Person Detection from a Top-View Perspective

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INTRODUCTION

Person Detection is performed from a Top-View Perspective by using most recent object detection frameworks.

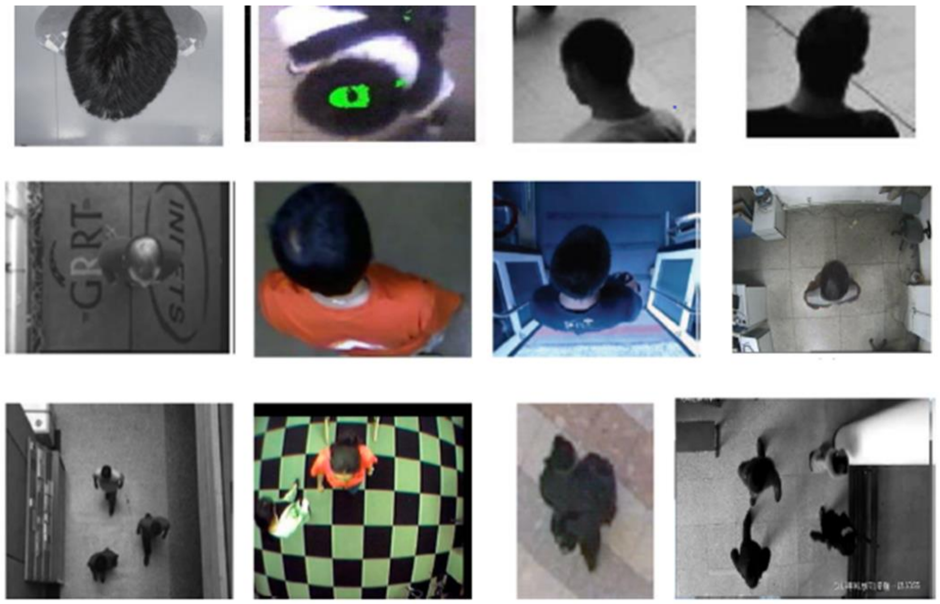
The aim is to build an efficient model to detect the people in the scene.

This framework is evaluated on a real-world scenario which is a retail environment.

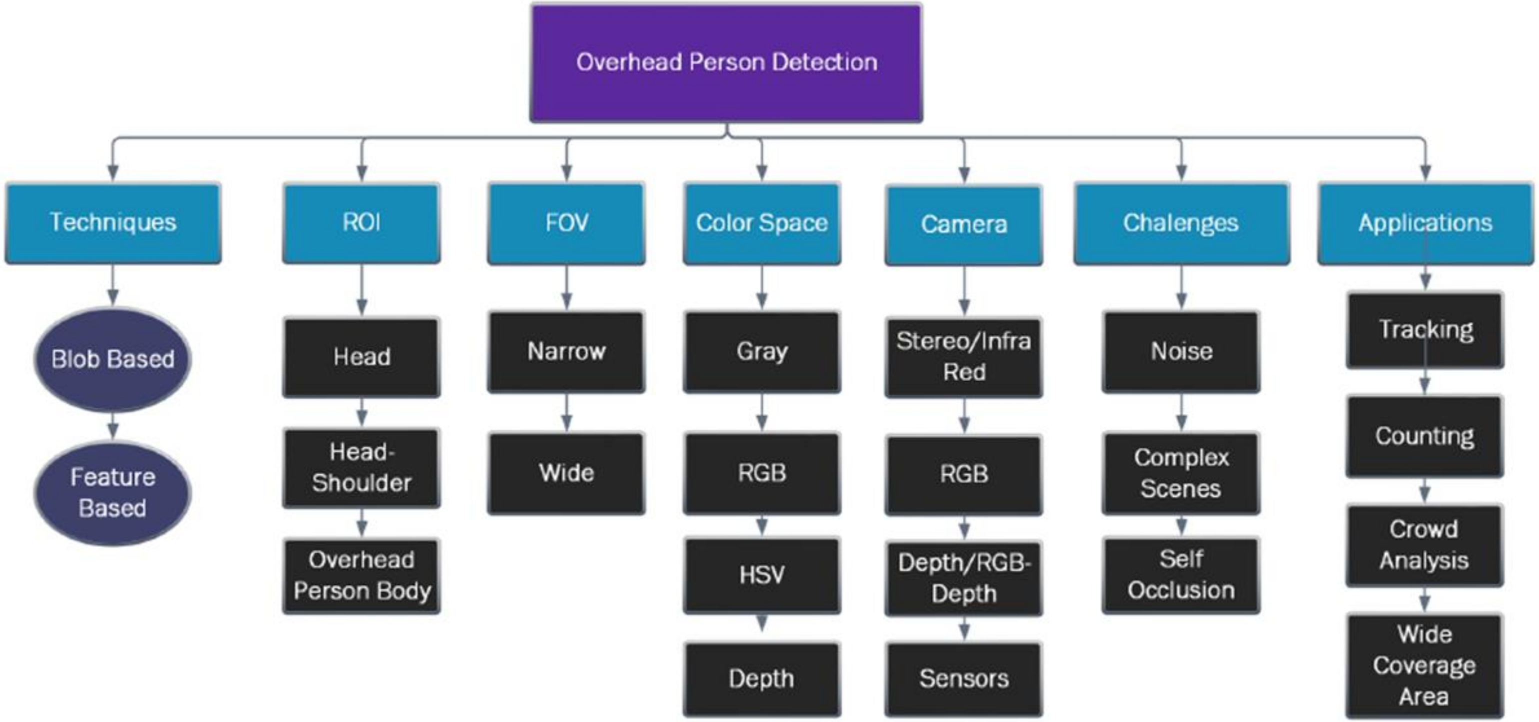
INTRODUCTION

MAIN STEPS:

- Definition of the **Region of Interest** (ROI);
- People localization.



