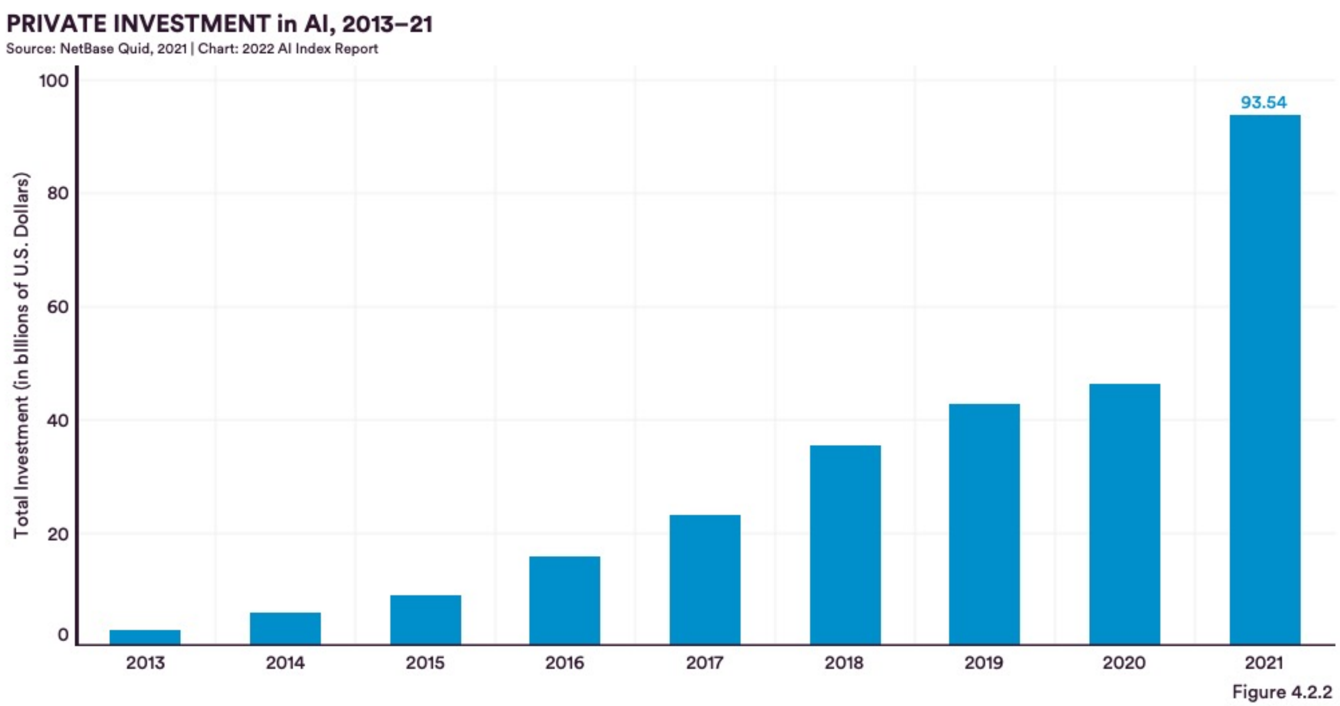
THE AI REVOLUTION

Satya Mallick,
CEO, OpenCV.org

Vikas Gupta
Director (Courses), OpenCV.org

PRIVATE INVESTMENT IN AI



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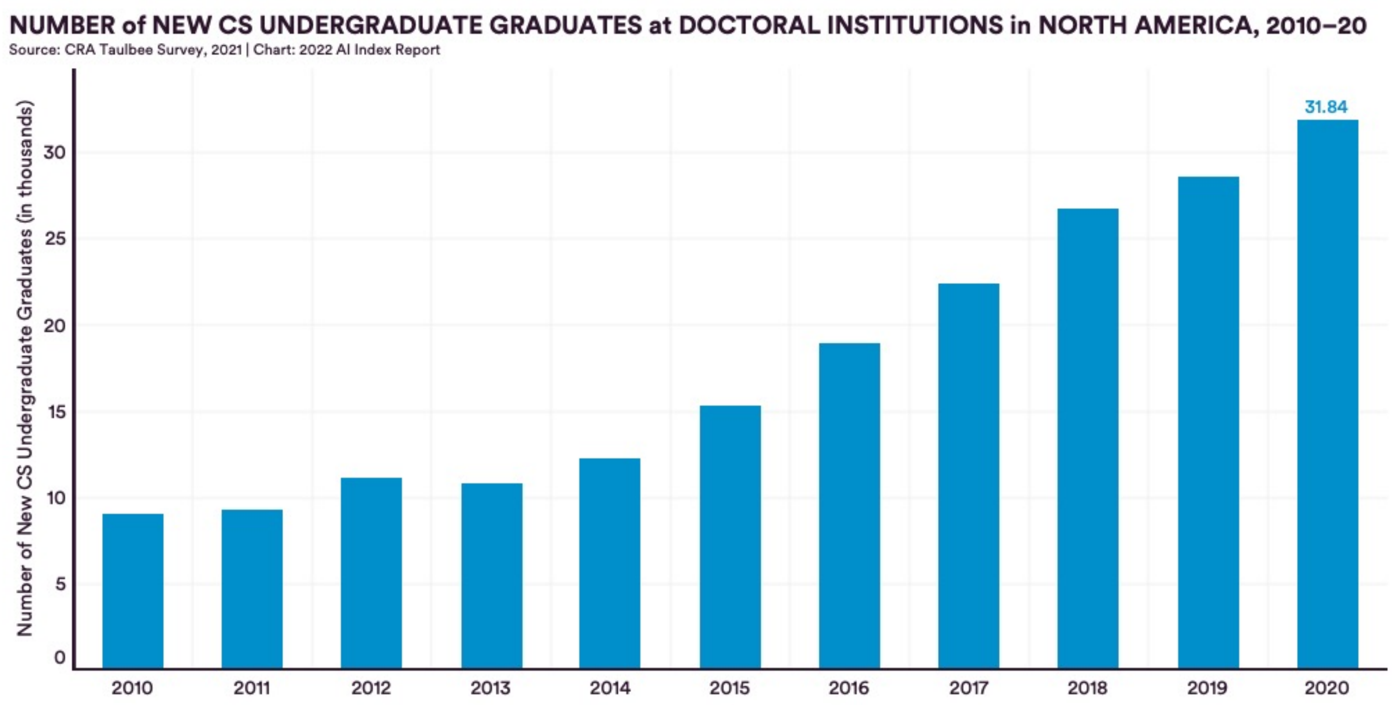
AI EDUCATION



