Lab 6: Object Localization with Fast R-CNN for Mobile Phone Detection

Objective

- the implementation of an object localization model using Fast R-CNN in PyTorch for detecting mobile phones. It involves:
- Understanding object localization vs. classification.
- Utilizing Fast R-CNN for bounding box predictions and class probabilities.
- Applying evaluation metrics like mAP (mean Average Precision) and IoU (Intersection over Union).

Dataset Information

- Dataset: Mobile Phone Detection Dataset - https://universe.roboflow.com/l-u7ala/productrecog-94bfc
- Format: COCO JSON annotations
- Classes: 1 (mobile-phone)

Splits:

- Training: 481 images (81%)
- Validation: 67 images (11%)
- Test: 49 images (8%)

Image Format: JPG

Annotation Format: COCO JSON with bounding boxes

Object Localization vs. Classification

Classification: Predicts only the class label of an object

Localization: Predicts both class label and object location (bounding box)

Output Format

- **Classification:** Class probabilities
- **Localization:** Class probabilities + Bounding box coordinates (x, y, width, height)

Mobile Phone Detection using Fast R-CNN

1. Environment Setup

Data Preparation

- Install necessary libraries:
  `pip install torch torchvision pycocotools albumentations matplotlib numpy pandas`
- Mount Google Drive to access datasets and annotations.

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2. Data Loading and Preparation

Custom Dataset Class:

- Implements PyTorch's `Dataset` for loading COCO annotations.
- Prepares image tensors and bounding box targets ([x1, y1, x2, y2]).
- Supports transformations (optional).

Key Methods:

- `__getitem__` : Loads images and bounding box annotations.
- `__len__` : Returns the size of the dataset.

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3. Model Setup

Fast R-CNN Architecture:

- **Base Model**: `fasterrcnn_resnet50_fpn_v2` (pre-trained).
- **Custom Head**:

- Replaces the pre-trained classification layer.
- Predicts bounding boxes and classes (background + mobile phones).

Key Function:

- `get_model(num_classes)` : Configures the model with a new head for custom classes.

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4. Training Pipeline

Tasks:

1. **Set Device**:
   - Use GPU if available:
     `device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')`
2. **Load Datasets**:
   - Train and validation datasets.
   - Use `DataLoader` for batching and shuffling.
3. **Optimizer and Scheduler**:
   - **Optimizer**: SGD with a learning rate of 0.001.
   - **Scheduler**: `StepLR` to decay learning rate.
4. **Training Loop**:
   - Perform forward and backward passes.
   - Update weights using calculated loss.

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5. Evaluation

Metrics:

- **IoU (Intersection over Union)**: Measures overlap between predicted and ground truth bounding boxes.
- **mAP (Mean Average Precision)**: Evaluates detection performance across classes.

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6. Inference and Visualization

Tasks:

1. **Inference Function**:
   - Loads test images.
   - Uses the trained model to predict bounding boxes and confidence scores.
2. **Visualization Function**:
   - Draws bounding boxes on images with confidence scores.

Key Functionality:

- `detect_phones` : Runs inference.
- `visualize_detection` : Plots predictions.

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run_inference('model_checkpoint.pth', 'test_image.jpg')

1. Environment Setup

In [3]:
```
# !pip install torch torchvision
# !pip install pycocotools
# !pip install albumentations
# !pip install matplotlib numpy pandas
```

In [4]:
```
# !pip install pycocotools
# !pip install albumentations
```

In [6]:
```
# 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=Tru
e).
```

In [1]:
```
# Import necessary libraries
import torch
```

```python
import torchvision
from torchvision.models.detection import fasterrcnn_resnet50_fpn_v2
from torchvision.models.detection.faster_rcnn import FastRCNNPredictor
import numpy as np
import matplotlib.pyplot as plt
import os
import json
from PIL import Image
from torchvision.transforms import functional as F
from pycocotools.coco import COCO
from torch.utils.data import Dataset, DataLoader
```

In [2]:
```python
# Set random seeds for reproducibility
torch.manual_seed(42)
np.random.seed(42)
```

2. Data Loading and Preparation

In [3]:
```python
class MobilePhoneDataset(Dataset):
    def __init__(self, root_dir, annotation_file, transforms=None):
        self.root_dir = root_dir
        self.transforms = transforms

        # Load COCO format annotations
        self.coco = COCO(annotation_file)
        self.ids = list(sorted(self.coco.imgs.keys()))

        # Filter for mobile phone class
        cat_ids = self.coco.getCatIds(catNms=['mobile-phone'])
        self.category_id_to_label = {cat_id: 1 for cat_id in cat_ids}  # Map to label 1

    def __getitem__(self, index):
        # Load image
        img_id = self.ids[index]
        img_info = self.coco.loadImgs(img_id)[0]
        image_path = os.path.join(self.root_dir, img_info['file_name'])
        image = Image.open(image_path).convert('RGB')

        # Convert PIL Image to tensor
        image = F.to_tensor(image)

        # Load annotations
        ann_ids = self.coco.getAnnIds(imgIds=img_id)
        anns = self.coco.loadAnns(ann_ids)

        boxes = []
        labels = []

        for ann in anns:
            boxes.append(ann['bbox'])  # [x, y, width, height]
            labels.append(1)  # 1 for mobile phone

        # Convert boxes to tensor
        boxes = torch.as_tensor(boxes, dtype=torch.float32)
        # Convert from [x, y, w, h] to [x1, y1, x2, y2]
        if len(boxes) > 0:
            boxes[:, 2] = boxes[:, 0] + boxes[:, 2]
            boxes[:, 3] = boxes[:, 1] + boxes[:, 3]

        # Prepare target
        target = {}
        target["boxes"] = boxes
        target["labels"] = torch.as_tensor(labels, dtype=torch.int64)
        target["image_id"] = torch.tensor([img_id])
        target["area"] = (boxes[:, 3] - boxes[:, 1]) * (boxes[:, 2] - boxes[:, 0])
        target["iscrowd"] = torch.zeros((len(boxes),), dtype=torch.int64)

        if self.transforms is not None:
            image = self.transforms(image)

        return image, target

    def __len__(self):
        return len(self.ids)
```

