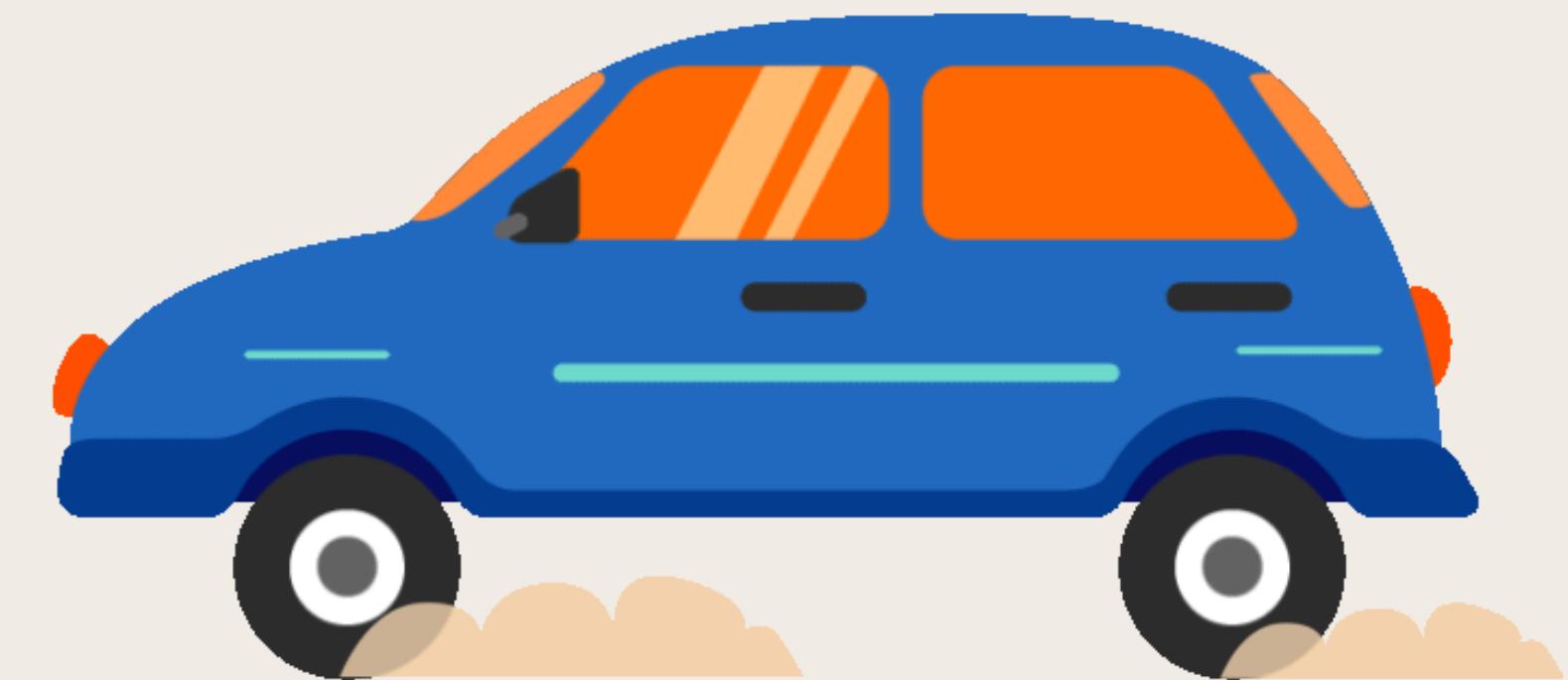


LICENSE PLATE DETECTION



Adrián, Pol, Nil, Xavi

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INTRODUCTION



Detect the license plate



2153 GYX

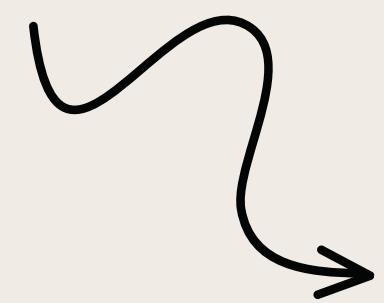
Extract the characters

CLASSICAL APPROACH: PREPROCESSING

Problems with morphological operators:

- Fine-grained solutions for each image.
- Not robust.

We decided to change the approach:



- Do the preprocess on a later stage of the pipeline.

So the new process consisted in:

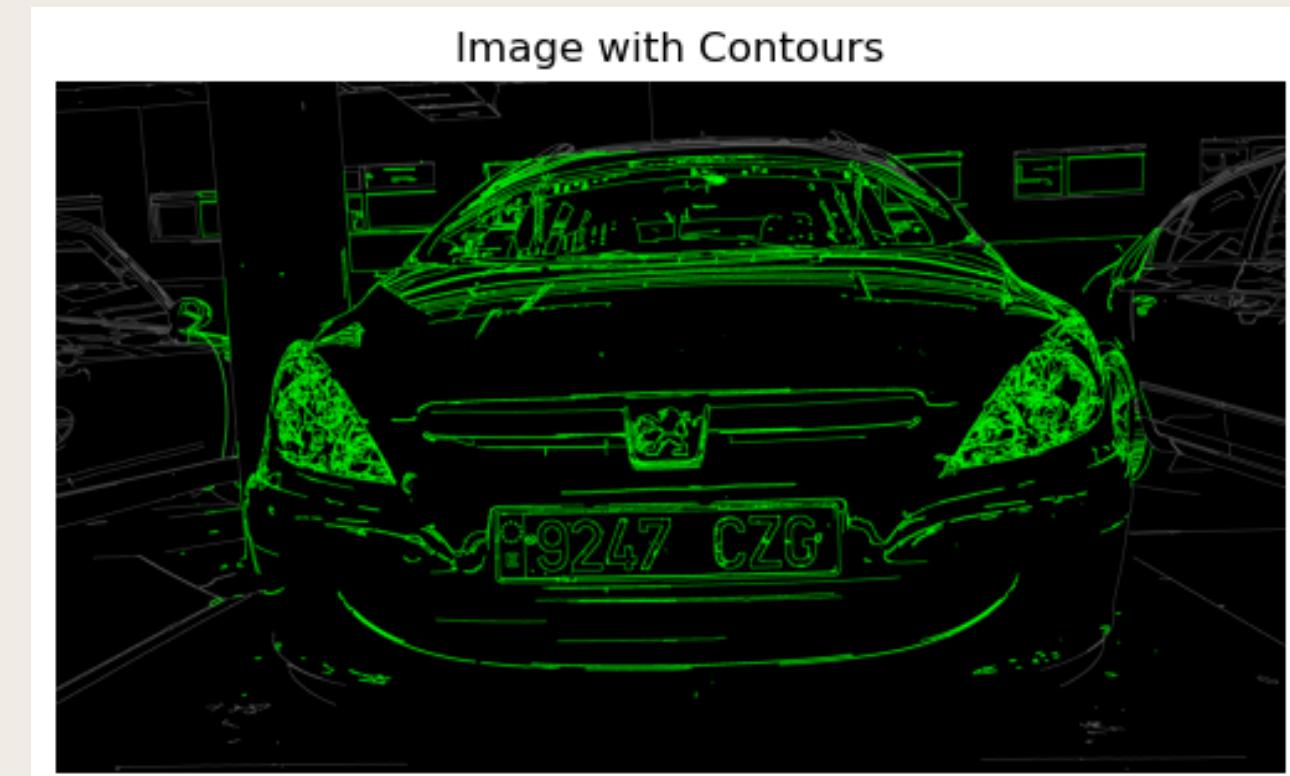
- Pass to gray scale Image.
- Use Canny to detect edges and extract boxes.
- If box didn't satisfy restrictions, omit detection.
- Else, run it through a classifier.



