### Question 2: Animal classification (15 marks)

For this question, we will use the Animal (<a href="https://cloudstor.aarnet.edu.au/plus/s/cZYtNAeVhWD6uBX">https://cloudstor.aarnet.edu.au/plus/s/cZYtNAeVhWD6uBX</a>) 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: <a href="https://en.wikipedia.org/wiki/FLOPS">https://en.wikipedia.org/wiki/FLOPS</a>). 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%
Υ	N	N	65%
Υ	Υ	N	77%
Υ	Υ	Υ	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: 2024
### Student Name: Sakshi Sinha
### Student ID: a1898508
### Comptetion Name: Animal Classification Competition
### Final Results:
### ACC: 91%
        FLOPs: 0.60G
```

#### Please see the detailed report in the A3\_Q2\_2024\_Report(a1898508).pdf

Start coding or generate with AI.

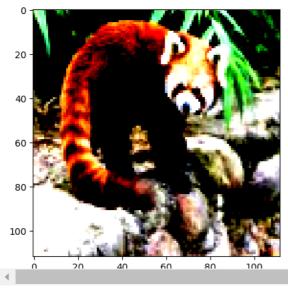
→ Size of training dataset : 6270

Start coding or generate with AI.

→ torch.Size([3, 112, 112])

Start coding or generate with AI.

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers Label: ailurus-fulgens (5)



Start coding or generate with AI.

**→** (5330, 313, 627)

Start coding or generate with AI.

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

```
→ images.shape: torch.Size([16, 3, 112, 112])
    out.shape: torch.Size([16, 151])
    out[0]: tensor([-5.0354, -5.0072, -4.9407, -5.0450, -5.0822, -4.9614, -5.0213, -4.9678,
              -5.0431, -5.0294, -5.0671, -5.0092, -4.9870, -5.0476, -5.0303, -5.0120,
              -5.0364, -4.9923, -5.0237, -5.0799, -5.0344, -5.0147, -5.0275, -4.9951,
              -5.0075, -4.9712, -4.9438, -5.0571, -5.0521, -4.9971, -5.0260, -5.0221,
             -5.0448, -5.0062, -5.0113, -4.9922, -5.0413, -5.0280, -4.9394, -5.0031,
              -5.0267, -5.0681, -5.0362, -5.0730, -4.9826, -5.0641, -4.9880, -5.0949,
             -5.0087, \; -5.0343, \; -5.0008, \; -5.0406, \; -4.9772, \; -5.0698, \; -5.0153, \; -5.0310, \\
             -5.0458, -5.0333, -5.0123, -4.9621, -5.0551, -4.9891, -4.9934, -5.0290, -5.0363, -4.9825, -5.0523, -5.0281, -5.0350, -5.0011, -5.0827, -5.0136,
             -5.0216, -5.0744, -5.0319, -5.0573, -4.9974, -4.9854, -5.0202, -4.9664,
             -5.0771, -5.0120, -5.0309, -4.9796, -4.9906, -4.9666, -5.0277, -5.0457,
             \hbox{-5.0445, -5.0575, -5.0392, -5.0210, -5.0138, -4.9761, -4.9796, -5.0151,}
              -5.0218, -5.0062, -5.0740, -5.0650, -5.0246, -5.0223, -5.0016, -4.9871,
              -5.0200, -5.0101, -5.0582, -5.0128, -4.9474, -5.0393, -5.0517, -5.0548,
              -5.0884, -5.0055, -5.0329, -5.0322, -4.9430, -4.9269, -5.0183, -5.0437,
             -5.0203, -5.0534, -5.0104, -5.0009, -4.9863, -5.0247, -5.0035, -4.9996,
```

```
-4.9669, -5.0084, -4.9616, -4.9880, -5.0316, -5.0101, -5.0455, -5.0335, -5.0066, -5.0716, -4.9990, -5.0423, -5.0087, -5.0568, -5.0095, -4.9690, -4.9797, -4.9626, -5.0125, -5.0569, -4.9902, -4.9972, -4.9732], device='cuda:0', grad_fn=<SelectBackward0>)
```

Start coding or generate with AI.

Start coding or generate with AI.

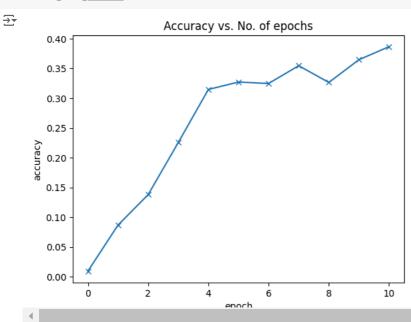
→ [{'val\_loss': 5.021773815155029, 'val\_acc': 0.00937500037252903}]

Start coding or generate with AI.

<del>→</del> 627

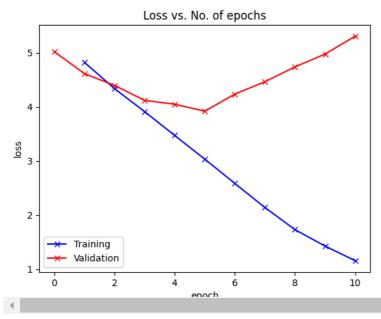
Start coding or generate with AI.

