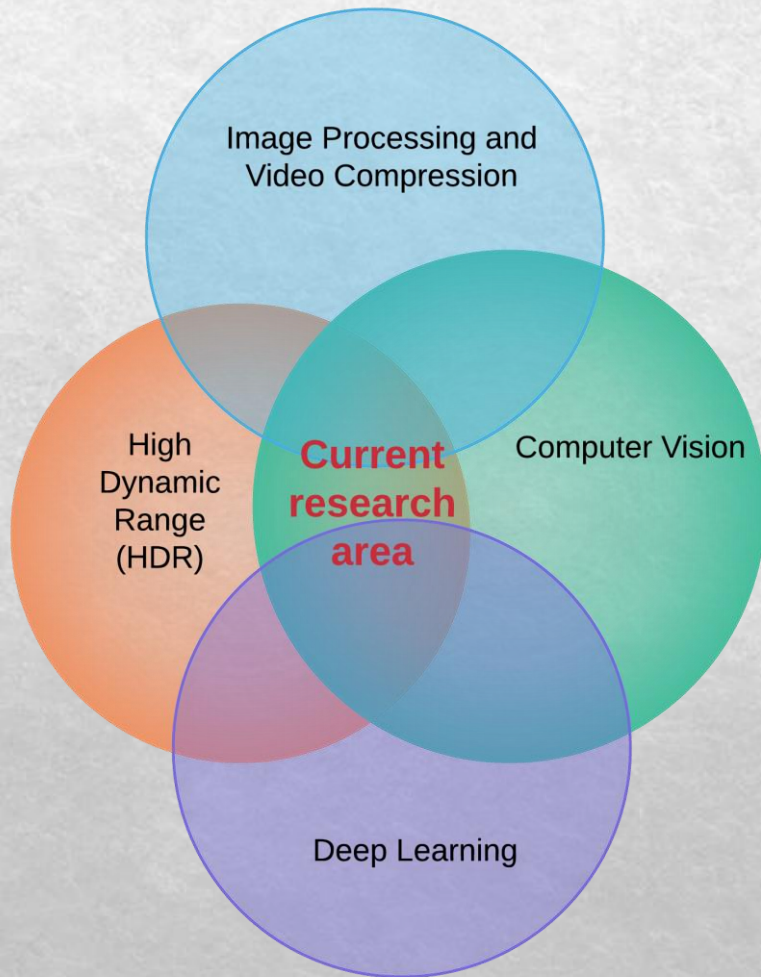


High Dynamic Range in Computer Vision

- Ratnajit Mukherjee
- Research Fellow, INESC TEC, Portugal
- Deep Learning Research Scientist, Navinfo Europe B.V., Netherlands

Research scope



- High Dynamic Range (HDR) in object detection encompasses
 1. High dynamic range image and video processing
 2. Explore traditional object detection and tracking techniques.
 3. Deep learning based:
 - Image generation (generative NNs)
 - CNN based object detection.

A few important tasks in Computer Vision

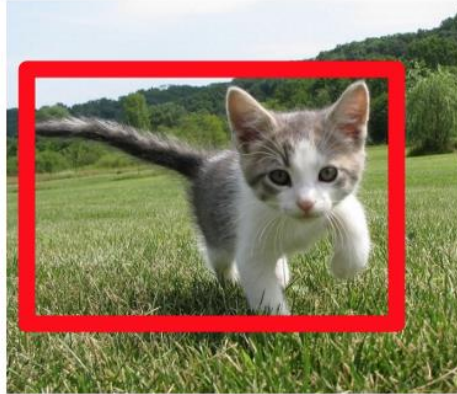
Classification



CAT

Single Object

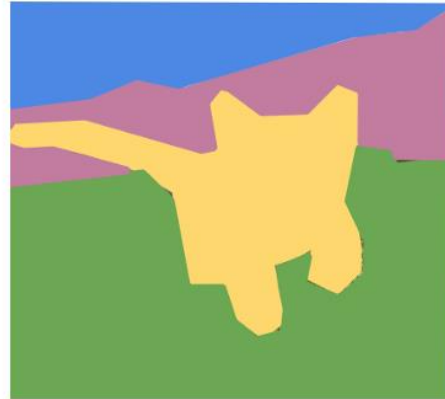
Classification + Localization



CAT

Single Object

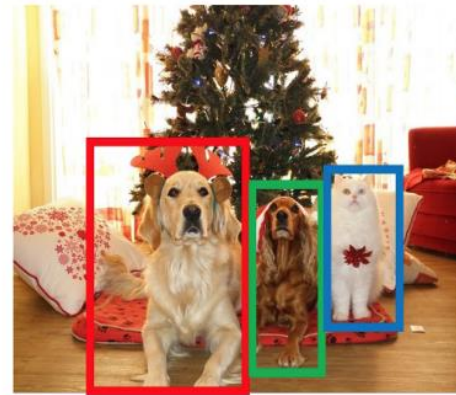
Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

Object Detection



DOG, DOG, CAT

Multiple Object

Instance Segmentation

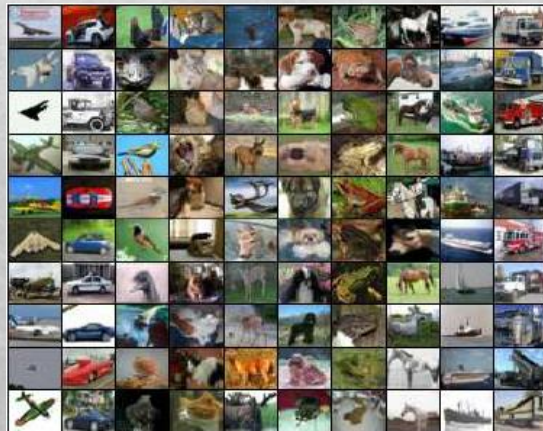


DOG, DOG, CAT

Some standardized datasets

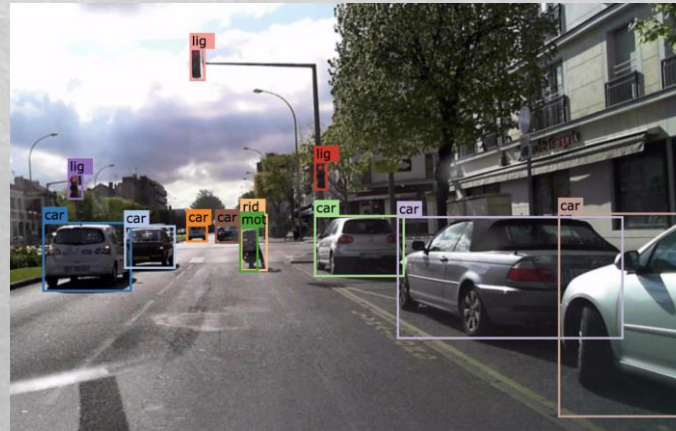
Classification:

- CIFAR 10 and 100
- Stanford cars
- ImageNet
- Open Images Dataset
- FER 2013 (emotion classification)



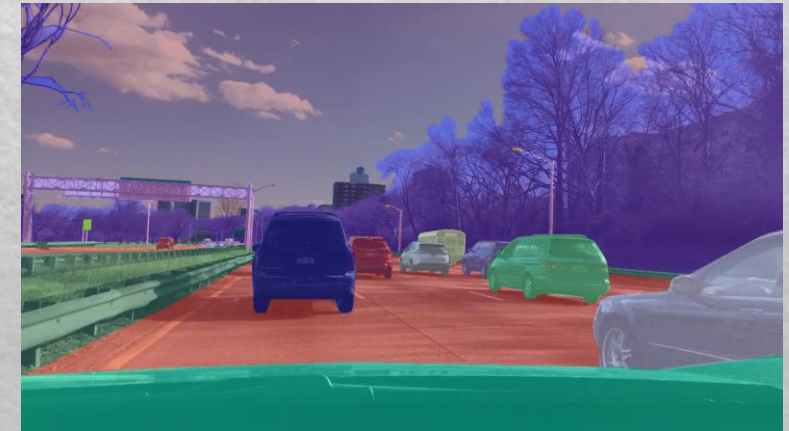
Object Detection:

- PASCAL VOC (2007 + 2012)
- MS COCO
- ILSVRC (detection subset)
- Open Images Dataset (subset)
- BDD100K



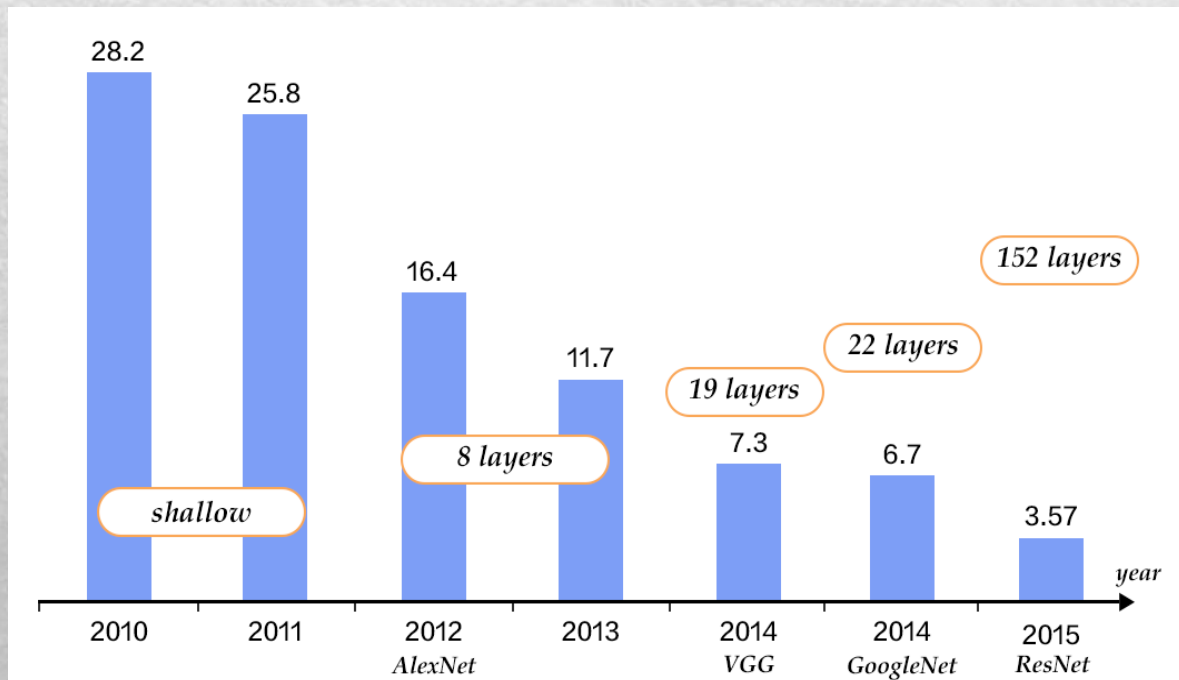
Semantic segmentation:

- CamVid
- KITTI
- CityScapes
- Mapillary
- BDD100K



Some state-of-the-art results (using deep learning)

- The introduction of deep neural networks (AlexNet, 2012) have changed the whole paradigm in computer vision with near human levels of accuracy.



Large scale **image classification** (error rate)

Algorithm	Dataset	mAP [AP 50]
SSD	Pascal VOC (07 + 12)	82.2
Faster RCNN	Pascal VOC (07 + 12)	75.9
R-FCN	Pascal VOC (07)	82.0
YOLO v2	Pascal VOC (07)	78.6
SSD	MS COCO (15)	48.5
YOLO v2	MS COCO (15)	44.2
Mask R-CNN	MS COCO (16)	63.2
CenterNet	MS COCO (15)	50.30

Large scale **object detection** (mAP)

The state-of-the-art results are scarily good...

So what is left to do ?

We shall see in the next slides...

So where do computer vision algorithms fail?

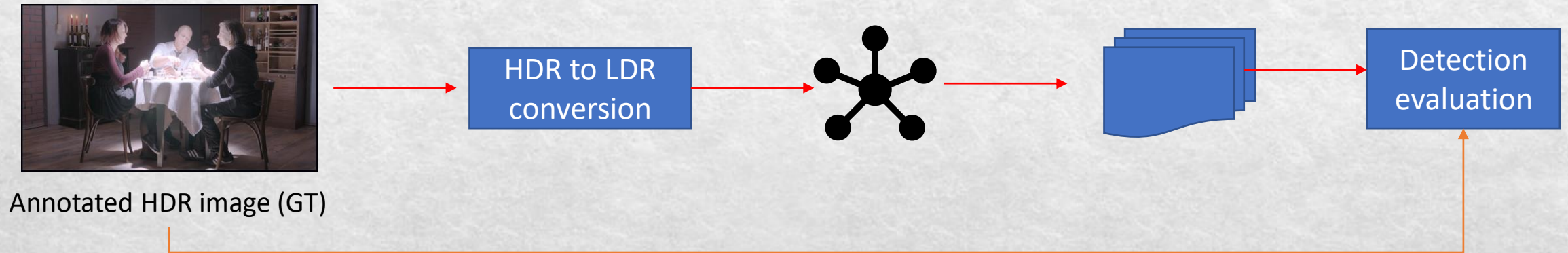
- Computer vision algorithms are mostly trained on LDR images i.e. 3 orders of magnitude of ambient lighting conditions.
- The limited DR in 8-bit data:
 - Fails to capture information in underexposed or overexposed scenarios.
 - Adverse conditions – (imagine night → blizzard)
 - High contrast scenarios
 - Rapidly changing lighting conditions (imagine tunnel)



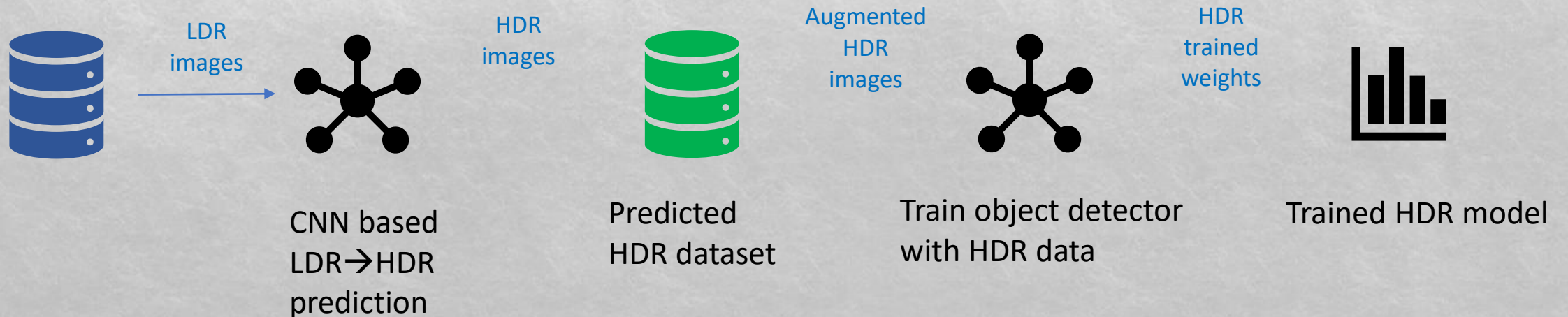
Example: extreme lighting condition leading to partial occlusion.

Research approach

1. Approach 1: Backward compatible HDR object detection using existing detectors



2. Approach 2: Generate HDR data and train HDR object detectors



But we have a BIG !! data problem



≈ 2000 HDR images are freely available from various sources



≈ 3000 HDR images (mobile photo-burst) are available from Google HDR dataset

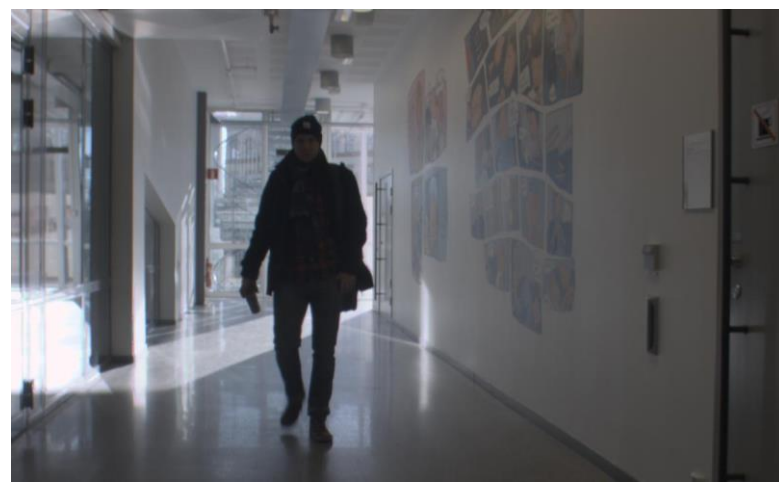
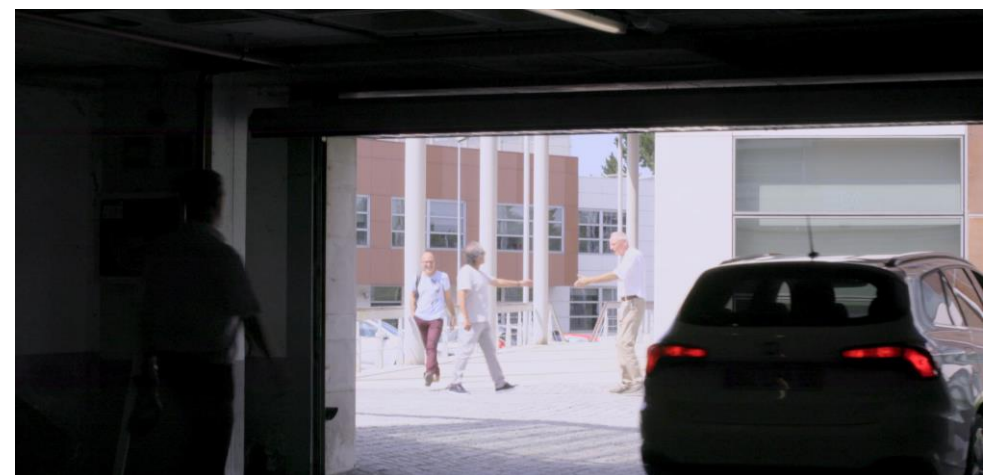


≈ 50 usable HDR video sequences (5-10 secs) are available.