STATE OF ART – Person Detection



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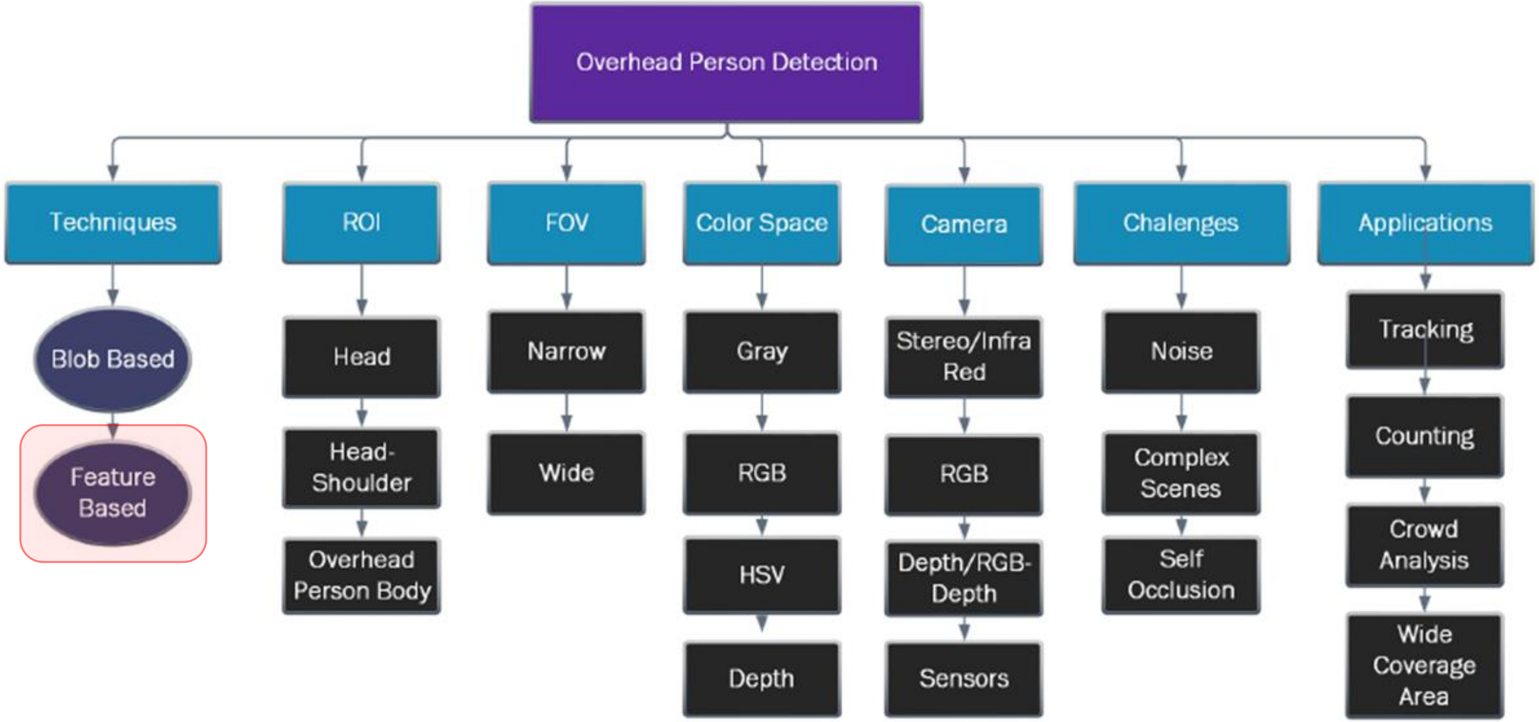
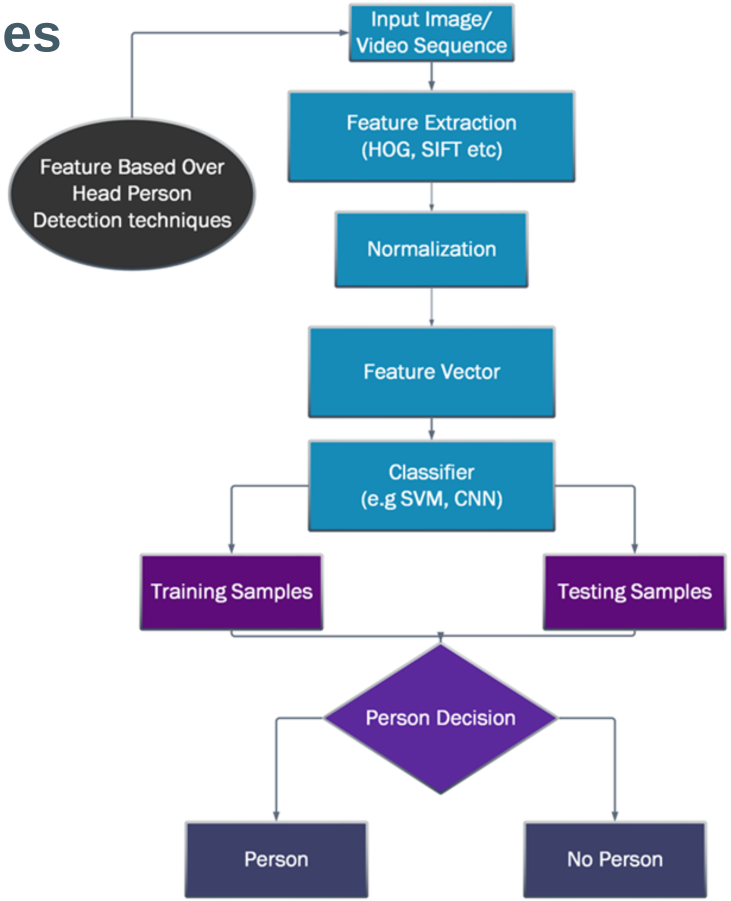


