1. Train/val data split

```
import os
import random
import shutil
# 원본 데이터 경로
label_folder_path = "./pneumonia_dataset"
# 새로운 데이터 경로
dataset folder path = "./xray dataset"
# train과 val 폴더 경로
train folder path = os.path.join(dataset folder path, "train")
val_folder_path = os.path.join(dataset_folder_path, "val")
#train과 val 폴더 생성
os.makedirs(train folder path, exist ok=True)
os.makedirs(val folder path, exist ok=True)
# 라벨 폴더
org_folders = os.listdir(label_folder_path)
for org_folder in org_folders:
    org_folder_full_path = os.path.join(label_folder_path, org_folder)
    images = os.listdir(org_folder_full_path)
    random.shuffle(images) # 이미지를 무작위로 섞음
    # 라벨 폴더 생성
    train label folder path = os.path.join(train_folder_path, org_folder)
    val label folder path = os.path.join(val folder path, org folder)
    os.makedirs(train label folder path, exist ok=True)
    os.makedirs(val_label_folder_path, exist_ok=True)
    # 이미지를 train 폴더로 이동
    split index = int(len(images) * 0.9)
    for image in images[:split index]:
        src_path = os.path.join(org_folder_full_path, image) # 원본 이미지 경로
        dst_path = os.path.join(train_label_folder_path, image)
#./dataset/train/라벨_폴더/이미지.jpg
        shutil.copyfile(src_path, dst_path)
    # 이미지를 val 폴더로 이동
    for image in images[split index:]:
        src_path = os.path.join(org_folder_full_path, image) # 원본 이미지 경로
        dst_path = os.path.join(val_label_folder_path, image)
#./dataset/val/라벨 폴더/이미지.ipg
```

2. CustomDataSet 함수 정의

```
import os
import cv2
import glob
from torch.utils.data import Dataset
class MyPneumoniaDataset(Dataset):
    def __init__(self, data_dir, transform=None):
        # 데이터 디렉토리 경로 설정
        self.data_dir = glob.glob(os.path.join(data_dir, "*", "*.jpeg"))
        self.transform = transform
        self.label_dict = self.create_label_dict()
    def create label dict(self):
        # 라벨 딕셔너리 생성
        label dict = {}
        for filepath in self.data_dir:
             label = os.path.basename(os.path.dirname(filepath))
             if label not in label_dict:
                 label_dict[label] = len(label_dict)
        return label_dict
    def __getitem__(self, item):
        # 데이터셋에서 아이템 가져오기
        image filepath = self.data dir[item]
        img = cv2.imread(image_filepath)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        label = os.path.basename(os.path.dirname(image_filepath))
        label_idx = self.label_dict[label]
        if self.transform is not None:
             # 이미지 변환 적용
             img = self.transform(image=img)['image']
        return img, label_idx
    def __len__(self):
        # 데이터셋의 총 길이 반환
        return len(self.data_dir)
```