All classification, detection and segmentation datasets are 8-bit LDR datasets

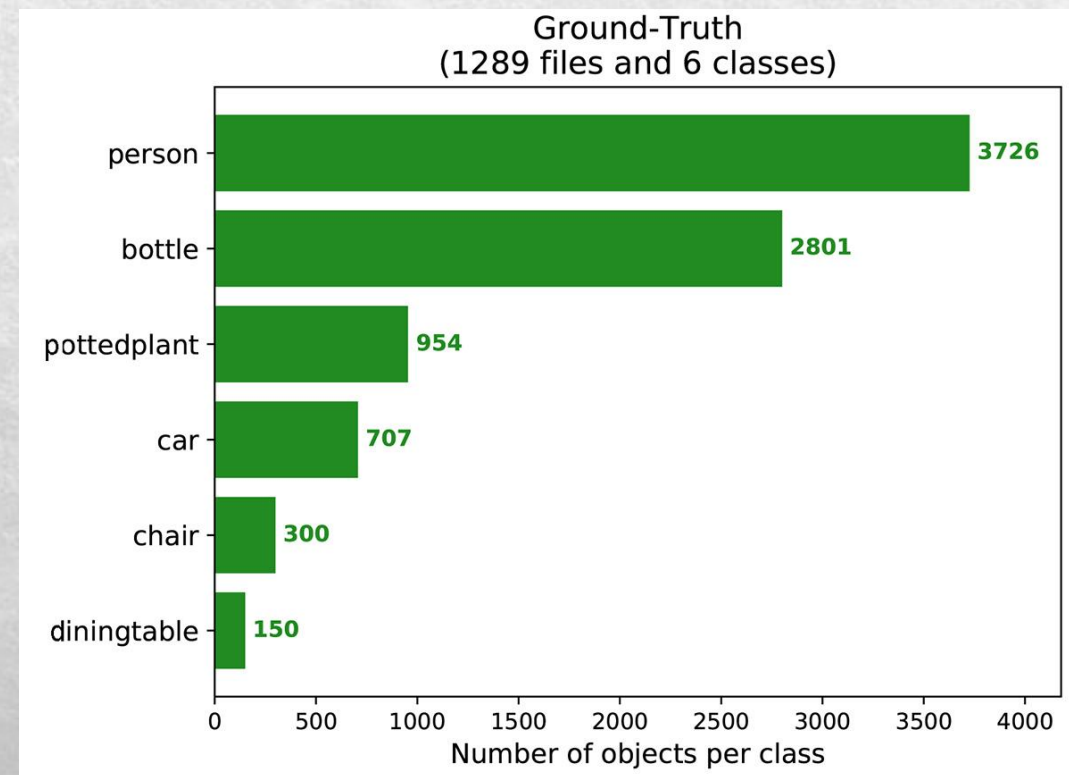
PART – I :

Dataset generation



Creation of mini-HDR dataset (OOD dataset)

- 6 video sequences
 - Varied capture sources (Canon, ARRI, Spheron)
 - Average dynamic range 18 ± 2 stops.
 - Shortlisted images \rightarrow GT \approx 1300 images.
 - Annotated and cross-verified by 4 annotators.
 - Object categories: 6 object categories.
 - To test both approaches 1 and 2.

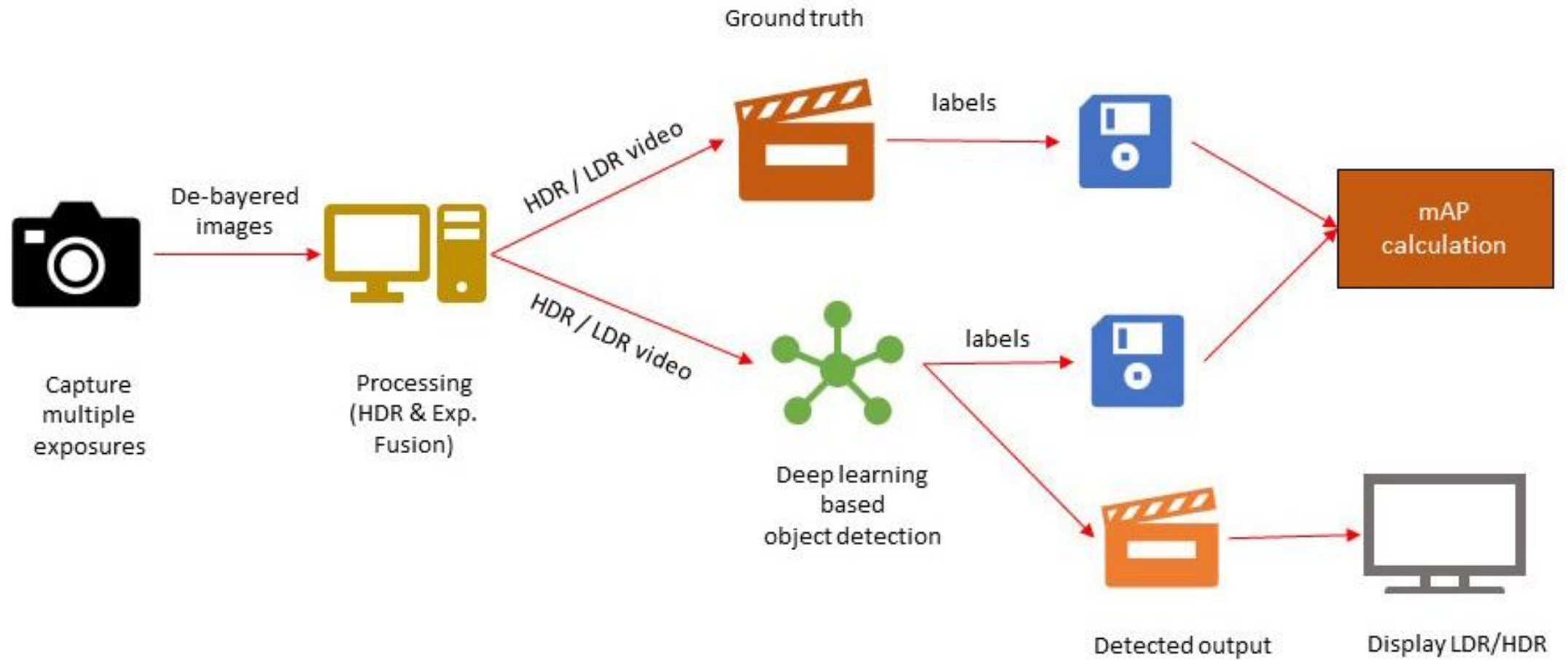


Later we shall highlight the key problems in annotating HDR images..

PART – II :

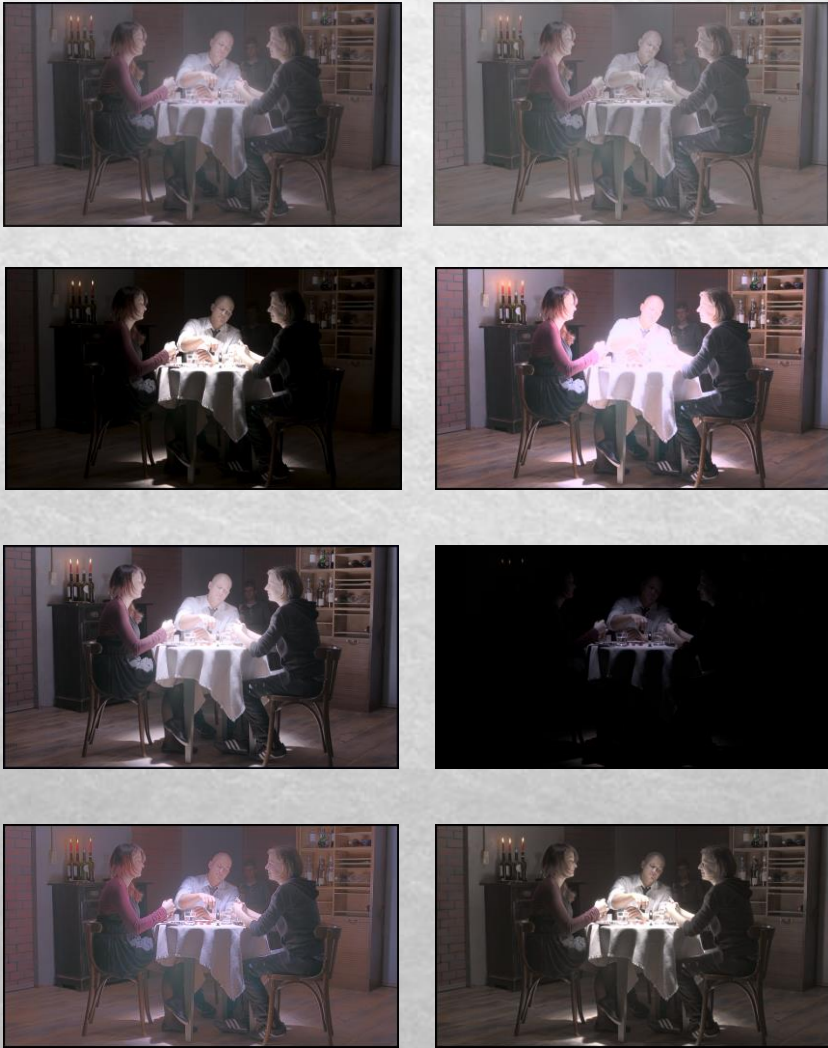
Setting up a detection pipeline

Designing a single HDR/LDR detection pipeline



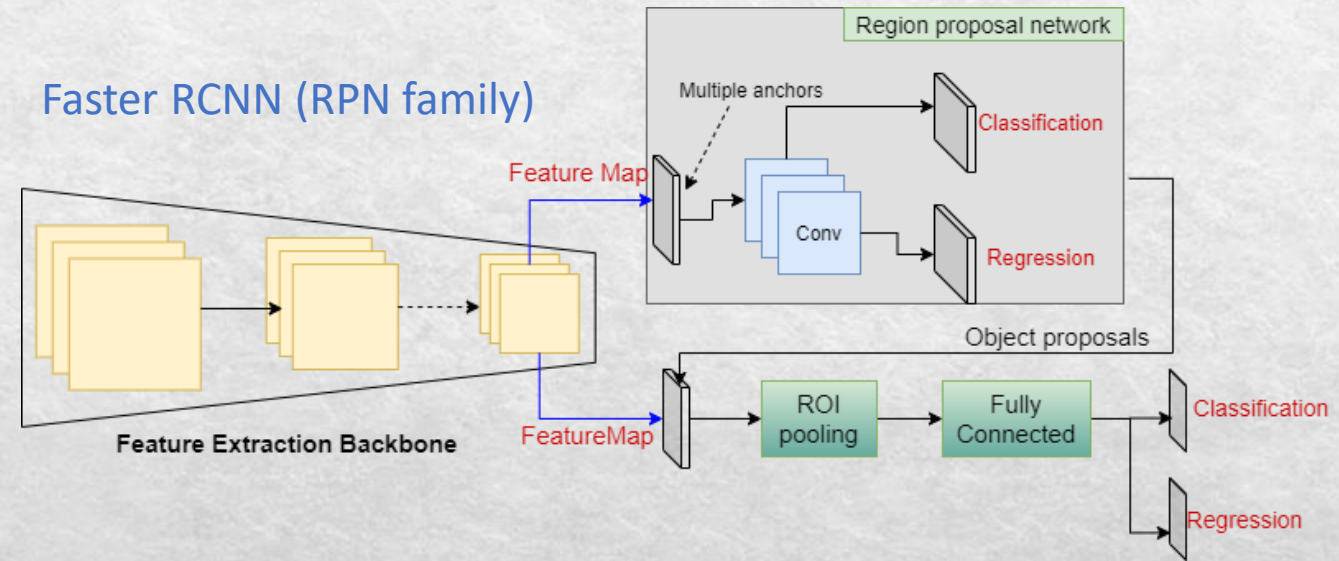
Pipeline works for both HDR & LDR videos

Materials

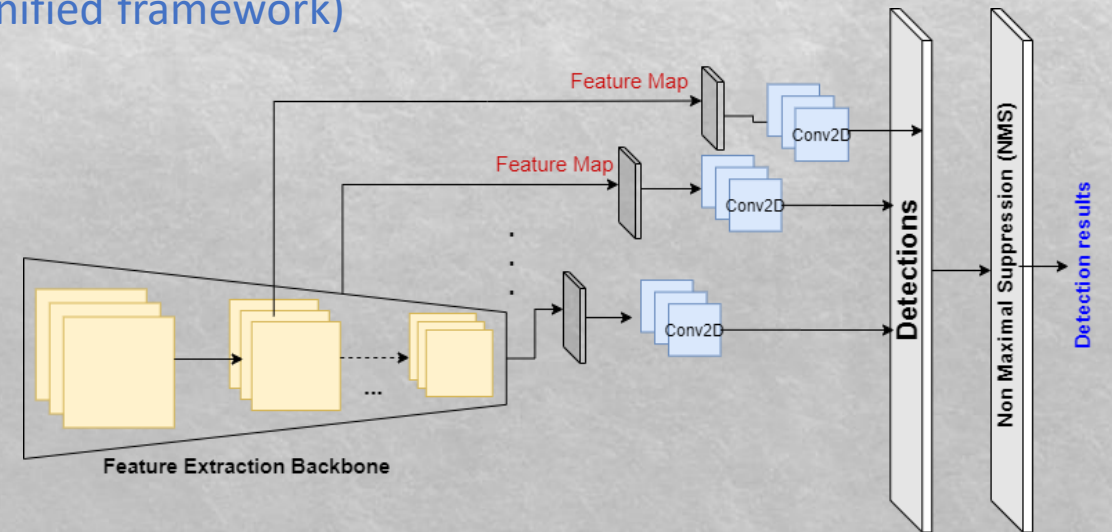


8 HDR to LDR mapping techniques

Faster RCNN (RPN family)



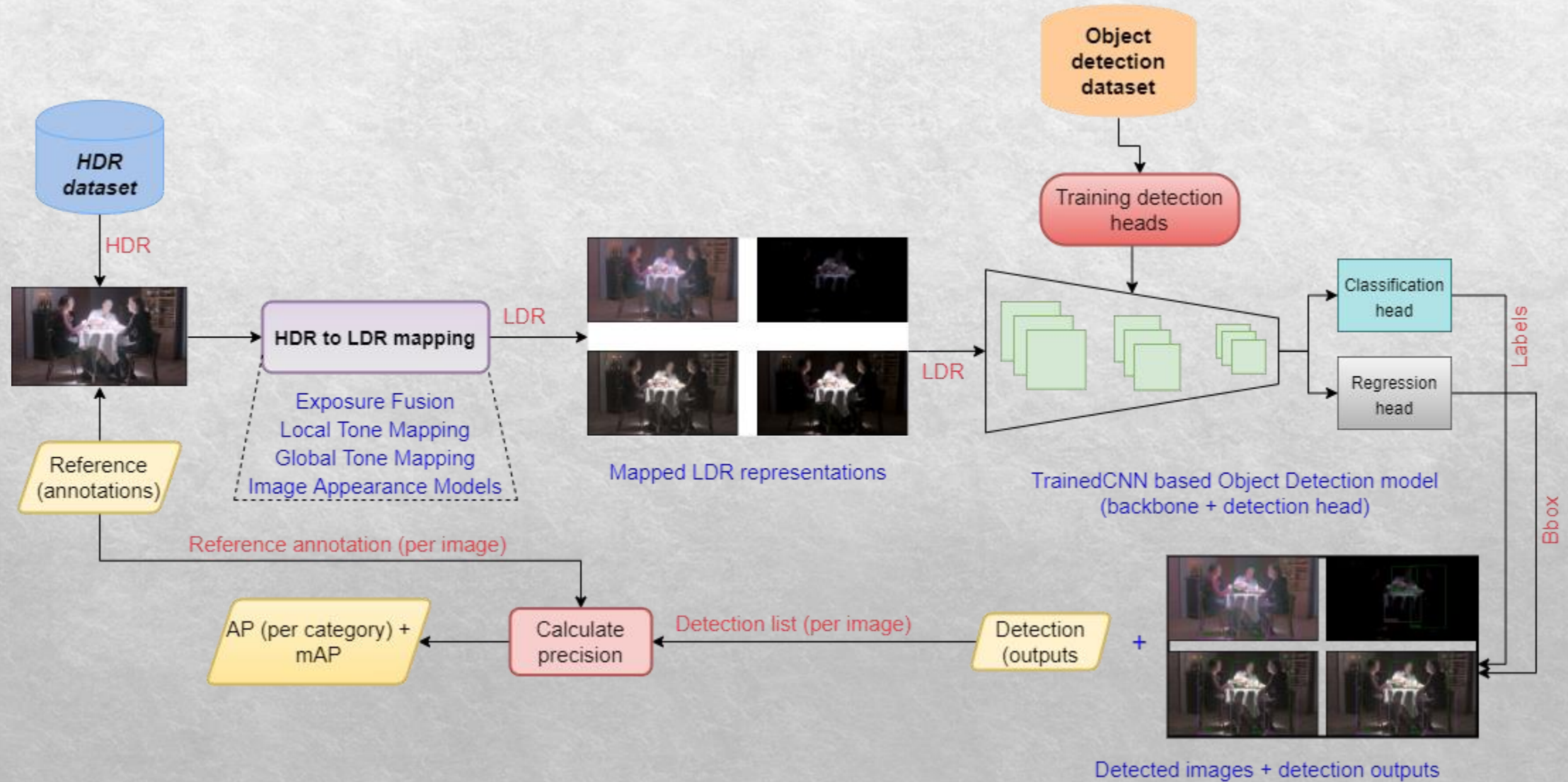
SSD (unified framework)



PART – III :

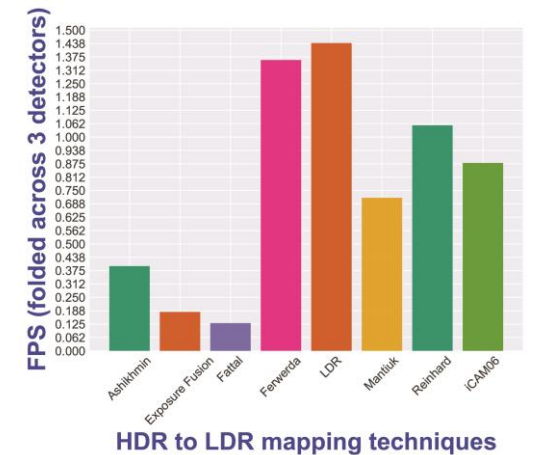
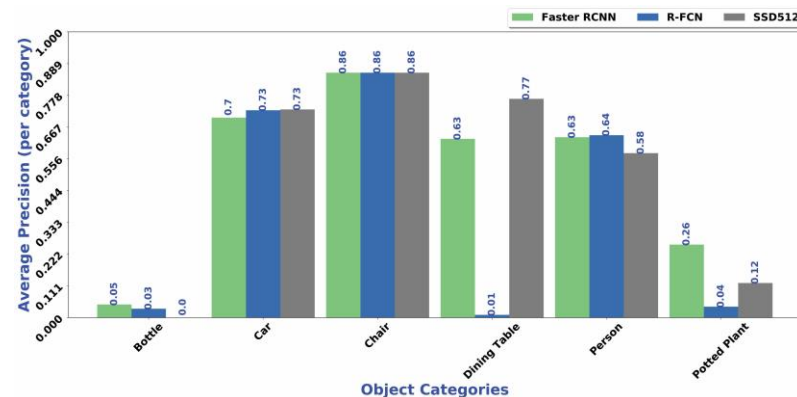
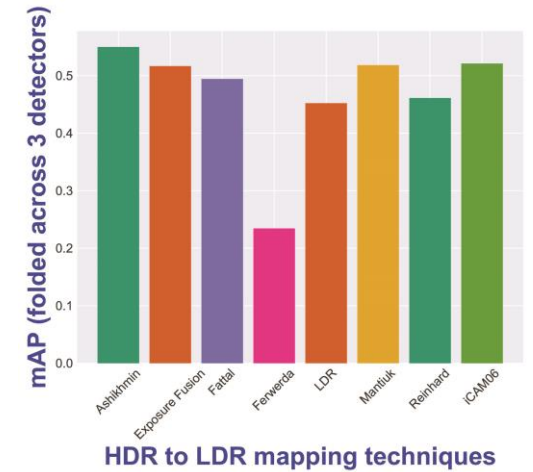
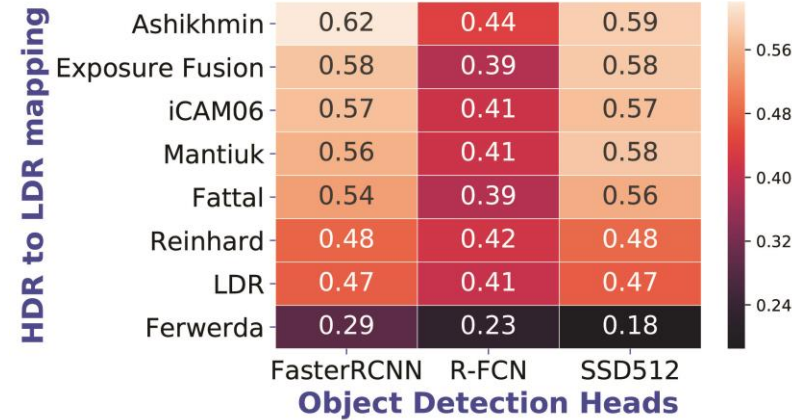
Backward compatible HDR object detection