STATE OF ART – Feature based Techniques

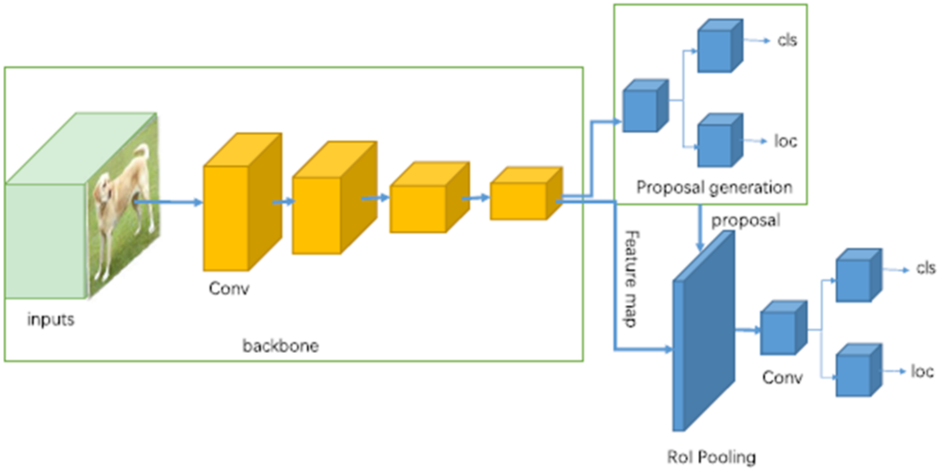
These **Feature based Techniques** operate on *features extracted* from overhead view videos and images.

The extracted features contain shape, color, texture, etc.… The images are often divided into samples for training and testing.



STATE OF ART – Feature based Techniques

Two-stage Detectors (R-CNN, Faster R-CNN, etc..) use a *Region Proposal Network* to generate regions of interests.



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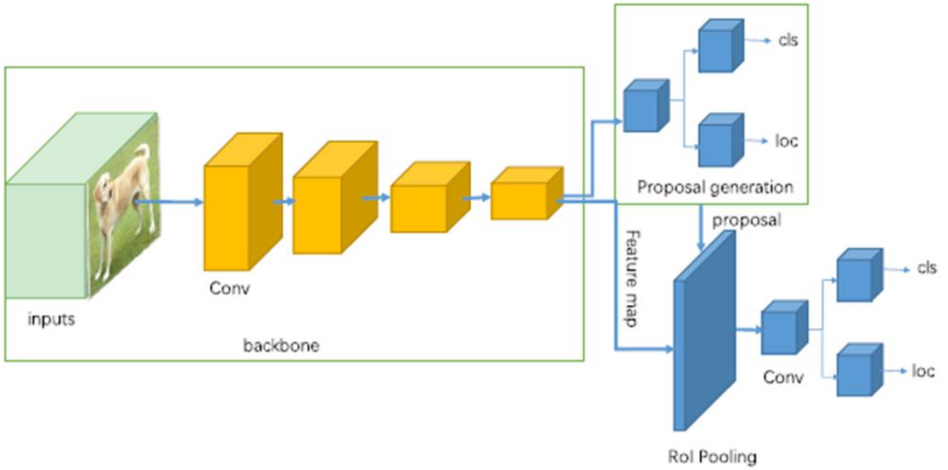
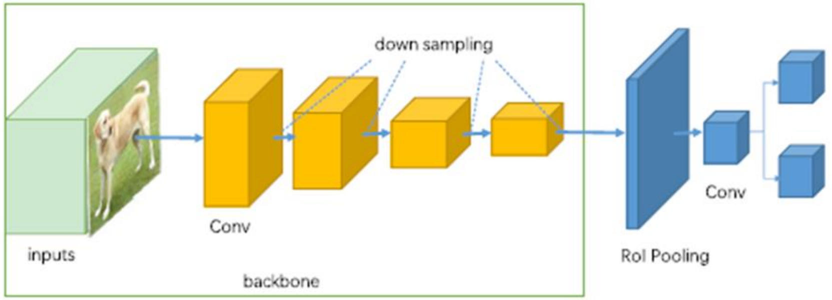
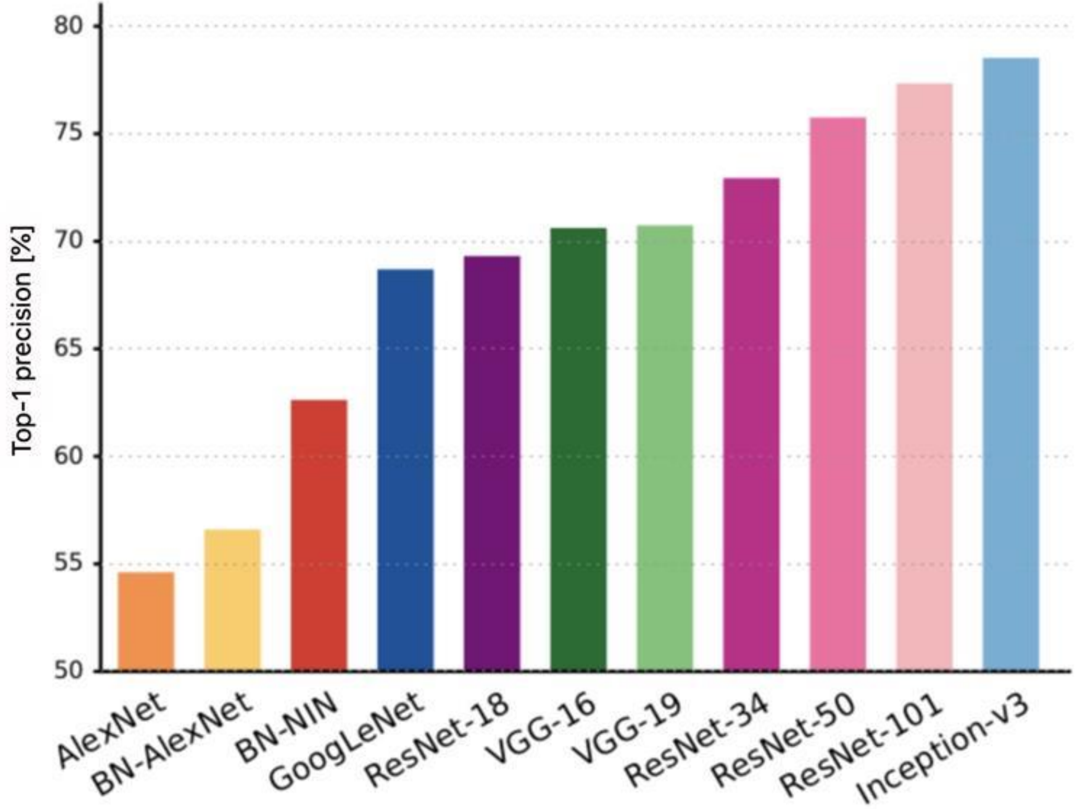