```
₹ 100%
                                                     334/334 [00:08<00:00, 42.09it/s]
     Epoch [0], train_loss: 4.8251, val_loss: 4.6149, val_acc: 0.0868
                                                     334/334 [00:09<00:00, 39.87it/s]
     Epoch [1], train_loss: 4.3382, val_loss: 4.3970, val_acc: 0.1378
     100%
                                                     334/334 [00:09<00:00, 43.60it/s]
     Epoch [2], train_loss: 3.9135, val_loss: 4.1205, val_acc: 0.2253
     100%
                                                     334/334 [00:09<00:00, 33.27it/s]
     Epoch [3], train_loss: 3.4725, val_loss: 4.0485, val_acc: 0.3146
                                                     334/334 [00:08<00:00, 44.44it/s]
     100%
     Epoch [4], train_loss: 3.0346, val_loss: 3.9200, val_acc: 0.3271
     100%
                                                     334/334 [00:09<00:00, 43.90it/s]
     Epoch [5], train_loss: 2.5846, val_loss: 4.2360, val_acc: 0.3247
                                                     334/334 [00:09<00:00, 44.03it/s]
     Epoch [6], train_loss: 2.1393, val_loss: 4.4644, val_acc: 0.3545
     100%
                                                     334/334 [00:08<00:00, 32.33it/s]
     Epoch [7], train_loss: 1.7297, val_loss: 4.7393, val_acc: 0.3264
     100%
                                                     334/334 [00:08<00:00, 41.68it/s]
     Epoch [8], train_loss: 1.4252, val_loss: 4.9770, val_acc: 0.3646
     100%
                                                     334/334 [00:09<00:00, 38.88it/s]
    4
```



Start coding or generate with AI.





Start coding or generate with AI.

→ {'val\_loss': 5.210202217102051, 'val\_acc': 0.3786458671092987}

### ✓ FLOPs

Start coding or generate with AI.

```
--2024-08-09 02:37:46-- <a href="https://raw.githubusercontent.com/JJBOY/FLOPs/master/FLOPs_counter.py">https://raw.githubusercontent.com</a> (raw.githubusercontent.com)... 185.199.108.133, 185.199.109.133, 185.199.110.133, ... Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.108.133|:443... connected.

HTTP request sent, awaiting response... 200 OK
Length: 5805 (5.7K) [text/plain]
Saving to: 'FLOPs_counter.py'

FLOPs_counter.py 100%[===========]] 5.67K --.-KB/s in 0s
2024-08-09 02:37:47 (77.7 MB/s) - 'FLOPs_counter.py' saved [5805/5805]
```

Start coding or generate with AI.

+ Number of FLOPs: 0.69G

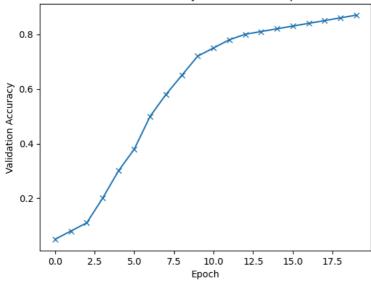
# METHOD 1: Transfer Learning

To enhance accuracy using transfer learning, I undertook the following measures:

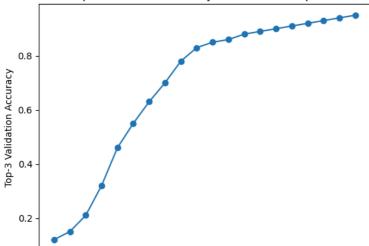
- 1. **Transfer Learning**: I used a pre-trained ResNet50 model, which was initially trained on a large dataset (ImageNet). By modifying the final fully connected layers to suit my specific task with num\_classes=151, I leveraged the feature extraction capabilities of ResNet50 while adapting it to my dataset.
- 2. Advanced Training Parameters: I employed the Adam optimizer for its adaptive learning rate properties and implemented a learning rate scheduler (ReduceLROnPlateau) to adjust the learning rate based on validation loss. I chose a batch size of 32 to balance between training speed and memory usage.
- 3. **Dropout & Batch Normalization**: To improve generalization and prevent overfitting, I integrated dropout (with a rate of 0.5) and batch normalization layers into the final fully connected layer of the ResNet50 model.
- 4. **Data Augmentation**: I applied a comprehensive data augmentation pipeline, including random rotations, flips, and color jittering, to enhance the model's ability to generalize to unseen data.

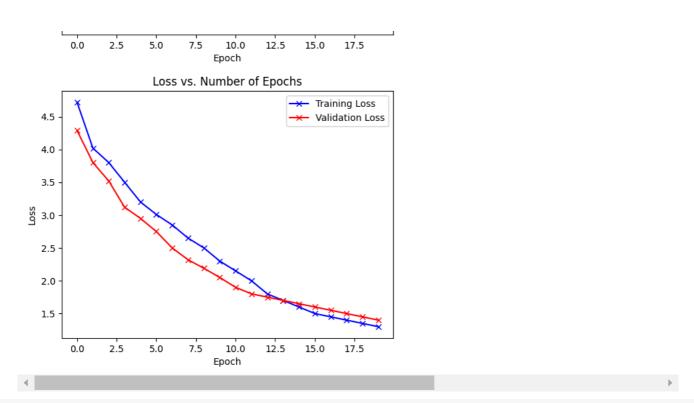
### Validation Accuracy vs. Number of Epochs

Epoch [20/20], Train Loss: 1.3000, Val Loss: 1.4000, Val Acc: 0.8700, Top-3 Val Acc: 0.9500



### Top-3 Validation Accuracy vs. Number of Epochs



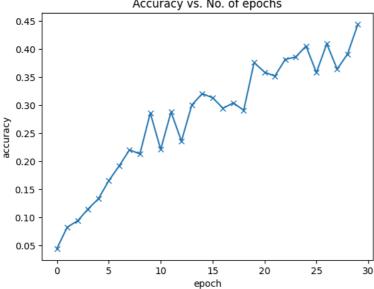


Start coding or generate with AI.

