```
import torch
from torchvision import datasets, transforms, models # datsets , transforms
from \ torch.utils.data.sampler \ import \ SubsetRandomSampler
import torch.nn as nn
import torch.nn.functional as F
from datetime import datetime
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import shutil
transform = transforms.Compose([transforms.Resize(255), transforms.CenterCrop(224), transforms.ToTensor()])
dataset = datasets.ImageFolder("/content/drive/MyDrive/plant/Plant_leave_diseases_dataset_with_augmentation", transform=tr
dataset
     Dataset ImageFolder
         Number of datapoints: 61486
         Root location: /content/drive/MyDrive/plant/Plant_leave_diseases_dataset_with_augmentation
         StandardTransform
     Transform: Compose(
                    Resize(size=255, interpolation=bilinear, max_size=None, antialias=warn)
                    CenterCrop(size=(224, 224))
                    ToTensor()
indices = list(range(len(dataset)))
split = int(np.floor(0.85 * len(dataset)))
validation = int(np.floor(0.70 * split))
print(0, validation, split, len(dataset))
     0 36584 52263 61486
print(f"length of train size :{validation}")
print(f"length of validation size :{split - validation}")
print(f"length of test size :{len(dataset)-validation}")
     length of train size :36584
     length of validation size :15679
     length of test size :24902
np.random.shuffle(indices)
train_indices, validation_indices, test_indices = (
    indices[:validation],
    indices[validation:split],
    indices[split:],
train_sampler = SubsetRandomSampler(train_indices)
validation_sampler = SubsetRandomSampler(validation_indices)
test_sampler = SubsetRandomSampler(test_indices)
targets_size = len(dataset.class_to_idx)
Convolution Aithmetic Equation: (W - F + 2P) / S + 1
W = Input Size
F = Filter Size
P = Padding Size
S = Stride
```

```
class CNN(nn.Module):
    def init (self, K):
        super(CNN, self).__init__()
        self.conv_layers = nn.Sequential(
            # conv1
            nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(32),
            nn.Conv2d(in_channels=32, out_channels=32, kernel_size=3, padding=1),
            nn.ReLU().
            nn.BatchNorm2d(32),
            nn.MaxPool2d(2),
            # conv2
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(64),
            nn.Conv2d(in_channels=64, out_channels=64, kernel_size=3, padding=1),
            nn.ReLU().
            nn.BatchNorm2d(64),
            nn.MaxPool2d(2),
            # conv3
            nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(128),
            nn.Conv2d(in_channels=128, out_channels=128, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(128),
            nn.MaxPool2d(2),
            # conv4
            nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(256),
            nn.Conv2d(in channels=256, out channels=256, kernel size=3, padding=1),
            nn.ReLU(),
            nn.BatchNorm2d(256),
            nn.MaxPool2d(2),
        self.dense_layers = nn.Sequential(
            nn.Dropout(0.4),
            nn.Linear(50176, 1024),
            nn.ReLU(),
            nn.Dropout(0.4),
            nn.Linear(1024, K),
        )
    def forward(self, X):
        out = self.conv_layers(X)
        # Flatten
       out = out.view(-1, 50176)
        # Fully connected
        out = self.dense_layers(out)
        return out
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
     cuda
device = "cuda"
model = CNN(targets size)
model.to(device)
     CNN (
       (conv_layers): Sequential(
         (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (3): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (4): ReLU()
         (5): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
         (7): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (8): ReLU()
         (9): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
         (10): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
         (12): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
(13): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (14): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (15): ReLU()
  (16): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (17): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (18): ReLU()
  (19): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track running stats=True)
  (20): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (21): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (22): ReLU()
  (23): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (24): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (25): ReLU()
  (26): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
 (27): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
(dense layers): Sequential(
 (0): Dropout(p=0.4, inplace=False)
  (1): Linear(in_features=50176, out_features=1024, bias=True)
  (2): ReLU()
  (3): Dropout(p=0.4, inplace=False)
 (4): Linear(in_features=1024, out_features=39, bias=True)
