Image Inpainting

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Problem

Requirements

Problem	Points
Semantic segmentation	1
Instance segmentation	3
Colourization	1
Depth estimation	1
Domain adaptation	3
Super-resolution	3
Image inpainting	3
Search engine	2
3D reconstruction	4

There can be no classification or regression as the primary problem, others are possible for discussion.

Selected Image inpainting.

Dataset

Minimal size of input image 200x200px.

Requirements

- At least 1000 photos
- not mnist

Additional points

- Evaluation on a set with at least 10000 photos +1pk
- Your own part of the dataset (> 500 photos) +1pk

Description

name: Animal Faces-HQ (AFHQ)

link: https://www.kaggle.com/datasets/andrewmvd/animal-faces

description:

This dataset, also known as Animal Faces-HQ (AFHQ), consists of 16,130 high-quality images at 512×512 resolution. There are three domains of classes, each providing about 5000 images. By having multiple (three) domains and diverse images of various breeds per each domain, AFHQ sets a challenging image-to-image translation problem. The classes are:

- Cat;
- Dog;
- Wildlife

For the model, only the Cat category was used.

Processing

Each image was scaled to size 256×256.



Then each image is processed to add a black square of size 100×100 and return a binary mask showing the square, the image with the square and the image with a blurred square.

```
def apply_random_mask(img):
    mask_size = 100
    y1, x1 = np.random.randint(0, img.shape[0] - mask_size, 1)[0], np.random.randint(0, img.shape[1] - mask_size, 1)[0]
    y2, x2 = y1 + mask_size, x1 + mask_size

    binary_mask = np.zeros((img.shape[0], img.shape[1]), dtype=np.uint8)
    binary_mask[y1:y2, x1:x2] = 1

    masked_img = img.copy()
    masked_img[y1:y2, x1:x2] = 0

    blurred_img = cv2.GaussianBlur(img, (35, 35), 0)
    blurred_version = img.copy()
    blurred_version[y1:y2, x1:x2] = blurred_img[y1:y2, x1:x2]

    return binary_mask, masked_img, blurred_version
```

The images are later normalised.

Training

Requirements

- The correctly selected loss function
- Split data into train, validation and test set
- Metrics (at least 2)

Additional points

- Hyperparameter tuning or estimation +1pk
- Architecture tuning (at least 3 architecture) +1pk
- Overfitting some examples from the training set +1pk
- Data augmentation +1pk
- Cross-validation +1pk
- Distributed learning +1pk
- Federated learning +2pk
- Testing a few optimizers (at least 3) +1pk
- Testing various loss functions (at least 3) +1pk
- Calculating intrinsic dimension +1pk

```
train_original, test_original, train_blurred, test_blurred, train_masks, test_masks = train_test_split(
    original_images, blurred_images, masked_images, test_size=0.2, random_state=42
)
```

Model

Requirements

1st model	Points
pre-trained model on the same problem	0
pre-trained model on the different problem (transfer-learning)	1
ready architecture trained from scratch	1
own architecture (over 50% of own layers)	2

Additional points:

- Each subsequent model with a different architecture +1pk, for next own architecture (over 50% of own layers) +2pk
- +1pk for a every non-trivial solution in own architecture (use of attention, GAN, RL, contrastive learning, metric learning)

GAN 1

Very bad, not in the final notebook on the GitHub.

```
def build_generator(input_shape=(256, 256, 3)):
    inputs = lavers.Input(shape=input shape)
    d1 = layers.Conv2D(64, kernel_size=4, strides=2, padding="same", activation="relu")(inputs)
    d2 = layers.Conv2D(128, kernel_size=4, strides=2, padding="same", activation="relu")(d1)
    d3 = layers.Conv2D(256, kernel_size=4, strides=2, padding="same", activation="relu")(d2)
    d4 = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(d3)
    d5 = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(d4)
    d6 = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(d5)
    d7 = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(d6)
    bottleneck = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(d7)
    u1 = layers.Conv2DTranspose(512, kernel_size=4, strides=2, padding="same", activation="relu")(bottleneck)
    u1 = layers.Dropout(0.5)(u1, training=True)
    u1 = layers.Concatenate()([u1, d7])
    u2 = layers.Conv2DTranspose(512, kernel_size=4, strides=2, padding="same", activation="relu")(u1)
    u2 = layers.Dropout(0.5)(u2, training=True)
    u2 = layers.Concatenate()([u2, d6])
    u3 = layers.Conv2DTranspose(512, kernel_size=4, strides=2, padding="same", activation="relu")(u2)
    u3 = layers.Dropout(0.5)(u3, training=True)
    u3 = layers.Concatenate()([u3, d5])
    u4 = layers.Conv2DTranspose(512, kernel_size=4, strides=2, padding="same", activation="relu")(u3)
    u4 = layers.Concatenate()([u4, d4])
    u5 = layers.Conv2DTranspose(256, kernel size=4, strides=2, padding="same", activation="relu")(u4)
    u5 = layers.Concatenate()([u5, d3])
    u6 = layers.Conv2DTranspose(128, kernel_size=4, strides=2, padding="same", activation="relu")(u5)
    u6 = layers.Concatenate()([u6, d2])
    u7 = layers.Conv2DTranspose(64, kernel_size=4, strides=2, padding="same", activation="relu")(u6)
    u7 = layers.Concatenate()([u7, d1])
    outputs = layers.Conv2DTranspose(3, kernel_size=4, strides=2, padding="same", activation="tanh")(u7)
    return Model(inputs, outputs)
def build_discriminator(input_shape=(256, 256, 3)):
    inputs = layers.Input(shape=input_shape)
    x = layers.Conv2D(64, kernel_size=4, strides=2, padding="same", activation="relu")(inputs)
    x = layers.Conv2D(128, kernel_size=4, strides=2, padding="same", activation="relu")(x)
    x = layers.Conv2D(256, kernel_size=4, strides=2, padding="same", activation="relu")(x)
    x = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(x)
    x = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(x)
    x = layers.Flatten()(x)
     # outputs = layers.Conv2D(1, kernel_size=4, strides=1, padding="same", activation="sigmoid")(x)
    outputs = layers.Dense(1, activation='sigmoid')(x)
    model = Model(inputs, outputs)
    model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5),
                 loss="binary_crossentropy",
                 metrics=["accuracy"])
    return model
def gan_model(g_model, d_model, input_shape=(256, 256, 3)):
    d_model.trainable = False
    inputs = layers.Input(shape=input_shape)
    gen_output = g_model(inputs)
    output = d_model(gen_output)
    model = Model(inputs, output)
    model.compile(optimizer=tf.keras.optimizers.Adam(0.0002,0.5), loss = "binary crossentropy")
    return model
```

```
def train_step(noise, real_images, real_labels, fake_labels):
    fake_images = g_model(noise, training=True)

d_loss_real = d_model.train_on_batch(real_images, real_labels)
    d_loss_fake = d_model.train_on_batch(fake_images, fake_labels)

d_loss = 0.5 * tf.add(d_loss_real[0], d_loss_fake[0])

g_loss = gan_model.train_on_batch(noise, np.ones((half_batch, 1)))

return d_loss, g_loss
```

```
for epoch in tqdm(range(epochs), desc="Training Progress", dynamic_ncols=True):
   idx = np.random.randint(0, train_blurred.shape[0], half_batch)
   real_images = train_blurred[idx]
   idx = np.random.randint(0, train_masks.shape[0], half_batch)
   noise = train_masks[idx]
   real labels = tf.ones((half batch, 1))
   fake_labels = tf.zeros((half_batch, 1))
   d_loss, g_loss = train_step(noise, real_images, real_labels, fake_labels)
   if epoch % 100 == 0:
       print(f"{epoch} [D loss: {d_loss} | G loss: {g_loss}]")
   if epoch % 5 == 0:
       generated_images = g_model.predict(np.random.normal(0, 1, (5, 256, 256, 3)))
       fig, axs = plt.subplots(1, 5, figsize=(15, 3))
       for i in range(5):
           axs[i].imshow((generated_images[i] + 1) / 2) # Rescale to [0, 1]
           axs[i].axis('off')
       plt.show()
```

GAN₂

```
def build_generator(input_shape=(256, 256, 3)):
   inputs = layers.Input(shape=input_shape)
   d1 = layers.Conv2D(64, kernel_size=4, strides=2, padding="same", activation="relu")(inputs)
    d2 = layers.Conv2D(128, kernel_size=4, strides=2, padding="same", activation="relu")(d1)
   d3 = layers.Conv2D(256, kernel_size=4, strides=2, padding="same", activation="relu")(d2)
   d4 = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(d3)
   d5 = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(d4)
   bottleneck = layers.Conv2D(512, kernel_size=4, strides=2, padding="same", activation="relu")(d5)
   u1 = layers.Conv2DTranspose(512, kernel_size=4, strides=2, padding="same", activation="relu")(bottleneck)
   u1 = layers.Dropout(0.5)(u1, training=True)
   u1 = layers.Concatenate()([u1, d5])
   u2 = layers.Conv2DTranspose(512, kernel_size=4, strides=2, padding="same", activation="relu")(u1)
   u2 = layers.Dropout(0.5)(u2, training=True)
   u2 = layers.Concatenate()([u2, d4])
   u3 = layers.Conv2DTranspose(256, kernel_size=4, strides=2, padding="same", activation="relu")(u2)
   u3 = layers.Concatenate()([u3, d3])
   u4 = layers.Conv2DTranspose(128, kernel_size=4, strides=2, padding="same", activation="relu")(u3)
   u4 = layers.Concatenate()([u4, d2])
   u5 = layers.Conv2DTranspose(64, kernel_size=4, strides=2, padding="same", activation="relu")(u4)
   u5 = layers.Concatenate()([u5, d1])
   outputs = layers.Conv2DTranspose(3, kernel_size=4, strides=2, padding="same", activation="tanh")(u5)
  return Model(inputs, outputs)
def build_discriminator(input_shape=(256, 256, 3)):
   inputs = layers.Input(shape=input_shape)
   x = layers.Conv2D(64, kernel_size=4, strides=2, padding="same")(inputs)
   x = layers.LeakyReLU(alpha=0.2)(x)
   x = layers.Conv2D(128, kernel_size=4, strides=2, padding="same")(x)
    x = layers.BatchNormalization()(x)
   x = layers.LeakyReLU(alpha=0.2)(x)
   x = layers.Conv2D(256, kernel_size=4, strides=2, padding="same")(x)
   x = lavers.BatchNormalization()(x)
   x = layers.LeakyReLU(alpha=0.2)(x)
   x = layers.Conv2D(512, kernel_size=4, strides=2, padding="same")(x)
    x = layers.BatchNormalization()(x)
   x = layers.LeakyReLU(alpha=0.2)(x)
   x = layers.Conv2D(512, kernel_size=4, strides=2, padding="same")(x)
    x = layers.BatchNormalization()(x)
   x = layers.LeakyReLU(alpha=0.2)(x)
   outputs = layers.Conv2D(1, kernel_size=4, strides=1, padding="same", activation="sigmoid")(x) # 16x16 output
    model = Model(inputs, outputs)
    model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5),
                 loss="binary_crossentropy",
                 metrics=["accuracy"])
    model.summary()
    return model
```

```
def gan_model(g_model, d_model, input_shape=(256, 256, 3)):
    inputs = layers.Input(shape=input_shape)
    gen_output = g_model(inputs)
    output = d_model(gen_output)
    model = Model(inputs, output)
    model.compile(optimizer=tf.keras.optimizers.Adam(0.0002, 0.5), loss="binary_crossentropy")
    return model
def train_step(noise, real_images, generator, discriminator, combined_model, batch_size, g_optimizer, d_optimizer):
    real_labels = tf.ones((batch_size, 16, 16, 1))
    fake_labels = tf.zeros((batch_size, 16, 16, 1))
    with tf.GradientTape() as tape_d:
        fake_images = generator(noise, training=True)
        real_output = discriminator(real_images, training=True)
        fake_output = discriminator(fake_images, training=True)
        d_loss = discriminator_loss(real_output, fake_output)
    gradients_d = tape_d.gradient(d_loss, discriminator.trainable_variables)
    d_optimizer.apply_gradients(zip(gradients_d, discriminator.trainable_variables))
    with tf.GradientTape() as tape g:
        fake_images = generator(noise, training=True)
        fake_output = discriminator(fake_images, training=True)
        g_loss = generator_loss(real_images, fake_images, fake_output)
    gradients_g = tape_g.gradient(g_loss, generator.trainable_variables)
    g_optimizer.apply_gradients(zip(gradients_g, generator.trainable_variables))
    return d_loss, g_loss
g_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)
d_optimizer = tf.keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)
for epoch in tqdm(range(epochs), desc="Training Progress", dynamic_ncols=True):
   for step in range(len(train_masks) // batch_size):
      idx = np.random.randint(0, train_masks.shape[0], batch_size)
       real_images = train_original[idx]
       noise = train_masks[idx]
       d_loss, g_loss = train_step(noise, real_images, g_model, d_model, gan_model, batch_size, g_optimizer, d_optimizer)
   if epoch % 2 == 0:
       print(f"{epoch} [D loss: {d_loss:.4f}] [G loss: {g_loss:.4f}]")
   if epoch % 5 == 0:
      idx = np.random.randint(0, val_blurred.shape[0], 5)
       val images = val masks[idx]
       generated_images = g_model.predict(val_images)
       fig, axs = plt.subplots(2, 5, figsize=(15, 6))
       for i in range(5):
          axs[0, i].imshow((val_masks[i] + 1) / 2)
          axs[0, i].axis('off')
           axs[1, i].imshow((generated_images[i] + 1) / 2)
           axs[1, i].axis('off')
      plt.show()
```

Custom loss

```
def discriminator_loss(real_output, fake_output):
    real_loss = tf.reduce_mean(tf.nn.sigmoid_cross_entropy_with_logits(labels=tf.ones_like(real_output), logits=real_output))
    fake_loss = tf.reduce_mean(tf.nn.sigmoid_cross_entropy_with_logits(labels=tf.zeros_like(fake_output), logits=fake_output))
    return real_loss + fake_loss

def generator_loss(y_true, y_pred, discriminator_output, gamma_L1=100):
    L1_loss = tf.reduce_mean(tf.abs(y_true - y_pred))
    adv_loss = tf.reduce_mean(tf.nn.sigmoid_cross_entropy_with_logits(labels=tf.ones_like(discriminator_output), logits=discriminator_output))
    return gamma_L1 * L1_loss + adv_loss
```

CNN

```
[ ] def autoencoder(input_shape=(256, 256, 3)):
         input_img = layers.Input(shape=input_shape)
         x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(input_img)
         x = layers.MaxPooling2D((2, 2), padding='same')(x)
         x = layers.Conv2D(64, (3, 3), activation='relu', padding='same')(x)
         x = layers.MaxPooling2D((2, 2), padding='same')(x)
         x = layers.Conv2D(128, (3, 3), activation='relu', padding='same')(x)
         encoded = layers.MaxPooling2D((2, 2), padding='same')(x)
         x = layers.Conv2D(128, (3, 3), activation='relu', padding='same')(encoded)
         x = layers.UpSampling2D((2, 2))(x)
         x = layers.Conv2D(64, (3, 3), activation='relu', padding='same')(x)
         x = layers.UpSampling2D((2, 2))(x)
         x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(x)
         x = layers.UpSampling2D((2, 2))(x)
         decoded = layers.Conv2D(3, (3, 3), activation='sigmoid', padding='same')(x)
         return Model(input_img, decoded)
```

Keras-SRGAN

Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network implemented in Keras by deepak112

https://github.com/deepak112/Keras-SRGAN

Tools

Requirements

Git with Readme

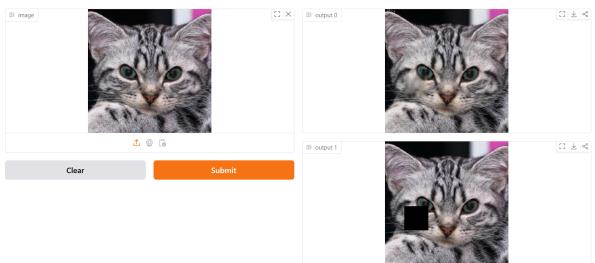
Additional points:

- MLflow, Tensorboard, Neptune, Weights & Biases (along with some analysis of experiments) +1pk
- Run as docker/ docker compose +1pk
- REST API or GUI for example Gradio, Streamlit +1pk
- DVC +2pk
- Every other MLOps tool +1pk
- Label Studio or other data labeling tools +1pk

https://huggingface.co/spaces/akrasi/CATastrophe

Image Inpainting Model

Upload an image. A random mask will be applied, and the model will attempt to fill it in.



Grading

Part	Points
Problem	3 (image inpainting)
Dataset	0
Model	2 (GAN2) +1 (GAN1) +2 (CNN) +1 (Keras-SRGAN) =6
Training	1+1=2

Tools	1 (Gradio)
Total	12