3. Model Setup

In [4]:
```python
def get_model(num_classes=1):
    # Load pre-trained model
    model = fasterrcnn_resnet50_fpn_v2(pretrained=True)

    # Get number of input features
    in_features = model.roi_heads.box_predictor.cls_score.in_features
```

```python
    # Replace the pre-trained head with a new one
    model.roi_heads.box_predictor = FastRCNNPredictor(in_features, num_classes)

    return model
```

In [5]:
```python
def train_one_epoch(model, optimizer, data_loader, device):
    model.train()
    total_loss = 0

    for images, targets in data_loader:
        images = list(image.to(device) for image in images)
        targets = [{k: v.to(device) for k, v in t.items()} for t in targets]

        loss_dict = model(images, targets)
        losses = sum(loss for loss in loss_dict.values())

        optimizer.zero_grad()
        losses.backward()
        optimizer.step()

        total_loss += losses.item()

    return total_loss / len(data_loader)
```

4. Training Pipeline

In [6]:
```python
# Set device
device = torch.device('cuda') if torch.cuda.is_available() else torch.device('cpu')
print(f"Using device: {device}")
```

```
Using device: cuda
```

In [ ]:
```python
# Dataset paths
train_root = '/content/drive/MyDrive/phone dataset/train'
train_annot = '/content/drive/MyDrive/phone dataset/train/_annotations.coco.json'
val_root = '/content/drive/MyDrive/phone dataset/valid'
val_annot = '/content/drive/MyDrive/phone dataset/valid/_annotations.coco.json'

# Create datasets
train_dataset = MobilePhoneDataset(train_root, train_annot)
val_dataset = MobilePhoneDataset(val_root, val_annot)

print(f"Number of training images: {len(train_dataset)}")
print(f"Number of validation images: {len(val_dataset)}")
```

In [ ]:
```python
# Create data loaders with smaller batch size for memory efficiency
train_loader = DataLoader(
    train_dataset,
    batch_size=2,
    shuffle=True,
    collate_fn=lambda x: tuple(zip(*x)),
    num_workers=2
)

val_loader = DataLoader(
    val_dataset,
    batch_size=1,
    shuffle=False,
    collate_fn=lambda x: tuple(zip(*x)),
    num_workers=2
)
```

In [7]:
```python
# Initialize model
model = get_model(num_classes=1)
model.to(device)

# Optimizer with lower learning rate
params = [p for p in model.parameters() if p.requires_grad]
optimizer = torch.optim.SGD(params, lr=0.001, momentum=0.9, weight_decay=0.0005)

# Learning rate scheduler
lr_scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=3, gamma=0.1)
```

```
d:\Nokia_DL_L3_lab\nokia\lib\site-packages\torchvision\models\_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weights' instead.
  warnings.warn(
d:\Nokia_DL_L3_lab\nokia\lib\site-packages\torchvision\models\_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=FasterRCNN_ResNet50_FPN_V2_Weights.COCO_V1`. You can also use `weights=FasterRCNN_ResNet50_FPN_V2_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
```

