

Light Skeleton Detection:

Utilizing vehicle light positions for angle agnostic signal state detection



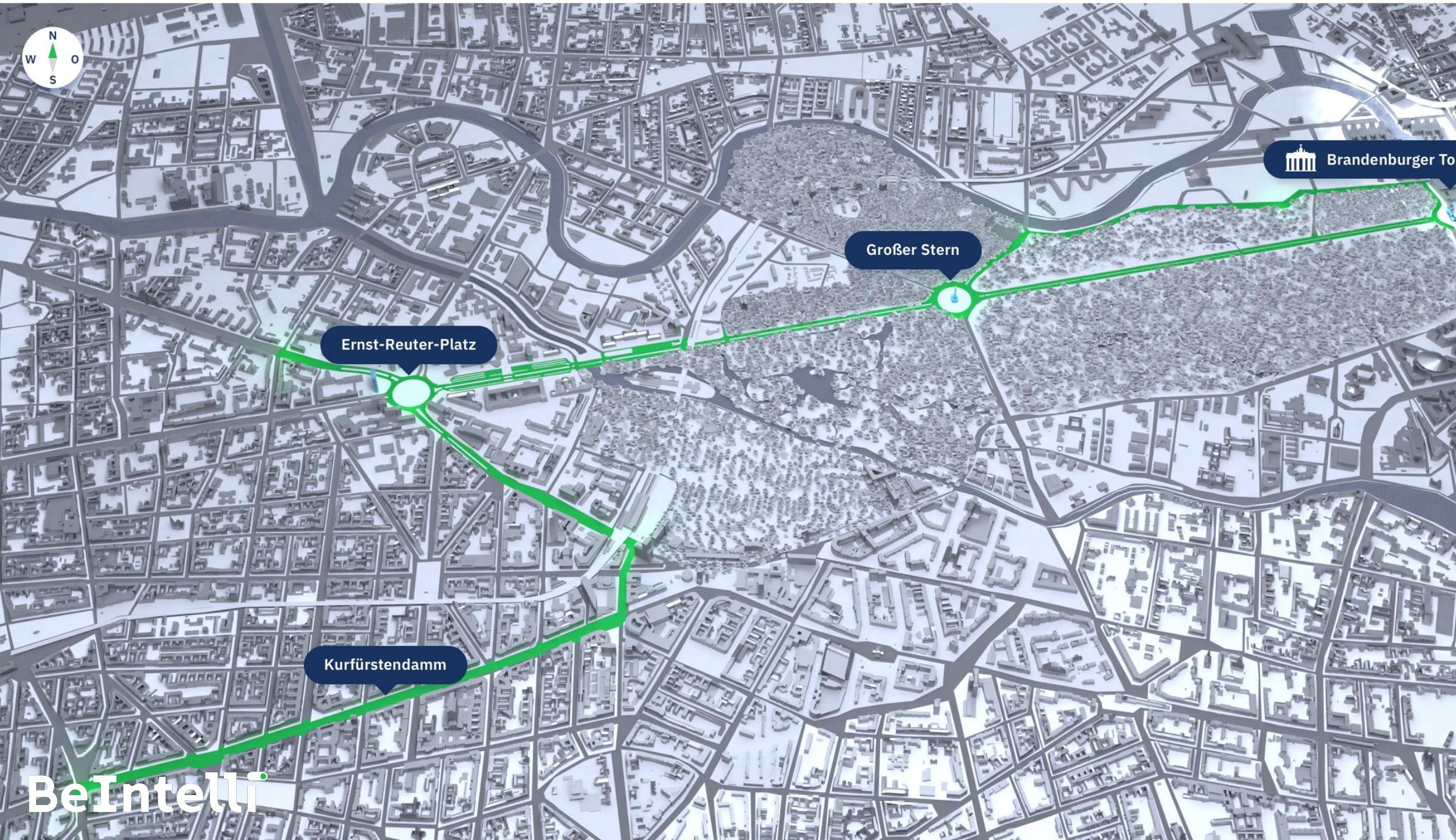
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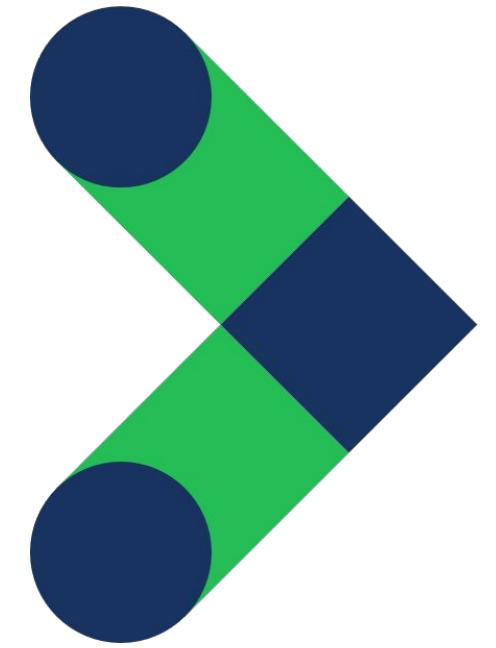


AI for autonomous mobility



DAI-Labor
TU Berlin

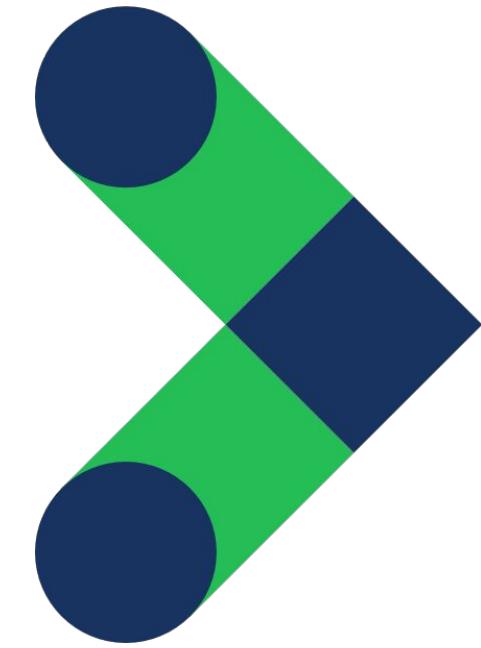




Introduction

- ❖ A vehicle's lights can give critical insight about its intended behaviour
- ❖ Autoware currently has no module to detect such lights and their state





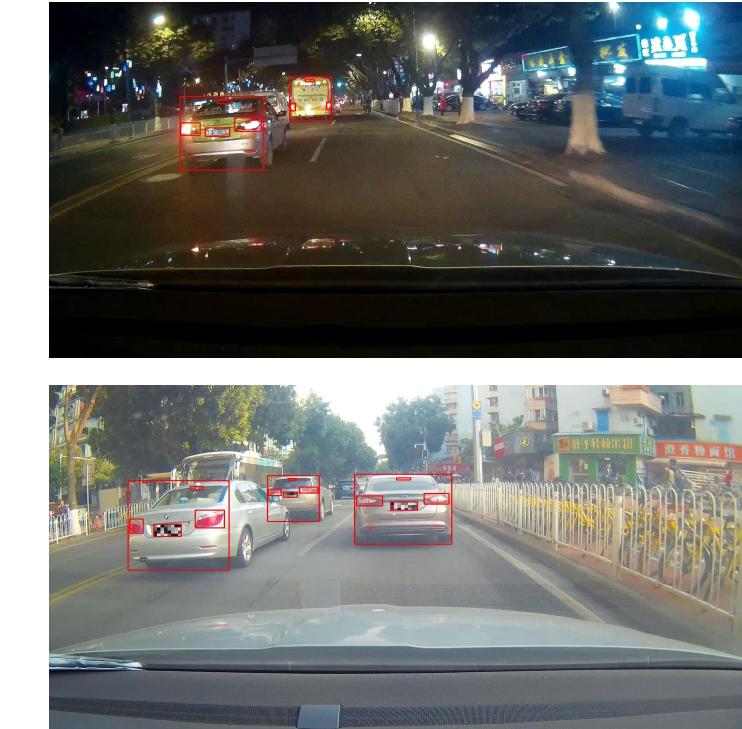
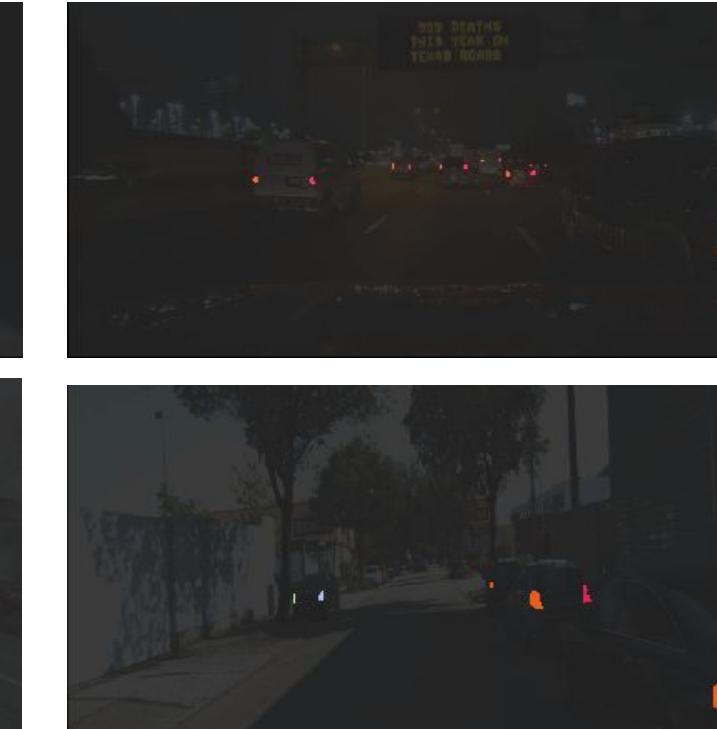
Background

Number of openly available datasets in relevant task domains (e.g., Vehicle Light Detection, Signal State Detection, etc.) is small & existing datasets largely share some common drawbacks:

