Convolution Neural Networks – CNN
Part I

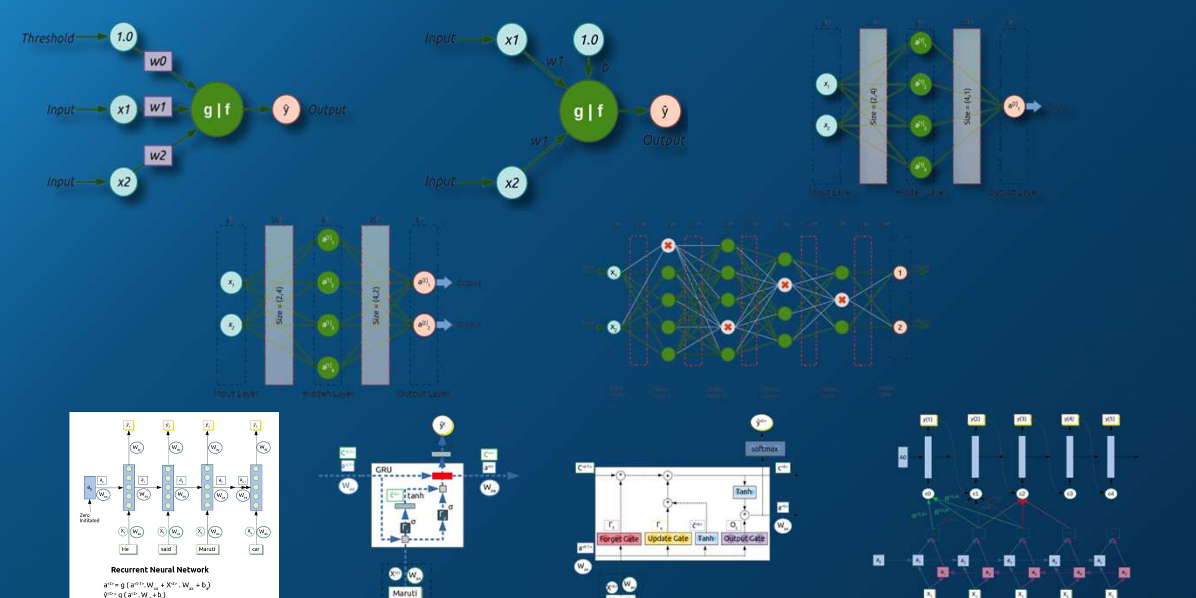
Deep Neural Network

Session 21

Pramod Sharma
pramod.sharma@prasami.com

2

Story So Far…



pra-sâmi

3

Agenda

- Computer Vision
- Convolution
- Padding
- Pooling
- Frameworks

pra-sâmi

4

Acknowledgement…

Geoffrey Everest Hinton CC FRS FRSC

- An English Canadian cognitive psychologist and computer scientist, most noted for his work on artificial neural networks.
- Since 2013, he divides his time working for Google (Google Brain) and the University of Toronto. In 2017, he cofounded and became the Chief Scientific Advisor of the Vector Institute in Toronto.
- With David Rumelhart and Ronald J. Williams, Hinton was co-author of a highly cited paper published in 1986 that popularized the **backpropagation algorithm** for training multi-layer neural networks, although they were not the first to propose the approach.
- Hinton is viewed as a **leading figure** in the deep learning community.
- The dramatic image-recognition milestone of the **AlexNet** designed in collaboration with his students Alex Krizhevsky and Ilya Sutskever for the ImageNet challenge 2012 was a breakthrough in the field of computer vision.

pra-sâmi

5

What is Computer Vision…

11/19/2025

pra-sâmi

6

Ambulance given green light all through….

11/19/2025

pra-sâmi

7

Computer vision is making progress in leaps and bounds…

pra-sâmi

8

Convolutional neural networks (CNN, ConvNet) is a class of deep, feed-forward (not recurrent) artificial neural networks that are applied to analyzing visual imagery

pra-sâmi

9

Computer Vision

- Self driving car
- Fully automated warehouse and ports
  - https://youtu.be/RFV8lkY52iY
- Image search services,
- Unlock phone
- Provide access to secure area
  - Open your house
  - Enter office without your access card
- Object identification Apps
  - Garment
  - Food,
  - Nature
- Natural style transfer
- Automatic video classification systems

11/19/2025

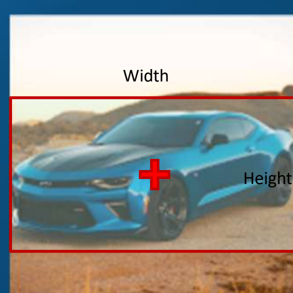
pra-sâmi

10

Object Classification - Localization - Detection

Classification:
Identify object
It's a Car!

- Pedestrian
- Car
- Truck
- Bike
- others



Classification with localization:
Identify object and mark its location

- Class of object
- Location of bounding box (mid point, height, width)
- $\hat{y}$ will be a vector

Detection:
Identify multiple object in the image

- Classes of all object
- Location of bounding box (mid point, height, width) of all objects
- $\hat{y}$ will be a vector

11/19/2025

pra-sâmi

11

Neural Style Transfer

11/19/2025

12

Neural Style Transfer









11/19/2025

13

Neural Style Transfer

11/19/2025

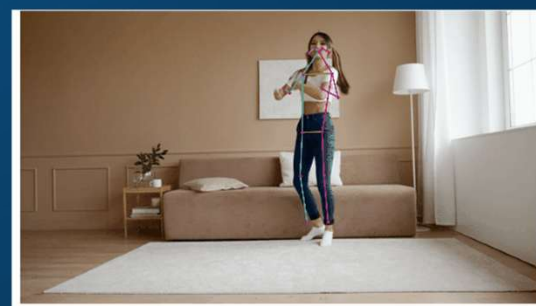
14

Landmark Detection

11/19/2025

15

Gait Detection



11/19/2025

16

Computer Vision

- Have been used in image recognition since the 1980s
- Increase in computational power, the amount of available training data, CNNs have managed to achieve better performance
- Rapid advancement
  - Newer and Newer products and applications are coming up
  - Some of you will get a chance to directly work on these advance applications
- The development community is also very kind in sharing their success stories
- The ideas can be borrowed in other applications:
  - Voice recognition
  - Natural language processing (NLP)

11/19/2025

17
Computer Vision

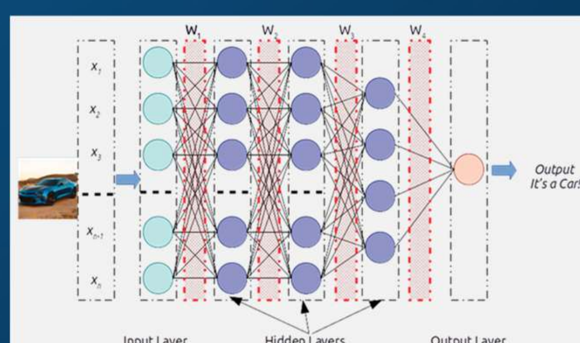
- What makes vision hard?
- Vision needs to be robust to a lot of transformations or distortions:
  - Change in pose/viewpoint
  - Change in illumination
  - Deformation
  - Occlusion (some objects are hidden behind others)
- Many object categories can vary wildly in appearance (e.g. chairs)

"Imaging a medical database in which the age of the patient sometimes hops to the input dimension which normally codes for weight!" - Geoff Hinton

11/19/2025

18
Why?

- Enough of sales pitch…
- Why not simply use a regular deep neural network with fully connected layers?
- Small (150 x 150 x 3) image has 67,500 pixels
- If we consider first hidden layer as 1000,
- First weight matrix (W1) will be 67,500 x 1000
- Do your math…… that size is huge



11/19/2025

19

Smaller Network: CNN

- We know it is good to learn a small model
- Fully connected model, each hidden unit is processing every input
  - Do we really need all the edges?
- Can some of these be shared?

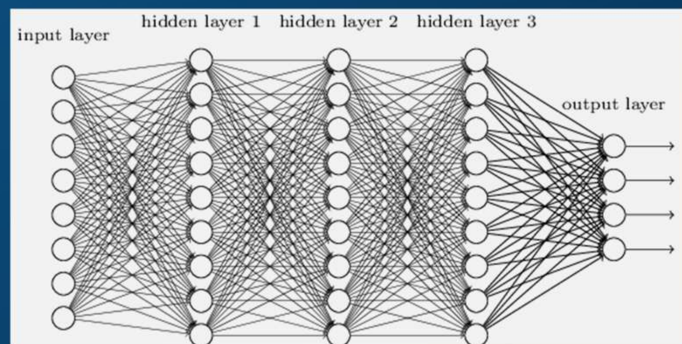


Image courtesy: University of Waterloo.

11/19/2025

pra-sâmi

20

Images are high-dimensional vectors. It would take a huge amount of parameters to characterize the network.

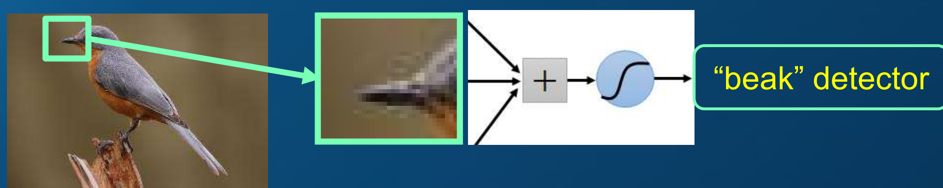
11/19/2025

pra-sâmi

21

Learning an image…

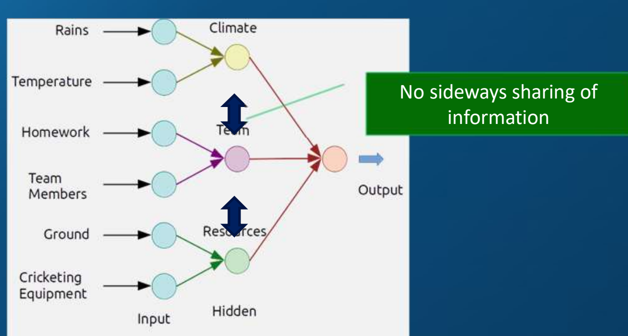
- Some patterns are much smaller than the whole image
- Can represent a small region with fewer parameters

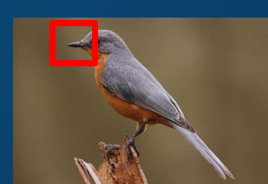


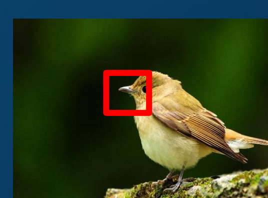
22

Learning an image…

- Same pattern appears in different places
  - Can they be compressed!
- What about training a lot of such “small” detectors and each detector must “move around”

