srrescycgan

July 30, 2025

[ ]:
```
!pip install --quiet fastmri
```

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
import fastmri
import h5py
import os
```

[3]:
```
OUTPUT     = "../working"
INPUT      = "../input"
DATA_PATH  = os.path.join(INPUT, "fastmri-knee", "fastmri")
TRAIN_PATH = os.path.join(DATA_PATH, "singlecoil_train")
TEST_PATH  = os.path.join(DATA_PATH, "singlecoil_test")
VAL_PATH   = os.path.join(DATA_PATH, "singlecoil_val")

sample_file = "file1000001.h5"
sample_path = os.path.join(TRAIN_PATH, sample_file)
```

1 Predstavitev podatkov

[4]:
```
sample = h5py.File(sample_path)
print(dict(sample.attrs), "\n\n", list(sample.keys()))
```

```
{'acquisition': 'CORPDFS_FBK', 'max': 0.000851878253624366, 'norm':
0.0596983310320022, 'patient_id':
'0beb8905d9b7fad304389b9d4263c57d5b069257ea0fdc5bf7f2675608a47406'}

 ['ismrmrd_header', 'kspace', 'reconstruction_esc', 'reconstruction_rss']
```

Podatki so razdeljeni na train, validation in test datasets. Vsaka binarna `h5` datoteka predstavlja eno MRI slikanje. Vsebuje: - `kspace`: k-space podatke - `reconstruction_rss`, `reconstruction_esc`: rekonstruirano MRI sliko (ground truth) - `attrs`: metapodatke o slikanju.

`k_space` so signali frekvenc (?) pridobljeni iz MRI naprave, torej surovi podatki, ki se nato s pomočjo inverzne Fouirerjeve preslikave transformirajo v MRI sliko.

TODO: kaj je reconstruction_esc?

[5]:
```
sample["kspace"].shape
```

[5]: (36, 640, 372)

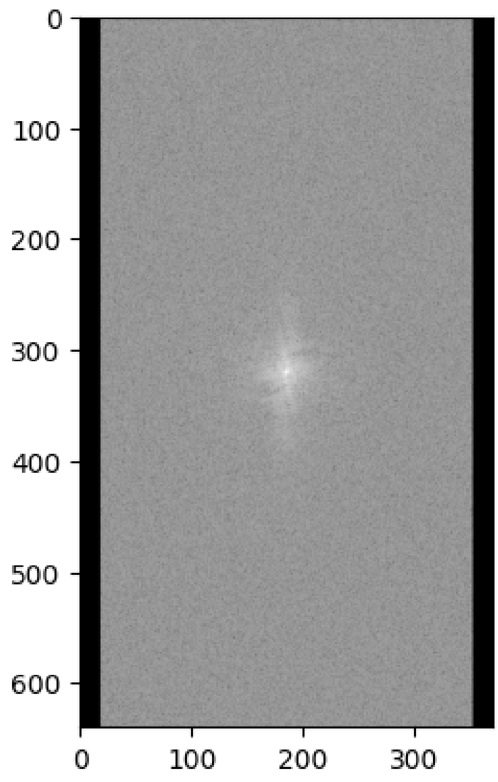
Slikanje vsebuje 36 slojev (posameznih slik) velikosti 640×372 px.

[6]:
```
slice = 10
kspace = np.array(sample["kspace"])
sample_slice = kspace[slice]
sample_slice[100:102, 100:102]
```

[6]:
```
array([[-5.6733791e-07+8.8030475e-07j, -1.2970555e-05-8.6704194e-06j],
       [-4.9417745e-06+3.0851206e-06j, -1.3465409e-05-7.6796363e-07j]],
      dtype=complex64)
```

`kspace` podatki so predstavljeni s kompleksnimi števili, zato jih je treba s pomočjo enačbe pretvoriti v realna števila.

[7]:
```
sample_slice_f = np.log(np.abs(sample_slice) + 1e-9)

plt.imshow(sample_slice_f, cmap="gray")
plt.show()
```



1.1 Primer transformacije *k-space* -> *image space*

[8]:
```python
from fastmri.data import transforms
```

[9]:
```python
kspace_tensor = transforms.to_tensor(kspace)
kspace_complex = fastmri.ifft2c(kspace_tensor)
kspace_complex.shape
```

[9]:
```
torch.Size([36, 640, 372, 2])
```

`to_tensor` pretvori `numpy.ndarray` kompleksnih podatkov v `torch.Tensor`, kjer sta v zadnji dimenziji ločeni realna in kompleksna komponenta.

`ifft2c` izvede inverzno Fourierjevo transformacijo.

[10]:
```python
kspace_complex[0, :3, :3, 0]  # Re
```

[10]:
```
tensor([[ 4.9065e-07,  1.4504e-06,  2.1026e-06],
        [ 1.9407e-06, -4.5079e-06,  3.7221e-06],
        [ 1.6579e-06, -4.1001e-06, -5.8950e-06]])
```

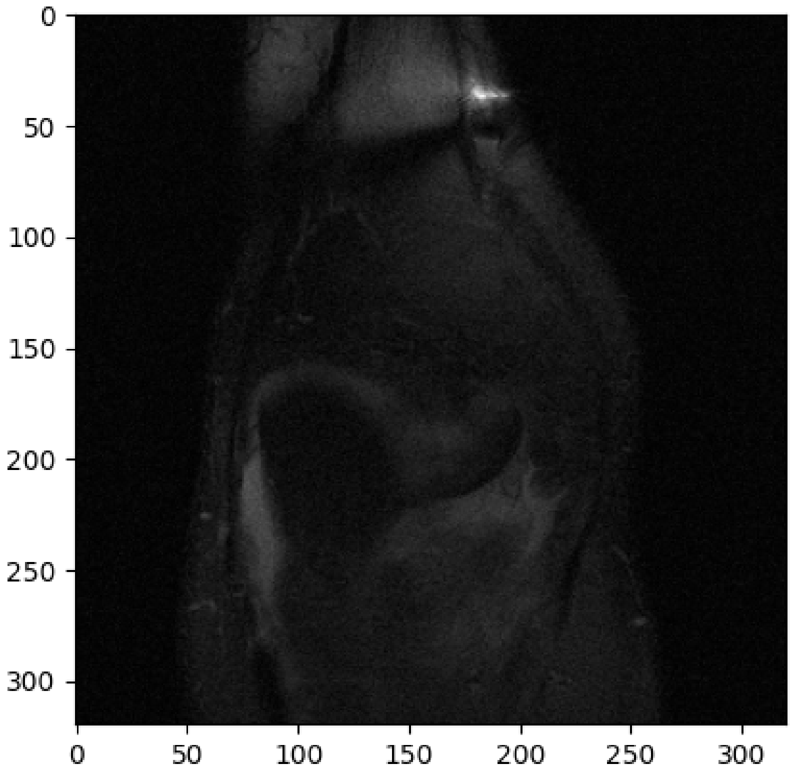
[11]:
```python
kspace_complex[0, :3, :3, 1]  # Img
```

[11]:
```
tensor([[ 1.2271e-06, -8.5122e-07,  2.1547e-07],
        [-2.8814e-06,  6.4273e-07,  1.9192e-07],
        [ 1.3289e-06, -1.2626e-06,  5.2304e-07]])
```

[12]:
```python
kspace_real = fastmri.complex_abs(kspace_complex)  # vrne realne komponente
kspace_real.shape
```

[12]:
```
torch.Size([36, 640, 372])
```

[13]:
```python
kspace_image = transforms.center_crop(kspace_real[slice], (320, 320))
plt.imshow(kspace_image, cmap="gray")
plt.show()
```



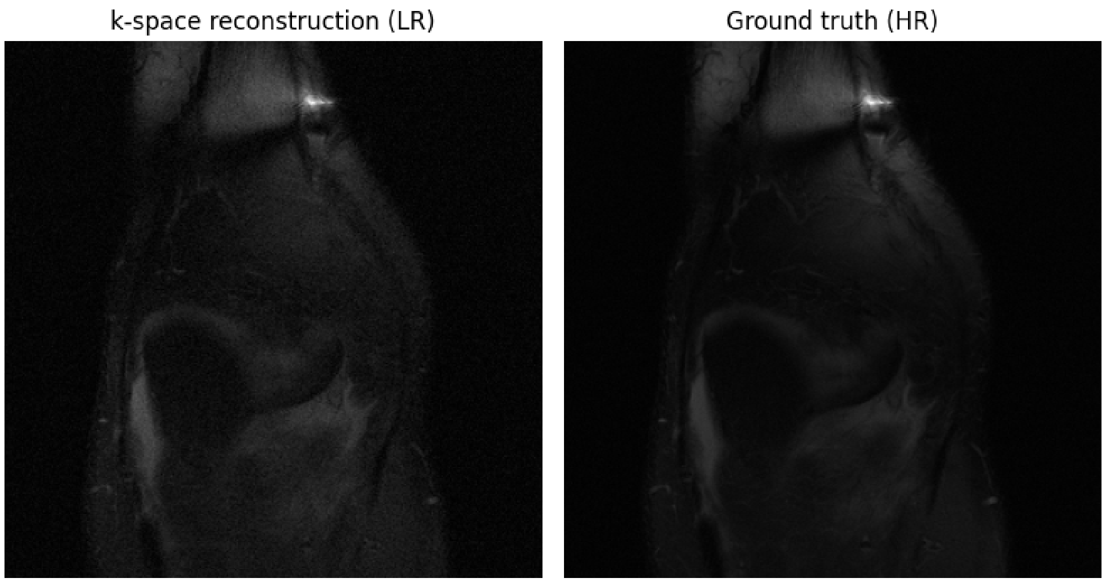
1.2 Primer rekonstruirane in očiščene slike

[14]:
```
ground_truth: h5py.Dataset = sample["reconstruction_rss"]
ground_truth.shape, ground_truth.dtype, ground_truth.dtype.type
```

[14]:
```
((36, 320, 320), dtype('<f4'), numpy.float32)
```

[15]:
```
ground_truth_image = ground_truth[slice]
```

[16]:
```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(8, 5))

axes[0].set_title("k-space reconstruction (LR)")
axes[0].imshow(kspace_image, cmap="gray")
axes[0].axis("off")
axes[1].set_title("Ground truth (HR)")
axes[1].imshow(ground_truth_image, cmap="gray")
axes[1].axis("off")

plt.tight_layout()
plt.show()
```



[17]:
```python
import imageio
from IPython.display import Image

fname_gif = ''.join([sample_file, '.gif'])
```

[18]:
```python
gt_np = np.array(ground_truth)

max_val = gt_np.max()
min_val = gt_np.min()

gt_norm = (gt_np - min_val) / (max_val - min_val) * 255
gt_norm = gt_norm.astype(np.uint8)
```

[19]:
```python
imageio.mimsave(fname_gif, gt_norm, duration=0.1, loop=0)
```

[20]:
```python
Image(os.path.join(OUTPUT, fname_gif))  # ta gif lah daš čiš gor v uvod
```

[20]:
```
<IPython.core.display.Image object>
```

V članku uporabljajo za LR slike downsampled HR slike, torej

2 SRResCycGAN

Izvorne datoteke so dostopne na kaggle-u in github-u.

[254]:
```python
from keras import Model, Loss, Optimizer, layers, metrics
from tensorflow import image, reduce_mean, abs, GradientTape, ones_like,␣
↪zeros_like, zeros
```

```
from keras.losses import MeanSquaredError, BinaryCrossentropy, MeanAbsoluteError
from keras.applications import VGG19
from keras.applications.vgg19 import preprocess_input
from keras.optimizers import Adam
from keras.optimizers.schedules import ExponentialDecay
```

[ ]:
```
LR_SHAPE = (80, 80, 3)
HR_SHAPE = (320, 320, 3)
```

2.1 Generatorja

[ ]:
```
def Generator_HR(input_shape=LR_SHAPE):
    """ Generator za HR (high resolution) slike.

    Deluje na principu "upscale -> refine". Sprejme sliko nizke ločljivosti in
    vrne izboljšano sliko visok ločljivosti. Arhitektura temelji na članku o␣
↪SRResCGAN.
    Ima 3 glavne dele:

    1. Encoder - upsampling vhodne slike in ekstrakcija značilnosti
    2. ResidualNet - predela zemljevid značilnosti (feature map) od encoderja
    3. Decoder - na podalagi izhoda ResNet-a ustvari zemljevid napak (proximal␣
↪map)

    `Subtract` sloj zmanjša prisotnost šuma in artefaktov upsampled slike s␣
↪pomočjo
    zemljevida napak. Zadnji `Conv2D` sloj poskrbi, da je izhod slika s tremi␣
↪kanali.

    Args:
        input_shape: dimenzija LR slike (width, height, channels)
    Returns:
        HR slika dimenzije (320, 320, 3)
    """
    lr_input = layers.Input(shape=input_shape)
    encoder_out = layers.Conv2DTranspose(
        filters=64,     # število kanalov izhoda; rgb slika ima 3, tu jih vrne␣
↪64)
        kernel_size=5,  # dimenzije jedra, ki bo procesiral sliko (5x5)
        strides=4,      # za koliko pikslov se premakne jedro (4 => 4x␣
↪upsampling => vodi v 320x320), ko je padding="same"
        padding="same"  # poskrbi, da se doda ravno prav ničel na robove, da je␣
↪končna dimenzija odvisna od strides
    )(lr_input)

    global_skip = encoder_out
```

```
    # služi kot vhod in izhod ResNet-a.
    x = layers.Conv2D(filters=64, kernel_size=5, padding="same")(encoder_out)

    for _ in range(5):
        block_skip = x
        x = layers.PReLU(shared_axes=[1, 2])(block_skip)
        x = layers.Conv2D(filters=64, kernel_size=3, strides=1, padding="same",␣
↪use_bias=False)(x)
        x = layers.GroupNormalization(groups=-1, axis=-1)(x)  # -1 za␣
↪InstanceNormalization

        x = layers.PReLU(shared_axes=[1, 2])(x)
        x = layers.Conv2D(filters=64, kernel_size=3, strides=1, padding="same",␣
↪use_bias=False)(x)
        x = layers.GroupNormalization(groups=-1, axis=-1)(x)
        x = layers.Add()([block_skip, x])

    decoder_out = layers.Conv2D(filters=64, kernel_size=5, strides=1,␣
↪padding="same")(x)
    decoder_out = layers.Conv2D(filters=64, kernel_size=5, strides=1,␣
↪padding="same")(decoder_out)

    subtracted = layers.Subtract()([global_skip, decoder_out])
    model_out = layers.Conv2D(filters=3, kernel_size=3, strides=1,␣
↪padding="same", use_bias=False)(subtracted)
    model_out = layers.ReLU(max_value=255)(model_out)  # vrednosti spravi na␣
↪interval [0,255]

    return Model(inputs=lr_input, outputs=model_out, name="G_HR")
```

[ ]:
```
def Generator_LR(input_shape=HR_SHAPE):
    """ Generator za LR (low resolution) slike.

    Sprejme sliko visoke ločljivosti in vrne degradirano sliko nizke␣
↪ločljivosti. Arhitektura temelji
    na G3 generatorju iz CinCGAN strukture, ki opravi downsampling s pomočjo␣
↪konvolucije.
    Ima 3 glavne dele:

    1. Glava - downsampling in ekstrakcija značilnosti
    2. ResidualNet - predela izdelan zemljevid značilnosti (feature map)
    3. Rep - transformacija nazaj v sliko s tremi kanali

    Args:
        input_shape: dimenzija HR slike (width, height, channels)
```

```python
    Returns:
        HR slika dimenzije (320, 320, 3)
    """
    hr_input = layers.Input(shape=input_shape)

    x = layers.Conv2D(filters=64, kernel_size=7, padding="same")(hr_input)
    x = layers.GroupNormalization(groups=-1, axis=-1)(x)
    x = layers.LeakyReLU(negative_slope=0.2)(x)

    for _ in range(2):  # downsample
        x = layers.Conv2D(filters=64, kernel_size=3, strides=2,␣
↪padding="same")(x)
        x = layers.GroupNormalization(groups=-1, axis=-1)(x)
        x = layers.LeakyReLU(negative_slope=0.2)(x)

    for _ in range(6): # ResNet
        block_skip = x
        x = layers.Conv2D(filters=64, kernel_size=3, padding="same")(x)
        x = layers.GroupNormalization(groups=-1, axis=-1)(x)
        x = layers.LeakyReLU(negative_slope=0.2)(x)

        x = layers.Conv2D(filters=64, kernel_size=3, padding="same")(x)
        x = layers.GroupNormalization(groups=-1, axis=-1)(x)
        x = layers.Add()([block_skip, x])
        x = layers.LeakyReLU(negative_slope=0.2)(x)

    for _ in range(2):
        x = layers.Conv2D(filters=64, kernel_size=3, padding="same")(x)
        x = layers.GroupNormalization(groups=-1, axis=-1)(x)
        x = layers.LeakyReLU(negative_slope=0.2)(x)

    x = layers.Conv2D(filters=3, kernel_size=7, padding="same")(x)
    model_out = layers.ReLU(max_value=255)(x)   # vrednosti spravi na interval␣
↪[0,255]

    return Model(inputs=hr_input, outputs=model_out, name="G_LR")
```

2.2 Diskriminatorja

[ ]:
```python
def Discriminator_HR(input_shape=HR_SHAPE):
    """ Diskriminator za HR (high resolution) slike.

    Sprejme HR sliko (pravo ali lažno) in vrne verjetnost,
    da je slika prava. Deluje kot binarni klasifikator.
    Arhitektura temelji na članku o SRResCGAN. Ima 3 glavne dele:

    1. Vhodni konvolucijski blok
```

```
    2. Zaporedje konvolucjiskih blokov, ki
       - postopoma zmanjšujejo dimenzijo slike,
       - normalizirajo vrednosti za stabilizacijo pri treniranju
       - večajo število filtrov za procesiranje lastnosti slike
    3. Fully connected sloji, ki poskrbijo, da se vrne ena float vrednost

    Args:
        input_shape: dimenzija HR slike (width, height, channels)
    Returns:
        float logit vrednost
    """
    hr_input = layers.Input(shape=input_shape)
    x = layers.Conv2D(filters=64, kernel_size=3, strides=1,␣
↪padding="valid")(hr_input)
    x = layers.LeakyReLU()(x)

    KERNEL_SIZE = (4, 3)
    STRIDES = (2, 1)
    FILTERS = (
        64,
        128, 128,
        256, 256,
        512, 512, 512, 512
    )

    for i in range(9):
        kernel_size = KERNEL_SIZE[0] if i % 2 == 0 else KERNEL_SIZE[1]
        strides = STRIDES[0] if i % 2 == 0 else STRIDES[1]

        x = layers.Conv2D(filters=FILTERS[i], kernel_size=kernel_size,␣
↪strides=strides, padding="valid")(x)
        # TODO: Spectral Normalization?
        x = layers.GroupNormalization(groups=-1, axis=-1)(x)
        x = layers.LeakyReLU()(x)

    x = layers.Flatten()(x)
    x = layers.Dense(units=100)(x)
    x = layers.LeakyReLU()(x)
    model_out = layers.Dense(units=1)(x)

    return Model(inputs=hr_input, outputs=model_out, name="D_HR")
```

[ ]:
```
def Discriminator_LR(input_shape=LR_SHAPE):
    """ Diskriminator za LR (low resolution) slike.

    Arhitektura temelji PatchGAN diskriminatorju, kot opisujejo v članku o␣
↪SRResCycGAN, ki vrne matriko
```

```
    ocen verjetnosti (logitov) namesto ene same vrednosti. Tak pristop spodbuja␣
↪generator, da se osredotoči
    na ustvarjanje realističnih lokalnih podrobnosti. Namesto␣
↪BatchNormalization je uporabljena
    InstanceNormalization, saj se obnese boljše med treniranjem.

    Args:
        input_shape: dimenzija LR slike (width, height, channels)
    Returns:
        matrika logitov oblike (20, 20, 1)
    """
    lr_input = layers.Input(shape=input_shape)
    KERNEL_SIZE = 5

    x = layers.Conv2D(filters=64, kernel_size=KERNEL_SIZE, strides=2,␣
↪padding="same")(lr_input)
    x = layers.GroupNormalization(groups=-1, axis=-1)(x)
    x = layers.LeakyReLU()(x)

    x = layers.Conv2D(filters=128, kernel_size=KERNEL_SIZE, strides=2,␣
↪padding="same")(x)
    x = layers.GroupNormalization(groups=-1, axis=-1)(x)
    x = layers.LeakyReLU()(x)

    x = layers.Conv2D(filters=256, kernel_size=KERNEL_SIZE, padding="same")(x)
    x = layers.GroupNormalization(groups=-1, axis=-1)(x)
    x = layers.LeakyReLU()(x)

    model_out = layers.Conv2D(filters=1, kernel_size=KERNEL_SIZE,␣
↪padding="same")(x)

    return Model(inputs=lr_input, outputs=model_out, name="D_LR")
```

2.3 Loss funckije

[ ]:
```
def total_variation(real_image, fake_image):
    """Total variation loss

    Primerja vodoravne in navpične gradiente resnične in generirane slike.␣
↪Imenovan tudi
    "gradient difference loss".

    Vrne vsoto razlik gradientov obeh slik.
    """
    real_dy, real_dx = image.image_gradients(real_image)
    fake_dy, fake_dx = image.image_gradients(fake_image)
```

```
    loss_dx = reduce_mean(abs(real_dx - fake_dx))
    loss_dy = reduce_mean(abs(real_dy - fake_dy))

    return loss_dx + loss_dy
```

[ ]:
```
class PerceptualLoss(Loss):
    """Perceptual loss

    Sliki primerja v prostoru značilnosti (feature space) namesto prostoru slik␣
↪(image space).
    Feature maps sta dobljena iz nekega umesnega konvolucijskega sloja VGG19␣
↪klasifikatorja.

    Vrne MSE (L2 loss) nad izhodom VGG19 za resnično in generirano sliko.
    """

    def __init__(self, hr_shape=HR_SHAPE) -> None:
        super(PerceptualLoss, self).__init__(name="perceptual_loss")
        self.vgg_model = self.__build_vgg_model(hr_shape)
        self.L2 = MeanSquaredError()

    def __build_vgg_model(self, hr_shape):
        vgg = VGG19(input_shape=hr_shape, include_top=False, weights="imagenet")
        vgg.trainable = False
        # Izhod enega od umesnih slojev
        output_layer = vgg.get_layer("block3_conv3").output
        return Model(inputs=vgg.input, outputs=output_layer,␣
↪name="vgg_perceptual")

    def call(self, y_true, y_pred):
        true_preproc = preprocess_input(y_true)
        pred_preproc = preprocess_input(y_pred)
        true_feat = self.vgg_model(true_preproc, training=False)
        pred_feat = self.vgg_model(pred_preproc, training=False)
        return self.L2(true_feat, pred_feat)
```

[ ]:
```
losses_dict = {
    "perceptual": PerceptualLoss(),
    "adversarial": BinaryCrossentropy(from_logits=True),
    "total_variation": total_variation,
    "content": MeanAbsoluteError(),
    "cyclic": MeanAbsoluteError(),
}
```

2.4 Primer generirane slike

[ ]:
```
import tensorflow as tf
t = tf.random.uniform(shape=(1, *LR_SHAPE), minval=0.0, maxval=255.0, dtype=tf.
 ↪float32)
ghr = Generator_HR()
generated_img = ghr(t)
plt.imshow(generated_img[0].numpy().astype(np.uint8))
```

[ ]:
```
dhr = Discriminator_HR()
dhr(generated_img)
```

2.5 Celotni model

[ ]:
```
class SRResCycGAN(Model):
    """
    Super Resolution Residual Cyclic GAN
    """
    def __init__(self, lambda_cyc=10.0, lambda_content=5.0) -> None:
        super(SRResCycGAN, self).__init__()

        self.G_HR = Generator_HR(input_shape=LR_SHAPE)
        self.G_LR = Generator_LR(input_shape=HR_SHAPE)
        self.D_HR = Discriminator_HR(input_shape=HR_SHAPE)
        self.D_LR = Discriminator_LR(input_shape=LR_SHAPE)
        self.lambda_cyc = lambda_cyc
        self.lambda_content = lambda_content

        # trackers
        self.d_hr_loss_tracker = metrics.Mean(name="d_hr_loss")
        self.d_lr_loss_tracker = metrics.Mean(name="d_lr_loss")
        self.g_adv_loss_tracker = metrics.Mean(name="g_adv_loss")
        self.g_cyc_loss_tracker = metrics.Mean(name="g_cyc_loss")
        self.g_content_loss_tracker = metrics.Mean(name="g_content_loss")
        self.g_perceptual_loss_tracker = metrics.Mean(name="g_perceptual_loss")
        self.g_tv_loss_tracker = metrics.Mean(name="g_tv_loss")
        self.total_gen_loss_tracker = metrics.Mean(name="total_g_loss")
        self.total_disc_loss_tracker = metrics.Mean(name="total_d_loss")

        self.mse_tracker = metrics.Mean(name="mse")
        self.psnr_tracker = metrics.Mean(name="psnr")

    def compile(self,
        g_hr_optimizer: Optimizer,
        d_hr_optimizer: Optimizer,
        g_lr_optimizer: Optimizer,
        d_lr_optimizer: Optimizer,
```

```
        losses: dict[str, Loss]
    ):
        super(SRResCycGAN, self).compile()

        self.g_hr_optimizer = g_hr_optimizer
        self.d_hr_optimizer = d_hr_optimizer
        self.g_lr_optimizer = g_lr_optimizer
        self.d_lr_optimizer = d_lr_optimizer

        self.adv_loss = losses["adversarial"]
        self.cyc_loss = losses["cyclic"]
        self.content_loss = losses["content"]
        self.perceptual_loss = losses["perceptual"]
        self.tv_loss = losses["total_variation"]


    def train_step(self, data):
        real_lr, real_hr = data

        with GradientTape(persistent=True) as disc_tape:
            # generira slike
            fake_hr = self.G_HR(real_lr, training=True)
            fake_lr = self.G_LR(real_hr, training=True)

            # diskriminira
            real_hr_pred = self.D_HR(real_hr, training=True)
            fake_hr_pred = self.D_HR(fake_hr, training=True)

            real_lr_pred = self.D_LR(real_lr, training=True)
            fake_lr_pred = self.D_LR(fake_lr, training=True)

            # discriminator losses
            dhr_real_loss = self.adv_loss(ones_like(real_hr_pred), real_hr_pred)
            dhr_fake_loss = self.adv_loss(zeros_like(fake_hr_pred),
↪fake_hr_pred)
            dhr_total_loss = (dhr_real_loss + dhr_fake_loss) * 0.5

            dlr_real_loss = self.adv_loss(ones_like(real_lr_pred), real_lr_pred)
            dlr_fake_loss = self.adv_loss(zeros_like(fake_lr_pred),
↪fake_lr_pred)
            dlr_total_loss = (dlr_real_loss + dlr_fake_loss) * 0.5

            total_disc_loss = dhr_total_loss + dlr_total_loss


        with GradientTape(persistent=True) as gen_tape:
            # generira slike
```

```
            fake_hr = self.G_HR(real_lr, training=True)
            fake_lr = self.G_LR(real_hr, training=True)
            cycled_hr = self.G_HR(fake_lr, training=True)
            cycled_lr = self.G_LR(fake_hr, training=True)

            # diskriminira za adversarial loss
            fake_hr_pred_gen = self.D_HR(fake_hr, training=True)
            fake_lr_pred_gen = self.D_LR(fake_lr, training=True)

            # generator losses
            perceptual_loss = self.perceptual_loss(real_hr, fake_hr)

            ghr_adv = self.adv_loss(ones_like(fake_hr_pred_gen),␣
↪fake_hr_pred_gen)
            glr_adv = self.adv_loss(ones_like(fake_lr_pred_gen),␣
↪fake_lr_pred_gen)
            adv_loss = ghr_adv + glr_adv

            tv_loss = self.tv_loss(real_hr, fake_hr)

            content_loss = self.content_loss(real_hr, fake_hr)

            # cyclic loss
            cyc_forward = self.cyc_loss(cycled_lr, real_lr)
            cyc_backward = self.cyc_loss(cycled_hr, real_hr)
            cyc_loss = cyc_forward + cyc_backward

            total_gen_loss = perceptual_loss + adv_loss + tv_loss + \
                            (content_loss * self.lambda_content) + \
                            (cyc_loss * self.lambda_cyc)


        # gradienti diskriminatorja
        dhr_grads = disc_tape.gradient(dhr_total_loss, self.D_HR.
↪trainable_variables)
        dlr_grads = disc_tape.gradient(dlr_total_loss, self.D_LR.
↪trainable_variables)

        self.d_hr_optimizer.apply_gradients(zip(dhr_grads, self.D_HR.
↪trainable_variables))
        self.d_lr_optimizer.apply_gradients(zip(dlr_grads, self.D_LR.
↪trainable_variables))

        # gradienti generatorja
        ghr_grads = gen_tape.gradient(total_gen_loss, self.G_HR.
↪trainable_variables)
```

```
        glr_grads = gen_tape.gradient(total_gen_loss, self.G_LR.
↪trainable_variables)

        self.g_hr_optimizer.apply_gradients(zip(ghr_grads, self.G_HR.
↪trainable_variables))
        self.g_lr_optimizer.apply_gradients(zip(glr_grads, self.G_LR.
↪trainable_variables))

        # Posodobi stanje trackerjev z novimi vrednostmi
        self.d_hr_loss_tracker.update_state(dhr_total_loss)
        self.d_lr_loss_tracker.update_state(dlr_total_loss)
        self.total_disc_loss_tracker.update_state(total_disc_loss)

        self.g_adv_loss_tracker.update_state(adv_loss)
        self.g_cyc_loss_tracker.update_state(cyc_loss)
        self.g_content_loss_tracker.update_state(content_loss)
        self.g_perceptual_loss_tracker.update_state(perceptual_loss)
        self.g_tv_loss_tracker.update_state(tv_loss)
        self.total_gen_loss_tracker.update_state(total_gen_loss)

        mse_metric = reduce_mean(square(real_hr - fake_hr))
        psnr_metric = image.psnr(real_hr, fake_hr, max_val=255.0)
        self.mse_tracker.update_state(mse_metric)
        self.psnr_tracker.update_state(psnr_metric)

        # za progress bar
        return {m.name: m.result() for m in self.metrics}

    def test_step(self, data):
        real_lr, real_hr = data

        # training=False ker nočemo da posodablja uteži
        fake_hr = self.G_HR(real_lr, training=False)
        fake_lr = self.G_LR(real_hr, training=False)
        cycled_hr = self.G_HR(fake_lr, training=False)
        cycled_lr = self.G_LR(fake_hr, training=False)

        real_hr_pred = self.D_HR(real_hr, training=False)
        fake_hr_pred = self.D_HR(fake_hr, training=False)
        real_lr_pred = self.D_LR(real_lr, training=False)
        fake_lr_pred = self.D_LR(fake_lr, training=False)

        # enako kot train_step
        dhr_real_loss = self.adv_loss(ones_like(real_hr_pred), real_hr_pred)
        dhr_fake_loss = self.adv_loss(zeros_like(fake_hr_pred), fake_hr_pred)
        dhr_total_loss = (dhr_real_loss + dhr_fake_loss) * 0.5
        dlr_real_loss = self.adv_loss(ones_like(real_lr_pred), real_lr_pred)
```

```
        dlr_fake_loss = self.adv_loss(zeros_like(fake_lr_pred), fake_lr_pred)
        dlr_total_loss = (dlr_real_loss + dlr_fake_loss) * 0.5
        total_disc_loss = dhr_total_loss + dlr_total_loss

        ghr_adv = self.adv_loss(ones_like(fake_hr_pred), fake_hr_pred)
        glr_adv = self.adv_loss(ones_like(fake_lr_pred), fake_lr_pred)
        adv_loss = ghr_adv + glr_adv
        tv_loss = self.tv_loss(real_hr, fake_hr)
        content_loss = self.content_loss(real_hr, fake_hr)
        cyc_forward = self.cyc_loss(cycled_lr, real_lr)
        cyc_backward = self.cyc_loss(cycled_hr, real_hr)
        cyc_loss = cyc_forward + cyc_backward
        total_gen_loss = perceptual_loss + adv_loss + tv_loss + \
                         (content_loss * self.lambda_content) + \
                         (cyc_loss * self.lambda_cyc)

        # Posodobi stanje trackerjev z novimi vrednostmi
        self.d_hr_loss_tracker.update_state(dhr_total_loss)
        self.d_lr_loss_tracker.update_state(dlr_total_loss)
        self.total_disc_loss_tracker.update_state(total_disc_loss)

        self.g_adv_loss_tracker.update_state(adv_loss)
        self.g_cyc_loss_tracker.update_state(cyc_loss)
        self.g_content_loss_tracker.update_state(content_loss)
        self.g_perceptual_loss_tracker.update_state(perceptual_loss)
        self.g_tv_loss_tracker.update_state(tv_loss)
        self.total_gen_loss_tracker.update_state(total_gen_loss)

        mse_metric = reduce_mean(square(real_hr - fake_hr))
        psnr_metric = image.psnr(real_hr, fake_hr, max_val=255.0)
        self.mse_tracker.update_state(mse_metric)
        self.psnr_tracker.update_state(psnr_metric)

        # za progress bar
        return {m.name: m.result() for m in self.metrics}

    def call(self, inputs, training=False):
        # samo vrne generirano HR sliko
        return self.G_HR(inputs, training=training)

    @property
    def metrics(self):
        return [
            self.d_hr_loss_tracker,
            self.d_lr_loss_tracker,
            self.total_disc_loss_tracker,
            self.g_adv_loss_tracker,
```

```
            self.g_cyc_loss_tracker,
            self.g_content_loss_tracker,
            self.g_perceptual_loss_tracker,
            self.g_tv_loss_tracker,
            self.total_gen_loss_tracker,
            self.mse_tracker,
            self.psnr_tracker,
        ]
```

2.6 Data loading

[ ]:
```
from typing import Generator
import tensorflow as tf
import keras
import numpy as np
import h5py
import os
```

[ ]:
```
BATCH_SIZE = 4
BUFFER_SIZE = 1000
BLOCK_LENGTH = 1
```

[ ]:
```
def h5_generator(filepath) -> Generator[tuple[np.ndarray, np.ndarray], None,␣
 ↪None]:
    """
    Generator, ki vrača (lr, hr) pare slik iz H5 datotek z uporabo NumPy.
    """
    with h5py.File(filepath.decode('utf-8'), "r") as hf:
        hr_images_raw = np.array(hf["reconstruction_rss"])

        channels = hr_images_raw.shape[0]

        for i in range(channels):
            hr_image = hr_images_raw[i].astype(np.float32)

            # zagotovi da je slika vsaj 3D (doda chanels dimenzijo, če manjka)
            if hr_image.ndim == 2:
                hr_image = np.expand_dims(hr_image, axis=-1) # (320, 320) ->␣
 ↪(320, 320, 1)

            # če ima slika 2 kanala, vzamemo samo prvega (morda lahko ostranim)
            if hr_image.shape[-1] == 2:
                hr_image = hr_image[..., 0:1] # (320, 320, 2) -> (320, 320, 1)

            # zagotovi da ima 3 kanale (nisem prepričan ali je to pravi pristop)
            # np.tile ponovi array po določeni osi.
            if hr_image.shape[-1] == 1:
```

```
                hr_image = np.tile(hr_image, (1, 1, 3)) # (320, 320, 1) ->␣
↪(320, 320, 3)

            assert hr_image.shape == HR_SHAPE

            # ustvari LR sliko z downsampling-om
            hr_image_tensor = tf.constant(hr_image)
            lr_image = tf.image.resize(hr_image_tensor, LR_SHAPE[:2], method=tf.
↪image.ResizeMethod.BICUBIC)

            yield lr_image.numpy(), hr_image
```

[ ]:
```
def create_paired_dataset(data_dir) -> tf.data.Dataset:
    """
    Ustvari `tf.data.Dataset` s parnimi podatki LR in HR slik. LR slike␣
↪predstavljajo transformirani k-space
    podatki, HR pa rekonstruirane in prečiščene slike dostopne znotraj datotek␣
↪pod `reconstruction_rss`.
    """
    filepaths_pattern = os.path.join(data_dir, "*.h5")

    # `from_generator` spodaj pričakuje signiature izhodnih podatkov
    # vsak `yield` bo vrnil dve sliki, LR in HR, primernih oblik
    out_sig = (
        tf.TensorSpec(shape=LR_SHAPE, dtype=tf.float32),
        tf.TensorSpec(shape=HR_SHAPE, dtype=tf.float32)
    )

    # dataset z imeni vseh datotek
    filepaths_dataset = tf.data.Dataset.list_files(filepaths_pattern,␣
↪shuffle=False)

    # z generatorjem odpre vsako datoteko posebej in postopoma z `yield` vrača␣
↪pare slik
    paired_dataset = filepaths_dataset.interleave(
        lambda filepath: tf.data.Dataset.from_generator(
            generator=h5_generator,
            output_signature=out_sig,
            args=(filepath,)  # vejica, ker mora biti sequence
        ),
        cycle_length=tf.data.AUTOTUNE,       # število vhodnih elementov, ki se␣
↪procesirajo istočasno
        block_length=BLOCK_LENGTH,           # da zajame vse slike v datoteki,␣
↪ker ni fiksnega števila slojev
        num_parallel_calls=tf.data.AUTOTUNE  # za hitrejše procesiranje
    )
```

```python
    paired_dataset = paired_dataset.shuffle(buffer_size=BUFFER_SIZE)
    paired_dataset = paired_dataset.batch(BATCH_SIZE)
    paired_dataset = paired_dataset.prefetch(tf.data.AUTOTUNE)

    return paired_dataset
```

2.7 Training

[ ]:
```python
EPOCHS = 1
```

[ ]:
```python
train = create_paired_dataset(TRAIN_PATH)
val = create_paired_dataset(VAL_PATH)
```

[ ]:
```python
model = SRResCycGAN(lambda_cyc=10.0, lambda_content=5.0)
```

[ ]:
```python
def adam_opt(lr=1e-4, b1=0.9, b2=0.999, decay_steps=1e4, decay_rate=0.5):
    lr_schedule = ExponentialDecay(
        initial_learning_rate=lr,
        decay_steps=decay_steps,
        decay_rate=decay_rate,
        staircase=True  # da se lr spremeni na vsakih 10k korakov
    )
    return Adam(learning_rate=lr_schedule, beta_1=b1, beta_2=b2,␣
 ↪weight_decay=False)
```

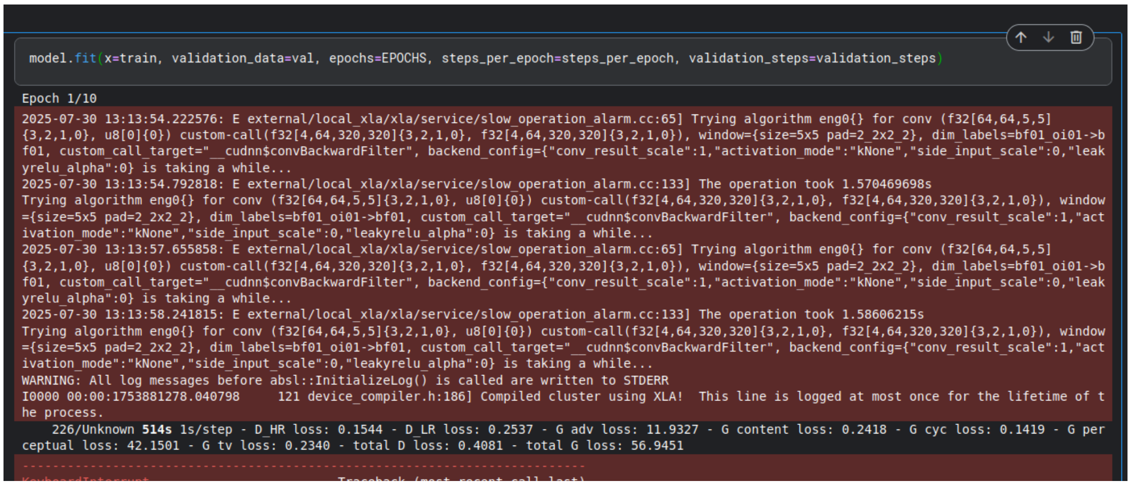
[ ]:
```python
g_hr_optimizer = adam_opt()
d_hr_optimizer = adam_opt()
g_lr_optimizer = adam_opt()
d_lr_optimizer = adam_opt()

model.compile(
    g_hr_optimizer=g_hr_optimizer,
    d_hr_optimizer=d_hr_optimizer,
    g_lr_optimizer=g_lr_optimizer,
    d_lr_optimizer=d_lr_optimizer,
    losses=losses_dict
)
```

[ ]:
```python
def calculate_slices(data_dir) -> int:
    print("Calculating slices for ", data_dir, "...")
    total_slices = 0
    for f in os.listdir(data_dir):
        with h5py.File(os.path.join(data_dir, f), "r") as hf:
            total_slices += hf["reconstruction_rss"].shape[0]
    print("Total slices:", total_slices)
    return total_slices
```

```
[ ]: total_train_slices = calculate_slices(TRAIN_PATH)
     total_val_slices = calculate_slices(VAL_PATH)
```

```
[ ]: steps_per_epoch = total_train_slices // BATCH_SIZE
     steps_per_epoch
```

```
[ ]: validation_steps = total_val_slices // BATCH_SIZE
     validation_steps
```



```
model.fit(x=train, validation_data=val, epochs=EPOCHS, steps_per_epoch=steps_per_epoch, validation_steps=validation_steps)

Epoch 1/10
2025-07-30 13:13:54.222576: E external/local_xla/xla/service/slow_operation_alarm.cc:65] Trying algorithm eng0{} for conv (f32[64,64,5,5]
{3,2,1,0}, u8[0]{0}) custom-call(f32[4,64,320,320]{3,2,1,0}, f32[4,64,320,320]{3,2,1,0}), window={size=5x5 pad=2_2x2_2}, dim_labels=bf01_oi01->b
f01, custom_call_target="__cudnn$convBackwardFilter", backend_config={"conv_result_scale":1,"activation_mode":"kNone","side_input_scale":0,"leak
yrelu_alpha":0} is taking a while...
2025-07-30 13:13:54.792818: E external/local_xla/xla/service/slow_operation_alarm.cc:133] The operation took 1.570469698s
Trying algorithm eng0{} for conv (f32[64,64,5,5]{3,2,1,0}, u8[0]{0}) custom-call(f32[4,64,320,320]{3,2,1,0}, f32[4,64,320,320]{3,2,1,0}), window
={size=5x5 pad=2_2x2_2}, dim_labels=bf01_oi01->bf01, custom_call_target="__cudnn$convBackwardFilter", backend_config={"conv_result_scale":1,"act
ivation_mode":"kNone","side_input_scale":0,"leakyrelu_alpha":0} is taking a while...
2025-07-30 13:13:57.655858: E external/local_xla/xla/service/slow_operation_alarm.cc:65] Trying algorithm eng0{} for conv (f32[64,64,5,5]
{3,2,1,0}, u8[0]{0}) custom-call(f32[4,64,320,320]{3,2,1,0}, f32[4,64,320,320]{3,2,1,0}), window={size=5x5 pad=2_2x2_2}, dim_labels=bf01_oi01->b
f01, custom_call_target="__cudnn$convBackwardFilter", backend_config={"conv_result_scale":1,"activation_mode":"kNone","side_input_scale":0,"leak
yrelu_alpha":0} is taking a while...
2025-07-30 13:13:58.241815: E external/local_xla/xla/service/slow_operation_alarm.cc:133] The operation took 1.58606215s
Trying algorithm eng0{} for conv (f32[64,64,5,5]{3,2,1,0}, u8[0]{0}) custom-call(f32[4,64,320,320]{3,2,1,0}, f32[4,64,320,320]{3,2,1,0}), window
={size=5x5 pad=2_2x2_2}, dim_labels=bf01_oi01->bf01, custom_call_target="__cudnn$convBackwardFilter", backend_config={"conv_result_scale":1,"act
ivation_mode":"kNone","side_input_scale":0,"leakyrelu_alpha":0} is taking a while...
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
I0000 00:00:1753881278.040798     121 device_compiler.h:186] Compiled cluster using XLA!  This line is logged at most once for the lifetime of t
he process.
    226/Unknown 514s 1s/step - D_HR loss: 0.1544 - D_LR loss: 0.2537 - G adv loss: 11.9327 - G content loss: 0.2418 - G cyc loss: 0.1419 - G per
ceptual loss: 42.1501 - G tv loss: 0.2340 - total D loss: 0.4081 - total G loss: 56.9451
---------------------------------------------------------------------------
```

S trenutnim naborom podatkov bi moral čakati kakšen teden, da se vse izvede. Namesto tega bom drastično zmanjšal število slik, ki bodo uporabljene.

```
[ ]: MAX_FILES_TO_USE = 300
```

```
[ ]: import random
     import glob

     all_train_files = glob.glob(os.path.join(TRAIN_PATH, "*.h5"))
     random.shuffle(all_train_files)

     train_files = all_train_files[:MAX_FILES_TO_USE]

     all_val_files = glob.glob(os.path.join(VAL_PATH, "*.h5"))
     random.shuffle(all_val_files)

     val_files = all_val_files[:int(MAX_FILES_TO_USE * 0.2)] # Npr. 20%
```

```
[ ]: def create_paired_dataset_from_list(filepaths: list) -> tf.data.Dataset:
         """
         Podobno kot `create_paired_dataset`, le da vzame kot parameter seznam␣
     ↪datotek.
         """
         # `from_generator` spodaj pričakuje signiature izhodnih podatkov
```

```
    # vsak `yield` bo vrnil dve sliki, LR in HR, primernih oblik
    out_sig = (
        tf.TensorSpec(shape=LR_SHAPE, dtype=tf.float32),
        tf.TensorSpec(shape=HR_SHAPE, dtype=tf.float32)
    )

    # dataset z imeni vseh datotek
    filepaths_dataset = tf.data.Dataset.from_tensor_slices(filepaths)

    # z generatorjem odpre vsako datoteko posebej in postopoma z `yield` vrača␣
↪pare slik
    paired_dataset = filepaths_dataset.interleave(
        lambda filepath: tf.data.Dataset.from_generator(
            generator=h5_generator,
            output_signature=out_sig,
            args=(filepath,)  # vejica, ker mora biti sequence
        ),
        cycle_length=tf.data.AUTOTUNE,       # število vhodnih elementov, ki se␣
↪procesirajo istočasno
        block_length=BLOCK_LENGTH,           # da zajame vse slike v datoteki,␣
↪ker ni fiksnega števila slojev
        num_parallel_calls=tf.data.AUTOTUNE  # za hitrejše procesiranje
    )

    paired_dataset = paired_dataset.shuffle(buffer_size=BUFFER_SIZE)
    paired_dataset = paired_dataset.batch(BATCH_SIZE)
    paired_dataset = paired_dataset.prefetch(tf.data.AUTOTUNE)

    return paired_dataset
```

[ ]:
```
def calculate_slices_v2(filepaths) -> int:
    total_slices = 0
    print("Calculating slices for ", filepaths[0][30:46], "...") # the string␣
↪slicing
    for f in filepaths:
        with h5py.File(f, "r") as hf:
            total_slices += hf["reconstruction_rss"].shape[0]
    print("Total slices:", total_slices)
    return total_slices
```

[ ]:
```
total_train_slices_sub = calculate_slices_v2(train_files)
total_val_slices_sub = calculate_slices_v2(val_files)
```

[ ]:
```
steps_per_epoch_sub = total_train_slices_sub // BATCH_SIZE
steps_per_epoch_sub
```

[ ]:
```
val_steps_sub = total_val_slices_sub // BATCH_SIZE
val_steps_sub
```

[ ]:
```
train_sub = create_paired_dataset_from_list(train_files)
val_sub = create_paired_dataset_from_list(val_files)
```

[ ]:
```
model.fit(x=train_sub, validation_data=val_sub, epochs=EPOCHS,␣
↪steps_per_epoch=steps_per_epoch_sub, validation_steps=val_steps_sub)
```