```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, Subset
from torchvision.transforms import Compose, Resize, ToTensor
from torchvision.datasets import ImageFolder
import matplotlib.pyplot as plt
import numpy as np
import cv2
from torch.cuda.amp import GradScaler, autocast
import kagglehub
```

```
# Download the dataset using kagglehub
path = kagglehub.dataset_download("adityamahimkar/iqothnccd-lung-cancer-dataset")
print("Path to dataset files:", path)
```

```
Path to dataset files: /root/.cache/kagglehub/datasets/adityamahimkar/iqothnccd-lung-cancer-dataset/versions/2
```

```
# Load the dataset (replace with your dataset folder structure)
# Assuming the dataset contains images and labels in subdirectories.
dataset = ImageFolder(root=path, transform=Compose([Resize((128, 128)), ToTensor()]))

# Use a subset for faster execution (you can use the full dataset for real training)
train_data = Subset(dataset, range(100))  # 100 samples for training
test_data = Subset(dataset, range(20))    # 20 samples for testing

train_loader = DataLoader(train_data, batch_size=2, shuffle=True)
test_loader = DataLoader(test_data, batch_size=2, shuffle=False)
```

```
# U-Net model definition (Small version for simplicity)
class SmallUNet(nn.Module):
    def __init__(self):
        super(SmallUNet, self).__init__()
        self.encoder = nn.Sequential(
            nn.Conv2d(3, 16, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2)
        )
        self.middle = nn.Sequential(
            nn.Conv2d(16, 32, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2)
        )
        self.decoder = nn.Sequential(
            nn.ConvTranspose2d(32, 16, kernel_size=2, stride=2),
            nn.ReLU(),
            nn.ConvTranspose2d(16, 1, kernel_size=2, stride=2),
            nn.Sigmoid()
        )

    def forward(self, x):
        enc = self.encoder(x)
        middle = self.middle(enc)
        dec = self.decoder(middle)
        return dec
```

```
# Initialize the model
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = SmallUNet().to(device)

# Criterion and optimizer
criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=1e-4)
scaler = GradScaler()  # Enable mixed precision training
```

```
<ipython-input-11-34000cb21645>:8: FutureWarning: `torch.cuda.amp.GradScaler(args...)` is deprecated. Please use `torch.amp.GradScal
  scaler = GradScaler()  # Enable mixed precision training
```

```
# Training loop (simplified for 1 epoch)
epochs = 3
for epoch in range(epochs):
    model.train()
```

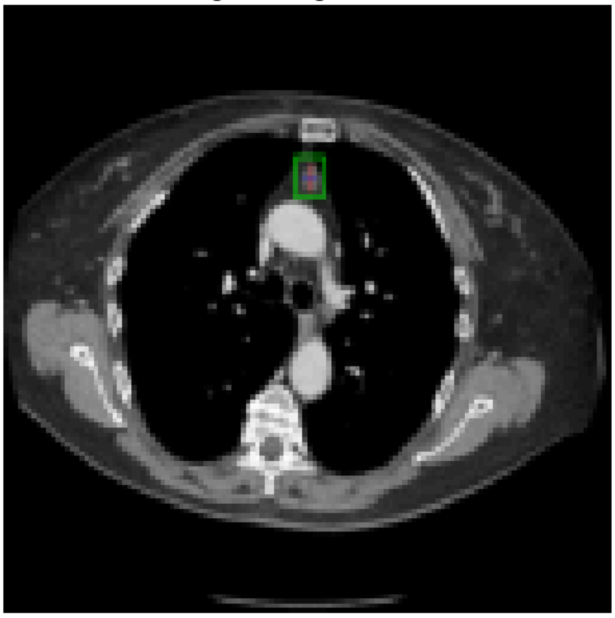
```
    train_loss = 0

    for images, _ in train_loader:
        images = images.to(device)
        masks = torch.rand_like(images[:, :1, :, :]).to(device)  # Placeholder masks

        optimizer.zero_grad()
        with autocast():  # Mixed precision
            outputs = model(images)
            loss = criterion(outputs, masks)
        scaler.scale(loss).backward()
        scaler.step(optimizer)
        scaler.update()

        train_loss += loss.item()

    print(f"Epoch {epoch+1}/{epochs}, Loss: {train_loss/len(train_loader):.4f}")
```

```
<ipython-input-12-f71c290c8706>:12: FutureWarning: `torch.cuda.amp.autocast(args...)` is deprecated. Please use `torch.amp.autocast
  with autocast():  # Mixed precision
Epoch 1/3, Loss: 0.7187
Epoch 2/3, Loss: 0.7156
Epoch 3/3, Loss: 0.7092
```

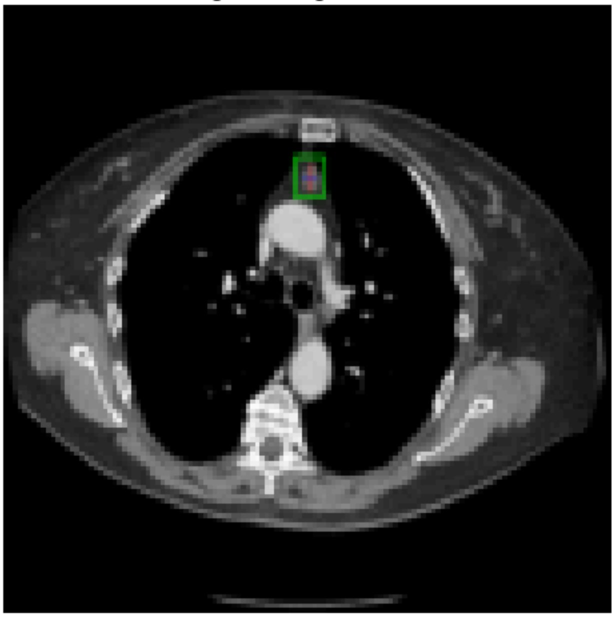
```
# Model evaluation (spotting dotted regions and marking them with red dots)
model.eval()
with torch.no_grad():
    images, _ = next(iter(test_loader))  # Take a batch from the test set
    images = images.to(device)
    outputs = model(images).cpu()  # Get predictions
    images = images.cpu()

    for i in range(len(images)):
        fig, axs = plt.subplots(2, 2, figsize=(10, 10))
        axs = axs.ravel()

        # Original image
        image = images[i].permute(1, 2, 0).numpy()  # Convert to numpy
        axs[0].imshow(image, cmap='gray')
        axs[0].set_title("Original Image - View 1")
        axs[0].axis("off")

        axs[1].imshow(image, cmap='gray')
        axs[1].set_title("Original Image - View 2")
        axs[1].axis("off")

        # Prediction
        prediction = outputs[i, 0].numpy()  # Single-channel prediction
        prediction = (prediction > 0.5).astype(float)  # Binary mask (threshold at 0.5)

        # Create overlay for prediction with red dots
        overlay = image.copy()
        prediction_coords = np.where(prediction == 1)  # Find coordinates of "dotted" regions (predicted areas)

        for y, x in zip(*prediction_coords):  # Mark red dots
            overlay[y, x, 0] = 255  # Red channel

        # Show prediction with red dots on top of the original image
        axs[2].imshow(image, cmap='gray')
        axs[2].set_title("Prediction (Red Dots for Dotted Regions)")
        axs[2].axis("off")

        axs[3].imshow(overlay, cmap='gray')
        axs[3].set_title("Prediction with Red Dots")
        axs[3].axis("off")

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

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integ
```