One-stage Detectors (YOLO, SSD, etc..) treat object detection as a *simple regression problem*.



STATE OF ART – Feature extraction architectures



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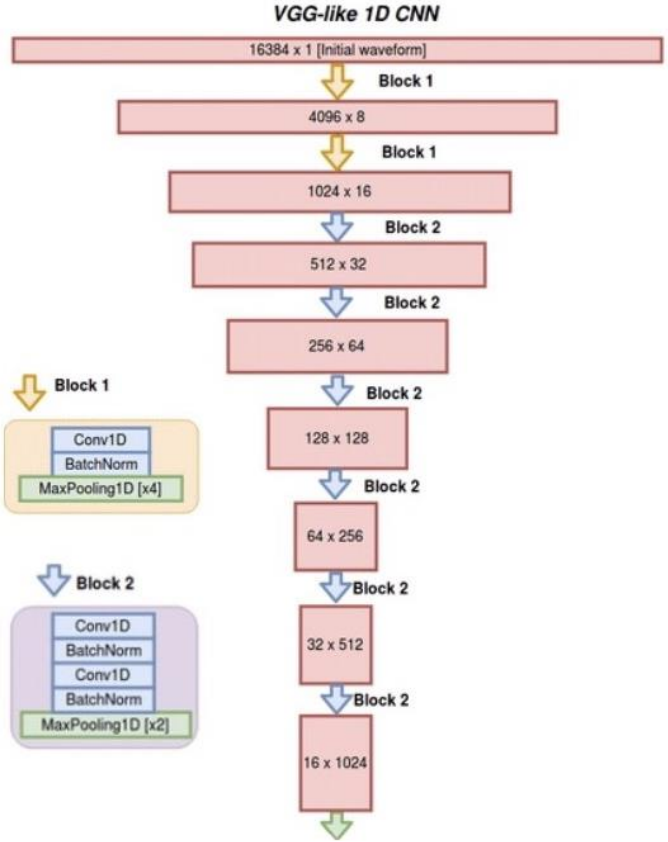
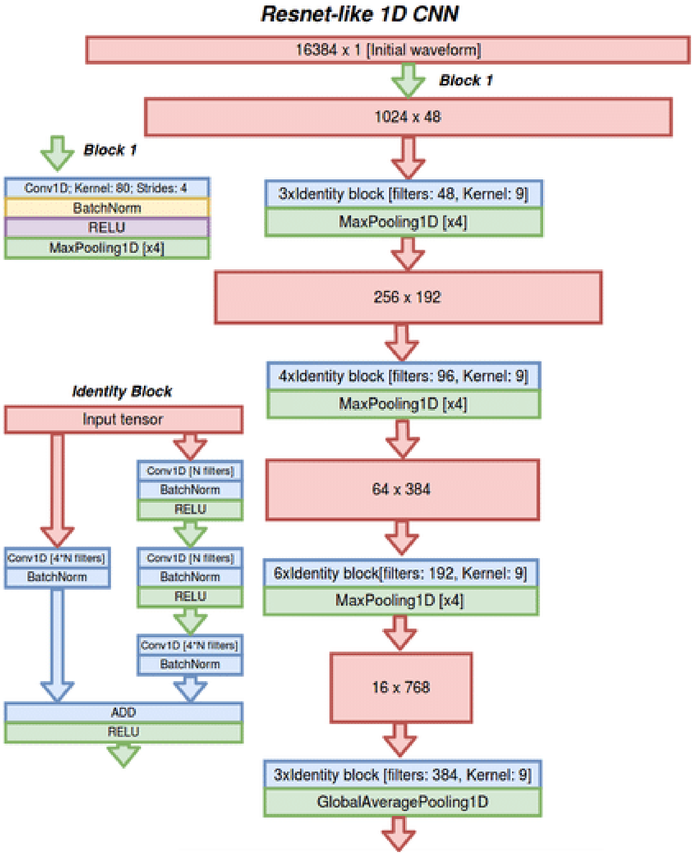




MATERIALS AND METHODS – Data Collection

The provided *Dataset* comes from video frames recorded by different cameras from a top-view, within a real environment: a supermarket.

