

# THEIA Innovation Project

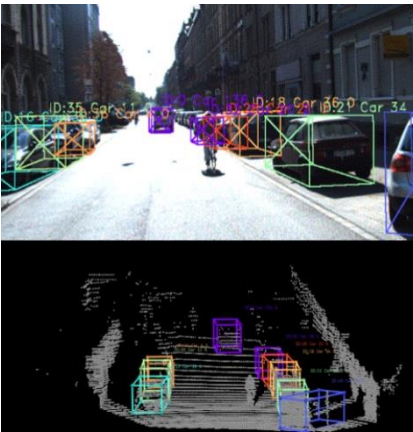
LiDAR based Accurate Perception

Cofinanciado por:

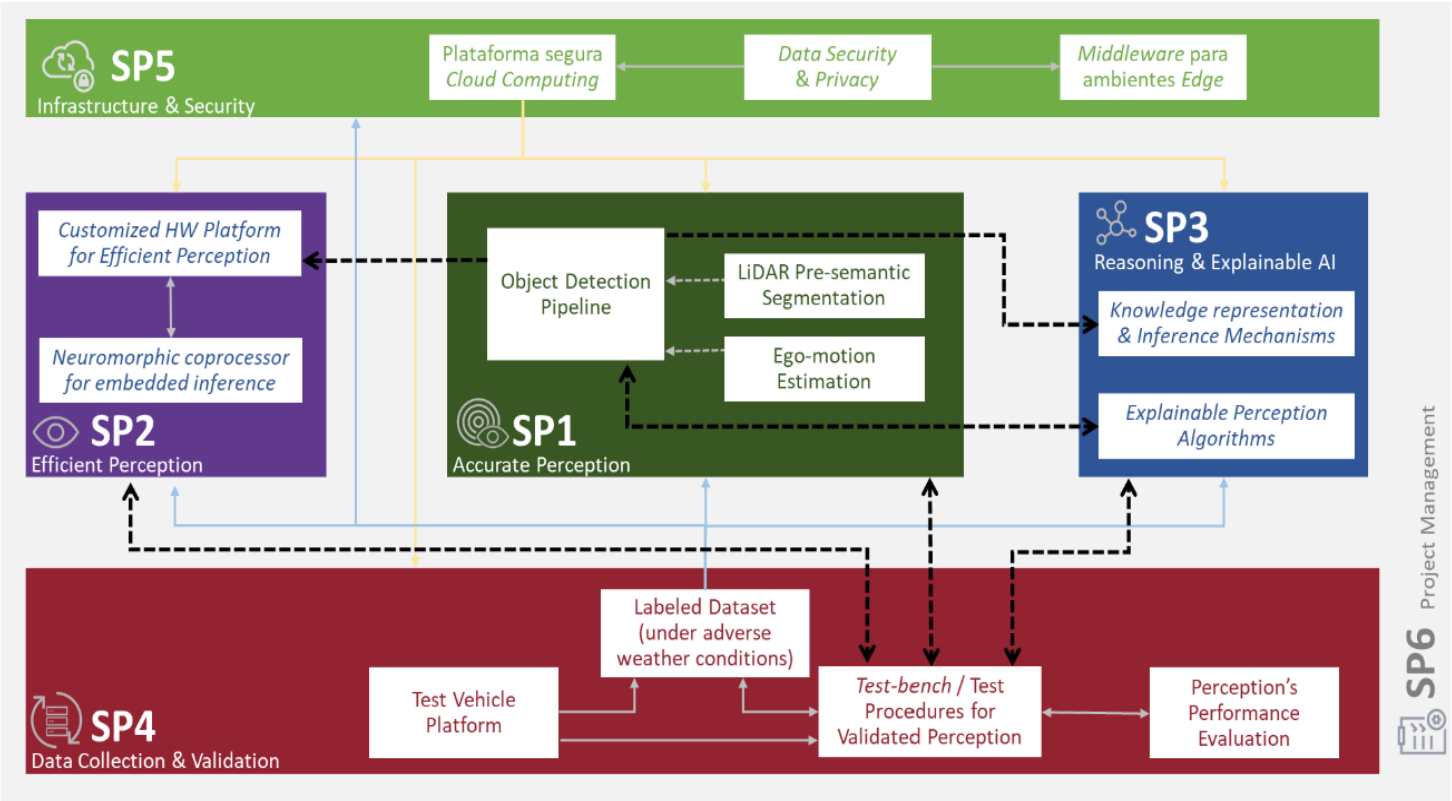


# THEIA Innovation Project

## Project Overview



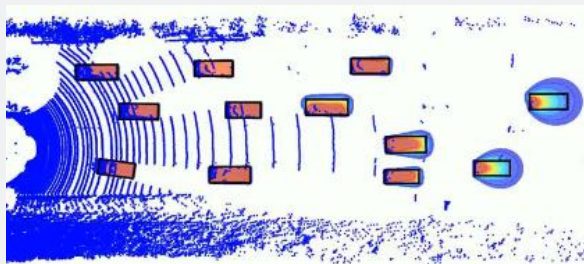
**AI Development**  
Innovation & Deep Learning for Perception



→ processing & storage capabilities    → Dataset input    --> input intermediate results    → internal dependencies

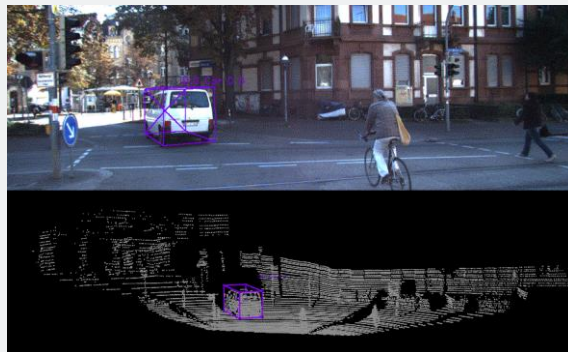
# THEIA Innovation Project

## Core Tasks



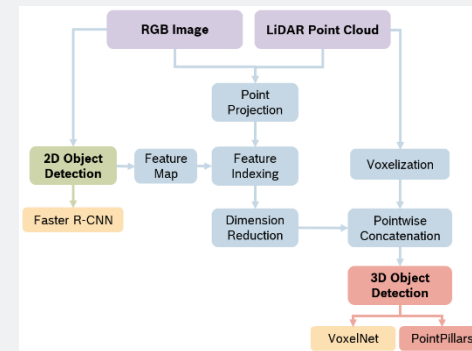
### Explainable and Safe AI

- Definition of Safety Aware KPIs
- Development of Uncertainty Quantification Methods



### Temporal Deep Learning

- Multi-sequence method
- Temporal consistency and context association



### Multi-Modal Deep Learning

- Multi-sensor scalable Fusion Architectures
- Multi-task Networks (i.e., Semantic Segmentation with Object Detection)

# THEIA Innovation Project

## PER AI Team



Filipe Gonçalves



João Teixeira



Ricardo Cerqueira



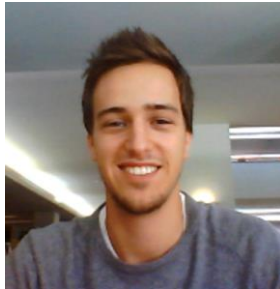
Bernardo Araújo



Sofia Beco



Carolina Pinto



Guilherme Santos



Mariana Xavier



José Guerra

### Points of Contact:

- [filipe.goncalves@pt.bosch.com](mailto:filipe.goncalves@pt.bosch.com) / [joaof.teixeira@pt.bosch.com](mailto:joaof.teixeira@pt.bosch.com)

# THEIA – Accurate Perception

LiDAR based Weather Estimation

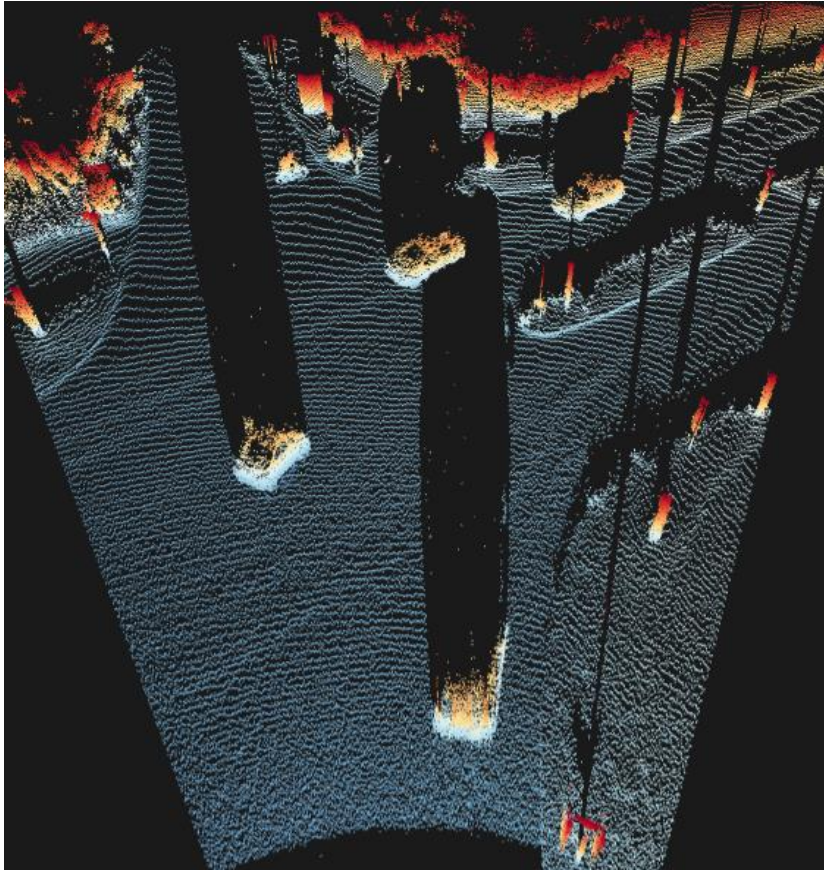
Cofinanciado por:





# THEIA Innovation Project

## What is a Point Cloud?



- List of points
- Accurate location of each
- Can be captured by:
  - LiDAR sensor (Light Detection And Ranging)
  - Stereo camera system
- Unordered
- Unstructured
- Sparse data
- Uneven density of points

LiDAR scanner



# LiDAR based Weather Estimation

## Overview & Objectives

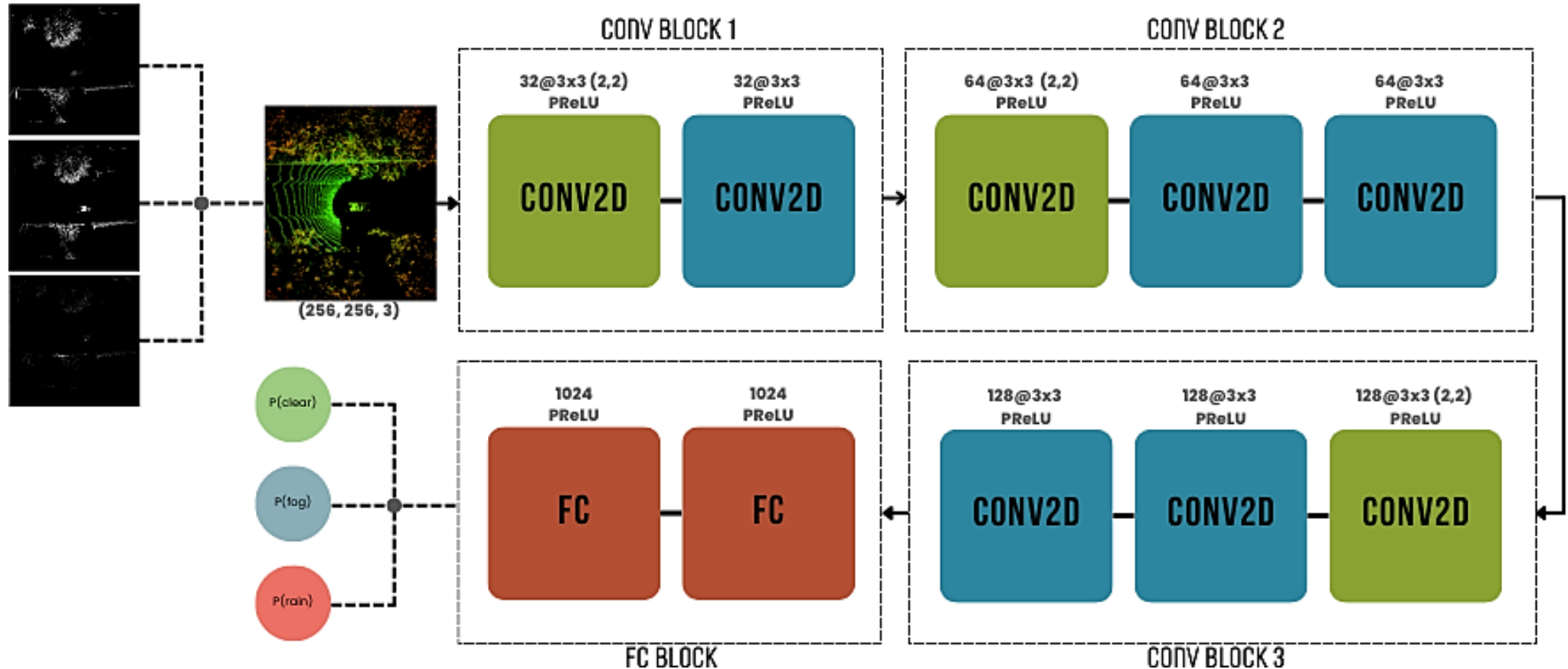
- Weather Estimation motivations for the Autonomous Driving (AD) domain:
  - Understand **LiDAR sensor's degradation caused by adverse weather**;
  - Provide an estimate of weather's **impact on vehicles visibility**;
  - **Enable safety adjustments** in AD behaviour in **real-time**.
- Classifying weather conditions will inform subsequent perception tasks about a degree of confidence or robustness regarding captured sensor data.

**Main Goal:** Develop new models/methods based on Machine/Deep Learning capable of detecting weather conditions (sun, rain, fog).

# LiDAR based Weather Estimation

## MobileWeatherNet Architecture

[1] M. P. Silva, D. Carneiro, J. Fernandes, and L. F. Teixeira. "MobileWeatherNet for LiDAR-only weather estimation". In 2023 International Joint Conference on Neural Networks (IJCNN), pages 1–8, 2023. doi: 10.1109/IJCNN54540.2023.10191333



Overview of the MobileWeatherNet input, architecture and output [1].



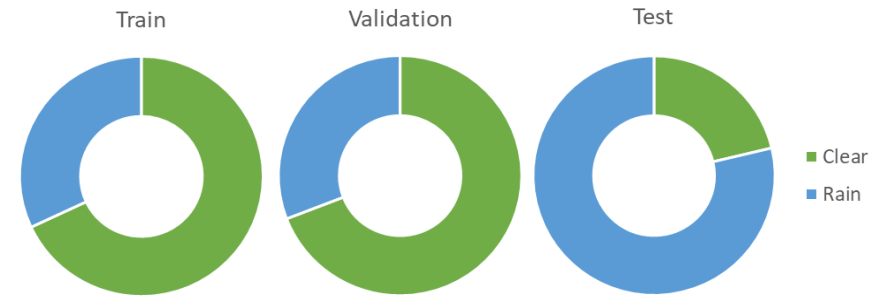
# LiDAR based Weather Estimation

## Results on THEIA\_DC#2

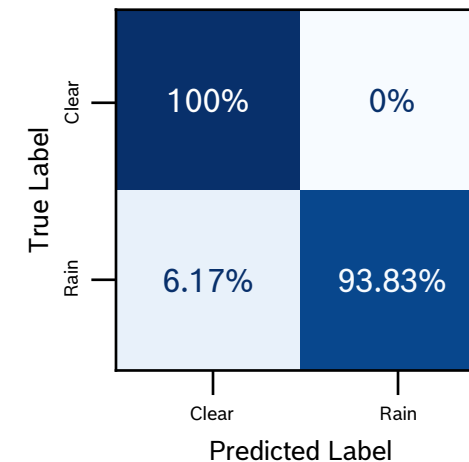
- **Dataset:** Theia\_DC#2 (LiDAR Bosch X)
  - Two weather conditions (**clear** weather, **rain**) under diverse driving scenarios (scenario, time of day, blockage).
  - Sequential test set, allowing post-processing for evaluation.

Key metrics obtained on test set with post-processing.

	Theia_DC#2
Cohen Kappa	0.87
F1-Score	93.29%
Balanced Accuracy	96.91%



Train, validation and test splits for weather estimation.



Confusion matrix on test set with post-processing.

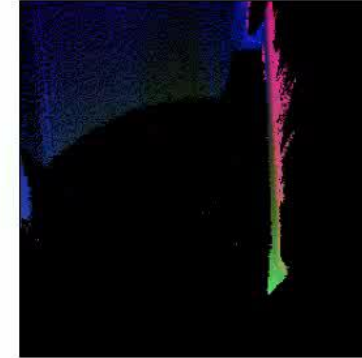
# LiDAR based Weather Estimation

## Results on THEIA\_DC#2

Range View



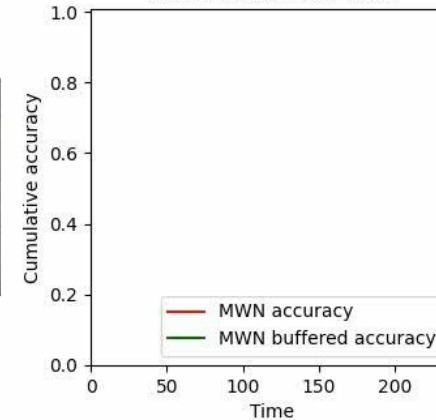
BEV



RGB



Performance over time



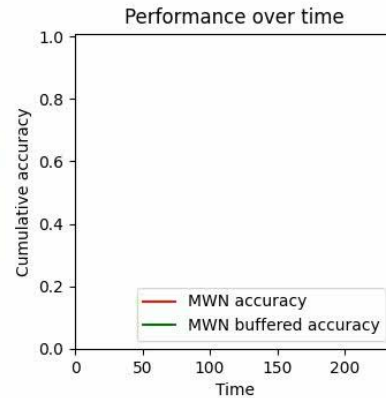
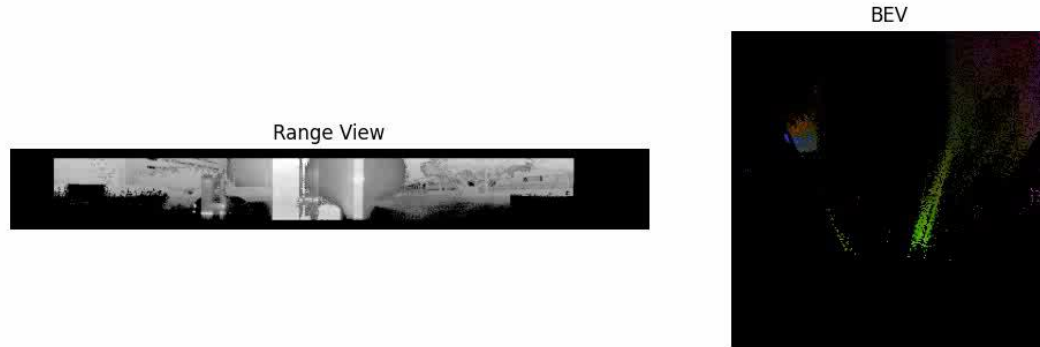
**MWN accuracy:** calculated from raw inferences.

**MWN buffered accuracy:** calculated from post-processed inferences – weighted moving average with sliding window of size 10.

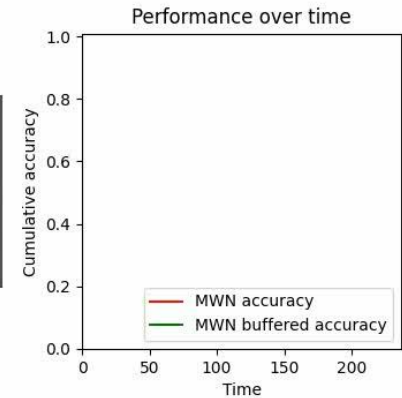
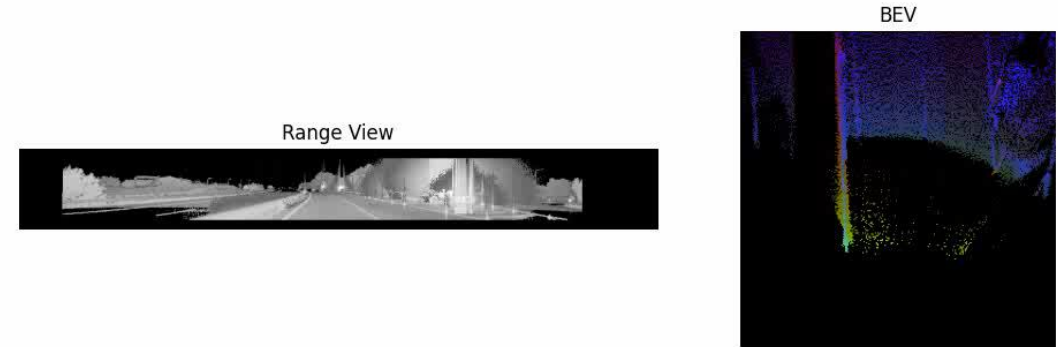
Ground truth: Clear  
Inference Prediction: Clear  
Buffered Prediction: Clear

# LiDAR based Weather Estimation

## Results on THEIA\_DC#2



Ground truth: Rain  
Inference Prediction: Rain  
Buffered Prediction: Rain



Ground truth: Rain  
Inference Prediction: Rain  
Buffered Prediction: Rain

# THEIA – Accurate Perception

LiDAR based Semantic Segmentation

Cofinanciado por:



# LiDAR based Semantic Segmentation

## Motivation and Objectives

### ▪ Semantic Segmentation:

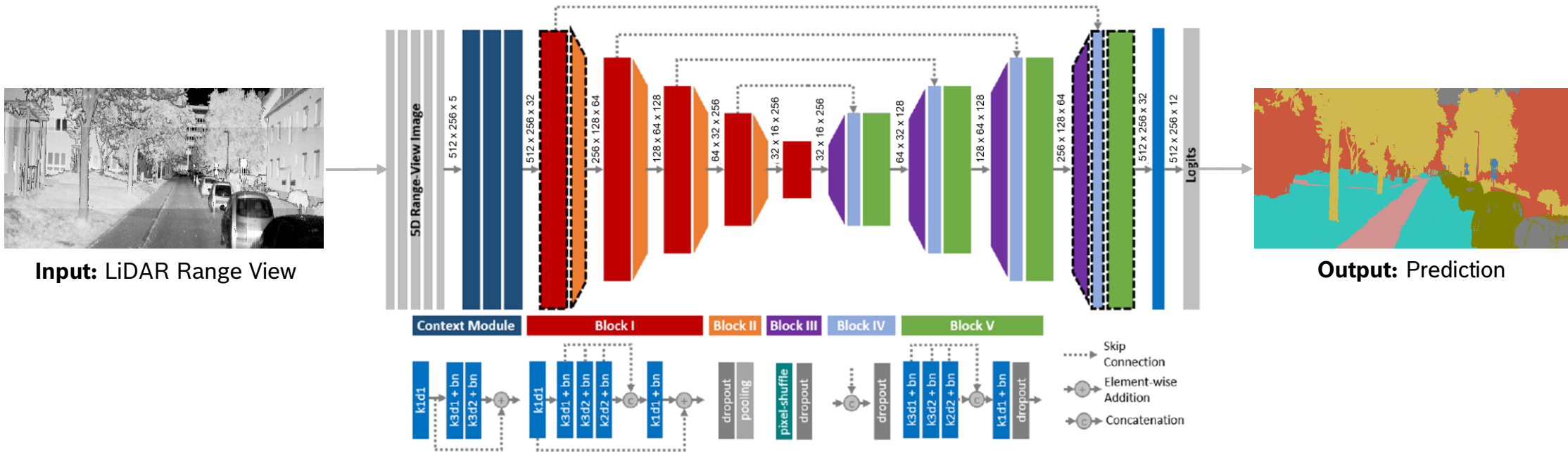
- **Autonomous driving** requires a **detailed and precise perception** of the surrounding environment, that goes **beyond object detection**.
- Essential for **safe vehicle navigation** as it enables perception of:
  - **Static environment:** road, buildings and vegetation.
  - **Dynamic environment:** vehicles, pedestrians and obstacles.
- LiDAR sensor pros & cons (compared to RGB images)

✓ <b>depth information</b>	✗ <b>data is sparse</b>
✓ <b>less vulnerable to light exposure</b>	✗ <b>sensitive to material reflection</b>
	✗ <b>sensitive to adverse weather conditions (also true for RGB)</b>

**Main Goal:** Develop a perception point-based algorithm using only LiDAR for semantic segmentation.

# LiDAR based Semantic Segmentation

## SalsaNext Architecture



Overview of the SalsaNext architecture. Adapted from [3].

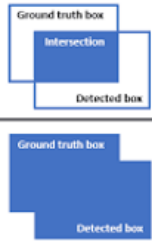
**Number of parameters:** 6.7M  
**Inference time:** 20.47 ms +/- 0.051

[3] Cortinhal, T., Tzelepis, G., & Aksoy, E. (2020). "SalsaNext: Fast, uncertainty-aware semantic segmentation of LiDAR point clouds."



# LiDAR based Semantic Segmentation

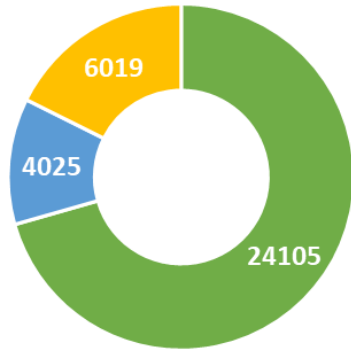
## Datasets and Results

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{\text{Intersection}}{\text{Ground truth box} + \text{Detected box} - \text{Intersection}}$$


<https://www.baeldung.com/wp-content/uploads/sites/4/2022/04/fig1.png>

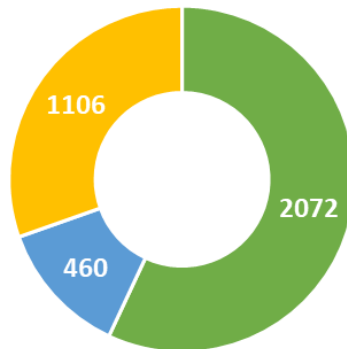
**nuScenes Dataset**

16 classes



**THEIA Dataset**

11 classes



■ Train ■ Validation ■ Test

	nuScenes	THEIA
IoU	0.6924	0.5522
Dice	0.8062	0.6550
Precision	0.7746	0.6693
Recall	0.8499	0.6580

# LiDAR based Semantic Segmentation

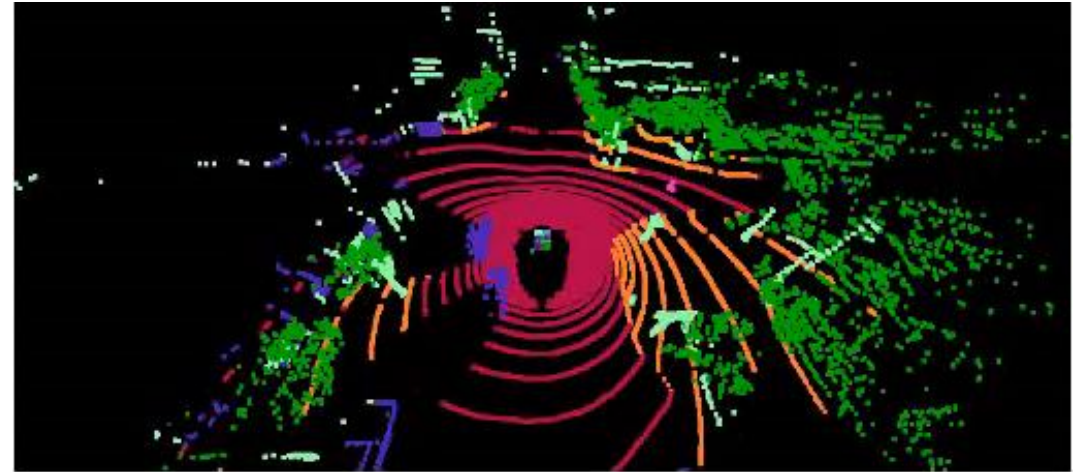
## Results: nuScenes dataset

- |                        |                     |              |
|------------------------|---------------------|--------------|
| ● noise                | ● motorcycle        | ● other_flat |
| ● barrier              | ● pedestrian        | ● sidewalk   |
| ● bicycle              | ● traffic_cone      | ● terrain    |
| ● bus                  | ● trailer           | ● manmade    |
| ● car                  | ● truck             | ● vegetation |
| ● construction_vehicle | ● driveable_surface |              |



RGB camera view.

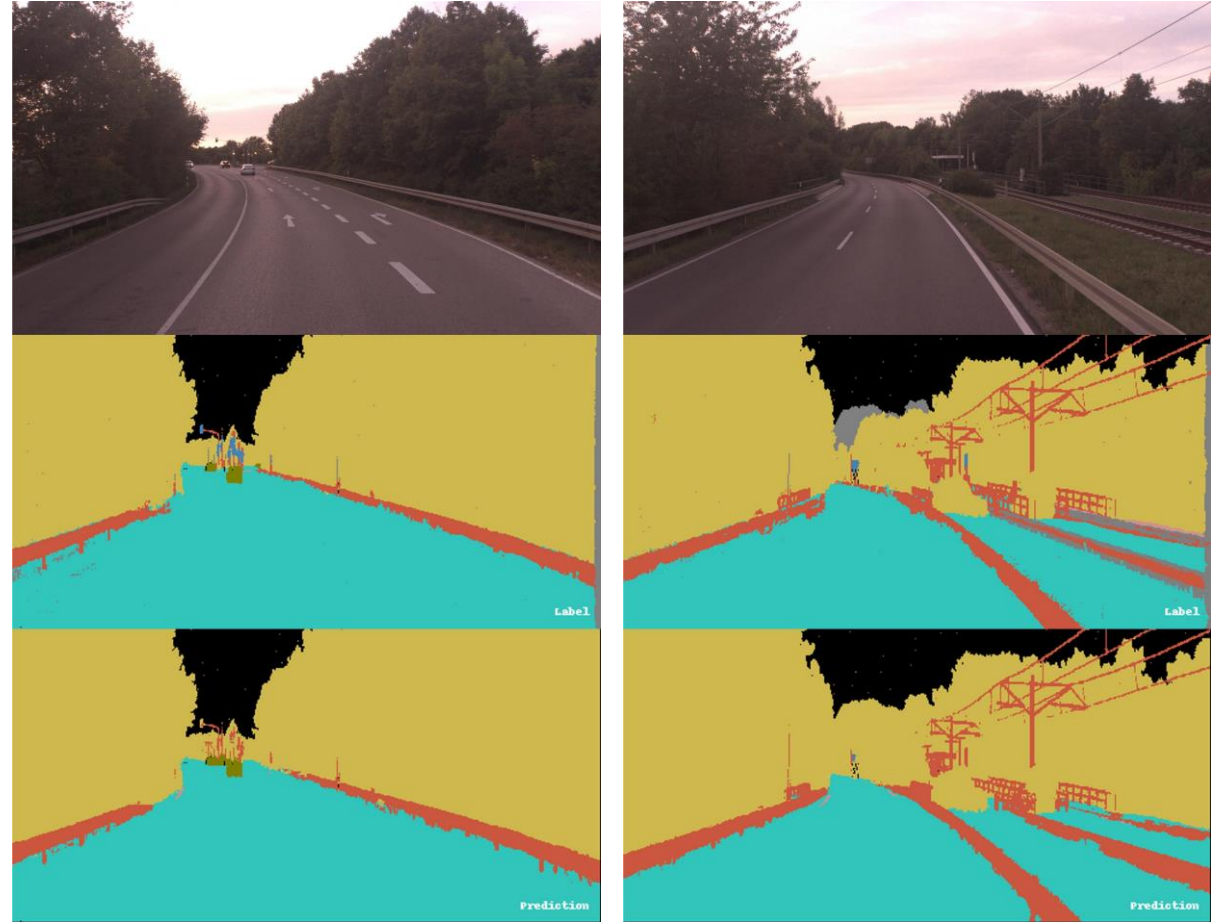
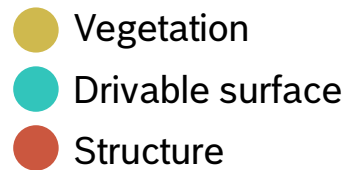
Bird-eye view results.



# LiDAR based Semantic Segmentation

## Results: THEIA dataset

- **Results with improved detail** thanks to LiDAR higher resolution
- **Top classes** with respect to IoU evaluation metric:
  - **Vegetation:** 87.1 %
  - **Drivable surface:** 86.2 %
  - **Structure:** 84.5 %

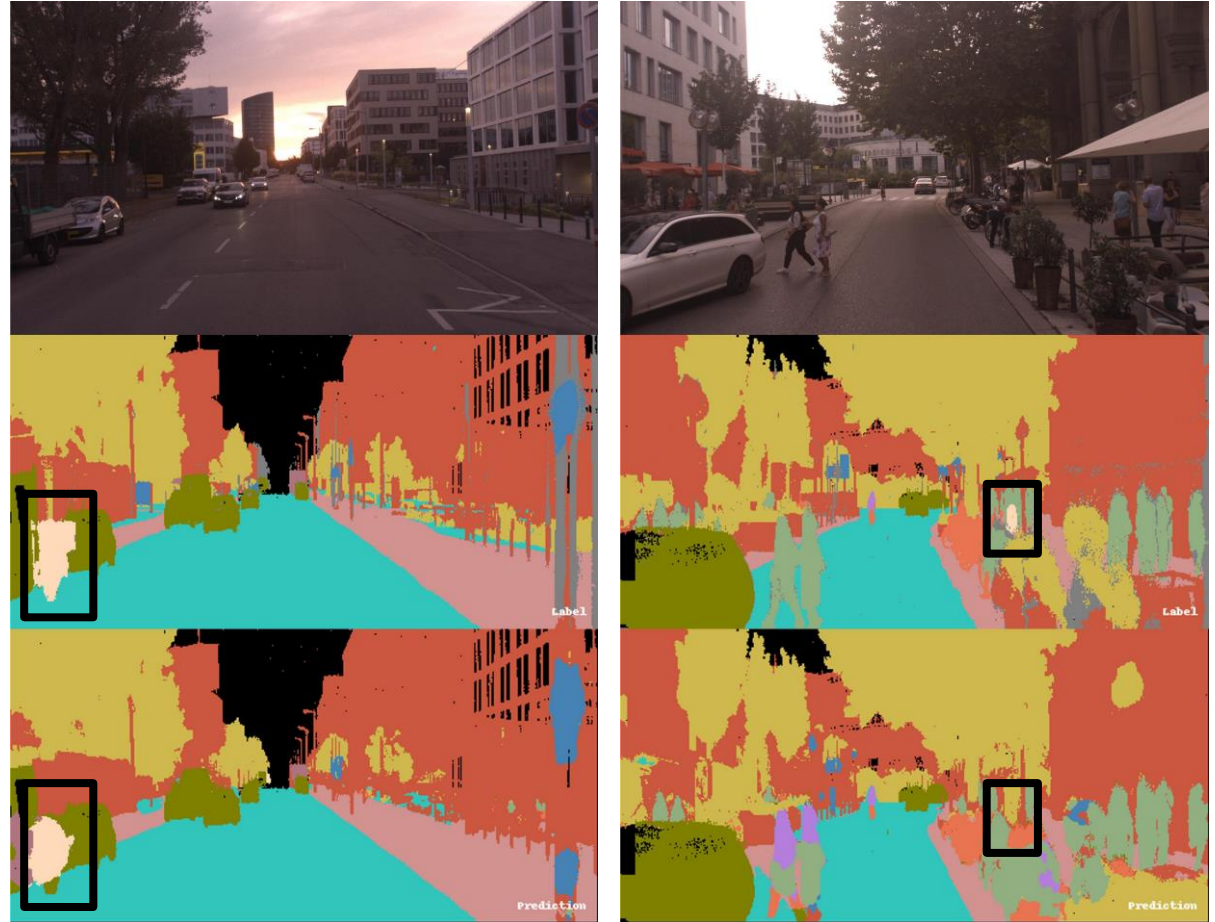


# LiDAR based Semantic Segmentation

## Results: THEIA dataset

- **Worst classes** with respect to IoU evaluation metric:
  - **Dynamic vehicle:** 2.6 %
  - **Rider:** 10.3 %
  - **Ridable vehicle:** 24.9 %

● Dynamic vehicle





# LiDAR based Semantic Segmentation

## Results: THEIA dataset

- **Worst classes** with respect to IoU evaluation metric:
  - **Dynamic vehicle:** 2.6 %
  - **Rider:** 10.3 %
  - **Ridable vehicle:** 24.9 %

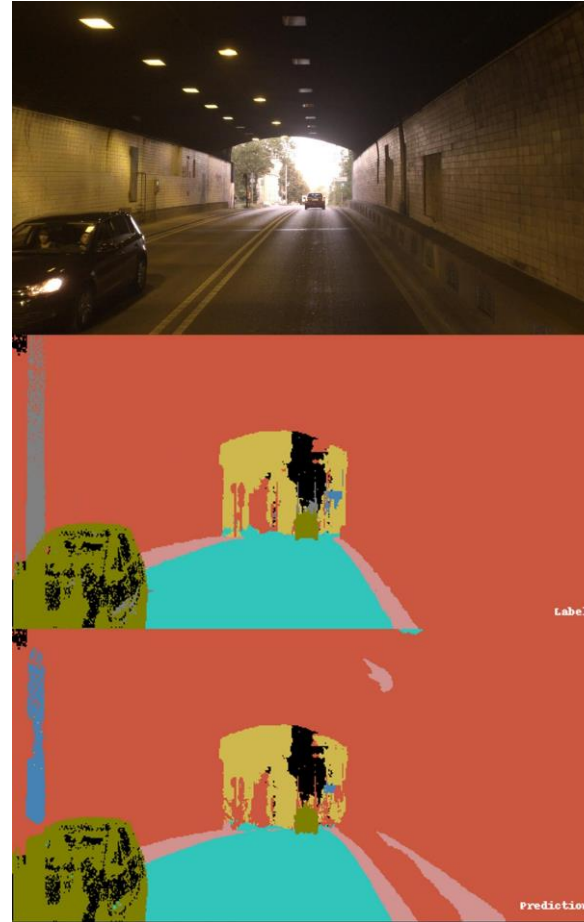
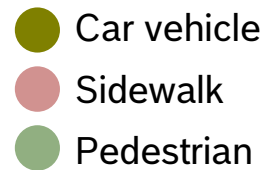
- Pedestrian
- Rider
- Ridable vehicle



# LiDAR based Semantic Segmentation

## Results: THEIA dataset

- Other **relevant classes** in Autonomous Driving context:
  - Car vehicle: 77.8 %
  - Sidewalk: 67.8 %
  - Pedestrian: 54.5 %





# THEIA – Accurate Perception

LiDAR based Lane Estimation

Cofinanciado por:

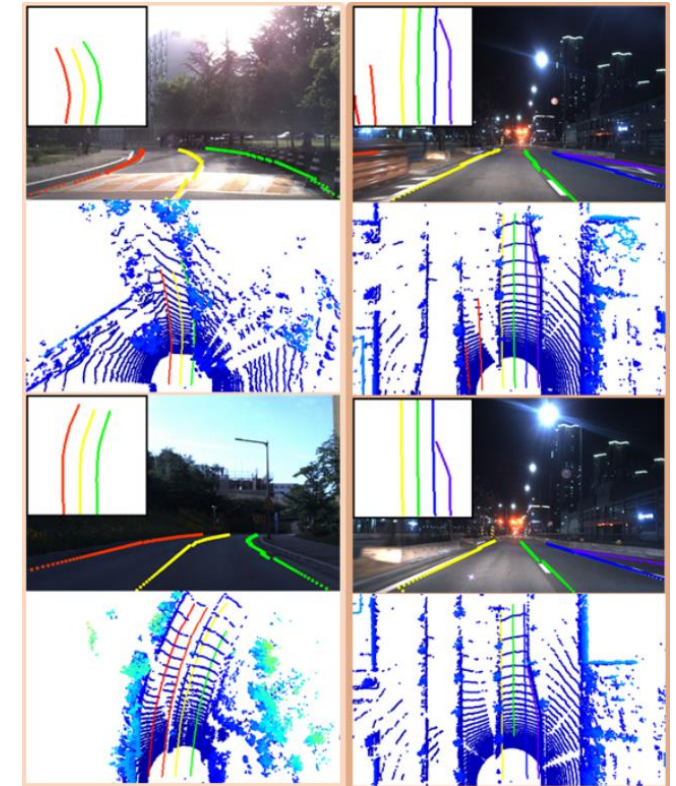


# LiDAR based Lane Estimation

## Motivation and Objectives

### ▪ Lane estimation:

- Essential for **safe vehicle navigation** as it enables perception of **drivable space** such as:
  - Lanes;
  - Lane markings;
  - Traffic arrows;
  - Crosswalks.
- **Supports** the layer of **planning** and **decision-making** for autonomous vehicles.



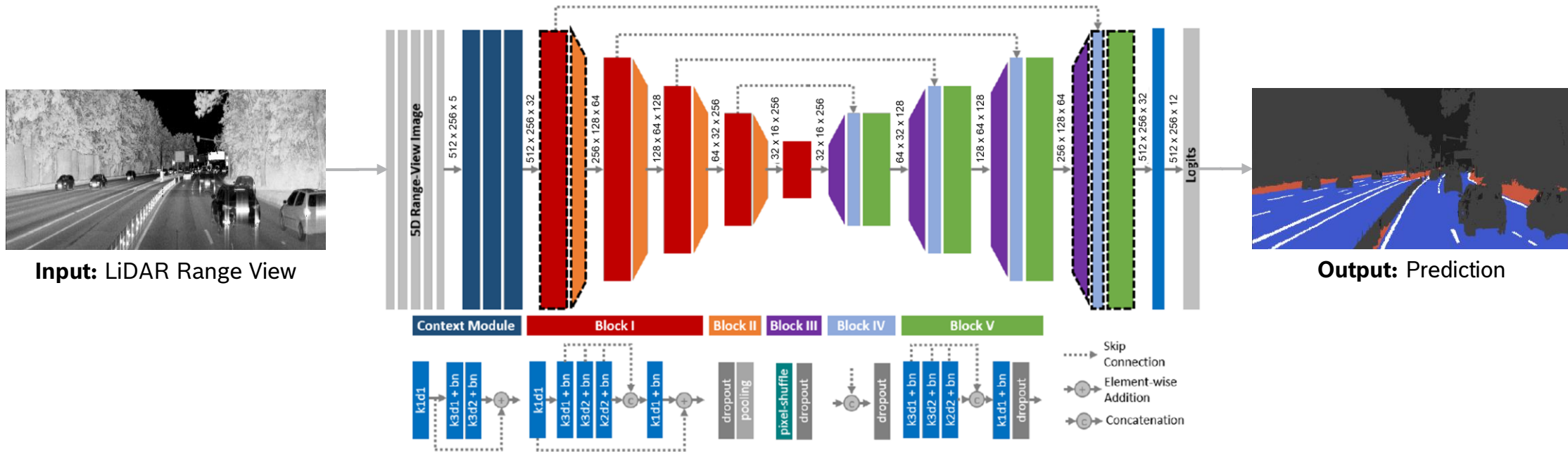
Examples of lane estimation. [4]

[4] Paek, D.-H. and Kong, S.-H. & Wijaya, K. T. (2022). K-Lane: Lidar Lane Dataset and Benchmark for Urban Roads and Highways.

**Main Goal:** Develop deep learning algorithms for lane marking detection.

# LiDAR based Lane Estimation

## SalsaNext Architecture



Overview of the SalsaNext architecture. Adapted from [5].

[5] Cortinhal, T., Tzelepis, G., & Aksoy, E. (2020). "SalsaNext: Fast, uncertainty-aware semantic segmentation of LiDAR point clouds."

# LiDAR based Lane Estimation

## Results: KITTI Road dataset

Overall metrics results on test set (%):

Task	Sensor	F1-score	Precision
Road	LiDAR	93.44	<b>88.92</b>
	RGB	<b>95.27</b>	88.80
Ego-Lane	LiDAR	<b>88.76</b>	<b>79.80</b>
	RGB	82.29	70.81





# LiDAR based Lane Estimation

## Results: THEIA dataset

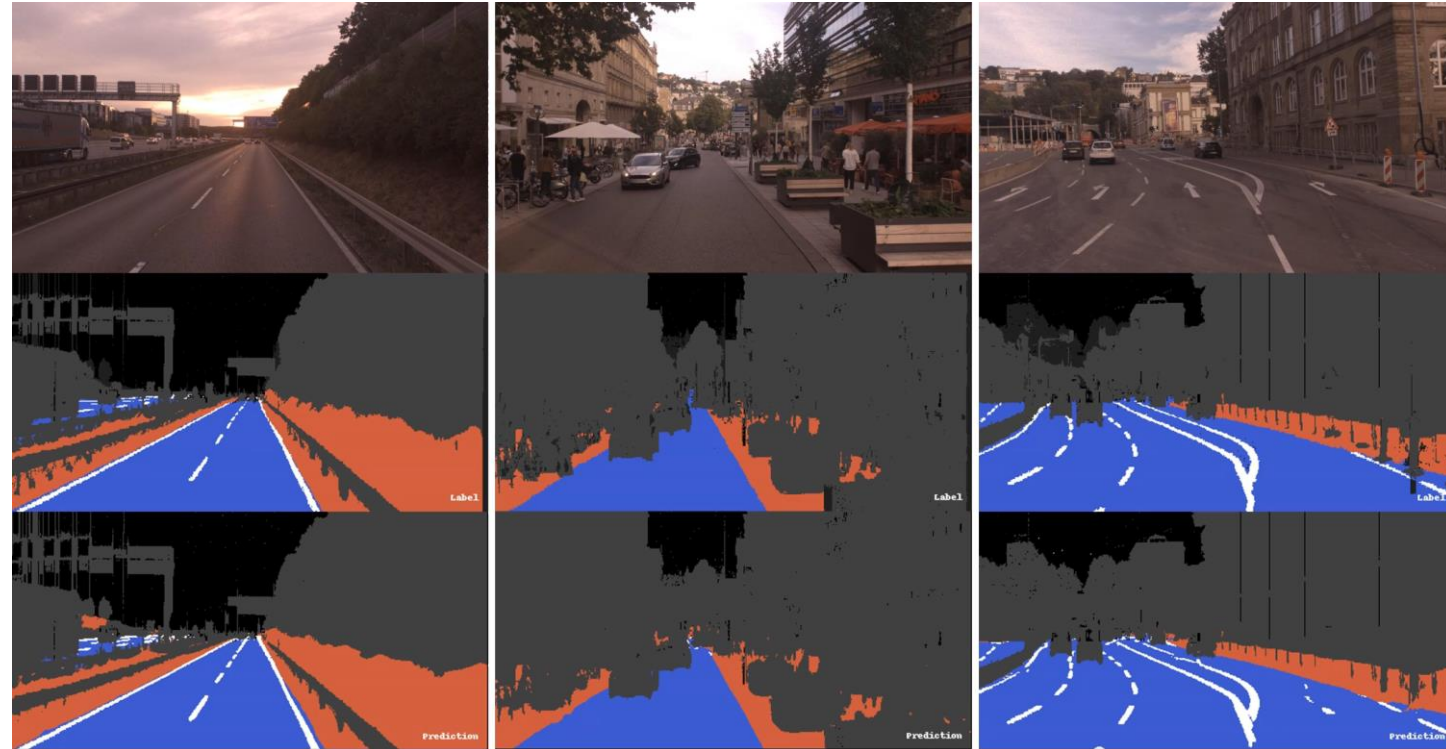
Line ○  
Road ●  
Other Surface ●  
Background ●