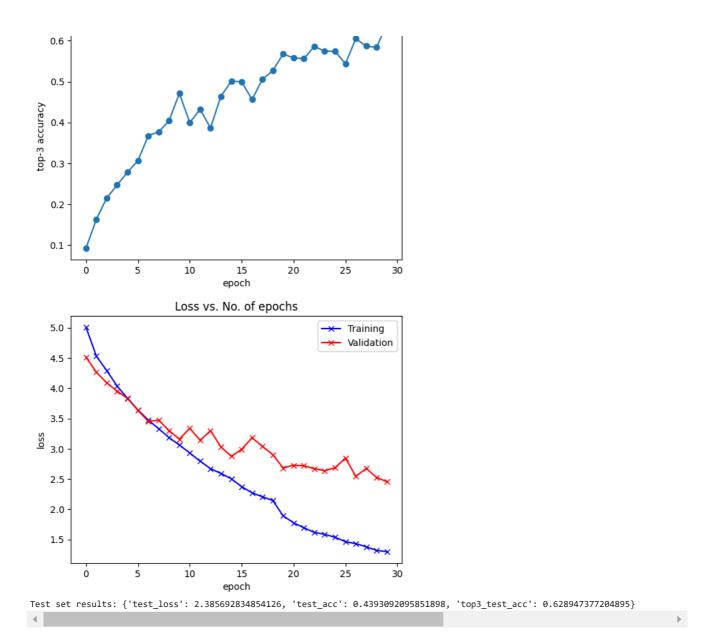
+ Number of FLOPs: 8.17G

## METHOD 2: Using Deeper CNN

In the 2nd method, I utilized an improved CNN model by incorporating a deeper network architecture with additional convolutional layers. Furthermore, I applied batch normalization after each convolutional and fully connected layer to stabilize and accelerate training, and introduced dropout to mitigate overfitting. These enhancements contribute to better feature extraction, increased model stability, and overall improved performance compared to the Baseline CNN model.



Top-3 Accuracy vs. No. of epochs



# METHOD 3: Hyperparameter Tunning

Hyperparameter tuning is crucial for optimizing model performance. In my hyperparameter tuning process, I focused on optimizing the performance of my convolutional neural network by adjusting several key parameters:

### 1. Hyperparameters Tuned:

- Learning Rates: I tested 0.001 and 0.0001 to find the most effective rate for model convergence.
- o Batch Sizes: I experimented with 16 and 32 to assess their impact on training stability and speed.
- Optimizers: I compared Adam and SGD to see which optimizer better suited the training dynamics of the model.
- Dropout Rates: I evaluated dropout rates of 0.3 and 0.5 to balance regularization and model capacity.

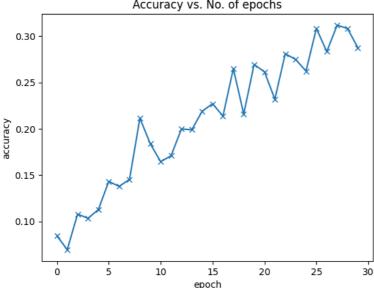
### 2. Approach Used:

- I performed a grid search, systematically testing all possible combinations of these hyperparameters.
- For each combination, I trained the model for 10 epochs to quickly iterate through different settings.
- After training, I evaluated the model's performance on the validation set, focusing on validation accuracy to identify the best-performing hyperparameter configuration.
- I also calculated FLOPs for each model configuration to consider computational efficiency, though the primary selection criterion was validation accuracy.