3-1. train 코드

efficientnet b0모델을 이용하여 모델을 학습했습니다.

```
import argparse
import os
import torch.nn as nn
import torch
import torchvision
import albumentations as A
import pandas as pd
import matplotlib.pyplot as plt
from albumentations.pytorch import ToTensorV2
from torchvision.models.efficientnet import efficientnet_b0
from torch.utils.data import DataLoader
from torch.optim import AdamW
from torch.nn import CrossEntropyLoss
from tgdm import tgdm
from ex02_0718_01_customdataset import MyPneumoniaDataset
class Classifier_XRay:
    def __init__(self):
         self.device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
         self.model = None
         self.train_losses = []
         self.valid_losses = []
         self.train_accs = []
         self.valid_accs = []
    def train(self, train loader, val loader, epochs, optimizer, criterion, start epoch=0):
         best val acc = 0.0
         print("Training....")
         for epoch in range(start_epoch, epochs):
             train loss = 0.0
             val loss = 0.0
             train_acc = 0.0
             val acc = 0.0
             self.model.train()
             train_loader_iter = tqdm(train_loader, desc=(f"Epoch : {epoch + 1}/{epochs}"),
leave=False)
             for index, (data, target) in enumerate(train_loader_iter):
                  data, target = data.float().to(self.device), target.to(self.device)
                  optimizer.zero_grad()
                  outputs = self.model(data)
                  loss = criterion(outputs, target)
                  loss.backward()
                  optimizer.step()
                  train loss += loss.item()
                   _, pred = torch.max(outputs, 1)
                  train_acc += (pred == target).sum().item()
```

```
train_loader_iter.set_postfix({"Loss": loss.item()})
         train_loss /= len(train_loader)
         train_acc = train_acc / len(train_loader.dataset)
         # eval()
         self.model.eval()
         with torch.no grad():
             for data, target in val loader:
                  data, target = data.float().to(self.device), target.to(self.device)
                  output = self.model(data)
                  pred = output.argmax(dim=1, keepdim=True)
                  val_acc += pred.eq(target.view_as(pred)).sum().item()
                  val loss += criterion(output, target).item()
         val loss /= len(val loader)
         val acc = val acc / len(val loader.dataset)
         self.train_losses.append(train_loss)
         self.train_accs.append(train_acc)
         self.valid_losses.append(val_loss)
         self.valid_accs.append(val_acc)
         print(f"Epoch [{epoch + 1}/{epochs}], Train loss: {train_loss:.4f}, "
                f"Val loss: {val loss:.4f}, Train ACC: {train acc:.4f}, Val ACC: {val acc:.4f}")
         if val acc > best val acc:
             torch.save(self.model.state_dict(), "./ex02_0718_efficientnet_b0_best.pt")
             best val acc = val acc
         # save the model state and optimizer state after each epoch
         torch.save({
              'epoch': epoch + 1,
              'model_state_dict': self.model.state_dict(),
              'optimizer state dict': optimizer.state dict(),
              'train_losses': self.train_losses,
              'train_accs': self.train_accs,
              'val_losses': self.valid_losses,
              'val_accs': self.valid_accs,
         }, "./weight/0718/ex02_0718_efficientnet_b0_checkpoint.pt")
    torch.save(self.model.state_dict(), "./ex02_0718_efficientnet_b0_last.pt")
    self.save result to csv()
    self.plot loss()
    self.plot_accuracy()
def save result to csv(self):
    df = pd.DataFrame({
         'Train Loss': self.train_losses,
         'Train ACC': self.train_accs,
         'Validation Loss': self.valid_losses,
         'Validation ACC': self.valid accs
    df.to csv('./train val result ex02.csv', index=False)
def plot_loss(self):
    plt.figure()
    plt.plot(self.train_losses, label="Train loss")
```

```
plt.plot(self.valid_losses, label="val loss")
         plt.xlabel("Epoch")
         plt.ylabel('Loss')
         plt.legend()
         plt.savefig("./ex02_loss_plot.jpg")
    def plot accuracy(self):
         plt.figure()
         plt.plot(self.train accs, label="Train Accuracy")
         plt.plot(self.valid accs, label="Valid Accuracy")
         plt.xlabel("Epoch")
         plt.ylabel('Loss')