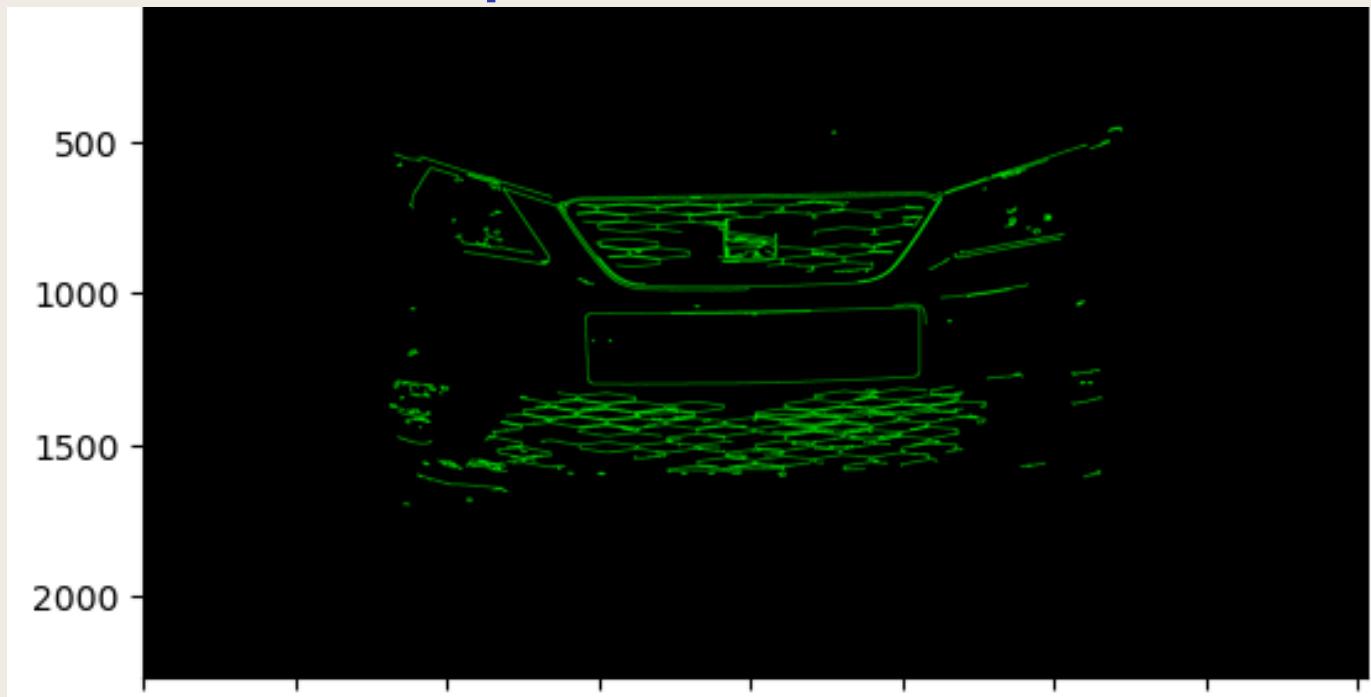
Input image



Output Canny



Filtered output



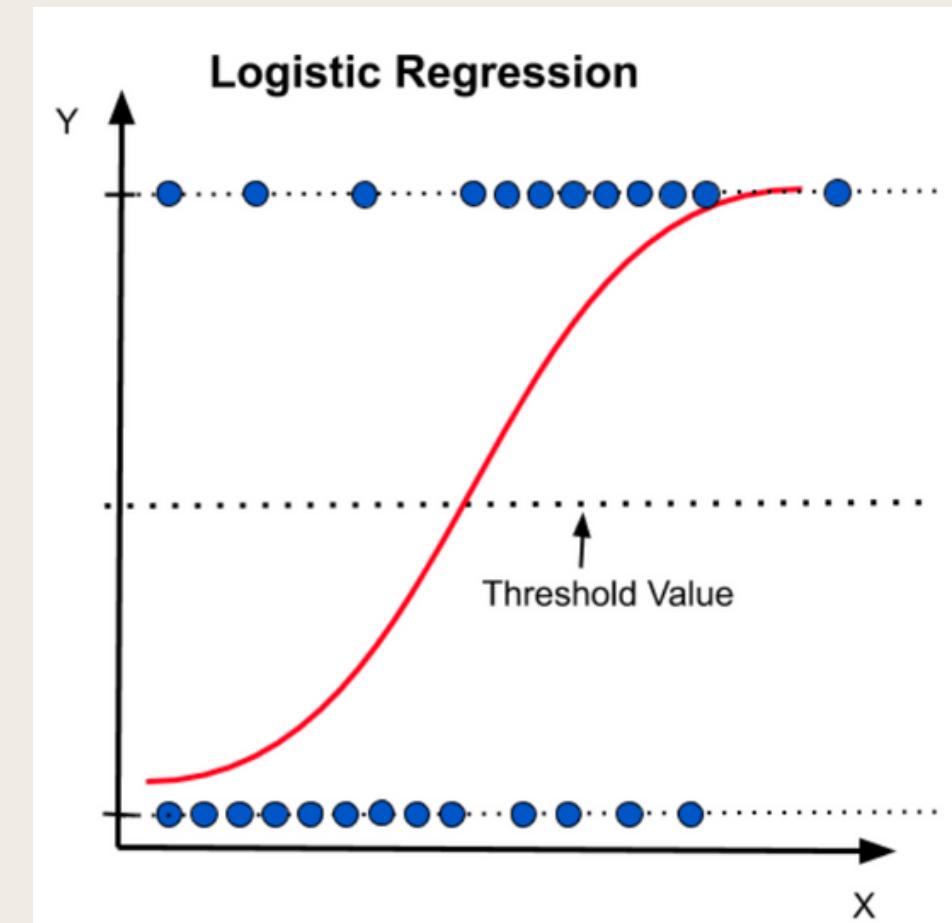
Logistic Regression Output

Licensplate	Licensplate	Not Licensplate
7153 JWD	7153 JWD	Not Licensplate
Not Licensplate	Not Licensplate	Not Licensplate
Not Licensplate	Not Licensplate	Not Licensplate
Not Licensplate	Not Licensplate	Not Licensplate

QUANTITATIVE RESULTS: CLASSIFICATION

Frontal images: **9 out of 15** images correctly detected

Lateral images: **5 out of 15** images correctly detected



Why were some images not detected?

- Logistic Regressor not assigning correctly the license plates labels to the crop images.
- Related to the quality of training data.

Not Licensplate		Not Licensplate		Not Licensplate		Not Licensplate	
Not Licensplate		Not Licensplate		Not Licensplate		Not Licensplate	
Not Licensplate		Not Licensplate		Not Licensplate		Licensplate	
Not Licensplate		Not Licensplate		Not Licensplate		Licensplate	
Not Licensplate		Not Licensplate		Not Licensplate		Licensplate	
Not Licensplate		Not Licensplate		Not Licensplate		Licensplate	
Not Licensplate		Not Licensplate		Not Licensplate		Licensplate	
Not Licensplate		Not Licensplate		Not Licensplate		Licensplate	

QUANTITATIVE RESULTS

OVERALL ACCURACY: **37'5%**

NUMBERS: **43'75%**

LETTERS: **43'75%**

FRONTAL IMAGES: **40%**

NUMBERS: **53'33%**

LETTERS: **46'67%**

LATERAL IMAGES: **35'29%**

NUMBERS: **35'29%**

LETTERS: **41'18%**



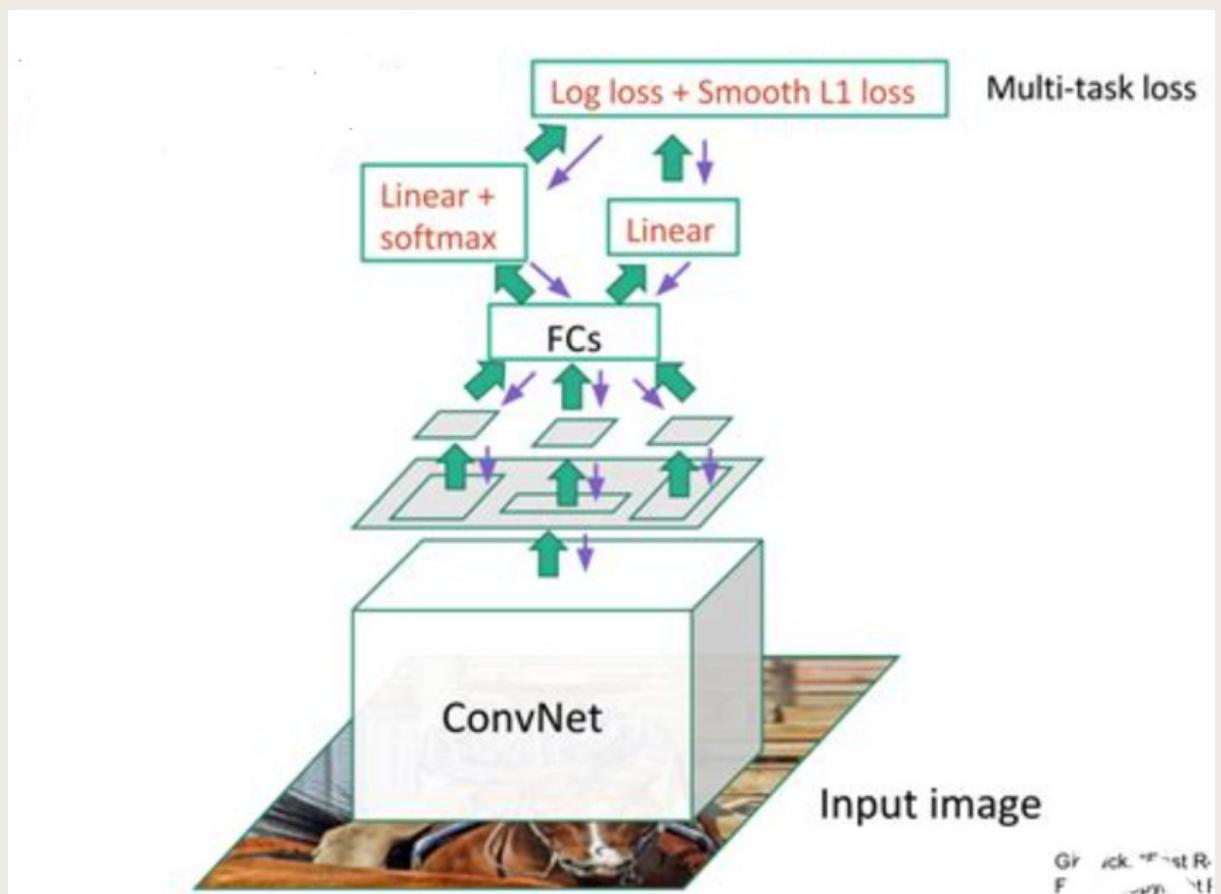
AVERAGE TIME OF COMPUTATION:
12'63 SECONDS

QUALITATIVE RESULTS

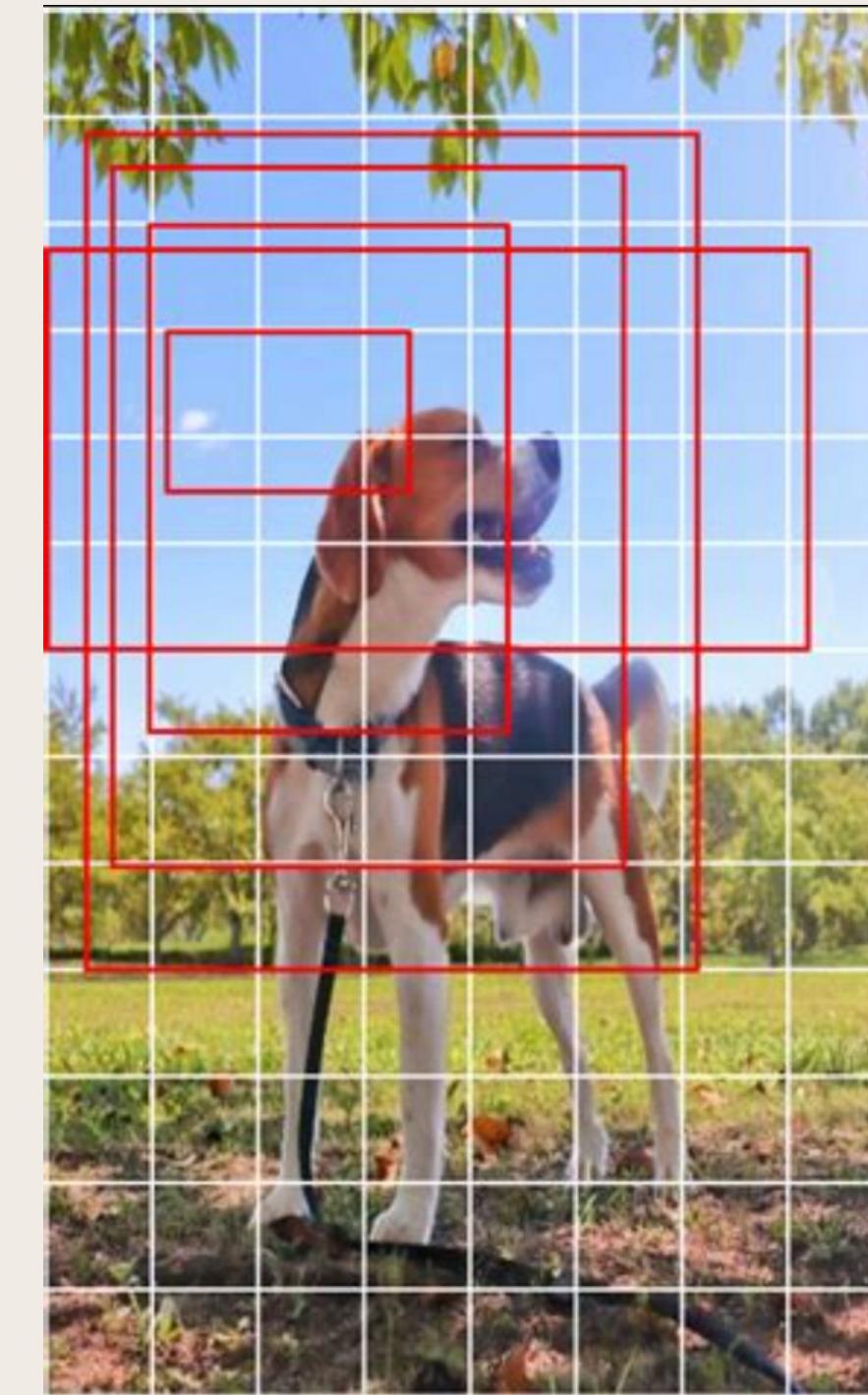


DEEP LEARNING APPROACH

TWO-STAGE FAST R-CNN



ONE-STAGE YOLO



2 STAGE : RCNN

Data augmentation:



HORIZONTAL FLIP



VERTICAL FLIP

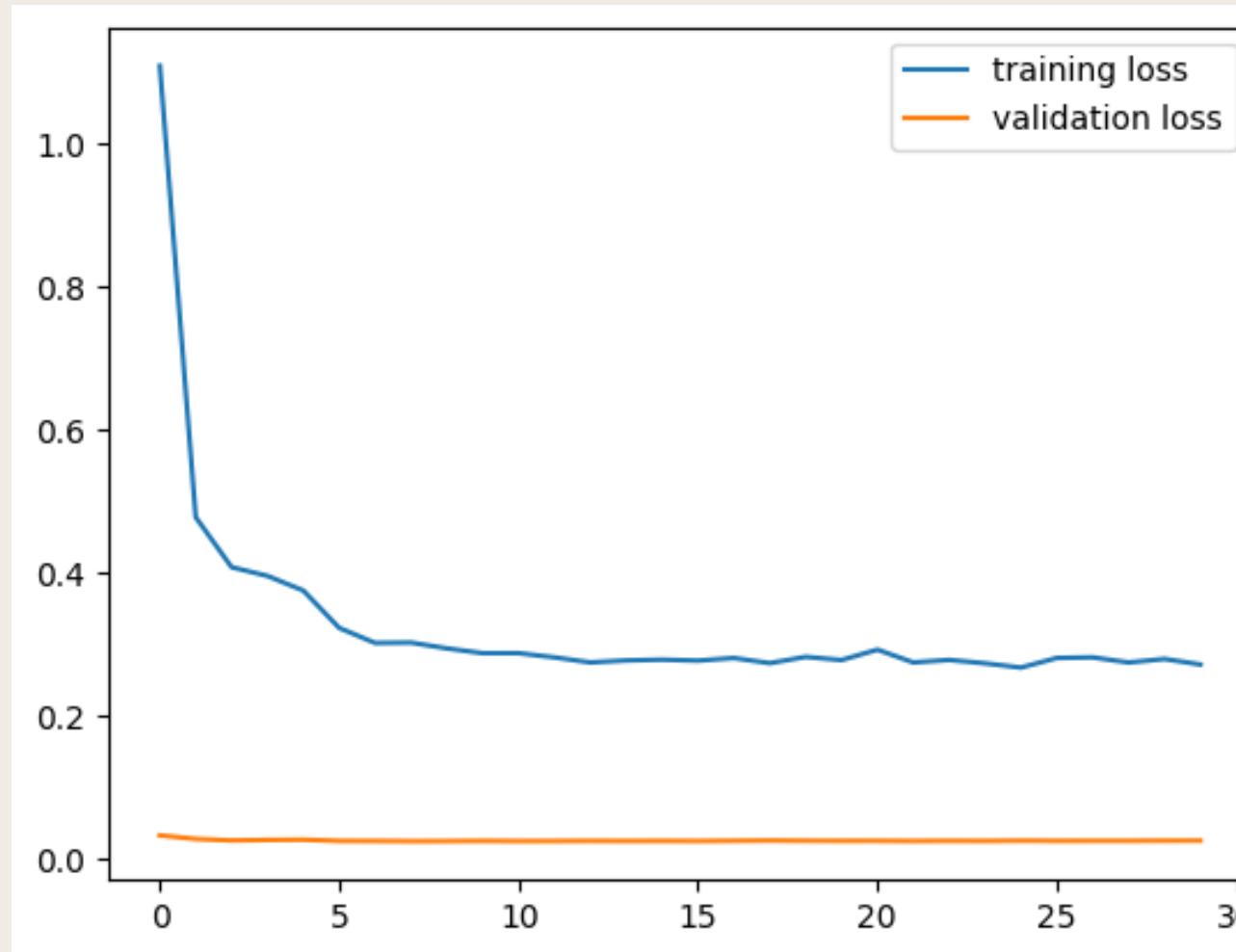


COLORJITTER



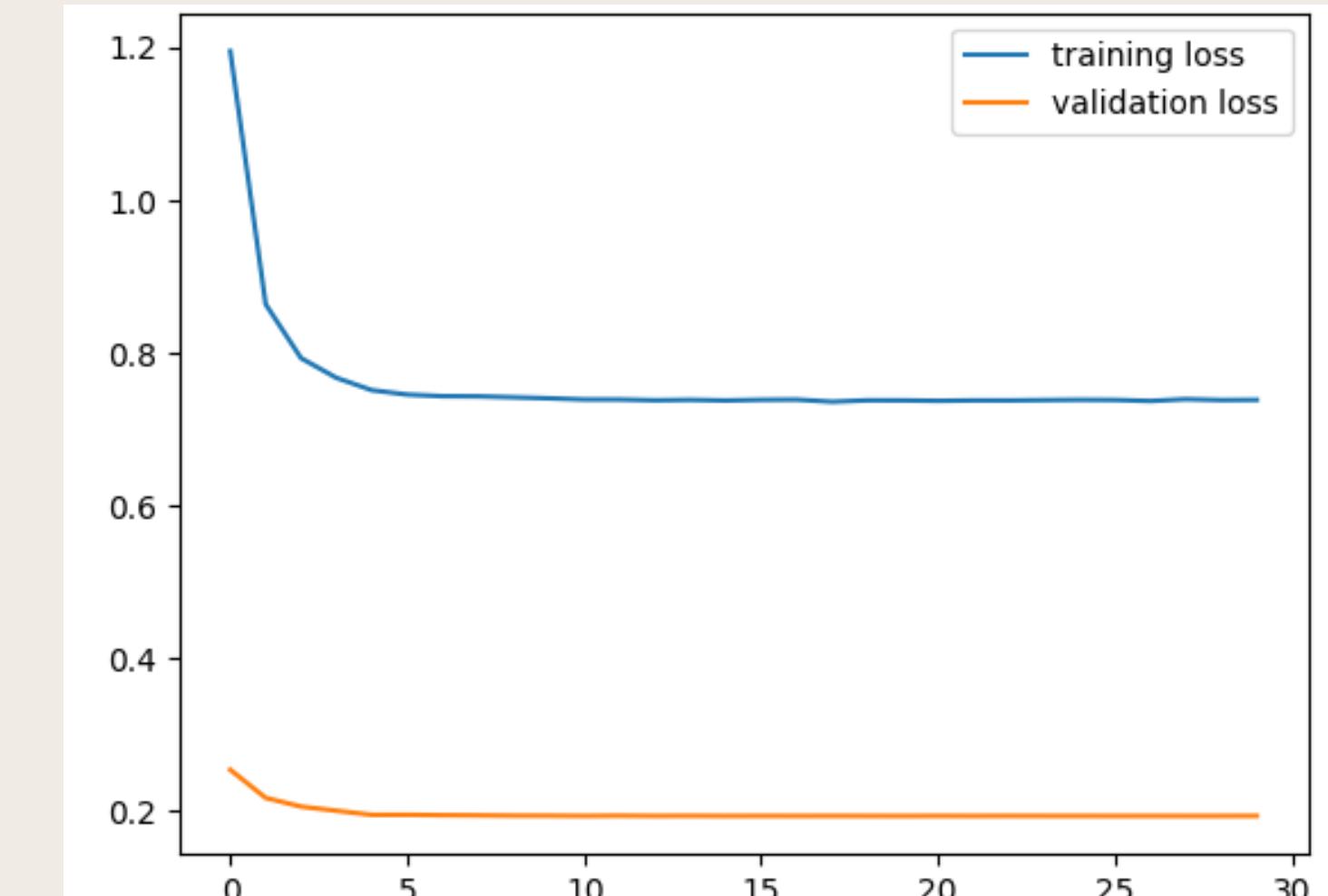
QUANTITATIVE RESULTS

PRETRAINED WEIGHTS



MAP 50 - 85%
MAP 75 - 50%
MAP - 54%

TRAINED FROM SCRATCH



MAP 50 - 33%
MAP 75 - 1%
MAP - 11%

QUALITATIVE RESULTS

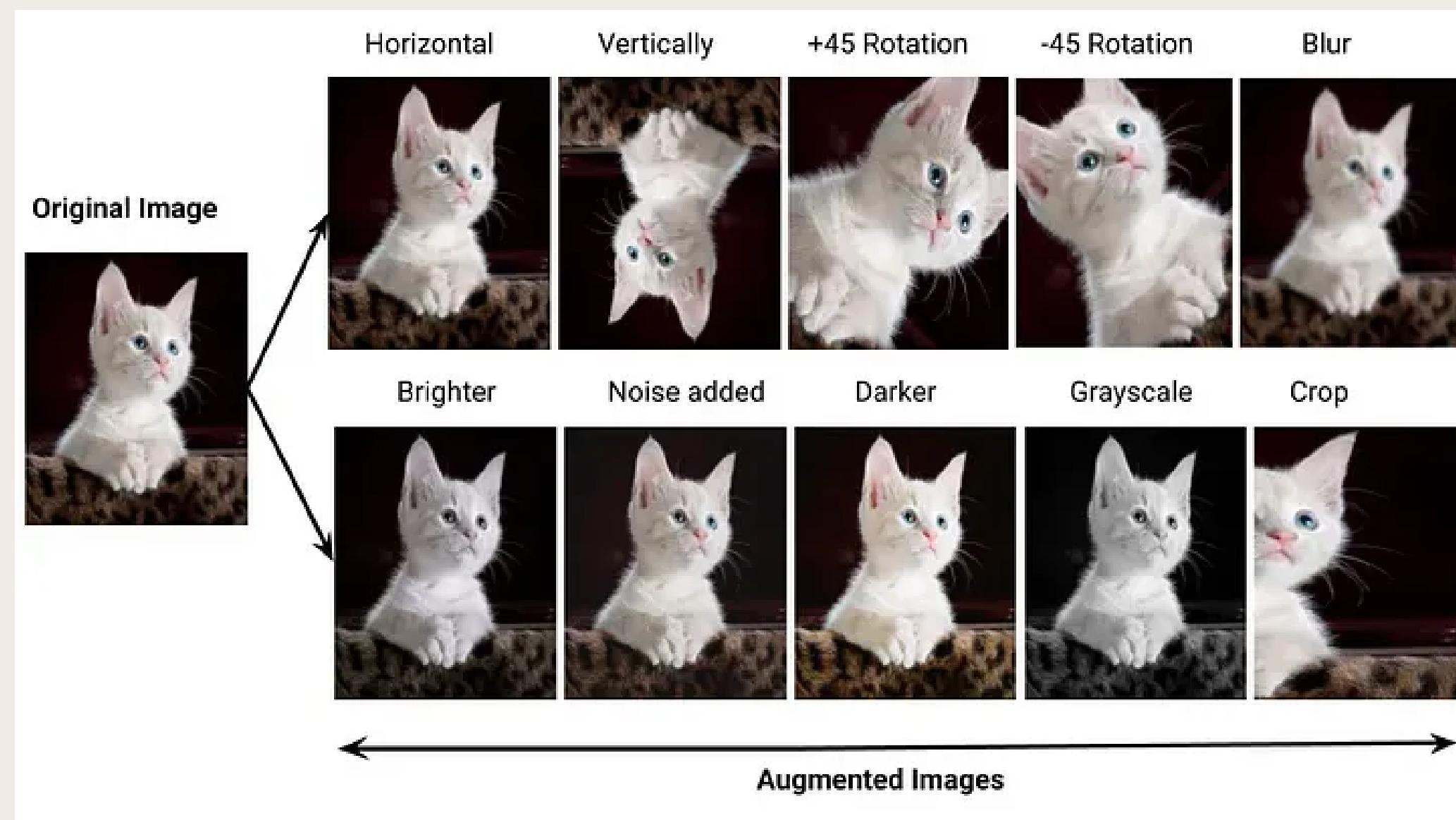


2 STAGE : RCNN

- **Epoch:** 30
- **GFLOPs:** 561.18 GFlops
- **Inference time:** 110 ms
- **Number of parameters:** 43.03 M

1 STAGE : YOLO V8

Data augmentation:



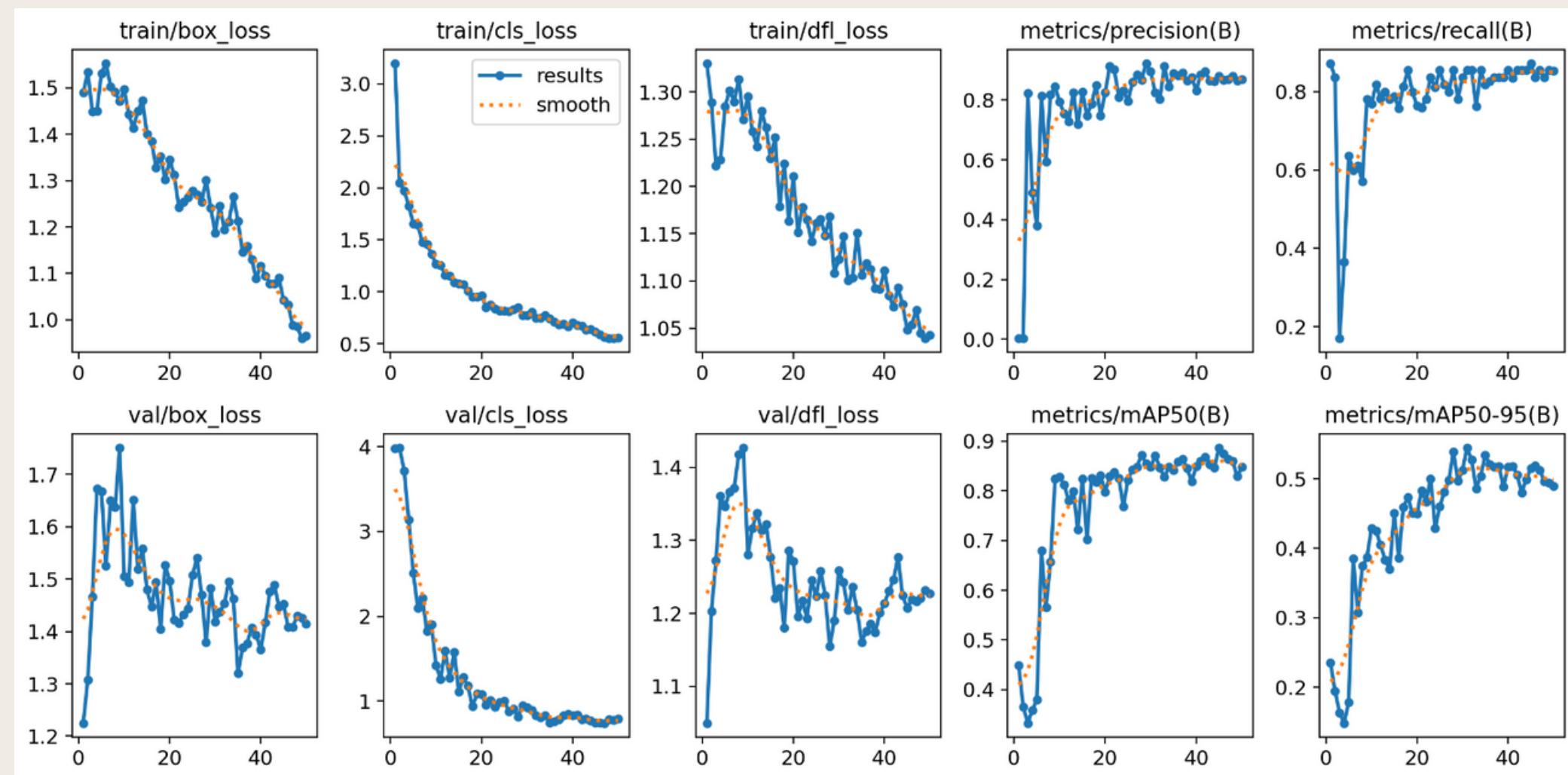
1 STAGE : YOLO V8

Quantitative results:

MAP-50: 93%

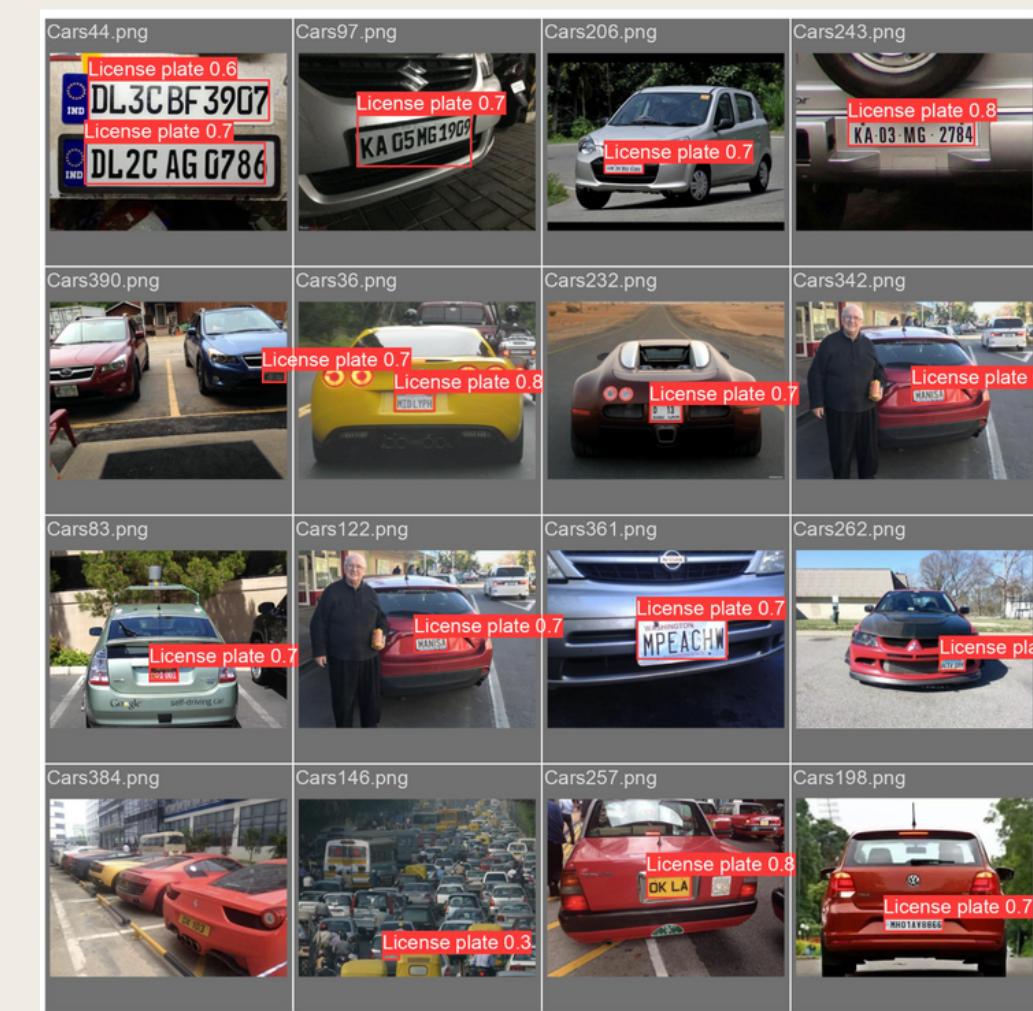
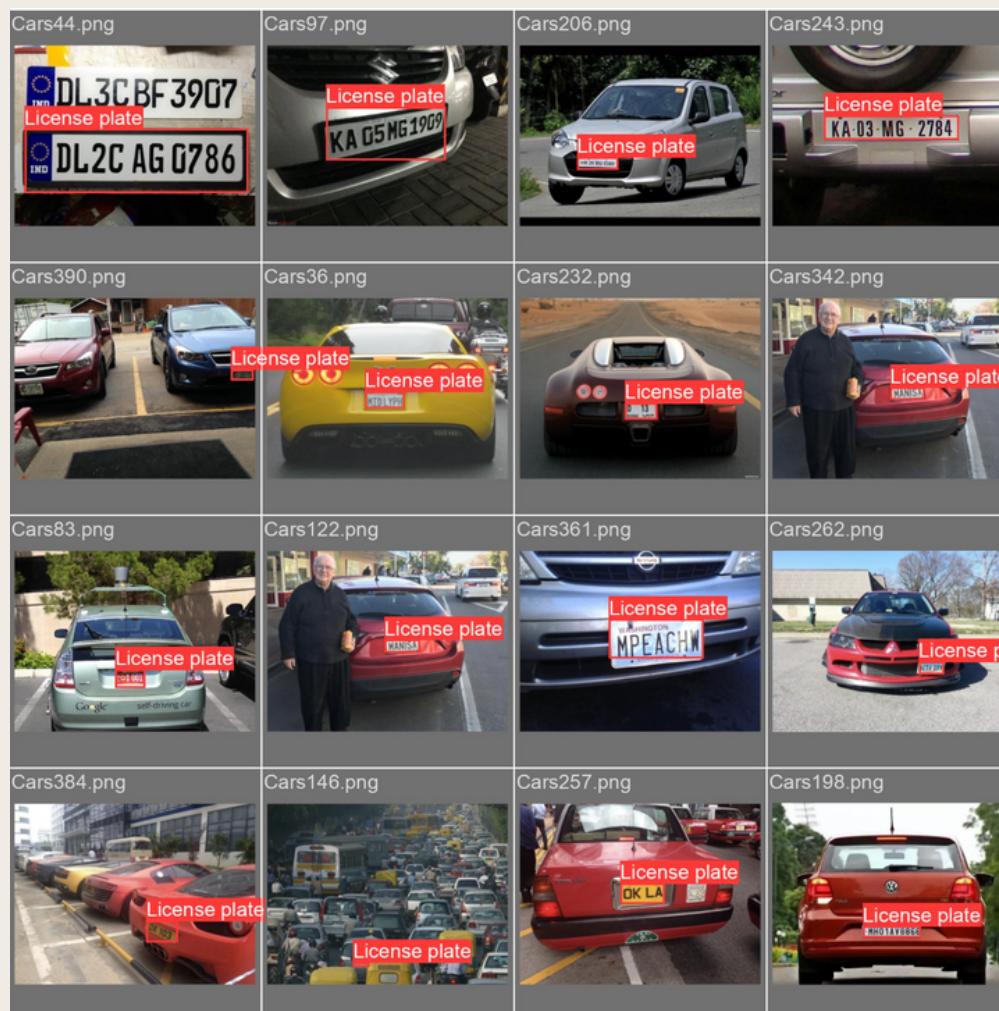
MAP-95: 53%

