Image-to-Image Translation is a task in computer vision and machine learning where the goal is to learn a mapping between an input image and an output image, such that the output image can be used to perform a specific task, such as style transfer, data augmentation, or image restoration.

It is a class of vision and graphics problems where the goal is to learn the mapping between an input image and an output image. It can be applied to a wide range of applications, such as collection style transfer, object transfiguration, season transfer and photo enhancement.

In the pix2pix cGAN, you condition on input images and generate corresponding output images. cGANs were first proposed in Conditional Generative Adversarial Nets (Mirza and Osindero, 2014)

The architecture of your network will contain:

- A generator with a U-Net-based architecture.
- A discriminator represented by a convolutional PatchGAN classifier

```
import tensorflow as tf

import os
import pathlib
import time
import datetime

from matplotlib import pyplot as plt
from IPython import display
```

```
/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
__init__.py:98: UserWarning: unable to load
libtensorflow_io_plugins.so: unable to open file:
libtensorflow_io_plugins.so, from paths:
['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
libtensorflow_io_plugins.so']
caused by:
['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
libtensorflow_io_plugins.so: undefined symbol:
_ZN3tsl6StatusC1EN10tensorflow5error4CodeESt17basic_string_viewIcSt11c
har_traitsIcEENS_14SourceLocationE']
  warnings.warn(f"unable to load libtensorflow_io_plugins.so: {e}")
/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/__ini
t__.py:104: UserWarning: file system plugins are not loaded: unable to
open file: libtensorflow_io.so, from paths:
['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
libtensorflow_io.so']
caused by:
['/opt/conda/lib/python3.10/site-packages/tensorflow_io/python/ops/
libtensorflow_io.so: undefined symbol:
_ZTVN10tensorflow13GcsFileSystemE']
  warnings.warn(f"file system plugins are not loaded: {e}")
```

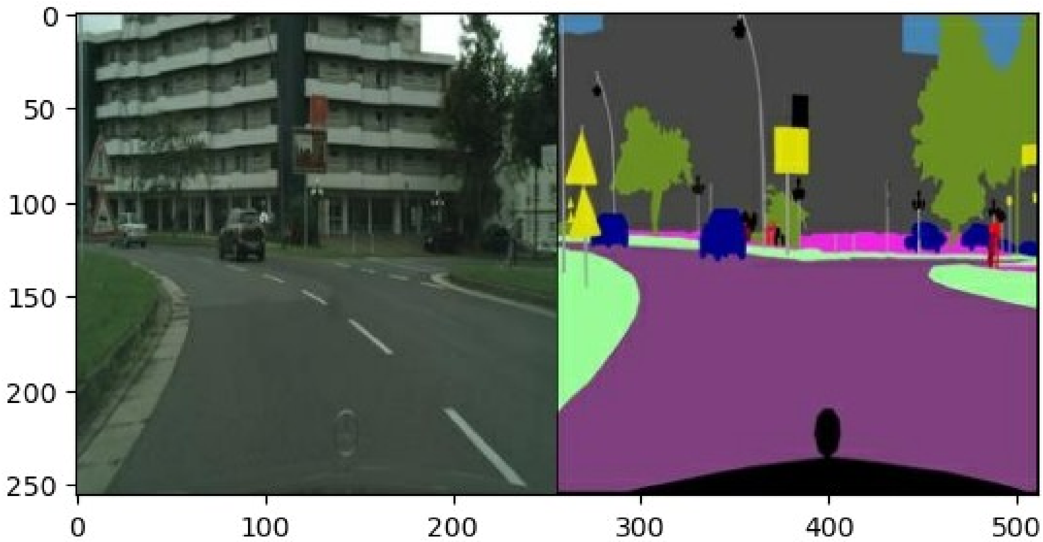
```python
dataset_name = "cityscapes"
_URL =
f'http://efrosgans.eecs.berkeley.edu/pix2pix/datasets/{dataset_name}.t
ar.gz'

path_to_zip = tf.keras.utils.get_file(
    fname=f"{dataset_name}.tar.gz",
    origin=_URL,
    extract=True)

path_to_zip  = pathlib.Path(path_to_zip)

PATH = path_to_zip.parent/dataset_name
```

```
Downloading data from
http://efrosgans.eecs.berkeley.edu/pix2pix/datasets/cityscapes.tar.gz
103441232/103441232 [==============================] - 31s 0us/step
```

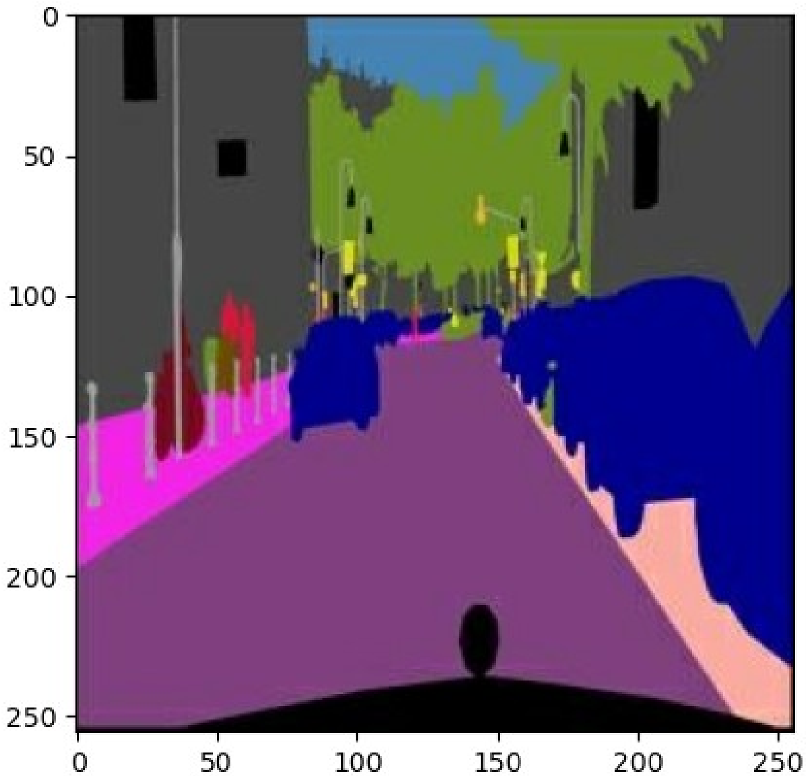
```python
sample_image = tf.io.read_file(str(PATH / 'train/1.jpg'))
sample_image = tf.io.decode_jpeg(sample_image)
print(sample_image.shape)
```

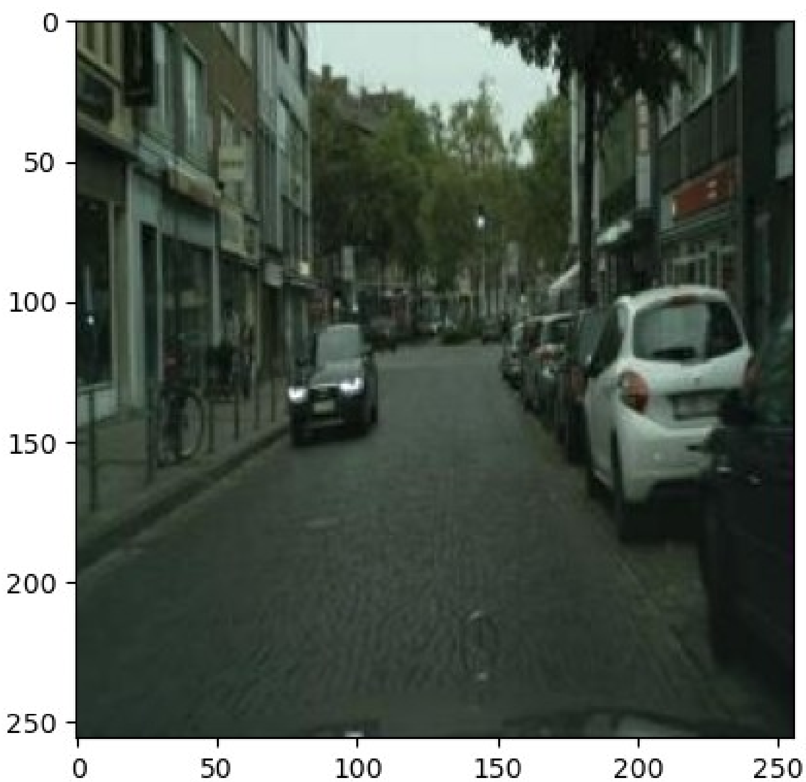
```
(256, 512, 3)
```

```python
plt.figure()
plt.imshow(sample_image)
plt.axis('on')
plt.show()
```




```
def load(image_file):
  # Read and decode an image file to a uint8 tensor
  image = tf.io.read_file(image_file)
  image = tf.io.decode_jpeg(image)

  # Split each image tensor into two tensors:
  # - one with a real building facade image
  # - one with an architecture label image
  w = tf.shape(image)[1]
  w = w // 2
  input_image = image[:, w:, :]
  real_image = image[:, :w, :]

  # Convert both images to float32 tensors
  input_image = tf.cast(input_image, tf.float32)
  real_image = tf.cast(real_image, tf.float32)

  return input_image, real_image

inp, re = load(str(PATH / 'train/100.jpg'))
# Casting to int for matplotlib to display the images
plt.figure()
plt.imshow(inp / 255.0)
plt.figure()
plt.imshow(re / 255.0)
plt.show()
```


0
50
100
150
200
250
0
50
100
150
200
250


0
50
100
150
200
250
0
50
100
150
200
250

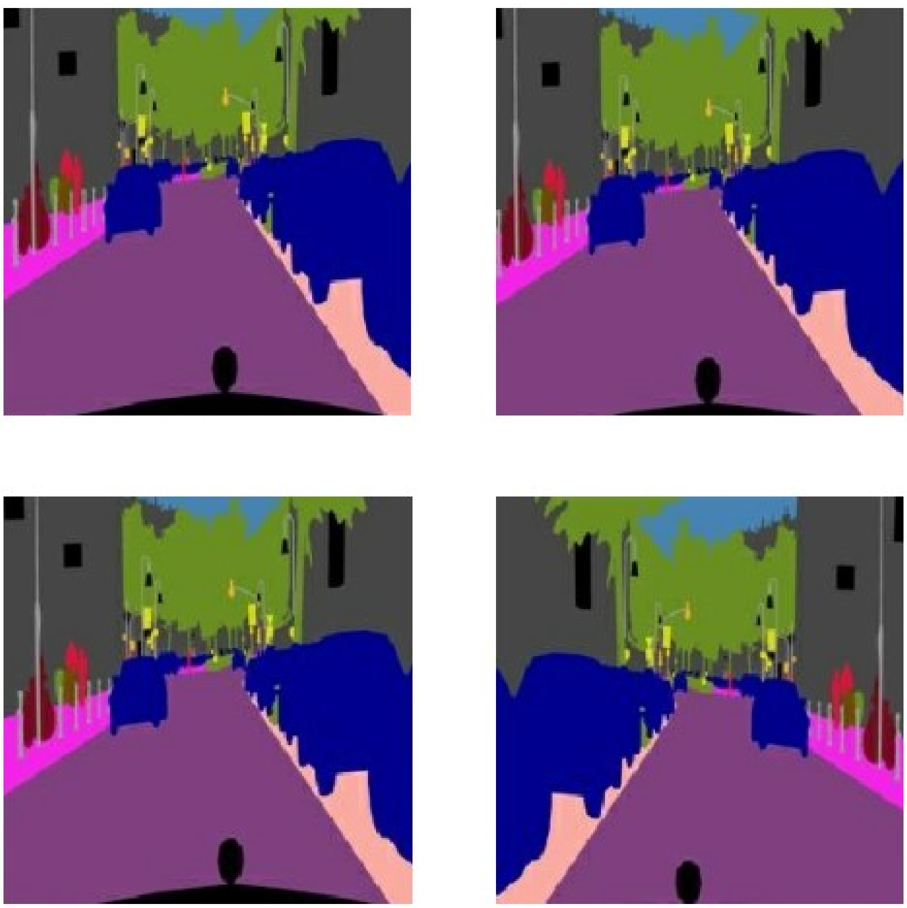
As described in the pix2pix paper, you need to apply random jittering and mirroring to preprocess the training set.

Define several functions that:

- Resize each 256 x 256 image to a larger height and width—286 x 286.
- Randomly crop it back to 256 x 256.
- Randomly flip the image horizontally i.e. left to right (random mirroring).
- Normalize the images to the [-1, 1] range.

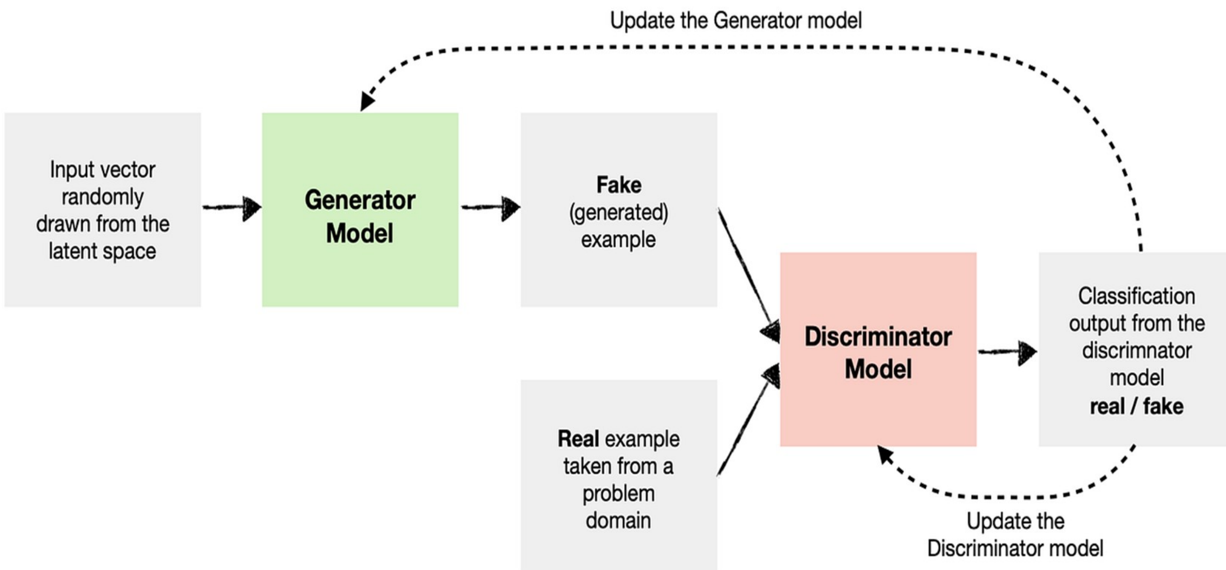
```
# The facade training set consist of 400 images
BUFFER_SIZE = 400
# The batch size of 1 produced better results for the U-Net in the
original pix2pix experiment
BATCH_SIZE = 1
# Each image is 256x256 in size
IMG_WIDTH = 256
IMG_HEIGHT = 256

def resize(input_image, real_image, height, width):
  input_image = tf.image.resize(input_image, [height, width],

method=tf.image.ResizeMethod.NEAREST_NEIGHBOR)
  real_image = tf.image.resize(real_image, [height, width],

method=tf.image.ResizeMethod.NEAREST_NEIGHBOR)

  return input_image, real_image


def random_crop(input_image, real_image):
  stacked_image = tf.stack([input_image, real_image], axis=0)
  cropped_image = tf.image.random_crop(
      stacked_image, size=[2, IMG_HEIGHT, IMG_WIDTH, 3])

  return cropped_image[0], cropped_image[1]


# Normalizing the images to [-1, 1]
def normalize(input_image, real_image):
  input_image = (input_image / 127.5) - 1
  real_image = (real_image / 127.5) - 1

  return input_image, real_image


@tf.function()
def random_jitter(input_image, real_image):
  # Resizing to 286x286
  input_image, real_image = resize(input_image, real_image, 286, 286)

  # Random cropping back to 256x256
```

```
  input_image, real_image = random_crop(input_image, real_image)

  if tf.random.uniform(()) > 0.5:
    # Random mirroring
    input_image = tf.image.flip_left_right(input_image)
    real_image = tf.image.flip_left_right(real_image)

  return input_image, real_image

plt.figure(figsize=(6, 6))
for i in range(4):
  rj_inp, rj_re = random_jitter(inp, re)
  plt.subplot(2, 2, i + 1)
  plt.imshow(rj_inp / 255.0)
  plt.axis('off')
plt.show()
```



Having checked that the loading and preprocessing works, let's define a couple of helper functions that load and preprocess the training and test sets:

```python
def load_image_train(image_file):
  input_image, real_image = load(image_file)
  input_image, real_image = random_jitter(input_image, real_image)
  input_image, real_image = normalize(input_image, real_image)

  return input_image, real_image

def load_image_test(image_file):
  input_image, real_image = load(image_file)
  input_image, real_image = resize(input_image, real_image,
                                   IMG_HEIGHT, IMG_WIDTH)
  input_image, real_image = normalize(input_image, real_image)

  return input_image, real_image

# Building an input pipeline with tf.data

train_dataset = tf.data.Dataset.list_files(str(PATH / 'train/*.jpg'))
train_dataset = train_dataset.map(load_image_train,
                                  num_parallel_calls=tf.data.AUTOTUNE)
train_dataset = train_dataset.shuffle(BUFFER_SIZE)
train_dataset = train_dataset.batch(BATCH_SIZE)


try:
  test_dataset = tf.data.Dataset.list_files(str(PATH / 'test/*.jpg'))
except tf.errors.InvalidArgumentError:
  test_dataset = tf.data.Dataset.list_files(str(PATH / 'val/*.jpg'))
test_dataset = test_dataset.map(load_image_test)
test_dataset = test_dataset.batch(BATCH_SIZE)
```



The architecture of your network will contain:

- A generator with a U-Net-based architecture.
- A discriminator represented by a convolutional PatchGAN classifier

Generator:

The generator of your pix2pix cGAN is a modified U-Net. A U-Net consists of an encoder (downsampler) and decoder (upsampler). (You can find out more about it in the Image segmentation tutorial and on the U-Net project website.)

- Each block in the encoder is: Convolution -> Batch normalization -> Leaky ReLU
- Each block in the decoder is: Transposed convolution -> Batch normalization -> Dropout (applied to the first 3 blocks) -> ReLU
- There are skip connections between the encoder and decoder (as in the U-Net).

Generator Loss:

GANs learn a loss that adapts to the data, while cGANs learn a structured loss that penalizes a possible structure that differs from the network output and the target image, as described in the pix2pix paper.

- The generator loss is a sigmoid cross-entropy loss of the generated images and an array of ones.
- The pix2pix paper also mentions the L1 loss, which is a MAE (mean absolute error) between the generated image and the target image.
- This allows the generated image to become structurally similar to the target image.
- The formula to calculate the total generator loss is gan_loss + LAMBDA * l1_loss, where LAMBDA = 100. - This value was decided by the authors of the paper.

```
# Buliding Generator

OUTPUT_CHANNELS = 3
```

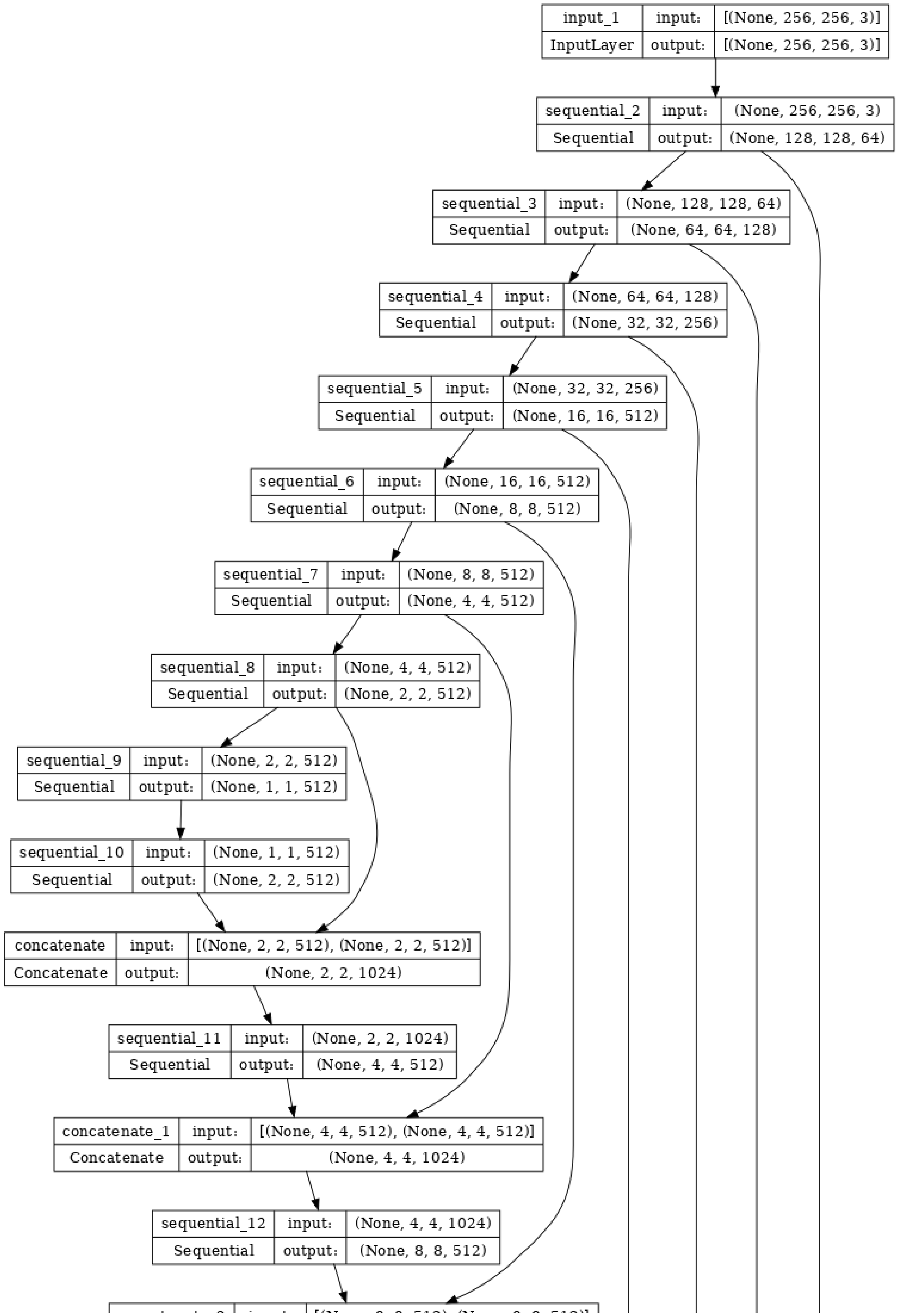
```
def downsample(filters, size, apply_batchnorm=True):
  initializer = tf.random_normal_initializer(0., 0.02)

  result = tf.keras.Sequential()
  result.add(
      tf.keras.layers.Conv2D(filters, size, strides=2, padding='same',
                             kernel_initializer=initializer,
use_bias=False))

  if apply_batchnorm:
    result.add(tf.keras.layers.BatchNormalization())

  result.add(tf.keras.layers.LeakyReLU())

  return result

down_model = downsample(3, 4)
down_result = down_model(tf.expand_dims(inp, 0))
print (down_result.shape)

def upsample(filters, size, apply_dropout=False):
  initializer = tf.random_normal_initializer(0., 0.02)

  result = tf.keras.Sequential()
  result.add(
    tf.keras.layers.Conv2DTranspose(filters, size, strides=2,
                                    padding='same',
                                    kernel_initializer=initializer,
                                    use_bias=False))

  result.add(tf.keras.layers.BatchNormalization())

  if apply_dropout:
      result.add(tf.keras.layers.Dropout(0.5))

  result.add(tf.keras.layers.ReLU())

  return result

up_model = upsample(3, 4)
up_result = up_model(down_result)
print (up_result.shape)
```

```
(1, 128, 128, 3)
(1, 256, 256, 3)
```

```
def Generator():
  inputs = tf.keras.layers.Input(shape=[256, 256, 3])

  down_stack = [
    downsample(64, 4, apply_batchnorm=False),  # (batch_size, 128,
```

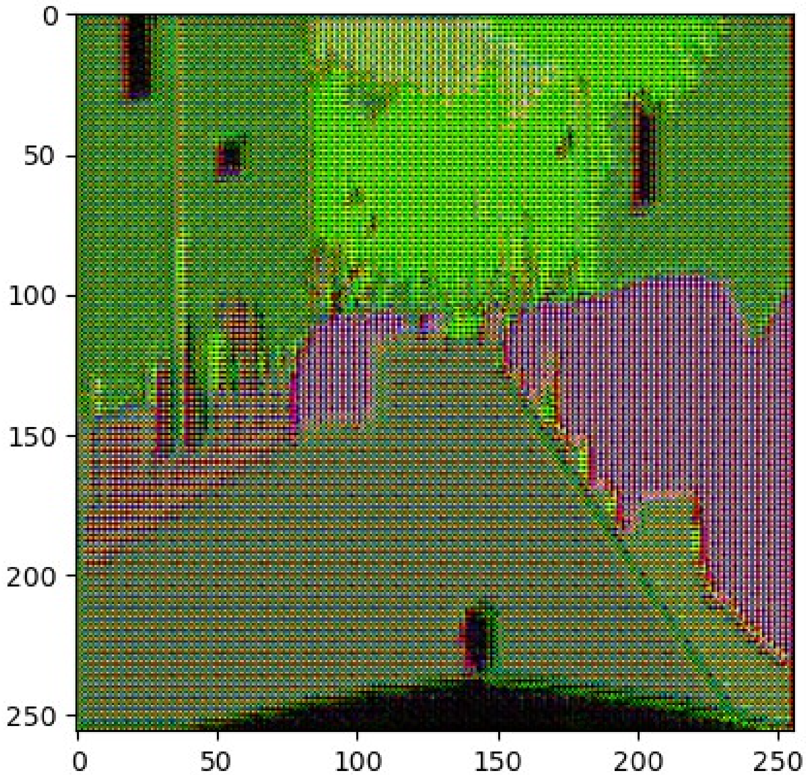
```
128, 64)
    downsample(128, 4),  # (batch_size, 64, 64, 128)
    downsample(256, 4),  # (batch_size, 32, 32, 256)
    downsample(512, 4),  # (batch_size, 16, 16, 512)
    downsample(512, 4),  # (batch_size, 8, 8, 512)
    downsample(512, 4),  # (batch_size, 4, 4, 512)
    downsample(512, 4),  # (batch_size, 2, 2, 512)
    downsample(512, 4),  # (batch_size, 1, 1, 512)
  ]

  up_stack = [
    upsample(512, 4, apply_dropout=True),  # (batch_size, 2, 2, 1024)
    upsample(512, 4, apply_dropout=True),  # (batch_size, 4, 4, 1024)
    upsample(512, 4, apply_dropout=True),  # (batch_size, 8, 8, 1024)
    upsample(512, 4),  # (batch_size, 16, 16, 1024)
    upsample(256, 4),  # (batch_size, 32, 32, 512)
    upsample(128, 4),  # (batch_size, 64, 64, 256)
    upsample(64, 4),  # (batch_size, 128, 128, 128)
  ]

  initializer = tf.random_normal_initializer(0., 0.02)
  last = tf.keras.layers.Conv2DTranspose(OUTPUT_CHANNELS, 4,
                                         strides=2,
                                         padding='same',

kernel_initializer=initializer,
                                         activation='tanh')  #
(batch_size, 256, 256, 3)

  x = inputs

  # Downsampling through the model
  skips = []
  for down in down_stack:
    x = down(x)
    skips.append(x)

  skips = reversed(skips[:-1])

  # Upsampling and establishing the skip connections
  for up, skip in zip(up_stack, skips):
    x = up(x)
    x = tf.keras.layers.Concatenate()([x, skip])

  x = last(x)

  return tf.keras.Model(inputs=inputs, outputs=x)
```

```
generator = Generator()
tf.keras.utils.plot_model(generator, show_shapes=True, dpi=64)
```



input_1 | input: | [(None, 256, 256, 3)]
InputLayer | output: | [(None, 256, 256, 3)]
sequential_2 | input: | (None, 256, 256, 3)
Sequential | output: | (None, 128, 128, 64)
sequential_3 | input: | (None, 128, 128, 64)
Sequential | output: | (None, 64, 64, 128)
sequential_4 | input: | (None, 64, 64, 128)
Sequential | output: | (None, 32, 32, 256)
sequential_5 | input: | (None, 32, 32, 256)
Sequential | output: | (None, 16, 16, 512)
sequential_6 | input: | (None, 16, 16, 512)
Sequential | output: | (None, 8, 8, 512)
sequential_7 | input: | (None, 8, 8, 512)
Sequential | output: | (None, 4, 4, 512)
sequential_8 | input: | (None, 4, 4, 512)
Sequential | output: | (None, 2, 2, 512)
sequential_9 | input: | (None, 2, 2, 512)
Sequential | output: | (None, 1, 1, 512)
sequential_10 | input: | (None, 1, 1, 512)
Sequential | output: | (None, 2, 2, 512)
concatenate | input: | [(None, 2, 2, 512), (None, 2, 2, 512)]
Concatenate | output: | (None, 2, 2, 1024)
sequential_11 | input: | (None, 2, 2, 1024)
Sequential | output: | (None, 4, 4, 512)
concatenate_1 | input: | [(None, 4, 4, 512), (None, 4, 4, 512)]
Concatenate | output: | (None, 4, 4, 1024)
sequential_12 | input: | (None, 4, 4, 1024)
Sequential | output: | (None, 8, 8, 512)

```
gen_output = generator(inp[tf.newaxis, ...], training=False)
plt.imshow(gen_output[0, ...])
plt.show()
```




```
# Generator Loss

LAMBDA = 100
loss_object = tf.keras.losses.BinaryCrossentropy(from_logits=True)

def generator_loss(disc_generated_output, gen_output, target):
  gan_loss = loss_object(tf.ones_like(disc_generated_output),
disc_generated_output)

  # Mean absolute error
  l1_loss = tf.reduce_mean(tf.abs(target - gen_output))

  total_gen_loss = gan_loss + (LAMBDA * l1_loss)

  return total_gen_loss, gan_loss, l1_loss
```

Discriminator:

The discriminator in the pix2pix cGAN is a convolutional PatchGAN classifier—it tries to classify if each image patch is real or not real, as described in the pix2pix paper.

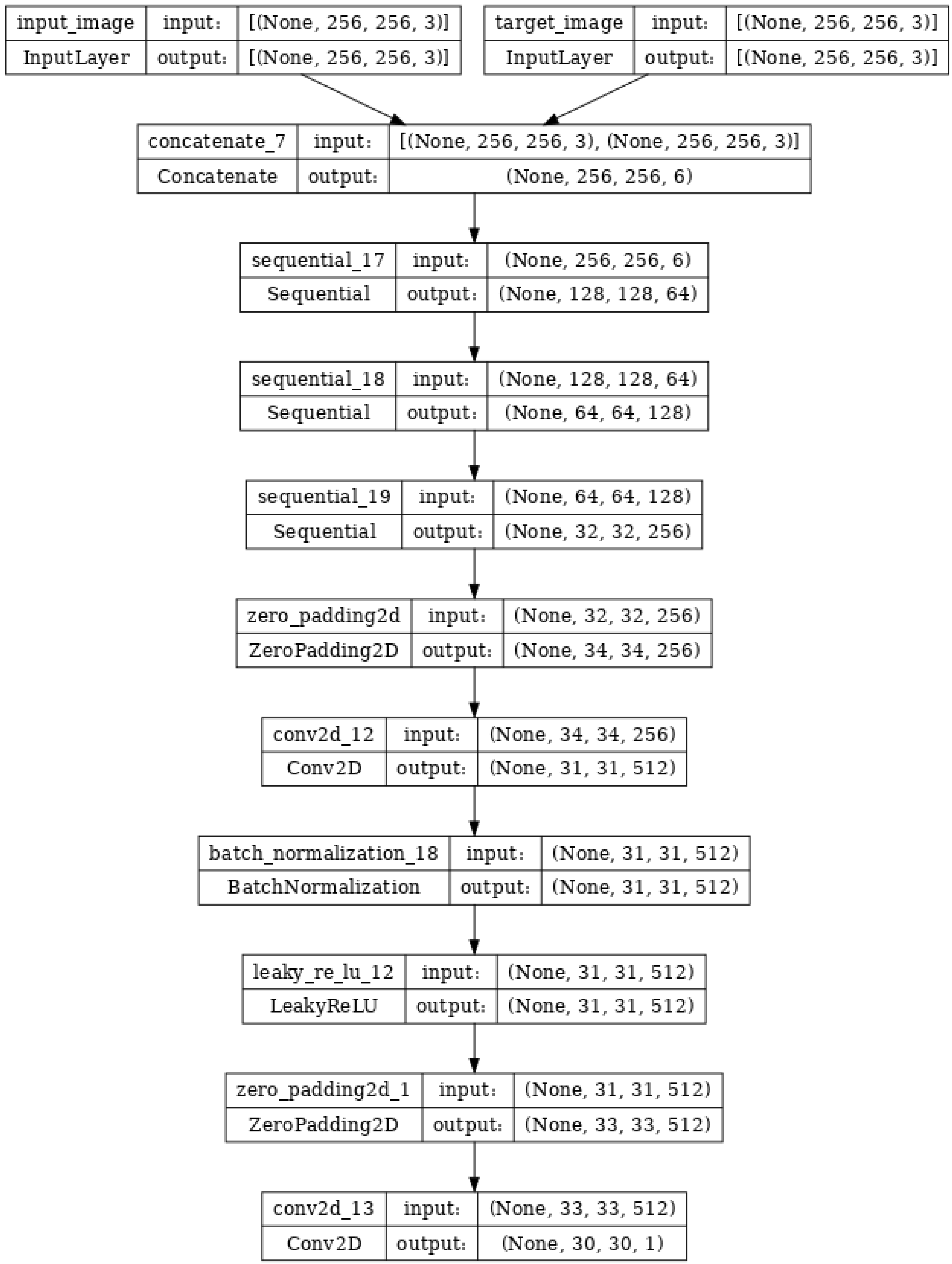
- Each block in the discriminator is: Convolution -> Batch normalization -> Leaky ReLU.
- The shape of the output after the last layer is (batch_size, 30, 30, 1).
- Each 30 x 30 image patch of the output classifies a 70 x 70 portion of the input image.
- The discriminator receives 2 inputs:
  - The input image and the target image, which it should classify as real.
  - The input image and the generated image (the output of the generator), which it should classify as fake.
  - Use tf.concat([inp, tar], axis=-1) to concatenate these 2 inputs together.

Discriminator Loss:

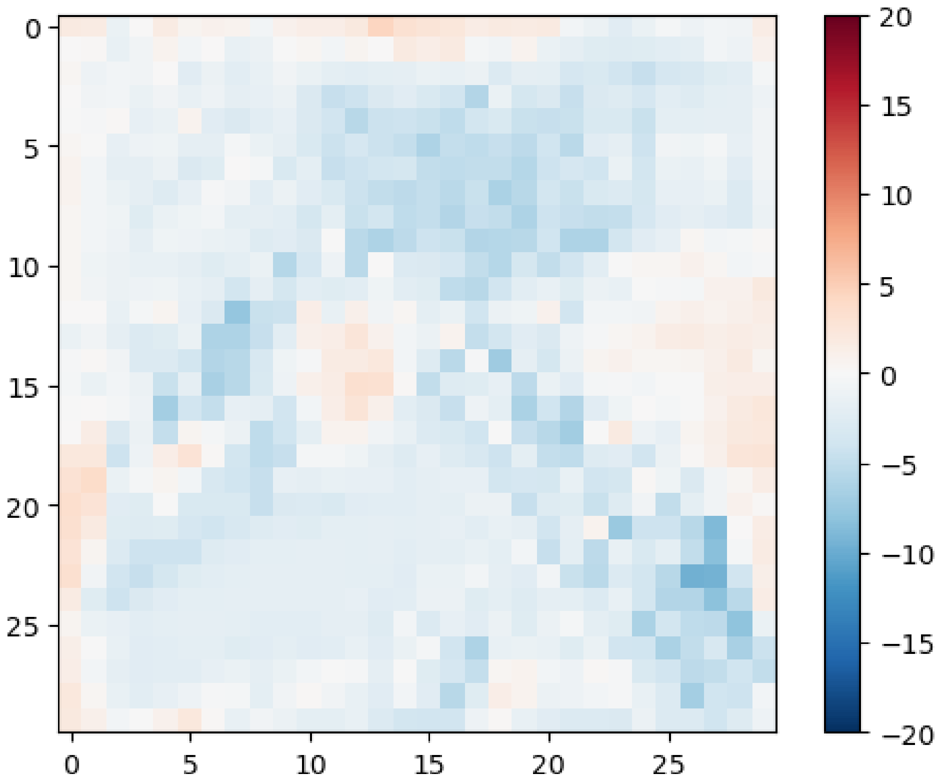
- The discriminator_loss function takes 2 inputs: real images and generated images.
- real_loss is a sigmoid cross-entropy loss of the real images and an array of ones(since these are the real images).
- generated_loss is a sigmoid cross-entropy loss of the generated images and an array of zeros (since these are the fake images).
- The total_loss is the sum of real_loss and generated_loss.

```
def Discriminator():
  initializer = tf.random_normal_initializer(0., 0.02)

  inp = tf.keras.layers.Input(shape=[256, 256, 3], name='input_image')
  tar = tf.keras.layers.Input(shape=[256, 256, 3],
name='target_image')

  x = tf.keras.layers.concatenate([inp, tar])  # (batch_size, 256,
256, channels*2)

  down1 = downsample(64, 4, False)(x)  # (batch_size, 128, 128, 64)
  down2 = downsample(128, 4)(down1)  # (batch_size, 64, 64, 128)
  down3 = downsample(256, 4)(down2)  # (batch_size, 32, 32, 256)

  zero_pad1 = tf.keras.layers.ZeroPadding2D()(down3)  # (batch_size,
34, 34, 256)
  conv = tf.keras.layers.Conv2D(512, 4, strides=1,
                                kernel_initializer=initializer,
                                use_bias=False)(zero_pad1)  #
(batch_size, 31, 31, 512)

  batchnorm1 = tf.keras.layers.BatchNormalization()(conv)

  leaky_relu = tf.keras.layers.LeakyReLU()(batchnorm1)

  zero_pad2 = tf.keras.layers.ZeroPadding2D()(leaky_relu)  #
(batch_size, 33, 33, 512)

  last = tf.keras.layers.Conv2D(1, 4, strides=1,
                                kernel_initializer=initializer)
(zero_pad2)  # (batch_size, 30, 30, 1)
```

```
  return tf.keras.Model(inputs=[inp, tar], outputs=last)


discriminator = Discriminator()
tf.keras.utils.plot_model(discriminator, show_shapes=True, dpi=64)
```


input_image
InputLayer
input:
output:
[(None, 256, 256, 3)]
[(None, 256, 256, 3)]
target_image
InputLayer
input:
output:
[(None, 256, 256, 3)]
[(None, 256, 256, 3)]
concatenate_7
Concatenate
input:
output:
[(None, 256, 256, 3), (None, 256, 256, 3)]
(None, 256, 256, 6)
sequential_17
Sequential
input:
output:
(None, 256, 256, 6)
(None, 128, 128, 64)
sequential_18
Sequential
input:
output:
(None, 128, 128, 64)
(None, 64, 64, 128)
sequential_19
Sequential
input:
output:
(None, 64, 64, 128)
(None, 32, 32, 256)
zero_padding2d
ZeroPadding2D
input:
output:
(None, 32, 32, 256)
(None, 34, 34, 256)
conv2d_12
Conv2D
input:
output:
(None, 34, 34, 256)
(None, 31, 31, 512)
batch_normalization_18
BatchNormalization
input:
output:
(None, 31, 31, 512)
(None, 31, 31, 512)
leaky_re_lu_12
LeakyReLU
input:
output:
(None, 31, 31, 512)
(None, 31, 31, 512)
zero_padding2d_1
ZeroPadding2D
input:
output:
(None, 31, 31, 512)
(None, 33, 33, 512)
conv2d_13
Conv2D
input:
output:
(None, 33, 33, 512)
(None, 30, 30, 1)

```
disc_out = discriminator([inp[tf.newaxis, ...], gen_output],
training=False)
plt.imshow(disc_out[0, ..., -1], vmin=-20, vmax=20, cmap='RdBu_r')
plt.colorbar()
plt.show()
```




```
# Discriminator Loss

def discriminator_loss(disc_real_output, disc_generated_output):
  real_loss = loss_object(tf.ones_like(disc_real_output),
disc_real_output)

  generated_loss = loss_object(tf.zeros_like(disc_generated_output),
disc_generated_output)

  total_disc_loss = real_loss + generated_loss

  return total_disc_loss

# Define the optimizers and a checkpoint-saver

generator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_1=0.5)
discriminator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_1=0.5)

checkpoint_dir = './training_checkpoints'
```

```
checkpoint_prefix = os.path.join(checkpoint_dir, "ckpt")
checkpoint =
tf.train.Checkpoint(generator_optimizer=generator_optimizer,

discriminator_optimizer=discriminator_optimizer,
                                 generator=generator,
                                 discriminator=discriminator)

def generate_images(model, test_input, tar):
  prediction = model(test_input, training=True)
  plt.figure(figsize=(15, 15))

  display_list = [test_input[0], tar[0], prediction[0]]
  title = ['Input Image', 'Ground Truth', 'Predicted Image']

  for i in range(3):
    plt.subplot(1, 3, i+1)
    plt.title(title[i])
    # Getting the pixel values in the [0, 1] range to plot.
    plt.imshow(display_list[i] * 0.5 + 0.5)
    plt.axis('off')
  plt.show()

for example_input, example_target in test_dataset.take(1):
  generate_images(generator, example_input, example_target)
```

Training:

- For each example input generates an output.
- The discriminator receives the input_image and the generated image as the first input. The second input is the input_image and the target_image.
- Next, calculate the generator and the discriminator loss.
- Then, calculate the gradients of loss with respect to both the generator and the discriminator variables(inputs) and apply those to the optimizer.
- Finally, log the losses to TensorBoard.

```
log_dir="logs/"

summary_writer = tf.summary.create_file_writer(
  log_dir + "fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M
%S"))

@tf.function
def train_step(input_image, target, step):
  with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
    gen_output = generator(input_image, training=True)

    disc_real_output = discriminator([input_image, target],
training=True)
    disc_generated_output = discriminator([input_image, gen_output],
training=True)

    gen_total_loss, gen_gan_loss, gen_l1_loss =
generator_loss(disc_generated_output, gen_output, target)
    disc_loss = discriminator_loss(disc_real_output,
disc_generated_output)

  generator_gradients = gen_tape.gradient(gen_total_loss,

generator.trainable_variables)
  discriminator_gradients = disc_tape.gradient(disc_loss,

discriminator.trainable_variables)

  generator_optimizer.apply_gradients(zip(generator_gradients,

generator.trainable_variables))
  discriminator_optimizer.apply_gradients(zip(discriminator_gradients,

discriminator.trainable_variables))

  with summary_writer.as_default():
    tf.summary.scalar('gen_total_loss', gen_total_loss,
step=step//1000)
    tf.summary.scalar('gen_gan_loss', gen_gan_loss, step=step//1000)
    tf.summary.scalar('gen_l1_loss', gen_l1_loss, step=step//1000)
    tf.summary.scalar('disc_loss', disc_loss, step=step//1000)

def fit(train_ds, test_ds, steps):
  example_input, example_target = next(iter(test_ds.take(1)))
  start = time.time()

  for step, (input_image, target) in
train_ds.repeat().take(steps).enumerate():
    if (step) % 1000 == 0:
      display.clear_output(wait=True)
```

```
      if step != 0:
        print(f'Time taken for 1000 steps: {time.time()-start:.2f} sec\n')

      start = time.time()

      generate_images(generator, example_input, example_target)
      print(f"Step: {step//1000}k")

    train_step(input_image, target, step)

    # Training step
    if (step+1) % 10 == 0:
      print('.', end='', flush=True)


    # Save (checkpoint) the model every 5k steps
    if (step + 1) % 5000 == 0:
      checkpoint.save(file_prefix=checkpoint_prefix)

fit(train_dataset, test_dataset, steps=15000)

Time taken for 1000 steps: 53.75 sec
```

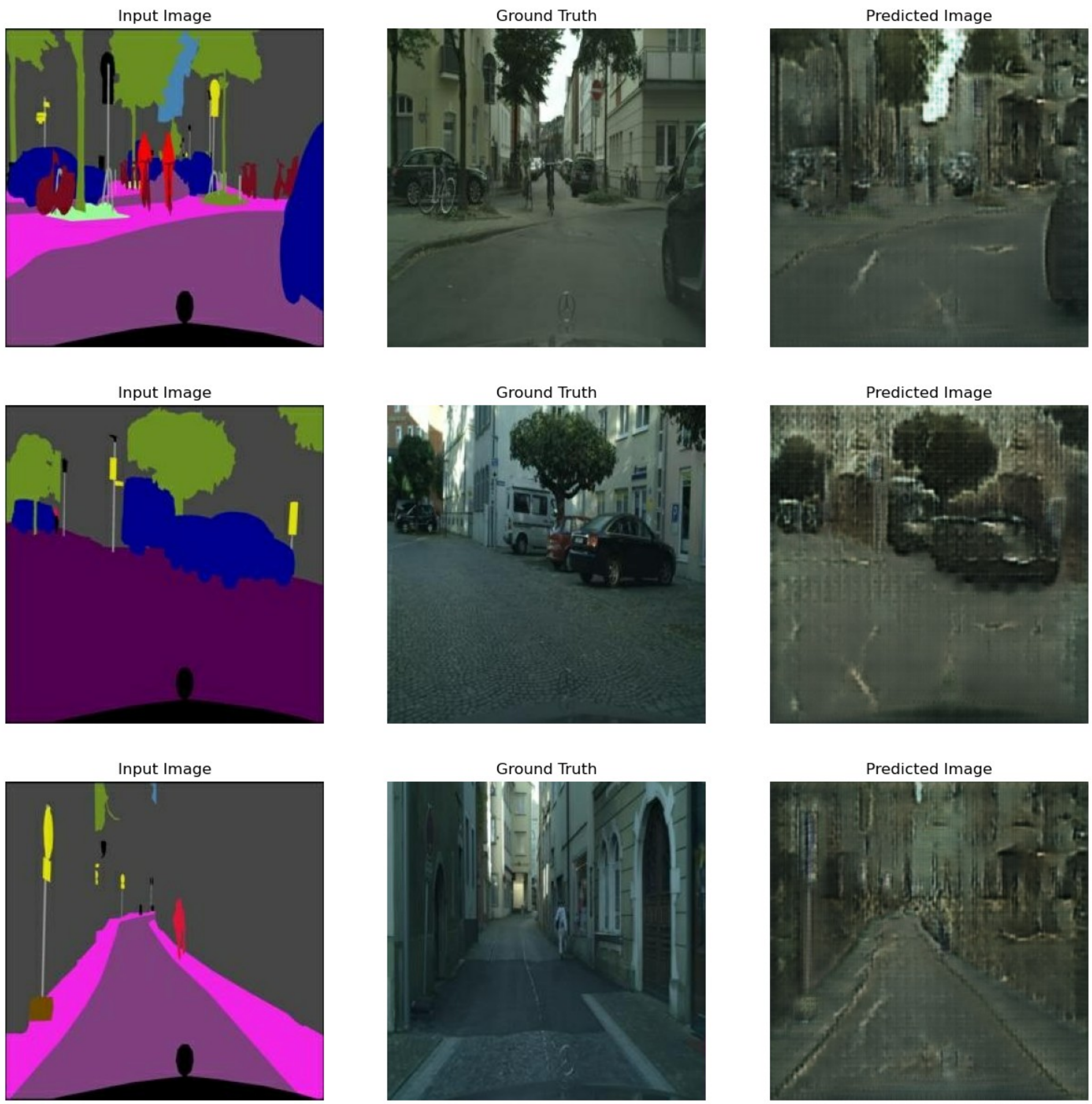

```
Step: 14k
......................................................................
..............................
```

Interpreting the logs is more subtle when training a GAN (or a cGAN like pix2pix) compared to a simple classification or regression model. Things to look for:

- Check that neither the generator nor the discriminator model has "won". If either the gen_gan_loss or the disc_loss gets very low, it's an indicator that this model is dominating the other, and you are not successfully training the combined model.
- The value log(2) = 0.69 is a good reference point for these losses, as it indicates a perplexity of 2 - the discriminator is, on average, equally uncertain about the two options.

- For the disc_loss, a value below 0.69 means the discriminator is doing better than random on the combined set of real and generated images.
- For the gen_gan_loss, a value below 0.69 means the generator is doing better than random at fooling the discriminator.
- As training progresses, the gen_l1_loss should go down.

```
# Run the trained model on a few examples from the test set
for inp, tar in test_dataset.take(5):
  generate_images(generator, inp, tar)
```




Input Image
Ground Truth
Predicted Image
Input Image
Ground Truth
Predicted Image