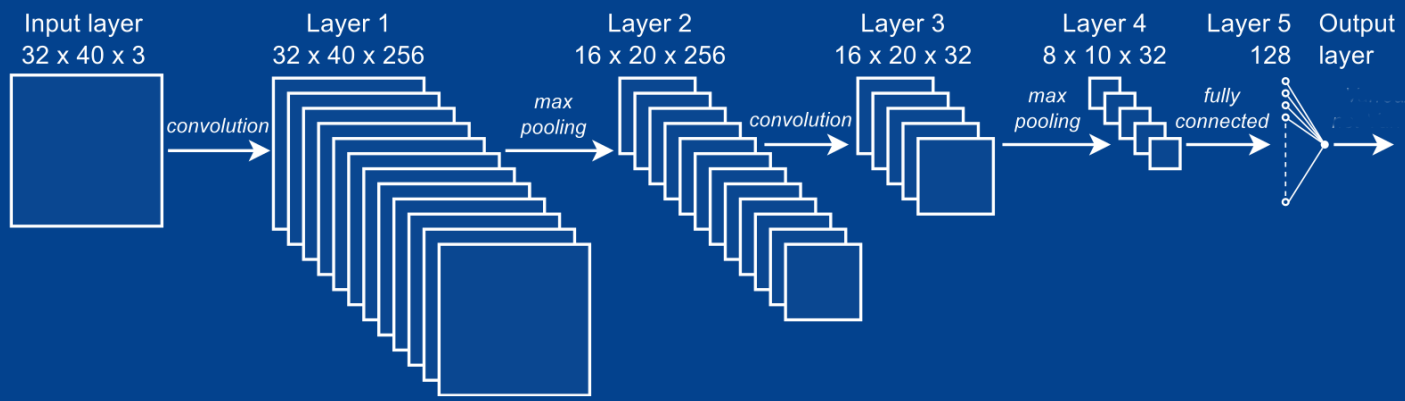
AARHUS UNIVERSITY

LESSON 07: Convolutional Neural Networks

CARSTEN EIE FRIGAARD

AUTUMN 2024



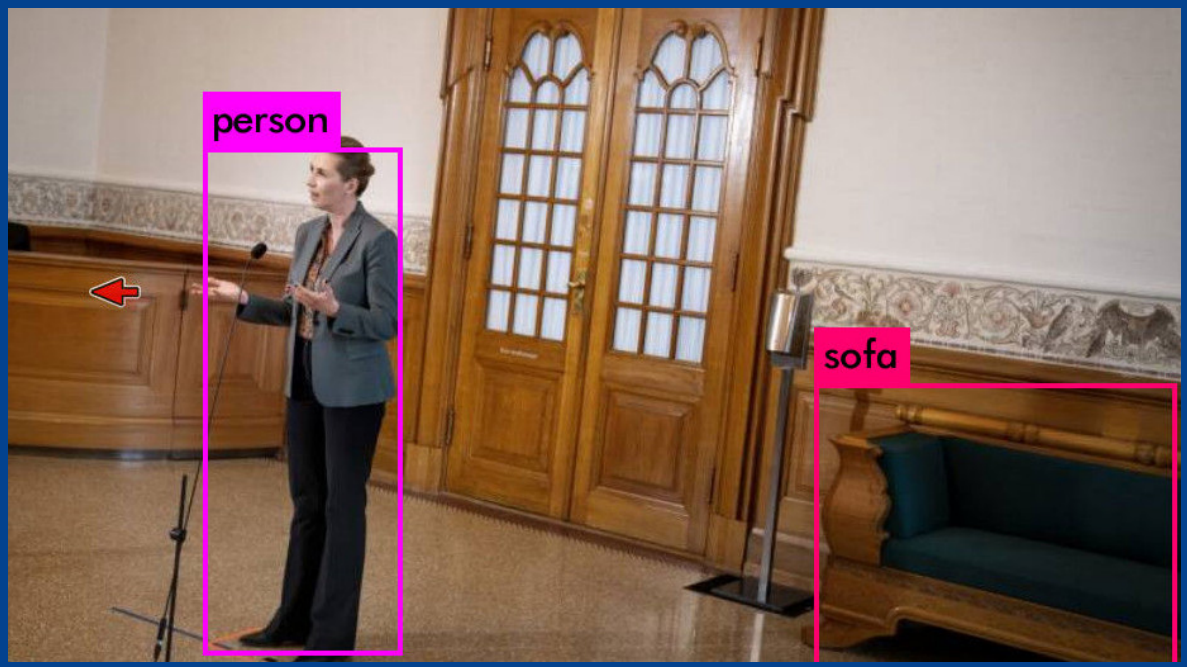
"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E." — Mitchell (1997).

L07: 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:

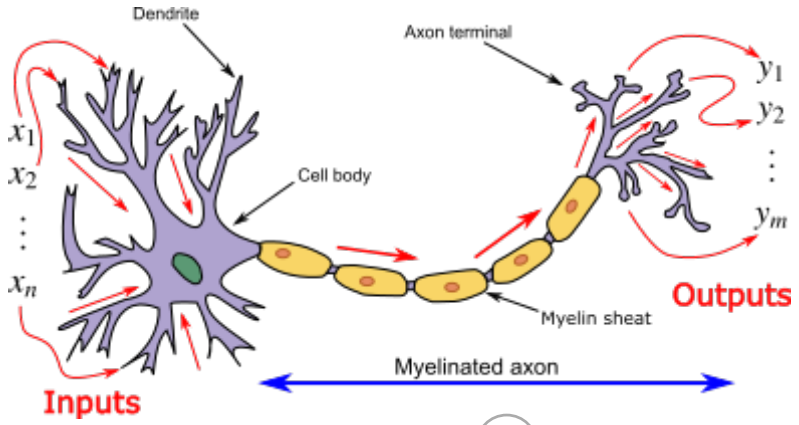
Mimicking the intelligence or behavioural pattern of humans or any other living entity.

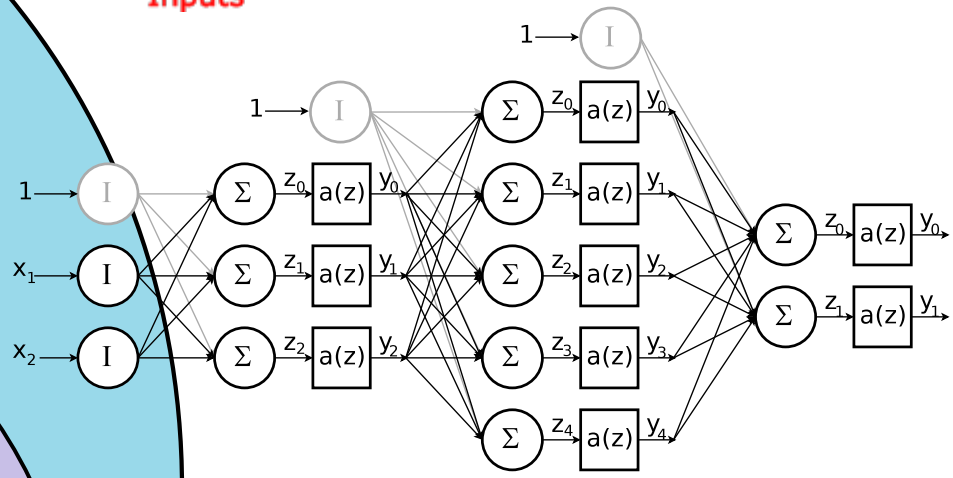
Machine Learning:

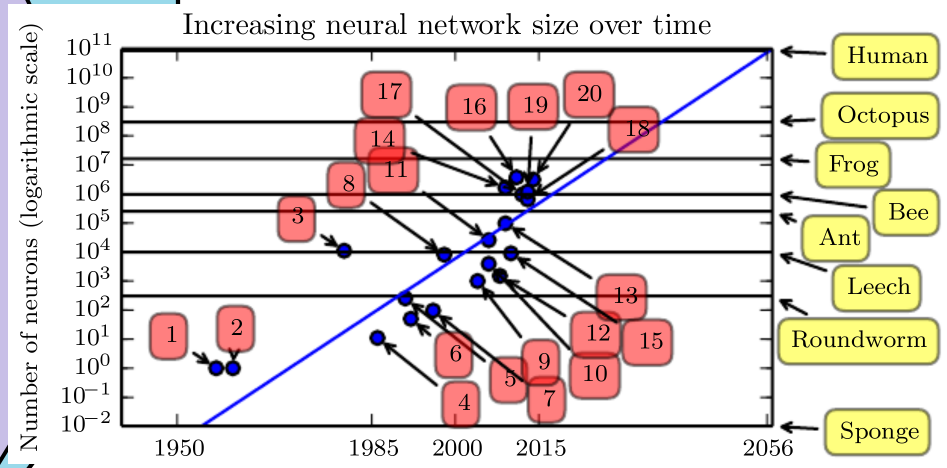
A technique by which a computer can "learn" from data, without using a complex set of different rules. This approach is mainly based on training a model from datasets.

