□ PLANT DISEASE CLASSIFICATION USING RESNET-9 □

Corresponding Kaggle notebook can be accessed [here]

□□□DISCLAIMER: This notebook is beginner friendly, so don't worry if you don't know much about CNNs and Pytorch. Even if you have used TensorFlow in the past and are new to PyTorch, hang in there, everything is explained clearly and concisely. You will get a good overview of how to use PyTorch for image classification problems.

Description of the dataset □

This dataset is created using offline augmentation from the original dataset. The original PlantVillage Dataset can be found here.This dataset consists of about 87K rgb images of healthy and diseased crop leaves which is categorized into 38 different classes. The total dataset is divided into 80/20 ratio of training and validation set preserving the directory structure. A new directory containing 33 test images is created later for prediction purpose.

Note: This description is given in the dataset itself

Our goal □

Goal is clear and simple. We need to build a model, which can classify between healthy and diseased crop leaves and also if the crop have any disease, predict which disease is it.

Let's get started....

Importing necessary libraries

Let's import required modules

In [1]:

```
!pip install torchsummary
```

```
Collecting torchsummary
  Downloading torchsummary-1.5.1-py3-none-any.whl (2.8 kB)
Installing collected packages: torchsummary
Successfully installed torchsummary-1.5.1
```

We would require torchsummary library to print the model's summary in keras style (nicely formatted and pretty to look) as Pytorch natively doesn't support that

In [2]:

```
import os                         # for working with files
import numpy as np                # for numerical computationss
import pandas as pd               # for working with dataframes
import torch                      # Pytorch module
import matplotlib.pyplot as plt # for plotting informations on graph and images using tensors
import torch.nn as nn             # for creating  neural networks
from torch.utils.data import DataLoader # for dataloaders
from PIL import Image             # for checking images
import torch.nn.functional as F # for functions for calculating loss
import torchvision.transforms as transforms   # for transforming images into tensors
from torchvision.utils import make_grid       # for data checking
```

```
from torchvision.datasets import ImageFolder  # for working with classes and images
from torchsummary import summary              # for getting the summary of our model

%matplotlib inline
```

□ Exploring the data □

Loading the data

In [3]:

```
data_dir = "../input/new-plant-diseases-dataset/New Plant Diseases Dataset(Augmented)/New Plant Diseases Dataset(Augmented)"
train_dir = data_dir + "/train"
valid_dir = data_dir + "/valid"
diseases = os.listdir(train_dir)
```

In [4]:

```
# printing the disease names
print(diseases)
```

```
['Tomato___Late_blight', 'Tomato___healthy', 'Grape___healthy', 'Orange___Haunglongbing_(Citrus_greening)', 'Soybean___healthy', 'Squash___Powdery_mildew', 'Potato___healthy', 'Corn_(maize)___Northern_Leaf_Blight', 'Tomato___Early_blight', 'Tomato___Septoria_leaf_spot', 'Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot', 'Strawberry___Leaf_scorch', 'Peach___healthy', 'Apple___Apple_scab', 'Tomato___Tomato_Yellow_Leaf_Curl_Virus', 'Tomato___Bacterial_spot', 'Apple___Black_rot', 'Blueberry___healthy', 'Cherry_(including_sour)___Powdery_mildew', 'Peach___Bacterial_spot', 'Apple___Cedar_apple_rust', 'Tomato___Target_Spot', 'Pepper,_bell___healthy', 'Grape___Leaf_blight_(Isariopsis_Leaf_Spot)', 'Potato___Late_blight', 'Tomato___Tomato_mosaic_virus', 'Strawberry___healthy', 'Apple___healthy', 'Grape___Black_rot', 'Potato___Early_blight', 'Cherry_(including_sour)___healthy', 'Corn_(maize)___Common_rust_', 'Grape___Esca_(Black_Measles)', 'Raspberry___healthy', 'Tomato___Leaf_Mold', 'Tomato___Spider_mites Two-spotted_spider_mite', 'Pepper,_bell___Bacterial_spot', 'Corn_(maize)___healthy']
```

In [5]:

```
print("Total disease classes are: {}".format(len(diseases)))
```

```
Total disease classes are: 38
```

