**1- Import all the libraries you may need here:**

```
import os
import random
import numpy as np
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
from PIL import Image
import glob
import shutil

import cv2
import matplotlib.pyplot as plt
from torchvision import transforms
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score, roc_curve
from torchvision.models import vgg19_bn
from torch import optim
import seaborn as sns

random.seed(0)
device = "cuda:0" if torch.cuda.is_available() else "cpu"
```

Clone dataset and read images

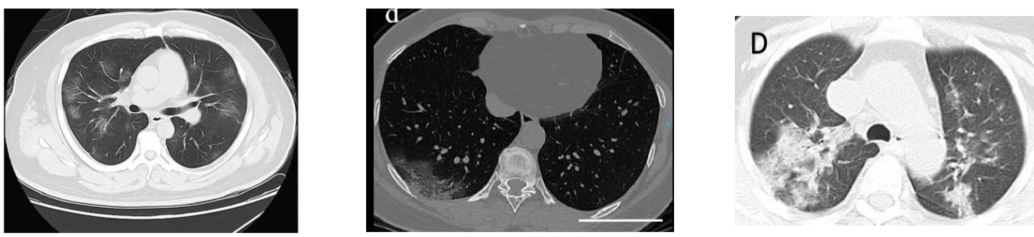
```
!git clone https://github.com/UCSD-AI4H/COVID-CT
!unzip COVID-CT/Images-processed/CT_COVID.zip
!unzip COVID-CT/Images-processed/CT_NonCOVID.zip
covid_files_path = 'CT_COVID/'
covid_files      = [os.path.join(covid_files_path, x) for x in os.listdir(covid_files_path)]
non_covid_files_path = 'CT_NonCOVID/'
non_covid_files      = [os.path.join(non_covid_files_path, x) for x in os.listdir(non_covid_files_path)]
```

```
Cloning into 'COVID-CT'...
remote: Enumerating objects: 5463, done.
remote: Counting objects: 100% (4/4), done.
remote: Compressing objects: 100% (4/4), done.
remote: Total 5463 (delta 0), reused 0 (delta 0), pack-reused 5459
Receiving objects: 100% (5463/5463), 1.09 GiB | 30.58 MiB/s, done.
Resolving deltas: 100% (360/360), done.
Checking out files: 100% (1048/1048), done.
Archive:  COVID-CT/Images-processed/CT_COVID.zip
   creating: CT_COVID/
  inflating: CT_COVID/2020.03.01.20029769-p21-73_1%1.png
   creating: __MACOSX/
   creating: __MACOSX/CT_COVID/
  inflating: __MACOSX/CT_COVID/._2020.03.01.20029769-p21-73_1%1.png
  inflating: CT_COVID/Recurrence-of-positive-SARS-CoV-2-RNA-in-C_2020_International-Journal-of-Inf-p1-21%1.png
  inflating: __MACOSX/CT_COVID/._Recurrence-of-positive-SARS-CoV-2-RNA-in-C_2020_International-Journal-of-Inf-p1-21%1.png
  inflating: CT_COVID/2020.03.12.20034686-p17-91-4.png
  inflating: __MACOSX/CT_COVID/._2020.03.12.20034686-p17-91-4.png
  inflating: CT_COVID/2020.02.25.20021568-p24-111%8.png
  inflating: __MACOSX/CT_COVID/._2020.02.25.20021568-p24-111%8.png
  inflating: CT_COVID/2020.03.13.20035212-p23-153.png
  inflating: __MACOSX/CT_COVID/._2020.03.13.20035212-p23-153.png
  inflating: CT_COVID/2020.03.21.20040691-p18-6-6.png
  inflating: __MACOSX/CT_COVID/._2020.03.21.20040691-p18-6-6.png
  inflating: CT_COVID/2020.03.04.20030395-p27-108%7.png
  inflating: __MACOSX/CT_COVID/._2020.03.04.20030395-p27-108%7.png
  inflating: CT_COVID/2020.02.22.20024927-p19-68%3.png
  inflating: __MACOSX/CT_COVID/._2020.02.22.20024927-p19-68%3.png
  inflating: CT_COVID/2020.03.07.20031393-p7-50%2.png
  inflating: __MACOSX/CT_COVID/._2020.03.07.20031393-p7-50%2.png
  inflating: CT_COVID/2020.03.09.20033118-p20-93%0.png
  inflating: __MACOSX/CT_COVID/._2020.03.09.20033118-p20-93%0.png
  inflating: CT_COVID/2020.03.09.20033118-p20-93%1.png
  inflating: __MACOSX/CT_COVID/._2020.03.09.20033118-p20-93%1.png
  inflating: CT_COVID/2020.03.07.20031393-p7-50%3.png
  inflating: __MACOSX/CT_COVID/._2020.03.07.20031393-p7-50%3.png
  inflating: CT_COVID/2020.02.22.20024927-p19-68%2.png
  inflating: __MACOSX/CT_COVID/._2020.02.22.20024927-p19-68%2.png
  inflating: CT_COVID/2020.03.04.20030395-p27-108%6.png
  inflating: __MACOSX/CT_COVID/._2020.03.04.20030395-p27-108%6.png
  inflating: CT_COVID/2020.03.13.20035212-p23-152.png
  inflating: __MACOSX/CT_COVID/._2020.03.13.20035212-p23-152.png
  inflating: CT_COVID/2020.03.22.20034041-p18-92-1.png
  inflating: __MACOSX/CT_COVID/._2020.03.22.20034041-p18-92-1.png
```