         plt.legend()
         plt.savefig("./ex02 accuracy plot.jpg")
    def run(self, args):
         self.model = efficientnet b0(pretrained=True)
         self.model.classifier[0] = nn.Dropout(p=0.5, inplace=True)
         self.model.classifier[1] = nn.Linear(1280, out_features=3)
         self.model.to(self.device)
         train_transforms = A.Compose([
             A.Resize(width=224, height=224),
             A.HorizontalFlip(),
             A. VerticalFlip(),
             A.Normalize().
             ToTensorV2()
        1)
         val_transforms = A.Compose([
             A.Resize(width=224, height=224),
             A.Normalize(),
             ToTensorV2()
         1)
         # dataset and dataloader
         train dataset = MyPneumoniaDataset(args.train dir, transform=train transforms)
         val dataset = MyPneumoniaDataset(args.val dir, transform=val transforms)
         train_loader = DataLoader(train_dataset, batch_size=args.batch_size, shuffle=True)
         val_loader = DataLoader(val_dataset, batch_size=args.batch_size, shuffle=True)
         epochs = args.epochs
         criterion = CrossEntropyLoss().to(self.device)
         optimizer = AdamW(self.model.parameters(), lr=args.learning rate,
weight decay=args.weight decay)
         start epoch = 0
         if args.resume training:
             checkpoint = torch.load(args.checkpoint_path)
             self.model.load_state_dict(checkpoint['model_state_dict'])
             optimizer.load_state_dict(checkpoint['optimizer_state_dict'])
             self.train_losses = checkpoint['train_losses']
             self.train_accs = checkpoint['train_accs']
             self.valid losses = checkpoint['val losses']
             self.valid accs = checkpoint['val accs']
             start_epoch = checkpoint['epoch']
         self.train(train_loader, val_loader, epochs, optimizer, criterion, start_epoch=start_epoch)
```

```
if __name__ == "__main__":
    파서는 사용자가 입력한 값들을 쉽게 읽고 사용하기 위한 도구정도로 이해하자
    parser = argparse.ArgumentParser()
    parser.add_argument("--train_dir", type=str, default="./xray_dataset/train/",
                          help='directory path to the training dataset')
    parser.add_argument("--val_dir", type=str, default="./xray_dataset/val/",
                          help="directory path to the validation dataset")
    parser.add_argument("--epochs", type=int, default=20,
                          help="number of epochs for training")
    parser.add_argument("--batch_size", type=int, default=32,
                          help='batch size for training and validation')
    parser.add argument("--learning rate", type=float, default=0.001,
                          help="learning rate for optimizer")
    parser.add_argument("--weight_decay", type=float, default=1e-4,
                          help='weight decay for optimizer')
    parser.add_argument("--resume_training", action='store_true',
                          help='resume training from the last checkpoint')
    parser.add argument("--checkpoint path", type=str,
                          default="./weight/0718/ex02_0718_efficientnet_b0_checkpoint.pt",
                          help="path to the checkpoint file")
    parser.add argument("--checkpoint folder path", type=str,
                          default="./weight/0718")
    args = parser.parse_args()
    weight_folder_path = args.checkpoint_folder_path
    os.makedirs(weight_folder_path, exist_ok=True)
    classifier = Classifier_XRay()
    classifier.run(args)
```

```
Epoch [11/20], Train loss: 0.2979, Val loss: 0.2265, Train ACC: 0.8780, Val ACC: 0.9092
Epoch [12/20], Train loss: 0.2595, Val loss: 0.2042, Train ACC: 0.8942, Val ACC: 0.9162
Epoch [13/20], Train loss: 0.2341, Val loss: 0.1650, Train ACC: 0.9010, Val ACC: 0.9331
Epoch [14/20], Train loss: 0.2081, Val loss: 0.1866, Train ACC: 0.9143, Val ACC: 0.9331
Epoch [15/20], Train loss: 0.2086, Val loss: 0.1952, Train ACC: 0.9134, Val ACC: 0.9242
Epoch [16/20], Train loss: 0.1902, Val loss: 0.1578, Train ACC: 0.9244, Val ACC: 0.9251
Epoch [17/20], Train loss: 0.1548, Val loss: 0.1062, Train ACC: 0.9404, Val ACC: 0.9621
Epoch [18/20], Train loss: 0.1627, Val loss: 0.1686, Train ACC: 0.9354, Val ACC: 0.9331
Epoch [19/20], Train loss: 0.1579, Val loss: 0.1305, Train ACC: 0.9354, Val ACC: 0.9521
Epoch [20/20], Train loss: 0.1429, Val loss: 0.1074, Train ACC: 0.9472, Val ACC: 0.9601
```

3-2. train 코드

ImageNet 데이터셋에서 이미지 분류를 위한 모델을 학습해봤습니다.

https://github.com/pytorch/examples/blob/main/imagenet/main.py 에서 코드 가져와서 Customdataset import 해주고 필요한 부분만 수정하고(모델, epochs, batch_size 등등)나서, 터미널에서 아래 명령어로 실행

python (파일명).py ./(daraset이름)/ --pretrained

```
Administrator: Anaconda Prompt - python .\\excup excup = \text{wexcup} = \text
        h: [0][41/42]
                                                                                                                                                                                                                                                       Acc@1 70.97 ( 64.50)
                                                                                                               Data 0.000 (0.539)
                                                                                                                                                                         Loss 7.5209e-01 (1.2377e+00)
                                                                                                                                                                                                                                                                                                                 Acc@5 100.00 ( 9
  14)
St: [1/9] Time 17.344 (17.344)
Acc@1 68.263 Acc@5 100.000
och: [1][ 1/42] Time 15.636 (15
                                                                                           Loss 4.6082e-01 (4.6082e-01)
                                                                                                                                                                         Acc@1 83.06 ( 83.06) Acc@5 100.00 (100.00)
                                                       100.000
Time 15.636 (15.636)
                                                                                                               Data 14.795 (14.795)
                                                                                                                                                                         Loss 6.4658e-01 (6.4658e-01)
                                                                                                                                                                                                                                                     Acc@1 72.58 ( 72.58)
                                                                                                                                                                                                                                                                                                                Acc@5 100.00 (10
 .00)
poch: [1][11/42]
                                                                                                                                                                         Loss 6.3467e-01 (6.1317e-01)
            [1][21/42]
                                                      Time 2.659 (3.324) Data 0.000 (0.921)
                                                                                                                                                                        Loss 6.3447e-01 (6.1653e-01) Acc@1 74.19 ( 74.54) Acc@5 100.00 (10
            [1][31/42]
                                                                                                               Data 0.000 ( 0.683)
                                                                                                                                                                         Loss 6.1476e-01 (6.0427e-01)
                                                                                                                                                                                                                                                                                                                Acc@5 100.00 (10
                                                       Time 2.642 ( 3.004)
                                                                                                               Data 0.000 ( 0.560)
                                                                                                                                                                         Loss 5.6572e-01 (6.1071e-01)
                                                                                                                                                                                                                                                      Acc@1 75.00 ( 74.11)
                                                                                                                                                                                                                                                                                                                 Acc@5 100.00 (10
 00) (17.069) (17.069) Loss 7

sst: [1/9] Time 17.069 (17.069) Loss 7

Acc@1 67.764 Acc@5 100.000

ooch: [2][ 1/42] Time 15.295 (15.295)
                                                                                                                                                                         Acc@1 70.16 ( 70.16) Acc@5 100.00 (100.00)
                                                                                        Loss 7.7603e-01 (7.7603e-01)
                                                                                                                                                                         Loss 5.7661e-01 (5.7661e-01) Acc@1 75.81 (75.81) Acc@5 100.00 (10
                                                                                                                                                                         Loss 5.8050e-01 (5.7392e-01) Acc@1 72.58 ( 75.73) Acc@5 100.00 (10
                                                     Time 2.661 (3.823) Data 0.000 (1.481)
                                                       Time 2.680 (3.278)
                                                                                                                                                                         Loss 4.3577e-01 (5.4888e-01)
                                                                                                                                                                                                                                                                                                                 Acc@5 100.00 (10
            [2][31/42]
                                                                                                                                                                                                                                                                                                               Acc@5 100.00 (10
                                                     Time 2.688 (3.086) Data 0.008 (0.643)
                                                                                                                                                                         Loss 5.4270e-01 (5.4392e-01)
                                                                                                                                                                                                                                                    Acc@1 75.81 ( 77.00)
            [2][41/42]
                                                                                                               Data 0.000 ( 0.531)
                                                                                                                                                                         Loss 4.5086e-01 (5.4763e-01)
                                                                                                                                                                                                                                                       Acc@1 79.84 ( 76.91) Acc@5 100.00 (10
         7
: [1/9]     Time 17.481 (17.481)
Acc@1 77.944 Acc@5 100.000
                                                                                                                                                                         Acc@1 99.19 ( 99.19) Acc@5 100.00 (100.00)
                                                                                        Loss 3.2404e-02 (3.2404e-02)
```