Question 2: Animal classification (15 marks)

For this question, we will use the Animal (https://cloudstor.aarnet.edu.au/plus/s/cZYtNAeVhWD6uBX) dataset. This dataset contains images of 151 different animals.

The dataset contains a total of 6270 images corresponding to the name of animal types.

All images are RGB images of 224 pixels wide by 224 pixels high in .jpg format. The images are separated in 151 folders according to their respective class.

The task is to categorize each animal into one of 151 categories.

We provide baseline code that includes the following features:

- Loading and Analysing the dataset using torchvision.
- Defining a simple convolutional neural network.
- How to use existing loss function for the model learning.
- Train the network on the training data.
- Test the trained network on the testing data.

The following changes could be considered:

1. "Transfer" Learning (ie use a model pre-trained another dataset)
2. Change of advanced training parameters: Learning Rate, Optimizer, Batch-size, Number of Max Epochs, and Drop-out.
3. Use of a new loss function.
4. Data augmentation
5. Architectural Changes: Batch Normalization, Residual layers, etc.
6. Others - please ask us on the Discussion Forums if you're not sure about an idea!

Your code should be modified from the provided baseline. A pdf report of a maximum of two pages is required to explain the changes you made from the baseline, why you chose those changes, and the improvements they achieved.

Marking Rules:

We will mark this question based on the final test accuracy on testing images and your report.

Final mark (out of 50) = acc_mark + efficiency mark + report mark

Acc_mark 10:

We will rank all the submission results based on their test accuracy. Zero improvement over the baseline yields 0 marks. Maximum improvement over the baseline will yield 10 marks. There will be a sliding scale applied in between.

Efficiency mark 10:

Efficiency considers not only the accuracy, but the computational cost of running the model (flops: https://en.wikipedia.org/wiki/FLOPS). Efficiency for our purposes is defined to be the ratio of accuracy (in %) to Gflops. Please report the computational cost for your final model and include the efficiency calculation in your report. Maximum improvement over the baseline will yield 10 marks. Zero improvement over the baseline yields zero marks, with a sliding scale in between.

Report mark 30:

Your report should comprise:

1. An introduction showing your understanding of the task and of the baseline model: [10 marks]
2. A description of how you have modified aspects of the system to improve performance. [10 marks]

A recommended way to present a summary of this is via an "ablation study" table, eg:

Method1	Method2	Method3	Accuracy
N	N	N	60%
Y	N	N	65%
Y	Y	N	77%
Y	Y	Y	82%

3. Explanation of the methods for reducing the computational cost and/or improve the trade-off between accuracy and cost: [5 marks]
4. Limitations/Conclusions: [5 marks]

```
####################################################################################################################################
### Subject: Computer Vision
### Year: 2023
### Student Name: ABC, XYZ
### Student ID: a123456, a654321
### Comptetion Name: Animal Classification Competition
### Final Results:
### ACC:         FLOPs:
####################################################################################################################################
```

```
# Importing libraries.

import os
import random
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
from tqdm.notebook import tqdm

# To avoid non-essential warnings
import warnings
warnings.filterwarnings('ignore')

from torchvision import datasets, transforms, models
from torchvision.datasets import ImageFolder
from torchvision.transforms import ToTensor
from torchvision.utils import make_grid
from torch.utils.data import random_split
from torch.utils.data.dataloader import DataLoader
import matplotlib.pyplot as plt
%matplotlib inline


from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import zipfile
with zipfile.ZipFile("/content/drive/MyDrive/animal.zip","r") as zip_ref:
    zip_ref.extractall()
```

```
# Mounting G-Drive to get your dataset.
# To access Google Colab GPU; Go To: Edit >>> Netebook Settings >>> Hardware Accelarator: Select GPU.
# Reference: https://towardsdatascience.com/google-colab-import-and-export-datasets-eccf801e2971
```

```
# Dataset path. You should change the dataset path to the location that you place the data.
data_dir = '/content/dataset/dataset'
classes = os.listdir(data_dir)
```

This is baseline transform

```
# Performing Image Transformations.
##Hints: Data Augmentation can be applied here. Have a look on RandomFlip, RandomRotation...
train_transform = transforms.Compose([
            transforms.Resize(112),
            transforms.RandomHorizontalFlip(),
            transforms.CenterCrop(112),
            transforms.ToTensor(),
            transforms.Normalize((0.488), (0.2172)),
        ])
```

```
# Checking the dataset training size.
dataset = ImageFolder(data_dir, transform=train_transform)
print('Size of training dataset :', len(dataset))
```

```
Size of training dataset : 6270
```

```
# Viewing one of images shape.
img, label = dataset[100]
print(img.shape)
```

```
torch.Size([3, 112, 112])
```

```
# Preview one of the images..
def show_image(img, label):
    print('Label: ', dataset.classes[label], "("+str(label)+")")
    plt.imshow(img.permute(1,2,0))
```

```
show_image(*dataset[200])
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGI
Label:  ailurus-fulgens (5)
```

```
# Setting seed so that value won't change everytime.
# Splitting the dataset to training, validation, and testing category.
torch.manual_seed(10)
val_size = len(dataset)//20
test_size = len(dataset)//10
train_size = len(dataset) - val_size - test_size
```

```
# Random Splitting.
train_ds, val_ds, test_ds = random_split(dataset, [train_size, val_size, test_size])
len(train_ds), len(val_ds),len(test_ds)
```

```
(5330, 313, 627)
```

```
batch_size = 16
train_loader = DataLoader(train_ds, batch_size, shuffle=True, num_workers=2, pin_memory=True)
val_loader = DataLoader(val_ds, batch_size, num_workers=2, pin_memory=True)
test_loader = DataLoader(test_ds, batch_size, num_workers=2, pin_memory=True)
```

```
# Multiple images preview.
for images, labels in train_loader:
    fig, ax = plt.subplots(figsize=(18,10))
    ax.set_xticks([])
    ax.set_yticks([])
    ax.imshow(make_grid(images, nrow=16).permute(1, 2, 0))
    break
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGI
```

```
 # Baseline model class for training and validation purpose. Evaluation metric function - Accuracy.
def accuracy(output, target, topk=(1,)):
    """
    Computes the accuracy over the k top predictions for the specified values of k
    In top-3 accuracy you give yourself credit for having the right answer
    if the right answer appears in your top five guesses.
    """
    with torch.no_grad():
        maxk = 3
        batch_size = target.size(0)

        # st()
        _, pred = output.topk(maxk, 1, True, True)
        pred = pred.t()
        # st()
        # correct = pred.eq(target.view(1, -1).expand_as(pred))
        # correct = (pred == target.view(1, -1).expand_as(pred))
        correct = (pred == target.unsqueeze(dim=0)).expand_as(pred)



        correct_3 = correct[:3].reshape(-1).float().sum(0, keepdim=True)

        return correct_3.mul_(1.0 / batch_size)
#def accuracy(outputs, labels):
 #   _, preds = torch.max(outputs, dim=1)
  #  return torch.tensor(torch.sum(preds == labels).item() / len(preds))

class ImageClassificationBase(nn.Module):
    def training_step(self, batch):
        images, labels = batch
        out = self(images)                  # Generate predictions
        loss = F.cross_entropy(out, labels) # Calculate loss, Hints: the loss function can be changed to improve the accuracy
        return loss

    def validation_step(self, batch):
        images, labels = batch
        out = self(images)                    # Generate predictions
        loss = F.cross_entropy(out, labels)   # Calculate loss
        acc = accuracy(out, labels, (5))           # Calculate accuracy
        return {'val_loss': loss.detach(), 'val_acc': acc}

    def validation_epoch_end(self, outputs):
        batch_losses = [x['val_loss'] for x in outputs]
        epoch_loss = torch.stack(batch_losses).mean()   # Combine losses
        batch_accs = [x['val_acc'] for x in outputs]
        epoch_acc = torch.stack(batch_accs).mean()      # Combine accuracies
        return {'val_loss': epoch_loss.item(), 'val_acc': epoch_acc.item()}

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

```
 # To check wether Google Colab GPU has been assigned/not.

def get_default_device():
    """Pick GPU if available, else CPU"""
    if torch.cuda.is_available():
        return torch.device('cuda')
    else:
        return None

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

class DeviceDataLoader():
    """Wrap a dataloader to move data to a device"""
    def __init__(self, dl, device):
        self.dl = dl
        self.device = device

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

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


device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
train_loader = DeviceDataLoader(train_loader, device)
val_loader = DeviceDataLoader(val_loader, device)
test_loader = DeviceDataLoader(test_loader, device)


input_size = 3*112*112
output_size = 151


# Convolutional Network - Baseline
class ConvolutionalNetwork(ImageClassificationBase):
    def __init__(self, classes):
        super().__init__()
        self.num_classes=classes
        self.conv1=nn.Conv2d(3,64,5,1)
        self.conv2=nn.Conv2d(64,128,3,1)
        self.conv3=nn.Conv2d(128,128,3,1)
        self.conv4=nn.Conv2d(128,128,3,1)
        self.fc1=nn.Linear(128*5*5,self.num_classes)
    def forward(self,X):
        X=F.relu(self.conv1(X))
        X=F.max_pool2d(X,2,2)
        X=F.relu(self.conv2(X))
        X=F.max_pool2d(X,2,2)
        X=F.relu(self.conv3(X))
```

```
        X=F.max_pool2d(X,2,2)
        X=F.relu(self.conv4(X))
        X=F.max_pool2d(X,2,2)
        X=X.view(-1,128*5*5)
        X=self.fc1(X)

        return F.log_softmax(X, dim=1)


# Model print
num_classes = 151
model = ConvolutionalNetwork(num_classes)
model = model.to(device)
#model.cuda()


# We can check the input and the output shape
for images, labels in train_loader:
    images = images.to(device)
    labels = labels.to(device)
    out = model(images)
    print('images.shape:', images.shape)
    print('out.shape:', out.shape)
    print('out[0]:', out[0])
    break
```

```
images.shape: torch.Size([16, 3, 112, 112])
out.shape: torch.Size([16, 151])
out[0]: tensor([-5.0253, -5.0075, -4.9627, -5.0596, -5.0815, -4.9866, -5.0008, -4.9870,
        -5.0678, -5.0146, -5.0684, -4.9802, -4.9810, -5.0258, -5.0535, -5.0307,
        -5.0418, -5.0117, -5.0337, -5.0770, -5.0106, -5.0112, -5.0253, -4.9587,
        -4.9998, -4.9620, -4.9563, -5.0806, -5.0266, -4.9681, -4.9688, -5.0341,
        -5.0871, -5.0054, -5.0148, -4.9946, -5.0253, -4.9978, -4.9086, -5.0187,
        -5.0609, -5.0372, -5.0035, -5.0826, -4.9326, -5.0396, -5.0156, -5.0929,
        -5.0151, -5.0075, -5.0279, -5.0491, -4.9886, -5.0747, -5.0234, -5.0762,
        -5.0536, -5.0433, -5.0373, -4.9688, -5.0567, -5.0227, -5.0481, -5.0432,
        -5.0580, -4.9815, -5.0384, -5.0471, -5.0285, -5.0213, -5.0451, -5.0055,
        -5.0277, -5.0750, -5.0670, -5.0840, -5.0346, -4.9949, -5.0220, -4.9649,
        -5.0837, -5.0014, -5.0467, -4.9690, -4.9925, -4.9640, -5.0435, -5.0278,
        -5.0357, -5.0496, -5.0517, -5.0088, -5.0177, -4.9542, -5.0016, -5.0400,
        -5.0196, -5.0168, -5.0874, -5.0769, -5.0624, -5.0368, -4.9610, -5.0215,
        -4.9595, -5.0215, -5.0327, -5.0223, -4.9540, -5.0473, -5.0826, -5.0351,
        -5.1066, -5.0157, -5.0138, -5.0146, -4.9556, -4.9345, -4.9744, -5.0310,
        -5.0230, -5.0704, -4.9948, -4.9817, -5.0034, -4.9679, -4.9537, -5.0187,
        -4.9682, -5.0083, -4.9759, -4.9625, -5.0273, -4.9851, -5.0317, -5.0196,
        -4.9901, -5.0643, -5.0197, -5.0291, -5.0257, -5.0060, -5.0191, -4.9599,
        -4.9919, -4.9667, -4.9805, -5.0451, -4.9737, -5.0820, -4.9577],
       device='cuda:0', grad_fn=<SelectBackward0>)
```

