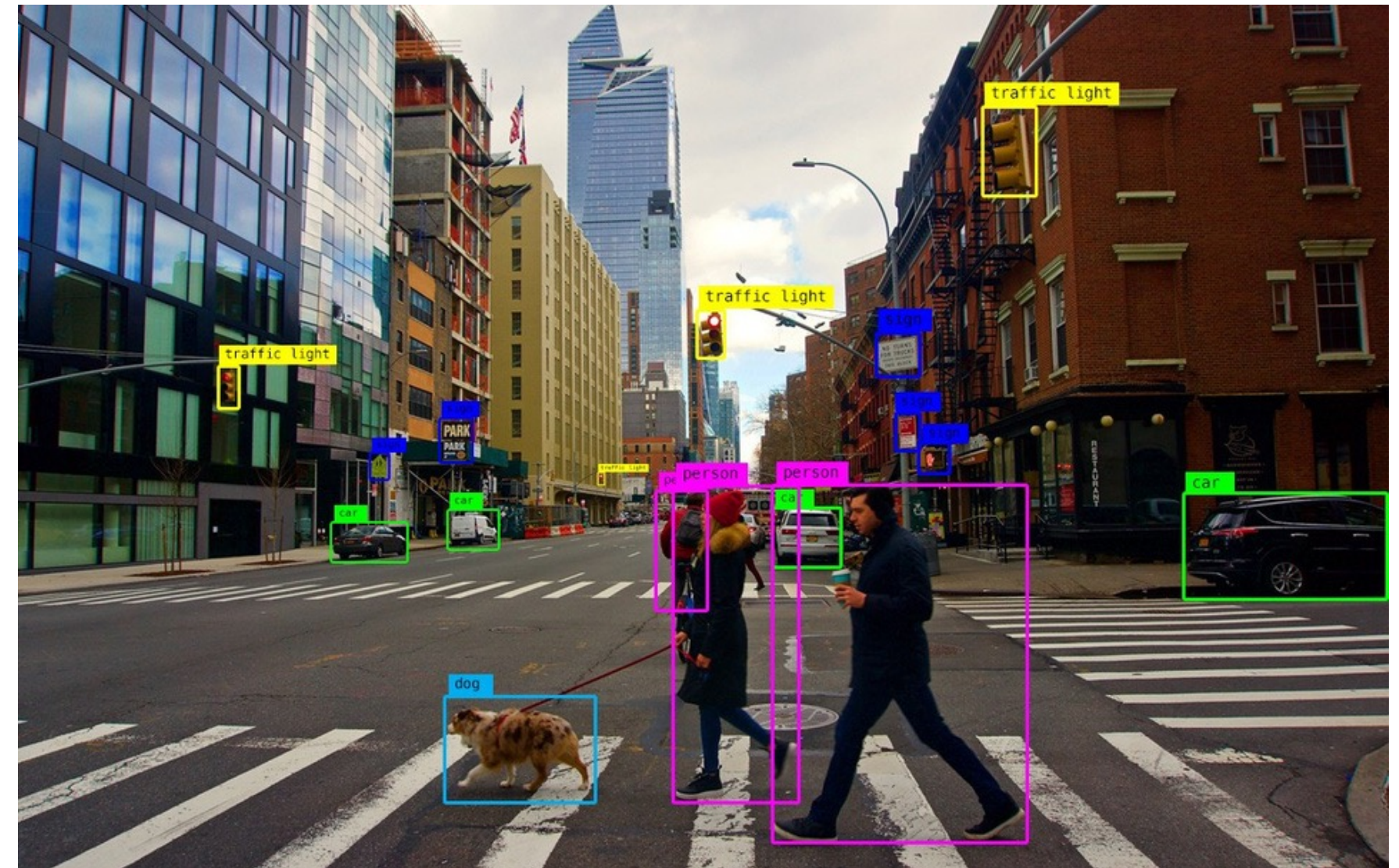


# Multi-Vision System for Autonomous Driving



## STUDENTS

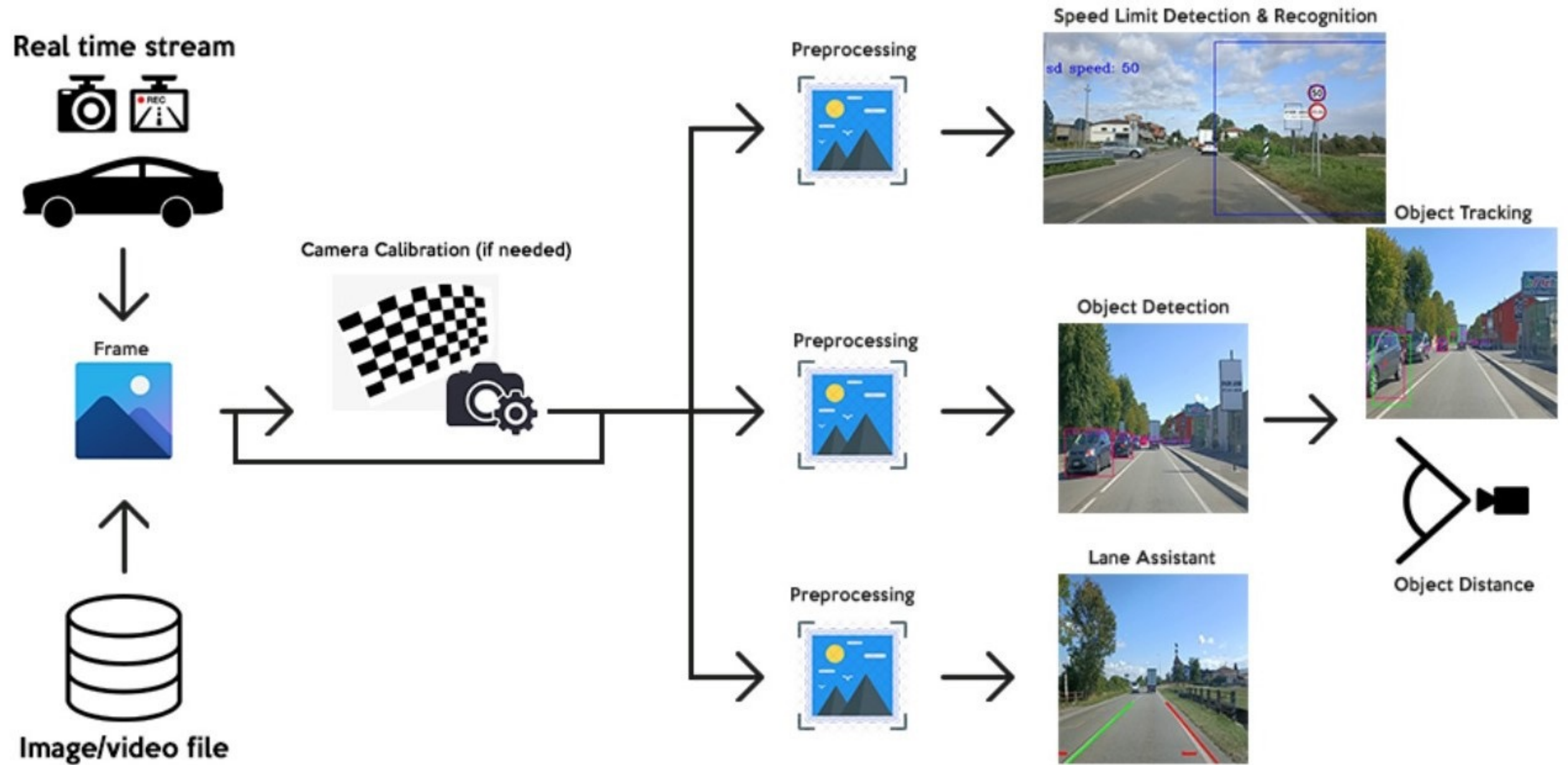
Daniel Rossi  
Riccardo Salami  
Filippo Ferrari

