

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

```
import re

folder = "C:/fire_detection/corsican_data/all_images"

for fname in os.listdir(folder):
    if any(tag in fname for tag in ['_rgb', '_nir', '_gt']):
        base, ext = os.path.splitext(fname)

        # Match patterns like seq01_rgb_001 or 001_rgb
        match = re.match(r'(.*)((_rgb|_nir|_gt)(_?\d+)?)', base)
        if match:
            group = match.group(1).replace('_', '-') # e.g., seq01 or 001
            ftype = match.group(2)[1:] # rgb / ir / gt
            frame = match.group(3) or '' # _001 or ''

            # Remove leading underscore from frame
            frame = frame.lstrip('_')

            new_name = f"{group}-{frame}_{ftype}{ext}" if frame else f"{group}_{ftype}{ext}"
            os.rename(os.path.join(folder, fname), os.path.join(folder, new_name))
            print(f"Renamed: {fname} → {new_name}")
```

```
Renamed: seq02_nir_266.png → seq02-266_nir.png
Renamed: seq02_nir_267.png → seq02-267_nir.png
Renamed: seq02_nir_268.png → seq02-268_nir.png
Renamed: seq03_nir_001.png → seq03-001_nir.png
Renamed: seq03_nir_002.png → seq03-002_nir.png
Renamed: seq03_nir_003.png → seq03-003_nir.png
```

```
base_names = sorted(list(set(
    f.split('_')[0]
    for f in os.listdir("C:\\fire_detection\\corsican_data\\all_images")
    if '_rgb' in f
)))
```

```
base_names
```

```
<>:3: SyntaxWarning: invalid escape sequence '\c'
<>:3: SyntaxWarning: invalid escape sequence '\c'
C:\Users\Admin\AppData\Local\Temp\ipykernel_26220\1792945694.py:3: SyntaxWarning: invalid escape sequence '\c'
    for f in os.listdir("C:\\fire_detection\\corsican_data\\all_images")
[ '001',
  '002',
  '003',
  '004',
  '005',
  '006',
  '007',
  '008',
  '009',
  '010',
  '011',
  '012',
  '013',
  '014',
  '015',
  '016',
  '017',
  '018',
  '019',
  '020',
  '021',
  '022',
  '023',
  '024',
  '025',
  '026',
  '027',
  '028',
  '029',
  '030',
  '031',
  '032',
  '033',
  '034',
  '035',
  '036',
  '037',
  '038',
  '039',
  '040',
  '041',
  '042',
  '043',
  '044',
  '045',
  '046',
  '047',
  '048',
  '049',
  '050',
  '051',
  '052',
  '053',
  '054',
```

```
class FireDatasetRGBIR(Dataset):
    def __init__(self, root_dir, image_size=(224, 224), use_ir=True):
        self.root_dir = root_dir
        self.image_size = image_size
        self.use_ir = use_ir

        # Collect base names (like img_001, img_002)
        self.base_names = sorted(list(set(
            f.split('_')[0]
            for f in os.listdir(root_dir)
            if '_rgb' in f
        )))
```

```

# Transforms
self.rgb_transform = T.Compose([
    T.Resize(self.image_size),
    T.ToTensor(),
    T.Normalize([0.485, 0.456, 0.406],
                [0.229, 0.224, 0.225])
])
self.ir_transform = T.Compose([
    T.Resize(self.image_size),
    T.ToTensor() # Will be [1, H, W]
])
self.mask_transform = T.Compose([
    T.Resize(self.image_size),
    T.ToTensor() # Assumes mask is binary (0 or 255)
])
def unnormalize(self, tensor):
    mean = torch.tensor([0.485, 0.456, 0.406]).reshape(3, 1, 1)
    std = torch.tensor([0.229, 0.224, 0.225]).reshape(3, 1, 1)
    return tensor * std + mean

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

def __getitem__(self, idx):
    base = self.base_names[idx]

    rgb_path = os.path.join(self.root_dir, f"{base}_rgb.png")
    mask_path = os.path.join(self.root_dir, f"{base}_gt.png")
    ir_path = os.path.join(self.root_dir, f"{base}_nir.png")

    rgb = Image.open(rgb_path).convert('RGB')
    mask = Image.open(mask_path).convert('L') # binary mask

    rgb = self.rgb_transform(rgb)
    mask = self.mask_transform(mask)

    if self.use_ir and os.path.exists(ir_path):
        ir = Image.open(ir_path).convert('L') # grayscale IR
        ir = self.ir_transform(ir)
        x = torch.cat([rgb, ir], dim=0) # [4, H, W]
    else:
        x = rgb # [3, H, W]

    # Make sure mask is binary (0 or 1)
    mask = (mask > 0).float()

    return x, mask

```

```

dataset = FireDatasetRGBIR(root_dir="corsican_data/all_images", use_ir= False)
len(dataset.base_names)

```

```
1135
```

```
first_x, first_y = dataset.__getitem__(0)
```

```

def unnormalize(tensor, mean, std):
    mean = torch.tensor(mean).reshape(3, 1, 1)
    std = torch.tensor(std).reshape(3, 1, 1)
    return tensor * std + mean

```

```

def show_image_and_mask(rgb, mask):
    mean = [0.485, 0.456, 0.406]
    std = [0.229, 0.224, 0.225]
    rgb = unnormalize(rgb, mean, std)

    # Prepare images
    rgb_np = rgb.permute(1, 2, 0).numpy().clip(0, 1) # [H, W, 3]
    if mask.ndim == 3:
        mask_np = mask.squeeze(0).numpy() # [H, W]
    else:
        mask_np = mask.numpy()

    # Plot side by side
    fig, ax = plt.subplots(1, 2, figsize=(10, 5))
    ax[0].imshow(rgb_np)