```
train_dl = DeviceDataLoader(train_loader, device)
val_dl = DeviceDataLoader(val_loader, device)
to_device(model, device)
```

```
ConvolutionalNetwork(
  (conv1): Conv2d(3, 64, kernel_size=(5, 5), stride=(1, 1))
  (conv2): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1))
  (conv3): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1))
  (conv4): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1))
```

```
      (fc1): Linear(in_features=3200, out_features=151, bias=True)
    )
```

```
# Functions for evaluation and training.

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

def fit(epochs, lr, model, train_loader, val_loader, opt_func=torch.optim.SGD):
    history = []
    optimizer = opt_func(model.parameters(), lr)
    for epoch in range(epochs):
        # Training Phase
        model.train()
        train_losses = []
        for batch in tqdm(train_loader):
            loss = model.training_step(batch)
            train_losses.append(loss)
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()
        # Validation phase
        result = evaluate(model, val_loader)
        result['train_loss'] = torch.stack(train_losses).mean().item()
        model.epoch_end(epoch, result)
        history.append(result)
    return history
```

```
model = to_device(model, device)
```

```
history=[evaluate(model, val_loader)]
history
```

```
[{'val_loss': 5.015639781951904, 'val_acc': 0.02187499962747097}]
```

```
# Hints: The following parameters can be changed to improve the accuracy
print(test_size)
num_epochs = 10
opt_func = torch.optim.Adam
lr = 0.001
```

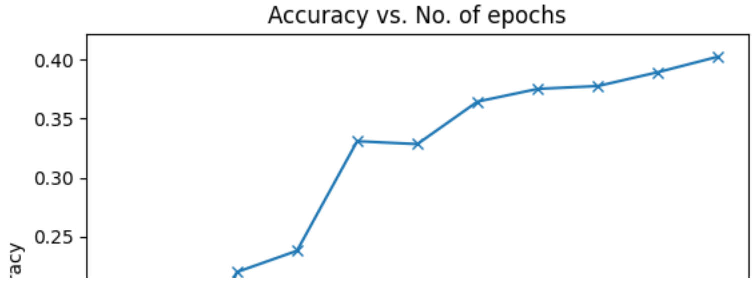
```
627
```

```
history+= fit(num_epochs, lr, model, train_dl, val_dl, opt_func)
```

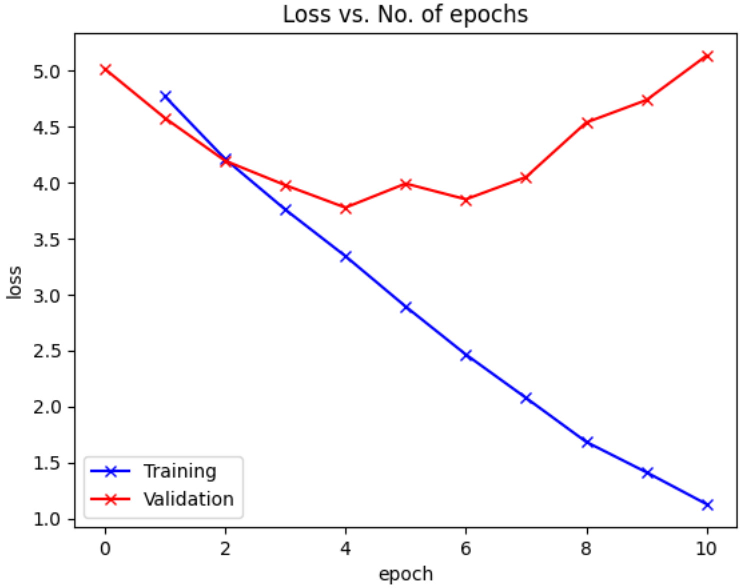
```
100%                                      334/334 [00:19<00:00, 12.48it/s]
Epoch [0], train_loss: 4.7693, val_loss: 4.5759, val_acc: 0.0844
100%                                      334/334 [00:09<00:00, 38.74it/s]
Epoch [1], train_loss: 4.2098, val_loss: 4.1940, val_acc: 0.2198
100%                                      334/334 [00:20<00:00, 12.75it/s]
Epoch [2], train_loss: 3.7580, val_loss: 3.9759, val_acc: 0.2378
100%                                      334/334 [00:15<00:00, 19.83it/s]
Epoch [3], train_loss: 3.3418, val_loss: 3.7755, val_acc: 0.3309
100%                                      334/334 [00:10<00:00, 21.38it/s]
Epoch [4], train_loss: 2.8917, val_loss: 3.9901, val_acc: 0.3285
100%                                      334/334 [00:09<00:00, 37.63it/s]
Epoch [5], train_loss: 2.4633, val_loss: 3.8495, val_acc: 0.3646
100%                                      334/334 [00:11<00:00, 24.77it/s]
Epoch [6], train_loss: 2.0755, val_loss: 4.0485, val_acc: 0.3753
100%                                      334/334 [00:14<00:00, 34.85it/s]
Epoch [7], train_loss: 1.6825, val_loss: 4.5356, val_acc: 0.3778
```

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

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

```
plot_accuracies(history)
```




```
plot_losses(history)
```




```
evaluate(model, test_loader)
```

```
{'val_loss': 5.279730796813965, 'val_acc': 0.34062501788139343}
```

The baseline model suggest a accuracy of 34% which is quite impressive, as it is a custom model, and it is not a pretrained, so it is only trianed with this small amount of data.

Pretrained Model (Efficient NET) [1]

In this experiment I will try to use a new transform model, using the model called Efficient NET (Tan, 2019), using crossEtropyLoss as criterion, optimizing using AdamW, and tried to use LRT. As the reason of this is my first apporach I tried to choose by my intuition and see the result.

