Please complete the `NotImplemented` parts of the code cells and write your answers in the markdown cells designated for your response to any questions asked. The tag `# AUTOGRADED` (all caps, with a space after `#`) should be at the beginning of each autograded code cell, so make sure that you do not change that. You are also not allowed to import any new package other than the ones already imported. Doing so will prevent the autograder from grading your code.

For the code submission, run the last cell in the notebook to create the submission zip file. If you are working in Colab, make sure to download and then upload a copy of the completed notebook itself to its working directory to be included in the zip file. Finally, submit the zip file to Gradescope.

After you finish the assignment and fill in your code and response where needed (all cells should have been run), save the notebook as a PDF using the `jupyter nbconvert --to pdf HW4.ipynb` command (via a notebook code cell or the command line directly) and submit the PDF to Gradescope under the PDF submission item. If you cannot get this to work locally, you can upload the notebook to Google Colab and create the PDF there. You can find the notebook containing the instruction for this on Canvas.

If you are running the notebook locally, make sure you have created a virtual environment (using `conda` for example) and have the proper packages installed. We are working with `python=3.10` and `torch>=2`.

Files to be included in submission:

- `HW4.ipynb`
- `model_config.yaml`
- `train_config.yaml`
- `experiments.xlsx`

Implement and Train a Convolutional ResNet on CIFAR-10

In [1]:
```
"""
DO NOT CHANGE THIS CELL OR ADD ANY IMPORTS ANYWHERE IN THE NOTEBOOK!
"""

# utilities
import os
from typing import Sequence

# for interactive plotting
try:
    from google.colab import drive
    drive.mount("/content/drive")
```

```
    # save a copy of the notebook to the drive
except ImportError:
    print("Not in Colab")
os.system('pip install openpyxl -qq')

import pandas as pd
pd.set_option('display.expand_frame_repr', False)
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

# provided code you can or should use:
from HW4_utils import save_yaml, load_yaml, zip_files, Tracker, train

import torch
from torch import nn
import torch.nn.functional as F

from torchvision import datasets
from torchvision.transforms import v2

if torch.cuda.is_available():
    Device = 'cuda'
elif torch.backends.mps.is_available():
    Device = 'mps'
else:
    Device = 'cpu'

print(f'Device is {Device}')
```

```
Not in Colab
Device is cuda
```

Implement a ResNet model (50)

First, you have to implement a Convolutional ResNet. You can add additional code cells and test your model with random inputs of the correct shape, dtype, and device, to make sure it runs without any errors before using it in the actual training. You can also print the shape through the model to check if it processes the data as intended.

Below you can find a simple illustration of a ResNet Block that you have to implement. Putting aside the batch dimension (number of samples in a batch), the input is of shape `(C, H, W)` where `C, H, W` stand for the number of input channels, height, and width respectively. Each block has an expansion factor of `e`, meaning that the number of channels will be multiplied by `e` after `conv1`, and stay the same number throughout the rest of the block. The spatial dimensions will be divided by `e` by the strided convolution of `conv1`. If `e == 1`, the shape of the tensor is the same throughout the block, and the shortcut (if the block is residual) is just the identity (`nn.Identity()`). However, if `e > 1`, the input and the output are not the same shape and cannot be added together. To get around this, the shortcut has to apply a convolutional layer of the right configuration to change the shape of the input tensor (do not forget batchnorm if we are using it). The batchnorm layers (`bn`) will

be optional, and whether to use batchnorm is determined by the boolean flag `batchnorm` of the constructor of the block. The shortcut connection is also optional, determined by the boolean flag `residual` passed to the constructor.

