CS182 Project: Introduction to EfficientNet

Part1: introduction

EfficientNet is a family of convolutional neural networks that were designed to provide state-of-the-art accuracy on image classification tasks while maintaining a high level of efficiency. Developed by a team of researchers at Google, EfficientNet models use a novel compound scaling method to balance the number of parameters in the network with its depth and width, resulting in a highly optimized architecture that achieves superior performance with fewer computational resources. EfficientNet models have achieved top scores in various computer vision benchmarks, including the ImageNet dataset, and have been widely adopted for a range of applications, including object detection, segmentation, and transfer learning.

In this HW, we're going to implement EfficientNet from scratch, and understand how EfficientNets are "efficient" in the sense of cost of compuation and number of parameters

Imports and preparations: (Run the cell below if you're using Google Colab)

In [ ]:
```
import os
from google.colab import drive
drive.mount('/content/gdrive')
DRIVE_PATH = '/content/gdrive/My\ Drive/cs182project_eq_efficientnet'
DRIVE_PYTHON_PATH = DRIVE_PATH.replace('\\', '')
if not os.path.exists(DRIVE_PYTHON_PATH):
  %mkdir $DRIVE_PATH

## the space in `My Drive` causes some issues,
## make a symlink to avoid this
SYM_PATH = '/content/cs182project_eq_efficientnet'
if not os.path.exists(SYM_PATH):
  !ln -s $DRIVE_PATH $SYM_PATH
```

In [ ]:
```
!pip install graphviz
!apt-get install graphviz
```

In [ ]:
```
import matplotlib.pyplot as plt
import numpy as np
from math import ceil

# Torch stuff
import torch
import torch.optim as optim
import torch.nn as nn
from torch.utils.data import random_split
from torchvision import transforms
from torch.utils.data import DataLoader
import torchvision
import torch.nn.init as init

import numpy as np
from matplotlib import pyplot as plt

#training part
import torch
from torch import nn
from torch.utils.data import DataLoader
import copy

import graphviz
from itertools import tee
```

In [ ]:
```
#@title Graphviz Utilities (run this)
def generate_dwr(csf):
  """
  Determins the depth, width and resolution from the scaling factor.
  Alpha, beta, gamma are taken from the efficientnet paper.
  """
  #From the paper
  alpha = 1.2
  beta = 1.1
  gamma = 1.15
  return (alpha ** csf, beta ** csf, gamma ** csf)

def pairwise(iterable):
  """
  Iterates through an iterable (list), pairwise.
  a, b, c -> (a,b), (b,c)
  """
  a, b = tee(iterable)
  next(b, None)
  return zip(a, b)

def compose_edges(g, nodes):
  """
  Forms the actual edges from a list of all the nodes, just sequentially.
  """
  for a, b, in list(pairwise(nodes)):
```

```
    g.edge(a, b, constraint='false')

def num_layers(n):
  # This is just a random constant
  return max(int(0.8*n), 1)

def generate_layers(g, rfactors, color, w_f, h_f, layer_name):
  """
  Generates a colored 'layer' in the graph, this could result in several
  Nodes being generated depending on the depth factor.
  """
  d, w, r = rfactors
  layers = num_layers(d)
  items = []
  for layer, index, in enumerate(range(layers)):
    name = layer_name + str(index)
    g.node(name, label = " ", color = color, style = "filled", width = str(w
    items.append(name)
  return items

def generate_visualization(csf = 1):
  factors = generate_dwr(csf)
  d, w, r = factors
  g = graphviz.Digraph('efficientNet', comment='efficientNet')
  all_items = []
  g.attr('node', shape='box')
  g.node('input','input' ,color = '#ffffff')
  all_items.append('input')
  all_items += generate_layers(g, factors, color = '#b873bf', w_f = 0.1, h_f
  all_items += generate_layers(g, factors, color = '#e3c062', w_f = 0.2, h_f
  all_items += generate_layers(g, factors, color = '#62e3a2', w_f = 0.2, h_f
  all_items += generate_layers(g, factors, color = '#62dfe3', w_f = 0.02, h_
  all_items += generate_layers(g, factors, color = '#e362d0', w_f = 0.02, h_
  g.node('output', 'output', color = '#ffffff')
  all_items.append('output')
  compose_edges(g, all_items)
  g.attr(label=r'EfficientNet Architecture Diagram \n Compound Scaling Facto
  return g
```

To better reinforce the intution about the compound scaling method, we have implemented a visualization generator function. The overall intution about just changing the compound scaling factor, then being able to affect overall change in the actual architecture, changing the depth, width, and resolution in a principled manner.