MAP: 49%



1 STAGE : YOLO V8

Qualitative results:



Labels

Predictions

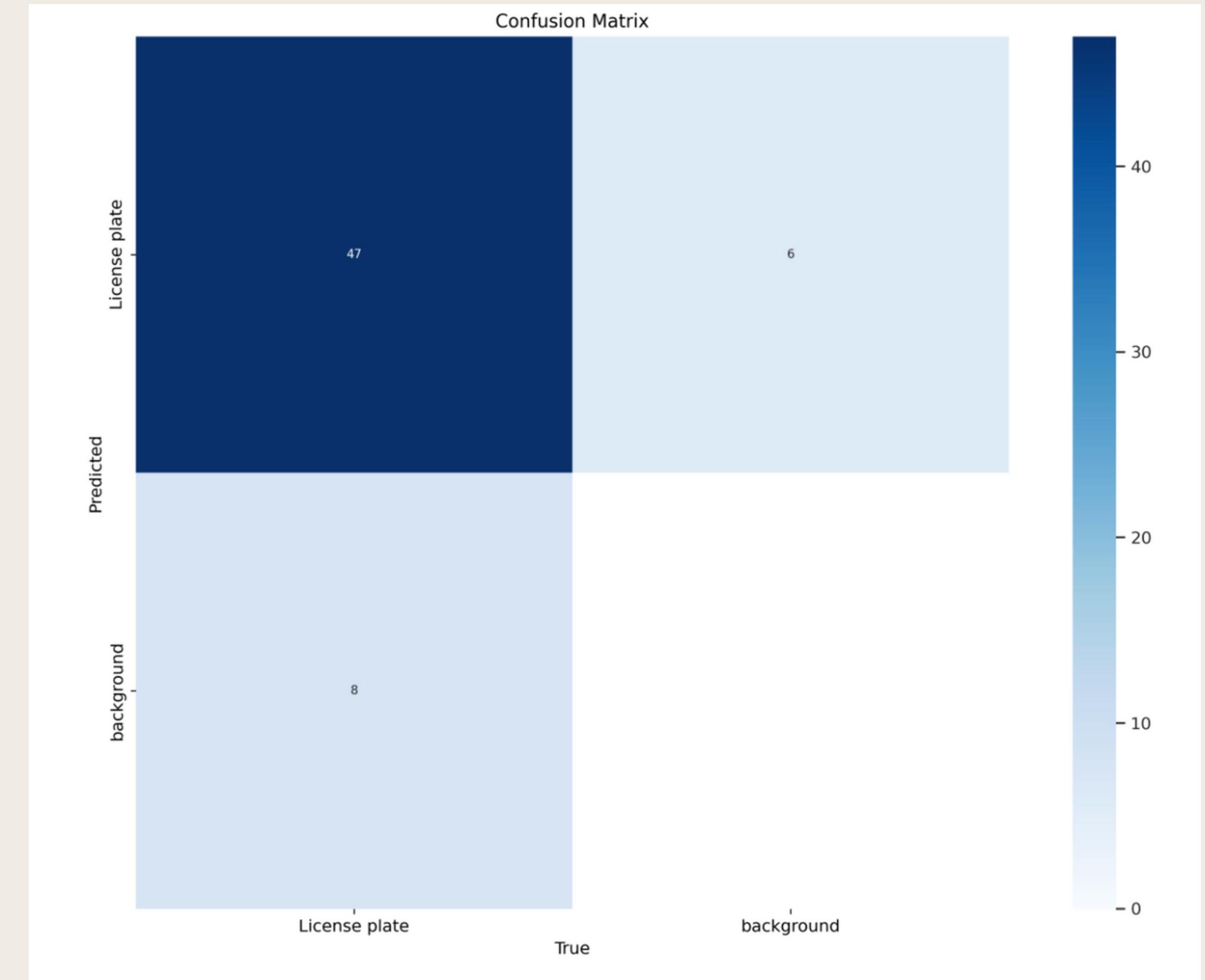
1 STAGE : YOLO V8

Qualitative results:



- The detected license plate is the following: **1062FNT**
- The confidence of the interval is the following: **0.78**

1 STAGE : YOLO CONFUSION MATRIX



1 STAGE : YOLO V8

- **Epochs:** 50
- **GFLOPs:** 8.7
- **GMAOs:** 5.9
- **Inference time:** 30,35 ms
- **Number of parameters:** 3M

1-STAGE

VS

2-STAGE

30ms

TIME PER IMAGE
X3

110ms

3M

PARAMETERS
X14

43M

8'7

GFLOPS
X64

561

49%

ACCURACIES (MAP)

54%

CLASSICAL

VS

DEEP

39,97 seconds

TIME TO TRAIN

3 hours

12,63 seconds

TIME TO INFER

110 ms

All features from images'
patches

DATA NEEDED

Images, plates'
coordinates and labels

37'5%

ACCURACIES

54%

CONCLUSIONS

- **Single Forward Pass:** YOLO performs both object localization and classification in a single forward pass through the neural network.
- **Fewer Operations:** RCNN involves generating region proposals, which usually require additional computational steps.
- **Real-time Processing:** YOLO architectures are often optimized for real-time processing, and every design decision is made with computational efficiency in mind.
- **Unified Detection:** YOLO uses a single network to perform both classification and localization, reducing the overall computational footprint. In contrast, RCNN-based methods typically use separate networks or stages for these tasks.

**THANKS FOR
YOUR
ATTENTION!**

