Team Debug Thugs

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Anime Image to Anime Name

Project Aim

We are given an image related to an anime movie. We need to identify the name of the Anime Movie through the image.

Brief Walkthrough

- DATASET BUILDING OF THE 6 ANIME MOVIES
- LOADING THE APPROPRIATE DATASET
- SPLITTING THE DATA INTO SETS
- IMAGE PRE-PROCESSING USING “Transformers in Torch”
- BUILDING THE CNN ARCHITECTURE
- COMPILING OUR MODEL USING LOSS, OPTIMIZERS (Adam) & METRICS
- TRAINING OUR MODEL WITH TRAINING SET AND SAVING OUR MODEL
- EVALUATING TESTING ACCURACY
- MAKING PREDICTIONS

Why CNN?

CNN uses convolutional layers which help in extracting the features using the many filters allowing the network to learn and identify local patterns such as edges, corners, and textures.

Tech Used

Following are the libraries in Python 3.11.1 which we used in this project:

- Bing Image Downloader
- Open-CV
- Split Folders
- TensorFlow
- Keras
- PyTorch (Building Model)
- NumPy
- Matplotlib

Following are the Environments and Apps we used in this project:

- Google Collab and Drive
- Anaconda
- Jupyter Notebook with GPU (“RTX 3050”) Setup
- VisiPics App
- Flask Framework

WORKING:

Database Collection

- First, we tried to extract the dataset using **bing-image-downloader** in python. But we did not get enough images for building a good model as well as the images were similar.

```
!pip install bing-image-downloader

from google.colab import drive
drive.mount('/content/drive')

!mkdir images
#mkdir-> make directories

from bing_image_downloader import downloader
downloader.download("death note anime images",limit=500,output_dir="/content/drive/MyDrive/images")

from bing_image_downloader import downloader
downloader.download("spirited away anime images",limit=1000,output_dir="/content/drive/MyDrive/images")

from bing_image_downloader import downloader
downloader.download("weathering with you anime images",limit=1000,output_dir="/content/drive/MyDrive/images")

from bing_image_downloader import downloader
downloader.download("death note anime images",limit=1000,output_dir="/content/drive/MyDrive/images")

from bing_image_downloader import downloader
downloader.download("another anime images",limit=1000,output_dir="/content/drive/MyDrive/images")

from bing_image_downloader import downloader
downloader.download("grand blue anime comedy images",limit=1000,output_dir="/content/drive/MyDrive/images")
```

```
!pip install opencv-python

Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: opencv-python in /usr/local/lib/python3.10/dist-packages (4.7.0.72)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from opencv

[ ] import cv2

[ ] cam = cv2.VideoCapture("/content/Untitled Folder/pexels-pressmaster-3195394-3840x2160-25fps.mp4")
    fps = cam.get(cv2.CAP_PROP_FPS)
    fps

    25.0

    n = 0
    i = 0
    while True:
      ret,frame = cam.read()
      if(n % fps == 0):
        cv2.imwrite("/content/Untitled Folder/images/%d.png" %i,frame)
        i+=1
      n+=1
      if ret == False:
        break
    cam.release()
```

- So, we decided to build our own dataset. We searched the web and came across a method which used frames taken from anime movie scenes. We downloaded selected movies and extracted frames using the **OPEN-CV** library. We extracted one frame per second approximately. The dataset still contained many similar images which were exact duplicates. So, we use **VisiPics** for eliminating duplicate images.

Splitting the Dataset

The dataset we created needed to be split into these 3 sets. Doing it manually was very hectic and time-consuming. Researching, we came across a method which uses a split-folders library to make these sets. The ratio which we decided for the splitting was (70%, 15%, 15%) for (train, validation, test) set.

```
!pip install split-folders[full]
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: split-folders[full] in /usr/local/lib/python3.10/dist-packages (0.5.1)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from split-folders[full]) (4.65.0)
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
import splitfolders
```

```
input_folder = '/content/drive/MyDrive/Anime_Images'
splitfolders.ratio(input_folder, output= "/content/drive/MyDrive/Dataset",seed = 42,ratio =(0.7,0.15,0.15),group_prefix=None, move=False)
```

```
Copying files: 10661 files [06:27, 27.53 files/s]
```

Preprocessing of Images

These are the transformations which we intended to apply on our image dataset before feeding them into the training model:

•**Size Reduction** – This was important to improve our model accuracy during training. So, we decided to resize our images to 256x256 pixels.

•**Greyscaling** – RGB images have ‘3’ input channels while the greyscale images only have ‘1’ input channel. This reduces the computations significantly by reducing the input channels from ‘3’ to ‘1’.

•**Normalizing** – It is done to ensure each pixel has an equal influence on the model's predictions. This also speeds up the convergence of the training process.

Preprocessing of Images through Open-CV :

Effort 1

We first tried to import the images from our anime directories and create a list of those images with the corresponding labels and then pre-process the image list by iterating through it.

```
import os
import cv2
import numpy as np

# Define the root directory where the images are stored
root_dir_1 = '/content/drive/MyDrive/Dataset/test/Grave of the Fireflies'
root_dir_2 = '/content/drive/MyDrive/Dataset/test/I want to eat your Pancreas'
root_dir_3 = '/content/drive/MyDrive/Dataset/test/Perfect Blue'
root_dir_4 = '/content/drive/MyDrive/Dataset/test/Spirited Away'
root_dir_5 = '/content/drive/MyDrive/Dataset/test/Weathering With You'
root_dir_6 = '/content/drive/MyDrive/Dataset/test/Your Name'

# Define a list to store the images and labels
images = []
labels = []

# Define a function to process a directory recursively
def process_directory(data_dir, label):

  # Loop through each file in the directory
  for filename in os.listdir(data_dir):

    # Get the full path of the file
    file_path = os.path.join(data_dir, filename)
```

```
    # Check if the path is a file or directory
    if os.path.isfile(file_path):
      # Process the file
      img = cv2.imread(file_path)
      img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
      img = cv2.resize(img, (256, 256))
      img = cv2.normalize(img.astype('float'), None, 0.0, 1.0, cv2.NORM_MINMAX)
      images.append(img)
      labels.append(label)
    elif os.path.isdir(file_path):
      # Recursively process files in subdirectories
      pass

process_directory(root_dir_1,0)
process_directory(root_dir_2,0)
process_directory(root_dir_3,0)
process_directory(root_dir_4,0)
process_directory(root_dir_5,0)
process_directory(root_dir_6,0)

# Convert the image and label lists to numpy arrays
images = np.array(images)
labels = np.array(labels)

# Print the shape of the image and label arrays
print('Image shape:', images.shape)
print('Label shape:', labels.shape)
```

But the issue we faced was creating 6 different lists for the 6 different anime directories as we were not able to append all the images into a single list.

Effort 2

So, to eliminate our previous problem, we decided to create another directory for the pre-processed images and save them after preprocessing. This was not only solving our problem but also helped in eliminating the time required every time for pre-processing.

```python
import os
import cv2
import numpy as np
from google.colab import drive

# Define paths to the input and output directories
input_path = '/content/drive/MyDrive/Dataset'
output_path = '/content/drive/MyDrive/final'

# Define the preprocessing function
def preprocess_image(image):
    # Resize the image
    image = cv2.resize(image, (256, 256))

    # Convert the image to grayscale
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

    return gray

# Loop over the input directories (train, test, split)
for split_dir in os.listdir(input_path):
    # Create the output directory if it doesn't exist
    output_split_dir = os.path.join(output_path, split_dir + '_Prepro')
    if not os.path.exists(output_split_dir):
        os.makedirs(output_split_dir)
```

```python
# Loop over the images in the input directory for each anime
input_anime_dir = os.path.join(input_split_dir, anime_dir)
for filename in os.listdir(input_anime_dir):
    # Load the image
    input_file = os.path.join(input_anime_dir, filename)
    image = cv2.imread(input_file)

    # Preprocess the image
    preprocessed_image = preprocess_image(image)

    # Save the preprocessed image
    output_file = os.path.join(output_anime_dir, filename)
    cv2.imwrite(output_file, preprocessed_image)
```

After we saved our images, we found out that the images were grayscale but they were still saved in the three channels which means the size of the images was still (3, 256, 256) instead of being (1, 256, 256).

Pre-Processing of Images through Transform in Torch

Due to previous issues, we dropped the idea of using open-cv to preprocess the dataset. We found a better option of using the transform feature of the PyTorch library. Here, we also transformed our images to Tensors which is important because the torch takes input in the form of tensors.

```python
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
from torchvision.transforms import ToTensor
from torchvision.transforms import Normalize
import torchvision.datasets as datasets
from torch.utils.data import DataLoader
from torchvision.datasets import ImageFolder
import numpy as np
import os
transform = transforms.Compose([
    transforms.Grayscale(),
    transforms.Resize((256,256)),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])
data_dir = 'C:\Aries\Dataset'
dataset = ImageFolder(data_dir+'/train', transform=transform)
dataset_val = ImageFolder(data_dir+'/val', transform=transform)
dataset_test = ImageFolder(data_dir+'/test', transform=transform)
```

Dataloading

```python
# Define the data loaders
batch_size = 32
train_loader = torch.utils.data.DataLoader(dataset, batch_size=batch_size, shuffle=True)
val_loader = torch.utils.data.DataLoader(dataset_val, batch_size=batch_size, shuffle=False)
test_loader = torch.utils.data.DataLoader(dataset_test, batch_size=batch_size, shuffle=False)
```

Building the CNN Architecture

We then started building our CNN model. Researching across, we decided to apply the following layers:

1. **Convolutional Layer**
2. **Activation Function Layer** with **ReLu** as activation function
3. **Max Pooling Layer**

We applied these layers in **4 Sets** each set containing these layers in the above sequence.

Then we **Flattened** the output convolutional arrays and passed them to **2 Fully Connected Layers** applying an activation layer in between them.

```
# Define the CNN model
class MyCNN(nn.Module):
    def __init__(self, num_classes):
        super(MyCNN, self).__init__()
        # Define the convolutional layers
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3, padding = 1, stride = 1)
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding = 1, stride = 1)
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding = 1, stride = 1)
        self.conv4 = nn.Conv2d(in_channels=128, out_channels=256, kernel_size=3, padding = 1, stride = 1)

        # Define the fully connected layers
        self.fc1 = nn.Linear(in_features=256 * 16 * 16, out_features=512)
        self.fc2 = nn.Linear(in_features=512, out_features=6)

        # Define the activation function
        self.relu = nn.ReLU()
```

```
        # Define the max pooling layer
        self.pool = nn.MaxPool2d(kernel_size=2, stride = 2)

    def forward(self, x):
        # Perform the forward pass through the convolutional layers
        x = self.conv1(x)
        x = self.relu(x)
        x = self.pool(x)

        x = self.conv2(x)
        x = self.relu(x)
        x = self.pool(x)

        x = self.conv3(x)
        x = self.relu(x)
        x = self.pool(x)

        x = self.conv4(x)
        x = self.relu(x)
        x = self.pool(x)

        # Flatten the output from the convolutional layers
        x = x.view(-1, 256 * 16 * 16)

        # Perform the forward pass through the fully connected layers
        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)

        return x
```

We then created an object named MyCNN and used **Adam** as **Optimizer** and took **Learning Rate = 0.001.**

```
# Initialize the model and the optimizer
model = MyCNN(num_classes=6)
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Define the loss function
criterion = nn.CrossEntropyLoss()
```

The Loss Function we used was **Cross Entropy Loss** .

Then, we trained our model and tested it.

Initially , We were training our model on Google Collab but it was taking very long time so we decided to do first train it on a smaller dataset which consists of only 2 anime movies and about 400 images and major advantage is that it will take very less time and we can debug the code relatively easily .

In the smaller dataset, we did not convert images to grayscale .

Our CNN Model on a Smaller Dataset

Batch size is **32**

```
# Define the convolutional layers
self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, stride = 1, padding = 1)
self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, stride = 1, padding = 1)
self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, stride = 1, padding = 1

# Define the fully connected layers
self.fc1 = nn.Linear(in_features=128 * 32 * 32, out_features=512)
self.fc2 = nn.Linear(in_features=512, out_features=num_classes)

# Define the activation function
self.relu = nn.ReLU()

# Define the max pooling layer
self.pool = nn.MaxPool2d(kernel_size=2, stride = 2)
```

```
# Train the model
num_epochs = 10
```

```
# Save the weights to Google Drive
file_name = f'weights_epoch_{epoch}.pth'
save_path = '/content/drive/MyDrive/images/' + file_name
torch.save(model.state_dict(), save_path)
```

Training Accuracy,Loss and Val Accuracy,Loss is:

```
Epoch [1/10], Train Loss: 1.4112, Train Acc: 0.6033, Val Loss: 0.6833, Val Acc: 0.5938
Epoch [2/10], Train Loss: 0.6180, Train Acc: 0.6100, Val Loss: 0.6239, Val Acc: 0.7188
Epoch [3/10], Train Loss: 0.5674, Train Acc: 0.6833, Val Loss: 0.5628, Val Acc: 0.7656
Epoch [4/10], Train Loss: 0.4178, Train Acc: 0.8067, Val Loss: 0.5968, Val Acc: 0.7656
Epoch [5/10], Train Loss: 0.3488, Train Acc: 0.8633, Val Loss: 0.4260, Val Acc: 0.8750
Epoch [6/10], Train Loss: 0.2843, Train Acc: 0.8733, Val Loss: 0.4104, Val Acc: 0.8750
Epoch [7/10], Train Loss: 0.1889, Train Acc: 0.9200, Val Loss: 0.5130, Val Acc: 0.8438
Epoch [8/10], Train Loss: 0.1183, Train Acc: 0.9667, Val Loss: 0.6192, Val Acc: 0.8594
Epoch [9/10], Train Loss: 0.0767, Train Acc: 0.9667, Val Loss: 0.6763, Val Acc: 0.8438
Epoch [10/10], Train Loss: 0.0427, Train Acc: 0.9900, Val Loss: 0.6651, Val Acc: 0.8750
```

As we can see that training accuracy has reached 99 percent there is a high chance of overfitting .

```
# Load the trained weights into the model
model.load_state_dict(torch.load('/content/drive/MyDrive/images/weights_epoch_9.pth'))
```

Testing Accuracy is:

```
Test Loss: 1.4281, Test Accuracy: 0.7761
```

VGG Model on Smaller Dataset

```
batch_size = 32
```

Training Accuracy, Loss and Val Accuracy, Loss is:

```
Epoch [1/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
Epoch [2/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
Epoch [3/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
Epoch [4/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
Epoch [5/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
Epoch [6/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
Epoch [7/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
Epoch [8/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
Epoch [9/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
Epoch [10/10], Train Loss: 0.0183, Train Acc: 0.9967, Val Loss: 0.6651, Val Acc: 0.8750
```

Testing Accuracy:

```
Test Loss: 1.4281, Test Accuracy: 0.7761
```

Training our CNN Architecture

We first define all the losses to zero and initialize the gradients to zero:

```
# Train the model
num_epochs = 10
for epoch in range(num_epochs):
    # Set the model to training mode
    model.train()

    # Initialize variables for tracking loss and accuracy
    train_loss = 0.0
    train_correct = 0

    # Iterate over the training data
    for images, labels in train_loader:
        # Zero the gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(images)

        # Compute the loss
        loss = criterion(outputs, labels)

        # Backward pass
        loss.backward()

        # Update the weights
        optimizer.step()

        # Update the training loss and accuracy
        train_loss += loss.item() * images.size(0)
        _, predicted = torch.max(outputs.data, 1)
        train_correct += (predicted == labels).sum().item()

    # Compute the average training loss and accuracy
    train_loss = train_loss / len(train_loader.dataset)
    train_acc = train_correct / len(train_loader.dataset)
```

Results:

The number of epochs we chose were ***10***. We saved our model and also the weight files so that we can use them in the test case (The weight file corresponding to the last epoch) .

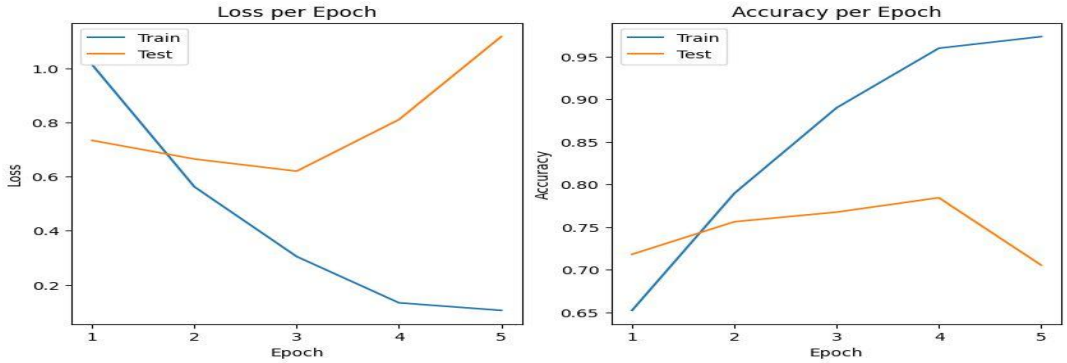
Here are the training accuracies, training losses, validation accuracies, validation losses and the graphs plotted between them:

Hyperparameter Tuning: We trained our model on different hyperparameters by changing the Batch Size and Number of Convolutional Layers to build the most accurate model.

(Accuracy, Loss and Graph)

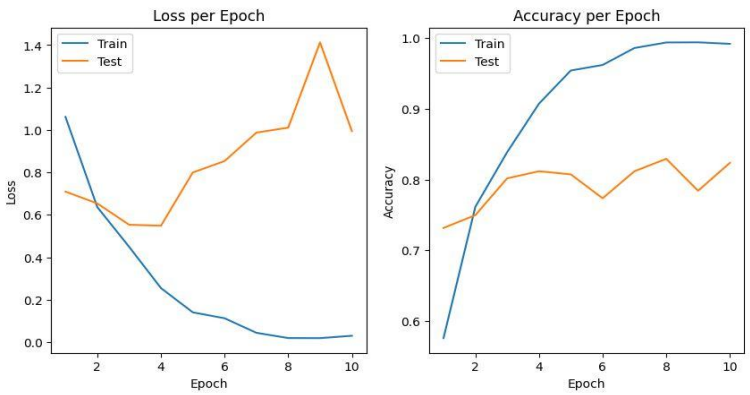
1) For convolutional layers = 2, batch size = 16:

```
Epoch [1/5], Train Loss: 1.0131,        Train Acc: 0.6521, Val Loss: 0.7334, Val Acc: 0.7179
Epoch [2/5], Train Loss: 0.5620,        Train Acc: 0.7894, Val Loss: 0.6648, Val Acc: 0.7561
Epoch [3/5], Train Loss: 0.3045,        Train Acc: 0.8898, Val Loss: 0.6199, Val Acc: 0.7674
Epoch [4/5], Train Loss: 0.1335,        Train Acc: 0.9597, Val Loss: 0.8105, Val Acc: 0.7843
Epoch [5/5], Train Loss: 0.1055,        Train Acc: 0.9733, Val Loss: 1.1170, Val Acc: 0.7053
```



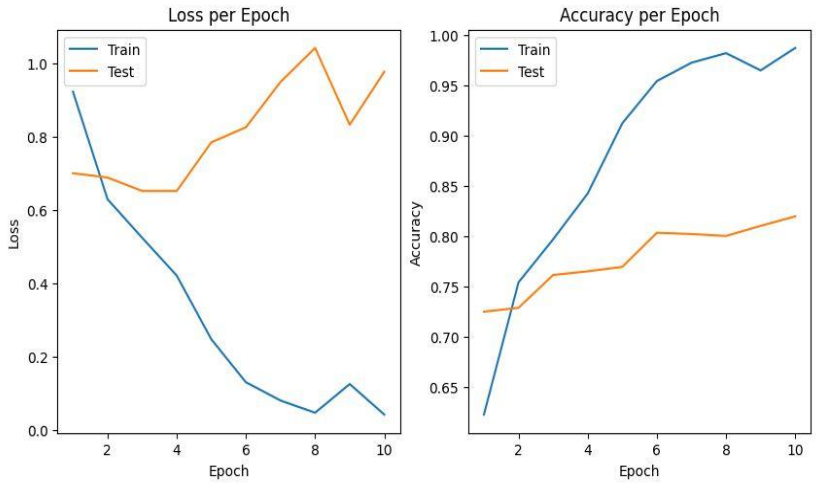
2) For convolutional layers = 3, batch size = 32:

```
Epoch [1/10], Train Loss: 1.0615,       Train Acc: 0.5759, Val Loss: 0.7095, Val Acc: 0.7317
Epoch [2/10], Train Loss: 0.6365,       Train Acc: 0.7616, Val Loss: 0.6538, Val Acc: 0.7498
Epoch [3/10], Train Loss: 0.4495,       Train Acc: 0.8389, Val Loss: 0.5534, Val Acc: 0.8019
Epoch [4/10], Train Loss: 0.2550,       Train Acc: 0.9075, Val Loss: 0.5488, Val Acc: 0.8119
Epoch [5/10], Train Loss: 0.1407,       Train Acc: 0.9544, Val Loss: 0.7996, Val Acc: 0.8075
Epoch [6/10], Train Loss: 0.1128,       Train Acc: 0.9622, Val Loss: 0.8535, Val Acc: 0.7737
Epoch [7/10], Train Loss: 0.0442,       Train Acc: 0.9862, Val Loss: 0.9875, Val Acc: 0.8119
Epoch [8/10], Train Loss: 0.0195,       Train Acc: 0.9940, Val Loss: 1.0110, Val Acc: 0.8295
Epoch [9/10], Train Loss: 0.0192,       Train Acc: 0.9942, Val Loss: 1.4128, Val Acc: 0.7843
Epoch [10/10], Train Loss: 0.0303,      Train Acc: 0.9921, Val Loss: 0.9945, Val Acc: 0.8238
```



3) For convolutional layers = 4, batch size = 32:

```
Epoch [1/10], Train Loss: 0.9225,       Train Acc: 0.6231, Val Loss: 0.7006, Val Acc: 0.7254
Epoch [2/10], Train Loss: 0.6297,       Train Acc: 0.7545, Val Loss: 0.6889, Val Acc: 0.7292
Epoch [3/10], Train Loss: 0.5247,       Train Acc: 0.7973, Val Loss: 0.6523, Val Acc: 0.7618
Epoch [4/10], Train Loss: 0.4217,       Train Acc: 0.8428, Val Loss: 0.6523, Val Acc: 0.7655
Epoch [5/10], Train Loss: 0.2481,       Train Acc: 0.9126, Val Loss: 0.7849, Val Acc: 0.7699
Epoch [6/10], Train Loss: 0.1311,       Train Acc: 0.9546, Val Loss: 0.8257, Val Acc: 0.8038
Epoch [7/10], Train Loss: 0.0814,       Train Acc: 0.9728, Val Loss: 0.9493, Val Acc: 0.8025
Epoch [8/10], Train Loss: 0.0481,       Train Acc: 0.9823, Val Loss: 1.0419, Val Acc: 0.8006
Epoch [9/10], Train Loss: 0.1263,       Train Acc: 0.9652, Val Loss: 0.8328, Val Acc: 0.8107
Epoch [10/10], Train Loss: 0.0431,      Train Acc: 0.9875, Val Loss: 0.9769, Val Acc: 0.8201
```



4) For convolutional layers = 4, batch size = 16:

```
Epoch [1/10], Train Loss: 0.8937,       Train Acc: 0.6429, Val Loss: 0.7521, Val Acc: 0.6878
Epoch [2/10], Train Loss: 0.6225,       Train Acc: 0.7613, Val Loss: 0.6148, Val Acc: 0.7630
Epoch [3/10], Train Loss: 0.5143,       Train Acc: 0.8077, Val Loss: 0.6734, Val Acc: 0.7643
Epoch [4/10], Train Loss: 0.3943,       Train Acc: 0.8591, Val Loss: 0.6593, Val Acc: 0.7812
Epoch [5/10], Train Loss: 0.2244,       Train Acc: 0.9204, Val Loss: 0.7884, Val Acc: 0.7850
Epoch [6/10], Train Loss: 0.1355,       Train Acc: 0.9550, Val Loss: 1.0219, Val Acc: 0.7793
Epoch [7/10], Train Loss: 0.1165,       Train Acc: 0.9625, Val Loss: 1.0254, Val Acc: 0.7900
Epoch [8/10], Train Loss: 0.0445,       Train Acc: 0.9849, Val Loss: 1.4399, Val Acc: 0.7875
Epoch [9/10], Train Loss: 0.0516,       Train Acc: 0.9820, Val Loss: 1.4595, Val Acc: 0.7699
Epoch [10/10], Train Loss: 0.0739,      Train Acc: 0.9796, Val Loss: 1.5040, Val Acc: 0.7705
```

Testing our CNN Architecture

(Evaluating our Performance)

```
# Define the path to the data directory
data_dir = 'C:\Aries\Dataset'

batch_size = 32

# Initialize the model
model = MyCNN(num_classes = 6)

# Load the trained weights into the model
model.load_state_dict(torch.load("C:\Aries\Weightsweights_epoch_9.pth"))

# Set the model to evaluation mode
model.eval()

# Define the loss function
criterion = nn.CrossEntropyLoss()

# Initialize variables for tracking loss and accuracy
test_loss = 0.0
test_correct = 0

# Iterate over the test data
for images, labels in test_loader:
    # Forward pass
    outputs = model(images)

    # Compute the loss
    loss = criterion(outputs, labels)

    # Update the test loss and accuracy
    test_loss += loss.item() * images.size(0)
    _, predicted = torch.max(outputs.data, 1)
    test_correct += (predicted == labels).sum().item()

# Compute the average test loss and accuracy
test_loss = test_loss / len(test_loader.dataset)
test_acc = test_correct / len(test_loader.dataset)

# Print the test loss and accuracy
print(f"Test Loss: {test_loss:.4f}, Test Accuracy: {test_acc:.4f}")
```

We set the batch size to 32 and initialize test loss = 0

Performance on different Hyperparameters

1) For convolutional layers = 2 , batch size = 16:

```
Test Loss: 0.7309, Test Accuracy: 0.7882
```

2) For convolutional layers = 3 , batch size = 32:

```
Test Loss: 1.0699, Test Accuracy: 0.8131
```

3) For convolutional layers = 4 , batch size = 32:

```
Test Loss: 0.9758, Test Accuracy: 0.8118
```

4) For convolutional layers = 4 , batch size = 16:

```
Test Loss: 1.4336, Test Accuracy: 0.7732
```

After testing, we got the best accuracy for 4 Convolutional Layers and taking the Batch Size as 32 which was our initial model.

VGG Model

First we downloaded the VGG model and extracted it, the code of which is:

```
# Load the pre-trained VGG19 model
model = models.vgg19(pretrained=True)

# Freeze the pre-trained layers
for param in model.parameters():
    param.requires_grad = False

# Add a custom classification layer on top of the pre-trained model
num_ftrs = model.classifier[6].in_features
model.classifier[6] = nn.Sequential(
                      nn.Linear(num_ftrs, 512),
                      nn.ReLU(),
                      nn.Dropout(0.5),
                      nn.Linear(512, 5),
                      nn.LogSoftmax(dim=1))

# Define the loss function and optimizer
criterion = nn.NLLLoss()
optimizer = optim.Adam(model.classifier.parameters(), lr=0.001)
```

Training Loss, Validation Accuracy and Validation Loss:

```
Epoch: 1        Training Loss: 0.8119
Epoch: 1        Validation Loss: 2.7208         Validation Accuracy: 0.5751
Epoch: 2        Training Loss: 0.4515
Epoch: 2        Validation Loss: 2.4757         Validation Accuracy: 0.5973
Epoch: 3        Training Loss: 0.3379
Epoch: 3        Validation Loss: 2.5310         Validation Accuracy: 0.5947
Epoch: 4        Training Loss: 0.2664
Epoch: 4        Validation Loss: 2.7515         Validation Accuracy: 0.5956
Epoch: 5        Training Loss: 0.2045
Epoch: 5        Validation Loss: 2.8725         Validation Accuracy: 0.6015
Epoch: 6        Training Loss: 0.1937
Epoch: 6        Validation Loss: 2.8363         Validation Accuracy: 0.6092
Epoch: 7        Training Loss: 0.1855
Epoch: 7        Validation Loss: 2.9123         Validation Accuracy: 0.6058
Epoch: 8        Training Loss: 0.1444
Epoch: 8        Validation Loss: 3.0179         Validation Accuracy: 0.6118
Epoch: 9        Training Loss: 0.1349
Epoch: 9        Validation Loss: 3.2216         Validation Accuracy: 0.6067
Epoch: 10       Training Loss: 0.1536
Epoch: 10       Validation Loss: 3.0937         Validation Accuracy: 0.6032
```

Test Accuracy:

```
Test Loss: 5.4125, Test Accuracy: 0.7341
```

The accuracy of our model is better than that of the VGG19 Model. These could be some potential reasons for the same:

- The VGG Model is trained for a large dataset whereas the dataset we created was not that large.
- It uses a high number of convolutional layers to extract features from a large dataset which here leads to overfitting.

Predictions

Now to test our model whether it gives correct output or not on giving any random image from internet, we take images from internet and try to predict their corresponding anime names:

Code

```
from PIL import Image

filename = '39.png'
image = Image.open(filename)


transform = transforms.Compose([
    transforms.Grayscale(),
    transforms.Resize((256, 256)),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

image = transform(image)

# Add a batch dimension to the image
image = image.unsqueeze(0)
model = MyCNN(num_classes = 6)

# Load the trained weights into the model
model.load_state_dict(torch.load("C:\Aries\Weightsweights_final_epoch_9.pth"))
# Get the predicted class probabilities
with torch.no_grad():
    outputs = model(image)

# Convert the predicted class probabilities to class labels
_, predicted = torch.max(outputs.data, 1)

# Print the predicted class label
print("Predicted class label:", classes[predicted.item()])
```

Results:

```
Predicted class label: Perfect Blue
```

```
Predicted class label: Your Name
```

```
Predicted class label: Grave of the Fireflies
```

```
Predicted class label: Spirited Away
```

The predictions made by the model were not so accurate. Here are the possible reasons for the same:

- The model may give accurate predictions when a large dataset is predicted.
- Our Dataset contained more images from the anime “Spirited Away” and “Weathering With You” as they were longer as compared to others in terms of duration, so the model became a little biased and was predicting them more frequently.
- Also graphics of the anime movies are similar like sharp edges and similar face features. This leads to less accurate predictions.
- The anime “Perfect Blue” had different graphics. So, the model was predicting it better than others.

We found that this issue can be resolved if we train our model for more movies which we will be trying later.