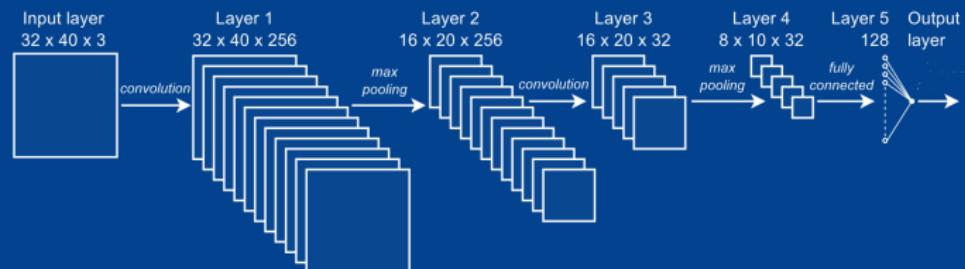




LESSON 07: Convolutional Neural Networks

CARSTEN EIE FRIGAARD

FALL 2023

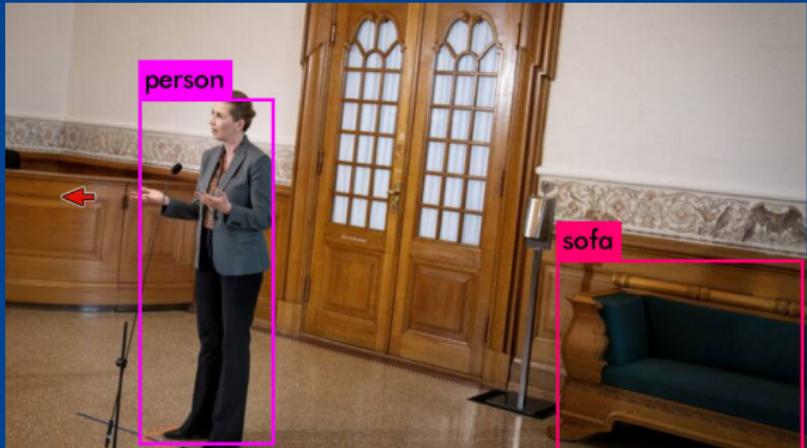


"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E." — Mitchell (1997).

L09: CNN's, Agenda

- ▶ Convolutional Neural Networks (CNN's),
 - ▶ and Deep-learning (DL).
 - ▶ CNN's In Practice,
 - ▶ YOLOV demo
 - ▶ The LeNET-5 Architecture.
 - ▶ GPU-cluster demo.
-
- ▶ Opgave: L07/CNN.ipynb

CONVOLUTIONAL NEURAL NETWORKS



Deep-learning (DL)

Artificial Intelligence:

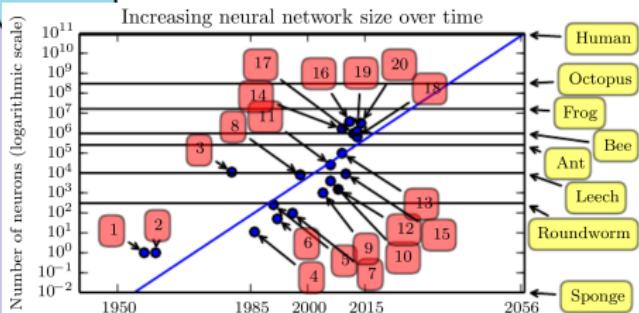
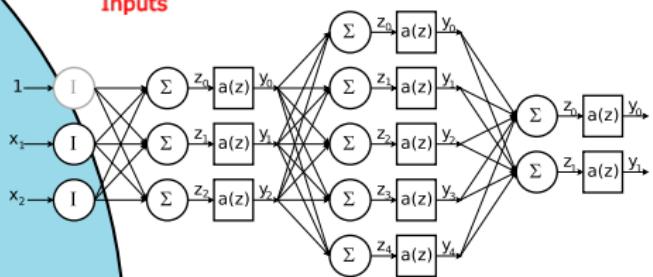
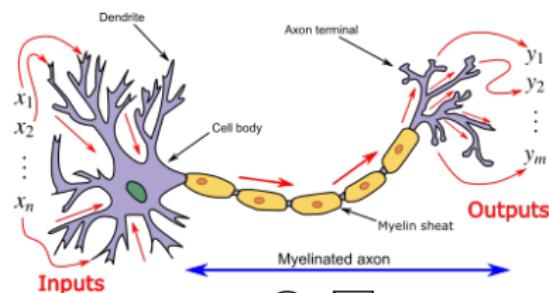
Mimicking the intelligence or behavioural pattern of humans or any other living entity.

Machine Learning:

A technique by which a computer can "learn" from data, without using a complex set of different rules. This approach is mainly based on training a model from datasets.

Deep Learning:

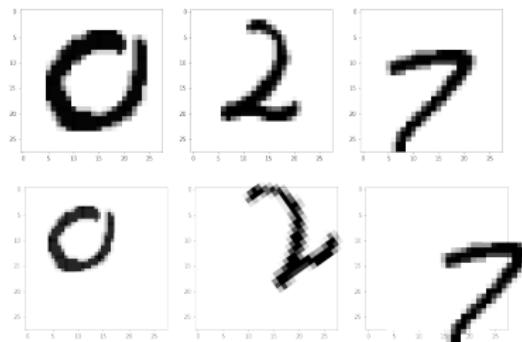
A technique to perform machine learning inspired by our brain's own network of neurons.



Definition of DL=??

Preprocessing/Feature-extraction + Machine Learning

Can your ML model handle simple image translation (rotation and scaling)?



..no problem for Your visual cortex, right?

Introducing the Convolutional Neural Networks: trade off

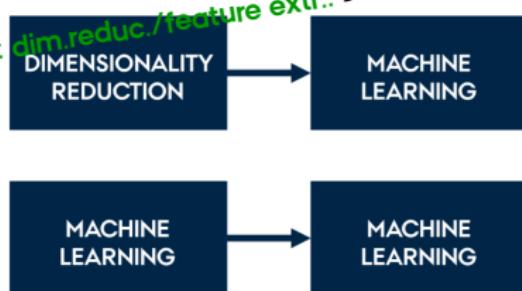
- ▶ preprocessing/feature-extraction + classification with:
- ▶ feature learning (CNN kernels) + classification (fully connected NN)

Convolutional Neural Networks

Feature Extraction vs. Feature Learning

- ▶ Smart filtering:
the distinction bewteen dimensionality reduction and machine learning blurs..

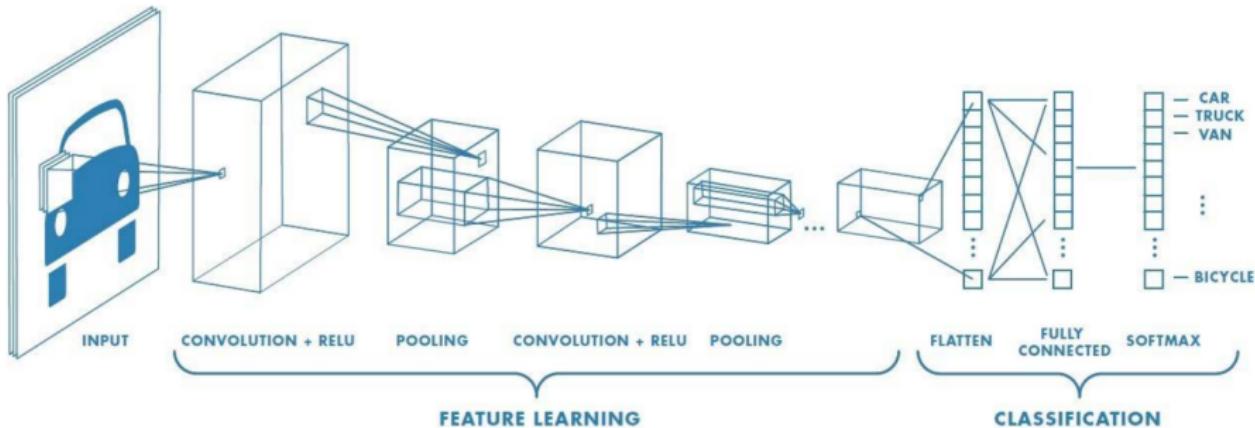
Preproces:



- ▶ Fundamental problem of filtering:
What is noise, what is signal?

Convolutional Neural Networks

Feature Extraction vs. Feature Learning

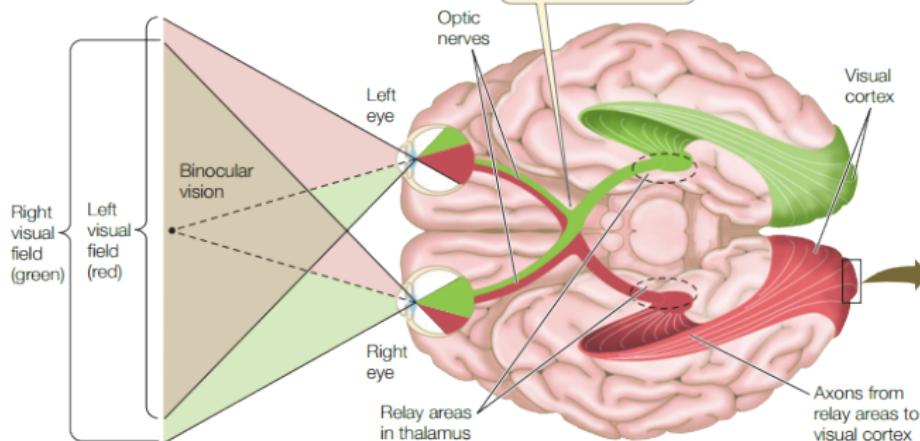


Convolutional Neural Networks

Human Eye and Brain Image Processing: Receptive Fields, Visual Cortex, and Neuro Cognition

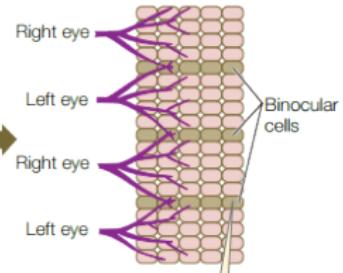
(A)

Human brain (viewed from underneath)



(B)

The visual cortex is organized in columns that receive input from the right eye and the left eye.



Binocular cells at the borders of columns receive input from both the right and left eyes.

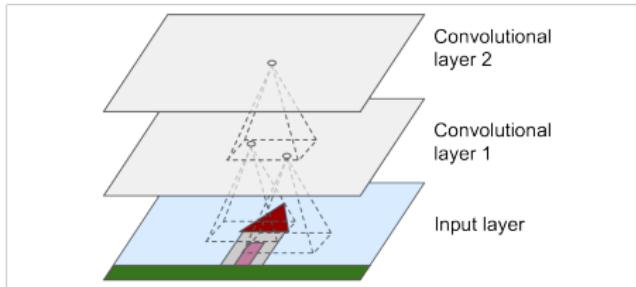


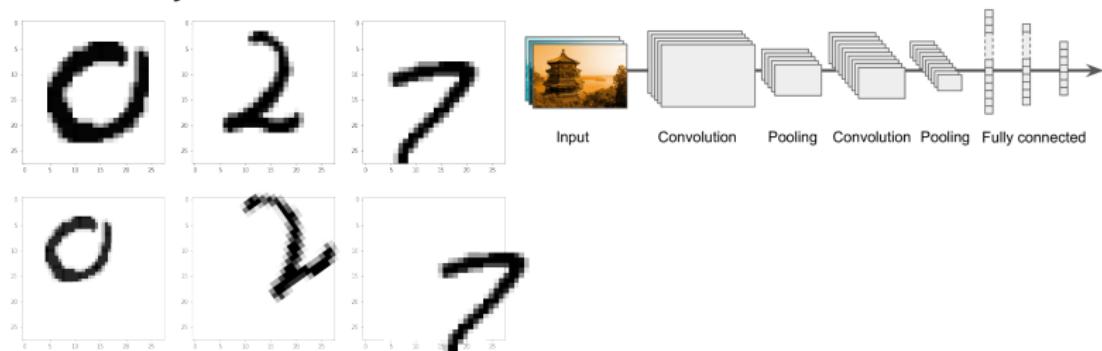
Figure 14-2. CNN layers with rectangular local receptive fields

Feature Learning + Machine Learning

CNN principle

Translation, rotation, and scaling invariant

- ▶ automatic image **feature extraction** that is **feature learning** via
 - ▶ 'convolutional', 'pooling' CNN layers, then a final fully connected NN



..no problem for Your CNN ML model, right?

Feature Learning + Machine Learning

CNN principle: Convolutional Layer (via CNN kernels)

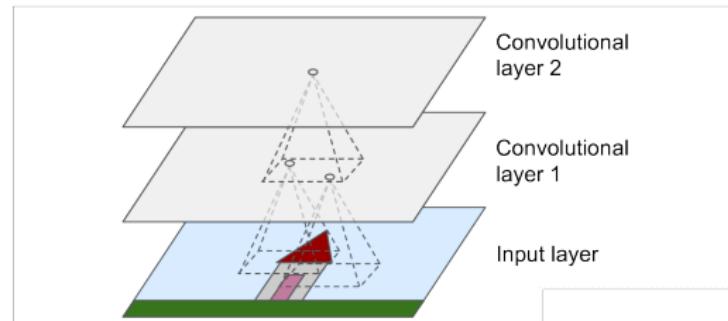


Figure 14-2. CNN layers with rectangular local receptive fields

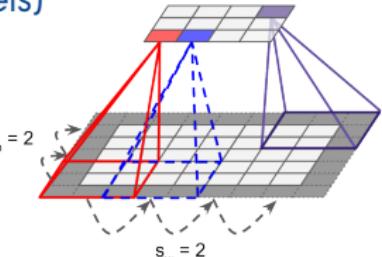
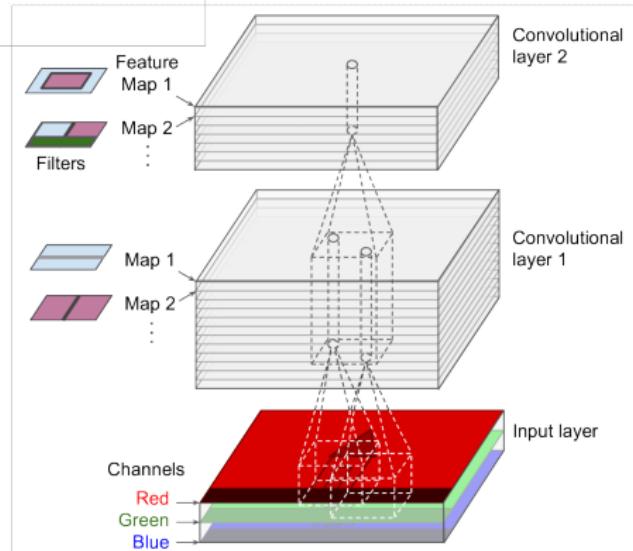


Figure 14-4. Reducing dimensionality using a stride of 2



Feature map 1 => with kernel 1

Feature map 2 => with kernel 2

Figure 14-6. Convolution layers with multiple feature maps, and images with three color channels

CNN Kernels

2D Convolution with a Kernel: Principle

0	0	0	0	0	0	0	0
0	60	113	56	139	85	0	0
0	73	121	54	84	128	0	0
0	131	99	70	129	127	0	0
0	80	57	115	69	134	0	0
0	104	126	123	95	130	0	0
0	0	0	0	0	0	0	0

Kernel

0	-1	0
-1	5	-1
0	-1	0

114				

$$5*60 + (-1)*113 + (-1)*73 = 114$$

CNN Kernels

2D Convolution with a Kernel: Different Kernels

-0.2	0.0	0.5
1.0	0.3	-0.6
0.0	0.0	0.8

0.0	0.0	0.0
0.8	-0.5	0.8
0.0	-0.2	0.0

0.4	0.2	-0.2
-0.8	0.0	0.8
0.0	-0.5	0.2



NOTE: GIMP demo on grey-scale Lenna: *Filters | Generic | Convolution Matrix..*

CNN Kernels in 3D

3D Convolution with a Kernel: Principle

0	0	0	0	0	0	...
0	156	155	156	158	158	...
0	153	154	157	159	159	...
0	149	151	155	158	159	...
0	146	146	149	153	158	...
0	145	143	148	148	158	...
...

Input Channel #1 (Red)

0	0	0	0	0	0	...
0	167	166	167	169	169	...
0	164	165	168	170	170	...
0	160	162	166	169	170	...
0	156	156	159	163	168	...
0	155	153	153	158	168	...
...

Input Channel #2 (Green)

0	0	0	0	0	0	...
0	163	162	163	165	165	...
0	160	161	164	166	166	...
0	156	158	162	165	166	...
0	155	155	158	162	167	...
0	154	152	152	157	167	...
...

Input Channel #3 (Blue)

-1	-1	1
0	1	-1
0	1	1

Kernel Channel #1



308

+

1	0	0
1	-1	-1
1	0	-1

Kernel Channel #2



-498

0	1	1
0	1	0
1	-1	1

Kernel Channel #3



164

+

-25				...
				...
				...
				...
...

Bias = 1

Output

CNN Pooling

The Principle

Max Pooling

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2
pool size

100	184
12	45

Average Pooling

31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2
pool size

36	80
12	15

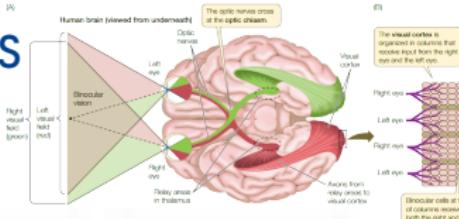
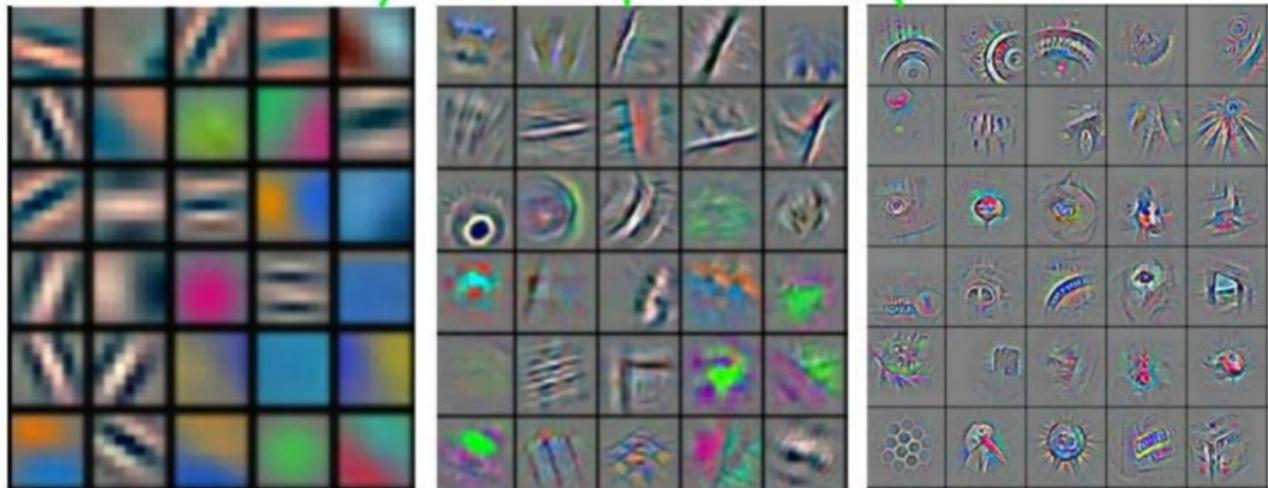
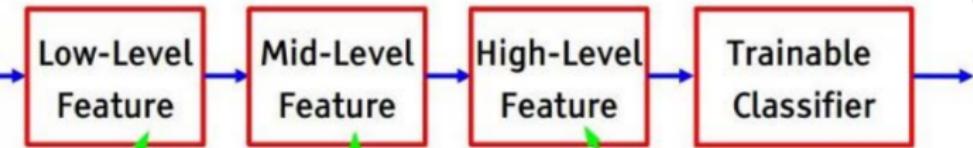
CNN Pooling

On real data (effectively subsampling)



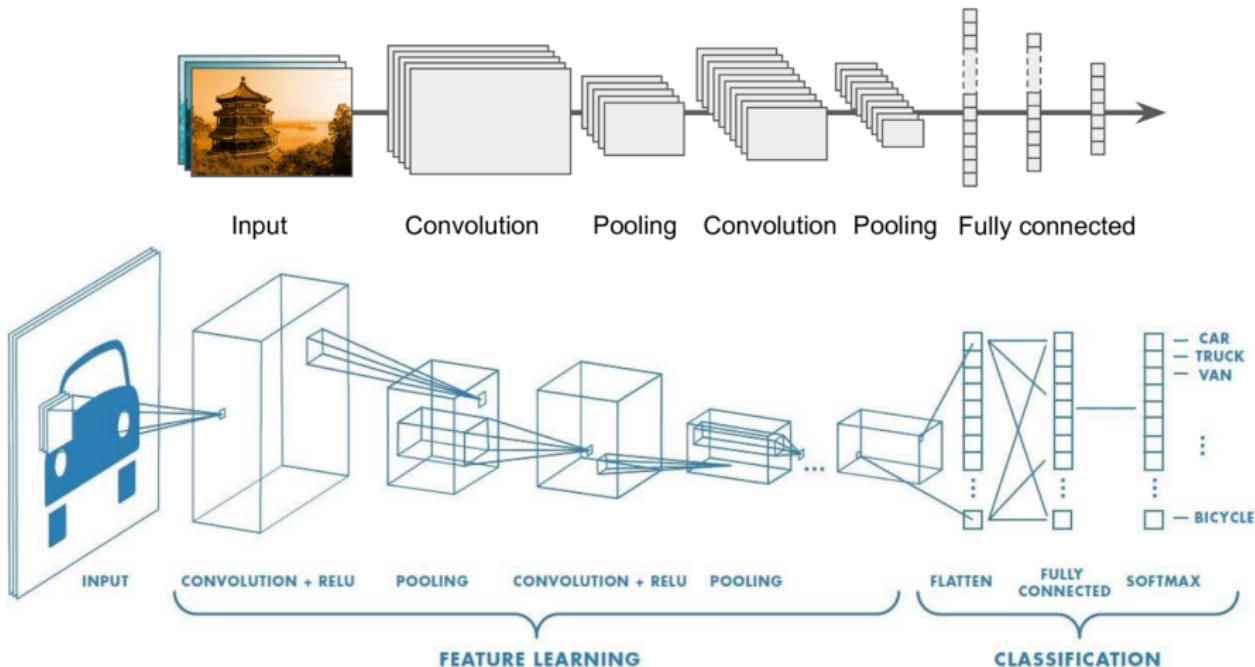
Convolutional Neural Networks

Low-, Mid-, and High-Level Feature Extraction



Convolutional Neural Networks

Stacking It All Up..

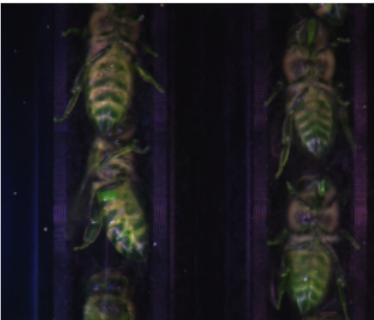
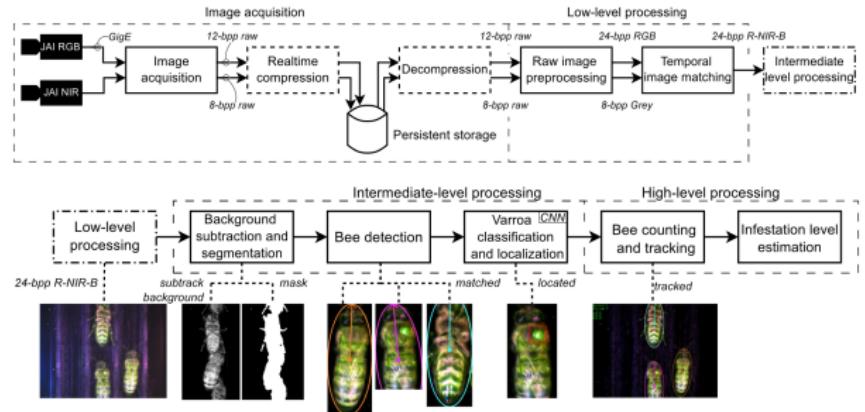


CNN'S IN PRACTICE

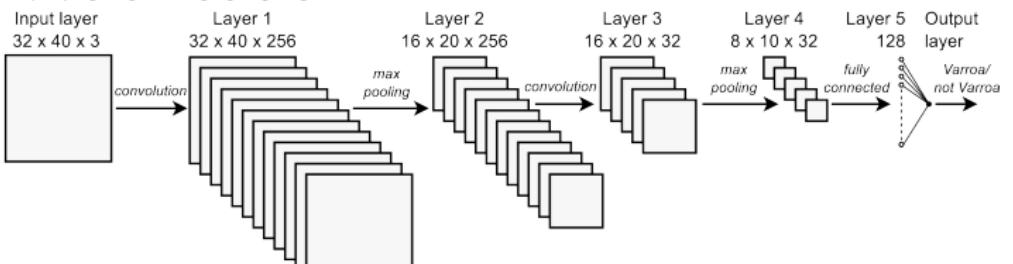
CNN's in Practice

Varroa mite detector—with a CNN somewhere in the pipeline

Image processing pipeline



CNN architecture



A recursive vision system to monitor the infestation level of Varroa destructor in a honeybee colony

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Received 20 April 2007; accepted 10 July 2007; available online 20 August 2007

Keywords: Varroa mite; CNN; recursive vision; Varroa detector; bee colony; multi-sensor illumination

1. Introduction

Background. Api-mite infestation, caused by the bee-killing Varroa mite, has become a major threat to honeybee colonies worldwide. Honeybees can also be attacked by a variety of diseases and parasites, and to help beekeepers to identify and treat such problems, an effective monitoring system for the health of the colony is required. Beekeepers can only identify the infestation level of their hives by physically inspecting the colony, which is a time-consuming and laborious process. Beekeepers need to count the number of bees and mites in each frame, spend lots of time and energy in this task, and the inspection result is often unreliable.

Proposed solution. A recursive vision system is proposed to monitor the infestation level of Varroa mites in a honeybee colony.

Contributions. A recursive vision system is proposed to automatically monitor the infestation level of Varroa mites in a honeybee colony. The system is designed to be simple, robust, and reliable.

Advantages. By using a recursive vision system, the mites can be tracked in the field, and the infestation level of the colony can be monitored more easily and quickly.

Scope. This paper focuses on the recursive vision system to monitor the infestation level of Varroa mites in a honeybee colony.

Outline. In Section 2, the system architecture is described. In Sections 3 and 4, the image processing and the learning methods are introduced, respectively. In Section 5, the experimental results are presented.

Abbreviations. The abbreviations used in this paper are defined as follows:

ICNN: image classification neural network; RGB: red-green-blue; R-NIR-B: red-near-infrared; UV: ultraviolet.

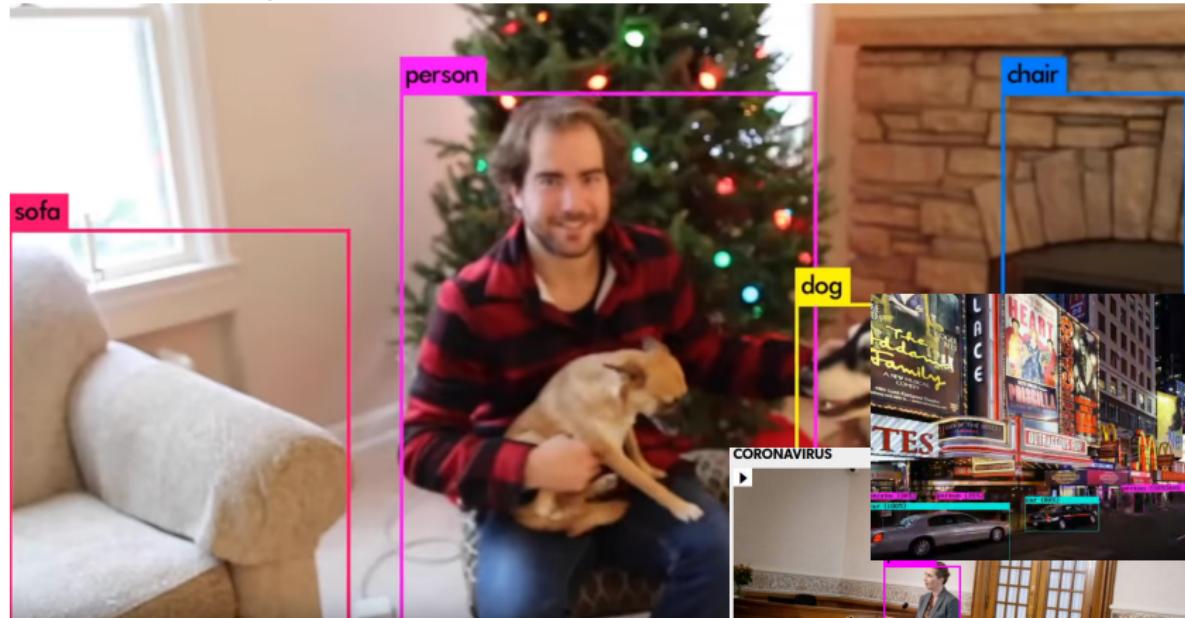
In this paper, we use the term "bee" to denote both the worker bee and the queen bee.

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CNN's in Practice

YOLOv2+3+4 (You Only Look Once)

Real-time object detection, demo..



[<https://homl.info/yolodemo>]

[<https://github.com/AlexeyAB/darknet>]

Mette Frederiksen: Uklogt og uholdbart at vi

Intro til YOLOV5..

YOLOV3/4/5 Family and Convolutional Neural Networks (CNN)

PyTorch Get Started Ecosystem Mobile Blog Tutorials Docs

YOLOV5

[View on Github](#) > [Open on Google Colab](#)



BEFORE YOU START

Start from a **Python>=3.8** environment with <https://pytorch.org/get-started/locally/>. To install YOLOv5, run:

```
pip install -qr https://raw.githubusercontent.com/ultralytics/yolov5/master/requirements.txt
```

MODEL DESCRIPTION

	Nano	Small	Medium	Large	XLarge
YOLOv5n					
4 MB _{FP16}	14 MB _{FP16}	41 MB _{FP16}	89 MB _{FP16}	166 MB _{FP16}	
6.3 ms ₁₀₀	6.4 ms ₁₀₀	8.2 ms ₁₀₀	10.1 ms ₁₀₀	12.1 ms ₁₀₀	
28.4 mAP _{COCO}	37.2 mAP _{COCO}	45.2 mAP _{COCO}	48.8 mAP _{COCO}	50.7 mAP _{COCO}	

YOLOV5: [https://pytorch.org/hub/ultralytics_yolov5/] Demo video: [https://www.youtube.com/watch?v=1_SiUOYUoOI]

CNN's in Practice

YOLOv2+3+4 (You Only Look Once)

```
[1] Terminal
o obj/art.o obj/tag.o obj/cifar.o obj/go.o obj/rnn.o obj/segmenter.o obj/regressor.o obj/classifier.o obj/coco.o
obj/yolo.o obj/detector.o obj/nightmare.o obj/instance-segmenter.o obj/darknet.o libdarknet.a -o darknet -lm -lpthread
-L/opt/opencv/opencv4/lib -lopencv_core -lopencv_imgproc -lopencv_imgcoders -lopencv_videoio -lopencv_highgui
-ltiff -lstdc++ libdarknet.a
layer      filters    size        input          output
  0 conv     32 3 x 3 / 1   256 x 256 x  3  ->  256 x 256 x 32  0.113
  1 max      2 x 2 / 2   256 x 256 x 32  ->  128 x 128 x 32
  2 conv     64 3 x 3 / 1   128 x 128 x 32  ->  128 x 128 x 64  0.604
  3 max      2 x 2 / 2   128 x 128 x 64  ->  64 x 64 x 64
  4 conv    128 3 x 3 / 1   64 x 64 x 64  ->  64 x 64 x 128  0.604
  5 conv     64 1 x 1 / 1   64 x 64 x 128 ->  64 x 64 x 64  0.067
  6 conv    128 3 x 3 / 1   64 x 64 x 64  ->  64 x 64 x 128  0.604
  7 max      2 x 2 / 2   64 x 64 x 128 ->  32 x 32 x 128
  8 conv    256 3 x 3 / 1   32 x 32 x 128 ->  32 x 32 x 256  0.604
  9 conv    128 1 x 1 / 1   32 x 32 x 256 ->  32 x 32 x 128  0.067
 10 conv   256 3 x 3 / 1   32 x 32 x 128 ->  32 x 32 x 256  0.604
 11 max      2 x 2 / 2   32 x 32 x 256 ->  16 x 16 x 256
 12 conv   512 3 x 3 / 1   16 x 16 x 256 ->  16 x 16 x 512  0.604
 13 conv   256 1 x 1 / 1   16 x 16 x 512 ->  16 x 16 x 256  0.067
 14 conv   512 3 x 3 / 1   16 x 16 x 256 ->  16 x 16 x 512  0.604
 15 conv   256 1 x 1 / 1   16 x 16 x 512 ->  16 x 16 x 256  0.067
 16 conv   512 3 x 3 / 1   16 x 16 x 256 ->  16 x 16 x 512  0.604
 17 max      2 x 2 / 2   16 x 16 x 512 ->  8 x 8 x 512
 18 conv   1024 3 x 3 / 1   8 x 8 x 512 ->  8 x 8 x 1024  0.604
 19 conv   512 1 x 1 / 1   8 x 8 x 1024 ->  8 x 8 x 512  0.067
 20 conv   1024 3 x 3 / 1   8 x 8 x 512 ->  8 x 8 x 1024  0.604
 21 conv   512 1 x 1 / 1   8 x 8 x 1024 ->  8 x 8 x 512  0.067
 22 conv   1024 3 x 3 / 1   8 x 8 x 512 ->  8 x 8 x 1024  0.604
 23 conv   1000 1 x 1 / 1   8 x 8 x 1024 ->  8 x 8 x 1000  0.131
 24 avg           8 x 8 x 1000 ->  1000
 25 softmax
Loading weights from darknet19.weights...Done!
test.jpg: Predicted in 1.965434 seconds.
64.68%: mountain bike
16.00%: web site
12.87%: bicycle-built-for-two
1.05%: crash helmet
0.86%: alp
cef@leno:~/textmal/darknet$
```

```
De danske cykellyttere har aldrig været bedre, siger cykelekspert Brian Nygaard efter Kasper Asgreens sejr i Flandern Rundt.
```



Kasper Asgreen slog Mathieu van der Poel i Flandern Rundt og vandt den sjette danske sejr på årets World Tour. Foto: AP/Bild ID: Stockom. © Scarpido



CNN's in Practice

The LeNET-5 Architecture

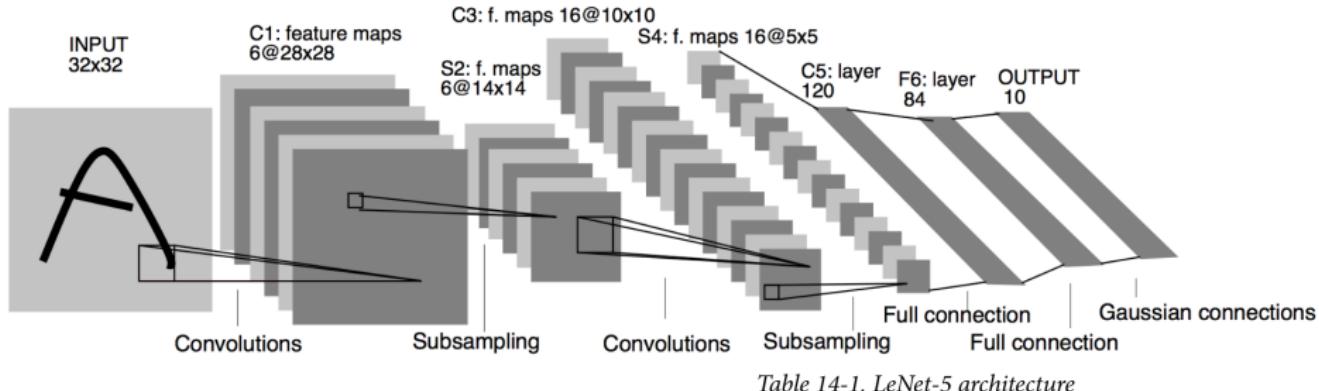


Table 14-1. LeNet-5 architecture

Other famous CNN-architectures:

- ▶ AlexNet,
- ▶ GoogLeNet (inception),
- ▶ ResNet (152 layers,
skip-connections),
- ▶ VGGNet,
- ▶ Inception-v4 (GoogLeNet + ResNet),
- ▶ ...

Layer	Type	Maps	Size	Kernel size	Stride	Activation
Out	Fully Connected	–	10	–	–	RBF
F6	Fully Connected	–	84	–	–	tanh
C5	Convolution	120	1 × 1	5 × 5	1	tanh
S4	Avg Pooling	16	5 × 5	2 × 2	2	tanh
C3	Convolution	16	10 × 10	5 × 5	1	tanh
S2	Avg Pooling	6	14 × 14	2 × 2	2	tanh
C1	Convolution	6	28 × 28	5 × 5	1	tanh
In	Input	1	32 × 32	–	–	–

CNN's in Practice

A LeNET-5 'Like' Architecture

In [9]:

```
1 import keras
2 from keras import layers
3
4 model = keras.Sequential()
5
6 model.add(layers.Conv2D(filters=6, kernel_size=(3, 3),
7                         activation='relu', input_shape=(32, 32, 1)))
8 model.add(layers.AveragePooling2D())
9
10 model.add(layers.Conv2D(filters=16, kernel_size=(3, 3), activation='relu'))
11 model.add(layers.AveragePooling2D())
12
13 model.add(layers.Flatten())
14
15 model.add(layers.Dense(units=120, activation='relu'))
16 model.add(layers.Dense(units=84, activation='relu'))
17 model.add(layers.Dense(units=10, activation='softmax'))
18
19 model.summary()
```

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 30, 30, 6)	60
average_pooling2d_5 (Average)	(None, 15, 15, 6)	0
conv2d_6 (Conv2D)	(None, 13, 13, 16)	880
average_pooling2d_6 (Average)	(None, 6, 6, 16)	0
flatten_3 (Flatten)	(None, 576)	0
dense_7 (Dense)	(None, 120)	69240
dense_8 (Dense)	(None, 84)	10164
dense_9 (Dense)	(None, 10)	850
<hr/>		
Total params: 81,194		
Trainable params: 81,194		
Non-trainable params: 0		

Table 14-1. LeNet-5 architecture

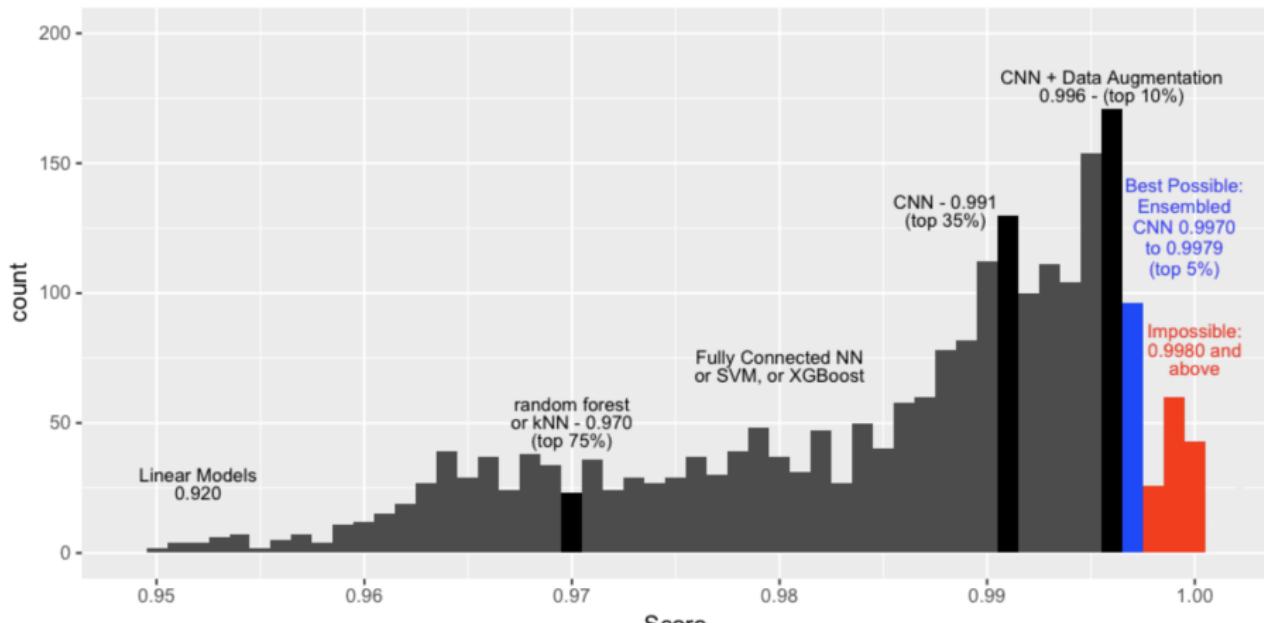
Layer	Type	Maps	Size	Kernel size	Stride	Activation
Out	Fully Connected	-	10	-	-	RBF
F6	Fully Connected	-	84	-	-	tanh
C5	Convolution	120	1 × 1	5 × 5	1	tanh
S4	Avg Pooling	16	5 × 5	2 × 2	2	tanh
C3	Convolution	16	10 × 10	5 × 5	1	tanh
S2	Avg Pooling	6	14 × 14	2 × 2	2	tanh
C1	Convolution	6	28 × 28	5 × 5	1	tanh
In	Input	1	32 × 32	-	-	-

CNN's in Practice

The LeNET-5 Architecture on MNIST

Histogram of Kaggle MNIST

public leaderboard scores, July 15 2018



- ▶ using pre-trained models => Transferred Learning,
- ▶ object detection,
- ▶ semantic segmentation,
- ▶ time series => RNN's, ...