Mempersiapkan

Mari kita mulai dengan mengunduh semua modul yang kita perlukan untuk bagian ini.

```
# For this notebook to run with updated APIs, we need torch 1.12+ and
torchvision 0.13+
try:
    import torch
    import torchvision
    assert int(torch.__version__.split(".")[1]) >= 12, "torch version
should be 1.12+"
    assert int(torchvision.__version__.split(".")[1]) >= 13,
"torchvision version should be 0.13+"
    print(f"torch version: {torch.__version__}")
    print(f"torchvision version: {torchvision.__version__}")
except:
    print(f"[INFO] torch/torchvision versions not as required,
installing nightly versions.")
    !pip3 install -U torch torchvision torchaudio --extra-index-url
https://download.pytorch.org/whl/cu113
    import torch
    import torchvision
    print(f"torch version: {torch.__version__}")
    print(f"torchvision version: {torchvision.__version__}")
```

```
torch version: 1.13.0.dev20220620+cu113
torchvision version: 0.14.0.dev20220620+cu113
```

```
# 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
try:
    from torchinfo import summary
except:
    print("[INFO] Couldn't find torchinfo... installing it.")
    !pip install -q torchinfo
    from torchinfo import summary

# Try to import the going_modular directory, download it from GitHub
if it doesn't work
try:
    from going_modular.going_modular import data_setup, engine
except:
```

```
    # Get the going_modular scripts
    print("[INFO] Couldn't find going_modular scripts... downloading them from GitHub.")
    !git clone https://github.com/mrdbourke/pytorch-deep-learning
    !mv pytorch-deep-learning/going_modular .
    !rm -rf pytorch-deep-learning
    from going_modular.going_modular import data_setup, engine

device = "cuda" if torch.cuda.is_available() else "cpu"
device
```

```
'cuda'
```

Buat fungsi pembantu untuk mengatur poin

Mari kita buat fungsi untuk "mengatur poin" yang disebut set_seeds().

```
# Set seeds
def set_seeds(seed: int=42):
    """Sets random sets for torch operations.

    Args:
        seed (int, optional): Random seed to set. Defaults to 42.
    """
    # Set the seed for general torch operations
    torch.manual_seed(seed)
    # Set the seed for CUDA torch operations (ones that happen on the GPU)
    torch.cuda.manual_seed(seed)
```

Dapatkan datanya

Untuk melakukannya, kita akan menggunakan kode yang mirip dengan bagian sebelumnya untuk mendownload pizza_steak_sushi.zip (jika datanya belum ada) kecuali kali ini sudah difungsikan.

```
import os
import zipfile

from pathlib import Path

import requests

def download_data(source: str,
                  destination: str,
                  remove_source: bool = True) -> Path:
    """Downloads a zipped dataset from source and unzips to destination.
```

```
    Args:
        source (str): A link to a zipped file containing data.
        destination (str): A target directory to unzip data to.
        remove_source (bool): Whether to remove the source after
downloading and extracting.

    Returns:
        pathlib.Path to downloaded data.

    Example usage:
        download_data(source="https://github.com/mrdbourke/pytorch-
deep-learning/raw/main/data/pizza_steak_sushi.zip",
                      destination="pizza_steak_sushi")
    """
    # Setup path to data folder
    data_path = Path("data/")
    image_path = data_path / destination

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

        # Download pizza, steak, sushi data
        target_file = Path(source).name
        with open(data_path / target_file, "wb") as f:
            request = requests.get(source)
            print(f"[INFO] Downloading {target_file} from
{source}...")
            f.write(request.content)

        # Unzip pizza, steak, sushi data
        with zipfile.ZipFile(data_path / target_file, "r") as zip_ref:
            print(f"[INFO] Unzipping {target_file} data...")
            zip_ref.extractall(image_path)

        # Remove .zip file
        if remove_source:
            os.remove(data_path / target_file)

    return image_path

image_path =
download_data(source="https://github.com/mrdbourke/pytorch-deep-
learning/raw/main/data/pizza_steak_sushi.zip",
```

```
                           destination="pizza_steak_sushi")
image_path
```

```
[INFO] data/pizza_steak_sushi directory exists, skipping download.
```

```
PosixPath('data/pizza_steak_sushi')
```

Buat Kumpulan Data dan Pemuat Data

Membuat DataLoaders menggunakan transformasi yang dibuat secara manual

```
# Setup directories
train_dir = image_path / "train"
test_dir = image_path / "test"

# Setup ImageNet normalization levels (turns all images into similar
distribution as ImageNet)
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])

# Create transform pipeline manually
manual_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    normalize
])
print(f"Manually created transforms: {manual_transforms}")

# Create data loaders
train_dataloader, test_dataloader, class_names =
data_setup.create_dataloaders(
    train_dir=train_dir,
    test_dir=test_dir,
    transform=manual_transforms, # use manually created transforms
    batch_size=32
)

train_dataloader, test_dataloader, class_names
```

```
Manually created transforms: Compose(
    Resize(size=(224, 224), interpolation=bilinear, max_size=None,
antialias=None)
    ToTensor()
    Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
)
```

```
(<torch.utils.data.dataloader.DataLoader at 0x7febf1d218e0>,
 <torch.utils.data.dataloader.DataLoader at 0x7febf1d216a0>,
 ['pizza', 'steak', 'sushi'])
```

