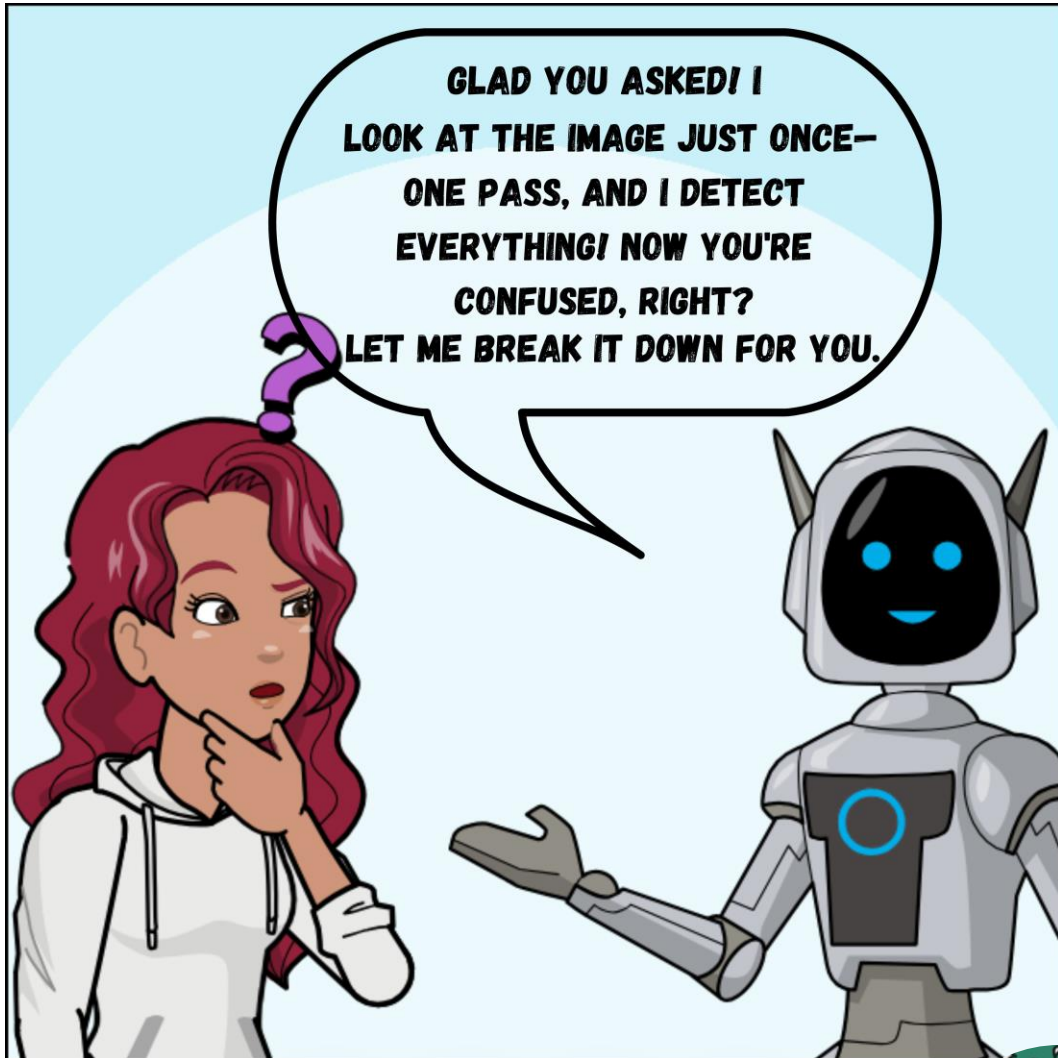


Visual Computing MAGAZiNE

Vol. 2, Issue 2
2024



CHRONICLE OF COMPUTER VISION



Visual Computing Magazine

The Foreword

In this issue, we feature a series of posters made by Visual Computing Master students of USTHB University, each highlighting specific moments that redefined computer vision. We begin with the concept of “Pandemonium” (1958), which laid the foundation for the perception of visual information through hierarchical processes. We then look at extracting 3D information from 2D images (1963) and highlight the landmark Summer Vision project (1966), which was an ambitious attempt to bring perception to machines at MIT.

Key breakthroughs followed: HOUGH's transformation (1972), optical flow and motion perception in 1981, and David Marr's paradigm of visual representation (1982). These developments were followed by tools such as the Canny Edge detector (1986) and object detection including the Viola-Jones detector (2001). The new millennium ushered in advances such as SIFT (2004) and SURF (2006), essential for primitive detection, and classifiers such as support vector machines (SVM, 2008).

The introduction of AlexNet in 2012 marked the beginning of the deep learning era, which saw models like GANs (2014), GoogleNet (2014) and ResNets (2015) bring remarkable advancements to the discipline. Recent innovations, including Vision Transformers (2021) and DALL-E 3 (2023), are pushing the boundaries of machine understanding and creative generation.

Each poster provides a window into these achievements, capturing the essence of the ideas and advances that have advanced computer vision over the decades.

Chief Editor, Prof. Slimane LARABI
Computer Science Faculty
USTHB University, Algeria

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Visual Computing: A quarterly magazine. Volume 2, Issue 2, 2024
ISSN: 2830-9820
Chief Editor: Prof. Slimane LARABI




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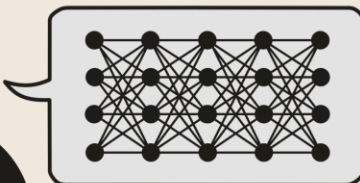
CHRONICLE OF COMPUTER VISION

EVENT: CONCEPT OF A "PANDEMONIUM", 1958

I. TIMSILINE, A. ABDENNOUZ, MASTER 2 VISUAL COMPUTING, USTHB



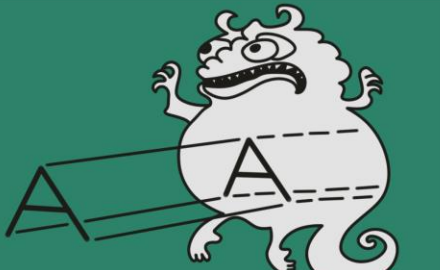
DEMONS!?



BUT HOW IS THAT RELATED TO COMPUTER VISION?

In Pandemonium, "demons" are simple detectors working together to recognize patterns (a foundational idea in AI vision).

IMAGE DEMON SCANS THE INPUT



1

FEATURE DEMONS DETECT DISTINCT FEATURES




2

LOUDEST IS PICKED BY DECISION DEMON



4

COGNITIVE DEMONS RECOGNIZE PATTERNS



3

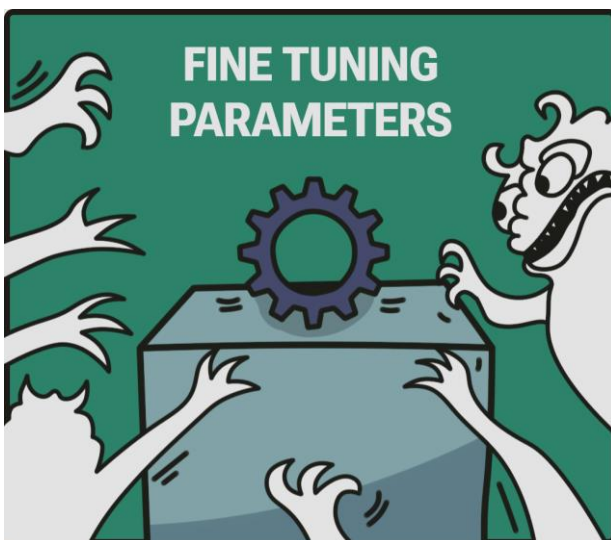


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CHRONICLE OF COMPUTER VISION

EVENT: CONCEPT OF A "PANDEMONIUM", 1958

I. TIMSILINE, A. ABDENNOUZ, MASTER 2 VISUAL COMPUTING, USTHB



PANDEMONIUM INFLUENCE

-  DEEP LEARNING MODELS
-  SPEECH RECOGNITION
-  OCR SYSTEMS
-  NLP CONTRIBUTION

REFERENCES

- O. G. Selfridge, "Pandemonium: a paradigm for learning," Mechanisation of Thought Processes: Proceedings of a Symposium Held at the National Physical Laboratory, November 1958
- Hinton, L. (1977). Illustration. In D. A. Lindsey & N. A. Norman (Eds.), Human Information Processing (p. 116). Academic Press, Inc.

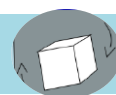
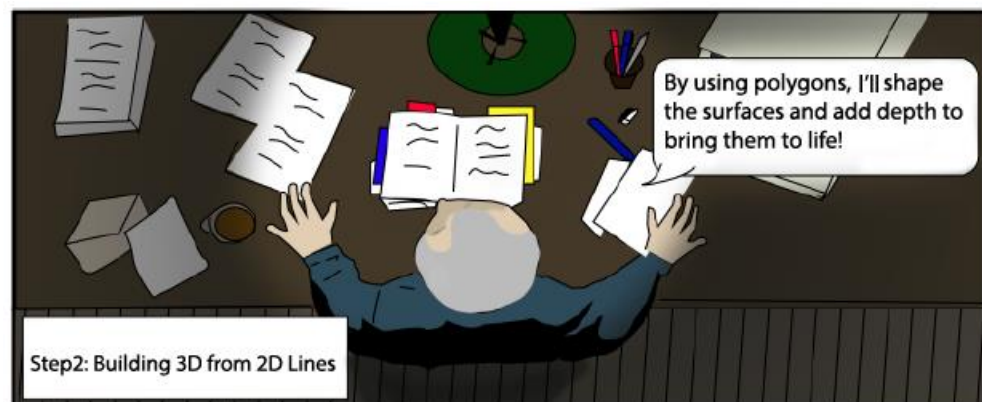
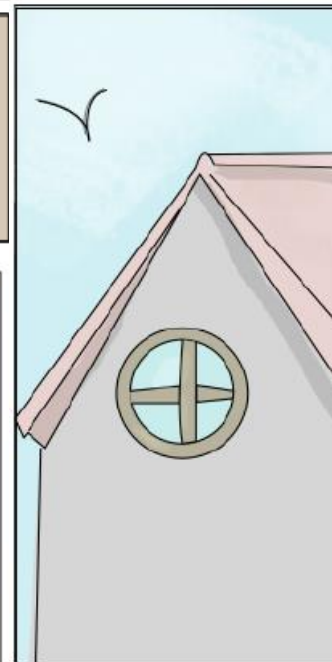
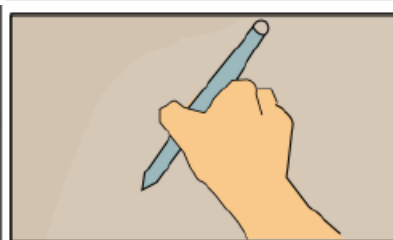
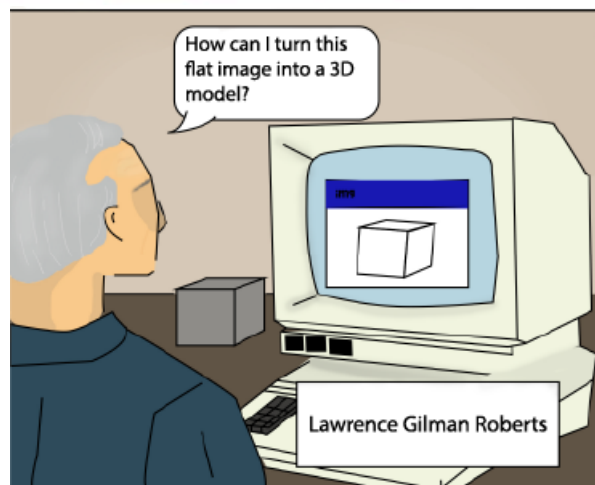


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EVENT: 3D information from 2D photographs , 1963

Y. ABOURA, M. LATIF, MASTER 2 VISUAL COMPUTING, USTHB

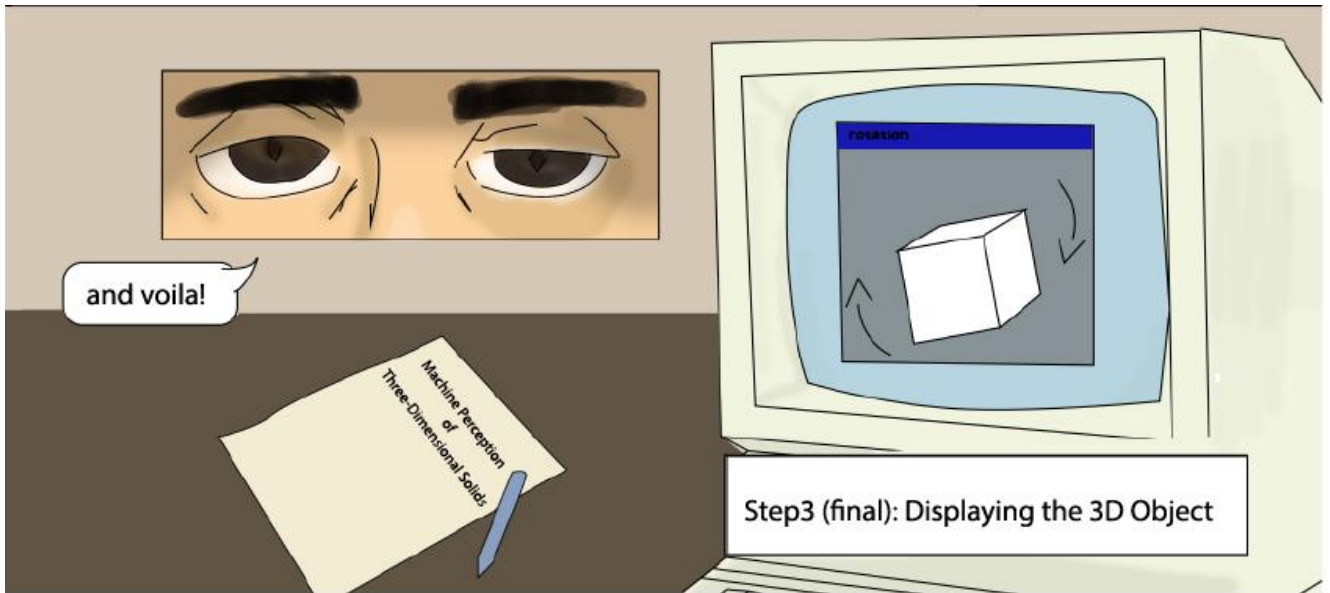


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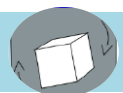
EVENT: 3D information from 2D photographs , 1963

Y. ABOURA, M. LATIF, MASTER 2 VISUAL COMPUTING, USTHB



Reference:

Roberts, Lawrence G., Machine perception of three-dimensional solids. Thesis (Ph. D.). Massachusetts Institute of Technology, Dept. of Electrical Engineering, 1963.