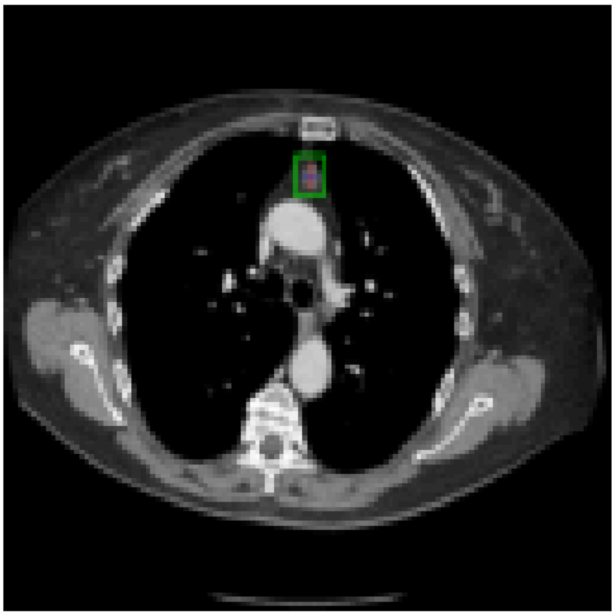
Original Image - View 1



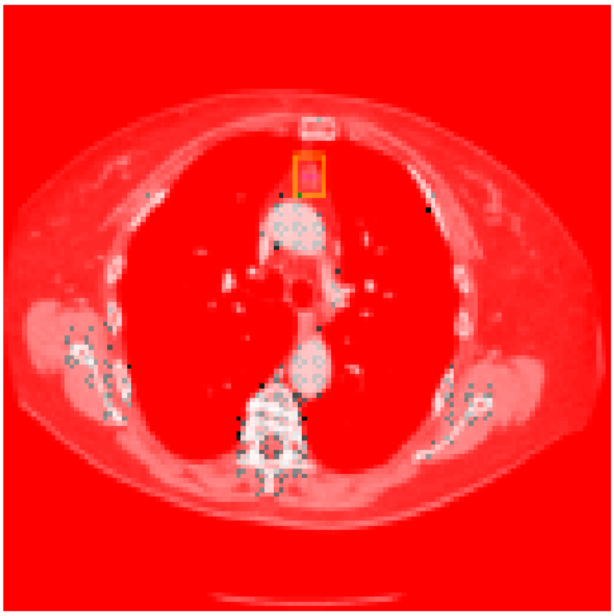
Original Image - View 2



Prediction (Red Dots for Dotted Regions)

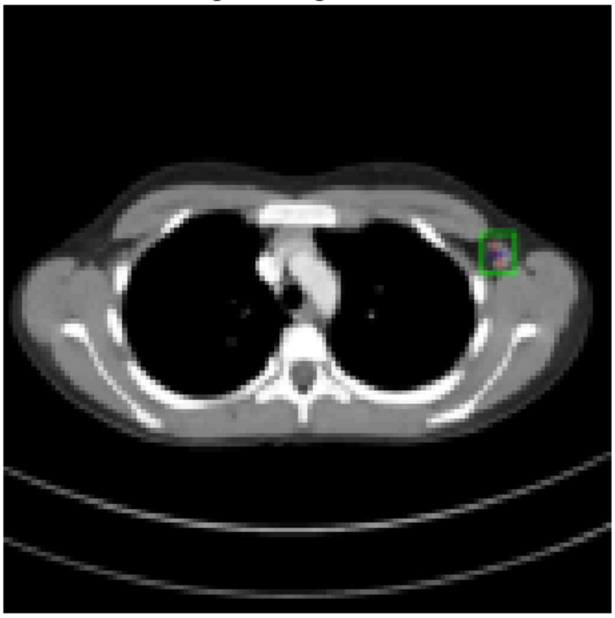


Prediction with Red Dots

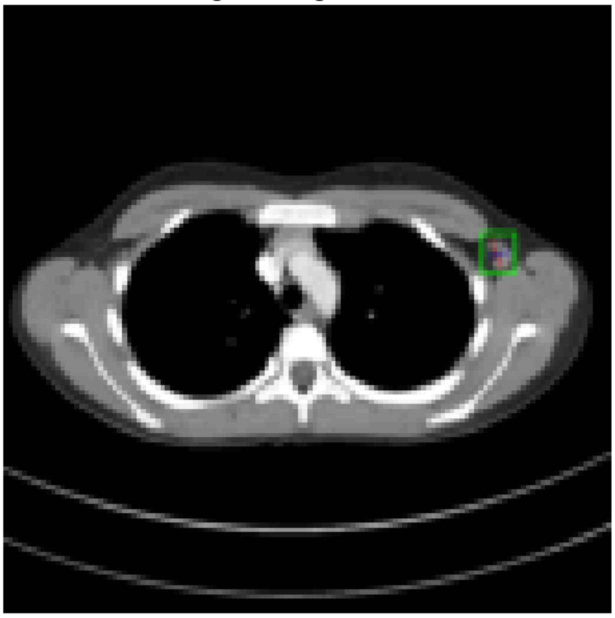


```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integ
```

Original Image - View 1



Original Image - View 2



Prediction (Red Dots for Dotted Regions)

Prediction with Red Dots