- This is intended to provide intuition about efficientNet, this is not how efficientNet literally scales.

Question: Play around with this function, at what point do you start to see new depth layers emerging? (You might also want to use this opportunity to check your intuition about the previous conceptual questions).

In [ ]:
```
generate_visualization(csf = 2) #Play around with this.
```

We're going to use CIFAR-10 dataset for this project. It is very commonly used while testing certain CV models. The dataset contains 60,000 32x32 color images in 10 different classes. The 10 different classes represent airplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks. There are 6,000 images of each class. We're going to use the torchvision package to load the dataset. The torchvision package consists of popular datasets, model architectures, and common image transformations for computer vision.

In this part we're going to implement a dataloader. The purpose of this is to build a convenient way to feed data from a dataset to a model during training or inference. With the DataLoader, users can easily handle large datasets and apply different data augmentation techniques to the input data. The PyTorch DataLoader is a flexible and efficient tool that has become a standard part of many deep learning workflows.

In [ ]:
```
train_transform = transforms.Compose(
    [
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))

    ]
)

test_transform = transforms.Compose(
    [
        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ]
)
```

In [ ]:
```
trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=train_trans

testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                        download=True, transform=test_transf
```

In [ ]:
```
train_size, val_size = 40000, 10000
train_ds, val_ds = random_split(trainset, [train_size, val_size])
len(train_ds), len(val_ds)
```

Question 1a): setup train_loader, train_dataset, val_loader, val_dataset, test_loader, test_dataset in the following block. You can use the code in the previous block as a reference. Hint: check out function: produce_dataloader_dataset

In [ ]:
```
#######################
# TODO: your code here#
#######################
trainloader = ...
valloader = ...
testloader = ...
#######################
#END OF YOUR CODE     #
#######################
```

In [ ]:
```
'''
You should be able to see some sample images from the training set if you co
'''
def draw_sample_images(data, labels):
    nrows = 4
    ncols = 10
    total_image = data.shape[0]
    samples = np.random.choice(total_image, nrows*ncols)
    plt.figure(figsize=(20, 5))
    for i in range(nrows*ncols):
        plt.subplot(nrows, ncols, i+1)
        image = np.moveaxis(data[samples[i]].numpy(), 0, -1)
        plt.imshow(image/2+0.5)
        plt.title(trainset.classes[labels[samples[i]]])
        plt.axis("off")
    plt.tight_layout()
    plt.show()

data_iterator = iter(trainloader)
images, labels = next(data_iterator)
draw_sample_images(images, labels)
```

In [ ]:
```
classes = trainset.classes
classes
```

Question: What's the shape of data in train_loader for a sigle batch? (in terms of [N, C, H, W])

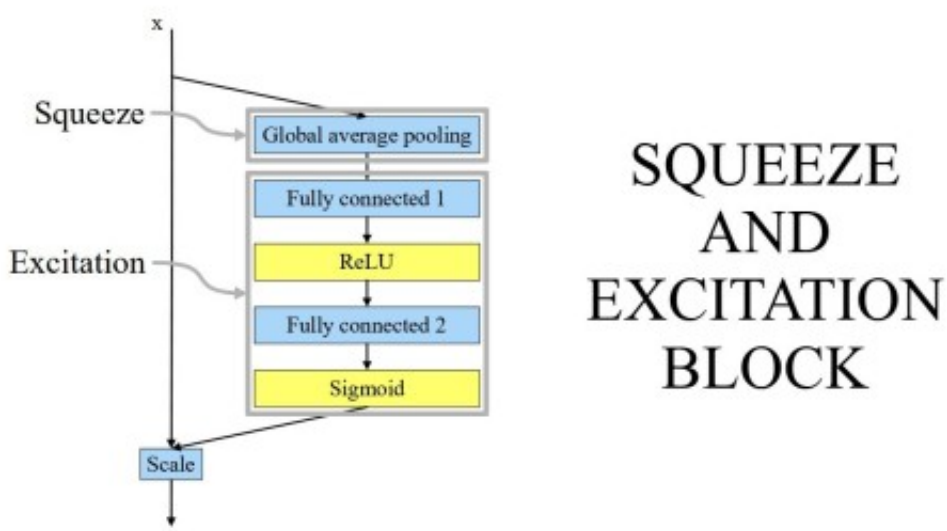
Part 2: Building the model

The "highlight" of EfficientNet is its use of compound scaling methods. Compound scaling in essence is to use a coefficient to uniformaly scale the 3 Dimensions (depth, width and resolution) of the model. The coefficient is denoted as ϕ in the paper. The scaling method is as follows:

$$\begin{gathered}
\text{depth} : d = \alpha^{\phi} \\
\text{width} : w = \beta^{\phi} \\
\text{resolution} : r = \gamma^{\phi} \\
\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \\
\alpha \geq 1, \beta \geq 1, \gamma \geq 1
\end{gathered}$$

The author created a family of EfficientNet models with different ϕ values, and the largest model is EfficientNet-B7 with $\phi = 2.0$. In this HW, we're going to implement EfficientNet, with the ability to scale from $b0$ to $b7$.

Firstly we'going to implement some tricks the author used that makes EfficientNet efficient. The first technique is called Squeeze and Excitation (SE). SE is very similiar to the attention mechanism. It is used to help the model to focus on the most important features. The SE module is implemented as follows:

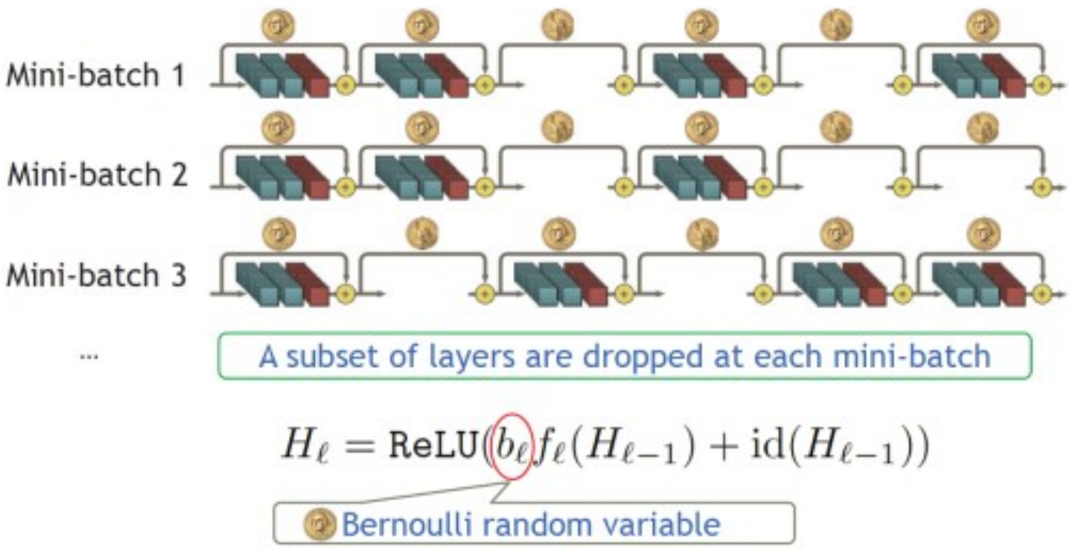


In [ ]:
```
# Implement the Squeeze and Excitation block down below
# Note that though the image above shows we're using ReLu as the activation
# as the author mentioned in the paper that it performed better than ReLU. W
# for the same reason.
# Hint: use nn.AdaptiveAvgPool2d(1) to replace nn.AvgPool2d(1) and nn.SiLU()
class SqueezeExcitation(nn.Module):
    def __init__(self, n_in, reduced_dim, fixed_params=False):
        super(SqueezeExcitation, self).__init__()
        self.conv1 = nn.Conv2d(n_in, reduced_dim, kernel_size=1)
        self.conv2 = nn.Conv2d(reduced_dim, n_in, kernel_size=1)
        if fixed_params:
          init.constant_(self.conv1.weight, 0.01)
          init.constant_(self.conv1.bias, 0.0)
          init.constant_(self.conv2.weight, 0.01)
          init.constant_(self.conv2.bias, 0.0)
        '''
        Hints: follow the pipeline in the image above to implement the forwa
        use nn.Sequential() to build the block.
        '''
        #######################
        # TODO: your code here#
        #######################
        self.se = ...
        #######################
        # End of your code    #
        #######################

    def forward(self, x):
        '''
        Hints: one line of code
        '''
        #######################
        # TODO: your code here#
        #######################
        raise NotImplementedError("Squeeze and Excitation forward pass not i
        #######################
        # End of your code    #
        #######################
        # Hint: consider why what the picture means by scaling and why we're
        return x * y
```

In [ ]:
```
# unit test for se
def test_se():
  data_iterator = iter(testloader)
  images, labels = next(data_iterator)
  x = images[0]
  se = SqueezeExcitation(3,2,fixed_params = True)
  y = se(x)
  y_test = y[0][0][:5].detach()
  y_true = torch.tensor([0.1196, 0.1235, 0.1471, 0.1510, 0.1274])
  assert torch.allclose(y_test,y_true,atol = 1e-3)
test_se()
```

Next we're going to implement the trick: Stochastic Depth, which makes the entire training process much faster. The gist of it is to randomly drop a subset of layers and bypass them with the identity function during training. And a full network is used during testing/inference.

The image below shows the implementation of Stochastic Depth, we suggest lo



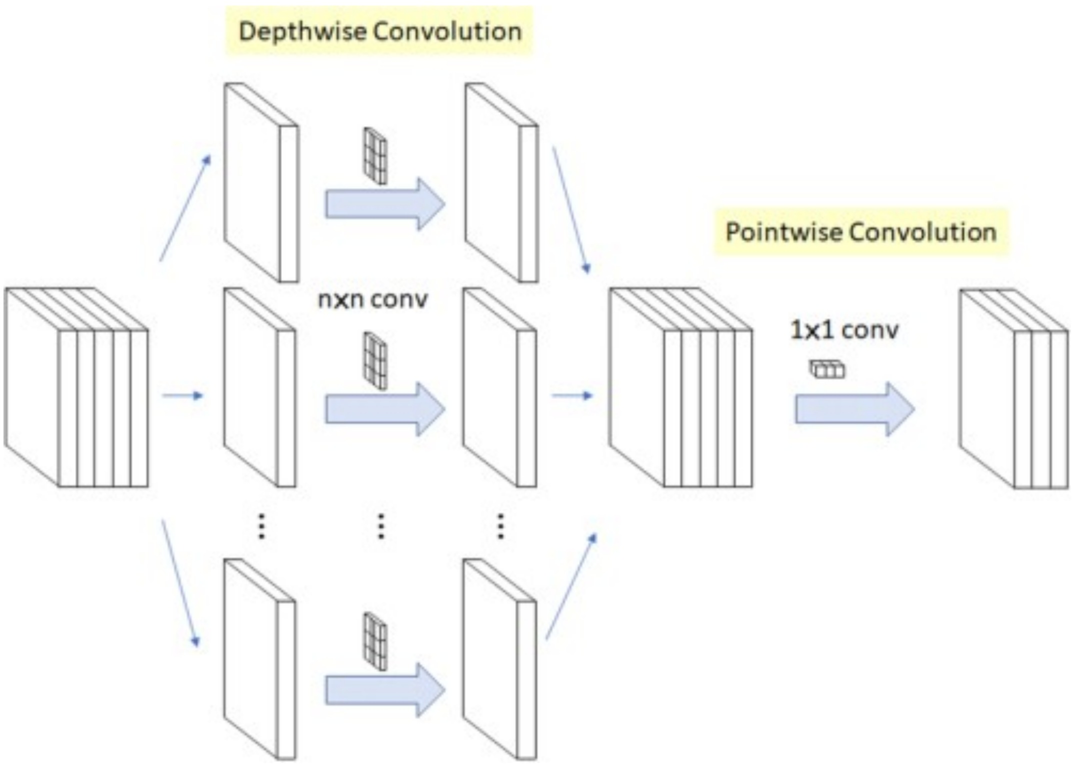
In [ ]:
```
# Implement the Stochastic Depth block down below
# Hint: use torch.rand() to generate a random number

class StochasticDepth(nn.Module):

    def __init__(self, survival_prob = 0.8, fixed_params=False):
        super(StochasticDepth, self).__init__()
        self.fixed_params = fixed_params
        self.p =  survival_prob

    def forward(self, x):
        '''
        Hints: what happens when self.training is True? What shall we do whe
        The idea is kind of similiar to Dropout and Masking.
        '''
        if self.fixed_params:
          if torch.cuda.is_available():
              torch.cuda.manual_seed(10)
          else:
              torch.manual_seed(10)
        #######################
        # TODO: your code here#
        #######################
        raise NotImplementedError("Stochastic Depth forward pass not impleme
        #######################
        # End of your code    #
        #######################
```