In [8]:
```python
## model architecture
print(model)
```

```
FasterRCNN(
  (transform): GeneralizedRCNNTransform(
      Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
      Resize(min_size=(800,), max_size=1333, mode='bilinear')
  )
  (backbone): BackboneWithFPN(
    (body): IntermediateLayerGetter(
      (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): Bottleneck(
          (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
          (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
          (downsample): Sequential(
            (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          )
        )
        (1): Bottleneck(
          (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
          (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
        )
        (2): Bottleneck(
          (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
          (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
        )
      )
      (layer2): Sequential(
        (0): Bottleneck(
          (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
          (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (relu): ReLU(inplace=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): Bottleneck(
          (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
          (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
        )
        (2): Bottleneck(
          (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
          (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
        )
        (3): Bottleneck(
          (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
          (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
          (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (relu): ReLU(inplace=True)
        )
      )
      (layer3): Sequential(
```

```
    (0): Bottleneck(
      (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (3): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (4): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (5): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=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)
```

```
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
      )
    )
  )
  (fpn): FeaturePyramidNetwork(
    (inner_blocks): ModuleList(
      (0): Conv2dNormActivation(
        (0): Conv2d(256, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (1): Conv2dNormActivation(
        (0): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (2): Conv2dNormActivation(
        (0): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (3): Conv2dNormActivation(
        (0): Conv2d(2048, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (layer_blocks): ModuleList(
      (0-3): 4 x Conv2dNormActivation(
        (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)
      )
    )
    (extra_blocks): LastLevelMaxPool()
  )
)
(rpn): RegionProposalNetwork(
  (anchor_generator): AnchorGenerator()
  (head): RPNHead(
    (conv): Sequential(
      (0): Conv2dNormActivation(
        (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        (1): ReLU(inplace=True)
      )
      (1): Conv2dNormActivation(
        (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        (1): ReLU(inplace=True)
      )
    )
    (cls_logits): Conv2d(256, 3, kernel_size=(1, 1), stride=(1, 1))
    (bbox_pred): Conv2d(256, 12, kernel_size=(1, 1), stride=(1, 1))
  )
)
(roi_heads): RoIHeads(
  (box_roi_pool): MultiScaleRoIAlign(featmap_names=['0', '1', '2', '3'], output_size=(7, 7), sampling_ratio=2)
  (box_head): FastRCNNConvFCHead(
    (0): Conv2dNormActivation(
      (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)
    )
    (1): Conv2dNormActivation(
      (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)
    )
    (2): Conv2dNormActivation(
      (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)
    )
    (3): Conv2dNormActivation(
      (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)
    )
    (4): Flatten(start_dim=1, end_dim=-1)
    (5): Linear(in_features=12544, out_features=1024, bias=True)
    (6): ReLU(inplace=True)
  )
  (box_predictor): FastRCNNPredictor(
    (cls_score): Linear(in_features=1024, out_features=2, bias=True)
    (bbox_pred): Linear(in_features=1024, out_features=8, bias=True)
  )
)
)
```