## TUTORS

Roberto Amoroso  
Silvia Cascianelli



# Pipeline

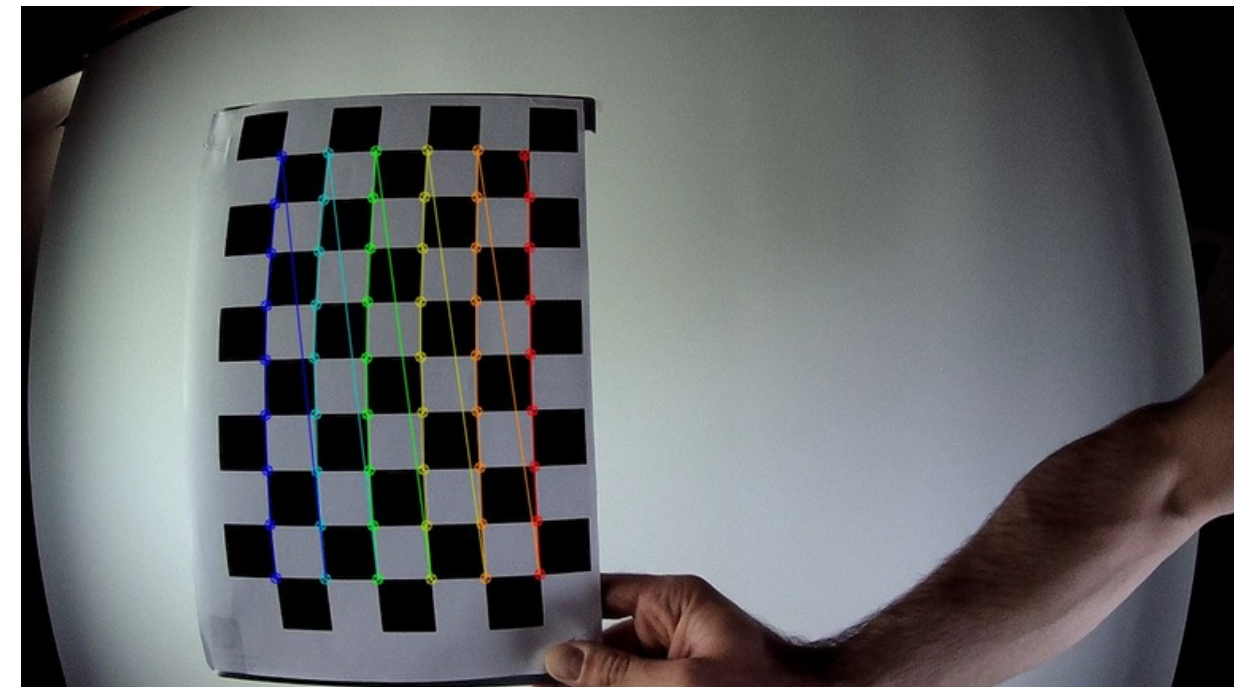
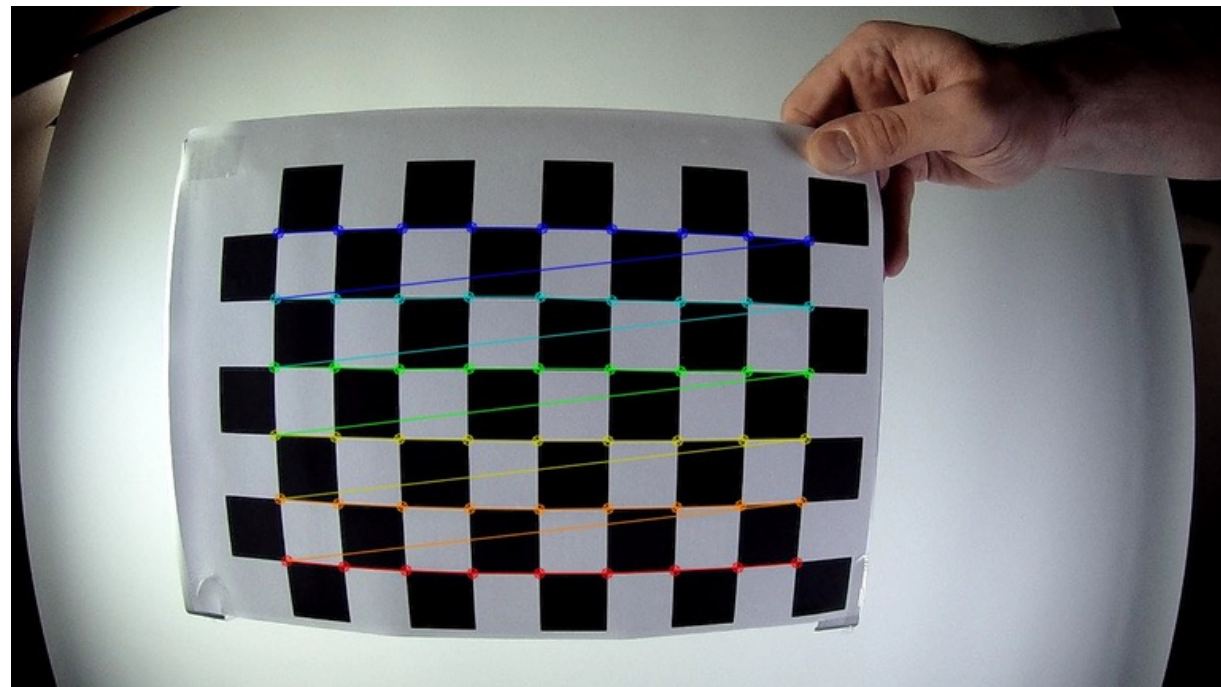