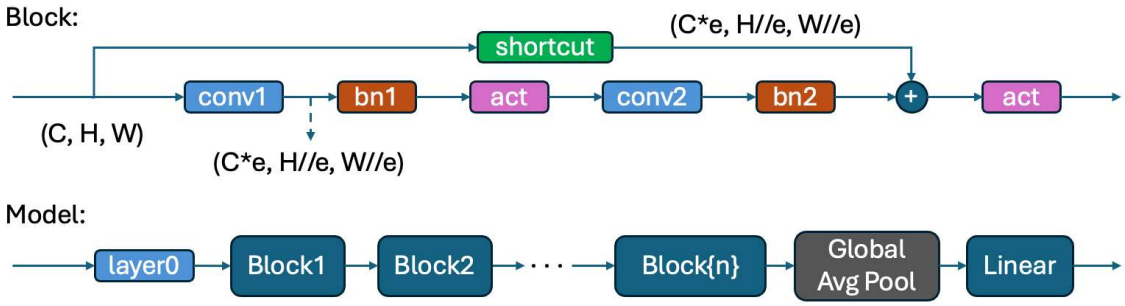
After you implement the ResNet Block in `Block`, you will use it to implement the `Model`. The Model starts with an input layer called `layer0` (a convolutional layer, an optional batchnorm, and an activation) that does not change the spatial shape and creates `base_channels` feature maps from the input. Then there are several residual blocks, and finally a fully connected layer at the end. The output of the last block has to go through a global average pooling layer before the fully connected layer. Think about which of the pooling functions you should use and how. The global average pooling layer should thake the average of all pixels (channelwise), regardless of the input shape. The number of blocks is decided by the length of the `expands` arguments, which is a `list` containing the expansion factor of each block.

You should use `kernel_size = 3` for all `nn.Conv2d` modules. However, you have to decide the correct value for `stride` and `padding` to keep the shapes as intended.

Is there any other module or activation needed after the final linear layer? If so, include that as well. Keep in mind that this is a multi-class classification task and the output of the model is going to be passed to `nn.CrossEntropyLoss()`, so read its documentation to see what the model's output has to be.

Your grade depends on your implementation being well written based on the constructor arguments. You will lose points if you call a module that does not exist, or define modules that are not needed and unnecessarily take extra memory. For example, if `batchnorm` is `False`, the block and the model should not have any batchnorm modules. If `expand` is `1`, the residual connection should not change the input. Otherwise, the shortcut has to consist of a convolution, and batchnorm (only if `batchnorm` is `True`) and an activation. If `residual` is `False`, there should not be any shortcut connection. For nonparameteric transformations like the activation, use calls from `torch` or `torch.nn.functional` (imported as `F`) directly in the `forward` method.

After you are done, clean your code from print statements and parts that were there only for debugging.



