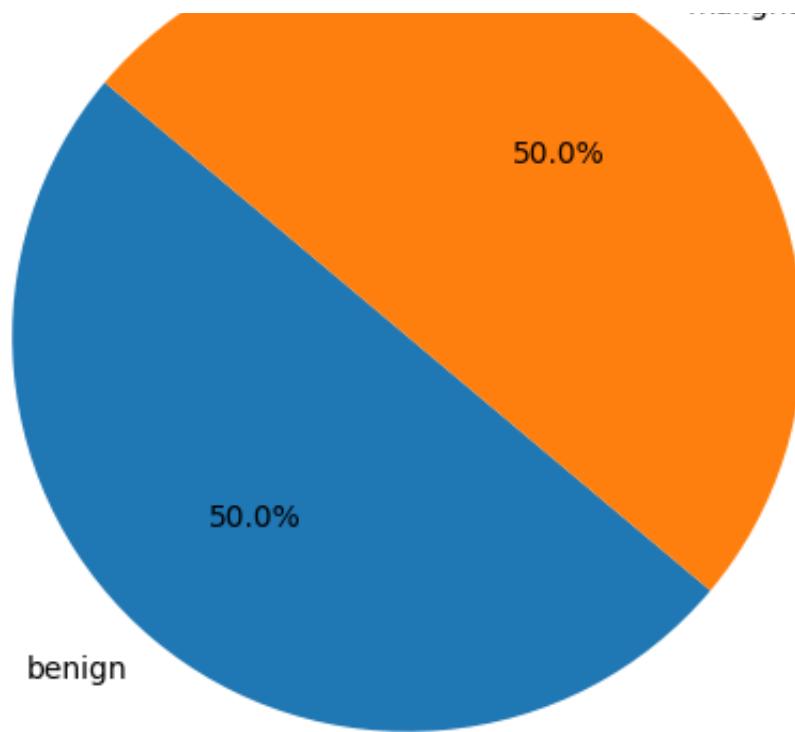
#####
# 12. Visualization 4: Confusion Matrix
#####
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(6,6))
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(train_dataset.classes))
plt.xticks(tick_marks, train_dataset.classes, rotation=45)
plt.yticks(tick_marks, train_dataset.classes)
thresh = cm.max() / 2.0
for i, j in np.ndindex(cm.shape):
    plt.text(j, i, format(cm[i, j], 'd'),
              horizontalalignment="center",
              color="white" if cm[i, j] > thresh else "black")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.tight_layout()
plt.show()

#####
# 13. Visualization 5: ROC Curve & AUC
#####
fpr, tpr, _ = roc_curve(all_labels, all_probs)
roc_auc = auc(fpr, tpr)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

→ Using device: cuda:0
Train Set Distribution:

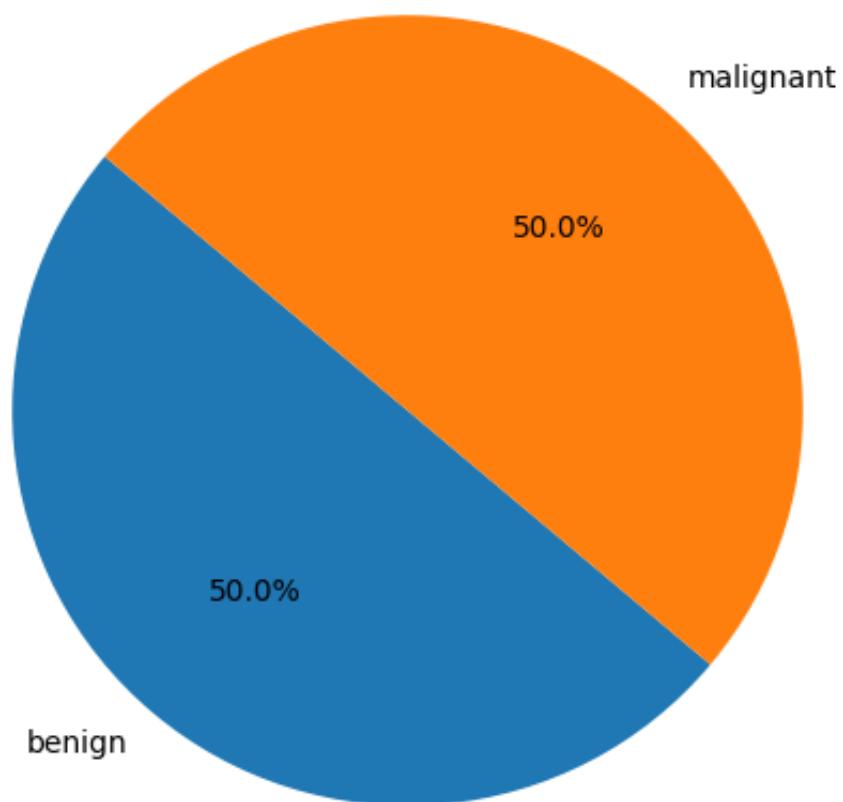
Train Set Distribution





Test Set Distribution:

Test Set Distribution



```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: U
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: U
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet50-0676ba61.pth" to
100%|██████████| 97.8M/97.8M [00:00<00:00, 213MB/s]
/usr/local/lib/python3.10/dist-packages/torch/nn/modules/transformer.py:379
  warnings.warn(
<ipython-input-1-a35db0ad61b9>:176: FutureWarning: `torch.cuda.amp.GradScal
  scaler = torch.cuda.amp.GradScaler()
Epoch 1/25
-----
train:  0%|          | 0/180 [00:00<?, ?it/s]<ipython-input-1-a35db0ad61b9
  with torch.cuda.amp.autocast():
train: 100%|██████████| 180/180 [00:21<00:00,  8.51it/s]
Train Loss: 0.9370 Acc: 0.6090
val: 100%|██████████| 45/45 [00:02<00:00, 21.67it/s]
Val Loss: 0.4069 Acc: 0.8028

Epoch 2/25
-----
train: 100%|██████████| 180/180 [00:19<00:00,  9.19it/s]
Train Loss: 0.5269 Acc: 0.7528
val: 100%|██████████| 45/45 [00:01<00:00, 24.52it/s]
Val Loss: 0.4315 Acc: 0.7958

Epoch 3/25
-----
train: 100%|██████████| 180/180 [00:19<00:00,  9.21it/s]
Train Loss: 0.4862 Acc: 0.7639
val: 100%|██████████| 45/45 [00:01<00:00, 25.14it/s]
Val Loss: 0.3881 Acc: 0.8069

Epoch 4/25
-----
train: 100%|██████████| 180/180 [00:19<00:00,  9.08it/s]
Train Loss: 0.4769 Acc: 0.7646
val: 100%|██████████| 45/45 [00:01<00:00, 25.01it/s]
Val Loss: 0.4175 Acc: 0.8153

Epoch 5/25
-----
train: 100%|██████████| 180/180 [00:19<00:00,  9.01it/s]
Train Loss: 0.4729 Acc: 0.7726
val: 100%|██████████| 45/45 [00:01<00:00, 24.38it/s]
Val Loss: 0.4650 Acc: 0.8083

Epoch 6/25
-----
train: 100%|██████████| 180/180 [00:20<00:00,  8.98it/s]
Train Loss: 0.4396 Acc: 0.7937
val: 100%|██████████| 45/45 [00:01<00:00, 24.42it/s]
Val Loss: 0.4556 Acc: 0.8069
```

Epoch 7/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.82it/s]  
Train Loss: 0.4239 Acc: 0.8063  
val: 100%|██████████| 45/45 [00:01<00:00, 24.03it/s]  
Val Loss: 0.4833 Acc: 0.7875
```

Epoch 8/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.73it/s]  
Train Loss: 0.4054 Acc: 0.8090  
val: 100%|██████████| 45/45 [00:01<00:00, 23.96it/s]  
Val Loss: 0.3431 Acc: 0.8431
```

