

```
In [1]: import os
import torch
import torchvision.transforms as T
import torchvision
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image
from google.colab import drive
import warnings
warnings.filterwarnings("ignore")
```

```
In [2]: # Mount Google Drive
drive.mount('/content/drive')
```

Mounted at /content/drive

```
In [3]: # Mount Google Drive and Paths to folders and model
drive.mount('/content/drive')
image_folder = "/content/drive/MyDrive/DL Project/Pics/images"
mask_folder = "/content/drive/MyDrive/DL Project/Pics/annotation_mask"
device = torch.device("cuda")
```

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

```
In [4]: # Define class colors
label_colors = {
    "background": (0, 0, 0),
    "grilled chicken": (255, 0, 0),
    "paneer": (0, 255, 0),
    "eggplant": (0, 0, 255)
}
color_to_class = {v: i for i, (k, v) in enumerate(
    label_colors.items())}
```

```
In [5]: # Custom Dataset Class
class FoodSegmentationDataset(Dataset):
    def __init__(self, image_dir, mask_dir, transform=None):
        self.image_dir = image_dir
        self.mask_dir = mask_dir
        self.transform = transform
        self.images = [f for f in os.listdir(image_dir)
                        if f.endswith('.png')]

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

    def __getitem__(self, idx):
        img_name = self.images[idx]
        img_path = os.path.join(self.image_dir, img_name)
        mask_path = os.path.join(self.mask_dir, img_name)

        # Load image and mask
        image = Image.open(img_path).convert("RGB")
        mask = Image.open(mask_path).convert("RGB")
        mask = self.rgb_to_class_indices(mask)

        if self.transform:
            image = self.transform(image)
            mask = torch.tensor(mask, dtype=torch.long)

        return image, mask

    def rgb_to_class_indices(self, mask):
        mask_np = np.array(mask)
        class_mask = np.zeros((mask_np.shape[0], mask_np.shape[1]),
                               dtype=np.int64)
        for color, class_idx in color_to_class.items():
            class_mask[(mask_np == color).all(axis=2)] = class_idx
        return class_mask
```

```
In [6]: # Data transformations
transform = T.Compose([
    T.Resize((512, 512)),
    T.ToTensor(),
])
```

```
In [7]: # Load dataset and split
dataset = FoodSegmentationDataset(image_folder, mask_folder,
                                   transform=transform)

train_size = int(0.8 * len(dataset))
val_size = len(dataset) - train_size
train_dataset, val_dataset = torch.utils.data.random_split(
    dataset, [train_size, val_size])
train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=8, shuffle=False)
```

```
In [9]: # EfficientNet model class
class EfficientNetSegmentation(nn.Module):
    def __init__(self, num_classes):
        super(EfficientNetSegmentation, self).__init__()
        self.backbone = torchvision.models.efficientnet_b0(
            pretrained=True).features
        self.classifier = nn.Sequential(
            nn.Conv2d(1280, num_classes, kernel_size=1),
            nn.Upsample(size=(512, 512), mode='bilinear',
                          align_corners=False)
        )

        # Freeze all layers
        for param in self.backbone.parameters():
            param.requires_grad = False

    def forward(self, x):
        x = self.backbone(x)
        x = self.classifier(x)
        return x
```

```
In [10]: # Initialize the model with the number of classes
model = EfficientNetSegmentation(num_classes=len(
    label_colors)).to(device)
```

Downloading: "https://download.pytorch.org/models/efficientnet\_b0\_rwightman-7f5810bc.pth" to /root/.cache/torch/hub/checkpoints/efficientnet\_b0\_rwightman-7f5810bc.pth  
 100%|██████████| 20.5M/20.5M [00:00<00:00, 164MB/s]

```
In [11]: # Criterion for evaluating performance
criterion = nn.CrossEntropyLoss()
```

```
In [12]: # Evaluation and loss calculation function
def evaluate_model(model, loader, criterion):
    total_loss = 0
    total_batches = 0
    with torch.no_grad():
        for images, masks in loader:
            images, masks = images.to(device), masks.to(device)
            outputs = model(images)
            loss = criterion(outputs, masks)
            total_loss += loss.item()
            total_batches += 1
    avg_loss = total_loss / total_batches
    return avg_loss
```

```
In [13]: # Calculate Training Loss and Validation loss
train_loss = evaluate_model(model, train_loader, criterion)
val_loss = evaluate_model(model, val_loader, criterion)
```

```
In [21]: # Visualization function for predictions
def visualize_predictions(model, dataloader):
    model.eval()
    with torch.no_grad():
        for images, masks in dataloader:
            images = images.to(device)
            outputs = model(images)
            preds = outputs.argmax(1).cpu().numpy()

            pred_rgb = np.zeros((preds[0].shape[0],
                                preds[0].shape[1], 3), dtype=np.uint8)
            mask_rgb = np.zeros((masks[0].shape[0],
                                masks[0].shape[1], 3), dtype=np.uint8)

            for color, class_idx in color_to_class.items():
                pred_rgb[preds[0] == class_idx] = color
                mask_rgb[masks[0].cpu().numpy() == class_idx] = color

            fig, axs = plt.subplots(1, 3, figsize=(15, 5))
            axs[0].imshow(images[0].cpu().permute(1, 2, 0))
            axs[0].set_title("Input Image")
            axs[1].imshow(mask_rgb)
            axs[1].set_title("Ground Truth Mask")
            axs[2].imshow(pred_rgb)
            axs[2].set_title("Prediction Mask")
            plt.show()
```

```
In [23]: # Evaluate and visualize
print("Average Training Loss:", train_loss)
print("Average Validation Loss:", val_loss)
print("Visualizing Predictions on Validation Data:")
visualize_predictions(model, val_loader)
```

Average Training Loss: 1.491151797771454  
 Average Validation Loss: 1.50767240524292  
 Visualizing Predictions on Validation Data:



