```
from google.colab import files
files.upload()
```

Choose Files no files selected Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving kaggle.json to kaggle.json
{'kaggle.json':
```

```
!mkdir ~/.kaggle/
```

```
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

```
!kaggle competitions download -c dogs-vs-cats
```

```
Downloading dogs-vs-cats.zip to /content
 98% 793M/812M [00:02<00:00, 287MB/s]
100% 812M/812M [00:03<00:00, 281MB/s]
```

```
!unzip -qq dogs-vs-cats.zip
```

```
!unzip -qq train.zip
```

1. 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 are initially taking the train sample of 1000 by taking first 1000 values in the dataset. Taking 500 validation samples starting from 1000 to 1500 values in the dataset, taking 500 test samples starting from 1500 to 2000 values in the dataset.

```
import os, shutil, pathlib

original_dir = pathlib.Path("train")
new_base_dir = pathlib.Path("cats_vs_dogs_small_1")

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

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)
```

Here we are preprocessing the data

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

Importing the numpy as np and creating the dataset with 1000 samples with vector 16.

```
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,)
```

Here we are taking 32 as batch size for the data

```
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)
```

Reshaping the dataset using dataset.map

```
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)
```

```
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,)
```

Using Keras with convolutions and Maxpooling: Creates convolutions kernel that is convolved with the layer

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

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

Configuring the model for training using biary crossentropy as loss function, adam optimizer and accuracy to measure the performance of the model.

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

```
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 (MaxPooling2  (None, 89, 89, 32)        0         
 D)                                                              
                                                                 
 conv2d_1 (Conv2D)           (None, 87, 87, 64)        18496     
                                                                 
 max_pooling2d_1 (MaxPoolin  (None, 43, 43, 64)        0         
 g2D)                                                            
                                                                 
 conv2d_2 (Conv2D)           (None, 41, 41, 128)       73856     
                                                                 
 max_pooling2d_2 (MaxPoolin  (None, 20, 20, 128)       0         
 g2D)                                                            
                                                                 
 conv2d_3 (Conv2D)           (None, 18, 18, 256)       295168    
                                                                 
 max_pooling2d_3 (MaxPoolin  (None, 9, 9, 256)         0         
 g2D)                                                            
                                                                 
 conv2d_4 (Conv2D)           (None, 7, 7, 256)         590080    
                                                                 
 flatten (Flatten)           (None, 12544)             0         
                                                                 
 dropout (Dropout)           (None, 12544)             0         
                                                                 
 dense (Dense)               (None, 1)                 12545     
                                                                 
=================================================================
Total params: 991041 (3.78 MB)
Trainable params: 991041 (3.78 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

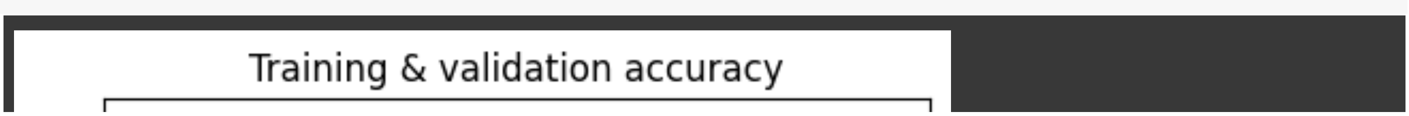
A record of the training measurements and loss values at different epochs, along with validation metrics and loss values, is called a history attribute.

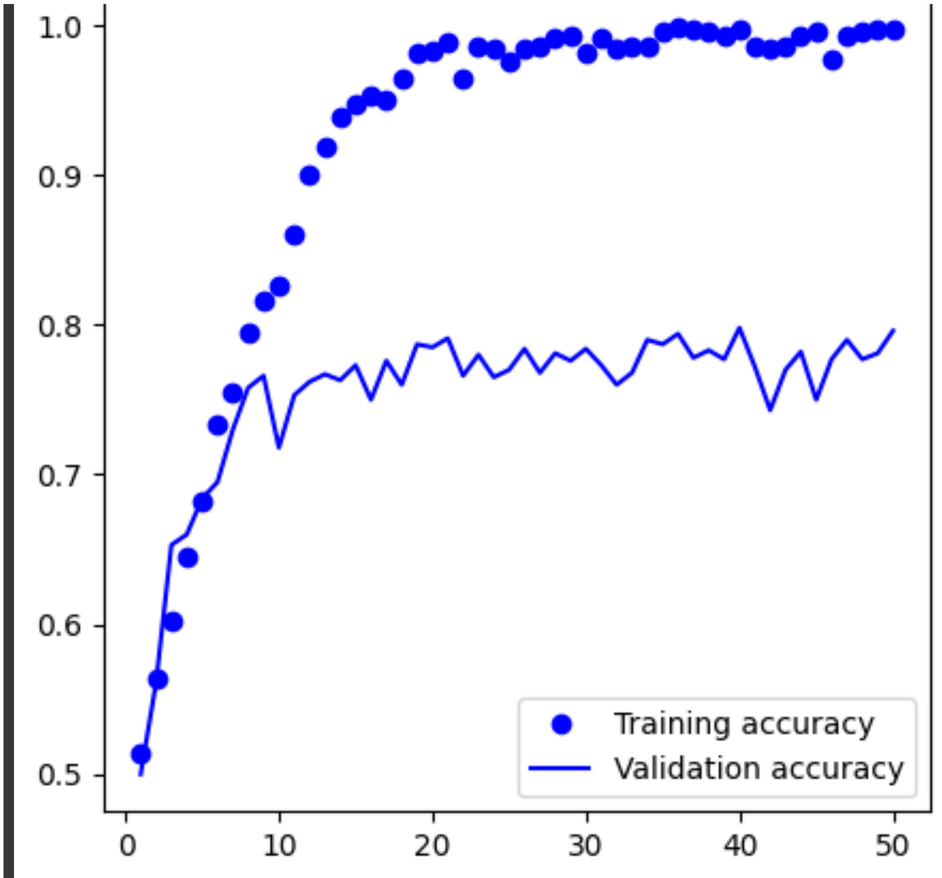
```
from keras.callbacks import ModelCheckpoint, EarlyStopping

callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=50,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 21/50
63/63 [==============================] - 4s 58ms/step - loss: 0.0354 - accura
Epoch 22/50
63/63 [==============================] - 6s 91ms/step - loss: 0.0903 - accura
Epoch 23/50
63/63 [==============================] - 4s 58ms/step - loss: 0.0468 - accura
Epoch 24/50
63/63 [==============================] - 4s 59ms/step - loss: 0.0433 - accura
Epoch 25/50
63/63 [==============================] - 5s 83ms/step - loss: 0.0574 - accura
Epoch 26/50
63/63 [==============================] - 5s 79ms/step - loss: 0.0563 - accura
Epoch 27/50
63/63 [==============================] - 4s 57ms/step - loss: 0.0431 - accura
Epoch 28/50
63/63 [==============================] - 4s 58ms/step - loss: 0.0359 - accura
Epoch 29/50
63/63 [==============================] - 6s 96ms/step - loss: 0.0208 - accura
Epoch 30/50
63/63 [==============================] - 4s 58ms/step - loss: 0.0596 - accura
Epoch 31/50
63/63 [==============================] - 4s 56ms/step - loss: 0.0276 - accura
Epoch 32/50
63/63 [==============================] - 6s 97ms/step - loss: 0.0396 - accura
Epoch 33/50
63/63 [==============================] - 5s 70ms/step - loss: 0.0381 - accura
Epoch 34/50
63/63 [==============================] - 4s 57ms/step - loss: 0.0326 - accura
Epoch 35/50
63/63 [==============================] - 5s 78ms/step - loss: 0.0139 - accura
Epoch 36/50
63/63 [==============================] - 6s 84ms/step - loss: 0.0079 - accura
Epoch 37/50
63/63 [==============================] - 4s 62ms/step - loss: 0.0096 - accura
Epoch 38/50
```

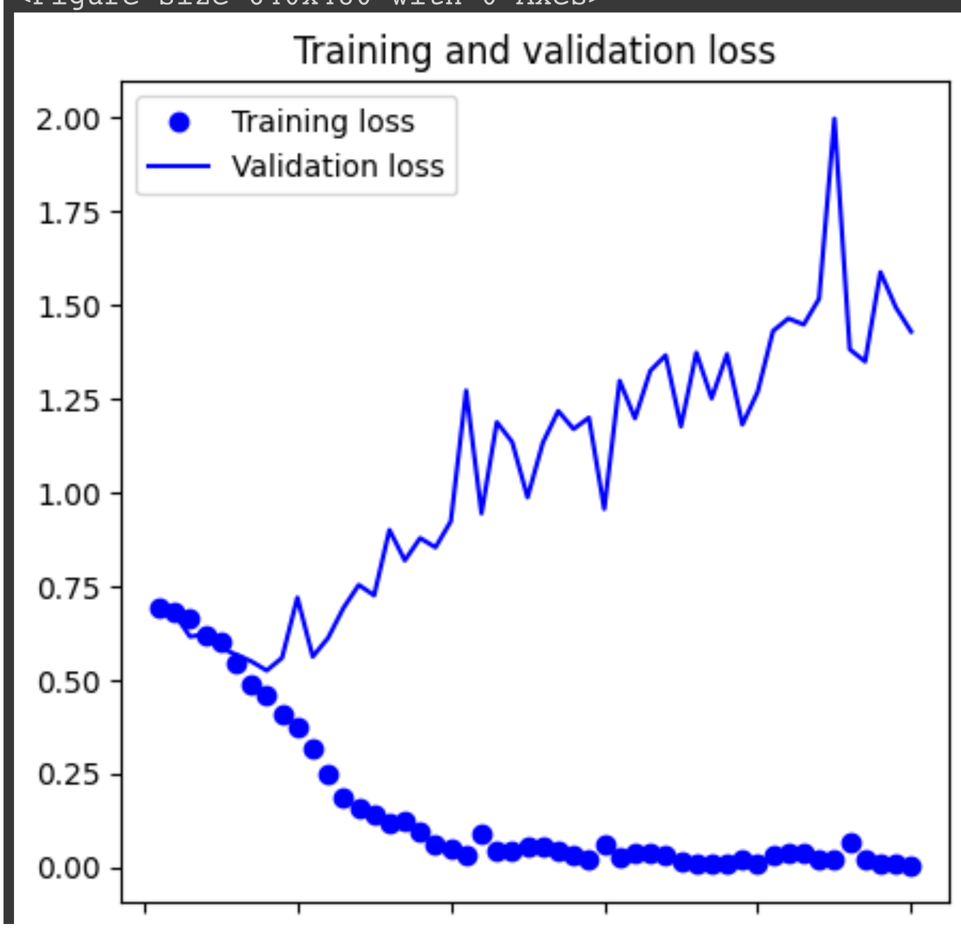
```
63/63 [==============================] - 4s 62ms/step - loss: 0.0126 - accura
Epoch 39/50
63/63 [==============================] - 6s 89ms/step - loss: 0.0218 - accura
Epoch 40/50
63/63 [==============================] - 4s 58ms/step - loss: 0.0120 - accura
Epoch 41/50
63/63 [==============================] - 4s 58ms/step - loss: 0.0345 - accura
Epoch 42/50
63/63 [==============================] - 7s 97ms/step - loss: 0.0403 - accura
Epoch 43/50
63/63 [==============================] - 4s 62ms/step - loss: 0.0370 - accura
Epoch 44/50
63/63 [==============================] - 4s 58ms/step - loss: 0.0235 - accura
Epoch 45/50
63/63 [==============================] - 5s 81ms/step - loss: 0.0203 - accura
Epoch 46/50
63/63 [==============================] - 6s 87ms/step - loss: 0.0674 - accura
Epoch 47/50
63/63 [==============================] - 4s 57ms/step - loss: 0.0206 - accura
Epoch 48/50
63/63 [==============================] - 4s 59ms/step - loss: 0.0113 - accura
Epoch 49/50
63/63 [==============================] - 7s 109ms/step - loss: 0.0095 - accura
Epoch 50/50
63/63 [==============================] - 4s 56ms/step - loss: 0.0059 - accura
```

```python
import matplotlib.pyplot as plt

plt.figure(figsize=(5, 5))
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 & validation accuracy")
plt.legend()
plt.figure()
plt.figure(figsize=(5, 5))
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()
```





<Figure size 640x480 with 0 Axes>




```
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}")
```

```
32/32 [==============================] - 1s 28ms/step - loss: 0.5921 - accura
Test accuracy: 0.719
```

2. Increase your training sample size. You may pick any amount. Keep the validation and test samples the same as above. Optimize your network (again training from scratch). What performance did you achieve?

Here we are incresing the train sample size to 1500 by taking the values from 2000 to 3500 and keeping the validation and test values constant i.e., 500.

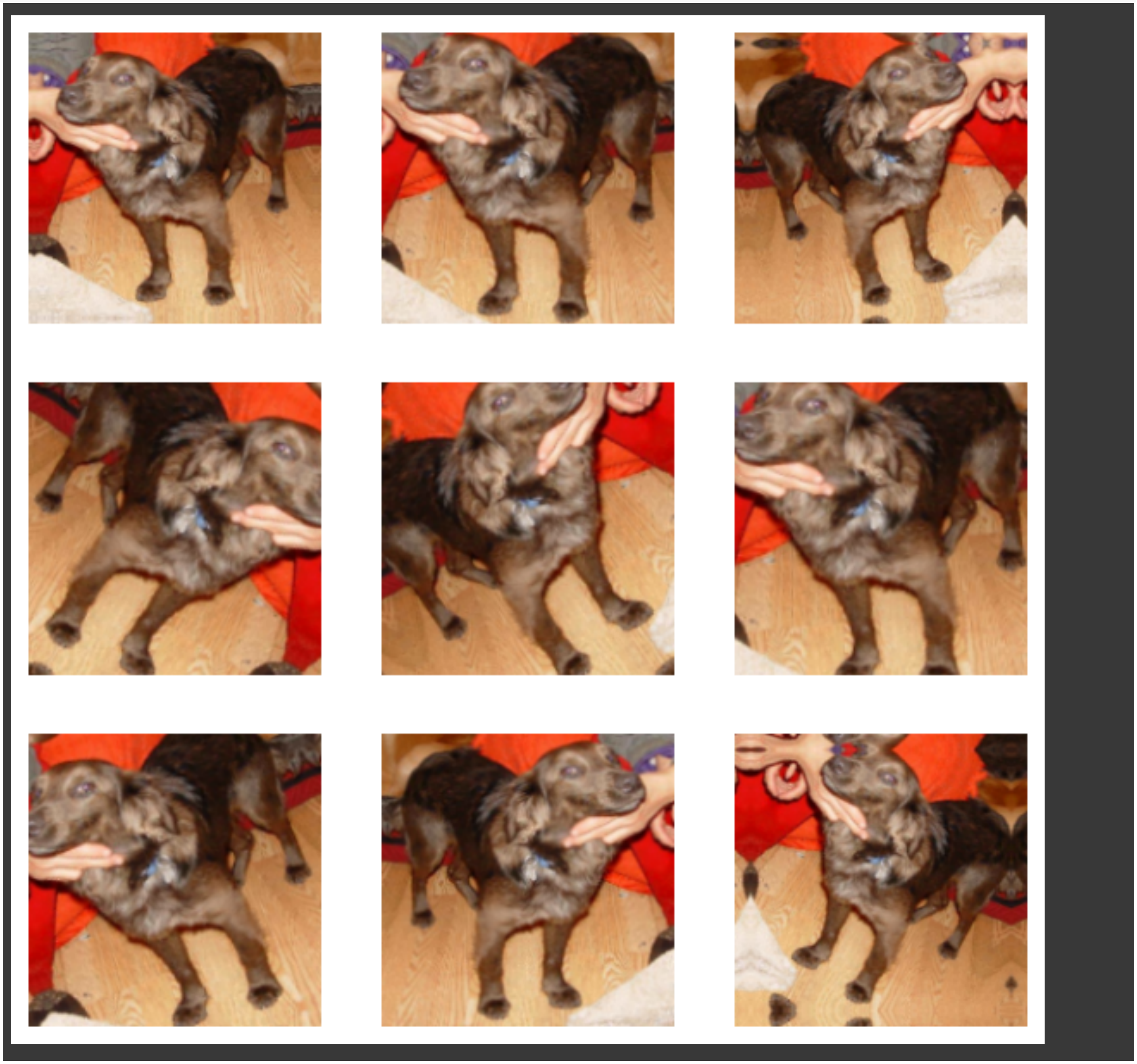
```
import os, shutil, pathlib

shutil.rmtree("./cats_vs_dogs_small_Q2", ignore_errors=True)

original_dir = pathlib.Path("train")
new_base_dir = pathlib.Path("cats_vs_dogs_small_Q2")

def make_subset(subset_name, start_index, end_index):
    for category in ("cat", "dog"):
        dir = new_base_dir / subset_name / category
        os.makedirs(dir)
        fnames = [f"{category}.{i}.jpg" for i in range(start_index, end_index)]
        for fname in fnames:
            shutil.copyfile(src=original_dir / fname,
                            dst=dir / fname)
#Creating training, Test and validation sets.
#Training has 1500 samples, test has 500 samples and validation has 500 samples.
make_subset("train", start_index=2000, end_index=3500)
make_subset("validation", start_index=3501, end_index=4001)
make_subset("test", start_index=4002, end_index=4502)
```

Here we are using the data augmentation technique to optimize the model performance as we are dealing with large datasets (increased the train sample size to 1500)

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

Display of few sample images in the dataset.

```
plt.figure(figsize=(7.5,7.5 ))
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")
```



Using Data Augmentation and Dropout to optimize the model. Dropout layer only applies when training is set to True such that no values are dropped during inference

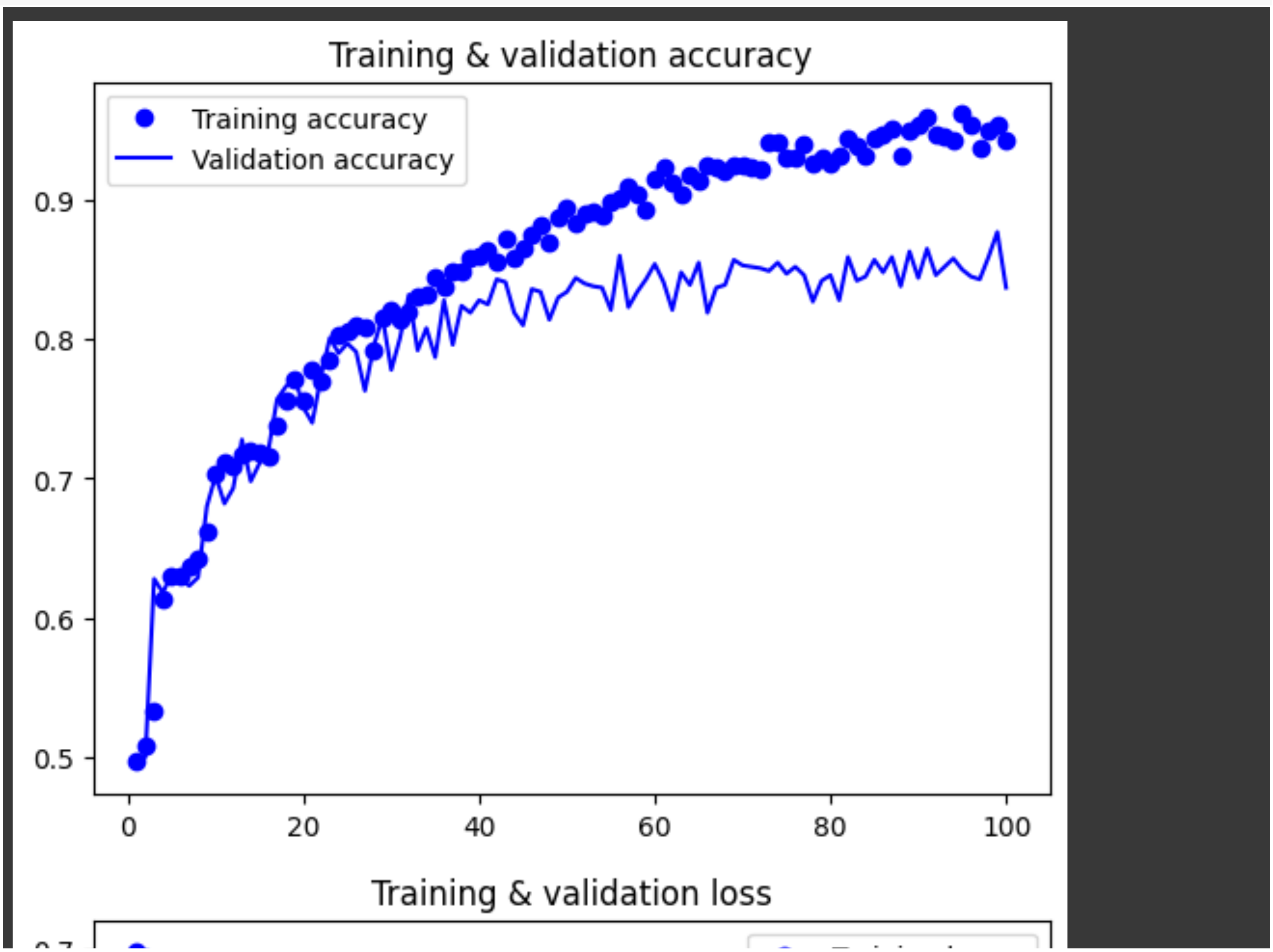
```
inputs = keras.Input(shape=(180, 180, 3))
x = data_augmentation(inputs)
x = layers.Rescaling(1./255)(x)
x = layers.Conv2D(filters=32, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
x = layers.Conv2D(filters=64, kernel_size=3, activation="relu")(x)
x = layers.MaxPooling2D(pool_size=2)(x)
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="adam",
              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=100,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

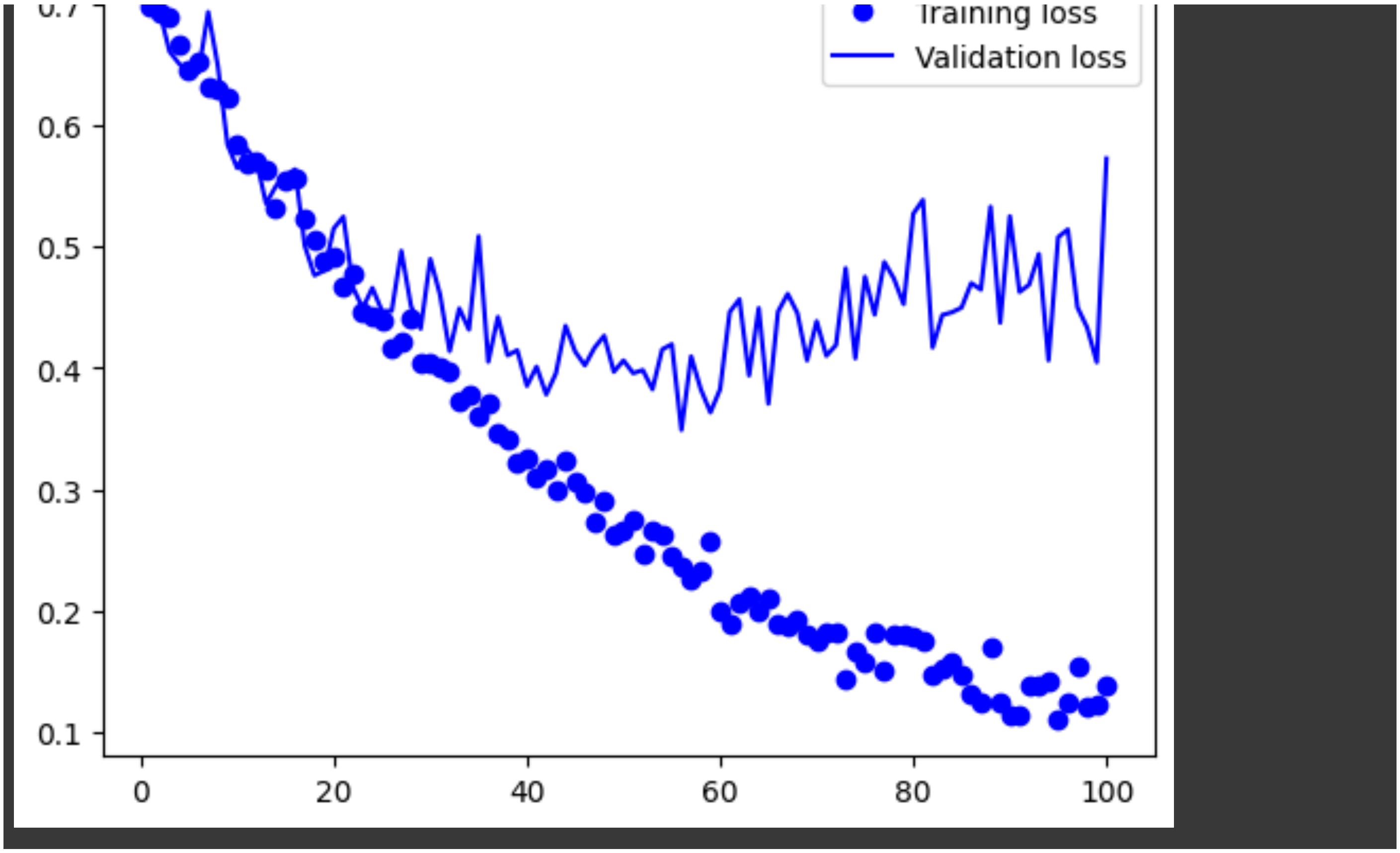
```
Epoch 71/100
63/63 [==============================] - 4s 62ms/step - loss: 0.1825 - accura
Epoch 72/100
63/63 [==============================] - 7s 112ms/step - loss: 0.1811 - accura
Epoch 73/100
63/63 [==============================] - 4s 58ms/step - loss: 0.1433 - accura
Epoch 74/100
63/63 [==============================] - 4s 58ms/step - loss: 0.1660 - accura
```

```
Epoch 75/100
63/63 [==============================] - 5s 82ms/step - loss: 0.1575 - accurac
Epoch 76/100
63/63 [==============================] - 6s 83ms/step - loss: 0.1816 - accurac
Epoch 77/100
63/63 [==============================] - 5s 83ms/step - loss: 0.1496 - accurac
Epoch 78/100
63/63 [==============================] - 6s 89ms/step - loss: 0.1799 - accurac
Epoch 79/100
63/63 [==============================] - 4s 58ms/step - loss: 0.1801 - accurac
Epoch 80/100
63/63 [==============================] - 4s 58ms/step - loss: 0.1783 - accurac
Epoch 81/100
63/63 [==============================] - 8s 114ms/step - loss: 0.1749 - accura
Epoch 82/100
63/63 [==============================] - 4s 60ms/step - loss: 0.1474 - accurac
Epoch 83/100
63/63 [==============================] - 4s 60ms/step - loss: 0.1519 - accurac
Epoch 84/100
63/63 [==============================] - 6s 88ms/step - loss: 0.1579 - accurac
Epoch 85/100
63/63 [==============================] - 5s 79ms/step - loss: 0.1471 - accurac
Epoch 86/100
63/63 [==============================] - 5s 71ms/step - loss: 0.1308 - accurac
Epoch 87/100
63/63 [==============================] - 6s 91ms/step - loss: 0.1237 - accurac
Epoch 88/100
63/63 [==============================] - 4s 59ms/step - loss: 0.1692 - accurac
Epoch 89/100
63/63 [==============================] - 4s 63ms/step - loss: 0.1248 - accurac
Epoch 90/100
63/63 [==============================] - 6s 93ms/step - loss: 0.1140 - accurac
Epoch 91/100
63/63 [==============================] - 4s 58ms/step - loss: 0.1136 - accurac
Epoch 92/100
63/63 [==============================] - 6s 89ms/step - loss: 0.1379 - accurac
Epoch 93/100
63/63 [==============================] - 4s 60ms/step - loss: 0.1380 - accurac
Epoch 94/100
63/63 [==============================] - 4s 66ms/step - loss: 0.1409 - accurac
Epoch 95/100
63/63 [==============================] - 7s 112ms/step - loss: 0.1093 - accura
Epoch 96/100
63/63 [==============================] - 4s 61ms/step - loss: 0.1250 - accurac
Epoch 97/100
63/63 [==============================] - 5s 73ms/step - loss: 0.1535 - accurac
Epoch 98/100
63/63 [==============================] - 6s 88ms/step - loss: 0.1207 - accurac
Epoch 99/100
63/63 [==============================] - 4s 59ms/step - loss: 0.1228 - accurac
```

Epoch 100/100

```
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 & 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 & validation loss")
plt.legend()
plt.show()
```






```
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}")
```

```
32/32 [==============================] - 1s 27ms/step - loss: 0.4353 - accura
Test accuracy: 0.840
```

3. Now change your training sample so that you achieve better performance than those from Steps 1 and 2. This sample size may be larger, or smaller than those in the previous steps. The objective is to find the ideal training sample size to get best prediction results.

Increasing the training sample size to 2000 taking the values from 4000 to 6000 from dataset and keeping the validation and test and validation sample sizes to 500 only.

```
original_dir = pathlib.Path("train")
new_base_dir = pathlib.Path("cats_vs_dogs_small_Q3")

def make_subset(subset_name, start_index, end_index):
    for category in ("cat", "dog"):
        dir = new_base_dir / subset_name / category
        os.makedirs(dir)
        fnames = [f"{category}.{i}.jpg" for i in range(start_index, end_index)]
        for fname in fnames:
            shutil.copyfile(src=original_dir / fname,
                            dst=dir / fname)
#Creating training, Test and validation sets.
#Training has 2000 samples, test has 500 samples and validation has 500 samples.
make_subset("train", start_index=4000, end_index=6000)
make_subset("validation", start_index=6001, end_index=6501)
make_subset("test", start_index=6502, end_index=7002)
```

A new convent:

```
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="adam",
              metrics=["accuracy"])
```

```
callbacks = [
    keras.callbacks.ModelCheckpoint(
```

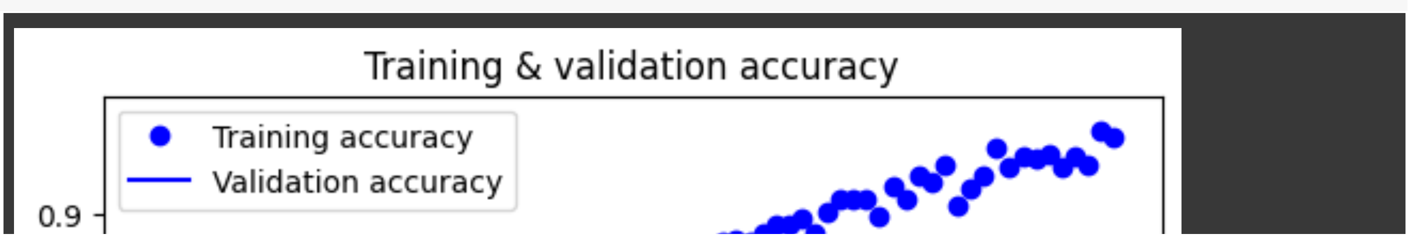
```
        filepath="convnet_from_scratch_with_augmentation1.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=75,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

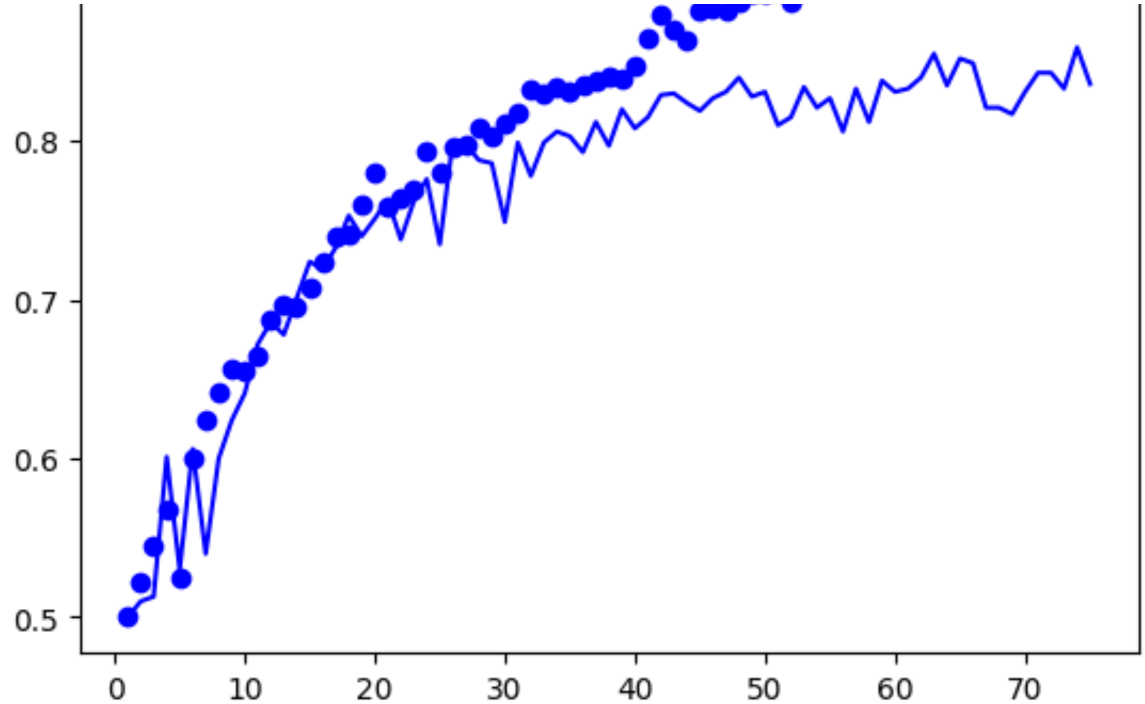
```
Epoch 1/75
63/63 [==============================] - 9s 90ms/step - loss: 0.6970 - accura
Epoch 2/75
63/63 [==============================] - 4s 60ms/step - loss: 0.6932 - accura
Epoch 3/75
63/63 [==============================] - 4s 60ms/step - loss: 0.6874 - accura
Epoch 4/75
63/63 [==============================] - 7s 106ms/step - loss: 0.6756 - accura
Epoch 5/75
63/63 [==============================] - 4s 60ms/step - loss: 0.6899 - accura
Epoch 6/75
63/63 [==============================] - 4s 62ms/step - loss: 0.6620 - accura
Epoch 7/75
63/63 [==============================] - 6s 93ms/step - loss: 0.6529 - accura
Epoch 8/75
63/63 [==============================] - 5s 73ms/step - loss: 0.6442 - accura
Epoch 9/75
63/63 [==============================] - 34s 545ms/step - loss: 0.6274 - accur
Epoch 10/75
63/63 [==============================] - 5s 81ms/step - loss: 0.6225 - accura
Epoch 11/75
63/63 [==============================] - 4s 61ms/step - loss: 0.6122 - accura
Epoch 12/75
63/63 [==============================] - 4s 64ms/step - loss: 0.5966 - accura
Epoch 13/75
63/63 [==============================] - 8s 116ms/step - loss: 0.5832 - accura
Epoch 14/75
63/63 [==============================] - 4s 60ms/step - loss: 0.5763 - accura
Epoch 15/75
63/63 [==============================] - 4s 60ms/step - loss: 0.5674 - accura
Epoch 16/75
63/63 [==============================] - 6s 90ms/step - loss: 0.5432 - accura
Epoch 17/75
63/63 [==============================] - 5s 77ms/step - loss: 0.5274 - accura
Epoch 18/75
63/63 [==============================] - 4s 60ms/step - loss: 0.5126 - accura
Epoch 19/75
63/63 [==============================] - 4s 64ms/step - loss: 0.5121 - accura
Epoch 20/75
```

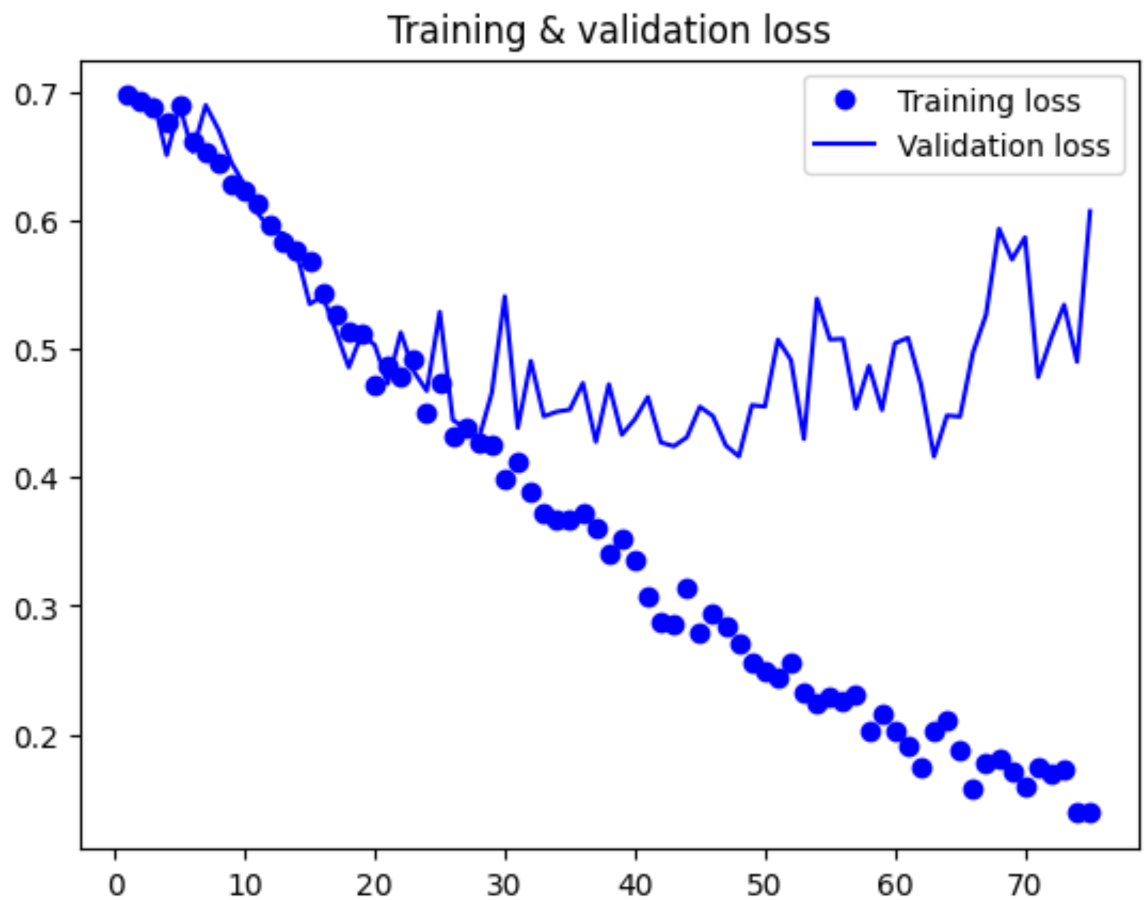
```
63/63 [==============================] - 6s 92ms/step - loss: 0.4720 - accura
Epoch 21/75
63/63 [==============================] - 4s 60ms/step - loss: 0.4859 - accura
Epoch 22/75
63/63 [==============================] - 8s 113ms/step - loss: 0.4789 - accura
Epoch 23/75
63/63 [==============================] - 4s 58ms/step - loss: 0.4916 - accura
Epoch 24/75
63/63 [==============================] - 5s 81ms/step - loss: 0.4497 - accura
Epoch 25/75
63/63 [==============================] - 4s 58ms/step - loss: 0.4727 - accura
Epoch 26/75
63/63 [==============================] - 4s 65ms/step - loss: 0.4315 - accura
Epoch 27/75
63/63 [==============================] - 6s 92ms/step - loss: 0.4388 - accura
Epoch 28/75
63/63 [==============================] - 4s 59ms/step - loss: 0.4277 - accura
Epoch 29/75
63/63 [==============================] - 4s 61ms/step - loss: 0.4254 - accura
Epoch 30/75
```

Graph of training and validation accuracy

```
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 & 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 & validation loss")
plt.legend()
plt.show()
```




0.8
0.7
0.6
0.5
0
10
20
30
40
50
60
70


Training & validation loss
Training loss
Validation loss
0.7
0.6
0.5
0.4
0.3
0.2
0
10
20
30
40
50
60
70

```
test_model = keras.models.load_model(
    "convnet_from_scratch_with_augmentation1.keras")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
32/32 [==============================] - 1s 28ms/step - loss: 0.4473 - accura
Test accuracy: 0.833
```

In the beginning as we took only 1000 samples in the first question and we acheived an accuracy of 74% but the same when we saw above with increasing the sample size to double we received 83% accuracy, the problem was overfitting and hence we generalized the model. As there was overfitting we used techniques like data augmentation and dropout to generalize the model.

4. Repeat Steps 1-3, but now using a pretrained network. The sample sizes you use in Steps 2 and 3 for the pretrained network may be the same or different from those using the network where you trained from scratch. Again, use any and all optimization techniques to get best performance.

Using pretrained model with Feature extraction technique

Using the VGG16 convolutional base which describes the first several layers of the the architecture, which are in charge of taking hierarchical features out of input images.

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

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applicat
58889256/58889256 [==============================] - 0s 0us/step
```

```
convolution_base.summary()
```

```
Model: "vgg16"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_7 (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: 14714688 (56.13 MB)
Trainable params: 14714688 (56.13 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Feature extraction without data augmentation using a pretrained model

```
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 = convolution_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)
```

```
1/1 [==============================] - 5s 5s/step
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 27ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 29ms/step
1/1 [==============================] - 0s 24ms/step
```

```
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 33ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 27ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 40ms/step
1/1 [==============================] - 0s 36ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 33ms/step
1/1 [==============================] - 0s 36ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 36ms/step
1/1 [==============================] - 0s 41ms/step
1/1 [==============================] - 0s 36ms/step
1/1 [==============================] - 0s 36ms/step
1/1 [==============================] - 0s 35ms/step
1/1 [==============================] - 0s 41ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 36ms/step
1/1 [==============================] - 0s 41ms/step
1/1 [==============================] - 0s 33ms/step
```

```
train_features.shape
```

```
(2000, 5, 5, 512)
```

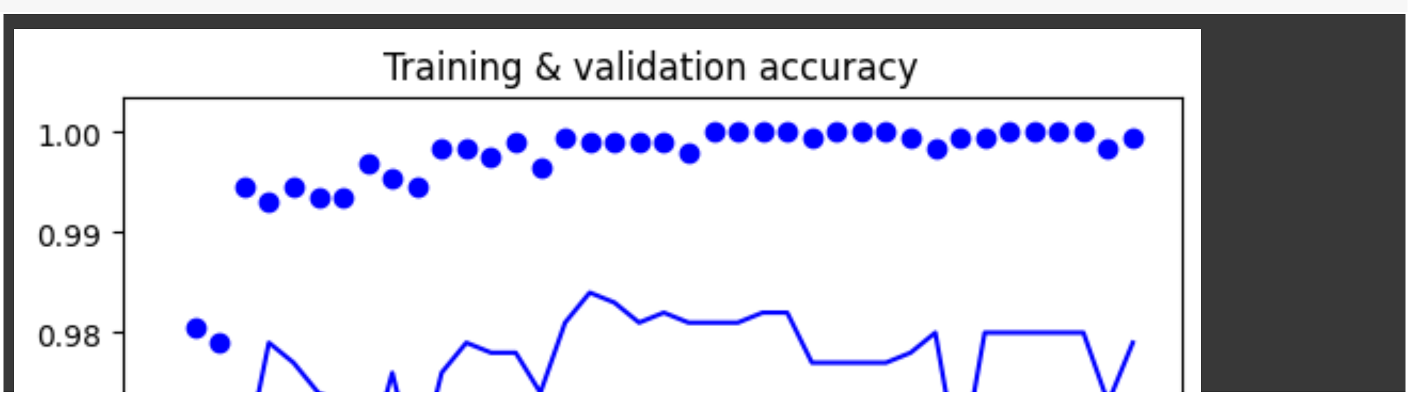
```
inputs = keras.Input(shape=(5, 5, 512))
x = layers.Flatten()(inputs)
x = layers.Dense(256)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.compile(loss="binary_crossentropy",
              optimizer="rmsprop",
          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

callbacks = [
    keras.callbacks.ModelCheckpoint(
```

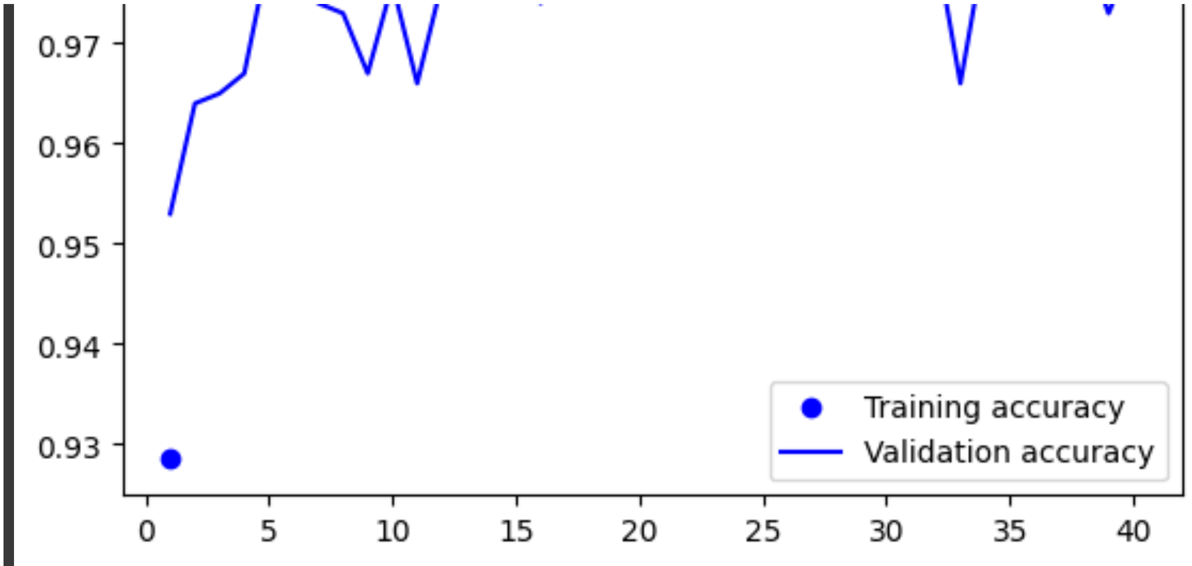
```
      filepath="feature_extraction.keras",
      save_best_only=True,
      monitor="val_loss")
]
history = model.fit(
    train_features, train_labels,
    epochs=40,
    validation_data=(val_features, val_labels),
    callbacks=callbacks)
```

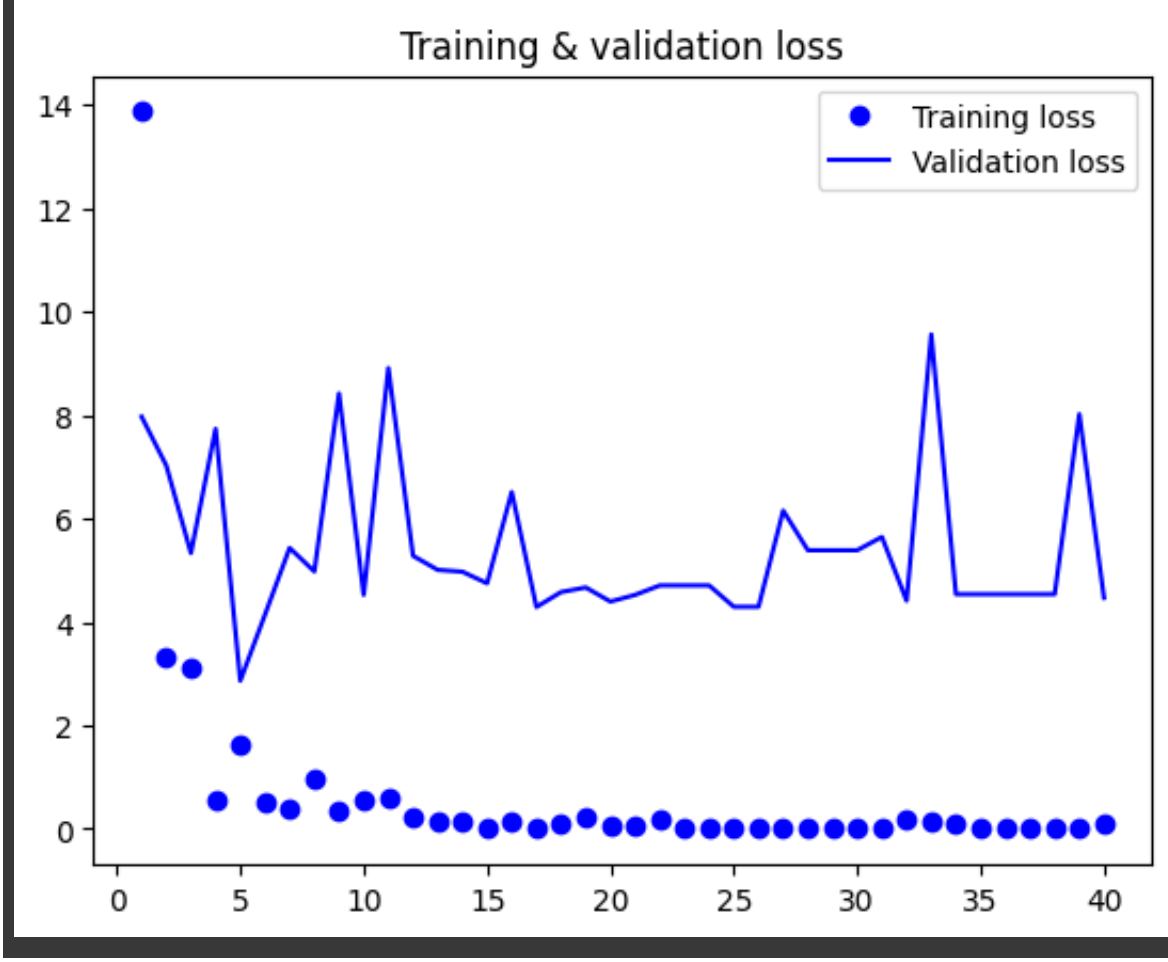
```
Epoch 1/40
63/63 [==============================] - 1s 10ms/step - loss: 13.8645 - accura
Epoch 2/40
63/63 [==============================] - 1s 8ms/step - loss: 3.3413 - accuracy
Epoch 3/40
63/63 [==============================] - 1s 8ms/step - loss: 3.1077 - accuracy
Epoch 4/40
63/63 [==============================] - 0s 6ms/step - loss: 0.5525 - accuracy
Epoch 5/40
63/63 [==============================] - 1s 8ms/step - loss: 1.6439 - accuracy
Epoch 6/40
63/63 [==============================] - 0s 6ms/step - loss: 0.5152 - accuracy
Epoch 7/40
63/63 [==============================] - 0s 5ms/step - loss: 0.4014 - accuracy
Epoch 8/40
63/63 [==============================] - 0s 5ms/step - loss: 0.9763 - accuracy
Epoch 9/40
63/63 [==============================] - 0s 6ms/step - loss: 0.3532 - accuracy
Epoch 10/40
63/63 [==============================] - 0s 5ms/step - loss: 0.5668 - accuracy
Epoch 11/40
63/63 [==============================] - 0s 5ms/step - loss: 0.5951 - accuracy
Epoch 12/40
63/63 [==============================] - 0s 6ms/step - loss: 0.2439 - accuracy
Epoch 13/40
63/63 [==============================] - 0s 5ms/step - loss: 0.1363 - accuracy
Epoch 14/40
63/63 [==============================] - 0s 5ms/step - loss: 0.1463 - accuracy
Epoch 15/40
63/63 [==============================] - 0s 6ms/step - loss: 0.0256 - accuracy
Epoch 16/40
63/63 [==============================] - 0s 6ms/step - loss: 0.1540 - accuracy
Epoch 17/40
63/63 [==============================] - 1s 8ms/step - loss: 0.0392 - accuracy
Epoch 18/40
63/63 [==============================] - 0s 7ms/step - loss: 0.1022 - accuracy
Epoch 19/40
63/63 [==============================] - 0s 7ms/step - loss: 0.2228 - accuracy
Epoch 20/40
```

```
63/63 [==============================] - 0s 8ms/step - loss: 0.0472 - accuracy
Epoch 21/40
63/63 [==============================] - 0s 7ms/step - loss: 0.0561 - accuracy
Epoch 22/40
63/63 [==============================] - 1s 9ms/step - loss: 0.1985 - accuracy
Epoch 23/40
63/63 [==============================] - 1s 9ms/step - loss: 0.0000e+00 - accu
Epoch 24/40
63/63 [==============================] - 0s 8ms/step - loss: 1.0615e-14 - accu
Epoch 25/40
63/63 [==============================] - 0s 8ms/step - loss: 5.1761e-06 - accu
Epoch 26/40
63/63 [==============================] - 1s 8ms/step - loss: 7.0063e-19 - accu
Epoch 27/40
63/63 [==============================] - 1s 9ms/step - loss: 0.0224 - accuracy
Epoch 28/40
63/63 [==============================] - 1s 8ms/step - loss: 1.1320e-06 - accu
Epoch 29/40
63/63 [==============================] - 1s 9ms/step - loss: 0.0000e+00 - accu
Epoch 30/40
```

```
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 & 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 & validation loss")
plt.legend()
plt.show()
```







Freezing the VGG16 convolutional base as in feature extraction we freeze the initial trained base

```
convolution_base  = keras.applications.vgg16.VGG16(
    weights="imagenet",
    include_top=False)
convolution_base.trainable = False
```

```
convolution_base.trainable = True
print("The number of trainable weights required to use the convolution base befor
```

```
The number of trainable weights required to use the convolution base before it
```

```
convolution_base.trainable = False
print("After the convolution base is frozen, this is the total quantity of traina
```

```
After the convolution base is frozen, this is the total quantity of trainable
```

Adding data augmentation:

```
augmentation2 = keras.Sequential(
[
layers.RandomFlip("horizontal"),
layers.RandomRotation(0.1),
layers.RandomZoom(0.2),
]
)
input22 = keras.Input(shape=(180, 180, 3))
x1 = augmentation2(input22)
x1 =keras.layers.Lambda(
lambda x: keras.applications.vgg16.preprocess_input(x))(x1)
x1 = convolution_base(x1)
x1 = layers.Flatten()(x1)
x1 = layers.Dense(256)(x1)
x1 = layers.Dropout(0.5)(x1)
outputs = layers.Dense(1, activation="sigmoid")(x1)
model = keras.Model(input22, outputs)
model.compile(loss="binary_crossentropy",
optimizer="rmsprop",
metrics=["accuracy"])
```

```
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="feature_extraction_with_data_augmentation.keras",
```

```
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=75,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 1/75
63/63 [==============================] - 11s 158ms/step - loss: 21.3565 - accu
Epoch 2/75
63/63 [==============================] - 11s 176ms/step - loss: 5.8368 - accur
Epoch 3/75
63/63 [==============================] - 11s 177ms/step - loss: 6.2118 - accur
Epoch 4/75
63/63 [==============================] - 9s 141ms/step - loss: 5.8927 - accura
Epoch 5/75
63/63 [==============================] - 11s 174ms/step - loss: 3.6089 - accur
Epoch 6/75
63/63 [==============================] - 10s 148ms/step - loss: 3.3797 - accur
Epoch 7/75
63/63 [==============================] - 9s 141ms/step - loss: 3.3175 - accura
Epoch 8/75
63/63 [==============================] - 10s 154ms/step - loss: 2.8912 - accur
Epoch 9/75
63/63 [==============================] - 9s 144ms/step - loss: 2.3200 - accura
Epoch 10/75
63/63 [==============================] - 9s 142ms/step - loss: 3.3377 - accura
Epoch 11/75
63/63 [==============================] - 9s 146ms/step - loss: 2.1499 - accura
Epoch 12/75
63/63 [==============================] - 9s 138ms/step - loss: 2.7613 - accura
Epoch 13/75
63/63 [==============================] - 10s 154ms/step - loss: 1.7239 - accur
Epoch 14/75
63/63 [==============================] - 11s 174ms/step - loss: 2.5592 - accur
Epoch 15/75
63/63 [==============================] - 9s 141ms/step - loss: 1.9904 - accura
Epoch 16/75
63/63 [==============================] - 9s 147ms/step - loss: 1.7074 - accura
Epoch 17/75
63/63 [==============================] - 12s 183ms/step - loss: 1.9545 - accur
Epoch 18/75
63/63 [==============================] - 9s 145ms/step - loss: 1.8268 - accura
Epoch 19/75
63/63 [==============================] - 9s 147ms/step - loss: 2.0651 - accura
Epoch 20/75
63/63 [==============================] - 10s 147ms/step - loss: 1.6846 - accur
```

```
Epoch 21/75
63/63 [==============================] - 9s 143ms/step - loss: 1.2312 - accura
Epoch 22/75
63/63 [==============================] - 9s 141ms/step - loss: 1.5208 - accura
Epoch 23/75
63/63 [==============================] - 9s 144ms/step - loss: 0.4468 - accura
Epoch 24/75
63/63 [==============================] - 9s 138ms/step - loss: 1.0485 - accura
Epoch 25/75
63/63 [==============================] - 9s 144ms/step - loss: 1.5633 - accura
Epoch 26/75
63/63 [==============================] - 11s 174ms/step - loss: 1.1490 - accur
Epoch 27/75
63/63 [==============================] - 10s 148ms/step - loss: 1.1046 - accur
Epoch 28/75
63/63 [==============================] - 10s 149ms/step - loss: 1.3581 - accur
Epoch 29/75
63/63 [==============================] - 9s 140ms/step - loss: 1.0131 - accura
Epoch 30/75
```

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

```
32/32 [==============================] - 4s 88ms/step - loss: 2.1661 - accurac
Test accuracy: 0.979
```

A pretrained VGG16 model with Fine-tuning

Fine-tuning the pretrained model which already discovered some useful characteristics from a large set of data, speed-to-convergence is accelerated as compared to training from scratch. The model may overfit the dataset that the model is tuned on if it is not fine-tunned on a new dataset. This may result in it meshing its learned features better to the features of this new dataset leading to improved generalization performance.

```
convolution_base.summary()
```

```
Model: "vgg16"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_9 (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: 14714688 (56.13 MB)
Trainable params: 0 (0.00 Byte)
Non-trainable params: 14714688 (56.13 MB)
_________________________________________________________________
```

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

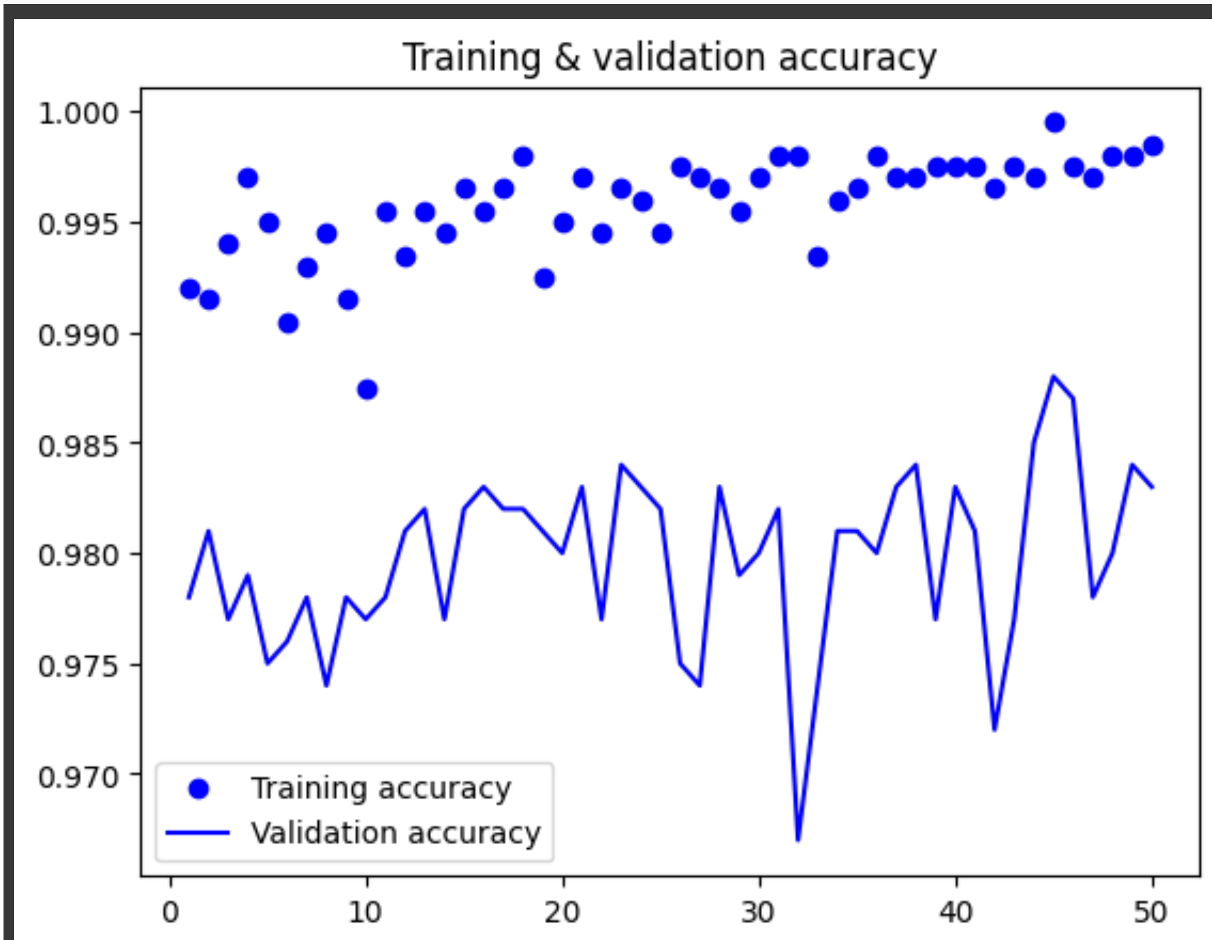
```
model.compile(loss="binary_crossentropy",
              optimizer=keras.optimizers.RMSprop(learning_rate=1e-5),
              metrics=["accuracy"])

callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="fine_tuning.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=50,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

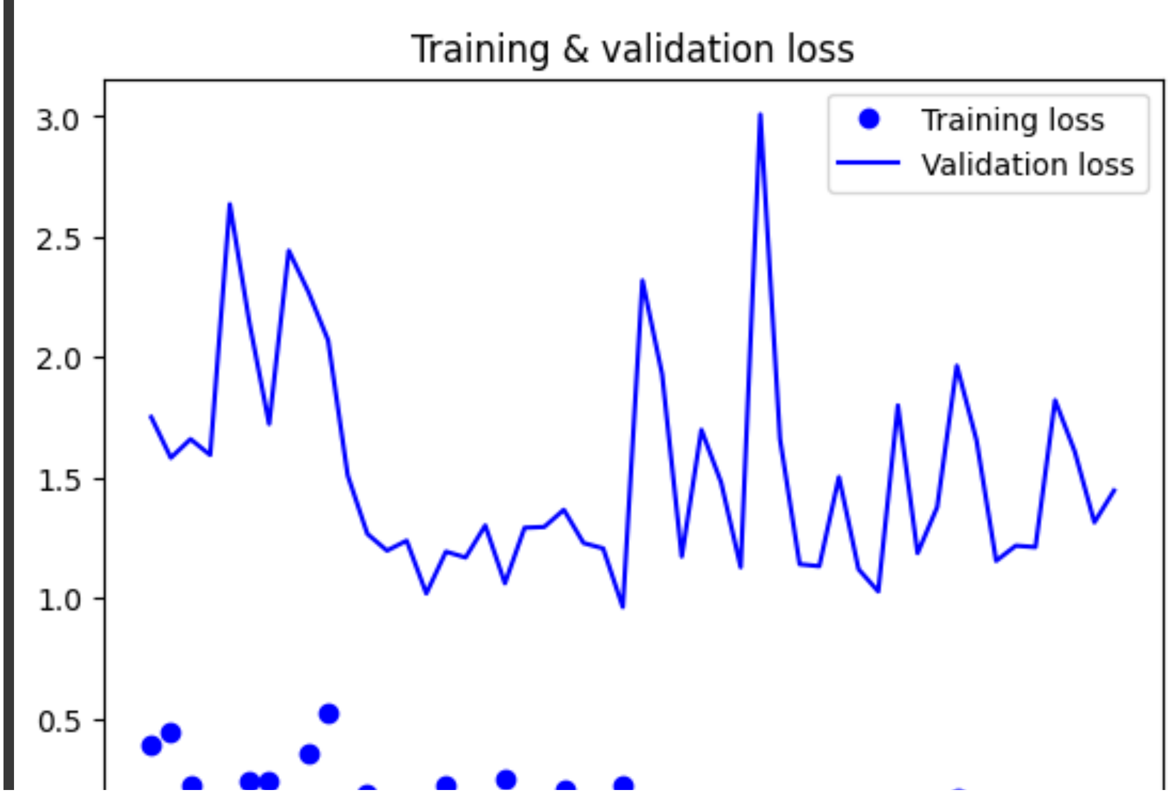
```
Epoch 1/50
63/63 [==============================] - 13s 178ms/step - loss: 0.3884 - accu
Epoch 2/50
63/63 [==============================] - 11s 170ms/step - loss: 0.4428 - accu
Epoch 3/50
63/63 [==============================] - 11s 166ms/step - loss: 0.2220 - accu
Epoch 4/50
63/63 [==============================] - 12s 192ms/step - loss: 0.0601 - accu
Epoch 5/50
63/63 [==============================] - 10s 161ms/step - loss: 0.0859 - accu
Epoch 6/50
63/63 [==============================] - 10s 154ms/step - loss: 0.2347 - accu
Epoch 7/50
63/63 [==============================] - 10s 163ms/step - loss: 0.2364 - accu
Epoch 8/50
63/63 [==============================] - 10s 155ms/step - loss: 0.1495 - accu
Epoch 9/50
63/63 [==============================] - 11s 165ms/step - loss: 0.3497 - accu
Epoch 10/50
63/63 [==============================] - 10s 157ms/step - loss: 0.5183 - accu
Epoch 11/50
63/63 [==============================] - 11s 169ms/step - loss: 0.0668 - accu
Epoch 12/50
63/63 [==============================] - 11s 173ms/step - loss: 0.1845 - accu
Epoch 13/50
63/63 [==============================] - 11s 165ms/step - loss: 0.0869 - accu
```

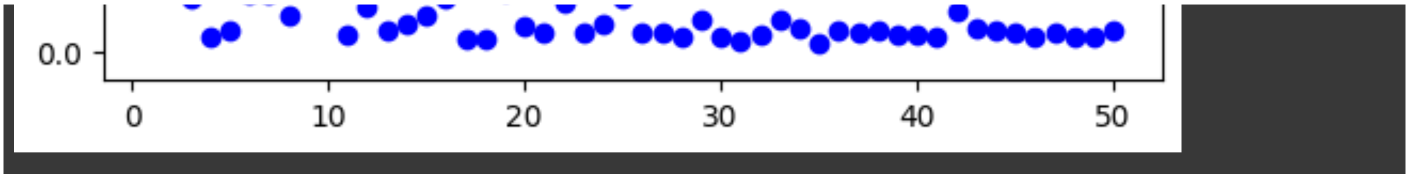
```
Epoch 14/50
63/63 [==============================] - 11s 162ms/step - loss: 0.1190 - accu
Epoch 15/50
63/63 [==============================] - 13s 198ms/step - loss: 0.1532 - accu
Epoch 16/50
63/63 [==============================] - 11s 164ms/step - loss: 0.2212 - accu
Epoch 17/50
63/63 [==============================] - 10s 157ms/step - loss: 0.0539 - accu
Epoch 18/50
63/63 [==============================] - 11s 163ms/step - loss: 0.0486 - accu
Epoch 19/50
63/63 [==============================] - 12s 189ms/step - loss: 0.2498 - accu
Epoch 20/50
63/63 [==============================] - 10s 158ms/step - loss: 0.1081 - accu
Epoch 21/50
63/63 [==============================] - 11s 165ms/step - loss: 0.0792 - accu
Epoch 22/50
63/63 [==============================] - 10s 155ms/step - loss: 0.2037 - accu
Epoch 23/50
63/63 [==============================] - 10s 160ms/step - loss: 0.0761 - accu
Epoch 24/50
63/63 [==============================] - 12s 190ms/step - loss: 0.1135 - accu
Epoch 25/50
63/63 [==============================] - 11s 170ms/step - loss: 0.2245 - accu
Epoch 26/50
63/63 [==============================] - 10s 157ms/step - loss: 0.0821 - accu
Epoch 27/50
63/63 [==============================] - 10s 160ms/step - loss: 0.0804 - accu
Epoch 28/50
63/63 [==============================] - 11s 161ms/step - loss: 0.0638 - accu
Epoch 29/50
63/63 [==============================] - 11s 167ms/step - loss: 0.1293 - accu
Epoch 30/50
```

```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.plot(epochs, accuracy, "bo", label="Training accuracy")
plt.plot(epochs, val_accuracy, "b", label="Validation accuracy")
plt.title("Training & 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 & validation loss")
```

```
plt.legend()
plt.show()
```








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

```
32/32 [==============================] - 3s 87ms/step - loss: 2.2782 - accura
Test accuracy: 0.974
```