Membuat DataLoader menggunakan transformasi yang dibuat secara otomatis

Kita dapat melakukan ini dengan terlebih dahulu membuat instance sekumpulan bobot yang telah dilatih sebelumnya (misalnya bobot = torchvision.models.EfficientNet_B0_Weights.DEFAULT) yang ingin kita gunakan dan memanggil metode transforms() di dalamnya.

```
# Setup dirs
train_dir = image_path / "train"
test_dir = image_path / "test"

# Setup pretrained weights (plenty of these available in
torchvision.models)
weights = torchvision.models.EfficientNet_B0_Weights.DEFAULT

# Get transforms from weights (these are the transforms that were used
to obtain the weights)
automatic_transforms = weights.transforms()
print(f"Automatically created transforms: {automatic_transforms}")

# Create data loaders
train_dataloader, test_dataloader, class_names =
data_setup.create_dataloaders(
    train_dir=train_dir,
    test_dir=test_dir,
    transform=automatic_transforms, # use automatic created transforms
    batch_size=32
)

train_dataloader, test_dataloader, class_names
```

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

```
(<torch.utils.data.dataloader.DataLoader at 0x7febf1d213a0>,
 <torch.utils.data.dataloader.DataLoader at 0x7febf1d21490>,
 ['pizza', 'steak', 'sushi'])
```

Mendapatkan model terlatih, membekukan lapisan dasar dan mengubah kepala pengklasifikasi

Mari unduh bobot terlatih untuk model torchvision.models.efisiennet_b0() dan persiapkan untuk digunakan dengan data kita sendiri.

```python
# Note: This is how a pretrained model would be created in torchvision > 0.13, it will be deprecated in future versions.
# model = torchvision.models.efficientnet_b0(pretrained=True).to(device) # OLD

# Download the pretrained weights for EfficientNet_B0
weights = torchvision.models.EfficientNet_B0_Weights.DEFAULT # NEW in torchvision 0.13, "DEFAULT" means "best weights available"

# Setup the model with the pretrained weights and send it to the target device
model = torchvision.models.efficientnet_b0(weights=weights).to(device)

# View the output of the model
# model

# Freeze all base layers by setting requires_grad attribute to False
for param in model.features.parameters():
    param.requires_grad = False

# Since we're creating a new layer with random weights (torch.nn.Linear),
# let's set the seeds
set_seeds()

# Update the classifier head to suit our problem
model.classifier = torch.nn.Sequential(
    nn.Dropout(p=0.2, inplace=True),
    nn.Linear(in_features=1280,
              out_features=len(class_names),
              bias=True).to(device))

from torchinfo import summary

# # Get a summary of the model (uncomment for full output)
# summary(model,
#         input_size=(32, 3, 224, 224), # make sure this is "input_size", not "input_shape" (batch_size, color_channels, height, width)
#         verbose=0,
#         col_names=["input_size", "output_size", "num_params", "trainable"],
#         col_width=20,
#         row_settings=["var_names"]
# )
```

Latih model dan lacak hasilnya

Dan kami akan tetap menggunakan torch.optim.Adam() dengan kecepatan pembelajaran 0,001 untuk pengoptimal.

```
# Define loss and optimizer
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

from torch.utils.tensorboard import SummaryWriter

# Create a writer with all default settings
writer = SummaryWriter()

from typing import Dict, List
from tqdm.auto import tqdm

from going_modular.going_modular.engine import train_step, test_step

# Import train() function from:
#
https://github.com/mrdbourke/pytorch-deep-learning/blob/main/going_mod
ular/going_modular/engine.py
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,
          epochs: int,
          device: torch.device) -> Dict[str, List]:
    """Trains and tests a PyTorch model.

    Passes a target PyTorch models through train_step() and
test_step()
    functions for a number of epochs, training and testing the model
    in the same epoch loop.

    Calculates, prints and stores evaluation metrics throughout.

    Args:
      model: A PyTorch model to be trained and tested.
      train_dataloader: A DataLoader instance for the model to be
trained on.
      test_dataloader: A DataLoader instance for the model to be
tested on.
      optimizer: A PyTorch optimizer to help minimize the loss
function.
      loss_fn: A PyTorch loss function to calculate loss on both
datasets.
      epochs: An integer indicating how many epochs to train for.
      device: A target device to compute on (e.g. "cuda" or "cpu").

    Returns:
      A dictionary of training and testing loss as well as training
and
```

```
      testing accuracy metrics. Each metric has a value in a list for
      each epoch.
      In the form: {train_loss: [...],
                train_acc: [...],
                test_loss: [...],
                test_acc: [...]}
      For example if training for epochs=2:
              {train_loss: [2.0616, 1.0537],
                train_acc: [0.3945, 0.3945],
                test_loss: [1.2641, 1.5706],
                test_acc: [0.3400, 0.2973]}
    """
    # Create empty results dictionary
    results = {"train_loss": [],
               "train_acc": [],
               "test_loss": [],
               "test_acc": []
    }

    # 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,
                                           device=device)
        test_loss, test_acc = test_step(model=model,
                                        dataloader=test_dataloader,
                                        loss_fn=loss_fn,
                                        device=device)

        # 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}"
        )

        # 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)

        ### New: Experiment tracking ###
        # Add loss results to SummaryWriter
        writer.add_scalars(main_tag="Loss",
```

```python
                           tag_scalar_dict={"train_loss": train_loss,
                                            "test_loss": test_loss},
                           global_step=epoch)

        # Add accuracy results to SummaryWriter
        writer.add_scalars(main_tag="Accuracy",
                           tag_scalar_dict={"train_acc": train_acc,
                                            "test_acc": test_acc},
                           global_step=epoch)

        # Track the PyTorch model architecture
        writer.add_graph(model=model,
                         # Pass in an example input
                         input_to_model=torch.randn(32, 3, 224,
224).to(device))

    # Close the writer
    writer.close()

    ### End new ###

    # Return the filled results at the end of the epochs
    return results

# Train model
# Note: Not using engine.train() since the original script isn't
updated to use writer
set_seeds()
results = train(model=model,
                train_dataloader=train_dataloader,
                test_dataloader=test_dataloader,
                optimizer=optimizer,
                loss_fn=loss_fn,
                epochs=5,
                device=device)
```