```

```
from torchsummary import summary
summary(model, (3, 224, 224))
```

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 32, 224, 224]	 896
ReLU-2	[-1, 32, 224, 224]	0
BatchNorm2d-3	[-1, 32, 224, 224]	64
Conv2d-4	[-1, 32, 224, 224]	9,248
ReLU-5	[-1, 32, 224, 224]	0
BatchNorm2d-6	[-1, 32, 224, 224]	64
MaxPool2d-7	[-1, 32, 112, 112]	0
Conv2d-8	[-1, 64, 112, 112]	18,496
ReLU-9	[-1, 64, 112, 112]	0
BatchNorm2d-10	[-1, 64, 112, 112]	128
Conv2d-11	[-1, 64, 112, 112]	36,928
ReLU-12	[-1, 64, 112, 112]	0
BatchNorm2d-13	[-1, 64, 112, 112]	128
MaxPool2d-14	[-1, 64, 56, 56]	0
Conv2d-15	[-1, 128, 56, 56]	73,856
ReLU-16	[-1, 128, 56, 56]	0
BatchNorm2d-17	[-1, 128, 56, 56]	256
Conv2d-18	[-1, 128, 56, 56]	147,584
ReLU-19	[-1, 128, 56, 56]	0
BatchNorm2d-20	[-1, 128, 56, 56]	256
MaxPool2d-21	[-1, 128, 28, 28]	0
Conv2d-22	[-1, 256, 28, 28]	295,168
ReLU-23	[-1, 256, 28, 28]	0
BatchNorm2d-24	[-1, 256, 28, 28]	512
Conv2d-25	[-1, 256, 28, 28]	590,080
ReLU-26	[-1, 256, 28, 28]	0
BatchNorm2d-27	[-1, 256, 28, 28]	512
MaxPool2d-28	[-1, 256, 14, 14]	0
Dropout-29	[-1, 50176]	0
Linear-30	[-1, 1024]	51,381,248
ReLU-31	[-1, 1024]	0
Dropout-32	[-1, 1024]	0
Linear-33	[-1, 39]	39,975

Total params: 52,595,399
Trainable params: 52,595,399
Non-trainable params: 0

Input size (MB): 0.57
Forward/backward pass size (MB): 143.96
Params size (MB): 200.64
Estimated Total Size (MB): 345.17

```
criterion = nn.CrossEntropyLoss() # this include softmax + cross entropy loss
optimizer = torch.optim.Adam(model.parameters())

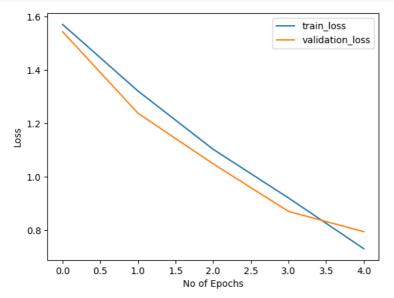
import numpy as np
from datetime import datetime # Import datetime module for time tracking

def batch_gd(model, criterion, train_loader, validation_loader, epochs, optimizer, device):
    train_losses = np.zeros(epochs)
    validation_losses = np.zeros(epochs) # Corrected variable name to match usage
```

```
for e in range(epochs):
                 t0 = datetime.now()
                 train_loss = []
                 for inputs, targets in train_loader:
                         inputs, targets = inputs.to(device), targets.to(device)
                         optimizer.zero grad()
                         output = model(inputs)
                         loss = criterion(output, targets)
                         train_loss.append(loss.item())
                         loss.backward()
                         optimizer.step()
                 train_loss = np.mean(train_loss)
                 validation_loss = []
                 for inputs, targets in validation_loader:
                          inputs, targets = inputs.to(device), targets.to(device)
                         output = model(inputs)
                         loss = criterion(output, targets)
                         validation_loss.append(loss.item())
                 validation_loss = np.mean(validation_loss)
                 train_losses[e] = train_loss
                 validation_losses[e] = validation_loss # Corrected variable name to match usage
                 dt = datetime.now() - t0
                 print(
                         f"Epoch: \{e+1\}/\{epochs\}\ Train\_loss: \{train\_loss:.3f\}\ Validation\_loss: \{validation\_loss:.3f\}\ Duration: \{dt\}'' = \{validation\_loss:.3f\}\ Duration: \{dt\}'' 
         return train_losses, validation_losses # Corrected variable name to match usage
device = "cuda'
batch_size = 32
train_loader = torch.utils.data.DataLoader(
        dataset, batch_size=batch_size, sampler=train_sampler
test_loader = torch.utils.data.DataLoader(
        {\tt dataset, batch\_size=batch\_size, sampler=test\_sampler}
validation loader = torch.utils.data.DataLoader(
        dataset, batch_size=batch_size, sampler=validation_sampler
torch.cuda.empty_cache()
train_losses, validation_losses = batch_gd(
        model, criterion, train_loader, validation_loader, 5, optimizer, device
           Epoch : 1/5 Train_loss:1.570 Validation_loss:1.543 Duration:0:05:05.075720
           Epoch: 2/5 Train_loss:1.321 Validation_loss:1.238 Duration:0:05:05.512447
           Epoch : 3/5 Train_loss:1.103 Validation_loss:1.048 Duration:0:05:05.808788
           Epoch: 4/5 Train_loss:0.921 Validation_loss:0.870 Duration:0:05:04.819274
           Epoch: 5/5 Train_loss:0.731 Validation_loss:0.794 Duration:0:05:04.904237
torch.save(model.state_dict() , 'plant_disease_model_1.pt')
targets_size = 39
model = CNN(targets_size)
model.load_state_dict(torch.load("plant_disease_model_1.pt"))
model.eval()
```

```
CNN(
  (conv_layers): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU()
    (2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (3): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): ReLU()
    (5): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (7): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU()
    (9): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (10): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU()
