```
# ========================================
# 03_deeplabv3_training.ipynb
# DeepLabV3+ Model Training
# ========================================

# ----- Cell 1: Mount Google Drive -----
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
# ----- Cell 2: Setup project paths -----
import os
import sys

PROJECT_ROOT = '/content/drive/MyDrive/SHBT 261/Mini_Project_2'
os.chdir(PROJECT_ROOT)

print(f"Working directory: {os.getcwd()}")
print(f"Project structure:")
!ls -lh
```

```
Working directory: /content/drive/MyDrive/SHBT 261/Mini_Project_2
Project structure:
total 1.9M
drwx------ 2 root root 4.0K Nov 15 04:09  data
-rw------- 1 root root 1.9M Nov 15 02:42 'Mini-Project 2.pdf'
drwx------ 2 root root 4.0K Nov 15 04:09  models
drwx------ 2 root root 4.0K Nov 15 04:09  notebooks
drwx------ 2 root root 4.0K Nov 15 04:09  results
-rw------- 1 root root   53 Nov 15 08:45  voc_data_path.txt
```

```
# ----- Cell 3: Install dependencies -----
!pip install -q segmentation-models-pytorch
!pip install -q albumentations
!pip install -q kagglehub

print("✓ Dependencies installed")
```

```
✓ Dependencies installed
```

```
# ----- Cell 4: Import libraries -----
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torchvision import transforms
from torchvision.datasets import VOCSegmentation
import segmentation_models_pytorch as smp

import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm
import time
from datetime import datetime

print(f"PyTorch version: {torch.__version__}")
print(f"CUDA available: {torch.cuda.is_available()}")
if torch.cuda.is_available():
    print(f"GPU: {torch.cuda.get_device_name(0)}")
    print(f"GPU Memory: {torch.cuda.get_device_properties(0).total_memory / 1e9:.2f} GB")
```

```
PyTorch version: 2.8.0+cu126
CUDA available: True
GPU: Tesla T4
GPU Memory: 15.83 GB
```

```
# ----- Cell 5: Load dataset path and setup data -----
import kagglehub

print("Loading Pascal VOC 2007 dataset...")
dataset_path = kagglehub.dataset_download("zaraks/pascal-voc-2007")

# Find VOC root
trainval_candidates = [
    'VOCtrainval_06-Nov-2007',
    'voctrainval_06-nov-2007',
]

VOC_ROOT = None
for candidate in trainval_candidates:
    candidate_path = os.path.join(dataset_path, candidate)
    if os.path.exists(os.path.join(candidate_path, 'VOCdevkit', 'VOC2007')):
        VOC_ROOT = candidate_path
        break

print(f"✓ VOC_ROOT: {VOC_ROOT}")

# Define classes
VOC_CLASSES = [
    "background", "aeroplane", "bicycle", "bird", "boat", "bottle", "bus",
    "car", "cat", "chair", "cow", "diningtable", "dog", "horse", "motorbike",
    "person", "pottedplant", "sheep", "sofa", "train", "tvmonitor"
]
NUM_CLASSES = len(VOC_CLASSES)
print(f"✓ Number of classes: {NUM_CLASSES}")
```

```
Loading Pascal VOC 2007 dataset...
Using Colab cache for faster access to the 'pascal-voc-2007' dataset.
✓ VOC_ROOT: /kaggle/input/pascal-voc-2007/VOCtrainval_06-Nov-2007
✓ Number of classes: 21
```

```
# ----- Cell 5: Load dataset path and setup data -----
import kagglehub

print("Loading Pascal VOC 2007 dataset...")
