Track_Activity_AI

March 26, 2025

1 Track Activity AI

1.1 Sujet : Reconnaissance d'activité humaine à partir d'un smartphone

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1.1.1 Importation des bibliothèques nécessaires

[12]:
```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from keras.utils import to_categorical
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Conv1D, MaxPooling1D, Flatten, Dense, Dropout,␣
  ↪BatchNormalization
from keras.callbacks import EarlyStopping
```

```
2025-03-20 12:24:09.046831: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2025-03-20 12:24:09.047675: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32]
Could not find cuda drivers on your machine, GPU will not be used.
2025-03-20 12:24:09.050073: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32]
Could not find cuda drivers on your machine, GPU will not be used.
2025-03-20 12:24:09.056945: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:467] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
E0000 00:00:1742487849.069228   13540 cuda_dnn.cc:8579] Unable to register cuDNN
factory: Attempting to register factory for plugin cuDNN when one has already
```

```
been registered
E0000 00:00:1742487849.072672   13540 cuda_blas.cc:1407] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
W0000 00:00:1742487849.081480   13540 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1742487849.081498   13540 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1742487849.081499   13540 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1742487849.081500   13540 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
2025-03-20 12:24:09.084433: I tensorflow/core/platform/cpu_feature_guard.cc:210]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other
operations, rebuild TensorFlow with the appropriate compiler flags.
```

1.1.2 Définition des chemins vers le dataset

[14]:
```python
base_path = 'UCI HAR Dataset'
train_path = os.path.join(base_path, 'train')
test_path = os.path.join(base_path, 'test')

train_inertial_path = os.path.join("train", "Inertial Signals")
test_inertial_path = os.path.join("test", "Inertial Signals")
```

1.1.3 Chargement des métadonnées

[16]:
```python
# Charger la liste des features qui servira de noms de colonnes pour les␣
 ↪données X
features = pd.read_csv('features.txt',
                       sep=r'\s+', header=None, names=['index', 'feature'])
feature_names = features['feature'].tolist()

# Charger les labels d'activité (pour associer un numéro d'activité à son␣
 ↪libellé)
activity_labels = pd.read_csv('activity_labels.txt',
                              sep=r'\s+', header=None, names=['index',␣
 ↪'activity'])
activity_dict = dict(zip(activity_labels['index'], activity_labels['activity']))
```

[17]:
```python
features.head()
```

[17]:
```
   index            feature
0      1  tBodyAcc-mean()-X
1      2  tBodyAcc-mean()-Y
2      3  tBodyAcc-mean()-Z
3      4   tBodyAcc-std()-X
4      5   tBodyAcc-std()-Y
```

[18]:
```
activity_labels.head()
```

[18]:
```
   index            activity
0      1             WALKING
1      2    WALKING_UPSTAIRS
2      3  WALKING_DOWNSTAIRS
3      4             SITTING
4      5            STANDING
```

1.1.4 Chargement des données d'entraînement

[20]:
```
# Fonction pour rendre les noms uniques
def make_unique(names):
    seen = {}
    unique_names = []
    for name in names:
        if name in seen:
            seen[name] += 1
            unique_names.append(f"{name}_{seen[name]}")
        else:
            seen[name] = 0
            unique_names.append(name)
    return unique_names

# Chargement des métadonnées avec des noms de colonnes uniques
features = pd.read_csv('features.txt', sep=r'\s+', header=None, names=['index',␣
 ↪'feature'])
feature_names = make_unique(features['feature'].tolist())

activity_labels = pd.read_csv('activity_labels.txt', sep=r'\s+', header=None,␣
 ↪names=['index', 'activity'])
activity_dict = dict(zip(activity_labels['index'], activity_labels['activity']))

# Chargement des données d'entraînement avec les noms de colonnes uniques
X_train = pd.read_csv('train/X_train.txt',
                      sep=r'\s+', header=None, names=feature_names)
y_train = pd.read_csv('train/y_train.txt',
                      sep=r'\s+', header=None, names=['activity'])
subject_train = pd.read_csv('train/subject_train.txt',
                            sep=r'\s+', header=None, names=['subject'])
```

[26]:
```
X_train.head()
```

[26]:
```
   tBodyAcc-mean()-X  tBodyAcc-mean()-Y  tBodyAcc-mean()-Z  tBodyAcc-std()-X  \
0           0.288585          -0.020294          -0.132905         -0.995279
1           0.278419          -0.016411          -0.123520         -0.998245
2           0.279653          -0.019467          -0.113462         -0.995380
3           0.279174          -0.026201          -0.123283         -0.996091
4           0.276629          -0.016570          -0.115362         -0.998139

   tBodyAcc-std()-Y  tBodyAcc-std()-Z  tBodyAcc-mad()-X  tBodyAcc-mad()-Y  \
0         -0.983111         -0.913526         -0.995112         -0.983185
1         -0.975300         -0.960322         -0.998807         -0.974914
2         -0.967187         -0.978944         -0.996520         -0.963668
3         -0.983403         -0.990675         -0.997099         -0.982750
4         -0.980817         -0.990482         -0.998321         -0.979672

   tBodyAcc-mad()-Z  tBodyAcc-max()-X  …  fBodyBodyGyroJerkMag-meanFreq()  \
0         -0.923527         -0.934724  …                        -0.074323
1         -0.957686         -0.943068  …                         0.158075
2         -0.977469         -0.938692  …                         0.414503
3         -0.989302         -0.938692  …                         0.404573
4         -0.990441         -0.942469  …                         0.087753

   fBodyBodyGyroJerkMag-skewness()  fBodyBodyGyroJerkMag-kurtosis()  \
0                        -0.298676                        -0.710304
1                        -0.595051                        -0.861499
2                        -0.390748                        -0.760104
3                        -0.117290                        -0.482845
4                        -0.351471                        -0.699205

   angle(tBodyAccMean,gravity)  angle(tBodyAccJerkMean),gravityMean)  \
0                    -0.112754                              0.030400
1                     0.053477                             -0.007435
2                    -0.118559                              0.177899
3                    -0.036788                             -0.012892
4                     0.123320                              0.122542

   angle(tBodyGyroMean,gravityMean)  angle(tBodyGyroJerkMean,gravityMean)  \
0                         -0.464761                             -0.018446
1                         -0.732626                              0.703511
2                          0.100699                              0.808529
3                          0.640011                             -0.485366
4                          0.693578                             -0.615971

   angle(X,gravityMean)  angle(Y,gravityMean)  angle(Z,gravityMean)
0             -0.841247              0.179941             -0.058627
1             -0.844788              0.180289             -0.054317
```

```
2              -0.848933              0.180637             -0.049118
3              -0.848649              0.181935             -0.047663
4              -0.847865              0.185151             -0.043892

[5 rows x 561 columns]
```

