Annexes

Classification des panneaux de signalisation par CNN :

❒ Importation des bibliothèques :

```
import os
import pathlib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing import image
from tensorflow.python.keras.preprocessing.image import ImageDataGenerator,
img_to_array, array_to_img, load_img
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.layers import Conv2D, maxPool2D, Dense, Flatten,
Dropout
from tensorflow.keras.models import Sequential
from sklearn.metrics import accuracy_score
```

❒ Définir les constantes (chemin et autres) :

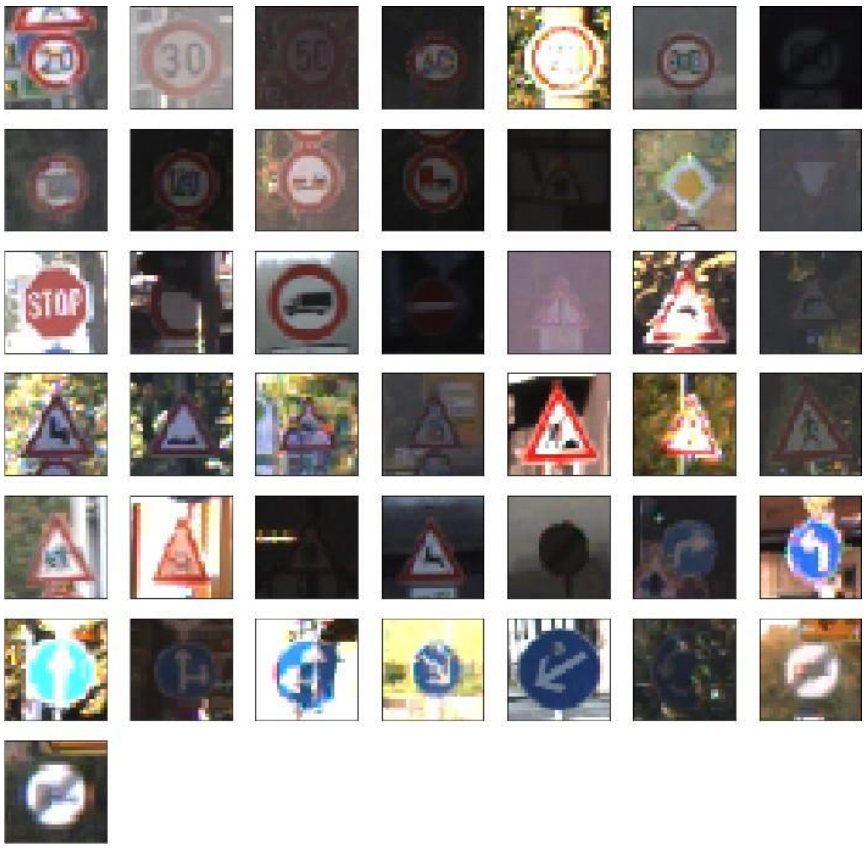
```
# directories
train_dir = '..\Train'
test_dir = '../'

# fixing width and height of each image
img_height = 30
img_width = 30
```

❒ Visualisation d’un échantillon de chaque classe :

```
# Visualizing all the categories
num_categories = len(os.listdir(train_dir))
img_dir = pathlib.Path(train_dir)
plt.figure(figsize = (14,14))
i = 0
for j in range(num_categories):
    plt.subplot(7,7,j+1)
    plt.grid(False)
    plt.xticks([])
    plt.yticks([])
    sign = list(img_dir.glob(f'{j}/*'))[0]
    img = load_img(sign,target_size = (img_width,img_height))
    plt.imshow(img)
plt.show()
num_categories
```

Output interpréteur:



❒ Création du model CNN à 3 couches :

```
#creating the model
model = Sequential()

#first convolutional layer
model.add(Conv2D(filters = 32,kernel_size = 3, activation = 'relu',
input_shape = (img_height, img_width,3)))
model.add(MaxPool2D(pool_size = (2,2)))
model.add(Dropout(rate = 0.25))

#second convolutional Layer
model.add(Conv2D(filters = 64,kernel_size = 3, activation = 'relu'))
model.add(MaxPool2D(pool_size = (2,2)))
model.add(Dropout(rate = 0.25))

#Third convolutional Layer
model.add(Conv2D(filters = 64,kernel_size = 3, activation = 'relu'))

# printing details
model.summary()
```

Output interpréteur :

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 28, 28, 32)        896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 14, 14, 32)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 12, 12, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 6, 6, 64)          0
_________________________________________________________________
dropout_2 (Dropout)          (None, 6, 6, 64)          0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 4, 4, 64)          36928
=================================================================
Total params: 56,320
```

❒ Aplanissement du couches et l'ajout d'une couche dense :

CNN se compose de $(\text{conv} - \text{pool})_n - (\text{flatten ou globalpool}) - (\text{Dense})_m$, où la partie $(\text{conv} - \text{pool})_n$ extrait les caractéristiques d'un signal 2D et $(\text{Dense})_m$ sélectionne les caractéristiques des couches précédentes.

La sortie de la dernière couche est $(4 \quad 4 \quad 64)$ qui sont 64 -*feature maps*- de taille 4 × 4 (signaux 2D). Nous les aplatissons ensuite pour obtenir un vecteur de dimension 4 × 4 × 64 = 1024 (à la place, nous pouvons également utiliser -*global max/avg pool*- pour obtenir un vecteur de dimension 64).