In [39]:

```
# Training Loop with try-except for debugging
num_epochs = 10
```

```python
print("Starting training...")

try:
    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        model.train()
        total_loss = 0
        num_batches = len(train_loader)

        for i, (images, targets) in enumerate(train_loader):
            # Move images and targets to device
            images = [image.to(device) for image in images]
            targets = [{k: v.to(device) for k, v in t.items()} for t in targets]

            # Forward pass
            loss_dict = model(images, targets)
            losses = sum(loss for loss in loss_dict.values())

            # Backward pass
            optimizer.zero_grad()
            losses.backward()
            optimizer.step()

            total_loss += losses.item()

            if i % 10 == 0:  # Print every 10 batches
                print(f"  Batch {i+1}/{num_batches}, Loss: {losses.item():.4f}")

        # Step the scheduler
        lr_scheduler.step()

        avg_loss = total_loss / len(train_loader)
        print(f"Epoch {epoch+1} completed. Average Loss: {avg_loss:.4f}")

        # Save model checkpoint
        torch.save({
            'epoch': epoch,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
            'loss': avg_loss,
        }, f'mobile_detector_epoch_{epoch+1}.pth')

except Exception as e:
    print(f"Error during training: {str(e)}")
    import traceback
    traceback.print_exc()
```

```
Using device: cuda
loading annotations into memory...
Done (t=0.01s)
creating index...
index created!
loading annotations into memory...
Done (t=0.00s)
creating index...
index created!
Number of training images: 481
Number of validation images: 67
Starting training...
Epoch 1/10
  Batch 1/241, Loss: 1.1296
  Batch 11/241, Loss: 0.7986
  Batch 21/241, Loss: 0.2058
  Batch 31/241, Loss: 0.7237
  Batch 41/241, Loss: 0.1686
  Batch 51/241, Loss: 0.2139
  Batch 61/241, Loss: 0.1602
  Batch 71/241, Loss: 0.1682
  Batch 81/241, Loss: 0.3659
  Batch 91/241, Loss: 0.1043
  Batch 101/241, Loss: 0.0908
  Batch 111/241, Loss: 0.2563
  Batch 121/241, Loss: 0.1163
  Batch 131/241, Loss: 0.1343
  Batch 141/241, Loss: 0.0981
  Batch 151/241, Loss: 0.1820
  Batch 161/241, Loss: 0.1195
  Batch 171/241, Loss: 0.1268
  Batch 181/241, Loss: 0.0790
  Batch 191/241, Loss: 0.1007
  Batch 201/241, Loss: 0.0813
  Batch 211/241, Loss: 0.1764
  Batch 221/241, Loss: 0.0943
  Batch 231/241, Loss: 0.0886
  Batch 241/241, Loss: 0.6243
Epoch 1 completed. Average Loss: 0.2092
Epoch 2/10
  Batch 1/241, Loss: 0.0905
  Batch 11/241, Loss: 0.0813
  Batch 21/241, Loss: 0.0982
  Batch 31/241, Loss: 0.1732
  Batch 41/241, Loss: 0.0833
  Batch 51/241, Loss: 0.0710
  Batch 61/241, Loss: 0.0695
  Batch 71/241, Loss: 0.0594
  Batch 81/241, Loss: 0.3237
  Batch 91/241, Loss: 0.0940
  Batch 101/241, Loss: 0.0511
  Batch 111/241, Loss: 0.0812
  Batch 121/241, Loss: 0.0898
  Batch 131/241, Loss: 0.1343
  Batch 141/241, Loss: 0.0864
  Batch 151/241, Loss: 0.0806
  Batch 161/241, Loss: 0.1615
  Batch 171/241, Loss: 0.7944
  Batch 181/241, Loss: 0.0354
  Batch 191/241, Loss: 0.1550
  Batch 201/241, Loss: 0.1128
  Batch 211/241, Loss: 0.0279
  Batch 221/241, Loss: 0.0768
  Batch 231/241, Loss: 0.0627
  Batch 241/241, Loss: 0.0393
Epoch 2 completed. Average Loss: 0.1048
Epoch 3/10
  Batch 1/241, Loss: 0.0555
  Batch 11/241, Loss: 0.0491
  Batch 21/241, Loss: 0.0533
  Batch 31/241, Loss: 0.0479
  Batch 41/241, Loss: 0.0685
  Batch 51/241, Loss: 0.0370
  Batch 61/241, Loss: 0.0503
  Batch 71/241, Loss: 0.0679
  Batch 81/241, Loss: 0.1048
  Batch 91/241, Loss: 0.0615
  Batch 101/241, Loss: 0.0378
  Batch 111/241, Loss: 0.0538
  Batch 121/241, Loss: 0.0405
  Batch 131/241, Loss: 0.1042
  Batch 141/241, Loss: 0.0238
  Batch 151/241, Loss: 0.0582
  Batch 161/241, Loss: 0.0775
  Batch 171/241, Loss: 0.2750
  Batch 181/241, Loss: 0.0272
  Batch 191/241, Loss: 0.0824
```

```
  Batch 201/241, Loss: 0.0604
  Batch 211/241, Loss: 0.1262
  Batch 221/241, Loss: 0.0410
  Batch 231/241, Loss: 0.0586
  Batch 241/241, Loss: 0.1317
Epoch 3 completed. Average Loss: 0.0865
Epoch 4/10
  Batch 1/241, Loss: 0.0421
  Batch 11/241, Loss: 0.1489
  Batch 21/241, Loss: 0.0306
  Batch 31/241, Loss: 0.0451
  Batch 41/241, Loss: 0.0792
  Batch 51/241, Loss: 0.0675
  Batch 61/241, Loss: 0.0531
  Batch 71/241, Loss: 0.0583
  Batch 81/241, Loss: 0.0599
  Batch 91/241, Loss: 0.0834
  Batch 101/241, Loss: 0.0358
  Batch 111/241, Loss: 0.0280
  Batch 121/241, Loss: 0.0642
  Batch 131/241, Loss: 0.0366
  Batch 141/241, Loss: 0.0423
  Batch 151/241, Loss: 0.0375
  Batch 161/241, Loss: 0.0377
  Batch 171/241, Loss: 0.0837
  Batch 181/241, Loss: 0.0232
  Batch 191/241, Loss: 0.0483
  Batch 201/241, Loss: 0.0257
  Batch 211/241, Loss: 0.0579
  Batch 221/241, Loss: 0.0506
  Batch 231/241, Loss: 0.0681