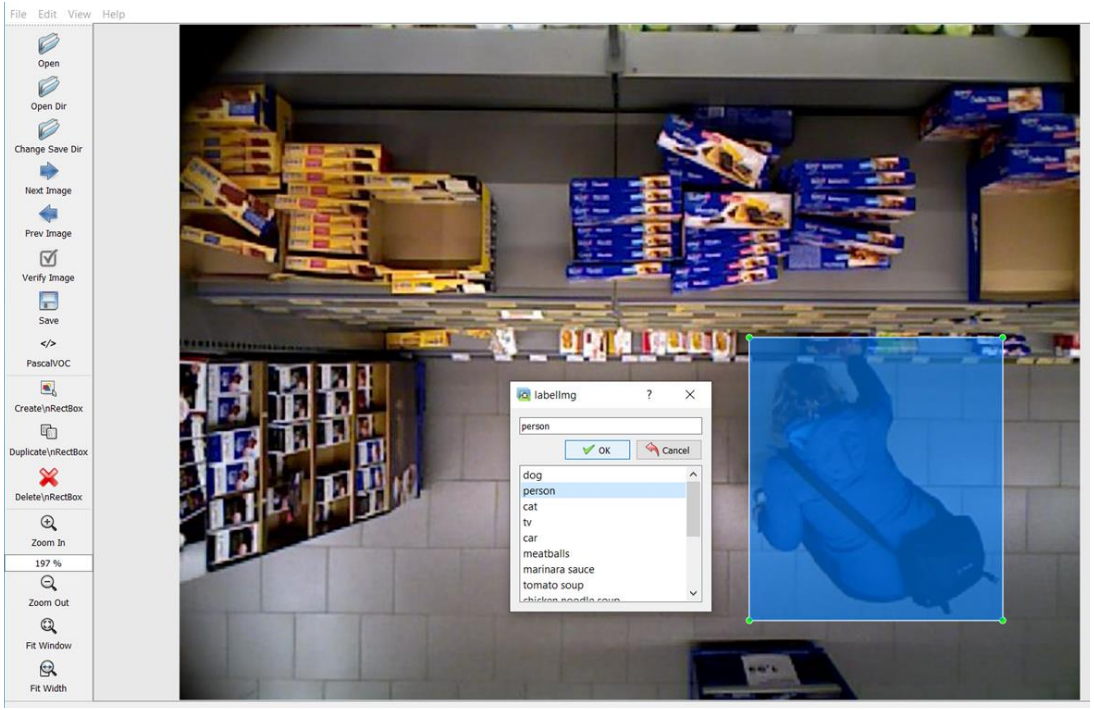
These 30.000 images needed a skim because some did not contain people.

MATERIALS AND METHODS – Labelling

Dataset annotation using **LabelImg**. LabelImg is a *graphical image annotation tool*.

About 17.000 images divided into:

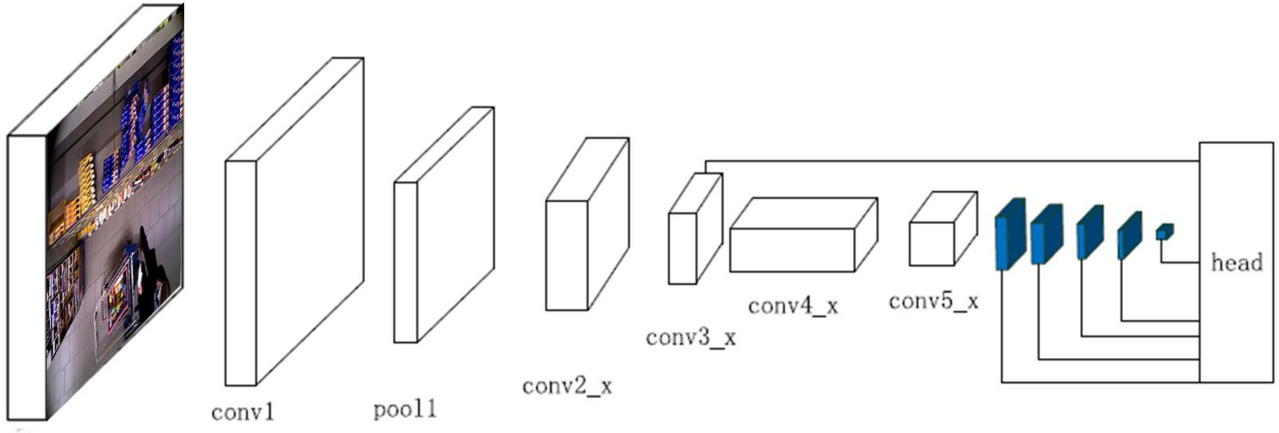
- **Testing set** → 30%
- **Training set** → 70%
- **Validation set** → 30% of training set



MATERIALS AND METHODS – Single-shot Detector

SSD (Single-shot Detector) discretizes the output space of *bounding boxes* into a set of default boxes over different aspect ratios and scales per feature map location.

In SSD the *prediction layer* is acting on fused features of different levels. Head module consists of a series of *convolutional layers* followed by several classification layers and localization layers.