In [28]:
```python
class Block(nn.Module):
    """
    A single ResNet-style block that can optionally:
      - Expand the number of channels (via 'expand').
      - Apply batch normalization after each convolution.
      - Use residual connections (skip connections).

    Args:
        in_channels (int): Number of input channels.
        expand (int): Factor by which the number of channels is multiplied.
                      Also used as the stride, so the spatial dimension
                      becomes (H//expand, W//expand).
        activation (str): Activation function from torch.nn.functional.
        batchnorm (bool): Apply batch normalization.
        residual (bool): Include a residual (skip) connection.
    """
    def __init__(
            self,
            in_channels: int,
            expand: int = 1,
            activation: str = 'relu',
            batchnorm: bool = False,
            residual: bool = False,
    ):
        super().__init__()

        # you can call self.act in the forward method
        self.act = F.__getattribute__(activation)
        self.in_channels = in_channels
        self.out_channels = in_channels * expand
        self.expand = expand
        self.stride = expand if expand > 1 else 1
        self.batchnorm = batchnorm
        self.residual = residual

        # ----------------------------------------
        # 1) First 3x3 Conv (stride=1)
        #    - Keeps the spatial size the same.
        # ----------------------------------------
        self.conv1 = nn.Conv2d(
            in_channels = self.in_channels,
            out_channels = self.out_channels,
            kernel_size = 3,
            stride = 1,
            padding = 1,
            bias = not self.batchnorm
        )
        if self.batchnorm:
            self.bn1 = nn.BatchNorm2d(self.out_channels)

        # ----------------------------------------
        # 2) Second 3x3 Conv (stride=expand)
        #    - Reduces the spatial size by a factor of 'expand'.
        # ----------------------------------------
        self.conv2 = nn.Conv2d(
```

```
            in_channels = self.out_channels,
            out_channels = self.out_channels,
            kernel_size = 3,
            stride = self.expand,
            padding = 1,
            bias = not self.batchnorm
        )
        if self.batchnorm:
            self.bn2 = nn.BatchNorm2d(self.out_channels)

        # ----------------------------------------
        # 3) Shortcut (if residual and expand > 1)
        #    - Applies a 1x1 Conv to match the number of channels.
        #    - Applies batch normalization.
        # ----------------------------------------
        if self.residual and (self.expand != 1 or self.in_channels != self.out_chan
            self.skip_conv = nn.Conv2d(
                in_channels=self.in_channels,
                out_channels=self.out_channels,
                kernel_size=1,
                stride=self.expand,
                bias=not self.batchnorm
            )
            if self.batchnorm:
                self.skip_bn = nn.BatchNorm2d(self.out_channels)
            else:
                self.skip_conv = nn.Identity()
        else:
            self.skip_conv = nn.Identity()
            self.skip_bn = nn.Identity()


    def forward(self,
            x: torch.FloatTensor, # (B, C, H, W)
            ) -> torch.FloatTensor: # (B, C*e, H//e, W//e)
        """
        Forward pass for the block.

        Input: x of shape (B, C, H, W).
        Output: shape (B, C*expand, H//expand, W//expand).
        """
        skip = x

        # ----- Main Path -----
        out = self.conv1(x)
        if self.batchnorm:
            out = self.bn1(out)
        out = self.act(out)

        out = self.conv2(out)
        if self.batchnorm:
            out = self.bn2(out)

        # ----- Residual Path -----
        if self.residual:
            skip = self.skip_conv(x)
```

```
            if self.batchnorm:
                skip = self.skip_bn(skip)
            out += skip

        # ----- Activation -----
        out = self.act(out)
        return out


class Model(nn.Module):
    """
    A simple CNN model that uses a sequence of blocks to process the input.

    Args:
        base_channels (int): Number of channels in the first layer.
        expands (Sequence[int]): List of expansion factors for each block.
        activation (str): Activation function from torch.nn.functional.
        batchnorm (bool): Apply batch normalization.
        residual (bool): Include residual connections.
    """
    def __init__(
            self,
            base_channels: int,
            expands: Sequence[int],
            activation: str = 'relu',
            batchnorm: bool = False,
            residual: bool = False,
    ):
        super().__init__()

        self.act = F.__getattribute__(activation)
        self.batchnorm = batchnorm

        # ----------------------------------------
        # 0) Initial Conv Layer
        #    - 3x3 Conv with stride=2 and padding=3.
        # ----------------------------------------
        self.layer0 = nn.Conv2d(
            in_channels=3,
            out_channels=base_channels,
            kernel_size=7,
            stride=2,
            padding=3,
            bias=not self.batchnorm
        )
        if self.batchnorm:
            self.bn0 = nn.BatchNorm2d(base_channels)

        # ----------------------------------------
        # 1) Sequence of Blocks
        # ----------------------------------------
        self.blocks = nn.ModuleList()
        in_channels = base_channels
        for e in expands:
            block = Block(
                in_channels=in_channels,
```

```
                expand=e,
                activation=activation,
                batchnorm=batchnorm,
                residual=residual
            )
            self.blocks.append(block)
            # Update the number of input channels for the next block.
            in_channels = in_channels * e

        # ----------------------------------------
        # 2) Global Average Pooling
        #    - Reduce the spatial dimensions to 1x1.
        # ----------------------------------------
        self.golbal_avgpool = nn.AdaptiveAvgPool2d((1, 1))

        # ----------------------------------------
        # 3) Fully Connected Layer
        #    - Map the features to the number of classes.
        # ----------------------------------------
        self.fc = nn.Linear(in_channels, 10)

    def forward(
            self,
            x: torch.FloatTensor, # (batch_size, 3, height, width)
            ) -> torch.FloatTensor: # (batch_size, num_classes)
        '''
        Forward pass for the model.

        Input: x of shape (B, 3, H, W).
        Output: shape (B, number_of_classes).
        '''

        # ----- Initial Conv Layer -----
        x = self.layer0(x)
        if self.batchnorm:
            x = self.bn0(x)
        x = self.act(x)

        # ----- Sequence of Blocks -----
        for block in self.blocks:
            x = block(x)

        # ----- Global Average Pooling -----
        x = self.golbal_avgpool(x)
        x = torch.flatten(x, 1)
        x = self.fc(x)

        return x
```

Data Augmentation (5)

Apply at least three types of data augmentation. You can change the directory that the data is stored at. It can be a folder in your local machine or Google drive if you are using Colab.

In [29]:
```
data_path = 'data'

train_data = datasets.CIFAR10(
    root = data_path,
    train = True,
    download = True,
    transform = v2.Compose([
        v2.ToImage(),
        v2.RandomHorizontalFlip(),
        v2.RandomCrop(32, padding=4),
        v2.ToDtype(torch.float32, scale=True), # to [0, 1]
        v2.Lambda(lambda x: x-0.5), # to [-0.5, 0.5]
        ])
        )

test_data = datasets.CIFAR10(
    root = data_path,
    train = False,
    download = True,
    transform = v2.Compose([
        v2.ToImage(),
        v2.ToDtype(torch.float32, scale=True), # to [0, 1]
        v2.Lambda(lambda x: x-0.5), # to [-0.5, 0.5]
        ])
        )
```

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

Training and Hyperparameter Tuning (20)

Next, you are going to explore the model hyperparameters. Later, you are going to verify the effectiveness of batchnorm and shortcut connections. To perform a fair comparison, first find a good configuration for the base model with batchnorm and residual connection. Then, we will do an ablation study by training a version of your successful model without those components. You will form your conclusions based on the results you observe. If you get the best grade at your first try, you have great luck, but **you have to run at least 5 experiments** with different configurations to get 5 points of this part. Try at least one model with `batchnorm = False` and one with `residual = False` and one with both `False`. The goal is to see the effect of these models. We suggest you find a successful model with both `True`, and perform an ablation study to see their effect by excluding them from the model.

In this assignment, we have to keep track of the previous experiments to compare the results later in a table. For that purpose, we will save the information about each experiment in a folder to access it later. The code is set up so that it counts the numbder of folders, and names them as their index in the order that they were conducted. The first experiment will create the first folder called `00`, the next one will be `01`, and so on.

To keep track of your past experiments more efficiently, you will have to use `pandas` to create a dataframe that collects the information about your past experiments. 15 points of

your grade depend on your dataframe. The dataframe you create should be displayed in the notebook in your submission. The rows should correspond to different experiments, and different columns are different hyperparameters (including both the model and the training) and the metrics (loss and accuracy on train and test dataset).

15 points of your grade depend on the best test accuracy you achieve:

$acc \geq 90\% \rightarrow$ 25 points (10 bonus)

$85\% \leq acc < 90\% \rightarrow$ 20 points (5 bonus)