In [6]:

```
plants = []
NumberOfDiseases = 0
for plant in diseases:
    if plant.split('___')[0] not in plants:
        plants.append(plant.split('___')[0])
    if plant.split('___')[1] != 'healthy':
        NumberOfDiseases += 1
```

The above cell extract the number of unique plants and number of unique diseases

In [7]:

```
# unique plants in the dataset
print(f"Unique Plants are: \n{plants}")
```

```
Unique Plants are:
['Tomato', 'Grape', 'Orange', 'Soybean', 'Squash', 'Potato', 'Corn_(maize)', 'Strawberry', 'Peach', 'Apple', 'Blueberry', 'Cherry_(including_sour)', 'Pepper,_bell', 'Raspberry']
```

In [8]:

```
# number of unique plants
print("Number of plants: {}".format(len(plants)))
```

```
Number of plants: 14
```

In [9]:

```
# number of unique diseases
print("Number of diseases: {}".format(NumberOfDiseases))
```

```
Number of diseases: 26
```

So we have images of leaves of 14 plants and while excluding healthy leaves, we have 26 types of images that show a particular disease in a particular plant.

In [10]:

```
# Number of images for each disease
nums = {}
for disease in diseases:
    nums[disease] = len(os.listdir(train_dir + '/' + disease))

# converting the nums dictionary to pandas dataframe passing index as plant
name and number of images as column

img_per_class = pd.DataFrame(nums.values(), index=nums.keys(),
columns=["no. of images"])
img_per_class
```

Out[10]:

	no. of images
Tomato___Late_blight	1851
Tomato___healthy	1926
Grape___healthy	1692
Orange___Haunglongbing_(Citrus_greening)	2010
Soybean___healthy	2022
Squash___Powdery_mildew	1736
Potato___healthy	1824
Corn_(maize)___Northern_Leaf_Blight	1908
Tomato___Early_blight	1920
Tomato___Septoria_leaf_spot	1745
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	1642

	no. of images
Strawberry___Leaf_scorch	1774
Peach___healthy	1728
Apple___Apple_scab	2016
Tomato___Tomato_Yellow_Leaf_Curl_Virus	1961
Tomato___Bacterial_spot	1702
Apple___Black_rot	1987
Blueberry___healthy	1816
Cherry_(including_sour)___Powdery_mildew	1683
Peach___Bacterial_spot	1838
Apple___Cedar_apple_rust	1760
Tomato___Target_Spot	1827
Pepper,_bell___healthy	1988
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1722
Potato___Late_blight	1939
Tomato___Tomato_mosaic_virus	1790
Strawberry___healthy	1824
Apple___healthy	2008
Grape___Black_rot	1888
Potato___Early_blight	1939
Cherry_(including_sour)___healthy	1826

	no. of images
Corn_(maize)___Common_rust_	1907
Grape___Esca_(Black_Measles)	1920
Raspberry___healthy	1781
Tomato___Leaf_Mold	1882
Tomato___Spider_mites Two-spotted_spider_mite	1741
Pepper,_bell___Bacterial_spot	1913
Corn_(maize)___healthy	1859

Visualizing the above information on a graph

In [11]:

```
# plotting number of images available for each disease
index = [n for n in range(38)]
plt.figure(figsize=(20, 5))
plt.bar(index, [n for n in nums.values()], width=0.3)
plt.xlabel('Plants/Diseases', fontsize=10)
plt.ylabel('No of images available', fontsize=10)
plt.xticks(index, diseases, fontsize=5, rotation=90)
plt.title('Images per each class of plant disease')
```

Out[11]:

```
Text(0.5, 1.0, 'Images per each class of plant disease')
```

We can see that the dataset is almost balanced for all classes, so we are good to go forward

Images available for training

In [12]:

```
n_train = 0
for value in nums.values():
    n_train += value
print(f"There are {n_train} images for training")
```

```
There are 70295 images for training
```

□ Data Preparation for training □

In [13]:

```
# datasets for validation and training
train = ImageFolder(train_dir, transform=transforms.ToTensor())
valid = ImageFolder(valid_dir, transform=transforms.ToTensor())
```

torchvision.datasets is a class which helps in loading all common and famous datasets. It also helps in loading custom datasets. I have used subclass torchvision.datasets.ImageFolder which helps in loading the image data when the data is arranged in this way:

---

root/dog/xxx.png

root/dog/xxy.png

root/dog/xxz.png

root/cat/123.png

root/cat/nsdf3.png

root/cat/asd932_.png

Next, after loading the data, we need to transform the pixel values of each image (0-255) to 0-1 as neural networks works quite good with normalized data. The entire array of pixel values is converted to torch tensor and then divided by 255. If you are not familiar why normalizing inputs help neural network, read this post.

