```
In [ ]:
            # Import library
            import torch
import torch.nn as nn
import torch.optim as optim
            from torch.utils.data import DataLoader
import torch.nn.functional as F
            import h5py
import torchvision
import torchvision.transforms as transforms
            from sklearn.metrics import confusion_matrix
            import seaborn as sns
import matplotlib.pyplot as plt
            import numpy as np
import pandas as pd
            from torchvision.models import resnet34
from torchsummary import summary
            from sklearn import preprocessing
            from sklearn.metrics import precision_recall_curve
           path = '/Users/woojaejeong/Desktop/Program/USC/Computational Introduction to Deep Learning/Homeworks/HW7/data/'
            transformation = torchvision.transforms.Compose([
    # Resize to 224 by 224
    transforms.Resize((224,224)),
                 transforms.ToTensor(),
transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,0.224,0.225]),
                 # Data augmentation
                 transforms.RandomRotation(20)
                 transforms.RandomHorizontalFlip(0.5).
                 transforms.RandomResizedCrop(224, scale=(0.8, 1.0), ratio=(0.99, 1.01)) # Scaling
            1)
            image\_data = torchvision.datasets.ImageFolder(root = path, transform = transformation)
            dataset_size = len(image_data)
data_split = [0.7, 0.2, 0.1]
            train\_set, \ val\_set, \ test\_set = torch.utils.data.random\_split(image\_data, \ [round(p * len(image\_data)) \ for \ p \ in \ data\_split])
            train_loader = torch.utils.data.DataLoader(train_set, batch_size = batch_size)
val_loader = torch.utils.data.DataLoader(val_set, batch_size = batch_size)
            test loader = torch.utils.data.DataLoader(test set, batch size = batch size)
           # Get cpu or gpu device for training.
device = "cuda" if torch.cuda.is_available() else "cpu"
           # Replace final classification output-layer to 3 class
            num_class = 3
model = resnet34(pretrained=True)
            model.fc = nn.Linear(model.fc.in features, num class)
            # Vanilla pretrained ResNet-34 model
            model_v = resnet34(pretrained=True)
model_v.fc = nn.Linear(model_v.fc.in_features, num_class)
            # Freeze all parameters in the model
for param in model.parameters():
                 param.requires_grad = False
            # Unfreeze the parameters of the new fully connected layer
            for param in model.fc.parameters():
    param.requires_grad = True
            # Loss function
criterion = nn.CrossEntropyLoss()
            # Optimizer
optimizer = optim.Adam(model.fc.parameters(), lr = 1e-4)
```

/Users/woojaejeong/opt/anaconda3/lib/python3.8/site-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated sin ce 0.13 and may be removed in the future, please use 'weights' instead.
warnings.warn(

/Users/woojaejeong/opt/anaconda3/lib/python3.8/site-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' are deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=ResNet34_Weights.IMAGEN ETIK_V1`. You can also use `weights=ResNet34_Weights.DEFAULT` to get the most up-to-date weights. warnings.warn(msg)

```
{'params': model.layer2.parameters()},
            {'params': model.fc.parameters()}], lr = 1e-7)
elif epoch == 8:
     for param in model.layer1.parameters():
    param.requires_grad = True
     for i, (inputs, labels) in enumerate(train_loader):
     # Forward
outputs = model(inputs)
          preds = torch.max(outputs.1)
      loss = criterion(outputs, labels)
     # Back propagation
optimizer.zero_grad()
      loss.backward(
      optimizer.step()
     train_running_loss += loss.item()
train_correct += torch.sum(preds == labels.data)
total += len(labels)
train_loss = np.append(train_loss, train_running_loss / len(train_loader))
train_acc = np.append(train_acc, 100 * train_correct.double() / total)
model.eval()
val_running_loss = 0.0
val_correct = 0
total = 0
          (inputs, labels) in enumerate(val_loader):
for i
     with torch.no_grad():
    # Forward
           outputs = model(inputs)
           _, preds = torch.max(outputs,1)
loss = criterion(outputs, labels)
           val_running_loss += loss.item()
val_correct += torch.sum(preds == labels.data)
            total += len(labels)
 \begin{tabular}{ll} val\_loss = np.append(val\_loss, val\_running\_loss / len(val\_loader)) \\ val\_acc = np.append(val\_acc, 100 * val\_correct.double() / total) \\ \end{tabular}
```

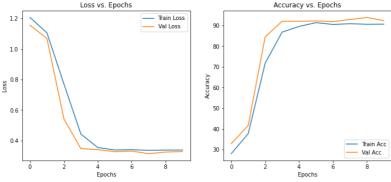
/Users/woojaejeong/opt/anaconda3/lib/python3.8/site-packages/torchvision/transforms/functional.py:1603: UserWarning: The default value of the antialias parameter of all the resizing transforms (Resize(), RandomResizedCrop(), etc.) will change from None to True in v0.17, in order to be consistent across the PIL and Tensor backends. To suppress this warning, directly pass antialias=True (recommended, future default), antialias=None (current default, which means False for Tensors and True for PIL), or antialias=False (only works on Tensors – PIL will still use antialiasing). This also applies if you are using the inference transforms from the models weights: update the call to weights.transforms(antialias=True).

warnings.warn(

```
In []:
    plt.figure(figsize=(12, 5))
    plt.subplot(1, 2, 1)
    plt.plot(train_loss, label='Train Loss')
    plt.plot(val_loss, tabel='Val Loss')
    plt.title('Loss vs. Epochs')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

plt.subplot(1, 2, 2)
    plt.plot(train_acc, label='Train Acc')
    plt.plot(val_acc, label='Val Acc')
    plt.title('Accuracy vs. Epochs')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.ylabel('Accuracy')
    plt.subout('Epochs')
    plt.show()

print('I unfreezed each layer starting from the layer 4 to layer 1 after every 2 epochs')
```



I unfreezed each layer starting from the layer 4 to layer 1 after every 2 epochs

```
image, _ = next(iter(single_loader))

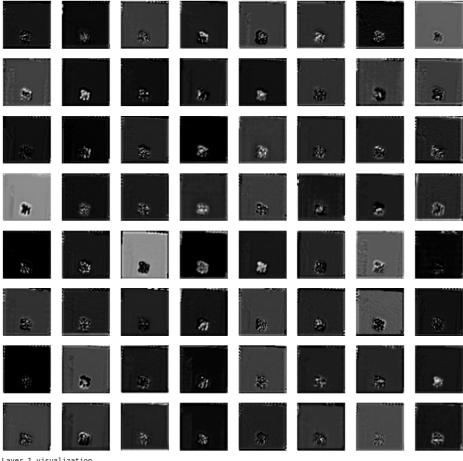
def visualize_hook(module, input, output):
    plt.figure(figsize = (15,15))
    for i in range(output.size(1)):
        plt.subplot(8,8,i+1)
        plt.axis("off")

plt.show()

def visualize_hook2(module, input, output):
    plt.figure(figsize = (15,15))
    for i in range(output.size(1)):
        plt.show()
```

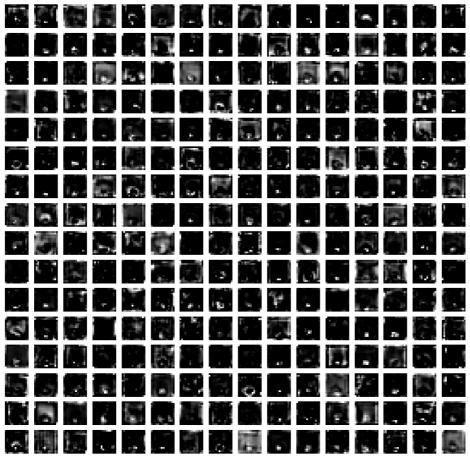
```
plt.imshow(output[0, i].detach().cpu().numpy(), cmap="gray")
         plt.axis("off"
    plt.show()
def remove_hook(model):
    for module in model.modules():
         module._forward_hooks.clear()
module._backward_hooks.clear()
remove_hook(model)
layer_to_visualize = model.layer1
hook = layer_to_visualize.register_forward_hook(visualize_hook)
_, = model(image)
print('Layer1 visualization')
```

/Users/woojaejeong/opt/anaconda3/lib/python3.8/site-packages/torchvision/transforms/functional.py:1603: UserWarning: The default value of the antialias parameter of all the resizing transforms (Resize(), RandomResizedCrop(), etc.) will change from None to True in v0.17, in order to be consistent across the PIL and Tensor backends. To suppress this warning, directly pass antialias=True (recommended, future default), antialias=None (current default, which means False for Tensors and True for PIL), or antialias=False (only works on Tensors – PIL will still use antialiasing). This also applies if you are using the inference transforms from the models weights: update the call to weights.transforms(antialias=True). warnings.warn(