In [ ]:
```
# unit test for stochastic depth
def test_sd():
  data_iterator = iter(testloader)
  images, labels = next(data_iterator)
  x = images[0]
  sd = StochasticDepth(fixed_params = True)
  y = sd(x)
  y_test = y[0][0][0][:5].detach()
  y_true = torch.tensor([0.2990, 0.3088, 0.3676, 0.3775, 0.3186])
  assert torch.allclose(y_test,y_true,atol = 1e-3)
test_sd()
```

In [ ]:
```
# Here we provide you with the simple Conv-BatchNorm-Activation block for yo
# Note that we're using SiLU (swish) as the activation function instead of R
# that it performed better than ReLU

class ConvBnAct(nn.Module):

    def __init__(self, n_in, n_out, kernel_size = 3, stride = 1,
                 padding = 0, groups = 1, bn = True, act = True,
                 bias = False, fixed_params = False
                ):

        super(ConvBnAct, self).__init__()
        self.conv = nn.Conv2d(n_in, n_out, kernel_size = kernel_size,
                              stride = stride, padding = padding,
                              groups = groups, bias = bias
                             )
        if fixed_params:
          init.constant_(self.conv.weight, 0.01)
        if bias:
          init.constant_(self.conv.bias, 0.0)

        self.batch_norm = nn.BatchNorm2d(n_out) if bn else nn.Identity()
        self.activation = nn.SiLU() if act else nn.Identity()

    def forward(self, x):

        x = self.conv(x)
        x = self.batch_norm(x)
        x = self.activation(x)

        return x
```

Finally here come the finally implementation of EfficientNet. Some additional tricks the author used here include Depthwise Separable Convolution, which is a combination of depthwise convolution and pointwise convolution. The depthwise convolution is used to extract features from each channel, and the pointwise convolution is used to combine the features from different channels.

The image below shows the implementation of Depthwise Separable Convolution, we suggest referencing this image when performing the implementation:



In [ ]:

```
# We start by implementing Residual Bottleneck Block with Expansion Factor =
# with Squeeze and Excitation Block and Stochastic Depth.
# The process of implementation: residual -> exapnd -> depthwise conv
# -> squeeze and excitation -> pointwise conv -> skip connection

class MBConvN(nn.Module):
    def __init__(self, n_in, n_out, kernel_size = 3,
                 stride = 1, expansion_factor = 6,
                 reduction = 4, # Squeeze and Excitation Block
                 survival_prob = 0.8, # Stochastic Depth
                 fixed_params = False
                ):

        super(MBConvN, self).__init__()
        '''
        Hints: self.skip_connection is True if stride == 1 and n_in == n_out
```

```
        For self.expand, you can use nn.Identity() if expansion_factor == 1
        for more details for the parameter you are going to use.

        For self.depthwise_conv, you can use ConvBnAct() with the correct pa

        self.se is something you implemented above.

        self.pointwise_conv is similar to self.depthwise_conv, but with diff

        self.drop_layers is something you implemented above as well.
        '''
        #######################
        # TODO: your code here#
        #######################
        self.skip_connection = ...
        self.expand = ...
        self.depthwise_conv = ...
        self.se = ...
        self.pointwise_conv = ...
        self.drop_layers = ...
        #######################
        # End of your code    #
        #######################

    def forward(self, x):
        residual = x
        '''
        Hints: if self.skip_connection is True, you should add residual to x
        Recollect the pipline of the MBConvN: residual -> exapnd -> depthwis
        -> pointwise conv -> skip connection
        '''
        #######################
        # TODO: your code here#
        #######################
        x = ...
        #######################
        # End of your code    #
        #######################
        return x
```

