

# Hope to Skills

Lecture# 24

Irfan Malik, Dr. Sheraz Naseer

# Agenda

- Limitations of simple Neural Network
- Convolutional Neural Networks (CNN)
- Basics for CNN
  - Images and features
  - Convolution
  - Pooling
- Quiz

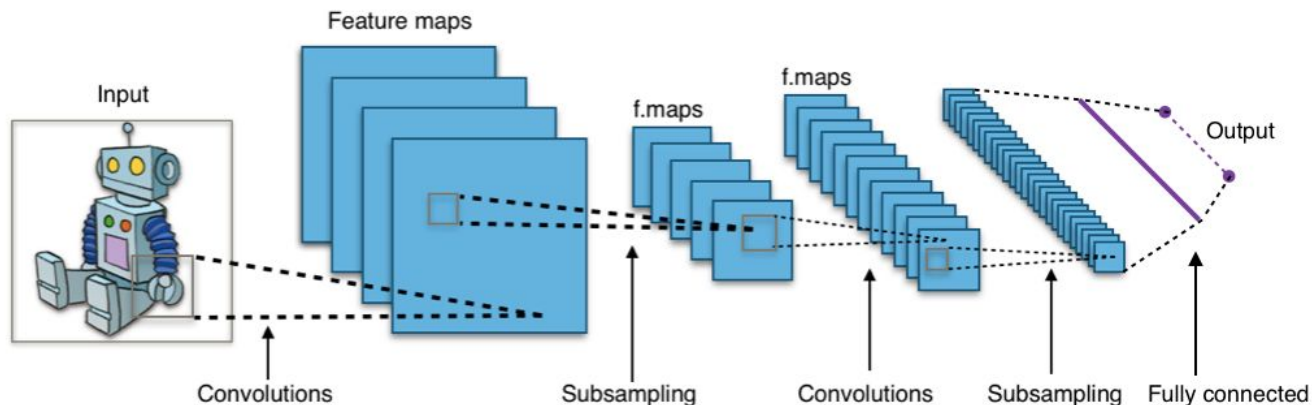
# Limitations of Simple Neural Networks

1. **Pixel Equality:** Simple neural networks treat all pixels in an image equally, regardless of their spatial relationships or positions
2. **High Dimensionality:** Large sized Image have more pixels and model needs more weights to learn.  $28 \times 28 = 784$ ,  $256 \times 256 = 65536$
3. **Limited Feature Extraction:** Simple networks lack specialized layers to automatically extract relevant features from images, making it harder to identify complex structures
4. **Large Computational Requirements:** Larger no of weights requires more computational resources to train.

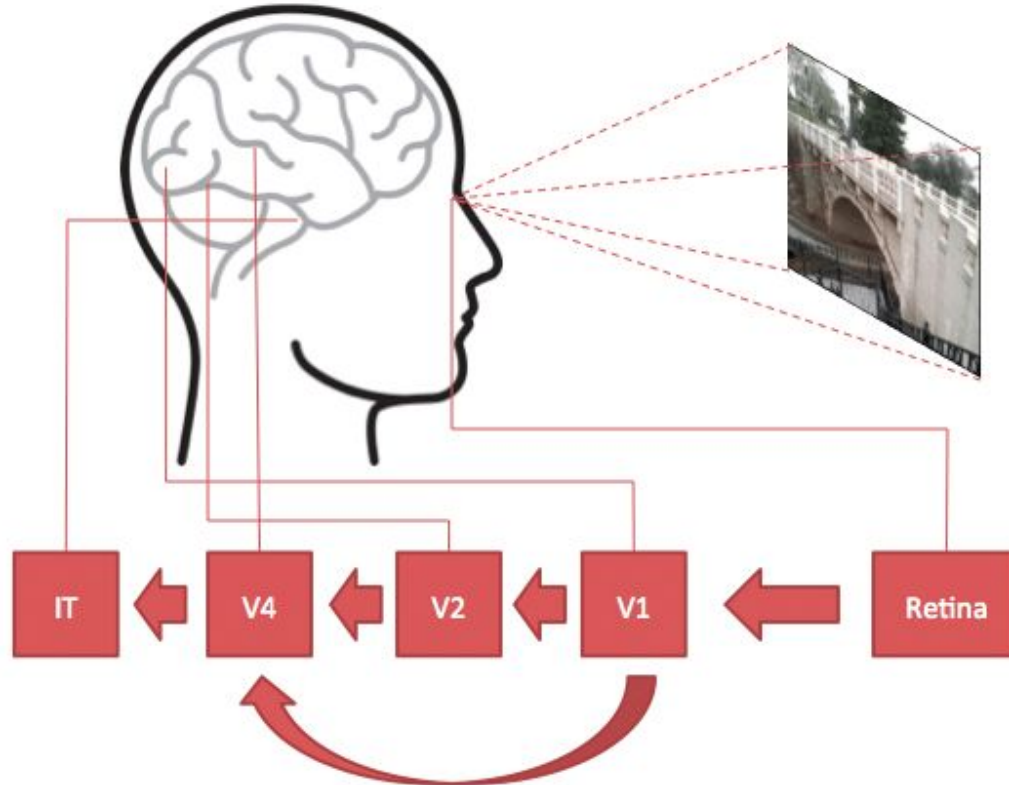
# Convolutional Neural Networks (CNN)

**CNNs** are a type of **Neural Networks** inspired by how our **brain** processes **visual information**.

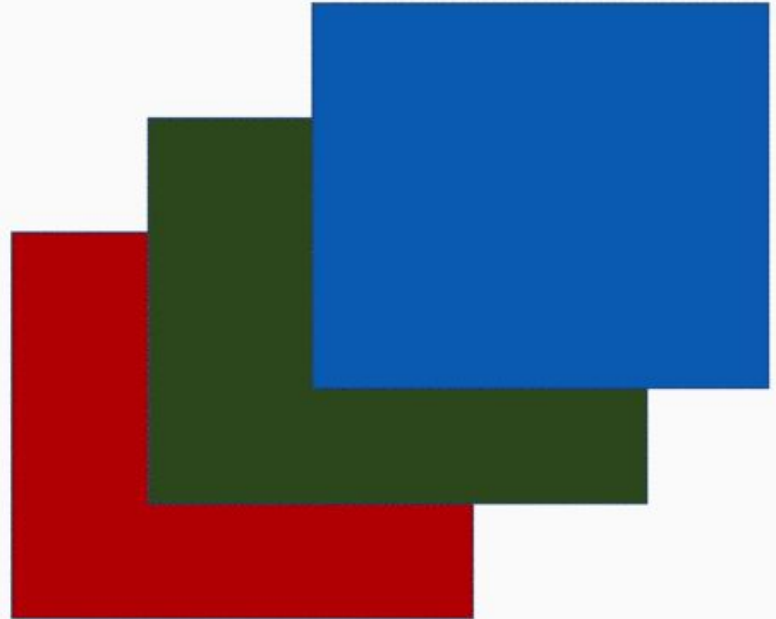
They're **specialized** for understanding **images**, making them powerful tools in image analysis, recognition, and more.



# Brain to AI: Visual Cortex



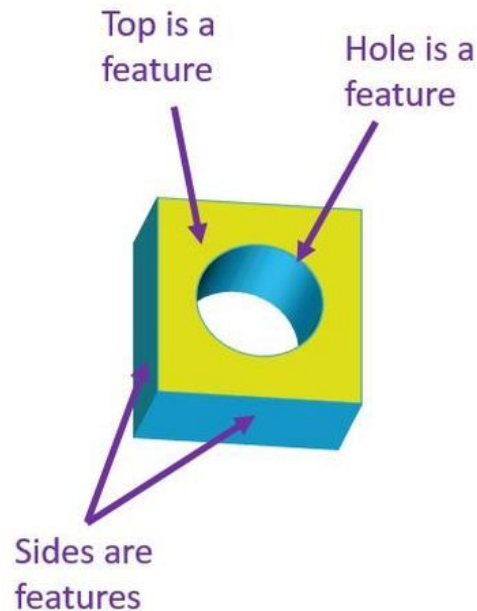
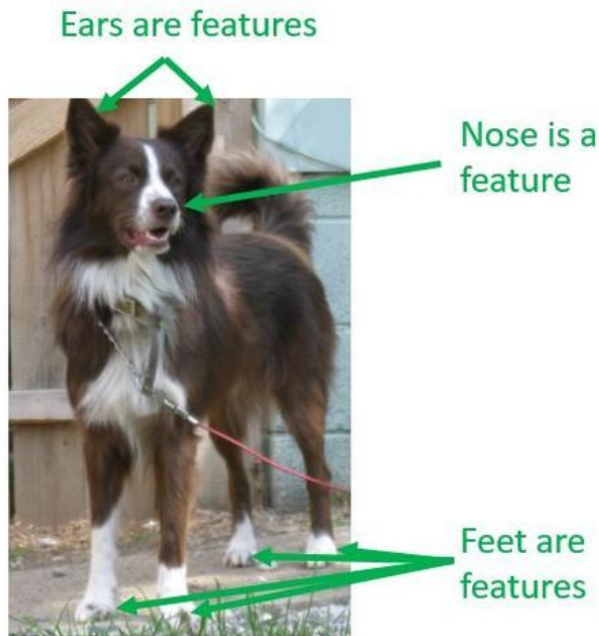
# Images in Computer



# Features for Images

Images are full of important parts called **features**.

