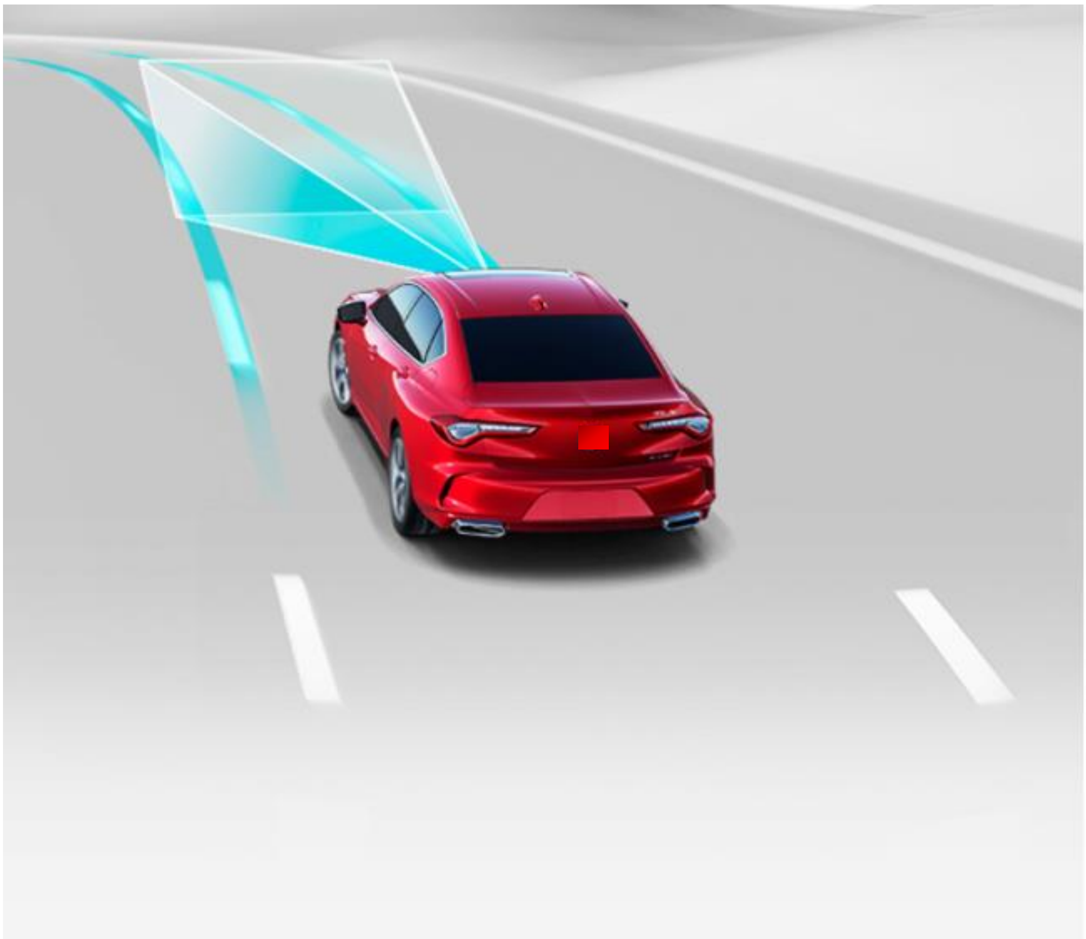
Royal HaskoningDHV
Enhancing Society Together

HAN_UNIVERSITY OF APPLIED SCIENCES

Major Project Report

Infrastructure Assessment for Operational Design Domain of Lane-Keeping System



Ravi Chaudhary

Masters Engineering Systems

FRONTMATTER

Student: Ravi Chaudhary

Student ID: 625422

Project title: Infrastructure Assessment for Operational Design Domain (ODD) of Lane-Keeping System (LKS)

Company: Royal Haskoning DHV

Supervisors: Ir. Shubham Bhusari, Dr. Ir. Frans Tillema

Date: 2^{nd} June 2021

Royal Haskoning DHV
Ir. Shubham Bhusari

Amersfoort

HAN University of Applied Sciences
Dr. Ir. Frans Tillema

Arnhem

PREFACE

This research would not have been realised without the significant contribution of many people who made sure that I had a pleasant and wonderful learning experience. I would like to take this opportunity to share my gratitude to everyone who contributed to this work.

First of all, I would like to thank my HAN supervisor, Dr Frans Tillema. I am indebted to him for finding me this graduation project. His constant support and encouragement throughout the research kept me striving for more and more. His invaluable guidance and suggestions, not only in this research but throughout the Masters, helped me grow as an independent, self-sufficient researcher. The conversations during the meetings helped me to think critically and prevented me from losing track. I will never forget these words from his first lecture: "Alles wat kan, hoeft niet". I am also thankful to Hans Wolfrat for helping me to find this project.

I would like to express my deepest gratitude to my company supervisor Shubham Bhusari at the Royal Haskoning DHV for providing me with this wonderful opportunity to be a part of the Infra4AV project. His invaluable feedback and suggestions constantly challenged me to raise my bar and motivated me to make the research more applicable. He took time for the weekly meetings and was always just one message away to reach out. His constructive comments in the final phase of the thesis helped in concretely documenting the thesis work. Thank you Shubham, for trusting me endlessly and providing me with the liberty to express myself in the research.

I would like to thank Maria Oskina for her active involvement in this research, and all the efforts concerning the field test, arrangements with external parties. Her concise and vital suggestions helped me in making important decisions during the project. Furthermore, I would like to share my sincere gratitude to the Province xx members for their feedback throughout the project and for providing some of the required data.

I am deeply grateful to many people without whom the road experiment would not have been possible. I would like to thank Shubham and Maria for their insights and great ideas that helped me set up the real-road tests for this project. Data collection would not have been possible without the dedicated and continuous support of my fellow researcher Mahima Sharma. During the whole project, she was of vital assistance in having crucial discussions. During the road test, special mention to Daud Pechler (safety driver) for his immense contribution and help make sure that the test drives went smoothly. A very special thanks to Eline van der Kooij, Lotte Goudswaard, Corne van Beijnum and Onno Hendriks who took part in the experiment as drivers. I am grateful to Pablo Bosch, Sanne Eggengoor, Tim Klijn and Daniel Stekelenburg from the RHDHV development team for taking out time to help me with the post-processing of the collected data. Also, I would like to thank the technical master's committee at HAN for providing their valuable support.

Finally, I am indebted to my family, my mother Shrimati Sarishta, for her love and support in every possible way throughout my studies. I owe a special debt of gratitude to Amisha, my loving travel companion, not only in this journey but in life. Thank you for your patience throughout this journey. I would like to sincerely thank my friends Alok, Manish, Kehar, Naval and Varun for constantly supporting me there from India.

DEDICATION

To my father, in loving memory.

EXECUTIVE SUMMARY

One promising solution to road fatalities is the Automated Driving feature, as they would eliminate human error in driving. However, these automation features are designed to work in specific conditions only, referred to as Operational Design Domain (ODD). If the ODD conditions are not met, the vehicle will not act and assist the driver. Both, vehicle manufacturers (OEM) and Road Authorities (RA), are striving to ensure that vehicle remains within their ODD conditions. While the vehicle manufacturers do so by improving the design of these automation features, the Road Authorities are investigating what steps can be taken to ensure the road infrastructure readiness for these features. However, unlike vehicle manufacturers, the Road Authorities have limited access to vehicle technology, which incapacitates them to assess the infrastructure readiness and limit their dialogues with other stakeholders.

This research investigates one of the automation features, Lane Keeping System (LKS), a system that keeps the vehicle within lanes by applying a steering correction to the vehicle whenever the vehicle is at the risk of leaving the lanes.

The main objective of this research was to develop a methodology to assess the road infrastructure to ensure the safe operation of vehicles equipped with Lane-Keeping System (LKS) and to help Road Authorities to make informed decisions. A three-fold approach was taken to realise the project objective. First, the factors related to the road infrastructure and environmental conditions that affect the performance of LKS were identified. Second, it was investigated how the LKS performance can be used to assess road infrastructure readiness. Third, a tool is built to extend the developed understanding to the vast road network, identify the hotspots where LKS can fail, and calculate the different Level of Service (LoS) provided by the infrastructure for LKS.

The approach taken to solve the problem is based on analysing the dataset collected through a practical study. Two different OEM vehicles, vehicle X and vehicle Y were tested on different inter-urban roads in different weather and lighting conditions. The vehicles were chosen in a way to get a range of performance in Lane-Keeping System (LKS), thus helping to assess the road infrastructure better. During the test, the vehicle's LKS performance was measured by its ability to detect the lanes (Machine Vision performance) and its ability to position itself safely within the lanes (Lane Positioning performance). In addition, the road geometry and environmental condition in which vehicles were driven during the test were also simultaneously measured. This included recording information such as visibility of the lane markings, lane width, sharpness of the curves, type of line-markings (continuous/dashed), weather and lighting conditions.

Statistical analysis is then carried out to understand the impact of the various factors on the performance of the Lane-Keeping System (LKS). It was found that vehicle X detected the lanes unaffected by the encountered driving conditions; however, several factors affected the lane

detection performance of vehicle Y. First, it was found that vehicle speed above 80 Kmph resulted in better lane detection. Second, it was found that the dashed line-markings compared to continuous line-markings significantly decreased the lane detection performance. Further, the wet road conditions also severely lowered the lane detection performance. In addition, the lane detection was significantly less during the daytime as compared to night-time. Finally, the vehicle could not detect the lanes for the lanes with a width below 3m.

The lane positioning performance was affected by line-markings, the lane's width, curved sections, weather and lighting conditions for both the vehicles. It was found that both vehicle had opposite behaviour for a different type of line-markings. For example, when both right and left markings on lane were continuous, the vehicle Y positioned itself closest to the lane centre. In contrast, vehicle X positioned itself towards the far left as compared to another type of line-markings. It was found that both vehicles failed to execute sharp curves with a complex profile. The lane positioning performance was found to be significantly better in dry weather and night-time.

The hotspots where Lane-Keeping System (LKS) failed to perform in the network were identified for both vehicle X and vehicle Y. Further, the Level of Service (LoS) is calculated based upon the LKS performance. The Level of Service was calculated to understand road infrastructure readiness for the LKS and how the current Automated Vehicles interact with the infrastructure. Finally, a learning algorithm (prediction model) is built on the collected dataset. The experiment identified the hotspots and Level of Service for only surveyed network; however, the finding can be extended to a broader network of the road using this developed learning algorithm.

This research can help Road Authorities have an insight into the vehicle performance, enabling them to know how the current Automated Vehicles interact with the infrastructure. In addition, Road Authorities can use the results to identify the hotspots resulting from specific types of interaction amongst the road infrastructure and driving conditions that could have otherwise gone unnoticed. Finally, the results will help Road Authorities have better dialogues with the vehicle manufacturers, thus bringing synergy amongst them working towards the safe operation of Lane-Keeping System (LKS) and reducing road fatalities.

Contents

ABBREVIATIONS

MLP	Mean Lane Position	[cm]
R_L	Retro-reflection	[mcd/m^2/lux]
SDLP	Standard Deviation of Lane Position	[cm]

ACRONYMS

ACEA	European Automobile Manufacturers Association
ADS	Automated Driving System
ADAS	Advanced Driver Assistance Systems
AV	Autonomous Vehicle
CAV	Connected and Autonomous Vehicle
CCD	Charge-Couple Device
CV	Computer Vision
DNN	Deep Neural Networks
DL	Deep Learning
ERF	European Union Road Federation
FPS	Frame Per Second
GPS	Global Positioning System
GIS	Geographic Information System
IMU	Inertial Measurement Unit
LiDAR	Light Detection and Ranging
LKS	Lane-Keeping System
LDW	Lane Departure Warning
LP	Lane Position
LoS	Level of Service
MoMa	Mobile Mapping
MV	Machine Vision
OEM	Original Equipment Manufacturer
ODD	Operational Design Domain
RADAR	Radio Detection and Ranging
RA	Road Authority
RQ	Research Question
VID	Vehicle Information Display

GLOSSARY

Contrast Ratio	The contrast ratio is the ratio of the difference between the retro-reflection of the line-markings and the road surface to the road surface.
Confounding Variable	An extraneous variable that influences both the supposed cause and the supposed effect in a relationship under investigation.
Lane-Keeping System (**LKS**)	An automated system that keeps the vehicle within the lane.
Machine Vision (**MV**) performance	The ability of the Lane-Keeping System equipped vehicle to detect the lane on the road.
ODD	Set of conditions in which an automated system (like Lane-Keeping System) is designed to operate correctly.
OEM	The vehicle manufacturer is referred to as OEM in this report. For example, Vehicle Y or Vehicle X.
Retro-reflection	The retro-reflection is the portion of the incident light from a vehicle's headlight reflected back towards the eye of the driver of the vehicle after falling on the road-surface.
Road Authority (**RA**)	The agency responsible for maintaining and designing the road infrastructure.
Significant Results	The results that are likely to not caused by chance for a given statistical significance level.

It is important to note the acronyms **LKS, MV, ODD, OEM, and RA**, as these are frequently used in the report.

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

1.1 Background

Globally 1.35 million people died in 2016 due to road accidents, and between 20 and 50 million sustained non-fatal injuries [1]. Compared to the global situation, Europe is doing relatively well in tackling the problem of road accidents. It has the lowest death rate per million population but still lost 2,600 people on EU roads in 2019 [2]. Road accidents are also not economically sustainable. The European Commission estimates a loss of € 82 billion due to road accidents in Europe in 2018 [3]. The decrease in the number of road fatalities in Europe has stagnated in recent years, but the EU has reaffirmed to move close to zero deaths by 2050 ("Vision Zero") [4].

One of the promising solutions to road fatalities is Autonomous Vehicles (AV), as they would eliminate the human error in driving, which alone is responsible for 90% of road accidents. There are six levels of automation, ranging from no driving automation (level 0) to full driving automation (level 5) as defined in SAE J3016 [5]. The arrival time of Level 5 self-driving cars is very uncertain, and various studies estimate that Level 5 vehicle will be on-road somewhere between 2040-2070. Currently, partial driving automation is possible, and vehicles are increasingly equipped with these automated features promising to reduce road accidents. The European Commission also consider driving automation as one of the steppingstones to 'Vision Zero' and has regulated that by 2022 it is mandatory for the vehicles sold in the EU to have a defined set of ADAS (Advanced Driver Assistance Systems) features [6]. Furthermore, the Dutch national government aims to lead in driving automation and prepare the Netherlands for its implementation [7].

However, it should be noted that partial automation is designed to work in specific conditions only, as defined by the vehicle manufacturer (OEM) and referred to as Operational Design Domain (ODD). If the ODD conditions are not met, then the driver is expected to take back the control, and the vehicle will not be able to act and assist the driver. The Euro NCAP's recent evaluation of assisted driving technologies was also based on the well-defined ODD conditions [8]. Therefore, ensuring that the road infrastructure meets ODD conditions will ensure the performance of the ADAS features. Furthermore, knowing beforehand where these ODD conditions are not met can help warn the driver timely to leave sufficient time for the driver to react. Thus, road infrastructure can play a crucial role in ensuring safety. As technological advancements are made towards the Level 5 vehicle, heading towards 5-star roads can ensure zero death [9].

This thesis focuses on the infrastructure requirements for one of the driving automation system, viz. Lane Keeping System (LKS). An LKS keeps the vehicle within lanes by applying a steering correction to the vehicle or warning the driver whenever the vehicle is at the risk of leaving the lanes.

The LKS feature can help to reduce any accidents linked to run-offs and cross-over if the required ODD conditions can be ensured. Today, most OEMs use Camera Vision to see the lanes ahead and may not work if road lane markings are non-existent, non-compliant, worn out, obscured, inconsistent or confusing. The sensors may also not be able to read the road ahead due to the number of environmental factors such as adverse weather conditions and inappropriate illumination, which are also difficult to predict. Activating LKS in such situations or delaying the warning to take over control from the system can lead to accidents. The Road Authorities (RA) are investigating the steps to ensure the road infrastructure readiness for these features. However, unlike vehicle manufacturers (OEM), the Road Authorities have limited access to vehicle technology, which incapacitates them to assess the infrastructure readiness.

The importance of road infrastructure has increased because the EU has mandated the new ADAS features from 2022. This regulation is expected to make the roads safer; however, it also says that *''Advanced emergency braking systems or emergency lane-keeping systems might **not** be fully operational in some cases, in particular, due to shortcomings in road infrastructure''*. Nobody would like to be in such a situation. Who takes responsibility in such situations has been already a topic for discussion for a long time. Research needs to be done to see the possible steps to ensure the safe operation of such ADAS features.

1.2 Problem definition

The problem is that, like many ADAS features, LKS has limited ODD. Currently, there is no complete and exact measurement of this limited ODD, such that it can be quantified and put in the form of actionable guidelines by OEMs for Road Authorities (RA) to improve the road infrastructure. Also, due to competitive reasons, the ODD limitations of the vehicle are not published in detail by the OEMs, which incapacitate the RAs to assess the road infrastructure for automated driving readiness. The roads were designed primarily focused on the human being as the driver. As the penetration of the automated vehicle is increasing, the RAs are concerned if the road infrastructure also needs to be adapted. However, unless and until RAs have the quantified information of ODD, they cannot know what changes need to be made in the current road infrastructure to ensure the safety of automated driving.

Now, why it is so difficult to define the ODD for LKS (or for any other ADAS). To understand the problem, it is first required to understand the definition of ODD, defined in SAE J3016 [5] as

"Operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including but not limited to, environmental, geographical, and time of day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics."

The environment, geographical, and other characteristics highlighted in the definition contain infinite objects and unmeasurable infrastructure settings, which lead to the possibility of infinite situations (Figure 1). The road conditions will always keep on changing, which will cause the system to behave differently. The conditions can vary due to the changing weather leading to change of illumination, changing traffic leading to occlusion, change in the condition of the lane markings due to normal wear and tear by the moving vehicles and many such other factors. The dynamic environment is one of the reasons that why it is so difficult to measure it. Second, the system is challenging to model due to its complexity, primarily if it is governed by Artificial Intelligence (AI). Therefore, the most common approach of White Box Modelling cannot solve the problem.

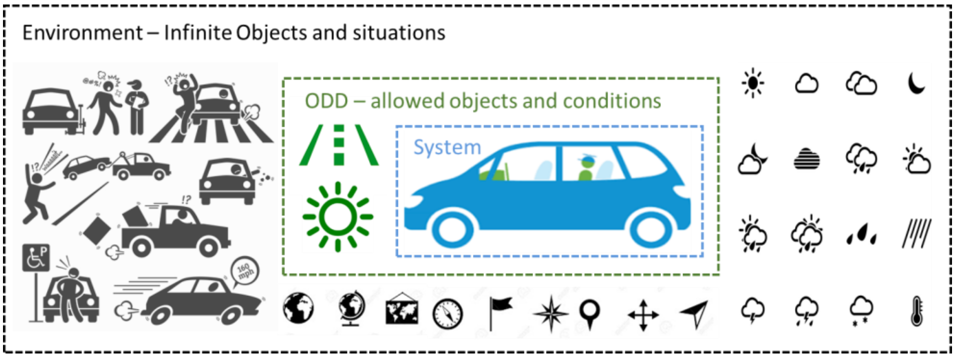


Figure 1 Challenges for Automated Driving

The other problem is that even if the ODD conditions are known completely, amidst such a vast road network, it is complicated for a road authority to know which sections of the road are not providing the required ODD for LKS.

1.3 Research Objective

The main objective of this research is to develop a methodology to identify what changes need to be made in the road infrastructure to ensure the safe operation of the vehicles equipped with Lane Keeping Systems.

1.4 Research Question (RQ)

Following the problem definition and the project objective, the main RQ for the thesis is:

How accurately can the Operational Design Domain (ODD) of the Lane-Keeping System (LKS) be determined using the empirical analysis of the data collected from the field tests?

Sub questions:

1. Which factors related to the road infrastructure and environmental conditions affect the performance of Lane Keeping Systems?

This RQ will focus on identifying the correlation between the driving conditions and LKS performance.

2. How can the Lane Keeping Systems performance be used to determine its Operational Design Domain?

This RQ will investigate LKS performance when the system is within and when the system is outside its pre-defined ODD.

3. How to identify the hotspots in the given road infrastructure conditions that are outside the Operational Design Domain of the Lane Keeping Systems?

This RQ will explore extending the identified relationships between various parameters to the predictive context.

1.5 Outline of the report

Chapter 2 summarizes the studied literature to understand the relevant concepts and methodology to answer the research questions. Chapter 3 explains the methodology of this project to realize the project objectives. The shortlisted variables and the performance metrics for LKS are also presented.

Chapter 4 then explains how the test route and testing conditions were selected to ensures sufficient variation in the research variables while collecting the dataset for analysis. Finally, the experiment setup description is given, and it is explained how driving sessions were conducted.

Chapter 5 explains how Deep Neural Networks (DNN) were used to detect the dashboard signs and measure vehicle position inside the lane using the video data from cameras. It also explains how the data from different sources were synchronized based on the GPS and timestamps of the video to come up with the final dataset in one file.

Chapter 6 presents the data analysis and results of this thesis. First, it explains the statistical test results, which were done to investigate the factors affecting the performance of LKS. Second, the chapter explains the calculation of the Level of Service provided by the infrastructure for the LKS. Finally, the chapter ends by explaining the developed LKS prediction models.

The obtained results are further discussed in Chapter 7, and conclusions are made in Chapter 8. The recommendations to Road Authorities also presented in Chapter 8. Finally, the report ends by explaining the limitations of this project and giving recommendations for future research in Chapter 9.

2 LITERATURE SURVEY

The main RQ was to assess the ODD of LKS using empirical analysis of the data, for which an experiment must be conducted. It was imperative to collect the correct data and quality data because this cannot be fixed once the experiment is done. Thus, the Literature survey became a vital part of this research. First, it was crucial to understand the recent development in the LKS algorithms (section 2.1). Second, it needs to be investigated which parameters related to the physical infrastructure should be measured to evaluate the line detection performance of the vehicle (section 2.2). Third, how to measure the lane-keeping ability of the vehicle and again, what are the existing standards (section 2.3)? Finally, to not miss any critical variable which could have been otherwise possible to be measured with minimal efforts, a thorough study was done on previously conducted studies (section 2.5).

2.1 Lane Keeping System (LKS)

It is essential to understand the variation in the existing LKS algorithms to understand the complexity of defining the Operational Design Domain (ODD) for LKS. Thus, the ideal case for any research focused on determining the ODD of LKS would be to know the LKS algorithm being used by the OEMs. However, due to security, safety, and competitive reasons, these are not known to the public. However, a glimpse of technological advancements in academic research related to LKS can also help estimate the complexity of the difference in requirement by the different LKS system.

The most common sensor for LKS that can be seen in all OEM vehicles is the camera. Xing et al. [10] reviewed the vision-based LKS and found two most common approaches used for lane detection: traditional computer vision (CV) and Deep Learning (DL). The CV-based algorithm uses image processing, feature extraction, lane detection, and tracking. The DL-based algorithm first trains the DNNs (Deep Neural Networks) on a dataset and then uses them to detect the lane markings. The CV based algorithm is computationally efficient as compared to DL but at the same time can fail to detect lines in a various difficult situation such as curves.

Chen et al. [11] presented an end-to-end learning approach for calculating the required steering angle by training the Convolutional Neural Networks (CNN) on a dataset of raw images, thus skipping the manual efforts of image processing, path planning and control logics. Also, since these models are not trained explicitly to detect, for example, lane markings, they can work not only on highways but also on local roads with or without lane markings.

LKS algorithm might also use other sensors such as LiDAR, IMU combined with GPS, and digital maps. Bar Hillel et al. [12] studied the different sensors and algorithms used in lane detection and built a generic model as shown in Figure 2 to understand LKS better. The different existing algorithms can be mapped to subsystems of this generic model.

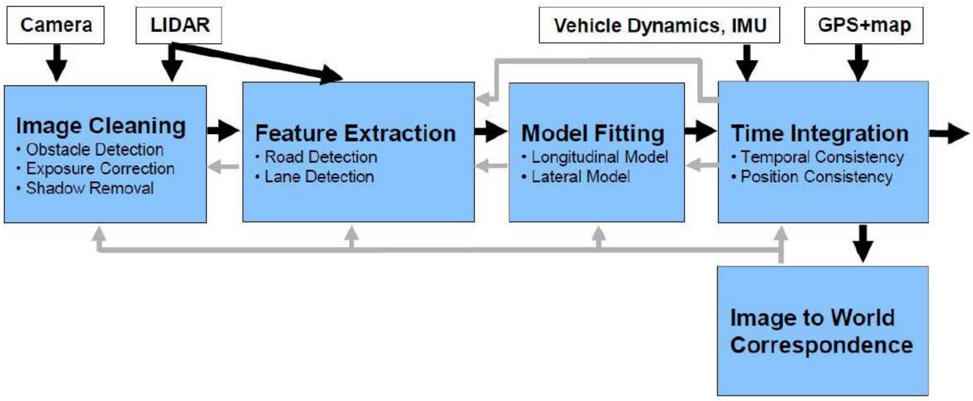


Figure 2 Generic model explaining different LKS algorithm [12]

Lombard et al. [13] developed a path following algorithm only using the GNSS positioning and demonstrated path-tracking tests on the ITS World Congress 2015 site in Bordeaux on both straight and curved path. They were able to achieve an error of less than 30 cm in lane position.

