In [1]:
```
# import to load dataset
import os
from torchvision import datasets, transforms
from torch.utils.data import random_split, DataLoader
import torch
import torch.nn as nn
import torch.nn.functional as F
import matplotlib.pyplot as plt
import numpy as np
import torch.optim as optim
from numba import cuda
use_cuda = torch.cuda.is_available()
import torchvision.transforms as T
import torchvision.datasets as D
import random
from torch.utils.data import Subset
```

In [2]:
```
# import the dataset
from google.colab import drive
drive.mount('/content/drive')

import os

small_dataset = ['CNV', 'DME', 'DRUSEN', 'NORMAL']
small_dataset_dir = '/content/drive/MyDrive/APS360 Project - Group 7/Code/OCT_split_NEWDATA'
# '/content/drive/MyDrive/UofT/Third Year/Summer/APS360/APS360 Project - Group 7/Code/small_dataset' ## change this based on your own google drive directory

def num_images(dir, folders):
    print(f"Number of images in each folder:")
    for folder in folders:
        path = os.path.join(dir, folder)
        if os.path.isdir(path):
            num_files = len(os.listdir(path))
            print(f"{folder}: {num_files}")
        else:
            print(f"Folder '{folder}' does not exist in the dataset directory.")

num_images(small_dataset_dir, small_dataset)
```

```
Mounted at /content/drive
Number of images in each folder:
CNV: 50
DME: 50
DRUSEN: 50
NORMAL: 50
```

In [3]:
```
# import to load dataset
from torchvision.datasets import ImageFolder
from torch.utils.data import random_split, DataLoader
import torch

transform = T.ToTensor()
dataset = ImageFolder(root=small_dataset_dir, transform=transform)

# split the data: 70% training, 15% validation, 15% testing
total_len = len(dataset)
train_len = int(0.7 * total_len)
val_len = int(0.15 * total_len)
test_len = total_len - train_len - val_len
train_data, val_data, test_data = random_split(dataset, [train_len, val_len, test_len], generator=torch.Generator().manual_seed(42))

# define dataloader parameters
batch_size = 32

# prepare data loaders
train_loader = DataLoader(train_data, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_data, batch_size=batch_size, shuffle=False)
test_loader = DataLoader(test_data, batch_size=batch_size, shuffle=False)

# check the number of training, validation, and test images alongside the percentage of training, validation, and testing (check)
print(f"Number of training images: {len(train_data)}  Percent: {100 * len(train_data)/total_len:.2f}")
print(f"Number of validation images: {len(val_data)}  Percent: {100 * len(val_data)/total_len:.2f}")
print(f"Number of test images: {len(test_data)}  Percent: {100 * len(test_data)/total_len:.2f}")
```

```
Number of training images: 140  Percent: 70.00
Number of validation images: 30  Percent: 15.00
Number of test images: 30  Percent: 15.00
```

In [4]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import models, transforms
from torch.utils.data import DataLoader
from torchvision.datasets import ImageFolder

resnet18 = models.resnet18(pretrained=True)
resnet18.fc = nn.Linear(resnet18.fc.in_features, 4)
```

```
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.11/dist-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=ResNet18_Weights.IMAGENET1K_V1`. You can also use `weights=ResNet18_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.cache/torch/hub/checkpoints/resnet18-f37072fd.pth
100%|██████████| 44.7M/44.7M [00:00<00:00, 75.7MB/s]
```

In [5]:
```
def get_accuracy(model, data_loader):
    correct = 0
    total = 0
    for imgs, labels in data_loader:
```

```
        ############################################
        #To Enable GPU Usage
        if use_cuda and torch.cuda.is_available():
          imgs = imgs.cuda()
          labels = labels.cuda()
        ############################################

        output = model(imgs)