# Classical Techniques

# Camera Calibration

The wide-angle lens of the camera we use creates a barrel distortion, so it was necessary to correct the image through camera calibration.

For the calibration task, we used **Zhang's technique**: we printed a chessboard and we acquired dozens of images of it, in order to estimate the camera parameters and obtain undistorted images.





# Lane assistant

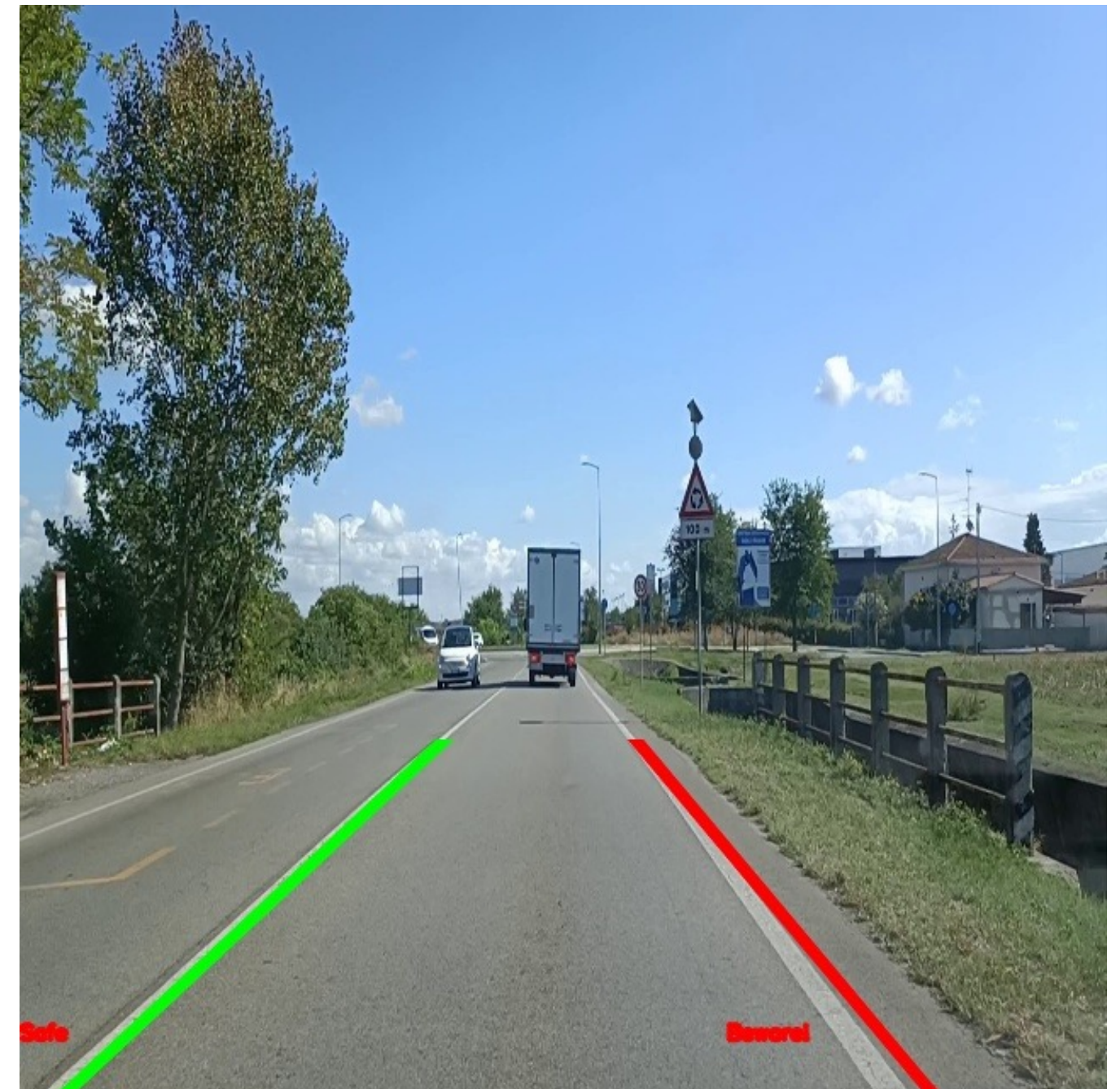
The lines at the sides of the road are detected and the driver is notified if he's crossing either the left or the right one, preventing him from endangering him and the other passengers.

The trickiest problem for this part was surely the removal of noise.

First, we remove the grass from the image, this removal is done using HSV color-space.

Then, based on the mean luminance of the entire image, we decide whether to enable Equalization or not and the parameters to use for the **bilateral filter**.

Finally, we apply **Canny** and we look for possible lines through the Hough transform.



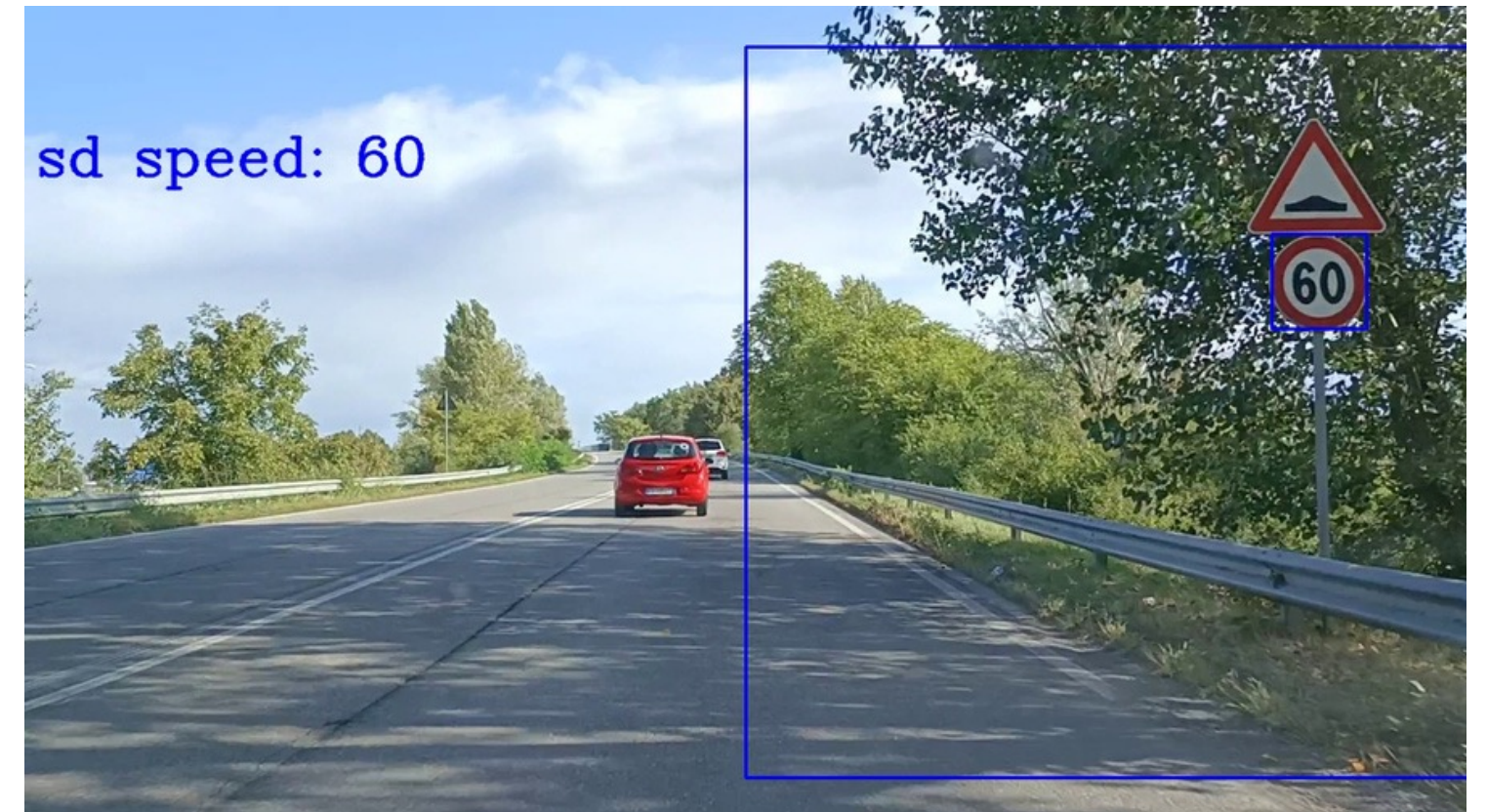


# Speed Limit Detection

We are able to locate the region of the sign with high accuracy by taking advantage of the red color present in the edge of the sign and using **Hough**.

We have collected a series of reference street sign images, specifically one for each speed limit that may be encountered on the street. We then pass these images to **SIFT**, along with the newly acquired and preprocessed street image, to extract keypoints.

Once the keypoints are extracted, we use the **KNN** algorithm to classify the main image.



# ItalianSigns

ItalianSigns is a dataset containing images of the road context captured by phone camera. It contains 362 labelled images: each image contains a road sign (speed limit only), of which the number associated with the speed limit, and the bounding box corresponding to the ROI of the sign were annotated.

To recognize the road signs, we applied preprocessing techniques clean the image, used HoughCircles to find the spatial location of the sign and extract the bounding box, and used a KNN on feature vectors extracted via SIFT between ground truth images, and the crop of the inference image



