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
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, c
all drive.mount("/content/gdrive", force_remount=True).
```

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

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/cola
b-wheels/public/simple/
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-p
ackages (0.20.1)
Reading package lists... Done
Building dependency tree
Reading state information... Done
graphviz is already the newest version (2.42.2-3build2).
0 upgraded, 0 newly installed, 0 to remove and 24 not upgraded.
```

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
```

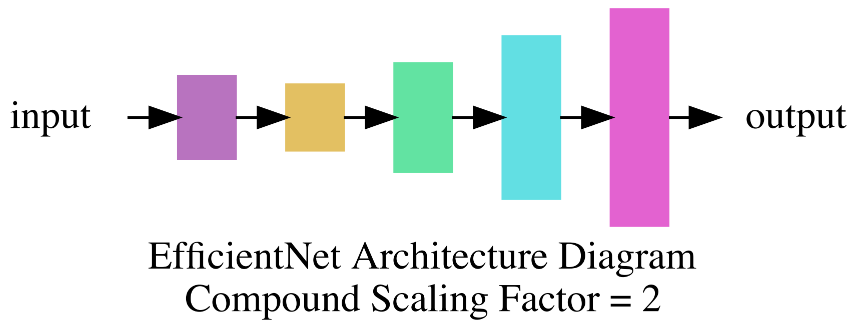
To better reinforce the intution about the compound scaling method, we have implemented a visualization generator function. The overall intution about just changing the compound scaling factor, then being able to affect overall change in the actual architecture, changing the depth, width, and resolution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

Out[ ]:



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
```

```
Files already downloaded and verified
Files already downloaded and verified
```

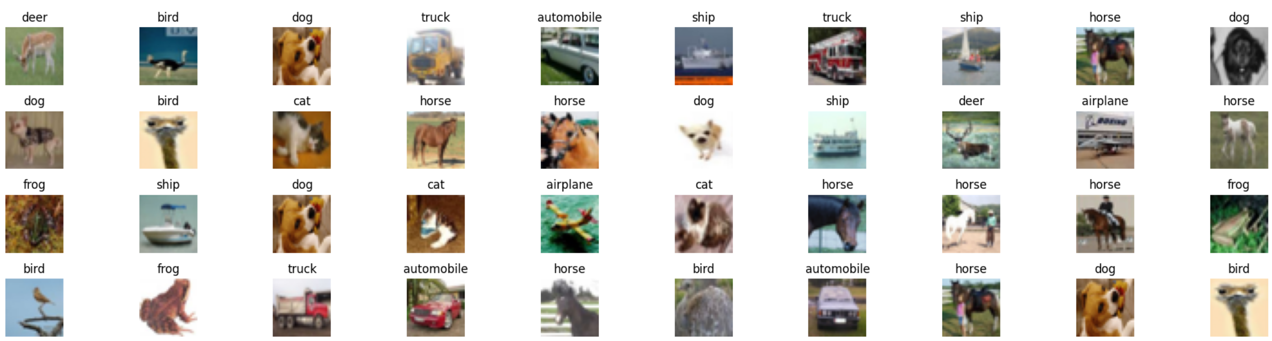
In [ ]:
```
train_size, val_size = 40000, 10000
train_ds, val_ds = random_split(trainset, [train_size, val_size])
len(train_ds), len(val_ds)
```

Out[ ]:
```
(40000, 10000)
```

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 = DataLoader(train_ds, batch_size=256,
                            shuffle=True, num_workers=2)
valloader = DataLoader(val_ds, batch_size=256,
                            shuffle=True, num_workers=2)
testloader = DataLoader(testset, batch_size=256,
                            shuffle=False, num_workers=2)
#######################
#END OF YOUR CODE    #
#######################
```

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

Out[ ]:
```
['airplane',
 'automobile',
 'bird',
 'cat',
 'deer',
 'dog',
 'frog',
 'horse',
 'ship',
 'truck']
```

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

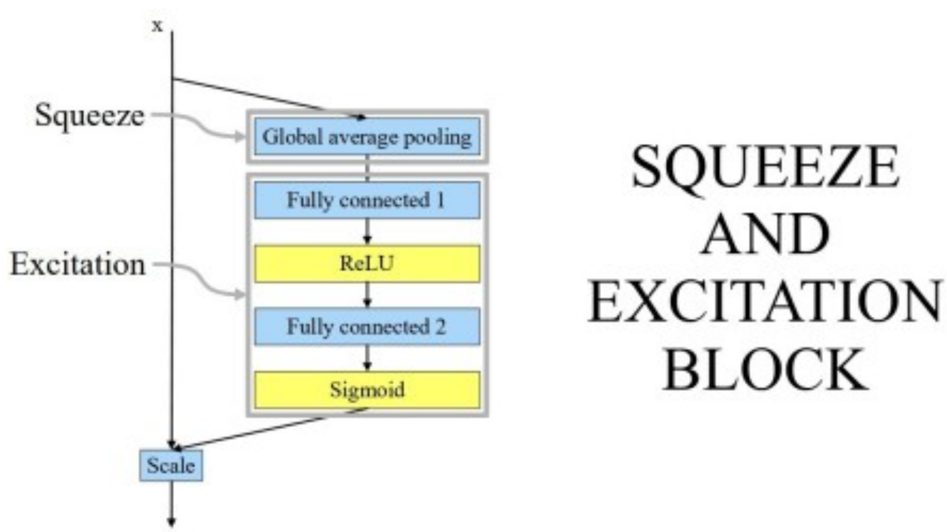
Part 2: Building the model

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:



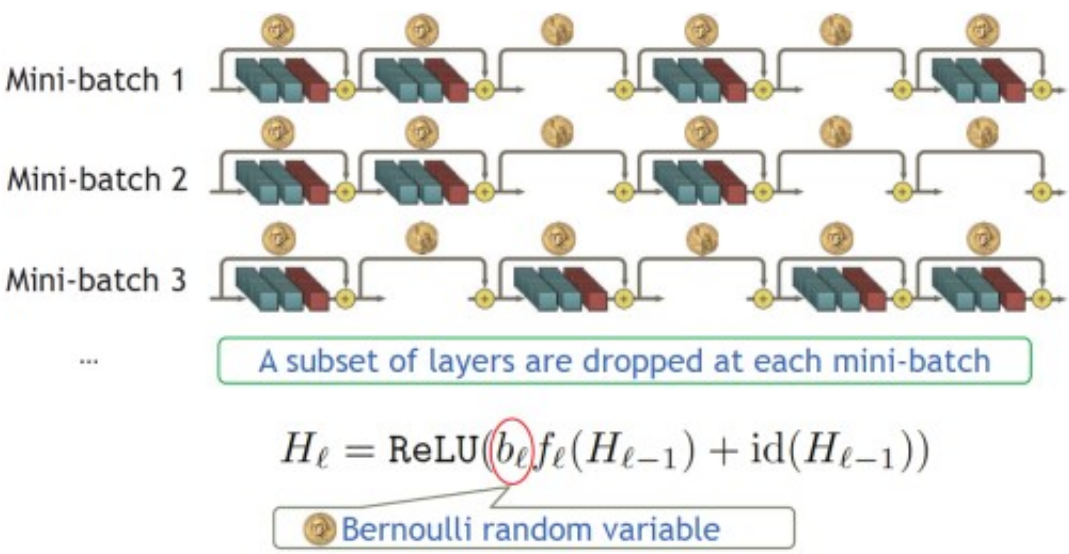
In [ ]:
```
# Implement the Squueze and Excitation block down below
# Note that though the image above shows we're using ReLu as the activation
# as the author mentioned in the paper that it performed better than ReLU. W
# for the same reason.
# Hint: use nn.AdaptiveAvgPool2d(1) to replace nn.AvgPool2d(1) 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 = nn.Sequential(
            nn.AdaptiveAvgPool2d(1),
            self.conv1,
            nn.SiLU(),
            self.conv2,
            nn.Sigmoid()
        )
        #######################
        # End of your code    #
        #######################

    def forward(self, x):
        '''
        Hints: one line of code
        '''
        #######################
        # TODO: your code here#
        #######################
        y = self.se(x)
        #######################
        # 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()
```

```
tensor([0.1196, 0.1235, 0.1471, 0.1510, 0.1274])
```

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



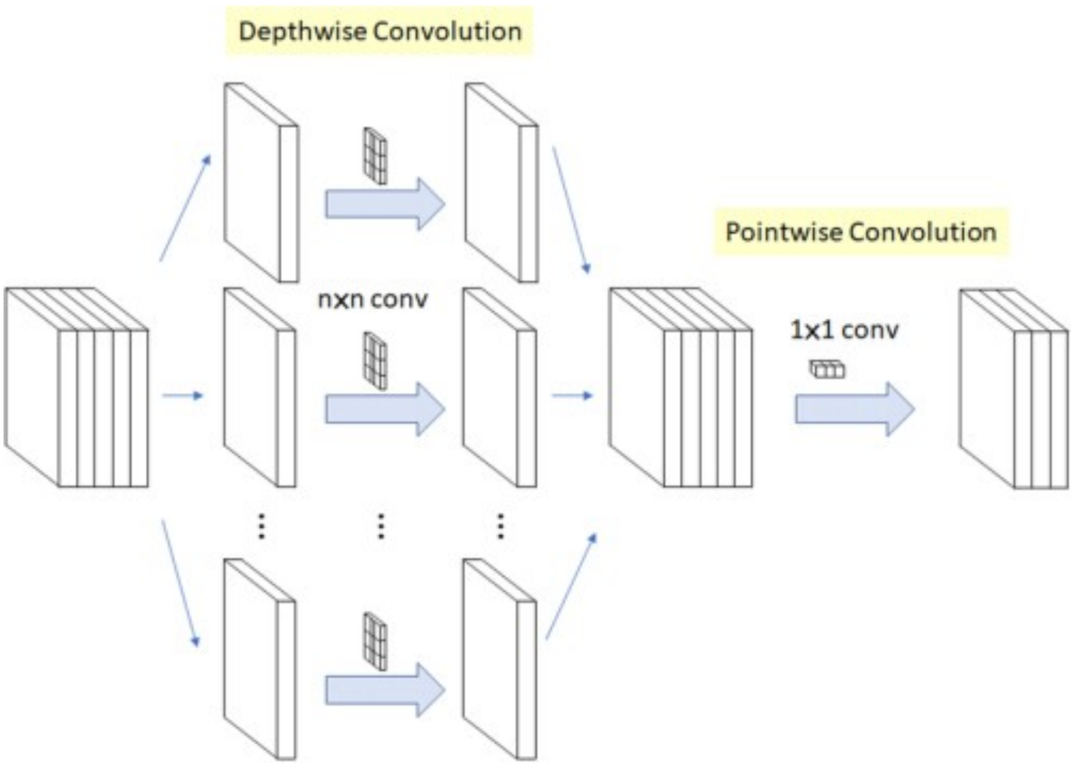
In [ ]:
```
# Implement the Stochastic Depth block down below
# Hint: use torch.rand() to generate a random number

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#
        #######################
        if not self.training:
            return x
        binary_tensor = torch.rand(x.shape[0], 1, 1, 1, device=x.device) < s
        return torch.div(x, self.p) * binary_tensor
        #######################
        # 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 = (stride == 1 and n_in == n_out)
        intermediate_channels = int(n_in * expansion_factor)
        padding = (kernel_size - 1)//2
        reduced_dim = int(n_in//reduction)

        self.expand = nn.Identity() if (expansion_factor == 1) else ConvBnAc
        self.depthwise_conv = ConvBnAct(intermediate_channels, intermediate_
                                        kernel_size = kernel_size, stride =
                                        padding = padding, groups = intermed
                                       )
        self.se = SqueezeExcitation(intermediate_channels, reduced_dim = red
        self.pointwise_conv = ConvBnAct(intermediate_channels, n_out,
                                        kernel_size = 1, act = False, fixed_
                                       )
        self.drop_layers = StochasticDepth(survival_prob = survival_prob, fi
        #######################
        # 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 = self.expand(x)
        x = self.depthwise_conv(x)
        x = self.se(x)
        x = self.pointwise_conv(x)

        if self.skip_connection:
```

```
            x = self.drop_layers(x)
            x += residual
        #######################
        # 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#
        #######################
        for i in range(len(scaled_num_channels)):
            layers += [MBConvN(in_channels if repeat==0 else scaled_num_char
                               scaled_num_channels[i],
                               kernel_size = kernels[i],
                               stride = strides[i] if repeat==0 else 1,
                               expansion_factor = expansions[i],
                               fixed_params = fixed_params
                               )
                       for repeat in range(scaled_num_layers[i])
                       ]
            in_channels = scaled_num_channels[i]
        #######################
        # 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, criterio

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

            optimizer.zero_grad() # zero the parameter gradients
            #######################
            # 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#
            #######################
```

```
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            #######################
            # 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
                  )
```

```
Epoch 1/30
------------------------------
Training Loss: 1.6205 Training Acc.: 0.1915
Found better model...
Updating the model weights....

Val Loss: 1.7733 Val Acc.: 0.3218


Epoch 2/30
------------------------------
Training Loss: 1.3543 Training Acc.: 0.2933
Found better model...
Updating the model weights....

Val Loss: 1.5587 Val Acc.: 0.4173


Epoch 3/30
------------------------------
Training Loss: 1.2134 Training Acc.: 0.3558
```

```
Found better model...
Updating the model weights....

Val Loss: 1.4404 Val Acc.: 0.4756


Epoch 4/30
------------------------------
Training Loss: 1.1185 Training Acc.: 0.3906
Found better model...
Updating the model weights....

Val Loss: 1.3485 Val Acc.: 0.5083


Epoch 5/30
------------------------------
Training Loss: 1.0529 Training Acc.: 0.4194
Found better model...
Updating the model weights....

Val Loss: 1.2764 Val Acc.: 0.5401


Epoch 6/30
------------------------------
Training Loss: 0.9913 Training Acc.: 0.4442
Found better model...
Updating the model weights....

Val Loss: 1.2210 Val Acc.: 0.5585


Epoch 7/30
------------------------------
Training Loss: 0.9393 Training Acc.: 0.4608
Found better model...
Updating the model weights....

Val Loss: 1.1949 Val Acc.: 0.5712


Epoch 8/30
------------------------------
Training Loss: 0.8939 Training Acc.: 0.4802
Found better model...
Updating the model weights....

Val Loss: 1.1419 Val Acc.: 0.5876
```

```
Epoch 9/30
------------------------------
Training Loss: 0.8509 Training Acc.: 0.4973
Found better model...
Updating the model weights....

Val Loss: 1.0880 Val Acc.: 0.6113


Epoch 10/30
------------------------------
Training Loss: 0.8141 Training Acc.: 0.5106
Found better model...
Updating the model weights....

Val Loss: 1.0592 Val Acc.: 0.6200


Epoch 11/30
------------------------------
Training Loss: 0.7720 Training Acc.: 0.5277
Found better model...
Updating the model weights....

Val Loss: 1.0268 Val Acc.: 0.6368


Epoch 12/30
------------------------------
Training Loss: 0.7339 Training Acc.: 0.5393
Found better model...
Updating the model weights....

Val Loss: 1.0070 Val Acc.: 0.6448


Epoch 13/30
------------------------------
Training Loss: 0.7065 Training Acc.: 0.5509
Found better model...
Updating the model weights....

Val Loss: 0.9806 Val Acc.: 0.6524


Epoch 14/30
------------------------------
Training Loss: 0.6781 Training Acc.: 0.5609
Found better model...
```

```
Updating the model weights....

Val Loss: 0.9748 Val Acc.: 0.6589


Epoch 15/30
------------------------------
Training Loss: 0.6512 Training Acc.: 0.5712
Found better model...
Updating the model weights....

Val Loss: 0.9654 Val Acc.: 0.6659


Epoch 16/30
------------------------------
Training Loss: 0.6267 Training Acc.: 0.5814
Found better model...
Updating the model weights....

Val Loss: 0.9330 Val Acc.: 0.6745


Epoch 17/30
------------------------------
Training Loss: 0.6008 Training Acc.: 0.5880
Found better model...
Updating the model weights....

Val Loss: 0.9439 Val Acc.: 0.6756


Epoch 18/30
------------------------------
Training Loss: 0.5773 Training Acc.: 0.5969
Found better model...
Updating the model weights....

Val Loss: 0.9269 Val Acc.: 0.6829


Epoch 19/30
------------------------------
```

```
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Traceback (most recent call last):
Exception ignored in:   File "/usr/local/lib/python3.10/dist-packages/torch
/utils/data/dataloader.py", line 1479, in __del__
    <function _MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>self
```

```
._shutdown_workers()

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
Traceback (most recent call last):
    if w.is_alive():  File "/usr/local/lib/python3.10/dist-packages/torch/u
tils/data/dataloader.py", line 1479, in __del__

  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    self._shutdown_workers()assert self._parent_pid == os.getpid(), 'can on
ly test a child process'

AssertionError:   File "/usr/local/lib/python3.10/dist-packages/torch/utils
/data/dataloader.py", line 1462, in _shutdown_workers
can only test a child process
    if w.is_alive():
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
        self._shutdown_workers()assert self._parent_pid == os.getpid(), 'ca
n only test a child process'

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
AssertionError    : if w.is_alive():can only test a child process

  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    Exception ignored in: assert self._parent_pid == os.getpid(), 'can only
test a child process'
<function _MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>
Traceback (most recent call last):
AssertionError  File "/usr/local/lib/python3.10/dist-packages/torch/utils/d
ata/dataloader.py", line 1479, in __del__
:     can only test a child processself._shutdown_workers()

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
Exception ignored in:     if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
```

```
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
<function _MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>  File "
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py", li
ne 1462, in _shutdown_workers

    Traceback (most recent call last):
if w.is_alive():
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
        if w.is_alive():
assert self._parent_pid == os.getpid(), 'can only test a child process'
File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_aliv
e

assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionErrorAssertionError: : can only test a child processcan only test
a child process

Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>Exception ignored in:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
<function _MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>    self
._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive

if w.is_alive():        assert self._parent_pid == os.getpid(), 'can only t
est a child process'
AssertionError: can only test a child process

Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
```

```
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
Training Loss: 0.5604 Training Acc.: 0.6030
Found better model...
Updating the model weights....

Val Loss: 0.9144 Val Acc.: 0.6842


Epoch 20/30
------------------------------
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
Exception ignored in:     <function _MultiProcessingDataLoaderIter.__del__
```

```
at 0x7f2e9a326050>assert self._parent_pid == os.getpid(), 'can only test a
child process'
Traceback (most recent call last):

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
AssertionError    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
:   File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_
alive
    can only test a child process
assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError:
can only test a child processException ignored in: <function _MultiProcessi
ngDataLoaderIter.__del__ at 0x7f2e9a326050>Exception ignored in: <function
_MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__

    self._shutdown_workers()  File "/usr/local/lib/python3.10/dist-packages
/torch/utils/data/dataloader.py", line 1462, in _shutdown_workers

    if w.is_alive():Traceback (most recent call last):

  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError    self._shutdown_workers(): can only test a child process

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
AssertionError  File "/usr/lib/python3.10/multiprocessing/process.py", line
160, in is_alive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
: can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
```

```
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
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    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
```

```
Training Loss: 0.5360 Training Acc.: 0.6127
```

```
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Exception ignored in: Traceback (most recent call last):
<function _MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>  File "
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py", li
ne 1479, in __del__

Traceback (most recent call last):
    self._shutdown_workers()  File "/usr/local/lib/python3.10/dist-packages
/torch/utils/data/dataloader.py", line 1479, in __del__

    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
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    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
```

```
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
    AssertionErrorif w.is_alive()::
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
can only test a child processAssertionError
: can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Exception ignored in: Traceback (most recent call last):
<function _MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>  File "
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py", li
ne 1479, in __del__

    Traceback (most recent call last):
self._shutdown_workers()  File "/usr/local/lib/python3.10/dist-packages/tor
ch/utils/data/dataloader.py", line 1479, in __del__

      File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/datalo
ader.py", line 1462, in _shutdown_workers
self._shutdown_workers()    if w.is_alive():
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers

      File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in i
s_alive
if w.is_alive():
assert self._parent_pid == os.getpid(), 'can only test a child process'  Fi
le "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_alive

    AssertionErrorassert self._parent_pid == os.getpid(), 'can only test a
child process':
can only test a child processAssertionError
: Exception ignored in: can only test a child process<function _MultiProces
singDataLoaderIter.__del__ at 0x7f2e9a326050>

Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
Exception ignored in:   File "/usr/local/lib/python3.10/dist-packages/torch
/utils/data/dataloader.py", line 1462, in _shutdown_workers
<function _MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>
if w.is_alive():Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
```

```
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
        assert self._parent_pid == os.getpid(), 'can only test a child proc
ess'assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError
AssertionError: : can only test a child processcan only test a child proces
s

Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
Found better model...
Updating the model weights....

Val Loss: 0.9070 Val Acc.: 0.6954


Epoch 21/30
------------------------------
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    Exception ignored in: if w.is_alive():<function _MultiProcessingDataLoa
derIter.__del__ at 0x7f2e9a326050>
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive

Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
        self._shutdown_workers()assert self._parent_pid == os.getpid(), 'ca
```

```
n only test a child process'

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():AssertionError
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
:
AssertionErrorcan only test a child process:
can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>Exception ignored in:
<function _MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>Tracebac
k (most recent call last):

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
Traceback (most recent call last):
      File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/datalo
ader.py", line 1479, in __del__
self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
self._shutdown_workers()    if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive

      File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/datalo
ader.py", line 1462, in _shutdown_workers
    if w.is_alive():assert self._parent_pid == os.getpid(), 'can only test
a child process'
AssertionError
: can only test a child process
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
Exception ignored in:     assert self._parent_pid == os.getpid(), 'can only
test a child process'<function _MultiProcessingDataLoaderIter.__del__ at 0x
7f2e9a326050>

Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
AssertionError:     can only test a child process
self._shutdown_workers()Exception ignored in:
<function _MultiProcessingDataLoaderIter.__del__ at 0x7f2e9a326050>
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
Traceback (most recent call last):
    if w.is_alive():
```

```
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
    self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    if w.is_alive():
    assert self._parent_pid == os.getpid(), 'can only test a child process'
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
AssertionError    assert self._parent_pid == os.getpid(), 'can only test a
child process'
AssertionError: : can only test a child process
can only test a child process
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at 0
x7f2e9a326050>Exception ignored in:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1479, in __del__
    self._shutdown_workers()<function _MultiProcessingDataLoaderIter.__del_
_ at 0x7f2e9a326050>

  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
Traceback (most recent call last):
      File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/datalo
ader.py", line 1479, in __del__
if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive
self._shutdown_workers()
  File "/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader
.py", line 1462, in _shutdown_workers
    assert self._parent_pid == os.getpid(), 'can only test a child process'
if w.is_alive():
  File "/usr/lib/python3.10/multiprocessing/process.py", line 160, in is_al
ive

assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionErrorAssertionError: can only test a child process:
can only test a child process
Training Loss: 0.5195 Training Acc.: 0.6168

Epoch 22/30
------------------------------
Training Loss: 0.4994 Training Acc.: 0.6243
Found better model...
Updating the model weights....
```

```
Val Loss: 0.8707 Val Acc.: 0.7037


Epoch 23/30
------------------------------
Training Loss: 0.4795 Training Acc.: 0.6339

Epoch 24/30
------------------------------
Training Loss: 0.4686 Training Acc.: 0.6354
Found better model...
Updating the model weights....

Val Loss: 0.8781 Val Acc.: 0.7060


Epoch 25/30
------------------------------
Training Loss: 0.4583 Training Acc.: 0.6394

Epoch 26/30
------------------------------
Training Loss: 0.4336 Training Acc.: 0.6477

Epoch 27/30
------------------------------
Training Loss: 0.4254 Training Acc.: 0.6508
Found better model...
Updating the model weights....

