

```
In [23]: import torch
import torch.nn as nn
import torch.nn.functional as F
# Acknowledgement to
# https://github.com/kuangliu/pytorch-cifar,
# https://github.com/BIGBALLON/CIFAR-ZOO,

''' Swish activation '''
class Swish(nn.Module): # Swish(x) = x*σ(x)
    def __init__(self):
        super().__init__()

    def forward(self, input):
        return input * torch.sigmoid(input)

''' MLP '''
class MLP(nn.Module):
    def __init__(self, channel, num_classes):
        super(MLP, self).__init__()
        self.fc_1 = nn.Linear(28*28*1 if channel==1 else 32*32*3, 128)
        self.fc_2 = nn.Linear(128, 128)
        self.fc_3 = nn.Linear(128, num_classes)

    def forward(self, x):
        out = x.view(x.size(0), -1)
        out = F.relu(self.fc_1(out))
        out = F.relu(self.fc_2(out))
        out = self.fc_3(out)
        return out

''' ConvNet '''
class ConvNet(nn.Module):
    def __init__(self, channel, num_classes, net_width, net_depth, net_act, net_norm):
        super(ConvNet, self).__init__()

        self.features, shape_feat = self._make_layers(channel, net_width, net_depth)
        num_feat = shape_feat[0]*shape_feat[1]*shape_feat[2]
        self.classifier = nn.Linear(num_feat, num_classes)

    def forward(self, x):
        out = self.features(x)
        out = out.view(out.size(0), -1)
        out = self.classifier(out)
        return out

    def embed(self, x):
        out = self.features(x)
        out = out.view(out.size(0), -1)
        return out
```

```
def _get_activation(self, net_act):
    if net_act == 'sigmoid':
        return nn.Sigmoid()
    elif net_act == 'relu':
        return nn.ReLU(inplace=True)
    elif net_act == 'leakyrelu':
        return nn.LeakyReLU(negative_slope=0.01)
    elif net_act == 'swish':
        return Swish()
    else:
        exit('unknown activation function: %s'%net_act)

def _get_pooling(self, net_pooling):
    if net_pooling == 'maxpooling':
        return nn.MaxPool2d(kernel_size=2, stride=2)
    elif net_pooling == 'avgpooling':
        return nn.AvgPool2d(kernel_size=2, stride=2)
    elif net_pooling == 'none':
        return None
    else:
        exit('unknown net_pooling: %s'%net_pooling)

def _get_normlayer(self, net_norm, shape_feat):
    # shape_feat = (c*h*w)
    if net_norm == 'batchnorm':
        return nn.BatchNorm2d(shape_feat[0], affine=True)
    elif net_norm == 'layernorm':
        return nn.LayerNorm(shape_feat, elementwise_affine=True)
    elif net_norm == 'instancenorm':
        return nn.GroupNorm(shape_feat[0], shape_feat[0], affine=True)
    elif net_norm == 'groupnorm':
        return nn.GroupNorm(4, shape_feat[0], affine=True)
    elif net_norm == 'none':
        return None
    else:
        exit('unknown net_norm: %s'%net_norm)

def _make_layers(self, channel, net_width, net_depth, net_norm, net_act, net_po
layers = []
in_channels = channel
if im_size[0] == 28:
    im_size = (32, 32)
shape_feat = [in_channels, im_size[0], im_size[1]]
for d in range(net_depth):
    layers += [nn.Conv2d(in_channels, net_width, kernel_size=3, padding=3 i
    shape_feat[0] = net_width
    if net_norm != 'none':
        layers += [self._get_normlayer(net_norm, shape_feat)]
    layers += [self._get_activation(net_act)]
    in_channels = net_width
    if net_pooling != 'none':
        layers += [self._get_pooling(net_pooling)]
        shape_feat[1] // 2
        shape_feat[2] // 2

return nn.Sequential(*layers), shape_feat
```

```
''' LeNet '''
class LeNet(nn.Module):
    def __init__(self, channel, num_classes):
        super(LeNet, self).__init__()
        self.features = nn.Sequential(
            nn.Conv2d(channel, 6, kernel_size=5, padding=2 if channel==1 else 0),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(6, 16, kernel_size=5),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )
        self.fc_1 = nn.Linear(16 * 5 * 5, 120)
        self.fc_2 = nn.Linear(120, 84)
        self.fc_3 = nn.Linear(84, num_classes)

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        x = F.relu(self.fc_1(x))
        x = F.relu(self.fc_2(x))
        x = self.fc_3(x)
        return x


''' AlexNet '''
class AlexNet(nn.Module):
    def __init__(self, channel, num_classes):
        super(AlexNet, self).__init__()
        self.features = nn.Sequential(
            nn.Conv2d(channel, 128, kernel_size=5, stride=1, padding=4 if channel==1 else 0),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(128, 192, kernel_size=5, padding=2),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(192, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 192, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(192, 192, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )
        self.fc = nn.Linear(192 * 4 * 4, num_classes)

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        x = self.fc(x)
        return x
```

```
def embed(self, x):
    x = self.features(x)
    x = x.view(x.size(0), -1)
    return x

''' AlexNetBN '''
class AlexNetBN(nn.Module):
    def __init__(self, channel, num_classes):
        super(AlexNetBN, self).__init__()
        self.features = nn.Sequential(
            nn.Conv2d(channel, 128, kernel_size=5, stride=1, padding=4 if channel==3 else 2),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(128, 192, kernel_size=5, padding=2),
            nn.BatchNorm2d(192),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(192, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 192, kernel_size=3, padding=1),
            nn.BatchNorm2d(192),
            nn.ReLU(inplace=True),
            nn.Conv2d(192, 192, kernel_size=3, padding=1),
            nn.BatchNorm2d(192),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )
        self.fc = nn.Linear(192 * 4 * 4, num_classes)

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        x = self.fc(x)
        return x

    def embed(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        return x

''' VGG '''
cfg_vgg = {
    'VGG11': [64, 'M', 128, 'M', 256, 256, 'M', 512, 512, 'M', 512, 512, 'M'],
    'VGG13': [64, 64, 'M', 128, 128, 'M', 256, 256, 'M', 512, 512, 'M', 512, 512, 'M'],
    'VGG16': [64, 64, 'M', 128, 128, 'M', 256, 256, 256, 'M', 512, 512, 512, 'M', 512, 512, 'M'],
    'VGG19': [64, 64, 'M', 128, 128, 'M', 256, 256, 256, 256, 'M', 512, 512, 512, 512, 'M']
}
class VGG(nn.Module):
    def __init__(self, vgg_name, channel, num_classes, norm='instancenorm'):
        super(VGG, self).__init__()
        self.channel = channel
        self.features = self._make_layers(cfg_vgg[vgg_name], norm)
```

```
        self.classifier = nn.Linear(512 if vgg_name != 'VGG5' else 128, num_classes)

    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        x = self.classifier(x)
        return x

    def embed(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        return x

    def _make_layers(self, cfg, norm):
        layers = []
        in_channels = self.channel
        for ic, x in enumerate(cfg):
            if x == 'M':
                layers += [nn.MaxPool2d(kernel_size=2, stride=2)]
            else:
                layers += [nn.Conv2d(in_channels, x, kernel_size=3, padding=1),
                           nn.GroupNorm(x, x, affine=True) if norm=='instancenorm'
                           nn.ReLU(inplace=True)]
                in_channels = x
        layers += [nn.AvgPool2d(kernel_size=1, stride=1)]
        return nn.Sequential(*layers)

def VGG11(channel, num_classes):
    return VGG('VGG11', channel, num_classes)
def VGG11BN(channel, num_classes):
    return VGG('VGG11', channel, num_classes, norm='batchnorm')
def VGG13(channel, num_classes):
    return VGG('VGG13', channel, num_classes)
def VGG16(channel, num_classes):
    return VGG('VGG16', channel, num_classes)
def VGG19(channel, num_classes):
    return VGG('VGG19', channel, num_classes)

''' ResNet_AP '''
# The conv(stride=2) is replaced by conv(stride=1) + avgpool(kernel_size=2, stride=2)

class BasicBlock_AP(nn.Module):
    expansion = 1

    def __init__(self, in_planes, planes, stride=1, norm='instancenorm'):
        super(BasicBlock_AP, self).__init__()
        self.norm = norm
        self.stride = stride
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=3, stride=1, padding=1)
        self.bn1 = nn.GroupNorm(planes, planes, affine=True) if self.norm == 'instancenorm'
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=1, padding=1)
        self.bn2 = nn.GroupNorm(planes, planes, affine=True) if self.norm == 'instancenorm'

        self.shortcut = nn.Sequential()
```

```
if stride != 1 or in_planes != self.expansion * planes:
    self.shortcut = nn.Sequential(
        nn.Conv2d(in_planes, self.expansion * planes, kernel_size=1, stride
        nn.AvgPool2d(kernel_size=2, stride=2), # modification
        nn.GroupNorm(self.expansion * planes, self.expansion * planes, affi
    )

def forward(self, x):
    out = F.relu(self.bn1(self.conv1(x)))
    if self.stride != 1: # modification
        out = F.avg_pool2d(out, kernel_size=2, stride=2)
    out = self.bn2(self.conv2(out))
    out += self.shortcut(x)
    out = F.relu(out)
    return out

class Bottleneck_AP(nn.Module):
    expansion = 4

    def __init__(self, in_planes, planes, stride=1, norm='instancenorm'):
        super(Bottleneck_AP, self).__init__()
        self.norm = norm
        self.stride = stride
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=1, bias=False)
        self.bn1 = nn.GroupNorm(planes, planes, affine=True) if self.norm == 'insta
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=1, padding=1,
        self.bn2 = nn.GroupNorm(planes, planes, affine=True) if self.norm == 'insta
        self.conv3 = nn.Conv2d(planes, self.expansion * planes, kernel_size=1, bias
        self.bn3 = nn.GroupNorm(self.expansion * planes, self.expansion * planes, a

        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != self.expansion * planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, self.expansion * planes, kernel_size=1, stride
                nn.AvgPool2d(kernel_size=2, stride=2), # modification
                nn.GroupNorm(self.expansion * planes, self.expansion * planes, affi
            )

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = F.relu(self.bn2(self.conv2(out)))
        if self.stride != 1: # modification
            out = F.avg_pool2d(out, kernel_size=2, stride=2)
        out = self.bn3(self.conv3(out))
        out += self.shortcut(x)
        out = F.relu(out)
        return out

class ResNet_AP(nn.Module):
    def __init__(self, block, num_blocks, channel=3, num_classes=10, norm='instance
        super(ResNet_AP, self).__init__()
        self.in_planes = 64
        self.norm = norm
```

```
self.conv1 = nn.Conv2d(channel, 64, kernel_size=3, stride=1, padding=1, bias=False)
self.bn1 = nn.GroupNorm(64, 64, affine=True) if self.norm == 'instancenorm'
self.layer1 = self._make_layer(block, 64, num_blocks[0], stride=1)
self.layer2 = self._make_layer(block, 128, num_blocks[1], stride=2)
self.layer3 = self._make_layer(block, 256, num_blocks[2], stride=2)
self.layer4 = self._make_layer(block, 512, num_blocks[3], stride=2)
self.classifier = nn.Linear(512 * block.expansion * 3 * 3 if channel==1 else 512, num_classes)

def _make_layer(self, block, planes, num_blocks, stride):
    strides = [stride] + [1] * (num_blocks - 1)
    layers = []
    for stride in strides:
        layers.append(block(self.in_planes, planes, stride, self.norm))
        self.in_planes = planes * block.expansion
    return nn.Sequential(*layers)

def forward(self, x):
    out = F.relu(self.bn1(self.conv1(x)))
    out = self.layer1(out)
    out = self.layer2(out)
    out = self.layer3(out)
    out = self.layer4(out)
    out = F.avg_pool2d(out, kernel_size=1, stride=1) # modification
    out = out.view(out.size(0), -1)
    out = self.classifier(out)
    return out

def embed(self, x):
    out = F.relu(self.bn1(self.conv1(x)))
    out = self.layer1(out)
    out = self.layer2(out)
    out = self.layer3(out)
    out = self.layer4(out)
    out = F.avg_pool2d(out, kernel_size=1, stride=1) # modification
    out = out.view(out.size(0), -1)
    return out

def ResNet18BN_AP(channel, num_classes):
    return ResNet_AP(BasicBlock_AP, [2,2,2,2], channel=channel, num_classes=num_classes)

def ResNet18_AP(channel, num_classes):
    return ResNet_AP(BasicBlock_AP, [2,2,2,2], channel=channel, num_classes=num_classes)

''' ResNet '''

class BasicBlock(nn.Module):
    expansion = 1

    def __init__(self, in_planes, planes, stride=1, norm='instancenorm'):
        super(BasicBlock, self).__init__()
        self.norm = norm
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=3, stride=stride, padding=1, bias=False)
        self.bn1 = nn.GroupNorm(planes, planes, affine=True) if self.norm == 'instancenorm'
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=1, padding=1, bias=False)
        self.bn2 = nn.GroupNorm(planes, planes, affine=True) if self.norm == 'instancenorm'
```

```
        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != self.expansion*planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, self.expansion*planes, kernel_size=1, stride=s
                nn.GroupNorm(self.expansion*planes, self.expansion*planes, affine=T
            )

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.bn2(self.conv2(out))
        out += self.shortcut(x)
        out = F.relu(out)
        return out

class Bottleneck(nn.Module):
    expansion = 4

    def __init__(self, in_planes, planes, stride=1, norm='instancenorm'):
        super(Bottleneck, self).__init__()
        self.norm = norm
        self.conv1 = nn.Conv2d(in_planes, planes, kernel_size=1, bias=False)
        self.bn1 = nn.GroupNorm(planes, planes, affine=True) if self.norm == 'instan
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3, stride=stride, paddin
        self.bn2 = nn.GroupNorm(planes, planes, affine=True) if self.norm == 'insta
        self.conv3 = nn.Conv2d(planes, self.expansion*planes, kernel_size=1, bias=F
        self.bn3 = nn.GroupNorm(self.expansion*planes, self.expansion*planes, affin

        self.shortcut = nn.Sequential()
        if stride != 1 or in_planes != self.expansion*planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, self.expansion*planes, kernel_size=1, stride=s
                nn.GroupNorm(self.expansion*planes, self.expansion*planes, affine=T
            )

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = F.relu(self.bn2(self.conv2(out)))
        out = self.bn3(self.conv3(out))
        out += self.shortcut(x)
        out = F.relu(out)
        return out

class ResNet(nn.Module):
    def __init__(self, block, num_blocks, channel=3, num_classes=10, norm='instanc
        super(ResNet, self).__init__()
        self.in_planes = 64
        self.norm = norm

        self.conv1 = nn.Conv2d(channel, 64, kernel_size=3, stride=1, padding=1, bia
        self.bn1 = nn.GroupNorm(64, 64, affine=True) if self.norm == 'instancenorm'
        self.layer1 = self._make_layer(block, 64, num_blocks[0], stride=1)
        self.layer2 = self._make_layer(block, 128, num_blocks[1], stride=2)
        self.layer3 = self._make_layer(block, 256, num_blocks[2], stride=2)
```

```
self.layer4 = self._make_layer(block, 512, num_blocks[3], stride=2)
self.classifier = nn.Linear(512*block.expansion, num_classes)

def _make_layer(self, block, planes, num_blocks, stride):
    strides = [stride] + [1]*(num_blocks-1)
    layers = []
    for stride in strides:
        layers.append(block(self.in_planes, planes, stride, self.norm))
        self.in_planes = planes * block.expansion
    return nn.Sequential(*layers)

def forward(self, x):
    out = F.relu(self.bn1(self.conv1(x)))
    out = self.layer1(out)
    out = self.layer2(out)
    out = self.layer3(out)
    out = self.layer4(out)
    out = F.avg_pool2d(out, 4)
    out = out.view(out.size(0), -1)
    out = self.classifier(out)
    return out

def embed(self, x):
    out = F.relu(self.bn1(self.conv1(x)))
    out = self.layer1(out)
    out = self.layer2(out)
    out = self.layer3(out)
    out = self.layer4(out)
    out = F.avg_pool2d(out, 4)
    out = out.view(out.size(0), -1)
    return out

def ResNet18BN(channel, num_classes):
    return ResNet(BasicBlock, [2,2,2,2], channel=channel, num_classes=num_classes)

def ResNet18(channel, num_classes):
    return ResNet(BasicBlock, [2,2,2,2], channel=channel, num_classes=num_classes)

def ResNet34(channel, num_classes):
    return ResNet(BasicBlock, [3,4,6,3], channel=channel, num_classes=num_classes)

def ResNet50(channel, num_classes):
    return ResNet(Bottleneck, [3,4,6,3], channel=channel, num_classes=num_classes)

def ResNet101(channel, num_classes):
    return ResNet(Bottleneck, [3,4,23,3], channel=channel, num_classes=num_classes)

def ResNet152(channel, num_classes):
    return ResNet(Bottleneck, [3,8,36,3], channel=channel, num_classes=num_classes)
```

