

cifar10

October 4, 2023

1 Deep Learning

1.0.1 Musel Tabares

1.0.2 A00830710

Importamos librerias

```
[ ]: #para utilizar tensores etc
import torch
#para el modelo
from torch import nn
#para importar datasets
import torchvision
#para transformar imagenes
import torchvision.transforms as transforms
#para visualizaciones
import matplotlib.pyplot as plt
#ver a detalle el modelo
from torchsummary import summary
# barra de progreso
from tqdm.auto import tqdm

#importamos funciones
from utils import *
```

```
c:\Users\musel\anaconda3\envs\pytorch\lib\site-packages\tqdm\auto.py:21:
TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
    from .autonotebook import tqdm as notebook_tqdm
```

1.1 Cifar10

Importamos datos

```
[ ]: trainset = torchvision.datasets.CIFAR10(root='./data',
    ↪train=True,download=True, transform=transforms.ToTensor())
testset = torchvision.datasets.CIFAR10(root='./data',
    ↪train=False,download=True, transform=transforms.ToTensor())
```

```
classes = ('plane', 'car', 'bird', 'cat','deer', 'dog', 'frog', 'horse',  
↪ 'ship', 'truck')
```

Files already downloaded and verified

Files already downloaded and verified

Observamos la dimension de las imagenes

```
[ ]: # desplegamos primer imagen  
image, label = trainset[0]  
image.shape, label
```

```
[ ]: (torch.Size([3, 32, 32]), 6)
```

Observamos cantidad de datos en train y test

```
[ ]: len(trainset.data), len(trainset.targets), len(testset.data), len(testset.  
↪ targets)
```

```
[ ]: (50000, 50000, 10000, 10000)
```

Creamos batches de los datos

```
[ ]: batch_size = 32  
trainloader = torch.utils.data.DataLoader(trainset,  
↪ batch_size=batch_size,shuffle=True, num_workers=2)  
testloader = torch.utils.data.DataLoader(testset,  
↪ batch_size=batch_size,shuffle=False, num_workers=2)
```

Observamos cuantos batches se crearon

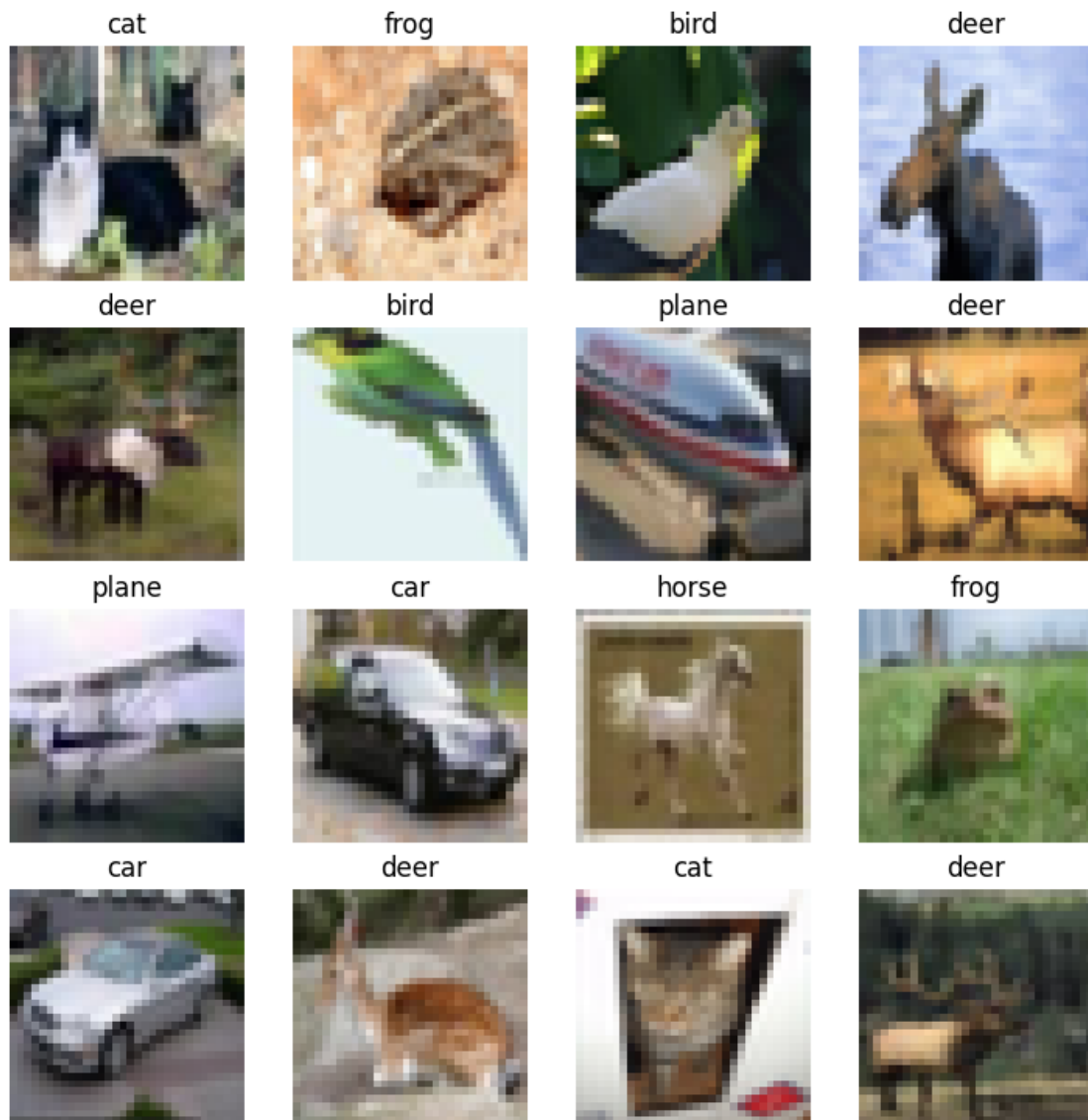
```
[ ]: print(f"Length of train dataloader: {len(trainloader)} batches of {batch_size}")  
print(f"Length of test dataloader: {len(testloader)} batches of {batch_size}")
```

Length of train dataloader: 782 batches of 64

Length of test dataloader: 157 batches of 64

visualizamos 16 imagenes de manera aleatoria

```
[ ]: plot_sample_images(trainset, classes, 4, 4)
```



Creamos modelo

```
[ ]: class conv(nn.Module):

    def __init__(self):
        super().__init__()
        self.block_1 = nn.Sequential(
            nn.Conv2d(3,32, kernel_size=(3,3), stride=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=(2, 2)),
            nn.Conv2d(32,64, kernel_size=(3,3), stride=1),
            nn.ReLU(),
```

```

        nn.MaxPool2d(kernel_size=(2, 2)),
        nn.Conv2d(64,256, kernel_size=(3,3), stride=1),
        nn.ReLU(),

    )
    self.block_2 = nn.Sequential(
        nn.Flatten(),
        nn.Linear(4096, 64),
        nn.ReLU(),
        nn.Linear(64, 10),
        nn.Sigmoid()
    )

    def forward(self, x):
        x = self.block_1(x)
        x = self.block_2(x)
        return x

```

instanciamos el modelo

```

[ ]: device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
model_0 = conv().to(device)
summary(model_0, (3,32,32))

```

```

-----
Layer (type)          Output Shape          Param #
=====
Conv2d-1              [-1, 32, 30, 30]      896
ReLU-2                [-1, 32, 30, 30]      0
MaxPool2d-3           [-1, 32, 15, 15]      0
Conv2d-4              [-1, 64, 13, 13]      18,496
ReLU-5                [-1, 64, 13, 13]      0
MaxPool2d-6           [-1, 64, 6, 6]        0
Conv2d-7              [-1, 256, 4, 4]       147,712
ReLU-8                [-1, 256, 4, 4]       0
Flatten-9             [-1, 4096]            0
Linear-10              [-1, 64]              262,208
ReLU-11               [-1, 64]              0
Linear-12              [-1, 10]              650
Sigmoid-13            [-1, 10]              0
=====
Total params: 429,962
Trainable params: 429,962
Non-trainable params: 0
-----
Input size (MB): 0.01
Forward/backward pass size (MB): 0.77
Params size (MB): 1.64

```

Estimated Total Size (MB): 2.42

definimos funcion de perdida y optimizador

```
[ ]: loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(params=model_0.parameters())
```

corremos modelo

```
[ ]: NUM_EPOCHS = 10
model_0_results = train(model=model_0,
                        train_dataloader=trainloader,
                        test_dataloader=testloader,
                        optimizer=optimizer,
                        loss_fn=loss_fn,
                        epochs=NUM_EPOCHS,
                        device=device)
```

10%| | 1/10 [00:10<01:38, 10.99s/it]

Epoch: 1 | train_loss: 2.0208 | train_acc: 0.3043 | test_loss: 1.9209 |
test_acc: 0.3851

20%| | 2/10 [00:22<01:28, 11.10s/it]

Epoch: 2 | train_loss: 1.9020 | train_acc: 0.4245 | test_loss: 1.8609 |
test_acc: 0.4719

30%| | 3/10 [00:35<01:25, 12.24s/it]

Epoch: 3 | train_loss: 1.8583 | train_acc: 0.4710 | test_loss: 1.8420 |
test_acc: 0.4918

40%| | 4/10 [00:49<01:18, 13.03s/it]

Epoch: 4 | train_loss: 1.8310 | train_acc: 0.5045 | test_loss: 1.8302 |
test_acc: 0.5021

50%| | 5/10 [01:04<01:08, 13.62s/it]

Epoch: 5 | train_loss: 1.8095 | train_acc: 0.5291 | test_loss: 1.8049 |
test_acc: 0.5448

60%| | 6/10 [01:19<00:55, 13.90s/it]

Epoch: 6 | train_loss: 1.7858 | train_acc: 0.5581 | test_loss: 1.7883 |
test_acc: 0.5737

70%| | 7/10 [01:33<00:42, 14.13s/it]

Epoch: 7 | train_loss: 1.7692 | train_acc: 0.5841 | test_loss: 1.7871 |
test_acc: 0.5632

80%| | 8/10 [01:48<00:28, 14.33s/it]

Epoch: 8 | train_loss: 1.7534 | train_acc: 0.6042 | test_loss: 1.7711 |
test_acc: 0.5850

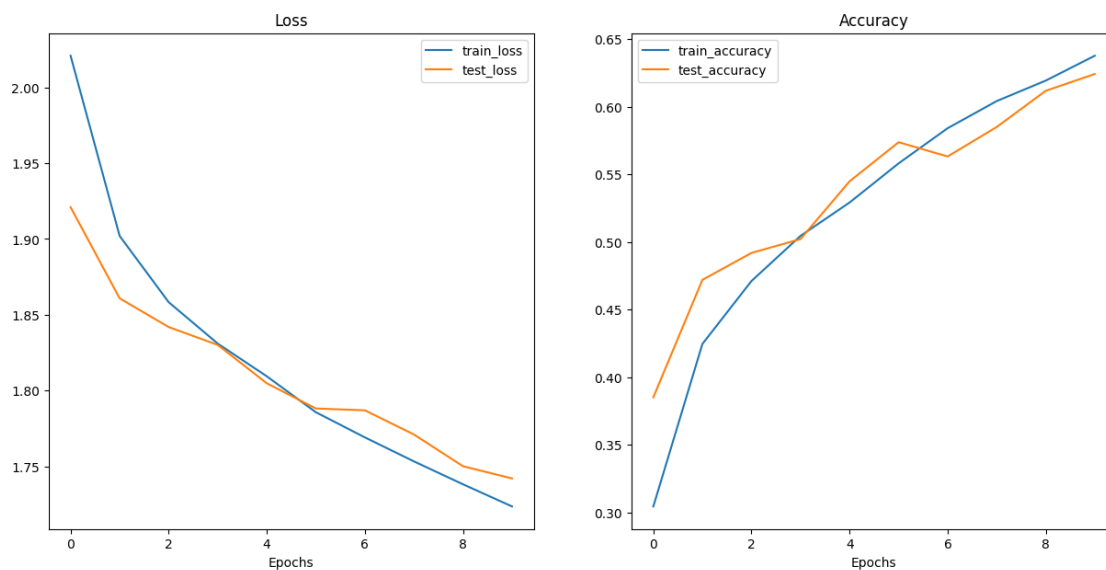
90%| | 9/10 [01:59<00:13, 13.20s/it]

Epoch: 9 | train_loss: 1.7383 | train_acc: 0.6193 | test_loss: 1.7502 |
test_acc: 0.6118

100%| | 10/10 [02:10<00:00, 13.07s/it]

Epoch: 10 | train_loss: 1.7237 | train_acc: 0.6377 | test_loss: 1.7421 |
test_acc: 0.6242

```
[ ]: plot_loss_curves(model_0_results)
```



obtenemos una muestra de los datos del test set

```
[ ]: import random

test_samples = []
test_labels = []

for sample, label in random.sample(list(testset), k=9):
    test_samples.append(sample)
    test_labels.append(label)
```

hacemos predicciones con la muestra que tomamos

```
[ ]: pred_classes= make_predictions(model=model_0, data=test_samples, device=device)
```

```
[ ]: classes[pred_classes[0]]
```

```
[ ]: 'plane'
```

visualizamos las predicciones

```
[ ]: plot_predictions(test_samples, test_labels, classes, pred_classes)
```

Pred: plane | Truth: deer



Pred: cat | Truth: cat



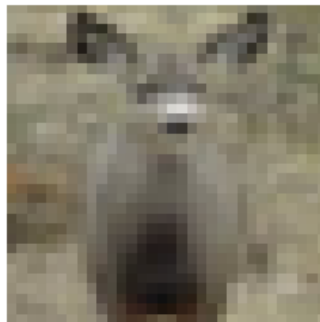
Pred: plane | Truth: plane



Pred: car | Truth: car



Pred: deer | Truth: deer



Pred: truck | Truth: truck



Pred: car | Truth: car



Pred: truck | Truth: truck



Pred: truck | Truth: truck



1.2 mejoramos accuracy

1.2.1 para ello aplicamos un poco de data augmentation, batch normalization y agregamos mas capas y filtros en el modelo

```
[ ]: from torchvision import transforms
```

```
[ ]: mean,std = mean_std(trainloader)
      print(mean)
      print(std)
```

```
tensor([0.4914, 0.4822, 0.4466])
```

```
tensor([0.2470, 0.2435, 0.2616])
```

```
[ ]: train_transform = transforms.Compose([
      transforms.RandomHorizontalFlip(p=0.5),
      transforms.ToTensor(),
      transforms.Normalize((mean),(std))])
```

```
test_transform = transforms.Compose([
      transforms.ToTensor(),
      transforms.Normalize((mean),(std))])
```

```
[ ]: trainset = torchvision.datasets.CIFAR10(root='./data',
      ↪train=True,download=True, transform=train_transform)
testset = torchvision.datasets.CIFAR10(root='./data',
      ↪train=False,download=True, transform=test_transform)

trainloader = torch.utils.data.DataLoader(trainset,
      ↪batch_size=batch_size,shuffle=True, num_workers=2)
testloader = torch.utils.data.DataLoader(testset,
      ↪batch_size=batch_size,shuffle=False, num_workers=2)
```

```
Files already downloaded and verified
```

```
Files already downloaded and verified
```

```
[ ]: plot_sample_images(trainset, classes, 4, 4)
```

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

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

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

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

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

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


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

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

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

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

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

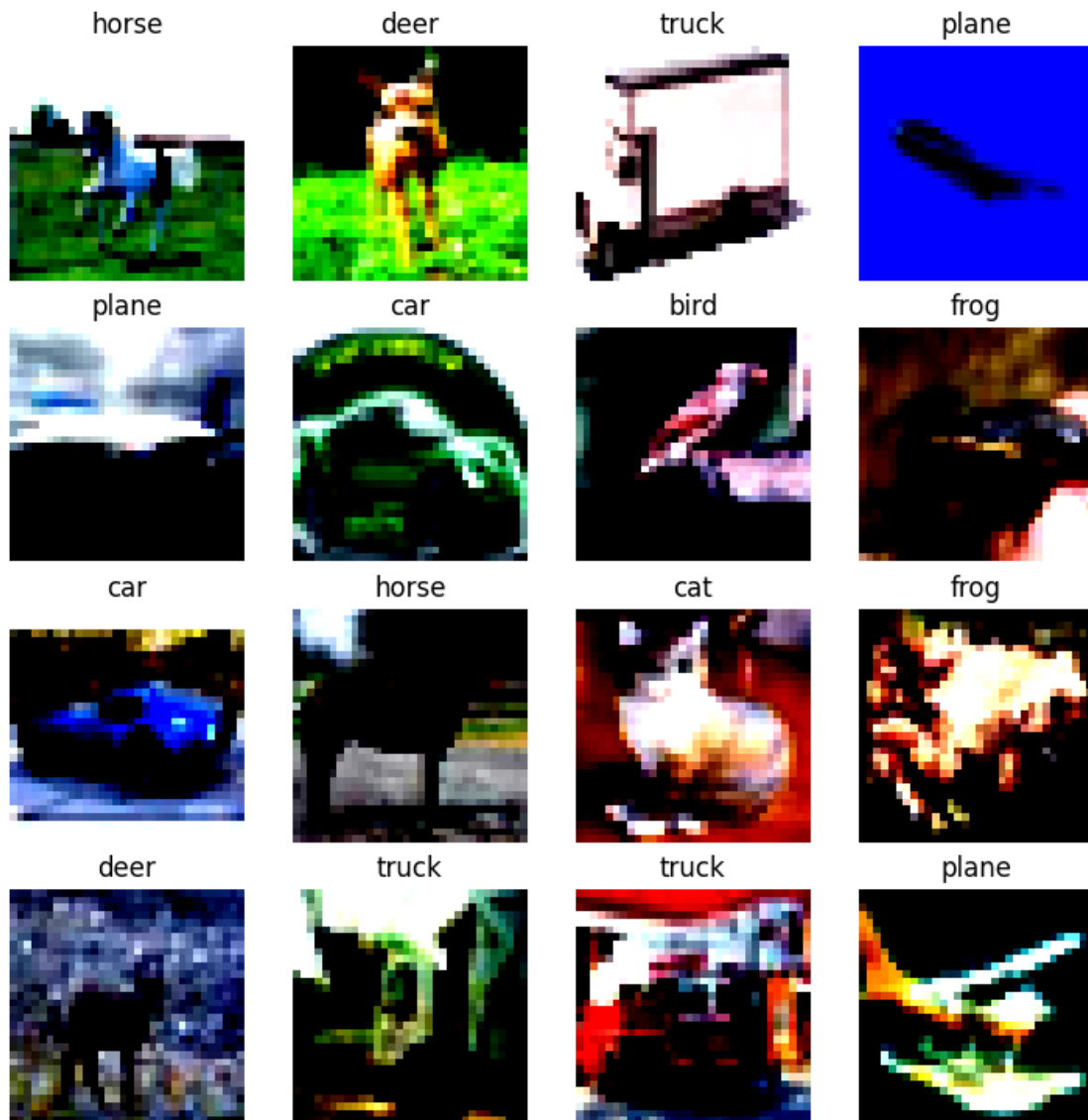
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

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

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

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

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



```
[ ]: class conv(nn.Module):

    def __init__(self):
        super().__init__()
        self.block_1 = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2, 2), # output: 64 x 16 x 16

            nn.Conv2d(64, 128, kernel_size=3, stride=1, padding=1),
```

```

        nn.ReLU(),
        nn.Conv2d(128, 128, kernel_size=3, stride=1, padding=1),
        nn.ReLU(),
        nn.MaxPool2d(2, 2), # output: 128 x 8 x 8

        nn.Conv2d(128, 256, kernel_size=3, stride=1, padding=1),
        nn.ReLU(),
        nn.Conv2d(256, 256, kernel_size=3, stride=1, padding=1),
        nn.ReLU(),
        nn.MaxPool2d(2, 2), # output: 256 x 4 x 4

    )

    self.block_2 = nn.Sequential(
        nn.Flatten(),
        nn.Linear(256*4*4, 1024),
        nn.ReLU(),
        nn.Linear(1024, 512),
        nn.ReLU(),
        nn.Linear(512, 10)
    )

    def forward(self, x):
        x = self.block_1(x)
        x = self.block_2(x)
        return x

```

```

[ ]: device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
model_0 = conv().to(device)
summary(model_0, (3,32,32))

```

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 32, 32, 32]	896
ReLU-2	[-1, 32, 32, 32]	0
Conv2d-3	[-1, 64, 32, 32]	18,496
ReLU-4	[-1, 64, 32, 32]	0
MaxPool2d-5	[-1, 64, 16, 16]	0
Conv2d-6	[-1, 128, 16, 16]	73,856
ReLU-7	[-1, 128, 16, 16]	0
Conv2d-8	[-1, 128, 16, 16]	147,584
ReLU-9	[-1, 128, 16, 16]	0
MaxPool2d-10	[-1, 128, 8, 8]	0
Conv2d-11	[-1, 256, 8, 8]	295,168
ReLU-12	[-1, 256, 8, 8]	0
Conv2d-13	[-1, 256, 8, 8]	590,080
ReLU-14	[-1, 256, 8, 8]	0

MaxPool2d-15	[-1, 256, 4, 4]	0
Flatten-16	[-1, 4096]	0
Linear-17	[-1, 1024]	4,195,328
ReLU-18	[-1, 1024]	0
Linear-19	[-1, 512]	524,800
ReLU-20	[-1, 512]	0
Linear-21	[-1, 10]	5,130

=====

Total params: 5,851,338

Trainable params: 5,851,338

Non-trainable params: 0

Input size (MB): 0.01

Forward/backward pass size (MB): 3.27

Params size (MB): 22.32

Estimated Total Size (MB): 25.61

```
[ ]: optimizer = torch.optim.Adam(params=model_0.parameters(), lr = 0.0001)
```

```
[ ]: NUM_EPOCHS = 10
model_0_results = train(model=model_0,
                        train_dataloader=trainloader,
                        test_dataloader=testloader,
                        optimizer=optimizer,
                        loss_fn=loss_fn,
                        epochs=NUM_EPOCHS,
                        device=device)
```

10%| | 1/10 [00:18<02:50, 18.99s/it]

Epoch: 1 | train_loss: 1.5957 | train_acc: 0.4056 | test_loss: 1.3171 |
test_acc: 0.5115

20%| | 2/10 [00:40<02:45, 20.63s/it]

Epoch: 2 | train_loss: 1.2102 | train_acc: 0.5595 | test_loss: 1.0964 |
test_acc: 0.6058

30%| | 3/10 [01:04<02:34, 22.12s/it]

Epoch: 3 | train_loss: 1.0035 | train_acc: 0.6430 | test_loss: 0.9250 |
test_acc: 0.6780

40%| | 4/10 [01:29<02:19, 23.24s/it]

Epoch: 4 | train_loss: 0.8501 | train_acc: 0.6998 | test_loss: 0.8487 |
test_acc: 0.7036

50%| | 5/10 [01:54<01:59, 23.99s/it]

Epoch: 5 | train_loss: 0.7391 | train_acc: 0.7412 | test_loss: 0.7852 |
test_acc: 0.7273

```

60%|          | 6/10 [02:20<01:38, 24.56s/it]
Epoch: 6 | train_loss: 0.6490 | train_acc: 0.7737 | test_loss: 0.6748 |
test_acc: 0.7639

70%|          | 7/10 [02:43<01:12, 24.13s/it]
Epoch: 7 | train_loss: 0.5688 | train_acc: 0.8013 | test_loss: 0.6730 |
test_acc: 0.7662

80%|          | 8/10 [03:04<00:46, 23.02s/it]
Epoch: 8 | train_loss: 0.5001 | train_acc: 0.8255 | test_loss: 0.6010 |
test_acc: 0.7936

90%|          | 9/10 [03:25<00:22, 22.29s/it]
Epoch: 9 | train_loss: 0.4351 | train_acc: 0.8495 | test_loss: 0.6145 |
test_acc: 0.7857

100%|         | 10/10 [03:46<00:00, 22.62s/it]
Epoch: 10 | train_loss: 0.3835 | train_acc: 0.8672 | test_loss: 0.6071 |
test_acc: 0.7975

```

```
[ ]: plot_loss_curves(model_0_results)
```

