Mission1

October 31, 2024

[ ]:
```
from google.colab import drive
import os, sys

#
drive.mount('/content/drive')

#
%cd /content/drive/MyDrive/

#
!mkdir -p Mission1
```

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

1 Mission 1:

1.1 Mission 1-1

1. "{W/T}{ *ID*}{ }{ }{ }.jpg" . 2. & . 3. Train Validation
.

[ ]:
```
import os
import pandas as pd
from IPython.display import display, display_html

#    (          )
training_image_list = os.listdir('dataset/origin_dataset/training_image')
validation_image_list = os.listdir('dataset/origin_dataset/validation_image')

# train  validation
print(f"train image: {len(training_image_list)}, validation image:␣
 ↪{len(validation_image_list)}")

#     ->     Pandas
def path2data(image_list):
    data = []
    for i in range(len(image_list)):
        meta_data = image_list[i].split('_')

        row = {
            'file_name': image_list[i][:-4],    # ".jpg"
            'wt': meta_data[0],
            'image_id': meta_data[1],
            'time': meta_data[2],
            'style': meta_data[3],
            'gender': meta_data[4][0]
        }
        data.append(row)
    return pd.DataFrame(data)

#
training_df = path2data(training_image_list)
validation_df = path2data(validation_image_list)

#       HTML
def display_left(*args):
    html_str = ''
    for df in args:
        html_str += f'<div style="margin-right:30px;">{df.to_html()}</div>'
    display_html(f'<div style="display: flex;">{html_str}</div>', raw=True)

#
display_left(training_df.head(), validation_df.head())

#
training_df.to_csv('Mission1/training_df.csv', index=False)
validation_df.to_csv('Mission1/validation_df.csv', index=False)
```

```
train image: 4070, validation image: 951
```

[ ]:
```
#
training_count_data = training_df[['gender', 'style', 'image_id']].
 ↪groupby(['gender', 'style']).count()
validation_count_data = validation_df[['gender', 'style', 'image_id']].
 ↪groupby(['gender', 'style']).count()

#
training_count_data.rename(columns={'image_id': 'training count'}, inplace=True)
validation_count_data.rename(columns={'image_id': 'validation count'},␣
 ↪inplace=True)

#
display_left(training_count_data, validation_count_data)
```

```
#
training_count_data.to_csv('Mission1/training_count_data.csv')
validation_count_data.to_csv('Mission1/validation_count_data.csv')
```

1.1.1

(1)

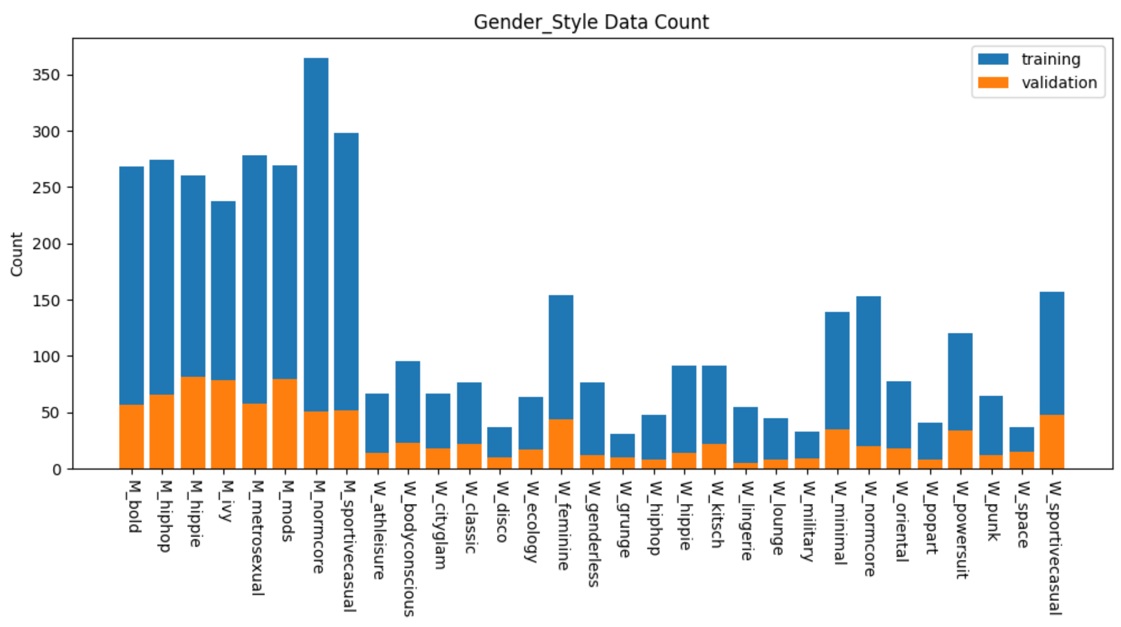
```
[ ]: import matplotlib.pyplot as plt

     # Group
     training_count_data_re = training_count_data.reset_index()
     validation_count_data_re = validation_count_data.reset_index()

     #           Gender  Style
     training_count_data_re['name'] = training_count_data_re['gender'] + '_' +␣
      ↪training_count_data_re['style']
     validation_count_data_re['name'] = validation_count_data_re['gender'] + '_' +␣
      ↪validation_count_data_re['style']

     #
     plt.figure(figsize=(12, 5))
     plt.title('Gender_Style Data Count')
     plt.ylabel('Count')
     plt.xticks(rotation=270)
     plt.bar(training_count_data_re['name'], training_count_data_re['training␣
      ↪count'], label="training")
     plt.bar(validation_count_data_re['name'], validation_count_data_re['validation␣
      ↪count'], label="validation")

     plt.legend()
     plt.savefig('Mission1/gender_style_data_count.png', bbox_inches='tight')    #␣
      ↪
     plt.show()
```



(2)

```
[ ]: import matplotlib.pyplot as plt

     #
     training_df_tt = training_df.copy()
     validation_df_tt = validation_df.copy()

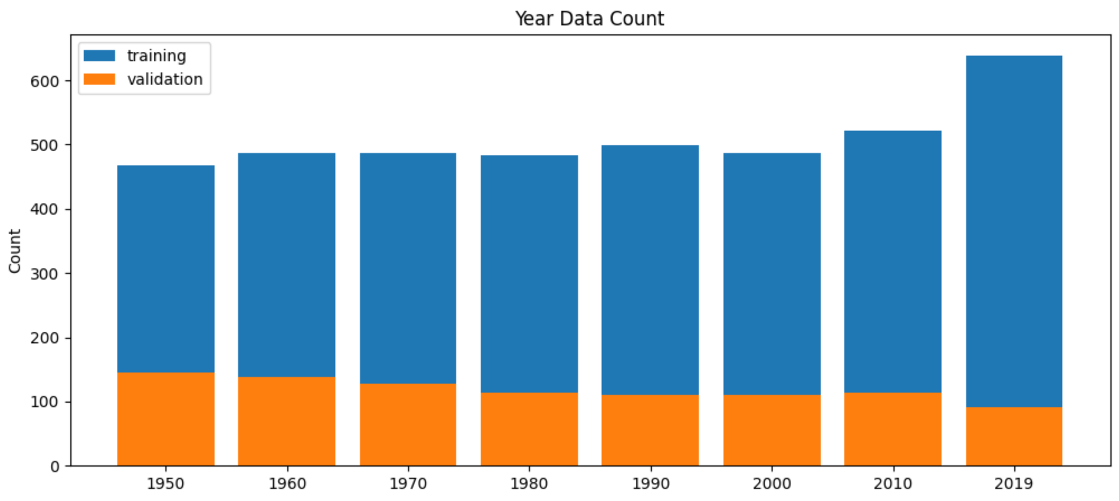
     #        00 -> 2000, 80 -> 1980
     def time2year(time):
         g20 = ['00', '10', '19']
         if time in g20:
             return '20' + time
         else:
             return '19' + time

     training_df_tt['time'] = training_df_tt['time'].apply(time2year)
     validation_df_tt['time'] = validation_df_tt['time'].apply(time2year)

     #
     training_by_year = training_df_tt.groupby('time').count()
     validation_by_year = validation_df_tt.groupby('time').count()

     #
     plt.figure(figsize=(12, 5))
     plt.title('Year Data Count')
     plt.ylabel('Count')
     plt.bar(training_by_year.index, training_by_year['image_id'], label="training")
     plt.bar(validation_by_year.index, validation_by_year['image_id'],␣
       ↪label="validation")

     plt.legend()
     plt.savefig('Mission1/year_data_count.png', bbox_inches='tight')    #
     plt.show()
```



(3) ID

- ID ,

[ ]:
```
import matplotlib.pyplot as plt

#   image_id
training_duplicates = training_df[training_df.duplicated(['image_id'],␣
  ↪keep=False)]
validation_duplicates = validation_df[validation_df.duplicated(['image_id'],␣
  ↪keep=False)]

#
training_duplicates.sort_values(by=['image_id'])
validation_duplicates.sort_values(by=['image_id'])

#
display_left(training_duplicates, validation_duplicates)
```

1.2 Mission 1-2

1. “ResNet18 & . 2. parameters , pretrained weights . 3. .

[ ]:
```
#       import
import os
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models
import random
import numpy as np

#
def set_random_seed(seed_value=42):
    # Python
    random.seed(seed_value)
    # NumPy
    np.random.seed(seed_value)
    # PyTorch       (CPU)
    torch.manual_seed(seed_value)
    # PyTorch       (GPU)
    torch.cuda.manual_seed(seed_value)
    torch.cuda.manual_seed_all(seed_value)


    # CuDNN
    torch.backends.cudnn.deterministic = True
    torch.backends.cudnn.benchmark = False

set_random_seed()
```

1.2.1 1.

1.   pandas
2. JSON   .

[ ]:
```
################################################################################
# Preprocessing Metadata
################################################################################
import json
import pandas as pd
from IPython.display import display, display_html

#
training_image_list = os.listdir('dataset/origin_dataset/training_image')
validation_image_list = os.listdir('dataset/origin_dataset/validation_image')

#     ->     Pandas
def path2data(image_list):
    data = []
    for i in range(len(image_list)):
        meta_data = image_list[i].split('_')

        wt = meta_data[0]
        image_id = meta_data[1]
        time = meta_data[2]
        style = meta_data[3]
        gender = meta_data[4][0]

        row = {
            'wt': wt,
            'image_id': image_id,
            'time': time,
            'style': style,
            'gender': gender,
            'image_name': image_list[i]
        }
        data.append(row)
    return pd.DataFrame(data)

#
training_df = path2data(training_image_list)
validation_df = path2data(validation_image_list)

#
training_df['label_name'] = training_df['gender'] + '_' + training_df['style']
validation_df['label_name'] = validation_df['gender'] + '_' +␣
 ↪validation_df['style']

#       HTML
def display_left(*args):
    html_str = ''
    for df in args:
        html_str += f'<div style="margin-right:30px;">{df.to_html()}</div>'
    display_html(f'<div style="display: flex;">{html_str}</div>', raw=True)


#
label_map = {}
for idx, label in enumerate(training_df['label_name'].unique()):
    label_map[label] = idx
    label_map[idx] = label


#
training_df['label'] = training_df['label_name'].map(label_map)
```

```
validation_df['label'] = validation_df['label_name'].map(label_map)

#
display_left(training_df.head(), validation_df.head())
print(len(training_df), len(validation_df))

#
training_df.to_csv('dataset/training_image_labels.csv', index=False)
validation_df.to_csv('dataset/validation_image_labels.csv', index=False)

#
with open('dataset/label_map.json', 'w') as f:
    json.dump(label_map, f)

#
print(f"{label_map[0]}, {label_map['W_minimal']}")
```

```
4070 951
W_minimal, 0
```

1.2.2 2.

1. ReSize .
2. Colab Google Drive I/O , Multi Thread .
3. I/O Tensor .

[ ]:
```
################################################################################
# Preprocessing File
################################################################################

import os
import torch
from torchvision import transforms
from tqdm.notebook import tqdm
from PIL import Image
import pandas as pd
from concurrent.futures import ThreadPoolExecutor

#
def process_single_image(args):
    image_name, label, image_dir, transform = args
    image_path = os.path.join(image_dir, image_name)
    try:
        #
        image = Image.open(image_path).convert('RGB')
        #
        image = transform(image)
        return image, label
    except Exception as e:
        print(f"Error processing {image_name}: {e}")
        return None


#
def process_images_parallel(metadata_df, image_dir, transform, cpu):
    inputs = [(row['image_name'], row['label'], image_dir, transform) for idx,␣
 ↪row in metadata_df.iterrows()]
    images = []
    labels = []

    # Thread Pool
    with ThreadPoolExecutor(max_workers=min(cpu, os.cpu_count())) as executor:
        # executer
        results = list(tqdm(executor.map(process_single_image, inputs),␣
 ↪total=len(inputs)))

    for result in results:
        if result is not None:
            image, label = result
            images.append(image)
            labels.append(label)

    #
    if not images:
        raise ValueError("No images were processed successfully.")

    images = torch.stack(images)
    labels = torch.tensor(labels, dtype=torch.long)
    return images, labels


#
def preprocess_image_to_tensor_pipeline(train_image_dir, val_image_dir,␣
 ↪tensor_dir, train_transform, test_transform, cpu=8):
    #
    os.makedirs(tensor_dir, exist_ok=True)

    #
    training_metadata_df = pd.read_csv('dataset/training_image_labels.csv')
    validation_metadata_df = pd.read_csv('dataset/validation_image_labels.csv')

    #
    print("Train Data Preprocessing")
    train_images, train_labels = process_images_parallel(training_metadata_df,␣
 ↪train_image_dir, train_transform, cpu=cpu)
```

```
    torch.save((train_images, train_labels), os.path.join(tensor_dir, 'train.
↪pt'))

    #
    print("Validation Data Preprocessing")
    val_images, val_labels = process_images_parallel(validation_metadata_df,␣
↪val_image_dir, test_transform, cpu=cpu)
    torch.save((val_images, val_labels), os.path.join(tensor_dir, 'val.pt'))

    print("Preprocessing Complete")
```

[ ]:
```
#        (    L4 GPU         . 12 )
os.cpu_count()
```

[ ]: 12

[ ]:
```
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor()
])

!mkdir -p dataset/tensor

#             (L4                 8 )
preprocess_image_to_tensor_pipeline(
    #
    train_image_dir = 'dataset/origin_dataset/training_image',
    val_image_dir = 'dataset/origin_dataset/validation_image',
    #
    tensor_dir = 'dataset/tensor/resize_tensor',
    #
    train_transform = transform,
    test_transform = transform,
    #       (                    .)
    cpu=8
)
```

```
Train Data Preprocessing

  0%|          | 0/4070 [00:00<?, ?it/s]

Validation Data Preprocessing

  0%|          | 0/951 [00:00<?, ?it/s]

Preprocessing Complete
```

1.2.3 3.

1. epoch .

```
[ ]: # GPU
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)
```

```
cuda:0
```

```
[ ]: ################################################################################
# Data Load
################################################################################

from torch.utils.data import DataLoader
from torchvision import datasets, transforms, models

#
class CustomDataset(torch.utils.data.Dataset):
    def __init__(self, images, labels, transform=None):
        self.images = images
        self.labels = labels
        self.transform = transform

    def __getitem__(self, index):
        image = self.images[index]
        label = self.labels[index]

        if self.transform:
            image = self.transform(image)

        return image, label

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

def data_loading(tensor_dir, batch_size, train_transform, val_transform):
    """
    tensor_dir:
    batch_size:
    train_transform:
    val_transform:
    """

    #
    train_images, train_labels = torch.load(os.path.join(tensor_dir, 'train.
  ↪pt'), weights_only=False)
    val_images, val_labels = torch.load(os.path.join(tensor_dir, 'val.pt'),␣
  ↪weights_only=False)

    #
    train_dataset = CustomDataset(train_images, train_labels,␣
↪transform=train_transform)
    val_dataset = CustomDataset(val_images, val_labels, transform=val_transform)

    #
    train_loader = DataLoader(train_dataset, batch_size=batch_size,␣
↪shuffle=True, pin_memory=True) # [3] Pin-Memory
    val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False,␣
↪pin_memory=True)

    #
    print(f"Train Dataset: {len(train_dataset)}, Val Dataset:␣
↪{len(val_dataset)}")

    return train_loader, val_loader
```

1.2.4 4.

1. .
2. **Overfitting, Local Minimum** .
3. .

[ ]:
```
################################################################################
# Training
################################################################################

import matplotlib.pyplot as plt
from tqdm.notebook import tqdm, trange


def training(experiment_name, save_dir, data_loader, optimizer, criterion,␣
↪scheduler=None):
    """
    experiment_name:
    save_dir:
    data_loader:
    optimizer:
    criterion:
    batch_size:
    scheduler:
    """

    train_loader, val_loader = data_loader



    os.makedirs(save_dir, exist_ok=True)
    os.makedirs(os.path.join(save_dir, experiment_name), exist_ok=True)

    train_loss_chart = []
    val_loss_chart = []

    train_acc_chart = []
    val_acc_chart = []

    for epoch in trange(NUM_EPOCHS):
        model.train()

        train_loss = 0
        train_correct = 0
        total = 0
        for images, labels in tqdm(train_loader, leave=False):
            images, labels = images.to(device), labels.to(device)
            images, labels = images.to(device, non_blocking=True), labels.
↪to(device, non_blocking=True) # [4]


            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            train_loss += loss.item()
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            train_correct += (predicted == labels).sum().item()

        train_loss /= len(train_loader)
        train_acc = 100 * train_correct / total

        train_loss_chart.append(train_loss)
        train_acc_chart.append(train_acc)

        print(f"Epoch [{epoch+1}/{NUM_EPOCHS}], Train Loss: {train_loss:.4f},␣
↪Train Acc: {train_acc:.2f}%")


        model.eval()
        val_loss = 0
        val_correct = 0
        total = 0
        with torch.no_grad():
            for images, labels in tqdm(val_loader, leave=False):
                images, labels = images.to(device), labels.to(device)

                outputs = model(images)
                loss = criterion(outputs, labels)
                val_loss += loss.item()

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

            val_loss /= len(val_loader)
            val_acc = 100 * val_correct / total

        # BestModel
        if epoch == 0 or val_acc > max(val_acc_chart):
            if experiment_name == 'best_acc_exp':
                torch.save(model.state_dict(), f'{save_dir}/{experiment_name}/
↪best_acc_model.pth')
            elif experiment_name == 'best_loss_exp':
                torch.save(model.state_dict(), f'{save_dir}/{experiment_name}/
↪best_loss_model.pth')
            else:
                torch.save(model.state_dict(), f'{save_dir}/{experiment_name}/
↪best_model.pth')

        val_loss_chart.append(val_loss)
        val_acc_chart.append(val_acc)

        print(f"Epoch [{epoch+1}/{NUM_EPOCHS}], Val Loss: {val_loss:.4f}, Val␣
↪Acc: {val_acc:.2f}%")

        #
        if scheduler is not None:
            scheduler.step()

        #
        if epoch+1 >= 20 and (epoch+1) % 5 == 0:
            torch.save(model.state_dict(), f'{save_dir}/{experiment_name}/
↪model_{epoch+1}.pth')
            print(f"Model saved at epoch -> {epoch+1}")

    #   loss, acc
    plt.figure(figsize=(10, 5))
    plt.subplot(1, 2, 1)
    plt.plot(train_loss_chart, label='Train Loss')
    plt.plot(val_loss_chart, label='Val Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.title('Training and Validation Loss')
    plt.grid(True)

    plt.subplot(1, 2, 2)
    plt.plot(train_acc_chart, label='Train Accuracy')
    plt.plot(val_acc_chart, label='Val Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.title('Training and Validation Accuracy')
    plt.grid(True)

    plt.tight_layout()

    #
    plt.savefig(f'{save_dir}/{experiment_name}/train_visualization.png')
    plt.show()

    #
    display(pd.DataFrame({
        'epoch': range(1, NUM_EPOCHS+1),
        'Train Acc': train_acc_chart,'Train Loss': train_loss_chart,
        'Val Acc': val_acc_chart, 'Val Loss': val_loss_chart
    }))
    #
    torch.save(model.state_dict(), f'{save_dir}/{experiment_name}/
↪model_final({epoch+1}).pth')
    print(f"Model saved at epoch {epoch+1}")
```

1.2.5 4.

1. , .
2. ACC .
3. 3-2 Loss .

1. Best Acc (Mission1-2) Best ACC

```
[ ]: #
LR = 0.001
BATCH_SIZE = 64
NUM_EPOCHS = 100
WEIGHT_DECAY = 5e-4


#    ,
EXP_NAME = 'best_acc_exp'
```

```
SAVE_DIR = "Mission1"

#
train_transform = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])
val_transform = transforms.Compose([
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])
data_loader = data_loading(
    tensor_dir='dataset/tensor/resize_tensor',
    batch_size=BATCH_SIZE,
    train_transform=train_transform,
    val_transform=val_transform
)

# ResNet18      (   X)
model = models.resnet18(weights=None, num_classes=31)
model = model.to(device)

#
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR, weight_decay=WEIGHT_DECAY)
scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=10, gamma=0.8)

#
training(
    experiment_name=EXP_NAME,
    save_dir=SAVE_DIR,
    data_loader=data_loader,
    optimizer=optimizer,
    criterion=criterion,
    scheduler=scheduler
)
```

```
Train Dataset: 4070, Val Dataset: 951

  0%|          | 0/100 [00:00<?, ?it/s]

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [1/100], Train Loss: 3.2918, Train Acc: 8.08%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [1/100], Val Loss: 3.2451, Val Acc: 8.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [2/100], Train Loss: 3.1859, Train Acc: 9.34%
```

```
  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [2/100], Val Loss: 3.1987, Val Acc: 8.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [3/100], Train Loss: 3.1537, Train Acc: 9.31%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [3/100], Val Loss: 3.2258, Val Acc: 7.57%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [4/100], Train Loss: 3.1275, Train Acc: 9.07%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [4/100], Val Loss: 3.1117, Val Acc: 8.94%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [5/100], Train Loss: 3.1097, Train Acc: 10.44%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [5/100], Val Loss: 3.1075, Val Acc: 10.30%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [6/100], Train Loss: 3.0818, Train Acc: 10.91%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [6/100], Val Loss: 3.1590, Val Acc: 8.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [7/100], Train Loss: 3.0633, Train Acc: 11.13%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [7/100], Val Loss: 3.2435, Val Acc: 8.73%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [8/100], Train Loss: 3.0566, Train Acc: 11.15%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [8/100], Val Loss: 3.0601, Val Acc: 10.83%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [9/100], Train Loss: 3.0382, Train Acc: 11.87%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [9/100], Val Loss: 3.0709, Val Acc: 9.04%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [10/100], Train Loss: 3.0268, Train Acc: 11.47%
```

```
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [10/100], Val Loss: 3.1901, Val Acc: 7.57%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [11/100], Train Loss: 2.9921, Train Acc: 12.83%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [11/100], Val Loss: 3.0055, Val Acc: 11.99%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [12/100], Train Loss: 2.9513, Train Acc: 13.69%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [12/100], Val Loss: 3.0223, Val Acc: 12.93%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [13/100], Train Loss: 2.9335, Train Acc: 14.08%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [13/100], Val Loss: 2.9870, Val Acc: 14.83%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [14/100], Train Loss: 2.8982, Train Acc: 14.99%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [14/100], Val Loss: 3.0593, Val Acc: 11.99%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [15/100], Train Loss: 2.8877, Train Acc: 15.33%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [15/100], Val Loss: 3.0125, Val Acc: 11.88%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [16/100], Train Loss: 2.8557, Train Acc: 14.79%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [16/100], Val Loss: 3.5437, Val Acc: 9.99%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [17/100], Train Loss: 2.8294, Train Acc: 15.95%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [17/100], Val Loss: 3.0565, Val Acc: 11.46%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [18/100], Train Loss: 2.7857, Train Acc: 16.93%
```

```
  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [18/100], Val Loss: 2.8335, Val Acc: 15.67%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [19/100], Train Loss: 2.7570, Train Acc: 17.71%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [19/100], Val Loss: 2.8939, Val Acc: 14.30%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [20/100], Train Loss: 2.7028, Train Acc: 18.33%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [20/100], Val Loss: 3.0122, Val Acc: 13.77%
Model saved at epoch -> 20

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [21/100], Train Loss: 2.6222, Train Acc: 20.54%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [21/100], Val Loss: 2.7618, Val Acc: 17.46%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [22/100], Train Loss: 2.5600, Train Acc: 21.72%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [22/100], Val Loss: 2.7890, Val Acc: 16.61%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [23/100], Train Loss: 2.5162, Train Acc: 23.24%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [23/100], Val Loss: 2.7798, Val Acc: 18.82%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [24/100], Train Loss: 2.4413, Train Acc: 24.69%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [24/100], Val Loss: 2.6720, Val Acc: 21.77%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [25/100], Train Loss: 2.3924, Train Acc: 26.58%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [25/100], Val Loss: 3.0593, Val Acc: 15.46%
Model saved at epoch -> 25

  0%|          | 0/64 [00:00<?, ?it/s]
```

```
Epoch [26/100], Train Loss: 2.2984, Train Acc: 29.12%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [26/100], Val Loss: 2.7446, Val Acc: 21.14%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [27/100], Train Loss: 2.1848, Train Acc: 32.46%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [27/100], Val Loss: 2.8954, Val Acc: 18.61%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [28/100], Train Loss: 2.0756, Train Acc: 36.63%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [28/100], Val Loss: 2.5430, Val Acc: 24.40%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [29/100], Train Loss: 1.9443, Train Acc: 38.62%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [29/100], Val Loss: 2.4288, Val Acc: 29.76%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [30/100], Train Loss: 1.7524, Train Acc: 45.87%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [30/100], Val Loss: 2.6128, Val Acc: 33.54%
Model saved at epoch -> 30

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [31/100], Train Loss: 1.4895, Train Acc: 56.09%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [31/100], Val Loss: 2.1838, Val Acc: 41.96%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [32/100], Train Loss: 1.1900, Train Acc: 65.65%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [32/100], Val Loss: 2.5570, Val Acc: 38.59%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [33/100], Train Loss: 1.0152, Train Acc: 70.34%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [33/100], Val Loss: 2.4625, Val Acc: 40.90%
```

```
  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [34/100], Train Loss: 0.8674, Train Acc: 75.36%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [34/100], Val Loss: 2.0145, Val Acc: 50.68%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [35/100], Train Loss: 0.6065, Train Acc: 84.28%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [35/100], Val Loss: 2.2470, Val Acc: 51.10%
Model saved at epoch -> 35

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [36/100], Train Loss: 0.4830, Train Acc: 87.49%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [36/100], Val Loss: 2.0714, Val Acc: 54.89%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [37/100], Train Loss: 0.3699, Train Acc: 91.99%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [37/100], Val Loss: 2.2142, Val Acc: 55.31%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [38/100], Train Loss: 0.3006, Train Acc: 93.22%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [38/100], Val Loss: 1.9557, Val Acc: 59.52%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [39/100], Train Loss: 0.2377, Train Acc: 95.33%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [39/100], Val Loss: 1.9628, Val Acc: 60.04%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [40/100], Train Loss: 0.1728, Train Acc: 96.90%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [40/100], Val Loss: 2.0490, Val Acc: 60.04%
Model saved at epoch -> 40

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [41/100], Train Loss: 0.1331, Train Acc: 98.11%

  0%|          | 0/15 [00:00<?, ?it/s]
```

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Epoch [41/100], Val Loss: 1.8955, Val Acc: 62.88%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [42/100], Train Loss: 0.0857, Train Acc: 98.94%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [42/100], Val Loss: 1.9432, Val Acc: 62.36%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [43/100], Train Loss: 0.0626, Train Acc: 99.29%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [43/100], Val Loss: 1.8554, Val Acc: 62.99%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [44/100], Train Loss: 0.0509, Train Acc: 99.29%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [44/100], Val Loss: 1.8924, Val Acc: 62.04%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [45/100], Train Loss: 0.0362, Train Acc: 99.63%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [45/100], Val Loss: 1.8690, Val Acc: 62.78%
Model saved at epoch -> 45

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [46/100], Train Loss: 0.0412, Train Acc: 99.43%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [46/100], Val Loss: 1.9843, Val Acc: 63.09%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [47/100], Train Loss: 0.0379, Train Acc: 99.46%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [47/100], Val Loss: 1.8964, Val Acc: 62.88%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [48/100], Train Loss: 0.0295, Train Acc: 99.66%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [48/100], Val Loss: 1.8491, Val Acc: 63.09%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [49/100], Train Loss: 0.0352, Train Acc: 99.43%
```

```
  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [49/100], Val Loss: 1.9199, Val Acc: 62.36%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [50/100], Train Loss: 0.0230, Train Acc: 99.73%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [50/100], Val Loss: 1.8550, Val Acc: 63.51%
Model saved at epoch -> 50

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [51/100], Train Loss: 0.0208, Train Acc: 99.73%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [51/100], Val Loss: 1.8992, Val Acc: 62.99%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [52/100], Train Loss: 0.0225, Train Acc: 99.68%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [52/100], Val Loss: 1.8359, Val Acc: 62.78%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [53/100], Train Loss: 0.0141, Train Acc: 99.85%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [53/100], Val Loss: 1.8487, Val Acc: 63.83%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [54/100], Train Loss: 0.0181, Train Acc: 99.73%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [54/100], Val Loss: 1.9157, Val Acc: 63.51%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [55/100], Train Loss: 0.0162, Train Acc: 99.75%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [55/100], Val Loss: 1.8973, Val Acc: 62.78%
Model saved at epoch -> 55

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [56/100], Train Loss: 0.0105, Train Acc: 99.88%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [56/100], Val Loss: 1.8523, Val Acc: 63.72%

  0%|          | 0/64 [00:00<?, ?it/s]
```

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Epoch [57/100], Train Loss: 0.0166, Train Acc: 99.83%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [57/100], Val Loss: 2.0611, Val Acc: 63.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [58/100], Train Loss: 0.0316, Train Acc: 99.58%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [58/100], Val Loss: 1.9757, Val Acc: 63.30%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [59/100], Train Loss: 0.0254, Train Acc: 99.73%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [59/100], Val Loss: 1.8608, Val Acc: 62.99%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [60/100], Train Loss: 0.0571, Train Acc: 99.12%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [60/100], Val Loss: 2.2762, Val Acc: 57.62%
Model saved at epoch -> 60

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [61/100], Train Loss: 0.2186, Train Acc: 95.18%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [61/100], Val Loss: 2.4833, Val Acc: 55.31%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [62/100], Train Loss: 0.2722, Train Acc: 93.00%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [62/100], Val Loss: 2.1811, Val Acc: 58.25%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [63/100], Train Loss: 0.2053, Train Acc: 95.14%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [63/100], Val Loss: 2.0399, Val Acc: 61.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [64/100], Train Loss: 0.1115, Train Acc: 97.84%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [64/100], Val Loss: 2.0098, Val Acc: 62.25%
```

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  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [65/100], Train Loss: 0.0646, Train Acc: 98.97%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [65/100], Val Loss: 1.9872, Val Acc: 62.04%
Model saved at epoch -> 65

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [66/100], Train Loss: 0.0411, Train Acc: 99.41%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [66/100], Val Loss: 1.9331, Val Acc: 63.72%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [67/100], Train Loss: 0.0244, Train Acc: 99.83%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [67/100], Val Loss: 1.8827, Val Acc: 63.20%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [68/100], Train Loss: 0.0257, Train Acc: 99.61%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [68/100], Val Loss: 1.9500, Val Acc: 62.36%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [69/100], Train Loss: 0.0157, Train Acc: 99.80%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [69/100], Val Loss: 1.8764, Val Acc: 63.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [70/100], Train Loss: 0.0109, Train Acc: 99.83%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [70/100], Val Loss: 1.9357, Val Acc: 63.20%
Model saved at epoch -> 70

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [71/100], Train Loss: 0.0137, Train Acc: 99.85%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [71/100], Val Loss: 1.8667, Val Acc: 63.41%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [72/100], Train Loss: 0.0092, Train Acc: 99.88%

  0%|          | 0/15 [00:00<?, ?it/s]
```

```
Epoch [72/100], Val Loss: 1.8557, Val Acc: 63.83%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [73/100], Train Loss: 0.0103, Train Acc: 99.83%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [73/100], Val Loss: 1.8857, Val Acc: 62.99%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [74/100], Train Loss: 0.0090, Train Acc: 99.78%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [74/100], Val Loss: 1.8600, Val Acc: 63.20%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [75/100], Train Loss: 0.0090, Train Acc: 99.83%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [75/100], Val Loss: 1.8760, Val Acc: 63.41%
Model saved at epoch -> 75

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [76/100], Train Loss: 0.0103, Train Acc: 99.80%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [76/100], Val Loss: 1.8436, Val Acc: 63.20%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [77/100], Train Loss: 0.0065, Train Acc: 99.90%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [77/100], Val Loss: 1.8139, Val Acc: 63.51%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [78/100], Train Loss: 0.0049, Train Acc: 99.95%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [78/100], Val Loss: 1.8206, Val Acc: 63.51%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [79/100], Train Loss: 0.0048, Train Acc: 99.95%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [79/100], Val Loss: 1.8322, Val Acc: 63.20%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [80/100], Train Loss: 0.0055, Train Acc: 99.93%
```

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  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [80/100], Val Loss: 1.7725, Val Acc: 63.41%
Model saved at epoch -> 80

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [81/100], Train Loss: 0.0067, Train Acc: 99.90%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [81/100], Val Loss: 1.8242, Val Acc: 63.41%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [82/100], Train Loss: 0.0072, Train Acc: 99.88%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [82/100], Val Loss: 1.7816, Val Acc: 63.41%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [83/100], Train Loss: 0.0047, Train Acc: 99.93%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [83/100], Val Loss: 1.7683, Val Acc: 63.41%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [84/100], Train Loss: 0.0048, Train Acc: 99.93%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [84/100], Val Loss: 1.7553, Val Acc: 63.72%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [85/100], Train Loss: 0.0052, Train Acc: 99.90%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [85/100], Val Loss: 1.7662, Val Acc: 63.41%
Model saved at epoch -> 85

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [86/100], Train Loss: 0.0077, Train Acc: 99.85%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [86/100], Val Loss: 1.7895, Val Acc: 63.72%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [87/100], Train Loss: 0.0064, Train Acc: 99.90%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [87/100], Val Loss: 1.7592, Val Acc: 63.20%

  0%|          | 0/64 [00:00<?, ?it/s]
```

```
Epoch [88/100], Train Loss: 0.0074, Train Acc: 99.90%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [88/100], Val Loss: 1.9057, Val Acc: 63.41%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [89/100], Train Loss: 0.0057, Train Acc: 99.98%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [89/100], Val Loss: 1.7421, Val Acc: 63.41%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [90/100], Train Loss: 0.0045, Train Acc: 99.95%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [90/100], Val Loss: 1.7699, Val Acc: 63.72%
Model saved at epoch -> 90

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [91/100], Train Loss: 0.0044, Train Acc: 99.98%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [91/100], Val Loss: 1.7647, Val Acc: 63.09%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [92/100], Train Loss: 0.0051, Train Acc: 99.98%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [92/100], Val Loss: 1.7200, Val Acc: 63.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [93/100], Train Loss: 0.0071, Train Acc: 99.93%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [93/100], Val Loss: 1.7834, Val Acc: 63.41%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [94/100], Train Loss: 0.0131, Train Acc: 99.85%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [94/100], Val Loss: 1.7928, Val Acc: 62.78%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [95/100], Train Loss: 0.0119, Train Acc: 99.93%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [95/100], Val Loss: 1.7267, Val Acc: 63.51%
Model saved at epoch -> 95
```

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  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [96/100], Train Loss: 0.0058, Train Acc: 99.93%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [96/100], Val Loss: 1.7158, Val Acc: 63.20%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [97/100], Train Loss: 0.0096, Train Acc: 99.88%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [97/100], Val Loss: 1.8301, Val Acc: 63.09%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [98/100], Train Loss: 0.0117, Train Acc: 99.90%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [98/100], Val Loss: 1.7184, Val Acc: 62.99%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [99/100], Train Loss: 0.0078, Train Acc: 99.90%

  0%|          | 0/15 [00:00<?, ?it/s]

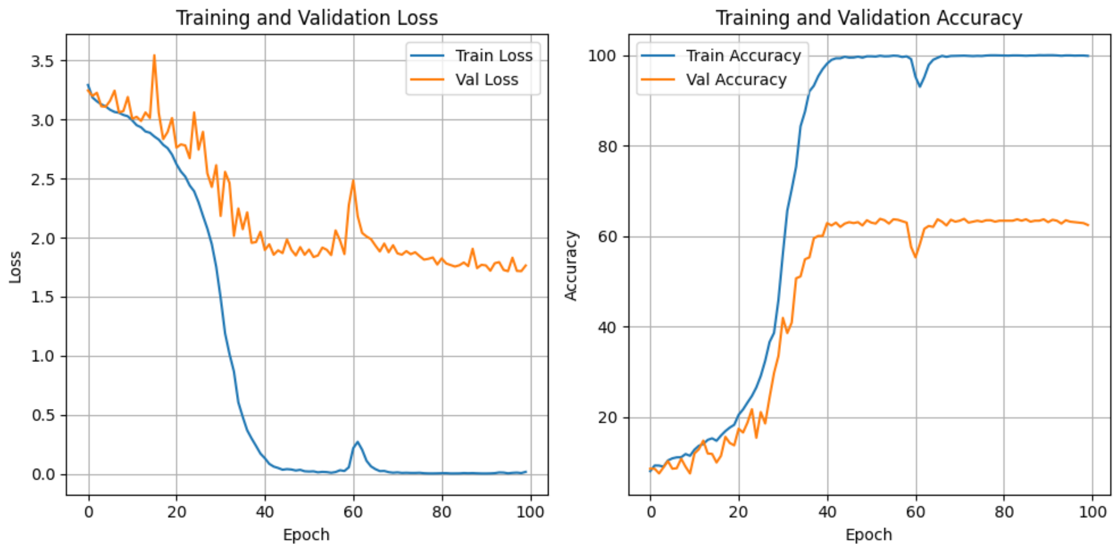
Epoch [99/100], Val Loss: 1.7163, Val Acc: 62.88%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [100/100], Train Loss: 0.0181, Train Acc: 99.83%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [100/100], Val Loss: 1.7643, Val Acc: 62.46%
Model saved at epoch -> 100
```



```
    epoch  Train Acc  Train Loss    Val Acc  Val Loss
0       1   8.083538    3.291836   8.622503  3.245087
1       2   9.336609    3.185947   8.622503  3.198747
2       3   9.312039    3.153689   7.570978  3.225753
3       4   9.066339    3.127509   8.937960  3.111717
4       5  10.442260    3.109712  10.304942  3.107517
..    …        …          …          …        …
95     96  99.926290    0.005755  63.196635  1.715781
96     97  99.877150    0.009593  63.091483  1.830147
97     98  99.901720    0.011737  62.986330  1.718449
98     99  99.901720    0.007828  62.881178  1.716350
99    100  99.828010    0.018127  62.460568  1.764270

[100 rows x 5 columns]

Model saved at epoch 100
```

2. Best Loss (Mission3-2) Mission3-2 .

```
[ ]: #
LR = 0.001
BATCH_SIZE = 64
NUM_EPOCHS = 50
WEIGHT_DECAY = 5e-4

#    ,
EXP_NAME = 'best_loss_exp'
SAVE_DIR = "Mission1"

#
train_transform = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])
val_transform = transforms.Compose([
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])
data_loader = data_loading(
    tensor_dir='dataset/tensor/resize_tensor',
    batch_size=BATCH_SIZE,
    train_transform=train_transform,
    val_transform=val_transform
)

# ResNet18     (   X)
```

```
model = models.resnet18(weights=None, num_classes=31)
model = model.to(device)

#
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=LR, weight_decay=WEIGHT_DECAY)
scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=20, gamma=0.1)

#
training(
    experiment_name=EXP_NAME,
    save_dir=SAVE_DIR,
    data_loader=data_loader,
    optimizer=optimizer,
    criterion=criterion,
    scheduler=scheduler
)
```

```
Train Dataset: 4070, Val Dataset: 951

  0%|          | 0/50 [00:00<?, ?it/s]

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [1/50], Train Loss: 3.2918, Train Acc: 8.08%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [1/50], Val Loss: 3.2451, Val Acc: 8.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [2/50], Train Loss: 3.1859, Train Acc: 9.34%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [2/50], Val Loss: 3.1987, Val Acc: 8.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [3/50], Train Loss: 3.1537, Train Acc: 9.31%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [3/50], Val Loss: 3.2258, Val Acc: 7.57%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [4/50], Train Loss: 3.1275, Train Acc: 9.07%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [4/50], Val Loss: 3.1117, Val Acc: 8.94%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [5/50], Train Loss: 3.1097, Train Acc: 10.44%
```

```
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [5/50], Val Loss: 3.1075, Val Acc: 10.30%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [6/50], Train Loss: 3.0818, Train Acc: 10.91%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [6/50], Val Loss: 3.1590, Val Acc: 8.62%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [7/50], Train Loss: 3.0633, Train Acc: 11.13%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [7/50], Val Loss: 3.2435, Val Acc: 8.73%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [8/50], Train Loss: 3.0566, Train Acc: 11.15%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [8/50], Val Loss: 3.0601, Val Acc: 10.83%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [9/50], Train Loss: 3.0382, Train Acc: 11.87%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [9/50], Val Loss: 3.0709, Val Acc: 9.04%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [10/50], Train Loss: 3.0268, Train Acc: 11.47%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [10/50], Val Loss: 3.1901, Val Acc: 7.57%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [11/50], Train Loss: 3.0122, Train Acc: 12.80%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [11/50], Val Loss: 3.0348, Val Acc: 11.25%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [12/50], Train Loss: 2.9758, Train Acc: 12.85%
  0%|          | 0/15 [00:00<?, ?it/s]
Epoch [12/50], Val Loss: 3.1681, Val Acc: 11.78%
  0%|          | 0/64 [00:00<?, ?it/s]
Epoch [13/50], Train Loss: 2.9698, Train Acc: 13.02%
```

```
  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [13/50], Val Loss: 3.1099, Val Acc: 9.57%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [14/50], Train Loss: 2.9270, Train Acc: 14.50%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [14/50], Val Loss: 3.2720, Val Acc: 8.62%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [15/50], Train Loss: 2.9132, Train Acc: 14.47%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [15/50], Val Loss: 2.9930, Val Acc: 12.41%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [16/50], Train Loss: 2.8835, Train Acc: 14.72%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [16/50], Val Loss: 3.4139, Val Acc: 11.46%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [17/50], Train Loss: 2.8584, Train Acc: 15.70%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [17/50], Val Loss: 3.1209, Val Acc: 11.78%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [18/50], Train Loss: 2.8288, Train Acc: 15.77%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [18/50], Val Loss: 2.9293, Val Acc: 14.09%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [19/50], Train Loss: 2.7936, Train Acc: 16.12%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [19/50], Val Loss: 2.8322, Val Acc: 16.82%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [20/50], Train Loss: 2.7467, Train Acc: 17.32%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [20/50], Val Loss: 3.2619, Val Acc: 12.72%
Model saved at epoch -> 20

  0%|          | 0/64 [00:00<?, ?it/s]
```

```
Epoch [21/50], Train Loss: 2.5913, Train Acc: 21.65%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [21/50], Val Loss: 2.6374, Val Acc: 21.98%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [22/50], Train Loss: 2.4718, Train Acc: 24.91%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [22/50], Val Loss: 2.5904, Val Acc: 23.66%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [23/50], Train Loss: 2.3967, Train Acc: 26.81%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [23/50], Val Loss: 2.5349, Val Acc: 24.71%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [24/50], Train Loss: 2.3303, Train Acc: 28.60%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [24/50], Val Loss: 2.5111, Val Acc: 24.50%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [25/50], Train Loss: 2.2680, Train Acc: 30.96%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [25/50], Val Loss: 2.4444, Val Acc: 28.50%
Model saved at epoch -> 25

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [26/50], Train Loss: 2.1860, Train Acc: 33.19%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [26/50], Val Loss: 2.4172, Val Acc: 27.87%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [27/50], Train Loss: 2.0888, Train Acc: 36.88%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [27/50], Val Loss: 2.3565, Val Acc: 30.39%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [28/50], Train Loss: 1.9911, Train Acc: 41.35%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [28/50], Val Loss: 2.2817, Val Acc: 35.23%
```

```
  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [29/50], Train Loss: 1.8681, Train Acc: 43.76%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [29/50], Val Loss: 2.3246, Val Acc: 33.23%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [30/50], Train Loss: 1.7188, Train Acc: 50.07%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [30/50], Val Loss: 2.2529, Val Acc: 37.43%
Model saved at epoch -> 30

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [31/50], Train Loss: 1.5857, Train Acc: 55.41%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [31/50], Val Loss: 2.1496, Val Acc: 41.54%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [32/50], Train Loss: 1.4051, Train Acc: 62.38%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [32/50], Val Loss: 2.1051, Val Acc: 45.43%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [33/50], Train Loss: 1.2533, Train Acc: 68.01%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [33/50], Val Loss: 1.9971, Val Acc: 45.74%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [34/50], Train Loss: 1.0661, Train Acc: 75.01%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [34/50], Val Loss: 1.9793, Val Acc: 50.89%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [35/50], Train Loss: 0.8798, Train Acc: 81.84%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [35/50], Val Loss: 1.9858, Val Acc: 51.52%
Model saved at epoch -> 35

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [36/50], Train Loss: 0.7236, Train Acc: 86.54%

  0%|          | 0/15 [00:00<?, ?it/s]
```

```
Epoch [36/50], Val Loss: 1.8308, Val Acc: 55.42%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [37/50], Train Loss: 0.5654, Train Acc: 91.28%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [37/50], Val Loss: 1.7918, Val Acc: 59.41%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [38/50], Train Loss: 0.4457, Train Acc: 94.08%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [38/50], Val Loss: 1.7235, Val Acc: 60.67%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [39/50], Train Loss: 0.3453, Train Acc: 96.68%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [39/50], Val Loss: 1.7110, Val Acc: 60.78%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [40/50], Train Loss: 0.2569, Train Acc: 97.81%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [40/50], Val Loss: 1.7076, Val Acc: 61.93%
Model saved at epoch -> 40

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [41/50], Train Loss: 0.1794, Train Acc: 98.89%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [41/50], Val Loss: 1.5368, Val Acc: 62.15%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [42/50], Train Loss: 0.1389, Train Acc: 99.29%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [42/50], Val Loss: 1.5244, Val Acc: 62.67%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [43/50], Train Loss: 0.1298, Train Acc: 99.43%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [43/50], Val Loss: 1.5173, Val Acc: 62.67%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [44/50], Train Loss: 0.1197, Train Acc: 99.53%
```

```
  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [44/50], Val Loss: 1.5095, Val Acc: 63.20%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [45/50], Train Loss: 0.1066, Train Acc: 99.63%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [45/50], Val Loss: 1.5105, Val Acc: 63.20%
Model saved at epoch -> 45

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [46/50], Train Loss: 0.1056, Train Acc: 99.71%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [46/50], Val Loss: 1.5112, Val Acc: 62.67%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [47/50], Train Loss: 0.1021, Train Acc: 99.61%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [47/50], Val Loss: 1.5080, Val Acc: 62.88%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [48/50], Train Loss: 0.0953, Train Acc: 99.68%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [48/50], Val Loss: 1.5056, Val Acc: 62.99%

  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [49/50], Train Loss: 0.0909, Train Acc: 99.75%

  0%|          | 0/15 [00:00<?, ?it/s]

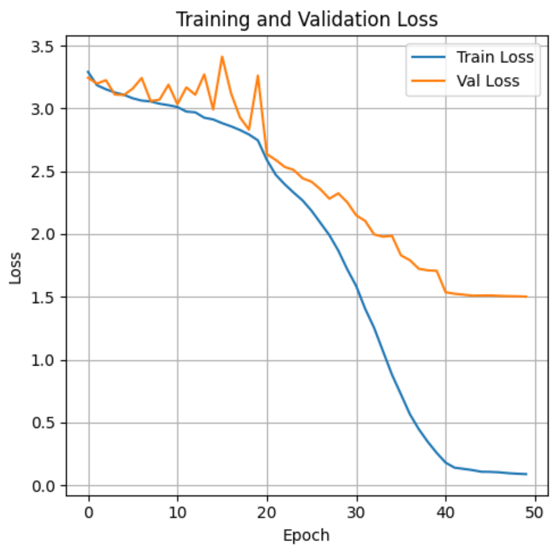
Epoch [49/50], Val Loss: 1.5046, Val Acc: 63.09%

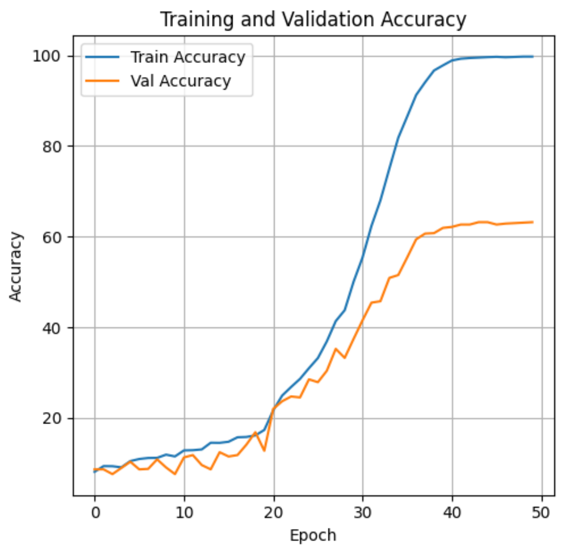
  0%|          | 0/64 [00:00<?, ?it/s]

Epoch [50/50], Train Loss: 0.0878, Train Acc: 99.75%

  0%|          | 0/15 [00:00<?, ?it/s]

Epoch [50/50], Val Loss: 1.5017, Val Acc: 63.20%
Model saved at epoch -> 50
```





```
    epoch  Train Acc  Train Loss    Val Acc  Val Loss
0       1   8.083538    3.291836   8.622503  3.245087
1       2   9.336609    3.185947   8.622503  3.198747
2       3   9.312039    3.153689   7.570978  3.225753
3       4   9.066339    3.127509   8.937960  3.111717
4       5  10.442260    3.109712  10.304942  3.107517
5       6  10.909091    3.081762   8.622503  3.158956
6       7  11.130221    3.063327   8.727655  3.243517
7       8  11.154791    3.056645  10.830705  3.060093
8       9  11.867322    3.038169   9.043113  3.070874
9      10  11.474201    3.026791   7.570978  3.190090
10     11  12.800983    3.012236  11.251314  3.034799
11     12  12.850123    2.975829  11.777077  3.168130
12     13  13.022113    2.969792   9.568875  3.109891
13     14  14.496314    2.927012   8.622503  3.271963
14     15  14.471744    2.913243  12.407992  2.992993
15     16  14.717445    2.883492  11.461619  3.413853
16     17  15.700246    2.858416  11.777077  3.120889
17     18  15.773956    2.828796  14.090431  2.929308
18     19  16.117936    2.793589  16.824395  2.832158
19     20  17.321867    2.746675  12.723449  3.261891
20     21  21.646192    2.591321  21.976866  2.637435
21     22  24.914005    2.471822  23.659306  2.590398
22     23  26.805897    2.396749  24.710831  2.534911
23     24  28.599509    2.330283  24.500526  2.511128
24     25  30.958231    2.267968  28.496320  2.444427
25     26  33.194103    2.186004  27.865405  2.417221
26     27  36.879607    2.088790  30.389064  2.356525
27     28  41.351351    1.991087  35.226078  2.281652
```

```
28     29  43.759214    1.868078  33.228181  2.324558
29     30  50.073710    1.718838  37.434280  2.252931
30     31  55.405405    1.585710  41.535226  2.149633
31     32  62.383292    1.405115  45.425868  2.105072
32     33  68.009828    1.253278  45.741325  1.997073
33     34  75.012285    1.066142  50.893796  1.979315
34     35  81.842752    0.879833  51.524711  1.985802
35     36  86.535627    0.723647  55.415352  1.830799
36     37  91.277641    0.565436  59.411146  1.791835
37     38  94.078624    0.445692  60.672976  1.723513
38     39  96.683047    0.345340  60.778128  1.711010
39     40  97.813268    0.256905  61.934805  1.707625
40     41  98.894349    0.179391  62.145110  1.536823
41     42  99.287469    0.138889  62.670873  1.524394
42     43  99.434889    0.129757  62.670873  1.517275
43     44  99.533170    0.119672  63.196635  1.509525
44     45  99.631450    0.106621  63.196635  1.510459
45     46  99.705160    0.105647  62.670873  1.511184
46     47  99.606880    0.102098  62.881178  1.507973
47     48  99.680590    0.095299  62.986330  1.505559
48     49  99.754300    0.090932  63.091483  1.504602
49     50  99.754300    0.087774  63.196635  1.501733

Model saved at epoch 50
```

1.2.6 5.

[ ]:
```python
# best acc model

SAVE_DIR = "Mission1"
EXP_NAME = "best_acc_exp"

best_path = f"./{SAVE_DIR}/{EXP_NAME}/best_model.pth"
model.load_state_dict(torch.load(best_path, weights_only=True))

def evaluate_model(model, data_loader):
    model.eval()
    val_loss = 0
    val_correct = 0
    total = 0
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for images, labels in tqdm(data_loader, leave=False):
            images, labels = images.to(device), labels.to(device)

            outputs = model(images)
            loss = criterion(outputs, labels)
            val_loss += loss.item()

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

            all_preds.extend(predicted.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

        val_loss /= len(data_loader)
        val_acc = 100 * val_correct / total

    print(f"Best Model Performance | Val Loss: {val_loss:.4f}, Val Acc:␣
 ↪{val_acc:.2f}%")

    return np.array(all_preds), np.array(all_labels), val_loss, val_acc

y_pred, y_true, val_loss, val_acc = evaluate_model(model, data_loader[1])
```

```
  0%|          | 0/15 [00:00<?, ?it/s]

Best Model Performance | Val Loss: 1.8487, Val Acc: 63.83%
```

1.2.7 6.

1. .

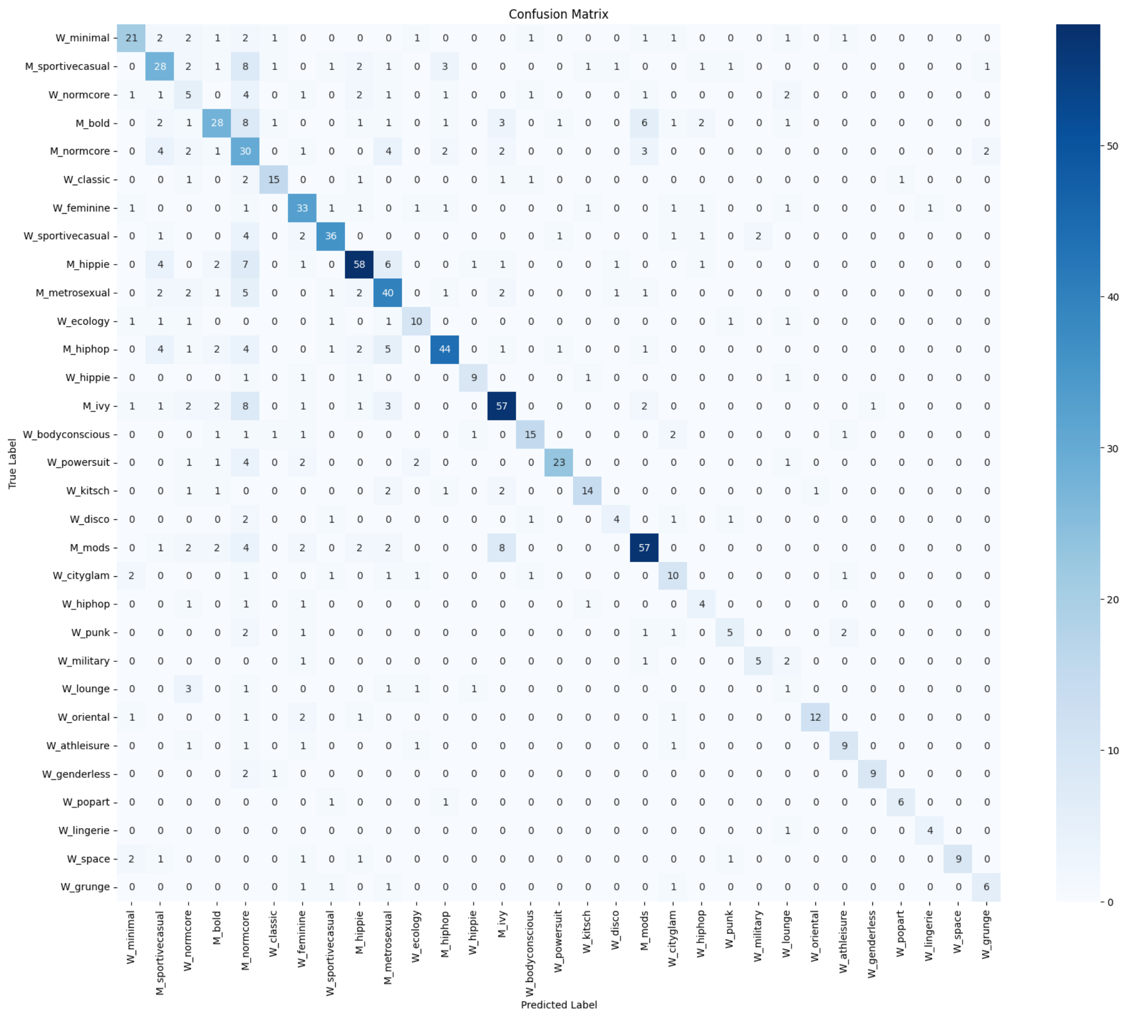
```
[ ]: #   class
import json
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report

#
def plot_confusion_matrix(y_true, y_pred, classes):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(20, 16))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=classes,␣
 ↪yticklabels=classes)
    plt.title('Confusion Matrix')
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.savefig(f'{SAVE_DIR}/{EXP_NAME}/pred_heatmap.png', bbox_inches='tight')
    plt.show()

#
def print_classification_report(y_true, y_pred, classes):
    report = classification_report(y_true, y_pred, target_names=classes,␣
  ↪digits=3)
    print(report)

#
label_map_ev = json.load(open('./dataset/label_map.json'))

#
class_names = [label_map_ev[str(i)] for i in range(31)]
plot_confusion_matrix(y_true, y_pred, class_names)
print_classification_report(y_true, y_pred, class_names)
```



```
                  precision    recall  f1-score   support

       W_minimal      0.700     0.600     0.646        35
M_sportivecasual      0.538     0.538     0.538        52
```

```
          W_normcore      0.179     0.250     0.208        20
              M_bold      0.651     0.491     0.560        57
          M_normcore      0.288     0.588     0.387        51
           W_classic      0.750     0.682     0.714        22
          W_feminine      0.623     0.750     0.680        44
    W_sportivecasual      0.800     0.750     0.774        48
            M_hippie      0.773     0.707     0.739        82
       M_metrosexual      0.580     0.690     0.630        58
           W_ecology      0.588     0.588     0.588        17
            M_hiphop      0.800     0.667     0.727        66
            W_hippie      0.750     0.643     0.692        14
               M_ivy      0.740     0.722     0.731        79
     W_bodyconscious      0.750     0.652     0.698        23
         W_powersuit      0.885     0.676     0.767        34
            W_kitsch      0.778     0.636     0.700        22
             W_disco      0.571     0.400     0.471        10
              M_mods      0.770     0.713     0.740        80
          W_cityglam      0.476     0.556     0.513        18
            W_hiphop      0.400     0.500     0.444         8
              W_punk      0.556     0.417     0.476        12
          W_military      0.714     0.556     0.625         9
            W_lounge      0.083     0.125     0.100         8
          W_oriental      0.923     0.667     0.774        18
        W_athleisure      0.643     0.643     0.643        14
        W_genderless      0.900     0.750     0.818        12
            W_popart      0.857     0.750     0.800         8
          W_lingerie      0.800     0.800     0.800         5
             W_space      1.000     0.600     0.750        15
            W_grunge      0.667     0.600     0.632        10

            accuracy                          0.638       951
           macro avg      0.662     0.603     0.625       951
        weighted avg      0.679     0.638     0.651       951
```

[ ]:
```
#          10
class_accuracy = classification_report(y_true, y_pred,␣
 ↪target_names=class_names, output_dict=True)
class_accuracy = {k: v['f1-score'] for k, v in class_accuracy.items() if k in␣
 ↪class_names}
worst_classes = sorted(class_accuracy.items(), key=lambda x: x[1])

print("Worst performing classes:")
for i, (cls, score) in enumerate(worst_classes):
    print(f"{cls}: {score:.3f}")
    if i == 9:
        print("==================================================")
```

```
Worst performing classes:
W_lounge: 0.100
W_normcore: 0.208
M_normcore: 0.387
W_hiphop: 0.444
W_disco: 0.471
W_punk: 0.476
W_cityglam: 0.513
M_sportivecasual: 0.538
M_bold: 0.560
W_ecology: 0.588
==================================================
W_military: 0.625
M_metrosexual: 0.630
W_grunge: 0.632
W_athleisure: 0.643
W_minimal: 0.646
W_feminine: 0.680
W_hippie: 0.692
W_bodyconscious: 0.698
W_kitsch: 0.700
W_classic: 0.714
M_hiphop: 0.727
M_ivy: 0.731
M_hippie: 0.739
M_mods: 0.740
W_space: 0.750
W_powersuit: 0.767
W_sportivecasual: 0.774
W_oriental: 0.774
W_popart: 0.800
W_lingerie: 0.800
W_genderless: 0.818
```