In [ ]:

```
# Here comes the acutal implmentation of EfficientNet
class EfficientNet(nn.Module):
    def __init__(self, width_mult = 1, depth_mult = 1,
                 dropout_rate = 0.2, num_classes = 1000, seed=42, fixed_param
        super(EfficientNet, self).__init__()
        last_channel = ceil(1280 * width_mult)
        self.features = self._feature_extractor(width_mult, depth_mult, last
        self.avgpool = nn.AdaptiveAvgPool2d(1)
        self.fc1 = nn.Linear(last_channel, num_classes)
        if fixed_params:
          init.constant_(self.fc1.weight, 0.01)
          init.constant_(self.fc1.bias, 0.0)
          self.classifier = nn.Sequential(
```

```
                self.fc1
            )
        else:
            self.classifier = nn.Sequential(
                nn.Dropout(dropout_rate),
                self.fc1
            )


    def forward(self, x):

        x = self.features(x)
        x = self.avgpool(x)
        x = self.classifier(x.view(x.shape[0], -1))

        return x

    def _feature_extractor(self, width_mult, depth_mult, last_channel, fixed

        channels = 4*ceil(int(32*width_mult) / 4)
        layers = [ConvBnAct(3, channels, kernel_size = 3, stride = 2, paddin
        in_channels = channels

        # These are from the paper
        kernels = [3, 3, 5, 3, 5, 5, 3]
        expansions = [1, 6, 6, 6, 6, 6, 6]
        num_channels = [16, 24, 40, 80, 112, 192, 320]
        num_layers = [1, 2, 2, 3, 3, 4, 1]
        strides =[1, 2, 2, 2, 1, 2, 1]

        # Scale channels and num_layers according to width and depth multipl
        scaled_num_channels = [4*ceil(int(c*width_mult) / 4) for c in num_ch
        scaled_num_layers = [int(d * depth_mult) for d in num_layers]

        '''
        Hints: save all layers in the list `layers` and we will use nn.Seque
        You first use a for loop to iterate through all scaled number of lay
        you use another for loop to iterate through all scaled number of cha
        append a MBConvN block to the list `layers`. Note that the first MBC
        should have a stride of `strides[i]` and the rest should have a stri
        block in each iteration should have an input channel of `in_channels
        channel of `scaled_num_channels[i]`. After each iteration, you updat
        `scaled_num_channels[i]`.
        '''
        #######################
        # TODO: your code here#
        #######################
        layers = []
        #######################
        # End of your code    #
        #######################

        layers.append(ConvBnAct(in_channels, last_channel, kernel_size = 1,
```

```
        return nn.Sequential(*layers)
```

In [ ]:
```
# unit test for efficientnet
def test_efficientnet():
  data_iterator = iter(testloader)
  images, labels = next(data_iterator)
  x = images[:2]
  net = EfficientNet(fixed_params=True)
  y = net(x)
  y_test = y[:,0].detach()
  y_true = torch.tensor([-3.4425,  9.3575])
  assert torch.allclose(y_test,y_true,atol = 1e-3)

test_efficientnet()
```

In [ ]:
```
# Compound scaling factors for efficient-net family.
efficient_net_config = {
    # tuple of width multiplier, depth multiplier, resolution, and Survival
    # from the paper
    "b0" : (1.0, 1.0, 224, 0.2),
    "b1" : (1.0, 1.1, 240, 0.2),
    "b2" : (1.1, 1.2, 260, 0.3),
    "b3" : (1.2, 1.4, 300, 0.3),
    "b4" : (1.4, 1.8, 380, 0.4),
    "b5" : (1.6, 2.2, 456, 0.4),
    "b6" : (1.8, 2.6, 528, 0.5),
    "b7" : (2.0, 3.1, 600, 0.5)
}
```

Finally we're going to train our implemented model. Follow the code instruction below to train the model. We recommend to use GPU to train the model.