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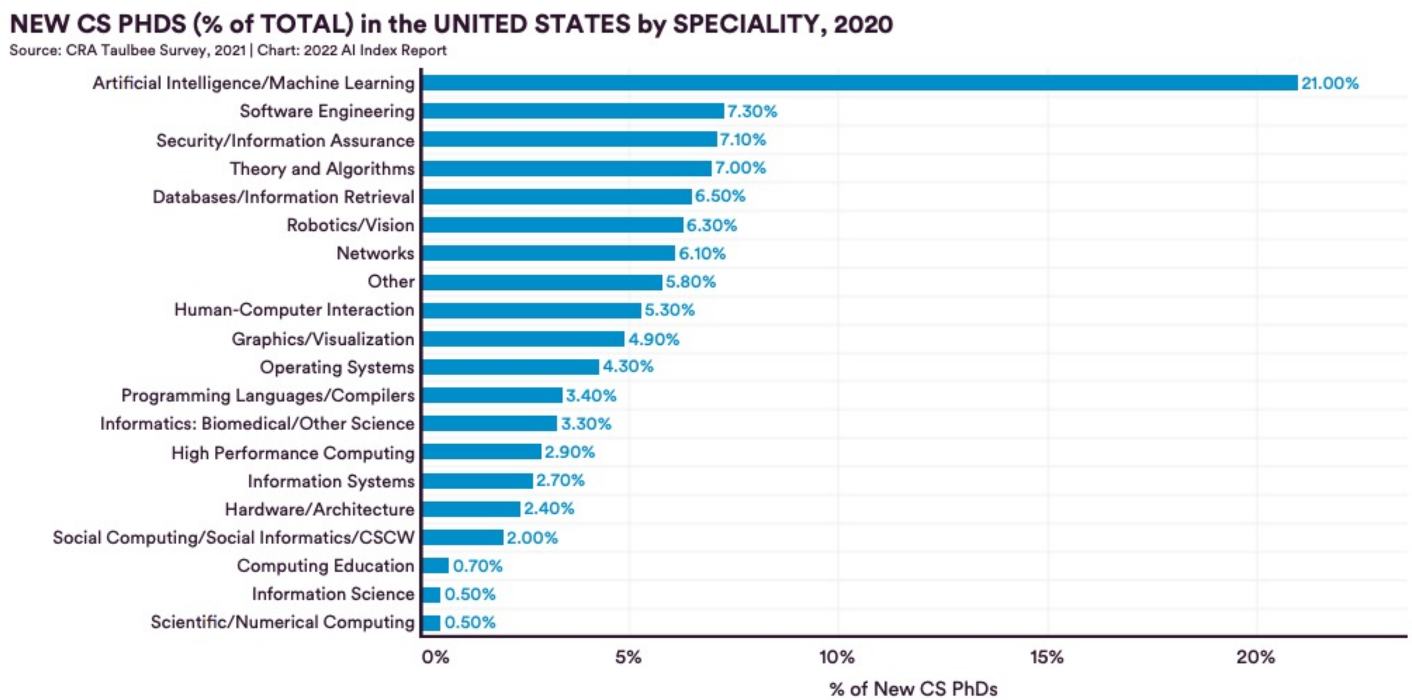

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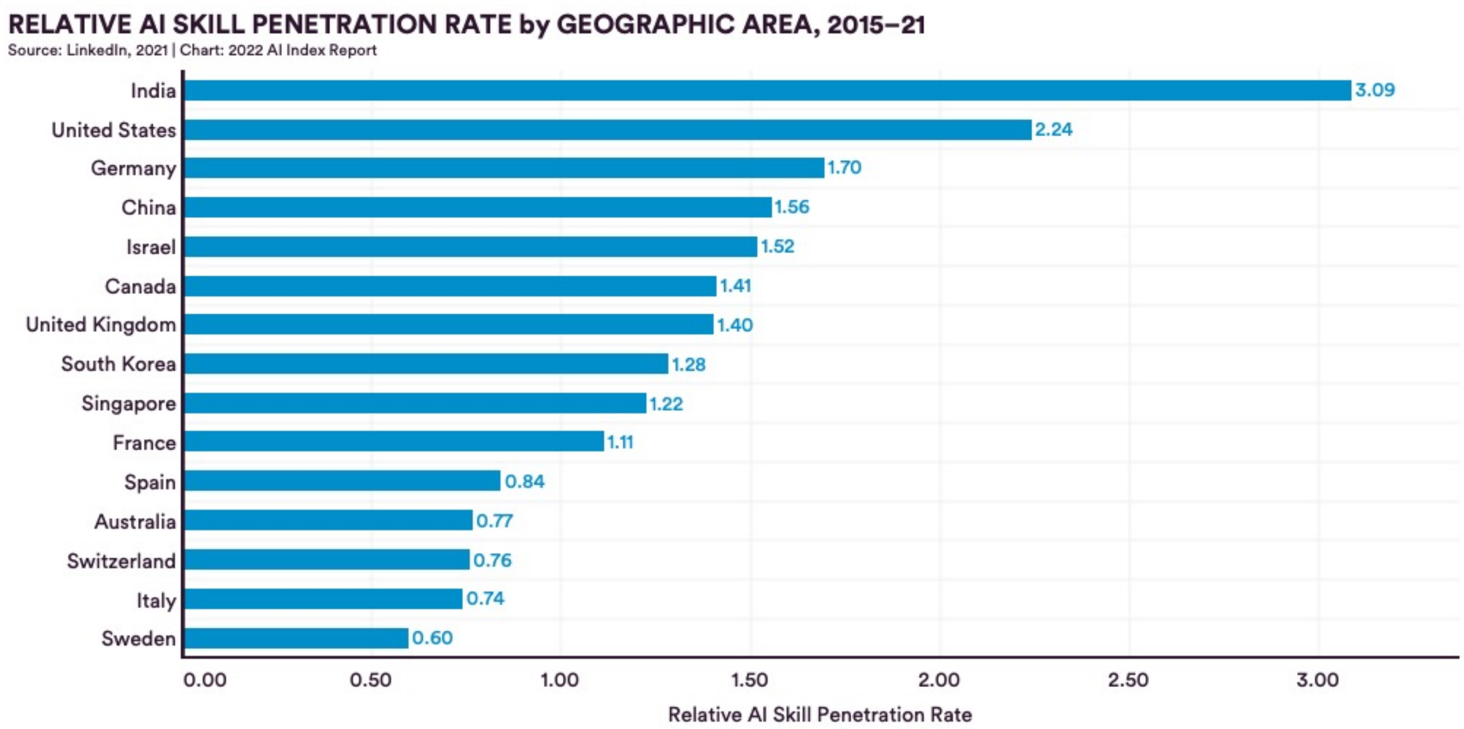
AI SKILL PENETRATION