[Wei Liu et al, 2016] Present a method for detecting objects in images using a single deep neural network. The approach, named SSD, discretizes the output space of bounding boxes into a set of default boxes. over different aspect ratios and scales feature map location.

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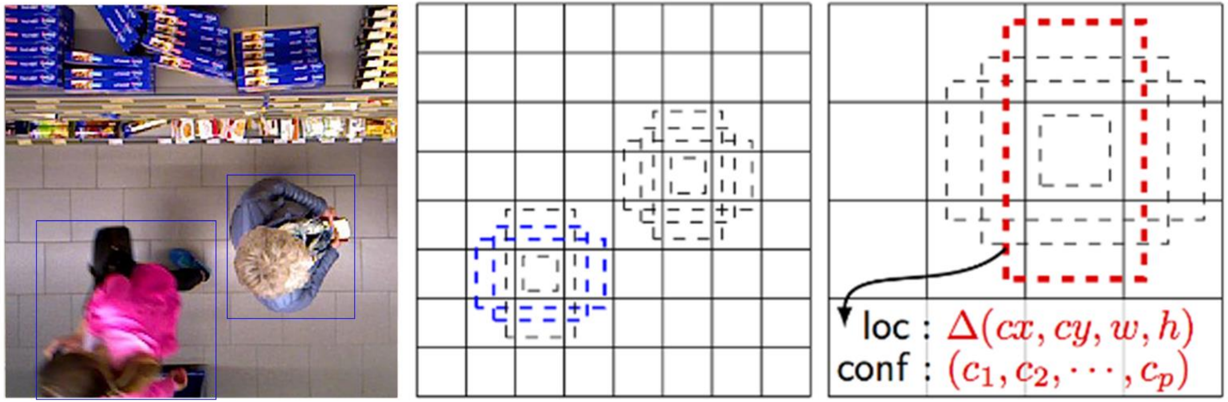
MATERIALS AND METHODS – Single-shot Detector



Each prediction is composed of:

- Bounding box with shape offset (Δcx, Δcy, w and h);
- *Confidences* for all object categories or all the classes.

MATERIALS AND METHODS – Settings

Three types of Single-shot Detectors were used: **SSD300**, **SSD512** and **SSD7**. The architecture of the first two is almost the same (9 and 10 layers respectively) while the SSD7 provides a simplified approach (7 layers).

Method	mAP	FPS	batch size	Input resolution
SSD300	74.3	46	1	300 × 300
SSD512	76.8	19	1	512 × 512
SSD300	74.3	59	8	300 × 300
SSD512	76.8	22	8	512 × 512

The default *backbone* was based on **VGG16**, then replaced with **ResNet50**.

Furthermore, a subsequent approach was fine tuning starting from a pre-trained model.

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		Batch size	Steps per epoch
VGG16	**SSD300**	32	260
	SSD512	16	520
ResNet50	**SSD300**	32	260
	SSD512	12	690

$$\text{Steps} = \frac{\text{Trainig set}}{\text{Batch size}}$$

Epochs = 40

Learning rate = 0,001

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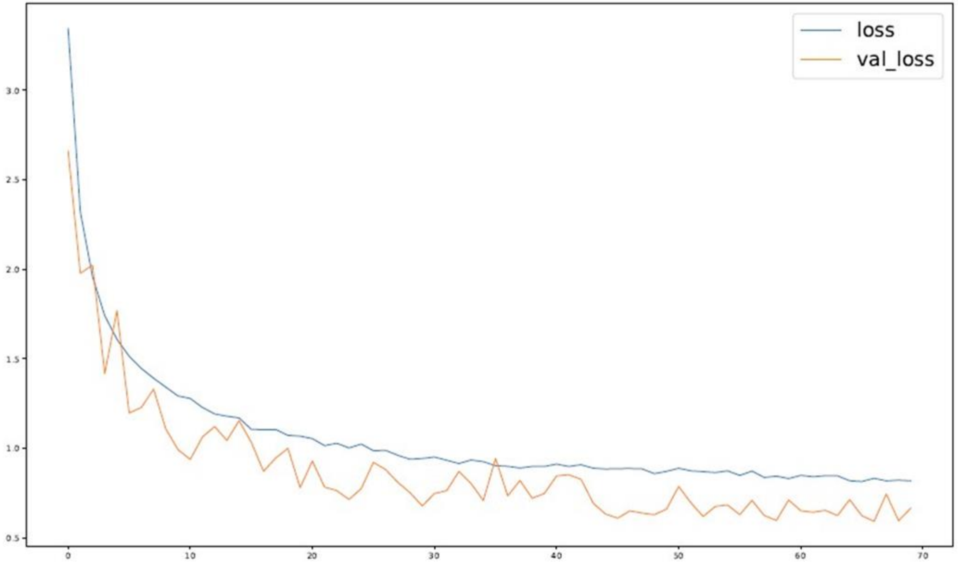


