Assignment-2

This project showcases the trade-offs between training from scratch and transfer learning in image classification:

From-scratch models can be ~70% accurate when well regularized, even with 1000 images.Bigger training sizes more than 1500 provide decreasing returns unless augmented with regularization.Transfer learning beats from-scratch models by a huge margin, with >85% accuracy on less data and lower test loss.Best overall performance was obtained using InceptionV3 trained on 1700 images, at 86.5% test accuracy and 0.32 loss.

Data Loading

```
from google.colab import drive
drive.mount('/content/drive')
```

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

Organizing images into training, validation, and testing directories

```
import os
import shutil
import pathlib

# Define original folders separately
train_src_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/train")
val_src_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/validation")
test_src_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/test")

# Define destination base directory
balanced_dataset_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/small_dataset_balanced")

def create_dataset_subset(subset_type, src_folder, start_index, end_index):

    print(f"\nCreating '{subset_type}' from {src_folder} indices {start_index} to {end_index}")

    for label_type in ["cats", "dogs"]:
        src_label_path = src_folder / label_type
        dest_label_path = balanced_dataset_path / subset_type / label_type

        os.makedirs(dest_label_path, exist_ok=True)

        files = sorted(os.listdir(src_label_path))


        if end_index > len(files):
            print(f"WARNING: end_index {end_index} exceeds available files ({len(files)}). Adjusting.")
            end_index = len(files)

        subset_files = files[start_index:end_index]
        print(f"Copying {len(subset_files)} '{label_type}' images to '{dest_label_path}'...")

        for fname in subset_files:
            src_file = src_label_path / fname
            dst_file = dest_label_path / fname
            shutil.copyfile(src_file, dst_file)

    print(f" {subset_type} created from {src_folder}.")

def main():



    create_dataset_subset("train", train_src_path, 0, 500)
    create_dataset_subset("validation", val_src_path,0,250)
    create_dataset_subset("test",   test_src_path, 0, 250)

if __name__ == "__main__":
    main()
```

```
Creating 'train' from /content/drive/MyDrive/cats_vs_dogs_small/train indices 0 to 500
Copying 500 'cats' images to '/content/drive/MyDrive/cats_vs_dogs_small/small_dataset_balanced/train/cats'...
Copying 500 'dogs' images to '/content/drive/MyDrive/cats_vs_dogs_small/small_dataset_balanced/train/dogs'...
 train created from /content/drive/MyDrive/cats_vs_dogs_small/train.
```

```
Creating 'validation' from /content/drive/MyDrive/cats_vs_dogs_small/validation indices 0 to 250
Copying 250 'cats' images to '/content/drive/MyDrive/cats_vs_dogs_small/small_dataset_balanced/validation/cats'...
Copying 250 'dogs' images to '/content/drive/MyDrive/cats_vs_dogs_small/small_dataset_balanced/validation/dogs'...
 validation created from /content/drive/MyDrive/cats_vs_dogs_small/validation.

Creating 'test' from /content/drive/MyDrive/cats_vs_dogs_small/test indices 0 to 250
Copying 250 'cats' images to '/content/drive/MyDrive/cats_vs_dogs_small/small_dataset_balanced/test/cats'...
Copying 250 'dogs' images to '/content/drive/MyDrive/cats_vs_dogs_small/small_dataset_balanced/test/dogs'...
 test created from /content/drive/MyDrive/cats_vs_dogs_small/test.
```

```
from tensorflow.keras.utils import image_dataset_from_directory

train_dataset = image_dataset_from_directory(
    balanced_dataset_path / "train",
    image_size=(180, 180),
    batch_size=32
)

val_dataset = image_dataset_from_directory(
    balanced_dataset_path / "validation",
    image_size=(180, 180),
    batch_size=32
)

test_dataset = image_dataset_from_directory(
    balanced_dataset_path / "test",
    image_size=(180, 180),
    batch_size=32
)
```

```
Found 1000 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
```

Training a convolutional neural network from scratch

Model 1:The dataset is divided into 1000 training samples, 500 validation samples, and 500 test samples.

```
from tensorflow import keras
from tensorflow.keras import layers
```

Designing a simple deep learning model to differentiate between cat and dog images.

```
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)
```

```
model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (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)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 43, 43, 64)	0
conv2d_2 (Conv2D)	(None, 41, 41, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 20, 20, 128)	0
conv2d_3 (Conv2D)	(None, 18, 18, 256)	295,168
max_pooling2d_3 (MaxPooling2D)	(None, 9, 9, 256)	0
conv2d_4 (Conv2D)	(None, 7, 7, 256)	590,080
flatten (Flatten)	(None, 12544)	0
dense (Dense)	(None, 1)	12,545

Total params: 991,041 (3.78 MB)
Trainable params: 991,041 (3.78 MB)
Non-trainable params: 0 (0.00 B)

Preparing the model for training

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

Data preparation

```
from tensorflow.keras.utils import image_dataset_from_directory

# Base directory for the subsets
balanced_subset_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/small_dataset_balanced")

# Load datasets
train_dataset = image_dataset_from_directory(
    balanced_subset_path / "train",
    image_size=(180, 180),
    batch_size=32
)

val_dataset = image_dataset_from_directory(
    balanced_subset_path / "validation",
    image_size=(180, 180),
    batch_size=32
)

test_dataset = image_dataset_from_directory(
    balanced_subset_path / "test",
    image_size=(180, 180),
    batch_size=32
)
```

```
Found 1000 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
```

```
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)


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

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

```
(16,)
```

```
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)
```

```
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)
```

Displaying the shape of input features and corresponding labels from the dataset

```
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,)
```

Model training using the dataset

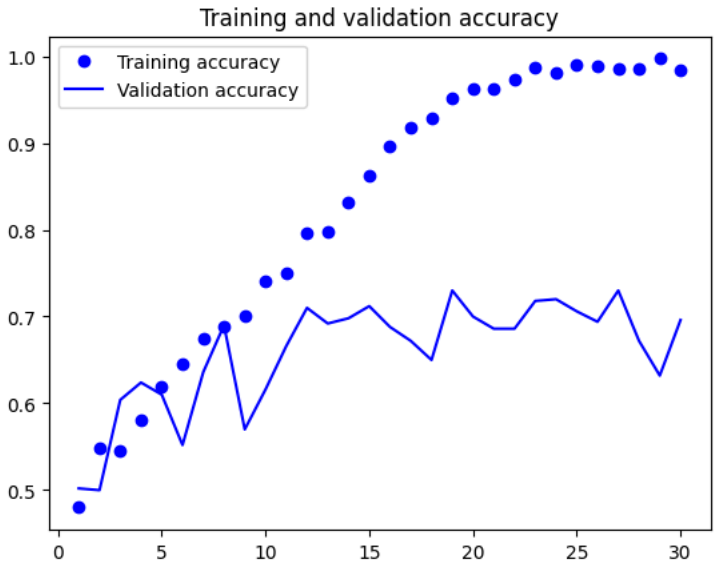
```
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=30,
    validation_data=val_dataset,
    callbacks=callbacks)
```

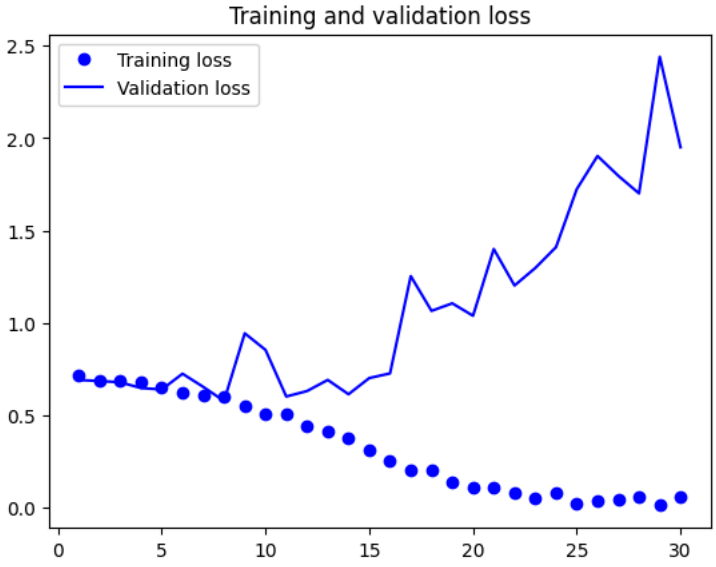
```
Epoch 2/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 168ms/step - accuracy: 0.5253 - loss: 0.6913 - val_accuracy: 0.5000 - val_loss: 0.6870
Epoch 3/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 192ms/step - accuracy: 0.5525 - loss: 0.6899 - val_accuracy: 0.6040 - val_loss: 0.6799
Epoch 4/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 153ms/step - accuracy: 0.5873 - loss: 0.6857 - val_accuracy: 0.6240 - val_loss: 0.6488
Epoch 5/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 154ms/step - accuracy: 0.6042 - loss: 0.6499 - val_accuracy: 0.6100 - val_loss: 0.6408
Epoch 6/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 187ms/step - accuracy: 0.6538 - loss: 0.6153 - val_accuracy: 0.5520 - val_loss: 0.7262
Epoch 7/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 185ms/step - accuracy: 0.6616 - loss: 0.6160 - val_accuracy: 0.6360 - val_loss: 0.6550
Epoch 8/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 186ms/step - accuracy: 0.6945 - loss: 0.5885 - val_accuracy: 0.6900 - val_loss: 0.5790
Epoch 9/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 185ms/step - accuracy: 0.7264 - loss: 0.5269 - val_accuracy: 0.5700 - val_loss: 0.9447
Epoch 10/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 169ms/step - accuracy: 0.7376 - loss: 0.5126 - val_accuracy: 0.6160 - val_loss: 0.8551
Epoch 11/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 12s 214ms/step - accuracy: 0.7228 - loss: 0.5506 - val_accuracy: 0.6660 - val_loss: 0.6030
Epoch 12/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 182ms/step - accuracy: 0.8024 - loss: 0.4456 - val_accuracy: 0.7100 - val_loss: 0.6324
Epoch 13/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 183ms/step - accuracy: 0.7831 - loss: 0.4266 - val_accuracy: 0.6920 - val_loss: 0.6927
Epoch 14/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 195ms/step - accuracy: 0.8313 - loss: 0.3689 - val_accuracy: 0.6980 - val_loss: 0.6153
Epoch 15/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 160ms/step - accuracy: 0.8637 - loss: 0.3024 - val_accuracy: 0.7120 - val_loss: 0.7028
Epoch 16/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 187ms/step - accuracy: 0.8814 - loss: 0.2717 - val_accuracy: 0.6880 - val_loss: 0.7279
Epoch 17/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 163ms/step - accuracy: 0.9056 - loss: 0.2141 - val_accuracy: 0.6720 - val_loss: 1.2541
Epoch 18/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 182ms/step - accuracy: 0.8969 - loss: 0.3036 - val_accuracy: 0.6500 - val_loss: 1.0661
```

```
Epoch 20/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 180ms/step - accuracy: 0.9517 - loss: 0.1190 - val_accuracy: 0.7000 - val_loss: 1.0398
Epoch 21/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 147ms/step - accuracy: 0.9700 - loss: 0.0873 - val_accuracy: 0.6860 - val_loss: 1.4006
Epoch 22/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 187ms/step - accuracy: 0.9873 - loss: 0.0446 - val_accuracy: 0.6860 - val_loss: 1.2032
Epoch 23/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 182ms/step - accuracy: 0.9905 - loss: 0.0457 - val_accuracy: 0.7180 - val_loss: 1.2979
Epoch 24/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 185ms/step - accuracy: 0.9912 - loss: 0.0360 - val_accuracy: 0.7200 - val_loss: 1.4110
Epoch 25/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 181ms/step - accuracy: 0.9769 - loss: 0.0440 - val_accuracy: 0.7060 - val_loss: 1.7246
Epoch 26/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 182ms/step - accuracy: 0.9901 - loss: 0.0359 - val_accuracy: 0.6940 - val_loss: 1.9039
Epoch 27/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 149ms/step - accuracy: 0.9748 - loss: 0.0664 - val_accuracy: 0.7300 - val_loss: 1.7970
Epoch 28/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 182ms/step - accuracy: 0.9888 - loss: 0.0481 - val_accuracy: 0.6720 - val_loss: 1.7015
Epoch 29/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 179ms/step - accuracy: 0.9969 - loss: 0.0139 - val_accuracy: 0.6320 - val_loss: 2.4406
Epoch 30/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 146ms/step - accuracy: 0.9871 - loss: 0.0366 - val_accuracy: 0.6960 - val_loss: 1.9511
```

Monitoring accuracy and loss curves throughout the training process

```
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.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.legend()
plt.show()
```





Evaluating the model on the test dataset

```
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}")
```

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 94ms/step - accuracy: 0.6797 - loss: 0.6229
Test accuracy: 0.684
```

Since the validation and the tes accuracy of the model is very low that is 68.4%

To enhance the performance of our CNN trained from scratch, we applied the following techniques during model development.

Model 1a: Applying Data Augmentation

```
from tensorflow import keras
from tensorflow.keras import layers
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 = 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)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs=inputs, outputs=outputs)

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


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=val_dataset,
     callbacks=callbacks)
```

```
Epoch 2/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 8s 198ms/step - accuracy: 0.5041 - loss: 0.6970 - val_accuracy: 0.5020 - val_loss: 0.6912
Epoch 3/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 183ms/step - accuracy: 0.5064 - loss: 0.6954 - val_accuracy: 0.5020 - val_loss: 0.6906
Epoch 4/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 172ms/step - accuracy: 0.5338 - loss: 0.6937 - val_accuracy: 0.5060 - val_loss: 0.6883
Epoch 5/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 195ms/step - accuracy: 0.5881 - loss: 0.6861 - val_accuracy: 0.5080 - val_loss: 0.6971
Epoch 6/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 145ms/step - accuracy: 0.5966 - loss: 0.6783 - val_accuracy: 0.5700 - val_loss: 0.6726
Epoch 7/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 184ms/step - accuracy: 0.6361 - loss: 0.6492 - val_accuracy: 0.6540 - val_loss: 0.6455
Epoch 8/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 181ms/step - accuracy: 0.6223 - loss: 0.6495 - val_accuracy: 0.5900 - val_loss: 0.6897
Epoch 9/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 142ms/step - accuracy: 0.6210 - loss: 0.6487 - val_accuracy: 0.5960 - val_loss: 0.7538
Epoch 10/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 179ms/step - accuracy: 0.6460 - loss: 0.6927 - val_accuracy: 0.5740 - val_loss: 0.7202
Epoch 11/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 151ms/step - accuracy: 0.6458 - loss: 0.6431 - val_accuracy: 0.5880 - val_loss: 0.6964
Epoch 12/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 142ms/step - accuracy: 0.6665 - loss: 0.5986 - val_accuracy: 0.6240 - val_loss: 0.6996
Epoch 13/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 8s 220ms/step - accuracy: 0.6604 - loss: 0.6224 - val_accuracy: 0.6540 - val_loss: 0.6121
Epoch 14/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 141ms/step - accuracy: 0.6850 - loss: 0.5877 - val_accuracy: 0.6480 - val_loss: 0.6169
Epoch 15/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 176ms/step - accuracy: 0.6965 - loss: 0.5999 - val_accuracy: 0.6760 - val_loss: 0.5833
Epoch 16/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 188ms/step - accuracy: 0.7106 - loss: 0.5714 - val_accuracy: 0.7060 - val_loss: 0.5676
Epoch 17/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 150ms/step - accuracy: 0.7348 - loss: 0.5369 - val_accuracy: 0.7020 - val_loss: 0.5686
Epoch 18/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 175ms/step - accuracy: 0.7169 - loss: 0.5504 - val_accuracy: 0.6460 - val_loss: 0.6427
Epoch 19/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 147ms/step - accuracy: 0.7172 - loss: 0.5593 - val_accuracy: 0.6640 - val_loss: 0.6898
Epoch 20/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 188ms/step - accuracy: 0.6764 - loss: 0.5817 - val_accuracy: 0.6300 - val_loss: 0.9670
Epoch 21/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 186ms/step - accuracy: 0.7023 - loss: 0.5771 - val_accuracy: 0.7220 - val_loss: 0.5389
Epoch 22/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 211ms/step - accuracy: 0.7572 - loss: 0.4932 - val_accuracy: 0.7100 - val_loss: 0.5573
Epoch 23/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 180ms/step - accuracy: 0.7307 - loss: 0.5107 - val_accuracy: 0.7380 - val_loss: 0.5495
Epoch 24/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 189ms/step - accuracy: 0.7655 - loss: 0.4892 - val_accuracy: 0.7360 - val_loss: 0.5446
Epoch 25/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 188ms/step - accuracy: 0.7766 - loss: 0.4800 - val_accuracy: 0.7040 - val_loss: 0.5712
Epoch 26/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 191ms/step - accuracy: 0.7836 - loss: 0.4926 - val_accuracy: 0.7380 - val_loss: 0.5318
Epoch 27/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 160ms/step - accuracy: 0.7449 - loss: 0.5242 - val_accuracy: 0.7060 - val_loss: 0.5903
Epoch 28/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 12s 221ms/step - accuracy: 0.7570 - loss: 0.4987 - val_accuracy: 0.7460 - val_loss: 0.5145
Epoch 29/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 185ms/step - accuracy: 0.8019 - loss: 0.4339 - val_accuracy: 0.6620 - val_loss: 1.0475
Epoch 30/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 190ms/step - accuracy: 0.7403 - loss: 0.5680 - val_accuracy: 0.7340 - val_loss: 0.5957
```

```
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}")
```

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 94ms/step - accuracy: 0.7337 - loss: 0.5534
Test accuracy: 0.736
```

Implementing image data augmentation for model training

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

Visualizing randomly augmented samples from the training dataset

```
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")
```

Model 1b: Applying the Dropout Technique

```
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)
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"])


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

```
Epoch 2/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 183ms/step - accuracy: 0.4913 - loss: 0.6934 - val_accuracy: 0.5000 - val_loss: 0.6923
Epoch 3/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 179ms/step - accuracy: 0.4840 - loss: 0.6936 - val_accuracy: 0.5000 - val_loss: 0.9418
Epoch 4/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 176ms/step - accuracy: 0.5760 - loss: 0.7400 - val_accuracy: 0.5000 - val_loss: 0.7059
Epoch 5/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 194ms/step - accuracy: 0.5389 - loss: 0.6901 - val_accuracy: 0.5020 - val_loss: 0.6954
Epoch 6/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 201ms/step - accuracy: 0.5410 - loss: 0.6864 - val_accuracy: 0.5320 - val_loss: 0.6812
Epoch 7/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 142ms/step - accuracy: 0.5741 - loss: 0.6782 - val_accuracy: 0.5280 - val_loss: 0.6784
Epoch 8/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 180ms/step - accuracy: 0.6130 - loss: 0.6637 - val_accuracy: 0.5780 - val_loss: 0.6514
Epoch 9/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 140ms/step - accuracy: 0.6373 - loss: 0.6312 - val_accuracy: 0.6140 - val_loss: 0.7329
Epoch 10/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 7s 210ms/step - accuracy: 0.6371 - loss: 0.6409 - val_accuracy: 0.6380 - val_loss: 0.6347
Epoch 11/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 8s 140ms/step - accuracy: 0.7278 - loss: 0.5454 - val_accuracy: 0.6540 - val_loss: 0.6431
Epoch 12/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 7s 216ms/step - accuracy: 0.7349 - loss: 0.5555 - val_accuracy: 0.6440 - val_loss: 0.7299
Epoch 13/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 167ms/step - accuracy: 0.7439 - loss: 0.5273 - val_accuracy: 0.5620 - val_loss: 1.0724
Epoch 14/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 160ms/step - accuracy: 0.7408 - loss: 0.5270 - val_accuracy: 0.6100 - val_loss: 0.7999
Epoch 15/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 148ms/step - accuracy: 0.7370 - loss: 0.5123 - val_accuracy: 0.6620 - val_loss: 0.6223
Epoch 16/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 7s 212ms/step - accuracy: 0.7949 - loss: 0.4660 - val_accuracy: 0.6920 - val_loss: 0.6123
Epoch 17/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 8s 146ms/step - accuracy: 0.7882 - loss: 0.4421 - val_accuracy: 0.6120 - val_loss: 0.8673
Epoch 18/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 174ms/step - accuracy: 0.7922 - loss: 0.4414 - val_accuracy: 0.6880 - val_loss: 0.5971
Epoch 19/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 195ms/step - accuracy: 0.8261 - loss: 0.3765 - val_accuracy: 0.6560 - val_loss: 0.7737
Epoch 20/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 180ms/step - accuracy: 0.8554 - loss: 0.3561 - val_accuracy: 0.6620 - val_loss: 0.8839
Epoch 21/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 181ms/step - accuracy: 0.8527 - loss: 0.3483 - val_accuracy: 0.6880 - val_loss: 0.9825
Epoch 22/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 186ms/step - accuracy: 0.8625 - loss: 0.3103 - val_accuracy: 0.6960 - val_loss: 0.7441
Epoch 23/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 181ms/step - accuracy: 0.8951 - loss: 0.2565 - val_accuracy: 0.6840 - val_loss: 0.7468
Epoch 24/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 163ms/step - accuracy: 0.9198 - loss: 0.2073 - val_accuracy: 0.6760 - val_loss: 1.1262
Epoch 25/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 186ms/step - accuracy: 0.9186 - loss: 0.2195 - val_accuracy: 0.6940 - val_loss: 0.8937
Epoch 26/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 140ms/step - accuracy: 0.9156 - loss: 0.2002 - val_accuracy: 0.7040 - val_loss: 0.8649
Epoch 27/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 171ms/step - accuracy: 0.9346 - loss: 0.1577 - val_accuracy: 0.7200 - val_loss: 0.9130
Epoch 28/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 177ms/step - accuracy: 0.9600 - loss: 0.1142 - val_accuracy: 0.6480 - val_loss: 1.5538
Epoch 29/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 139ms/step - accuracy: 0.9209 - loss: 0.1480 - val_accuracy: 0.7160 - val_loss: 1.0177
Epoch 30/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 177ms/step - accuracy: 0.9580 - loss: 0.1130 - val_accuracy: 0.7080 - val_loss: 1.1780
```

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

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 91ms/step - accuracy: 0.6541 - loss: 0.6612
Test accuracy: 0.658
```

Model 1c: Applying both Image Augmentation and Dropout techniques

```
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 = 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"])


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

```
Epoch 2/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 201ms/step - accuracy: 0.5056 - loss: 0.6927 - val_accuracy: 0.5000 - val_loss: 0.7182
Epoch 3/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 193ms/step - accuracy: 0.5408 - loss: 0.6936 - val_accuracy: 0.5820 - val_loss: 0.6783
Epoch 4/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 159ms/step - accuracy: 0.5826 - loss: 0.6849 - val_accuracy: 0.6380 - val_loss: 0.6673
Epoch 5/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 7s 206ms/step - accuracy: 0.6042 - loss: 0.6781 - val_accuracy: 0.6400 - val_loss: 0.6388
Epoch 6/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 189ms/step - accuracy: 0.5973 - loss: 0.6694 - val_accuracy: 0.6260 - val_loss: 0.6360
Epoch 7/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 175ms/step - accuracy: 0.6285 - loss: 0.6606 - val_accuracy: 0.5960 - val_loss: 0.6845
Epoch 8/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 154ms/step - accuracy: 0.6358 - loss: 0.6401 - val_accuracy: 0.5840 - val_loss: 0.6501
Epoch 9/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 189ms/step - accuracy: 0.6557 - loss: 0.6347 - val_accuracy: 0.6700 - val_loss: 0.5977
Epoch 10/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 185ms/step - accuracy: 0.6563 - loss: 0.6036 - val_accuracy: 0.6080 - val_loss: 0.6918
Epoch 11/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 173ms/step - accuracy: 0.6391 - loss: 0.6270 - val_accuracy: 0.6780 - val_loss: 0.6153
Epoch 12/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 184ms/step - accuracy: 0.6950 - loss: 0.5908 - val_accuracy: 0.6340 - val_loss: 0.6147
Epoch 13/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 182ms/step - accuracy: 0.6983 - loss: 0.5829 - val_accuracy: 0.6480 - val_loss: 0.6033
Epoch 14/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 185ms/step - accuracy: 0.6970 - loss: 0.5890 - val_accuracy: 0.6660 - val_loss: 0.5822
Epoch 15/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 181ms/step - accuracy: 0.6807 - loss: 0.5941 - val_accuracy: 0.6460 - val_loss: 0.6266
Epoch 16/30
```

```
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 153ms/step - accuracy: 0.7216 - loss: 0.5656 - val_accuracy: 0.7020 - val_loss: 0.5599
Epoch 18/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 189ms/step - accuracy: 0.7120 - loss: 0.5470 - val_accuracy: 0.6780 - val_loss: 0.6197
Epoch 19/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 150ms/step - accuracy: 0.7094 - loss: 0.5595 - val_accuracy: 0.7060 - val_loss: 0.6341
Epoch 20/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 181ms/step - accuracy: 0.7341 - loss: 0.5201 - val_accuracy: 0.6620 - val_loss: 0.6268
Epoch 21/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 168ms/step - accuracy: 0.7382 - loss: 0.5229 - val_accuracy: 0.7100 - val_loss: 0.5435
Epoch 22/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 11s 201ms/step - accuracy: 0.7508 - loss: 0.5174 - val_accuracy: 0.6040 - val_loss: 0.9094
Epoch 23/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 8s 141ms/step - accuracy: 0.7420 - loss: 0.5336 - val_accuracy: 0.7260 - val_loss: 0.5459
Epoch 24/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 182ms/step - accuracy: 0.7335 - loss: 0.5199 - val_accuracy: 0.6460 - val_loss: 0.6467
Epoch 25/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 159ms/step - accuracy: 0.7352 - loss: 0.5349 - val_accuracy: 0.7120 - val_loss: 0.6223
Epoch 26/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 203ms/step - accuracy: 0.7559 - loss: 0.4917 - val_accuracy: 0.7520 - val_loss: 0.5276
Epoch 27/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 10s 196ms/step - accuracy: 0.7721 - loss: 0.4923 - val_accuracy: 0.7060 - val_loss: 0.6232
Epoch 28/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 9s 142ms/step - accuracy: 0.7810 - loss: 0.4707 - val_accuracy: 0.7200 - val_loss: 0.6158
Epoch 29/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 6s 182ms/step - accuracy: 0.7761 - loss: 0.4888 - val_accuracy: 0.7320 - val_loss: 0.5235
Epoch 30/30
32/32 ━━━━━━━━━━━━━━━━━━━━ 5s 149ms/step - accuracy: 0.7772 - loss: 0.4602 - val_accuracy: 0.7580 - val_loss: 0.5158
```

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

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 95ms/step - accuracy: 0.7176 - loss: 0.5982
Test accuracy: 0.722
```

Model 2) Expanded the training dataset to 1500 samples and enhanced the model using MaxPooling layers, data augmentation techniques, and Dropout regularization with a 0.5 rate.

```
import os
import shutil
import pathlib

# Define original folders (your dataset path)
train_src_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/train")
val_src_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/validation")
test_src_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/test")

# Destination for balanced dataset subsets
balanced_dataset_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset")

def create_dataset_subset(subset_type, src_folder, start_index, end_index):
    print(f"\nCreating '{subset_type}' subset from {src_folder} [{start_index}:{end_index}]")

    for label_type in ["cats", "dogs"]:
        src_label_path = src_folder / label_type
        dest_label_path = balanced_dataset_path / subset_type / label_type

        # Clean old files if they exist
        if dest_label_path.exists():
            shutil.rmtree(dest_label_path)

        os.makedirs(dest_label_path, exist_ok=True)

        files = sorted(os.listdir(src_label_path))

        # Validate end_index
        if end_index > len(files):
            print(f" WARNING: end_index {end_index} exceeds available files ({len(files)}). Adjusting.")
            end_index = len(files)

        subset_files = files[start_index:end_index]
        print(f"Copying {len(subset_files)} '{label_type}' images to '{dest_label_path}'...")

        for fname in subset_files:
            src_file = src_label_path / fname
            dst_file = dest_label_path / fname
            shutil.copyfile(src_file, dst_file)

    print(f" Subset '{subset_type}' created.")

def main():
```

```
    create_dataset_subset("train", train_src_path, 0, 750)
    create_dataset_subset("validation", val_src_path, 0, 300)
    create_dataset_subset("test",   test_src_path, 0, 300)

if __name__ == "__main__":
    main()
```

```
Creating 'train' subset from /content/drive/MyDrive/cats_vs_dogs_small/train [0:750]
Copying 750 'cats' images to '/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/train/cats'...
Copying 750 'dogs' images to '/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/train/dogs'...
 Subset 'train' created.

Creating 'validation' subset from /content/drive/MyDrive/cats_vs_dogs_small/validation [0:300]
Copying 300 'cats' images to '/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/validation/cats'...
Copying 300 'dogs' images to '/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/validation/dogs'...
 Subset 'validation' created.

Creating 'test' subset from /content/drive/MyDrive/cats_vs_dogs_small/test [0:300]
Copying 300 'cats' images to '/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/test/cats'...
Copying 300 'dogs' images to '/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/test/dogs'...
 Subset 'test' created.
```

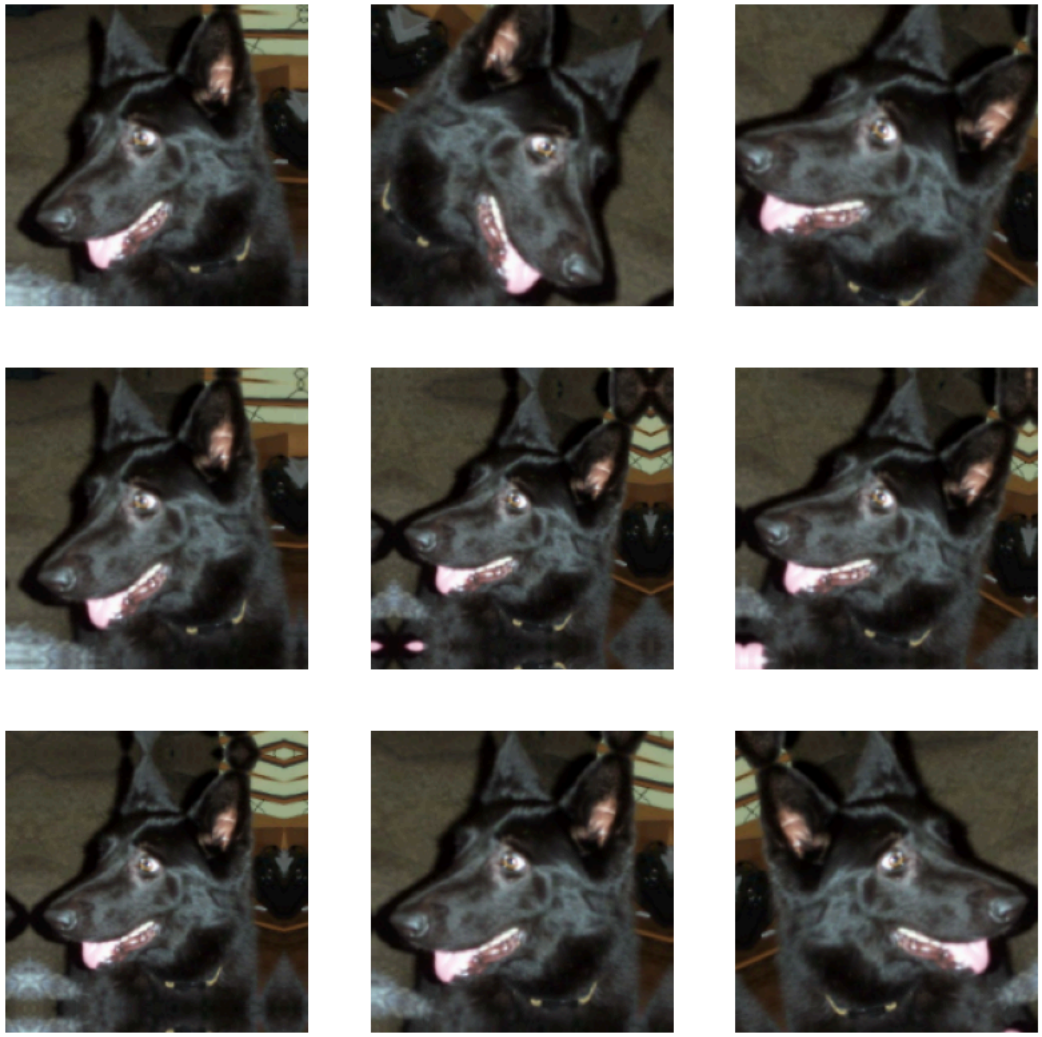
```
from tensorflow.keras.utils import image_dataset_from_directory
from pathlib import Path

balanced_dataset_path = Path("/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset")

train_dataset = image_dataset_from_directory(
    balanced_dataset_path / "train",
    image_size=(180, 180),
    batch_size=32
)

val_dataset = image_dataset_from_directory(
    balanced_dataset_path / "validation",
    image_size=(180, 180),
    batch_size=32
)

test_dataset = image_dataset_from_directory(
    balanced_dataset_path / "test",
    image_size=(180, 180),
    batch_size=32
)

# Prefetch for speed
AUTOTUNE = tf.data.AUTOTUNE
train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)
val_dataset = val_dataset.prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.prefetch(buffer_size=AUTOTUNE)
```

```
Found 1500 files belonging to 2 classes.
Found 600 files belonging to 2 classes.
Found 600 files belonging to 2 classes.
```

Developing a custom CNN architecture incorporating image augmentation and dropout for improved generalization.

```
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
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)
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"])
```

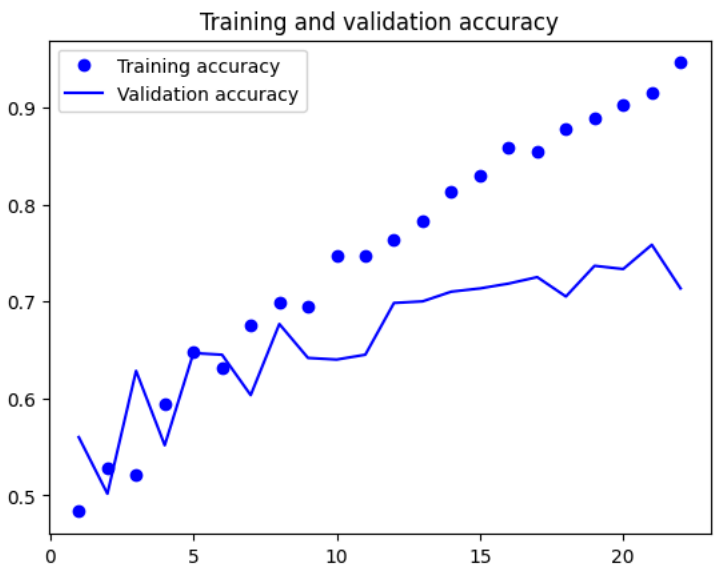
```
from tensorflow import keras
from tensorflow.keras import layers
import matplotlib.pyplot as plt
from keras.callbacks import EarlyStopping
from keras import regularizers

# used early stopping to stop optimization when it isn't helping any more.
early_stopping_monitor = EarlyStopping(patience=10)


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



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")
```

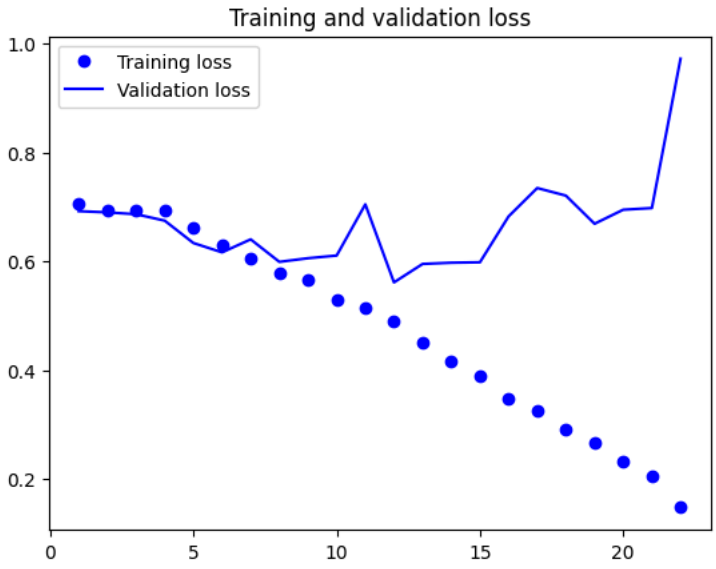


```
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch.keras",
        save_best_only=True,
        monitor="val_loss"), early_stopping_monitor
]
history = model.fit(
    train_dataset,
    epochs=30,
    validation_data=val_dataset,
    callbacks=callbacks)
```

```
Epoch 1/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 18s 325ms/step - accuracy: 0.4780 - loss: 0.7347 - val_accuracy: 0.5600 - val_loss: 0.6922
Epoch 2/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 148ms/step - accuracy: 0.5181 - loss: 0.6943 - val_accuracy: 0.5017 - val_loss: 0.6900
Epoch 3/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 146ms/step - accuracy: 0.5092 - loss: 0.6945 - val_accuracy: 0.6283 - val_loss: 0.6866
Epoch 4/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 159ms/step - accuracy: 0.5771 - loss: 0.6901 - val_accuracy: 0.5517 - val_loss: 0.6747
Epoch 5/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 12s 202ms/step - accuracy: 0.6197 - loss: 0.6777 - val_accuracy: 0.6467 - val_loss: 0.6336
Epoch 6/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 224ms/step - accuracy: 0.6002 - loss: 0.6405 - val_accuracy: 0.6450 - val_loss: 0.6165
Epoch 7/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 8s 172ms/step - accuracy: 0.6668 - loss: 0.6102 - val_accuracy: 0.6033 - val_loss: 0.6404
Epoch 8/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 188ms/step - accuracy: 0.6885 - loss: 0.5802 - val_accuracy: 0.6767 - val_loss: 0.5990
Epoch 9/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 222ms/step - accuracy: 0.6925 - loss: 0.5678 - val_accuracy: 0.6417 - val_loss: 0.6057
Epoch 10/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 7s 153ms/step - accuracy: 0.7374 - loss: 0.5309 - val_accuracy: 0.6400 - val_loss: 0.6106
Epoch 11/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 187ms/step - accuracy: 0.7321 - loss: 0.5352 - val_accuracy: 0.6450 - val_loss: 0.7047
Epoch 12/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 183ms/step - accuracy: 0.7415 - loss: 0.5238 - val_accuracy: 0.6983 - val_loss: 0.5613
Epoch 13/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 7s 157ms/step - accuracy: 0.7744 - loss: 0.4558 - val_accuracy: 0.7000 - val_loss: 0.5952
Epoch 14/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 8s 181ms/step - accuracy: 0.7783 - loss: 0.4504 - val_accuracy: 0.7100 - val_loss: 0.5974
Epoch 15/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 163ms/step - accuracy: 0.8125 - loss: 0.4043 - val_accuracy: 0.7133 - val_loss: 0.5982
Epoch 16/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 137ms/step - accuracy: 0.8386 - loss: 0.3701 - val_accuracy: 0.7183 - val_loss: 0.6826
Epoch 17/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 8s 180ms/step - accuracy: 0.8406 - loss: 0.3878 - val_accuracy: 0.7250 - val_loss: 0.7347
Epoch 18/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 7s 141ms/step - accuracy: 0.8710 - loss: 0.2989 - val_accuracy: 0.7050 - val_loss: 0.7207
Epoch 19/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 7s 156ms/step - accuracy: 0.8703 - loss: 0.2939 - val_accuracy: 0.7367 - val_loss: 0.6690
Epoch 20/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 177ms/step - accuracy: 0.8881 - loss: 0.2632 - val_accuracy: 0.7333 - val_loss: 0.6948
Epoch 21/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 152ms/step - accuracy: 0.9119 - loss: 0.2086 - val_accuracy: 0.7583 - val_loss: 0.6979
Epoch 22/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 154ms/step - accuracy: 0.9423 - loss: 0.1560 - val_accuracy: 0.7133 - val_loss: 0.9723
```

```
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.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.legend()
plt.show()
```






```
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}")
```

```
19/19 ━━━━━━━━━━━━━━━━━━━━ 3s 92ms/step - accuracy: 0.7038 - loss: 0.6168
Test accuracy: 0.695
```

Model 3: Increasing the Training sample size to 1700

```
import os
import shutil
import pathlib
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.utils import image_dataset_from_directory

# 1. Function to Create Subsets
def make_subset(subset_type, original_dir, balanced_dataset_path, start_index, end_index):
    print(f"\nCreating subset: {subset_type} from {original_dir} [{start_index}:{end_index}]")

    for label_type in ["cats", "dogs"]:
        src_label_path = original_dir / label_type
        dest_label_path = balanced_dataset_path / subset_type / label_type

        if dest_label_path.exists():
            shutil.rmtree(dest_label_path)

        os.makedirs(dest_label_path, exist_ok=True)

        files = sorted(os.listdir(src_label_path))

        if end_index > len(files):
            print(f" end_index {end_index} exceeds available files ({len(files)}). Adjusting...")
```

```
            end_index = len(files)

        subset_files = files[start_index:end_index]

        print(f"Copying {len(subset_files)} files from {src_label_path} to {dest_label_path}...")

        for fname in subset_files:
            src_file = src_label_path / fname
            dst_file = dest_label_path / fname

            shutil.copyfile(src_file, dst_file)

    print(f"Subset '{subset_type}' created successfully!")

# 2. Paths Setup
train_src_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/train")
val_src_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/validation")
test_src_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/test")

balanced_dataset_path = pathlib.Path("/content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset")

# 3. Create Subsets
make_subset("train_4", train_src_path, balanced_dataset_path, 0, 850)
make_subset("validation_4", val_src_path, balanced_dataset_path, 0, 250)
make_subset("test_4",   test_src_path, balanced_dataset_path, 0, 250)

# 4. Load the Subset Datasets
train_dataset_4 = image_dataset_from_directory(
    balanced_dataset_path / "train_4",
    image_size=(180, 180),
    batch_size=32
)

val_dataset_4 = image_dataset_from_directory(
    balanced_dataset_path / "validation_4",
    image_size=(180, 180),
    batch_size=32
)

test_dataset_4 = image_dataset_from_directory(
    balanced_dataset_path / "test_4",
    image_size=(180, 180),
    batch_size=32
)

# 5. Define the Callbacks
early_stopping_monitor = keras.callbacks.EarlyStopping(
    monitor="val_loss",
    patience=3,
    restore_best_weights=True
)

callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch.keras",
        save_best_only=True,
        monitor="val_loss"
    ),
    early_stopping_monitor
]

# 6. Build Your Model
model = keras.Sequential([
    keras.layers.Rescaling(1./255, input_shape=(180, 180, 3)),
    keras.layers.Conv2D(32, (3, 3), activation='relu'),
    keras.layers.MaxPooling2D(),
    keras.layers.Conv2D(64, (3, 3), activation='relu'),
    keras.layers.MaxPooling2D(),
    keras.layers.Conv2D(128, (3, 3), activation='relu'),
    keras.layers.MaxPooling2D(),
    keras.layers.Flatten(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(512, activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')
])

model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy']
)
```

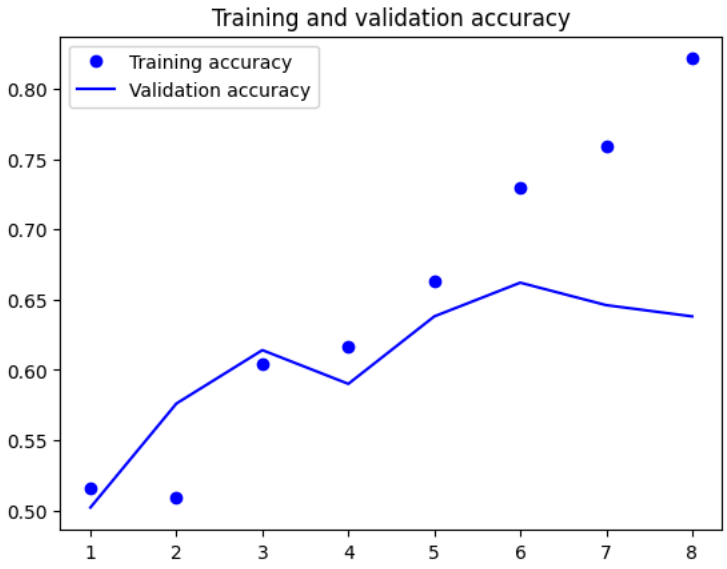
```
# 7. Train the Model
history = model.fit(
    train_dataset_4,
    epochs=30,
    validation_data=val_dataset_4,
    callbacks=callbacks
)
```

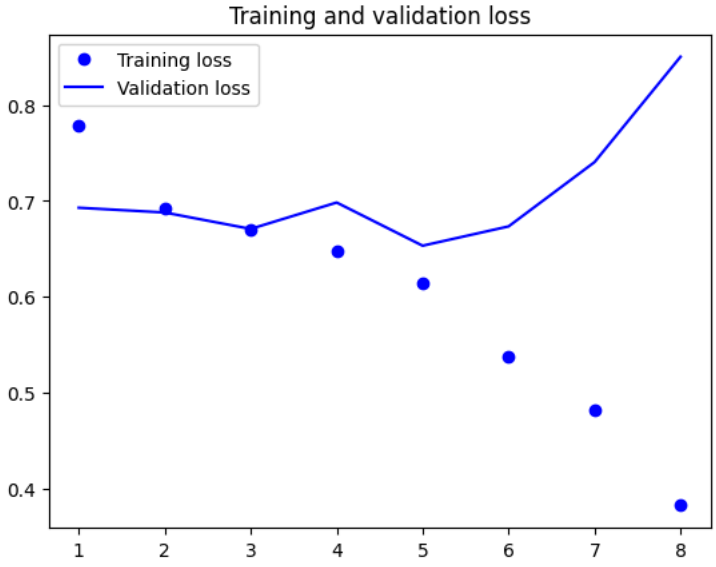
```
Creating subset: train_4 from /content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/train [0:850]
 end_index 850 exceeds available files (750). Adjusting...
Copying 750 files from /content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/train/cats to /content/drive/
Copying 750 files from /content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/train/dogs to /content/drive/
Subset 'train_4' created successfully!

Creating subset: validation_4 from /content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/validation [0:250
Copying 250 files from /content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/validation/cats to /content/d
Copying 250 files from /content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/validation/dogs to /content/d
Subset 'validation_4' created successfully!

Creating subset: test_4 from /content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/test [0:250]
Copying 250 files from /content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/test/cats to /content/drive/M
Copying 250 files from /content/drive/MyDrive/cats_vs_dogs_small/cats_vs_dogs_small_subset/test/dogs to /content/drive/M
Subset 'test_4' created successfully!
Found 1500 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
Found 500 files belonging to 2 classes.
Epoch 1/30
/usr/local/lib/python3.11/dist-packages/keras/src/layers/preprocessing/tf_data_layer.py:19: UserWarning: Do not pass an
  super().__init__(**kwargs)
47/47 ━━━━━━━━━━━━━━━━━━━━ 21s 273ms/step - accuracy: 0.5057 - loss: 0.9617 - val_accuracy: 0.5020 - val_loss: 0.6930
Epoch 2/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 13s 234ms/step - accuracy: 0.4999 - loss: 0.6939 - val_accuracy: 0.5760 - val_loss: 0.6880
Epoch 3/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 205ms/step - accuracy: 0.5959 - loss: 0.6812 - val_accuracy: 0.6140 - val_loss: 0.6709
Epoch 4/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 7s 145ms/step - accuracy: 0.5938 - loss: 0.6648 - val_accuracy: 0.5900 - val_loss: 0.6984
Epoch 5/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 16s 271ms/step - accuracy: 0.6591 - loss: 0.6378 - val_accuracy: 0.6380 - val_loss: 0.6534
Epoch 6/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 16s 170ms/step - accuracy: 0.7164 - loss: 0.5587 - val_accuracy: 0.6620 - val_loss: 0.6735
Epoch 7/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 7s 141ms/step - accuracy: 0.7433 - loss: 0.5090 - val_accuracy: 0.6460 - val_loss: 0.7406
Epoch 8/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 156ms/step - accuracy: 0.8055 - loss: 0.4039 - val_accuracy: 0.6380 - val_loss: 0.8505
```

```
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
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)
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"])


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



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")
```

```
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.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()
plt.plot(epochs, loss, "bo", label="Training loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.legend()
plt.show()
```






```
test_model = keras.models.load_model("convnet_from_scratch.keras")
test_loss, test_acc = test_model.evaluate(test_dataset_4)
print(f"Test accuracy: {test_acc:.3f}")
```

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 131ms/step - accuracy: 0.6025 - loss: 0.6756
Test accuracy: 0.628
```

Feature extraction enhanced through data augmentation

Creating and locking the VGG16 convolutional base

Pre-Trained Model - 1000 Training samples

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

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_t
58889256/58889256 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

```
conv_base.summary()
```

Model: "vgg16"

Layer (type)	Output Shape	Param #
input_layer_12 (InputLayer)	(None, 180, 180, 3)	0
block1_conv1 (Conv2D)	(None, 180, 180, 64)	1,792
block1_conv2 (Conv2D)	(None, 180, 180, 64)	36,928
block1_pool (MaxPooling2D)	(None, 90, 90, 64)	0
block2_conv1 (Conv2D)	(None, 90, 90, 128)	73,856
block2_conv2 (Conv2D)	(None, 90, 90, 128)	147,584
block2_pool (MaxPooling2D)	(None, 45, 45, 128)	0
block3_conv1 (Conv2D)	(None, 45, 45, 256)	295,168
block3_conv2 (Conv2D)	(None, 45, 45, 256)	590,080
block3_conv3 (Conv2D)	(None, 45, 45, 256)	590,080
block3_pool (MaxPooling2D)	(None, 22, 22, 256)	0
block4_conv1 (Conv2D)	(None, 22, 22, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 22, 22, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 22, 22, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 11, 11, 512)	0
block5_conv1 (Conv2D)	(None, 11, 11, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 11, 11, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 11, 11, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 5, 5, 512)	0

Total params: 14,714,688 (56.13 MB)
Trainable params: 14,714,688 (56.13 MB)
Non-trainable params: 0 (0.00 B)

```
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
```

```
**Integrating a data augmentation pipeline and a classificatio
of the convolutional base.**
```

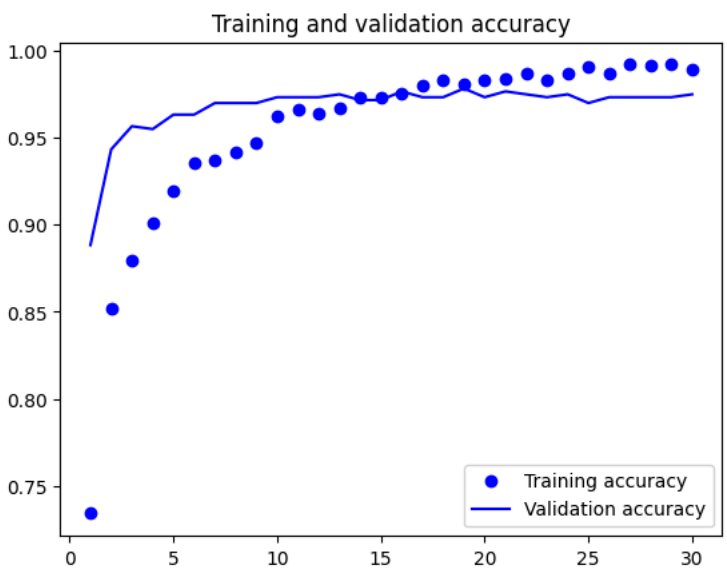
Integrating a data augmentation pipeline and a classification head on top of the convolutional base.

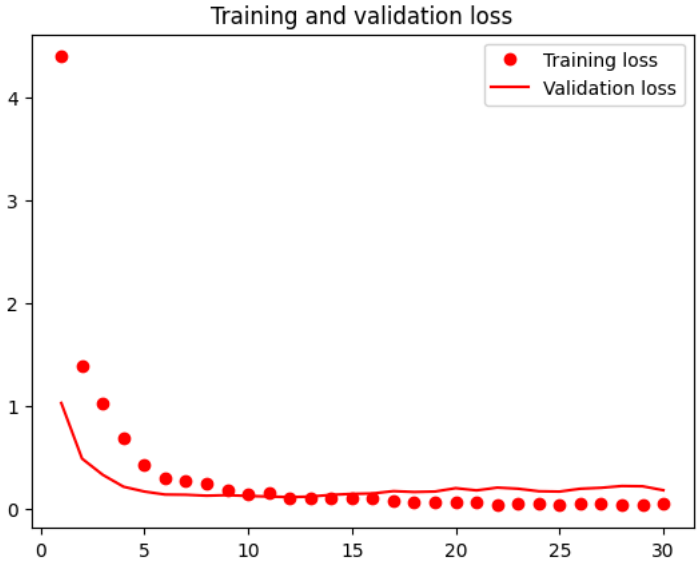
```
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)


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_tuning.keras",
```

```
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=30,
    validation_data=val_dataset,
    callbacks=callbacks)
```

```
Epoch 2/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 12s 185ms/step - accuracy: 0.8336 - loss: 1.6062 - val_accuracy: 0.9433 - val_loss: 0.4845
Epoch 3/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 181ms/step - accuracy: 0.8763 - loss: 1.0595 - val_accuracy: 0.9567 - val_loss: 0.3266
Epoch 4/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 207ms/step - accuracy: 0.9040 - loss: 0.7964 - val_accuracy: 0.9550 - val_loss: 0.2109
Epoch 5/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 245ms/step - accuracy: 0.9139 - loss: 0.4335 - val_accuracy: 0.9633 - val_loss: 0.1640
Epoch 6/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 189ms/step - accuracy: 0.9392 - loss: 0.2720 - val_accuracy: 0.9633 - val_loss: 0.1348
Epoch 7/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 162ms/step - accuracy: 0.9350 - loss: 0.2994 - val_accuracy: 0.9700 - val_loss: 0.1329
Epoch 8/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 200ms/step - accuracy: 0.9516 - loss: 0.1791 - val_accuracy: 0.9700 - val_loss: 0.1236
Epoch 9/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 235ms/step - accuracy: 0.9515 - loss: 0.1792 - val_accuracy: 0.9700 - val_loss: 0.1292
Epoch 10/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 17s 166ms/step - accuracy: 0.9706 - loss: 0.1092 - val_accuracy: 0.9733 - val_loss: 0.1206
Epoch 11/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 12s 189ms/step - accuracy: 0.9698 - loss: 0.1424 - val_accuracy: 0.9733 - val_loss: 0.1156
Epoch 12/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 219ms/step - accuracy: 0.9733 - loss: 0.0820 - val_accuracy: 0.9733 - val_loss: 0.1100
Epoch 13/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 8s 161ms/step - accuracy: 0.9701 - loss: 0.0958 - val_accuracy: 0.9750 - val_loss: 0.1148
Epoch 14/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 163ms/step - accuracy: 0.9751 - loss: 0.0781 - val_accuracy: 0.9717 - val_loss: 0.1318
Epoch 15/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 166ms/step - accuracy: 0.9743 - loss: 0.0951 - val_accuracy: 0.9717 - val_loss: 0.1412
Epoch 16/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 178ms/step - accuracy: 0.9769 - loss: 0.0795 - val_accuracy: 0.9767 - val_loss: 0.1454
Epoch 17/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 8s 162ms/step - accuracy: 0.9829 - loss: 0.0726 - val_accuracy: 0.9733 - val_loss: 0.1681
Epoch 18/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 153ms/step - accuracy: 0.9839 - loss: 0.0406 - val_accuracy: 0.9733 - val_loss: 0.1596
Epoch 19/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 158ms/step - accuracy: 0.9808 - loss: 0.0635 - val_accuracy: 0.9783 - val_loss: 0.1641
Epoch 20/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 180ms/step - accuracy: 0.9770 - loss: 0.0768 - val_accuracy: 0.9733 - val_loss: 0.1969
Epoch 21/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 220ms/step - accuracy: 0.9873 - loss: 0.0465 - val_accuracy: 0.9767 - val_loss: 0.1751
Epoch 22/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 7s 151ms/step - accuracy: 0.9888 - loss: 0.0334 - val_accuracy: 0.9750 - val_loss: 0.2023
Epoch 23/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 189ms/step - accuracy: 0.9806 - loss: 0.0489 - val_accuracy: 0.9733 - val_loss: 0.1916
Epoch 24/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 8s 168ms/step - accuracy: 0.9888 - loss: 0.0368 - val_accuracy: 0.9750 - val_loss: 0.1669
Epoch 25/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 152ms/step - accuracy: 0.9917 - loss: 0.0246 - val_accuracy: 0.9700 - val_loss: 0.1637
Epoch 26/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 150ms/step - accuracy: 0.9857 - loss: 0.0522 - val_accuracy: 0.9733 - val_loss: 0.1915
Epoch 27/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 172ms/step - accuracy: 0.9891 - loss: 0.0525 - val_accuracy: 0.9733 - val_loss: 0.2004
Epoch 28/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 227ms/step - accuracy: 0.9937 - loss: 0.0367 - val_accuracy: 0.9733 - val_loss: 0.2179
Epoch 29/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 17s 158ms/step - accuracy: 0.9935 - loss: 0.0205 - val_accuracy: 0.9733 - val_loss: 0.2154
Epoch 30/30
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 174ms/step - accuracy: 0.9910 - loss: 0.0362 - val_accuracy: 0.9750 - val_loss: 0.1769
```

```
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.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()
plt.plot(epochs, loss, "ro", label="Training loss")
plt.plot(epochs, val_loss, "r", label="Validation loss")
plt.title("Training and validation loss")
plt.legend()
plt.show()
```






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

```
19/19 ━━━━━━━━━━━━━━━━━━━━ 3s 127ms/step - accuracy: 0.9619 - loss: 0.2732
Test accuracy: 0.963
```

Pre-Trained Model Utilizing 1500 Training Samples

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


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


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=10,
    validation_data=val_dataset,
    callbacks=callbacks)
```

```
Epoch 1/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 181ms/step - accuracy: 0.7279 - loss: 4.7850 - val_accuracy: 0.9467 - val_loss: 0.7728
Epoch 2/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 197ms/step - accuracy: 0.8726 - loss: 1.4896 - val_accuracy: 0.9550 - val_loss: 0.5806
Epoch 3/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 189ms/step - accuracy: 0.8888 - loss: 1.0350 - val_accuracy: 0.9633 - val_loss: 0.4393
Epoch 4/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 8s 175ms/step - accuracy: 0.9307 - loss: 0.6375 - val_accuracy: 0.9650 - val_loss: 0.3539
Epoch 5/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 182ms/step - accuracy: 0.9414 - loss: 0.4189 - val_accuracy: 0.9683 - val_loss: 0.3067
Epoch 6/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 188ms/step - accuracy: 0.9528 - loss: 0.2771 - val_accuracy: 0.9650 - val_loss: 0.2771
Epoch 7/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 208ms/step - accuracy: 0.9482 - loss: 0.3108 - val_accuracy: 0.9683 - val_loss: 0.2327
Epoch 8/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 185ms/step - accuracy: 0.9580 - loss: 0.1995 - val_accuracy: 0.9717 - val_loss: 0.2093
Epoch 9/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 202ms/step - accuracy: 0.9510 - loss: 0.2260 - val_accuracy: 0.9683 - val_loss: 0.2021
Epoch 10/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 168ms/step - accuracy: 0.9584 - loss: 0.1424 - val_accuracy: 0.9683 - val_loss: 0.2206
```

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

```
19/19 ━━━━━━━━━━━━━━━━━━━━ 3s 140ms/step - accuracy: 0.9800 - loss: 0.1081
Test accuracy: 0.968
```

Pre-Trained Model Utilizing 1700 Training Samples

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

```
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
```

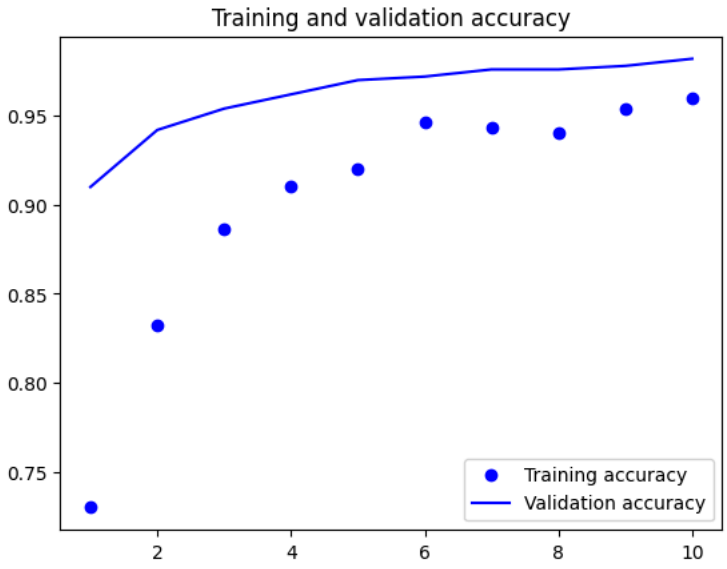
```
data_augmentation = keras.Sequential(
    [
        layers.RandomFlip("horizontal"),
        layers.RandomRotation(0.1),
        layers.RandomZoom(0.2),
    ]
)
```

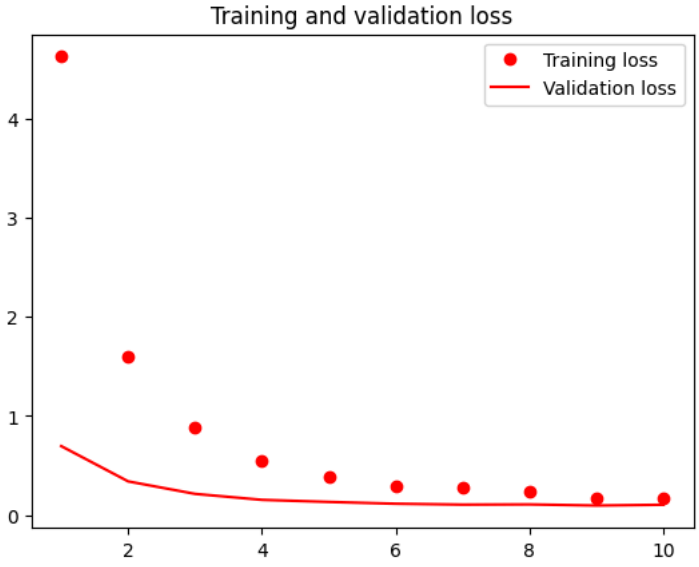
```
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
```

```
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_4,
    epochs=10,
    validation_data=val_dataset_4,
    callbacks=callbacks)
```

```
Epoch 1/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 12s 221ms/step - accuracy: 0.6586 - loss: 7.1900 - val_accuracy: 0.9100 - val_loss: 0.6967
Epoch 2/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 18s 162ms/step - accuracy: 0.8097 - loss: 2.0329 - val_accuracy: 0.9420 - val_loss: 0.3413
Epoch 3/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 181ms/step - accuracy: 0.8771 - loss: 0.9488 - val_accuracy: 0.9540 - val_loss: 0.2153
Epoch 4/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 8s 164ms/step - accuracy: 0.9049 - loss: 0.5581 - val_accuracy: 0.9620 - val_loss: 0.1551
Epoch 5/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 11s 174ms/step - accuracy: 0.9158 - loss: 0.4496 - val_accuracy: 0.9700 - val_loss: 0.1341
Epoch 6/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 9s 186ms/step - accuracy: 0.9324 - loss: 0.3564 - val_accuracy: 0.9720 - val_loss: 0.1160
Epoch 7/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 180ms/step - accuracy: 0.9320 - loss: 0.2760 - val_accuracy: 0.9760 - val_loss: 0.1071
Epoch 8/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 165ms/step - accuracy: 0.9306 - loss: 0.2936 - val_accuracy: 0.9760 - val_loss: 0.1092
Epoch 9/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 8s 180ms/step - accuracy: 0.9440 - loss: 0.2471 - val_accuracy: 0.9780 - val_loss: 0.0980
Epoch 10/10
47/47 ━━━━━━━━━━━━━━━━━━━━ 10s 167ms/step - accuracy: 0.9580 - loss: 0.1596 - val_accuracy: 0.9820 - val_loss: 0.1056
```

```
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.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training and validation accuracy")
plt.legend()
plt.figure()
plt.plot(epochs, loss, "ro", label="Training loss")
plt.plot(epochs, val_loss, "r", label="Validation loss")
plt.title("Training and validation loss")
plt.legend()
plt.show()
```






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

```
19/19 ━━━━━━━━━━━━━━━━━━━━ 3s 105ms/step - accuracy: 0.9687 - loss: 0.3499
Test accuracy: 0.967
```

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