assignment2_proj

February 20, 2024

1 Deep Learning Course

1.1 Assignment 2

1.1.1 Assignment Goals

- Design and implementation of CNNs.
- CNN visualization.
- Implementation of ResNet.

In this assignment, you will be asked to learn CNN models for an image dataset. Different experiments will help you achieve a better understanding of CNNs.

1.1.2 Dataset

The dataset consists of around 9K images (some grayscale and some RGB) belonging to 101 classes. The shape of each image is (64,64,3). Every image is labeled with one of the classes. The image file is contained in the folder named after the class name.

1.1.3 Requirements

1. **(40 points) Implement and improve a CNN model.**

   (a) We are aiming to learn a CNN on the given dataset. Download the dataset, and use PyTorch to implement LeNet5 to classify instances. Use a one-hot encoding for labels. Split the dataset into training (90 percent) and validation (10 percent) and report the model loss (cross-entropy) and accuracy on both training and validation sets. (20 points)

   The LeNet5 configuration is:

   - Convolutional layer (kernel size 5 x 5, 32 filters, stride 1 x 1 and followed by ReLU)
   - Max Pooling layer with size 4 and stride 4 x 4
   - Convolutional layer (kernel size 5 x 5, 64 filters, stride 1 x 1 and followed by ReLU)
   - Max Pooling layer with size 4 and stride 4 x 4
   - Fully Connected ReLU layer that has 1021 neurons
   - Fully Connected ReLU layer with 84 neurons
   - Fully Connected Softmax layer that has input 84 and output which is equal to the number of classes (one node for each of the classes).

   (b) Try to improve model accuracy on the validation dataset by tuning the model hyperparameters. You can use any improvement methods you prefer. You are expected to reach at least 65 percent accuracy on validation set. (20 points)

Here are some improvement methods you can use, of course you can use others which are not mentioned here:

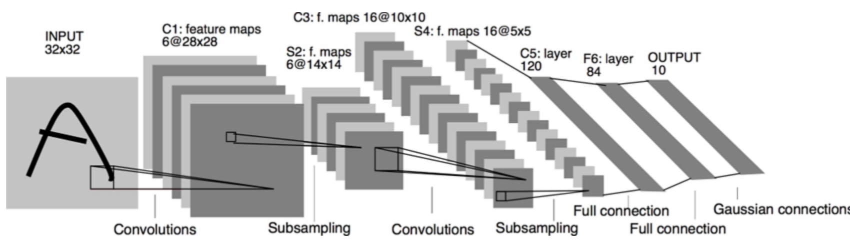
- Dropout
- L1, L2 regularization
- Try improved initialization (e.g., Xavier initialier)
- Batch Normalization

The grading of part (b) is based on the correctness of your implementation (5 points) and the performance of your improvement on the validation set. The validation accuracy and corresponding score is:

- 65% (5 points)
- 67% (8 points)
- 69% (12 points)
- 71% (15 points)

Structure of LENET-5

This following LENET-5 structure is for 10-class dataset. Therefore, the layer size is not exactly the same as ours.



2. **(20 points) Visualize layer activation**

   There are several approaches to understand and visualize convolutional Networks, including visualizing the activations and layers weights. The most straight-forward visualization technique is to show the activations of the network during the forward pass. The second most common strategy is to visualize the weights. For more information we recommend the course notes on "Visualizing what ConvNets learn". More advanced techniques can be found in "Visualizing and Understanding Convolutional Networks" paper by Matthew D.Zeiler and Rob Fergus.

   Please visualize the layer activation of **the first conv layer** and **the second conv layer** of your above CNN model (after completing Q1), on the following 2 images:

   - accordion/image_0001
   - camera/image_0001

   Visualizing a CNN layer activation means to visualize the result of the activation layer as an image. Specifically, the activation of the first conv layer is the output of the first (conv + ReLU) layer during forward propagation. Since we have 32 filters in the first conv layer, you should draw 32 activation images for the first conv layer. Please display multiple images side by side in a row to make your output more readable (Hint: matplotlib.pyplot.subplot).

3. **(40 points) ResNet Implementation**

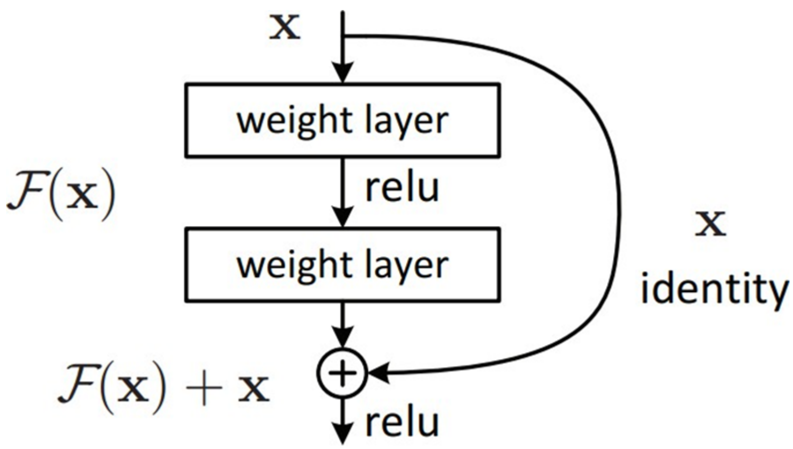
Use PyTorch to implement ResNet 18 to classify the given dataset. Same as above, please use a one-hot encoding for labels, split the dataset into training (90 percent) and validation (10 percent) and report the model loss (cross-entropy) and accuracy on both training and validation sets. See the paper Deep Residual Learning for Image Recognition for detailed introduction of ResNet.

The grading of this part is mainly based on the implementation and performance on validation set. If you need more resources to complete the training, consider using Google Colab.

The ResNet 18 configuration is:

- conv_1 (kernel size 7 x 7, 64 filters, stride 2 x 2)
- conv_2 (max pooling layer with size 3 x 3, followed by 2 blocks.Each block contains two conv layers. Each conv layer has kernel size 3 x 3, 64 filters, stride 2 x 2)
- conv_3 (2 blocks, each contains 2 conv layers with kernel size 3*3, 128 filters)
- conv_4 (2 blocks, each contains 2 conv layers with kernel size 3*3, 256 filters)
- conv_5 (2 blocks, each contains 2 conv layers with kernel size 3*3, 512 filters)

A block has the structure:



1.1.4 Submission Notes

Please use Jupyter Notebook. The notebook should include the final code, results and your answers. You should submit your Notebook in (.pdf or .html) and .ipynb format. (penalty 10 points)

1.2 Your Implementation

[3]:
```
# You can use the following helper functions

from typing import Any
from torch.utils.data import Dataset, DataLoader
import pandas as pd
import os
from torchvision.io import read_image
from torchvision import transforms
from sklearn.preprocessing import OneHotEncoder
import numpy as np
```

```python
import torch
from torch import nn
from tqdm import tqdm
from matplotlib import pyplot as plt
```

[4]:
```python
device = 'cuda' if torch.cuda.is_available() else 'cpu'
```

[5]:
```python
#no transformer
class ImageDataset( Dataset ):

    def __init__(self, is_val= False, transform = None) -> None:


        if is_val:
            self.df = pd.read_csv( 'validation.csv', index_col=0 )
        else:
            self.df = pd.read_csv( 'train.csv', index_col= 0 )

        self.cls_names = self.df['cls_name'].unique().tolist()
        self.df['label'] = self.df['cls_name'].apply( self.cls_names.index )

        self.transform = transform


    def get_num_classes(self):
        return len( self.cls_names )

    def __len__(self):
        return len( self.df )

    def __getitem__(self, index):
        path = self.df.iloc[index]['path']
        img = read_image( path ).type( torch.float32 )

        target = self.df.iloc[index]['label']

        if self.transform is not None:
            img = self.transform( img )

        target = torch.tensor( target )

        return img/255 , target

# def collate_fn( batch ):
#     imgs, targets = [], []

#     for img, target in batch:
```

```
#         imgs.append( img )
#         targets.append( target )

#     imgs = torch.stack( imgs, dim= 0 )
#     targets = torch.stack( targets, dim= 0 )
#     return imgs, targets
def collate_fn(batch):
    imgs, targets = [], []
    for img, target in batch:
        # Convert img and target to tensors if they're not already.
        img = torch.tensor(img) if not isinstance(img, torch.Tensor) else img
        target = torch.tensor(target) if not isinstance(target, torch.Tensor)␣
 ↪else target
        imgs.append(img)
        targets.append(target)

    imgs = torch.stack(imgs, dim=0)
    targets = torch.stack(targets, dim=0)
    return imgs, targets
```

[6]:

```
#transformer
import pandas as pd
import torch
from torchvision.io import read_image
from torch.utils.data import Dataset
from PIL import Image

class ImageDataset_t(Dataset):
    def __init__(self, is_val=False, transform=None):
        super(ImageDataset_t, self).__init__()
        if is_val:
            self.df = pd.read_csv('validation.csv', index_col=0)
        else:
            self.df = pd.read_csv('train.csv', index_col=0)

        self.cls_names = self.df['cls_name'].unique().tolist()
        self.df['label'] = self.df['cls_name'].apply(self.cls_names.index)
        self.transform = transform

    def get_num_classes(self):
        return len(self.cls_names)

    def __len__(self):
        return len(self.df)

    def __getitem__(self, index):
        path = self.df.iloc[index]['path']
```

```
        # Load image as PIL Image
        img = Image.open(path).convert('RGB')

        target = self.df.iloc[index]['label']

        if self.transform is not None:
            img = self.transform(img)

        target = torch.tensor(target, dtype=torch.long)  # here

        return img, target

def collate_fn(batch):
    imgs, targets = [], []
    for img, target in batch:
        imgs.append(img)
        targets.append(target)

    imgs = torch.stack(imgs, dim=0)
    targets = torch.stack(targets, dim=0)
    return imgs, targets
```

[7]:

```
from torchvision import transforms, datasets
from torch.utils.data import DataLoader,random_split



# Assuming ImageDataset is a custom dataset class you've defined
# that properly handles the is_val flag and applies transformations.

# transform = {
#     'train': transforms.Compose([
#         # transforms.RandomResizedCrop(64),
#         # transforms.RandomHorizontalFlip(),
#         # transforms.ToTensor(),
#         transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
#     ]),
# }
# total_size_train = len(ImageDataset(is_val=False))
# split_size_train = int(0.2 * total_size_train)  # 20% of the total size
# train_size_train = total_size_train - split_size_train  # The remaining 80%


# total_size_val = len(ImageDataset(is_val=True))
# split_size_val = int(0.2 * total_size_val)  # 20% of the total size
# train_size_val = total_size_val - split_size_val  # The remaining 80%
```

```
# Split the dataset
# train_dataset = random_split(ImageDataset(is_val=False), [train_size_train,␣
↪split_size_train])
# val_dataset = random_split(ImageDataset(is_val=True), [train_size_val,␣
↪split_size_val])

# train_transforms = transforms.Compose([
#     transforms.RandomResizedCrop(224),  # Example size, adjust to your needs
#     transforms.RandomHorizontalFlip(),
#     transforms.RandomRotation(20),
#     transforms.ColorJitter(brightness=0.1, contrast=0.1, saturation=0.1, hue=0.
↪1),
#     transforms.ToTensor(),  # Converts PIL Image or numpy.ndarray (H x W x C)␣
↪in the range [0, 255] to torch.FloatTensor of shape (C x H x W) in the range␣
↪[0.0, 1.0]
# ])

# val_transforms = transforms.Compose([
#     transforms.Resize(256),
#     transforms.CenterCrop(224),
#     transforms.ToTensor(),
# ])









train_dataset = ImageDataset(is_val=False )
val_dataset = ImageDataset(is_val=True)

train_dataloader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_dataloader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False) ␣
↪# No need to shuffle validation data
print(type(train_dataloader))
```

```
<class 'torch.utils.data.dataloader.DataLoader'>
```

[9]:
```
def init_weights( m ):
    if isinstance(m, nn.Linear):
        torch.nn.init.xavier_uniform_(m.weight)
        m.bias.data.fill_(0.01)
```

[10]:
```
df = pd.read_csv( 'train.csv', index_col= 0 )
df.head()
```

[10]:

	file_name	cls_name	path
0	image_0019.jpg	cougar_body	Dataset/train/cougar_body/image_0019.jpg
1	image_0001.jpg	cougar_body	Dataset/train/cougar_body/image_0001.jpg
2	image_0002.jpg	cougar_body	Dataset/train/cougar_body/image_0002.jpg
3	image_0003.jpg	cougar_body	Dataset/train/cougar_body/image_0003.jpg
4	image_0004.jpg	cougar_body	Dataset/train/cougar_body/image_0004.jpg

[ ]:
```

```

[ ]:
```

```

1.2.1 Implement and improve a CNN model

[11]:
```
# implement your Lenet5 here
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torchvision import transforms
```

