
Simple explanation of convolutional neural network | Deep Learning Tutorial 23 (Tensorflow & Python)

Location shifted

1	1	1	-1	-1
1	-1	1	-1	-1
1	1	1	-1	-1
-1	-1	1	-1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1
1	-1	-1	-1	-1

→

1	1	1	-1	-1
1	-1	1	-1	-1
1	1	1	-1	-1
-1	-1	1	-1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1
1	-1	-1	-1	-1

✗

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

↳

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Variation 1

-1	-1	1	-1	-1
-1	1	-1	1	-1
-1	1	1	-1	-1
-1	-1	1	-1	-1
-1	-1	1	-1	-1
-1	-1	1	-1	-1
-1	-1	1	-1	-1



-1	-1	1	-1	-1
-1	1	-1	1	-1
-1	1	1	-1	-1
-1	-1	1	-1	-1
-1	-1	1	-1	-1
-1	-1	1	-1	-1
-1	-1	1	-1	-1



-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

To handle **variety** in digits we can use simple artificial neural network (ANN)



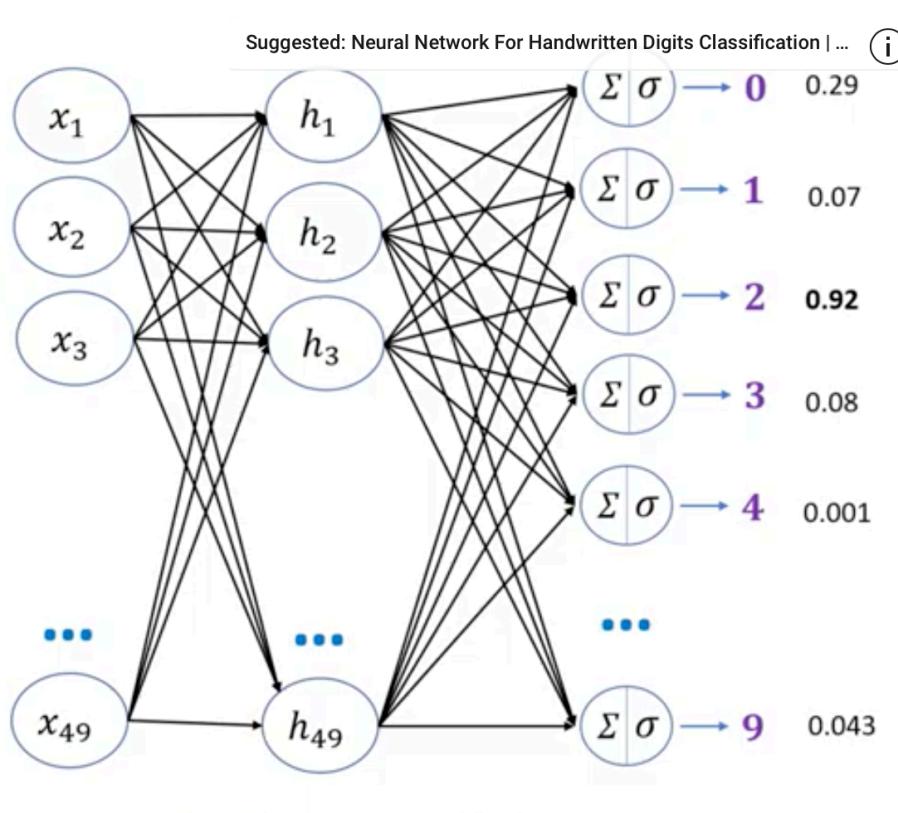


0	0	0	0	0	0	0	0
0	87	240	210	24	0	0	0
0	13	0	101	195	0	0	0
0	35	167	99	210	0	0	0
0	145	230	240	201	189	140	0
0	0	102	67	17	13	0	0
0	0	0	0	0	0	0	0

7 by 7 grid

0	0	0	0	0	0	0	0
0	87	240	210	24	0	0	0
0	13	0	101	195	0	0	0
0	35	167	99	210	0	0	0
0	145	230	240	201	189	140	0
0	0	102	67	17	13	0	0
0	0	0	0	0	0	0	0

0
87
240
210
24
0
...
0



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Image size = $1920 \times 1080 \times 3$

First layer neurons = $1920 \times 1080 \times 3 \sim 6$ million



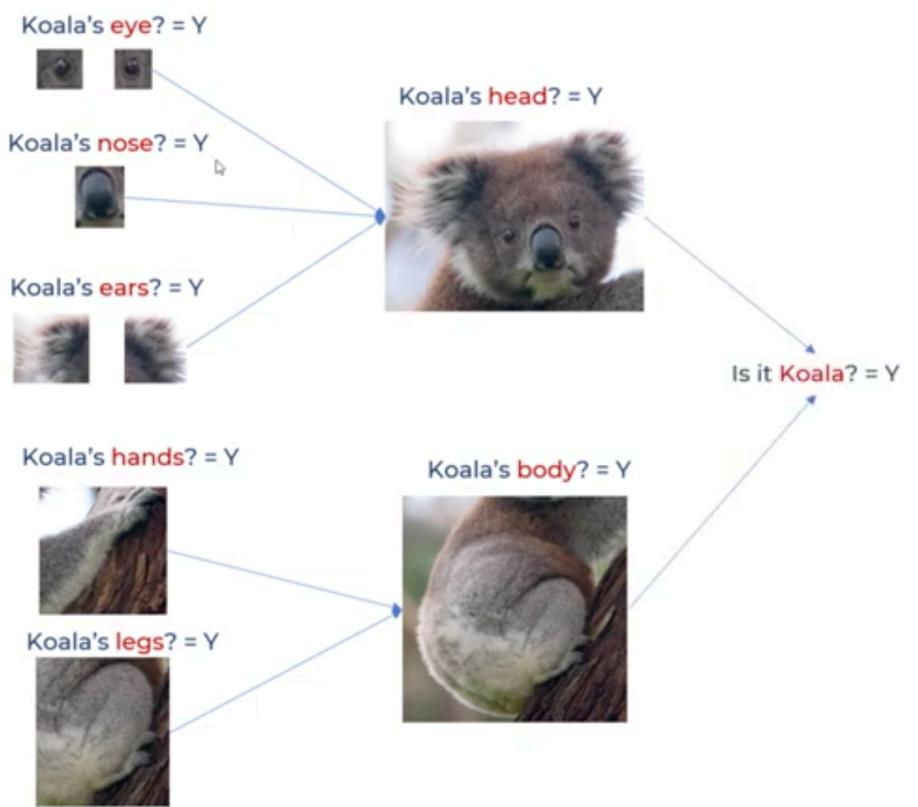
Hidden layer neurons = Let's say you keep it ~ 4 million

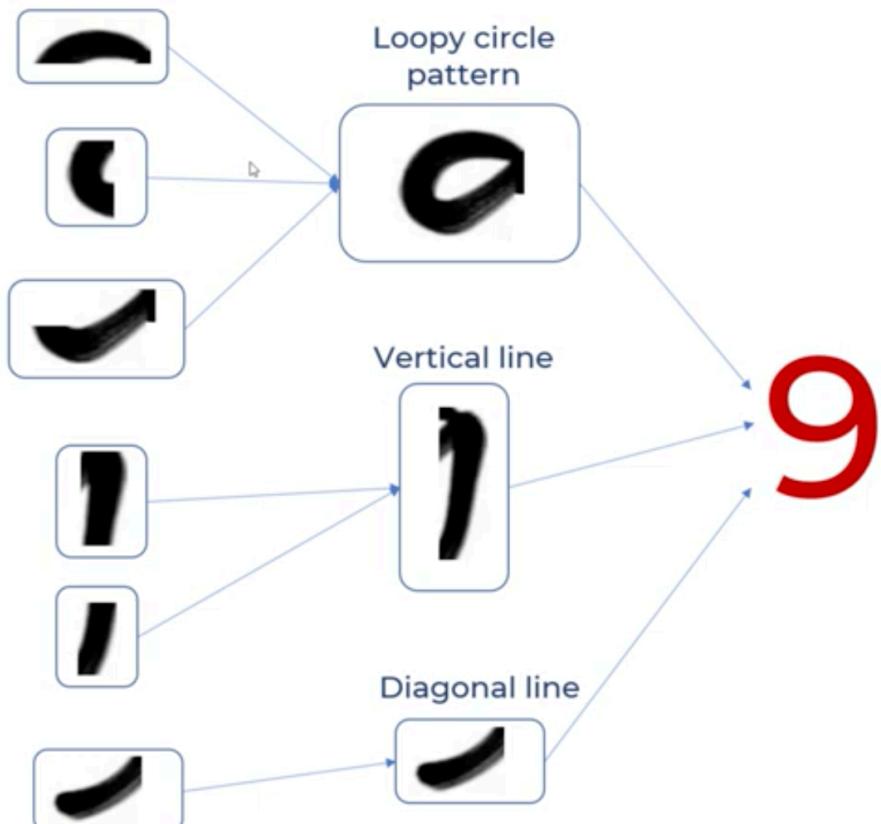
Weights between input and hidden layer = $6 \text{ mil} * 4 \text{ mil}$
 $= 24$ million

Disadvantages of using ANN for image classification

1. Too much computation
2. Treats local pixels same as pixels far apart
3. Sensitive to location of an object in an image







-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	1	-1	-1	-1
-1	1	-1	-1	-1

Loopy pattern
filter

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	1	-1	-1	-1
-1	1	-1	-1	-1

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	1	-1	-1	-1
-1	1	-1	-1	-1

Vertical line
filter

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	1	-1	-1	-1
-1	1	-1	-1	-1

Diagonal line
filter

$$-1+1+1-1-1-1+1+1 = -1 \rightarrow -1/9 = -0.11$$

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

*

1	1	1
1	-1	1
1	1	1

-0.11		

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-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

*

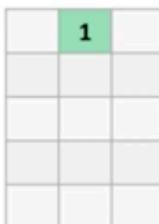
1	1	1
1	-1	1
1	1	1

-0.11	1	-0.11
-0.55	0.11	-0.33
-0.33	0.33	-0.33
-0.22	-0.11	-0.22
-0.33	-0.33	-0.33

Feature Map

9 * **Loopy pattern detector**

1	1	1
1	-1	1
1	1	1

= 

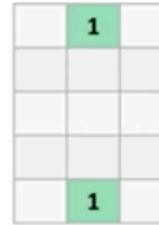
6 * **Loopy pattern detector**

1	1	1
1	-1	1
1	1	1

= 

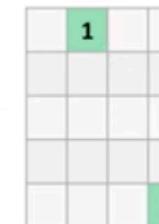
8 * **Loopy pattern detector**

1	1	1
1	-1	1
1	1	1

= 

96 * **Loopy pattern detector**

1	1	1
1	-1	1
1	1	1

= 

**Filters are nothing
but the feature
detectors**



$$* \begin{array}{|c|c|c|} \hline \text{eye} & & \\ \hline \text{detector} & & \\ \hline \end{array} = \boxed{\begin{array}{|c|c|} \hline 1 & 1 \\ \hline \end{array}}$$

Location invariant: It can detect eyes in any location of the image

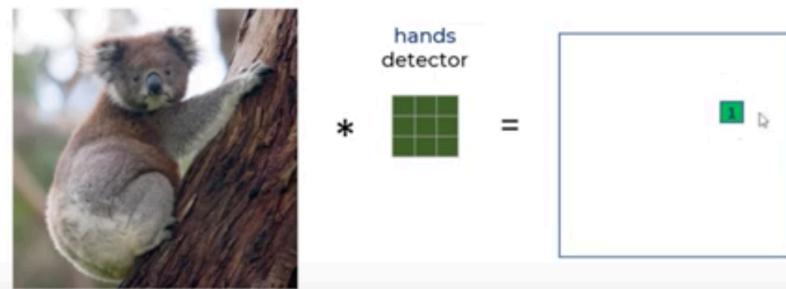


$$\begin{array}{|c|c|c|} \hline \text{eye} & & \\ \hline \text{detector} & & \\ \hline \end{array} = \boxed{\begin{array}{|c|c|} \hline 1 & 1 \\ \hline \end{array}}$$



$$* \begin{array}{|c|c|c|} \hline \text{eye} & & \\ \hline \text{detector} & & \\ \hline \end{array} = \boxed{\begin{array}{|c|c|c|c|} \hline 1 & & 1 & 1 \\ \hline & 1 & 1 & \\ \hline \end{array}}$$

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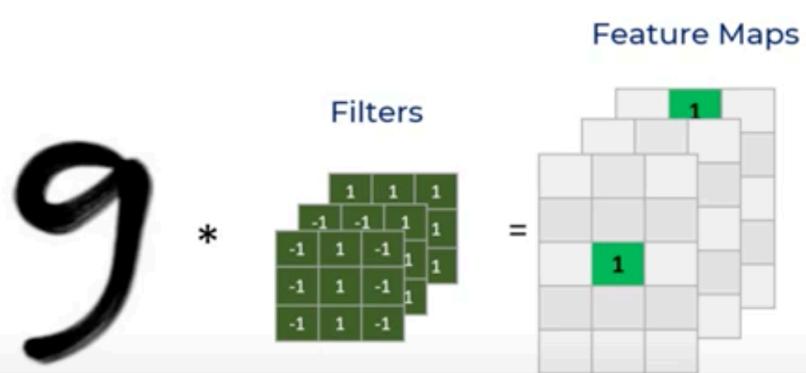


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$$* \begin{array}{|c|c|} \hline \text{eye} & \\ \hline \end{array} = \boxed{\begin{array}{|c|c|} \hline 1 & 1 \\ \hline \end{array}}$$

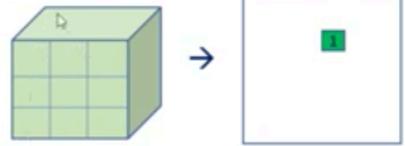


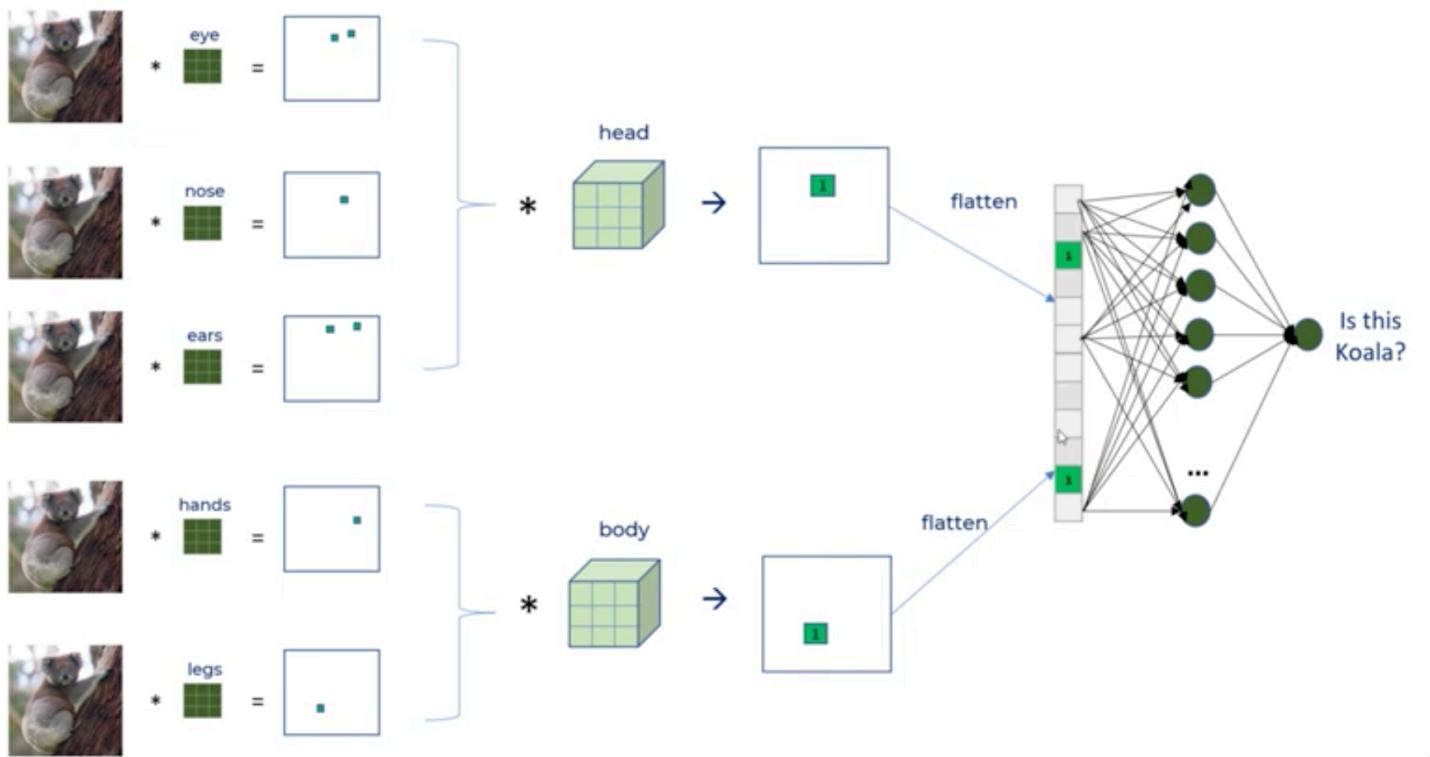
$$* \begin{array}{|c|c|} \hline \text{nose} & \\ \hline \end{array} = \boxed{\begin{array}{|c|} \hline 1 \\ \hline \end{array}}$$

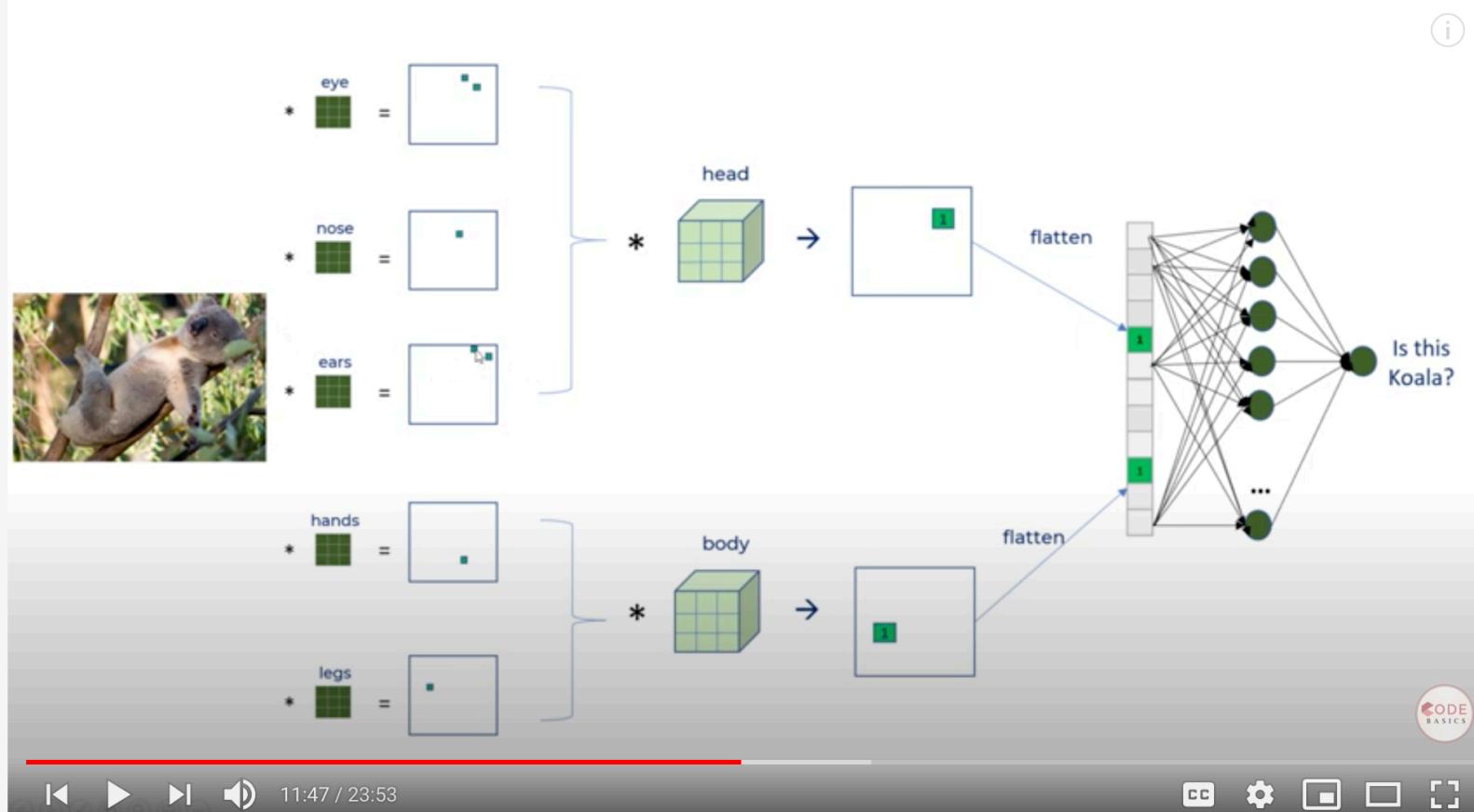


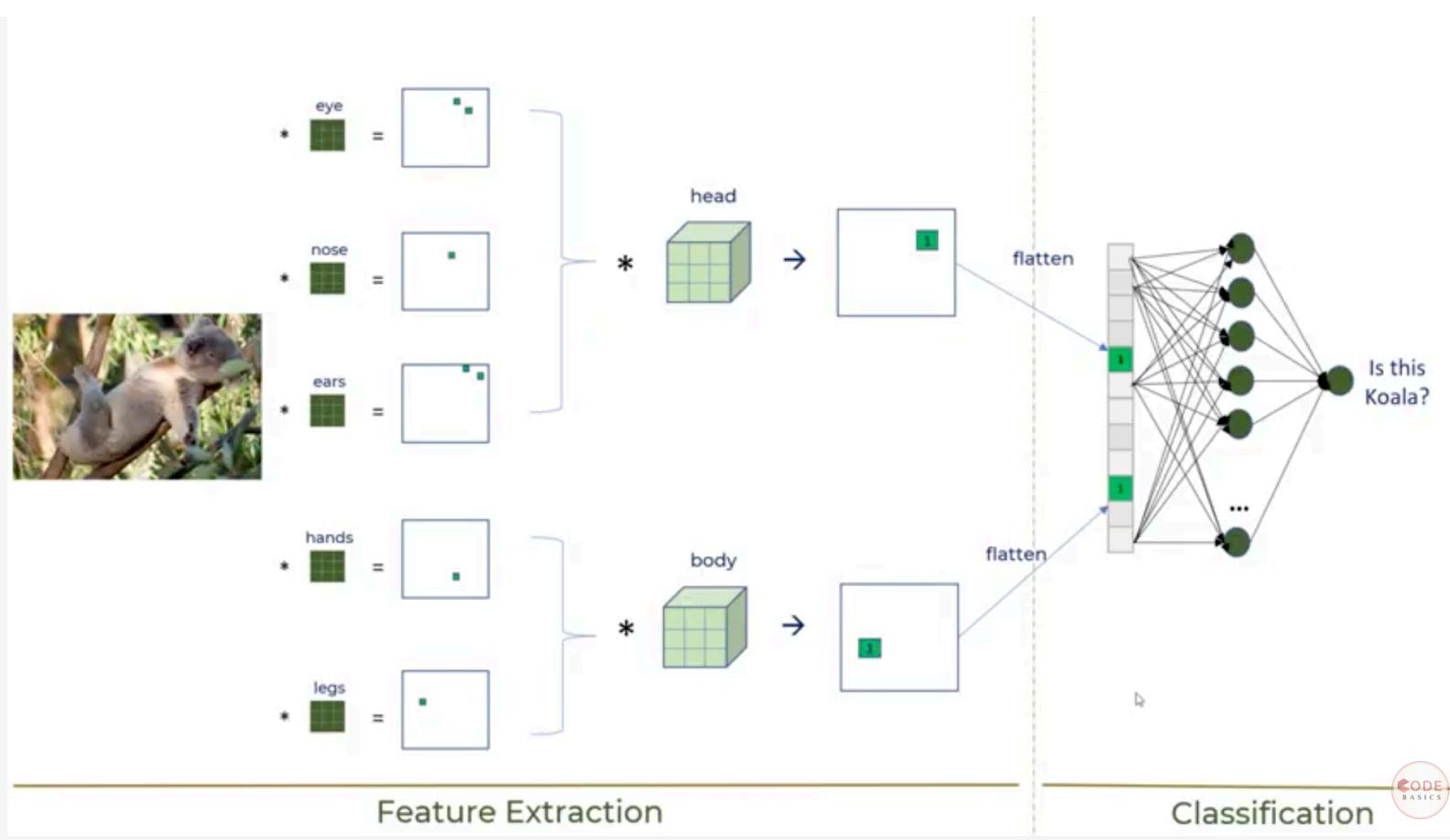
$$* \begin{array}{|c|c|} \hline \text{ears} & \\ \hline \end{array} = \boxed{\begin{array}{|c|c|} \hline 1 & 1 \\ \hline \end{array}}$$

Filter for head









-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

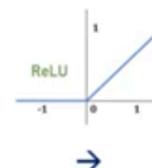
*

Loopy pattern filter

1	1	1
1	-1	1
1	1	1

→

-0.11	1	-0.11
-0.55	0.11	-0.33
-0.33	0.33	-0.33
-0.22	-0.11	-0.22
-0.33	-0.33	-0.33



0	1	0
0	0.11	0
0	0.33	0
0	0	0
0	0	0

ReLU helps with making the model nonlinear

4



We didn't
address the issue
of too much
computation



Image credit: <https://giphy.com/> (@rabbids)



**Pooling layer is used to
reduce the size**



5	1	3	4
8	2	9	2
1	3	0	1
2	2	2	0

8	9
3	2

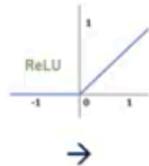
2 by 2 filter with stride = 2

-1	1	1	1	-1
-1	1	-1	1	-1
-1	1	1	1	-1
-1	-1	-1	1	-1
-1	-1	-1	1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1

Loopy pattern
filter

$$* \quad \begin{matrix} 1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & 1 \end{matrix} \rightarrow$$

-0.11	1	-0.11
-0.55	0.11	-0.33
-0.33	0.33	-0.33
-0.22	-0.11	-0.22
-0.33	-0.33	-0.33



0	1	0
0	0.11	0
0	0.33	0
0	0	0
0	0	0

Max
pooling
→

1	1
0.33	0.33
0.33	0.33
0	0

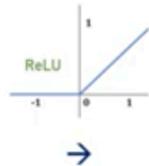
Shifted 9 at
different position

1	1	1	-1	-1
1	-1	1	-1	-1
1	1	1	-1	-1
-1	-1	1	-1	-1
-1	-1	1	-1	-1
-1	1	-1	-1	-1
1	-1	-1	-1	-1

Loopy pattern
filter

$$* \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \rightarrow$$

1	-0.11	-0.11
0.11	-0.33	0.33
0.33	-0.33	-0.33
-0.11	-0.55	-0.33
-0.55	-0.33	-0.55



1	0	0
0.11	0	0.33
0.33	0	0
0	0	0
0	0	0

Max
pooling
→

1	0.33
0.33	0.33
0.33	0
0	0

There is average pooling also...

5	1	3	4
8	2	9	2
1	3	0	1
2	2	2	0

4	4.5
2	0.75

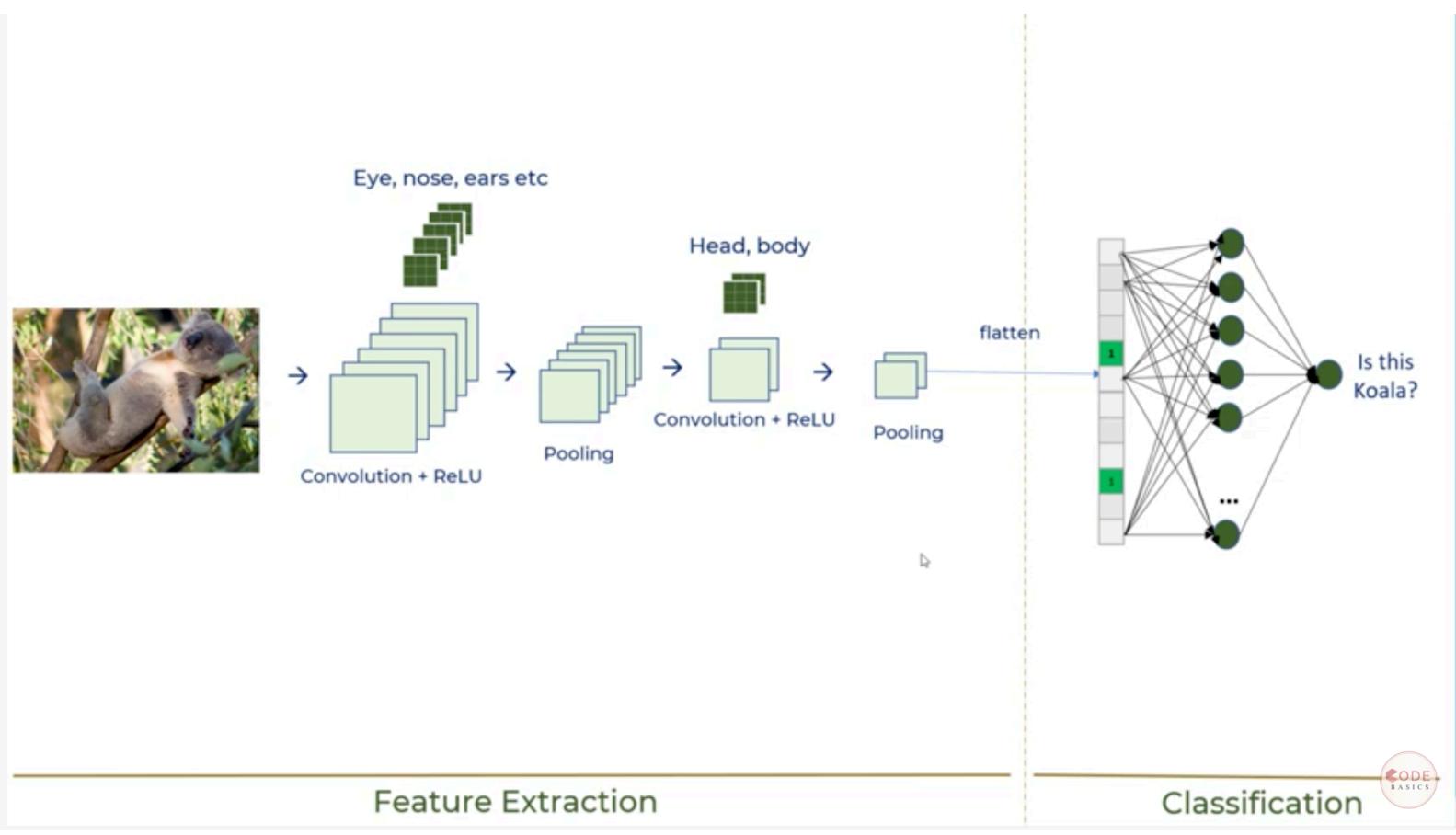
Benefits of pooling

Reduces dimensions & computation

Reduce overfitting as there are less parameters

Model is tolerant towards variations, distortions





Convolution

- Connections sparsity reduces overfitting
- Conv + Pooling gives location invariant feature detection
- Parameter sharing

ReLU

- Introduces nonlinearity
- Speeds up training, faster to compute

Pooling

- Reduces dimensions and computation
- Reduces overfitting
- Makes the model tolerant towards small distortion and variations

CNN by itself doesn't take care of rotation and scale

- You need to have rotated, scaled samples in training dataset
- If you don't have such samples than use **data augmentation** methods to generate new rotated/scaled samples from existing training samples



Rotation



Thickness