    (12): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (13): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (14): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
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    (20): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (21): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
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    (25): ReLU()
    (26): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (27): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (dense_layers): Sequential(
    (0): Dropout(p=0.4, inplace=False)
    (1): Linear(in_features=50176, out_features=1024, bias=True)
    (2): ReLU()
    (3): Dropout(p=0.4, inplace=False)
    (4): Linear(in_features=1024, out_features=39, bias=True)
)
```

```
plt.plot(train_losses , label = 'train_loss')
plt.plot(validation_losses , label = 'validation_loss')
plt.xlabel('No of Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
# Move the model to the GPU (if not already on the GPU)
model.to(device)

def accuracy(loader):
    n_correct = 0
    n_total = 0

model.eval() # Set the model to evaluation mode

with torch.no_grad(): # Disable gradient computation for inference
    for inputs, targets in loader:
        inputs, targets = inputs.to(device), targets.to(device)
```

```
outputs = model(inputs)
                             _, predictions = torch.max(outputs, 1)
                             n_correct += (predictions == targets).sum().item()
                             n_total += targets.shape[0]
         model.train() # Set the model back to training mode
          acc = n_correct / n_total
          return acc
\ensuremath{\mathtt{\#}} 
 Now calculate accuracies for train, test, and validation loaders
train_acc = accuracy(train_loader)
test_acc = accuracy(test_loader)
validation_acc = accuracy(validation_loader)
print(
         f"Train\ Accuracy : \{train\_acc\} \land Test\_acc\} \land Accuracy : \{test\_acc\} \land Accura
            Train Accuracy : 0.9075278810408922
            Test Accuracy : 0.881491922367993
            Validation Accuracy : 0.8718030486638179
transform_index_to_disease = dataset.class_to_idx
transform_index_to_disease = dict(
         [(value, key) for key, value in transform_index_to_disease.items()]
transform_index_to_disease
            {0: 'Apple__Apple_scab',
              1: 'Apple___Black_rot',
              2: 'Apple___Cedar_apple_rust',
              3: 'Apple___healthy',
              4: 'Background_without_leaves',
              5: 'Blueberry__healthy',
6: 'Cherry__Powdery_mildew',
              7: 'Cherry__healthy',
8: 'Corn__Cercospora_leaf_spot Gray_leaf_spot',
              9: 'Corn___Common_rust'
              10: 'Corn___Northern_Leaf_Blight',
              11: 'Corn___healthy',
              12: 'Grape___Black_rot',
13: 'Grape___Esca_(Black_Measles)',
              14: 'Grape__Leaf_blight_(Isariopsis_Leaf_Spot)',
15: 'Grape__healthy',
              16: 'Orange__Haunglongbing_(Citrus_greening)',
17: 'Peach__Bacterial_spot',
              18: 'Peach___healthy',
              19: 'Pepper,_bell___Bacterial_spot',
              20: 'Pepper,_bell___healthy',
              21: 'Potato___Early_blight',
              22: 'Potato___Late_blight',
23: 'Potato___healthy',
              24: 'Raspberry_healthy',
25: 'Soybean_healthy',
26: 'Squash_Powdery_mildew',
              27: 'Strawberry__Leaf_scorch', 28: 'Strawberry__healthy',
              29: 'Tomato___Bacterial_spot',
              30: 'Tomato___Early_blight',
              31: 'Tomato___Late_blight',
              32: 'Tomato___Leaf_Mold'
              33: 'Tomato___Septoria_leaf_spot',
              34: 'Tomato___Spider_mites Two-spotted_spider_mite',
              35: 'Tomato___Target_Spot',
              36: 'Tomato__ Tomato_Yellow_Leaf_Curl_Virus',
37: 'Tomato__ Tomato_mosaic_virus',
              38: 'Tomato___healthy'}
from PIL import Image
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
\tt def \ single\_prediction(image\_path, \ model, \ transform\_index\_to\_disease, \ device):
          image = Image.open(image_path)
          image = image.resize((224, 224))
          # Use torchvision.transforms.ToTensor() to convert the image to a tensor
```

```
transform = transforms.Compose([transforms.ToTensor()])
input_data = transform(image)
input_data = input_data.view((-1, 3, 224, 224))

# Move the input data to the same device as the model
input_data = input_data.to(device)

output = model(input_data)
output = output.detach().cpu().numpy() # Move output to CPU for further processing
index = np.argmax(output)

print("Original : ", image_path[12:-4])
pred = transform_index_to_disease[index]

plt.imshow(image)
plt.title("Disease Prediction: " + pred)
plt.show()

# Example usage:
single_prediction("/content/drive/MyDrive/Plant_leave_diseases_dataset_with_augmentation/Apple___healthy/image (1004).JPG'
```

 ${\tt Original: ve/MyDrive/Plant_leave_diseases_dataset_with_augmentation/Apple__healthy/image~(1004)}$