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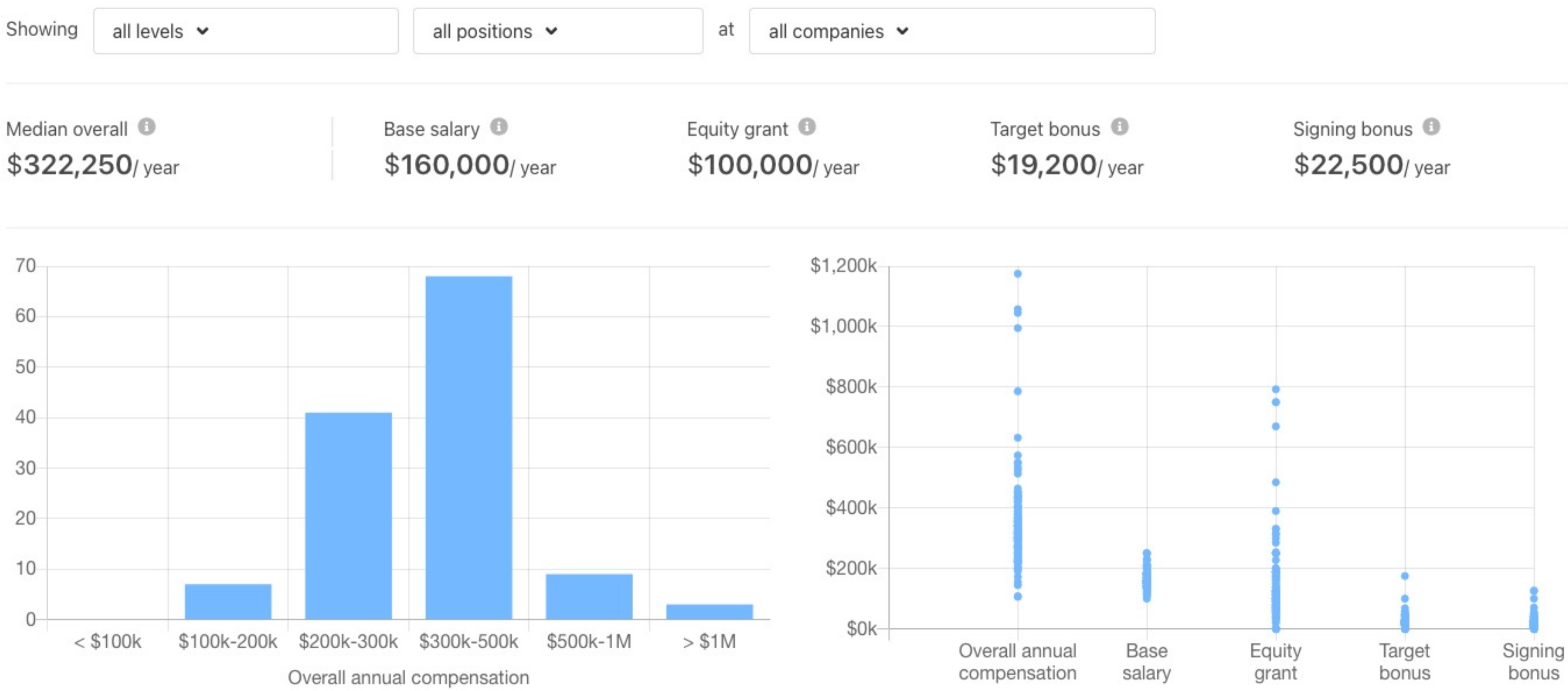
AI PAYGRADES



https://aipaygrad.es/

A TALE OF 3 LIBRARIES

OpenCV

PyTorch

+

TensorFlow

COMPUTER VISION COURSES

1

OpenCV for Beginners

A short, fun, and affordable course for beginners.

2

Computer Vision I: Introduction

An introductory course for beginners in computer vision and machine learning. Available in C++ and Python.

3

Computer Vision II: Applications

A computer vision course focussed on building real world applications.

https://opencv.org/courses

Email us at courses@opencv.org for discount code

DEEP LEARNING COURSES

4

Deep Learning with PyTorch

An introductory hands-on course for beginners in deep learning for computer vision.

5

Deep Learning with Tensorflow & Keras

An introductory hands-on course for beginners in deep learning for computer vision

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DEEP LEARNING

IMAGE CLASSIFICATION / OBJECT DETECTION

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2001

Viola and Jones

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Deep Learning based AlexNet won ILSVRC 2012 by a huge margin.

WHY NOW ? THREE REASONS

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LARGE DATASETS

ILSVRC proved large datasets
will keep improving performance

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PARALLEL COMPUTING

We figured out how to use
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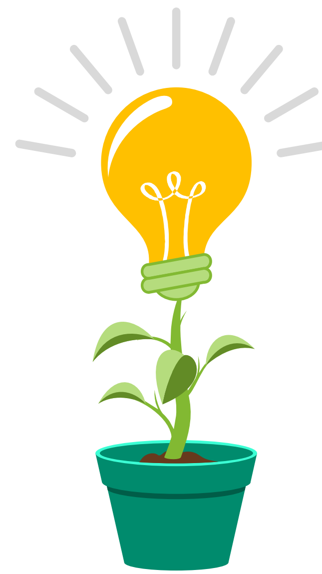

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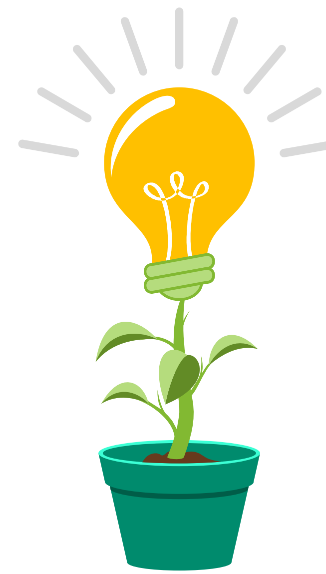

