```
In [79]: import numpy as np
         import matplotlib.pyplot as plt
         import torch
         import torch.nn as nn
         import torch.nn.functional as F
         from torchvision import models, transforms
         from torch.utils.data import Dataset, DataLoader
         import cv2
         import os
         import glob
         import scipy.io as sio
         import pandas as pd
         from sklearn.metrics import precision recall curve, average precision score
In [80]: # Device configuration
         device = torch.device('cuda' if torch.cuda.is available() else 'cpu')
In [81]: # Define transformations
         transform = transforms.Compose([
             transforms.ToTensor(),
             transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
         1)
In [82]: import urllib.request
         import tarfile
         import os
         def download and extract dataset():
             dataset url = "https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/BSR/BSR bsds500.tgz"
             tgz file = "BSR bsds500.tgz"
             if not os.path.exists('BSR'):
                 print("Downloading BSDS500 dataset...")
                 urllib.request.urlretrieve(dataset url, tgz file)
                 print("Extracting dataset...")
                 with tarfile.open(tgz file, 'r:gz') as tar:
                     tar.extractall()
```

```
print("Dataset extracted successfully!")
         # Call the function to download and extract the dataset
         download and extract dataset()
In [83]: # Define paths
         data dir = 'BSR/BSDS500/data'
         images dir = os.path.join(data dir, 'images')
         gt dir = os.path.join(data dir, 'groundTruth')
In [84]: # Dataset class
         class BSDS500Dataset(Dataset):
             def init (self, split='test', transform=None, target size=(320, 320)):
                 self.split = split
                 self.transform = transform
                 self.target size = target size
                 self.img paths = glob.glob(f'BSR/BSDS500/data/images/{split}/*.jpg')
                 self.gt paths = [p.replace('images', 'groundTruth').replace('.jpg', '.mat')
                                for p in self.img paths]
             def len (self): return len(self.img paths)
             def getitem (self, idx):
                 img = cv2.resize(cv2.cvtColor(cv2.imread(self.img paths[idx]), cv2.COLOR BGR2RGB), self.target size)
                 gt edges = np.sum([cv2.resize(sio.loadmat(self.gt paths[idx])['groundTruth'][0,i]['Boundaries'][0,0].astype(np.float32
                                             self.target size) for i in range(4)], axis=0)
                 return transform(img) if self.transform else img, torch.from numpy((gt edges > 0).astype(np.float32)).unsqueeze(0)
In [85]: # Define the Simple CNN Model
         class SimpleCNN(nn.Module):
             def init (self):
                 super(SimpleCNN, self). init ()
                 # First conv layer: 3 input channels (RGB), 8 output channels, 3x3 kernel
                 self.conv1 = nn.Conv2d(3, 8, kernel size=3, padding=1)
                 self.relu1 = nn.ReLU(inplace=True)
                 # Second conv layer: 8 input channels, 16 output channels, 3x3 kernel
                 self.conv2 = nn.Conv2d(8, 16, kernel size=3, padding=1)
                 self.relu2 = nn.ReLU(inplace=True)
```

```
self.conv3 = nn.Conv2d(16, 1, kernel size=3, padding=1)
                 self.sigmoid = nn.Sigmoid()
             def forward(self, x):
                 x = self.relu1(self.conv1(x))
                 x = self.relu2(self.conv2(x))
                 x = self.sigmoid(self.conv3(x))
                 return x
In [86]: # Define the VGG16-based Edge Detection Model with transpose convolution
         class VGG16EdgeDetection(nn.Module):
             def init (self, use bilinear=False):
                 super(VGG16EdgeDetection, self). init ()
                 # Load pretrained VGG16 model
                 vgg16 = models.vgg16(pretrained=True)
                 # Get feature layers up to the last pooling layer (excluding it)
                 features = list(vgg16.features.children())[:-1]
                 self.features = nn.Sequential(*features)
                 # Upsampling method: transpose convolution or bilinear interpolation
                 self.use bilinear = use bilinear
                 if not use bilinear:
                     # Transpose convolution to upsample feature maps back to original size
                     self.upconv1 = nn.ConvTranspose2d(512, 256, kernel size=3, stride=2, padding=1, output padding=1)
                     self.relu1 = nn.ReLU(inplace=True)
                     # 256 -> 128
                     self.upconv2 = nn.ConvTranspose2d(256, 128, kernel size=3, stride=2, padding=1, output padding=1)
                     self.relu2 = nn.ReLU(inplace=True)
                     # 128 -> 64
                     self.upconv3 = nn.ConvTranspose2d(128, 64, kernel size=3, stride=2, padding=1, output padding=1)
                     self.relu3 = nn.ReLU(inplace=True)
                     # 64 -> 32
```