        # select index with maximum prediction score
        pred = output.max(1, keepdim=True)[1]
        correct += pred.eq(labels.view_as(pred)).sum().item()
        total += imgs.shape[0]
    return correct / total
```

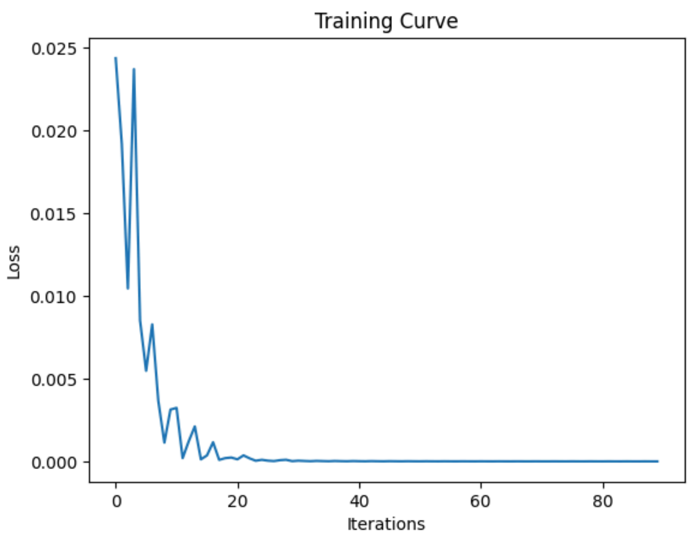
In [6]:

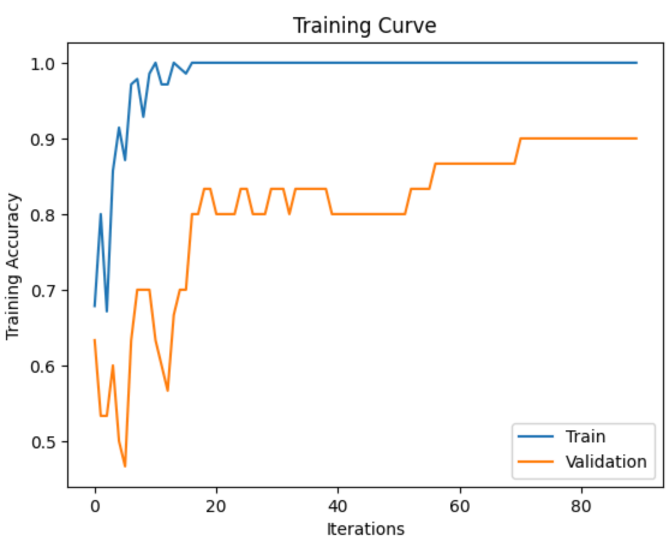
```
def train(model, train_data, val_data, batch_size=64, learning_rate = 0.001, num_epochs=20):
    train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size)
    val_loader = torch.utils.data.DataLoader(val_data, batch_size=batch_size)

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=learning_rate)

    iters, losses, train_acc, val_acc = [], [], [], []

    # training
    n = 0 # the number of iterations
    for epoch in range(num_epochs):
        for imgs, labels in iter(train_loader):


            ############################################
            #To Enable GPU Usage
            if use_cuda and torch.cuda.is_available():
              imgs = imgs.cuda()
              labels = labels.cuda()
            ############################################


            out = model(imgs)             # forward pass
            loss = criterion(out, labels) # compute the total loss
            loss.backward()               # backward pass (compute parameter updates)
            optimizer.step()              # make the updates for each parameter
            optimizer.zero_grad()         # a clean up step for PyTorch

            # save the current training information
            iters.append(n)
            losses.append(float(loss)/batch_size)             # compute *average* loss
            train_acc.append(get_accuracy(model, train_loader)) # compute training accuracy
            val_acc.append(get_accuracy(model, val_loader))  # compute validation accuracy
            n += 1

        print(f"Epoch {epoch+1}: Train acc: {train_acc[-1]:.4f} | Validation acc: {val_acc[-1]:.4f}")
        #model_path = get_model_name(model.name, batch_size, learning_rate, epoch)
        #torch.save(model.state_dict(), model_path)

    # plotting
    plt.title("Training Curve")
    plt.plot(iters, losses, label="Train")
    plt.xlabel("Iterations")
    plt.ylabel("Loss")
    plt.show()

    plt.title("Training Curve")
    plt.plot(iters, train_acc, label="Train")
    plt.plot(iters, val_acc, label="Validation")
    plt.xlabel("Iterations")
    plt.ylabel("Training Accuracy")
    plt.legend(loc='best')
    plt.show()

    print("Final Training Accuracy: {}".format(train_acc[-1]))
    print("Final Validation Accuracy: {}".format(val_acc[-1]))
```

In [7]:

```
use_cuda = True

if use_cuda and torch.cuda.is_available():
  resnet18 = resnet18.to('cuda:0')
  device = 'cuda:0'
  print('CUDA is available!  Training on GPU ...')
else:
  device = 'cpu'
  print('CUDA is not available.  Training on CPU ...')

train(resnet18, train_data, val_data, batch_size=64, num_epochs=30)
```

```
CUDA is available!  Training on GPU ...
Epoch 1: Train acc: 0.6714 | Validation acc: 0.5333
Epoch 2: Train acc: 0.8714 | Validation acc: 0.4667
Epoch 3: Train acc: 0.9286 | Validation acc: 0.7000
Epoch 4: Train acc: 0.9714 | Validation acc: 0.6000
Epoch 5: Train acc: 0.9929 | Validation acc: 0.7000
Epoch 6: Train acc: 1.0000 | Validation acc: 0.8000
Epoch 7: Train acc: 1.0000 | Validation acc: 0.8000
Epoch 8: Train acc: 1.0000 | Validation acc: 0.8000
Epoch 9: Train acc: 1.0000 | Validation acc: 0.8000
Epoch 10: Train acc: 1.0000 | Validation acc: 0.8333
Epoch 11: Train acc: 1.0000 | Validation acc: 0.8000
Epoch 12: Train acc: 1.0000 | Validation acc: 0.8333
Epoch 13: Train acc: 1.0000 | Validation acc: 0.8333
Epoch 14: Train acc: 1.0000 | Validation acc: 0.8000
Epoch 15: Train acc: 1.0000 | Validation acc: 0.8000
Epoch 16: Train acc: 1.0000 | Validation acc: 0.8000
Epoch 17: Train acc: 1.0000 | Validation acc: 0.8000
Epoch 18: Train acc: 1.0000 | Validation acc: 0.8333
Epoch 19: Train acc: 1.0000 | Validation acc: 0.8667
Epoch 20: Train acc: 1.0000 | Validation acc: 0.8667
Epoch 21: Train acc: 1.0000 | Validation acc: 0.8667
Epoch 22: Train acc: 1.0000 | Validation acc: 0.8667
Epoch 23: Train acc: 1.0000 | Validation acc: 0.8667
Epoch 24: Train acc: 1.0000 | Validation acc: 0.9000
Epoch 25: Train acc: 1.0000 | Validation acc: 0.9000
Epoch 26: Train acc: 1.0000 | Validation acc: 0.9000
Epoch 27: Train acc: 1.0000 | Validation acc: 0.9000
Epoch 28: Train acc: 1.0000 | Validation acc: 0.9000
Epoch 29: Train acc: 1.0000 | Validation acc: 0.9000
Epoch 30: Train acc: 1.0000 | Validation acc: 0.9000
```