Val Loss: 0.8840 Val Acc.: 0.7103


Epoch 28/30
------------------------------
Training Loss: 0.3997 Training Acc.: 0.6605

Epoch 29/30
------------------------------
Training Loss: 0.3868 Training Acc.: 0.6654
Found better model...
Updating the model weights....

Val Loss: 0.9020 Val Acc.: 0.7118


Epoch 30/30
------------------------------
Training Loss: 0.3816 Training Acc.: 0.6659
```

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)
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: U
serWarning: Arguments other than a weight enum or `None` for 'weights' are
deprecated since 0.13 and may be removed in the future. The current behavio
r is equivalent to passing `weights=None`.
  warnings.warn(msg)
```

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)
```

```
Epoch 1/30
------------------------------
Training Loss: 1.4407 Training Acc.: 0.3436
Found better model...
Updating the model weights....

Val Loss: 1.3945 Val Acc.: 0.4979


Epoch 2/30
------------------------------
Training Loss: 0.9452 Training Acc.: 0.4592
Found better model...
Updating the model weights....

Val Loss: 1.1795 Val Acc.: 0.5797


Epoch 3/30
------------------------------
Training Loss: 0.8057 Training Acc.: 0.5131
Found better model...
Updating the model weights....

Val Loss: 1.0660 Val Acc.: 0.6181


Epoch 4/30
------------------------------
Training Loss: 0.7102 Training Acc.: 0.5477
Found better model...
Updating the model weights....

Val Loss: 1.0133 Val Acc.: 0.6399


Epoch 5/30
------------------------------
Training Loss: 0.6251 Training Acc.: 0.5800
Found better model...
Updating the model weights....
```

```
Val Loss: 0.9901 Val Acc.: 0.6562


Epoch 6/30
------------------------------
Training Loss: 0.5536 Training Acc.: 0.6054
Found better model...
Updating the model weights....

Val Loss: 0.9931 Val Acc.: 0.6619


Epoch 7/30
------------------------------
Training Loss: 0.4955 Training Acc.: 0.6258
Found better model...
Updating the model weights....

Val Loss: 0.9511 Val Acc.: 0.6755


Epoch 8/30
------------------------------
Training Loss: 0.4401 Training Acc.: 0.6461
Found better model...
Updating the model weights....

Val Loss: 0.9420 Val Acc.: 0.6848


Epoch 9/30
------------------------------
Training Loss: 0.3880 Training Acc.: 0.6657
Found better model...
Updating the model weights....

Val Loss: 0.9484 Val Acc.: 0.6926


Epoch 10/30
------------------------------
Training Loss: 0.3397 Training Acc.: 0.6822

Epoch 11/30
------------------------------
Training Loss: 0.3089 Training Acc.: 0.6948
Found better model...
Updating the model weights....

Val Loss: 1.0342 Val Acc.: 0.6936
```

```
Epoch 12/30
------------------------------
Training Loss: 0.2762 Training Acc.: 0.7046
Found better model...
Updating the model weights....

Val Loss: 0.9825 Val Acc.: 0.7016


Epoch 13/30
------------------------------
Training Loss: 0.2432 Training Acc.: 0.7171
Found better model...
Updating the model weights....

Val Loss: 1.0064 Val Acc.: 0.7090


Epoch 14/30
------------------------------
Training Loss: 0.2125 Training Acc.: 0.7267

Epoch 15/30
------------------------------
Training Loss: 0.1968 Training Acc.: 0.7324

Epoch 16/30
------------------------------
Training Loss: 0.1823 Training Acc.: 0.7375
Found better model...
Updating the model weights....

Val Loss: 1.0733 Val Acc.: 0.7095


Epoch 17/30
------------------------------
Training Loss: 0.1643 Training Acc.: 0.7435

Epoch 18/30
------------------------------
Training Loss: 0.1503 Training Acc.: 0.7481
Found better model...
Updating the model weights....

Val Loss: 1.1304 Val Acc.: 0.7148
```

```
Epoch 19/30
------------------------------
Training Loss: 0.1325 Training Acc.: 0.7538

Epoch 20/30
------------------------------
Training Loss: 0.1276 Training Acc.: 0.7560

Epoch 21/30
------------------------------
Training Loss: 0.1165 Training Acc.: 0.7589
Found better model...
Updating the model weights....

Val Loss: 1.2096 Val Acc.: 0.7183


Epoch 22/30
------------------------------
Training Loss: 0.1164 Training Acc.: 0.7585

Epoch 23/30
------------------------------
Training Loss: 0.1036 Training Acc.: 0.7641
Found better model...
Updating the model weights....

Val Loss: 1.2055 Val Acc.: 0.7229


Epoch 24/30
------------------------------
Training Loss: 0.0983 Training Acc.: 0.7652

Epoch 25/30
------------------------------
Training Loss: 0.0920 Training Acc.: 0.7681

Epoch 26/30
------------------------------
Training Loss: 0.0883 Training Acc.: 0.7691

Epoch 27/30
------------------------------
Training Loss: 0.0857 Training Acc.: 0.7701

Epoch 28/30
------------------------------
Training Loss: 0.0786 Training Acc.: 0.7723
Found better model...
```

```
Updating the model weights....

Val Loss: 1.2852 Val Acc.: 0.7279


Epoch 29/30
------------------------------
Training Loss: 0.0750 Training Acc.: 0.7739

Epoch 30/30
------------------------------
Training Loss: 0.0885 Training Acc.: 0.7694
final validation statistics, loss : 1.2749816423416138, accuracy : tensor(0
.7291, device='cuda:0')
```

In [ ]:

```
mobile_params = train_model(mobilenetv2)
```

```
Epoch 1/30
------------------------------
Training Loss: 1.8835 Training Acc.: 0.1552
Found better model...
Updating the model weights....

Val Loss: 2.0235 Val Acc.: 0.2370


Epoch 2/30
------------------------------
Training Loss: 1.5204 Training Acc.: 0.2223
Found better model...
Updating the model weights....

