

```
!pip install roboflow
```

```
from roboflow import Roboflow
rf = Roboflow(api_key="FmCTXKicdAcgH2ZRPNlJ")
project = rf.workspace("jim-ps1mt").project("jim_sem")
version = project.version(2)
dataset = version.download("png-mask-semantic")
```

→ Collecting roboflow

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  Downloading roboflow-1.1.61-py3-none-any.whl.metadata (9.7 kB)
Requirement already satisfied: certifi in /usr/local/lib/python3.11/dist-packages (from roboflow) (2025
Collecting idna==3.7 (from roboflow)
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Requirement already satisfied: numpy>=1.18.5 in /usr/local/lib/python3.11/dist-packages (from roboflow)
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Requirement already satisfied: Pillow>=7.1.2 in /usr/local/lib/python3.11/dist-packages (from roboflow)
Collecting pillow-heif>=0.18.0 (from roboflow)
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Requirement already satisfied: python-dateutil in /usr/local/lib/python3.11/dist-packages (from robofl
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Downloading python_dotenv-1.1.0-py3-none-any.whl (20 kB)
Installing collected packages: filetype, python-dotenv, pillow-heif, opencv-python-headless, idna, robo
Attempting uninstall: opencv-python-headless
  Found existing installation: opencv-python-headless 4.11.0.86
  Uninstalling opencv-python-headless-4.11.0.86:
    Successfully uninstalled opencv-python-headless-4.11.0.86
Attempting uninstall: idna
  Found existing installation: idna 3.10
  Uninstalling idna-3.10:
    Successfully uninstalled idna-3.10
Successfully installed filetype-1.2.0 idna-3.7 opencv-python-headless-4.10.0.84 pillow-heif-0.22.0 pyth
loading Roboflow workspace...
loading Roboflow project...
```

Downloading Dataset Version Zip in Jim_sem-2 to png-mask-semantic::: 100%|██████████| 22769/22769 [00:00]

Extracting Dataset Version Zip to Jim_sem-2 in png-mask-semantic::: 100%|██████████| 1048/1048 [00:00<00]

```
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```

```
from roboflow import Roboflow
rf = Roboflow(api_key="FmCTXKicdAcgH2ZRPNlJ")
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→ Collecting roboflow

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  Downloading roboflow-1.1.62-py3-none-any.whl.metadata (9.7 kB)
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  Downloading python_dotenv-1.1.0-py3-none-any.whl (20 kB)
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```
  Installing collected packages: filetype, python-dotenv, pillow-heif, opencv-python-headless, idna, robo
  Attempting uninstall: opencv-python-headless
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    Found existing installation: opencv-python-headless 4.11.0.86
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```
    Uninstalling opencv-python-headless-4.11.0.86:
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      Successfully uninstalled opencv-python-headless-4.11.0.86
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  Attempting uninstall: idna
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    Found existing installation: idna 3.10
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```
    Uninstalling idna-3.10:
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      Successfully uninstalled idna-3.10
```

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Successfully installed filetype-1.2.0 idna-3.7 opencv-python-headless-4.10.0.84 pillow-heif-0.22.0 pyth
loading Roboflow workspace...
loading Roboflow project...
Downloading Dataset Version Zip in Jim_sem-3 to png-mask-semantic:: 100%|██████████| 22638/22638 [00:00
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Extracting Dataset Version Zip to Jim_sem-3 in png-mask-semantic:: 100%|██████████| 1048/1048 [00:00<00
```

```
import cv2
```

```
!pip install segmentation-models-pytorch
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→ Collecting segmentation-models-pytorch
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```

```
import os

base_path = "/content/Jim_sem-3/train"
print("Train Images:", os.listdir(os.path.join(base_path))[:5])
print("Train Masks:", os.listdir(os.path.join(base_path))[:5])
```

```
→ Train Images: ['IMG_0988.jpg.rf.2c2364074ff019f7626ef70bd9d79733.jpg', 'IMG_0994.jpg.rf.9ef1e2831c8a2be
Train Masks: ['IMG_0988.jpg.rf.2c2364074ff019f7626ef70bd9d79733.jpg', 'IMG_0994.jpg.rf.9ef1e2831c8a2be6
```

```
import os
import shutil

def sort_images_masks(folder_path):
    images_path = os.path.join(folder_path)
    masks_path = os.path.join(folder_path)

    for filename in os.listdir(images_path):
        if "_mask.png" in filename:
            shutil.move(os.path.join(images_path, filename), os.path.join(masks_path, filename))

    for filename in os.listdir(masks_path):
        if "_mask.png" not in filename:
            shutil.move(os.path.join(masks_path, filename), os.path.join(images_path, filename))

sort_images_masks("/content/Jim_sem-3/train")
sort_images_masks("/content/Jim_sem-3/valid")
sort_images_masks("/content/Jim_sem-3/test")
```

```
import os
import shutil

def sort_images_masks(folder_path):
    images_path = os.path.join(folder_path, "images")
    masks_path = os.path.join(folder_path, "masks")

    os.makedirs(images_path, exist_ok=True)
    os.makedirs(masks_path, exist_ok=True)

    for filename in os.listdir(folder_path):
        file_path = os.path.join(folder_path, filename)
        if os.path.isfile(file_path):
            if "_mask.png" in filename:
                shutil.move(file_path, os.path.join(masks_path, filename))
            else:
```

```
shutil.move(file_path, os.path.join(images_path, filename))
```

```
sort_images_masks("/content/Jim_sem-3/train")
sort_images_masks("/content/Jim_sem-3/valid")
sort_images_masks("/content/Jim_sem-3/test")
```

```
os.listdir("/content/Jim_sem-3/train/images")[:5]
os.listdir("/content/Jim_sem-3/train/masks")[:5]
```

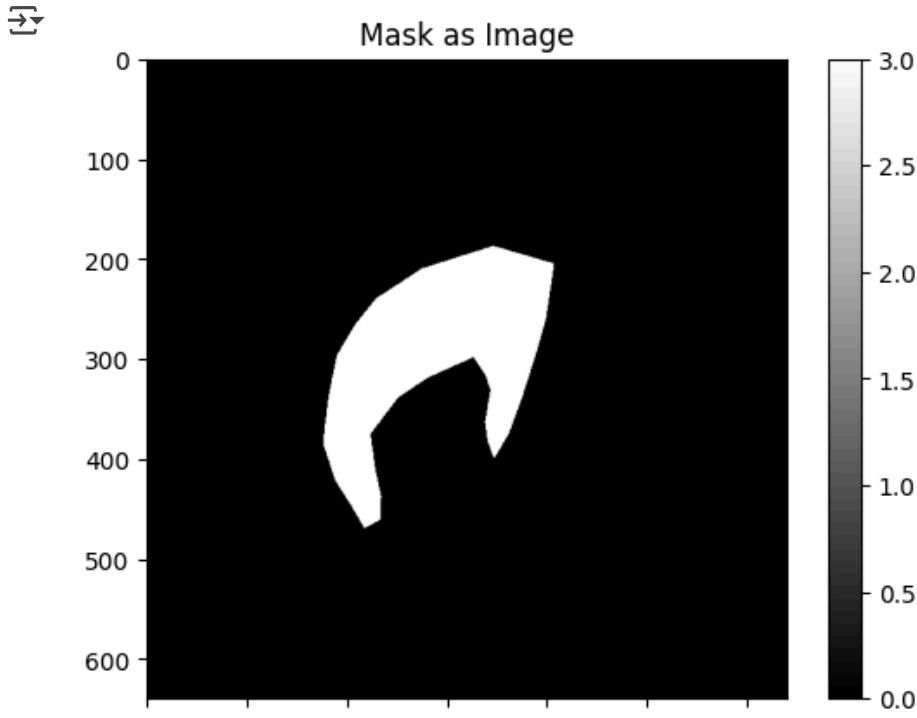
```
→ ['IMG_0980.jpg.rf.a28e5b034139bff74b3958ff8ade9433_mask.png',
    'IMG_0963.jpg.rf.a8123b1bd726db8c07e8530247d97ae1_mask.png',
    'IMG_1018.jpg.rf.0ba7a96411f867abd6599e4f86d8bb9d_mask.png',
    'IMG_0994.jpg.rf.ebf1ff1a1468d018c2490d2bf0e05498_mask.png',
    'IMG_0992.jpg.rf.1ec21a48476fa73f877858a29ad24463_mask.png']
```

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

mask_path = "/content/Jim_sem-3/train/masks/IMG_0879.jpg.rf.a3264c77d05c2a975bf47b9bf61485e9_mask.png"
mask = Image.open(mask_path)
mask_np = np.array(mask)

plt.imshow(mask_np, cmap='gray')
plt.title("Mask as Image")
plt.colorbar()
plt.show()

print("Unique pixel values (class labels):", np.unique(mask_np))
```



```
!pip install -q albumentations
```

```
import albumentations as A
from albumentations.pytorch import ToTensorV2

train_transform = A.Compose([
    A.Resize(256, 256),
    A.HorizontalFlip(p=0.5),
    A.VerticalFlip(p=0.5),
    A.RandomRotate90(p=0.5),
    A.ShiftScaleRotate(shift_limit=0.05, scale_limit=0.1, rotate_limit=10, p=0.5),
    A.ColorJitter(p=0.3),
    A.Normalize(mean=(0.485, 0.456, 0.406),
               std=(0.229, 0.224, 0.225)),
    ToTensorV2()
])

val_transform = A.Compose([
    A.Resize(256, 256),
    A.Normalize(mean=(0.485, 0.456, 0.406),
               std=(0.229, 0.224, 0.225)),
    ToTensorV2()
])
```

→ ShiftScaleRotate is a special case of Affine transform. Please use Affine transform instead.

```
import os
import cv2
import torch
from torch.utils.data import Dataset

class SegmentationDataset(Dataset):
    def __init__(self, image_dir, mask_dir, transform=None):
        self.image_dir = image_dir
        self.mask_dir = mask_dir
        self.transform = transform

        self.image_paths = sorted([
            os.path.join(image_dir, fname) for fname in os.listdir(image_dir)
            if fname.endswith('.jpg', '.jpeg', '.png')
        ])
        self.mask_paths = sorted([
            os.path.join(mask_dir, fname) for fname in os.listdir(mask_dir)
            if fname.endswith('.jpg', '.jpeg', '.png')
        ])

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

    def __getitem__(self, idx):
        image = cv2.imread(self.image_paths[idx])
        image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

        mask = cv2.imread(self.mask_paths[idx], cv2.IMREAD_GRAYSCALE)

        if self.transform:
```

```
augmented = self.transform(image=image, mask=mask)
image = augmented['image']
mask = augmented['mask']

return image, mask.long()
```

Start coding or [generate](#) with AI.

