# Classification des images histopathologiques de cancer: Using DeepLearning CNN

#### Réaliser par:

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### Dataset

Le cancer du sein est la forme la plus courante de cancer chez les femmes, et le carcinome canalaire invasif (IDC) est la forme la plus courante de cancer du sein. L'identification et la catégorisation précises des sous-types de cancer du sein est une tâche clinique importante, et des méthodes automatisées peuvent être utilisées pour gagner du temps et réduire les erreurs.

1. Install the Kaggle library

```
1 ! pip install -q kaggle

1 from google.colab import files
2 uploaded = files.upload()
```

6

3. Make a directory named kaggle

```
1 ! mkdir ~/.kaggle
```

4. Copy the "kaggle.json" into this new directory

```
1 ! cp kaggle.json ~/.kaggle/
```

## ▼ 5. Allocate the required permission for this file.

```
1! chmod 600 ~/.kaggle/kaggle.json
```

## 6-Download datasets

```
1 #downlod dataset
2 ! kaggle datasets download -d paultimothymooney/breast-histopathology-images
    Downloading breast-histopathology-images.zip to /content
    100% 3.10G/3.10G [00:49<00:00, 96.7MB/s]
    100% 3.10G/3.10G [00:49<00:00, 67.6MB/s]</pre>
```

## → 7-Extract the data:

1 ! unzip breast-histopathology-images.zip -d breast\_cancer\_images

```
Le flux de sortie a été tronqué et ne contient que les 5000 dernières lignes.
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
  inflating: breast cancer images/IDC regular ps50 idx5/9346/0/9346 idx5 x2351
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
  inflating: breast cancer images/IDC regular ps50 idx5/9346/0/9346 idx5 x2351
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
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  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2351_
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2401_
  inflating: breast cancer images/IDC regular ps50 idx5/9346/0/9346 idx5 x2401
  inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2401_
```

```
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2401_
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2401_
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inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2401_
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2401_
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inflating: breast cancer images/IDC regular ps50 idx5/9346/0/9346 idx5 x2451
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inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2501_
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2501_
inflating: breast cancer images/IDC regular ps50 idx5/9346/0/9346 idx5 x2501
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2501_
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2501_
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2501_
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x2501_
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x251_y
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x251_y
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x251_y
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x251_y
inflating: breast_cancer_images/IDC_regular_ps50_idx5/9346/0/9346_idx5_x251_y
```

```
1 import pandas as pd
 2 import numpy as np
 3 import os
4 from glob import glob
 5 import random
 6 import matplotlib.pylab as plt
7 import keras.backend as K
8 from sklearn.model selection import train test split
9 import tensorflow as tf
10 import keras
11 from keras.utils.np utils import to categorical
12 from keras.models import Sequential
13 from keras.layers import Dense, Dropout, Activation, Flatten, Conv2D, MaxPool2D, Max
14 %matplotlib inline
 1 try:
 2
       tpu = tf.distribute.cluster resolver.TPUClusterResolver()
 3
       print('Running on TPU ', tpu.master())
 4 except ValueError:
 5
       tpu = None
 7 if tpu:
 8
       tf.config.experimental connect to cluster(tpu)
       tf.tpu.experimental.initialize tpu system(tpu)
```

```
1 import numpy as np
2 import glob
3 import random
4 import warnings
5 warnings.filterwarnings(action = 'ignore')
6 import matplotlib.pyplot as plt
7
8 from PIL import Image
```

```
9
10 random.seed(98)
11 np.random.seed(98)
 1 breast img = glob.glob('/breast-histopathology-images/IDC_regular_ps50_idx5/**/*.png
 2
 3 for imgname in breast_img[:3]:
4
      print(imgname)
 5
 1 imagePatches = glob.glob("breast_cancer_images/**/*.png", recursive=True)
 2 for filename in imagePatches[0:10]:
 3
      print(filename)
 4
    breast cancer images/13458/0/13458 idx5 x851 y1001 class0.png
    breast_cancer_images/13458/0/13458_idx5_x801_y1001_class0.png
    breast_cancer_images/13458/0/13458_idx5_x151_y1001_class0.png
    breast_cancer_images/13458/0/13458_idx5_x1101_y1351_class0.png
    breast_cancer_images/13458/0/13458_idx5_x1301_y1351_class0.png
    breast cancer images/13458/0/13458 idx5 x501 y1051 class0.png
    breast_cancer_images/13458/0/13458_idx5_x251_y851_class0.png
    breast cancer images/13458/0/13458 idx5 x801 y901 class0.png
    breast_cancer_images/13458/0/13458_idx5_x1101_y1201_class0.png
    breast_cancer_images/13458/0/13458_idx5_x1301_y1401_class0.png
 1 non_img = []
 2 can_img = []
 3
4 for img in imagePatches:
 5
       if img[-5] == '0':
 6
           non img.append(img)
 7
      elif img[-5] == '1' :
 8
9
           can img.append(img)
 1 \text{ non num} = \text{len(non img)}
 2 can_num = len(can_img)
 4 total img num = non num + can num
 6 print('Number of Images in IDC (-): {}' .format(non_num))
 7 print('Number of Images in IDC (+) : {}' .format(can num))
 8 print('Total Number of Images : {}' .format(total_img_num))
    Number of Images in IDC (-): 397476
    Number of Images in IDC (+): 157572
    Total Number of Images: 555048
```