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BETTER ALGORITHMS

Deeper networks could be trained

DEEP LEARNING vs TRADITIONAL LEARNING

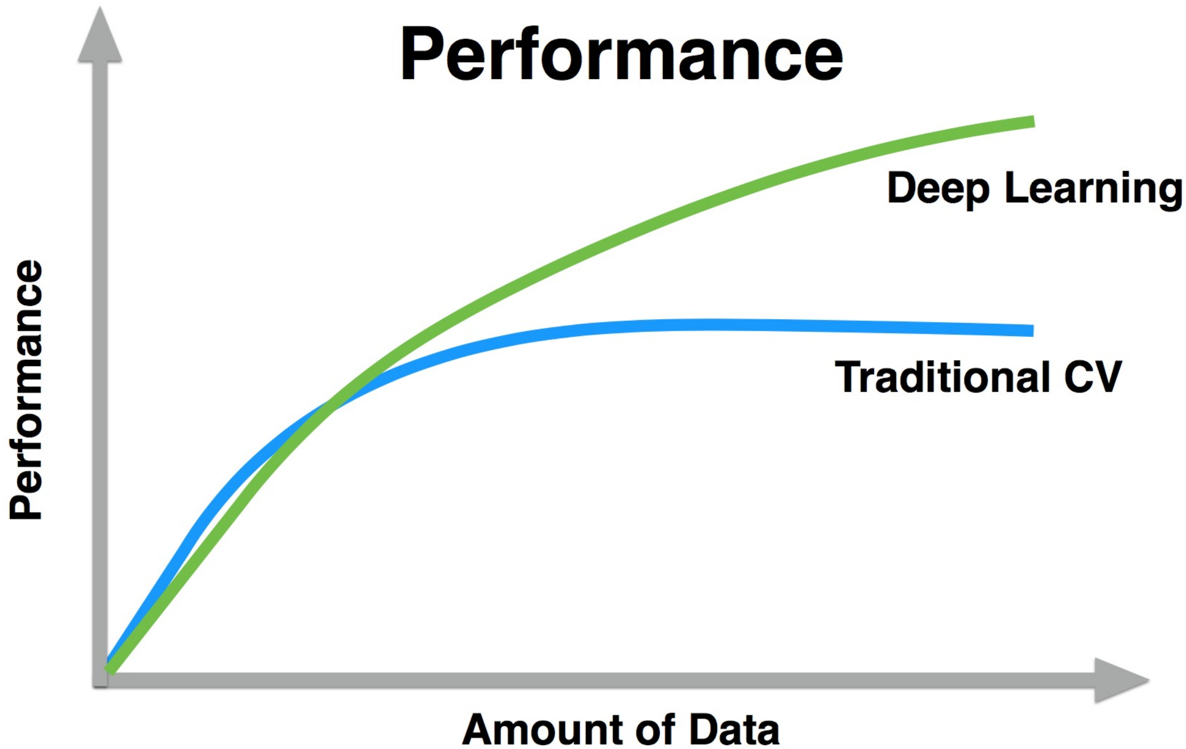
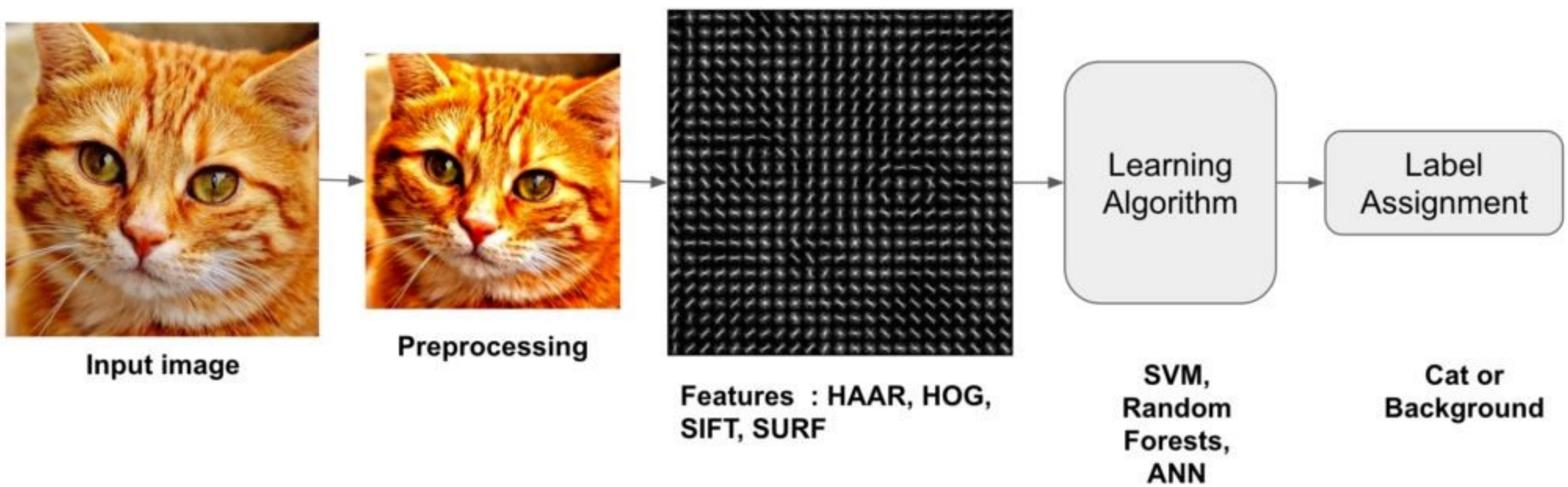
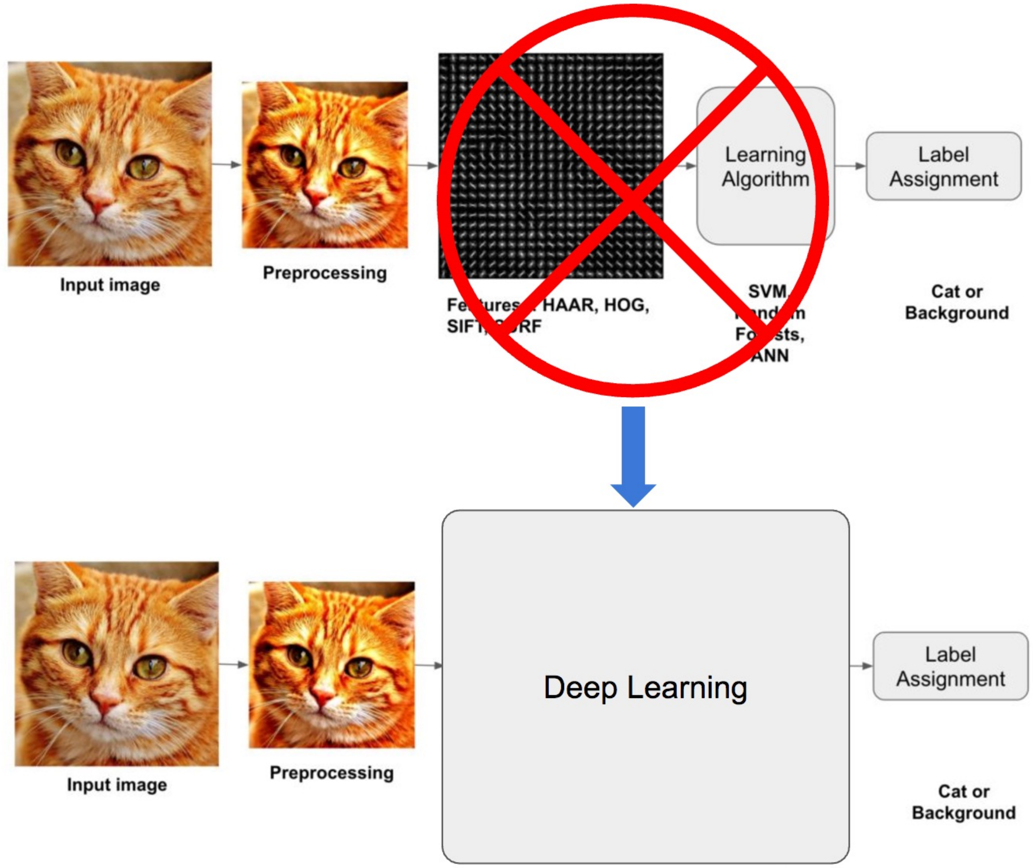


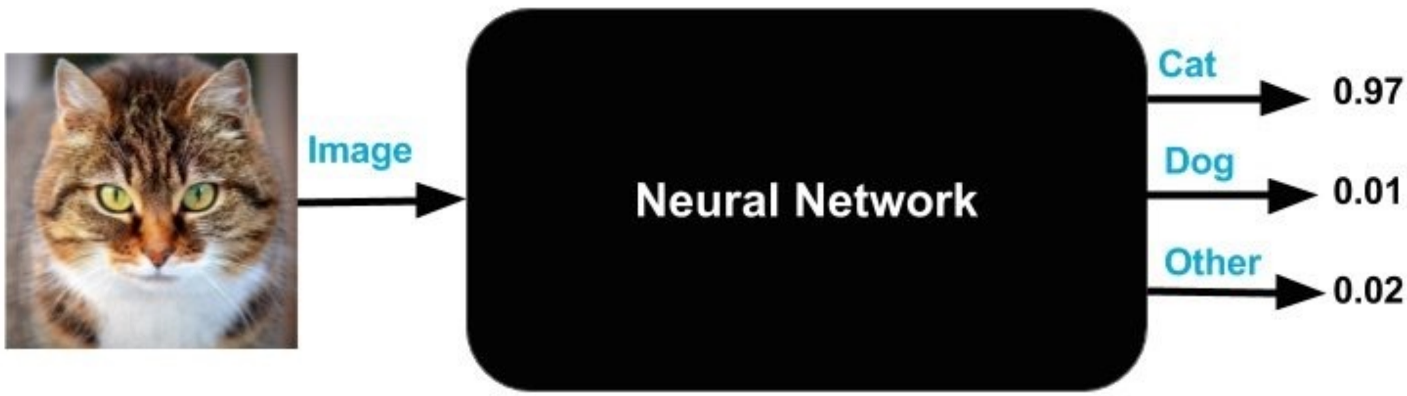
IMAGE CLASSIFICATION PIPELINE



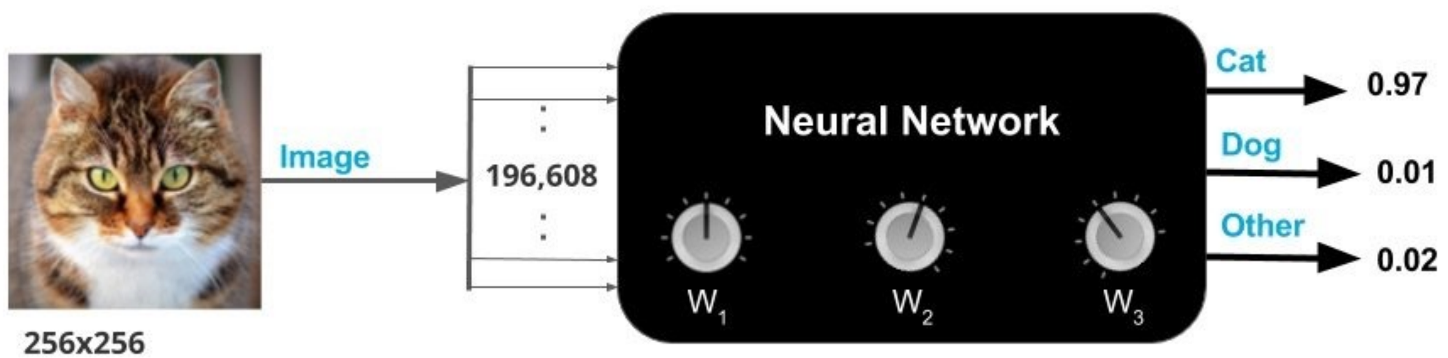
DEEP LEARNING



CONVOLUTIONAL NEURAL NETWORK



TRAINING A NETWORK



TRAINING REQUIREMENTS

1. Training data
   - Thousands of images.

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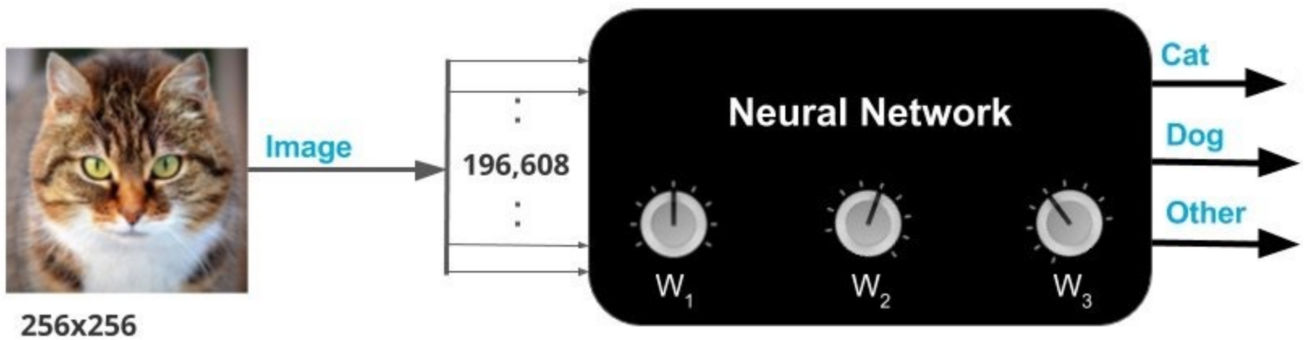
    - Thousands of images with class labels.