```
train_dataset = SegmentationDataset(
    image_dir="/content/Jim_sem-3/train/images",
    mask_dir="/content/Jim_sem-3/train/masks",
    #transform=train_transform
)

val_dataset = SegmentationDataset(
    image_dir="/content/Jim_sem-3/valid/images",
    mask_dir="/content/Jim_sem-3/valid/masks",
    #transform=val_transform
)

import torch
import torch.nn as nn
import torch.nn.functional as F

class UNet(nn.Module):
    def __init__(self, num_classes):
        super(UNet, self).__init__()

        def conv_block(in_channels, out_channels):
            return nn.Sequential(
                nn.Conv2d(in_channels, out_channels, kernel_size=3, padding=1),
                nn.ReLU(inplace=True),
                nn.Conv2d(out_channels, out_channels, kernel_size=3, padding=1),
                nn.ReLU(inplace=True),
            )

        self.encoder1 = conv_block(3, 64)
        self.pool1 = nn.MaxPool2d(2)
        self.encoder2 = conv_block(64, 128)
        self.pool2 = nn.MaxPool2d(2)
        self.encoder3 = conv_block(128, 256)
        self.pool3 = nn.MaxPool2d(2)
        self.encoder4 = conv_block(256, 512)
        self.pool4 = nn.MaxPool2d(2)

        self.bottleneck = conv_block(512, 1024)

        self.upconv4 = nn.ConvTranspose2d(1024, 512, kernel_size=2, stride=2)
        self.decoder4 = conv_block(1024, 512)
        self.upconv3 = nn.ConvTranspose2d(512, 256, kernel_size=2, stride=2)
        self.decoder3 = conv_block(512, 256)
        self.upconv2 = nn.ConvTranspose2d(256, 128, kernel_size=2, stride=2)
        self.decoder2 = conv_block(256, 128)
        self.upconv1 = nn.ConvTranspose2d(128, 64, kernel_size=2, stride=2)
        self.decoder1 = conv_block(128, 64)
```

```
self.final_conv = nn.Conv2d(64, num_classes, kernel_size=1)

def forward(self, x):
    enc1 = self.encoder1(x)
    enc2 = self.encoder2(self.pool1(enc1))
    enc3 = self.encoder3(self.pool2(enc2))
    enc4 = self.encoder4(self.pool3(enc3))

    bottleneck = self.bottleneck(self.pool4(enc4))

    dec4 = self.upconv4(bottleneck)
    dec4 = torch.cat((dec4, enc4), dim=1)
    dec4 = self.decoder4(dec4)

    dec3 = self.upconv3(dec4)
    dec3 = torch.cat((dec3, enc3), dim=1)
    dec3 = self.decoder3(dec3)

    dec2 = self.upconv2(dec3)
    dec2 = torch.cat((dec2, enc2), dim=1)
    dec2 = self.decoder2(dec2)

    dec1 = self.upconv1(dec2)
    dec1 = torch.cat((dec1, enc1), dim=1)
    dec1 = self.decoder1(dec1)

    return self.final_conv(dec1)
```

```
!pip install segmentation-models-pytorch
```

Collecting segmentation-models-pytorch

```
  Downloading segmentation_models_pytorch-0.5.0-py3-none-any.whl.metadata (17 kB)
Requirement already satisfied: huggingface-hub>=0.24 in /usr/local/lib/python3.11/dist-packages (from segmentation-models-pytorch)
Requirement already satisfied: numpy>=1.19.3 in /usr/local/lib/python3.11/dist-packages (from segmentation-models-pytorch)
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Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub)
Requirement already satisfied: networkx in /usr/local/lib/python3.11/dist-packages (from torch>=1.8->segmentation-models-pytorch)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.11/dist-packages (from torch>=1.8->segmentation-models-pytorch)
Collecting nvidia-cuda-nvrtc-cu12==12.4.127 (from torch>=1.8->segmentation-models-pytorch)
  Downloading nvidia_cuda_nvrtc_cu12-12.4.127-py3-none-manylinux2014_x86_64.whl.metadata (1.5 kB)
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  Downloading nvidia_cuda_runtime_cu12-12.4.127-py3-none-manylinux2014_x86_64.whl.metadata (1.5 kB)
Collecting nvidia-cuda-cupti-cu12==12.4.127 (from torch>=1.8->segmentation-models-pytorch)
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```

```
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    Downloading nvidia_nvjitlink_cu12-12.4.127-py3-none-manylinux2014_x86_64.whl.metadata (1.5 kB)
Requirement already satisfied: triton==3.2.0 in /usr/local/lib/python3.11/dist-packages (from torch>=1.8->segmentation-models-pytorch)
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Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from torch>=1.8->segmentation-models-pytorch)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-packages (from jinja2<3.1,>=3.0.3->segmentation-models-pytorch)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests<3.0,>=2.27.0->segmentation-models-pytorch)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests<3.0,>=2.27.0->segmentation-models-pytorch)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests<3.0,>=2.27.0->segmentation-models-pytorch)
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Downloading nvidia_cublas_cu12-12.4.5.8-py3-none-manylinux2014_x86_64.whl (363.4 kB)
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    24.6/24.6 kB 75.7 MB/s eta 0:00:00
```

```
import segmentation_models_pytorch as smp
import torch

NUM_CLASSES = 4

model = smp.Unet(
    encoder_name="resnet34",
    encoder_weights="imagenet",
    in_channels=3,
    classes=NUM_CLASSES
)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)
```



The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (<https://huggingface.org>).
You will be able to reuse this secret in all of your notebooks.

Please note that authentication is recommended but still optional to access public models or dataset

config.json: 100%	156/156 [00:00<00:00, 9.52kB/s]
model.safetensors: 100%	87.3M/87.3M [00:00<00:00, 118MB/s]

```
Unet(
  (encoder): ResNetEncoder(
    (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
    (layer1): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (2): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (layer2): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (2): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (3): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
  )
)
```

```

(conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(relu): ReLU(inplace=True)
(conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
)
(layer3): Sequential(
(0): BasicBlock(
(conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
(bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(relu): ReLU(inplace=True)
(conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(downsample): Sequential(
(0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
(1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
)
(1): BasicBlock(
(conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(relu): ReLU(inplace=True)
(conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
(2): BasicBlock(
(conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(relu): ReLU(inplace=True)
(conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
(3): BasicBlock(
(conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(relu): ReLU(inplace=True)
(conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
(4): BasicBlock(
(conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(relu): ReLU(inplace=True)
(conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
(5): BasicBlock(
(conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(relu): ReLU(inplace=True)
(conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
)
(layer4): Sequential(
(0): BasicBlock(
(conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
(bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(relu): ReLU(inplace=True)
(conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
(bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(downsample): Sequential(
(0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
(1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
)

```

```
        )
    (1): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (2): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
)
)
(decoder): UnetDecoder(
    (center): Identity()
    (blocks): ModuleList(
        (0): UnetDecoderBlock(
            (conv1): Conv2dReLU(
                (0): Conv2d(768, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                (2): ReLU(inplace=True)
            )
            (attention1): Attention(
                (attention): Identity()
            )
            (conv2): Conv2dReLU(
                (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                (2): ReLU(inplace=True)
            )
            (attention2): Attention(
                (attention): Identity()
            )
        )
        (1): UnetDecoderBlock(
            (conv1): Conv2dReLU(
                (0): Conv2d(384, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                (2): ReLU(inplace=True)
            )
            (attention1): Attention(
                (attention): Identity()
            )
            (conv2): Conv2dReLU(
                (0): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                (2): ReLU(inplace=True)
            )
            (attention2): Attention(
                (attention): Identity()
            )
        )
        (2): UnetDecoderBlock(
            (conv1): Conv2dReLU(
                (0): Conv2d(192, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                (2): ReLU(inplace=True)
            )
            (attention1): Attention(
                (attention): Identity()
            )
        )
    )
)
```

```
(conv2): Conv2dReLU(  
    (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)  
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
    (2): ReLU(inplace=True)  
)  
(attention2): Attention(  
    (attention): Identity()  
)  
)  
(3): UnetDecoderBlock(  
    (conv1): Conv2dReLU(  
        (0): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)  
        (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
        (2): ReLU(inplace=True)  
)  
    (attention1): Attention(  
        (attention): Identity()  
)  
    (conv2): Conv2dReLU(  
        (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)  
        (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
        (2): ReLU(inplace=True)  
)  
    (attention2): Attention(  
        (attention): Identity()  
)  
)  
(4): UnetDecoderBlock(  
    (conv1): Conv2dReLU(  
        (0): Conv2d(32, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)  
        (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
        (2): ReLU(inplace=True)  
)  
    (attention1): Attention(  
        (attention): Identity()  
)  
    (conv2): Conv2dReLU(  
        (0): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)  
        (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)  
        (2): ReLU(inplace=True)  
)  
    (attention2): Attention(  
        (attention): Identity()  
)  
)  
)  
)  
(segmentation_head): SegmentationHead(  
    (0): Conv2d(16, 4, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (1): Identity()  
    (2): Activation(  
        (activation): Identity()  
)  
)  
)
```

```
import torch.nn as nn

loss_fn = nn.CrossEntropyLoss()

import torch.optim as optim

optimizer = optim.Adam(model.parameters(), lr=1e-4)

Start coding or generate with AI.

def train_one_epoch(model, loader, optimizer, loss_fn, device):
    model.train()
    total_loss = 0

    for images, masks in loader:
        images = images.to(device)
        masks = masks.to(device)

        outputs = model(images)
        loss = loss_fn(outputs, masks)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

    return total_loss / len(loader)

def evaluate(model, loader, loss_fn, device):
    model.eval()
    total_loss = 0

    with torch.no_grad():
        for images, masks in loader:
            images = images.to(device)
            masks = masks.to(device)

            outputs = model(images)
            loss = loss_fn(outputs, masks)

            total_loss += loss.item()

    return total_loss / len(loader)

import os
import cv2
import torch
from torch.utils.data import Dataset

class SegmentationDataset(Dataset):
    def __init__(self, image_dir, mask_dir, transform=None):
```

```

self.image_dir = image_dir
self.mask_dir = mask_dir
self.transform = transform

self.image_paths = sorted([
    os.path.join(image_dir, fname) for fname in os.listdir(image_dir)
    if fname.endswith('.jpg', '.jpeg', '.png'))
])

self.mask_paths = sorted([
    os.path.join(mask_dir, fname) for fname in os.listdir(mask_dir)
    if fname.endswith('.jpg', '.jpeg', '.png'))
])

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

def __getitem__(self, idx):
    image = cv2.imread(self.image_paths[idx])
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

    mask = cv2.imread(self.mask_paths[idx], cv2.IMREAD_GRAYSCALE)

    if self.transform:
        augmented = self.transform(image=image, mask=mask)
        image = augmented['image']
        mask = augmented['mask']

    return image, mask.long()