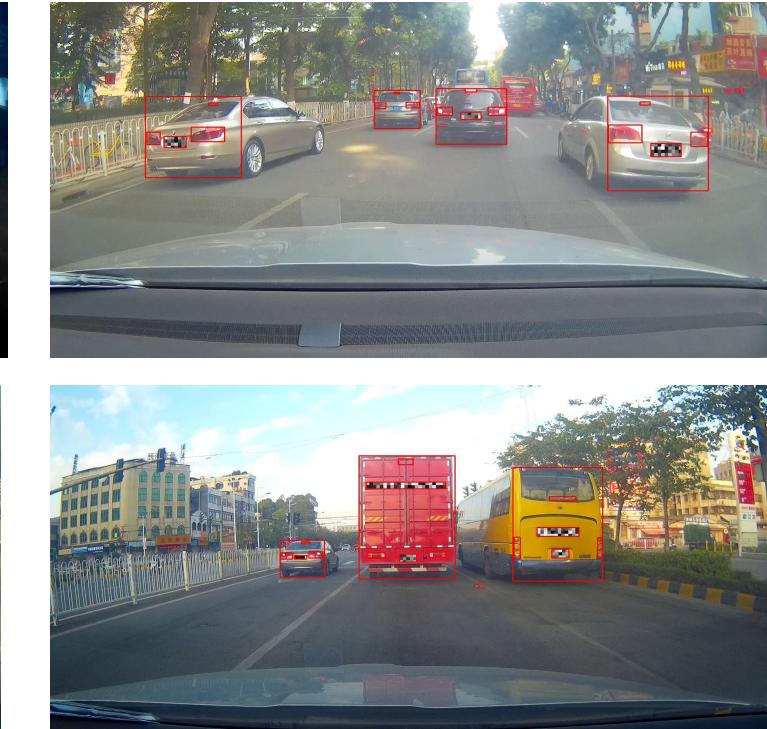
- ❖ existing datasets focus mainly on the rear or front of observed vehicles
- ❖ often only a (single) front mounted camera is used to capture traffic scene
- ❖ annotated side views or different angles are often severely underrepresented or non-existent

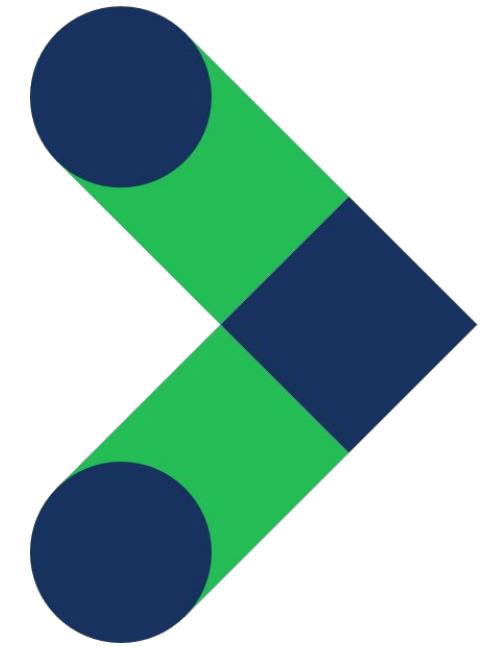


Vehicle Lights Dataset @AUT



Vehicle Light Signal (VLS) Dataset

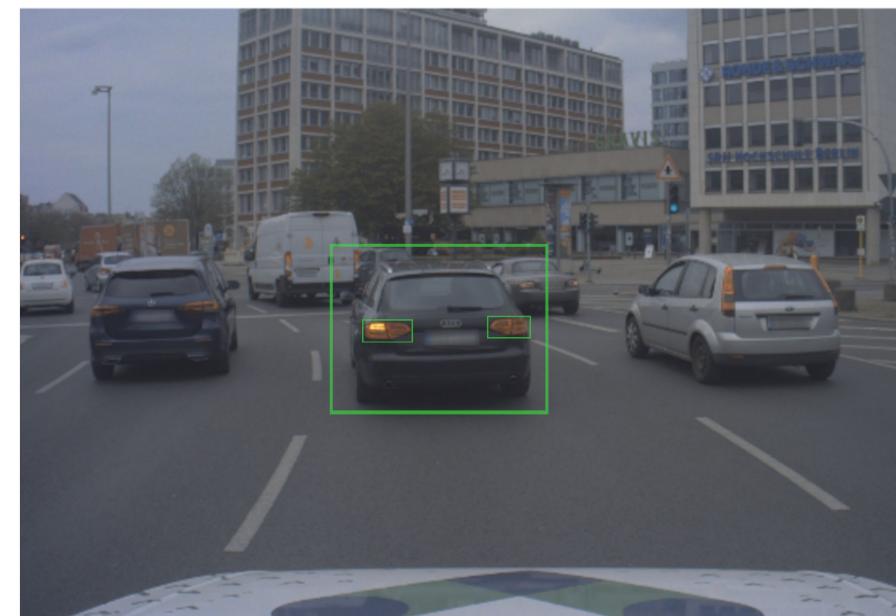




Background

Proposed solutions overwhelmingly (partly due to nature of available data) focus on detecting brake or turn signals based mainly / solely on the rear lights of observed vehicles:

- ❖ Solutions typically utilize (implicitly or explicitly) two-phase approach



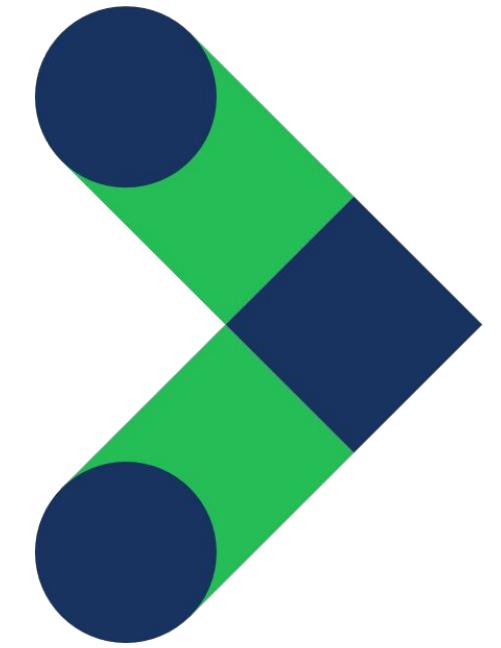
Vehicle and/or Vehicle Light Detection



Signal State Detection

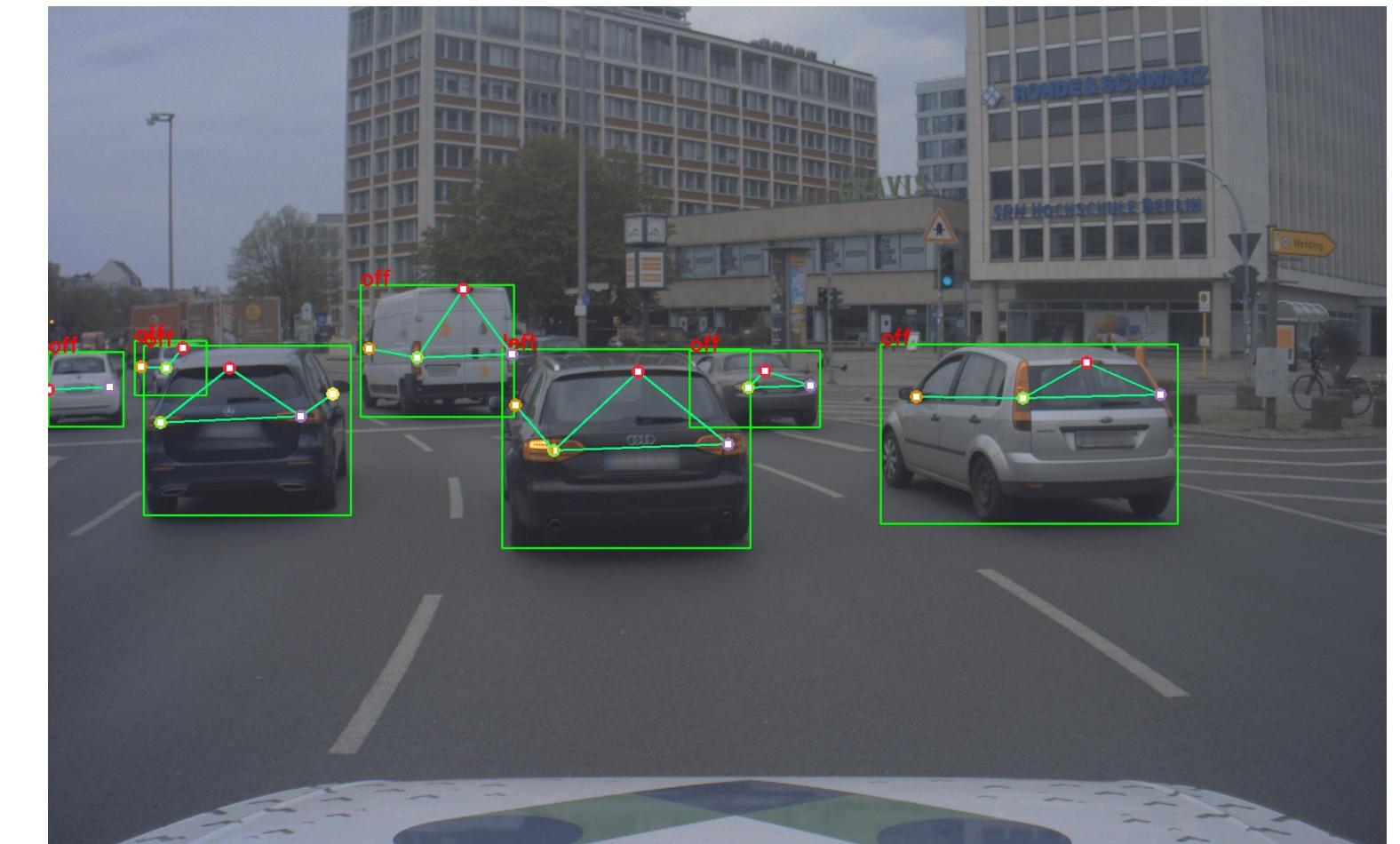
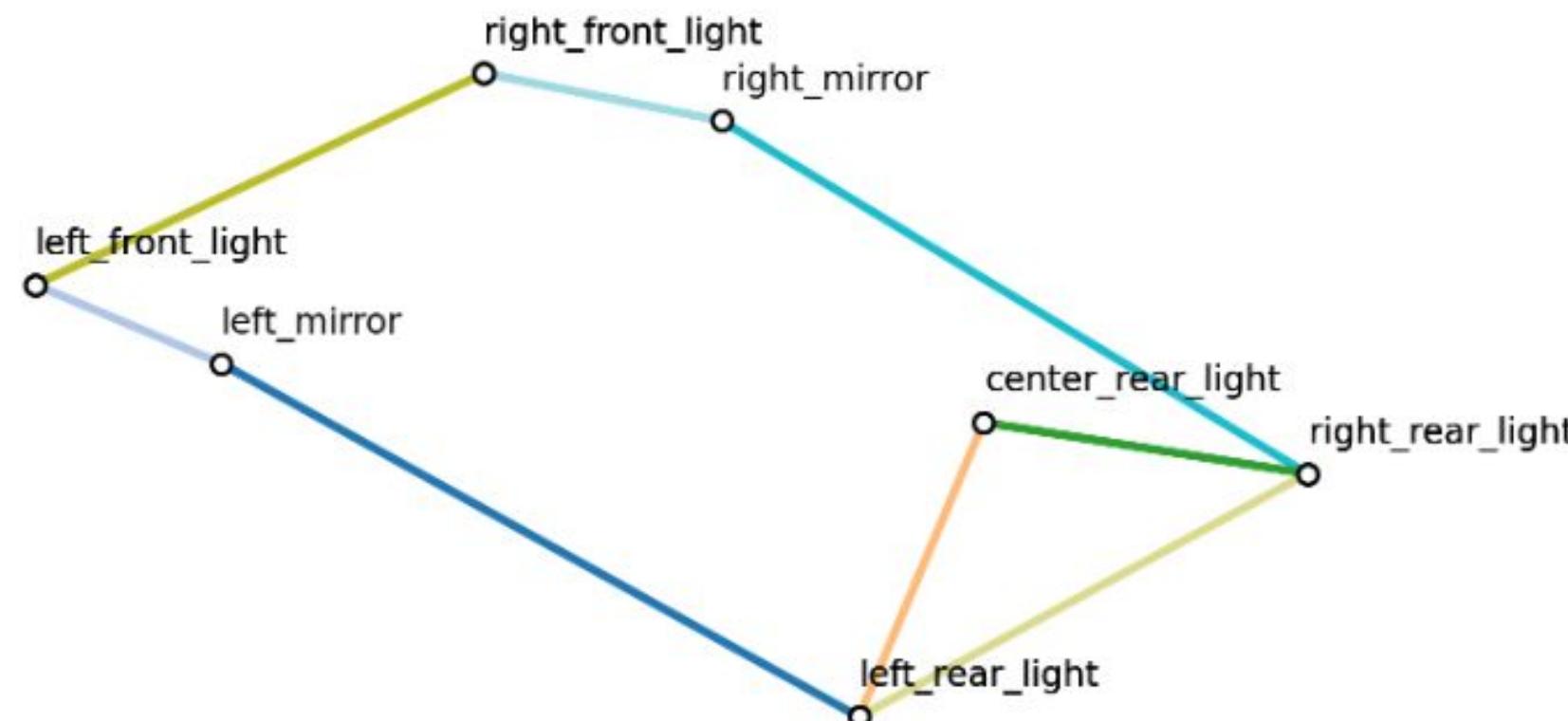
Currently, Autoware lacks any implementation for detecting vehicle lights / signal states
&