[28]:
```
y_train.head()
```

[28]:
```
   activity
0         5
1         5
2         5
3         5
4         5
```

[31]:
```
subject_train.head()
```

[31]:
```
   subject
0        1
1        1
2        1
3        1
4        1
```

1.1.5 Chargement des données de test

[34]:
```
X_test = pd.read_csv('test/X_test.txt',
                     sep=r'\s+', header=None, names=feature_names)
y_test = pd.read_csv('test/y_test.txt',
                     sep=r'\s+', header=None, names=['activity'])
subject_test = pd.read_csv('test/subject_test.txt',
                           sep=r'\s+', header=None, names=['subject'])
```

[36]:
```
X_test.head()
```

[36]:
```
   tBodyAcc-mean()-X  tBodyAcc-mean()-Y  tBodyAcc-mean()-Z  tBodyAcc-std()-X  \
0           0.257178          -0.023285          -0.014654         -0.938404
1           0.286027          -0.013163          -0.119083         -0.975415
2           0.275485          -0.026050          -0.118152         -0.993819
3           0.270298          -0.032614          -0.117520         -0.994743
4           0.274833          -0.027848          -0.129527         -0.993852

   tBodyAcc-std()-Y  tBodyAcc-std()-Z  tBodyAcc-mad()-X  tBodyAcc-mad()-Y  \
0         -0.920091         -0.667683         -0.952501         -0.925249
1         -0.967458         -0.944958         -0.986799         -0.968401
2         -0.969926         -0.962748         -0.994403         -0.970735
3         -0.973268         -0.967091         -0.995274         -0.974471
```

```
4        -0.967445        -0.978295        -0.994111        -0.965953

   tBodyAcc-mad()-Z  tBodyAcc-max()-X  …  fBodyBodyGyroJerkMag-meanFreq()  \
0         -0.674302         -0.894088  …                         0.071645
1         -0.945823         -0.894088  …                        -0.401189
2         -0.963483         -0.939260  …                         0.062891
3         -0.968897         -0.938610  …                         0.116695
4         -0.977346         -0.938610  …                        -0.121711

   fBodyBodyGyroJerkMag-skewness()  fBodyBodyGyroJerkMag-kurtosis()  \
0                        -0.330370                        -0.705974
1                        -0.121845                        -0.594944
2                        -0.190422                        -0.640736
3                        -0.344418                        -0.736124
4                        -0.534685                        -0.846595

   angle(tBodyAccMean,gravity)  angle(tBodyAccJerkMean),gravityMean)  \
0                     0.006462                              0.162920
1                    -0.083495                              0.017500
2                    -0.034956                              0.202302
3                    -0.017067                              0.154438
4                    -0.002223                             -0.040046

   angle(tBodyGyroMean,gravityMean)  angle(tBodyGyroJerkMean,gravityMean)  \
0                         -0.825886                              0.271151
1                         -0.434375                              0.920593
2                          0.064103                              0.145068
3                          0.340134                              0.296407
4                          0.736715                             -0.118545

   angle(X,gravityMean)  angle(Y,gravityMean)  angle(Z,gravityMean)
0             -0.720009              0.276801             -0.057978
1             -0.698091              0.281343             -0.083898
2             -0.702771              0.280083             -0.079346
3             -0.698954              0.284114             -0.077108
4             -0.692245              0.290722             -0.073857

[5 rows x 561 columns]
```

[38]:
```python
y_test.head()
```

[38]:
```
   activity
0         5
1         5
2         5
3         5
4         5
```

[40]:
```
subject_test.head()
```

[40]:

	subject
0	2
1	2
2	2
3	2
4	2

1.1.6 Exploration et analyse des données

[43]:
```
print("Statistiques descriptives de X_train :")
X_train.describe()
```

Statistiques descriptives de X_train :

[43]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	\
count	7352.000000	7352.000000	7352.000000	
mean	0.274488	-0.017695	-0.109141	
std	0.070261	0.040811	0.056635	
min	-1.000000	-1.000000	-1.000000	
25%	0.262975	-0.024863	-0.120993	
50%	0.277193	-0.017219	-0.108676	
75%	0.288461	-0.010783	-0.097794	
max	1.000000	1.000000	1.000000	

	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	\
count	7352.000000	7352.000000	7352.000000	7352.000000	
mean	-0.605438	-0.510938	-0.604754	-0.630512	
std	0.448734	0.502645	0.418687	0.424073	
min	-1.000000	-0.999873	-1.000000	-1.000000	
25%	-0.992754	-0.978129	-0.980233	-0.993591	
50%	-0.946196	-0.851897	-0.859365	-0.950709	
75%	-0.242813	-0.034231	-0.262415	-0.292680	
max	1.000000	0.916238	1.000000	1.000000	

	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	…	\
count	7352.000000	7352.000000	7352.000000	…	
mean	-0.526907	-0.606150	-0.468604	…	
std	0.485942	0.414122	0.544547	…	
min	-1.000000	-1.000000	-1.000000	…	
25%	-0.978162	-0.980251	-0.936219	…	
50%	-0.857328	-0.857143	-0.881637	…	
75%	-0.066701	-0.265671	-0.017129	…	
max	0.967664	1.000000	1.000000	…	

	fBodyBodyGyroJerkMag-meanFreq()	fBodyBodyGyroJerkMag-skewness()	\
count	7352.000000	7352.000000	

mean	0.125293	-0.307009
std	0.250994	0.321011
min	-1.000000	-0.995357
25%	-0.023692	-0.542602
50%	0.134000	-0.343685
75%	0.289096	-0.126979
max	0.946700	0.989538

	fBodyBodyGyroJerkMag-kurtosis()	angle(tBodyAccMean,gravity) \
count	7352.000000	7352.000000
mean	-0.625294	0.008684
std	0.307584	0.336787
min	-0.999765	-0.976580
25%	-0.845573	-0.121527
50%	-0.711692	0.009509
75%	-0.503878	0.150865
max	0.956845	1.000000

	angle(tBodyAccJerkMean),gravityMean)	angle(tBodyGyroMean,gravityMean) \
count	7352.000000	7352.000000
mean	0.002186	0.008726
std	0.448306	0.608303
min	-1.000000	-1.000000
25%	-0.289549	-0.482273
50%	0.008943	0.008735
75%	0.292861	0.506187
max	1.000000	0.998702