Epoch 9/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.80it/s]  
Train Loss: 0.3523 Acc: 0.8361  
val: 100%|██████████| 45/45 [00:01<00:00, 24.18it/s]  
Val Loss: 0.3414 Acc: 0.8486
```

Epoch 10/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.84it/s]  
Train Loss: 0.3560 Acc: 0.8351  
val: 100%|██████████| 45/45 [00:01<00:00, 24.31it/s]  
Val Loss: 0.3379 Acc: 0.8500
```

Epoch 11/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.80it/s]  
Train Loss: 0.3517 Acc: 0.8299  
val: 100%|██████████| 45/45 [00:01<00:00, 24.23it/s]  
Val Loss: 0.3267 Acc: 0.8472
```

Epoch 12/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.81it/s]  
Train Loss: 0.3445 Acc: 0.8406  
val: 100%|██████████| 45/45 [00:01<00:00, 22.97it/s]  
Val Loss: 0.3224 Acc: 0.8514
```

Epoch 13/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.86it/s]  
Train Loss: 0.3537 Acc: 0.8354  
val: 100%|██████████| 45/45 [00:01<00:00, 24.24it/s]  
Val Loss: 0.3259 Acc: 0.8569
```

Epoch 14/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.82it/s]  
Train Loss: 0.3474 Acc: 0.8462  
val: 100%|██████████| 45/45 [00:01<00:00, 24.15it/s]
```

Val Loss: 0.3227 Acc: 0.8611

Epoch 15/25

train: 100%|██████████| 180/180 [00:20<00:00, 8.83it/s]
Train Loss: 0.3172 Acc: 0.8556
val: 100%|██████████| 45/45 [00:01<00:00, 24.21it/s]
Val Loss: 0.3224 Acc: 0.8583

Epoch 16/25

train: 100%|██████████| 180/180 [00:20<00:00, 8.82it/s]
Train Loss: 0.3200 Acc: 0.8670
val: 100%|██████████| 45/45 [00:01<00:00, 23.42it/s]
Val Loss: 0.3212 Acc: 0.8639

Epoch 17/25

train: 100%|██████████| 180/180 [00:20<00:00, 8.79it/s]
Train Loss: 0.3155 Acc: 0.8545
val: 100%|██████████| 45/45 [00:01<00:00, 24.23it/s]
Val Loss: 0.3223 Acc: 0.8625

Epoch 18/25

train: 100%|██████████| 180/180 [00:20<00:00, 8.83it/s]
Train Loss: 0.3224 Acc: 0.8500
val: 100%|██████████| 45/45 [00:01<00:00, 24.16it/s]
Val Loss: 0.3173 Acc: 0.8611

Epoch 19/25

train: 100%|██████████| 180/180 [00:20<00:00, 8.85it/s]
Train Loss: 0.3114 Acc: 0.8573
val: 100%|██████████| 45/45 [00:01<00:00, 24.30it/s]
Val Loss: 0.3161 Acc: 0.8625

Epoch 20/25

train: 100%|██████████| 180/180 [00:20<00:00, 8.82it/s]
Train Loss: 0.3200 Acc: 0.8521
val: 100%|██████████| 45/45 [00:01<00:00, 24.09it/s]
Val Loss: 0.3189 Acc: 0.8625

Epoch 21/25

train: 100%|██████████| 180/180 [00:20<00:00, 8.86it/s]
Train Loss: 0.3096 Acc: 0.8576
val: 100%|██████████| 45/45 [00:01<00:00, 24.15it/s]
Val Loss: 0.3178 Acc: 0.8611