```
train_transform = transforms.Compose([
    transforms.Resize(128),  # Resizing to 128x128 for better training
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(15),
    transforms.ColorJitter(brightness=0.1, contrast=0.1, saturation=0.1, hue=0.1),
    transforms.RandomResizedCrop(112),
    transforms.ToTensor(),
    transforms.Normalize((0.488), (0.2172))
])



dataset = ImageFolder(data_dir, transform=train_transform)


# Setting seed so that value won't change everytime.
# Splitting the dataset to training, validation, and testing category.
torch.manual_seed(10)
val_size = len(dataset)//20
test_size = len(dataset)//10
train_size = len(dataset) - val_size - test_size


train_ds, val_ds, test_ds = random_split(dataset, [train_size, val_size, test_size])
len(train_ds), len(val_ds),len(test_ds)
```

```
(5330, 313, 627)
```

```
# Set up data loaders
loaders = {
    'train': DataLoader(train_ds, batch_size=32, shuffle=True, num_workers=4),
    'val': DataLoader(val_ds, batch_size=32, shuffle=False, num_workers=4),
    'test': DataLoader(test_ds, batch_size=32, shuffle=False, num_workers=4)
}
```

```
!pip install timm
import timm
import copy
# Load a pretrained EfficientNet model
model_name = 'efficientnet_b0'  # You can change this to another version if needed
model = timm.create_model(model_name, pretrained=True, num_classes=151)
model = model.to(device)
```

```
Collecting timm
  Downloading timm-0.9.5-py3-none-any.whl (2.2 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.2/2.2 MB 15.3 MB/s eta 0:00:00
Requirement already satisfied: torch>=1.7 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: torchvision in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: pyyaml in /usr/local/lib/python3.10/dist-packages (1
Collecting huggingface-hub (from timm)
  Downloading huggingface_hub-0.16.4-py3-none-any.whl (268 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 268.8/268.8 kB 20.2 MB/s eta 0:00:00
Collecting safetensors (from timm)
  Downloading safetensors-0.3.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x8
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.3/1.3 MB 33.3 MB/s eta 0:00:00
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.10/dist-
Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (f
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (1
Requirement already satisfied: triton==2.0.0 in /usr/local/lib/python3.10/dist-pacl
Requirement already satisfied: cmake in /usr/local/lib/python3.10/dist-packages (f
Requirement already satisfied: lit in /usr/local/lib/python3.10/dist-packages (fro
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (1
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages
```

```
criterion = nn.CrossEntropyLoss().to(device)
optimizer = torch.optim.AdamW(model.parameters(), lr=0.001)
scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=3, gamma=0.97)
```

```
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3..
```

```
@torch.no_grad()
def evaluate(model, val_loader, criterion):
    model.eval()
    total_loss = 0.0
    total_correct = 0

    for batch in val_loader:
        inputs, labels = batch
        inputs, labels = inputs.to(device), labels.to(device)

        # Get model outputs
        outputs = model(inputs)

        # Compute loss
        loss = criterion(outputs, labels)
        total_loss += loss.item() * inputs.size(0)

        # Compute number of correct predictions
        _, preds = torch.max(outputs, 1)
        total_correct += torch.sum(preds == labels.data)

    avg_loss = total_loss / len(val_loader.dataset)
    avg_accuracy = total_correct.double() / len(val_loader.dataset)

    return {'val_loss': avg_loss, 'val_acc': avg_accuracy}


def train_model(model, criterion, optimizer, scheduler, num_epochs=25):
    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0
```

```
for epoch in range(num_epochs):
    print(f"Epoch {epoch}/{num_epochs - 1}")
    print('-' * 10)

    # Each epoch has a training and validation phase
    for phase in ['train', 'val']:
        if phase == 'train':
            model.train()  # Set model to training mode
        else:
            model.eval()   # Set model to evaluate mode

        running_loss = 0.0
        running_corrects = 0

        # Iterate over data.
        for inputs, labels in loaders[phase]:
            inputs = inputs.to(device)
            labels = labels.to(device)

            # Zero the parameter gradients
            optimizer.zero_grad()

            # Forward
            # Track history if only in train
            with torch.set_grad_enabled(phase == 'train'):
                outputs = model(inputs)
                _, preds = torch.max(outputs, 1)
                loss = criterion(outputs, labels)

                # Backward + optimize only if in training phase
                if phase == 'train':
                    loss.backward()
                    optimizer.step()

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

        if phase == 'train':
            scheduler.step()

        epoch_loss = running_loss / len(loaders[phase].dataset)
        epoch_acc = running_corrects.double() / len(loaders[phase].dataset)

        print(f"{phase} Loss: {epoch_loss:.4f} Acc: {epoch_acc:.4f}")

        # Deep copy the model
        if phase == 'val' and epoch_acc > best_acc:
            best_acc = epoch_acc
            best_model_wts = copy.deepcopy(model.state_dict())

    print()

print(f"Best val Acc: {best_acc:.4f}")
```

```
    # Load best model weights
    model.load_state_dict(best_model_wts)
    return model
```

```
trained_model = train_model(model, criterion, optimizer, scheduler, num_epochs=25)
```

```
Epoch 0/24
----------
train Loss: 3.3570 Acc: 0.2640
val Loss: 2.4076 Acc: 0.4089

Epoch 1/24
----------
train Loss: 1.9746 Acc: 0.5182
val Loss: 2.1249 Acc: 0.5176

Epoch 2/24
----------
train Loss: 1.5052 Acc: 0.6128
val Loss: 1.7375 Acc: 0.5655

Epoch 3/24
----------
train Loss: 1.2789 Acc: 0.6668
val Loss: 1.6319 Acc: 0.6102

Epoch 4/24
----------
train Loss: 1.1251 Acc: 0.7060
val Loss: 1.6754 Acc: 0.5719

Epoch 5/24
----------
train Loss: 1.0154 Acc: 0.7285
val Loss: 1.7262 Acc: 0.5942

Epoch 6/24
----------
train Loss: 0.9228 Acc: 0.7568
val Loss: 1.6230 Acc: 0.6134