  Batch 241/241, Loss: 0.1381
Epoch 4 completed. Average Loss: 0.0747
Epoch 5/10
  Batch 1/241, Loss: 0.0549
  Batch 11/241, Loss: 0.1368
  Batch 21/241, Loss: 0.0397
  Batch 31/241, Loss: 0.0179
  Batch 41/241, Loss: 0.0931
  Batch 51/241, Loss: 0.0755
  Batch 61/241, Loss: 0.0245
  Batch 71/241, Loss: 0.0419
  Batch 81/241, Loss: 0.0438
  Batch 91/241, Loss: 0.0281
  Batch 101/241, Loss: 0.0497
  Batch 111/241, Loss: 0.0536
  Batch 121/241, Loss: 0.1042
  Batch 131/241, Loss: 0.0338
  Batch 141/241, Loss: 0.0544
  Batch 151/241, Loss: 0.0540
  Batch 161/241, Loss: 0.0457
  Batch 171/241, Loss: 0.0258
  Batch 181/241, Loss: 0.1039
  Batch 191/241, Loss: 0.0364
  Batch 201/241, Loss: 0.0506
  Batch 211/241, Loss: 0.0326
  Batch 221/241, Loss: 0.0282
  Batch 231/241, Loss: 0.0875
  Batch 241/241, Loss: 0.0421
Epoch 5 completed. Average Loss: 0.0725
Epoch 6/10
  Batch 1/241, Loss: 0.1391
  Batch 11/241, Loss: 0.0395
  Batch 21/241, Loss: 0.0299
  Batch 31/241, Loss: 0.0306
  Batch 41/241, Loss: 0.1657
  Batch 51/241, Loss: 0.0424
  Batch 61/241, Loss: 0.0257
  Batch 71/241, Loss: 0.0828
  Batch 81/241, Loss: 0.2437
  Batch 91/241, Loss: 0.0260
  Batch 101/241, Loss: 0.0203
  Batch 111/241, Loss: 0.0444
  Batch 121/241, Loss: 0.1942
  Batch 131/241, Loss: 0.0339
  Batch 141/241, Loss: 0.0246
  Batch 151/241, Loss: 0.0509
  Batch 161/241, Loss: 0.0514
  Batch 171/241, Loss: 0.0476
  Batch 181/241, Loss: 0.1060
  Batch 191/241, Loss: 0.0890
  Batch 201/241, Loss: 0.0294
  Batch 211/241, Loss: 0.0588
  Batch 221/241, Loss: 0.0706
  Batch 231/241, Loss: 0.0666
  Batch 241/241, Loss: 0.0873
Epoch 6 completed. Average Loss: 0.0718
```

```
Epoch 7/10
  Batch 1/241, Loss: 0.0390
  Batch 11/241, Loss: 0.0588
  Batch 21/241, Loss: 0.0398
  Batch 31/241, Loss: 0.0280
  Batch 41/241, Loss: 0.0981
  Batch 51/241, Loss: 0.0635
  Batch 61/241, Loss: 0.0645
  Batch 71/241, Loss: 0.1039
  Batch 81/241, Loss: 0.0650
  Batch 91/241, Loss: 0.0881
  Batch 101/241, Loss: 0.0537
  Batch 111/241, Loss: 0.0348
  Batch 121/241, Loss: 0.0370
  Batch 131/241, Loss: 0.0698
  Batch 141/241, Loss: 0.0522
  Batch 151/241, Loss: 0.2601
  Batch 161/241, Loss: 0.0891
  Batch 171/241, Loss: 0.0324
  Batch 181/241, Loss: 0.0499
  Batch 191/241, Loss: 0.0489
  Batch 201/241, Loss: 0.0632
  Batch 211/241, Loss: 0.0412
  Batch 221/241, Loss: 0.0263
  Batch 231/241, Loss: 0.0890
  Batch 241/241, Loss: 0.0689
Epoch 7 completed. Average Loss: 0.0705
Epoch 8/10
  Batch 1/241, Loss: 0.0462
  Batch 11/241, Loss: 0.0271
  Batch 21/241, Loss: 0.0802
  Batch 31/241, Loss: 0.0815
  Batch 41/241, Loss: 0.0259
  Batch 51/241, Loss: 0.0458
  Batch 61/241, Loss: 0.0861
  Batch 71/241, Loss: 0.1310
  Batch 81/241, Loss: 0.0350
  Batch 91/241, Loss: 0.0375
  Batch 101/241, Loss: 0.0428
  Batch 111/241, Loss: 0.0433
  Batch 121/241, Loss: 0.0544
  Batch 131/241, Loss: 0.2503
  Batch 141/241, Loss: 0.0343
  Batch 151/241, Loss: 0.0518
  Batch 161/241, Loss: 0.0955
  Batch 171/241, Loss: 0.0746
  Batch 181/241, Loss: 0.0375
  Batch 191/241, Loss: 0.0692
  Batch 201/241, Loss: 0.0514
  Batch 211/241, Loss: 0.1147
  Batch 221/241, Loss: 0.0911
  Batch 231/241, Loss: 0.0401
  Batch 241/241, Loss: 0.0370
Epoch 8 completed. Average Loss: 0.0699
Epoch 9/10
  Batch 1/241, Loss: 0.2133
  Batch 11/241, Loss: 0.0345
  Batch 21/241, Loss: 0.0283
  Batch 31/241, Loss: 0.0544
  Batch 41/241, Loss: 0.0688
  Batch 51/241, Loss: 0.0271
  Batch 61/241, Loss: 0.4754
  Batch 71/241, Loss: 0.0270
  Batch 81/241, Loss: 0.0325
  Batch 91/241, Loss: 0.0721
  Batch 101/241, Loss: 0.0402
  Batch 111/241, Loss: 0.0553
  Batch 121/241, Loss: 0.1474
  Batch 131/241, Loss: 0.1807
  Batch 141/241, Loss: 0.0981
  Batch 151/241, Loss: 0.1659
  Batch 161/241, Loss: 0.0409
  Batch 171/241, Loss: 0.0627
  Batch 181/241, Loss: 0.0399
  Batch 191/241, Loss: 0.0671
  Batch 201/241, Loss: 0.0266
  Batch 211/241, Loss: 0.0535
  Batch 221/241, Loss: 0.0675
  Batch 231/241, Loss: 0.1131
  Batch 241/241, Loss: 0.1545
Epoch 9 completed. Average Loss: 0.0719
Epoch 10/10
  Batch 1/241, Loss: 0.0344
  Batch 11/241, Loss: 0.0440
  Batch 21/241, Loss: 0.0463
  Batch 31/241, Loss: 0.0975
  Batch 41/241, Loss: 0.0249
```

```
  Batch 51/241, Loss: 0.0589
  Batch 61/241, Loss: 0.0378
  Batch 71/241, Loss: 0.0568
  Batch 81/241, Loss: 0.0400
  Batch 91/241, Loss: 0.0524
  Batch 101/241, Loss: 0.0594
  Batch 111/241, Loss: 0.0348
  Batch 121/241, Loss: 0.0373
  Batch 131/241, Loss: 0.0302
  Batch 141/241, Loss: 0.0474
  Batch 151/241, Loss: 0.0551
  Batch 161/241, Loss: 0.0537
  Batch 171/241, Loss: 0.1010
  Batch 181/241, Loss: 0.0782
  Batch 191/241, Loss: 0.0535
  Batch 201/241, Loss: 0.0944
  Batch 211/241, Loss: 0.0392
  Batch 221/241, Loss: 0.0471
  Batch 231/241, Loss: 0.0650
  Batch 241/241, Loss: 0.0437
Epoch 10 completed. Average Loss: 0.0705
```

5. Evaluation

In [47]:
```python
from collections import defaultdict
from torchvision.ops import box_iou
from tqdm import tqdm
```

In [ ]:
```python
def get_model(num_classes=2):
    model = fasterrcnn_resnet50_fpn_v2(pretrained=True)
    in_features = model.roi_heads.box_predictor.cls_score.in_features
    model.roi_heads.box_predictor = FastRCNNPredictor(in_features, num_classes)
    return model
```

In [ ]:
```python
def evaluate_single_image(pred_boxes, pred_scores, target_boxes, iou_threshold=0.5):
    """
    Evaluate predictions for a single image
    """
    if len(pred_boxes) == 0:
        return {'precision': 0.0, 'recall': 0.0, 'f1': 0.0}
    if len(target_boxes) == 0:
        return {'precision': 0.0, 'recall': 0.0, 'f1': 0.0}

    # Calculate IoU between predicted and ground truth boxes
    iou_matrix = box_iou(pred_boxes, target_boxes)

    # Get maximum IoU for each predicted box
    max_ious, _ = iou_matrix.max(dim=1)

    # True positives: predicted boxes with IoU > threshold
    true_positives = (max_ious >= iou_threshold).sum().item()

    # Calculate metrics
    precision = true_positives / len(pred_boxes)
    recall = true_positives / len(target_boxes)
    f1 = 2 * (precision * recall) / (precision + recall + 1e-10)

    return {
        'precision': precision,
        'recall': recall,
        'f1': f1
    }
```

In [ ]:
```python
def calculate_ap_at_threshold(all_predictions, all_targets, iou_threshold):
    """
    Calculate Average Precision at a specific IoU threshold
    """
    all_detections = []
    num_positives = sum(len(target_boxes) for target_boxes in all_targets)

    # Collect all detections
    for (pred_boxes, pred_scores), target_boxes in zip(all_predictions, all_targets):
        if len(pred_boxes) == 0:
            continue

        iou_matrix = box_iou(pred_boxes, target_boxes)
        max_ious, _ = iou_matrix.max(dim=1)

        for score, iou in zip(pred_scores, max_ious):
            all_detections.append({
                'score': score.item(),
                'tp': iou >= iou_threshold
            })

    # Sort detections by confidence
```

```python
    all_detections.sort(key=lambda x: x['score'], reverse=True)

    # Calculate precision and recall
    precisions = []
    recalls = []
    num_correct = 0
    for i, detection in enumerate(all_detections):
        if detection['tp']:
            num_correct += 1
        precision = num_correct / (i + 1)
        recall = num_correct / num_positives
        precisions.append(precision)
        recalls.append(recall)

    if not precisions:
        return 0.0

    # Calculate AP using all points
    ap = np.trapz(precisions, recalls) if recalls else 0.0
    return ap
```

In [ ]:
```python
def calculate_map(all_predictions, all_targets, iou_thresholds=None):
    """
    Calculate mean Average Precision
    """
    if iou_thresholds is None:
        iou_thresholds = np.linspace(0.5, 0.95, 10)

    aps = []
    for iou_threshold in iou_thresholds:
        ap = calculate_ap_at_threshold(all_predictions, all_targets, iou_threshold)
        aps.append(ap)

    mAP = np.mean(aps)
    return mAP
```

In [ ]:
```python
def evaluate_model(model, data_loader, device, confidence_threshold=0.5):
    """
    Evaluate model performance on the validation set
    """
    model.eval()
    total_metrics = defaultdict(float)
    all_predictions = []
    all_targets = []
    num_images = 0

    print("\nEvaluating model...")
    with torch.no_grad():
        for images, targets in tqdm(data_loader):
            # Move images to device
            images = [image.to(device) for image in images]
            predictions = model(images)

            # Process each image in the batch
            for pred, target in zip(predictions, targets):
                # Filter predictions by confidence
                mask = pred['scores'] >= confidence_threshold
                pred_boxes = pred['boxes'][mask].cpu()
                pred_scores = pred['scores'][mask].cpu()
                target_boxes = target['boxes'].cpu()

                # Store predictions and targets for mAP calculation
                all_predictions.append((pred_boxes, pred_scores))
                all_targets.append(target_boxes)

                # Calculate metrics for this image
                metrics = evaluate_single_image(pred_boxes, pred_scores, target_boxes)
                for k, v in metrics.items():
                    total_metrics[k] += v
                num_images += 1

    # Calculate average metrics
    avg_metrics = {k: v / num_images for k, v in total_metrics.items()}

    # Calculate mAP
    mAP = calculate_map(all_predictions, all_targets)
    avg_metrics['mAP'] = mAP

    return avg_metrics
```

