Msc Computer Engineering

Intelligent Systems

Food Recogniser

Lorenzo Bataloni
Edoardo Pantè
Claudio Daka

Accademic Year 22/23

1.Introduction

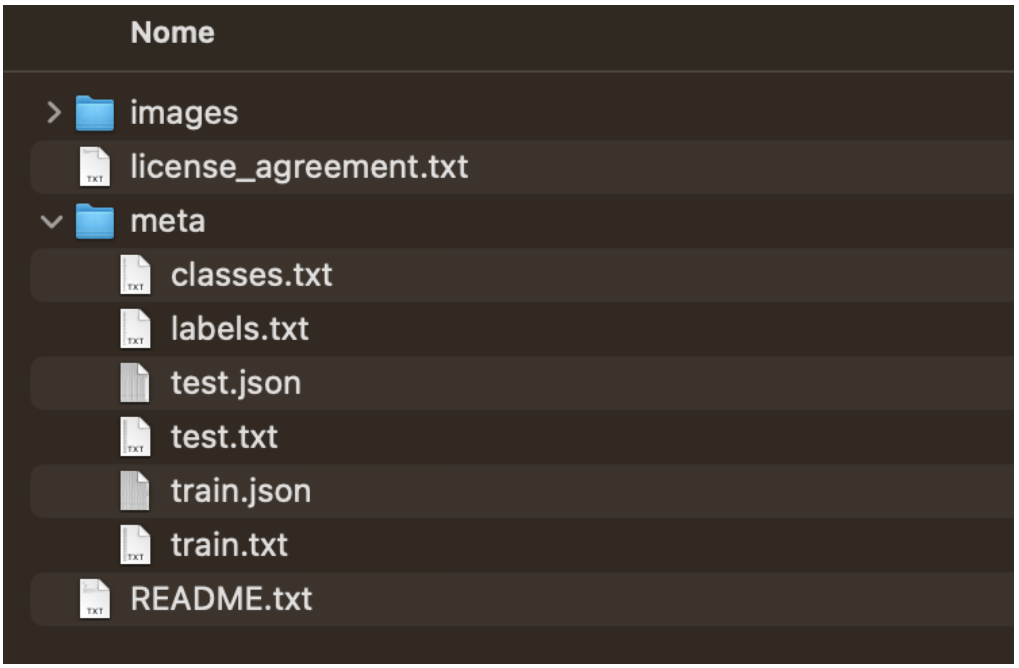
Food Recognition is an image recognition system that can recognize and identify up to 101 different categories of food. The use of this type of system is very broad and can range from use in apps for example for diet or meal management to use to help people with visual impairments for example interpret menus or otherwise overcome any barriers.
To carry out this task, different technologies were used to also make comparisons to determine which system offered the best performance. A CNN was created from scratch using tuning techniques to improve performance, two pre-trained CNNs were then used using fine tuning techniques. Of these, one was trained using images similar to those in the dataset used by us.

2.Dataset

The dataset used is the food-101 dataset. A dataset containing images of food, these images belong to 101 different classes. For each class there are 1000 images of different sizes, for a total of about 5 GB of dataset.

2.1. Dataset Structure

Unlike standard datasets, this dataset does not have a ready-to-use structure, and a scripting step was required to process the images and create a suitable structure. As we can see in the image, the dataset contains a single images folder, with a folder for each class inside, and within these are all the images, both test and train images.



In addition to the images folder we have the meta folder that contains files that contain information about the dataset. Specifically, the files test.json and train.json contain the names of the files to be used for test and train, respectively.

A script was made that would go to read these files and extract the files so that we would have a structure suitable for use with our networks. In addition, a portion of the images for the train is used for validation.
The final structure of the dataset is as follows, with three different directories for train, test, and validation. Each directory within it has 101 directories, one per class, containing the relevant images.









As we can see from the graph below, the dataset is perfectly balanced:

2.2. Dataset Elaboration

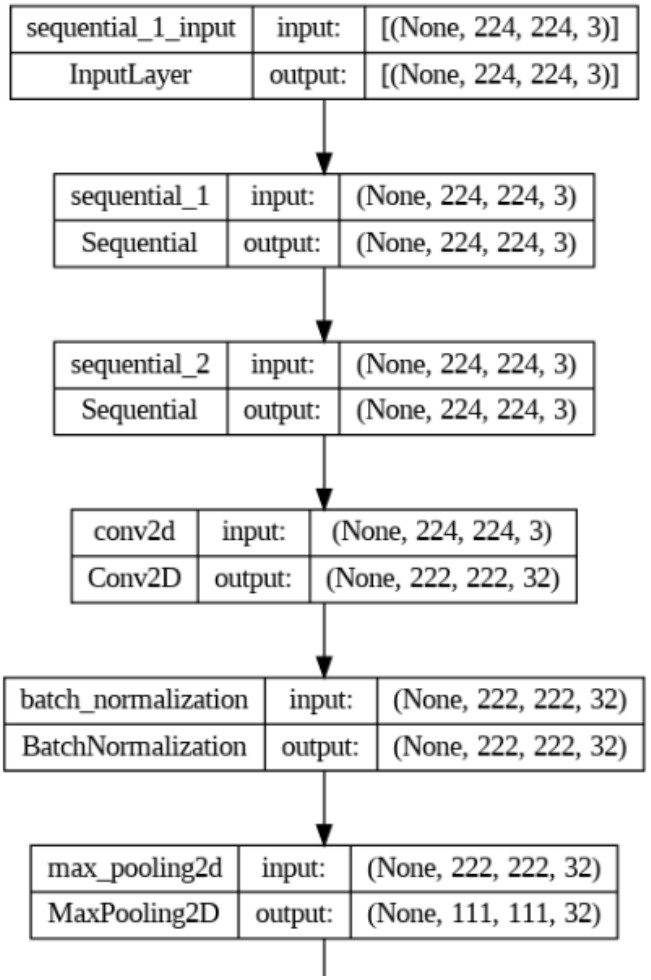
Following processing, initial tests were carried out with both the from scratch and pre-trained models. Problems were immediately encountered due to the size of the dataset and the number of classes. A major problem was the tool used, namely google colab. This tool in fact has limitations for use, especially with regard to the GPU. It was therefore decided to go for thinning the images and use a few hundred images rather than a thousand per class so as not to have any impediments.

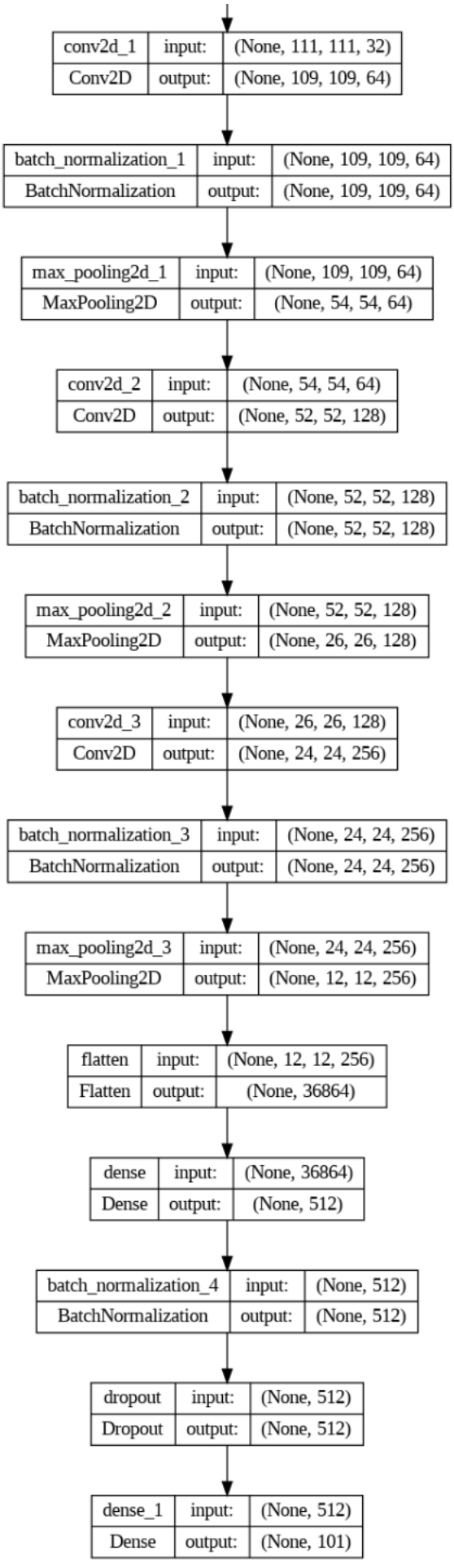
3.Model From Scratch

For the from scratch models, we started with simple networks and then went on to use more complex models to counteract any overfitting.

3.1. First Model

The first model is the simplest one we used; it has 4 convolutional blocks starting from 32 filters up to 256. All blocks are separated by batch normalization and max pooling layers. We ran a train with 25 epochs with a learning rate ranging from 0.1 up to 1e-5.

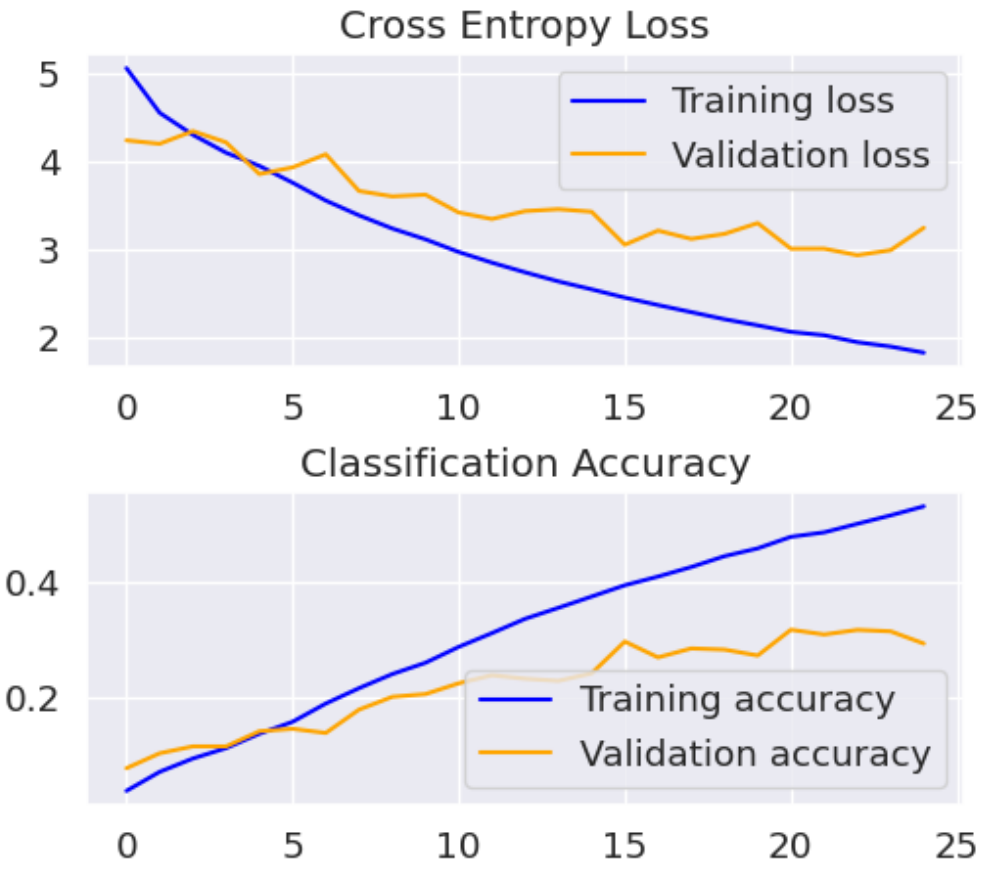


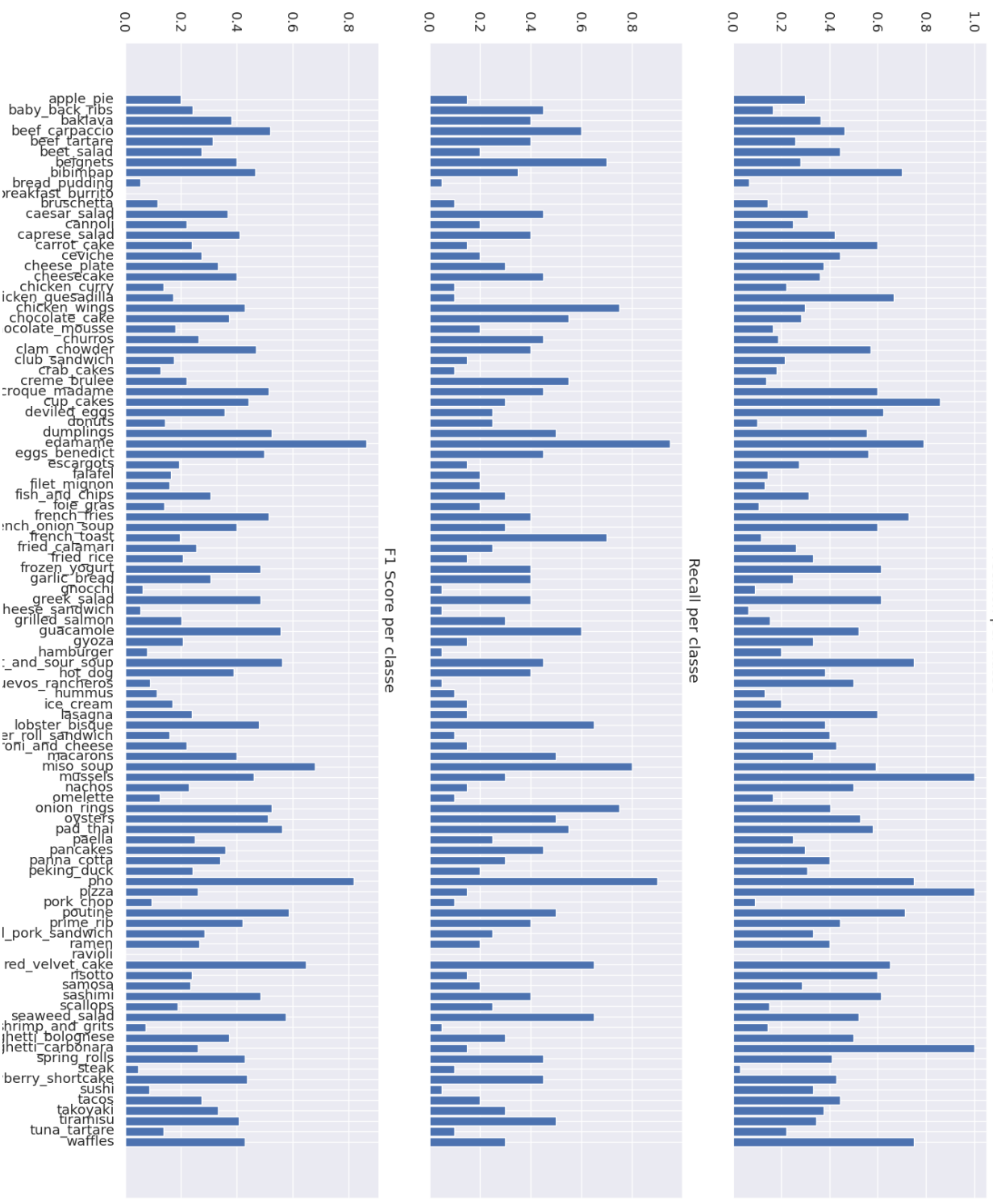

conv2d_1 input: (None, 111, 111, 32)
Conv2D output: (None, 109, 109, 64)
batch_normalization_1 input: (None, 109, 109, 64)
BatchNormalization output: (None, 109, 109, 64)
max_pooling2d_1 input: (None, 109, 109, 64)
MaxPooling2D output: (None, 54, 54, 64)
conv2d_2 input: (None, 54, 54, 64)
Conv2D output: (None, 52, 52, 128)
batch_normalization_2 input: (None, 52, 52, 128)
BatchNormalization output: (None, 52, 52, 128)
max_pooling2d_2 input: (None, 52, 52, 128)
MaxPooling2D output: (None, 26, 26, 128)
conv2d_3 input: (None, 26, 26, 128)
Conv2D output: (None, 24, 24, 256)
batch_normalization_3 input: (None, 24, 24, 256)
BatchNormalization output: (None, 24, 24, 256)
max_pooling2d_3 input: (None, 24, 24, 256)
MaxPooling2D output: (None, 12, 12, 256)
flatten input: (None, 12, 12, 256)
Flatten output: (None, 36864)
dense input: (None, 36864)
Dense output: (None, 512)
batch_normalization_4 input: (None, 512)
BatchNormalization output: (None, 512)
dropout input: (None, 512)
Dropout output: (None, 512)
dense_1 input: (None, 512)
Dense output: (None, 101)

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential_1 (Sequential)   (None, 224, 224, 3)       0

 sequential_2 (Sequential)   (None, 224, 224, 3)       0

 conv2d (Conv2D)             (None, 222, 222, 32)      896

 batch_normalization (BatchN  (None, 222, 222, 32)     128
 ormalization)

 max_pooling2d (MaxPooling2D  (None, 111, 111, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 109, 109, 64)      18496

 batch_normalization_1 (Batc  (None, 109, 109, 64)     256
 hNormalization)

 max_pooling2d_1 (MaxPooling  (None, 54, 54, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 52, 52, 128)       73856

 conv2d_3 (Conv2D)           (None, 50, 50, 128)       147584

 batch_normalization_2 (Batc  (None, 50, 50, 128)      512
 hNormalization)

 max_pooling2d_2 (MaxPooling  (None, 25, 25, 128)      0
 2D)

 dropout (Dropout)           (None, 25, 25, 128)       0

 conv2d_4 (Conv2D)           (None, 23, 23, 256)       295168

 conv2d_5 (Conv2D)           (None, 21, 21, 256)       590080

 batch_normalization_3 (Batc  (None, 21, 21, 256)      1024
 hNormalization)

 max_pooling2d_3 (MaxPooling  (None, 10, 10, 256)      0
 2D)

 dropout_1 (Dropout)         (None, 10, 10, 256)       0

 flatten (Flatten)           (None, 25600)             0

 dense (Dense)               (None, 512)               13107712

 batch_normalization_4 (Batc  (None, 512)              2048
 hNormalization)

 dropout_2 (Dropout)         (None, 512)               0

 dense_1 (Dense)             (None, 101)               51813

=================================================================
Total params: 14,289,573
Trainable params: 14,287,589
Non-trainable params: 1,984
_________________________________________________________________
```

3.1.3. Result

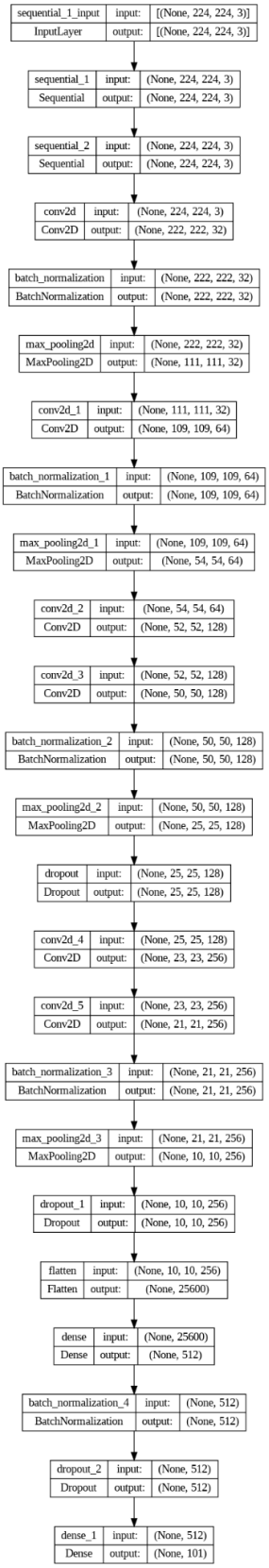
Despite the presence of the data augmentation and dropout layer, as we can see from the graphs, overfitting is present. In fact, the curve related to validation goes to a plateau after a certain number of epochs and tends to stabilize. After training the accuracy of the network settles around 29% with the test dataset.





3.2. Second Model

For the second model, we modified the convolutional layers by adding a convolutional layer to the last 2 layers to try to increase the accuracy of the model. We then added dropout layers to try to decrease overfitting.

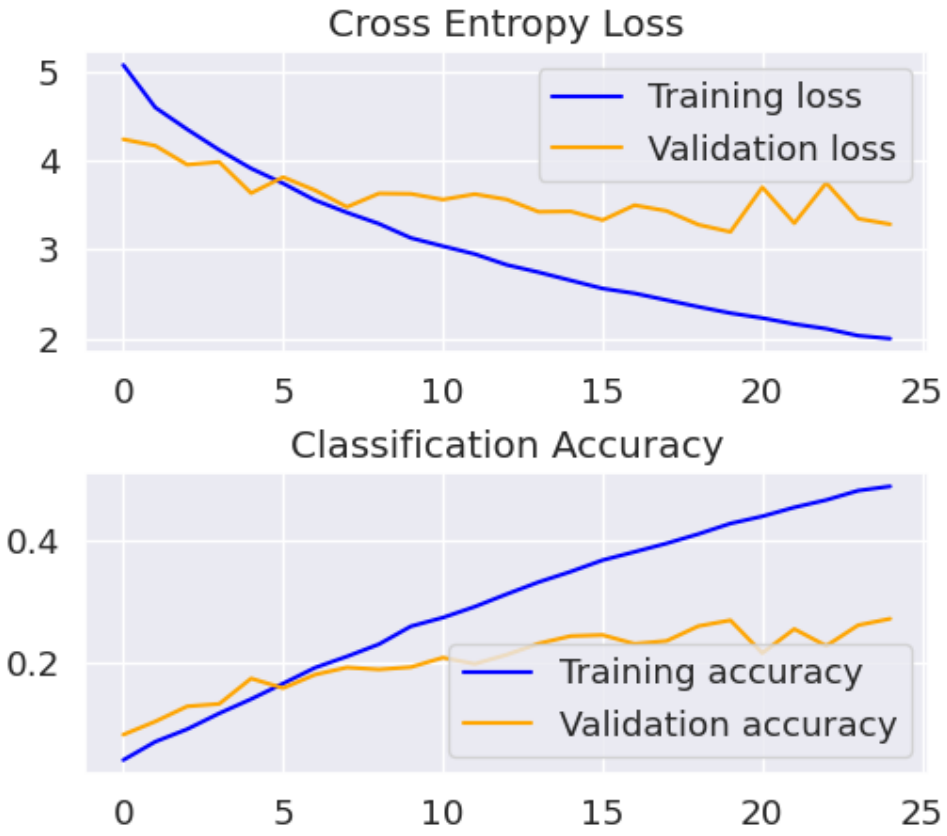

sequential_1_input | input: | [(None, 224, 224, 3)]
InputLayer | output: | [(None, 224, 224, 3)]
sequential_1 | input: | (None, 224, 224, 3)
Sequential | output: | (None, 224, 224, 3)
sequential_2 | input: | (None, 224, 224, 3)
Sequential | output: | (None, 224, 224, 3)
conv2d | input: | (None, 224, 224, 3)
Conv2D | output: | (None, 222, 222, 32)
batch_normalization | input: | (None, 222, 222, 32)
BatchNormalization | output: | (None, 222, 222, 32)
max_pooling2d | input: | (None, 222, 222, 32)
MaxPooling2D | output: | (None, 111, 111, 32)
conv2d_1 | input: | (None, 111, 111, 32)
Conv2D | output: | (None, 109, 109, 64)
batch_normalization_1 | input: | (None, 109, 109, 64)
BatchNormalization | output: | (None, 109, 109, 64)
max_pooling2d_1 | input: | (None, 109, 109, 64)
MaxPooling2D | output: | (None, 54, 54, 64)
conv2d_2 | input: | (None, 54, 54, 64)
Conv2D | output: | (None, 52, 52, 128)
conv2d_3 | input: | (None, 52, 52, 128)
Conv2D | output: | (None, 50, 50, 128)
batch_normalization_2 | input: | (None, 50, 50, 128)
BatchNormalization | output: | (None, 50, 50, 128)
max_pooling2d_2 | input: | (None, 50, 50, 128)
MaxPooling2D | output: | (None, 25, 25, 128)
dropout | input: | (None, 25, 25, 128)
Dropout | output: | (None, 25, 25, 128)
conv2d_4 | input: | (None, 25, 25, 128)
Conv2D | output: | (None, 23, 23, 256)
conv2d_5 | input: | (None, 23, 23, 256)
Conv2D | output: | (None, 21, 21, 256)
batch_normalization_3 | input: | (None, 21, 21, 256)
BatchNormalization | output: | (None, 21, 21, 256)
max_pooling2d_3 | input: | (None, 21, 21, 256)
MaxPooling2D | output: | (None, 10, 10, 256)
dropout_1 | input: | (None, 10, 10, 256)
Dropout | output: | (None, 10, 10, 256)
flatten | input: | (None, 10, 10, 256)
Flatten | output: | (None, 25600)
dense | input: | (None, 25600)
Dense | output: | (None, 512)
batch_normalization_4 | input: | (None, 512)
BatchNormalization | output: | (None, 512)
dropout_2 | input: | (None, 512)
Dropout | output: | (None, 512)
dense_1 | input: | (None, 512)
Dense | output: | (None, 101)

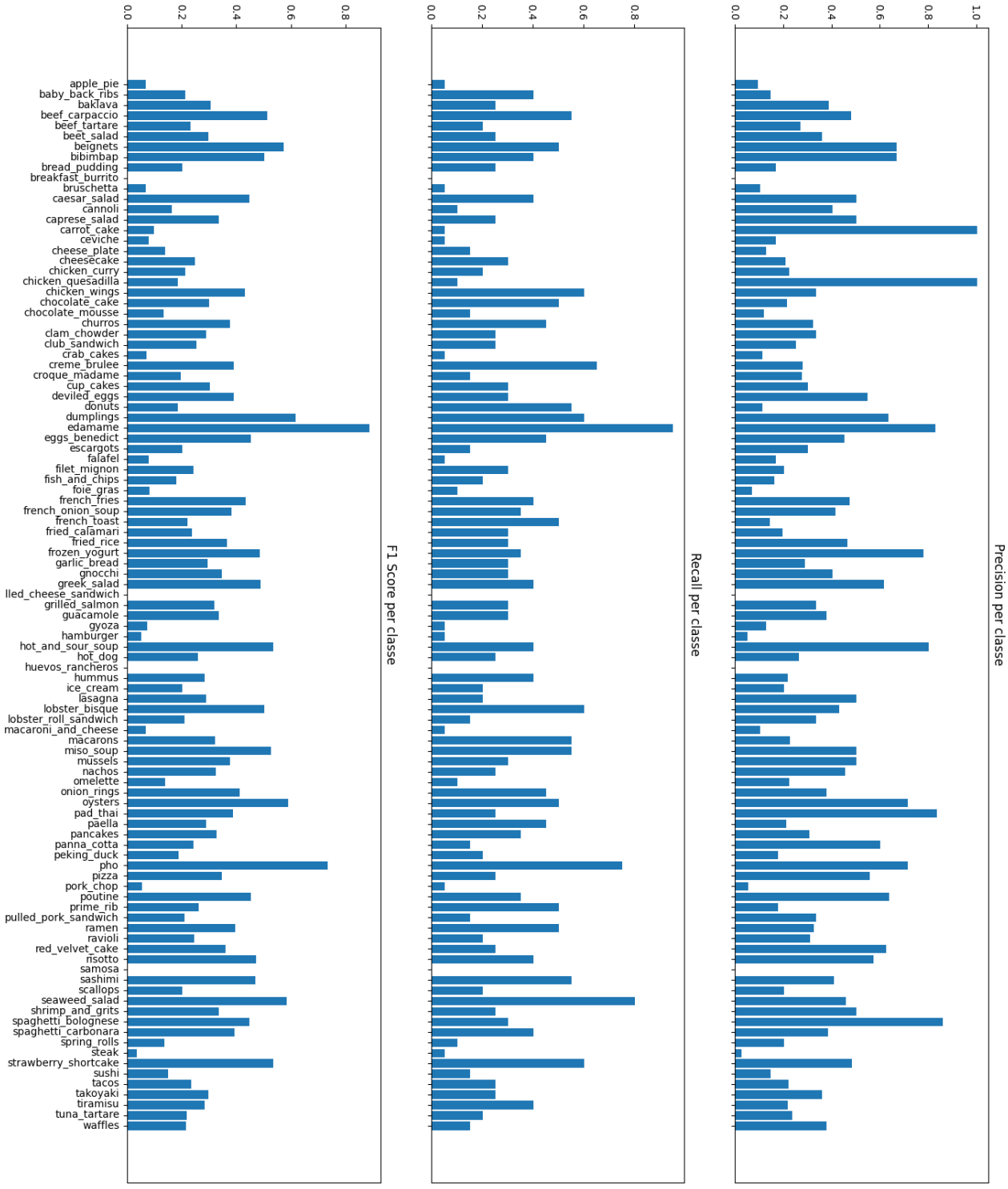
Layer (type)	Output Shape	Param #
sequential_1 (Sequential)	(None, 224, 224, 3)	0
sequential_2 (Sequential)	(None, 224, 224, 3)	0
conv2d (Conv2D)	(None, 222, 222, 32)	896
batch_normalization (BatchNormalization)	(None, 222, 222, 32)	128
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18496
batch_normalization_1 (BatchNormalization)	(None, 109, 109, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73856
conv2d_3 (Conv2D)	(None, 50, 50, 128)	147584
batch_normalization_2 (BatchNormalization)	(None, 50, 50, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 25, 25, 128)	0
dropout (Dropout)	(None, 25, 25, 128)	0
conv2d_4 (Conv2D)	(None, 23, 23, 256)	295168
conv2d_5 (Conv2D)	(None, 21, 21, 256)	590080
batch_normalization_3 (BatchNormalization)	(None, 21, 21, 256)	1024
max_pooling2d_3 (MaxPooling2D)	(None, 10, 10, 256)	0
dropout_1 (Dropout)	(None, 10, 10, 256)	0
flatten (Flatten)	(None, 25600)	0
dense (Dense)	(None, 512)	13107712
batch_normalization_4 (BatchNormalization)	(None, 512)	2048
dropout_2 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 101)	51813

Total params: 14,289,573
Trainable params: 14,287,589
Non-trainable params: 1,984

3.2.2. Result

As we expected, the model achieves a better accuracy of around 35%. However, efforts to reduce overfitting are not enough. In fact, as we can see from the graphs, again the curves related to validation go to settling and again reach a plateau.





3.2.3. Model without data augmentation

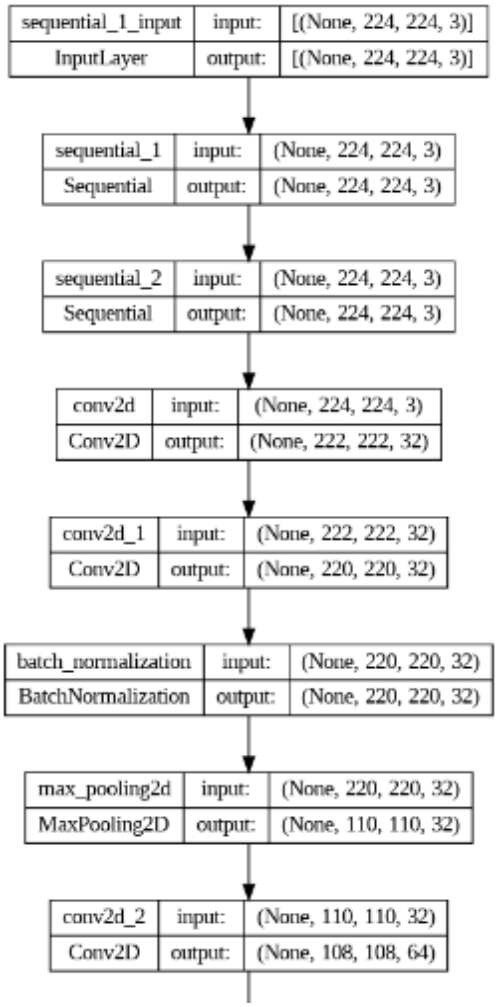
Surprised by the difficulty of combating this overfitting, we tried running a new train by removing the data augmentation layer. The result reassured us, in fact, already from the first epochs the difference between the train and validation curves is very marked and far exceeds the difference found in previous experiments. This indicates good progress in

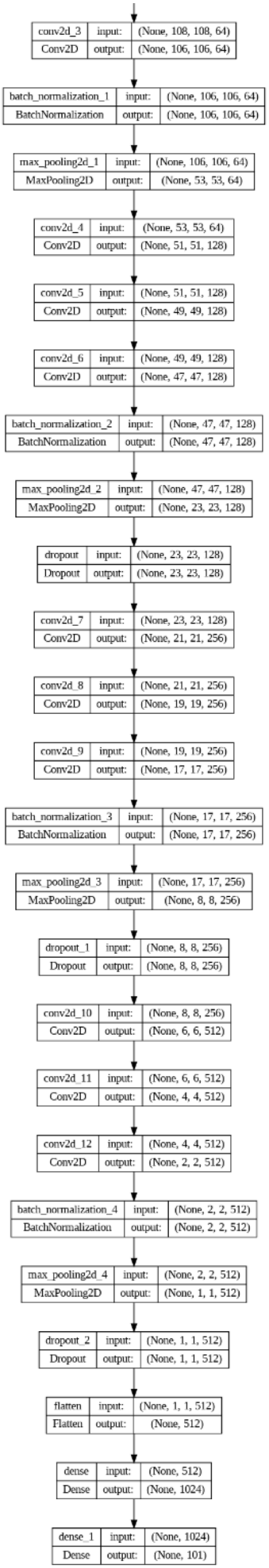
combating overfitting despite the fact that it remained even in the experiments already completed.

```
757/757 [==============================] - 183s 242ms/step - loss: 1.2929 - accuracy: 0.7013 - val_loss: 4.2040 - val_accuracy: 0.1463
Epoch 7/25
757/757 [==============================] - ETA: 0s - loss: 0.6179 - accuracy: 0.8878
Epoch 7: val_accuracy did not improve from 0.14633
757/757 [==============================] - 182s 241ms/step - loss: 0.6179 - accuracy: 0.8878 - val_loss: 4.1720 - val_accuracy: 0.1419
Epoch 8/25
757/757 [==============================] - ETA: 0s - loss: 0.3018 - accuracy: 0.9599
Epoch 8: val_accuracy did not improve from 0.14633
757/757 [==============================] - 181s 239ms/step - loss: 0.3018 - accuracy: 0.9599 - val_loss: 4.3199 - val_accuracy: 0.1374
Epoch 9/25
757/757 [==============================] - ETA: 0s - loss: 0.1641 - accuracy: 0.9840
Epoch 9: val_accuracy did not improve from 0.14633
757/757 [==============================] - 181s 239ms/step - loss: 0.1641 - accuracy: 0.9840 - val_loss: 4.3072 - val_accuracy: 0.1434
Epoch 10/25
757/757 [==============================] - ETA: 0s - loss: 0.1077 - accuracy: 0.9906
Epoch 10: val_accuracy did not improve from 0.14633
757/757 [==============================] - 159s 210ms/step - loss: 0.1077 - accuracy: 0.9906 - val_loss: 4.3982 - val_accuracy: 0.1347
Epoch 11/25
757/757 [==============================] - ETA: 0s - loss: 0.0872 - accuracy: 0.9923
Epoch 11: val_accuracy did not improve from 0.14633
757/757 [==============================] - 162s 214ms/step - loss: 0.0872 - accuracy: 0.9923 - val_loss: 4.5704 - val_accuracy: 0.1262
Epoch 12/25
757/757 [==============================] - ETA: 0s - loss: 0.0868 - accuracy: 0.9918
Epoch 12: val_accuracy did not improve from 0.14633
757/757 [==============================] - 161s 213ms/step - loss: 0.0868 - accuracy: 0.9918 - val_loss: 4.7791 - val_accuracy: 0.1240
```

3.3. Third Model

To try to increase performance, we added complexity to the model and added additional dropout levels. We added new convolutional layers with additional filters. We also tried increasing epochs but as we will see it did not help.

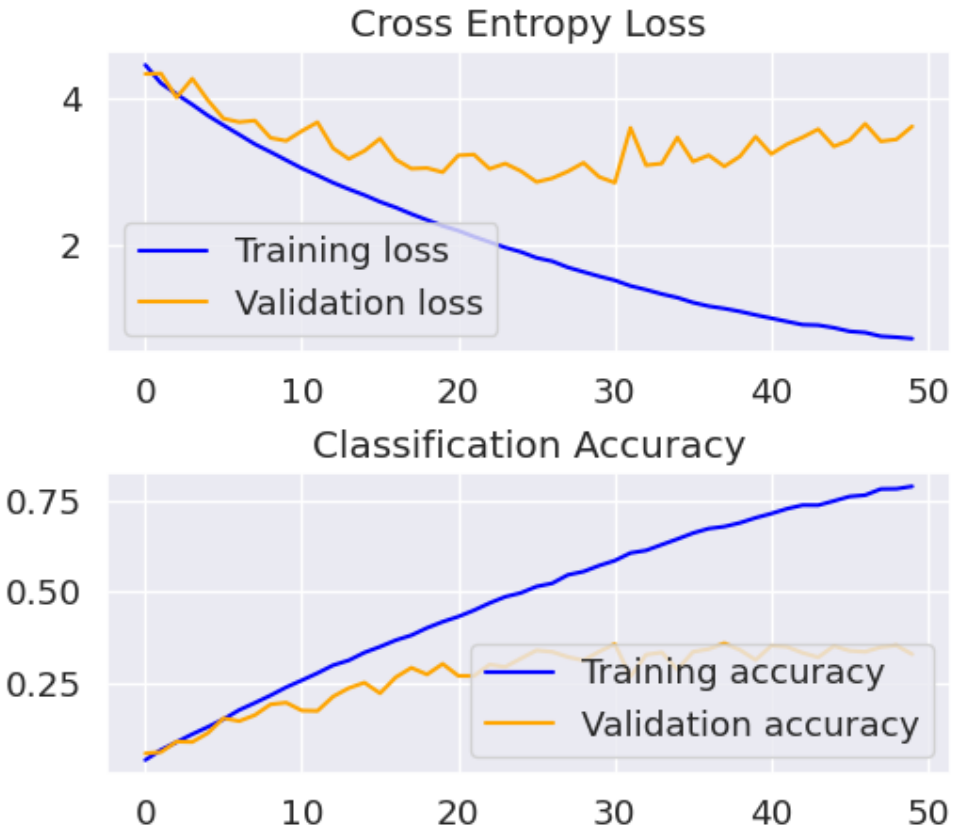


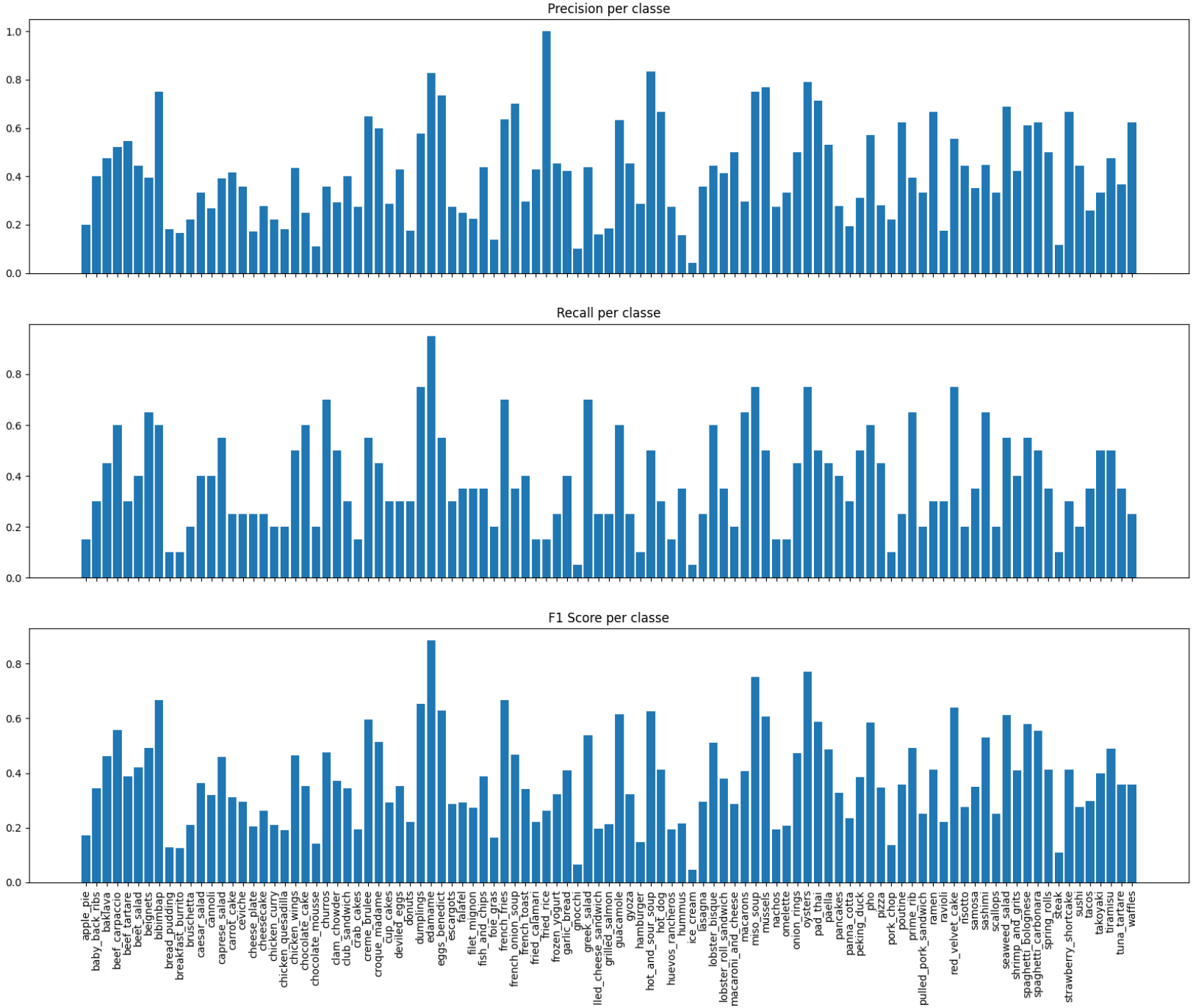

conv2d_3 | input: | (None, 108, 108, 64)
Conv2D | output: | (None, 106, 106, 64)
batch_normalization_1 | input: | (None, 106, 106, 64)
BatchNormalization | output: | (None, 106, 106, 64)
max_pooling2d_1 | input: | (None, 106, 106, 64)
MaxPooling2D | output: | (None, 53, 53, 64)
conv2d_4 | input: | (None, 53, 53, 64)
Conv2D | output: | (None, 51, 51, 128)
conv2d_5 | input: | (None, 51, 51, 128)
Conv2D | output: | (None, 49, 49, 128)
conv2d_6 | input: | (None, 49, 49, 128)
Conv2D | output: | (None, 47, 47, 128)
batch_normalization_2 | input: | (None, 47, 47, 128)
BatchNormalization | output: | (None, 47, 47, 128)
max_pooling2d_2 | input: | (None, 47, 47, 128)
MaxPooling2D | output: | (None, 23, 23, 128)
dropout | input: | (None, 23, 23, 128)
Dropout | output: | (None, 23, 23, 128)
conv2d_7 | input: | (None, 23, 23, 128)
Conv2D | output: | (None, 21, 21, 256)
conv2d_8 | input: | (None, 21, 21, 256)
Conv2D | output: | (None, 19, 19, 256)
conv2d_9 | input: | (None, 19, 19, 256)
Conv2D | output: | (None, 17, 17, 256)
batch_normalization_3 | input: | (None, 17, 17, 256)
BatchNormalization | output: | (None, 17, 17, 256)
max_pooling2d_3 | input: | (None, 17, 17, 256)
MaxPooling2D | output: | (None, 8, 8, 256)
dropout_1 | input: | (None, 8, 8, 256)
Dropout | output: | (None, 8, 8, 256)
conv2d_10 | input: | (None, 8, 8, 256)
Conv2D | output: | (None, 6, 6, 512)
conv2d_11 | input: | (None, 6, 6, 512)
Conv2D | output: | (None, 4, 4, 512)
conv2d_12 | input: | (None, 4, 4, 512)
Conv2D | output: | (None, 2, 2, 512)
batch_normalization_4 | input: | (None, 2, 2, 512)
BatchNormalization | output: | (None, 2, 2, 512)
max_pooling2d_4 | input: | (None, 2, 2, 512)
MaxPooling2D | output: | (None, 1, 1, 512)
dropout_2 | input: | (None, 1, 1, 512)
Dropout | output: | (None, 1, 1, 512)
flatten | input: | (None, 1, 1, 512)
Flatten | output: | (None, 512)
dense | input: | (None, 512)
Dense | output: | (None, 1024)
dense_1 | input: | (None, 1024)
Dense | output: | (None, 101)

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential_1 (Sequential)    (None, 224, 224, 3)       0

sequential_2 (Sequential)    (None, 224, 224, 3)       0

conv2d (Conv2D)              (None, 222, 222, 32)      896

batch_normalization (BatchN  (None, 222, 222, 32)      128
ormalization)

max_pooling2d (MaxPooling2D  (None, 111, 111, 32)      0
)

conv2d_1 (Conv2D)            (None, 109, 109, 64)      18496

batch_normalization_1 (Batc  (None, 109, 109, 64)      256
hNormalization)

max_pooling2d_1 (MaxPooling  (None, 54, 54, 64)        0
2D)

conv2d_2 (Conv2D)            (None, 52, 52, 128)       73856

conv2d_3 (Conv2D)            (None, 50, 50, 128)       147584

batch_normalization_2 (Batc  (None, 50, 50, 128)       512
hNormalization)

max_pooling2d_2 (MaxPooling  (None, 25, 25, 128)       0
2D)

dropout (Dropout)            (None, 25, 25, 128)       0

conv2d_4 (Conv2D)            (None, 23, 23, 256)       295168

conv2d_5 (Conv2D)            (None, 21, 21, 256)       590080

batch_normalization_3 (Batc  (None, 21, 21, 256)       1024
hNormalization)

max_pooling2d_3 (MaxPooling  (None, 10, 10, 256)       0
2D)

dropout_1 (Dropout)          (None, 10, 10, 256)       0

flatten (Flatten)            (None, 25600)             0

dense (Dense)                (None, 512)               13107712

batch_normalization_4 (Batc  (None, 512)               2048
hNormalization)

dropout_2 (Dropout)          (None, 512)               0

dense_1 (Dense)              (None, 101)               51813

=================================================================
Total params: 14,289,573
Trainable params: 14,287,589
Non-trainable params: 1,984
_________________________________________________________________
```

3.3.2. Results

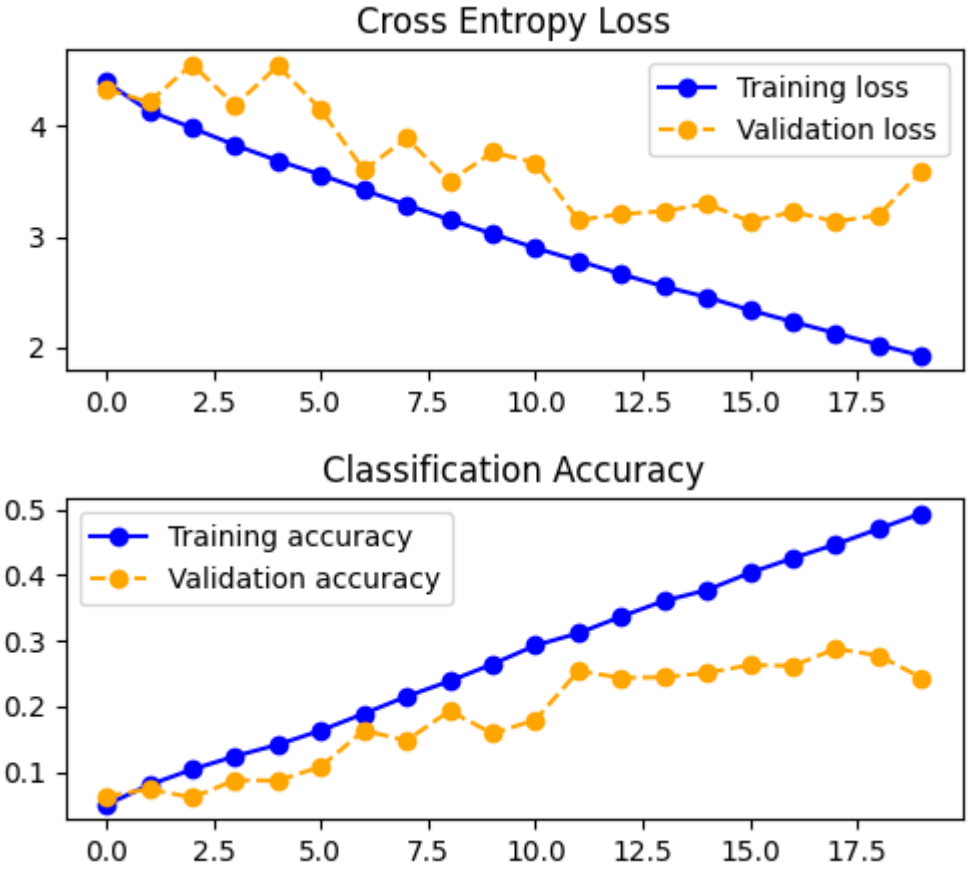
This third model, given the larger number of filters, allows accuracy close to 40 percent. However as we see from the graphs there remains a large component of overfitting despite efforts to try to lower it.




Precision per classe
Recall per classe
F1 Score per classe
0.0
0.2
0.4
0.6
0.8
1.0
apple_pie
baby_back_ribs
baklava
beef_carpaccio
beef_tartare
beet_salad
beignets
bibimbap
bread_pudding
breakfast_burrito
bruschetta
caesar_salad
cannoli
caprese_salad
carrot_cake
ceviche
cheese_plate
cheesecake
chicken_curry
chicken_quesadilla
chicken_wings
chocolate_cake
chocolate_mousse
churros
clam_chowder
club_sandwich
crab_cakes
creme_brulee
croque_madame
cup_cakes
deviled_eggs
donuts
dumplings
edamame
eggs_benedict
escargots
falafel
filet_mignon
fish_and_chips
foie_gras
french_fries
french_onion_soup
french_toast
fried_calamari
fried_rice
frozen_yogurt
garlic_bread
gnocchi
greek_salad
lled_cheese_sandwich
grilled_salmon
guacamole
gyoza
hamburger
hot_and_sour_soup
hot_dog
huevos_rancheros
hummus
ice_cream
lasagna
lobster_bisque
lobster_roll_sandwich
macaroni_and_cheese
macarons
miso_soup
mussels
nachos
omelette
onion_rings
oysters
pad_thai
paella
pancakes
panna_cotta
peking_duck
pho
pizza
pork_chop
poutine
prime_rib
pulled_pork_sandwich
ramen
ravioli
red_velvet_cake
risotto
samosa
sashimi
scallops
seaweed_salad
shrimp_and_grits
spaghetti_bolognese
spaghetti_carbonara
spring_rolls
steak
strawberry_shortcake
sushi
tacos
takoyaki
tiramisu
tuna_tartare
waffles

3.4. Tuned Third Model

We then finally tried tuning the third model to see the differences in performance. We used fewer epochs given the previous performance and obtained a better result from the overfitting point of view.



As we can see from the graphs, the phenomenon of overfitting remains present but the gap between the curves remains controlled, despite the fact that a plateau tends to occur here as well.

4.Pre-trained Networks

4.1. Introduction

This section describes the results obtained using two different pretrained models (MobileNet and InceptionV3) that were pretrained on other large-scale image datasets.

These networks have been widely used for tasks such as image classification, semantic segmentation, and real-time image processing on mobile devices.

We have taken these pretrained models from the tensorflow.keras.application module and we choose the models with the weights obtained during training with the ImageNet dataset.

We choose an input of (224,224,3).

For each experiment, we use the Adam optimizer and the categorical cross-entropy as loss function.

For each network we computed some of the most important metrics: precision, recall and f1 score.

Due to the fact that we are dealing with 101 classes it is impossible to represent the confusion matrix in an understandable way.

4.2. Feature Extraction

Feature extraction consists of using the representations learned by a previous network to extract interesting features from new samples. The convolutional bases of the MobileNetV2 and InceptionV3 are frozen and the features that they extract are then sent to new classifiers, which are trained from scratch.

4.3. Pre-processing

Pre-processing the dataset is an important step before training a deep learning model like MobileNetV2 or InceptionV3. Here are the pre-processing steps we used for these pre-trained networks:

Resize Images: these networks expect images of a specific size as input. Resize all the images in the dataset to a consistent size, such as 224x224 pixels, to match the input size expected by the networks. Resizing ensures that all images have the same dimensions.

Normalization: Convert the resized images into a floating-point representation, typically in the range of 0 to 1. Divide the pixel values by 255, which is the maximum pixel value for an 8-bit image representation, to normalize the values between 0 and 1.

Data Augmentation: Augmenting the dataset with additional variations of the images can help improve the model's generalization ability. We have applied techniques such as random

rotations, flips, and zooms to generate new training samples from existing ones. Data augmentation helps models to learn robust features and reduces the risk of overfitting.

Splitting the Dataset: Divide the dataset into training, validation, and testing subsets. We have used 300 images per class and we have divided each set of images in this way:

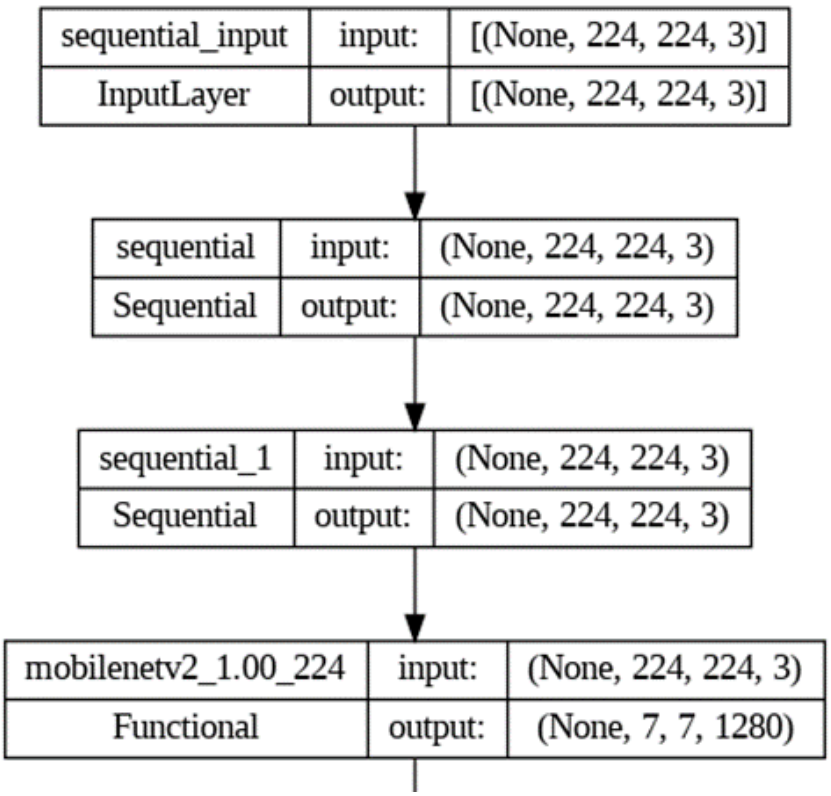
- Training : 240 images
- Validation: 40 images
- Test: 20 images

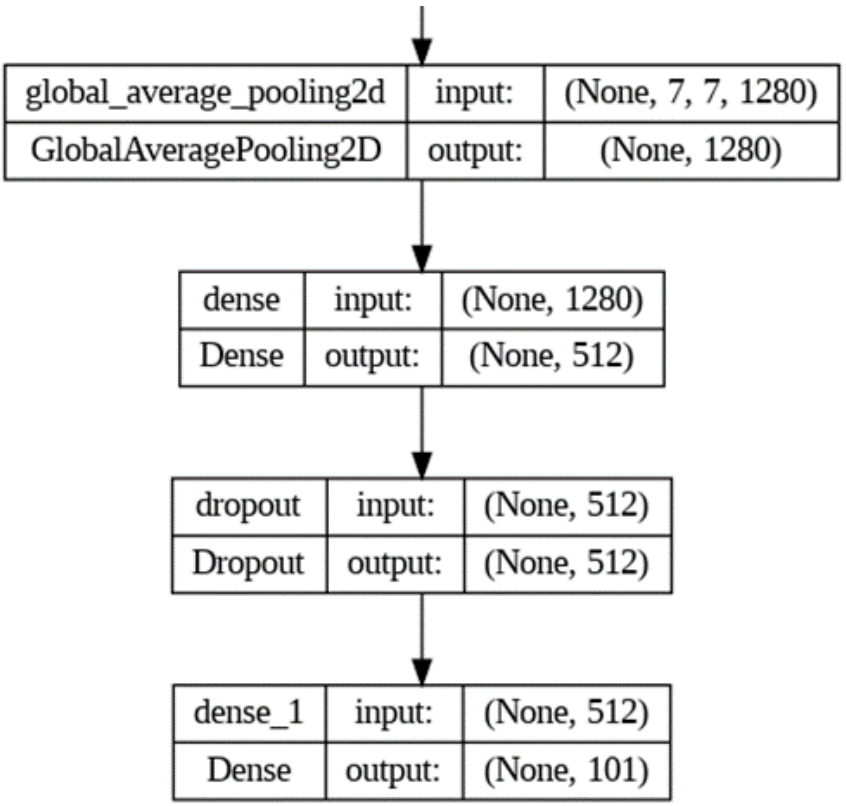
4.4. MobileNetV2

MobileNetV2 is a convolutional neural network architecture proposed for mobile and embedded vision applications. Designed for image processing on mobile devices. It is an improved and optimized version of MobileNetV1, developed by Google.

4.4.1. Experiment 0 - Base model

The MobileNetV2 has been taken as base model (with frozen weights) and on top of it has been built a GlobalAveragePooling2D layer, a dense layer, a dropout layer and an output layer. MobileNetV2 uses a Global Average Pooling layer to reduce the spatial dimensions of the feature map obtained from the convolutional layers, while retaining the important information. It computes the average of all activation values across all spatial dimensions and contains information about the spatial hierarchy. We could use a Flatten layer instead, but it may not be optimal because it simply takes the output of the previous layer and flattens it into a single long vector, losing all spatial information.

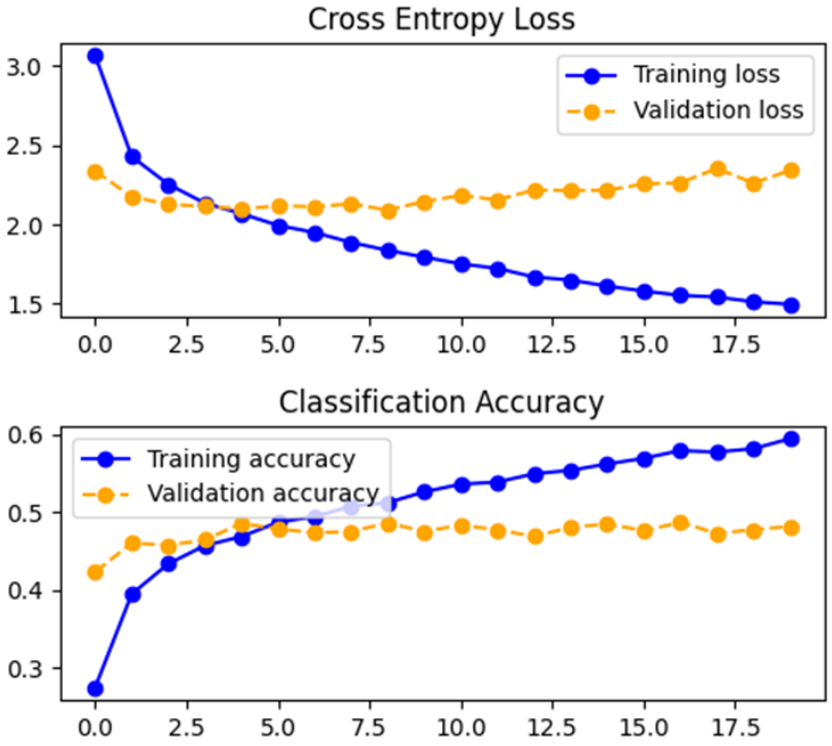




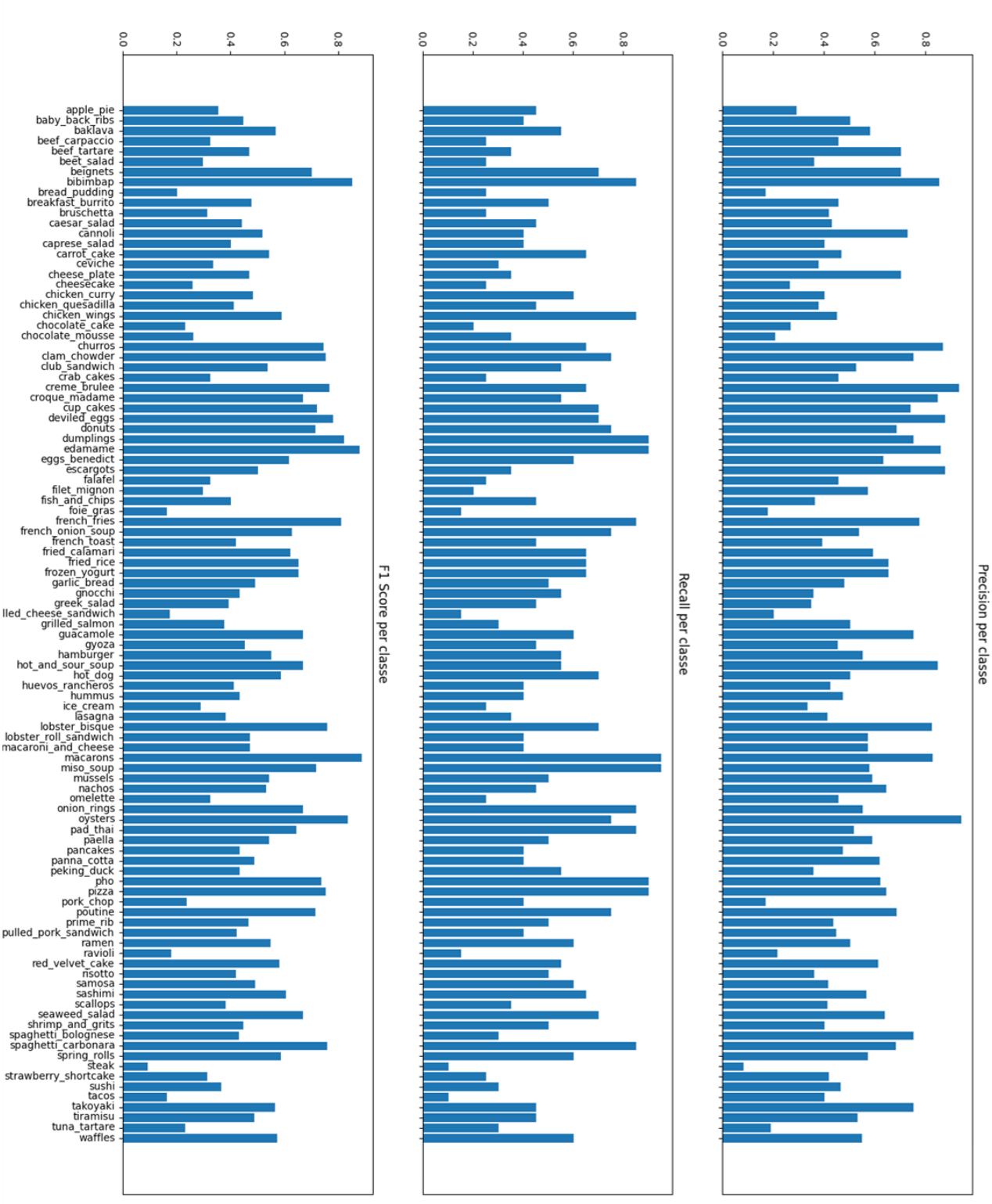
Total params: 2,965,669

Trainable params: 707,685

Non-trainable params: 2,257,984



After 5 epochs, we observe overfitting: the accuracy on the training set is larger than the one on the validation set and the accuracy on the validation set does not increase significantly anymore, which means that the network starts to memorize the training data.

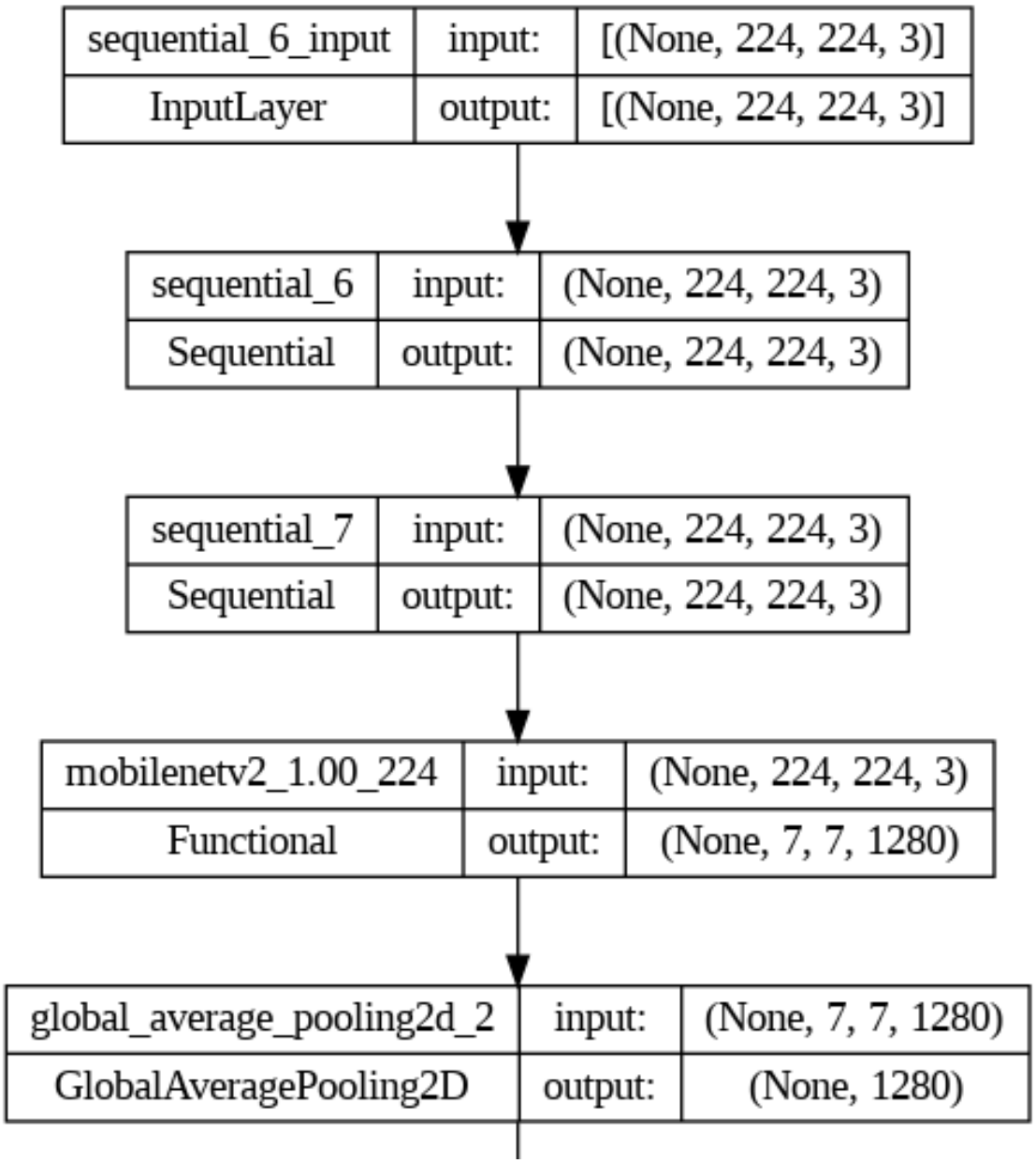


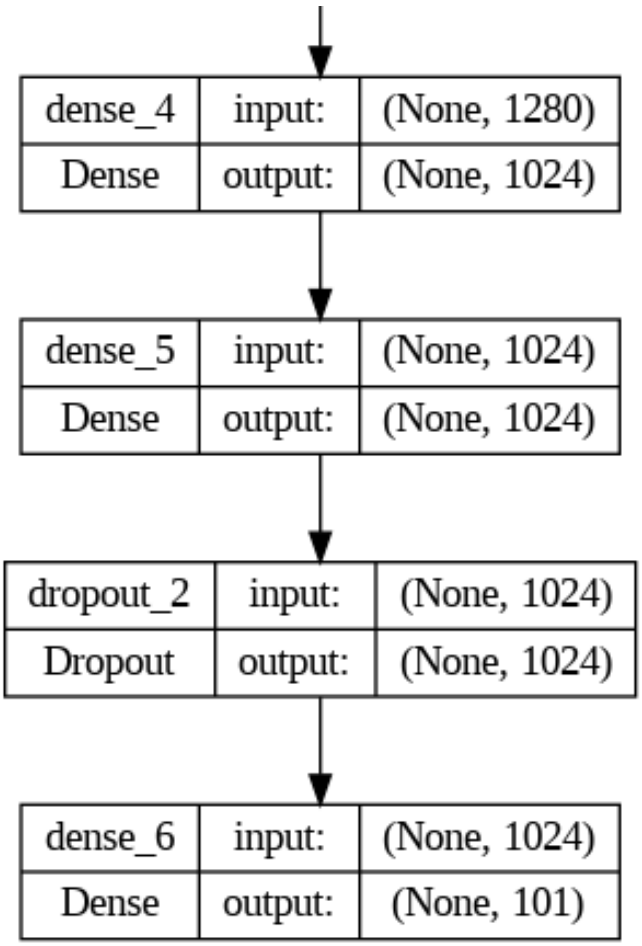
4.4.2. Tuned base model

Due to the bad performance in terms of accuracy and overfitting we decided to make a hyper-parameters tuning to find the better ones and see the results that we can obtain. The hyperparameters that we have tried to tune are the following:

- Dense hidden layer number of neurons
- Dropout percentage
- Learning rate

At the end of the tuning we have build the following network:



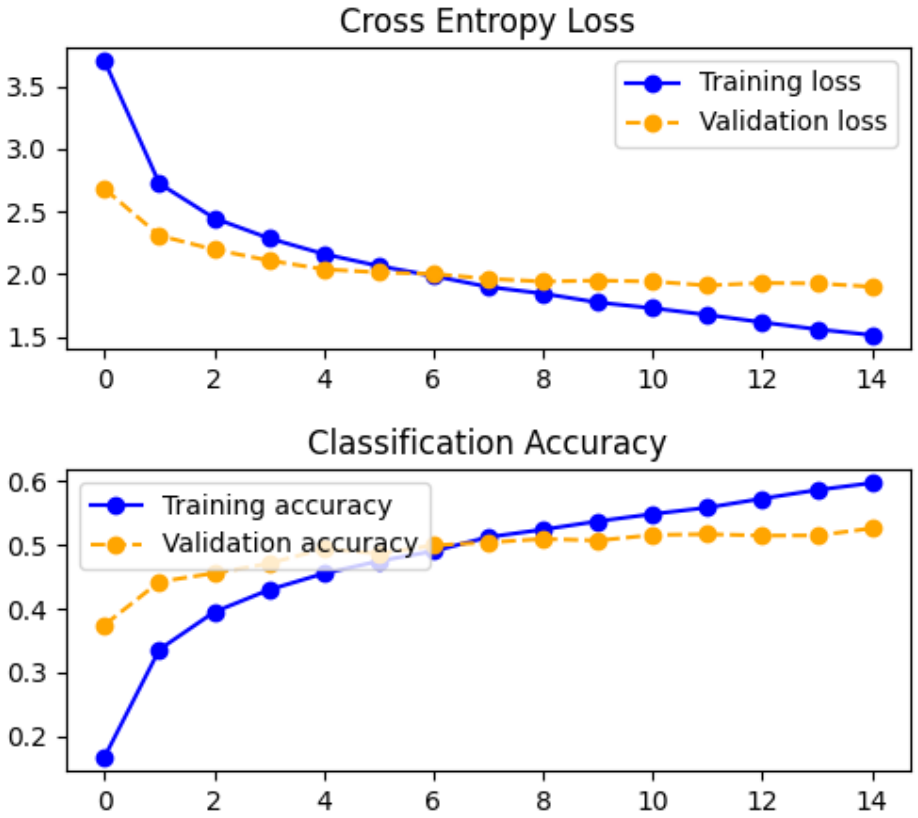


Total params: 4,722,853
Trainable params: 2,464,869
Non-trainable params: 2,257,984

Since we use an early stop callback to stop the training when there is no improvement in the accuracy on the validation set with a patience of 3, we need to retrain the network with the best number of epochs. The values reported in the following are the ones that we get with the network trained with the best number of epochs. The same procedure is applied for all the experiments of this section.

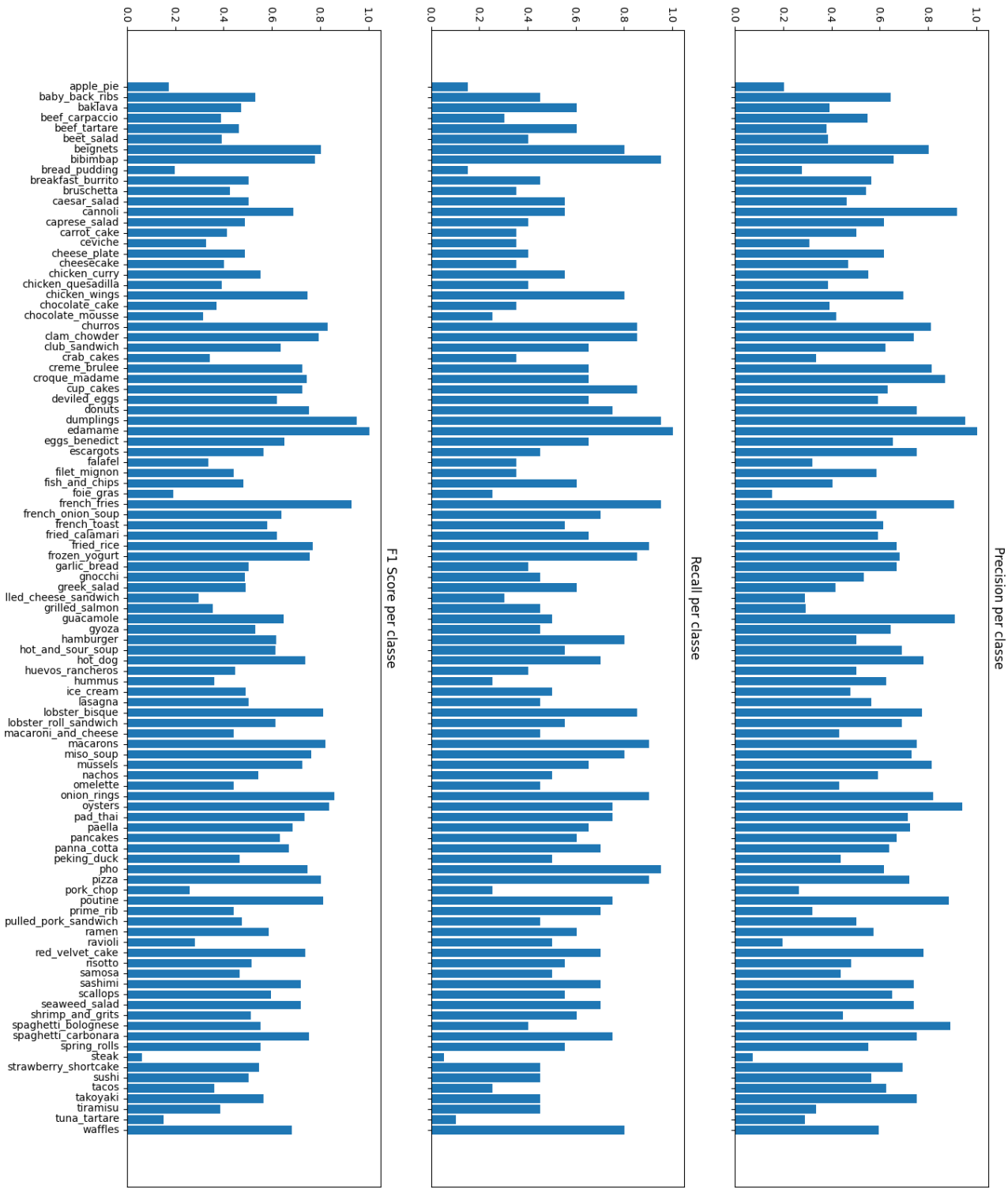
4.4.3. Experiment 1 - Tuned freezed model

The first experiment is done by using the optimal hyper-parameters found in the previous experiment.



As we can see, this network has performance far better than the previous one: loss and accuracy have a much more consistent trend.

Best epoch	Validation accuracy	Test accuracy	Validation loss	Test loss
15	0.5258	0.5628	1.8987	1.6687



4.4.4. Fine tuning

Fine tuning consists in unfreezing a few of the top layers of a frozen model base used for feature extraction, and jointly training both the classifier we added and and these top layers.

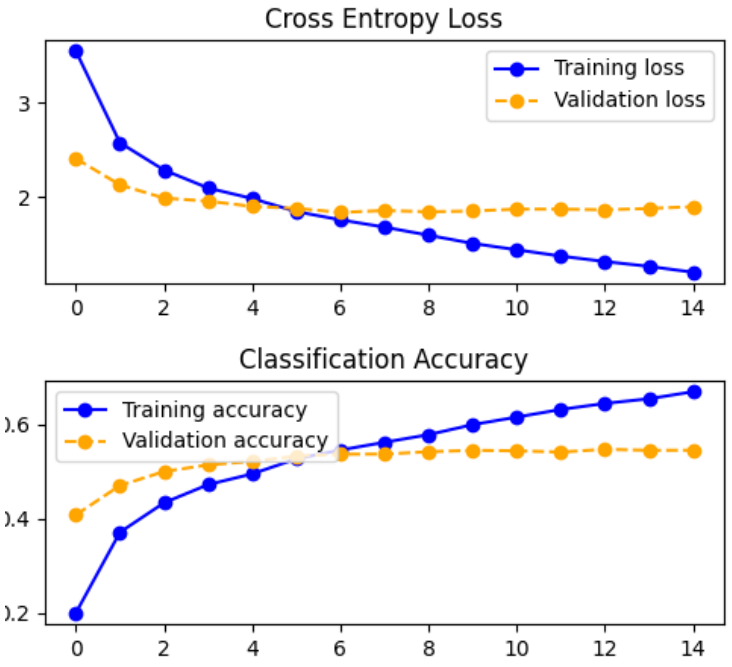
This is called ”fine-tuning” because it slightly adjusts the more abstract representations of the model being reused, in order to make them more relevant for the problem at hand. Fine tuning can be useful when the new dataset is large and very different from the original dataset like in this case. We can either train a CNN from scratch or fine-tuning a larger number of layers. Indeed, when we have a lot of data, we do not run the risk of overfitting. And when the data is different, we could benefit from the weight initialization of a pre-trained network and fine-tune even the earlier layers.

4.4.4. Experiment 2 - Unfreeze 1

The third experiment is done by unfreezing the last convolutional block of MobileNetV2. The architecture is the same as previously, except that the total number of parameters is 4,722,853 (2,877,029 trainable and 1,845,824 non-trainable).

Layer (type)	Output Shape	Param #
sequential_6 (Sequential)	(None, 224, 224, None)	0
sequential_7 (Sequential)	(None, 224, 224, None)	0
mobilenetv2_1.00_224 (Functional)	(None, 7, 7, 1280)	2257984
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 1280)	0
dense_4 (Dense)	(None, 1024)	1311744
dense_5 (Dense)	(None, 1024)	1049600
dropout_2 (Dropout)	(None, 1024)	0
dense_6 (Dense)	(None, 101)	103525

Total params: 4,722,853
Trainable params: 2,877,029
Non-trainable params: 1,845,824



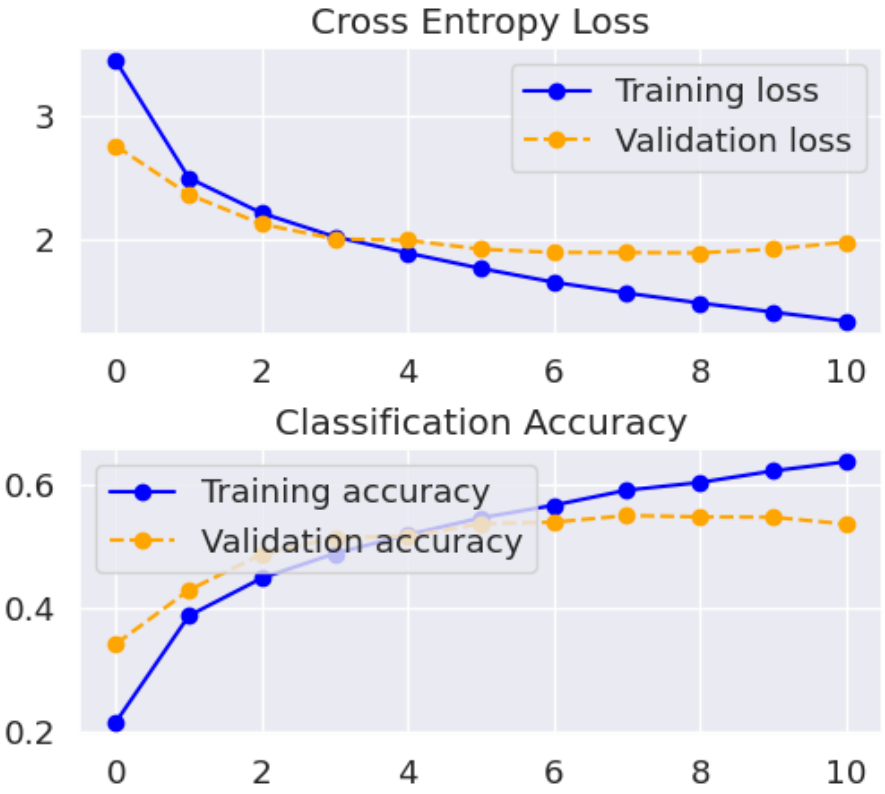
Best epoch	Validation accuracy	Test accuracy	Validation loss	Test loss
15	0.5451	0.5821	1.8954	1.6216

4.4.5. Experiment 3 - Unfreeze 2

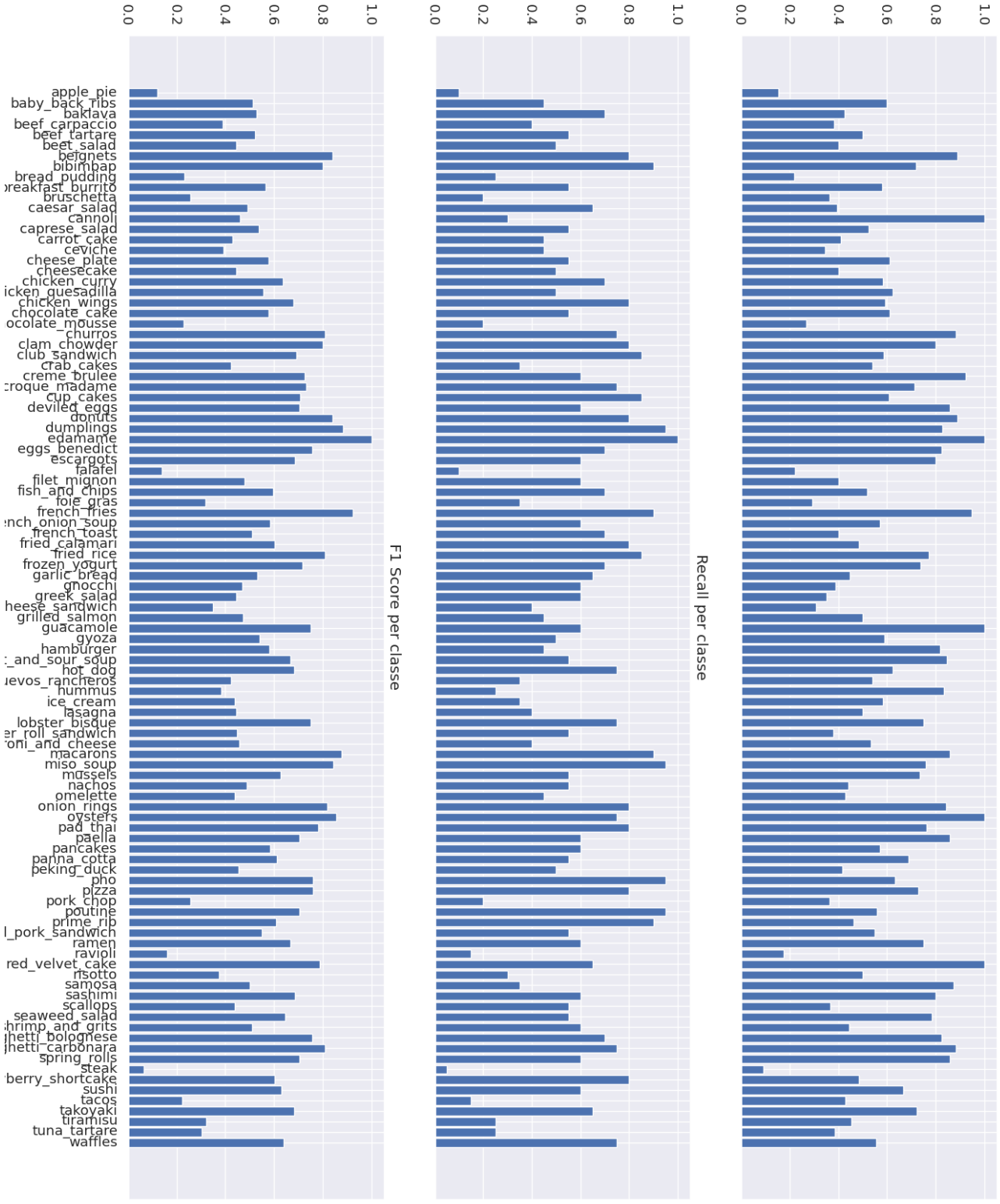
The fourth experiment is done by unfreezing the 2 last convolutional blocks of MobileNetV2. The architecture is the same as previously, except that the total number of parameters is 4,722,853 (3,184,869 trainable and 1,537,984 non trainable).

Layer (type)	Output Shape	Param #
sequential_6 (Sequential)	(None, 224, 224, None)	0
sequential_7 (Sequential)	(None, 224, 224, None)	0
mobilenetv2_1.00_224 (Functional)	(None, 7, 7, 1280)	2257984
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 1280)	0
dense_4 (Dense)	(None, 1024)	1311744
dense_5 (Dense)	(None, 1024)	1049600
dropout_2 (Dropout)	(None, 1024)	0
dense_6 (Dense)	(None, 101)	103525

Total params: 4,722,853
Trainable params: 3,184,869
Non-trainable params: 1,537,984



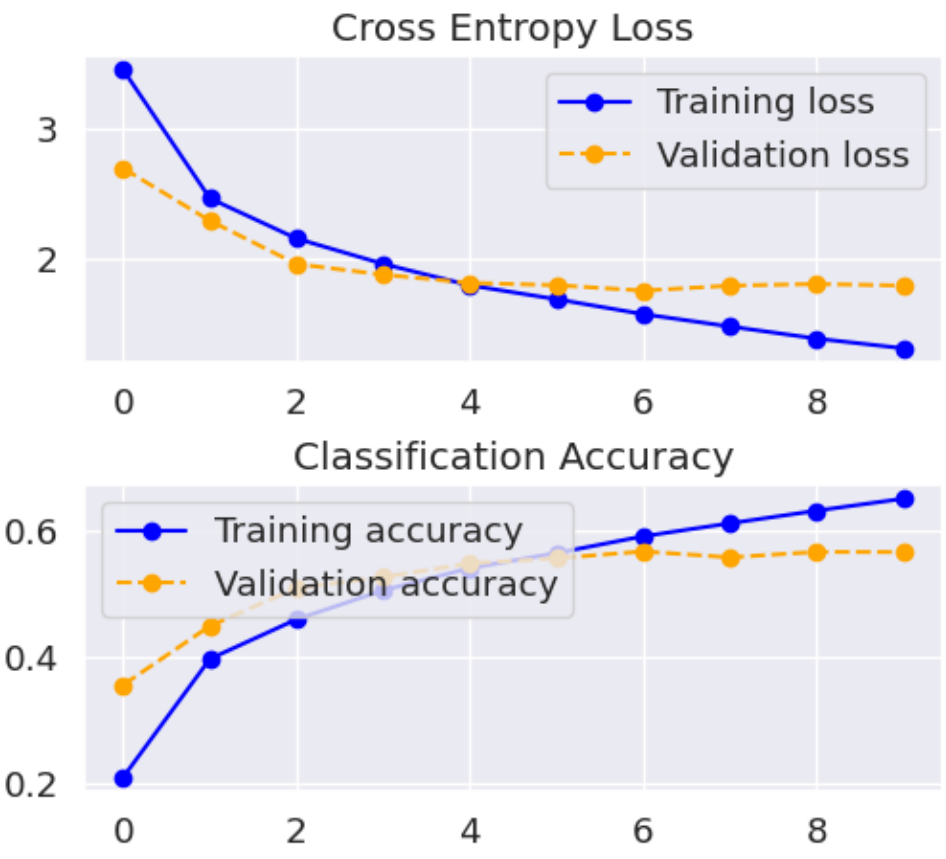
Best epoch	Validation accuracy	Test accuracy	Validation loss	Test loss
11	0.5360	0.5777	1.3301	1.6149



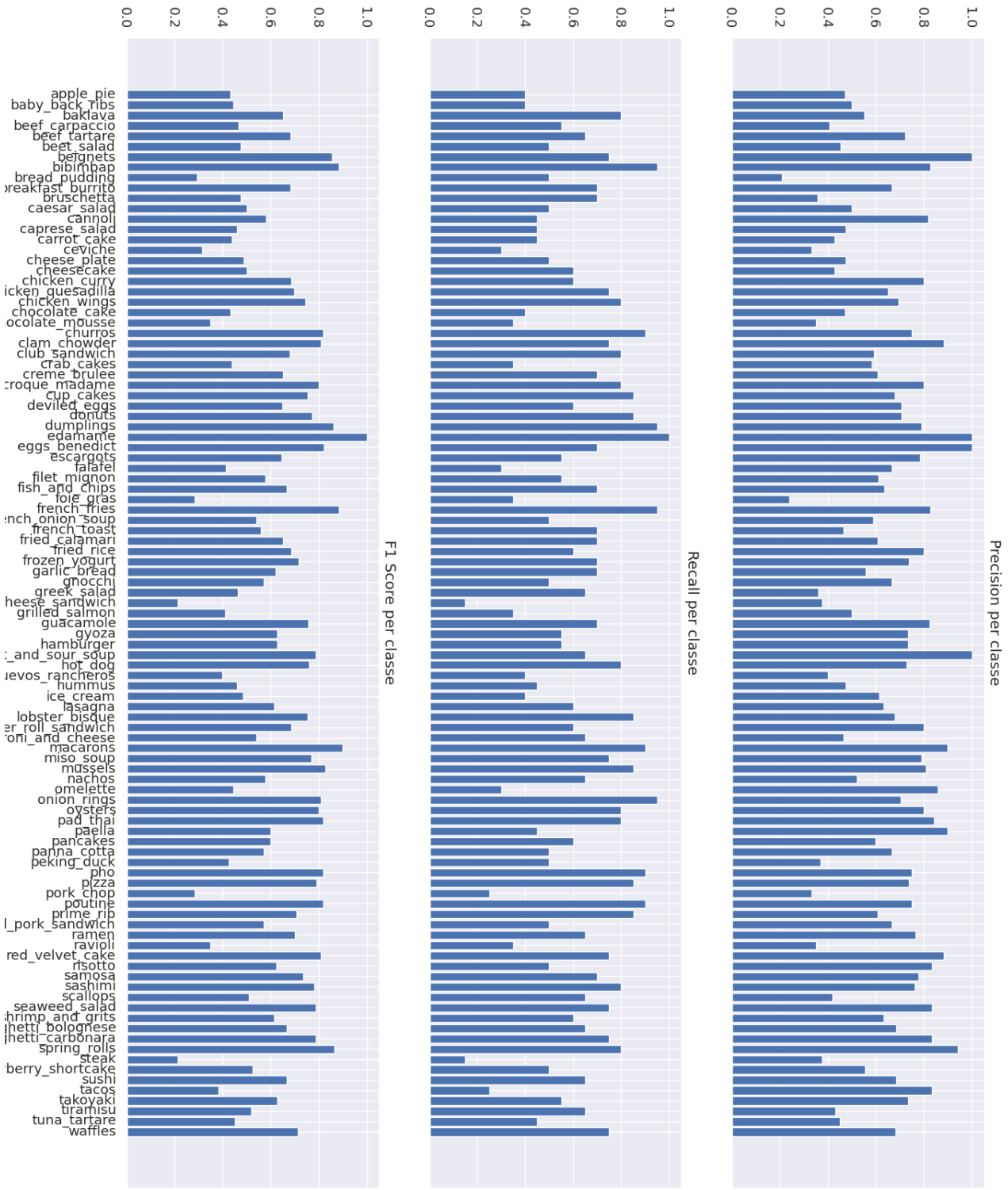
4.4.6. Experiment 4 - Unfreeze 3

The fifth experiment is done by unfreezing the 3 last convolutional blocks of MobileNetV2. The architecture is the same as previously, except that the total number of parameters is 4,722,853 (3,350,949 trainable and 1,371,904 non-trainable).

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential_6 (Sequential)   (None, 224, 224, None)    0

 sequential_7 (Sequential)   (None, 224, 224, None)    0

 mobilenetv2_1.00_224 (Funct  (None, 7, 7, 1280)       2257984
 ional)

 global_average_pooling2d_2   (None, 1280)             0
 (GlobalAveragePooling2D)

 dense_4 (Dense)             (None, 1024)              1311744

 dense_5 (Dense)             (None, 1024)              1049600

 dropout_2 (Dropout)         (None, 1024)              0

 dense_6 (Dense)             (None, 101)               103525

=================================================================
Total params: 4,722,853
Trainable params: 3,350,949
Non-trainable params: 1,371,904
```

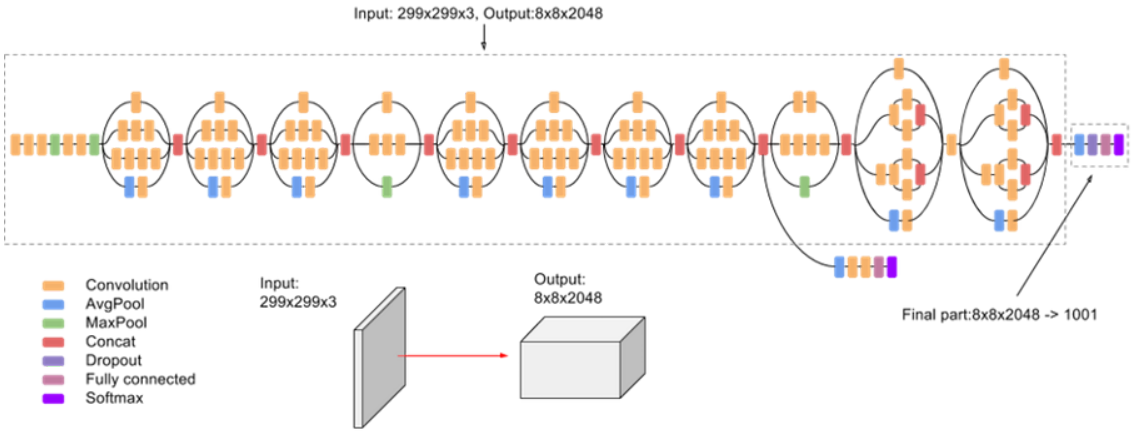


Best epoch	Validation accuracy	Test accuracy	Validation loss	Test loss
10	0.5667	0.6203	1.7860	1.4669



4.5. InceptionV3

InceptionV3 is a convolutional neural network for assisting in image analysis and object detection and got its start as a module for GoogLeNet. It is the third edition of Google's Inception Convolutional Neural Network, originally introduced during the ImageNet Recognition Challenge.



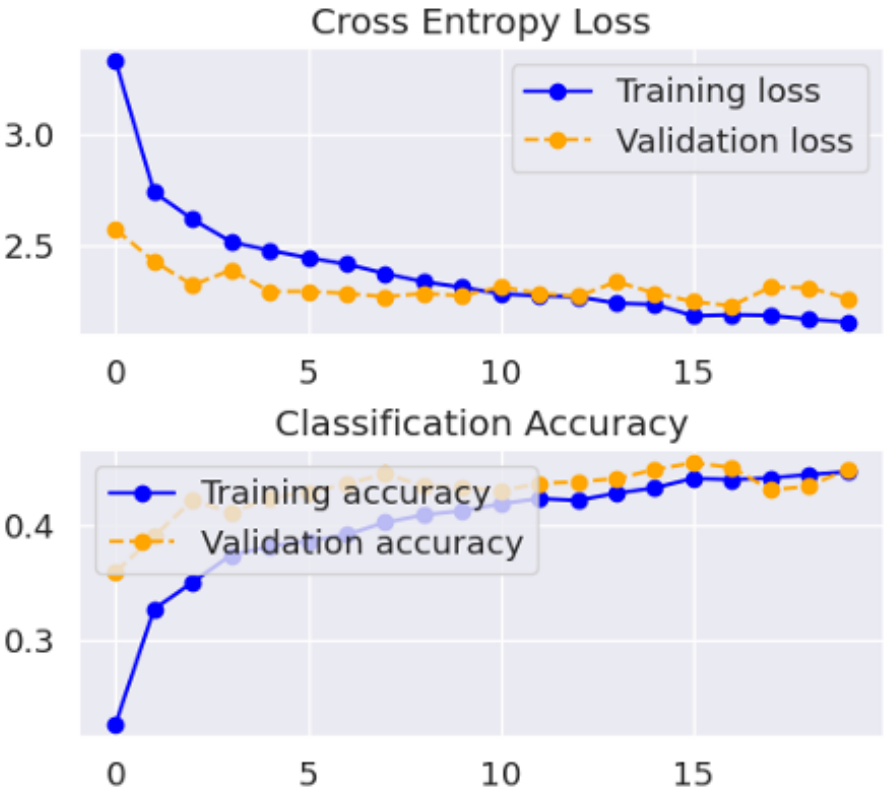
The third version was introduced by Szegedy et al. in Rethinking the Inception Architecture for Computer Vision. Makes several improvements from the previous models including using Label Smoothing, factorized 7 x 7 convolutions, and the use of an auxiliary classifier to propagate label information lower down the network (along with the use of batch normalization for layers in the sidehead).

4.5.1 Experiment 0 - Base model

The experiment was performed by using as base model the InceptionV3 (with frozen weights) and placing on top of this base the following layers: GlobalAveragePooling2D, Dense, Dropout and another Dense as an output layer.

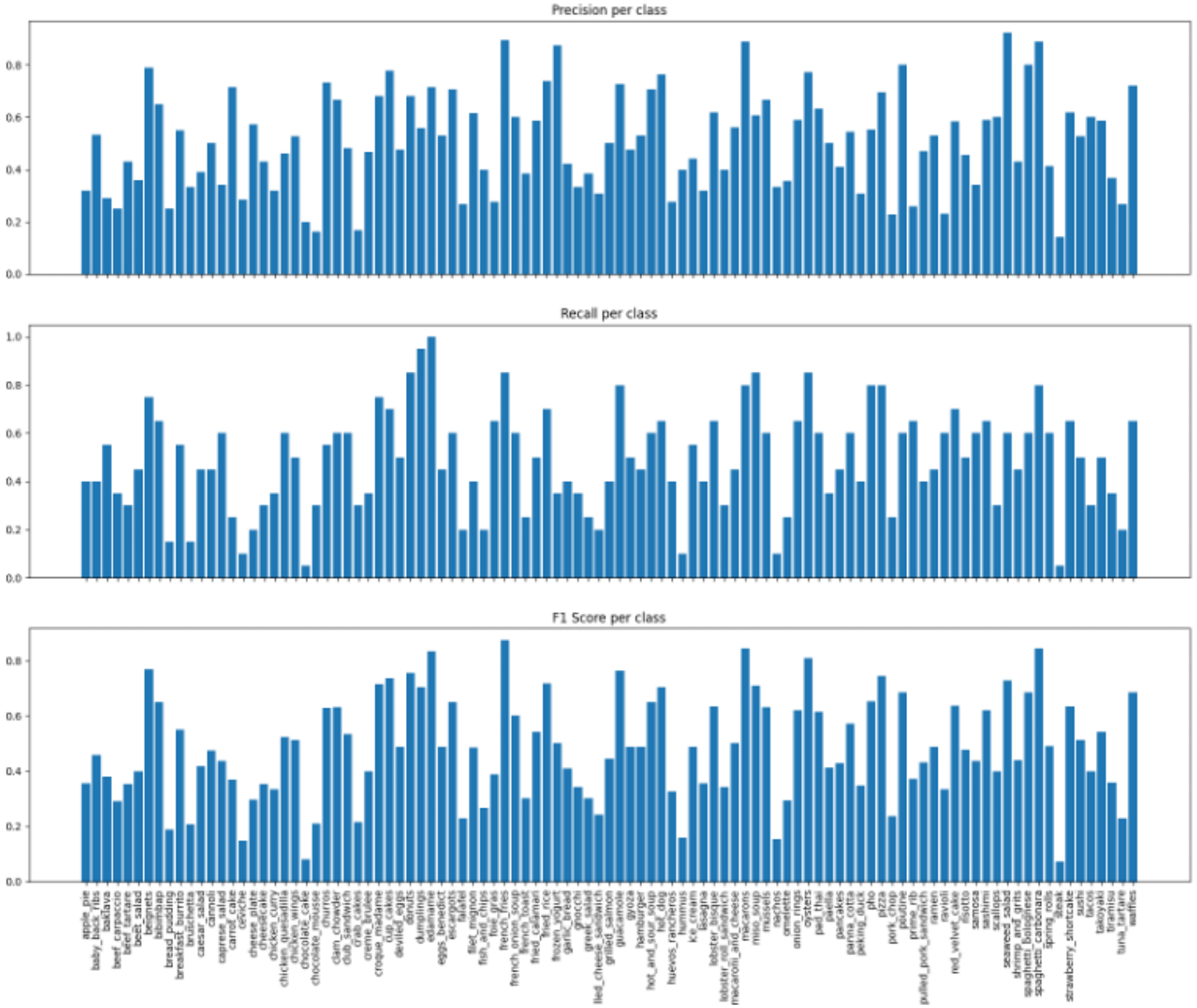
```
Layer (type)                 Output Shape              Param #
=================================================================
sequential (Sequential)      (None, 224, 224, 3)       0

sequential_1 (Sequential)    (None, 224, 224, 3)       0

inception_v3 (Functional)    (None, 5, 5, 2048)        21802784

global_average_pooling2d (G  (None, 2048)              0
lobalAveragePooling2D)

dense (Dense)                (None, 1024)              2098176

dropout (Dropout)            (None, 1024)              0

dense_1 (Dense)              (None, 101)               103525

=================================================================
Total params: 24,004,485
Trainable params: 2,201,701
Non-trainable params: 21,802,784
_________________________________________________________________
```

The above pictures show the different layers of the model and the trainable (and non-trainable) params.



After 16 epochs, we observe overfitting: the accuracy on the training set is larger than the one on the validation set. And the accuracy on the validation set does not increase significantly anymore, which means that the network stats to memorize the training data.

Best epoch	Validation accuracy	Test accuracy	Validation loss	Test loss
20	0.44	0.48	2.26	2.02


Precision per class
Recall per class
F1 Score per class
0.0
0.2
0.4
0.6
0.8
1.0
apple_pie
baby_back_ribs
baklava
beef_carpaccio
beef_tartare
beet_salad
beignets
bibimbap
bread_pudding
breakfast_burrito
bruschetta
caesar_salad
cannoli
caprese_salad
carrot_cake
ceviche
cheese_plate
cheesecake
chicken_curry
chicken_quesadilla
chicken_wings
chocolate_cake
chocolate_mousse
churros
clam_chowder
club_sandwich
crab_cakes
creme_brulee
croque_madame
cup_cakes
deviled_eggs
donuts
dumplings
edamame
eggs_benedict
escargots
falafel
filet_mignon
fish_and_chips
foie_gras
french_fries
french_onion_soup
french_toast
fried_calamari
fried_rice
frozen_yogurt
garlic_bread
gnocchi
greek_salad
grilled_cheese_sandwich
grilled_salmon
guacamole
gyoza
hamburger
hot_and_sour_soup
hot_dog
huevos_rancheros
hummus
ice_cream
lasagna
lobster_bisque
lobster_roll_sandwich
macaroni_and_cheese
macarons
miso_soup
mussels
nachos
omelette
onion_rings
oysters
pad_thai
paella
pancakes
panna_cotta
peking_duck
pho
pizza
pork_chop
poutine
prime_rib
pulled_pork_sandwich
ramen
ravioli
red_velvet_cake
risotto
samosa
sashimi
scallops
seaweed_salad
shrimp_and_grits
spaghetti_bolognese
spaghetti_carbonara
spring_rolls
steak
strawberry_shortcake
sushi
tacos
takoyaki
tiramisu
tuna_tartare
waffles

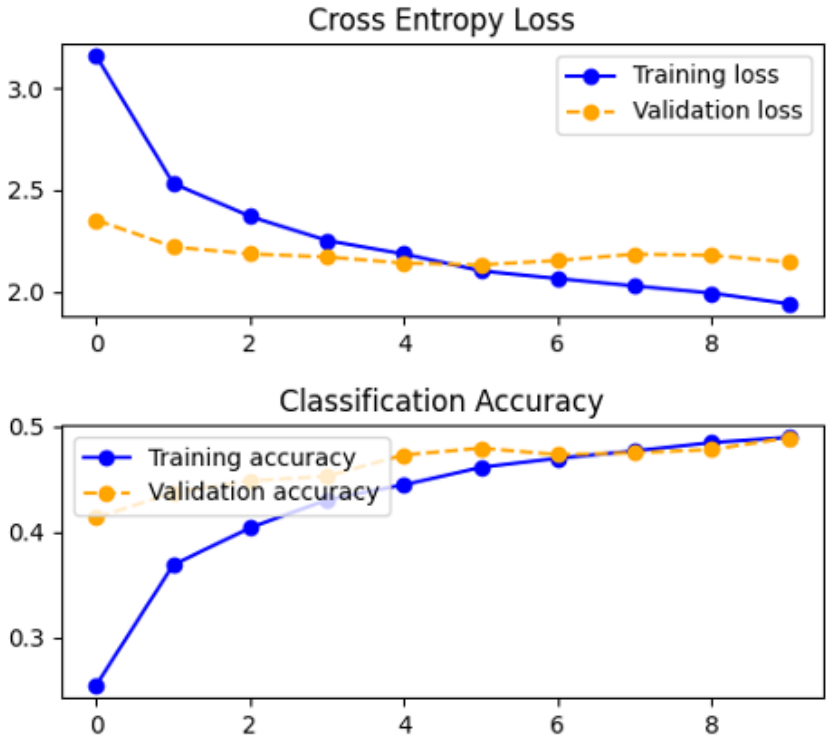
4.5.2. Experiment 1 - Unfreeze 1

From the following experiment to the last one (Experiment 3) was performed the fine-tuning. The process of fine-tuning consists of unfreezing some layers of the model (in particular the one of the InceptionV3 that was chosen as our base).

Layer (type)	Output Shape	Param #
sequential (Sequential)	(None, 224, 224, 3)	0
sequential_1 (Sequential)	(None, 224, 224, 3)	0
inception_v3 (Functional)	(None, 5, 5, 2048)	21802784
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dense (Dense)	(None, 1024)	2098176
dropout (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 101)	103525

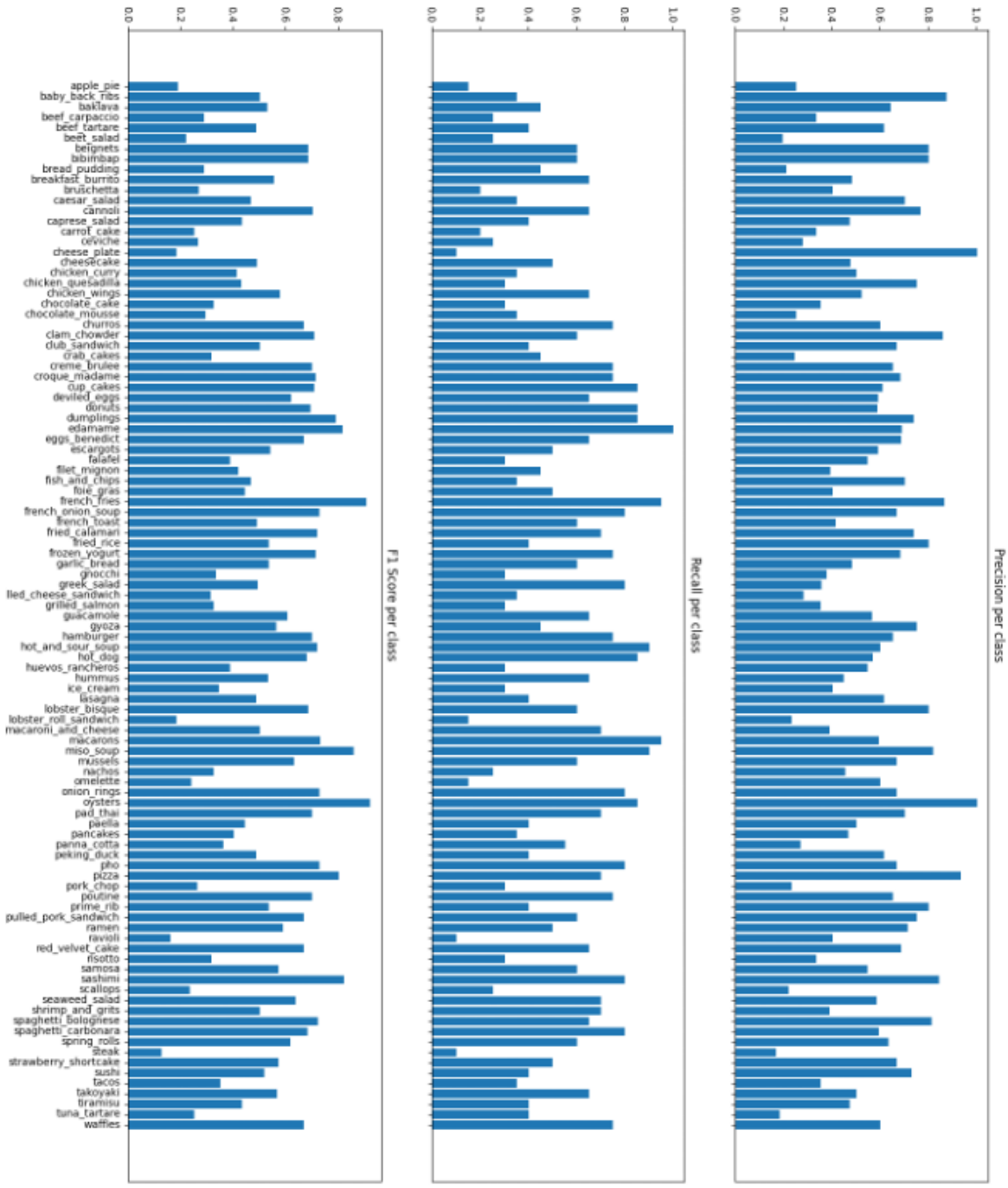
Total params: 24,004,485
Trainable params: 2,595,429
Non-trainable params: 21,409,056

The above pictures show the different layers of the model and the trainable (and non-trainable) params.



After 8 epochs, we observe overfitting: the accuracy on the training set is larger than the one on the validation set. And the accuracy on the validation set does not increase significantly anymore, which means that the network starts to memorize the training data.

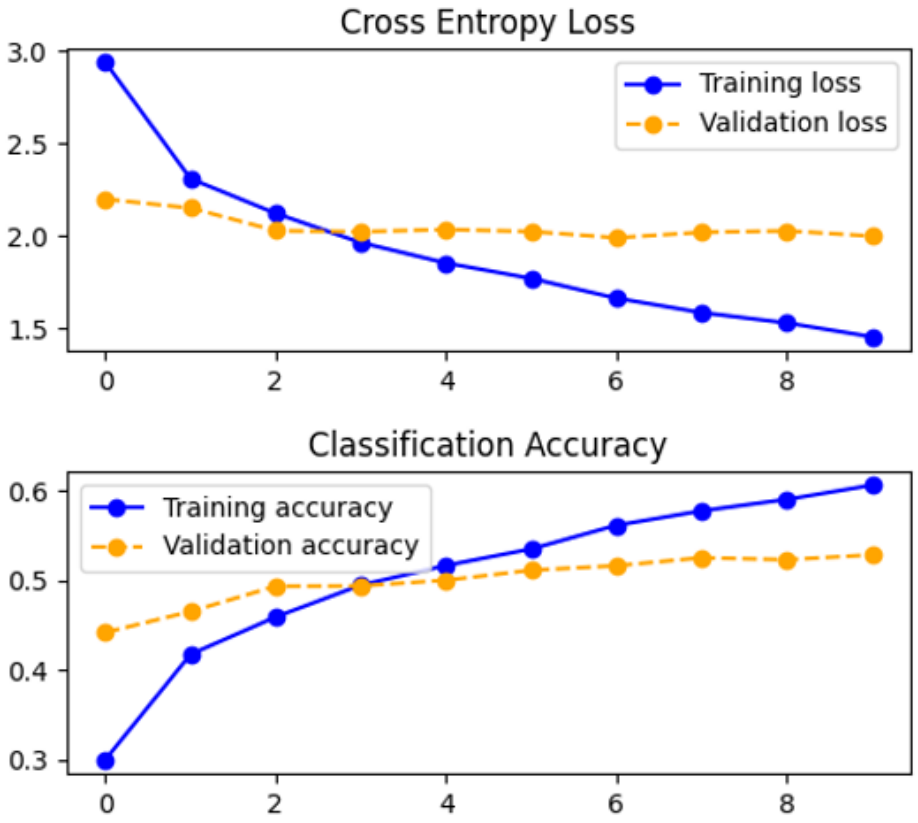
Best epoch	Validation accuracy	Test accuracy	Validation loss	Test loss
10	0.48	0.52	2.14	1.80



4.5.3. Experiment 2 - Unfreeze 2

Following with experiment 2 was performed the unfreezing of other layers as we can see in the picture below.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential (Sequential)      (None, 224, 224, 3)       0

sequential_1 (Sequential)    (None, 224, 224, 3)       0

inception_v3 (Functional)    (None, 5, 5, 2048)        21802784

global_average_pooling2d (G  (None, 2048)              0
lobalAveragePooling2D)

dense (Dense)                (None, 1024)              2098176

dropout (Dropout)            (None, 1024)              0

dense_1 (Dense)              (None, 101)               103525

=================================================================
Total params: 24,004,485
Trainable params: 3,252,325
Non-trainable params: 20,752,160
```



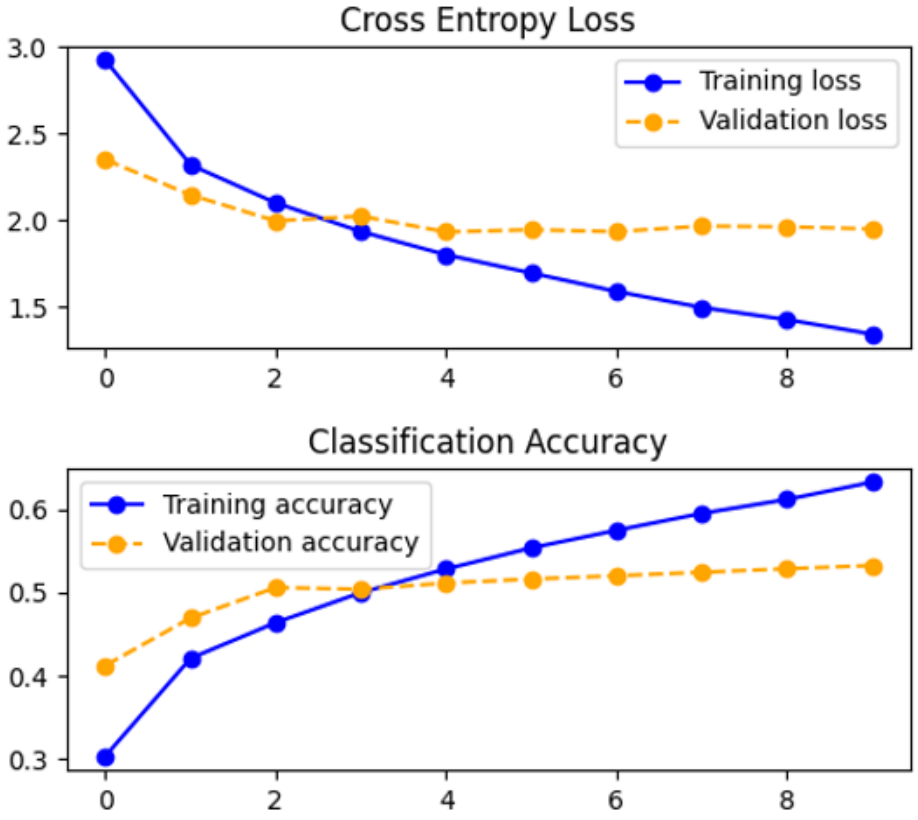
After 4 epochs, we observe overfitting: the accuracy on the training set is larger than the one on the validation set. And the accuracy on the validation set does not increase significantly anymore, which means that the network stats to memorize the training data.

Best epoch	Validation accuracy	Test accuracy	Validation loss	Test loss
10	0.60	0.57	1.98	1.65

4.5.4. Experiment 3 - Unfreeze 3

In the last experiment covering the fine-tuning we can do some math and see that we moved from experiment 1 with a total of 2,595,429 trainable params to the model of this experiment that has a total of 5,021,797 trainable params.

```
 Layer (type)                 Output Shape              Param #
=================================================================
 sequential (Sequential)      (None, 224, 224, 3)       0

 sequential_1 (Sequential)    (None, 224, 224, 3)       0

 inception_v3 (Functional)    (None, 5, 5, 2048)        21802784

 global_average_pooling2d (G  (None, 2048)              0
 lobalAveragePooling2D)

 dense (Dense)                (None, 1024)              2098176

 dropout (Dropout)            (None, 1024)              0

 dense_1 (Dense)              (None, 101)               103525

=================================================================
Total params: 24,004,485
Trainable params: 5,021,797
Non-trainable params: 18,982,688
```



After 5 epochs, we observe overfitting: the accuracy on the training set is larger than the one on the validation set. And the accuracy on the validation set does not increase significantly anymore, which means that the network starts to memorize the training data.

Best epoch	Validation accuracy	Test accuracy	Validation loss	Test loss
10	0.53	0.58	1.94	1.64