```

```

import albumentations as A
from albumentations.pytorch import ToTensorV2
imagenet_mean = (0.485, 0.456, 0.406)
imagenet_std = (0.229, 0.224, 0.225)

```

```

train_transform = A.Compose([
    A.Resize(256, 256),
    A.Normalize(mean=imagenet_mean, std=imagenet_std),
    ToTensorV2()
])

```

```

val_transform = A.Compose([
    A.Resize(256, 256),
    A.Normalize(mean=imagenet_mean, std=imagenet_std),
    ToTensorV2()
])

```

A new version of Albumentations is available: '2.0.6' (you have '2.0.5'). Upgrade using: pip install -U

```
from torch.utils.data import DataLoader
```

```

train_dataset = SegmentationDataset(
    image_dir="/content/Jim_sem-3/train/images",
    mask_dir="/content/Jim_sem-3/train/masks",

```

```

        transform=train_transform
    )

val_dataset = SegmentationDataset(
    image_dir="/content/Jim_sem-3/valid/images",
    mask_dir="/content/Jim_sem-3/valid/masks",
    transform=val_transform
)

train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=8, shuffle=False)

```

```
!pip install torchmetrics
```

→ Collecting torchmetrics

 Downloading torchmetrics-1.7.1-py3-none-any.whl.metadata (21 kB)

Requirement already satisfied: numpy>1.20.0 in /usr/local/lib/python3.11/dist-packages (from torchmetri

Requirement already satisfied: packaging>17.1 in /usr/local/lib/python3.11/dist-packages (from torchmet

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Collecting lightning-utilities>=0.8.0 (from torchmetrics)

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Requirement already satisfied: setuptools in /usr/local/lib/python3.11/dist-packages (from lightning-ut

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Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.11/dist-packages (from torch>=2.

Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from symp

Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-packages (from jinja2-

Downloading torchmetrics-1.7.1-py3-none-any.whl (961 kB)

961.5/961.5 kB 14.6 MB/s eta 0:00:00

Downloading lightning_utilities-0.14.3-py3-none-any.whl (28 kB)

Installing collected packages: lightning-utilities, torchmetrics

Successfully installed lightning-utilities-0.14.3 torchmetrics-1.7.1



```

from torchmetrics.classification import MulticlassAccuracy

def evaluate_accuracy(model, loader, device, num_classes=4):
    model.eval()
    acc_metric = MulticlassAccuracy(num_classes=num_classes, average='macro').to(device)

    with torch.no_grad():
        for images, masks in loader:

```

```

images = images.to(device)
masks = masks.to(device)

outputs = model(images)
preds = torch.argmax(outputs, dim=1)

acc_metric.update(preds, masks)

return acc_metric.compute().item()

num_epochs = 10
train_losses = []
val_losses = []

for epoch in range(num_epochs):
    train_loss = train_one_epoch(model, train_loader, optimizer, loss_fn, device)
    val_loss = evaluate(model, val_loader, loss_fn, device)

    train_losses.append(train_loss)
    val_losses.append(val_loss)

    print(f"Epoch {epoch+1}/{num_epochs} - Train Loss: {train_loss:.4f} - Val Loss: {val_loss:.4f}")

```

→ Epoch 1/10 - Train Loss: 1.3227 - Val Loss: 0.8911
 Epoch 2/10 - Train Loss: 0.7824 - Val Loss: 0.6249
 Epoch 3/10 - Train Loss: 0.5179 - Val Loss: 0.4059
 Epoch 4/10 - Train Loss: 0.3453 - Val Loss: 0.2785
 Epoch 5/10 - Train Loss: 0.2480 - Val Loss: 0.2078
 Epoch 6/10 - Train Loss: 0.1878 - Val Loss: 0.1759
 Epoch 7/10 - Train Loss: 0.1479 - Val Loss: 0.1543
 Epoch 8/10 - Train Loss: 0.1190 - Val Loss: 0.1119
 Epoch 9/10 - Train Loss: 0.0978 - Val Loss: 0.0968
 Epoch 10/10 - Train Loss: 0.0831 - Val Loss: 0.0831

```

import torch.optim as optim
from torch.optim.lr_scheduler import ReduceLROnPlateau

optimizer = optim.Adam(model.parameters(), lr=1e-4)
scheduler = ReduceLROnPlateau(optimizer, mode='min', patience=3, factor=0.5)

loss_fn = nn.CrossEntropyLoss()

num_epochs = 30
train_losses = []
val_losses = []
train_accuracies = []
val_accuracies = []

best_val_loss = float('inf')
save_path = "best_model_checkpoint.pth"

for epoch in range(num_epochs):
    train_loss = train_one_epoch(model, train_loader, optimizer, loss_fn, device)
    val_loss = evaluate(model, val_loader, loss_fn, device)

    scheduler.step(val_loss)
    train_losses.append(train_loss)

```

```
val_losses.append(val_loss)
train_acc = evaluate_accuracy(model, train_loader, device)
val_acc = evaluate_accuracy(model, val_loader, device)

train_accuracies.append(train_acc)
val_accuracies.append(val_acc)

print(f"Epoch {epoch+1}/{num_epochs} | Train Loss: {train_loss:.4f} | Val Loss: {val_loss:.4f} | Train Acc: {train_acc:.4f} | Val Acc: {val_acc:.4f}")

if val_loss < best_val_loss:
    best_val_loss = val_loss
    torch.save({
        'epoch': epoch,
        'model_state_dict': model.state_dict(),
        'optimizer_state_dict': optimizer.state_dict(),
        'val_loss': val_loss
    }, save_path)
    print(f"Saved Best Model at Epoch {epoch+1}")
```

→ Epoch 1/30 | Train Loss: 0.9181 | Val Loss: 0.7398 | Train Acc: 0.3033 | Val Acc: 0.2674
Saved Best Model at Epoch 1
Epoch 2/30 | Train Loss: 0.6193 | Val Loss: 0.4993 | Train Acc: 0.3479 | Val Acc: 0.3038
Saved Best Model at Epoch 2
Epoch 3/30 | Train Loss: 0.4083 | Val Loss: 0.3078 | Train Acc: 0.4341 | Val Acc: 0.3058
Saved Best Model at Epoch 3
Epoch 4/30 | Train Loss: 0.2628 | Val Loss: 0.2027 | Train Acc: 0.5464 | Val Acc: 0.3704
Saved Best Model at Epoch 4
Epoch 5/30 | Train Loss: 0.1879 | Val Loss: 0.1506 | Train Acc: 0.5494 | Val Acc: 0.3772
Saved Best Model at Epoch 5
Epoch 6/30 | Train Loss: 0.1468 | Val Loss: 0.1193 | Train Acc: 0.5894 | Val Acc: 0.3847
Saved Best Model at Epoch 6
Epoch 7/30 | Train Loss: 0.1192 | Val Loss: 0.0998 | Train Acc: 0.6896 | Val Acc: 0.4424
Saved Best Model at Epoch 7
Epoch 8/30 | Train Loss: 0.1015 | Val Loss: 0.0782 | Train Acc: 0.7878 | Val Acc: 0.5242
Saved Best Model at Epoch 8
Epoch 9/30 | Train Loss: 0.0863 | Val Loss: 0.0692 | Train Acc: 0.8321 | Val Acc: 0.5242
Saved Best Model at Epoch 9
Epoch 10/30 | Train Loss: 0.0731 | Val Loss: 0.0624 | Train Acc: 0.7887 | Val Acc: 0.5161
Saved Best Model at Epoch 10
Epoch 11/30 | Train Loss: 0.0628 | Val Loss: 0.0579 | Train Acc: 0.8937 | Val Acc: 0.5557
Saved Best Model at Epoch 11
Epoch 12/30 | Train Loss: 0.0552 | Val Loss: 0.0558 | Train Acc: 0.9188 | Val Acc: 0.5747
Saved Best Model at Epoch 12
Epoch 13/30 | Train Loss: 0.0523 | Val Loss: 0.0517 | Train Acc: 0.9054 | Val Acc: 0.5514
Saved Best Model at Epoch 13
Epoch 14/30 | Train Loss: 0.0450 | Val Loss: 0.0500 | Train Acc: 0.8345 | Val Acc: 0.5263
Saved Best Model at Epoch 14
Epoch 15/30 | Train Loss: 0.0415 | Val Loss: 0.0478 | Train Acc: 0.8604 | Val Acc: 0.5162
Saved Best Model at Epoch 15
Epoch 16/30 | Train Loss: 0.0366 | Val Loss: 0.0432 | Train Acc: 0.8828 | Val Acc: 0.5491
Saved Best Model at Epoch 16
Epoch 17/30 | Train Loss: 0.0325 | Val Loss: 0.0473 | Train Acc: 0.9160 | Val Acc: 0.5622
Epoch 18/30 | Train Loss: 0.0301 | Val Loss: 0.0420 | Train Acc: 0.9071 | Val Acc: 0.5754
Saved Best Model at Epoch 18
Epoch 19/30 | Train Loss: 0.0288 | Val Loss: 0.0393 | Train Acc: 0.8929 | Val Acc: 0.5595
Saved Best Model at Epoch 19
Epoch 20/30 | Train Loss: 0.0261 | Val Loss: 0.0407 | Train Acc: 0.9166 | Val Acc: 0.5566
Epoch 21/30 | Train Loss: 0.0251 | Val Loss: 0.0409 | Train Acc: 0.9481 | Val Acc: 0.5953
Epoch 22/30 | Train Loss: 0.0231 | Val Loss: 0.0392 | Train Acc: 0.9040 | Val Acc: 0.5593
Saved Best Model at Epoch 22
Epoch 23/30 | Train Loss: 0.0219 | Val Loss: 0.0409 | Train Acc: 0.9199 | Val Acc: 0.5892
Epoch 24/30 | Train Loss: 0.0202 | Val Loss: 0.0391 | Train Acc: 0.9313 | Val Acc: 0.5666

```
Saved Best Model at Epoch 24
Epoch 25/30 | Train Loss: 0.0194 | Val Loss: 0.0399 | Train Acc: 0.9610 | Val Acc: 0.5988
Epoch 26/30 | Train Loss: 0.0186 | Val Loss: 0.0378 | Train Acc: 0.9253 | Val Acc: 0.5665
Saved Best Model at Epoch 26
Epoch 27/30 | Train Loss: 0.0173 | Val Loss: 0.0390 | Train Acc: 0.9332 | Val Acc: 0.5541
Epoch 28/30 | Train Loss: 0.0163 | Val Loss: 0.0387 | Train Acc: 0.9568 | Val Acc: 0.5766
Epoch 29/30 | Train Loss: 0.0152 | Val Loss: 0.0393 | Train Acc: 0.9402 | Val Acc: 0.5573
Epoch 30/30 | Train Loss: 0.0147 | Val Loss: 0.0411 | Train Acc: 0.9461 | Val Acc: 0.5723
```