1. Backward compatible HDR object detection



Evaluation and results

- 7 HDR to LDR mapping techniques (each representing a class of mapping techniques) + LDR image
- 3 object detectors (two RPN family and 1 unified framework)
- Faster RCNN & SSD 512 > R-FCN
- Most TMOs > LDR image
- Gradient based TMOs best and fastest
- Smaller objects difficult to detect



PART – IV : HDR object detection

Key challenges & solutions for HDR object detection

Challenges

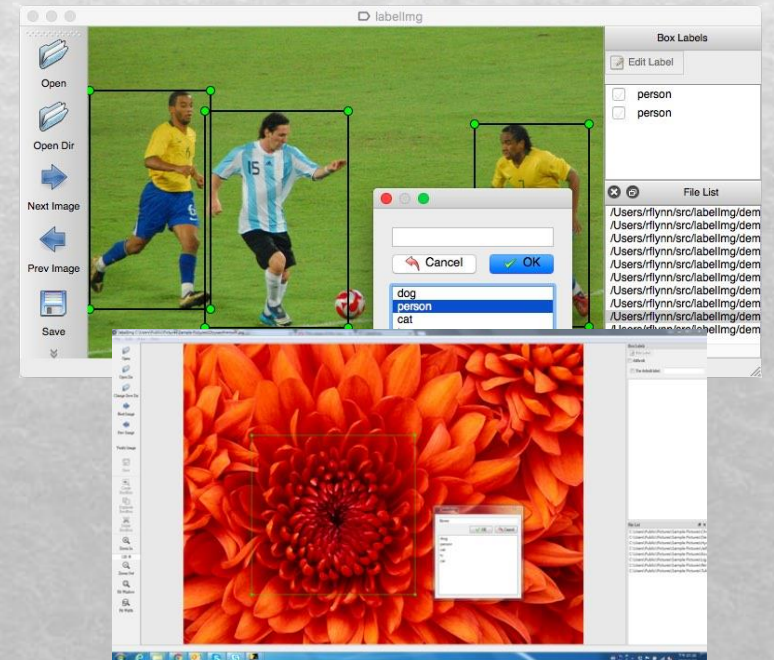
- No HDR capture software / hardware has a complete pipeline
- No annotated HDR image / video dataset exists to date
- No annotation tool supports HDR images
- No object detector trained for HDR images to date.

Solutions

- Use LDR image datasets to create pseudo-HDR datasets (already contains annotations)
- Explore LDR to HDR expansion techniques and evaluate them.
- Use pseudo-HDR datasets to train existing detectors with HDR augmentation
- Test and refine detector based on actual OOD dataset

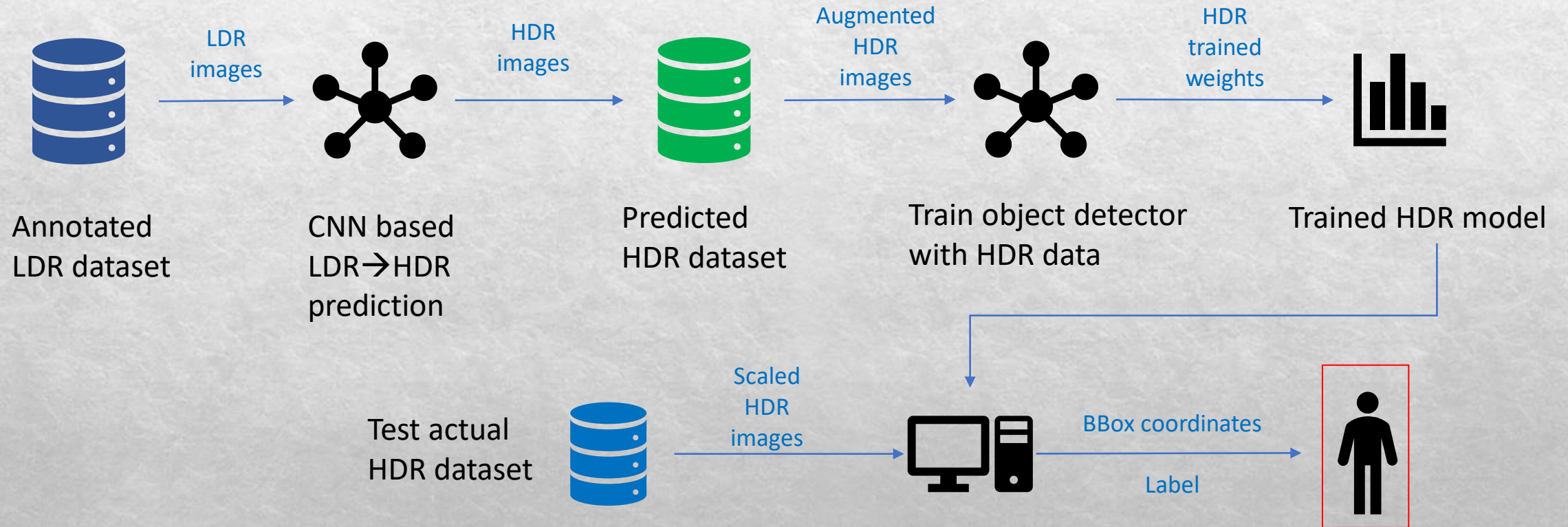


HDR image/video content

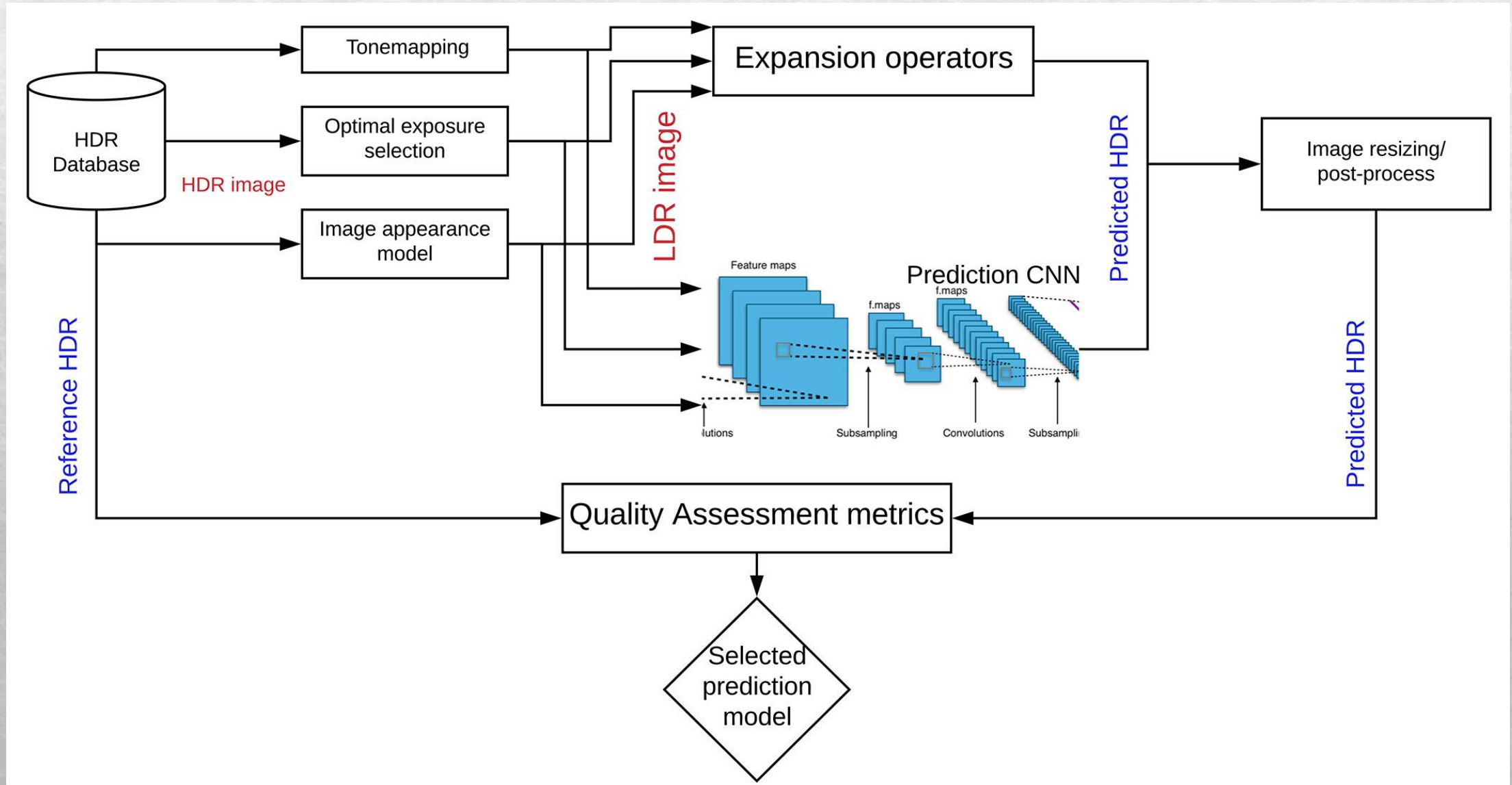


Annotation tool

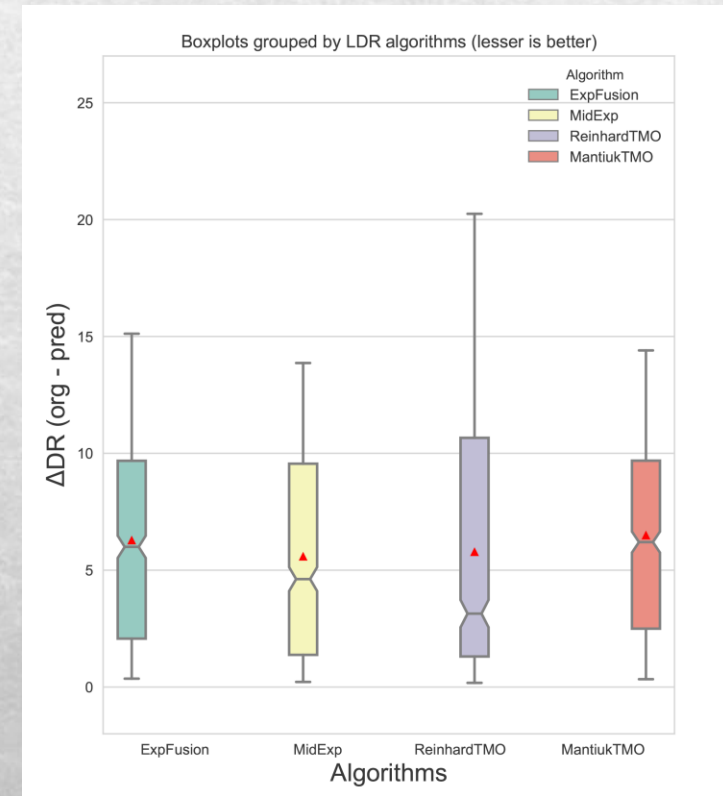
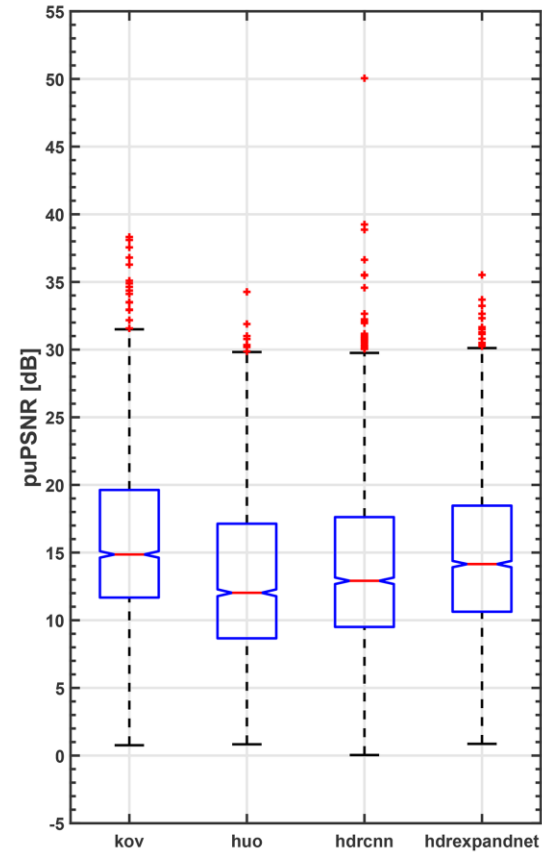
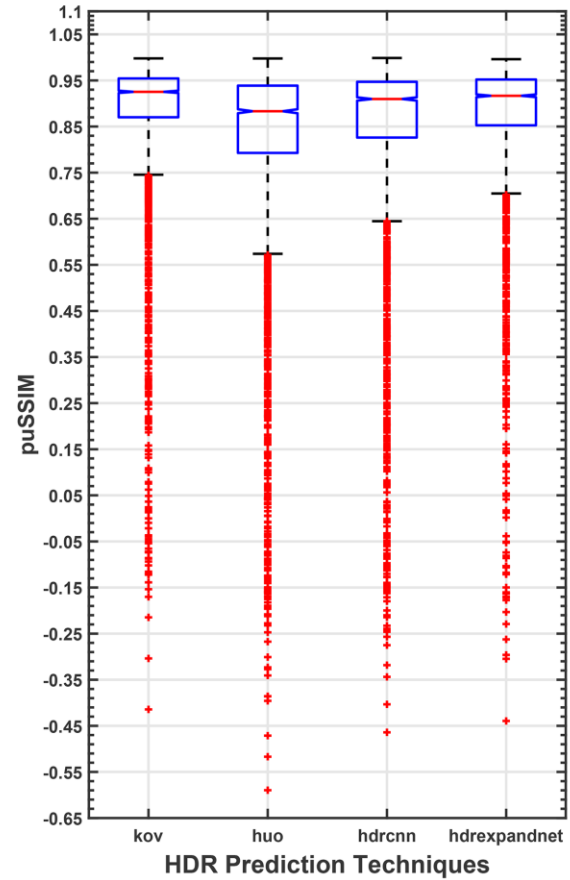
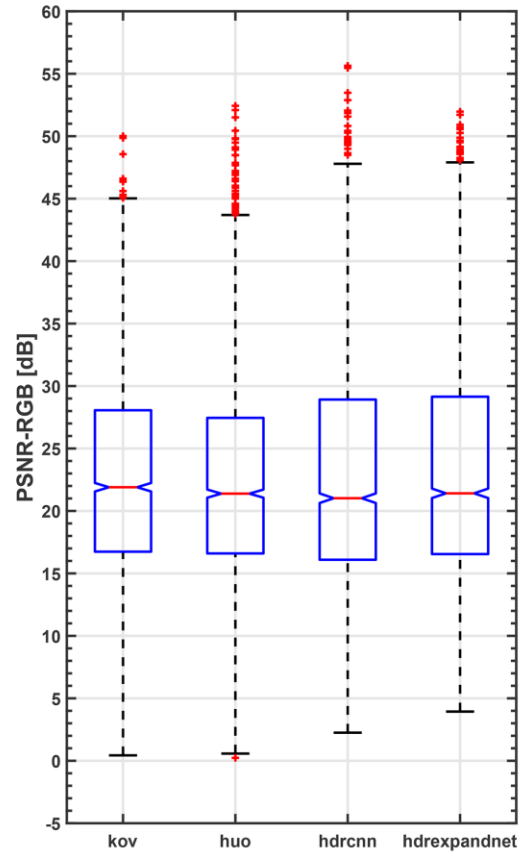
HDR object detection pipeline



LDR expansion evaluation pipeline

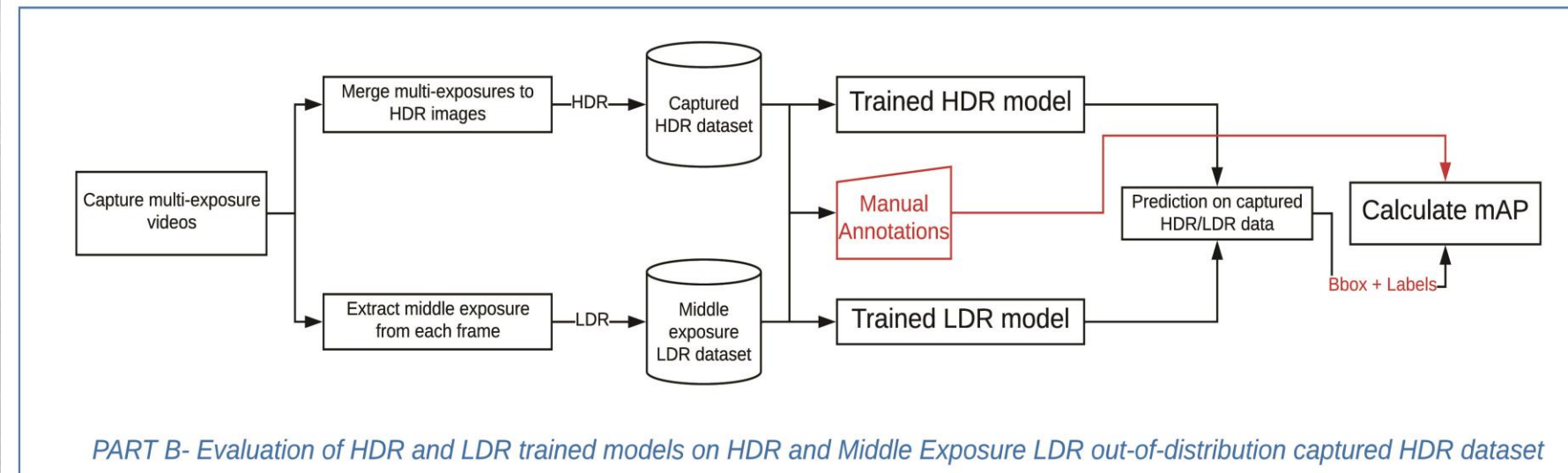
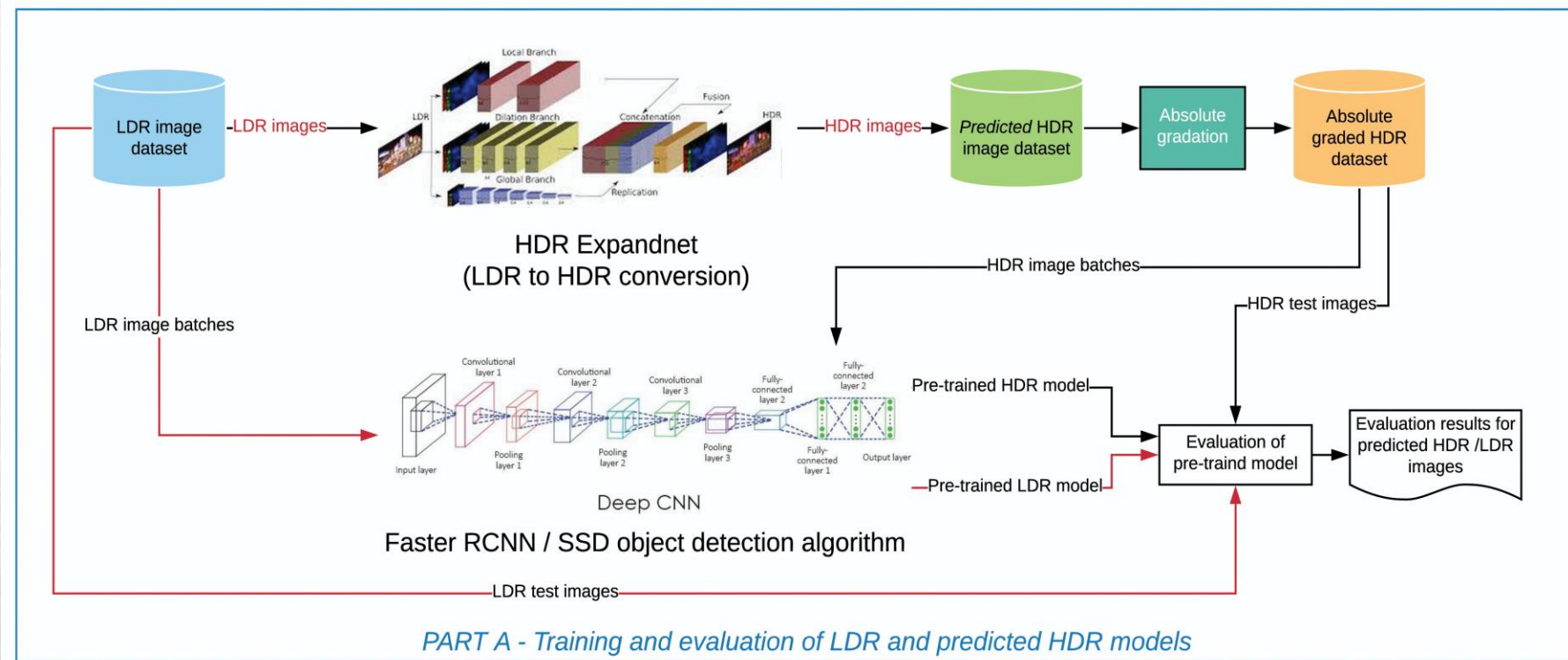


Expansion evaluation results...

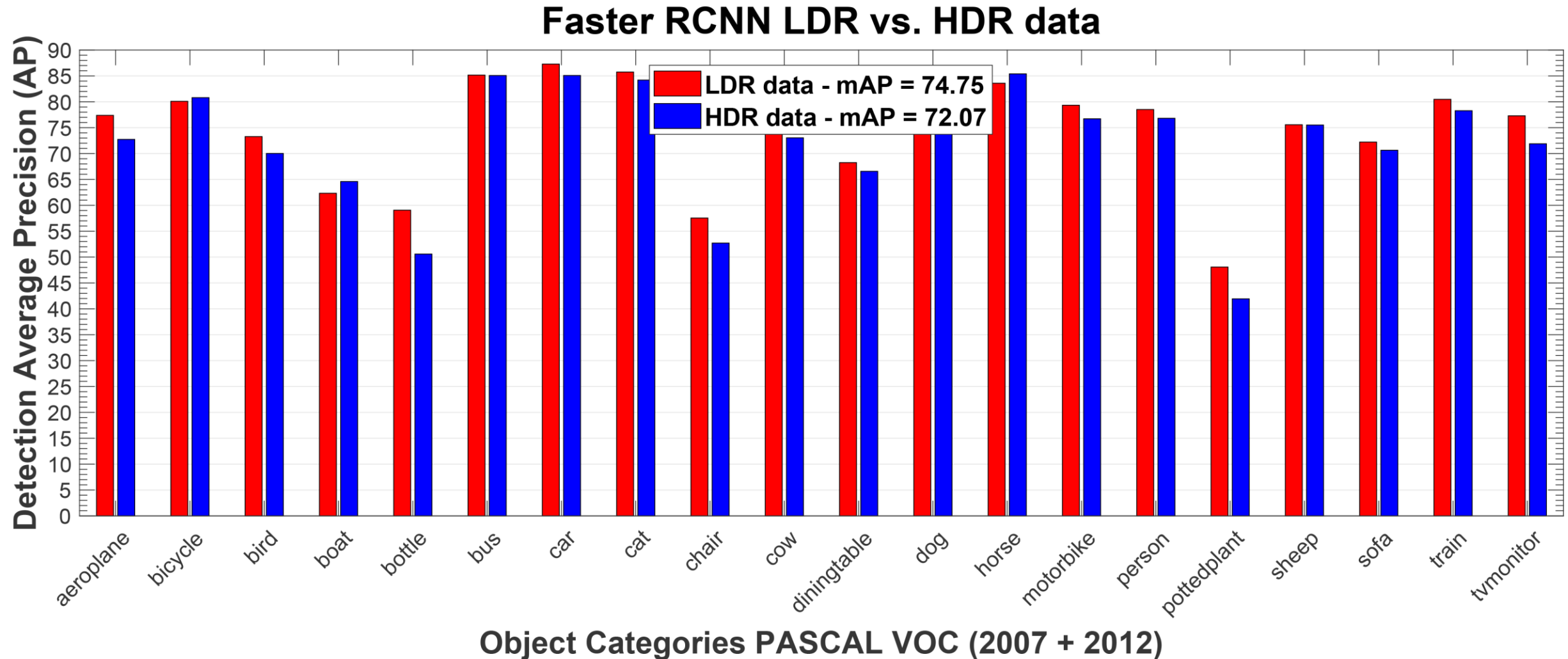


HDR object detection

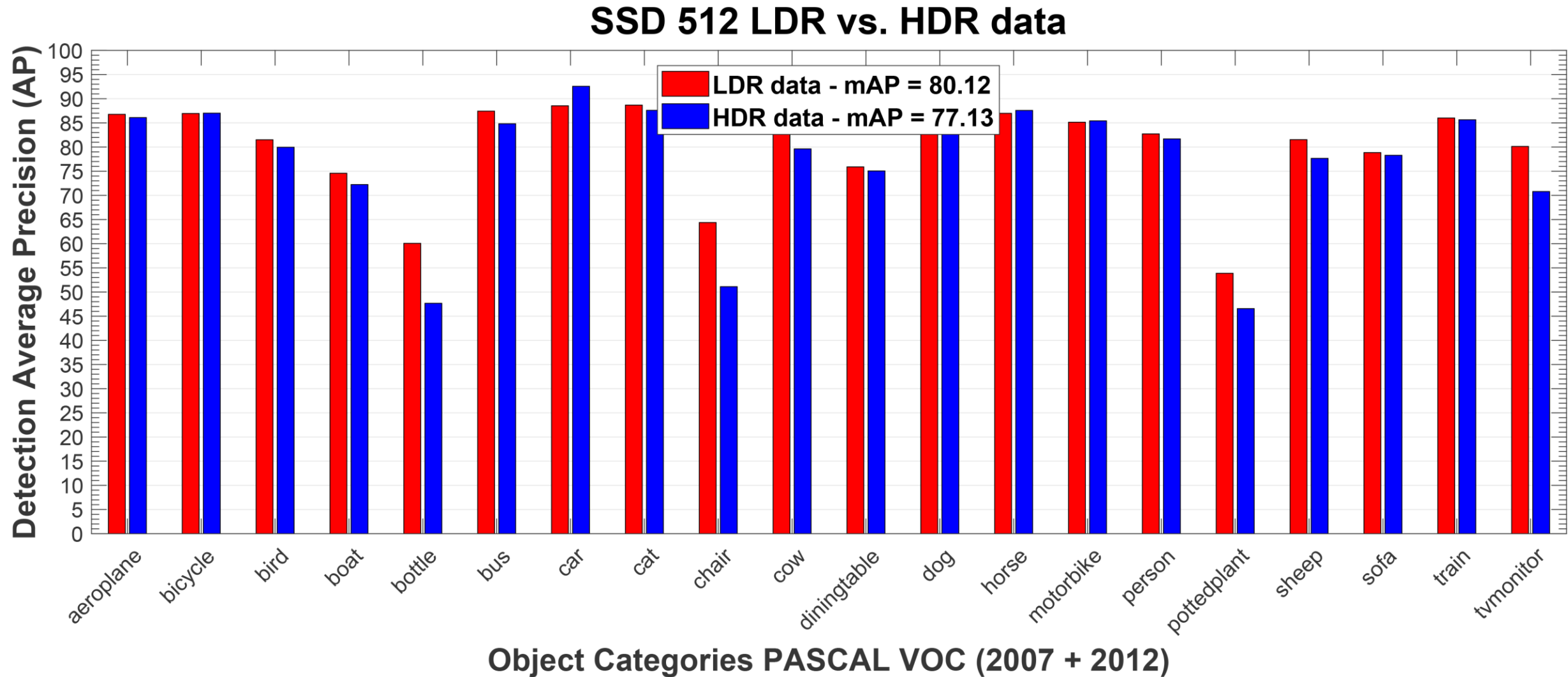
- Dataset selected:
 - PASCAL VOC (small)
 - Contains 20K images
 - 52K annotations
- LDR2HDR:
 - Deep learning based HDR expandnet
- Object detectors:
 - Faster RCNN
 - SSD
- Test dataset:
 - OOD dataset 1289 images

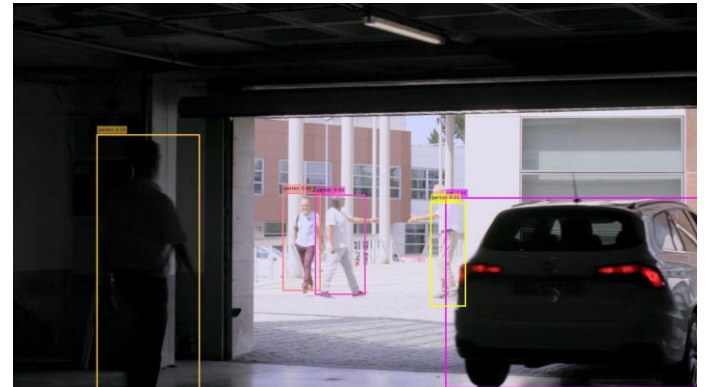
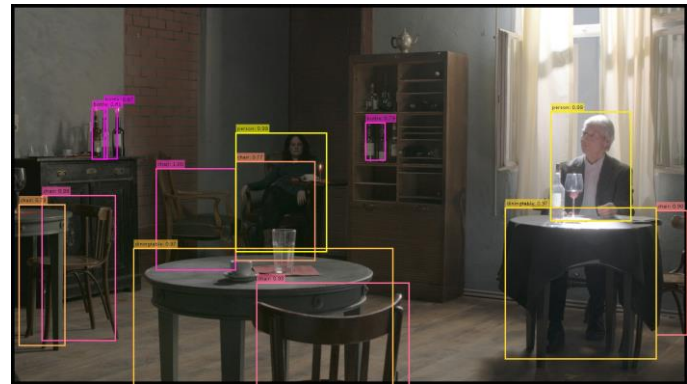


PASCAL VOC test (in distribution) – Faster RCNN



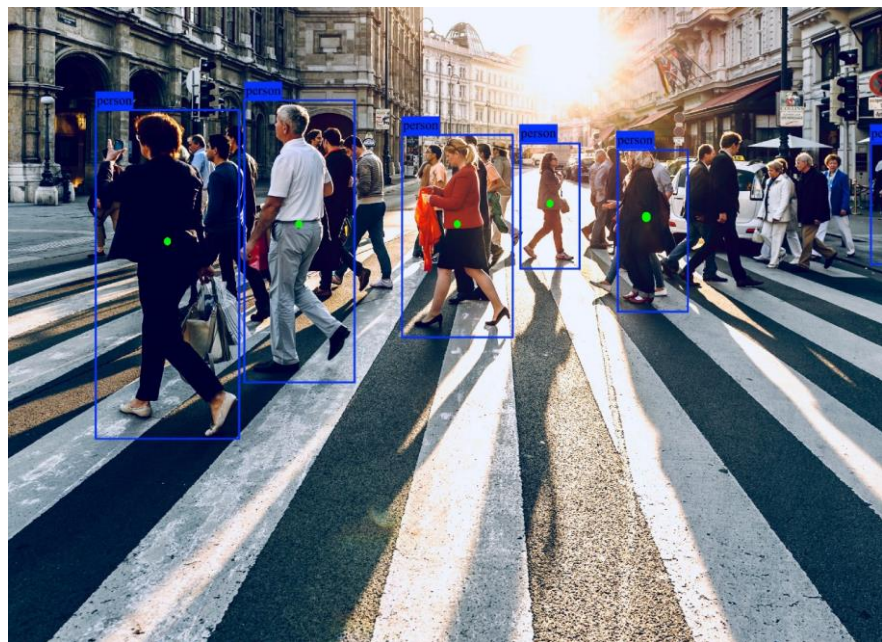
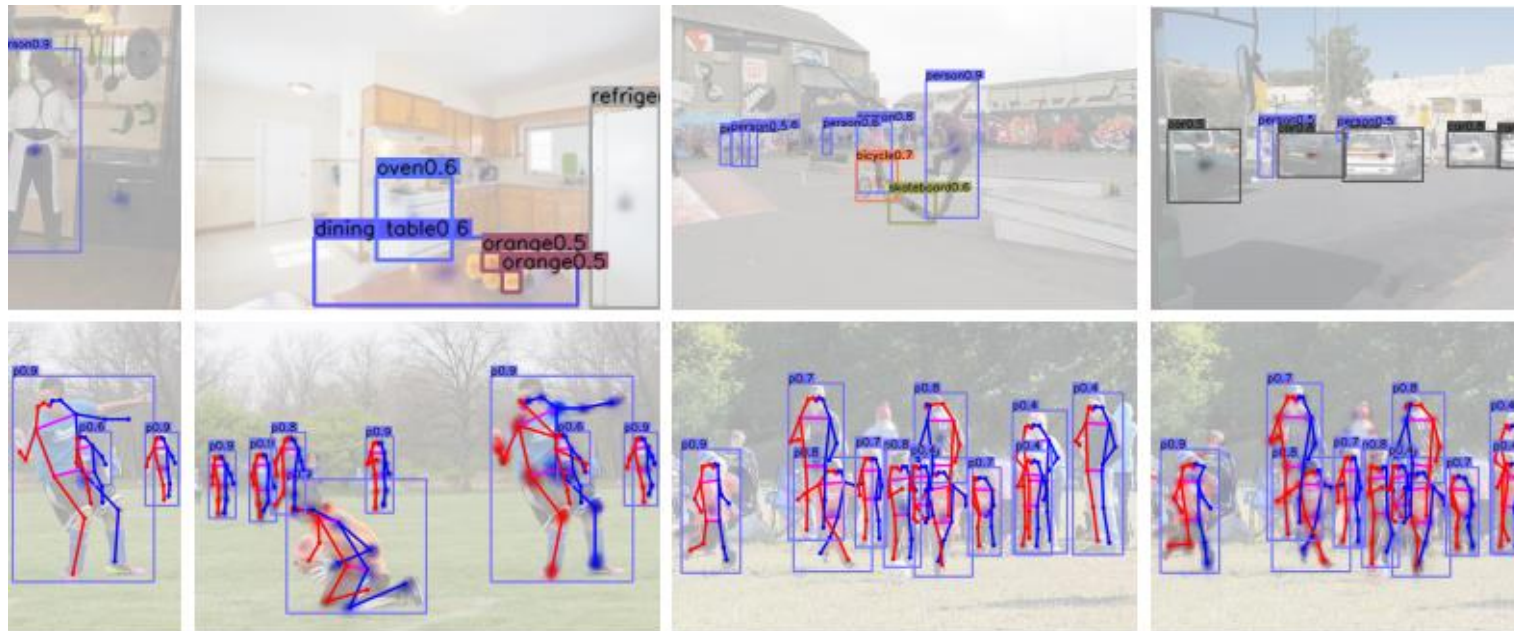
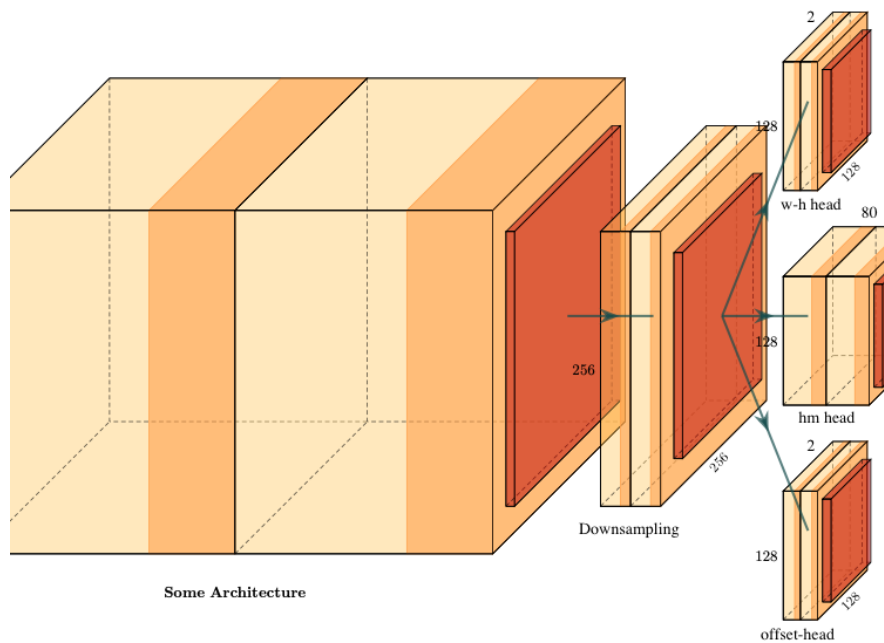
PASCAL VOC test – SSD 512





- results HDR vs LDR evaluation

PART – V :
The future...



Keypoint estimation

Real time scene understanding – panoptic segmentation





thank you..