Reef Support — SEAVIEW_ATL DataLoader (PyTorch)

This Colab notebook mounts Google Drive and constructs a **PyTorch Dataset + DataLoader** for the Reef Support dataset located at:

/content/drive/MyDrive/benthic_datasets/mask_labels/reef_support/SEAVIEW_ATL

It expects the following folder structure (typical for past exports):

```
SEAVIEW_ATL/
├── images/               # original RGB images (various extensions)
├── masks/                # multiple single-class color masks per image (optional for this loader)
└── masks_stitched/       # one color mask per image, with suffix "_mask.png"
```

Matching rule: an image named `foo.jpg` should have a stitched mask named `foo_mask.png` inside `masks_stitched/`.

1) Setup & Mount Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
#Change ROOT_DIR to the location where you have short cutted the dataset to
ROOT_DIR = "/content/drive/MyDrive/Data Challenge 3 - JBG060 AY2526/01_data/benthic_datasets/mask_labels/reef_support/SEAVIEW_ATL"
IMAGES_DIR = f"{ROOT_DIR}/images"
MASKS_STITCHED_DIR = f"{ROOT_DIR}/masks_stitched"  # required by this loader
MASKS_DIR = f"{ROOT_DIR}/masks"                     # optional

import os
assert os.path.isdir(IMAGES_DIR), f"Images folder not found: {IMAGES_DIR}"
assert os.path.isdir(MASKS_STITCHED_DIR), f"Stitched masks folder not found: {MASKS_STITCHED_DIR}"

print('Images:', IMAGES_DIR)
print('Masks (stitched):', MASKS_STITCHED_DIR)
print('Masks (single, optional):', os.path.isdir(MASKS_DIR) and MASKS_DIR)
```

```
Images: /content/drive/MyDrive/Data Challenge 3 - JBG060 AY2526/01_data/benthic_datasets/mask_labels/reef_support/SEAVIEW_ATL/images
Masks (stitched): /content/drive/MyDrive/Data Challenge 3 - JBG060 AY2526/01_data/benthic_datasets/mask_labels/reef_support/SEAVIEW_ATL/
Masks (single, optional): /content/drive/MyDrive/Data Challenge 3 - JBG060 AY2526/01_data/benthic_datasets/mask_labels/reef_support/SEAV
```

2) Install dependencies

```
!pip -q install torch torchvision pillow tqdm
```

3) Imports

```
import os
from glob import glob
from typing import List, Tuple, Optional, Dict

import numpy as np
from PIL import Image
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader, random_split
import torchvision.transforms as T
from tqdm import tqdm

# Utilities for visualization
import matplotlib.pyplot as plt
```

4) Scan dataset & basic sanity checks

```
def list_images(images_dir: str, exts=('.jpg', '.jpeg', '.png', '.JPG', '.JPEG', '.PNG')) -> List[str]:
    files = []
    for e in exts:
        files.extend(glob(os.path.join(images_dir, f"*{e}")))
    return sorted(files)

def infer_mask_path(img_path: str, masks_stitched_dir: str) -> Optional[str]:
    base = os.path.splitext(os.path.basename(img_path))[0]
    mask_name = f"{base}_mask.png"
    cand = os.path.join(masks_stitched_dir, mask_name)
    return cand if os.path.isfile(cand) else None

all_images = list_images(IMAGES_DIR)
print(f"Found {len(all_images)} images")

paired = 0
unpaired_examples = []
for p in all_images[:1000]:  # quick sample check
    m = infer_mask_path(p, MASKS_STITCHED_DIR)
    if m is not None:
        paired += 1
    else:
        if len(unpaired_examples) < 10:
            unpaired_examples.append(p)

print(f"Sample check — stitched mask pairs found: {paired}/{min(len(all_images),1000)}")
if unpaired_examples:
    print("Examples lacking stitched masks (first 10):")
    for u in unpaired_examples:
        print(" -", os.path.basename(u))
```

```
Found 659 images
Sample check — stitched mask pairs found: 659/659
```

5) PyTorch Dataset

```
class ReefSegDataset(Dataset):
    """Dataset that returns (image_tensor, mask_tensor, meta).