Deep Learning:

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





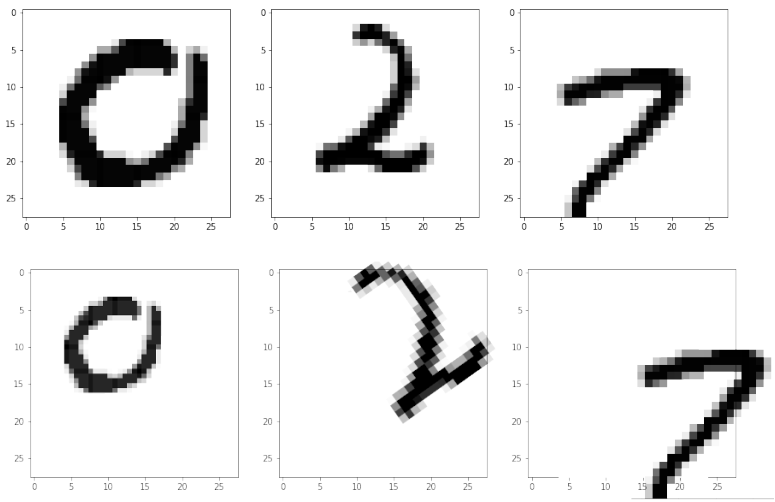


[Deep Learning, Ian Goodfellow et. al., The MIT Press, 2016],
[Prof. Loc Vu-Quoc, commons.wikimedia.org/w/index.php?curid=72816083],
[Tukijaaliwa, commons.wikimedia.org/w/index.php?curid=9013135]

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 of

- preprocessing/feature-extraction + classification

with:

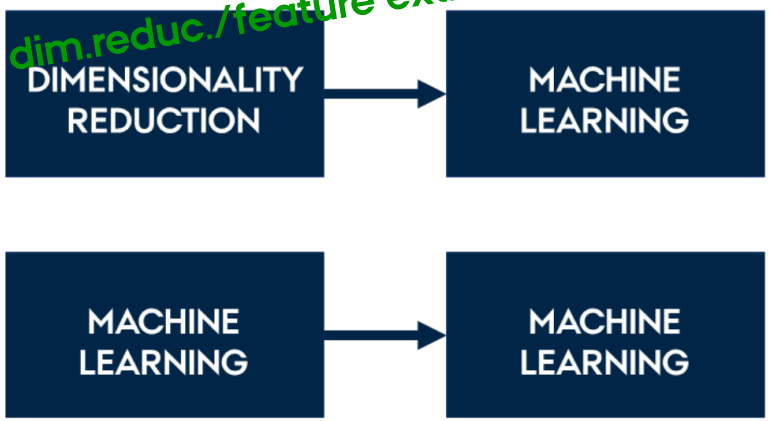
- feature learning (CNN kernels) + classification (fully connected NN)

Convolutional Neural Networks

Feature Extraction vs. Feature Learning

- Smart filtering:
  the distriction bewteen dimensionality reduction (/feature extraction) and machine learning blurs..

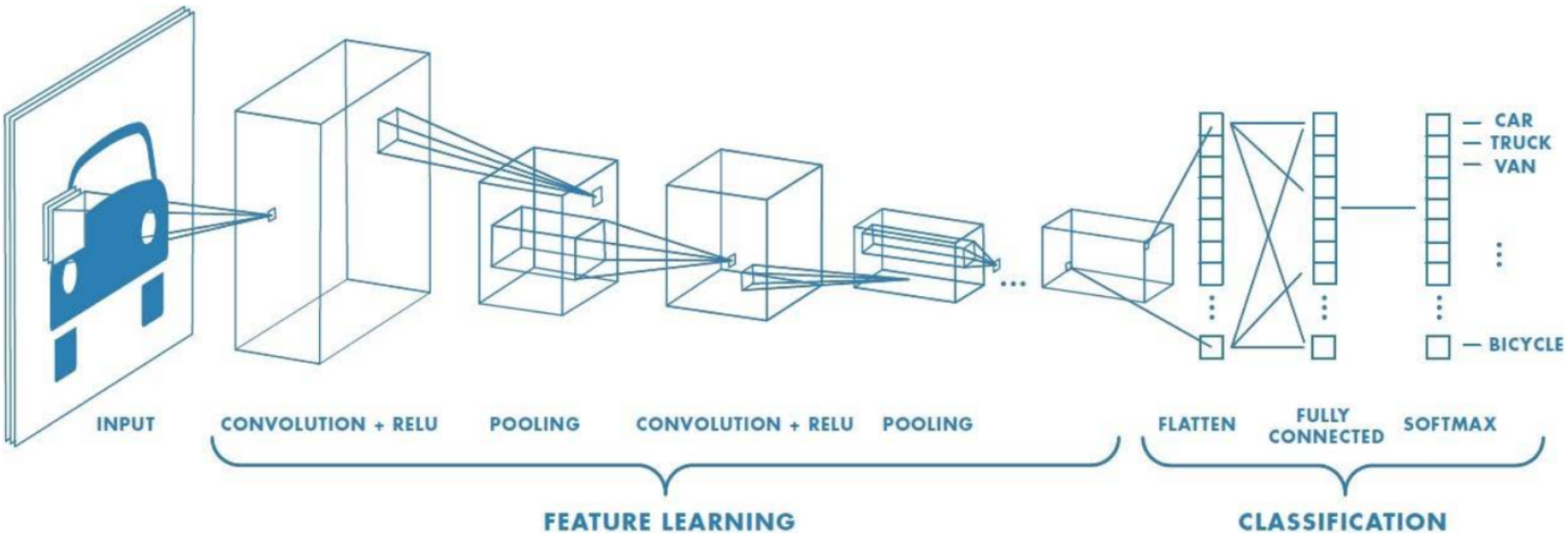
Preproces: dim.reduc./feature extr..

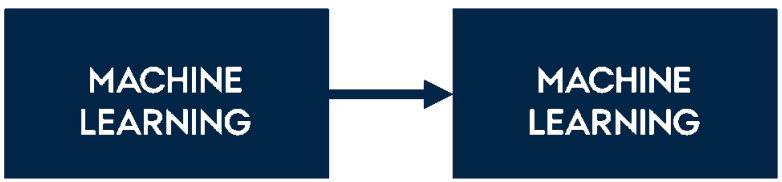


- Fundamental problem of filtering:
  What is noise, what is signal?

Convolutional Neural Networks

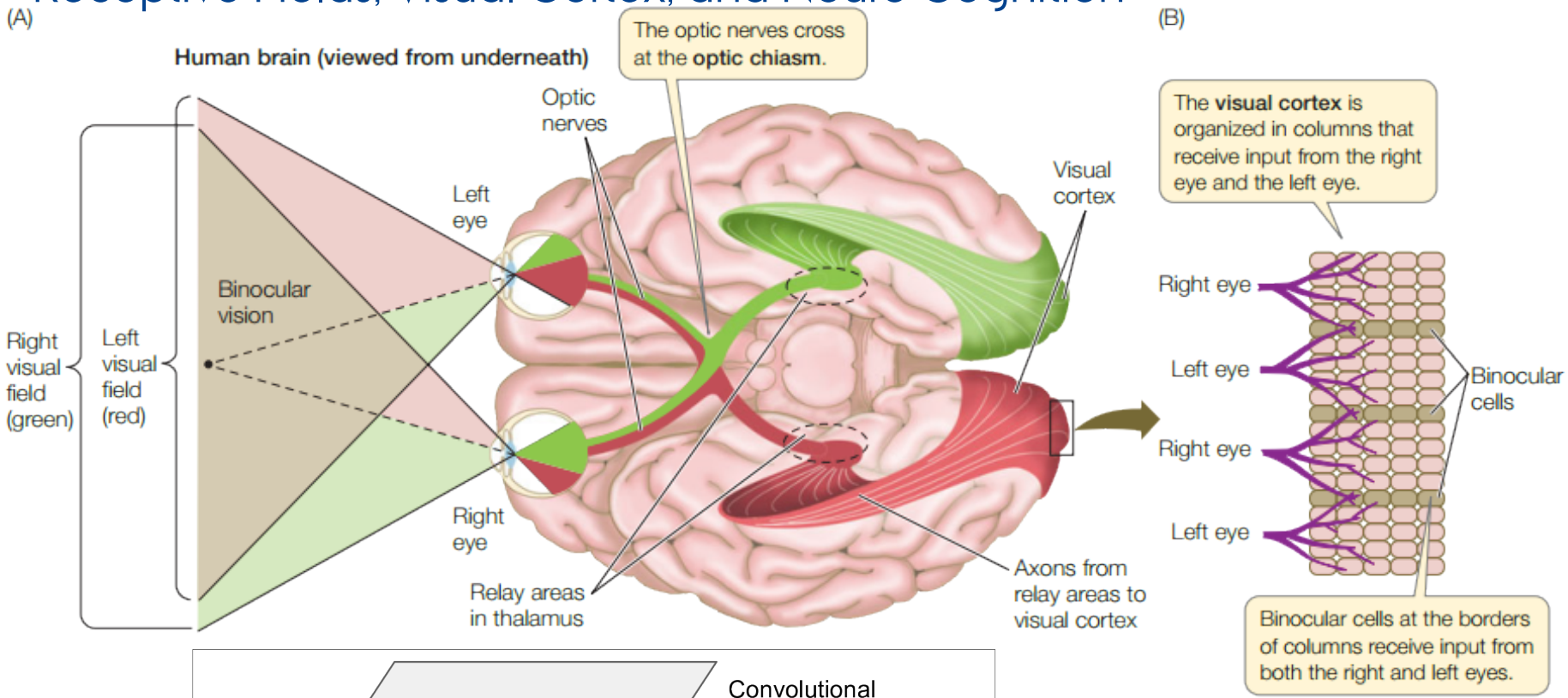
Feature Extraction vs. Feature Learning





Convolutional Neural Networks

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



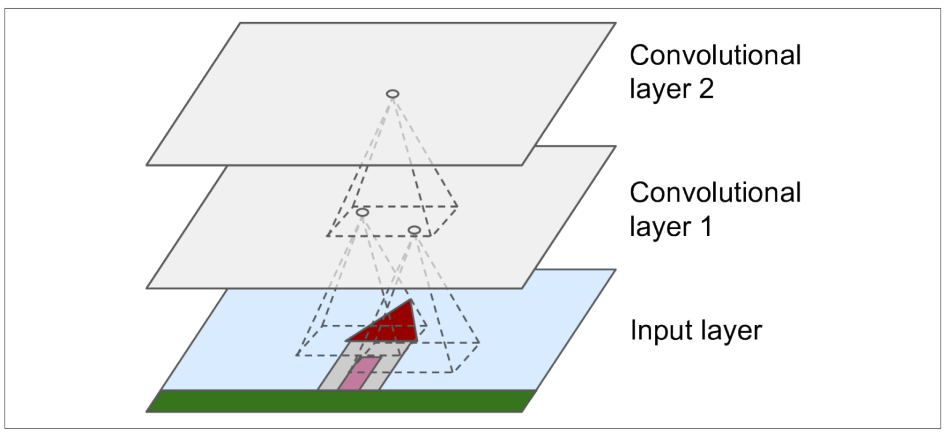


Figure 14-2. CNN layers with rectangular local receptive fields

Feature Learning + Machine Learning

CNN principle

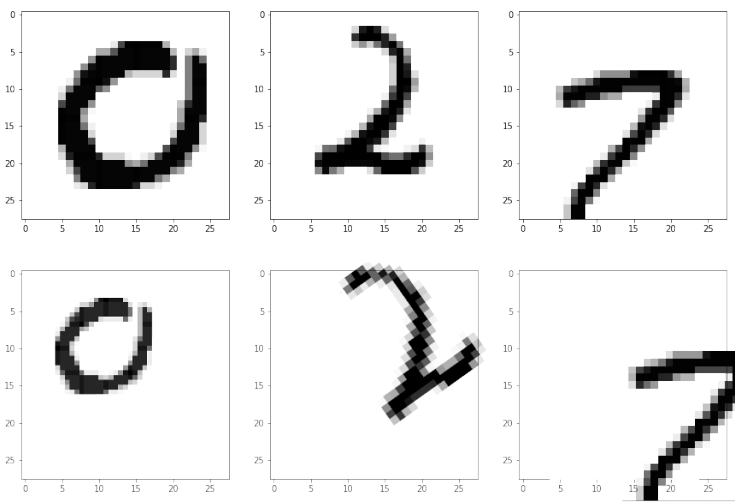
Translation, rotation, and scaling invariant