Epoch 7/24
----------
train Loss: 0.8941 Acc: 0.7591
val Loss: 1.6236 Acc: 0.6422

Epoch 8/24
----------
train Loss: 0.8460 Acc: 0.7764
val Loss: 1.8094 Acc: 0.6262

Epoch 9/24
----------
train Loss: 0.7356 Acc: 0.8024
val Loss: 1.5655 Acc: 0.6198

Epoch 10/24
----------
train Loss: 0.7394 Acc: 0.8028
val Loss: 1.8386 Acc: 0.5942
```

```
Epoch 11/24
----------
```

```
# Evaluate the model on the test set
test_results = evaluate(trained_model, loaders['test'], criterion)

print(f"Test Loss: {test_results['val_loss']:.4f}")
print(f"Test Accuracy: {test_results['val_acc']:.4f}")
```

```
Test Loss: 1.5512
Test Accuracy: 0.6651
```

Resnet18 [2]

Instead of improving everytime the efficient net, which will give the better result after improving, I started to use resnet18 to better compare between which one is better, and what parameter can be used.

```
train_transform  = transforms.Compose([
            transforms.RandomHorizontalFlip(),
            transforms.RandomVerticalFlip(),
            transforms.RandomApply(transforms=[
                transforms.GaussianBlur(kernel_size=(5, 9), sigma=(0.1, 5))
            ], p=0.2),
            transforms.Resize(256),
            transforms.CenterCrop(224),
            transforms.ToTensor(),
            transforms.Normalize((0.485, 0.456, 0.406), (0.229, 0.224, 0.225)),
        ])
dataset = ImageFolder(data_dir, transform=train_transform)
torch.manual_seed(10)
val_size = len(dataset)//20
test_size = len(dataset)//10
train_size = len(dataset) - val_size - test_size
# Random Splitting.
train_ds, val_ds, test_ds = random_split(dataset, [train_size, val_size, test_size])
len(train_ds), len(val_ds),len(test_ds)
```

```
(5330, 313, 627)
```

```
batch_size = 32
train_loader = DataLoader(train_ds, batch_size, shuffle=True, num_workers=2, pin_memory=True)
val_loader = DataLoader(val_ds, batch_size, num_workers=2, pin_memory=True)
test_loader = DataLoader(test_ds, batch_size, num_workers=2, pin_memory=True)
```

