In-Service Monitoring and Assessment of Autonomous Driving Vehicles with AI based Algorithms

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Academy:

M.Tech in Computer science from Indian Institute of technology, Kolkata, India (2005)

Research Assistant at Frankfurt institute of Advance Studies (FIAS), Germany. (2010-2012)

Research Associate at Goethe University, Frankfurt, Germany (2012-2016).

Industry:

2022-2023: AI Engineer (Computer vision and perception), Continental Automotive Technologies, Frankfurt. Germany.
2016-2022: SW Engineer at Continental Teves. Frankfurt, Germany.
2008-2010: Research Associate, Infosys Technology Ltd. Hyderabad, India.
2005-2008: Senior Engineer, Honeywell Technology solution, Bangalore, India.

Core subject area: AI, Machine learning, Computer vision.
Domain: Automotive, Surveillance, Inspection, Power train.

Conference attended- CVPR'18, ICCV'19, ECCV'20, NIPS'21.

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2. In-Service Monitoring Framework

3. Related Work

4. Types of In-Service Monitoring and Assessment

5.Examplary Trigger Development

5. Conclusion and Future Work

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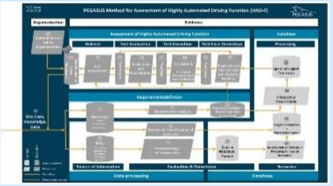
VVMethoden PEGASUS Family – Publicly-funded Projects in Germany

- The **PEGASUS Family** focuses on development / testing methods and tools for AD systems on highways and in urban environments

PEGASUS
https://www.pegasusprojekt.de/en/home

PEGASUS

- Scope: **Basic methodological framework**
- Use-Case: L3/4 on highways
- Partners: 17



PEGASUS FAMILY

VV-Methods

VERIFICATION VALIDATION METHODS

- Scope: **Methods, toolchains, specifications for technical assurance**
- Use-Case: L4/5 in urban environments
- Partners: 23 partners
- Timeline: 07/2019 – 06/2023

SET Level 4to5

SET Level 4to5

- Scope: **Simulation platform, toolchains, definitions for simulation-based testing**
- Use-Case: L4/5 in urban environments
- Partners: 20 partners
- Timeline: 03/2019 – 08/2022

\+ future projects of the PEGASUS Family

2016 2019 2023

Time

VVMethoden – Project Setup

IARIA
VERIFICATION VALIDATION METHODS
Continental

- **Funded by** Federal Ministry for Economic Affairs and Climate Actions (BMWK)
- **Start - End** 07/2019 - 12/2023
- **Budget total** 47M€
- **Objectives** Development of methods and tools for the testing of highly automated and autonomous vehicles (SAE level 4/5) for homologation in urban environments
- **Partners**

OEM	BMW, Ford
Tier-1	BOSCH, Valeo, Continental, ZF
Tech	AVL, PROSTEP integrate the future, dSPACE
Eval	TÜV SÜD, bast
Science	ika, RWTH AACHEN UNIVERSITY, Fraunhofer, TECHNISCHE UNIVERSITÄT DARMSTADT, Technische Universität Braunschweig, OFFIS, FZI, DLR

Continental Contribution	**Development of a In-Service Monitoring & Assessment System & prototype implementation**

In-Service Monitoring - Motivation

How can our AD System react to unexpected changes in such an complex and uncertain environment ?

→

We should be able to monitor continuously rare new events and be able to adapt and Improve

→

In-Service Monitoring and Assessment

To increase confidence in AD safety we need to drive many millions of kilometers.How can we achieve this challenge in cost efficient way ?

→

We should have an big vehicle fleet monitoring the safety performance + select situations which are needed for the validation

→

In-Service Monitoring and Assessment

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Objectives

Objective: Monitoring, Data Collection & Assessment of an AD Vehicle during operation

- **Monitoring**
  - to ensure that all safety risk controls are effective throughout the product life cycle
  - and to identify and evaluate previously unknown unsafe events.
- **Data Collection**
  - for analysis purposes
- **Assessment**
  - to identify new safety risks
  - to modify ineffective safety risk controls
  - ..or to eliminate those that are no longer needed due to changes in the operational environment.

The Approach

Data Acquisition

In-Service Monitoring

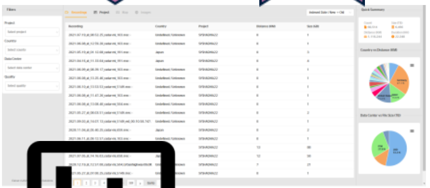
Trigger Event

Data Recording

Data Transfer

Data Management

Server / Data Lake



User Interface

Data Analysis / Reporting

MATLAB

jBEAM

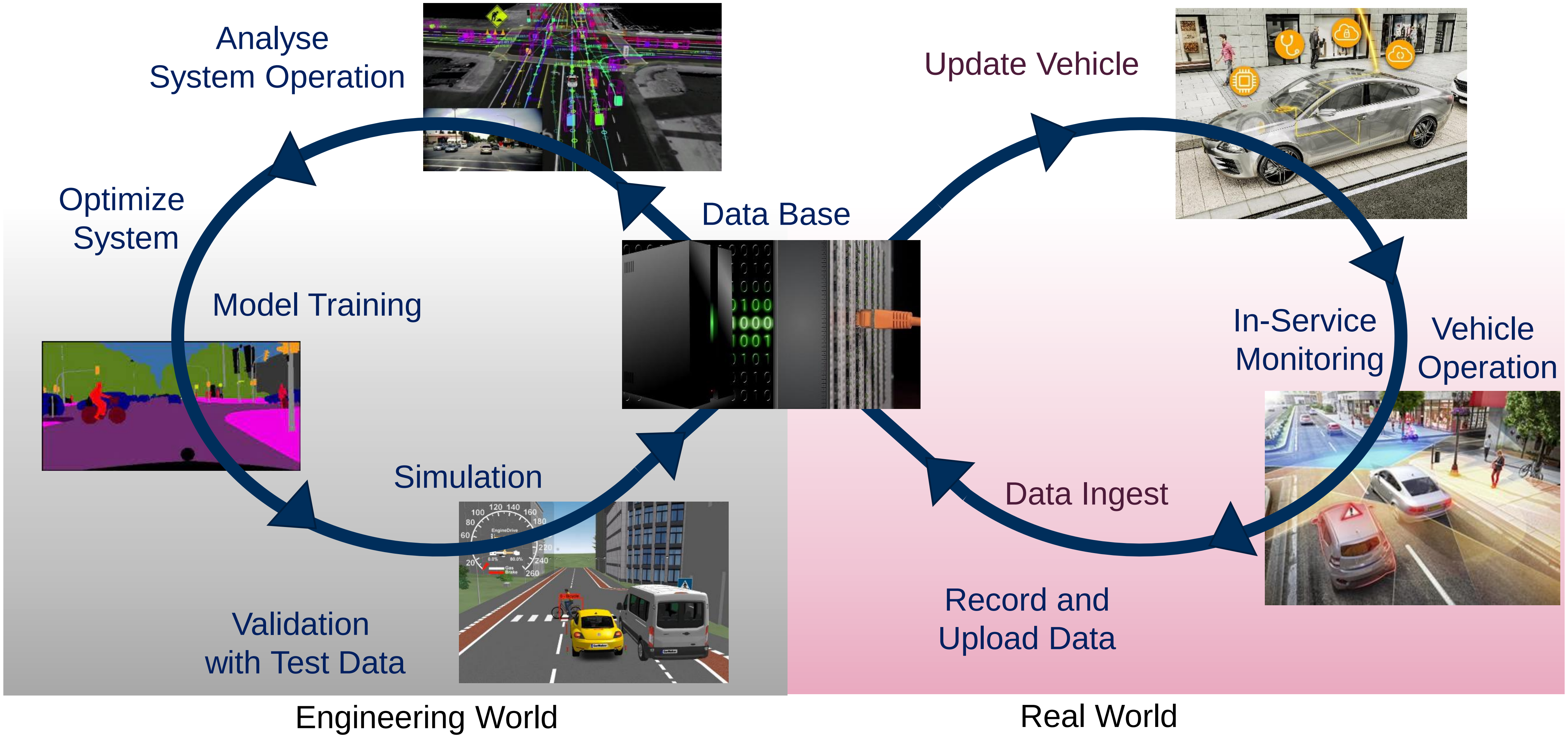
+ a b | e a u

Data Analysis Tools

Visualization

Report

In-Service Monitoring and Assessment in the Context of DevOps



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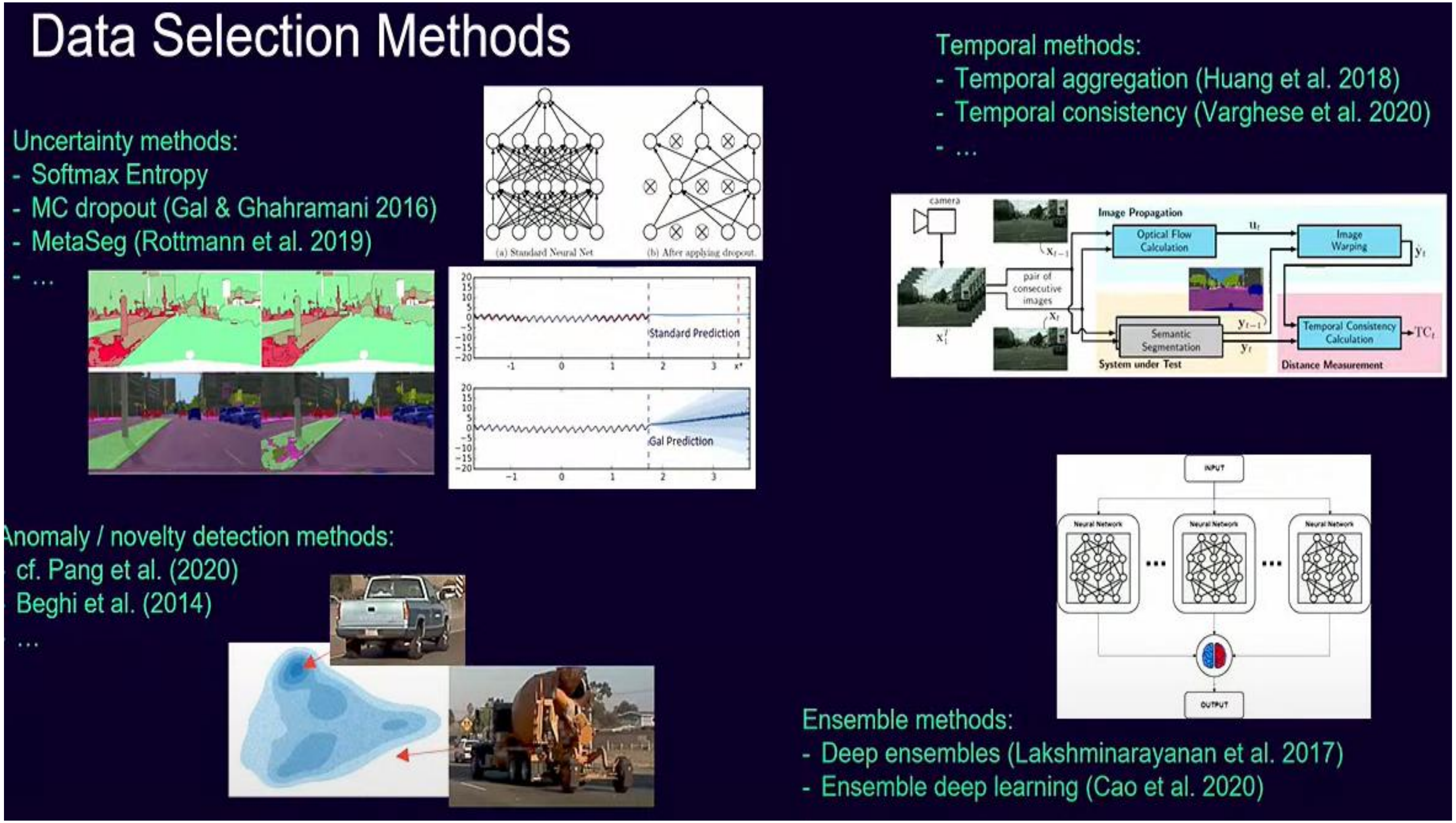
Related Work: Smart Monitoring

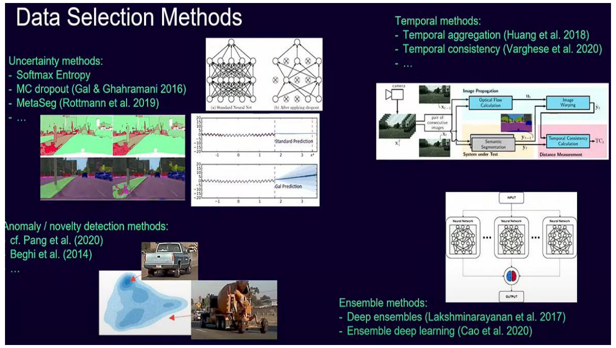
Smart data monitoring and Safety standards

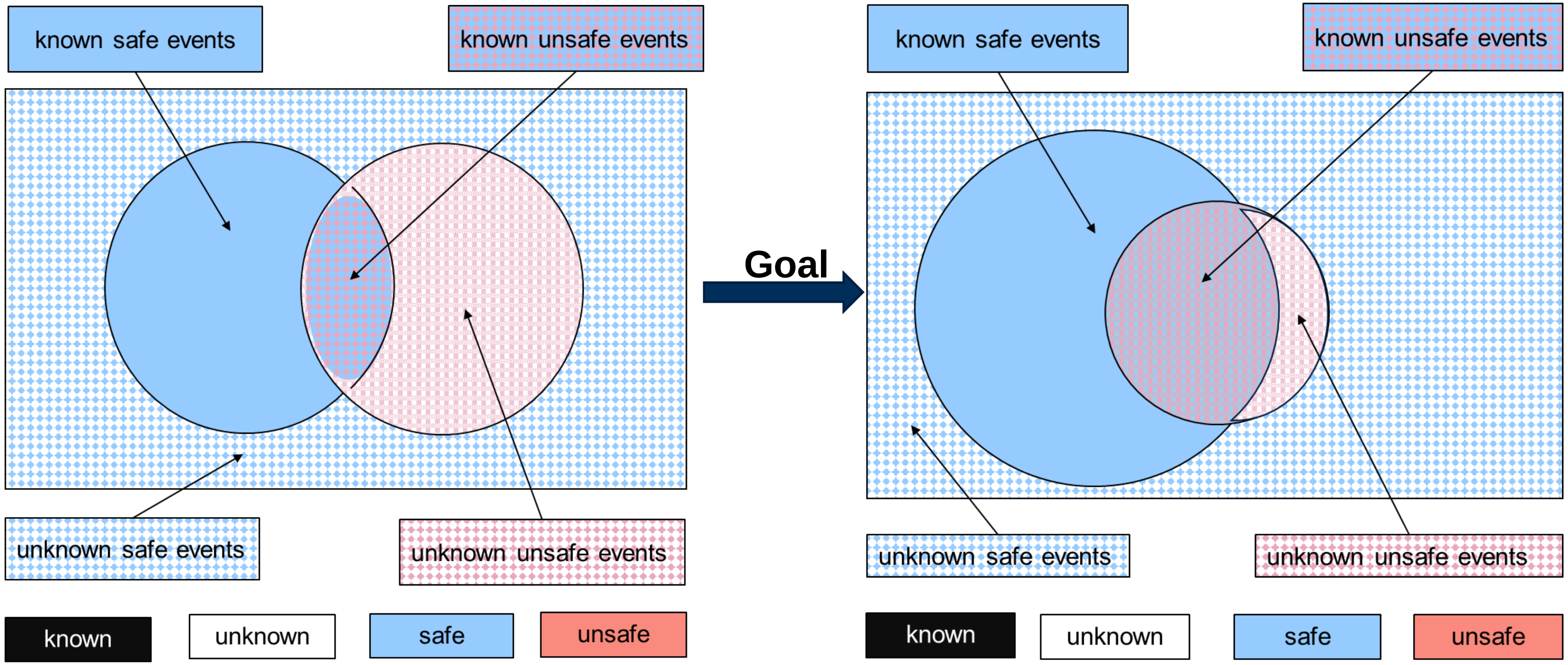


[24]

Related Work: Smart Monitoring

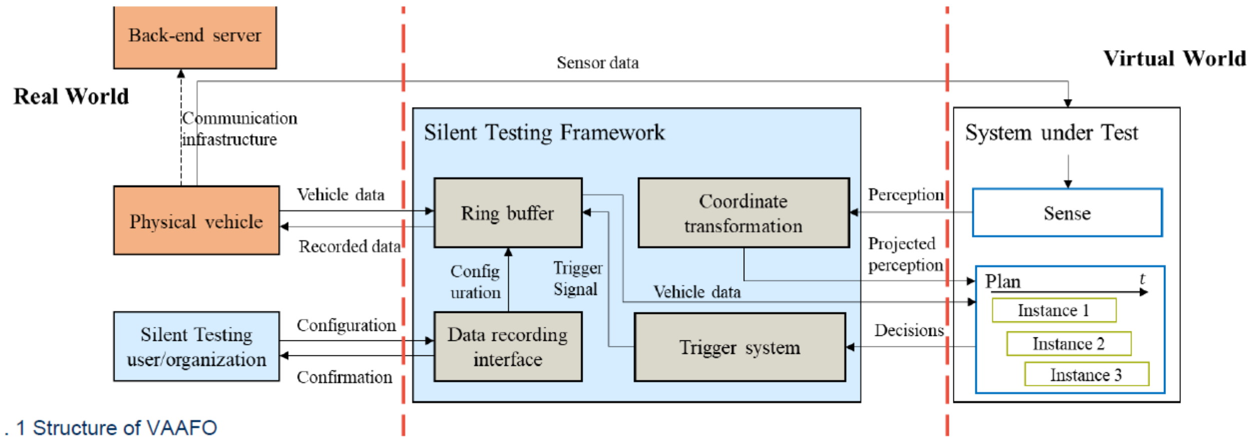
Smart data monitoring and Safety standards





Related Work: Testing approaches

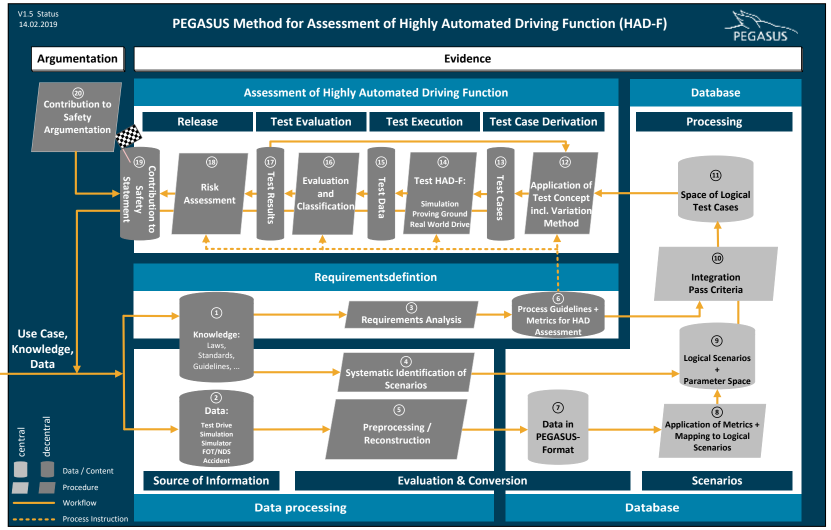
Major testing approaches motivates this work



. 1 Structure of VAAFO

- Virtual Assessment of Automation in Field Operation (VAAFO)[10]

- Shadow mode testing[7]



- Scenario based testing[6]

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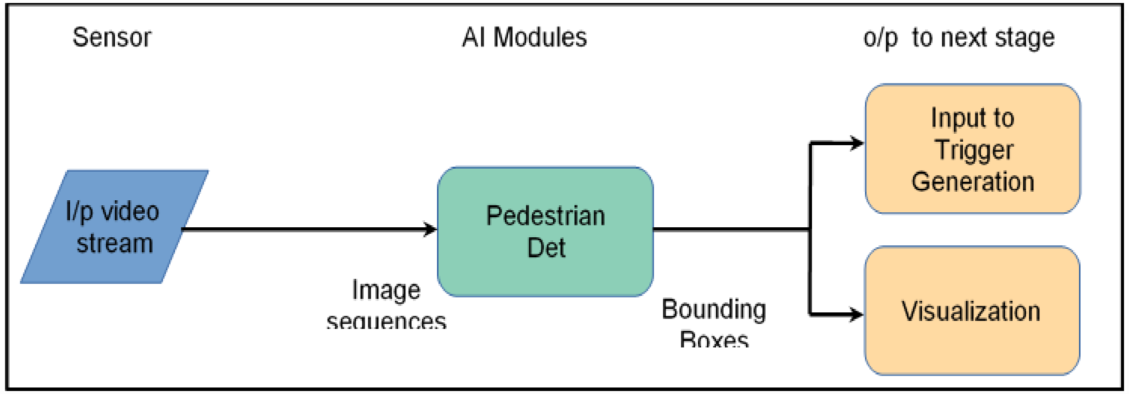
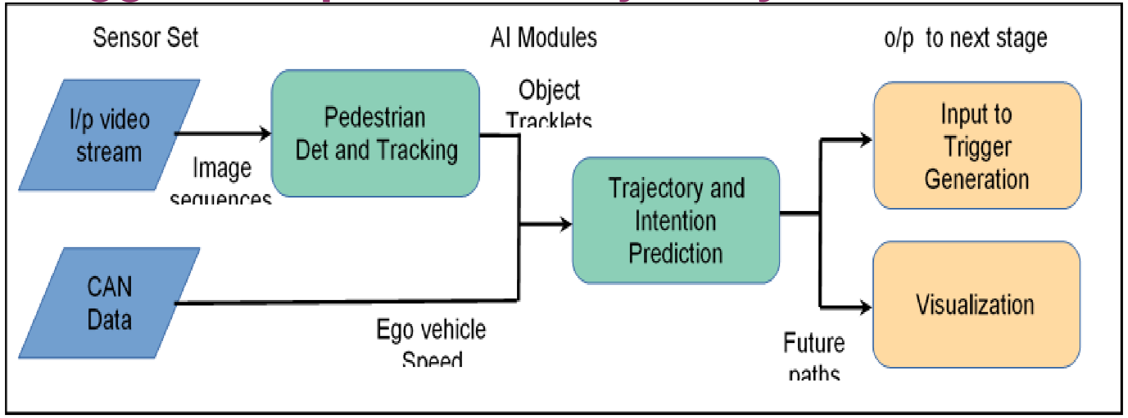
Smart Monitoring : Rule Based Approach

Pedestrian detection within defined ROI



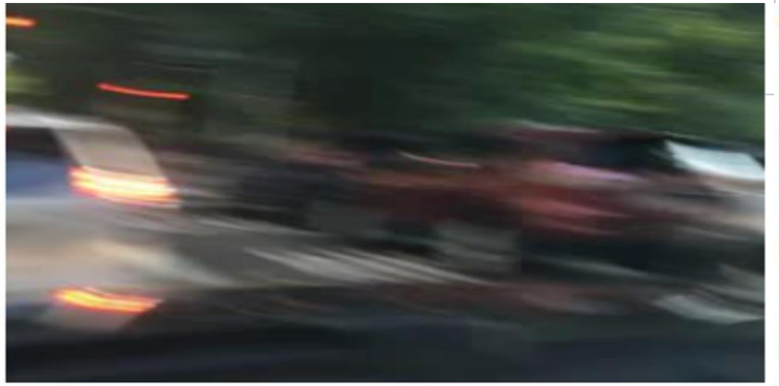
Trigger with predicted trajectory



Smart Monitoring : Data Driven Approach

Event Classification and Discovery [23, 19]

Normal Driving	Sudden breaking event	Left turn Event: Camera view
		

Anomaly- Camera jittering	Anomaly – Camera falling	Low visibility
		

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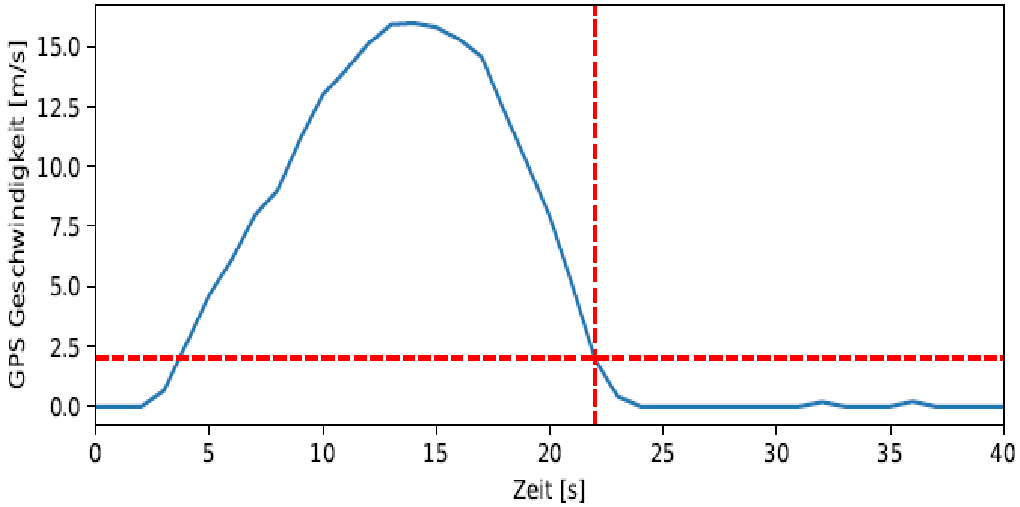
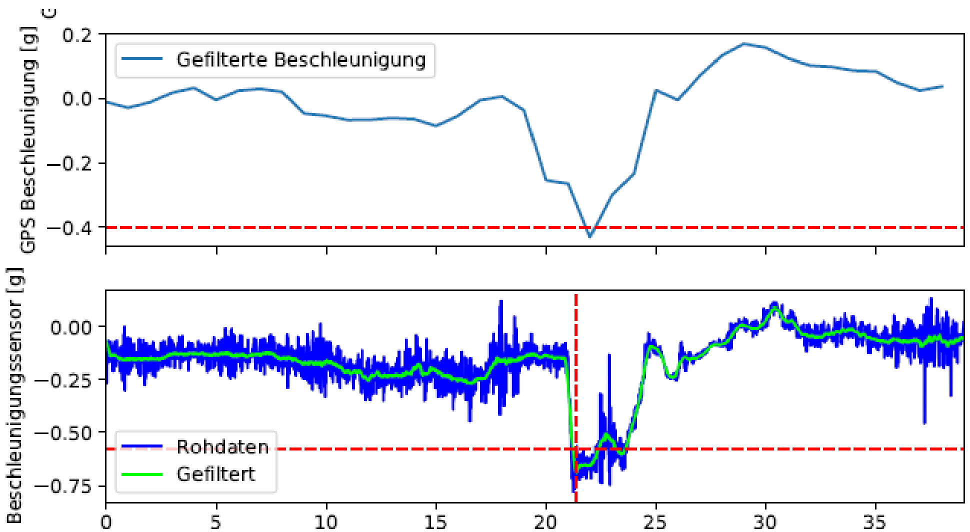
Data Preparation:

Event class definitions (Weakly supervised approach) [23]

Stop: Speed below 2 m/s and stay for more than 5 sec



Sudden Break: Speed drops suddenly



Event Detection

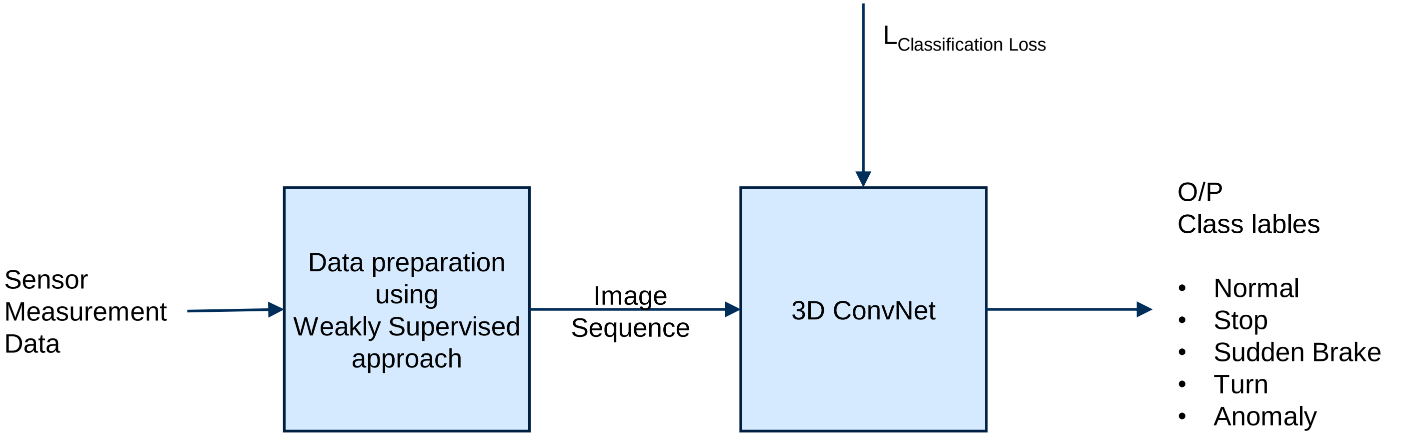


Fig 1: Training pipeline for Event Detection

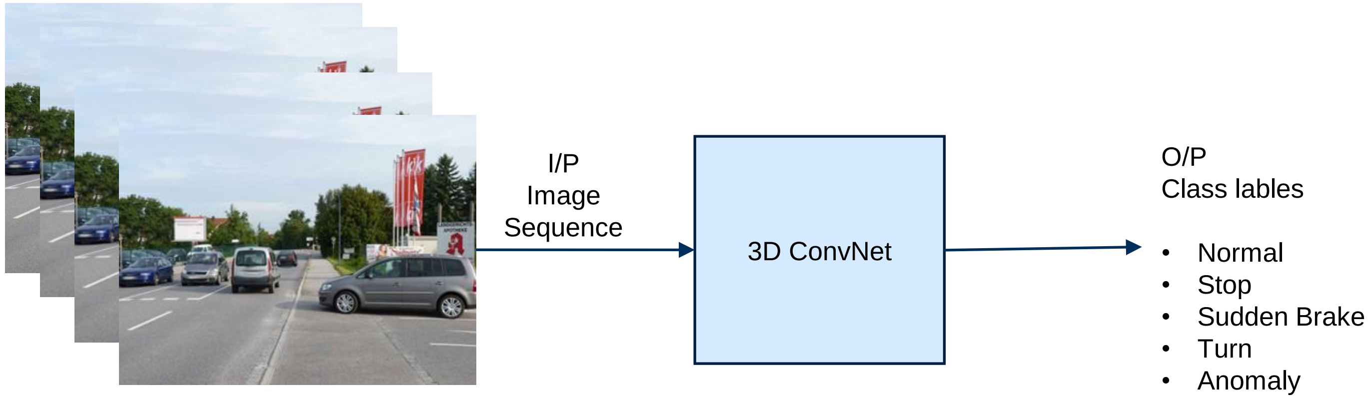


Fig 2: Inference pipeline for Event Detection [23]

- I/P - 16 frames/sample
- The original BDD100k dataset is grouped based on usecase using the sensor data **- Weakly Supervised Approach**
- Available sensor data - **GPS, accelerometer, gyroscope**
- 3D ResNet-34 trained on BDD100k dataset for **Event Detection**
- **5 classes -** Stop, Sudden Brake, Turn, Normal & Anomaly

Results on Event Detection:
BDD100k dataset

Fig 4: Video Sample - Sudden Brake

Fig 5: Video Sample - Turn

Fig 6: Video Sample - Anomaly

True Label \ Predicted Label	Normal	Stop	Sudden Brake	Turn	Anomaly
Normal	3467	282	260	45	545
Stop	594	6120	547	103	106
Sudden Brake	31	42	396	6	21
Turn	11	9	13	1200	50
Anomaly	114	17	45	56	287

- Event Detection accuracy on the BDD100k val set **79.85%**
- Weakly Supervised approch are less reliable

Results on Event Detection:
ADAS (Conti) data

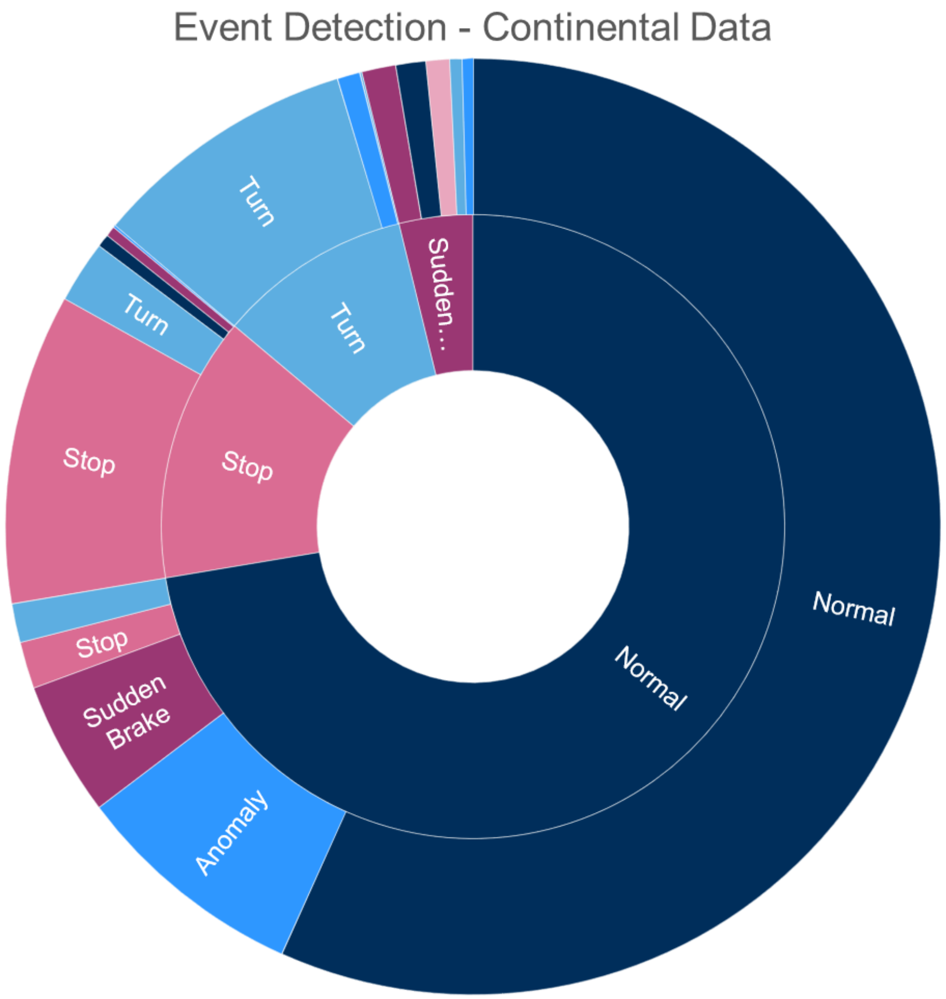
True Label \ Predicted Label	Normal	Stop	Sudden Brake	Turn	Anomaly
Normal	919	26	75	22	131
Stop	7	174	6	35	1
Sudden Brake	17	13	19	7	6
Turn	0	1	0	149	13
Anomaly	0	0	0	0	0

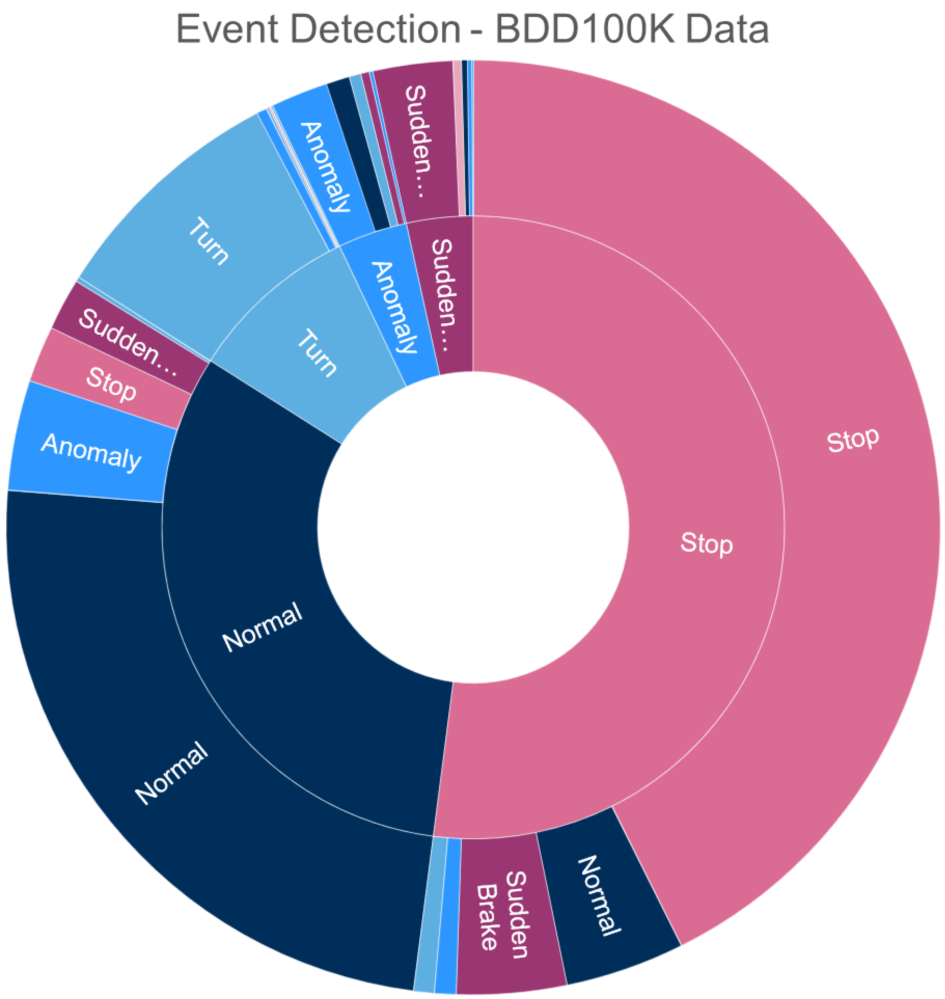
Fig 7: Confusion Matrix for Event Detection evaluated on ADAS data

- Event Detection accuracy on the ADAS val set **77.79%**
- The real-world samples where the instances can have multiple class labels
- Model recognized few anomaly events such as, vibrations due to the unevenness of the road, low visibility, and blockage in the camera view

Fig 8: RGB frame in four video samples predicted as Anomaly event class in ADAS data

Event Detection – Results comparison





Generalized Category Discovery (GCD) [19]

- Given a **labelled** and **unlabelled** set of images, the task is to <u>categorize all images in the unlabelled set</u>
- The **unlabelled** images may come from <u>labelled classes</u> or *<u>novel ones</u>*

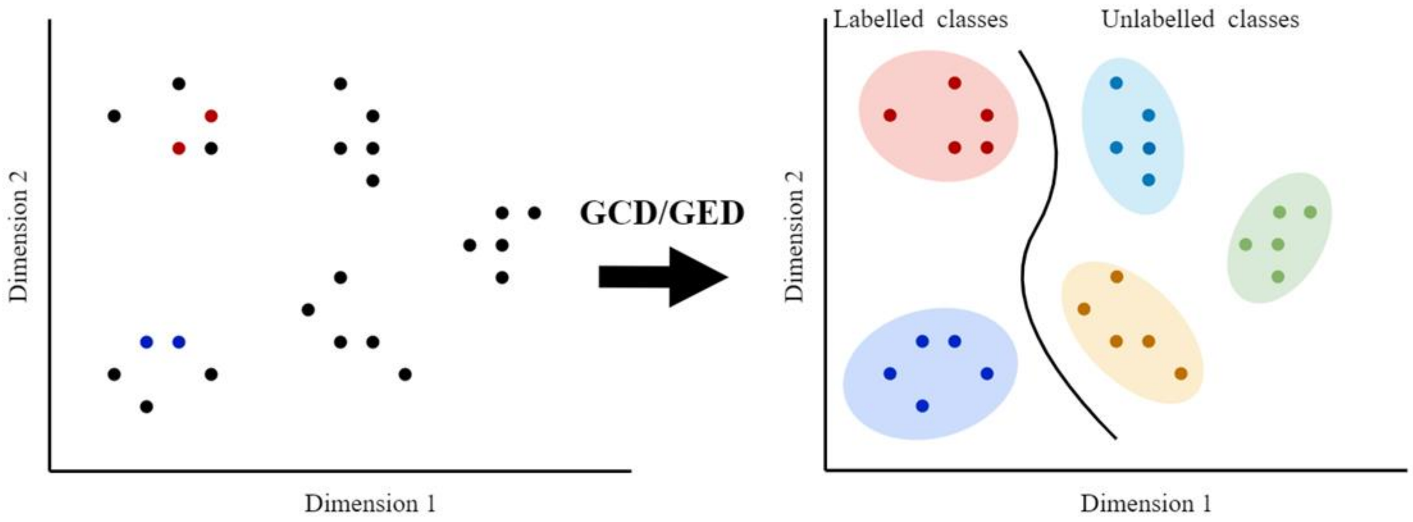
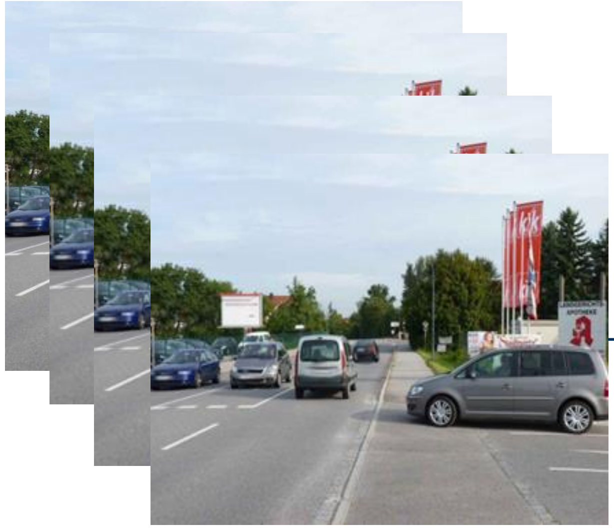