# Third conv layer: 16 input channels, 1 output channel (edge map), 3x3 kernel

```
self.upconv4 = nn.ConvTranspose2d(64, 32, kernel size=3, stride=2, padding=1, output padding=1)
       self.relu4 = nn.ReLU(inplace=True)
    else:
        # Use convolutional layers after bilinear upsampling
       self.conv1 = nn.Conv2d(512, 256, kernel size=3, padding=1)
       self.relu1 = nn.ReLU(inplace=True)
        self.conv2 = nn.Conv2d(256, 128, kernel size=3, padding=1)
       self.relu2 = nn.ReLU(inplace=True)
       self.conv3 = nn.Conv2d(128, 64, kernel size=3, padding=1)
       self.relu3 = nn.ReLU(inplace=True)
        self.conv4 = nn.Conv2d(64, 32, kernel size=3, padding=1)
        self.relu4 = nn.ReLU(inplace=True)
   # Final convolution to output edge map
   self.final conv = nn.Conv2d(32, 1, kernel size=1)
    self.sigmoid = nn.Sigmoid()
def forward(self, x):
   # Original input size for reference
   input size = x.size()[2:]
   # Extract features using VGG16
   features = self.features(x)
   if not self.use bilinear:
       # Upsample using transpose convolutions
       x = self.relu1(self.upconv1(features))
       x = self.relu2(self.upconv2(x))
       x = self.relu3(self.upconv3(x))
       x = self.relu4(self.upconv4(x))
   else:
       # Upsample using bilinear interpolation + conv
       x = self.relu1(self.conv1(features))
       x = nn.functional.interpolate(x, scale factor=2, mode='bilinear', align corners=True)
       x = self.relu2(self.conv2(x))
       x = nn.functional.interpolate(x, scale factor=2, mode='bilinear', align corners=True)
```

```
x = self.relu3(self.conv3(x))
                     x = nn.functional.interpolate(x, scale factor=2, mode='bilinear', align corners=True)
                     x = self.relu4(self.conv4(x))
                     x = nn.functional.interpolate(x, scale factor=2, mode='bilinear', align corners=True)
                 # Final adjustment to match input size exactly (if needed)
                 if x.size()[2:] != input size:
                     x = nn.functional.interpolate(x, size=input size, mode='bilinear', align corners=True)
                 # Final convolution and sigmoid to get edge probabilities
                 x = self.sigmoid(self.final conv(x))
                 return x
In [87]: class HED(nn.Module):
             def init (self):
                 super(HED, self). init ()
                 # Load pretrained VGG16 without fully connected layers
                 vgg16 = models.vgg16(pretrained=True)
                 # Extract features before each pooling layer (excluding the final pooling)
                 # VGG16 structure: 2 conv -> pool -> 2 conv -> pool -> 3 conv -> pool -> 3 conv -> pool -> 3 conv -> pool
                 features = list(vgg16.features.children())
                 # Create feature extractors for each stage
                 self.stage1 = nn.Sequential(*features[:4]) # Before first pooling
                 self.stage2 = nn.Sequential(*features[4:9]) # Before second pooling
                 self.stage3 = nn.Sequential(*features[9:16]) # Before third pooling
                 self.stage4 = nn.Sequential(*features[16:23]) # Before fourth pooling
                 self.stage5 = nn.Sequential(*features[23:30]) # Before fifth pooling (exclude final pooling)
                 # Side output layers (1x1 convolutions)
                 self.side1 = nn.Conv2d(64, 1, kernel size=1)
                 self.side2 = nn.Conv2d(128, 1, kernel size=1)
                 self.side3 = nn.Conv2d(256, 1, kernel size=1)
                 self.side4 = nn.Conv2d(512, 1, kernel size=1)
                 self.side5 = nn.Conv2d(512, 1, kernel_size=1)
                 # Fusion layer (learnable weights)
```

```
self.fuse = nn.Conv2d(5, 1, kernel size=1)
   # Initialize weights for side outputs and fusion
    self. initialize weights()
def initialize weights(self):
   for m in [self.side1, self.side2, self.side3, self.side4, self.side5, self.fuse]:
       if isinstance(m, nn.Conv2d):
            nn.init.xavier normal (m.weight)
           if m.bias is not None:
                nn.init.constant (m.bias, 0)
def forward(self, x):
   # Store original input size for upsampling
   input_size = x.size()[2:]
   # Forward pass through VGG stages
   stage1 = self.stage1(x)
    stage2 = self.stage2(stage1)
   stage3 = self.stage3(stage2)
   stage4 = self.stage4(stage3)
   stage5 = self.stage5(stage4)
   # Side outputs with upsampling to original size
   side1 = self.side1(stage1)
   side1 = F.interpolate(side1, size=input size, mode='bilinear', align corners=True)
   side2 = self.side2(stage2)
    side2 = F.interpolate(side2, size=input size, mode='bilinear', align corners=True)
    side3 = self.side3(stage3)
    side3 = F.interpolate(side3, size=input size, mode='bilinear', align corners=True)
    side4 = self.side4(stage4)
   side4 = F.interpolate(side4, size=input size, mode='bilinear', align corners=True)
    side5 = self.side5(stage5)