Epoch 22/25

train: 100%|██████████| 180/180 [00:20<00:00, 8.84it/s]

```
Train Loss: 0.3276 Acc: 0.8562
val: 100%|██████████| 45/45 [00:01<00:00, 24.38it/s]
Val Loss: 0.3134 Acc: 0.8611
```

Epoch 23/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.79it/s]
Train Loss: 0.3168 Acc: 0.8604
val: 100%|██████████| 45/45 [00:01<00:00, 24.33it/s]
Val Loss: 0.3155 Acc: 0.8611
```

Epoch 24/25

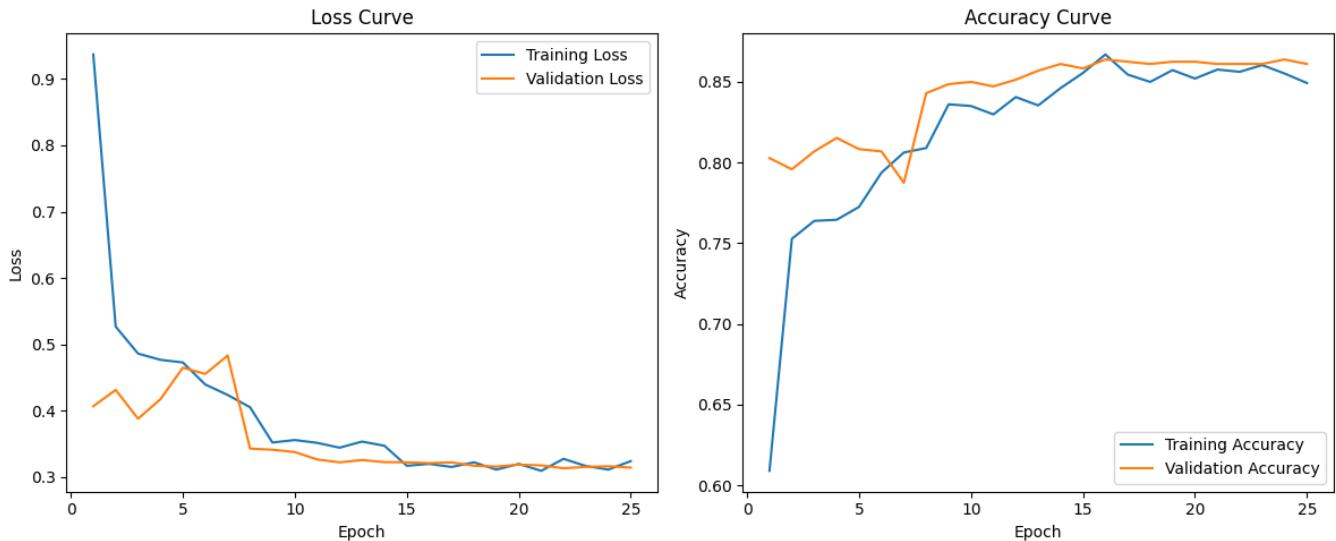
```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.86it/s]
Train Loss: 0.3115 Acc: 0.8552
val: 100%|██████████| 45/45 [00:01<00:00, 24.44it/s]
Val Loss: 0.3165 Acc: 0.8639
```

Epoch 25/25

```
-----  
train: 100%|██████████| 180/180 [00:20<00:00, 8.88it/s]
Train Loss: 0.3242 Acc: 0.8493
val: 100%|██████████| 45/45 [00:01<00:00, 22.62it/s]
Val Loss: 0.3145 Acc: 0.8611
```

Training complete in 9m 15s

Best Validation Acc: 0.8639



```
Testing: 100%|██████████| 45/45 [00:03<00:00, 11.85it/s]
```

Classification Report:

	precision	recall	f1-score	support
benign	0.87	0.86	0.86	360
malignant	0.86	0.87	0.86	360
accuracy			0.86	720
macro avg	0.86	0.86	0.86	720
weighted avg	0.86	0.86	0.86	720