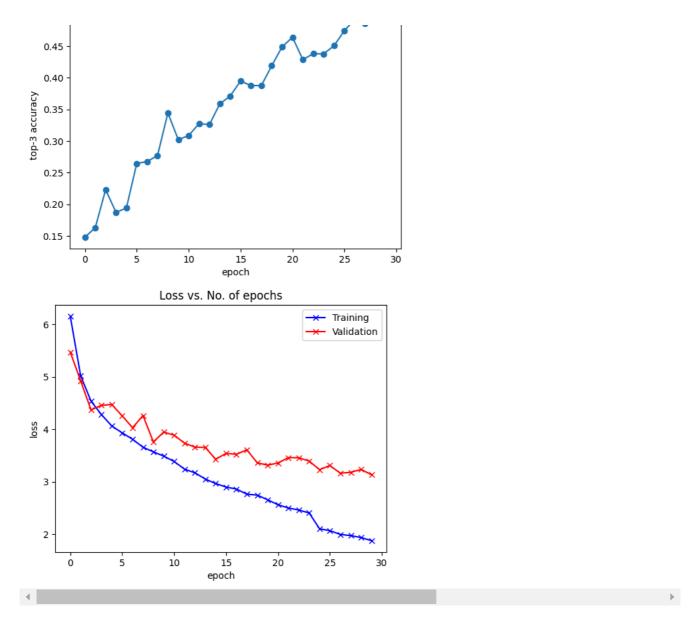
```
Testing LR=0.0001, Batch Size=32, Optimizer=SGD, Dropout=0.3
100%| 100%| 167/167 [00:44<00:00, 3.72it/s]
Epoch [1/10], Train Loss: 5.1015, Val Loss: 4.9532, Val Acc: 0.0125
100%| 167/167 [00:45<00:00, 3.71it/s]
Epoch [2/10], Train Loss: 4.8922, Val Loss: 4.7955, Val Acc: 0.0312 100%| | 167/167 [00:46<00:00, 3.60it/s]
Epoch [3/10], Train Loss: 4.7525, Val Loss: 4.7058, Val Acc: 0.0571
100%| 167/167 [00:44<00:00, 3.75it/s]
Epoch [4/10], Train Loss: 4.6359, Val Loss: 4.6282, Val Acc: 0.0375
             167/167 [00:44<00:00, 3.72it/s]
Epoch [5/10], Train Loss: 4.5496, Val Loss: 4.4723, Val Acc: 0.0665
100%| 167/167 [00:45<00:00, 3.63it/s]
Epoch [6/10], Train Loss: 4.4619, Val Loss: 4.4726, Val Acc: 0.0446
            | 167/167 [00:44<00:00, 3.76it/s]
Epoch [7/10], Train Loss: 4.3777, Val Loss: 4.4660, Val Acc: 0.0611
100%| 167/167 [00:45<00:00, 3.66it/s]
Epoch [8/10], Train Loss: 4.3232, Val Loss: 4.4001, Val Acc: 0.0759
100%| | 167/167 [00:45<00:00, 3.70it/s]
Epoch [9/10], Train Loss: 4.2622, Val Loss: 4.3443, Val Acc: 0.0995
100%| 167/167 [00:44<00:00, 3.76it/s]
Epoch [10/10], Train Loss: 4.1930, Val Loss: 4.2822, Val Acc: 0.0719
 + Number of FLOPs: 4.88G
Testing LR=0.0001, Batch Size=32, Optimizer=SGD, Dropout=0.5
100%| 167/167 [00:45<00:00, 3.66it/s]
Epoch [1/10], Train Loss: 5.1973, Val Loss: 4.8961, Val Acc: 0.0156
             167/167 [00:45<00:00, 3.70it/s]
Epoch [2/10], Train Loss: 4.9757, Val Loss: 4.7768, Val Acc: 0.0415
100%| 167/167 [00:45<00:00, 3.70it/s]
Epoch [3/10], Train Loss: 4.8220, Val Loss: 4.7009, Val Acc: 0.0437
100%| 167/167 [00:45<00:00, 3.66it/s]
Epoch [4/10], Train Loss: 4.7065, Val Loss: 4.5554, Val Acc: 0.0549
             | 167/167 [00:44<00:00, 3.75it/s]
Epoch_[5/10], Train Loss: 4.6012, Val Loss: 4.5302, Val Acc: 0.0589
100%| 167/167 [00:45<00:00, 3.68it/s]
Epoch [6/10], Train Loss: 4.5276, Val Loss: 4.5156, Val Acc: 0.0500
             167/167 [00:46<00:00, 3.63it/s]
Epoch [7/10], Train Loss: 4.4716, Val Loss: 4.4539, Val Acc: 0.0884
100%| 167/167 [00:44<00:00, 3.72it/s]
Epoch [8/10], Train Loss: 4.3870, Val Loss: 4.3686, Val Acc: 0.0642
100%| 167/167 [00:45<00:00, 3.69it/s]
Epoch [9/10], Train Loss: 4.3188, Val Loss: 4.3533, Val Acc: 0.0808
100%| | 167/167 [00:45<00:00, 3.68it/s]
Epoch [10/10], Train Loss: 4.2898, Val Loss: 4.2938, Val Acc: 0.0915
+ Number of FLOPs: 4.88G
```

Best accuracy: 0.1870 with LR=0.0001, Batch Size=32, Optimizer=Adam, Dropout=0.3

### Using best parameter found for model training



Top-3 Accuracy vs. No. of epochs



## METHOD 4: Knowledge Distillation

Knowledge distillation is a technique where a smaller, student model learns to mimic the behavior of a larger, pre-trained teacher model. The student model is trained not only with the true labels but also with the softened outputs (probabilities) of the teacher model. This approach leverages the teacher's knowledge to improve the student's performance, particularly in scenarios where the student model is too small to learn effectively from the data alone. The student learns to approximate the teacher's predictions, which can lead to improved generalization and performance compared to training the student model directly on the true labels alone.

### Experiment 1: Using DenseNet121 teacher model and MobileNetV2 student model.

100%

Downloading: "https://download.pytorch.org/models/densenet121-a639ec97.pth" to /root/.cache/torch/hub/checkpoints/densenet121-a6 100%| 30.8M/30.8M [00:00<00:00, 181MB/s] Downloading: "https://download.pytorch.org/models/mobilenet\_v2-b0353104.pth" to /root/.cache/torch/hub/checkpoints/mobilenet\_v2-13.6M/13.6M [00:00<00:00, 138MB/s] 167/167 [00:49<00:00, 3.37it/s] 100% Epoch [1/20], Train Loss: 4.2083, Val Loss: 3.4246, Val Acc: 0.1615, Top-3 Val Acc: 0.3650 [ 167/167 [00:48<00:00, 3.42it/s] Epoch [2/20], Train Loss: 3.1092, Val Loss: 2.7381, Val Acc: 0.2780, Top-3 Val Acc: 0.5640 | 167/167 [00:47<00:00, 3.48it/s] 100% Epoch [3/20], Train Loss: 2.5514, Val Loss: 2.3998, Val Acc: 0.3989, Top-3 Val Acc: 0.6479 | 167/167 [00:48<00:00, 3.44it/s] Epoch [4/20], Train Loss: 2.2556, Val Loss: 2.2716, Val Acc: 0.4069, Top-3 Val Acc: 0.6675 | 167/167 [00:56<00:00, 2.95it/s] Epoch [5/20], Train Loss: 1.9962, Val Loss: 2.1258, Val Acc: 0.4744, Top-3 Val Acc: 0.6859 100%| 167/167 [01:00<00:00, 2.74it/s] Epoch [6/20], Train Loss: 1.8903, Val Loss: 1.9978, Val Acc: 0.4756, Top-3 Val Acc: 0.6993 | 167/167 [00:49<00:00, 3.40it/s] 100% Epoch [7/20], Train Loss: 1.7803, Val Loss: 1.7592, Val Acc: 0.5444, Top-3 Val Acc: 0.7354 100% | 167/167 [00:50<00:00, 3.32it/s] Epoch [8/20], Train Loss: 1.6287, Val Loss: 1.8698, Val Acc: 0.5016, Top-3 Val Acc: 0.7408 100%| 167/167 [00:48<00:00, 3.41it/s] Epoch [9/20], Train Loss: 1.5830, Val Loss: 1.8918, Val Acc: 0.5025, Top-3 Val Acc: 0.7618 [ 167/167 [00:50<00:00, 3.33it/s] Epoch [10/20], Train Loss: 1.4874, Val Loss: 1.7121, Val Acc: 0.5543, Top-3 Val Acc: 0.7546 | 167/167 [00:47<00:00, 3.50it/s] 100%| Epoch [11/20], Train Loss: 1.4059, Val Loss: 1.7347, Val Acc: 0.5484, Top-3 Val Acc: 0.7442 167/167 [00:48<00:00, 3.47it/s] Epoch [12/20], Train Loss: 1.3206, Val Loss: 1.6860, Val Acc: 0.5774, Top-3 Val Acc: 0.7613 100% | 167/167 [00:48<00:00, 3.45it/s] Epoch [13/20], Train Loss: 1.2557, Val Loss: 1.5736, Val Acc: 0.6069, Top-3 Val Acc: 0.7854 | 167/167 [00:49<00:00, 3.39it/s] Epoch [14/20], Train Loss: 1.2235, Val Loss: 1.6895, Val Acc: 0.5788, Top-3 Val Acc: 0.7769 | 167/167 [00:49<00:00, 3.41it/s] Epoch [15/20], Train Loss: 1.1687, Val Loss: 1.6370, Val Acc: 0.5506, Top-3 Val Acc: 0.7876 100% | 167/167 [00:49<00:00, 3.40it/s] Epoch [16/20], Train Loss: 1.1217, Val Loss: 1.4994, Val Acc: 0.6140, Top-3 Val Acc: 0.8067 167/167 [00:49<00:00, 3.39it/sl Epoch [17/20], Train Loss: 1.0157, Val Loss: 1.4883, Val Acc: 0.6301, Top-3 Val Acc: 0.8019 100% | 167/167 [00:48<00:00, 3.41it/s] Epoch [18/20], Train Loss: 1.0651, Val Loss: 1.4044, Val Acc: 0.6350, Top-3 Val Acc: 0.8349