```
# Multiple images preview.
for images, labels in train_loader:
    fig, ax = plt.subplots(figsize=(18,10))
    ax.set_xticks([])
    ax.set_yticks([])
    ax.imshow(make_grid(images, nrow=16).permute(1, 2, 0))
    break
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

```
import torchvision.models as models

model = models.resnet18(pretrained=True)
num_ftrs = model.fc.in_features
model.fc = nn.Linear(num_ftrs, 151)  # Assuming 151 classes
model = model.to(device)


device = get_default_device()
device
train_loader = DeviceDataLoader(train_loader, device)
val_loader = DeviceDataLoader(val_loader, device)
test_loader = DeviceDataLoader(test_loader, device)
```

```
train_dl = DeviceDataLoader(train_loader, device)
val_dl = DeviceDataLoader(val_loader, device)
to_device(model, device)
```

```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (layer3): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
```

```
# Loss Function with Label Smoothing
class LabelSmoothingCrossEntropy(nn.Module):
    def __init__(self, epsilon: float = 0.1):
        super().__init__()
        self.epsilon = epsilon

    def forward(self, outputs, targets):
        num_classes = outputs.size()[-1]
        log_preds = F.log_softmax(outputs, dim=-1)
        loss = (-log_preds.sum(dim=-1)).mean()
        nll = F.nll_loss(log_preds, targets)
        return (1. - self.epsilon) * nll + self.epsilon * loss / num_classes

criterion = LabelSmoothingCrossEntropy()

# Optimizer
optimizer = torch.optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4)

# Learning Rate Scheduler
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, 'min', patience=5, factor=0.5)
```

```
num_epochs = 40
```

```
def train_one_epoch(model, train_loader, criterion, optimizer):
    model.train()
    total_loss = 0.0
    for inputs, labels in train_loader:
        inputs, labels = inputs.to(device), labels.to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        # Backward and optimize
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

    return total_loss / len(train_loader)

def validate(model, val_loader, criterion):
    model.eval()
    total_loss = 0.0
    correct = 0
    total = 0
    with torch.no_grad():
        for inputs, labels in val_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = model(inputs)
            loss = criterion(outputs, labels)
            total_loss += loss.item()

            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    accuracy = 100 * correct / total
    return total_loss / len(val_loader), accuracy

for epoch in range(num_epochs):
    train_loss = train_one_epoch(model, train_loader, criterion, optimizer)
    val_loss, val_acc = validate(model, val_loader, criterion)

    # Step the scheduler
    scheduler.step(val_loss)

    print(f"Epoch {epoch+1}/{num_epochs}, Train Loss: {train_loss:.4f}, Val Loss: {val_loss:.4f}, Val Acc: {val_acc:.2f}%")
```

```
Epoch 1/40, Train Loss: 4.0921, Val Loss: 4.5324, Val Acc: 12.46%
Epoch 2/40, Train Loss: 3.0560, Val Loss: 3.1677, Val Acc: 36.10%
Epoch 3/40, Train Loss: 2.6184, Val Loss: 3.3024, Val Acc: 33.87%
Epoch 4/40, Train Loss: 2.3324, Val Loss: 2.6621, Val Acc: 48.88%
Epoch 5/40, Train Loss: 2.0981, Val Loss: 2.6663, Val Acc: 47.92%
Epoch 6/40, Train Loss: 1.9246, Val Loss: 2.7880, Val Acc: 45.37%
```

```
Epoch 7/40, Train Loss: 1.7705, Val Loss: 2.5139, Val Acc: 53.99%
Epoch 8/40, Train Loss: 1.6801, Val Loss: 2.5534, Val Acc: 49.84%
Epoch 9/40, Train Loss: 1.6325, Val Loss: 2.5672, Val Acc: 52.72%
Epoch 10/40, Train Loss: 1.5525, Val Loss: 2.3501, Val Acc: 57.83%
Epoch 11/40, Train Loss: 1.4579, Val Loss: 2.2356, Val Acc: 61.66%
Epoch 12/40, Train Loss: 1.3890, Val Loss: 2.3826, Val Acc: 57.51%
Epoch 13/40, Train Loss: 1.3853, Val Loss: 2.2855, Val Acc: 61.02%
Epoch 14/40, Train Loss: 1.3701, Val Loss: 2.2134, Val Acc: 61.34%
Epoch 15/40, Train Loss: 1.3364, Val Loss: 2.4859, Val Acc: 53.99%
Epoch 16/40, Train Loss: 1.3232, Val Loss: 2.2715, Val Acc: 57.83%
Epoch 17/40, Train Loss: 1.2563, Val Loss: 2.1947, Val Acc: 62.94%
Epoch 18/40, Train Loss: 1.2565, Val Loss: 2.4099, Val Acc: 56.55%
Epoch 19/40, Train Loss: 1.2346, Val Loss: 2.2857, Val Acc: 60.06%
Epoch 20/40, Train Loss: 1.2268, Val Loss: 2.3072, Val Acc: 58.79%
Epoch 21/40, Train Loss: 1.2393, Val Loss: 2.1991, Val Acc: 65.81%
Epoch 22/40, Train Loss: 1.2310, Val Loss: 2.3410, Val Acc: 57.51%
Epoch 23/40, Train Loss: 1.2222, Val Loss: 2.2500, Val Acc: 59.11%
Epoch 24/40, Train Loss: 1.0834, Val Loss: 1.9087, Val Acc: 68.37%
Epoch 25/40, Train Loss: 1.0160, Val Loss: 1.8391, Val Acc: 71.57%
Epoch 26/40, Train Loss: 0.9980, Val Loss: 1.8769, Val Acc: 70.29%
Epoch 27/40, Train Loss: 0.9845, Val Loss: 1.8659, Val Acc: 72.52%
Epoch 28/40, Train Loss: 0.9780, Val Loss: 1.8853, Val Acc: 70.93%
Epoch 29/40, Train Loss: 0.9705, Val Loss: 1.8313, Val Acc: 74.76%
Epoch 30/40, Train Loss: 0.9707, Val Loss: 1.8798, Val Acc: 72.20%
Epoch 31/40, Train Loss: 0.9729, Val Loss: 1.8674, Val Acc: 70.93%
Epoch 32/40, Train Loss: 0.9858, Val Loss: 2.1258, Val Acc: 65.81%
Epoch 33/40, Train Loss: 0.9905, Val Loss: 1.9817, Val Acc: 69.65%
Epoch 34/40, Train Loss: 1.0097, Val Loss: 2.0222, Val Acc: 66.13%
Epoch 35/40, Train Loss: 1.0152, Val Loss: 1.9929, Val Acc: 68.69%
Epoch 36/40, Train Loss: 0.9693, Val Loss: 1.8750, Val Acc: 72.84%
Epoch 37/40, Train Loss: 0.9394, Val Loss: 1.8443, Val Acc: 69.33%
Epoch 38/40, Train Loss: 0.9299, Val Loss: 1.8151, Val Acc: 72.52%
Epoch 39/40, Train Loss: 0.9210, Val Loss: 1.8043, Val Acc: 73.16%
Epoch 40/40, Train Loss: 0.9179, Val Loss: 1.8293, Val Acc: 73.48%
```

```
def evaluate(model, data_loader, criterion):
    model.eval()  # Set the model to evaluation mode
    total_loss = 0.0
    correct_predictions = 0
    total_predictions = 0

    with torch.no_grad():  # Disable gradient computation during evaluation
        for inputs, labels in data_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            # Forward pass
            outputs = model(inputs)
            loss = criterion(outputs, labels)

            total_loss += loss.item()

            _, predicted = torch.max(outputs.data, 1)
            total_predictions += labels.size(0)
            correct_predictions += (predicted == labels).sum().item()

    average_loss = total_loss / len(data_loader)
    accuracy = (correct_predictions / total_predictions) * 100
    return average_loss, accuracy
```

```
val_loss, val_accuracy = evaluate(model, val_loader, criterion)
print(f"Validation Loss: {val_loss:.4f}, Validation Accuracy: {val_accuracy:.2f}%")
```

```
Validation Loss: 1.8068, Validation Accuracy: 74.76%
```

```
test_loss, test_accuracy = evaluate(model, test_loader, criterion)
print(f"Test Loss: {test_loss:.4f}, Test Accuracy: {test_accuracy:.2f}%")
```

```
Test Loss: 1.7621, Test Accuracy: 76.08%
```