Val Loss: 1.8410 Val Acc.: 0.3111


Epoch 3/30
------------------------------
Training Loss: 1.3917 Training Acc.: 0.2807
Found better model...
Updating the model weights....

Val Loss: 1.7202 Val Acc.: 0.3629


Epoch 4/30
------------------------------
Training Loss: 1.2973 Training Acc.: 0.3196
Found better model...
Updating the model weights....
```

```
Val Loss: 1.6093 Val Acc.: 0.4031


Epoch 5/30
------------------------------
Training Loss: 1.2253 Training Acc.: 0.3482
Found better model...
Updating the model weights....

Val Loss: 1.5614 Val Acc.: 0.4195


Epoch 6/30
------------------------------
Training Loss: 1.1690 Training Acc.: 0.3655
Found better model...
Updating the model weights....

Val Loss: 1.5022 Val Acc.: 0.4445


Epoch 7/30
------------------------------
Training Loss: 1.1272 Training Acc.: 0.3860
Found better model...
Updating the model weights....

Val Loss: 1.4881 Val Acc.: 0.4545


Epoch 8/30
------------------------------
Training Loss: 1.0866 Training Acc.: 0.4036
Found better model...
Updating the model weights....

Val Loss: 1.4560 Val Acc.: 0.4766


Epoch 9/30
------------------------------
Training Loss: 1.0474 Training Acc.: 0.4159
Found better model...
Updating the model weights....

Val Loss: 1.4084 Val Acc.: 0.4859


Epoch 10/30
------------------------------
```

```
Training Loss: 1.0158 Training Acc.: 0.4294
Found better model...
Updating the model weights....

Val Loss: 1.3947 Val Acc.: 0.4966


Epoch 11/30
------------------------------
Training Loss: 0.9765 Training Acc.: 0.4469
Found better model...
Updating the model weights....

Val Loss: 1.3693 Val Acc.: 0.5035


Epoch 12/30
------------------------------
Training Loss: 0.9493 Training Acc.: 0.4555

Epoch 13/30
------------------------------
Training Loss: 0.9173 Training Acc.: 0.4683
Found better model...
Updating the model weights....

Val Loss: 1.3349 Val Acc.: 0.5245


Epoch 14/30
------------------------------
Training Loss: 0.8915 Training Acc.: 0.4811
Found better model...
Updating the model weights....

Val Loss: 1.3328 Val Acc.: 0.5246


Epoch 15/30
------------------------------
Training Loss: 0.8708 Training Acc.: 0.4882
Found better model...
Updating the model weights....

Val Loss: 1.3113 Val Acc.: 0.5304


Epoch 16/30
------------------------------
Training Loss: 0.8381 Training Acc.: 0.5018
```

```
Found better model...
Updating the model weights....

Val Loss: 1.3112 Val Acc.: 0.5364


Epoch 17/30
------------------------------
Training Loss: 0.8128 Training Acc.: 0.5107
Found better model...
Updating the model weights....

Val Loss: 1.3131 Val Acc.: 0.5393


Epoch 18/30
------------------------------
Training Loss: 0.7921 Training Acc.: 0.5188
Found better model...
Updating the model weights....

Val Loss: 1.2908 Val Acc.: 0.5476


Epoch 19/30
------------------------------
Training Loss: 0.7663 Training Acc.: 0.5275
Found better model...
Updating the model weights....

Val Loss: 1.2968 Val Acc.: 0.5490


Epoch 20/30
------------------------------
Training Loss: 0.7510 Training Acc.: 0.5326

Epoch 21/30
------------------------------
Training Loss: 0.7225 Training Acc.: 0.5429
Found better model...
Updating the model weights....

Val Loss: 1.2887 Val Acc.: 0.5639


Epoch 22/30
------------------------------
Training Loss: 0.7026 Training Acc.: 0.5484
```

```
Epoch 23/30
------------------------------
Training Loss: 0.6856 Training Acc.: 0.5580

Epoch 24/30
------------------------------
Training Loss: 0.6653 Training Acc.: 0.5634
Found better model...
Updating the model weights....

Val Loss: 1.2922 Val Acc.: 0.5723


Epoch 25/30
------------------------------
Training Loss: 0.6407 Training Acc.: 0.5747

Epoch 26/30
------------------------------
Training Loss: 0.6336 Training Acc.: 0.5770
Found better model...
Updating the model weights....

Val Loss: 1.3072 Val Acc.: 0.5755


Epoch 27/30
------------------------------
Training Loss: 0.6135 Training Acc.: 0.5831
Found better model...
Updating the model weights....

Val Loss: 1.2871 Val Acc.: 0.5804


Epoch 28/30
------------------------------
Training Loss: 0.5895 Training Acc.: 0.5925

Epoch 29/30
------------------------------
Training Loss: 0.5730 Training Acc.: 0.5980

Epoch 30/30
------------------------------
Training Loss: 0.5619 Training Acc.: 0.6013
Found better model...
Updating the model weights....

Val Loss: 1.2950 Val Acc.: 0.5811
```

```
final validation statistics, loss : 1.301525839805603, accuracy : tensor(0.
5754, device='cuda:0')
```

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

```
Epoch 1/30
------------------------------
Training Loss: 1.6549 Training Acc.: 0.2270
Found better model...
Updating the model weights....

Val Loss: 1.7677 Val Acc.: 0.3719


Epoch 2/30
------------------------------
Training Loss: 1.2636 Training Acc.: 0.3439
Found better model...
Updating the model weights....

Val Loss: 1.5424 Val Acc.: 0.4548


Epoch 3/30
------------------------------
Training Loss: 1.1139 Training Acc.: 0.4022
Found better model...
Updating the model weights....

Val Loss: 1.4477 Val Acc.: 0.4837


Epoch 4/30
------------------------------
Training Loss: 1.0128 Training Acc.: 0.4433
Found better model...
Updating the model weights....

Val Loss: 1.3754 Val Acc.: 0.5207


Epoch 5/30
------------------------------
Training Loss: 0.9318 Training Acc.: 0.4712
Found better model...
Updating the model weights....

Val Loss: 1.3383 Val Acc.: 0.5310
```

```
Epoch 6/30
------------------------------
Training Loss: 0.8504 Training Acc.: 0.5005
Found better model...
Updating the model weights....

Val Loss: 1.2753 Val Acc.: 0.5464


Epoch 7/30
------------------------------
Training Loss: 0.7785 Training Acc.: 0.5271
Found better model...
Updating the model weights....

Val Loss: 1.2191 Val Acc.: 0.5686


Epoch 8/30
------------------------------
Training Loss: 0.7190 Training Acc.: 0.5498
Found better model...
Updating the model weights....

Val Loss: 1.2306 Val Acc.: 0.5704


Epoch 9/30
------------------------------
Training Loss: 0.6682 Training Acc.: 0.5673
Found better model...
Updating the model weights....

Val Loss: 1.2245 Val Acc.: 0.5856


Epoch 10/30
------------------------------
Training Loss: 0.6070 Training Acc.: 0.5870
Found better model...
Updating the model weights....

Val Loss: 1.1786 Val Acc.: 0.6051


Epoch 11/30
------------------------------
Training Loss: 0.5721 Training Acc.: 0.6017
Found better model...
```

```
Updating the model weights....

Val Loss: 1.2021 Val Acc.: 0.6059


Epoch 12/30
------------------------------
Training Loss: 0.5325 Training Acc.: 0.6144
Found better model...
Updating the model weights....

Val Loss: 1.2007 Val Acc.: 0.6096


Epoch 13/30
------------------------------
Training Loss: 0.4818 Training Acc.: 0.6327
Found better model...
Updating the model weights....

Val Loss: 1.1854 Val Acc.: 0.6144


Epoch 14/30
------------------------------
Training Loss: 0.4486 Training Acc.: 0.6452
Found better model...
Updating the model weights....

Val Loss: 1.2104 Val Acc.: 0.6193


Epoch 15/30
------------------------------
Training Loss: 0.4807 Training Acc.: 0.6320
Found better model...
Updating the model weights....

Val Loss: 1.1812 Val Acc.: 0.6262


Epoch 16/30
------------------------------
Training Loss: 0.4154 Training Acc.: 0.6564

Epoch 17/30
------------------------------
Training Loss: 0.3804 Training Acc.: 0.6697
Found better model...
Updating the model weights....
```

```
Val Loss: 1.2178 Val Acc.: 0.6365


Epoch 18/30
------------------------------
Training Loss: 0.3145 Training Acc.: 0.6924

Epoch 19/30
------------------------------
Training Loss: 0.2865 Training Acc.: 0.7005
Found better model...
Updating the model weights....

Val Loss: 1.2631 Val Acc.: 0.6464


Epoch 20/30
------------------------------
Training Loss: 0.2863 Training Acc.: 0.7034

Epoch 21/30
------------------------------
Training Loss: 0.2785 Training Acc.: 0.7042

Epoch 22/30
------------------------------
Training Loss: 0.2461 Training Acc.: 0.7151
Found better model...
Updating the model weights....

Val Loss: 1.2902 Val Acc.: 0.6556


Epoch 23/30
------------------------------
Training Loss: 0.2586 Training Acc.: 0.7105

Epoch 24/30
------------------------------
Training Loss: 0.2531 Training Acc.: 0.7132

Epoch 25/30
------------------------------
Training Loss: 0.2844 Training Acc.: 0.7038

Epoch 26/30
------------------------------
Training Loss: 0.2342 Training Acc.: 0.7186
```

```
Epoch 27/30
------------------------------
Training Loss: 0.1815 Training Acc.: 0.7375
Found better model...
Updating the model weights....

Val Loss: 1.3696 Val Acc.: 0.6611


Epoch 28/30
------------------------------
Training Loss: 0.1520 Training Acc.: 0.7474

Epoch 29/30
------------------------------
Training Loss: 0.1557 Training Acc.: 0.7467
Found better model...
Updating the model weights....

Val Loss: 1.3651 Val Acc.: 0.6666


Epoch 30/30
------------------------------
Training Loss: 0.1483 Training Acc.: 0.7483
final validation statistics, loss : 1.3941359251022338, accuracy : tensor(0
.6586, device='cuda:0')
```

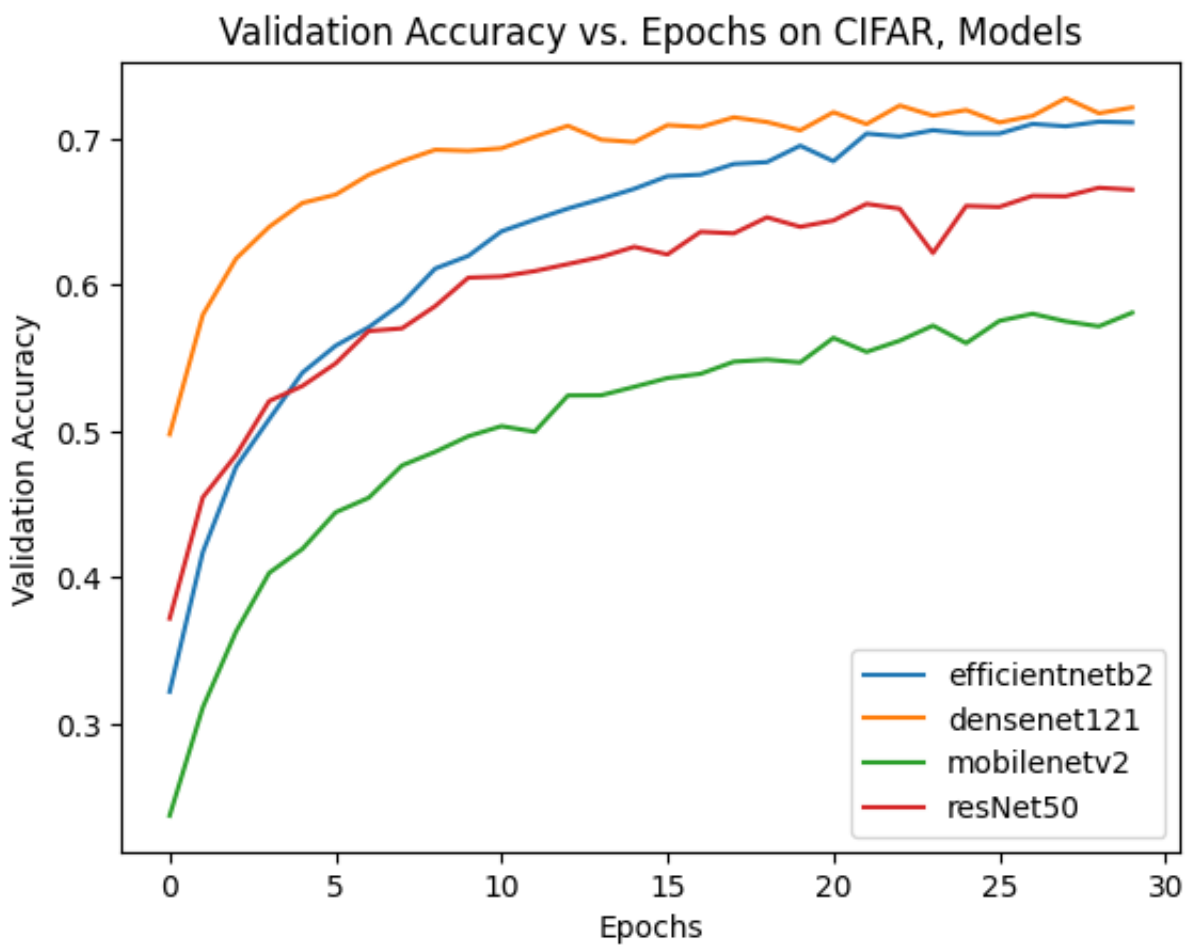
In [ ]:
```
den_model, den_losses, den_acc = dense_params
mobile_model, mobile_losses, mobile_acc = mobile_params
res_model, res_losses, res_acc = res_params
```

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.

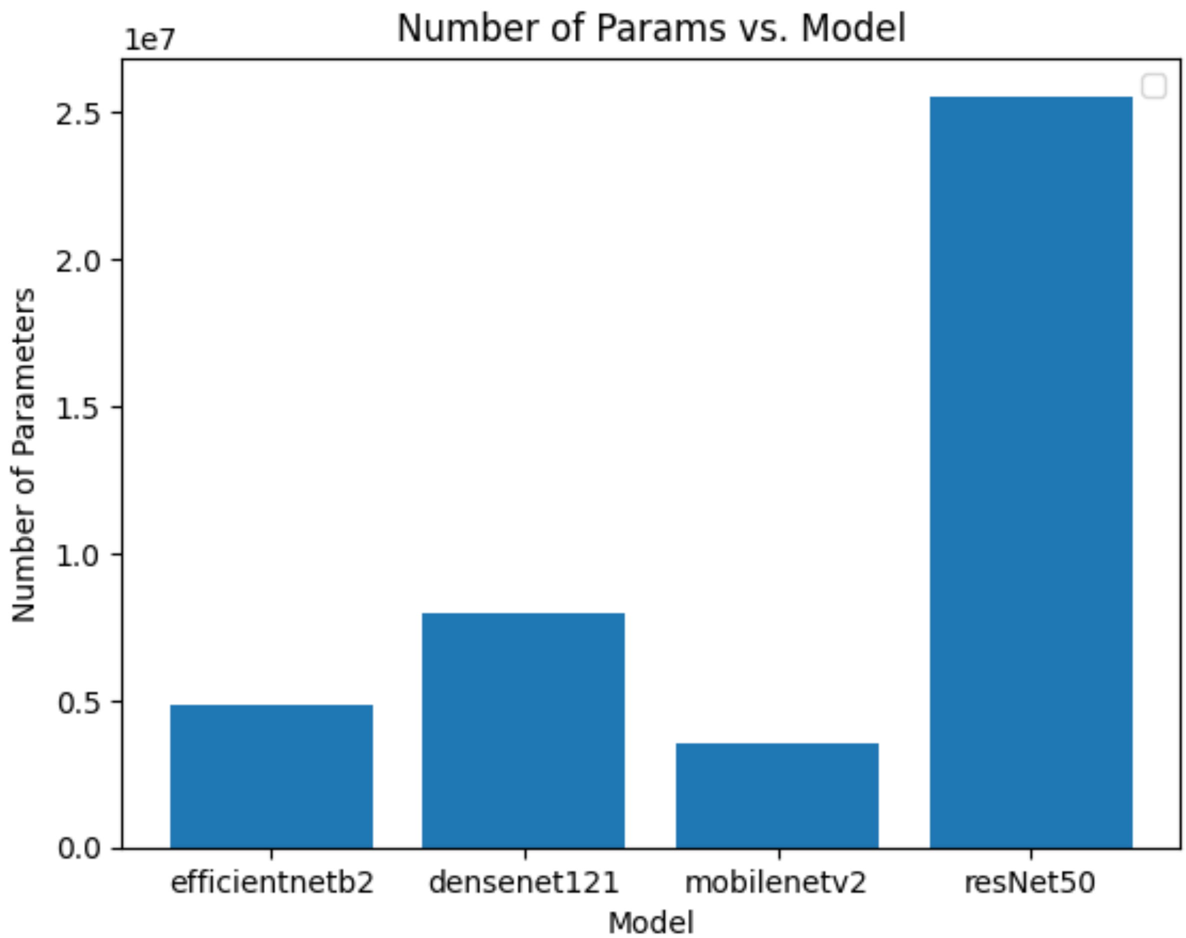
In [ ]:
```
def calculate_parameters(model, model_name):
  num_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
  print("%s has %s params" %(model_name, num_params))
  return num_params
```

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")
```

```
efficientnetb2 has 4872811 params
densenet121 has 7978856 params
mobilenetv2 has 3504872 params
resNet50 has 25557032 params
```

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

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  N
ote that artists whose label start with an underscore are ignored when lege
nd() is called with no argument.
```



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