FORWARD PASS



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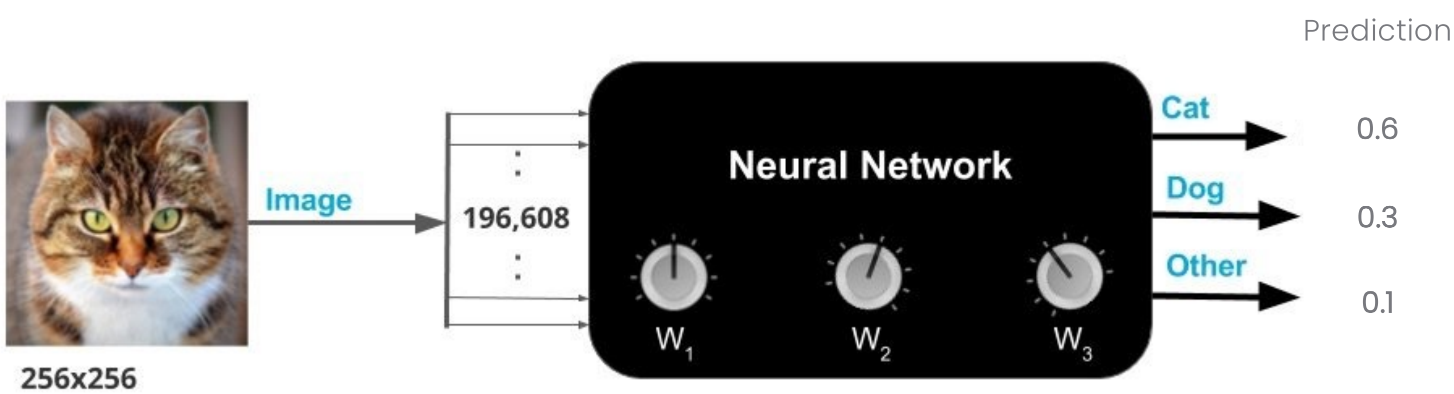

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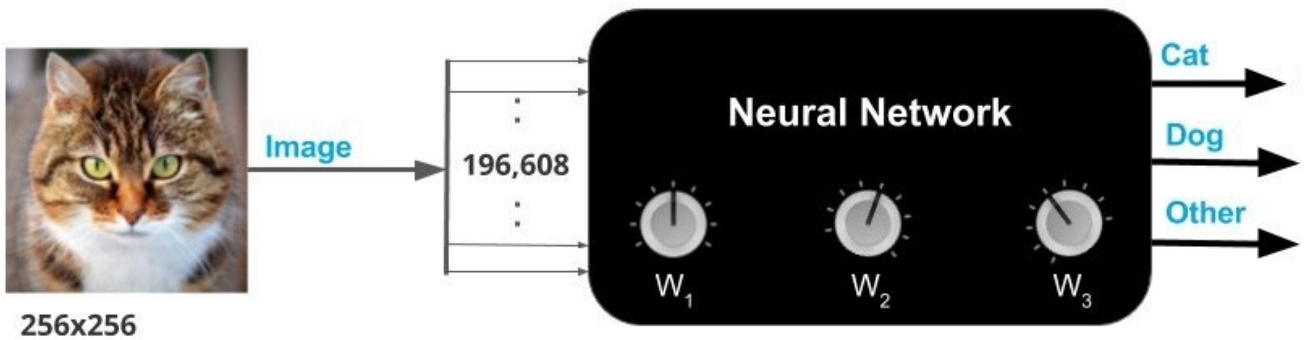
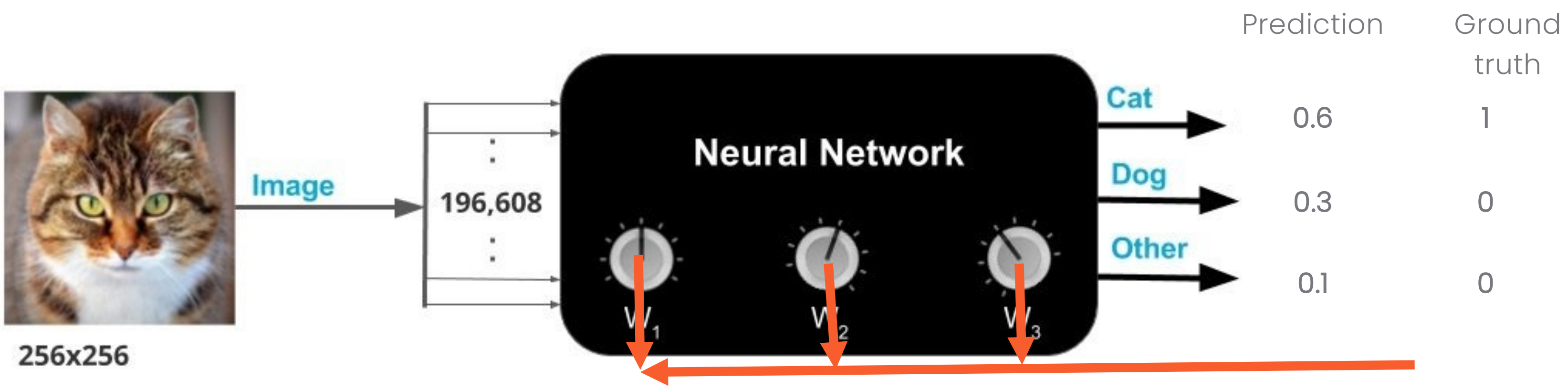


	Prediction	Ground truth
Cat	0.6	1
Dog	0.3	0
Other	0.1	0

CHANGE WEIGHTS



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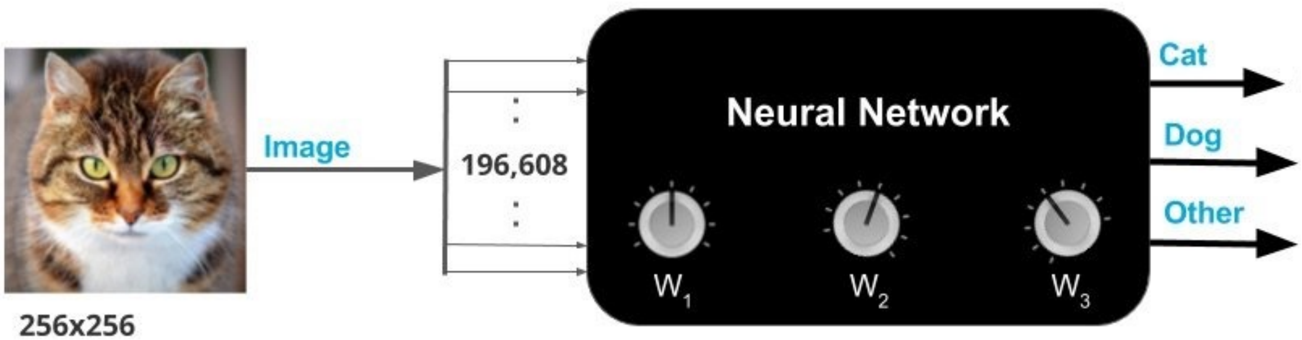
   - Returns low value when the network is accurate on training data.