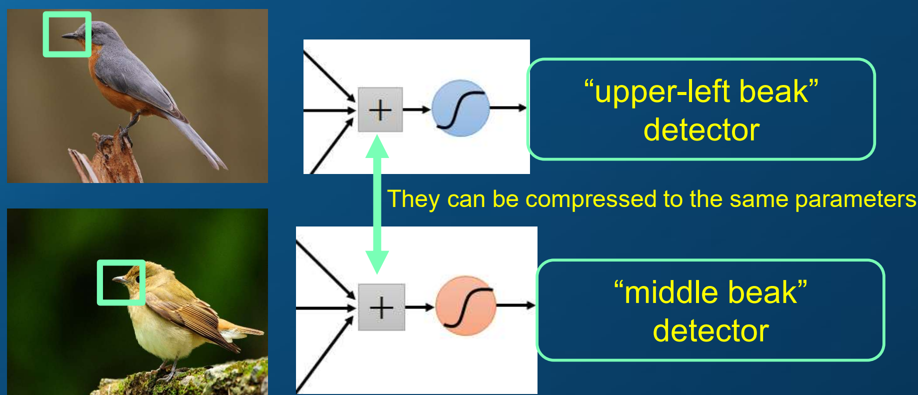






23

Learning an image…



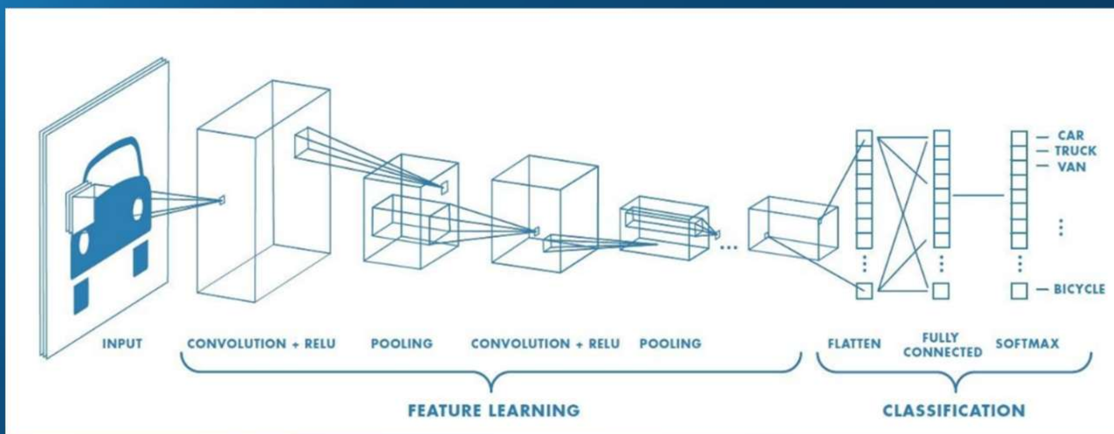
24

Learning an image…

- The same sorts of features that are useful in analyzing one part of the image will probably be useful for analyzing other parts as well.
  - E.g., edges, corners, contours, object parts
- We want a neural net architecture that lets us learn a set of feature detectors that are applied at all image locations
- So far, we’ve seen a bunch of types of layers
  - Fully connected layers (dense)
  - Embedding layers (i.e. lookup tables)
  - A few more in RNNs (GRU, LSTMs, etc.)
- Different layers could be stacked together to build powerful models
- Let’s add another set of layers: the convolution layer, pooling layer…

25

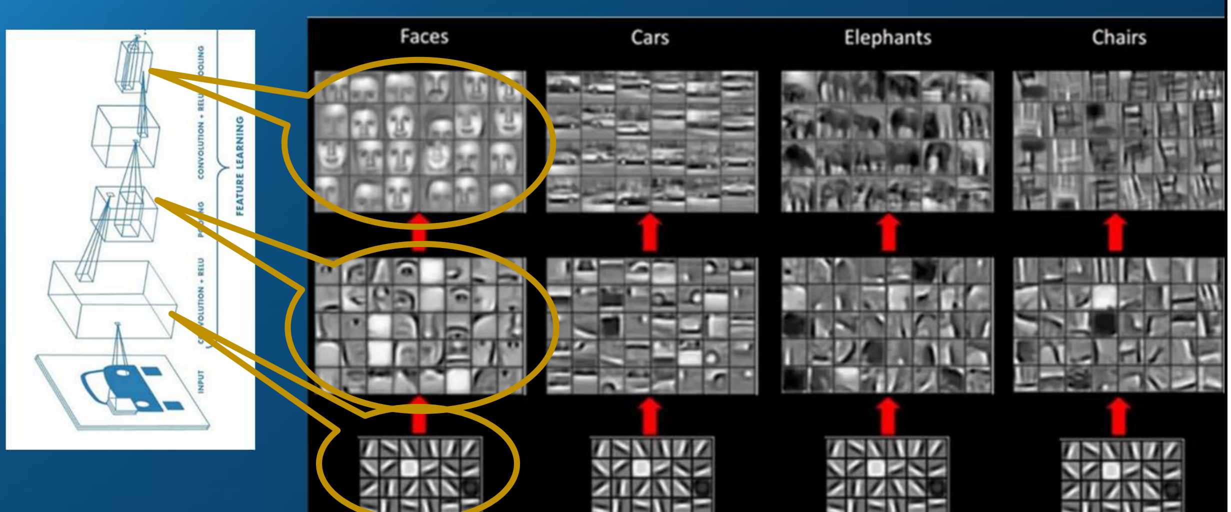
Overall Layout



11/19/2025

26

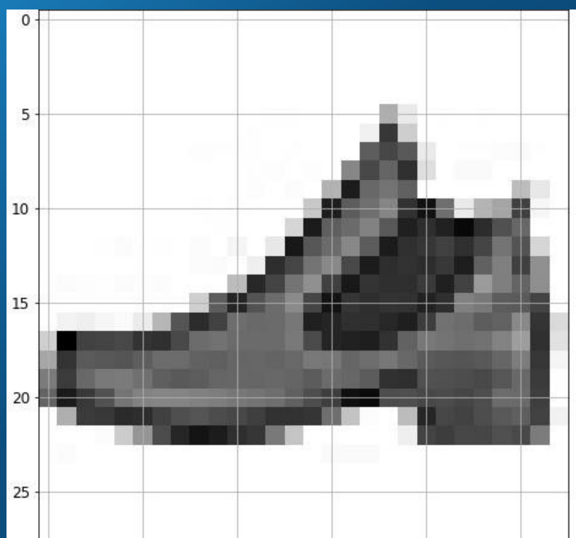
Successive Layers Do!

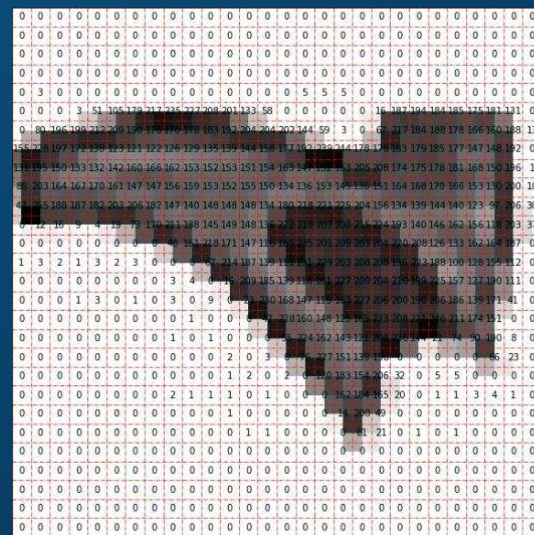


11/19/2025

27

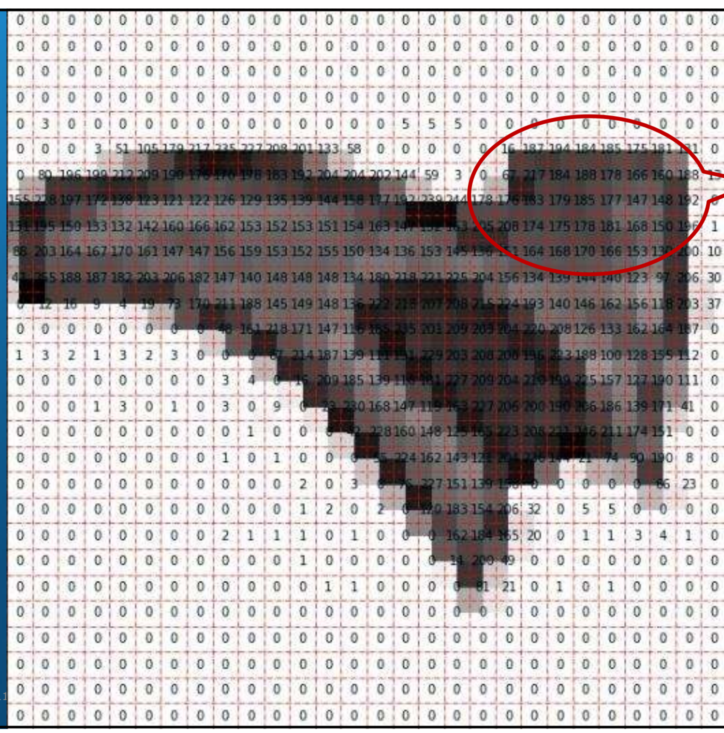
What computer sees…

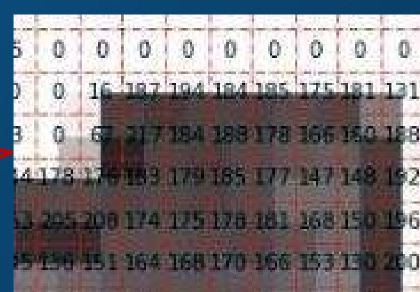




11/19/2025

28

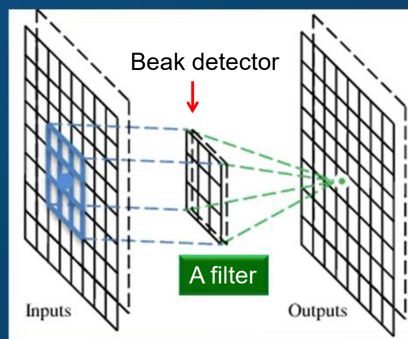




29

A Convolutional Layer

- A CNN is a neural network with some convolutional layers
  - And, of course, a few other layers
- A convolutional layer has a number of filters that does convolutional operation
  - Some of the literature would call it **Kernel**

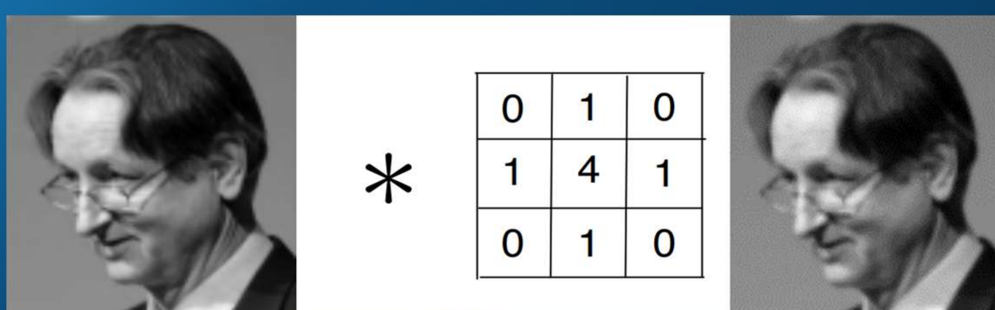


11/19/2025

pra-sâmi

30

What does this Convolution Filter/ Kernel do?

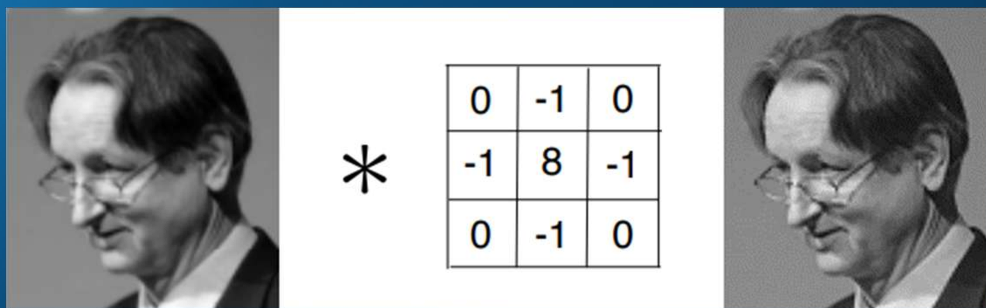


11/19/2025

pra-sâmi

31

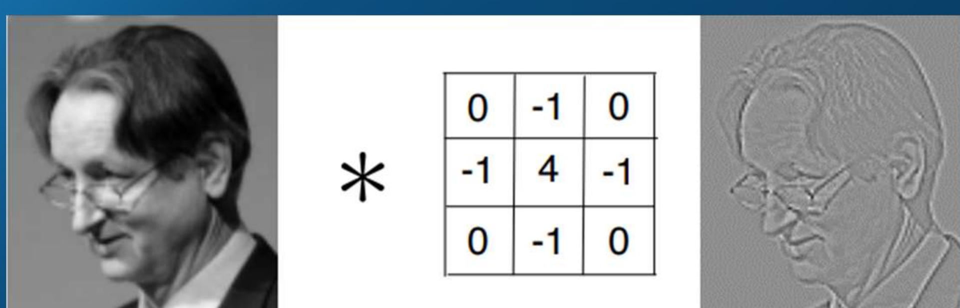
What does this Convolution Filter/ Kernel do?



11/19/2025

32

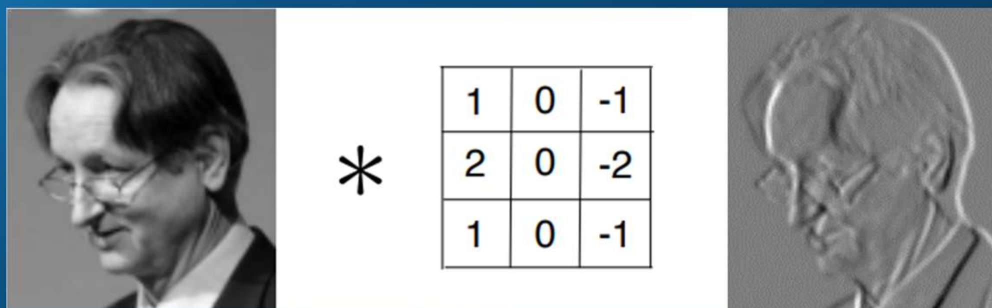
What does this Convolution Filter/ Kernel do?



11/19/2025

33

What does this Convolution Filter/ Kernel do?



11/19/2025

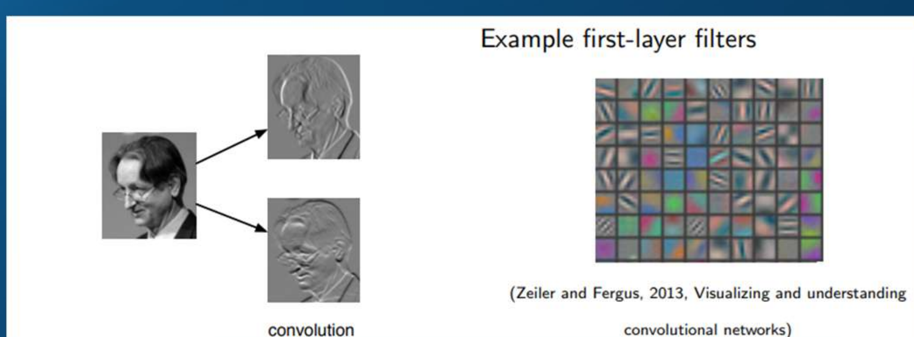
pra-sâmi

34

Convolutional Networks

- Two kinds of layers:
  - Detection layers (or convolution layers)
  - Pooling layers

- The convolution layer has a set of filters.
  - Output is a set of feature maps, each one obtained by convolving the image with a filter.



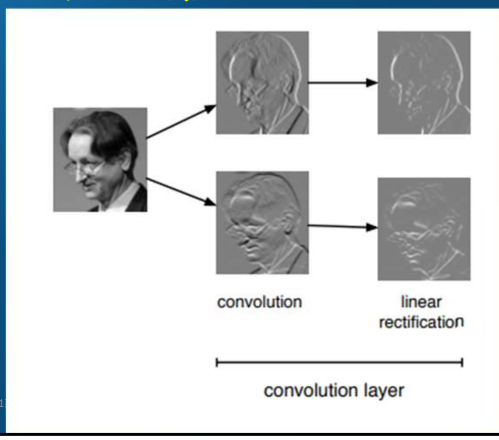
11/19/2025

pra-sâmi

35

Convolutional Networks

- It's common to apply a linear rectification (activations) nonlinearity or even something else:
  - y_i = Relu(z_i),
  - May be, Tanh(z_i), etc.



- Convolution is a linear operation
- Therefore, we need a nonlinearity:
  - Otherwise two convolution layers would be no more powerful than one
- Two edges in opposite directions shouldn't cancel
- Non-linearity makes the gradients sparse, which helps optimization

36

Image with a edge

- Convolution is basic building block of image recognition
- Using edge detection as an example in following image…

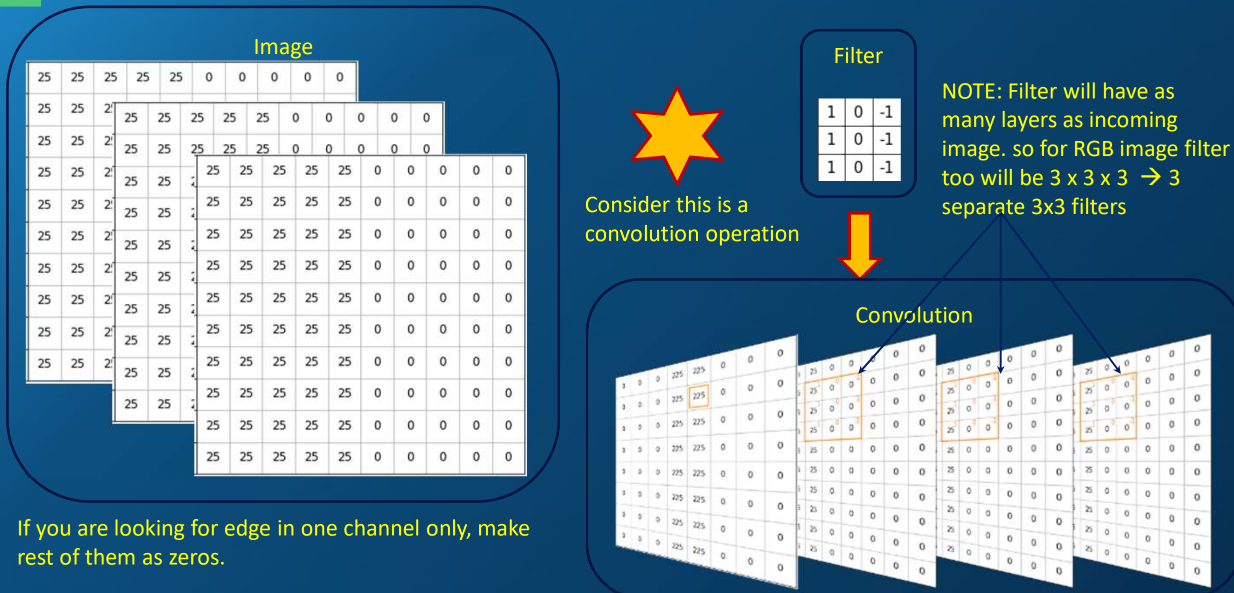
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

- Apply filters on the image!

37

Convolution on 3D images (RGB)



If you are looking for edge in one channel only, make rest of them as zeros.

11/19/2025

pra-sâmi

38

Convolution on 3D images (RGB)

- First convolution

25^{1}	25^{0}	25^{-1}	25	25	0	0	0	0	0
25^{1}	25^{0}	25^{-1}	25	25	0	0	0	0	0
25^{1}	25^{0}	25^{-1}	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

- Layer R
  - = 25*1 + 25*1 + 25*1 + 0 + 0 + 0 – 1*25 – 1*25 – 1*25
  - = 0
- Layer G
  - = 25*1 + 25*1 + 25*1 + 0 + 0 + 0 – 1*25 – 1*25 – 1*25
  - = 0
- Layer B
  - = 25*1 + 25*1 + 25*1 + 0 + 0 + 0 – 1*25 – 1*25 – 1*25
  - = 0
- Total = 0 + 0 + 0 = 0

11/19/2025

pra-sâmi

39

Convolution on 3D images (RGB)

- Second convolution
  - It will be identical to First

25	25^{1}	25^{0}	25^{-1}	25	0	0	0	0	0
25	25^{1}	25^{0}	25^{-1}	25	0	0	0	0	0
25	25^{1}	25^{0}	25^{-1}	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

- Layer R
  - = 25 + 25 + 25 + 0 + 0 + 0 – 25 – 25 – 25
  - = 0
- Layer G
  - = 25 + 25 + 25 + 0 + 0 + 0 – 25 – 25 – 25
  - = 0
- Layer B
  - = 25 + 25 + 25 + 0 + 0 + 0 – 25 – 25 – 25
  - = 0
- Total = 0 + 0 + 0 = 0

11/19/2025

pra-sâmi

40

Convolution on 3D images (RGB)

- What happens 4th step

25	25	25	25^{1}	25^{0}	0^{-1}	0	0	0	0
25	25	25	25^{1}	25^{0}	0^{-1}	0	0	0	0
25	25	25	25^{1}	25^{0}	0^{-1}	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

- Layer R
  - = 25 + 25 + 25 + 0 + 0 + 0 – 0 – 0 – 0
  - = 75
- Layer G
  - = 25 + 25 + 25 + 0 + 0 + 0 – 0 – 0 – 0
  - = 75
- Layer B
  - = 25 + 25 + 25 + 0 + 0 + 0 – 0 – 0 – 0
  - = 75
- Total = 75 + 75 + 75 = 225

11/19/2025

pra-sâmi

41

Convolution on 3D images (RGB)

- And for 5th Step

25	25	25	25	25^{1}	0^{0}	0^{-1}	0	0	0
25	25	25	25	25^{1}	0^{0}	0^{-1}	0	0	0
25	25	25	25	25^{1}	0^{0}	0^{-1}	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

- Layer R
  - = 25 + 25 + 25 + 0 + 0 + 0 – 0 – 0 – 0
  - = 75
- Layer G
  - = 25 + 25 + 25 + 0 + 0 + 0 – 0 – 0 – 0
  - = 75
- Layer B
  - = 25 + 25 + 25 + 0 + 0 + 0 – 0 – 0 – 0
  - = 75
- Total = 75 + 75 + 75 = 225

11/19/2025

pra-sâmi

42

Convolution on 3D images (RGB)

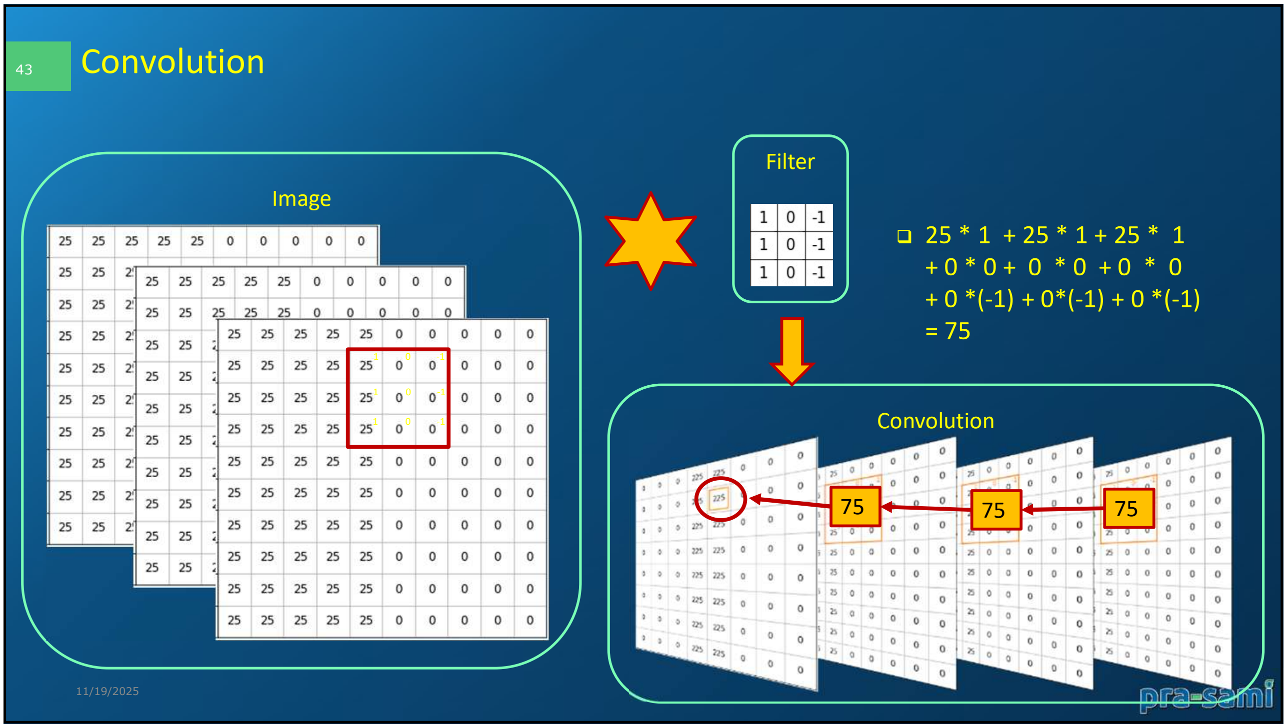
- 6th Step onwards again all values are 0