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CHRONICLE OF COMPUTER VISION

EVENT: Summer Vision Project, 1966

H. KADIRI, MASTER 2 VISUAL COMPUTING, USTHB

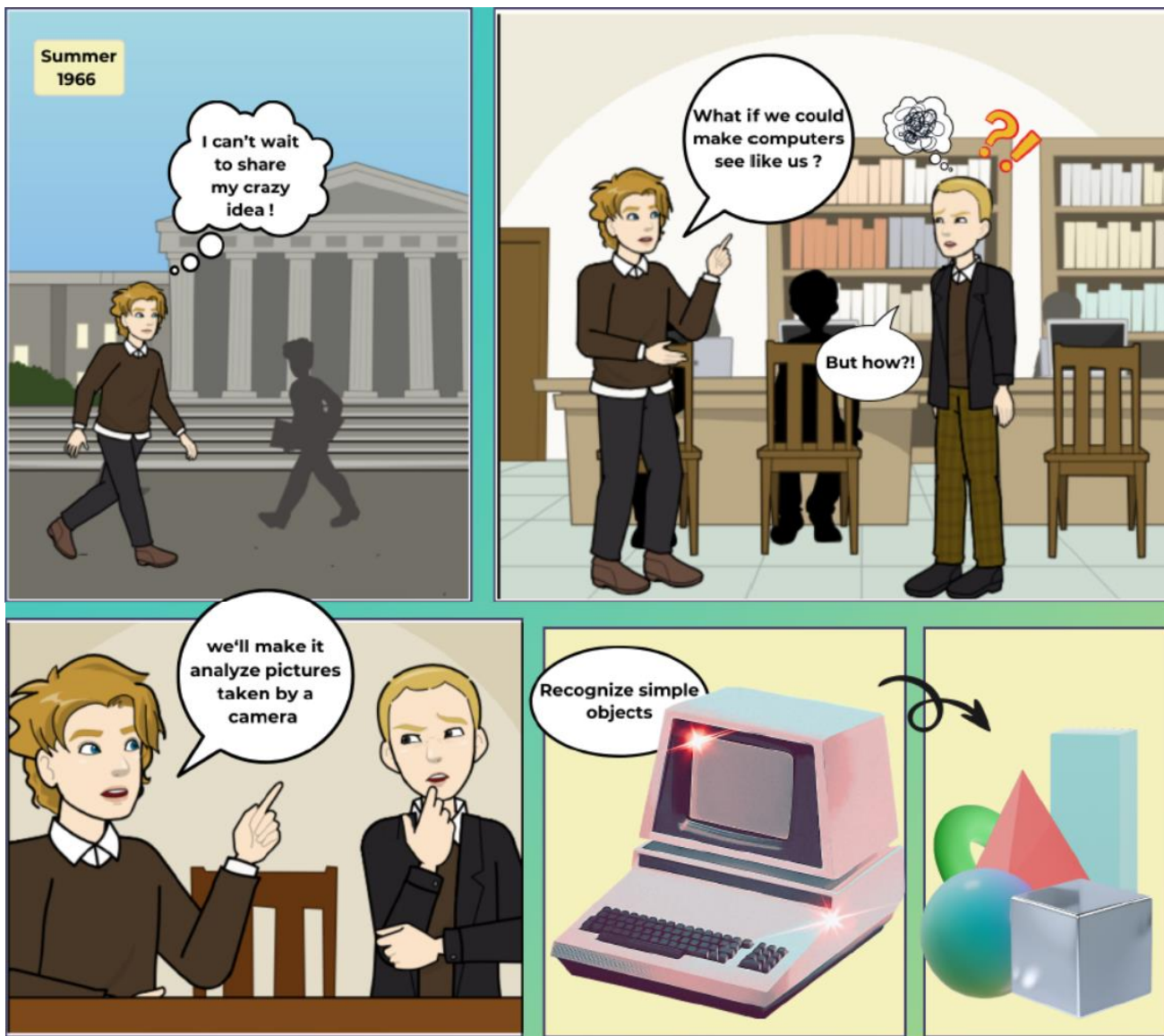


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CHRONICLE OF COMPUTER VISION

EVENT: Summer Vision Project, 1966

H. KADIRI, MASTER 2 VISUAL COMPUTING, USTHB

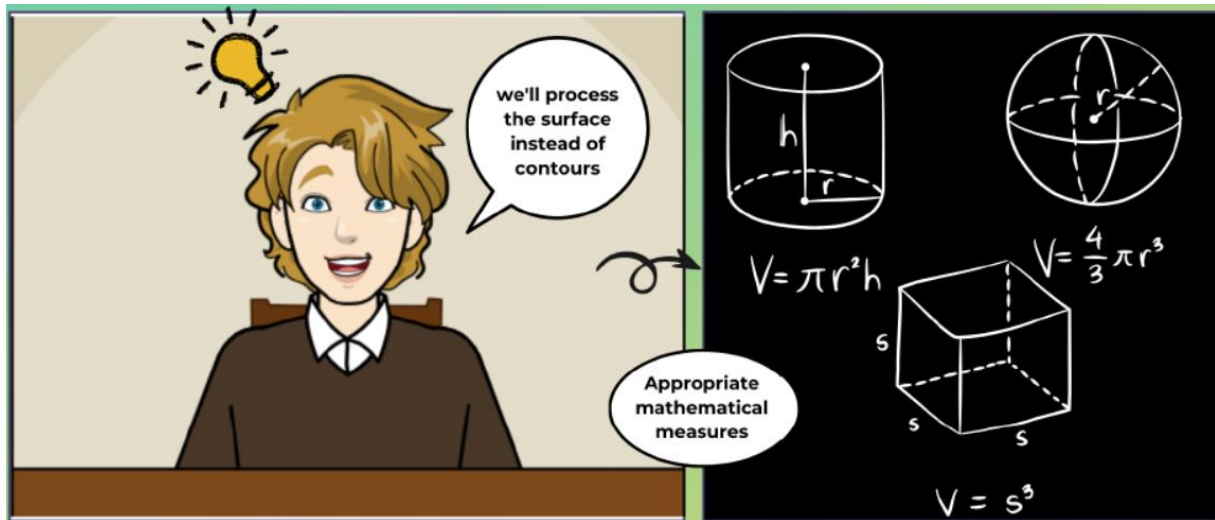


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CHRONICLE OF COMPUTER VISION

EVENT: Summer Vision Project, 1966

H. KADIRI, MASTER 2 VISUAL COMPUTING, USTHB



Reference:

Seymour Papert, The summer vision project, MIT, 1966
<https://people.csail.mit.edu/brooks/idocs/AIM-100.pdf>

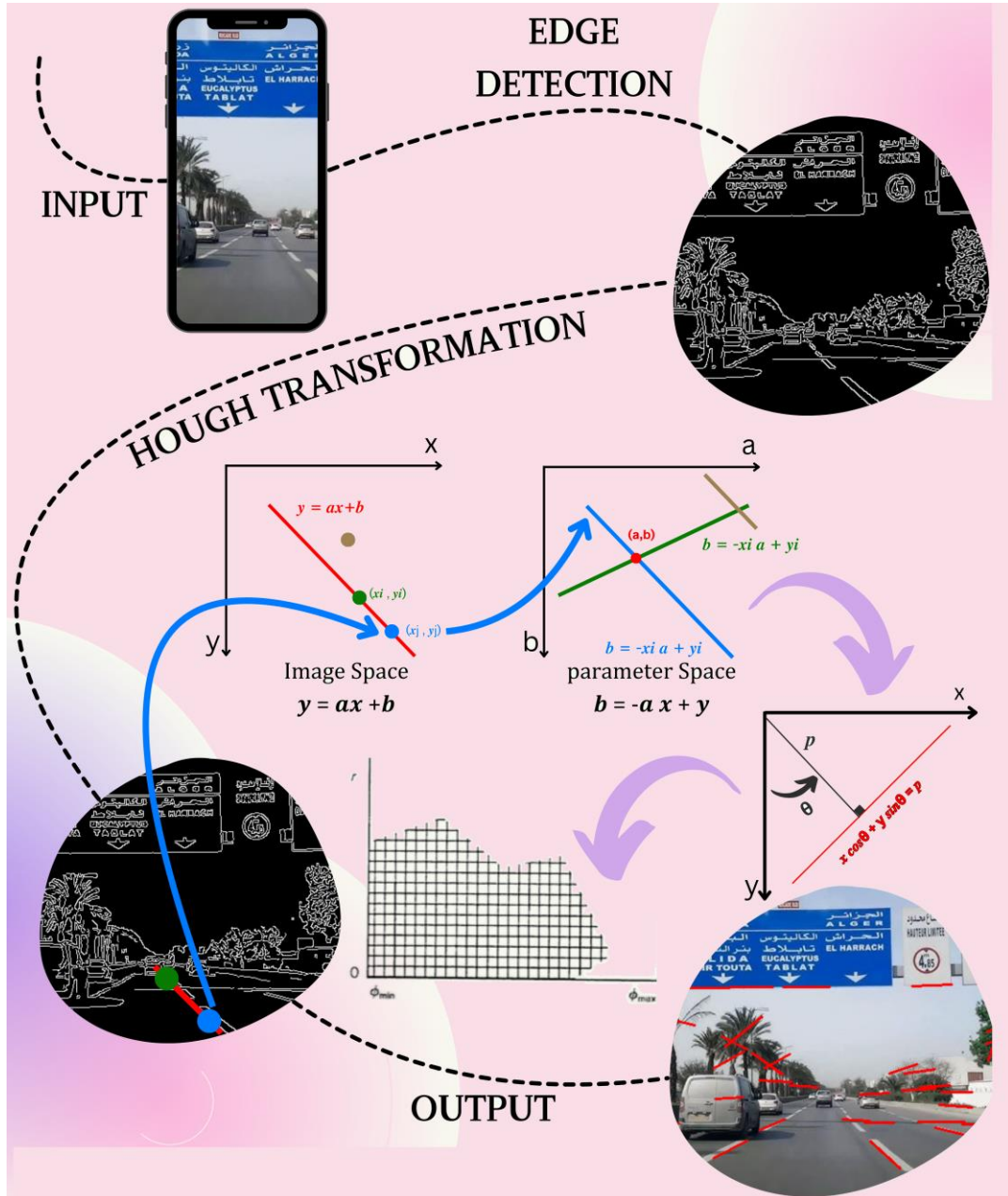


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CHRONICLE OF COMPUTER VISION

EVENT: HOUGH Transform, 1972

A. BOUCENNA, A. OUHIB, MASTER 2 VISUAL COMPUTING, USTHB



Reference: Richard O. Duda, Peter E. Hart. Use of the Hough transformation to detect lines and curves in pictures. Communications of the ACM, Volume 15, Issue 2, 1972



CHRONICLE OF COMPUTER VISION

EVENT: SFM Structure From Motion, 1981

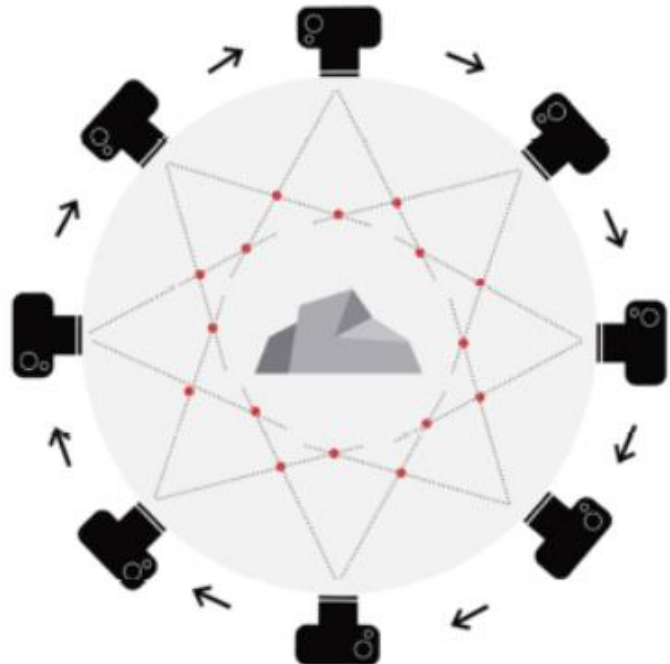
H. SAAD, M. MEZIANI, MASTER 2 VISUAL COMPUTING, USTHB

Structure from Motion is an algorithm that allows to recreate 3D objects into a cloud of points by simply taking a few images from different angles



Image Acquisition

Capture multiple 2D images of an object or scene from different angles using a regular camera



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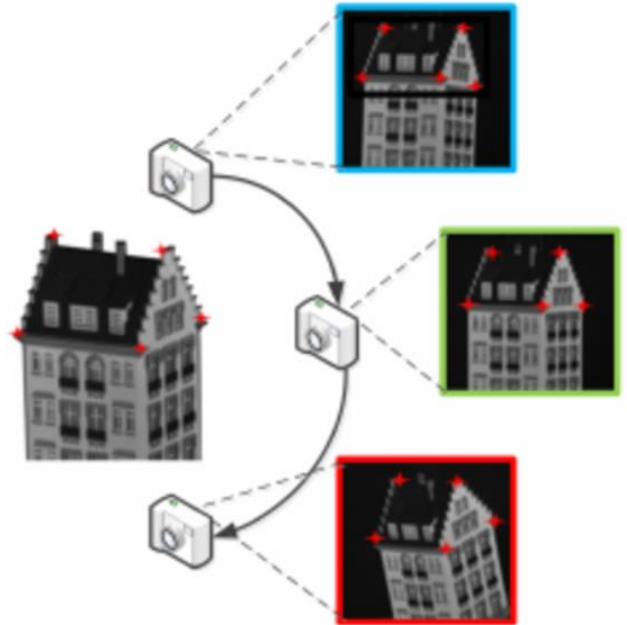
CHRONICLE OF COMPUTER VISION

EVENT: SFM Structure From Motion, 1981

H. SAAD, M. MEZIANI, MASTER 2 VISUAL COMPUTING, USTHB

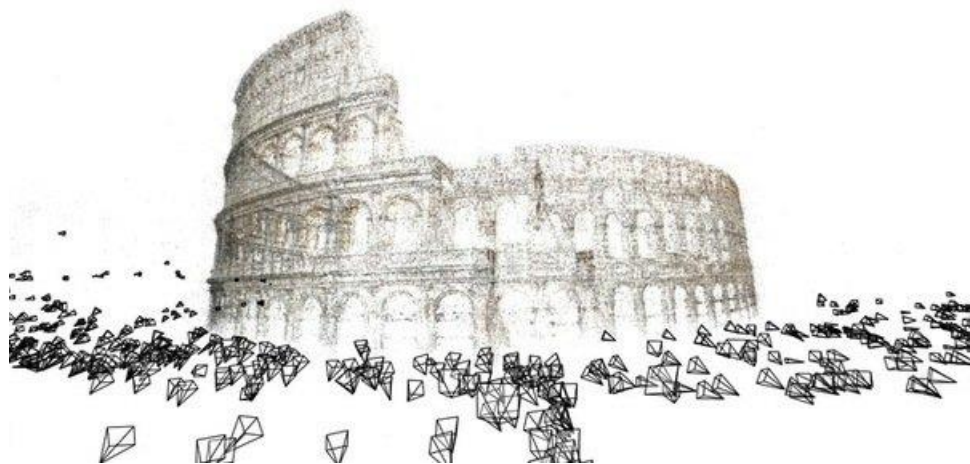
Feature Detection & Matching

The system identifies key features across the images and matches them to find overlapping parts between different pictures.