```

```
ax[0].set_title("RGB Image")
ax[0].axis("off")

ax[1].imshow(mask_np, cmap="gray")
ax[1].set_title("Ground Truth Mask")
ax[1].axis("off")

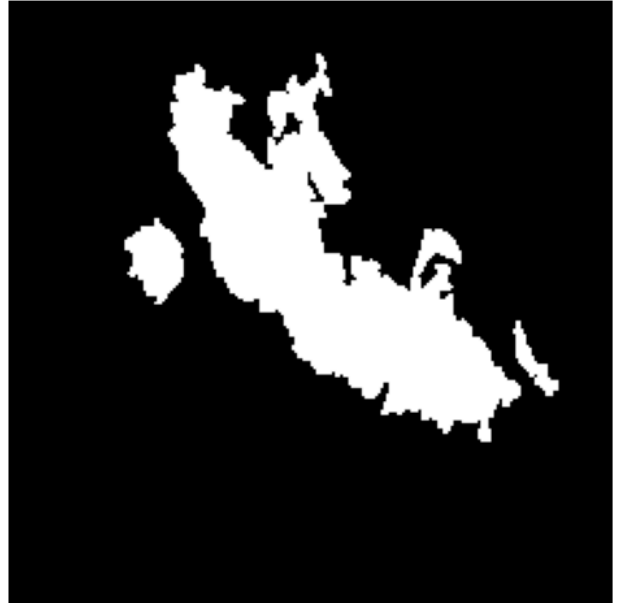
plt.tight_layout()
plt.show()
```

```
show_image_and_mask(first_x, first_y)
```

RGB Image



Ground Truth Mask



```
print(torch.unique(first_y)) # Black or white image
```

```
tensor([0., 1.])
```

```
class UNetSimple(nn.Module):
    def __init__(self, in_channels=3):
        super().__init__()
        def CBR(in_c, out_c): # conv → BN → ReLU
            return nn.Sequential(
                nn.Conv2d(in_c, out_c, kernel_size=3, padding=1),
                nn.BatchNorm2d(out_c),
                nn.ReLU(inplace=True)
            )

        self.enc1 = CBR(in_channels, 64)
        self.enc2 = CBR(64, 128)
        self.enc3 = CBR(128, 256)

        self.pool = nn.MaxPool2d(2, 2) # halves the dimensions

        self.up2 = nn.ConvTranspose2d(256, 128, 2, 2)
        self.dec2 = CBR(256, 128)
        self.up1 = nn.ConvTranspose2d(128, 64, 2, 2)
        self.dec1 = CBR(128, 64)

        self.out = nn.Conv2d(64, 1, kernel_size=1)

    def forward(self, x):
        e1 = self.enc1(x)
        e2 = self.enc2(self.pool(e1))
        e3 = self.enc3(self.pool(e2))

        d2 = self.dec2(torch.cat([self.up2(e3), e2], dim=1))
        d1 = self.dec1(torch.cat([self.up1(d2), e1], dim=1))

        return self.out(d1) # output logits (no sigmoid here!)

flatten = nn.Flatten()

model = UNetSimple()
model.state_dict()
```

```

OrderedDict([('enc1.0.weight',
              tensor([[[[-0.0357, -0.0824, -0.1113],
                        [-0.0841,  0.1787, -0.0649],
                        [-0.1577, -0.1701, -0.0916]],

                        [[ 0.1625, -0.1517,  0.0804],
                        [ 0.0887, -0.0836,  0.0017],
                        [ 0.0096, -0.0435, -0.1298]],

                        [[ 0.1012, -0.1492, -0.1738],
                        [ 0.1173,  0.0988,  0.1744],
                        [ 0.1669,  0.1300, -0.1632]]],

              [[ 0.1653, -0.1332, -0.1690],
               [-0.1002,  0.1150, -0.0074],
               [-0.1517, -0.0620,  0.0639]],

              [[-0.1470,  0.0160, -0.1225],
               [-0.1224,  0.0354,  0.1270],
               [ 0.1378,  0.0750, -0.0683]],

              [[-0.0765,  0.1209, -0.0020],
               [-0.0552, -0.0943, -0.1848],
               [ 0.1494,  0.1666,  0.0599]]],

              [[[ 0.0902, -0.0896,  0.1117],
                [-0.0339, -0.0520, -0.1326],
                [-0.0682, -0.1025, -0.1518]],

               [[ 0.1261, -0.0964,  0.1923],
                [-0.1115,  0.0891,  0.1162],
                [ 0.0090, -0.1179, -0.1347]],

               [[-0.0353,  0.1378, -0.1890],
                [ 0.0450, -0.0594,  0.1453],
                [-0.0429, -0.1912, -0.0728]]],

              ...],

              [[[-0.0326, -0.1228, -0.1258],
                [ 0.0858, -0.0480, -0.1205],
                [-0.1408, -0.1892,  0.0749]],

               [[-0.1013,  0.1730, -0.0138],
                [ 0.1919, -0.0622, -0.0649],
                [-0.0423, -0.1240,  0.1579]],

               [[-0.1001, -0.0071, -0.0208],
                [-0.0253,  0.1257, -0.0507],
                [-0.0559, -0.1889, -0.1548]]],

              [[[ 0.0060, -0.0559,  0.1549],
                [ 0.1468, -0.0118, -0.0628],

```

```

total_params = sum(p.numel() for p in model.parameters())
print(f"Total parameters: {total_params:,}")

```

Total parameters: 905,025

```

from torch.utils.data import random_split

torch.manual_seed(42)

train_size = int(0.8 * len(dataset))
test_size = len(dataset) - train_size

# Randomly split
train_dataset, test_dataset = random_split(dataset, [train_size, test_size])

```

```
len(train_dataset), len(test_dataset)
```

(908, 227)

```

train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=8, shuffle=False)

X, y = next(iter(train_loader))
# len(X), len(y)

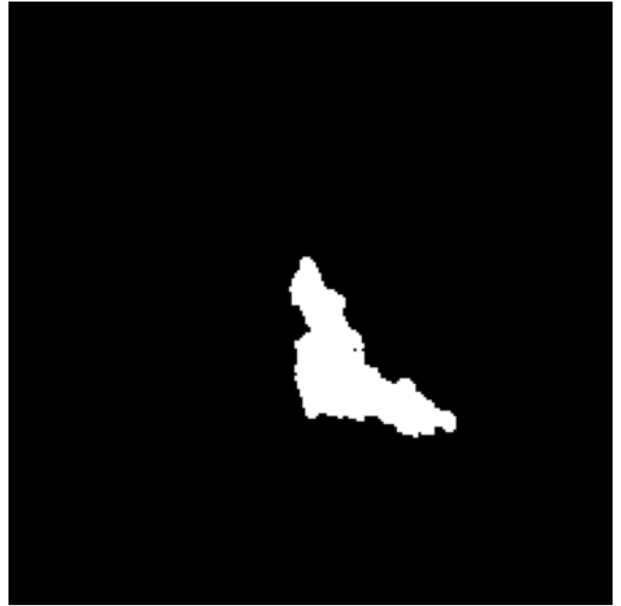
```

snow_image_and_mask(x[z], y[z])