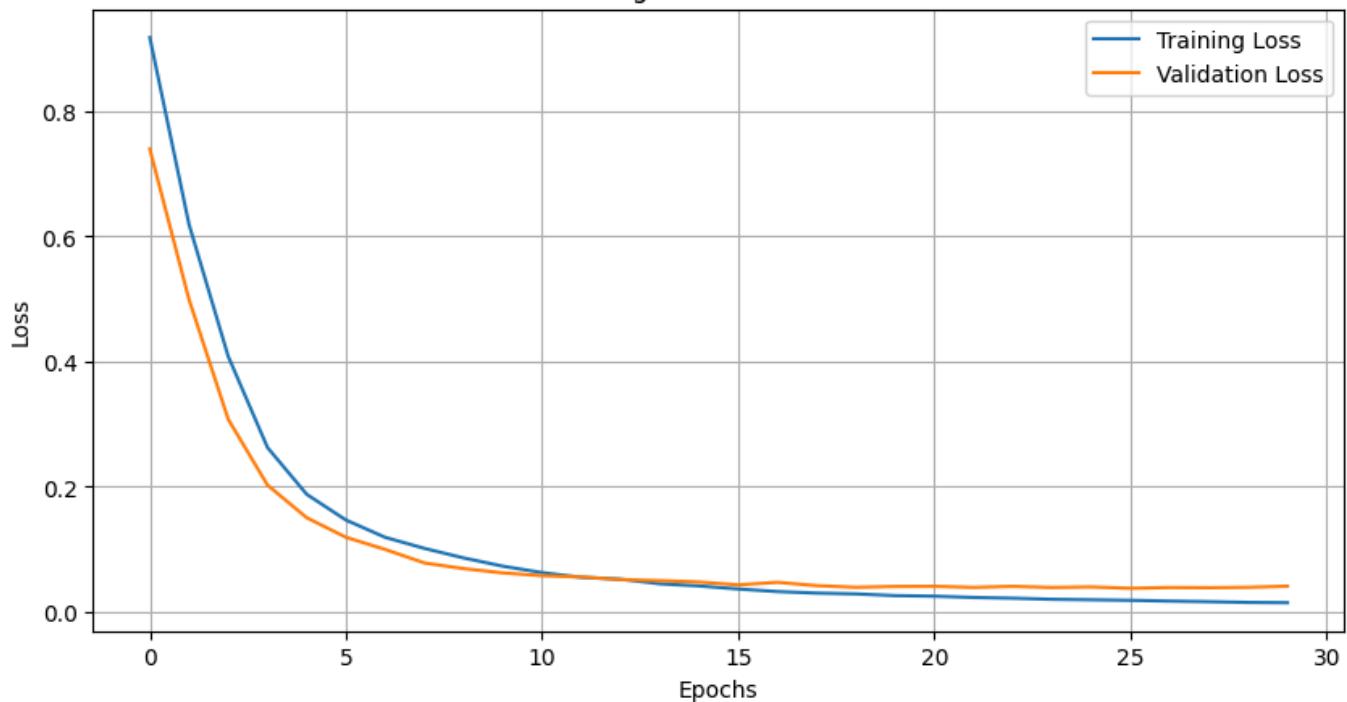
```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,5))
plt.plot(train_losses, label='Training Loss')
plt.plot(val_losses, label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training vs Validation Loss')
plt.legend()
plt.grid()
plt.show()

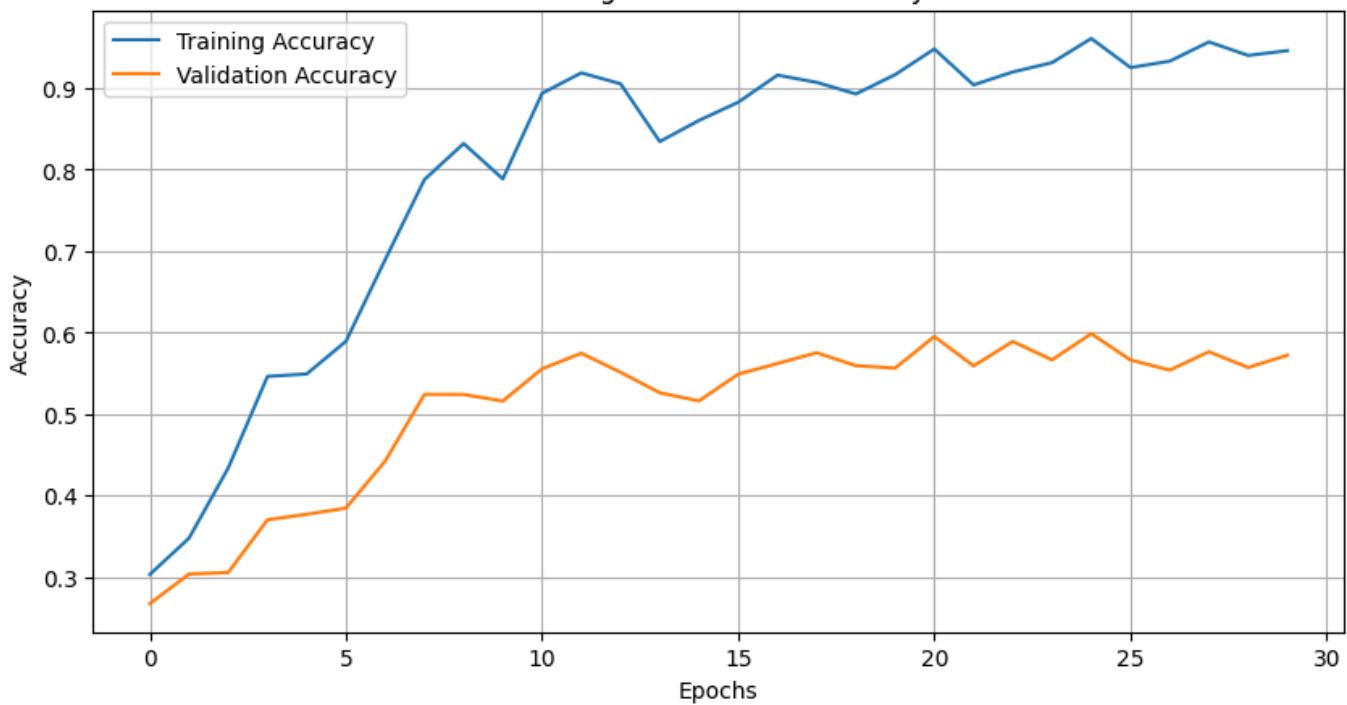
plt.figure(figsize=(10,5))
plt.plot(train_accuracies, label='Training Accuracy')
plt.plot(val_accuracies, label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training vs Validation Accuracy')
plt.legend()
plt.grid()
plt.show()
```



Training vs Validation Loss



Training vs Validation Accuracy



```
checkpoint = torch.load("best_model_checkpoint.pth")
model.load_state_dict(checkpoint['model_state_dict'])
model.eval()
```



Unet(

(encoder): ResNetEncoder(

(conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)

```

(bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(relu): ReLU(inplace=True)
(maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
(layer1): Sequential(
    (0): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (2): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
)
(layer2): Sequential(
    (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
            (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
            (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
    )
    (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (2): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (3): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
)

```

```
from torchmetrics.classification import MulticlassAccuracy, MulticlassJaccardIndex
```

```
def final_evaluate_metrics(model, dataloader, device, num_classes=4):
    model.eval()
```

```
acc_metric = MulticlassAccuracy(num_classes=num_classes, average='macro').to(device)
iou_metric = MulticlassJaccardIndex(num_classes=num_classes, average='macro').to(device)
```

```

with torch.no_grad():
    for images, masks in dataloader:
        images = images.to(device)
        masks = masks.to(device)

        outputs = model(images)
        preds = torch.argmax(outputs, dim=1)

        acc_metric.update(preds, masks)
        iou_metric.update(preds, masks)

    accuracy = acc_metric.compute().item()
    miou = iou_metric.compute().item()

    print(f" Final Validation Accuracy: {accuracy:.4f}")
    print(f" Final Validation Mean IoU: {miou:.4f}")

final_evaluate_metrics(model, val_loader, device)

```

→ Final Validation Accuracy: 0.5665
 Final Validation Mean IoU: 0.5165

Start coding or generate with AI.

```

from torchmetrics import ConfusionMatrix
from torchmetrics.classification import MulticlassAccuracy, MulticlassPrecision, MulticlassRecall

acc_metric = MulticlassAccuracy(num_classes=4, average='macro').to(device)
prec_metric = MulticlassPrecision(num_classes=4, average='macro').to(device)
rec_metric = MulticlassRecall(num_classes=4, average='macro').to(device)

confmat = ConfusionMatrix(num_classes=4, task="multiclass").to(device)

with torch.no_grad():
    for imgs, masks in val_loader:
        imgs, masks = imgs.to(device), masks.to(device)
        preds = torch.argmax(model(imgs), dim=1)

        acc_metric.update(preds, masks)
        prec_metric.update(preds, masks)
        rec_metric.update(preds, masks)
        confmat.update(preds.flatten(), masks.flatten())

    accuracy = acc_metric.compute().item()
    precision = prec_metric.compute().item()
    recall = rec_metric.compute().item()
    cm = confmat.compute().cpu().numpy()

print(f"Mean Accuracy: {accuracy:.4f}")
print(f"Mean Precision: {precision:.4f}")
print(f"Mean Recall: {recall:.4f}")
print("Confusion Matrix:\n", cm)