<https://www.kaggle.com/datasets/officialprojecto/italiansigns>

# Deep Learning Techniques



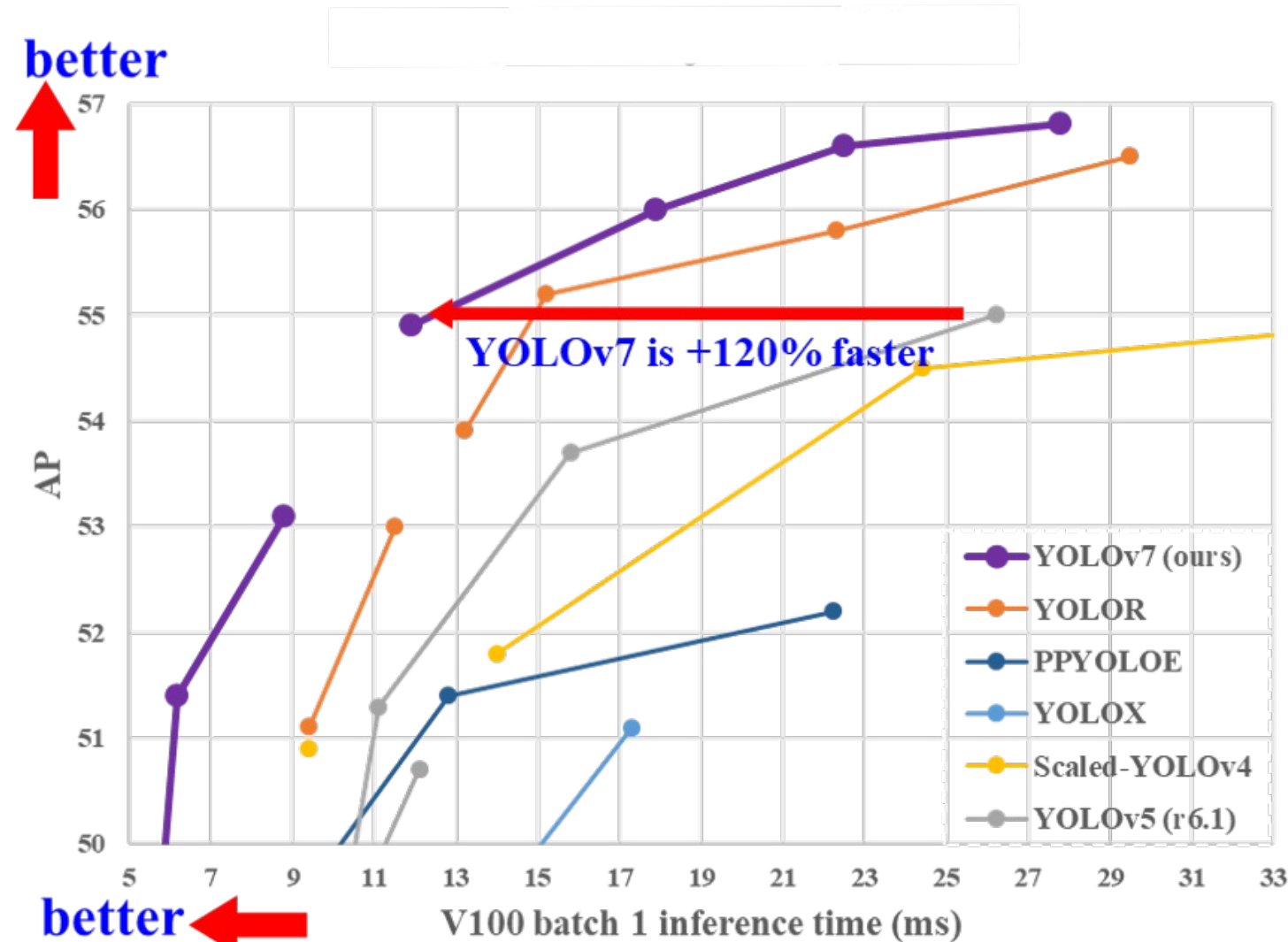
# YOLOv7

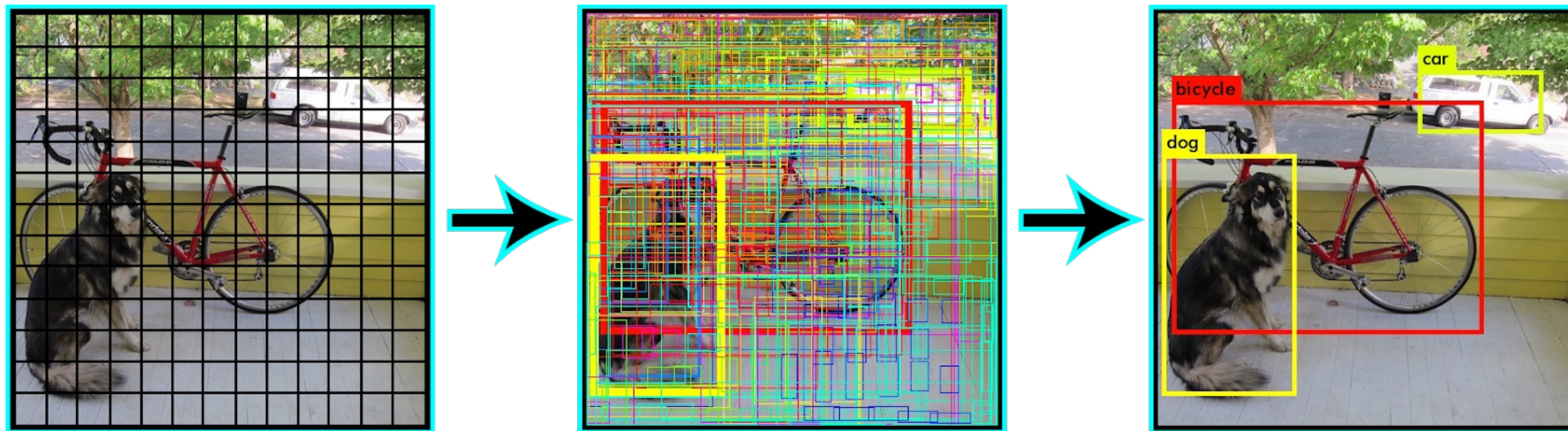
YOLO is one of the premiere **object detection** networks.

YOLOv7 is the latest version of the popular algorithm, and improves significantly on its predecessors.

A number of new changes were made for YOLOv7:

- the model scales the network depth and width simultaneously while concatenating layers together
- the technique "Extended efficient layer aggregation networks" or E-ELAN is used to accelerate inference time
- used gradient flow propagation paths to analyze how re-parameterized convolution should be combined with different networks
- uses the lead head prediction as guidance to generate coarse-to-fine hierarchical labels, which are used for auxiliary head and lead head learning, respectively





## How does YOLO work ?

YOLO works to perform object detection in a single stage by first separating the image into  $N$  grids. For each grid, bounding box coordinates,  $B$ , for the potential object(s) are predicted with an object label and a probability score for the predicted object's presence.

To handle this redundancy and reduce the predicted objects down to those of interest, YOLO uses Non-Maximal Suppression to suppress all the bounding boxes with comparatively lower probability scores.



# CustomYOLOv7



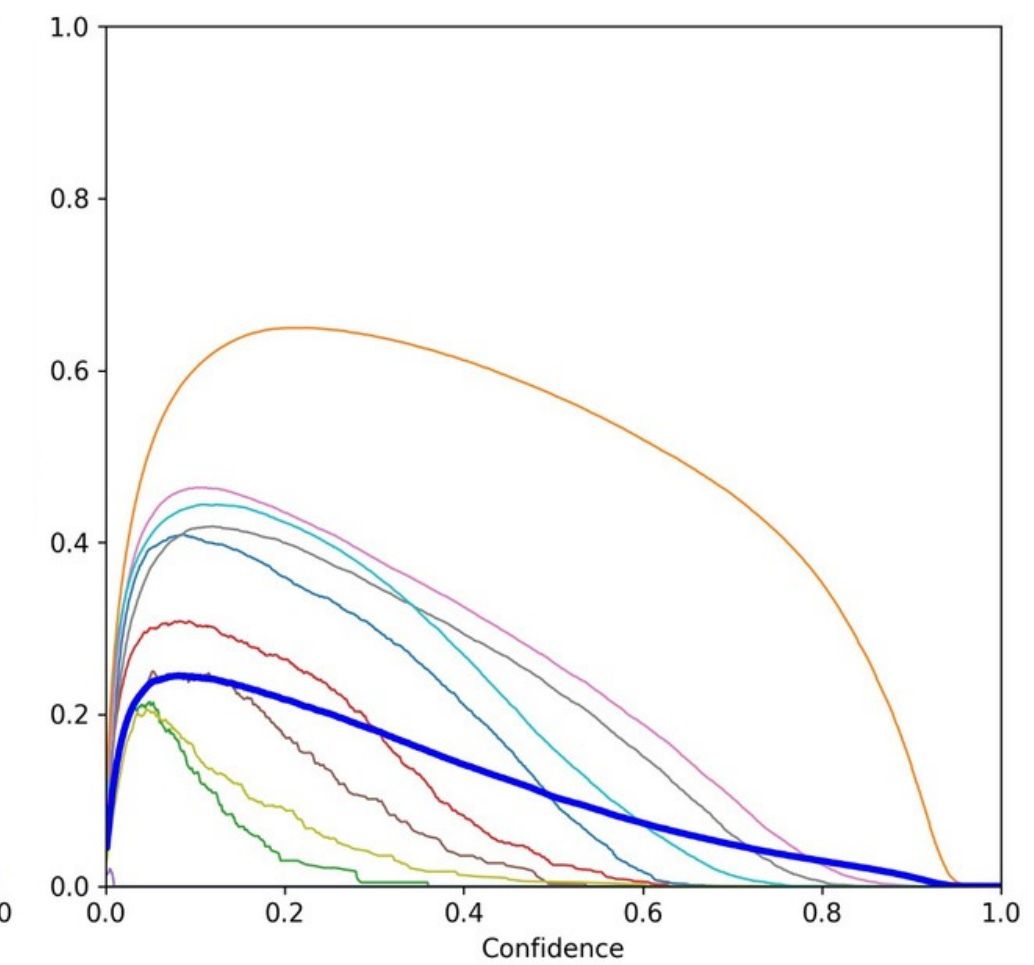
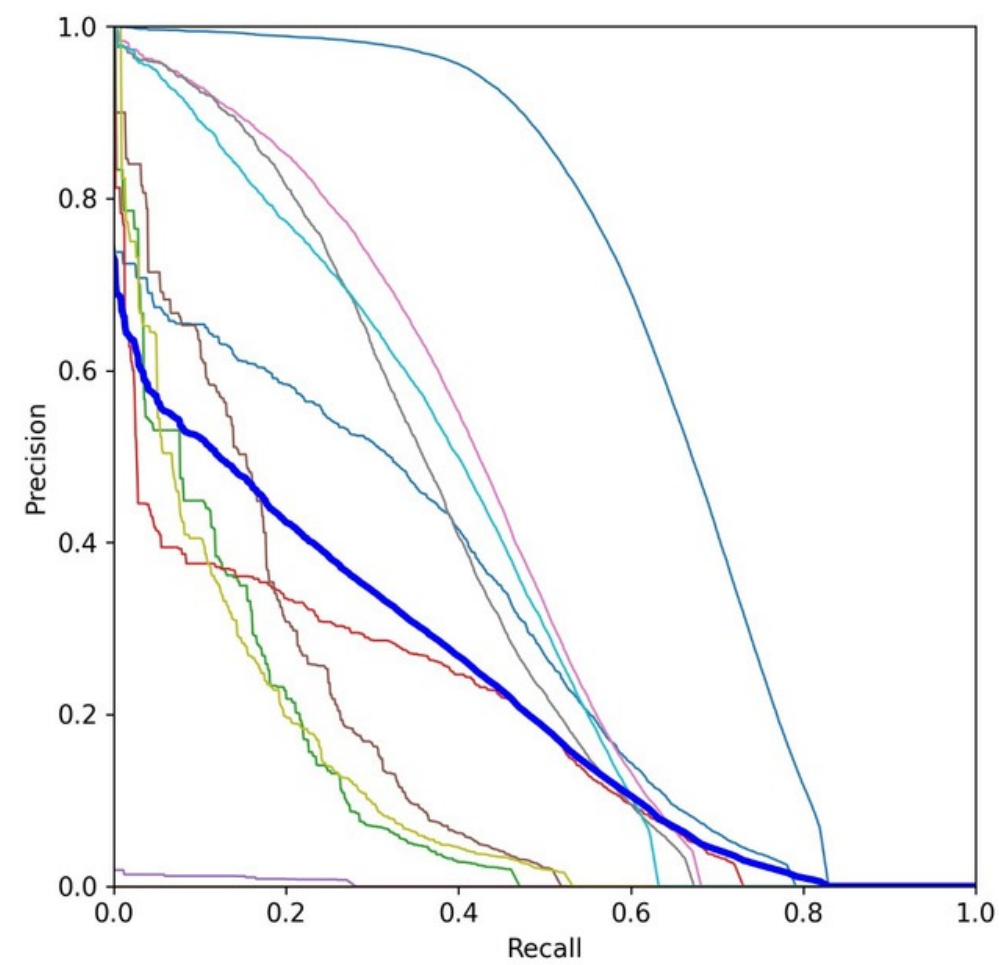
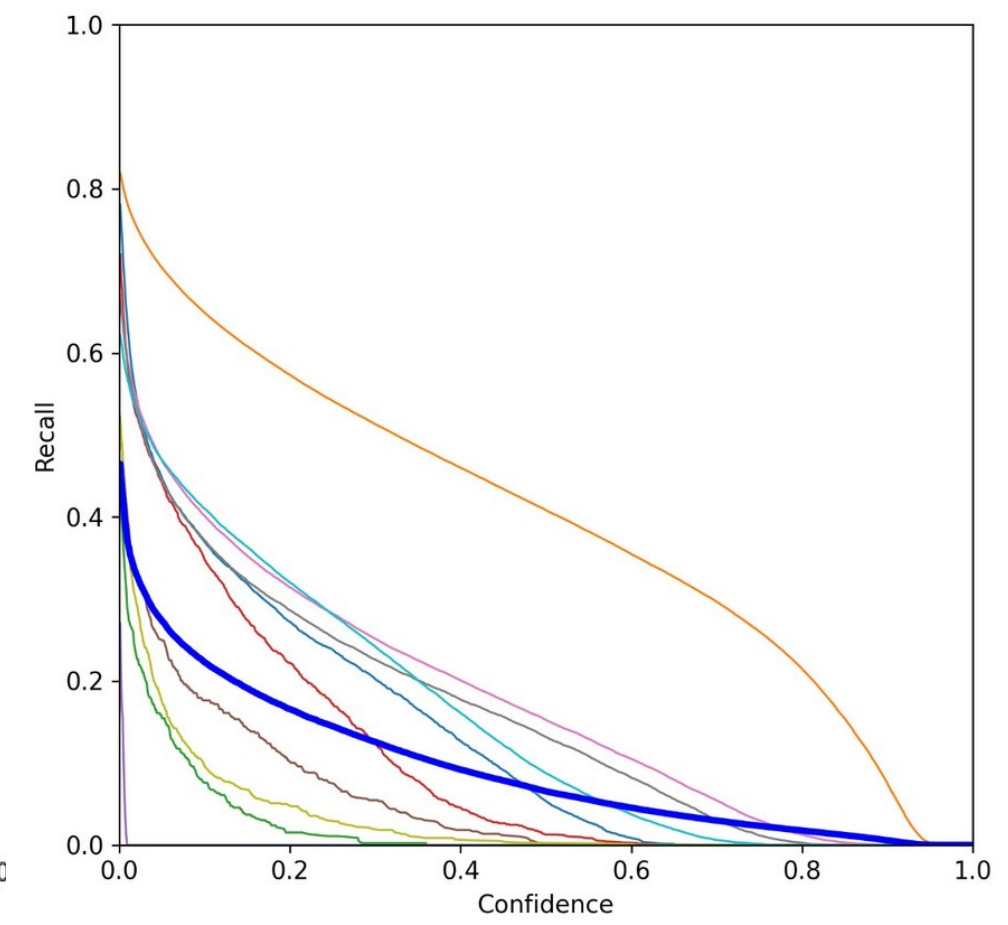
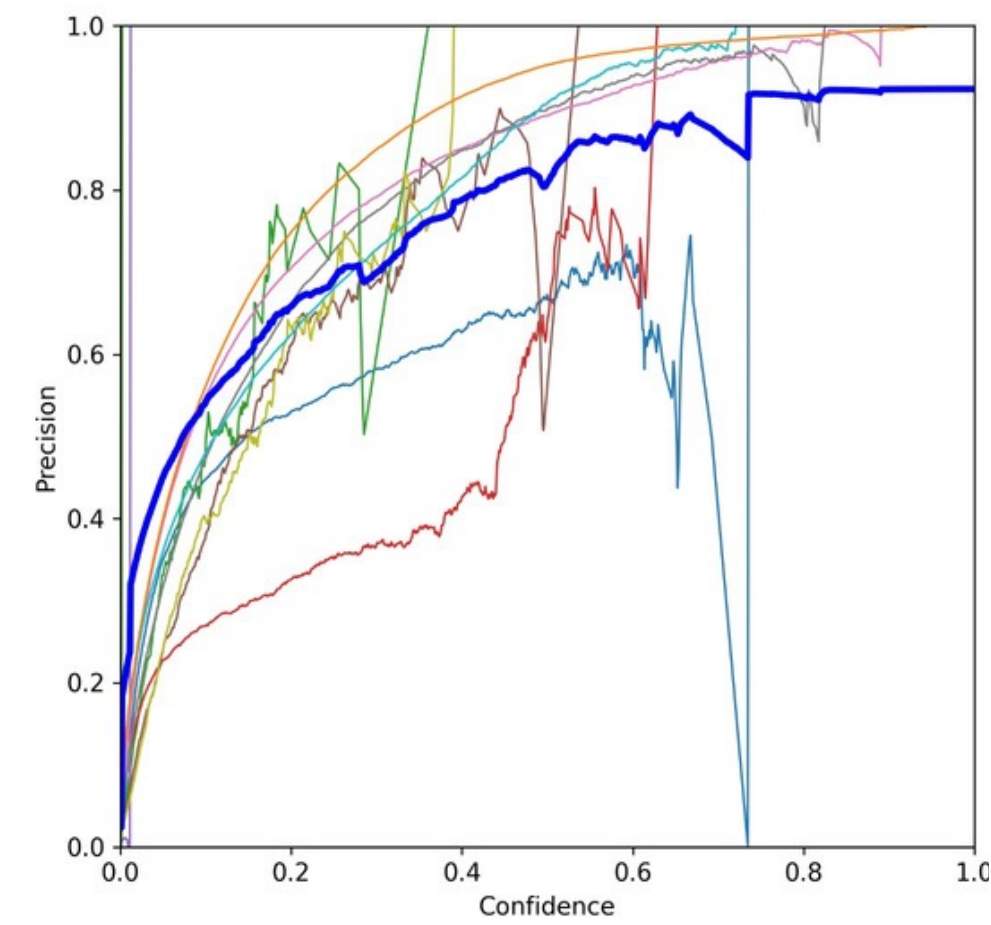
We use [BDD100K](#) to fine tune YOLOv7's detection layer. We chose to use this dataset because we mount the camera inside the cockpit as in the images of BDD.

BDD100K can be used for different tasks: we used it by taking advantage of the object detection labels, which include 10 classes: pedestrian, rider, car, truck, bus, train, motorcycle, bicycle, traffic light, traffic sign.

To do the training, we obtained a partnership with the company [LeaderGPU](#). Which made available to us for 15 hours 5 GPU rtx 3090.



# Results



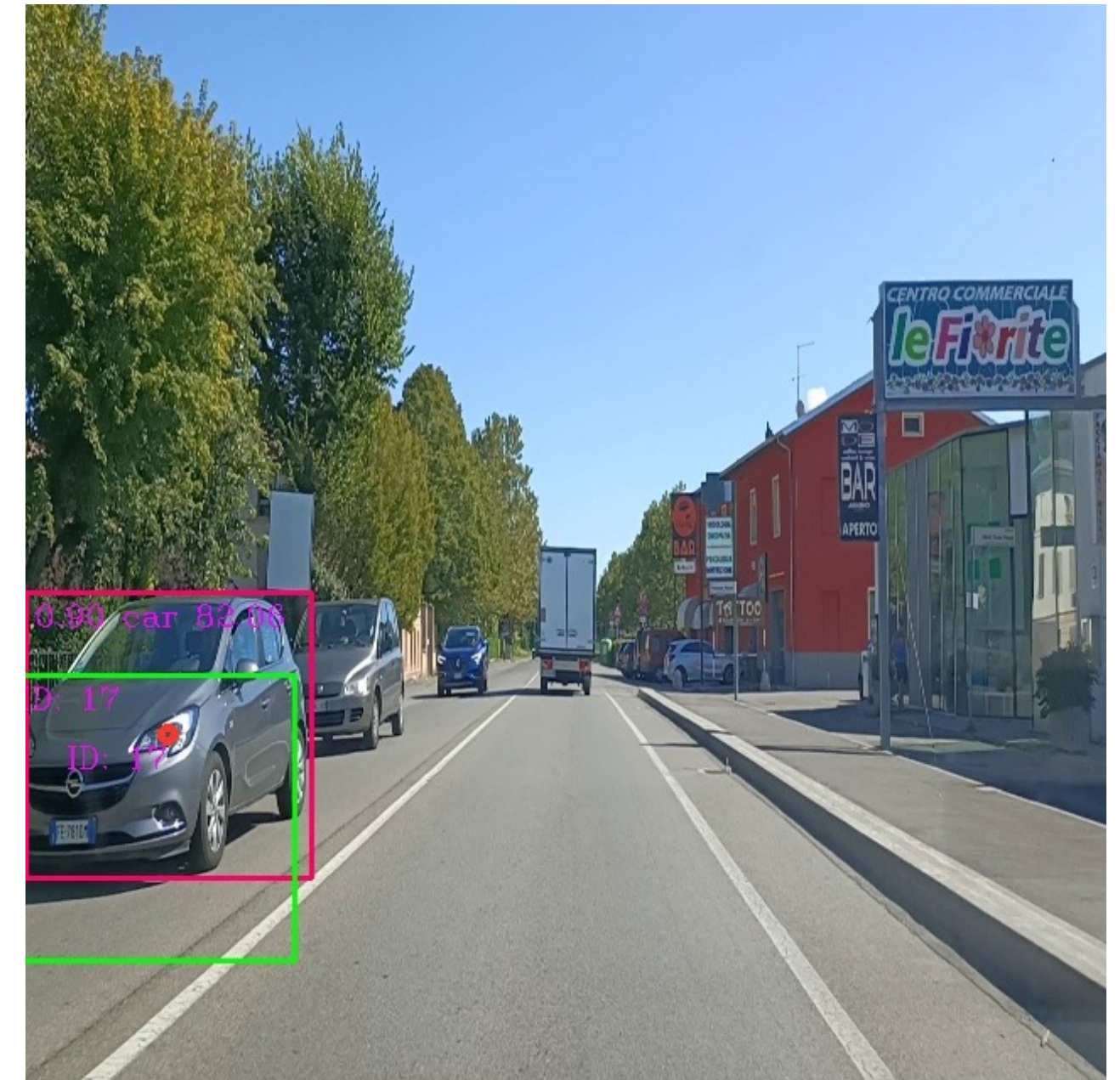
# Future Developments

# Tracking

Starting with the bounding box which describe where the object is located, we carry out the tracking of it using Kalman filters. These filters tend to produce increasingly accurate estimates of the object's future location as we add information about the trajectory it has traveled so far.

The **Kalman filter** at work then takes advantage of the current bounding box and the ROI in HSV format to update the model that it exploits to perform the estimation and to subsequently provide us with a prediction of future position.

During testing, we noticed that the Kalman Filters produce an accurate prediction of the future position of the object only when the bounding box is large enough.





# Object distance

To calculate the distance we use a very simple procedure: we have a reference frame in which we recognize an object, whose size and distance from the camera we know. From this data we are able to extract the **focal length**, which we then use to calculate the distance to a generic object. This method is rather inaccurate and needs appropriate calibration according to the camera being used.

To improve the distance calculation technique it would be sufficient to use a stereo vision camera, which unfortunately we were unable to add to the project for mainly economic reasons.





Speed Limit: 60km/h, 1

truck: 1  
car: 1

0.56 truck 167.09  
0.78 car 364.96

Safe

Safe



# Some tools used



Partnership with [e-con Systems](#)



The End

**Thank you  
for listening**