In [24]:

```
import time
import os
import numpy as np
import torch
import torch.nn as nn
```

```
import torch.nn.functional as F
from torch.utils.data import Dataset
from torchvision import datasets, transforms
from scipy.ndimage.interpolation import rotate as scipyrotate
#from networks import MLP, ConvNet, LeNet, AlexNet, AlexNetBN, VGG11, VGG11BN, ResN

def get_dataset(dataset, data_path):
    if dataset == 'MNIST':
        channel = 1
        im_size = (28, 28)
        num_classes = 10
        mean = [0.1307]
        std = [0.3081]
        transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize(0.1307, 0.3081)])
        dst_train = datasets.MNIST(data_path, train=True, download=True, transform=transform)
        dst_test = datasets.MNIST(data_path, train=False, download=True, transform=transform)
        class_names = [str(c) for c in range(num_classes)]

    elif dataset == 'FashionMNIST':
        channel = 1
        im_size = (28, 28)
        num_classes = 10
        mean = [0.2861]
        std = [0.3530]
        transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize(0.2861, 0.3530)])
        dst_train = datasets.FashionMNIST(data_path, train=True, download=True, transform=transform)
        dst_test = datasets.FashionMNIST(data_path, train=False, download=True, transform=transform)
        class_names = dst_train.classes

    elif dataset == 'SVHN':
        channel = 3
        im_size = (32, 32)
        num_classes = 10
        mean = [0.4377, 0.4438, 0.4728]
        std = [0.1980, 0.2010, 0.1970]
        transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize(0.4377, 0.4438, 0.4728)])
        dst_train = datasets.SVHN(data_path, split='train', download=True, transform=transform)
        dst_test = datasets.SVHN(data_path, split='test', download=True, transform=transform)
        class_names = [str(c) for c in range(num_classes)]

    elif dataset == 'CIFAR10':
        channel = 3
        im_size = (32, 32)
        num_classes = 10
        mean = [0.4914, 0.4822, 0.4465]
        std = [0.2023, 0.1994, 0.2010]
        transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize(0.4914, 0.4822, 0.4465)])
        dst_train = datasets.CIFAR10(data_path, train=True, download=True, transform=transform)
        dst_test = datasets.CIFAR10(data_path, train=False, download=True, transform=transform)
        class_names = dst_train.classes

    elif dataset == 'CIFAR100':
        channel = 3
        im_size = (32, 32)
        num_classes = 100
        mean = [0.5071, 0.4866, 0.4409]
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    std = [0.2673, 0.2564, 0.2762]
    transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize(
        dst_train = datasets.CIFAR100(data_path, train=True, download=True, transform=transform)
        dst_test = datasets.CIFAR100(data_path, train=False, download=True, transform=transform)
        class_names = dst_train.classes

    elif dataset == 'TinyImageNet':
        channel = 3
        im_size = (64, 64)
        num_classes = 200
        mean = [0.485, 0.456, 0.406]
        std = [0.229, 0.224, 0.225]
        data = torch.load(os.path.join(data_path, 'tinyimagenet.pt'), map_location='cpu')
        class_names = data['classes']

        images_train = data['images_train']
        labels_train = data['labels_train']
        images_train = images_train.detach().float() / 255.0
        labels_train = labels_train.detach()
        for c in range(channel):
            images_train[:,c] = (images_train[:,c] - mean[c])/std[c]
        dst_train = TensorDataset(images_train, labels_train) # no augmentation

        images_val = data['images_val']
        labels_val = data['labels_val']
        images_val = images_val.detach().float() / 255.0
        labels_val = labels_val.detach()

        for c in range(channel):
            images_val[:, c] = (images_val[:, c] - mean[c]) / std[c]

        dst_test = TensorDataset(images_val, labels_val) # no augmentation

    else:
        exit('unknown dataset: %s' % dataset)

    testloader = torch.utils.data.DataLoader(dst_test, batch_size=256, shuffle=False)
    return channel, im_size, num_classes, class_names, mean, std, dst_train, dst_test
```



```
class TensorDataset(Dataset):
    def __init__(self, images, labels): # images: n x c x h x w tensor
        self.images = images.detach().float()
        self.labels = labels.detach()

    def __getitem__(self, index):
        return self.images[index], self.labels[index]

    def __len__(self):
        return self.images.shape[0]
```

```
def get_default_convnet_setting():
    net_width, net_depth, net_act, net_norm, net_pooling = 128, 3, 'relu', 'instanc
    return net_width, net_depth, net_act, net_norm, net_pooling

def get_network(model, channel, num_classes, im_size=(32, 32)):
    torch.random.manual_seed(int(time.time() * 1000) % 100000)
    net_width, net_depth, net_act, net_norm, net_pooling = get_default_convnet_setting()

    if model == 'MLP':
        net = MLP(channel=channel, num_classes=num_classes)
    elif model == 'ConvNet':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'LeNet':
        net = LeNet(channel=channel, num_classes=num_classes)
    elif model == 'AlexNet':
        net = AlexNet(channel=channel, num_classes=num_classes)
    elif model == 'AlexNetBN':
        net = AlexNetBN(channel=channel, num_classes=num_classes)
    elif model == 'VGG11':
        net = VGG11(channel=channel, num_classes=num_classes)
    elif model == 'VGG11BN':
        net = VGG11BN(channel=channel, num_classes=num_classes)
    elif model == 'ResNet18':
        net = ResNet18(channel=channel, num_classes=num_classes)
    elif model == 'ResNet18BN_AP':
        net = ResNet18BN_AP(channel=channel, num_classes=num_classes)
    elif model == 'ResNet18BN':
        net = ResNet18BN(channel=channel, num_classes=num_classes)

    elif model == 'ConvNetD1':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetD2':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetD3':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetD4':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetD7':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)

    elif model == 'ConvNetW32':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=32, net_d
    elif model == 'ConvNetW64':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=64, net_d
    elif model == 'ConvNetW128':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=128, net_
    elif model == 'ConvNetW256':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=256, net_

    elif model == 'ConvNetAS':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetAR':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetAL':
```

```
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetASwish':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetASwishBN':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)

    elif model == 'ConvNetNN':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetBN':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetLN':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetIN':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetGN':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)

    elif model == 'ConvNetNP':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetMP':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)
    elif model == 'ConvNetAP':
        net = ConvNet(channel=channel, num_classes=num_classes, net_width=net_width)

    else:
        net = None
        exit('unknown model: %s' %model)

    gpu_num = torch.cuda.device_count()
    if gpu_num>0:
        device = 'cuda'
        if gpu_num>1:
            net = nn.DataParallel(net)
    else:
        device = 'cpu'
    net = net.to(device)

    return net


def get_time():
    return str(time.strftime("%Y-%m-%d %H:%M:%S"), time.localtime()))


def distance_wb(gwr, gws):
    shape = gwr.shape
    if len(shape) == 4: # conv, out*in*h*w
        gwr = gwr.reshape(shape[0], shape[1] * shape[2] * shape[3])
        gws = gws.reshape(shape[0], shape[1] * shape[2] * shape[3])
    elif len(shape) == 3: # Layernorm, C*h*w
        gwr = gwr.reshape(shape[0], shape[1] * shape[2])
        gws = gws.reshape(shape[0], shape[1] * shape[2])
    elif len(shape) == 2: # Linear, out*in
        tmp = 'do nothing'
```

```
    elif len(shape) == 1: # batchnorm/instancenorm, C; groupnorm x, bias
        gwr = gwr.reshape(1, shape[0])
        gws = gws.reshape(1, shape[0])
        return torch.tensor(0, dtype=torch.float, device=gwr.device)

    dis_weight = torch.sum(1 - torch.sum(gwr * gws, dim=-1)) / (torch.norm(gwr, dim=1))
    dis = dis_weight
    return dis

def match_loss(gw_syn, gw_real, args):
    dis = torch.tensor(0.0).to(args.device)

    if args.dis_metric == 'ours':
        for ig in range(len(gw_real)):
            gwr = gw_real[ig]
            gws = gw_syn[ig]
            dis += distance_wb(gwr, gws)

    elif args.dis_metric == 'mse':
        gw_real_vec = []
        gw_syn_vec = []
        for ig in range(len(gw_real)):
            gw_real_vec.append(gw_real[ig].reshape((-1)))
            gw_syn_vec.append(gw_syn[ig].reshape((-1)))
        gw_real_vec = torch.cat(gw_real_vec, dim=0)
        gw_syn_vec = torch.cat(gw_syn_vec, dim=0)
        dis = torch.sum((gw_syn_vec - gw_real_vec)**2)

    elif args.dis_metric == 'cos':
        gw_real_vec = []
        gw_syn_vec = []
        for ig in range(len(gw_real)):
            gw_real_vec.append(gw_real[ig].reshape((-1)))
            gw_syn_vec.append(gw_syn[ig].reshape((-1)))
        gw_real_vec = torch.cat(gw_real_vec, dim=0)
        gw_syn_vec = torch.cat(gw_syn_vec, dim=0)
        dis = 1 - torch.sum(gw_real_vec * gw_syn_vec, dim=-1) / (torch.norm(gw_real_vec, dim=1))

    else:
        exit('unknown distance function: %s' % args.dis_metric)

    return dis

def get_loops(ipc):
    # Get the two hyper-parameters of outer-Loop and inner-Loop.
    # The following values are empirically good.
    if ipc == 1:
        outer_loop, inner_loop = 1, 1
    elif ipc == 10:
        outer_loop, inner_loop = 10, 50
    elif ipc == 20:
        outer_loop, inner_loop = 20, 25
```

```
        elif ipc == 30:
            outer_loop, inner_loop = 30, 20
        elif ipc == 40:
            outer_loop, inner_loop = 40, 15
        elif ipc == 50:
            outer_loop, inner_loop = 50, 10
        else:
            outer_loop, inner_loop = 0, 0
            exit('loop hyper-parameters are not defined for %d ipc'%ipc)
    return outer_loop, inner_loop

def epoch(mode, dataloader, net, optimizer, criterion, args, aug):
    loss_avg, acc_avg, num_exp = 0, 0, 0
    net = net.to(args.device)
    criterion = criterion.to(args.device)

    if mode == 'train':
        net.train()
    else:
        net.eval()

    for i_batch, datum in enumerate(dataloader):

        img = datum[0].float().to(args.device)
        #print(datum, img)
        #datum[0] = torch.tensor(datum[0])
        if aug:
            if args.dsa:
                img = DiffAugment(img, args.dsa_strategy, param=args.dsa_param)
            else:
                img = augment(img, args.dc_aug_param, device=args.device)
        # Ensure `lab` is 1D by adding an extra dimension if it's a scalar
        lab = datum[1].to(args.device).long()
        if lab.ndim == 0: # If Lab is a scalar
            lab = lab.unsqueeze(0)
        #print(lab)
        #Lab = Lab.unsqueeze(0)
        if img.ndim == 3: # If shape is [128, 32, 32]
            img = img.unsqueeze(0)

        n_b = lab.shape[0]

        output = net(img)
        loss = criterion(output, lab)
        acc = np.sum(np.equal(np.argmax(output.cpu().data.numpy(), axis=-1), lab.cpu().data.numpy()))

        loss_avg += loss.item()*n_b
        acc_avg += acc
        num_exp += n_b

        if mode == 'train':
            optimizer.zero_grad()
            loss.backward()
```

```
        optimizer.step()

    loss_avg /= num_exp
    acc_avg /= num_exp

    return loss_avg, acc_avg


def evaluate_synset(it_eval, net, images_train, labels_train, testloader, args):
    net = net.to(args.device)
    images_train = images_train.to(args.device)
    labels_train = labels_train.to(args.device)
    lr = float(args.lr_net)
    Epoch = int(args.epoch_eval_train)
    lr_schedule = [Epoch//2+1]
    optimizer = torch.optim.SGD(net.parameters(), lr=lr, momentum=0.9, weight_decay
    criterion = nn.CrossEntropyLoss().to(args.device)

    dst_train = TensorDataset(images_train, labels_train)
    trainloader = torch.utils.data.DataLoader(dst_train, batch_size=args.batch_trai

    start = time.time()
    for ep in range(Epoch+1):
        loss_train, acc_train = epoch('train', trainloader, net, optimizer, criteri
        if ep in lr_schedule:
            lr *= 0.1
            optimizer = torch.optim.SGD(net.parameters(), lr=lr, momentum=0.9, weig

        time_train = time.time() - start
        loss_test, acc_test = epoch('test', testloader, net, optimizer, criterion, args
        print('%s Evaluate_%02d: epoch = %04d train time = %d s train loss = %.6f train

    return net, acc_train, acc_test


def augment(images, dc_aug_param, device):
    # This can be sped up in the future.

    if dc_aug_param != None and dc_aug_param['strategy'] != 'none':
        scale = dc_aug_param['scale']
        crop = dc_aug_param['crop']
        rotate = dc_aug_param['rotate']
        noise = dc_aug_param['noise']
        strategy = dc_aug_param['strategy']

        shape = images.shape
        mean = []
        for c in range(shape[1]):
            mean.append(float(torch.mean(images[:,c])))

        def cropfun(i):
            im_ = torch.zeros(shape[1],shape[2]+crop*2,shape[3]+crop*2, dtype=torch
            for c in range(shape[1]):
                im_[c] = mean[c]
```

```
im_[:, crop:crop+shape[2], crop:crop+shape[3]] = images[i]
r, c = np.random.permutation(crop*2)[0], np.random.permutation(crop*2)[1]
images[i] = im_[:, r:r+shape[2], c:c+shape[3]]


def scalefun(i):
    h = int((np.random.uniform(1 - scale, 1 + scale)) * shape[2])
    w = int((np.random.uniform(1 - scale, 1 + scale)) * shape[2])
    tmp = F.interpolate(images[i:i + 1], [h, w], )[0]
    mhw = max(h, w, shape[2], shape[3])
    im_ = torch.zeros(shape[1], mhw, mhw, dtype=torch.float, device=device)
    r = int((mhw - h) / 2)
    c = int((mhw - w) / 2)
    im_[:, r:r + h, c:c + w] = tmp
    r = int((mhw - shape[2]) / 2)
    c = int((mhw - shape[3]) / 2)
    images[i] = im_[:, r:r + shape[2], c:c + shape[3]]


def rotatefun(i):
    im_ = scipyrotate(images[i].cpu().data.numpy(), angle=np.random.randint(-45, 45))
    r = int((im_.shape[-2] - shape[-2]) / 2)
    c = int((im_.shape[-1] - shape[-1]) / 2)
    images[i] = torch.tensor(im_[:, r:r + shape[-2], c:c + shape[-1]], dtype=torch.float).to(device)
    images[i] = images[i].float()


def noisefun(i):
    images[i] = images[i] + noise * torch.randn(shape[1:], dtype=torch.float).to(device)
    images[i] = images[i].float()

augs = strategy.split('_')

for i in range(shape[0]):
    choice = np.random.permutation(augs)[0] # randomly implement one augmentation
    if choice == 'crop':
        cropfun(i)
    elif choice == 'scale':
        scalefun(i)
    elif choice == 'rotate':
        rotatefun(i)
    elif choice == 'noise':
        noisefun(i)

return images


def get_daparam(dataset, model, model_eval, ipc):
    # We find that augmentation doesn't always benefit the performance.
    # So we do augmentation for some of the settings.

    dc_aug_param = dict()
    dc_aug_param['crop'] = 4
    dc_aug_param['scale'] = 0.2
    dc_aug_param['rotate'] = 45
    dc_aug_param['noise'] = 0.001
    dc_aug_param['strategy'] = 'none'

    if dataset == 'MNIST':
```

```
dc_aug_param['strategy'] = 'crop_scale_rotate'

if model_eval in ['ConvNetBN']: # Data augmentation makes model training with BN
    dc_aug_param['strategy'] = 'crop_noise'

return dc_aug_param

def get_eval_pool(eval_mode, model, model_eval):
    if eval_mode == 'M': # multiple architectures
        model_eval_pool = ['MLP', 'ConvNet', 'LeNet', 'AlexNet', 'VGG11', 'ResNet18']
    elif eval_mode == 'B': # multiple architectures with BatchNorm for DM experiments
        model_eval_pool = ['ConvNetBN', 'ConvNetASwishBN', 'AlexNetBN', 'VGG11BN', 'ResNet18BN']
    elif eval_mode == 'W': # ablation study on network width
        model_eval_pool = ['ConvNetW32', 'ConvNetW64', 'ConvNetW128', 'ConvNetW256']
    elif eval_mode == 'D': # ablation study on network depth
        model_eval_pool = ['ConvNetD1', 'ConvNetD2', 'ConvNetD3', 'ConvNetD4']
    elif eval_mode == 'A': # ablation study on network activation function
        model_eval_pool = ['ConvNetAS', 'ConvNetAR', 'ConvNetAL', 'ConvNetASwish']
    elif eval_mode == 'P': # ablation study on network pooling layer
        model_eval_pool = ['ConvNetNP', 'ConvNetMP', 'ConvNetAP']
    elif eval_mode == 'N': # ablation study on network normalization Layer
        model_eval_pool = ['ConvNetNN', 'ConvNetBN', 'ConvNetLN', 'ConvNetIN', 'ConvNetAS']
    elif eval_mode == 'S': # itself
        if 'BN' in model:
            print('Attention: Here I will replace BN with IN in evaluation, as the BN is not supported by PyTorch')
            model_eval_pool = [model[:model.index('BN')]] if 'BN' in model else [model]
        else:
            model_eval_pool = [model]
    else:
        model_eval_pool = [model_eval]
return model_eval_pool

class ParamDiffAug():
    def __init__(self):
        self.aug_mode = 'S' #'multiple or single'
        self.prob_flip = 0.5
        self.ratio_scale = 1.2
        self.ratio_rotate = 15.0
        self.ratio_crop_pad = 0.125
        self.ratio_cutout = 0.5 # the size would be 0.5x0.5
        self.brightness = 1.0
        self.saturation = 2.0
        self.contrast = 0.5

    def set_seed_DiffAug(self):
        if param.latestseed == -1:
            return
        else:
            torch.random.manual_seed(param.latestseed)
            param.latestseed += 1

    def DiffAugment(x, strategy='', seed = -1, param = None):
```

```

if strategy == 'None' or strategy == 'none' or strategy == '':
    return x

if seed == -1:
    param.Siamese = False
else:
    param.Siamese = True

param.latestseed = seed

if strategy:
    if param.aug_mode == 'M': # original
        for p in strategy.split('_'):
            for f in AUGMENT_FNS[p]:
                x = f(x, param)
    elif param.aug_mode == 'S':
        pbties = strategy.split('_')
        set_seed_DiffAug(param)
        p = pbties[torch.randint(0, len(pbties), size=(1,)).item()]
        for f in AUGMENT_FNS[p]:
            x = f(x, param)
    else:
        exit('unknown augmentation mode: %s'%param.aug_mode)
    x = x.contiguous()
return x

# We implement the following differentiable augmentation strategies based on the co
def rand_scale(x, param):
    # x>1, max scale
    # sx, sy: (0, +oo), 1: orignal size, 0.5: enlarge 2 times
    ratio = param.ratio_scale
    set_seed_DiffAug(param)
    sx = torch.rand(x.shape[0]) * (ratio - 1.0/ratio) + 1.0/ratio
    set_seed_DiffAug(param)
    sy = torch.rand(x.shape[0]) * (ratio - 1.0/ratio) + 1.0/ratio
    theta = [[[sx[i], 0, 0],
              [0, sy[i], 0],] for i in range(x.shape[0])]
    theta = torch.tensor(theta, dtype=torch.float)
    if param.Siamese: # Siamese augmentation:
        theta[:] = theta[0]
    grid = F.affine_grid(theta, x.shape).to(x.device)
    x = F.grid_sample(x, grid)
    return x

def rand_rotate(x, param): # [-180, 180], 90: anticlockwise 90 degree
    ratio = param.ratio_rotate
    set_seed_DiffAug(param)
    theta = (torch.rand(x.shape[0]) - 0.5) * 2 * ratio / 180 * float(np.pi)
    theta = [[[torch.cos(theta[i]), torch.sin(-theta[i]), 0],
              [torch.sin(theta[i]), torch.cos(theta[i]), 0],] for i in range(x.shape[0])]
    theta = torch.tensor(theta, dtype=torch.float)
    if param.Siamese: # Siamese augmentation:
        theta[:] = theta[0]
    grid = F.affine_grid(theta, x.shape).to(x.device)