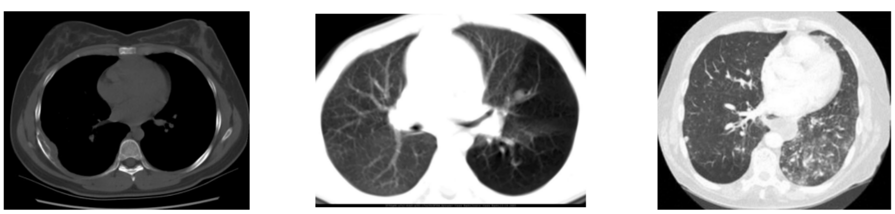
```
    inflating: CT_COVID/2020.02.25.20021568-p24-111%9.png
    inflating: __MACOSX/CT_COVID/._2020.02.25.20021568-p24-111%9.png
    inflating: CT_COVID/2020.03.12.20034686-p17-91-5.png
    inflating: __MACOSX/CT_COVID/._2020.03.12.20034686-p17-91-5.png
    inflating: CT_COVID/Recurrence-of-positive-SARS-CoV-2-RNA-in-C_2020_International-Journal-of-Inf-p1-21%0.png
    inflating: __MACOSX/CT_COVID/._Recurrence-of-positive-SARS-CoV-2-RNA-in-C_2020_International-Journal-of-Inf-p1-21%0.png
    inflating: CT_COVID/2020.03.01.20029769-p21-73_1%0.png
    inflating: __MACOSX/CT_COVID/._2020.03.01.20029769-p21-73_1%0.png
    inflating: CT_COVID/2020.03.01.20029769-p21-73_1%2.png
    inflating: __MACOSX/CT_COVID/._2020.03.01.20029769-p21-73_1%2.png
    inflating: CT_COVID/2020.02.26.20027938-p6-80_2%0.png
    inflating: __MACOSX/CT_COVID/._2020.02.26.20027938-p6-80_2%0.png
    inflating: CT_COVID/2020.03.22.20034041-p18-92-3.png
```

```python
def plot_3random_img(files):
  images =  [cv2.imread(x) for x in random.sample(files, 3)] # reading 3 random Samples from files

  plt.figure(figsize=(20,15))
  for i, img in enumerate(images):
      plt.subplot(len(images), 3, i + 1)
      plt.axis('off')
      plt.imshow(img)
```

```python
plot_3random_img(covid_files) #positive Covid19 samples
```




```python
plot_3random_img(non_covid_files) #non-Covid19 samples
```



The dataset is divided into three splits: the train set (425 examples), validation set (118 examples), and the test set (203 examples). Information for this split has been provided in the folder Data-split folder. This folder contains text files which explain what files belong to each split.

We write a function to read these files and put them into a list of strings:

```python
def read_txt(txt_path):
    with open(txt_path) as f:
        lines = f.readlines()
    txt_data = [line.strip() for line in lines]
    return txt_data
```

We then create the COVIDCTDataset class which basically subclasses the torch.utils.data.Dataset class:

```python
class CovidCTDataset(Dataset):
    def __init__(self, root_dir, classes, covid_files, non_covid_files, transform=None):
        self.root_dir = root_dir
        self.classes = classes
```

```
        self.files_path = [non_covid_files, covid_files]
        self.image_list = []

        # read the files from data split text files
        covid_files = read_txt(covid_files)
        non_covid_files = read_txt(non_covid_files)

        # combine the positive and negative files into a cummulative files list
        for cls_index in range(len(self.classes)):

            class_files = [[os.path.join(self.root_dir, self.classes[cls_index], x), cls_index] \
                            for x in read_txt(self.files_path[cls_index])]
            self.image_list += class_files

        self.transform = transform

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

    def __getitem__(self, idx):
        path = self.image_list[idx][0]

        # Read the image
        image = Image.open(path).convert('RGB')

        # Apply transforms
        if self.transform:
            image = self.transform(image)

        label = int(self.image_list[idx][1])

        data = {'img':   image,
                'label': label,
                'paths' : path}

        return data
```

## Preprocessing

```
train_transformer = transforms.Compose([transforms.Resize(256),
                                        transforms.RandomResizedCrop((224),scale=(0.5, 1.0)),
                                        transforms.RandomHorizontalFlip(),
                                        transforms.ToTensor(),
                                        transforms.Normalize(mean=[0, 0, 0], std=[1, 1, 1])])


val_transformer = transforms.Compose([transforms.Resize((224,224)),
                                      transforms.ToTensor(),
                                      transforms.Normalize(mean=[0, 0, 0], std=[1, 1, 1])])
```

## Training

```
batchsize = 8

trainset = CovidCTDataset(root_dir='/content/',
                          classes = ['CT_NonCOVID', 'CT_COVID'],
                          covid_files='COVID-CT/Data-split/COVID/trainCT_COVID.txt',
                          non_covid_files='/content/COVID-CT/Data-split/NonCOVID/trainCT_NonCOVID.txt',
                          transform = train_transformer)
valset = CovidCTDataset(root_dir='/content/',
                          classes = ['CT_NonCOVID', 'CT_COVID'],
                          covid_files='COVID-CT/Data-split/COVID/valCT_COVID.txt',
                          non_covid_files = '/content/COVID-CT/Data-split/NonCOVID/valCT_NonCOVID.txt',
                          transform = val_transformer)
testset = CovidCTDataset(root_dir='/content/',
                          classes = ['CT_NonCOVID', 'CT_COVID'],
                          covid_files='COVID-CT/Data-split/COVID/testCT_COVID.txt',
                          non_covid_files='/content/COVID-CT/Data-split/NonCOVID/testCT_NonCOVID.txt',
                          transform = val_transformer)

train_loader = DataLoader(trainset, batch_size=batchsize, drop_last=False, shuffle=True)
```

```
val_loader = DataLoader(valset, batch_size=batchsize, drop_last=False, shuffle=False)