1 from keras.preprocessing import image

```
3 plt.figure(figsize = (15, 15))
 5 some_non = np.random.randint(0, len(non_img), 18)
 6 some_can = np.random.randint(0, len(can_img), 18)
 8 s = 0
 9 for num in some_non:
10
11
           img = image.load_img((non_img[num]), target_size=(100, 100))
12
           img = image.img_to_array(img)
13
           plt.subplot(6, 6, 2*s+1)
14
15
           plt.axis('off')
           plt.title('IDC (-)')
16
17
           plt.imshow(img.astype('uint8'))
18
           s += 1
19
20 s = 1
21 for num in some_can:
22
23
           img = image.load_img((can_img[num]), target_size=(100, 100))
           img = image.img_to_array(img)
24
25
           plt.subplot(6, 6, 2*s)
26
27
           plt.axis('off')
           plt.title('IDC (+)')
28
29
           plt.imshow(img.astype('uint8'))
           s += 1
30
```

```
1 from matplotlib.image import imread
 2 import cv2
 3
 4 some_non_img = random.sample(non_img, len(can_img))
 5 some can img = random.sample(can img, len(can img))
 7 non img arr = []
 8 can img_arr = []
10 for img in some_non_img:
11
12
       n img = cv2.imread(img, cv2.IMREAD COLOR)
13
       n_img_size = cv2.resize(n_img, (50, 50), interpolation = cv2.INTER_LINEAR)
14
       non_img_arr.append([n_img_size, 0])
15
16 for img in some_can_img:
17
       c_img = cv2.imread(img, cv2.IMREAD_COLOR)
18
19
       c img size = cv2.resize(c img, (50, 50), interpolation = cv2.INTER LINEAR)
20
       can_img_arr.append([c_img_size, 1])
21
 1 X = []
 2 y = []
 4 breast_img_arr = np.concatenate((non_img_arr, can_img_arr))
 5 random.shuffle(breast_img_arr)
 6
 7 for feature, label in breast_img_arr:
      X.append(feature)
```

```
9
      y.append(label)
10
11 X = np.array(X)
12 y = np.array(y)
13
14 print('X shape : {}' .format(X.shape))
    X shape: (315144, 50, 50, 3)
 1 from sklearn.model_selection import train_test_split
 2 from keras.utils.np utils import to categorical
 4 X train, X predict, y train, y true = train test split(X, y, test size = 0.3, random
 6 \text{ rate} = 0.5
 7 num = int(X.shape[0] * rate)
 9 X test = X train[num:]
10 X train = X train[:num]
11
12 y_test = y_train[num:]
13 y_train = y_train[:num]
14
15 y train = to categorical(y train, 2)
16 y test = to_categorical(y_test, 2)
17 y true = to_categorical(y true, 2)
18
19 print('X_train shape : {}' .format(X_train.shape))
20 print('X_test shape : {}' .format(X_test.shape))
21 print('X_predict shape : {}' .format(X_predict.shape))
22 print('y_train shape : {}' .format(y_train.shape))
23 print('y test shape : {}' .format(y test.shape))
24 print('y true shape : {}' .format(y true.shape))
    X_train shape : (157572, 50, 50, 3)
    X test shape: (63028, 50, 50, 3)
    X predict shape: (94544, 50, 50, 3)
    y_train shape : (157572, 2)
    y_test shape : (63028, 2)
    y_true shape : (94544, 2)
 1 from keras.models import Sequential
 2 from keras.layers import Conv2D, MaxPooling2D, Dropout, Flatten, Dense
 3
 4 model = Sequential()
 6 model.add(Conv2D(32, (3, 3), padding = 'same', activation = 'relu', input_shape = (5
 7 model.add(MaxPooling2D(2, 2))