[12]:
```
# class LeNet5(nn.Module):
#     def __init__(self, num_classes=101):
#         super(LeNet5, self).__init__()
#         self.features = nn.Sequential(
#             nn.Conv2d(3, 32, kernel_size=5, stride=1),
#             nn.ReLU(inplace=True),
#             nn.BatchNorm2d(32),
#             nn.MaxPool2d(kernel_size=4, stride=4),
#             nn.Conv2d(32, 64, kernel_size=5, stride=1),
#             nn.ReLU(inplace=True),
#             nn.BatchNorm2d(64),
#             nn.MaxPool2d(kernel_size=4, stride=4),
#         )
#         self.classifier = nn.Sequential(
#             nn.Linear(256, 1021),  # Adjusted for the actual output size
#             nn.ReLU(inplace=True),
#             nn.BatchNorm1d(1021),
#             nn.Dropout(p=0.5),
#             nn.Linear(1021, 84),
#             nn.ReLU(inplace=True),
#             nn.BatchNorm1d(84),
#             nn.Dropout(p=0.5),
#             nn.Linear(84, num_classes),
#             nn.Softmax(dim=1)
```

```
#         )

#     def forward(self, x):
#         x = self.features(x)
#         x = torch.flatten(x, 1)
#         x = self.classifier(x)
#       #  print(x.size())
#         return x

# def init_weights(m):
#     if isinstance(m, nn.Conv2d) or isinstance(m, nn.Linear):
#         nn.init.xavier_uniform_(m.weight)
#         if m.bias is not None:
#             nn.init.constant_(m.bias, 0)
```

[13]:

```
# import torch
# import torch.nn as nn
# import torch.optim as optim
# from torch.optim.lr_scheduler import StepLR


# # Model, loss function, optimizer, and scheduler setup
# num_epochs = 500
# batch_size = 64
# learning_rate = 0.001
# weight_decay = 0.00005

# model = LeNet5(num_classes=101).apply(init_weights)  # Apply Xavier␣
↪initialization here
# criterion = nn.CrossEntropyLoss()
# optimizer = optim.Adam(model.parameters(), lr=learning_rate,␣
↪weight_decay=weight_decay)
# scheduler = StepLR(optimizer, step_size=30, gamma=0.1)

# # Training and validation loops
# for epoch in range(num_epochs):
#     model.train()
#     running_loss = 0.0
#     correct = 0
#     total = 0
#     for images, labels in train_dataloader:  # Assume train_dataloader is␣
↪defined elsewhere
#         optimizer.zero_grad()
#         outputs = model(images)
#         loss = criterion(outputs, labels)
#         loss.backward()
#         optimizer.step()
```

```
#         running_loss += loss.item()
#         _, predicted = torch.max(outputs.data, 1)
#         total += labels.size(0)
#         correct += (predicted == labels).sum().item()

#     train_loss = running_loss / len(train_dataloader)
#     train_accuracy = 100 * correct / total
#     print(f'Epoch {epoch+1}, Train Loss: {train_loss:.4f}, Accuracy:␣
↪{train_accuracy:.2f}%')
#     scheduler.step()  # Update the learning rate

#     # Validation loop
#     model.eval()
#     val_loss = 0.0
#     correct = 0
#     total = 0
#     with torch.no_grad():
#         for images, labels in val_dataloader:  # Assume val_dataloader is␣
↪defined elsewhere
#             outputs = model(images)
#             loss = criterion(outputs, labels)
#             val_loss += loss.item()
#             _, predicted = torch.max(outputs.data, 1)
#             total += labels.size(0)
#             correct += (predicted == labels).sum().item()

#     val_loss = val_loss / len(val_dataloader)
#     val_accuracy = 100 * correct / total
#     print(f'Epoch {epoch+1}, Validation Loss: {val_loss:.4f}, Accuracy:␣
↪{val_accuracy:.2f}%')
```

[14]:

```
import torch
import torch.nn as nn
import torch.nn.functional as F
dropout_rate = 0.14775549228794788
class LeNet5_with_dropout_layers(nn.Module):
    def __init__(self, num_classes=101):
        super(LeNet5_with_dropout_layers, self).__init__()
        self.features = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=5, stride=1, padding=2),  # Added␣
↪padding to maintain feature map size
            nn.ReLU(inplace=True),
            nn.BatchNorm2d(32),
            nn.MaxPool2d(kernel_size=2, stride=2),  # Changed pooling size for␣
↪less aggressive reduction
            nn.Dropout2d(p=dropout_rate),  # Added dropout for regularization
            nn.Conv2d(32, 64, kernel_size=5, stride=1, padding=2),
```

```
            nn.ReLU(inplace=True),
            nn.BatchNorm2d(64),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Dropout2d(p=dropout_rate),
        )
        self.classifier = nn.Sequential(
            nn.Linear(64 * 16 * 16, 1024),  # Adjusted due to pooling changes
            nn.ReLU(inplace=True),
            nn.Dropout(p=0.5),
            nn.Linear(1024, num_classes),
        )

    def forward(self, x):
        x = self.features(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)
        return x

def init_weights(m):
    if isinstance(m, nn.Conv2d) or isinstance(m, nn.Linear):
        nn.init.xavier_uniform_(m.weight)
        if m.bias is not None:
            nn.init.constant_(m.bias, 0)
```

[15]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim.lr_scheduler import StepLR


# Model, loss function, optimizer, and scheduler setup
num_epochs = 500
batch_size = 64
learning_rate = 0.013500536424062414
weight_decay = 0.00005
momentum=0.5938519353289676
model = LeNet5_with_dropout_layers(num_classes=101).apply(init_weights)  # Apply␣
 ↪Xavier initialization here
criterion = nn.CrossEntropyLoss()
# optimizer = optim.Adam(model.parameters(), lr=learning_rate,␣
 ↪weight_decay=weight_decay)
optimizer = optim.SGD(model.parameters(), lr=learning_rate, momentum=momentum)

scheduler = StepLR(optimizer, step_size=30, gamma=0.1)

# Training and validation loops
for epoch in range(num_epochs):
```

```python
    model.train()
    running_loss = 0.0
    correct = 0
    total = 0
    for images, labels in train_dataloader:  # Assume train_dataloader is␣
↪defined elsewhere
        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

    train_loss = running_loss / len(train_dataloader)
    train_accuracy = 100 * correct / total
    print(f'Epoch {epoch+1}, Train Loss: {train_loss:.4f}, Accuracy:␣
↪{train_accuracy:.2f}%')
    scheduler.step()  # Update the learning rate

    # Validation loop
    model.eval()
    val_loss = 0.0
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in val_dataloader:  # Assume val_dataloader is␣
↪defined elsewhere
            outputs = model(images)
            loss = criterion(outputs, labels)
            val_loss += loss.item()
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    val_loss = val_loss / len(val_dataloader)
    val_accuracy = 100 * correct / total
    print(f'Epoch {epoch+1}, Validation Loss: {val_loss:.4f}, Accuracy:␣
↪{val_accuracy:.2f}%')
```

```
Epoch 1, Train Loss: 3.7950, Accuracy: 30.31%
Epoch 1, Validation Loss: 2.8575, Accuracy: 41.82%
Epoch 2, Train Loss: 2.5780, Accuracy: 44.23%
Epoch 2, Validation Loss: 2.4383, Accuracy: 49.51%
Epoch 3, Train Loss: 2.0008, Accuracy: 53.98%
```

```
Epoch 3, Validation Loss: 2.1900, Accuracy: 53.68%
Epoch 4, Train Loss: 1.5295, Accuracy: 62.92%
Epoch 4, Validation Loss: 1.9896, Accuracy: 56.42%
Epoch 5, Train Loss: 1.1818, Accuracy: 70.23%
Epoch 5, Validation Loss: 1.9107, Accuracy: 59.50%
Epoch 6, Train Loss: 0.8552, Accuracy: 76.99%
Epoch 6, Validation Loss: 1.9803, Accuracy: 58.95%
Epoch 7, Train Loss: 0.6210, Accuracy: 83.39%
Epoch 7, Validation Loss: 1.8884, Accuracy: 61.91%
Epoch 8, Train Loss: 0.4479, Accuracy: 88.17%
Epoch 8, Validation Loss: 1.8660, Accuracy: 61.14%
Epoch 9, Train Loss: 0.3500, Accuracy: 90.15%
Epoch 9, Validation Loss: 2.0635, Accuracy: 61.47%
Epoch 10, Train Loss: 0.2598, Accuracy: 92.84%
Epoch 10, Validation Loss: 1.8126, Accuracy: 61.80%
Epoch 11, Train Loss: 0.2142, Accuracy: 94.24%
Epoch 11, Validation Loss: 1.9193, Accuracy: 63.23%
Epoch 12, Train Loss: 0.1599, Accuracy: 95.72%
Epoch 12, Validation Loss: 1.8320, Accuracy: 63.45%
Epoch 13, Train Loss: 0.1346, Accuracy: 96.27%
Epoch 13, Validation Loss: 1.8239, Accuracy: 64.65%
Epoch 14, Train Loss: 0.1135, Accuracy: 97.04%
Epoch 14, Validation Loss: 1.8985, Accuracy: 64.11%
Epoch 15, Train Loss: 0.1011, Accuracy: 97.24%
Epoch 15, Validation Loss: 1.9857, Accuracy: 64.76%
Epoch 16, Train Loss: 0.0953, Accuracy: 97.26%
Epoch 16, Validation Loss: 1.9109, Accuracy: 63.89%
Epoch 17, Train Loss: 0.0825, Accuracy: 97.94%
Epoch 17, Validation Loss: 1.9562, Accuracy: 64.65%
Epoch 18, Train Loss: 0.0751, Accuracy: 98.08%
Epoch 18, Validation Loss: 1.8891, Accuracy: 64.87%
Epoch 19, Train Loss: 0.0643, Accuracy: 98.29%
Epoch 19, Validation Loss: 1.8898, Accuracy: 64.87%
Epoch 20, Train Loss: 0.0539, Accuracy: 98.61%
Epoch 20, Validation Loss: 1.9167, Accuracy: 64.43%
Epoch 21, Train Loss: 0.0497, Accuracy: 98.64%
Epoch 21, Validation Loss: 2.0047, Accuracy: 65.31%
Epoch 22, Train Loss: 0.0462, Accuracy: 98.87%
Epoch 22, Validation Loss: 1.9393, Accuracy: 65.31%
Epoch 23, Train Loss: 0.0437, Accuracy: 98.87%
Epoch 23, Validation Loss: 1.9267, Accuracy: 66.30%
Epoch 24, Train Loss: 0.0392, Accuracy: 99.03%
Epoch 24, Validation Loss: 2.0198, Accuracy: 65.09%
Epoch 25, Train Loss: 0.0358, Accuracy: 99.07%
Epoch 25, Validation Loss: 1.8645, Accuracy: 65.09%
Epoch 26, Train Loss: 0.0324, Accuracy: 99.23%
Epoch 26, Validation Loss: 1.9241, Accuracy: 65.64%
Epoch 27, Train Loss: 0.0348, Accuracy: 99.18%
```

```
Epoch 27, Validation Loss: 2.1919, Accuracy: 64.87%
Epoch 28, Train Loss: 0.0268, Accuracy: 99.43%
Epoch 28, Validation Loss: 1.9782, Accuracy: 64.65%
Epoch 29, Train Loss: 0.0290, Accuracy: 99.33%
Epoch 29, Validation Loss: 2.0148, Accuracy: 65.20%
Epoch 30, Train Loss: 0.0296, Accuracy: 99.39%
Epoch 30, Validation Loss: 2.0349, Accuracy: 66.74%
Epoch 31, Train Loss: 0.0239, Accuracy: 99.30%
Epoch 31, Validation Loss: 1.9824, Accuracy: 66.74%
Epoch 32, Train Loss: 0.0241, Accuracy: 99.48%
Epoch 32, Validation Loss: 1.9716, Accuracy: 66.85%
Epoch 33, Train Loss: 0.0193, Accuracy: 99.59%
Epoch 33, Validation Loss: 1.9805, Accuracy: 66.96%
Epoch 34, Train Loss: 0.0202, Accuracy: 99.54%
Epoch 34, Validation Loss: 1.9528, Accuracy: 66.85%
Epoch 35, Train Loss: 0.0203, Accuracy: 99.55%
Epoch 35, Validation Loss: 1.9605, Accuracy: 67.18%
Epoch 36, Train Loss: 0.0201, Accuracy: 99.56%
Epoch 36, Validation Loss: 1.9489, Accuracy: 67.40%
Epoch 37, Train Loss: 0.0179, Accuracy: 99.58%
Epoch 37, Validation Loss: 1.9636, Accuracy: 67.29%
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
Cell In[15], line 30
     28 outputs = model(images)
     29 loss = criterion(outputs, labels)
---> 30 loss.backward()
     31 optimizer.step()
     32 running_loss += loss.item()