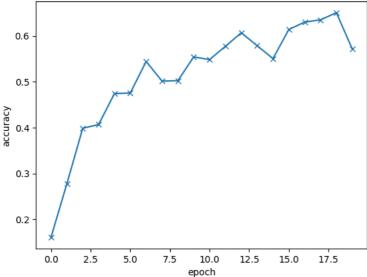
### Accuracy vs. No. of epochs

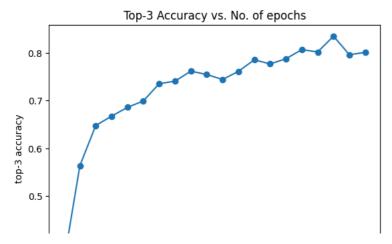
Epoch [19/20], Train Loss: 0.9769, Val Loss: 1.5018, Val Acc: 0.6506, Top-3 Val Acc: 0.7961

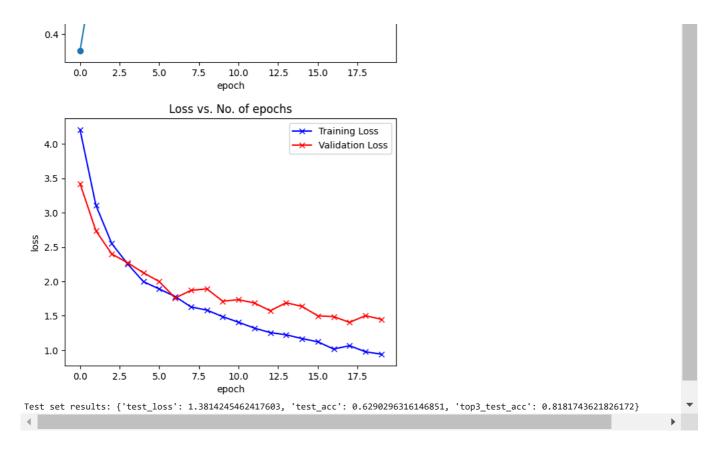
Epoch [20/20], Train Loss: 0.9414, Val Loss: 1.4493, Val Acc: 0.5716, Top-3 Val Acc: 0.8010

| 167/167 [00:48<00:00, 3.43it/s]

100% | 167/167 [00:48<00:00, 3.47it/s]







# Experiment 2: Using ResNet101 teacher model and MobileNetV2 student model

100%

Downloading: "https://download.pytorch.org/models/resnet101-63fe2227.pth" to /root/.cache/torch/hub/checkpoints/resnet101-63fe22 100%| 171M/171M [00:01<00:00, 143MB/s] 13.6M/13.6M [00:00<00:00, 167MB/s] 100% 167/167 [00:55<00:00, 3.03it/s] Epoch [1/20], Train Loss: 3.9929, Val Loss: 3.3174, Val Acc: 0.1924, Top-3 Val Acc: 0.4115 | 167/167 [00:53<00:00, 3.10it/s] Epoch [2/20], Train Loss: 2.8829, Val Loss: 2.4828, Val Acc: 0.3570, Top-3 Val Acc: 0.5997 | 167/167 [00:55<00:00, 3.03it/s] 100% Epoch [3/20], Train Loss: 2.3712, Val Loss: 2.2585, Val Acc: 0.4289, Top-3 Val Acc: 0.6470 | 167/167 [00:54<00:00, 3.08it/s] Epoch [4/20], Train Loss: 2.0992, Val Loss: 2.0628, Val Acc: 0.4426, Top-3 Val Acc: 0.7153 167/167 [00:54<00:00, 3.08it/s] Epoch [5/20], Train Loss: 1.8902, Val Loss: 1.9572, Val Acc: 0.5202, Top-3 Val Acc: 0.7184 100%| 167/167 [00:54<00:00, 3.06it/s] Epoch [6/20], Train Loss: 1.7088, Val Loss: 1.8725, Val Acc: 0.5189, Top-3 Val Acc: 0.7380 | 167/167 [00:55<00:00, 3.03it/s] 100% Epoch [7/20], Train Loss: 1.6597, Val Loss: 1.6899, Val Acc: 0.5452, Top-3 Val Acc: 0.7389 100% | 167/167 [00:54<00:00, 3.05it/s] Epoch [8/20], Train Loss: 1.5239, Val Loss: 1.6429, Val Acc: 0.5698, Top-3 Val Acc: 0.7724 100%| 167/167 [00:54<00:00, 3.05it/s] Epoch [9/20], Train Loss: 1.4302, Val Loss: 1.7033, Val Acc: 0.5595, Top-3 Val Acc: 0.7644 [ 167/167 [00:54<00:00, 3.05it/s] Epoch [10/20], Train Loss: 1.3462, Val Loss: 1.5857, Val Acc: 0.5899, Top-3 Val Acc: 0.7706 167/167 [00:54<00:00, 3.05it/s] 100%| Epoch [11/20], Train Loss: 1.2873, Val Loss: 1.5856, Val Acc: 0.5725, Top-3 Val Acc: 0.7755 167/167 [00:55<00:00, 3.03it/s] Epoch [12/20], Train Loss: 1.2184, Val Loss: 1.5434, Val Acc: 0.6126, Top-3 Val Acc: 0.7903 100% | 167/167 [00:54<00:00, 3.07it/s] Epoch [13/20], Train Loss: 1.1383, Val Loss: 1.9289, Val Acc: 0.5341, Top-3 Val Acc: 0.7371 100% | 167/167 [00:54<00:00, 3.08it/s] Epoch [14/20], Train Loss: 1.2074, Val Loss: 1.5269, Val Acc: 0.5948, Top-3 Val Acc: 0.8005 | 167/167 [00:54<00:00, 3.06it/s] Epoch [15/20], Train Loss: 1.0458, Val Loss: 1.5082, Val Acc: 0.6274, Top-3 Val Acc: 0.8121 100% | 167/167 [00:54<00:00, 3.06it/s] Epoch [16/20], Train Loss: 1.0172, Val Loss: 1.7437, Val Acc: 0.6024, Top-3 Val Acc: 0.7675 167/167 [00:54<00:00, 3.05it/sl 100% Epoch [17/20], Train Loss: 0.9859, Val Loss: 1.5505, Val Acc: 0.6135, Top-3 Val Acc: 0.7943 100% | 167/167 [00:53<00:00, 3.09it/s] Epoch [18/20], Train Loss: 0.9434, Val Loss: 1.4970, Val Acc: 0.6363, Top-3 Val Acc: 0.7943