Image shape

In [14]:

```
img, label = train[0]
print(img.shape, label)
```

```
torch.Size([3, 256, 256]) 0
```

We can see the shape (3, 256 256) of the image. 3 is the number of channels (RGB) and 256 x 256 is the width and height of the image

In [15]:

```
# total number of classes in train set
len(train.classes)
```

Out[15]:

```
38
```

In [16]:

```
# for checking some images from training dataset
def show_image(image, label):
    print("Label :" + train.classes[label] + "(" + str(label) + ")")
    plt.imshow(image.permute(1, 2, 0))
```

□ Some Images from training dataset □

In [17]:

```
show_image(*train[0])
```

```
Label :Apple___Apple_scab(0)
```

In [18]:

```
show_image(*train[70000])
```

```
Label :Tomato___healthy(37)
```

In [19]:

```
show_image(*train[30000])
```

```
Label :Peach___Bacterial_spot(16)
```

In [20]:

```
# Setting the seed value
random_seed = 7
torch.manual_seed(random_seed)
```

Out[20]:

In [21]:

```
# setting the batch size
batch_size = 32
```

batch_size is the total number of images given as input at once in forward propagation of the CNN. Basically, batch size defines the number of samples that will be propagated through the network.

For instance, let's say you have 1050 training samples and you want to set up a batch_size equal to 100. The algorithm takes the first 100 samples (from 1st to 100th) from the training dataset and trains the network. Next, it takes the second 100 samples (from 101st to 200th) and trains the network again. We can keep doing this procedure until we have propagated all samples through of the network.

In [22]:

```
# DataLoaders for training and validation
train_dl = DataLoader(train, batch_size, shuffle=True, num_workers=2, 
pin_memory=True)
valid_dl = DataLoader(valid, batch_size, num_workers=2, pin_memory=True)
```

- DataLoader is a subclass which comes from torch.utils.data. It helps in loading large and memory consuming datasets. It takes in batch_size which denotes the number of samples contained in each generated batch.
- Setting shuffle=True shuffles the dataset. It is heplful so that batches between epochs do not look alike. Doing so will eventually make our model more robust.
- num_workers, denotes the number of processes that generate batches in parallel. If you have more cores in your CPU, you can set it to number of cores in your CPU. Since, Kaggle provides a 2 core CPU, I have set it to 2

In [23]:

```
# helper function to show a batch of training instances
def show_batch(data):
    for images, labels in data:
        fig, ax = plt.subplots(figsize=(30, 30))
        ax.set_xticks([]); ax.set_yticks([])
        ax.imshow(make_grid(images, nrow=8).permute(1, 2, 0))
        break
```

In [24]:

```
# Images for first batch of training
show_batch(train_dl)
```

□ Modelling □

It is advisable to use GPU instead of CPU when dealing with images dataset because CPUs are generalized for general purpose and GPUs are optimized for training deep learning models as they can process multiple computations simultaneously. They have a large number of cores, which allows for better computation of multiple parallel processes. Additionally, computations in deep learning need to handle huge amounts of data — this makes a GPU's memory bandwidth most suitable. To seamlessly use a GPU, if one is available, we define a couple of helper functions (get_default_device & to_device) and a helper class DeviceDataLoader to move our model & data to the GPU as required

Some helper functions

In [25]:

```
# for moving data into GPU (if available)
def get_default_device():
    """Pick GPU if available, else CPU"""
    if torch.cuda.is_available:
        return torch.device("cuda")
    else:
        return torch.device("cpu")

# for moving data to device (CPU or GPU)
def to_device(data, device):
    """Move tensor(s) to chosen device"""
    if isinstance(data, (list,tuple)):
        return [to_device(x, device) for x in data]
    return data.to(device, non_blocking=True)

# for loading in the device (GPU if available else CPU)
class DeviceDataLoader():
    """Wrap a dataloader to move data to a device"""
    def __init__(self, dl, device):
        self.dl = dl
        self.device = device

    def __iter__(self):
        """Yield a batch of data after moving it to device"""
        for b in self.dl:
            yield to_device(b, self.device)

    def __len__(self):
        """Number of batches"""
        return len(self.dl)
```