dataset_path = kagglehub.dataset_download("zaraks/pascal-voc-2007")
```

```
# Find VOC root
trainval_candidates = [
    'VOCtrainval_06-Nov-2007',
    'voctrainval_06-nov-2007',
]

VOC_ROOT = None
for candidate in trainval_candidates:
    candidate_path = os.path.join(dataset_path, candidate)
    if os.path.exists(os.path.join(candidate_path, 'VOCdevkit', 'VOC2007')):
        VOC_ROOT = candidate_path
        break

print(f"✓ VOC_ROOT: {VOC_ROOT}")

# Define classes
VOC_CLASSES = [
    "background", "aeroplane", "bicycle", "bird", "boat", "bottle", "bus",
    "car", "cat", "chair", "cow", "diningtable", "dog", "horse", "motorbike",
    "person", "pottedplant", "sheep", "sofa", "train", "tvmonitor"
]
NUM_CLASSES = len(VOC_CLASSES)
print(f"✓ Number of classes: {NUM_CLASSES}")
```

```
Loading Pascal VOC 2007 dataset...
Using Colab cache for faster access to the 'pascal-voc-2007' dataset.
✓ VOC_ROOT: /kaggle/input/pascal-voc-2007/VOCtrainval_06-Nov-2007
✓ Number of classes: 21
```

```
# ----- Cell 6: Data transforms with augmentation -----
import albumentations as A
from albumentations.pytorch import ToTensorV2

# Training transforms (with augmentation)
train_transform = A.Compose([
    A.Resize(256, 256),
    A.HorizontalFlip(p=0.5),
    A.RandomBrightnessContrast(p=0.2),
    A.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
    ToTensorV2(),
])

# Validation transforms (no augmentation)
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(),
])

print("✓ Data transforms defined")
```

```
✓ Data transforms defined
```

```
# ----- Cell 7: Custom Dataset wrapper -----
from torch.utils.data import Dataset
from PIL import Image

class VOCSegmentationAlbumentations(Dataset):
    """
    Wrapper for VOCSegmentation to use Albumentations transforms
    """
    def __init__(self, root, year, image_set, transform=None):
        self.voc = VOCSegmentation(
            root=root,
            year=year,
            image_set=image_set,
            download=False
        )
        self.transform = transform

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

    def __getitem__(self, idx):
        image, mask = self.voc[idx]

        # Convert PIL to numpy
        image = np.array(image)
        mask = np.array(mask)

        # Clean mask
        mask[mask == 255] = 0

        # Apply transforms
        if self.transform:
            transformed = self.transform(image=image, mask=mask)
            image = transformed['image']
            mask = transformed['mask']

        # Convert mask to long tensor
        if not isinstance(mask, torch.Tensor):
            mask = torch.from_numpy(mask)
        mask = mask.long()

        return image, mask

print("✓ Custom dataset class defined")
```

```
✓ Custom dataset class defined
```

```
# ----- Cell 8: Create datasets and dataloaders -----
# Create datasets
train_dataset = VOCSegmentationAlbumentations(
    root=VOC_ROOT,
    year="2007",
    image_set="train",
    transform=train_transform
)

val_dataset = VOCSegmentationAlbumentations(
```

```
    root=VOC_ROOT,
    year="2007",
    image_set="val",
    transform=val_transform
)

# Create dataloaders
BATCH_SIZE = 8
NUM_WORKERS = 2

train_loader = DataLoader(
    train_dataset,
    batch_size=BATCH_SIZE,
    shuffle=True,