RGB Image



Ground Truth Mask



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

```
'cuda'
```

```
model = model.to(device)
```

```
loss_fn = nn.BCEWithLogitsLoss()
optimizer = torch.optim.Adam(params=model.parameters(), lr = 1e-3)
```

```
from tqdm import tqdm

def train_segmentation_model(model, train_loader, val_loader, device, num_epochs=10, loss_fn=loss_fn, optimizer=optimizer)
    # model = model.to(device)

    # criterion = torch.nn.BCEWithLogitsLoss()
    # optimizer = torch.optim.Adam(model.parameters(), lr=1e-3)

    for epoch in range(num_epochs):
        model.train()
        train_loss = 0.0

        for images, masks in tqdm(train_loader, desc=f"Epoch {epoch+1}/{num_epochs} - Training"):
            images = images.to(device)          # [B, 3 or 4, H, W]
            masks = masks.to(device).float()     # [B, 1, H, W], float

            outputs = model(images)              # [B, 1, H, W], logits
            loss = loss_fn(outputs, masks)
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            train_loss += loss.item() * images.size(0)

        avg_train_loss = train_loss / len(train_loader.dataset)

        # ----- Validation -----
        model.eval()
        val_loss = 0.0
        with torch.no_grad():
            for images, masks in tqdm(val_loader, desc=f"Epoch {epoch+1}/{num_epochs} - Validation"):
                images = images.to(device)
                masks = masks.to(device).float()

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

                val_loss += loss.item() * images.size(0)

            avg_val_loss = val_loss / len(val_loader.dataset)
```

```

        print(f"\nEpoch {epoch+1}:")
        print(f"Train Loss: {avg_train_loss:.4f} | Val Loss: {avg_val_loss:.4f}")
        print("-" * 50)

    return model

```

```

train_segmentation_model(model=model,
                        train_loader=train_loader,
                        val_loader=test_loader,
                        device=device,
                        num_epochs=5,
                        )

```

```

Epoch 1/5 - Training: 100%|██████████| 114/114 [02:14<00:00, 1.18s/it]
Epoch 1/5 - Validation: 100%|██████████| 29/29 [00:25<00:00, 1.12it/s]

```

```

Epoch 1:
Train Loss: 0.2762 | Val Loss: 0.1713
-----

```

```

Epoch 2/5 - Training: 100%|██████████| 114/114 [01:28<00:00, 1.29it/s]
Epoch 2/5 - Validation: 100%|██████████| 29/29 [00:24<00:00, 1.21it/s]

```

```

Epoch 2:
Train Loss: 0.1543 | Val Loss: 0.1383
-----

```

```

Epoch 3/5 - Training: 100%|██████████| 114/114 [01:28<00:00, 1.28it/s]
Epoch 3/5 - Validation: 100%|██████████| 29/29 [00:19<00:00, 1.48it/s]

```

```

Epoch 3:
Train Loss: 0.1404 | Val Loss: 0.1340
-----

```

```

Epoch 4/5 - Training: 100%|██████████| 114/114 [01:29<00:00, 1.27it/s]
Epoch 4/5 - Validation: 100%|██████████| 29/29 [00:18<00:00, 1.58it/s]

```

```

Epoch 4:
Train Loss: 0.1359 | Val Loss: 0.1230
-----

```

```

Epoch 5/5 - Training: 100%|██████████| 114/114 [01:32<00:00, 1.24it/s]
Epoch 5/5 - Validation: 100%|██████████| 29/29 [00:21<00:00, 1.36it/s]

```

```

Epoch 5:
Train Loss: 0.1355 | Val Loss: 0.1248
-----

```

```

UNetSimple(
  (enc1): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
  )
  (enc2): Sequential(
    (0): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
  )
  (enc3): Sequential(
    (0): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
  )
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (up2): ConvTranspose2d(256, 128, kernel_size=(2, 2), stride=(2, 2))
  (dec2): Sequential(
    (0): Conv2d(256, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
  )
  (up1): ConvTranspose2d(128, 64, kernel_size=(2, 2), stride=(2, 2))
  (dec1): Sequential(
    (0): Conv2d(128, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
  )
)

```

```

torch.save(model.state_dict(), 'unet_simple_fire_segmentation.pth')

```

```

def show_prediction_and_mask(pred, mask):

    pred = torch.round(torch.sigmoid(pred)).detach().cpu()
    mask = mask.detach().cpu()
    if mask.ndim == 3:
        mask_np = mask.squeeze(0).numpy() # [H, W]
    else:
        mask_np = mask.numpy()

```

```

if pred.ndim == 3:
    pred_np = pred.squeeze(0).numpy()
elif pred.ndim == 4:
    pred_np = pred.squeeze(0).squeeze(0).numpy()          # [H, W]
else:
    pred_np = pred.numpy()

fig, ax = plt.subplots(1, 2, figsize=(10, 5))
ax[0].imshow(pred_np, cmap="gray")
ax[0].set_title("Prediction Mask")
ax[0].axis("off")

ax[1].imshow(mask_np, cmap="gray")
ax[1].set_title("Ground Truth Mask")
ax[1].axis("off")

plt.tight_layout()
plt.show()

```

```

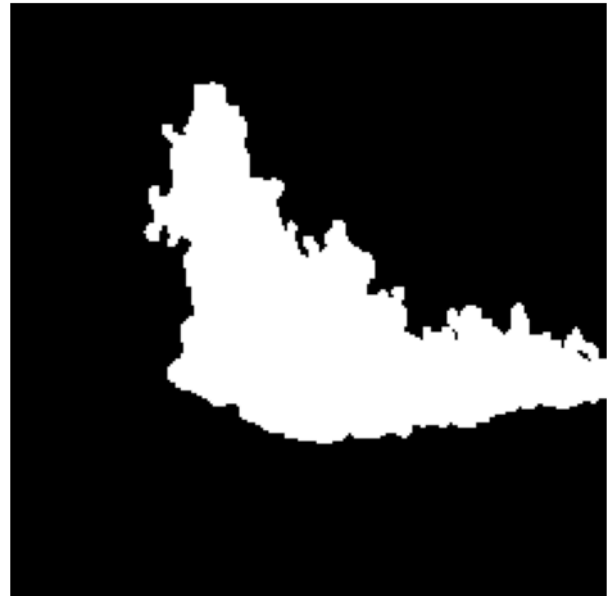
X_first, y_first = train_dataset[1]
X_first = X_first.to(device)
y_first_pred = model(X_first.unsqueeze(dim=0))
show_prediction_and_mask(torch.round(torch.sigmoid(y_first_pred)).squeeze().detach().cpu(), y_first.squeeze())
show_image_and_mask(X_first.cpu(), y_first.squeeze())

```

Prediction Mask



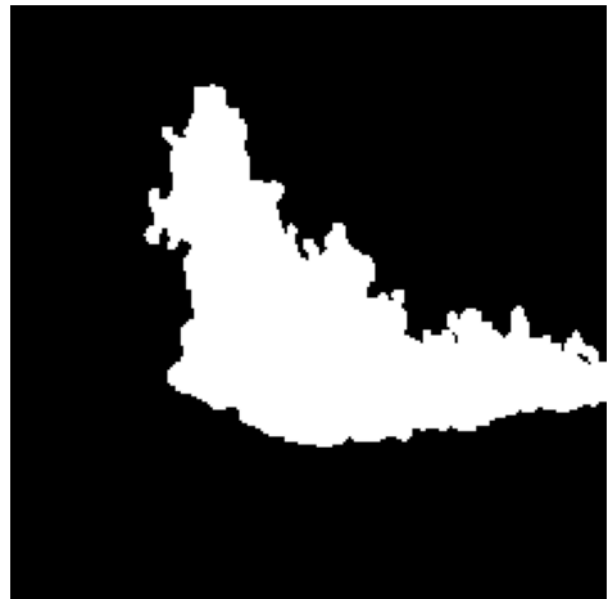
Ground Truth Mask



RGB Image



Ground Truth Mask



```

X, y = test_dataset[4]
X = X.to(device)

```



```

y_pred = model(X.unsqueeze(dim = 0))
# y_pred = y_pred.cpu().detach().numpy()
y_pred = torch.round(torch.sigmoid(y_pred)).squeeze().detach().cpu()

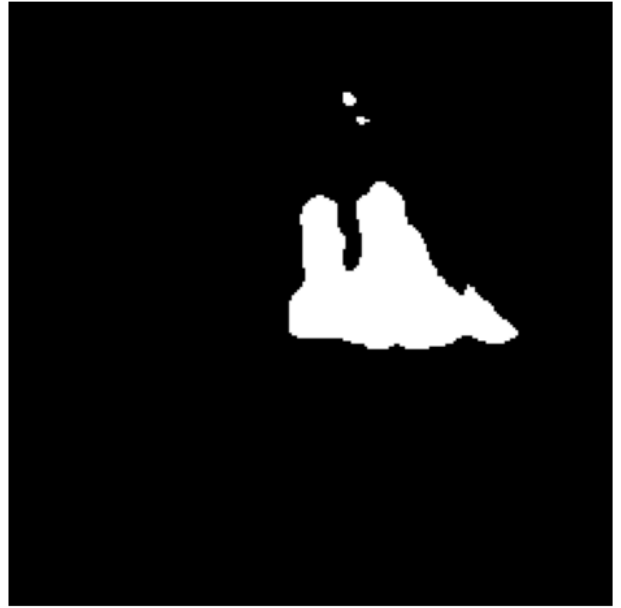
show_image_and_mask(X.cpu(), y_pred)

```

RGB Image



Ground Truth Mask



```

def accuracy_fn(pred_mask, gt):

    pred_mask = torch.round(torch.sigmoid(torch.flatten(pred_mask))).cpu()
    gt = torch.flatten(gt).cpu()

    correct_pixels = torch.eq(pred_mask, gt).sum().item()
    acc_score = correct_pixels/len(gt)
    return acc_score

```

```

def intersection_over_union(preds: torch.Tensor, targets: torch.Tensor) -> float:
    eps = 1e-5
    probs = torch.sigmoid(preds)
    preds_bin = (probs < 0.5).float() # fire=1, background=0

    targets = 1.0 - targets # Flip: fire=1, background=0

    preds_flat = preds_bin.view(preds.size(0), -1)
    targets_flat = targets.view(targets.size(0), -1)

    intersection = (preds_flat * targets_flat).sum(dim=1)
    union = preds_flat.sum(dim=1) + targets_flat.sum(dim=1) - intersection

    iou = (intersection + eps) / (union + eps)
    return iou.mean().item()

```

```

def dice_coefficient(preds: torch.Tensor, targets: torch.Tensor) -> float:
    eps = 1e-5
    probs = torch.sigmoid(preds)
    preds_bin = (probs < 0.5).float() # fire=1, background=0

    targets = 1.0 - targets # Flip: fire=1, background=0

    preds_flat = preds_bin.view(preds.size(0), -1)
    targets_flat = targets.view(targets.size(0), -1)

    intersection = (preds_flat * targets_flat).sum(dim=1)
    union = preds_flat.sum(dim=1) + targets_flat.sum(dim=1)

    dc = (2 * (intersection + eps)) / (union + eps)
    return dc.mean().item()

```

```
# Validation loop
total_acc = 0.0
total_iou = 0.0
with torch.no_grad():
    for images, masks in test_loader:
        images = images.to(device)
        masks = masks.to(device)

        logits = model(images)
        loss = loss_fn(logits, masks.float())

        acc = accuracy_fn(logits, masks)
        iou = intersection_over_union(logits, masks)
        total_iou += iou * images.size(0)
        total_acc += acc * images.size(0)

avg_test_iou = total_iou / len(test_loader.dataset)
avg_test_acc = total_acc / len(test_loader.dataset)
print(f"Testing Accuracy: {avg_test_acc:.4f}")
print(f"Testing Intersection Over Union: {avg_test_iou:.4f}")
```

Testing Accuracy: 0.9627
Testing Intersection Over Union: 0.9547

```
train_acc = 0.0
train_iou = 0.0
with torch.no_grad():
    for images, masks in train_loader:
        images = images.to(device)
        masks = masks.to(device)

        logits = model(images)
        loss = loss_fn(logits, masks.float())

        acc = accuracy_fn(logits, masks)
        iou = intersection_over_union(logits, masks)
        train_iou += iou * images.size(0)
        train_acc += acc * images.size(0)

avg_train_iou = train_iou / len(train_loader.dataset)
avg_train_acc = train_acc / len(train_loader.dataset)
print(f"Training Accuracy: {avg_train_acc:.4f}")
print(f"Training Intersection Over Union: {avg_train_iou:.4f}")
```

Training Accuracy: 0.9596
Training Intersection Over Union: 0.9485

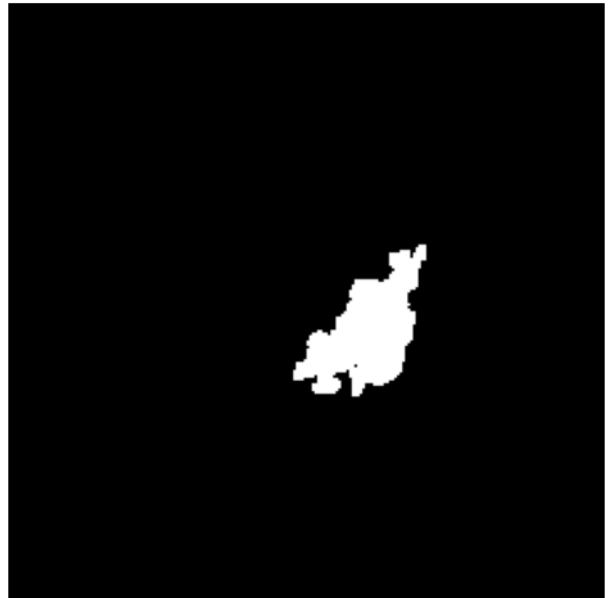
```
X, y = train_dataset[667]
X = X.to(device)
y_pred = model(X.unsqueeze(dim=0))
print(accuracy_fn(y_pred, y))
show_image_and_mask(X.cpu(), y)
show_prediction_and_mask(y_pred, y)
```

0.994140625

RGB Image



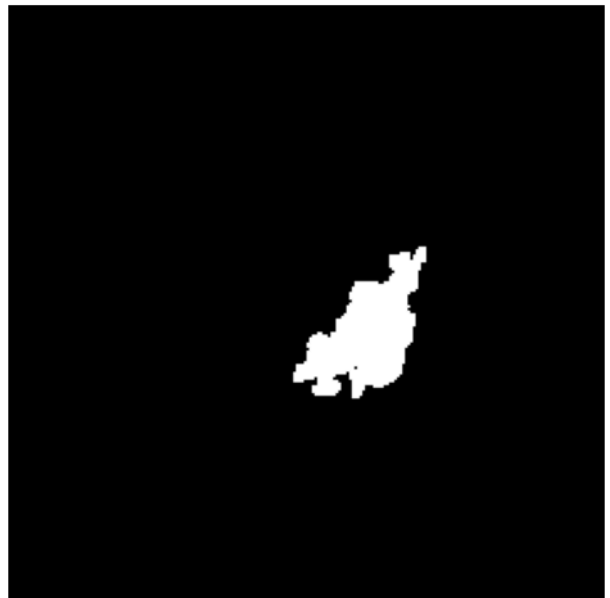
Ground Truth Mask



Prediction Mask



Ground Truth Mask



```
accuracies = {"light_model": None, "unet": None, "deeplab": None}
ious = {"light_model": None, "unet": None, "deeplab": None}
```

```
class LighterUnet(nn.Module):
    def __init__(self, in_channels=3):
        super().__init__()
        def CBR(in_c, out_c): # conv → BN → ReLU
            return nn.Sequential(
                nn.Conv2d(in_c, out_c, kernel_size=3, padding=1),
                nn.BatchNorm2d(out_c),
                nn.ReLU(inplace=True)
            )

        self.enc1 = CBR(in_channels, 32)
        self.enc2 = CBR(32, 64)
        self.enc3 = CBR(64, 128)

        self.pool = nn.MaxPool2d(2, 2) # halves the dimensions

        self.up2 = nn.ConvTranspose2d(128, 64, 2, 2)
        self.dec2 = CBR(128, 64)
        self.up1 = nn.ConvTranspose2d(64, 32, 2, 2)
        self.dec1 = CBR(64, 32)

        self.out = nn.Conv2d(32, 1, kernel_size=1)
```

```

def forward(self, x):

    e1 = self.enc1(x)
    e2 = self.enc2(self.pool(e1))
    e3 = self.enc3(self.pool(e2))

    d2 = self.dec2(torch.cat([self.up2(e3), e2], dim=1))
    d1 = self.dec1(torch.cat([self.up1(d2), e1], dim=1))

    return self.out(d1) # output logits (no sigmoid here!)

light_model = LighterUnet().to(device)
loss_fn = nn.BCEWithLogitsLoss()
light_optimizer = torch.optim.Adam(params=light_model.parameters(), lr=1e-3 )

```

```

total_params = sum(p.numel() for p in light_model.parameters())
print(f"Total parameters: {total_params:,}")

```

Total parameters: 227,233

```

train_segmentation_model(model=light_model,
                        train_loader=train_loader,
                        val_loader=test_loader,
                        device=device,
                        num_epochs=10,
                        optimizer=light_optimizer,
                        loss_fn=loss_fn
                        )

```

```

Epoch 1/10 - Training: 100%|██████████| 114/114 [02:24<00:00, 1.27s/it]
Epoch 1/10 - Validation: 100%|██████████| 29/29 [00:24<00:00, 1.18it/s]

```

```

Epoch 1:
Train Loss: 0.2759 | Val Loss: 0.1586
-----

```

```

Epoch 2/10 - Training: 100%|██████████| 114/114 [01:44<00:00, 1.09it/s]
Epoch 2/10 - Validation: 100%|██████████| 29/29 [00:22<00:00, 1.27it/s]

```

```

Epoch 2:
Train Loss: 0.1628 | Val Loss: 0.1332
-----

```

```

Epoch 3/10 - Training: 100%|██████████| 114/114 [01:44<00:00, 1.09it/s]
Epoch 3/10 - Validation: 100%|██████████| 29/29 [00:25<00:00, 1.12it/s]

```

```

Epoch 3:
Train Loss: 0.1443 | Val Loss: 0.1276
-----

```

```

Epoch 4/10 - Training: 100%|██████████| 114/114 [01:44<00:00, 1.09it/s]
Epoch 4/10 - Validation: 100%|██████████| 29/29 [00:21<00:00, 1.32it/s]

```

```

Epoch 4:
Train Loss: 0.1346 | Val Loss: 0.1224
-----

```

```

Epoch 5/10 - Training: 100%|██████████| 114/114 [01:52<00:00, 1.01it/s]
Epoch 5/10 - Validation: 100%|██████████| 29/29 [00:25<00:00, 1.13it/s]

```

```

Epoch 5:
Train Loss: 0.1277 | Val Loss: 0.1239
-----

```

```

Epoch 6/10 - Training: 100%|██████████| 114/114 [01:43<00:00, 1.10it/s]
Epoch 6/10 - Validation: 100%|██████████| 29/29 [00:23<00:00, 1.21it/s]

```

```

Epoch 6:
Train Loss: 0.1284 | Val Loss: 0.1099
-----

```

```

Epoch 7/10 - Training: 100%|██████████| 114/114 [01:58<00:00, 1.04s/it]
Epoch 7/10 - Validation: 100%|██████████| 29/29 [00:21<00:00, 1.32it/s]

```

```

Epoch 7:
Train Loss: 0.1213 | Val Loss: 0.1089
-----

```

```

Epoch 8/10 - Training: 100%|██████████| 114/114 [01:50<00:00, 1.03it/s]
Epoch 8/10 - Validation: 100%|██████████| 29/29 [00:27<00:00, 1.04it/s]

```

```

Epoch 8:
Train Loss: 0.1226 | Val Loss: 0.1170
-----

```

```

Epoch 9/10 - Training: 100%|██████████| 114/114 [02:09<00:00, 1.13s/it]
Epoch 9/10 - Validation: 100%|██████████| 29/29 [00:30<00:00, 1.05s/it]

```

```

Epoch 9:
Train Loss: 0.1173 | Val Loss: 0.1155

```

```
-----
Epoch 10/10 - Training: 100%|██████████| 114/114 [02:16<00:00, 1.19s/it]
Epoch 10/10 - Validation: 100%|██████████| 29/29 [00:32<00:00, 1.11s/it]
Epoch 10:
Train Loss: 0.1140 | Val Loss: 0.1051
```

```
torch.save(light_model.state_dict(), 'light_model.pth')
```

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

```
import segmentation_models_pytorch as smp

def get_model(name: str, in_channels=3):
    if name == "unet":
        return smp.Unet(encoder_name="resnet34", encoder_weights="imagenet",
                        in_channels=in_channels, classes=1)
    elif name == "deeplabv3":
        return smp.DeepLabV3(encoder_name="resnet34", encoder_weights="imagenet",
                             in_channels=in_channels, classes=1)
    elif name == "segnet":
        return smp.SegmentationModel(
            encoder_name="vgg11_bn",
            encoder_weights="imagenet",
            decoder_channels=(256, 128, 64, 32, 16),
            in_channels=in_channels,
            classes=1
        )
    else:
        raise ValueError("Unsupported model")
```

```
c:\Users\Admin\AppData\Local\Programs\Python\Python312\Lib\site-packages\tqdm\auto.py:21: TqdmWarning: IPProgress not found.
from .autonotebook import tqdm as notebook_tqdm
```

```
# Validation loop
total_acc = 0.0
total_iou = 0.0
with torch.no_grad():
    for images, masks in test_loader:
        images = images.to(device)
        masks = masks.to(device)

        logits = light_model(images)
        loss = loss_fn(logits, masks.float())

        acc = accuracy_fn(logits, masks)
        iou = intersection_over_union(logits, masks)
        total_iou += iou * images.size(0)
        total_acc += acc * images.size(0)

avg_test_iou = total_iou / len(test_loader.dataset)
avg_test_acc = total_acc / len(test_loader.dataset)
print(f"Testing Accuracy: {avg_test_acc:.4f}")
accuracies['light_model'] = avg_test_acc
print(f"Testing Intersection Over Union: {avg_test_iou:.4f}")
ious['light_model'] = avg_test_iou
```

```
Testing Accuracy: 0.9685
Testing Intersection Over Union: 0.9632
```

```
X, y = train_dataset[11]
X = X.to(device)
y_pred = light_model(X.unsqueeze(dim=0))
show_prediction_and_mask(y_pred, y)
show_image_and_mask(X.cpu(), y)
```

Prediction Mask



Ground Truth Mask



RGB Image



Ground Truth Mask



```
UNET_MODEL = get_model("UNET")
total_params = sum(p.numel() for p in UNET_MODEL.parameters())
print(f"Total parameters (UNET): {total_params:,}")
```

Total parameters (UNET): 24,436,369

```
DEEPLAB_MODEL = get_model("deeplabv3")
total_params = sum(p.numel() for p in DEEPLAB_MODEL.parameters())
print(f"Total parameters (DeeplabV3): {total_params:,}")
```

Total parameters (DeeplabV3): 26,007,105

```
UNET_MODEL = UNET_MODEL.to(device)
DEEPLAB_MODEL = DEEPLAB_MODEL.to(device)
```

```
loss_fn = nn.BCEWithLogitsLoss()
UNET_OPTIM = torch.optim.Adam(params=UNET_MODEL.parameters(), lr=1e-3)
```

```

train_segmentation_model(model=UNET_model,
                        train_loader=train_loader,
                        val_loader=test_loader,
                        device=device,
                        num_epochs=10,
                        loss_fn=loss_fn,
                        optimizer=UNET_optim)

```

```

Epoch 1/10 - Training: 100%|██████████| 114/114 [02:06<00:00, 1.11s/it]
Epoch 1/10 - Validation: 100%|██████████| 29/29 [00:23<00:00, 1.25it/s]

```

```

Epoch 1:
Train Loss: 0.2308 | Val Loss: 0.1194

```

```

Epoch 2/10 - Training: 100%|██████████| 114/114 [01:50<00:00, 1.03it/s]
Epoch 2/10 - Validation: 100%|██████████| 29/29 [00:23<00:00, 1.25it/s]

```

```

Epoch 2:
Train Loss: 0.1336 | Val Loss: 0.1404

```

```

Epoch 3/10 - Training: 100%|██████████| 114/114 [01:43<00:00, 1.10it/s]
Epoch 3/10 - Validation: 100%|██████████| 29/29 [00:22<00:00, 1.26it/s]

```

```

Epoch 3:
Train Loss: 0.1290 | Val Loss: 0.1166

```

```

Epoch 4/10 - Training: 100%|██████████| 114/114 [01:48<00:00, 1.05it/s]
Epoch 4/10 - Validation: 100%|██████████| 29/29 [00:23<00:00, 1.23it/s]

```

```

Epoch 4:
Train Loss: 0.1173 | Val Loss: 0.1114

```

```

Epoch 5/10 - Training: 100%|██████████| 114/114 [01:48<00:00, 1.06it/s]
Epoch 5/10 - Validation: 100%|██████████| 29/29 [00:23<00:00, 1.26it/s]

```

```

Epoch 5:
Train Loss: 0.1076 | Val Loss: 0.0996

```

```

Epoch 6/10 - Training: 100%|██████████| 114/114 [01:51<00:00, 1.02it/s]
Epoch 6/10 - Validation: 100%|██████████| 29/29 [00:25<00:00, 1.15it/s]

```

```

Epoch 6:
Train Loss: 0.1117 | Val Loss: 0.1082

```

```

Epoch 7/10 - Training: 100%|██████████| 114/114 [02:31<00:00, 1.33s/it]
Epoch 7/10 - Validation: 100%|██████████| 29/29 [00:32<00:00, 1.14s/it]

```

```

Epoch 7:
Train Loss: 0.1003 | Val Loss: 0.0975

```

```

Epoch 8/10 - Training: 100%|██████████| 114/114 [02:22<00:00, 1.25s/it]
Epoch 8/10 - Validation: 100%|██████████| 29/29 [00:28<00:00, 1.00it/s]

```

```

Epoch 8:
Train Loss: 0.1035 | Val Loss: 0.0942

```

```

Epoch 9/10 - Training: 100%|██████████| 114/114 [02:49<00:00, 1.49s/it]
Epoch 9/10 - Validation: 100%|██████████| 29/29 [00:31<00:00, 1.09s/it]

```

```

Epoch 9:
Train Loss: 0.0996 | Val Loss: 0.1262

```

```

Epoch 10/10 - Training: 100%|██████████| 114/114 [02:09<00:00, 1.13s/it]
Epoch 10/10 - Validation: 100%|██████████| 29/29 [00:28<00:00, 1.03it/s]

```

```

Epoch 10:
Train Loss: 0.0998 | Val Loss: 0.0915

```

```

# Validation loop
total_acc = 0.0
total_iou = 0.0
with torch.no_grad():
    for images, masks in test_loader:
        images = images.to(device)
        masks = masks.to(device)

        logits = UNET_model(images)
        loss = loss_fn(logits, masks.float())

        acc = accuracy_fn(logits, masks)
        iou = intersection_over_union(logits, masks)
        total_iou += iou * images.size(0)
        total_acc += acc * images.size(0)

avg_test_iou = total_iou / len(test_loader.dataset)
avg_test_acc = total_acc / len(test_loader.dataset)
print(f"Testing Accuracy (UNET): {avg_test_acc:.4f}")
accuracies['UNET'] = avg_test_acc
print(f"Testing Intersection Over Union (UNET): {avg_test_iou:.4f}")

```

```
print('Testing Intersection Over Union (UNET):', avg_test_iou) ,
ious['unet'] = avg_test_iou
```

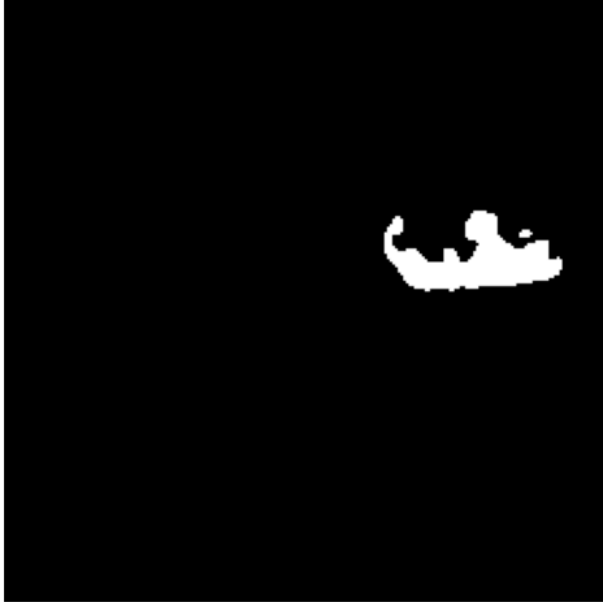
Testing Accuracy (UNET): 0.9707

Testing Intersection Over Union (UNET): 0.9664

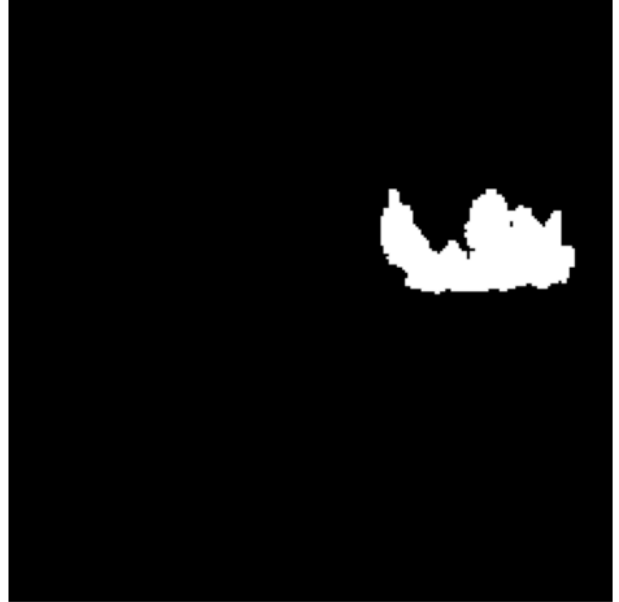
```
X, y = test_dataset[12]
X = X.to(device)
y_pred = unet_model(X.unsqueeze(dim=0))

show_prediction_and_mask(y_pred, y)
```

Prediction Mask



Ground Truth Mask



```
loss_fn = nn.BCEWithLogitsLoss()
deeplab_optim = torch.optim.Adam(params=deeplab_model.parameters(), lr=1e-3)
```

```
train_segmentation_model(model=deeplab_model,
                          train_loader=train_loader,
                          val_loader=test_loader,
                          device=device,
                          num_epochs=10,
                          loss_fn=loss_fn,
                          optimizer=deeplab_optim)
```

```
Epoch 1/10 - Training: 100%|██████████| 114/114 [02:46<00:00, 1.46s/it]
Epoch 1/10 - Validation: 100%|██████████| 29/29 [00:29<00:00, 1.01s/it]
```

Epoch 1:
Train Loss: 0.2313 | Val Loss: 0.1349

```
Epoch 2/10 - Training: 100%|██████████| 114/114 [03:12<00:00, 1.69s/it]
Epoch 2/10 - Validation: 100%|██████████| 29/29 [00:22<00:00, 1.30it/s]
```

Epoch 2:
Train Loss: 0.1230 | Val Loss: 0.1021

```
Epoch 3/10 - Training: 100%|██████████| 114/114 [02:23<00:00, 1.26s/it]
Epoch 3/10 - Validation: 100%|██████████| 29/29 [00:25<00:00, 1.12it/s]
```

Epoch 3:
Train Loss: 0.1176 | Val Loss: 0.2466

```
Epoch 4/10 - Training: 100%|██████████| 114/114 [02:18<00:00, 1.22s/it]
Epoch 4/10 - Validation: 100%|██████████| 29/29 [00:28<00:00, 1.01it/s]
```

Epoch 4:
Train Loss: 0.1347 | Val Loss: 0.1045

```
Epoch 5/10 - Training: 100%|██████████| 114/114 [02:47<00:00, 1.47s/it]
Epoch 5/10 - Validation: 100%|██████████| 29/29 [00:32<00:00, 1.11s/it]
```

Epoch 5:
Train Loss: 0.1060 | Val Loss: 0.0992

```
Epoch 6/10 - Training: 100%|██████████| 114/114 [02:47<00:00, 1.47s/it]
Epoch 6/10 - Validation: 100%|██████████| 29/29 [00:39<00:00, 1.35s/it]
```

Epoch 6:

Train Loss: 0.1026 | Val Loss: 0.0801

Epoch 7/10 - Training: 100%|██████████| 114/114 [03:18<00:00, 1.74s/it]
Epoch 7/10 - Validation: 100%|██████████| 29/29 [00:39<00:00, 1.38s/it]

Epoch 7:

Train Loss: 0.1021 | Val Loss: 0.1159

Epoch 8/10 - Training: 100%|██████████| 114/114 [02:30<00:00, 1.32s/it]
Epoch 8/10 - Validation: 100%|██████████| 29/29 [00:24<00:00, 1.19it/s]

Epoch 8:

Train Loss: 0.1041 | Val Loss: 0.0825

Epoch 9/10 - Training: 100%|██████████| 114/114 [02:01<00:00, 1.07s/it]
Epoch 9/10 - Validation: 100%|██████████| 29/29 [00:25<00:00, 1.16it/s]

Epoch 9:

Train Loss: 0.0897 | Val Loss: 0.0935

Epoch 10/10 - Training: 100%|██████████| 114/114 [02:00<00:00, 1.06s/it]
Epoch 10/10 - Validation: 100%|██████████| 29/29 [00:25<00:00, 1.14it/s]

Epoch 10:

Train Loss: 0.0839 | Val Loss: 0.1118

```
# Validation loop
total_acc = 0.0
total_iou = 0.0
with torch.no_grad():
    for images, masks in test_loader:
        images = images.to(device)
        masks = masks.to(device)

        logits = deeplab_model(images)
        loss = loss_fn(logits, masks.float())

        acc = accuracy_fn(logits, masks)
        iou = intersection_over_union(logits, masks)
        total_iou += iou * images.size(0)
        total_acc += acc * images.size(0)

avg_test_iou = total_iou / len(test_loader.dataset)
avg_test_acc = total_acc / len(test_loader.dataset)
print(f"Testing Accuracy (DeepLabV3): {avg_test_acc:.4f}")
accuracies["deeplab"] = avg_test_acc
print(f"Testing Intersection Over Union (DeepLabV3): {avg_test_iou:.4f}")
ious["deeplab"] = avg_test_iou
```

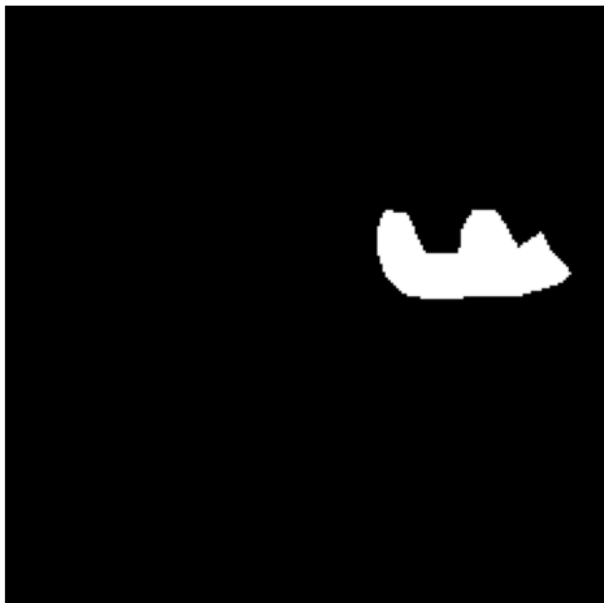
Testing Accuracy (DeepLabV3): 0.9677

Testing Intersection Over Union (DeepLabV3): 0.9624

```
X, y = test_dataset[12]
X = X.to(device)
y_pred = deeplab_model(X.unsqueeze(dim=0))

show_prediction_and_mask(y_pred, y)
```

Prediction Mask



Ground Truth Mask



```
X, y = test_dataset[12]
X = X.to(device)
y_pred = light_model(X.unsqueeze(dim=0))

show_prediction_and_mask(y_pred, y)
```

Prediction Mask



Ground Truth Mask



```
accuracies, ious
```

```
{'light_model': 0.9684641340016183,
 'unet': 0.9706624751359796,
 'deeplab': 0.9676577214723995},
 {'light_model': 0.9631991893184343,
 'unet': 0.9664005729070319,
 'deeplab': 0.962432961369401}}
```

```
torch.save(unet_model.state_dict(), "unet_weights.pth")
```

```
torch.save(deeplab_model.state_dict(), "deeplab_weights.pth")
```

```
models = list(ious.keys())
ious = list(ious.values())
accs = list(accuracies.values())
```

```
# Colors
colors = ['royalblue', 'orange', 'green']

# Plot
x = range(len(models))
bar_width = 0.35

plt.figure(figsize=(8, 5))

# Plot IoU
plt.bar([i - bar_width/2 for i in x], ious, width=bar_width, label='IoU', color=colors)
# Plot Accuracy
plt.bar([i + bar_width/2 for i in x], accs, width=bar_width, label='Accuracy', color=colors, alpha=0.5)

# Labels and Title
plt.xticks(x, models)
plt.ylabel("Score")
plt.title("Model Comparison (10 epochs each): IoU vs Accuracy")
plt.ylim(0.95, 0.975)
plt.legend()

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