    - Images are loaded as RGB and transformed to float tensors [0,1].
    - Stitched masks are loaded as RGB color masks (uint8). By default we return them as tensors [0..255].
      If you have a color->class mapping, you can plug in a converter to map colors to class indices.
    """
    def __init__(
        self,
        images_dir: str,
        masks_stitched_dir: str,
        resize: Optional[Tuple[int, int]] = None,   # e.g., (512, 512)
        image_transform: Optional[T.Compose] = None,
        mask_transform: Optional[T.Compose] = None,
        return_paths: bool = False,
        drop_unpaired: bool = True,
    ):
        self.images_dir = images_dir
        self.masks_stitched_dir = masks_stitched_dir
        self.resize = resize
        self.image_transform = image_transform
        self.mask_transform = mask_transform
        self.return_paths = return_paths

        images = list_images(images_dir)
        pairs = []
        misses = 0
        for img in images:
            m = infer_mask_path(img, masks_stitched_dir)
            if m is None:
                misses += 1
                if not drop_unpaired:
                    pairs.append((img, None))
            else:
```

```
                pairs.append((img, m))

        self.pairs = pairs
        print(f"Dataset init — total images: {len(images)}, usable pairs: {len(self.pairs)}, missing stitched masks: {misses}")

        # Default image_transform if none provided
        if self.image_transform is None:
            tfms = [T.ToTensor()]  # converts PIL to [0,1] float tensor CHW
            if self.resize is not None:
                tfms.insert(0, T.Resize(self.resize, antialias=True))
            self.image_transform = T.Compose(tfms)

        # Default mask_transform: keep as tensor with values [0..255]
        if self.mask_transform is None:
            tfms_m = []
            if self.resize is not None:
                tfms_m.append(T.Resize(self.resize, interpolation=T.InterpolationMode.NEAREST))
            tfms_m.append(T.PILToTensor())  # uint8 CxHxW
            self.mask_transform = T.Compose(tfms_m)

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

    def __getitem__(self, idx: int):
        img_path, mask_path = self.pairs[idx]

        # Load image
        img = Image.open(img_path).convert('RGB')

        # Load mask (stitched color mask)
        if mask_path is not None and os.path.isfile(mask_path):
            mask = Image.open(mask_path).convert('RGB')
        else:
            # create an empty mask if missing
            mask = Image.fromarray(np.zeros((img.height, img.width, 3), dtype=np.uint8))

        # Apply transforms
        img_t = self.image_transform(img) if self.image_transform else img
        mask_t = self.mask_transform(mask) if self.mask_transform else mask

        meta = {
            "image_path": img_path,
            "mask_path": mask_path
        }

        if self.return_paths:
            return img_t, mask_t, meta
        else:
            return img_t, mask_t
```

(Optional) Convert color masks to class index masks

If your stitched masks use **specific colors per class**, define a mapping from RGB colors to integer class IDs and convert the color mask to a single-channel class index mask.

```
# Example color map (edit to your export's colors)
COLOR_TO_CLASS = {
    (255,   0,   0): 1,  # class 1
    (  0,   0, 255): 2,  # class 2
    # Add more as needed...
}

def color_mask_to_index(mask_tensor: torch.Tensor) -> torch.Tensor:
    """mask_tensor: uint8 tensor with shape [3, H, W]. Returns [H, W] long tensor with class indices."""
    # Move to HWC for easier comparison
    mask_np = mask_tensor.permute(1, 2, 0).numpy()
    out = np.zeros(mask_np.shape[:2], dtype=np.int64)
    for rgb, cls in COLOR_TO_CLASS.items():
        match = np.all(mask_np == np.array(rgb, dtype=np.uint8), axis=-1)
        out[match] = cls
    return torch.from_numpy(out)  # [H, W] long
```

6) Create Dataset & DataLoader

```
RESIZE = (512, 512)  # change or set to None
BATCH_SIZE = 4
NUM_WORKERS = 2  # on Colab CPU; increase if GPU with enough memory

dataset = ReefSegDataset(
    images_dir=IMAGES_DIR,
    masks_stitched_dir=MASKS_STITCHED_DIR,
    resize=RESIZE,
    return_paths=True,
)

# Split into train/val
val_ratio = 0.1
val_size = int(len(dataset) * val_ratio)
train_size = len(dataset) - val_size
train_ds, val_ds = random_split(dataset, [train_size, val_size])

train_loader = DataLoader(train_ds, batch_size=BATCH_SIZE, shuffle=True, num_workers=NUM_WORKERS, pin_memory=True)
val_loader = DataLoader(val_ds, batch_size=BATCH_SIZE, shuffle=False, num_workers=NUM_WORKERS, pin_memory=True)

print(f"Train size: {len(train_ds)}, Val size: {len(val_ds)}")
```

```
Dataset init — total images: 659, usable pairs: 659, missing stitched masks: 0
Train size: 594, Val size: 65
```

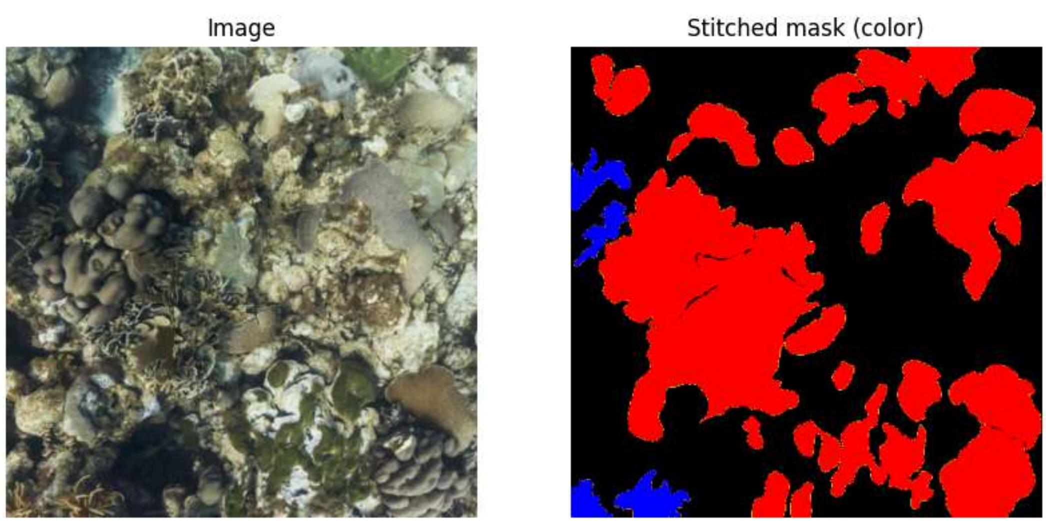
7) Visualize a batch (image + stitched color mask)

```
batch = next(iter(train_loader))
imgs, masks, _ = batch

# show first sample
i = 1
img = imgs[i].permute(1,2,0).numpy()
mask = masks[i].permute(1,2,0).numpy().astype(np.uint8)

plt.figure(figsize=(10,5))
plt.subplot(1,2,1)
plt.imshow(img)
plt.title('Image')
plt.axis('off')

plt.subplot(1,2,2)
plt.imshow(mask)
plt.title('Stitched mask (color)')
plt.axis('off')
plt.show()
```



8) (Optional) Convert color mask to class indices for training

```
imgs_b, masks_b, metas_b = next(iter(train_loader))
idx_mask = color_mask_to_index(masks_b[0])  # [H, W] long
print("Index mask shape:", idx_mask.shape, "unique classes:", torch.unique(idx_mask))
```

```
Index mask shape: torch.Size([512, 512]) unique classes: tensor([0, 1, 2])
```

9) Quick dataset stats

```
total = len(dataset)
paired = sum(1 for _ in dataset)  # counts items; if missing masks were dropped, this is equal to len
print(f"Total pairs (usable): {paired}/{total}")

# Resolution stats (sampled)
heights, widths = [], []
for k in range(min(200, len(dataset))):
    _, _, meta = dataset[k]
    img = Image.open(meta['image_path']).convert('RGB')
    w, h = img.size
    widths.append(w); heights.append(h)

print("Sampled image size stats:")
print(" - mean WxH:", int(np.mean(widths)), "x", int(np.mean(heights)))
print(" - min WxH:", np.min(widths), "x", np.min(heights))
print(" - max WxH:", np.max(widths), "x", np.max(heights))
```

```
Total pairs (usable): 659/659
Sampled image size stats:
 - mean WxH: 1157 x 1157
 - min WxH: 868 x 868
 - max WxH: 2375 x 2375
```

10) Using the DataLoader in training

Below is a tiny template for how you'd iterate batches during model training (replace `your_model` and loss accordingly).

```
# Pseudo-training loop (skeleton)
device = 'cuda' if torch.cuda.is_available() else 'cpu'
print('Device:', device)

# your_model = ...
# your_model.to(device)
# optimizer = torch.optim.Adam(your_model.parameters(), lr=1e-3)
# criterion = ...  # e.g., CrossEntropyLoss for class index masks

for epoch in range(1):
    # Train
    # your_model.train()
    for imgs, masks, _ in train_loader:
        imgs = imgs.to(device)
        # Convert color mask to indices if using a segmentation criterion expecting classes
        idx_masks = torch.stack([color_mask_to_index(m) for m in masks]).to(device)  # [B, H, W]
        # logits = your_model(imgs)  # [B, C, H, W]
        # loss = criterion(logits, idx_masks)
        # optimizer.zero_grad()
        # loss.backward()
        # optimizer.step()
        pass

    # Validate
    # your_model.eval()
    # with torch.no_grad():
    #     for imgs, masks, _ in val_loader:
    #         ...

print("DataLoader is ready for integration with your training code.")
```

Baseline model for coral segmentation

Here is a pretrained U-Net model on a random subset of 100 images and corresponding masks for 20 epochs.

When you decide to use this code and Google Colab for model training, make sure to connect to GPU. You can change your runtime type in the top left menu.

Runtime > Change runtime type > T4 GPU

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

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 154.8/154.8 kB 6.7 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 983.0/983.0 kB 21.9 MB/s eta 0:00:00
```

```
from torchmetrics.classification import MulticlassJaccardIndex
import segmentation_models_pytorch as smp


# Replace the simple model with a pretrained U-Net
# Choose a suitable encoder (e.g., 'resnet34')
# num_classes should be the number of classes in your dataset (len(COLOR_TO_CLASS) + 1 for background)
model = smp.Unet(
    encoder_name="resnet34",  # choose encoder, e.g. resnet34 or efficientnet-b0
    encoder_weights="imagenet",     # use imagenet pretrained weights
    in_channels=3,                  # model input channels (images are RGB)
    classes=len(COLOR_TO_CLASS) + 1, # model output channels (number of segmentation classes)
)

# Print the model architecture
print(model)
```

```
/usr/local/lib/python3.12/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
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.co/settings/tokens), set it as sec
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 datasets.
  warnings.warn(
```

config.json: 100% 156/156 [00:00<00:00, 15.4kB/s]

model.safetensors: 100% 87.3M/87.3M [00:01<00:00, 65.6MB/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)
      )
    )
    (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, 3, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): Identity()
    (2): Activation(
      (activation): Identity()
    )
  )
)
```

```
# Pseudo-training loop (skeleton)
device = 'cuda' if torch.cuda.is_available() else 'cpu'
print('Device:', device)

# Move the model to the selected device
model.to(device)

# Define the loss function (CrossEntropyLoss for segmentation)
criterion = nn.CrossEntropyLoss()

# Define the optimizer (Adam optimizer)
optimizer = torch.optim.Adam(model.parameters(), lr=1e-3)

print("Training loop configuration (device, loss, optimizer) is ready for the U-Net model.")
```

```
Device: cuda
Training loop configuration (device, loss, optimizer) is ready for the U-Net model.
```

```
# Set the number of training epochs
num_epochs = 20

print(f"Starting training for {num_epochs} epochs on {device}")

for epoch in range(num_epochs):
    # Set the model to training mode
    model.train()
    running_loss = 0.0
    # Use tqdm for a progress bar
    for i, (imgs, masks, _) in enumerate(tqdm(train_loader, desc=f"Epoch {epoch+1}/{num_epochs}")):
        # Move images and masks to the selected device
        imgs = imgs.to(device)
        # Convert color mask to indices and stack them
        idx_masks = torch.stack([color_mask_to_index(m.cpu()) for m in masks]).to(device)  # [B, H, W]

        # Pass images through the model to get predicted logits
        logits = model(imgs)  # [B, C, H, W]

        # Calculate the loss
        loss = criterion(logits, idx_masks)

        # Perform a backward pass to calculate gradients
        loss.backward()

        # Update the model's weights
        optimizer.step()

        # Zero the optimizer's gradients
        optimizer.zero_grad()

        running_loss += loss.item()

    # Print loss for each epoch
    epoch_loss = running_loss / len(train_loader)
    print(f'Epoch [{epoch+1}/{num_epochs}], Average Loss: {epoch_loss:.4f}')

print("Training finished.")
```

```
Starting training for 20 epochs on cuda
Epoch 1/20: 100%|██████████| 149/149 [00:50<00:00,  2.94it/s]
Epoch [1/20], Average Loss: 0.4900
Epoch 2/20: 100%|██████████| 149/149 [00:41<00:00,  3.57it/s]
Epoch [2/20], Average Loss: 0.3814
Epoch 3/20: 100%|██████████| 149/149 [00:43<00:00,  3.46it/s]
Epoch [3/20], Average Loss: 0.3431
Epoch 4/20: 100%|██████████| 149/149 [00:40<00:00,  3.65it/s]
Epoch [4/20], Average Loss: 0.3329
Epoch 5/20: 100%|██████████| 149/149 [00:41<00:00,  3.60it/s]
Epoch [5/20], Average Loss: 0.3121
Epoch 6/20: 100%|██████████| 149/149 [00:41<00:00,  3.62it/s]
Epoch [6/20], Average Loss: 0.2873
Epoch 7/20: 100%|██████████| 149/149 [00:42<00:00,  3.51it/s]
Epoch [7/20], Average Loss: 0.2833
Epoch 8/20: 100%|██████████| 149/149 [00:41<00:00,  3.61it/s]
Epoch [8/20], Average Loss: 0.2655
Epoch 9/20: 100%|██████████| 149/149 [00:40<00:00,  3.66it/s]
Epoch [9/20], Average Loss: 0.2456
Epoch 10/20: 100%|██████████| 149/149 [00:42<00:00,  3.53it/s]
Epoch [10/20], Average Loss: 0.2334
```