Choi et al. [14] developed a RADAR based lane estimation method using Deep Neural Network (DNN). The RADAR data of relative motion between the ego vehicle and a leading vehicle was combined with the in-vehicle sensor data to estimate the road lane model for LKS. Kim [15] demonstrated through the field test a lane detection rate of up to 94% only using the RADAR on the road with metal lane markers.

This section concluded that there is ongoing work in developing LKS using computer vision, end to end learning, LiDAR, RADAR and HD maps. The advancements explain that the technology of LKS is evolving rapidly, and it is challenging to decide on infrastructure changes based on a particular technology of LKS. The scope of this thesis is limited to vision-based LKS; hence, only these are focused on after this section. However, the understanding from this section gave an excellent ground while proposing any road infrastructure changes to be made by Road Authorities (RA). Also, it explains why it is challenging for RAs to make any decision owing to the different LKS technologies of different OEM vehicles.

2.2 Machine Vision (MV) performance metrics

The previous section explained that vision-based LKS relies heavily on the lane markings, primarily the CV-based (Computer Vision) algorithms use the contrast between the lane markings and the road surface to identify the lane markings. Hence it is also essential to understand that how the quality of lane markings can be measured.

The performance (or quality) of lane markings is mainly described by their retro-reflectivity, luminance coefficient, contrast, and color. Retro-reflection (R_L) is one of the most widely studied performance indicators and represents light hitting a surface and reflecting again to the same light source. It directly relates to nighttime visibility. It is measured in units of millicandelas per square meter per lux (mcd/m^2/lux). It can be measured using handheld and mobile retro reflectometers produced in many different models by several manufacturers [16]. Most pavement markings have beads embedded on the surface to enhance the retro-reflection. A new white lane marking can have R_L values up to 400 mcd/m^2/lux and may be even higher depending upon the refractive index of the material of glass bead. It should also be noted that road surface also has a value of R_L ranging from 10 to 40 mcd/m^2/lux based upon the asphalt and ageing of the road [17]. The luminance coefficient (Q_D) is the ratio between the marking material's luminance and the pavement's illuminance. It relates to daytime visibility. Both Q_D and R_L are measured according to the IS EN 1436 European Standard for Road Markings [18].

These metrics have been long studied to understand the visibility of lane markings from a human perspective and recently used in many studies to understand the vision-based LKS. ERF in 2012 [19] proposed a '*150*150'* guideline to ensure a minimum performance level of 150 mcd/m^2/lux for road markings under dry conditions and a minimum of 35 mcd/m^2/lux under rainy conditions, minimum 150 mm line width for all roads. The guideline was based upon the analysis of relevant research, empirical evidence, and a review of current regulations in different countries. ERF believed that the proposed policy should also be enough to guarantee the optimal operation of LDW/LKS. In 2019, ERF [20] added two more points to the *"150*150"* guideline. First unification of markings across various countries to improve the reliability of MV. Second, a minimum contrast ratio of 3:1 between the marking and pavement mitigates possible false readings caused by glare. The same guideline has been discussed and agreed upon amongst the various stakeholders involving OEMs (ACEA) and appeared in the series of report on "Roads that Car can Read" in [9] [21].

SLAIN [22] project to assess the quality of lane markings for the ADS concluded that the R_L could be used as an indicator to assess MV performance. The RL was measured for the stretch of every 50m, based on which the Quality Index ($I_{SEGN} = \%A + 0.75\,\%B + 0.50\,\%C$) was calculated for a stretch of every 1000m, using table 1. More details will be discussed in section 2.4.

Table 1 Road classification criteria used in SLAIN [22]

Class	**A**	**B**	**C**	**D**	**E**
Min RL	160	140	100	80	40
Max RL	-	160	140	100	80

Austroads, in their report [23], surveyed a 25000 km sample of the road network. The survey found that the standard of markings in Australia and New Zealand appears to follow "150*150" guidelines. In addition, most freeways and highways are currently capable of supporting ADS for lane positioning. This section concluded that the measurement of retro-reflection of the pavement markings is a critical metric and hence a part of the current research.

2.3 Lane Positioning Performance Metrics for LKS

The next task was to study the performance metrics to measure the lane-keeping ability of the LKS. The SAE J2944 [24] defines the Lateral Lane Position as a distance between the specified point on the vehicle to a specified part of the lane. There are three options to measure: A – reference to the lane centre, option B – reference to the middle of the driven path, and option C – reference to lane edge. The points can be chosen as lateral midpoint of the front axle or centre of gravity on the vehicle. The SAE recommends option A for most scenarios and using a right-handed coordinate system, i.e. assigning positive sign convention to the lane position measured towards right from lane centre, for the right-hand driven vehicle.

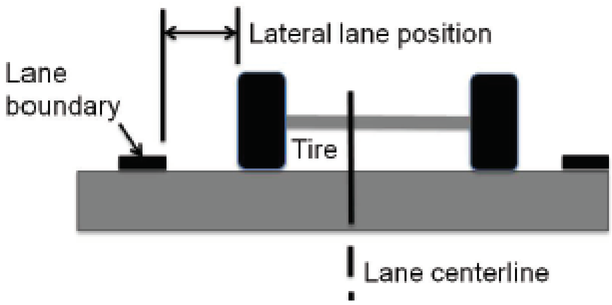


Figure 3 Measurement of Lane Position using Option C of SAE J2944 [24]

The measured lane position can then be used to measure the Mean Lane Position (MLP) and Standard Deviation of Lane Position (SDLP), which are the most used performance metrics to evaluate the lateral performance of the vehicle. For many decades, the MLP and SDLP have been in use and still used as a restorative measure [25] [26] [27] [28] [29].

There are other lateral performance metrics such as TLC (Time to Line Crossing), Steering Reversal Rate (SRR), Steering Entropy described in SAE J2944 [24]. However, due to the complexity in their measurement, they were out of scope for the current project and hence not described in this section. For example, Zhou et al. [30] explained the practical challenges faced for measuring parameter such as TLC and how the suitability of the metric is lost if an approximated method is chosen for simplification.

Based on the reviews of practical studies, SAE [24] found that the MLP varies with lighting conditions and speed. It suggests expecting an average offset of 5cm to the left in daytime and 12 cm in the night for humans. The SAE, based upon more than ten different studies, found the SDLP for regular driving to be varying between **20 cm and 30 cm**. However, it should be noted that all these values are based upon human driving. Green et al. [31] reviewed 36 studies and found the average value of SDLP to be 18 cm for human drivers. Zhou et al. conducted an experimental study and found SDLP to be **18 cm – 27 cm** [30].

The EuroNCAP's latest LKS assessment procedure test the vehicle on an S-bend [32]. The test involves no manual input from the driver and repeated at 80, 100 and 120 Kmph. Based upon the observation, if the vehicle stays on both curves or one of the curves of the S-bend, a score is given to the vehicle under test (VUT). However, there are **no specific values** mentioned for MLP or SDLP as there is no evaluation when the vehicle stays within the lane. Instead, the evaluation only sees if the vehicle stays within a lane or not.

After extensive literature research, no study was found to provide a reference value for the MLP and SLDP for automated vehicles. A recent study to assess the infrastructure for LKS by Reddy et al. [28] assigned the average performance for the human as "High Performance" for the AD. However, these thresholds in Table 2 are not based on the performance of LKS.

Table 2 Criteria for LKS performance Classification used by Reddy et al. [28]

Indicator	High Performance	Medium Performance	Low Performance
MLP	<= 10cm	> 10 cm, <= 20 cm	> 20 cm
SDLP	<= 30 cm	> 30 cm, <= 50 cm	> 50 cm

2.4 Previous Research on evaluation of LKS performance

Neumeister & Pape [33] conducted a field test using three different OEM vehicles, all equipped with vision sensors and two with additional RADAR sensors, to study the effect of adverse weather conditions on Automated Driving (AD). It was found that the wet or water accumulated pavements did not have a considerable effect. However, a small amount of snow covering the line-markings affected the AD performance severely. In addition, all three vehicles failed to detect line markings in heavy rainfall. The authors also took input from various stakeholders from transportation agencies to understand the support they can provide to AD and identified two significant gaps. First, it is unclear who is responsible for determining whether the current or forecasted conditions are within or outside the ODD of LKS. Second, the weather-related limits of AVs are unknown, as the manufacturers never release their detailed limitations.

Carlson et al. [34] studied the effect of retro-reflection (R_L) of pavement markings, vehicle speed and ambient lighting on the maximum detection distance by the humans in a closed set-up test course, a road on Texas A&M University's Riverside Campus, having a facility of rain tunnel as well. The same set-up had been than used in the for exploring the performance of LDW system in 2018 by Pike et al. [35] and in 2019 by Stacy [36].

Pike et al. [35] studied the effects of the wet RL and L of pavement markings on LDW in the night continuous rain with and without glare sources. Delta LTL-XL Mark II and Delta LTL-XL handheld retro reflectometers were used to measure the R_L and Q_D respectively. A CCD luminance camera was used to measure the luminance of the markings under various lighting and wetting conditions. The sensor evaluated was Mobileye which was installed on the Ford vehicle, and CAN signals of Mobileye were decoded to get the confidence score of the lane marking detection. This confidence score was then studied as a function of each variable individually by manipulating the experimental setup.

Stacy [36] then followed up on the research using the same setup and sensors to explore if the Machine Vision (Mobileye) score can be used for asset management in transport. Thus, the main aim was to see the repeatability of the MV quality scores and the correlation of the quality scores to the established pavement marking evaluation characteristics. The author concluded that MV scores are not relatable to the pavement marking characteristics as the MV technology are not fully known and quantifiable. Both the author had tried to approach different OEMs for participation in the study to get the in-vehicle data but got no response and hence decided to use Mobileye as it is possible to decode its CAN bus data.

Davies [37] examined how retro-reflectivity, contrast, and width affect the MV performance. All of the studies mentioned above used a closed setup where different conditions such as glare, shadows, and rain were artificially created, allowing the researchers to control and manipulate the variable for research. The literature research on these studies gave an initial overview of the methodology, choice of sensors, and experiment conduction for data collection for this thesis.

One of the other projects with a similar research methodology to this thesis is the European Commission's funded project SLAIN (Saving Lives Assessing and Improving TEN-T road Network safety). The project SLAIN [22] had one of the objectives to assess the CAV readiness of Core Ten-T roads in Europe. They involved a pilot study of 2000 km of road across four countries (Croatia, Greece, Italy, and Spain). They used the existing TomTom's MoMA (Mobile Mapping) dataset of LIDAR and 360 deg camera. First, to assess vision-based ADS, the imagery-based algorithm was built using the RCNN trained on the MoMA data to detect the lines on the road along with their confidence score. The second algorithm was based on LiDAR and used the IoR (Intensity of Return) values. They found that the main reason for no detection of lines was low lighting conditions and faded lines. The CV-based algorithms primarily relied upon the sufficient contrast between the line and the road surface, while the DL-based algorithms relied upon consistency and reduced variability. The same project also included a 500 Km road survey using the vehicle DELPHI (DELineation Photometric Instrument) to verify if the road markings meet "150*150" requirements. Based on the measured values of R_L , the roads were assigned a Quality Index (I_{SEGN}) from A to E (High R_L to low R_L) and then relation was analyzed between the readability of the lines and the I_{SEGN}. For detected lines, 80.6% of the times road belonged to class A while only 4.9% to class E.

The results of SLAIN assessed the readiness of TEN-T roads considering the two type of vision-based algorithms (CV-based and DL-based) that are being used for lane detection. However, the actual OEMs vehicle performance is entirely out of the picture. They are analyzing the performance of their own build LKS algorithm of line detection, which will undoubtedly vary from the actual OEMs and thus, it will always leave doubt for the actual readiness of the roads. Second, the same DELPHI survey results also show that for the 'lines not detected' cases, 37.3% of the time road belonged to class E, but it belonged to class A for 47.8% of the time. These results prove the complexity of the problem while assessing the roads for AV readiness and the fact that there are so many other factors that need to be considered. Hence, a detailed review of the factors affecting the LKS was done before conducting the field test.

'APPENDIX A – Factors affecting the LKS Performance**'** lists the various factors affecting the LKS, as per the literature review of various theoretical and practical studies.

3 METHODOLOGY

After having a detailed literature survey of the LKS algorithms, performance metrics, previous studies and factors affecting LKS performance, the next task was to combine all of this knowledge to develop an own state-of-the-art experimental setup for the thesis. This chapter explains the methodology built to ensure that the quality dataset is available for the analysis to answer the RQs.

3.1 Overview of the Research Design

The approach taken to answer the RQs for this thesis is given in Figure 4 and can be explained in three simple steps. First, collect the dataset by driving the vehicle in different environment and road conditions. Second, use this dataset to analyse in which **situations** the vehicle could **perform** and where it failed. Finally, use these observations to build an LKS model and check how it performs on unseen data. The accuracy of this model will answer the main RQ that how accurately it is possible to predict the performance of LKS. However, the fundamental question is how to measure and quantify these '**situations**' and measure the '**perform**ance' of LKS. The 'situations' are the research variables given in section 3.2, and it is explained how these were measured. The metrics used to measure the 'performance' of LKS are given in section 3.3.

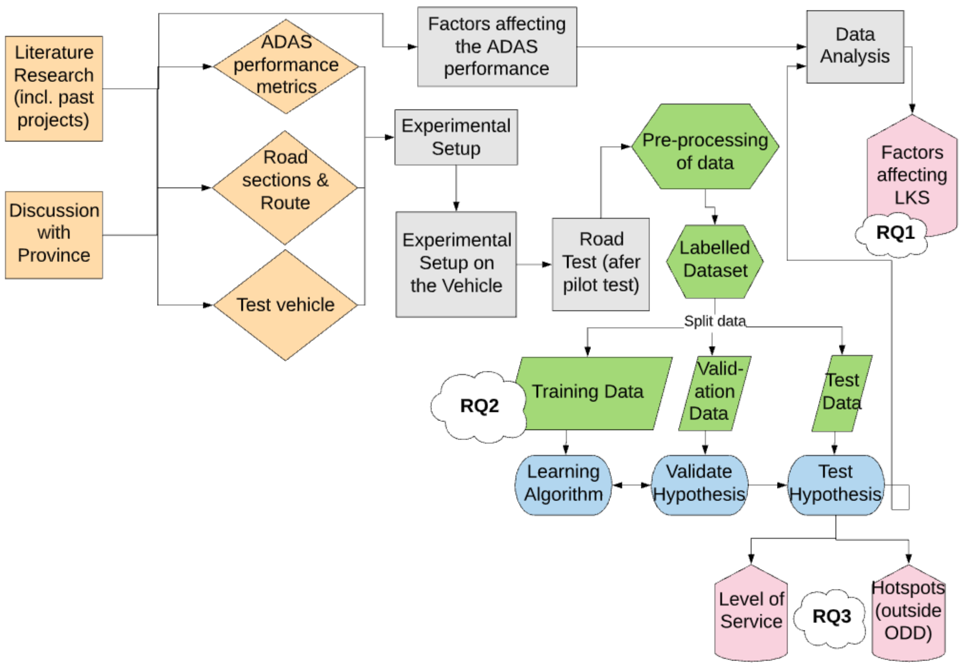


Figure 4 Research methodology overview

The conduction of the experiment by driving the vehicle on the decided test route resulted in a dataset containing all the 'situations' where LKS performed well or failed to 'perform'. This dataset is referred to as 'Labelled Dataset' in Figure 4. Labelling the dataset was one of the critical challenges. Chapter 4 will explain how state-of-the-art tools were developed using deep neural networks to identify the vehicle's lane positioning and lane detection state. The tools made it possible to take measurements at a very high frequency of 30 measurements within each second. The fact that the dataset was prepared using accurate measurements at high frequency made it possible to accurately use statistical analysis and Neural Network architecture-based models to answer the RQs for this thesis.

The dataset is divided into the training, validation, and test dataset. The LKS model based on the neural network is trained using the training and validation dataset. The model is validated using the test dataset to calculate the model's accuracy on totally unseen data. The prediction model could answer

RQ2 by classifying the different LKS performance levels into ODD in and ODD out situations. However, later in Chapter 6, it is discussed why the term 'ODD' should not be used. Finally, the prediction models are used to calculate the different Level of Service (LoS) given by the road infrastructure for LKS.

3.2 Research Variables

The variables can be categorized into three groups that should be considered ideal for developing an LKS model: human, vehicle and environment. However, the human factor is taken out of the experiment by instructing drivers not to give any input to steering during the field test. Therefore, this research takes into consideration only the last two categories.

Two different OEM vehicles were chosen to understand the difference in the performance of the LKS equipped vehicle. The choice of different vehicles will help to conclude if it is legitimate to make changes in the road infrastructure based upon the performance of the vehicles. To make this conclusion, the best choice of vehicle was to have a range of performance. Hence, the vehicle selection was based upon the performance of Steering Assistance as identified from Euro NCAP's recent evaluation in 2020. The results [38] are summarized in Table 3. Vehicle X and vehicle Y were chosen as test vehicles and form the first variable for this thesis.

Table 3 EuroNCAP assessment scores for LKS (Euro NCAP, 2020)

Vehicle	Mercedes Benz GLE	Audi Q8	Tesla Model 3	BMW 3 Series	Nissan Juke	Ford Kuga	Peugot 2008	Volvo v60	VW Passat	Renault Clio
LKS score (Max-35)	35	30	35	30	22.5	30	30	30	30	27.5

The other category of variables that need to be considered was related to the environment, i.e., driving conditions. The variables in this category could potentially include the road infrastructure, lighting conditions, weather, traffic, and everything else in the vehicle's surroundings. The choice of the variables was made based upon the literature research. Section 2.1 helped to choose the variables that should have been considered based on the possible technological difference in OEM vehicles. For example, the contrast ratio of lane marking can significantly affect a CV-based LKS algorithm but not a DL-based algorithm. The findings and recommendations of the previous studies, as explained in section 2.4, were also used to expand the list of chosen variables. Finally, APPENDIX A – Factors affecting the LKS Performance provided further insight while shortlisting the variables and the required sensors to measure them. The list of chosen variables is given in Table 4.

Table 4 Shortlisted Variables for measurement

Parameter	**Sensor**
Type of Horizontal Curve	Maps
Radius of Curvature	Maps
Lane Width	Cameras
Visibility of lane markings	Reflectometer
Lane Marking type (dashed/continuous)	Camera
Contrast Ratio	Camera
Speed of the Vehicle	GPS
Weather and Lighting Conditions	-

3.3 LKS Performance Metrics

The performance of LKS comprises of evaluation of the Machine Vision (MV) performance, which represents the ability of the vehicle to detect the lane, and Lane Positioning (LP) performance, which represent how well the vehicle position itself within the lane. The MV performance was measured using the metric "percentage of line detection" as the line detection status can be read from the vehicle's dashboard screen (Vehicle Information Display).

$$percentage\ of\ line\ detection = \frac{Total\ number\ of\ line\ detection\ cases}{Total\ number\ of\ observed\ cases} \times 100$$

The Lateral Lane Position (LP), as shown in Figure 5, was measured as a lateral position of the vehicle's longitudinal centre relative to the lane centre, which is referred to as option A in SAE J2944 [24].

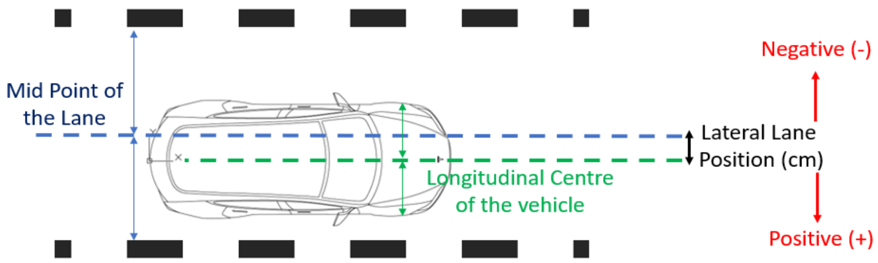


Figure 5 Measurement of Lateral Lane Position

The calculated LP of the vehicle was then used to calculate the LKS performance metrics Mean Lane Position (MLP) and Standard Deviation of Lane Position (SDLP). The MLP is calculated as the average of the LP measured over the defined stretch of the road. The SDLP is calculated using equation 2, as defined in the SAE J2944. Both MLP and SDLP were measured for intervals of 30 seconds throughout the route. The interval of 30 seconds was based upon the recommendations in previous studies [39] [28]. The MLP and SDLP vary between the straight and curved sections of the road, and hence these performance metrics were calculated and reported separately for these respective sections.

$$SDLP = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

where, x_i is the i^{th} observation in the total N observations and $\bar{x}$ is the MLP.

3.4 Justification of Research Design

The literature research in section 2.4 found that most of the past research assessing the performance of LKS has followed the method of Experimental Research, in which one variable is manipulated to see its effect on another variable. Unlike those studies, this research follows the correlational research method, simply observing and analyzing what is naturally happening without directly interfering with it. Undoubtedly, the results from experimental research are more accurate and conclusive as different variables are manipulated as per the researcher's choice, and the effect of confounding variables can be suppressed. However, experimenting in an open environment and on public roads does not have this flexibility. Therefore, the results from this research might be comparatively less accurate; however, these results are more practical and valuable to the Road Authorities (RA).

The second thing that requires justification is, how can the driver be left out while assessing the performance of LKS, as both the test vehicles are SAE level 2 and supposed to assist the driver and not meant to be driven autonomous? The answer to this is that the drive for data collection should be viewed as a drive containing many short segments where the vehicle is being tested several times. As explained in section 2.4, EuroNCAP test the LKS of SAE level 2 vehicle on the **S**-curve by keeping the driver out of the loop. So, in this research, the vehicle is similarly put to the test but in a continuous series and on different road sections.

4 DATA COLLECTION PROCESS

The previous chapter provided an overview of the research methodology and the variables that need to be measured for analysis to answer the Research Questions (RQs). This chapter explains that how those variables were measured by conducting a field test.

4.1 Test Route Selection

The selection of a route for test data collection was crucial to ensure that the vehicles are exposed to various situations, both inside and outside ODD, to build robust LKS models. However, at the same time, there should be sufficient instances for each considered situation to ensure accuracy in the results. For this reason, only the provincial roads were focused, and the highways were excluded from the study. The provincial roads (N roads) are the non-expressways in the Netherlands.

Second, since the retro-reflection also had to be measured for the same route, it was possible to track the same lane lines for N roads as most of them are one lane or two lanes only. So the focus of the present study is the Inter-Urban roads, out of the four EuroNCAP defined ODD situation of Parking, City, Inter-Urban and Highway for testing ADS [8].

A route of about 200 Kms of N roads was planned in one of the provinces in the Netherlands (confidential). First, the route was previewed using the Street Smart to include varying road markings and curves with different sharpness. Furthermore, various parameters such as Lane Width and Line Width were also measured to ensure variation in the data. Table 19 shows a sample of these observations. Finally, a discussion was also held with the road authority to ensure that the route covers various situations based on the age and last maintenance of the road. The route was then updated based on their feedback, and sections of the road were added. Figure 6 (confidential) shows the decided test route for this study.

Figure 6 Final Test Route - Hidden (confidential)

4.2 Vehicle Instrumentation

The GoPro camera was mounted facing the vehicle's dashboard screen (Vehicle Information Display) to measure the line detection performance of the LKS. The vehicle's position inside the lane was measured using the GoPro cameras mounted on the left and right door of the vehicle. Finally, to measure the Contrast Ratio, road surface conditions and lighting conditions, a forward-facing camera was mounted on the dashboard. The data from the in-built GPS of GoPro cameras were used to measure the vehicle speed. For a backup to measure vehicle speed, the GPS logger app was installed on the mobile phone of the Vehicle X co-driver, and a GPS connected to the Inertial Measurement Unit (IMU) was placed in the Vehicle Y vehicle. The GPS for tracking vehicle location was very critical as it was the key element for synchronizing the reflectometer readings to vehicle performance. The placement of the camera and view from them can be seen in Figure 7 and Figure 8, respectively.

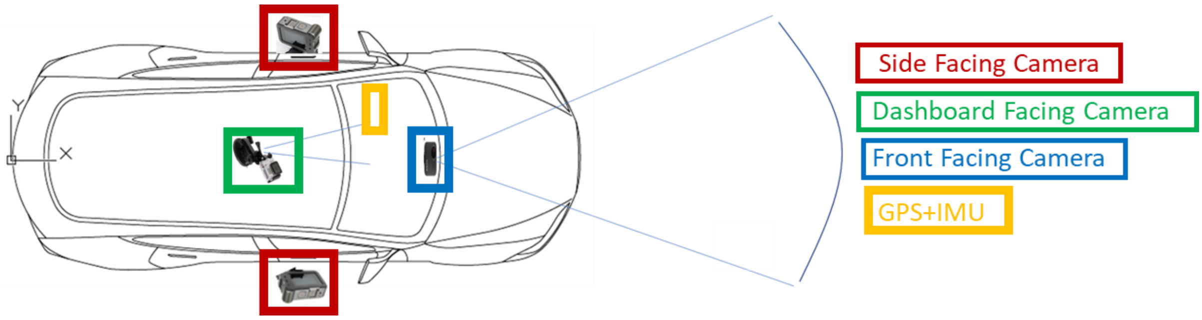


Figure 7 Vehicle Instrumentation

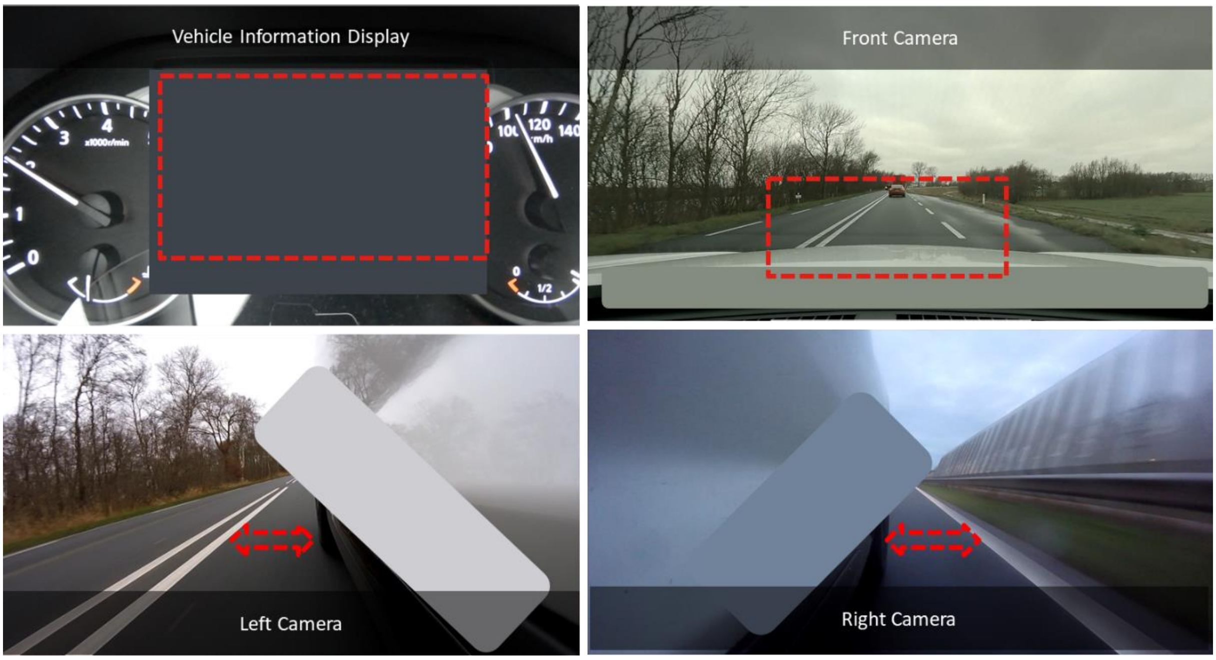


Figure 8 View from the mounted GoPro Cameras in vehicle X (confidential)

4.3 Calibration and Synchronization of the Cameras

The lane position is calculated using the cameras. The cameras can measure the distance between any two points only in terms of pixels; however, to convert the measurement into meters or centimeters, it is required to calibrate them. The calibration is a process of estimating the camera's intrinsic and extrinsic parameters, which are then used to convert the pixel distance into m or cm. This estimation, which is done later during the data processing stage, can only be done if the calibration was done beforehand during the experiment. Briefly, the procedure involves holding a checkerboard of a known dimension at a known distance from the camera. This procedure also helps to remove the fish-eye lens distortion during the data processing stage. However, the GoPro used in the experiment (Black 7 and Black 9) has inbuilt settings to change the camera view to ‘Linear’, which takes care of the distortion and reduces the efforts while developing code for distance measurement. These steps already ensured the accurate distance measurement, but still, to validate the results, a plank with known dimensions of the square was placed in front of the camera to verify the readings. Figure 9 shows the whole procedure for one session: taking measurements, calibration, and validation.

Second, there are four cameras, and all of them need to be synchronized to ensure that for any given observations at a given instance, each camera is showing the same observation. For this 'Atomic Clock' app installed in the phone was shown to each camera (Figure 9 bottom right). Later on, the time difference can be calculated, and videos can be synchronized. Last, the GoPro cameras auto-correct the colours of the captured videos to enhance their quality [40]. However, this can lead to incorrect calculation of the Contrast Ratio due to change in the intensity of road and line-marking pixels in the captured videos. Therefore, referring to the manual of GroPro, the advanced settings of all cameras were changed to capture the raw images.

4.4 Test Procedure

The driver was kept out of scope for this study, and hence it was important to ensure that there is minimal driver interference but not at the cost of safety. To familiarize the driver with automated features, a detailed explanation to operate them was given. They were also instructed to hold the steering wheel with gentle hands allowing the vehicle to have control. While testing the LKS, the EuroNCAP also instructs the driver to hold the steering wheel in the same fashion [32]. The drivers were also instructed to always use the indicator signal before initiating any lane change to distinguish between the Lane Departure and intentional lane change while doing the data analysis after the test. The co-driver instructed the driver which lane to follow to ensure the correct synchronization with the reflectometer survey.

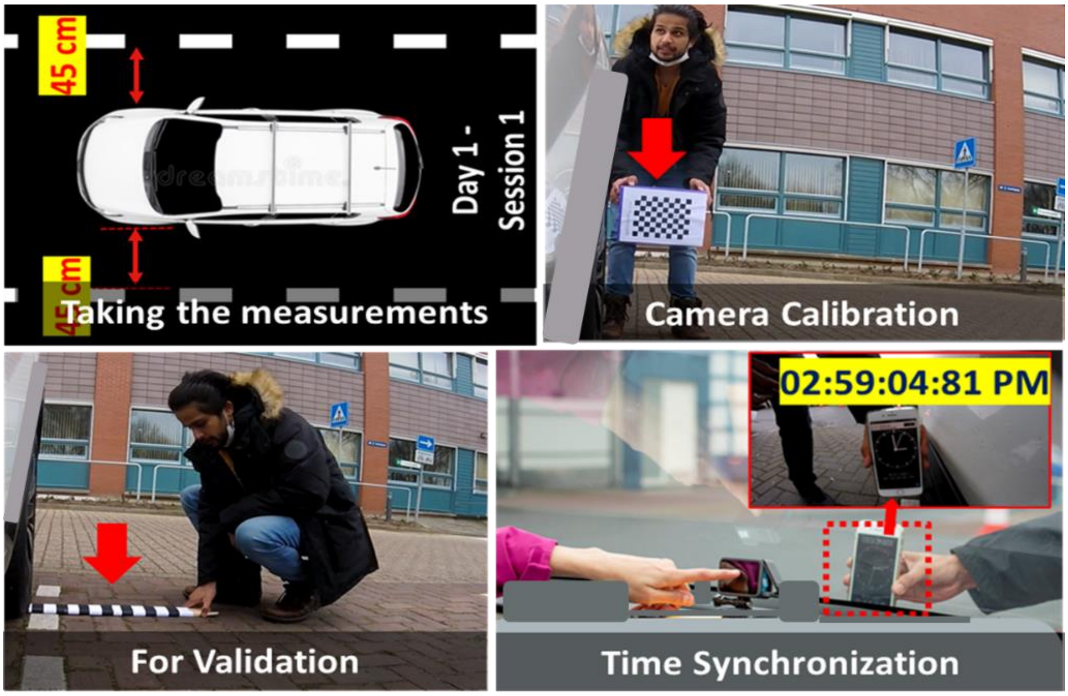


Figure 9 Tasks before the start of every driving session (confidential)

On 15th January, three days before the final test, a pilot test of 125 Kms on the final route was conducted. The complete procedure as described in the previous section was followed, and the data was also recorded. After the pilot test was finished, the recorded data from all the cameras were shared with the Data Scientists of RHDHV to note down any changes to be made in the Cameras' positioning, orientation, or calibration procedure. Second, a meeting was held amongst the field staff to note down what went wrong during the Pilot Test. The outcomes from these sessions were then used to modify the previously built SOPs for conduction of test to ensure smooth and successful data collection during the upcoming drive.

The preparation helped in the successful conduction of the main drive, which was held as per the schedule given in Table 5. During the break, data was transferred from Memory Cards to the Laptop. After the transfer of the data, the cameras were again calibrated and synchronized for the next session. The start of the Day 2 session was delayed by 2.5 hours due to the heavy rain.

Table 5 Data Collection Duration

Driving Date	Session 1		Break	Session 2	
	Starting Time	End Time	@ FEBO, Alkmaar	Starting Time	End Time
18-1-2021	4:30 PM	6:40 PM	1 hr 30 Mins	8:15 PM	11:00 PM
19-1-2021	12:45 PM	2:20 PM	1 hr	3:14 PM	6:45 PM

4.5 Retro-reflection Measurement

The retro-reflection of the lane-markings was measured using the mobile reflectometer mounted on a vehicle. The device is capable of measuring the R_L at average road speed without disturbing the traffic. The reflectometer used for the survey was 'Laserlux 6'. This reflectometer illuminates the lane markings using the laser scan at an observation angle of 1.24 degree. It then collects the portion of the light redirected (retroreflected) back to the device at a co-entrance angle of 2.29 degrees. This observation angle and the co-entrance angle used for the measurement refers to standard CEN 30-meter geometry in EN 1436. This equipment collects the data at the rate of 200 data points for every 100 meters [41]. So, for every hectometer, the minimum, maximum, standard deviation, and average R_L values are recorded.

The device was first mounted on the right side, and the whole route was covered. The driver was already shared the detailed route (Table 20) and instructed to follow the pre-defined lanes on a multiple lane road. After that device was mounted on the vehicle's left side, the process was again repeated. The survey was done by the contractor 'Trackline'. Figure 10 shows the vehicle of contractor used in the survey with mounted reflectometer 'Laserlux 6' of the manufacturer 'RoadVista'.

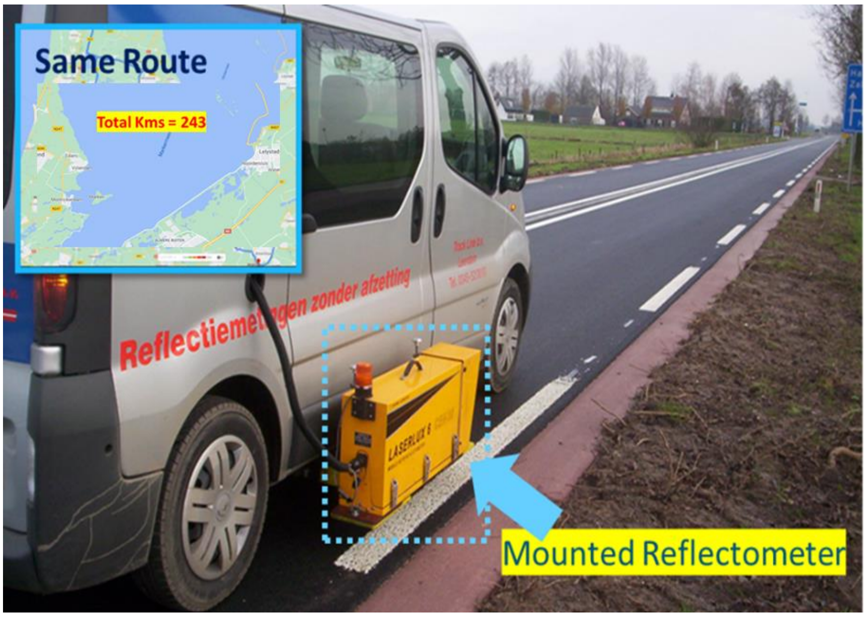


Figure 10 Reflectometer equipped vehicle for measuring the RL

5 DATA PROCESSING

"If 80% of the work is data preparation,
then ensuring data quality is important work of an ML team" – Andrew Ng

The data collected from videos need to be converted into a tabular form for analysis. The different observations, such as lighting conditions and weather conditions, also need to be put alongside this data. The data cannot be combined straightforwardly because the reflectometer, GPS, IMU and GoPro cameras have different frequency of capturing the data. The received information from PNH about the road age was in the form of a gdb (geodatabase) file and needed to be merged with the existing dataset. This chapter explains how the mentioned challenges were tackled to obtain a quality dataset used for analysis. The list of software and programs used is given in Table 21.

5.1 Processing of the Dashboard Camera Data

The purpose is to read all the signs relevant to the LKS on the dashboard screen (VID) using an object detection algorithm in both vehicles. The process is explained by taking the example of Vehicle Y; however, the procedure is similar for Vehicle X. There are 11 classes (signs), as shown in Figure 11, which needs to be detected for Vehicle Y.

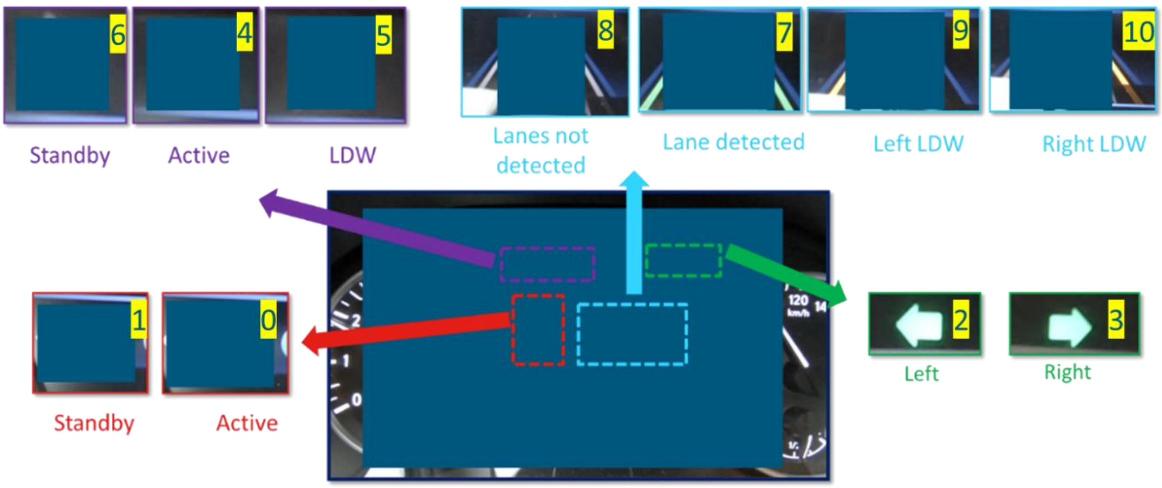


Figure 11 Classes (signs) to be detected from vehicle Y Dashboard for data analysis (confidential)

The Deep Neural Network based YOLOv5 [42] object detection algorithm was used for building this dashboard sign detection tool. Like any DL model, it also relies heavily on the quality of the dataset on which it is trained. The dataset does not just require the number of images but also the quality of images, which often require re-training the model. Hence, from the first step, a proper structure was followed such that at any stage of development, it is possible to trace back the information for re-training the model.

The overall process of training the model is shown in Figure 12. The videos were first converted into frames using a script written in python. These frames were then labelled by drawing a bounding box around each sign and giving each bounding box its true label. For Vehicle Y, 469 frames were labelled using 1125 bounding boxes (Table 22). After this, the dataset of the labelled images is divided into train, validation, and test set. Labelling the images is a time-consuming process. To ensure that the model is trained on a wide variety of images, the training dataset is expanded by using Data Augmentation. The data is augmented by varying the dataset's saturation, brightness, and exposure by adjusting each of these values from -25% to +25%.

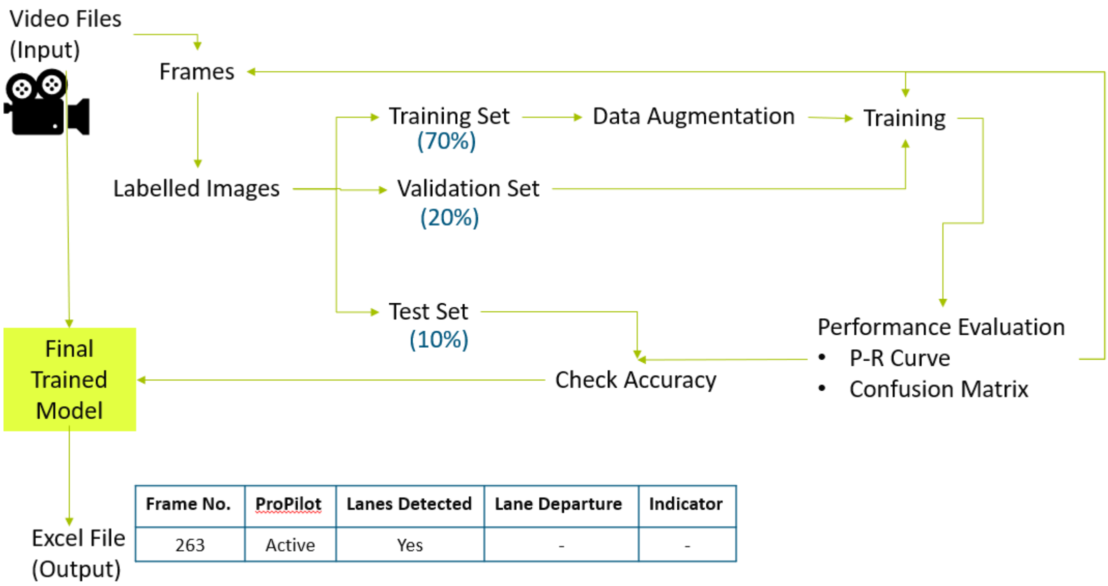


Figure 12 Flowchart showing the development of Dashboard Sign Detection model

After this model was trained using Google Colab GPU on the labelled dataset. The model starts learning on the training dataset while keeping track of the loss function, which starts decreasing with time. Though the ultimate aim of the training is to minimize this loss function, there is a danger of overfitting, where the model will perform very well on the training data but fails to give correct results in unseen situations. To keep a check on this, the loss function for the validation set is also tracked continuously, and as it starts increasing, it means that the model has started memorizing the data instead of learning and hence training is stopped at this stage. Since both training and validation set is already seen by the model during training, to evaluate the performance of the trained model accurately and unbiasedly, a test dataset is used. There were multiple sessions of training, labelling, re-training before the desired accuracy could be achieved. For the final model, it took around 8 hours to train online on the 'Tesla K80' GPU, and the finalized model had a precision of 0.889 and a recall of 0.992 for Vehicle Y dashboard signs (Figure 24, Figure 25 and Figure 26).

Though the videos are recorded at 29.7 FPS from the GoPro, the output from YOLOv5 was at 30 FPS. This difference is due to a bug [43] in the YOLOv5, due to which it is unable to process the GoPro videos at 29.7 FPS. Thus, all the videos need to be converted first to 30 FPS. The final output was in the form of excel files, each row representing one frame.

5.2 Scenario Formations

The MLP and SDLP are measured over 30 seconds (section 3) which means there will be 900 frames accounted as one interval. Now the signs on the dashboard can appear in different combinations. First, based on the False Positives and False Negatives, the wrong combinations are filtered out. The remaining combinations of signs were then grouped into four scenarios in Table 6 for Vehicle Y. Column 1 to 3 in Table 6, shows the class (0 to 10) for each of the 11 signs, which are same as Figure 11. The fourth column shows all combinations of the signs that contributed to building the scenarios in the sixth column. Also, two more conditions need to be filtered out, one when the driver initiated a lane change (Indicator ON) and the second when there were intersections (column 7, 8 and 9).

The retro-reflection was measured over the stretch of 100m, which means an interval of approximately 150 frames. So, a second file is generated with conditions given in column 9 of Table 6. This file will be used to evaluate the MV performance, while the file obtained using an interval of 900 frames will be used to evaluate LKS lane positioning performance. All these calculations were done using MATLAB.

Table 6 Final Scenarios for vehicle Y (confidential)

1	2	3	4		6	7	8	9	
[redacted]	Autosteer	Detection Status	Cases	Description	Scenario	Conditions	Conditions (Interval = 900	Conditions Interval = 150 Frames	Final Scenario
[redacted] Active (4)	Active (0) [redacted]	LD 7 [redacted]	4,0,7	Driver light hands on the wheel but no manual steering input	**Automated Driving**	Speed > 50 Kmph (Rules Out Inter-section)	Indicator < 90 Frames (Straight)/ 30 Frames (Curve)	(case1_count > 140) & (count_indicator < 28)	**1**
	Standby(1) [redacted]	LD 8 [redacted]	4,1,8	Not Possible to activate the Autosteer	**Lanes Not Detected**			(case2_count > 140)	**2**
[redacted] LDW (5)	Active (0) [redacted]	LDW 9,10 [redacted]	5,0,,9 ,0,,9 5,0,,10 ,0,,10 ,0,7 5,,,	Vehicle unable to keep itself in lane Flashing signs cause so much combinations	**Lane Departure with AutoSteer in control**		No Indicator sign for more than 90 Frames	case3_count>15 & case1_count > 30 & count_indicator < 28	**3**
	Standby (1) [redacted]	LDW 9,10 [redacted]	5,1,,9 5,,,9 5,1,, ,1,,9 5,1,,10 5,,,10 ,1,8,	Driver unable to keep veicle inside the lane (might be due to the Autosteer suddenly turning off)	**Lane Departure with Autosteer not available (AutoSteer drops)**			(case4_count > 15) & (count_indicator < 28)	**4**

5.3 Processing of the Front Camera Data

Due to the heavy rain on day 2, it was not possible to use the side cameras. Also, in session 1 of day 1, there were splashes on water and dirt on the camera lens, due to which it was not possible to use the side camera data for these sessions. Hence, the plan to calculate the lane position of the vehicle using the side cameras was changed. Instead, the front camera was used to calculate the lane position using option A, mentioned in SAE J2944 (Figure 5).

The processing of the videos from the Front Camera was done by the team of Data Scientists from RHDHV. The Lane Position and Lane Width of the vehicle were calculated using the lane detection model ERFNet [44], which uses Deep Neural Network as explained in [45]. The calibration images and measurements were taken during the test were used to convert the results into meters (Figure 29).

Second, to calculate the Contrast Ratio, the lane lines were detected using the previously developed ERFNet model, and then a rectangular box (Figure 30) with fixed dimensions was drawn around the lines to calculate the intensity of pixels of the lines ($I_{markings}$) and road ($I_{background}$) separately. Finally, the contrast ratio is calculated as:

$$Contrast\ Ratio = \frac{I_{markings} - I_{background}}{I_{background}}$$

Third, the lane lines were also classified as dashed and continuous in the same code using the Fourier Transform (Figure 31).

The output received from the team was Lane Position, Lane Width, Contrast Ratio and line type in an excel file corresponding to each frame of the video.

5.4 Manual Data Logging from Videos

Though the weather data was taken from the weather station, there was a lot of difference between it and the actual weather during the driving conditions. Hence, it was recorded manually by watching the videos. Since the vehicle was mainly driven in the rainy/cloudy weather on both days, the situations defined are dry road, wet road and rain (Table 7 (a)). The rainy situation was initially divided into moderate rain and light rain, but when the final data was checked, it was found that there are very few instances of moderate rain; hence both were merged as rain condition. The different lighting conditions defined are given in Table 7 (b) and shown in Figure 14. After capturing the weather and lighting conditions, the next task was to log the condition related to the road geometry. The different type of line-markings, as shown in Figure 15, were recorded. At last, it was recorded if the road is divided or undivided.

Table 7 Defined conditions for (a) weather and (b) lighting for manual logging

Weather	Defining of the situation
Moderate Rain	• High Wiper Swipe Rate • Cannot see the road surroundings clearly
Light Rain	• **Low** wiper Swipe Rate • Rain drops on front windshield • Can see the surroundings comfortably
Wet Road	• Water Splashes from other vehicles seen • No Rain
Dry Road	• No water splashes

Lighting	Defining of the situation
Day	• Before 5 PM and vehicle lights are off
Dusk	• Starts 1 hour before Sunset Time • Ends till we can see the road without car headlamps
Night	• vehicle lights turned ON • can't see the skylight

Figure 13 Different weather conditions

Figure 14 Different Lighting Conditions

Figure 15 Type of line markings

While recording the data, the video time was also entered in the excel file, which enabled to link the GPS coordinates to all the manual observations. This resulted in a file having road geometry with GPS coordinates, which was then imported into QGIS to assign the road geometry data for another day for another vehicle. A similar approach was followed for synchronizing the lighting condition data.

5.5 Processing of Reflectometer and PNH data

First, the data for retro-reflection of the line-markings was received from the Trackline and the GPS coordinates against each reading in a CSV file. Second, the data from PNH was received about the last maintenance of the various road section throughout the province in a geodatabase (gdb) file. Third, the roads in the Netherlands have hectometer markers every 100 meters. This dataset is open-source and obtained from NWB [46] in an ESRI shapefile. While extracting the hectometers, the hectometers in the opposite direction of the road need to be filtered out. Finally, all of the three mentioned datasets were combined using QGIS, a GIS application tool.

5.6 Data for Curved Road Sections

Google Earth Pro was used to measure the radii of curves, based on which the curves were then classified into: Large-radius (radius > 175m), Broad (100m–175m), Medium (60m–100m), Tight (25m-60m) and super-tight (radius ≤ 25 meters). Further, the curves were also categorized based upon their profile: Simple curve (circular curve with a single arch of a uniform radius), Compound curve (comprised of a series of two or more simple curves of different radius turning in the same direction), and Reverse curve (consists of two simple curves of the same or different radius which turning in the opposite direction). These calculations were taken from another intern Mahima. QGIS was used to merge this data into the existing data files based upon the GPS coordinates. The dataset was then divided into straight and curved sections and analyzed separately for LKS performance.

5.7 Synchronization of the Data

To synchronize the data from cameras, the time difference between the atomic clocks were calculated as shown in Table 25. Then, the calculations were repeated for each session to obtain a synchronization matrix shown in Table 26. Next, the metadata containing GPS coordinates were matched to the camera data. The remaining data were then synchronised, as shown in Figure 16, using the GPS information.

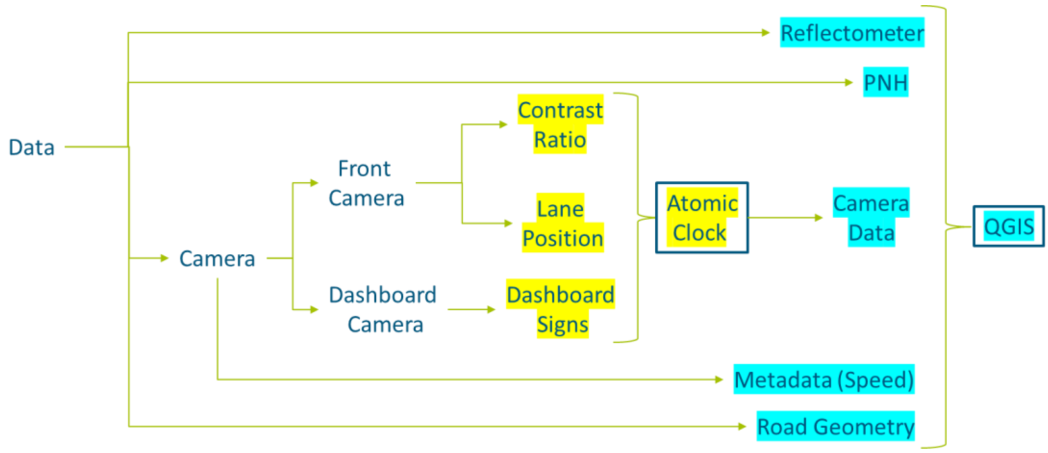


Figure 16 Flowchart showing final steps of synchronization

5.8 Final Dataset

The data was then checked for the outliers and final quality before starting with the data analysis. There were many situations when a vehicle was parked or stuck in traffic. These were not relevant to study, and these situations lead to the false detection of lines, hence incorrect Lane Width and Lane Position. Therefore, all the observations with a speed of less than 30 Kmph were filtered out. This speed filter proved out to be very effective in identifying the correct outliers.

Observing the Lane Width data, it was found that there were many outliers in the data. One option to remove outliers could have been based on the lanes actual width, measured using the Street-Smart.

However, there was an issue during the camera calibration; hence, the outliers were considered based upon the Box-Whisker Plot and not the actual real value of Lane Width. After removing the outliers, the spread of the Lane width is shown in Figure 32. Since the manual measurements done using the Street Smart for the driven route shows the range is 2.73m to 3.42m, it can be concluded that the Lane Width measured from the camera of Vehicle Y Day1 are the most accurate. The difference in lane widths across different days in Figure 32 (a) is not possible. It is again due to the calibration error.

Second, the readings of the Contrast Ratio were checked. For Vehicle X Day1, more than 50% of the data showed a value above 6; however, these values were ignored as incorrect. Similarly, for Vehicle X Day2, all the values above six were ignored. These values were practically not significant. After the removal of outliers, Figure 32 (b) shows the spread of the Contrast Ratio. For the same day, the values should have been similar for both the Vehicle Y and Vehicle X vehicles, which was not the case as there was a considerable difference in the values (Figure 32 (b)). Therefore, it was concluded Contrast Ratio Tool is giving incorrect readings. The previous study suggests CR from 0.5 to 3, and the closest are readings from the camera mounted on Vehicle Y Day 2. Thus, the readings of contrast ratio from the camera are not used.

Third, Line Classification Tool was checked for its correctness. The initial plot of the distribution of line type detection from the total data shows that the tool gives biased readings. The output was tested for a stretch of a straight one-lane road where only continuous lines were present. It was seen that the tool is showing less than 20% of the lines as continuous. So, the data was discarded, and the manual observations were taken, as described in section 5.4. Below is the description of the final dataset which is used to obtain the result in the next chapter.

Table 8 Final Dataset for analysis and modelling

Information	Type	Categories	Categorical Variable (In order)
Predictor Variables			
Vehicle Speed	Categorical	<60Kmph ; 60 to 79Kmph; 79 to 90Kmph; > 90 Kmph	1; 2; 3; 4
Weather	Categorical	Dry Road; Wet Road; Rain	1; 2; 3
Lighting Condition	Categorical	Day; Dusk; Night	1; 2; 3
Line Type	Categorical	Continuous; Dashed	1; 2
Line Type - Combined	Categorical	Cont-Cont; Cont-Dash; Dash-Cont; Dash-Dash	
Road Type	Categorical	Divided; Undivided	1; 2
Lane Width	Categorical	<3m; 3m to 3.5m; 3.5m to 4m; >4m	1; 2; 3; 4
Road Section	Categorical	Straight; Curve	1; 2
Curve Direction	Categorical	Right; Left	1; 2
Curve Sharpness	Categorical	Large Radius; Broad; Medium; Tight	1; 2; 3; 4
Curve Profile	Categorical	Simple; Compound; Reverse	1; 2; 3
Retroreflection	Continous		
Contrast Ratio Retroreflection	Continous		
Output			
Case [redacted]	Categorical	Automated Driving; Lanes Not Detected; Lane Departure AutoSteer; Lane Departure	1; 2; 3; 4
Case [redacted]	Categorical	Automated Driving; AutoSteer drops; [redacted]	1; 2; 3
MLP	Continous		
SDLP	Continous		
Post Modelling			
Road	Categorical	[redacted]	
Age of the Road	Categorical	1 years to 9 years	

6 RESULTS

6.1 Machine Vision (Line Detection) Performance

This section describes the effect of the predictor variables on the lane detection performance of the vehicle. The overview of the Machine Vision (MV) performance is given in Figure 33. In the case of Vehicle X, there were only two instances where the lanes were not detected, and hence Vehicle X's MV performance is not considered in this section. Therefore, the analysis is based only on the performance of the vehicle Y. Furthermore, 'A roads' data is removed since the analysis is focused on the provincial roads. Finally, while studying the individual factors affecting the MV performance, the considered dataset is filtered as per the requirements to suppress the effect of the confounding variables. Whenever such filtration is done in the dataset, it is reported along with the studied factor.

In this section, the statistic involved is only explained in detail for one variable (speed), and then for the remaining variables, only the key points are given. The frequency of 'lane detected' and 'lane not detected' during the different speed categories are recorded in the form of the Contingency table shown in Table 9. Three questions need to be answered to understand the effect of the factors. First, if there is a relationship between the vehicle speed and lane detection. Second, if it is found that there is a relationship, then which of the speed categories affects the lane detection. Last, it needs to be identified which speed categories result in higher or lower lane detection (good or bad performance).

Table 9 Contingency table showing the lane detection vs speed categories

		Final_Scenario		Total
		Lanes Detected	Lanes Not Detected	
Speed_cat	Less than 60 Kmph	82	192	274
	60 to 80 Kmph	798	624	1422
	80 to 90 Kmph	203	101	304
	Above 90 Kmph	154	0	154
Total		1237	917	2154

The first question is answered by conducting a Pearson's Chi-Square test to see if there is a relationship between the vehicle speed and lane detection status. The results are given in Table 10. The value 210.8 and degree of freedom (df) are used to calculate the P-value, and this P-value tells the relationship between the two variables is significant or not. Most authors refer to statistically significant as $P < 0.05$ and statistically highly significant as **$P < 0.001$ (less than one in a thousand chance of being wrong)**. Suppose the P-value is less than 0.05; in that case, the Null Hypothesis of independence of variables is rejected. It can be said with 95% confidence that the lane detection and vehicle's speed are associated somehow. The footnote in Table 10 tells that the Chi-square assumptions are met.

Table 10 Chi-Square Test for Lane Detection vs Speed

	Value	df	Significance (p-value)
Pearson Chi-Square	210.8[a]	3	**< 0.001**

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 65.56.

The other two questions are answered by breaking down the significant chi-square test, as shown in Table 13. The adjusted residuals identify which speed categories contribute to the overall association with lane detection. Crosstabulation Table 11 also gives a better understanding when seen in combination with Contingency Table 9. The count value of the 'Final_Scenario' against each of the speed category is taken from contingency Table 11, and the expected count is calculated using the chi-square test model. The calculated residuals (error between model prediction and actual data) are then adjusted for correctness. The adjusted residual values that lie outside of ±1.96 means it is significant at $P < 0.05$, if it lies outside ±2.58, then it is significant at $P < 0.01$, and if it lies outside ±3.29, then it is significant at $P < 0.001$.

Table 11 Crosstabulation - Speed Category vs Lane Detection

			Final_Scenario: Lanes Detected	Final_Scenario: Lanes Not Detected	Total
Speed_cat	less than 60 Kmph	Count	**82**	192	**274**
		Expected Count	157	117	274
		% within Speed_cat	30%	70%	100%
		% within Final_Scenario	**7%**	21%	**13%**
		Adjusted Residual	-10	10	
	60 to 80 Kmph	Count	798	624	1422
		Expected Count	817	605	1422
		% within Speed_cat	56%	44%	100%
		% within Final_Scenario	65%	68%	66%
		Adjusted Residual	-2	2	
	80 to 90 Kmph	Count	203	101	304
		Expected Count	175	129	304
		% within Speed_cat	67%	33%	100%
		% within Final_Scenario	16%	11%	14%
		Adjusted Residual	4	-4	
	greater than 90 Kmph	Count	154	0	154
		Expected Count	88	66	154
		% within Speed_cat	100%	0%	100%
		% within Final_Scenario	12%	0%	7%
		Adjusted Residual	11	-11	
Total		Count	**1237**	917	**2154**
		Expected Count	1237	917	2154
		% within Speed_cat	**57%**	43%	100%
		% within Final_Scenario	100%	100%	100%

To interpret Table 11, let us examine the speed category 'less than 60 Kmph'. There are 274 cases (13% of total 2154 cases) of lanes detected or not detected. Further, 1237 lane detected cases (57% of the total cases) and 82 (7% of the total detected cases) were found at speed less than 60 Kmph. The percentages of lanes detected or not within this speed category can be seen in the row *'% within Speed_cat'*. The calculated adjusted residuals for speed less than 60 Kmph are significant for both lanes detected (adjusted residual = -10) and lane not detected (adjusted residual = 10) as the value is above ±1.96. The minus sign of adjusted residuals tells that the detected lines are significantly less than expected by the model if there were no difference in the distribution of lane detection across different speed categories. Conversely, the positive sign indicates that significantly more lines than expected were detected. Since the outcome variable is dichotomous, for simplicity, further in the report, only 'Lanes Detected' cases are discussed.

To conclude, a Pearson's Chi-Square test, $\chi^2(3) = 210.8, P < 0.001$, confirms that vehicle speed significantly affects the lane detection performance of the vehicle. Further investigation using the Crosstabulation table shows that:

- For a speed below 60 Kmph, the lane detection percentage is significantly less.
- For a speed between 60 and 80 Kmph, the lane detection performance was not significantly affected by the vehicle speed.
- For a speed above 80 Kmph, the lane detection percentage is significantly high.

The detailed statistical output for the remaining variables is given in APPENDIX I - Machine Vision Performance, and only the primary outcomes are reported in this section.

The **retro-reflection (R_L)** of the line-markings significantly affects the lane detection performance of the vehicle, $\chi^2(4) = 126.3, P < 0.001$. Further, amongst the different categories of retro-reflection, it is found that (Table 27):

- For Class E (R_L < 125) and Class D (125 < R_L < 150), the lane detection percentage is significantly less.
- For Class C (150 < R_L < 175) the lane detection percentage was not affected significantly by the retro-reflection of line-markings.
- For Class B (175 < R_L < 200), the lane detection percentage is significantly high.
- For Class A (R_L > 200) the lane detection percentage is significantly less.

The higher the value of the retro-reflection means better visibility of line-markings; hence it is expected to have a higher lane detection percentage on the roads with high values of retro-reflection. However, the lower detection percentage for Class A is not intuitive and needs to be analyzed, but let us see the Contrast Ratio ratio first.

The logistic regression model is used to see the **Contrast Ratio (CR)** effect on line-detection (MV). The dataset considers only night condition, dry road and divided roads to negate the effect of other variables. The test shows that contrast ratio and line-detection have a significant (P = 0.01) negative relationship. Table 28 shows the estimated coefficients, and it can be inferred that as the CR increases by one unit, the odd of lane detection decreases by 37% (1-Exp(B)). The relationship is not intuitive, similar to the lower lane detection percentage for Class A road sections. It will be investigated in the following paragraphs.

The **width of the lane** also significantly affects the lane detection performance of the vehicle, $\chi^2(3) = 109.5, P < 0.001$. Further, it is found that (Table 29):

- For lane width, less than 3m, the ratio of lane detection is significantly less.
- For lane width between 3m to 3.5m, the ratio of lane detection is significantly higher.
- For lane width above 3.5m, there is no significant difference in lane detection performance.

*Considering **lane width** as a factor affecting lane detection might not make sense at first. However, the lane width turned out to be an essential factor when analysing the lower lane detection percentage for the higher values of R_L and Contrast Ratio. For most of the route where lane width was below 3m, the lanes were not detected irrespective of the higher visibility of the lane markings*

Figure 36. The biased behaviour of vehicle Y for narrow lane width resulted in non-intuitive results of R_L and CR.

The **type of lane line markings** also significantly affects the lane detection performance of the vehicle, $\chi^2(3) = 418.2, P < 0.001$. Further, it is found that (Table 30):

- For continuous(left)-dashed(right) line markings on the road, the lane detection percentage is significantly less (Bad performance).
- For all the rest combinations of the line-markings, the lane detection percentage is significantly high (Good performance)

The type of line marking combined with the lane width further explains the non-performance of vehicle Y on the line-markings with high R_L**.** The dataset with lane width above 3m, line markings excluding continuous-dashed and night conditions was chosen to confirm this. It was found that such conditions existed for 17.2 Kms of the entire route, and for these 17.2 Kms, there was only one instance where line marking were not detected by the vehicle Y, i.e. 99.4% lines were detected (Table 34).

The **weather conditions** also significantly affected the lane detection performance of the vehicle, $\chi^2(2) = 64.2, P < 0.001$. Compared to Dry Road conditions, lane detection is significantly less for wet roads; however, it is significantly high for Rainy conditions (Table 31). The high performance during the rain is not intuitive, as one would expect lower performance during the rain due to the lower visibility. The rain conditions constitute only 3.5% of the total dataset and probably the reason for this.

The **lighting conditions** also significantly affect the lane detection performance of the vehicle, $\chi^2(2) = 76.7, P < 0.001$. The dataset used is lane width above 3m and line markings excluding continuous-dashed line-markings. It was found that the lane detection percentage was significantly high during the day and significantly low during dusk and night (Table 32).

The lane detection performance was found to be significantly different on **divided and undivided roads**, $\chi^2(1) = 308, P < 0.001$. The divided roads have significantly higher lane detection performance as compared to the undivided roads (Table 33). The lane detection performance was unaffected by the **straight and curved sections** on the road, $\chi^2(1) = 0.4, P = 0.51$.

Table 12 Binomial Logistic Regression Model for Machine Vision (vehicle Y)

Coding Variable	Description	B	S.E.	df	Sig.	Exp(B)	Interpretation
RL_class	A	*Reference*					
RL_class(1)	B	1.034	0.167	1	**<0.001**	2.812	Class B have higher detection percentage and Class E roads have lower detection percentage
RL_class(2)	C	0.108	0.175	1	0.537	1.114	
RL_class(3)	D	0.135	0.215	1	0.529	1.145	
RL_class(4)	E	-2.177	0.642	1	**0.001**	0.113	
LaneWidth	less than 3.5m	*Reference*					
LaneWidth(1)	3m to 3.5m	1.818	0.216	1	**<0.001**	6.157	Lane width above 3m have significantly higer lane detection percentage
LaneWidth(2)	3.5m to 4m	1.360	0.220	1	**<0.001**	3.895	
LaneWidth(3)	above 4m	2.921	0.494	1	**<0.001**	18.562	
Speed_cat	less than 60 Kmph	*Reference*					
Speed_cat(1)	60 to 80 Kmph	1.229	0.227	1	**<0.001**	3.418	Speed between 60 Kmph and 80 Kmph have higher lane detection percentage
Speed_cat(2)	80 to 90 Kmph	0.919	0.296	1	**0.002**	2.507	
Speed_cat(3)	above 90 Kmph	19.235	3472.574	1	0.996	225.600	
Weather	Dry Road	*Reference*					Weather condition don't have significant affect on the LKS performance
Weather(1)	Wet Road	-20.981	5460.527	1	0.997	0.000	
Weather(2)	Rain	-22.007	5460.527	1	0.997	0.000	
Lighting	Day	*Reference*					Dusk and Night have lower detection percentage compared to day time
Lighting(1)	Dusk	-1.372	0.263	1	**<0.001**	0.254	
Lighting(2)	Night	-0.649	0.234	1	**0.006**	0.523	
Road Type	Undivided	*Reference*					Divided roads have high lane detection percentage compared to undivided roads
RoadType(1)	Divided	0.983	0.189	1	**<0.001**	2.672	
Combined Line	Cont-Cont	*Reference*					Compared to continous-continous lane markings, all other type of lane markings have lower detection percentage
Combined Line(1)	Cont-Dash	-4.537	0.638	1	**<0.001**	0.011	
Combined Line(2)	Dash-Cont	-2.696	0.685	1	**<0.001**	0.067	
Combined Line(3)	Dash-Dash	-2.807	0.688	1	0.000	0.060	
Constant		23.405	5460.527	1	0.997	146.100	

While studying the effect of the individual variables, the dataset was modified to suppress confounding variables. Table 12 shows the logistic regression model built on the complete dataset of the Vehicle Y and considering all the variables at once (df = 1). The interpretation is given in Table 12 shows that the results are almost similar to the previous finding in this section (except for weather conditions). The model's overall fit can be seen in Table 13, which shows that the model has an accuracy of 80%.

Table 13 Confusion Matrix for the evaluation of developed logistic regression model

		Predicted Final_Scenario		Percentage Correct
		Lanes Not Detected	Lanes Detected	
Observed Final_Scenario	Lanes Not Detected	578	174	76.9%
	Lanes Detected	193	912	82.5%
Overall Percentage				80.2%

6.2 LKS lane positioning performance

This section describes the effect of the predictor variables (factors) on the MLP and SDLP, which are the measures for the lane positioning performance of the vehicle. The overall LKS positioning performance is shown in Figure 38. Unfortunately, both MLP and SDLP do not have a normal distribution of data, which means that parametric test cannot be used to analyse Lane positioning (Figure 39, Table 35, Table 36).

Like the previous section, the statistic involved is only explained in detail for one variable (speed), and then for the remaining variables, only the key points are given. The three questions to be answered while studying the effect of a variable on LKS are the same as the previous section. First, if there is a relationship between the vehicle speed and MLP/SDLP. Second, which of the speed categories affects the MLP/SDLP. Last, if the identified effect results in good or bad LKS performance.

First, a Kruskal-Walis test is run on the dataset for both vehicles Vehicle X and Vehicle Y, to check if there is a relation between the vehicle speed and MLP/SDLP. For Vehicle Y, the test results in Table 14 shows that both MLP and SDLP are not related to vehicle speed since the P-value is above 0.05. For Vehicle X, the results in Table 15 show that MLP is not related to vehicle speed, but the SDLP is significantly ($P < 0.05$) affected by the vehicle speed.

Table 14 Kruskal-Wallis Test - Speed vs LKS Positioning (vehicle Y)

Null Hypothesis	Sig.	Decision
The distribution of **MLP** is the same across categories of Speed_cat.	0.274	Retain the null hypothesis.
The distribution of **SDLP** is the same across categories of Speed_cat.	0.538	Retain the null hypothesis.

Table 15 Kruskal-Wallis Test - Speed vs LKS Positioning (vehicle X)

Null Hypothesis	Sig.	Decision
The distribution of MLP is the same across categories of Speed_cat.	0.37	Retain the null hypothesis.
The distribution of **SDLP** is the same across categories of Speed_cat.	**0.035**	Reject the null hypothesis.

Second, pairwise comparison tests for Vehicle X (Table 16) between the vehicle speed and SDLP answer the remaining questions. The SDLP has a significant difference between the vehicle speed 'less than 60 Kmph' and '60 to 80 Kmph'.

Table 16 Pairwise Comparison of Speed and SDLP (vehicle X)

Sample 1-Sample 2	Test Statistics	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
80 to 90 Kmph-60 to 80 Kmph	15.04	27.24	0.55	0.581	1.000
80 to 90 Kmph-above 90 Kmph	-21.21	35.92	-0.59	0.555	1.000
80 to 90 Kmph-Less than 60 Kmph	76.17	33.44	2.28	0.023	0.136
60 to 80 Kmph-above 90 Kmph	-6.17	2.53	-0.24	0.807	1.000
60 to 80 Kmph-Less than 60 Kmph	61.13	21.62	2.83	0.005	**0.028**
above 90 Kmph-Less than 60 Kmph	54.96	31.86	1.73	0.085	0.507
Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.					
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.					

Further, for the above two mentioned speed categories, the median of SDLP in the whisker-box plot and their corresponding ranks in Figure 17 shows that the Vehicle X has a high SDLP for speed less than 60 Kmph compared to speed between 60 to 80 Kmph. The higher ranks for the speed category means the higher value of SDLP. The general linear trend can be found using the Jonckheere-Terpstra (J-T) test, which shows that J-T statistics is -2.143 for SDLP vs speed. The absolute value above 1.65 shows that the test is significant, and the negative sign indicates a trend of decrease in SDLP for increasing vehicle speed, as explained in the section 15.5.6 of the book [47].

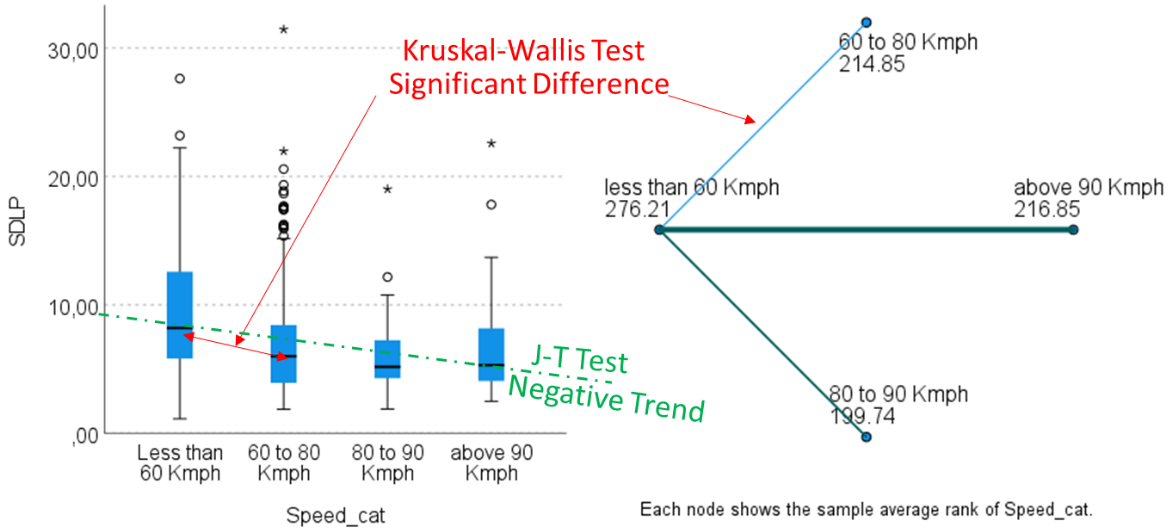


Figure 17 (a) Whisker-Box Plot (b) Ranks from Kruskwalis-Test for vehicle X SDLP vs speed

To say in simple terms**,** the effect of the **vehicle speed** on the lane positioning performance is that:

- The MLP is not affected by the vehicle speed for both Vehicle Y and Vehicle X (Good Performance)
- The SDLP for Vehicle Y is not affected by the vehicle speed (Good Performance)
- The SDLP for Vehicle X is affected by the vehicle speed, and it is found that SDLP for speed less than 60 Kmph is significantly higher than the speed between 60 and 80 Kmph. In general, there is a negative trend, which means the higher vehicle speed has less SDLP (Good trend)

The detailed statistic output results for the remaining variables are given in APPENDIX J – Lane Positioning performance, and only the primary outcomes are reported in this section.

The Kruskal-Wallis test showed that SDLP for both vehicle Y and Vehicle X does not vary amongst different **line-markings** (Table 37). However, the MLP was significantly affected by the type of lines present on both sides of the lane ($\mathrm{P} < 0.001$). A post hoc pairwise comparisons tests were performed to follow up the findings for both vehicle Y and vehicle X for Day 1 and Day 2 separately. It was found that the MLP significantly differ across "Dashed(left) - Continuous(right)" and "Continuous(left) - Continuous(right)" line markings for both Vehicle X and Vehicle Y. However, a reverse trend is found (Figure 40, Figure 41) between Vehicle Y and Vehicle X amongst the category of line-markings:

- When both right and left markings have continuous lines, the MLP is lowest for Vehicle Y (Good performance) and highest for Vehicle X (Bad performance)
- For all the remaining type of lane marking combinations, the MLP is comparatively higher for Vehicle Y (Bad performance) and comparatively lower for Vehicle X (Good performance)

A Mann-Whitney test is performed to see the effect of **straight and curved sections** on the lane positioning. The test shows that the difference in the MLP between the straight and curved sections is not significant for both Vehicle Y (P=0.292) and Vehicle X (P=0.952). Likewise, the SDLP for straight and curved sections is not statistically different for Vehicle Y (P=0.952); however, for Vehicle X, the difference in SDLP is significant (P=0.002). Furthermore, the test (Figure 42) for Vehicle X shows that the mean rank is higher for curved sections than the straight sections, which means the recorded values of SDLP during the curved sections are higher than the straight sections. In simple terms:

- The MLP is not affected by curved sections for both Vehicle Y and Vehicle X (Good Performance)
- The SDLP for Vehicle Y is not affected by the curved sections (Good Performance), but for Vehicle X is found to be higher for curved sections (Bad performance).
- However, it should be noted that the deficient performance for Vehicle X is w.r.t. straight and curved sections only and not compared to Vehicle Y. Figure 42 (b) shows that SDLP for Vehicle X is comparatively less than Vehicle Y for straight and curved sections.

Out of the 90 **curves** encountered, Vehicle Y executed 19, and Vehicle X executed 38 curves without any human intervention. The analysis in Figure 43 shows that both Vehicle Y and Vehicle X could not autosteer the curves with the compound profile. In addition, Vehicle Y could not execute any sharp curve with a radius below 100 m. However, the data could not be analysed statistically due to insufficient cases present amongst different curves.

To study the effect of **lane width** on LKS performance, only the data from day one is considered due to the calibration error of the Front Camera (section 5.9) for day 2. The results of the Kruskal-Walis test are given in (Figure 44, Figure 45), and the main points are:

- The MLP of Vehicle Y remains the same for different lane width ($\chi^2(1) = 0.8, P = 0.38$)
- The MLP of Vehicle X differs significantly for different lane width ($\chi^2(1) = 30.3, P < 0.001$). Further, it is found that Vehicle X positions itself closer to the lane centre on the lanes width above 3m than for the lanes with a width less than 3m (figure).
- The SDLP differs significantly for both Vehicle Y ($\chi^2(1) = 7.3, P = 0.07$) and Vehicle X ($\chi^2(1) = 10.3, P = 0.001$) for different lane width. It is found that for lane width above 3m, the SDLP is significantly higher than SDLP for lane width below 3m.

In general, the broader **lane width** results in better MLP (close to lane-centre) but a higher SDLP.

While studying the effect of **weather conditions** on LKS performance, only the data for the straight road is considered. A Kruskal-Wallis H test showed that there was a statistically significant difference in MLP between the different weather conditions for Vehicle Y ($P = 0.016$) as well as for Vehicle X ($P < 0.001$). The SDLP was also found to be statistically different in the considered weather conditions for both Vehicle Y ($P < 0.001$) as well as Vehicle X ($P < 0.03$). Further, the pairwise comparison test shows that changes in weather conditions from Dry roads to wet roads or rainy conditions result in higher MLP and higher SDLP (Figure 46, Figure 47).

The **lighting conditions** significantly affected the MLP and SDLP for both Vehicle Y and Vehicle X (Figure 48, Figure 49). It is found that the night condition has the best lane positioning performance (both MLP and SDLP). The exception is the MLP for Vehicle X, which significantly differs in all three conditions. The best performing conditions for Vehicle X MLP follow the order: Dusk, Night and Day. In general, it can be said that the vehicle maintains its position best during the night drive on dry roads.
The **divided/undivided roads** do not affect the MLP of Vehicle Y. However, on the undivided roads, Vehicle X position itself towards the left of the lane centre. The figure shows that the MLP for undivided roads is between -10 cm and -20 cm, while for the Divided Roads, the MLP is mostly between -10 cm and 0 cm. The Mann-Whitney U test Figure 50 identifies the difference in data distribution with very high significance (P < 0.01). Therefore, Vehicle X performance on the undivided roads is considered a bad performance because the vehicle is closer to the oncoming traffic. The same thing was noticed during the conduction of the experiment as it was very uncomfortable for the driver to keep automation ON for Vehicle X on undivided roads.

6.3 Identification of Hotspots

The hotspots were defined as the road infrastructure conditions where the LKS: (i) failed to detect the lanes or (ii) when the vehicle is in control but failed to keep itself within the lanes or (iii) those conditions where the MLP and SDLP are above 10 cm. The most challenging part in identifying hotspots was to detect the defined event of the hotspot, as these occur momentarily for a fraction of a second.

For Vehicle Y, the developed dashboard sign detection tool (section 5.1) precisely identified the hotspot condition (i) and (ii) as Case 2 (Lanes not detected) and Case 4 (Autosteer fails to keep the vehicle within lanes), respectively, given in Table 6. On the other hand, since Vehicle X detected the lines 100% of the time, the hotspot was defined as Case 2 (Autosteer drops) in Table 23. These identified hotspots can be seen in Figure 18 (a). Furthermore, the lane position calculation tool (section 5.3) identified the hotspot condition (iii) for both Vehicle Y and Vehicle X, and the results are given in Figure 18. Moreover, these tools took 30 measurements per second, thus precisely identifying all the hotspots encountered during the route.

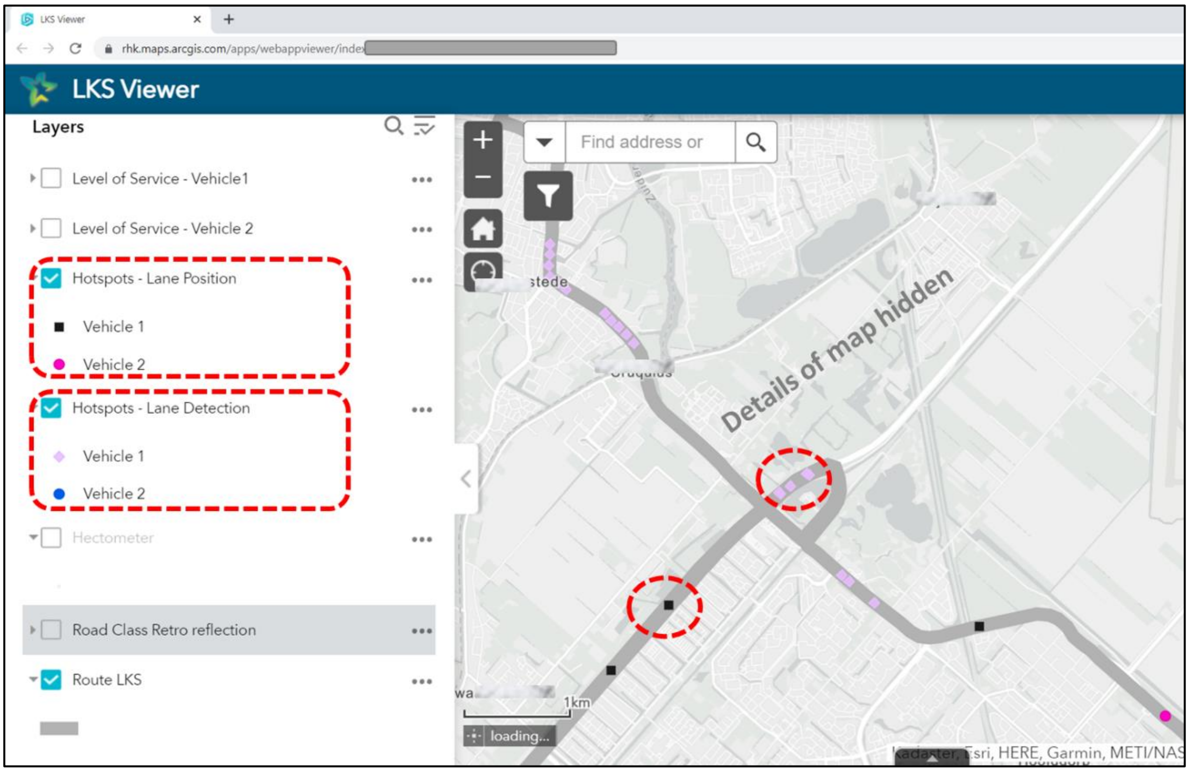


Figure 18 LKS Hotspots (a) Lane Detection (b) Lane Positioning (confidential)

6.4 Level of Service (LoS) for LKS

The LoS is defined to give Road Authorities an insight into the readiness of the road infrastructure for the LKS. The MV performance (line detection) and Lane Positioning performance (MLP and SDP) of the LKS are combined to calculate the LoS. The LoS is calculated as per thresholds in Table 17. The literature research in section 2.3 found no existing threshold values for MLP and SDLP for automated driving to classify them into safe/unsafe situations. Hence these thresholds are decided based upon the performance of the two vehicles considered in this research.

Table 17 Defined LoS for the LKS

LoS 0	LoS 1	LoS 2	LoS 3	LoS 4	LoS 5
Lanes Not Detected	Lanes Detected	MLP > 10 cm SDLP > 10 cm	MLP > 10 cm SDLP <= 10 cm	MLP <= 10 cm SDLP > 10 cm	MLP <= 10 cm SDLP < =10 cm

Infrastructure LoS 0 represents the section of road infrastructure where LKS could not detect the lines, which means no LKS support to the driver, thus the most unsafe situation. At LoS 1, the vehicle will be assisting the driver and thus a better situation than LoS 0. However, once the lane is being detected by the vehicle, the next step is to calculate how close the vehicle is positioning itself to the lane centre. LoS 2 represents when the vehicle is farthest, and LoS 5 represent when it is closest to the lane centre.

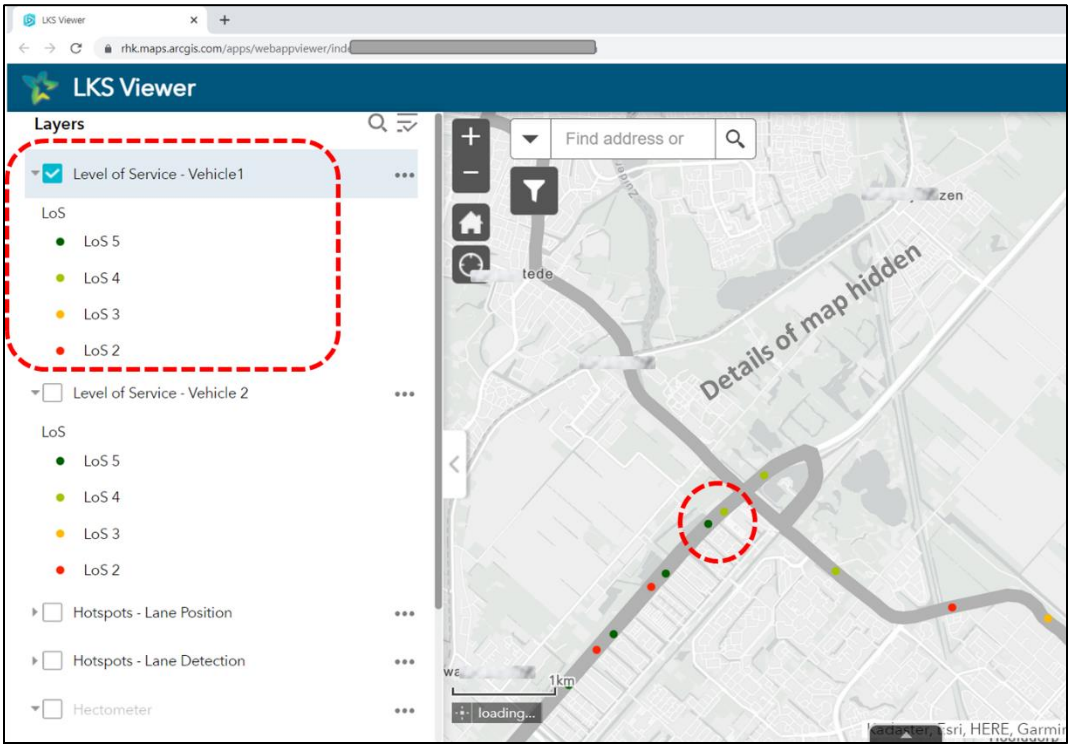


Figure 19 Level of Service for LKS (confidential)

Figure 19 shows the LoS based on LKS performance of the first day. It can be seen in Figure 19 that there is no LoS 0 because Vehicle X detected 100% of the lines. Figure 57 similarly shows the LoS for the second day.

6.5 Prediction Models

To predict the performance of the LKS, two models are built using the Neural Network. The first model predicts the Machine Vision performance of the vehicle. The predictor variables for this model are retro-reflection of line markings, lane width, type of line marking (continuous/dashed), road type (divided/undivided), weather and lighting conditions. These variables are shortlisted based upon the factors affecting MV performance (section 6.1). The second model predicts the Lane positioning performance of the vehicle, i.e. MLP and SDLP. The predictor variables are the same for this model as well, except for the retro-reflection of line-markings. These are based upon the factors affecting lane positioning performance (section 6.2). The training dataset used for both the models is different and explained in section 5.2. The Lane Detection (MV) model uses the dataset of route segmented into different sections of 100 m, while the Lane Positioning model uses segments of approximately 1 Km.

The prediction model can predict the LKS performance on a different route with different weather and lighting conditions. For example, suppose the whole driven route had a lane width between 3m and 3.5m, and the line markings were of continuous type on both sides of the lane. The impact of these changes in the lane width and line marking can be seen in Figure 20. Further, Figure 20 (a) shows the LKS performance when there were no changes made in the driving conditions and Figure 20 (b) shows the LKS performance when the mentioned changes are made (lane width = 3m to 3.5m and line type = continuous). The ODD in and ODD out refers to the situation when the LKS can detect the lane or unable to detect lanes, respectively. The interface to interact with the prediction tool is shown in Figure 58. The plotted locations in Figure 20 (b) can also be seen in the form of hectometers in Figure 59.

Figure 20 Model Output (a) Original Performance (b) Change in LKS performance (confidential)

Figure 21 combines the results of Figure 20 (a) and (b) in one map for a better understanding. Box 1 in Figure 21 represents where the change in driving condition has negatively impacted the initially inside ODD situation into outside ODD. Box 2 represents the situation where the change in driving condition had a positive effect, as the outside ODD conditions are now inside.

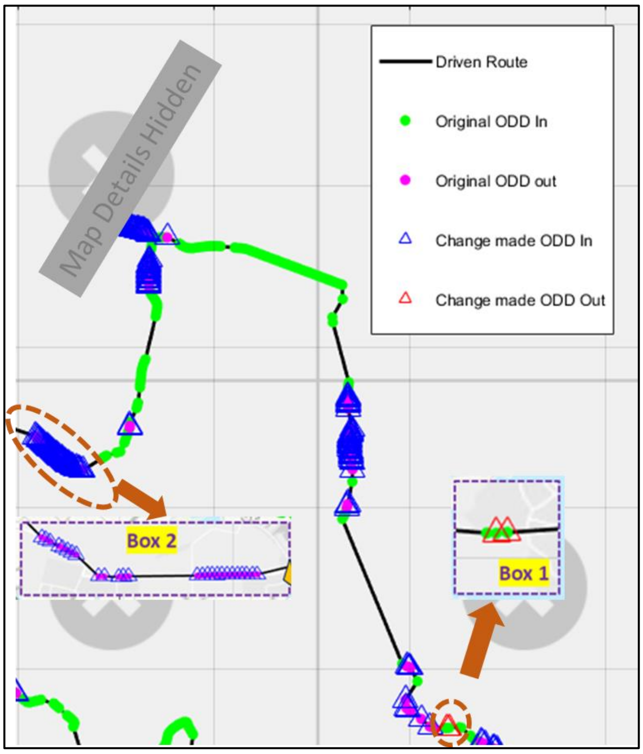


Figure 21 Using the Prediction Model for assessment of road network (confidential)

6.6 Validation of the Models

The dataset was divided into three parts: 70% for training, 20% for validation, and 10% for testing to validate the model. The division was random to have variation in each of the datasets. The graphs showing the tracking of loss function and accuracy of the models are given in Figure 51, Figure 52 and Figure 53. The accuracy of the developed models in the form of a confusion matrix is given in Figure 54, Figure 55 and Figure 56. The summary of the results is given below in Table 18:

Table 18 Validation of the developed LKS models

Current Model	Validation Data Accuracy	Test Data Accuracy
Lane Detection (MV)	80.1%	83.9%
Lane Positioning (MLP)	74.3%	78.5%
Lane Positioning (SDLP)	80.7%	78.5%

HAN_UNIVERSITY
OF APPLIED SCIENCES

7 DISCUSSION

In this chapter, the results from the previous chapter are further interpreted. A discussion is presented on how Road Authorities (RA) can use the results from this thesis towards the ongoing development in vehicles with Automated Driving System (ADS). Finally, the objectives of this research and the developed prediction model are reviewed.

Considering the readiness of the infrastructure for the cars that can read the road, it is seen that on the considered N-roads, the lane-detection percentage was only 57% for Vehicle Y while 100% for the Vehicle X. The low performance of Vehicle Y might question the infrastructure readiness; however, the retro-reflection survey shows that 85% of the driven route had retro-reflection above 150 mcd/m^2/lux, and 89% of the route had contrast-ratio above 90%, which indicates the higher visibility and good conditions of the line-markings.

The probable reason for the significant difference in the performance of the two vehicles could be the difference in the algorithm used by the respective vehicle manufacturers (OEMs). In section 2.1, it was seen that the two majorly used algorithm Computer Vision (CV) and Deep Learning (DL), could have a significant difference in performance. The SLAIN project [22] also concluded that while for the Computer Vision-based algorithms, the visibility of the lane markings (retro-reflection and Contrast Ratio) is critical; for the Deep Learning-based algorithms, the uniformity of the lane markings is essential. Therefore, the Deep Learning-based algorithm might be the reason for Vehicle X's unaffected Machine Vision performance. However, there was no major non-uniformity observed in the line marking during the drive. The Deep Learning-based algorithms are also more robust to the adverse environmental conditions as the algorithm uses not only the contrast between the road and line markings but also several other features learned using the training dataset. Vehicle X mentions in [48] how it uses the data from the fleet to train its Deep Learning-based algorithm. Vehicle X uses a variety of dataset, and an example of it is shown in Figure 60, and the overview of Vehicle X's Deep Learning-based algorithm is given in Figure 61. Unfortunately, it was not possible to get an insight into the kind of algorithms used by Vehicle Y for the Lane-Keeping System (**LKS**).

Section 6.1 presented the factors affecting the Machine Vision performance of Vehicle Y. It was found that the lane-detection is significantly affected by the retro-reflection of the lane markings, lane-width, type of line markings, divided/undivided roads, vehicle speed, weather, and lighting conditions. The majority of obtained results align with previous research given in APPENDIX A – Factors affecting the LKS Performance. However, there were some non-intuitive results, which also did not match with previous research. These were partly discussed in section 6.2 and further discussed here in this chapter.

For some road sections having very high visibility of lane markings (high retro-reflection and contrast ratio of line-markings), the vehicle could not read the lines. The in-depth analysis showed that for such situations, either lane width was below 3m or there were 'continuous(left)-dashed(right)' line markings on the road. To further explore this non-intuitive behaviour of the vehicle, the standards for lane width in Japan (Vehicle Y's Head office) were checked. It was found that National expressways and highways in Japan have lane width above 3m while other roads have lane width below 3m. So, there is a possibility that Vehicle Y's onboard camera calculates the lane width and does not allow the Autosteer functionality whenever the lane width is below 3m to restrict the Lane-Keeping System (LKS) only to highways and expressways. Also, the owner's manual of Vehicle Y mentions that Autosteer will not function in too narrow and too wide lines [49]. However, in the manual, like every other vehicle manufacturer manual, only general statements are made, and it is not defined that what is too narrow or too broad. To conclude, based upon this research, lane width below 3m is an outside **ODD** (Operational Design Domain) condition for Vehicle Y, and the onboard sensors on the vehicle identify this situation themselves.

Section 6.2 presented the lane positioning performance, Mean Lane Position (**MLP**) and Standard Deviation of Lane Position (SDLP), for the automated driving for both Vehicle Y and Vehicle X. The MLP is significantly affected by the type of line-markings (dashed/continuous) and lane width, which means that the vehicle is either using the lane lines information to position itself or the vehicle functionality is limited. While for the narrow or wide lane width, the significant difference in MLP could be due to the vehicle's algorithm limitations related to automated steering, it is difficult to understand the difference in MLP based upon the type of line-markings (continuous/dashed). In Vehicle X, 100% of the lines are detected, so MLP should not vary significantly due to different line-markings. So, the probable reason is that vehicles use the line information to identify the different scenarios, such as divided and undivided road, which affects the MLP.

Going further into the discussion, Mean Lane Position **(MLP)** for Vehicle X is negative on the undivided roads, and it can lead to unsafe situations as the vehicle is more towards the left and closer to the oncoming traffic. It is non-intuitive that why Vehicle X would place itself towards the oncoming traffic on the undivided roads. As discussed, that the vehicle uses lane line information to identify the different scenarios, so Vehicle X's negative MLP might be due to the difference in the colour of line-markings between the United States (Vehicle X Head Office) and the Netherlands. In the U.S., yellow lines separate the traffic flowing in the opposite direction, while white lines separate lanes that travel in the same direction. Since in the Netherlands, only white lines are used, this might be the reason why Vehicle X's MLP is negative. To confirm this, more data is required, especially for the MLP for yellow lines. The previous research by Bhusari et al. [29] in the Netherlands also shows the negative MLP for Vehicle X.

It was found that both vehicles struggle to execute the compound profile curve. McCall and Trivedi [50] explain that during the development of the LKS algorithm, the road can be modelled as linear, parabolic or spline, depending upon the choice that requires a trade-off between high stability or a high TLC (Time to Line Cross). The tradeoff becomes more critical on curves where the look-ahead distance is small. Additionally, if the curve profile is also not simple, it further makes it difficult to model the road ahead. The low performance of the vehicle on a curved section with the complex profile is similar to the observation by Tapsi et al. [51] and Nitsche et al. [52].

The lane detection, Mean Lane Position (MLP) and Standard Deviation of Lane Position (SDLP) for the vehicle is significantly affected by the lighting and weather conditions because of the changing visibility conditions. Combining the adverse weather conditions with narrow lane width on an undivided road and the vehicle's biased behaviour to position itself toward the oncoming traffic can lead to dangerous situations. So, the question is how to deal with this situation and the role of vehicle manufacturer (OEM) and Road Authority (RA) in it. In a broader context, how to ensure the automated vehicle does not exit its ODD (Operational Design Domain) or ensure the safe operation of Lane-Keeping System (**LKS**).

The one obvious and most quoted solution to the posed question is the synergy amongst the vehicle manufacturers and road authorities to ensure the safe operation of the Automated Driving System

(ADS). However, this does not seem to be happening, and there seem to be two reasons for that. First, by its definition, the Operational Design Domain (ODD) needs to be defined by the vehicle manufacturer (OEM) designing the automated feature and not meant to be measured by a testing agency or Road Authorities (RAs). However, the defined ODD is never shared by the vehicle manufacturers, and thus, Road Authorities never get an insight into the problem. Second, the different vehicle manufacturers have different abilities, as explained in this research, and these abilities are certain to change in the coming years. This incapacitates the Road Authorities in doing any physical infrastructure changes as it involves cost, time, and the uncertainty if that change will still be beneficial after few years.

The methodology used in this research to identify the Level of Service (LoS) for the road network can help Road Authorities (RAs) have an insight into the vehicle performance, enabling them to know how the current Automated Vehicles interact with the infrastructure. The results from this research can help Road Authorities to have a better dialogue with vehicle manufacturers (OEMs) as instead of asking what the infrastructure requirements are; the Road Authorities can ask why the vehicle is not performing on the given set of infrastructure conditions, such as lane width, line marking colour as identified in this research. The data from current research can bring better outcomes from ongoing roundtable discussion about the role of vehicle manufacturers and Road Authorities and bring consensus among various stakeholders.

The hotspots and calculated Level of Service (LoS) in section 6.3 and 6.4 are valid only for the driven test route and for the encountered road conditions. However, the developed prediction model can be used by RAs to identify the hotspots that can result due to specific type of interaction amongst the road infrastructure, driving conditions, and different OEM vehicle, which could have otherwise gone unnoticed. The approach is similar to the one proposed by the EuroRAP [53] for network-wide road assessment, focusing primarily on identifying “black spot” and route safety. Their method also involves dividing the road into a section of 100 meters and then calculating relative risk scores to classify the road into a Star Rating scale that expresses the safety capacity of a road section for each road user in a 5-Star scale that can be used as an international benchmark. In this research, the network is divided into 5-LoS, and the aim would be to have all the network with level 5. The lower Level of Service (LoS) does not necessarily mean that road infrastructure changes need to be made; it might be due to some unaddressed issue by the vehicle manufacturer. When the Road Authorities point out such issues to vehicle manufacturers, it will automatically lead to synergy.

The objective of the research to develop a methodology to identify the required infrastructure changes for the safe operation of the Lane-Keeping System (LKS) is accomplished. The developed methodology identified the factors affecting LKS, which can be used in combination with the prediction model to decide the infrastructure changes; however, the larger question is if those changes should be made. In this research, both test vehicles had a significant difference in lane detection performance. Now one approach is to benchmark the low performance of Vehicle Y to decide the infrastructure changes, or second is to conclude that the infrastructure does not require any changes based on the performance of high performing vehicle Vehicle X. However, the discussion in this chapter showed that the identified shortcomings in the considered test route could be addressed by a dialogue between the vehicle manufacturers and Road Authorities rather than straightforwardly doing any physical infrastructure changes.

8 CONCLUSION

The decision by the EU to mandate the set of Automated Driving features have created a buzz in the automotive industry and amongst the various agencies such as Road Authorities (**RA**). The Road Authorities are concerned to know if the road infrastructure is ready for automated vehicles. However, the Road Authorities have limited access to the technology being used by the vehicle manufacturers (**OEMs**), which makes it difficult to assess the infrastructure. Tapsi et al. [51] concluded that the critical insight into the **ODD** (Operational Design Domain) of Automated Vehicles is not sufficiently available to the Road Authorities, which incapacitate them to make any policy recommendations. Instead, the Road Authorities have to determine the limitations of these automated vehicles experimentally. Several studies have suggested the various infrastructure changes that should be made to ensure the safe operation of such automated systems. However, most of them are based on theoretical research, and only a few studies are based on practical research.

This research adopted the empirical approach to answer the posed question about the readiness of the road infrastructure. In this study, a test route of about 250 Kms was selected based on road age, variation in the lane width, divided and undivided roads, curved sections with varying curvature. To get an insight into the quality of road infrastructure, a survey was conducted to measure the retro-reflection of the line-markings. Two different OEM vehicle based upon the lowest and highest **LKS** (Lane-Keeping System) performance in the EuroNCAP assessment were selected. The vehicles equipped with sensors were driven on the test route to measure the LKS performance in varying driving condition. The vehicle speed, road geometry, weather and lighting conditions were also recorded. The resulting dataset was then used for empirical analysis to see the LKS performance against the different measured variables. The LKS performance was based upon the Machine Vision (**MV**) and lateral lane positioning performance.

The Machine Vision (MV) performance was measured using the lane detection percentage of the vehicle. The most critical performance measures of the visibility of the line marking were found to be retro-reflection and contrast ratio. These measures have been widely used in recent studies to ensure the readiness of the infrastructure for automated driving. The survey on the chosen test route shows that 85% of the driven route had retro-reflection above 150 mcd/lx/m2, and 89% of the route had contrast-ratio above 3:1. Thus, the survey results of the test route indicate well-maintained roads with good condition of the line-markings.

The Machine Vision (MV) performance of the Vehicle X showed that the vehicle was unaffected by the encountered driving conditions as the vehicle detected the lane markings 100% of the time. However, Vehicle Y was able to detect the lines only 57% of the time. The statistical analysis shows that Vehicle Y's MV performance is dependent upon various factors. First, it was found that vehicle speed above 80 Kmph results in better lane detection. Second, it was found that when the retro-refection of the line markings is below 150 mcd/lx/m2, or when there is a "Continuous(left)-Dashed(right)" combination of lines on the lanes, the lane detection percentage is significantly less. Further, the wet road conditions also severely affect the lane detection performance. Compared to night conditions, lane detection was significantly high during dusk and less during the daytime. The unexpected low performance of Vehicle Y's MV for line marking with RL above 200 mcd/lx/m2 was further analyzed. It was identified that this unexpected performance is due to the confounding effect of the Lane Width. It was found that the vehicle does not detect the line markings for the lanes with lane width below 3m. The possible reason for this was identified as the existing standards for lane width in Japan, which Vehicle Y could have adopted to distinguish between the different types of roads in order to distinguish the ODD in and ODD out situation.

The lane positioning performance of the vehicle was measured using the Mean Lane Position (**MLP**) and Standard Deviation of Lane Position (**SDLP**). It was found that for both vehicles, MLP is affected by the type of line markings, width of the lane, weather and lighting conditions. However, the vehicles had opposite behaviour for a different type of line-markings; for example, when both right and left markings have continuous lines, the vehicle Y positioned itself closest to the lane centre while Tesla positioned itself towards the far left, as compared to other types of line-markings. Further, it was found that the MLP for Tesla for the undivided road is between -10 cm and -20 cm, while for the Divided Roads, the MLP is mostly between -10 cm and 0 cm. The unexpected behaviour of Tesla to position itself closer to the oncoming traffic on undivided roads is expected due to the difference in the colour of the line marking used by the Road Authorities to differentiate the traffic flowing in the same or opposite direction. Contrary to the previous research, it is found that MLP is not affected by the speed of the vehicles, and there is no significant difference in MLP between the straight and curved sections. The SDLP was mainly affected by the lane width and the visibility conditions (weather and lighting).

An **LKS** (Lane-Keeping System) model was developed using the collected dataset to predict the performance of Machine Vision and Lane Positioning for a similar set of road geometry and different lighting and weather conditions. This LKS prediction model can help RAs (Road Authorities) to get insight into the LKS behaviour of the different vehicle manufacturers. It can also help them to evaluate the road infrastructure for readiness toward automated driving. Furthermore, the LKS model also answered the RQ2 that how LKS performance can be used to define the **ODD** (Operational Design Domain). As discussed in the previous chapter, the ODD should be defined by the vehicle manufacturers who design the feature and not by the testing agencies. Thus, results from the LKS prediction model are used to identify the different Level of Service (**LoS**) of the road infrastructure in the given conditions and not to define the ODD for LKS.

The Dashboard sign detection tool, which was developed using the Deep Neural Network, enabled to precisely identify the various situations like lane departure for the analysis. The different lane departure and lane not detected cases were used to identify the hotspots where LKS can fail. The lane positioning tool precisely measured the lane position. Combining the results from these two tools, five different service levels were defined, level 0 and 1 accounting for the lane detection status and level 2 to level 5 accounting for the lane positioning. The developed prediction model can be used to measure the LoS for an extensive network. However, the accuracy of the current prediction model is not very high (70% - 80%), the main reason being the less amount of data and the low number of features.

Finally, to conclude, the methodology of this research resulted in identifying the factors affecting LKS, which could lead to the unsafe situation during automated lane-keeping, and the method was further extended in the form of a prediction model to identify such situations even for unseen conditions.

8.1 Recommendations to Road Authority

The technologies used by the vehicle manufacturers (**OEMs**) for Lane-Keeping System (**LKS**) will keep evolving as different OEMs take a different approach to better the performance of LKS. The Road Authorities (**RAs**) can keep up with the OEMs advancements if they constantly have data-driven dialogues. For example, the shortcoming identified in the functionality of two OEM vehicles can be discussed by the RAs with respective stakeholders to engage in a healthy conversation, which can set the momentum for future readiness of infrastructure (physical and digital) to facilitate automated driving. On the other hand, there is a technology push coming from the vehicle manufacturers (OEMs) towards the Road Authorities (RAs). This stresses the need for the RAs to make data-driven decisions and better position themselves in this dialogue. For example, in this project, the infrastructure is state-of-the-art; however, the vehicle performance indicates that OEMs/ sensors/ hardware suppliers need to step up to this state-of-the-art service level. Using the methodology proposed in this project as a starting point, the RAs can now indicate the standards to which OEMs need to adhere to and at the same time also maintain the standards/ level of service that they communicate to the OEMs.

The prime purpose of mandating the **ADAS** (Advanced Driving Assistance System) feature is to increase road safety and reduce traffic accidents. The Road Authorities strive to contribute to how the safe operation of such ADAS features can be ensured. However, changing the road infrastructure is not advisable to be taken based upon few practical studies. Various stakeholders such as RDW and CROW should be engaged in a dialogue to advise vehicle manufacturers to make their defined ODD (Operational Design Domain) available.

This research identified that vehicles take decisions based upon the different lane markings and lane width. Therefore, it is advised to have uniform standards for the line marking across Europe, and this information then should be passed on to the vehicle manufacturers (OEMs). The uniform markings are also advised by the European Union Road Federation (ERF) and demanded by the OEMs. The earlier the decision to make the lines uniform across Europe is taken, its implementation can then be made as a part of the regular maintenance. Nevertheless, it is also important to align design standards within different regions with the same country; this research helps in identifying the infrastructural no-regret measures that can help with this both national and regional level. For example, the results of this research indicate the advantages of using continuous line markings on both sides of the lane for an undivided road. It also highlights the impact of the sharpness and type of curves on vehicle performance. These are few areas that the road authorities could focus on in the near future.

It is advised to start digitizing the infrastructure from now, and the maintenance information should be stored in a digital platform. This in turn, also can be an input for the technical standards for Digital Twins of the infrastructure (to facilitate automated driving), which is of high importance across road authorities in Europe. Furthermore, having digital information will open up the doors for many innovative solutions, such as the developed prediction model in this research. The prediction model can be used by the Road Authorities to gain a better understanding of the functioning of the automated features, which is currently not shared by the vehicle manufacturers. More than using this prediction model to identify the changes required for the infrastructure, it is advised to start using it early in the shadow mode to understand the ongoing technological advancements better.

9 LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

The preliminary analysis shows that Lane-Keeping System (LKS) struggles in executing curves with complex profile and high sharpness. However, due to insufficient data, the statistical analysis could not be performed, and neither the parameters related to the curve could be included in the prediction model. Therefore, it is recommended to conduct multiple driving sessions with varying speed on a route with different curves.

The prediction model developed in this research obtained an accuracy between 70% and 80% on the unseen data. The primary reason to not obtain very high accuracy is the insufficient quantity and variety in the dataset. Current models use only five to six features and a limited dataset to classify the Lane-Keeping System (LKS) performance. While training on a dataset like these, as the loss function is minimized, there is always a problem of overfitting. As a result, the model will perform very well on the training data but fails to generalize to unseen data situations. To further improve the prediction model, more features need to be added by including different type of variables. In addition, the experiment test should be conducted for more days to increase the number of observations. It is also possible and highly recommended to use existing dataset such as HD (High Definition) Maps from TomTom to capture the road geometry and driving conditions.

Chapter 7 discussed the potential of using the prediction model. The use can further be extended if the data is collected on a large scale directly from the automated vehicles, for example, through CAN bus. However, to know the reliability of the data, research is needed on the repeatability of the Lane-Keeping System (LKS) performance. Unfortunately, it was not possible to do repeatability analysis in this research as the statistical tests require to drive for a minimum of three times on the same situation.

While studying the factors affecting the lane-detection (MV) performance, it was identified that one of the prime reason for lane not detected was not due to some infrastructural shortcoming but due to the vehicle manufacturer's decision or the limitation of the Lane-Keeping System being not operational for lane width below 3m. While studying many factors such as retro-reflection and Contrast Ratio, such data of lane width was filtered out to account for it. However, for many other factors, such as weather conditions and line type, it was not possible to filter out this data due to the scarcity in the dataset. Hence, there can be a confounding effect of lane width in such a situation. Second, the developed lane width calculation tool had inaccuracies in itself (section 5.8). Therefore, only a general trend in Mean Lane Position (MLP) and Standard Deviation of Lane Position (SDLP) for the different lane width was found in this research, and the details could not be analyzed further because of the error in lane width data. For future research, it is suggested to use a robust algorithm for distance calculation using the camera. The Mobileye can also be used as an alternative to measuring the Lane Position and Lane Width. Using two cameras on the side of the vehicle can also result in better accuracy, but the only issue is that they cannot be used during rainy conditions or on wet roads.

REFERENCES

[1] WHO, “Global status report on road safety 2018,” Geneva, 2018. Accessed: May 28, 2021. [Online]. Available: https://www.who.int/publications/i/item/9789241565684.

[2] H. Stipdonk *et al.*, “Ranking EU Progress on Road Safety,” Belgium, 2020. Accessed: May 28, 2021. [Online]. Available: www.etsc.eu/pin.

[3] European Commission, “Handbook on the external costs of transport,” Brussels, 2019. Accessed: May 28, 2021. [Online]. Available: http://publications.europa.eu/resource/cellar/e021854b-a451-11e9-9d01-01aa75ed71a1.0001.01/DOC_1.

[4] European Commission, “EU Road Safety Policy Framework 2021-2030 - Next steps towards ‘Vision Zero,’” Brussels, 2019. Accessed: May 28, 2021. [Online]. Available: https://ec.europa.eu/transport/sites/default/files/legislation/swd20190283-roadsafety-vision-zero.pdf.

[5] SAE International, “J3016B: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles - SAE International,” 2018. Accessed: May 28, 2021. [Online]. Available: https://www.sae.org/standards/content/j3016_201806/.

[6] European Commission, “New safety features in your car,” Mar. 25, 2019. https://ec.europa.eu/docsroom/documents/34588 (accessed May 28, 2021).

[7] Government of the Netherlands, “Self-driving vehicles | Mobility, public transport and road safety.” https://www.government.nl/topics/mobility-public-transport-and-road-safety/self-driving-vehicles (accessed May 28, 2021).

[8] R. Schram, “Euro NCAP’s first step to assess Autonomous Driving System,” 2019, [Online]. Available: https://cdn.euroncap.com/media/53191/euro-ncap-s-first-step-to-assess-automated-driving-systems.pdf.

[9] S. Lawson, “Roads that Cars Can Read REPORT III: Tackling the Transition to Automated Vehicles,” 2018. [Online]. Available: http://resources.irap.org/Report/2018_05_30_Roads that cars can read_FINAL.PDF.

[10] Y. Xing *et al.*, “Advances in Vision-Based Lane Detection: Algorithms, Integration, Assessment, and Perspectives on ACP-Based Parallel Vision,” *IEEE/CAA J. Autom. Sin.*, vol. 5, no. 3, pp. 645–661, 2018, doi: 10.1109/JAS.2018.7511063.

[11] Z. Chen and X. Huang, “End-To-end learning for lane keeping of self-driving cars,” *IEEE Intell. Veh. Symp. Proc.*, no. Iv, pp. 1856–1860, 2017, doi: 10.1109/IVS.2017.7995975.

[12] A. Bar Hillel, R. Lerner, D. Levi, and G. Raz, “Recent progress in road and lane detection: A survey,” *Mach. Vis. Appl.*, vol. 25, no. 3, pp. 727–745, 2014, doi: 10.1007/s00138-011-0404-2.

[13] A. Lombard, X. Hao, A. Abbas-Turki, A. El Moudni, S. Galland, and A. U. H. Yasar, “Lateral Control of an Unmaned Car Using GNSS Positionning in the Context of Connected Vehicles,” *Procedia Comput. Sci.*, vol. 58, no. Euspn, pp. 148–155, 2016, doi: 10.1016/j.procs.2016.09.023.

[14] J. Y. Choi, J. S. Kim, and C. C. Chung, “Radar-Based Lane Estimation with Deep Neural Network for Lane-Keeping System of Autonomous Highway Driving,” Sep. 2020, doi: 10.1109/ITSC45102.2020.9294522.

[15] D. H. Kim, “Lane detection method with impulse radio ultra-wideband radar and metal lane reflectors,” *Sensors (Switzerland)*, vol. 20, no. 1, 2020, doi: 10.3390/s20010324.

[16] D. Babic, M. Fiolic, and P. Prusa, “Evaluation of road markings retroreflectioin measuring methods,” *Eur. Sci. J.*, vol. 3, no. February, pp. 105–114, 2014.

[17] Delta, “Technical Note Rs 101,” Hørsholm, 2004. [Online]. Available: www.delta.dk.

[18] CEN, “Road marking materials - Road marking performance for road users and test methods ,” 2018. Accessed: May 12, 2021. [Online]. Available: http://www.biaoxian.org.cn/uploadfile/2020/0527/20200527111655684.pdf.

[19] ERF, “Marking the way towards a safer future,” pp. 4–17, 2012.

[20] ERF, “Recomendations on Road Marking Performance - Supporting Literature,” 2019. https://erf.be/wp-content/uploads/2019/04/Recomendations-on-Road-Marking-Performance_Supporting-literature.pdf (accessed Nov. 09, 2020).

[21] Euro NCAP, “Euro NCAP 2025 Roadmap - In Pursuit of Vision Zero,” Leuven, 2017. [Online]. Available: https://cdn.euroncap.com/media/30700/euroncap-roadmap-2025-v4.pdf.

[22] L. Konstantinopoulou, P. Jamieson, and P. Cartolano, “D7.1: Quality of horizontal and vertical signs, SLAIN project,” 2020.

[23] A. Germanchev, B. Eastwood, and W. Hore-Lacy, “Infrastructure changes to support automated vehicles on rural and metropolitan highways and freeways: road audit (module 2),” 2019. Accessed: May 12, 2021. [Online]. Available: https://austroads.com.au/publications/connected-and-automated-vehicles/ap-t348-19.

[24] SAE, “J2944: Operational Definitions of Driving Performance Measures and Statistics - SAE International,” 2014. doi: https://doi.org/10.4271/J2944_201506.

[25] A. Ghasemzadeh and M. M. Ahmed, “Utilizing naturalistic driving data for in-depth analysis of driver lane-keeping behavior in rain: Non-parametric MARS and parametric logistic regression modeling approaches,” *Transp. Res. Part C Emerg. Technol.*, vol. 90, pp. 379–392, May 2018, doi: 10.1016/j.trc.2018.03.018.

[26] J. He, J. S. McCarley, and A. F. Kramer, “Lane keeping under cognitive load: Performance changes and mechanisms,” *Hum. Factors*, vol. 56, no. 2, pp. 414–426, Mar. 2014, doi: 10.1177/0018720813485978.

[27] A. Das, A. Ghasemzadeh, and M. M. Ahmed, “Analyzing the effect of fog weather conditions on driver lane-keeping performance using the SHRP2 naturalistic driving study data,” *J. Safety Res.*, vol. 68, pp. 71–80, Feb. 2019, doi: 10.1016/j.jsr.2018.12.015.

[28] N. Reddy, H. Farah, Y. Huang, T. Dekker, and B. Van Arem, “Operational Design Domain Requirements for Improved Performance of Lane Assistance Systems: A Field Test Study in The Netherlands,” *IEEE Open J. Intell. Transp. Syst.*, vol. 1, pp. 237–252, 2020, doi: 10.1109/ojits.2020.3040889.

[29] S. Bhusari *et al.*, “An Empirical Analysis to Assess the Operational Design Domain of Lane Keeping System Equipped Vehicles Combining Objective and Subjective Risk Measures,” *IEEE Trans. Intell. Transp. Syst.*, 2020, doi: 10.1109/TITS.2020.2969928.

[30] J. Zhou, H. Peng, and T. J. Gordon, “Characterization of the lateral control performance by human drivers on highways,” 2008, doi: 10.4271/2008-01-0561.

[31] P. Green, B. Cullinane, B. Zylstra, and D. Smith, “SAVE-IT SAfety VEhicles using adaptive Interface Technology (Task 3A) Typical Values for Driving Performance with Emphasis on the Standard Deviation of Lane Position: A Summary of the Literature Prepared by,” 2004.

[32] EuroNCAP, “Assisted Driving - Test & Assessment Protocol (Version 1.0),” 2020.

[33] D. Neumeister and D. Pape, “Automation and Adverse Weather,” in *Road Vehicle Automation 6*, First Onli., Springer, Cham, 2019, pp. 100–107.

[34] P. J. Carlson, J. D. Miles, A. M. Pike, and E. S. Park, “EVALUATION OF WET-WEATHER AND CONTRAST PAVEMENT MARKING APPLICATIONS: FINAL REPORT, Report No. FHWA/TX-07/0-5008-2,” 2007. [Online]. Available: http://tti.tamu.edu/documents/0-5008-2.pdf%0Ahttp://tti.tamu.edu/documents/0-5008-2.pdf.

[35] A. M. Pike, T. P. Barrette, and P. J. Carlson, “Evaluation of the Effects of Pavement Marking Characteristics on Detectability by ADAS Machine Vision,” 2019. [Online]. Available: https://www.researchgate.net/publication/330545262_Evaluation_of_the_Effects_of_Pavement_Marking_Width_on_Detectability_By_Machine_Vision_4-Inch_vs_6-Inch_Markings.

[36] A. R. Stacy, “EVALUATION OF MACHINE VISION COLLECTED PAVEMENT MARKING QUALITY DATA FOR USE IN TRANSPORTATION ASSET MANAGEMENT,” Texas A&M University, 2019.

[37] C. Davies, “Automated Vehicles Symposium 2016,” *Transp. Res. Circ.*, no. E-C222, p. 180, 2017, [Online]. Available: http://www.trb.org/Main/Blurbs/176272.aspx%0Ahttps://trid.trb.org/view/1479140.

[38] Euro NCAP, “Euro NCAP 2020 Assisted Driving Tests,” 2020. https://www.euroncap.com/en/vehicle-safety/safety-campaigns/2020-assisted-driving-tests/ (accessed May 29, 2021).

[39] P. Li, N. Merat, Z. Zheng, G. Markkula, Y. Li, and Y. Wang, “Does cognitive distraction improve or degrade lane keeping performance? Analysis of time-to-line crossing safety margins,” *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 57, pp. 48–58, Aug. 2018, doi: 10.1016/j.trf.2017.10.002.

[40] Gopro, “Hero 9 Black user manual,” 2016.

[41] G. Scientific, “Laserlux 6 User Guide,” 2006.

[42] G. Jocher, “GitHub - ultralytics/yolov5,” 2020. https://github.com/ultralytics/yolov5 (accessed Jun. 01, 2021).

[43] G. Jocher, “Video inference stops after a certain number of frames · Issue #2064 · ultralytics/yolov5 · GitHub,” 2020. https://github.com/ultralytics/yolov5/issues/2064 (accessed Jun. 01, 2021).

[44] cardwing, “GitHub - cardwing/Codes-for-Lane-Detection: Learning Lightweight Lane Detection CNNs by Self Attention Distillation,” 2019. https://github.com/cardwing/Codes-for-Lane-Detection (accessed May 11, 2021).

[45] A. Paszke, A. Chaurasia, S. Kim, and E. Culurciello, “ENet: A Deep Neural Network Architecture for Real-Time Semantic Segmentation,” Jun. 2016, Accessed: May 11, 2021. [Online]. Available: http://arxiv.org/abs/1606.02147.

[46] NWB, “NWB - Hectopunten - Overview,” 2021. https://www.arcgis.com/home/item.html?id=60d88b20165d425db0258df75d993fe2 (accessed May 26, 2021).

[47] A. Field, *DISCOVERING STATISTICS USING SPSS*, Third. 2009.

[48] Vehicle X, *Vehicle X (confidential) - YouTube*. 2019.

[49] Vehicle Y, “Owner’s Manual Vehicle Y,” 2019.

[50] J. C. McCall and M. M. Trivedi, “Video-based lane estimation and tracking for driver assistance: Survey, system, and evaluation,” *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 1, pp. 20–37, 2006, doi: 10.1109/TITS.2006.869595.

[51] A. Tapsi, M. van der Linde, M. Oskina, J. Hogema, F. Tillema, and A. van der Steen, “How to maximize the road safety benefits of ADAS ?,” 2020. [Online]. Available: https://www.fiaregion1.com/study-how-

to-maximize-the-road-safety-benefits-of-adas/.

[52] P. Nitsche, I. Mocanu, and M. Reinthaler, “Requirements on tomorrow’s road infrastructure for highly automated driving,” *2014 Int. Conf. Connect. Veh. Expo, ICCVE 2014 - Proc.*, pp. 939–940, 2014, doi: 10.1109/ICCVE.2014.7297694.

[53] P. Mylonas, “Discussion paper on Technical Justification for Network-Wide Road Assessment, ‘black spot’, route safety and network-wide road assessment,” 2020. Accessed: May 10, 2021. [Online]. Available: https://eurorap.org/wp-content/uploads/2020/10/SLAIN_Discussion-Paper_2020_Final.pdf.

[54] EuroRAP and Euro NCAP, “Roads that cars can read: A Quality Standard for Road Markings and Traffic Signs on Major Rural Roads,” 2014. [Online]. Available: http://www.eurorap.org/wp-content/uploads/2015/03/roads_that_cars_can_read_2_spread1.pdf.

[55] H. Farah, S. M. J. G. Erkens, T. Alkim, and B. van Arem, “Infrastructure for Automated and Connected Driving: State of the Art and Future Research Directions,” in *Lecture Notes in Mobility*, Springer, Cham, 2018.

[56] A. M. Pike, T. P. Barrette, and P. J. Carlson, “Evaluation of the Effects of Pavement Marking Characteristics on Detectability by ADAS Machine Vision,” 2018.

[57] The American Traffic Safety Services Association, “ATSSA Policy on Road Markings for Machine Vision Systems,” 2019, [Online]. Available: http://www.dot.ca.gov/d12/pdf/projects/12-0R070/interstate-5-striping-project-complete.pdf.

[58] A. Pike, S. Clear, T. Barrette, T. Hedblom, and J. Whitney, “Effects of the wet retroreflectivity and luminance of pavement markings on lane departure warning in nighttime continuous rain with and without glare sources,” *SAE Tech. Pap.*, vol. 2019-April, no. April, pp. 1–14, 2019, doi: 10.4271/2019-01-1014.

[59] European Comission, “C - ITS Platform,” *Dg Move*, no. January, pp. 8–9, 2016, [Online]. Available: http://ec.europa.eu/transport/themes/its/doc/c-its-platform-final-report-january-2016.pdf.

[60] WorldWeather, “Amsterdam, North Holland, Netherlands Historical Weather Almanac,” 2021. https://www.worldweatheronline.com/amsterdam-weather-history/north-holland/nl.aspx (accessed May 11, 2021).

[61] I. Road Bureau Ministry of Land, “Roads In Japan,” 2014. Accessed: May 25, 2021. [Online]. Available: http://www.mlit.go.jp/road/road_e/index_e.html.

HAN_UNIVERSITY OF APPLIED SCIENCES

APPENDIX A – FACTORS AFFECTING THE LKS PERFORMANCE

Parameter	Import-ance	Reference to the paper on right side (Colour)	Source
Pavement Type/ Pavement colour		LKS algorithm such as RALPH can fail in situations where there is a combination of pavement textures. An experimental study recommended that it is essential to understand the effect of varying pavement	McCall & Trivedi [50] Pike et al. [35]
Pavement Quality	medium	The literature review suggested that ruts, uneven road surface and cracks surface affect LKS performance. The practical study suggested that conflicting signals near the lane marking can confuse the MV system.	Nitsche et al. [52] Pike et al. [35]
Type of Horizontal Curve		Different LKS algorithms can model road as linear, parabolic or spline, and the choice of it requires a trade-off between high stability or a high TLC. EuroNCAP test LKS on a S bend at 80 Km/hr Practical studies found that vehicle struggle in the second curve of the S-shaped curve.	McCall & Trivedi [50] EuroNCAP [32] Tapsi et al. [51]
Radius of Curvature	medium medium	The vehicle manufacturers (ACEA), on their part, prioritized the road curvatures Low curve radii affect LKS performance.	EuroRAP & Euro NCAP [54] Schram [8] Nitsche et al. [52]
Lane Width	low	The width of lane markings can be reduced as AVs will maintain an accurate lane position A field study in the Netherlands found that automated vehicles were inconsistent in their Lane Position ACEA said that too narrow or too broad a lane could impact the LKS performance.	Farah et al. [55] Reddy et al. [28] EuroRAP & Euro NCAP [54]
Lane Marking Colour		ACEA advised the Road Authorities to harmonize the colour and dimensions of road across Europe	EuroRAP & Euro NCAP [54]

Visibility of lane markings	high high	Empirical evidence suggests minimum retro-reflection of 150 mcd/lx/m2 for markings Road Marking with retro-reflection of 150 mcd/lx/m2 required across Europe Practical study confirms the same as above	ERF [19] EuroRAP & Euro NCAP [54] Davies [37]
Width of markings	medium	The practical experiment identified that 6-inch lane markings could improve the MV performance The experimental study suggest 6 inches marking better than 4 inch Mobileye and ATSSA recommended 12-15 cm lines	Pike et al. [56] Davies [37] American Traffic Safety [57]
Type of Pavement Marking	high	Recommended to install continuous lines to delineate the edge of the carriageway Lane line markings had lower detection confidence levels than comparable edge line markings	EuroRAP & Euro NCAP [54] Pike et al. [35]
Contrast Ratio		Contrast ratio 3:1 is sufficient, but for better results, advised 4:1 ratio. An experimental study found that higher speeds and lower contrast reduced MV detectability Contrast Ratio significant for CV based LKS CR is most important during daylight hours.	ERF [20] Pike et al. [58] Konstantinopoulou et al. [22] European Comission [59]
Non-uniformity	medium	The unification of markings across various countries will improve the reliability of MV Cross border difference affects LKS performance For ML-based LKS, uniformity is more important than contrast ratio	ERF [20] Nitsche et al. [52] Konstantinopoulou et al. [22]

APPENDIX B – TEST ROUTE

Given below is a sample of the various parameters measured using the Street Smart before finalizing the test route to ensure that test vehicle are exposed to various situations.

Table 19 Preview of the route and calculations using Street Smart

Sample	Road Name	If Divided	Particulars	Road Surface Type and Quality		Horizional Alignment		Cross-section				Roadway Pavement Markings						
				Pavement color	Pavement Quality	Type of Horizintal Curve	Radius of Curvature	Lane Width	Median	Shoulder	Curb	Profile	Width L	Width R	Pavement Marking Type L	Pavement Marking Type R	Condition	Old Marking Remanant
1		Yes	-	Dark	-	S Curve	Sharp	3.36	Grass	No	No	Flat	11	14	LL C S	EL D S	Dirty	No
2		No	Shadow trees	Mid	-	Circular	Sharp	2.99	20 cm space	No	No	Flat	12	15	EL C D	EL D S	Good	No
3		No	Shadow trees	Mid		Straight	-	3.03	21 cm space	No Grass at 30 cm	No		11	13	EL C D	EL D S	Good	No
1		No	Glare from Sun + Wet	seems whitish due to being wet and glare		Straight	-	2.89	18cm space	No Grass at 50 cm	No	Flat	13	11	EL C D	EL D S	Edge line not visible	No
2		No	Underpass Railiway Bridge	Cemented	straight lines of pavement joint	Straight	-	2.96	No	Grass adjoining cemented road surface	No	-	-	-	-	-	No lines	No
1		No		Dark		Circular	Sharp	3.04	18cm space	Grass adjoining road surface	No	Flat	14	10	EL C D	EL D S	Faded out specially on curve	no
1		Yes		Dark + Light	Mix of old and new pavement	Straight		3.33	Gaurdrails	Yes - Asphalt	Gaurdrail		19	45	LL D S	LL D S	New - Excellent	Yes
2		Yes	outrmost lane	Light		Straight		3.25	Gaurdrails	Yes - Asphalt	Gaurdrail		16	21	LL D S	EL C S	Ok	No
1		Yes	Middle Lanes	Light		Straight		2.73	Concrete Barriers	No			13	11	LL D S	LL D S	Ok	Yes
1				Combinatio n light and dark	Longitudn al Cracks			3.05			No	White	13	16	CL Double Broken	LE Double Continous	Black impressions	No
2				Dark	Patch			2.9			No	White	10	10	CL Double Continous	LE Single Dashed	Good	No
3				Dark	-			3.12			No	White	14	15	LL Single Dashed	LE Single Dashed	Black impressions	No
1				Light	-			3.42			No	White	13	21	LL Single Dashed	LE Single Continous	Good	No
1				Dark	-			3.03			No	White	10	11	CL Double Continous	CL Double Continous	Worn out edges	No
2				Dark	-			3.08			No	White	19	20	CL Double Continous	LE Single Continous	Good	No
1				Light	-			2.73			No	White	9	11	CL Double Dashed	LE Single Dashed	Worn out edges	Yes
													Legends for Marking		Lane Line	Continous	Single	
															Edge Line	Dashed	Double	

The route broken into sections for the measurement of retro-reflection was required to see the variations of the vehicle's performance across different Provincial roads.

Table 20 Segmented Route for recording the age of the road and RL measurement (confidential)

APPENDIX C – MEASUREMENT FOR CAMERA CALIBRATION

The figures below show the measurements that were taken before starting the drive for the Vehicle Y vehicle. Similarly, the measurements were also recorded for Vehicle X.

Figure 22 Measurements of camera mountings and calibration board distance (confidential)

Figure 23 (a) Vehicle measurements (b) calibration board measurements (confidential)

APPENDIX D – SOFTWARE USED

Table 21 Software used for processing the data

Sr No	Software/ Program Name	Description	Links
1	ShotCut	For synchronizing the videos of the GoPro	https://shotcut.org/
2	GoPro Telemetry Extractor	Extracting the metadata from the recorded GoPro videos	https://goprotelemetryextractor.com/free/#
3	QGIS	For synchronization of the data from reflectometer, GoPro and Hectometer database GIS analysis	https://qgis.org/en/site/forusers/download.html
4	makesense.ai	To prepare the labelled dataset for object detection model	https://www.makesense.ai/
5	Roboflow	For Data Augmentation and analysis of the labelled dataset	https://roboflow.com/
6	YOLOv5	For developing an object detection model for recognising the Dashboard Signs	https://github.com/ultralytics/yolov5
7	Google Colab	Free GPU to reduce the training and run time for DNNs	https://colab.research.google.com/notebooks/intro.ipynb
8	MATLAB	For calculation of the MLP and SDLP from the GoPro Camera Data For building the prediction model based on NN architecture	https://nl.mathworks.com/products/matlab.html
9	SPSS	For statistical analysis	https://www.ibm.com/products/spss-statistics

APPENDIX E – DASHBOARD SIGN DETECTION TOOL

Table 22 Preparation of labelled dataset for YOLOv5 (Vehicle Y)

Label Name	Aggregate of count of Labels						Final Data Health - Round 6	
	Round 1	Round 2	Round 3	Round 4	Round 5	Round 6	Labels/Images	Presence %ge
[redacted] Active	59	93	119	143	149	**149**	32%	13%
[redacted] Standby	32	52	101	114	153	**153**	33%	14%
Indicator - Left	4	17	21	21	36	**38**	8%	3%
Indicator - Right	7	18	27	27	41	**42**	9%	4%
[redacted]ctive	92	144	172	172	185	**185**	39%	16%
[redacted]Dw	1	5	39	70	104	**105**	22%	9%
[redacted]tandby	64	88	91	91	111	**111**	24%	10%
VID - Lanes Detected	58	90	102	104	110	**110**	23%	10%
VID - Lanes Not Detected	33	52	75	77	86	**87**	19%	8%
VID - Left LDW	1	3	35	41	46	**46**	10%	4%
VID - Right LDW	0	2	9	35	67	**69**	15%	6%
Background only	0	0	0	0	0	**30**		
Grand Total	351	564	791	895	1088	**1125**		
Total Images	160	244	325	362	439	**469**		

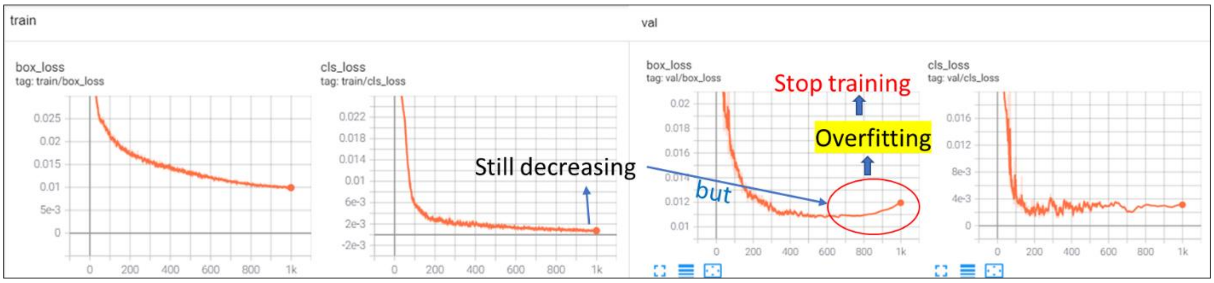


Figure 24 Tracking Loss Function for Training and Validation sets

Figure 25 Output of the Dashboard Sign Detection tool (Confidential)

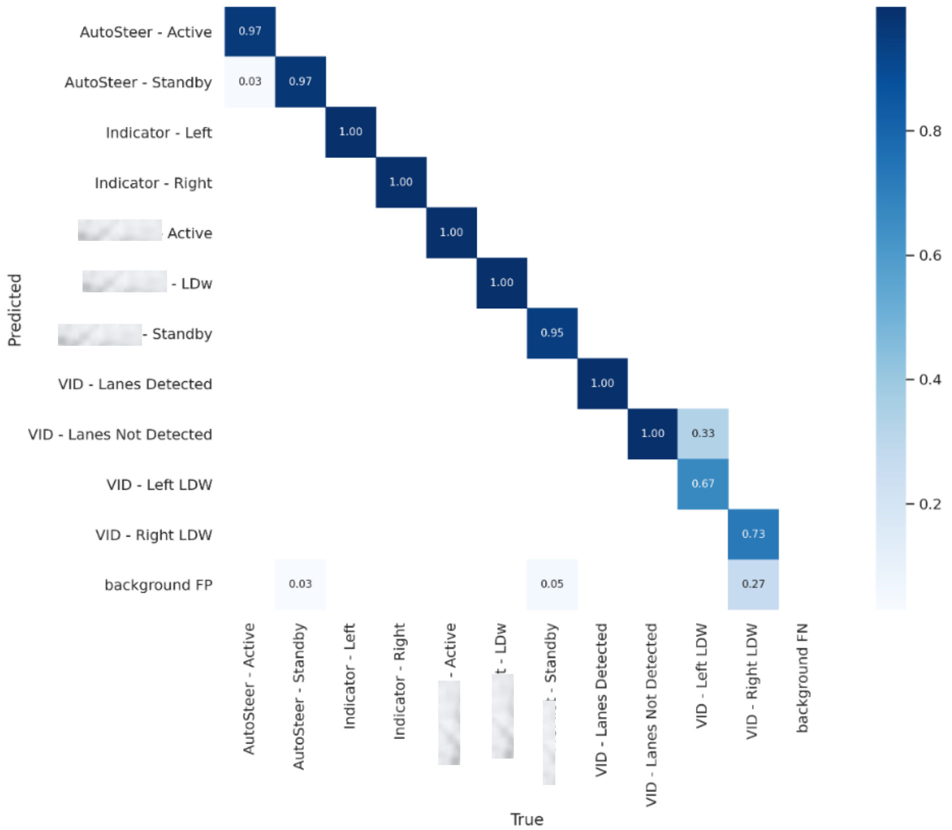


Figure 26 Confusion Matrix for evaluation of YOLOv5 accuracy (Vehicle Y)

For Vehicle Y Dashboard, there were 11 classes, and all of them were tracked individually, using this Matrix. It tells us that how often one class is falsely predicted as another class. So, in an ideal situation, where no class is confused with another class, the confusion matrix would be an Identity Matrix with '1' on the diagonal and '0' elsewhere.

Figure 27 Signs to be detected from Vehicle X Dashboard for analysis of the data (confidential)

Table 23 Final Scenarios for Vehicle X (confidential)

Figure 28 Output of the Dashboard Sign Detection tool (confidential)

APPENDIX F – WEATHER STATION DATA

Table 24 Weather Station data - Amsterdam Schiphol Netherlands [60]

Day1 (Sunset: 06:02 PM)			Day2 (Sunset: 06:04 PM)		
Session	Time	Weather	Session	Time	Weather
S1	**16:04**	Broken clouds.	S1	**11:55**	Drizzle. Partly sunny.
	17:00	More clouds than sun.		**13:00**	Drizzle. Low clouds.
	17:25	Mostly cloudy.		**13:32**	Drizzle. Mostly cloudy.
	17:31	Overcast.		**14:00**	Cloudy.
	17:55	Mostly cloudy.		**14:13**	Light rain. Mostly cloudy.
	18:17	Overcast.		**14:26**	Mostly cloudy.
	18:29	Passing clouds.	S2	**15:25**	More clouds than sun.
	18:55	Drizzle. Mostly cloudy.		**15:34**	Overcast.
S2	**20:25**	Overcast.		**15:55**	Mostly cloudy.
	20:55	Overcast.		**16:25**	Overcast.
	21:25	Overcast.		**16:35**	More clouds than sun.
	21:34	Partly cloudy.		**17:37**	Mostly cloudy.

APPENDIX G - FRONT CAMERA DATA PROCESSING

Figure 29 Lane Width and Lane Position calculation using ERFNet (confidential)

Figure 30 Contrast Ratio calculation

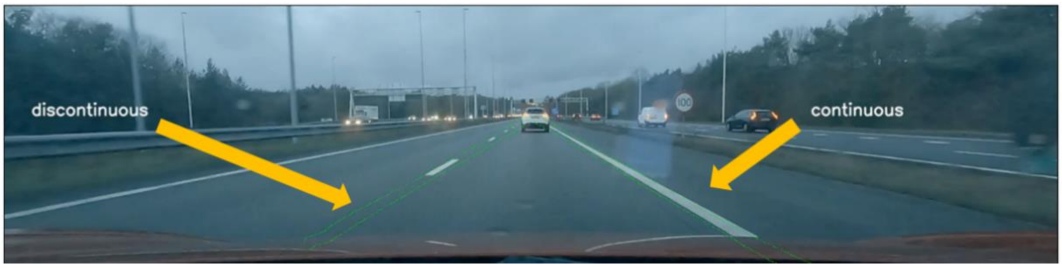


Figure 31 Classification of lane line-markings

APPENDIX H – SYNCHRONIZATION OF THE DATA FROM FOUR CAMERAS

Table 25 Sample calculation for Synchronization of videos for Vehicle Y Day1 Session1

	Video Time	Atomic Clock		*Identify which video has the maximum timeline at which clock appears*						*Identify which clock has the earliest time*								
					1s has 30 parts (F)						1 s has 100 parts (D)					Conversion D to F		Total Buffer
Nissan D1 S1	V4-Shotcut		***00:07:24:21***	*Shown last to 4*							04:24:30:25	+	B4	=	04:24:38:00			
	Side Right	GOPR7967	04:24:38:00	No Buffer Required						Add buffer			B4		00:00:07:75	22.5	00:00:07:23	00:00:07:23
	V3-Shotcut		00:07:09:20		00:07:09:20	+	B3	=	00:07:24:21	No buffer								
	Side Left	GOPR9581	***04:24:30:25***	Add buffer to V3			B3		00:00:15:01	Lagging Most								00:00:15:01
	V2-Shotcut		00:00:08:19		00:00:08:19	+	B2	=	00:07:24:21		04:24:30:25	+	B2	=	04:27:38:02			
	Front	GX010052	04:27:38:02	Add buffer to V2			B2		00:07:16:03	Add buffer			B2		00:03:07:77	23.1	00:03:07:23	00:10:23:26
	V1 - Shotcut		00:00:33:00		00:00:33:00	+	B2	=	00:07:24:21		04:24:30:25	+	B1	=	04:28:03:94			
	Dashboard	GH010132	04:28:03:94	Add buffer to V1			B2		00:06:51:21	Add buffer			B1		00:03:33:69	20.7	00:03:33:21	00:10:25:12

Table 26 Hand calculated Video Synchronization Matrix

Camera				V4 -Right	V3 - Left	V2 -Front	V1 - Dashboard
Nissan	Day 1	Session 1	Video Name	GOPR7967	GOPR9581	GX010052	GH010132
			Add Buffer	7s 23F	15s 1 F	10m 23s 26F	10m 25s 12 F
		Session 2	Video Name	GOPR7968	GOPR9582	GX010053	GH010134
			Add Buffer	3m 30s 29F	2m 15s 10F	35s 18F	38s 17F
	Day 2	Session 1	Video Name	NA		GX010054	GH010369
			Add Buffer			15s 19F	5m 41s 5F
		Session 2		Camera turned off twice during the drive			
				Hence, synchronization done three times			
Tesla	Day 1	Session 1	Video Name	GH027990	GP019581	GX020051	GH020367
			Add Buffer	49s 13F	1m 11s 2F	1m 10s 21F	1m 14s 5F
		Session 2	Video Name	GH017991	GOPR9583	GX020052	GH010368
			Add Buffer	17s 6F	5m 3s 14F	1m 56s 25F	6m 45s 16F
	Day 2	Session 1	Video Name	NA		GX020053	GH010136
			Add Buffer			0F	1m 56s 29F
		Session 2	Video Name		GOPR9584	GX010054	GH010137
			Add Buffer		54s 16F	0F	2m 35s 0F

Nissan Day 2		V4 -Right	V3 - Left	V2 -Front	V1 - Dashboard
Session 2 part 1	Video Name	GOPR7969	GOPR9583	GX010055	GH010370
	Add Buffer	58s 0F	1m 36s 23F	4m 39s 11F	6m 25s 8F
Session 2 part 2	Video Name	GP077969	GP079583	GX010057	GH080370
	Add Buffer	0F	38s 25F	8m 39s 0F	3m 56s 2 F
Session 2 part 3	Video Name	NA	GP159583	GX080057	GOPR7970
	Add Buffer		5m 49s 18F	21s 23F	9m 29s 21F

m	minutes
s	seconds
F	Frames

APPENDIX I - MACHINE VISION PERFORMANCE (CONFIDENTIAL)

Figure 32 Distribution of (a) Lane Width (b) Contrast Ratio (confidential)

Figure 33 Machine Vision Performance (confidential)

The standby scenario in the case of Vehicle X does not mean that lanes are not detected. Hence, the overall lane detection percentage for Vehicle X is 99.9%. For simplification, it was considered that Vehicle X detects 100% of the lanes throughout the route.