   side5 = F.interpolate(side5, size=input size, mode='bilinear', align corners=True)
   # Concatenate side outputs and apply fusion layer
   fused = torch.cat([side1, side2, side3, side4, side5], dim=1)
```

```
fused = self.fuse(fused)
                 # Return all outputs (side outputs and fused output)
                 return [side1, side2, side3, side4, side5, fused]
In [88]: # Apply Canny edge detection with different blurring parameters
         def canny edge detection(img, low threshold=50, high threshold=150, sigma=1.0):
             # Convert to grayscale if needed
             if len(img.shape) == 3:
                 gray = cv2.cvtColor(img, cv2.COLOR RGB2GRAY)
             else:
                 gray = img
             # Calculate kernel size based on sigma
             kernel size = int(2 * np.ceil(3 * sigma) + 1)
             # Apply Gaussian blur
             blurred = cv2.GaussianBlur(gray, (kernel size, kernel size), sigma)
             # Run Canny edge detector
             edges = cv2.Canny(blurred, low threshold, high threshold)
             # Normalize to [0, 1]
             edges = edges / 255.0
             return edges
In [89]: def load models():
             models_dict = {}
             # Simple CNN
             models dict['CNN'] = SimpleCNN().to(device)
             models dict['CNN'].load state dict(torch.load('/kaggle/input/edge-detection/pytorch/default/1/simple cnn edge detector.pth
             # VGG16
             models dict['VGG16'] = VGG16EdgeDetection().to(device)
             models dict['VGG16'].load state dict(torch.load('/kaggle/input/edge-detection/pytorch/default/1/vgg16 edge detector 100epo
             # HED
```

```
models dict['HED'] = HED().to(device)
              hed checkpoint = torch.load('/kaggle/input/edge-detection/pytorch/default/1/best hed model.pth', map location=device)
              models dict['HED'].load state dict(hed checkpoint['model state dict'])
              return models dict
In [90]: # Evaluation metrics
          def calculate metrics(pred, target, threshold=0.5):
              pred bin = (pred > threshold).astype(np.float32)
              tp = np.sum(pred bin * target)
              fp = np.sum(pred bin * (1-target))
              fn = np.sum((1-pred bin) * target)
              precision = tp/(tp+fp+1e-10)
              recall = tp/(tp+fn+1e-10)
              return precision, recall, 2*precision*recall/(precision+recall+1e-10)
          def compare all(models dict, test loader, num images=4):
In [110...
              dataiter = iter(test loader)
              images, targets = next(dataiter)
              results = {'Canny': []}
              with torch.no grad():
                  for name, model in models dict.items():
                      if name == 'HED':
                          outputs = model(images.to(device))[-1].sigmoid().cpu().numpy()
                      elif name != 'Canny':
                          outputs = model(images.to(device)).sigmoid().cpu().numpy()
                      results[name] = outputs
              for i in range(num images):
                  plt.figure(figsize=(24, 5))
                  # Original image
                  plt.subplot(1,6,1)
                  img = images[i].permute(1,2,0).numpy() * [0.229,0.224,0.225] + [0.485,0.456,0.406]
                  plt.imshow(np.clip(img,0,1))
                  plt.title('Original')
                  plt.axis('off')
                  # Ground truth
```

```
plt.subplot(1,6,2)
                  plt.imshow(targets[i,0], cmap='gray')
                  plt.title('Ground Truth')
                  plt.axis('off')
                  # Model predictions
                  for j, (model name, preds) in enumerate(results.items()):
                      if model name == 'Canny': continue
                      plt.subplot(1,6,3+j-1)
                      if model name == 'CNN':
                          plt.imshow((preds[i,0]).astype(float), cmap='gray')
                      else:
                          plt.imshow((preds[i,0] > 0.5).astype(float), cmap='gray')
                      plt.title(model name)
                      plt.axis('off')
                  # Canny
                  plt.subplot(1,6,6)
                  img_np = images[i].cpu().permute(1,2,0).numpy()
                  img np = (img np * [0.229, 0.224, 0.225] + [0.485, 0.456, 0.406]) * 255
                  img np = img np.astype('uint8')
                  edges = canny edge detection(img np)
                  results['Canny'].append(edges)
                  plt.imshow(edges, cmap='gray')
                  plt.title('Canny')
                  plt.axis('off')
                  plt.show()
In [112...
          def main():
              models = load models()
              test dataset = BSDS500Dataset(split='test', transform=transform)
              test loader = DataLoader(test dataset, batch size=4, shuffle=True)
              print("Visualizing comparisons...")
              compare all(models, test loader)
```

print("\nQuantitative Metrics:")

metrics = {}

```
for name, model in models.items():
        if name == 'Canny': continue
        prec, rec, f1 = [], [], []
        for img, target in test loader:
            with torch.no grad():
                if name == 'HED':
                    pred = model(img.to(device))[-1].sigmoid().cpu().numpy()
                else:
                    pred = model(img.to(device)).sigmoid().cpu().numpy()
            for i in range(pred.shape[0]):
                p, r, f = calculate metrics(pred[i,0], target[i,0].numpy())
                prec.append(p); rec.append(r); f1.append(f)
        metrics[name] = {
            'Precision': np.mean(prec),
            'Recall': np.mean(rec),
            'F1-Score': np.mean(f1)
    # Add Canny metrics
    prec, rec, f1 = [], [], []
    for img, target in test loader:
        img = img.permute(0,2,3,1).numpy() * [0.229,0.224,0.225] + [0.485,0.456,0.406]
        for i in range(img.shape[0]):
            rgb image = (img[i] * 255).astype('uint8')
            gray = cv2.cvtColor(rgb image, cv2.COLOR RGB2GRAY)
            pred = canny edge detection(gray)
            p, r, f = calculate metrics(pred, target[i,0].numpy())
            prec.append(p); rec.append(r); f1.append(f)
    metrics['Canny'] = {
        'Precision': np.mean(prec),
        'Recall': np.mean(rec),
        'F1-Score': np.mean(f1)
    print(pd.DataFrame(metrics).T)
if __name__ == "__main__":
    main()
```

<ipython-input-89-9ac600bac3eb>:6: FutureWarning: You are using `torch.load` with `weights\_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary 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 executed 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 experimental feature.

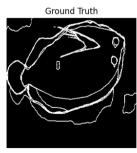
models\_dict['CNN'].load\_state\_dict(torch.load('/kaggle/input/edge-detection/pytorch/default/1/simple\_cnn\_edge\_detector.pth')) <ipython-input-89-9ac600bac3eb>:10: FutureWarning: You are using `torch.load` with `weights\_only=False` (the current default value), which uses the default pickle module 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 executed 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.

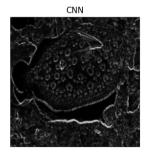
models\_dict['VGG16'].load\_state\_dict(torch.load('/kaggle/input/edge-detection/pytorch/default/1/vgg16\_edge\_detector\_100epoch
s.pth'))

cipython-input-89-9ac600bac3eb>:14: FutureWarning: You are using `torch.load` with `weights\_only=False` (the current default value), 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.

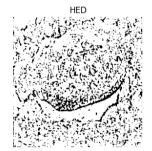
hed\_checkpoint = torch.load('/kaggle/input/edge-detection/pytorch/default/1/best\_hed\_model.pth', map\_location=device)
Visualizing comparisons...

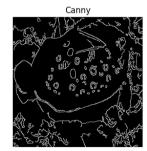


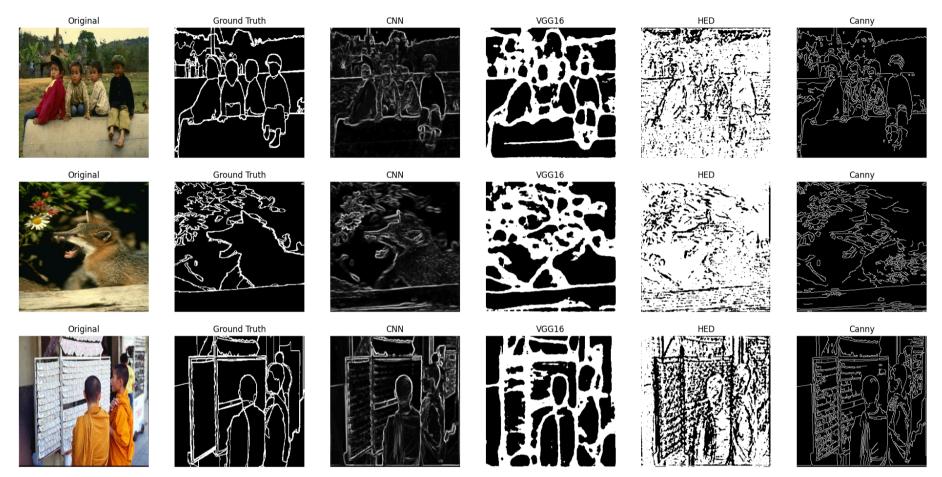












Quantitative Metrics:

	Precision	Recall	F1-Score
CNN	0.097347	1.000000	0.175830
VGG16	0.241982	0.841096	0.371135
HED	0.081753	0.663718	0.143595
Cannv	0.267305	0.217969	0.225288