File ~/miniconda3/lib/python3.11/site-packages/torch/_tensor.py:522, in Tensor.
 ↪backward(self, gradient, retain_graph, create_graph, inputs)
    512 if has_torch_function_unary(self):
    513     return handle_torch_function(
    514         Tensor.backward,
    515         (self,),
   (...)
    520         inputs=inputs,
    521     )
--> 522 torch.autograd.backward(
    523     self, gradient, retain_graph, create_graph, inputs=inputs
    524 )

File ~/miniconda3/lib/python3.11/site-packages/torch/autograd/__init__.py:266, in␣
 ↪backward(tensors, grad_tensors, retain_graph, create_graph, grad_variables,␣
 ↪inputs)
    261     retain_graph = create_graph
```

```
    263 # The reason we repeat the same comment below is that
    264 # some Python versions print out the first line of a multi-line function
    265 # calls in the traceback and some print out the last line
--> 266 Variable._execution_engine.run_backward(  # Calls into the C++ engine to run t e backward pa
    267     tensors,
    268     grad_tensors_,
    269     retain_graph,
    270     create_graph,
    271     inputs,
    272     allow_unreachable=True,
    273     accumulate_grad=True,
    274 )

KeyboardInterrupt:
```

2 67.40% validation accuracy on LeNet_5

[ ]:

[ ]:

[ ]:

[16]:
```
# torch.save(LeNet5_with_dropout_layers, 'LeNet5-67%validation_accuracy.pth')
```

3 optuna parameter tuning

[64]:
```
# import optuna
# import torch
# import torch.nn as nn
# import torch.optim as optim
# from torch.optim.lr_scheduler import StepLR
# from torchvision import datasets, transforms
# from torch.utils.data import DataLoader
# import numpy as np

# def objective(trial):
#     # Hyperparameters to tune
#     lr = trial.suggest_float("lr", 1e-5, 1e-1, log=True)
#     momentum = trial.suggest_float("momentum", 0.5, 0.9)  # Adding momentum to be tuned
#     batch_size = trial.suggest_categorical("batch_size", [16, 32, 64, 128])
#     dropout_rate = trial.suggest_float("dropout_rate", 0.1, 0.5)
```

```
#     negative_slope = trial.suggest_float("negative_slope", 1e-2, 2e-1)  #␣
↪Suggest a value for Leaky ReLU negative slope

#     # Adjust model initialization to use the suggested negative slope
#     model = leaky_LeNet5_with_dropout_layers(num_classes=101,␣
↪negative_slope=negative_slope)
#     # Continue with the rest of your objective function as before

#     for module in model.modules():
#         if isinstance(module, nn.Dropout2d) or isinstance(module, nn.Dropout):
#             module.p = dropout_rate

#     # Using SGD with the momentum parameter
#     optimizer = optim.SGD(model.parameters(), lr=lr, momentum=momentum)
#     scheduler = StepLR(optimizer, step_size=50, gamma=0.1)
#     criterion = nn.CrossEntropyLoss()

#     # Training loop (simplified for brevity)
#     for epoch in range(10):  # Using a smaller number of epochs for tuning
#         model.train()
#         for images, labels in train_dataloader:  # train_dataloader needs to␣
↪be defined
#             optimizer.zero_grad()
#             outputs = model(images)
#             loss = criterion(outputs, labels)
#             loss.backward()
#             optimizer.step()
#         scheduler.step()

#     # Validation loop
#     model.eval()
#     total = correct = 0
#     with torch.no_grad():
#         for images, labels in val_dataloader:  # val_dataloader needs to be␣
↪defined
#             outputs = model(images)
#             _, predicted = torch.max(outputs.data, 1)
#             total += labels.size(0)
#             correct += (predicted == labels).sum().item()

#     accuracy = correct / total
#     return accuracy

# study = optuna.create_study(direction="maximize")
# study.optimize(objective, n_trials=20)  # Adjust the number of trials based on␣
↪computational budget
```

```python
# print("Best trial:")
# trial = study.best_trial
# print(f"  Value: {trial.value}")
# print("  Params: ")
# for key, value in trial.params.items():
#     print(f"    {key}: {value}")
```

```
[I 2024-02-19 17:50:47,493] A new study created in memory with name: no-
name-9809a127-b3f3-42db-b01c-0050ae878ef6
[I 2024-02-19 17:55:11,607] Trial 0 finished with value: 0.48518111964873767 and
parameters: {'lr': 0.00025292093741957036, 'momentum': 0.7902762896192698,
'batch_size': 128, 'dropout_rate': 0.3361590990873793, 'negative_slope':
0.19879177469157208}. Best is trial 0 with value: 0.48518111964873767.
[I 2024-02-19 17:59:35,177] Trial 1 finished with value: 0.424807903402854 and
parameters: {'lr': 0.0005174447458335915, 'momentum': 0.5255072464936988,
'batch_size': 64, 'dropout_rate': 0.4417744587465644, 'negative_slope':
0.13061025197680634}. Best is trial 0 with value: 0.48518111964873767.
[I 2024-02-19 18:04:00,148] Trial 2 finished with value: 0.6739846322722283 and
parameters: {'lr': 0.0074212021190408995, 'momentum': 0.6540140539914326,
'batch_size': 128, 'dropout_rate': 0.18711802633096586, 'negative_slope':
0.1755725058294685}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:08:33,515] Trial 3 finished with value: 0.6158068057080132 and
parameters: {'lr': 0.0005142639002172103, 'momentum': 0.8395656811986605,
'batch_size': 64, 'dropout_rate': 0.18229831715186393, 'negative_slope':
0.08982123828259748}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:13:11,714] Trial 4 finished with value: 0.4588364434687157 and
parameters: {'lr': 0.0003200215713501991, 'momentum': 0.6062682843459604,
'batch_size': 128, 'dropout_rate': 0.20389944721775435, 'negative_slope':
0.02770438781253111}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:17:47,182] Trial 5 finished with value: 0.5916575192096597 and
parameters: {'lr': 0.07620697222448304, 'momentum': 0.7368438472116667,
'batch_size': 128, 'dropout_rate': 0.34277929591991374, 'negative_slope':
0.054614509065929906}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:22:33,371] Trial 6 finished with value: 0.570801317233809 and
parameters: {'lr': 0.001511707920887111, 'momentum': 0.6183969894665711,
'batch_size': 128, 'dropout_rate': 0.47519155801163304, 'negative_slope':
0.10965546485200142}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:27:24,178] Trial 7 finished with value: 0.5850713501646543 and
parameters: {'lr': 0.0007872663132962706, 'momentum': 0.7247370656838592,
'batch_size': 16, 'dropout_rate': 0.32029503655509595, 'negative_slope':
0.07164270482102345}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:32:13,203] Trial 8 finished with value: 0.6355653128430296 and
parameters: {'lr': 0.022316384402927762, 'momentum': 0.5952244812291294,
'batch_size': 16, 'dropout_rate': 0.3902467254493416, 'negative_slope':
0.11266377773391531}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:37:04,487] Trial 9 finished with value: 0.6454445664105378 and
parameters: {'lr': 0.003041646870579173, 'momentum': 0.5556744205111703,
'batch_size': 32, 'dropout_rate': 0.1706519050413649, 'negative_slope':
```