Layer 1 visualization

```
In [ ]:
           remove_hook(model)
            layer_to_visualize = model.layer3
hook = layer_to_visualize.register_forward_hook(visualize_hook2)
            _, = model(image)
            remove_hook(model)
print('Layer3 visualization')
```



Layer3 visualization

```
In [ ]: | # Vanilla pretrained ResNet-34 model
            model_v.eval()
            test_running_loss = 0.0
test_correct = 0
            total = 0
            with torch.no_grad():
                  for i, (inputs, labels) in enumerate(test_loader):
    inputs, labels = inputs.to(device), labels.to(device)
                       # Forward
outputs = model_v(inputs)
_, preds = torch.max(outputs,1)
                        loss = criterion(outputs, labels)
                        test_running_loss += loss.item()
test_correct += torch.sum(preds == labels.data)
total += len(labels)
            test_loss_vanilla = test_running_loss / len(test_loader)
            test_acc_vanilla = 100 * test_correct.double() / total
            # Fine-tuned ResNet-34 model
            model.eval()
             test_running_loss = 0.0
            test correct = 0
            total = 0
            with torch.no_grad():
    for i, (inputs, labels) in enumerate(test_loader):
        inputs, labels = inputs.to(device), labels.to(device)
                       # Forward
outputs = model(inputs)
_, preds = torch.max(outputs,1)
                        loss = criterion(outputs, labels)
                        test_running_loss += loss.item()
                        test_correct += torch.sum(preds == labels.data)
                        total += len(labels)
            test_loss= test_running_loss / len(test_loader)
test_acc = 100 * test_correct.double() / total
```

/Users/woojaejeong/opt/anaconda3/lib/python3.8/site-packages/torchvision/transforms/functional.py:1603: UserWarning: The default value of the antialias parameter of all the resizing transforms (Resize(), RandomResizedCrop(), etc.) will change from None to True in v0.17, in order to be consistent across the PIL and Tensor backends. To suppress this warning, directly pass antialias=True (recommended, future default), antialias=None (current default, which means False for Tensors and True for PIL), or antialias=False (only works on Tensors – PIL will still use antialiasing). This also applies if you are using the inference transforms from the models weights: update the call to weights.transforms(antialias=True).

```
In [ ]:
    print('The accuracy of the fine-tuned model is:',test_acc.item())
    print('The accuracy of the vanilla pretrained model is:',test_acc_vanilla.item())
```

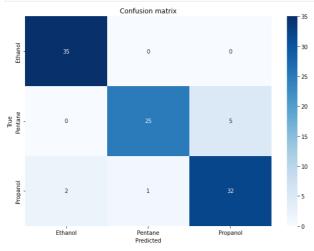
The accuracy of the fine-tuned model is: 93.0 The accuracy of the vanilla pretrained model is: 38.66666666666666

```
In []: # Confusion matrix
    preds_c = preds.cpu().numpy()
    labels_c = labels.cpu().numpy()

    cm = confusion_matrix(labels_c, preds_c)

    class_names = ['Ethanol', 'Pentane', 'Propanol']
    df_cm = pd.DataFrame(cm, index = class_names, columns = class_names)

    plt.figure(figsize=(10,7))
    sns.heatmap(df_cm, annot=True, cmap = 'Blues', fmt ='g')
    plt.xlabel('Predicted')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()
```



```
all_labels = np.array(labels)
all_preds = np.array(preds)

all_labels_binarized = preprocessing.label_binarize(all_labels, classes = range(num_class))

precision = dict()
recall = dict()

for i in range(num_class):
    precision[i], recall[i], _ = precision_recall_curve(all_labels_binarized[:, i], all_preds == i)

for i in range(num_class):
    plt.plot(recall[i], precision[i], lw=2, label='class {}'.format(i))

plt.xlabel("Recall")
    plt.ylabel("Precision")
    plt.legend(loc="best")
    plt.legend(loc="best")
    plt.title("Precision vs. Recall curve")
    plt.title("Precision vs. Recall curve")
    plt.show()
```