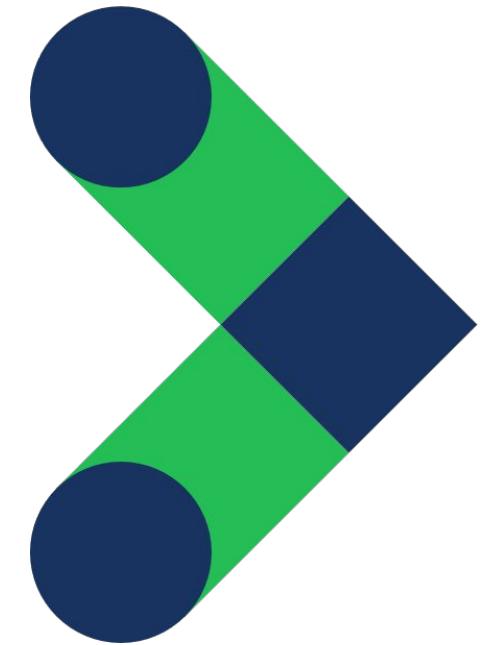
Proposed solutions can be seen as inherently limited as they generally lack the holistic consideration of the entire surrounding environment, e.g., vehicles viewed perpendicular



Proposed Solution

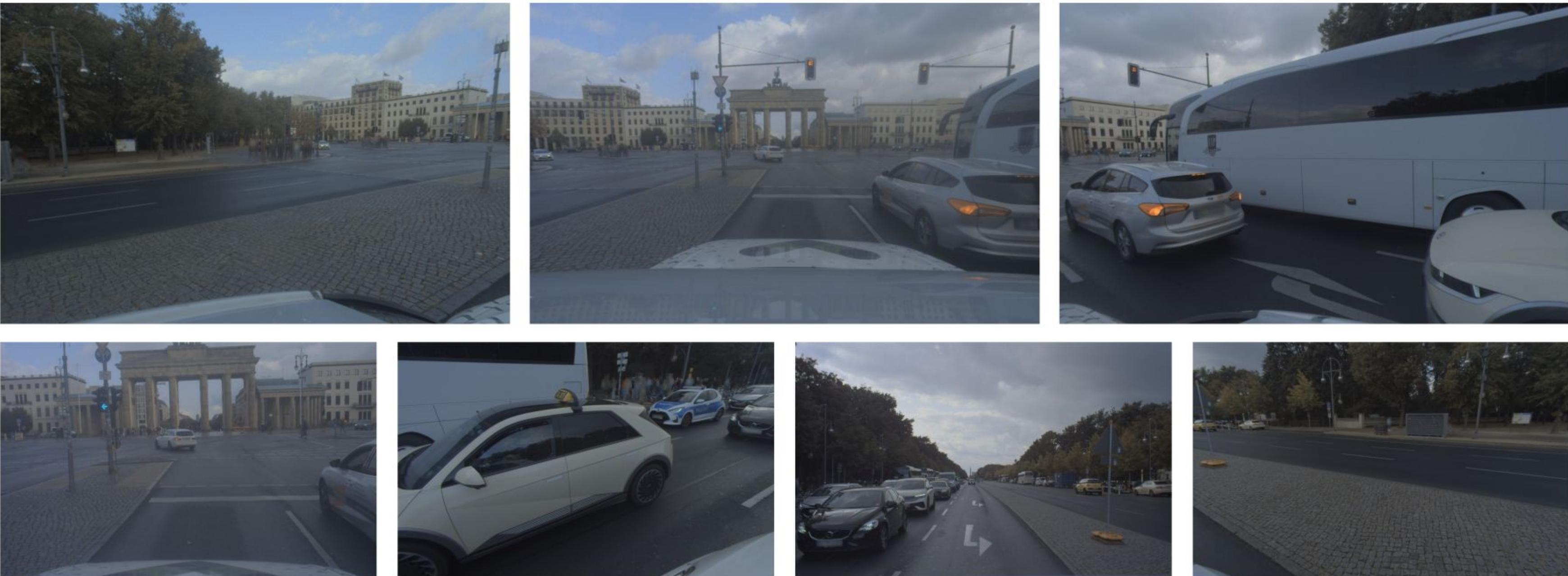
- ❖ Light Skeleton Detection (LSD)
- ❖ Detect the location of each car's lights and their states individually
- ❖ Not constrained to the back of vehicles

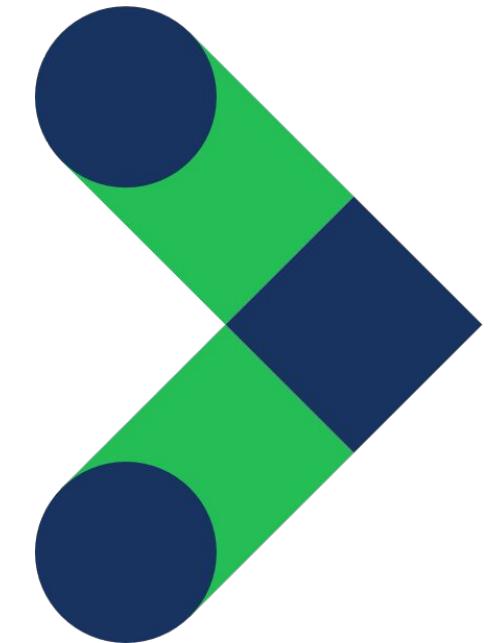




Data Capture

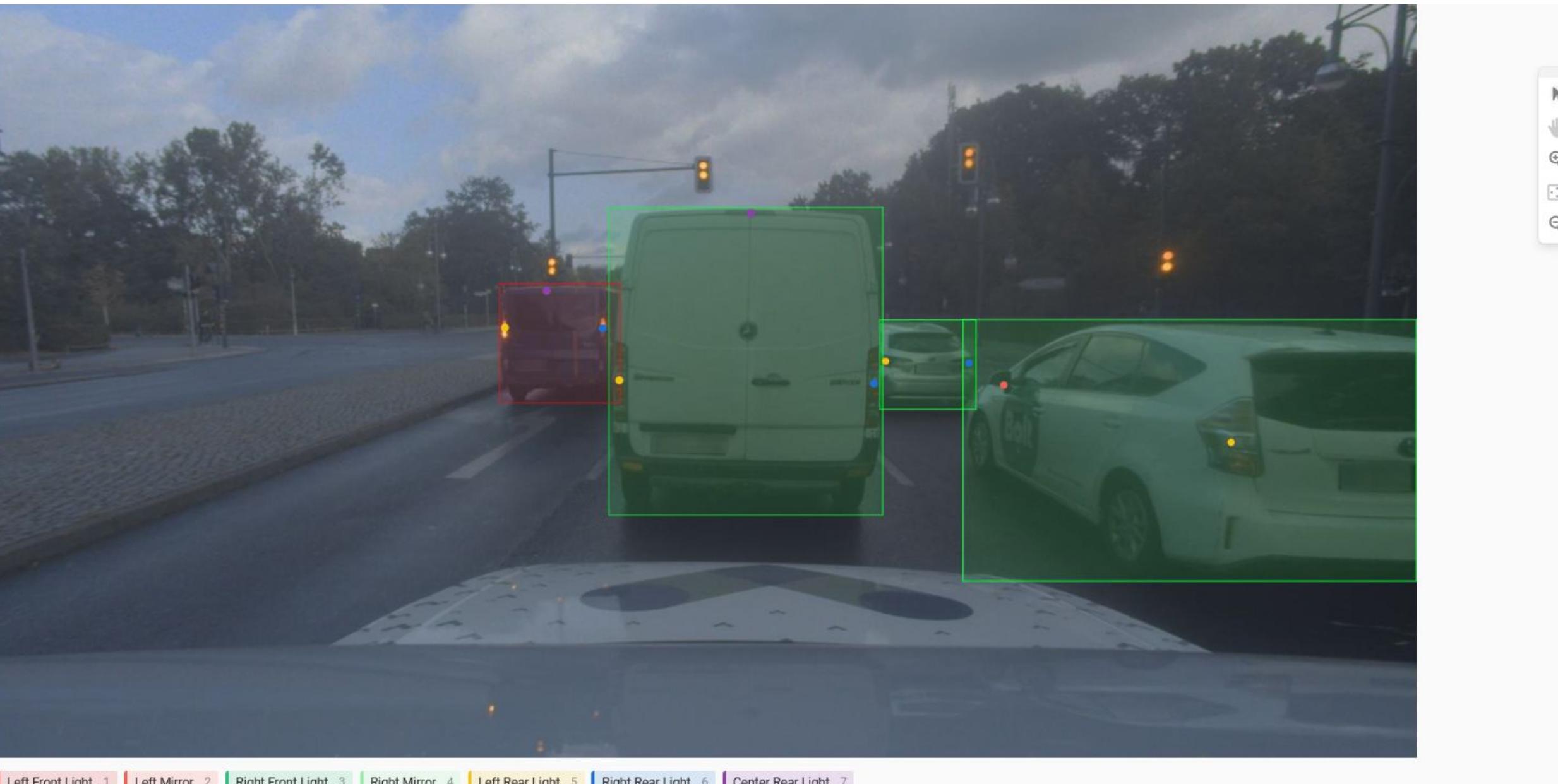
- ❖ Surround view (capturing vehicles from all angles)
- ❖ Custom daytime dataset
- ❖ Custom labeling setup with ML Backends



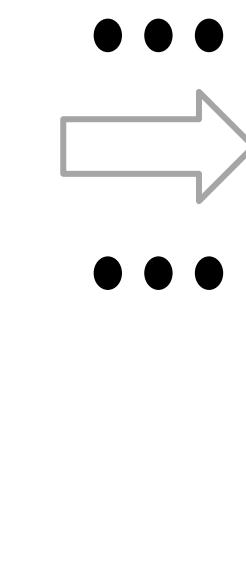


Input Image

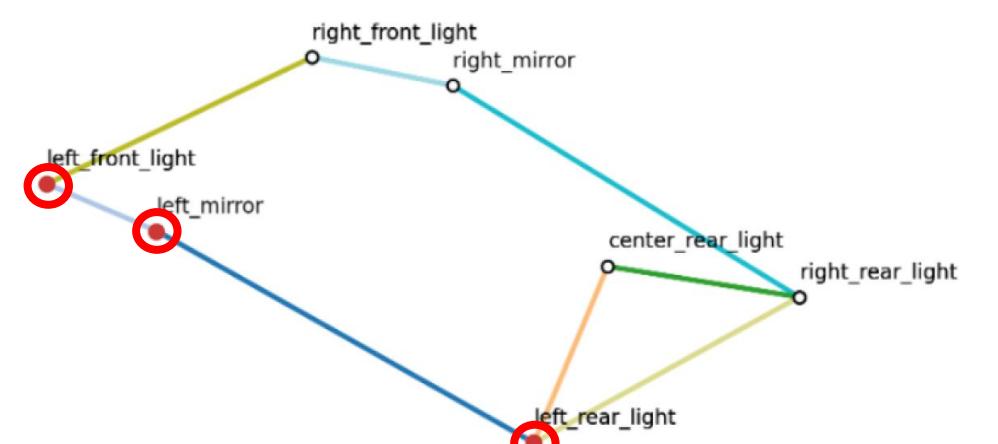
Data Labeling



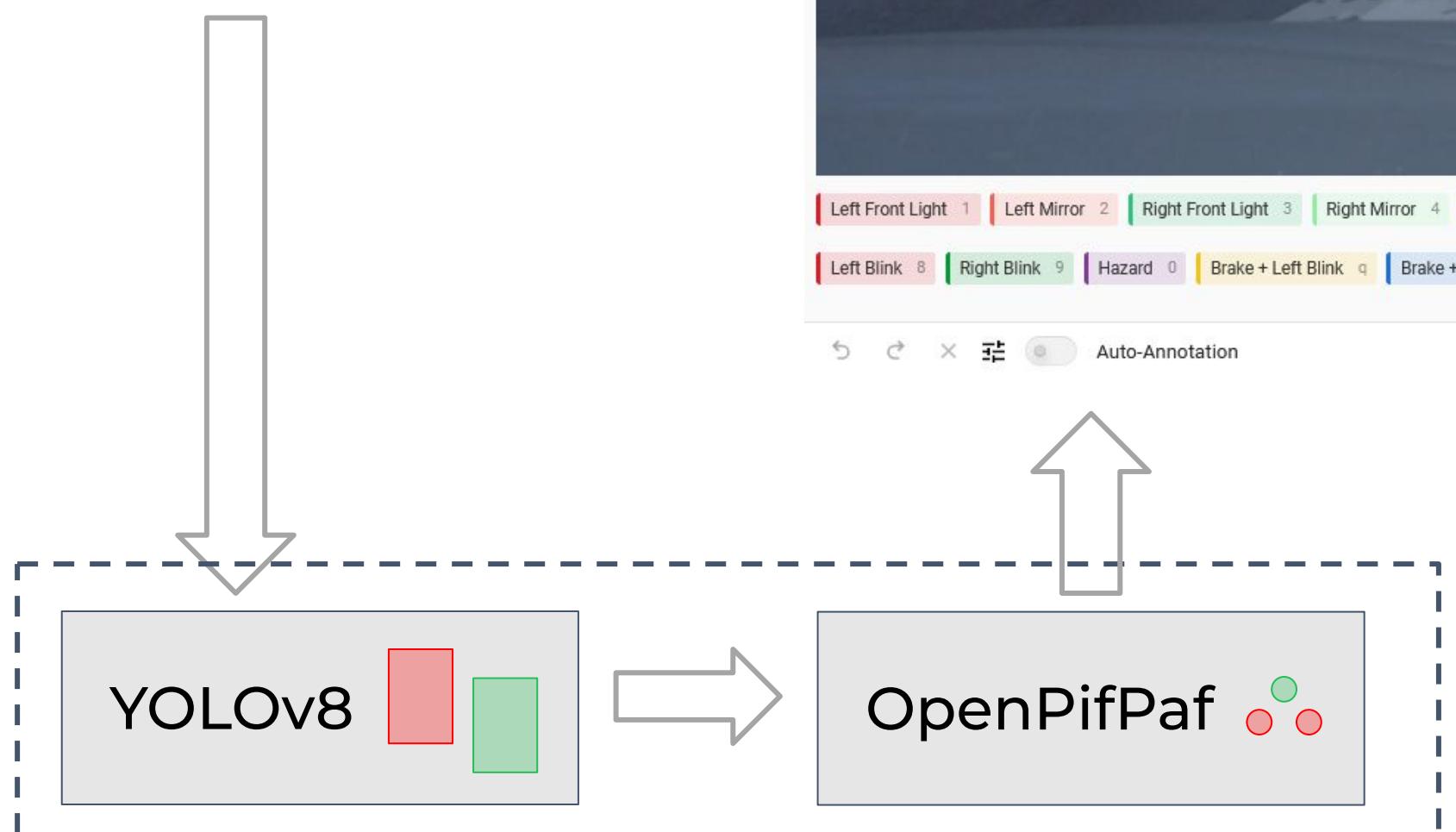
Labeling Interface



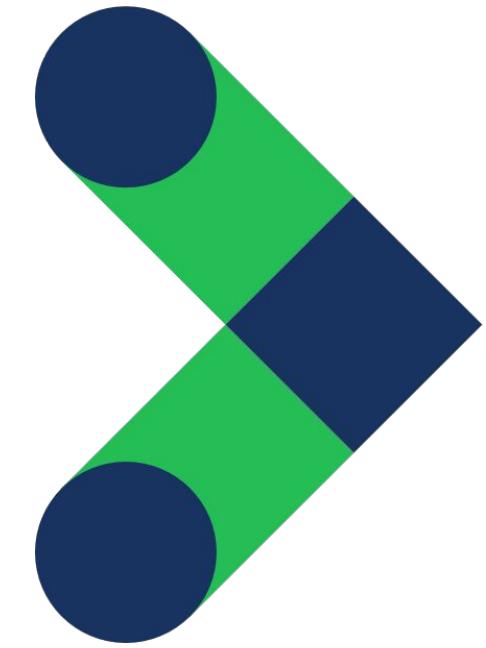
Bbox w/ Keypoints



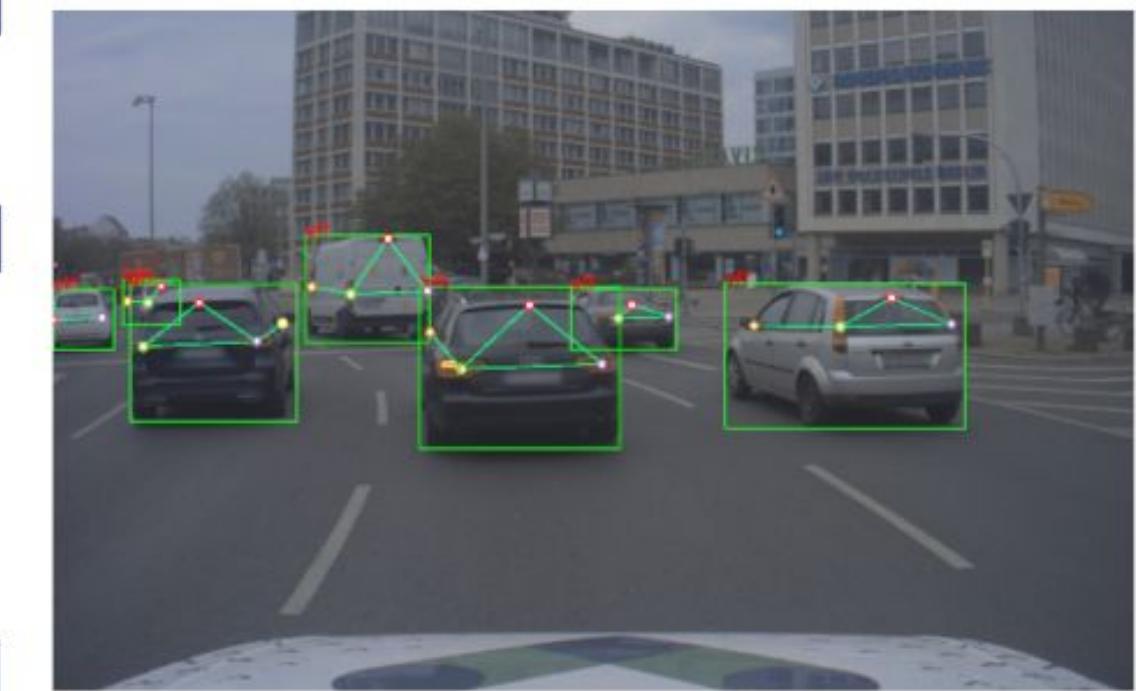
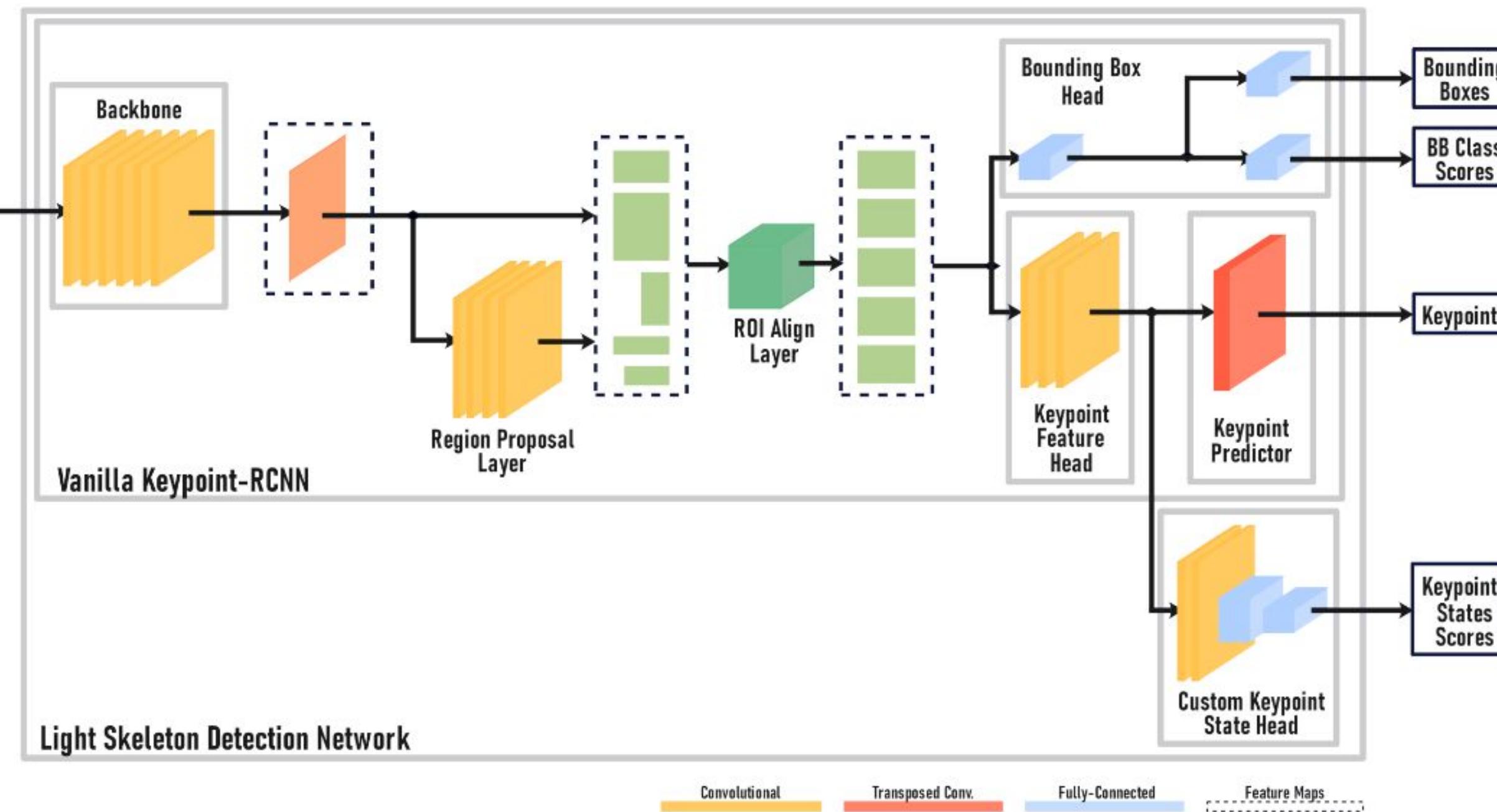
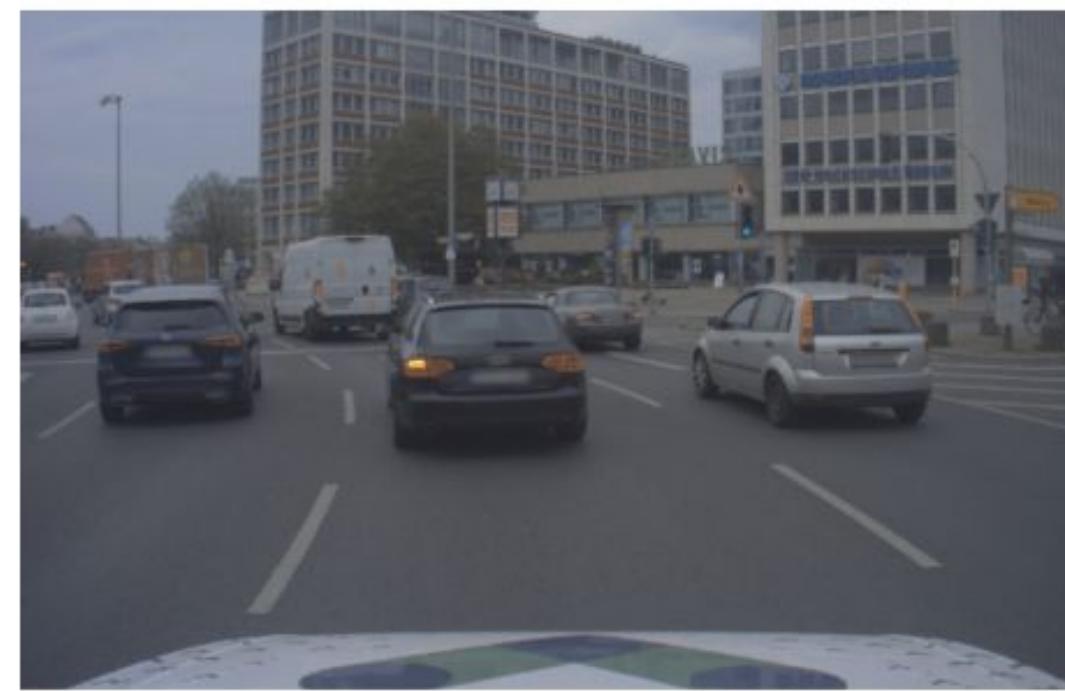
Keypoint States



ML Backend for Pre-Annotation

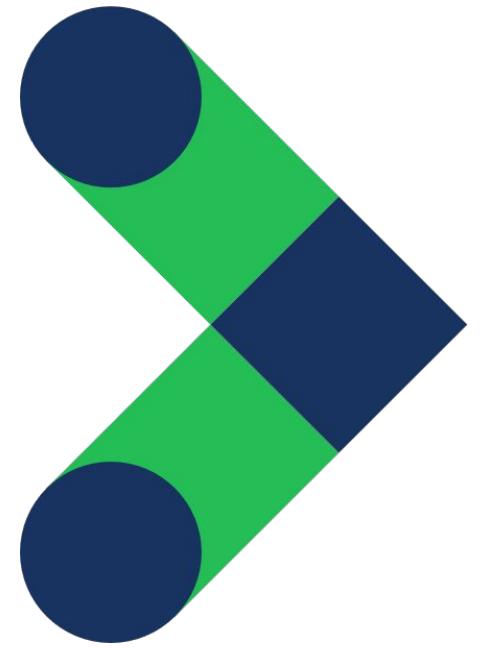


Model

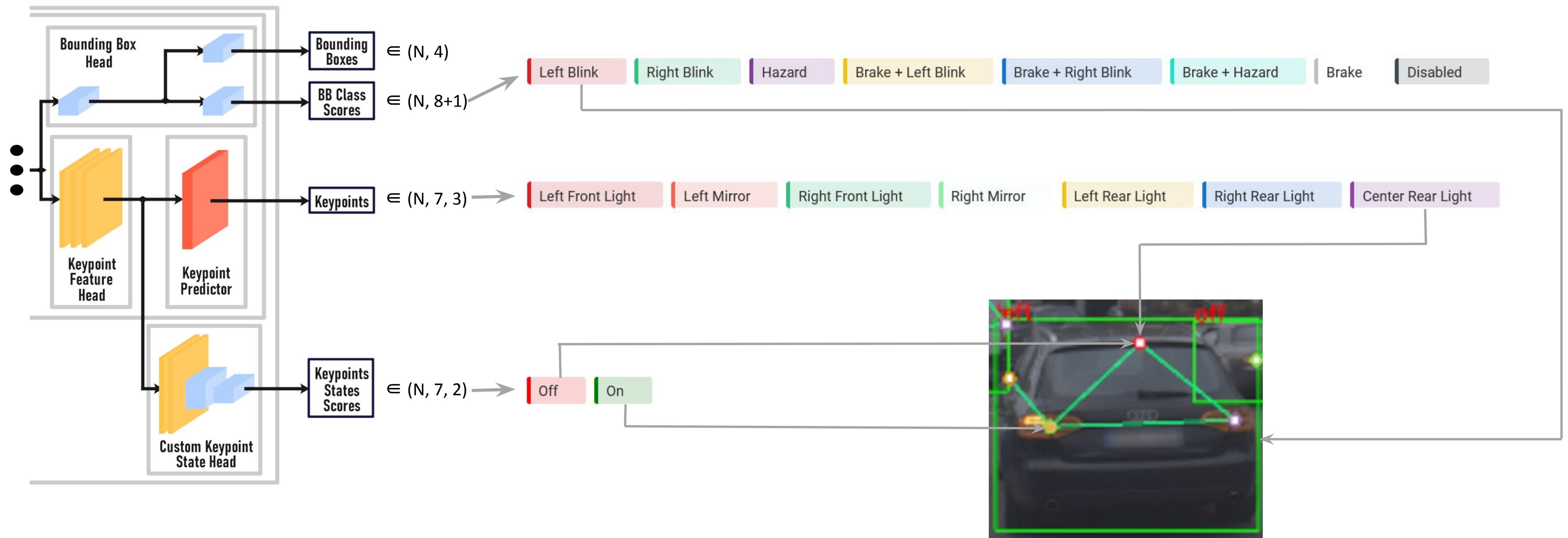


1. **Custom Keypoint State Head**
Modified Keypoint-RCNN with custom head to predict two additional states per keypoint.

2. **Custom Output Classes**
Set number of bounding box (bb) classes to 9 and number of keypoints (x, y, visibility) to 7 per bb.

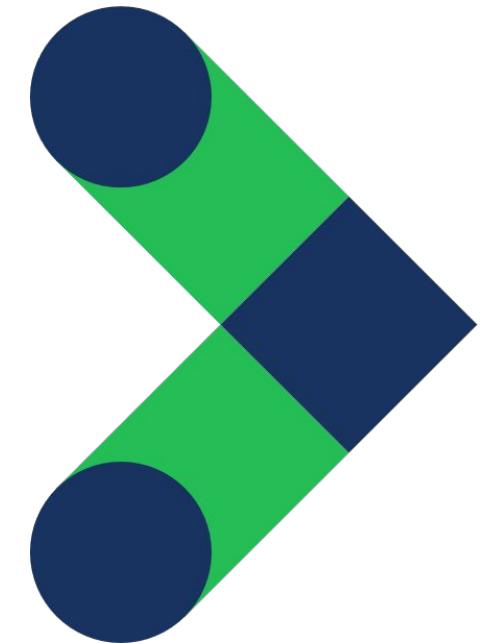


Model



- Custom Keypoint State Head**
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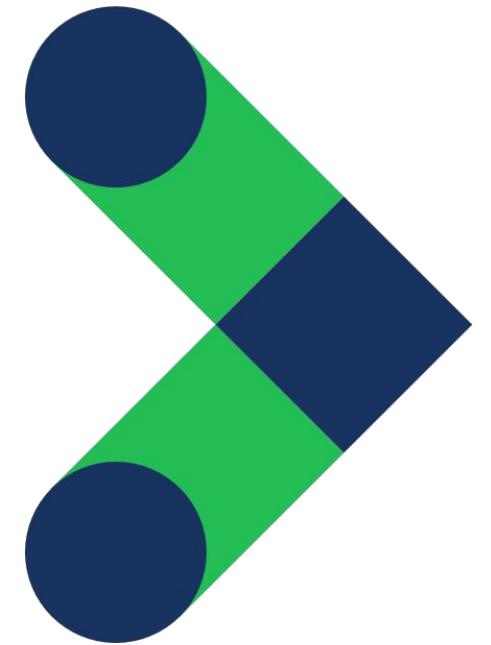
Results

On evaluation set...

Metric	Average
IoU	0.891
Bounding-Box Label Accuracy	0.953
Split Light State Accuracy	0.984

Performance...

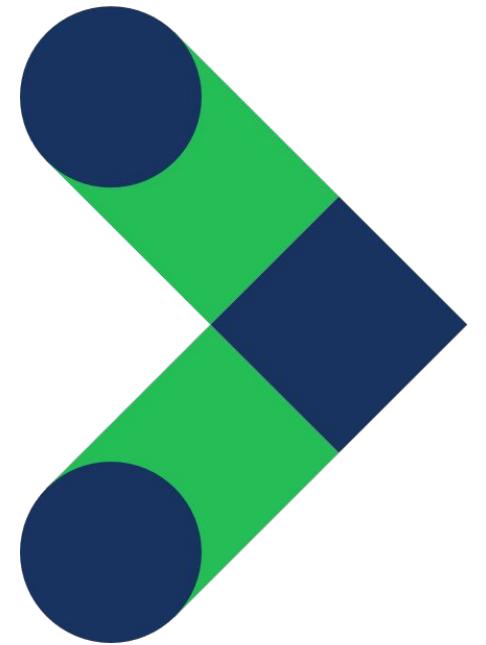
Metric	Average
ROS2 Node Frequency (RTX3070m)	11Hz
Model Latency (RTX3070m)	81.5ms



Results

- ❖ Should only be seen as a proof of concept, since the training set is quite small
- ❖ Shows generalization performance

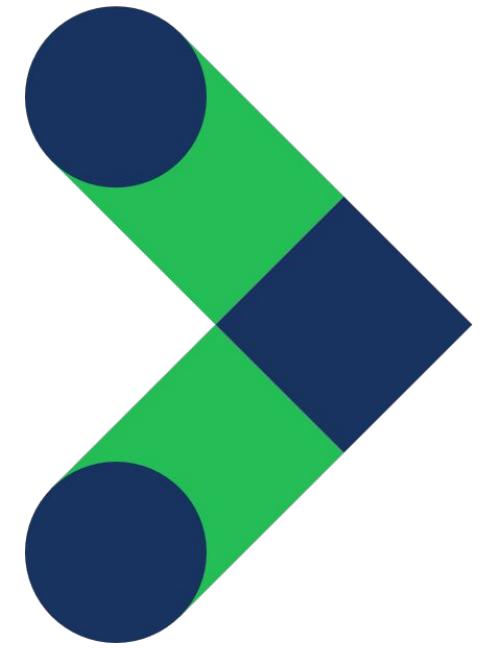




Results

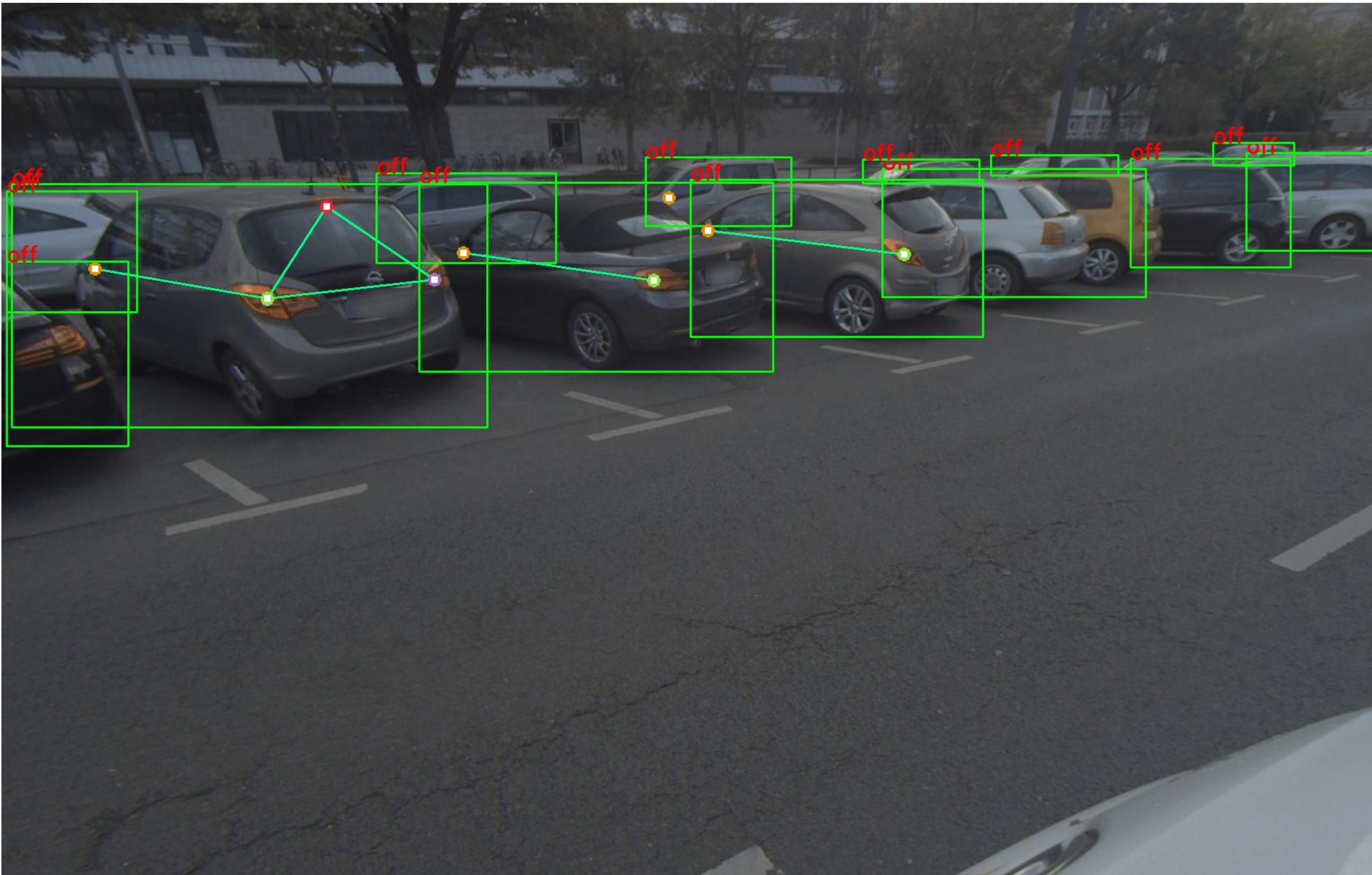
- ❖ Accurately detects vehicle lights

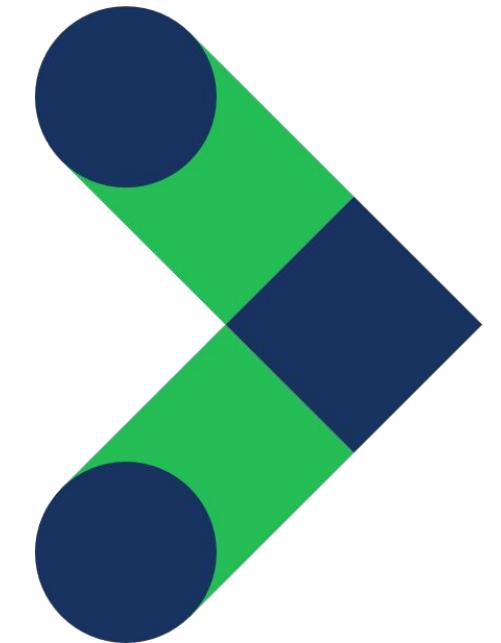




Results

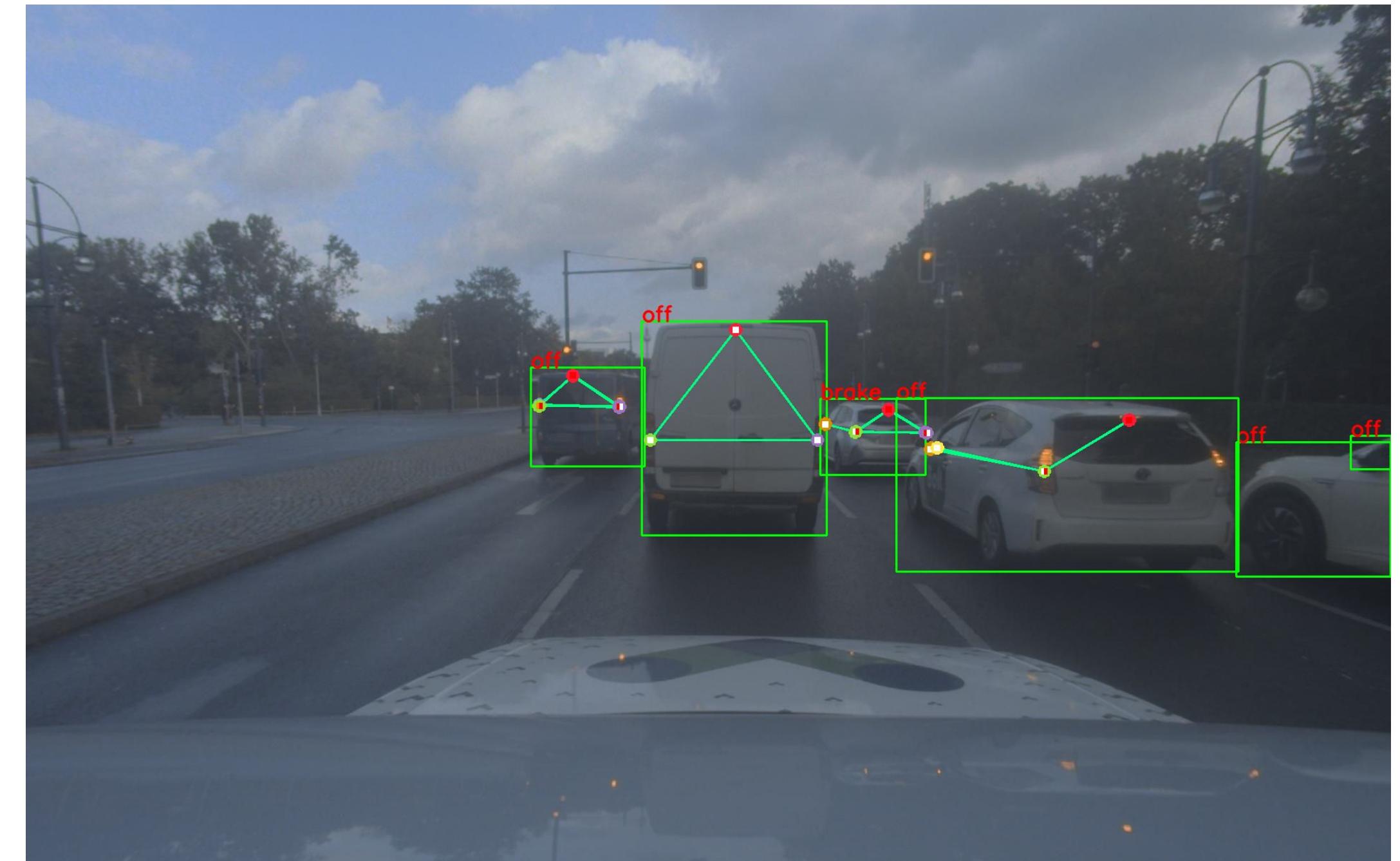
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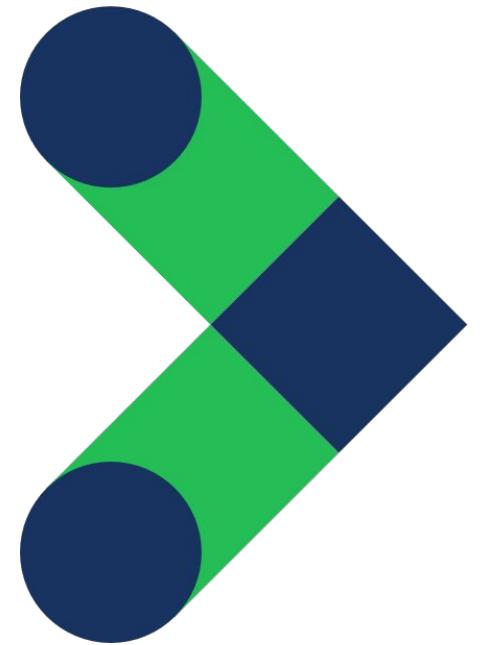




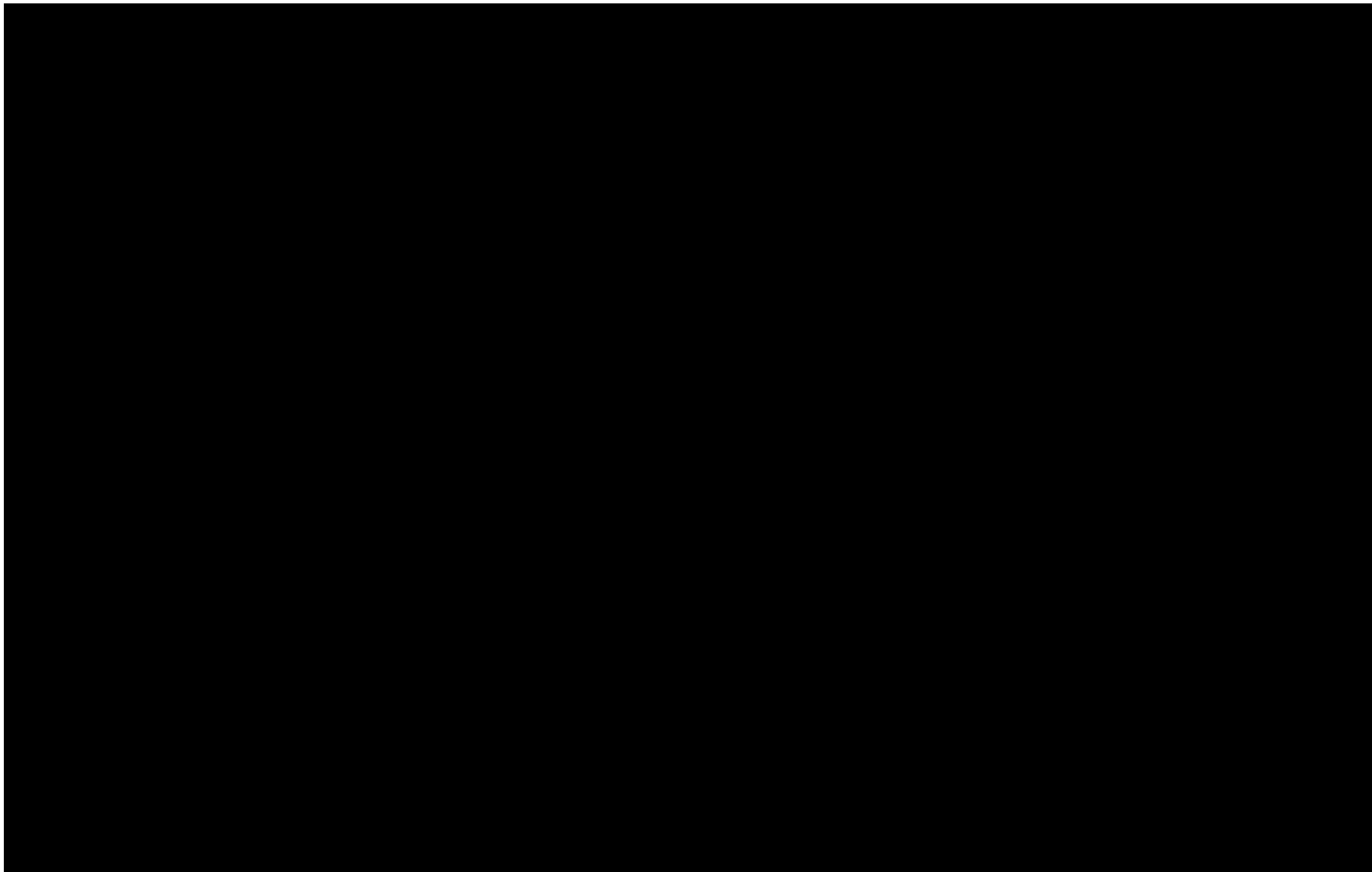
Results

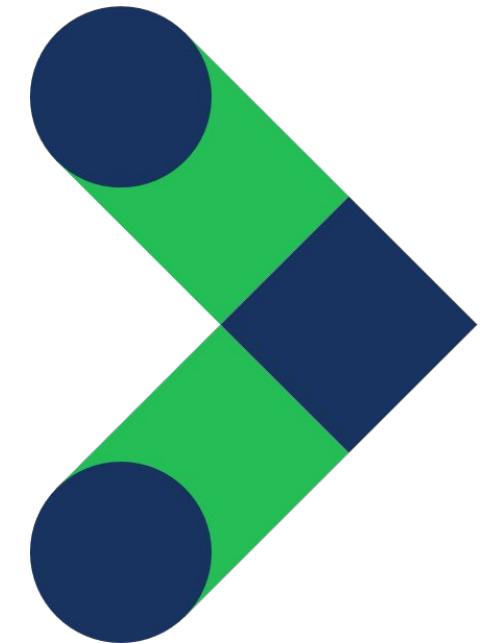
- ❖ Predicted light states can be more accurate than bounding box labels