```

```
x = F.grid_sample(x, grid)
return x

def rand_flip(x, param):
    prob = param.prob_flip
    set_seed_DiffAug(param)
    randf = torch.rand(x.size(0), 1, 1, 1, device=x.device)
    if param.Siamese: # Siamese augmentation:
        randf[:] = randf[0]
    return torch.where(randf < prob, x.flip(3), x)

def rand_brightness(x, param):
    ratio = param.brightness
    set_seed_DiffAug(param)
    randb = torch.rand(x.size(0), 1, 1, 1, dtype=x.dtype, device=x.device)
    if param.Siamese: # Siamese augmentation:
        randb[:] = randb[0]
    x = x + (randb - 0.5)*ratio
    return x

def rand_saturation(x, param):
    ratio = param.saturation
    x_mean = x.mean(dim=1, keepdim=True)
    set_seed_DiffAug(param)
    rands = torch.rand(x.size(0), 1, 1, 1, dtype=x.dtype, device=x.device)
    if param.Siamese: # Siamese augmentation:
        rands[:] = rands[0]
    x = (x - x_mean) * (rands * ratio) + x_mean
    return x

def rand_contrast(x, param):
    ratio = param.contrast
    x_mean = x.mean(dim=[1, 2, 3], keepdim=True)
    set_seed_DiffAug(param)
    randc = torch.rand(x.size(0), 1, 1, 1, dtype=x.dtype, device=x.device)
    if param.Siamese: # Siamese augmentation:
        randc[:] = randc[0]
    x = (x - x_mean) * (randc + ratio) + x_mean
    return x

def rand_crop(x, param):
    # The image is padded on its surrounding and then cropped.
    ratio = param.ratio_crop_pad
    shift_x, shift_y = int(x.size(2) * ratio + 0.5), int(x.size(3) * ratio + 0.5)
    set_seed_DiffAug(param)
    translation_x = torch.randint(-shift_x, shift_x + 1, size=[x.size(0), 1, 1], de
    set_seed_DiffAug(param)
    translation_y = torch.randint(-shift_y, shift_y + 1, size=[x.size(0), 1, 1], de
    if param.Siamese: # Siamese augmentation:
        translation_x[:] = translation_x[0]
        translation_y[:] = translation_y[0]
```

```

grid_batch, grid_x, grid_y = torch.meshgrid(
    torch.arange(x.size(0), dtype=torch.long, device=x.device),
    torch.arange(x.size(2), dtype=torch.long, device=x.device),
    torch.arange(x.size(3), dtype=torch.long, device=x.device),
)
grid_x = torch.clamp(grid_x + translation_x + 1, 0, x.size(2) + 1)
grid_y = torch.clamp(grid_y + translation_y + 1, 0, x.size(3) + 1)
x_pad = F.pad(x, [1, 1, 1, 1, 0, 0, 0, 0])
x = x_pad.permute(0, 2, 3, 1).contiguous()[grid_batch, grid_x, grid_y].permute()
return x

def rand_cutout(x, param):
    ratio = param.ratio_cutout
    cutout_size = int(x.size(2) * ratio + 0.5), int(x.size(3) * ratio + 0.5)
    set_seed_DiffAug(param)
    offset_x = torch.randint(0, x.size(2) + (1 - cutout_size[0] % 2), size=[x.size(
    set_seed_DiffAug(param)
    offset_y = torch.randint(0, x.size(3) + (1 - cutout_size[1] % 2), size=[x.size(
    if param.Siamese: # Siamese augmentation:
        offset_x[:] = offset_x[0]
        offset_y[:] = offset_y[0]
    grid_batch, grid_x, grid_y = torch.meshgrid(
        torch.arange(x.size(0), dtype=torch.long, device=x.device),
        torch.arange(cutout_size[0], dtype=torch.long, device=x.device),
        torch.arange(cutout_size[1], dtype=torch.long, device=x.device),
    )
    grid_x = torch.clamp(grid_x + offset_x - cutout_size[0] // 2, min=0, max=x.size
    grid_y = torch.clamp(grid_y + offset_y - cutout_size[1] // 2, min=0, max=x.size
    mask = torch.ones(x.size(0), x.size(2), x.size(3), dtype=x.dtype, device=x.dev
    mask[grid_batch, grid_x, grid_y] = 0
    x = x * mask.unsqueeze(1)
    return x

AUGMENT_FNS = {
    'color': [rand_brightness, rand_saturation, rand_contrast],
    'crop': [rand_crop],
    'cutout': [rand_cutout],
    'flip': [rand_flip],
    'scale': [rand_scale],
    'rotate': [rand_rotate],
}

```

C:\Users\rupin\AppData\Local\Temp\ipykernel_19572\760089213.py:9: DeprecationWarning : Please import `rotate` from the `scipy.ndimage` namespace; the `scipy.ndimage.interpolation` namespace is deprecated and will be removed in SciPy 2.0.0.

```
from scipy.ndimage.interpolation import rotate as scipyrotate
```

In [25]:

```

import torch
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset, random_split, ConcatDataset
import time
from torchvision import transforms
import matplotlib.pyplot as plt
from torchvision.utils import make_grid

```

```
import os
from PIL import Image
import pandas as pd

In [26]: # MHIST LOADER

class MHISTDataset(Dataset):
    def __init__(self, annotations_file, img_dir, partition='train', transform=None):

        self.img_labels = pd.read_csv(annotations_file)
        self.img_dir = img_dir
        self.transform = transform
        self.partition = partition

        self.img_labels = self.img_labels[self.img_labels['Partition'] == partition]

        self.label_mapping = {'SSA': 0, 'HP': 1}

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

    def __getitem__(self, idx):
        img_name = os.path.join(self.img_dir, self.img_labels.iloc[idx, 0])
        image = Image.open(img_name).convert("RGB")

        label_str = self.img_labels.iloc[idx, 1]
        label = self.label_mapping[label_str]

        if self.transform:
            image = self.transform(image)

        return image, label
```

```
In [27]: class Args:
    def __init__(self):
        self.device = 'cpu'
        self.lr_net = 0.01
        self.epoch_eval_train = 20
        self.batch_train = 128
        self.dsa = False
        self.dsa_strategy = ''
        self.dc_aug_param = None
        self.dis_metric = 'cos'

args = Args()
```

```
In [28]: # Task 1 - Question 2 - Part a

img_dir = "C:/Users/rupin/Downloads/ECE1512_2024F_ProjectA_submission_files/submiss
annotations_file = r"C:\Users\rupin\Downloads\ECE1512_2024F_ProjectA_submission_fil

import torch
import torch.optim as optim
from torch.optim.lr_scheduler import CosineAnnealingLR
from torch.utils.data import DataLoader
```

```
from torchvision import transforms
import torch.nn.functional as F
from tqdm import tqdm
import time

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

# Define the image transformations
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])

# Load MHIST Dataset
mhist_dataset = MHISTDataset(annotations_file=annotations_file, img_dir=img_dir, tr
batch_size = 128
num_classes = 2

# Split into training and testing sets
train_size = int(0.8 * len(mhist_dataset))
test_size = len(mhist_dataset) - train_size
train_dataset, test_dataset = torch.utils.data.random_split(mhist_dataset, [train_s

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

model_name = 'ConvNetW64'
channel = 3 # RGB images
im_size = (224, 224) # Image size
model = get_network(model_name, channel, num_classes, im_size).to(device)

optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9, weight_decay=5e-4)
scheduler = CosineAnnealingLR(optimizer, T_max=20)
criterion = nn.CrossEntropyLoss()

def compute_flops(model, input_size):
    inputs = torch.randn(input_size).to(device)
    macs = profile_macs(model, inputs)
    flops = macs * 2
    return flops

def evaluate_model(model, test_loader):
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in test_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    accuracy = 100 * correct / total
```

```
    return accuracy

epochs = 20
for epoch_num in range(epochs):
    model.train()
    running_loss = 0.0
    correct = 0
    total = 0

    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)
        optimizer.zero_grad()

        outputs = model(images)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

        running_loss += loss.item()
    scheduler.step()

    train_acc = 100 * correct / total
    print(f"Epoch {epoch_num + 1}/{epochs}, Loss: {running_loss:.4f}, Accuracy: {train_acc:.2f}%")

test_accuracy = evaluate_model(model, test_loader)
print(f"Test Accuracy: {test_accuracy:.2f}%")
```

Using device: cpu
Epoch 1/20, Loss: 144.1497, Accuracy: 58.74%
Epoch 2/20, Loss: 45.0875, Accuracy: 64.77%
Epoch 3/20, Loss: 14.1904, Accuracy: 75.23%
Epoch 4/20, Loss: 5.9388, Accuracy: 82.76%
Epoch 5/20, Loss: 4.0381, Accuracy: 87.18%
Epoch 6/20, Loss: 3.0991, Accuracy: 91.15%
Epoch 7/20, Loss: 2.3857, Accuracy: 94.94%
Epoch 8/20, Loss: 2.0017, Accuracy: 96.44%
Epoch 9/20, Loss: 1.6930, Accuracy: 97.64%
Epoch 10/20, Loss: 1.4931, Accuracy: 98.16%
Epoch 11/20, Loss: 1.2817, Accuracy: 98.91%
Epoch 12/20, Loss: 1.1753, Accuracy: 99.25%
Epoch 13/20, Loss: 1.0687, Accuracy: 99.60%
Epoch 14/20, Loss: 1.0172, Accuracy: 99.83%
Epoch 15/20, Loss: 0.9650, Accuracy: 99.83%
Epoch 16/20, Loss: 0.9304, Accuracy: 100.00%
Epoch 17/20, Loss: 0.9088, Accuracy: 100.00%
Epoch 18/20, Loss: 0.8980, Accuracy: 100.00%
Epoch 19/20, Loss: 0.8838, Accuracy: 100.00%
Epoch 20/20, Loss: 0.8820, Accuracy: 100.00%
Test Accuracy: 71.72%

