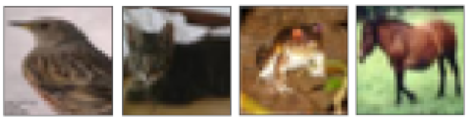
PRACTICAL SESSION 2 Supervised DEEP LEARNING

The dataset is a *subset* of CIFAR10 (a very popular dataset in Machine Learning) with only 4 classes: **BIRD**, **CAT**, **FROG**, **HORSE**. We will call our dataset **CIFAR4**. It is composed of 24000 images from 4 types of animals.

Input data are square color images (RGB). The size of a picture is 32x32. So we have an input tensor of size [32,32,3]. Each pixel has a red, green and blue UINT8 values, i.e. in [0,255].



The dataset is available on **ECAMPUS**

The main objective is to train different deep neural network models to classify an image into one of the 4 classes.

The goal of this practical session is to experiment! Everything you need is easily available in the TENSORFLOW documentation that contains many examples.

BONUS STRIKE

You can make additional experiences. In that case, please add bonus works at the end of your notebook in the **[BONUS]** section.

Bonus works could bring bonus points on the global note for the practical sessions ***if and only if*** all the mandatory jobs have been done correctly.

IMPORT LIBS

We will use TENSORFLOW, the Deep Learning platform from Google.

TensorFlow is easy to understand and the documentation and tutorials are (very) useful when learning Deep Learning.

I already know how to develop DL models and I want to use PyTorch instead. Is it possible?

==> *YES*. PYTORCH (from Meta) is the other big reference for DL libraries. Note that, in that case, *it's your choice* and you must be *self-sufficient* in case of development issues.

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import urllib
import zipfile
import matplotlib.pyplot as plt
from PIL import Image
import tensorflow as tf
```

[WARNING] About the use of COLAB and GPU

On the top-right of the colab environment, you can chose the execution environment ("Modify the execution type") between CPU and GPU (Nvidia T4). With a free google account, there is no limitation with the CPU-only mode. With the GPU, you have a limitation that is dynamically set by Google regarding the overall load on their infrastructure. Usually, it could be 1 hour per day.

For this practical session, you can keep the CPU mode for the MLP part. For the CNN section, you can swith to the GPU mode if you consider the processing are too slow. But, be careful and not too GPU-enthusiast.

NB: You can check the CPU info with `!cat /proc/cpuinfo`

```
#Get CPU info
!cat /proc/cpuinfo
#Get GPU info
#!nividia-smi
```

```
processor       : 0
vendor_id       : GenuineIntel
cpu family      : 6
model           : 79
model name      : Intel(R) Xeon(R) CPU @ 2.20GHz
stepping        : 0
microcode       : 0xffffffff
cpu MHz         : 2199.998
cache size      : 56320 KB
physical id     : 0
siblings        : 2
core id         : 0
cpu cores       : 1
apicid          : 0
initial apicid  : 0
fpu             : yes
fpu_exception   : yes
cpuid level     : 13
wp              : yes
flags           : fpu vme de pse tsc msr pae mce cx8 apic sep mtrr pge mca cmov pat pse36 clflush mmx fxsr sse sse
bugs            : cpu_meltdown spectre_v1 spectre_v2 spec_store_bypass l1tf mds swapgs taa mmio_stale_data retblee
bogomips        : 4399.99
clflush size    : 64
cache_alignment : 64
address sizes   : 46 bits physical, 48 bits virtual
power management:

processor       : 1
vendor_id       : GenuineIntel
cpu family      : 6
model           : 79
model name      : Intel(R) Xeon(R) CPU @ 2.20GHz
stepping        : 0
microcode       : 0xffffffff
cpu MHz         : 2199.998
cache size      : 56320 KB
physical id     : 0
siblings        : 2
core id         : 0
cpu cores       : 1
apicid          : 1
initial apicid  : 1
fpu             : yes
fpu_exception   : yes
cpuid level     : 13
wp              : yes
flags           : fpu vme de pse tsc msr pae mce cx8 apic sep mtrr pge mca cmov pat pse36 clflush mmx fxsr sse sse
bugs            : cpu_meltdown spectre_v1 spectre_v2 spec_store_bypass l1tf mds swapgs taa mmio_stale_data retblee
bogomips        : 4399.99
clflush size    : 64
cache_alignment : 64
address sizes   : 46 bits physical, 48 bits virtual
power management:
```

DOWNLOAD AND CHECK THE DATASET [3 pts]

Data must be located in a ./data directory at the same level as this notebook

```
#IF YOU USE Google COLAB, you can mount your Google Drive:
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
#Create a 'data/' directory, put the numpy files and load. With Colab case, create 'data' here:
X_cifar4=np.load("/content/drive/MyDrive/Colab Notebooks/data/CIFAR4_X.npy")
Y_cifar4=np.load("/content/drive/MyDrive/Colab Notebooks/data/CIFAR4_Y.npy")
print(np.shape(X_cifar4))
print(np.shape(Y_cifar4))
nb_labels=4
```

```
(24000, 32, 32, 3)
(24000,)
```

[QUESTION] Display some images from X_cifar4 with the corresponding label

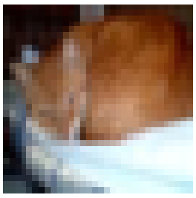
NB: Since the pictures are very small, use `plt.figure(figsize=(2, 2), dpi=80)` before `plt.imshow()` to display something *"watchable"*.

```
j = 11995  # Starting index
for i in range(j, j + 9):  # Display 9 images sequentially
    plt.figure(figsize=(2, 2), dpi=80)  # Set figure size for each image
    plt.imshow(X_cifar4[i])  # Display the image
    plt.title(f"Label: {Y_cifar4[i]}")  # Add the label as the title
    plt.axis('off')  # Remove axis for clarity
    plt.show()  # Show the image
```

Label: 1

Label: 1

Label: 1



Label: 1

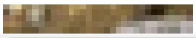
Label: 1

Label: 2

Label: 2

Label: 2

Label: 2



A pixel is an UINT8 value, so in [0;255]. We will normalize data in [0,1]:

```
print("First pixel (r,g,b) of the first image:", X_cifar4[0,0,0,:])
X = X_cifar4/255.0
print("Now in [0,1] ==> ", X[0,0,0,:])
```

```
First pixel (r,g,b) of the first image: [164 206  84]
Now in [0,1] ==>  [0.64313725 0.80784314 0.32941176]
```

For the labels **Y**, usually, we prefer to process "one-hot encodings" i.e., a vector with '0' everywhere except for the corresponding label where you have '1'.

Example : let's say you have 4 labels and 10 training data with the original Y:

```
Y=[0,1,1,3,3,3,2,2,1,0]
shape(Y)=[10,]
```

Then the "one-hot encoding" version of Y will be:

```
Y_onehot=
[1,0,0,0;
 0,1,0,0;
 0,1,0,0;
 0,0,0,1;
 0,0,0,1;
 0,0,0,1;
 0,0,1,0;
 0,0,1,0;
 0,1,0,0;
 1,0,0,0]
shape(Y_onehot)=[10,4]
```

[QUESTION] Use the tensorflow method *tf.keras.utils.to_categorical()* to transform your Y_cifar4 into Y and check the shape of your new Y.

```
import keras
#Your code here

Y = keras.utils.to_categorical(Y_cifar4, num_classes=4)
print(Y)
```

```
[[1. 0. 0. 0.]
 [1. 0. 0. 0.]
 [1. 0. 0. 0.]
 ...
 [0. 0. 0. 1.]
 [0. 0. 0. 1.]
 [0. 0. 0. 1.]]
```

CREATE A TRAINING/VALIDATION/TEST dataset [2 pt]

NB: This step is similar to the supervised section in TP1.

[QUESTION] Use the SKLEARN method train_test_split in order to create:

- a TRAIN set (X_train,Y_train) *[advice: use 70% of the whole dataset]*
- a VALIDATION set (X_val, Y_val) *[advice: 15%]*
- a TEST set (X_test, Y_test) *[advice: 15%]*

Print the shape of the 3 datasets.

The TRAIN and VALIDATION sets will be used at training time. The TEST set will be used, after the training, at the inference time.

NOTE that we could only use a single VALIDATION/TEST set for both the training and the inference stages.

```
#Your code here
#CREATE A TRAINING/ VALIDATION/TEST dataset
from sklearn.model_selection import train_test_split

# Split the dataset into training and test sets
X_train, X_test, Y_train, Y_test= train_test_split(X, Y, train_size=0.7, random_state=42)
X_val, X_test, Y_val, Y_test= train_test_split(X_test, Y_test, train_size=0.5, random_state=42)

# Check the sizes of the resulting datasets
print(f"Size of X_train: {X_train.shape}")
print(f"Size of Y_train: {Y_train.shape}")
print(f"Size of X_test: {X_test.shape}")
print(f"Size of Y_test: {Y_test.shape}")
print(f"Size of X_val: {X_val.shape}")
print(f"Size of Y_val: {Y_val.shape}")
```

```
Size of X_train: (16800, 32, 32, 3)
Size of Y_train: (16800, 4)
Size of X_test: (3600, 32, 32, 3)
Size of Y_test: (3600, 4)
Size of X_val: (3600, 32, 32, 3)
Size of Y_val: (3600, 4)
```

[**QUESTION**] Why the train/val/test split is important in our case? What is the main interest of the validation data at training time?

[**ANSWER**]

Splitting the data into training, validation, and test sets is crucial for building a model that generalizes well to new data.

The training set is used to learn the model parameters, while the validation set serves to fine-tune hyperparameters and monitor performance during training.

This helps prevent overfitting by providing feedback on how the model might perform on unseen data before using the test set for a final, unbiased evaluation.

MULTI-LAYER PERCEPTRON (MLP) MODEL [12 pts]

Analyse of a MLP code [6pts]

It's time to build our first deep neural network...

Below, we provide a small code **THAT IS NOT WORKING**, because something are missing or wrong.

The model is a very simple MLP with only one hidden layer (20 neurons). So we have :

```
x --> "input" layer ==> hidden layer ==> output layer --> ŷ
```

Have a look at the code, and understand how it works.

```
# (1) DEFINE THE ARCHITECTURE OF MY MODEL
#first, I define all the layers and the way they are connected
inputs = tf.keras.Input(shape=(32,32,3)) #my input layer
x = tf.keras.layers.Flatten()(inputs) #cf. question below...
x = tf.keras.layers.Dense(20, activation='tanh')(x) #a first hidden layer with 20 neurons
outputs = tf.keras.layers.Dense(4, activation='softmax')(x) # my output layer
#Then, I define my model with the input layer, the output layer and a name
my_mlp_model = tf.keras.Model(inputs=inputs, outputs=outputs, name="my_mlp_model")
```

```
#PRINT A SUMMARY OF THE ARCHITECTURE OF MY MODEL WITH THE NUMBER OF TRAINABLE PARAMETERS
my_mlp_model.summary()

# (2) DEFINE THE TRAINING HYPER-PARAMETERS WITH THE "COMPILE" METHOD:
'''
(1) Set the "optimizer" [pick 'adam', 'sgd' or 'rmsprop']
(2) Set the loss [cf. lesson #3, we pick the categorical cross-entropy]
(3) Set the final performance metric to evaluate the model
'''

my_mlp_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# (3) NOW, LET'S TRAIN ON MY DATA WITH THE "FIT" METHOD
'''
(1) Set the number of epochs
(2) Set the size of the (mini)batch
(3) Set the training dataset ==> here, X_train with Y_train
(4) Set the validation dataset (X_val, Y_val)
'''
nb_epochs=4
batch_size=100
training_history = my_mlp_model.fit(X_train,Y_train,
                                    validation_data=(X_val, Y_val),
                                    epochs=nb_epochs,
                                    batch_size=batch_size)

#COMPUTE THE ACCURACY ON THE TRAINING AND TEST SETS
loss_train, acc_train = my_mlp_model.evaluate(X_train, Y_train, batch_size=batch_size)
loss_test, acc_test = my_mlp_model.evaluate(X_test, Y_test, batch_size=batch_size)

print("Performance on the TRAIN set, ACCURACY=",acc_train)
print("Performance on the TEST set, ACCURACY=",acc_test)
```

Model: "my_mlp_model"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 32, 32, 3)	0
flatten (Flatten)	(None, 3072)	0
dense (Dense)	(None, 20)	61,460
dense_1 (Dense)	(None, 4)	84

```
 Total params: 61,544 (240.41 KB)
 Trainable params: 61,544 (240.41 KB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/4
168/168 ━━━━━━━━━━━━━━━━━━━━ 4s 11ms/step - accuracy: 0.3182 - loss: 1.4029 - val_accuracy: 0.4394 - val_loss: 1.2
Epoch 2/4
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4721 - loss: 1.2175 - val_accuracy: 0.4858 - val_loss: 1.18
Epoch 3/4
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4962 - loss: 1.1642 - val_accuracy: 0.5194 - val_loss: 1.14
Epoch 4/4
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5228 - loss: 1.1251 - val_accuracy: 0.5028 - val_loss: 1.13
168/168 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5067 - loss: 1.1247
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5046 - loss: 1.1481
Performance on the TRAIN set, ACCURACY= 0.5057737827301025
Performance on the TEST set, ACCURACY= 0.5033333301544189
```

[QUESTION]

- (1) What is the activation function for the hidden layer?
- (2) What is the most used activation function in deep learning?
- (3) How many time an image sample will be used during the training?
- (4) How many training iterations (i.e., params update) in total will be processed?

[ANSWER]

(1) The activation function for the hidden layer is tanh().

(2) The the most used activation function in deep learning is relu() because ,even with its cons , it is a great way to avoid vanishing gradient and it allows a sparse activation of our network.

(3) Because this deep learning algorithm runs on 4 epochs, each image sample will be used 4 times during the training.

(4) The training dataset have 70% of image samples of our ciphar4 dataset, which means 16800 pictures. Furthermore, the MLP algorithm above is doing a mini-batch Stochastic Gradient Descent with batches of size 100, which means the training dataset have 168 batches. And this algorithm runs on 4 epochs, so in total 672(=4x 24000x0.7 / 100) training iterations will be processed.

[QUESTION]

- (1) Regarding the previous questions, copy and change the code above to make it runs on **10 EPOCHS**. Comment the resulting performance of the model.
- (2) For our MLP, why do we need this line `x = tf.keras.layers.Flatten()(inputs)` ?
- (3) Give the calculation of the number of trainable parameters

```
# (1) DEFINE THE ARCHITECTURE OF MY MODEL
#first, I define all the layers and the way they are connected
inputs = tf.keras.Input(shape=(32,32,3)) #my input layer
x = tf.keras.layers.Flatten()(inputs) #cf. question below...
x = tf.keras.layers.Dense(20, activation='tanh')(x) #a first hidden layer with 20 neurons
outputs = tf.keras.layers.Dense(4, activation='softmax')(x) # my output layer
#Then, I define my model with the input layer, the output layer and a name
my_mlp_model = tf.keras.Model(inputs=inputs, outputs=outputs, name="my_mlp_model")

#PRINT A SUMMARY OF THE ARCHITECTURE OF MY MODEL WITH THE NUMBER OF TRAINABLE PARAMETERS
my_mlp_model.summary()

# (2) DEFINE THE TRAINING HYPER-PARAMETERS WITH THE "COMPILE" METHOD:
'''
(1) Set the "optimizer" [pick 'adam', 'sgd' or 'rmsprop']
(2) Set the loss [cf. lesson #3, we pick the categorical cross-entropy]
(3) Set the final performance metric to evaluate the model
'''

my_mlp_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# (3) NOW, LET'S TRAIN ON MY DATA WITH THE "FIT" METHOD
'''
(1) Set the number of epochs
(2) Set the size of the (mini)batch
(3) Set the training dataset ==> here, X_train with Y_train
(4) Set the validation dataset (X_val, Y_val)
'''
nb_epochs=10
batch_size=100
training_history = my_mlp_model.fit(X_train,Y_train,
                                    validation_data=(X_val, Y_val),
                                    epochs=nb_epochs,
                                    batch_size=batch_size)

#COMPUTE THE ACCURACY ON THE TRAINING AND TEST SETS
loss_train, acc_train = my_mlp_model.evaluate(X_train, Y_train, batch_size=batch_size)
loss_test, acc_test = my_mlp_model.evaluate(X_test, Y_test, batch_size=batch_size)

print("Performance on the TRAIN set, ACCURACY=",acc_train)
print("Performance on the TEST set, ACCURACY=",acc_test)
```

```
Model: "my_mlp_model"
```

Layer (type)	Output Shape	Param #
input_layer_8 (InputLayer)	(None, 32, 32, 3)	0
flatten (Flatten)	(None, 3072)	0
dense_6 (Dense)	(None, 20)	61,460
dense_7 (Dense)	(None, 4)	84

```
 Total params: 61,544 (240.41 KB)
 Trainable params: 61,544 (240.41 KB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.3477 - loss: 1.4195 - val_accuracy: 0.4447 - val_loss: 1.23
Epoch 2/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.4740 - loss: 1.2049 - val_accuracy: 0.4919 - val_loss: 1.16
Epoch 3/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5178 - loss: 1.1427 - val_accuracy: 0.5217 - val_loss: 1.10
Epoch 4/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5264 - loss: 1.1104 - val_accuracy: 0.5342 - val_loss: 1.11
Epoch 5/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5358 - loss: 1.1036 - val_accuracy: 0.4997 - val_loss: 1.14
Epoch 6/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5400 - loss: 1.0842 - val_accuracy: 0.5353 - val_loss: 1.09
Epoch 7/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5534 - loss: 1.0593 - val_accuracy: 0.5372 - val_loss: 1.08
Epoch 8/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5490 - loss: 1.0676 - val_accuracy: 0.5467 - val_loss: 1.06
Epoch 9/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5638 - loss: 1.0315 - val_accuracy: 0.5506 - val_loss: 1.05
Epoch 10/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5582 - loss: 1.0398 - val_accuracy: 0.5497 - val_loss: 1.05
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5813 - loss: 1.0084
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.5424 - loss: 1.0668
Performance on the TRAIN set, ACCURACY= 0.5773214101791382
Performance on the TEST set, ACCURACY= 0.5416666865348816
```

[ANSWER] *Your answer here*

(1) After training, the model achieved roughly 57% accuracy on the training set and 54% accuracy on the test set. This indicates that while the network is learning, its performance is still modest. The small gap between training and test accuracy suggests that the model is not overfitting but might be **underfitting** due to its simple architecture or limited training duration.

(2) The line x = tf.keras.layers.Flatten()(inputs) is essential for preparing the input data for the Dense (fully connected) layers in the MLP architecture.

The input data has the shape (32, 32, 3), representing an RGB image of size 32×32 with 3 color channels. However dense Layers Require 1D Input. This is why we have a Flatten layer (x = tf.keras.layers.Flatten()(inputs)) that converts the 3D input tensor (height, width, channels) into a 1D vector.

(3) Model.summary() gives us a total of 61544 parameters trainable in our model. Let's explain this number :

- We have 3072 inputs (=32x32x3)
- The first layer is a fully connected layer of 20 neurons so this layers gives us (3072+1)x20= 61460 trainable parameters with the biases counted
- And we have a final fully connected layer of 4 neurons which means this layer have (20+1)x4= 84 trainables parameters with the biases counted

So the total numbers of trainable parameters in this model is 61460+84= 61544 which is indeed the result of model.summary()

It is always good to have a look on the training curves. That is the role of the "**training_history**" object that we defined in the code as the output of the **fit** method. In this object, we collect all the loss and metric values after each epoch.

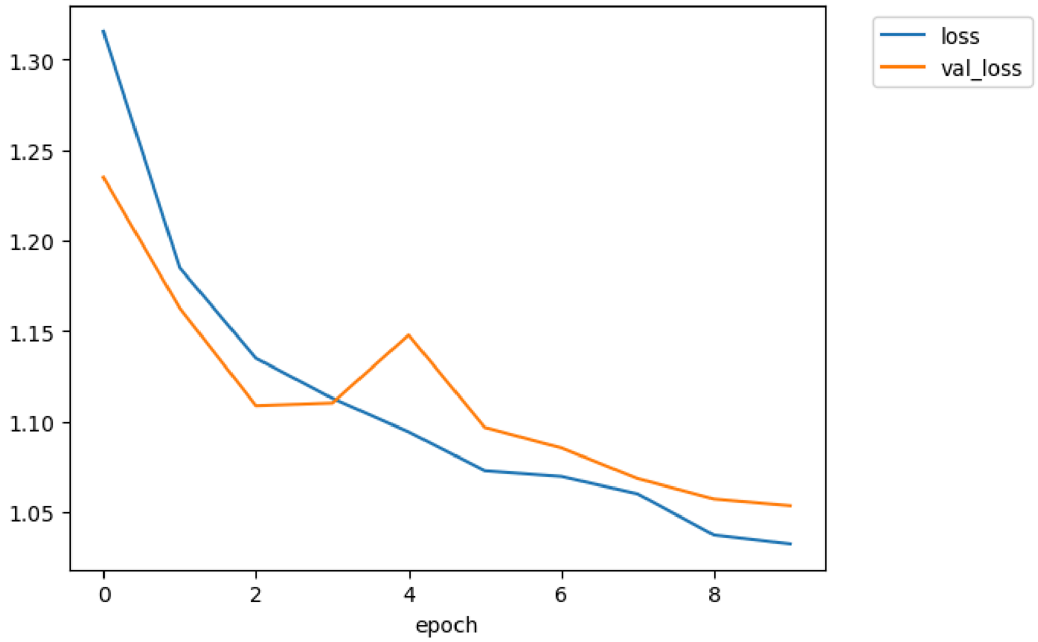
You can use the following **method** to display the train/val curves (loss and accuracy):

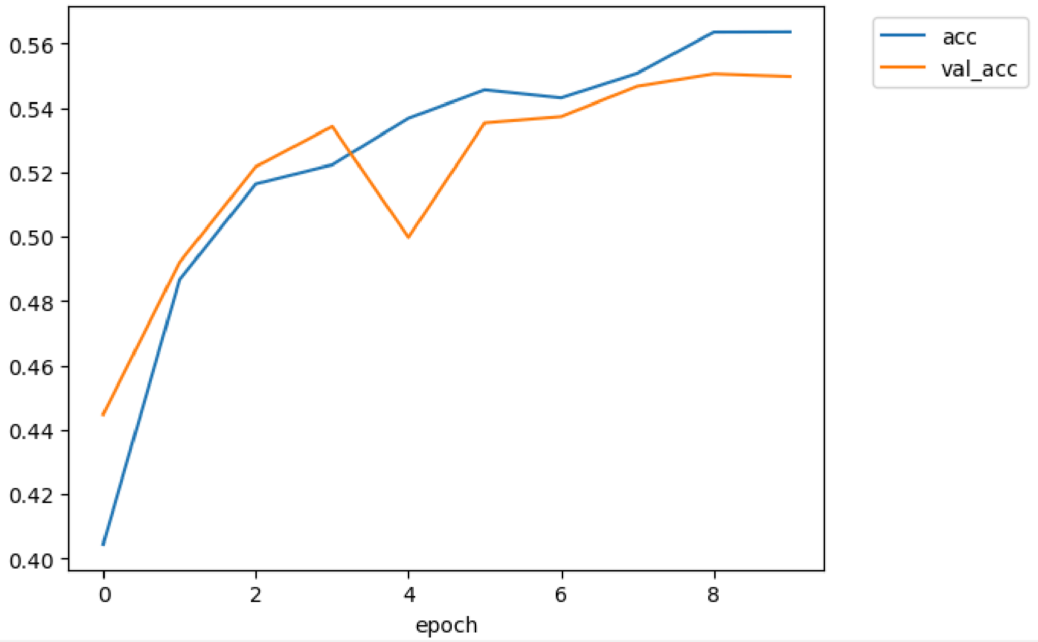
```
def display_training_curves(training_history):
  # display loss
  plt.plot(training_history.history['loss'],label='loss')
```

```
    plt.plot(training_history.history['val_loss'], label='val_loss')
    plt.xlabel("epoch")
    plt.legend(bbox_to_anchor=(1.05, 1), loc=2)
    plt.show()
    #display accuracy
    plt.plot(training_history.history['accuracy'],label='acc')
    plt.plot(training_history.history['val_accuracy'], label='val_acc')
    plt.xlabel("epoch")
    plt.legend(bbox_to_anchor=(1.05, 1), loc=2)
    plt.show()
```

[QUESTION] Display the training curves from your MLP model.

```
display_training_curves(training_history)
```





Improvements and overfitting [6 pts]

[QUESTION] Use the previous MLP code to build your own model and try to reach a better accuracy performance (e.g., above/around 60%, both train and test)

```
#Your code here
# (1) DEFINE THE ARCHITECTURE OF MY MODEL
#first, I define all the layers and the way they are connected
inputs = tf.keras.Input(shape=(32,32,3)) #my input layer
x = tf.keras.layers.Flatten()(inputs) #cf. question below...
x = tf.keras.layers.Dense(200, activation='tanh')(x) #a first hidden layer with 20 neurons
x = tf.keras.layers.Dense(70, activation='relu')(x) #a first hidden layer with 20 neurons
#x = tf.keras.layers.Dropout(0.)(x)  #Drop 10% of neurons on the first layer
outputs = tf.keras.layers.Dense(4, activation='softmax')(x) # my output layer
#Then, I define my model with the input layer, the output layer and a name
my_mlp_model = tf.keras.Model(inputs=inputs, outputs=outputs, name="my_mlp_model")

#PRINT A SUMMARY OF THE ARCHITECTURE OF MY MODEL WITH THE NUMBER OF TRAINABLE PARAMETERS
my_mlp_model.summary()

# (2) DEFINE THE TRAINING HYPER-PARAMETERS WITH THE "COMPILE" METHOD:
'''
(1) Set the "optimizer" [pick 'adam', 'sgd' or 'rmsprop']
(2) Set the loss [cf. lesson #3, we pick the categorical cross-entropy]
(3) Set the final performance metric to evaluate the model
'''

my_mlp_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# (3) NOW, LET'S TRAIN ON MY DATA WITH THE "FIT" METHOD
'''
(1) Set the number of epochs
(2) Set the size of the (mini)batch
(3) Set the training dataset ==> here, X_train with Y_train
(4) Set the validation dataset (X_val, Y_val)
'''
nb_epochs=30
batch_size=100
training_history = my_mlp_model.fit(X_train,Y_train,
                                    validation_data=(X_val, Y_val),
                                    epochs=nb_epochs,
                                    batch_size=batch_size)

#COMPUTE THE ACCURACY ON THE TRAINING AND TEST SETS
loss_train, acc_train = my_mlp_model.evaluate(X_train, Y_train, batch_size=batch_size)
loss_test, acc_test = my_mlp_model.evaluate(X_test, Y_test, batch_size=batch_size)

print("Performance on the TRAIN set, ACCURACY=",acc_train)
print("Performance on the TEST set, ACCURACY=",acc_test)
```

```
Model: "my_mlp_model"
```

Layer (type)	Output Shape	Param #
input_layer_40 (InputLayer)	(None, 32, 32, 3)	0
flatten_40 (Flatten)	(None, 3072)	0
dense_131 (Dense)	(None, 200)	614,600
dense_132 (Dense)	(None, 70)	14,070
dense_133 (Dense)	(None, 4)	284

```
 Total params: 628,954 (2.40 MB)
 Trainable params: 628,954 (2.40 MB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 4s 7ms/step - accuracy: 0.3524 - loss: 1.4419 - val_accuracy: 0.4850 - val_loss: 1.16
Epoch 2/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4948 - loss: 1.1547 - val_accuracy: 0.5361 - val_loss: 1.11
Epoch 3/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5243 - loss: 1.1106 - val_accuracy: 0.5486 - val_loss: 1.06
Epoch 4/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5446 - loss: 1.0714 - val_accuracy: 0.5686 - val_loss: 1.05
Epoch 5/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5501 - loss: 1.0605 - val_accuracy: 0.5694 - val_loss: 1.02
Epoch 6/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5646 - loss: 1.0321 - val_accuracy: 0.5606 - val_loss: 1.06
Epoch 7/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5716 - loss: 1.0166 - val_accuracy: 0.5606 - val_loss: 1.04
Epoch 8/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.5847 - loss: 0.9940 - val_accuracy: 0.5697 - val_loss: 1.02
Epoch 9/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5765 - loss: 1.0001 - val_accuracy: 0.5572 - val_loss: 1.05
Epoch 10/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5926 - loss: 0.9785 - val_accuracy: 0.5883 - val_loss: 1.01
Epoch 11/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5989 - loss: 0.9614 - val_accuracy: 0.5822 - val_loss: 1.00
Epoch 12/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5932 - loss: 0.9701 - val_accuracy: 0.5792 - val_loss: 1.01
Epoch 13/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6003 - loss: 0.9700 - val_accuracy: 0.5778 - val_loss: 1.04
Epoch 14/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6067 - loss: 0.9507 - val_accuracy: 0.5733 - val_loss: 1.01
Epoch 15/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6138 - loss: 0.9295 - val_accuracy: 0.5906 - val_loss: 0.99
Epoch 16/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6249 - loss: 0.9232 - val_accuracy: 0.5844 - val_loss: 1.01
Epoch 17/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6228 - loss: 0.9138 - val_accuracy: 0.5683 - val_loss: 1.06
Epoch 18/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6135 - loss: 0.9419 - val_accuracy: 0.5772 - val_loss: 1.01
Epoch 19/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6148 - loss: 0.9381 - val_accuracy: 0.5844 - val_loss: 1.00
Epoch 20/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6389 - loss: 0.8906 - val_accuracy: 0.5994 - val_loss: 0.99
Epoch 21/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6359 - loss: 0.8896 - val_accuracy: 0.5972 - val_loss: 0.97
Epoch 22/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6378 - loss: 0.8942 - val_accuracy: 0.5917 - val_loss: 0.99
Epoch 23/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6432 - loss: 0.8754 - val_accuracy: 0.5733 - val_loss: 1.03
Epoch 24/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6273 - loss: 0.9050 - val_accuracy: 0.5956 - val_loss: 0.98
Epoch 25/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6373 - loss: 0.8845 - val_accuracy: 0.5975 - val_loss: 0.99
Epoch 26/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6518 - loss: 0.8686 - val_accuracy: 0.6106 - val_loss: 0.98
Epoch 27/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6535 - loss: 0.8531 - val_accuracy: 0.5914 - val_loss: 1.00
Epoch 28/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6414 - loss: 0.8731 - val_accuracy: 0.6044 - val_loss: 0.98
Epoch 29/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6608 - loss: 0.8393 - val_accuracy: 0.5969 - val_loss: 0.99
Epoch 30/30
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6679 - loss: 0.8398 - val_accuracy: 0.5978 - val_loss: 0.98
168/168 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.6744 - loss: 0.8217
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.5898 - loss: 0.9947
```

```
Performance on the TRAIN set, ACCURACY= 0.6747024059295654
Performance on the TEST set, ACCURACY= 0.5933333039283752
```

[QUESTION] For illustration/educational purpose, use the code of your last model and adapt it so that your model clearly **OVERFITS**.

We need to see the overfitting issue on the training curve!

(Think about the reasons of overfitting?)

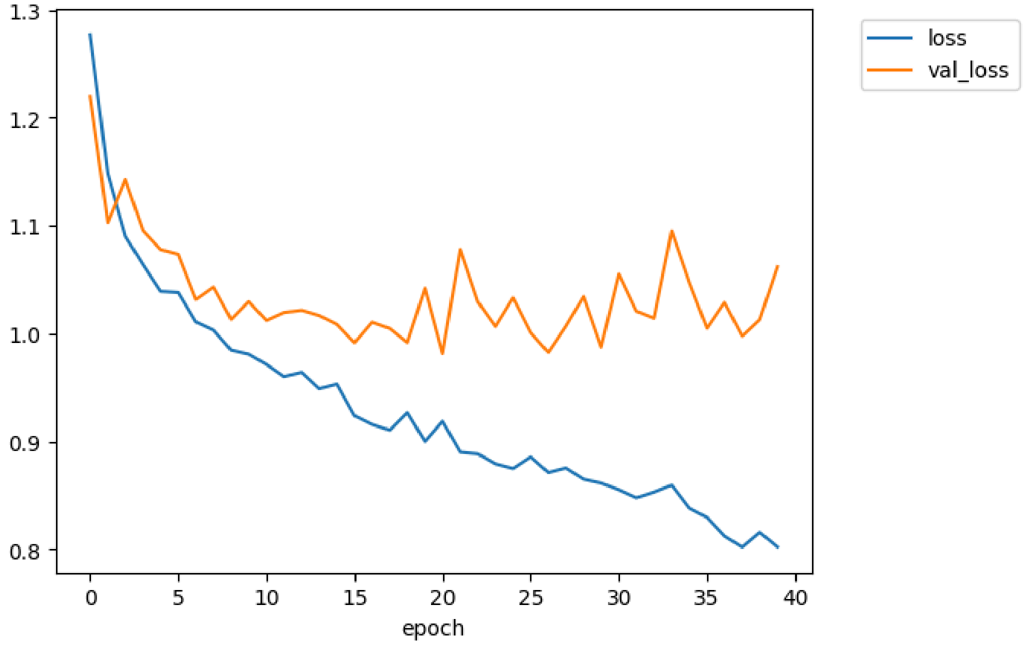
```
#Your code here
# (1) DEFINE THE ARCHITECTURE OF MY MODEL
#first, I define all the layers and the way they are connected
inputs = tf.keras.Input(shape=(32,32,3)) #my input layer
x = tf.keras.layers.Flatten()(inputs) #cf. question below...
x = tf.keras.layers.Dense(200, activation='tanh')(x) #a first hidden layer with 20 neurons
x = tf.keras.layers.Dense(70, activation='relu')(x) #a first hidden layer with 20 neurons
outputs = tf.keras.layers.Dense(4, activation='softmax')(x) # my output layer
#Then, I define my model with the input layer, the output layer and a name
my_mlp_model = tf.keras.Model(inputs=inputs, outputs=outputs, name="my_mlp_model")

#PRINT A SUMMARY OF THE ARCHITECTURE OF MY MODEL WITH THE NUMBER OF TRAINABLE PARAMETERS
my_mlp_model.summary()

# (2) DEFINE THE TRAINING HYPER-PARAMETERS WITH THE "COMPILE" METHOD:
'''
(1) Set the "optimizer" [pick 'adam', 'sgd' or 'rmsprop']
(2) Set the loss [cf. lesson #3, we pick the categorical cross-entropy]
(3) Set the final performance metric to evaluate the model
'''

my_mlp_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# (3) NOW, LET'S TRAIN ON MY DATA WITH THE "FIT" METHOD
'''
(1) Set the number of epochs
(2) Set the size of the (mini)batch
(3) Set the training dataset ==> here, X_train with Y_train
(4) Set the validation dataset (X_val, Y_val)
'''
nb_epochs=40
batch_size=100
training_history = my_mlp_model.fit(X_train,Y_train,
                                    validation_data=(X_val, Y_val),
                                    epochs=nb_epochs,
                                    batch_size=batch_size)

#COMPUTE THE ACCURACY ON THE TRAINING AND TEST SETS
loss_train, acc_train = my_mlp_model.evaluate(X_train, Y_train, batch_size=batch_size)
loss_test, acc_test = my_mlp_model.evaluate(X_test, Y_test, batch_size=batch_size)

print("Performance on the TRAIN set, ACCURACY=",acc_train)
print("Performance on the TEST set, ACCURACY=",acc_test)

display_training_curves(training_history)
```

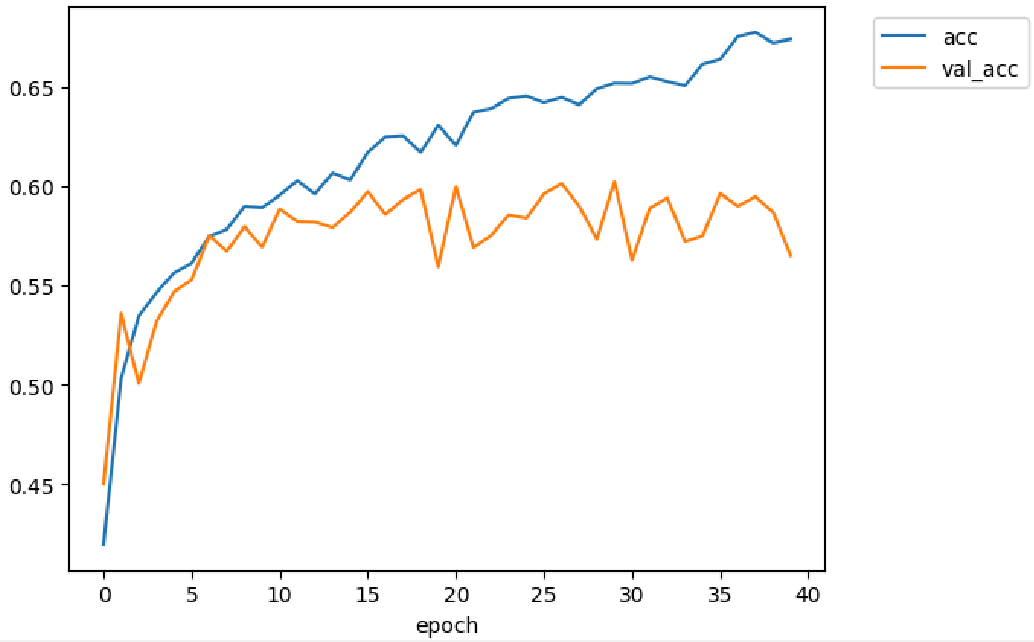
```
Model: "my_mlp_model"
```

Layer (type)	Output Shape	Param #
input_layer_42 (InputLayer)	(None, 32, 32, 3)	0
flatten_42 (Flatten)	(None, 3072)	0
dense_137 (Dense)	(None, 200)	614,600
dense_138 (Dense)	(None, 70)	14,070
dense_139 (Dense)	(None, 4)	284

```
 Total params: 628,954 (2.40 MB)
 Trainable params: 628,954 (2.40 MB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.3549 - loss: 1.3809 - val_accuracy: 0.4503 - val_loss: 1.22
Epoch 2/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4917 - loss: 1.1679 - val_accuracy: 0.5361 - val_loss: 1.10
Epoch 3/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5311 - loss: 1.1002 - val_accuracy: 0.5006 - val_loss: 1.14
Epoch 4/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5404 - loss: 1.0727 - val_accuracy: 0.5317 - val_loss: 1.09
Epoch 5/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5474 - loss: 1.0500 - val_accuracy: 0.5469 - val_loss: 1.07
Epoch 6/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5536 - loss: 1.0458 - val_accuracy: 0.5528 - val_loss: 1.07
Epoch 7/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5745 - loss: 1.0122 - val_accuracy: 0.5753 - val_loss: 1.03
Epoch 8/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5794 - loss: 1.0069 - val_accuracy: 0.5672 - val_loss: 1.04
Epoch 9/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5847 - loss: 0.9908 - val_accuracy: 0.5797 - val_loss: 1.01
Epoch 10/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.5856 - loss: 0.9913 - val_accuracy: 0.5694 - val_loss: 1.02
Epoch 11/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.5978 - loss: 0.9663 - val_accuracy: 0.5886 - val_loss: 1.01
Epoch 12/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6054 - loss: 0.9585 - val_accuracy: 0.5822 - val_loss: 1.01
Epoch 13/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5981 - loss: 0.9519 - val_accuracy: 0.5819 - val_loss: 1.02
Epoch 14/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6100 - loss: 0.9426 - val_accuracy: 0.5792 - val_loss: 1.01
Epoch 15/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6116 - loss: 0.9424 - val_accuracy: 0.5869 - val_loss: 1.00
Epoch 16/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6200 - loss: 0.9177 - val_accuracy: 0.5972 - val_loss: 0.99
Epoch 17/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6293 - loss: 0.9067 - val_accuracy: 0.5858 - val_loss: 1.01
Epoch 18/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6275 - loss: 0.9070 - val_accuracy: 0.5933 - val_loss: 1.00
Epoch 19/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6110 - loss: 0.9381 - val_accuracy: 0.5983 - val_loss: 0.99
Epoch 20/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6312 - loss: 0.9054 - val_accuracy: 0.5594 - val_loss: 1.04
Epoch 21/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6141 - loss: 0.9253 - val_accuracy: 0.5997 - val_loss: 0.98
Epoch 22/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6443 - loss: 0.8764 - val_accuracy: 0.5692 - val_loss: 1.07
Epoch 23/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6302 - loss: 0.9001 - val_accuracy: 0.5753 - val_loss: 1.02
Epoch 24/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6451 - loss: 0.8703 - val_accuracy: 0.5856 - val_loss: 1.00
Epoch 25/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6420 - loss: 0.8819 - val_accuracy: 0.5839 - val_loss: 1.03
Epoch 26/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6467 - loss: 0.8759 - val_accuracy: 0.5961 - val_loss: 1.00
Epoch 27/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6432 - loss: 0.8685 - val_accuracy: 0.6014 - val_loss: 0.98
Epoch 28/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6471 - loss: 0.8626 - val_accuracy: 0.5900 - val_loss: 1.00
Epoch 29/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6555 - loss: 0.8516 - val_accuracy: 0.5733 - val_loss: 1.03
Epoch 30/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6491 - loss: 0.8645 - val_accuracy: 0.6022 - val_loss: 0.98
Epoch 31/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6527 - loss: 0.8558 - val_accuracy: 0.5628 - val_loss: 1.05
```

```
Epoch 32/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6612 - loss: 0.8412 - val_accuracy: 0.5889 - val_loss: 1.02
Epoch 33/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6589 - loss: 0.8463 - val_accuracy: 0.5942 - val_loss: 1.01
Epoch 34/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6618 - loss: 0.8420 - val_accuracy: 0.5722 - val_loss: 1.09
Epoch 35/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6594 - loss: 0.8388 - val_accuracy: 0.5750 - val_loss: 1.04
Epoch 36/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6625 - loss: 0.8250 - val_accuracy: 0.5964 - val_loss: 1.00
Epoch 37/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6736 - loss: 0.8166 - val_accuracy: 0.5900 - val_loss: 1.02
Epoch 38/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6723 - loss: 0.8140 - val_accuracy: 0.5947 - val_loss: 0.99
Epoch 39/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6730 - loss: 0.8105 - val_accuracy: 0.5869 - val_loss: 1.01
Epoch 40/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6750 - loss: 0.7979 - val_accuracy: 0.5650 - val_loss: 1.06
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6512 - loss: 0.8442
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5494 - loss: 1.0961
Performance on the TRAIN set, ACCURACY= 0.6534523963928223
Performance on the TEST set, ACCURACY= 0.5569444298744202
```





[ANSWER] Overfitting occurs when the model learns not only the underlying patterns in the training data but also the noise, reducing its ability to generalize.

In this example, overfitting is likely due to a high number of parameters relative to the available data, lack of regularization techniques (like dropout or weight decay), and the loss of spatial structure from flattening the image inputs.

[QUESTION] Try to find an optimal architecture without overfitting by using a regularization (or other) technique of your choice. The goal is to have a performance > 60% without overfitting after **20** epochs.

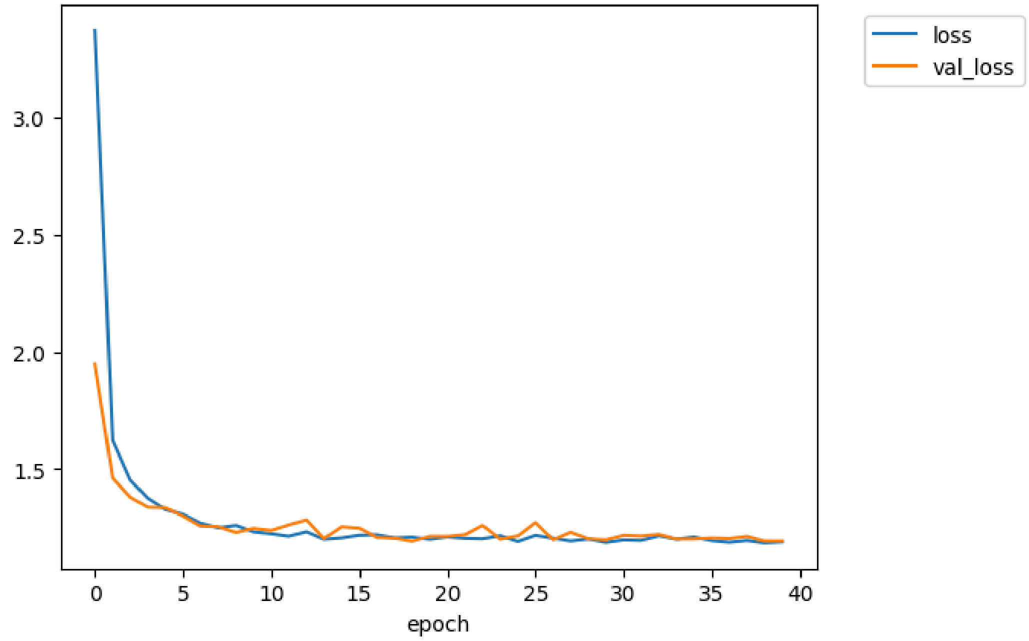
```
#x = tf.keras.layers.Dense(1024, activation='relu',kernel_regularizer=tf.keras.regularizers.l2(0.01))(x) gives us an a
#x = tf.keras.layers.BatchNormalization()(x)
#x = tf.keras.layers.Dropout(0.1)(x)

#Your code here
# (1) DEFINE THE ARCHITECTURE OF MY MODEL
#first, I define all the layers and the way they are connected
inputs = tf.keras.Input(shape=(32,32,3)) #my input layer
x = tf.keras.layers.Flatten()(inputs) #cf. question below...
x = tf.keras.layers.Dense(200, activation='tanh',kernel_regularizer=tf.keras.regularizers.l2(0.01))(x) #a first hidden
x = tf.keras.layers.Dense(70, activation='relu',kernel_regularizer=tf.keras.regularizers.l2(0.01))(x) #a first hidden
outputs = tf.keras.layers.Dense(4, activation='softmax',kernel_regularizer=tf.keras.regularizers.l2(0.01))(x) # my out
#Then, I define my model with the input layer, the output layer and a name
my_mlp_model = tf.keras.Model(inputs=inputs, outputs=outputs, name="my_mlp_model")

#PRINT A SUMMARY OF THE ARCHITECTURE OF MY MODEL WITH THE NUMBER OF TRAINABLE PARAMETERS
my_mlp_model.summary()

# (2) DEFINE THE TRAINING HYPER-PARAMETERS WITH THE "COMPILE" METHOD:
'''
(1) Set the "optimizer" [pick 'adam', 'sgd' or 'rmsprop']
(2) Set the loss [cf. lesson #3, we pick the categorical cross-entropy]
(3) Set the final performance metric to evaluate the model
'''

my_mlp_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# (3) NOW, LET'S TRAIN ON MY DATA WITH THE "FIT" METHOD
'''
(1) Set the number of epochs
(2) Set the size of the (mini)batch
(3) Set the training dataset ==> here, X_train with Y_train
(4) Set the validation dataset (X_val, Y_val)
'''
nb_epochs=40
batch_size=100
training_history = my_mlp_model.fit(X_train,Y_train,
                                    validation_data=(X_val, Y_val),
                                    epochs=nb_epochs,
                                    batch_size=batch_size)

#COMPUTE THE ACCURACY ON THE TRAINING AND TEST SETS
loss_train, acc_train = my_mlp_model.evaluate(X_train, Y_train, batch_size=batch_size)
loss_test, acc_test = my_mlp_model.evaluate(X_test, Y_test, batch_size=batch_size)

print("Performance on the TRAIN set, ACCURACY=",acc_train)
print("Performance on the TEST set, ACCURACY=",acc_test)

display_training_curves(training_history)
```

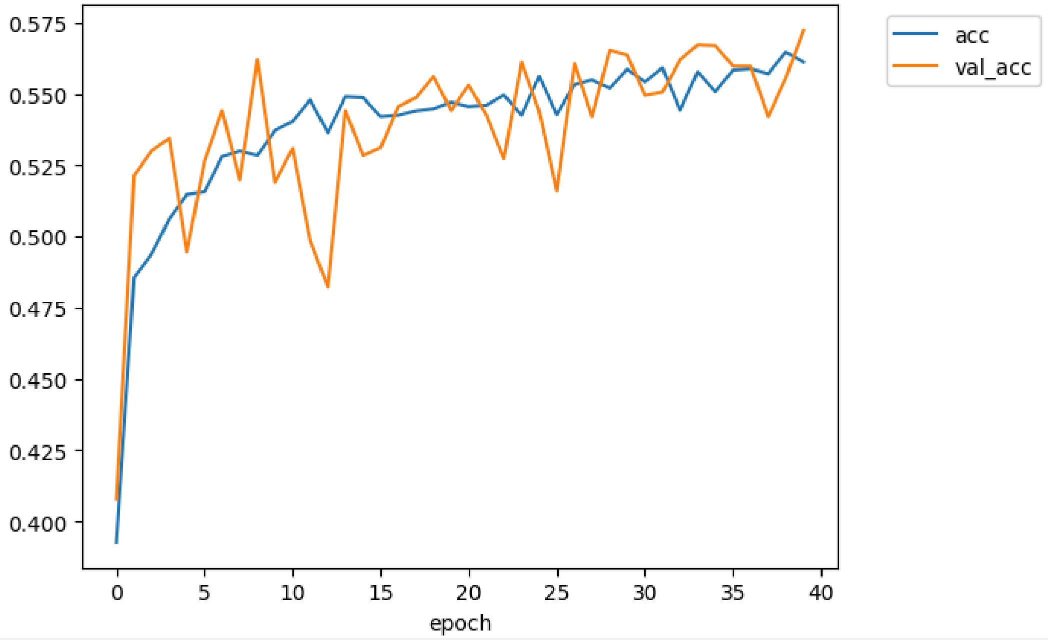
```
Model: "my_mlp_model"
```

Layer (type)	Output Shape	Param #
input_layer_6 (InputLayer)	(None, 32, 32, 3)	0
flatten_6 (Flatten)	(None, 3072)	0
dense_17 (Dense)	(None, 200)	614,600
dense_18 (Dense)	(None, 70)	14,070
dense_19 (Dense)	(None, 4)	284

```
 Total params: 628,954 (2.40 MB)
 Trainable params: 628,954 (2.40 MB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - accuracy: 0.3327 - loss: 4.7137 - val_accuracy: 0.4078 - val_loss: 1.94
Epoch 2/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4623 - loss: 1.7408 - val_accuracy: 0.5214 - val_loss: 1.46
Epoch 3/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.4889 - loss: 1.4779 - val_accuracy: 0.5300 - val_loss: 1.38
Epoch 4/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5128 - loss: 1.3803 - val_accuracy: 0.5344 - val_loss: 1.33
Epoch 5/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5223 - loss: 1.3315 - val_accuracy: 0.4944 - val_loss: 1.33
Epoch 6/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5145 - loss: 1.3108 - val_accuracy: 0.5264 - val_loss: 1.29
Epoch 7/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5321 - loss: 1.2719 - val_accuracy: 0.5442 - val_loss: 1.25
Epoch 8/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5308 - loss: 1.2521 - val_accuracy: 0.5197 - val_loss: 1.25
Epoch 9/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5364 - loss: 1.2498 - val_accuracy: 0.5619 - val_loss: 1.23
Epoch 10/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5387 - loss: 1.2397 - val_accuracy: 0.5189 - val_loss: 1.24
Epoch 11/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5368 - loss: 1.2286 - val_accuracy: 0.5308 - val_loss: 1.23
Epoch 12/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5471 - loss: 1.2180 - val_accuracy: 0.4986 - val_loss: 1.26
Epoch 13/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5411 - loss: 1.2226 - val_accuracy: 0.4822 - val_loss: 1.28
Epoch 14/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5473 - loss: 1.2015 - val_accuracy: 0.5442 - val_loss: 1.20
Epoch 15/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5510 - loss: 1.2025 - val_accuracy: 0.5283 - val_loss: 1.25
Epoch 16/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5411 - loss: 1.2200 - val_accuracy: 0.5311 - val_loss: 1.24
Epoch 17/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5382 - loss: 1.2300 - val_accuracy: 0.5456 - val_loss: 1.20
Epoch 18/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5543 - loss: 1.1915 - val_accuracy: 0.5486 - val_loss: 1.20
Epoch 19/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5473 - loss: 1.2061 - val_accuracy: 0.5561 - val_loss: 1.19
Epoch 20/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5508 - loss: 1.1937 - val_accuracy: 0.5442 - val_loss: 1.21
Epoch 21/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5391 - loss: 1.2188 - val_accuracy: 0.5531 - val_loss: 1.21
Epoch 22/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5451 - loss: 1.2109 - val_accuracy: 0.5425 - val_loss: 1.22
Epoch 23/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5523 - loss: 1.1968 - val_accuracy: 0.5272 - val_loss: 1.26
Epoch 24/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.5435 - loss: 1.2170 - val_accuracy: 0.5611 - val_loss: 1.20
Epoch 25/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step - accuracy: 0.5639 - loss: 1.1855 - val_accuracy: 0.5439 - val_loss: 1.21
Epoch 26/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5533 - loss: 1.2036 - val_accuracy: 0.5158 - val_loss: 1.27
Epoch 27/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5502 - loss: 1.2084 - val_accuracy: 0.5606 - val_loss: 1.19
Epoch 28/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5559 - loss: 1.1864 - val_accuracy: 0.5419 - val_loss: 1.23
Epoch 29/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5545 - loss: 1.1989 - val_accuracy: 0.5653 - val_loss: 1.20
Epoch 30/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5682 - loss: 1.1719 - val_accuracy: 0.5636 - val_loss: 1.19
Epoch 31/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5573 - loss: 1.1901 - val_accuracy: 0.5494 - val_loss: 1.21
```

```
Epoch 32/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5599 - loss: 1.1908 - val_accuracy: 0.5506 - val_loss: 1.21
Epoch 33/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5560 - loss: 1.1955 - val_accuracy: 0.5619 - val_loss: 1.22
Epoch 34/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5637 - loss: 1.1995 - val_accuracy: 0.5672 - val_loss: 1.20
Epoch 35/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5600 - loss: 1.2010 - val_accuracy: 0.5669 - val_loss: 1.20
Epoch 36/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5637 - loss: 1.1871 - val_accuracy: 0.5597 - val_loss: 1.20
Epoch 37/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5476 - loss: 1.2011 - val_accuracy: 0.5597 - val_loss: 1.20
Epoch 38/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5632 - loss: 1.1806 - val_accuracy: 0.5419 - val_loss: 1.21
Epoch 39/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5727 - loss: 1.1731 - val_accuracy: 0.5556 - val_loss: 1.19
Epoch 40/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5577 - loss: 1.1827 - val_accuracy: 0.5722 - val_loss: 1.19
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5896 - loss: 1.1585
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5672 - loss: 1.2054
Performance on the TRAIN set, ACCURACY= 0.588273823261261
Performance on the TEST set, ACCURACY= 0.5616666674613953
```





CONVOLUTIONAL NEURAL NETWORK (CNN) [12 pts]

Build a first architecture [6 pts]

MLPs are great but CNNs should work better for our image classification problem...

For that, we will use new layers from TF.KERAS:

- tf.keras.layers.Conv2D() an example is:

  ```
  l = tf.keras.layers.Conv2D(32,kernel_size=3,activation='relu')(l_input)
  ```

  Here, we ask for 32 convolutional kernels of size [3,3]. By default the stride is set to '1' and the padding is 'valid'.
- tf.keras.layers.MaxPooling2D() an example is:

  ```
  l = tf.keras.layers.MaxPooling2D()(l_input)
  ```

  By default the stride is set to '2' and the padding is 'valid'.

[QUESTION] With the default parameters of *Conv2D()*, do you expect to have the same shape for the output tensor?

[ANSWER] Not at all, because of the padding='valid' (so no padding added around the input) by default, the output tensor will at least shrink by 1 in height and width.

[QUESTION] With the default parameters of *MaxPooling2D()*, what do you expect on the shape of the output tensor?

[ANSWER] With those default parameters, after a MaxPooling2D(), the output tensor will have the integer part of the half of both the height and width of the input tensor.

[QUESTION] Try to build a first CNN model with this architecture:

```
x --> Conv2D (32 filters) ==> MaxPooling ==> Conv2D (64 filters) ==> MaxPooling ==> Flatten ==> Dense (4) --> ŷ
```

```
#Your code here

# (1) DEFINE THE ARCHITECTURE OF MY MODEL
#first, I define all the layers and the way they are connected
inputs = tf.keras.Input(shape=(32,32,3)) #my input layer

x = tf.keras.layers.Conv2D(32,kernel_size=3,activation='relu')(inputs)
x = tf.keras.layers.MaxPooling2D()(x)
x = tf.keras.layers.Conv2D(64,kernel_size=3,activation='relu')(x)
x = tf.keras.layers.MaxPooling2D()(x)

x = tf.keras.layers.Flatten()(x) #cf. question below...

outputs = tf.keras.layers.Dense(4, activation='softmax')(x) # my output layer
#Then, I define my model with the input layer, the output layer and a name
my_cnn_model = tf.keras.Model(inputs=inputs, outputs=outputs, name="my_cnn_model")

#PRINT A SUMMARY OF THE ARCHITECTURE OF MY MODEL WITH THE NUMBER OF TRAINABLE PARAMETERS
my_cnn_model.summary()

# (2) DEFINE THE TRAINING HYPER-PARAMETERS WITH THE "COMPILE" METHOD:
'''
(1) Set the "optimizer" [pick 'adam', 'sgd' or 'rmsprop']
(2) Set the loss [cf. lesson #3, we pick the categorical cross-entropy]
```

```
(3) Set the final performance metric to evaluate the model
'''

my_cnn_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# (3) NOW, LET'S TRAIN ON MY DATA WITH THE "FIT" METHOD
'''
(1) Set the number of epochs
(2) Set the size of the (mini)batch
(3) Set the training dataset ==> here, X_train with Y_train
(4) Set the validation dataset (X_val, Y_val)
'''
nb_epochs=7
batch_size=100
training_history = my_cnn_model.fit(X_train,Y_train,
                                    validation_data=(X_val, Y_val),
                                    epochs=nb_epochs,
                                    batch_size=batch_size)

#COMPUTE THE ACCURACY ON THE TRAINING AND TEST SETS
loss_train, acc_train = my_cnn_model.evaluate(X_train, Y_train, batch_size=batch_size)
loss_test, acc_test = my_cnn_model.evaluate(X_test, Y_test, batch_size=batch_size)

print("Performance on the TRAIN set, ACCURACY=",acc_train)
print("Performance on the TEST set, ACCURACY=",acc_test)
```

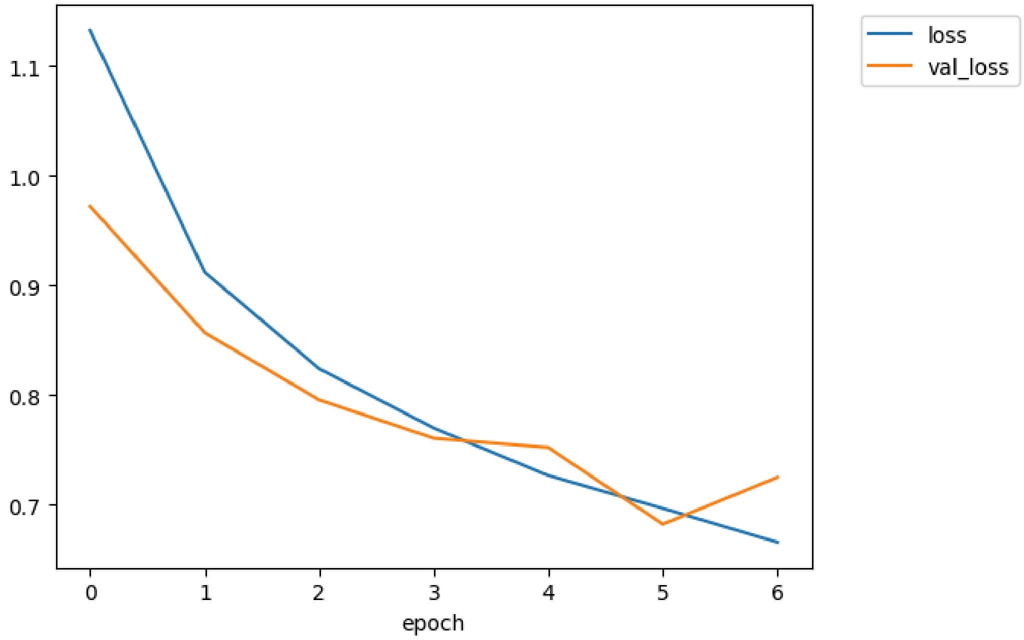
Model: "my_cnn_model"

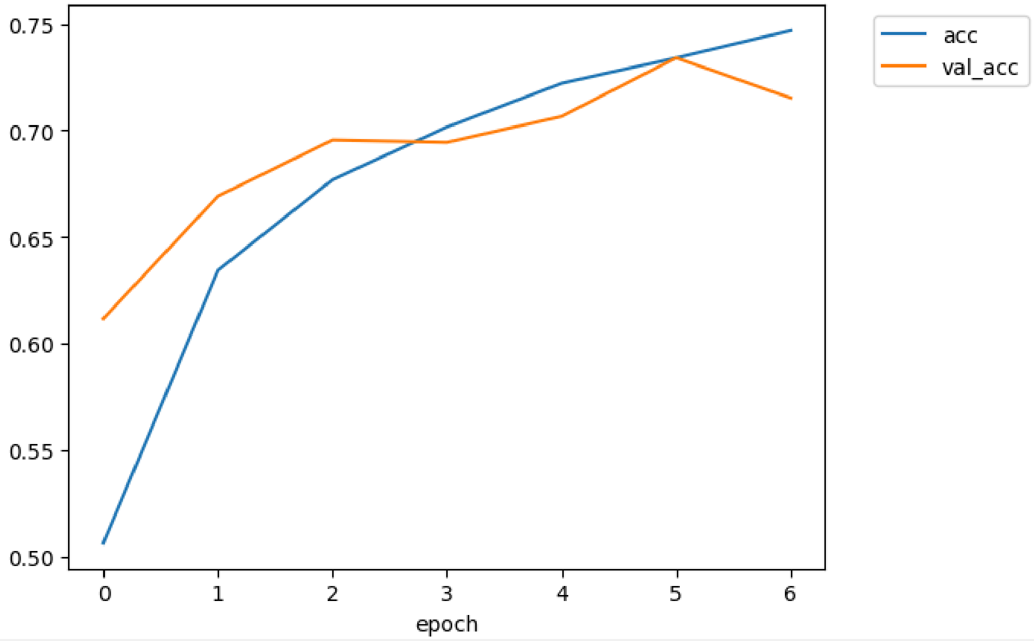
Layer (type)	Output Shape	Param #
input_layer_9 (InputLayer)	(None, 32, 32, 3)	0
conv2d_4 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_4 (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_5 (Conv2D)	(None, 13, 13, 64)	18,496
max_pooling2d_5 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten_9 (Flatten)	(None, 2304)	0
dense_22 (Dense)	(None, 4)	9,220

```
 Total params: 28,612 (111.77 KB)
 Trainable params: 28,612 (111.77 KB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/7
168/168 ━━━━━━━━━━━━━━━━━━━━ 4s 10ms/step - accuracy: 0.4236 - loss: 1.2456 - val_accuracy: 0.6117 - val_loss: 0.9
Epoch 2/7
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6159 - loss: 0.9434 - val_accuracy: 0.6692 - val_loss: 0.85
Epoch 3/7
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6781 - loss: 0.8240 - val_accuracy: 0.6956 - val_loss: 0.79
Epoch 4/7
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6924 - loss: 0.7880 - val_accuracy: 0.6944 - val_loss: 0.76
Epoch 5/7
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7201 - loss: 0.7327 - val_accuracy: 0.7067 - val_loss: 0.75
Epoch 6/7
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7294 - loss: 0.7042 - val_accuracy: 0.7342 - val_loss: 0.68
Epoch 7/7
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7476 - loss: 0.6637 - val_accuracy: 0.7153 - val_loss: 0.72
168/168 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7340 - loss: 0.6804
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7114 - loss: 0.7353
Performance on the TRAIN set, ACCURACY= 0.7329761981964111
Performance on the TEST set, ACCURACY= 0.7163888812065125
```

[QUESTION] Display the training curves from your CNN model.

```
#Your code here
display_training_curves(training_history)
```





Improvements and overfitting [6 pts]

[QUESTION] Use, the code of your last model and adapt it so that your model **OVERFITS**.

We need to see the overfitting issue on the training curve!

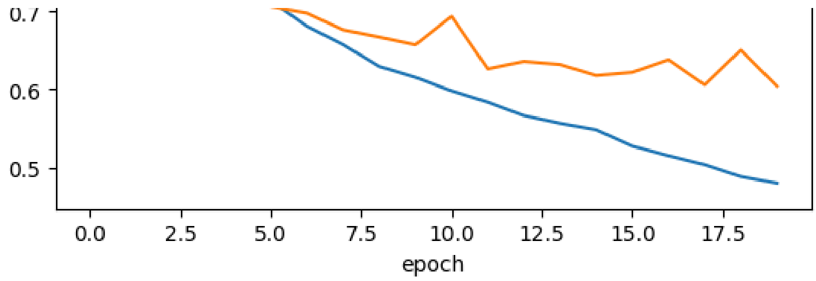
```
#Your code here

# (1) DEFINE THE ARCHITECTURE OF MY MODEL
#first, I define all the layers and the way they are connected
inputs = tf.keras.Input(shape=(32,32,3)) #my input layer

x = tf.keras.layers.Conv2D(32,kernel_size=3,activation='relu')(inputs)
x = tf.keras.layers.MaxPooling2D()(x)
x = tf.keras.layers.Conv2D(64,kernel_size=3,activation='relu')(x)
x = tf.keras.layers.MaxPooling2D()(x)

x = tf.keras.layers.Flatten()(x) #cf. question below...

outputs = tf.keras.layers.Dense(4, activation='softmax')(x) # my output layer
#Then, I define my model with the input layer, the output layer and a name
my_cnn_model = tf.keras.Model(inputs=inputs, outputs=outputs, name="my_cnn_model")
```

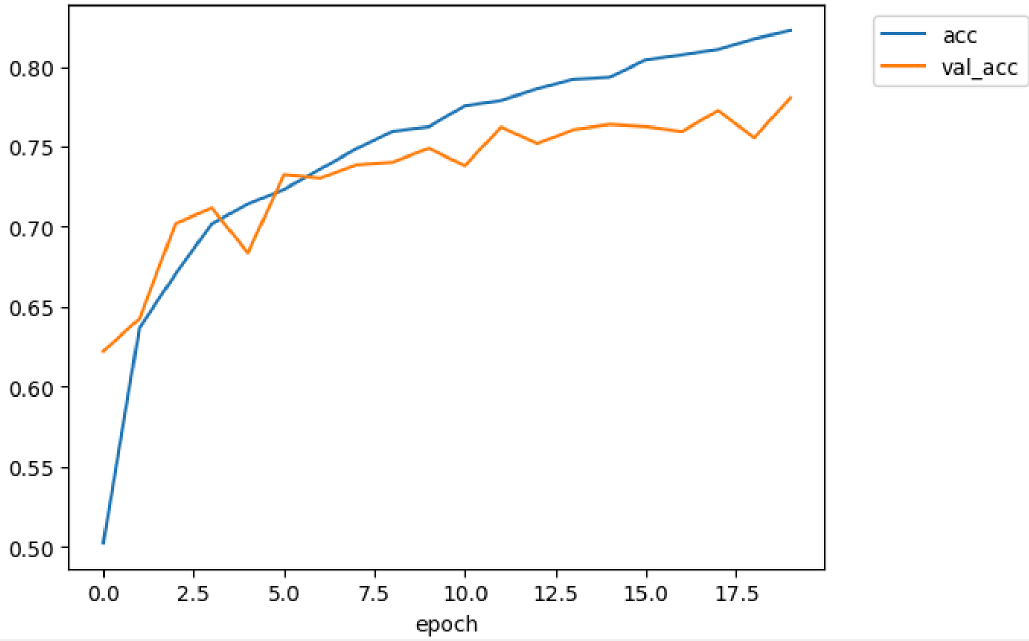
```
#PRINT A SUMMARY OF THE ARCHITECTURE OF MY MODEL WITH THE NUMBER OF TRAINABLE PARAMETERS
my_cnn_model.summary()

# (2) DEFINE THE TRAINING HYPER-PARAMETERS WITH THE "COMPILE" METHOD:
'''
(1) Set the "optimizer" [pick 'adam', 'sgd' or 'rmsprop']
(2) Set the loss [cf. lesson #3, we pick the categorical cross-entropy]
(3) Set the final performance metric to evaluate the model
'''

my_cnn_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# (3) NOW, LET'S TRAIN ON MY DATA WITH THE "FIT" METHOD
'''
(1) Set the number of epochs
(2) Set the size of the (mini)batch
(3) Set the training dataset ==> here, X_train with Y_train
(4) Set the validation dataset (X_val, Y_val)
'''
nb_epochs=20
batch_size=100
training_history = my_cnn_model.fit(X_train,Y_train,
                                    validation_data=(X_val, Y_val),
                                    epochs=nb_epochs,
                                    batch_size=batch_size)

#COMPUTE THE ACCURACY ON THE TRAINING AND TEST SETS
loss_train, acc_train = my_cnn_model.evaluate(X_train, Y_train, batch_size=batch_size)
loss_test, acc_test = my_cnn_model.evaluate(X_test, Y_test, batch_size=batch_size)

print("Performance on the TRAIN set, ACCURACY=",acc_train)
print("Performance on the TEST set, ACCURACY=",acc_test)

display_training_curves(training_history)
```

Model: "my_cnn_model"

Layer (type)	Output Shape	Param #
input_layer_10 (InputLayer)	(None, 32, 32, 3)	0
conv2d_6 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_6 (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_7 (Conv2D)	(None, 13, 13, 64)	18,496
max_pooling2d_7 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten_10 (Flatten)	(None, 2304)	0
dense_23 (Dense)	(None, 4)	9,220

```
Total params: 28,612 (111.77 KB)
Trainable params: 28,612 (111.77 KB)
Non-trainable params: 0 (0.00 B)
Epoch 1/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - accuracy: 0.4169 - loss: 1.2469 - val_accuracy: 0.6222 - val_loss: 0.96
Epoch 2/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6211 - loss: 0.9384 - val_accuracy: 0.6425 - val_loss: 0.88
Epoch 3/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6631 - loss: 0.8563 - val_accuracy: 0.7019 - val_loss: 0.77
Epoch 4/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6996 - loss: 0.7715 - val_accuracy: 0.7117 - val_loss: 0.73
Epoch 5/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7146 - loss: 0.7428 - val_accuracy: 0.6836 - val_loss: 0.78
Epoch 6/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7236 - loss: 0.7105 - val_accuracy: 0.7325 - val_loss: 0.70
Epoch 7/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7401 - loss: 0.6715 - val_accuracy: 0.7303 - val_loss: 0.69
Epoch 8/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7476 - loss: 0.6617 - val_accuracy: 0.7386 - val_loss: 0.67
Epoch 9/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7595 - loss: 0.6371 - val_accuracy: 0.7403 - val_loss: 0.66
Epoch 10/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7669 - loss: 0.6064 - val_accuracy: 0.7489 - val_loss: 0.65
Epoch 11/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7749 - loss: 0.6018 - val_accuracy: 0.7381 - val_loss: 0.69
Epoch 12/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7760 - loss: 0.5866 - val_accuracy: 0.7622 - val_loss: 0.62
Epoch 13/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7865 - loss: 0.5684 - val_accuracy: 0.7519 - val_loss: 0.63
Epoch 14/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7918 - loss: 0.5568 - val_accuracy: 0.7606 - val_loss: 0.63
Epoch 15/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7906 - loss: 0.5524 - val_accuracy: 0.7639 - val_loss: 0.61
Epoch 16/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8039 - loss: 0.5288 - val_accuracy: 0.7625 - val_loss: 0.62
Epoch 17/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8017 - loss: 0.5121 - val_accuracy: 0.7594 - val_loss: 0.63
Epoch 18/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8068 - loss: 0.5096 - val_accuracy: 0.7725 - val_loss: 0.60
Epoch 19/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8163 - loss: 0.4910 - val_accuracy: 0.7556 - val_loss: 0.65
Epoch 20/20
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8249 - loss: 0.4774 - val_accuracy: 0.7806 - val_loss: 0.60
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8342 - loss: 0.4580
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7704 - loss: 0.6196
Performance on the TRAIN set, ACCURACY= 0.8330952525138855
Performance on the TEST set, ACCURACY= 0.7702777981758118
```





[ANSWER 2] Let's overfit our CNN in a different method that is to say without simply increasing the number of epochs.

In other words, **let's increase the capacity of our model** until it learns the data by heart :

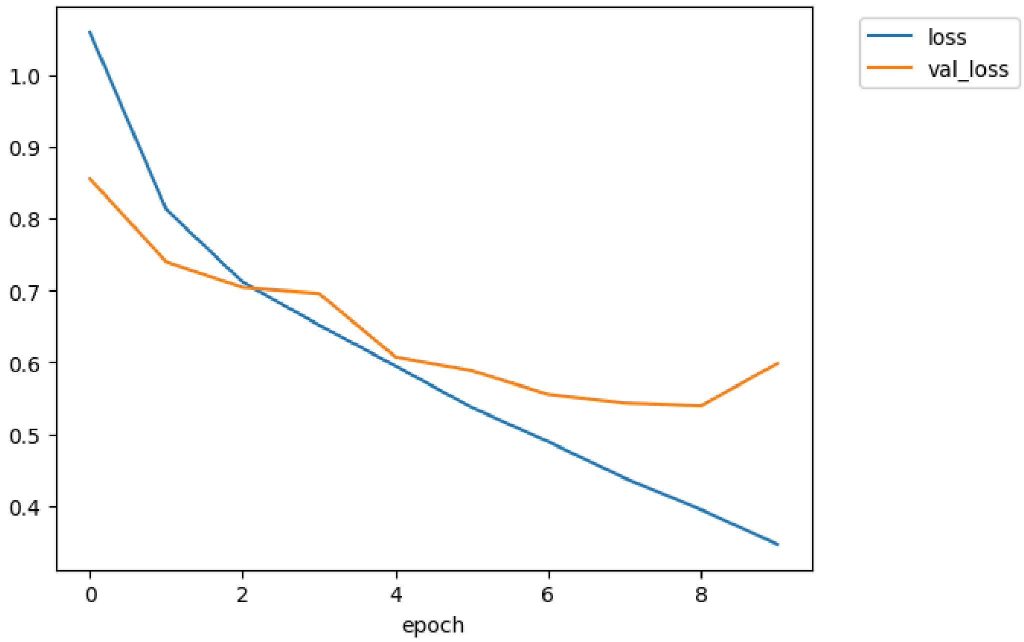
```
#Your code here

# (1) DEFINE THE ARCHITECTURE OF MY MODEL
#first, I define all the layers and the way they are connected
inputs = tf.keras.Input(shape=(32,32,3)) #my input layer

x = tf.keras.layers.Conv2D(32,kernel_size=3,activation='relu')(inputs)
x = tf.keras.layers.MaxPooling2D()(x)
x = tf.keras.layers.Conv2D(128,kernel_size=3,activation='relu')(x)
x = tf.keras.layers.MaxPooling2D()(x)
x = tf.keras.layers.Conv2D(256,kernel_size=3,activation='relu')(x)
x = tf.keras.layers.MaxPooling2D()(x)

x = tf.keras.layers.Flatten()(x) #cf. question below...

outputs = tf.keras.layers.Dense(4, activation='softmax')(x) # my output layer
#Then, I define my model with the input layer, the output layer and a name
my_cnn_model = tf.keras.Model(inputs=inputs, outputs=outputs, name="my_cnn_model")

#PRINT A SUMMARY OF THE ARCHITECTURE OF MY MODEL WITH THE NUMBER OF TRAINABLE PARAMETERS
my_cnn_model.summary()

# (2) DEFINE THE TRAINING HYPER-PARAMETERS WITH THE "COMPILE" METHOD:
'''
(1) Set the "optimizer" [pick 'adam', 'sgd' or 'rmsprop']
(2) Set the loss [cf. lesson #3, we pick the categorical cross-entropy]
(3) Set the final performance metric to evaluate the model
'''

my_cnn_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# (3) NOW, LET'S TRAIN ON MY DATA WITH THE "FIT" METHOD
'''
```

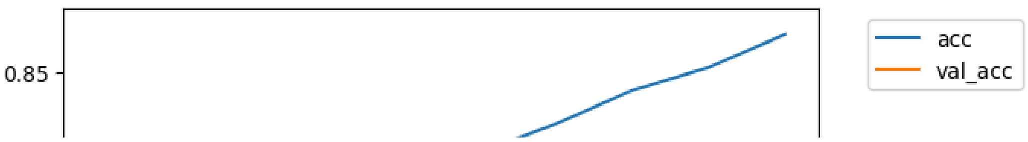
```
(1) Set the number of epochs
(2) Set the size of the (mini)batch
(3) Set the training dataset ==> here, X_train with Y_train
(4) Set the validation dataset (X_val, Y_val)
'''
nb_epochs=10
batch_size=100
training_history = my_cnn_model.fit(X_train,Y_train,
                                    validation_data=(X_val, Y_val),
                                    epochs=nb_epochs,
                                    batch_size=batch_size)

#COMPUTE THE ACCURACY ON THE TRAINING AND TEST SETS
loss_train, acc_train = my_cnn_model.evaluate(X_train, Y_train, batch_size=batch_size)
loss_test, acc_test = my_cnn_model.evaluate(X_test, Y_test, batch_size=batch_size)

print("Performance on the TRAIN set, ACCURACY=",acc_train)
print("Performance on the TEST set, ACCURACY=",acc_test)

display_training_curves(training_history)
```

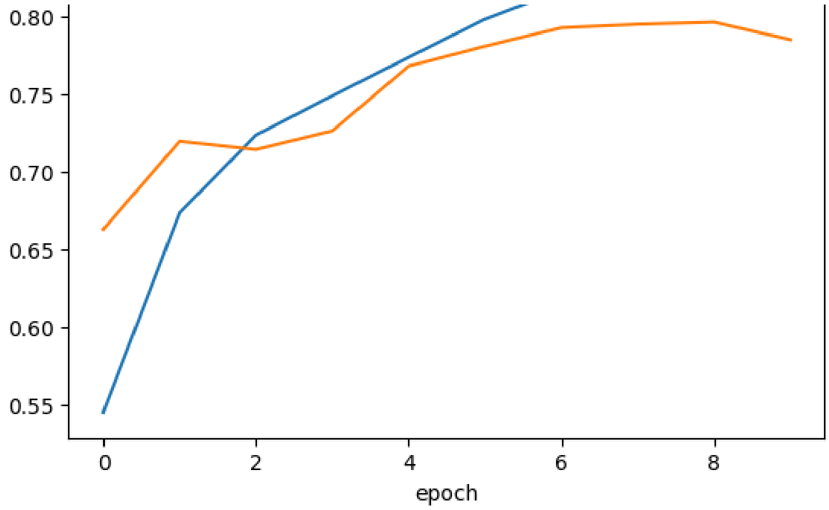
Model: "my_cnn_model"

Layer (type)	Output Shape	Param #
input_layer_14 (InputLayer)	(None, 32, 32, 3)	0
conv2d_17 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_17 (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_18 (Conv2D)	(None, 13, 13, 128)	36,992
max_pooling2d_18 (MaxPooling2D)	(None, 6, 6, 128)	0
conv2d_19 (Conv2D)	(None, 4, 4, 256)	295,168
max_pooling2d_19 (MaxPooling2D)	(None, 2, 2, 256)	0
flatten_14 (Flatten)	(None, 1024)	0
dense_27 (Dense)	(None, 4)	4,100

```
 Total params: 337,156 (1.29 MB)
 Trainable params: 337,156 (1.29 MB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 6s 14ms/step - accuracy: 0.4561 - loss: 1.1857 - val_accuracy: 0.6628 - val_loss: 0.8
Epoch 2/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6590 - loss: 0.8495 - val_accuracy: 0.7194 - val_loss: 0.73
Epoch 3/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7161 - loss: 0.7256 - val_accuracy: 0.7142 - val_loss: 0.70
Epoch 4/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7458 - loss: 0.6643 - val_accuracy: 0.7261 - val_loss: 0.69
Epoch 5/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7662 - loss: 0.6107 - val_accuracy: 0.7678 - val_loss: 0.60
Epoch 6/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7938 - loss: 0.5463 - val_accuracy: 0.7806 - val_loss: 0.58
Epoch 7/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8280 - loss: 0.4669 - val_accuracy: 0.7925 - val_loss: 0.55
Epoch 8/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8395 - loss: 0.4342 - val_accuracy: 0.7947 - val_loss: 0.54
Epoch 9/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.8546 - loss: 0.3871 - val_accuracy: 0.7961 - val_loss: 0.53
Epoch 10/10
168/168 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.8819 - loss: 0.3389 - val_accuracy: 0.7847 - val_loss: 0.59
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8792 - loss: 0.3445
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7798 - loss: 0.6184
Performance on the TRAIN set, ACCURACY= 0.876369059085846
Performance on the TEST set, ACCURACY= 0.7752777934074402
```







[QUESTION] Fix your overfitting issue with a technique of your choice.

```
#Your code here

#To fight overfitting with CNN, we can use the exact same techniques of dropping out, regularization and batch normali

#this time let's do data augmentation
from tensorflow.keras.preprocessing.image import ImageDataGenerator

#here we can see that data augmentation is by far the best method to fight overfitting, and at the same time it improv

datagen = ImageDataGenerator(
    rotation_range=15,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True
)
datagen.fit(X_train)


# (1) DEFINE THE ARCHITECTURE OF MY MODEL
#first, I define all the layers and the way they are connected
inputs = tf.keras.Input(shape=(32,32,3)) #my input layer

x = tf.keras.layers.Conv2D(32,kernel_size=3,activation='relu')(inputs)
x = tf.keras.layers.MaxPooling2D()(x)
x = tf.keras.layers.Conv2D(64,kernel_size=3,activation='relu')(x)
x = tf.keras.layers.MaxPooling2D()(x)

x = tf.keras.layers.Flatten()(x) #cf. question below...

outputs = tf.keras.layers.Dense(4, activation='softmax')(x) # my output layer
#Then, I define my model with the input layer, the output layer and a name
my_cnn_model = tf.keras.Model(inputs=inputs, outputs=outputs, name="my_cnn_model")

#PRINT A SUMMARY OF THE ARCHITECTURE OF MY MODEL WITH THE NUMBER OF TRAINABLE PARAMETERS
my_cnn_model.summary()

# (2) DEFINE THE TRAINING HYPER-PARAMETERS WITH THE "COMPILE" METHOD:
'''
(1) Set the "optimizer" [pick 'adam', 'sgd' or 'rmsprop']
(2) Set the loss [cf. lesson #3, we pick the categorical cross-entropy]
(3) Set the final performance metric to evaluate the model
'''

my_cnn_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# (3) NOW, LET'S TRAIN ON MY DATA WITH THE "FIT" METHOD
'''
(1) Set the number of epochs
(2) Set the size of the (mini)batch
(3) Set the training dataset ==> here, X_train with Y_train
(4) Set the validation dataset (X_val, Y_val)
```

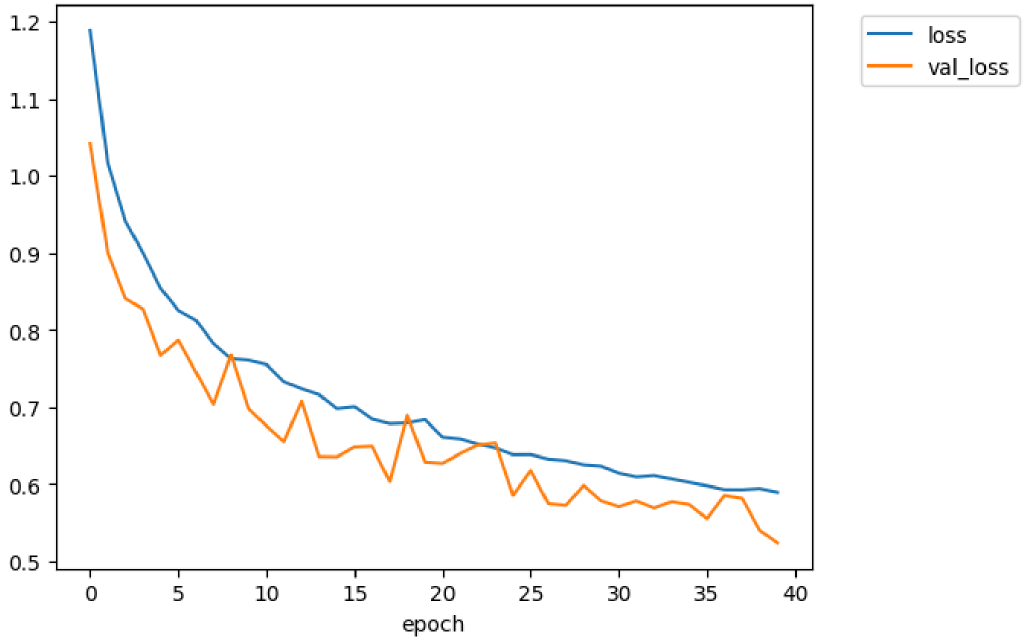
```
'''
nb_epochs=40
batch_size=100
training_history = my_cnn_model.fit(datagen.flow(X_train, Y_train, batch_size=batch_size),
                                    validation_data=(X_val, Y_val),
                                    epochs=nb_epochs)

#COMPUTE THE ACCURACY ON THE TRAINING AND TEST SETS
loss_train, acc_train = my_cnn_model.evaluate(X_train, Y_train, batch_size=batch_size)
loss_test, acc_test = my_cnn_model.evaluate(X_test, Y_test, batch_size=batch_size)

print("Performance on the TRAIN set, ACCURACY=",acc_train)
print("Performance on the TEST set, ACCURACY=",acc_test)

display_training_curves(training_history)
```

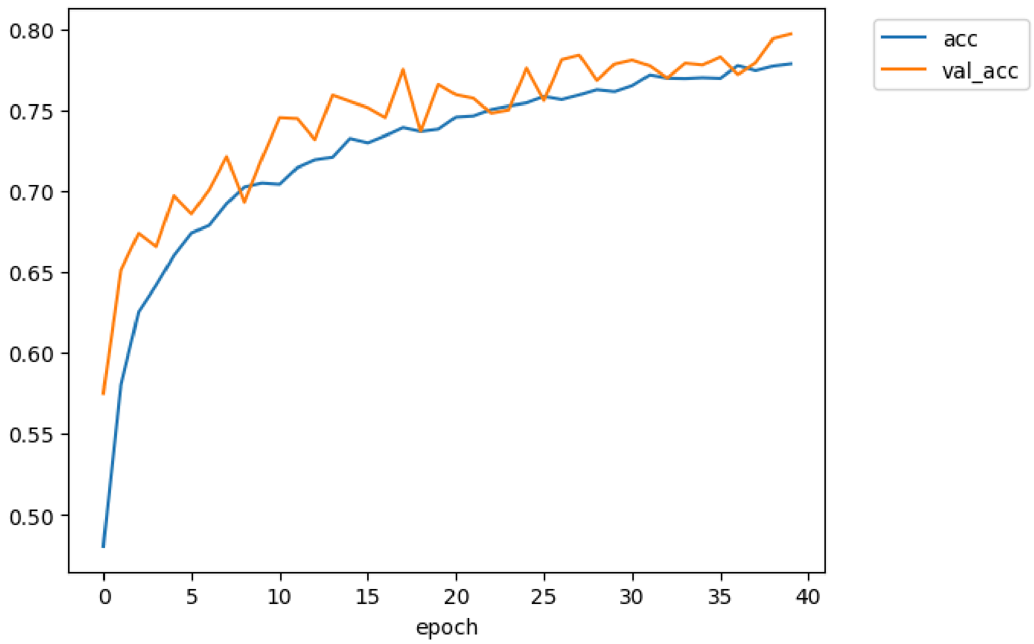
```
Model: "my_cnn_model"
```

Layer (type)	Output Shape	Param #
input_layer_15 (InputLayer)	(None, 32, 32, 3)	0
conv2d_20 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_20 (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_21 (Conv2D)	(None, 13, 13, 64)	18,496
max_pooling2d_21 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten_15 (Flatten)	(None, 2304)	0
dense_28 (Dense)	(None, 4)	9,220

```
 Total params: 28,612 (111.77 KB)
 Trainable params: 28,612 (111.77 KB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/40
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Y
  self._warn_if_super_not_called()
168/168 ━━━━━━━━━━━━━━━━━━━━ 13s 67ms/step - accuracy: 0.4129 - loss: 1.2706 - val_accuracy: 0.5750 - val_loss: 1.
Epoch 2/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 61ms/step - accuracy: 0.5710 - loss: 1.0317 - val_accuracy: 0.6511 - val_loss: 0.
Epoch 3/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 9s 52ms/step - accuracy: 0.6264 - loss: 0.9396 - val_accuracy: 0.6739 - val_loss: 0.8
Epoch 4/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 61ms/step - accuracy: 0.6406 - loss: 0.9037 - val_accuracy: 0.6656 - val_loss: 0.
Epoch 5/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.6520 - loss: 0.8656 - val_accuracy: 0.6969 - val_loss: 0.
Epoch 6/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 19s 55ms/step - accuracy: 0.6693 - loss: 0.8319 - val_accuracy: 0.6858 - val_loss: 0.
Epoch 7/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 60ms/step - accuracy: 0.6666 - loss: 0.8363 - val_accuracy: 0.7006 - val_loss: 0.
Epoch 8/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 58ms/step - accuracy: 0.6814 - loss: 0.7902 - val_accuracy: 0.7211 - val_loss: 0.
Epoch 9/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 9s 53ms/step - accuracy: 0.7035 - loss: 0.7633 - val_accuracy: 0.6931 - val_loss: 0.7
Epoch 10/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 60ms/step - accuracy: 0.7022 - loss: 0.7640 - val_accuracy: 0.7200 - val_loss: 0.
Epoch 11/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.7013 - loss: 0.7679 - val_accuracy: 0.7453 - val_loss: 0.
Epoch 12/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 9s 51ms/step - accuracy: 0.7166 - loss: 0.7320 - val_accuracy: 0.7447 - val_loss: 0.6
Epoch 13/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 12s 74ms/step - accuracy: 0.7227 - loss: 0.7187 - val_accuracy: 0.7317 - val_loss: 0.
Epoch 14/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.7211 - loss: 0.7131 - val_accuracy: 0.7592 - val_loss: 0.
Epoch 15/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 9s 55ms/step - accuracy: 0.7310 - loss: 0.6992 - val_accuracy: 0.7553 - val_loss: 0.6
Epoch 16/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 9s 55ms/step - accuracy: 0.7222 - loss: 0.7162 - val_accuracy: 0.7514 - val_loss: 0.6
Epoch 17/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.7313 - loss: 0.6861 - val_accuracy: 0.7453 - val_loss: 0.
Epoch 18/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 60ms/step - accuracy: 0.7413 - loss: 0.6760 - val_accuracy: 0.7750 - val_loss: 0.
Epoch 19/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 9s 52ms/step - accuracy: 0.7352 - loss: 0.6920 - val_accuracy: 0.7369 - val_loss: 0.6
Epoch 20/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.7426 - loss: 0.6735 - val_accuracy: 0.7658 - val_loss: 0.
Epoch 21/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 60ms/step - accuracy: 0.7488 - loss: 0.6527 - val_accuracy: 0.7594 - val_loss: 0.
Epoch 22/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 11s 63ms/step - accuracy: 0.7536 - loss: 0.6507 - val_accuracy: 0.7572 - val_loss: 0.
Epoch 23/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 11s 62ms/step - accuracy: 0.7477 - loss: 0.6593 - val_accuracy: 0.7481 - val_loss: 0.
Epoch 24/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 11s 64ms/step - accuracy: 0.7519 - loss: 0.6461 - val_accuracy: 0.7500 - val_loss: 0.
Epoch 25/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 13s 76ms/step - accuracy: 0.7524 - loss: 0.6416 - val_accuracy: 0.7758 - val_loss: 0.
Epoch 26/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 9s 54ms/step - accuracy: 0.7593 - loss: 0.6386 - val_accuracy: 0.7558 - val_loss: 0.6
Epoch 27/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.7601 - loss: 0.6259 - val_accuracy: 0.7811 - val_loss: 0.
Epoch 28/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 61ms/step - accuracy: 0.7644 - loss: 0.6229 - val_accuracy: 0.7839 - val_loss: 0.
```

```
Epoch 29/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 19s 51ms/step - accuracy: 0.7677 - loss: 0.6121 - val_accuracy: 0.7683 - val_loss: 0.
Epoch 30/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.7622 - loss: 0.6206 - val_accuracy: 0.7783 - val_loss: 0.
Epoch 31/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 19s 56ms/step - accuracy: 0.7668 - loss: 0.6120 - val_accuracy: 0.7808 - val_loss: 0.
Epoch 32/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 53ms/step - accuracy: 0.7696 - loss: 0.6108 - val_accuracy: 0.7772 - val_loss: 0.
Epoch 33/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.7728 - loss: 0.6018 - val_accuracy: 0.7697 - val_loss: 0.
Epoch 34/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 61ms/step - accuracy: 0.7749 - loss: 0.5985 - val_accuracy: 0.7789 - val_loss: 0.
Epoch 35/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 8s 51ms/step - accuracy: 0.7702 - loss: 0.5993 - val_accuracy: 0.7778 - val_loss: 0.5
Epoch 36/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 60ms/step - accuracy: 0.7723 - loss: 0.6009 - val_accuracy: 0.7828 - val_loss: 0.
Epoch 37/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 59ms/step - accuracy: 0.7737 - loss: 0.6002 - val_accuracy: 0.7719 - val_loss: 0.
Epoch 38/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 9s 50ms/step - accuracy: 0.7754 - loss: 0.5894 - val_accuracy: 0.7792 - val_loss: 0.5
Epoch 39/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 11s 53ms/step - accuracy: 0.7734 - loss: 0.5994 - val_accuracy: 0.7942 - val_loss: 0.
Epoch 40/40
168/168 ━━━━━━━━━━━━━━━━━━━━ 10s 62ms/step - accuracy: 0.7827 - loss: 0.5856 - val_accuracy: 0.7969 - val_loss: 0.
168/168 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8190 - loss: 0.4904
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7943 - loss: 0.5261
Performance on the TRAIN set, ACCURACY= 0.8186309337615967
Performance on the TEST set, ACCURACY= 0.7975000143051147
```





[**QUESTION**] Regarding these experiences, compare MLP vs. CNN

[**ANSWER**] The CNN clearly outperforms the MLP in these experiments. Here's a concise comparison:

- **Performance:**
  The CNN achieves about 82% accuracy on the training set and nearly 80% on the test set, whereas the MLP only reaches around 59% on training and 56% on testing. This indicates that the CNN generalizes better to unseen data.
- **Architecture and Feature Extraction:**
  The CNN uses convolutional layers and pooling operations to capture local spatial features and hierarchical patterns within images. In contrast, the MLP flattens the image into a one-dimensional vector, thereby discarding the spatial relationships inherent in image data. This difference means the CNN can learn more relevant features for classification with fewer parameters and less risk of overfitting.
- **Regularization and Data Augmentation:**
  In the CNN experiment, data augmentation further improves generalization by artificially increasing the diversity of the training data. Although regularization (like L2 penalties) is applied in the MLP, it cannot compensate for the loss of spatial context.

In summary, for image classification tasks, the CNN is superior because it efficiently exploits spatial structure and benefits more from techniques like data augmentation, resulting in higher accuracy and better generalization.

BONUS

[Bonus 1] let's now explore **Transfer Learning** trough our Ciphar-4 dataset and a classic **model ResNet**.

```
# ===== RESNET TRANSFER LEARNING MODEL =====

# Load pre-trained ResNet50 base (frozen)
base_model = tf.keras.applications.ResNet50(
    include_top=False,
    weights='imagenet',
    input_shape=(32, 32, 3)
)
base_model.trainable = False  # Freeze layers

# Define the model architecture
inputs = tf.keras.Input(shape=(32, 32, 3))

# Pass through ResNet base
x = base_model(inputs, training=False)
# Add classification head
x = tf.keras.layers.GlobalAveragePooling2D()(x)
x = tf.keras.layers.Dense(256, activation='relu')(x)
x = tf.keras.layers.Dropout(0.5)(x)
outputs = tf.keras.layers.Dense(4, activation='softmax')(x)

# Build and compile the model
resnet_model = tf.keras.Model(inputs, outputs, name="resnet_model")
resnet_model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=1e-3),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

# Print model summary
resnet_model.summary()

# Train the model
resnet_history = resnet_model.fit(
    X_train, Y_train,
    validation_data=(X_val, Y_val),
    epochs=7,
    batch_size=64
```

```
)

# Evaluate performance
loss_train, acc_train = resnet_model.evaluate(X_train, Y_train, batch_size=64
loss_test, acc_test = resnet_model.evaluate(X_test, Y_test, batch_size=64)

print(f"Train Accuracy: {acc_train:.4f}")
print(f"Test Accuracy: {acc_test:.4f}")

# Plot training curves
```

Model: "resnet_model"

Layer (type)	Output Shape	Param #
input_layer_7 (InputLayer)	(None, 32, 32, 3)	0
resnet50 (Functional)	(None, 1, 1, 2048)	23,587,712
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 2048)	0
dense_4 (Dense)	(None, 256)	524,544
dropout_2 (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 4)	1,028

Total params: 24,113,284 (91.98 MB)
Trainable params: 525,572 (2.00 MB)