```

→ Mean Accuracy: 0.5665
 Mean Precision: 0.6116
 Mean Recall: 0.5665
 Confusion Matrix:
 [[1279592 1076 0 4136]]

```
[ 3313 12449 0 0]
[ 275 0 0 0]
[ 5111 23 0 4745]]
```

```
import cv2
import numpy as np
import torch
import matplotlib.pyplot as plt
from albumentations.pytorch import ToTensorV2
import albumentations as A

single_image_transform = A.Compose([
    A.Resize(256, 256),
    A.Normalize(mean=(0.485, 0.456, 0.406),
               std=(0.229, 0.224, 0.225)),
    ToTensorV2()
])

def predict_single_image(model, image_path, device):
    model.eval()
    image = cv2.imread(image_path)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    augmented = single_image_transform(image=image)
    input_tensor = augmented['image'].unsqueeze(0).to(device)
    with torch.no_grad():
        output = model(input_tensor)
    pred_mask = torch.argmax(output, dim=1).squeeze(0).cpu().numpy()

    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    plt.imshow(image)
    plt.title("Input Image")
    plt.axis("off")

    plt.subplot(1, 2, 2)
    plt.imshow(pred_mask, cmap='tab10')
    plt.title("Predicted Segmentation Mask")
    plt.axis("off")

    plt.tight_layout()
    plt.show()

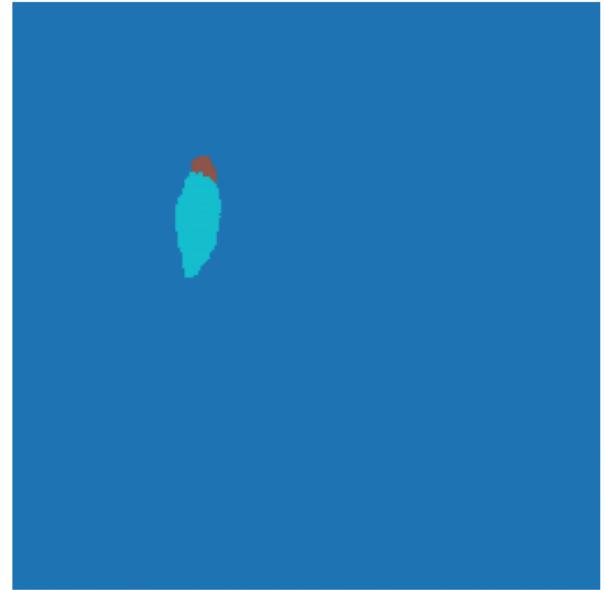
predict_single_image(model, "/content/Jim_sem-3/test/images/IMG_0954.jpg.rf.d764f05dd55ef5e315b3cdf029b7906
```



Input Image



Predicted Segmentation Mask



```

import cv2
import numpy as np
import torch
import matplotlib.pyplot as plt
from albumentations.pytorch import ToTensorV2
import albumentations as A

single_image_transform = A.Compose([
    A.Resize(256, 256),
    A.Normalize(mean=(0.485, 0.456, 0.406),
               std=(0.229, 0.224, 0.225)),
    ToTensorV2()
])

def predict_single_image(model, image_path, device):
    model.eval()
    image = cv2.imread(image_path)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    augmented = single_image_transform(image=image)
    input_tensor = augmented['image'].unsqueeze(0).to(device)
    with torch.no_grad():
        output = model(input_tensor)
        pred_mask = torch.argmax(output, dim=1).squeeze(0).cpu().numpy()

    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    plt.imshow(image)
    plt.title("Input Image")
    plt.axis("off")

    plt.subplot(1, 2, 2)
    plt.imshow(pred_mask, cmap='tab10')
    plt.title("Predicted Segmentation Mask")
    plt.axis("off")

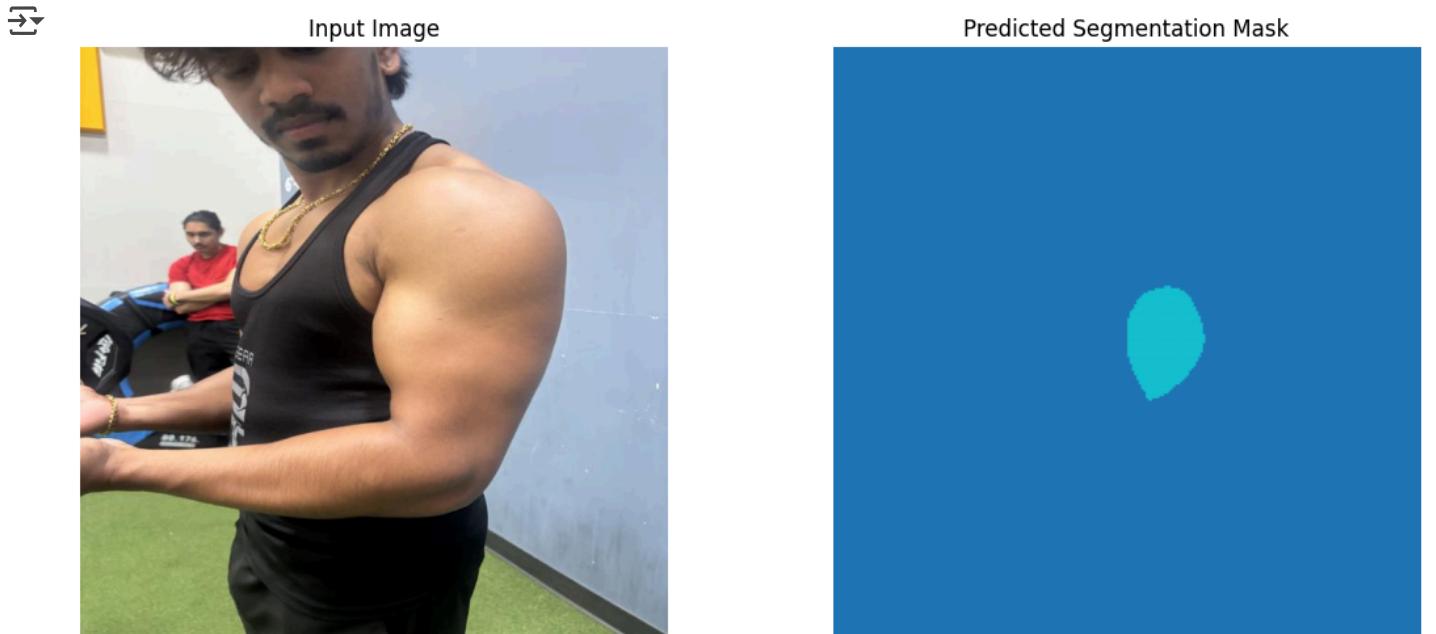
```

```

plt.tight_layout()
plt.show()

predict_single_image(model, "/content/Jim_sem-3/test/images/IMG_0954.jpg.rf.d764f05dd55ef5e315b3cdf029b7906

```



```

import cv2
import numpy as np
import torch
import matplotlib.pyplot as plt
from albumentations.pytorch import ToTensorV2
import albumentations as A

single_image_transform = A.Compose([
    A.Resize(256, 256),
    A.Normalize(mean=(0.485, 0.456, 0.406),
               std=(0.229, 0.224, 0.225)),
    ToTensorV2()
])

def predict_single_image(model, image_path, device):
    model.eval()
    image = cv2.imread(image_path)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    augmented = single_image_transform(image=image)
    input_tensor = augmented['image'].unsqueeze(0).to(device)
    with torch.no_grad():
        output = model(input_tensor)
        pred_mask = torch.argmax(output, dim=1).squeeze(0).cpu().numpy()

    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    plt.imshow(image)

    plt.subplot(1, 2, 2)
    plt.imshow(pred_mask)

```

```

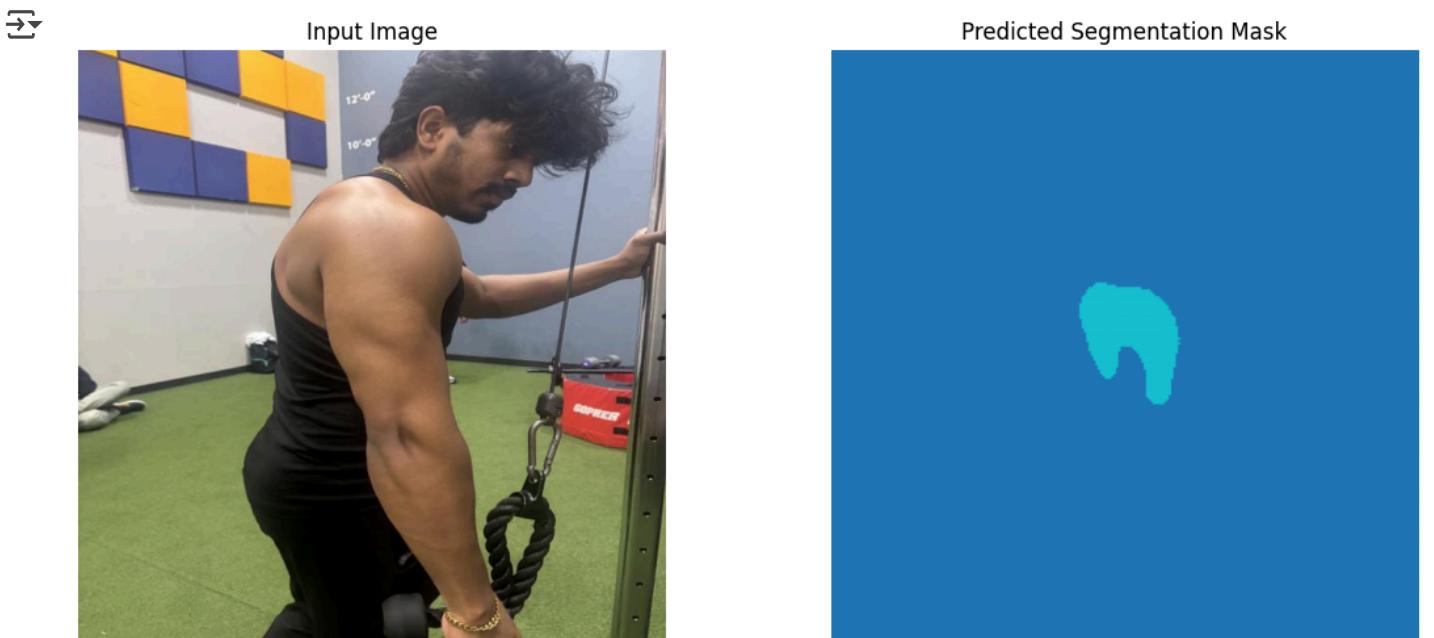
plt.title("Input Image")
plt.axis("off")

plt.subplot(1, 2, 2)
plt.imshow(pred_mask, cmap='tab10')
plt.title("Predicted Segmentation Mask")
plt.axis("off")

plt.tight_layout()
plt.show()

predict_single_image(model, "/content/Jim_sem-3/train/images/IMG_0963.jpg.rf.33fab83a3b64b4a117f3a1c2cb6469"

```



Start coding or [generate](#) with AI.

```

import itertools
import pandas as pd
import torch
import torch.nn as nn
from torch.optim import Adam, SGD
from torchmetrics.classification import MulticlassJaccardIndex

learning_rates = [1e-3, 5e-4, 1e-5]
batch_sizes    = [4, 8, 16]
optimizers     = ['adam', 'sgd']

iou_metric = MulticlassJaccardIndex(num_classes=4, average='macro').to(device)

results = []

for lr, bs, opt_name in itertools.product(learning_rates, batch_sizes, optimizers):
    print(f"\n  LR={lr}, BS={bs}, OPT={opt_name.upper()}")

    train_loader = DataLoader(train_dataset, batch_size=bs, shuffle=True)