 8 model.add(Dropout(0.25))
 9
10 model.add(Conv2D(64, (3, 3), padding = 'same', activation = 'relu', input_shape = (5
11 model.add(MaxPooling2D(2, 2))
```

```
12 model.add(Dropout(0.25))
13
14 model.add(Conv2D(128, (3, 3), padding = 'same', activation = 'relu', input_shape = (
15 model.add(MaxPooling2D(2, 2))
16 model.add(Dropout(0.25))
17
18 model.add(Conv2D(128, (3, 3), padding = 'same', activation = 'relu', input_shape = (
19 model.add(MaxPooling2D(2, 2))
20 model.add(Dropout(0.25))
21
22 model.add(Flatten())
23 model.add(Dense(128, activation = 'relu'))
25 model.add(Dropout(0.5))
26 model.add(Dense(2, activation = 'sigmoid'))
27
28 model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 50, 50, 32)	896
<pre>max_pooling2d (MaxPooling2D )</pre>	(None, 25, 25, 32)	0
dropout (Dropout)	(None, 25, 25, 32)	0
conv2d_1 (Conv2D)	(None, 25, 25, 64)	18496
<pre>max_pooling2d_1 (MaxPooling 2D)</pre>	(None, 12, 12, 64)	0
dropout_1 (Dropout)	(None, 12, 12, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	73856
<pre>max_pooling2d_2 (MaxPooling 2D)</pre>	(None, 6, 6, 128)	0
dropout_2 (Dropout)	(None, 6, 6, 128)	0
conv2d_3 (Conv2D)	(None, 6, 6, 128)	147584
<pre>max_pooling2d_3 (MaxPooling 2D)</pre>	(None, 3, 3, 128)	0
dropout_3 (Dropout)	(None, 3, 3, 128)	0
flatten (Flatten)	(None, 1152)	0
dense (Dense)	(None, 128)	147584
dropout_4 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 2)	258

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```
Total params: 388,674
 Trainable params: 388,674
 Non-trainable params: 0
1 #from keras.optimizers import Adam
2 from tensorflow.keras.optimizers import Adam
3
4
5 Adam = Adam(learning_rate = 0.0001)
6 model.compile(loss = 'binary_crossentropy', optimizer = Adam, metrics = ['accuracy']
1 history = model.fit(X train, y train, validation_data = (X test, y test), epochs = 1
 Epoch 1/15
 Epoch 2/15
 3152/3152 [=============== ] - 116s 37ms/step - loss: 0.3139 - accu
 Epoch 3/15
 Epoch 4/15
 Epoch 5/15
 Epoch 6/15
 Epoch 7/15
 Epoch 8/15
 Epoch 9/15
 Epoch 10/15
 Epoch 11/15
 Epoch 12/15
 Epoch 13/15
 Epoch 14/15
 Epoch 15/15
 1 model.save("model TP.h5")
1 P = model.predict(X predict)
2
3 \text{ true} = 0
4 for i in range(X_predict.shape[0]):
  if(np.argmax(P[i]) == np.argmax(y_true[i])):
```

1

```
6
        true = true + 1
7
8 pre_accuracy = 100 * float(true/X_predict.shape[0])
9 print('Predict Accuracy: {}' .format(pre_accuracy))
   Predict Accuracy: 90.53245049923845
1 result = model.evaluate(X test, y test, batch size = 50)
2 print('Test Loss, Test Accuracy :', result)
   Test Loss, Test Accuracy : [0.2760542035102844, 0.9058672189712524]
1 plt.plot(history.history['accuracy'])
2 plt.plot(history.history['val_accuracy'])
3 plt.title('Model Accuracy')
4 plt.xlabel('epoch')
5 plt.ylabel('accuracy')
6 plt.legend(['train', 'test'], loc='upper left')
7 plt.show()
```

```
1 plt.plot(history.history['loss'])
2 plt.plot(history.history['val_loss'])
3 plt.title('Model Loss')
4 plt.xlabel('epoch')
5 plt.ylabel('loss')
6 plt.legend(['train', 'test'], loc='upper left')
7 plt.show()
```

×