assignment-aml-cats

April 4, 2024

Group - 03 Assignment by Gaurav Kudeshia & Anurodh Singh

Assignment-2: Exploring Convolutional Neural Networks (CNNs)

The primary aim of this assignment is to explore the capabilities of Convolutional Neural Networks in identifying and classifying objects within images. Students will engage in practical application of CNNs on image datasets, leveraging pre-trained models to evaluate their effectiveness and performance.

[1]:

```
!unzip -/fs/ess/PGS0341/BA_64061_KSU_SEC1/data/dogs-vs-cats.zip
```

```
UnZip 6.00 of 20 April 2009, by Info-ZIP.  Maintained by C. Spieler.  Send
bug reports using http://www.info-zip.org/zip-bug.html; see README for details.

Usage: unzip [-Z] [-opts[modifiers]] file[.zip] [list] [-x xlist] [-d exdir]
  Default action is to extract files in list, except those in xlist, to exdir;
  file[.zip] may be a wildcard.  -Z => ZipInfo mode ("unzip -Z" for usage).

  -p  extract files to pipe, no messages     -l  list files (short format)
  -f  freshen existing files, create none    -t  test compressed archive data
  -u  update files, create if necessary      -z  display archive comment only
  -v  list verbosely/show version info       -T  timestamp archive to latest
  -x  exclude files that follow (in xlist)   -d  extract files into exdir
modifiers:
  -n  never overwrite existing files         -q  quiet mode (-qq => quieter)
  -o  overwrite files WITHOUT prompting      -a  auto-convert any text files
  -j  junk paths (do not make directories)   -aa treat ALL files as text
  -U  use escapes for all non-ASCII Unicode  -UU ignore any Unicode fields
  -C  match filenames case-insensitively     -L  make (some) names lowercase
  -X  restore UID/GID info                   -V  retain VMS version numbers
  -K  keep setuid/setgid/tacky permissions   -M  pipe through "more" pager
  -O CHARSET  specify a character encoding for DOS, Windows and OS/2 archives
  -I CHARSET  specify a character encoding for UNIX and other archives

See "unzip -hh" or unzip.txt for more help.  Examples:
  unzip data1 -x joe   => extract all files except joe from zipfile data1.zip
  unzip -p foo | more  => send contents of foo.zip via pipe into program more
  unzip -fo foo ReadMe => quietly replace existing ReadMe if archive file newer
```

[2]:
```
!unzip -o -qq /fs/ess/PGS0341/BA_64061_KSU_SEC1/data/dogs-vs-cats.zip
```

[3]:
```
!unzip -qq/fs/ess/PGS0341/BA_64061_KSU_SEC1/data/dogs-vs-cats train.zip
```

```
UnZip 6.00 of 20 April 2009, by Info-ZIP.  Maintained by C. Spieler.  Send
bug reports using http://www.info-zip.org/zip-bug.html; see README for details.

Usage: unzip [-Z] [-opts[modifiers]] file[.zip] [list] [-x xlist] [-d exdir]
  Default action is to extract files in list, except those in xlist, to exdir;
  file[.zip] may be a wildcard.  -Z => ZipInfo mode ("unzip -Z" for usage).

  -p  extract files to pipe, no messages     -l  list files (short format)
  -f  freshen existing files, create none    -t  test compressed archive data
  -u  update files, create if necessary      -z  display archive comment only
  -v  list verbosely/show version info       -T  timestamp archive to latest
  -x  exclude files that follow (in xlist)   -d  extract files into exdir
modifiers:
  -n  never overwrite existing files         -q  quiet mode (-qq => quieter)
  -o  overwrite files WITHOUT prompting      -a  auto-convert any text files
  -j  junk paths (do not make directories)   -aa treat ALL files as text
  -U  use escapes for all non-ASCII Unicode  -UU ignore any Unicode fields
  -C  match filenames case-insensitively     -L  make (some) names lowercase
  -X  restore UID/GID info                   -V  retain VMS version numbers
  -K  keep setuid/setgid/tacky permissions   -M  pipe through "more" pager
  -O CHARSET  specify a character encoding for DOS, Windows and OS/2 archives
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  unzip -p foo | more  => send contents of foo.zip via pipe into program more
  unzip -fo foo ReadMe => quietly replace existing ReadMe if archive file newer
```

Q1, Consider the Cats & Dogs example. Start initially with a training sample of 1000, a validation sample of 500, and a test sample of 500 (like in the text). Use any technique to reduce overfitting and improve performance in developing a network that you train from scratch. What performance did you achieve?

We're going to build a convolutional neural network from the ground up. Having loaded our dataset, it's time to split it into distinct subsets for training, validation, and testing. For this project, we'll allocate 1,000 images for training purposes, 500 images for validation, and another 500 images will be used for the test set.

Organizing the Dataset into Training, Validation, and Testing Groups

[4]:
```python
import os, shutil, pathlib

original_dir = pathlib.Path("train")
new_base_dir = pathlib.Path("cats_vs_dogs_small")
```

```python
def make_subset(subset_name, start_index, end_index):
    for category in ("cat", "dog"):
        dir = new_base_dir / subset_name / category
        os.makedirs(dir, exist_ok=True)
        fnames = [f"{category}.{i}.jpg" for i in range(start_index, end_index)]
        for fname in fnames:
            src = original_dir / fname
            dst = dir / fname
            shutil.copyfile(src, dst)

make_subset("train", start_index=0, end_index=1000)
make_subset("validation", start_index=1000, end_index=1500)
make_subset("test", start_index=1500, end_index=2000)
```

0.0.1 Constructing the Model

For this network, we begin by processing images, represented as 3D tensors, which are initially reshaped. The process involves applying convolution operations using a 3x3 window (referred to as kernel_size), followed by max pooling operations with a 2x2 window (known as pool_size).

The objective of this task is to categorize the images into two classes: "cat" or "dog". To achieve this, the architecture incorporates a dense layer towards the end, which plays a crucial role in determining the classification of the output as either "cat" or "dog". This classification is facilitated by a single output node corresponding to these categories. Before reaching the dense layer, it's necessary to transform the 3D tensor structure into a 1D format, a step accomplished by introducing a flattening layer.

Creating a Compact Convolutional Network for Cat vs. Dog Classification

[5]:
```python
from tensorflow import keras
from tensorflow.keras import layers

inputs = keras.Input(shape=(180, 180, 3))
x = layers.Rescaling(1./255)(inputs)
x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.Flatten()(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)
```

[6]:
```python
model.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
input_1 (InputLayer)        [(None, 180, 180, 3)]     0

rescaling (Rescaling)       (None, 180, 180, 3)       0

conv2d (Conv2D)             (None, 178, 178, 32)      896

max_pooling2d (MaxPooling2D) (None, 89, 89, 32)       0

conv2d_1 (Conv2D)           (None, 87, 87, 64)        18496

max_pooling2d_1 (MaxPooling2 (None, 43, 43, 64)       0

conv2d_2 (Conv2D)           (None, 41, 41, 128)       73856

max_pooling2d_2 (MaxPooling2 (None, 20, 20, 128)      0

conv2d_3 (Conv2D)           (None, 18, 18, 256)       295168

max_pooling2d_3 (MaxPooling2 (None, 9, 9, 256)        0

conv2d_4 (Conv2D)           (None, 7, 7, 256)         590080

flatten (Flatten)           (None, 12544)             0

dense (Dense)               (None, 1)                 12545
=================================================================
Total params: 991,041
Trainable params: 991,041
Non-trainable params: 0

_________________________________________________________________
```

Setting Up the Model for Training

[7]:
```
model.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
              metrics=["accuracy"])
```

- Performed Data preprocessing process of cleaning and organizing raw data to make it suitable for analysis or modeling

Reading Images with image_dataset_from_directory

[8]:
```
from tensorflow.keras.utils import image_dataset_from_directory

train_dataset = image_dataset_from_directory(
```

```
    new_base_dir / "train",
    image_size=(180, 180),
    batch_size=32)
validation_dataset = image_dataset_from_directory(
    new_base_dir / "validation",
    image_size=(180, 180),
    batch_size=32)
test_dataset = image_dataset_from_directory(
    new_base_dir / "test",
    image_size=(180, 180),
    batch_size=32)
```

```
Found 2000 files belonging to 2 classes.
Found 1000 files belonging to 2 classes.
Found 2000 files belonging to 2 classes.
```

[9]:
```
import numpy as np
import tensorflow as tf
random_numbers = np.random.normal(size=(1000, 16))
dataset = tf.data.Dataset.from_tensor_slices(random_numbers)
```