Resnet + ImageclassificationBase(Initial model)

```
import torch.nn as nn
from torchvision.models import resnet50
import torchvision.models as models

class ImageClassificationBase(nn.Module):
    def training_step(self, batch):
        images, labels = batch
        out = self(images)                  # Generate predictions
        loss = FocalLoss(logits=True)(out, labels) # Calculate loss
        return loss

    def validation_step(self, batch):
        images, labels = batch
        out = self(images)                    # Generate predictions
        loss = FocalLoss(logits=True)(out, labels)   # Calculate loss
        acc = accuracy(out, labels, (5))           # Calculate accuracy
        return {'val_loss': loss.detach(), 'val_acc': acc}

    def validation_epoch_end(self, outputs):
        batch_losses = [x['val_loss'] for x in outputs]
        epoch_loss = torch.stack(batch_losses).mean()   # Combine losses
        batch_accs = [x['val_acc'] for x in outputs]
        epoch_acc = torch.stack(batch_accs).mean()      # Combine accuracies
        return {'val_loss': epoch_loss.item(), 'val_acc': epoch_acc.item()}

    def epoch_end(self, epoch, result):
        print("Epoch [{}], train_loss: {:.4f}, val_loss: {:.4f}, val_acc: {:.4f}".format(
            epoch, result['train_loss'], result['val_loss'], result['val_acc']))


class PretrainedResNet(ImageClassificationBase):
    def __init__(self, num_classes=151):
        super(PretrainedResNet, self).__init__()

        # Load the pretrained ResNet-18 model
        self.model = models.resnet18(pretrained=True)

        # Replace the final layer to match the number of classes in your dataset
        num_ftrs = self.model.fc.in_features
        self.model.fc = nn.Linear(num_ftrs, num_classes)
```

```
    def forward(self, x):
        return self.model(x)

# Create an instance of the modified ResNet model
model = PretrainedResNet(num_classes=151)
model = model.to(device)


train_dl = DeviceDataLoader(train_loader, device)
val_dl = DeviceDataLoader(val_loader, device)
test_dl = DeviceDataLoader(test_loader, device)
to_device(model, device)
```

```
PretrainedResNet(
  (model): ResNet(
    (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
    (layer1): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (layer2): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (layer3): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
```

```
            (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (downsample): Sequential(
              (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
              (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            )
          )
          (1): BasicBlock(
            (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (relu): ReLU(inplace=True)
```

```
model = to_device(model, device)
val_dl = DeviceDataLoader(val_loader, device)
history = [evaluate(model, val_dl,criterion)]
history
```

```
[{'val_loss': 5.5590434074401855, 'val_acc': 0.012500000186264515}]
```

```
from tqdm import tqdm
def evaluate(model, val_loader, criterion):
    model.eval()
    outputs = [model.validation_step(batch) for batch in val_loader]
    batch_losses = [x['val_loss'] for x in outputs]
    epoch_loss = torch.stack(batch_losses).mean()
    batch_accs = [x['val_acc'] for x in outputs]
    epoch_acc = torch.stack(batch_accs).mean()

    return {'val_loss': epoch_loss.item(), 'val_acc': epoch_acc.item()}
def fit(epochs, model, train_loader, val_loader, optimizer, criterion):
    history = []

    for epoch in range(epochs):
        # Training Phase
        model.train()
        train_losses = []

        for batch in tqdm(train_loader):
            loss = model.training_step(batch)
            train_losses.append(loss)
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()

        avg_train_loss = torch.stack(train_losses).mean().item()

        # Validation phase
        result = evaluate(model, val_loader, criterion)
        result['train_loss'] = avg_train_loss
        model.epoch_end(epoch, result)
        history.append(result)

    return history

class FocalLoss(nn.Module):
    def __init__(self, alpha=1., gamma=2., logits=False, reduction='mean'):
        super(FocalLoss, self).__init__()
```

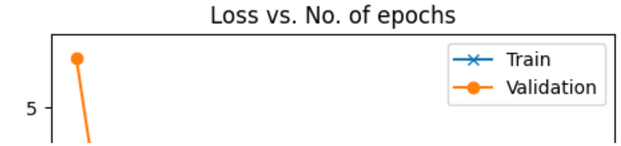
```
        self.alpha = alpha
        self.gamma = gamma
        self.logits = logits
        self.reduction = reduction

    def forward(self, inputs, targets):
        if self.logits:
            inputs = torch.nn.functional.softmax(inputs, dim=1)
            inputs = inputs.gather(1, targets.unsqueeze(1))
            inputs = inputs.squeeze(1)
            BCE_loss = F.binary_cross_entropy(inputs, torch.ones_like(inputs), reduction='none')
        else:
            BCE_loss = F.binary_cross_entropy(inputs, targets, reduction='none')

        pt = torch.exp(-BCE_loss)
        F_loss = self.alpha * (1-pt)**self.gamma * BCE_loss

        if self.reduction == 'sum':
            return F_loss.sum()
        elif self.reduction == 'mean':
            return F_loss.mean()
```