Sparse 3D Reconstruction

With camera poses known, the algorithm builds a basic 3D model by plotting key points in 3D space.



Reference: H.C. Longuet-Higgins. A computer algorithm for reconstructing a scene from two projections. Nature, vol. 293, pp. 133-135, 1981



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CHRONICLE OF COMPUTER VISION

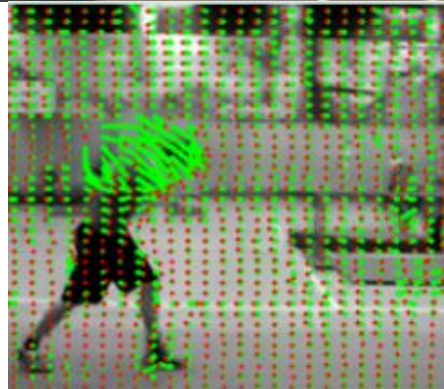
EVENT: Optical Flow, 1981

K. AMROUNI, R. KADOUM, MASTER 2 VISUAL COMPUTING, USTHB

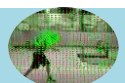
Optical flow is used in computer vision to estimate the motion of objects between consecutive frames in a video. It looks at how pixels in an image move from one frame to the next and creates motion maps.



- Motion flow can be used for :
- object tracking
 - Robotics
 - VR, to make a more interactive world



Constraints :

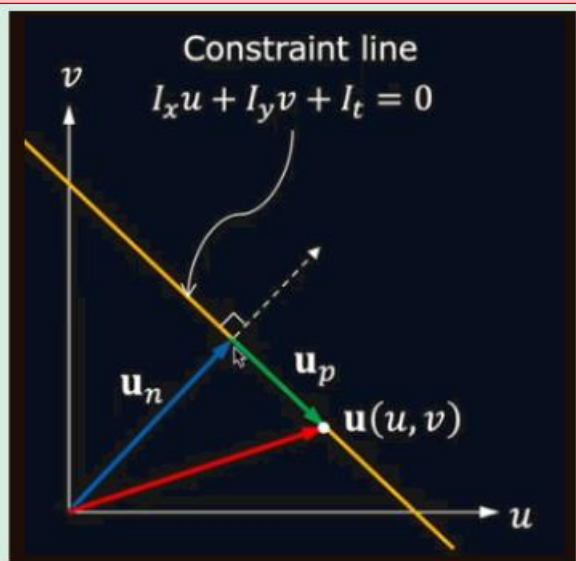


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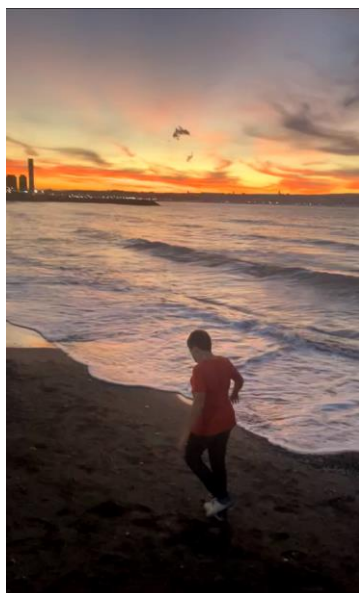
CHRONICLE OF COMPUTER VISION

EVENT: Optical Flow, 1981

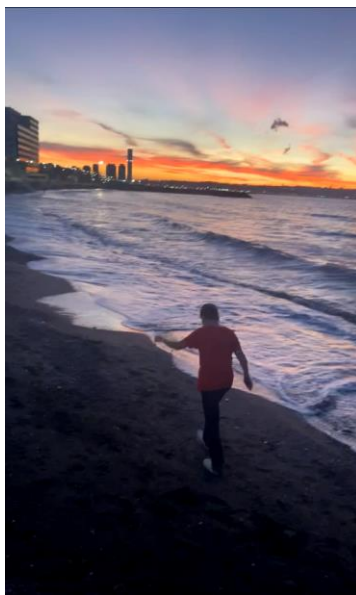
K. AMROUNI, R. KADOUM, MASTER 2 VISUAL COMPUTING, USTHB



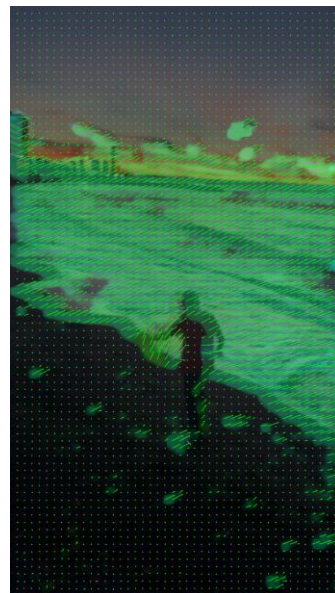
The value of the optical flow is on the constraint line.



Frame 1

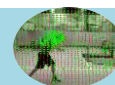


Frame 2



Optical flow

Reference: Berthold K.P. Horn, Brian G. Schunck. Determining optical flow. Artificial Intelligence. Volume 17, Issues 1-3, August 1981, Pages 185-203



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CHRONICLE OF COMPUTER VISION

EVENT: David Marr's Paradigm, 1982

H. KACIOUSSALEH, Z. BISKRI, MASTER 2 VISUAL COMPUTING, USTHB



David Marr

David Marr (1945–1980): a British psychologist and neuroscientist known for his extensive research on vision and visual information processing.



general theoretical framework for understanding visual perception



information processing process



1 computational



Describe the problem solved by an information processing system.

2 algorithmic



Transformation of information

3 implementation



Implementation of algorithmic in physical hardware

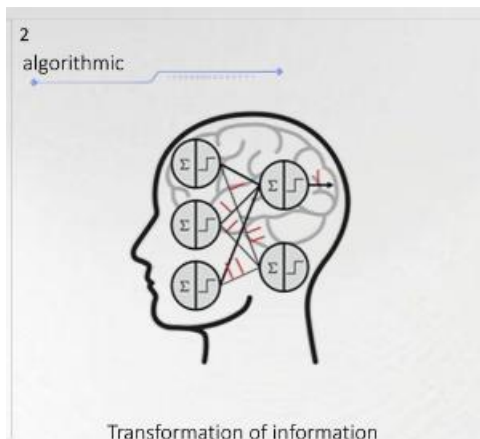
REFERENCE :David Marr. Vision: A Computational Investigation into the Human Representation and Processing of Visual Information. 1982.



CHRONICLE OF COMPUTER VISION

EVENT: David Marr's Paradigm, 1982

H. KACIOUSSALEH, Z. BISKRI, MASTER 2 VISUAL COMPUTING, USTHB



❖ Primal sketch



Raw primal sketch



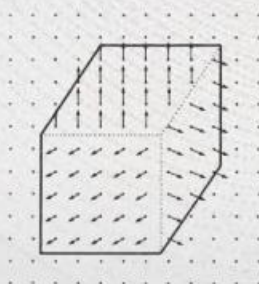
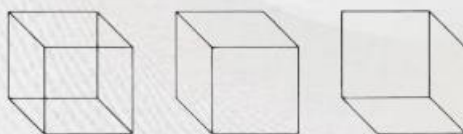
Level 1 solens



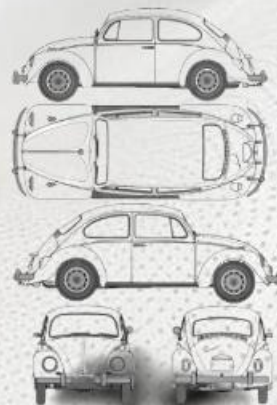
Level 2 boundary



❖ 2- 1/2 D sketch:



❖ Representation 3D model:

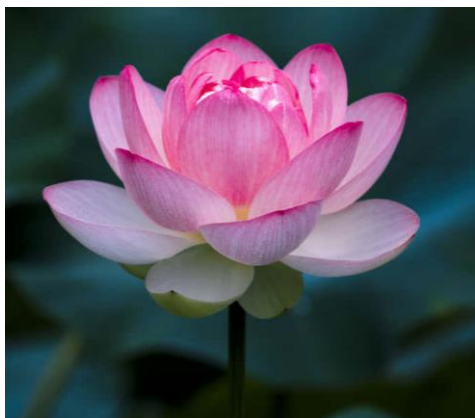


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CHRONICLE OF COMPUTER VISION

EVENT: Canny Edge Detector, 1986

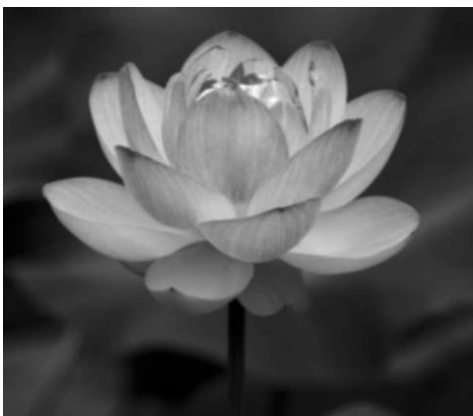
A. R. BADRI, A. MEKKAOUI, MASTER 2 VISUAL COMPUTING, USTHB



Original image



Conversion to Grayscale



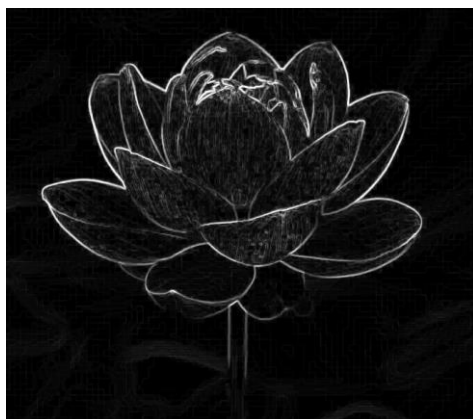
Blurring with a Gaussian



X-Gradient



Y-Gradient



Sobel result magnitude



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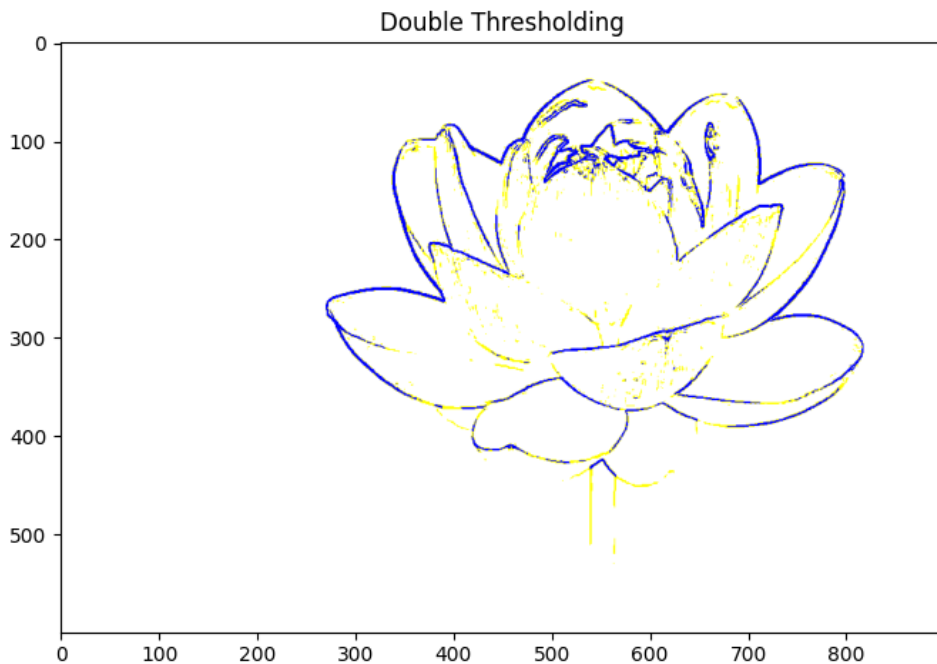
CHRONICLE OF COMPUTER VISION

EVENT: Canny Edge Detector, 1986

A. R. BADRI, A. MEKKAOUI, MASTER 2 VISUAL COMPUTING, USTHB



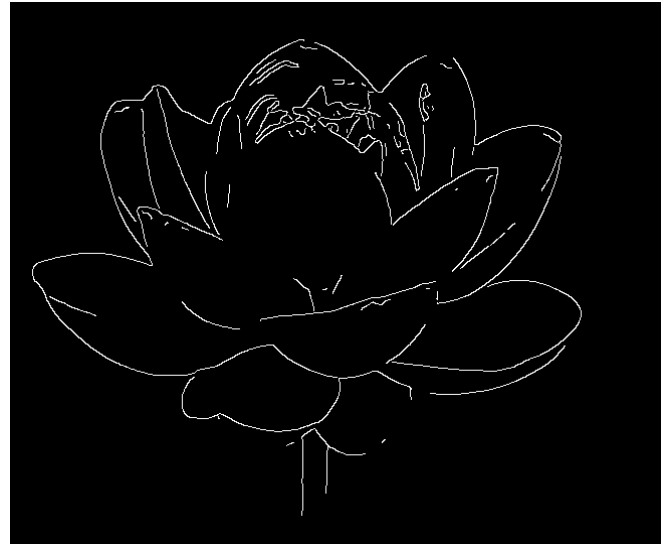
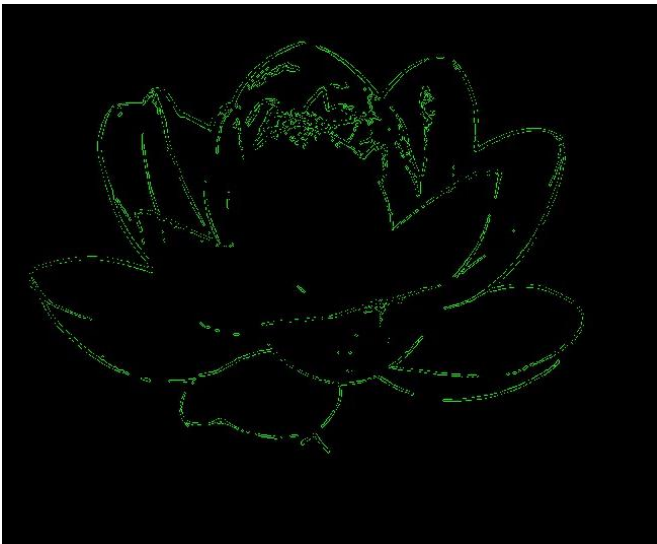
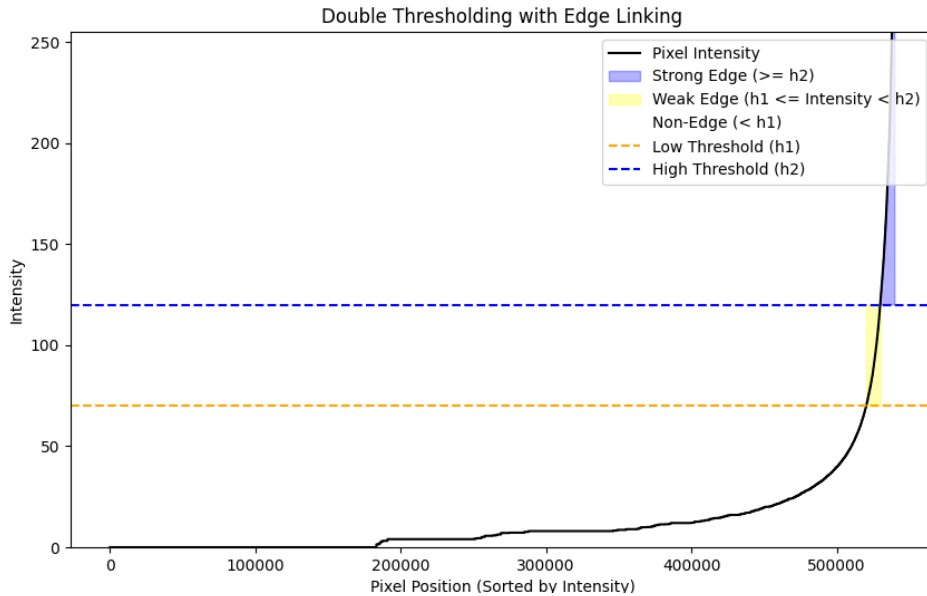
Non Maxima suppression