In [29]: # Task 1 - Question 2 - Part b

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

img_dir = "C:/Users/rupin/Downloads/ECE1512_2024F_ProjectA_submission_files/submiss
annotations_file = r"C:\Users\rupin\Downloads\ECE1512_2024F_ProjectA_submission_fil

transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])
mhist_dataset = MHISTDataset(annotations_file=annotations_file, img_dir=img_dir, tr
batch_size = 128
real_data_loader = DataLoader(mhist_dataset, batch_size=batch_size, shuffle=True)

num_classes = 2
channel = 3
im_size = (224, 224)
synthetic_data = torch.randn(num_classes, channel, im_size[0], im_size[1], requires
requires_grad=False)

model_name = 'ConvNetD7'
model = get_network(model_name, channel, num_classes, im_size).to(device)

K = 200
T = 10
eta_S = 0.1
lambda_param = 0.01

optimizer_syn = optim.SGD([synthetic_data], lr=eta_S)

class Args:
    def __init__(self, device, dis_metric='cos'):
        self.device = device
        self.dis_metric = dis_metric

args = Args(device=device)

for k in range(K):
    # Randomly initialize the model parameters
    model.apply(lambda m: m.reset_parameters() if hasattr(m, 'reset_parameters') el
    optimizer_model = optim.SGD(model.parameters(), lr=0.01)

    for t in range(T):
        optimizer_syn.zero_grad()
        optimizer_model.zero_grad()

        real_images, real_labels = next(iter(real_data_loader))
        real_images, real_labels = real_images.to(device), real_labels.to(device)

        indices = torch.randperm(real_images.size(0))[:2]
        real_images_subset = real_images[indices]
        real_labels_subset = real_labels[indices]

        outputs_real = model(real_images_subset)
        outputs_syn = model(synthetic_data)
```

```
loss = match_loss(outputs_syn, outputs_real, args) + lambda_param  
loss.backward()  
optimizer_syn.step()  
  
print(f"Iteration {k + 1}/{K}, SAM Loss: {loss.item()}")
```

```
Using device: cpu
Iteration 1/200, SAM Loss: 1.3139328956604004
Iteration 2/200, SAM Loss: 0.055756933987140656
Iteration 3/200, SAM Loss: 0.028593668714165688
Iteration 4/200, SAM Loss: 0.07843620330095291
Iteration 5/200, SAM Loss: 0.8124338984489441
Iteration 6/200, SAM Loss: 0.018386075273156166
Iteration 7/200, SAM Loss: 0.04344416409730911
Iteration 8/200, SAM Loss: 0.46725964546203613
Iteration 9/200, SAM Loss: 0.0379529669880867
Iteration 10/200, SAM Loss: 0.15229232609272003
Iteration 11/200, SAM Loss: 0.18234969675540924
Iteration 12/200, SAM Loss: 0.027177700772881508
Iteration 13/200, SAM Loss: 0.05029202252626419
Iteration 14/200, SAM Loss: 0.12217003852128983
Iteration 15/200, SAM Loss: 0.029774555936455727
Iteration 16/200, SAM Loss: 0.2619844675064087
Iteration 17/200, SAM Loss: 0.18472470343112946
Iteration 18/200, SAM Loss: 0.10635150223970413
Iteration 19/200, SAM Loss: 0.01598329283297062
Iteration 20/200, SAM Loss: 0.8956540822982788
Iteration 21/200, SAM Loss: 0.13103307783603668
Iteration 22/200, SAM Loss: 0.12565208971500397
Iteration 23/200, SAM Loss: 0.20528562366962433
Iteration 24/200, SAM Loss: 0.13512666523456573
Iteration 25/200, SAM Loss: 0.046334750950336456
Iteration 26/200, SAM Loss: 0.06733299046754837
Iteration 27/200, SAM Loss: 0.03697068244218826
Iteration 28/200, SAM Loss: 0.10944540053606033
Iteration 29/200, SAM Loss: 0.028074750676751137
Iteration 30/200, SAM Loss: 0.05312085896730423
Iteration 31/200, SAM Loss: 0.5923842191696167
Iteration 32/200, SAM Loss: 0.4121595025062561
Iteration 33/200, SAM Loss: 0.7208618521690369
Iteration 34/200, SAM Loss: 0.07303036004304886
Iteration 35/200, SAM Loss: 0.3168885111808777
Iteration 36/200, SAM Loss: 0.27961277961730957
Iteration 37/200, SAM Loss: 0.3464624881744385
Iteration 38/200, SAM Loss: 0.05675721913576126
Iteration 39/200, SAM Loss: 0.014644155278801918
Iteration 40/200, SAM Loss: 0.017499634996056557
Iteration 41/200, SAM Loss: 0.060796745121479034
Iteration 42/200, SAM Loss: 0.2036859542131424
Iteration 43/200, SAM Loss: 0.4300534129142761
Iteration 44/200, SAM Loss: 0.13352538645267487
Iteration 45/200, SAM Loss: 0.013445386663079262
Iteration 46/200, SAM Loss: 0.730274498462677
Iteration 47/200, SAM Loss: 0.0894930437207222
Iteration 48/200, SAM Loss: 0.07865387946367264
Iteration 49/200, SAM Loss: 0.017155298963189125
Iteration 50/200, SAM Loss: 0.03130365163087845
Iteration 51/200, SAM Loss: 0.9145160913467407
Iteration 52/200, SAM Loss: 0.29158735275268555
Iteration 53/200, SAM Loss: 0.16154684126377106
Iteration 54/200, SAM Loss: 0.488844096660614
Iteration 55/200, SAM Loss: 0.18342776596546173
```

Iteration 56/200, SAM Loss: 0.556141197681427
Iteration 57/200, SAM Loss: 0.04204631596803665
Iteration 58/200, SAM Loss: 0.18076808750629425
Iteration 59/200, SAM Loss: 0.057893164455890656
Iteration 60/200, SAM Loss: 0.2028353363275528
Iteration 61/200, SAM Loss: 1.4177563190460205
Iteration 62/200, SAM Loss: 0.10621834546327591
Iteration 63/200, SAM Loss: 0.2961006760597229
Iteration 64/200, SAM Loss: 0.09224671870470047
Iteration 65/200, SAM Loss: 0.041900403797626495
Iteration 66/200, SAM Loss: 0.3097159266471863
Iteration 67/200, SAM Loss: 0.04921329766511917
Iteration 68/200, SAM Loss: 0.11981392651796341
Iteration 69/200, SAM Loss: 0.052866704761981964
Iteration 70/200, SAM Loss: 0.2298167496919632
Iteration 71/200, SAM Loss: 0.01836235262453556
Iteration 72/200, SAM Loss: 0.18103273212909698
Iteration 73/200, SAM Loss: 0.9353293776512146
Iteration 74/200, SAM Loss: 0.04379863291978836
Iteration 75/200, SAM Loss: 0.1429019719362259
Iteration 76/200, SAM Loss: 0.08967519551515579
Iteration 77/200, SAM Loss: 0.12837345898151398
Iteration 78/200, SAM Loss: 0.0851140096783638
Iteration 79/200, SAM Loss: 0.1856357604265213
Iteration 80/200, SAM Loss: 0.7789507508277893
Iteration 81/200, SAM Loss: 0.038852520287036896
Iteration 82/200, SAM Loss: 0.17865528166294098
Iteration 83/200, SAM Loss: 0.4380595088005066
Iteration 84/200, SAM Loss: 0.06497205048799515
Iteration 85/200, SAM Loss: 1.6494450569152832
Iteration 86/200, SAM Loss: 0.12168533354997635
Iteration 87/200, SAM Loss: 0.3360442519187927
Iteration 88/200, SAM Loss: 0.17928190529346466
Iteration 89/200, SAM Loss: 0.4882991313934326
Iteration 90/200, SAM Loss: 0.03550858050584793
Iteration 91/200, SAM Loss: 0.2750948667526245
Iteration 92/200, SAM Loss: 0.035171933472156525
Iteration 93/200, SAM Loss: 0.02189774252474308
Iteration 94/200, SAM Loss: 0.056023187935352325
Iteration 95/200, SAM Loss: 0.901598334312439
Iteration 96/200, SAM Loss: 0.08635527640581131
Iteration 97/200, SAM Loss: 0.037247784435749054
Iteration 98/200, SAM Loss: 0.04878927022218704
Iteration 99/200, SAM Loss: 0.7768771648406982
Iteration 100/200, SAM Loss: 0.03758091479539871
Iteration 101/200, SAM Loss: 0.06361640244722366
Iteration 102/200, SAM Loss: 0.1293358951807022
Iteration 103/200, SAM Loss: 0.12589241564273834
Iteration 104/200, SAM Loss: 0.04025036841630936
Iteration 105/200, SAM Loss: 1.40143620967865
Iteration 106/200, SAM Loss: 0.12335003167390823
Iteration 107/200, SAM Loss: 0.1777672916650772
Iteration 108/200, SAM Loss: 0.09422386437654495
Iteration 109/200, SAM Loss: 0.08362198621034622
Iteration 110/200, SAM Loss: 0.09149707108736038
Iteration 111/200, SAM Loss: 0.056076712906360626

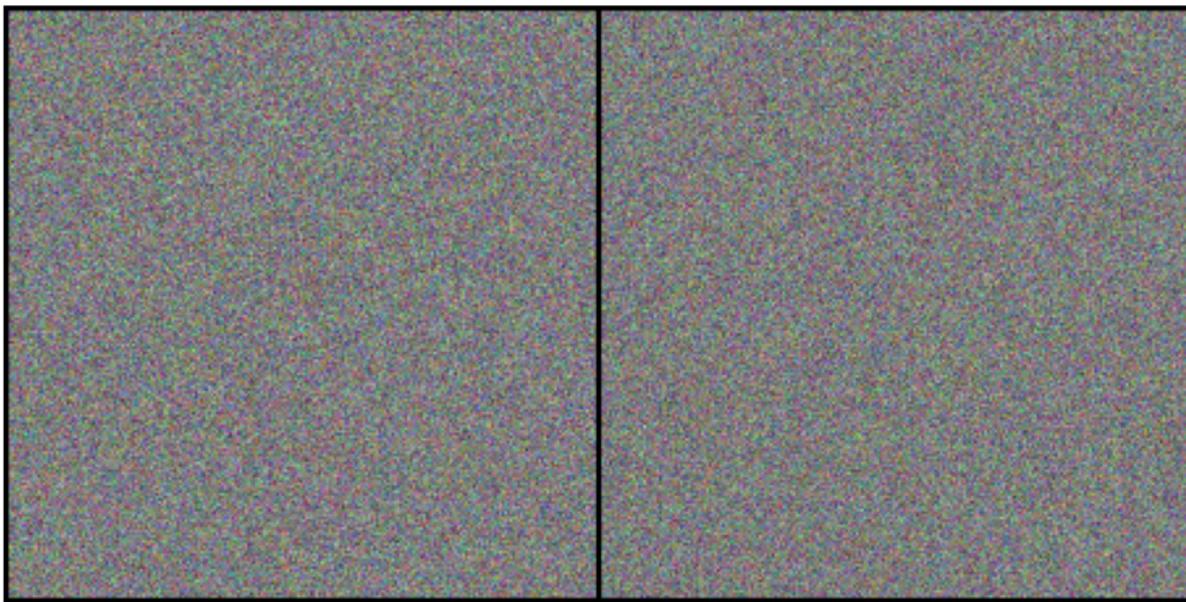
Iteration 112/200, SAM Loss: 0.10251093655824661
Iteration 113/200, SAM Loss: 0.17539937794208527
Iteration 114/200, SAM Loss: 0.14913715422153473
Iteration 115/200, SAM Loss: 0.040385372936725616
Iteration 116/200, SAM Loss: 0.3145732283592224
Iteration 117/200, SAM Loss: 0.9944014549255371
Iteration 118/200, SAM Loss: 0.16574300825595856
Iteration 119/200, SAM Loss: 0.12929768860340118
Iteration 120/200, SAM Loss: 0.011812636628746986
Iteration 121/200, SAM Loss: 0.09460318833589554
Iteration 122/200, SAM Loss: 0.2634100317955017
Iteration 123/200, SAM Loss: 0.023177990689873695
Iteration 124/200, SAM Loss: 0.65901118516922
Iteration 125/200, SAM Loss: 0.1145550087094307
Iteration 126/200, SAM Loss: 0.01931900717318058
Iteration 127/200, SAM Loss: 0.2848992347717285
Iteration 128/200, SAM Loss: 0.08674246817827225
Iteration 129/200, SAM Loss: 0.03563458472490311
Iteration 130/200, SAM Loss: 0.15088321268558502
Iteration 131/200, SAM Loss: 0.05276186019182205
Iteration 132/200, SAM Loss: 0.20345087349414825
Iteration 133/200, SAM Loss: 0.1742432862520218
Iteration 134/200, SAM Loss: 0.23587454855442047
Iteration 135/200, SAM Loss: 0.0864834263920784
Iteration 136/200, SAM Loss: 0.18447668850421906
Iteration 137/200, SAM Loss: 0.12528397142887115
Iteration 138/200, SAM Loss: 0.043340571224689484
Iteration 139/200, SAM Loss: 0.2584289312362671
Iteration 140/200, SAM Loss: 0.17891110479831696
Iteration 141/200, SAM Loss: 0.12719793617725372
Iteration 142/200, SAM Loss: 0.09743870049715042
Iteration 143/200, SAM Loss: 0.12190795689821243
Iteration 144/200, SAM Loss: 0.019382664933800697
Iteration 145/200, SAM Loss: 0.6601561307907104
Iteration 146/200, SAM Loss: 0.0401153638958931
Iteration 147/200, SAM Loss: 0.1899731308221817
Iteration 148/200, SAM Loss: 0.18624962866306305
Iteration 149/200, SAM Loss: 1.2885663509368896
Iteration 150/200, SAM Loss: 0.07364512234926224
Iteration 151/200, SAM Loss: 0.10921234637498856
Iteration 152/200, SAM Loss: 0.06036479026079178
Iteration 153/200, SAM Loss: 0.042135901749134064
Iteration 154/200, SAM Loss: 0.08090157061815262
Iteration 155/200, SAM Loss: 0.06906045228242874
Iteration 156/200, SAM Loss: 0.23410262167453766
Iteration 157/200, SAM Loss: 0.2601439356803894
Iteration 158/200, SAM Loss: 0.37946122884750366
Iteration 159/200, SAM Loss: 0.1223728135228157
Iteration 160/200, SAM Loss: 0.05875105410814285
Iteration 161/200, SAM Loss: 0.05905861407518387
Iteration 162/200, SAM Loss: 0.04800880700349808
Iteration 163/200, SAM Loss: 0.17412038147449493
Iteration 164/200, SAM Loss: 0.05366212874650955
Iteration 165/200, SAM Loss: 0.2351330667734146
Iteration 166/200, SAM Loss: 0.24699975550174713
Iteration 167/200, SAM Loss: 0.09325189143419266

