

Convolutional Neural Networks

RAMAN LAB @PLS

<https://drrajshkumar.wordpress.com>

Agenda

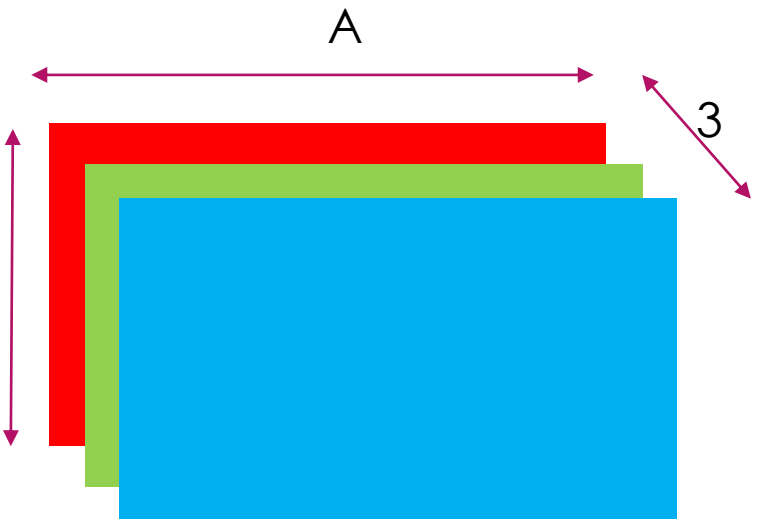
- ▶ How Computer Reads an Image?
- ▶ Why not fully connected Networks for Image Recognition?
- ▶ What is Convolutional Neural Network?
- ▶ How Convolutional Neural Network works?
- ▶ Real world Applications

How computer reads an image



Channels

Size of Image $B \times A \times 3$



Pixels value of RGB

B: Rows | A: Columns | 3: Channels

How computer reads an image



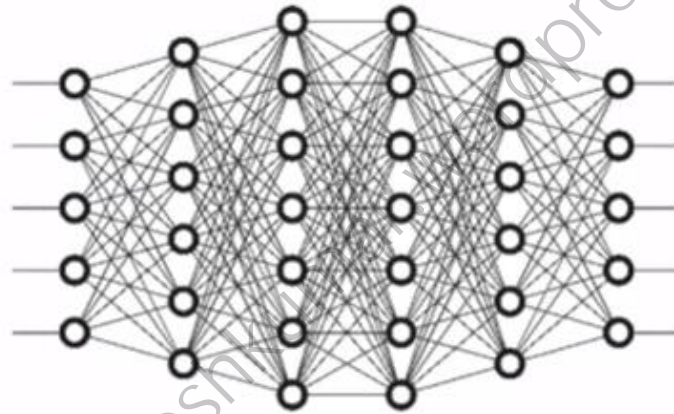
What We See

08 02 22 97 38 15 00 40 00 75 04 05 07 78 52 12 50 77 91 08
49 49 99 40 17 81 18 57 60 87 17 40 98 43 69 48 04 56 62 00
81 49 31 73 55 79 14 29 93 71 40 67 53 88 30 03 49 13 36 65
52 70 95 23 04 60 11 42 69 24 68 56 01 32 56 71 37 02 36 91
22 31 16 71 51 67 63 89 41 92 36 54 22 40 40 28 66 33 13 80
24 47 32 60 99 03 45 02 44 75 33 53 78 36 84 20 35 17 12 50
32 98 81 28 64 23 67 10 26 38 40 67 59 54 70 66 18 38 64 70
67 26 20 68 02 62 12 20 95 63 94 39 63 08 40 91 66 49 94 21
24 55 58 05 66 73 99 26 97 17 78 78 96 83 14 88 34 89 63 72
21 36 23 09 75 00 76 44 20 45 35 14 00 61 33 97 34 31 33 95
78 17 53 28 22 75 31 67 15 94 03 80 04 62 16 14 09 53 56 92
16 39 05 42 96 35 31 47 55 58 88 24 00 17 54 24 36 29 85 57
86 56 00 48 35 71 89 07 05 44 44 37 44 60 21 58 51 54 17 58
19 80 81 68 05 94 47 69 28 73 92 13 86 52 17 77 04 89 55 40
04 52 08 83 97 35 99 16 07 97 57 32 16 26 26 79 33 27 98 66
88 16 68 87 57 62 20 72 03 46 33 67 46 55 12 32 63 93 53 69
04 42 16 73 38 25 39 11 24 94 72 18 08 46 29 32 40 62 76 36
20 69 36 41 72 30 23 88 34 62 99 69 82 67 59 85 74 04 36 16
20 73 35 29 78 31 90 01 74 31 49 71 48 86 81 16 23 57 05 54
01 70 54 71 83 51 54 69 16 92 33 48 61 43 52 01 89 19 67 48

What Computers See

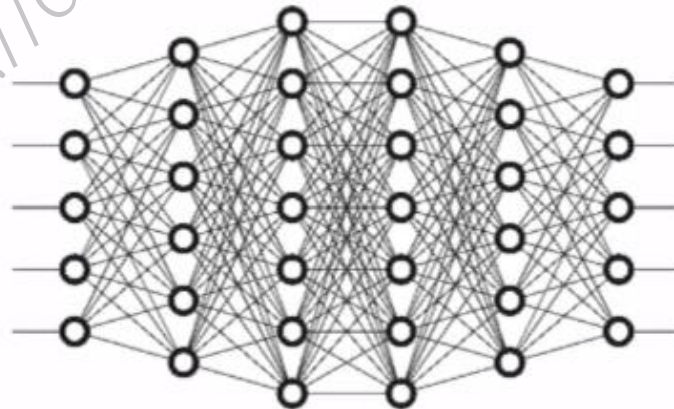
Why not fully connected networks

Image with
28 x 28 x 3
Pixels
(MNIST)



*Number of weights in
the first hidden layer
will be 2352*

Image with
200 x 200 x 3
pixels



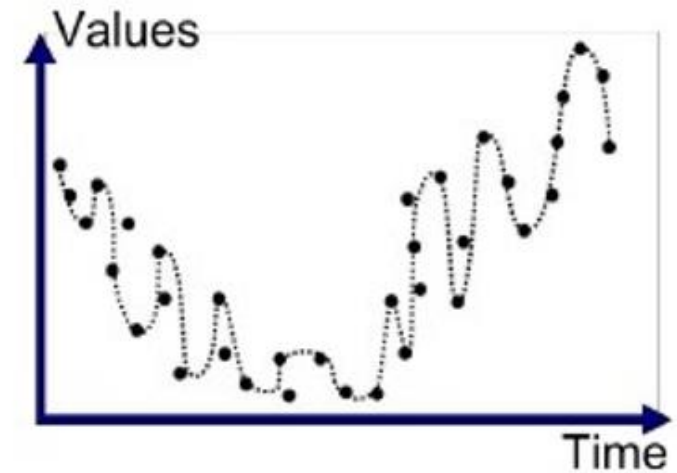
*Number of weights in
the first hidden layer
will be 120,000*

Why not fully connected networks

High computational
Resources

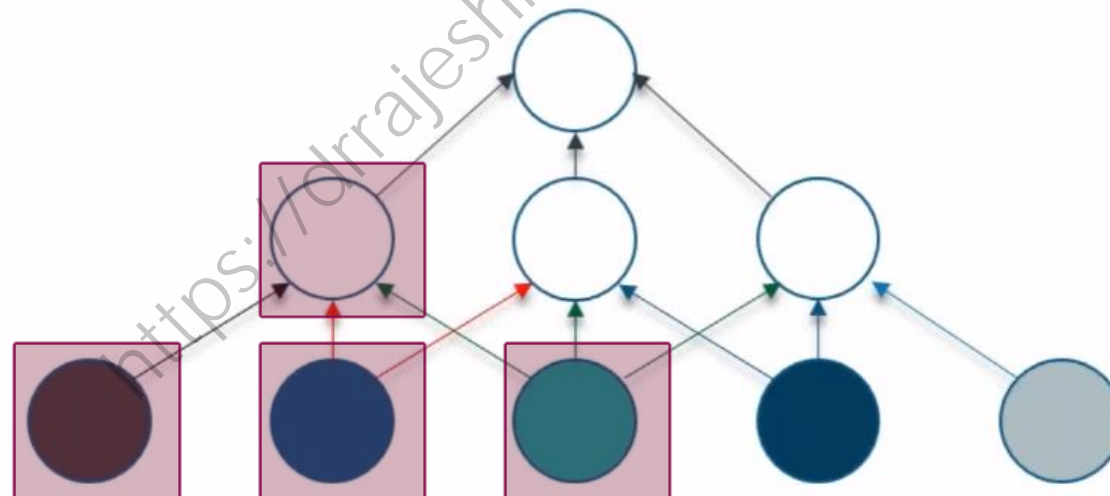


Overfitting



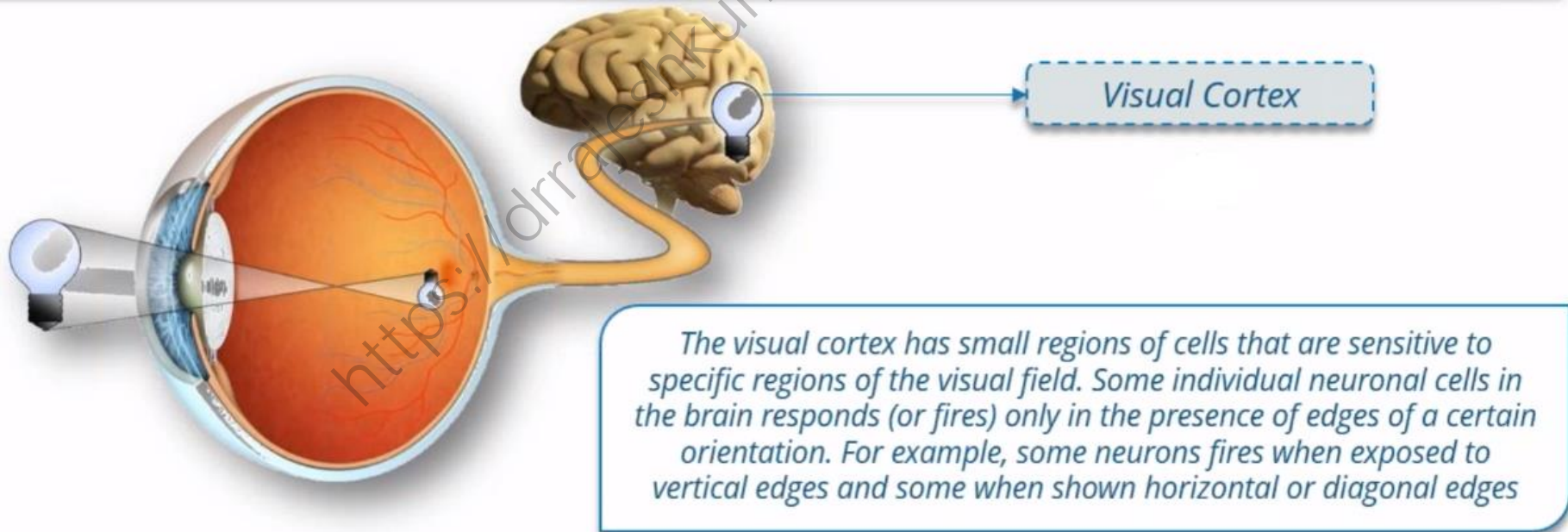
Why Convolutional Neural Networks

In case of CNN, the neuron in a layer will only be connected to a small region of layer before it, Instead of all neurons in a fully-connected manner.



What is Convolutional Neural Network

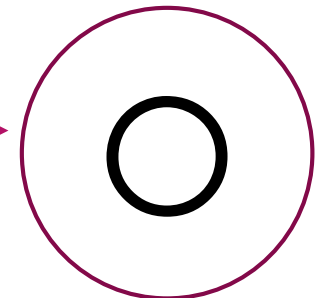
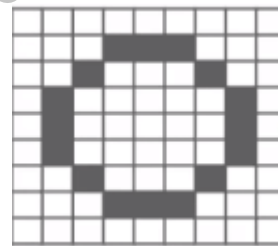
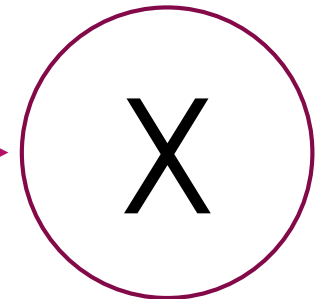
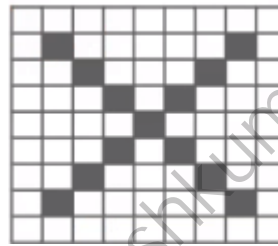
Convolutional Neural Network (CNN) is a type of feed-forward artificial neural network in which the Connectivity pattern between its neuron is inspired by organization of animal visual cortex.



How CNN works?

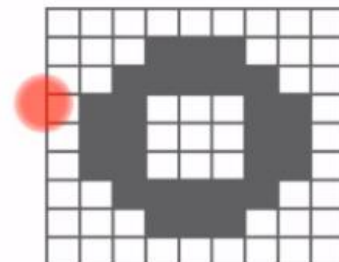
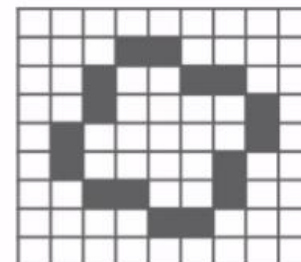
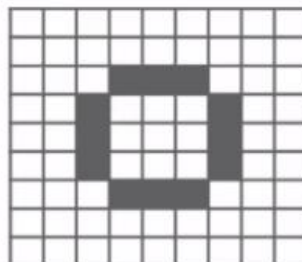
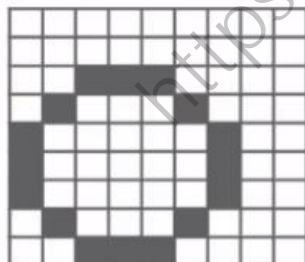
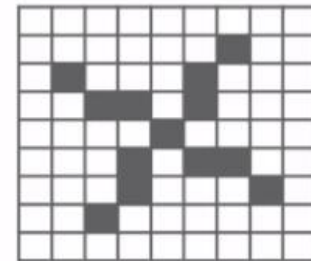
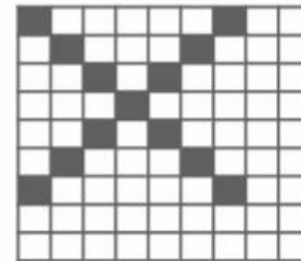
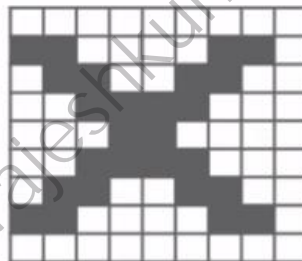
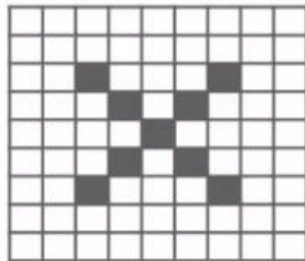
Convolutional Neural Network has following layers:

- ✓ Convolutional Layer
- ✓ ReLU Layer
- ✓ Pooling Layer
- ✓ Fully Connected Layer



Trickier Case

Here we will have some problems, because X and O images won't always have the same images. There can be certain deformations. Consider the diagram below



works?

an image using

considered that
d a white pixel will

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

works?

an image using

considered that
d a white pixel will

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

works?

an image using

considered that
d a white pixel will

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

works?

an image using

considered that
d a white pixel will

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

How CNN works?

Using normal techniques, computers compare these images as:

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

Correct X

+

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

Deformed X

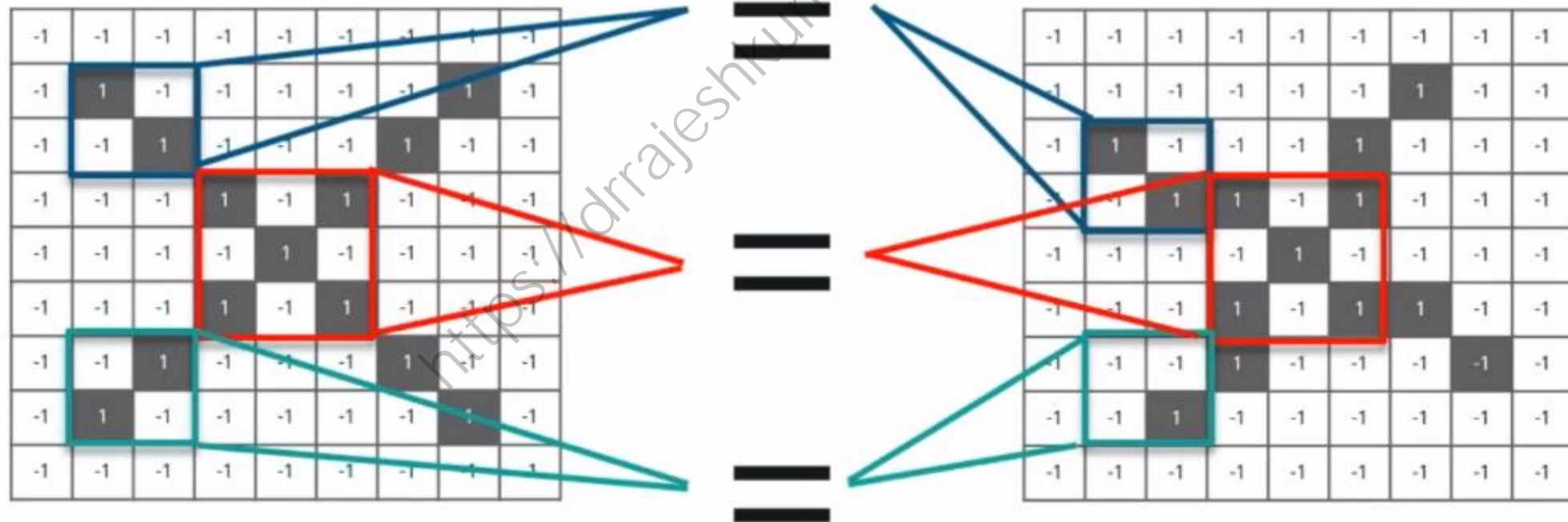
=

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	x	-1	-1	-1	-1	x	x	-1
-1	x	x	-1	-1	x	x	-1	-1
-1	-1	x	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	x	-1	-1
-1	-1	x	x	-1	-1	x	x	-1
-1	x	x	-1	-1	-1	-1	x	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Computer unable to recognize if it is X or not

How CNN works?

CNN compares the images piece by piece. The pieces that it looks for are called features. By finding rough feature matches in roughly the same position in two images, CNN gets a lot better at seeing similarity than whole-image matching scheme.



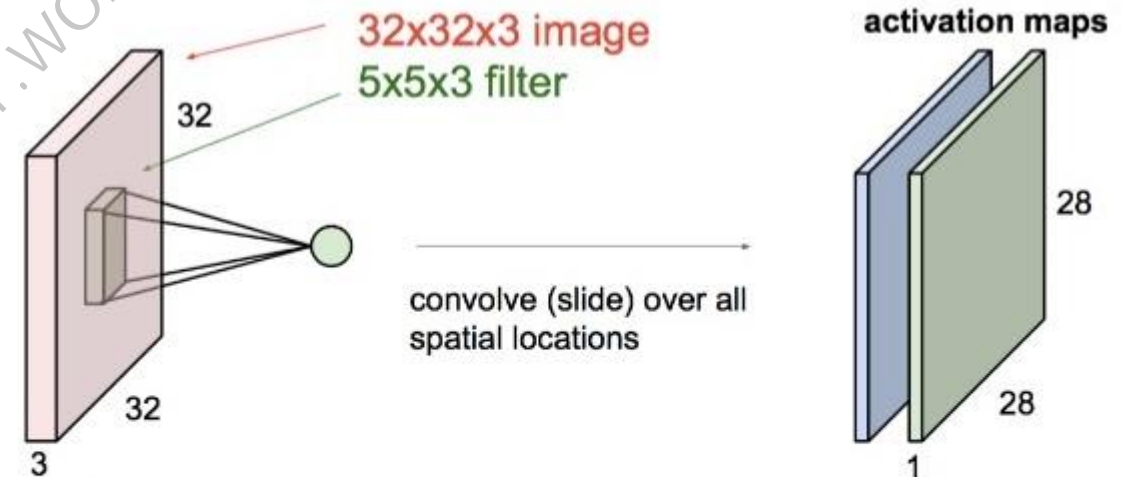
Convolutional Layer

CONVOLUTE THROUGHOUT THE IMAGE

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Steps involved in Convolutional Layer

- ▶ Here we move the feature/filter to every possible position on the image.
- ▶ Steps involved in Convolutional Layer are as follows
 1. Line Up the image.
 2. Multiply each image pixel by corresponding feature pixel.
 3. Add them up.
 4. Divide by total number of pixel in the feature.



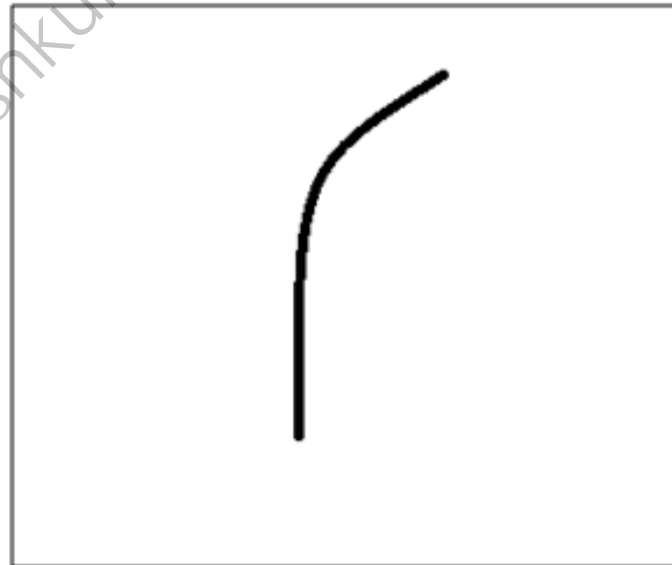
- **Convolution** (3-dim dot product) image and filter
- Stack filter in one layer (See blue and green output, called **channel**)

What are filters?

- ▶ Each of these filters can be thought of as **feature identifiers**
- ▶ By Feature, we here means things like straight edges, simple colors, and curves.

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

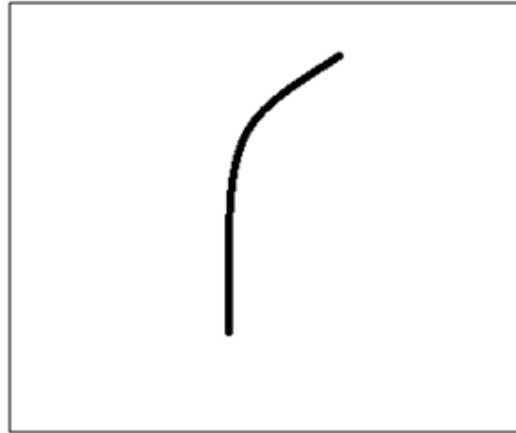


Visualization of a curve detector filter

What are filters?

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

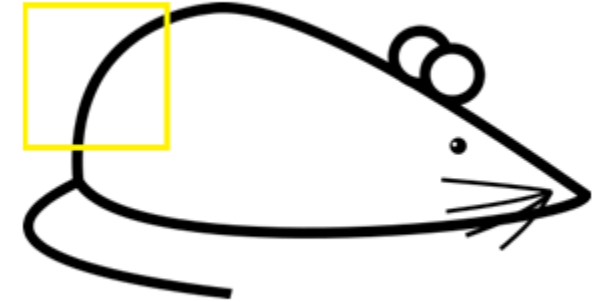
Pixel representation of filter



Visualization of a curve detector filter



Original image



Visualization of the filter on the image



Visualization of the receptive field

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Convolutional Layer

Weights/parameters

Filter pixels value are multiplied with the corresponding input image pixel value and is saved in another result matrix.

Filter / neuron / kernel

Receptive field

Result Matrix

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

$$1 \times 1 = 1$$

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

1	

Convolutional Layer

Add and divide by
total number of pixel.

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

$$\frac{1+1+1+1+1+1+1+1+1}{9} = 1$$

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

1	1	1
1	1	1
1	1	1

Result of the above Filter: 1

Convolutional Layer

Create a map to put value of filter

Now to keep track of where that feature was, we create a map and put value of the filter at the place.

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



		1						

Feature Map

Convolutional Layer

Similarly we move the filter to every other positions of the image and will how the feature matches the area.

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

9 x 9 matrices



			1					
				0.55				



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.0	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.0	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

(Activation/Feature Map : 7 x 7 Matrices)

Convolution Layer Output

After performing the same convolution, with every filter, we get all the filter/feature maps.

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



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



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.0	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.0	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77



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



0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.11	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33



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



0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

ReLU Layer

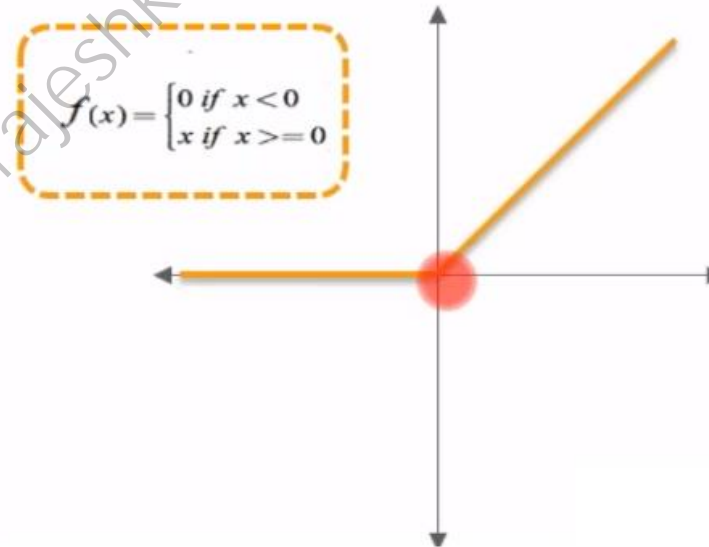
ACTIVATION FUNCTION

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ReLU Layer – Activation Function

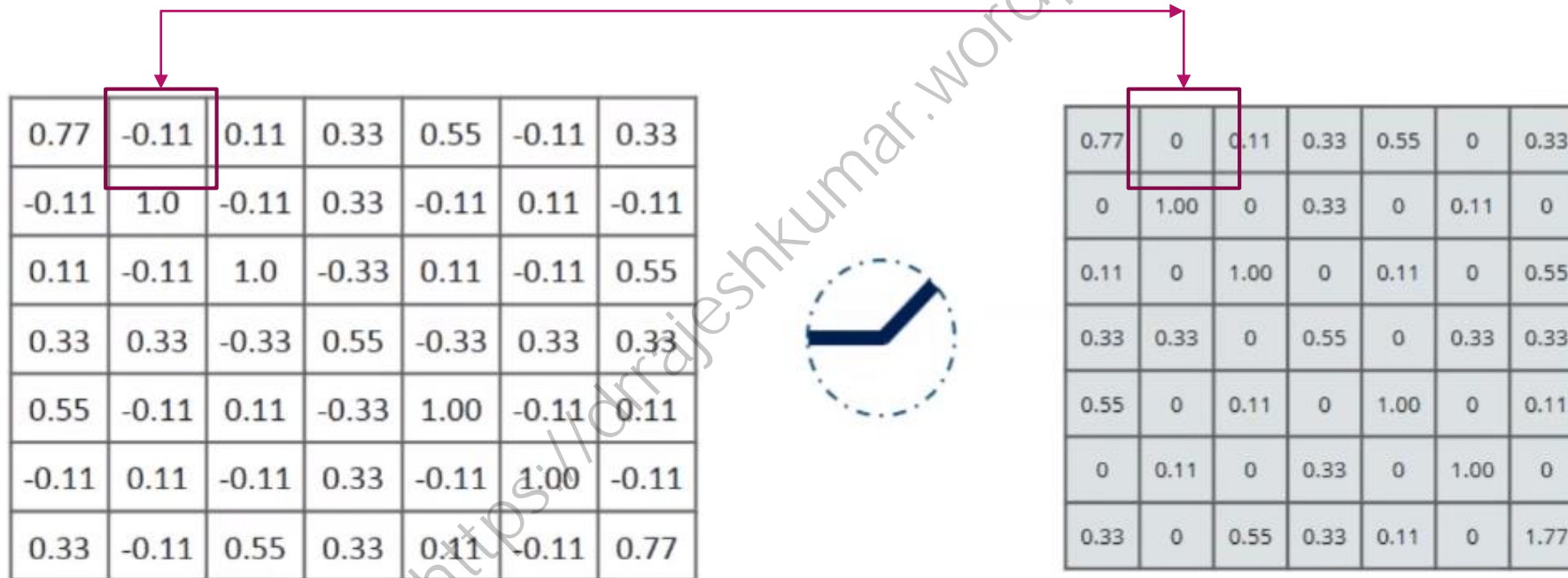
Rectified Linear Unit (ReLU) transform function only activates a node if the input is above a certain quantity, while input is below zero, output is zero, but when the input rises above threshold, it has linear relationship with dependent variable.

- ▶ In this layer we remove every negative values from the filtered images and replace it with zero's.
- ▶ This is done to avoid the values from summing up to zeros



x	$f(x)=x$	F(x)
-3	$f(-3) = 0$	0
-5	$f(-5) = 0$	0
3	$f(3) = 3$	3
5	$f(5) = 5$	5

ReLU function applied on One feature



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.0	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.0	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.77	0	0.11	0.33	0.55	0	0.33
0	1.00	0	0.33	0	0.11	0
0.11	0	1.00	0	0.11	0	0.55
0.33	0.33	0	0.55	0	0.33	0.33
0.55	0	0.11	0	1.00	0	0.11
0	0.11	0	0.33	0	1.00	0
0.33	0	0.55	0.33	0.11	0	1.77

Negative values transformed to 0. We have to perform ReLU function for all features.

Pooling Layer

IN THIS LAYER WE SHRINK THE IMAGE STACK INTO SMALLER SIZE.

Pooling Layer

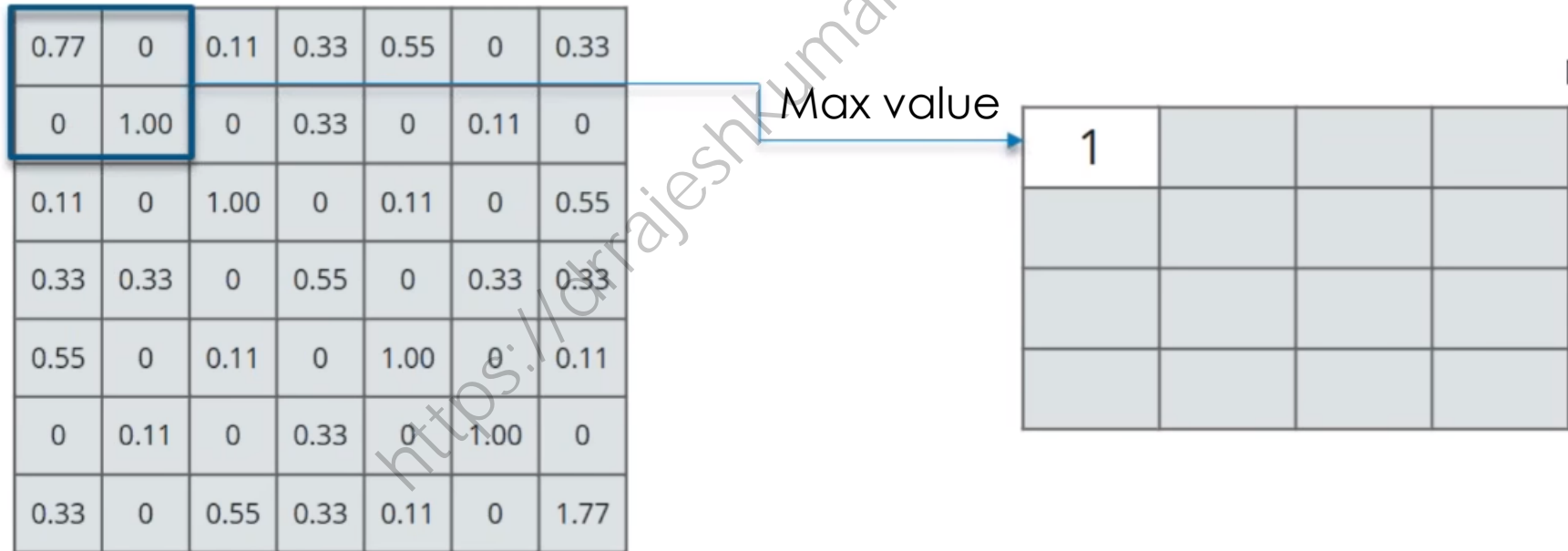
- ▶ POOL layer will perform a down sampling operation along the spatial dimensions (width, height), resulting in lower volume.
- ▶ In this layer we shrink the image stack into smaller size.
- ▶ Steps:
 1. Pick a window size (usually 2-3)
 2. Pick a stride (usually 2)
 3. Walk your window across filtered images.
 4. From each window, take maximum value

Symbol:



Pooling Layer

- Choose the highest value in the window and move the window two strides.



Pooling Layer

Moving the windows across entire image

0.77	0	0.11	0.33	0.55	0	0.33
0	1.00	0	0.33	0	0.11	0
0.11	0	1.00	0	0.11	0	0.55
0.33	0.33	0	0.55	0	0.33	0.33
0.55	0	0.11	0	1.00	0	0.11
0	0.11	0	0.33	0	1.00	0
0.33	0	0.55	0.33	0.11	0	1.77

7 x 7 matrix

1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

4 x 4 matrix

Output after passing through pooling layer.

The basic role of pooling layer is to shrink the size of our image matrix.

Here we have converted a 7x7 matrix to a 4x4 matrix.

Since we took 3 features in the beginning, we have 3 outputs after pooling layer.

Now next we have to stack up all the layers.

0.77	0	0.11	0.33	0.55	0	0.33
0	1.00	0	0.33	0	0.11	0
0.11	0	1.00	0	0.11	0	0.55
0.33	0.33	0	0.55	0	0.33	0.33
0.55	0	0.11	0	1.00	0	0.11
0	0.11	0	0.33	0	1.00	0
0.33	0	0.55	0.33	0.11	0	1.77

0.33	0	0.11	0	0.11	0	0.33
0	0.55	0	0.33	0	0.55	0
0.11	0	0.55	0	0.55	0	0.11
0	0.33	0	1.00	0	0.33	0
0.11	0	0.55	0	0.55	0	0.11
0	0.55	0	0.33	0	0.55	0
0.33	0	0.11	0	0.11	0	0.33

0.33	0	0.55	0.33	0.77	0	0.77
0	0.11	0	0.33	0	1.00	0
0.55	0	0.11	1.00	0	0.11	
0.33	0.33	0	0.55	0	0.33	0.33
0.11	0	1.00	0	0.11	0	0.55
0	1.00	0	0.33	0	0.11	0
0.77	0	0.11	0.33	0.55	0	0.33



1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

0.55	0.33	0.55	0.33
0.33	1.00	0.55	0.11
0.55	0.55	0.55	0.11
0.33	0.11	0.11	0.33

0.33	0.55	1.00	0.77
0.55	0.55	1.00	0.33
1.00	1.00	0.11	0.55
0.77	0.33	0.55	0.33

Stacking up the layers

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

Input Image

Convolution



ReLU



Pooling



1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

0.55	0.33	0.55	0.33
0.33	1.00	0.55	0.11
0.55	0.55	0.55	0.11
0.33	0.11	0.11	0.33

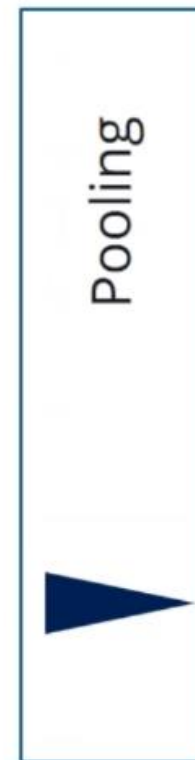
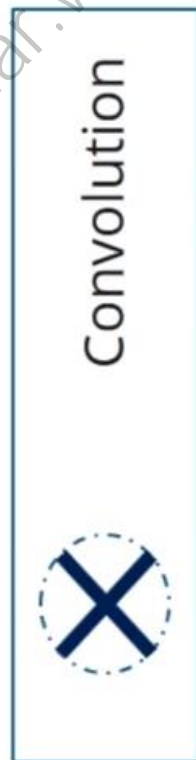
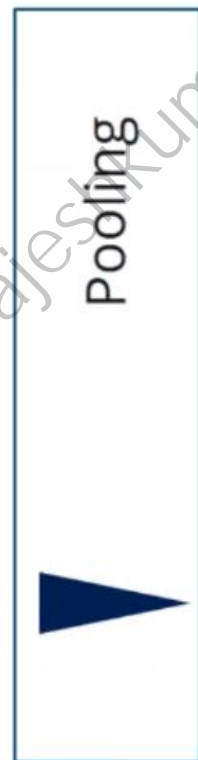
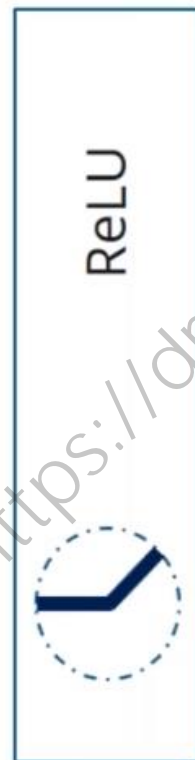
0.33	0.55	1.00	0.77
0.55	0.55	1.00	0.33
1.00	1.00	0.11	0.55
0.77	0.33	0.55	0.33

4x4 matrices

Stacking up the layers

Here we have applied one more layer of each convolution, ReLU and pooling, in order to downsize 4x4 matrix to 2x2 matrices.

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



1	0.55
0.55	1.00

1	0.55
0.55	0.55

0.55	1.00
1.00	0.55

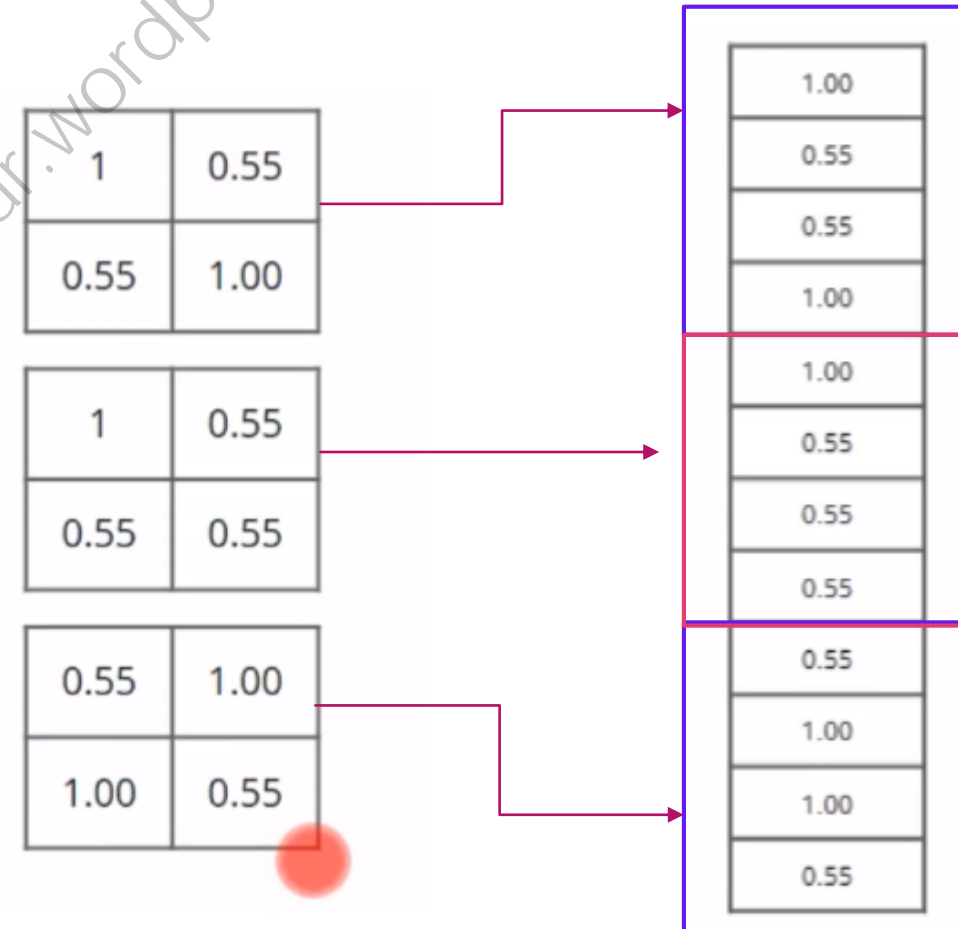
Fully Connected Layer

ACTUAL CLASSIFICATION TAKE PLACE IN FULLY CONNECTED LAYER.

Fully Connected layer

This is the final layer where the actual classification happens.

Here we take our filter and shrunk image and put them in into single list.



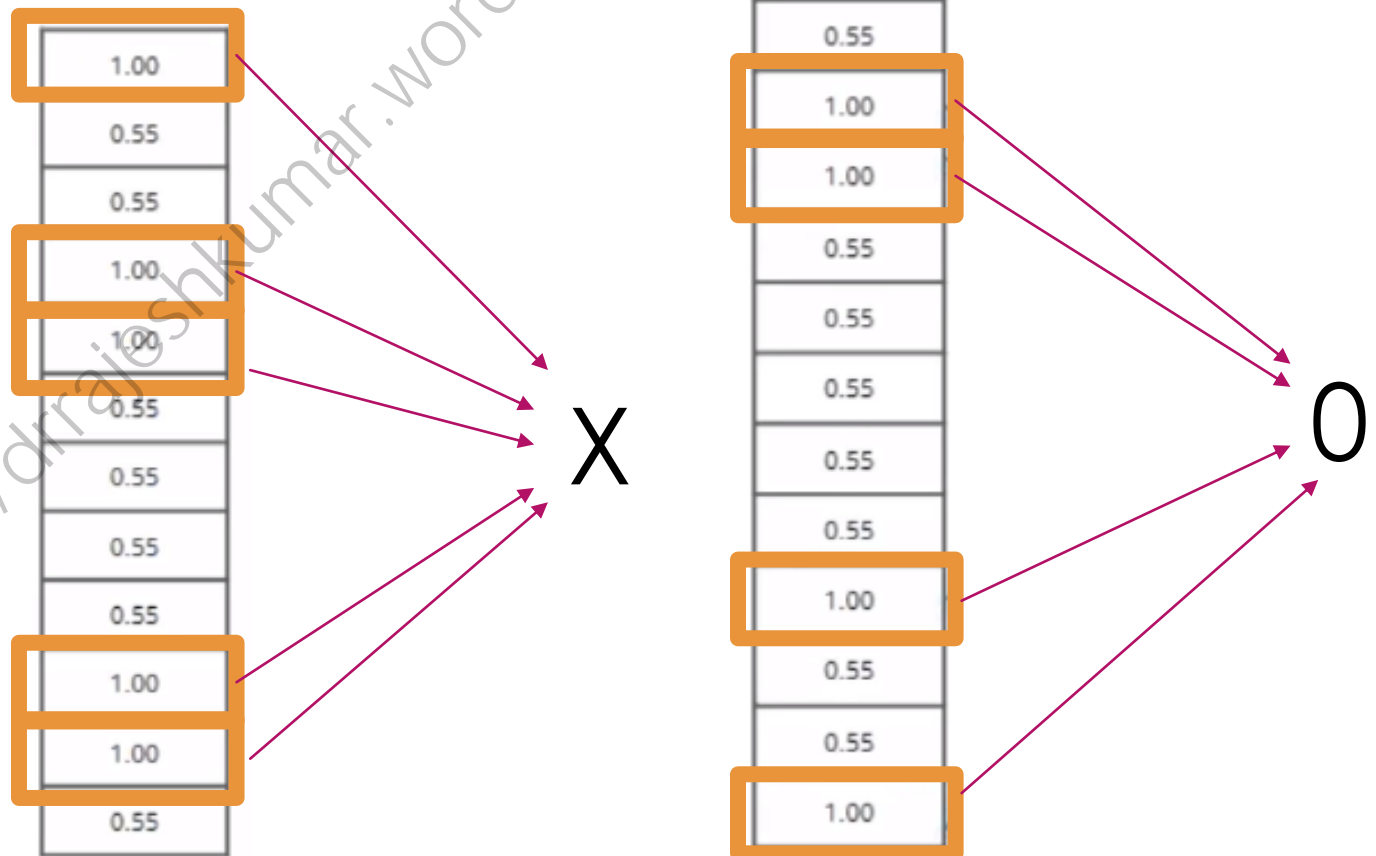
Output

When we feed in, 'X' and 'O'.
Then there will be some element that will be high.

Now if we have an input image with 1st, 4th, 5th, 10th, 11th value high we can say that the image is X

Similarly, if we have an image with 2nd, 3rd, 9th and 12th value high, we can say that it is O

This completes the training of our model. Now let's see results on some unseen images.



Prediction

After passing an input image through 4 layers of CNN, we have received the list of the image, we need to classify the image as X or O based on the model we learned earlier.

0.9
0.65
0.45
0.87
0.96
0.73
0.23
0.63
0.44
0.89
0.94
0.53

Let's compare with the list of 'X' and 'O'

Compare the input Vector with X

0.9
0.65
0.45
0.87
0.96
0.73
0.23
0.63
0.44
0.89
0.94
0.53

Input Image

1.00
0.55
0.55
1.00
1.00
0.55
0.55
0.55
0.55
1.00
1.00
0.55

Vector for 'X'

Compare the input Vector with O

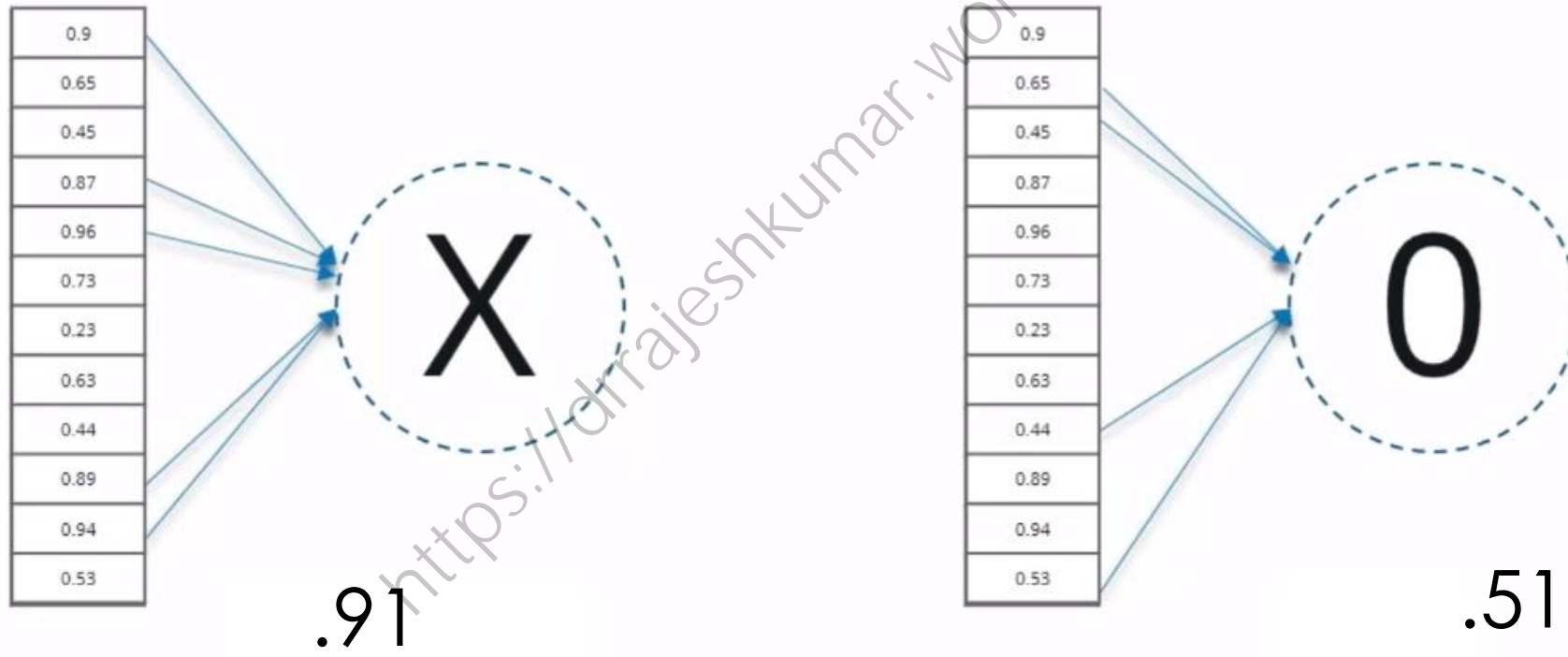
0.9
0.65
0.45
0.87
0.96
0.73
0.23
0.63
0.44
0.89
0.94
0.53

Input Image

0.55
1.00
1.00
0.55
0.55
0.55
0.55
0.55
1.00
0.55
0.55
1.00

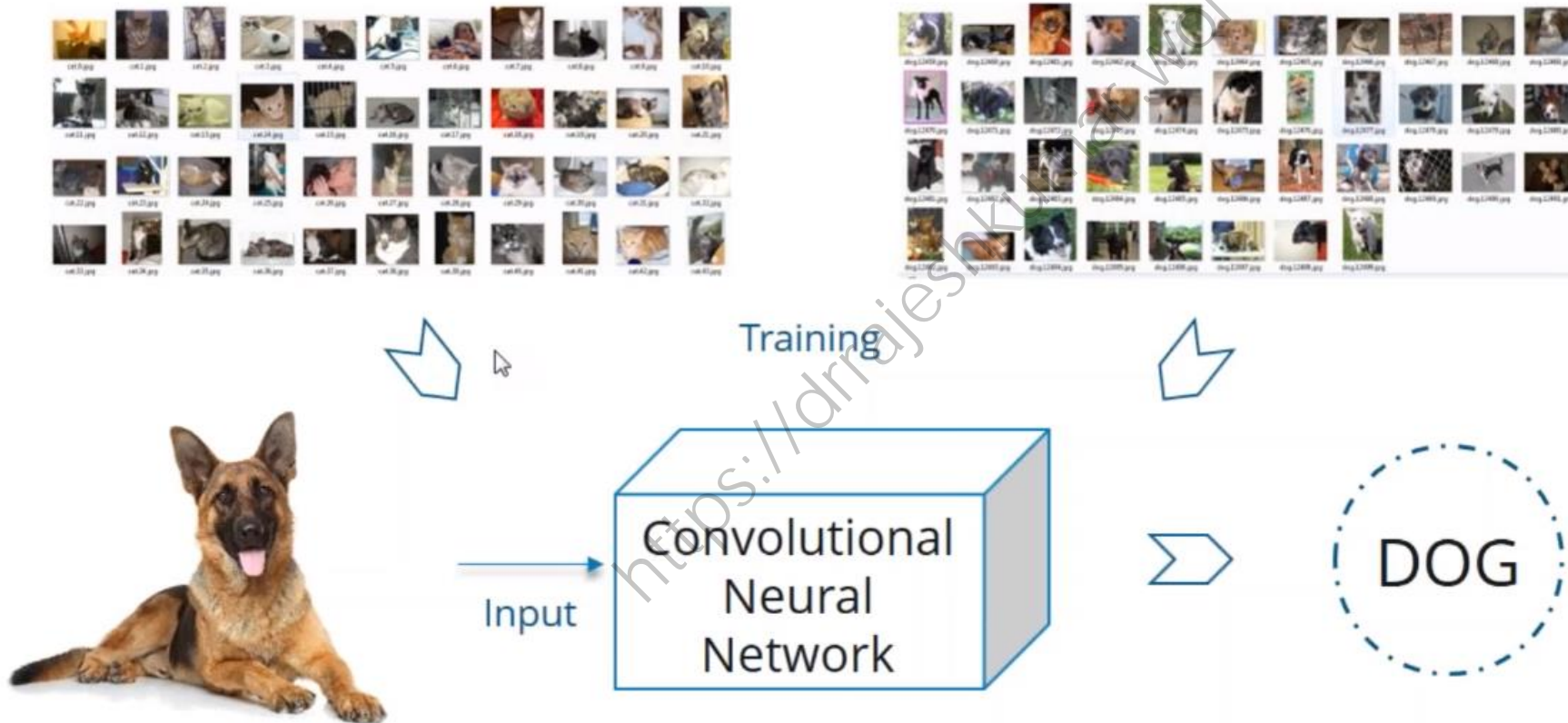
Vector for 'O'

Result



The new input image is classified as 'X'

Use case



Similarly, If we train our model with dataset of Dogs and cats. Once training is done, our model will be able to predict a new unlabeled input correctly.

Applications of CNN

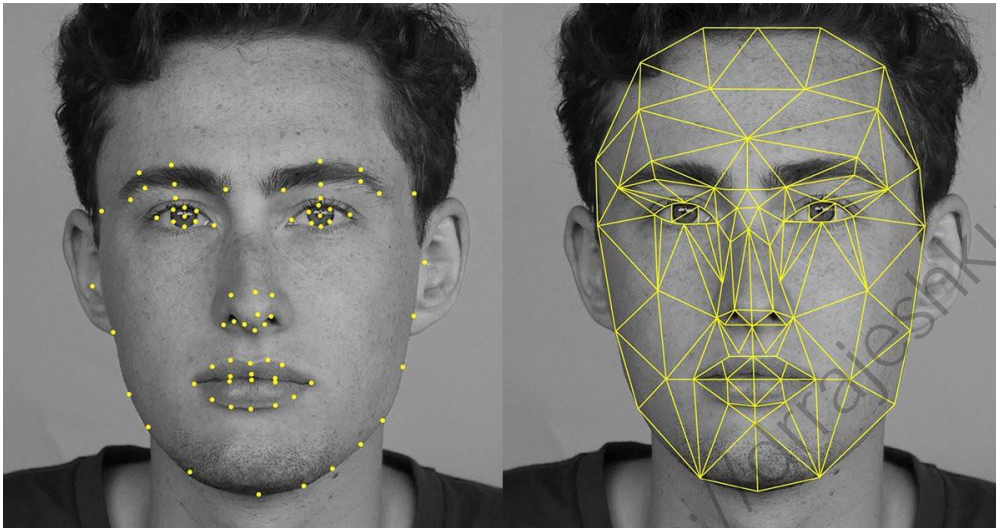
- Image processing and Character Recognition.



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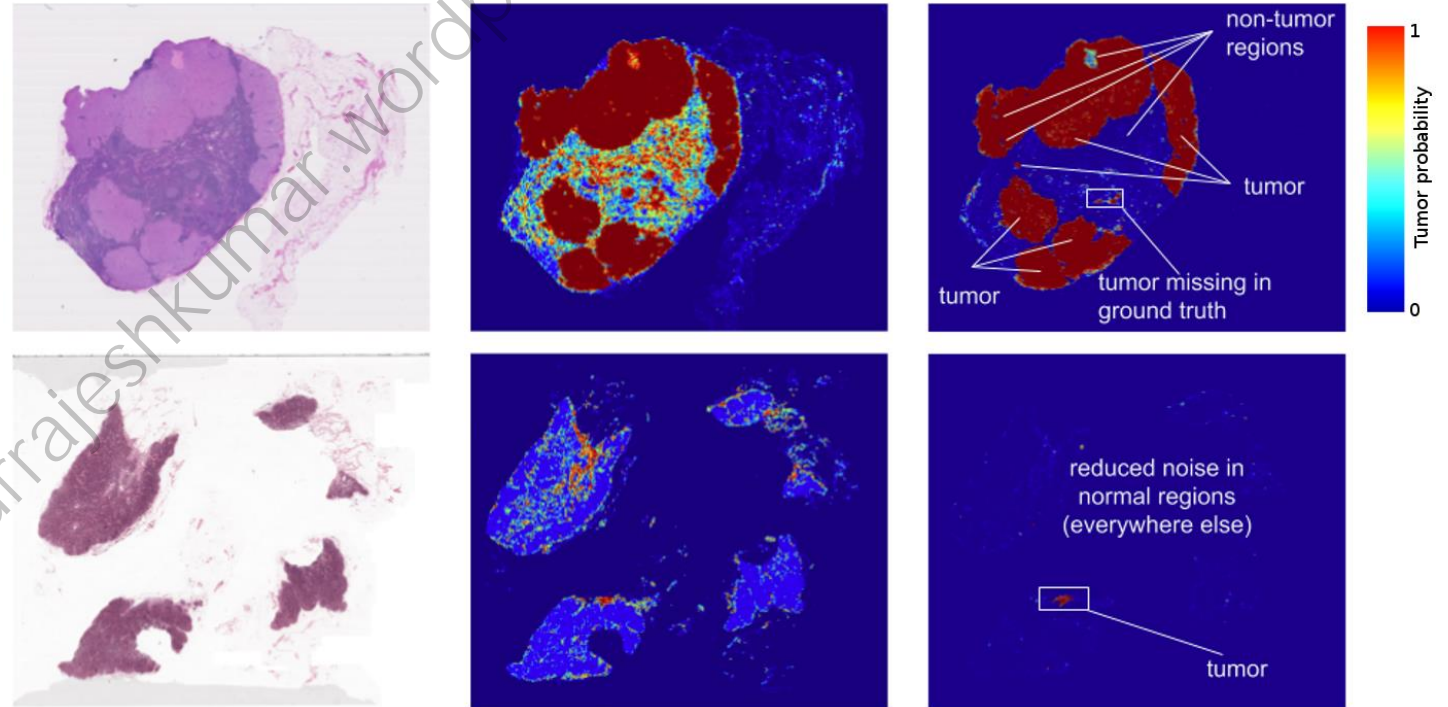
Applications of CNN

➤ Face Detection



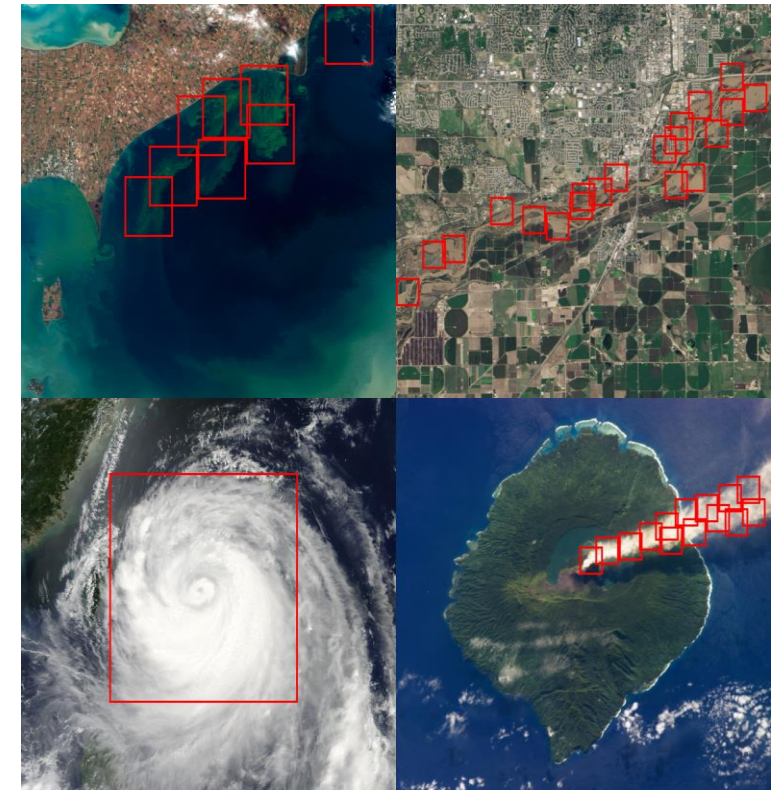
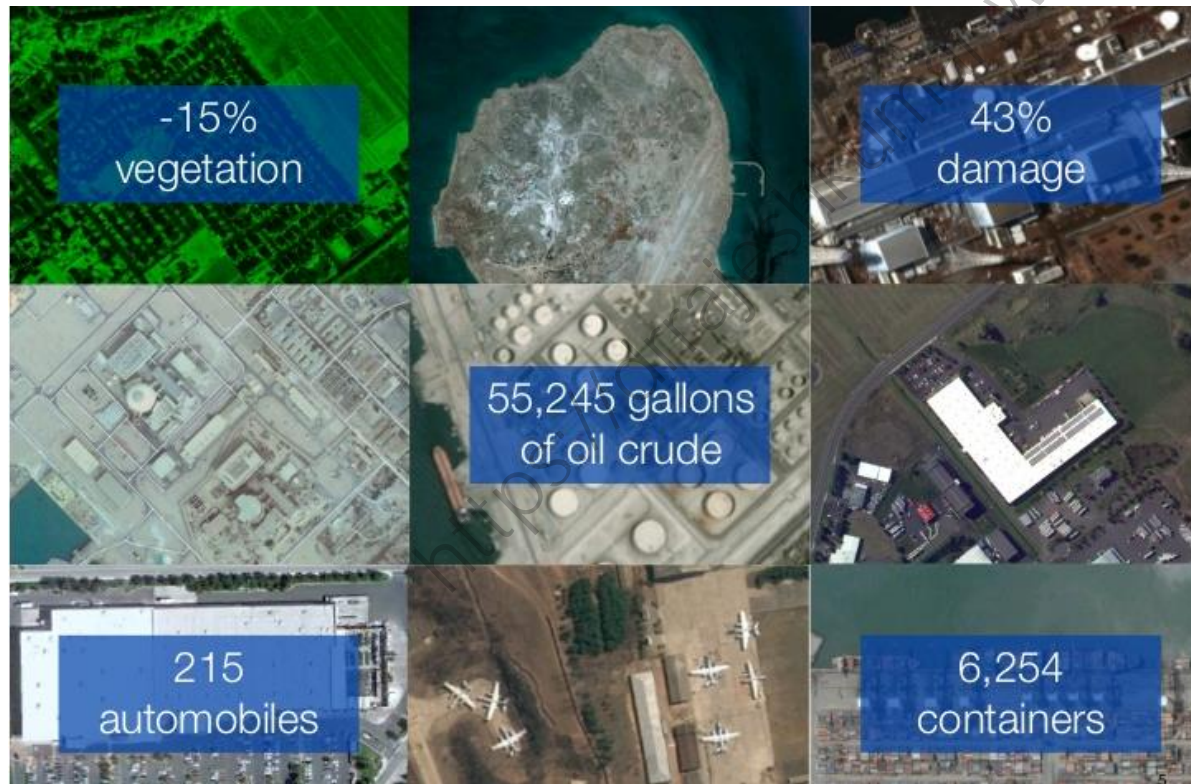
Applications of CNN

➤ Cancer Detection



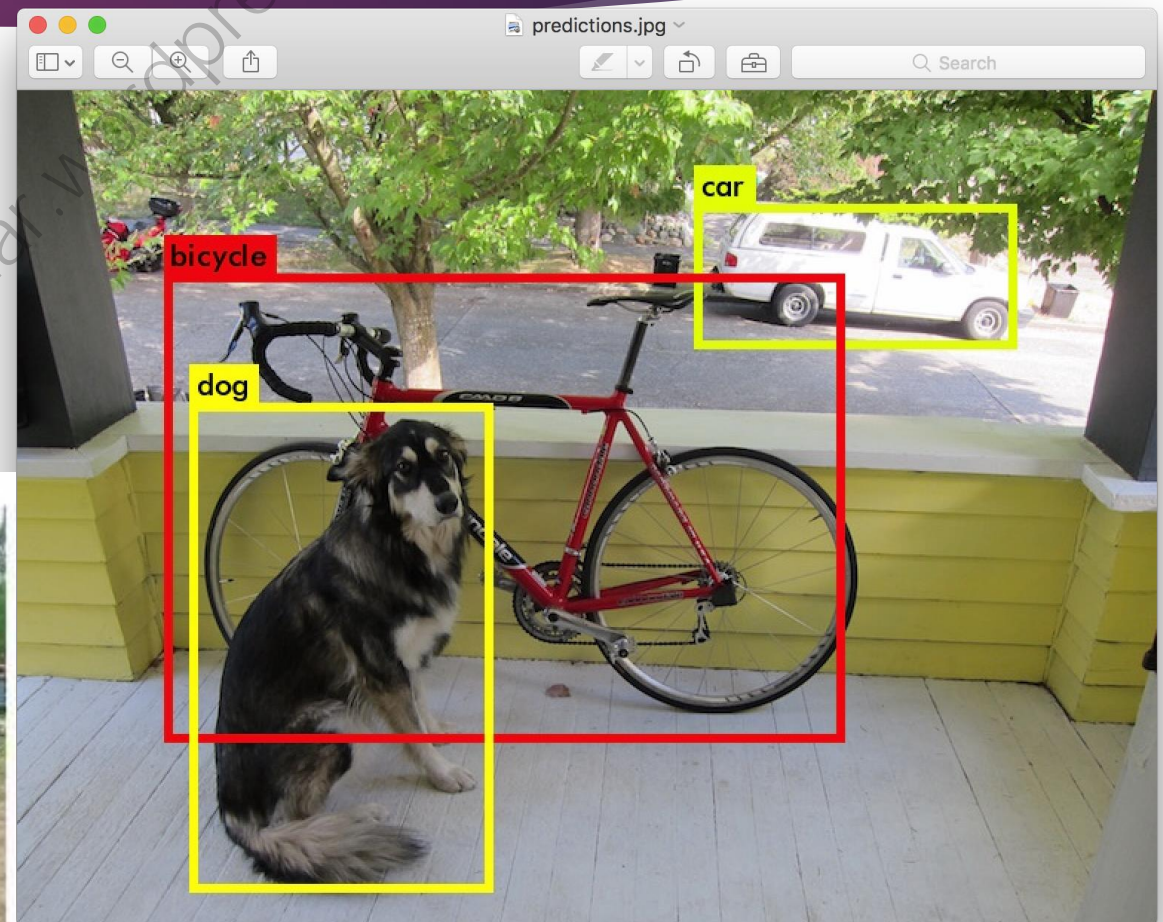
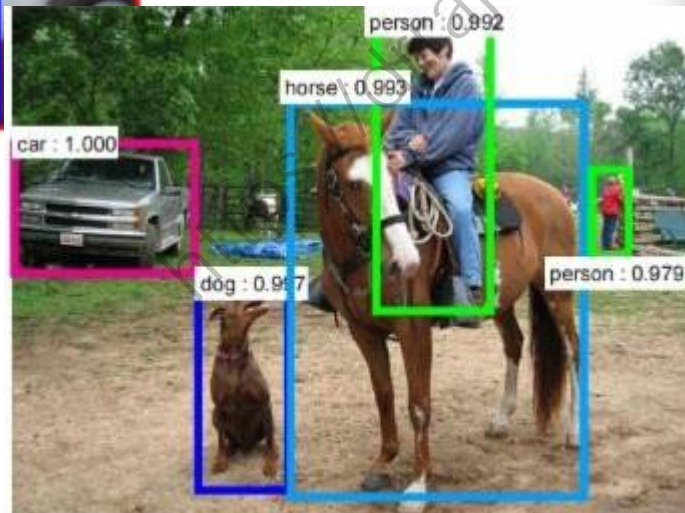
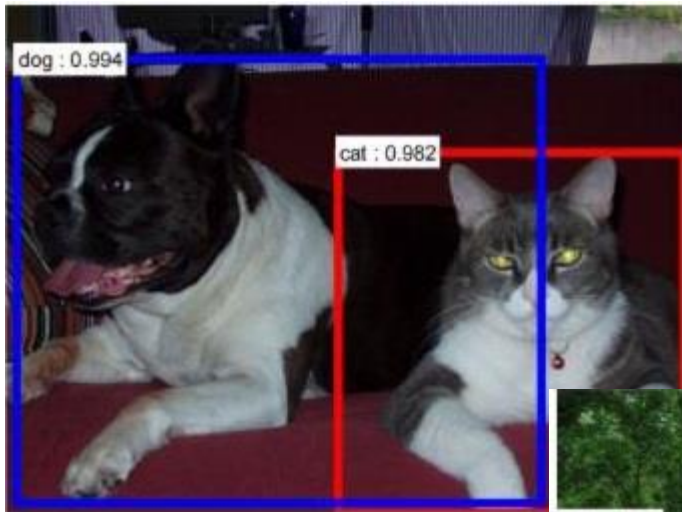
Applications of CNN

- Satellite imagery processing



Applications of CNN

► Object detection



Thank you

<https://drrajeshkumar.wordpress.com>