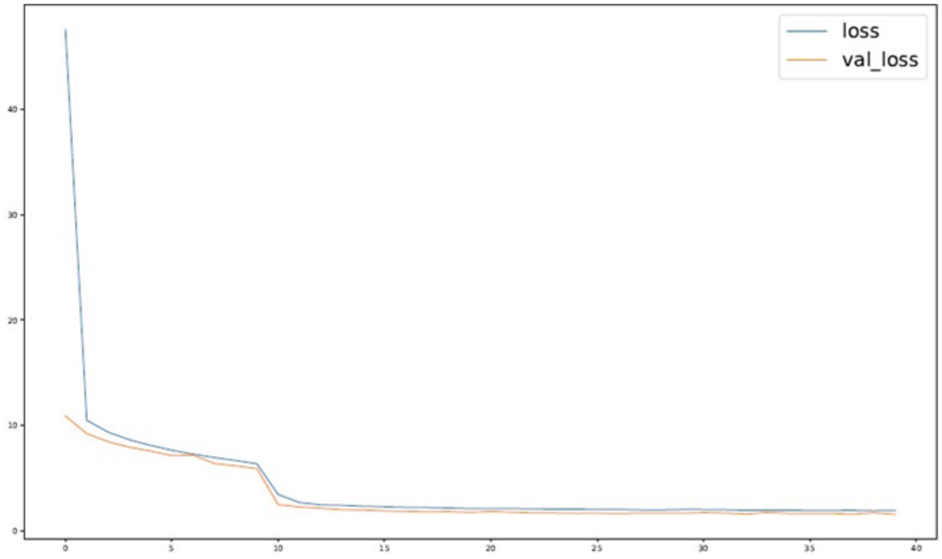
SSD7

Epochs = 70

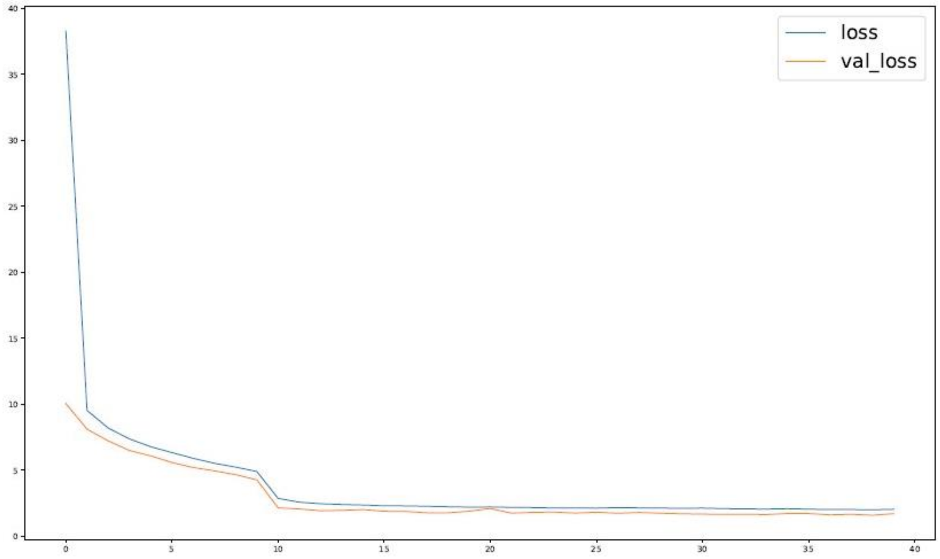
Learning rate = 0,001

MATERIALS AND METHODS – Settings

SSD300



SSD512



VGG16

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MATERIALS AND METHODS – Loss Function

The **Loss function** consists of two terms: L_{conf} and L_{loc} where N is the matched default boxes.

$$L(x, c, l, g) = \frac{1}{N}(L_{conf}(x, c) + \alpha L_{loc}(x, l, g))$$

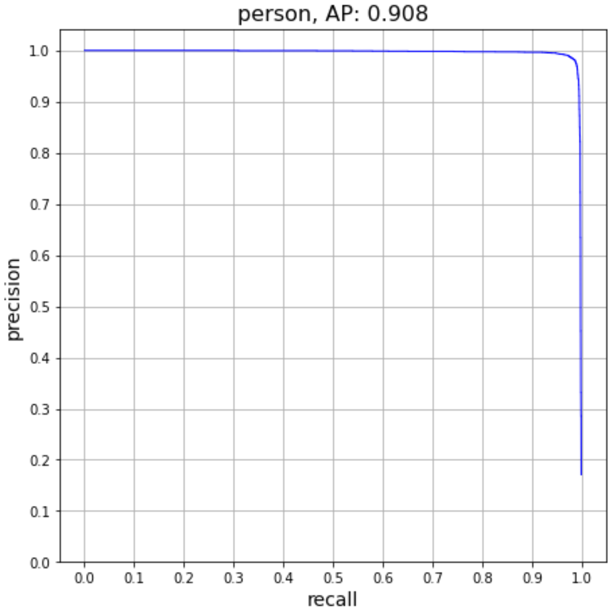
L_{loc} is the **Localization Loss** which is the smooth L1 loss between the predicted box (l) and the ground-truth box (g) parameters. L_{conf} is the **Confidence Loss** which is the softmax loss over confidences (c).

RESULTS AND DISCUSSIONS

The metrics used for the evaluation are **AP** (*Average Precision*), **Recall**, **F1 Score** and **IoU** *(Intersection over Union).*

SSD300	AP	Recall	F1 Score	IoU
VGG16	0,908	0,818	0,861	0,879
ResNet50	<u>0,909</u>	0,618	0,736	0,842

SSD512	AP	Recall	F1 Score	IoU
VGG16	0,908	<u>0,912</u>	0,910	0,801
ResNet50	<u>0,909</u>	0,872	0,890	0,846



SSD512 (VGG16)

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SSD512 (VGG16)