$80\% \leq acc < 85\% \rightarrow$ 15 points

$75\% \leq acc < 80\% \rightarrow$ 10 points

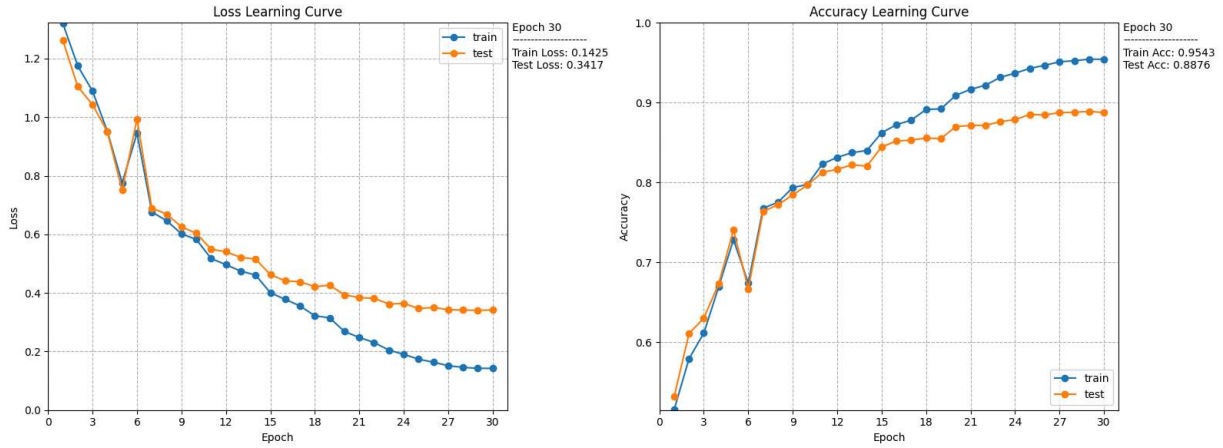
$70\% \leq acc < 75\% \rightarrow$ 5 points

$acc < 70\% \rightarrow$ 0 points

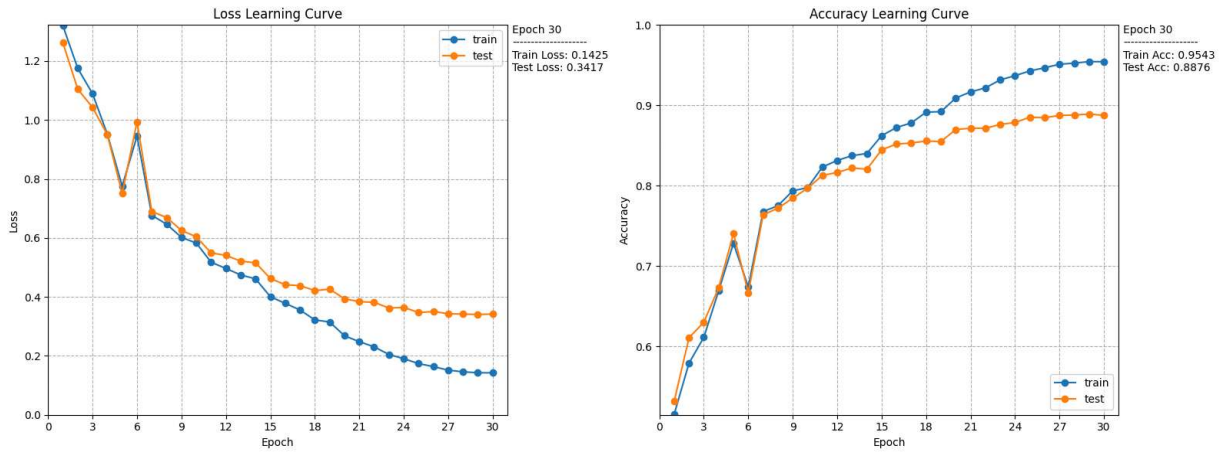
In [30]:
```
"""
Choose the folder to save model checkpoints and results.
In Colab, this is a folder in your drive (somewhere in /content/drive/MyDrive/...)
"""
results_dir = 'results'
os.makedirs(results_dir, exist_ok=True)
```

In [ ]:
```
"""
Find a good model config and train config.

You can run this cell as many times as you want.
Each time, a new experiment will run and the information will be saved in the save_
"""

model_config = dict(
    base_channels = 96,
    expands = [1, 2, 2, 3],
    activation = 'relu',
    # activation = 'leaky_relu',
    batchnorm = True,
    residual = True,
    )

train_config = dict(
    optim_name = 'Adam',
    optim_config = dict(lr=5e-4, weight_decay=1e-3),
    # lr_scheduler_name = 'StepLR',
    # lr_scheduler_config = dict(step_size=10, gamma=0.5),
    lr_scheduler_name = 'CosineAnnealingLR',
    lr_scheduler_config = dict(T_max=30, eta_min=1e-6),
    n_epochs = 30,
    batch_size = 64,
    )
```

```
n_experiments = len(os.listdir(results_dir))
name = f'{n_experiments:02d}'
save_path = f'{results_dir}/{name}'
os.makedirs(save_path, exist_ok=False) # Not Overwrite

save_yaml(model_config, f'{save_path}/model_config.yaml')
save_yaml(train_config, f'{save_path}/train_config.yaml')

train(
    save_path = save_path,
    model = Model(**model_config).to(Device),
    train_data = train_data,
    test_data = test_data,
    loss_fn = nn.CrossEntropyLoss(),
    device = Device,
    train_pbar = False,
    val_pbar = False,
    plot_freq = 1, # plot the curve every how many epochs
    save_freq = 1, # save the model state dict every how many epochs
    **train_config,
)
```




```
epochs: 100%|██████████| 30/30 [26:56<00:00, 53.89s/epoch]
```



Create a table from the experiments to summarize the results (15)

Create a `pandas` dataframe from the saved information about the experiments.

The rows should be the different experiments, with the index being called `name`, which is the name of the experiment folder as a two digit format.

The columns should be the hyperparameters for the model and training, with the same name as the keys in the `model_config` and `train_config` dictionaries.

The columns should also include the following:

- `train_loss`: the final training loss
- `test_loss`: the final test loss
- `train_acc`: the final training accuracy
- `test_acc`: the final test accuracy

You can retrieve these values using the Tracker's `load_results` method, and access them through the tracker.

After you are done, save the dataframe as an excel file and display it in the notebook.

For the PDF submission, assign the pages corresponding to the output of the following cell for the table, and the cell output for the results, to be graded. If you do not assign the correct pages of the PDF, you will be penalized.

In [108…

```
# results folder path
results_dir = 'results'

# sorted list of experiment directories
experiment_dirs = sorted([d for d in os.listdir(results_dir) if os.path.isdir(os.pa

# list to store the results
entries = []

for exp in experiment_dirs:
    exp_path = os.path.join(results_dir, exp)

    # Skip if not a directory
    if not os.path.isdir(exp_path):
        continue

    # load the model and training config from the YAML files
    model_config_path = os.path.join(exp_path, 'model_config.yaml')
    train_config_path = os.path.join(exp_path, 'train_config.yaml')
    model_config = load_yaml(model_config_path)
    train_config = load_yaml(train_config_path)

    # Check if tracker file exists
    tracker_file = os.path.join(exp_path, 'results.pkl')
    if not os.path.exists(tracker_file):
```

```
        print(f"Skipping {exp}: results.pkl not found.")
        continue

    # load the results (metrics) using the Tracker class
    n_epochs = train_config.get('n_epochs')
    tracker = Tracker(n_epochs)
    tracker.load_results(tracker_file)

    # log the results
    entry = dict(
        name = exp,
        **model_config,
        **train_config,
        train_loss = tracker.train_losses[-1],
        train_acc = tracker.train_accs[-1],
        test_loss = tracker.test_losses[-1],
        test_acc = tracker.test_accs[-1],
    )
    entries.append(entry)


# table: pd.DataFrame = NotImplemented
table = pd.DataFrame(entries)
table.set_index('name', inplace=True)

# save to excel
table.to_excel(f'{results_dir}/experiments.xlsx')

# get the best experiment
best_experiment = table['test_acc'].idxmax()
print(f'Best experiment was {best_experiment} with test accuracy of {table.loc[best

# display in notebook
table
```

```
Best experiment was 05 with test accuracy of 90.11%
```