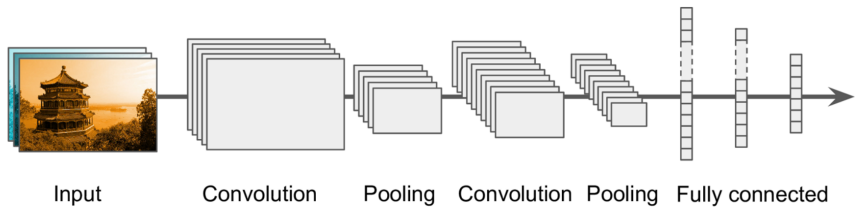
- automatic image feature extraction

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)

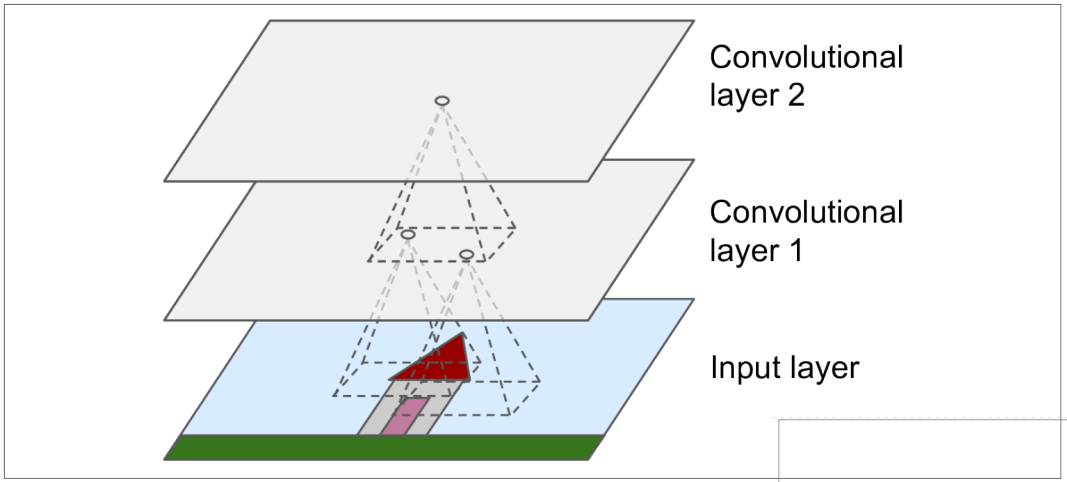


Figure 14-2. CNN layers with rectangular local receptive fields

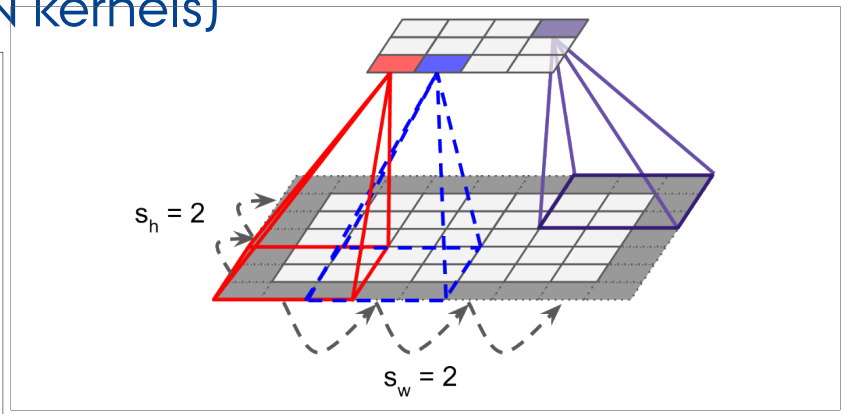


Figure 14-4. Reducing dimensionality using a stride of 2

Feature map 1 => with kernel 1

Feature map 2 => with kernel 2

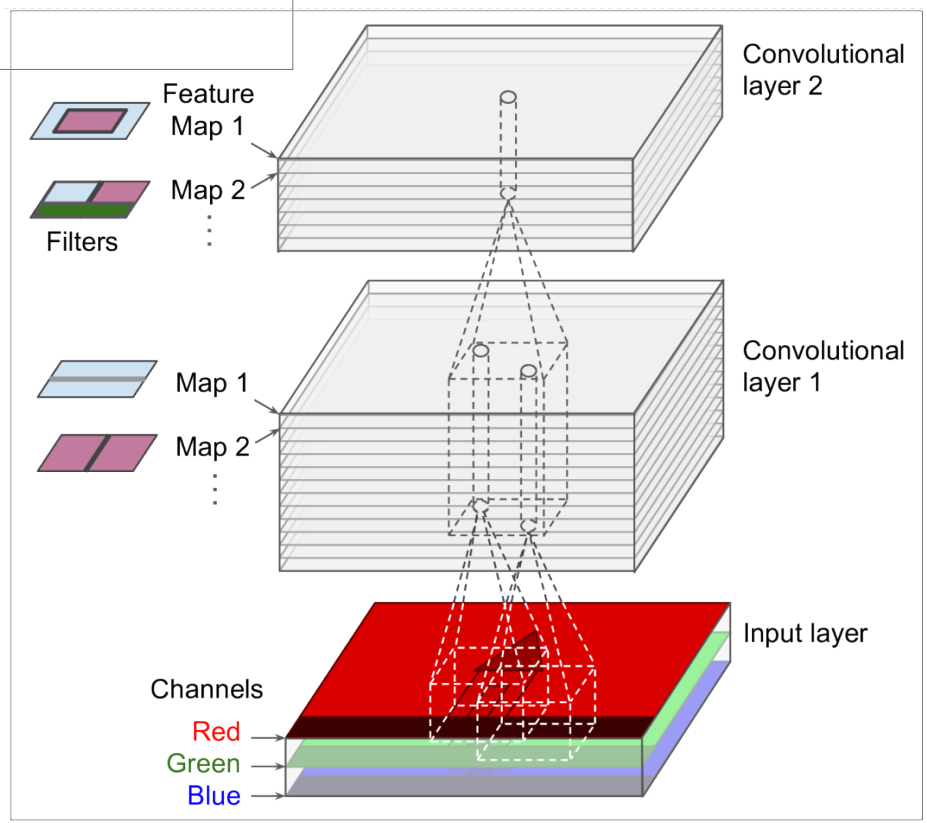
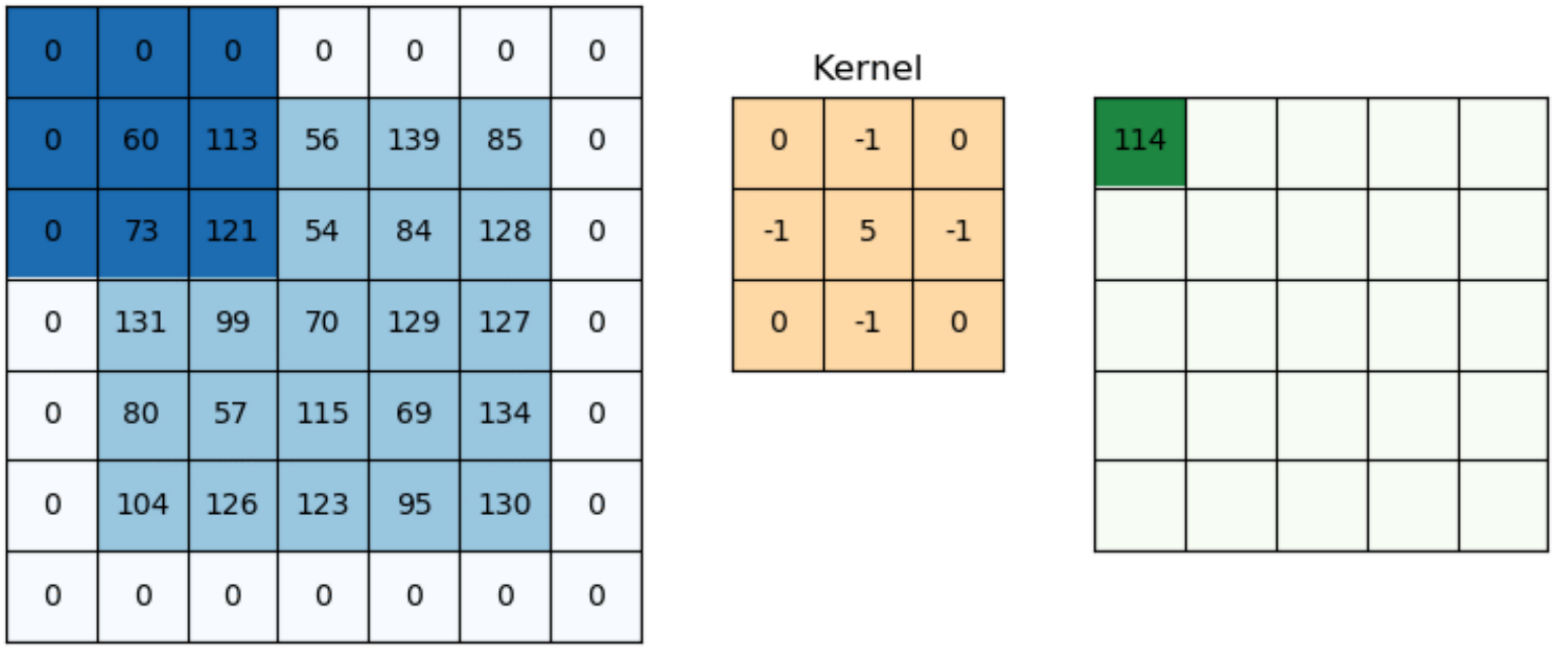