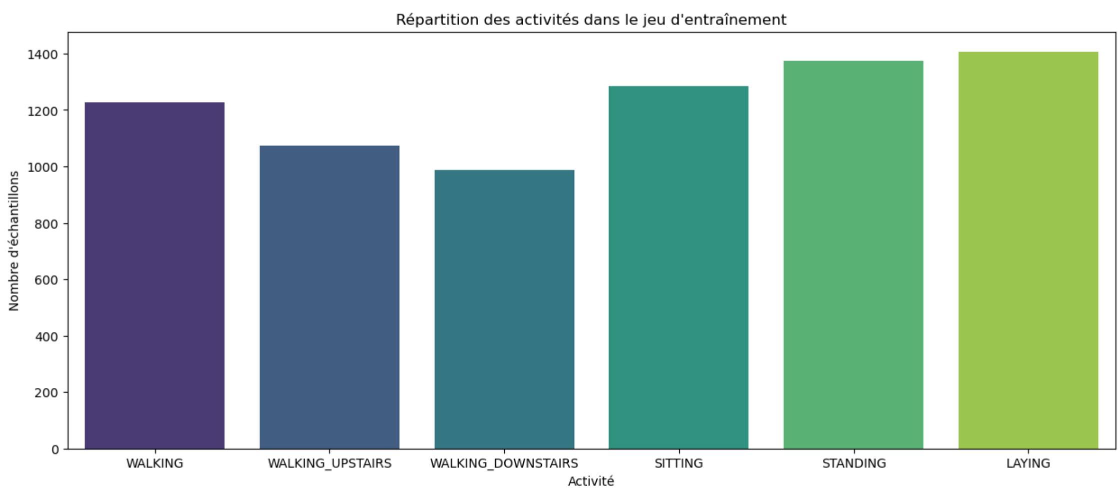
	angle(tBodyGyroJerkMean,gravityMean)	angle(X,gravityMean) \
count	7352.000000	7352.000000
mean	-0.005981	-0.489547
std	0.477975	0.511807
min	-1.000000	-1.000000
25%	-0.376341	-0.812065
50%	-0.000368	-0.709417
75%	0.359368	-0.509079
max	0.996078	1.000000

	angle(Y,gravityMean)	angle(Z,gravityMean)
count	7352.000000	7352.000000
mean	0.058593	-0.056515
std	0.297480	0.279122
min	-1.000000	-1.000000
25%	-0.017885	-0.143414
50%	0.182071	0.003181
75%	0.248353	0.107659
max	0.478157	1.000000

```
[8 rows x 561 columns]
```

Visualisation de la répartition des activités dans y__train

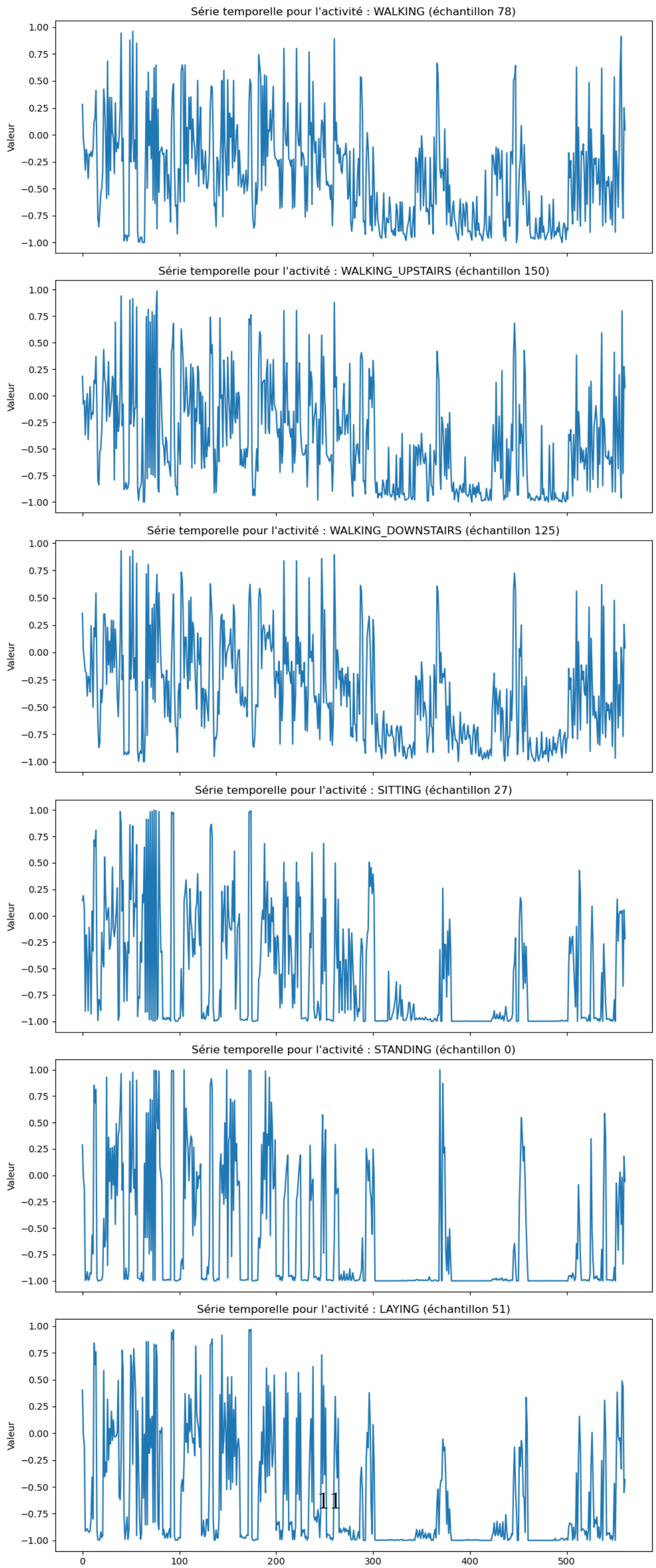
[46]:
```python
# Récupération du nombre d'échantillons pour chaque activité
activity_counts = y_train['activity'].value_counts().sort_index()
# Conversion des codes en noms d'activités via activity_dict
activity_names = [activity_dict[code] for code in activity_counts.index]

plt.figure(figsize=(15, 6))
sns.barplot(x=activity_names, y=activity_counts.values, hue=activity_names,␣
 ↪palette="viridis", dodge=False)
plt.xlabel("Activité")
plt.ylabel("Nombre d'échantillons")
plt.title("Répartition des activités dans le jeu d'entraînement")
plt.legend([], [], frameon=False)
plt.show()
```



