

Practice 1: Convolutional Neural Network - Deep Learning course

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```
In [ ]: import plotly
        plotly.offline.init_notebook_mode()
```

```
In [ ]: import tensorflow as tf
        from keras.optimizers import Adam
        from keras.metrics import SparseCategoricalAccuracy
        from logging import ERROR
        tf.get_logger().setLevel(ERROR)
        import warnings, os
        import plotly.express as px
        warnings.filterwarnings("ignore")
        from utils import *
        from models import *
        from typing import List, Tuple
        model_accuracies: List[Tuple[str, int]] = []

        # global variables
        IMG_SIZE = 100
        BATCH_SIZE = 258
        base_dir = 'animals/'
        model_dir = 'results/'
        if not os.path.exists(model_dir):
            os.mkdir(model_dir)
```

```
2024-03-07 11:56:17.619575: I tensorflow/core/util/port.cc:113] oneDNN cus
tom operations are on. You may see slightly different numerical results du
e to floating-point round-off errors from different computation orders. To
turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-03-07 11:56:17.640942: E external/local_xla/xla/stream_executor/cuda/
cuda_dnn.cc:9261] Unable to register cuDNN factory: Attempting to register
factory for plugin cuDNN when one has already been registered
2024-03-07 11:56:17.640961: E external/local_xla/xla/stream_executor/cuda/
cuda_fft.cc:607] Unable to register cuFFT factory: Attempting to register
factory for plugin cuFFT when one has already been registered
2024-03-07 11:56:17.641561: E external/local_xla/xla/stream_executor/cuda/
cuda_blas.cc:1515] Unable to register cuBLAS factory: Attempting to regist
er factory for plugin cuBLAS when one has already been registered
2024-03-07 11:56:17.645228: I tensorflow/core/platform/cpu_feature_guard.c
c:182] This TensorFlow binary is optimized to use available CPU instructio
ns in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operatio
ns, rebuild TensorFlow with the appropriate compiler flags.
2024-03-07 11:56:18.014887: W tensorflow/compiler/tf2tensorrt/utils/py_uti
ls.cc:38] TF-TRT Warning: Could not find TensorRT
```

Note: Some figures of this notebook have been rendered using [Plotly](#). Depending on the server the notebook is executed in, the Plotly renderer should be modified to

properly display the figures:

```
In [ ]: import plotly.io as pio
pio.renderers.default = 'vscode' # In our case, we used visual studio cod
```

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Exercise 1. Dataset preprocessing

We decided to use for the image resolution 100×100 for retrieving similar results than considering higher resolutions with the simpler architectures. The batch size is adapted to fit the GPU capabilities of the local machine. We used the original validation set for evaluation a split a 15% of the data for validation. All the input images were normalized to fit the range $[0, 1]$ with the [Rescaling layer](#).

```
In [ ]: train_dataset, val_dataset, test_dataset = load_data(base_dir, IMG_SIZE,
Found 13474 files belonging to 5 classes.
Using 11453 files for training.
Using 2021 files for validation.
```

```
2024-03-07 11:56:18.884797: I external/local_xla/xla/stream_executor/cuda/cuda_executor.cc:901] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero. See more at https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-pci#L344-L355
2024-03-07 11:56:18.906855: I external/local_xla/xla/stream_executor/cuda/cuda_executor.cc:901] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero. See more at https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-pci#L344-L355
2024-03-07 11:56:18.906967: I external/local_xla/xla/stream_executor/cuda/cuda_executor.cc:901] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero. See more at https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-pci#L344-L355
2024-03-07 11:56:18.907937: I external/local_xla/xla/stream_executor/cuda/cuda_executor.cc:901] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero. See more at https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-pci#L344-L355
2024-03-07 11:56:18.908009: I external/local_xla/xla/stream_executor/cuda/cuda_executor.cc:901] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero. See more at https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-pci#L344-L355
2024-03-07 11:56:18.908051: I external/local_xla/xla/stream_executor/cuda/cuda_executor.cc:901] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero. See more at https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-pci#L344-L355
2024-03-07 11:56:18.957630: I external/local_xla/xla/stream_executor/cuda/cuda_executor.cc:901] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero. See more at https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-pci#L344-L355
2024-03-07 11:56:18.957716: I external/local_xla/xla/stream_executor/cuda/cuda_executor.cc:901] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero. See more at https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-pci#L344-L355
2024-03-07 11:56:18.957767: I external/local_xla/xla/stream_executor/cuda/cuda_executor.cc:901] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero. See more at https://github.com/torvalds/linux/blob/v6.0/Documentation/ABI/testing/sysfs-bus-pci#L344-L355
2024-03-07 11:56:18.957810: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1929] Created device /job:localhost/replica:0/task:0/device:GPU:0 with 22146 MB memory: -> device: 0, name: NVIDIA GeForce RTX 3090 Ti, pci bus id: 0000:01:00.0, compute capability: 8.6
2024-03-07 11:56:19.194639: I external/local_tsl/tsl/platform/default/subprocess.cc:304] Start cannot spawn child process: No such file or directory
Found 1497 files belonging to 5 classes.
```

Exercise 2. Custom Convolutional Models

For this exercise, we prepared four different convolutional architectures with increasing complexity and regularization methods to tackle the animal classification problem: (1) a simple linear approach with 2 convolutional layers interleaved with max-

pooling, (2) a more complex convolutional-linear model with 3 blocks of paired convolutions and max-poolings, (3) a convolutional architecture based on residual connections (He et al., 2015), (4) the integration of the Inception block (Szegedy et al., 2014). We used the validation split to tune each hyperparameter configuration (although not all experiments are included in this notebook to facilitate the readability) and applied some regularization methods learnt in previous practical lessons to avoid overfitting.

2.1. Simple Model

```
In [ ]: simple_model = SimpleModel(num_classes=5)
optimizer = Adam(learning_rate=1e-3)
simple_model.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
simple_model_history = train_model(simple_model, train_dataset, val_dataset)
print(
    f"Final loss: training -> {simple_model_history['loss'][-1]:.2f}, val
)
print(
    f"Final accuracy: training -> {simple_model_history['acc'][-1]:.2f},
    validation -> {simple_model_history['val_acc'][-1]:.2f}"
)
```

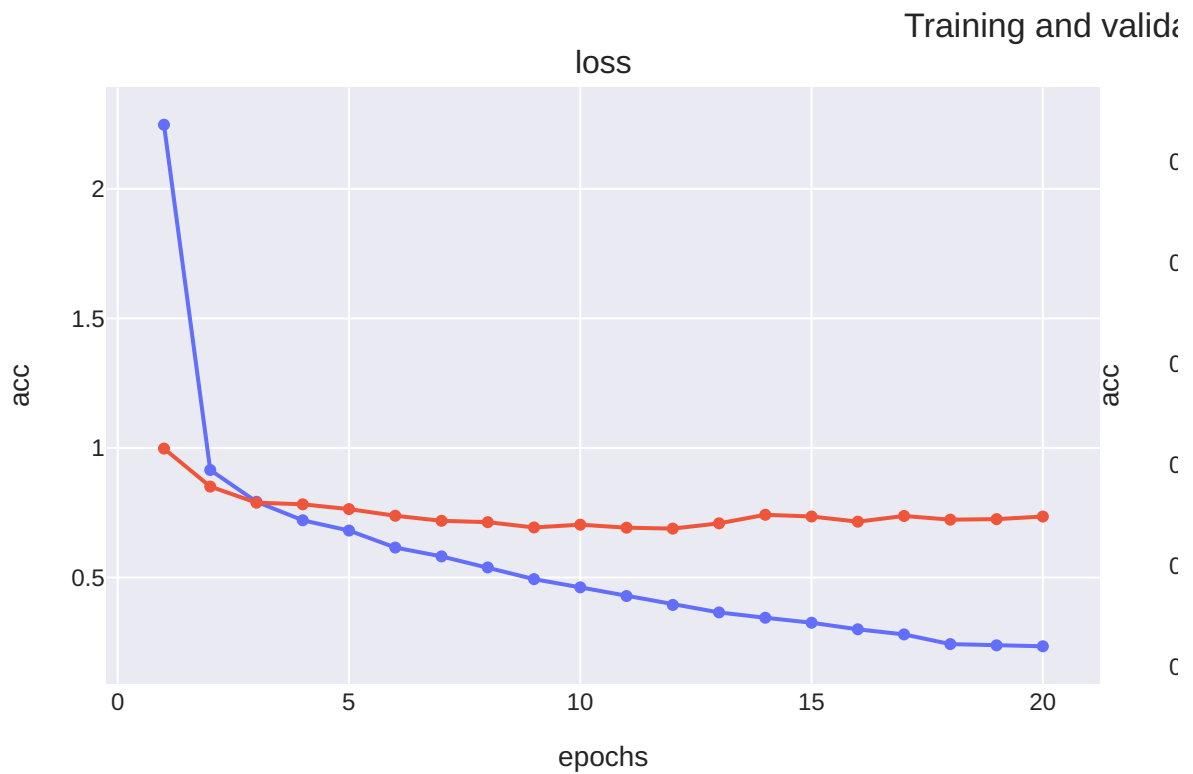
Epoch 1/20

```
2024-03-07 11:56:20.945884: I external/local_xla/xla/stream_executor/cuda/
cuda_dnn.cc:454] Loaded cuDNN version 8904
2024-03-07 11:56:21.015085: I external/local_tsl/tsl/platform/default/subp
rocess.cc:304] Start cannot spawn child process: No such file or directory
2024-03-07 11:56:21.395381: I external/local_xla/xla/service/service.cc:16
8] XLA service 0x7fcc386be2a0 initialized for platform CUDA (this does not
guarantee that XLA will be used). Devices:
2024-03-07 11:56:21.395397: I external/local_xla/xla/service/service.cc:17
6] StreamExecutor device (0): NVIDIA GeForce RTX 3090 Ti, Compute Capabi
lity 8.6
2024-03-07 11:56:21.398714: I tensorflow/compiler/mlir/tensorflow/utils/du
mp_mlir_util.cc:269] disabling MLIR crash reproducer, set env var `MLIR_CR
ASH_REPRODUCER_DIRECTORY` to enable.
WARNING: All log messages before absl::InitializeLog() is called are writt
en to STDERR
I0000 00:00:1709808981.458911 222545 device_compiler.h:186] Compiled clus
ter using XLA! This line is logged at most once for the lifetime of the p
rocess.
```

```
45/45 [=====] - 8s 112ms/step - loss: 2.2477 - acc
c: 0.4202 - val_loss: 0.9977 - val_acc: 0.6378 - lr: 0.0010
Epoch 2/20
45/45 [=====] - 5s 84ms/step - loss: 0.9149 - acc
: 0.6693 - val_loss: 0.8510 - val_acc: 0.6784 - lr: 0.0010
Epoch 3/20
45/45 [=====] - 5s 87ms/step - loss: 0.7922 - acc
: 0.7127 - val_loss: 0.7887 - val_acc: 0.7006 - lr: 0.0010
Epoch 4/20
45/45 [=====] - 5s 85ms/step - loss: 0.7207 - acc
: 0.7392 - val_loss: 0.7825 - val_acc: 0.6972 - lr: 0.0010
Epoch 5/20
45/45 [=====] - 5s 86ms/step - loss: 0.6811 - acc
: 0.7508 - val_loss: 0.7639 - val_acc: 0.7180 - lr: 0.0010
Epoch 6/20
45/45 [=====] - 5s 86ms/step - loss: 0.6156 - acc
: 0.7795 - val_loss: 0.7383 - val_acc: 0.7229 - lr: 0.0010
Epoch 7/20
45/45 [=====] - 5s 86ms/step - loss: 0.5814 - acc
: 0.7924 - val_loss: 0.7188 - val_acc: 0.7303 - lr: 0.0010
Epoch 8/20
45/45 [=====] - 5s 85ms/step - loss: 0.5388 - acc
: 0.8108 - val_loss: 0.7135 - val_acc: 0.7338 - lr: 0.0010
Epoch 9/20
45/45 [=====] - 5s 87ms/step - loss: 0.4936 - acc
: 0.8272 - val_loss: 0.6931 - val_acc: 0.7378 - lr: 0.0010
Epoch 10/20
45/45 [=====] - 5s 84ms/step - loss: 0.4619 - acc
: 0.8441 - val_loss: 0.7039 - val_acc: 0.7353 - lr: 0.0010
Epoch 11/20
45/45 [=====] - 5s 87ms/step - loss: 0.4283 - acc
: 0.8558 - val_loss: 0.6922 - val_acc: 0.7467 - lr: 0.0010
Epoch 12/20
45/45 [=====] - 5s 87ms/step - loss: 0.3941 - acc
: 0.8707 - val_loss: 0.6886 - val_acc: 0.7481 - lr: 0.0010
Epoch 13/20
45/45 [=====] - 5s 86ms/step - loss: 0.3651 - acc
: 0.8874 - val_loss: 0.7090 - val_acc: 0.7392 - lr: 0.0010
Epoch 14/20
45/45 [=====] - 5s 84ms/step - loss: 0.3446 - acc
: 0.8900 - val_loss: 0.7420 - val_acc: 0.7234 - lr: 0.0010
Epoch 15/20
45/45 [=====] - 5s 83ms/step - loss: 0.3253 - acc
: 0.9008 - val_loss: 0.7353 - val_acc: 0.7373 - lr: 0.0010
Epoch 16/20
45/45 [=====] - 5s 84ms/step - loss: 0.3000 - acc
: 0.9060 - val_loss: 0.7155 - val_acc: 0.7496 - lr: 0.0010
Epoch 17/20
45/45 [=====] - 5s 85ms/step - loss: 0.2802 - acc
: 0.9150 - val_loss: 0.7373 - val_acc: 0.7402 - lr: 0.0010
Epoch 18/20
45/45 [=====] - 5s 83ms/step - loss: 0.2429 - acc
: 0.9347 - val_loss: 0.7233 - val_acc: 0.7427 - lr: 2.0000e-04
Epoch 19/20
45/45 [=====] - 5s 83ms/step - loss: 0.2381 - acc
: 0.9367 - val_loss: 0.7252 - val_acc: 0.7407 - lr: 2.0000e-04
Epoch 20/20
45/45 [=====] - 5s 84ms/step - loss: 0.2344 - acc
: 0.9364 - val_loss: 0.7352 - val_acc: 0.7397 - lr: 2.0000e-04
Final loss: training -> 0.23, validation -> 0.74
```

Final accuracy: training -> 0.94, validation -> 0.74

```
In [ ]: plot_history(simple_model_history, ['loss', 'acc'], name='Simple Model')
```



```
In [ ]: test_loss, test_accuracy = simple_model.evaluate(test_dataset, batch_size=32)
print(f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_accuracy}")
print(simple_model.summary())
model accuracies.append(("SimpleModel", test_accuracy))
```

6/6 [=====] - 1s 68ms/step - loss: 0.6367 - acc: 0.7695

Model evaluated: Test Loss-> 0.6366969347000122, Test Accuracy -> 76.95%
Model: "SimpleModel"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	multiple	0
conv2d (Conv2D)	multiple	896
max_pooling2d (MaxPooling2D)	multiple	0
conv2d_1 (Conv2D)	multiple	18496
max_pooling2d_1 (MaxPooling2D)	multiple	0 (unused)
flatten (Flatten)	multiple	0
dense (Dense)	multiple	706885

=====
Total params: 726277 (2.77 MB)
Trainable params: 726277 (2.77 MB)
Non-trainable params: 0 (0.00 Byte)

None

As can be seen, the accuracy of both the test and the validation is not high, as it is a "toy" model and very simple, so it will not capture well certain characteristics of the images, resulting in this low accuracy.

2.2 Mid Complex Model

```
In [ ]: mid_model = MidModel(num_classes=5)
optimizer = Adam(learning_rate=1e-3)
mid_model.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
mid_model_history = train_model(
    mid_model,
    train_dataset,
    val_dataset,
    epochs=30,
    batch_size=BATCH_SIZE,
    verbose=1,
    path=model_dir,
    lr_patience=5,
    val_patience=10
).history
print(
    f"Final loss: training -> {mid_model_history['loss'][-1]:.2f}, validation -> {mid_model_history['val_loss'][-1]:.2f}"
)
print(
    f"Final accuracy: training -> {mid_model_history['acc'][-1]:.2f}, validation -> {mid_model_history['val_acc'][-1]:.2f}"
)
```

Epoch 1/30

```
2024-03-07 11:57:58.546442: E tensorflow/core/grappler/optimizers/meta_optimizer.cc:961] layout failed: INVALID_ARGUMENT: Size of values 0 does not match size of permutation 4 @ fanin shape inMidModel/dropout/dropout/SelectV2-2-TransposeNHWCToNCHW-LayoutOptimizer
```



```

45/45 [=====] - 12s 135ms/step - loss: 1.3207 - a
cc: 0.4573 - val_loss: 0.9567 - val_acc: 0.6393 - lr: 0.0010
Epoch 2/30
45/45 [=====] - 5s 86ms/step - loss: 0.8289 - acc
: 0.6846 - val_loss: 0.7033 - val_acc: 0.7338 - lr: 0.0010
Epoch 3/30
45/45 [=====] - 5s 85ms/step - loss: 0.6622 - acc
: 0.7439 - val_loss: 0.6313 - val_acc: 0.7506 - lr: 0.0010
Epoch 4/30
45/45 [=====] - 5s 86ms/step - loss: 0.5746 - acc
: 0.7725 - val_loss: 0.6024 - val_acc: 0.7719 - lr: 0.0010
Epoch 5/30
45/45 [=====] - 5s 85ms/step - loss: 0.5285 - acc
: 0.7910 - val_loss: 0.5485 - val_acc: 0.7862 - lr: 0.0010
Epoch 6/30
45/45 [=====] - 5s 86ms/step - loss: 0.4775 - acc
: 0.8122 - val_loss: 0.5855 - val_acc: 0.7803 - lr: 0.0010
Epoch 7/30
45/45 [=====] - 5s 86ms/step - loss: 0.4587 - acc
: 0.8204 - val_loss: 0.5352 - val_acc: 0.8011 - lr: 0.0010
Epoch 8/30
45/45 [=====] - 5s 86ms/step - loss: 0.4139 - acc
: 0.8376 - val_loss: 0.5116 - val_acc: 0.8046 - lr: 0.0010
Epoch 9/30
45/45 [=====] - 5s 88ms/step - loss: 0.3732 - acc
: 0.8546 - val_loss: 0.4778 - val_acc: 0.8204 - lr: 0.0010
Epoch 10/30
45/45 [=====] - 5s 85ms/step - loss: 0.3223 - acc
: 0.8759 - val_loss: 0.4984 - val_acc: 0.8144 - lr: 0.0010
Epoch 11/30
45/45 [=====] - 5s 84ms/step - loss: 0.3063 - acc
: 0.8798 - val_loss: 0.5119 - val_acc: 0.8140 - lr: 0.0010
Epoch 12/30
45/45 [=====] - 5s 85ms/step - loss: 0.2621 - acc
: 0.8983 - val_loss: 0.5139 - val_acc: 0.8238 - lr: 0.0010
Epoch 13/30
45/45 [=====] - 5s 86ms/step - loss: 0.2232 - acc
: 0.9171 - val_loss: 0.5413 - val_acc: 0.8328 - lr: 0.0010
Epoch 14/30
45/45 [=====] - 5s 86ms/step - loss: 0.1888 - acc
: 0.9258 - val_loss: 0.6093 - val_acc: 0.8204 - lr: 0.0010
Epoch 15/30
45/45 [=====] - 5s 85ms/step - loss: 0.1175 - acc
: 0.9575 - val_loss: 0.5355 - val_acc: 0.8496 - lr: 2.0000e-04
Epoch 16/30
45/45 [=====] - 5s 85ms/step - loss: 0.0861 - acc
: 0.9695 - val_loss: 0.5710 - val_acc: 0.8481 - lr: 2.0000e-04
Epoch 17/30
45/45 [=====] - 5s 85ms/step - loss: 0.0767 - acc
: 0.9740 - val_loss: 0.6264 - val_acc: 0.8456 - lr: 2.0000e-04
Epoch 18/30
45/45 [=====] - 5s 87ms/step - loss: 0.0663 - acc
: 0.9779 - val_loss: 0.6477 - val_acc: 0.8481 - lr: 2.0000e-04
Epoch 19/30
45/45 [=====] - 5s 86ms/step - loss: 0.0583 - acc
: 0.9829 - val_loss: 0.6639 - val_acc: 0.8496 - lr: 2.0000e-04
Final loss: training -> 0.06, validation -> 0.66
Final accuracy: training -> 0.98, validation -> 0.85

```

```
In [ ]: plot_history(mid_model_history, ['loss', 'acc'], name='Mid Complex Model')
```



```
In [ ]: test_loss, test_accuracy = mid_model.evaluate(test_dataset, batch_size=BA
print(
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_ac
)
model accuracies.append(('MidModel', test_accuracy))
mid_model.summary()
```

6/6 [=====] - 1s 99ms/step - loss: 0.5026 - acc: 0.8764

Model evaluated: Test Loss-> 0.5025559067726135, Test Accuracy -> 87.64%
Model: "MidModel"

Layer (type)	Output Shape	Param #
rescaling_1 (Rescaling)	multiple	0
conv2d_2 (Conv2D)	multiple	896
conv2d_3 (Conv2D)	multiple	9248
max_pooling2d_2 (MaxPooling2D)	multiple	0
dropout (Dropout)	multiple	0
conv2d_4 (Conv2D)	multiple	18496
conv2d_5 (Conv2D)	multiple	36928
conv2d_6 (Conv2D)	multiple	73856
conv2d_7 (Conv2D)	multiple	147584
flatten_1 (Flatten)	multiple	0
dense_1 (Dense)	multiple	1327232
dense_2 (Dense)	multiple	645
Total params: 1614885 (6.16 MB)		
Trainable params: 1614885 (6.16 MB)		
Non-trainable params: 0 (0.00 Byte)		

In the medium complexity model, it can be seen that it starts to overfit, although not to a great extent, from the middle of its epochs. This model has dropout, which means that this overfitting is reduced both in time and magnitude, benefiting the model, although with more complex models and other more sophisticated techniques its performance can be improved.

2.3 Model with residual connections

```
In [ ]: resnet = CustomResNet(num_classes=5)
optimizer = Adam(learning_rate=1e-3)
resnet.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
resnet_history = train_model(
    resnet,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=5,
```

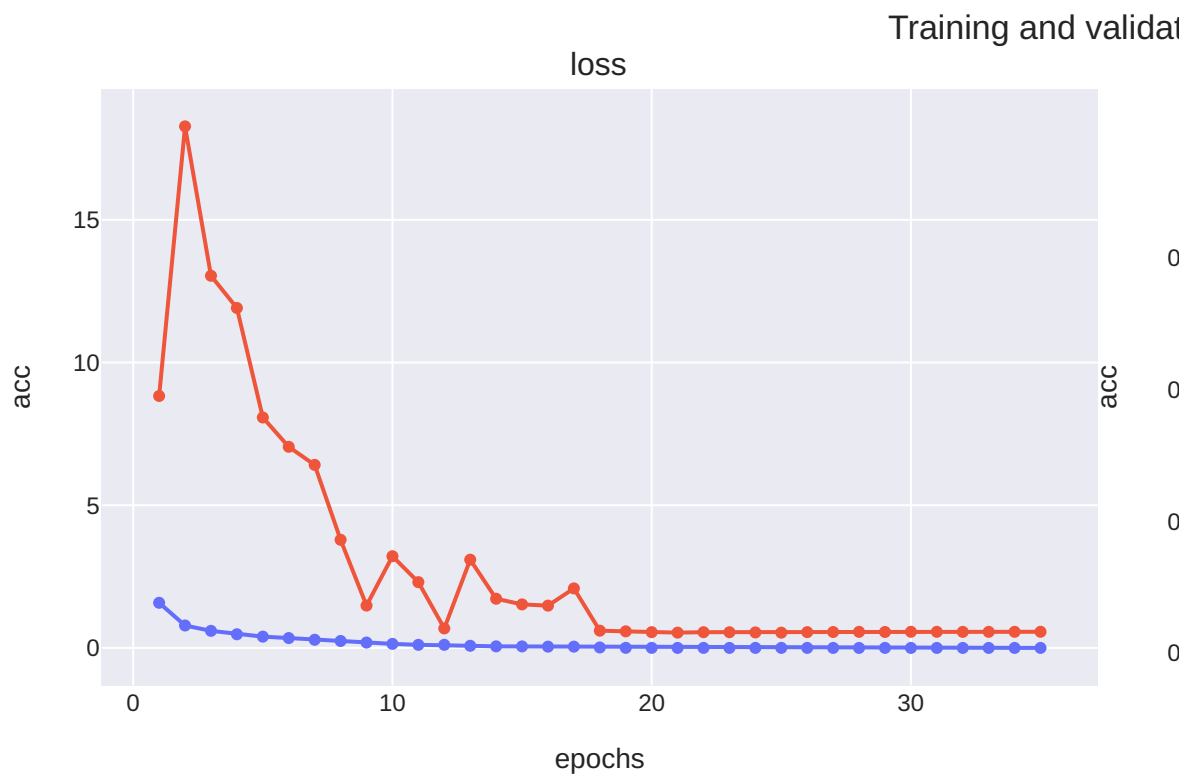
```
        val_patience=10,  
    ).history  
    print(  
        f"Final loss: training -> {resnet_history['loss'][-1]:.2f}, validation  
    )  
    print(  
        f"Final accuracy: training -> {resnet_history['acc'][-1]:.2f}, validation  
    )
```

Epoch 1/50

```
45/45 [=====] - 14s 162ms/step - loss: 1.5817 - a
cc: 0.4257 - val_loss: 8.8287 - val_acc: 0.2088 - lr: 0.0010
Epoch 2/50
45/45 [=====] - 5s 88ms/step - loss: 0.7860 - acc
: 0.6844 - val_loss: 18.2752 - val_acc: 0.2088 - lr: 0.0010
Epoch 3/50
45/45 [=====] - 5s 87ms/step - loss: 0.5990 - acc
: 0.7636 - val_loss: 13.0407 - val_acc: 0.2088 - lr: 0.0010
Epoch 4/50
45/45 [=====] - 5s 87ms/step - loss: 0.4790 - acc
: 0.8108 - val_loss: 11.9123 - val_acc: 0.2078 - lr: 0.0010
Epoch 5/50
45/45 [=====] - 5s 95ms/step - loss: 0.3959 - acc
: 0.8446 - val_loss: 8.0744 - val_acc: 0.2345 - lr: 0.0010
Epoch 6/50
45/45 [=====] - 5s 93ms/step - loss: 0.3466 - acc
: 0.8634 - val_loss: 7.0475 - val_acc: 0.2608 - lr: 0.0010
Epoch 7/50
45/45 [=====] - 5s 94ms/step - loss: 0.2861 - acc
: 0.8895 - val_loss: 6.4130 - val_acc: 0.2217 - lr: 0.0010
Epoch 8/50
45/45 [=====] - 5s 94ms/step - loss: 0.2437 - acc
: 0.9037 - val_loss: 3.7884 - val_acc: 0.3360 - lr: 0.0010
Epoch 9/50
45/45 [=====] - 5s 95ms/step - loss: 0.1887 - acc
: 0.9285 - val_loss: 1.4852 - val_acc: 0.5804 - lr: 0.0010
Epoch 10/50
45/45 [=====] - 5s 90ms/step - loss: 0.1418 - acc
: 0.9476 - val_loss: 3.2144 - val_acc: 0.4043 - lr: 0.0010
Epoch 11/50
45/45 [=====] - 5s 86ms/step - loss: 0.1086 - acc
: 0.9584 - val_loss: 2.3050 - val_acc: 0.4790 - lr: 0.0010
Epoch 12/50
45/45 [=====] - 5s 96ms/step - loss: 0.1096 - acc
: 0.9602 - val_loss: 0.6837 - val_acc: 0.7956 - lr: 0.0010
Epoch 13/50
45/45 [=====] - 5s 88ms/step - loss: 0.0752 - acc
: 0.9728 - val_loss: 3.0924 - val_acc: 0.4923 - lr: 0.0010
Epoch 14/50
45/45 [=====] - 5s 89ms/step - loss: 0.0557 - acc
: 0.9811 - val_loss: 1.7241 - val_acc: 0.6724 - lr: 0.0010
Epoch 15/50
45/45 [=====] - 5s 89ms/step - loss: 0.0534 - acc
: 0.9814 - val_loss: 1.5253 - val_acc: 0.6685 - lr: 0.0010
Epoch 16/50
45/45 [=====] - 5s 87ms/step - loss: 0.0455 - acc
: 0.9831 - val_loss: 1.4823 - val_acc: 0.7209 - lr: 0.0010
Epoch 17/50
45/45 [=====] - 5s 86ms/step - loss: 0.0452 - acc
: 0.9844 - val_loss: 2.0859 - val_acc: 0.6091 - lr: 0.0010
Epoch 18/50
45/45 [=====] - 5s 94ms/step - loss: 0.0164 - acc
: 0.9949 - val_loss: 0.6046 - val_acc: 0.8615 - lr: 2.0000e-04
Epoch 19/50
45/45 [=====] - 5s 91ms/step - loss: 0.0031 - acc
: 0.9996 - val_loss: 0.5810 - val_acc: 0.8659 - lr: 2.0000e-04
Epoch 20/50
45/45 [=====] - 5s 93ms/step - loss: 0.0018 - acc
: 0.9998 - val_loss: 0.5525 - val_acc: 0.8728 - lr: 2.0000e-04
Epoch 21/50
```

```
45/45 [=====] - 5s 94ms/step - loss: 0.0012 - acc
: 0.9998 - val_loss: 0.5361 - val_acc: 0.8778 - lr: 2.0000e-04
Epoch 22/50
45/45 [=====] - 5s 86ms/step - loss: 0.0012 - acc
: 0.9998 - val_loss: 0.5511 - val_acc: 0.8758 - lr: 2.0000e-04
Epoch 23/50
45/45 [=====] - 5s 88ms/step - loss: 0.0011 - acc
: 0.9997 - val_loss: 0.5506 - val_acc: 0.8783 - lr: 2.0000e-04
Epoch 24/50
45/45 [=====] - 5s 88ms/step - loss: 9.8771e-04 -
acc: 0.9997 - val_loss: 0.5432 - val_acc: 0.8793 - lr: 2.0000e-04
Epoch 25/50
45/45 [=====] - 5s 94ms/step - loss: 8.4224e-04 -
acc: 0.9998 - val_loss: 0.5350 - val_acc: 0.8808 - lr: 2.0000e-04
Epoch 26/50
45/45 [=====] - 5s 88ms/step - loss: 9.8657e-04 -
acc: 0.9997 - val_loss: 0.5533 - val_acc: 0.8798 - lr: 2.0000e-04
Epoch 27/50
45/45 [=====] - 5s 85ms/step - loss: 7.0752e-04 -
acc: 0.9998 - val_loss: 0.5574 - val_acc: 0.8812 - lr: 2.0000e-04
Epoch 28/50
45/45 [=====] - 5s 87ms/step - loss: 7.8093e-04 -
acc: 0.9998 - val_loss: 0.5640 - val_acc: 0.8788 - lr: 2.0000e-04
Epoch 29/50
45/45 [=====] - 5s 89ms/step - loss: 0.0011 - acc
: 0.9997 - val_loss: 0.5594 - val_acc: 0.8808 - lr: 2.0000e-04
Epoch 30/50
45/45 [=====] - 5s 87ms/step - loss: 5.3720e-04 -
acc: 0.9997 - val_loss: 0.5662 - val_acc: 0.8788 - lr: 2.0000e-04
Epoch 31/50
45/45 [=====] - 5s 88ms/step - loss: 7.3354e-04 -
acc: 0.9998 - val_loss: 0.5647 - val_acc: 0.8803 - lr: 4.0000e-05
Epoch 32/50
45/45 [=====] - 5s 85ms/step - loss: 4.7854e-04 -
acc: 0.9998 - val_loss: 0.5626 - val_acc: 0.8803 - lr: 4.0000e-05
Epoch 33/50
45/45 [=====] - 5s 89ms/step - loss: 5.4136e-04 -
acc: 0.9999 - val_loss: 0.5634 - val_acc: 0.8808 - lr: 4.0000e-05
Epoch 34/50
45/45 [=====] - 5s 88ms/step - loss: 6.9059e-04 -
acc: 0.9997 - val_loss: 0.5646 - val_acc: 0.8808 - lr: 4.0000e-05
Epoch 35/50
45/45 [=====] - 5s 86ms/step - loss: 5.3650e-04 -
acc: 0.9998 - val_loss: 0.5660 - val_acc: 0.8808 - lr: 4.0000e-05
Final loss: training -> 0.00, validation -> 0.57
Final accuracy: training -> 1.00, validation -> 0.88
```

```
In [ ]: plot_history(resnet_history, ['loss', 'acc'], name='Custom ResNet')
```



```
In [ ]: test_loss, test_accuracy = resnet.evaluate(test_dataset, batch_size=BATCH_SIZE)
print(f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_accuracy}")
model accuracies.append(("ResNet", test_accuracy))
resnet.summary()
```

6/6 [=====] - 1s 145ms/step - loss: 0.5762 - acc: 0.8891

Model evaluated: Test Loss-> 0.5761938095092773, Test Accuracy -> 88.91%

Model: "ResNet"

Layer (type)	Output Shape	Param #
rescaling_2 (Rescaling)	multiple	0
zero_padding2d (ZeroPadding2D)	multiple	0
conv2d_8 (Conv2D)	multiple	9472
batch_normalization (Batch Normalization)	multiple	256
max_pooling2d_3 (MaxPooling2D)	multiple	0
identity_block (IdentityBlock)	multiple	74368
identity_block_1 (IdentityBlock)	multiple	74368
convolution_block (ConvolutionBlock)	multiple	230784
identity_block_2 (IdentityBlock)	multiple	296192
convolution_block_1 (ConvolutionBlock)	multiple	920320
identity_block_3 (IdentityBlock)	multiple	1182208
convolution_block_2 (ConvolutionBlock)	multiple	3675648
identity_block_4 (IdentityBlock)	multiple	4723712
dense_3 (Dense)	multiple	513000
dense_4 (Dense)	multiple	5005

=====
Total params: 11705333 (44.65 MB)

Trainable params: 11697525 (44.62 MB)

Non-trainable params: 7808 (30.50 KB)

Among the more complex models we have decided on two customised implementations, a model with residual connections and a model based on the "inception" technique, with its corresponding blocks. This allows these models to be deeper without the problem of gradient fading and can better capture the characteristics of the data and result in better performance. We first tested a residual

model with 4 blocks and filter size 64, which already gives a better accuracy than the previous ones. This model would be an "approximation" to a resnet14, although differing in certain aspects. It can be seen that the model does not overfit despite having a large number of epochs, which is a good indication.

2.4. Inception block

```
In [ ]: inception = InceptionModel(num_classes=5, num_blocks=3, n_filters=[(32, 3
optimizer = Adam(learning_rate=1e-4)
inception.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
inception_history = train_model(
    inception,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=5,
    val_patience=10
).history
print(
    f"Final loss: training -> {inception_history['loss'][-1]:.2f}, validation -> {inception_history['val_loss'][-1]:.2f}"
)
print(
    f"Final accuracy: training -> {inception_history['acc'][-1]:.2f}, validation -> {inception_history['val_acc'][-1]:.2f}"
)
```

Epoch 1/50

```
45/45 [=====] - 106s 1s/step - loss: 1.0687 - acc
: 0.6346 - val_loss: 2.0058 - val_acc: 0.2519 - lr: 1.0000e-04
Epoch 2/50
45/45 [=====] - 17s 361ms/step - loss: 0.5435 - a
cc: 0.7950 - val_loss: 2.0530 - val_acc: 0.2736 - lr: 1.0000e-04
Epoch 3/50
45/45 [=====] - 17s 362ms/step - loss: 0.3665 - a
cc: 0.8637 - val_loss: 2.0429 - val_acc: 0.2810 - lr: 1.0000e-04
Epoch 4/50
45/45 [=====] - 17s 361ms/step - loss: 0.2545 - a
cc: 0.9069 - val_loss: 2.2570 - val_acc: 0.2677 - lr: 1.0000e-04
Epoch 5/50
45/45 [=====] - 17s 361ms/step - loss: 0.1513 - a
cc: 0.9494 - val_loss: 2.1995 - val_acc: 0.3597 - lr: 1.0000e-04
Epoch 6/50
45/45 [=====] - 17s 368ms/step - loss: 0.1031 - a
cc: 0.9676 - val_loss: 1.5280 - val_acc: 0.5191 - lr: 1.0000e-04
Epoch 7/50
45/45 [=====] - 17s 361ms/step - loss: 0.0608 - a
cc: 0.9837 - val_loss: 1.5663 - val_acc: 0.4696 - lr: 1.0000e-04
Epoch 8/50
45/45 [=====] - 18s 368ms/step - loss: 0.0326 - a
cc: 0.9944 - val_loss: 1.2253 - val_acc: 0.5764 - lr: 1.0000e-04
Epoch 9/50
45/45 [=====] - 17s 368ms/step - loss: 0.0266 - a
cc: 0.9955 - val_loss: 1.0802 - val_acc: 0.6363 - lr: 1.0000e-04
Epoch 10/50
45/45 [=====] - 17s 368ms/step - loss: 0.0137 - a
cc: 0.9992 - val_loss: 0.8429 - val_acc: 0.7219 - lr: 1.0000e-04
Epoch 11/50
45/45 [=====] - 17s 368ms/step - loss: 0.0094 - a
cc: 0.9997 - val_loss: 0.7322 - val_acc: 0.7694 - lr: 1.0000e-04
Epoch 12/50
45/45 [=====] - 17s 368ms/step - loss: 0.0073 - a
cc: 0.9997 - val_loss: 0.6378 - val_acc: 0.8070 - lr: 1.0000e-04
Epoch 13/50
45/45 [=====] - 18s 368ms/step - loss: 0.0048 - a
cc: 0.9997 - val_loss: 0.6061 - val_acc: 0.8135 - lr: 1.0000e-04
Epoch 14/50
45/45 [=====] - 17s 368ms/step - loss: 0.0063 - a
cc: 0.9997 - val_loss: 0.5978 - val_acc: 0.8258 - lr: 1.0000e-04
Epoch 15/50
45/45 [=====] - 17s 361ms/step - loss: 0.0054 - a
cc: 0.9997 - val_loss: 0.6083 - val_acc: 0.8318 - lr: 1.0000e-04
Epoch 16/50
45/45 [=====] - 17s 360ms/step - loss: 0.0052 - a
cc: 0.9997 - val_loss: 0.6162 - val_acc: 0.8357 - lr: 1.0000e-04
Epoch 17/50
45/45 [=====] - 17s 361ms/step - loss: 0.0062 - a
cc: 0.9997 - val_loss: 0.6337 - val_acc: 0.8382 - lr: 1.0000e-04
Epoch 18/50
45/45 [=====] - 17s 361ms/step - loss: 0.0046 - a
cc: 0.9997 - val_loss: 0.6328 - val_acc: 0.8357 - lr: 1.0000e-04
Epoch 19/50
45/45 [=====] - 17s 361ms/step - loss: 0.0050 - a
cc: 0.9997 - val_loss: 0.6576 - val_acc: 0.8323 - lr: 1.0000e-04
Epoch 20/50
45/45 [=====] - 17s 361ms/step - loss: 0.0028 - a
cc: 0.9998 - val_loss: 0.6543 - val_acc: 0.8382 - lr: 2.0000e-05
Epoch 21/50
```

```

45/45 [=====] - 17s 361ms/step - loss: 0.0021 - a
cc: 0.9997 - val_loss: 0.6582 - val_acc: 0.8382 - lr: 2.0000e-05
Epoch 22/50
45/45 [=====] - 17s 361ms/step - loss: 0.0018 - a
cc: 0.9997 - val_loss: 0.6628 - val_acc: 0.8382 - lr: 2.0000e-05
Epoch 23/50
45/45 [=====] - 17s 361ms/step - loss: 0.0019 - a
cc: 0.9997 - val_loss: 0.6665 - val_acc: 0.8422 - lr: 2.0000e-05
Epoch 24/50
45/45 [=====] - 17s 361ms/step - loss: 0.0020 - a
cc: 0.9997 - val_loss: 0.6690 - val_acc: 0.8402 - lr: 2.0000e-05
Final loss: training -> 0.00, validation -> 0.67
Final accuracy: training -> 1.00, validation -> 0.84

```

```
In [ ]: plot_history(inception_history, ['loss', 'acc'], name='Inception Model')
```



```
In [ ]: test_loss, test_accuracy = inception.evaluate(test_dataset, batch_size=BA
print(
    f"Model evaluated: Test Loss -> {test_loss}, Test Accuracy -> {test_a
)
model_accuracies.append(("Inception", test_accuracy))
inception.summary()
```

6/6 [=====] - 7s 1s/step - loss: 0.5857 - acc: 0.8484

Model evaluated: Test Loss -> 0.5856717228889465, Test Accuracy -> 84.84%
Model: "InceptionModel"

Layer (type)	Output Shape	Param #
rescaling_3 (Rescaling)	multiple	0
inception (Inception)	multiple	83872
inception_1 (Inception)	multiple	95584
inception_2 (Inception)	multiple	95584
conv2d_35 (Conv2D)	multiple	602176
conv2d_43 (Conv2D)	multiple	602176
conv2d_51 (Conv2D)	multiple	602176
batch_normalization_17 (Batch Normalization)	multiple	768
batch_normalization_18 (Batch Normalization)	multiple	768
batch_normalization_19 (Batch Normalization)	multiple	768
dense_5 (Dense)	multiple	12545000
dropout_1 (Dropout)	multiple	0
dense_6 (Dense)	multiple	5005

=====
Total params: 14633877 (55.82 MB)
Trainable params: 14632725 (55.82 MB)
Non-trainable params: 1152 (4.50 KB)

For the second deep model, an inception architecture has been chosen. It can be seen in the graphs how at the beginning it was difficult to start generalising, as reflected in the metrics of the validation set, but as the model learned, it also started to generalise, although its accuracy does not surpass that of the residual model. This model does not overfit either, but because of the above, it is somewhat distant from training performance.

2.5 What if we add Data Augmentation?

```
In [ ]: from keras.models import Sequential
resnet_data_aug = Sequential([
    layers.RandomFlip("horizontal"),
    layers.RandomRotation(0.1),
    layers.RandomZoom(0.2),
    layers.GaussianNoise(0.01),
```

```
        CustomResNet(num_classes=5)
    ], name='ResNetAug')

resnet_data_aug.compile(optimizer="adam", loss="sparse_categorical_crossentropy")
resnet_data_aug_history = train_model(
    resnet_data_aug,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=5,
    val_patience=10,
).history

print(
    f"Final loss: training -> {resnet_data_aug_history['loss'][-1]:.2f},
)
print(
    f"Final accuracy: training -> {resnet_data_aug_history['acc'][-1]:.2f}
)
```

Epoch 1/50

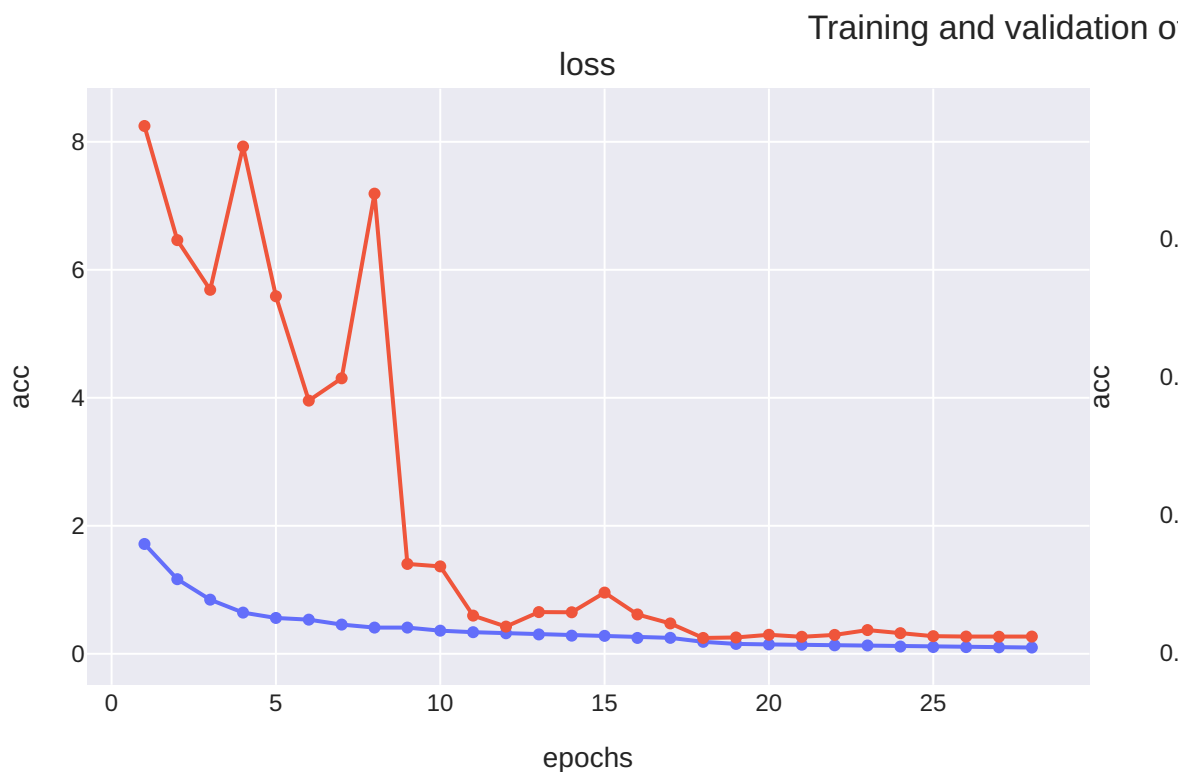
```
45/45 [=====] - 9s 99ms/step - loss: 1.7157 - acc
: 0.3624 - val_loss: 8.2472 - val_acc: 0.2088 - lr: 0.0010
Epoch 2/50
45/45 [=====] - 5s 92ms/step - loss: 1.1655 - acc
: 0.5241 - val_loss: 6.4635 - val_acc: 0.2068 - lr: 0.0010
Epoch 3/50
45/45 [=====] - 5s 95ms/step - loss: 0.8457 - acc
: 0.6654 - val_loss: 5.6873 - val_acc: 0.2143 - lr: 0.0010
Epoch 4/50
45/45 [=====] - 5s 90ms/step - loss: 0.6436 - acc
: 0.7465 - val_loss: 7.9266 - val_acc: 0.2815 - lr: 0.0010
Epoch 5/50
45/45 [=====] - 5s 96ms/step - loss: 0.5598 - acc
: 0.7761 - val_loss: 5.5866 - val_acc: 0.2825 - lr: 0.0010
Epoch 6/50
45/45 [=====] - 5s 92ms/step - loss: 0.5336 - acc
: 0.7929 - val_loss: 3.9558 - val_acc: 0.2578 - lr: 0.0010
Epoch 7/50
45/45 [=====] - 5s 89ms/step - loss: 0.4562 - acc
: 0.8275 - val_loss: 4.3048 - val_acc: 0.2905 - lr: 0.0010
Epoch 8/50
45/45 [=====] - 5s 88ms/step - loss: 0.4093 - acc
: 0.8400 - val_loss: 7.1897 - val_acc: 0.2380 - lr: 0.0010
Epoch 9/50
45/45 [=====] - 5s 95ms/step - loss: 0.4094 - acc
: 0.8417 - val_loss: 1.4042 - val_acc: 0.5923 - lr: 0.0010
Epoch 10/50
45/45 [=====] - 5s 94ms/step - loss: 0.3613 - acc
: 0.8601 - val_loss: 1.3657 - val_acc: 0.5710 - lr: 0.0010
Epoch 11/50
45/45 [=====] - 5s 96ms/step - loss: 0.3377 - acc
: 0.8718 - val_loss: 0.5966 - val_acc: 0.7768 - lr: 0.0010
Epoch 12/50
45/45 [=====] - 5s 95ms/step - loss: 0.3205 - acc
: 0.8768 - val_loss: 0.4250 - val_acc: 0.8427 - lr: 0.0010
Epoch 13/50
45/45 [=====] - 5s 89ms/step - loss: 0.3024 - acc
: 0.8861 - val_loss: 0.6516 - val_acc: 0.7679 - lr: 0.0010
Epoch 14/50
45/45 [=====] - 5s 89ms/step - loss: 0.2835 - acc
: 0.8902 - val_loss: 0.6484 - val_acc: 0.7640 - lr: 0.0010
Epoch 15/50
45/45 [=====] - 5s 90ms/step - loss: 0.2803 - acc
: 0.8905 - val_loss: 0.9562 - val_acc: 0.7125 - lr: 0.0010
Epoch 16/50
45/45 [=====] - 5s 87ms/step - loss: 0.2480 - acc
: 0.9068 - val_loss: 0.6148 - val_acc: 0.7937 - lr: 0.0010
Epoch 17/50
45/45 [=====] - 5s 90ms/step - loss: 0.2491 - acc
: 0.9051 - val_loss: 0.4744 - val_acc: 0.8238 - lr: 0.0010
Epoch 18/50
45/45 [=====] - 5s 95ms/step - loss: 0.1869 - acc
: 0.9308 - val_loss: 0.2474 - val_acc: 0.9075 - lr: 2.0000e-04
Epoch 19/50
45/45 [=====] - 5s 89ms/step - loss: 0.1544 - acc
: 0.9431 - val_loss: 0.2554 - val_acc: 0.9060 - lr: 2.0000e-04
Epoch 20/50
45/45 [=====] - 5s 87ms/step - loss: 0.1467 - acc
: 0.9467 - val_loss: 0.2968 - val_acc: 0.8882 - lr: 2.0000e-04
Epoch 21/50
```

```

45/45 [=====] - 5s 86ms/step - loss: 0.1417 - acc
: 0.9488 - val_loss: 0.2656 - val_acc: 0.9015 - lr: 2.0000e-04
Epoch 22/50
45/45 [=====] - 5s 89ms/step - loss: 0.1326 - acc
: 0.9527 - val_loss: 0.2950 - val_acc: 0.8902 - lr: 2.0000e-04
Epoch 23/50
45/45 [=====] - 5s 91ms/step - loss: 0.1300 - acc
: 0.9514 - val_loss: 0.3706 - val_acc: 0.8758 - lr: 2.0000e-04
Epoch 24/50
45/45 [=====] - 5s 89ms/step - loss: 0.1131 - acc
: 0.9572 - val_loss: 0.3223 - val_acc: 0.8906 - lr: 4.0000e-05
Epoch 25/50
45/45 [=====] - 5s 91ms/step - loss: 0.1058 - acc
: 0.9612 - val_loss: 0.2754 - val_acc: 0.9075 - lr: 4.0000e-05
Epoch 26/50
45/45 [=====] - 5s 89ms/step - loss: 0.1047 - acc
: 0.9625 - val_loss: 0.2694 - val_acc: 0.9080 - lr: 4.0000e-05
Epoch 27/50
45/45 [=====] - 5s 90ms/step - loss: 0.1015 - acc
: 0.9635 - val_loss: 0.2663 - val_acc: 0.9070 - lr: 4.0000e-05
Epoch 28/50
45/45 [=====] - 5s 87ms/step - loss: 0.0978 - acc
: 0.9640 - val_loss: 0.2690 - val_acc: 0.9095 - lr: 4.0000e-05
Final loss: training -> 0.10, validation -> 0.27
Final accuracy: training -> 0.96, validation -> 0.91

```

```
In [ ]: plot_history(resnet_data_aug_history, ['loss', 'acc'], name='Augmented Re
```



```
In [ ]: test_loss, test_accuracy = resnet_data_aug.evaluate(test_dataset, batch_s
print(
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_ac
)
model_accuracies.append(("AugmentedResNet", test_accuracy))
resnet_data_aug.summary()
```

```
6/6 [=====] - 0s 21ms/step - loss: 0.2016 - acc: 0.9365
Model evaluated: Test Loss-> 0.20161490142345428, Test Accuracy -> 93.65%
Model: "ResNetAug"
```

Layer (type)	Output Shape	Param #
random_flip (RandomFlip)	(None, 100, 100, 3)	0
random_rotation (RandomRotation)	(None, 100, 100, 3)	0
random_zoom (RandomZoom)	(None, 100, 100, 3)	0
gaussian_noise (GaussianNoise)	(None, 100, 100, 3)	0
ResNet (CustomResNet)	(None, 5)	11705333

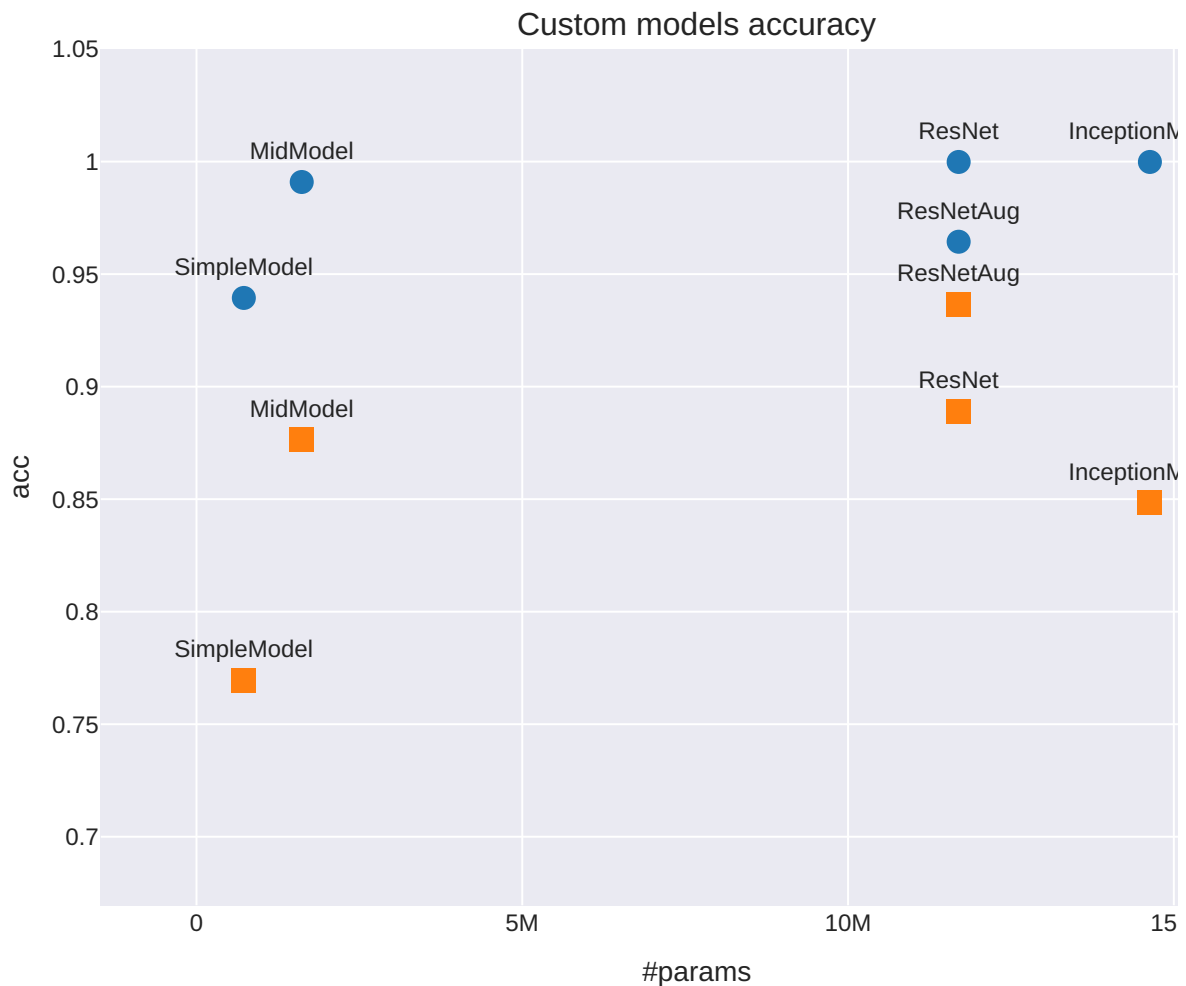
=====
Total params: 11705333 (44.65 MB)
Trainable params: 11697525 (44.62 MB)
Non-trainable params: 7808 (30.50 KB)
=====

To enhance the model's generalisation and prevent it from overfitting to the training set, we decided to use data augmentation. We selected the residual model, which was the best model available, and added four stages of data augmentation: horizontal flip, rotation, zoom, and Gaussian noise. The results demonstrate that this technique has significantly improved the model's performance, achieving over 90% accuracy in the test set, which is impressive for a non-pretrained model. Additionally, the model appears to be free of overfitting, as evidenced by the consistent loss of training and validation across epochs.

2.6. Custom models comparison

In the next output we have displayed the accuracy performance of each custom model in the train and test set to analyze the overfitting behavior.

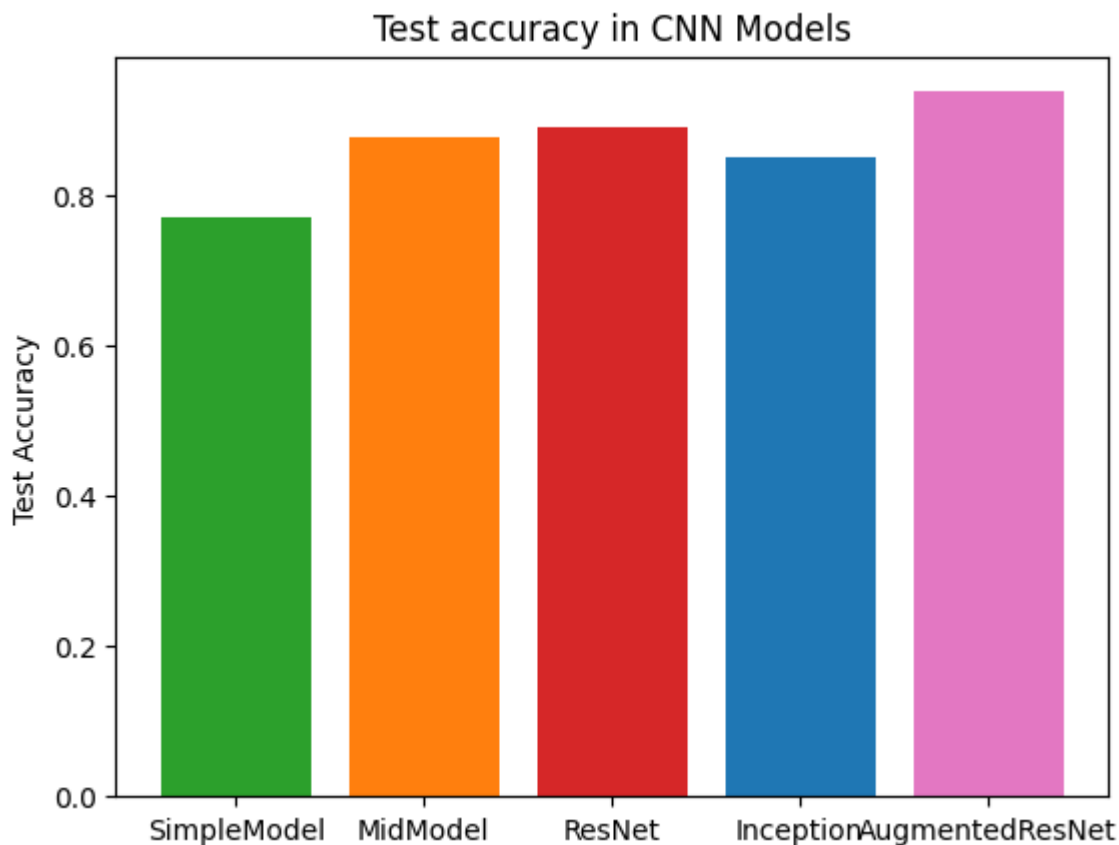
```
In [ ]: models = [simple_model, mid_model, inception, resnet, resnet_data_aug]
        comparison(models, (train_dataset, test_dataset))
```

The left figure shows each model performance in the train (blue) and test (orange) sets. We see that for all models the performance is considerably better in the train set (99%) than in the evaluation samples (75-85%), proving the network is learning the train set characteristics instead of generalizing image information for the given task. The right figure shows the disadvantage of using larger networks with more complex connections (Inception), inducing a higher difference between the train and test set. In the other hand, we can see that a simple model like the first that was trained, without any type of regularization technique, is clearly overfitted, shows a great difference meaning that simpler models tends to learn the training set instead of learning to generalize. Additionally, we see the impact of regularizing the network via data augmentation (ResNetAug). The result is the smaller difference between the train and test set.

```
In [ ]: fig, ax = plt.subplots()
models = [name for name, _ in model_accuracies]
accuracies = [accuracy for _, accuracy in model_accuracies]
bar_colors = ["tab:green", "tab:orange", "tab:red", "tab:blue", "tab:pink"]
ax.bar(models, accuracies, label=models, color=bar_colors)

ax.set_ylabel("Test Accuracy")
ax.set_title("Test accuracy in CNN Models")
plt.show()
```



Exercise 3. Pretrained models

For this exercise we conducted experiments with three pretrained models available in the [Keras Applications website](#) pretrained with ImageNet dataset: [ResNet-50](#) (He et al., 2016), [MobileNet-V2](#) (Sandler et al., 2018) and [EfficientNet-B0](#) (Tan & Le, 2019). Our first approach uses transfer learning, using the pretrained models freezed to use that previous knowledge and only train our classifier. The second round is fine-tuning, where we train the model with the feature-extractor freezed, to train the top (classifier) and then do a little round of epochs with very low learning rate with the pretrained model unfreezed to adapt its weights to our dataset. The last approaches explores defreezing only the last 10 layers of each architecture to test if maintaining a large ratio of trainable weights does not impact in the overall performance.

3.1. Transfer-learning

ResNet-50 V2

```
In [ ]: resnet_t = PretrainedModel(num_classes=5, img_size=IMG_SIZE, pretrained='
optimizer = Adam(learning_rate=1e-4)
resnet_t.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
resnet_t_history = train_model(
    resnet_t,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
```

```
        lr_patience=5,  
        val_patience=10  
    ).history  
    print(  
        f"Final loss: training -> {resnet_t_history['loss'][-1]:.2f}, validation  
    )  
    print(  
        f"Final accuracy: training -> {resnet_t_history['acc'][-1]:.2f}, validation  
    )  
    test_loss, test_accuracy = resnet_t.evaluate(test_dataset, batch_size=BATCH_SIZE)  
    print(  
        f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_accuracy}  
    )  
    resnet_t.summary()
```

```

Epoch 1/50
45/45 [=====] - 9s 136ms/step - loss: 0.8935 - acc: 0.8552 - val_loss: 0.2917 - val_acc: 0.9095 - lr: 1.0000e-04
Epoch 2/50
45/45 [=====] - 6s 109ms/step - loss: 0.0984 - acc: 0.9701 - val_loss: 0.2475 - val_acc: 0.9184 - lr: 1.0000e-04
Epoch 3/50
45/45 [=====] - 5s 96ms/step - loss: 0.0243 - acc: 0.9960 - val_loss: 0.2590 - val_acc: 0.9198 - lr: 1.0000e-04
Epoch 4/50
45/45 [=====] - 5s 93ms/step - loss: 0.0104 - acc: 0.9994 - val_loss: 0.2704 - val_acc: 0.9198 - lr: 1.0000e-04
Epoch 5/50
45/45 [=====] - 5s 93ms/step - loss: 0.0064 - acc: 0.9997 - val_loss: 0.2796 - val_acc: 0.9213 - lr: 1.0000e-04
Epoch 6/50
45/45 [=====] - 5s 92ms/step - loss: 0.0043 - acc: 0.9998 - val_loss: 0.2883 - val_acc: 0.9198 - lr: 1.0000e-04
Epoch 7/50
45/45 [=====] - 5s 92ms/step - loss: 0.0036 - acc: 0.9998 - val_loss: 0.2921 - val_acc: 0.9218 - lr: 1.0000e-04
Epoch 8/50
45/45 [=====] - 5s 89ms/step - loss: 0.0029 - acc: 0.9998 - val_loss: 0.2942 - val_acc: 0.9198 - lr: 2.0000e-05
Epoch 9/50
45/45 [=====] - 5s 91ms/step - loss: 0.0026 - acc: 0.9998 - val_loss: 0.2956 - val_acc: 0.9189 - lr: 2.0000e-05
Epoch 10/50
45/45 [=====] - 5s 91ms/step - loss: 0.0025 - acc: 0.9997 - val_loss: 0.2968 - val_acc: 0.9193 - lr: 2.0000e-05
Epoch 11/50
45/45 [=====] - 5s 92ms/step - loss: 0.0024 - acc: 0.9997 - val_loss: 0.2976 - val_acc: 0.9193 - lr: 2.0000e-05
Epoch 12/50
45/45 [=====] - 5s 90ms/step - loss: 0.0023 - acc: 0.9997 - val_loss: 0.2988 - val_acc: 0.9203 - lr: 2.0000e-05
Final loss: training -> 0.00, validation -> 0.30
Final accuracy: training -> 1.00, validation -> 0.92
6/6 [=====] - 1s 142ms/step - loss: 0.2515 - acc: 0.9446
Model evaluated: Test Loss-> 0.25145092606544495, Test Accuracy -> 94.46%
Model: "ResNet-t"

```

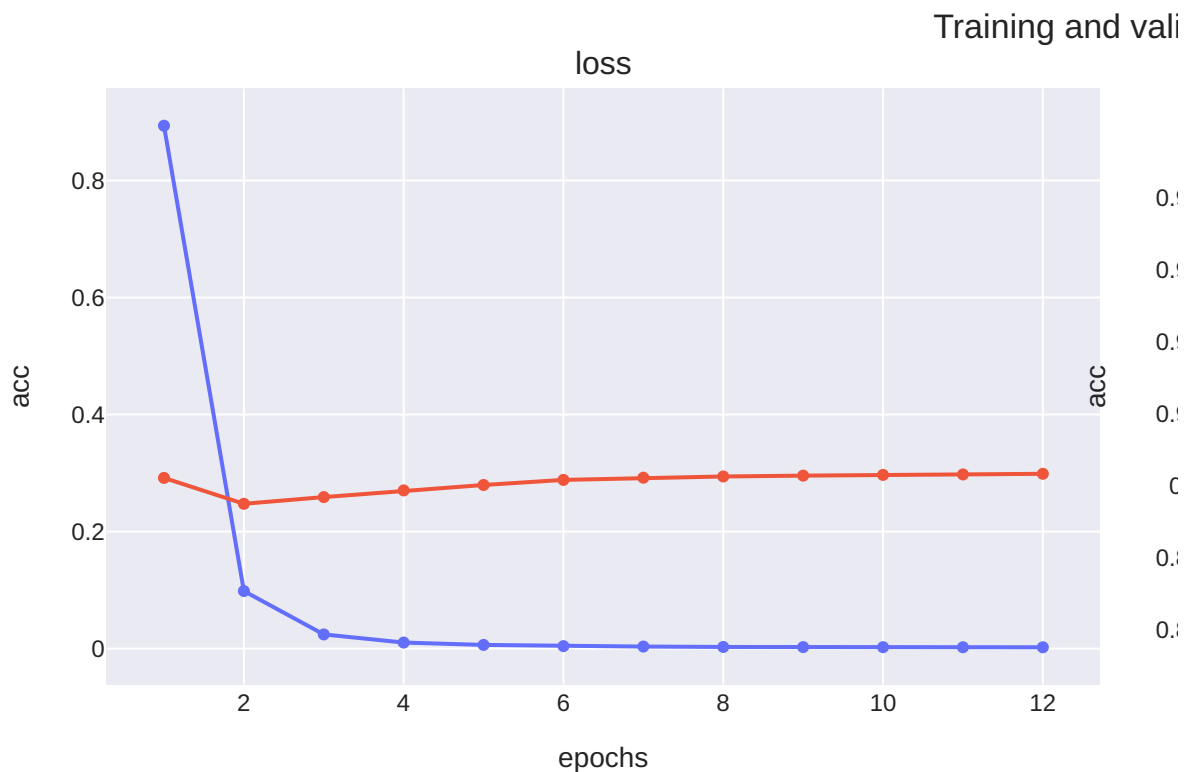
Layer (type)	Output Shape	Param #
rescaling_5 (Rescaling)	multiple	0
resnet50v2 (Functional)	(None, 4, 4, 2048)	23564800
flatten_2 (Flatten)	multiple	0
dense_9 (Dense)	multiple	32769000
dense_10 (Dense)	multiple	5005

```

=====
Total params: 56338805 (214.92 MB)
Trainable params: 32774005 (125.02 MB)
Non-trainable params: 23564800 (89.89 MB)

```

```
In [ ]: plot_history(resnet_t_history, ['loss', 'acc'], name=f'{resnet_t.name} Mo
```



MobileNet V2

```
In [ ]: mobile_t = PretrainedModel(num_classes=5, img_size=IMG_SIZE, pretrained='
optimizer = Adam(learning_rate=1e-4)
mobile_t.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
mobile_t_history = train_model(
    mobile_t,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=5,
    val_patience=10
).history
print(
    f"Final loss: training -> {mobile_t_history['loss'][-1]:.2f}, validation -> {mobile_t_history['val_loss'][-1]:.2f}"
)
print(
    f"Final accuracy: training -> {mobile_t_history['acc'][-1]:.2f}, validation -> {mobile_t_history['val_acc'][-1]:.2f}"
)
test_loss, test_accuracy = mobile_t.evaluate(test_dataset, batch_size=BATCH_SIZE)
print(
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_accuracy}"
)
mobile_t.summary()
```

```

Epoch 1/50
45/45 [=====] - 7s 106ms/step - loss: 1.4484 - acc: 0.8216 - val_loss: 0.2129 - val_acc: 0.9139 - lr: 1.0000e-04
Epoch 2/50
45/45 [=====] - 5s 96ms/step - loss: 0.1558 - acc: 0.9416 - val_loss: 0.1809 - val_acc: 0.9233 - lr: 1.0000e-04
Epoch 3/50
45/45 [=====] - 5s 97ms/step - loss: 0.0911 - acc: 0.9706 - val_loss: 0.1735 - val_acc: 0.9317 - lr: 1.0000e-04
Epoch 4/50
45/45 [=====] - 5s 89ms/step - loss: 0.0563 - acc: 0.9862 - val_loss: 0.1784 - val_acc: 0.9352 - lr: 1.0000e-04
Epoch 5/50
45/45 [=====] - 5s 98ms/step - loss: 0.0349 - acc: 0.9954 - val_loss: 0.1660 - val_acc: 0.9396 - lr: 1.0000e-04
Epoch 6/50
45/45 [=====] - 5s 87ms/step - loss: 0.0210 - acc: 0.9984 - val_loss: 0.1695 - val_acc: 0.9436 - lr: 1.0000e-04
Epoch 7/50
45/45 [=====] - 5s 87ms/step - loss: 0.0138 - acc: 0.9992 - val_loss: 0.1698 - val_acc: 0.9446 - lr: 1.0000e-04
Epoch 8/50
45/45 [=====] - 5s 85ms/step - loss: 0.0098 - acc: 0.9997 - val_loss: 0.1694 - val_acc: 0.9431 - lr: 1.0000e-04
Epoch 9/50
45/45 [=====] - 5s 86ms/step - loss: 0.0073 - acc: 0.9997 - val_loss: 0.1751 - val_acc: 0.9426 - lr: 1.0000e-04
Epoch 10/50
45/45 [=====] - 5s 87ms/step - loss: 0.0061 - acc: 0.9997 - val_loss: 0.1762 - val_acc: 0.9416 - lr: 1.0000e-04
Epoch 11/50
45/45 [=====] - 5s 87ms/step - loss: 0.0045 - acc: 0.9998 - val_loss: 0.1753 - val_acc: 0.9426 - lr: 2.0000e-05
Epoch 12/50
45/45 [=====] - 5s 86ms/step - loss: 0.0043 - acc: 0.9998 - val_loss: 0.1763 - val_acc: 0.9431 - lr: 2.0000e-05
Epoch 13/50
45/45 [=====] - 5s 86ms/step - loss: 0.0040 - acc: 0.9998 - val_loss: 0.1769 - val_acc: 0.9441 - lr: 2.0000e-05
Epoch 14/50
45/45 [=====] - 5s 86ms/step - loss: 0.0039 - acc: 0.9997 - val_loss: 0.1780 - val_acc: 0.9426 - lr: 2.0000e-05
Epoch 15/50
45/45 [=====] - 5s 88ms/step - loss: 0.0038 - acc: 0.9997 - val_loss: 0.1787 - val_acc: 0.9426 - lr: 2.0000e-05
Final loss: training -> 0.00, validation -> 0.18
Final accuracy: training -> 1.00, validation -> 0.94
6/6 [=====] - 1s 46ms/step - loss: 0.1589 - acc: 0.9519
Model evaluated: Test Loss-> 0.1589222103357315, Test Accuracy -> 95.19%
Model: "Mobile-t"

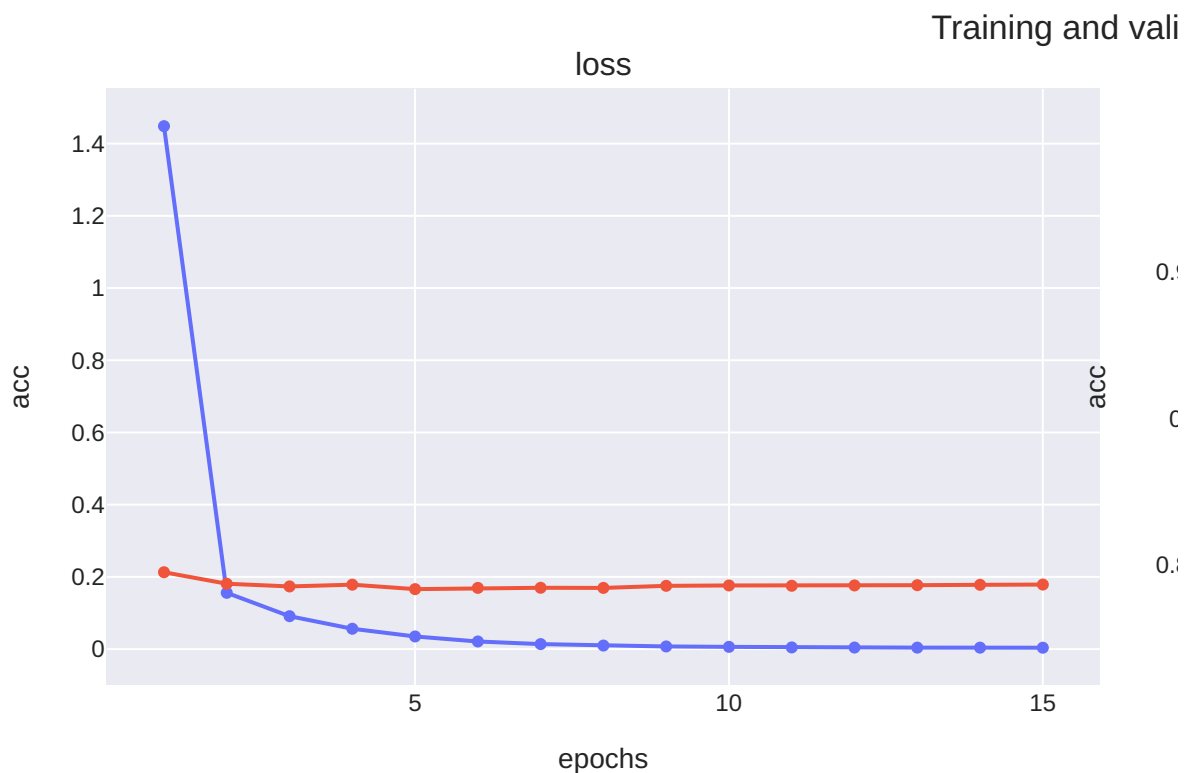
```

Layer (type)	Output Shape	Param #
rescaling_6 (Rescaling)	multiple	0
mobilenetv2_1.00_224 (Functional)	(None, 4, 4, 1280)	2257984
flatten_3 (Flatten)	multiple	0

dense_11 (Dense)	multiple	20481000
dense_12 (Dense)	multiple	5005

```
=====
Total params: 22743989 (86.76 MB)
Trainable params: 20486005 (78.15 MB)
Non-trainable params: 2257984 (8.61 MB)
```

```
In [ ]: plot_history(mobile_t_history, ['loss', 'acc'], name=f'{mobile_t.name} Mo
```



Xception

```
In [ ]: xception_t = PretrainedModel(num_classes=5, img_size=IMG_SIZE, pretrained
optimizer = Adam(learning_rate=1e-4)
xception_t.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
xception_t_history = train_model(
    xception_t,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=5,
    val_patience=10
).history
print(
    f"Final loss: training -> {xception_t_history['loss'][-1]:.2f}, valid
)
print(
    f"Final accuracy: training -> {xception_t_history['acc'][-1]:.2f}, va
)
test_loss, test_accuracy = xception_t.evaluate(test_dataset, batch_size=B
```

```
print(  
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_ac  
)  
exception_t.summary()
```



```

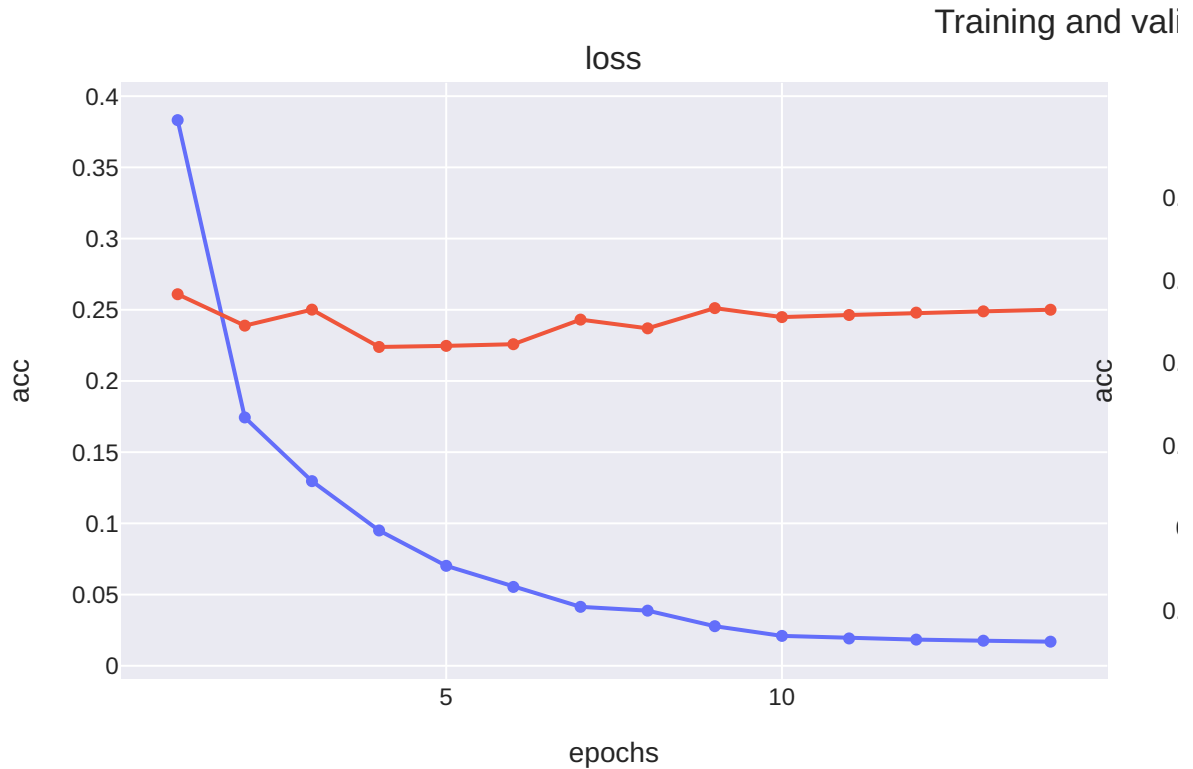
Epoch 1/50
45/45 [=====] - 8s 120ms/step - loss: 0.3832 - acc: 0.8724 - val_loss: 0.2609 - val_acc: 0.8996 - lr: 1.0000e-04
Epoch 2/50
45/45 [=====] - 6s 104ms/step - loss: 0.1744 - acc: 0.9361 - val_loss: 0.2389 - val_acc: 0.9134 - lr: 1.0000e-04
Epoch 3/50
45/45 [=====] - 5s 92ms/step - loss: 0.1297 - acc: 0.9548 - val_loss: 0.2501 - val_acc: 0.9095 - lr: 1.0000e-04
Epoch 4/50
45/45 [=====] - 5s 101ms/step - loss: 0.0950 - acc: 0.9697 - val_loss: 0.2239 - val_acc: 0.9253 - lr: 1.0000e-04
Epoch 5/50
45/45 [=====] - 5s 91ms/step - loss: 0.0702 - acc: 0.9807 - val_loss: 0.2247 - val_acc: 0.9218 - lr: 1.0000e-04
Epoch 6/50
45/45 [=====] - 5s 88ms/step - loss: 0.0554 - acc: 0.9866 - val_loss: 0.2258 - val_acc: 0.9263 - lr: 1.0000e-04
Epoch 7/50
45/45 [=====] - 5s 89ms/step - loss: 0.0414 - acc: 0.9914 - val_loss: 0.2431 - val_acc: 0.9243 - lr: 1.0000e-04
Epoch 8/50
45/45 [=====] - 5s 89ms/step - loss: 0.0387 - acc: 0.9921 - val_loss: 0.2370 - val_acc: 0.9273 - lr: 1.0000e-04
Epoch 9/50
45/45 [=====] - 5s 90ms/step - loss: 0.0278 - acc: 0.9962 - val_loss: 0.2512 - val_acc: 0.9248 - lr: 1.0000e-04
Epoch 10/50
45/45 [=====] - 5s 93ms/step - loss: 0.0210 - acc: 0.9982 - val_loss: 0.2449 - val_acc: 0.9258 - lr: 2.0000e-05
Epoch 11/50
45/45 [=====] - 5s 91ms/step - loss: 0.0192 - acc: 0.9983 - val_loss: 0.2463 - val_acc: 0.9268 - lr: 2.0000e-05
Epoch 12/50
45/45 [=====] - 5s 90ms/step - loss: 0.0184 - acc: 0.9988 - val_loss: 0.2480 - val_acc: 0.9273 - lr: 2.0000e-05
Epoch 13/50
45/45 [=====] - 5s 92ms/step - loss: 0.0176 - acc: 0.9988 - val_loss: 0.2489 - val_acc: 0.9273 - lr: 2.0000e-05
Epoch 14/50
45/45 [=====] - 5s 91ms/step - loss: 0.0169 - acc: 0.9987 - val_loss: 0.2500 - val_acc: 0.9278 - lr: 2.0000e-05
Final loss: training -> 0.02, validation -> 0.25
Final accuracy: training -> 1.00, validation -> 0.93
6/6 [=====] - 1s 99ms/step - loss: 0.1698 - acc: 0.9432
Model evaluated: Test Loss-> 0.16977046430110931, Test Accuracy -> 94.32%
Model: "Xception-t"

```

Layer (type)	Output Shape	Param #
rescaling_7 (Rescaling)	multiple	0
xception (Functional)	(None, 3, 3, 2048)	20861480
flatten_4 (Flatten)	multiple	0
dense_13 (Dense)	multiple	18433000
dense_14 (Dense)	multiple	5005

```
=====
Total params: 39299485 (149.92 MB)
Trainable params: 18438005 (70.34 MB)
Non-trainable params: 20861480 (79.58 MB)
=====
```

```
In [ ]: plot_history(xception_t_history, ['loss', 'acc'], name=f'{xception_t.name
```



3.2. Fine-tuning

To finetune the pre-trained models we will first freeze the model and train only the "top", i.e. the classifier. After this, the whole model is unfrozen and trained for a few epochs with a very low learning rate in order to slightly modify the weights of our model and adapt it better to the dataset.

ResNet-50 V2

```
In [ ]: resnet_f = PretrainedModel(num_classes=5, img_size=IMG_SIZE, pretrained='
optimizer = Adam(learning_rate=1e-3)
resnet_f.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")

print("Training only the classifier")
train_model(
    resnet_f,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=3,
    val_patience=5,
)
```

```
print("Finetuning the model with a learning rate of 1e-5")
resnet_f.trainable = True
optimizer = Adam(learning_rate=5e-5)
resnet_f.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")

resnet_f_history = train_model(
    resnet_f,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=3,
    val_patience=10,
).history

print(
    f"Final loss: training -> {resnet_f_history['loss'][-1]:.2f}, validation -> {resnet_f_history['val_loss'][-1]:.2f}"
)
print(
    f"Final accuracy: training -> {resnet_f_history['acc'][-1]:.2f}, validation -> {resnet_f_history['val_acc'][-1]:.2f}"
)
test_loss, test_accuracy = resnet_f.evaluate(test_dataset, batch_size=BATCH_SIZE)
print(
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_accuracy}"
)
resnet_f.summary()
```

Training only the classifier

Epoch 1/50

45/45 [=====] - 7s 115ms/step - loss: 4.8100 - acc: 0.8467 - val_loss: 0.6332 - val_acc: 0.8936 - lr: 0.0010

Epoch 2/50

45/45 [=====] - 6s 111ms/step - loss: 0.2195 - acc: 0.9454 - val_loss: 0.3765 - val_acc: 0.9124 - lr: 0.0010

Epoch 3/50

45/45 [=====] - 6s 109ms/step - loss: 0.0665 - acc: 0.9804 - val_loss: 0.3454 - val_acc: 0.9124 - lr: 0.0010

Epoch 4/50

45/45 [=====] - 5s 90ms/step - loss: 0.0256 - acc: 0.9944 - val_loss: 0.3512 - val_acc: 0.9203 - lr: 0.0010

Epoch 5/50

45/45 [=====] - 6s 108ms/step - loss: 0.0116 - acc: 0.9986 - val_loss: 0.3418 - val_acc: 0.9208 - lr: 0.0010

Epoch 6/50

45/45 [=====] - 5s 91ms/step - loss: 0.0062 - acc: 0.9995 - val_loss: 0.3484 - val_acc: 0.9238 - lr: 0.0010

Epoch 7/50

45/45 [=====] - 5s 91ms/step - loss: 0.0044 - acc: 0.9997 - val_loss: 0.3576 - val_acc: 0.9253 - lr: 0.0010

Epoch 8/50

45/45 [=====] - 5s 91ms/step - loss: 0.0033 - acc: 0.9997 - val_loss: 0.3649 - val_acc: 0.9258 - lr: 0.0010

Epoch 9/50

45/45 [=====] - 5s 93ms/step - loss: 0.0021 - acc: 0.9998 - val_loss: 0.3686 - val_acc: 0.9228 - lr: 2.0000e-04

Epoch 10/50

45/45 [=====] - 5s 90ms/step - loss: 0.0020 - acc: 0.9997 - val_loss: 0.3710 - val_acc: 0.9228 - lr: 2.0000e-04

Finetuning the model with a learning rate of 1e-5

Epoch 1/50

45/45 [=====] - 27s 247ms/step - loss: 0.4672 - acc: 0.8630 - val_loss: 0.7456 - val_acc: 0.8906 - lr: 5.0000e-05

Epoch 2/50

45/45 [=====] - 8s 160ms/step - loss: 0.0475 - acc: 0.9885 - val_loss: 0.4840 - val_acc: 0.9075 - lr: 5.0000e-05

Epoch 3/50

45/45 [=====] - 8s 161ms/step - loss: 0.0098 - acc: 0.9990 - val_loss: 0.4431 - val_acc: 0.9060 - lr: 5.0000e-05

Epoch 4/50

45/45 [=====] - 7s 137ms/step - loss: 0.0040 - acc: 0.9997 - val_loss: 0.4491 - val_acc: 0.9060 - lr: 5.0000e-05

Epoch 5/50

45/45 [=====] - 8s 161ms/step - loss: 0.0023 - acc: 0.9997 - val_loss: 0.4388 - val_acc: 0.9050 - lr: 5.0000e-05

Epoch 6/50

45/45 [=====] - 7s 137ms/step - loss: 0.0020 - acc: 0.9997 - val_loss: 0.4407 - val_acc: 0.9025 - lr: 5.0000e-05

Epoch 7/50

45/45 [=====] - 7s 136ms/step - loss: 0.0014 - acc: 0.9998 - val_loss: 0.4405 - val_acc: 0.9035 - lr: 5.0000e-05

Epoch 8/50

45/45 [=====] - 7s 137ms/step - loss: 0.0011 - acc: 0.9997 - val_loss: 0.4392 - val_acc: 0.9035 - lr: 5.0000e-05

Epoch 9/50

45/45 [=====] - 8s 161ms/step - loss: 6.4849e-04 - acc: 0.9998 - val_loss: 0.4369 - val_acc: 0.9030 - lr: 1.0000e-05

Epoch 10/50

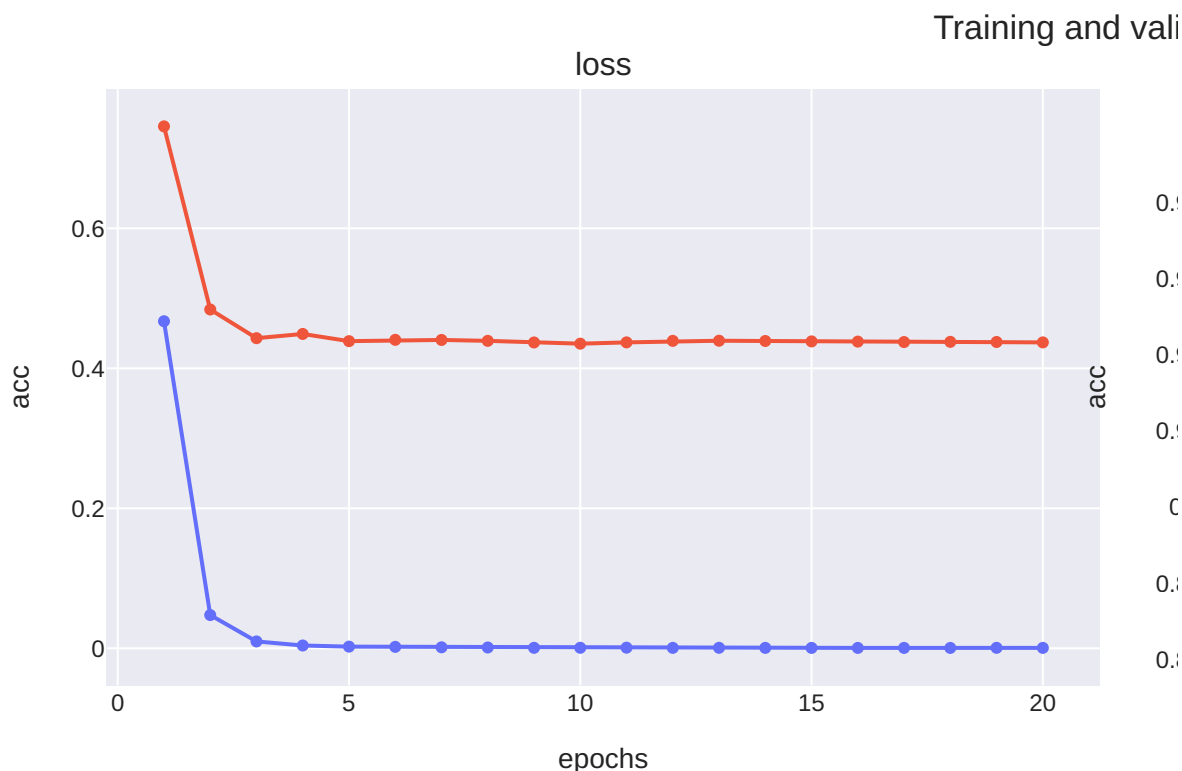
```

45/45 [=====] - 8s 161ms/step - loss: 7.2401e-04
- acc: 0.9997 - val_loss: 0.4352 - val_acc: 0.8996 - lr: 1.0000e-05
Epoch 11/50
45/45 [=====] - 7s 136ms/step - loss: 8.7058e-04
- acc: 0.9996 - val_loss: 0.4370 - val_acc: 0.8981 - lr: 1.0000e-05
Epoch 12/50
45/45 [=====] - 7s 136ms/step - loss: 6.1167e-04
- acc: 0.9997 - val_loss: 0.4392 - val_acc: 0.8991 - lr: 1.0000e-05
Epoch 13/50
45/45 [=====] - 7s 137ms/step - loss: 6.9154e-04
- acc: 0.9997 - val_loss: 0.4394 - val_acc: 0.8986 - lr: 1.0000e-05
Epoch 14/50
45/45 [=====] - 7s 137ms/step - loss: 5.6919e-04
- acc: 0.9997 - val_loss: 0.4390 - val_acc: 0.8991 - lr: 2.0000e-06
Epoch 15/50
45/45 [=====] - 7s 137ms/step - loss: 5.5034e-04
- acc: 0.9998 - val_loss: 0.4384 - val_acc: 0.8991 - lr: 2.0000e-06
Epoch 16/50
45/45 [=====] - 7s 136ms/step - loss: 5.3281e-04
- acc: 0.9999 - val_loss: 0.4381 - val_acc: 0.8991 - lr: 2.0000e-06
Epoch 17/50
45/45 [=====] - 7s 136ms/step - loss: 5.3672e-04
- acc: 0.9997 - val_loss: 0.4375 - val_acc: 0.8991 - lr: 4.0000e-07
Epoch 18/50
45/45 [=====] - 7s 137ms/step - loss: 5.1441e-04
- acc: 0.9998 - val_loss: 0.4378 - val_acc: 0.8991 - lr: 4.0000e-07
Epoch 19/50
45/45 [=====] - 7s 138ms/step - loss: 6.6209e-04
- acc: 0.9998 - val_loss: 0.4376 - val_acc: 0.8991 - lr: 4.0000e-07
Epoch 20/50
45/45 [=====] - 7s 137ms/step - loss: 5.5975e-04
- acc: 0.9997 - val_loss: 0.4370 - val_acc: 0.8991 - lr: 8.0000e-08
Final loss: training -> 0.00, validation -> 0.44
Final accuracy: training -> 1.00, validation -> 0.90
6/6 [=====] - 1s 49ms/step - loss: 0.3587 - acc:
0.9212
Model evaluated: Test Loss-> 0.3587038516998291, Test Accuracy -> 92.12%
Model: "ResNet-f"

```

Layer (type)	Output Shape	Param #
rescaling_8 (Rescaling)	multiple	0
resnet50v2 (Functional)	(None, 4, 4, 2048)	23564800
flatten_5 (Flatten)	multiple	0
dense_15 (Dense)	multiple	32769000
dense_16 (Dense)	multiple	5005
=====		
Total params: 56338805 (214.92 MB)		
Trainable params: 56293365 (214.74 MB)		
Non-trainable params: 45440 (177.50 KB)		

```
In [ ]: plot_history(resnet_f_history, ['loss', 'acc'], name=f'{resnet_f.name} Mo
```



MobileNet V2

```
In [ ]: mobile_f = PretrainedModel(num_classes=5, img_size=IMG_SIZE, pretrained='
optimizer = Adam(learning_rate=1e-3)
mobile_f.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")

print("Training only the classifier")
train_model(
    mobile_f,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=3,
    val_patience=5,
)

print("Finetuning the model with a learning rate of 1e-5")
mobile_f.trainable = True
optimizer = Adam(learning_rate=1e-5)
mobile_f.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")

mobile_f_history = train_model(
    mobile_f,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=2,
    val_patience=2,
).history
```

```
print(
    f"Final loss: training -> {mobile_f_history['loss'][-1]:.2f}, validation loss -> {mobile_f_history['val_loss'][-1]:.2f}"
)
print(
    f"Final accuracy: training -> {mobile_f_history['acc'][-1]:.2f}, validation accuracy -> {mobile_f_history['val_acc'][-1]:.2f}"
)
test_loss, test_accuracy = mobile_f.evaluate(test_dataset, batch_size=BATCH_SIZE)
print(
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_accuracy}"
)
mobile_f.summary()
```

Training only the classifier

Epoch 1/50

45/45 [=====] - 7s 102ms/step - loss: 8.0062 - acc: 0.8124 - val_loss: 0.2656 - val_acc: 0.9203 - lr: 0.0010

Epoch 2/50

45/45 [=====] - 5s 98ms/step - loss: 0.1860 - acc: 0.9368 - val_loss: 0.2131 - val_acc: 0.9312 - lr: 0.0010

Epoch 3/50

45/45 [=====] - 5s 98ms/step - loss: 0.0900 - acc: 0.9699 - val_loss: 0.1972 - val_acc: 0.9337 - lr: 0.0010

Epoch 4/50

45/45 [=====] - 5s 87ms/step - loss: 0.0683 - acc: 0.9766 - val_loss: 0.2179 - val_acc: 0.9381 - lr: 0.0010

Epoch 5/50

45/45 [=====] - 5s 88ms/step - loss: 0.0386 - acc: 0.9900 - val_loss: 0.1982 - val_acc: 0.9406 - lr: 0.0010

Epoch 6/50

45/45 [=====] - 5s 87ms/step - loss: 0.0237 - acc: 0.9966 - val_loss: 0.1981 - val_acc: 0.9401 - lr: 0.0010

Epoch 7/50

45/45 [=====] - 5s 98ms/step - loss: 0.0149 - acc: 0.9990 - val_loss: 0.1943 - val_acc: 0.9416 - lr: 2.0000e-04

Epoch 8/50

45/45 [=====] - 5s 87ms/step - loss: 0.0133 - acc: 0.9990 - val_loss: 0.1955 - val_acc: 0.9421 - lr: 2.0000e-04

Epoch 9/50

45/45 [=====] - 5s 86ms/step - loss: 0.0122 - acc: 0.9991 - val_loss: 0.1971 - val_acc: 0.9416 - lr: 2.0000e-04

Epoch 10/50

45/45 [=====] - 5s 87ms/step - loss: 0.0112 - acc: 0.9993 - val_loss: 0.1990 - val_acc: 0.9421 - lr: 2.0000e-04

Epoch 11/50

45/45 [=====] - 5s 89ms/step - loss: 0.0102 - acc: 0.9995 - val_loss: 0.1984 - val_acc: 0.9416 - lr: 4.0000e-05

Epoch 12/50

45/45 [=====] - 5s 89ms/step - loss: 0.0100 - acc: 0.9995 - val_loss: 0.1988 - val_acc: 0.9411 - lr: 4.0000e-05

Finetuning the model with a learning rate of 1e-5

Epoch 1/50

45/45 [=====] - 20s 157ms/step - loss: 0.5810 - acc: 0.7985 - val_loss: 0.2606 - val_acc: 0.9307 - lr: 1.0000e-05

Epoch 2/50

45/45 [=====] - 5s 93ms/step - loss: 0.2888 - acc: 0.8928 - val_loss: 0.3084 - val_acc: 0.9253 - lr: 1.0000e-05

Epoch 3/50

45/45 [=====] - 5s 92ms/step - loss: 0.2174 - acc: 0.9205 - val_loss: 0.3450 - val_acc: 0.9208 - lr: 1.0000e-05

Final loss: training -> 0.22, validation -> 0.34

Final accuracy: training -> 0.92, validation -> 0.92

6/6 [=====] - 0s 30ms/step - loss: 0.2889 - acc: 0.9352

Model evaluated: Test Loss-> 0.28893202543258667, Test Accuracy -> 93.52%

Model: "Mobile-f"

Layer (type)	Output Shape	Param #
rescaling_9 (Rescaling)	multiple	0
mobilenetv2_1.00_224 (Functional)	(None, 4, 4, 1280)	2257984

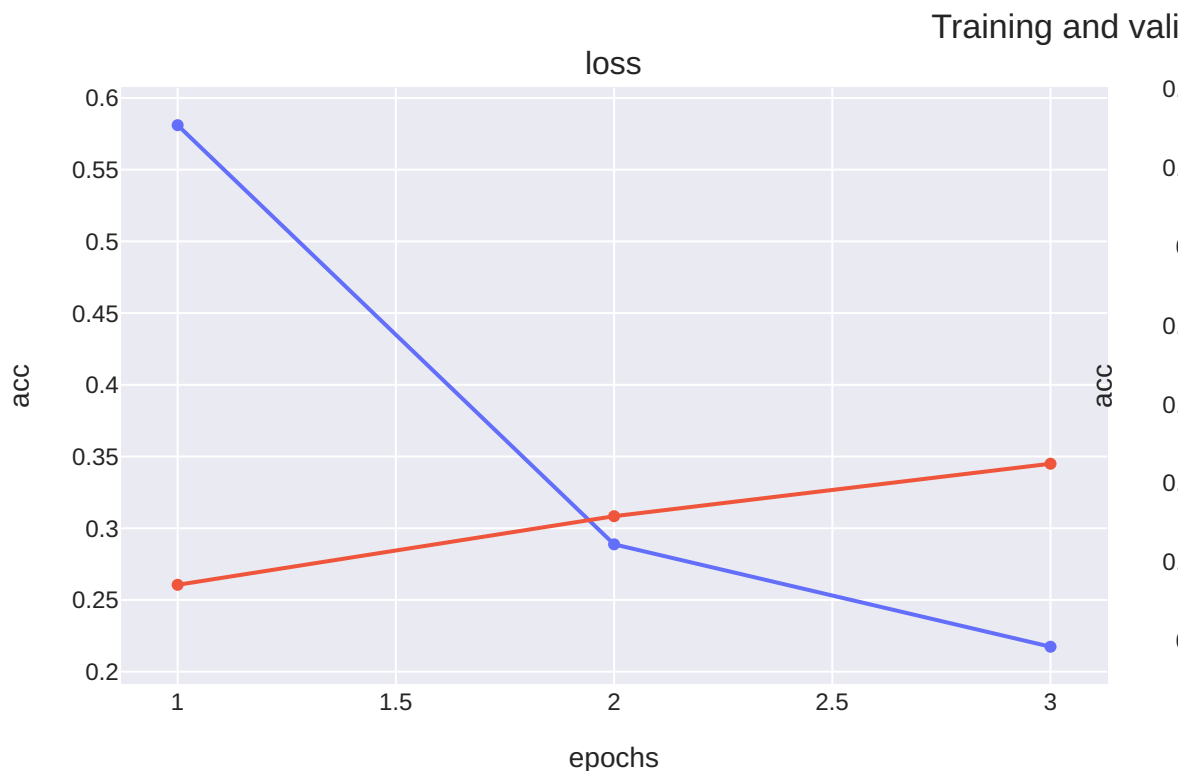
flatten_6 (Flatten)	multiple	0
dense_17 (Dense)	multiple	20481000
dense_18 (Dense)	multiple	5005

```

=====
Total params: 22743989 (86.76 MB)
Trainable params: 22709877 (86.63 MB)
Non-trainable params: 34112 (133.25 KB)
=====

```

```
In [ ]: plot_history(mobile_f_history, ['loss', 'acc'], name=f'{mobile_f.name} Mo
```



Xception

```
In [ ]: xception_f = PretrainedModel(num_classes=5, img_size=IMG_SIZE, pretrained
optimizer = Adam(learning_rate=1e-3)
xception_f.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")

print("Training only the classifier")
xception_f_history = train_model(
    xception_f,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=3,
    val_patience=5,
).history

print("Finetuning the model with a learning rate of 1e-5")
xception_f.trainable = True
```

```
optimizer = Adam(learning_rate=1e-5)
xception_f.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")

xception_f_history = train_model(
    xception_f,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=2,
    val_patience=2,
).history

print(
    f"Final loss: training -> {xception_f_history['loss'][-1]:.2f}, valid
)
print(
    f"Final accuracy: training -> {xception_f_history['acc'][-1]:.2f}, va
)
test_loss, test_accuracy = xception_f.evaluate(test_dataset, batch_size=B
print(
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_ac
)
xception_f.summary()
```

Training only the classifier

Epoch 1/50

45/45 [=====] - 7s 109ms/step - loss: 3.1739 - acc: 0.8092 - val_loss: 0.4876 - val_acc: 0.8936 - lr: 0.0010

Epoch 2/50

45/45 [=====] - 6s 104ms/step - loss: 0.2881 - acc: 0.9221 - val_loss: 0.3135 - val_acc: 0.9065 - lr: 0.0010

Epoch 3/50

45/45 [=====] - 6s 104ms/step - loss: 0.1798 - acc: 0.9403 - val_loss: 0.2606 - val_acc: 0.9184 - lr: 0.0010

Epoch 4/50

45/45 [=====] - 5s 92ms/step - loss: 0.1568 - acc: 0.9437 - val_loss: 0.2925 - val_acc: 0.9075 - lr: 0.0010

Epoch 5/50

45/45 [=====] - 5s 92ms/step - loss: 0.1160 - acc: 0.9564 - val_loss: 0.2681 - val_acc: 0.9134 - lr: 0.0010

Epoch 6/50

45/45 [=====] - 5s 92ms/step - loss: 0.1087 - acc: 0.9601 - val_loss: 0.2931 - val_acc: 0.9174 - lr: 0.0010

Epoch 7/50

45/45 [=====] - 5s 90ms/step - loss: 0.0717 - acc: 0.9761 - val_loss: 0.2623 - val_acc: 0.9144 - lr: 2.0000e-04

Epoch 8/50

45/45 [=====] - 6s 103ms/step - loss: 0.0602 - acc: 0.9828 - val_loss: 0.2582 - val_acc: 0.9149 - lr: 2.0000e-04

Epoch 9/50

45/45 [=====] - 5s 93ms/step - loss: 0.0555 - acc: 0.9854 - val_loss: 0.2591 - val_acc: 0.9154 - lr: 2.0000e-04

Epoch 10/50

45/45 [=====] - 5s 91ms/step - loss: 0.0529 - acc: 0.9866 - val_loss: 0.2611 - val_acc: 0.9179 - lr: 2.0000e-04

Epoch 11/50

45/45 [=====] - 5s 94ms/step - loss: 0.0475 - acc: 0.9896 - val_loss: 0.2585 - val_acc: 0.9189 - lr: 2.0000e-04

Epoch 12/50

45/45 [=====] - 6s 102ms/step - loss: 0.0426 - acc: 0.9909 - val_loss: 0.2576 - val_acc: 0.9164 - lr: 4.0000e-05

Epoch 13/50

45/45 [=====] - 5s 90ms/step - loss: 0.0417 - acc: 0.9917 - val_loss: 0.2580 - val_acc: 0.9174 - lr: 4.0000e-05

Epoch 14/50

45/45 [=====] - 5s 92ms/step - loss: 0.0411 - acc: 0.9920 - val_loss: 0.2582 - val_acc: 0.9169 - lr: 4.0000e-05

Epoch 15/50

45/45 [=====] - 5s 90ms/step - loss: 0.0401 - acc: 0.9921 - val_loss: 0.2586 - val_acc: 0.9164 - lr: 4.0000e-05

Epoch 16/50

45/45 [=====] - 5s 91ms/step - loss: 0.0393 - acc: 0.9924 - val_loss: 0.2584 - val_acc: 0.9203 - lr: 8.0000e-06

Epoch 17/50

45/45 [=====] - 5s 91ms/step - loss: 0.0388 - acc: 0.9926 - val_loss: 0.2585 - val_acc: 0.9198 - lr: 8.0000e-06

Finetuning the model with a learning rate of 1e-5

Epoch 1/50

45/45 [=====] - 25s 237ms/step - loss: 0.7941 - acc: 0.7098 - val_loss: 0.2801 - val_acc: 0.8996 - lr: 1.0000e-05

Epoch 2/50

45/45 [=====] - 8s 153ms/step - loss: 0.4428 - acc: 0.8434 - val_loss: 0.2804 - val_acc: 0.8971 - lr: 1.0000e-05

Epoch 3/50

```

45/45 [=====] - 8s 154ms/step - loss: 0.2844 - ac
c: 0.8967 - val_loss: 0.2906 - val_acc: 0.8926 - lr: 1.0000e-05
Final loss: training -> 0.28, validation -> 0.29
Final accuracy: training -> 0.90, validation -> 0.89
6/6 [=====] - 1s 51ms/step - loss: 0.2098 - acc:
0.9185
Model evaluated: Test Loss-> 0.20984682440757751, Test Accuracy -> 91.85%
Model: "Xception-f"

```

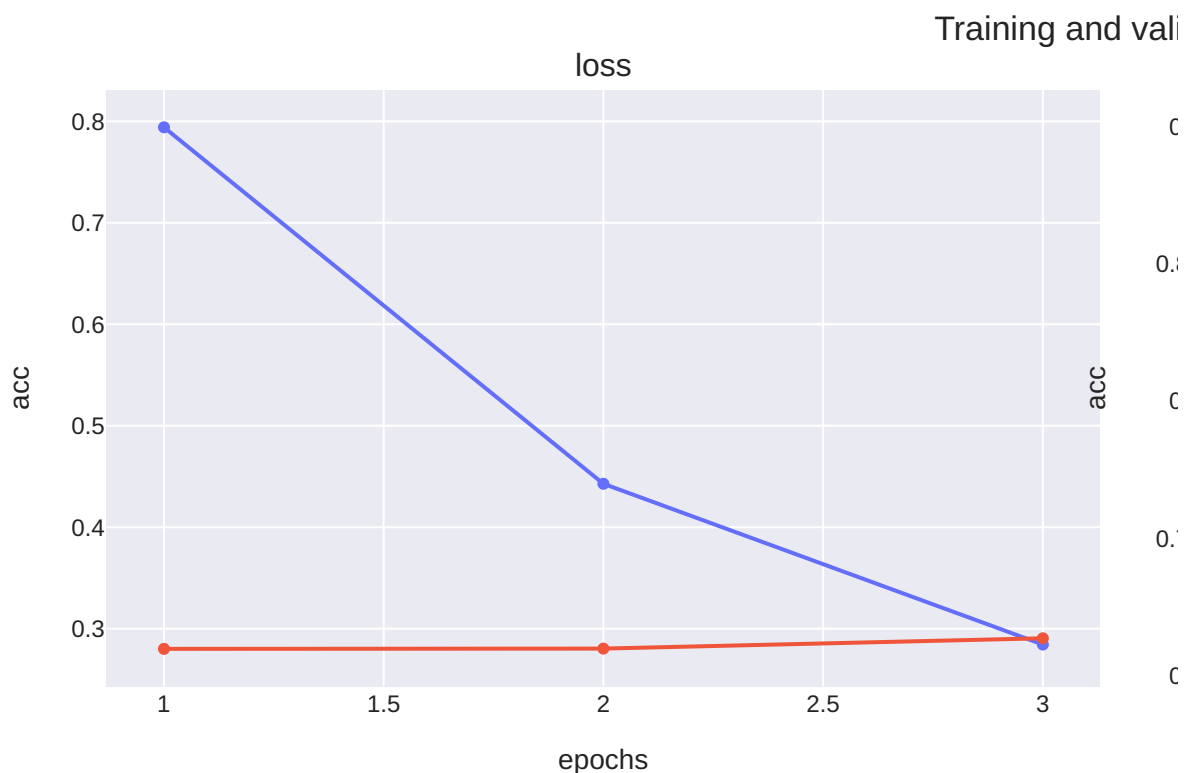
Layer (type)	Output Shape	Param #
rescaling_10 (Rescaling)	multiple	0
xception (Functional)	(None, 3, 3, 2048)	20861480
flatten_7 (Flatten)	multiple	0
dense_19 (Dense)	multiple	18433000
dense_20 (Dense)	multiple	5005

```

=====
Total params: 39299485 (149.92 MB)
Trainable params: 39244957 (149.71 MB)
Non-trainable params: 54528 (213.00 KB)

```

```
In [ ]: plot_history(xception_f_history, ['loss', 'acc'], name=f'{xception_f.name}
```



3.3. Partial fine-tuning

ResNet-50 V2

```
In [ ]: resnet_d = PretrainedModel(num_classes=5, img_size=IMG_SIZE, pretrained=''
```

```
optimizer = Adam(learning_rate=1e-4)
resnet_d.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
resnet_d_history = train_model(
    resnet_d,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=5,
    val_patience=10
).history
print(
    f"Final loss: training -> {resnet_d_history['loss'][-1]:.2f}, validation loss -> {resnet_d_history['val_loss'][-1]:.2f}"
)
print(
    f"Final accuracy: training -> {resnet_d_history['acc'][-1]:.2f}, validation accuracy -> {resnet_d_history['val_acc'][-1]:.2f}"
)
test_loss, test_accuracy = resnet_d.evaluate(test_dataset, batch_size=BATCH_SIZE)
print(
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_accuracy}"
)
resnet_d.summary()
```

```

Epoch 1/50
45/45 [=====] - 18s 168ms/step - loss: 0.6909 - acc: 0.7916 - val_loss: 0.5427 - val_acc: 0.8946 - lr: 1.0000e-04
Epoch 2/50
45/45 [=====] - 8s 159ms/step - loss: 0.0937 - acc: 0.9708 - val_loss: 0.3556 - val_acc: 0.9164 - lr: 1.0000e-04
Epoch 3/50
45/45 [=====] - 7s 135ms/step - loss: 0.0135 - acc: 0.9967 - val_loss: 0.3649 - val_acc: 0.9218 - lr: 1.0000e-04
Epoch 4/50
45/45 [=====] - 7s 136ms/step - loss: 0.0031 - acc: 0.9994 - val_loss: 0.4143 - val_acc: 0.9159 - lr: 1.0000e-04
Epoch 5/50
45/45 [=====] - 7s 137ms/step - loss: 0.0015 - acc: 0.9997 - val_loss: 0.3986 - val_acc: 0.9208 - lr: 1.0000e-04
Epoch 6/50
45/45 [=====] - 7s 135ms/step - loss: 0.0010 - acc: 0.9997 - val_loss: 0.3972 - val_acc: 0.9213 - lr: 1.0000e-04
Epoch 7/50
45/45 [=====] - 7s 135ms/step - loss: 7.2656e-04 - acc: 0.9997 - val_loss: 0.3969 - val_acc: 0.9198 - lr: 1.0000e-04
Epoch 8/50
45/45 [=====] - 7s 135ms/step - loss: 6.2142e-04 - acc: 0.9998 - val_loss: 0.3918 - val_acc: 0.9184 - lr: 2.0000e-05
Epoch 9/50
45/45 [=====] - 7s 135ms/step - loss: 5.8788e-04 - acc: 0.9997 - val_loss: 0.3894 - val_acc: 0.9189 - lr: 2.0000e-05
Epoch 10/50
45/45 [=====] - 7s 136ms/step - loss: 5.1186e-04 - acc: 0.9997 - val_loss: 0.3876 - val_acc: 0.9184 - lr: 2.0000e-05
Epoch 11/50
45/45 [=====] - 7s 136ms/step - loss: 4.7585e-04 - acc: 0.9997 - val_loss: 0.3882 - val_acc: 0.9169 - lr: 2.0000e-05
Epoch 12/50
45/45 [=====] - 7s 132ms/step - loss: 5.2060e-04 - acc: 0.9997 - val_loss: 0.3874 - val_acc: 0.9169 - lr: 2.0000e-05
Final loss: training -> 0.00, validation -> 0.39
Final accuracy: training -> 1.00, validation -> 0.92
6/6 [=====] - 1s 52ms/step - loss: 0.3425 - acc: 0.9279
Model evaluated: Test Loss-> 0.3424745500087738, Test Accuracy -> 92.79%
Model: "ResNet-d"

```

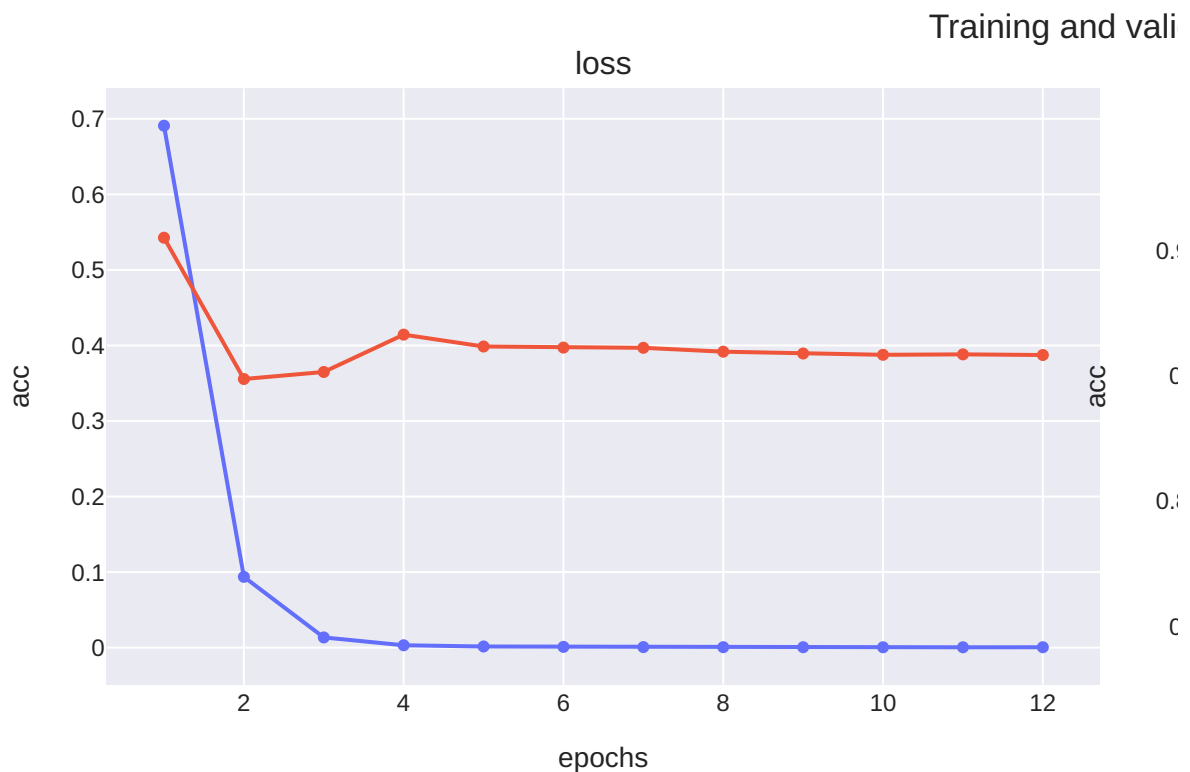
Layer (type)	Output Shape	Param #
rescaling_11 (Rescaling)	multiple	0
resnet50v2 (Functional)	(None, 4, 4, 2048)	23564800
flatten_8 (Flatten)	multiple	0
dense_21 (Dense)	multiple	32769000
dense_22 (Dense)	multiple	5005

```

=====
Total params: 56338805 (214.92 MB)
Trainable params: 52877301 (201.71 MB)
Non-trainable params: 3461504 (13.20 MB)

```

```
In [ ]: plot_history(resnet_d_history, ['loss', 'acc'], name=f'{resnet_d.name} Mo
```



MobileNet V2

```
In [ ]: mobile_d = PretrainedModel(num_classes=5, img_size=IMG_SIZE, pretrained='
optimizer = Adam(learning_rate=1e-4)
mobile_d.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
mobile_d_history = train_model(
    mobile_d,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=5,
    val_patience=10
).history
print(
    f"Final loss: training -> {mobile_d_history['loss'][-1]:.2f}, validation
)
print(
    f"Final accuracy: training -> {mobile_d_history['acc'][-1]:.2f}, validation
)
test_loss, test_accuracy = mobile_d.evaluate(test_dataset, batch_size=BATCH_SIZE)
print(
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_accuracy}
)
mobile_d.summary()
```

```

Epoch 1/50
45/45 [=====] - 14s 112ms/step - loss: 0.9545 - acc: 0.7648 - val_loss: 0.4478 - val_acc: 0.8822 - lr: 1.0000e-04
Epoch 2/50
45/45 [=====] - 6s 113ms/step - loss: 0.1360 - acc: 0.9521 - val_loss: 0.4290 - val_acc: 0.8966 - lr: 1.0000e-04
Epoch 3/50
45/45 [=====] - 5s 91ms/step - loss: 0.0524 - acc: 0.9856 - val_loss: 0.5211 - val_acc: 0.8916 - lr: 1.0000e-04
Epoch 4/50
45/45 [=====] - 5s 92ms/step - loss: 0.0193 - acc: 0.9974 - val_loss: 0.5562 - val_acc: 0.8951 - lr: 1.0000e-04
Epoch 5/50
45/45 [=====] - 5s 92ms/step - loss: 0.0082 - acc: 0.9994 - val_loss: 0.5790 - val_acc: 0.8966 - lr: 1.0000e-04
Epoch 6/50
45/45 [=====] - 5s 90ms/step - loss: 0.0050 - acc: 0.9997 - val_loss: 0.6040 - val_acc: 0.8976 - lr: 1.0000e-04
Epoch 7/50
45/45 [=====] - 5s 92ms/step - loss: 0.0033 - acc: 0.9997 - val_loss: 0.5802 - val_acc: 0.9015 - lr: 1.0000e-04
Epoch 8/50
45/45 [=====] - 5s 90ms/step - loss: 0.0025 - acc: 0.9998 - val_loss: 0.5748 - val_acc: 0.9010 - lr: 2.0000e-05
Epoch 9/50
45/45 [=====] - 5s 91ms/step - loss: 0.0020 - acc: 0.9999 - val_loss: 0.5766 - val_acc: 0.9010 - lr: 2.0000e-05
Epoch 10/50
45/45 [=====] - 5s 93ms/step - loss: 0.0018 - acc: 0.9997 - val_loss: 0.5791 - val_acc: 0.9015 - lr: 2.0000e-05
Epoch 11/50
45/45 [=====] - 5s 92ms/step - loss: 0.0017 - acc: 0.9998 - val_loss: 0.5578 - val_acc: 0.9045 - lr: 2.0000e-05
Epoch 12/50
45/45 [=====] - 5s 92ms/step - loss: 0.0015 - acc: 0.9998 - val_loss: 0.5395 - val_acc: 0.9065 - lr: 2.0000e-05
Final loss: training -> 0.00, validation -> 0.54
Final accuracy: training -> 1.00, validation -> 0.91
6/6 [=====] - 0s 29ms/step - loss: 0.3581 - acc: 0.9359
Model evaluated: Test Loss-> 0.3581494092941284, Test Accuracy -> 93.59%
Model: "Mobile-d"

```

Layer (type)	Output Shape	Param #
rescaling_12 (Rescaling)	multiple	0
mobilenetv2_1.00_224 (Functional)	(None, 4, 4, 1280)	2257984
flatten_9 (Flatten)	multiple	0
dense_23 (Dense)	multiple	20481000
dense_24 (Dense)	multiple	5005

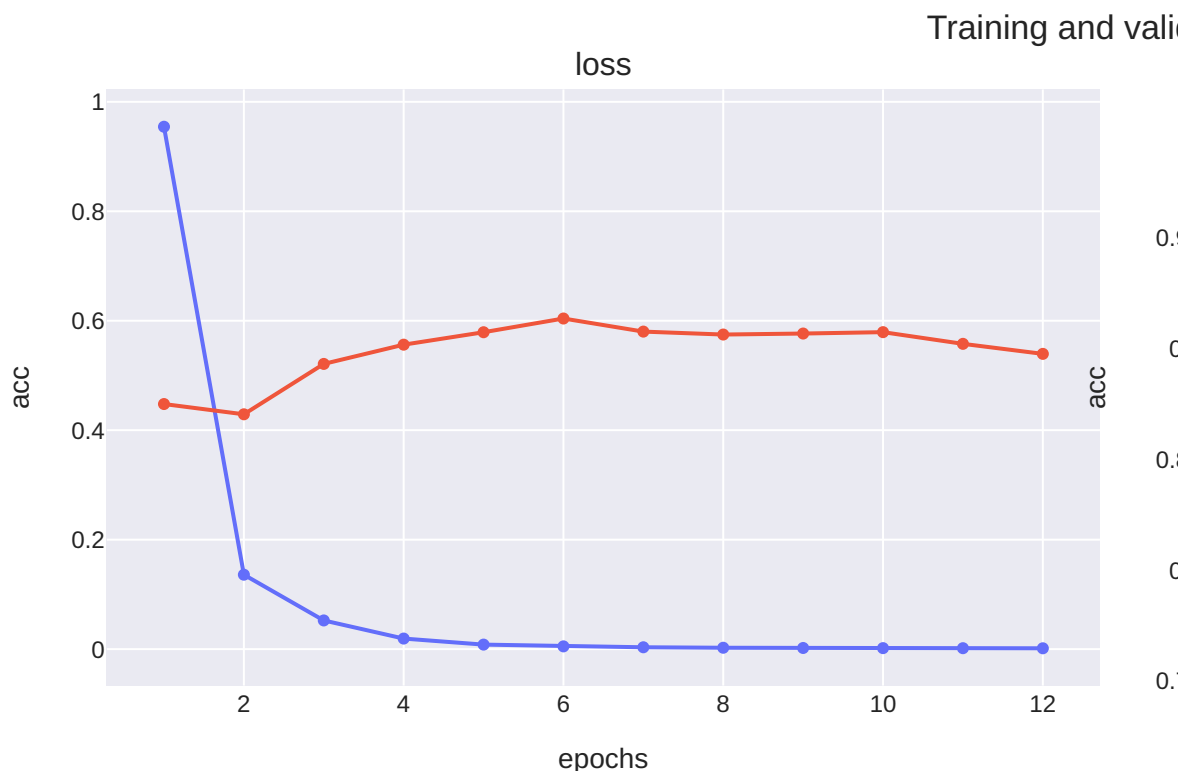
```

=====
Total params: 22743989 (86.76 MB)
Trainable params: 21977397 (83.84 MB)
Non-trainable params: 766592 (2.92 MB)

```



```
In [ ]: plot_history(mobile_d_history, ['loss', 'acc'], name=f'{mobile_d.name} Mo
```



Xception

```
In [ ]: xception_d = PretrainedModel(num_classes=5, img_size=IMG_SIZE, pretrained
optimizer = Adam(learning_rate=1e-4)
xception_d.compile(optimizer=optimizer, loss="sparse_categorical_crossentropy")
xception_d_history = train_model(
    xception_d,
    train_dataset,
    val_dataset,
    path=model_dir,
    epochs=50,
    verbose=1,
    lr_patience=5,
    val_patience=10
).history
print(
    f"Final loss: training -> {xception_d_history['loss'][-1]:.2f}, validation -> {xception_d_history['val_loss'][-1]:.2f}"
)
print(
    f"Final accuracy: training -> {xception_d_history['acc'][-1]:.2f}, validation -> {xception_d_history['val_acc'][-1]:.2f}"
)
test_loss, test_accuracy = xception_d.evaluate(test_dataset, batch_size=BATCH_SIZE)
print(
    f"Model evaluated: Test Loss-> {test_loss}, Test Accuracy -> {test_accuracy}"
)
xception_d.summary()
```

```

Epoch 1/50
45/45 [=====] - 16s 170ms/step - loss: 1.8568 - acc: 0.5821 - val_loss: 0.6590 - val_acc: 0.7848 - lr: 1.0000e-04
Epoch 2/50
45/45 [=====] - 8s 163ms/step - loss: 0.3390 - acc: 0.8896 - val_loss: 0.2381 - val_acc: 0.9144 - lr: 1.0000e-04
Epoch 3/50
45/45 [=====] - 8s 164ms/step - loss: 0.1013 - acc: 0.9652 - val_loss: 0.1830 - val_acc: 0.9391 - lr: 1.0000e-04
Epoch 4/50
45/45 [=====] - 8s 148ms/step - loss: 0.0284 - acc: 0.9921 - val_loss: 0.1851 - val_acc: 0.9426 - lr: 1.0000e-04
Epoch 5/50
45/45 [=====] - 8s 147ms/step - loss: 0.0101 - acc: 0.9975 - val_loss: 0.1981 - val_acc: 0.9436 - lr: 1.0000e-04
Epoch 6/50
45/45 [=====] - 8s 146ms/step - loss: 0.0051 - acc: 0.9989 - val_loss: 0.2235 - val_acc: 0.9461 - lr: 1.0000e-04
Epoch 7/50
45/45 [=====] - 8s 147ms/step - loss: 0.0024 - acc: 0.9996 - val_loss: 0.2336 - val_acc: 0.9461 - lr: 1.0000e-04
Epoch 8/50
45/45 [=====] - 8s 146ms/step - loss: 0.0021 - acc: 0.9996 - val_loss: 0.2445 - val_acc: 0.9471 - lr: 1.0000e-04
Epoch 9/50
45/45 [=====] - 8s 147ms/step - loss: 0.0011 - acc: 0.9998 - val_loss: 0.2484 - val_acc: 0.9476 - lr: 2.0000e-05
Epoch 10/50
45/45 [=====] - 8s 147ms/step - loss: 9.8106e-04 - acc: 0.9997 - val_loss: 0.2540 - val_acc: 0.9461 - lr: 2.0000e-05
Epoch 11/50
45/45 [=====] - 8s 147ms/step - loss: 8.8258e-04 - acc: 0.9997 - val_loss: 0.2531 - val_acc: 0.9461 - lr: 2.0000e-05
Epoch 12/50
45/45 [=====] - 8s 147ms/step - loss: 7.6186e-04 - acc: 0.9997 - val_loss: 0.2559 - val_acc: 0.9461 - lr: 2.0000e-05
Epoch 13/50
45/45 [=====] - 8s 146ms/step - loss: 8.8458e-04 - acc: 0.9997 - val_loss: 0.2575 - val_acc: 0.9456 - lr: 2.0000e-05
Final loss: training -> 0.00, validation -> 0.26
Final accuracy: training -> 1.00, validation -> 0.95
6/6 [=====] - 1s 50ms/step - loss: 0.2511 - acc: 0.9486
Model evaluated: Test Loss-> 0.2511465847492218, Test Accuracy -> 94.86%
Model: "Xception-d"

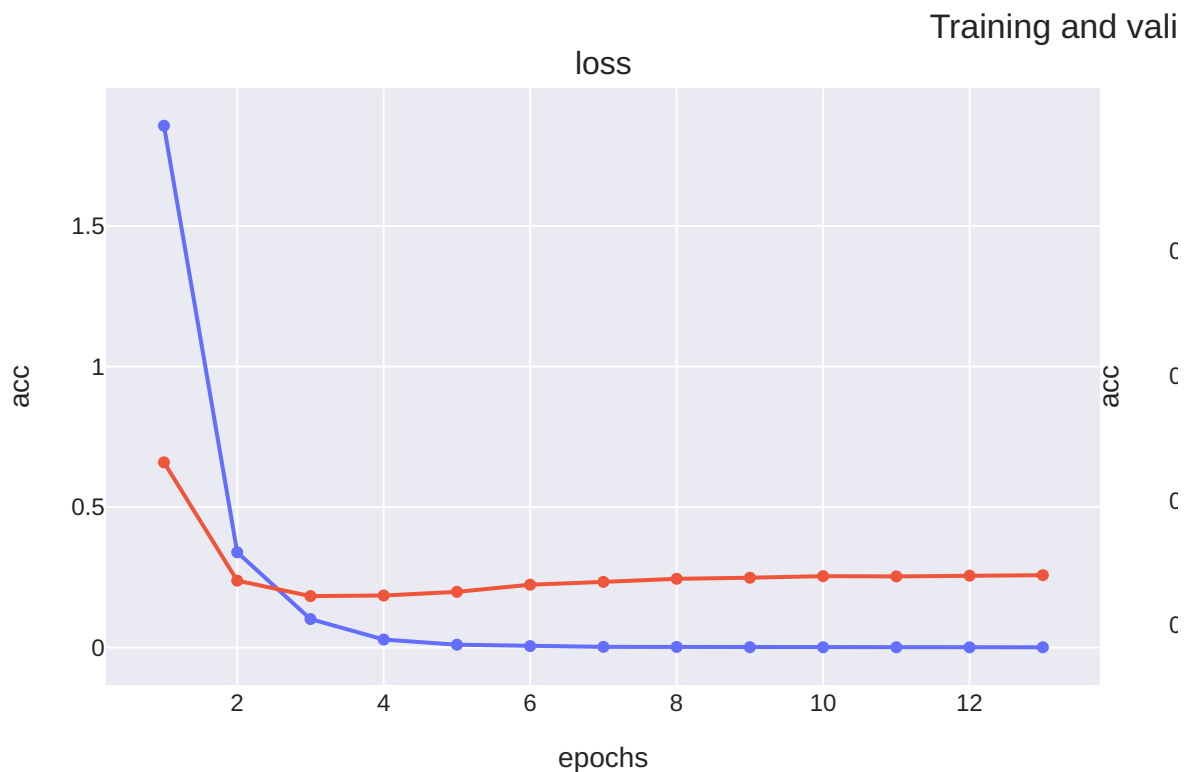
```

Layer (type)	Output Shape	Param #
rescaling_13 (Rescaling)	multiple	0
xception (Functional)	(None, 3, 3, 2048)	20861480
flatten_10 (Flatten)	multiple	0
dense_25 (Dense)	multiple	18433000
dense_26 (Dense)	multiple	5005

=====
Total params: 39299485 (149.92 MB)

Trainable params: 33748637 (128.74 MB)
 Non-trainable params: 5550848 (21.17 MB)

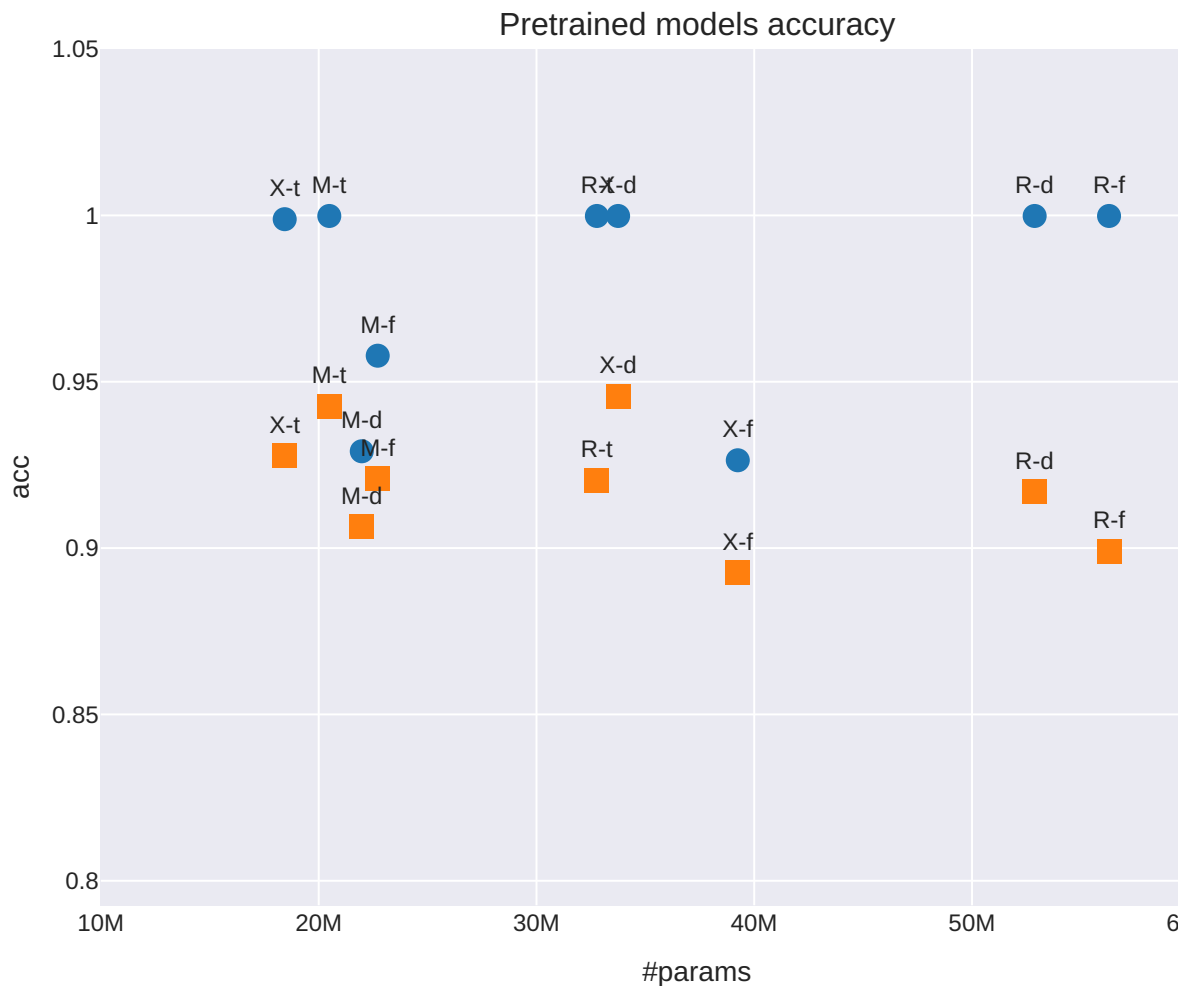
```
In [ ]: plot_history(xception_d_history, ['loss', 'acc'], name=f'{xception_d.name}
```



3.4. Comparison between pretrained approaches

The next figure shows the train and test performance of each pretrained model with the number of trainable parameters. We have abbreviated the names with the first character and a suffix indicating the transfer-learning (t), finetuning (f) and partial-finetuning (d) approaches.

```
In [ ]: # abbreviate names
names = ['R-t', 'R-f', 'R-d', 'M-t', 'M-f', 'M-d', 'X-t', 'X-f', 'X-d']
models = [resnet_t, resnet_f, resnet_d, mobile_t, mobile_f, mobile_d, xce
for model, name in zip(models, names):
    model._name = name
comparison(models, (train_dataset, val_dataset), titles=['Pretrained mode
```



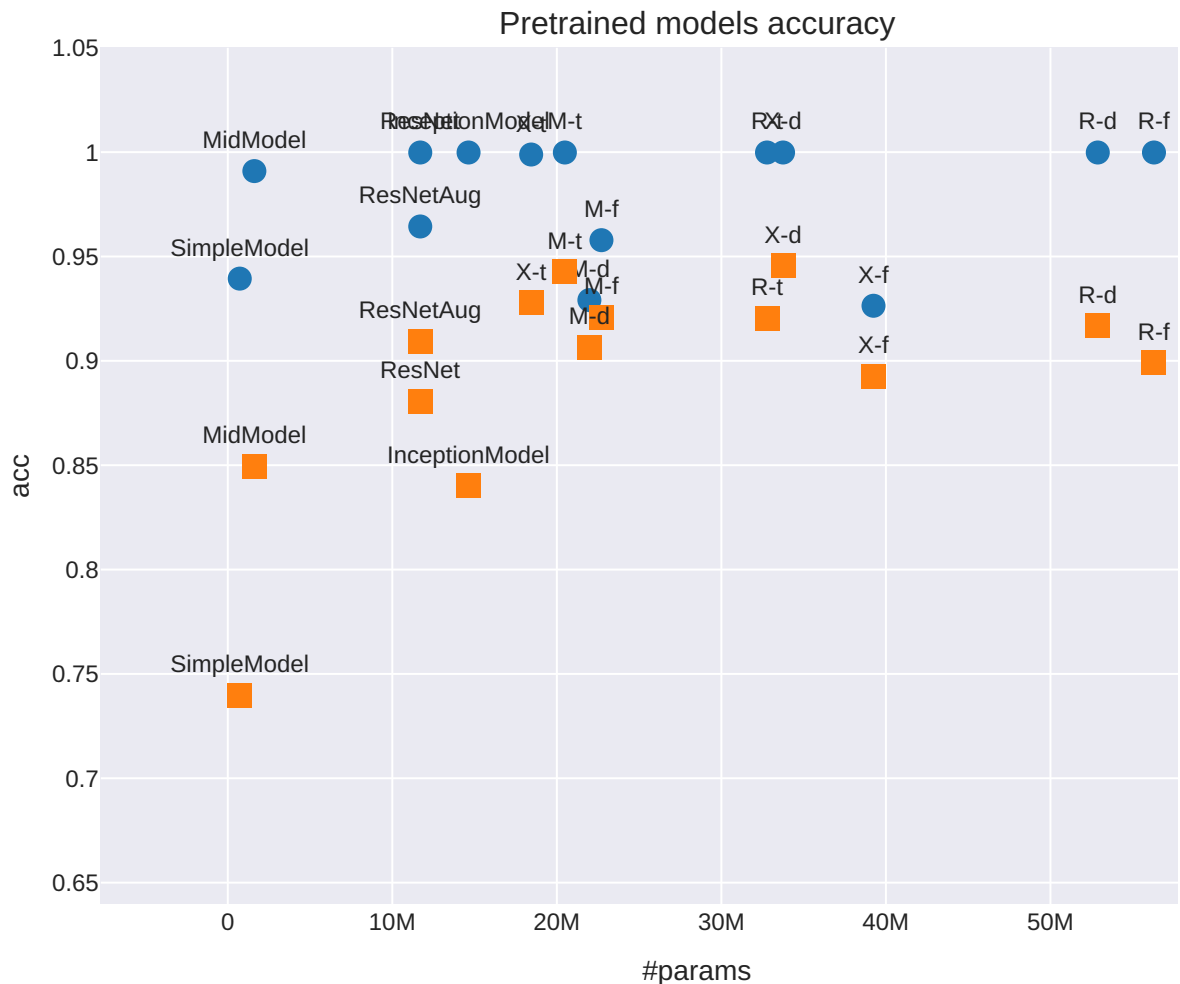
We can derive some conclusions about the above figure:

1. The best performance is achieved with the MobileNetV2 with transfer learning and Xception with partial fine-tuning.
2. In general terms, MobileNetV2 retrieves the better results, followed by Xception and finally ResNet50-V2.
3. Fine-tuning with Xception and ResNet50-V2 obtains the worst results (less than 90% of accuracy).
4. Although the number of trainable parameters is higher in the fine-tuning approaches, they yield the less overfitting results. This behavior might be due to the difference between the original pretraining image resolution (224×224) and the image resolution used for the animals dataset. Forcing the first layers to maintain the same weights might cause the models to skip some local features that are used to generalize the classification information.

4. Results and comparison

```
In [ ]: models = [
    simple_model, mid_model, inception, resnet, resnet_data_aug,
    resnet_t, resnet_f, resnet_d, mobile_t, mobile_f, mobile_d, xception_
]

comparison(models, (train_dataset, val_dataset), titles=['Pretrained mode
```



The figure above shows a final comparison of all models trained in this notebook. In general terms, the pretrained architectures retrieve the best performance and overfitting level. Although the pretrained architectures are larger than the custom models, they can maintain the accuracy and generalization (avoiding overfitting) for encoding a lot of image information in their hidden layers and use a smaller learning rate to finetune them. Only the ResNet custom model is able to reach a lower overfitting level (similar to pretrained models): this success is obtained due to the data augmentation technique, which simulates the pretraining process by allowing the model to see a large number of diverse images.