CHRONICLE OF COMPUTER VISION

EVENT: Canny Edge Detector, 1986

A. R. BADRI, A. MEKKAOU, MASTER 2 VISUAL COMPUTING, USTHB



Reference: J. Canny, "A Computational Approach to Edge Detection," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-8, no. 6, pp. 679-698, Nov. 1986

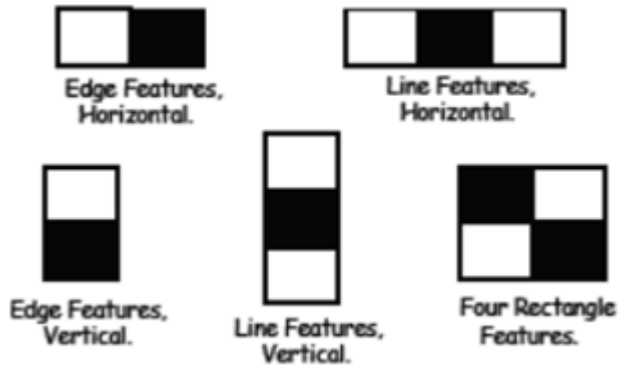
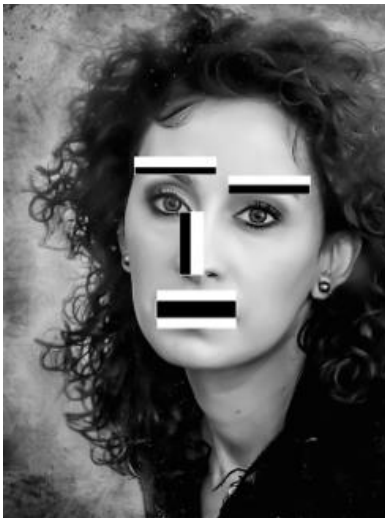
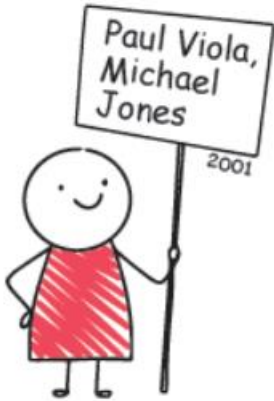


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CHRONICLE OF COMPUTER VISION

EVENT: Viola-John Detector, 2001

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Extraction of Haar features



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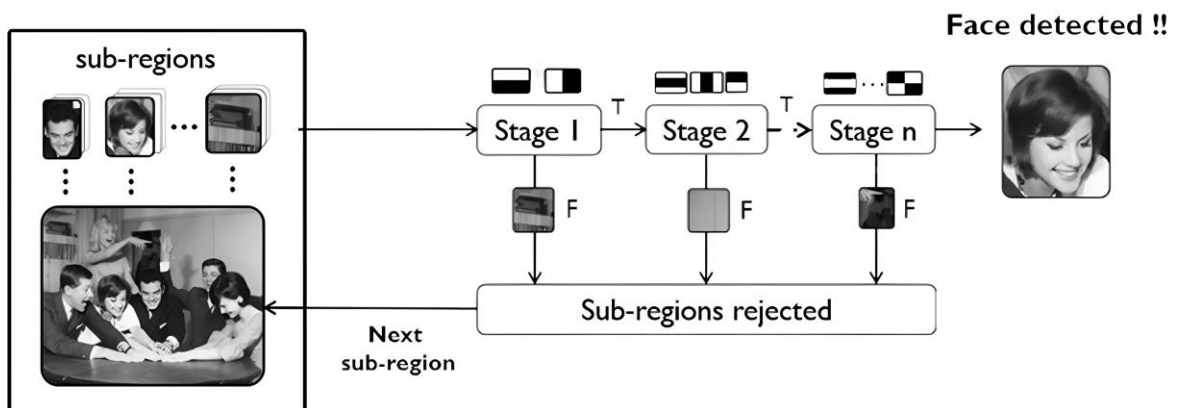
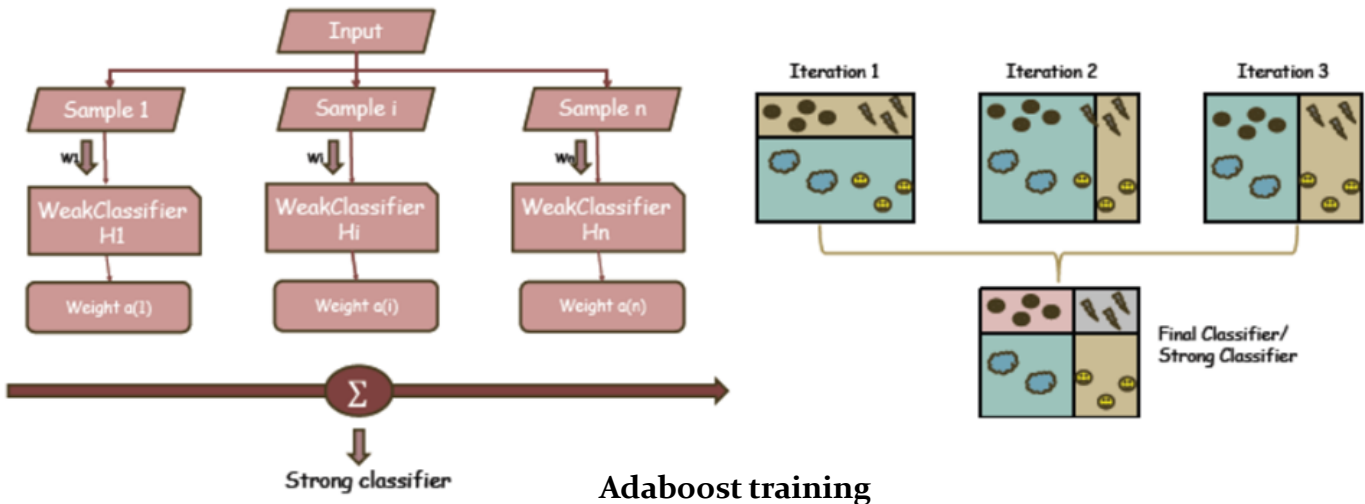
EVENT: Viola-John Detector, 2001

Y. BELAIDI, K. MAZROU, MASTER 2 VISUAL COMPUTING, USTHB

Source image				Integral image			
0	1	1	1	0	1	2	3
1	2	2	3	1	4	7	11
1	2	1	1	2	7	11	16
1	3	1	0	3	11	16	21

$$0+1+1+1+2+2=7$$

Compute the Integral of image

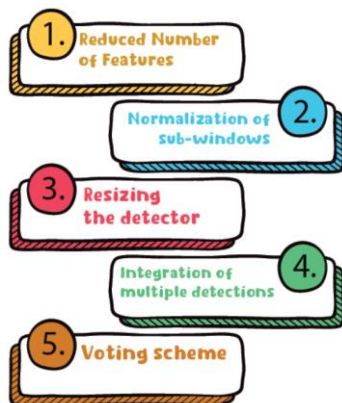


CHRONICLE OF COMPUTER VISION

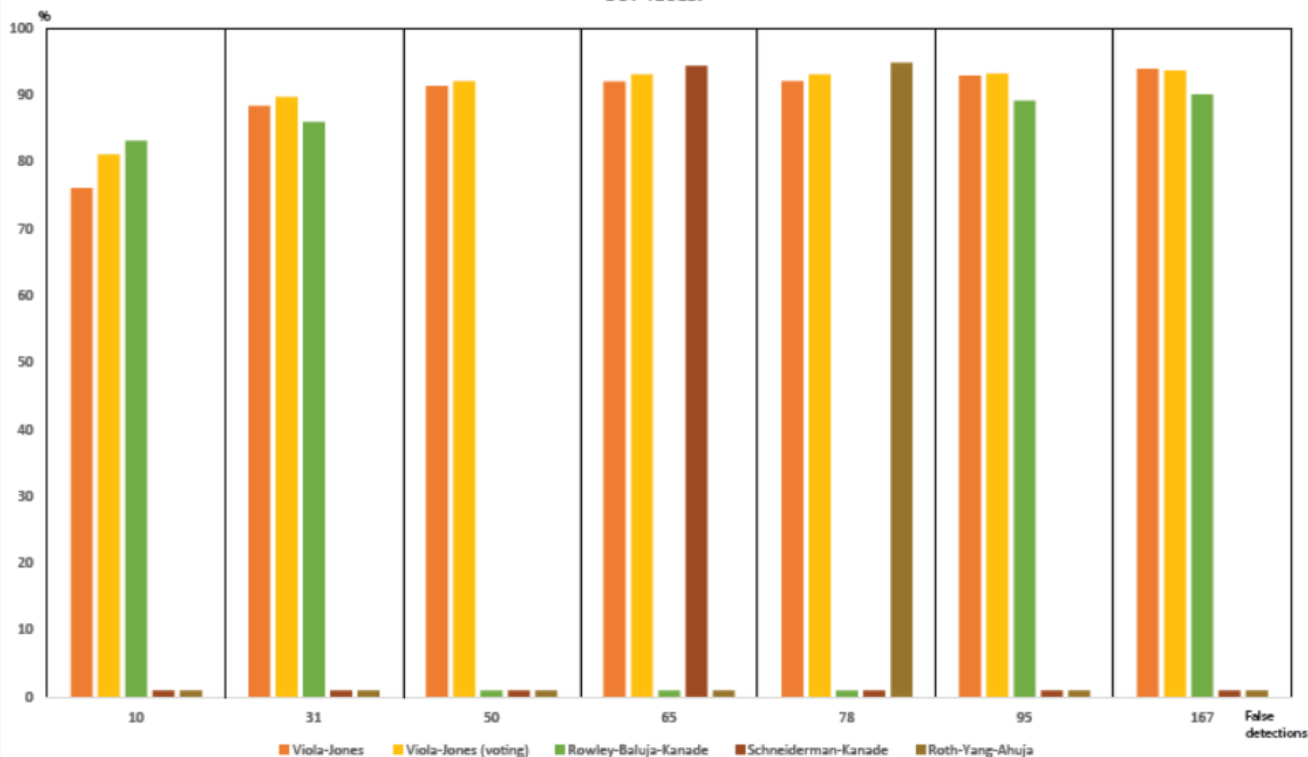
EVENT: Viola-John Detector, 2001

Y. BELAIDI, K. MAZROU, MASTER 2 VISUAL COMPUTING, USTHB

Improvements



Detection rates for various numbers of false positives on the MIT+CMU test set containing 130 images and 507 faces.



Reference: Paul Viola, Michael Jones. Rapid Object Detection using a Boosted Cascade of Simple Features, CVPR 2001



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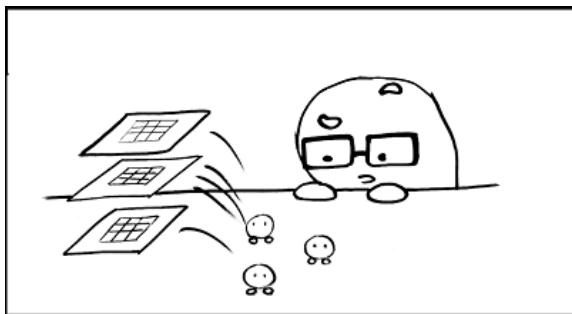
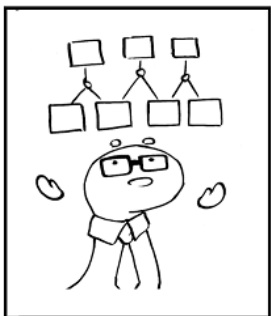
CHRONICLE OF COMPUTER VISION

EVENT: SIFT, 2004

L.R. BOUGUERRA, MASTER 2 VISUAL COMPUTING, USTHB

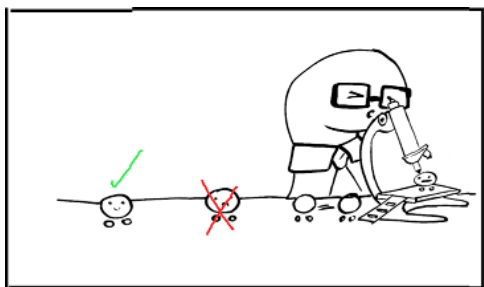


SIFT



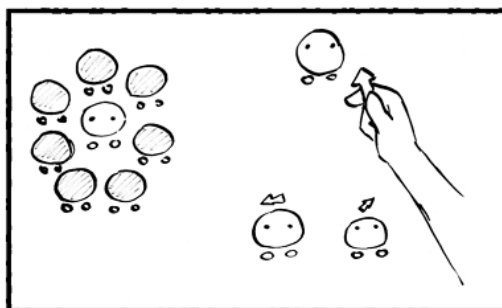
First we create a Scale-Space. We apply the gaussian with value σ and up scale it. then for each two pairs apply the DoG.

we detect the "Key points". using a 3×3 block and choosing the minima or maxima .

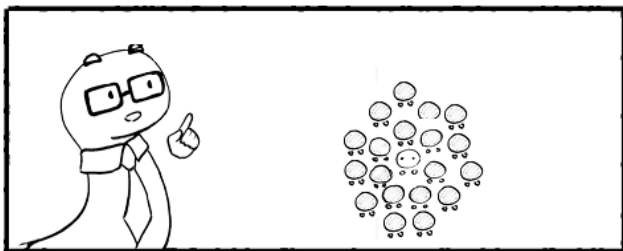


we have to get rid of unstable points:

- the series of Taylor with the expansion of DoG for low-contrast points
- Hessian matrix to eliminait edges.



