

# Relatorio\_Multiclasse\_Imagens\_Satelitais\_result4\_dropout2\_ReLU\_64

December 21, 2023

Classificação multiclasse de imagens satelitais

PAVIC-Lab

Módulo III - Aprendizado de Máquina

Professor: Salomão Mafalda

Autor: Wallison Ferreira

[Link para o trabalho relacionado](#)

## 0.1 0 Importar bibliotecas

```
[ ]: import torch
    from torch import nn

    import warnings
    warnings.filterwarnings('ignore')

    torch.__version__
```

```
[ ]: '2.1.2+cu121'
```

```
[2]: # Continue with regular imports
    import matplotlib.pyplot as plt
    import torch
    import torchvision

    from torch import nn
    from torchvision import transforms

    # Try to get torchinfo, install it if it doesn't work
    from torchinfo import summary
    from pavic_treinamento_ml.going_modular.going_modular import data_setup, engine
```

```
/home/wallison/Downloads/relatorio_final_pavic/venv/lib/python3.10/site-
packages/tqdm/auto.py:21: TqdmWarning: IPProgress not found. Please update
```

jupyter and ipywidgets. See  
[https://ipywidgets.readthedocs.io/en/stable/user\\_install.html](https://ipywidgets.readthedocs.io/en/stable/user_install.html)  
from .autonotebook import tqdm as notebook\_tqdm

```
[3]: device = "cuda" if torch.cuda.is_available() else "cpu"  
device
```

```
[3]: 'cpu'
```

## 0.2 1 Aquisição de dados

### 0.2.1 Varredura do dataset

```
[4]: import os  
  
def walk_dir(dir_path):  
    for dirpath, dirnames, filenames in os.walk(dir_path):  
        print(f"{len(dirnames)} pastas e {len(filenames)} imagens em [{dirpath}].")
```

```
[5]: import requests  
import zipfile  
from pathlib import Path  
  
data_path = Path("dataset/dataset_splitted_smokers_min")  
image_path = data_path
```

```
[6]: walk_dir(image_path)
```

```
3 pastas e 0 imagens em [dataset/dataset_splitted_smokers_min].  
3 pastas e 0 imagens em [dataset/dataset_splitted_smokers_min/train].  
0 pastas e 807 imagens em [dataset/dataset_splitted_smokers_min/train/Dust].  
0 pastas e 812 imagens em [dataset/dataset_splitted_smokers_min/train/Smoke].  
0 pastas e 931 imagens em [dataset/dataset_splitted_smokers_min/train/Cloud].  
3 pastas e 0 imagens em [dataset/dataset_splitted_smokers_min/test].  
0 pastas e 102 imagens em [dataset/dataset_splitted_smokers_min/test/Dust].  
0 pastas e 103 imagens em [dataset/dataset_splitted_smokers_min/test/Smoke].  
0 pastas e 117 imagens em [dataset/dataset_splitted_smokers_min/test/Cloud].  
3 pastas e 0 imagens em [dataset/dataset_splitted_smokers_min/val].  
0 pastas e 100 imagens em [dataset/dataset_splitted_smokers_min/val/Dust].  
0 pastas e 101 imagens em [dataset/dataset_splitted_smokers_min/val/Smoke].  
0 pastas e 116 imagens em [dataset/dataset_splitted_smokers_min/val/Cloud].
```

```
[7]: train_dir = image_path / "train"  
test_dir = image_path / "test"  
train_dir, test_dir
```

```
[7]: (PosixPath('dataset/dataset_splitted_smokers_min/train'),  
      PosixPath('dataset/dataset_splitted_smokers_min/test'))
```

```
[8]: # Visualizar uma imagem

import random
from PIL import Image

#1 ler todos 'caminhos' das imagens
image_path_list = list(image_path.glob("*/*/*.tif"))

#2 selecionar imagem random
random_image_path = random.choice(image_path_list)

#3 selecionar classe
image_class = random_image_path.parent.stem

#4 ler img
img = Image.open(random_image_path)

print("Path: ", random_image_path)
print("Class: ", image_class)
print("Height: ", img.height)
print("Width: ", img.width)
img
```

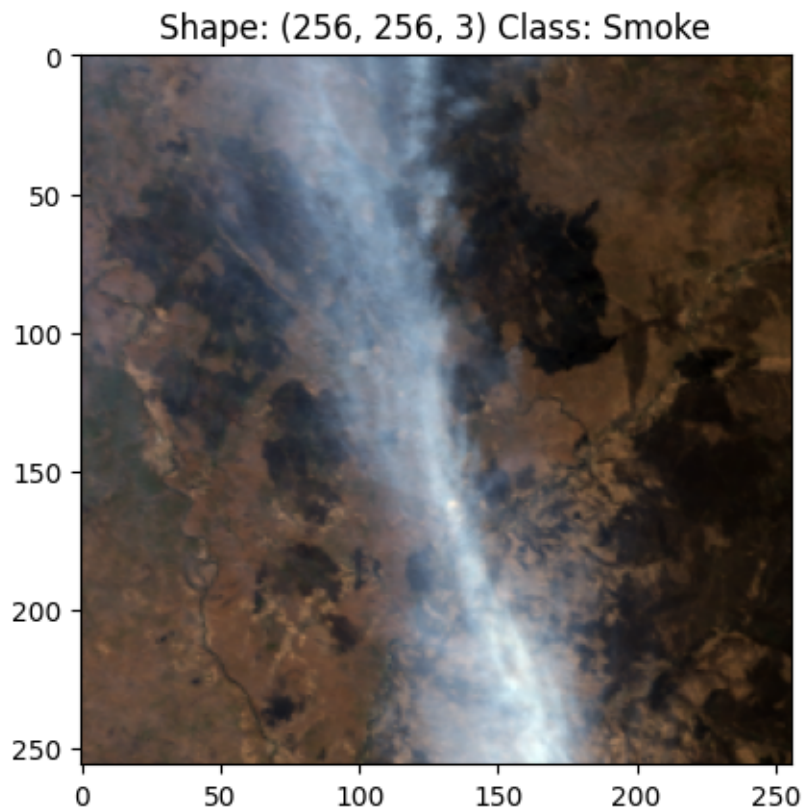
```
Path: dataset/dataset_splitting_smokers_min/train/Smoke/smoke_955.tif
Class: Smoke
Height: 256
Width: 256
```

[8]:



```
[9]: import numpy as np
import matplotlib.pyplot as plt

img_array = np.asarray(img)
plt.imshow(img_array);
plt.title(f"Shape: {img_array.shape} Class: {image_class}");
```



### 0.3 2 Load to Tensors

```
[10]: import torch
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
```

```
[11]: data_transform = transforms.Compose([
    transforms.Resize(size=(128, 128)),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.ToTensor()
])
```

```
[12]: def plot_transformed_images(image_paths,
                                transform,
                                n=3):

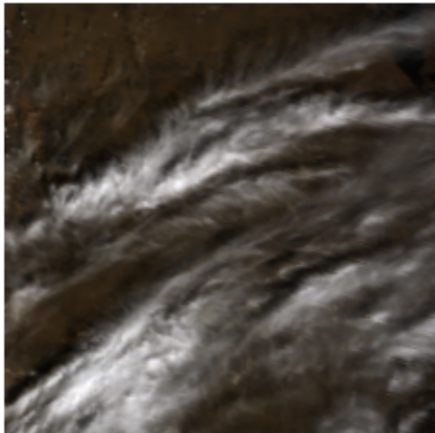
    random_image_paths = random.sample(image_paths, k=n)
    for image_path in random_image_paths:
        with Image.open(image_path) as f:
            fig, ax = plt.subplots(1, 2)
            ax[0].imshow(f)
            ax[0].set_title(f"Original \n Size:{f.size}")
            ax[0].axis("off")
            # [C, H, W] - [3, 64, 64] - [0, 1, 2] - [64, 64, 3] - [H, W, C]
            transformed_image = transform(f).permute(1, 2, 0)
            ax[1].imshow(transformed_image)
            ax[1].set_title(f"Transformed \n Size: {transformed_image.shape}")
            ax[1].axis("off")

        fig.suptitle(f"Class: {image_path.parent.stem}", fontsize=16)

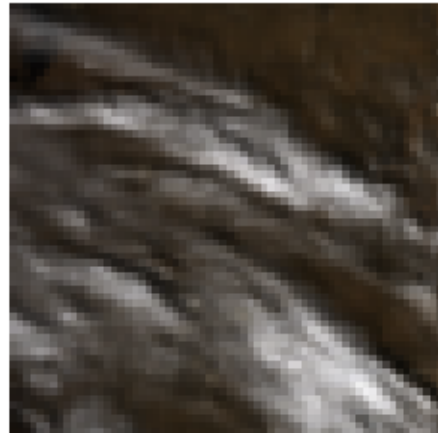
[13]: plot_transformed_images(image_path_list,
                              transform=data_transform,
                              n=3)
```

## Class: Cloud

Original  
Size:(256, 256)

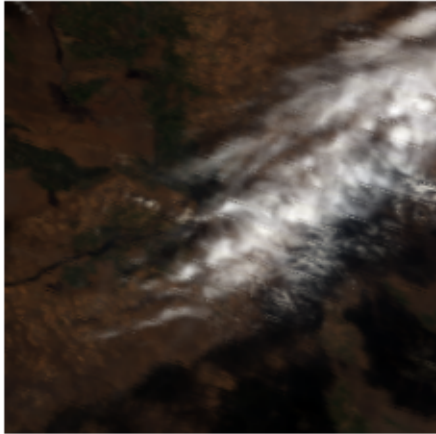


Transformed  
Size: torch.Size([64, 64, 3])

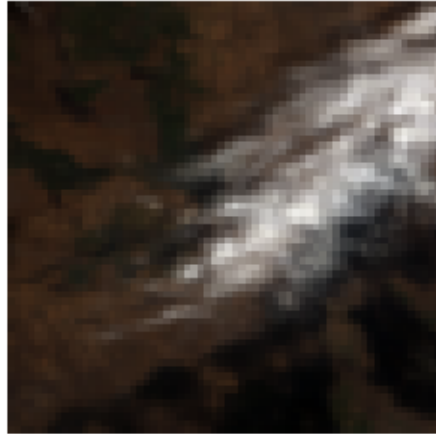


## Class: Cloud

Original  
Size:(256, 256)



Transformed  
Size: torch.Size([64, 64, 3])

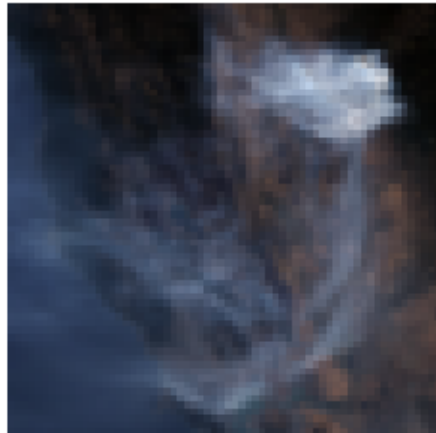


## Class: Smoke

Original  
Size:(256, 256)



Transformed  
Size: torch.Size([64, 64, 3])



## 0.4 Opção 1: Carregar os dados com Image Folder

```
[13]: from torchvision import datasets
train_data = datasets.ImageFolder(root=train_dir,
                                   transform=data_transform,
                                   target_transform=None)

test_data = datasets.ImageFolder(root=test_dir,
                                  transform=data_transform)

train_data
```

```
[13]: Dataset ImageFolder
      Number of datapoints: 2550
      Root location: dataset/dataset_splitted_smokers_min/train
      StandardTransform
      Transform: Compose(
        Resize(size=(128, 128), interpolation=bilinear, max_size=None,
        antialias=warn)
        RandomHorizontalFlip(p=0.5)
        ToTensor()
      )
```

```
[14]: #get class
class_names = train_data.classes
class_names
```

```
[14]: ['Cloud', 'Dust', 'Smoke']
```

## 0.5 3 Carregar para o Dataloader

## 0.6 Opção 2: Carregar os dados com Custom Dataset

```
[15]: import os
import pathlib
import torch

from PIL import Image
from torch.utils.data import Dataset
from torchvision import transforms
from typing import Tuple, Dict, List
```

```
[17]: #função para retornar lista de classes e dicionario de classes
def find_classes(directory: str) -> Tuple[List[str], Dict[str, int]]:
    classes = sorted(entry.name for entry in os.scandir(directory) if entry.
    ↪is_dir())

    if not classes:
```

```

        raise FileNotFoundError(f"Classes nao encontradas na pasta {directory}.")

    class_to_idx = {cls_name: i for i, cls_name in enumerate(classes)}
    return classes, class_to_idx

```

```
[18]: find_classes(train_dir)
```

```
[18]: (['Cloud', 'Dust', 'Smoke'], {'Cloud': 0, 'Dust': 1, 'Smoke': 2})
```

## 0.7 3 Preparando a Rede Neural Efficient Net

```
[16]: import torchvision

      from torch import nn
      from torchvision import transforms

```

```
[17]: weights = torchvision.models.EfficientNet_B1_Weights.DEFAULT
      model = torchvision.models.efficientnet_b1(weights=weights).to(device)

```

Define transformers manuais

```
[18]: manual_transforms = transforms.Compose([
      transforms.Resize((256,256)),
      transforms.ToTensor(),
      transforms.Normalize(mean=[0.485, 0.456, 0.406],
                           std=[0.229, 0.224, 0.225])
    ])

```

Define transformers automático

```
[19]: #carregamento automatico do transform
      weights = torchvision.models.EfficientNet_B0_Weights.DEFAULT
      auto_transforms = weights.transforms()
      auto_transforms

```

```
[19]: ImageClassification(
      crop_size=[224]
      resize_size=[256]
      mean=[0.485, 0.456, 0.406]
      std=[0.229, 0.224, 0.225]
      interpolation=InterpolationMode.BICUBIC
    )

```

```
[20]: #criar o dataloader
      train_dataloader, test_dataloader, class_names = data_setup.create_dataloaders(
          train_dir=train_dir,
          test_dir=test_dir,
          transform=manual_transforms,

```



```

        batch_size=16
    )

```

Summary

```

[21]: summary(model=model,
            input_size=(16, 3, 256, 256),
            col_names=["input_size", "output_size", "num_params", "trainable"],
            col_width=20,
            row_settings=["var_names"]
        )

```

```

[21]: =====
=====
Layer (type (var_name))                Input Shape
Output Shape      Param #              Trainable
=====
=====
EfficientNet (EfficientNet)              [16, 3, 256, 256]
[16, 1000]          --                  True
  Sequential (features)                  [16, 3, 256, 256]
[16, 1280, 8, 8]    --                  True
    Conv2dNormActivation (0)              [16, 3, 256, 256]
[16, 32, 128, 128]  --                  True
      Conv2d (0)                          [16, 3, 256, 256]
[16, 32, 128, 128]  864                  True
        BatchNorm2d (1)                  [16, 32, 128, 128]
[16, 32, 128, 128]  64                   True
          SiLU (2)                       [16, 32, 128, 128]
[16, 32, 128, 128]  --                   --
            Sequential (1)                [16, 32, 128, 128]
[16, 16, 128, 128]  --                   True
              MBConv (0)                  [16, 32, 128, 128]
[16, 16, 128, 128]  1,448                 True
                MBConv (1)                [16, 16, 128, 128]
[16, 16, 128, 128]  612                  True
                  Sequential (2)           [16, 16, 128, 128]
[16, 24, 64, 64]    --                   True
                    MBConv (0)             [16, 16, 128, 128]
[16, 24, 64, 64]    6,004                 True
                      MBConv (1)           [16, 24, 64, 64]
[16, 24, 64, 64]    10,710                True
                        MBConv (2)          [16, 24, 64, 64]
[16, 24, 64, 64]    10,710                True
                          Sequential (3)    [16, 24, 64, 64]
[16, 40, 32, 32]    --                   True
                            MBConv (0)      [16, 24, 64, 64]

```

[16, 40, 32, 32]	15,350	True	[16, 40, 32, 32]
MBConv (1)			
[16, 40, 32, 32]	31,290	True	[16, 40, 32, 32]
MBConv (2)			
[16, 40, 32, 32]	31,290	True	[16, 40, 32, 32]
Sequential (4)			
[16, 80, 16, 16]	--	True	[16, 40, 32, 32]
MBConv (0)			
[16, 80, 16, 16]	37,130	True	[16, 40, 32, 32]
MBConv (1)			
[16, 80, 16, 16]	102,900	True	[16, 80, 16, 16]
MBConv (2)			
[16, 80, 16, 16]	102,900	True	[16, 80, 16, 16]
MBConv (3)			
[16, 80, 16, 16]	102,900	True	[16, 80, 16, 16]
Sequential (5)			
[16, 112, 16, 16]	--	True	[16, 80, 16, 16]
MBConv (0)			
[16, 112, 16, 16]	126,004	True	[16, 80, 16, 16]
MBConv (1)			
[16, 112, 16, 16]	208,572	True	[16, 112, 16, 16]
MBConv (2)			
[16, 112, 16, 16]	208,572	True	[16, 112, 16, 16]
MBConv (3)			
[16, 112, 16, 16]	208,572	True	[16, 112, 16, 16]
Sequential (6)			
[16, 192, 8, 8]	--	True	[16, 112, 16, 16]
MBConv (0)			
[16, 192, 8, 8]	262,492	True	[16, 112, 16, 16]
MBConv (1)			
[16, 192, 8, 8]	587,952	True	[16, 192, 8, 8]
MBConv (2)			
[16, 192, 8, 8]	587,952	True	[16, 192, 8, 8]
MBConv (3)			
[16, 192, 8, 8]	587,952	True	[16, 192, 8, 8]
MBConv (4)			
[16, 192, 8, 8]	587,952	True	[16, 192, 8, 8]
Sequential (7)			
[16, 320, 8, 8]	--	True	[16, 192, 8, 8]
MBConv (0)			
[16, 320, 8, 8]	717,232	True	[16, 192, 8, 8]
MBConv (1)			
[16, 320, 8, 8]	1,563,600	True	[16, 320, 8, 8]
Conv2dNormActivation (8)			
[16, 1280, 8, 8]	--	True	[16, 320, 8, 8]
Conv2d (0)			
[16, 1280, 8, 8]	409,600	True	[16, 320, 8, 8]

BatchNorm2d (1)			[16, 1280, 8, 8]
[16, 1280, 8, 8]	2,560	True	
SiLU (2)			[16, 1280, 8, 8]
[16, 1280, 8, 8]	--	--	
AdaptiveAvgPool2d (avgpool)			[16, 1280, 8, 8]
[16, 1280, 1, 1]	--	--	
Sequential (classifier)			[16, 1280]
[16, 1000]	--	True	
Dropout (0)			[16, 1280]
[16, 1280]	--	--	
Linear (1)			[16, 1280]
[16, 1000]	1,281,000	True	

=====

Total params: 7,794,184  
Trainable params: 7,794,184  
Non-trainable params: 0  
Total mult-adds (G): 11.89

=====

Input size (MB): 12.58  
Forward/backward pass size (MB): 3125.12  
Params size (MB): 31.18  
Estimated Total Size (MB): 3168.88

=====

### 0.7.1 Congelar camadas

```
[22]: for param in model.features.parameters():
      param.requires_grad = False
```

```
[23]: output_shape = len(class_names)

model.classifier = torch.nn.Sequential(
    torch.nn.Dropout(p=0.2, inplace=True),
    torch.nn.Linear(in_features=1280,
                    out_features=output_shape,
                    bias=True),
    torch.nn.ReLU(),
    torch.nn.Linear(in_features=output_shape,
                    out_features=output_shape,
                    bias=True)).to(device)
```

```
[24]: summary(model=model,
            input_size=(1, 3, 16, 16),
            col_names=["input_size", "output_size", "num_params", "trainable"],
            col_width=20,
            row_settings=["var_names"]
        )
```

```
[24]: =====
=====
Layer (type (var_name))                                Input Shape
Output Shape      Param #          Trainable
=====
EfficientNet (EfficientNet)                             [1, 3, 16, 16]
[1, 3]            --                Partial
  Sequential (features)                                  [1, 3, 16, 16]
    [1, 1280, 1, 1]  --                False
      Conv2dNormActivation (0)                        [1, 3, 16, 16]
        [1, 32, 8, 8]  --                False
          Conv2d (0)                                     [1, 3, 16, 16]
            [1, 32, 8, 8]      (864)          False
              BatchNorm2d (1)                        [1, 32, 8, 8]
                [1, 32, 8, 8]      (64)          False
                  SiLU (2)                             [1, 32, 8, 8]
                    [1, 32, 8, 8]  --                --
                      Sequential (1)                    [1, 32, 8, 8]
                        [1, 16, 8, 8]  --                False
                          MBConv (0)                     [1, 32, 8, 8]
                            [1, 16, 8, 8]      (1,448)          False
                              MBConv (1)                   [1, 16, 8, 8]
                                [1, 16, 8, 8]      (612)          False
                                  Sequential (2)            [1, 16, 8, 8]
                                    [1, 24, 4, 4]  --                False
                                      MBConv (0)            [1, 16, 8, 8]
                                        [1, 24, 4, 4]      (6,004)          False
                                          MBConv (1)         [1, 24, 4, 4]
                                            [1, 24, 4, 4]      (10,710)          False
                                              MBConv (2)       [1, 24, 4, 4]
                                                [1, 24, 4, 4]      (10,710)          False
                                                  Sequential (3)    [1, 24, 4, 4]
                                                    [1, 40, 2, 2]  --                False
                                                      MBConv (0)    [1, 24, 4, 4]
                                                        [1, 40, 2, 2]      (15,350)          False
                                                          MBConv (1)    [1, 40, 2, 2]
                                                            [1, 40, 2, 2]      (31,290)          False
                                                              MBConv (2)    [1, 40, 2, 2]
                                                                [1, 40, 2, 2]      (31,290)          False
```

Sequential (4)			[1, 40, 2, 2]
[1, 80, 1, 1]	--	False	
MBConv (0)			[1, 40, 2, 2]
[1, 80, 1, 1]	(37,130)	False	
MBConv (1)			[1, 80, 1, 1]
[1, 80, 1, 1]	(102,900)	False	
MBConv (2)			[1, 80, 1, 1]
[1, 80, 1, 1]	(102,900)	False	
MBConv (3)			[1, 80, 1, 1]
[1, 80, 1, 1]	(102,900)	False	
Sequential (5)			[1, 80, 1, 1]
[1, 112, 1, 1]	--	False	
MBConv (0)			[1, 80, 1, 1]
[1, 112, 1, 1]	(126,004)	False	
MBConv (1)			[1, 112, 1, 1]
[1, 112, 1, 1]	(208,572)	False	
MBConv (2)			[1, 112, 1, 1]
[1, 112, 1, 1]	(208,572)	False	
MBConv (3)			[1, 112, 1, 1]
[1, 112, 1, 1]	(208,572)	False	
Sequential (6)			[1, 112, 1, 1]
[1, 192, 1, 1]	--	False	
MBConv (0)			[1, 112, 1, 1]
[1, 192, 1, 1]	(262,492)	False	
MBConv (1)			[1, 192, 1, 1]
[1, 192, 1, 1]	(587,952)	False	
MBConv (2)			[1, 192, 1, 1]
[1, 192, 1, 1]	(587,952)	False	
MBConv (3)			[1, 192, 1, 1]
[1, 192, 1, 1]	(587,952)	False	
MBConv (4)			[1, 192, 1, 1]
[1, 192, 1, 1]	(587,952)	False	
Sequential (7)			[1, 192, 1, 1]
[1, 320, 1, 1]	--	False	
MBConv (0)			[1, 192, 1, 1]
[1, 320, 1, 1]	(717,232)	False	
MBConv (1)			[1, 320, 1, 1]
[1, 320, 1, 1]	(1,563,600)	False	
Conv2dNormActivation (8)			[1, 320, 1, 1]
[1, 1280, 1, 1]	--	False	
Conv2d (0)			[1, 320, 1, 1]
[1, 1280, 1, 1]	(409,600)	False	
BatchNorm2d (1)			[1, 1280, 1, 1]
[1, 1280, 1, 1]	(2,560)	False	
SiLU (2)			[1, 1280, 1, 1]
[1, 1280, 1, 1]	--	--	
AdaptiveAvgPool2d (avgpool)			[1, 1280, 1, 1]

```

[1, 1280, 1, 1]      --          --          [1, 1280]
  Sequential (classifier)
[1, 3]               --          True         [1, 1280]
    Dropout (0)
[1, 1280]            --          --          [1, 1280]
    Linear (1)
[1, 3]               3,843       True         [1, 1280]
    ReLU (2)
[1, 3]               --          --          [1, 3]
    Linear (3)
[1, 3]               12         True         [1, 3]
=====
=====
Total params: 6,517,039
Trainable params: 3,855
Non-trainable params: 6,513,184
Total mult-adds (M): 7.30
=====
=====
Input size (MB): 0.00
Forward/backward pass size (MB): 1.10
Params size (MB): 26.07
Estimated Total Size (MB): 27.17
=====
=====

```

```

[25]: loss_fn = nn.CrossEntropyLoss()
      optimizer = torch.optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-5)

```

```

[26]: from timeit import default_timer as timer
      start_time = timer()

      results = engine.train(model=model,
                             train_dataloader=train_dataloader,
                             test_dataloader=test_dataloader,
                             optimizer=optimizer,
                             loss_fn=loss_fn,
                             epochs=50,
                             device=device)

      end_time = timer()

      print(f"Tempo de treinamento: {end_time-start_time:.3f} segundos")

```

```

0%|          | 0/50 [00:00<?, ?it/s]  2%|          | 1/50 [04:54<4:00:27,
294.44s/it]

```

```

Epoch: 1 | train_loss: 0.8359 | train_acc: 0.6785 | test_loss: 0.6429 |
test_acc: 0.8304

```

4%| | 2/50 [08:58<3:31:49, 264.79s/it]  
Epoch: 2 | train\_loss: 0.5980 | train\_acc: 0.8193 | test\_loss: 0.4696 |  
test\_acc: 0.8869

6%| | 3/50 [13:30<3:30:01, 268.11s/it]  
Epoch: 3 | train\_loss: 0.4833 | train\_acc: 0.8535 | test\_loss: 0.3840 |  
test\_acc: 0.8869

8%| | 4/50 [18:00<3:26:06, 268.83s/it]  
Epoch: 4 | train\_loss: 0.4203 | train\_acc: 0.8590 | test\_loss: 0.3162 |  
test\_acc: 0.9137

10%| | 5/50 [22:33<3:22:50, 270.46s/it]  
Epoch: 5 | train\_loss: 0.3652 | train\_acc: 0.8762 | test\_loss: 0.2915 |  
test\_acc: 0.9107

12%| | 6/50 [26:29<3:09:36, 258.56s/it]  
Epoch: 6 | train\_loss: 0.3400 | train\_acc: 0.8820 | test\_loss: 0.2648 |  
test\_acc: 0.9226

14%| | 7/50 [30:40<3:03:28, 256.02s/it]  
Epoch: 7 | train\_loss: 0.3090 | train\_acc: 0.8938 | test\_loss: 0.2397 |  
test\_acc: 0.9256

16%| | 8/50 [35:12<3:02:51, 261.23s/it]  
Epoch: 8 | train\_loss: 0.3050 | train\_acc: 0.8892 | test\_loss: 0.2190 |  
test\_acc: 0.9226

18%| | 9/50 [39:46<3:01:19, 265.35s/it]  
Epoch: 9 | train\_loss: 0.2967 | train\_acc: 0.8921 | test\_loss: 0.2224 |  
test\_acc: 0.9226

20%| | 10/50 [44:02<2:54:56, 262.40s/it]  
Epoch: 10 | train\_loss: 0.2879 | train\_acc: 0.8973 | test\_loss: 0.2150 |  
test\_acc: 0.9256

22%| | 11/50 [47:45<2:42:39, 250.23s/it]  
Epoch: 11 | train\_loss: 0.2976 | train\_acc: 0.8999 | test\_loss: 0.2133 |  
test\_acc: 0.9256

24%| | 12/50 [52:18<2:42:52, 257.18s/it]  
Epoch: 12 | train\_loss: 0.2687 | train\_acc: 0.9061 | test\_loss: 0.2293 |  
test\_acc: 0.9167

26%| | 13/50 [56:51<2:41:36, 262.08s/it]  
Epoch: 13 | train\_loss: 0.2919 | train\_acc: 0.8887 | test\_loss: 0.2166 |  
test\_acc: 0.9286

28%| | 14/50 [1:01:03<2:35:25, 259.05s/it]  
Epoch: 14 | train\_loss: 0.2892 | train\_acc: 0.8930 | test\_loss: 0.2156 |  
test\_acc: 0.9256

30%| | 15/50 [1:04:46<2:24:46, 248.17s/it]  
Epoch: 15 | train\_loss: 0.2647 | train\_acc: 0.9036 | test\_loss: 0.2110 |  
test\_acc: 0.9137

32%| | 16/50 [1:08:26<2:15:43, 239.50s/it]  
Epoch: 16 | train\_loss: 0.2475 | train\_acc: 0.9055 | test\_loss: 0.2027 |  
test\_acc: 0.9256

34%| | 17/50 [1:12:05<2:08:19, 233.33s/it]  
Epoch: 17 | train\_loss: 0.2701 | train\_acc: 0.9009 | test\_loss: 0.2016 |  
test\_acc: 0.9286

36%| | 18/50 [1:16:13<2:06:55, 238.00s/it]  
Epoch: 18 | train\_loss: 0.2675 | train\_acc: 0.8986 | test\_loss: 0.1943 |  
test\_acc: 0.9256

38%| | 19/50 [1:20:22<2:04:33, 241.09s/it]  
Epoch: 19 | train\_loss: 0.2384 | train\_acc: 0.9091 | test\_loss: 0.2077 |  
test\_acc: 0.9315

40%| | 20/50 [1:24:01<1:57:20, 234.68s/it]  
Epoch: 20 | train\_loss: 0.2737 | train\_acc: 0.8954 | test\_loss: 0.2062 |  
test\_acc: 0.9315

42%| | 21/50 [1:27:41<1:51:12, 230.09s/it]  
Epoch: 21 | train\_loss: 0.2555 | train\_acc: 0.9076 | test\_loss: 0.2040 |  
test\_acc: 0.9405

44%| | 22/50 [1:31:45<1:49:19, 234.27s/it]  
Epoch: 22 | train\_loss: 0.2474 | train\_acc: 0.9130 | test\_loss: 0.2090 |  
test\_acc: 0.9375

46%| | 23/50 [1:35:58<1:47:55, 239.83s/it]  
Epoch: 23 | train\_loss: 0.2469 | train\_acc: 0.9189 | test\_loss: 0.2207 |  
test\_acc: 0.9226

48%| | 24/50 [1:39:39<1:41:33, 234.35s/it]  
Epoch: 24 | train\_loss: 0.2399 | train\_acc: 0.9109 | test\_loss: 0.1884 |  
test\_acc: 0.9315

50%| | 25/50 [1:43:20<1:35:54, 230.20s/it]  
Epoch: 25 | train\_loss: 0.2419 | train\_acc: 0.9098 | test\_loss: 0.1999 |  
test\_acc: 0.9315



52%| | 26/50 [1:47:00<1:30:55, 227.32s/it]  
Epoch: 26 | train\_loss: 0.2322 | train\_acc: 0.9145 | test\_loss: 0.1822 |  
test\_acc: 0.9345

54%| | 27/50 [1:50:40<1:26:17, 225.11s/it]  
Epoch: 27 | train\_loss: 0.2598 | train\_acc: 0.9090 | test\_loss: 0.2053 |  
test\_acc: 0.9286

56%| | 28/50 [1:54:21<1:22:00, 223.64s/it]  
Epoch: 28 | train\_loss: 0.2337 | train\_acc: 0.9158 | test\_loss: 0.1984 |  
test\_acc: 0.9345

58%| | 29/50 [1:58:24<1:20:19, 229.48s/it]  
Epoch: 29 | train\_loss: 0.2483 | train\_acc: 0.9160 | test\_loss: 0.2058 |  
test\_acc: 0.9345

60%| | 30/50 [2:02:54<1:20:35, 241.79s/it]  
Epoch: 30 | train\_loss: 0.2142 | train\_acc: 0.9207 | test\_loss: 0.2014 |  
test\_acc: 0.9286

62%| | 31/50 [2:07:19<1:18:46, 248.78s/it]  
Epoch: 31 | train\_loss: 0.2474 | train\_acc: 0.9066 | test\_loss: 0.1893 |  
test\_acc: 0.9315

64%| | 32/50 [2:11:33<1:15:04, 250.26s/it]  
Epoch: 32 | train\_loss: 0.2396 | train\_acc: 0.9099 | test\_loss: 0.1899 |  
test\_acc: 0.9315

66%| | 33/50 [2:15:12<1:08:17, 241.03s/it]  
Epoch: 33 | train\_loss: 0.2524 | train\_acc: 0.9056 | test\_loss: 0.2049 |  
test\_acc: 0.9315

68%| | 34/50 [2:19:29<1:05:28, 245.55s/it]  
Epoch: 34 | train\_loss: 0.2440 | train\_acc: 0.9134 | test\_loss: 0.2081 |  
test\_acc: 0.9286

70%| | 35/50 [2:23:51<1:02:40, 250.71s/it]  
Epoch: 35 | train\_loss: 0.2231 | train\_acc: 0.9187 | test\_loss: 0.2022 |  
test\_acc: 0.9286

72%| | 36/50 [2:27:54<57:57, 248.38s/it]  
Epoch: 36 | train\_loss: 0.2090 | train\_acc: 0.9195 | test\_loss: 0.1919 |  
test\_acc: 0.9345

74%| | 37/50 [2:31:35<52:00, 240.04s/it]  
Epoch: 37 | train\_loss: 0.2382 | train\_acc: 0.9168 | test\_loss: 0.2048 |  
test\_acc: 0.9345

76%| | 38/50 [2:35:29<47:40, 238.40s/it]  
Epoch: 38 | train\_loss: 0.2289 | train\_acc: 0.9145 | test\_loss: 0.1824 |  
test\_acc: 0.9435

78%| | 39/50 [2:39:38<44:15, 241.38s/it]  
Epoch: 39 | train\_loss: 0.2445 | train\_acc: 0.9086 | test\_loss: 0.2203 |  
test\_acc: 0.9256

80%| | 40/50 [2:43:41<40:18, 241.81s/it]  
Epoch: 40 | train\_loss: 0.2306 | train\_acc: 0.9115 | test\_loss: 0.1965 |  
test\_acc: 0.9286

82%| | 41/50 [2:48:02<37:10, 247.81s/it]  
Epoch: 41 | train\_loss: 0.2328 | train\_acc: 0.9189 | test\_loss: 0.2198 |  
test\_acc: 0.9315

84%| | 42/50 [2:52:33<33:57, 254.72s/it]  
Epoch: 42 | train\_loss: 0.2608 | train\_acc: 0.9025 | test\_loss: 0.2167 |  
test\_acc: 0.9315

86%| | 43/50 [2:57:26<31:03, 266.25s/it]  
Epoch: 43 | train\_loss: 0.2261 | train\_acc: 0.9165 | test\_loss: 0.2198 |  
test\_acc: 0.8988

88%| | 44/50 [3:02:09<27:07, 271.30s/it]  
Epoch: 44 | train\_loss: 0.2516 | train\_acc: 0.9107 | test\_loss: 0.1858 |  
test\_acc: 0.9286

90%| | 45/50 [3:06:09<21:48, 261.72s/it]  
Epoch: 45 | train\_loss: 0.2258 | train\_acc: 0.9195 | test\_loss: 0.2049 |  
test\_acc: 0.9345

92%| | 46/50 [3:09:57<16:46, 251.68s/it]  
Epoch: 46 | train\_loss: 0.2311 | train\_acc: 0.9120 | test\_loss: 0.2037 |  
test\_acc: 0.9107

94%| | 47/50 [3:13:55<12:22, 247.64s/it]  
Epoch: 47 | train\_loss: 0.2264 | train\_acc: 0.9141 | test\_loss: 0.2003 |  
test\_acc: 0.9286

96%| | 48/50 [3:18:05<08:16, 248.17s/it]  
Epoch: 48 | train\_loss: 0.2333 | train\_acc: 0.9187 | test\_loss: 0.1903 |  
test\_acc: 0.9345

98%| | 49/50 [3:22:26<04:12, 252.19s/it]  
Epoch: 49 | train\_loss: 0.2337 | train\_acc: 0.9121 | test\_loss: 0.2147 |  
test\_acc: 0.9315

100%| | 50/50 [3:26:47<00:00, 248.16s/it]

Epoch: 50 | train\_loss: 0.2365 | train\_acc: 0.9121 | test\_loss: 0.1957 |  
test\_acc: 0.9375

Tempo de treinamento: 12408.576 segundos

```
[27]: results.keys()
```

```
[27]: dict_keys(['train_loss', 'train_acc', 'test_loss', 'test_acc'])
```

## 0.7.2 5.1 Plot train info

```
[28]: def plot_loss_curves(results: Dict[str, List[float]]):  
    loss = results["train_loss"]  
    test_loss = results["test_loss"]  
    accuracy = results["train_acc"]  
    test_accuracy = results["test_acc"]  
    epochs = range(len(results['train_loss']))  
  
    plt.figure(figsize=(15,7))  
    #plot loss  
    plt.subplot(1, 2, 1)  
    plt.plot(epochs, loss, label="train_loss")  
    plt.plot(epochs, test_loss, label="test_loss")  
    plt.title("Loss")  
    plt.xlabel("Epochs")  
    plt.legend()  
    #plot accuracy  
    plt.subplot(1, 2, 2)  
    plt.plot(epochs, accuracy, label="train_acc")  
    plt.plot(epochs, test_accuracy, label="test_acc")  
    plt.title("Accuracy")  
    plt.xlabel("Epochs")  
    plt.legend();
```

```
[29]: plot_loss_curves(results)
```

