```
!pip install segmentation-models-pytorch --quiet
!pip install torch torchvision pillow tqdm matplotlib opencv-python
```

```
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Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (2.9.0.post0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib) (1.17.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-packages (from jinja2->torch) (3.0.2)
```

```
import os
import json
import cv2
import numpy as np
from PIL import Image
from collections import defaultdict
import torch
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms
import torchvision.transforms.functional as TF
import random
import matplotlib.pyplot as plt
import segmentation_models_pytorch as smp
```

```
from google.colab import files
uploaded = files.upload()  # Upload Vehicle_Damage.zip

import zipfile
zip_path = 'archive (13).zip'
unzip_dir = 'Vehicle_Damage'
with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(unzip_dir)
```

Choose Files archive (13).zip

- **archive (13).zip**(application/x-zip-compressed) - 15120245 bytes, last modified: 7/17/2025 - 100% done

```
Saving archive (13).zip to archive (13).zip
```

```
def create_multiclass_masks_from_coco(coco_json, mask_folder):
    with open(coco_json, 'r') as f:
        coco = json.load(f)
    imgid_to_info = {img['id']: img for img in coco['images']}
    perimg_segments = defaultdict(list)
    all_classes = set()
    for ann in coco['annotations']:
        perimg_segments[ann['image_id']].append(ann)
        all_classes.add(ann['category_id'])
    num_classes = max(all_classes) + 1

    os.makedirs(mask_folder, exist_ok=True)
    for img_id, info in imgid_to_info.items():
        height, width = info['height'], info['width']
        mask = np.zeros((height, width), dtype=np.uint8)
        anns = perimg_segments.get(img_id, [])
        for ann in anns:
            cat = ann['category_id']
            if 'segmentation' in ann:
                for seg in ann['segmentation']:
                    coords = np.array(seg).reshape((-1, 2)).astype(np.int32)
                    cv2.fillPoly(mask, [coords], cat)
        mask_name = info['file_name'].replace('.jpg', '_mask.png')
        Image.fromarray(mask).save(os.path.join(mask_folder, mask_name))
    return num_classes
```

```
num_classes_train = create_multiclass_masks_from_coco(
    'Vehicle_Damage/train/COCO_mul_train_annos.json',
    'Vehicle_Damage/train/masks'
)
num_classes_val = create_multiclass_masks_from_coco(
    'Vehicle_Damage/val/COCO_mul_val_annos.json',
    'Vehicle_Damage/val/masks'
)
num_classes = max(num_classes_train, num_classes_val)


def compute_class_counts(mask_dir):
    mask_files = [f for f in os.listdir(mask_dir) if f.endswith('.png')]
    max_class = 0
    for mfile in mask_files:
        mask = np.array(Image.open(os.path.join(mask_dir, mfile)))
        this_max = mask.max()
        if this_max > max_class:
            max_class = this_max
    num_classes = max_class + 1
    class_counts = np.zeros(num_classes, dtype=np.int64)
    for mfile in mask_files:
        mask = np.array(Image.open(os.path.join(mask_dir, mfile)))
        for class_idx in range(num_classes):
            class_counts[class_idx] += np.sum(mask == class_idx)
    return class_counts

mask_dir = 'Vehicle_Damage/train/masks'
class_counts = compute_class_counts(mask_dir)
print("Pixel counts per class:", class_counts.tolist())
```

```
Pixel counts per class: [40698472, 1908459, 4714480, 5246303, 3489282, 5808988]
```

```
class CarDamageMulticlassSegmentationDataset(Dataset):
    def __init__(self, image_dir, mask_dir, image_size=(256, 256), aug=False, num_classes=None):
        self.image_dir = image_dir
        self.mask_dir = mask_dir
        self.image_size = image_size
        self.aug = aug
        self.num_classes = num_classes
        self.images = sorted([
            f for f in os.listdir(image_dir)
            if f.lower().endswith(('.jpg', '.jpeg', '.png'))
        ])
        self.resize = transforms.Resize(self.image_size)
        self.to_tensor = transforms.ToTensor()
    def augment(self, image, mask):
        if random.random() > 0.5:
            image, mask = TF.hflip(image), TF.hflip(mask)
        if random.random() > 0.9:
            image, mask = TF.vflip(image), TF.vflip(mask)
        angle = random.uniform(-15, 15)
        image, mask = TF.rotate(image, angle), TF.rotate(mask, angle)
        if random.random() > 0.7:
            image = TF.adjust_brightness(image, brightness_factor=random.uniform(0.8, 1.2))
            image = TF.adjust_contrast(image, contrast_factor=random.uniform(0.8, 1.2))
        return image, mask
    def __len__(self):
        return len(self.images)
    def __getitem__(self, idx):
        img_name = self.images[idx]
        base = os.path.splitext(img_name)[0]
        img_path = os.path.join(self.image_dir, img_name)
        mask_path = os.path.join(self.mask_dir, base + '_mask.png')
        image = Image.open(img_path).convert('RGB')
        mask = Image.open(mask_path).convert('L')
        image = self.resize(image)
        mask = mask.resize(self.image_size, resample=Image.NEAREST)
        if self.aug:
            image, mask = self.augment(image, mask)
        image = self.to_tensor(image)
        mask_np = np.array(mask, dtype=np.uint8)
        mask_tensor = torch.from_numpy(mask_np).long()
        # --- Data checks
        if mask_tensor.min() < 0 or mask_tensor.max() >= self.num_classes:
            raise ValueError(
                f"Mask in {mask_path} out-of-range indices: {mask_tensor.min()} to {mask_tensor.max()}"
            )
        if mask_tensor.ndim != 2:
            raise ValueError(
                f"Mask in {mask_path} should have 2 dims, got {mask_tensor.shape}"
            )
        return image, mask_tensor



train_dataset = CarDamageMulticlassSegmentationDataset(
    image_dir='Vehicle_Damage/train',
    mask_dir='Vehicle_Damage/train/masks',
    aug=True,
    num_classes=num_classes
)
val_dataset = CarDamageMulticlassSegmentationDataset(
    image_dir='Vehicle_Damage/val',
    mask_dir='Vehicle_Damage/val/masks',
    aug=False,
    num_classes=num_classes
)
from torch.utils.data import DataLoader
train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=8, shuffle=False)
```

```
import torch.nn as nn
import torch

weights = 1. / torch.tensor(class_counts, dtype=torch.float32)
weights = weights / weights.sum()
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
weights = weights.to(device)
criterion = nn.CrossEntropyLoss(weight=weights)
```

```
import segmentation_models_pytorch as smp

model = smp.Unet(
    encoder_name='resnet34',           # Or try: 'resnet50', 'efficientnet-b0', etc.
    encoder_weights='imagenet',        # Pretrained weights
    in_channels=3,
    classes=num_classes
).to(device)
```

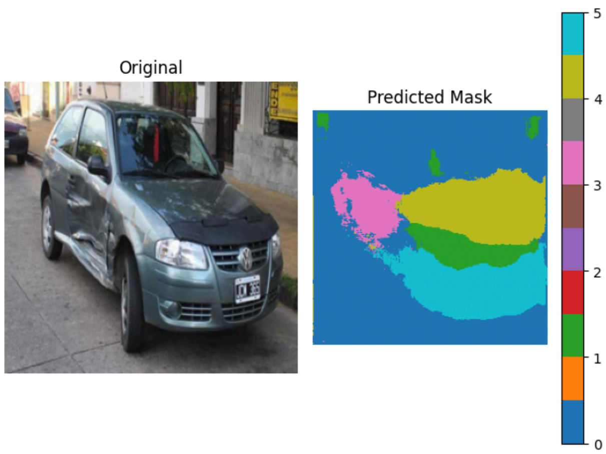
```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set it as secret in your Google Colab and restart your session.
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, 16.1kB/s]
model.safetensors: 100%   87.3M/87.3M [00:00<00:00, 162MB/s]
```

```
import torch.optim as optim
from tqdm import tqdm

optimizer = optim.Adam(model.parameters(), lr=1e-4)
epochs = 20

for epoch in range(epochs):
    model.train()
    train_loss = 0
    for images, masks in tqdm(train_loader):
        images, masks = images.to(device), masks.to(device)
        outputs = model(images)
        loss = criterion(outputs, masks)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        train_loss += loss.item()
        # Debug: check classes in batch
        print("Batch GT classes:", torch.unique(masks).tolist())
        print("Batch pred classes:", torch.unique(outputs.argmax(dim=1)).tolist())
    print(f"Epoch {epoch+1}/{epochs}, Train Loss: {train_loss/len(train_loader):.4f}")

    # Validation
    model.eval()
    val_loss = 0
    with torch.no_grad():
        for images, masks in val_loader:
            images, masks = images.to(device), masks.to(device)
            outputs = model(images)
            val_loss += criterion(outputs, masks).item()
            print("Val GT classes:", torch.unique(masks).tolist())
            print("Val pred classes:", torch.unique(outputs.argmax(dim=1)).tolist())
    print(f"Validation Loss: {val_loss/len(val_loader):.4f}")
```

```
 12%|█         | 1/8 [00:01<00:07,  1.10s/it]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 25%|██        | 2/8 [00:01<00:03,  1.52it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 38%|███       | 3/8 [00:01<00:02,  1.98it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 50%|█████     | 4/8 [00:02<00:01,  2.35it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 62%|██████    | 5/8 [00:02<00:01,  2.63it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 75%|███████   | 6/8 [00:02<00:00,  2.81it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
100%|██████████| 8/8 [00:03<00:00,  2.54it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
Batch GT classes: [0, 1, 2, 3]
Batch pred classes: [0, 1, 2, 3, 4, 5]
Epoch 1/20, Train Loss: 2.1550

Val GT classes: [0, 1, 2, 3, 4, 5]
Val pred classes: [0, 1, 2, 3, 4, 5]
Val GT classes: [0, 1, 3, 4, 5]
Val pred classes: [0, 1, 2, 3, 4, 5]
Validation Loss: 1.7521
 12%|█         | 1/8 [00:00<00:01,  4.42it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 25%|██        | 2/8 [00:00<00:01,  4.33it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 38%|███       | 3/8 [00:00<00:01,  4.35it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 50%|█████     | 4/8 [00:00<00:00,  4.28it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 62%|██████    | 5/8 [00:01<00:00,  4.21it/s]Batch GT classes: [0, 1, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 75%|███████   | 6/8 [00:01<00:00,  4.27it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
100%|██████████| 8/8 [00:01<00:00,  4.61it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
Batch GT classes: [0, 1, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
Epoch 2/20, Train Loss: 1.8461
```

```
Val GT classes: [0, 1, 2, 3, 4, 5]
Val pred classes: [0, 1, 2, 3, 4, 5]
Val GT classes: [0, 1, 3, 4, 5]
Val pred classes: [0, 1, 2, 3, 4, 5]
Validation Loss: 1.7065
 12%|█         | 1/8 [00:00<00:01,  4.39it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 25%|██        | 2/8 [00:00<00:01,  4.37it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 38%|███▊      | 3/8 [00:00<00:01,  4.32it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 50%|█████     | 4/8 [00:00<00:00,  4.29it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 62%|██████▎   | 5/8 [00:01<00:00,  4.29it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
 75%|███████▌  | 6/8 [00:01<00:00,  4.25it/s]Batch GT classes: [0, 1, 2, 3, 4, 5]
Batch pred classes: [0, 1, 2, 3, 4, 5]
```

```python
def show_multiclass_mask(model, img_path, device, num_classes):
    import torchvision.transforms as T
    model.eval()
    img = Image.open(img_path).convert('RGB').resize((256, 256))
    img_tensor = T.ToTensor()(img).unsqueeze(0).to(device)
    with torch.no_grad():
        out = model(img_tensor)
        pred = out.argmax(dim=1)[0].cpu().numpy()
    plt.subplot(1, 2, 1)
    plt.imshow(img)
    plt.title("Original")
    plt.axis('off')
    plt.subplot(1, 2, 2)
    plt.imshow(pred, cmap='tab10', vmin=0, vmax=num_classes-1)
    plt.colorbar(ticks=range(num_classes))
    plt.title("Predicted Mask")
    plt.axis('off')
    plt.tight_layout()
    plt.show()
show_multiclass_mask(model, 'Vehicle_Damage/test/28.jpg', device, num_classes)
```