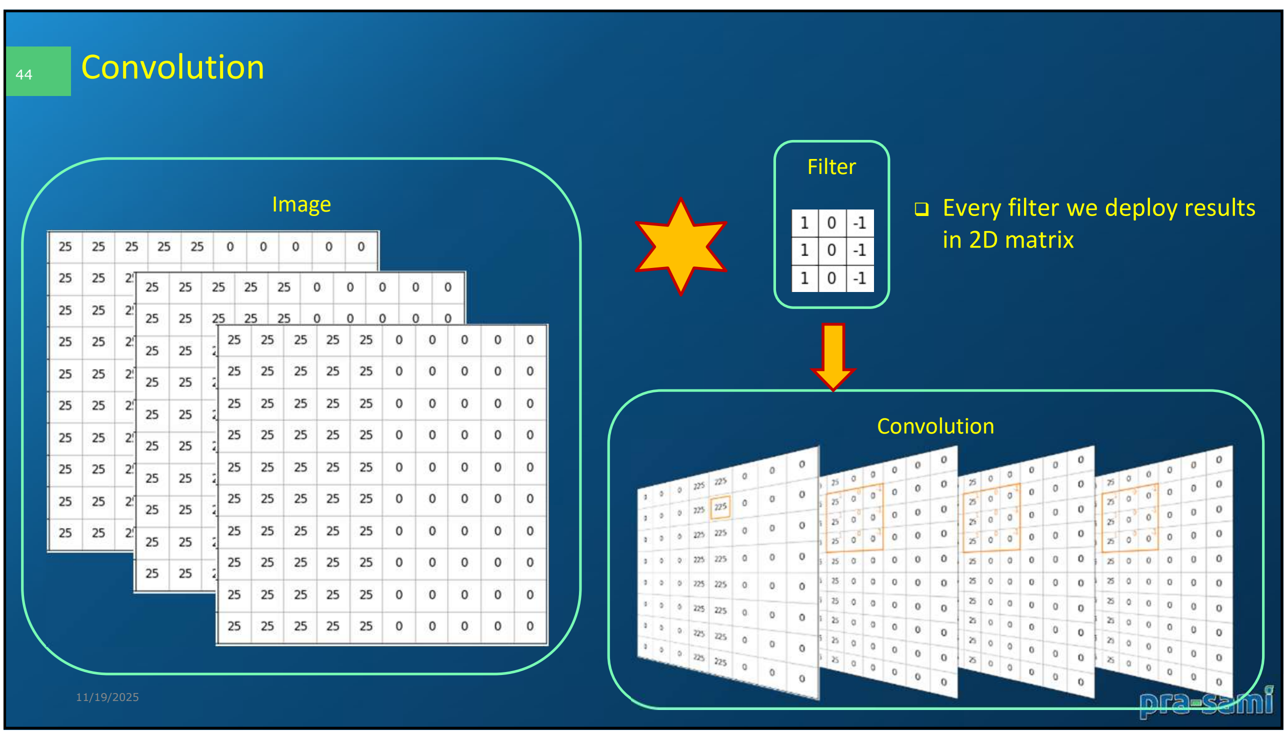
25	25	25	25	25	0^{1}	0^{0}	0^{-1}	0	0
25	25	25	25	25	0^{1}	0^{0}	0^{-1}	0	0
25	25	25	25	25	0^{1}	0^{0}	0^{-1}	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

- Layer R
  - = 0 + 0 + 0 + 0 + 0 + 0 – 0 – 0 – 0
  - = 0
- Layer G
  - = 0 + 0 + 0 + 0 + 0 + 0 – 0 – 0 – 0
  - = 0
- Layer B
  - = 0 + 0 + 0 + 0 + 0 + 0 – 0 – 0 – 0
  - = 0
- Total = 0 + 0 + 0 = 0

11/19/2025

pra-sâmi


43
Convolution
Image
Filter
1 0 -1
1 0 -1
1 0 -1
25 * 1 + 25 * 1 + 25 * 1
+ 0 * 0 + 0 * 0 + 0 * 0
+ 0 *(-1) + 0*(-1) + 0 *(-1)
= 75
Convolution
75
75
75
11/19/2025
pra-sami


44
Convolution
Image
Filter
1 0 -1
1 0 -1
1 0 -1
Every filter we deploy results in 2D matrix
Convolution
11/19/2025
pra-sami

45

Convolution

- How many steps filter can take before it goes out of image?
- 10 – 3 + 1 = 8 in either direction…

25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

46

Convolution

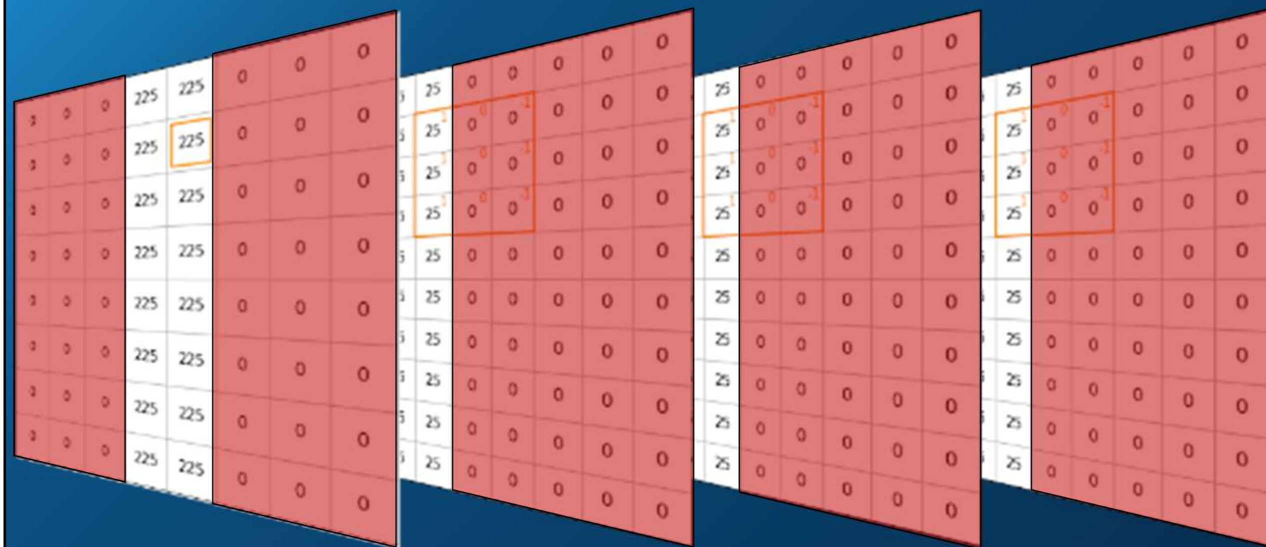
- 10 – 3 + 1 = 8 x 8

25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

- Output will be a 2D Matrix
- Assuming it moves by one step
- Given that size of the image is 10 and size of the filter is 3
- Taking : 10- 3 +1 = 8 steps
- Output image will have 8 cells
- Hence, Output image size $= \{ nH_{in} - nF + 1 \} x \{ nW_{in} - nF + 1 \}$

47

Has it detected the edge?



pra-sâmi

48

What if we move two steps at a time

pra-sâmi

49

Stride

25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	

- Steps are called stride
- If we move 2 steps at a time, we can move 4 steps only
- In other word with stride of 2
  - Given that size of the image is 10 and size of the filter is 3
- Output image size will be : (10 – 3)/2 + 1 = 4.5 or 4
- For fractions pick lower integer
- Over flow not permitted

11/19/2025

50

Stride

- (10 – 3)/2 + 1 = 4 x 4

25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0
25	25	25	25	25	0	0	0	0	0

- Steps are called stride
- Hence, Output image size =

$$\{ (nH_{in} - nF) / stride + 1 \}$$
$$x$$
$$\{ (nW_{in} - nF) / stride + 1 \}$$

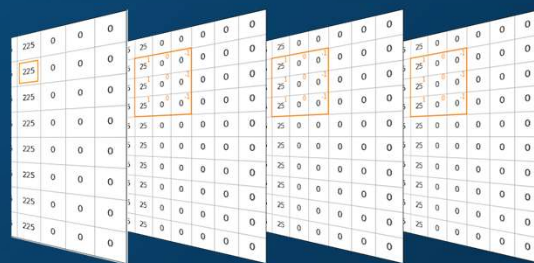
- If we apply multiple filters ➔ this layer will have 3D matrix.
  - Each layer corresponding to one filter.

11/19/2025

51

Convolution

- Apply filters and stack filtered layers together to make a 3D matrix
- Hence from 3 layer RGB, we can construct as many layers as number of filters applied…
- Move “stride” steps, generally one or two
  - one in most cases…
- Strongly advisable to keep filters as odd shape (3,3) or (5,5)
- Two strong reason..
- We do not want asymmetric padding
  - Not good for learning features
  - It’s better to have central point of the filter



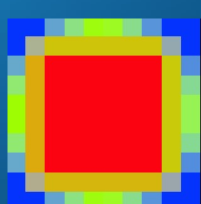
11/19/2025

pra-sâmi

52

Another image

- This image has a few distinct edges



3	3	98	140	158	157	137	87	3	3
3	170	206	206	206	206	206	206	148	3
102	220	252	252	252	252	252	252	201	82
145	220	252	252	252	252	252	252	201	134
158	220	252	252	252	252	252	252	201	151
158	220	252	252	252	252	252	252	201	151
145	220	252	252	252	252	252	252	201	134
102	220	252	252	252	252	252	252	201	82
3	177	213	213	213	213	213	213	154	3
3	3	98	140	158	157	137	87	3	3

51	51	163	225	252	250	220	148	51	51
51	178	196	196	196	196	196	196	169	51
169	170	3	3	3	3	3	3	203	141
233	170	3	3	3	3	3	3	203	217
252	170	3	3	3	3	3	3	203	242
252	170	3	3	3	3	3	3	203	242
233	170	3	3	3	3	3	3	203	217
169	170	3	3	3	3	3	3	203	141
51	172	182	182	182	182	182	182	166	51
51	51	163	225	252	250	220	148	51	51

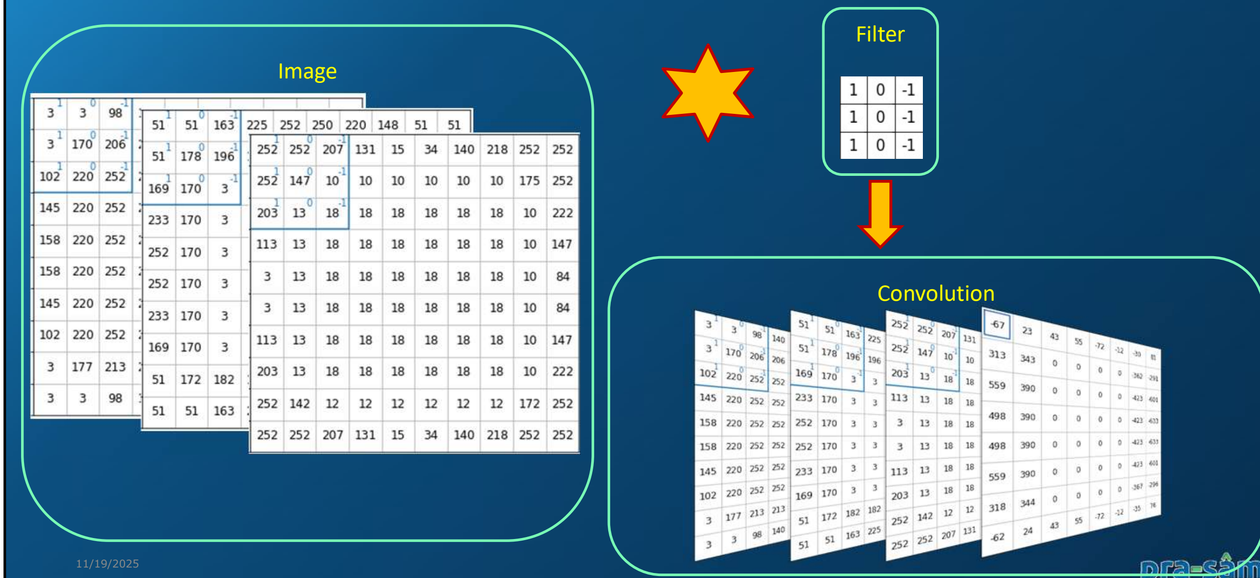
252	252	207	131	15	34	140	218	252	252
252	147	10	10	10	10	10	10	175	252
203	13	18	18	18	18	18	18	10	222
113	13	18	18	18	18	18	18	10	147
3	13	18	18	18	18	18	18	10	84
3	13	18	18	18	18	18	18	10	84
113	13	18	18	18	18	18	18	10	147
203	13	18	18	18	18	18	18	10	222
252	142	12	12	12	12	12	12	172	252
252	252	207	131	15	34	140	218	252	252

11/19/2025

pra-sâmi

53

Another Convolution

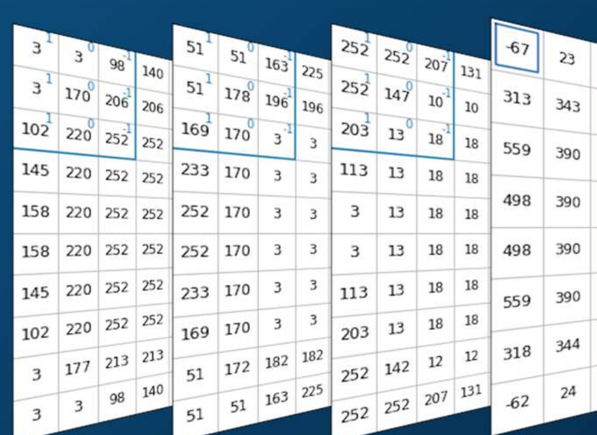


11/19/2025

54

Another Convolution

- Layer R = 3 + 3 + 102 - 98 - 206 – 252 = -448
- Layer G = 51 + 51 + 169 - 163 - 196 - 3 = -91
- Layer B = 252 + 252 + 203 - 207 - 10 - 18 = 472
- Total = -448 + -91 + 472 = -67

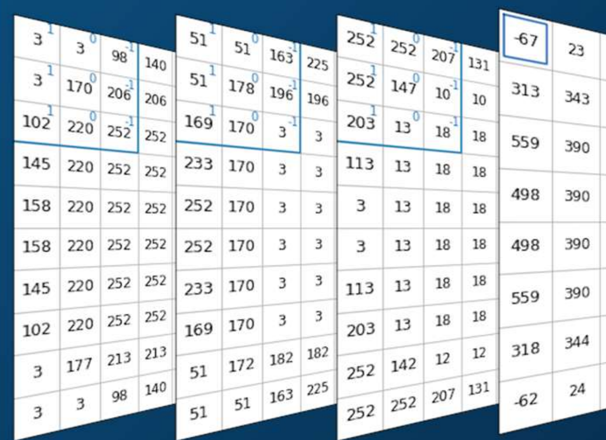


11/19/2025

55

Another Convolution

- Incoming Image shape = (10,10,3)
  - $nH_{in} = 10$; $nW_{in} = 10$, nC = 3
- Filter shape = (3, 3, 3)
  - nF = 3 ; nF = 3, nC = 3
- Stride = 1
- Hence the size will be 8 x 8 after convolution



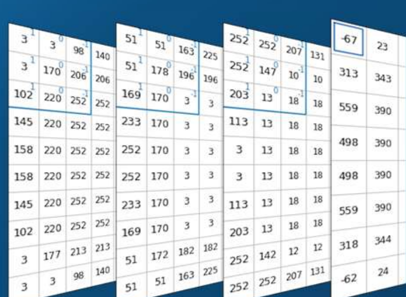
11/19/2025

pra-sâmi

56

Another Convolution

- Single filter convolution:
- Layer R = 3 + 3 + 102 - 98 - 206 – 252 = -448
- Layer G = 51 + 51 + 169 - 163 - 196 - 3 = -91
- Layer B = 252 + 252 + 203 - 207 - 10 - 18 = 472
- Total = -448 + -91 + 472 = -67



- Incoming Image shape = (10,10,3)
  - nHin = 10 ; nWin = 10, nC = 3
- Filter shape = (3, 3, 3)
  - ➔ nF = 3 ; nF = 3, nC = 3
- Stride = 1
- Hence the size will be 8 x 8 after convolution

In convolution,:

- With every convolution image is shrinking
- Corners and edges of image are used less frequently than the middle

11/19/2025

pra-sâmi

57

Other filters

- We have seen vertical filter… How about horizontal Filter….
- No surprises there….

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

- The math will be exactly the same and we would get horizontal edge

11/19/2025

pra-sâmi

58

Horizontal Edge…

11/19/2025

pra-sâmi

59

Other filters

- Sobel Filter…

-1	0	1
-2	0	2
-1	0	1

- There was a lot of debate on filters….
- Researchers kept trying various numbers…
- Why not learn these parameters…

w_1	w_4	w_7
w_2	w_5	w_8
w_3	w_6	w_9

11/19/2025

pra-sâmi

60

Shade Reversal

- So far we have seen lighter to darker shade filters…
- What happens if we move from darker shade to lighter

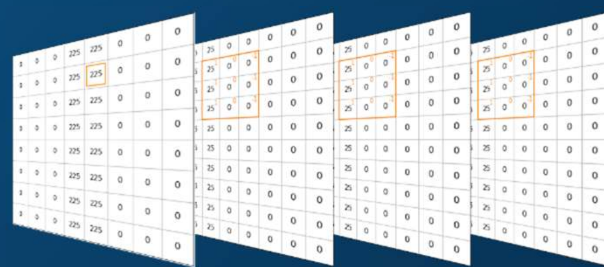
11/19/2025

pra-sâmi

61

Shade Reversal

- So far we have seen lighter to darker shade filters…
- What happens if we move from darker shade to lighter
- We will again get the edge only it will be negative this time…



62

Convolving a Volume

- So far we have shown that same filter is applied to all layers
- In theory, it is possible to have a filter which is looking for edges in red channel alone…

$$\begin{matrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{matrix} \qquad \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} \qquad \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix}$$

- So far we have been showing that 3D image converts to 2D image when we apply filter
- By applying a number of filters to detect different edges, we can have 3d Convolutional Volumes.

63

Two Issues with the Convolution…

- With every convolution image is shrinking
  - Knowing that 100s of layer is not uncommon in the architecture
  - Image can soon become 1px X 1px

- Corners and edges of image are used less frequently than the middle

11/19/2025

pra-sâmi

64

What if we zero pad the image all around… will it help?

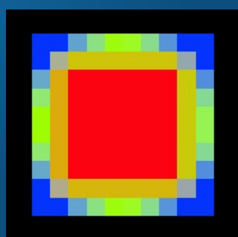
11/19/2025

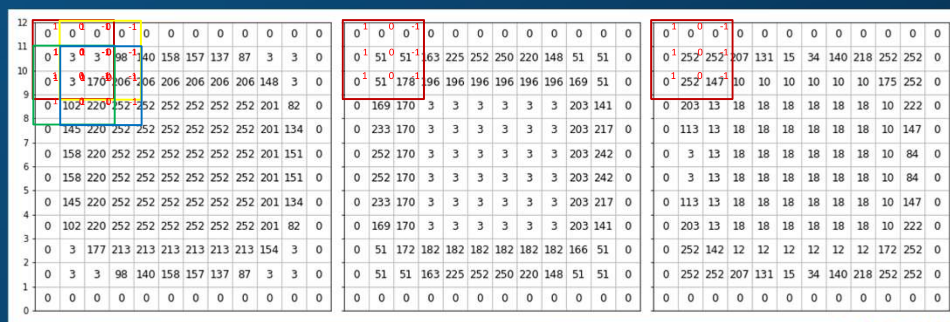
pra-sâmi

65

Zero Padding

- If we do not want our images to shrink during convolution and to take maximum advantage of edges,
- Pad the image by adding zeros all around.
- Now we will be using corner cell 4 times at least…
- Edge cells will be used more….

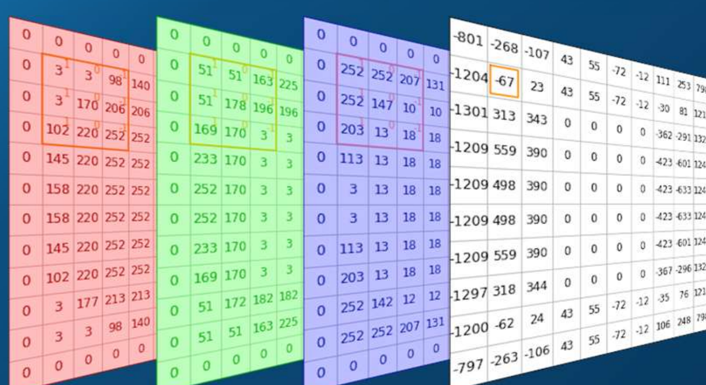




66

Convolution after Padding

- The respective cell values remain same



- and we are back with original image size

67

Convolution after Padding

- Incoming image shape = (10, 10, 3)
  - i.e $nH_{in} = 10$; $nW_{in} = 10$; $nC = 3$
- Padding p = 1
- Padded image shape = (12, 12, 3)
  - i.e $nH_{in} = 12$; $nW_{in} = 12$; $nC = 3$
- Filter shape = (3, 3, 3)
  - i.e. nF = 3 ; nF = 3, nC = 3
- Assuming we move "stride" steps at any time
  - i.e. stride = 1

- Output image size:

$$= \{ \frac{nH_{in} - nF + 2*p}{stride} + 1 \}$$

x

$$\{ \frac{nW_{in} - nF + 2*p}{stride} + 1 \}$$

- Image Size $= \{ \frac{10 - 3 + 2*1}{1} + 1 \}$

x

$$\{ \frac{10 - 3 + 2*1}{1} + 1 \}$$

= 10 x 10

We are back to original size...

11/19/2025 pra-sâmi

68

How much to pad???

- There are two recommended mechanism
- **Valid** : output is calculated as

$$\{ \frac{nH_{in} - nF}{stride} + 1 \} \text{ x } \{ \frac{nW_{in} - nF}{stride} + 1 \}$$

  - So for 10 x 10 image a 3 x 3 filter with 1 px padding, image size will be 8 x 8

- padding = 0
- kernel stays inside the boundary
- output shrinks

- **Same** : do the padding in such a way so that resultant image is of same size

$$\{ \frac{nH_{in} - nF + 2*p}{stride} + 1 \} \text{ x } \{ (\frac{nW_{in} - nF + 2*p}{stride} + 1 \} = nH_{in} \; x \; nW_{in}$$

  - or p = (nF -1)/2 for stride = 1
  - So for 10 x 10 image a 5 x 5 filter with 1 px padding, image size will be 8 x 8

Full convolution

- Exists in math.
- Add padding to use all pixels
- Size grows,

Short Answer – Not used in CNN layers

11/19/2025 pra-sâmi

69

How much to pad???

- With p = (nF -1)/2 for stride = 1;
- We want p to be an integer and hence
  - Need nF to be odd
- For even value of nF we would end up in asymmetric padding.
- Unless we feel one edge of the image is more important than other, there is no need to have asymmetric padding

70

Cross-Correlation vs. Convolution

71

Cross-Correlation vs. Convolution

- In Signal Theory and Maths
- Convolution involves multiplying the filter after mirroring on both axis
- i.e. for filter $\begin{bmatrix} 3 & 4 & 5 \\ 1 & 0 & 2 \\ -1 & 9 & 7 \end{bmatrix}$
- It will be mirrored along both axis… $\begin{bmatrix} 7 & 9 & -1 \\ 2 & 0 & 1 \\ 5 & 4 & 3 \end{bmatrix}$
- Then we do element wise multiplication.
- Signal Engineers will agree with me… ☺
- Such correlations have properties like associative (a*b)*c = a*(b*c) and all other properties

11/19/2025

pra-sâmi

72

Cross-Correlation vs. Convolution

- So that we are correct semantically…
- What we are doing is called Cross-Correlation….
- However, Data Scientists across the world have been using filters without reversing it and still call it Convolution…

Now you know… don't write home about it… yet…. ☺

11/19/2025

pra-sâmi

73

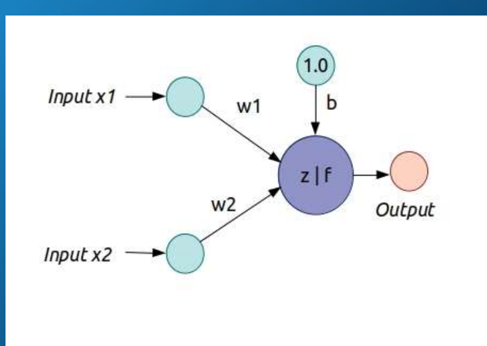
One layer of Convolutional Net

11/19/2025

pra-sâmi

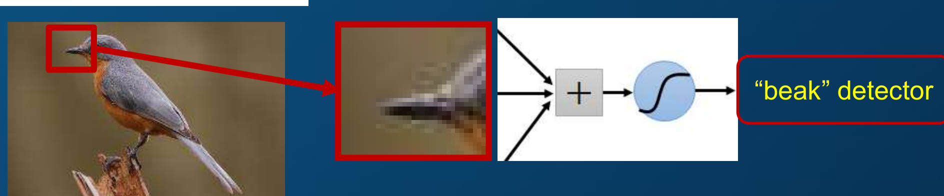
74

One layer of Conv Net



$Z_1 = a_0 . W_1 + b_1$

$a_1 = Relu(Z_1)$

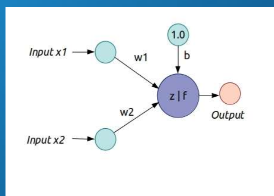


11/19/2025

pra-sâmi

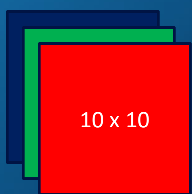
75

One Layer of Conv Net



$Z_1 = a_0 . W_1 + b_1$

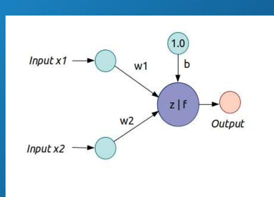
$a_1 = \text{Relu}(Z_1)$



11/19/2025

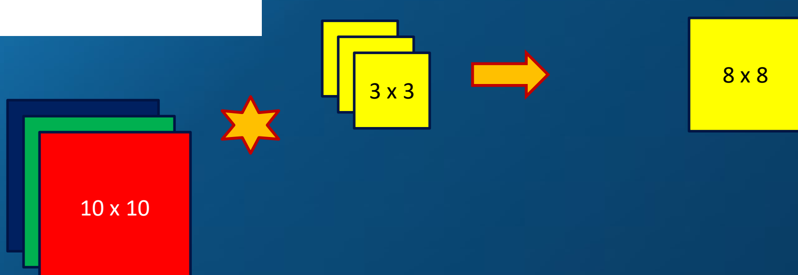
76

One Layer of Conv Net

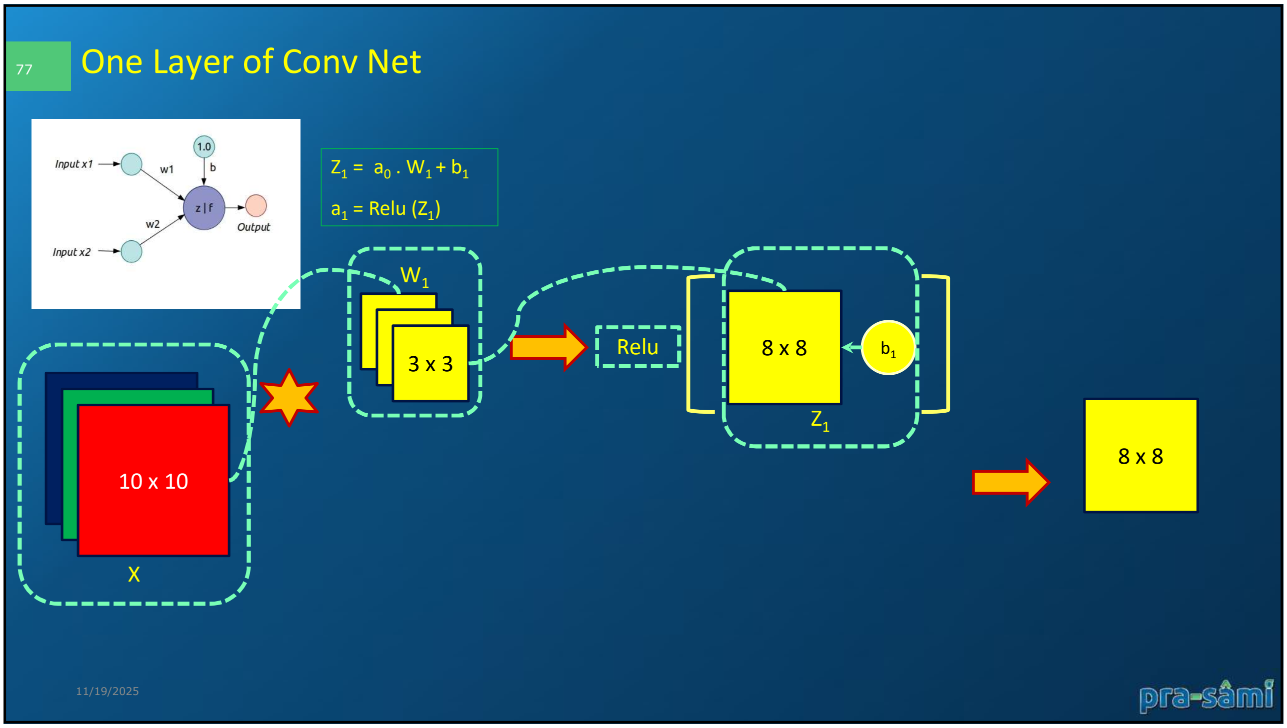


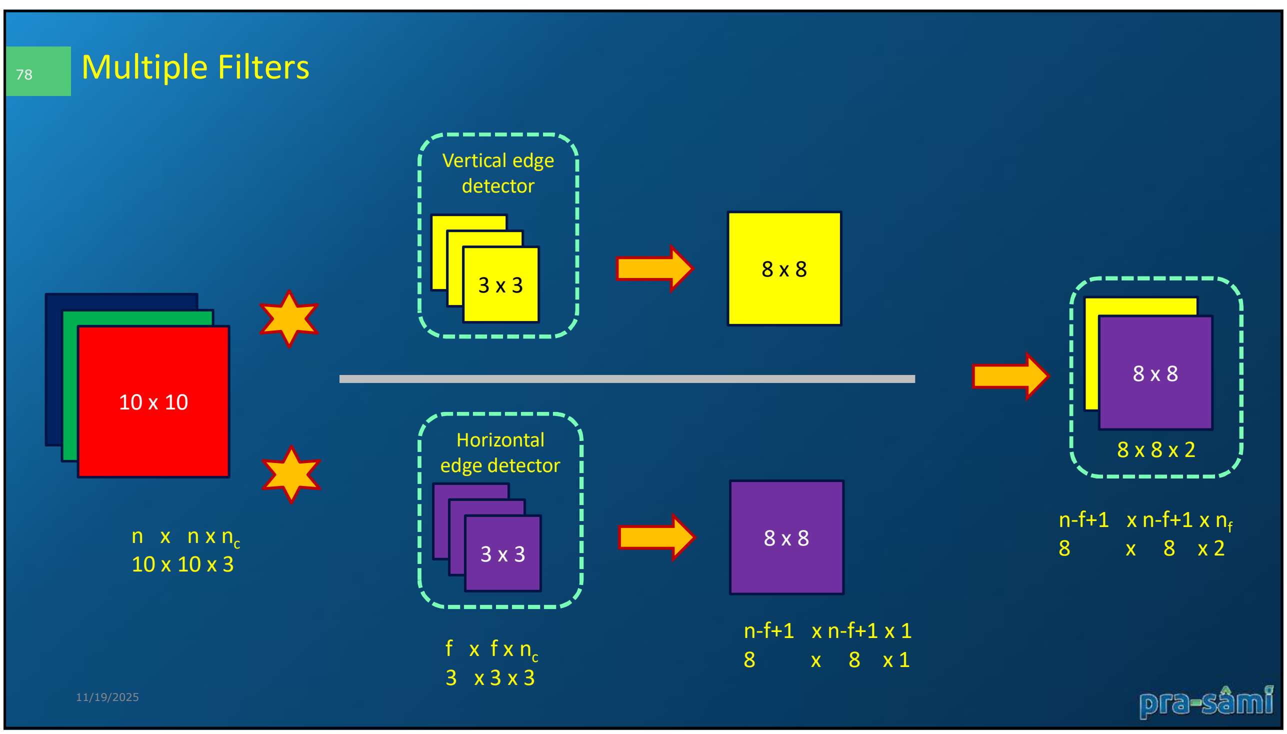
$Z_1 = a_0 . W_1 + b_1$

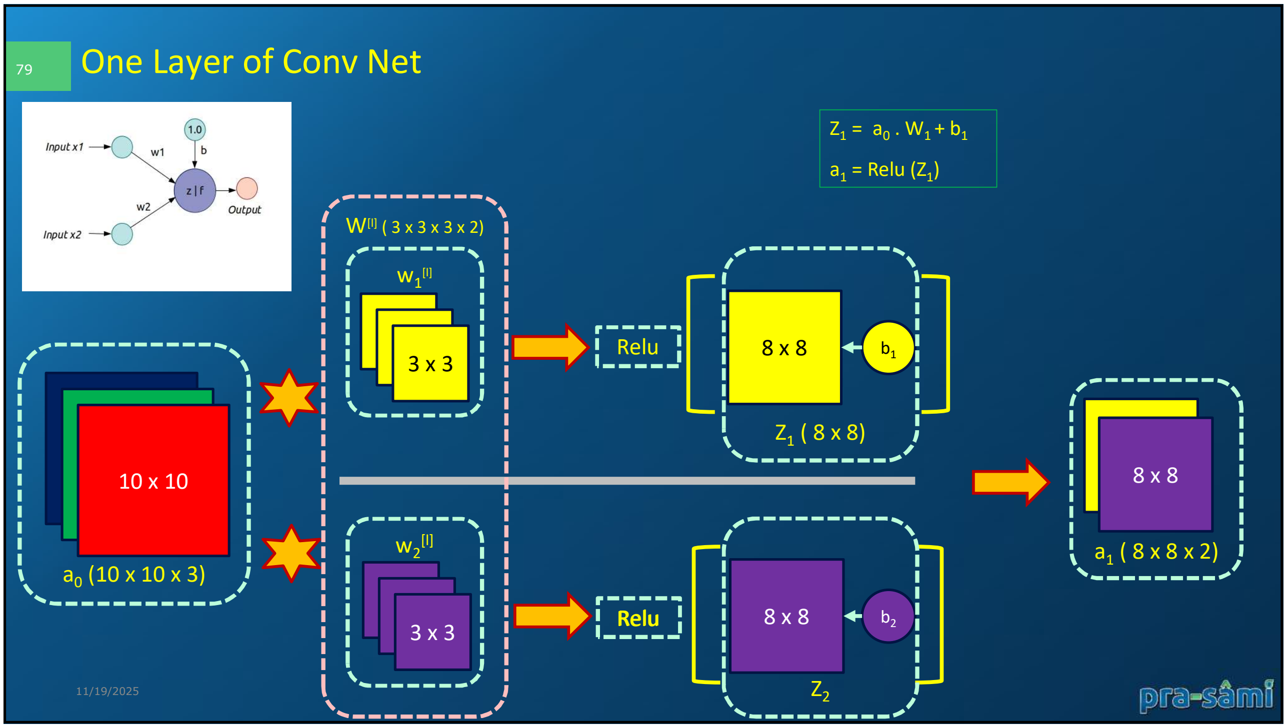
$a_1 = \text{Relu}(Z_1)$



11/19/2025


77
One Layer of Conv Net
Input x1
Input x2
w1
w2
1.0
b
z | f
Output
Z1 = a0 . W1 + b1
a1 = Relu (Z1)
W1
3 x 3
Relu
8 x 8
b1
Z1
10 x 10
X
8 x 8
11/19/2025
pra-sāmi


78
Multiple Filters
Vertical edge detector
3 x 3
8 x 8
10 x 10
Horizontal edge detector
3 x 3
8 x 8
8 x 8
8 x 8 x 2
n x n x nc
10 x 10 x 3
f x f x nc
3 x 3 x 3
n-f+1 x n-f+1 x 1
8 x 8 x 1
n-f+1 x n-f+1 x nf
8 x 8 x 2
11/19/2025
pra-sāmi

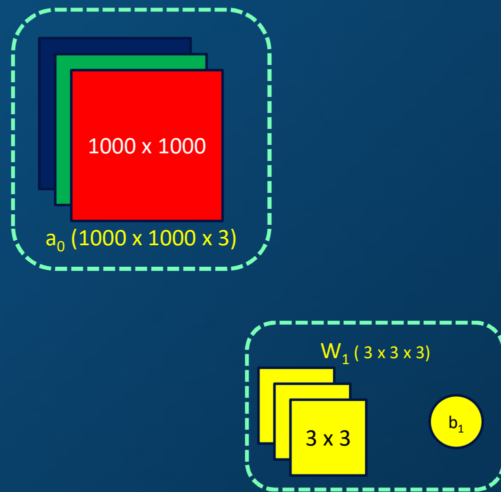

79
One Layer of Conv Net
Input x1
Input x2
w1
w2
1.0
b
z | f
Output
Z1 = a0 . W1 + b1
a1 = Relu (Z1)
W[l] (3 x 3 x 3 x 2)
w1[l]
3 x 3
Relu
8 x 8
b1
Z1 (8 x 8)
10 x 10
a0 (10 x 10 x 3)
8 x 8
a1 (8 x 8 x 2)
w2[l]
3 x 3
Relu
8 x 8
b2
Z2
11/19/2025
pra-sâmi


80
One Layer of Conv Net
If we apply 10 filters, size of a1 will be 8 x 8 x 10

81

How Many Parameters…

- Imagine using 10 filters in a convolutional layer
- How many parameters in the layer?
  - Number of weights per filter: 3 x 3 x 3 = 27
  - Add a bias ➔ total 28 parameters
- For 10 filters = total 280 parameters
- Key take away:
  - No matter how large input image is, This conv layer still has 280 learnable parameters…. Yay!!!
- Helps in prevention of over-fitting, reduced memory



11/19/2025

82

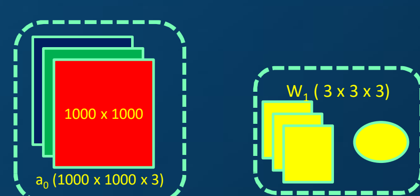
Lets Look at the Dimensions…

$f^{[l]}$:	Filter Size		Input:	$n^{[l-1]}_H \times n^{[l-1]}_W \times n^{[l-1]}_c$
$p^{[l]}$:	Padding size		Output:	$n^{[l]}_H \times n^{[l]}_W \times n^{[l]}_c$
$s^{[l]}$:	Stride		$n^{[l]}_H$:	$(n^{[l-1]}_H + 2\, p^{[l]} - f^{[l]}) / s^{[l]} + 1$
$n^{[l]}_c$:	Number of filters		$n^{[l]}_W$:	$(n^{[l-1]}_W + 2\, p^{[l]} - f^{[l]}) / s^{[l]} + 1$
Filter size:	$f^{[l]} \times f^{[l]} \times n^{[l-1]}_c$		Activations $a^{[l]}$:	$n^{[l]}_H \times n^{[l]}_W \times n^{[l]}_c$
Weights (all filters):	$f^{[l]} \times f^{[l]} \times n^{[l-1]}_c \times n^{[l]}_c$		Biases:	$n^{[l]}_c$

Weights are tensors of rank 4

Activation for all m training examples m
$m \times n^{[l]}_H \times n^{[l]}_W \times n^{[l]}_c$

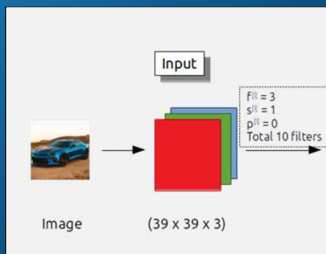
Don't be surprised if you see Filter number first



11/19/2025

83

A Simple CNN with Conv Layers

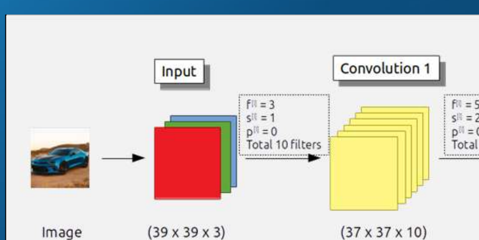


11/19/2025

pra-sâmi

84

A Simple CNN with Conv Layers

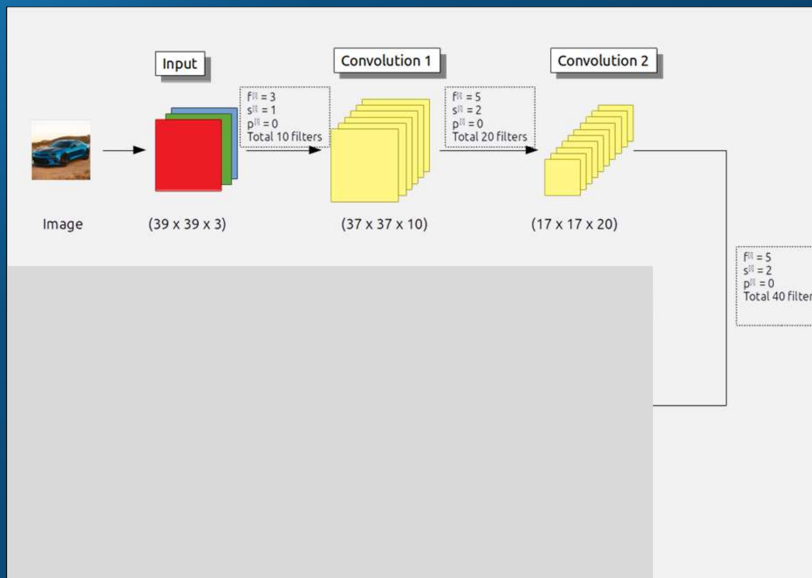


11/19/2025

pra-sâmi

85

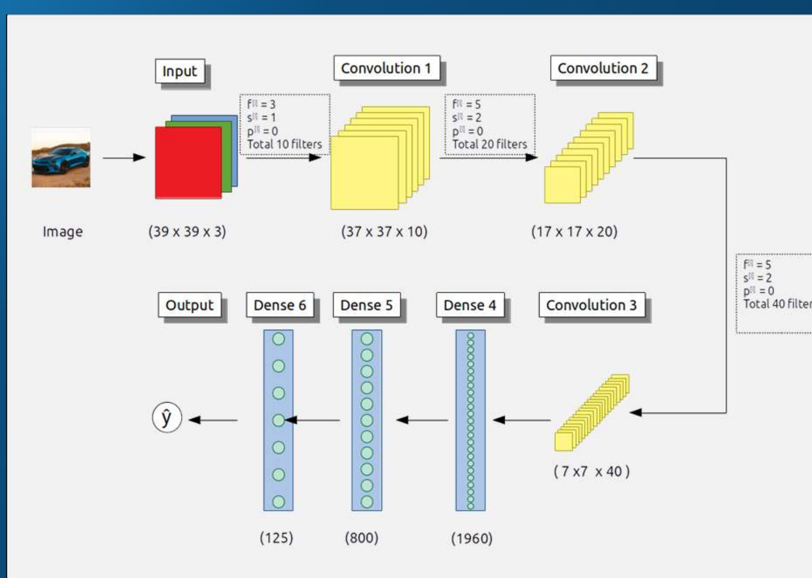
A Simple CNN with Conv Layers



11/19/2025

86

A Simple CNN with Conv Layers

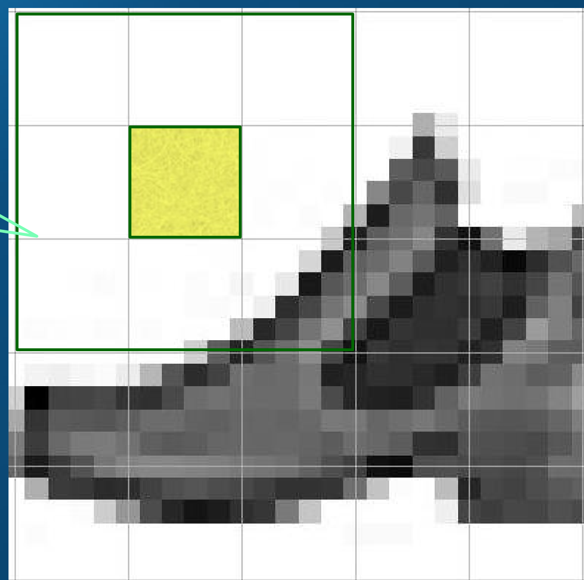


11/19/2025

87

Convolution – Applying Filters

9 datapoints result in one



pra-sâmi

88

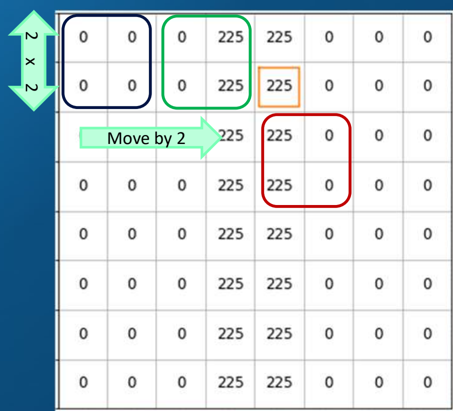
Pooling…
What is most significant in this area…

pra-sâmi

89

Pooling

- Two methods of Pooling – 'Max' and 'Average'
- Max : maximum value of the from the cells being filtered
- Average : Average Values from the cells



0	0	0	225	225	0	0	0
0	0	0	225	225	0	0	0
			225	225	0	0	0
0	0	0	225	225	0	0	0
0	0	0	225	225	0	0	0
0	0	0	225	225	0	0	0
0	0	0	225	225	0	0	0
0	0	0	225	225	0	0	0

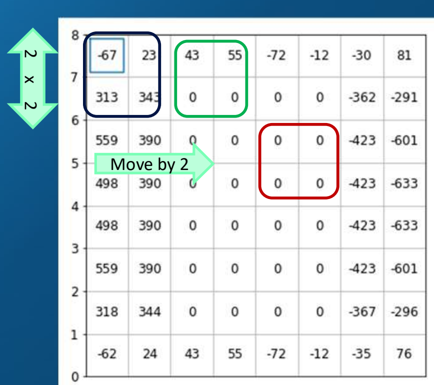
- Mode = 'max'; pool = 2; stride = 2

0	225	225	0
0	225	225	0
0	225	225	0
0	225	225	0

90

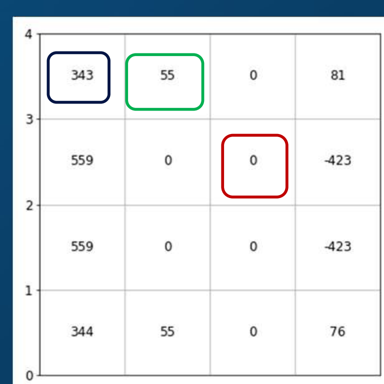
Other image

- Image Size = 10,10,3; filter Size = 3,3,3; stride = 1
- After Convolution = 8, 8, 1



-67	23	43	55	-72	-12	-30	81
313	343	0	0	0	0	-362	-291
559	390	0	0	0	0	-423	-601
498	390	0	0	0	0	-423	-633
498	390	0	0	0	0	-423	-633
559	390	0	0	0	0	-423	-601
318	344	0	0	0	0	-367	-296
-62	24	43	55	-72	-12	-35	76

- Input size = 8,8,1; pool = 2; Stride = 2
- After pooling = 4,4,1



343	55	0	81
559	0	0	-423
559	0	0	-423
344	55	0	76

91

Pooling

- Image Size = 10,10,3; filter Size = 3,3,3; stride = 1
- After Convolution = 8, 8, 1

-67	23	43	55	-72	-12	-30	81
313	343	0	0	0	0	-362	-291
559	390	0	0	0	0	-423	-601
498	390	0	0	0	0	-423	-633
498	390	0	0	0	0	-423	-633
559	390	0	0	0	0	-423	-601
318	344	0	0	0	0	-367	-296
-62	24	43	55	-72	-12	-35	76

- Input size = 8,8,1; pool = 2; Stride = 2
- After pooling = 4,4,1
- Formula for size are still applicable,
- Its independently done on each channels
- Other option is to use Average instead of Max
  - But not used frequently.

343	55	0	81
559	0	0	-423
559	0	0	-423
344	55	0	76

11/19/2025

pra-sâmi

92

Pooling

- Image Size = 10,10,3; filter Size = 3,3,3; stride = 1
- After Convolution = 8, 8, 1
- Input size = 8,8,1; pool = 2; Stride = 2
- After pooling = 4,4,1
- Formula for size are still applicable,
- Its independently done on each channels

- Other is Average as expected but not used frequently.

Consider that each area represents presence of some feature in the image and high number represents, presence of that feature…

It has three (mode, pool and stride) hyperparameters to tune…

but no parameters to learn…

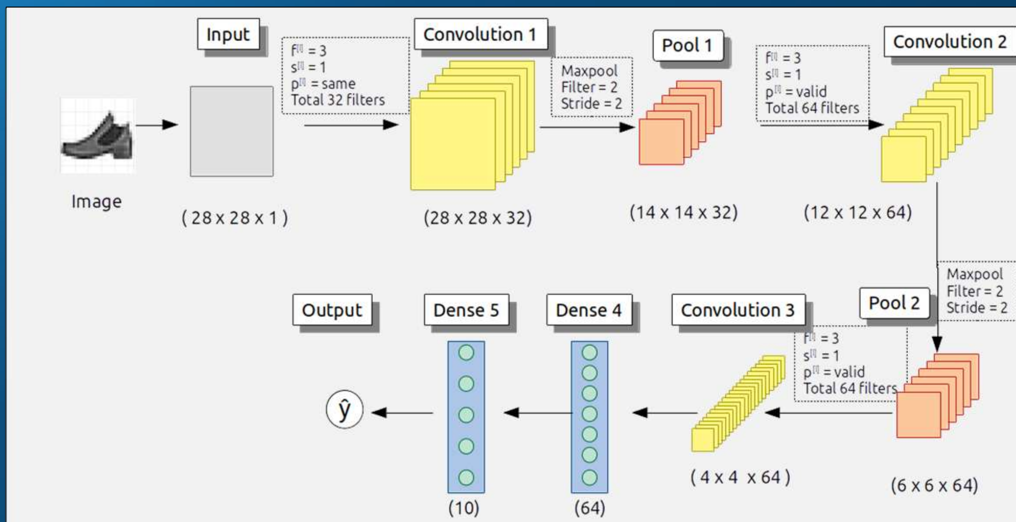
Gradient descent is not going to do anything here…. ☺

11/19/2025

pra-sâmi

93

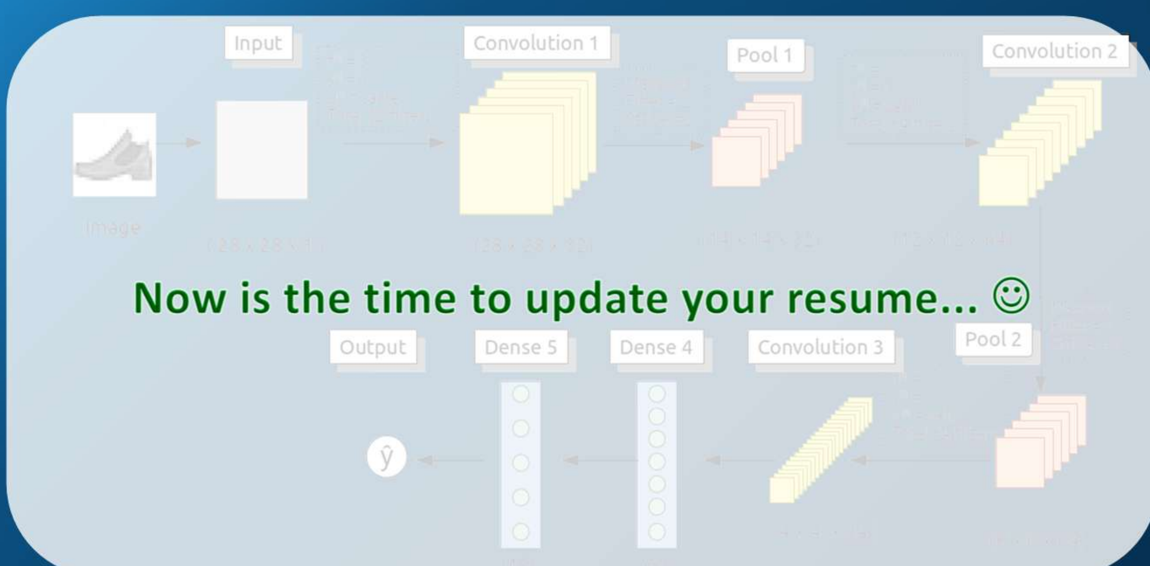
Demo Example – Fashion MNIST



11/19/2025

94

Congratulations!!!!



Now is the time to update your resume… ☺

11/19/2025

95

Reflect…

- What is the main purpose of Convolutional Neural Networks (CNNs)?
  - A) Text generation
  - B) Image and video recognition
  - C) Time series analysis
  - D) Natural language processing
- Answer: B) Image and video recognition
- Which of the following layers is a key component of CNNs?
  - A) Recurrent layer
  - B) Convolutional layer
  - C) Dropout layer
  - D) Activation layer
- Answer: B) Convolutional layer
- What is the role of the pooling layer in a CNN?
  - A) To increase the dimensions of the input
  - B) To extract features from the input data
  - C) To reduce the spatial dimensions (width and height) of the input
  - D) To combine multiple input channels
- Answer: C) To reduce the spatial dimensions (width and height) of the input
- Which operation is performed by a convolutional layer in a CNN?
  - A) Element-wise addition of the input matrix
  - B) Cross Correlation between a filter (kernel) and portions of the input matrix
  - C) Subtraction of one input channel from another
  - D) Matrix inversion
- Answer: B) Cross Correlation between a filter (kernel) and portions of the input matrix

11/19/2025

pra-sâmi

96

Reflect…

- What is the function of a kernel (filter) in a CNN?
  - A) To resize images
  - B) To detect specific features like edges or textures in the input
  - C) To add noise to the image
  - D) To combine multiple images into one
- Answer: B) To detect specific features like edges or textures in the input
- What does stride refer to in a CNN?
  - A) The number of filters used
  - B) The number of steps the filter moves across the input matrix
  - C) The size of the input image
  - D) The number of output channels
- Answer: B) The number of steps the filter moves across the input matrix
- Which of the following is a common activation function used in CNNs?
  - A) Sigmoid
  - B) Tanh
  - C) ReLU (Rectified Linear Unit)
  - D) SoftMax
- Answer: C) ReLU (Rectified Linear Unit)
- In CNNs, what is the effect of padding?
  - A) To increase the number of filters
  - B) To prevent the reduction of spatial dimensions by adding zeros around the input matrix
  - C) To reduce the memory footprint of the model
  - D) To change the size of the kernel
- Answer: B) To prevent the reduction of spatial dimensions by adding zeros around the input matrix

11/19/2025

pra-sâmi

97

Reflect…

- Why do deeper CNNs typically perform better than shallow CNNs?
  - A) Deeper CNNs have more parameters and can memorize the training data better
  - B) Deeper CNNs can learn hierarchical representations, capturing complex features
  - C) Deeper CNNs require fewer data points for training
  - D) Deeper CNNs prevent overfitting
- Answer: B) Deeper CNNs can learn hierarchical representations, capturing complex features
- What is the vanishing gradient problem in the context of CNNs?
  - A) The gradients become too small to update the weights effectively in deeper networks
  - B) The model loses information about small details in images
  - C) The network stops learning after a certain number of epochs
  - D) The gradients become too large, leading to unstable training
- Answer: A) The gradients become too small to update the weights effectively in deeper networks
- What is the purpose of the fully connected (dense) layer at the end of a CNN?
  - A) To downsample the input
  - B) To map the learned features to the final output classes
  - C) To combine the pooling layers into a single layer
  - D) To prevent overfitting by regularizing the model
- Answer: B) To map the learned features to the final output classes
- What is a common method to reduce overfitting in a CNN?
  - A) Use a very large filter size
  - B) Add more fully connected layers
  - C) Use techniques like dropout, data augmentation, or early stopping
  - D) Increase the learning rate
- Answer: C) Use techniques like dropout, data augmentation, or early stopping

11/19/2025

pra-sâmi

98

11/19/2025

pra-sâmi