```
Iteration 168/200, SAM Loss: 0.021676549687981606
Iteration 169/200, SAM Loss: 0.0848841741681099
Iteration 170/200, SAM Loss: 0.015975603833794594
Iteration 171/200, SAM Loss: 0.03523535281419754
Iteration 172/200, SAM Loss: 0.09027958661317825
Iteration 173/200, SAM Loss: 0.01706922985613346
Iteration 174/200, SAM Loss: 0.31566476821899414
Iteration 175/200, SAM Loss: 0.021218368783593178
Iteration 176/200, SAM Loss: 0.06326103955507278
Iteration 177/200, SAM Loss: 0.3945666551589966
Iteration 178/200, SAM Loss: 0.03763110190629959
Iteration 179/200, SAM Loss: 0.028428802266716957
Iteration 180/200, SAM Loss: 0.17561109364032745
Iteration 181/200, SAM Loss: 0.20935262739658356
Iteration 182/200, SAM Loss: 0.16602130234241486
Iteration 183/200, SAM Loss: 0.15656007826328278
Iteration 184/200, SAM Loss: 0.2584623694419861
Iteration 185/200, SAM Loss: 0.06478668004274368
Iteration 186/200, SAM Loss: 1.2721495628356934
Iteration 187/200, SAM Loss: 0.17611391842365265
Iteration 188/200, SAM Loss: 0.16923590004444122
Iteration 189/200, SAM Loss: 0.236149862408638
Iteration 190/200, SAM Loss: 0.01703990437090397
Iteration 191/200, SAM Loss: 0.012336382642388344
Iteration 192/200, SAM Loss: 0.482740581035614
Iteration 193/200, SAM Loss: 0.11776978522539139
Iteration 194/200, SAM Loss: 0.16575898230075836
Iteration 195/200, SAM Loss: 0.07751632481813431
Iteration 196/200, SAM Loss: 0.13500483334064484
Iteration 197/200, SAM Loss: 0.09604383260011673
Iteration 198/200, SAM Loss: 0.23090530931949615
Iteration 199/200, SAM Loss: 0.03170258551836014
Iteration 200/200, SAM Loss: 0.01573331095278263
```

```
In [30]: # Task 1 - Question 2 - Part c
def visualize_synthetic_images(synthetic_data, num_classes=2):
    grid_img = make_grid(synthetic_data, nrow=num_classes, normalize=True, scale_ea

    plt.figure(figsize=(10, 5))
    plt.imshow(grid_img.permute(1, 2, 0).cpu().numpy())
    plt.title("Visualized Synthetic (Condensed) Images")
    plt.axis('off')
    plt.show()
visualize_synthetic_images(synthetic_data, num_classes=num_classes)
```

Visualized Synthetic (Condensed) Images



In [31]: # Task 1 - Question 2 - Part d

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

img_dir = "C:/Users/rupin/Downloads/ECE1512_2024F_ProjectA_submission_files/submiss
annotations_file = r"C:\Users\rupin\Downloads\ECE1512_2024F_ProjectA_submission_fil

transform = transforms.Compose([
    transforms.Resize((224, 224)), # Resize images to a fixed size (e.g., 224x224
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])

mhist_dataset = MHISTDataset(annotations_file=annotations_file, img_dir=img_dir, tr
batch_size = 128
real_data_loader = DataLoader(mhist_dataset, batch_size=batch_size, shuffle=True)

num_classes = 2
channel = 3
im_size = (224, 224)

# Gaussian initialization for synthetic data
mean = 0.0
std = 1.0
synthetic_data = torch.normal(mean=mean, std=std, size=(num_classes, channel, im_si

def visualize_synthetic_images(synthetic_data, num_classes=2):

    grid_img = make_grid(synthetic_data.detach().cpu(), nrow=num_classes, normalize

    plt.figure(figsize=(10, 5))
    plt.imshow(grid_img.permute(1, 2, 0).numpy())
    plt.title("Visualized Synthetic (Condensed) Images")
    plt.axis('off')
```

```
plt.show()

model_name = 'ConvNetD3'
model = get_network(model_name, channel, num_classes, im_size).to(device)

K = 200
T = 10
eta_S = 0.1
lambda_param = 0.01

optimizer_syn = optim.SGD([synthetic_data], lr=eta_S)

class Args:
    def __init__(self, device, dis_metric='cos'):
        self.device = device
        self.dis_metric = dis_metric

args = Args(device=device)

for k in range(K):
    model.apply(lambda m: m.reset_parameters() if hasattr(m, 'reset_parameters') else None)
    optimizer_model = optim.SGD(model.parameters(), lr=0.01)

    for t in range(T):
        optimizer_syn.zero_grad()
        optimizer_model.zero_grad()

        real_images, real_labels = next(iter(real_data_loader))
        real_images, real_labels = real_images.to(device), real_labels.to(device)

        indices = torch.randperm(real_images.size(0))[:2]
        real_images_subset = real_images[indices]
        real_labels_subset = real_labels[indices]

        outputs_real = model(real_images_subset)
        outputs_syn = model(synthetic_data)

        loss = match_loss(outputs_syn, outputs_real, args) + lambda_param
        loss.backward()
        optimizer_syn.step()

        print(f"Iteration {k + 1}/{K}, SAM Loss: {loss.item()}")

    if (k + 1) % 5 == 0:
        visualize_synthetic_images(synthetic_data, num_classes=num_classes)
```

Using device: cpu
Iteration 1/200, SAM Loss: 0.9179607033729553
Iteration 2/200, SAM Loss: 0.1470094472169876
Iteration 3/200, SAM Loss: 0.5626929998397827
Iteration 4/200, SAM Loss: 0.5002634525299072
Iteration 5/200, SAM Loss: 0.9048941135406494

Visualized Synthetic (Condensed) Images



Iteration 6/200, SAM Loss: 1.8179564476013184

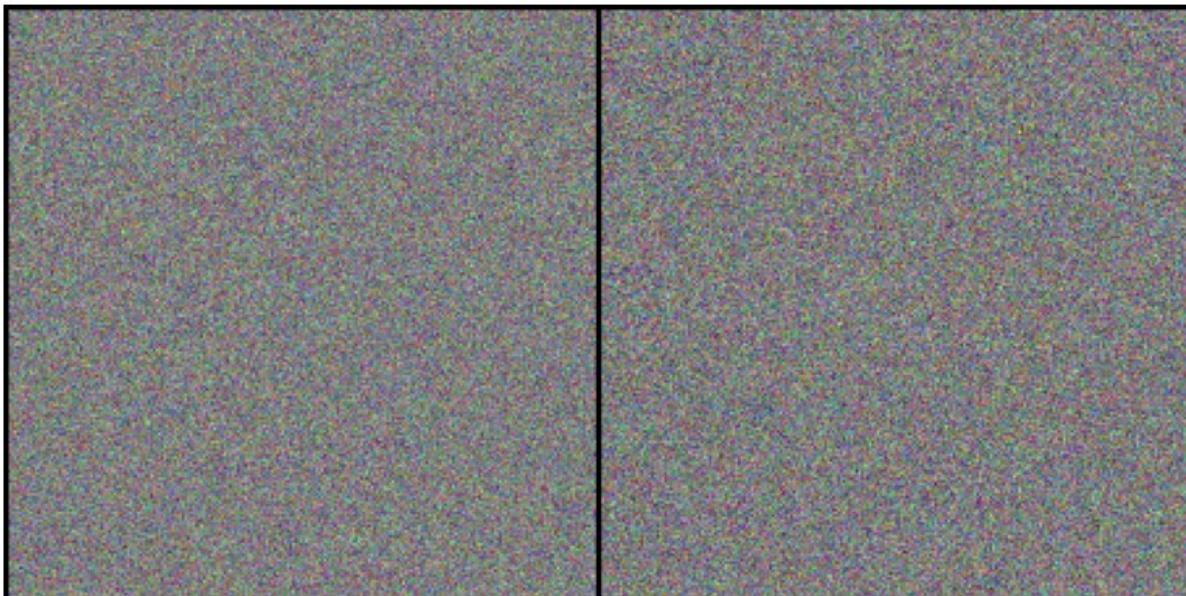
Iteration 7/200, SAM Loss: 0.08841288834810257

Iteration 8/200, SAM Loss: 0.2776220440864563

Iteration 9/200, SAM Loss: 0.2009405642747879

Iteration 10/200, SAM Loss: 1.1365973949432373

Visualized Synthetic (Condensed) Images



Iteration 11/200, SAM Loss: 0.6865944862365723

Iteration 12/200, SAM Loss: 0.35522574186325073

Iteration 13/200, SAM Loss: 0.2988209128379822

Iteration 14/200, SAM Loss: 0.849730908870697

Iteration 15/200, SAM Loss: 0.24848605692386627

Visualized Synthetic (Condensed) Images

Iteration 16/200, SAM Loss: 0.3352375030517578

Iteration 17/200, SAM Loss: 0.19285400211811066

Iteration 18/200, SAM Loss: 0.09616471081972122

Iteration 19/200, SAM Loss: 0.4356839656829834

Iteration 20/200, SAM Loss: 0.9015045762062073

Visualized Synthetic (Condensed) Images

Iteration 21/200, SAM Loss: 0.055659420788288116

Iteration 22/200, SAM Loss: 0.17004425823688507

Iteration 23/200, SAM Loss: 0.34715574979782104

Iteration 24/200, SAM Loss: 0.10108990222215652

Iteration 25/200, SAM Loss: 1.3104461431503296

Visualized Synthetic (Condensed) Images

Iteration 26/200, SAM Loss: 0.2708700895309448

Iteration 27/200, SAM Loss: 0.624534010887146

Iteration 28/200, SAM Loss: 0.28962600231170654

Iteration 29/200, SAM Loss: 1.2376420497894287

Iteration 30/200, SAM Loss: 0.04275406152009964

Visualized Synthetic (Condensed) Images

Iteration 31/200, SAM Loss: 0.3156421184539795

Iteration 32/200, SAM Loss: 1.8774863481521606

Iteration 33/200, SAM Loss: 0.19170619547367096

Iteration 34/200, SAM Loss: 0.13342483341693878

Iteration 35/200, SAM Loss: 0.07021690160036087

Visualized Synthetic (Condensed) Images



Iteration 36/200, SAM Loss: 0.20692963898181915

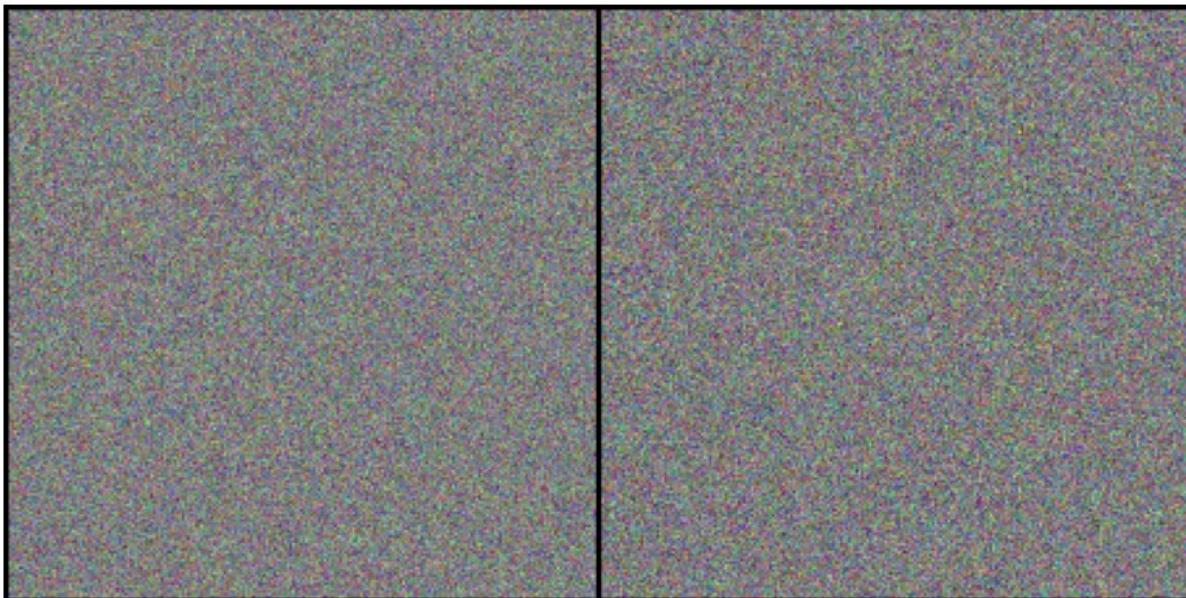
Iteration 37/200, SAM Loss: 0.4833504557609558

Iteration 38/200, SAM Loss: 0.4885404706001282

Iteration 39/200, SAM Loss: 0.2422472983598709

Iteration 40/200, SAM Loss: 1.0475369691848755

Visualized Synthetic (Condensed) Images



Iteration 41/200, SAM Loss: 1.2698590755462646

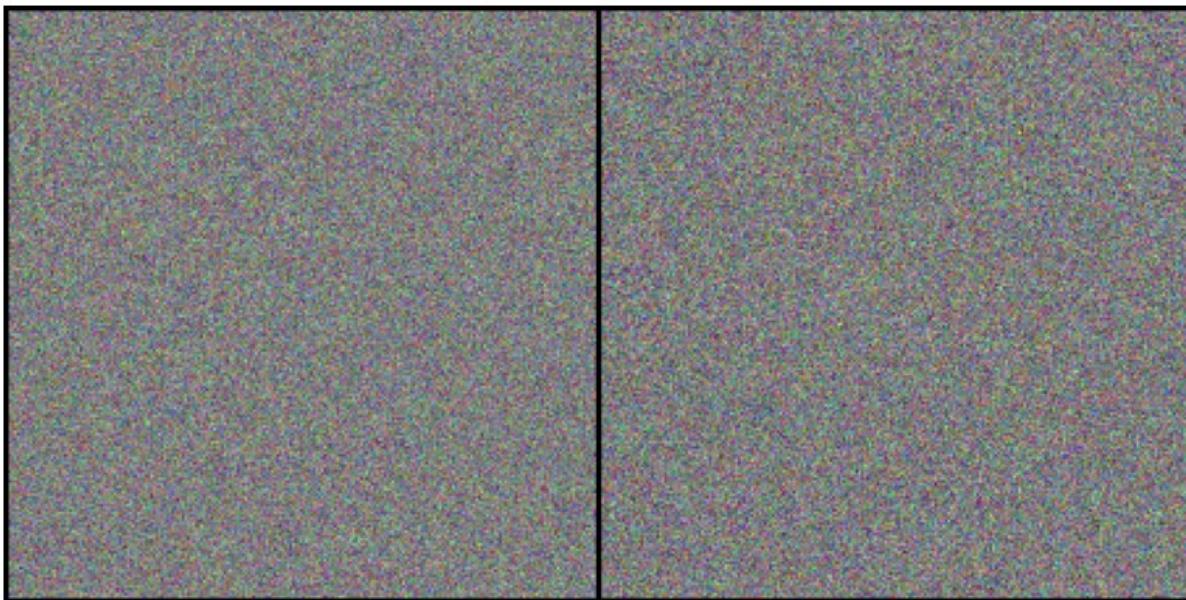
Iteration 42/200, SAM Loss: 0.7923212051391602

