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

!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 99% 803M/812M [00:09<00:00, 61.4MB/s] 100% 812M/812M [00:09<00:00, 89.3MB/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?

Copying pictures to the test, validation, and training sets.

Convolutional neural networks are used.

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

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
<pre>max_pooling2d (MaxPooling2 D)</pre>	(None, 89, 89, 32)	0
conv2d_1 (Conv2D)	(None, 87, 87, 64)	18496
<pre>max_pooling2d_1 (MaxPoolin g2D)</pre>	(None, 43, 43, 64)	0
conv2d_2 (Conv2D)	(None, 41, 41, 128)	73856
<pre>max_pooling2d_2 (MaxPoolin g2D)</pre>	(None, 20, 20, 128)	0
conv2d_3 (Conv2D)	(None, 18, 18, 256)	295168
<pre>max_pooling2d_3 (MaxPoolin g2D)</pre>	(None, 9, 9, 256)	0
conv2d_4 (Conv2D)	(None, 7, 7, 256)	590080
flatten (Flatten)	(None, 12544)	0
dense (Dense)	(None, 1)	12545

Total params: 991041 (3.78 MB)
Trainable params: 991041 (3.78 MB)
Non-trainable params: 0 (0.00 Byte)

Given that the model may overfit, regularization techniques are employed at the DATA PREPROCESSING step.

Here, every image is transformed into a tensor.

```
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.
```

Callback can be either used for saveage the model's weights at the end of every epoch or for early stopping if the model is not improving. Besides that callbacks, such as logging metrics, visualizing the model performance, or scheduling a learning rate changes may be used in the same way.

```
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch1.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=30,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

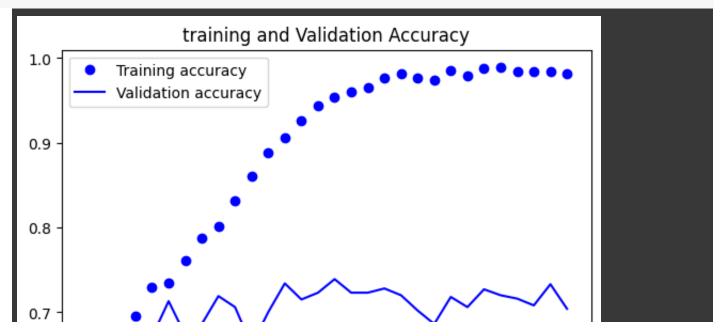
Epoch 1/30

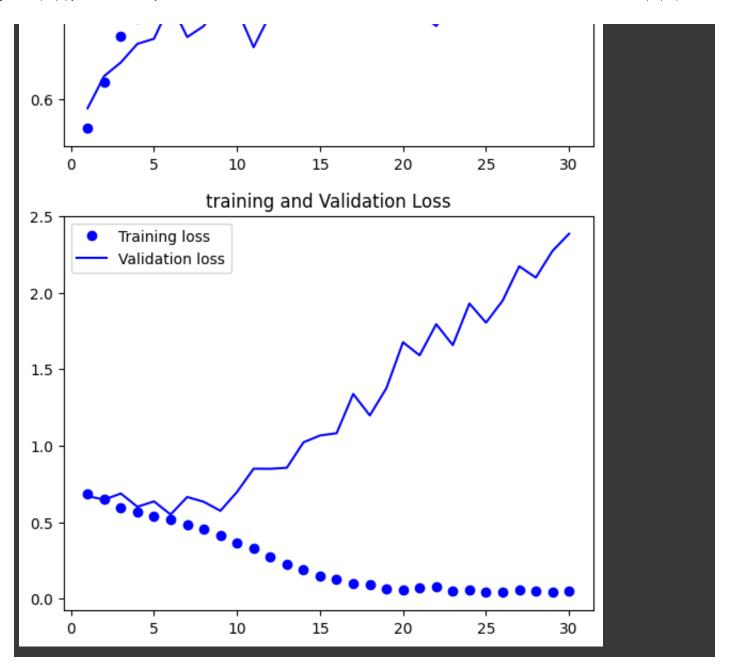
· •	
	==] - 6s 96ms/step - loss: 0.6868 - accurac
Epoch 2/30	1 /s F7ms/stop loss, 0.6497 loss,
63/63 [====================================	==] - 4s 57ms/step - loss: 0.6487 - accurac
	==] - 4s 56ms/step - loss: 0.5969 - accurac
Epoch 4/30	
	==] - 5s 72ms/step - loss: 0.5681 - accurac
Epoch 5/30	
63/63 [====================================	==] - 6s 84ms/step - loss: 0.5399 - accurac
Epoch 6/30	
	==] - 4s 57ms/step - loss: 0.5165 - accurac
Epoch 7/30	
	==] - 7s 103ms/step - loss: 0.4856 - accura
Epoch 8/30	1 40 56mg/oton 1000 0 4560 000000
63/63 [====================================	==] - 4s 56ms/step - loss: 0.4560 - accurac
•	==] - 4s 56ms/step - loss: 0.4115 - accurac
Epoch 10/30	
	==] - 6s 97ms/step - loss: 0.3636 - accurac
Epoch 11/30	
63/63 [====================================	==] - 4s 57ms/step - loss: 0.3278 - accurac
Epoch 12/30	
	==] - 4s 60ms/step - loss: 0.2721 - accurac
Epoch 13/30	
	==] - 6s 83ms/step - loss: 0.2251 - accurac
Epoch 14/30	==] - 4s 58ms/step - loss: 0.1930 - accurac
Epoch 15/30	==] - 45 36ms/step - toss: 0.1930 - accurac
	==] - 4s 57ms/step - loss: 0.1472 - accurac
Epoch 16/30	
	==] - 5s 80ms/step - loss: 0.1295 - accurac
Epoch 17/30	
	==] - 4s 56ms/step - loss: 0.0976 - accurac
Epoch 18/30	
	==] - 6s 90ms/step - loss: 0.0945 - accurac
Epoch 19/30	1 4- 57/ 1 0.0674
	==] - 4s 57ms/step - loss: 0.0674 - accurac
Epoch 20/30	==] - 4s 56ms/step - loss: 0.0546 - accurac
Epoch 21/30] - 45 Johns/Step - toss. 0.0340 - accurat
•	==] - 6s 87ms/step - loss: 0.0719 - accurac
Epoch 22/30	1 00 075, 5 top 10051 010715 400414.
1	==] - 4s 57ms/step - loss: 0.0767 - accurac
Epoch 23/30	·
63/63 [====================================	==] - 6s 95ms/step - loss: 0.0494 - accurac
Epoch 24/30	
	==] - 5s 66ms/step - loss: 0.0561 - accurac
Epoch 25/30	
63/63 [====================================	==] - 4s 61ms/step - loss: 0.0406 - accurac
LPUCII 20/30	

Accuracy appears to be rising with the number of epochs.

Accuracy=71.3 Val_acc=70.4 test_acc=71.3

```
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()
```





```
test_model = keras.models.load_model("convnet_from_scratch1.keras")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

Test accuracy with no data augmentation=71.3

Data Augmentation

Data augmentation acts like a master artist adding new custom made artwork to the training dataset by artfully modifying the original data. Apart from assisting in curbing overfitting, this aesthetic touch also leads to the development of a broader capability of recognizing more generalized cases by the model.

```
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"])
```

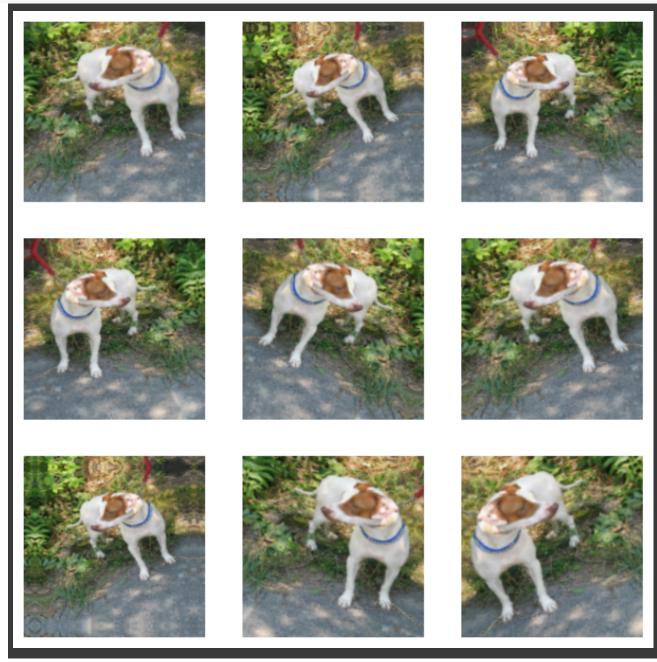
```
callbacks = [
   keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch_with_augmentation1.keras",
```

```
Epoch 1/50
Epoch 2/50
Epoch 3/50
Epoch 4/50
Epoch 5/50
Epoch 6/50
Epoch 7/50
Epoch 8/50
Epoch 9/50
Epoch 10/50
Epoch 11/50
Epoch 12/50
Epoch 13/50
Epoch 14/50
Epoch 15/50
Epoch 16/50
Epoch 17/50
Epoch 18/50
Epoch 19/50
Epoch 20/50
```

```
Epoch 21/50
Epoch 22/50
Epoch 23/50
Epoch 24/50
Epoch 25/50
Epoch 26/50
Epoch 27/50
Epoch 28/50
63/63 [============== ] - 4s 62ms/step - loss: 0.4309 - accurac
Epoch 29/50
Epoch 30/50
```

Displaying some randomly augmented training images:

```
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")
```



2. Increase your training sample size. You may pick any amount. Keep the validation and test samples the same as above

Tried to raise the 1000–1500 training sample size.

```
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 3000 files belonging to 2 classes. Found 1000 files belonging to 2 classes. Found 1000 files belonging to 2 classes.
```

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

```
callbacks = [
    keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch2.keras",
        save_best_only=True,
        monitor="val_loss")
]
history = model.fit(
    train_dataset,
    epochs=70,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

94/94 [====================================	- 6c 64mc/cton - locci 0 4537 - accu	ıraı
Epoch 8/70	- 03 041113/312p - 1033. 01433/ - acco	II at
94/94 [====================================	– 5s 51ms/step – loss: 0.4003 – accu	ırac
Epoch 9/70		
94/94 [====================================	– 7s 75ms/step – loss: 0.3641 – accu	ırac
Epoch 10/70	C- C1/-t 1 0 2000	
94/94 [====================================	- 65 61ms/step - loss: 0.2999 - accu	ırac
94/94 [====================================	- 6s 57ms/sten - loss: 0.2355 - accu	ıraı
Epoch 12/70	03 37m3/3ccp	
94/94 [====================================	– 9s 93ms/step – loss: 0.1936 – accu	ırac
Epoch 13/70		
94/94 [====================================	– 5s 54ms/step – loss: 0.1570 – accu	ırac
Epoch 14/70 94/94 [====================================	7s 70ms/ston loss, 0 1067 assu	ıraı
Epoch 15/70	- /5 /0ms/step - toss: 0.100/ - acco	II at
94/94 [====================================	- 5s 51ms/step - loss: 0.0928 - accu	ırac
Epoch 16/70		
94/94 [====================================	– 7s 72ms/step – loss: 0.0842 – accu	ırac
Epoch 17/70		
94/94 [====================================	– 7s 64ms/step – loss: 0.0665 – accu	ıraı
Epoch 18/70 94/94 [====================================	- 7s 73ms/sten - loss: 0 0608 - accu	ıraı
Epoch 19/70	- 73 751113/312p - 1033. 0.0000 - acco	II at
94/94 [====================================	- 6s 63ms/step - loss: 0.0555 - accu	ırac
Epoch 20/70		
94/94 [====================================	– 5s 51ms/step – loss: 0.0509 – accu	ırac
Epoch 21/70		
94/94 [====================================	- 8s 83ms/step - loss: 0.0356 - accu	ırac
94/94 [========================	- 5s 52ms/sten - loss: 0.0377 - accu	ıraı
Epoch 23/70	33 32m3/3cep (0331 0103// deed	
94/94 [====================================	– 9s 92ms/step – loss: 0.0521 – accu	ırac
Epoch 24/70		
94/94 [====================================	– 5s 51ms/step – loss: 0.0394 – accu	ırac
Epoch 25/70	Co 57mg/stan lagge 0 0220 sage	
94/94 [====================================	- 65 5/ms/step - toss: 0.0336 - accu	irac
94/94 [====================================	- 8s 77ms/sten - loss: 0.0472 - accu	ırac
Epoch 27/70	03 //ms/seep	
94/94 [====================================	– 5s 51ms/step – loss: 0.0496 – accu	ırac
Epoch 28/70		
94/94 [====================================	– 7s 69ms/step – loss: 0.0310 – accu	ırac
Epoch 29/70	7c 70mc/cton local 0 0512	LEG :
94/94 [====================================	- /S /WIIIS/Step - LOSS: W.WSIZ - accu	II d(
Epoch Juliu		

Accuracy=75.8 val_acc=74.6 test_acc=75.8

Applying data augmentation

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 augmentation2.keras",
      save_best_only=True,
      monitor="val_loss")
history = model.fit(
   train_dataset,
   epochs=80,
   validation_data=validation_dataset,
   callbacks=callbacks)
   Epoch 1/80
   Epoch 2/80
   Epoch 3/80
                    94/94 [======
   Epoch 4/80
   Epoch 5/80
                     ==========] - 5s 55ms/step - loss: 0.6494 - accurac
   94/94 [=========
```

Epoch 6/80

94/94	[======]	_	7s	68ms/step - loss: 0.6400 - accurac
Epoch			-	52ma (atau) 1 a a a 0 6266
94/94 Epoch		_	55	53ms/step - loss: 0.6266 - accurac
		_	7s	72ms/step - loss: 0.5966 - accurac
Epoch	9/80			
		-	5s	53ms/step - loss: 0.5968 - accurac
Epoch		_	7 c	69ms/step - loss: 0.5732 - accurac
Epoch			73	03113/31Cp - 1033. 013/32 - accurat
94/94	[=======]	_	7s	72ms/step - loss: 0.5598 - accurac
Epoch			_	
94/94 Epoch		-	bs	63ms/step - loss: 0.5337 - accurac
		_	5s	53ms/step - loss: 0.5350 - accurac
Epoch	14/80			
		-	6s	56ms/step - loss: 0.4995 - accurac
Epoch			E c	F2mc/ston loss, 0 F0F2 popular
Epoch		_	55	52ms/step - loss: 0.5053 - accurac
		_	8s	85ms/step - loss: 0.4901 - accurac
Epoch	17/80			
		-	5s	52ms/step - loss: 0.4780 - accurac
Epoch		_	<u>۵</u> د	78ms/step - loss: 0.4719 - accurac
Epoch			03	701113/312p - 1033. 0.4/13 - accurac
		_	5s	56ms/step - loss: 0.4754 - accurac
Epoch			_	70 () 0 4445
94/94 Epoch		_	/s	72ms/step - loss: 0.4445 - accurac
		_	6s	63ms/step - loss: 0.4477 - accurac
Epoch				
		-	7s	68ms/step - loss: 0.4319 - accurac
	23/80	_	5.0	53ms/step - loss: 0.4268 - accurac
Epoch			23	33//31cμ - 1033. 0.4200 - accurat
	•	_	6s	64ms/step - loss: 0.4227 - accurac
Epoch			_	
	[=======] 26/80	-	5s	52ms/step - loss: 0.4176 - accurac
	•	_	7s	72ms/step - loss: 0.3990 - accurac
Epoch			, 5	, zms, step 18331 013330 accurac
		-	5s	53ms/step - loss: 0.3953 - accurac
Epoch			7.	71mg/gton 1000 0 2004
94/94 Epoch		_	/5	71ms/step - loss: 0.3984 - accurac
		_	7s	68ms/step - loss: 0.3863 - accurac
Epoch	30/80			
04/04	r 1		-	70/_± 1 0 0700

Accuracy=93.8 val_acc=85.2 test_acc=84.8

```
test_model = keras.models.load_model(
    "convnet_from_scratch_with_augmentation2.keras")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

3. The objective is to find the ideal training sample size to get best prediction

The sizes of the training, validation, and test sets were established at 1500, 1000, and 500, respectively.

```
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 3000 files belonging to 2 classes.
    Found 2000 files belonging to 2 classes.
    Found 1000 files belonging to 2 classes.
```

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)

```
callbacks = [
   keras.callbacks.ModelCheckpoint(
        filepath="convnet_from_scratch3.keras",
        save_best_only=True,
        monitor="val_loss")
```

model.compile(loss="binary_crossentropy",

optimizer="rmsprop",
metrics=["accuracy"])

```
history = model.fit(
    train_dataset,
    epochs=90,
    validation_data=validation_dataset,
    callbacks=callbacks)
```

```
Epoch 1/90
Epoch 2/90
Epoch 3/90
Epoch 4/90
Epoch 5/90
Epoch 6/90
94/94 [============== ] - 6s 61ms/step - loss: 0.5029 - accurac
Epoch 7/90
Epoch 8/90
Epoch 9/90
Epoch 10/90
94/94 [============== ] - 7s 67ms/step - loss: 0.3092 - accurac
Epoch 11/90
Epoch 12/90
Epoch 13/90
Epoch 14/90
Epoch 15/90
Epoch 16/90
Epoch 17/90
94/94 [============== ] - 7s 67ms/step - loss: 0.0660 - accurac
Epoch 18/90
Epoch 19/90
Epoch 20/90
94/94 [============== ] - 9s 89ms/step - loss: 0.0588 - accurac
Epoch 21/90
```

```
94/94 [============== ] - 7s 67ms/step - loss: 0.0366 - accurac
 Epoch 22/90
 Epoch 23/90
 Epoch 24/90
 Epoch 25/90
 Epoch 26/90
 Epoch 27/90
 Epoch 28/90
 Epoch 29/90
 Epoch 30/90
test_model = keras.models.load_model(
 "convnet_from_scratch3.keras")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test acc:.3f}")
 Test accuracy: 0.752
```

Accuracy=99.3 val_Acc=75.0 test_Acc=75.2

Utilizing Augmented Data

```
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 augmentation3.keras",
      save_best_only=True,
      monitor="val_loss")
history = model.fit(
   train_dataset,
   epochs=100,
   validation_data=validation_dataset,
   callbacks=callbacks)
   Epoch 1/100
   Epoch 2/100
   94/94 [============== ] - 9s 94ms/step - loss: 0.6943 - accurac
   Epoch 3/100
   Epoch 4/100
   Epoch 5/100
   Epoch 6/100
```

Epoch 7/100	
	:] - 10s 104ms/step - loss: 0.6934 - accu
Epoch 8/100	
	e] - 6s 61ms/step - loss: 0.6934 - accurac
Epoch 9/100	1 00 00mg/stan loss, 0 60F0 seems
94/94 [====================================	e] - 9s 89ms/step - loss: 0.6958 - accurac
	e] - 6s 62ms/step - loss: 0.6934 - accurac
Epoch 11/100	1 03 02m3/3ccp (0331 010331 decurat
	e] - 7s 69ms/step - loss: 0.6921 - accurac
Epoch 12/100	
94/94 [===========	e] - 10s 109ms/step - loss: 0.6945 - accu
Epoch 13/100	
	e] - 6s 62ms/step - loss: 0.6933 - accurac
Epoch 14/100	1 0-04/
	:] - 8s 84ms/step - loss: 0.6933 - accurac
Epoch 15/100] - 9s 96ms/step - loss: 0.6932 - accurac
Epoch 16/100	.] - 95 90ms/step - toss. 0.0932 - accurat
	e] - 7s 68ms/step - loss: 0.6927 - accurac
Epoch 17/100	,,,,,
	e] - 9s 96ms/step - loss: 0.6932 - accurac
Epoch 18/100	
	:] - 7s 66ms/step - loss: 0.6934 - accurac
Epoch 19/100	
	:] - 7s 71ms/step - loss: 0.6931 - accurac
Epoch 20/100	1 00 06mg/stan lagge 0 6020 aggregation
94/94 [====================================	:] - 9s 86ms/step - loss: 0.6938 - accurac
	e] - 6s 61ms/step - loss: 0.6929 - accurac
Epoch 22/100	1 03 01m3/3ccp (0331 010323 deceird)
	e] - 12s 122ms/step - loss: 0.6932 - accu
Epoch 23/100	
94/94 [============	e] - 6s 61ms/step - loss: 0.6930 - accurac
Epoch 24/100	
	:] - 7s 65ms/step - loss: 0.6930 - accurac
Epoch 25/100	1 0- 06 (-+ 1 0 6020
	:] - 9s 96ms/step - loss: 0.6929 - accurac
Epoch 26/100] - 6s 62ms/step - loss: 0.6942 - accurac
Epoch 27/100	.] - 03 021113/312p - 1033. 0:0342 - accurat
•	e] - 8s 81ms/step - loss: 0.6933 - accurac
Epoch 28/100	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
•	e] - 8s 75ms/step - loss: 0.6926 - accurac
Epoch 29/100	
	:] - 7s 68ms/step - loss: 0.6936 - accurac
Epoch 30/100	

Accuracy=48.9 val_acc=50.0 test_acc=52.4

Test accuracy: 0.524

4. Now using a pretrained network.

This pre-trained network is modeled by VGG16.

Creating the VGG16 convolutional basis is the first step in feature extraction.

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

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
<pre>block1_pool (MaxPooling2D)</pre>	(None, 90, 90, 64)	0
block2_conv1 (Conv2D)	(None, 90, 90, 128)	73856
block2_conv2 (Conv2D)	(None, 90, 90, 128)	147584
<pre>block2_pool (MaxPooling2D)</pre>	(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
<pre>block3_pool (MaxPooling2D)</pre>	(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
<pre>block4_pool (MaxPooling2D)</pre>	(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
<pre>block5_pool (MaxPooling2D)</pre>	(None, 5, 5, 512)	0

Total params: 14714688 (56.13 MB)
Trainable params: 14714688 (56.13 MB)
Non-trainable params: 0 (0.00 Byte)

Extraction of features and associated labels is known as feature extraction.

```
import numpy as np

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

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

```
1/1 [======= ] - 0s 30ms/step
1/1 [======= ] - 0s 36ms/step
1/1 [======= ] - 0s 38ms/step
1/1 [======= ] - 0s 29ms/step
1/1 [======= ] - 0s 50ms/step
1/1 [======= ] - 0s 31ms/step
1/1 [======= ] - 0s 45ms/step
1/1 [======= ] - 0s 32ms/step
1/1 [======= ] - 0s 49ms/step
1/1 [======= ] - 0s 47ms/step
1/1 [======= ] - 0s 34ms/step
1/1 [======= ] - 0s 38ms/step
1/1 [======= ] - 0s 40ms/step
1/1 [======= ] - 0s 38ms/step
1/1 [======= ] - 0s 43ms/step
1/1 [======= ] - 0s 51ms/step
1/1 [======= ] - 0s 36ms/step
1/1 [======= ] - 0s 39ms/step
1/1 [======= ] - 0s 32ms/step
1/1 [======= ] - 0s 30ms/step
1/1 [======= ] - 0s 34ms/step
1/1 [======= ] - 0s 35ms/step
1/1 [======= ] - 0s 32ms/step
1/1 [======= ] - 0s 33ms/step
```

1/1 [=======] - 5s 5s/step

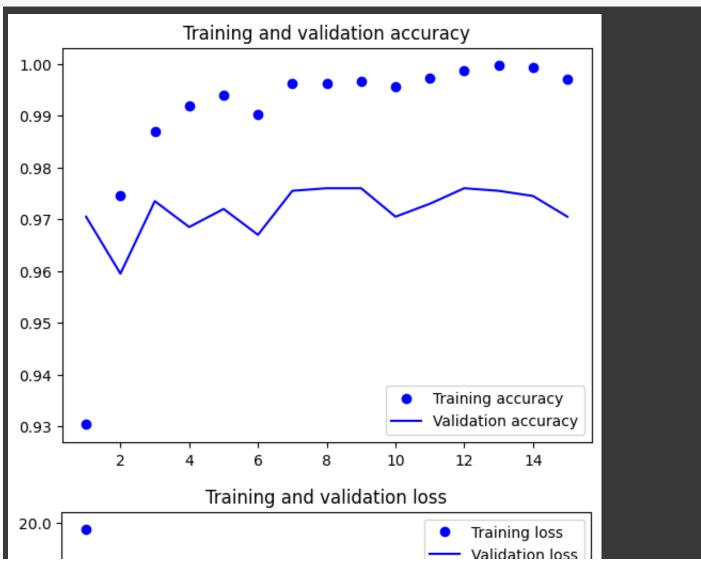
```
1/1 [======= ] - 0s 30ms/step
1/1 [=================== ] - 0s 34ms/step
1/1 [======= ] - 0s 23ms/step
1/1 [=================== ] - 0s 22ms/step
1/1 [============= ] - 0s 24ms/step
1/1 [=============== ] - 0s 23ms/step
1/1 [=================== ] - 0s 24ms/step
1/1 [=================== ] - 0s 22ms/step
1/1 [======= ] - 0s 27ms/step
1/1 [======= ] - 0s 23ms/step
1/1 [======= ] - 0s 23ms/step
1/1 [======= ] - 0s 23ms/step
1/1 [=================== ] - 0s 22ms/step
1/1 [======= ] - 0s 27ms/step
1/1 [=================== ] - 0s 22ms/step
1/1 [======= ] - 0s 23ms/step
1/1 [======= ] - 0s 25ms/step
1/1 [======= ] - 0s 23ms/step
1/1 [======= ] - 0s 24ms/step
1/1 [======= ] - 0s 22ms/step
1/1 [======] - 0s 23ms/step
1/1 [======= ] - 0s 23ms/step
1/1 [======] - 0s 22ms/step
1/1 [======= ] - 0s 28ms/step
1/1 [======= ] - 0s 22ms/step
1/1 [=================== ] - 0s 22ms/step
1/1 [======= ] - 0s 23ms/step
```

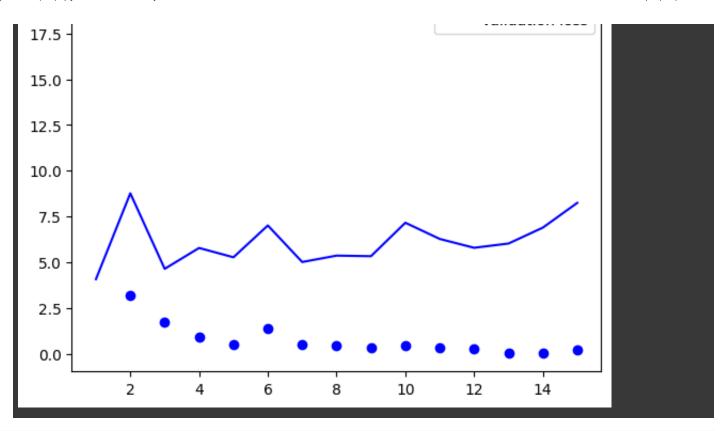
The densely connected classifier is defined and trained throughout the feature extraction process.

```
callbacks = [
 keras.callbacks.ModelCheckpoint(
  filepath="feature extractionPT1.keras",
  save_best_only=True,
  monitor="val_loss")
history = model.fit(
 train_features, train_labels,
 epochs=15,
 validation_data=(val_features, val_labels),
 callbacks=callbacks)
 Epoch 1/15
 Epoch 2/15
 Epoch 3/15
 Epoch 4/15
 Epoch 5/15
 Epoch 6/15
 Epoch 7/15
 Epoch 8/15
 Epoch 9/15
 Epoch 10/15
 94/94 [============== ] - 1s 8ms/step - loss: 0.4261 - accuracy
 Epoch 11/15
 94/94 [============== ] - 1s 8ms/step - loss: 0.3498 - accuracy
 Epoch 12/15
 Epoch 13/15
 Epoch 14/15
 94/94 [============== ] - 1s 7ms/step - loss: 0.0149 - accuracy
 Epoch 15/15
```

accuracy=99.7 val_acc=97.5

```
import matplotlib.pyplot as plt
acc = history.history["accuracy"]
val acc = history.history["val accuracy"]
loss = history.history["loss"]
val_loss = history.history["val_loss"]
epochs = range(1, len(acc) + 1)
plt.plot(epochs, acc, "bo", label="Training accuracy")
plt.plot(epochs, val_acc, "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()
```





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

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

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

This is the number of trainable weights before freezing the conv base: 26 This is the number of trainable weights after freezing the conv base: 0

Utilizing data augmentation for feature extraction

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

import tensorflow as tf
from tensorflow import keras

!pip install tensorflow

```
Requirement already satisfied: tensorflow in /usr/local/lib/python3.10/dist-page 1.0.
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dis
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10,
Requirement already satisfied: flatbuffers>=23.5.26 in /usr/local/lib/python3.
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in /usr/loc
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.1
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.10/dist-
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/c
Requirement already satisfied: ml-dtypes~=0.2.0 in /usr/local/lib/python3.10/c
Requirement already satisfied: numpy<2.0.0,>=1.23.5 in /usr/local/lib/python3.
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10,
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packaging in /usr/local/lib/python3
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-r
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/c
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/pyth
Requirement already satisfied: wrapt<1.15,>=1.11.0 in /usr/local/lib/python3.1
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/lc
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.1
Requirement already satisfied: tensorboard<2.16,>=2.15 in /usr/local/lib/pythc
Requirement already satisfied: tensorflow-estimator<2.16,>=2.15.0 in /usr/location
Requirement already satisfied: keras<2.16,>=2.15.0 in /usr/local/lib/python3.1
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/python?
Requirement already satisfied: google-auth-oauthlib<2,>=0.5 in /usr/local/lib,
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/d:
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.1
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/d:
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/pythor
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python?
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.10/dist
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/pyth
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/pyth
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10,
Requirement already satisfied: pyasn1<0.7.0,>=0.4.6 in /usr/local/lib/python3.
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.10/d:
```

```
import tensorflow as tf
from tensorflow import keras

callbacks = [
```

```
keras.callbacks.ModelCheckpoint(
    filepath="feature_extraction_with_data_augmentationPT2.keras",
    save_best_only=True,
    monitor="val_loss",
    save_weights_only=True)
]
history = model.fit(
    train_dataset,
    epochs=30,
    validation_data=validation_dataset,
    callbacks=callbacks)
Epoch 1/30
```

```
Epoch 1/30
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Epoch 12/30
Epoch 13/30
Epoch 14/30
Epoch 15/30
Epoch 16/30
Epoch 17/30
Epoch 18/30
Epoch 19/30
```

```
Epoch 20/30
 Epoch 21/30
 Epoch 22/30
 Epoch 23/30
 Epoch 24/30
 Epoch 25/30
 Epoch 26/30
 94/94 [============== ] - 16s 166ms/step - loss: 0.4109 - accur
 Epoch 27/30
 94/94 [============== ] - 20s 209ms/step - loss: 0.3969 - accur
 Epoch 28/30
 Epoch 29/30
 Epoch 30/30
                 16- 167--/---
test model = keras.models.load model(
 "feature extraction with data augmentationPT2.keras")
test_loss, test_acc = test_model.evaluate(test_dataset)
print(f"Test accuracy: {test_acc:.3f}")
```

```
32/32 [=========================] - 3s 89ms/step - loss: 4.2593 - accuracy: 0.9690 Test accuracy: 0.969 accuracy=96.9% val_Acc=97.4% test_acc=97.4%
```