SSE LOSS



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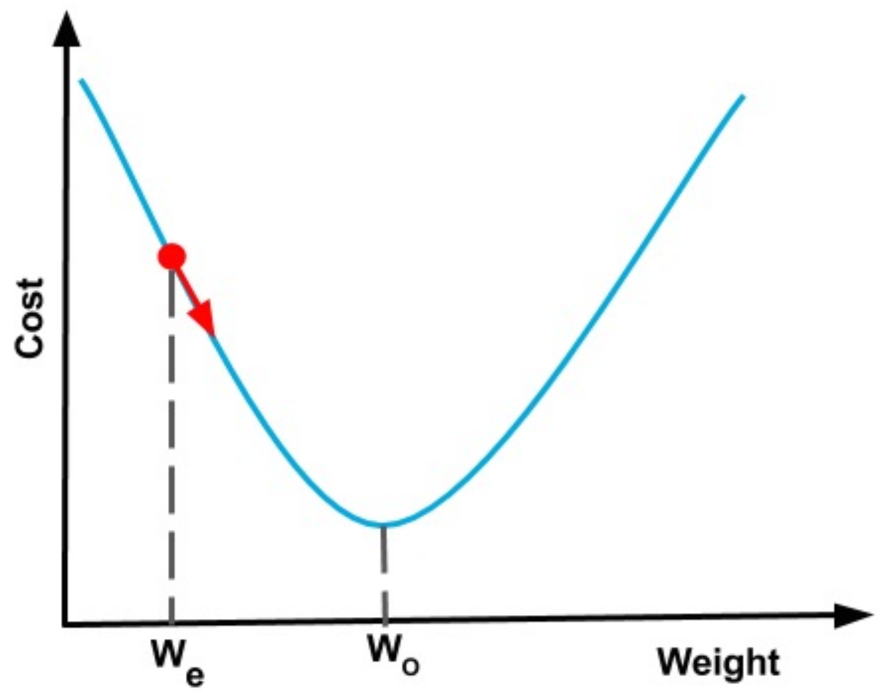
SSE LOSS =

$$(0.6 - 1.0)^2 + (0.3 - 0.0)^2 + (0.1 - 0.0)^2 = 0.26$$

GRADIENT DESCENT



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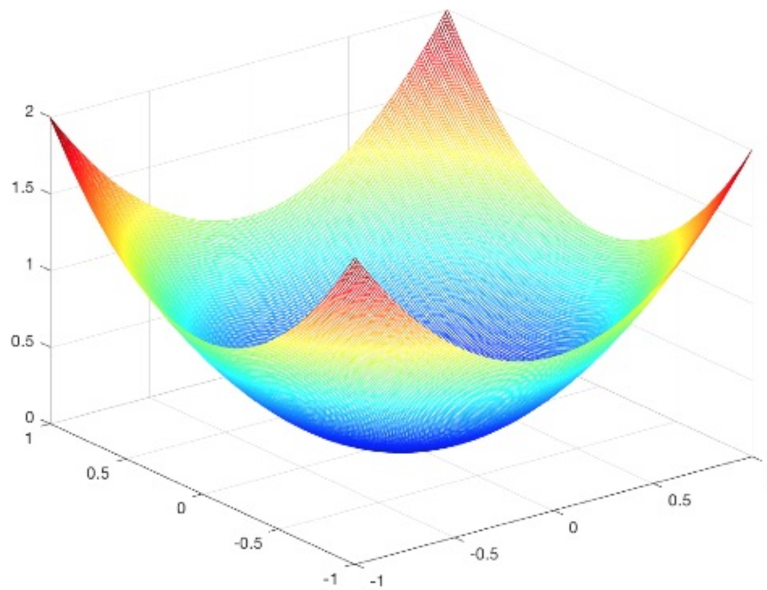

BACKPROPAGATION

The algorithm used for estimating the gradient of the loss function is called **Backpropagation**.

Backpropagation is essentially chain rule applied repeatedly.

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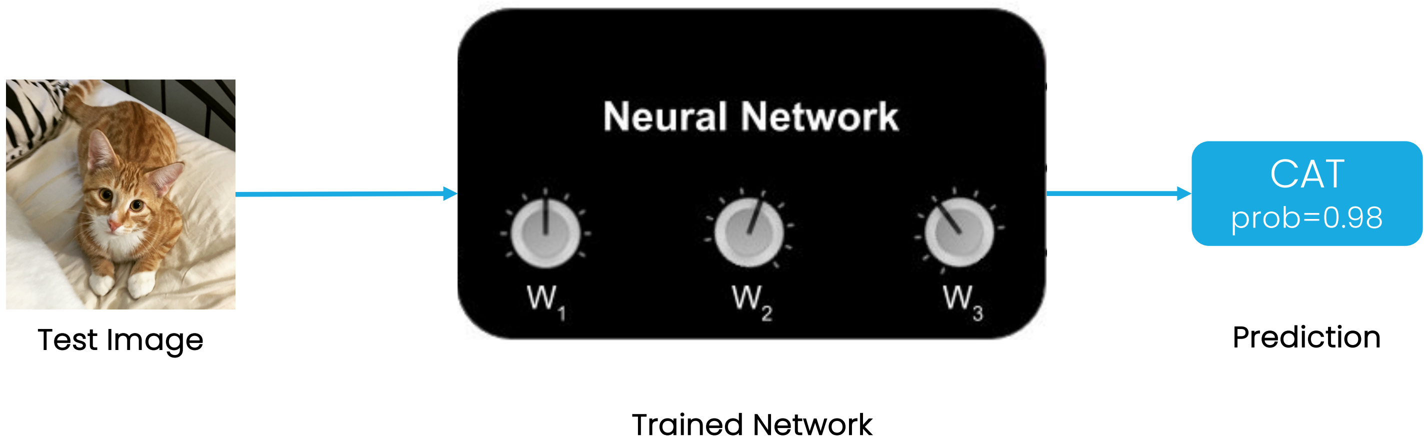
5. Training is done by showing the network data with known answers.
6. Backpropagation is used to estimate the gradient of the loss function with respect to parameters.
7. An optimizer like Gradient Descent is used to find the minimum for the loss function.