```

```

val_loader = DataLoader(val_dataset, batch_size=bs, shuffle=False)

model = smp.Unet(
    encoder_name="resnet34",
    encoder_weights="imagenet",
    in_channels=3,
    classes=4
).to(device)

if opt_name == 'adam':
    optimizer = Adam(model.parameters(), lr=lr)
else:
    optimizer = SGD(model.parameters(), lr=lr, momentum=0.9)

loss_fn = nn.CrossEntropyLoss()

for epoch in range(2):
    model.train()
    for imgs, masks in train_loader:
        imgs, masks = imgs.to(device), masks.to(device)
        preds = model(imgs)
        loss = loss_fn(preds, masks)
        optimizer.zero_grad(); loss.backward(); optimizer.step()

    model.eval()
    val_loss = 0.0
    iou_metric.reset()
    with torch.no_grad():
        for imgs, masks in val_loader:
            imgs, masks = imgs.to(device), masks.to(device)
            preds = model(imgs)
            val_loss += loss_fn(preds, masks).item()
            iou_metric.update(torch.argmax(preds, dim=1), masks)
    val_loss /= len(val_loader)
    val_iou = iou_metric.compute().item()

    print(f" → Val Loss: {val_loss:.4f}, Val mIoU: {val_iou:.4f}")

results.append({
    'lr': lr,
    'batch_size': bs,
    'optimizer': opt_name,
    'val_loss': val_loss,
    'val_mIoU': val_iou
})

df = pd.DataFrame(results)
df = df.sort_values('val_mIoU', ascending=False).reset_index(drop=True)
print("\n Top 3 configs by mIoU:")
print(df.head(3))

best = df.iloc[0]
print(f"\n Best config → LR={best['lr']}, BS={best['batch_size']}, OPT={best['optimizer'].upper()}, mIoU={best['val_mIoU']:.4f}")

```



LR=0.001, BS=4, OPT=ADAM
→ Val Loss: 0.0874, Val mIoU: 0.3006

LR=0.001, BS=4, OPT=SGD

```
→ Val Loss: 0.1065, Val mIoU: 0.2451

LR=0.001, BS=8, OPT=ADAM
→ Val Loss: 0.0895, Val mIoU: 0.2451

LR=0.001, BS=8, OPT=SGD
→ Val Loss: 0.1331, Val mIoU: 0.2451

LR=0.001, BS=16, OPT=ADAM
→ Val Loss: 0.0917, Val mIoU: 0.2451

LR=0.001, BS=16, OPT=SGD
→ Val Loss: 0.1632, Val mIoU: 0.2451

LR=0.0005, BS=4, OPT=ADAM
→ Val Loss: 0.0761, Val mIoU: 0.2451

LR=0.0005, BS=4, OPT=SGD
→ Val Loss: 0.1386, Val mIoU: 0.2451

LR=0.0005, BS=8, OPT=ADAM
→ Val Loss: 0.1154, Val mIoU: 0.2451

LR=0.0005, BS=8, OPT=SGD
→ Val Loss: 0.1894, Val mIoU: 0.2450

LR=0.0005, BS=16, OPT=ADAM
→ Val Loss: 0.1628, Val mIoU: 0.3000

LR=0.0005, BS=16, OPT=SGD
→ Val Loss: 0.2746, Val mIoU: 0.2449

LR=1e-05, BS=4, OPT=ADAM
→ Val Loss: 1.0547, Val mIoU: 0.1943

LR=1e-05, BS=4, OPT=SGD
→ Val Loss: 1.3151, Val mIoU: 0.1000

LR=1e-05, BS=8, OPT=ADAM
→ Val Loss: 1.5187, Val mIoU: 0.0906

LR=1e-05, BS=8, OPT=SGD
→ Val Loss: 1.5767, Val mIoU: 0.0592

LR=1e-05, BS=16, OPT=ADAM
```

```
from google.colab import files
files.download('best_model_checkpoint.pth')
```



```
print(f"Epoch {epoch+1}/{num_epochs} - Train Loss: {train_loss:.4f} - Val Loss: {val_loss:.4f}")
```

```
Epoch 10/10 - Train Loss: 0.0831 - Val Loss: 0.0831
```

```
torch.save({
    'epoch': num_epochs,
    'model_state_dict': model.state_dict(),
    'optimizer_state_dict': optimizer.state_dict(),
    'loss': val_losses[-1],
```

```
}, "unet_checkpoint.pth")
print("Full training checkpoint saved as unet_checkpoint.pth")
```

→ Full training checkpoint saved as unet_checkpoint.pth

```
import matplotlib.pyplot as plt
import torch
import numpy as np

def denormalize(tensor):
    # Undo ImageNet normalization
    mean = torch.tensor([0.485, 0.456, 0.406]).view(3, 1, 1)
    std = torch.tensor([0.229, 0.224, 0.225]).view(3, 1, 1)
    return tensor * std + mean

def visualize_prediction(model, dataloader, device):
    model.eval()
    with torch.no_grad():
        for images, masks in dataloader:
            images = images.to(device)
            masks = masks.to(device)

            outputs = model(images)
            preds = torch.argmax(outputs, dim=1)

            for i in range(images.shape[0]):
                image = denormalize(images[i].cpu()).permute(1, 2, 0).numpy()
                true_mask = masks[i].cpu().numpy()
                pred_mask = preds[i].cpu().numpy()

                fig, axs = plt.subplots(1, 3, figsize=(15, 5))

                axs[0].imshow(image)
                axs[0].set_title("Input Image")
                axs[0].axis("off")

                axs[1].imshow(true_mask, cmap='tab10')
                axs[1].set_title("Ground Truth Mask")
                axs[1].axis("off")

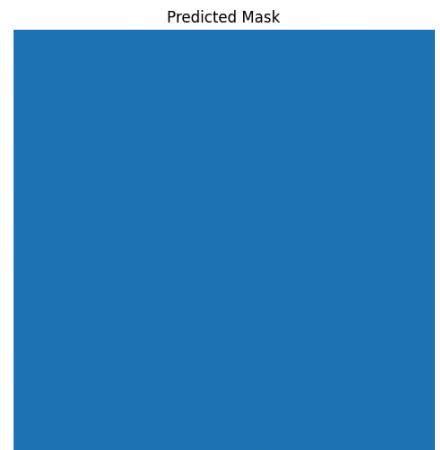
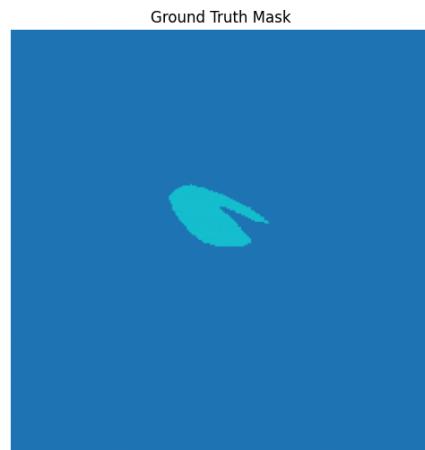
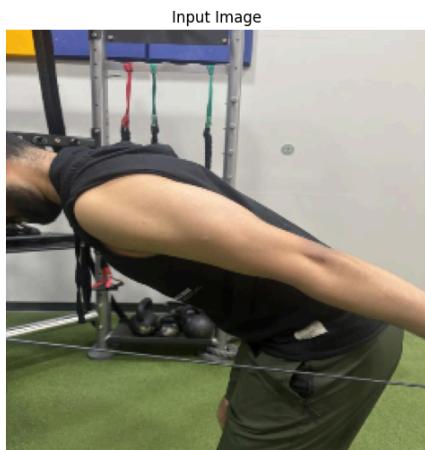
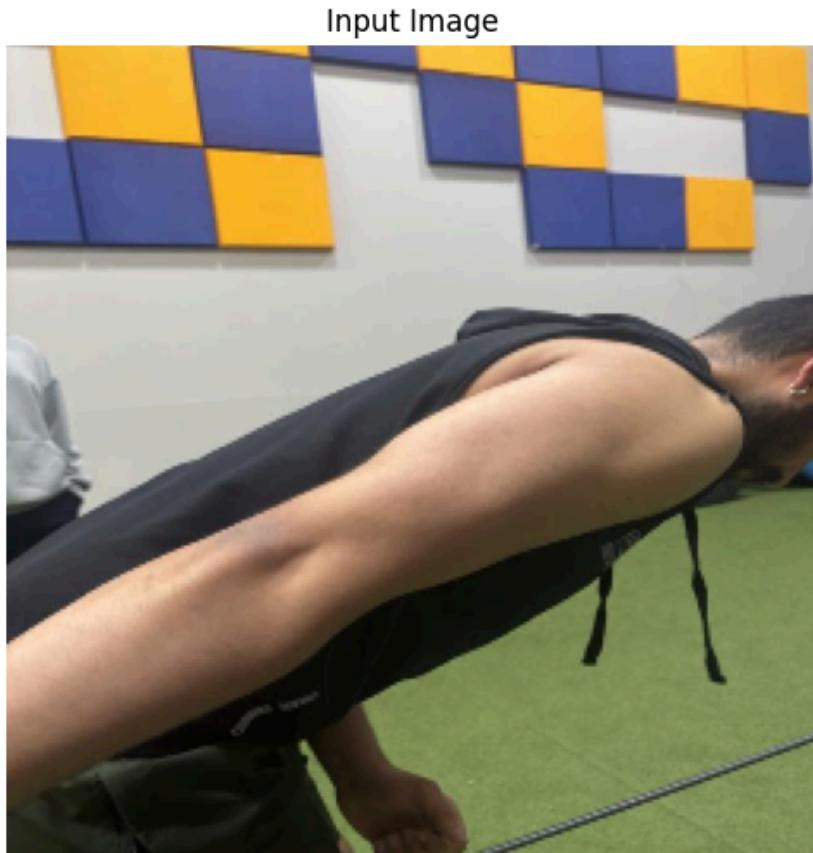
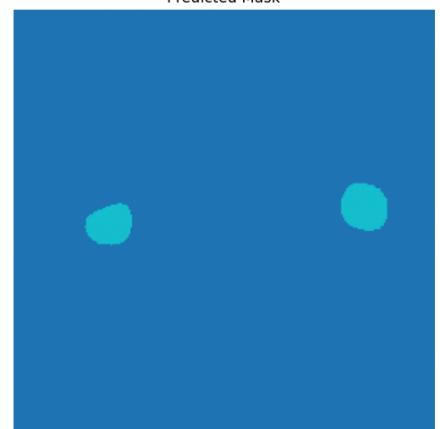
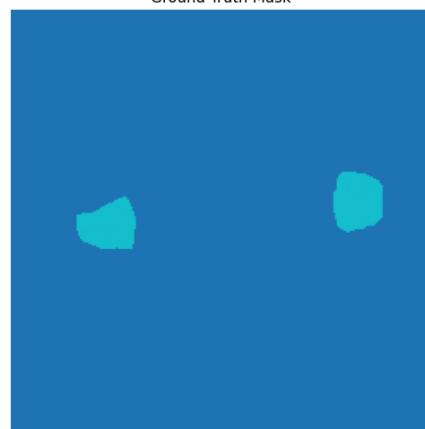
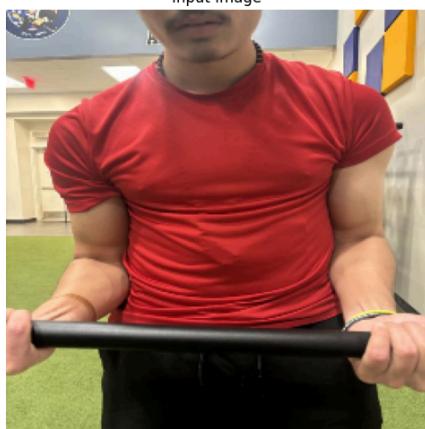
                axs[2].imshow(pred_mask, cmap='tab10')
                axs[2].set_title("Predicted Mask")
                axs[2].axis("off")

                plt.tight_layout()
                plt.show()

        break
```

