Kumpulan Data Khusus PyTorch

##Mengimpor PyTorch dan menyiapkan kode agnostik perangkat

```
import torch
from torch import nn

# Note: this notebook requires torch >= 1.10.0
torch.__version__
```

```
'1.12.1+cu113'
```

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

```
'cuda'
```

Dapatkan datanya

Hal pertama yang pertama kita perlukan beberapa data.

Data yang akan kita gunakan adalah subset dari dataset Food101.

Mari tulis beberapa kode untuk mengunduh data yang diformat dari GitHub.

```
import requests
import zipfile
from pathlib import Path

# Setup path to data folder
data_path = Path("data/")
image_path = data_path / "pizza_steak_sushi"

# If the image folder doesn't exist, download it and prepare it...
if image_path.is_dir():
    print(f"{image_path} directory exists.")
else:
    print(f"Did not find {image_path} directory, creating one...")
    image_path.mkdir(parents=True, exist_ok=True)

    # Download pizza, steak, sushi data
    with open(data_path / "pizza_steak_sushi.zip", "wb") as f:
        request = requests.get("https://github.com/mrdbourke/pytorch-
deep-learning/raw/main/data/pizza_steak_sushi.zip")
        print("Downloading pizza, steak, sushi data...")
        f.write(request.content)
```

```
    # Unzip pizza, steak, sushi data
    with zipfile.ZipFile(data_path / "pizza_steak_sushi.zip", "r") as
zip_ref:
        print("Unzipping pizza, steak, sushi data...")
        zip_ref.extractall(image_path)
```

```
data/pizza_steak_sushi directory exists.
```

Menjadi satu dengan data (persiapan data)

Kumpulan data diunduh!

Untuk melakukannya, kita akan menggunakan os.walk() bawaan Python.

```
import os
def walk_through_dir(dir_path):
  """
  Walks through dir_path returning its contents.
  Args:
    dir_path (str or pathlib.Path): target directory

  Returns:
    A print out of:
      number of subdiretories in dir_path
      number of images (files) in each subdirectory
      name of each subdirectory
  """
  for dirpath, dirnames, filenames in os.walk(dir_path):
    print(f"There are {len(dirnames)} directories and {len(filenames)}
images in '{dirpath}'.")

walk_through_dir(image_path)
```

```
There are 2 directories and 1 images in 'data/pizza_steak_sushi'.
There are 3 directories and 0 images in 'data/pizza_steak_sushi/test'.
There are 0 directories and 19 images in
'data/pizza_steak_sushi/test/steak'.
There are 0 directories and 31 images in
'data/pizza_steak_sushi/test/sushi'.
There are 0 directories and 25 images in
'data/pizza_steak_sushi/test/pizza'.
There are 3 directories and 0 images in
'data/pizza_steak_sushi/train'.
There are 0 directories and 75 images in
'data/pizza_steak_sushi/train/steak'.
There are 0 directories and 72 images in
'data/pizza_steak_sushi/train/sushi'.
There are 0 directories and 78 images in
'data/pizza_steak_sushi/train/pizza'.
```

siapkan jalur pelatihan dan pengujian kita.

```
# Setup train and testing paths
train_dir = image_path / "train"
test_dir = image_path / "test"

train_dir, test_dir
```

```
(PosixPath('data/pizza_steak_sushi/train'),
 PosixPath('data/pizza_steak_sushi/test'))
```

Visualisasikan gambar

kita tulis beberapa kode

1. Dapatkan semua jalur gambar menggunakan pathlib.Path.glob() untuk menemukan semua file yang diakhiri dengan .jpg.
2. Pilih jalur gambar acak menggunakan random.choice() Python.
3. Dapatkan nama kelas gambar menggunakan pathlib.Path.parent.stem.
4. Dan karena kita bekerja dengan gambar, kita akan membuka jalur gambar acak menggunakan PIL.Image.open() (PIL adalah singkatan dari Python Image Library).
5. Kami kemudian akan menampilkan gambar dan mencetak beberapa metadata.

```
import random
from PIL import Image

# Set seed
random.seed(42) # <- try changing this and see what happens

# 1. Get all image paths (* means "any combination")
image_path_list = list(image_path.glob("*/*/*.jpg"))

# 2. Get random image path
random_image_path = random.choice(image_path_list)

# 3. Get image class from path name (the image class is the name of
the directory where the image is stored)
image_class = random_image_path.parent.stem

# 4. Open image
img = Image.open(random_image_path)

# 5. Print metadata
print(f"Random image path: {random_image_path}")
print(f"Image class: {image_class}")
print(f"Image height: {img.height}")
print(f"Image width: {img.width}")
img
```

```
Random image path: data/pizza_steak_sushi/test/pizza/2124579.jpg
Image class: pizza
Image height: 384
Image width: 512
```

Kita dapat melakukan hal yang sama dengan matplotlib.pyplot.imshow(), kecuali kita harus mengonversi gambar menjadi array NumPy terlebih dahulu.

```
import numpy as np
import matplotlib.pyplot as plt

# Turn the image into an array
img_as_array = np.asarray(img)

# Plot the image with matplotlib
plt.figure(figsize=(10, 7))
plt.imshow(img_as_array)
plt.title(f"Image class: {image_class} | Image shape:
{img_as_array.shape} -> [height, width, color_channels]")
plt.axis(False);
```

Image class: pizza | Image shape: (384, 512, 3) -> [height, width, color_channels]

Transformasi data

```
import torch
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
```

Mentransformasi data dengan torchvision.transforms

Kita dapat mengkompilasi semua langkah ini menggunakan torchvision.transforms.Compose().

```
# Write transform for image
data_transform = transforms.Compose([
    # Resize the images to 64x64
    transforms.Resize(size=(64, 64)),
    # Flip the images randomly on the horizontal
    transforms.RandomHorizontalFlip(p=0.5), # p = probability of flip,
0.5 = 50% chance
    # Turn the image into a torch.Tensor
    transforms.ToTensor() # this also converts all pixel values from 0
```

```
to 255 to be between 0.0 and 1.0
])
```

Sekarang kita mempunyai komposisi transformasi, mari kita tulis sebuah fungsi untuk mencobanya pada berbagai gambar

```
def plot_transformed_images(image_paths, transform, n=3, seed=42):
    """Plots a series of random images from image_paths.

    Will open n image paths from image_paths, transform them
    with transform and plot them side by side.

    Args:
        image_paths (list): List of target image paths.
        transform (PyTorch Transforms): Transforms to apply to images.
        n (int, optional): Number of images to plot. Defaults to 3.
        seed (int, optional): Random seed for the random generator.
Defaults to 42.
    """
    random.seed(seed)
    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 \nSize: {f.size}")
            ax[0].axis("off")

            # Transform and plot image
            # Note: permute() will change shape of image to suit
matplotlib
            # (PyTorch default is [C, H, W] but Matplotlib is [H, W,
C])
            transformed_image = transform(f).permute(1, 2, 0)
            ax[1].imshow(transformed_image)
            ax[1].set_title(f"Transformed \nSize:
{transformed_image.shape}")
            ax[1].axis("off")

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

plot_transformed_images(image_path_list,
                        transform=data_transform,
                        n=3)
```

Class: pizza

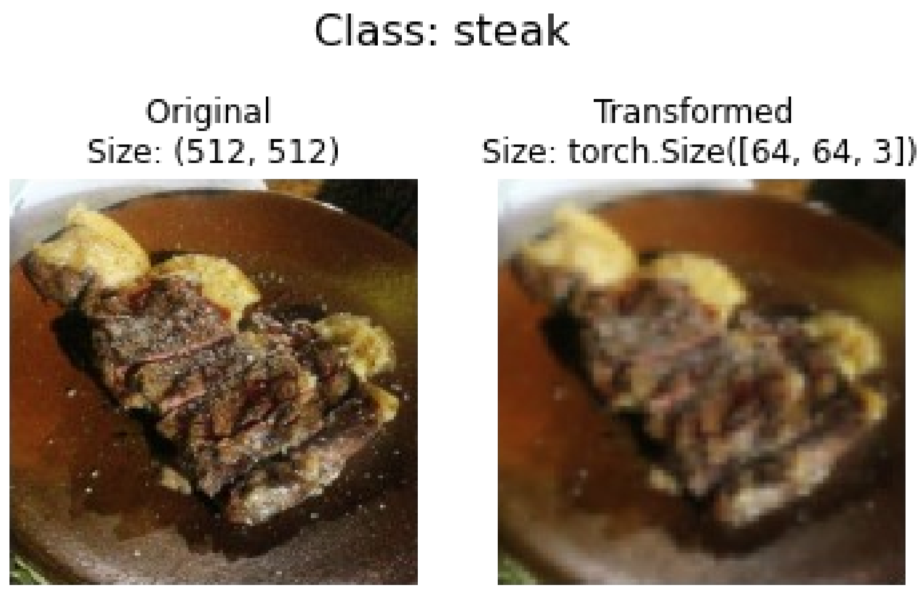
Original
Size: (512, 384)

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

Class: steak

Original
Size: (512, 512)

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



Opsi 1: Memuat Data Gambar Menggunakan ImageFolder

Mari kita uji pada folder data train_dir dan test_dir dengan meneruskan transform=data_transform untuk mengubah gambar kita menjadi tensor.

```
# Use ImageFolder to create dataset(s)
from torchvision import datasets
train_data = datasets.ImageFolder(root=train_dir, # target folder of images
                                  transform=data_transform, # transforms to perform on data (images)
                                  target_transform=None) # transforms to perform on labels (if necessary)

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

print(f"Train data:\n{train_data}\nTest data:\n{test_data}")
```

```
Train data:
Dataset ImageFolder
    Number of datapoints: 225
    Root location: data/pizza_steak_sushi/train
    StandardTransform
Transform: Compose(
               Resize(size=(64, 64), interpolation=bilinear, max_size=None, antialias=None)
               RandomHorizontalFlip(p=0.5)
               ToTensor()
           )
Test data:
```

```
Dataset ImageFolder
    Number of datapoints: 75
    Root location: data/pizza_steak_sushi/test
    StandardTransform
Transform: Compose(
               Resize(size=(64, 64), interpolation=bilinear,
max_size=None, antialias=None)
               RandomHorizontalFlip(p=0.5)
               ToTensor()
           )
```

```
# Get class names as a list
class_names = train_data.classes
class_names
```

```
['pizza', 'steak', 'sushi']
```

```
# Can also get class names as a dict
class_dict = train_data.class_to_idx
class_dict
```

```
{'pizza': 0, 'steak': 1, 'sushi': 2}
```

```
# Check the lengths
len(train_data), len(test_data)
```

```
(225, 75)
```

Kita dapat mengindeks Kumpulan Data train_data dan test_data untuk menemukan sampel dan label targetnya.

```
img, label = train_data[0][0], train_data[0][1]
print(f"Image tensor:\n{img}")
print(f"Image shape: {img.shape}")
print(f"Image datatype: {img.dtype}")
print(f"Image label: {label}")
print(f"Label datatype: {type(label)}")
```

```
Image tensor:
tensor([[[0.1137, 0.1020, 0.0980,  ..., 0.1255, 0.1216, 0.1176],
         [0.1059, 0.0980, 0.0980,  ..., 0.1294, 0.1294, 0.1294],
         [0.1020, 0.0980, 0.0941,  ..., 0.1333, 0.1333, 0.1333],
         ...,
         [0.1098, 0.1098, 0.1255,  ..., 0.1686, 0.1647, 0.1686],
         [0.0863, 0.0941, 0.1098,  ..., 0.1686, 0.1647, 0.1686],
         [0.0863, 0.0863, 0.0980,  ..., 0.1686, 0.1647, 0.1647]],

        [[0.0745, 0.0706, 0.0745,  ..., 0.0588, 0.0588, 0.0588],
         [0.0706, 0.0706, 0.0745,  ..., 0.0627, 0.0627, 0.0627],
         [0.0706, 0.0745, 0.0745,  ..., 0.0706, 0.0706, 0.0706],
         ...,
```

```
         [0.1255, 0.1333, 0.1373,  ..., 0.2510, 0.2392, 0.2392],
         [0.1098, 0.1176, 0.1255,  ..., 0.2510, 0.2392, 0.2314],
         [0.1020, 0.1059, 0.1137,  ..., 0.2431, 0.2353, 0.2275]],

        [[0.0941, 0.0902, 0.0902,  ..., 0.0196, 0.0196, 0.0196],
         [0.0902, 0.0863, 0.0902,  ..., 0.0196, 0.0157, 0.0196],
         [0.0902, 0.0902, 0.0902,  ..., 0.0157, 0.0157, 0.0196],
         ...,
         [0.1294, 0.1333, 0.1490,  ..., 0.1961, 0.1882, 0.1804],
         [0.1098, 0.1137, 0.1255,  ..., 0.1922, 0.1843, 0.1804],
         [0.1059, 0.1020, 0.1059,  ..., 0.1843, 0.1804, 0.1765]]])
Image shape: torch.Size([3, 64, 64])
Image datatype: torch.float32
Image label: 0
Label datatype: <class 'int'>
```

Gambar kita sekarang berbentuk tensor (dengan bentuk [3, 64, 64]) dan labelnya berbentuk bilangan bulat yang berkaitan dengan kelas tertentu (direferensikan oleh atribut class_to_idx).

Saat ini dimensi gambar kita dalam format CHW (saluran warna, tinggi, lebar) tetapi matplotlib lebih memilih HWC (tinggi, lebar, saluran warna).

```
# Rearrange the order of dimensions
img_permute = img.permute(1, 2, 0)

# Print out different shapes (before and after permute)
print(f"Original shape: {img.shape} -> [color_channels, height,
width]")
print(f"Image permute shape: {img_permute.shape} -> [height, width,
color_channels]")

# Plot the image
plt.figure(figsize=(10, 7))
plt.imshow(img.permute(1, 2, 0))
plt.axis("off")
plt.title(class_names[label], fontsize=14);
```

```
Original shape: torch.Size([3, 64, 64]) -> [color_channels, height,
width]
Image permute shape: torch.Size([64, 64, 3]) -> [height, width,
color_channels]
```

Notice the image is now more pixelated (less quality).

This is due to it being resized from `512x512` to `64x64` pixels.

The intuition here is that if you think the image is harder to recognize what's going on, chances are a model will find it harder to understand too.

Ubah gambar yang dimuat menjadi milik DataLoader

```
# Turn train and test Datasets into DataLoaders
from torch.utils.data import DataLoader
train_dataloader = DataLoader(dataset=train_data,
                              batch_size=1, # how many samples per 
batch?
                              num_workers=1, # how many subprocesses 
to use for data loading? (higher = more)
                              shuffle=True) # shuffle the data?
```

```
test_dataloader = DataLoader(dataset=test_data,
                             batch_size=1,
                             num_workers=1,
                             shuffle=False) # don't usually need to
shuffle testing data

train_dataloader, test_dataloader
```

```
(<torch.utils.data.dataloader.DataLoader at 0x7f53c0b9dca0>,
 <torch.utils.data.dataloader.DataLoader at 0x7f53c0b9de50>)
```

Mari kita coba dan periksa bentuknya.

```
img, label = next(iter(train_dataloader))

# Batch size will now be 1, try changing the batch_size parameter
above and see what happens
print(f"Image shape: {img.shape} -> [batch_size, color_channels,
height, width]")
print(f"Label shape: {label.shape}")
```

```
Image shape: torch.Size([1, 3, 64, 64]) -> [batch_size,
color_channels, height, width]
Label shape: torch.Size([1])
```

Opsi 2: Memuat Data Gambar dengan Kumpulan Data Khusus

```
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

# Instance of torchvision.datasets.ImageFolder()
train_data.classes, train_data.class_to_idx
```

```
(['pizza', 'steak', 'sushi'], {'pizza': 0, 'steak': 1, 'sushi': 2})
```

Membuat fungsi pembantu untuk mendapatkan nama kelas

```
# Setup path for target directory
target_directory = train_dir
print(f"Target directory: {target_directory}")

# Get the class names from the target directory
```

```
class_names_found = sorted([entry.name for entry in
list(os.scandir(image_path / "train"))])
print(f"Class names found: {class_names_found}")
```

```
Target directory: data/pizza_steak_sushi/train
Class names found: ['pizza', 'steak', 'sushi']
```

```
# Make function to find classes in target directory
def find_classes(directory: str) -> Tuple[List[str], Dict[str, int]]:
    """Finds the class folder names in a target directory.

    Assumes target directory is in standard image classification
format.

    Args:
        directory (str): target directory to load classnames from.

    Returns:
        Tuple[List[str], Dict[str, int]]: (list_of_class_names,
dict(class_name: idx...))

    Example:
        find_classes("food_images/train")
        >>> (["class_1", "class_2"], {"class_1": 0, ...})
    """
    # 1. Get the class names by scanning the target directory
    classes = sorted(entry.name for entry in os.scandir(directory) if
entry.is_dir())

    # 2. Raise an error if class names not found
    if not classes:
        raise FileNotFoundError(f"Couldn't find any classes in
{directory}.")

    # 3. Create a dictionary of index labels (computers prefer
numerical rather than string labels)
    class_to_idx = {cls_name: i for i, cls_name in enumerate(classes)}
    return classes, class_to_idx

find_classes(train_dir)
```

```
(['pizza', 'steak', 'sushi'], {'pizza': 0, 'steak': 1, 'sushi': 2})
```

Buat Kumpulan Data khusus untuk mereplikasi ImageFolder

```
# Write a custom dataset class (inherits from
torch.utils.data.Dataset)
from torch.utils.data import Dataset

# 1. Subclass torch.utils.data.Dataset
class ImageFolderCustom(Dataset):
```

```python
    # 2. Initialize with a targ_dir and transform (optional) parameter
    def __init__(self, targ_dir: str, transform=None) -> None:

        # 3. Create class attributes
        # Get all image paths
        self.paths = list(pathlib.Path(targ_dir).glob("*/*.jpg")) #
note: you'd have to update this if you've got .png's or .jpeg's
        # Setup transforms
        self.transform = transform
        # Create classes and class_to_idx attributes
        self.classes, self.class_to_idx = find_classes(targ_dir)

    # 4. Make function to load images
    def load_image(self, index: int) -> Image.Image:
        "Opens an image via a path and returns it."
        image_path = self.paths[index]
        return Image.open(image_path)

    # 5. Overwrite the __len__() method (optional but recommended for
subclasses of torch.utils.data.Dataset)
    def __len__(self) -> int:
        "Returns the total number of samples."
        return len(self.paths)

    # 6. Overwrite the __getitem__() method (required for subclasses
of torch.utils.data.Dataset)
    def __getitem__(self, index: int) -> Tuple[torch.Tensor, int]:
        "Returns one sample of data, data and label (X, y)."
        img = self.load_image(index)
        class_name  = self.paths[index].parent.name # expects path in
data_folder/class_name/image.jpeg
        class_idx = self.class_to_idx[class_name]

        # Transform if necessary
        if self.transform:
            return self.transform(img), class_idx # return data, label
(X, y)
        else:
            return img, class_idx # return data, label (X, y)

# Augment train data
train_transforms = transforms.Compose([
    transforms.Resize((64, 64)),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.ToTensor()
])

# Don't augment test data, only reshape
test_transforms = transforms.Compose([
```

```
    transforms.Resize((64, 64)),
    transforms.ToTensor()
])

train_data_custom = ImageFolderCustom(targ_dir=train_dir,
                                      transform=train_transforms)
test_data_custom = ImageFolderCustom(targ_dir=test_dir,
                                     transform=test_transforms)
train_data_custom, test_data_custom
```

```
(<__main__.ImageFolderCustom at 0x7f5461f70c70>,
 <__main__.ImageFolderCustom at 0x7f5461f70c40>)
```

```
len(train_data_custom), len(test_data_custom)
```

```
(225, 75)
```

```
train_data_custom.classes
```

```
['pizza', 'steak', 'sushi']
```

```
train_data_custom.class_to_idx
```

```
{'pizza': 0, 'steak': 1, 'sushi': 2}
```

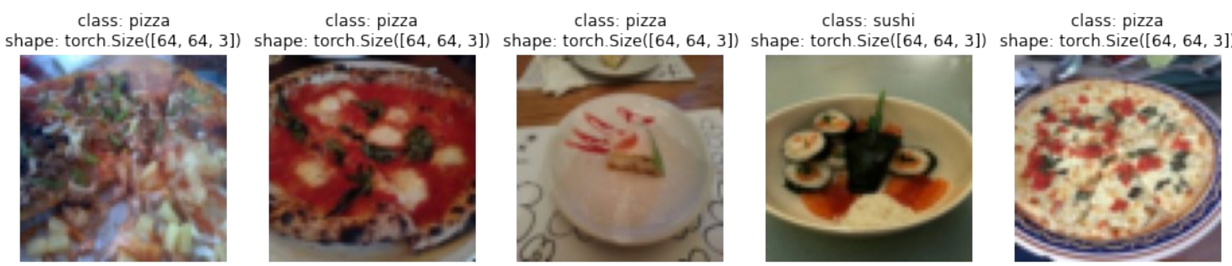
```
# Check for equality amongst our custom Dataset and ImageFolder
Dataset
print((len(train_data_custom) == len(train_data)) &
(len(test_data_custom) == len(test_data)))
print(train_data_custom.classes == train_data.classes)
print(train_data_custom.class_to_idx == train_data.class_to_idx)
```

```
True
True
True
```

Buat fungsi untuk menampilkan gambar acak

```
# 1. Take in a Dataset as well as a list of class names
def display_random_images(dataset: torch.utils.data.dataset.Dataset,
                          classes: List[str] = None,
                          n: int = 10,
                          display_shape: bool = True,
                          seed: int = None):

    # 2. Adjust display if n too high
    if n > 10:
        n = 10
        display_shape = False
        print(f"For display purposes, n shouldn't be larger than 10,
setting to 10 and removing shape display.")
```

```
    # 3. Set random seed
    if seed:
        random.seed(seed)

    # 4. Get random sample indexes
    random_samples_idx = random.sample(range(len(dataset)), k=n)

    # 5. Setup plot
    plt.figure(figsize=(16, 8))

    # 6. Loop through samples and display random samples
    for i, targ_sample in enumerate(random_samples_idx):
        targ_image, targ_label = dataset[targ_sample][0],
dataset[targ_sample][1]

        # 7. Adjust image tensor shape for plotting: [color_channels,
height, width] -> [color_channels, height, width]
        targ_image_adjust = targ_image.permute(1, 2, 0)

        # Plot adjusted samples
        plt.subplot(1, n, i+1)
        plt.imshow(targ_image_adjust)
        plt.axis("off")
        if classes:
            title = f"class: {classes[targ_label]}"
            if display_shape:
                title = title + f"\nshape: {targ_image_adjust.shape}"
        plt.title(title)

# Display random images from ImageFolder created Dataset
display_random_images(train_data,
                      n=5,
                      classes=class_names,
                      seed=None)
```




```
# Display random images from ImageFolderCustom Dataset
display_random_images(train_data_custom,
                      n=12,
                      classes=class_names,
                      seed=None) # Try setting the seed for
reproducible images
```

```
For display purposes, n shouldn't be larger than 10, setting to 10 and
removing shape display.
```

Ubah gambar yang dimuat khusus menjadi milik DataLoader

```
# Turn train and test custom Dataset's into DataLoader's
from torch.utils.data import DataLoader
train_dataloader_custom = DataLoader(dataset=train_data_custom, # use
custom created train Dataset
                                     batch_size=1, # how many samples
per batch?
                                     num_workers=0, # how many
subprocesses to use for data loading? (higher = more)
                                     shuffle=True) # shuffle the data?

test_dataloader_custom = DataLoader(dataset=test_data_custom, # use
custom created test Dataset
                                    batch_size=1,
                                    num_workers=0,
                                    shuffle=False) # don't usually
need to shuffle testing data

train_dataloader_custom, test_dataloader_custom
```

```
(<torch.utils.data.dataloader.DataLoader at 0x7f5460ab8400>,
 <torch.utils.data.dataloader.DataLoader at 0x7f5460ab8490>)
```

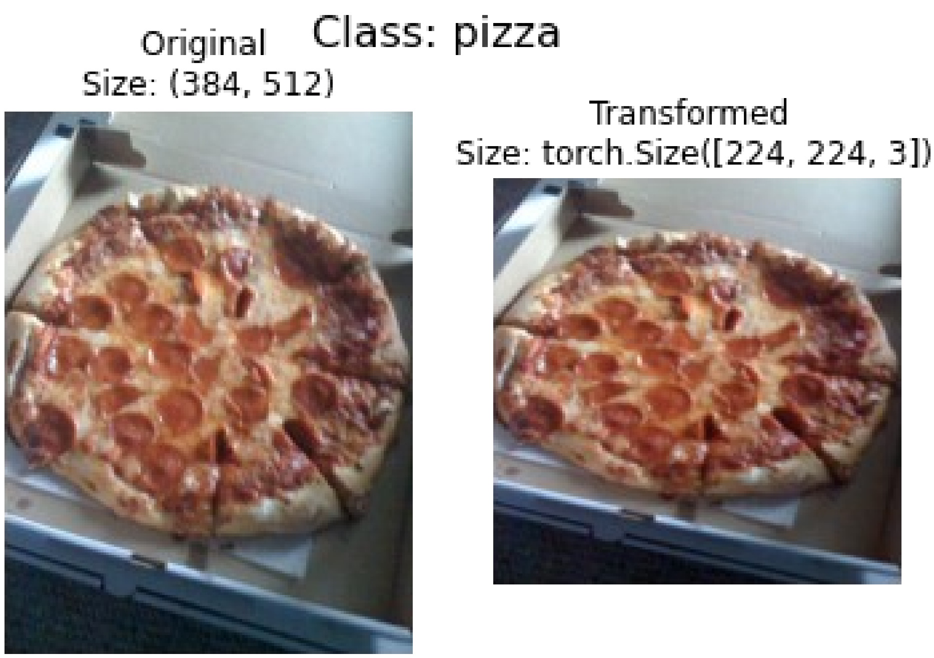
```
# Get image and label from custom DataLoader
img_custom, label_custom = next(iter(train_dataloader_custom))

# Batch size will now be 1, try changing the batch_size parameter
above and see what happens
print(f"Image shape: {img_custom.shape} -> [batch_size,
color_channels, height, width]")
print(f"Label shape: {label_custom.shape}")
```

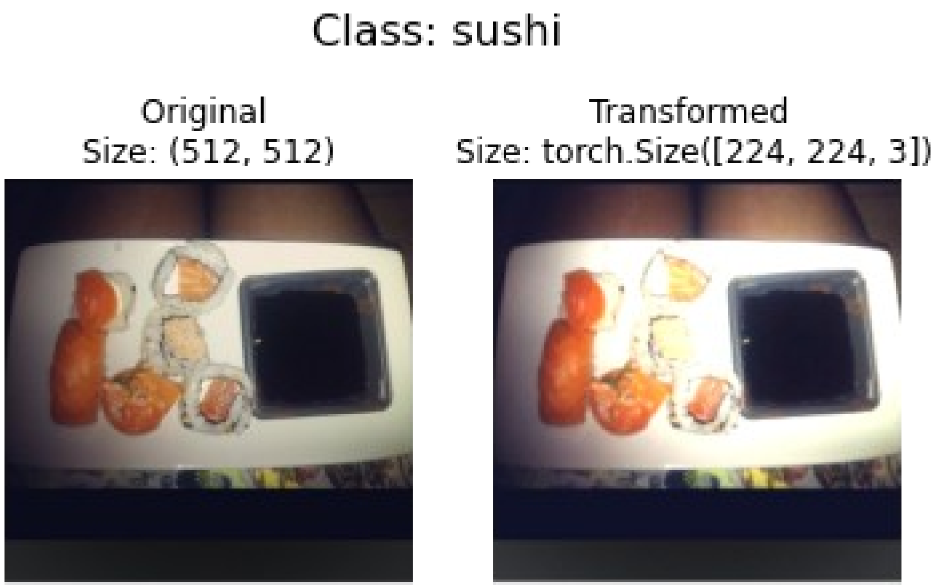
```
Image shape: torch.Size([1, 3, 64, 64]) -> [batch_size,
color_channels, height, width]
Label shape: torch.Size([1])
```

Bentuk transformasi lainnya (augmentasi data)

```
from torchvision import transforms

train_transforms = transforms.Compose([
```

```
    transforms.Resize((224, 224)),
    transforms.TrivialAugmentWide(num_magnitude_bins=31), # how
intense
    transforms.ToTensor() # use ToTensor() last to get everything
between 0 & 1
])

# Don't need to perform augmentation on the test data
test_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor()
])

# Get all image paths
image_path_list = list(image_path.glob("*/*/*.jpg"))

# Plot random images
plot_transformed_images(
    image_paths=image_path_list,
    transform=train_transforms,
    n=3,
    seed=None
)
```





Model 0: TinyVGG tanpa augmentasi data

Membuat transformasi dan memuat data untuk Model 0

```
# Create simple transform
simple_transform = transforms.Compose([
    transforms.Resize((64, 64)),
    transforms.ToTensor(),
])

# 1. Load and transform data
from torchvision import datasets
train_data_simple = datasets.ImageFolder(root=train_dir,
```

```
transform=simple_transform)
test_data_simple = datasets.ImageFolder(root=test_dir,
transform=simple_transform)

# 2. Turn data into DataLoaders
import os
from torch.utils.data import DataLoader

# Setup batch size and number of workers
BATCH_SIZE = 32
NUM_WORKERS = os.cpu_count()
print(f"Creating DataLoader's with batch size {BATCH_SIZE} and
{NUM_WORKERS} workers.")

# Create DataLoader's
train_dataloader_simple = DataLoader(train_data_simple,
                                     batch_size=BATCH_SIZE,
                                     shuffle=True,
                                     num_workers=NUM_WORKERS)

test_dataloader_simple = DataLoader(test_data_simple,
                                    batch_size=BATCH_SIZE,
                                    shuffle=False,
                                    num_workers=NUM_WORKERS)

train_dataloader_simple, test_dataloader_simple
```

```
Creating DataLoader's with batch size 32 and 16 workers.
```

```
(<torch.utils.data.dataloader.DataLoader at 0x7f5460ad2f70>,
 <torch.utils.data.dataloader.DataLoader at 0x7f5460ad23d0>)
```

Membuat kelas model TinyVGG

```
class TinyVGG(nn.Module):
    """
    Model architecture copying TinyVGG from:
    https://poloclub.github.io/cnn-explainer/
    """
    def __init__(self, input_shape: int, hidden_units: int,
output_shape: int) -> None:
        super().__init__()
        self.conv_block_1 = nn.Sequential(
            nn.Conv2d(in_channels=input_shape,
                      out_channels=hidden_units,
                      kernel_size=3, # how big is the square that's
going over the image?
                      stride=1, # default
                      padding=1), # options = "valid" (no padding) or
"same" (output has same shape as input) or int for specific number
```

```
            nn.ReLU(),
            nn.Conv2d(in_channels=hidden_units,
                      out_channels=hidden_units,
                      kernel_size=3,
                      stride=1,
                      padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2,
                         stride=2) # default stride value is same as
kernel_size
        )
        self.conv_block_2 = nn.Sequential(
            nn.Conv2d(hidden_units, hidden_units, kernel_size=3,
padding=1),
            nn.ReLU(),
            nn.Conv2d(hidden_units, hidden_units, kernel_size=3,
padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2)
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            # Where did this in_features shape come from?
            # It's because each layer of our network compresses and
changes the shape of our inputs data.
            nn.Linear(in_features=hidden_units*16*16,
                      out_features=output_shape)
        )

    def forward(self, x: torch.Tensor):
        x = self.conv_block_1(x)
        # print(x.shape)
        x = self.conv_block_2(x)
        # print(x.shape)
        x = self.classifier(x)
        # print(x.shape)
        return x
        # return
self.classifier(self.conv_block_2(self.conv_block_1(x))) # <- leverage
the benefits of operator fusion

torch.manual_seed(42)
model_0 = TinyVGG(input_shape=3, # number of color channels (3 for
RGB)
                  hidden_units=10,
                  output_shape=len(train_data.classes)).to(device)
model_0

TinyVGG(
  (conv_block_1): Sequential(
```

```
    (0): Conv2d(3, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (1): ReLU()
    (2): Conv2d(10, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (3): ReLU()
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (conv_block_2): Sequential(
    (0): Conv2d(10, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (1): ReLU()
    (2): Conv2d(10, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (3): ReLU()
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Linear(in_features=2560, out_features=3, bias=True)
  )
)
```

Mencoba forward pass pada satu gambar (untuk menguji model)

```
# 1. Get a batch of images and labels from the DataLoader
img_batch, label_batch = next(iter(train_dataloader_simple))

# 2. Get a single image from the batch and unsqueeze the image so its
shape fits the model
img_single, label_single = img_batch[0].unsqueeze(dim=0),
label_batch[0]
print(f"Single image shape: {img_single.shape}\n")

# 3. Perform a forward pass on a single image
model_0.eval()
with torch.inference_mode():
    pred = model_0(img_single.to(device))

# 4. Print out what's happening and convert model logits -> pred probs
-> pred label
print(f"Output logits:\n{pred}\n")
print(f"Output prediction probabilities:\n{torch.softmax(pred,
dim=1)}\n")
print(f"Output prediction label:\n{torch.argmax(torch.softmax(pred,
dim=1), dim=1)}\n")
print(f"Actual label:\n{label_single}")
```

```
Single image shape: torch.Size([1, 3, 64, 64])

Output logits:
tensor([[0.0578, 0.0634, 0.0352]], device='cuda:0')

Output prediction probabilities:
tensor([[0.3352, 0.3371, 0.3277]], device='cuda:0')

Output prediction label:
tensor([1], device='cuda:0')

Actual label:
2
```

Gunakan torchinfo untuk mendapatkan gambaran tentang bentuk yang ada pada model kita

```python
# Install torchinfo if it's not available, import it if it is
try:
    import torchinfo
except:
    !pip install torchinfo
    import torchinfo

from torchinfo import summary
summary(model_0, input_size=[1, 3, 64, 64]) # do a test pass through
of an example input size
```

```
======================================================================
====================
Layer (type:depth-idx)                   Output Shape
Param #
======================================================================
====================
TinyVGG                                  [1, 3]                    --
├─Sequential: 1-1                        [1, 10, 32, 32]           --
│    └─Conv2d: 2-1                       [1, 10, 64, 64]           280
│    └─ReLU: 2-2                         [1, 10, 64, 64]           --
│    └─Conv2d: 2-3                       [1, 10, 64, 64]           910
│    └─ReLU: 2-4                         [1, 10, 64, 64]           --
│    └─MaxPool2d: 2-5                    [1, 10, 32, 32]           --
├─Sequential: 1-2                        [1, 10, 16, 16]           --
│    └─Conv2d: 2-6                       [1, 10, 32, 32]           910
│    └─ReLU: 2-7                         [1, 10, 32, 32]           --
│    └─Conv2d: 2-8                       [1, 10, 32, 32]           910
│    └─ReLU: 2-9                         [1, 10, 32, 32]           --
│    └─MaxPool2d: 2-10                   [1, 10, 16, 16]           --
├─Sequential: 1-3                        [1, 3]                    --
│    └─Flatten: 2-11                     [1, 2560]                 --
│    └─Linear: 2-12                      [1, 3]
```

```
7,683
======================================================================
====================
Total params: 10,693
Trainable params: 10,693
Non-trainable params: 0
Total mult-adds (M): 6.75
======================================================================
====================
Input size (MB): 0.05
Forward/backward pass size (MB): 0.82
Params size (MB): 0.04
Estimated Total Size (MB): 0.91
======================================================================
====================
```

Membuat fungsi train & test loop

```python
def train_step(model: torch.nn.Module,
               dataloader: torch.utils.data.DataLoader,
               loss_fn: torch.nn.Module,
               optimizer: torch.optim.Optimizer):
    # Put model in train mode
    model.train()

    # Setup train loss and train accuracy values
    train_loss, train_acc = 0, 0

    # Loop through data loader data batches
    for batch, (X, y) in enumerate(dataloader):
        # Send data to target device
        X, y = X.to(device), y.to(device)

        # 1. Forward pass
        y_pred = model(X)

        # 2. Calculate  and accumulate loss
        loss = loss_fn(y_pred, y)
        train_loss += loss.item()

        # 3. Optimizer zero grad
        optimizer.zero_grad()

        # 4. Loss backward
        loss.backward()

        # 5. Optimizer step
        optimizer.step()

        # Calculate and accumulate accuracy metric across all batches
```

```
        y_pred_class = torch.argmax(torch.softmax(y_pred, dim=1), 
dim=1)
        train_acc += (y_pred_class == y).sum().item()/len(y_pred)

    # Adjust metrics to get average loss and accuracy per batch
    train_loss = train_loss / len(dataloader)
    train_acc = train_acc / len(dataloader)
    return train_loss, train_acc

def test_step(model: torch.nn.Module,
              dataloader: torch.utils.data.DataLoader,
              loss_fn: torch.nn.Module):
    # Put model in eval mode
    model.eval()

    # Setup test loss and test accuracy values
    test_loss, test_acc = 0, 0

    # Turn on inference context manager
    with torch.inference_mode():
        # Loop through DataLoader batches
        for batch, (X, y) in enumerate(dataloader):
            # Send data to target device
            X, y = X.to(device), y.to(device)

            # 1. Forward pass
            test_pred_logits = model(X)

            # 2. Calculate and accumulate loss
            loss = loss_fn(test_pred_logits, y)
            test_loss += loss.item()

            # Calculate and accumulate accuracy
            test_pred_labels = test_pred_logits.argmax(dim=1)
            test_acc += ((test_pred_labels == 
y).sum().item()/len(test_pred_labels))

    # Adjust metrics to get average loss and accuracy per batch
    test_loss = test_loss / len(dataloader)
    test_acc = test_acc / len(dataloader)
    return test_loss, test_acc
```

Membuat fungsi train() untuk menggabungkan train_step() dan test_step()

```
from tqdm.auto import tqdm

# 1. Take in various parameters required for training and test steps
def train(model: torch.nn.Module,
          train_dataloader: torch.utils.data.DataLoader,
```

```
          test_dataloader: torch.utils.data.DataLoader,
          optimizer: torch.optim.Optimizer,
          loss_fn: torch.nn.Module = nn.CrossEntropyLoss(),
          epochs: int = 5):

    # 2. Create empty results dictionary
    results = {"train_loss": [],
        "train_acc": [],
        "test_loss": [],
        "test_acc": []
    }

    # 3. Loop through training and testing steps for a number of
epochs
    for epoch in tqdm(range(epochs)):
        train_loss, train_acc = train_step(model=model,

dataloader=train_dataloader,
                                           loss_fn=loss_fn,
                                           optimizer=optimizer)
        test_loss, test_acc = test_step(model=model,
            dataloader=test_dataloader,
            loss_fn=loss_fn)

        # 4. Print out what's happening
        print(
            f"Epoch: {epoch+1} | "
            f"train_loss: {train_loss:.4f} | "
            f"train_acc: {train_acc:.4f} | "
            f"test_loss: {test_loss:.4f} | "
            f"test_acc: {test_acc:.4f}"
        )

        # 5. Update results dictionary
        results["train_loss"].append(train_loss)
        results["train_acc"].append(train_acc)
        results["test_loss"].append(test_loss)
        results["test_acc"].append(test_acc)

    # 6. Return the filled results at the end of the epochs
    return results
```

Melatih dan Mengevaluasi Model 0

```
# Set random seeds
torch.manual_seed(42)
torch.cuda.manual_seed(42)

# Set number of epochs
NUM_EPOCHS = 5
```

```
# Recreate an instance of TinyVGG
model_0 = TinyVGG(input_shape=3, # number of color channels (3 for
RGB)
                  hidden_units=10,
                  output_shape=len(train_data.classes)).to(device)

# Setup loss function and optimizer
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(params=model_0.parameters(), lr=0.001)

# Start the timer
from timeit import default_timer as timer
start_time = timer()

# Train model_0
model_0_results = train(model=model_0,
                        train_dataloader=train_dataloader_simple,
                        test_dataloader=test_dataloader_simple,
                        optimizer=optimizer,
                        loss_fn=loss_fn,
                        epochs=NUM_EPOCHS)

# End the timer and print out how long it took
end_time = timer()
print(f"Total training time: {end_time-start_time:.3f} seconds")
```

{"model_id":"b566c3ddf5bc4a8b98a6db06c8825c9d","version_major":2,"vers
ion_minor":0}

```
Epoch: 1 | train_loss: 1.1078 | train_acc: 0.2578 | test_loss: 1.1360
| test_acc: 0.2604
Epoch: 2 | train_loss: 1.0847 | train_acc: 0.4258 | test_loss: 1.1620
| test_acc: 0.1979
Epoch: 3 | train_loss: 1.1157 | train_acc: 0.2930 | test_loss: 1.1697
| test_acc: 0.1979
Epoch: 4 | train_loss: 1.0956 | train_acc: 0.4141 | test_loss: 1.1384
| test_acc: 0.1979
Epoch: 5 | train_loss: 1.0985 | train_acc: 0.2930 | test_loss: 1.1426
| test_acc: 0.1979
Total training time: 4.935 seconds
```

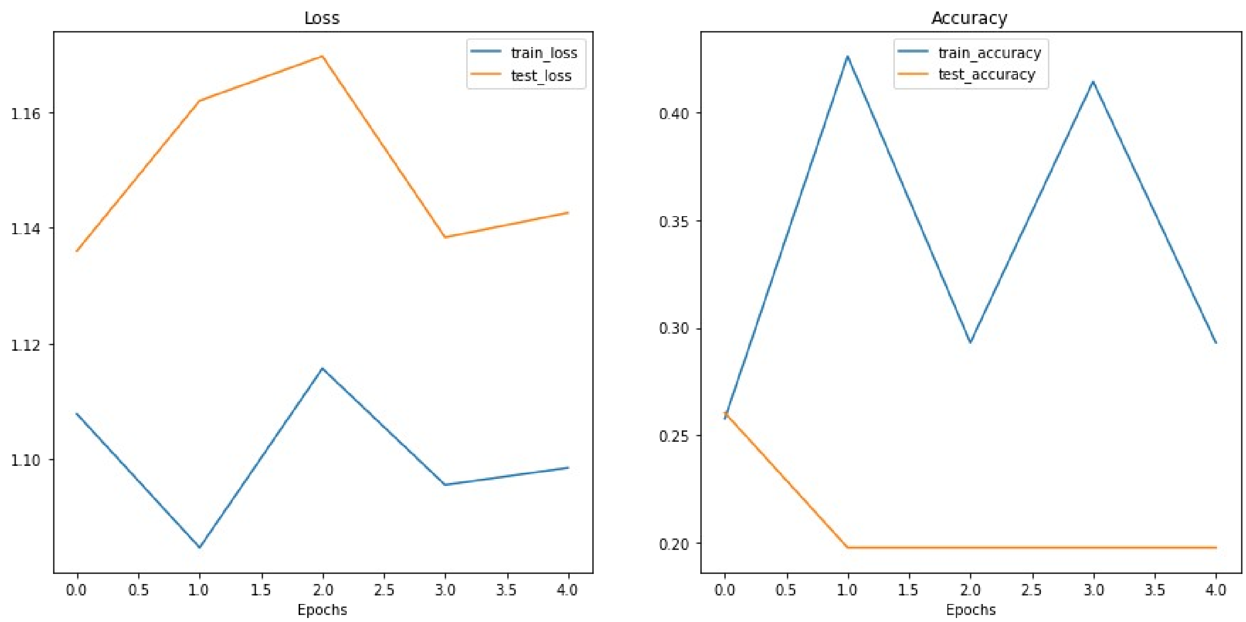
Plot kurva kerugian Model 0

```
# Check the model_0_results keys
model_0_results.keys()
```

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

```
def plot_loss_curves(results: Dict[str, List[float]]):
    """Plots training curves of a results dictionary.
```

```
    Args:
        results (dict): dictionary containing list of values, e.g.
            {"train_loss": [...],
             "train_acc": [...],
             "test_loss": [...],
             "test_acc": [...]}
    """

    # Get the loss values of the results dictionary (training and
test)
    loss = results['train_loss']
    test_loss = results['test_loss']

    # Get the accuracy values of the results dictionary (training and
test)
    accuracy = results['train_acc']
    test_accuracy = results['test_acc']

    # Figure out how many epochs there were
    epochs = range(len(results['train_loss']))

    # Setup a plot
    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_accuracy')
    plt.plot(epochs, test_accuracy, label='test_accuracy')
    plt.title('Accuracy')
    plt.xlabel('Epochs')
    plt.legend();

plot_loss_curves(model_0_results)
```



Seperti apa seharusnya kurva kerugian yang ideal?

Cara mengatasi overfitting

Cara mengatasi underfitting

Keseimbangan antara overfitting dan underfitting

Model 1: TinyVGG dengan Augmentasi Data

Buat transformasi dengan augmentasi data

```
# Create training transform with TrivialAugment
train_transform_trivial_augment = transforms.Compose([
    transforms.Resize((64, 64)),
    transforms.TrivialAugmentWide(num_magnitude_bins=31),
    transforms.ToTensor()
])

# Create testing transform (no data augmentation)
test_transform = transforms.Compose([
    transforms.Resize((64, 64)),
    transforms.ToTensor()
])
```

Membuat latih dan uji Kumpulan Data dan DataLoader

```
# Turn image folders into Datasets
train_data_augmented = datasets.ImageFolder(train_dir,
```

```
transform=train_transform_trivial_augment)
test_data_simple = datasets.ImageFolder(test_dir,
transform=test_transform)

train_data_augmented, test_data_simple
```

```
(Dataset ImageFolder
     Number of datapoints: 225
     Root location: data/pizza_steak_sushi/train
     StandardTransform
 Transform: Compose(
                Resize(size=(64, 64), interpolation=bilinear,
max_size=None, antialias=None)
                TrivialAugmentWide(num_magnitude_bins=31,
interpolation=InterpolationMode.NEAREST, fill=None)
                ToTensor()
            ),
 Dataset ImageFolder
     Number of datapoints: 75
     Root location: data/pizza_steak_sushi/test
     StandardTransform
 Transform: Compose(
                Resize(size=(64, 64), interpolation=bilinear,
max_size=None, antialias=None)
                ToTensor()
            ))
```

```
# Turn Datasets into DataLoader's
import os
BATCH_SIZE = 32
NUM_WORKERS = os.cpu_count()

torch.manual_seed(42)
train_dataloader_augmented = DataLoader(train_data_augmented,
                                        batch_size=BATCH_SIZE,
                                        shuffle=True,
                                        num_workers=NUM_WORKERS)

test_dataloader_simple = DataLoader(test_data_simple,
                                    batch_size=BATCH_SIZE,
                                    shuffle=False,
                                    num_workers=NUM_WORKERS)

train_dataloader_augmented, test_dataloader
```

```
(<torch.utils.data.dataloader.DataLoader at 0x7f53c6d64040>,
 <torch.utils.data.dataloader.DataLoader at 0x7f53c0b9de50>)
```

Membangun dan melatih Model 1

```
# Create model_1 and send it to the target device
torch.manual_seed(42)
model_1 = TinyVGG(
    input_shape=3,
    hidden_units=10,
    output_shape=len(train_data_augmented.classes)).to(device)
model_1
```

```
TinyVGG(
  (conv_block_1): Sequential(
    (0): Conv2d(3, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (1): ReLU()
    (2): Conv2d(10, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (3): ReLU()
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (conv_block_2): Sequential(
    (0): Conv2d(10, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (1): ReLU()
    (2): Conv2d(10, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
    (3): ReLU()
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Linear(in_features=2560, out_features=3, bias=True)
  )
)
```

```
# Set random seeds
torch.manual_seed(42)
torch.cuda.manual_seed(42)

# Set number of epochs
NUM_EPOCHS = 5

# Setup loss function and optimizer
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(params=model_1.parameters(), lr=0.001)

# Start the timer
from timeit import default_timer as timer
start_time = timer()
```

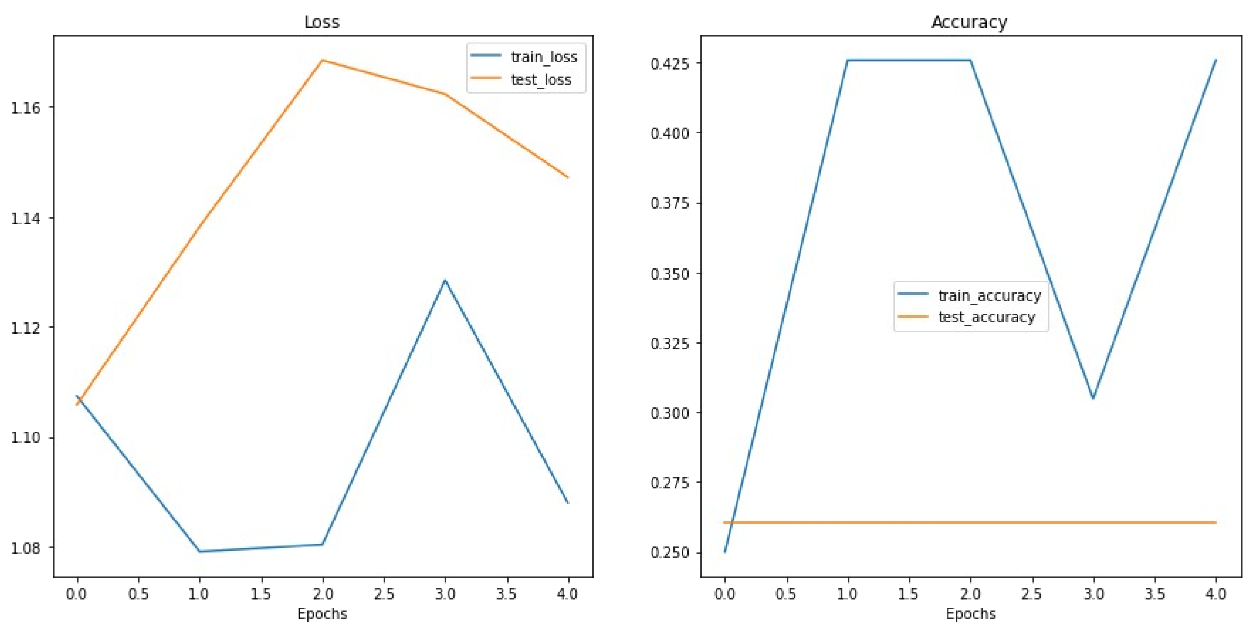
```python
# Train model_1
model_1_results = train(model=model_1,
                        train_dataloader=train_dataloader_augmented,
                        test_dataloader=test_dataloader_simple,
                        optimizer=optimizer,
                        loss_fn=loss_fn,
                        epochs=NUM_EPOCHS)

# End the timer and print out how long it took
end_time = timer()
print(f"Total training time: {end_time-start_time:.3f} seconds")
```

{"model_id":"cf64499894624ea2a5c2da2f27c1b765","version_major":2,"version_minor":0}

```
Epoch: 1 | train_loss: 1.1074 | train_acc: 0.2500 | test_loss: 1.1058
| test_acc: 0.2604
Epoch: 2 | train_loss: 1.0791 | train_acc: 0.4258 | test_loss: 1.1382
| test_acc: 0.2604
Epoch: 3 | train_loss: 1.0803 | train_acc: 0.4258 | test_loss: 1.1685
| test_acc: 0.2604
Epoch: 4 | train_loss: 1.1285 | train_acc: 0.3047 | test_loss: 1.1623
| test_acc: 0.2604
Epoch: 5 | train_loss: 1.0880 | train_acc: 0.4258 | test_loss: 1.1472
| test_acc: 0.2604
Total training time: 4.924 seconds
```

Plot kurva kerugian Model 1

```python
plot_loss_curves(model_1_results)
```

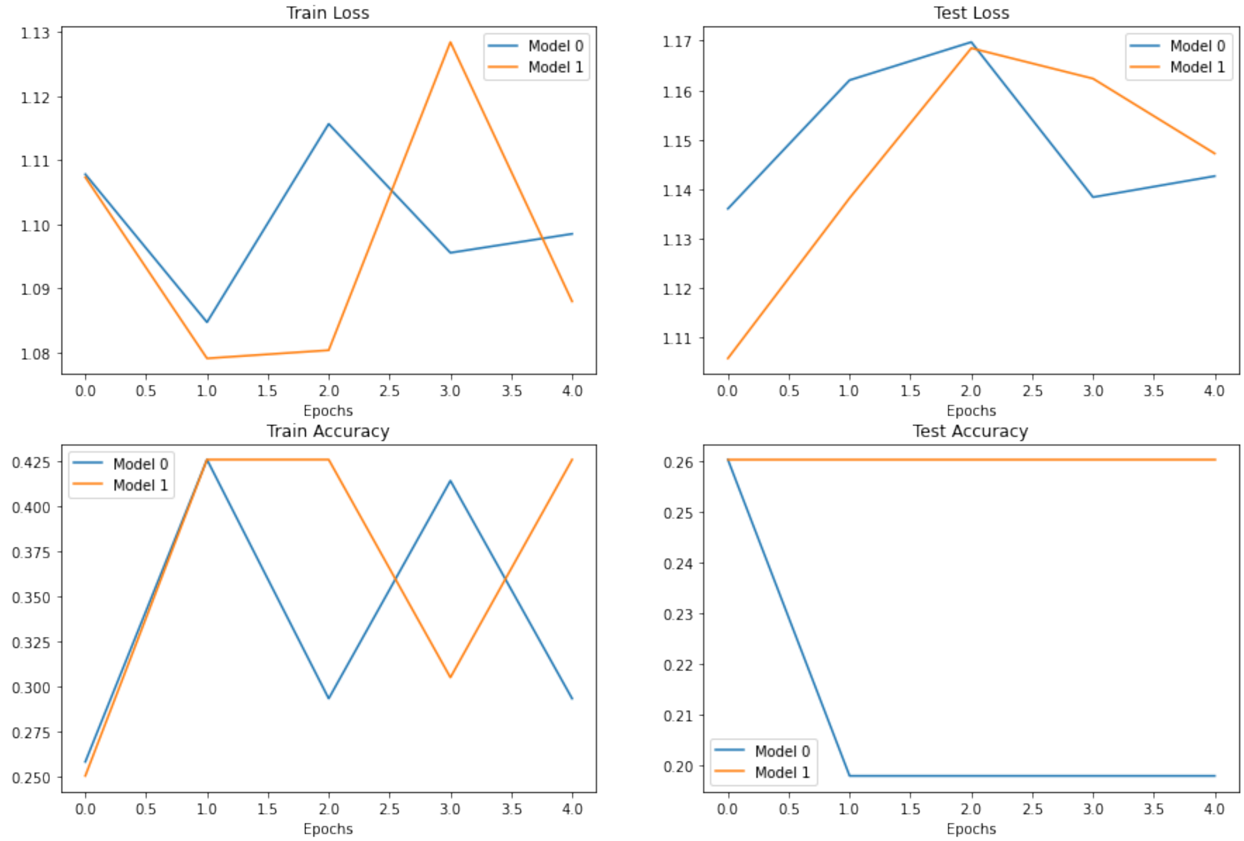


Bandingkan hasil model

```
import pandas as pd
model_0_df = pd.DataFrame(model_0_results)
model_1_df = pd.DataFrame(model_1_results)
model_0_df
```

	train_loss	train_acc	test_loss	test_acc
0	1.107833	0.257812	1.136041	0.260417
1	1.084713	0.425781	1.162014	0.197917
2	1.115697	0.292969	1.169704	0.197917
3	1.095564	0.414062	1.138373	0.197917
4	1.098520	0.292969	1.142631	0.197917

```
# Setup a plot
plt.figure(figsize=(15, 10))

# Get number of epochs
epochs = range(len(model_0_df))

# Plot train loss
plt.subplot(2, 2, 1)
plt.plot(epochs, model_0_df["train_loss"], label="Model 0")
plt.plot(epochs, model_1_df["train_loss"], label="Model 1")
plt.title("Train Loss")
plt.xlabel("Epochs")
plt.legend()

# Plot test loss
plt.subplot(2, 2, 2)
plt.plot(epochs, model_0_df["test_loss"], label="Model 0")
plt.plot(epochs, model_1_df["test_loss"], label="Model 1")
plt.title("Test Loss")
plt.xlabel("Epochs")
plt.legend()

# Plot train accuracy
plt.subplot(2, 2, 3)
plt.plot(epochs, model_0_df["train_acc"], label="Model 0")
plt.plot(epochs, model_1_df["train_acc"], label="Model 1")
plt.title("Train Accuracy")
plt.xlabel("Epochs")
plt.legend()

# Plot test accuracy
plt.subplot(2, 2, 4)
plt.plot(epochs, model_0_df["test_acc"], label="Model 0")
plt.plot(epochs, model_1_df["test_acc"], label="Model 1")
plt.title("Test Accuracy")
plt.xlabel("Epochs")
plt.legend();
```



Membuat prediksi pada gambar kustom

```
# Download custom image
import requests

# Setup custom image path
custom_image_path = data_path / "04-pizza-dad.jpeg"

# Download the image if it doesn't already exist
if not custom_image_path.is_file():
    with open(custom_image_path, "wb") as f:
        # When downloading from GitHub, need to use the "raw" file
link
        request =
requests.get("https://raw.githubusercontent.com/mrdbourke/pytorch-
deep-learning/main/images/04-pizza-dad.jpeg")
        print(f"Downloading {custom_image_path}...")
        f.write(request.content)
else:
    print(f"{custom_image_path} already exists, skipping download.")
```

```
data/04-pizza-dad.jpeg already exists, skipping download.
```

Memuat gambar khusus dengan PyTorch

```
import torchvision

# Read in custom image
custom_image_uint8 = torchvision.io.read_image(str(custom_image_path))

# Print out image data
print(f"Custom image tensor:\n{custom_image_uint8}\n")
print(f"Custom image shape: {custom_image_uint8.shape}\n")
print(f"Custom image dtype: {custom_image_uint8.dtype}")

Custom image tensor:
tensor([[[154, 173, 181,  ...,  21,  18,  14],
         [146, 165, 181,  ...,  21,  18,  15],
         [124, 146, 172,  ...,  18,  17,  15],
         ...,
         [ 72,  59,  45,  ..., 152, 150, 148],
         [ 64,  55,  41,  ..., 150, 147, 144],
         [ 64,  60,  46,  ..., 149, 146, 143]],

        [[171, 190, 193,  ...,  22,  19,  15],
         [163, 182, 193,  ...,  22,  19,  16],
         [141, 163, 184,  ...,  19,  18,  16],
         ...,
         [ 55,  42,  28,  ..., 107, 104, 103],
         [ 47,  38,  24,  ..., 108, 104, 102],
         [ 47,  43,  29,  ..., 107, 104, 101]],

        [[119, 138, 147,  ...,  17,  14,  10],
         [111, 130, 145,  ...,  17,  14,  11],
         [ 87, 111, 136,  ...,  14,  13,  11],
         ...,
         [ 35,  22,   8,  ...,  52,  52,  48],
         [ 27,  18,   4,  ...,  50,  49,  44],
         [ 27,  23,   9,  ...,  49,  46,  43]]], dtype=torch.uint8)

Custom image shape: torch.Size([3, 4032, 3024])

Custom image dtype: torch.uint8

# Try to make a prediction on image in uint8 format (this will error)
model_1.eval()
with torch.inference_mode():
    model_1(custom_image_uint8.to(device))

----------------------------------------------------------------------
-----
RuntimeError                              Traceback (most recent call
last)
Input In [61], in <cell line: 3>()
```

```
      2 model_1.eval()
      3 with torch.inference_mode():
----> 4     model_1(custom_image_uint8.to(device))

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/module
.py:1130, in Module._call_impl(self, *input, **kwargs)
   1126 # If we don't have any hooks, we want to skip the rest of the
logic in
   1127 # this function, and just call forward.
   1128 if not (self._backward_hooks or self._forward_hooks or
self._forward_pre_hooks or _global_backward_hooks
   1129         or _global_forward_hooks or
_global_forward_pre_hooks):
-> 1130     return forward_call(*input, **kwargs)
   1131 # Do not call functions when jit is used
   1132 full_backward_hooks, non_full_backward_hooks = [], []

Input In [41], in TinyVGG.forward(self, x)
     39 def forward(self, x: torch.Tensor):
---> 40     x = self.conv_block_1(x)
     41     # print(x.shape)
     42     x = self.conv_block_2(x)

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/module
.py:1130, in Module._call_impl(self, *input, **kwargs)
   1126 # If we don't have any hooks, we want to skip the rest of the
logic in
   1127 # this function, and just call forward.
   1128 if not (self._backward_hooks or self._forward_hooks or
self._forward_pre_hooks or _global_backward_hooks
   1129         or _global_forward_hooks or
_global_forward_pre_hooks):
-> 1130     return forward_call(*input, **kwargs)
   1131 # Do not call functions when jit is used
   1132 full_backward_hooks, non_full_backward_hooks = [], []

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/contai
ner.py:139, in Sequential.forward(self, input)
    137 def forward(self, input):
    138     for module in self:
--> 139         input = module(input)
    140     return input

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/module
.py:1130, in Module._call_impl(self, *input, **kwargs)
   1126 # If we don't have any hooks, we want to skip the rest of the
```

```
logic in
   1127 # this function, and just call forward.
   1128 if not (self._backward_hooks or self._forward_hooks or
self._forward_pre_hooks or _global_backward_hooks
   1129         or _global_forward_hooks or
_global_forward_pre_hooks):
-> 1130     return forward_call(*input, **kwargs)
   1131 # Do not call functions when jit is used
   1132 full_backward_hooks, non_full_backward_hooks = [], []

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/conv.p
y:457, in Conv2d.forward(self, input)
    456 def forward(self, input: Tensor) -> Tensor:
--> 457     return self._conv_forward(input, self.weight, self.bias)

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/conv.p
y:453, in Conv2d._conv_forward(self, input, weight, bias)
    449 if self.padding_mode != 'zeros':
    450     return F.conv2d(F.pad(input,
self._reversed_padding_repeated_twice, mode=self.padding_mode),
    451                     weight, bias, self.stride,
    452                     _pair(0), self.dilation, self.groups)
--> 453 return F.conv2d(input, weight, bias, self.stride,
    454                 self.padding, self.dilation, self.groups)

RuntimeError: Input type (torch.cuda.ByteTensor) and weight type
(torch.cuda.FloatTensor) should be the same
```

```python
# Load in custom image and convert the tensor values to float32
custom_image =
torchvision.io.read_image(str(custom_image_path)).type(torch.float32)

# Divide the image pixel values by 255 to get them between [0, 1]
custom_image = custom_image / 255.

# Print out image data
print(f"Custom image tensor:\n{custom_image}\n")
print(f"Custom image shape: {custom_image.shape}\n")
print(f"Custom image dtype: {custom_image.dtype}")
```

```
Custom image tensor:
tensor([[[0.6039, 0.6784, 0.7098,  ..., 0.0824, 0.0706, 0.0549],
         [0.5725, 0.6471, 0.7098,  ..., 0.0824, 0.0706, 0.0588],
         [0.4863, 0.5725, 0.6745,  ..., 0.0706, 0.0667, 0.0588],
         ...,
         [0.2824, 0.2314, 0.1765,  ..., 0.5961, 0.5882, 0.5804],
         [0.2510, 0.2157, 0.1608,  ..., 0.5882, 0.5765, 0.5647],
         [0.2510, 0.2353, 0.1804,  ..., 0.5843, 0.5725, 0.5608]],
```

```
        [[0.6706, 0.7451, 0.7569,  ..., 0.0863, 0.0745, 0.0588],
         [0.6392, 0.7137, 0.7569,  ..., 0.0863, 0.0745, 0.0627],
         [0.5529, 0.6392, 0.7216,  ..., 0.0745, 0.0706, 0.0627],
         ...,
         [0.2157, 0.1647, 0.1098,  ..., 0.4196, 0.4078, 0.4039],
         [0.1843, 0.1490, 0.0941,  ..., 0.4235, 0.4078, 0.4000],
         [0.1843, 0.1686, 0.1137,  ..., 0.4196, 0.4078, 0.3961]],

        [[0.4667, 0.5412, 0.5765,  ..., 0.0667, 0.0549, 0.0392],
         [0.4353, 0.5098, 0.5686,  ..., 0.0667, 0.0549, 0.0431],
         [0.3412, 0.4353, 0.5333,  ..., 0.0549, 0.0510, 0.0431],
         ...,
         [0.1373, 0.0863, 0.0314,  ..., 0.2039, 0.2039, 0.1882],
         [0.1059, 0.0706, 0.0157,  ..., 0.1961, 0.1922, 0.1725],
         [0.1059, 0.0902, 0.0353,  ..., 0.1922, 0.1804, 0.1686]]])

Custom image shape: torch.Size([3, 4032, 3024])

Custom image dtype: torch.float32
```

Memprediksi gambar khusus dengan model PyTorch terlatih

```
# Plot custom image
plt.imshow(custom_image.permute(1, 2, 0)) # need to permute image dimensions from CHW -> HWC otherwise matplotlib will error
plt.title(f"Image shape: {custom_image.shape}")
plt.axis(False);
```

Image shape: torch.Size([3, 4032, 3024])

```python
# Create transform pipleine to resize image
custom_image_transform = transforms.Compose([
    transforms.Resize((64, 64)),
])

# Transform target image
custom_image_transformed = custom_image_transform(custom_image)

# Print out original shape and new shape
print(f"Original shape: {custom_image.shape}")
print(f"New shape: {custom_image_transformed.shape}")
```

```
Original shape: torch.Size([3, 4032, 3024])
New shape: torch.Size([3, 64, 64])
```

```python
model_1.eval()
with torch.inference_mode():
    custom_image_pred = model_1(custom_image_transformed)
```

```
-----------------------------------------------------------------------
-----
RuntimeError                              Traceback (most recent call
last)
Input In [65], in <cell line: 2>()
      1 model_1.eval()
      2 with torch.inference_mode():
----> 3     custom_image_pred = model_1(custom_image_transformed)

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/module
.py:1130, in Module._call_impl(self, *input, **kwargs)
   1126 # If we don't have any hooks, we want to skip the rest of the
logic in
   1127 # this function, and just call forward.
   1128 if not (self._backward_hooks or self._forward_hooks or
self._forward_pre_hooks or _global_backward_hooks
   1129         or _global_forward_hooks or
_global_forward_pre_hooks):
-> 1130     return forward_call(*input, **kwargs)
   1131 # Do not call functions when jit is used
   1132 full_backward_hooks, non_full_backward_hooks = [], []

Input In [41], in TinyVGG.forward(self, x)
     39 def forward(self, x: torch.Tensor):
---> 40     x = self.conv_block_1(x)
     41     # print(x.shape)
     42     x = self.conv_block_2(x)

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/module
```

```
.py:1130, in Module._call_impl(self, *input, **kwargs)
   1126 # If we don't have any hooks, we want to skip the rest of the
logic in
   1127 # this function, and just call forward.
   1128 if not (self._backward_hooks or self._forward_hooks or
self._forward_pre_hooks or _global_backward_hooks
   1129         or _global_forward_hooks or
_global_forward_pre_hooks):
-> 1130     return forward_call(*input, **kwargs)
   1131 # Do not call functions when jit is used
   1132 full_backward_hooks, non_full_backward_hooks = [], []

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/contai
ner.py:139, in Sequential.forward(self, input)
    137 def forward(self, input):
    138     for module in self:
--> 139         input = module(input)
    140     return input

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/module
.py:1130, in Module._call_impl(self, *input, **kwargs)
   1126 # If we don't have any hooks, we want to skip the rest of the
logic in
   1127 # this function, and just call forward.
   1128 if not (self._backward_hooks or self._forward_hooks or
self._forward_pre_hooks or _global_backward_hooks
   1129         or _global_forward_hooks or
_global_forward_pre_hooks):
-> 1130     return forward_call(*input, **kwargs)
   1131 # Do not call functions when jit is used
   1132 full_backward_hooks, non_full_backward_hooks = [], []

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/conv.p
y:457, in Conv2d.forward(self, input)
    456 def forward(self, input: Tensor) -> Tensor:
--> 457     return self._conv_forward(input, self.weight, self.bias)

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/conv.p
y:453, in Conv2d._conv_forward(self, input, weight, bias)
    449 if self.padding_mode != 'zeros':
    450     return F.conv2d(F.pad(input,
self._reversed_padding_repeated_twice, mode=self.padding_mode),
    451                     weight, bias, self.stride,
    452                     _pair(0), self.dilation, self.groups)
--> 453 return F.conv2d(input, weight, bias, self.stride,
    454                 self.padding, self.dilation, self.groups)
```

```
RuntimeError: Expected all tensors to be on the same device, but found
at least two devices, cpu and cuda:0! (when checking argument for
argument weight in method wrapper___slow_conv2d_forward)

model_1.eval()
with torch.inference_mode():
    custom_image_pred = model_1(custom_image_transformed.to(device))

----------------------------------------------------------------------
-----
RuntimeError                              Traceback (most recent call
last)
Input In [66], in <cell line: 2>()
      1 model_1.eval()
      2 with torch.inference_mode():
----> 3     custom_image_pred =
model_1(custom_image_transformed.to(device))

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/module
.py:1130, in Module._call_impl(self, *input, **kwargs)
   1126 # If we don't have any hooks, we want to skip the rest of the
logic in
   1127 # this function, and just call forward.
   1128 if not (self._backward_hooks or self._forward_hooks or
self._forward_pre_hooks or _global_backward_hooks
   1129         or _global_forward_hooks or
_global_forward_pre_hooks):
-> 1130     return forward_call(*input, **kwargs)
   1131 # Do not call functions when jit is used
   1132 full_backward_hooks, non_full_backward_hooks = [], []

Input In [41], in TinyVGG.forward(self, x)
     42 x = self.conv_block_2(x)
     43 # print(x.shape)
---> 44 x = self.classifier(x)
     45 # print(x.shape)
     46 return x

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/module
.py:1130, in Module._call_impl(self, *input, **kwargs)
   1126 # If we don't have any hooks, we want to skip the rest of the
logic in
   1127 # this function, and just call forward.
   1128 if not (self._backward_hooks or self._forward_hooks or
self._forward_pre_hooks or _global_backward_hooks
   1129         or _global_forward_hooks or
_global_forward_pre_hooks):
```

```
-> 1130     return forward_call(*input, **kwargs)
   1131 # Do not call functions when jit is used
   1132 full_backward_hooks, non_full_backward_hooks = [], []

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/contai
ner.py:139, in Sequential.forward(self, input)
    137 def forward(self, input):
    138     for module in self:
--> 139         input = module(input)
    140     return input

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/module
.py:1130, in Module._call_impl(self, *input, **kwargs)
   1126 # If we don't have any hooks, we want to skip the rest of the
logic in
   1127 # this function, and just call forward.
   1128 if not (self._backward_hooks or self._forward_hooks or
self._forward_pre_hooks or _global_backward_hooks
   1129         or _global_forward_hooks or
_global_forward_pre_hooks):
-> 1130     return forward_call(*input, **kwargs)
   1131 # Do not call functions when jit is used
   1132 full_backward_hooks, non_full_backward_hooks = [], []

File
~/code/pytorch/env/lib/python3.8/site-packages/torch/nn/modules/linear
.py:114, in Linear.forward(self, input)
    113 def forward(self, input: Tensor) -> Tensor:
--> 114     return F.linear(input, self.weight, self.bias)

RuntimeError: mat1 and mat2 shapes cannot be multiplied (10x256 and
2560x3)

model_1.eval()
with torch.inference_mode():
    # Add an extra dimension to image
    custom_image_transformed_with_batch_size =
custom_image_transformed.unsqueeze(dim=0)

    # Print out different shapes
    print(f"Custom image transformed shape:
{custom_image_transformed.shape}")
    print(f"Unsqueezed custom image shape:
{custom_image_transformed_with_batch_size.shape}")

    # Make a prediction on image with an extra dimension
    custom_image_pred =
model_1(custom_image_transformed.unsqueeze(dim=0).to(device))
```

```
Custom image transformed shape: torch.Size([3, 64, 64])
Unsqueezed custom image shape: torch.Size([1, 3, 64, 64])
```

```
custom_image_pred
```

```
tensor([[ 0.1172,  0.0160, -0.1425]], device='cuda:0')
```

```
# Print out prediction logits
print(f"Prediction logits: {custom_image_pred}")

# Convert logits -> prediction probabilities (using torch.softmax()
for multi-class classification)
custom_image_pred_probs = torch.softmax(custom_image_pred, dim=1)
print(f"Prediction probabilities: {custom_image_pred_probs}")

# Convert prediction probabilities -> prediction labels
custom_image_pred_label = torch.argmax(custom_image_pred_probs, dim=1)
print(f"Prediction label: {custom_image_pred_label}")
```

```
Prediction logits: tensor([[ 0.1172,  0.0160, -0.1425]],
device='cuda:0')
Prediction probabilities: tensor([[0.3738, 0.3378, 0.2883]],
device='cuda:0')
Prediction label: tensor([0], device='cuda:0')
```

```
# Find the predicted label
custom_image_pred_class = class_names[custom_image_pred_label.cpu()] #
put pred label to CPU, otherwise will error
custom_image_pred_class
```

```
'pizza'
```

```
# The values of the prediction probabilities are quite similar
custom_image_pred_probs
```

```
tensor([[0.3738, 0.3378, 0.2883]], device='cuda:0')
```

Menyatukan prediksi gambar khusus: membangun suatu fungsi

```
def pred_and_plot_image(model: torch.nn.Module,
                        image_path: str,
                        class_names: List[str] = None,
                        transform=None,
                        device: torch.device = device):
    """Makes a prediction on a target image and plots the image with
its prediction."""

    # 1. Load in image and convert the tensor values to float32
    target_image =
torchvision.io.read_image(str(image_path)).type(torch.float32)
```

```
    # 2. Divide the image pixel values by 255 to get them between [0,
1]
    target_image = target_image / 255.

    # 3. Transform if necessary
    if transform:
        target_image = transform(target_image)

    # 4. Make sure the model is on the target device
    model.to(device)

    # 5. Turn on model evaluation mode and inference mode
    model.eval()
    with torch.inference_mode():
        # Add an extra dimension to the image
        target_image = target_image.unsqueeze(dim=0)

        # Make a prediction on image with an extra dimension and send
it to the target device
        target_image_pred = model(target_image.to(device))

    # 6. Convert logits -> prediction probabilities (using
torch.softmax() for multi-class classification)
    target_image_pred_probs = torch.softmax(target_image_pred, dim=1)

    # 7. Convert prediction probabilities -> prediction labels
    target_image_pred_label = torch.argmax(target_image_pred_probs,
dim=1)

    # 8. Plot the image alongside the prediction and prediction
probability
    plt.imshow(target_image.squeeze().permute(1, 2, 0)) # make sure
it's the right size for matplotlib
    if class_names:
        title = f"Pred: {class_names[target_image_pred_label.cpu()]} |
Prob: {target_image_pred_probs.max().cpu():.3f}"
    else:
        title = f"Pred: {target_image_pred_label} | Prob:
{target_image_pred_probs.max().cpu():.3f}"
    plt.title(title)
    plt.axis(False);

# Pred on our custom image
pred_and_plot_image(model=model_1,
                    image_path=custom_image_path,
                    class_names=class_names,
                    transform=custom_image_transform,
                    device=device)
```

Pred: pizza | Prob: 0.374