INFERENCE


Neural Network
W1
W2
W3
CAT
prob=0.98
Test Image
Trained Network
Prediction

OPENCV DNN MODULE

OPENCV DNN MODULE

TRAINING

TensorFlow

PyTorch

Caffe

Darknet

OPENCV DNN MODULE

TRAINING	INFERENCE
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TensorFlow	TensorFlow
PyTorch	PyTorch
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OPENCV DNN MODULE

PROS

1. Simply import models in your OpenCV C++ or Python applications.
2. OpenCV DNN module is much faster than other frameworks

OPENCV DNN MODULE

PROS	CONS
1. Simply import models in your OpenCV C++ or Python applications. 2. OpenCV DNN module is much faster than other frameworks	1. New layers may not be supported

OPENCV MODEL ZOO

CLASSIFICATION

AlexNet
GoogleNet
CaffeNet
RCNN_ILSVRC13
ZFNet512
VGG16, VGG16_bn
ResNet-18v1, ResNet-50v1
CNN Mnist
MobileNetv2
LResNet100E-IR
Emotion FERPlus
Squeezenet
DenseNet121
Inception v1, v2
Shufflenet

OBJECT DETECTION

YOLOv3
SSD VGG
MobileNet-SSD
Faster-RCNN
R-FCN
OpenCV face detector
TinyYolov2

SEGMENTATION

FCN
ENet
ResNet101_DUC_HDC
Mask R-CNN

OTHER

OpenPose
EAST Text Detection
Style Transfer
Colorization

OPENCV DNN MODULE

READ NET

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Read the network using **`readNet`**

1. Config File
2. Weights file

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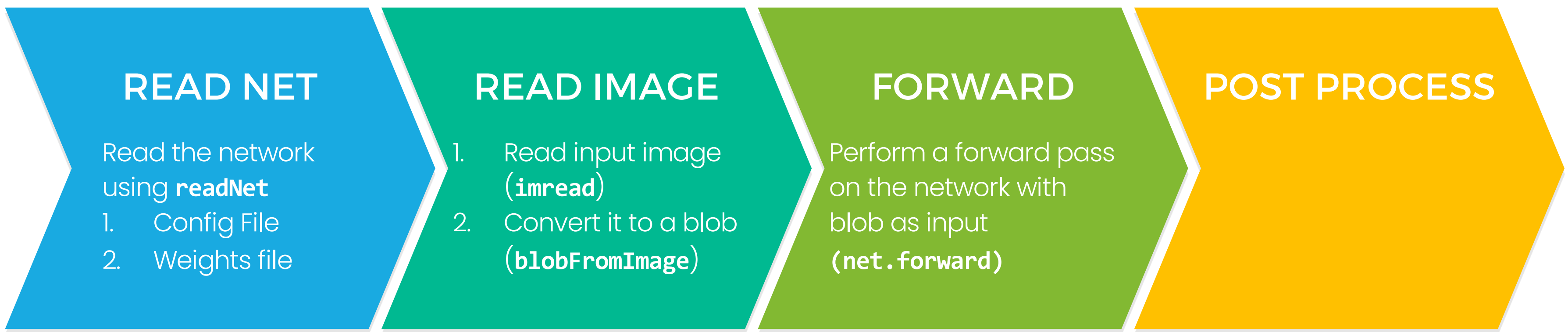
Perform a forward pass on the network with blob as input **`(net.forward)`**

OPENCV DNN MODULE



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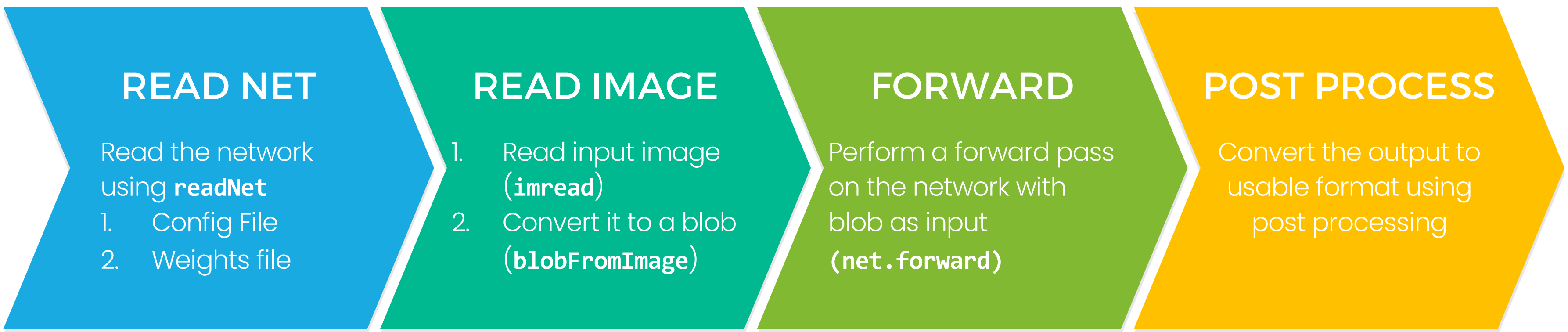
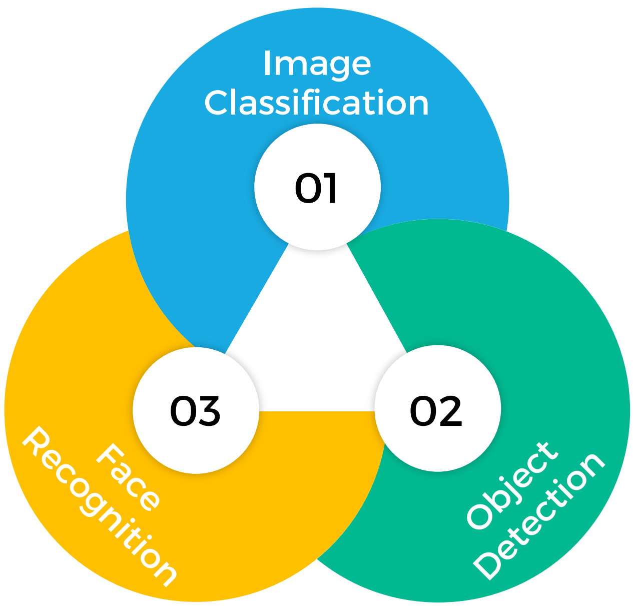


TOPICS COVERED



01 **Image Classification**

DenseNet

02 **Object Detection**

YOLO v4

03 **Face Recognition**

YuNet Face Detection

SFace Recognition

THANK YOU