Overall metrics results on test set (%):

IoU	Dice	Precision	Recall
75.50	84.49	84.52	84.81

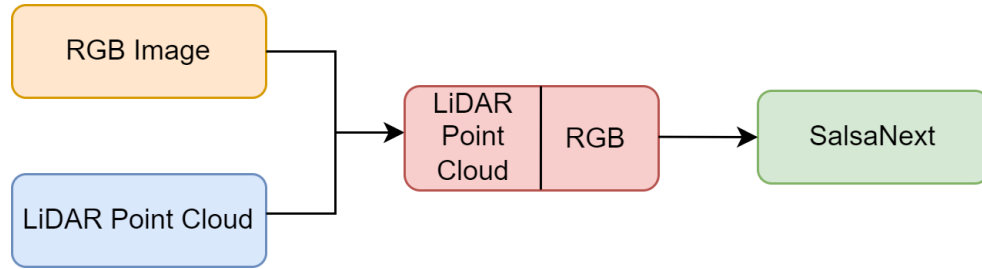
- **Most important classes** for the lane estimation task and respective results:

	IoU (%)	Precision (%)	Recall (%)
<b>Line</b>	44.70	65.13	55.78
<b>Road</b>	85.96	94.29	90.68

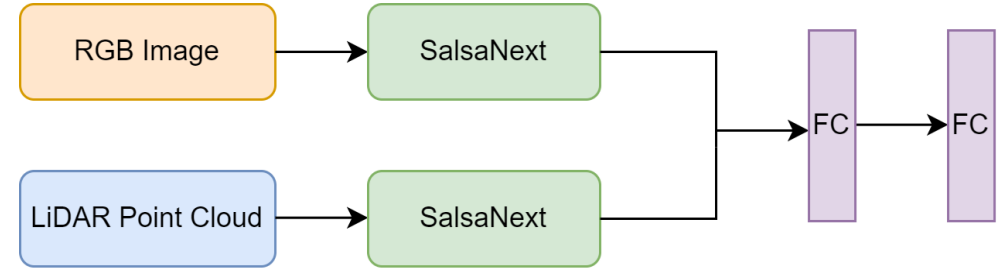


# LiDAR based Lane Estimation

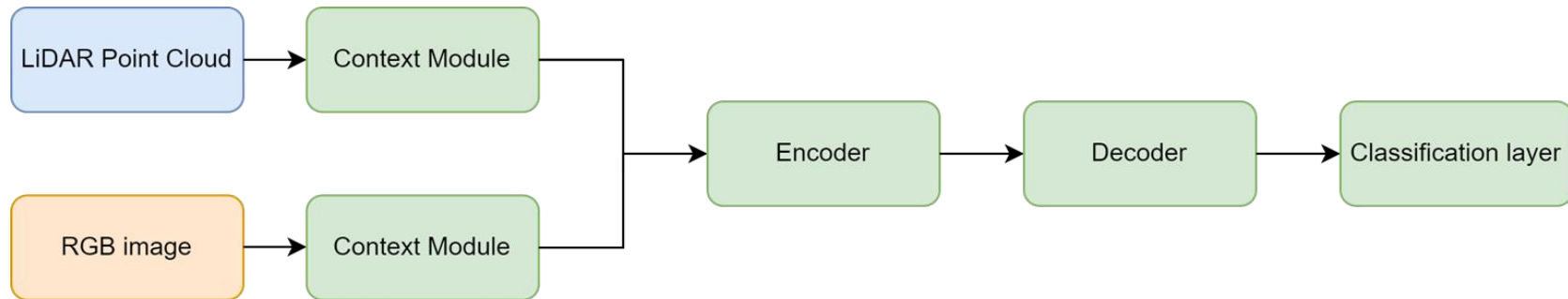
## Multi-Modal Approaches



**Early-fusion**



**Late-fusion**



**Middle-fusion**



# LiDAR based Lane Estimation

## Results: Multi-Modal

**KITTI Road Dataset  
(Road Segmentation)**

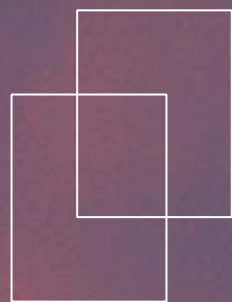
	RGB	LiDAR	LiDAR +RGB (Early)	LiDAR +RGB (Middle)	LiDAR +RGB (Late)
<b>F1-score</b>	95.68	96.10	96.38	<b>96.69</b>	95.59
<b>Precision</b>	90.16	90.25	90.15	<b>91.18</b>	90.17

**KITTI Road Dataset  
(Ego-lane Segmentation)**

	RGB	LiDAR	LiDAR +RGB (Early)	LiDAR +RGB (Middle)	LiDAR +RGB (Late)
<b>F1-score</b>	82.29	88.76	90.02	<b>91.42</b>	90.97
<b>Precision</b>	70.81	79.80	77.09	78.95	<b>83.95</b>

**THEIA Dataset**

	RGB	LiDAR	LiDAR +RGB (Early)	LiDAR +RGB (Middle)	LiDAR +RGB (Late)
<b>F1-score</b>	-	<b>64.08</b>	-	62.29	-
<b>Precision</b>	-	<b>77.04</b>	-	76.90	-



QUESTIONS?