Checking the device we are working with

In [26]:

```
device = get_default_device()
device
```

Out[26]:

```
device(type='cuda')
```

Wrap up our training and validation data loaders using DeviceDataLoader for automatically transferring batches of data to the GPU (if available)

In [27]:

```
# Moving data into GPU
train_dl = DeviceDataLoader(train_dl, device)
valid_dl = DeviceDataLoader(valid_dl, device)
```

□ Building the model architecture □

We are going to use ResNet, which have been one of the major breakthrough in computer vision since they were introduced in 2015.

If you want to learn more about ResNets read the following articles:

- Understanding and Visualizing ResNets
- Overview of ResNet and its variants
- Paper with code implementation

In ResNets, unlike in traditional neural networks, each layer feeds into the next layer, we use a network with residual blocks, each layer feeds into the next layer and directly into the layers about 2–3 hops away, to avoid over-fitting (a situation when validation loss stop decreasing at a point and then keeps increasing while training loss still decreases). This also helps in preventing vanishing gradient problem and allow us to train deep neural networks. Here is a simple residual block:

Residual Block code implementation

In [28]:

```
class SimpleResidualBlock(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=3, 
kernel_size=3, stride=1, padding=1)
        self.relu1 = nn.ReLU()
        self.conv2 = nn.Conv2d(in_channels=3, out_channels=3, 
kernel_size=3, stride=1, padding=1)
        self.relu2 = nn.ReLU()

    def forward(self, x):
        out = self.conv1(x)
        out = self.relu1(out)
        out = self.conv2(out)
        return self.relu2(out) + x # ReLU can be applied before or after 
adding the input
```

Then we define our ImageClassificationBase class whose functions are:

- training_step - To figure out how "wrong" the model is going after training or validation step.We are using this function other than just an accuracy metric that is likely not going to be differentiable (this would mean that the gradient can't be determined, which is necessary for the model to improve during training)

A quick look at the PyTorch docs that yields the cost function: cross_entropy.

- validation_step - Because an accuracy metric can't be used while training the model, doesn't mean it shouldn't be implemented! Accuracy in this case would be measured by a threshold, and counted if the difference between the model's prediction and the actual label is lower than that threshold.
- validation_epoch_end - We want to track the validation losses/accuracies and train losses after each epoch, and every time we do so we have to make sure the gradient is not being tracked.
- epoch_end - We also want to print validation losses/accuracies, train losses and learning rate too because we are using learning rate scheduler (which will change the learning rate after every batch of training) after each epoch.

We also define an accuracy function which calculates the overall accuracy of the model on an entire batch of outputs, so that we can use it as a metric in fit_one_cycle

In [29]:

```
# for calculating the accuracy
def accuracy(outputs, labels):
    _, preds = torch.max(outputs, dim=1)
    return torch.tensor(torch.sum(preds == labels).item() / len(preds))


# base class for the model
class ImageClassificationBase(nn.Module):

    def training_step(self, batch):
        images, labels = batch
        out = self(images)                  # Generate predictions
        loss = F.cross_entropy(out, labels) # Calculate loss
        return loss

    def validation_step(self, batch):
```

```
        images, labels = batch
        out = self(images)                    # Generate prediction
        loss = F.cross_entropy(out, labels)   # Calculate loss
        acc = accuracy(out, labels)           # Calculate accuracy
        return {"val_loss": loss.detach(), "val_accuracy": acc}

    def validation_epoch_end(self, outputs):
        batch_losses = [x["val_loss"] for x in outputs]
        batch_accuracy = [x["val_accuracy"] for x in outputs]
        epoch_loss = torch.stack(batch_losses).mean()       # Combine loss
        epoch_accuracy = torch.stack(batch_accuracy).mean()
        return {"val_loss": epoch_loss, "val_accuracy": epoch_accuracy} #
Combine accuracies

    def epoch_end(self, epoch, result):
        print("Epoch [{}], last_lr: {:.5f}, train_loss: {:.4f}, val_loss:
{:.4f}, val_acc: {:.4f}".format(
            epoch, result['lrs'][-1], result['train_loss'],
result['val_loss'], result['val_accuracy']))
```