Mask Generation from COCO

```python
def create_binary_masks_from_coco(coco_json, mask_folder):
    with open(coco_json, 'r') as f:
        coco = json.load(f)
    imgid_to_info = {img['id']: img for img in coco['images']}
    perimg_segments = defaultdict(list)
    for ann in coco['annotations']:
        perimg_segments[ann['image_id']].append(ann)
    os.makedirs(mask_folder, exist_ok=True)
    for img_id, info in imgid_to_info.items():
        height, width = info['height'], info['width']
        mask = np.zeros((height, width), dtype=np.uint8)
        anns = perimg_segments.get(img_id, [])
        for ann in anns:
            if 'segmentation' in ann:
                for seg in ann['segmentation']:
                    coords = np.array(seg).reshape((-1, 2)).astype(np.int32)
                    cv2.fillPoly(mask, [coords], color=1)
        mask_name = info['file_name'].replace('.jpg', '_mask.png')
        Image.fromarray(mask * 255).save(os.path.join(mask_folder, mask_name))
```

Generate mask

```python
create_binary_masks_from_coco(
    coco_json='Vehicle_Damage/train/COCO_train_annos.json',
    mask_folder='Vehicle_Damage/train/masks'
)
```

Calculate Pixel Class Balance for Binary Masks

```python
def compute_binary_class_counts(mask_dir):
    mask_files = [f for f in os.listdir(mask_dir) if f.endswith('.png')]
```

```
    class_counts = np.zeros(2, dtype=np.int64)
    for mfile in mask_files:
        mask = np.array(Image.open(os.path.join(mask_dir, mfile)))
        class_counts[0] += np.sum(mask == 0)
        class_counts[1] += np.sum(mask > 0)
    return class_counts

mask_dir = 'Vehicle_Damage/train/masks'
class_counts = compute_binary_class_counts(mask_dir)
print("Pixel counts per class:", class_counts.tolist())  # [background_pixels, damage_pixels]
```

```
Pixel counts per class: [55770811, 6095173]
```

Binary and Multiclass Segmentation Dataset

```
from torch.utils.data import Dataset
from torchvision import transforms
import torchvision.transforms.functional as TF
import random

class CarDamageBinarySegmentationDataset(Dataset):
    def __init__(self, image_dir, mask_dir, image_size=(256, 256), aug=False):
        self.image_dir = image_dir
        self.mask_dir = mask_dir
        self.image_size = image_size
        self.aug = aug
        self.images = sorted([
            f for f in os.listdir(image_dir)
            if f.lower().endswith(('.jpg', '.jpeg', '.png'))
        ])
        self.resize = transforms.Resize(self.image_size)
        self.to_tensor = transforms.ToTensor()

    def augment(self, image, mask):
        if random.random() > 0.5:
            image, mask = TF.hflip(image), TF.hflip(mask)
        if random.random() > 0.9:
            image, mask = TF.vflip(image), TF.vflip(mask)
        angle = random.uniform(-15, 15)
        image, mask = TF.rotate(image, angle), TF.rotate(mask, angle)
        if random.random() > 0.7:
            image = TF.adjust_brightness(image, brightness_factor=random.uniform(0.8, 1.2))
            image = TF.adjust_contrast(image, contrast_factor=random.uniform(0.8, 1.2))
        return image, mask

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

    def __getitem__(self, idx):
        img_name = self.images[idx]
        base = os.path.splitext(img_name)[0]
        img_path = os.path.join(self.image_dir, img_name)
        mask_path = os.path.join(self.mask_dir, base + '_mask.png')
        image = Image.open(img_path).convert('RGB')
        mask = Image.open(mask_path).convert('L')
        image = self.resize(image)
        mask = mask.resize(self.image_size, resample=Image.NEAREST)
        if self.aug:
            image, mask = self.augment(image, mask)
        image = self.to_tensor(image)
        mask_np = np.array(mask, dtype=np.uint8)
        mask_tensor = torch.from_numpy((mask_np > 127).astype(np.float32))  # [H, W], float32; 0/1
        return image, mask_tensor.unsqueeze(0)  # [3,H,W], [1,H,W]
```

Create train & val loaders:

```
from torch.utils.data import DataLoader

train_dataset = CarDamageBinarySegmentationDataset(
    image_dir='Vehicle_Damage/train',
    mask_dir='Vehicle_Damage/train/masks',
    aug=True
)
val_dataset = CarDamageBinarySegmentationDataset(
    image_dir='Vehicle_Damage/val',
    mask_dir='Vehicle_Damage/val/masks',
    aug=False
)

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

Weighted Loss for Class Imbalance

```
import torch.nn as nn
import torch

# Compute pos_weight for BCEWithLogitsLoss: (background / (damage + epsilon))
background, damage = class_counts
epsilon = 1e-6
pos_weight = torch.tensor([background / (damage + epsilon)], dtype=torch.float32)
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
pos_weight = pos_weight.to(device)
criterion = nn.BCEWithLogitsLoss(pos_weight=pos_weight)
```

Pretrained U-Net Model Initialization

```
import segmentation_models_pytorch as smp

model = smp.Unet(
    encoder_name='resnet34',      # Pretrained backbone
    encoder_weights='imagenet',   # Pretrained on ImageNet
    in_channels=3,
    classes=1                     # Binary mask output (1 channel)
).to(device)
```

```
import torch.optim as optim
from tqdm import tqdm

optimizer = optim.Adam(model.parameters(), lr=1e-4)
epochs = 20

for epoch in range(epochs):
    model.train()
    train_loss = 0
    for images, masks in tqdm(train_loader):
        images = images.to(device)
        masks = masks.to(device)
        outputs = model(images)
        loss = criterion(outputs, masks)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        train_loss += loss.item()
    print(f"Epoch {epoch+1}/{epochs}, Train Loss: {train_loss/len(train_loader):.4f}")

    model.eval()
    val_loss = 0
    with torch.no_grad():
        for images, masks in val_loader:
            images = images.to(device)
            masks = masks.to(device)
            outputs = model(images)
            val_loss += criterion(outputs, masks).item()
    print(f"Validation Loss: {val_loss/len(val_loader):.4f}")
```