Results



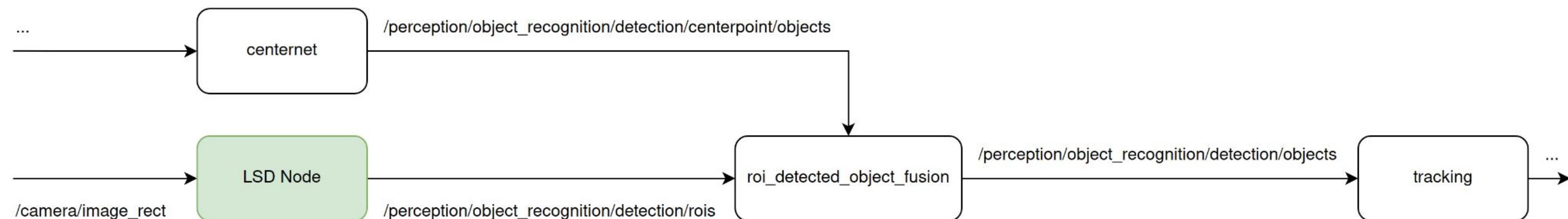


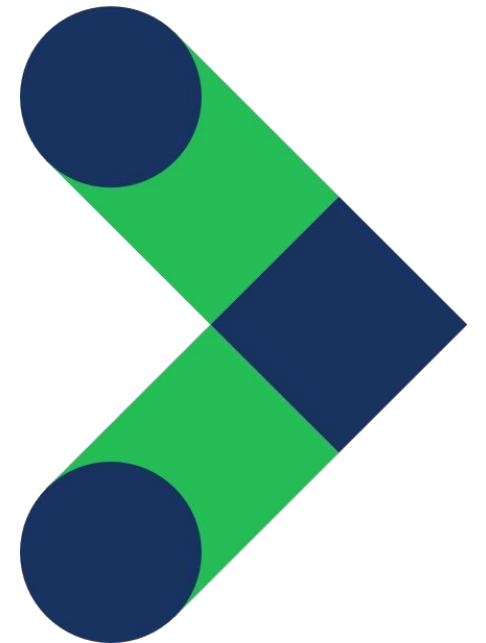
Autoware Integration

Publish custom classification in `DetectedObjectsWithFeature` message

Classification label	Label value
Brake	100
Left indicator on	101
Right indicator on	102

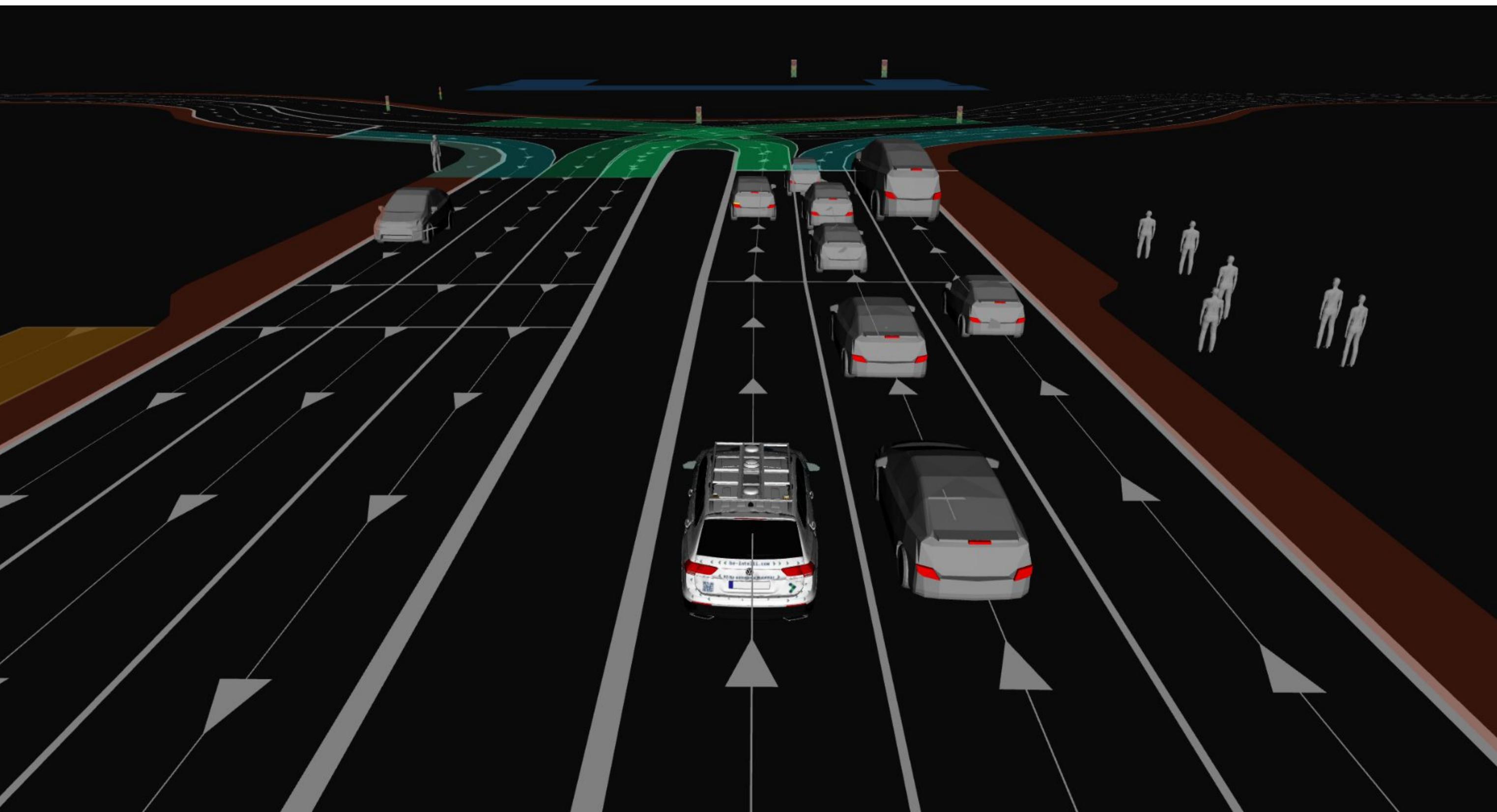
- ❖ Fused to detected objects
- ❖ Disabled filtering of custom classifications in fusion node

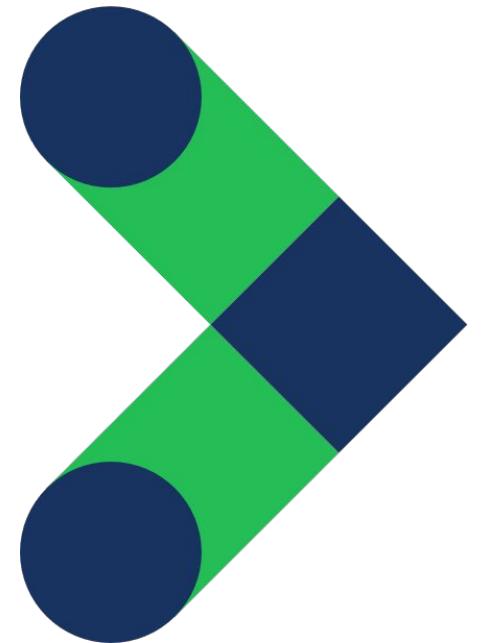




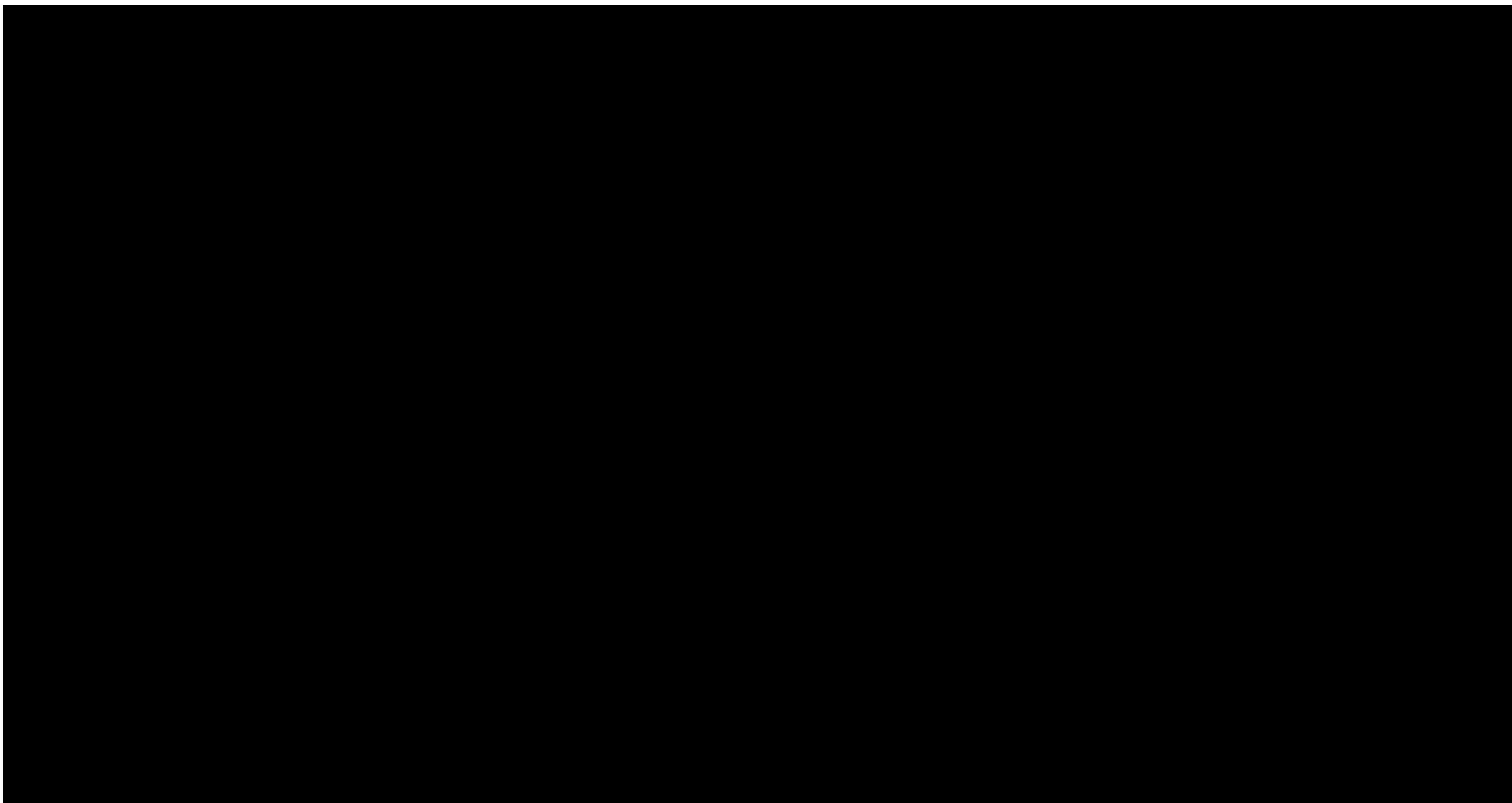
Autoware Integration

- ❖ RViz Visualization





Autoware Integration



Outlook



- 1.** **Train on more data**
To improve the models robustness
- 2.** **Optimize the model for inference hardware**
To improve the execution speed
- 3.** **Extend the prediction model in Autoware**
To utilize the light state predictions

Conclusion



1.

Novel approach for angle agnostic light state detection

Addressing a current gap in literature

2.

Evaluation on real world data

Showing promising results

3.

Integrated in to Autoware

And 3D visualization in RViz



Get in touch

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