test_loader = DataLoader(testset, batch_size=batchsize, drop_last=False, shuffle=False)


#CODE HERE

def calculating_metrics(model, test_loader, plot_roc_curve = False):

    # Evaluation the pytorch model with val_loader
    model.eval()

    # For saving losses of (log cross entropy) function loss
    # Each iteration (Adding them together)
    val_loss = 0

    # For saving number of correctly predicted output by the model
    val_correct = 0

    # Using cross entropy loss for classification (Final layer is a linear with two neurons)
    # That's why we use "CrossEntropyLoss()" instead of "BCEloss()"
    # Note: It is actually "Softmax + Cross entropy loss"
    # Softmax will be used for the output for classification purpose
    criterion = nn.CrossEntropyLoss()

    # For Bookkeeping
    # self.long() is equivalent to self.to(torch.int64)
    score_list  = torch.Tensor([]).to(device)
    pred_list   = torch.Tensor([]).to(device).long()
    target_list = torch.Tensor([]).to(device).long()
    path_list   = []


    for iter, data in enumerate(test_loader):

        # Converting img data into single channel data
        image, target = data['img'].to(device), data['label'].to(device)
        paths = data['paths']
        path_list.extend(paths)

        # Forward pass for the model
        with torch.no_grad():
            output = model(image)

        # Calculating loss
        val_loss += criterion(output, target.long()).item()

        # Number of correctly classified predicted outputs
        pred = output.argmax(dim=1, keepdim=True)
        val_correct += pred.eq(target.long().view_as(pred)).sum().item()

        # We pass the output (final linear layer with one having 2 neurons) through softmax
        score_list   = torch.cat([score_list, nn.Softmax(dim = 1)(output)[:,1].squeeze()])
        pred_list    = torch.cat([pred_list, pred.squeeze()])
        target_list  = torch.cat([target_list, target.squeeze()])


    classification_metrics = classification_report(target_list.tolist(), pred_list.tolist(),
                                                    target_names = ['CT_NonCOVID', 'CT_COVID'],
                                                    output_dict= True,
                                                    )


    # sensitivity is the recall of the positive class
    sensitivity = classification_metrics['CT_COVID']['recall']

    # specificity is the recall of the negative class
    specificity = classification_metrics['CT_NonCOVID']['recall']

    # accuracy
    acc = classification_metrics['accuracy']

    # confusion matrix
    con_matrix = confusion_matrix(target_list.tolist(), pred_list.tolist())

    # roc score
    roc_score = roc_auc_score(target_list.tolist(), score_list.tolist())
```

```
    # plot the roc curve
    if plot_roc_curve:
        false_prate, true_prate, _ = roc_curve(target_list.tolist(), score_list.tolist())
        plt.plot(false_prate, true_prate, label = "Area under ROC = {:.4f}".format(roc_score))
        plt.legend(loc = 'best')
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.show()


    # put together values
    metrics_dict = {"Accuracy": acc,
                    "Sensitivity": sensitivity,
                    "Specificity": specificity,
                    "Roc_score"  : roc_score,
                    "Confusion Matrix": con_matrix,
                    "Validation Loss": val_loss / len(test_loader)}

    # A dictionary of all the metrics we want
    return metrics_dict
```

```
model = vgg19_bn(pretrained=True)
```