Figure 14-6. Convolution layers with multiple feature maps, and images with three color

CNN Kernels

2D Convolution with a Kernel: Principle




```
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

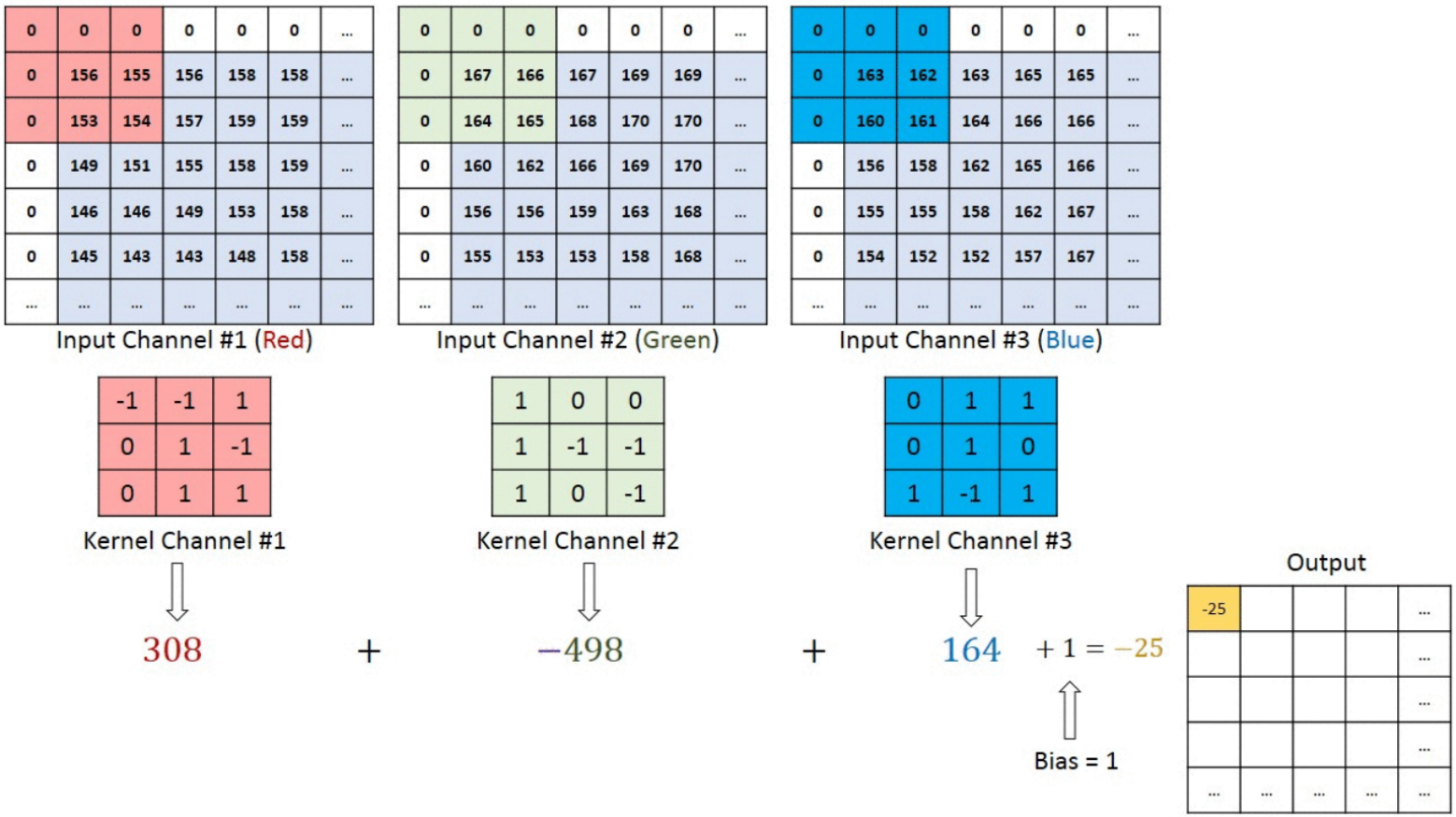
0.0	0.0	0.0
0.8	-0.5	0.8
0.0	-0.2	0.0

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..*

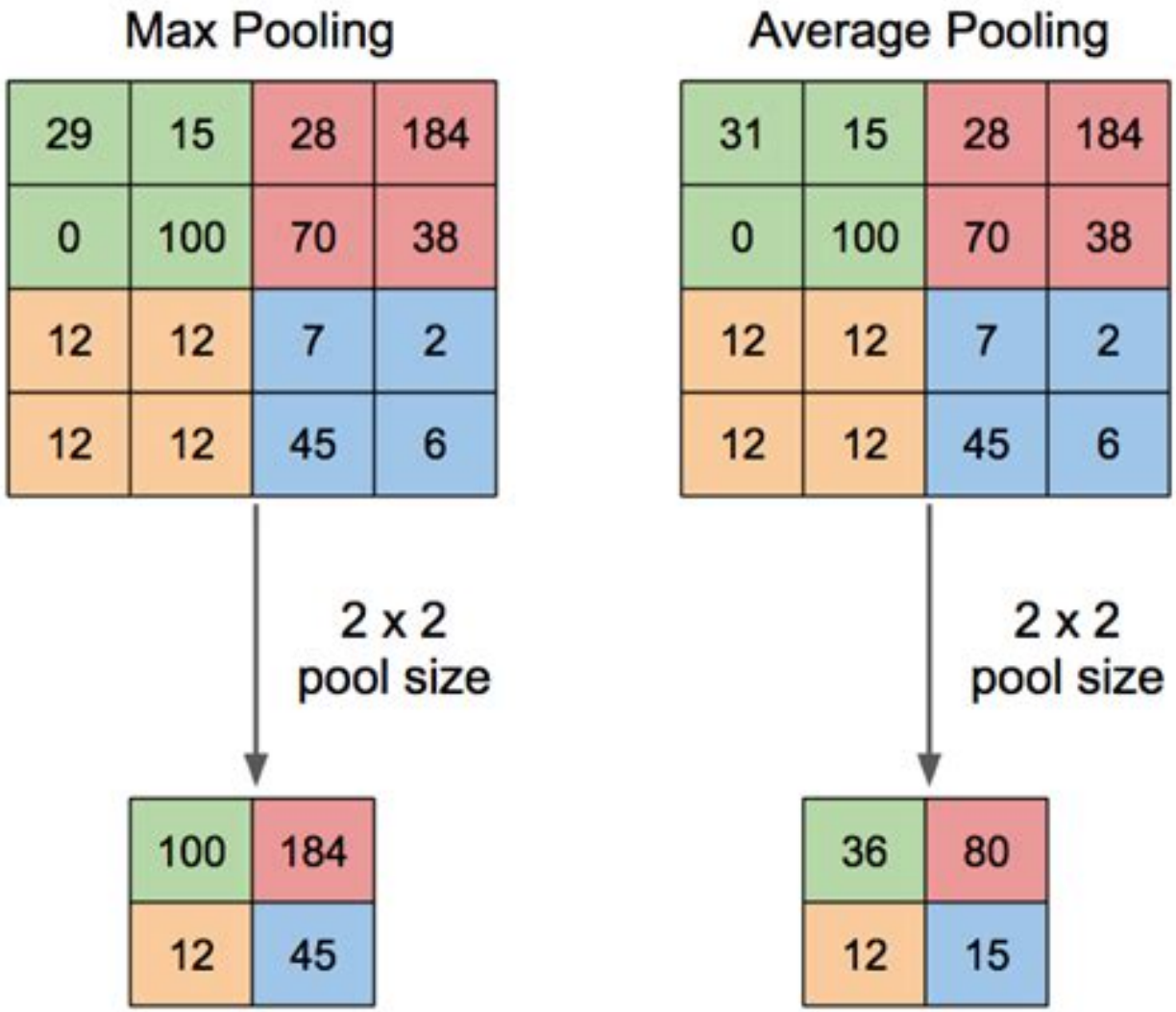
CNN Kernels in 3D

3D Convolution with a Kernel: Principle



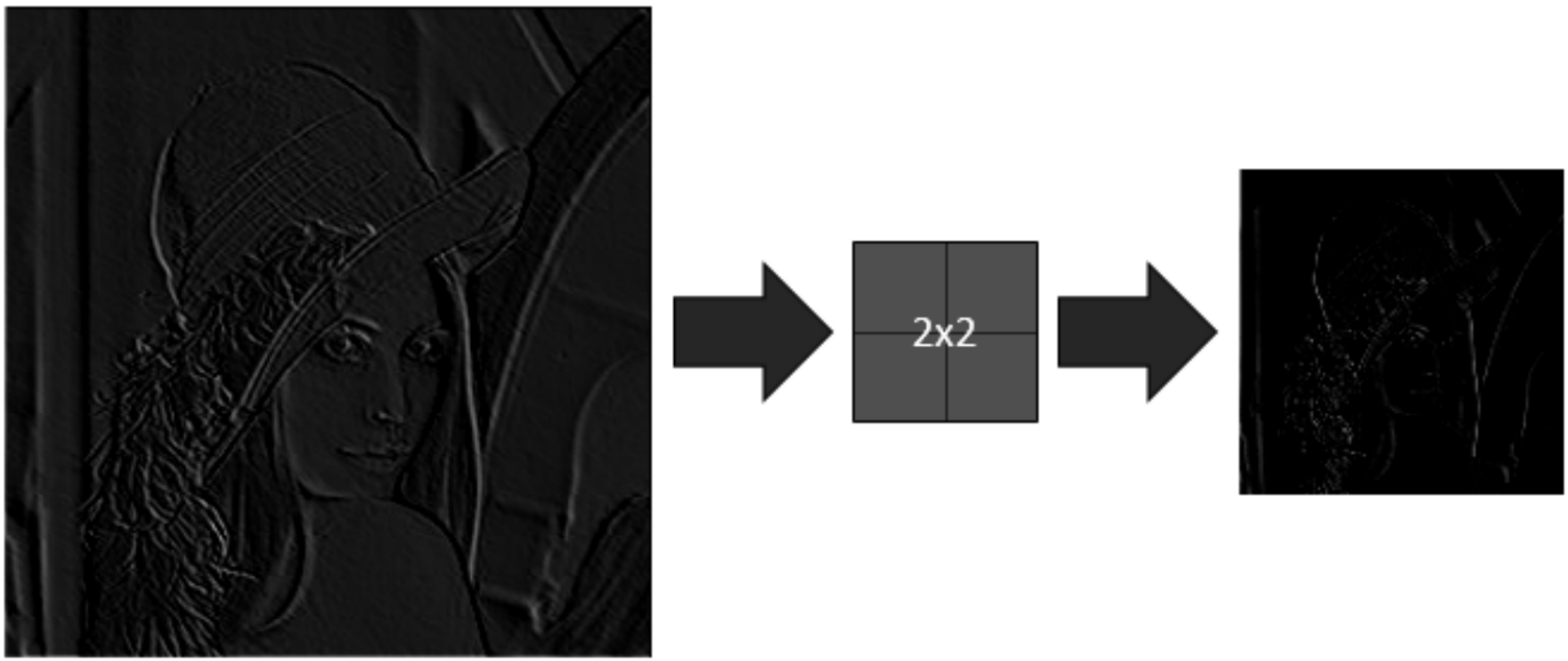
CNN Pooling

The Principle



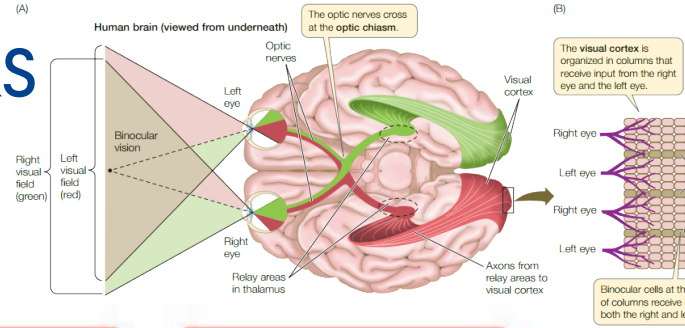
CNN Pooling

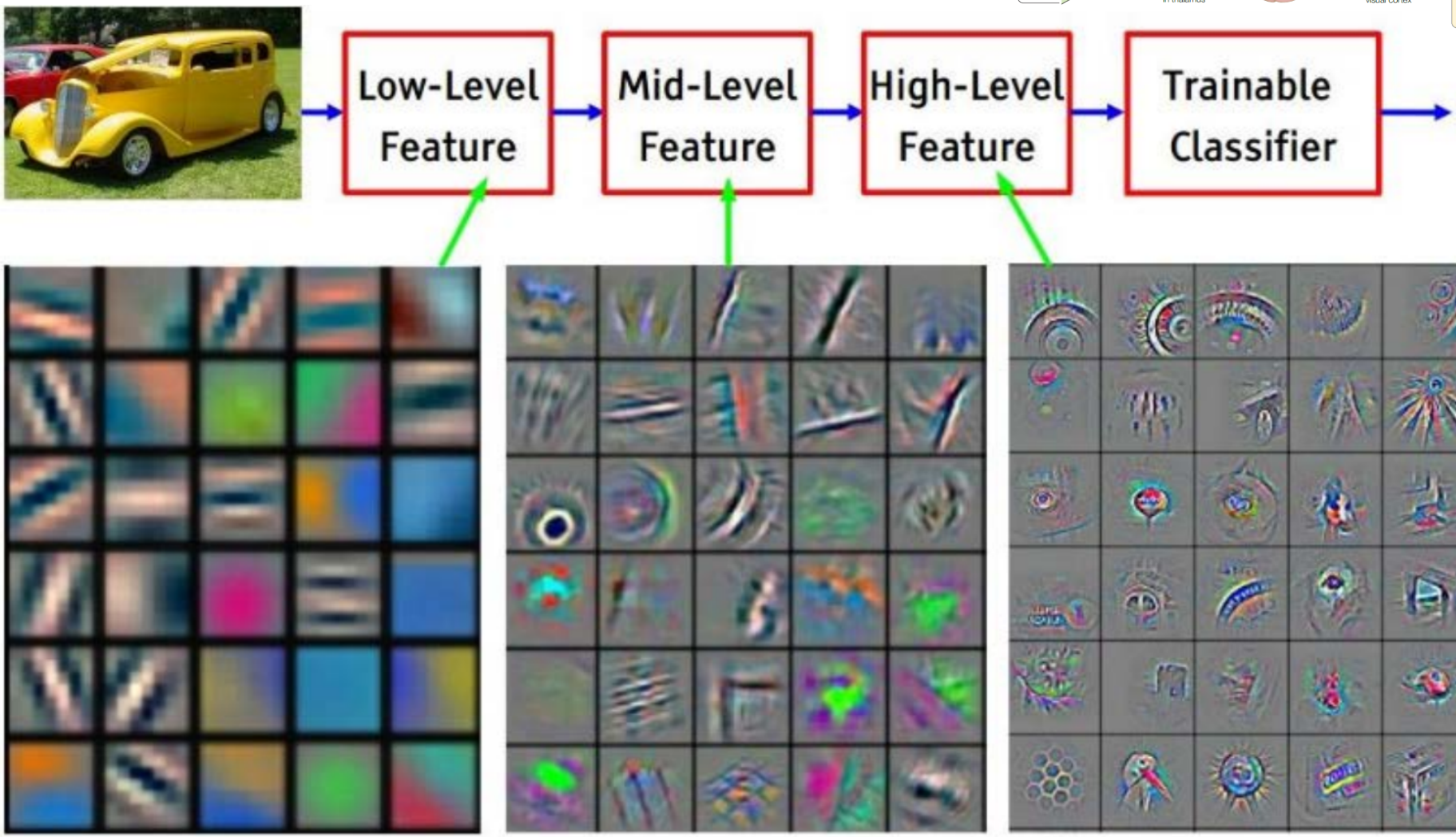
On real data (effectivly subsampling)



Convolutional Neural Networks

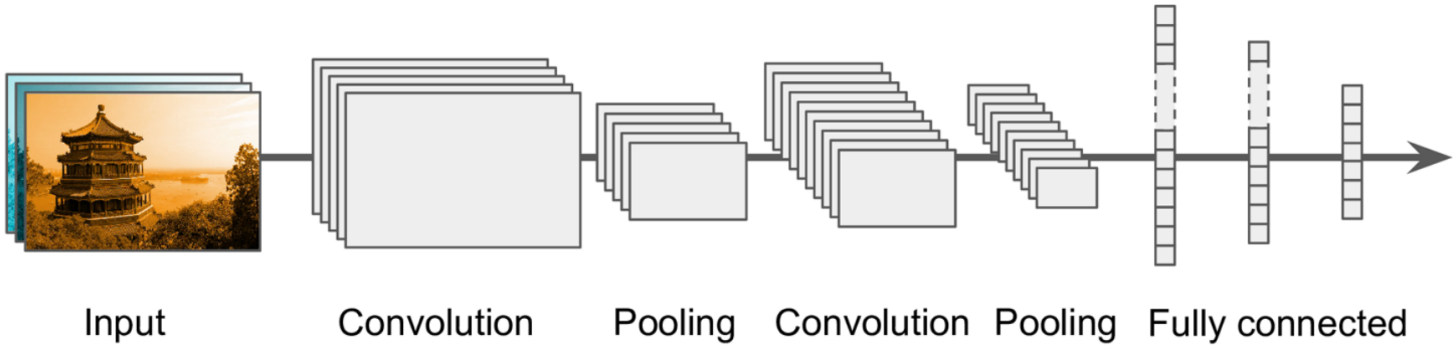
Low-, Mid-, and High-Level Feature Extraction

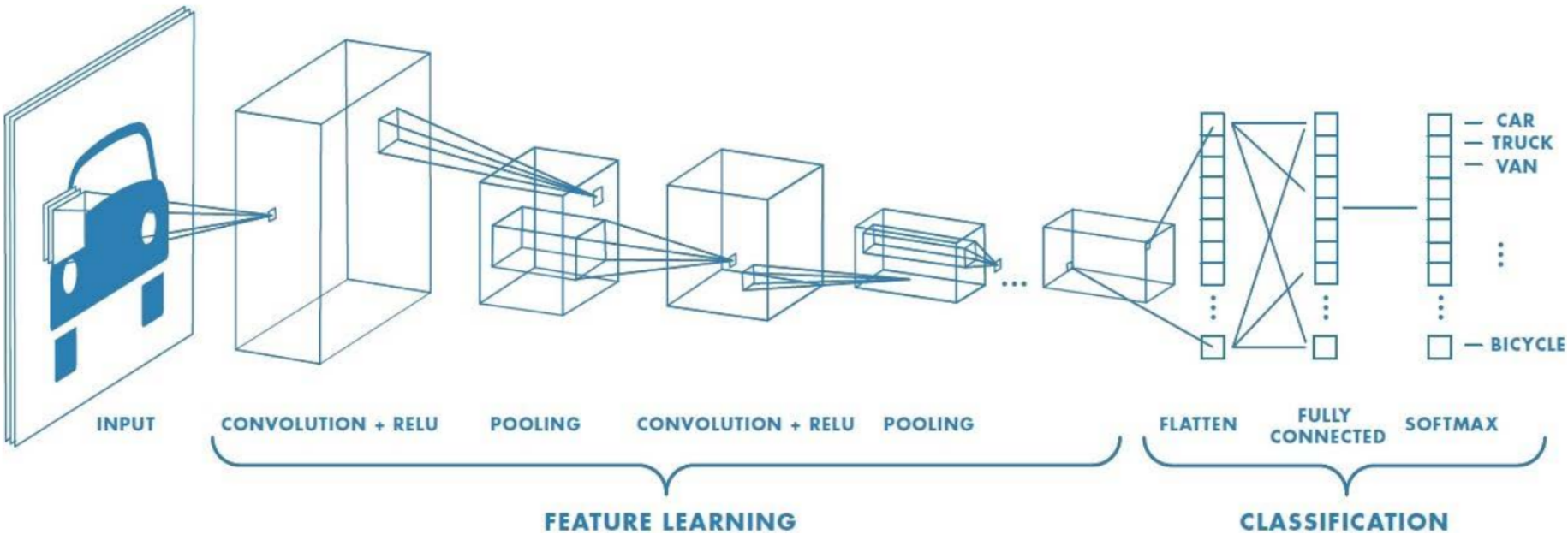




Convolutional Neural Networks

Stacking It All Up..





CNN'S IN PRACTICE

CNN's in Practice

Varroa mite detector—with a CNN somewhere in the pipeline


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

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[b]*Department of Agroecology - Entomology and Plant Pathology, Aarhus University, Flakkebjerg, Forsøgsvej 1, 4200 Slagelse, Denmark*

Abstract

This paper presents a portable computer vision system, that is able to monitor the infestation level of the *Varroa destructor* mite in a beehive by recording a video sequence of live honeybees *Apis mellifera* for 5-20 minutes. A video monitoring unit with multispectral illumination and camera was designed to be placed in front of the beehive, where bees from a selected frame were shaken off. Subsequently, a computer vision algorithm (denoted as the *Infestation Level Estimator*) based on deep learning analysis of the video stream counted the number of honeybees and found the position of identified varroa mites. In this paper, the design and the algorithm that were used to determine the number of bees and mites are presented. Based on a video sequence with 1,775 bees and 98 visual mites, the algorithm measured the infestation level to 5.80% compared to a ground truth of 5.52% The algorithm had a high F_1-score accuracy for counting bees (0.97), while the F_1-score for detecting varroa mites was lower (0.91). The latter was due to misperdictions, which can be resolved by improving both the trained varroa classifier and the mechanical setup. Overall, the proposed computer vision system and algorithm showed a promising results in nondestructive and automatic monitoring of infestation levels in honeybee colonies and should be considered as an alternative to traditional methods, which require the killing of bees.

Keywords: Computer Vision, Deep Learning, *Varroa destructor*, *Apis mellifera*, Multi-spectral Illumination
2018 MSC: 00-01, 99-00

1. Introduction

Honeybees, *Apis mellifera*, are important in the pollination of plants and crops [1, 2]. The ectoparasitic mite *Varroa destructor* has been identified as a main driver for mortality of honeybees and particularly in honeybee colonies [3, 4], due to virus transmission [5, 6]. Beehives must be inspected for the infestation level of mites to provide the needed treatment before the damage threshold level is reached [7]. Due to the exponential growth rate of the mites and the difficulties in detecting low infection levels, optimal timing of varroa treatment is a challenge for many beekeepers [8]. A variety of methods have been developed including collecting a few hundred bees with mites and washing them with detergent or ethanol to detach the mites, passing the suspension through a sieve to determine the infestation level, or de-lodging the mites with powdered sugar [9]. These methods are the ones most commonly used to monitor the infestation level of honeybee colonies today. Ideally, a sample of 300 bees should be used for comparison between colonies as shown by Lee et al. [10]. The disadvantages of these methods are that the samples of bees and mites are killed and that it is a time consuming operation to wash, separate and count the number of bees and mites. In addition, we observed that in practice, the number of bees is not actually counted, but rather estimated based on volume or weight, which may lead to inaccurate measurements.

In this paper, we describe a new method for auto-

Preprint submitted to Journal of Computers and Electronics in Agriculture *July 4, 2019*

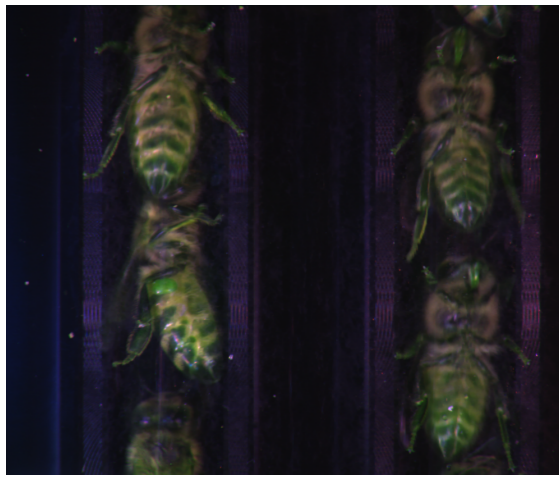
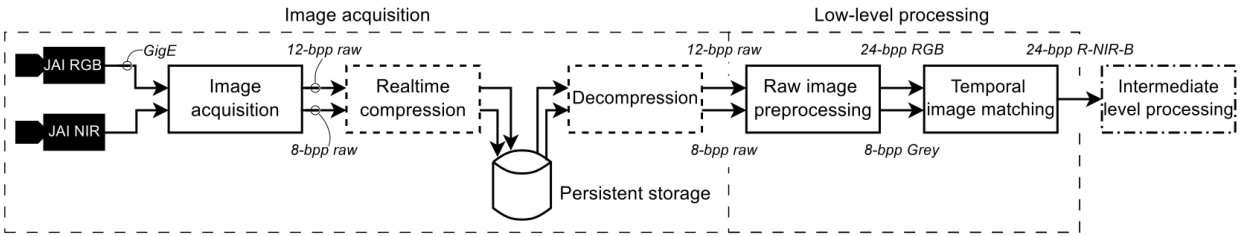
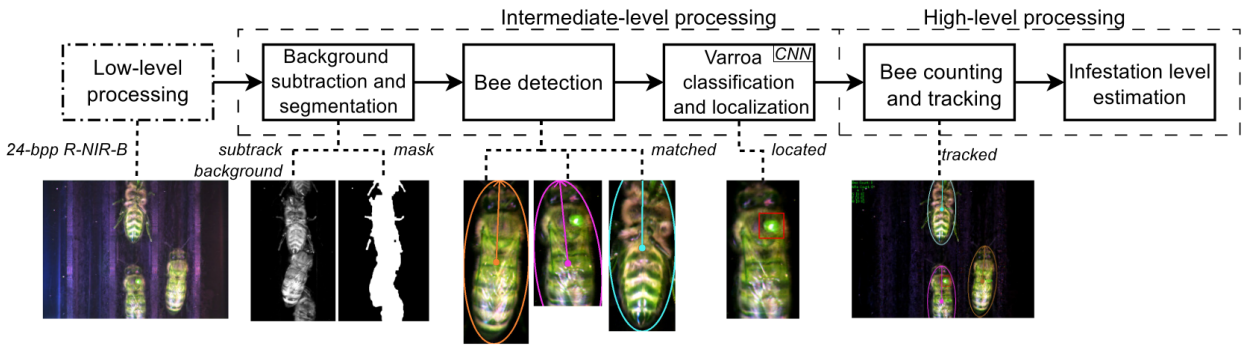
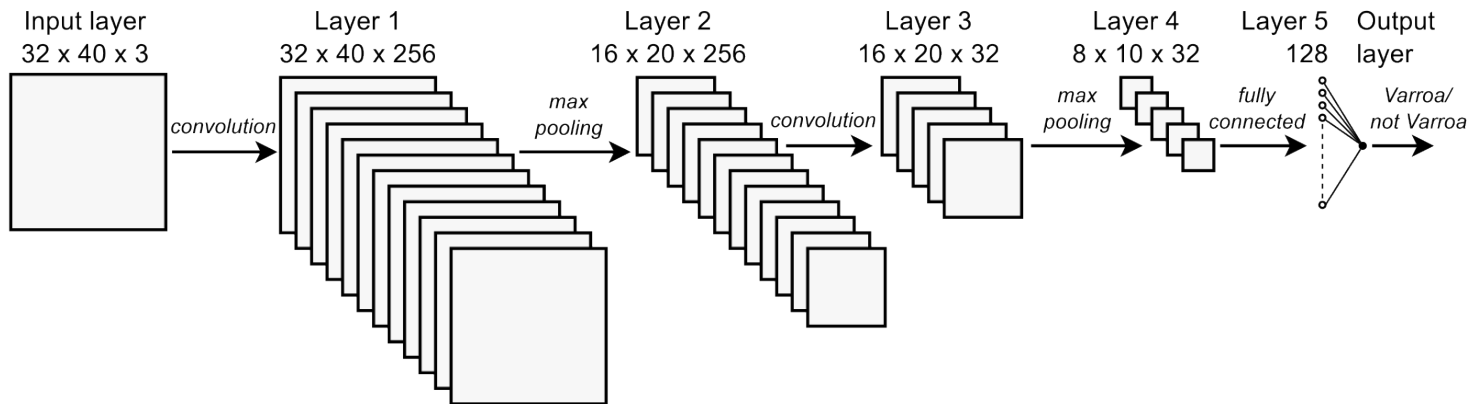


Image processing pipeline





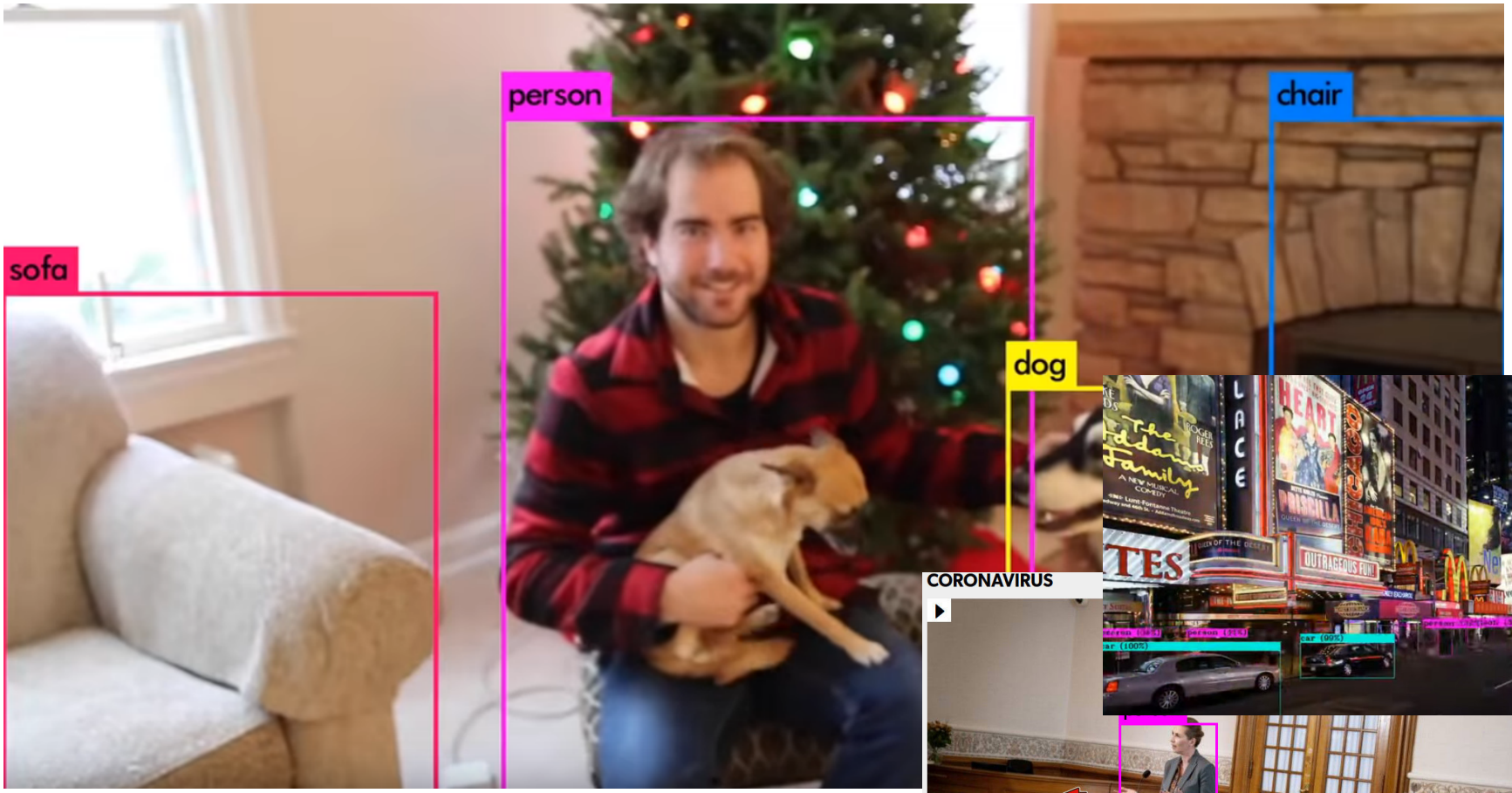
CNN architecture



CNN's in Practice

YOLOv2+3+4 (You Only Look Once)

Real-time object detection, demo..

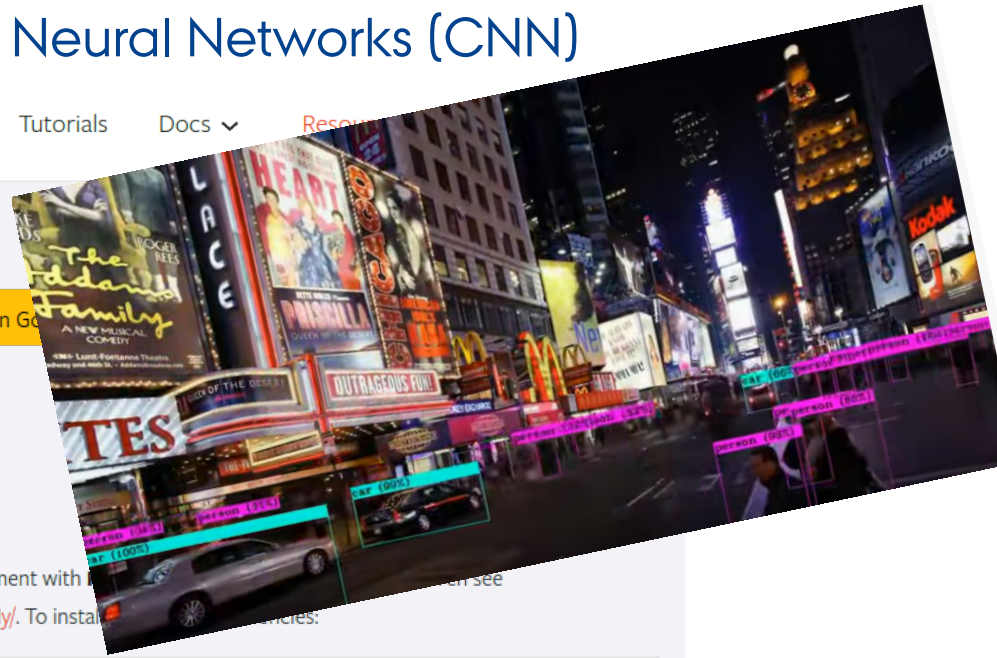


[https://homl.info/yolodemo]

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

Intro til YOLOV5..

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



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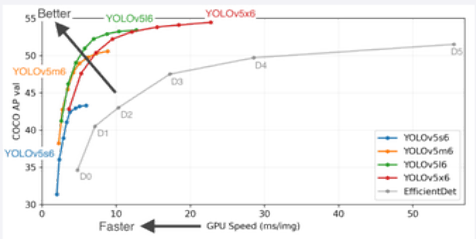
YOLOV5

View on Github Open on G



BEFORE YOU START

Start from a **Python>=3.8** environment with

https://pytorch.org/get-started/locally/. To instal

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

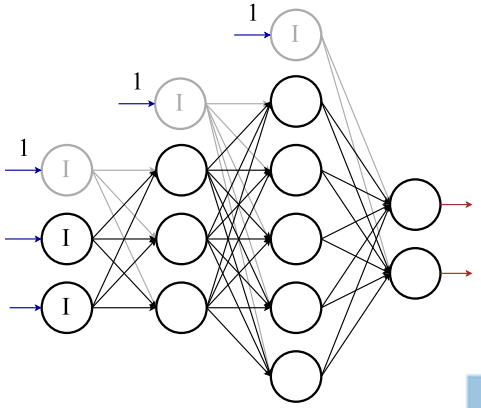
MODEL DESCRIPTION

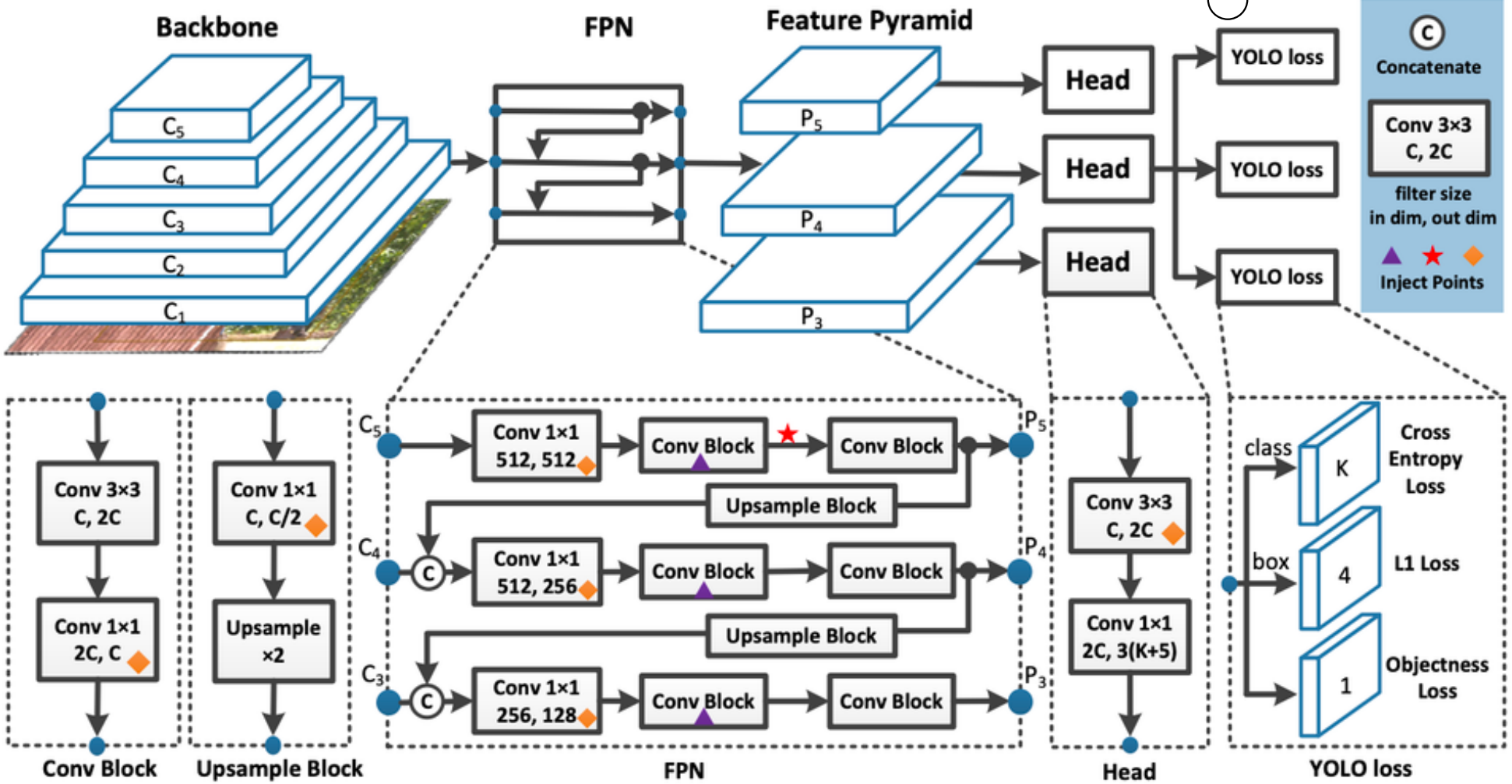
Nano	Small	Medium	Large	XLarge
YOLOv5n	YOLOv5s	YOLOv5m	YOLOv5l	YOLOv5x
4 MB_{FP16}	14 MB_{FP16}	41 MB_{FP16}	89 MB_{FP16}	166 MB_{FP16}
6.3 ms_{V100}	6.4 ms_{V100}	8.2 ms_{V100}	10.1 ms_{V100}	12.1 ms_{V100}
28.4 mAP_{COCO}	37.2 mAP_{COCO}	45.2 mAP_{COCO}	48.8 mAP_{COCO}	50.7 mAP_{COCO}

YOLOV5: [https://pytorch.org/hub/ultralytics_yolov5/]
Demo video: [https://www.youtube.com/watch?v=1_SiU0YUo0I]

Intro til YOLOV7..

YOLOV7 Architecture





[https://blog.roboflow.com/yolov7-breakdown/]

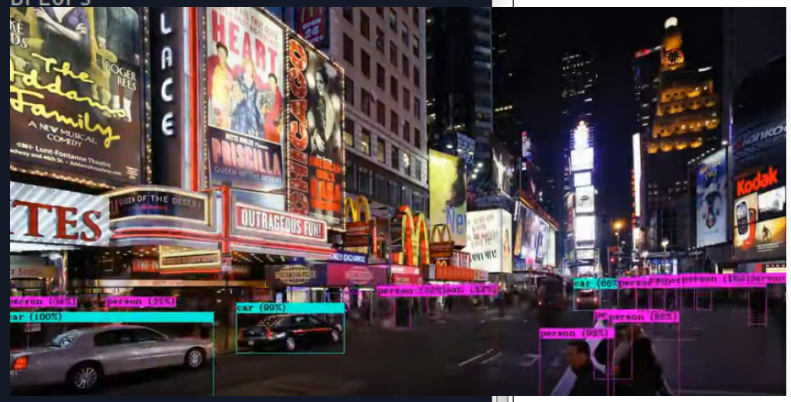
CNN's in Practice

YOLOv2+3+4 (You Only Look Once)

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 -p
thread  -L/opt/opencv/opencv4/lib -lopencv_core -lopencv_imgproc -lopencv_imgcodecs -lopencv_videoio -lopencv_hi
ghgui  -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 x1024  0.604
   19 conv    512  1 x 1 / 1     8 x   8 x1024   ->     8 x   8 x 512  0.067
   20 conv   1024  3 x 3 / 1     8 x   8 x 512   ->     8 x   8 x1024  0.604
   21 conv    512  1 x 1 / 1     8 x   8 x1024   ->     8 x   8 x 512  0.067
   22 conv   1024  3 x 3 / 1     8 x   8 x 512   ->     8 x   8 x1024  0.604
   23 conv   1000  1 x 1 / 1     8 x   8 x1024   ->     8 x   8 x1000  0.131
   24 avg                        8 x   8 x1000   ->  1000
   25 softmax                                       1000
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:~/texitmal/darknet$
```

BFLOPs
BFLOPs



CNN's in Practice

The LeNET-5 Architecture

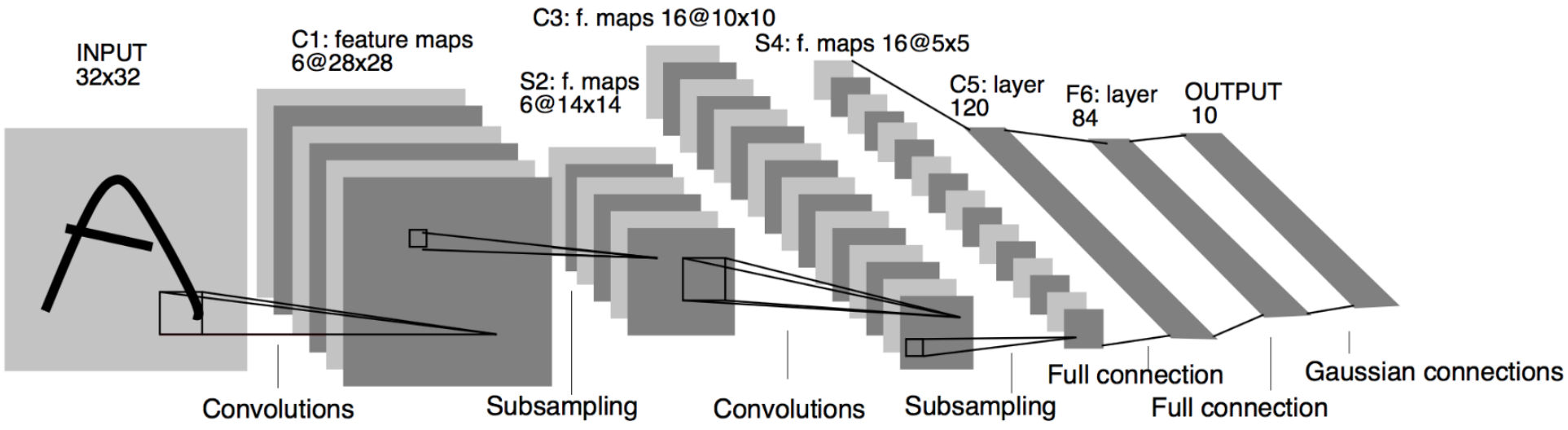


Table 14-1. LeNet-5 architecture

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	–	–	–

Other famours CNN-architectures:

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

CNN's in Practice

A LeNET-5 'Like' Architecture

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	–	–	–

In [9]:

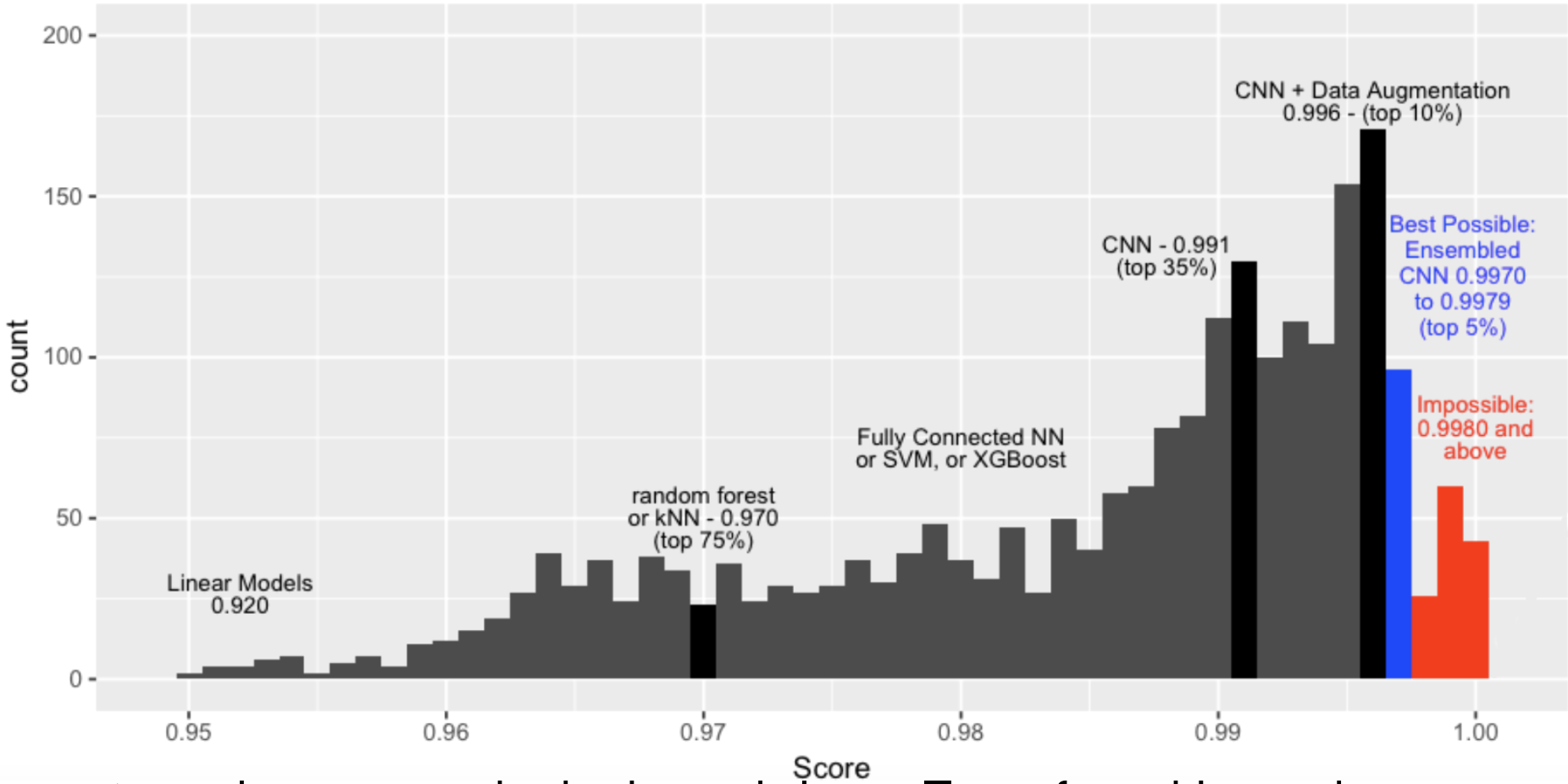
```
import keras
from keras import layers

model = keras.Sequential()

model.add(layers.Conv2D(filters=6, kernel_size=(3, 3),
                        activation='relu', input_shape=(32,32,1)))
model.add(layers.AveragePooling2D())

model.add(layers.Conv2D(filters=16, kernel_size=(3, 3), activation='relu'))
model.add(layers.AveragePooling2D())

model.add(layers.Flatten())

model.add(layers.Dense(units=120, activation='relu'))
model.add(layers.Dense(units=84,  activation='relu'))
model.add(layers.Dense(units=10,  activation='softmax'))

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
=================================================================
Total params: 81,194
Trainable params: 81,194
Non-trainable params: 0
```

[https://colab.research.google.com/drive/1CVm50PGE4vhtB5I_a_yc4h5F-itKOVL9]

CNN's in Practice

The LeNET-5 Architecture on MNIST



- using pre-trainded models => Transfered Learning,
- object detection,
- semantic segmentation,
- time series => RNN's, ...

[https://www.kaggle.com/datasets/numbersareuseful/public-leaderboard-mnist]