```
100%|██████████| 8/8 [00:01<00:00,  4.14it/s]
Epoch 1/20, Train Loss: 1.2763
Validation Loss: 0.7504
100%|██████████| 8/8 [00:01<00:00,  4.67it/s]
Epoch 2/20, Train Loss: 1.1689
Validation Loss: 0.7415
100%|██████████| 8/8 [00:01<00:00,  4.74it/s]
Epoch 3/20, Train Loss: 1.0576
Validation Loss: 0.6579
100%|██████████| 8/8 [00:02<00:00,  3.84it/s]
Epoch 4/20, Train Loss: 0.9539
Validation Loss: 0.6999
100%|██████████| 8/8 [00:01<00:00,  4.70it/s]
Epoch 5/20, Train Loss: 0.8678
Validation Loss: 0.7092
100%|██████████| 8/8 [00:01<00:00,  4.77it/s]
Epoch 6/20, Train Loss: 0.8190
Validation Loss: 0.7632
100%|██████████| 8/8 [00:01<00:00,  4.74it/s]
Epoch 7/20, Train Loss: 0.7918
Validation Loss: 0.7354
100%|██████████| 8/8 [00:01<00:00,  4.83it/s]
Epoch 8/20, Train Loss: 0.7277
Validation Loss: 0.5893
100%|██████████| 8/8 [00:01<00:00,  4.81it/s]
Epoch 9/20, Train Loss: 0.6929
Validation Loss: 0.6521
100%|██████████| 8/8 [00:01<00:00,  4.06it/s]
Epoch 10/20, Train Loss: 0.6666
Validation Loss: 0.5347
100%|██████████| 8/8 [00:01<00:00,  4.36it/s]
Epoch 11/20, Train Loss: 0.6210
Validation Loss: 0.5132
100%|██████████| 8/8 [00:01<00:00,  4.61it/s]
Epoch 12/20, Train Loss: 0.6132
Validation Loss: 0.4576
100%|██████████| 8/8 [00:01<00:00,  4.74it/s]
Epoch 13/20, Train Loss: 0.6182
Validation Loss: 0.4958
100%|██████████| 8/8 [00:01<00:00,  4.72it/s]
Epoch 14/20, Train Loss: 0.5636
Validation Loss: 0.4469
100%|██████████| 8/8 [00:01<00:00,  4.69it/s]
Epoch 15/20, Train Loss: 0.5625
Validation Loss: 0.4518
100%|██████████| 8/8 [00:01<00:00,  4.06it/s]
Epoch 16/20, Train Loss: 0.5306
Validation Loss: 0.4682
100%|██████████| 8/8 [00:01<00:00,  4.10it/s]
Epoch 17/20, Train Loss: 0.5146
Validation Loss: 0.4506
100%|██████████| 8/8 [00:01<00:00,  4.65it/s]
Epoch 18/20, Train Loss: 0.5161
Validation Loss: 0.3945
100%|██████████| 8/8 [00:01<00:00,  4.71it/s]
Epoch 19/20, Train Loss: 0.4838
Validation Loss: 0.4913
100%|██████████| 8/8 [00:01<00:00,  4.71it/s]
```

```
import matplotlib.pyplot as plt
import torchvision.transforms as T
import cv2
import numpy as np
```

```
from PIL import Image

def show_mask_outline_on_image(model, img_path, device, threshold=0.5):
    # Load image and predict mask
    image = Image.open(img_path).convert('RGB').resize((256, 256))
    image_tensor = T.ToTensor()(image).unsqueeze(0).to(device)
    model.eval()
    with torch.no_grad():
        out = torch.sigmoid(model(image_tensor))
        pred_mask = (out[0, 0].cpu().numpy() > threshold).astype(np.uint8)

    img_disp = np.array(image)
    contours, _ = cv2.findContours(pred_mask, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
    img_with_contours = img_disp.copy()
    cv2.drawContours(img_with_contours, contours, -1, (0, 0, 255), thickness=2)
    img_with_contours = cv2.cvtColor(img_with_contours, cv2.COLOR_BGR2RGB)
    plt.figure(figsize=(12, 6))
    plt.subplot(1, 2, 1)
    plt.imshow(img_disp)
    plt.title("Original Image")
    plt.axis('off')
    plt.subplot(1, 2, 2)
    plt.imshow(img_with_contours)
    plt.title("Predicted Damage Outline")
    plt.axis('off')
    plt.show()
```

```
show_mask_outline_on_image(model, 'Vehicle_Damage/test/11.jpg', device, threshold=0.5)
```

Start coding or generate with AI.