```
# Flattening the layer and adding Dense Layer
model.add(Flatten())
model.add(Dense(units = 64, activation = 'relu'))
model.add(Dense(num_categories, activation = 'softmax'))

# Printing details
model.summary()
```

Output interpréteur :

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 28, 28, 32)        896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 14, 14, 32)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 12, 12, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 6, 6, 64)          0
_________________________________________________________________
dropout_2 (Dropout)          (None, 6, 6, 64)          0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 4, 4, 64)          36928
_________________________________________________________________
flatten (Flatten)            (None, 1024)              0
_________________________________________________________________
dense (Dense)                (None, 64)                65600
_________________________________________________________________
dense_1 (Dense)              (None, 43)                2795
=================================================================
Total params: 124,715
```

❒ Compilation du model :

```
#compiling the model
model.compile(
loss = 'categorical_crossentropy',
optimizer = 'adam',
metrics = ['accuracy']
)
```

❒ Diviser les données en -training data- et -validation data- :

```
def load_data(train_dir):
    images = list()
    labels = list()
    for cat in range(num_categories):
        cats_train = os.path.join(train_dir, str(cat))
        for img in os.listdir(cats_train):
            img = load_img(os.path.join(cats_train, img),target_size =
(30,30))
            image = img_to_array(img)
            images.append(image)
            labels.append(cat)
    return images, labels

images, labels = load_data(train_dir)
# Converting labels to categorical data matrix
labels = to_categorical(labels)
# Splitting the dataset into training and test set
x_train, x_test, y_train, y_test = train_test_split(np.array(images),
labels, test_size = 0.3)
```

❒ Fitting the model :

```
## Fitting the model
Epochs = 30
history = model.fit(
    x_train,
    y_train,
    validation_data = (x_test, y_test),
    epochs = Epochs,
    steps_per_epoch = 60
)
```

Output interpréteur (last 3 epochs) :

```
Epoch 28/30
60/60 [==============================] - 40s 672ms/step - loss: 0.0996 - accuracy: 0.9703 - val_loss: 0.0590 - val_accuracy: 0.9856
Epoch 29/30
60/60 [==============================] - 40s 675ms/step - loss: 0.0988 - accuracy: 0.9709 - val_loss: 0.0502 - val_accuracy: 0.9862
Epoch 30/30
60/60 [==============================] - 43s 711ms/step - loss: 0.0930 - accuracy: 0.9730 - val_loss: 0.0509 - val_accuracy: 0.9878
```

❒ Validation du model et performances :

```
# printing the val_loss and val_accuracy
loss, accuracy = model.evaluate(x_test,y_test)
print('test set accuracy : ', accuracy* 100)accuracy : ', accuracy*
100)
```

Output interpréteur :

```
368/368 [==============================] - 9s 25ms/step - loss: 0.0509 -
accuracy: 0.9878
test set accuracy : 98.7758219242096
```

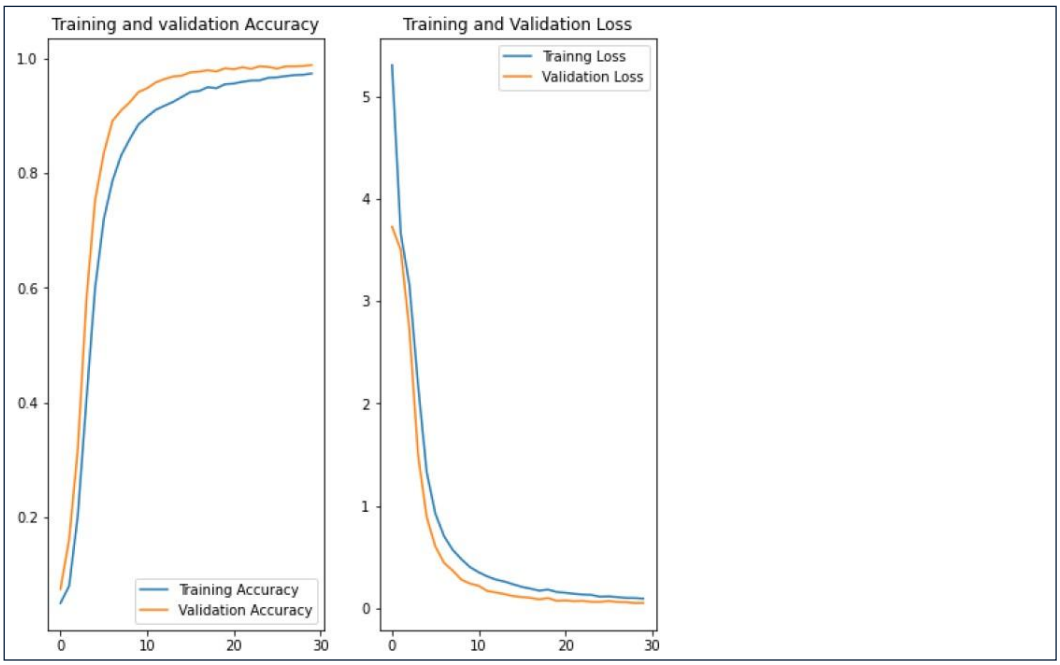
❒ Traçage du fonctions loss et accuracy :

```
# Plotting the accuracy and loss values with the training data
accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(Epochs)
plt.figure(figsize = (8,8))
plt.subplot(1,2,1)
plt.plot(epochs_range, accuracy, label = 'Training Accuracy')
plt.plot(epochs_range, val_accuracy, label = 'Validation Accuracy')
plt.legend(loc = 'lower right')
plt.title('Training and validation Accuracy')
plt.subplot(1,2,2)
plt.plot(epochs_range, loss, label = 'Trainng Loss')
plt.plot(epochs_range, val_loss, label = 'Validation Loss')
plt.legend(loc = 'upper right')
plt.title('Training and Validation Loss')
plt.show()
```

Output interpréteur :



❒ Phase du test :

```
Y_test = pd.read_csv(test_dir+'Test.csv')
test_labels = Y_test["ClassId"].values
test_images = Y_test["Path"].values

output = list()
for img in test_images :
    image = load_img(os.path.join(test_dir, img), target_size = (30,30))
    output.append(np.array(image))

X_test = np.array(output)
pred = model.predict_classes(X_test)

# Printing Accuracy with the test data
print('Test Data Accuracy : ', accuracy_score(test_labels, pred) * 100)
```

Output interpréteur :

```
Test Data Accuracy : 94.87727632620744
```

❒ Test PAR Webcam :

Classification et détection des panneaux de signalisation par YOLO V5 :

❒ Importation des bibliothèques

```
# install dependencies as necessary
!pip install -qr requirements.txt  # install dependencies (ignore errors)
import torch

from IPython.display import Image, clear_output  # to display images
from utils.google_utils import gdrive_download  # to download models/datasets

# clear_output()
print('Setup complete. Using torch %s %s' % (torch._version_, torch.cuda.get_
device_properties(0) if torch.cuda.is_available() else 'CPU'))
```

❒ Importation du modèle YOLO V5 de roboflow

```
#follow the link below to get your download code from from Roboflow
!pip install  -q  roboflow
from roboflow import Roboflow
rf = Roboflow(model_format="yolov5", notebook="roboflow-yolov5"
```

❒ Téléchargement de la data générée par roboflow

```
%cd /content/yolov5
#after following the link above, recieve python code with these fields filledin
from roboflow import Roboflow
rf = Roboflow(api_key="AFTOPTikJBOv6TMlqQDF")
project = rf.workspace().project("tsr-system")
dataset = project.version(8).download("yolov5")
```

❒ Vérification des classes

```
# this is the YAML file Roboflow wrote for us that we're loading into this not
ebook with our data
%cat {dataset.location}/data.yam
```

```
names:
- speed limit 120 km-h
- speed limit 20 km-h
- speed limit 60 km-h
- speed limit 80 km-h
- stop
nc: 5
train: TSR-System-8/train/images
val: TSR-System-8/valid/images
```