```
Final Training Accuracy: 1.0
Final Validation Accuracy: 0.9
```

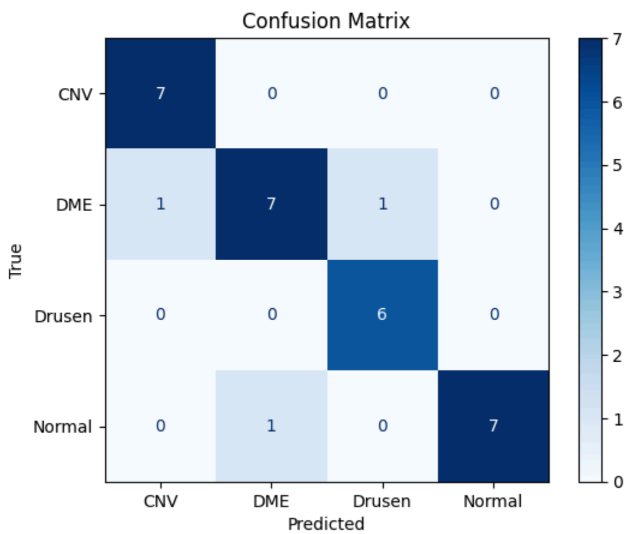
In [8]:
```
# compute the test accuracy for restnet18
test_acc = get_accuracy(resnet18, test_loader)
print(f"Test accuracy: {test_acc:.4f}")
```

```
Test accuracy: 0.9000
```

In [9]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# confusion matrix
def plot_confusion_matrix(model, data_loader, class_names):
    # set model into evaluation mode
    model.eval()
    all_preds = []
    all_labels = []

    with torch.no_grad():
```

```python
        for imgs, labels in data_loader:
            if use_cuda and torch.cuda.is_available():
                imgs = imgs.cuda()
                labels = labels.cuda()

            output = model(imgs)
            preds = output.argmax(dim=1)

            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    # compute the confusion matrix
    cm = confusion_matrix(all_labels, all_preds)

    # plot the confusion matrix
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
    disp.plot(cmap='Blues', values_format='d')
    plt.title("Confusion Matrix")
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.title('Confusion Matrix')
    plt.show()

    return cm
```

In [10]:
```python
class_names = ['CNV', 'DME', 'Drusen', 'Normal']
plot_confusion_matrix(resnet18, test_loader, class_names)
```



Out[10]:
```
array([[7, 0, 0, 0],
       [1, 7, 1, 0],
       [0, 0, 6, 0],
       [0, 1, 0, 7]])
```

In [11]:
```python
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize

# plot roc curve
def plot_roc_curve(model, data_loader, class_names):
    model.eval()
    all_labels = []
    all_probs = []

    with torch.no_grad():
        for imgs, labels in data_loader:
            if use_cuda and torch.cuda.is_available():
                imgs = imgs.cuda()
                labels = labels.cuda()

            output = model(imgs)
            probs = torch.softmax(output, dim=1)

            all_probs.extend(probs.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    all_probs = np.array(all_probs)
    all_labels = np.array(all_labels)

    # binarize the labels for multi-class ROC
    y_true = label_binarize(all_labels, classes=np.arange(len(class_names)))
    n_classes = y_true.shape[1]

    # compute ROC and AUC for each class
    fpr = dict()
    tpr = dict()
    roc_auc = dict()

    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_true[:, i], all_probs[:, i])
        roc_auc[i] = auc(fpr[i], tpr[i])

    # plot the ROC curve
    plt.figure()
    for i in range(n_classes):
        plt.plot(fpr[i], tpr[i], label=f"{class_names[i]} (AUC = {roc_auc[i]:.2f})")

    plt.plot([0, 1], [0, 1], 'k--')  # random classfier
```

```python
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc='lower right')
    plt.grid(True)
    plt.show()

    return roc_auc
```

In [12]:
```python
roc_auc = plot_roc_curve(resnet18, test_loader, class_names)
```