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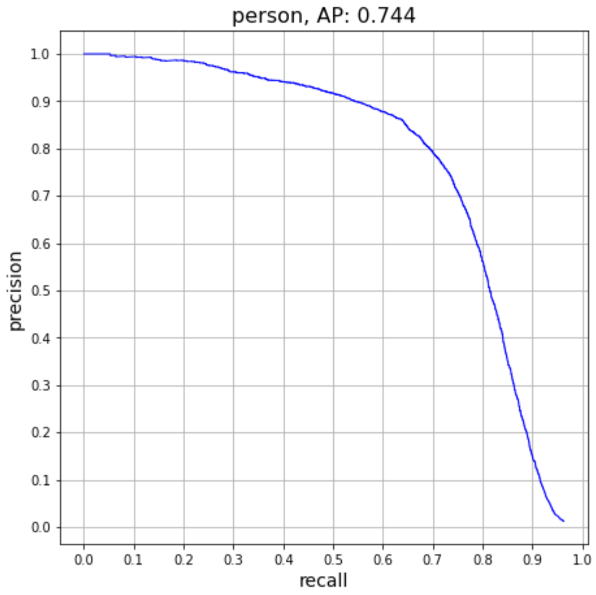
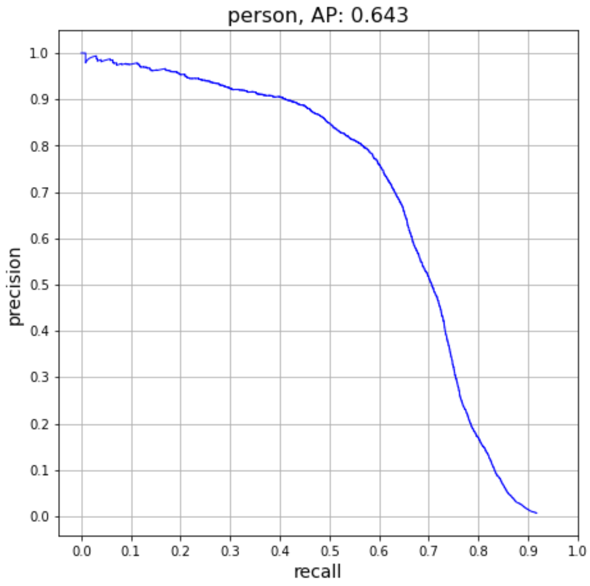
RESULTS AND DISCUSSIONS

The SSD300 and SSD512 presented *weights* related to models already trained on the Pascal VOC 07 + 12 dataset; a **fine tuning** of the weights was made to go from 20 classes to the only <**person**> class.



SSD512



SSD300

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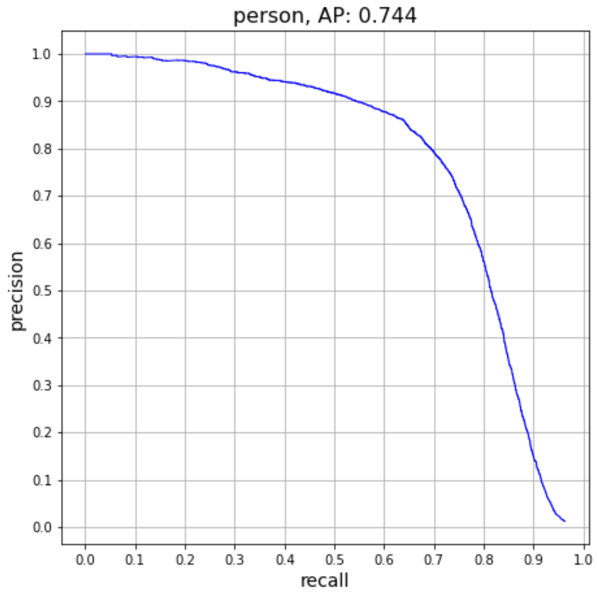
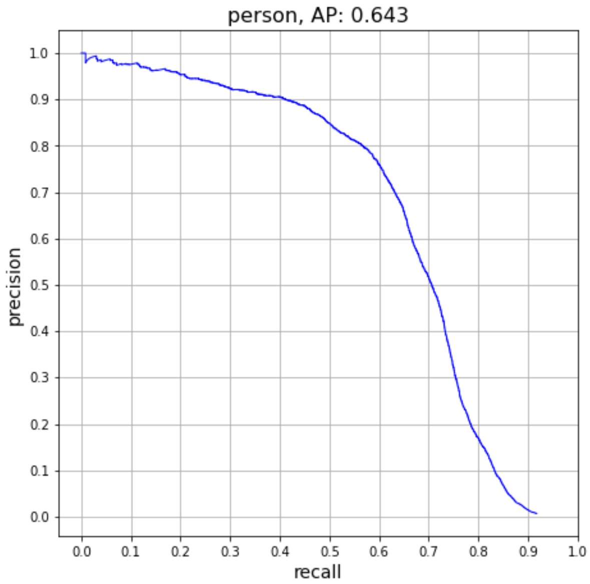


SSD512

FINE-TUNE	SSD300	SSD512
AP	0,643	0,744
Recall	0,887	0,934
F1 Score	0,746	0,828
IoU	0,712	0,885



SSD300

CONCLUSION AND FUTURE WORKS

- ✓ Labelling the Dataset (~17.000);
- ✓ Replacement of VGG16 with ResNet50;
- ✓ Training from scratch and fine-tuning;
- ✓ Average Precision not less than 90%.

The proposed approach, i.e. replacing the feature extractor, proved to be excellent to solve the detection problem. The best architecture remains the SSD512 with the VGG16.

CONCLUSION AND FUTURE WORKS

- Changing the feature extractor with other architectures ResNet-like, for example DenseNet;
- Changing the type of feature extractor, i.e. Feature Pyramid Networks (FPN)

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“Some people call it Artificial Intelligence but the reality is, this technology will enhance us. So, instead of Artificial Intelligence I think we will Augment our Intelligence”

Ginni Rometty, President & CEO of IBM