Features can be **edges**, **textures**, **shapes**, or even **faces**.



# Convolution

Convolution is like a special way of looking at data. It's a **mathematical** operation that brings out **patterns**.

The filter slides over the image, one small piece at a time.

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

5 x 5 – Image Matrix



1	0	1
0	1	0
1	0	1

3 x 3 – Filter Matrix



# Convolution

1 <sub>x1</sub>	1 <sub>x0</sub>	1 <sub>x1</sub>	0	0
0 <sub>x0</sub>	1 <sub>x1</sub>	1 <sub>x0</sub>	1	0
0 <sub>x1</sub>	0 <sub>x0</sub>	1 <sub>x1</sub>	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved  
Feature

# Filter as Magnifier

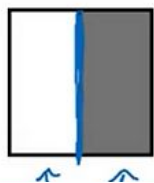


# Vertical edge detection

↓ ↓

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	<u>10</u>	<u>10</u>	<u>0</u>	0	0
10	<u>10</u>	<u>10</u>	<u>0</u>	0	0
10	<u>10</u>	<u>10</u>	<u>0</u>	0	0

6x6



\*

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

3x3

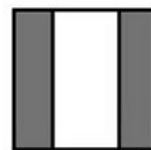
=

↓

0	30	30	0
0	30	30	0
0	30	30	0
0	<u>30</u>	30	0

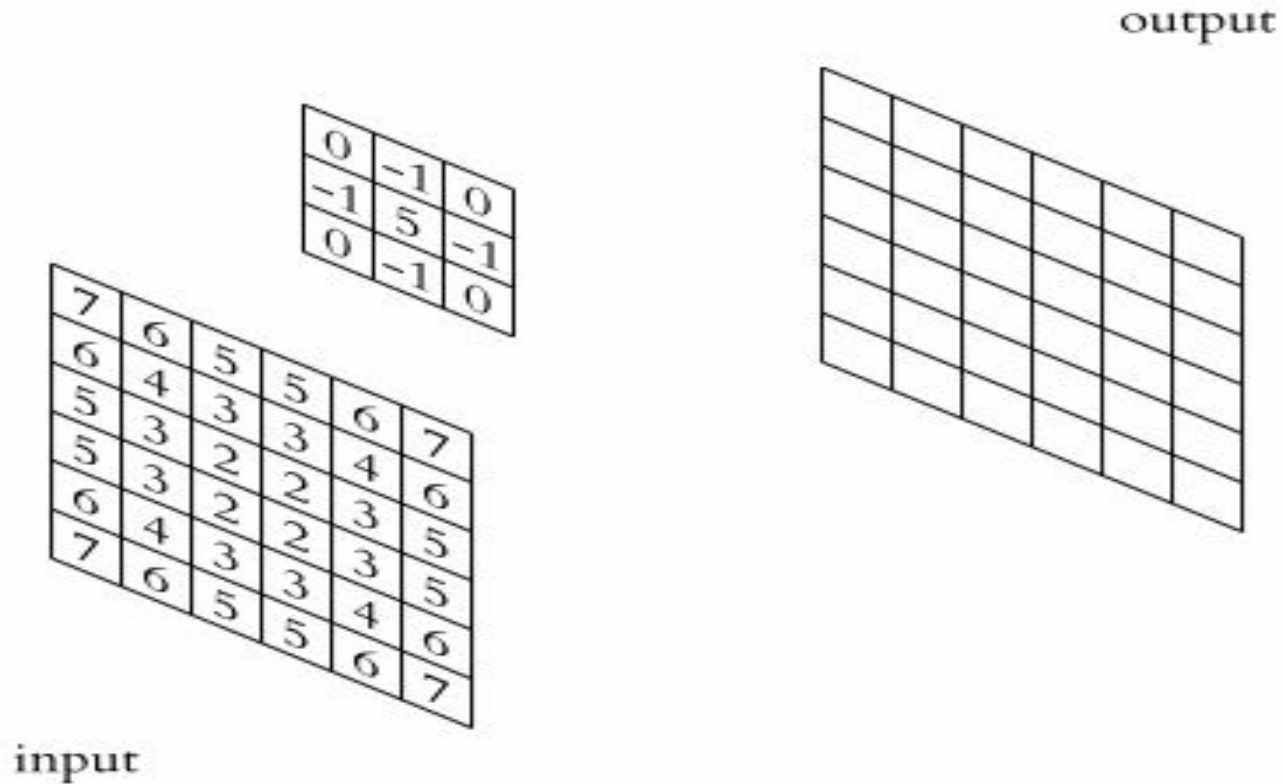
↑

\*



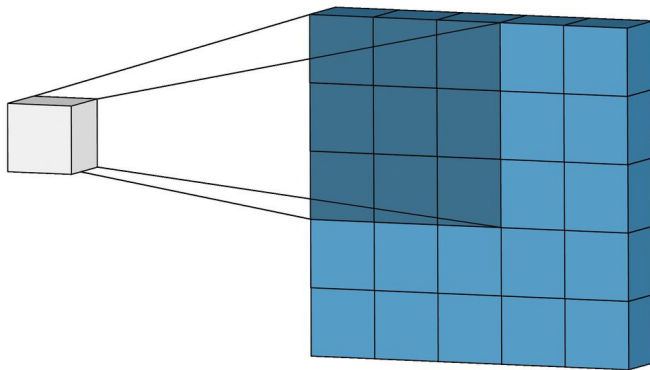
Andrew Ng

# Convolution



# Pooling

Pooling is like **summarizing information**, keeping what's **important**.  
It helps **reduce** the **dimensionality** while retaining **important information**.  
**Pooling = Downsizing + Information Summary.**



# Types of Pooling

## Feature Map

6	6	6	6
4	5	5	4
2	4	4	2
2	4	4	2

Max  
Pooling


Average  
Pooling


Sum  
Pooling


# Types of Pooling

## Feature Map

6	6	6	6
4	5	5	4
2	4	4	2
2	4	4	2

## Max Pooling


# Advantages of Max Pooling:

**Feature Retention:** Keeps dominant features intact.

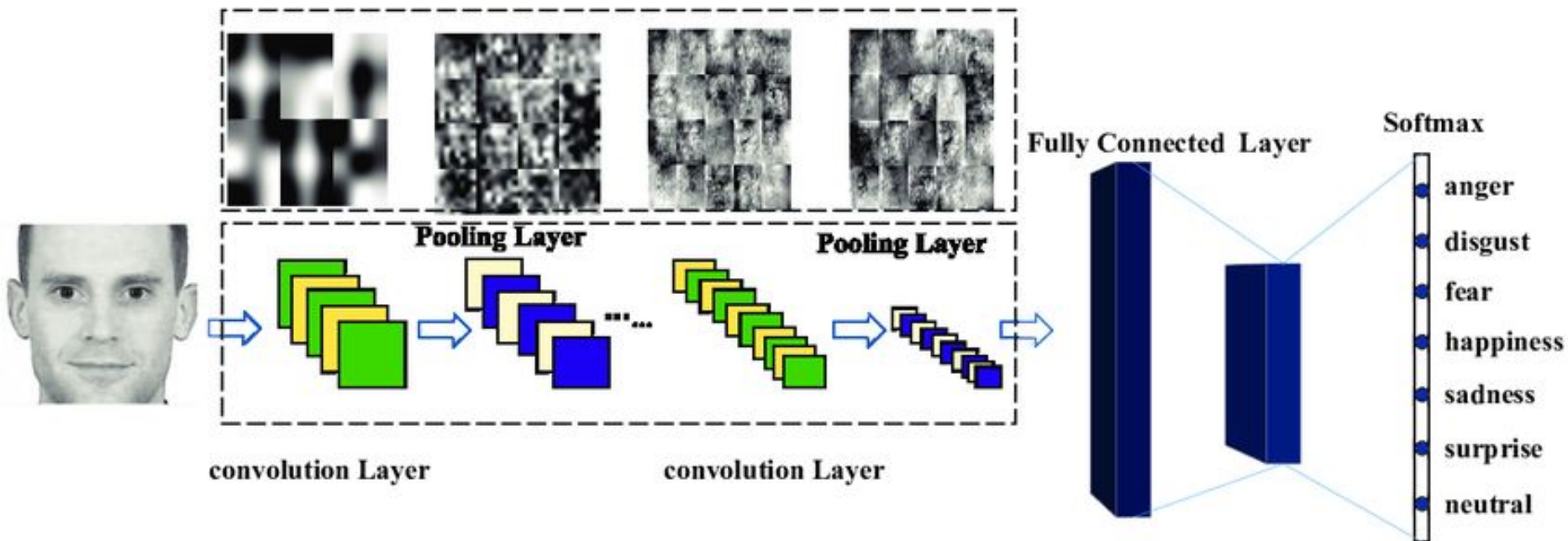
**Translation Invariance:** Recognizes features regardless of exact location.

**Dimension Reduction:** Reduces data size, providing efficiency.





# CNN Architecture



# CNN Architecture