{"model_id":"bf70c256625142c283475bdf9af948a1","version_major":2,"vers
ion_minor":0}

```
Epoch: 1 | train_loss: 1.0924 | train_acc: 0.3984 | test_loss: 0.9133
| test_acc: 0.5398
Epoch: 2 | train_loss: 0.8975 | train_acc: 0.6562 | test_loss: 0.7838
| test_acc: 0.8561
Epoch: 3 | train_loss: 0.8037 | train_acc: 0.7461 | test_loss: 0.6723
| test_acc: 0.8864
Epoch: 4 | train_loss: 0.6769 | train_acc: 0.8516 | test_loss: 0.6698
| test_acc: 0.8049
Epoch: 5 | train_loss: 0.7065 | train_acc: 0.7188 | test_loss: 0.6746
| test_acc: 0.7737
```

```python
# Check out the model results
results
```

```
{'train_loss': [1.0923754647374153,
  0.8974628075957298,
  0.803724929690361,
  0.6769256368279457,
  0.7064960040152073],
 'train_acc': [0.3984375, 0.65625, 0.74609375, 0.8515625, 0.71875],
 'test_loss': [0.9132757981618246,
  0.7837507526079813,
  0.6722926497459412,
  0.6698453426361084,
  0.6746167540550232],
 'test_acc': [0.5397727272727273,
  0.8560606060606061,
  0.8863636363636364,
  0.8049242424242425,
  0.7736742424242425]}
```

Lihat hasil model kita di TensorBoard

```python
# Example code to run in Jupyter or Google Colab Notebook (uncomment
to try it out)
# %load_ext tensorboard
# %tensorboard --logdir runs
```

Buat fungsi pembantu untuk membangun instance SummaryWriter()

```python
def create_writer(experiment_name: str,
                  model_name: str,
                  extra: str=None) ->
torch.utils.tensorboard.writer.SummaryWriter():
    """Creates a torch.utils.tensorboard.writer.SummaryWriter()
instance saving to a specific log_dir.

    log_dir is a combination of
runs/timestamp/experiment_name/model_name/extra.

    Where timestamp is the current date in YYYY-MM-DD format.

    Args:
        experiment_name (str): Name of experiment.
        model_name (str): Name of model.
        extra (str, optional): Anything extra to add to the directory.
Defaults to None.

    Returns:
```

```
        torch.utils.tensorboard.writer.SummaryWriter(): Instance of a
writer saving to log_dir.

    Example usage:
        # Create a writer saving to
"runs/2022-06-04/data_10_percent/effnetb2/5_epochs/"
        writer = create_writer(experiment_name="data_10_percent",
                               model_name="effnetb2",
                               extra="5_epochs")
        # The above is the same as:
        writer =
SummaryWriter(log_dir="runs/2022-06-04/data_10_percent/effnetb2/5_epoc
hs/")
    """
    from datetime import datetime
    import os

    # Get timestamp of current date (all experiments on certain day
live in same folder)
    timestamp = datetime.now().strftime("%Y-%m-%d") # returns current
date in YYYY-MM-DD format

    if extra:
        # Create log directory path
        log_dir = os.path.join("runs", timestamp, experiment_name,
model_name, extra)
    else:
        log_dir = os.path.join("runs", timestamp, experiment_name,
model_name)

    print(f"[INFO] Created SummaryWriter, saving to: {log_dir}...")
    return SummaryWriter(log_dir=log_dir)

# Create an example writer
example_writer = create_writer(experiment_name="data_10_percent",
                               model_name="effnetb0",
                               extra="5_epochs")

[INFO] Created SummaryWriter, saving to:
runs/2022-06-23/data_10_percent/effnetb0/5_epochs...
```

Perbarui fungsi train() untuk menyertakan parameter penulis

Untuk menyesuaikan fungsi train() kita akan menambahkan parameter penulis ke fungsi tersebut dan kemudian kita akan menambahkan beberapa kode untuk melihat apakah ada penulis dan jika demikian, kita akan melacak informasi kita di sana.

```
from typing import Dict, List
from tqdm.auto import tqdm
```

```python
# Add writer parameter to train()
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,
          epochs: int,
          device: torch.device,
          writer: torch.utils.tensorboard.writer.SummaryWriter # new
parameter to take in a writer
          ) -> Dict[str, List]:
    """Trains and tests a PyTorch model.

    Passes a target PyTorch models through train_step() and
test_step()
    functions for a number of epochs, training and testing the model
    in the same epoch loop.

    Calculates, prints and stores evaluation metrics throughout.

    Stores metrics to specified writer log_dir if present.

    Args:
      model: A PyTorch model to be trained and tested.
      train_dataloader: A DataLoader instance for the model to be
trained on.
      test_dataloader: A DataLoader instance for the model to be
tested on.
      optimizer: A PyTorch optimizer to help minimize the loss
function.
      loss_fn: A PyTorch loss function to calculate loss on both
datasets.
      epochs: An integer indicating how many epochs to train for.
      device: A target device to compute on (e.g. "cuda" or "cpu").
      writer: A SummaryWriter() instance to log model results to.

    Returns:
      A dictionary of training and testing loss as well as training
and
      testing accuracy metrics. Each metric has a value in a list for
      each epoch.
      In the form: {train_loss: [...],
                train_acc: [...],
                test_loss: [...],
                test_acc: [...]}
      For example if training for epochs=2:
              {train_loss: [2.0616, 1.0537],
                train_acc: [0.3945, 0.3945],
                test_loss: [1.2641, 1.5706],
                test_acc: [0.3400, 0.2973]}
```

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

    # 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,
                                          device=device)
        test_loss, test_acc = test_step(model=model,
          dataloader=test_dataloader,
          loss_fn=loss_fn,
          device=device)

        # 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}"
        )

        # 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)


        ### New: Use the writer parameter to track experiments ###
        # See if there's a writer, if so, log to it
        if writer:
            # Add results to SummaryWriter
            writer.add_scalars(main_tag="Loss",
                               tag_scalar_dict={"train_loss":
train_loss,
                                                "test_loss":
test_loss},
                               global_step=epoch)
            writer.add_scalars(main_tag="Accuracy",
                               tag_scalar_dict={"train_acc":
train_acc,
                                                "test_acc": test_acc},
```

```
                                global_step=epoch)

            # Close the writer
            writer.close()
        else:
            pass
    ### End new ###

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

Menyiapkan rangkaian percobaan pemodelan

Eksperimen seperti apa yang harus Anda jalankan?

Eksperimen apa yang akan kita jalankan?

Unduh kumpulan data yang berbeda

```
# Download 10 percent and 20 percent training data (if necessary)
data_10_percent_path = 
download_data(source="https://github.com/mrdbourke/pytorch-deep-
learning/raw/main/data/pizza_steak_sushi.zip",
                                     destination="pizza_steak_sushi")

data_20_percent_path = 
download_data(source="https://github.com/mrdbourke/pytorch-deep-
learning/raw/main/data/pizza_steak_sushi_20_percent.zip",

destination="pizza_steak_sushi_20_percent")
```

```
[INFO] data/pizza_steak_sushi directory exists, skipping download.
[INFO] data/pizza_steak_sushi_20_percent directory exists, skipping
download.
```

```
# Setup training directory paths
train_dir_10_percent = data_10_percent_path / "train"
train_dir_20_percent = data_20_percent_path / "train"

# Setup testing directory paths (note: use the same test dataset for
both to compare the results)
test_dir = data_10_percent_path / "test"

# Check the directories
print(f"Training directory 10%: {train_dir_10_percent}")
print(f"Training directory 20%: {train_dir_20_percent}")
print(f"Testing directory: {test_dir}")
```

```
Training directory 10%: data/pizza_steak_sushi/train
Training directory 20%: data/pizza_steak_sushi_20_percent/train
Testing directory: data/pizza_steak_sushi/test
```

Transformasi Kumpulan Data dan membuat DataLoader

```
from torchvision import transforms

# Create a transform to normalize data distribution to be inline with
ImageNet
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406], # values
per colour channel [red, green, blue]
                                 std=[0.229, 0.224, 0.225]) # values
per colour channel [red, green, blue]

# Compose transforms into a pipeline
simple_transform = transforms.Compose([
    transforms.Resize((224, 224)), # 1. Resize the images
    transforms.ToTensor(), # 2. Turn the images into tensors with
values between 0 & 1
    normalize # 3. Normalize the images so their distributions match
the ImageNet dataset
])

BATCH_SIZE = 32

# Create 10% training and test DataLoaders
train_dataloader_10_percent, test_dataloader, class_names =
data_setup.create_dataloaders(train_dir=train_dir_10_percent,
    test_dir=test_dir,
    transform=simple_transform,
    batch_size=BATCH_SIZE
)

# Create 20% training and test data DataLoders
train_dataloader_20_percent, test_dataloader, class_names =
data_setup.create_dataloaders(train_dir=train_dir_20_percent,
    test_dir=test_dir,
    transform=simple_transform,
    batch_size=BATCH_SIZE
)

# Find the number of samples/batches per dataloader (using the same
test_dataloader for both experiments)
print(f"Number of batches of size {BATCH_SIZE} in 10 percent training
data: {len(train_dataloader_10_percent)}")
print(f"Number of batches of size {BATCH_SIZE} in 20 percent training
data: {len(train_dataloader_20_percent)}")
print(f"Number of batches of size {BATCH_SIZE} in testing data:
{len(train_dataloader_10_percent)} (all experiments will use the same
```

```
test set)")
print(f"Number of classes: {len(class_names)}, class names:
{class_names}")
```

```
Number of batches of size 32 in 10 percent training data: 8
Number of batches of size 32 in 20 percent training data: 15
Number of batches of size 32 in testing data: 8 (all experiments will
use the same test set)
Number of classes: 3, class names: ['pizza', 'steak', 'sushi']
```

Membuat model ekstraktor fitur

```
import torchvision
from torchinfo import summary

# 1. Create an instance of EffNetB2 with pretrained weights
effnetb2_weights = torchvision.models.EfficientNet_B2_Weights.DEFAULT
# "DEFAULT" means best available weights
effnetb2 =
torchvision.models.efficientnet_b2(weights=effnetb2_weights)

# # 2. Get a summary of standard EffNetB2 from torchvision.models
(uncomment for full output)
# summary(model=effnetb2,
#         input_size=(32, 3, 224, 224), # make sure this is
"input_size", not "input_shape"
#         # col_names=["input_size"], # uncomment for smaller output
#         col_names=["input_size", "output_size", "num_params",
"trainable"],
#         col_width=20,
#         row_settings=["var_names"]
# )

# 3. Get the number of in_features of the EfficientNetB2 classifier
layer
print(f"Number of in_features to final layer of EfficientNetB2:
{len(effnetb2.classifier.state_dict()['1.weight'][0])}")
```

```
Number of in_features to final layer of EfficientNetB2: 1408
```

```
import torchvision
from torch import nn

# Get num out features (one for each class pizza, steak, sushi)
OUT_FEATURES = len(class_names)

# Create an EffNetB0 feature extractor
def create_effnetb0():
    # 1. Get the base mdoel with pretrained weights and send to target
device
```

```
    weights = torchvision.models.EfficientNet_B0_Weights.DEFAULT
    model = 
torchvision.models.efficientnet_b0(weights=weights).to(device)

    # 2. Freeze the base model layers
    for param in model.features.parameters():
        param.requires_grad = False

    # 3. Set the seeds
    set_seeds()

    # 4. Change the classifier head
    model.classifier = nn.Sequential(
        nn.Dropout(p=0.2),
        nn.Linear(in_features=1280, out_features=OUT_FEATURES)
    ).to(device)

    # 5. Give the model a name
    model.name = "effnetb0"
    print(f"[INFO] Created new {model.name} model.")
    return model

# Create an EffNetB2 feature extractor
def create_effnetb2():
    # 1. Get the base model with pretrained weights and send to target 
device
    weights = torchvision.models.EfficientNet_B2_Weights.DEFAULT
    model = 
torchvision.models.efficientnet_b2(weights=weights).to(device)

    # 2. Freeze the base model layers
    for param in model.features.parameters():
        param.requires_grad = False

    # 3. Set the seeds
    set_seeds()

    # 4. Change the classifier head
    model.classifier = nn.Sequential(
        nn.Dropout(p=0.3),
        nn.Linear(in_features=1408, out_features=OUT_FEATURES)
    ).to(device)

    # 5. Give the model a name
    model.name = "effnetb2"
    print(f"[INFO] Created new {model.name} model.")
    return model

effnetb0 = create_effnetb0()
```

```
# Get an output summary of the layers in our EffNetB0 feature
extractor model (uncomment to view full output)
# summary(model=effnetb0,
#         input_size=(32, 3, 224, 224), # make sure this is
"input_size", not "input_shape"
#         # col_names=["input_size"], # uncomment for smaller output
#         col_names=["input_size", "output_size", "num_params",
"trainable"],
#         col_width=20,
#         row_settings=["var_names"]
# )
```

```
[INFO] Created new effnetb0 model.
```

```
effnetb2 = create_effnetb2()

# Get an output summary of the layers in our EffNetB2 feature
extractor model (uncomment to view full output)
# summary(model=effnetb2,
#         input_size=(32, 3, 224, 224), # make sure this is
"input_size", not "input_shape"
#         # col_names=["input_size"], # uncomment for smaller output
#         col_names=["input_size", "output_size", "num_params",
"trainable"],
#         col_width=20,
#         row_settings=["var_names"]
# )
```

```
[INFO] Created new effnetb2 model.
```

Membuat eksperimen dan menyiapkan kode pelatihan

```
# 1. Create epochs list
num_epochs = [5, 10]

# 2. Create models list (need to create a new model for each
experiment)
models = ["effnetb0", "effnetb2"]

# 3. Create dataloaders dictionary for various dataloaders
train_dataloaders = {"data_10_percent": train_dataloader_10_percent,
                     "data_20_percent": train_dataloader_20_percent}

%%time
from going_modular.going_modular.utils import save_model

# 1. Set the random seeds
set_seeds(seed=42)

# 2. Keep track of experiment numbers
experiment_number = 0
```

```
# 3. Loop through each DataLoader
for dataloader_name, train_dataloader in train_dataloaders.items():

    # 4. Loop through each number of epochs
    for epochs in num_epochs:

        # 5. Loop through each model name and create a new model based
on the name
        for model_name in models:

            # 6. Create information print outs
            experiment_number += 1
            print(f"[INFO] Experiment number: {experiment_number}")
            print(f"[INFO] Model: {model_name}")
            print(f"[INFO] DataLoader: {dataloader_name}")
            print(f"[INFO] Number of epochs: {epochs}")

            # 7. Select the model
            if model_name == "effnetb0":
                model = create_effnetb0() # creates a new model each
time (important because we want each experiment to start from scratch)
            else:
                model = create_effnetb2() # creates a new model each
time (important because we want each experiment to start from scratch)

            # 8. Create a new loss and optimizer for every model
            loss_fn = nn.CrossEntropyLoss()
            optimizer = torch.optim.Adam(params=model.parameters(),
lr=0.001)

            # 9. Train target model with target dataloaders and track
experiments
            train(model=model,
                  train_dataloader=train_dataloader,
                  test_dataloader=test_dataloader,
                  optimizer=optimizer,
                  loss_fn=loss_fn,
                  epochs=epochs,
                  device=device,

writer=create_writer(experiment_name=dataloader_name,
                                       model_name=model_name,
                                       extra=f"{epochs}_epochs"))

            # 10. Save the model to file so we can get back the best
model
            save_filepath =
f"07_{model_name}_{dataloader_name}_{epochs}_epochs.pth"
            save_model(model=model,
```

```
                       target_dir="models",
                       model_name=save_filepath)
            print("-"*50 + "\n")
```

```
[INFO] Experiment number: 1
[INFO] Model: effnetb0
[INFO] DataLoader: data_10_percent
[INFO] Number of epochs: 5
[INFO] Created new effnetb0 model.
[INFO] Created SummaryWriter, saving to:
runs/2022-06-23/data_10_percent/effnetb0/5_epochs...
```

{"model_id":"7f724e8d22604328b6f2c69ab0b3948f","version_major":2,"version_minor":0}

```
Epoch: 1 | train_loss: 1.0528 | train_acc: 0.4961 | test_loss: 0.9217
| test_acc: 0.4678
Epoch: 2 | train_loss: 0.8747 | train_acc: 0.6992 | test_loss: 0.8138
| test_acc: 0.6203
Epoch: 3 | train_loss: 0.8099 | train_acc: 0.6445 | test_loss: 0.7175
| test_acc: 0.8258
Epoch: 4 | train_loss: 0.7097 | train_acc: 0.7578 | test_loss: 0.5897
| test_acc: 0.8864
Epoch: 5 | train_loss: 0.5980 | train_acc: 0.9141 | test_loss: 0.5676
| test_acc: 0.8864
[INFO] Saving model to:
models/07_effnetb0_data_10_percent_5_epochs.pth
--------------------------------------------------

[INFO] Experiment number: 2
[INFO] Model: effnetb2
[INFO] DataLoader: data_10_percent
[INFO] Number of epochs: 5
[INFO] Created new effnetb2 model.
[INFO] Created SummaryWriter, saving to:
runs/2022-06-23/data_10_percent/effnetb2/5_epochs...
```

{"model_id":"36ca9faf96d443b38c6e3f71c427c567","version_major":2,"version_minor":0}

```
Epoch: 1 | train_loss: 1.0928 | train_acc: 0.3711 | test_loss: 0.9557
| test_acc: 0.6610
Epoch: 2 | train_loss: 0.9247 | train_acc: 0.6445 | test_loss: 0.8711
| test_acc: 0.8144
Epoch: 3 | train_loss: 0.8086 | train_acc: 0.7656 | test_loss: 0.7511
| test_acc: 0.9176
Epoch: 4 | train_loss: 0.7191 | train_acc: 0.8867 | test_loss: 0.7150
| test_acc: 0.9081
Epoch: 5 | train_loss: 0.6851 | train_acc: 0.7695 | test_loss: 0.7076
| test_acc: 0.8873
```

```
[INFO] Saving model to:
models/07_effnetb2_data_10_percent_5_epochs.pth
--------------------------------------------------

[INFO] Experiment number: 3
[INFO] Model: effnetb0
[INFO] DataLoader: data_10_percent
[INFO] Number of epochs: 10
[INFO] Created new effnetb0 model.
[INFO] Created SummaryWriter, saving to:
runs/2022-06-23/data_10_percent/effnetb0/10_epochs...
```

{"model_id":"85b88ac8b65a41139edf9ef59763f6cc","version_major":2,"version_minor":0}

```
Epoch: 1 | train_loss: 1.0528 | train_acc: 0.4961 | test_loss: 0.9217
| test_acc: 0.4678
Epoch: 2 | train_loss: 0.8747 | train_acc: 0.6992 | test_loss: 0.8138
| test_acc: 0.6203
Epoch: 3 | train_loss: 0.8099 | train_acc: 0.6445 | test_loss: 0.7175
| test_acc: 0.8258
Epoch: 4 | train_loss: 0.7097 | train_acc: 0.7578 | test_loss: 0.5897
| test_acc: 0.8864
Epoch: 5 | train_loss: 0.5980 | train_acc: 0.9141 | test_loss: 0.5676
| test_acc: 0.8864
Epoch: 6 | train_loss: 0.5611 | train_acc: 0.8984 | test_loss: 0.5949
| test_acc: 0.8864
Epoch: 7 | train_loss: 0.5573 | train_acc: 0.7930 | test_loss: 0.5566
| test_acc: 0.8864
Epoch: 8 | train_loss: 0.4702 | train_acc: 0.9492 | test_loss: 0.5176
| test_acc: 0.8759
Epoch: 9 | train_loss: 0.5728 | train_acc: 0.7773 | test_loss: 0.5095
| test_acc: 0.8873
Epoch: 10 | train_loss: 0.4794 | train_acc: 0.8242 | test_loss: 0.4640
| test_acc: 0.9072
[INFO] Saving model to:
models/07_effnetb0_data_10_percent_10_epochs.pth
--------------------------------------------------

[INFO] Experiment number: 4
[INFO] Model: effnetb2
[INFO] DataLoader: data_10_percent
[INFO] Number of epochs: 10
[INFO] Created new effnetb2 model.
[INFO] Created SummaryWriter, saving to:
runs/2022-06-23/data_10_percent/effnetb2/10_epochs...
```

{"model_id":"b4df178559d448539d3e159fb9a3b0fb","version_major":2,"version_minor":0}

```
Epoch: 1 | train_loss: 1.0928 | train_acc: 0.3711 | test_loss: 0.9557
| test_acc: 0.6610
Epoch: 2 | train_loss: 0.9247 | train_acc: 0.6445 | test_loss: 0.8711
| test_acc: 0.8144
Epoch: 3 | train_loss: 0.8086 | train_acc: 0.7656 | test_loss: 0.7511
| test_acc: 0.9176
Epoch: 4 | train_loss: 0.7191 | train_acc: 0.8867 | test_loss: 0.7150
| test_acc: 0.9081
Epoch: 5 | train_loss: 0.6851 | train_acc: 0.7695 | test_loss: 0.7076
| test_acc: 0.8873
Epoch: 6 | train_loss: 0.6111 | train_acc: 0.7812 | test_loss: 0.6325
| test_acc: 0.9280
Epoch: 7 | train_loss: 0.6127 | train_acc: 0.8008 | test_loss: 0.6404
| test_acc: 0.8769
Epoch: 8 | train_loss: 0.5202 | train_acc: 0.9336 | test_loss: 0.6200
| test_acc: 0.8977
Epoch: 9 | train_loss: 0.5425 | train_acc: 0.8008 | test_loss: 0.6227
| test_acc: 0.8466
Epoch: 10 | train_loss: 0.4908 | train_acc: 0.8125 | test_loss: 0.5870
| test_acc: 0.8873
[INFO] Saving model to:
models/07_effnetb2_data_10_percent_10_epochs.pth
--------------------------------------------------

[INFO] Experiment number: 5
[INFO] Model: effnetb0
[INFO] DataLoader: data_20_percent
[INFO] Number of epochs: 5
[INFO] Created new effnetb0 model.
[INFO] Created SummaryWriter, saving to:
runs/2022-06-23/data_20_percent/effnetb0/5_epochs...
```

{"model_id":"067d7002a70443edb72e0dc5f61b60d1","version_major":2,"vers
ion_minor":0}

```
Epoch: 1 | train_loss: 0.9577 | train_acc: 0.6167 | test_loss: 0.6545
| test_acc: 0.8655
Epoch: 2 | train_loss: 0.6881 | train_acc: 0.8438 | test_loss: 0.5798
| test_acc: 0.9176
Epoch: 3 | train_loss: 0.5798 | train_acc: 0.8604 | test_loss: 0.4575
| test_acc: 0.9176
Epoch: 4 | train_loss: 0.4930 | train_acc: 0.8646 | test_loss: 0.4458
| test_acc: 0.9176
Epoch: 5 | train_loss: 0.4886 | train_acc: 0.8500 | test_loss: 0.3909
| test_acc: 0.9176
[INFO] Saving model to:
models/07_effnetb0_data_20_percent_5_epochs.pth
--------------------------------------------------

[INFO] Experiment number: 6
```

```
[INFO] Model: effnetb2
[INFO] DataLoader: data_20_percent
[INFO] Number of epochs: 5
[INFO] Created new effnetb2 model.
[INFO] Created SummaryWriter, saving to:
runs/2022-06-23/data_20_percent/effnetb2/5_epochs...
```

{"model_id":"50eee46e57ec47948c11b0b51a2460e3","version_major":2,"version_minor":0}

```
Epoch: 1 | train_loss: 0.9830 | train_acc: 0.5521 | test_loss: 0.7767
| test_acc: 0.8153
Epoch: 2 | train_loss: 0.7298 | train_acc: 0.7604 | test_loss: 0.6673
| test_acc: 0.8873
Epoch: 3 | train_loss: 0.6022 | train_acc: 0.8458 | test_loss: 0.5622
| test_acc: 0.9280
Epoch: 4 | train_loss: 0.5435 | train_acc: 0.8354 | test_loss: 0.5679
| test_acc: 0.9186
Epoch: 5 | train_loss: 0.4404 | train_acc: 0.9042 | test_loss: 0.4462
| test_acc: 0.9489
[INFO] Saving model to:
models/07_effnetb2_data_20_percent_5_epochs.pth
--------------------------------------------------

[INFO] Experiment number: 7
[INFO] Model: effnetb0
[INFO] DataLoader: data_20_percent
[INFO] Number of epochs: 10
[INFO] Created new effnetb0 model.
[INFO] Created SummaryWriter, saving to:
runs/2022-06-23/data_20_percent/effnetb0/10_epochs...
```

{"model_id":"564c35143a874dd1ad829e03034101f2","version_major":2,"version_minor":0}

```
Epoch: 1 | train_loss: 0.9577 | train_acc: 0.6167 | test_loss: 0.6545
| test_acc: 0.8655
Epoch: 2 | train_loss: 0.6881 | train_acc: 0.8438 | test_loss: 0.5798
| test_acc: 0.9176
Epoch: 3 | train_loss: 0.5798 | train_acc: 0.8604 | test_loss: 0.4575
| test_acc: 0.9176
Epoch: 4 | train_loss: 0.4930 | train_acc: 0.8646 | test_loss: 0.4458
| test_acc: 0.9176
Epoch: 5 | train_loss: 0.4886 | train_acc: 0.8500 | test_loss: 0.3909
| test_acc: 0.9176
Epoch: 6 | train_loss: 0.3705 | train_acc: 0.8854 | test_loss: 0.3568
| test_acc: 0.9072
Epoch: 7 | train_loss: 0.3551 | train_acc: 0.9250 | test_loss: 0.3187
| test_acc: 0.9072
Epoch: 8 | train_loss: 0.3745 | train_acc: 0.8938 | test_loss: 0.3349
```

```
| test_acc: 0.8873
Epoch: 9 | train_loss: 0.2972 | train_acc: 0.9396 | test_loss: 0.3092
| test_acc: 0.9280
Epoch: 10 | train_loss: 0.3620 | train_acc: 0.8479 | test_loss: 0.2780
| test_acc: 0.9072
[INFO] Saving model to:
models/07_effnetb0_data_20_percent_10_epochs.pth
--------------------------------------------------

[INFO] Experiment number: 8
[INFO] Model: effnetb2
[INFO] DataLoader: data_20_percent
[INFO] Number of epochs: 10
[INFO] Created new effnetb2 model.
[INFO] Created SummaryWriter, saving to:
runs/2022-06-23/data_20_percent/effnetb2/10_epochs...
```

{"model_id":"c53f44132ccf45d4aeb1e8cc18383798","version_major":2,"version_minor":0}

```
Epoch: 1 | train_loss: 0.9830 | train_acc: 0.5521 | test_loss: 0.7767
| test_acc: 0.8153
Epoch: 2 | train_loss: 0.7298 | train_acc: 0.7604 | test_loss: 0.6673
| test_acc: 0.8873
Epoch: 3 | train_loss: 0.6022 | train_acc: 0.8458 | test_loss: 0.5622
| test_acc: 0.9280
Epoch: 4 | train_loss: 0.5435 | train_acc: 0.8354 | test_loss: 0.5679
| test_acc: 0.9186
Epoch: 5 | train_loss: 0.4404 | train_acc: 0.9042 | test_loss: 0.4462
| test_acc: 0.9489
Epoch: 6 | train_loss: 0.3889 | train_acc: 0.9104 | test_loss: 0.4555
| test_acc: 0.8977
Epoch: 7 | train_loss: 0.3483 | train_acc: 0.9271 | test_loss: 0.4227
| test_acc: 0.9384
Epoch: 8 | train_loss: 0.3862 | train_acc: 0.8771 | test_loss: 0.4344
| test_acc: 0.9280
Epoch: 9 | train_loss: 0.3308 | train_acc: 0.8979 | test_loss: 0.4242
| test_acc: 0.9384
Epoch: 10 | train_loss: 0.3383 | train_acc: 0.8896 | test_loss: 0.3906
| test_acc: 0.9384
[INFO] Saving model to:
models/07_effnetb2_data_20_percent_10_epochs.pth
--------------------------------------------------

CPU times: user 29.5 s, sys: 1min 28s, total: 1min 58s
Wall time: 2min 33s
```

Lihat eksperimen di TensorBoard

```
# Viewing TensorBoard in Jupyter and Google Colab Notebooks (uncomment
to view full TensorBoard instance)
# %load_ext tensorboard
# %tensorboard --logdir runs

# # Upload the results to TensorBoard.dev (uncomment to try it out)
# !tensorboard dev upload --logdir runs \
#     --name "07. PyTorch Experiment Tracking: FoodVision Mini model
results" \
#     --description "Comparing results of different model size,
training data amount and training time."
```

Masukkan model terbaik dan buat prediksi dengannya

```
# Setup the best model filepath
best_model_path = "models/07_effnetb2_data_20_percent_10_epochs.pth"

# Instantiate a new instance of EffNetB2 (to load the saved
state_dict() to)
best_model = create_effnetb2()

# Load the saved best model state_dict()
best_model.load_state_dict(torch.load(best_model_path))
```

```
[INFO] Created new effnetb2 model.
```

```
<All keys matched successfully>
```

```
# Check the model file size
from pathlib import Path

# Get the model size in bytes then convert to megabytes
effnetb2_model_size = Path(best_model_path).stat().st_size //
(1024*1024)
print(f"EfficientNetB2 feature extractor model size:
{effnetb2_model_size} MB")
```

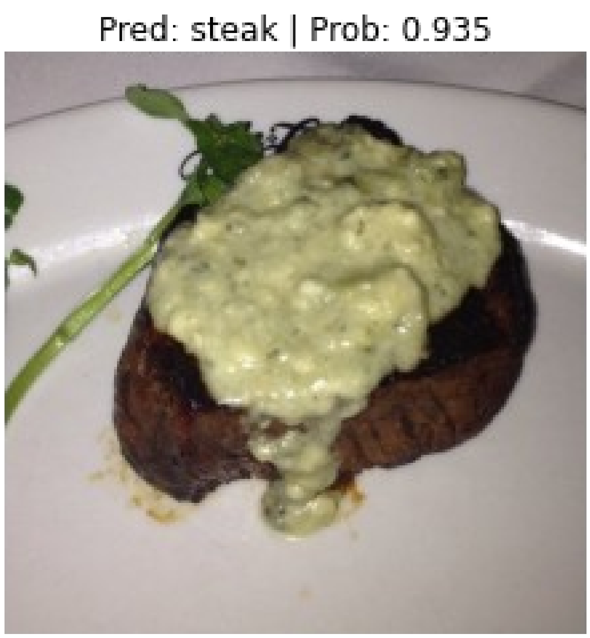
```
EfficientNetB2 feature extractor model size: 29 MB
```

```
# Import function to make predictions on images and plot them
# See the function previously created in section:
https://www.learnpytorch.io/06_pytorch_transfer_learning/#6-make-
predictions-on-images-from-the-test-set
from going_modular.going_modular.predictions import
pred_and_plot_image

# Get a random list of 3 images from 20% test set
import random
num_images_to_plot = 3
```

```
test_image_path_list = list(Path(data_20_percent_path /
"test").glob("*/*.jpg")) # get all test image paths from 20% dataset
test_image_path_sample =
random.sample(population=test_image_path_list,
                                       k=num_images_to_plot) #
randomly select k number of images

# Iterate through random test image paths, make predictions on them
and plot them
for image_path in test_image_path_sample:
    pred_and_plot_image(model=best_model,
                        image_path=image_path,
                        class_names=class_names,
                        image_size=(224, 224))
```



Memprediksi gambar khusus dengan model terbaik

```
# Download custom image
import requests

# Setup custom image path
custom_image_path = Path("data/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.")

# Predict on custom image
pred_and_plot_image(model=model,
                    image_path=custom_image_path,
                    class_names=class_names)
```

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