    num_workers=NUM_WORKERS,
    pin_memory=True,
    drop_last=True  # Drop last incomplete batch to avoid BatchNorm error
)

val_loader = DataLoader(
    val_dataset,
    batch_size=BATCH_SIZE,
    shuffle=False,
    num_workers=NUM_WORKERS,
    pin_memory=True,
    drop_last=False  # Keep all validation samples
)

print(f"✓ Train samples: {len(train_dataset)}")
print(f"✓ Val samples: {len(val_dataset)}")
print(f"✓ Batch size: {BATCH_SIZE}")
print(f"✓ Train batches: {len(train_loader)}")
print(f"✓ Val batches: {len(val_loader)}")
```

```
✓ Train samples: 209
✓ Val samples: 213
✓ Batch size: 8
✓ Train batches: 26
✓ Val batches: 27
```

```
# ----- Cell 9: Define DeepLabV3+ model -----
# Create DeepLabV3+ model using segmentation_models_pytorch
model = smp.DeepLabV3Plus(
    encoder_name="resnet50",        # Encoder backbone
    encoder_weights="imagenet",     # Use pretrained weights
    in_channels=3,                  # RGB images
    classes=NUM_CLASSES,            # 21 classes
)

# Move model to GPU
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = model.to(device)

print(f"✓ DeepLabV3+ model created")
print(f"✓ Encoder: ResNet50 (pretrained on ImageNet)")
print(f"✓ Device: {device}")

# Count parameters
total_params = sum(p.numel() for p in model.parameters())
trainable_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
print(f"✓ Total parameters: {total_params:,}")
print(f"✓ Trainable parameters: {trainable_params:,}")
```

```
✓ DeepLabV3+ model created
✓ Encoder: ResNet50 (pretrained on ImageNet)
✓ Device: cuda
✓ Total parameters: 26,682,725
✓ Trainable parameters: 26,682,725
```

```
# ----- Cell 10: Define loss function and optimizer -----
# Loss function (Cross Entropy)
criterion = nn.CrossEntropyLoss()

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

# Learning rate scheduler
scheduler = optim.lr_scheduler.ReduceLROnPlateau(
    optimizer,
    mode='min',
    factor=0.5,
    patience=5
)

print(f"✓ Loss: CrossEntropyLoss")
print(f"✓ Optimizer: Adam (lr={LEARNING_RATE})")
print(f"✓ Scheduler: ReduceLROnPlateau")
```

```
✓ Loss: CrossEntropyLoss
✓ Optimizer: Adam (lr=0.0001)
✓ Scheduler: ReduceLROnPlateau
```

```
# ----- Cell 11: Define metrics -----
def calculate_iou(pred, target, num_classes=21):
    """
    Calculate IoU for each class
    """
    ious = []
    pred = pred.view(-1)
    target = target.view(-1)

    for cls in range(num_classes):
        pred_inds = pred == cls
        target_inds = target == cls
        intersection = (pred_inds & target_inds).sum().float()
        union = (pred_inds | target_inds).sum().float()

        if union == 0:
            ious.append(float('nan'))
```

```
        else:
            ious.append((intersection / union).item())

    return ious

def calculate_pixel_accuracy(pred, target):
    """
    Calculate pixel-wise accuracy
    """
    pred = pred.view(-1)
    target = target.view(-1)
    correct = (pred == target).sum().float()
    total = target.numel()
    return (correct / total).item()

print("✓ Metrics defined: IoU, Pixel Accuracy")
```

```
✓ Metrics defined: IoU, Pixel Accuracy
```

```
# ----- Cell 12: Training function -----
def train_epoch(model, dataloader, criterion, optimizer, device):
    """
    Train for one epoch
    """
    model.train()
    running_loss = 0.0
    running_iou = []
    running_acc = 0.0

    pbar = tqdm(dataloader, desc='Training')
    for images, masks in pbar:
        images = images.to(device)
        masks = masks.to(device)

        # Forward pass
        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, masks)

        # Backward pass
        loss.backward()
        optimizer.step()

        # Calculate metrics
        preds = torch.argmax(outputs, dim=1)
        batch_iou = calculate_iou(preds, masks, NUM_CLASSES)
        batch_acc = calculate_pixel_accuracy(preds, masks)

        # Update running metrics
        running_loss += loss.item()
        running_iou.append(batch_iou)
        running_acc += batch_acc

        # Update progress bar
        pbar.set_postfix({
            'loss': f'{loss.item():.4f}',
            'acc': f'{batch_acc:.4f}'
        })

    # Calculate epoch metrics
    epoch_loss = running_loss / len(dataloader)
    epoch_iou = np.nanmean(running_iou)
    epoch_acc = running_acc / len(dataloader)

    return epoch_loss, epoch_iou, epoch_acc

print("✓ Training function defined")
```

```
✓ Training function defined
```

```
# ----- Cell 13: Validation function -----
def validate(model, dataloader, criterion, device):
    """
    Validate the model
    """
    model.eval()
    running_loss = 0.0
    running_iou = []
    running_acc = 0.0

    with torch.no_grad():
        pbar = tqdm(dataloader, desc='Validation')
        for images, masks in pbar:
            images = images.to(device)
            masks = masks.to(device)

            # Forward pass
            outputs = model(images)
            loss = criterion(outputs, masks)

            # Calculate metrics
            preds = torch.argmax(outputs, dim=1)
            batch_iou = calculate_iou(preds, masks, NUM_CLASSES)
            batch_acc = calculate_pixel_accuracy(preds, masks)

            # Update running metrics
            running_loss += loss.item()
            running_iou.append(batch_iou)
            running_acc += batch_acc

            # Update progress bar
            pbar.set_postfix({
                'loss': f'{loss.item():.4f}',
                'acc': f'{batch_acc:.4f}'
            })

    # Calculate epoch metrics
    epoch_loss = running_loss / len(dataloader)
    epoch_iou = np.nanmean(running_iou)
    epoch_acc = running_acc / len(dataloader)
```

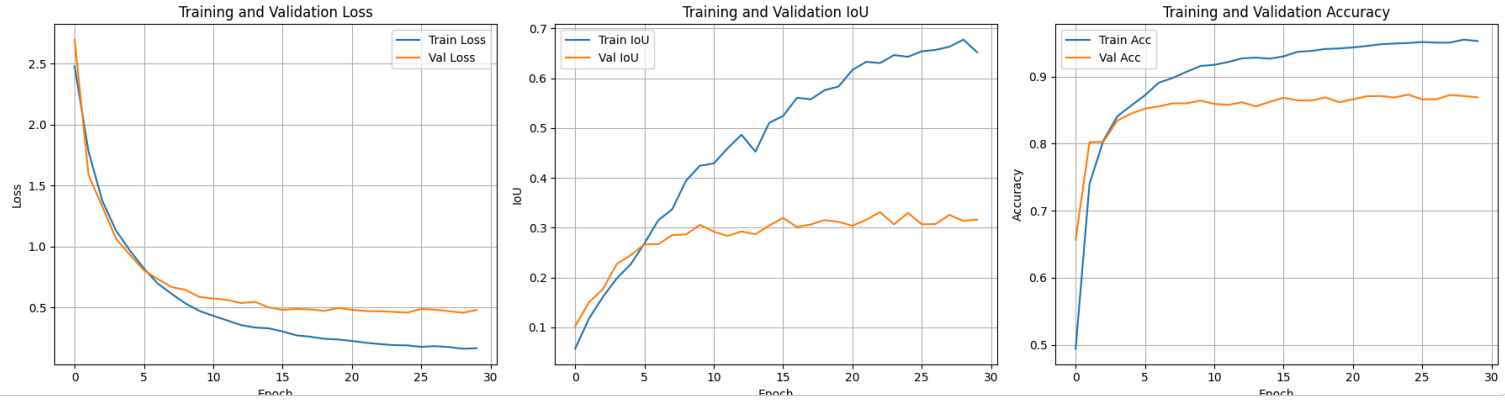
```
    return epoch_loss, epoch_iou, epoch_acc

print("✓ Validation function defined")
```

```
✓ Validation function defined
```

```
# ----- Cell 14: Training loop -----
NUM_EPOCHS = 30

# Initialize tracking
best_val_iou = 0.0
history = {
    'train_loss': [],
    'train_iou': [],
    'train_acc': [],
    'val_loss': [],
    'val_iou': [],
    'val_acc': [],
}

# Create models directory
os.makedirs(f'{PROJECT_ROOT}/models', exist_ok=True)

print("=" * 70)
print(f"Starting DeepLabV3+ Training")
print(f"Epochs: {NUM_EPOCHS}")
print(f"Device: {device}")
print("=" * 70)

start_time = time.time()

for epoch in range(NUM_EPOCHS):
    print(f"\nEpoch {epoch+1}/{NUM_EPOCHS}")
    print("-" * 70)

    # Train
    train_loss, train_iou, train_acc = train_epoch(
        model, train_loader, criterion, optimizer, device
    )

    # Validate
    val_loss, val_iou, val_acc = validate(
        model, val_loader, criterion, device
    )

    # Update scheduler
    scheduler.step(val_loss)

    # Save metrics
    history['train_loss'].append(train_loss)
    history['train_iou'].append(train_iou)
    history['train_acc'].append(train_acc)
    history['val_loss'].append(val_loss)
    history['val_iou'].append(val_iou)
    history['val_acc'].append(val_acc)

    # Print epoch summary
    print(f"\nEpoch {epoch+1} Summary:")
    print(f"  Train Loss: {train_loss:.4f} | Train IoU: {train_iou:.4f} | Train Acc: {train_acc:.4f}")
    print(f"  Val Loss:   {val_loss:.4f} | Val IoU:   {val_iou:.4f} | Val Acc:   {val_acc:.4f}")

    # Save best model
    if val_iou > best_val_iou:
        best_val_iou = val_iou
        torch.save({
            'epoch': epoch,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
            'val_iou': val_iou,
            'val_loss': val_loss,
        }, f'{PROJECT_ROOT}/models/deeplabv3_best.pth')
        print(f"  ✓ Best model saved! (IoU: {val_iou:.4f})")

    # Save checkpoint every 10 epochs
    if (epoch + 1) % 10 == 0:
        torch.save({
            'epoch': epoch,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
            'history': history,
        }, f'{PROJECT_ROOT}/models/deeplabv3_checkpoint_epoch_{epoch+1}.pth')
        print(f"  ✓ Checkpoint saved at epoch {epoch+1}")

# Training complete
end_time = time.time()
training_time = end_time - start_time

print("\n" + "=" * 70)
print("TRAINING COMPLETE!")
print("=" * 70)
print(f"Total training time: {training_time/60:.2f} minutes")
print(f"Best validation IoU: {best_val_iou:.4f}")
print(f"Models saved to: {PROJECT_ROOT}/models/")
```

```
Training: 100%|██████████| 26/26 [00:05<00:00,  4.62it/s, loss=0.1425, acc=0.9649]
Validation: 100%|██████████| 27/27 [00:01<00:00, 14.33it/s, loss=0.4279, acc=0.8568]

Epoch 27 Summary:
  Train Loss: 0.1822 | Train IoU: 0.6568 | Train Acc: 0.9507
  Val Loss:   0.4814 | Val IoU:   0.3073 | Val Acc:   0.8662

Epoch 28/30
----------------------------------------------------------------------
Training: 100%|██████████| 26/26 [00:05<00:00,  5.05it/s, loss=0.1024, acc=0.9728]
Validation: 100%|██████████| 27/27 [00:02<00:00, 11.29it/s, loss=0.5573, acc=0.8239]

Epoch 28 Summary:
  Train Loss: 0.1748 | Train IoU: 0.6632 | Train Acc: 0.9508
  Val Loss:   0.4689 | Val IoU:   0.3258 | Val Acc:   0.8725

Epoch 29/30
----------------------------------------------------------------------
Training: 100%|██████████| 26/26 [00:05<00:00,  4.90it/s, loss=0.1462, acc=0.9594]
Validation: 100%|██████████| 27/27 [00:01<00:00, 14.15it/s, loss=0.4277, acc=0.8699]

Epoch 29 Summary:
  Train Loss: 0.1608 | Train IoU: 0.6775 | Train Acc: 0.9551
  Val Loss:   0.4567 | Val IoU:   0.3135 | Val Acc:   0.8711

Epoch 30/30
----------------------------------------------------------------------
Training: 100%|██████████| 26/26 [00:05<00:00,  5.11it/s, loss=0.1589, acc=0.9539]
Validation: 100%|██████████| 27/27 [00:02<00:00, 11.05it/s, loss=0.4601, acc=0.8656]

Epoch 30 Summary:
  Train Loss: 0.1649 | Train IoU: 0.6521 | Train Acc: 0.9530
  Val Loss:   0.4790 | Val IoU:   0.3163 | Val Acc:   0.8690
  ✓ Checkpoint saved at epoch 30

======================================================================
TRAINING COMPLETE!
======================================================================
Total training time: 4.17 minutes
Best validation IoU: 0.3312
Models saved to: /content/drive/MyDrive/SHBT 261/Mini_Project_2/models/
```

```
# ----- Cell 15: Plot training history -----
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Plot loss
axes[0].plot(history['train_loss'], label='Train Loss')
axes[0].plot(history['val_loss'], label='Val Loss')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
axes[0].set_title('Training and Validation Loss')
axes[0].legend()
axes[0].grid(True)

# Plot IoU
axes[1].plot(history['train_iou'], label='Train IoU')
axes[1].plot(history['val_iou'], label='Val IoU')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('IoU')
axes[1].set_title('Training and Validation IoU')
axes[1].legend()
axes[1].grid(True)

# Plot Accuracy
axes[2].plot(history['train_acc'], label='Train Acc')
axes[2].plot(history['val_acc'], label='Val Acc')
axes[2].set_xlabel('Epoch')
axes[2].set_ylabel('Accuracy')
axes[2].set_title('Training and Validation Accuracy')
axes[2].legend()
axes[2].grid(True)

plt.tight_layout()
plt.savefig(f'{PROJECT_ROOT}/results/deeplabv3_training_history.png', dpi=150, bbox_inches='tight')
plt.show()

print(f"✓ Training history saved")
```




```
# ----- Cell 16: Save final model -----
torch.save({
    'model_state_dict': model.state_dict(),
    'history': history,
    'best_val_iou': best_val_iou,
    'training_time': training_time,
}, f'{PROJECT_ROOT}/models/deeplabv3_final.pth')

print(f"✓ Final model saved to: {PROJECT_ROOT}/models/deeplabv3_final.pth")
```

```
✓ Final model saved to: /content/drive/MyDrive/SHBT 261/Mini_Project_2/models/deeplabv3_final.pth
```

```
# ----- Cell 17: Load best model for inference -----
checkpoint = torch.load(f'{PROJECT_ROOT}/models/deeplabv3_best.pth', weights_only=False)
```

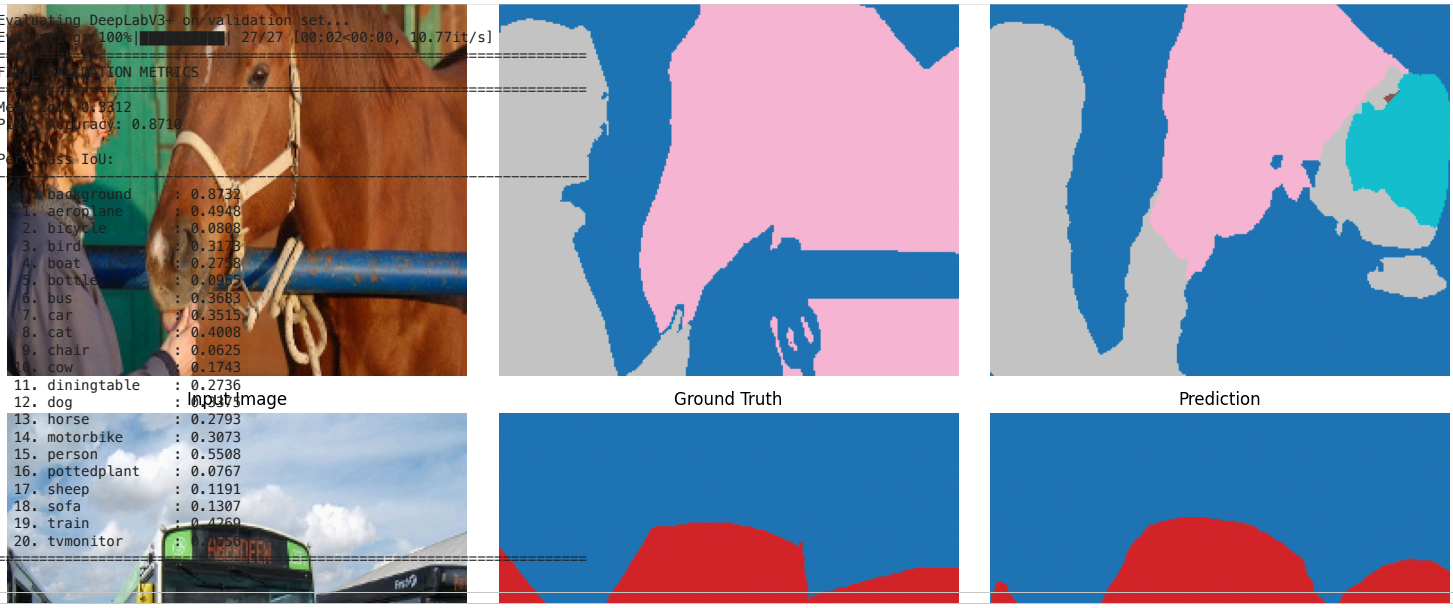
```
model.load_state_dict(checkpoint['model_state_dict'])
model.eval()

print(f"✓ Best model loaded (from epoch {checkpoint['epoch']+1})")
print(f"  Validation IoU: {checkpoint['val_iou']:.4f}")
print(f"  Validation Loss: {checkpoint['val_loss']:.4f}")
```

```
✓ Best model loaded (from epoch 23)
  Validation IoU: 0.3312
  Validation Loss: 0.4684
```

```
# ----- Cell 18: Visualize predictions -----
import matplotlib.pyplot as plt
import numpy as np

def visualize_predictions(model, dataset, device, num_samples=5, save_dir=None):
    """
    Visualize model predictions
    """
    model.eval()

    if save_dir:
        os.makedirs(save_dir, exist_ok=True)

    fig, axes = plt.subplots(num_samples, 3, figsize=(15, 5*num_samples))
    if num_samples == 1:
        axes = axes.reshape(1, -1)

    with torch.no_grad():
        for i in range(num_samples):
            idx = np.random.randint(0, len(dataset))
            image, mask = dataset[idx]

            image_input = image.unsqueeze(0).to(device)
            output = model(image_input)
            pred = torch.argmax(output, dim=1).squeeze(0).cpu().numpy()

            # Denormalize image
            img_display = image.cpu().numpy().transpose(1, 2, 0)
            mean = np.array([0.485, 0.456, 0.406])
            std = np.array([0.229, 0.224, 0.225])
            img_display = std * img_display + mean
            img_display = np.clip(img_display, 0, 1)

            mask_gt = mask.cpu().numpy()

            # Plot
            axes[i, 0].imshow(img_display)
            axes[i, 0].set_title('Input Image')
            axes[i, 0].axis('off')

            axes[i, 1].imshow(mask_gt, cmap='tab20', vmin=0, vmax=20)
            axes[i, 1].set_title('Ground Truth')
            axes[i, 1].axis('off')

            axes[i, 2].imshow(pred, cmap='tab20', vmin=0, vmax=20)
            axes[i, 2].set_title('Prediction')
            axes[i, 2].axis('off')

    plt.tight_layout()

    if save_dir:
        save_path = os.path.join(save_dir, 'deeplabv3_predictions.png')
        plt.savefig(save_path, dpi=150, bbox_inches='tight')
        print(f"✓ Predictions saved to: {save_path}")

    plt.show()

print("Visualizing predictions on validation set...")
visualize_predictions(
    model,
    val_dataset,
    device,
    num_samples=5,
    save_dir=f'{PROJECT_ROOT}/results'
)
```

```
# ----- Cell 19: Calculate final metrics -----
def evaluate_model(model, dataloader, device, num_classes=21):
    """
    Comprehensive evaluation
    """
    model.eval()

    all_ious = []
    all_accs = []
    class_ious = [[] for _ in range(num_classes)]

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

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

            batch_iou = calculate_iou(preds, masks, num_classes)
            batch_acc = calculate_pixel_accuracy(preds, masks)

            all_ious.append(batch_iou)
            all_accs.append(batch_acc)

            for cls in range(num_classes):
                if not np.isnan(batch_iou[cls]):
                    class_ious[cls].append(batch_iou[cls])

    mean_iou = np.nanmean(all_ious)
    mean_acc = np.mean(all_accs)
    per_class_iou = [np.mean(ious) if len(ious) > 0 else 0.0 for ious in class_ious]

    return mean_iou, mean_acc, per_class_iou

print("Evaluating DeepLabV3+ on validation set...")
val_iou, val_acc, per_class_iou = evaluate_model(model, val_loader, device)

print("\n" + "=" * 70)
print("FINAL VALIDATION METRICS")
print("=" * 70)
print(f"Mean IoU: {val_iou:.4f}")
print(f"Pixel Accuracy: {val_acc:.4f}")
print("\nPer-class IoU:")
print("-" * 70)
for idx, iou in enumerate(per_class_iou):
    print(f"  {idx:2d}. {VOC_CLASSES[idx]:15s}: {iou:.4f}")
print("=" * 70)
```

```
Evaluating DeepLabV3+ on validation set...
Evaluating: 100%|██████████| 27/27 [00:02<00:00, 10.77it/s]
======================================================================
FINAL VALIDATION METRICS
======================================================================
Mean IoU: 0.3312
Pixel Accuracy: 0.8710

Per-class IoU:
----------------------------------------------------------------------
   0. background     : 0.8732
   1. aeroplane      : 0.4948
   2. bicycle        : 0.0808
   3. bird           : 0.3178
   4. boat           : 0.2758
   5. bottle         : 0.0952
   6. bus            : 0.3683
   7. car            : 0.3515
   8. cat            : 0.4008
   9. chair          : 0.0625
  10. cow            : 0.1743
  11. diningtable    : 0.2736
  12. dog            : 0.2537
  13. horse          : 0.2793
  14. motorbike      : 0.3073
  15. person         : 0.5508
  16. pottedplant    : 0.0767
  17. sheep          : 0.1191
  18. sofa           : 0.1307
  19. train          : 0.4769
  20. tvmonitor      : 0.4226
======================================================================
```




```
# ----- Cell 20: Save training summary -----
import json

summary = {
    'model': 'DeepLabV3+',
    'encoder': 'ResNet50',
    'pretrained': True,
    'num_epochs': NUM_EPOCHS,
    'batch_size': BATCH_SIZE,
    'learning_rate': LEARNING_RATE,
    'optimizer': 'Adam',
    'loss_function': 'CrossEntropyLoss',
    'training_time_minutes': training_time / 60,
    'best_val_iou': float(best_val_iou),
    'final_val_iou': float(val_iou),
    'final_val_acc': float(val_acc),
    'num_parameters': trainable_params,
    'train_samples': len(train_dataset),
```