Visualisation d'un échantillon de série temporelle de chaque activité

[49]:
```python
# Récupérer la liste des activités distinctes présentes dans y_train, triées␣
 ↪par ordre croissant
unique_activities = sorted(y_train['activity'].unique())
n_activities = len(unique_activities)

# Créer une figure avec un sous-graphe par activité
fig, axs = plt.subplots(n_activities, 1, figsize=(10, 4 * n_activities),␣
 ↪sharex=True)
```

```python
# Pour chaque activité, sélectionner le premier échantillon et tracer sa série␣
 ↪temporelle
for ax, act in zip(axs, unique_activities):
    # Trouver l'indice du premier échantillon correspondant à l'activité act
    sample_index = y_train[y_train['activity'] == act].index[0]
    # Tracer la série temporelle pour cet échantillon
    ax.plot(X_train.iloc[sample_index].values)
    ax.set_title(f"Série temporelle pour l'activité : {activity_dict[act]}␣
 ↪(échantillon {sample_index})")
    ax.set_ylabel("Valeur")

ax.set_xlabel("Index de la feature")
plt.tight_layout()
plt.show()
```


Série temporelle pour l'activité : WALKING (échantillon 78)
Série temporelle pour l'activité : WALKING_UPSTAIRS (échantillon 150)
Série temporelle pour l'activité : WALKING_DOWNSTAIRS (échantillon 125)
Série temporelle pour l'activité : SITTING (échantillon 27)
Série temporelle pour l'activité : STANDING (échantillon 0)
Série temporelle pour l'activité : LAYING (échantillon 51)
Valeur
Index de la feature
0
100
200
300
400
500
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

1.1.7 Conception du modèle de réseau de neurones profond

[52]:
```
# Les étiquettes vont de 1 à 6, donc on soustrait 1 pour obtenir des indices de␣
↪0 à 5
y_train_cat = to_categorical(y_train['activity'].values - 1, num_classes=6)
y_test_cat = to_categorical(y_test['activity'].values - 1, num_classes=6)

# Création d'un jeu de validation à partir de X_train et y_train
X_train_split, X_val, y_train_split, y_val = train_test_split(X_train,␣
↪y_train_cat, test_size=0.2, random_state=42)
```

[54]:
```
# Construction du modèle de réseau de neurones profond
model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(256, activation='relu', input_shape=(X_train.
↪shape[1],)),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Dropout(0.3),

    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Dropout(0.3),

    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Dropout(0.3),

    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Dropout(0.3),

    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Dropout(0.3),

    tf.keras.layers.Dense(6, activation='softmax')  # 6 classes pour les␣
↪activités
])

# Compilation du modèle
#model.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
from keras.optimizers import SGD

model.compile(optimizer=SGD(learning_rate=0.01, momentum=0.9),
```

```python
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Affichage du résumé du modèle
model.summary()
```

```
/home/userdepinfo/anaconda3/lib/python3.12/site-
packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
2025-03-20 12:24:20.689106: E
external/local_xla/xla/stream_executor/cuda/cuda_platform.cc:51] failed call to
cuInit: INTERNAL: CUDA error: Failed call to cuInit: UNKNOWN ERROR (303)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 256)	143,872
batch_normalization (BatchNormalization)	(None, 256)	1,024
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32,896
batch_normalization_1 (BatchNormalization)	(None, 128)	512
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 128)	16,512
batch_normalization_2 (BatchNormalization)	(None, 128)	512
dropout_2 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 128)	16,512
batch_normalization_3 (BatchNormalization)	(None, 128)	512
dropout_3 (Dropout)	(None, 128)	0

```
dense_4 (Dense)                  (None, 64)                    8,256

batch_normalization_4            (None, 64)                      256
(BatchNormalization)

dropout_4 (Dropout)              (None, 64)                        0

dense_5 (Dense)                  (None, 6)                       390
```

Total params: 221,254 (864.27 KB)

Trainable params: 219,846 (858.77 KB)

Non-trainable params: 1,408 (5.50 KB)

[84]:
```python
early_stopping = EarlyStopping(monitor='val_loss', patience=5,␣
 ↪restore_best_weights=True)

# Entraînement du modèle
history = model.fit(X_train_split, y_train_split,
                    epochs=50, batch_size=32,
                    validation_data=(X_val, y_val),
                    callbacks=[early_stopping])

# Évaluation du modèle sur le jeu de test
test_loss, test_acc = model.evaluate(X_test, y_test_cat)
print("Précision sur le jeu de test : {:.2f}%".format(test_acc * 100))
```

```
Epoch 1/50
184/184               1s 3ms/step -
accuracy: 0.9831 - loss: 0.0513 - val_accuracy: 0.9796 - val_loss: 0.0630
Epoch 2/50
184/184               1s 3ms/step -
accuracy: 0.9743 - loss: 0.0718 - val_accuracy: 0.9844 - val_loss: 0.0451
Epoch 3/50
184/184               0s 3ms/step -
accuracy: 0.9797 - loss: 0.0721 - val_accuracy: 0.9816 - val_loss: 0.0544
Epoch 4/50
184/184               0s 3ms/step -
accuracy: 0.9763 - loss: 0.0619 - val_accuracy: 0.9789 - val_loss: 0.0616
Epoch 5/50
184/184               1s 3ms/step -
accuracy: 0.9816 - loss: 0.0505 - val_accuracy: 0.9422 - val_loss: 0.1696
Epoch 6/50
```