We then replace its final linear layer with one having 2 neurons at its output, and perform transfer learning over our dataset.

```
model.classifier[6] = nn.Linear(4096, 2)
model.to(device)
```

```
         (7): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (8): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (9): ReLU(inplace=True)
         (10): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (11): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (12): ReLU(inplace=True)
         (13): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
         (14): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (15): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (16): ReLU(inplace=True)
         (17): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (18): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (19): ReLU(inplace=True)
         (20): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (21): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (22): ReLU(inplace=True)
         (23): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (24): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (25): ReLU(inplace=True)
         (26): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
         (27): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (28): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (29): ReLU(inplace=True)
         (30): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (31): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (32): ReLU(inplace=True)
         (33): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (34): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (35): ReLU(inplace=True)
         (36): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (37): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (38): ReLU(inplace=True)
         (39): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
         (40): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (41): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (42): ReLU(inplace=True)
         (43): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (44): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (45): ReLU(inplace=True)
         (46): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (47): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (48): ReLU(inplace=True)
```

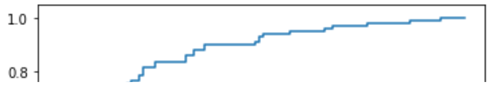
```
        (2): Dropout(p=0.5, inplace=False)
        (3): Linear(in_features=4096, out_features=4096, bias=True)
        (4): ReLU(inplace=True)
        (5): Dropout(p=0.5, inplace=False)
        (6): Linear(in_features=4096, out_features=2, bias=True)
      )
    )
```

```
# Hyperparameters
learning_rate = 0.01
momentum = 0.9


optimizer = optim.SGD(model.parameters(), lr = learning_rate, momentum = momentum)
scheduler = optim.lr_scheduler.StepLR(optimizer, step_size = 8, gamma = 0.1)


best_model = model #initialization
best_validation_acc = 0

criterion = nn.CrossEntropyLoss()

for epoch in range(40):
    model.train()
    train_loss = 0
    train_correct = 0

    for iter, data in enumerate(train_loader):
        image, target = data['img'].to(device), data['label'].to(device)

        #Forward pass
        output = model(image)

        #Calculating loss
        ## divide the loss by 8 since we are adding updates for 8 iterations
        loss = criterion(output, target.long()) / 8
        train_loss += loss.item()

        #Backward pass
        loss.backward()

        # Gradient Update --> updating every 8 iteration
        if iter % 8 == 0:
            optimizer.step()
            optimizer.zero_grad()
            scheduler.step()



        # Calculate the number of correctly classified examples
        pred = output.argmax(dim=1, keepdim=True)
        train_correct += pred.eq(target.long().view_as(pred)).sum().item()

    # Checking the performance metrics for every 5 epoch
    if epoch == 0 or (epoch + 1) % 5 == 0:
        metrics_dict = calculating_metrics(model, val_loader)
        print('------------------------------ Epoch {}/{} ---------------------------------'.format(epoch+1, 40))
        print("Accuracy \t {:.3f}".format(metrics_dict['Accuracy']))
        print("Sensitivity \t {:.3f}".format(metrics_dict['Sensitivity']))
        print("Specificity \t {:.3f}".format(metrics_dict['Specificity']))
        print("Area Under ROC \t {:.3f}".format(metrics_dict['Roc_score']))
        print("Val Loss \t {}".format(metrics_dict["Validation Loss"]))
        print("------------------------------------------------------------------------------")
        print('\n')

    # Save the model with best validation accuracy
    if metrics_dict['Accuracy'] > best_validation_acc:
        torch.save(model, "best_model.pkl")
        best_validation_acc = metrics_dict['Accuracy']
```

```
Area Under ROC   0.840
Val Loss         0.9500029095758994
------------------------------------------------------------------------------


------------------------------- Epoch 20/40 ----------------------------------
Accuracy         0.771
Sensitivity      0.867
Specificity      0.672
Area Under ROC   0.857
Val Loss         0.8720451972136894
------------------------------------------------------------------------------


------------------------------- Epoch 25/40 ----------------------------------
Accuracy         0.712
Sensitivity      0.867
Specificity      0.552
Area Under ROC   0.855
Val Loss         1.3098768473224482
------------------------------------------------------------------------------


------------------------------- Epoch 30/40 ----------------------------------
Accuracy         0.763
Sensitivity      0.850
Specificity      0.672
Area Under ROC   0.868
Val Loss         0.8936457291866342
------------------------------------------------------------------------------


------------------------------- Epoch 35/40 ----------------------------------
Accuracy         0.720
Sensitivity      0.933
Specificity      0.500
Area Under ROC   0.849
Val Loss         1.3699102925253102
------------------------------------------------------------------------------


------------------------------- Epoch 40/40 ----------------------------------
Accuracy         0.797
Sensitivity      0.900
Specificity      0.690
Area Under ROC   0.884
Val Loss         0.7174764371166626
------------------------------------------------------------------------------
```

## Testing

```
model = torch.load("best_model.pkl")

metrics_dict = calculating_metrics(model, test_loader, plot_roc_curve = True)
print('---------------------- Test Performance -------------------------------------')
print("Accuracy·\t·{:.3f}".format(metrics_dict['Accuracy']))
print("Sensitivity·\t·{:.3f}".format(metrics_dict['Sensitivity']))
print("Specificity·\t·{:.3f}".format(metrics_dict['Specificity']))
print("Area Under ROC \t {:.3f}".format(metrics_dict['Roc_score']))
print("-----------------------------------------------------------------------------")
```




```
con_matrix = metrics_dict["Confusion Matrix"]

fig = plt.figure()
fig.set_size_inches(10, 7)
ax= plt.subplot()
sns.heatmap(con_matrix, annot=True, ax = ax); #annot=True to annotate cells


ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels');
ax.set_title('Confusion Matrix');
ax.xaxis.set_ticklabels(['CoViD', 'NonCoViD']); ax.yaxis.set_ticklabels(['CoViD', 'NonCoViD']);
```