

# Convolutional Neural Networks - CNN

The Power of Deep Learning for Image Recognition

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# Agenda

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# Top growing technologies in 2022

According to the latest ifiCLAIMS report<sup>1</sup>, the fastest growing technology was:

- ▶ AUTONOMOUS DRIVING
- ▶ modern EV cars have 20+ sensors and cameras
- ▶ 9th place: Machine learning

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<sup>1</sup><https://www.ificlaims.com/rankings-tech-growth-2022.htm>

# Why good vision is important?

By far the most important organs of sense are our eyes.

What per cent of all impressions do we perceive by means of our sight?

- ▶ 80%

As vision plays a crucial role in our daily lives, CNNs have made it possible for machines to mimic human vision and process images effectively, improving efficiency and accuracy in various fields.

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# How computers "see"?



```

0 2 15 0 0 11 10 0 0 0 0 0 0 9 9 0 0 0
0 0 4 60 157 236 255 255 177 95 61 32 0 0 29
0 10 16 119 238 255 244 245 243 250 249 255 222 103 10 0
0 14 170 255 255 244 254 254 255 253 245 255 249 253 251 124 1
2 98 255 228 255 251 254 211 141 116 122 215 251 238 255 49
13 217 243 255 155 33 226 52 2 0 10 13 232 255 255 36
16 229 252 254 49 12 0 0 7 7 0 70 237 252 235 62
6 141 245 255 212 25 11 9 3 0 115 236 243 255 137 0
0 87 252 250 248 215 60 0 1 121 252 255 248 144 6 0
0 13 113 255 255 245 255 182 181 248 252 242 208 36 0 19
1 0 5 117 251 255 241 255 247 255 241 162 17 0 7 0
0 0 0 4 58 251 255 246 254 253 255 120 11 0 1 0
0 0 4 97 255 255 248 252 255 244 255 182 10 0 4
0 22 206 252 246 251 241 100 24 113 255 245 255 194 9 0
0 111 255 242 255 150 24 0 0 6 39 255 232 230 56 0
0 218 251 250 137 7 11 0 0 0 2 62 255 250 125 3
0 173 255 255 101 9 20 0 13 3 3 13 182 251 245 61 0
0 107 251 241 255 230 98 55 19 118 217 248 253 255 52 4
0 18 146 250 255 247 255 255 249 255 240 255 129 0 5
0 0 23 113 215 255 250 248 255 255 248 248 118 14 12 0
0 0 6 1 0 52 153 233 255 252 147 37 0 0 4 1
0 0 5 5 0 0 0 0 0 14 1 0 6 6 0 0

```

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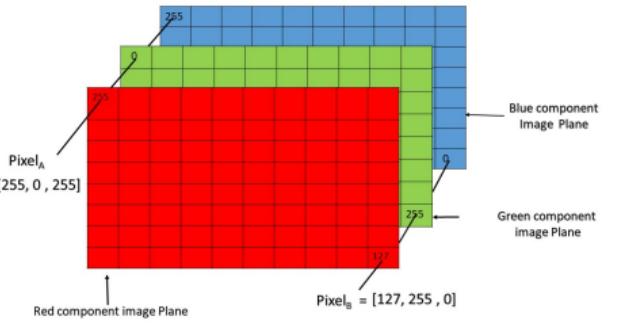
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# How computers "see"?



Pixel of an RGB image are formed from the corresponding pixel of the three component images

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# How humans recognize objects?

How do we recognize a car?



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# Is this electric car?



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# CNN architecture

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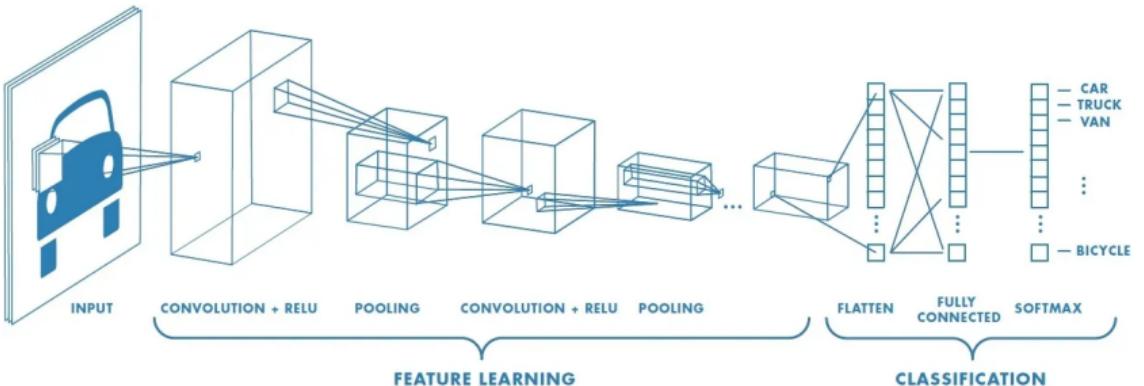
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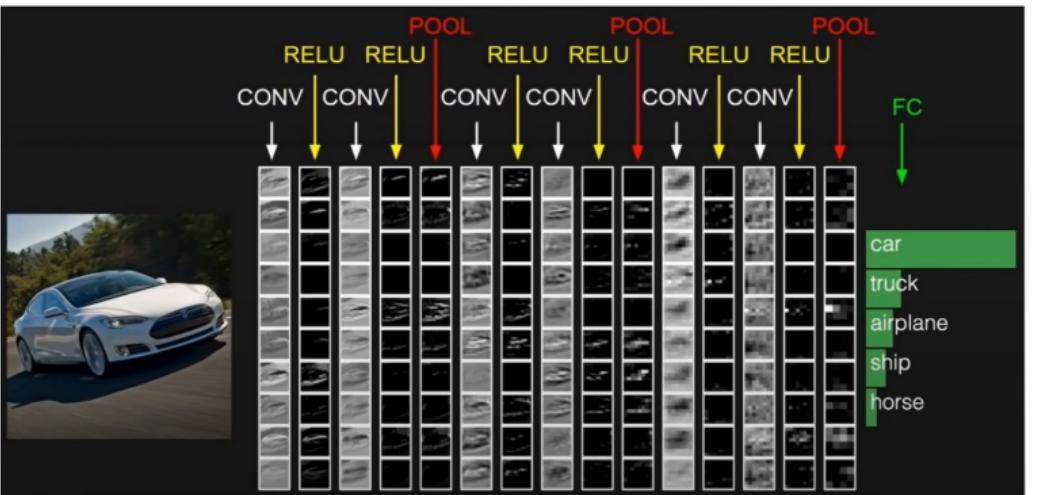
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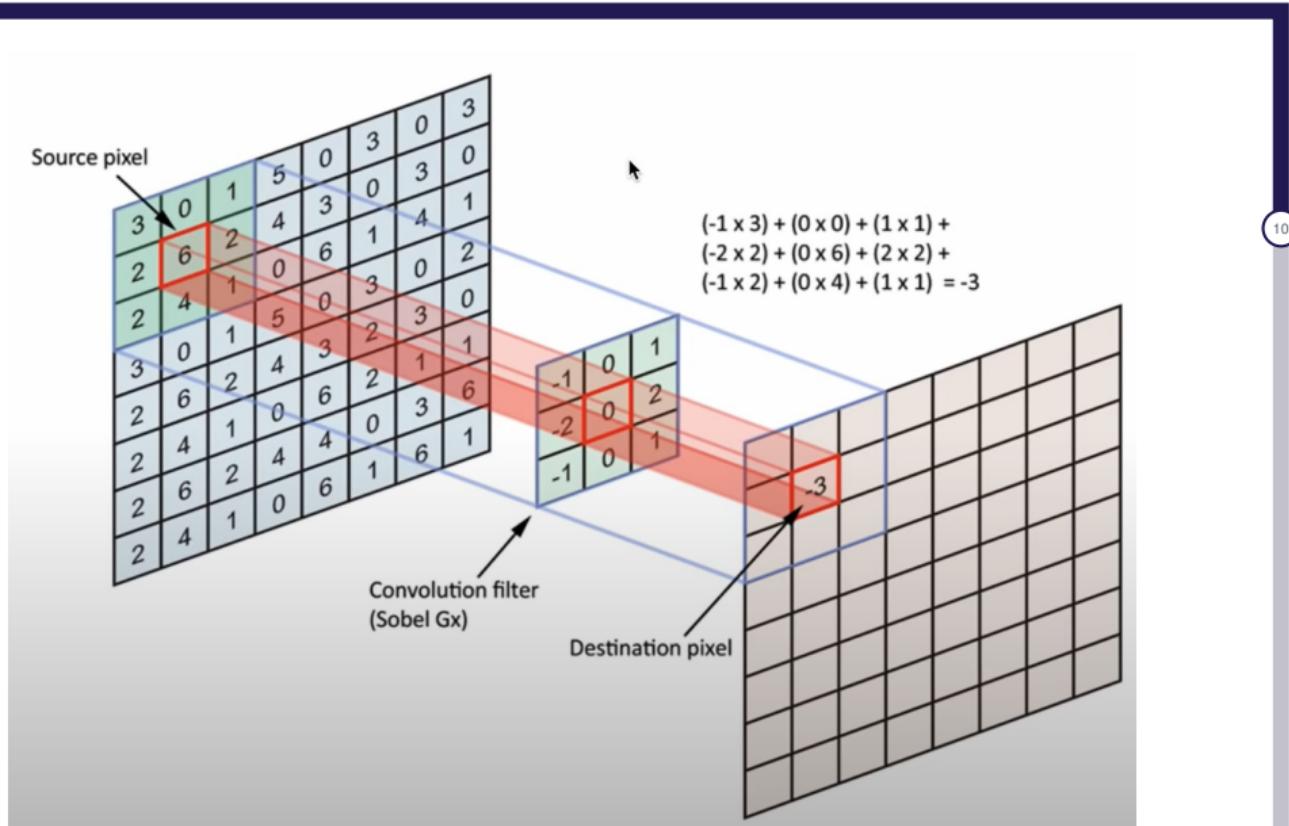
# Visual process



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# Convolution layer



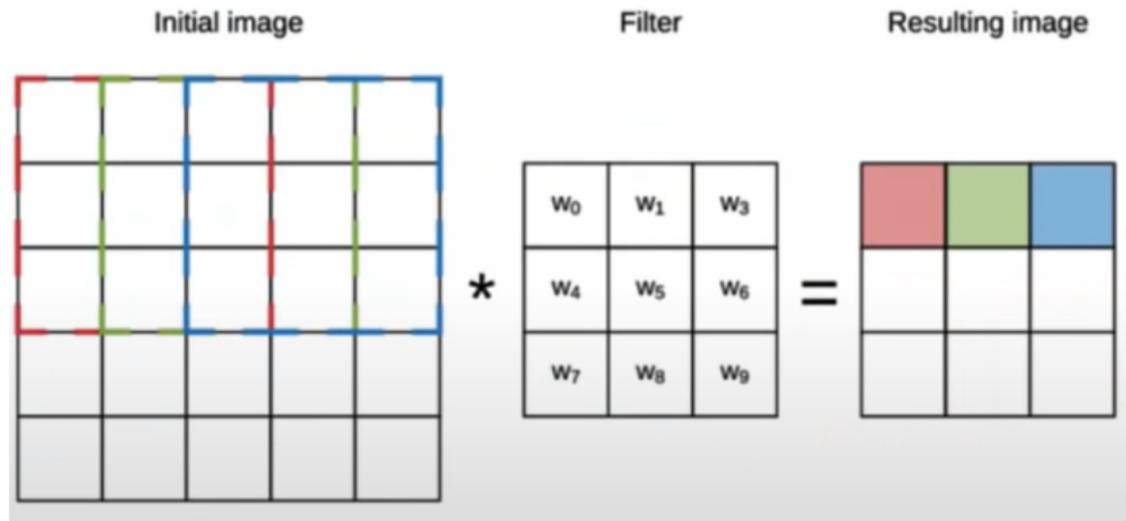
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# Convolution filter

Operation	Filter	Convolved Image
<b>Identity</b>	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
<b>Edge detection</b>	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
<b>Sharpen</b>	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
<b>Box blur (normalized)</b>	$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
<b>Gaussian blur (approximation)</b>	$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

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# Convolution layer



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# Downsampling

12	20	30	0
8	12	2	0
34	70	37	4
112	100	25	12

$2 \times 2$  Max-Pool

20	30
112	37

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# Fully connected layers

First fully connected layers take the output of the previous layers, “flattens” them and turns them into a single vector that can be an input for the next stage.

Fully connected output layer gives the final probabilities for each label.

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# R-CNN

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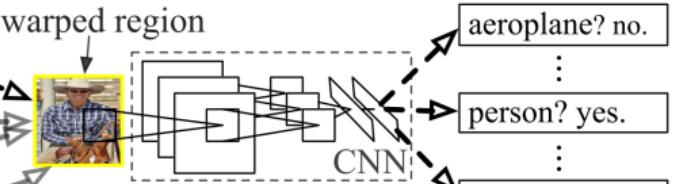
## R-CNN: *Regions with CNN features*



1. Input image



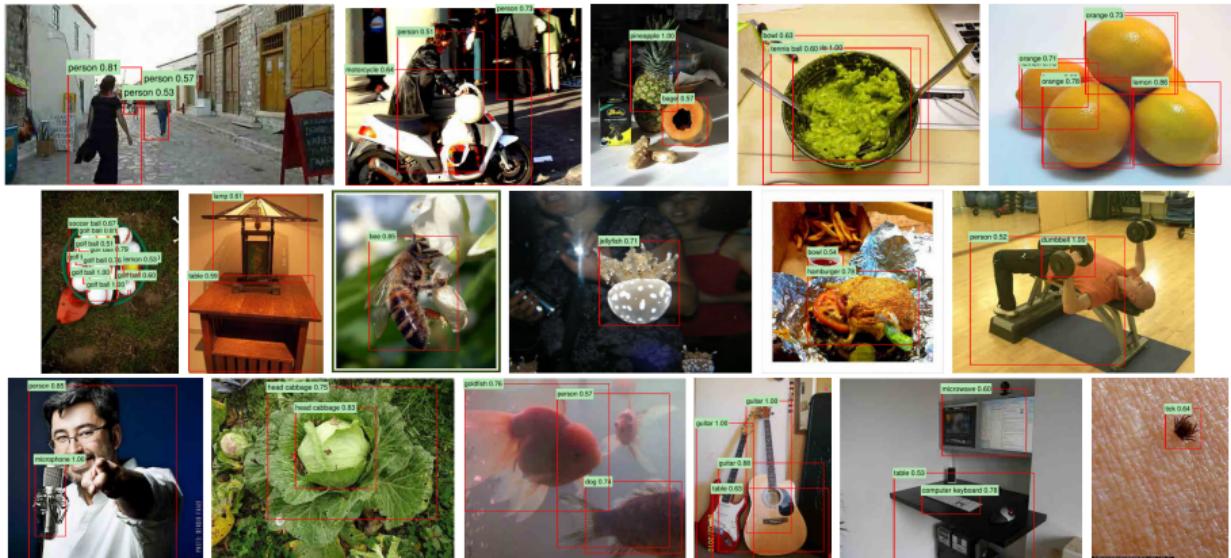
2. Extract region proposals (~2k)



3. Compute CNN features

4. Classify regions

# R-CNN



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# Dataset CIFAR-10

- ▶ 60.000 images
- ▶ RGB (3 channels)
- ▶ 32x32 pixel images
- ▶ 10 classes (5000 train 1000 test for each class)

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# Dataset CIFAR-10



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# Results

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Model Name	Accuracy of the network:
e6, b4, r00.1	51.69%
e8, b4, r00.1	54.70%
e10, b4, r00.1	58.57%
e10, b4, r00.3	62.41%

# Results

## Class:

Accuracy of the network:	62.41 %
Accuracy of plane:	54.2 %
Accuracy of car:	74.4 %
Accuracy of bird:	57.3 %
Accuracy of cat:	54.3 %
Accuracy of deer:	53.6 %
Accuracy of dog:	43.5 %
Accuracy of frog:	78.7 %
Accuracy of horse:	61.3 %
Accuracy of ship:	80.9 %
Accuracy of truck:	65.9 %

## Accuracy:

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# Model optimization

- ▶ Hyper-parameter tuning: learning rate, batch size, epochs, number of filters in each convolutional layer
- ▶ Data augmentation: increase dataset size by rotating, flipping, scaling
- ▶ Transfer learning: using a pre-trained models and fine-tune with your dataset
- ▶ Regularization: dropout, L1/L2 regularization, and early stopping
- ▶ Change architecture: find the optimal network architecture for a given problem (use academic articles)
- ▶ ...

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# Business applications

what, how, why, and for who

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- ▶ Albawi, S., Mohammed, T. A., Al-Zawi, S. (2017). **Understanding of a convolutional neural network.** In 2017 international conference on engineering and technology (ICET) (pp. 1-6). Ieee.
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