```
184/184             1s 3ms/step -
accuracy: 0.9732 - loss: 0.0765 - val_accuracy: 0.9776 - val_loss: 0.0681
Epoch 7/50
184/184             1s 3ms/step -
accuracy: 0.9803 - loss: 0.0568 - val_accuracy: 0.9728 - val_loss: 0.0645
93/93             0s 1ms/step -
accuracy: 0.9601 - loss: 0.1551
Précision sur le jeu de test : 96.64%
```

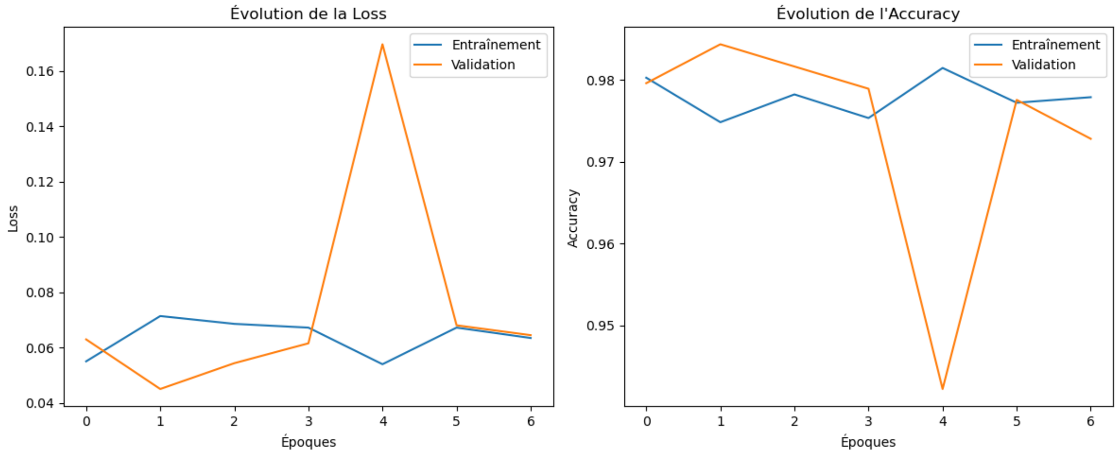
1.1.8 Exportation du model

[91]:
```
model.save("model.h5")
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```

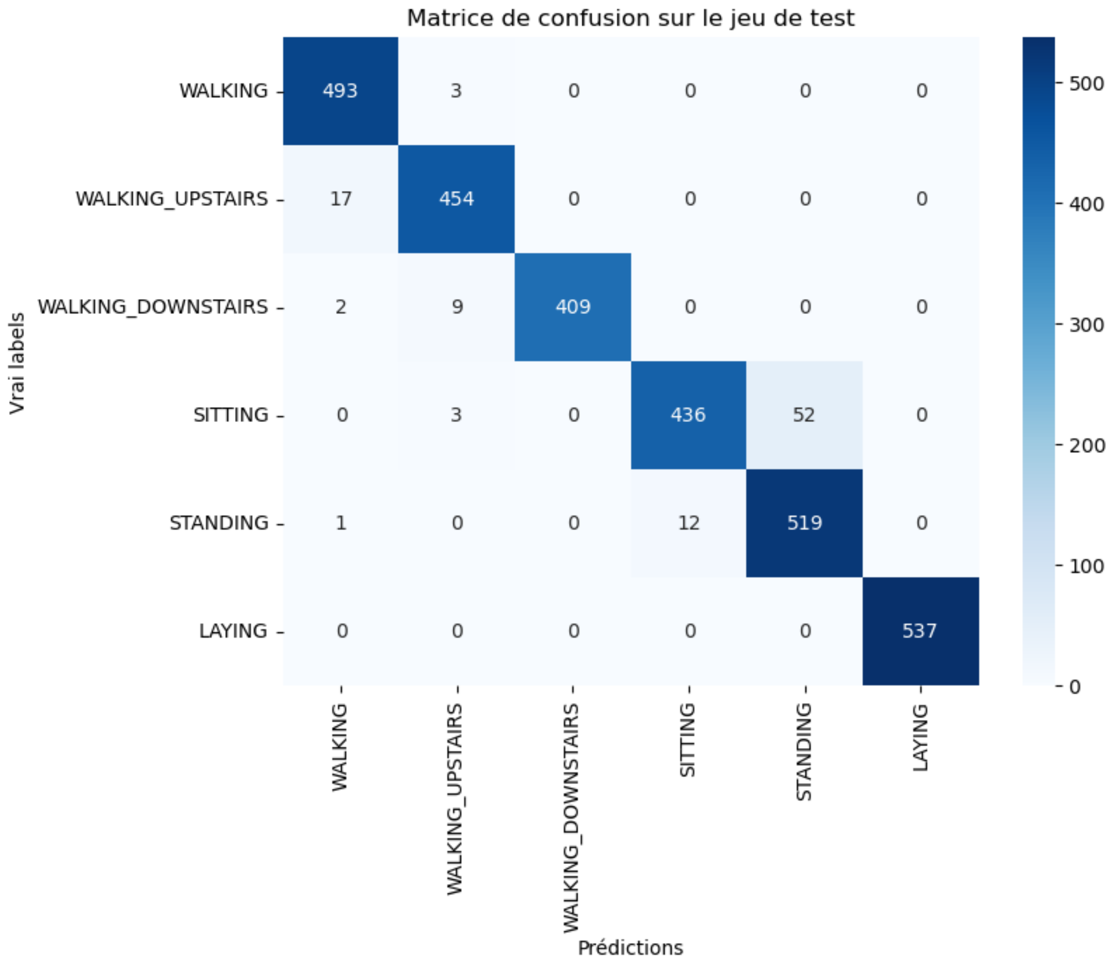
1.1.9 Visualisation du model de réseau de neurones profond

[86]:
```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Entraînement')
plt.plot(history.history['val_loss'], label='Validation')
plt.xlabel('Époques')
plt.ylabel('Loss')
plt.title('Évolution de la Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Entraînement')
plt.plot(history.history['val_accuracy'], label='Validation')
plt.xlabel('Époques')
plt.ylabel('Accuracy')
plt.title('Évolution de l\'Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



[88]:
```python
# Prédictions sur le jeu de test
y_pred_prob = model.predict(X_test)
# On obtient les indices des classes prédites. On ajoute 1 pour revenir aux labels d'origine (1 à 6)
y_pred = np.argmax(y_pred_prob, axis=1) + 1
# Extraction des labels réels du DataFrame y_test
y_true = y_test['activity'].values

# Calcul et affichage de la matrice de confusion
from sklearn.metrics import confusion_matrix, classification_report
cm = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(8,6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=[activity_dict[i] for i in sorted(activity_dict.keys())],
            yticklabels=[activity_dict[i] for i in sorted(activity_dict.keys())])
plt.xlabel('Prédictions')
plt.ylabel('Vrai labels')
plt.title('Matrice de confusion sur le jeu de test')
plt.show()

# Affichage du rapport de classification
print("Rapport de classification :")
print(classification_report(y_true, y_pred))
```