For the orientation, we select it neighborhood and compute the gradient magnitude and direction, then create a direction histogram, it peak will be the orientation.



We'll repeat the same step except with a bigger neighborhood. and the collection of histograms is the ID.



We add it in the data base.

Reference: Lowe, D.G. Distinctive Image Features from Scale-Invariant Keypoints. International Journal of Computer Vision 60, 91-110 (2004).

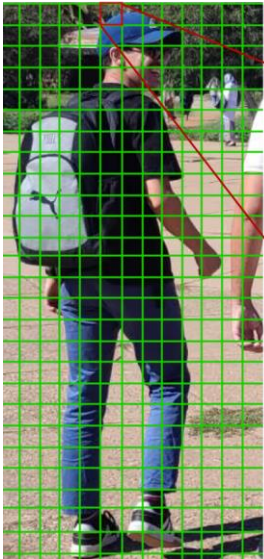


CHRONICLE OF COMPUTER VISION

EVENT: HOG: Histogram of Oriented Gradients, 2005

A. AOUDJ, Y. CHELBI, MASTER 2 VISUAL COMPUTING, USTHB

HOG Computation Process

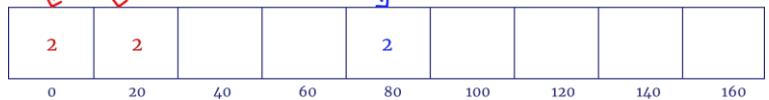


2	3	4	4	3	4	2	2
5	11	17	13	7	9	3	4
11	21	23	27	22	17	4	6
23	99	165	135	85	31	26	2
91	155	133	136	144	152	57	28
98	196	76	38	26	60	170	51
165	60	60	27	77	85	43	136
71	13	34	23	108	27	48	110

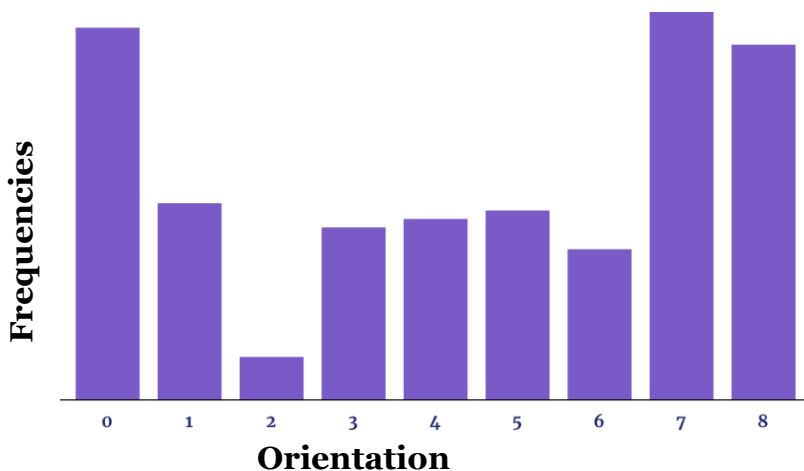
80	36	5	10	0	64	90	73
37	9	9	179	78	27	169	166
87	136	173	39	102	163	152	176
76	13	1	168	159	22	125	143
120	70	14	150	145	144	145	143
58	86	119	98	100	101	133	113
30	65	157	75	78	165	145	124
11	179	91	4	110	17	133	110

Magnitude

Orientation



Histogram of gradients



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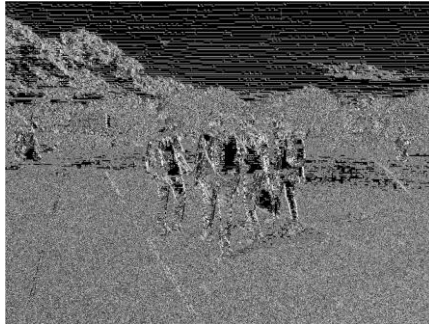
EVENT: HOG: Histogram of Oriented Gradients, 2005

A. AOUDJ, Y. CHELBI, MASTER 2 VISUAL COMPUTING, USTHB

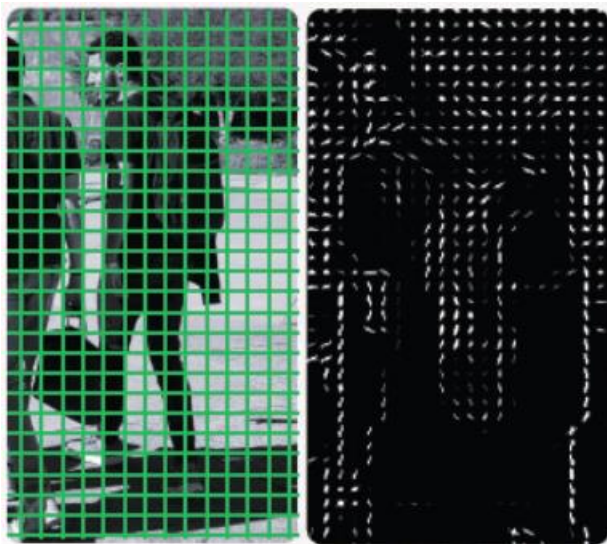
HOG in Action: Real Images Analysis



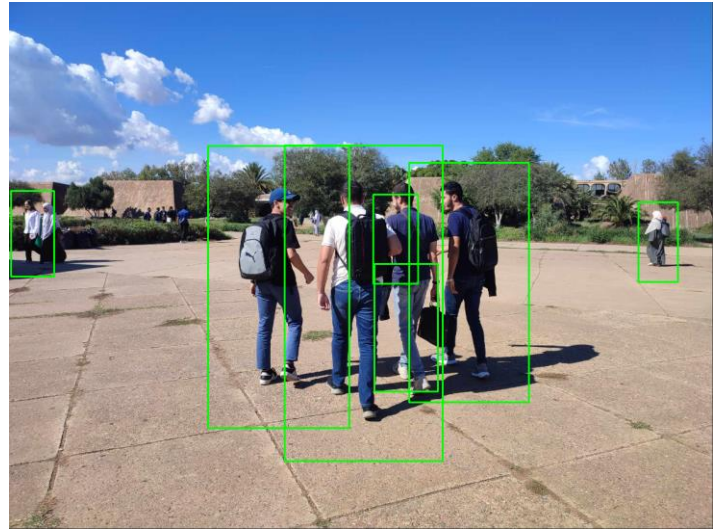
Grayscale conversion



Computation of Gradient (Magnitude, Orientation)



Grouping cells into blocks and computing histogram for each block.



Block normalization, classification using SVM to detect humans.

Reference: Dalal, N., & Triggs, B. (2005). Histograms of Oriented Gradients for Human Detection. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), Vol. 1, pp. 886-893.

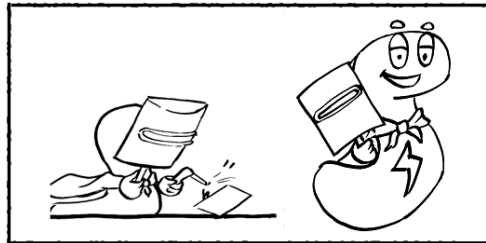


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CHRONICLE OF COMPUTER VISION

EVENT: SURF, 2006

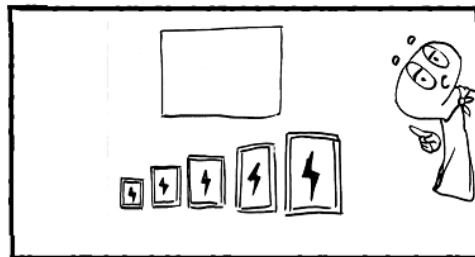
L.R. BOUGUERRA, MASTER 2 VISUAL COMPUTING, USTHB



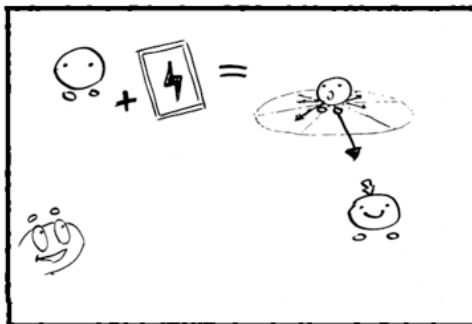
The first thing is to create an integral image from the original image.



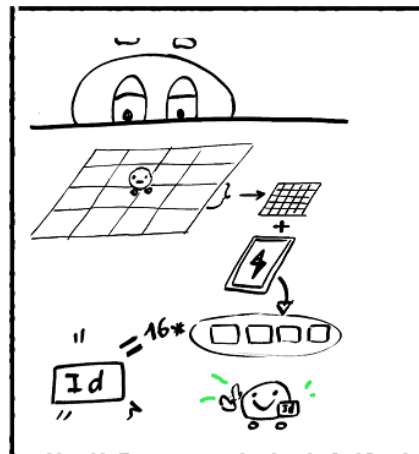
To detect key points we'll manipulate the integral image by using *Magic Cards*.



No more changes will occur on the image instead the magic cards will upscale.



we get the orientation by applying a magic card "Haar-wavelet", The point will follow it strongest direction.



We'll repeat the earlier step with a wider neighborhood. The collection of all the values across all regions will be our ID.

Reference: Bay, H., Tuytelaars, T., Van Gool, L. (2006). SURF: Speeded Up Robust Features. In: Leonardis, A., Bischof, H., Pinz, A. (eds) Computer Vision – ECCV 2006. ECCV 2006.



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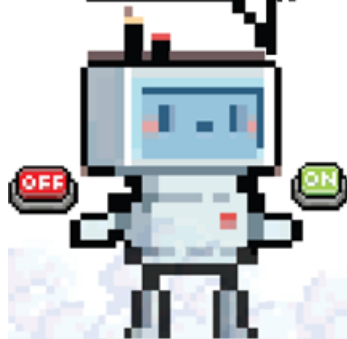
EVENT: SVM, 2008

A. TAREB, A. KHOUAS, MASTER 2 VISUAL COMPUTING, USTHB

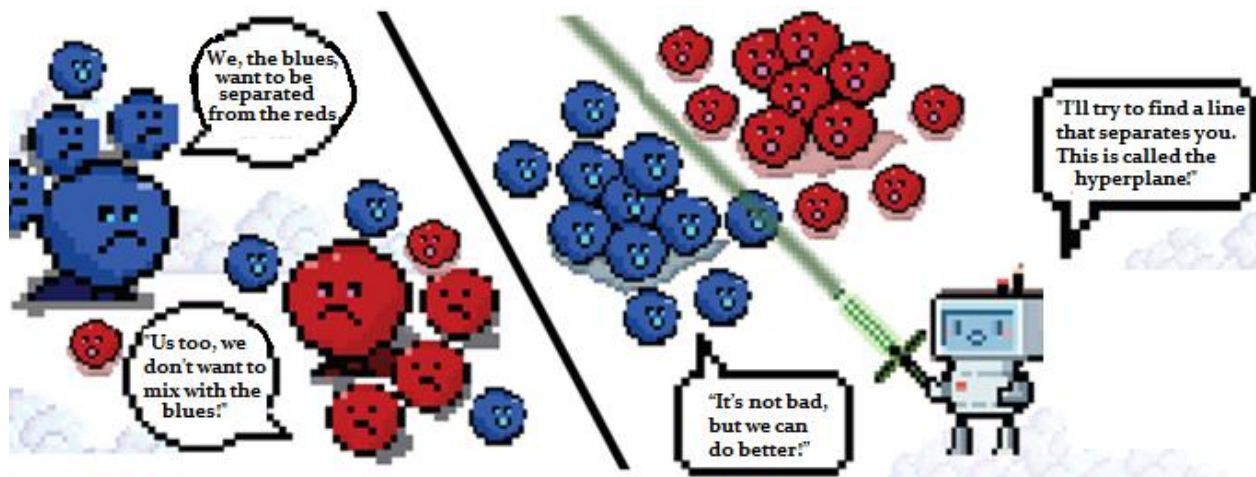
"Hi, we're the red class! We represent one type of data!"



"Hi, I'm SVM! I'm a machine learning classification algorithm, here to help separate your data!"



"And we're the blue class! We represent another type of data!"

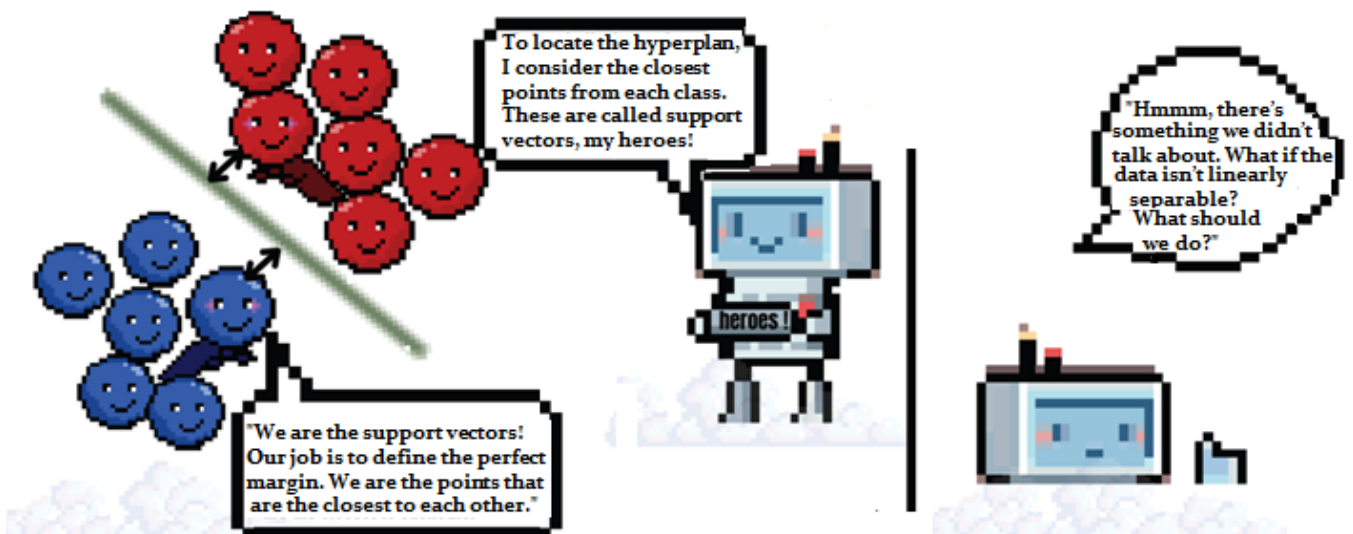
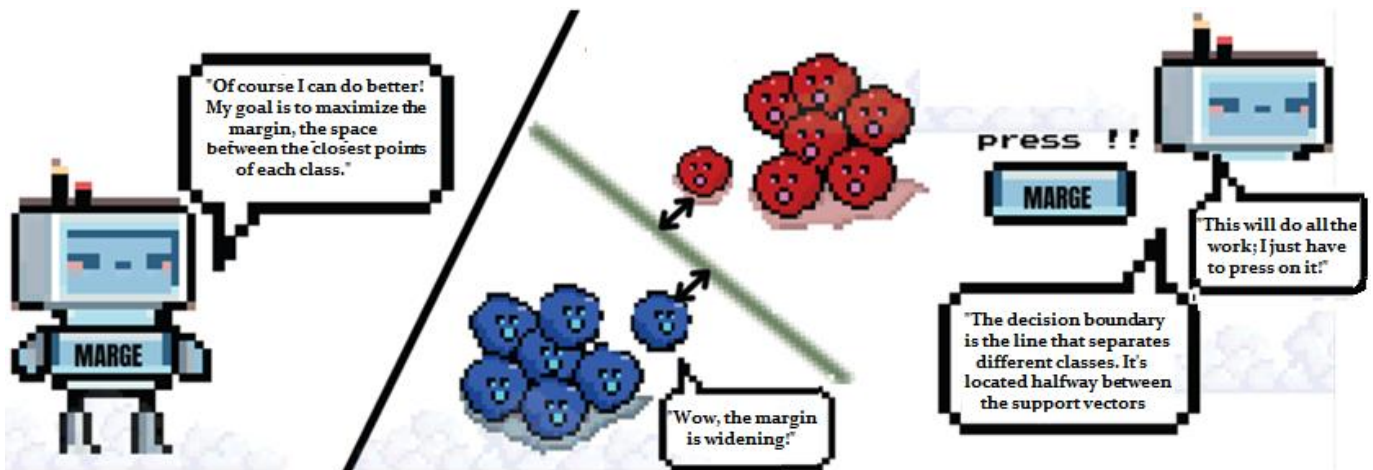