In [48]:
```python
def visualize_predictions(model, dataset, device, num_images=5, confidence_threshold=0.5):
    """
    Visualize model predictions on sample images
    """
    model.eval()
    fig, axes = plt.subplots(1, num_images, figsize=(20, 4))
```

```python
    with torch.no_grad():
        for i in range(num_images):
            # Get random image
            img, target = dataset[np.random.randint(len(dataset))]

            # Get prediction
            prediction = model([img.to(device)])
            pred = prediction[0]

            # Filter predictions by confidence
            mask = pred['scores'] >= confidence_threshold
            boxes = pred['boxes'][mask].cpu()
            scores = pred['scores'][mask].cpu()

            # Convert tensor image to numpy for plotting
            img = img.cpu().permute(1, 2, 0).numpy()

            # Plot image
            ax = axes[i]
            ax.imshow(img)

            # Draw predicted boxes
            for box, score in zip(boxes, scores):
                x1, y1, x2, y2 = box.tolist()
                rect = plt.Rectangle((x1, y1), x2-x1, y2-y1,
                                   fill=False, color='red', linewidth=2)
                ax.add_patch(rect)
                ax.text(x1, y1-5, f'{score:.2f}',
                       bbox=dict(facecolor='white', alpha=0.7))

            ax.axis('off')

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

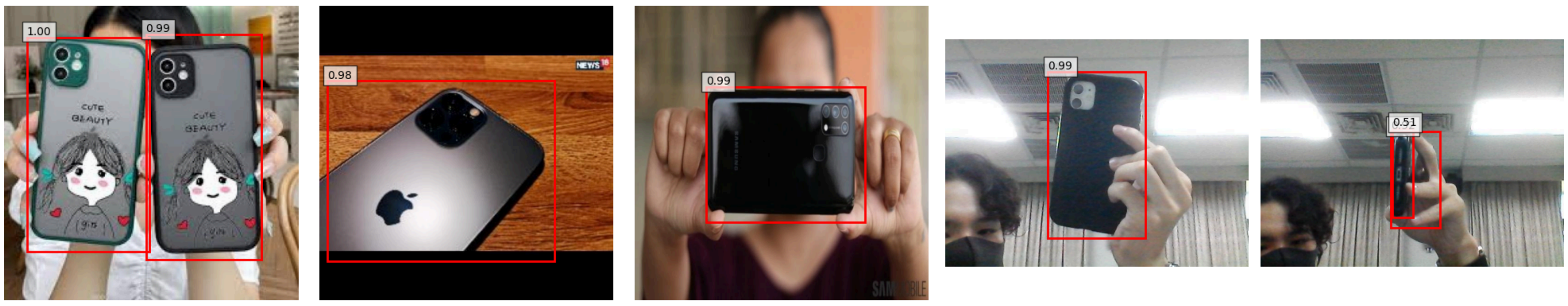
In [ ]:

```python
def run_evaluation(model_path, val_loader, device):
    """
    Run complete model evaluation
    """
    # Load model
    model = get_model(num_classes=2)
    checkpoint = torch.load(model_path, map_location=device)
    model.load_state_dict(checkpoint['model_state_dict'])
    model.to(device)

    # Evaluate model
    metrics = evaluate_model(model, val_loader, device)

    # Print results
    print("\n=== Evaluation Results ===")
    print(f"Mean Average Precision (mAP): {metrics['mAP']:.4f}")
    print(f"Average Precision: {metrics['precision']:.4f}")
    print(f"Average Recall: {metrics['recall']:.4f}")
    print(f"Average F1 Score: {metrics['f1']:.4f}")

    # Visualize some predictions
    print("\nGenerating visualization of predictions...")
    visualize_predictions(model, val_loader.dataset, device)

    return metrics
```

In [49]:

```python
results = run_evaluation(
    model_path='/content/mobile_detector_epoch_10.pth',
    val_loader=val_loader,
    device=device
)
```

```
<ipython-input-48-d6730a283150>:186: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default v
alue), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute ar
bitrary code during unpickling (See https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for more detail
s). In a future release, the default value for `weights_only` will be flipped to `True`. This limits the functions that could b
e executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly
allowlisted by the user via `torch.serialization.add_safe_globals`. We recommend you start setting `weights_only=True` for any
use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this ex
perimental feature.
  checkpoint = torch.load(model_path, map_location=device)
Evaluating model...
100%|██████████| 67/67 [00:12<00:00,  5.23it/s]
=== Evaluation Results ===
Mean Average Precision (mAP): 0.6545
Average Precision: 0.8893
Average Recall: 0.9739
Average F1 Score: 0.9143