Iteration 43/200, SAM Loss: 0.12087655812501907

Iteration 44/200, SAM Loss: 1.7781665325164795

Iteration 45/200, SAM Loss: 0.23434562981128693

Visualized Synthetic (Condensed) Images



Iteration 46/200, SAM Loss: 0.5981769561767578

Iteration 47/200, SAM Loss: 0.8074577450752258

Iteration 48/200, SAM Loss: 0.779705822467804

Iteration 49/200, SAM Loss: 1.1527538299560547

Iteration 50/200, SAM Loss: 1.2970821857452393

Visualized Synthetic (Condensed) Images



Iteration 51/200, SAM Loss: 0.929925799369812

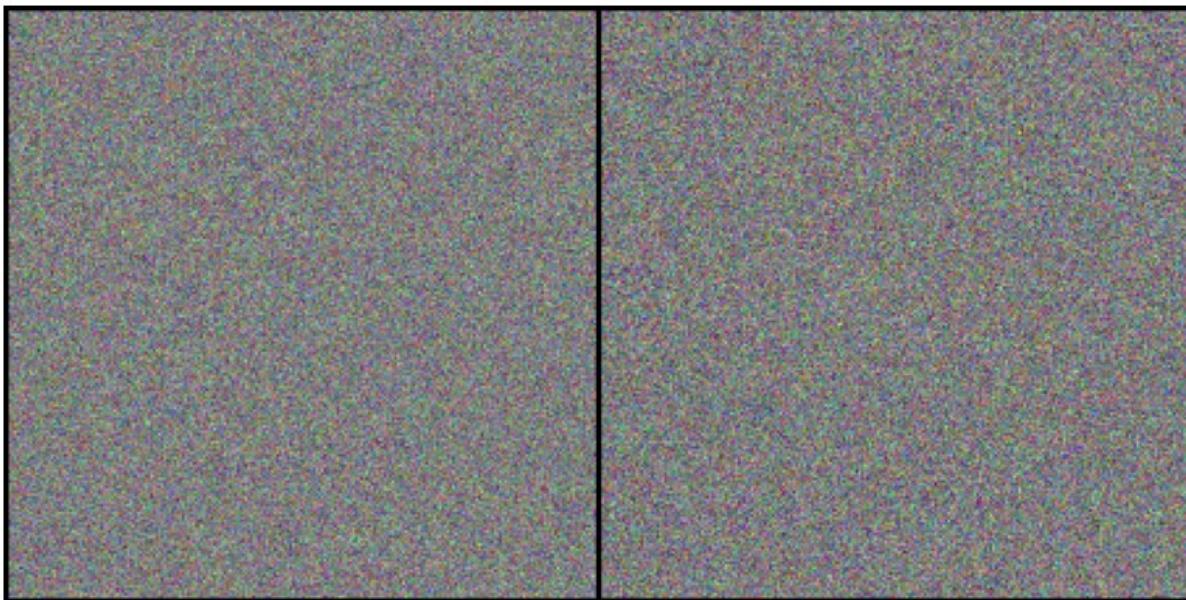
Iteration 52/200, SAM Loss: 0.6338505148887634

Iteration 53/200, SAM Loss: 0.5299016237258911

Iteration 54/200, SAM Loss: 0.8199635744094849

Iteration 55/200, SAM Loss: 0.7014877796173096

Visualized Synthetic (Condensed) Images



Iteration 56/200, SAM Loss: 0.48689669370651245

Iteration 57/200, SAM Loss: 0.8280671834945679

Iteration 58/200, SAM Loss: 0.28113895654678345

Iteration 59/200, SAM Loss: 0.8929292559623718

Iteration 60/200, SAM Loss: 0.1844901591539383

Visualized Synthetic (Condensed) Images



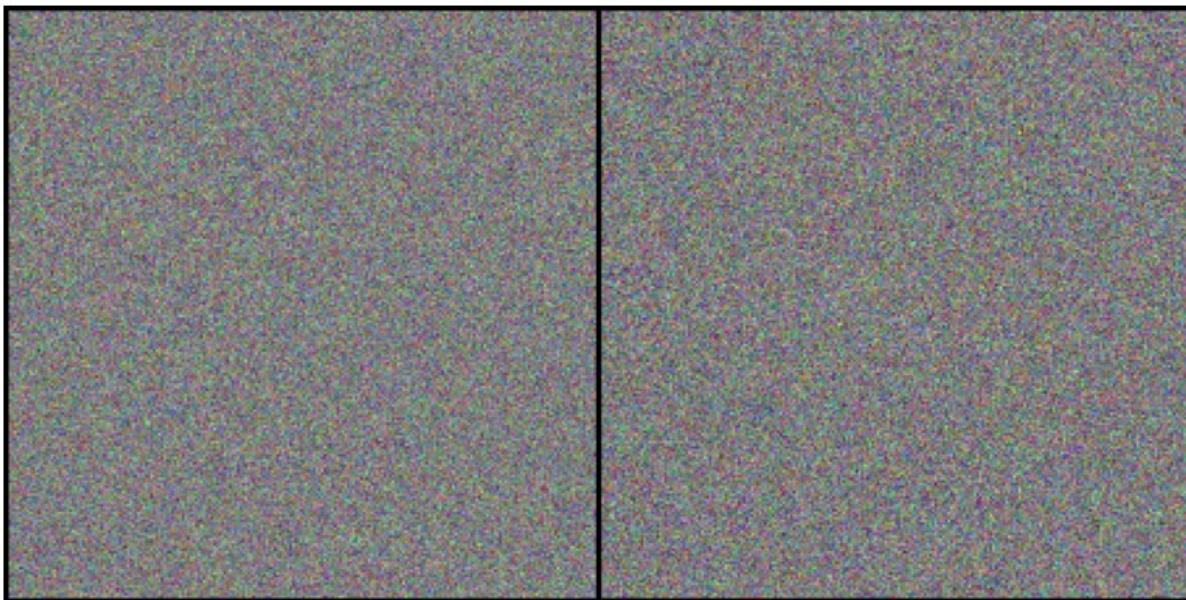
Iteration 61/200, SAM Loss: 1.4877256155014038

Iteration 62/200, SAM Loss: 0.2398625761270523

Iteration 63/200, SAM Loss: 0.05707252770662308

Iteration 64/200, SAM Loss: 0.2723240852355957

Iteration 65/200, SAM Loss: 0.05459136515855789

Visualized Synthetic (Condensed) Images

Iteration 66/200, SAM Loss: 1.4643038511276245

Iteration 67/200, SAM Loss: 0.13547058403491974

Iteration 68/200, SAM Loss: 1.4923608303070068

Iteration 69/200, SAM Loss: 0.4486526846885681

Iteration 70/200, SAM Loss: 1.1434181928634644

Visualized Synthetic (Condensed) Images

Iteration 71/200, SAM Loss: 0.36154747009277344

Iteration 72/200, SAM Loss: 0.2010027915239334

Iteration 73/200, SAM Loss: 1.9803974628448486

Iteration 74/200, SAM Loss: 0.04549182206392288

Iteration 75/200, SAM Loss: 0.10815901309251785

Visualized Synthetic (Condensed) Images



Iteration 76/200, SAM Loss: 1.8181475400924683

Iteration 77/200, SAM Loss: 0.44463932514190674

Iteration 78/200, SAM Loss: 0.5830071568489075

Iteration 79/200, SAM Loss: 1.0093008279800415

Iteration 80/200, SAM Loss: 0.34474319219589233

Visualized Synthetic (Condensed) Images



Iteration 81/200, SAM Loss: 1.2075139284133911

Iteration 82/200, SAM Loss: 0.436687707901001

Iteration 83/200, SAM Loss: 0.5907412767410278

Iteration 84/200, SAM Loss: 0.12464792281389236

Iteration 85/200, SAM Loss: 0.5070674419403076

Visualized Synthetic (Condensed) Images



Iteration 86/200, SAM Loss: 0.2898673415184021

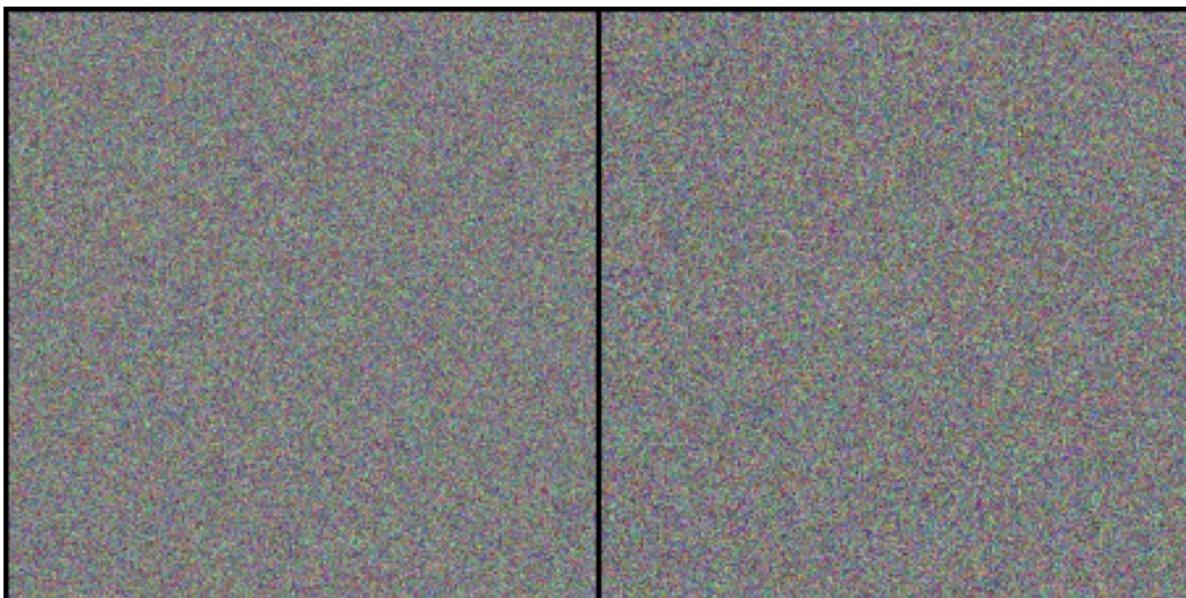
Iteration 87/200, SAM Loss: 0.31589192152023315

Iteration 88/200, SAM Loss: 0.20805145800113678

Iteration 89/200, SAM Loss: 0.27298516035079956

Iteration 90/200, SAM Loss: 0.2989266514778137

Visualized Synthetic (Condensed) Images



Iteration 91/200, SAM Loss: 0.20211602747440338

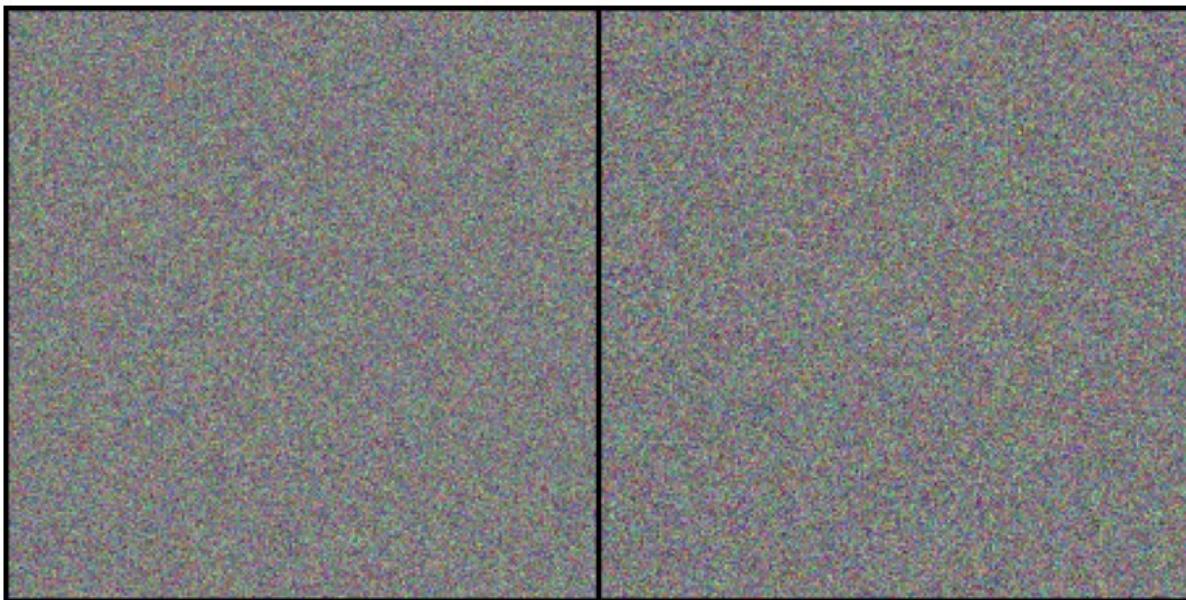
Iteration 92/200, SAM Loss: 1.1478629112243652

Iteration 93/200, SAM Loss: 0.5389487743377686

Iteration 94/200, SAM Loss: 0.7608807682991028

Iteration 95/200, SAM Loss: 0.4418078660964966

Visualized Synthetic (Condensed) Images



Iteration 96/200, SAM Loss: 0.5567556619644165

Iteration 97/200, SAM Loss: 0.08664382249116898

Iteration 98/200, SAM Loss: 0.9840946197509766

Iteration 99/200, SAM Loss: 0.9028469324111938

Iteration 100/200, SAM Loss: 1.974325180053711

Visualized Synthetic (Condensed) Images



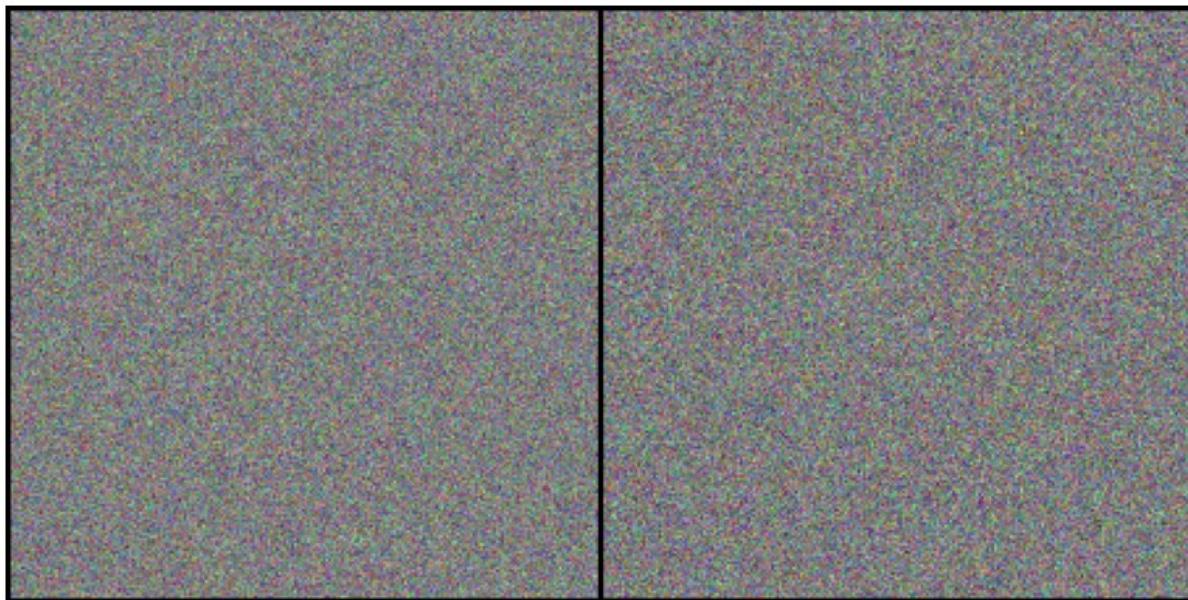
Iteration 101/200, SAM Loss: 0.05050665885210037

Iteration 102/200, SAM Loss: 0.01140511967241764

Iteration 103/200, SAM Loss: 0.06415707617998123

Iteration 104/200, SAM Loss: 0.32100796699523926

Iteration 105/200, SAM Loss: 0.19438536465168

Visualized Synthetic (Condensed) Images

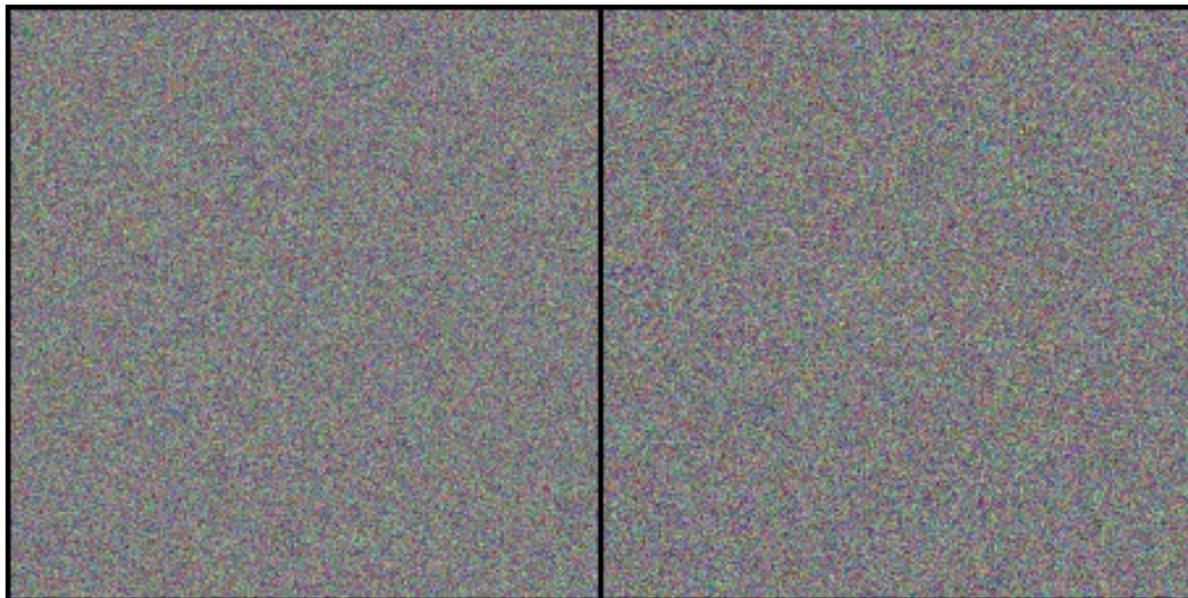
Iteration 106/200, SAM Loss: 0.4670848846435547

Iteration 107/200, SAM Loss: 0.36153435707092285

Iteration 108/200, SAM Loss: 0.08046186715364456

Iteration 109/200, SAM Loss: 0.7123156189918518

Iteration 110/200, SAM Loss: 1.3961918354034424

Visualized Synthetic (Condensed) Images

Iteration 111/200, SAM Loss: 0.08320791274309158

Iteration 112/200, SAM Loss: 0.6007540225982666

Iteration 113/200, SAM Loss: 0.181448832154274

Iteration 114/200, SAM Loss: 0.1727975755929947

Iteration 115/200, SAM Loss: 1.3906774520874023

Visualized Synthetic (Condensed) Images

Iteration 116/200, SAM Loss: 0.14346767961978912

Iteration 117/200, SAM Loss: 0.671867847442627

Iteration 118/200, SAM Loss: 0.40972310304641724

Iteration 119/200, SAM Loss: 0.06658560782670975

Iteration 120/200, SAM Loss: 0.42051035165786743

Visualized Synthetic (Condensed) Images

Iteration 121/200, SAM Loss: 0.7531847953796387

Iteration 122/200, SAM Loss: 0.40031421184539795

Iteration 123/200, SAM Loss: 0.3954012989997864

Iteration 124/200, SAM Loss: 0.11514837294816971

Iteration 125/200, SAM Loss: 0.9670853614807129

Visualized Synthetic (Condensed) Images

Iteration 126/200, SAM Loss: 0.48582708835601807

Iteration 127/200, SAM Loss: 0.5928347110748291

Iteration 128/200, SAM Loss: 0.11420298367738724

Iteration 129/200, SAM Loss: 0.638157308101654

Iteration 130/200, SAM Loss: 0.5357222557067871

Visualized Synthetic (Condensed) Images

Iteration 131/200, SAM Loss: 1.1997615098953247

Iteration 132/200, SAM Loss: 0.2857159376144409

Iteration 133/200, SAM Loss: 0.12626107037067413

Iteration 134/200, SAM Loss: 0.10883898288011551

Iteration 135/200, SAM Loss: 0.07292408496141434

Visualized Synthetic (Condensed) Images

Iteration 136/200, SAM Loss: 0.047876425087451935

Iteration 137/200, SAM Loss: 0.08579916507005692

Iteration 138/200, SAM Loss: 0.06914681941270828

Iteration 139/200, SAM Loss: 0.29878270626068115

Iteration 140/200, SAM Loss: 0.8300502300262451

Visualized Synthetic (Condensed) Images

Iteration 141/200, SAM Loss: 0.675663948059082

Iteration 142/200, SAM Loss: 0.6147029399871826

Iteration 143/200, SAM Loss: 1.3402807712554932

Iteration 144/200, SAM Loss: 1.086564302444458

Iteration 145/200, SAM Loss: 0.273964524269104

Visualized Synthetic (Condensed) Images

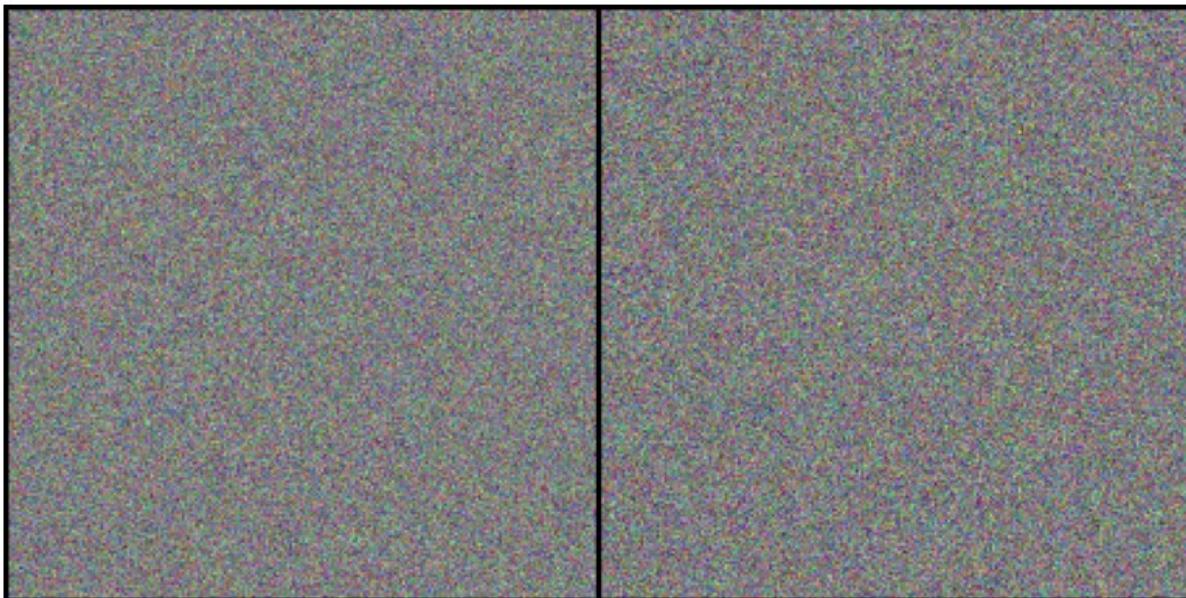
Iteration 146/200, SAM Loss: 0.11010397225618362

Iteration 147/200, SAM Loss: 0.13847823441028595

Iteration 148/200, SAM Loss: 1.2674968242645264

Iteration 149/200, SAM Loss: 1.735368251800537

Iteration 150/200, SAM Loss: 0.43955087661743164

Visualized Synthetic (Condensed) Images

Iteration 151/200, SAM Loss: 0.5145469903945923

Iteration 152/200, SAM Loss: 0.587695300579071

Iteration 153/200, SAM Loss: 0.819360613822937

Iteration 154/200, SAM Loss: 0.15936626493930817

Iteration 155/200, SAM Loss: 0.2758117914199829

Visualized Synthetic (Condensed) Images

Iteration 156/200, SAM Loss: 0.8227286338806152

Iteration 157/200, SAM Loss: 0.4915117025375366

Iteration 158/200, SAM Loss: 0.09718889743089676

Iteration 159/200, SAM Loss: 0.8133030533790588

Iteration 160/200, SAM Loss: 1.123751163482666

Visualized Synthetic (Condensed) Images

Iteration 161/200, SAM Loss: 0.9222137928009033

Iteration 162/200, SAM Loss: 0.11858690530061722

Iteration 163/200, SAM Loss: 0.26395732164382935

Iteration 164/200, SAM Loss: 0.6197378635406494

Iteration 165/200, SAM Loss: 1.2812974452972412

Visualized Synthetic (Condensed) Images

Iteration 166/200, SAM Loss: 0.06185764819383621

Iteration 167/200, SAM Loss: 1.125948429107666

Iteration 168/200, SAM Loss: 0.09742606431245804

Iteration 169/200, SAM Loss: 0.24399800598621368

Iteration 170/200, SAM Loss: 0.413662850856781

Visualized Synthetic (Condensed) Images

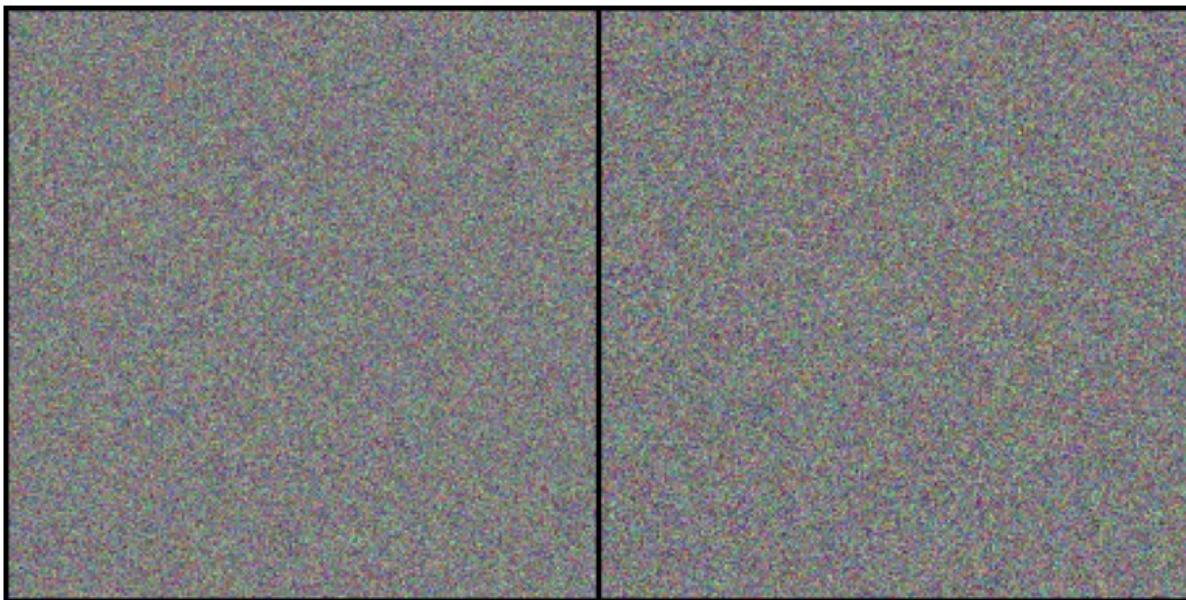
Iteration 171/200, SAM Loss: 0.31732791662216187

Iteration 172/200, SAM Loss: 0.30036675930023193

Iteration 173/200, SAM Loss: 0.047031112015247345

Iteration 174/200, SAM Loss: 0.17348714172840118

Iteration 175/200, SAM Loss: 0.3493116497993469

Visualized Synthetic (Condensed) Images

Iteration 176/200, SAM Loss: 0.3099749684333801

Iteration 177/200, SAM Loss: 0.7088462114334106

Iteration 178/200, SAM Loss: 1.9418553113937378

Iteration 179/200, SAM Loss: 0.19808097183704376

Iteration 180/200, SAM Loss: 1.5228946208953857

Visualized Synthetic (Condensed) Images

Iteration 181/200, SAM Loss: 0.12810786068439484

Iteration 182/200, SAM Loss: 1.5827234983444214

Iteration 183/200, SAM Loss: 0.6552492380142212

Iteration 184/200, SAM Loss: 0.82565838098526

Iteration 185/200, SAM Loss: 0.298545241355896

Visualized Synthetic (Condensed) Images

Iteration 186/200, SAM Loss: 0.17319132387638092

Iteration 187/200, SAM Loss: 0.07210607081651688

Iteration 188/200, SAM Loss: 0.11654055863618851

Iteration 189/200, SAM Loss: 0.6630160808563232

Iteration 190/200, SAM Loss: 0.92356276512146

Visualized Synthetic (Condensed) Images

Iteration 191/200, SAM Loss: 0.25965720415115356

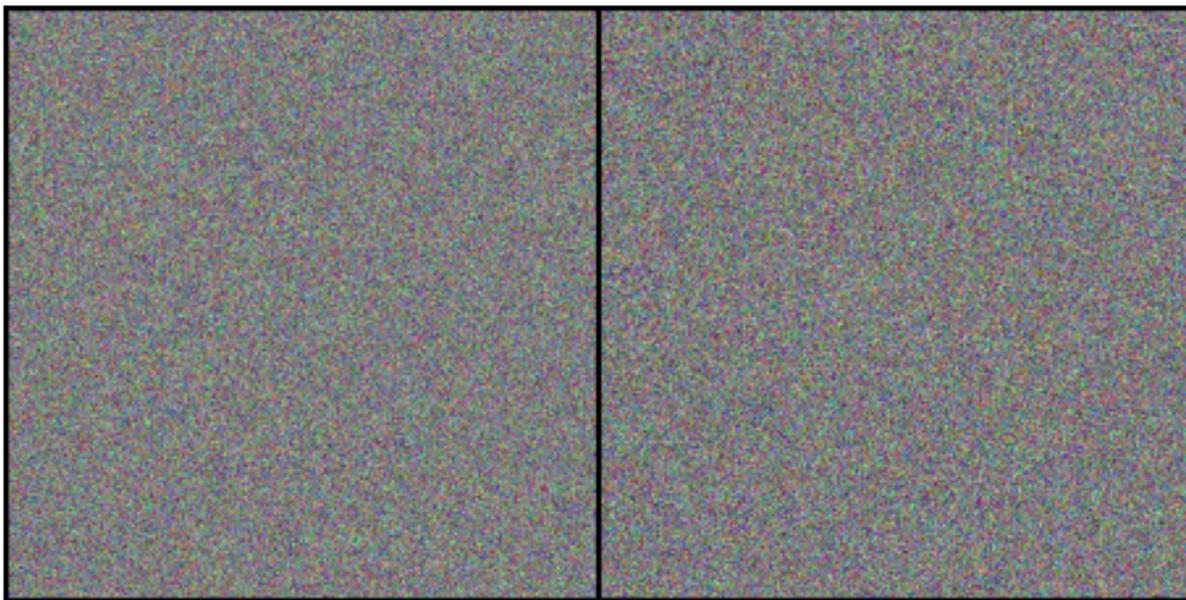
Iteration 192/200, SAM Loss: 0.29672902822494507