[10]:
```
for i, element in enumerate(dataset):
    print(element.shape)
    if i >= 2:
        break
```

```
(16,)
(16,)
(16,)
```

[11]:
```
batched_dataset = dataset.batch(32)
for i, element in enumerate(batched_dataset):
    print(element.shape)
    if i >= 2:
        break
```

```
(32, 16)
(32, 16)
(32, 16)
```

[12]:
```
reshaped_dataset = dataset.map(lambda x: tf.reshape(x, (4, 4)))
for i, element in enumerate(reshaped_dataset):
    print(element.shape)
    if i >= 2:
        break
```

```
(4, 4)
(4, 4)
```

```
(4, 4)
```

Showing the Dimensions of Data and Labels Provided by the Dataset

[13]:
```python
for data_batch, labels_batch in train_dataset:
    print("data batch shape:", data_batch.shape)
    print("labels batch shape:", labels_batch.shape)
    break
```

```
data batch shape: (32, 180, 180, 3)
labels batch shape: (32,)
```

Training the Model with a Dataset

[14]:
```python
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=25,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 1/25
63/63 [==============================] - 45s 704ms/step - loss: 0.7334 -
accuracy: 0.5230 - val_loss: 0.6929 - val_accuracy: 0.5000
Epoch 2/25
63/63 [==============================] - 44s 698ms/step - loss: 0.6945 -
accuracy: 0.5090 - val_loss: 0.6858 - val_accuracy: 0.6290
Epoch 3/25
63/63 [==============================] - 44s 695ms/step - loss: 0.6947 -
accuracy: 0.6055 - val_loss: 0.6708 - val_accuracy: 0.5700
Epoch 4/25
63/63 [==============================] - 43s 687ms/step - loss: 0.6471 -
accuracy: 0.6425 - val_loss: 0.6278 - val_accuracy: 0.6490
Epoch 5/25
63/63 [==============================] - 44s 695ms/step - loss: 0.5958 -
accuracy: 0.6925 - val_loss: 0.6844 - val_accuracy: 0.5950
Epoch 6/25
63/63 [==============================] - 44s 695ms/step - loss: 0.5815 -
accuracy: 0.7025 - val_loss: 0.6396 - val_accuracy: 0.6790
Epoch 7/25
63/63 [==============================] - 44s 692ms/step - loss: 0.5408 -
accuracy: 0.7375 - val_loss: 1.0853 - val_accuracy: 0.5790
Epoch 8/25
63/63 [==============================] - 44s 692ms/step - loss: 0.4801 -
```

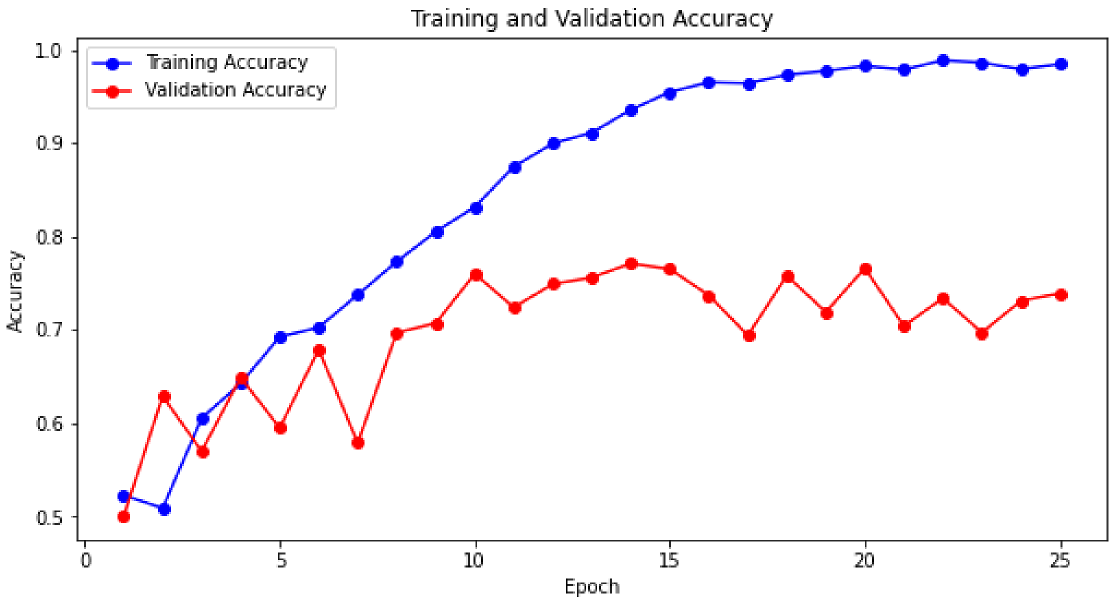
```
accuracy: 0.7730 - val_loss: 0.6306 - val_accuracy: 0.6970
Epoch 9/25
63/63 [==============================] - 43s 689ms/step - loss: 0.4313 -
accuracy: 0.8050 - val_loss: 0.6851 - val_accuracy: 0.7070
Epoch 10/25
63/63 [==============================] - 43s 689ms/step - loss: 0.3686 -
accuracy: 0.8315 - val_loss: 0.5503 - val_accuracy: 0.7600
Epoch 11/25
63/63 [==============================] - 44s 692ms/step - loss: 0.3113 -
accuracy: 0.8745 - val_loss: 0.7121 - val_accuracy: 0.7240
Epoch 12/25
63/63 [==============================] - 44s 700ms/step - loss: 0.2547 -
accuracy: 0.8995 - val_loss: 0.6244 - val_accuracy: 0.7490
Epoch 13/25
63/63 [==============================] - 44s 695ms/step - loss: 0.2186 -
accuracy: 0.9110 - val_loss: 0.7321 - val_accuracy: 0.7560
Epoch 14/25
63/63 [==============================] - 44s 692ms/step - loss: 0.1600 -
accuracy: 0.9355 - val_loss: 0.7764 - val_accuracy: 0.7710
Epoch 15/25
63/63 [==============================] - 44s 695ms/step - loss: 0.1267 -
accuracy: 0.9545 - val_loss: 0.8855 - val_accuracy: 0.7650
Epoch 16/25
63/63 [==============================] - 44s 698ms/step - loss: 0.0955 -
accuracy: 0.9650 - val_loss: 0.9541 - val_accuracy: 0.7370
Epoch 17/25
63/63 [==============================] - 43s 688ms/step - loss: 0.1012 -
accuracy: 0.9640 - val_loss: 1.4772 - val_accuracy: 0.6940
Epoch 18/25
63/63 [==============================] - 43s 689ms/step - loss: 0.0835 -
accuracy: 0.9730 - val_loss: 1.2734 - val_accuracy: 0.7580
Epoch 19/25
63/63 [==============================] - 44s 695ms/step - loss: 0.0641 -
accuracy: 0.9770 - val_loss: 1.9459 - val_accuracy: 0.7190
Epoch 20/25
63/63 [==============================] - 44s 697ms/step - loss: 0.0655 -
accuracy: 0.9825 - val_loss: 1.2097 - val_accuracy: 0.7660
Epoch 21/25
63/63 [==============================] - 44s 694ms/step - loss: 0.0578 -
accuracy: 0.9785 - val_loss: 1.5644 - val_accuracy: 0.7040
Epoch 22/25
63/63 [==============================] - 44s 693ms/step - loss: 0.0519 -
accuracy: 0.9885 - val_loss: 1.4130 - val_accuracy: 0.7340
Epoch 23/25
63/63 [==============================] - 44s 698ms/step - loss: 0.0553 -
accuracy: 0.9860 - val_loss: 2.4004 - val_accuracy: 0.6970
Epoch 24/25
63/63 [==============================] - 44s 692ms/step - loss: 0.0538 -
```

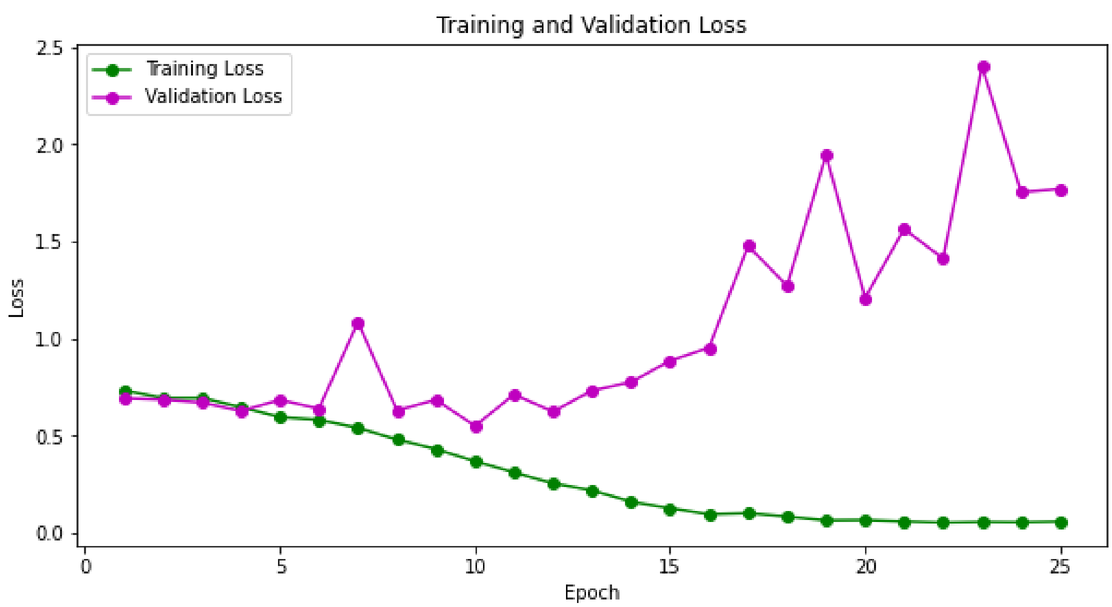
```
accuracy: 0.9790 - val_loss: 1.7538 - val_accuracy: 0.7310
Epoch 25/25
63/63 [==============================] - 44s 690ms/step - loss: 0.0571 -
accuracy: 0.9845 - val_loss: 1.7714 - val_accuracy: 0.7390
```

Visualizing Training Loss and Accuracy Curves

- This code plots training and validation accuracy and loss over epochs for a model's training process, using matplotlib for visualization, with distinct colors to differentiate between training and validation metrics.

[15]:
```python
import matplotlib.pyplot as plt
accuracy = history.history["accuracy"]
val_accuracy = history.history["val_accuracy"]
loss = history.history["loss"]
val_loss = history.history["val_loss"]
epochs = range(1, len(accuracy) + 1)
plt.figure(figsize=(10, 5))
plt.plot(epochs, accuracy, "bo-", label="Training Accuracy")
plt.plot(epochs, val_accuracy, "ro-", label="Validation Accuracy")
plt.title("Training and Validation Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
plt.figure(figsize=(10, 5))
plt.plot(epochs, loss, "go-", label="Training Loss")
plt.plot(epochs, val_loss, "mo-", label="Validation Loss")
plt.title("Training and Validation Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.show()
```





Assessing the model's performance using the test dataset.

[16]:
```
test_model = keras.models.load_model("convnet_from_scratch.keras")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
63/63 [==============================] - 10s 158ms/step - loss: 0.5856 -
accuracy: 0.7230
```

Test accuracy: 0.723

The model's validation and test accuracy currently stands at a relatively low 73%. - To enhance the model's performance, we plan to implement several strategies, including:

a) Data Augmentation

b) Dropout Technique

c) A combination of Data Augmentation and the Dropout Technique

0.0.2 a, By employing data augmentation

Implement a Data Augmentation Stage for an Image Processing Model

[17]:
```
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)
```

Displaying some randomly augmented training images

[18]:
```
plt.figure(figsize=(10, 10))
for images, _ in train_dataset.take(1):
    for i in range(9):
        augmented_images = data_augmentation(images)
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow(augmented_images[0].numpy().astype("uint8"))
        plt.axis("off")
```

Q2. Increasing Training sample size to 2870 samples

[19]:
```
import os, shutil, pathlib

original_dir = pathlib.Path("train")
new_base_dir = pathlib.Path("cats_vs_dogs_small_01")

def make_subset(subset_name, start_index, end_index):
    for category in ("cat", "dog"):
        dir = new_base_dir / subset_name / category
        os.makedirs(dir, exist_ok=True)
        fnames = [f"{category}.{i}.jpg" for i in range(start_index, end_index)]
        for fname in fnames:
            src = original_dir / fname
```

```
            dst = dir / fname
            shutil.copyfile(src, dst)

make_subset("train", start_index=0, end_index=1870)
make_subset("validation", start_index=1870, end_index=2370)
make_subset("test", start_index=2370, end_index=2870)
```

Defining a new convnet that includes image augmentation and dropout

[20]:
```
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = layers.Rescaling(1./255)(x)
x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.Flatten()(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)

model.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
              metrics=["accuracy"])
```

Training the regularized convnet

[22]:
```
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch_with_augmentation.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=35,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 1/35
63/63 [==============================] - 45s 722ms/step - loss: 0.6907 -
accuracy: 0.5510 - val_loss: 0.7387 - val_accuracy: 0.5110
Epoch 2/35
```

```
63/63 [==============================] - 45s 721ms/step - loss: 0.6913 -
accuracy: 0.5815 - val_loss: 0.9297 - val_accuracy: 0.5100
Epoch 3/35
63/63 [==============================] - 45s 722ms/step - loss: 0.6571 -
accuracy: 0.6095 - val_loss: 0.6376 - val_accuracy: 0.6360
Epoch 4/35
63/63 [==============================] - 46s 723ms/step - loss: 0.6472 -
accuracy: 0.6450 - val_loss: 0.5952 - val_accuracy: 0.6810
Epoch 5/35
63/63 [==============================] - 46s 722ms/step - loss: 0.6470 -
accuracy: 0.6610 - val_loss: 0.6258 - val_accuracy: 0.6370
Epoch 6/35
63/63 [==============================] - 45s 722ms/step - loss: 0.6066 -
accuracy: 0.6795 - val_loss: 0.5720 - val_accuracy: 0.6860
Epoch 7/35
63/63 [==============================] - 46s 723ms/step - loss: 0.5778 -
accuracy: 0.6950 - val_loss: 0.6102 - val_accuracy: 0.6630
Epoch 8/35
63/63 [==============================] - 45s 722ms/step - loss: 0.5806 -
accuracy: 0.7045 - val_loss: 0.5716 - val_accuracy: 0.7090
Epoch 9/35
63/63 [==============================] - 45s 722ms/step - loss: 0.5585 -
accuracy: 0.7165 - val_loss: 0.5480 - val_accuracy: 0.7290
Epoch 10/35
63/63 [==============================] - 45s 720ms/step - loss: 0.5590 -
accuracy: 0.7230 - val_loss: 0.5703 - val_accuracy: 0.7010
Epoch 11/35
63/63 [==============================] - 45s 721ms/step - loss: 0.5584 -
accuracy: 0.7315 - val_loss: 0.4896 - val_accuracy: 0.7660
Epoch 12/35
63/63 [==============================] - 45s 721ms/step - loss: 0.5282 -
accuracy: 0.7380 - val_loss: 0.4857 - val_accuracy: 0.7630
Epoch 13/35
63/63 [==============================] - 45s 722ms/step - loss: 0.5061 -
accuracy: 0.7520 - val_loss: 1.0203 - val_accuracy: 0.6330
Epoch 14/35
63/63 [==============================] - 45s 714ms/step - loss: 0.5178 -
accuracy: 0.7575 - val_loss: 0.5314 - val_accuracy: 0.7500
Epoch 15/35
63/63 [==============================] - 46s 724ms/step - loss: 0.5121 -
accuracy: 0.7480 - val_loss: 0.4698 - val_accuracy: 0.7740
Epoch 16/35
63/63 [==============================] - 46s 722ms/step - loss: 0.4759 -
accuracy: 0.7680 - val_loss: 0.4851 - val_accuracy: 0.7660
Epoch 17/35
63/63 [==============================] - 46s 726ms/step - loss: 0.4602 -
accuracy: 0.7805 - val_loss: 0.6508 - val_accuracy: 0.7310
Epoch 18/35
```

```
63/63 [==============================] - 45s 722ms/step - loss: 0.4938 -
accuracy: 0.7695 - val_loss: 0.4623 - val_accuracy: 0.7720
Epoch 19/35
63/63 [==============================] - 46s 723ms/step - loss: 0.4713 -
accuracy: 0.7870 - val_loss: 0.4883 - val_accuracy: 0.7600
Epoch 20/35
63/63 [==============================] - 46s 726ms/step - loss: 0.4420 -
accuracy: 0.7995 - val_loss: 0.5557 - val_accuracy: 0.7230
Epoch 21/35
63/63 [==============================] - 45s 720ms/step - loss: 0.4492 -
accuracy: 0.7960 - val_loss: 0.5078 - val_accuracy: 0.7700
Epoch 22/35
63/63 [==============================] - 46s 724ms/step - loss: 0.4387 -
accuracy: 0.7975 - val_loss: 0.4926 - val_accuracy: 0.7940
Epoch 23/35
63/63 [==============================] - 46s 725ms/step - loss: 0.4290 -
accuracy: 0.8000 - val_loss: 0.4811 - val_accuracy: 0.7700
Epoch 24/35
63/63 [==============================] - 45s 721ms/step - loss: 0.4143 -
accuracy: 0.8125 - val_loss: 0.5426 - val_accuracy: 0.7900
Epoch 25/35
63/63 [==============================] - 46s 726ms/step - loss: 0.4071 -
accuracy: 0.8110 - val_loss: 0.7852 - val_accuracy: 0.7400
Epoch 26/35
63/63 [==============================] - 46s 727ms/step - loss: 0.4192 -
accuracy: 0.8040 - val_loss: 0.4348 - val_accuracy: 0.7990
Epoch 27/35
63/63 [==============================] - 46s 725ms/step - loss: 0.3830 -
accuracy: 0.8315 - val_loss: 0.4999 - val_accuracy: 0.7770
Epoch 28/35
63/63 [==============================] - 46s 727ms/step - loss: 0.4046 -
accuracy: 0.8265 - val_loss: 0.4750 - val_accuracy: 0.7960
Epoch 29/35
63/63 [==============================] - 46s 725ms/step - loss: 0.3807 -
accuracy: 0.8265 - val_loss: 0.4735 - val_accuracy: 0.8040
Epoch 30/35
63/63 [==============================] - 46s 730ms/step - loss: 0.3669 -
accuracy: 0.8380 - val_loss: 0.6172 - val_accuracy: 0.7610
Epoch 31/35
63/63 [==============================] - 46s 730ms/step - loss: 0.3662 -
accuracy: 0.8445 - val_loss: 0.4408 - val_accuracy: 0.8140
Epoch 32/35
63/63 [==============================] - 46s 731ms/step - loss: 0.3606 -
accuracy: 0.8360 - val_loss: 0.6227 - val_accuracy: 0.7520
Epoch 33/35
63/63 [==============================] - 46s 726ms/step - loss: 0.3536 -
accuracy: 0.8460 - val_loss: 0.4926 - val_accuracy: 0.7640
Epoch 34/35
```

```
63/63 [==============================] - 46s 729ms/step - loss: 0.3661 -
accuracy: 0.8310 - val_loss: 0.4792 - val_accuracy: 0.8030
Epoch 35/35
63/63 [==============================] - 46s 724ms/step - loss: 0.3342 -
accuracy: 0.8590 - val_loss: 0.4606 - val_accuracy: 0.8210
```

Assessment of the Model Using the Test Data

[23]:
```
test_model = keras.models.load_model(
    "convnet_from_scratch_with_augmentation.keras")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
63/63 [==============================] - 10s 156ms/step - loss: 0.4613 -
accuracy: 0.8060
Test accuracy: 0.806
```

Q3. Increasing Training sample size to 3100 samples

The number of training samples has been expanded to 3100, and the impact on model performance is discussed in the provided summary.

[24]:
```
import os, shutil, pathlib

original_dir = pathlib.Path("train")
new_base_dir = pathlib.Path("cats_vs_dogs_small_02")

def make_subset(subset_name, start_index, end_index):
    for category in ("cat", "dog"):
        dir = new_base_dir / subset_name / category
        os.makedirs(dir, exist_ok=True)
        fnames = [f"{category}.{i}.jpg" for i in range(start_index, end_index)]
        for fname in fnames:
            src = original_dir / fname
            dst = dir / fname
            shutil.copyfile(src, dst)

make_subset("train", start_index=0, end_index=2100)
make_subset("validation", start_index=2100, end_index=2600)
make_subset("test", start_index=2600, end_index=3100)
```

Defining a new convnet that includes image augmentation and dropout

[25]:
```
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = layers.Rescaling(1./255)(x)
x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
```

```
x = layers.Conv2D(filters=128, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=256, kernel_size=3, activation="relu")(x)
x = layers.Flatten()(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)

model.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
              metrics=["accuracy"])
```

Now, we proceed to train the convnet that has been regularized.

[26]:
```
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch_with_augmentation.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=30,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 1/30
63/63 [==============================] - 47s 738ms/step - loss: 0.7166 -
accuracy: 0.4935 - val_loss: 0.6979 - val_accuracy: 0.5000
Epoch 2/30
63/63 [==============================] - 46s 730ms/step - loss: 0.7024 -
accuracy: 0.5295 - val_loss: 0.7651 - val_accuracy: 0.5020
Epoch 3/30
63/63 [==============================] - 46s 727ms/step - loss: 0.6912 -
accuracy: 0.5735 - val_loss: 0.6773 - val_accuracy: 0.5280
Epoch 4/30
63/63 [==============================] - 46s 722ms/step - loss: 0.6817 -
accuracy: 0.5725 - val_loss: 0.7610 - val_accuracy: 0.5180
Epoch 5/30
63/63 [==============================] - 45s 718ms/step - loss: 0.6530 -
accuracy: 0.6135 - val_loss: 0.6120 - val_accuracy: 0.6490
Epoch 6/30
63/63 [==============================] - 46s 724ms/step - loss: 0.6345 -
accuracy: 0.6365 - val_loss: 0.5809 - val_accuracy: 0.7000
Epoch 7/30
63/63 [==============================] - 46s 722ms/step - loss: 0.6238 -
```

```
accuracy: 0.6535 - val_loss: 0.6259 - val_accuracy: 0.6430
Epoch 8/30
63/63 [==============================] - 46s 726ms/step - loss: 0.6072 -
accuracy: 0.6715 - val_loss: 0.6125 - val_accuracy: 0.6390
Epoch 9/30
63/63 [==============================] - 46s 726ms/step - loss: 0.6031 -
accuracy: 0.6760 - val_loss: 0.6262 - val_accuracy: 0.6690
Epoch 10/30
63/63 [==============================] - 46s 724ms/step - loss: 0.5815 -
accuracy: 0.7025 - val_loss: 0.5756 - val_accuracy: 0.7080
Epoch 11/30
63/63 [==============================] - 46s 724ms/step - loss: 0.5794 -
accuracy: 0.6880 - val_loss: 0.5776 - val_accuracy: 0.7100
Epoch 12/30
63/63 [==============================] - 46s 726ms/step - loss: 0.5669 -
accuracy: 0.7165 - val_loss: 0.5758 - val_accuracy: 0.6970
Epoch 13/30
63/63 [==============================] - 46s 725ms/step - loss: 0.5680 -
accuracy: 0.7155 - val_loss: 0.5694 - val_accuracy: 0.7130
Epoch 14/30
63/63 [==============================] - 45s 718ms/step - loss: 0.5455 -
accuracy: 0.7175 - val_loss: 0.5811 - val_accuracy: 0.7210
Epoch 15/30
63/63 [==============================] - 46s 724ms/step - loss: 0.5231 -
accuracy: 0.7610 - val_loss: 0.6174 - val_accuracy: 0.7100
Epoch 16/30
63/63 [==============================] - 46s 724ms/step - loss: 0.5385 -
accuracy: 0.7420 - val_loss: 0.5854 - val_accuracy: 0.6860
Epoch 17/30
63/63 [==============================] - 45s 722ms/step - loss: 0.5081 -
accuracy: 0.7595 - val_loss: 0.5701 - val_accuracy: 0.7380
Epoch 18/30
63/63 [==============================] - 45s 721ms/step - loss: 0.4947 -
accuracy: 0.7675 - val_loss: 0.4653 - val_accuracy: 0.7760
Epoch 19/30
63/63 [==============================] - 46s 724ms/step - loss: 0.5004 -
accuracy: 0.7670 - val_loss: 0.5739 - val_accuracy: 0.7220
Epoch 20/30
63/63 [==============================] - 45s 722ms/step - loss: 0.4810 -
accuracy: 0.7755 - val_loss: 0.4851 - val_accuracy: 0.7430
Epoch 21/30
63/63 [==============================] - 45s 721ms/step - loss: 0.4805 -
accuracy: 0.7710 - val_loss: 0.4980 - val_accuracy: 0.7700
Epoch 22/30
63/63 [==============================] - 45s 722ms/step - loss: 0.4604 -
accuracy: 0.7815 - val_loss: 0.4482 - val_accuracy: 0.7710
Epoch 23/30
63/63 [==============================] - 45s 721ms/step - loss: 0.4585 -
```

```
accuracy: 0.7775 - val_loss: 0.5678 - val_accuracy: 0.7140
Epoch 24/30
63/63 [==============================] - 45s 722ms/step - loss: 0.4442 -
accuracy: 0.7945 - val_loss: 0.5032 - val_accuracy: 0.7740
Epoch 25/30
63/63 [==============================] - 46s 724ms/step - loss: 0.4345 -
accuracy: 0.8090 - val_loss: 0.4494 - val_accuracy: 0.8010
Epoch 26/30
63/63 [==============================] - 46s 726ms/step - loss: 0.4257 -
accuracy: 0.8020 - val_loss: 0.4452 - val_accuracy: 0.7810
Epoch 27/30
63/63 [==============================] - 46s 722ms/step - loss: 0.4352 -
accuracy: 0.8095 - val_loss: 0.4306 - val_accuracy: 0.7940
Epoch 28/30
63/63 [==============================] - 46s 724ms/step - loss: 0.4342 -
accuracy: 0.8045 - val_loss: 0.4493 - val_accuracy: 0.7910
Epoch 29/30
63/63 [==============================] - 45s 722ms/step - loss: 0.4079 -
accuracy: 0.8225 - val_loss: 0.4519 - val_accuracy: 0.7940
Epoch 30/30
63/63 [==============================] - 46s 723ms/step - loss: 0.3755 -
accuracy: 0.8275 - val_loss: 0.4563 - val_accuracy: 0.7920
```

Evaluating the test dataset

[27]:
```
test_model = keras.models.load_model(
    "convnet_from_scratch_with_augmentation.keras")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
63/63 [==============================] - 10s 153ms/step - loss: 0.5019 -
accuracy: 0.7725
Test accuracy: 0.772
```

Q4.Fine Tuning of the pretrained models

We will adjust the pretrained model by experimenting with various sizes of training samples and then assess its effectiveness based on the performance of the models we previously constructed.

Pre-Trained Model with 1000 Training Samples

Initializing the VGG16 convolutional base and setting it to a non-trainable state

Instantiating the VGG16 convolutional base

[28]:
```
conv_base = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False,
    input_shape=(180, 180, 3))
```

[29]:
```
conv_base.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_4 (InputLayer)         [(None, 180, 180, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 180, 180, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 180, 180, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 90, 90, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 90, 90, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 90, 90, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 45, 45, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 45, 45, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 45, 45, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 45, 45, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 22, 22, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 22, 22, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 22, 22, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 22, 22, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 11, 11, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 11, 11, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 11, 11, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 11, 11, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 5, 5, 512)         0
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0

_________________________________________________________________
```

Fast feature extraction without data augmentation **Extracting the VGG16 features and corresponding labels**

[31]:
```
import numpy as np

def get_features_and_labels(dataset):
    all_features = []
    all_labels = []
    for images, labels in dataset:
        preprocessed_images = keras.applications.vgg16.preprocess_input(images)
        features = conv_base.predict(preprocessed_images)
        all_features.append(features)
        all_labels.append(labels)
    return np.concatenate(all_features), np.concatenate(all_labels)

train_features, train_labels =  get_features_and_labels(train_dataset)
val_features, val_labels =  get_features_and_labels(validation_dataset)
test_features, test_labels =  get_features_and_labels(test_dataset)
```

[32]:
```
train_features.shape
```

[32]:
```
(2000, 5, 5, 512)
```

Defining and training the densely connected classifier

[34]:
```
inputs = keras.Input(shape=(5, 5, 512))
x = layers.Flatten()(inputs)
x = layers.Dense(256)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
              metrics=["accuracy"])

callbacks = [
    keras.callbacks.ModelCheckpoint(
      filepath="feature_extraction.keras",
      save_best_only=True,
      monitor="val_loss")
]
history = model.fit(
    train_features, train_labels,
    epochs=130,
    validation_data=(val_features, val_labels),
    callbacks=callbacks)
```

```
Epoch 1/130
```

```
63/63 [==============================] - 2s 33ms/step - loss: 15.4349 -
accuracy: 0.9265 - val_loss: 3.4968 - val_accuracy: 0.9750
Epoch 2/130
63/63 [==============================] - 2s 32ms/step - loss: 4.0122 - accuracy:
0.9700 - val_loss: 5.3281 - val_accuracy: 0.9660
Epoch 3/130
63/63 [==============================] - 2s 32ms/step - loss: 1.1995 - accuracy:
0.9895 - val_loss: 5.2322 - val_accuracy: 0.9690
Epoch 4/130
63/63 [==============================] - 2s 32ms/step - loss: 1.2835 - accuracy:
0.9875 - val_loss: 6.7933 - val_accuracy: 0.9650
Epoch 5/130
63/63 [==============================] - 2s 32ms/step - loss: 1.4363 - accuracy:
0.9910 - val_loss: 6.3728 - val_accuracy: 0.9720
Epoch 6/130
63/63 [==============================] - 2s 32ms/step - loss: 0.7145 - accuracy:
0.9950 - val_loss: 6.0059 - val_accuracy: 0.9680
Epoch 7/130
63/63 [==============================] - 2s 32ms/step - loss: 0.5798 - accuracy:
0.9935 - val_loss: 4.9726 - val_accuracy: 0.9720
Epoch 8/130
63/63 [==============================] - 2s 32ms/step - loss: 0.1666 - accuracy:
0.9980 - val_loss: 5.3776 - val_accuracy: 0.9690
Epoch 9/130
63/63 [==============================] - 2s 32ms/step - loss: 0.3782 - accuracy:
0.9955 - val_loss: 5.8746 - val_accuracy: 0.9720
Epoch 10/130
63/63 [==============================] - 2s 32ms/step - loss: 0.2794 - accuracy:
0.9980 - val_loss: 6.5317 - val_accuracy: 0.9670
Epoch 11/130
63/63 [==============================] - 2s 32ms/step - loss: 0.2695 - accuracy:
0.9975 - val_loss: 4.0863 - val_accuracy: 0.9760
Epoch 12/130
63/63 [==============================] - 2s 32ms/step - loss: 0.7043 - accuracy:
0.9970 - val_loss: 4.9878 - val_accuracy: 0.9730
Epoch 13/130
63/63 [==============================] - 2s 33ms/step - loss: 0.1020 - accuracy:
0.9980 - val_loss: 4.8264 - val_accuracy: 0.9770
Epoch 14/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0907 - accuracy:
0.9995 - val_loss: 5.9126 - val_accuracy: 0.9710
Epoch 15/130
63/63 [==============================] - 2s 32ms/step - loss: 0.1272 - accuracy:
0.9990 - val_loss: 6.3353 - val_accuracy: 0.9710
Epoch 16/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0341 - accuracy:
0.9990 - val_loss: 5.7382 - val_accuracy: 0.9770
Epoch 17/130
```

```
63/63 [==============================] - 2s 32ms/step - loss: 0.1020 - accuracy:
0.9980 - val_loss: 5.3296 - val_accuracy: 0.9750
Epoch 18/130
63/63 [==============================] - 2s 32ms/step - loss: 8.1959e-26 -
accuracy: 1.0000 - val_loss: 5.3296 - val_accuracy: 0.9750
Epoch 19/130
63/63 [==============================] - 2s 32ms/step - loss: 2.4769e-10 -
accuracy: 1.0000 - val_loss: 5.3035 - val_accuracy: 0.9760
Epoch 20/130
63/63 [==============================] - 2s 32ms/step - loss: 2.5584e-35 -
accuracy: 1.0000 - val_loss: 5.3035 - val_accuracy: 0.9760
Epoch 21/130
63/63 [==============================] - 2s 32ms/step - loss: 4.2438e-26 -
accuracy: 1.0000 - val_loss: 5.3035 - val_accuracy: 0.9760
Epoch 22/130
63/63 [==============================] - 2s 32ms/step - loss: 0.1145 - accuracy:
0.9985 - val_loss: 5.7997 - val_accuracy: 0.9740
Epoch 23/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0631 - accuracy:
0.9995 - val_loss: 5.9653 - val_accuracy: 0.9710
Epoch 24/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0232 - accuracy:
0.9990 - val_loss: 5.5400 - val_accuracy: 0.9730
Epoch 25/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0940 - accuracy:
0.9990 - val_loss: 5.1268 - val_accuracy: 0.9770
Epoch 26/130
63/63 [==============================] - 2s 32ms/step - loss: 8.3362e-11 -
accuracy: 1.0000 - val_loss: 5.1227 - val_accuracy: 0.9770
Epoch 27/130
63/63 [==============================] - 2s 32ms/step - loss: 1.2329e-18 -
accuracy: 1.0000 - val_loss: 5.1227 - val_accuracy: 0.9770
Epoch 28/130
63/63 [==============================] - 2s 32ms/step - loss: 2.0056e-12 -
accuracy: 1.0000 - val_loss: 5.1215 - val_accuracy: 0.9770
Epoch 29/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.1215 - val_accuracy: 0.9770
Epoch 30/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0635 - accuracy:
0.9985 - val_loss: 4.8735 - val_accuracy: 0.9750
Epoch 31/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0142 - accuracy:
0.9990 - val_loss: 4.7102 - val_accuracy: 0.9760
Epoch 32/130
63/63 [==============================] - 2s 33ms/step - loss: 0.0128 - accuracy:
0.9995 - val_loss: 5.2985 - val_accuracy: 0.9730
Epoch 33/130
```

```
63/63 [==============================] - 2s 32ms/step - loss: 0.0884 - accuracy:
0.9985 - val_loss: 6.3055 - val_accuracy: 0.9730
Epoch 34/130
63/63 [==============================] - 2s 32ms/step - loss: 9.5969e-08 -
accuracy: 1.0000 - val_loss: 5.6765 - val_accuracy: 0.9790
Epoch 35/130
63/63 [==============================] - 2s 33ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.6765 - val_accuracy: 0.9790
Epoch 36/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0462 - accuracy:
0.9990 - val_loss: 5.9722 - val_accuracy: 0.9780
Epoch 37/130
63/63 [==============================] - 2s 33ms/step - loss: 2.0346e-26 -
accuracy: 1.0000 - val_loss: 5.9722 - val_accuracy: 0.9780
Epoch 38/130
63/63 [==============================] - 2s 32ms/step - loss: 0.1434 - accuracy:
0.9980 - val_loss: 5.8941 - val_accuracy: 0.9770
Epoch 39/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.8941 - val_accuracy: 0.9770
Epoch 40/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0756 - accuracy:
0.9990 - val_loss: 6.0057 - val_accuracy: 0.9770
Epoch 41/130
63/63 [==============================] - 2s 32ms/step - loss: 1.0528e-36 -
accuracy: 1.0000 - val_loss: 6.0057 - val_accuracy: 0.9770
Epoch 42/130
63/63 [==============================] - 2s 32ms/step - loss: 0.1124 - accuracy:
0.9985 - val_loss: 6.8627 - val_accuracy: 0.9740
Epoch 43/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0075 - accuracy:
0.9995 - val_loss: 6.6571 - val_accuracy: 0.9710
Epoch 44/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0438 - accuracy:
0.9995 - val_loss: 5.4400 - val_accuracy: 0.9780
Epoch 45/130
63/63 [==============================] - 2s 32ms/step - loss: 1.8405e-20 -
accuracy: 1.0000 - val_loss: 5.4400 - val_accuracy: 0.9780
Epoch 46/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.4400 - val_accuracy: 0.9780
Epoch 47/130
63/63 [==============================] - 2s 32ms/step - loss: 7.3847e-30 -
accuracy: 1.0000 - val_loss: 5.4400 - val_accuracy: 0.9780
Epoch 48/130
63/63 [==============================] - 2s 32ms/step - loss: 2.8423e-34 -
accuracy: 1.0000 - val_loss: 5.4400 - val_accuracy: 0.9780
Epoch 49/130
```

```
63/63 [==============================] - 2s 32ms/step - loss: 0.0136 - accuracy:
0.9995 - val_loss: 7.1067 - val_accuracy: 0.9740
Epoch 50/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0174 - accuracy:
0.9995 - val_loss: 5.8323 - val_accuracy: 0.9770
Epoch 51/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0727 - accuracy:
0.9990 - val_loss: 4.8314 - val_accuracy: 0.9790
Epoch 52/130
63/63 [==============================] - 2s 32ms/step - loss: 3.7032e-30 -
accuracy: 1.0000 - val_loss: 4.8314 - val_accuracy: 0.9790
Epoch 53/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0921 - accuracy:
0.9990 - val_loss: 4.7112 - val_accuracy: 0.9810
Epoch 54/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0746 - accuracy:
0.9980 - val_loss: 5.7422 - val_accuracy: 0.9810
Epoch 55/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0019 - accuracy:
0.9995 - val_loss: 7.6202 - val_accuracy: 0.9690
Epoch 56/130
63/63 [==============================] - 2s 32ms/step - loss: 0.1375 - accuracy:
0.9990 - val_loss: 4.9396 - val_accuracy: 0.9810
Epoch 57/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 4.9396 - val_accuracy: 0.9810
Epoch 58/130
63/63 [==============================] - 2s 32ms/step - loss: 1.0192e-23 -
accuracy: 1.0000 - val_loss: 4.9396 - val_accuracy: 0.9810
Epoch 59/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0324 - accuracy:
0.9995 - val_loss: 5.7003 - val_accuracy: 0.9780
Epoch 60/130
63/63 [==============================] - 2s 32ms/step - loss: 3.5633e-29 -
accuracy: 1.0000 - val_loss: 5.7003 - val_accuracy: 0.9780
Epoch 61/130
63/63 [==============================] - 2s 32ms/step - loss: 5.9241e-32 -
accuracy: 1.0000 - val_loss: 5.7003 - val_accuracy: 0.9780
Epoch 62/130
63/63 [==============================] - 2s 33ms/step - loss: 0.0517 - accuracy:
0.9990 - val_loss: 5.9997 - val_accuracy: 0.9780
Epoch 63/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0121 - accuracy:
0.9995 - val_loss: 8.2004 - val_accuracy: 0.9700
Epoch 64/130
63/63 [==============================] - 2s 31ms/step - loss: 0.0215 - accuracy:
0.9995 - val_loss: 6.0644 - val_accuracy: 0.9780
Epoch 65/130
```

```
63/63 [==============================] - 2s 32ms/step - loss: 0.1455 - accuracy:
0.9990 - val_loss: 6.0006 - val_accuracy: 0.9780
Epoch 66/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0006 - val_accuracy: 0.9780
Epoch 67/130
63/63 [==============================] - 2s 33ms/step - loss: 0.1177 - accuracy:
0.9990 - val_loss: 5.9410 - val_accuracy: 0.9790
Epoch 68/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.9410 - val_accuracy: 0.9790
Epoch 69/130
63/63 [==============================] - 2s 33ms/step - loss: 0.0132 - accuracy:
0.9995 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 70/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 71/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 72/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 73/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 74/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 75/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 76/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 77/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 78/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 79/130
63/63 [==============================] - 2s 33ms/step - loss: 4.7593e-33 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 80/130
63/63 [==============================] - 2s 32ms/step - loss: 1.0483e-36 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 81/130
```

```
63/63 [==============================] - 2s 33ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.7684 - val_accuracy: 0.9790
Epoch 82/130
63/63 [==============================] - 2s 32ms/step - loss: 1.7050e-07 -
accuracy: 1.0000 - val_loss: 7.0673 - val_accuracy: 0.9720
Epoch 83/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0629 - accuracy:
0.9995 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 84/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 85/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 86/130
63/63 [==============================] - 2s 33ms/step - loss: 4.4261e-12 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 87/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 88/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 89/130
63/63 [==============================] - 2s 32ms/step - loss: 1.3902e-30 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 90/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 91/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 92/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 93/130
63/63 [==============================] - 2s 32ms/step - loss: 1.7793e-31 -
accuracy: 1.0000 - val_loss: 5.9954 - val_accuracy: 0.9780
Epoch 94/130
63/63 [==============================] - 2s 32ms/step - loss: 2.1768e-07 -
accuracy: 1.0000 - val_loss: 9.5803 - val_accuracy: 0.9690
Epoch 95/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0472 - accuracy:
0.9995 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 96/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 97/130
```

```
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 98/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 99/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 100/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 101/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 102/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 103/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 104/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 105/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 106/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 107/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 108/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 109/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 110/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 111/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 112/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 113/130
```

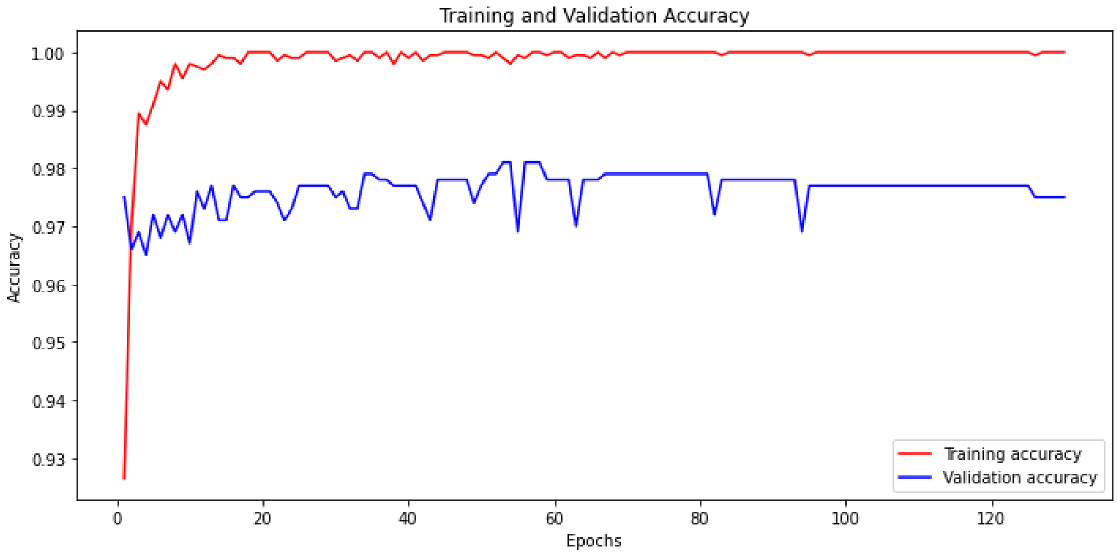
```
63/63 [==============================] - 2s 32ms/step - loss: 2.4231e-18 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 114/130
63/63 [==============================] - 2s 33ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 115/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 116/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 117/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 118/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 119/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 120/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 121/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 122/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 123/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 124/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 125/130
63/63 [==============================] - 2s 32ms/step - loss: 8.3834e-30 -
accuracy: 1.0000 - val_loss: 6.0492 - val_accuracy: 0.9770
Epoch 126/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0047 - accuracy:
0.9995 - val_loss: 6.3387 - val_accuracy: 0.9750
Epoch 127/130
63/63 [==============================] - 2s 33ms/step - loss: 2.9434e-30 -
accuracy: 1.0000 - val_loss: 6.3387 - val_accuracy: 0.9750
Epoch 128/130
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.3387 - val_accuracy: 0.9750
Epoch 129/130
```

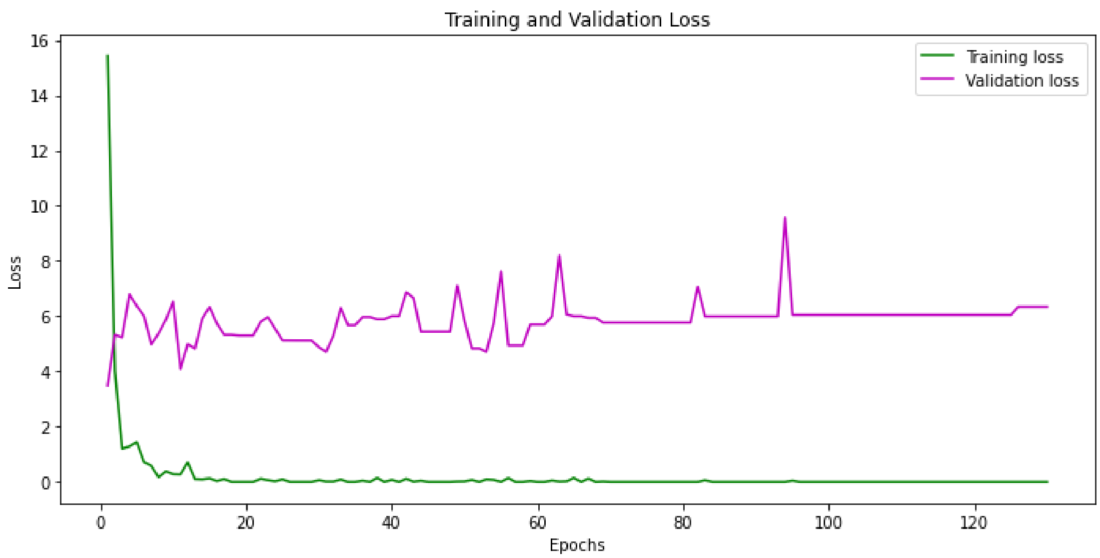
```
63/63 [==============================] - 2s 32ms/step - loss: 0.0000e+00 -
accuracy: 1.0000 - val_loss: 6.3387 - val_accuracy: 0.9750
Epoch 130/130
63/63 [==============================] - 2s 32ms/step - loss: 7.0039e-23 -
accuracy: 1.0000 - val_loss: 6.3387 - val_accuracy: 0.9750
```

Plotting the results

[35]:

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(acc) + 1)

fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(10, 10))

ax1.plot(epochs, acc, 'r', label='Training accuracy')
ax1.plot(epochs, val_acc, 'b', label='Validation accuracy')
ax1.set_title('Training and Validation Accuracy')
ax1.set_xlabel('Epochs')
ax1.set_ylabel('Accuracy')
ax1.legend()

ax2.plot(epochs, loss, 'g', label='Training loss')
ax2.plot(epochs, val_loss, 'm', label='Validation loss')
ax2.set_title('Training and Validation Loss')
ax2.set_xlabel('Epochs')
ax2.set_ylabel('Loss')
ax2.legend()

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





Feature extraction together with data augmentation Instantiating and freezing the VGG16 convolutional base

[36]:
```
conv_base  = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False)
conv_base.trainable = False
```

Printing the list of trainable weights before and after freezing

[37]:
```
conv_base.trainable = True
print("This is the number of trainable weights "
      "before freezing the conv base:", len(conv_base.trainable_weights))
```

```
This is the number of trainable weights before freezing the conv base: 26
```

[38]:

```python
conv_base.trainable = False
print("This is the number of trainable weights "
      "after freezing the conv base:", len(conv_base.trainable_weights))
```

```
This is the number of trainable weights after freezing the conv base: 0
```

Adding a data augmentation stage and a classifier to the convolutional base

[39]:

```python
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)

inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = keras.applications.vgg16.preprocess_input(x)
x = conv_base(x)
x = layers.Flatten()(x)
x = layers.Dense(256)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
              metrics=["accuracy"])
```

[42]:

```python
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="feature_extraction_with_data_augmentation.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=5,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 1/5
63/63 [==============================] - 165s 3s/step - loss: 5.6375 - accuracy:
0.9620 - val_loss: 4.9509 - val_accuracy: 0.9720
Epoch 2/5
63/63 [==============================] - 165s 3s/step - loss: 4.8123 - accuracy:
```

```
0.9600 - val_loss: 5.8528 - val_accuracy: 0.9680
Epoch 3/5
63/63 [==============================] - 165s 3s/step - loss: 4.4011 - accuracy:
0.9670 - val_loss: 5.7027 - val_accuracy: 0.9720
Epoch 4/5
63/63 [==============================] - 165s 3s/step - loss: 3.9860 - accuracy:
0.9690 - val_loss: 3.9207 - val_accuracy: 0.9720
Epoch 5/5
63/63 [==============================] - 165s 3s/step - loss: 3.7545 - accuracy:
0.9710 - val_loss: 5.4095 - val_accuracy: 0.9670
```

Evaluating the model on the test set

[43]:
```python
test_model = keras.models.load_model(
    "feature_extraction_with_data_augmentation.keras")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
63/63 [==============================] - 107s 2s/step - loss: 4.2241 - accuracy:
0.9745
Test accuracy: 0.975
```

0.0.3 Fine-tuning a pretrained model

[44]:
```python
conv_base.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
input_7 (InputLayer)        [(None, None, None, 3)]   0

_________________________________________________________________
block1_conv1 (Conv2D)       (None, None, None, 64)    1792

_________________________________________________________________
block1_conv2 (Conv2D)       (None, None, None, 64)    36928

_________________________________________________________________
block1_pool (MaxPooling2D)  (None, None, None, 64)    0

_________________________________________________________________
block2_conv1 (Conv2D)       (None, None, None, 128)   73856

_________________________________________________________________
block2_conv2 (Conv2D)       (None, None, None, 128)   147584

_________________________________________________________________
block2_pool (MaxPooling2D)  (None, None, None, 128)   0

_________________________________________________________________
block3_conv1 (Conv2D)       (None, None, None, 256)   295168

_________________________________________________________________
block3_conv2 (Conv2D)       (None, None, None, 256)   590080

_________________________________________________________________
```

```
block3_conv3 (Conv2D)        (None, None, None, 256)   590080

_________________________________________________________________
block3_pool (MaxPooling2D)   (None, None, None, 256)   0

_________________________________________________________________
block4_conv1 (Conv2D)        (None, None, None, 512)   1180160

_________________________________________________________________
block4_conv2 (Conv2D)        (None, None, None, 512)   2359808

_________________________________________________________________
block4_conv3 (Conv2D)        (None, None, None, 512)   2359808

_________________________________________________________________
block4_pool (MaxPooling2D)   (None, None, None, 512)   0

_________________________________________________________________
block5_conv1 (Conv2D)        (None, None, None, 512)   2359808

_________________________________________________________________
block5_conv2 (Conv2D)        (None, None, None, 512)   2359808

_________________________________________________________________
block5_conv3 (Conv2D)        (None, None, None, 512)   2359808

_________________________________________________________________
block5_pool (MaxPooling2D)   (None, None, None, 512)   0
=================================================================
Total params: 14,714,688
Trainable params: 0
Non-trainable params: 14,714,688
_________________________________________________________________
```

Freezing all layers until the fourth from the last

[45]:
```
conv_base.trainable = True
for layer in conv_base.layers[:-4]:
    layer.trainable = False
```

Fine-tuning the model

[46]:
```
model.compile(loss="binary_crossentropy",
              optimizer=keras.optimizers.RMSprop(learning_rate=1e-5),
              metrics=["accuracy"])

callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="fine_tuning.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=5,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 1/5
63/63 [==============================] - 192s 3s/step - loss: 2.4510 - accuracy:
0.9765 - val_loss: 3.3270 - val_accuracy: 0.9800
Epoch 2/5
63/63 [==============================] - 190s 3s/step - loss: 0.7606 - accuracy:
0.9915 - val_loss: 3.2980 - val_accuracy: 0.9780
Epoch 3/5
63/63 [==============================] - 190s 3s/step - loss: 1.0761 - accuracy:
0.9850 - val_loss: 3.1059 - val_accuracy: 0.9810
Epoch 4/5
63/63 [==============================] - 191s 3s/step - loss: 0.8716 - accuracy:
0.9840 - val_loss: 3.0539 - val_accuracy: 0.9770
Epoch 5/5
63/63 [==============================] - 190s 3s/step - loss: 0.8123 - accuracy:
0.9885 - val_loss: 3.0518 - val_accuracy: 0.9790
```

[47]:
```
model = keras.models.load_model("fine_tuning.keras")
test_loss, test_acc = model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
63/63 [==============================] - 107s 2s/step - loss: 2.4981 - accuracy:
0.9735
Test accuracy: 0.974
```

Pre-Trained Model - 5000 Training samples

Instantiating and freezing the VGG16 convolutional base

[48]:
```
conv_base  = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False,
    input_shape=(180, 180, 3))
```

[49]:
```
conv_base  = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False)

conv_base.trainable = True
for layer in conv_base.layers[:-4]:
    layer.trainable = False
```

[50]:
```
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)
```

```
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = keras.applications.vgg16.preprocess_input(x)
x = conv_base(x)
x = layers.Flatten()(x)
x = layers.Dense(256)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.compile(loss="binary_crossentropy",
              optimizer=keras.optimizers.RMSprop(learning_rate=1e-5),
              metrics=["accuracy"])

callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="fine_tuning2.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=5,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 1/5
63/63 [==============================] - 192s 3s/step - loss: 3.4654 - accuracy:
0.7505 - val_loss: 0.7099 - val_accuracy: 0.9180
Epoch 2/5
63/63 [==============================] - 192s 3s/step - loss: 1.1883 - accuracy:
0.8600 - val_loss: 0.3784 - val_accuracy: 0.9470
Epoch 3/5
63/63 [==============================] - 191s 3s/step - loss: 0.6065 - accuracy:
0.9110 - val_loss: 0.2704 - val_accuracy: 0.9570
Epoch 4/5
63/63 [==============================] - 191s 3s/step - loss: 0.3379 - accuracy:
0.9245 - val_loss: 0.2123 - val_accuracy: 0.9580
Epoch 5/5
63/63 [==============================] - 191s 3s/step - loss: 0.2489 - accuracy:
0.9395 - val_loss: 0.1800 - val_accuracy: 0.9580
```

[51]:
```
model = keras.models.load_model("fine_tuning2.keras")
test_loss, test_acc = model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
63/63 [==============================] - 107s 2s/step - loss: 0.1697 - accuracy:
0.9700
Test accuracy: 0.970
```

Pre-Trained Model - 10000 samples

Instantiating and freezing the VGG16 convolutional base

[52]:
```
conv_base  = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False,
    input_shape=(180, 180, 3))
```

[53]:
```
conv_base  = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False)

conv_base.trainable = True
for layer in conv_base.layers[:-4]:
    layer.trainable = False
```

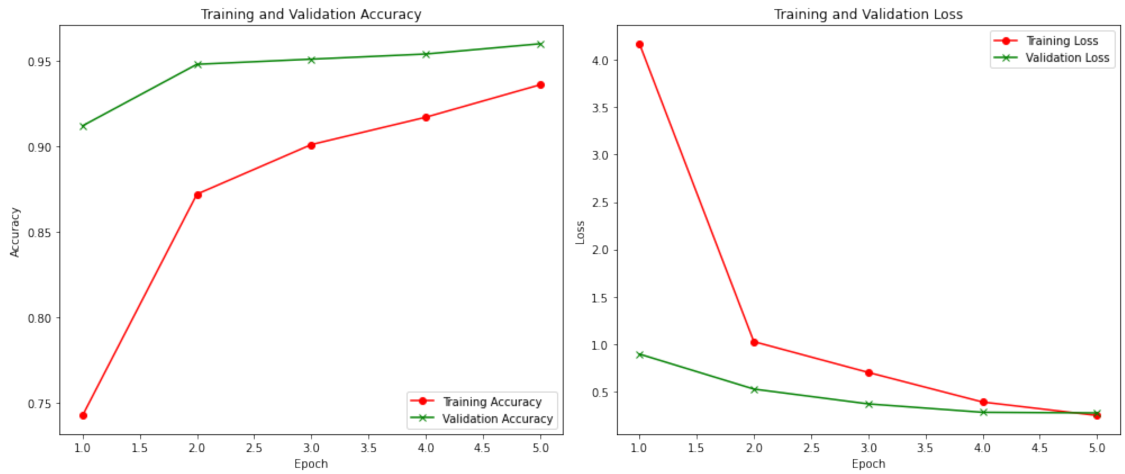
[54]:
```
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)

inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = keras.applications.vgg16.preprocess_input(x)
x = conv_base(x)
x = layers.Flatten()(x)
x = layers.Dense(256)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.compile(loss="binary_crossentropy",
              optimizer=keras.optimizers.RMSprop(learning_rate=1e-5),
              metrics=["accuracy"])

callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="fine_tuning3.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=5,
    validation_data=validation_dataset,
```

```
    callbacks=callbacks)
```

```
Epoch 1/5
63/63 [==============================] - 192s 3s/step - loss: 4.1675 - accuracy:
0.7425 - val_loss: 0.8961 - val_accuracy: 0.9120
Epoch 2/5
63/63 [==============================] - 191s 3s/step - loss: 1.0275 - accuracy:
0.8720 - val_loss: 0.5272 - val_accuracy: 0.9480
Epoch 3/5
63/63 [==============================] - 192s 3s/step - loss: 0.7030 - accuracy:
0.9010 - val_loss: 0.3709 - val_accuracy: 0.9510
Epoch 4/5
63/63 [==============================] - 192s 3s/step - loss: 0.3906 - accuracy:
0.9170 - val_loss: 0.2823 - val_accuracy: 0.9540
Epoch 5/5
63/63 [==============================] - 192s 3s/step - loss: 0.2492 - accuracy:
0.9360 - val_loss: 0.2759 - val_accuracy: 0.9600
```

Code plots training and validation accuracy and loss side by side in a single figure using Matplotlib. It uses different colors and markers to distinguish between training and validation metrics, enhancing visualization and comparison across training epochs.

[55]:
```
accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(accuracy) + 1)
plt.figure(figsize=(14, 6))
plt.subplot(1, 2, 1)
plt.plot(epochs, accuracy, 'r-', label='Training Accuracy', marker='o')
plt.plot(epochs, val_accuracy, 'g-', label='Validation Accuracy', marker='x')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(epochs, loss, 'r-', label='Training Loss', marker='o')
plt.plot(epochs, val_loss, 'g-', label='Validation Loss', marker='x')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
```



[56]:
```
model = keras.models.load_model("fine_tuning3.keras")
test_loss, test_acc = model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
63/63 [==============================] - 107s 2s/step - loss: 0.1968 - accuracy:
0.9575
Test accuracy: 0.957
```

[ ]: