Charger les données et les transformer en images de 28 x 28 pixels

```
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error
from tensorflow.keras.utils import to_categorical, plot_model
from tensorflow.keras.layers import Input, Dense, Conv2D,
MaxPooling2D, AveragePooling2D, Flatten, Dropout, RandomFlip,
RandomRotation, RandomZoom, RandomTranslation
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam, RMSprop

X_train = pd.read_csv("./sign_mnist_train.csv")
X_test = pd.read_csv("./sign_mnist_test.csv")

X_train.head(10)
```

```
   label  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7
pixel8  \
0      3     107     118     127     134     139     143     146
150
1      6     155     157     156     156     156     157     156
158
2      2     187     188     188     187     187     186     187
188
3      2     211     211     212     212     211     210     211
210
4     13     164     167     170     172     176     179     180
184
5     16     161     168     172     173     178     184     189
193
6      8     134     134     135     135     136     137     137
138
7     22     114      42      74      99     104     109     117
127
8      3     169     174     176     180     183     185     187
188
9      3     189     189     189     190     190     191     190
190

   pixel9  ...  pixel775  pixel776  pixel777  pixel778  pixel779
pixel780  \
0     153  ...       207       207       207       207       206
206
1     158  ...        69       149       128        87        94
163
```

```
2     187  ...       202       201       200       199       198
199
3     210  ...       235       234       233       231       230
226
4     185  ...        92       105       105       108       133
163
5     196  ...        76        74        68        62        53
55
6     138  ...       109       102        91        65       138
189
7     142  ...       214       218       220       223       223
225
8     190  ...       119       118       123       120       118
114
9     190  ...        13        53       200       204       201
201

   pixel781  pixel782  pixel783  pixel784
0       206       204       203       202
1       175       103       135       149
2       198       195       194       195
3       225       222       229       163
4       157       163       164       179
5        48       238       255       255
6       179       181       181       179
7       227       227       228       228
8        94        74        61        57
9       193       175       178       156

[10 rows x 785 columns]
```

```
X_test.head(10)
```

```
   label  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7
pixel8  \
0      6     149     149     150     150     150     151     151
150
1      5     126     128     131     132     133     134     135
135
2     10      85      88      92      96     105     123     135
143
3      0     203     205     207     206     207     209     210
209
4      3     188     191     193     195     199     201     202
203
5     21      72      79      87     101     115     124     131
135
6     10      93     100     112     118     123     127     131
133
7     14     177     177     177     177     177     178     179
```

```
179
8      3     191     194     196     198     201     203     204
205
9      7     171     172     172     173     173     173     173
173

   pixel9  ...  pixel775  pixel776  pixel777  pixel778  pixel779
pixel780  \
0     151  ...       138       148       127        89        82
96
1     136  ...        47       104       194       183       186
184
2     147  ...        68       166       242       227       230
227
3     210  ...       154       248       247       248       253
236
4     203  ...        26        40        64        48        29
46
5     139  ...       187       189       192       193       194
194
6     136  ...       173       175       177       178       180
180
7     178  ...       232       223       224       224       223
221
8     205  ...        43        57        78        64        47
62
9     172  ...       199       199       198       196       195
194

   pixel781  pixel782  pixel783  pixel784
0       106       112       120       107
1       184       184       182       180
2       226       225       224       222
3       230       240       253       255
4        49        46        46        53
5       194       195       195       194
6       181       181       181       183
7       221       221       220       219
8        65        62        62        68
9       183        85        65       124

[10 rows x 785 columns]
```

```python
X_train, X_val = train_test_split(X_train, test_size=1/6)

target = "label"

y_train = X_train[target]
y_val = X_val[target]
y_test = X_test[target]
```

```
X_train = X_train.drop(target, axis=1)
X_val = X_val.drop(target, axis=1)
X_test = X_test.drop(target, axis=1)

print(X_train.shape)
print(X_val.shape)
print(X_test.shape)
print(y_train.shape)
print(y_val.shape)
print(y_test.shape)
```

```
(22879, 784)
(4576, 784)
(7172, 784)
(22879,)
(4576,)
(7172,)
```

```
image_w = 28
image_h = 28

df_filtered = y_test[y_test == 10]

df_filtered
```

```
2       10
6       10
24      10
60      10
65      10
        ..
7083    10
7124    10
7127    10
7138    10
7162    10
Name: label, Length: 331, dtype: int64
```

```
labels = {
    'A': 0,
    'B': 1,
    'C': 2,
    'D': 3,
    'E': 4,
    'F': 5,
    'G': 6,
    'H': 7,
    'I': 8,
    # 'J' est exclu
    'K': 10,
    'L': 11,
```

```
    'M': 12,
    'N': 13,
    'O': 14,
    'P': 15,
    'Q': 16,
    'R': 17,
    'S': 18,
    'T': 19,
    'U': 20,
    'V': 21,
    'W': 22,
    'X': 23,
    'Y': 24
    # 'Z' est exclu
}

X_train_image = X_train.to_numpy().reshape(X_train.shape[0], image_w,
image_h)

X_train_image.shape
```

```
(22879, 28, 28)
```

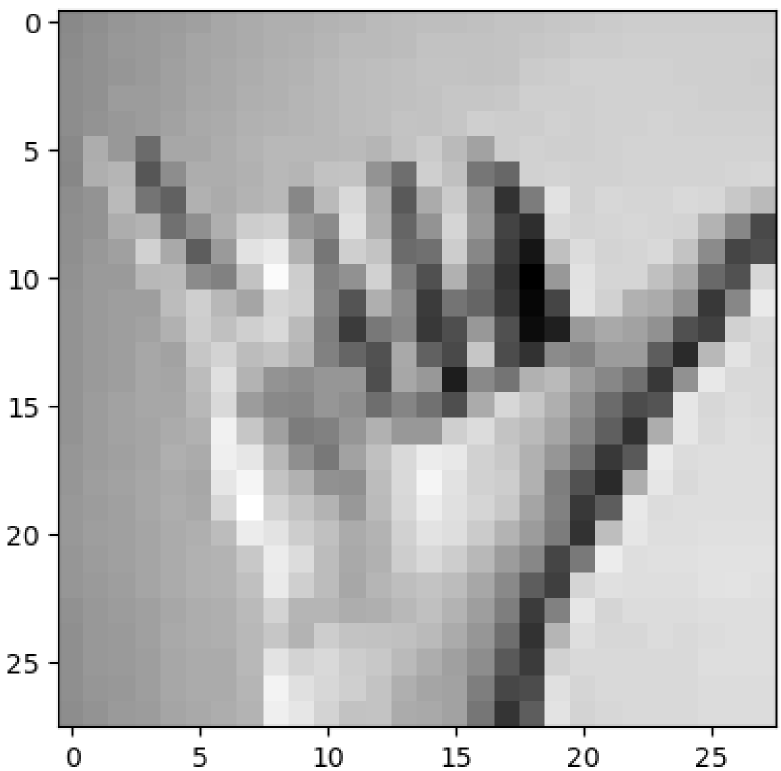
```
print(y_train.unique())  # Affiche les valeurs uniques de y_train pour
comprendre son contenu
```

```
[24  7 17 15 19  4 20 23 21 10  8 18 13 12  2 11 22  3 16  0  1 14  5
6]
```

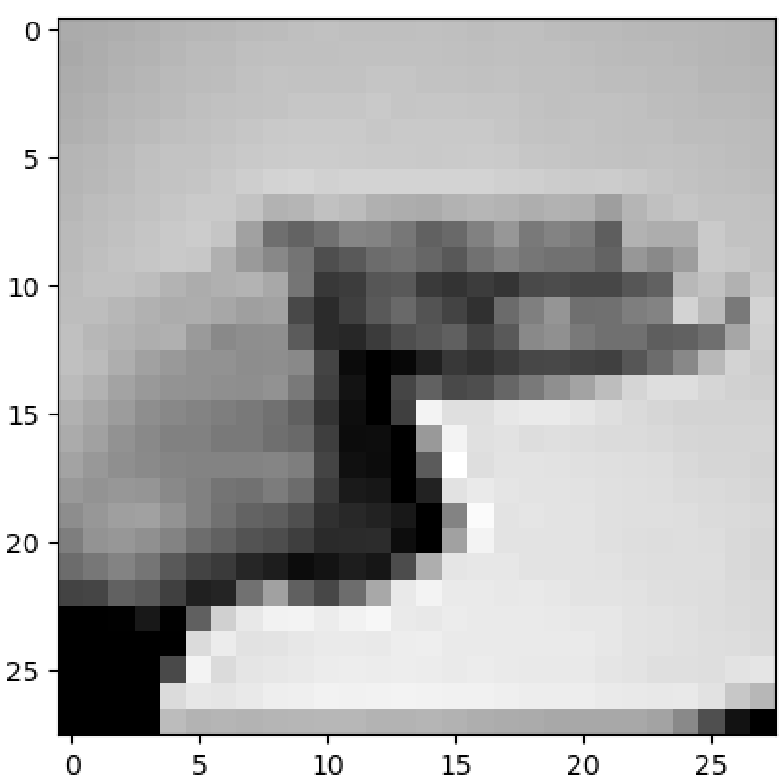
```
# Inverser le dictionnaire labels pour obtenir une correspondance de
nombre à lettre
inv_labels = {v: k for k, v in labels.items()}

plt.gray()
for i in range(10):
    print(inv_labels[y_train.iloc[i]])  # Utiliser le dictionnaire
inversé
    plt.imshow(X_train_image[i])
    plt.show()
```

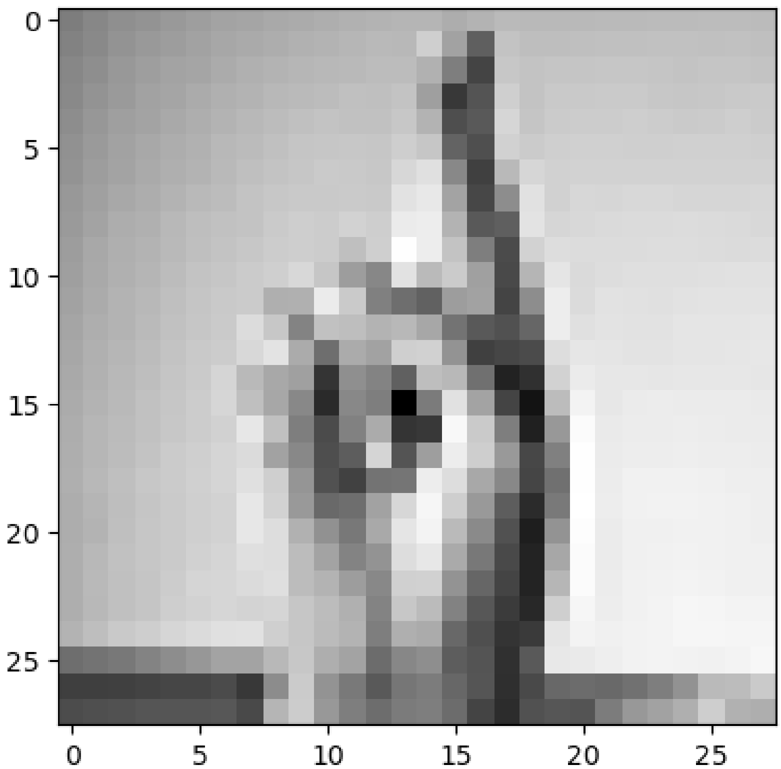
```
Y
```



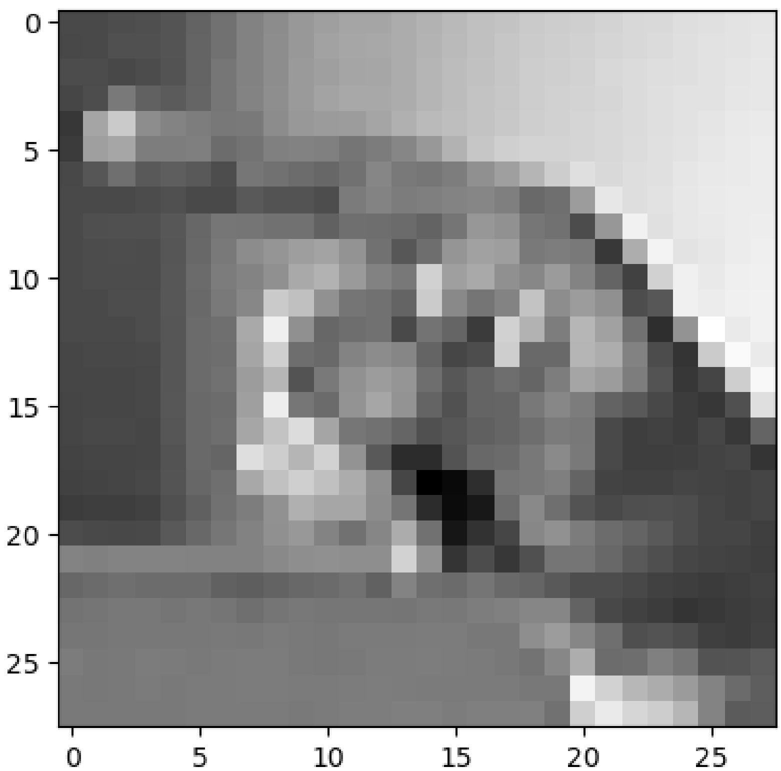
H



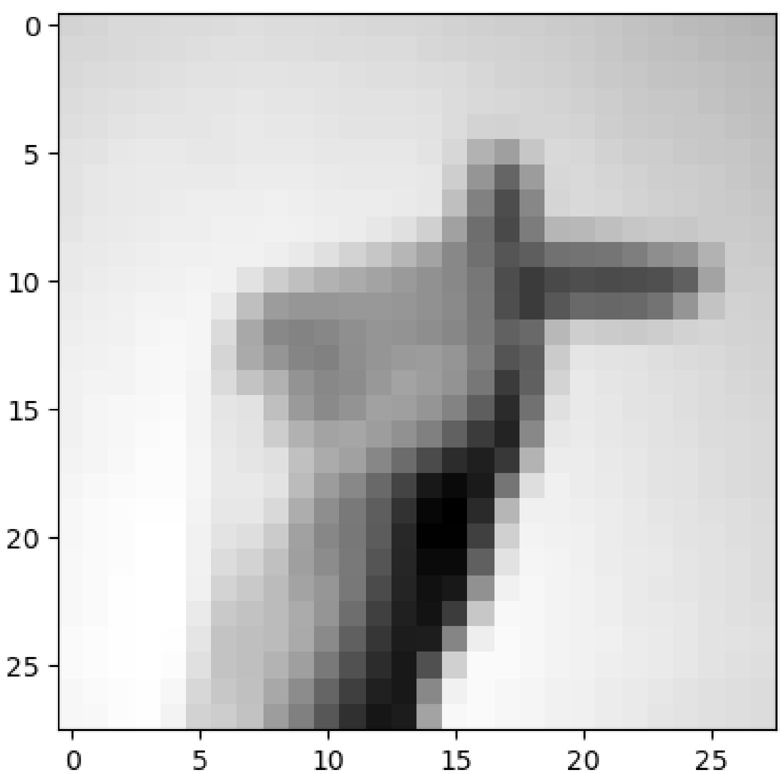
```
R
```



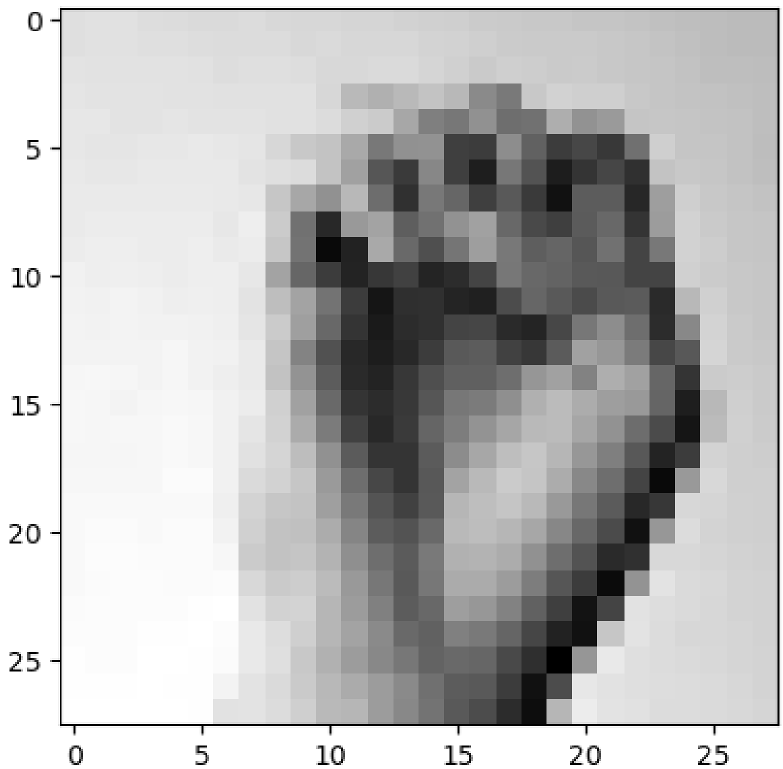

```
P
```



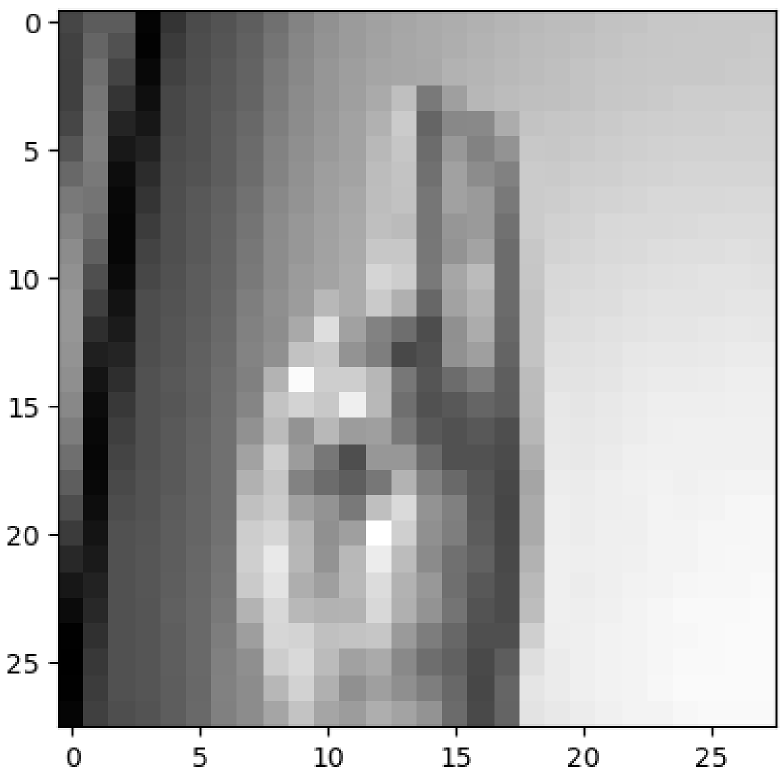
T



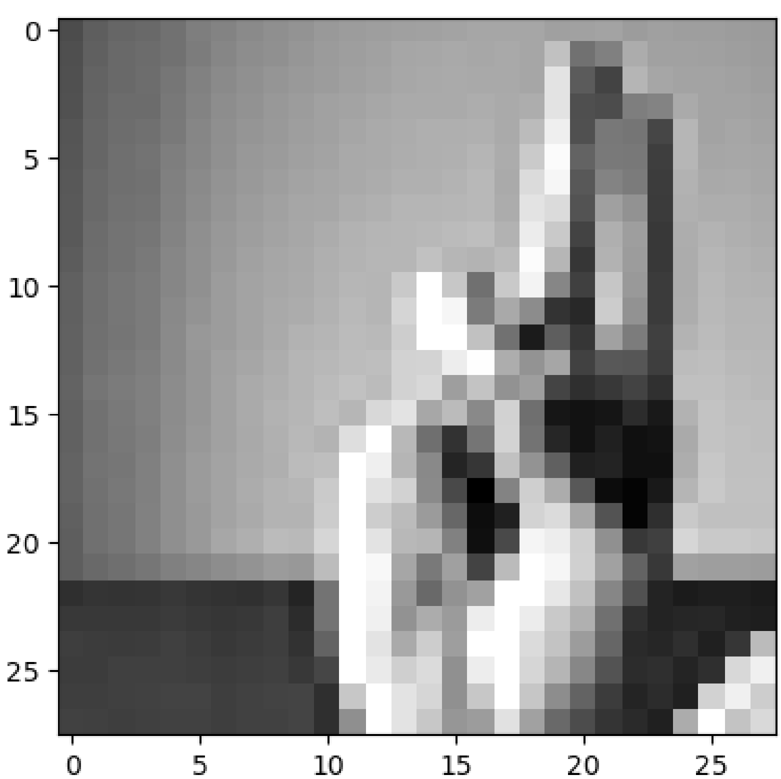
```
E
```



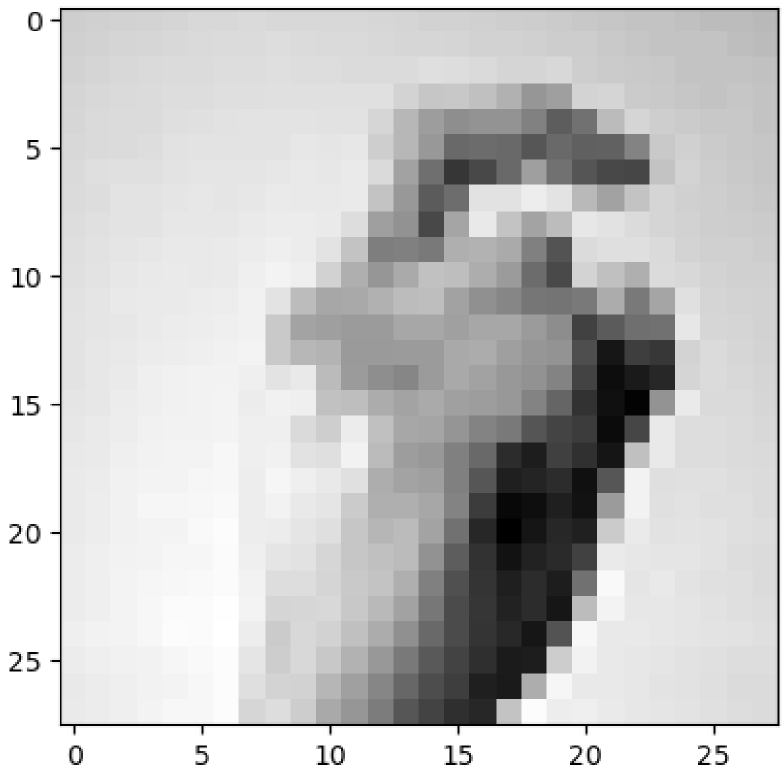

```
U
```



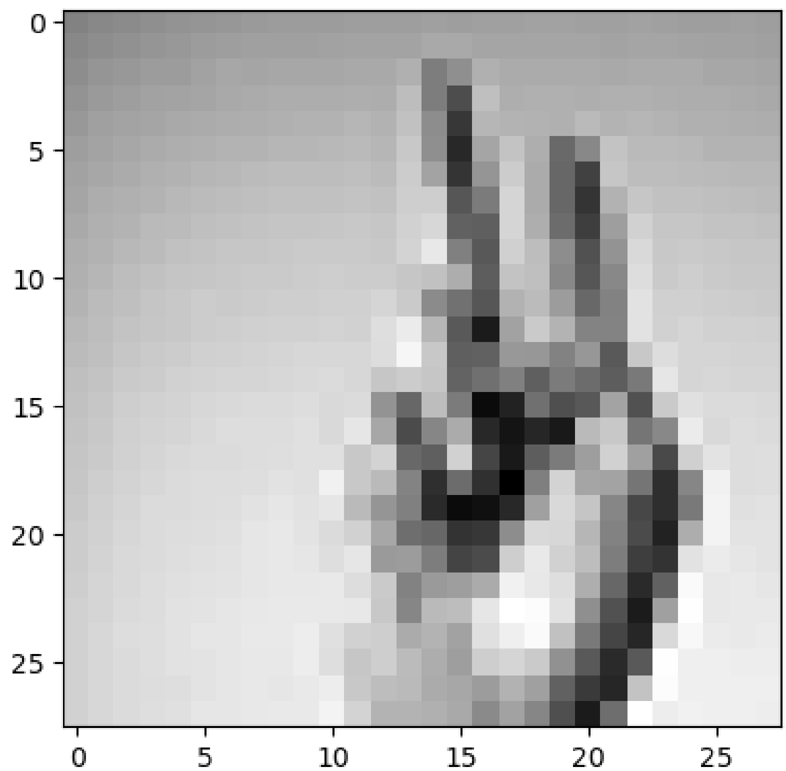
U



X



V



Ce dataset est-il équilibré ? Est-il nécessaire de rééquilibrer les données ? Le faire si besoin

```python
# Compter le nombre d'occurrences de chaque classe
class_distribution = y_train.value_counts()
print(class_distribution)
```

```
label
17    1083
16    1066
11    1047
22    1013
5     1004
14     998
18     995
3      993
19     988
8      975
20     968
2      968
23     967
13     947
10     927
0      925
24     924
```

```
6     921
15    906
21    902
12    872
7     842
1     837
4     811
Name: count, dtype: int64
```

```
!pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in c:\users\anasa\
appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages
(0.12.3)
Requirement already satisfied: numpy>=1.17.3 in c:\users\anasa\
appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
imbalanced-learn) (1.26.4)
Requirement already satisfied: scipy>=1.5.0 in c:\users\anasa\appdata\
roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
imbalanced-learn) (1.12.0)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\anasa\
appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
imbalanced-learn) (1.4.2)
Requirement already satisfied: joblib>=1.1.1 in c:\users\anasa\
appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
imbalanced-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\anasa\
appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
imbalanced-learn) (3.5.0)
```

```
from imblearn.over_sampling import SMOTE
from collections import Counter

# Initialiser SMOTE
smote = SMOTE(random_state=42)

# Appliquer SMOTE sur les données d'entraînement
X_train, y_train = smote.fit_resample(X_train, y_train)

# Afficher la nouvelle distribution des classes après rééquilibrage
print(Counter(y_train))
```

```
Counter({24: 1083, 7: 1083, 17: 1083, 15: 1083, 19: 1083, 4: 1083, 20:
1083, 23: 1083, 21: 1083, 10: 1083, 8: 1083, 18: 1083, 13: 1083, 12:
1083, 2: 1083, 11: 1083, 22: 1083, 3: 1083, 16: 1083, 0: 1083, 1:
1083, 14: 1083, 5: 1083, 6: 1083})
```

Construire un réseau de neurones convolutif pour résoudre ce problème de classification. Il devra contenir au minimum les éléments suivants : couches de convolution, couche de "pooling", "dropout", couches cachées complètement connectées. Vous êtes libres d'ajouter d'autres éléments

Prétraitement des données

```
X_train_norm = X_train/255
X_val_norm = X_val/255
X_test_norm = X_test/255

y_train_cat = to_categorical(y_train, num_classes=25)
y_val_cat = to_categorical(y_val, num_classes=25)
y_test_cat = to_categorical(y_test, num_classes=25)

print(y_train_cat.shape)
print(y_val_cat.shape)
print(y_test_cat.shape)
```

```
(25992, 25)
(4576, 25)
(7172, 25)
```

Création du modèle de convolution

```
X_train_image = X_train.to_numpy().reshape(X_train.shape[0], image_w,
image_h, 1)
X_val_image = X_val.to_numpy().reshape(X_val.shape[0], image_w,
image_h, 1)
X_test_image = X_test.to_numpy().reshape(X_test.shape[0], image_w,
image_h, 1)

X_train_image.shape
```

```
(25992, 28, 28, 1)
```

```
input_shape = X_train_image.shape[1:]
output_dim = y_train_cat.shape[1]

print(input_shape)
print(output_dim)
```

```
(28, 28, 1)
25
```

```
X_train_image_norm = X_train_image/255
X_val_image_norm = X_val_image/255
X_test_image_norm = X_test_image/255
```

```
def create_cnn_model(activation='relu', optimizer='adam',
nb_hidden_layers=2, nb_units=64):
    model = Sequential()

    model.add(Input(shape=input_shape))

    model.add(Conv2D(32, kernel_size=(3, 3), activation="relu",
padding="same"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))

    model.add(Conv2D(64, kernel_size=(3, 3), activation="relu",
padding="same"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))

    model.add(Conv2D(128, kernel_size=(3, 3), activation="relu",
padding="same"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.4))

    model.add(Flatten())

    model.add(Dense(128, activation="relu"))
    model.add(Dropout(0.5))
    model.add(Dense(64, activation="relu"))

    model.add(Dense(output_dim, activation="softmax"))

    model.compile(optimizer=Adam(), loss="categorical_crossentropy",
metrics=["categorical_accuracy"])

    model.summary()

    return model

model_cnn = create_cnn_model(activation='relu', optimizer='adam',
nb_hidden_layers=2, nb_units=64)
```

```
Model: "sequential"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━
━━━━━┓
┃ Layer (type)                     ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━
━━━━━┩
│ conv2d (Conv2D)                  │ (None, 28, 28, 32)     │
320 │
├──────────────────────────────────┼────────────────────────┼──────────
─────┤
```

```
│ max_pooling2d (MaxPooling2D)     │ (None, 14, 14, 32)       │
0 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ dropout (Dropout)                │ (None, 14, 14, 32)       │
0 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ conv2d_1 (Conv2D)                │ (None, 14, 14, 64)       │
18,496 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d_1 (MaxPooling2D)   │ (None, 7, 7, 64)         │
0 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ dropout_1 (Dropout)              │ (None, 7, 7, 64)         │
0 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ conv2d_2 (Conv2D)                │ (None, 7, 7, 128)        │
73,856 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d_2 (MaxPooling2D)   │ (None, 3, 3, 128)        │
0 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ dropout_2 (Dropout)              │ (None, 3, 3, 128)        │
0 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ flatten (Flatten)                │ (None, 1152)             │
0 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ dense (Dense)                    │ (None, 128)              │
147,584 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ dropout_3 (Dropout)              │ (None, 128)              │
0 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ dense_1 (Dense)                  │ (None, 64)               │
8,256 │
├──────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ dense_2 (Dense)                  │ (None, 25)               │
```

```
1,625 │
└──────────────────────────────────┴─────────────────────────┴──────────
──────┘

 Total params: 250,137 (977.10 KB)

 Trainable params: 250,137 (977.10 KB)

 Non-trainable params: 0 (0.00 B)

nb_epochs = 50
```

Entraîner le modèle construit à la question précédente et mesurer sa performance

```
history_cnn = model_cnn.fit(
    X_train_image_norm,
    y_train_cat,
    epochs=nb_epochs,
    validation_data=(X_val_image_norm, y_val_cat),
    callbacks=[EarlyStopping(patience=3)]
)

Epoch 1/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 19s 20ms/step - categorical_accuracy:
0.1304 - loss: 2.8528 - val_categorical_accuracy: 0.8590 - val_loss:
0.5267
Epoch 2/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 19ms/step - categorical_accuracy:
0.7392 - loss: 0.7399 - val_categorical_accuracy: 0.9771 - val_loss:
0.1213
Epoch 3/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 19ms/step - categorical_accuracy:
0.8632 - loss: 0.3908 - val_categorical_accuracy: 0.9919 - val_loss:
0.0456
Epoch 4/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 19ms/step - categorical_accuracy:
0.9136 - loss: 0.2542 - val_categorical_accuracy: 0.9996 - val_loss:
0.0109
Epoch 5/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 17s 21ms/step - categorical_accuracy:
0.9420 - loss: 0.1690 - val_categorical_accuracy: 0.9993 - val_loss:
0.0078
Epoch 6/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9562 - loss: 0.1317 - val_categorical_accuracy: 0.9989 - val_loss:
0.0059
Epoch 7/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9617 - loss: 0.1185 - val_categorical_accuracy: 1.0000 - val_loss:
```

```
9.8250e-04
Epoch 8/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 19ms/step - categorical_accuracy:
0.9674 - loss: 0.1019 - val_categorical_accuracy: 1.0000 - val_loss:
4.2531e-04
Epoch 9/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9714 - loss: 0.0869 - val_categorical_accuracy: 0.9998 - val_loss:
0.0013
Epoch 10/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9722 - loss: 0.0815 - val_categorical_accuracy: 1.0000 - val_loss:
4.3157e-04
Epoch 11/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9732 - loss: 0.0793 - val_categorical_accuracy: 1.0000 - val_loss:
3.5599e-04
Epoch 12/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9738 - loss: 0.0788 - val_categorical_accuracy: 1.0000 - val_loss:
1.3619e-04
Epoch 13/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9763 - loss: 0.0749 - val_categorical_accuracy: 1.0000 - val_loss:
5.0121e-05
Epoch 14/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9808 - loss: 0.0633 - val_categorical_accuracy: 1.0000 - val_loss:
4.3160e-05
Epoch 15/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9802 - loss: 0.0590 - val_categorical_accuracy: 1.0000 - val_loss:
3.0494e-04
Epoch 16/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 16s 20ms/step - categorical_accuracy:
0.9804 - loss: 0.0644 - val_categorical_accuracy: 1.0000 - val_loss:
4.1746e-05
Epoch 17/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 17s 21ms/step - categorical_accuracy:
0.9806 - loss: 0.0608 - val_categorical_accuracy: 1.0000 - val_loss:
3.5827e-05
Epoch 18/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 17s 21ms/step - categorical_accuracy:
0.9841 - loss: 0.0488 - val_categorical_accuracy: 1.0000 - val_loss:
1.2387e-05
Epoch 19/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 17s 21ms/step - categorical_accuracy:
0.9838 - loss: 0.0495 - val_categorical_accuracy: 1.0000 - val_loss:
1.3797e-05
```

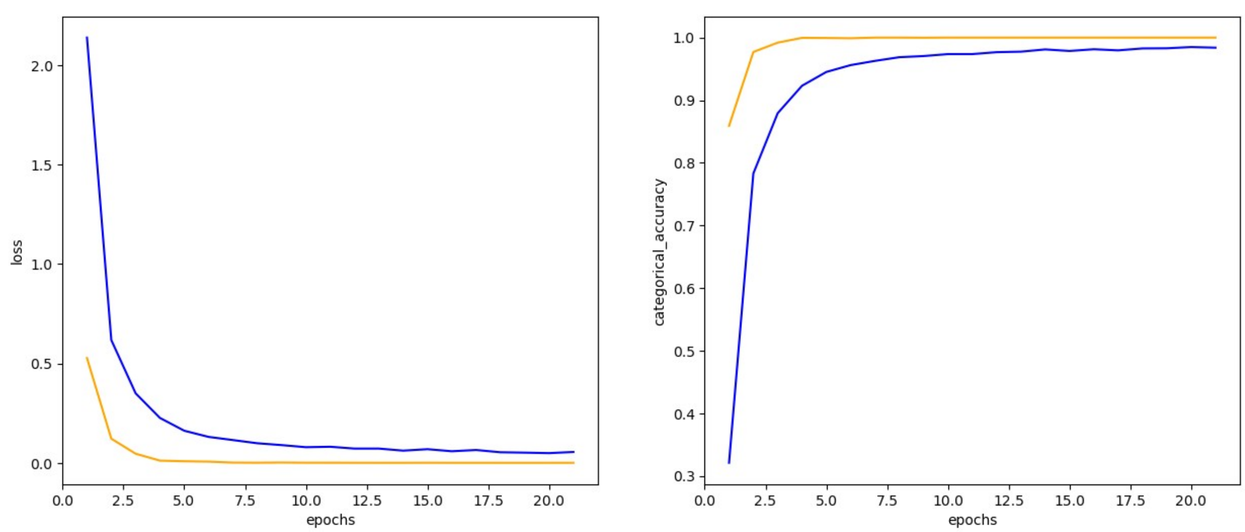
```
Epoch 20/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 17s 21ms/step - categorical_accuracy: 0.9851 - loss: 0.0458 - val_categorical_accuracy: 1.0000 - val_loss: 1.3130e-05
Epoch 21/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 17s 21ms/step - categorical_accuracy: 0.9824 - loss: 0.0560 - val_categorical_accuracy: 1.0000 - val_loss: 7.2383e-05
```

```
def plot_history(history):
    fig, axes = plt.subplots(1,2, figsize=(15,6))
    hist_data = history.history
    hist_data["epochs"] = list(range(1, len(history.history["loss"])+1))

    hist_data = pd.DataFrame(hist_data)
    sns.lineplot(data=hist_data, x="epochs", y="loss", ax=axes[0], color = "blue")
    sns.lineplot(data=hist_data, x="epochs", y="val_loss", ax=axes[0], color = "orange")

    sns.lineplot(data=hist_data, x="epochs", y="categorical_accuracy", ax=axes[1], color = "blue")
    sns.lineplot(data=hist_data, x="epochs", y="val_categorical_accuracy", ax=axes[1], color = "orange")

plot_history(history_cnn)
```



Evaluation du modèle

```
loss, accuracy = model_cnn.evaluate(X_test_image_norm, y_test_cat)
print(f"Loss: {loss}")
print(f"Accuracy: {accuracy}")
```

```
225/225 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - categorical_accuracy:
0.9706 - loss: 0.1324
Loss: 0.11798509210348129
Accuracy: 0.9712771773338318
```

```
y_pred = model_cnn.predict(X_test_image_norm)
```

```
225/225 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step
```

```
y_pred_final = np.argmax(y_pred,axis=1)+1
y_test_final = np.argmax(y_test_cat,axis=1)+1
```

```
mean_absolute_error(y_pred_final, y_test_final)
```

```
0.3318460680423871
```

Faire une recherche de meilleurs hyperparamètres avec la fonction "GridSearchCV"

```
!pip install scikeras
```

```
Requirement already satisfied: scikeras in c:\users\anasa\appdata\
roaming\jupyterlab-desktop\jlab_server\lib\site-packages (0.13.0)
Requirement already satisfied: keras>=3.2.0 in c:\users\anasa\appdata\
roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
scikeras) (3.3.3)
Requirement already satisfied: scikit-learn>=1.4.2 in c:\users\anasa\
appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
scikeras) (1.4.2)
Requirement already satisfied: absl-py in c:\users\anasa\appdata\
roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
keras>=3.2.0->scikeras) (2.1.0)
Requirement already satisfied: numpy in c:\users\anasa\appdata\
roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
keras>=3.2.0->scikeras) (1.26.4)
Requirement already satisfied: rich in c:\users\anasa\appdata\roaming\
jupyterlab-desktop\jlab_server\lib\site-packages (from keras>=3.2.0-
>scikeras) (13.7.1)
Requirement already satisfied: namex in c:\users\anasa\appdata\
roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
keras>=3.2.0->scikeras) (0.0.8)
Requirement already satisfied: h5py in c:\users\anasa\appdata\roaming\
jupyterlab-desktop\jlab_server\lib\site-packages (from keras>=3.2.0-
>scikeras) (3.11.0)
Requirement already satisfied: optree in c:\users\anasa\appdata\
roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
keras>=3.2.0->scikeras) (0.11.0)
Requirement already satisfied: ml-dtypes in c:\users\anasa\appdata\
roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from
keras>=3.2.0->scikeras) (0.3.2)
```

```
Requirement already satisfied: scipy>=1.6.0 in c:\users\anasa\appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from scikit-learn>=1.4.2->scikeras) (1.12.0)
Requirement already satisfied: joblib>=1.2.0 in c:\users\anasa\appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from scikit-learn>=1.4.2->scikeras) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\anasa\appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from scikit-learn>=1.4.2->scikeras) (3.5.0)
Requirement already satisfied: typing-extensions>=4.0.0 in c:\users\anasa\appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from optree->keras>=3.2.0->scikeras) (4.10.0)
Requirement already satisfied: markdown-it-py>=2.2.0 in c:\users\anasa\appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from rich->keras>=3.2.0->scikeras) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in c:\users\anasa\appdata\roaming\python\python312\site-packages (from rich->keras>=3.2.0->scikeras) (2.17.2)
Requirement already satisfied: mdurl~=0.1 in c:\users\anasa\appdata\roaming\jupyterlab-desktop\jlab_server\lib\site-packages (from markdown-it-py>=2.2.0->rich->keras>=3.2.0->scikeras) (0.1.2)
```

```python
from sklearn.model_selection import GridSearchCV
from scikeras.wrappers import KerasClassifier

def create_cnn_model_2(activation='relu', optimizer='adam', nb_units=64):
    model = Sequential()

    model.add(Input(shape=input_shape))

    model.add(Conv2D(nb_units//2, kernel_size=(3, 3), activation=activation, padding="same"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))

    model.add(Conv2D(nb_units, kernel_size=(3, 3), activation=activation, padding="same"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))

    model.add(Conv2D(nb_units*2, kernel_size=(3, 3), activation=activation, padding="same"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.4))

    model.add(Flatten())

    model.add(Dense(128, activation=activation))
    model.add(Dropout(0.5))
```

```
    model.add(Dense(64, activation=activation))

    model.add(Dense(output_dim, activation="softmax"))

    model.compile(optimizer=optimizer,
loss="categorical_crossentropy", metrics=["categorical_accuracy"])

    return model

hyperparameters = {
    'model__activation': ['relu', 'sigmoid'],
    'model__optimizer': ['adam', 'rmsprop'],
    'model__nb_units': [64, 128]
}

model = KerasClassifier(build_fn=create_cnn_model_2, verbose=0)

grid = GridSearchCV(estimator=model, param_grid=hyperparameters, cv=2)

grid_result = grid.fit(X_train_image_norm, y_train_cat)
```

```
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
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C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
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C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
```

```
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
```

```
  X, y = self._initialize(X, y)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\scikeras\wrappers.py:925: UserWarning: ``build_fn`` will
be renamed to ``model`` in a future release, at which point use of
``build_fn`` will raise an Error instead.
  X, y = self._initialize(X, y)
```

```
# Meilleurs hyperparamètres trouvés
best_params = grid_result.best_params_
print("Meilleurs paramètres :", best_params)

# Meilleur estimateur (modèle)
best_model = grid_result.best_estimator_
print("Meilleur modèle :", best_model)

# Meilleur score de validation croisée
best_score = grid_result.best_score_
print("Meilleur score :", best_score)
```

```
Meilleurs paramètres : {'model__activation': 'relu',
'model__nb_units': 128, 'model__optimizer': 'adam'}
Meilleur modèle : KerasClassifier(
	model=None
	build_fn=<function create_cnn_model_2 at 0x0000019BAD1271A0>
	warm_start=False
	random_state=None
	optimizer=rmsprop
	loss=None
	metrics=None
	batch_size=None
	validation_batch_size=None
	verbose=0
	callbacks=None
	validation_split=0.0
	shuffle=True
	run_eagerly=False
	epochs=1
	class_weight=None
	model__activation=relu
	model__nb_units=128
	model__optimizer=adam
)
Meilleur score : 0.3668436441982148
```

Sauvegarder votre meilleur modèle

```
# Évaluation de model_cnn (modèle de base) sur les données de test
loss_cnn, accuracy_cnn = model_cnn.evaluate(X_test_image_norm,
y_test_cat, verbose=0)
print(f"Loss (model_cnn): {loss_cnn}")
```

```python
print(f"Accuracy (model_cnn): {accuracy_cnn}")

# Meilleurs hyperparamètres trouvés par GridSearchCV
best_params = grid_result.best_params_
print("Meilleurs paramètres :", best_params)

# Meilleur score de validation croisée (GridSearchCV)
best_score = grid_result.best_score_
print(f"Best cross-validation score (best_model): {best_score}")

# Comparaison des scores
if accuracy_cnn > best_score:
    best_model = model_cnn
else:
    best_model = best_model.model
```

```
Loss (model_cnn): 0.11798509210348129
Accuracy (model_cnn): 0.9712771773338318
Meilleurs paramètres : {'model__activation': 'relu',
'model__nb_units': 128, 'model__optimizer': 'adam'}
Best cross-validation score (best_model): 0.3668436441982148
```

Utiliser une technique d'augmentation d'images. Les résultats de vos modèles s'en trouvent-ils améliorés ? Était-ce prévisible ?

```python
def create_cnn_model_with_augmentation(activation='relu',
optimizer='adam', nb_units=64):
    model = Sequential()

    # Couche d'entrée avec augmentation des données
    model.add(Input(shape=input_shape))
    model.add(RandomFlip("horizontal"))
    model.add(RandomRotation(0.05))
    model.add(RandomZoom(0.2))
    model.add(RandomTranslation(height_factor=0.1, width_factor=0.1))

    # Couches de convolution
    model.add(Conv2D(nb_units//2, kernel_size=(3, 3),
activation=activation, padding="same"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))

    model.add(Conv2D(nb_units, kernel_size=(3, 3),
activation=activation, padding="same"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Dropout(0.25))

    model.add(Conv2D(nb_units*2, kernel_size=(3, 3),
activation=activation, padding="same"))
    model.add(MaxPooling2D(pool_size=(2, 2)))
```

```
    model.add(Dropout(0.4))

    # Applatissement des images convoluées
    model.add(Flatten())

    # Couches denses servant à la classification
    model.add(Dense(128, activation=activation))
    model.add(Dropout(0.5))
    model.add(Dense(64, activation=activation))

    model.add(Dense(output_dim, activation="softmax"))

    model.compile(optimizer=optimizer,
loss="categorical_crossentropy", metrics=["categorical_accuracy"])

    return model

model_cnn_augmentation =
create_cnn_model_with_augmentation(activation=best_params['model__acti
vation'],

optimizer=best_params['model__optimizer'],

nb_units=best_params['model__nb_units'])
```

Remplacer les paramètres du fit par best_params

```
history_cnn_augmentation = model_cnn_augmentation.fit(
    X_train_image_norm,
    y_train_cat,
    epochs=nb_epochs,
    validation_data=(X_val_image_norm, y_val_cat),
    callbacks=[EarlyStopping(patience=3)]
)
```

```
Epoch 1/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 56s 66ms/step - categorical_accuracy:
0.0481 - loss: 3.1822 - val_categorical_accuracy: 0.1954 - val_loss:
2.4039
Epoch 2/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 52s 64ms/step - categorical_accuracy:
0.2067 - loss: 2.4789 - val_categorical_accuracy: 0.4816 - val_loss:
1.5291
Epoch 3/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 52s 64ms/step - categorical_accuracy:
0.4016 - loss: 1.7816 - val_categorical_accuracy: 0.7242 - val_loss:
0.8598
Epoch 4/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 54s 67ms/step - categorical_accuracy:
0.5178 - loss: 1.3960 - val_categorical_accuracy: 0.8099 - val_loss:
```

```
0.5609
Epoch 5/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 53s 65ms/step - categorical_accuracy:
0.5975 - loss: 1.1509 - val_categorical_accuracy: 0.8440 - val_loss:
0.4721
Epoch 6/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 54s 67ms/step - categorical_accuracy:
0.6476 - loss: 1.0286 - val_categorical_accuracy: 0.8676 - val_loss:
0.3679
Epoch 7/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 52s 64ms/step - categorical_accuracy:
0.6813 - loss: 0.9144 - val_categorical_accuracy: 0.9025 - val_loss:
0.3293
Epoch 8/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 53s 65ms/step - categorical_accuracy:
0.6973 - loss: 0.8635 - val_categorical_accuracy: 0.9115 - val_loss:
0.2586
Epoch 9/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 52s 64ms/step - categorical_accuracy:
0.7216 - loss: 0.7912 - val_categorical_accuracy: 0.9159 - val_loss:
0.2346
Epoch 10/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 53s 65ms/step - categorical_accuracy:
0.7348 - loss: 0.7606 - val_categorical_accuracy: 0.9480 - val_loss:
0.1845
Epoch 11/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 54s 66ms/step - categorical_accuracy:
0.7523 - loss: 0.7118 - val_categorical_accuracy: 0.9683 - val_loss:
0.1498
Epoch 12/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 53s 65ms/step - categorical_accuracy:
0.7591 - loss: 0.7046 - val_categorical_accuracy: 0.9427 - val_loss:
0.1626
Epoch 13/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 55s 67ms/step - categorical_accuracy:
0.7729 - loss: 0.6475 - val_categorical_accuracy: 0.9489 - val_loss:
0.1531
Epoch 14/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 53s 65ms/step - categorical_accuracy:
0.7818 - loss: 0.6229 - val_categorical_accuracy: 0.9633 - val_loss:
0.1223
Epoch 15/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 54s 66ms/step - categorical_accuracy:
0.7930 - loss: 0.6003 - val_categorical_accuracy: 0.9766 - val_loss:
0.0899
Epoch 16/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 62s 76ms/step - categorical_accuracy:
0.8000 - loss: 0.5864 - val_categorical_accuracy: 0.9729 - val_loss:
0.0869
```

```
Epoch 17/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 59s 72ms/step - categorical_accuracy:
0.8148 - loss: 0.5458 - val_categorical_accuracy: 0.9742 - val_loss:
0.0830
Epoch 18/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 63s 78ms/step - categorical_accuracy:
0.8147 - loss: 0.5310 - val_categorical_accuracy: 0.9738 - val_loss:
0.0828
Epoch 19/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 57s 71ms/step - categorical_accuracy:
0.8206 - loss: 0.5275 - val_categorical_accuracy: 0.9753 - val_loss:
0.0818
Epoch 20/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 55s 68ms/step - categorical_accuracy:
0.8237 - loss: 0.5070 - val_categorical_accuracy: 0.9779 - val_loss:
0.0782
Epoch 21/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 56s 68ms/step - categorical_accuracy:
0.8336 - loss: 0.5003 - val_categorical_accuracy: 0.9812 - val_loss:
0.0637
Epoch 22/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 56s 69ms/step - categorical_accuracy:
0.8386 - loss: 0.4787 - val_categorical_accuracy: 0.9753 - val_loss:
0.0680
Epoch 23/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 58s 71ms/step - categorical_accuracy:
0.8406 - loss: 0.4789 - val_categorical_accuracy: 0.9777 - val_loss:
0.0627
Epoch 24/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 59s 72ms/step - categorical_accuracy:
0.8456 - loss: 0.4617 - val_categorical_accuracy: 0.9797 - val_loss:
0.0654
Epoch 25/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 63s 77ms/step - categorical_accuracy:
0.8452 - loss: 0.4652 - val_categorical_accuracy: 0.9851 - val_loss:
0.0487
Epoch 26/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 59s 72ms/step - categorical_accuracy:
0.8567 - loss: 0.4323 - val_categorical_accuracy: 0.9812 - val_loss:
0.0605
Epoch 27/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 75s 93ms/step - categorical_accuracy:
0.8537 - loss: 0.4453 - val_categorical_accuracy: 0.9790 - val_loss:
0.0598
Epoch 28/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 61s 75ms/step - categorical_accuracy:
0.8533 - loss: 0.4426 - val_categorical_accuracy: 0.9869 - val_loss:
0.0366
Epoch 29/50
```

```
813/813 ━━━━━━━━━━━━━━━━━━━━ 90s 110ms/step - categorical_accuracy:
0.8605 - loss: 0.4024 - val_categorical_accuracy: 0.9812 - val_loss:
0.0547
Epoch 30/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 92s 114ms/step - categorical_accuracy:
0.8690 - loss: 0.3971 - val_categorical_accuracy: 0.9882 - val_loss:
0.0429
Epoch 31/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 103s 66ms/step - categorical_accuracy:
0.8635 - loss: 0.4030 - val_categorical_accuracy: 0.9899 - val_loss:
0.0332
Epoch 32/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 56s 69ms/step - categorical_accuracy:
0.8678 - loss: 0.3959 - val_categorical_accuracy: 0.9926 - val_loss:
0.0264
Epoch 33/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 57s 70ms/step - categorical_accuracy:
0.8716 - loss: 0.3904 - val_categorical_accuracy: 0.9928 - val_loss:
0.0269
Epoch 34/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 77s 63ms/step - categorical_accuracy:
0.8728 - loss: 0.3815 - val_categorical_accuracy: 0.9893 - val_loss:
0.0303
Epoch 35/50
813/813 ━━━━━━━━━━━━━━━━━━━━ 53s 66ms/step - categorical_accuracy:
0.8769 - loss: 0.3721 - val_categorical_accuracy: 0.9886 - val_loss:
0.0357
```

```python
# Modèle sans augmentation d'images
loss_no_aug, acc_no_aug = best_model.evaluate(X_test_image_norm,
y_test_cat, verbose=0)
print(f"Accuracy without augmentation: {acc_no_aug}")

# Modèle avec augmentation d'images
loss_aug, acc_aug = model_cnn_augmentation.evaluate(X_test_image_norm,
y_test_cat, verbose=0)
print(f"Accuracy with augmentation: {acc_aug}")

# Comparaison des résultats
if acc_aug > acc_no_aug:
    print("Le modèle avec augmentation d'images est meilleur.")
    best_model.save('best_model.keras')
else:
    print("Le modèle sans augmentation d'images est meilleur.")
    model_cnn_augmentation.save('best_model.keras')
```

```
Accuracy without augmentation: 0.9712771773338318
Accuracy with augmentation: 0.9765755534172058
Le modèle avec augmentation d'images est meilleur.
```

```
# Initialiser une figure pour afficher les images
plt.figure(figsize=(15, 10))

# Parcourir les lettres de A à Z
for letter in range(26):
    # Trouver un indice pour chaque lettre
    indices = [i for i, label in enumerate(y_train) if label ==
letter]
    if indices:  # Vérifier si des images existent pour cette lettre
        plt.subplot(5, 6, letter + 1)  # 5 lignes, 6 colonnes
        plt.imshow(X_train_image[indices[0]])  # Afficher la première
image pour cette lettre
        plt.title(inv_labels[letter])  # Titre de la lettre
        plt.axis('off')  # Pas d'axes

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