In [ ]:
```
def calculate_loss_and_accuracy(model, dataloader, size_of_dataset, criteric

    # Now set model to validation mode.
    running_loss = 0
    running_accuracy = 0

    # Processing the Test Loader
    for (inputs, labels) in dataloader:

        # Load data to device.
        inputs = inputs.to(device)
        labels = labels.to(device)

        # Outputs
        outputs = model(inputs)
        _ , preds = torch.max(outputs, 1)

        # Outputs
```

```
        outputs = model(inputs)
        _ , preds = torch.max(outputs, 1)

        # Loss and Backpropagation.
        loss = criterion(outputs, labels)

        # Statistics
        running_loss += loss.item()*inputs.size(0)
        running_accuracy += torch.sum(preds == labels.data)

    epoch_loss = running_loss/size_of_dataset
    epoch_accuracy = running_accuracy/size_of_dataset

    return epoch_loss, epoch_accuracy

def train(model, criterion, optimizer, scheduler, num_of_epochs):

    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0
    track_training_loss = []
    track_val_loss = []
    track_val_acc = []

    for epoch in range(num_of_epochs):

        print(f'\nEpoch {epoch + 1}/{num_of_epochs}')
        print('-'*30)

        model.train() # Setting model to train.
        running_loss = 0
        running_accuracy = 0

        # Processing the Train Loader
        for (inputs, labels) in trainloader:

            '''
            Load data to device.
            Hints: use .to(device) to load data to device
            remember to zero the parameter gradients
            '''
            #######################
            # TODO: your code here#
            #######################
            raise NotImplementedError("Training not implemented")
            #######################
            # End of your code    #
            #######################

            # Outputs
            outputs = model(inputs)
            _ , preds = torch.max(outputs, 1)

            '''
```

```
            Loss and Backpropagation.
            Hints: use criterion to calculate loss
            remember to perform backpropagation
            '''
            #######################
            # TODO: your code here#
            #######################
            raise NotImplementedError("Training not implemented")
            #######################
            # End of your code    #
            #######################
            # Statistics
            running_loss += loss.item()*inputs.size(0)
            running_accuracy += torch.sum(preds == labels.data)

        scheduler.step()
        epoch_loss = running_loss/len(trainset)
        epoch_accuracy = running_accuracy/len(trainset)
        track_training_loss.append(epoch_loss) # Loss Tracking

        print(f'Training Loss: {epoch_loss:.4f} Training Acc.: {epoch_accura

        # Now set model to validation mode.
        model.eval()

        val_loss, val_accuracy = calculate_loss_and_accuracy(model, valloade
        track_val_loss.append(val_loss)
        track_val_acc.append(val_accuracy)
        if val_accuracy > best_acc:
            print("Found better model...")
            print('Updating the model weights....\n')
            print(f'Val Loss: {val_loss:.4f} Val Acc.: {val_accuracy:.4f}\n'

            best_acc = val_accuracy
            best_model_wts = copy.deepcopy(model.state_dict())

    model.load_state_dict(best_model_wts) # update model

    return  model, track_val_loss, track_val_acc
```

In [ ]:
```
device = torch.device('cuda')

NUM_OF_CLASSES = 10
BATCH_SIZE = 32
NUM_OF_EPOCHS = 30

# Initialize Efficientnet model
# We are training the b2 version here
version = 'b2'
width_mult, depth_mult, res, dropout_rate = efficient_net_config[version]
model = EfficientNet(width_mult, depth_mult, dropout_rate, num_classes = NUM
model = model.to(device) # Load model to device.

# Criterion.
criterion = nn.CrossEntropyLoss()
optimizer = optim.AdamW(model.parameters(), lr=1e-6, weight_decay=1e-2)


exp_lr_scheduler = optim.lr_scheduler.OneCycleLR(optimizer, max_lr=1e-2,
                                                 steps_per_epoch=len(trainloader

# Training
best_model = train(model = model,
                   criterion = criterion,
                   optimizer = optimizer,
                   scheduler = exp_lr_scheduler,
                   num_of_epochs = NUM_OF_EPOCHS
                  )
```

Question: What is the best accuracy you can get? What is the best accuracy you can get with the same number of parameters as the EfficientNet-B2 model? Feel free to use different models and find the one with the best validation accuracy.