□ Defining the final architecture of our model □

In [30]:

```
# Architecture for training

# convolution block with BatchNormalization
def ConvBlock(in_channels, out_channels, pool=False):
    layers = [nn.Conv2d(in_channels, out_channels, kernel_size=3,
padding=1),
             nn.BatchNorm2d(out_channels),
             nn.ReLU(inplace=True)]
    if pool:
        layers.append(nn.MaxPool2d(4))
    return nn.Sequential(*layers)


# resnet architecture
class ResNet9(ImageClassificationBase):
    def __init__(self, in_channels, num_diseases):
        super().__init__()

        self.conv1 = ConvBlock(in_channels, 64)
        self.conv2 = ConvBlock(64, 128, pool=True) # out_dim : 128 x 64 x
64
        self.res1 = nn.Sequential(ConvBlock(128, 128), ConvBlock(128, 128))

        self.conv3 = ConvBlock(128, 256, pool=True) # out_dim : 256 x 16 x
16
        self.conv4 = ConvBlock(256, 512, pool=True) # out_dim : 512 x 4 x
44
        self.res2 = nn.Sequential(ConvBlock(512, 512), ConvBlock(512, 512))

        self.classifier = nn.Sequential(nn.MaxPool2d(4),
                                       nn.Flatten(),
                                       nn.Linear(512, num_diseases))

    def forward(self, xb): # xb is the loaded batch
        out = self.conv1(xb)
        out = self.conv2(out)
```

```
        out = self.res1(out) + out
        out = self.conv3(out)
        out = self.conv4(out)
        out = self.res2(out) + out
        out = self.classifier(out)
        return out
```

Now, we define a model object and transfer it into the device with which we are working...

In [31]:

```
# defining the model and moving it to the GPU
model = to_device(ResNet9(3, len(train.classes)), device)
model
```

Out[31]:

```
ResNet9(
  (conv1): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU(inplace=True)
  )
  (conv2): Sequential(
    (0): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=4, stride=4, padding=0, dilation=1,
ceil_mode=False)
  )
  (res1): Sequential(
    (0): Sequential(
      (0): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): ReLU(inplace=True)
    )
    (1): Sequential(
      (0): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): ReLU(inplace=True)
    )
  )
  (conv3): Sequential(
    (0): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=4, stride=4, padding=0, dilation=1,
ceil_mode=False)
  )
  (conv4): Sequential(
    (0): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=4, stride=4, padding=0, dilation=1,
ceil_mode=False)
```

```
  )
  (res2): Sequential(
    (0): Sequential(
      (0): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): ReLU(inplace=True)
    )
    (1): Sequential(
      (0): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): ReLU(inplace=True)
    )
  )
  (classifier): Sequential(
    (0): MaxPool2d(kernel_size=4, stride=4, padding=0, dilation=1,
ceil_mode=False)
    (1): Flatten(start_dim=1, end_dim=-1)
    (2): Linear(in_features=512, out_features=38, bias=True)
  )
)
```

Getting a nicely formatted summary of our model (like in Keras). Pytorch doesn't support it natively. So, we need to install the torchsummary *library (discussed earlier)*

In [32]:

```
# getting summary of the model
INPUT_SHAPE = (3, 256, 256)
print(summary(model.cuda(), (INPUT_SHAPE)))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1        [-1, 64, 256, 256]           1,792
       BatchNorm2d-2        [-1, 64, 256, 256]             128
              ReLU-3        [-1, 64, 256, 256]               0
            Conv2d-4       [-1, 128, 256, 256]          73,856
       BatchNorm2d-5       [-1, 128, 256, 256]             256
              ReLU-6       [-1, 128, 256, 256]               0
         MaxPool2d-7         [-1, 128, 64, 64]               0
            Conv2d-8         [-1, 128, 64, 64]         147,584
       BatchNorm2d-9         [-1, 128, 64, 64]             256
             ReLU-10         [-1, 128, 64, 64]               0
           Conv2d-11         [-1, 128, 64, 64]         147,584
      BatchNorm2d-12         [-1, 128, 64, 64]             256
             ReLU-13         [-1, 128, 64, 64]               0
           Conv2d-14         [-1, 256, 64, 64]         295,168
      BatchNorm2d-15         [-1, 256, 64, 64]             512
             ReLU-16         [-1, 256, 64, 64]               0
        MaxPool2d-17         [-1, 256, 16, 16]               0
           Conv2d-18         [-1, 512, 16, 16]       1,180,160
      BatchNorm2d-19         [-1, 512, 16, 16]           1,024
             ReLU-20         [-1, 512, 16, 16]               0
        MaxPool2d-21           [-1, 512, 4, 4]               0
           Conv2d-22           [-1, 512, 4, 4]       2,359,808
      BatchNorm2d-23           [-1, 512, 4, 4]           1,024
             ReLU-24           [-1, 512, 4, 4]               0
           Conv2d-25           [-1, 512, 4, 4]       2,359,808
      BatchNorm2d-26           [-1, 512, 4, 4]           1,024
             ReLU-27           [-1, 512, 4, 4]               0
```

```
        MaxPool2d-28          [-1, 512, 1, 1]               0
          Flatten-29                [-1, 512]               0
           Linear-30                 [-1, 38]          19,494
================================================================
Total params: 6,589,734
Trainable params: 6,589,734
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 343.95
Params size (MB): 25.14
Estimated Total Size (MB): 369.83
----------------------------------------------------------------
None
```

□ Training the model □

Before we train the model, Let's define a utility functionan evaluate function, which will perform the validation phase, and a fit_one_cycle function which will perform the entire training process. In fit_one_cycle, we have use some techniques:

- **Learning Rate Scheduling**: Instead of using a fixed learning rate, we will use a learning rate scheduler, which will change the learning rate after every batch of training. There are many strategies for varying the learning rate during training, and the one we'll use is called the *"One Cycle Learning Rate Policy"*, which involves starting with a low learning rate, gradually increasing it batch-by-batch to a high learning rate for about 30% of epochs, then gradually decreasing it to a very low value for the remaining epochs.

- **Weight Decay**: We also use weight decay, which is a regularization technique which prevents the weights from becoming too large by adding an additional term to the loss function.

- **Gradient Clipping**: Apart from the layer weights and outputs, it also helpful to limit the values of gradients to a small range to prevent undesirable changes in parameters due to large gradient values. This simple yet effective technique is called gradient clipping.

We'll also record the learning rate used for each batch.

In [33]:

```
# for training
@torch.no_grad()
def evaluate(model, val_loader):
    model.eval()
    outputs = [model.validation_step(batch) for batch in val_loader]
    return model.validation_epoch_end(outputs)


def get_lr(optimizer):
    for param_group in optimizer.param_groups:
        return param_group['lr']


def fit_OneCycle(epochs, max_lr, model, train_loader, val_loader, 
weight_decay=0,
                grad_clip=None, opt_func=torch.optim.SGD):
    torch.cuda.empty_cache()
    history = []

    optimizer = opt_func(model.parameters(), max_lr, 
weight_decay=weight_decay)
    # scheduler for one cycle learniing rate
    sched = torch.optim.lr_scheduler.OneCycleLR(optimizer, max_lr, 
epochs=epochs, steps_per_epoch=len(train_loader))
```

```
    for epoch in range(epochs):
        # Training
        model.train()
        train_losses = []
        lrs = []
        for batch in train_loader:
            loss = model.training_step(batch)
            train_losses.append(loss)
            loss.backward()

            # gradient clipping
            if grad_clip:
                nn.utils.clip_grad_value_(model.parameters(), grad_clip)

            optimizer.step()
            optimizer.zero_grad()

            # recording and updating learning rates
            lrs.append(get_lr(optimizer))
            sched.step()


        # validation
        result = evaluate(model, val_loader)
        result['train_loss'] = torch.stack(train_losses).mean().item()
        result['lrs'] = lrs
        model.epoch_end(epoch, result)
        history.append(result)

    return history
```

Let's check our validation loss and accuracy

In [34]:

```
%%time
history = [evaluate(model, valid_dl)]
history
```

```
CPU times: user 44 s, sys: 3.28 s, total: 47.3 s
Wall time: 1min 32s
```

Out[34]:

```
[{'val_loss': tensor(3.6397, device='cuda:0'), 'val_accuracy':
tensor(0.0191)}]
```

Since there are randomly initialized weights, that is why accuracy come to near 0.019 (that is 1.9% chance of getting the right answer or you can say model randomly chooses a class). Now, declare some hyper parameters for the training of the model. We can change it if result is not satisfactory.

In [35]:

```
epochs = 2
max_lr = 0.01
grad_clip = 0.1
weight_decay = 1e-4
opt_func = torch.optim.Adam
```

Let's start training our model ....

Note: The following cell may take 15 mins to 45 mins to run depending on your GPU. In kaggle (P100 GPU) it took around 20 mins of Wall Time.

In [36]:

```
%%time
history += fit_OneCycle(epochs, max_lr, model, train_dl, valid_dl,
```

```
                                 grad_clip=grad_clip,
                                 weight_decay=1e-4,
                                 opt_func=opt_func)
```

```
Epoch [0], last_lr: 0.00812, train_loss: 0.7466, val_loss: 0.5865, val_acc:
0.8319
Epoch [1], last_lr: 0.00000, train_loss: 0.1248, val_loss: 0.0269, val_acc:
0.9923
CPU times: user 11min 16s, sys: 7min 13s, total: 18min 30s
Wall time: 19min 53s
```

We got an accuracy of 99.2 % □□

□ Plotting □

Helper functions for plotting

In [37]:

```
def plot_accuracies(history):
    accuracies = [x['val_accuracy'] for x in history]
    plt.plot(accuracies, '-x')
    plt.xlabel('epoch')
    plt.ylabel('accuracy')
    plt.title('Accuracy vs. No. of epochs');

def plot_losses(history):
    train_losses = [x.get('train_loss') for x in history]
    val_losses = [x['val_loss'] for x in history]
    plt.plot(train_losses, '-bx')
    plt.plot(val_losses, '-rx')
    plt.xlabel('epoch')
    plt.ylabel('loss')
    plt.legend(['Training', 'Validation'])
    plt.title('Loss vs. No. of epochs');

def plot_lrs(history):
    lrs = np.concatenate([x.get('lrs', []) for x in history])
    plt.plot(lrs)
    plt.xlabel('Batch no.')
    plt.ylabel('Learning rate')
    plt.title('Learning Rate vs. Batch no.');
```

Validation Accuracy

In [38]:

```
plot_accuracies(history)
```

Validation loss

In [39]:

```
plot_losses(history)
```

Learning Rate overtime

In [40]:

```
plot_lrs(history)
```

Testing model on test data

We only have 33 images in test data, so let's check the model on all images

In [41]:

```
test_dir = "../input/new-plant-diseases-dataset/test"
test = ImageFolder(test_dir, transform=transforms.ToTensor())
```

In [42]:

```
test_images = sorted(os.listdir(test_dir + '/test')) # since images in test folder are in alphabetical order
test_images
```

Out[42]:

```
['AppleCedarRust1.JPG',
 'AppleCedarRust2.JPG',
 'AppleCedarRust3.JPG',
 'AppleCedarRust4.JPG',
 'AppleScab1.JPG',
 'AppleScab2.JPG',
 'AppleScab3.JPG',
 'CornCommonRust1.JPG',
 'CornCommonRust2.JPG',
 'CornCommonRust3.JPG',
 'PotatoEarlyBlight1.JPG',
 'PotatoEarlyBlight2.JPG',
 'PotatoEarlyBlight3.JPG',
 'PotatoEarlyBlight4.JPG',
 'PotatoEarlyBlight5.JPG',
 'PotatoHealthy1.JPG',
 'PotatoHealthy2.JPG',
 'TomatoEarlyBlight1.JPG',
 'TomatoEarlyBlight2.JPG',
 'TomatoEarlyBlight3.JPG',
 'TomatoEarlyBlight4.JPG',
 'TomatoEarlyBlight5.JPG',
 'TomatoEarlyBlight6.JPG',
 'TomatoHealthy1.JPG',
 'TomatoHealthy2.JPG',
 'TomatoHealthy3.JPG',
 'TomatoHealthy4.JPG',
 'TomatoYellowCurlVirus1.JPG',
 'TomatoYellowCurlVirus2.JPG',
 'TomatoYellowCurlVirus3.JPG',
 'TomatoYellowCurlVirus4.JPG',
 'TomatoYellowCurlVirus5.JPG',
 'TomatoYellowCurlVirus6.JPG']
```

In [43]:

```
def predict_image(img, model):
    """Converts image to array and return the predicted class
        with highest probability"""
    # Convert to a batch of 1
    xb = to_device(img.unsqueeze(0), device)
```

```
    # Get predictions from model
    yb = model(xb)
    # Pick index with highest probability
    _, preds  = torch.max(yb, dim=1)
    # Retrieve the class label

    return train.classes[preds[0].item()]
```

In [44]:

```
# predicting first image
img, label = test[0]
plt.imshow(img.permute(1, 2, 0))
print('Label:', test_images[0], ', Predicted:', predict_image(img, model))
```

```
Label: AppleCedarRust1.JPG , Predicted: Apple___Cedar_apple_rust
```

In [45]:

```
# getting all predictions (actual label vs predicted)
for i, (img, label) in enumerate(test):
    print('Label:', test_images[i], ', Predicted:', predict_image(img,
model))
```

```
Label: AppleCedarRust1.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleCedarRust2.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleCedarRust3.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleCedarRust4.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleScab1.JPG , Predicted: Apple___Apple_scab
Label: AppleScab2.JPG , Predicted: Apple___Apple_scab
Label: AppleScab3.JPG , Predicted: Apple___Apple_scab
Label: CornCommonRust1.JPG , Predicted: Corn_(maize)___Common_rust_
Label: CornCommonRust2.JPG , Predicted: Corn_(maize)___Common_rust_
Label: CornCommonRust3.JPG , Predicted: Corn_(maize)___Common_rust_
Label: PotatoEarlyBlight1.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight2.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight3.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight4.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight5.JPG , Predicted: Potato___Early_blight
Label: PotatoHealthy1.JPG , Predicted: Potato___healthy
Label: PotatoHealthy2.JPG , Predicted: Potato___healthy
Label: TomatoEarlyBlight1.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight2.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight3.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight4.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight5.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight6.JPG , Predicted: Tomato___Early_blight
Label: TomatoHealthy1.JPG , Predicted: Tomato___healthy
Label: TomatoHealthy2.JPG , Predicted: Tomato___healthy
Label: TomatoHealthy3.JPG , Predicted: Tomato___healthy
Label: TomatoHealthy4.JPG , Predicted: Tomato___healthy
Label: TomatoYellowCurlVirus1.JPG , Predicted:
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus2.JPG , Predicted:
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus3.JPG , Predicted:
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus4.JPG , Predicted:
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus5.JPG , Predicted:
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus6.JPG , Predicted:
Tomato___Tomato_Yellow_Leaf_Curl_Virus
```

We can see that the model predicted all the test images perfectly!!!!

Saving the model

There are several ways to save the model in Pytorch, following are the two most common ways

1. **Save/Load state_dict (Recommended)**

When saving a model for inference, it is only necessary to save the trained model's learned parameters. Saving the model's state_dict with the torch.save() function will give you the most flexibility for restoring the model later, which is why it is the recommended method for saving models.

A common PyTorch convention is to save models using either a .pt or .pth file extension.

Remember that you must call model.eval() to set dropout and batch normalization layers to evaluation mode before running inference. Failing to do this will yield inconsistent inference results.

In [46]:

```
# saving to the kaggle working directory
PATH = './plant-disease-model.pth'
torch.save(model.state_dict(), PATH)
```

2. **Save/Load Entire Model**

This save/load process uses the most intuitive syntax and involves the least amount of code. Saving a model in this way will save the entire module using Python's pickle module. The disadvantage of this approach is that the serialized data is bound to the specific classes and the exact directory structure used when the model is saved. The reason for this is because pickle does not save the model class itself. Rather, it saves a path to the file containing the class, which is used during load time. Because of this, your code can break in various ways when used in other projects or after refactors.

In [47]:

```
# saving the entire model to working directory
PATH = './plant-disease-model-complete.pth'
torch.save(model, PATH)
```

Conclusion

ResNets perform significantly well for image classification when some of the parameters are tweaked and techniques like scheduling learning rate, gradient clipping and weight decay are applied. The model is able to predict every image in test set perfectly without any errors !!!!

References

- CIFAR10 ResNet Implementation
- PyTorch docs

Hope you all learned something from this kernel. Do upvote if you find this useful.

Happy Learning....

Catch you guys on the next one

Peace ☒