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EVENT: SVM, 2008

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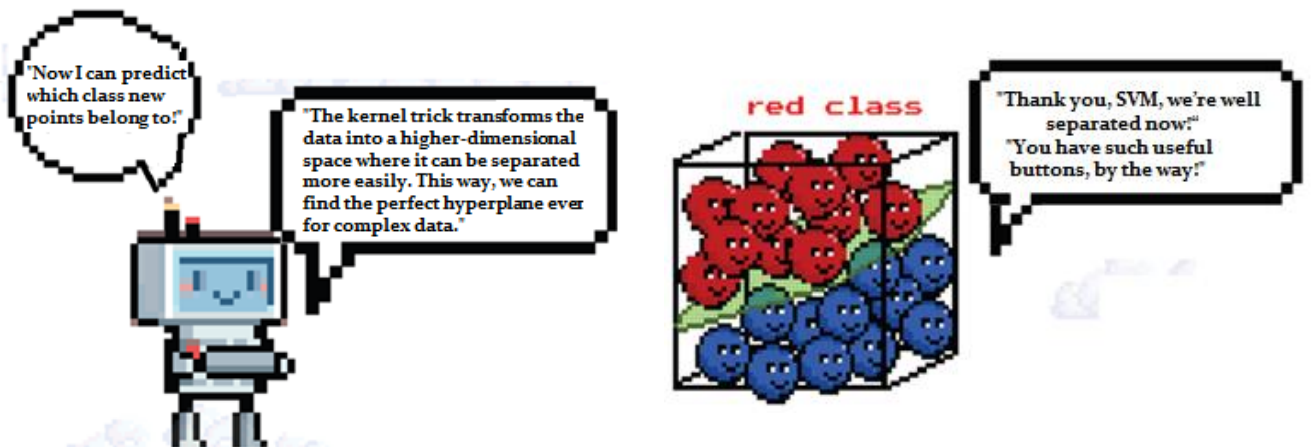
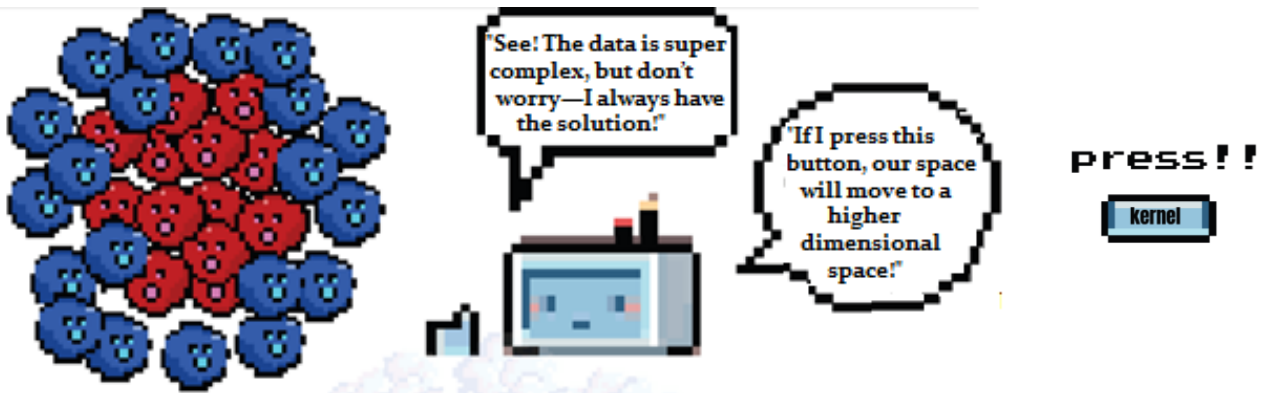


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CHRONICLE OF COMPUTER VISION

EVENT: SVM, 2008

A. TAREB, A. KHOUAS, MASTER 2 VISUAL COMPUTING, USTHB



Reference: Tzotsos, A. Argialas, D. (2008). Support Vector Machine Classification for Object-Based Image Analysis. Object-Based Image Analysis. Lecture Notes in Geoinformation and Cartography. https://doi.org/10.1007/978-3-540-77058-9_36



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CHRONICLE OF COMPUTER VISION

EVENT: AlexNet CNN, 2012

A. ADLAOUI, A. BELLOULA, MASTER 2 VISUAL COMPUTING, USTHB

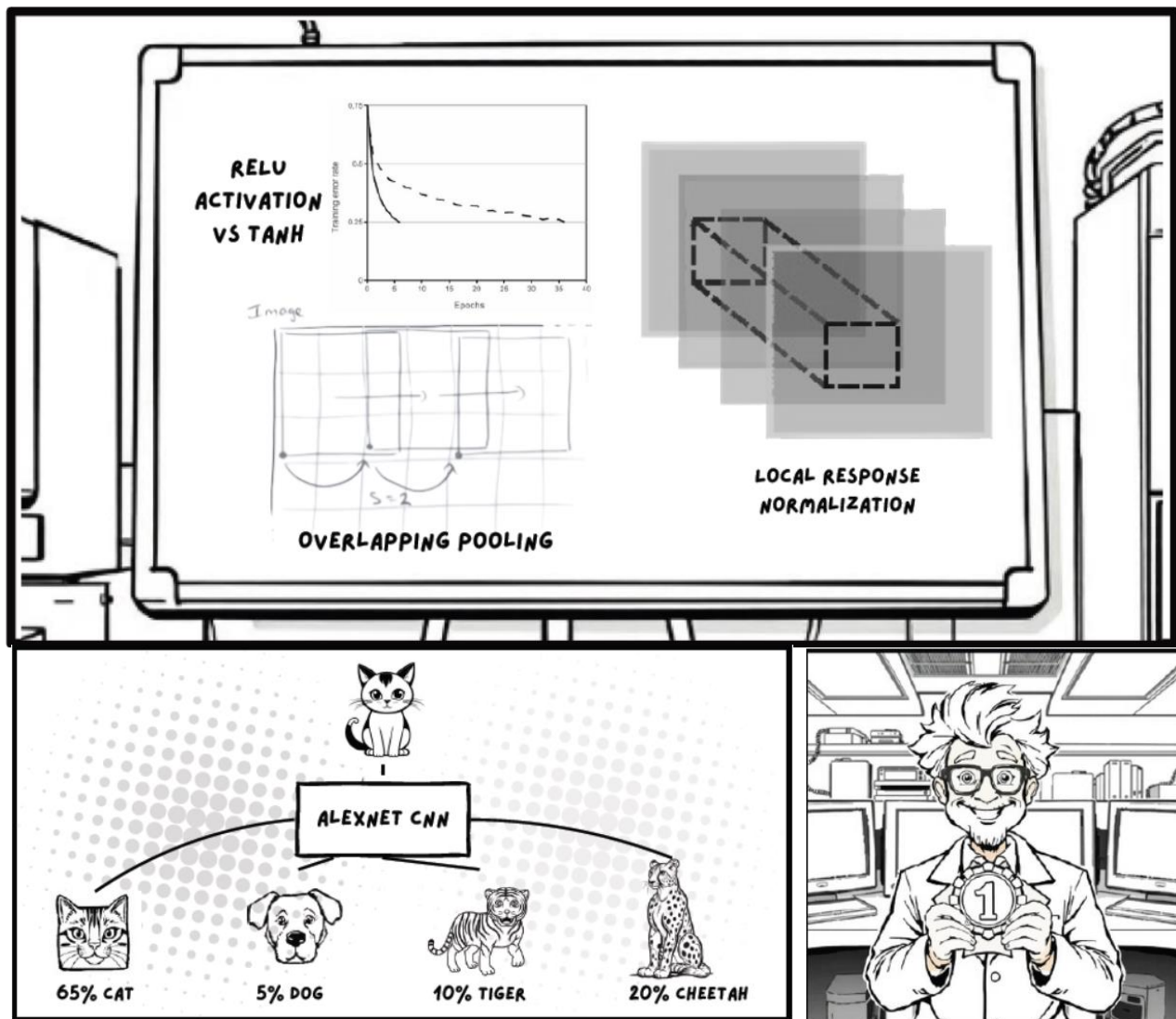


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CHRONICLE OF COMPUTER VISION

EVENT: AlexNet CNN, 2012

A. ADLAOUI, A. BELLOULA, MASTER 2 VISUAL COMPUTING, USTHB



Reference: Authors: Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, ImageNet classification with deep convolutional neural networks », NIPS'12: Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1 Pages 1097 - 1105



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CHRONICLE OF COMPUTER VISION

EVENT: Generative Adversarial Networks , 2014.

A. KACI AISSA, R. NINE, MASTER 2 VISUAL COMPUTING, USTHB

GENERATOR



Objective :

Create data that mimics the real dataset.

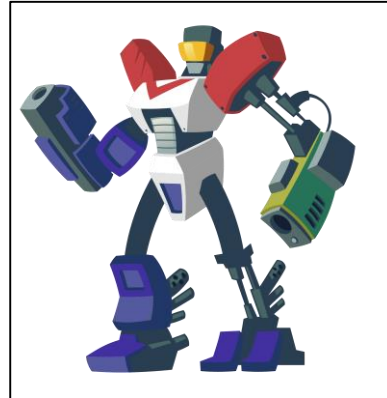
Purpose of training:

Deceiving the discriminator.

Type of loss :

Minimize the success rate.

DISCRIMINATOR



Objective :

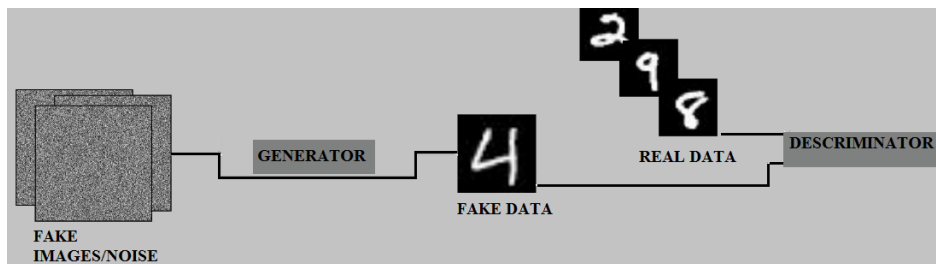
Distinguish between real data from generated data.

Purpose of training:

Correctly classify real and fake data..

Type of loss :

Maximize classification accuracy.



Reference: Goodfellow, Ian & Pouget-Abadie, Jean & Mirza, Mehdi & Xu, Bing & Warde-Farley, David & Ozair, Sherjil & Courville, Aaron & Bengio, Y.. (2014). Generative Adversarial Networks. Advances in Neural Information Processing Systems.



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CHRONICLE OF COMPUTER VISION

EVENT: GoogleNet, 2014, VGGNet, 2015.

S. BELKACEMI, L. ROUBAH, MASTER 2 VISUAL COMPUTING, USTHB



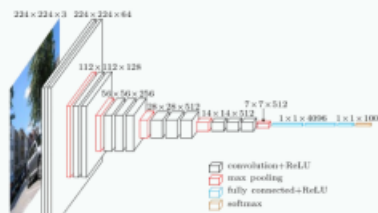
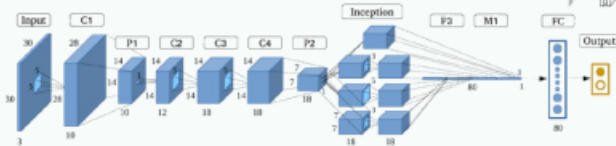
what CNN should i use for image processing?

I think **Visual Geometry Group** :

- VGG-16 & VGG-19
- very high precision

No no **Googlenet** :

- 22 layer
- Concept of Inception



Performance

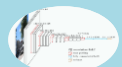
Googlenet achieves a **top-5** test accuracy of nearly **93.3%** in ImageNet with **7 million** parammeters only

VGG achieves a **top-5** test accuracy of nearly **92.7%** in ImageNet with **138 million** parammeters

Applications

- Analyse vidéo
- Autonomous driving
- Satellite image analysis
- Image classification
- Object detection
- Medical imaging

- Image classification
- Feature extraction
- Facial recognition
- Medical image analysis
- Object detection and recognition



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CHRONICLE OF COMPUTER VISION

EVENT: GoogleNet, 2014, VGGNet, 2015.

S. BELKACEMI, L. ROUIBAH, MASTER 2 VISUAL COMPUTING, USTHB



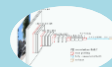
I get it now so **VGG** is used for tasks requiring high accuracy and feature extraction in image-related fields .

and **Googlenet** is used in efficient deep learning tasks where parameter efficiency and multi-scale feature extraction are important.

References:

1- Karen Simonyan and Andrew Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition, 2015, <https://arxiv.org/abs/1409.1556>. GoogleNet:

2- Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich. Going Deeper with Convolutions 2014, <https://arxiv.org/abs/1409.4842>



CHRONICLE OF COMPUTER VISION

EVENT: Deep Residual Networks, 2015

W. KESBI, M. SAADI, MASTER 2 VISUAL COMPUTING, USTHB

Hi NeoBot, i have a problem, my model isn't performing well, what should i do ?



Have you tried adding more layers ?

Its even worst now...