Out[108…

name	base_channels	expands	activation	batchnorm	residual	optim_name	optim_confi
00	32	[1, 2, 2, 4]	relu	True	True	Adam	{'lr': 0.00 'weight_decay 0.000
01	64	[1, 2, 2, 3]	relu	True	True	Adam	{'lr': 0.000 'weight_decay 0.000
02	64	[1, 2, 2, 3]	relu	True	True	Adam	{'lr': 0.000 'weight_decay 0.000
03	64	[1, 2, 2, 3]	leaky_relu	True	True	Adam	{'lr': 0.000 'weight_decay 0.00
04	96	[1, 2, 3, 4]	leaky_relu	True	True	Adam	{'lr': 0.000 'weight_decay 0.00
05	96	[1, 2, 2, 3]	relu	True	True	Adam	{'lr': 0.000 'weight_decay 0.00
06	64	[1, 2, 3, 4]	relu	True	True	Adam	{'lr': 0.000 'weight_decay 0.00

In [107…

```
"""
Optional: Write code that deletes the folders you want to discard (if you hate them
and renames the remaining ones to have sequential numbers with format {n:02d} again

You can use os.listdir, os.rename, os.remove, os.path.join, ...
"""

# Delete the experiment entries that do not contain results.pkl
for exp in experiment_dirs:
    exp_path = os.path.join(results_dir, exp)
    if not os.path.exists(os.path.join(exp_path, 'results.pkl')):
        print(f"Deleting {exp_path} as it does not contain results.pkl")
        for root, dirs, files in os.walk(exp_path, topdown=False):
            for file in files:
                os.remove(os.path.join(root, file))
            for d in dirs:
                os.rmdir(os.path.join(root, d))
        os.rmdir(exp_path)

# Get the remaining experiment directories
remain_dirs = sorted([d for d in os.listdir(results_dir) if os.path.isdir(os.path.j

# Rename the remaining experiments
```

```
for i, exp in enumerate(remain_dirs):
    exp_path = os.path.join(results_dir, exp)
    new_exp = f'{i:02d}'
    new_exp_path = os.path.join(results_dir, new_exp)
    os.rename(exp_path, new_exp_path)
```

Conclusion (10)

Explain your findings from your hyperparameter search. What were the most and least effective factors?

RESPONSE:

From my hyperparameter search, the most effective factors are:

- Extended Training Duration: Increasing the number of epochs improved the test accuracy.
- Learning Rate Schedule: Switching from a StepLR to a CosineAnnealingLR scheduler—and tuning parameters such as T_max and eta_min—yielded smoother learning rate transitions.

From my hyperparameter search, the least effective factors are:

- Minor Architectural Tweaks: Adjustments such as slight variations in the expansion factors or small modifications in the base channel size did not yield significant performance improvements.
- Activation Function Variations: Switching between standard ReLU and LeakyReLU resulted in only marginal differences.
- Weight Decay Adjustments: Fine-tuning the weight decay had less effect on test accuracy than the effects of training duration and learning rate schedule.

Zip submission files

You can run the following cell to zip the generated files for submission.

If you are on Colab, make sure to download and then upload a completed copy of the notebook to the working directory so the code can detect and include it in the zip file for submission.

In [129…

```
# copying the best model to the working directory
# load table from excel
table = pd.read_excel(f'{results_dir}/experiments.xlsx', index_col='name')

best_experiment = table['test_acc'].idxmax()
# print(f'Best experiment was {best_experiment} with test accuracy of {table.loc[be

# os.system(f'cp {results_dir}/{best_experiment:02d}/model_config.yaml .')
```

```
# os.system(f'cp {results_dir}/{best_experiment:02d}/train_config.yaml .')

# copying the excel files to the working directory
# os.system(f'cp {results_dir}/experiments.xlsx .')

os.system(f'cmd /c copy "{results_dir}\\{best_experiment:02d}\\model_config.yaml" .
os.system(f'cmd /c copy "{results_dir}\\{best_experiment:02d}\\train_config.yaml" .

# copying the excel file to the working directory
os.system(f'cmd /c copy "{results_dir}\\experiments.xlsx" .')

# creating the zip file consisting of the notebook and the above files
files_to_zip = ['HW4.ipynb', 'model_config.yaml', 'train_config.yaml', 'experiments
zip_files('HW4_submission.zip', *files_to_zip)
```