Generating visualization of predictions...
```



6. Inference and Visualization

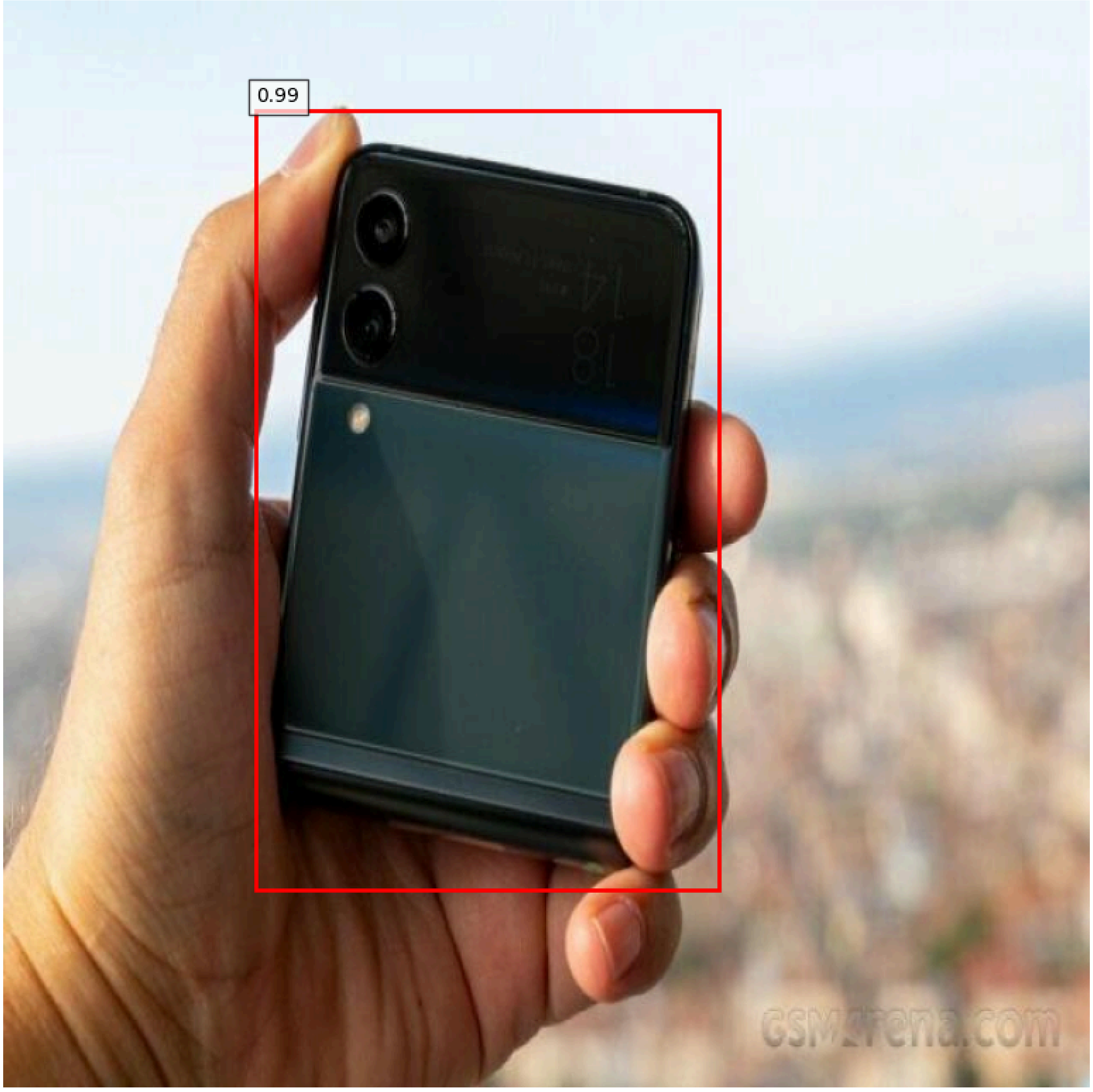
In [ ]:
```python
# Inference function
def detect_phones(model, image_path, device, conf_threshold=0.5):
    model.eval()
    image = Image.open(image_path).convert('RGB')
    image_tensor = F.to_tensor(image).unsqueeze(0).to(device)

    with torch.no_grad():
        prediction = model(image_tensor)

    # Filter predictions by confidence
    boxes = prediction[0]['boxes'][prediction[0]['scores'] > conf_threshold]
    scores = prediction[0]['scores'][prediction[0]['scores'] > conf_threshold]

    return image, boxes.cpu(), scores.cpu()
```

In [ ]:
```python
# Visualization function
def visualize_detection(image, boxes, scores):
    fig, ax = plt.subplots(1, figsize=(10, 10))
    ax.imshow(image)

    for box, score in zip(boxes, scores):
        x1, y1, x2, y2 = box
        rect = plt.Rectangle((x1, y1), x2-x1, y2-y1, fill=False, color='red', linewidth=2)
        ax.add_patch(rect)
        ax.text(x1, y1-5, f'{score:.2f}', bbox=dict(facecolor='white', alpha=0.7))

    plt.axis('off')
    plt.show()
```

In [40]:
```python
# Function to run inference on a test image
def run_inference(model_path, image_path):
    # Load model
    model = get_model(num_classes=2)
    checkpoint = torch.load(model_path)
    model.load_state_dict(checkpoint['model_state_dict'])
    model.to(device)
    model.eval()

    # Run detection
    image, boxes, scores = detect_phones(model, image_path, device)
    visualize_detection(image, boxes, scores)

    return boxes, scores
```

In [51]:
```python
run_inference('/content/mobile_detector_epoch_10.pth', '/content/drive/MyDrive/phone dataset/test/59381278d7b7ab85dfaa44e35c67
```

```
<ipython-input-40-90fb1b5ff341>:34: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default va
lue), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arb
itrary code during unpickling (See https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for more details).
In a future release, the default value for `weights_only` will be flipped to `True`. This limits the functions that could be ex
ecuted during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly all
owlisted by the user via `torch.serialization.add_safe_globals`. We recommend you start setting `weights_only=True` for any use
case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experi
mental feature.
  checkpoint = torch.load(model_path)
```



Out[51]: (tensor([[148.6618, 64.4105, 420.5332, 522.9233]]), tensor([0.9915]))

In [ ]:

In [ ]:

In [ ]: