TP - Traitement d'images

Séance2: Prise en main d'un UNet

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Master 2 Data Science, Université d'Angers

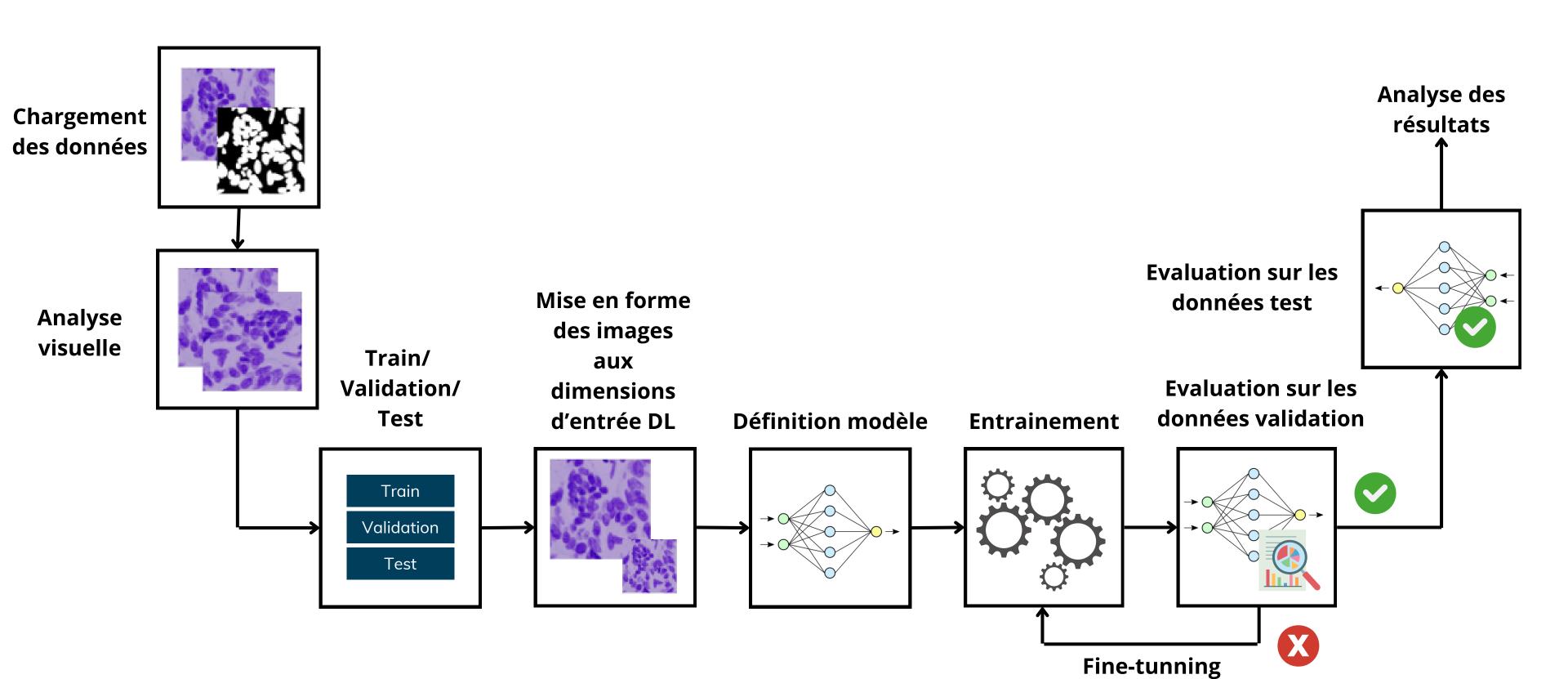
30 Janvier 2025



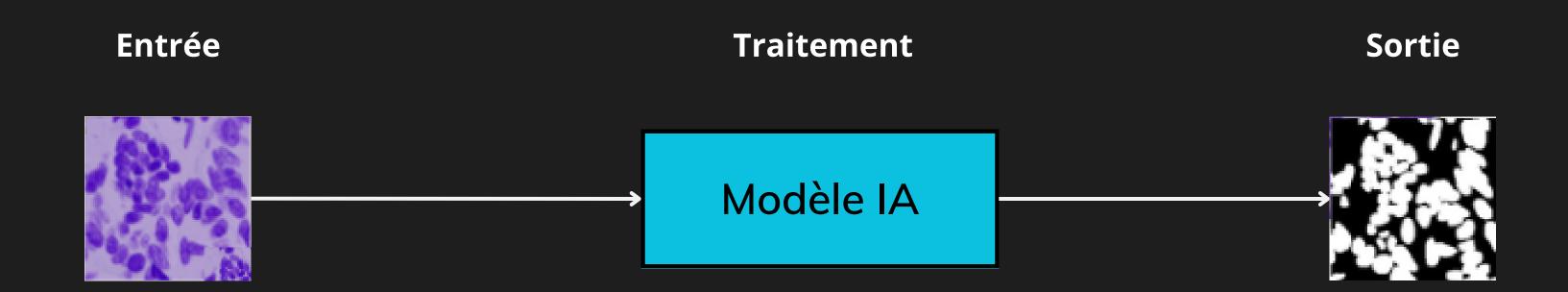
Plan de la séance

Guide pour concevoir un modèle DL de traitement d'images TP

Guide pour concevoir un modèle de traitement d'images



Objectif de ce TP : Concevoir un modèle de segmentation d'images

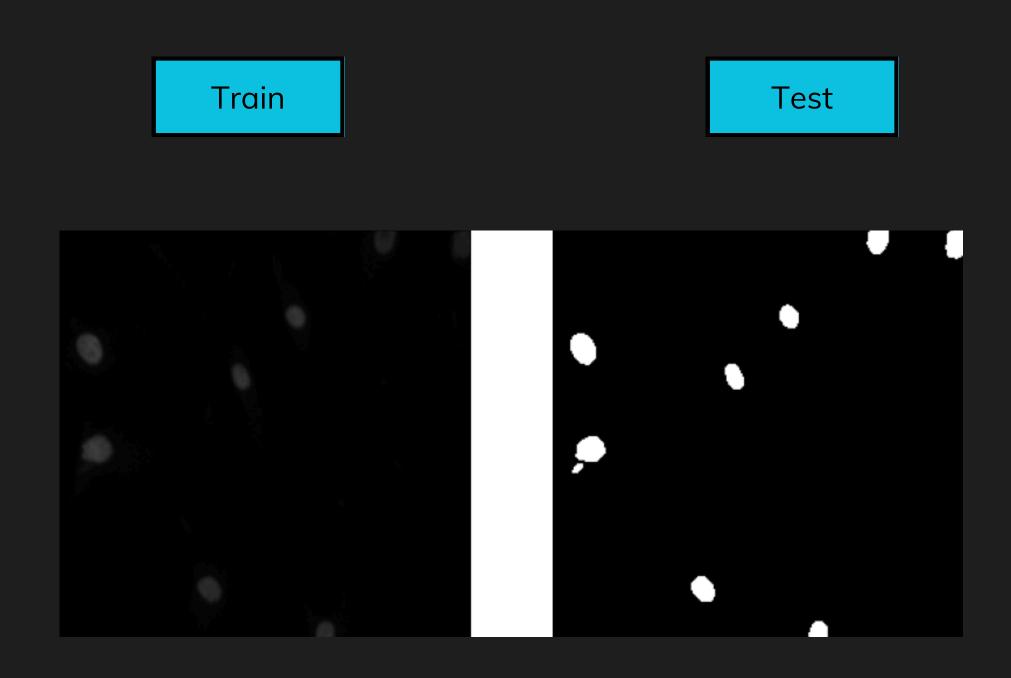


Prérequis : Importation des librairies et définition de fonctions utiles

```
import os
import sys
import random
import warnings
import numpy as np
import pandas as pd
import imageio
import matplotlib.pyplot as plt
from tadm import tadm
from itertools import chain
from skimage.io import imread, imshow, imread_collection, concatenate_images
from skimage.transform import resize
from skimage.morphology import label
from tensorflow.keras.models import Model, load model
from tensorflow.keras.layers import Input, Conv2D, Conv2DTranspose, MaxPooling2D, concatenate
from tensorflow.keras.layers import BatchNormalization, Activation, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras import backend as K
from tensorflow.keras.optimizers import Adam
import cv2
import tensorflow as tf
import matplotlib.patches as mpatches
```

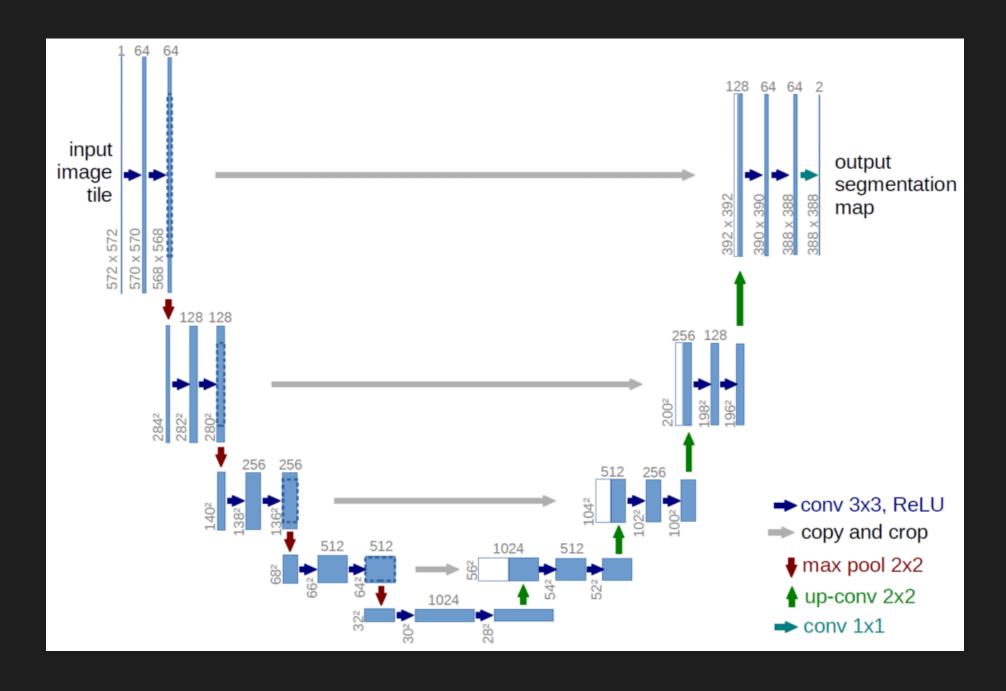
```
def show_image(ix,x_train,y_train):
 fig = plt.figure(figsize=(10, 10))
 plt.subplot(121)
 plt.imshow(x_train[ix,:,:])
 plt.subplot(122)
 plt.imshow(y_train[ix, :, :, 0],cmap='gray')
 plt.axis('off')
 plt.show()
def get_data(path, train=True):
   Loads and preprocesses image data.
   Args:
       path (str): Path to the directory containing the image data.
       train (bool, optional): Flag indicating if the data is for training.
                                Defaults to True.
   Returns:
        tuple or ndarray: If train is True, returns a tuple containing the
                         image data (X) and corresponding masks (Y).
                         If train is False, returns only the image data (X).
   # Get the list of image IDs
   ids = next(os.walk(path))[1]
   # Initialize arrays to store image data and masks
   X = np.zeros((len(ids), IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS), dtype=np.uint8)
   # Initialize masks array only if train is True
   if train:
       Y = np.zeros((len(ids), IMG_HEIGHT, IMG_WIDTH, 1), dtype=bool)
   print('Getting and resizing images ... ')
   sys.stdout.flush()
   # Iterate through each image ID
   for n, id_ in tqdm(enumerate(ids), total=len(ids)):
       path_new = path + id_
       # Read and resize the image
        img = imread(path_new + '/images/' + id_ + '.png')[:,:,:IMG_CHANNELS]
        img = resize(img, (IMG_HEIGHT, IMG_WIDTH), mode='constant', preserve_range=True)
```

I- Importation et visualisation des données



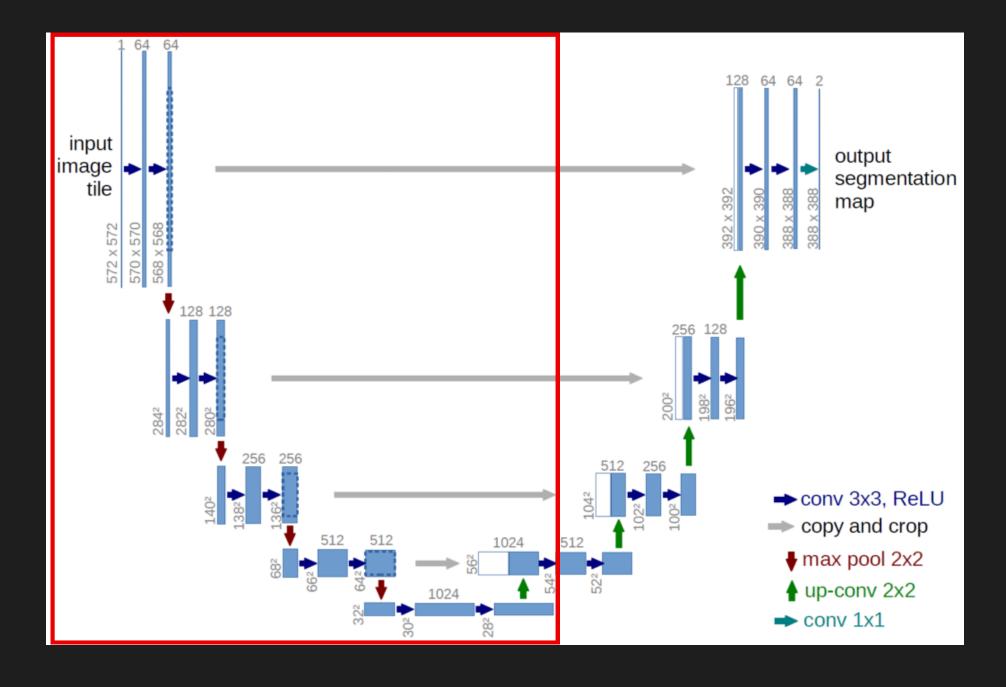
```
#Each block of u-net architecture consist of two Convolution layers
# These two layers are written in a function to make our code clean
def conv2d_block(input_tensor, n_filters,kernel_size=3):
    x = Conv2D(filters=n_filters,kernel_size=(kernel_size, kernel_size),activation='relu', padding="same")(input_tensor)
   x = Conv2D(filters=n_filters,kernel_size=(kernel_size, kernel_size),activation='relu', padding="same")(x)
   return x
# The u-net architecture consists of contracting and expansive paths which
# shrink and expands the inout image respectivly.
# Output image have the same size of input image
def get_unet(input_img, n_filters):
   # contracting path
   c1 = conv2d_block(input_img, n_filters=n_filters*4, kernel_size=3) #The first block of U-net
   p1 = MaxPooling2D((2, 2)) (c1)
   c2 = conv2d_block(p1, n_filters=n_filters*8, kernel_size=3)
    p2 = MaxPooling2D((2, 2)) (c2)
    c3 = conv2d_block(p2, n_filters=n_filters*16, kernel_size=3)
    p3 = MaxPooling2D((2, 2)) (c3)
    c4 = conv2d_block(p3, n_filters=n_filters*32, kernel_size=3)
   p4 = MaxPooling2D(pool_size=(2, 2)) (c4)
    c5 = conv2d_block(p4, n_filters=n_filters*64, kernel_size=3) # last layer on encoding path
   # expansive path
    u6 = Conv2DTranspose(n_filters*32, (3, 3), strides=(2, 2), padding='same') (c5) #upsampling included
    u6 = concatenate([u6, c4])
   c6 = conv2d_block(u6, n_filters=n_filters*32, kernel_size=3)
    u7 = Conv2DTranspose(n_filters*16, (3, 3), strides=(2, 2), padding='same') (c6)
    u7 = concatenate([u7, c3])
    c7 = conv2d_block(u7, n_filters=n_filters*16, kernel_size=3)
    u8 = Conv2DTranspose(n_filters*8, (3, 3), strides=(2, 2), padding='same') (c7)
   u8 = concatenate([u8, c2])
   c8 = conv2d_block(u8, n_filters=n_filters*8, kernel_size=3)
   u9 = Conv2DTranspose(n_filters*4, (3, 3), strides=(2, 2), padding='same') (c8)
    u9 = concatenate([u9, c1], axis=3)
    c9 = conv2d_block(u9, n_filters=n_filters*4, kernel_size=3)
   outputs = Conv2D(1, (1, 1), activation='sigmoid') (c9)
   model = Model(inputs=[input_img], outputs=[outputs])
    return model
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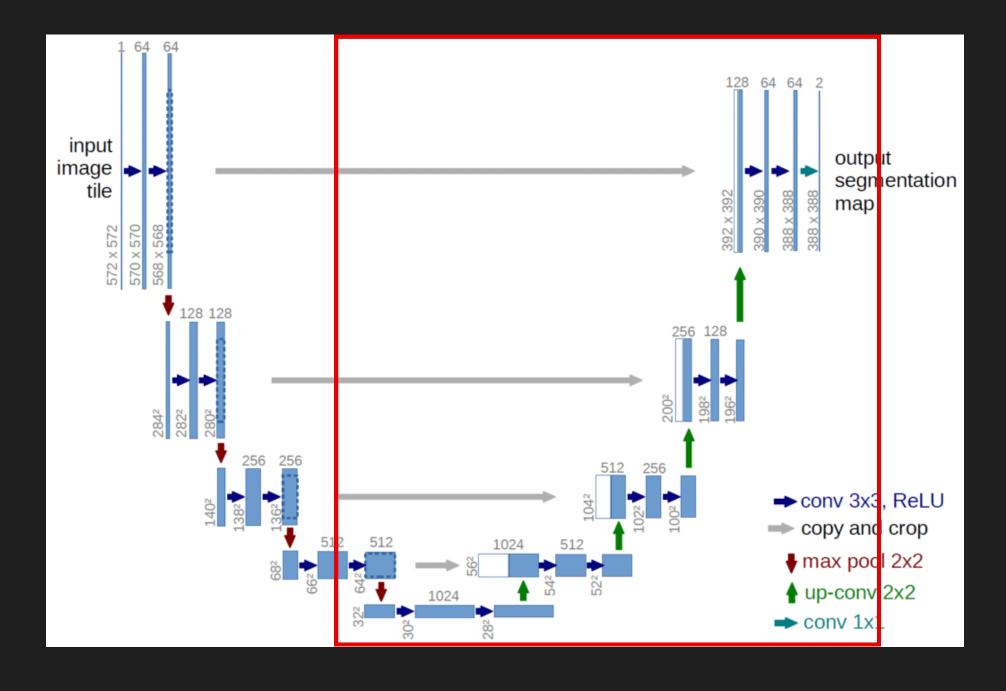


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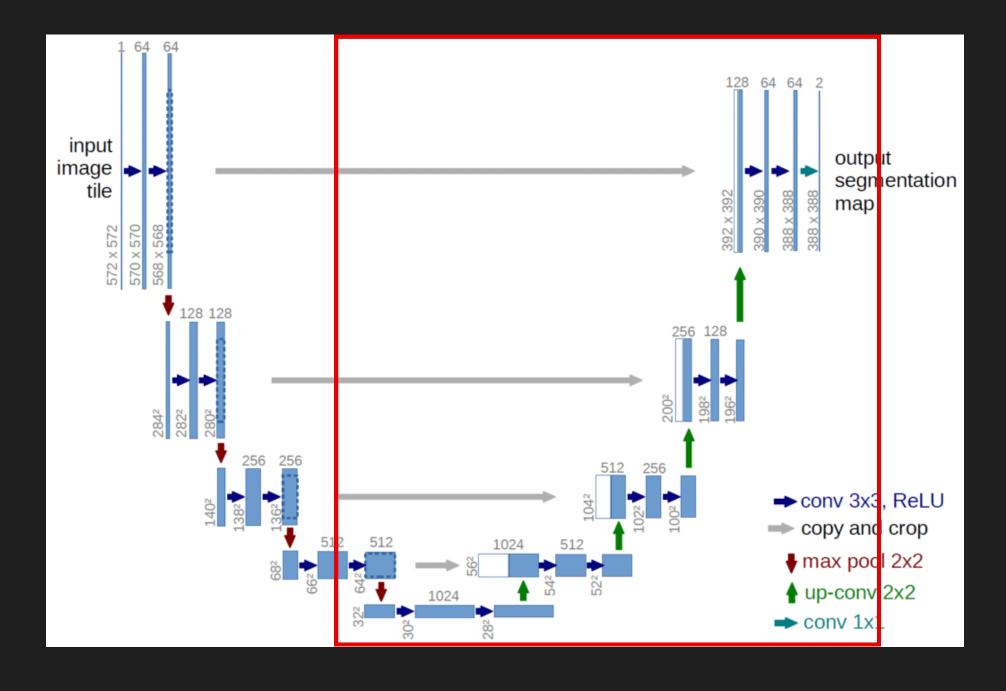
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    model = Model(inputs=[input_img], outputs=[outputs])
   return model
```



Sigmoid Function #Each bl 1.0 $\sigma(x) = \frac{1}{1 + e^{-x}}$ # These def conv 0.8 ing="same")(x) X = reti # The # shrink 0.6 # Outpu def get c1 **p1** c2 0.2 p2 с3 рЗ с4 -10.0 -7.5 -5.0-2.50.0 2.5 5.0 7.5 10.0 c5 = conv2d_block(p4, n_filters=n_filters*64, kernel_size=3) # last layer on encoding path # expansive path u6 = Conv2DTranspose(n_filters*32, (3, 3), strides=(2, 2), padding='same') (c5) #upsampling included u6 = concatenate([u6, c4]) c6 = conv2d_block(u6, n_filters=n_filters*32, kernel_size=3) u7 = Conv2DTranspose(n_filters*16, (3, 3), strides=(2, 2), padding='same') (c6) u7 = concatenate([u7, c3]) c7 = conv2d_block(u7, n_filters=n_filters*16, kernel_size=3) u8 = Conv2DTranspose(n_filters*8, (3, 3), strides=(2, 2), padding='same') (c7) u8 = concatenate([u8, c2]) c8 = conv2d_block(u8, n_filters=n_filters*8, kernel_size=3)

u9 = Conv2DTranspose(n_filters*4, (3, 3), strides=(2, 2), padding='same') (c8)

c9 = conv2d_block(u9, n_filters=n_filters*4, kernel_size=3)

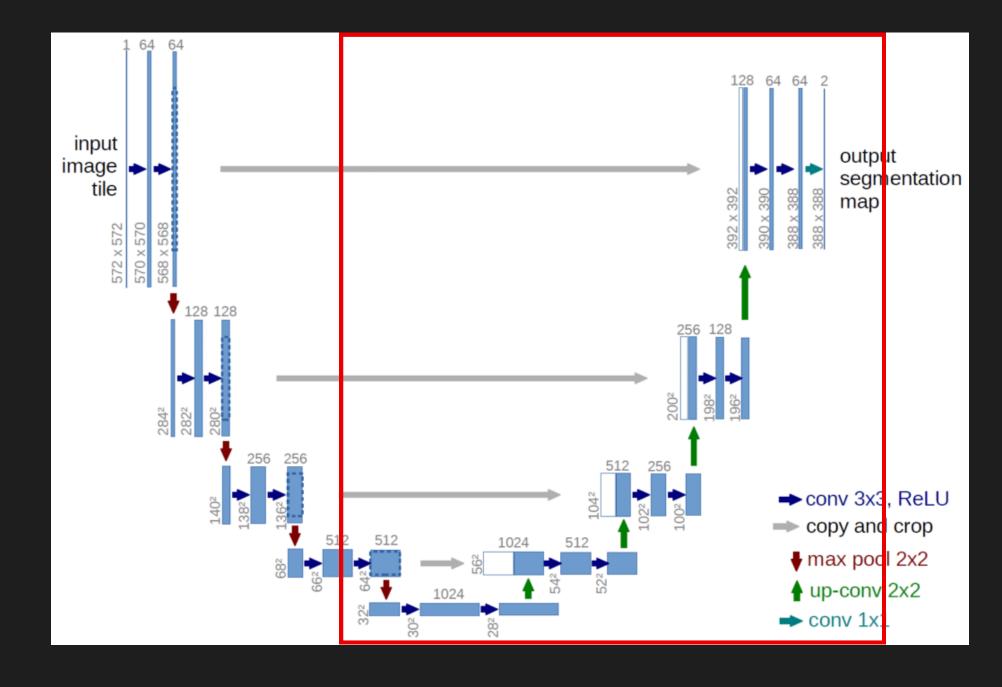
outputs = Conv2D(1, (1, 1), activation='sigmoid') (c9) model = Model(inputs=[input_img], outputs=[outputs])

u9 = concatenate([u9, c1], axis=3)

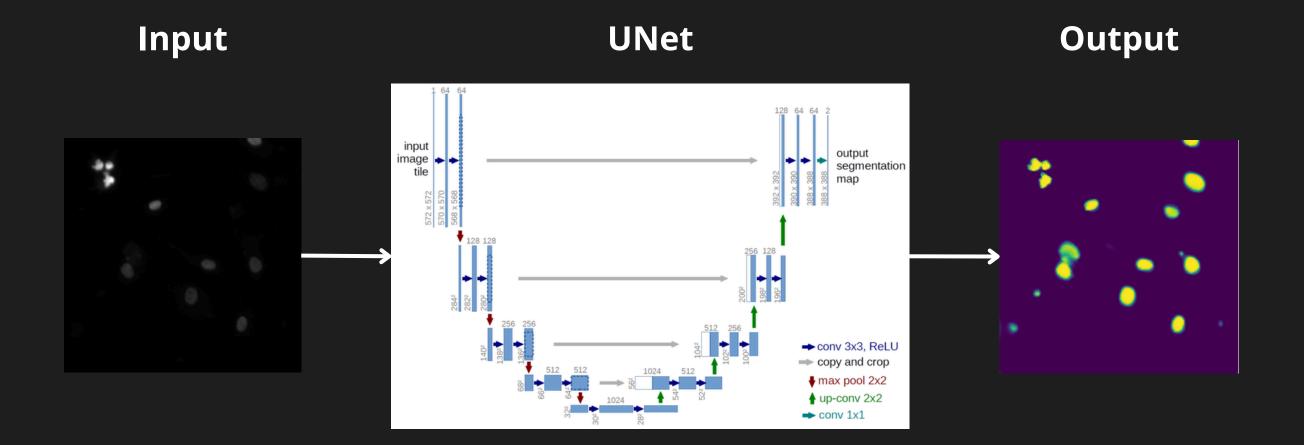
return model

V- Définition du modèle

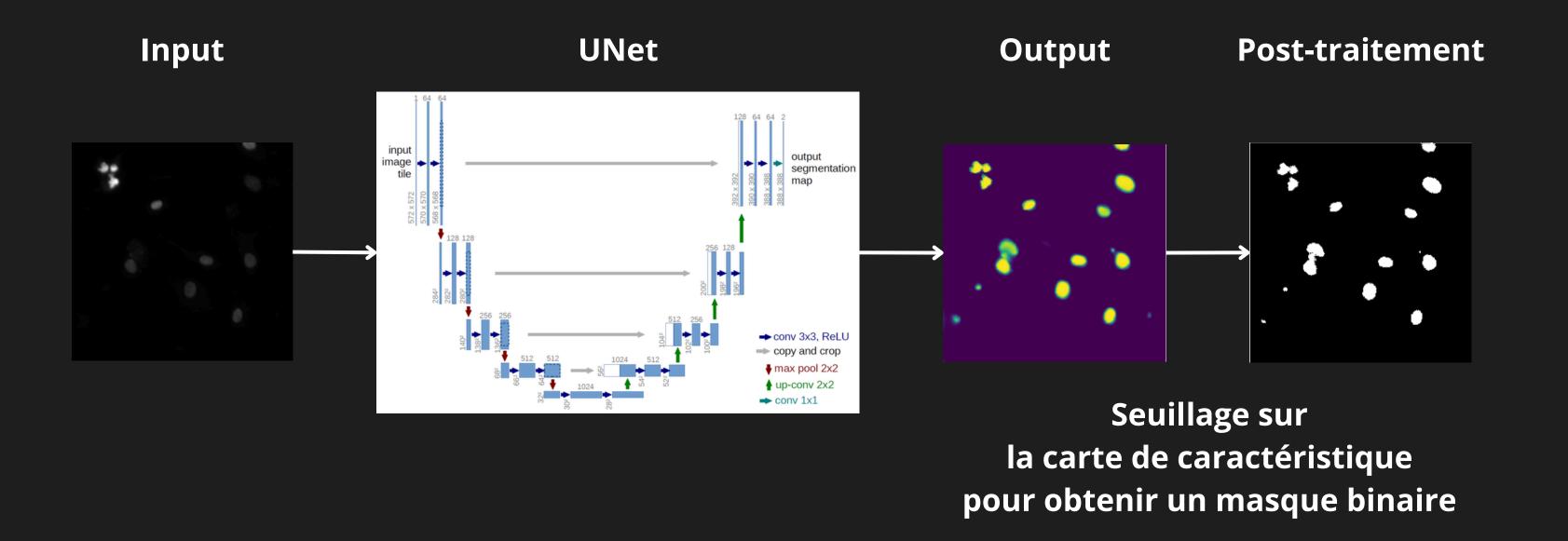
ing="same")(input_tensor)



Résumé

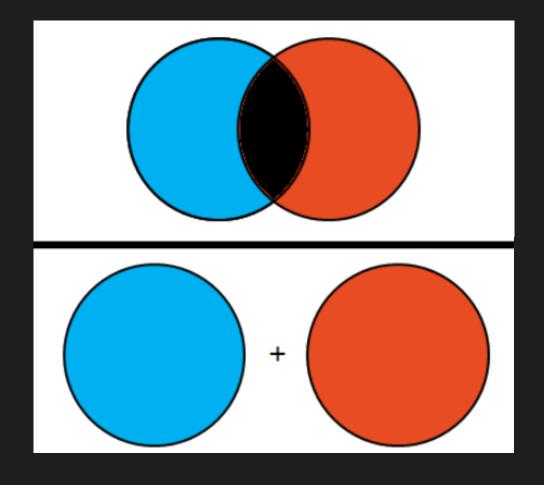


Résumé

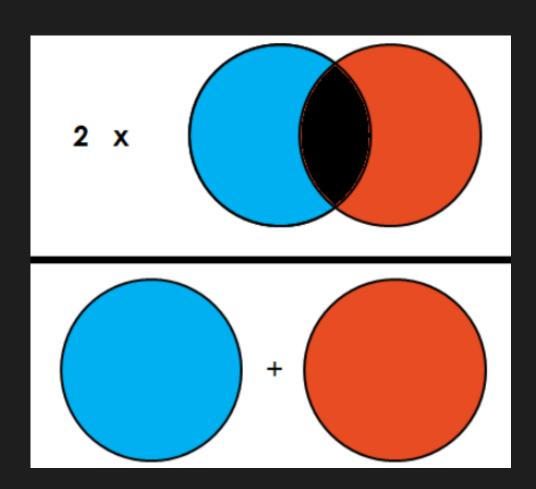


Métrique

IoU score



Dice score



Fonction de perte

Binary cross entropy

$$ext{BCE} = -rac{1}{N}\sum_{i=1}^{N}\left[y_i\log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)
ight]$$

N is the number of samples,

 y_i is the true binary label (0 or 1),

 \hat{y}_i is the predicted probability for the positive class (i.e., the model's output), \log is the natural logarithm.

Weighted binary cross entropy

$$ext{WBCE} = -rac{1}{N} \sum_{i=1}^{N} \left[w_{+} y_{i} \log(\hat{y}_{i}) + w_{-} (1-y_{i}) \log(1-\hat{y}_{i})
ight]$$

N is the number of samples,

 y_i is the true label (0 or 1),

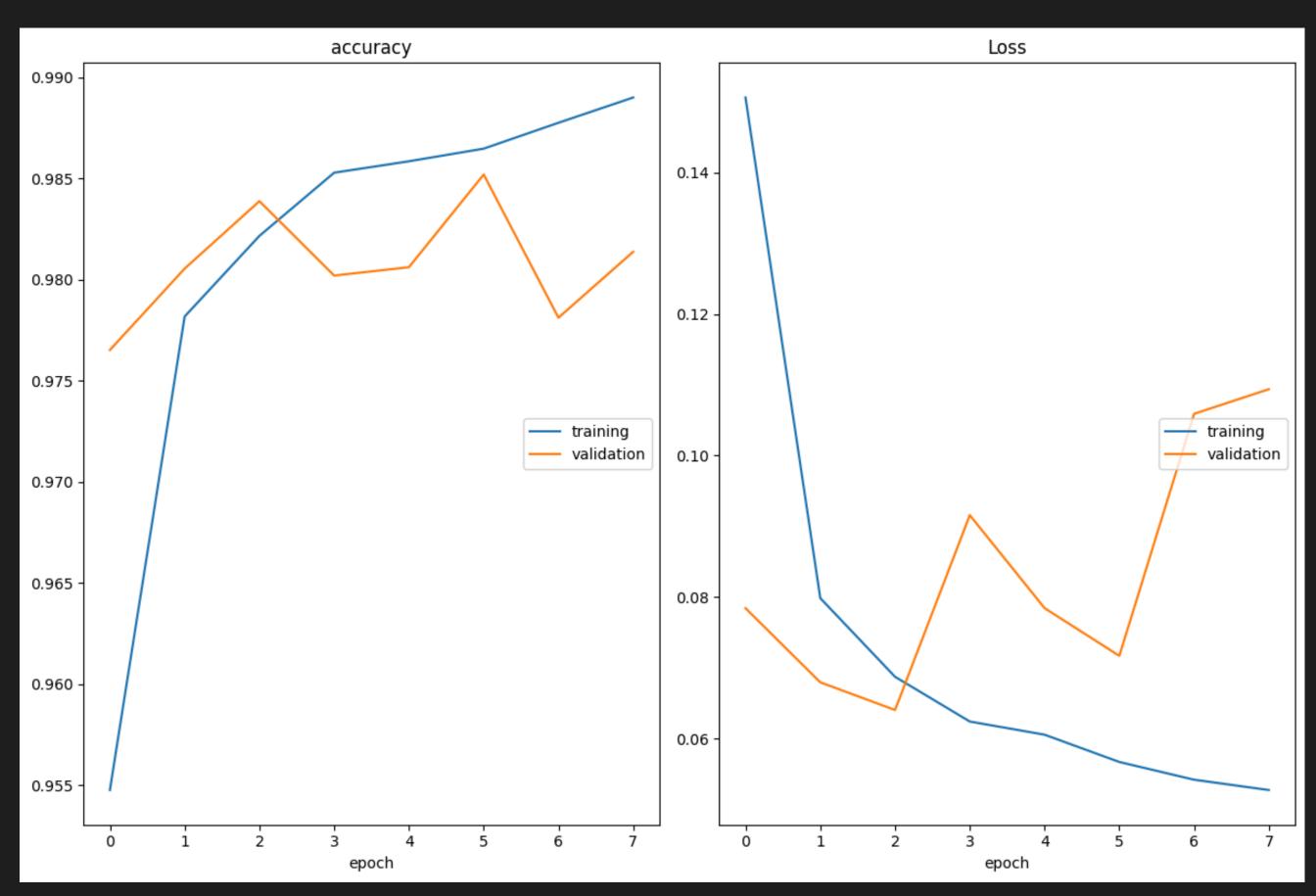
 \hat{y}_i is the predicted probability of the positive class,

 w_{+} is the weight for the positive class (label 1),

 w_{-} is the weight for the negative class (label 0),

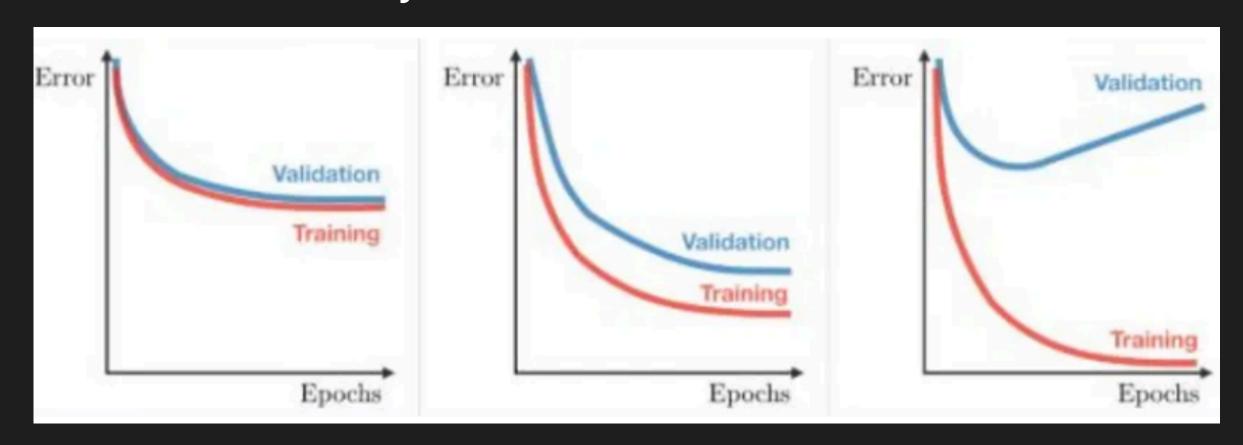
log is the natural logarithm.

Entrainement du modèle et évaluation sur les données de validation



Entrainement du modèle et évaluation sur les données de validation

Analyse des courbes d'entrainement



Underfitting

Good fitting

Overfitting

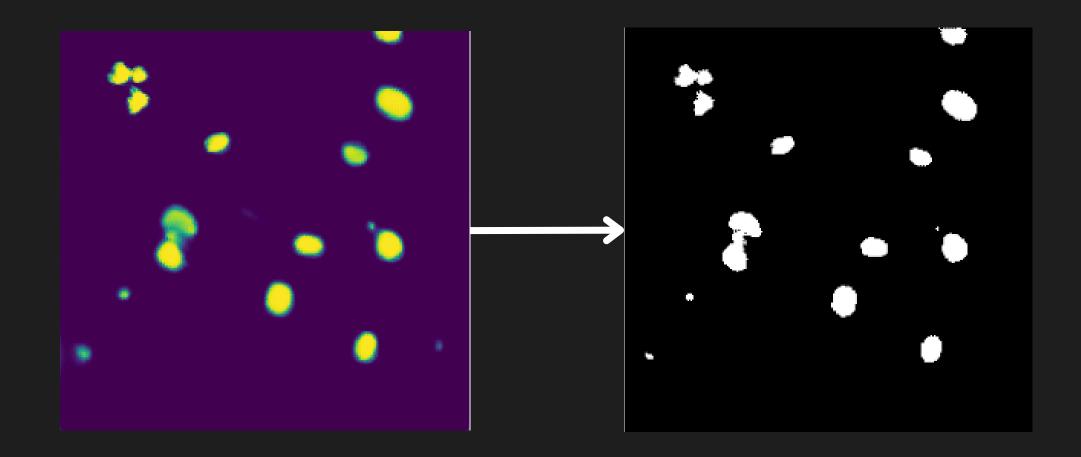
Si overfitting ou underfitting:

- 1- Appliquer un fine tunning
- 2- Réinitialiser le modèle
- 3- Lancer un nouveau entrainement

Fine tunning (ou réglage sans fin)

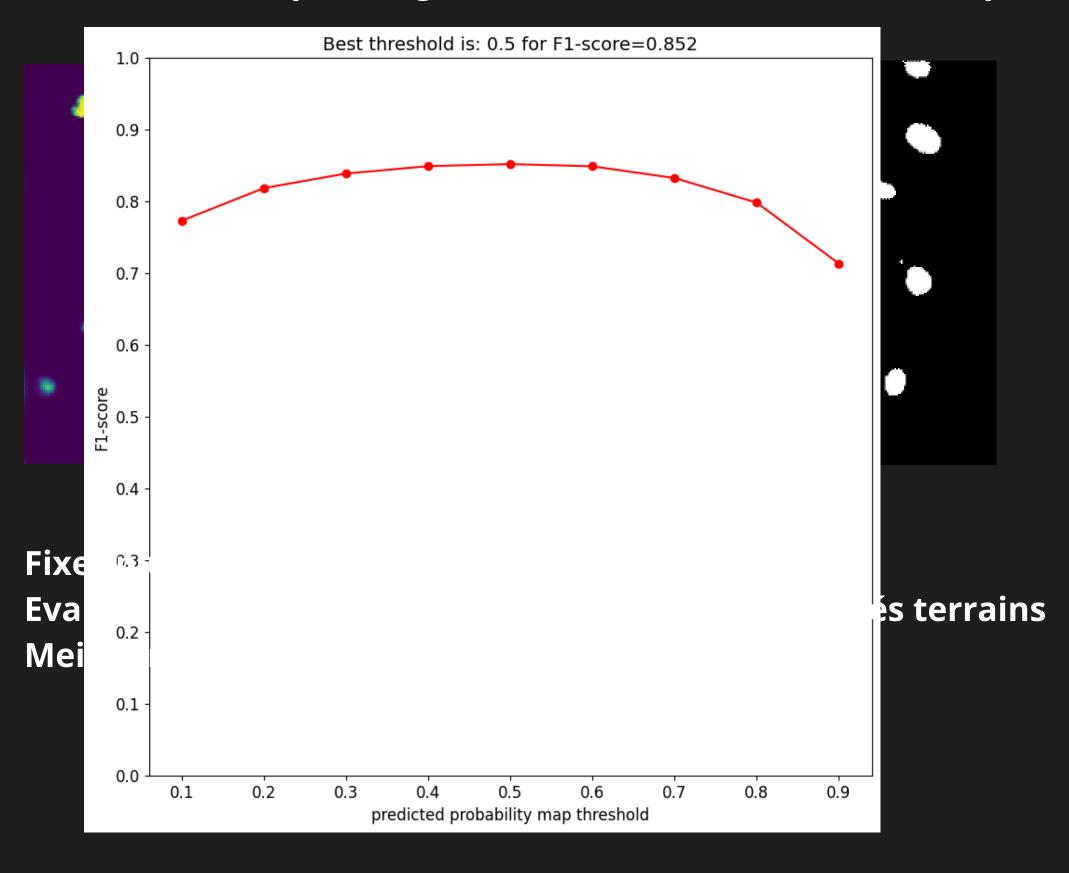
Ajustement des hyperparamètres du modèle ou de l'entrainement

Recherche du seuil pour segmenter les cartes de caractéristiques



Fixer plusieurs seuils : 0, 0.1, 0.2, ..., 0.9, 1 Evaluer avec f1 score les segmentations et les vérités terrains Meilleur seuil est associé au plus grand f1 score

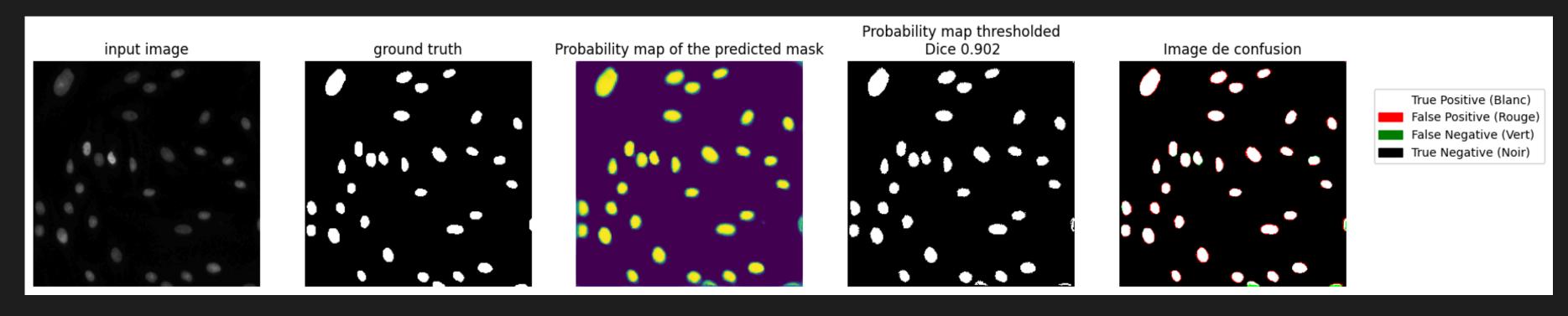
Recherche du seuil pour segmenter les cartes de caractéristiques



Evaluation sur les données test

5/5 29s 5s/step Dice coefficient: 0.959

Analyse visuelle avec l'image confusion



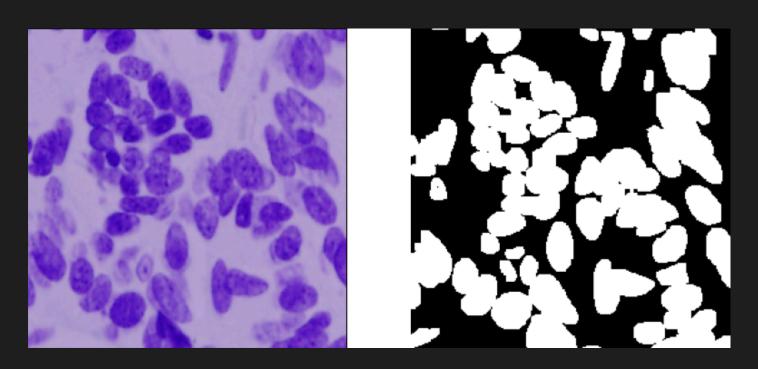
Prochaines séances

Séance 2 -

i) Prise en main d'un code de segmentation d'images UNet

ii) Techniques classiques pour améliorer un modèle : focus sur la Data Augmentation et le transfert

learning



Séance 3 - Prise en main de Napari

Séance 4 - Évaluation