Iteration 193/200, SAM Loss: 1.6893587112426758

Iteration 194/200, SAM Loss: 0.12827540934085846

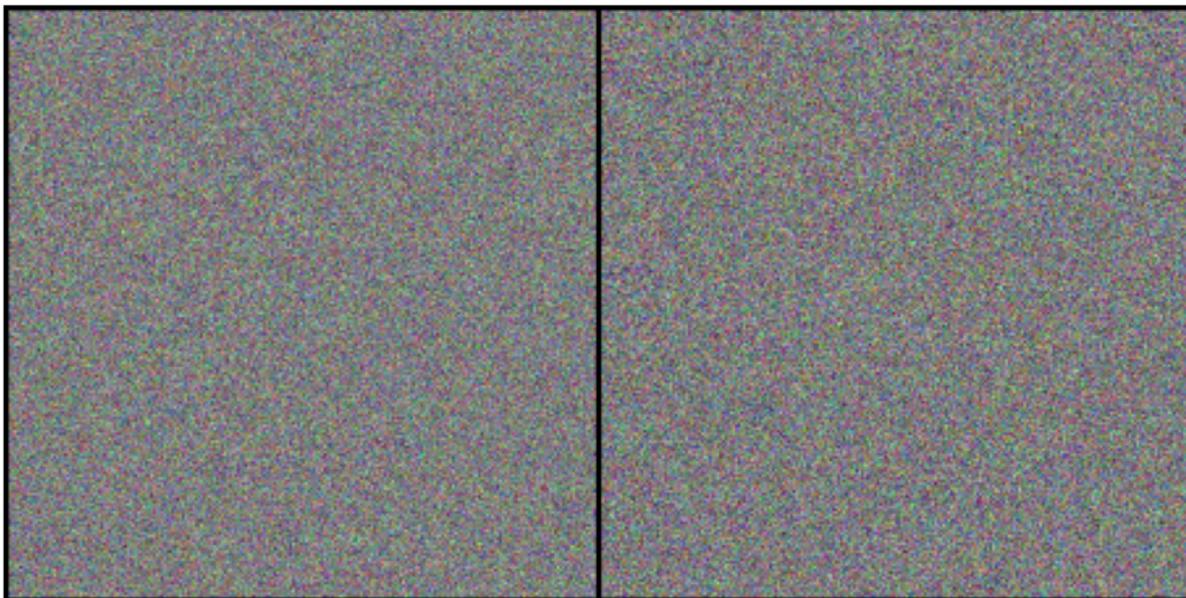
Iteration 195/200, SAM Loss: 0.6120777726173401

Visualized Synthetic (Condensed) Images



```
Iteration 196/200, SAM Loss: 0.08390320092439651  
Iteration 197/200, SAM Loss: 0.09214503318071365  
Iteration 198/200, SAM Loss: 0.5700350999832153  
Iteration 199/200, SAM Loss: 0.02359355427324772  
Iteration 200/200, SAM Loss: 0.3157395124435425
```

Visualized Synthetic (Condensed) Images



```
In [50]: # Task 1 - Question 2 - Part e  
  
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")  
print(f"Using device: {device}")  
  
num_classes = 2  
num_samples_per_class = 50  
synthetic_data_expanded = synthetic_data.repeat_interleave(num_samples_per_class, d  
  
synthetic_labels = torch.cat([torch.zeros(num_samples_per_class, dtype=torch.long),
```

```
synthetic_dataset = TensorDataset(synthetic_data_expanded, synthetic_labels)
synthetic_loader = DataLoader(synthetic_dataset, batch_size=16, shuffle=True)

model_name = 'ConvNetD3'
model_synthetic = get_network(model_name, channel=3, num_classes=num_classes, im_si

optimizer_synthetic = optim.SGD(model_synthetic.parameters(), lr=0.01)
criterion = torch.nn.CrossEntropyLoss()

epochs = 10
start_time = time.time()

print("Training on Synthetic Dataset...")
for epoch in range(epochs):
    model_synthetic.train()
    epoch_loss, correct, total = 0, 0, 0
    for images, labels in synthetic_loader:
        images, labels = images.to(device), labels.to(device)

        optimizer_synthetic.zero_grad()
        outputs = model_synthetic(images)
        loss = criterion(outputs, labels)

        loss.backward()
        optimizer_synthetic.step()

        epoch_loss += loss.item() * labels.size(0)
        _, predicted = outputs.max(1)
        total += labels.size(0)
        correct += predicted.eq(labels).sum().item()

    accuracy = 100 * correct / total
    print(f"Epoch [{epoch+1}/{epochs}], Loss: {epoch_loss/total:.4f}, Accuracy: {ac

training_time_synthetic = time.time() - start_time
print(f"Training Time on Synthetic Dataset: {training_time_synthetic:.2f} seconds")

test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False) # Assuming `t

def evaluate_model(model, test_loader):
    model.eval()
    correct, total = 0, 0
    with torch.no_grad():
        for images, labels in test_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, predicted = outputs.max(1)
            total += labels.size(0)
            correct += predicted.eq(labels).sum().item()
    accuracy = 100 * correct / total
    return accuracy

test_accuracy_synthetic = evaluate_model(model_synthetic, test_loader)
print(f"Test Accuracy on Real Data (trained on synthetic data): {test_accuracy_synt
```

```
Using device: cpu
Training on Synthetic Dataset...
Epoch [1/10], Loss: 0.1136, Accuracy: 93.00%
Epoch [2/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [3/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [4/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [5/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [6/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [7/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [8/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [9/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [10/10], Loss: 0.0000, Accuracy: 100.00%
Training Time on Synthetic Dataset: 3764.23 seconds
Test Accuracy on Real Data (trained on synthetic data): 29.89%
```

```
In [41]: # Task 1 - Question 3
```

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

num_samples_per_class = 50
synthetic_data_expanded = synthetic_data.repeat_interleave(num_samples_per_class, dim=0)

synthetic_labels = torch.cat([
    torch.zeros(num_samples_per_class, dtype=torch.long),
    torch.ones(num_samples_per_class, dtype=torch.long)
]).to(device)

synthetic_dataset = TensorDataset(synthetic_data_expanded, synthetic_labels)
synthetic_loader = DataLoader(synthetic_dataset, batch_size=16, shuffle=True)

num_classes = 2
channel = 3
im_size = (224, 224)

convnet_model = ConvNet(channel=channel, num_classes=num_classes, net_width=64, net_depth=4)
optimizer = optim.SGD(convnet_model.parameters(), lr=0.01, momentum=0.9)
criterion = torch.nn.CrossEntropyLoss()

epochs = 10
print("Training ConvNetW64 on Condensed Synthetic Dataset...")

for epoch in range(epochs):
    convnet_model.train()
    epoch_loss, correct, total = 0, 0, 0

    for images, labels in synthetic_loader:
        images, labels = images.to(device), labels.to(device)

        optimizer.zero_grad()
        outputs = convnet_model(images)
        loss = criterion(outputs, labels)

        loss.backward()
        optimizer.step()
```

```
epoch_loss += loss.item() * labels.size(0)
_, predicted = outputs.max(1)
total += labels.size(0)
correct += predicted.eq(labels).sum().item()

accuracy = 100 * correct / total
print(f"Epoch [{epoch + 1}/{epochs}], Loss: {epoch_loss/total:.4f}, Accuracy: {accuracy:.2f}")

def evaluate_model(model, test_loader):
    model.eval()
    correct, total = 0, 0
    with torch.no_grad():
        for images, labels in test_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, predicted = outputs.max(1)
            total += labels.size(0)
            correct += predicted.eq(labels).sum().item()
    accuracy = 100 * correct / total
    return accuracy

test_accuracy = evaluate_model(convnet_model, test_loader)
print(f"Test Accuracy on Real Data (trained on condensed data with ConvNetW64): {test_accuracy:.2f}")
```

```
Using device: cpu
Training ConvNetW64 on Condensed Synthetic Dataset...
Epoch [1/10], Loss: 2.4998, Accuracy: 71.00%
Epoch [2/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [3/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [4/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [5/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [6/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [7/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [8/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [9/10], Loss: 0.0000, Accuracy: 100.00%
Epoch [10/10], Loss: 0.0000, Accuracy: 100.00%
Test Accuracy on Real Data (trained on condensed data with ConvNetW64): 70.11%
```

```
In [42]: # Task 1 - Question 4
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

num_phases = 3
phase_datasets = random_split(mhist_dataset, [len(mhist_dataset) // num_phases] * n)

num_classes = 2
print(f"synthetic_data shape: {synthetic_data.shape}")

if synthetic_data.shape[0] != 100:
    synthetic_data = torch.randn(100, 3, 224, 224, requires_grad=True, device=device)

print(f"synthetic_labels shape: {synthetic_labels.shape}")

synthetic_labels = torch.cat([torch.zeros(50, dtype=torch.long), torch.ones(50, dtype=torch.long)])
```

```
print(f"New synthetic_data shape: {synthetic_data.shape}")
print(f"New synthetic_labels shape: {synthetic_labels.shape}")

synthetic_dataset = TensorDataset(synthetic_data, synthetic_labels)
synthetic_loader = DataLoader(synthetic_dataset, batch_size=16, shuffle=True)

model = ConvNet(channel=3, num_classes=num_classes, net_width=64, net_depth=3, net_
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)
criterion = torch.nn.CrossEntropyLoss()

epochs = 5
for phase, phase_data in enumerate(phase_datasets, start=1):
    phase_loader = DataLoader(phase_data, batch_size=16, shuffle=True)

    phase_images = []
    phase_labels = []
    for image, label in phase_data:
        phase_images.append(image)
        phase_labels.append(label)

    phase_images = torch.stack(phase_images)
    phase_labels = torch.tensor(phase_labels, dtype=torch.long)

    phase_dataset_with_replay = ConcatDataset([TensorDataset(phase_images, phase_la
phase_loader_with_replay = DataLoader(phase_dataset_with_replay, batch_size=16,

    print(f"--- Training Phase {phase} ---")
    for epoch in range(epochs):
        model.train()
        total_loss, correct, total = 0, 0, 0
        for images, labels in phase_loader_with_replay:
            images, labels = images.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            total_loss += loss.item() * labels.size(0)
            _, predicted = outputs.max(1)
            total += labels.size(0)
            correct += predicted.eq(labels).sum().item()

        accuracy = 100 * correct / total
        print(f"Phase {phase}, Epoch {epoch+1}/{epochs}, Loss: {total_loss/total:.4f}, Accuracy: {accuracy:.2f}%")

    test_accuracy = evaluate_model(model, test_loader)
    print(f"Test Accuracy after Phase {phase}: {test_accuracy:.2f}%")

print("Continual Learning with Synthetic Replay Buffer Complete.")
```

```
Using device: cpu
synthetic_data shape: torch.Size([2, 3, 224, 224])
synthetic_labels shape: torch.Size([100])
New synthetic_data shape: torch.Size([100, 3, 224, 224])
New synthetic_labels shape: torch.Size([100])
--- Training Phase 1 ---
Phase 1, Epoch 1/5, Loss: 5.9463, Accuracy: 62.30%
Phase 1, Epoch 2/5, Loss: 0.6159, Accuracy: 69.45%
Phase 1, Epoch 3/5, Loss: 0.6080, Accuracy: 69.45%
Phase 1, Epoch 4/5, Loss: 0.5957, Accuracy: 69.45%
Phase 1, Epoch 5/5, Loss: 0.5825, Accuracy: 69.58%
Test Accuracy after Phase 1: 70.11%
--- Training Phase 2 ---
Phase 2, Epoch 1/5, Loss: 0.6130, Accuracy: 68.24%
Phase 2, Epoch 2/5, Loss: 0.5979, Accuracy: 68.24%
Phase 2, Epoch 3/5, Loss: 0.5817, Accuracy: 67.88%
Phase 2, Epoch 4/5, Loss: 0.5685, Accuracy: 69.21%
Phase 2, Epoch 5/5, Loss: 0.5318, Accuracy: 74.18%
Test Accuracy after Phase 2: 71.49%
--- Training Phase 3 ---
Phase 3, Epoch 1/5, Loss: 0.5836, Accuracy: 70.91%
Phase 3, Epoch 2/5, Loss: 0.5130, Accuracy: 74.42%
Phase 3, Epoch 3/5, Loss: 0.4549, Accuracy: 78.67%
Phase 3, Epoch 4/5, Loss: 0.3811, Accuracy: 83.27%
Phase 3, Epoch 5/5, Loss: 0.3017, Accuracy: 87.52%
Test Accuracy after Phase 3: 73.56%
Continual Learning with Synthetic Replay Buffer Complete.
```

In [97]: # Task 2 - Question 2

```
import torch
import torch.optim as optim
from torch.utils.data import DataLoader, Subset, TensorDataset
from torchvision import transforms
import torch.nn as nn
import numpy as np
from torch.utils.data import Dataset
from PIL import Image
import pandas as pd
import os

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

class MHISTDataset(Dataset):
    def __init__(self, annotations_file, img_dir, transform=None):
        self.img_labels = pd.read_csv(annotations_file)
        self.img_dir = img_dir
        self.transform = transform
        self.label_mapping = {'SSA': 0, 'HP': 1}

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

    def __getitem__(self, idx):
        img_name = os.path.join(self.img_dir, self.img_labels.iloc[idx, 0])
        image = Image.open(img_name).convert("RGB")
```

```
label_str = self.img_labels.iloc[idx, 1]
label = self.label_mapping[label_str]

if self.transform:
    image = self.transform(image)
return image, label

transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])

img_dir = "C:/Users/rupin/Downloads/ECE1512_2024F_ProjectA_submission_files/submiss
annotations_file = r"C:\Users\rupin\Downloads\ECE1512_2024F_ProjectA_submission_file
mhist_dataset = MHISTDataset(annotations_file=annotations_file, img_dir=img_dir, tr

batch_size = 16
real_data_loader = DataLoader(mhist_dataset, batch_size=batch_size, shuffle=True)

def calculate_el2n_scores(model, dataloader, device):
    model.eval()
    el2n_scores = []
    with torch.no_grad():
        for images, labels in dataloader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            probs = torch.softmax(outputs, dim=1)
            correct_probs = probs.gather(1, labels.unsqueeze(1)).squeeze()
            el2n_scores.extend((1 - correct_probs).cpu().numpy())
    return el2n_scores

channel, num_classes = 3, 2
model = ConvNet(channel=3, num_classes=num_classes, net_width=64, net_depth=3, net_
el2n_scores = calculate_el2n_scores(model, real_data_loader, device)

num_samples = 100
sorted_indices = np.argsort(el2n_scores)
selected_indices = np.concatenate([sorted_indices[:num_samples // 2], sorted_index
distilled_dataset = Subset(mhist_dataset, selected_indices)
distilled_loader = DataLoader(distilled_dataset, batch_size=16, shuffle=True)

def match_loss_with_trajectory(outputs_syn, outputs_real):
    loss = torch.norm(outputs_syn - outputs_real)
    return loss

epochs = 5
learning_rate = 0.01
synthetic_data = torch.randn(num_classes, channel, 224, 224, requires_grad=True, de
optimizer_syn = optim.SGD([synthetic_data], lr=learning_rate)
criterion = nn.CrossEntropyLoss()

for epoch in range(epochs):
    model.train()
    for images, labels in distilled_loader:
        images, labels = images.to(device), labels.to(device)
```

```
optimizer_syn.zero_grad()

repeated_synthetic_data = synthetic_data.repeat(images.size(0) // synthetic_size)

outputs_real = model(images)
outputs_syn = model(repeated_synthetic_data)

loss = match_loss_with_trajectory(outputs_syn, outputs_real) + criterion(outputs_syn, outputs_real)

loss.backward()
optimizer_syn.step()

print(f"Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}")

model.eval()
correct, total = 0, 0
with torch.no_grad():
    for images, labels in distilled_loader:
        images, labels = images.to(device), labels.to(device)
        outputs = model(images)
        _, predicted = torch.max(outputs, 1)
        correct += (predicted == labels).sum().item()
        total += labels.size(0)

accuracy = 100 * correct / total
print(f"Accuracy on distilled dataset: {accuracy:.2f}%")
```

```
Epoch [1/5], Loss: 1.3374
Epoch [2/5], Loss: 1.5557
Epoch [3/5], Loss: 1.1639
Epoch [4/5], Loss: 1.3493
Epoch [5/5], Loss: 1.2279
Accuracy on distilled dataset: 70.00%
```