Imports

```
# standard imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import torch
from torch import nn
import torch.nn.functional as F
from torch.utils.data import Subset, DataLoader, Dataset
import torchvision
from torchvision.io import read_image
from torchvision import datasets as torchV_datasets
from torchvision import transforms, utils
from torchvision.utils import make_grid
from torchvision.models import resnet50, ResNet50_Weights
from torch import optim
from tqdm.auto import tqdm

# sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# others
import os
import shutil
from distutils.dir_util import copy_tree
import glob as glob
import random
import collections
import time

# --- Setup ---
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

```
print(f"Using device: {device}")

# seeding
random.seed(42)
np.random.seed(42)
torch.manual_seed(42)
if torch.cuda.is_available():
    torch.cuda.manual_seed_all(42)
```

```
Using device: cuda
```

```
from google.colab import drive
drive.mount('/content/drive')
# for dataset files
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive",
```

```
from matplotlib import pyplot as plt

def plot_training_curves(train_losses, val_accuracies):
    """Plot training loss and validation accuracy curves."""
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))

    ax1.plot(train_losses)
    ax1.set_title('Training Loss')
    ax1.set_xlabel('Epoch')
    ax1.set_ylabel('Loss')
    ax1.grid(True)

    ax2.plot(val_accuracies)
    ax2.set_title('Validation Accuracy')
    ax2.set_xlabel('Epoch')
    ax2.set_ylabel('Accuracy (0.0 to 1.0)')
    ax2.grid(True)

    plt.tight_layout()
    plt.show()
```

Utility Class

This class will move anime image folders from the dataset called anime-images-dataset to local colab directory

```
class UtilityWorker():
    """
    Utility class for selecting anime datasets.

    Parameters:
        num_anime (int): Number of anime to include (used only for random selection).
        anime_list (list, optional): Specific list of anime names to include.
        seed (int): Random seed for reproducibility (only used for random selection).

    Notes:
        - If `anime_list` is provided, it overrides random selection.
        - Chosen anime are copied to the local working directory.
    """
    def __init__(self, num_anime=None, anime_list=None, seed=42):
        self.ANIME_IMAGES = "/content/drive/MyDrive/372 final project/datasets/anime_images"
        self.INPUT = "/content/subset_data"

        self._cleanup_subset_data()

        all_anime = os.listdir(self.ANIME_IMAGES)

        if anime_list is not None:
            # Validate provided anime list
            missing = [a for a in anime_list if a not in all_anime]
            if missing:
                raise ValueError(f"The following anime are not found in dataset: {missing}")
            selected_anime = anime_list
        else:
            # Fallback to random selection
            if num_anime is None:
                raise ValueError("Either 'anime_list' or 'num_anime' must be provided.")
```

```
            random.seed(seed)
            selected_anime = random.sample(all_anime, k=num_anime)

        print(f"The anime chosen are:\n{selected_anime}")

        # Copy chosen anime to local folder
        self.copy_folder_helper(selected_anime)

        print(f"These anime can be found within folders of their own name in: {self.INPUT}")

    def _cleanup_subset_data(self):
        """Helper function to clean up the subset_data directory."""
        if os.path.exists(self.INPUT):
            print(f"Cleaning up existing data in: {self.INPUT}")
            shutil.rmtree(self.INPUT)
        os.makedirs(self.INPUT, exist_ok=True)

    def copy_folder_helper(self, animelist):
        """Helper function that does the actual copying."""
        for anime in animelist:
            src = os.path.join(self.ANIME_IMAGES, anime)
            dest = os.path.join(self.INPUT, anime)
            os.makedirs(dest, exist_ok=True) # Ensure destination subdirectory exists
            copy_tree(src, dest)
```

```
my_anime_list = [
    "A Silent Voice",
    "Attack on Titan",
    "Death Parade",
    "Haikyu!!",
    "Hunter x Hunter",
    "ReLife",
    "Steins Gate",
    "Violet Evergarden",
    "Yona of the Dawn",
    "Your Lie in April"
]
```

```
#utility = UtilityWorker(anime_list=my_anime_list)
utility = UtilityWorker(num_anime=30)
```

```
Cleaning up existing data in: /content/subset_data
The anime chosen are:
['Nichijou', 'Angel Beats!', 'A Place Further Than The Universe', 'Ping Pong the Animation', 'Death Parade',
These anime can be found within folders of their own name in: /content/subset_data
```

Data Class

```
class Data():
    def __init__(self):
        self.INPUT = "/content/subset_data"
        self.separator = ""

    def get_full_dataset(self, transform=None):
        """
        Loads the dataset with a specified transform.
        If transform is None, uses basic ToTensor for splitting.
        """
        if transform is None:
            transform = transforms.Compose([transforms.ToTensor()]) # Basic transform for splitting

        self.full_dataset = torchV_datasets.ImageFolder(self.INPUT, transform=transform)
        print(f"Full dataset details:")
        print(self.full_dataset)
        print(f"Classes: {self.full_dataset.classes}")
        print(self.separator)
        return self.full_dataset

    def get_train_val_test_splits(self, dataset, val_split=0.2, test_split=0.2):
        """
        Splits the dataset into train, validation, and test sets.
        Uses stratification to ensure class distribution is maintained.
        """
        dataset_size = len(dataset)
        indices = list(range(dataset_size))
```

```
        indices = list(range(dataset_size))
        try:
            targets = dataset.targets
        except AttributeError:
            print("Warning: Could not find .targets attribute. Falling back to slow label extraction.")
            targets = [label for _, label in dataset]

        # Split 1: Create train_val and test
        train_val_idx, test_idx = train_test_split(
            indices,
            test_size=test_split,
            stratify=targets,
            random_state=42
        )

        # Get targets for the remaining train_val set
        train_val_targets = [targets[i] for i in train_val_idx]
        val_split_adjusted = val_split / (1.0 - test_split)

        # Split 2: Create train and val from train_val
        train_idx, val_idx = train_test_split(
            train_val_idx,
            test_size=val_split_adjusted,
            stratify=train_val_targets,
            random_state=42
        )

        print(f"Full dataset size: {dataset_size}")
        print(f"Train indices: {len(train_idx)}")
        print(f"Validation indices: {len(val_idx)}")
        print(f"Test indices: {len(test_idx)}")
        print(self.separator)

        # Return *indices* now
        return train_idx, val_idx, test_idx


    def count_labels_in_dataset(self, dataset, indices, dataset_name="optional"):
        """Counts labels given a dataset and a list of indices."""
```

```
        Counts labels given a dataset and a list of indices.
    if dataset_name != "optional":
         print(f"Counting labels in {dataset_name} dataset....")

    # Get labels from the original dataset using indices
    labels = [dataset.targets[i] for i in indices]

    print(f"Label counts are:\n{collections.Counter(labels)}")
    print(f"Number of classes: {len(collections.Counter(labels))}")
    print(self.separator)
```

```
# --- Data Loading and Splitting ---
data_obj = Data()

# 1. Load dataset *once* with basic transform just to get targets/indices
full_dataset_for_splitting = data_obj.get_full_dataset(transform=None)

# 2. Get the indices for train, val, and test
train_idx, val_idx, test_idx = data_obj.get_train_val_test_splits(
    full_dataset_for_splitting, val_split=0.15, test_split=0.15
)

# 3. Count labels
data_obj.count_labels_in_dataset(full_dataset_for_splitting, train_idx, "train")
data_obj.count_labels_in_dataset(full_dataset_for_splitting, val_idx, "validation")
data_obj.count_labels_in_dataset(full_dataset_for_splitting, test_idx, "test")
```

```
Full dataset details:
Dataset ImageFolder
    Number of datapoints: 11097
    Root location: /content/subset_data
    StandardTransform
Transform: Compose(
               ToTensor()
           )
Classes: ['A Place Further Than The Universe', 'A Silent Voice', 'Angel Beats!', 'Attack on Titan', 'Bakemon

Full dataset size: 11097
Train indices: 7767
```

```
Validation indices: 1665
Test indices: 1665

Counting labels in train dataset....
Label counts are:
Counter({21: 266, 18: 266, 13: 266, 12: 266, 19: 266, 4: 266, 29: 266, 14: 266, 23: 266, 27: 266, 28: 266, 1
Number of classes: 30

Counting labels in validation dataset....
Label counts are:
Counter({4: 57, 3: 57, 16: 57, 12: 57, 19: 57, 20: 57, 7: 57, 2: 57, 13: 57, 5: 57, 6: 57, 15: 57, 11: 57, 2
Number of classes: 30

Counting labels in test dataset....
Label counts are:
Counter({10: 57, 11: 57, 5: 57, 18: 57, 27: 57, 16: 57, 3: 57, 28: 57, 20: 57, 7: 57, 2: 57, 17: 57, 4: 57,
Number of classes: 30
```

Dataloaders

Creating the train and test dataloaders in preparation for training.

```
# with augmentation

# Define the mean and std for normalization (must be consistent)
normalize_mean = [0.485, 0.456, 0.406]
normalize_std = [0.229, 0.224, 0.225]
data_root = "/content/subset_data" # From Data class

# 1. Define the training transforms with augmentations
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224, scale=(0.8, 1.0)), # Cropping (and resizing)
    transforms.RandomHorizontalFlip(),                  # Flipping
    transforms.RandomRotation(15),                      # Rotation
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1), # Color Jitter
    transforms.ToTensor(),
```

```
    transforms.Normalize(mean=normalize_mean, std=normalize_std)
])

# 2. Define the validation/test transforms (no augmentation)
#    We use Resize(256) -> CenterCrop(224) as is standard practice for evaluation.
val_test_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=normalize_mean, std=normalize_std)
])

# 3. Create *separate* ImageFolder datasets for each transform
#    We can reuse the indices (train_idx, val_idx, test_idx) because they
#    refer to the *files*, which are the same.

train_dataset_full = torchV_datasets.ImageFolder(
    data_root,
    transform=train_transforms
)

val_test_dataset_full = torchV_datasets.ImageFolder(
    data_root,
    transform=val_test_transforms
)

# 4. Create Subsets using the *correct* base dataset and the indices
train_dataset = Subset(train_dataset_full, train_idx)
val_dataset = Subset(val_test_dataset_full, val_idx)
test_dataset = Subset(val_test_dataset_full, test_idx)

print("Created separate transforms for train and val/test sets.")
print(f"Train transforms: {train_transforms}")
print(f"Val/Test transforms: {val_test_transforms}")

# --- Dataloaders ---
BATCH_SIZE = 32
train_dataloader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True)
```

```
val_dataloader = DataLoader(val_dataset, batch_size=BATCH_SIZE, shuffle=False)
test_dataloader = DataLoader(test_dataset, batch_size=BATCH_SIZE, shuffle=False)

x,y = next(iter(train_dataloader))
print(f"Train batch data shapes: {x.shape, y.shape}")
x,y = next(iter(val_dataloader))
print(f"Validation batch data shapes: {x.shape, y.shape}")
x,y = next(iter(test_dataloader))
print(f"Test batch data shapes: {x.shape, y.shape}")
```