❒ Configuration et architecture du modèle

```
#this is the model configuration we will use for our tutorial
%cat /content/yolov5/models/yolov5s.yaml
```

```
# parameters
nc: {num_classes} # number of classes
depth_multiple: 0.33 # model depth multiple
width_multiple: 0.50  # layer channel multiple
# anchors
anchors:
  - [10,13, 16,30, 33,23]  # P3/8
  - [30,61, 62,45, 59,119]  # P4/16
  - [116,90, 156,198, 373,326]  # P5/32
# YOLOv5 backbone
backbone:
  # [from, number, module, args]
  [[-1, 1, Focus, [64, 3]],  # 0-P1/2
   [-1, 1, Conv, [128, 3, 2]],  # 1-P2/4
   [-1, 3, BottleneckCSP, [128]],
   [-1, 1, Conv, [256, 3, 2]],  # 3-P3/8
   [-1, 9, BottleneckCSP, [256]],
   [-1, 1, Conv, [512, 3, 2]],  # 5-P4/16
   [-1, 9, BottleneckCSP, [512]],
   [-1, 1, Conv, [1024, 3, 2]],  # 7-P5/32
   [-1, 1, SPP, [1024, [5, 9, 13]]],
   [-1, 3, BottleneckCSP, [1024, False]],  # 9
  ]
```

```
# YOLOv5 head
head:
  [[-1, 1, Conv, [512, 1, 1]],
   [-1, 1, nn.Upsample, [None, 2, 'nearest']],
   [[-1, 6], 1, Concat, [1]],  # cat backbone P4
   [-1, 3, BottleneckCSP, [512, False]],  # 1
   [-1, 1, Conv, [256, 1, 1]],
   [-1, 1, nn.Upsample, [None, 2, 'nearest']],
   [[-1, 4], 1, Concat, [1]],  # cat backbone P3
   [-1, 3, BottleneckCSP, [256, False]],  # 17 (P3/8-small)
```

```
   [-1, 1, Conv, [256, 3, 2]],
   [[-1, 14], 1, Concat, [1]],  # cat head P4
   [-1, 3, BottleneckCSP, [512, False]],  # 20 (P4/16-medium)

   [-1, 1, Conv, [512, 3, 2]],
   [[-1, 10], 1, Concat, [1]],  # cat head P5
   [-1, 3, BottleneckCSP, [1024, False]],  # 23 (P5/32-large)

   [[17, 20, 23], 1, Detect, [nc, anchors]],  # Detect(P3, P4, P5)
  ]
```

❒ Training du modèle

```
# train yolov5s on custom data for 100 epochs
# time its performance
%%time
%cd /content/yolov5/
!python train.py --img 416 --batch 16 --epochs 100 --
data {dataset.location}/data.yaml --cfg ./models/custom_yolov5s.yaml --
weights '' --name yolov5s_results --cache
```

```
Starting training for 100 epochs...

     Epoch   gpu_mem       box       obj       cls     total   targets  img_size
      0/99     1.79G   0.09273   0.02085   0.05035    0.1639         2       416: 100% 88/88 [00:55<00:00,  1.59it/s]
                Class      Images     Targets           P           R      mAP@.5  mAP@.5:.95: 100% 4/4 [00:04<00:00,
  1.08s/it]
                  all         108         110     0.00081       0.279    0.000751    0.000116

     Epoch   gpu_mem       box       obj       cls     total   targets  img_size
      1/99     1.84G   0.08241   0.02215   0.04753    0.1521         3       416: 100% 88/88 [00:50<00:00,  1.75it/s]
                Class      Images     Targets           P           R      mAP@.5  mAP@.5:.95: 100% 4/4 [00:01<00:00,
  2.11it/s]
                  all         108         110      0.0112       0.125     0.00446    0.000786

     Epoch   gpu_mem       box       obj       cls     total   targets  img_size
      2/99     1.84G   0.08033   0.02243     0.046    0.1488         1       416: 100% 88/88 [00:48<00:00,  1.80it/s]
                Class      Images     Targets           P           R      mAP@.5  mAP@.5:.95: 100% 4/4 [00:01<00:00,
  2.13it/s]
                  all         108         110       0.096      0.0434      0.0252      0.0175

     Epoch   gpu_mem       box       obj       cls     total   targets  img_size
      3/99     1.84G    0.0773   0.02261   0.04476    0.1447         1       416: 100% 88/88 [00:48<00:00,  1.80it/s]
                Class      Images     Targets           P           R      mAP@.5  mAP@.5:.95: 100% 4/4 [00:01<00:00,
  2.12it/s]
                  all         108         110       0.422      0.0211      0.0125      0.0016

     Epoch   gpu_mem       box       obj       cls     total   targets  img_size
      4/99     1.84G    0.0711   0.02436   0.04425    0.1397         1       416: 100% 88/88 [00:48<00:00,  1.80it/s]
                Class      Images     Targets           P           R      mAP@.5  mAP@.5:.95: 100% 4/4 [00:01<00:00,
  2.16it/s]
                  all         108         110     0.00848       0.366      0.0106     0.00212
...
```

❒ Test sur des images

```
# when we ran this, we saw .007 second inference time. That is 140 FPS on a TE
SLA P100!
# use the best weights!
%cd /content/yolov5/
!python detect.py --weights runs/train/yolov5s_results/weights/best.pt -
img 416 --conf 0.4 --source ../images
```

❒ Test avec webcam

CONTRIBUTORS:

ACHRAF FAYTOUT

ENGINEERING STUDENT - ARTIFICIAL INTELLIGENCE & DATA SCIENCE

MOURAD IZEM

ENGINEERING STUDENT - ARTIFICIAL INTELLIGENCE & DATA SCIENCE