```
93/93                 0s 2ms/step
```




```
Rapport de classification :
              precision    recall  f1-score   support

           1       0.96      0.99      0.98       496
           2       0.97      0.96      0.97       471
           3       1.00      0.97      0.99       420
           4       0.97      0.89      0.93       491
           5       0.91      0.98      0.94       532
           6       1.00      1.00      1.00       537

    accuracy                           0.97      2947
   macro avg       0.97      0.97      0.97      2947
weighted avg       0.97      0.97      0.97      2947
```

[ ]:

1.1.10 Autre méthode : CNN 1D

Preparation du TRAIN brut

[62]:
```
train_signal_files = [
    "body_acc_x_train.txt",
    "body_acc_y_train.txt",
    "body_acc_z_train.txt",
    "body_gyro_x_train.txt",
    "body_gyro_y_train.txt",
    "body_gyro_z_train.txt",
    "total_acc_x_train.txt",
    "total_acc_y_train.txt",
    "total_acc_z_train.txt"
]

# Chargement des signaux dans une liste
signals = []
for file in train_signal_files:
    file_path_train = os.path.join(train_inertial_path, file)
    # Chaque fichier contient une matrice de forme (n_samples, timesteps)
    signal_data = np.loadtxt(file_path_train)
    signals.append(signal_data)

# Combinaison des 9 signaux en un tenseur de forme (n_samples, timesteps,␣
↪n_channels)
# On empile les arrays le long d'une nouvelle dimension à la fin.
X_train_raw = np.stack(signals, axis=-1)
print("X_train_raw shape:", X_train_raw.shape)

y_train_cat = to_categorical(y_train['activity'].values - 1, num_classes=6)
```

```
X_train_raw shape: (7352, 128, 9)
```

Preparation du TEST brut

[65]:
```
test_signal_files = [
    "body_acc_x_test.txt",
    "body_acc_y_test.txt",
    "body_acc_z_test.txt",
    "body_gyro_x_test.txt",
    "body_gyro_y_test.txt",
    "body_gyro_z_test.txt",
    "total_acc_x_test.txt",
    "total_acc_y_test.txt",
    "total_acc_z_test.txt"
]

# Chargement des signaux dans une liste
signals = []
```

```
for file in test_signal_files:
    file_path_test = os.path.join(test_inertial_path, file)
    # Chaque fichier contient une matrice de forme (n_samples, timesteps)
    signal_data = np.loadtxt(file_path_test)
    signals.append(signal_data)

# Combinaison des 9 signaux en un tenseur de forme (n_samples, timesteps,␣
 ↪n_channels)
# On empile les arrays le long d'une nouvelle dimension à la fin.
X_test_raw = np.stack(signals, axis=-1)
print("X_test_raw shape:", X_test_raw.shape)

y_test_cat = to_categorical(y_test['activity'].values - 1, num_classes=6)
```

```
X_test_raw shape: (2947, 128, 9)
```

La Conception du CNN 1D

[76]:
```
from keras.models import Sequential
from keras.layers import Conv1D, MaxPooling1D, Flatten, Dense, Dropout,␣
 ↪BatchNormalization

input_shape = X_train_raw.shape[1:]  # (timesteps, n_channels) ex.: (128, 9)

model_cnn = Sequential([
    Conv1D(filters=128, kernel_size=5, activation='relu', padding='same',␣
 ↪input_shape=input_shape),
    BatchNormalization(),
    Conv1D(filters=128, kernel_size=5, activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling1D(pool_size=2),
    Dropout(0.3),  # Réduction du dropout pour ne pas trop perdre d'informations

    Conv1D(filters=256, kernel_size=5, activation='relu', padding='same'),
    BatchNormalization(),
    Conv1D(filters=256, kernel_size=5, activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling1D(pool_size=2),
    Dropout(0.3),

    Conv1D(filters=512, kernel_size=5, activation='relu', padding='same'),
    BatchNormalization(),
    Conv1D(filters=512, kernel_size=5, activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling1D(pool_size=2),
    Dropout(0.3),

    Flatten(),
```

```python
    Dense(256, activation='relu'),
    Dropout(0.4),
    Dense(6, activation='softmax')  # 6 classes pour la classification
])

# Compilation du modèle
#model_cnn.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])
from keras.optimizers import SGD

model_cnn.compile(optimizer=SGD(learning_rate=0.01, momentum=0.9),
              loss='categorical_crossentropy',
              metrics=['accuracy'])


# Affichage du résumé du modèle
model_cnn.summary()
```

```
/home/userdepinfo/anaconda3/lib/python3.12/site-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv1d_6 (Conv1D)	(None, 128, 128)	5,888
batch_normalization_11 (BatchNormalization)	(None, 128, 128)	512
conv1d_7 (Conv1D)	(None, 128, 128)	82,048
batch_normalization_12 (BatchNormalization)	(None, 128, 128)	512
max_pooling1d_3 (MaxPooling1D)	(None, 64, 128)	0
dropout_9 (Dropout)	(None, 64, 128)	0
conv1d_8 (Conv1D)	(None, 64, 256)	164,096
batch_normalization_13 (BatchNormalization)	(None, 64, 256)	1,024

conv1d_9 (Conv1D)	(None, 64, 256)	327,936
batch_normalization_14 (BatchNormalization)	(None, 64, 256)	1,024
max_pooling1d_4 (MaxPooling1D)	(None, 32, 256)	0
dropout_10 (Dropout)	(None, 32, 256)	0
conv1d_10 (Conv1D)	(None, 32, 512)	655,872
batch_normalization_15 (BatchNormalization)	(None, 32, 512)	2,048
conv1d_11 (Conv1D)	(None, 32, 512)	1,311,232
batch_normalization_16 (BatchNormalization)	(None, 32, 512)	2,048
max_pooling1d_5 (MaxPooling1D)	(None, 16, 512)	0
dropout_11 (Dropout)	(None, 16, 512)	0
flatten_1 (Flatten)	(None, 8192)	0
dense_8 (Dense)	(None, 256)	2,097,408
dropout_12 (Dropout)	(None, 256)	0
dense_9 (Dense)	(None, 6)	1,542

Total params: 4,653,190 (17.75 MB)

Trainable params: 4,649,606 (17.74 MB)

Non-trainable params: 3,584 (14.00 KB)

[78]:
```
early_stopping_cnn = EarlyStopping(monitor='val_loss', patience=5,␣
↪restore_best_weights=True)

# Entraînement du modèle
history_cnn = model_cnn.fit(X_train_raw, y_train_cat,
                            epochs=25, batch_size=32,
```

```
                    validation_split=0.2,
                    callbacks=[early_stopping])


# Évaluation du modèle sur le jeu de test
test_cnn_loss, test_cnn_acc = model_cnn.evaluate(X_test_raw, y_test_cat)
print("Précision sur le jeu de test : {:.2f}%".format(test_cnn_acc * 100))
```

```
Epoch 1/25
184/184              36s 188ms/step -
accuracy: 0.7266 - loss: 1.4595 - val_accuracy: 0.8001 - val_loss: 0.4365
Epoch 2/25
184/184              33s 180ms/step -
accuracy: 0.9050 - loss: 0.2834 - val_accuracy: 0.8994 - val_loss: 0.3370
Epoch 3/25
184/184              42s 185ms/step -
accuracy: 0.9339 - loss: 0.1853 - val_accuracy: 0.9184 - val_loss: 0.2709
Epoch 4/25
184/184              30s 161ms/step -
accuracy: 0.9037 - loss: 0.2849 - val_accuracy: 0.9205 - val_loss: 0.5298
Epoch 5/25
184/184              31s 168ms/step -
accuracy: 0.9280 - loss: 0.1868 - val_accuracy: 0.9232 - val_loss: 0.5057
93/93              4s 42ms/step -
accuracy: 0.7852 - loss: 0.6850
Précision sur le jeu de test : 78.15%
```

[82]:
```
# Entraînement du modèle sur les données brutes
history_cnn = model_cnn.fit(X_train_raw, y_train_cat, epochs=15, batch_size=32,␣
 ↪validation_split=0.2)

# Évaluation du modèle sur le jeu de test
test_cnn_loss, test_cnn_acc = model_cnn.evaluate(X_test_raw, y_test_cat)
print("Précision sur le jeu de test : {:.2f}%".format(test_cnn_acc * 100))
```

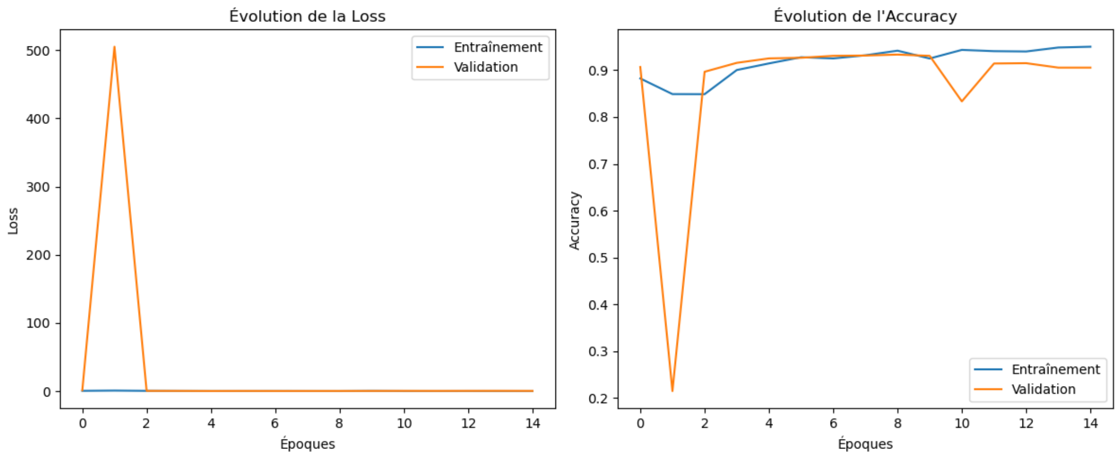
```
Epoch 1/15
184/184              33s 177ms/step -
accuracy: 0.8995 - loss: 0.3542 - val_accuracy: 0.9069 - val_loss: 1.2103
Epoch 2/15
184/184              31s 167ms/step -
accuracy: 0.8919 - loss: 0.5435 - val_accuracy: 0.2148 - val_loss: 505.0779
Epoch 3/15
184/184              41s 165ms/step -
accuracy: 0.8165 - loss: 0.5459 - val_accuracy: 0.8967 - val_loss: 0.4378
Epoch 4/15
184/184              36s 195ms/step -
accuracy: 0.9012 - loss: 0.3062 - val_accuracy: 0.9157 - val_loss: 0.3858
Epoch 5/15
```

```
184/184              38s 208ms/step -
accuracy: 0.9195 - loss: 0.2111 - val_accuracy: 0.9252 - val_loss: 0.2416
Epoch 6/15
184/184              34s 187ms/step -
accuracy: 0.9290 - loss: 0.1770 - val_accuracy: 0.9266 - val_loss: 0.3310
Epoch 7/15
184/184              33s 182ms/step -
accuracy: 0.9235 - loss: 0.2767 - val_accuracy: 0.9307 - val_loss: 0.2665
Epoch 8/15
184/184              33s 179ms/step -
accuracy: 0.9260 - loss: 0.2058 - val_accuracy: 0.9313 - val_loss: 0.2829
Epoch 9/15
184/184              33s 177ms/step -
accuracy: 0.9412 - loss: 0.1636 - val_accuracy: 0.9334 - val_loss: 0.2960
Epoch 10/15
184/184              36s 195ms/step -
accuracy: 0.9159 - loss: 0.7995 - val_accuracy: 0.9307 - val_loss: 0.3543
Epoch 11/15
184/184              32s 175ms/step -
accuracy: 0.9387 - loss: 0.1724 - val_accuracy: 0.8334 - val_loss: 0.4240
Epoch 12/15
184/184              35s 192ms/step -
accuracy: 0.9343 - loss: 0.1730 - val_accuracy: 0.9143 - val_loss: 0.3642
Epoch 13/15
184/184              37s 170ms/step -
accuracy: 0.9376 - loss: 0.1693 - val_accuracy: 0.9150 - val_loss: 0.4320
Epoch 14/15
184/184              32s 172ms/step -
accuracy: 0.9447 - loss: 0.1421 - val_accuracy: 0.9055 - val_loss: 0.4764
Epoch 15/15
184/184              31s 168ms/step -
accuracy: 0.9497 - loss: 0.1265 - val_accuracy: 0.9055 - val_loss: 0.3913
93/93              5s 53ms/step -
accuracy: 0.8926 - loss: 0.4733
Précision sur le jeu de test : 93.38%
```

Visualisation du CNN 1D

[88]:
```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history_cnn.history['loss'], label='Entraînement')
plt.plot(history_cnn.history['val_loss'], label='Validation')
plt.xlabel('Époques')
plt.ylabel('Loss')
plt.title('Évolution de la Loss')
plt.legend()
```

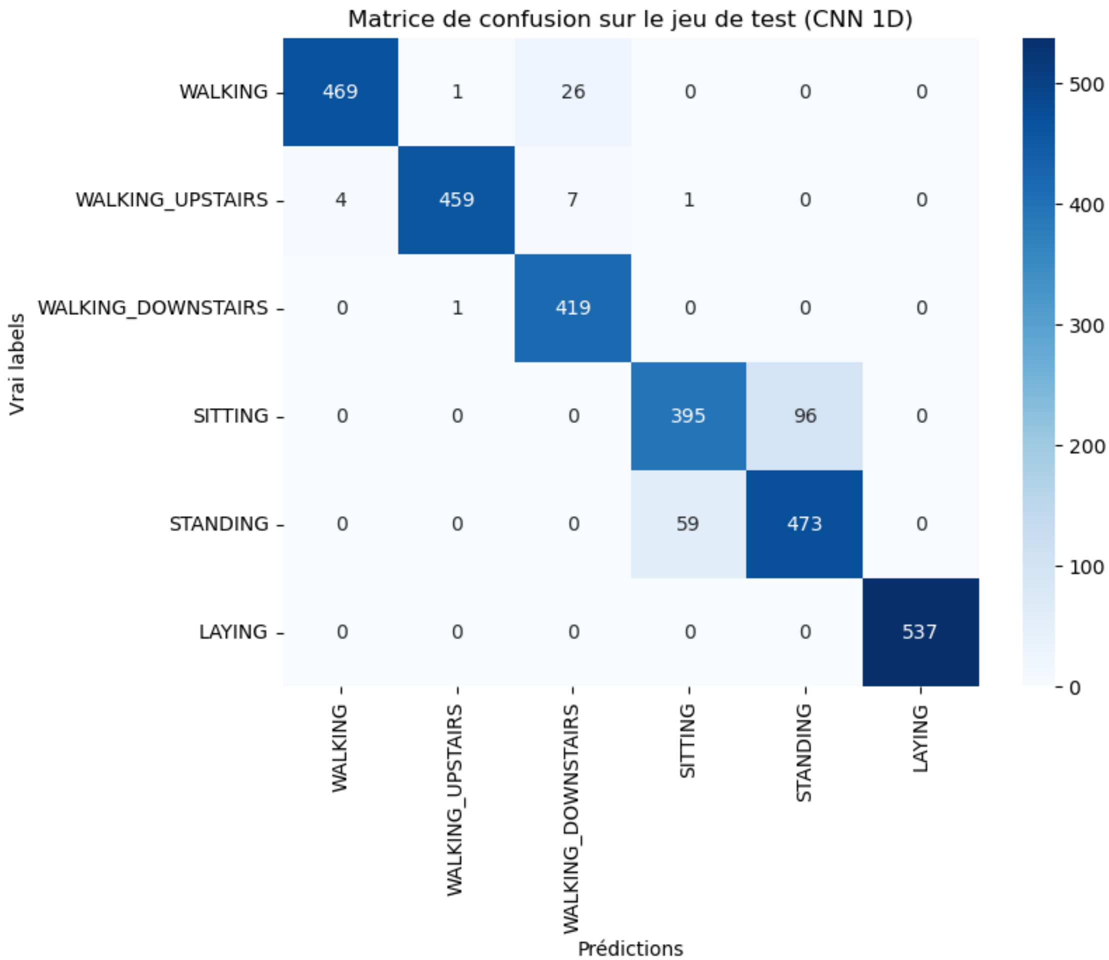
```
plt.subplot(1, 2, 2)
plt.plot(history_cnn.history['accuracy'], label='Entraînement')
plt.plot(history_cnn.history['val_accuracy'], label='Validation')
plt.xlabel('Époques')
plt.ylabel('Accuracy')
plt.title('Évolution de l\'Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



[98]:
```
# Prédictions sur le jeu de test avec le modèle CNN 1D
y_pred_prob = model_cnn.predict(X_test_raw)
# On obtient l'indice de la classe prédite pour chaque échantillon, puis on␣
↪ajoute 1 pour revenir aux labels originaux (1 à 6)
y_pred = np.argmax(y_pred_prob, axis=1) + 1
# Extraction des labels réels à partir du DataFrame y_test
y_true = y_test['activity'].values

# Calcul de la matrice de confusion et du rapport de classification
from sklearn.metrics import confusion_matrix, classification_report
cm = confusion_matrix(y_true, y_pred)

plt.figure(figsize=(8,6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=[activity_dict[i] for i in sorted(activity_dict.
↪keys())],
            yticklabels=[activity_dict[i] for i in sorted(activity_dict.
↪keys())])
plt.xlabel('Prédictions')
plt.ylabel('Vrai labels')
```

```
plt.title('Matrice de confusion sur le jeu de test (CNN 1D)')
plt.show()

print("Rapport de classification :")
print(classification_report(y_true, y_pred))
```

```
93/93                  4s 46ms/step
```




```
Rapport de classification :
              precision    recall  f1-score   support

           1       0.99      0.95      0.97       496
           2       1.00      0.97      0.98       471
           3       0.93      1.00      0.96       420
           4       0.87      0.80      0.84       491
           5       0.83      0.89      0.86       532
           6       1.00      1.00      1.00       537
```

```
    accuracy                           0.93      2947
   macro avg       0.94      0.94      0.93      2947
weighted avg       0.94      0.93      0.93      2947
```

Comparaison des modeles

[7]:
```
print("MLP    : précision sur le jeu de test : {:.2f}% avec un F1-score de 0.
↪97".format(test_acc * 100))
print("CNN 1D : précision sur le jeu de test : {:.2f}% avec un F1-score de 0.
↪93".format(test_cnn_acc * 100))
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[7], line 1
----> 1 print("MLP    : précision sur le jeu de test : {:.2f}% avec un F1-score
↪de 0.97".format(test_acc * 100))
      2 print("CNN 1D : précision sur le jeu de test : {:.2f}% avec un F1-score
↪de 0.93".format(test_cnn_acc * 100))

NameError: name 'test_acc' is not defined
```

Cependant on ne peut s'empecher de remarquer que le CNN 1D est bien plus stable que le RNP.