```
Created separate transforms for train and val/test sets.
Train transforms: Compose(
    RandomResizedCrop(size=(224, 224), scale=(0.8, 1.0), ratio=(0.75, 1.3333), interpolation=bilinear, antia
    RandomHorizontalFlip(p=0.5)
    RandomRotation(degrees=[-15.0, 15.0], interpolation=nearest, expand=False, fill=0)
    ColorJitter(brightness=(0.8, 1.2), contrast=(0.8, 1.2), saturation=(0.8, 1.2), hue=(-0.1, 0.1))
    ToTensor()
    Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
)
Val/Test transforms: Compose(
    Resize(size=256, interpolation=bilinear, max_size=None, antialias=True)
    CenterCrop(size=(224, 224))
    ToTensor()
    Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
)
Train batch data shapes: (torch.Size([32, 3, 224, 224]), torch.Size([32]))
Validation batch data shapes: (torch.Size([32, 3, 224, 224]), torch.Size([32]))
Test batch data shapes: (torch.Size([32, 3, 224, 224]), torch.Size([32]))
```

Plotting Images

The following two functions were borrowed from this nice tutorial.

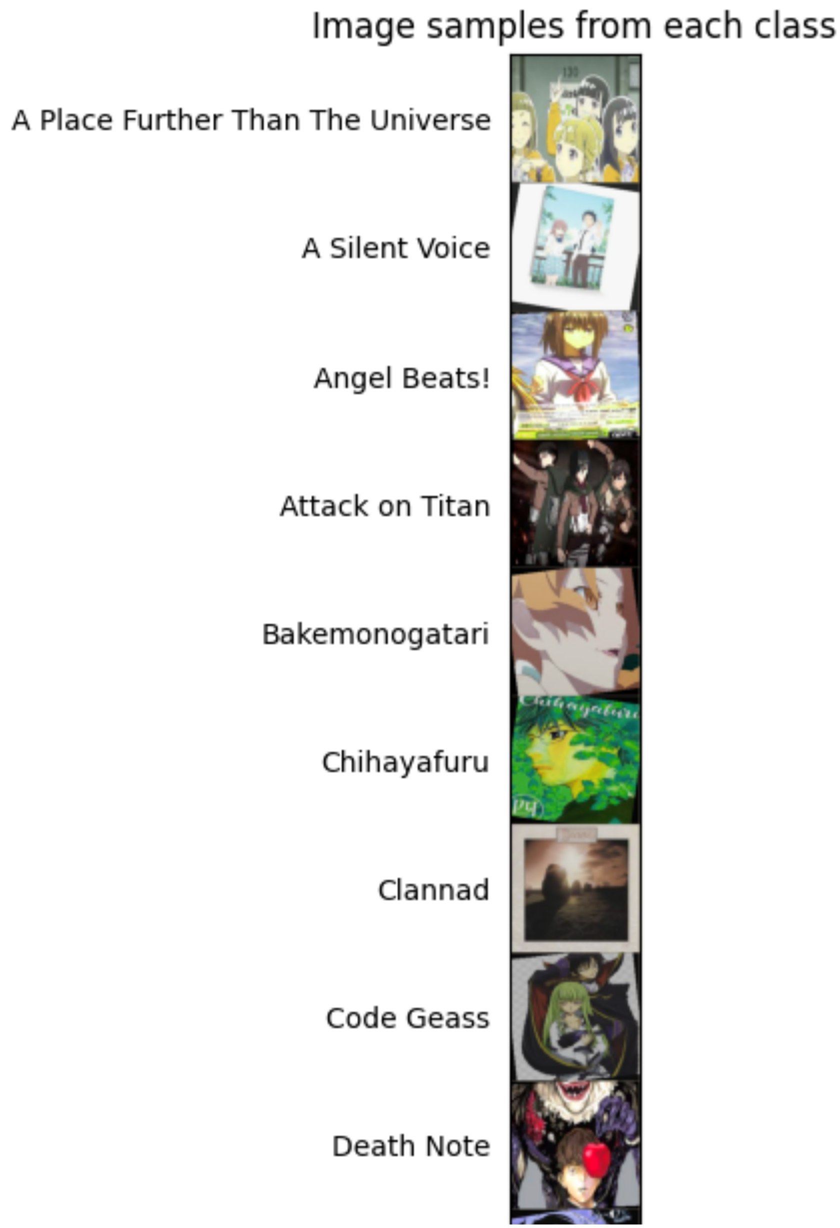
```
def plot_img(img, y=None, color=True, class_names=None, num_classes=None, images_per_row=None):
    # Define mean and std based on the unified_transforms used for normalization
    mean = torch.tensor([0.485, 0.456, 0.406]).to(img.device)
    std = torch.tensor([0.229, 0.224, 0.225]).to(img.device)
```

```
    # Inverse normalization
    img_unnormalized = img * std[:, None, None] + mean[:, None, None]

    # Clip values to [0, 1] after unnormalization
    img_unnormalized = torch.clamp(img_unnormalized, 0, 1)

    npimg = img_unnormalized.cpu().numpy()
    npimg_T = np.transpose(npimg, (1, 2, 0))

    ax = plt.gca() # Get current axes to plot on
    ax.imshow(npimg_T)
    ax.set_title('Image samples from each class')

    # Customizing axes based on class_names
    if class_names and num_classes and images_per_row:
        original_img_height = 224 # Assuming 224x224 from unified_transforms
        padding = 1 # From make_grid(padding=1)

        y_tick_positions = []
        for i in range(num_classes):
            # Calculate the center y-coordinate for each row of images
            pos = i * (original_img_height + padding) + padding + (original_img_height / 2)
            y_tick_positions.append(pos)

        ax.set_yticks(y_tick_positions)
        ax.set_yticklabels(class_names)
        ax.set_ylabel('Anime Class', rotation=0, ha='right', va='center', fontsize=12)
        ax.tick_params(axis='x', which='both', bottom=False, top=False, labelbottom=False) # Remove x-axis
        ax.tick_params(axis='y', which='both', left=False, right=False) # Remove y-axis ticks
        ax.set_xticks([]) # Ensure no x-axis labels
    else:
        ax.axis('on') # Default behavior if no class names are provided

def plot_tensor(tensor):
    # Assume data_obj is globally accessible and initialized from the Data class
    # to get class names.
    if 'data_obj' in globals() and hasattr(data_obj, 'full_dataset') and hasattr(data_obj.full_dataset, 'cl
```

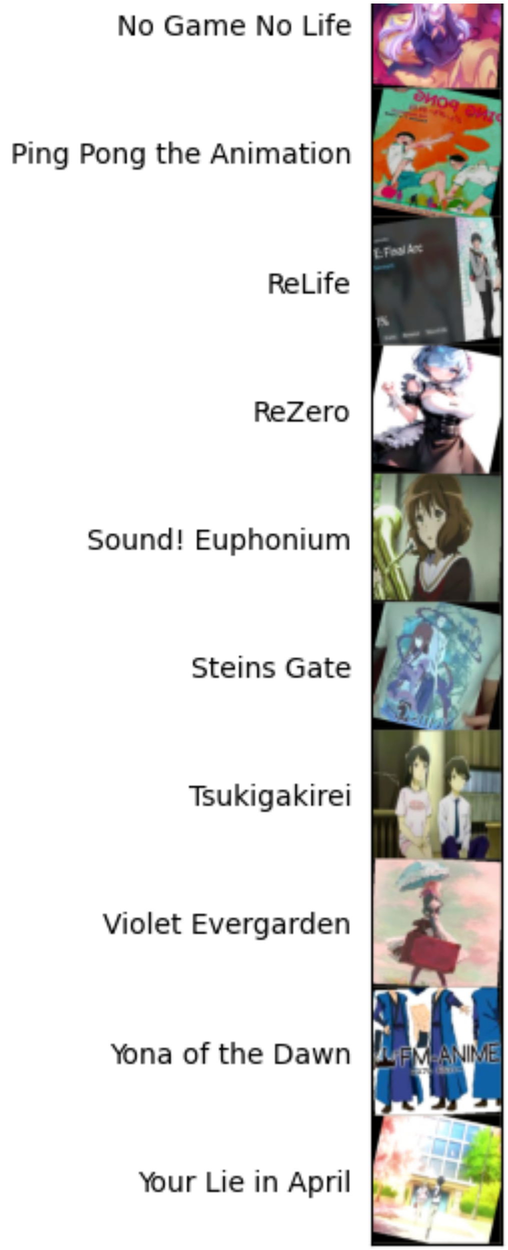
```
    all_class_names = data_obj.full_dataset.classes
else:
    all_class_names = None
    print("Warning: Could not retrieve class names from data_obj. Displaying default axes.")

num_images_to_show_per_class = 1 # Changed to 1
num_images_per_row = num_images_to_show_per_class # Fixed as nrow in utils.make_grid

plt.figure(figsize=(60,25))

images_by_class = collections.defaultdict(list)
classes_found = set() # Track classes for which an image has been found

for i in range(len(tensor)): # Iterate through the subset to collect images
    img, label = tensor[i]
    if label not in classes_found: # Only take one image per class
        images_by_class[label].append(img)
        classes_found.add(label)
    if len(classes_found) == len(all_class_names): # Optimization: stop if all classes found
        break

# Get sorted list of actual classes present in the tensor
actual_labels_in_tensor = sorted(images_by_class.keys())
num_classes_in_display = len(actual_labels_in_tensor)

# Get class names for only the displayed classes
class_names_to_display = [all_class_names[label] for label in actual_labels_in_tensor] if all_class_nam

X_show = []
for label in actual_labels_in_tensor:
    X_show.extend(images_by_class[label])

X_grid = utils.make_grid(X_show, nrow=num_images_per_row, padding=1)

plot_img(X_grid, y=None, color=True,
         class_names=class_names_to_display,
         num_classes=num_classes_in_display,
         images_per_row=num_images_per_row)
```

```
    plt.show()
```

```
plot_tensor(train_dataset)
```




Anime Class
Death Parade
Haikyu!!
Hunter x Hunter
Hyouka
Kamisama Kiss
Laid-Back Camp
Maid Sama!
My Teen Romantic Comedy
Nana
Neon Genesis Evangelion
Nichijou


No Game No Life
Ping Pong the Animation
ReLife
ReZero
Sound! Euphonium
Steins Gate
Tsukigakirei
Violet Evergarden
Yona of the Dawn
Your Lie in April

Training

```
# --- Model Definition ---
model = resnet50(weights="IMAGENET1K_V2")
num_classes = len(data_obj.full_dataset.classes)

# Fine-tuning: (uncomment to freeze layers for feature extraction)
for param in model.parameters():
    param.requires_grad = False

print(f"ImageNet Defaults: {model.fc}")
fc_inputs = model.fc.in_features
model.fc = nn.Sequential(
    nn.Linear(fc_inputs, 256),
    nn.ReLU(),
    nn.Dropout(0.4),
    nn.Linear(256, num_classes),
)
model = model.to(device)
print(f"After update: {model.fc}")
print(data_obj.separator)

criterion = nn.CrossEntropyLoss(reduction="mean", label_smoothing=0.1)
optimizer = optim.Adam(model.parameters(), lr=0.0001, weight_decay=1e-5)
epochs = 25
```

```
ImageNet Defaults: Linear(in_features=2048, out_features=1000, bias=True)
After update: Sequential(
  (0): Linear(in_features=2048, out_features=256, bias=True)
  (1): ReLU()
  (2): Dropout(p=0.4, inplace=False)
  (3): Linear(in_features=256, out_features=30, bias=True)
)
```

```
def train(epochs, model, train_loader, val_loader, criterion, optimizer, device):
    """
    Main training and validation loop with mixed precision support.
    """
    print("Starting training...")
```

```
train_losses, val_accuracies = [], []

best_val_accuracy = 0.0
epochs_no_improve_ctr = 0
patience = 5
start_time = time.time()

# Initialize GradScaler for mixed precision
scaler = torch.amp.GradScaler('cuda')

for epoch in range(epochs):
    # --- Training Phase ---
    model.train()
    total_train_loss = 0.0
    train_correct = 0
    train_total = 0

    train_pbar = tqdm(train_loader, desc=f"Epoch {epoch+1}/{epochs} [Train]", leave=False)
    for inputs, labels in train_pbar:
        inputs, labels = inputs.to(device), labels.to(device)
        optimizer.zero_grad()

        # Forward pass with autocast
        with torch.amp.autocast('cuda'):
            outputs = model(inputs)
            loss = criterion(outputs, labels)

        # Backward pass and optimization with scaler
        scaler.scale(loss).backward()
        scaler.step(optimizer)
        scaler.update()

        total_train_loss += loss.item()
        predicted_class = outputs.argmax(dim=1)
        train_total += labels.size(0)
        train_correct += (predicted_class == labels).sum().item()
        train_pbar.set_postfix({'loss': loss.item()})
```

```
avg_train_loss = total_train_loss / len(train_loader)
epoch_train_acc = train_correct / train_total
train_losses.append(avg_train_loss)

# --- Validation Phase ---
model.eval()
total_val_loss = 0.0
val_correct = 0
val_total = 0

val_pbar = tqdm(val_loader, desc=f"Epoch {epoch+1}/{epochs} [Valid]", leave=False)
with torch.no_grad():
    for inputs, labels in val_pbar:
        inputs, labels = inputs.to(device), labels.to(device)
        # Forward pass with autocast
        with torch.amp.autocast('cuda'):
            outputs = model(inputs)
            loss = criterion(outputs, labels)

        total_val_loss += loss.item()
        predicted_class = outputs.argmax(dim=1)
        val_total += labels.size(0)
        val_correct += (predicted_class == labels).sum().item()
        val_pbar.set_postfix({'loss': loss.item()})

avg_val_loss = total_val_loss / len(val_loader)
epoch_val_acc = val_correct / val_total
val_accuracies.append(epoch_val_acc)

print(f"Epoch {epoch+1}/{epochs} | "
      f"Train Loss: {avg_train_loss:.4f} | "
      f"Train Acc: {epoch_train_acc*100:.2f}% | "
      f"Val Loss: {avg_val_loss:.4f} | "
      f"Val Acc: {epoch_val_acc*100:.2f}%")

# --- Early Stopping Logic ---
if epoch_val_acc > best_val_accuracy:
    best_val_accuracy = epoch_val_acc
```

```python
            best_val_accuracy = epoch_val_acc
            epochs_no_improve_ctr = 0
            # (Optional: Save best model)
            # ...
        else:
            epochs_no_improve_ctr += 1
            if epochs_no_improve_ctr >= patience:
                print(f"Early stopping after {epoch+1} epochs. No improvement for {patience} epochs.")
                break

    total_time = time.time() - start_time
    print(f"\nTraining finished in {total_time:.2f} seconds.")

    return train_losses, val_accuracies
```

```python
train_losses_list, val_accuracies_list = train(
    epochs=epochs,
    model=model,
    train_loader=train_dataloader,
    val_loader=val_dataloader,
    criterion=criterion,
    optimizer=optimizer,
    device=device
)
```

```
Starting training...



Epoch 1/25 | Train Loss: 3.3405 | Train Acc: 11.60% | Val Loss: 3.2386 | Val Acc: 24.08%



Epoch 2/25 | Train Loss: 3.1234 | Train Acc: 25.67% | Val Loss: 3.0067 | Val Acc: 30.93%
```

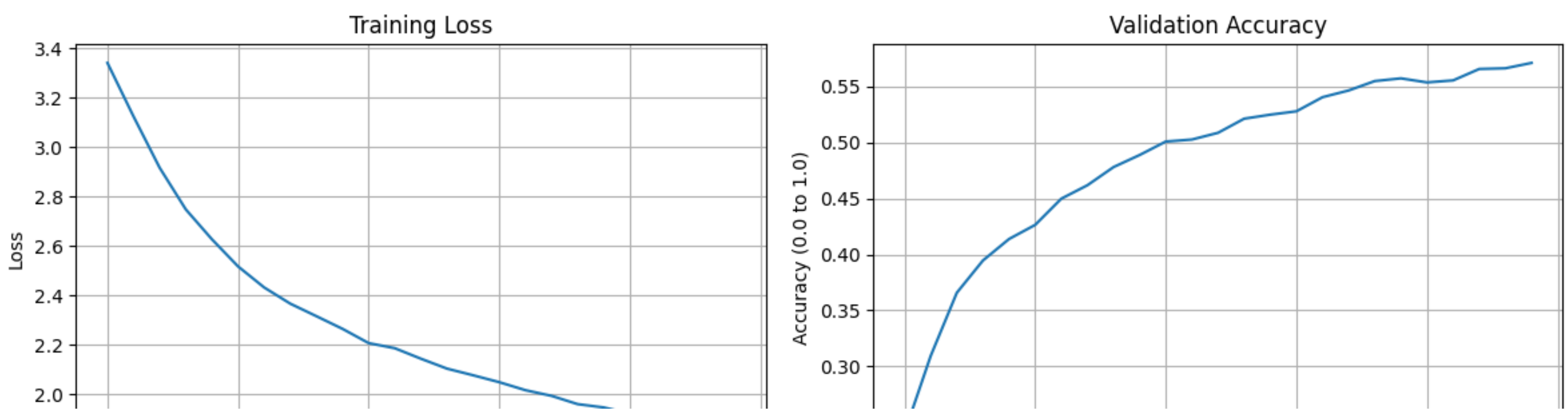
```
Epoch 3/25 | Train Loss: 2.9158 | Train Acc: 30.44% | Val Loss: 2.8190 | Val Acc: 36.58%

Epoch 4/25 | Train Loss: 2.7474 | Train Acc: 35.32% | Val Loss: 2.6733 | Val Acc: 39.46%

Epoch 5/25 | Train Loss: 2.6264 | Train Acc: 39.23% | Val Loss: 2.5784 | Val Acc: 41.38%

Epoch 6/25 | Train Loss: 2.5166 | Train Acc: 41.44% | Val Loss: 2.4978 | Val Acc: 42.64%

Epoch 7/25 | Train Loss: 2.4314 | Train Acc: 44.46% | Val Loss: 2.4196 | Val Acc: 44.98%

Epoch 8/25 | Train Loss: 2.3658 | Train Acc: 46.03% | Val Loss: 2.3645 | Val Acc: 46.19%

Epoch 9/25 | Train Loss: 2.3151 | Train Acc: 47.08% | Val Loss: 2.3336 | Val Acc: 47.81%

Epoch 10/25 | Train Loss: 2.2638 | Train Acc: 49.27% | Val Loss: 2.2832 | Val Acc: 48.89%

Epoch 11/25 | Train Loss: 2.2061 | Train Acc: 50.42% | Val Loss: 2.2379 | Val Acc: 50.09%
```

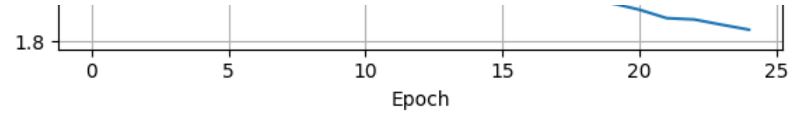
```
Epoch 12/25 | Train Loss: 2.1855 | Train Acc: 50.46% | Val Loss: 2.2198 | Val Acc: 50.27%

Epoch 13/25 | Train Loss: 2.1430 | Train Acc: 52.45% | Val Loss: 2.1934 | Val Acc: 50.87%

Epoch 14/25 | Train Loss: 2.1028 | Train Acc: 54.17% | Val Loss: 2.1651 | Val Acc: 52.13%

Epoch 15/25 | Train Loss: 2.0759 | Train Acc: 54.62% | Val Loss: 2.1419 | Val Acc: 52.49%

Epoch 16/25 | Train Loss: 2.0480 | Train Acc: 55.75% | Val Loss: 2.1243 | Val Acc: 52.79%

Epoch 17/25 | Train Loss: 2.0157 | Train Acc: 57.02% | Val Loss: 2.0953 | Val Acc: 54.05%

Epoch 18/25 | Train Loss: 1.9927 | Train Acc: 56.77% | Val Loss: 2.0883 | Val Acc: 54.65%

Epoch 19/25 | Train Loss: 1.9591 | Train Acc: 58.23% | Val Loss: 2.0662 | Val Acc: 55.50%

Epoch 20/25 | Train Loss: 1.9457 | Train Acc: 58.72% | Val Loss: 2.0584 | Val Acc: 55.74%
```

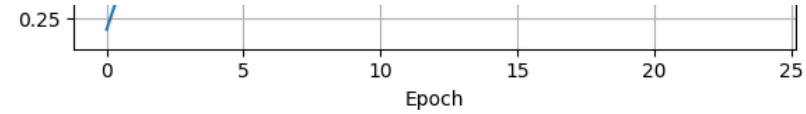
```
Epoch 21/25 | Train Loss: 1.9207 | Train Acc: 58.85% | Val Loss: 2.0456 | Val Acc: 55.38%

Epoch 22/25 | Train Loss: 1.8883 | Train Acc: 60.27% | Val Loss: 2.0251 | Val Acc: 55.56%

Epoch 23/25 | Train Loss: 1.8833 | Train Acc: 60.78% | Val Loss: 2.0139 | Val Acc: 56.58%

Epoch 24/25 | Train Loss: 1.8631 | Train Acc: 61.35% | Val Loss: 2.0058 | Val Acc: 56.64%

Epoch 25/25 | Train Loss: 1.8441 | Train Acc: 61.21% | Val Loss: 1.9991 | Val Acc: 57.12%

Training finished in 2118.70 seconds.
```

```
print("Plotting training curves...")
plot_training_curves(train_losses_list, val_accuracies_list)
```

```
Plotting training curves...
```








```
save_dir = "/content/drive/MyDrive/372 final project/models/"
if not os.path.exists(save_dir):
    os.makedirs(save_dir)
final_model_path = os.path.join(save_dir, "trained_resnet50_final_simple.pt")
torch.save(model.state_dict(), final_model_path)
print(f"Final model saved to {final_model_path}")
print(data_obj.separator)
```

```
Final model saved to /content/drive/MyDrive/372 final project/models/trained_resnet50_final_simple.pt
```

Final Evaluation on Test Set

```
# loading saved weights if needed
final_model_path = "/content/drive/MyDrive/372 final project/models/trained_resnet50_final_simple.pt"

model.load_state_dict(torch.load(final_model_path, map_location=device))
model.to(device)
```

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

```
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer2): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
```

```
      (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): Bottleneck(
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
```

```
print("\n--- Final Test Evaluation ---")
model.eval()
correct = 0
total = 0
test_loss = 0.0
all_true_labels = []
all_predicted_labels = []

with torch.no_grad():
    for inputs, labels in tqdm(test_dataloader, desc="Testing"):
        inputs, labels = inputs.to(device), labels.to(device)
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        test_loss += loss.item()

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

        all_true_labels.extend(labels.cpu().numpy())
        all_predicted_labels.extend(predicted.cpu().numpy())

avg_test_loss = test_loss / len(test_dataloader)
test_accuracy = correct / total
print(f"\nFinal Test Accuracy: {test_accuracy*100:.2f}%")
print(f"Average Test Loss: {avg_test_loss:.4f}")
```

```
--- Final Test Evaluation ---
Testing: 100%                                   53/53 [00:09<00:00,  6.58it/s]

Final Test Accuracy: 58.26%
Average Test Loss: 1.9703
```

Error Analysis

Generate and visualize a confusion matrix

Report the top 10 misclassifications from the confusion matrix, showing predicted class, actual class, and the number of instances for each

Future: summarize error analysis findings

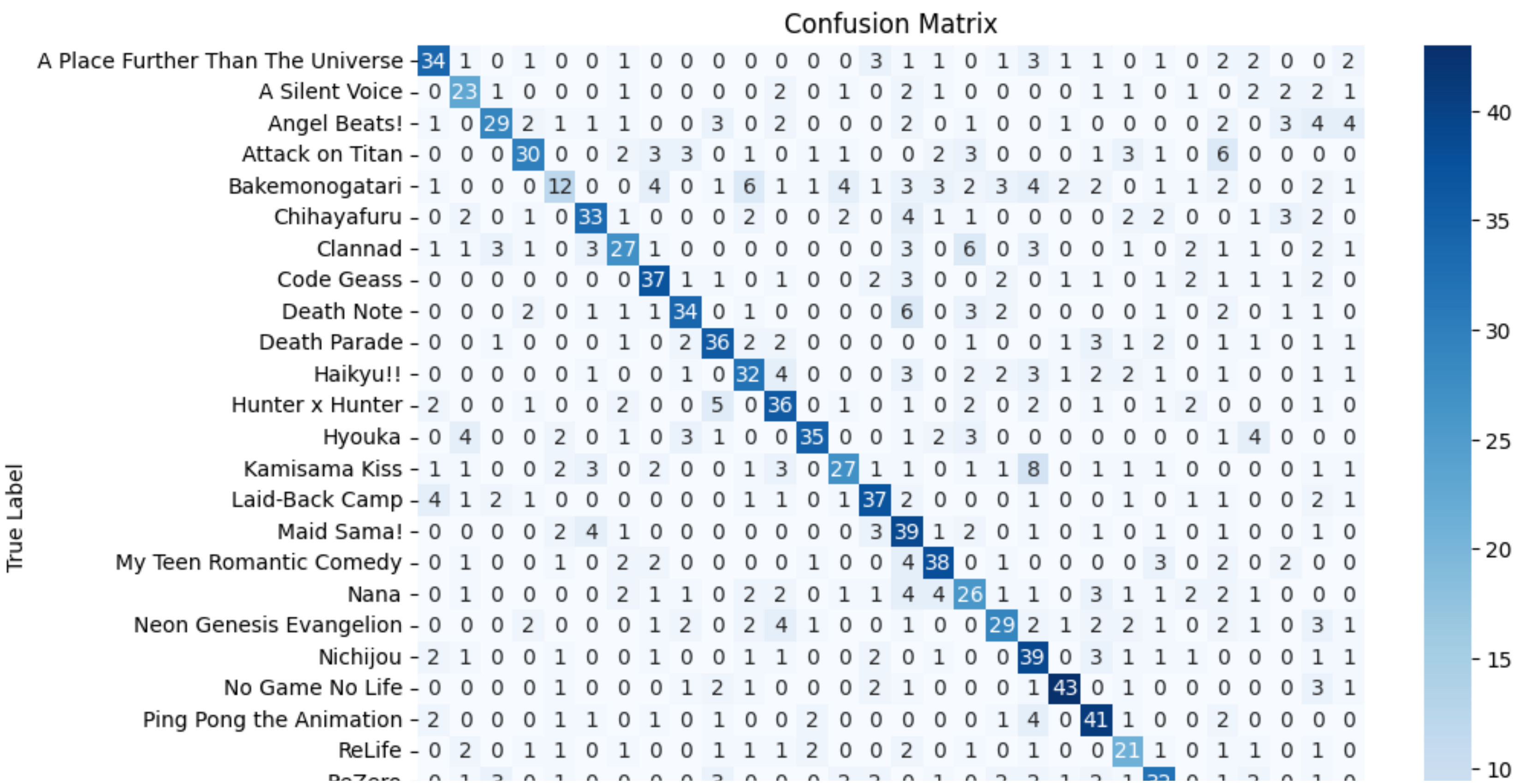
```
# Create a confusion matrix using the collected true labels and predicted labels.

from sklearn.metrics import confusion_matrix

# Retrieve class names
class_names = data_obj.full_dataset.classes

# Generate the confusion matrix
conf_matrix = confusion_matrix(all_true_labels, all_predicted_labels)

print("Confusion Matrix:")
print(conf_matrix)
```

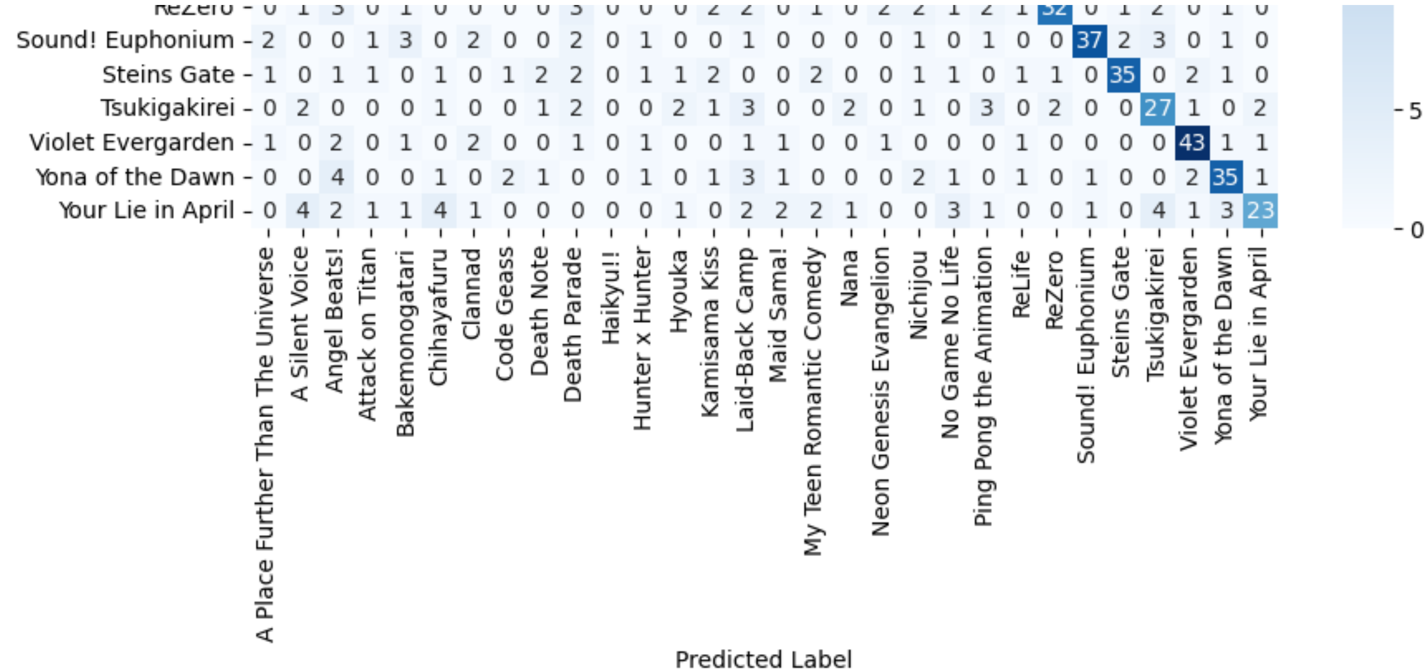
```
Confusion Matrix:
[[34  1  0  1  0  0  1  0  0  0  0  0  0  0  3  1  1  0  1  3  1  1  0  1
   0  2  2  0  0  2]
 [ 0 23  1  0  0  0  1  0  0  0  0  2  0  1  0  2  1  0  0  0  0  1  1  0
   1  0  2  2  2  1]
 [ 1  0 29  2  1  1  1  0  0  3  0  2  0  0  0  2  0  1  0  0  1  0  0  0
   0  2  0  3  4  4]
 [ 0  0  0 30  0  0  2  3  3  0  1  0  1  1  0  0  2  3  0  0  0  1  3  1
```

```
  0  6  0  0  0  0]
 [ 1  0  0  0 12  0  0  4  0  1  6  1  1  4  1  3  3  2  3  4  2  2  0  1
   1  2  0  0  2  1]
 [ 0  2  0  1  0 33  1  0  0  0  2  0  0  2  0  4  1  1  0  0  0  0  2  2
   0  0  1  3  2  0]
 [ 1  1  3  1  0  3 27  1  0  0  0  0  0  0  0  3  0  6  0  3  0  0  1  0
   2  1  1  0  2  1]
 [ 0  0  0  0  0  0  0 37  1  1  0  1  0  0  2  3  0  0  2  0  1  1  0  1
   2  1  1  1  2  0]
 [ 0  0  0  2  0  1  1  1 34  0  1  0  0  0  0  6  0  3  2  0  0  0  0  1
   0  2  0  1  1  0]
 [ 0  0  1  0  0  0  1  0  2 36  2  2  0  0  0  0  0  1  0  0  1  3  1  2
   0  1  1  0  1  1]
 [ 0  0  0  0  0  1  0  0  1  0 32  4  0  0  0  3  0  2  2  3  1  2  2  1
   0  1  0  0  1  1]
 [ 2  0  0  1  0  0  2  0  0  5  0 36  0  1  0  1  0  2  0  2  0  1  0  1
   2  0  0  0  1  0]
 [ 0  4  0  0  2  0  1  0  3  1  0  0 35  0  0  1  2  3  0  0  0  0  0  0
   0  1  4  0  0  0]
 [ 1  1  0  0  2  3  0  2  0  0  1  3  0 27  1  1  0  1  1  8  0  1  1  1
   0  0  0  0  1  1]
 [ 4  1  2  1  0  0  0  0  0  0  1  1  0  1 37  2  0  0  0  1  0  0  1  0
   1  1  0  0  2  1]
 [ 0  0  0  0  2  4  1  0  0  0  0  0  0  0  3 39  1  2  0  1  0  1  0  1
   0  1  0  0  1  0]
 [ 0  1  0  0  1  0  2  2  0  0  0  0  1  0  0  4 38  0  1  0  0  0  0  3
   0  2  0  2  0  0]
 [ 0  1  0  0  0  0  2  1  1  0  2  2  0  1  1  4  4 26  1  1  0  3  1  1
   2  2  1  0  0  0]
 [ 0  0  0  2  0  0  0  1  2  0  2  4  1  0  0  1  0  0 29  2  1  2  2  1
   0  2  1  0  3  1]
 [ 2  1  0  0  1  0  0  1  0  0  1  1  0  0  2  0  1  0  0 39  0  3  1  1
   1  0  0  0  1  1]
 [ 0  0  0  0  1  0  0  0  1  2  1  0  0  0  2  1  0  0  0  1 43  0  1  0
   0  0  0  0  3  1]
 [ 2  0  0  0  1  1  0  1  0  1  0  0  2  0  0  0  0  0  1  4  0 41  1  0
   0  2  0  0  0  0]
 [ 0  2  0  1  1  0  1  0  0  1  1  1  2  0  0  2  0  1  0  1  0  0 21  1
   0  1  1  0  1  0]
 [ 0  1  3  0  1  0  0  0  0  3  0  0  0  2  2  0  1  0  2  2  1  2  1 32
   0  1  2  0  1  0]
 [ 2  0  0  1  3  0  2  0  0  2  0  1  0  0  1  0  0  0  0  1  0  1  0  0
```

```
 37  2  3  0  1  0]
[ 1  0  1  1  0  1  0  1  2  2  0  1  1  2  0  0  2  0  0  1  1  0  1  1
  0 35  0  2  1  0]
[ 0  2  0  0  0  1  0  0  1  2  0  0  2  1  3  0  0  2  0  1  0  3  0  2
  0  0 27  1  0  2]
[ 1  0  2  0  1  0  2  0  0  1  0  1  0  0  1  1  0  0  1  0  0  0  1  0
  0  0  0 43  1  1]
[ 0  0  4  0  0  1  0  2  1  0  0  1  0  1  3  1  0  0  0  2  1  0  1  0
```

```
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=class_names, yticklabels=class_name
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```






```
# top 10 misclassifications

misclassifications = []
for i in range(len(class_names)): # True labels
    for j in range(len(class_names)): # Predicted labels
        if i != j: # Only consider misclassifications
            count = conf_matrix[i, j]
            if count > 0:
                misclassifications.append({
                    'true_class': class_names[i],
```

```python
                    'predicted_class': class_names[j],
                    'count': count
                })

    # Sort misclassifications by count in descending order
    top_misclassifications = sorted(misclassifications, key=lambda x: x['count'], reverse=True)[:10]

    print("\nTop 10 Misclassifications:")
    for item in top_misclassifications:
        print(f"  True: {item['true_class']}, Predicted: {item['predicted_class']}, Instances: {item['count']}"
```

```
Top 10 Misclassifications:
  True: Kamisama Kiss, Predicted: Nichijou, Instances: 8
  True: Attack on Titan, Predicted: Steins Gate, Instances: 6
  True: Bakemonogatari, Predicted: Haikyu!!, Instances: 6
  True: Clannad, Predicted: Nana, Instances: 6
  True: Death Note, Predicted: Maid Sama!, Instances: 6
  True: Hunter x Hunter, Predicted: Death Parade, Instances: 5
  True: Angel Beats!, Predicted: Yona of the Dawn, Instances: 4
  True: Angel Beats!, Predicted: Your Lie in April, Instances: 4
  True: Bakemonogatari, Predicted: Code Geass, Instances: 4
  True: Bakemonogatari, Predicted: Kamisama Kiss, Instances: 4
```