st123012-11-Transformer

April 13, 2023

1 Lab 11: Transformers

[1]:
```python
id = 123012
name = 'Todsavad Tangtortan'
```

1. Manage your available resources and continue fine-tune on the same dataset. The pretrained weights at 30th epoch (accuracy = 80%) is giving below link: (Hint: for batch_size = 8 on Puffer will used up 5GB of RAM in one GPU)

   https://drive.google.com/file/d/1P_f5OKNJuk_xpV6efLD5rFOjIyVhMW7I/view?usp=sharinghttps://driv

   Feel free to download the file and continue fine-tuning with different settings. Make a challenge to achieve a better performance than my result. There is no bound for the number of epochs to continue. (please don't forget to change the epoch_number=30)

[2]:
```python
# !pip install opencv-python
# !apt-get update
# !apt install libgl1-mesa-glx
```

[3]:
```python
# !pip install pandas
# !pip install scikit-image
```

[4]:
```python
# !pip install torch torchvision --upgrade
# !pip install vit_pytorch
```

[2]:
```python
import os
import time
import torch
import torch.nn as nn
from torchvision.models import vit_b_16 as ViT, ViT_B_16_Weights

from torchvision import transforms
from torch.utils.data import DataLoader
import pandas as pd

from tqdm import tqdm

import os
os.environ['http_proxy']="http://192.41.170.23:3128"
```

```
os.environ['https_proxy']="http://192.41.170.23:3128"

# Set the GPU Device
device = 'cuda:1' if torch.cuda.is_available() else 'cpu'
print(device)
```

```
cuda:1
```

[3]:
```
model = ViT(weights=ViT_B_16_Weights.DEFAULT)

# Count trainable parameters
total_params = sum(p.numel() for p in model.parameters() if p.requires_grad)

print(model)
print(f"{total_params/1000000}M")
```

```
VisionTransformer(
  (conv_proj): Conv2d(3, 768, kernel_size=(16, 16), stride=(16, 16))
  (encoder): Encoder(
    (dropout): Dropout(p=0.0, inplace=False)
    (layers): Sequential(
      (encoder_layer_0): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_1): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
```

```
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_2): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_3): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_4): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
```

```
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_5): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_6): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_7): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
```

```
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_8): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_9): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_10): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
```

```
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
      (encoder_layer_11): EncoderBlock(
        (ln_1): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (self_attention): MultiheadAttention(
          (out_proj): NonDynamicallyQuantizableLinear(in_features=768,
out_features=768, bias=True)
        )
        (dropout): Dropout(p=0.0, inplace=False)
        (ln_2): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
        (mlp): MLPBlock(
          (0): Linear(in_features=768, out_features=3072, bias=True)
          (1): GELU(approximate='none')
          (2): Dropout(p=0.0, inplace=False)
          (3): Linear(in_features=3072, out_features=768, bias=True)
          (4): Dropout(p=0.0, inplace=False)
        )
      )
    )
    (ln): LayerNorm((768,), eps=1e-06, elementwise_affine=True)
  )
  (heads): Sequential(
    (head): Linear(in_features=768, out_features=1000, bias=True)
  )
)
86.567656M
```

[4]:
```
# Changed to out_features = 100
model.heads = nn.Sequential(nn.Linear(in_features=768, out_features=100,␣
↪bias=True))

# Move the model to Device
model.to(device)
print("Classifier Head: ", model.heads)
```

```
Classifier Head:  Sequential(
  (0): Linear(in_features=768, out_features=100, bias=True)
)
```

[5]:
```
# Initiate the weights and biases
for m in model.heads:
    if isinstance(m, nn.Linear):
        nn.init.xavier_uniform_(m.weight)
        if m.bias is not None:
```

```
            nn.init.normal_(m.bias, std=1e-6)

train_transform = transforms.Compose(
    [
    transforms.ToPILImage(mode='RGB'),
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.RandomHorizontalFlip(0.5),
    transforms.ToTensor()
    ]
)

val_transform = transforms.transforms.Compose(
    [
    transforms.ToPILImage(mode='RGB'),
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor()
    ]
)
```

[6]:
```
# !pip install Pillow --upgrade
# !pip install matplotlib
```

[7]:
```
from dataset import SportDataset

csv_file = '/root/Datasets/Sports/sports.csv'
class_file = '/root/Datasets/Sports/class_dict.csv'
root_dir = '/root/Datasets/Sports'

train_ds = SportDataset(csv_file=csv_file, class_file=class_file,␣
 ↪root_dir=root_dir, train=True, transform=train_transform)
val_ds = SportDataset(csv_file=csv_file, class_file=class_file,␣
 ↪root_dir=root_dir, train=False, transform=val_transform)

train_loader = DataLoader(train_ds, batch_size=32, shuffle=True)
val_loader = DataLoader(val_ds, batch_size=32, shuffle=False)
```

[8]:
```
# !pip install tensorboardX
```

[9]:
```
# tensorboard --logdir=/root/lab11Transformer/runs
```

[10]:
```
from logger import Logger
from tensorboardX import SummaryWriter # have to install pip3 install␣
 ↪tensorboardX

lr = 1e-5
```

```python
epoch_number = 30 # describe the starting epoch if you are continuing training
EPOCHS = 91 # number of epochs to train
model_name = 'vit_b16'
dataset_name = 'sport_dataset'

loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=lr, momentum=0.9)

logger = Logger(model_name, dataset_name)
```

[14]:

```python
print("### Start Loading Model ###")
model.load_state_dict(torch.load('Ep.30.pth',  map_location=device))
print("### Finished Loading Model ###")
```

[14]: <All keys matched successfully>

[15]:

```python
best_vloss = 100000.
# timestamp = datetime.now().strftime('%Y%m%d_%H%M%S')
timestamp = time.time()

for epoch in range(EPOCHS):
    print('EPOCH {}:'.format(epoch_number + 1))
    since = time.time()
    # Make sure gradient tracking is on, and do a pass over the data
    model.train(True)
    running_loss = 0.
    last_loss = 0.
    running_acc = 0.
    train_loop = tqdm(train_loader)
    # Here, we use enumerate(training_loader) instead of
    # iter(training_loader) so that we can track the batch
    # index and do some intra-epoch reporting
    for i, data in enumerate(train_loop):
        # Every data instance is an input + label pair
        inputs, labels = data['image'].to(device), data['labels'].long().
↪to(device)

        # Zero your gradients for every batch!
        optimizer.zero_grad()

        # Make predictions for this batch
        outputs = model(inputs)

        # Compute the loss and its gradients
        loss = loss_fn(outputs, labels)
        loss.backward()
```

```
        # print(labels.shape, outputs.shape)
        _, prediction = torch.max(outputs, dim=1)
        corrects = (labels == (prediction)).sum() / len(labels)
        running_acc += corrects

        # Adjust learning weights
        optimizer.step()

        # Gather data and report
        running_loss += loss.item()

        train_loop.set_postfix(loss=loss.item())

    avg_train_acc = running_acc/len(train_loader)
    avg_train_loss = running_loss/len(train_loader)

    print('Epoch {} loss: {}'.format(epoch_number+1, avg_train_loss))


    # We don't need gradients on to do reporting
    model.train(False)

    vloop = tqdm(val_loader)
    running_vloss = 0.0
    running_vacc = 0.0
    for i, data in enumerate(vloop):
        inputs, labels = data['image'].to(device), data['labels'].long().
↪to(device)
        outputs = model(inputs)
        loss = loss_fn(outputs, labels)
        running_vloss += loss.item()

        _, prediction = torch.max(outputs, dim=1)

        corrects = (prediction == labels).sum() / len(labels)
        running_vacc += corrects

        vloop.set_postfix(loss=loss.item())

    avg_vloss = running_vloss / len(val_loader)
    print('LOSS train {} valid {}'.format(avg_train_loss, avg_vloss))

    avg_vacc = running_vacc / len(val_loader)
    print('Accuracy train {} valid {}'.format(avg_train_acc, avg_vacc))

    # Log the running loss averaged per batch
    # for both training and validation
```

```
    logger.loss_log( train_loss=avg_train_loss,
                     val_loss=avg_vloss, nth_epoch=epoch_number+1)

    logger.acc_log( train_acc=avg_train_acc,
                     val_acc=avg_vacc, nth_epoch=epoch_number+1)

    # Track best performance, and save the model's state
    if avg_vloss < best_vloss:
        best_vloss = avg_vloss
        model_path = 'model_{}_{}'.format(timestamp, epoch_number+1)
        if epoch+1 % 10 == 0:
            logger.save_models(model=model, nth_epoch=epoch_number+1)

    ep_duration = time.time() - since
    print("Epoch time taken: {:.0f}m {:.0f}s".format(ep_duration // 60,␣
 ↪ep_duration % 60))
    epoch_number += 1

total_time = time.time() - timestamp
print("Total time taken: {:.0f}m {:.0f}s".format(total_time // 60, total_time %␣
 ↪60))
```

```
EPOCH 31:

100%|      | 425/425 [03:49<00:00,  1.85it/s, loss=0.608]

Epoch 31 loss: 0.9092286489991581

100%|      | 16/16 [00:03<00:00,  4.18it/s, loss=0.908]

LOSS train 0.9092286489991581 valid 0.9122011810541153
Accuracy train 0.8447058200836182 valid 0.836718738079071
Epoch time taken: 3m 53s
EPOCH 32:

100%|      | 425/425 [03:48<00:00,  1.86it/s, loss=0.306]

Epoch 32 loss: 0.8706562424407286

100%|      | 16/16 [00:03<00:00,  4.21it/s, loss=0.885]

LOSS train 0.8706562424407286 valid 0.8748568072915077
Accuracy train 0.851102888584137 valid 0.836718738079071
Epoch time taken: 3m 53s
EPOCH 33:

100%|      | 425/425 [03:52<00:00,  1.83it/s, loss=0.725]

Epoch 33 loss: 0.8351266033509198

100%|      | 16/16 [00:03<00:00,  4.06it/s, loss=0.822]
```

```
LOSS train 0.8351266033509198 valid 0.8403701893985271
Accuracy train 0.8586764335632324 valid 0.840624988079071
Epoch time taken: 3m 56s
EPOCH 34:

100%|     | 425/425 [03:50<00:00,  1.84it/s, loss=0.912]

Epoch 34 loss: 0.800339147273232

100%|     | 16/16 [00:03<00:00,  4.15it/s, loss=0.774]

LOSS train 0.800339147273232 valid 0.8082048706710339
Accuracy train 0.8641176223754883 valid 0.846484363079071
Epoch time taken: 3m 55s
EPOCH 35:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.647]

Epoch 35 loss: 0.7704856484076557

100%|     | 16/16 [00:03<00:00,  4.12it/s, loss=0.75]

LOSS train 0.7704856484076557 valid 0.7782379277050495
Accuracy train 0.8680881857872009 valid 0.856249988079071
Epoch time taken: 3m 53s
EPOCH 36:

100%|     | 425/425 [03:48<00:00,  1.86it/s, loss=1.99]

Epoch 36 loss: 0.7439536636717179

100%|     | 16/16 [00:03<00:00,  4.15it/s, loss=0.722]

LOSS train 0.7439536636717179 valid 0.7525982726365328
Accuracy train 0.8733087778091431 valid 0.862109363079071
Epoch time taken: 3m 53s
EPOCH 37:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.469]

Epoch 37 loss: 0.71425305611947

100%|     | 16/16 [00:03<00:00,  4.20it/s, loss=0.678]

LOSS train 0.71425305611947 valid 0.7262177933007479
Accuracy train 0.8778676390647888 valid 0.87109375
Epoch time taken: 3m 53s
EPOCH 38:

100%|     | 425/425 [03:48<00:00,  1.86it/s, loss=0.645]

Epoch 38 loss: 0.6879269759795245

100%|     | 16/16 [00:03<00:00,  4.17it/s, loss=0.666]

LOSS train 0.6879269759795245 valid 0.7000140994787216
Accuracy train 0.8824264407157898 valid 0.867968738079071
```

```
Epoch time taken: 3m 53s
EPOCH 39:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.558]

Epoch 39 loss: 0.6655448083316579

100%|     | 16/16 [00:03<00:00,  4.10it/s, loss=0.629]

LOSS train 0.6655448083316579 valid 0.6797144245356321
Accuracy train 0.8861764073371887 valid 0.876953125
Epoch time taken: 3m 53s
EPOCH 40:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=1]

Epoch 40 loss: 0.6441204338915207

100%|     | 16/16 [00:03<00:00,  4.14it/s, loss=0.599]

LOSS train 0.6441204338915207 valid 0.6579332742840052
Accuracy train 0.8891911506652832 valid 0.876953125
Epoch time taken: 3m 54s
EPOCH 41:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.382]

Epoch 41 loss: 0.6220995396025041

100%|     | 16/16 [00:04<00:00,  3.92it/s, loss=0.57]

LOSS train 0.6220995396025041 valid 0.6371945086866617
Accuracy train 0.8958088159561157 valid 0.873046875
Epoch time taken: 3m 54s
EPOCH 42:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.452]

Epoch 42 loss: 0.6007460845919217

100%|     | 16/16 [00:03<00:00,  4.19it/s, loss=0.559]

LOSS train 0.6007460845919217 valid 0.6208793614059687
Accuracy train 0.8997058272361755 valid 0.876953125
Epoch time taken: 3m 54s
EPOCH 43:

100%|     | 425/425 [03:50<00:00,  1.85it/s, loss=0.663]

Epoch 43 loss: 0.5840735389204587

100%|     | 16/16 [00:03<00:00,  4.21it/s, loss=0.54]

LOSS train 0.5840735389204587 valid 0.6042516101151705
Accuracy train 0.9004411697387695 valid 0.875
Epoch time taken: 3m 54s
EPOCH 44:
```

```
100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=1.17]

Epoch 44 loss: 0.5668106150627136

100%|     | 16/16 [00:03<00:00,  4.20it/s, loss=0.521]

LOSS train 0.5668106150627136 valid 0.5873925685882568
Accuracy train 0.9047793745994568 valid 0.880859375
Epoch time taken: 3m 53s
EPOCH 45:

100%|     | 425/425 [03:50<00:00,  1.84it/s, loss=0.444]

Epoch 45 loss: 0.5490735148682314

100%|     | 16/16 [00:03<00:00,  4.19it/s, loss=0.501]

LOSS train 0.5490735148682314 valid 0.5750409960746765
Accuracy train 0.909044086933136 valid 0.8828125
Epoch time taken: 3m 55s
EPOCH 46:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.731]

Epoch 46 loss: 0.5336992430686951

100%|     | 16/16 [00:03<00:00,  4.20it/s, loss=0.478]

LOSS train 0.5336992430686951 valid 0.556655440479517
Accuracy train 0.912573516368866 valid 0.888671875
Epoch time taken: 3m 54s
EPOCH 47:

100%|     | 425/425 [03:48<00:00,  1.86it/s, loss=0.343]

Epoch 47 loss: 0.5175997879925897

100%|     | 16/16 [00:03<00:00,  4.17it/s, loss=0.473]

LOSS train 0.5175997879925897 valid 0.5439559333026409
Accuracy train 0.9133087992668152 valid 0.888671875
Epoch time taken: 3m 53s
EPOCH 48:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.196]

Epoch 48 loss: 0.5021809340224547

100%|     | 16/16 [00:03<00:00,  4.17it/s, loss=0.449]

LOSS train 0.5021809340224547 valid 0.53105104342103
Accuracy train 0.916985273361206 valid 0.892578125
Epoch time taken: 3m 54s
EPOCH 49:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=1.2]

Epoch 49 loss: 0.4903567162682028
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100%|     | 16/16 [00:03<00:00,  4.22it/s, loss=0.445]

LOSS train 0.4903567162682028 valid 0.5175435785204172
Accuracy train 0.9199264049530029 valid 0.89453125
Epoch time taken: 3m 53s
EPOCH 50:

100%|     | 425/425 [03:49<00:00,  1.86it/s, loss=0.543]

Epoch 50 loss: 0.47693637700641855

100%|     | 16/16 [00:03<00:00,  4.17it/s, loss=0.437]

LOSS train 0.47693637700641855 valid 0.5065863076597452
Accuracy train 0.9238234758377075 valid 0.89453125
Epoch time taken: 3m 53s
EPOCH 51:

100%|     | 425/425 [03:48<00:00,  1.86it/s, loss=0.55]

Epoch 51 loss: 0.4633128080648534

100%|     | 16/16 [00:04<00:00,  3.99it/s, loss=0.42]

LOSS train 0.4633128080648534 valid 0.49515455961227417
Accuracy train 0.9266911149024963 valid 0.8984375
Epoch time taken: 3m 53s
EPOCH 52:

100%|     | 425/425 [03:50<00:00,  1.84it/s, loss=0.505]

Epoch 52 loss: 0.4523327289609348

100%|     | 16/16 [00:03<00:00,  4.01it/s, loss=0.406]

LOSS train 0.4523327289609348 valid 0.48461744748055935
Accuracy train 0.9283823370933533 valid 0.900390625
Epoch time taken: 3m 55s
EPOCH 53:

100%|     | 425/425 [03:51<00:00,  1.84it/s, loss=0.395]

Epoch 53 loss: 0.4401604563699049

100%|     | 16/16 [00:03<00:00,  4.16it/s, loss=0.389]

LOSS train 0.4401604563699049 valid 0.4746447019279003
Accuracy train 0.9308087825775146 valid 0.904296875
Epoch time taken: 3m 55s
EPOCH 54:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.559]

Epoch 54 loss: 0.4287885188705781

100%|     | 16/16 [00:03<00:00,  4.18it/s, loss=0.382]
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LOSS train 0.4287885188705781 valid 0.46531920321285725
Accuracy train 0.9327205419540405 valid 0.904296875
Epoch time taken: 3m 53s
EPOCH 55:

100%|     | 425/425 [03:49<00:00,  1.86it/s, loss=0.801]

Epoch 55 loss: 0.4186297613732955

100%|     | 16/16 [00:03<00:00,  4.05it/s, loss=0.373]

LOSS train 0.4186297613732955 valid 0.45740762539207935
Accuracy train 0.934926450252533 valid 0.908203125
Epoch time taken: 3m 53s
EPOCH 56:

100%|     | 425/425 [03:53<00:00,  1.82it/s, loss=0.111]

Epoch 56 loss: 0.40743775018874334

100%|     | 16/16 [00:04<00:00,  3.97it/s, loss=0.357]

LOSS train 0.40743775018874334 valid 0.4471710678189993
Accuracy train 0.9378675818443298 valid 0.91015625
Epoch time taken: 3m 57s
EPOCH 57:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=1.17]

Epoch 57 loss: 0.40076577884309433

100%|     | 16/16 [00:04<00:00,  3.98it/s, loss=0.345]

LOSS train 0.40076577884309433 valid 0.439258037135005
Accuracy train 0.9392646551132202 valid 0.912109375
Epoch time taken: 3m 56s
EPOCH 58:

100%|     | 425/425 [03:55<00:00,  1.80it/s, loss=0.349]

Epoch 58 loss: 0.3888860802790698

100%|     | 16/16 [00:04<00:00,  3.93it/s, loss=0.34]

LOSS train 0.3888860802790698 valid 0.4315406568348408
Accuracy train 0.9406617283821106 valid 0.9140625
Epoch time taken: 3m 60s
EPOCH 59:

100%|     | 425/425 [03:54<00:00,  1.82it/s, loss=0.103]

Epoch 59 loss: 0.37919777828104356

100%|     | 16/16 [00:03<00:00,  4.05it/s, loss=0.328]

LOSS train 0.37919777828104356 valid 0.4229041524231434
Accuracy train 0.943823516368866 valid 0.91796875
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Epoch time taken: 3m 58s
EPOCH 60:

100%|     | 425/425 [03:51<00:00,  1.84it/s, loss=0.219]

Epoch 60 loss: 0.3705185336225173

100%|     | 16/16 [00:03<00:00,  4.15it/s, loss=0.323]

LOSS train 0.3705185336225173 valid 0.4159801471978426
Accuracy train 0.9449264407157898 valid 0.91796875
Epoch time taken: 3m 55s
EPOCH 61:

100%|     | 425/425 [03:50<00:00,  1.85it/s, loss=0.2]

Epoch 61 loss: 0.3622961117239559

100%|     | 16/16 [00:03<00:00,  4.05it/s, loss=0.312]

LOSS train 0.3622961117239559 valid 0.4091479955241084
Accuracy train 0.9472793936729431 valid 0.919921875
Epoch time taken: 3m 54s
EPOCH 62:

100%|     | 425/425 [03:50<00:00,  1.84it/s, loss=0.308]

Epoch 62 loss: 0.35479932739454156

100%|     | 16/16 [00:03<00:00,  4.01it/s, loss=0.31]

LOSS train 0.35479932739454156 valid 0.4017239222303033
Accuracy train 0.9465440511703491 valid 0.91796875
Epoch time taken: 3m 55s
EPOCH 63:

100%|     | 425/425 [03:54<00:00,  1.81it/s, loss=0.564]

Epoch 63 loss: 0.34748892465058495

100%|     | 16/16 [00:03<00:00,  4.06it/s, loss=0.304]

LOSS train 0.34748892465058495 valid 0.39551400672644377
Accuracy train 0.9491176009178162 valid 0.919921875
Epoch time taken: 3m 59s
EPOCH 64:

100%|     | 425/425 [03:53<00:00,  1.82it/s, loss=0.146]

Epoch 64 loss: 0.33851986976230847

100%|     | 16/16 [00:03<00:00,  4.13it/s, loss=0.296]

LOSS train 0.33851986976230847 valid 0.3897798294201493
Accuracy train 0.9505146741867065 valid 0.91796875
Epoch time taken: 3m 57s
EPOCH 65:
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100%|     | 425/425 [03:54<00:00,  1.81it/s, loss=0.0597]

Epoch 65 loss: 0.33229362948852426

100%|     | 16/16 [00:03<00:00,  4.10it/s, loss=0.284]

LOSS train 0.33229362948852426 valid 0.3836500942707062
Accuracy train 0.9515441060066223 valid 0.921875
Epoch time taken: 3m 59s
EPOCH 66:

100%|     | 425/425 [03:56<00:00,  1.80it/s, loss=0.221]

Epoch 66 loss: 0.3240241616263109

100%|     | 16/16 [00:04<00:00,  3.97it/s, loss=0.28]

LOSS train 0.3240241616263109 valid 0.3782455828040838
Accuracy train 0.9544117450714111 valid 0.9296875
Epoch time taken: 4m 0s
EPOCH 67:

100%|     | 425/425 [03:55<00:00,  1.81it/s, loss=0.169]

Epoch 67 loss: 0.3178333565417458

100%|     | 16/16 [00:03<00:00,  4.00it/s, loss=0.275]

LOSS train 0.3178333565417458 valid 0.37268697284162045
Accuracy train 0.9561764597892761 valid 0.927734375
Epoch time taken: 3m 59s
EPOCH 68:

100%|     | 425/425 [03:57<00:00,  1.79it/s, loss=0.201]

Epoch 68 loss: 0.31131692374453823

100%|     | 16/16 [00:03<00:00,  4.13it/s, loss=0.272]

LOSS train 0.31131692374453823 valid 0.3666380802169442
Accuracy train 0.957352876663208 valid 0.9296875
Epoch time taken: 4m 1s
EPOCH 69:

100%|     | 425/425 [03:54<00:00,  1.81it/s, loss=0.225]

Epoch 69 loss: 0.3050002656964695

100%|     | 16/16 [00:03<00:00,  4.15it/s, loss=0.267]

LOSS train 0.3050002656964695 valid 0.3617017325013876
Accuracy train 0.957352876663208 valid 0.93359375
Epoch time taken: 3m 59s
EPOCH 70:

100%|     | 425/425 [03:55<00:00,  1.80it/s, loss=0.118]

Epoch 70 loss: 0.29832651064676396
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100%|     | 16/16 [00:03<00:00,  4.02it/s, loss=0.262]

LOSS train 0.29832651064676396 valid 0.3564029289409518
Accuracy train 0.9594852328300476 valid 0.9375
Epoch time taken: 3m 60s
EPOCH 71:

100%|     | 425/425 [03:55<00:00,  1.80it/s, loss=0.436]

Epoch 71 loss: 0.29207999439800486

100%|     | 16/16 [00:04<00:00,  3.96it/s, loss=0.254]

LOSS train 0.29207999439800486 valid 0.3538771718740463
Accuracy train 0.9605882167816162 valid 0.931640625
Epoch time taken: 3m 60s
EPOCH 72:

100%|     | 425/425 [03:55<00:00,  1.81it/s, loss=0.117]

Epoch 72 loss: 0.2865275741675321

100%|     | 16/16 [00:04<00:00,  3.86it/s, loss=0.252]

LOSS train 0.2865275741675321 valid 0.3468138091266155
Accuracy train 0.9622793793678284 valid 0.9375
Epoch time taken: 3m 59s
EPOCH 73:

100%|     | 425/425 [03:56<00:00,  1.80it/s, loss=0.209]

Epoch 73 loss: 0.28069135585251975

100%|     | 16/16 [00:03<00:00,  4.03it/s, loss=0.237]

LOSS train 0.28069135585251975 valid 0.34336353093385696
Accuracy train 0.9613969922065735 valid 0.939453125
Epoch time taken: 4m 0s
EPOCH 74:

100%|     | 425/425 [03:53<00:00,  1.82it/s, loss=0.0817]

Epoch 74 loss: 0.2759015065080979

100%|     | 16/16 [00:03<00:00,  4.03it/s, loss=0.234]

LOSS train 0.2759015065080979 valid 0.3376178443431854
Accuracy train 0.9633088111877441 valid 0.94140625
Epoch time taken: 3m 57s
EPOCH 75:

100%|     | 425/425 [03:51<00:00,  1.84it/s, loss=0.355]

Epoch 75 loss: 0.27083146351225235

100%|     | 16/16 [00:03<00:00,  4.17it/s, loss=0.235]
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LOSS train 0.27083146351225235 valid 0.33384233247488737
Accuracy train 0.9654411673545837 valid 0.94140625
Epoch time taken: 3m 55s
EPOCH 76:

100%|     | 425/425 [03:53<00:00,  1.82it/s, loss=0.0754]

Epoch 76 loss: 0.264225233056966

100%|     | 16/16 [00:03<00:00,  4.06it/s, loss=0.236]

LOSS train 0.264225233056966 valid 0.33077449910342693
Accuracy train 0.9663970470428467 valid 0.9375
Epoch time taken: 3m 58s
EPOCH 77:

100%|     | 425/425 [03:50<00:00,  1.85it/s, loss=0.296]

Epoch 77 loss: 0.26070594091625776

100%|     | 16/16 [00:04<00:00,  3.97it/s, loss=0.223]

LOSS train 0.26070594091625776 valid 0.3267780588939786
Accuracy train 0.966985285282135 valid 0.939453125
Epoch time taken: 3m 54s
EPOCH 78:

100%|     | 425/425 [03:50<00:00,  1.84it/s, loss=0.152]

Epoch 78 loss: 0.2549304789304733

100%|     | 16/16 [00:03<00:00,  4.09it/s, loss=0.22]

LOSS train 0.2549304789304733 valid 0.32247672602534294
Accuracy train 0.9683088064193726 valid 0.94140625
Epoch time taken: 3m 55s
EPOCH 79:

100%|     | 425/425 [03:50<00:00,  1.85it/s, loss=0.139]

Epoch 79 loss: 0.2502949786186218

100%|     | 16/16 [00:03<00:00,  4.04it/s, loss=0.215]

LOSS train 0.2502949786186218 valid 0.3192863706499338
Accuracy train 0.9680882096290588 valid 0.943359375
Epoch time taken: 3m 54s
EPOCH 80:

100%|     | 425/425 [03:50<00:00,  1.84it/s, loss=0.635]

Epoch 80 loss: 0.2466217808863696

100%|     | 16/16 [00:03<00:00,  4.04it/s, loss=0.212]

LOSS train 0.2466217808863696 valid 0.3147279964759946
Accuracy train 0.9688234925270081 valid 0.943359375
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Epoch time taken: 3m 55s
EPOCH 81:

100%|     | 425/425 [03:50<00:00,  1.85it/s, loss=0.104]

Epoch 81 loss: 0.24159161972648957

100%|     | 16/16 [00:04<00:00,  3.94it/s, loss=0.21]

LOSS train 0.24159161972648957 valid 0.31229472160339355
Accuracy train 0.9700734615325928 valid 0.943359375
Epoch time taken: 3m 54s
EPOCH 82:

100%|     | 425/425 [03:51<00:00,  1.83it/s, loss=0.23]

Epoch 82 loss: 0.23688337061335057

100%|     | 16/16 [00:03<00:00,  4.09it/s, loss=0.212]

LOSS train 0.23688337061335057 valid 0.3077662819996476
Accuracy train 0.9724999666213989 valid 0.943359375
Epoch time taken: 3m 56s
EPOCH 83:

100%|     | 425/425 [03:50<00:00,  1.84it/s, loss=0.216]

Epoch 83 loss: 0.23316618177820655

100%|     | 16/16 [00:04<00:00,  3.94it/s, loss=0.205]

LOSS train 0.23316618177820655 valid 0.3056129990145564
Accuracy train 0.9730146527290344 valid 0.9453125
Epoch time taken: 3m 54s
EPOCH 84:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=0.115]

Epoch 84 loss: 0.2288807518341962

100%|     | 16/16 [00:04<00:00,  3.90it/s, loss=0.201]

LOSS train 0.2288807518341962 valid 0.3025565482676029
Accuracy train 0.9735293984413147 valid 0.947265625
Epoch time taken: 3m 57s
EPOCH 85:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.203]

Epoch 85 loss: 0.22463837723521626

100%|     | 16/16 [00:03<00:00,  4.20it/s, loss=0.197]

LOSS train 0.22463837723521626 valid 0.2990518547594547
Accuracy train 0.9749999642372131 valid 0.9453125
Epoch time taken: 3m 53s
EPOCH 86:
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100%|     | 425/425 [03:51<00:00,  1.84it/s, loss=0.333]

Epoch 86 loss: 0.22119925472666235

100%|     | 16/16 [00:04<00:00,  3.92it/s, loss=0.196]

LOSS train 0.22119925472666235 valid 0.2963058724999428
Accuracy train 0.975147008895874 valid 0.947265625
Epoch time taken: 3m 55s
EPOCH 87:

100%|     | 425/425 [04:05<00:00,  1.73it/s, loss=0.156]

Epoch 87 loss: 0.2171853703786345

100%|     | 16/16 [00:04<00:00,  3.83it/s, loss=0.193]

LOSS train 0.2171853703786345 valid 0.2939000427722931
Accuracy train 0.975073516368866 valid 0.947265625
Epoch time taken: 4m 10s
EPOCH 88:

100%|     | 425/425 [04:45<00:00,  1.49it/s, loss=0.0451]

Epoch 88 loss: 0.213690664768219

100%|     | 16/16 [00:04<00:00,  3.54it/s, loss=0.187]

LOSS train 0.213690664768219 valid 0.2913897028192878
Accuracy train 0.9753676056861877 valid 0.947265625
Epoch time taken: 4m 50s
EPOCH 89:

100%|     | 425/425 [04:05<00:00,  1.73it/s, loss=0.0946]

Epoch 89 loss: 0.20943065964123783

100%|     | 16/16 [00:03<00:00,  4.03it/s, loss=0.184]

LOSS train 0.20943065964123783 valid 0.2889753170311451
Accuracy train 0.9769852757453918 valid 0.943359375
Epoch time taken: 4m 10s
EPOCH 90:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.0461]

Epoch 90 loss: 0.20629795174388324

100%|     | 16/16 [00:03<00:00,  4.02it/s, loss=0.182]

LOSS train 0.20629795174388324 valid 0.28535670787096024
Accuracy train 0.977867603302002 valid 0.94921875
Epoch time taken: 3m 54s
EPOCH 91:

100%|     | 425/425 [03:51<00:00,  1.84it/s, loss=0.246]

Epoch 91 loss: 0.2028302293489961
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100%|     | 16/16 [00:03<00:00,  4.12it/s, loss=0.186]

LOSS train 0.2028302293489961 valid 0.28241574484854937
Accuracy train 0.9785293936729431 valid 0.951171875
Epoch time taken: 3m 55s
EPOCH 92:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=0.257]

Epoch 92 loss: 0.20009364441913716

100%|     | 16/16 [00:04<00:00,  3.98it/s, loss=0.175]

LOSS train 0.20009364441913716 valid 0.2820408847182989
Accuracy train 0.9791176319122314 valid 0.947265625
Epoch time taken: 3m 56s
EPOCH 93:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=0.101]

Epoch 93 loss: 0.19623387473471024

100%|     | 16/16 [00:04<00:00,  3.99it/s, loss=0.179]

LOSS train 0.19623387473471024 valid 0.27906804997473955
Accuracy train 0.9796323180198669 valid 0.951171875
Epoch time taken: 3m 56s
EPOCH 94:

100%|     | 425/425 [03:53<00:00,  1.82it/s, loss=0.215]

Epoch 94 loss: 0.19334076537805445

100%|     | 16/16 [00:03<00:00,  4.03it/s, loss=0.175]

LOSS train 0.19334076537805445 valid 0.2769497698172927
Accuracy train 0.9801470041275024 valid 0.94921875
Epoch time taken: 3m 58s
EPOCH 95:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=0.383]

Epoch 95 loss: 0.18994102676125132

100%|     | 16/16 [00:03<00:00,  4.01it/s, loss=0.171]

LOSS train 0.18994102676125132 valid 0.2733333110809326
Accuracy train 0.9811028838157654 valid 0.947265625
Epoch time taken: 3m 57s
EPOCH 96:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=0.234]

Epoch 96 loss: 0.1867006697900155

100%|     | 16/16 [00:03<00:00,  4.14it/s, loss=0.174]
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LOSS train 0.1867006697900155 valid 0.2718238439410925
Accuracy train 0.9808822870254517 valid 0.947265625
Epoch time taken: 3m 56s
EPOCH 97:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.184]

Epoch 97 loss: 0.18361573641791062

100%|     | 16/16 [00:03<00:00,  4.17it/s, loss=0.167]

LOSS train 0.18361573641791062 valid 0.26931706070899963
Accuracy train 0.9821323156356812 valid 0.947265625
Epoch time taken: 3m 53s
EPOCH 98:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=0.324]

Epoch 98 loss: 0.18113731364993488

100%|     | 16/16 [00:03<00:00,  4.07it/s, loss=0.168]

LOSS train 0.18113731364993488 valid 0.2681800639256835
Accuracy train 0.982279360294342 valid 0.947265625
Epoch time taken: 3m 56s
EPOCH 99:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=0.124]

Epoch 99 loss: 0.1774675845661584

100%|     | 16/16 [00:03<00:00,  4.03it/s, loss=0.162]

LOSS train 0.1774675845661584 valid 0.2663507033139467
Accuracy train 0.9824999570846558 valid 0.9453125
Epoch time taken: 3m 56s
EPOCH 100:

100%|     | 425/425 [03:53<00:00,  1.82it/s, loss=0.129]

Epoch 100 loss: 0.17482008523800793

100%|     | 16/16 [00:04<00:00,  3.96it/s, loss=0.165]

LOSS train 0.17482008523800793 valid 0.2639252860099077
Accuracy train 0.9838234782218933 valid 0.947265625
Epoch time taken: 3m 58s
EPOCH 101:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=0.0813]

Epoch 101 loss: 0.172611723103944

100%|     | 16/16 [00:03<00:00,  4.09it/s, loss=0.16]

LOSS train 0.172611723103944 valid 0.2626511277630925
Accuracy train 0.9836764335632324 valid 0.947265625
```

```
Epoch time taken: 3m 56s
EPOCH 102:

100%|     | 425/425 [03:52<00:00,  1.83it/s, loss=0.425]

Epoch 102 loss: 0.17030577282695208

100%|     | 16/16 [00:03<00:00,  4.04it/s, loss=0.158]

LOSS train 0.17030577282695208 valid 0.25969488359987736
Accuracy train 0.984044075012207 valid 0.9453125
Epoch time taken: 3m 56s
EPOCH 103:

100%|     | 425/425 [03:49<00:00,  1.85it/s, loss=0.0281]

Epoch 103 loss: 0.16725907338892712

100%|     | 16/16 [00:03<00:00,  4.18it/s, loss=0.155]

LOSS train 0.16725907338892712 valid 0.25676382426172495
Accuracy train 0.9843382239341736 valid 0.94921875
Epoch time taken: 3m 54s
EPOCH 104:

100%|     | 425/425 [03:55<00:00,  1.81it/s, loss=0.24]

Epoch 104 loss: 0.16534918846452937

100%|     | 16/16 [00:03<00:00,  4.18it/s, loss=0.154]

LOSS train 0.16534918846452937 valid 0.25642019137740135
Accuracy train 0.9849264025688171 valid 0.9453125
Epoch time taken: 3m 59s
EPOCH 105:

100%|     | 425/425 [03:53<00:00,  1.82it/s, loss=0.247]

Epoch 105 loss: 0.16265263117411558

100%|     | 16/16 [00:03<00:00,  4.05it/s, loss=0.158]

LOSS train 0.16265263117411558 valid 0.2544843815267086
Accuracy train 0.9855881929397583 valid 0.94921875
Epoch time taken: 3m 58s
EPOCH 106:

100%|     | 425/425 [03:52<00:00,  1.82it/s, loss=0.2]

Epoch 106 loss: 0.1600733779107823

100%|     | 16/16 [00:04<00:00,  3.89it/s, loss=0.152]

LOSS train 0.1600733779107823 valid 0.25215839873999357
Accuracy train 0.9858823418617249 valid 0.94921875
Epoch time taken: 3m 57s
EPOCH 107:
```

```
100%|      | 425/425 [03:51<00:00,  1.83it/s, loss=0.263]

Epoch 107 loss: 0.157791401927962

100%|      | 16/16 [00:03<00:00,  4.08it/s, loss=0.152]

LOSS train 0.157791401927962 valid 0.2504274323582649
Accuracy train 0.9863970279693604 valid 0.94921875
Epoch time taken: 3m 56s
EPOCH 108:

100%|      | 425/425 [03:49<00:00,  1.85it/s, loss=0.125]

Epoch 108 loss: 0.1547462284389664

100%|      | 16/16 [00:03<00:00,  4.24it/s, loss=0.149]

LOSS train 0.1547462284389664 valid 0.24864165764302015
Accuracy train 0.986764669418335 valid 0.94921875
Epoch time taken: 3m 53s
EPOCH 109:

100%|      | 425/425 [03:47<00:00,  1.87it/s, loss=0.213]

Epoch 109 loss: 0.15332963254521875

100%|      | 16/16 [00:03<00:00,  4.21it/s, loss=0.144]

LOSS train 0.15332963254521875 valid 0.24741909559816122
Accuracy train 0.9868382215499878 valid 0.94921875
Epoch time taken: 3m 51s
EPOCH 110:

100%|      | 425/425 [03:48<00:00,  1.86it/s, loss=0.205]

Epoch 110 loss: 0.15123620068325716

100%|      | 16/16 [00:03<00:00,  4.19it/s, loss=0.143]

LOSS train 0.15123620068325716 valid 0.24524625204503536
Accuracy train 0.9874999523162842 valid 0.951171875
Epoch time taken: 3m 52s
EPOCH 111:

100%|      | 425/425 [03:48<00:00,  1.86it/s, loss=0.0863]

Epoch 111 loss: 0.14848096951842307

100%|      | 16/16 [00:03<00:00,  4.03it/s, loss=0.143]

LOSS train 0.14848096951842307 valid 0.24405852239578962
Accuracy train 0.9874264597892761 valid 0.94921875
Epoch time taken: 3m 52s
EPOCH 112:

100%|      | 425/425 [03:48<00:00,  1.86it/s, loss=0.293]

Epoch 112 loss: 0.146409753946697
```

```
100%|     | 16/16 [00:03<00:00,  4.19it/s, loss=0.14]

LOSS train 0.146409753946697 valid 0.24336411617696285
Accuracy train 0.9876469969749451 valid 0.947265625
Epoch time taken: 3m 52s
EPOCH 113:

100%|     | 425/425 [03:48<00:00,  1.86it/s, loss=0.238]

Epoch 113 loss: 0.1445304005110965

100%|     | 16/16 [00:03<00:00,  4.26it/s, loss=0.138]

LOSS train 0.1445304005110965 valid 0.24088024348020554
Accuracy train 0.9880146384239197 valid 0.94921875
Epoch time taken: 3m 52s
EPOCH 114:

100%|     | 425/425 [03:48<00:00,  1.86it/s, loss=0.0784]

Epoch 114 loss: 0.14190886706113814

100%|     | 16/16 [00:03<00:00,  4.19it/s, loss=0.139]

LOSS train 0.14190886706113814 valid 0.2397499131038785
Accuracy train 0.9888970255851746 valid 0.953125
Epoch time taken: 3m 52s
EPOCH 115:

100%|     | 425/425 [03:48<00:00,  1.86it/s, loss=0.168]

Epoch 115 loss: 0.14022423986126395

100%|     | 16/16 [00:03<00:00,  4.20it/s, loss=0.138]

LOSS train 0.14022423986126395 valid 0.23717800620943308
Accuracy train 0.9885293841362 valid 0.953125
Epoch time taken: 3m 52s
EPOCH 116:

100%|     | 425/425 [03:48<00:00,  1.86it/s, loss=0.0711]

Epoch 116 loss: 0.13847211527473785

100%|     | 16/16 [00:03<00:00,  4.28it/s, loss=0.136]

LOSS train 0.13847211527473785 valid 0.23623186722397804
Accuracy train 0.988602876663208 valid 0.953125
Epoch time taken: 3m 52s
EPOCH 117:

100%|     | 425/425 [03:46<00:00,  1.87it/s, loss=0.119]

Epoch 117 loss: 0.1367047748232589

100%|     | 16/16 [00:03<00:00,  4.23it/s, loss=0.136]
```

```
LOSS train 0.1367047748232589 valid 0.23541664611548185
Accuracy train 0.9890440702438354 valid 0.953125
Epoch time taken: 3m 51s
EPOCH 118:

100%|      | 425/425 [03:48<00:00,  1.86it/s, loss=0.137]

Epoch 118 loss: 0.13455437739982323

100%|      | 16/16 [00:03<00:00,  4.14it/s, loss=0.137]

LOSS train 0.13455437739982323 valid 0.2347709136083722
Accuracy train 0.9894852638244629 valid 0.953125
Epoch time taken: 3m 53s
EPOCH 119:

100%|      | 425/425 [03:48<00:00,  1.86it/s, loss=0.112]

Epoch 119 loss: 0.13283952348372516

100%|      | 16/16 [00:03<00:00,  4.21it/s, loss=0.134]

LOSS train 0.13283952348372516 valid 0.23205858562141657
Accuracy train 0.9898529052734375 valid 0.953125
Epoch time taken: 3m 52s
EPOCH 120:

100%|      | 425/425 [03:47<00:00,  1.87it/s, loss=0.172]

Epoch 120 loss: 0.1315960278055247

100%|      | 16/16 [00:03<00:00,  4.24it/s, loss=0.133]

LOSS train 0.1315960278055247 valid 0.23147412855178118
Accuracy train 0.9899999499320984 valid 0.95703125
Epoch time taken: 3m 52s
EPOCH 121:

100%|      | 425/425 [03:47<00:00,  1.87it/s, loss=0.0805]

Epoch 121 loss: 0.12873743884703692

100%|      | 16/16 [00:03<00:00,  4.24it/s, loss=0.132]

LOSS train 0.12873743884703692 valid 0.23023033700883389
Accuracy train 0.9908823370933533 valid 0.955078125
Epoch time taken: 3m 51s
Total time taken: 357m 54s
```

[17]:
```
# torch.save(model.state_dict(), './saved/vit_b16/Ep.121.pth')
```

[ ]:
```
# logger.save_models(model=model, nth_epoch=120+1)
```

2. With your final fine-tuned weights, try to inference and get the result on images from "test" and "images to predict" directories in sport_dataset. Visualize some random inferenced images with their predictions.

[23]:
```
import matplotlib.pyplot as plt
from utils import *
import torchvision

print("### Start Loading Model ###")
model.load_state_dict(torch.load('./saved/vit_b16/Ep.121.pth', ␣
↪map_location=device))
model = model.to(device)

model.eval()

class_df = pd.read_csv(class_file, usecols=['class_index', 'class'])
class_dict = { row[0]:row[1] for i, row in class_df.iterrows()}
print("class dict: ", class_dict)

dataiter = iter(val_loader)
data = next(dataiter)
```

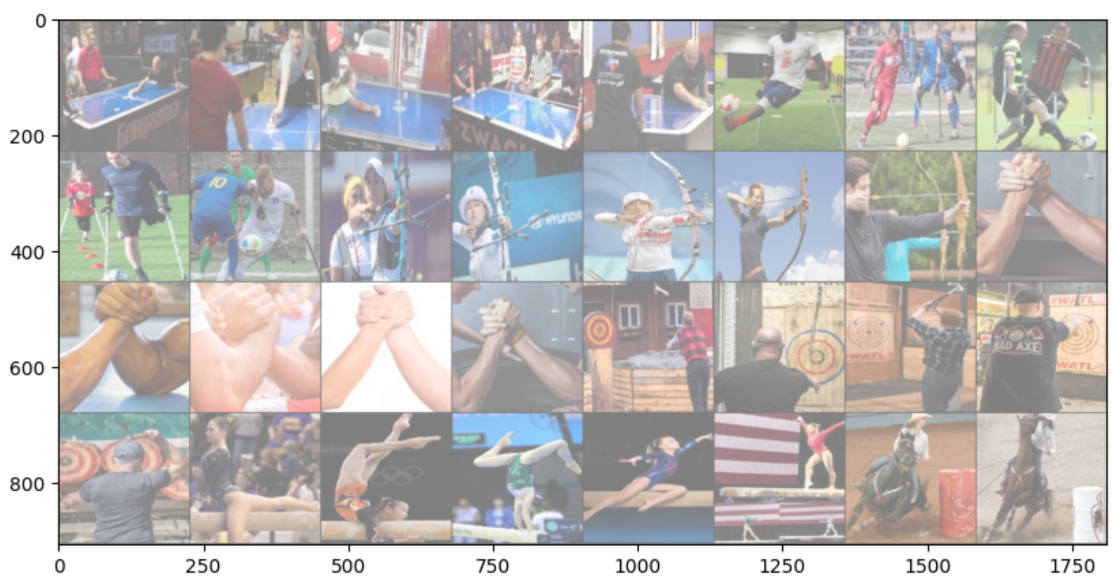
```
### Start Loading Model ###
class dict:  {0: 'air hockey', 1: 'ampute football', 2: 'archery', 3: 'arm
wrestling', 4: 'axe throwing', 5: 'balance beam', 6: 'barell racing', 7:
'baseball', 8: 'basketball', 9: 'baton twirling', 10: 'bike polo', 11:
'billiards', 12: 'bmx', 13: 'bobsled', 14: 'bowling', 15: 'boxing', 16: 'bull
riding', 17: 'bungee jumping', 18: 'canoe slamon', 19: 'cheerleading', 20:
'chuckwagon racing', 21: 'cricket', 22: 'croquet', 23: 'curling', 24: 'disc
golf', 25: 'fencing', 26: 'field hockey', 27: 'figure skating men', 28: 'figure
skating pairs', 29: 'figure skating women', 30: 'fly fishing', 31: 'football',
32: 'formula 1 racing', 33: 'frisbee', 34: 'gaga', 35: 'giant slalom', 36:
'golf', 37: 'hammer throw', 38: 'hang gliding', 39: 'harness racing', 40: 'high
jump', 41: 'hockey', 42: 'horse jumping', 43: 'horse racing', 44: 'horseshoe
pitching', 45: 'hurdles', 46: 'hydroplane racing', 47: 'ice climbing', 48: 'ice
yachting', 49: 'jai alai', 50: 'javelin', 51: 'jousting', 52: 'judo', 53:
'lacrosse', 54: 'log rolling', 55: 'luge', 56: 'motorcycle racing', 57:
'mushing', 58: 'nascar racing', 59: 'olympic wrestling', 60: 'parallel bar', 61:
'pole climbing', 62: 'pole dancing', 63: 'pole vault', 64: 'polo', 65: 'pommel
horse', 66: 'rings', 67: 'rock climbing', 68: 'roller derby', 69: 'rollerblade
racing', 70: 'rowing', 71: 'rugby', 72: 'sailboat racing', 73: 'shot put', 74:
'shuffleboard', 75: 'sidecar racing', 76: 'ski jumping', 77: 'sky surfing', 78:
'skydiving', 79: 'snow boarding', 80: 'snowmobile racing', 81: 'speed skating',
82: 'steer wrestling', 83: 'sumo wrestling', 84: 'surfing', 85: 'swimming', 86:
'table tennis', 87: 'tennis', 88: 'track bicycle', 89: 'trapeze', 90: 'tug of
war', 91: 'ultimate', 92: 'uneven bars', 93: 'volleyball', 94: 'water cycling',
95: 'water polo', 96: 'weightlifting', 97: 'wheelchair basketball', 98:
'wheelchair racing', 99: 'wingsuit flying'}
```

[26]:
```python
plt.rcParams['figure.figsize'] = [15, 5]
# Create a grid from the images and show them
img_grid = torchvision.utils.make_grid(data['image'])
matplotlib_imshow(img_grid, one_channel=False)
# print(','.join(class_dict[data['labels'][j].item()] for j in range(8)))

inputs, labels = data['image'].to(device), data['labels'].long().to(device)
outputs = model(inputs)
_, prediction = torch.max(outputs, dim=1)

print(f'Predict Result : {[class_dict[c] for c in prediction.tolist()]}')
print(f'Actual  Result : {[class_dict[c] for c in labels.tolist()]}')
```

```
Predict Result : ['air hockey', 'air hockey', 'air hockey', 'air hockey', 'air
hockey', 'ampute football', 'ampute football', 'ampute football', 'ampute
football', 'ampute football', 'archery', 'archery', 'archery', 'archery',
'archery', 'arm wrestling', 'arm wrestling', 'arm wrestling', 'arm wrestling',
'arm wrestling', 'axe throwing', 'axe throwing', 'axe throwing', 'axe throwing',
'axe throwing', 'balance beam', 'balance beam', 'balance beam', 'balance beam',
'balance beam', 'barell racing', 'barell racing']
Actual  Result : ['air hockey', 'air hockey', 'air hockey', 'air hockey', 'air
hockey', 'ampute football', 'ampute football', 'ampute football', 'ampute
football', 'ampute football', 'archery', 'archery', 'archery', 'archery',
'archery', 'arm wrestling', 'arm wrestling', 'arm wrestling', 'arm wrestling',
'arm wrestling', 'axe throwing', 'axe throwing', 'axe throwing', 'axe throwing',
'axe throwing', 'balance beam', 'balance beam', 'balance beam', 'balance beam',
'balance beam', 'barell racing', 'barell racing']
```



3. Describe your experience on fine-turning and show the graphs from tensorboardX.

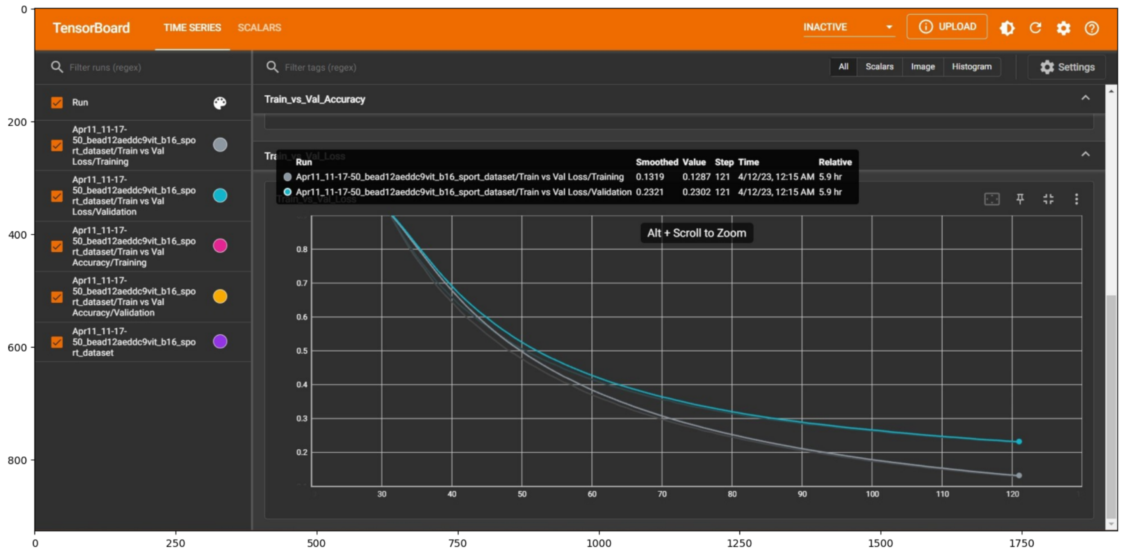
[13]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

plt.figure(figsize=(30,20))
img1 = mpimg.imread('./figure/01loss.jpg')
img2 = mpimg.imread('./figure/02acc.jpg')

plt.title('Train vs Validation')
plt.subplot(2,1,1)
plt.imshow(img1)
plt.subplot(2,1,2)
plt.imshow(img2)
```

```
/tmp/ipykernel_5350/537292868.py:10: MatplotlibDeprecationWarning: Auto-removal
of overlapping axes is deprecated since 3.6 and will be removed two minor
releases later; explicitly call ax.remove() as needed.
  plt.subplot(2,1,1)
```

[13]:
```
<matplotlib.image.AxesImage at 0x7f9c6e247160>
```



In conclusion, I has continued to fine-tuned more 91 (totally epochs is 121). It shown surprisely that accuracy and loss are always improve more and more. Training and Validation loss are 0.139 and 0.2321 respectively, and Training and Validation Accuracy are 99.01 % and 95.51 % respectively. From testing image, the model is able to predict outputs correctly.