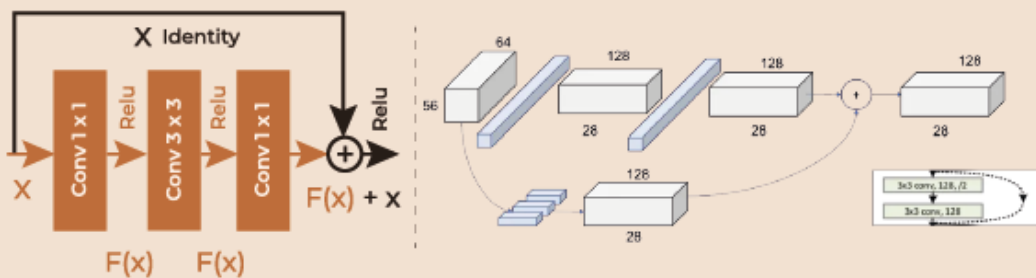


I think you should try ResNet

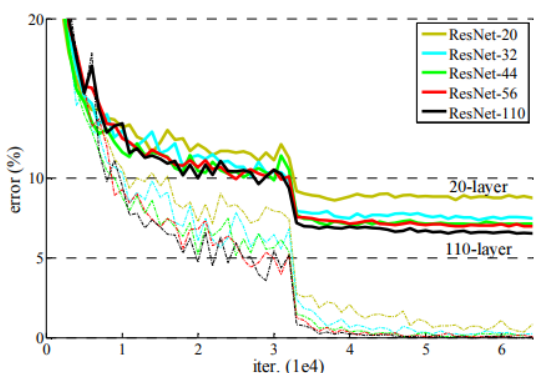
Huh, what's that ?



This architecture allows ResNet to perform complex tasks such as image recognition, object detection and segmentation.



Here are some results of training a ResNet model:



	Model	Train acc	Validation acc	Time
1	ResNet18	0,83	0,87	2701s
2	ResNet34	0,8651	0,8519	4800s
3	ResNet50	0,8662	0,8095	5580s
4	ResNet101	0,8594	0,7884	6112s
5	ResNet152	0,8798	0,8836	9248s

Intresting!! i will try that

Reference: Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, Deep Residual Learning for Image Recognition, Microsoft Research, 10 Dec 2015.

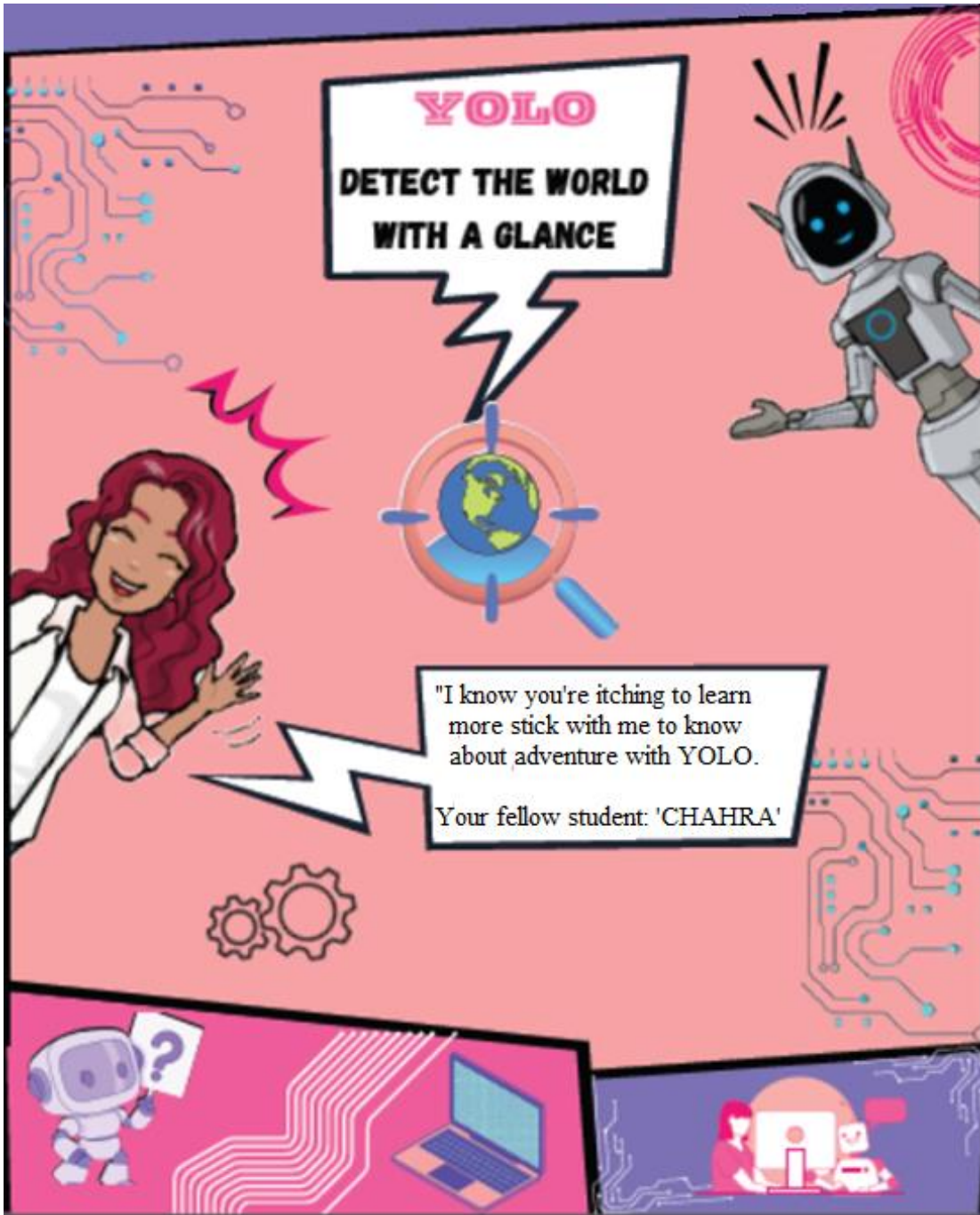


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CHRONICLE OF COMPUTER VISION

EVENT: YOLO, 2016

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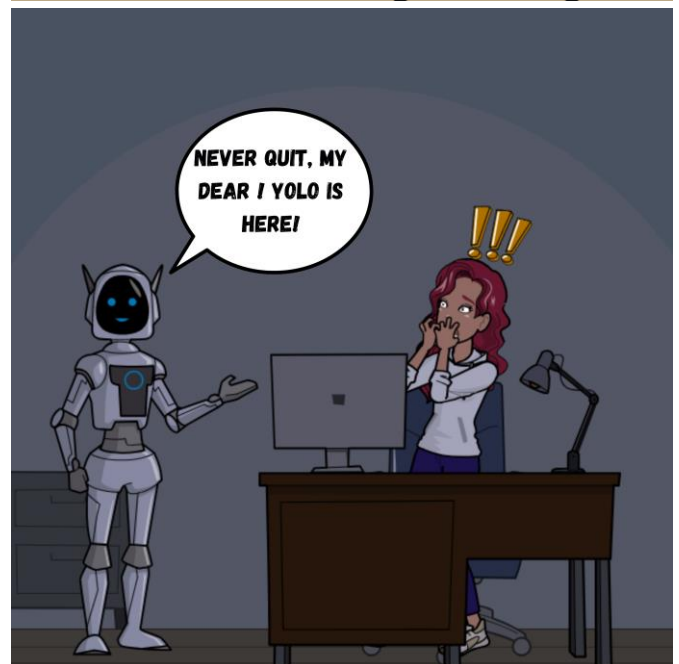
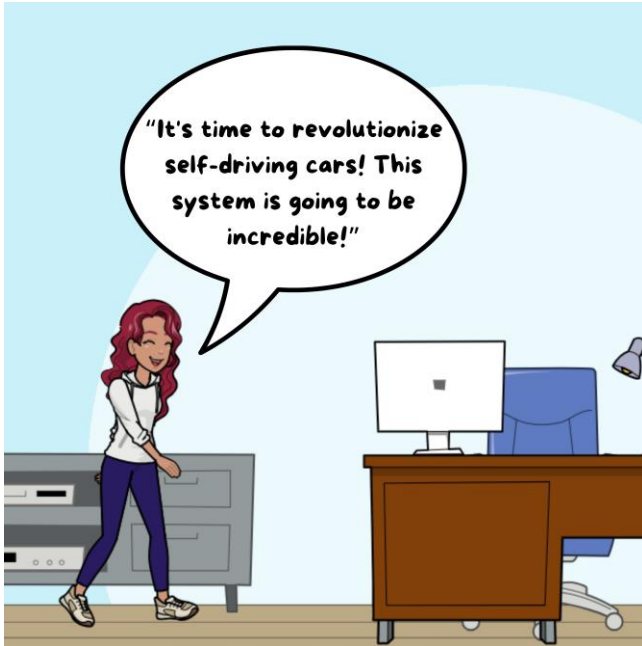


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EVENT: YOLO, 2016

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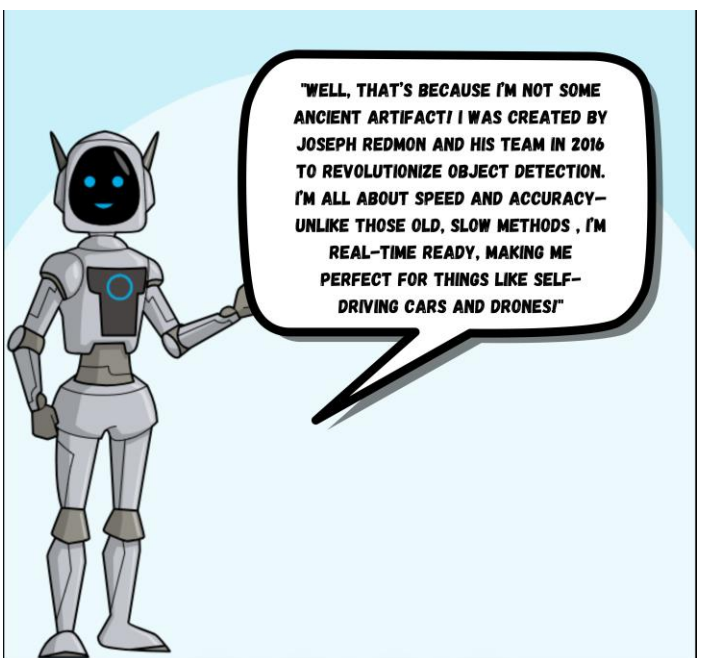
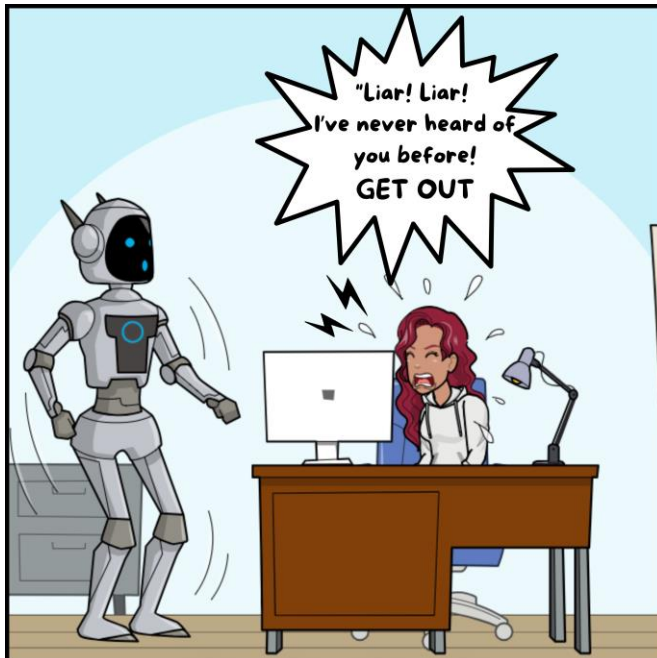
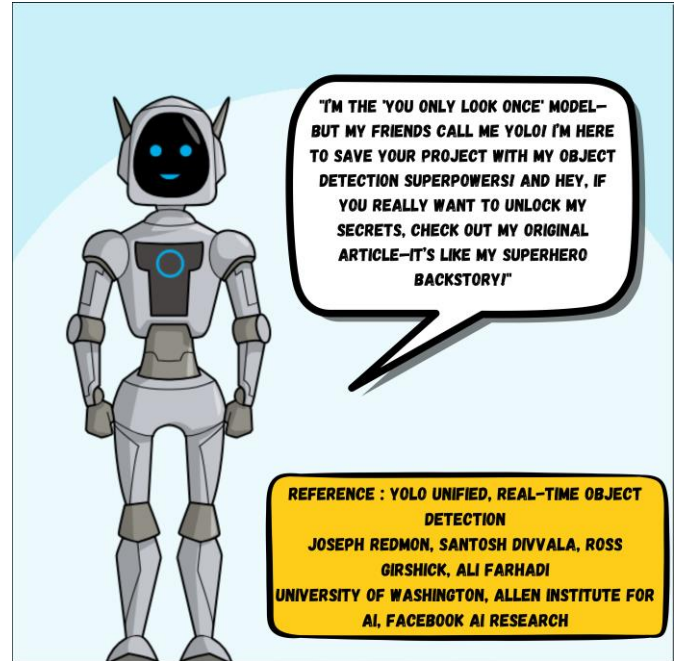


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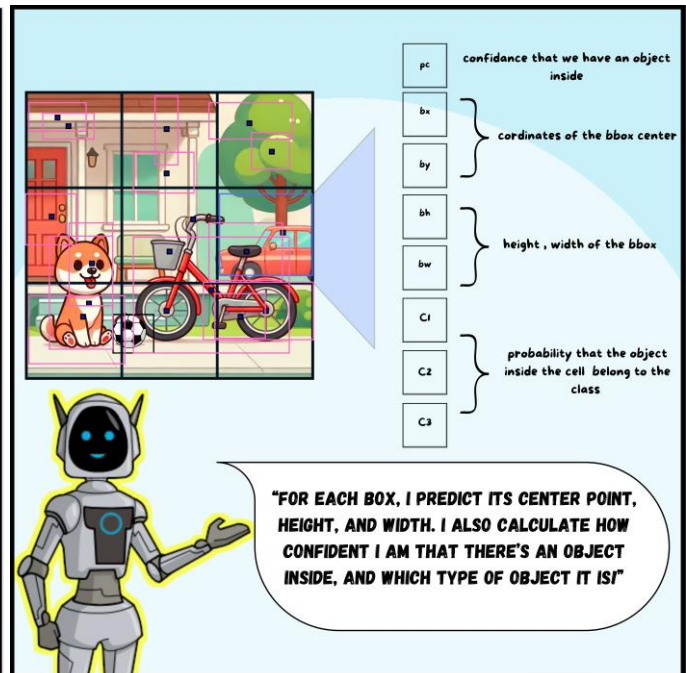
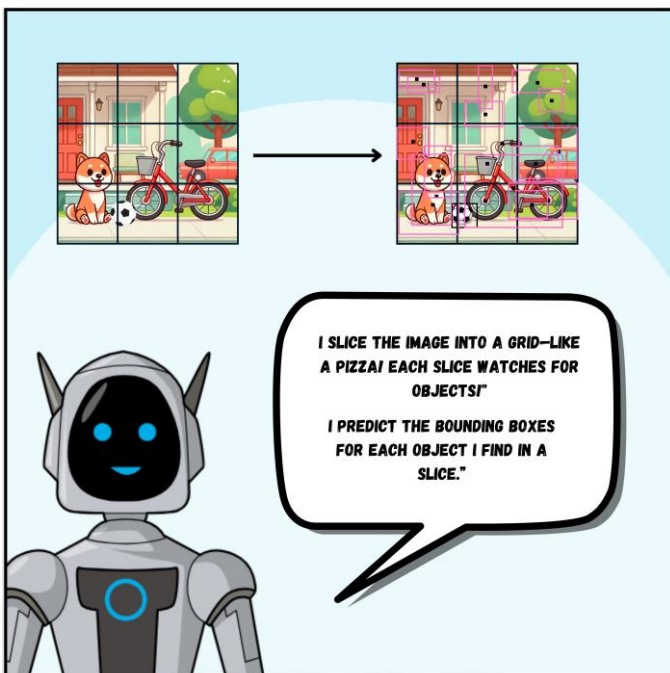
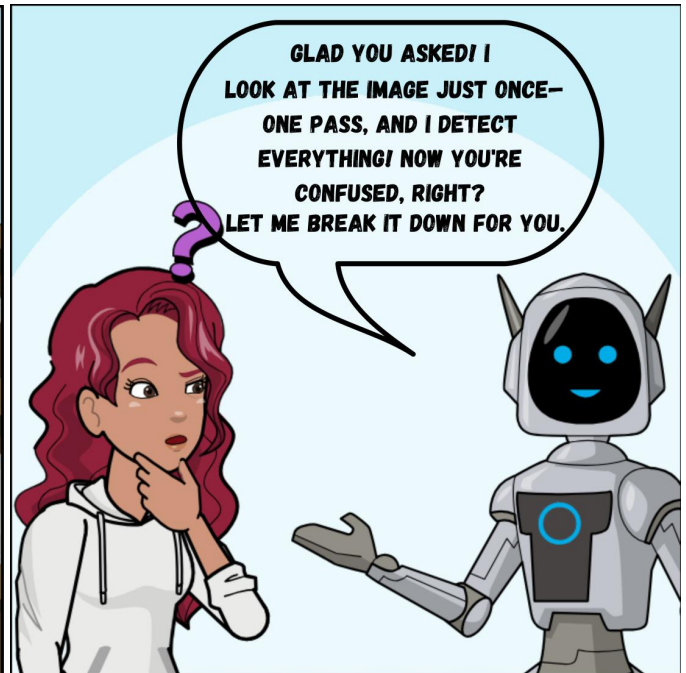
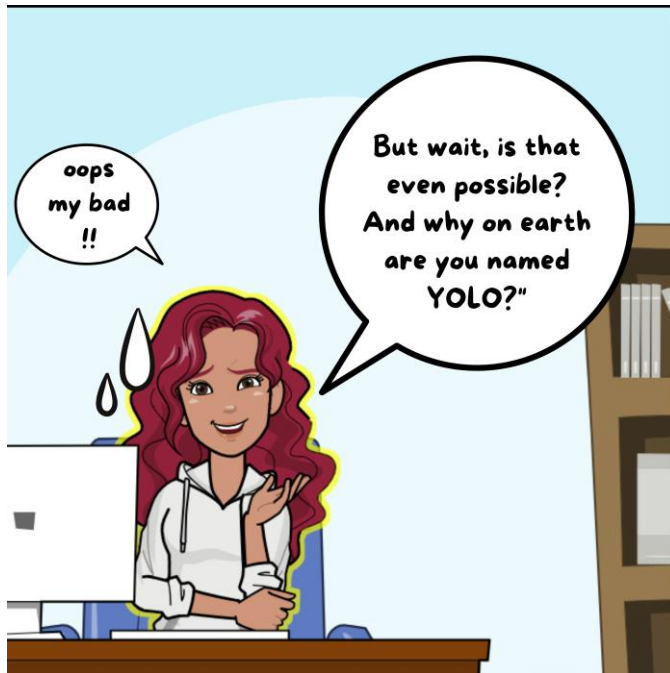


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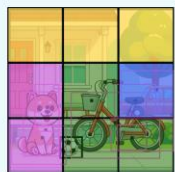
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EVENT: YOLO, 2016

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filtered boxes

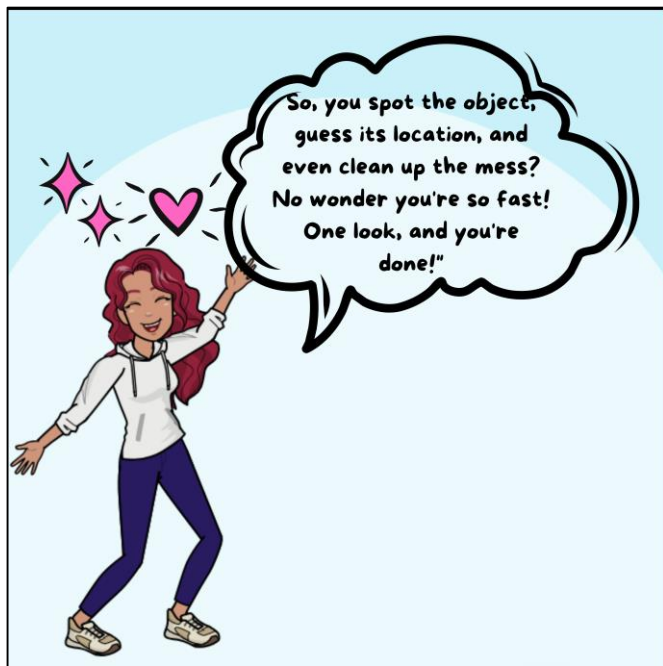


class mapping



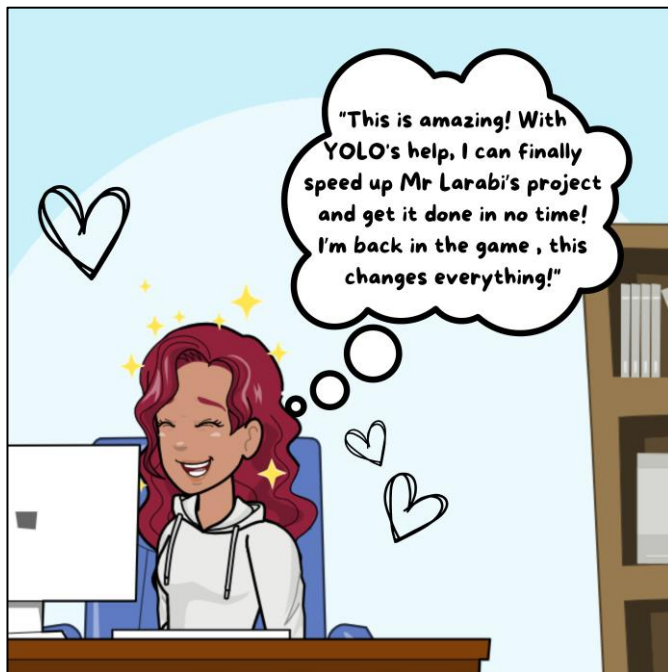
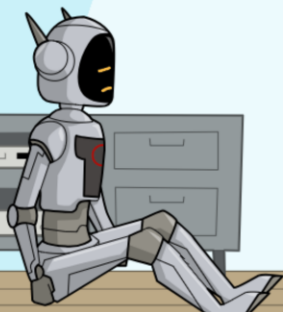
final output

"I DON'T JUST DRAW BOXES—I ALSO TELL YOU WHICH CLASS THE OBJECT BELONGS TO, LIKE A CAR OR BICYCLE! PLUS, I FILTER OUT LOW-CONFIDENCE BOXES, IGNORING CELLS WITHOUT REAL OBJECTS."



"BUT I'VE GOT TO BE HONEST WITH YOU—I CAN'T CATCH EVERYTHING IN MY ORIGINAL FORM. I DO HAVE A FEW LIMITS. BUT DON'T WORRY, I WON'T LEAVE YOU HANGING! I ALWAYS RECOMMEND CHECKING OUT MY NEWER VERSIONS—THEY'VE GOT WAY MORE TRICKS UP THEIR SLEEVE!"

it's okay
i understand



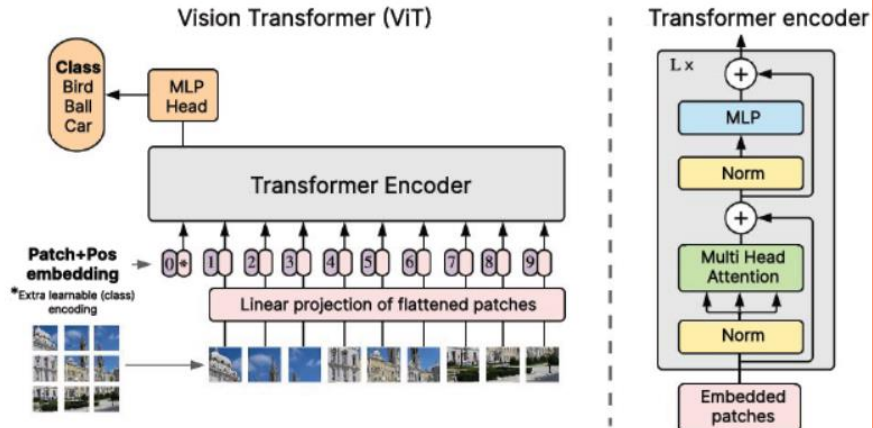
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CHRONICLE OF COMPUTER VISION

EVENT: Vision Transformers, 2021

B. ABADLI, R. KEMMOUN, MASTER 2 VISUAL COMPUTING, USTHB

The vision transformer (ViT)'s architecture



First we need to prepare the **patches!**

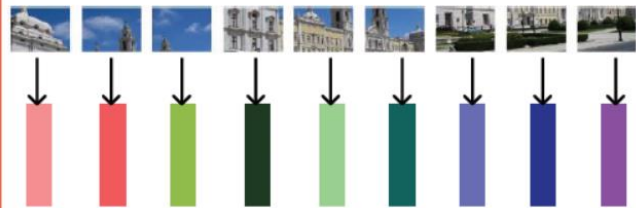


An image is taken as input, in RGB format.



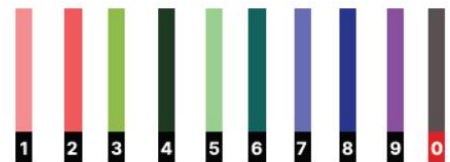
The image is divided into smaller, non-overlapping patches

Then we reshape them into **embeddings**



We convert the patches from RGB to numerical vectors

We then add the **positions** and the **class token!**



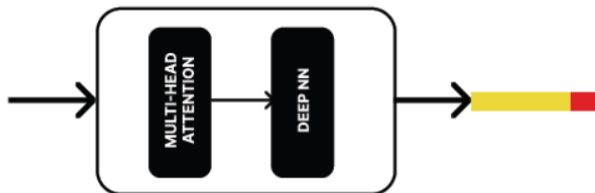
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EVENT: Vision Transformers, 2021

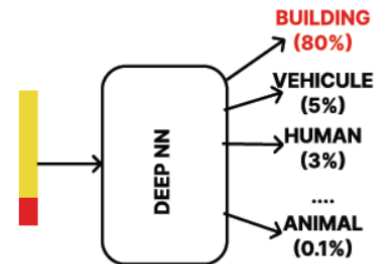
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We feed them into the transformer encoder to capture **relationships between patches!**

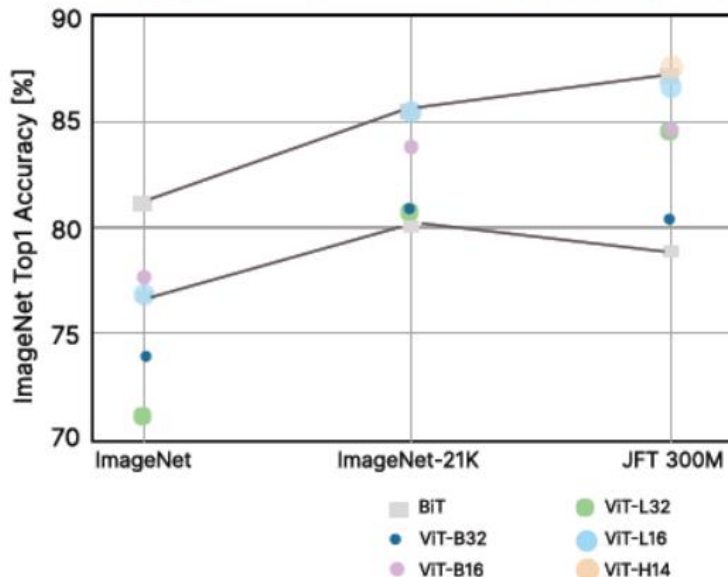


The sequence is processed through multiple layers of the Transformer architecture

The output is fed into a MLP for **classification!**



How does ViTs compare to CNN models?



Reference: Alexey Dosovitskiy , Lucas Beyer , Alexander Kolesnikov , Dirk Weissenborn , Xiaohua Zhai , Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby, AN IMAGE IS WORTH 16X16 WORDS:TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE, ICLR 2021



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EVENT: DALL-E 3, 2023

R. BOUSSIS, W. WASSIM, MASTER 2 VISUAL COMPUTING, USTHB



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Reference: <https://openai.com/index/dall-e-3/>

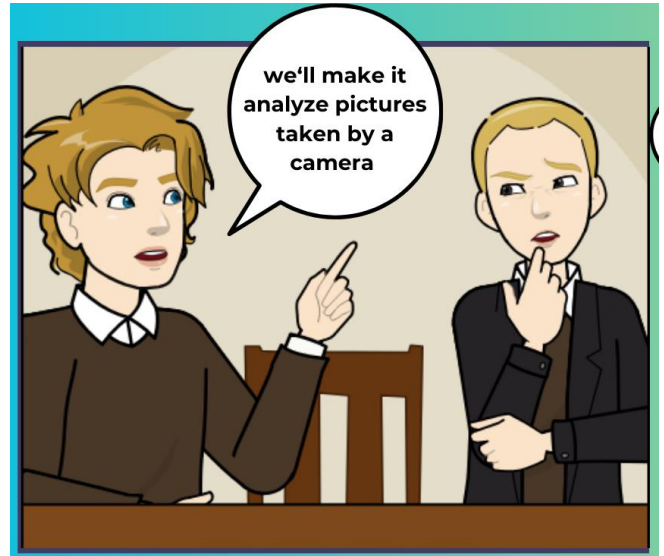


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