Start coding or [generate](#) with AI.

```
visualize_prediction(model, val_loader, device)
```

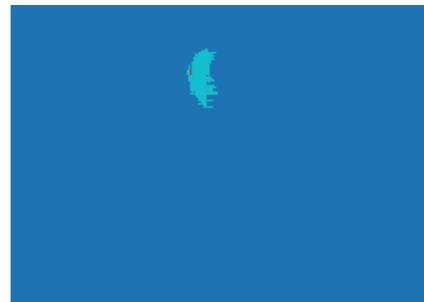




Input Image



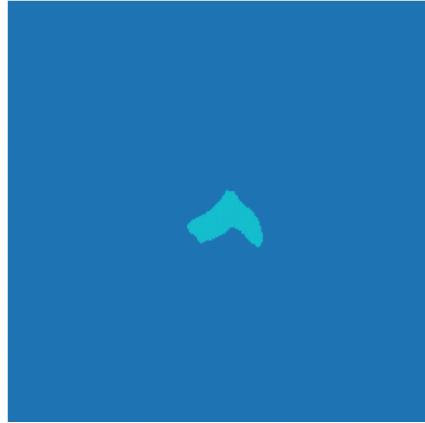
Ground Truth Mask



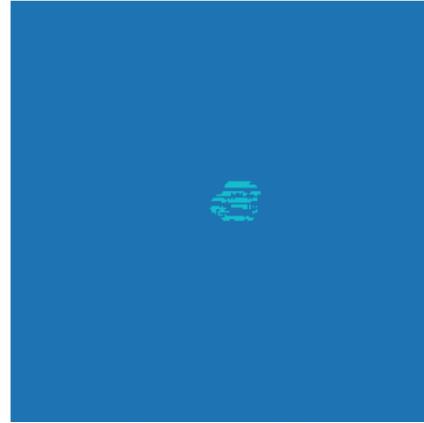
Predicted Mask



Input Image



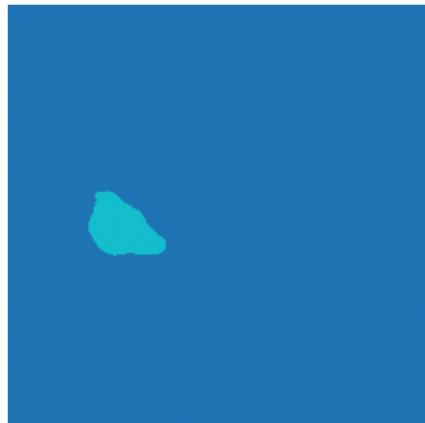
Ground Truth Mask



Predicted Mask



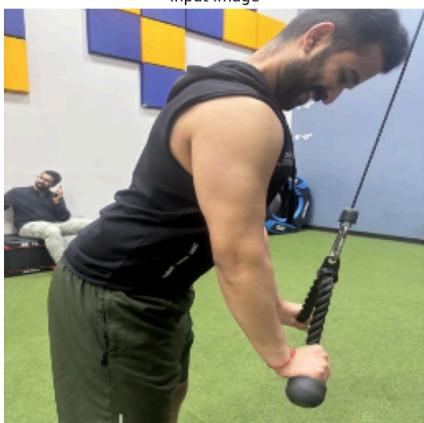
Input Image



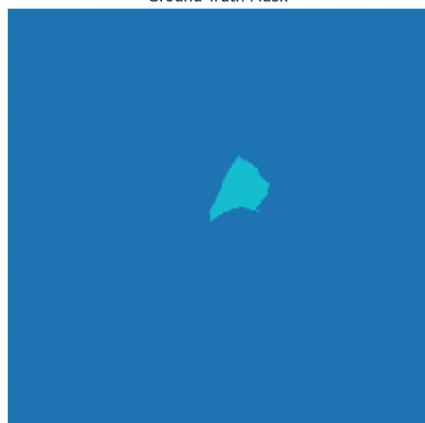
Ground Truth Mask



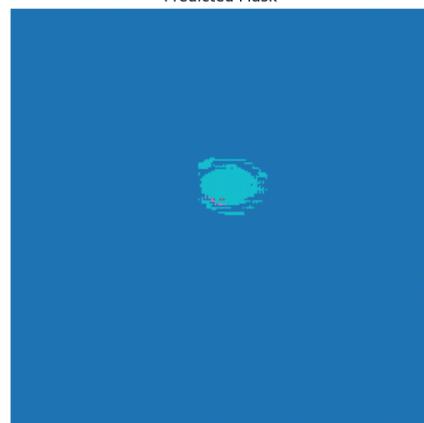
Predicted Mask



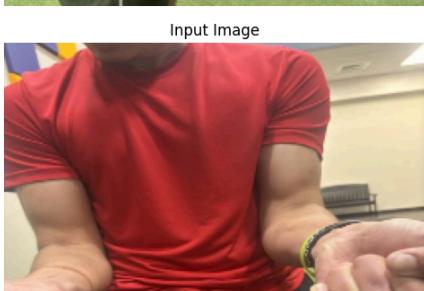
Input Image



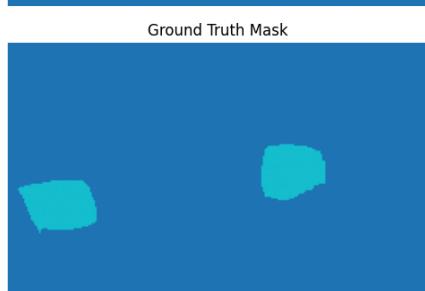
Ground Truth Mask



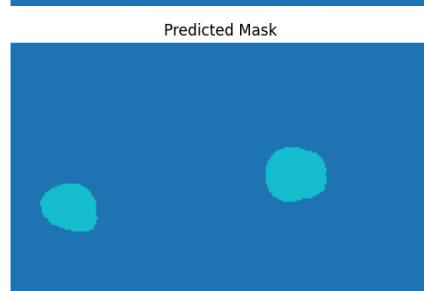
Predicted Mask



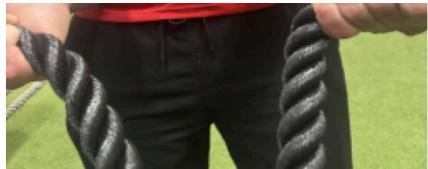
Input Image



Ground Truth Mask



Predicted Mask



```
import cv2
import numpy as np
import torch
import matplotlib.pyplot as plt
from albuminations.pytorch import ToTensorV2

single_image_transform = A.Compose([
    A.Resize(256, 256),
    A.Normalize(mean=(0.485, 0.456, 0.406),
               std=(0.229, 0.224, 0.225)),
    ToTensorV2()
])

def predict_single_image(model, image_path, device):
    model.eval()

    # Load and preprocess image
    image = cv2.imread(image_path)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    transformed = single_image_transform(image=image)
    input_tensor = transformed['image'].unsqueeze(0).to(device)  # Add batch dim

    # Prediction
    with torch.no_grad():
        output = model(input_tensor)
        pred_mask = torch.argmax(output, dim=1).squeeze(0).cpu().numpy()

    # Denormalized image for display
    img_display = image.astype(np.uint8)

    # Visualization
    plt.figure(figsize=(10, 4))
    plt.subplot(1, 2, 1)
    plt.imshow(img_display)
    plt.title("Input Image")
    plt.axis("off")

    plt.subplot(1, 2, 2)
    plt.imshow(pred_mask, cmap='tab10')
    plt.title("Predicted Segmentation")
    plt.axis("off")

    plt.tight_layout()
    plt.show()

predict_single_image(model, "/content/Jim_sem-3/test/images/calf9.jpeg.rf.8253fa10f98dee9ed2647bdda454626d.
```



Input Image



Predicted Segmentation



```
import torch.nn.functional as F

def evaluate(model, dataloader):
    model.eval()
    total_loss = 0
    criterion = nn.CrossEntropyLoss()

    with torch.no_grad():
        for images, masks in dataloader:
            images, masks = images.to(device), masks.to(device)
            outputs = model(images)
            loss = criterion(outputs, masks)
            total_loss += loss.item()

    avg_loss = total_loss / len(dataloader)
    return avg_loss

device = "cuda" if torch.cuda.is_available() else "cpu"
train_loss = evaluate(model, train_loader)
val_loss = evaluate(model, val_loader)

print(f"Train Avg Loss: {train_loss:.4f}")
print(f"Val Avg Loss: {val_loss:.4f}")
```

→ Train Avg Loss: 1.3971
Val Avg Loss: 1.3968

Start coding or generate with AI.