In [ ]:
```
def train_model(model):
  criterion = nn.CrossEntropyLoss()

  optimizer = optim.AdamW(model.parameters(), lr=1e-6, weight_decay=1e-2)


  exp_lr_scheduler = optim.lr_scheduler.OneCycleLR(optimizer, max_lr=1e-2,
                                                   steps_per_epoch=len(trainloade

  best_model, val_losses, val_accs = train(model = model,
                                  criterion = criterion,
                                  optimizer = optimizer,
                                  scheduler = exp_lr_scheduler,
                                  num_of_epochs = NUM_OF_EPOCHS
                                  )

  val_loss, val_accuracy = calculate_loss_and_accuracy(best_model, valloader
  print("final validation statistics, loss : %s, accuracy : %s" %(val_loss,

  return best_model, val_losses, val_accs
```

Now, let us compare with some other recent architecture models, which torchvision conveniently packages. Generally, we want to consider 2 things, the number of parameters, and the actual performance of the architecture.

For this, let us consider densenet121, mobilenetv2 and resNet50, which are all fairly recent models.

Warning: this part takes roughly half an hour to train

In [ ]:
```
densenet121 = torchvision.models.densenet121(weights = False).to(device)
mobilenetv2 = torchvision.models.mobilenet_v2(weights = False).to(device)
resNet50 = torchvision.models.resnet50(weights = False).to(device)
```

In [ ]:
```
def calculate_parameters(model, model_name):
  num_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
  print("%s has %s params" %(model_name, num_params))
  return num_params
```

In [ ]:
```
dense_params = train_model(densenet121)
```

In [ ]:
```
mobile_params = train_model(mobilenetv2)
```

In [ ]:
```
res_params = train_model(resNet50)
```

In [ ]:
```
den_model, den_losses, den_acc = dense_params
mobile_model, mobile_losses, mobile_acc = mobile_params
res_model, res_losses, res_acc = res_params
```

In [ ]:
```
den_acc = np.array([i.to('cpu').numpy() for i in den_acc])
mobile_acc = np.array([i.to('cpu').numpy() for i in mobile_acc])
res_acc = np.array([i.to('cpu').numpy() for i in res_acc])
```

In [ ]:
```
best_model, efficientnet_val_losses, efficientnet_val_accs = best_model
efficientnet_val_accs = np.array([i.to('cpu').numpy() for i in efficientnet_
```

Let us see how EfficientNet performs against them!

In [ ]:
```
plt.plot(range(NUM_OF_EPOCHS), efficientnet_val_accs, label = 'efficientnetb
plt.plot(range(NUM_OF_EPOCHS), den_acc, label = 'densenet121')
plt.plot(range(NUM_OF_EPOCHS), mobile_acc, label = 'mobilenetv2')
plt.plot(range(NUM_OF_EPOCHS), res_acc, label = 'resNet50')
plt.title("Validation Accuracy vs. Epochs on CIFAR, Models")
plt.xlabel("Epochs")
plt.ylabel("Validation Accuracy")
plt.legend()
plt.show()
```

Question: Looking at the accuracy of EfficientNet compared to other state-of-the-art model architectures, how does the validation accuracy compare? Anything else interesting you've noticed about these plots?

We now examine the number of parameters within the different models. We provide a calculate_parameters function to just sum all the parameters for a model. We also provide some code for a quick bar plot.

In [ ]:
```
def calculate_parameters(model, model_name):
  num_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
  print("%s has %s params" %(model_name, num_params))
  return num_params
```

In [ ]:
```
eff_num_params = calculate_parameters(best_model, "efficientnetb2")
den_num_params = calculate_parameters(den_model, "densenet121")
mob_num_params = calculate_parameters(mobile_model, "mobilenetv2")
res_num_params = calculate_parameters(res_model, "resNet50")
```

In [ ]:
```
plt.bar(['efficientnetb2', 'densenet121', 'mobilenetv2', 'resNet50'], [eff_n
plt.legend()
plt.title("Number of Params vs. Model")
plt.xlabel("Model")
plt.ylabel("Number of Parameters")
plt.show()
```

Question: Examine the number of parameters of the different models, does anything stand out to you? If we take this as context, is there anything you want to comment about the validation performance of the models?

This is the end of the notebook. We hope you've learned something about EfficientNet!

References

[1] Mingxing Tan, Quoc V. Le. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. https://arxiv.org/abs/1905.11946