

Projet : Deep Food

Nous utilisons le GPU pour bénéficier de l'entraînement en précision mixte.

```
!nvidia-smi -L
```

```
GPU 0: NVIDIA GeForce RTX 2060 (UUID: GPU-a2b4317d-436b-2cc1-0fe3-ac16673637a5)
```

Obtenir des fonctions d'assistance.

```
# Importer une série de fonctions d'assistance pour le notebook
from helper_functions import create_tensorboard_callback,
plot_loss_curves, compare_historys
```

Nous utilisons Utilisez TensorFlow datasets pour télécharger les données.

- Si vous voulez un aperçu, lisez le guide : <https://www.tensorflow.org/datasets/overview?hl=fr>
- Documentation de food101 sur TensorFlow : https://data.vision.ee.ethz.ch/cvl/datasets_extra/food-101/

```
# Obtenir les datasets de TensorFlow
```

```
import tensorflow_datasets as tfds
```

```
# Lister tous les datasets disponibles
```

```
tfds_list = tfds.list_builders()
```

```
tfds_list
```

```
['abstract_reasoning',
'accentdb',
'aeslc',
'aflw2k3d',
'ag_news_subset',
'ai2_arc',
'ai2_arc_with_ir',
'aloha_mobile',
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'civil_comments',
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```

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```



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'xtreme_xnli',
'yahoo_ltrc',
'yelp_polarity_reviews',
'yes_no',
'youtube_vis']
```

```
# Vérifiez si food101 est dans la liste des datasets
print("food101" in tfds_list)
```

```
True
```

Chargement des données (prend environ 5 - 6 minutes)

```
(train_data, test_data), ds_info = tfds.load(
    name="food101",
    split=["train", "validation"],
    shuffle_files=True,
    as_supervised=True, # Les données seront retournées sous forme de
tuple (données, étiquette)
    with_info=True # Donne des métadonnées (ds_info)
)
```

Remarque : Si le dataset a déjà été téléchargé, le code précédent ne le téléchargera pas à nouveau.

Caractéristiques de food101

```
ds_info.features
```

```
FeaturesDict({
    'image': Image(shape=(None, None, 3), dtype=uint8),
    'label': ClassLabel(shape=(), dtype=int64, num_classes=101),
})
```

```
# Obtenir les noms des classes
```

```
class_names = ds_info.features["label"].names
```

```
# Affiche les 10 premiers aliments du dataset
```

```
class_names[:10]
```

```
['apple_pie',
'baby_back_ribs',
'baklava',
'beef_carpaccio',
'beef_tartare',
```

```
'beet_salad',  
'beignets',  
'bibimbap',  
'bread_pudding',  
'breakfast_burrito']
```

Explorer le dataset Food

- Noms des classes
- Forme de notre entrée (tenseurs d'images)
- Le type de données de nos entrées
- À quoi ressemblent les étiquettes ? (sont-elles encodées en one-hot ou label encoded)
- Les étiquettes correspondent-elles aux noms des classes ?

Prendre un échantillon des données d'entraînement

```
train_one_simple = train_data.take(1)  
  
train_one_simple # Les échantillons sont au format format (image  
tesneur), (label)  
  
<TakeDataset element_spec=(TensorSpec(shape=(None, None, 3),  
dtype=tf.uint8, name=None), TensorSpec(shape=(), dtype=tf.int64,  
name=None))>  
  
# Afficher des informations sur notre échantillon d'entraînement  
for image, label in train_one_simple:  
    print(f"""  
    Image shape : {image.shape}  
    Image datatype : {image.dtype}  
    Target class : {label}  
    Class names string form : {class_names[label.numpy()]}  
    """)  
  
    Image shape : (384, 512, 3)  
    Image datatype : <dtype: 'uint8'>  
    Target class : 70  
    Class names string form : pad_thai  
  
# À quoi ressemble notre tenseur d'image ?  
image  
  
<tf.Tensor: shape=(384, 512, 3), dtype=uint8, numpy=  
array([[ [230, 229, 183],  
        [231, 230, 184],  
        [232, 231, 183],  
        ...,  
        [232, 233, 202],  
        [229, 234, 204],
```

```

        [229, 236, 205]],
        [[228, 227, 179],
         [227, 226, 178],
         [226, 226, 176],
         ...,
         [234, 235, 204],
         [232, 237, 207],
         [234, 241, 210]],
        [[229, 229, 175],
         [229, 229, 175],
         [227, 227, 175],
         ...,
         [233, 234, 202],
         [232, 237, 205],
         [235, 242, 209]],
        ...,
        [[119, 97, 58],
         [131, 109, 70],
         [131, 109, 70],
         ...,
         [239, 241, 220],
         [238, 240, 219],
         [238, 240, 219]],
        [[120, 98, 61],
         [133, 111, 74],
         [135, 113, 76],
         ...,
         [240, 242, 221],
         [240, 242, 221],
         [240, 242, 221]],
        [[136, 114, 77],
         [135, 113, 76],
         [129, 107, 70],
         ...,
         [243, 245, 224],
         [244, 246, 225],
         [245, 247, 226]]], dtype=uint8)>

```

Quelles sont les valeurs minimales et maximales de l'image, censées être entre 0 et 255 ?

```

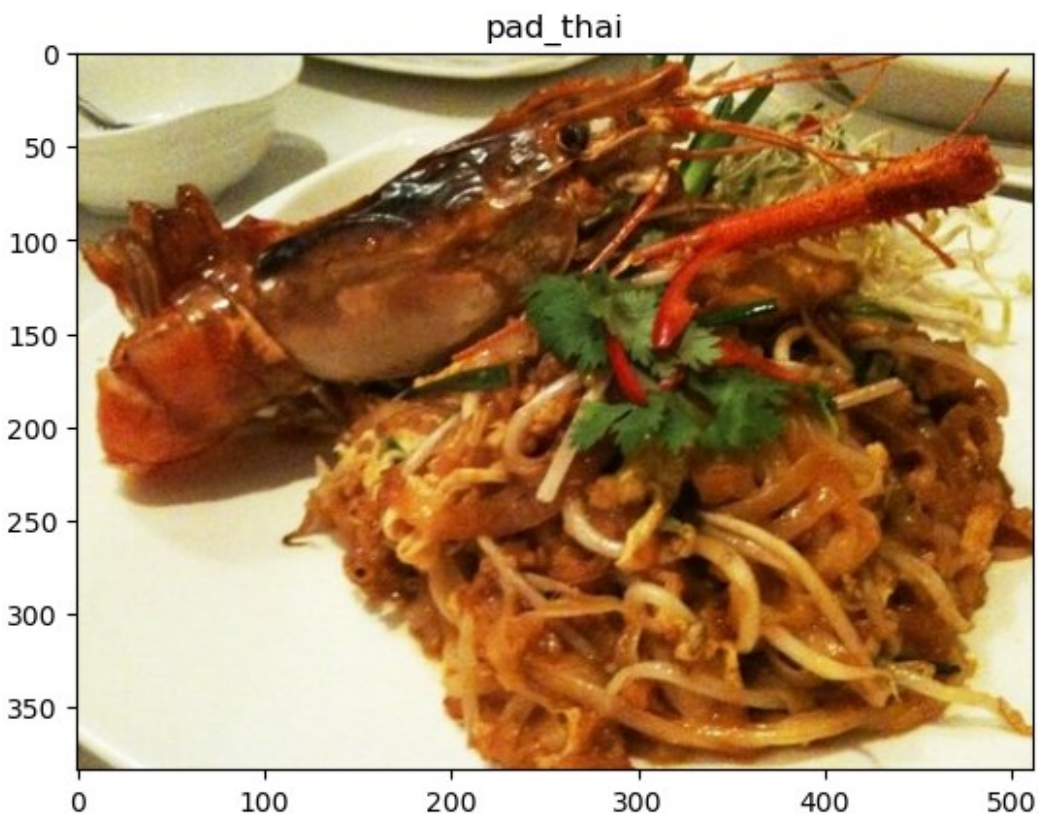
import tensorflow as tf
tf.reduce_min(image), tf.reduce_max(image)

```

```
(<tf.Tensor: shape=(), dtype=uint8, numpy=0>,  
<tf.Tensor: shape=(), dtype=uint8, numpy=255>)
```

Neural networks like images to be encoded between 0 and 1

```
# Afficher une image du dataset TensorFlow  
import matplotlib.pyplot as plt  
  
plt.imshow(image)  
plt.title(class_names[label.numpy()])  
Text(0.5, 1.0, 'pad_thai')
```



Créer des fonctions de prétraitement pour nos données

Ce que nous savons sur nos données :

- Type de données 'uint8'
- Composé de tailles variées de tenseurs (images de tailles différentes)
- Non mises à l'échelle (les valeurs des pixels sont comprises entre 0 et 255)
- Ce que nous savons sur les modèles :

Données en 'float32'

- TensorFlow préfère que toutes les images d'un lot aient la même taille
- Mises à l'échelle (valeurs entre 0 et 1, également appelé normalisé)

- Avec cela en tête, nous avons plusieurs choses à aborder avec une fonction de prétraitement.

Comme nous allons utiliser EfficientNetBx pré-entraîné de tf.keras.applications, nous n'avons pas besoin de redimensionner nos données (ces architectures ont un redimensionnement intégré).

Notre fonction doit :

- Redimensionner toutes nos images à la même taille
- Convertir le type de données de nos tenseurs d'image de 'uint8' à 'float32'

```
# Créer une fonction pour le prétraitement des images
def preprocess_img(image, label, img_shape=244):
    """
    Convertir le type de données de l'image de 'uint8' à 'float32' et
    redimensionner l'image à (img_shape, img_shape, 3).
    """
    image = tf.image.resize(image, [img_shape, img_shape]) # Reshape
    target image
    return tf.cast(image, tf.float32), label

# Prétraiter une seule image échantillon et vérifier le résultat
preprocessed_img = preprocess_img(image, label)[0] # retourne un tuple
et nous voulons seulement l'image
print(f"Image before preprocessing:\n {image[:2]}")
print(f"Image shape: {image.shape}")
print(f"Image dtype: {image.dtype}")
print(f"#####")
print(f"Image after preprocessing:\n {preprocessed_img[:2]}")
print(f"Image shape: {preprocessed_img.shape}")
print(f"Image dtype: {preprocessed_img.dtype}")

Image before preprocessing:
[[[230 229 183]
  [231 230 184]
  [232 231 183]
  ...
  [232 233 202]
  [229 234 204]
  [229 236 205]]

  [[228 227 179]
  [227 226 178]
  [226 226 176]
  ...
  [234 235 204]
  [232 237 207]
  [234 241 210]]]
Image shape: (384, 512, 3)
Image dtype: <dtype: 'uint8'>
#####
Image after preprocessing:
```

```

[[[229.66031 228.66031 182.08653]
 [230.00269 229.28958 180.7158 ]
 [224.9142  224.9142  173.4224 ]
 ...
 [237.75494 231.47707 201.58101]
 [235.6259  233.38799 203.68315]
 [230.11931 236.02092 205.57011]]

 [[228.78413 228.64479 175.48085]
 [226.39359 226.39359 174.67227]
 [227.06     227.06     175.1308 ]
 ...
 [237.92068 232.17474 200.24554]
 [235.17233 233.49176 202.36893]
 [233.2896  239.19121 207.01909]]]
Image shape: (244, 244, 3)
Image dtype: <dtype: 'float32'>

```

Batcher et préparer les datasets

Nous allons maintenant rendre notre pipeline d'entrée de données vraiment rapide.

```

# Mapper la fonction de prétraitement sur les données d'entraînement
(AUTOTUNE utilise autant de processus que possible)
# Prétraiter et batcher les données d'entraînement
train_data = train_data.map(lambda x, y: preprocess_img(x, y,
img_shape=224), num_parallel_calls=tf.data.AUTOTUNE)
train_data =
train_data.shuffle(buffer_size=1000).batch(batch_size=32).prefetch(tf.
data.AUTOTUNE)

# Prétraiter et batcher les données de test
test_data = test_data.map(lambda x, y: preprocess_img(x, y,
img_shape=224), num_parallel_calls=tf.data.AUTOTUNE)
test_data = test_data.batch(batch_size=32).prefetch(tf.data.AUTOTUNE)

train_data, test_data

(<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 224, 224, 3),
dtype=tf.float32, name=None), TensorSpec(shape=(None,),
dtype=tf.int64, name=None))>,
 <_PrefetchDataset element_spec=(TensorSpec(shape=(None, 224, 224, 3),
dtype=tf.float32, name=None), TensorSpec(shape=(None,),
dtype=tf.int64, name=None))>)

```

Créer des callbacks pour le modèle

Nous allons créer plusieurs callbacks pour nous aider pendant l'entraînement du modèle :

- Callback TensorBoard pour enregistrer les résultats de l'entraînement (pour que nous puissions les visualiser plus tard si nécessaire)

- Callback ModelCheckpoint pour sauvegarder la progression de notre modèle après l'extraction des caractéristiques

```
# Créer le callback TensorBoard (importé depuis helper_functions.py)
from helper_functions import create_tensorboard_callback

# Sauvegarder les poids au lieu de sauvegarder tout le modèle, ce qui
est plus rapide
checkpoint_path = "model_checkpoints/cp.weights.h5"
model_checkpoint = tf.keras.callbacks.ModelCheckpoint(checkpoint_path,

monitor="val_acc",

save_best_only=True,

save_weights_only=True,

verbose=0)
# verbose = 0, ne rien afficher si le modèle est sauvegardé ou non
```

Configurer l'entraînement en précision mixte

```
# Activer l'entraînement en précision mixte
from tensorflow.keras import mixed_precision
mixed_precision.set_global_policy("mixed_float16") # Définir la
politique de données globale en précision mixte
# Utiliser les types de données float16 et float32 pour accélérer les
performances du modèle

mixed_precision.global_policy()

<FloatDTypePolicy "mixed_float16">
```

Construire un modèle d'extraction de caractéristiques

```
len(class_names)

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from tensorflow.keras import layers

# Créer le modèle de base
input_shape = (224, 224, 3)
base_model = tf.keras.applications.EfficientNetV2B0(include_top=False)
# Geler les poids des paramètres du modèle de base
base_model.trainable = False

# Créer un modèle fonctionnel
inputs = layers.Input(shape=input_shape, name="input_layer")

x = base_model(inputs, training=False)
x = layers.GlobalAveragePooling2D()(x)
```



```

x = layers.Dense(len(class_names))(x)
outputs = layers.Activation("softmax", dtype=tf.float32,
name="softmax_float32")(x)

model = tf.keras.Model(inputs, outputs)

# Compiler le modèle
model.compile(loss="sparse_categorical_crossentropy",
optimizer=tf.keras.optimizers.Adam(), metrics=["accuracy"])

model.summary()

Model: "functional_1"

```

Layer (type) Param #	Output Shape	
input_layer (InputLayer) 0	(None, 224, 224, 3)	
efficientnetv2-b0 (Functional) 5,919,312	(None, 7, 7, 1280)	
global_average_pooling2d 0 (GlobalAveragePooling2D)	(None, 1280)	
dense (Dense) 129,381	(None, 101)	
softmax_float32 (Activation) 0	(None, 101)	

Total params: 6,048,693 (23.07 MB)

Trainable params: 129,381 (505.39 KB)

Non-trainable params: 5,919,312 (22.58 MB)

Vérifier les politiques dtype des couches : utilisons-nous la précision mixte ?

```
# Vérifier les attributs dtype_policy des couches de notre modèle
for layer in model.layers:
    print(layer.name, layer.trainable, layer.dtype,
          layer.dtype_policy)

input_layer True float32 <FloatDTypePolicy "mixed_float16">
efficientnetv2-b0 False float32 <FloatDTypePolicy "mixed_float16">
global_average_pooling2d True float32 <FloatDTypePolicy
"mixed_float16">
dense True float32 <FloatDTypePolicy "mixed_float16">
softmax_float32 True float32 <FloatDTypePolicy "float32">

# Vérifier les attributs dtype_policy des couches du modèle
EfficientV2NetB0
for layer in base_model.layers:
    print(layer.name, layer.trainable, layer.dtype,
          layer.dtype_policy)

input_layer False float32 <FloatDTypePolicy "mixed_float16">
rescaling False float32 <FloatDTypePolicy "mixed_float16">
normalization False float32 <FloatDTypePolicy "mixed_float16">
stem_conv False float32 <FloatDTypePolicy "mixed_float16">
stem_bn False float32 <FloatDTypePolicy "mixed_float16">
stem_activation False float32 <FloatDTypePolicy "mixed_float16">
block1a_project_conv False float32 <FloatDTypePolicy "mixed_float16">
block1a_project_bn False float32 <FloatDTypePolicy "mixed_float16">
block1a_project_activation False float32 <FloatDTypePolicy
"mixed_float16">
block2a_expand_conv False float32 <FloatDTypePolicy "mixed_float16">
block2a_expand_bn False float32 <FloatDTypePolicy "mixed_float16">
block2a_expand_activation False float32 <FloatDTypePolicy
"mixed_float16">
block2a_project_conv False float32 <FloatDTypePolicy "mixed_float16">
block2a_project_bn False float32 <FloatDTypePolicy "mixed_float16">
block2b_expand_conv False float32 <FloatDTypePolicy "mixed_float16">
block2b_expand_bn False float32 <FloatDTypePolicy "mixed_float16">
block2b_expand_activation False float32 <FloatDTypePolicy
"mixed_float16">
block2b_project_conv False float32 <FloatDTypePolicy "mixed_float16">
block2b_project_bn False float32 <FloatDTypePolicy "mixed_float16">
block2b_drop False float32 <FloatDTypePolicy "mixed_float16">
block2b_add False float32 <FloatDTypePolicy "mixed_float16">
block3a_expand_conv False float32 <FloatDTypePolicy "mixed_float16">
block3a_expand_bn False float32 <FloatDTypePolicy "mixed_float16">
block3a_expand_activation False float32 <FloatDTypePolicy
"mixed_float16">
block3a_project_conv False float32 <FloatDTypePolicy "mixed_float16">
block3a_project_bn False float32 <FloatDTypePolicy "mixed_float16">
block3b_expand_conv False float32 <FloatDTypePolicy "mixed_float16">
```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```

block6h_dwconv2 False float32 <FloatDTypePolicy "mixed_float16">
block6h_bn False float32 <FloatDTypePolicy "mixed_float16">
block6h_activation False float32 <FloatDTypePolicy "mixed_float16">
block6h_se_squeeze False float32 <FloatDTypePolicy "mixed_float16">
block6h_se_reshape False float32 <FloatDTypePolicy "mixed_float16">
block6h_se_reduce False float32 <FloatDTypePolicy "mixed_float16">
block6h_se_expand False float32 <FloatDTypePolicy "mixed_float16">
block6h_se_excite False float32 <FloatDTypePolicy "mixed_float16">
block6h_project_conv False float32 <FloatDTypePolicy "mixed_float16">
block6h_project_bn False float32 <FloatDTypePolicy "mixed_float16">
block6h_drop False float32 <FloatDTypePolicy "mixed_float16">
block6h_add False float32 <FloatDTypePolicy "mixed_float16">
top_conv False float32 <FloatDTypePolicy "mixed_float16">
top_bn False float32 <FloatDTypePolicy "mixed_float16">
top_activation False float32 <FloatDTypePolicy "mixed_float16">

mixed_precision.global_policy()

<FloatDTypePolicy "mixed_float16">

```

Entraîner le modèle d'extraction de caractéristiques

```

# Entraîner le modèle d'extraction de caractéristiques avec des
callbacks
history_101_food_classes_feature_extract = model.fit(train_data,
                                                       epochs=3,

steps_per_epoch=len(train_data),
validation_data=test_data,
validation_steps=int(0.15 * len(test_data)),
callbacks=[create_tensorboard_callback(dir_name="training_logs",
experiment_name="efficientnetb0_101_classes_all_data_feature_extract")
,
model_checkpoint])

Saving TensorBoard log files to:
training_logs/efficientnetb0_101_classes_all_data_feature_extract/
20241003-090308
Epoch 1/3
2368/2368 ————— 3742s 2s/step - accuracy: 0.4600 -
loss: 2.3543 - val_accuracy: 0.6962 - val_loss: 1.1668
Epoch 2/3

C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
site-packages\keras\src\callbacks\model_checkpoint.py:206:
UserWarning: Can save best model only with val_acc available,

```



```

skipping.
    self._save_model(epoch=epoch, batch=None, logs=logs)
C:\Users\anasa\AppData\Roaming\jupyterlab-desktop\jlab_server\Lib\
contextlib.py:158: UserWarning: Your input ran out of data;
interrupting training. Make sure that your dataset or generator can
generate at least `steps_per_epoch * epochs` batches. You may need to
use the `.repeat()` function when building your dataset.
    self.gen.throw(value)

2368/2368 _____ 168s 71ms/step - accuracy: 0.0000e+00 -
loss: 0.0000e+00 - val_accuracy: 0.6841 - val_loss: 1.1820
Epoch 3/3
2368/2368 _____ 3672s 2s/step - accuracy: 0.6586 -
loss: 1.3329 - val_accuracy: 0.7142 - val_loss: 1.0480

# Évaluer le modèle sur l'ensemble du dataset de test
results_feature_extract_model = model.evaluate(test_data)
results_feature_extract_model

790/790 _____ 1159s 1s/step - accuracy: 0.7168 - loss:
1.0524

[1.0519026517868042, 0.7169108986854553]

# Sauvegarder le modèle localement (si vous utilisez Google Colab, le
modèle sauvegardé sera supprimé lorsque l'instance Colab sera
terminée)
save_dir =
"07_efficientnetb0_feature_extract_model_mixed_precision.keras"
model.save(save_dir)

# Charger le modèle précédemment sauvegardé
loaded_saved_model = tf.keras.models.load_model(save_dir)

# Vérifier les couches du modèle de base et voir quelle politique
dtype elles utilisent
for layer in loaded_saved_model.layers[1].layers[:20]: # vérifier
uniquement les 20 premières couches pour limiter la sortie
    print(layer.name, layer.trainable, layer.dtype,
layer.dtype_policy)

input_layer True float32 <FloatDTypePolicy "mixed_float16">
rescaling False float32 <FloatDTypePolicy "mixed_float16">
normalization False float32 <FloatDTypePolicy "mixed_float16">
stem_conv False float32 <FloatDTypePolicy "mixed_float16">
stem_bn False float32 <FloatDTypePolicy "mixed_float16">
stem_activation False float32 <FloatDTypePolicy "mixed_float16">
block1a_project_conv False float32 <FloatDTypePolicy "mixed_float16">
block1a_project_bn False float32 <FloatDTypePolicy "mixed_float16">
block1a_project_activation False float32 <FloatDTypePolicy
"mixed_float16">

```

```

block2a_expand_conv False float32 <FloatDTypePolicy "mixed_float16">
block2a_expand_bn False float32 <FloatDTypePolicy "mixed_float16">
block2a_expand_activation False float32 <FloatDTypePolicy
"mixed_float16">
block2a_project_conv False float32 <FloatDTypePolicy "mixed_float16">
block2a_project_bn False float32 <FloatDTypePolicy "mixed_float16">
block2b_expand_conv False float32 <FloatDTypePolicy "mixed_float16">
block2b_expand_bn False float32 <FloatDTypePolicy "mixed_float16">
block2b_expand_activation False float32 <FloatDTypePolicy
"mixed_float16">
block2b_project_conv False float32 <FloatDTypePolicy "mixed_float16">
block2b_project_bn False float32 <FloatDTypePolicy "mixed_float16">
block2b_drop False float32 <FloatDTypePolicy "mixed_float16">

```

Vérifier les performances du modèle chargé (cela devrait être les mêmes que celles du modèle d'extraction de caractéristiques)

```

results_loaded_saved_model = loaded_saved_model.evaluate(test_data)
results_loaded_saved_model

```

```

790/790 ————— 1169s 1s/step - accuracy: 0.7166 - loss:
1.0528

```

```
[1.0519040822982788, 0.7169108986854553]
```

Les résultats du modèle chargé doivent être égaux (ou du moins très proches) de ceux du modèle avant la sauvegarde

Remarque : cela ne fonctionnera que si vous avez instancié des variables de résultats

```

# import numpy as np
# assert np.isclose(results_feature_extract_model,
results_loaded_saved_model, rtol=1e-05, atol=1e-08).all()

```

Obtenir un résumé de notre modèle téléchargé

```
loaded_saved_model.summary()
```

```
Model: "functional_1"
```

Layer (type) Param #	Output Shape	
input_layer (InputLayer) 0	(None, 224, 224, 3)	
efficientnetv2-b0 (Functional) 5,919,312	(None, 7, 7, 1280)	

0	global_average_pooling2d	(None, 1280)	
	(GlobalAveragePooling2D)		
<hr/>			
	dense (Dense)	(None, 101)	
129,381			
<hr/>			
0	softmax_float32 (Activation)	(None, 101)	
<hr/>			

Total params: 6,307,461 (24.06 MB)

Trainable params: 129,381 (505.39 KB)

Non-trainable params: 5,919,312 (22.58 MB)

Optimizer params: 258,768 (1010.82 KB)

```
# Configurer le callback EarlyStopping pour arrêter l'entraînement si
la val_loss du modèle n'améliore pas pendant 3 époques
early_stopping = tf.keras.callbacks.EarlyStopping(monitor="val_loss",
# Surveiller la métrique val_loss
                                                    patience=3) # Si la
val_loss diminue pendant 3 époques d'affilée, arrêter l'entraînement

# Créer un callback ModelCheckpoint pour sauvegarder le meilleur
modèle pendant le fine-tuning
checkpoint_path = "fine_tune_checkpoints/fine_tune_checkpoints.keras"
model_checkpoint = tf.keras.callbacks.ModelCheckpoint(checkpoint_path,
save_best_only=True,
monitor="val_loss")

# Créer un callback de réduction du taux d'apprentissage
reduce_lr = tf.keras.callbacks.ReduceLROnPlateau(monitor="val_loss",
                                                    factor=0.2, #
multiply the learning rate by 0.2 (reduce by 5x)
                                                    patience=2,
                                                    verbose=1, # print
out when learning rate goes down
                                                    min_lr=1e-7)

# Compiler le modèle
loaded_saved_model.compile(loss="sparse_categorical_crossentropy", #
sparse_categorical_crossentropy car les labels ne sont pas one-hot
```

```

optimizer=tf.keras.optimizers.Adam(0.0001), #
10x moins que le taux d'apprentissage par défaut
metrics=["accuracy"])

# Commencer le fine-tuning (pour toutes les couches)
history_101_food_classes_all_data_fine_tune =
loaded_saved_model.fit(train_data,
                                                                    epochs=100, #
Affiner pour un maximum de 100 époques

steps_per_epoch=len(train_data),

validation_data=test_data,

validation_steps=int(0.15 * len(test_data)), # Validation pendant
l'entraînement sur 15% des données de test

callbacks=[create_tensorboard_callback("training_logs",
"efficientb0_101_classes_all_data_fine_tuning"), # Garder trace des
logs du modèle pendant l'entraînement

model_checkpoint, # Sauvegarder uniquement le meilleur modèle pendant
l'entraînement

early_stopping, # Arrêter le modèle après X époques sans améliorations

reduce_lr]) # Réduire le taux d'apprentissage après X époques sans
améliorations

Saving TensorBoard log files to:
training_logs/efficientb0_101_classes_all_data_fine_tuning/20241003-
114824
Epoch 1/100
2368/2368 _____ 3656s 2s/step - accuracy: 0.7011 -
loss: 1.1496 - val_accuracy: 0.7381 - val_loss: 1.0137 -
learning_rate: 1.0000e-04
Epoch 2/100
2368/2368 _____ 167s 71ms/step - accuracy: 0.0000e+00 -
loss: 0.0000e+00 - val_accuracy: 0.7256 - val_loss: 1.0239 -
learning_rate: 1.0000e-04
Epoch 3/100
2368/2368 _____ 3800s 2s/step - accuracy: 0.7087 -
loss: 1.1279 - val_accuracy: 0.7336 - val_loss: 0.9921 -
learning_rate: 1.0000e-04
Epoch 4/100
2368/2368 _____ 181s 76ms/step - accuracy: 0.0000e+00 -
loss: 0.0000e+00 - val_accuracy: 0.7370 - val_loss: 0.9848 -
learning_rate: 1.0000e-04
Epoch 5/100
2368/2368 _____ 3849s 2s/step - accuracy: 0.7141 -

```

```
loss: 1.1101 - val_accuracy: 0.7264 - val_loss: 0.9995 -  
learning_rate: 1.0000e-04  
Epoch 6/100
```

```
Epoch 6: ReduceLROnPlateau reducing learning rate to  
1.9999999494757503e-05.
```

```
2368/2368 _____ 196s 83ms/step - accuracy: 0.0000e+00 -  
loss: 0.0000e+00 - val_accuracy: 0.7301 - val_loss: 1.0164 -  
learning_rate: 1.0000e-04
```

```
Epoch 7/100
```

```
2368/2368 _____ 3689s 2s/step - accuracy: 0.7208 -  
loss: 1.0872 - val_accuracy: 0.7263 - val_loss: 1.0203 -  
learning_rate: 2.0000e-05
```

```
# Sauvegarder le modèle localement
```

```
loaded_saved_model.save("07_efficientnetb0_fine_tuned_101_classes_mixed_precision.keras")
```

```
# Charger le modèle fine-tuné depuis Google Storage et évaluer
```

```
loaded_fine_tuned_gs_model =  
tf.keras.models.load_model("07_efficientnetb0_fine_tuned_101_classes_mixed_precision.keras")
```

```
# Obtenir un résumé du modèle (même architecture que ci-dessus)
```

```
loaded_fine_tuned_gs_model.summary()
```

```
Model: "functional_1"
```

Layer (type) Param #	Output Shape	
input_layer (InputLayer) 0	(None, 224, 224, 3)	
efficientnetv2-b0 (Functional) 5,919,312	(None, 7, 7, 1280)	
global_average_pooling2d 0 (GlobalAveragePooling2D)	(None, 1280)	
dense (Dense) 129,381	(None, 101)	

softmax_float32 (Activation)	(None, 101)	
0		

Total params: 6,307,461 (24.06 MB)

Trainable params: 129,381 (505.39 KB)

Non-trainable params: 5,919,312 (22.58 MB)

Optimizer params: 258,768 (1010.82 KB)

```
results_downloaded_fine_tuned_gs_model =
loaded_fine_tuned_gs_model.evaluate(test_data)
results_downloaded_fine_tuned_gs_model
```

790/790 ————— 1214s 2s/step - accuracy: 0.7362 - loss: 0.9983

[0.9974470138549805, 0.7340593934059143]