Start coding or generate with AI.

```
%matplotlib inline
import matplotlib.pyplot as plt
```

Start coding or generate with AI.

```
print(len(val_loader.dataset))
```

20

```
import matplotlib.pyplot as plt
import torch

def visualize_prediction(model, dataloader, device):
    model.eval()

    with torch.no_grad():
        for batch in dataloader:

            if isinstance(batch, (list, tuple)):
                images, masks = batch
            elif isinstance(batch, dict):
                images = batch['image']
                masks = batch['mask']
            else:
                raise TypeError("Unexpected batch format!")

            images = images.to(device)
            masks = masks.to(device)
            outputs = model(images)
            preds = torch.argmax(outputs, dim=1)
            img = images[0].cpu().permute(1, 2, 0).numpy() # [C,H,W] -> [H,W,C]
            mask = masks[0].cpu().numpy()
            pred = preds[0].cpu().numpy()

            plt.figure(figsize=(12, 4))
            plt.subplot(1, 3, 1)
            plt.imshow(img)
            plt.title("Input Image")
            plt.axis("off")

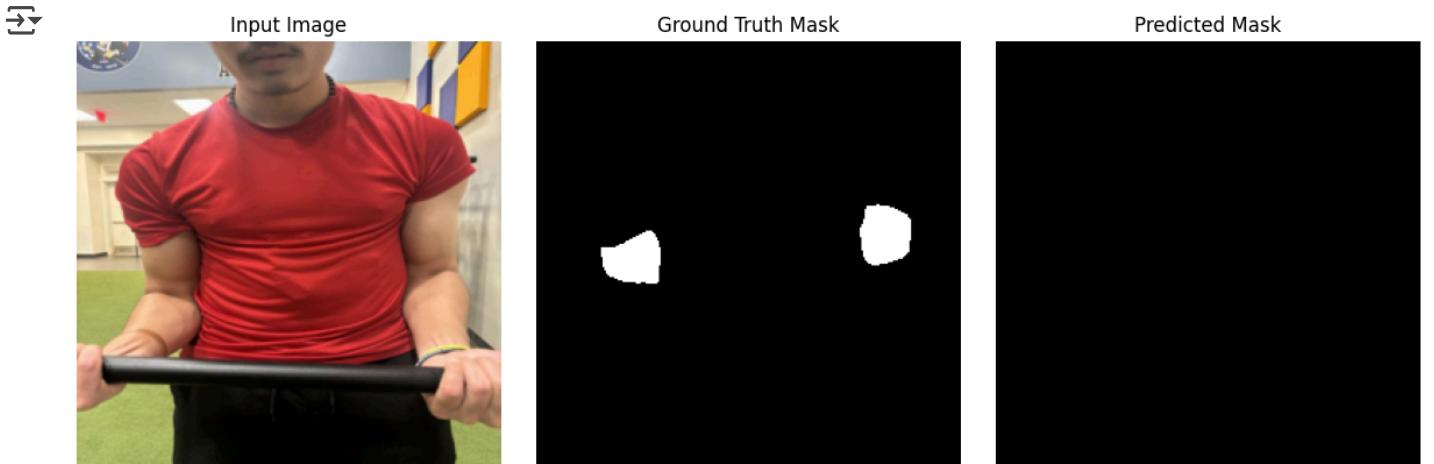
            plt.subplot(1, 3, 2)
            plt.imshow(mask, cmap='gray')
            plt.title("Ground Truth Mask")
            plt.axis("off")

            plt.subplot(1, 3, 3)
            plt.imshow(pred, cmap='gray')
            plt.title("Predicted Mask")
            plt.axis("off")

            plt.tight_layout()
            plt.show()
            print("Unique values in predicted mask:", torch.unique(preds[0]))
```

```
break
```

```
visualize_prediction(model, val_loader, device)
```



```
Unique values in predicted mask: tensor([3])
```

Start coding or [generate](#) with AI.

```
import torch
import matplotlib.pyplot as plt
import numpy as np

def denormalize(img_tensor):
    img = img_tensor.cpu().numpy().transpose(1, 2, 0)
    img = np.clip(img, 0, 1)
    return img

def visualize_prediction(model, dataloader, device):
    model.eval()
    cmap = plt.get_cmap('tab10')

    with torch.no_grad():
        for batch in dataloader:
            images, masks = batch
            images = images.to(device)
            masks = masks.to(device)

            outputs = model(images)
            preds = torch.argmax(outputs, dim=1)

            batch_size = images.size(0)

            for i in range(batch_size):
                image_np = denormalize(images[i])
                mask_np = masks[i].cpu().numpy()
                pred_np = preds[i].cpu().numpy()

                fig, axs = plt.subplots(1, 3, figsize=(12, 4))
                axs[0].imshow(image_np)
                axs[0].set_title('Input Image')
```

```
        axs[0].axis('off')

        axs[1].imshow(mask_np, cmap='tab10', vmin=0, vmax=4)
        axs[1].set_title(f'Ground Truth (Unique: {np.unique(mask_np)}')
        axs[1].axis('off')

        axs[2].imshow(pred_np, cmap='tab10', vmin=0, vmax=4)
        axs[2].set_title(f'Predicted Mask (Unique: {np.unique(pred_np)}')
        axs[2].axis('off')

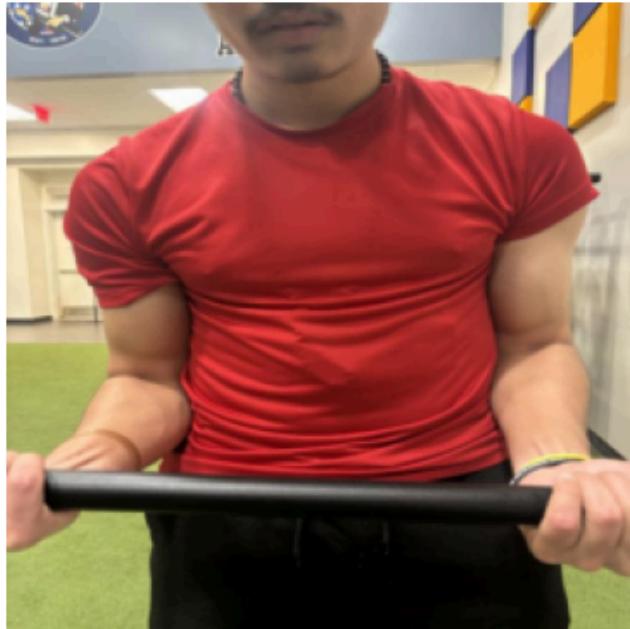
        plt.tight_layout()
        plt.show()

break

visualize_prediction(model, val_loader, device)
```



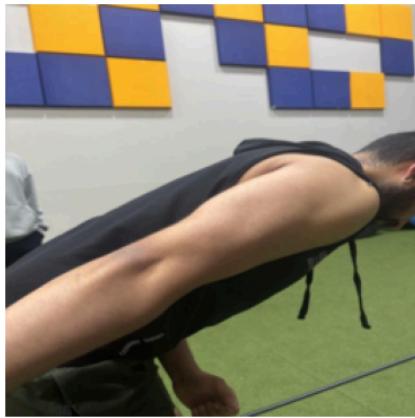
Input Image



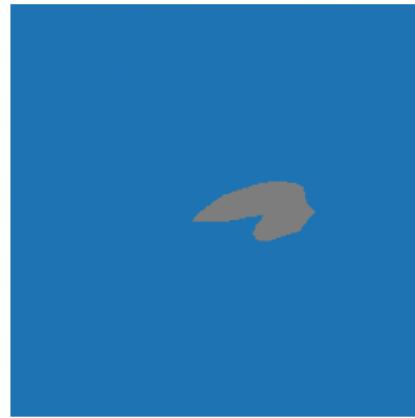
Ground Truth (Unique: [0 1])



Input Image



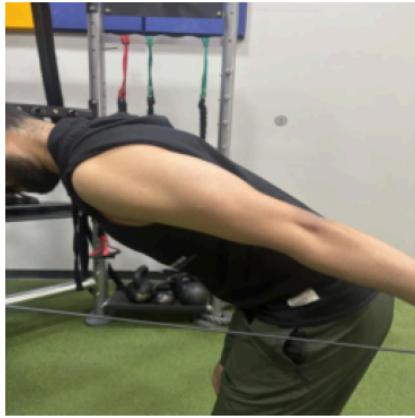
Ground Truth (Unique: [0 3])



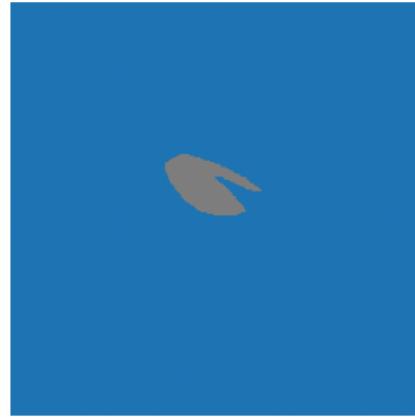
Predicted Mask (Unique: [3])



Input Image



Ground Truth (Unique: [0 3])



Predicted Mask (Unique: [3])



Input Image



Ground Truth (Unique: [0 3])



Predicted Mask (Unique: [3])





Input Image



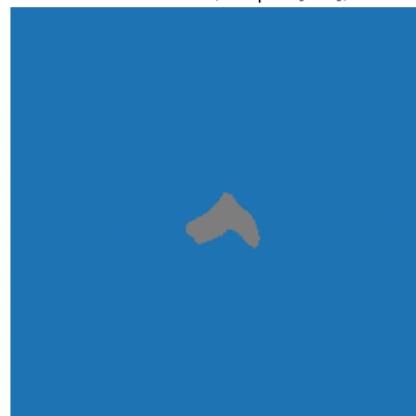
Ground Truth (Unique: [0 3])



Predicted Mask (Unique: [3])



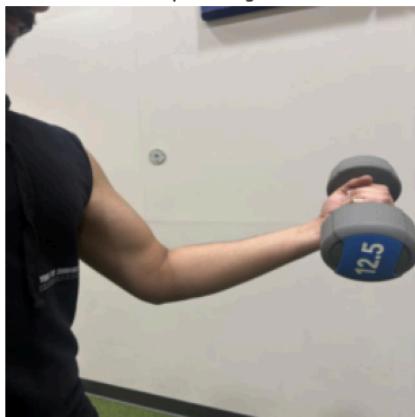
Input Image



Ground Truth (Unique: [0 3])



Predicted Mask (Unique: [3])



Input Image



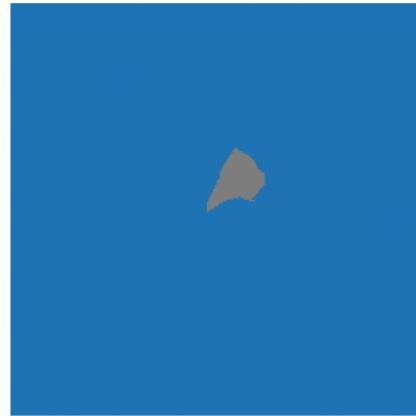
Ground Truth (Unique: [0 1])



Predicted Mask (Unique: [3])



Input Image



Ground Truth (Unique: [0 3])



Predicted Mask (Unique: [3])



Input Image



Ground Truth (Unique: [0 1])



Predicted Mask (Unique: [3])