Fig 11: GCD setting. Black data points represent unlabelled instances. Coloured data points represent labelled instances.

Event Discovery Pipeline

Class ID
(Labeled Data)
&
Clustering Parameter



Feature Vector

K-Means ++
Clustering Algorithm

Cluster Indices

Results on Data for Event Discovery (BDD100k dataset)

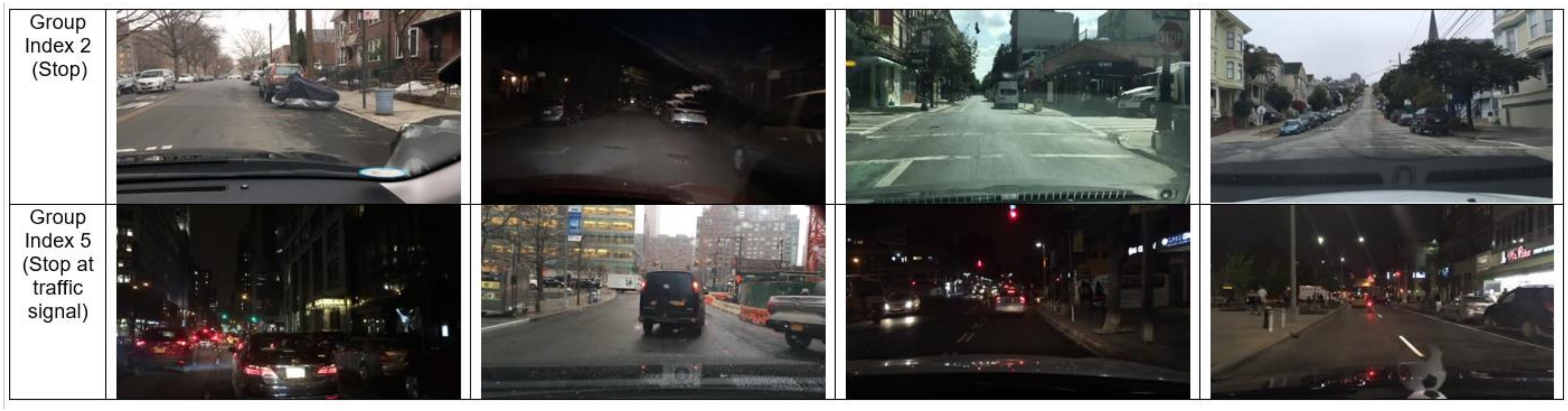


Fig 18: RGB frames from video samples predicted as group index 2 and group index 5

Results on Data for Event Discovery (BDD100k dataset)

Fig 19. Video Sample:
Group Index-2
Stop event

Fig 20. Video Sample:
Group Index-5
Stop at traffic signal

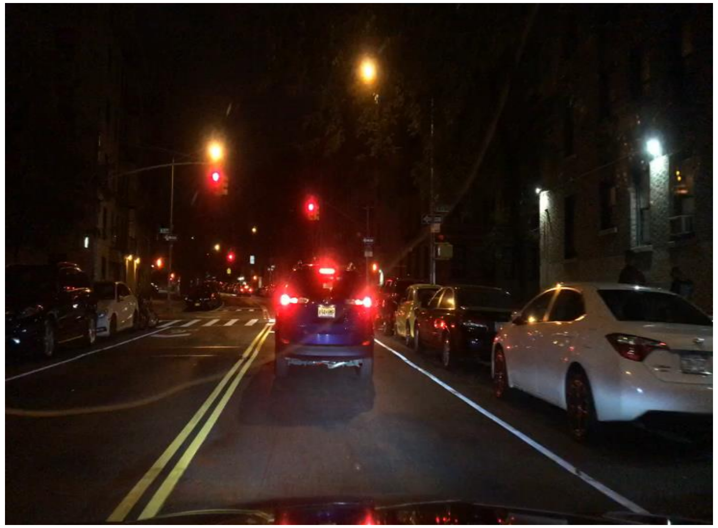


Fig 21. Video Sample:
Group Index-2
Finer Normal event

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Conclusion and Future works

- The approach of In-Service Monitoring and Assessment is presented as a new method for safety validation of highly automated driving
- State of the art works on verification and validation, different approaches for monitoring of HAD **Systems during operation** is covered and that motivates the presented exemplary trigger development.
- Results are shown with both rule based, and data driven approach of triggers for Smart Monitoring to **filter *out anomaly & unknown events*** *for* ***self adaptive*** systems like HAD.

Our future works includes:

- Exploration of appropriate set of triggers, define suitable metrices for their evaluation and context specific trigger subset selection for improving validation systems during operation.
- Use of safety critical data for continuous learning and model improvement is also a topic needs further study.

IARIA

VERIFICATION
VALIDATION
METHODS

Continental

Thank you!

Rudra N. Hota

PROJECT of the PEGASUS FAMILY

A project developed by the
VDA Leitinitiative
autonomous and connected driving

Supported by:
Federal Ministry for Economic Affairs and Climate Action
on the basis of a decision by the German Bundestag

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