```
0.06864099996082854}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:41:47,063] Trial 10 finished with value: 0.2030735455543359 and
parameters: {'lr': 1.6439767454652183e-05, 'momentum': 0.6580772224569967,
'batch_size': 32, 'dropout_rate': 0.10870685343688496, 'negative_slope':
0.17667180758371412}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:46:21,074] Trial 11 finished with value: 0.6597145993413831 and
parameters: {'lr': 0.006839142820314523, 'momentum': 0.5060883201442838,
'batch_size': 32, 'dropout_rate': 0.2212411884220794, 'negative_slope':
0.14773051381712787}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:51:02,126] Trial 12 finished with value: 0.6553238199780461 and
parameters: {'lr': 0.009552248305295228, 'momentum': 0.5069476366691533,
'batch_size': 32, 'dropout_rate': 0.2433523855435512, 'negative_slope':
0.15179826004939498}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 18:55:36,830] Trial 13 finished with value: 0.6344676180021954 and
parameters: {'lr': 0.011382945762788973, 'momentum': 0.8992741430499166,
'batch_size': 32, 'dropout_rate': 0.2601013787513715, 'negative_slope':
0.15832017754990255}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 19:00:17,522] Trial 14 finished with value: 0.6673984632272228 and
parameters: {'lr': 0.004168414549631733, 'momentum': 0.6683715979414224,
'batch_size': 128, 'dropout_rate': 0.10123593664879255, 'negative_slope':
0.19743218741355398}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 19:04:54,395] Trial 15 finished with value: 0.3424807903402854 and
parameters: {'lr': 8.234591191942955e-05, 'momentum': 0.6889074943614542,
'batch_size': 128, 'dropout_rate': 0.10917159369790976, 'negative_slope':
0.19523663307912972}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 19:09:28,830] Trial 16 finished with value: 0.6443468715697036 and
parameters: {'lr': 0.045878422778867764, 'momentum': 0.6695145927960873,
'batch_size': 128, 'dropout_rate': 0.1521399372400083, 'negative_slope':
0.16838786189550536}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 19:14:09,360] Trial 17 finished with value: 0.6498353457738749 and
parameters: {'lr': 0.0025782474590825078, 'momentum': 0.7703303417187694,
'batch_size': 128, 'dropout_rate': 0.13560656590034206, 'negative_slope':
0.18201257572038815}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 19:18:45,584] Trial 18 finished with value: 0.6564215148188803 and
parameters: {'lr': 0.004521539633270048, 'momentum': 0.6419609127650515,
'batch_size': 128, 'dropout_rate': 0.26690721536695855, 'negative_slope':
0.13238245541660357}. Best is trial 2 with value: 0.6739846322722283.
[I 2024-02-19 19:23:18,527] Trial 19 finished with value: 0.681668496158068 and
parameters: {'lr': 0.02136592803704019, 'momentum': 0.5681462855644005,
'batch_size': 64, 'dropout_rate': 0.14052104631674633, 'negative_slope':
0.1852020139731246}. Best is trial 19 with value: 0.681668496158068.

Best trial:
  Value: 0.681668496158068
  Params:
    lr: 0.02136592803704019
    momentum: 0.5681462855644005
    batch_size: 64
```

```
dropout_rate: 0.14052104631674633
negative_slope: 0.1852020139731246
```

Best trial: Value: 0.6426271732131359 Params: lr: 0.00021972321552983008 batch_size: 32 dropout_rate: 0.14161254759360675

Best trial: Value: 0.672886937431394 Params: lr: 0.013500536424062414 momentum: 0.5938519353289676 batch_size: 64 dropout_rate: 0.14775549228794788

Best trial: Value: 0.681668496158068 Params: lr: 0.02136592803704019 momentum: 0.5681462855644005 batch_size: 64 dropout_rate: 0.14052104631674633 negative_slope: 0.1852020139731246

4 Visualize layer activation

[49]:
```
# implement your visualization here
activation = {}
def get_activation(name):
    def hook(model, input, output):
        activation[name] = output.detach()
    return hook

model = LeNet5(num_classes=101)
model.apply(init_weights)  # Apply Xavier initialization

# Register hooks
model.features[0].register_forward_hook(get_activation('conv1'))
model.features[4].register_forward_hook(get_activation('conv2'))
```

[49]:
```
<torch.utils.hooks.RemovableHandle at 0x158468e90>
```

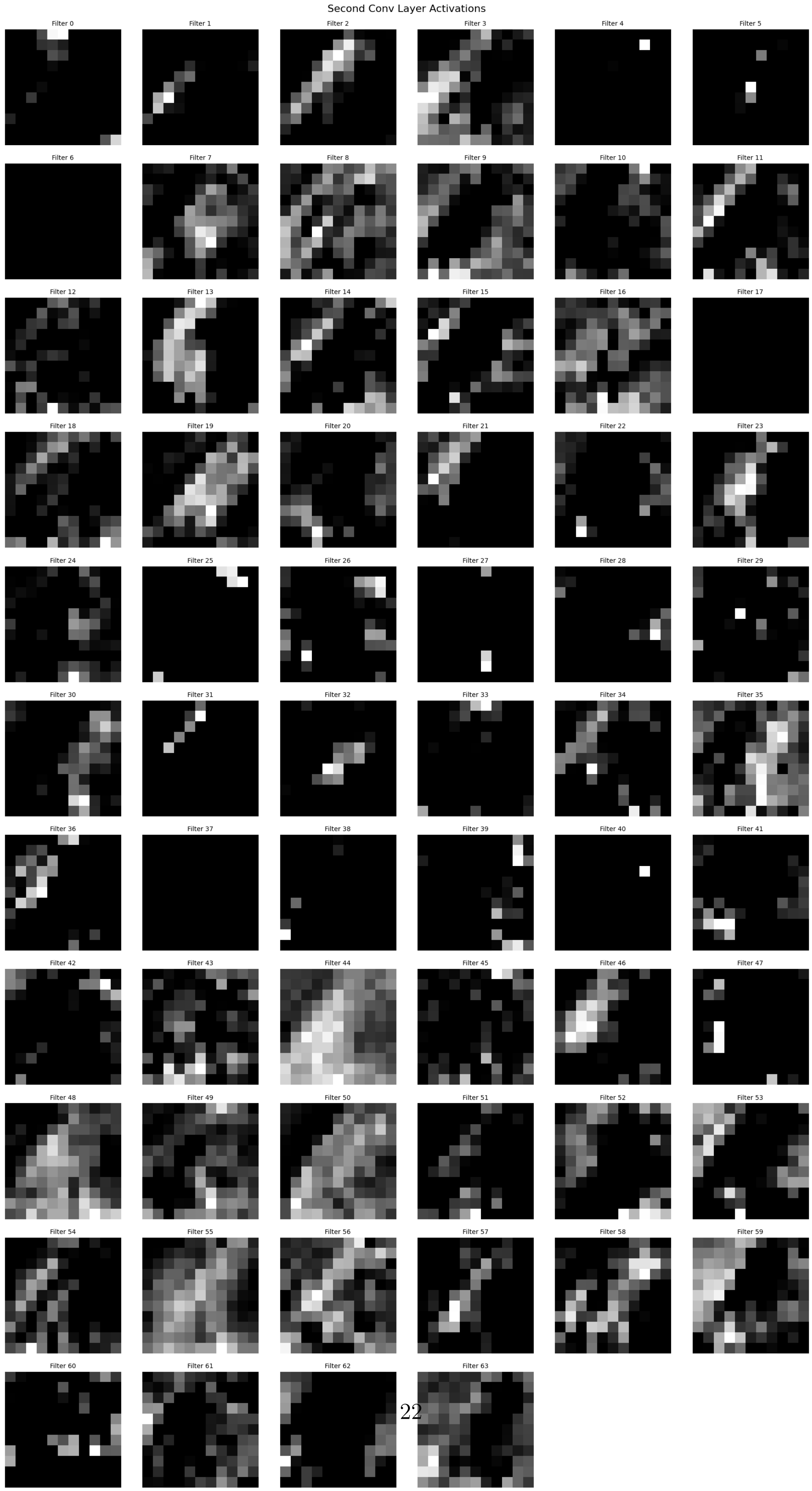
[50]:
```
from torchvision import transforms
from PIL import Image

# Replace these paths with the actual paths to your images
img_accordion = Image.open('Dataset/train/cougar_body/image_0001.jpg')
img_camera = Image.open('Dataset/train/cougar_body/image_0001.jpg')

transform = transforms.Compose([
    transforms.Resize((64, 64)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])

input_accordion = transform(img_accordion).unsqueeze(0)  # Add batch dimension
input_camera = transform(img_camera).unsqueeze(0)  # Add batch dimension
```

[55]:
```python
from IPython.display import Image

# Display the image
Image(filename='Dataset/train/cougar_body/image_0001.jpg', width=200, height=200)
```

[55]:

[51]:
```python
# Forward pass
model.eval()
_ = model(input_accordion)
_ = model(input_camera)

# Visualization function
def visualize_activation_grid_with_titles(activation, title, num_cols=8):
    num_filters = activation.shape[1]
    num_rows = num_filters // num_cols + int(num_filters % num_cols != 0)
    fig_size = num_cols * 3  # Adjust the figure size for larger images
    fig, axes = plt.subplots(num_rows, num_cols, figsize=(fig_size, num_rows *␣
↪3))
    axes = axes.flatten()  # Flatten the axes array for easier indexing

    for i in range(num_rows * num_cols):
        if i < num_filters:
            axes[i].imshow(activation[0][i].cpu().numpy(), cmap='gray')
            axes[i].set_title(f"Filter {i}", fontsize=10)  # Title indicating␣
↪filter index
            axes[i].axis('off')
        else:  # Hide axes for empty subplots
            axes[i].axis('off')

    plt.suptitle(title, fontsize=16)
    plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=1.5)  # Adjust padding to␣
↪accommodate titles
    plt.show()



# Visualize activations
# Example usage
visualize_activation_grid_with_titles(activation['conv1'], 'First Conv Layer␣
↪Activations\n', num_cols=6)
```

```
visualize_activation_grid_with_titles(activation['conv2'], 'Second Conv Layer Activations\n \n \n', num_cols=6)
```


Second Conv Layer Activations
Filter 0
Filter 1
Filter 2
Filter 3
Filter 4
Filter 5
Filter 6
Filter 7
Filter 8
Filter 9
Filter 10
Filter 11
Filter 12
Filter 13
Filter 14
Filter 15
Filter 16
Filter 17
Filter 18
Filter 19
Filter 20
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Filter 22
Filter 23
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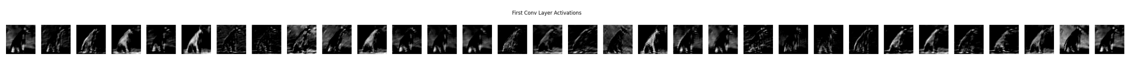
Filter 48
Filter 49
Filter 50
Filter 51
Filter 52
Filter 53
Filter 54
Filter 55
Filter 56
Filter 57
Filter 58
Filter 59
Filter 60
Filter 61
Filter 62
Filter 63

[ ]:

```

```

[52]:

```
def visualize_activation(activation, title):
    num_filters = activation.shape[1]
    fig, axes = plt.subplots(1, num_filters, figsize=(num_filters * 1.5, 2))
    for i, ax in enumerate(axes):
        ax.imshow(activation[0][i].cpu().numpy(), cmap='gray')
        ax.axis('off')
    plt.suptitle(title)
    plt.show()

# Visualize activations
visualize_activation(activation['conv1'], 'First Conv Layer Activations')
visualize_activation(activation['conv2'], 'Second Conv Layer Activations')
```



4.0.1 ResNet Implementation

[19]:

```
# implement a ResNet model here
import torch
import torch.nn as nn
import torch.nn.functional as F
from torchvision import datasets, transforms, models
from torch.utils.data.dataset import Subset
from torch.utils.data import DataLoader, random_split
import numpy as np

class BasicBlock(nn.Module):
    expansion = 1

    def __init__(self, in_channels, out_channels, stride=1):
        super(BasicBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=3,␣
↪stride=stride, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.conv2 = nn.Conv2d(out_channels, out_channels, kernel_size=3,␣
↪stride=1, padding=1, bias=False)
```

```
        self.bn2 = nn.BatchNorm2d(out_channels)

        self.shortcut = nn.Sequential()
        if stride != 1 or in_channels != self.expansion * out_channels:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_channels, self.expansion * out_channels,␣
↪kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(self.expansion * out_channels)
            )

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.bn2(self.conv2(out))
        out += self.shortcut(x)
        out = F.relu(out)
        return out

class ResNet(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
        super(ResNet, self).__init__()
        self.in_channels = 64
        self.conv1 = nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3,␣
↪bias=False)
        self.bn1 = nn.BatchNorm2d(64)
        self.layer1 = self._make_layer(block, 64, num_blocks[0], stride=1)
        self.layer2 = self._make_layer(block, 128, num_blocks[1], stride=2)
        self.layer3 = self._make_layer(block, 256, num_blocks[2], stride=2)
        self.layer4 = self._make_layer(block, 512, num_blocks[3], stride=2)
        self.linear = nn.Linear(512 * block.expansion, num_classes)

    def _make_layer(self, block, out_channels, num_blocks, stride):
        strides = [stride] + [1] * (num_blocks - 1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_channels, out_channels, stride))
            self.in_channels = out_channels * block.expansion
        return nn.Sequential(*layers)

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = F.max_pool2d(out, kernel_size=3, stride=2, padding=1)
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.layer4(out)
        out = F.avg_pool2d(out, 4)
        out = out.view(out.size(0), -1)
```

```
        out = self.linear(out)
        return out

def ResNet18(num_classes=10):
    return ResNet(BasicBlock, [2, 2, 2, 2], num_classes)
```

[35]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import transforms
from torch.utils.data import DataLoader



device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Adjustments for the ResNet model initialization
def ResNet18(num_classes=10):
    model = ResNet(BasicBlock, [2, 2, 2, 2], num_classes)
    return model

model = ResNet18(num_classes=train_dataset.get_num_classes()).to(device)


transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])

train_dataset = ImageDataset_t(is_val=False,transform = transform)
val_dataset = ImageDataset_t(is_val=True,transform = transform)

train_loader = DataLoader(dataset=train_dataset, batch_size=64, shuffle=True,␣
 ↪num_workers=0)
val_loader = DataLoader(dataset=val_dataset, batch_size=64, shuffle=False,␣
 ↪num_workers=0)

# Loss, optimizer, and scheduler
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9,␣
 ↪weight_decay=5e-4)
scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=30, gamma=0.1)

# Training loop
num_epochs = 10
```

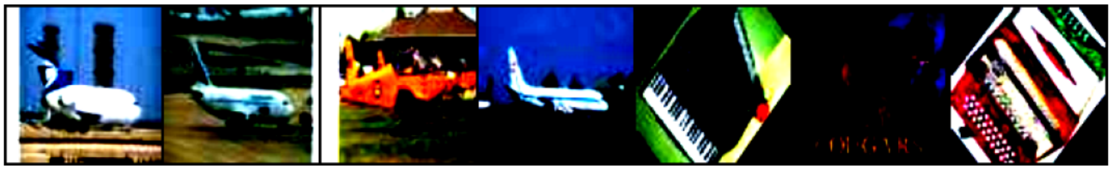
```python
for epoch in range(num_epochs):
    model.train()
    running_loss, correct, total = 0.0, 0, 0
    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)
        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
    print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {running_loss/
 ↪len(train_loader):.4f}, Accuracy: {100*correct/total:.2f}%')
    scheduler.step()

# Validation loop
model.eval()
total, correct = 0, 0
with torch.no_grad():
    for images, labels in val_loader:
        images, labels = images.to(device), labels.to(device)
        outputs = model(images)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
print(f'Validation Accuracy: {100*correct/total:.2f}%')
```

```
Epoch [1/10], Loss: 3.2640, Accuracy: 30.40%
Epoch [2/10], Loss: 2.3670, Accuracy: 45.75%
Epoch [3/10], Loss: 1.8101, Accuracy: 55.79%
Epoch [4/10], Loss: 1.4010, Accuracy: 64.63%
Epoch [5/10], Loss: 1.0600, Accuracy: 72.61%
Epoch [6/10], Loss: 0.7686, Accuracy: 79.82%
Epoch [7/10], Loss: 0.5244, Accuracy: 86.39%
Epoch [8/10], Loss: 0.3087, Accuracy: 92.17%
Epoch [9/10], Loss: 0.1352, Accuracy: 97.49%
Epoch [10/10], Loss: 0.0527, Accuracy: 99.34%
Validation Accuracy: 73.11%
```

5 73.11 % validation accuracy on ResNet_18

[48]:
```
import matplotlib.pyplot as plt
import numpy as np
import torchvision

# Function to display a row of images with their predictions and truths
def show_images_predictions(images, labels, predicted, num_images=7):
    # Select a random subset of images
    indices = np.random.choice(range(len(images)), num_images, replace=False)
    selected_images = images[indices]
    selected_labels = labels[indices]
    selected_predictions = predicted[indices]


    resized_images = torch.nn.functional.interpolate(selected_images,␣
↪scale_factor=0.5)

    # Display images in a row
    img_grid = torchvision.utils.make_grid(resized_images, nrow=num_images)
    npimg = img_grid.numpy()
    plt.figure(figsize=(17, 2))  # Adjust figure size to accommodate the row of␣
↪images
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.axis('off')
    plt.show()

    # Print predicted and expected labels for each selected image
    for i in range(num_images):
        print(f'Image {i+1}: Predicted: "{get_class_name(selected_predictions[i].
↪item())}", Expected: "{get_class_name(selected_labels[i].item())}"')

# Fetch a single batch from the validation loader
dataiter = iter(val_loader)
images, labels = next(dataiter)

# Transfer to device, compute outputs
images, labels = images.to(device), labels.to(device)
outputs = model(images)

# Get the index of the highest score for each image
_, predicted = torch.max(outputs, 1)

# Display images and their labels
show_images_predictions(images.cpu(), labels.cpu(), predicted.cpu(),␣
↪num_images=7)  # Adjust num_images as needed
```

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



```
Image 1: Predicted: "airplanes", Expected: "airplanes"
Image 2: Predicted: "airplanes", Expected: "airplanes"
Image 3: Predicted: "airplanes", Expected: "airplanes"
Image 4: Predicted: "airplanes", Expected: "airplanes"
Image 5: Predicted: "accordion", Expected: "accordion"
Image 6: Predicted: "Leopards", Expected: "cougar_body"
Image 7: Predicted: "accordion", Expected: "accordion"
```

[49]:
```
torch.save(ResNet18, 'ResNet18-73%validation_accuracy.pth')
```

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