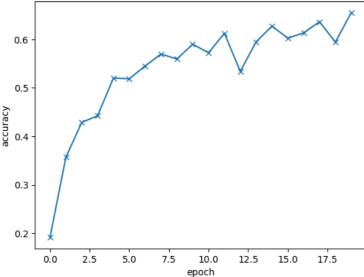
### Accuracy vs. No. of epochs

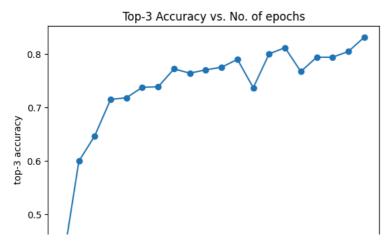
Epoch [19/20], Train Loss: 0.9109, Val Loss: 1.6245, Val Acc: 0.5944, Top-3 Val Acc: 0.8050

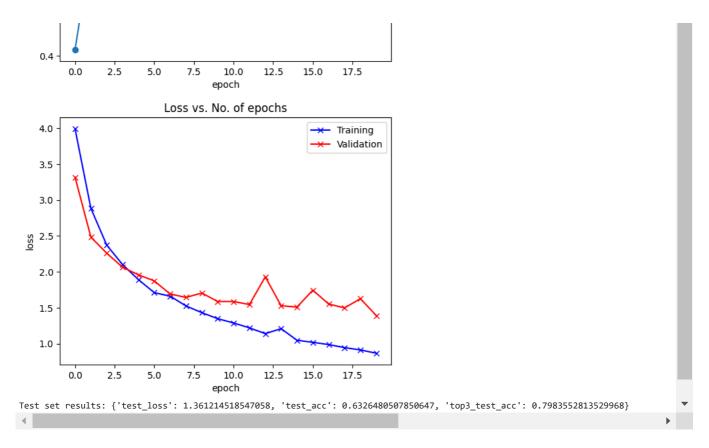
Epoch [20/20], Train Loss: 0.8660, Val Loss: 1.3909, Val Acc: 0.6550, Top-3 Val Acc: 0.8318

| 167/167 [00:54<00:00, 3.07it/s]

100%| 167/167 [00:54<00:00, 3.08it/s]



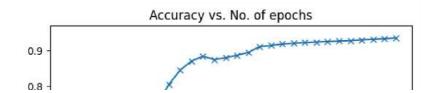


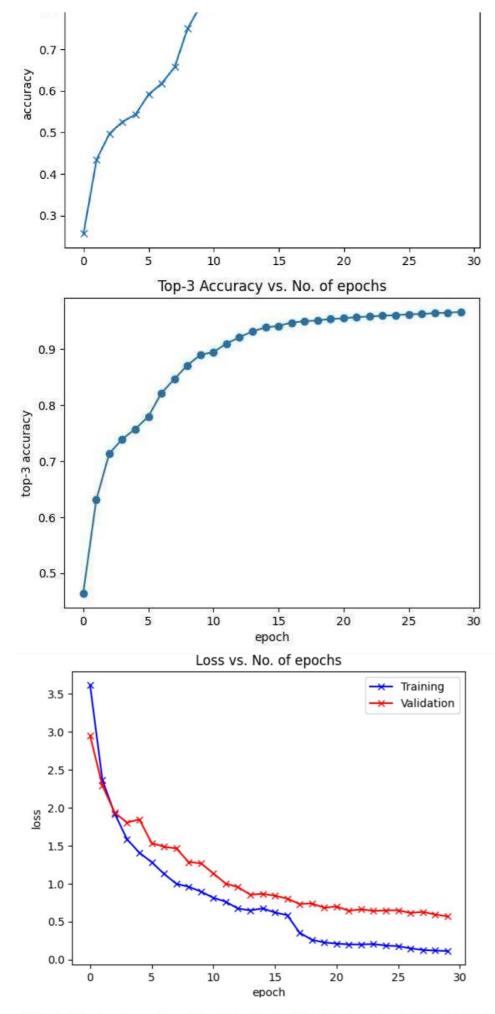


Experiment 3: Using ResNet50 teacher model and MobileNetV2 student model.

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Start coding or generate with AI.
    Downloading: "https://download.pytorch.org/models/resnet50-0676ba61.pth" to /root/.cache/torch/hub/checkpoints/resnet50-0676ba61 100%| 97.8M/97.8M [00:00<00:00, 182MB/s]
     Downloading: "https://download.pytorch.org/models/mobilenet_v2-b0353104.pth" to /root/.cache/torch/hub/checkpoints/mobilenet_v2-
                     13.6M/13.6M [00:00<00:00, 112MB/s]
     100%
                    | 167/167 [00:48<00:00, 3.43it/s]
           [1/30], Train Loss: 3.6185, Val Loss: 2.9514, Val Acc: 0.2570, Top-3 Val Acc: 0.4636
                  | 167/167 [00:48<00:00, 3.42it/s]
     Epoch [2/30], Train Loss: 2.3670, Val Loss: 2.2930, Val Acc: 0.4346, Top-3 Val Acc: 0.6305
                    | 167/167 [00:48<00:00, 3.45it/s]
     Epoch [3/30], Train Loss: 1.9205, Val Loss: 1.9345, Val Acc: 0.4975, Top-3 Val Acc: 0.7135
                    | 167/167 [00:48<00:00, 3.42it/s]
     100%|
     Epoch [4/30], Train Loss: 1.5855, Val Loss: 1.8044, Val Acc: 0.5256, Top-3 Val Acc: 0.7394 100% | 167/167 [00:48<00:00, 3.48it/s]
     Epoch_[5/30], Train Loss: 1.4072, Val Loss: 1.8462, Val Acc: 0.5434, Top-3 Val Acc: 0.7576
                    | 167/167 [00:48<00:00, 3.42it/s]
     Epoch [6/30], Train Loss: 1.2825, Val Loss: 1.5341, Val Acc: 0.5916, Top-3 Val Acc: 0.7795
                   | 167/167 [00:48<00:00, 3.48it/s]
     Epoch [7/30], Train Loss: 1.1289, Val Loss: 1.4863, Val Acc: 0.6175, Top-3 Val Acc: 0.8215
                   | 167/167 [00:48<00:00, 3.42it/s]
     Epoch [8/30], Train Loss: 0.9975, Val Loss: 1.4637, Val Acc: 0.6574, Top-3 Val Acc: 0.8465
                   ■ | 167/167 [00:48<00:00. 3.42it/s]