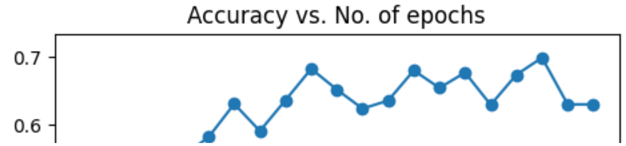
```
num_epochs = 20
optimizer = torch.optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4)
criterion = FocalLoss(logits=True)  # Ensure you have defined FocalLoss before this
history += fit(num_epochs, model, train_dl, val_dl, optimizer, criterion)
```

```
100%|██████████| 334/334 [00:12<00:00, 26.57it/s]
Epoch [0], train_loss: 4.2097, val_loss: 3.6542, val_acc: 0.3097
100%|██████████| 334/334 [00:09<00:00, 34.17it/s]
Epoch [1], train_loss: 3.0104, val_loss: 3.2318, val_acc: 0.4028
100%|██████████| 334/334 [00:10<00:00, 31.51it/s]
Epoch [2], train_loss: 2.3853, val_loss: 2.9070, val_acc: 0.4622
100%|██████████| 334/334 [00:11<00:00, 28.80it/s]
Epoch [3], train_loss: 1.9355, val_loss: 2.4682, val_acc: 0.5538
100%|██████████| 334/334 [00:11<00:00, 29.45it/s]
Epoch [4], train_loss: 1.5817, val_loss: 2.4168, val_acc: 0.5819
100%|██████████| 334/334 [00:11<00:00, 29.17it/s]
Epoch [5], train_loss: 1.3233, val_loss: 2.0438, val_acc: 0.6309
100%|██████████| 334/334 [00:13<00:00, 25.52it/s]
Epoch [6], train_loss: 1.0667, val_loss: 2.1607, val_acc: 0.5910
100%|██████████| 334/334 [00:09<00:00, 35.32it/s]
Epoch [7], train_loss: 0.8498, val_loss: 2.1010, val_acc: 0.6365
100%|██████████| 334/334 [00:13<00:00, 24.54it/s]
Epoch [8], train_loss: 0.7714, val_loss: 2.1233, val_acc: 0.6826
100%|██████████| 334/334 [00:11<00:00, 29.84it/s]
Epoch [9], train_loss: 0.7188, val_loss: 1.9796, val_acc: 0.6521
100%|██████████| 334/334 [00:11<00:00, 28.72it/s]
Epoch [10], train_loss: 0.5492, val_loss: 2.2692, val_acc: 0.6240
100%|██████████| 334/334 [00:11<00:00, 28.42it/s]
Epoch [11], train_loss: 0.5022, val_loss: 2.2513, val_acc: 0.6358
100%|██████████| 334/334 [00:11<00:00, 28.69it/s]
Epoch [12], train_loss: 0.4844, val_loss: 2.2090, val_acc: 0.6802
100%|██████████| 334/334 [00:11<00:00, 29.14it/s]
Epoch [13], train_loss: 0.4276, val_loss: 2.1697, val_acc: 0.6545
```

```
100%|██████████| 334/334 [00:13<00:00, 25.47it/s]
Epoch [14], train_loss: 0.4250, val_loss: 2.4049, val_acc: 0.6771
100%|██████████| 334/334 [00:18<00:00, 17.97it/s]
Epoch [15], train_loss: 0.4368, val_loss: 2.2800, val_acc: 0.6295
100%|██████████| 334/334 [00:12<00:00, 26.62it/s]
Epoch [16], train_loss: 0.3554, val_loss: 2.2440, val_acc: 0.6740
100%|██████████| 334/334 [00:11<00:00, 28.65it/s]
Epoch [17], train_loss: 0.3578, val_loss: 2.1529, val_acc: 0.6990
100%|██████████| 334/334 [00:11<00:00, 29.27it/s]
Epoch [18], train_loss: 0.3741, val_loss: 2.3115, val_acc: 0.6302
100%|██████████| 334/334 [00:09<00:00, 33.84it/s]
Epoch [19], train_loss: 0.3132, val_loss: 2.4945, val_acc: 0.6302
```

```python
def plot_history(history):
    # Extract training and validation loss from history
    train_losses = [x['train_loss'] for x in history if isinstance(x, dict) and 'train_loss' in x]
    val_losses = [x['val_loss'] for x in history if isinstance(x, dict) and 'val_loss' in x]
    val_accs = [x['val_acc'] for x in history if isinstance(x, dict) and 'val_acc' in x]

    # Plotting train and validation loss
    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    plt.plot(train_losses, '-x', label='Train')
    plt.plot(val_losses, '-o', label='Validation')
    plt.title('Loss vs. No. of epochs')
    plt.legend()

    # Plotting validation accuracy
    plt.subplot(1, 2, 2)
    plt.plot(val_accs, '-o', label='Validation Accuracy')
    plt.title('Accuracy vs. No. of epochs')
    plt.legend()

    plt.show()


plot_history(history)
```






```
def evaluate(model, test_loader, criterion):
    model.eval()  # set the model to evaluation mode
    outputs = [model.validation_step(batch) for batch in test_loader]
    return model.validation_epoch_end(outputs)
result = evaluate(model, test_dl, criterion)
print(f"Test Loss: {result['val_loss']:.4f}")
print(f"Test Accuracy: {result['val_acc']:.4f}")
```

```
Test Loss: 2.4210
Test Accuracy: 0.6531
```

FLOPs

[ ] ↳ 2 cells hidden

0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5 20.0 0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5 20.0

Report

Introduction In the course of this assignment, I explored various techniques to optimize and enhance the performance of an image classification model. This involved leveraging different image transformers, integrating pretrained image models, and experimenting with parameters like optimizers and criterion.

Modifications & Attempts The starting point was a baseline model that already demonstrated decent performance, achieving an accuracy of around 40%. This model was simple, without pretraining, and used basic image transformation methods along with elementary parameters.

First Try: EfficientNet Inspired by SHARAN SAJIV MENON's 2019 publication [3], which indicated that using EfficientNet could achieve an impressive accuracy of 94% on Kaggle, I decided to give it a go. While the evaluation and training methods from the publication weren't a direct fit for our use case, I adapted them for our context. Conversations with peers and further research fortified my belief in EfficientNet's potential. However, post-adaptation and some modifications, the model's accuracy was 65%, a significant improvement from the baseline.

Second Try: ResNet with Improved Transformations The ResNet architecture delivered the best results. This success can be attributed to the superior image transformations employed. The transformed images were of such quality that the distinct characteristics of animals were easily discernible. Furthermore, integrating the LabelSmoothingCrossEntropy loss function boosted the model's performance.

Third Try: ResNet18 + Baseline Model In the final attempt, I combined the ResNet18 model with our baseline model, which achieved an accuracy of 65%.

Transform	Optimizer	Criterion	Model	Accuracy
Re+RHF+CC+N	Cross Entropy	None	Base	34%
Re+RHF+RR+CoJ+RRC+N	AdamW	CrossEntropyLoss	efficientnet_b0	65%
RHF+RV+RA+GB+RE+CC+N	Adam	LabelSmoothingCrossEntropy	ResNet18	74%
RHF+RV+RA+GB+RE+CC+N	Adam	Custom Focal Loss	Resnet+Baseline Model	65%

Transform Key:

RE: Resize RHF: RandomHorizontalFlip CC: CenterCrop N: Normalize RR: RandomRotation CoJ: ColorJitter RRC: RandomResizedCrop GB: GaussianBlur RA: RandomApply Methods for Reducing Computational Cost and Improving Trade-off: [Please fill this section based on the notebook's content or your understanding. Some general pointers can include leveraging efficient architectures like EfficientNet or ResNet, data augmentation techniques to minimize overfitting, or using learning rate schedulers.]

Limitations/Conclusions: While significant progress was made in enhancing the model's accuracy, the constraints of time limited the exploration of all potential configurations. Among the various techniques tried, the parameters and methods from the second attempt proved most effective. Combining this with EfficientNet could potentially yield even better results in the future.

Reference

1. Tan M., Le Q. Efficientnet: Rethinking model scaling for convolutional neural networks //International conference on machine learning. – PMLR, 2019. – C. 6105-6114.
2. He K. et al. Deep residual learning for image recognition //Proceedings of the IEEE conference on computer vision and pattern recognition. – 2016. – C. 770-778.
3. Sharan, 2019, "Animals 151 ViT | DeIT 94%" https://www.kaggle.com/code/sharansmenon/animals-151-vit-deit-94