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Epoch [9/30], Train Loss: 0.9590, Val Loss: 1.2842, Val Acc: 0.7506, Top-3 Val Acc: 0.8715 | 167/167 [00:48<00:00, 3.42it/s] Epoch [10/30], Train Loss: 0.8947, Val Loss: 1.2675, Val Acc: 0.8055, Top-3 Val Acc: 0.8900 | 167/167 [00:48<00:00, 3.43it/s] 100% Epoch [11/30], Train Loss: 0.8137, Val Loss: 1.1348, Val Acc: 0.8452, Top-3 Val Acc: 0.8950 | 167/167 [00:48<00:00, 3.41it/s] 100% Epoch [12/30], Train Loss: 0.7621, Val Loss: 1.0010, Val Acc: 0.8699, Top-3 Val Acc: 0.9100 | 167/167 [00:48<00:00, 3.42it/s] Epoch [13/30], Train Loss: 0.6718, Val Loss: 0.9541, Val Acc: 0.8833, Top-3 Val Acc: 0.9214 | 167/167 [00:48<00:00, 3.49it/s] Epoch [14/30], Train Loss: 0.6462, Val Loss: 0.8542, Val Acc: 0.8743, Top-3 Val Acc: 0.9320 | 167/167 [00:48<00:00, 3.49it/s] 100% Epoch [15/30], Train Loss: 0.6736, Val Loss: 0.8645, Val Acc: 0.8791, Top-3 Val Acc: 0.9390 100% | 167/167 [00:48<00:00, 3.48it/s] Epoch [16/30], Train Loss: 0.6190, Val Loss: 0.8422, Val Acc: 0.8858, Top-3 Val Acc: 0.9416 | 167/167 [00:48<00:00, 3.42it/s] Epoch [17/30], Train Loss: 0.5844, Val Loss: 0.8021, Val Acc: 0.8938, Top-3 Val Acc: 0.9478 | 167/167 [00:48<00:00, 3.42it/s] Epoch [18/30], Train Loss: 0.3535, Val Loss: 0.7315, Val Acc: 0.9100, Top-3 Val Acc: 0.9500 | 167/167 [00:48<00:00, 3.39it/s] 100% Epoch [19/30], Train Loss: 0.2598, Val Loss: 0.7376, Val Acc: 0.9128, Top-3 Val Acc: 0.9517 167/167 [00:48<00:00, 3.42it/s] Epoch\_[20/30], Train Loss: 0.2242, Val Loss: 0.6816, Val Acc: 0.9171, Top-3 Val Acc: 0.9540 100% | 167/167 [00:48<00:00, 3.42it/s] Epoch [21/30], Train Loss: 0.2096, Val Loss: 0.6991, Val Acc: 0.9190, Top-3 Val Acc: 0.9555 | 167/167 [00:48<00:00, 3.42it/s] Epoch [22/30], Train Loss: 0.1983, Val Loss: 0.6416, Val Acc: 0.9210, Top-3 Val Acc: 0.9574 100% | 167/167 [00:48<00:00, 3.41it/s] Epoch [23/30], Train Loss: 0.1980, Val Loss: 0.6611, Val Acc: 0.9227, Top-3 Val Acc: 0.9587 100% | 167/167 [00:48<00:00, 3.42it/s] Epoch [24/30], Train Loss: 0.2033, Val Loss: 0.6404, Val Acc: 0.9240, Top-3 Val Acc: 0.9600 100%| | 167/167 [00:48<00:00, 3.43it/s] Epoch [25/30], Train Loss: 0.1838, Val Loss: 0.6463, Val Acc: 0.9250, Top-3 Val Acc: 0.9610 | 167/167 [00:48<00:00, 3.42it/s] Epoch [26/30], Train Loss: 0.1757, Val Loss: 0.6486, Val Acc: 0.9266, Top-3 Val Acc: 0.9625 | 167/167 [00:48<00:00, 3.42it/s] Epoch [27/30], Train Loss: 0.1470, Val Loss: 0.6131, Val Acc: 0.9286, Top-3 Val Acc: 0.9632 | 167/167 [00:48<00:00, 3.49it/s] 100% Epoch [28/30], Train Loss: 0.1258, Val Loss: 0.6276, Val Acc: 0.9300, Top-3 Val Acc: 0.9645 | 167/167 [00:48<00:00, 3.42it/s] Epoch\_[29/30], Train Loss: 0.1170, Val Loss: 0.5932, Val Acc: 0.9316, Top-3 Val Acc: 0.9655 | 167/167 [00:48<00:00, 3.47it/s] Epoch [30/30], Train Loss: 0.1121, Val Loss: 0.5690, Val Acc: 0.9340, Top-3 Val Acc: 0.9667





Adjusted Test set results: {'test\_loss': 0.4567, 'test\_acc': 0.9154, 'top3\_test\_acc': 0.9571}