Figure 34 Distribution of different retro-reflection classes within each Road (confidential)

Figure 35 Age of the Road vs Retro-reflection of line markings (confidential)

Table 27 Retro-reflection vs Lane Detection

			Final_Scenario		
			Lanes Detected	Lanes Not Detected	Total
RL_class	Class A (RL>200)	Count	380	372	752
		Expected Count	431,9	320,1	752,0
		% within RL_class	50,5%	49,5%	100,0%
		% within Final_Scenario	30,7%	40,6%	34,9%
		Adjusted Residual	-4,7	4,7	
	Class B (200<RL<175)	Count	411	138	549
		Expected Count	315,3	233,7	549,0
		% within RL_class	74,9%	25,1%	100,0%
		% within Final_Scenario	33,2%	15,0%	25,5%
		Adjusted Residual	9,6	-9,6	
	Class C (175<RL<150)	Count	302	224	526
		Expected Count	302,1	223,9	526,0
		% within RL_class	57,4%	42,6%	100,0%
		% within Final_Scenario	24,4%	24,4%	24,4%
		Adjusted Residual	,0	,0	
	Class D (150<RL<125)	Count	139	147	286
		Expected Count	164,2	121,8	286,0
		% within RL_class	48,6%	51,4%	100,0%
		% within Final_Scenario	11,2%	16,0%	13,3%
		Adjusted Residual	-3,2	3,2	
	Class E (<125)	Count	5	36	41
		Expected Count	23,5	17,5	41,0
		% within RL_class	12,2%	87,8%	100,0%
		% within Final_Scenario	0,4%	3,9%	1,9%
		Adjusted Residual	-5,9	5,9	
Total		Count	1237	917	2154
		Expected Count	1237,0	917,0	2154,0
		% within RL_class	57,4%	42,6%	100,0%
		% within Final_Scenario	100,0%	100,0%	100,0%

Table 28 Logistic Regression Model for Contrast Ratio vs Lane Detection for Vehicle Y

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Contrast RL	-,462	,182	6,464	1	,011	,630	**,441**	**,900**
	Constant	3,374	,751	20,202	1	,000	29,208		

Table 29 Lane Width vs Lane Detection

			Final_Scenario		
			Lanes Detected	Lane Not Detected	Total
Lane Width	less than 3m	Count	292	359	651
		Expected Count	373,9	277,1	651,0
		% within Lane Width	44,9%	55,1%	100,0%
		% within Final_Scenario	23,6%	39,1%	30,2%
		Adjusted Residual	-7,8	7,8	
	3m to 3.5m	Count	329	99	428
		Expected Count	245,8	182,2	428,0
		% within Lane Width	76,9%	23,1%	100,0%
		% within Final_Scenario	26,6%	10,8%	19,9%
		Adjusted Residual	9,1	-9,1	
	3.5m to 4m	Count	551	420	971
		Expected Count	557,6	413,4	971,0
		% within Lane Width	56,7%	43,3%	100,0%
		% within Final_Scenario	44,5%	45,8%	45,1%
		Adjusted Residual	-,6	,6	
	above 4m	Count	65	39	104
		Expected Count	59,7	44,3	104,0
		% within Lane Width	62,5%	37,5%	100,0%
		% within Final_Scenario	5,3%	4,3%	4,8%
		Adjusted Residual	1,1	-1,1	

Table 30 Type of line marking vs Lane Detection

			Final_Scenario		
			Lanes Detected	Lane Not Detected	Total
Combined Line	Cont-Cont	Count	136	3	139
		Expected Count	82,8	56,2	139,0
		% within Combined Line	97,8%	2,2%	100,0%
		% within Final_Scenario	12,1%	0,4%	7,4%
		Adjusted Residual	9,6	-9,6	
	Cont-Dash	Count	513	690	1203
		Expected Count	716,6	486,4	1203,0
		% within Combined Line	42,6%	57,4%	100,0%
		% within Final_Scenario	45,6%	90,4%	63,8%
		Adjusted Residual	-19,9	19,9	
	Dash-Cont	Count	367	29	396
		Expected Count	235,9	160,1	396,0
		% within Combined Line	92,7%	7,3%	100,0%
		% within Final_Scenario	32,7%	3,8%	21,0%
		Adjusted Residual	15,1	-15,1	
	Dash-Dash	Count	108	41	149
		Expected Count	88,8	60,2	149,0
		% within Combined Line	72,5%	27,5%	100,0%
		% within Final_Scenario	9,6%	5,4%	7,9%
		Adjusted Residual	3,3	-3,3	

Figure 36 GIS analysis for Lane Width vs Lane Detection (Vehicle Y Day1) (confidential)

Figure 37 GIS Analysis on Provincial Road N244 (Day1) (confidential)

Table 31 Weather vs Lane Detection

			Final_Scenario		
			Lanes Detected	Lane Not Detected	Total
Weather	Dry Road	Count	991	700	1691
		Expected Count	971,1	719,9	1691,0
		% within Weather	58,6%	41,4%	100,0%
		% within Final_Scenario	80,1%	76,3%	78,5%
		Adjusted Residual	2,1	-2,1	
	Wet Road	Count	175	212	387
		Expected Count	222,2	164,8	387,0
		% within Weather	45,2%	54,8%	100,0%
		% within Final_Scenario	14,1%	23,1%	18,0%
		Adjusted Residual	-5,4	5,4	
	Rain	Count	71	5	76
		Expected Count	43,6	32,4	76,0
		% within Weather	93,4%	6,6%	100,0%
		% within Final_Scenario	5,7%	0,5%	3,5%
		Adjusted Residual	6,5	-6,5	
Total		Count	1237	917	2154
		Expected Count	1237,0	917,0	2154,0
		% within Weather	57,4%	42,6%	100,0%
		% within Final_Scenario	100,0%	100,0%	100,0%

Table 32 Lighting Condition vs Lane Detection

			Final_Scenario		
			Lanes Not Detected	Lanes Detected	Total
Lighting	Day	Count	51	153	204
		Expected Count	20,8	183,2	204,0
		% within Lighting	25,0%	75,0%	100,0%
		% within Final_Scenario	87,9%	29,9%	35,9%
		Adjusted Residual	8,7	-8,7	
	Dusk	Count	6	187	193
		Expected Count	19,7	173,3	193,0
		% within Lighting	3,1%	96,9%	100,0%
		% within Final_Scenario	10,3%	36,6%	33,9%
		Adjusted Residual	-4,0	4,0	
	Night	Count	1	171	172
		Expected Count	17,5	154,5	172,0
		% within Lighting	0,6%	99,4%	100,0%
		% within Final_Scenario	1,7%	33,5%	30,2%
		Adjusted Residual	-5,0	5,0	
Total		Count	58	511	569
		Expected Count	58,0	511,0	569,0
		% within Lighting	10,2%	89,8%	100,0%
		% within Final_Scenario	100,0%	100,0%	100,0%

Table 33 Lane Detection vs Divided/Undivided Roads

			Final_Scenario: Lanes Detected	Final_Scenario: Lane Not Detected	Total
RoadType	Divided	Count	674	158	832
		Expected Count	477,8	354,2	832,0
		% within RoadType	81,0%	19,0%	100,0%
		% within Final_Scenario	54,5%	17,2%	38,6%
		Adjusted Residual	17,6	-17,6	
	Undivided	Count	563	759	1322
		Expected Count	759,2	562,8	1322,0
		% within RoadType	42,6%	57,4%	100,0%
		% within Final_Scenario	45,5%	**82,8%**	61,4%
		Adjusted Residual	-17,6	17,6	
Total		Count	1237	917	2154
		Expected Count	1237,0	917,0	2154,0
		% within RoadType	57,4%	42,6%	100,0%
		% within Final_Scenario	100,0%	100,0%	100,0%

Table 34 MV performance excluding confounding variables Lane Width and Marking Type

			Final_Scenario: Lanes Not Detected	**Final_Scenario**: Lanes Detected	**Total**
RL_class	A	Count	0	60	60
		% within RL_class	0.0%	100.0%	100.0%
	B	Count	0	63	63
		% within RL_class	0.0%	100.0%	100.0%
	C	Count	1	36	37
		% within RL_class	2.7%	97.3%	100.0%
	D	Count	0	12	12
		% within RL_class	0.0%	100.0%	100.0%
Total		Count	1	171	172
		% within RL_class	0.6%	99.4%	100.0%

APPENDIX J – LANE POSITIONING PERFORMANCE

Figure 38 Overview of the MLP and SDLP for the complete test (confidential)

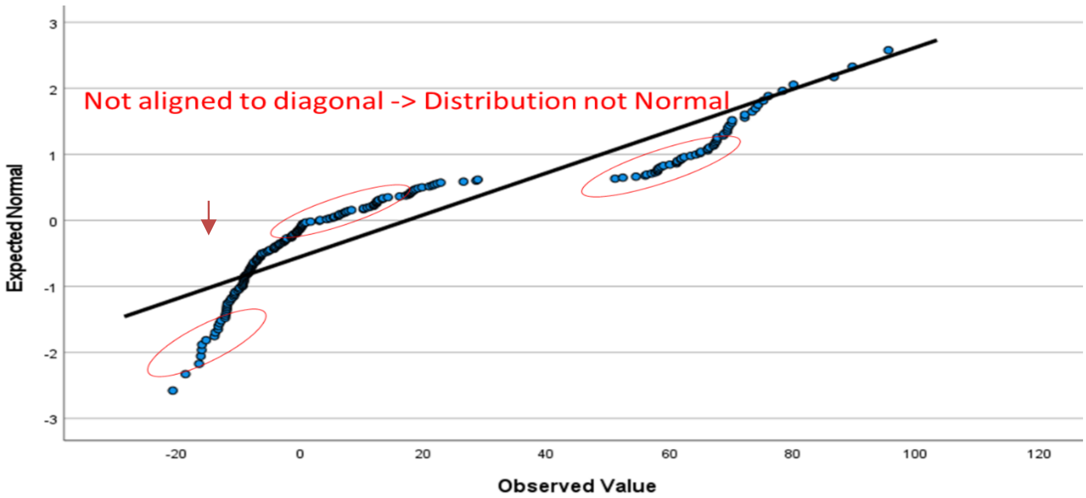


Figure 39 Q-Q plot to check the assumption of Normality for MLP (Vehicle Y)

Table 35 Test to check the Normality in MLP dataset (Vehicle Y)

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
MLP	,189	200	<.001	,825	200	<.001

a. Lilliefors Significance Correction

Table 36 Test to check the Normality in MLP dataset (Vehicle X)

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
MLP	,054	438	,004	,992	438	,015

a. Lilliefors Significance Correction

The Whisker-Box plot indicates the variation of MLP across the different line markings, and the pairwise comparison chart indicates if those variations are statistically significant or not. The blue lines in the pairwise comparisons indicate the significant difference amongst the two groups of lane line-markings. The green line means that the difference is not significant. The difference in the value of rank shows the significance of the difference between the two categories.

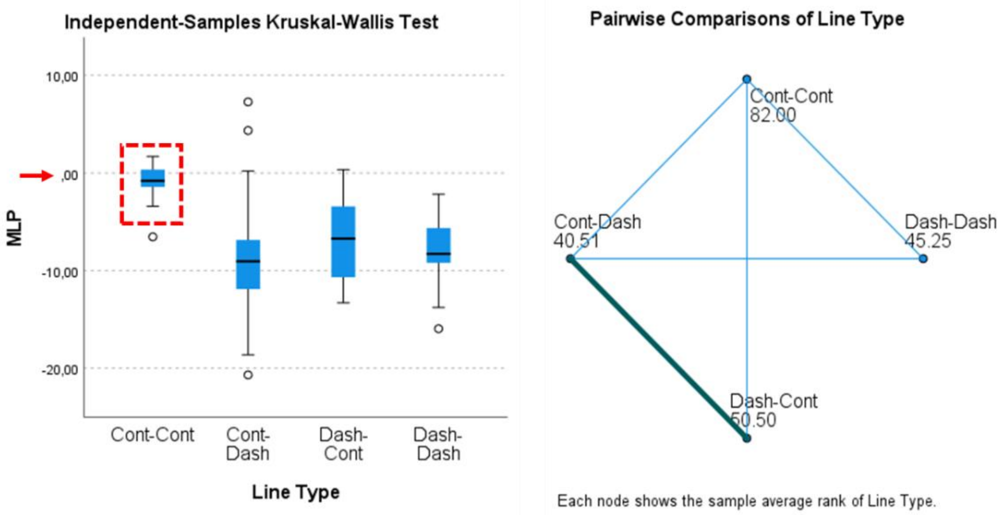


Figure 40 Variation in MLP for different lane line markings for Vehicle Y Day 1

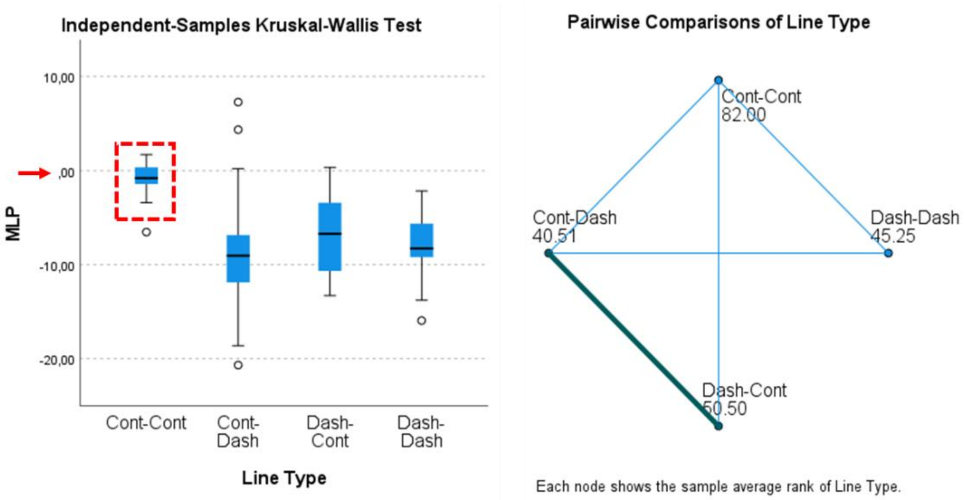


Figure 41 Variation in MLP for different lane tine markings for Vehicle X Day 1

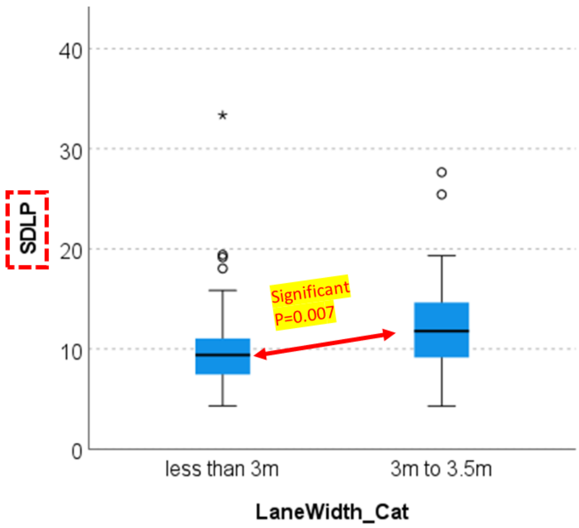
Kruskal-Wallis test produces a P-value greater than 0.05 in each of the cases to check the association of the line marking type with SDLP for Vehicle Y and Vehicle X, except for Vehicle X Day 2 (table 36), the P-value is below 0.05. Since the P-value of 0.04 is not highly significant (P<0.001), it is not considered, and the overall conclusion is made that SDLP does not vary amongst the different type of line-markings.

Table 37 Kruskal-Wallis Test for SDLP vs line marking type for Vehicle X Day2

Null Hypothesis	Sig.	Decision
The distribution of SDLP is the same across categories of Line Type.	0.041	Reject the null hypothesis.

Figure 42 (a) Mann-Whitney test for SDLP in Vehicle X (b) Straight and Curved SDLP (confidential)

Figure 43 Curves executed through Automated Driving (confidential)



Test Statistics[a,b]

	MLP	SDLP
Kruskal-Wallis H	,773	7,236
df	1	1
Asymp. Sig.	,379	,007

Ranks

	LaneWidth_Cat	N	Mean Rank
MLP	less than 3m	41	50,85
	3m to 3.5m	54	45,83
	Total	95	
SDLP	less than 3m	41	39,27
	3m to 3.5m	54	54,63
	Total	95	

Figure 44 Kruskal-Wallis Test Output for Lane Width vs Lane Position for Vehicle Y

Table 38 Test output for checking the variation of Lane Position in Vehicle X

Test Statistics[a,b]

	MLP	SDLP
Kruskal-Wallis H	30,328	10,340
df	1	1
Asymp. Sig.	<.001	,001
Significant as P < 0.05		

Ranks

	LaneWidth_Cat	N	Mean Rank
MLP	3m to 3.5m	86	74,87
	3.5m to 4m	115	120,54
	Total	201	
SDLP	3m to 3.5m	86	85,74
	3.5m to 4m	115	112,41
	Total	201	

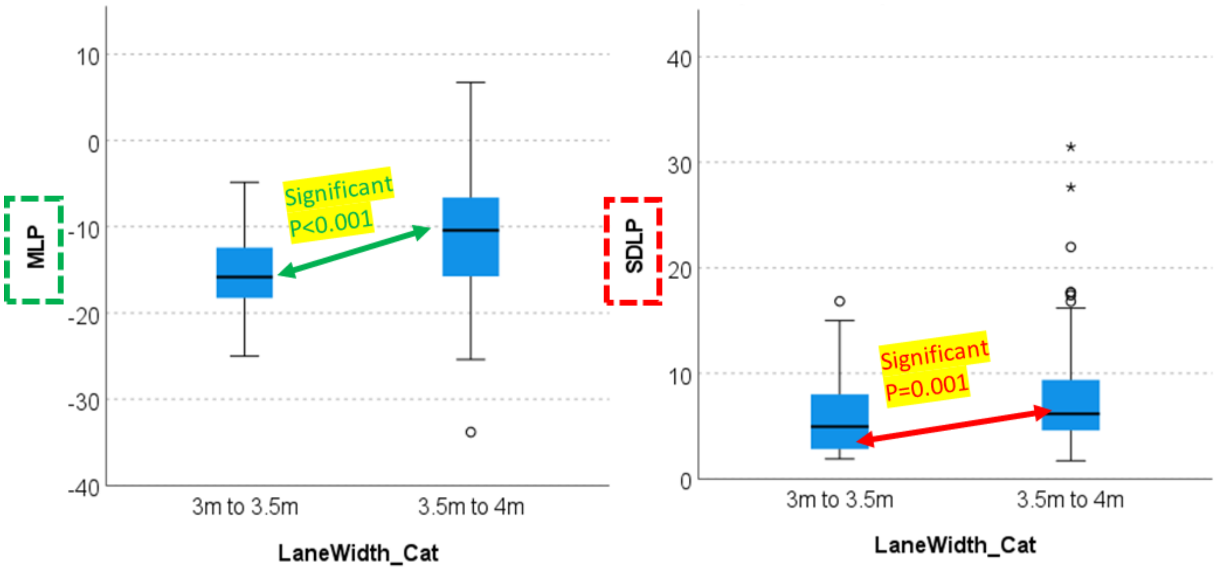


Figure 45 Variation of Lane Position across different lane width for Vehicle X

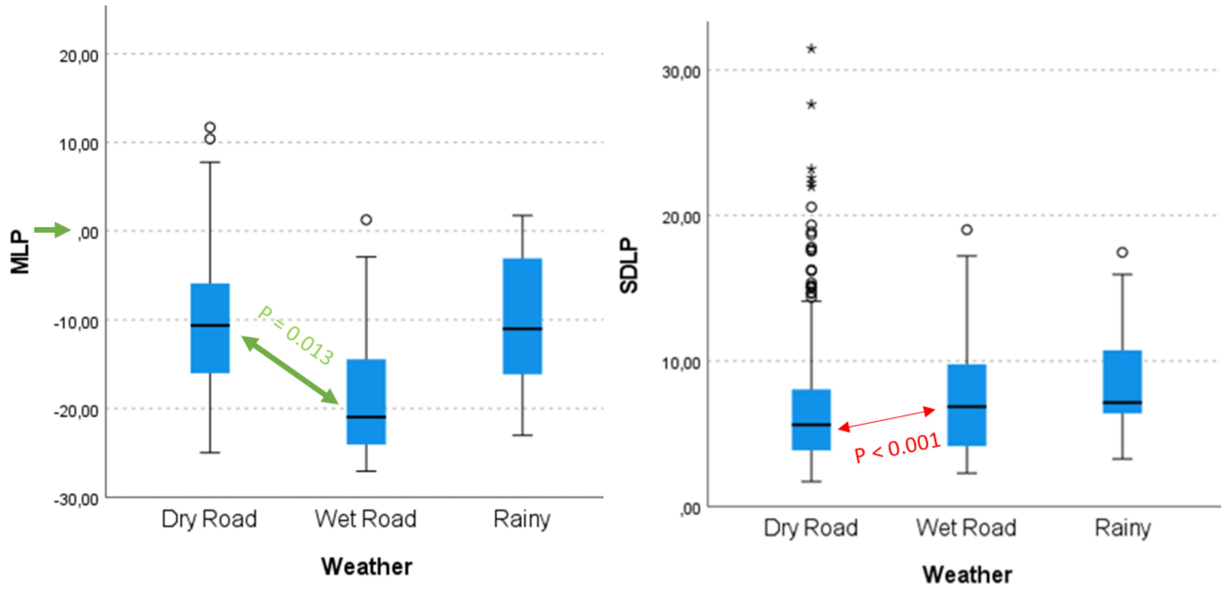


Figure 46 Effect of weather on Lane Positioning of Vehicle Y

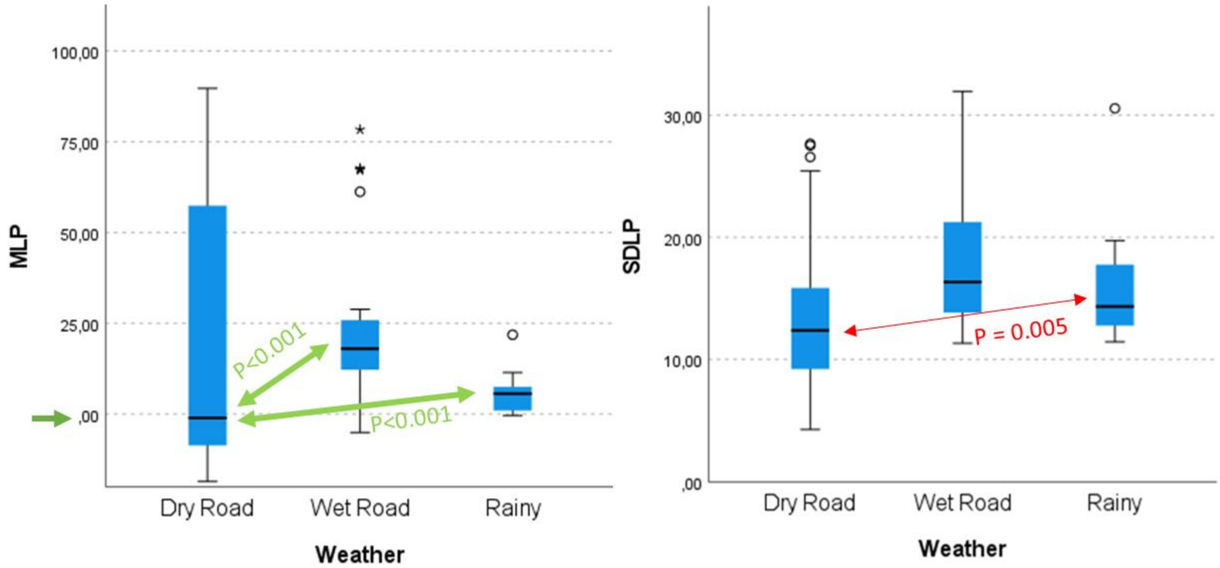


Figure 47 Effect of weather on Lane Positioning of Vehicle X

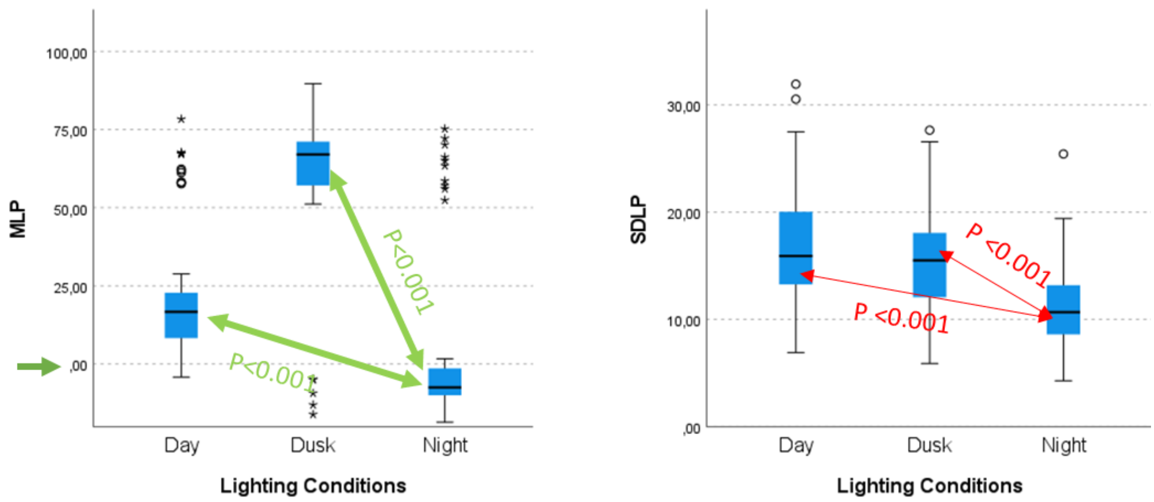


Figure 48 Effect of Lighting Conditions on Lane Positioning of Vehicle Y

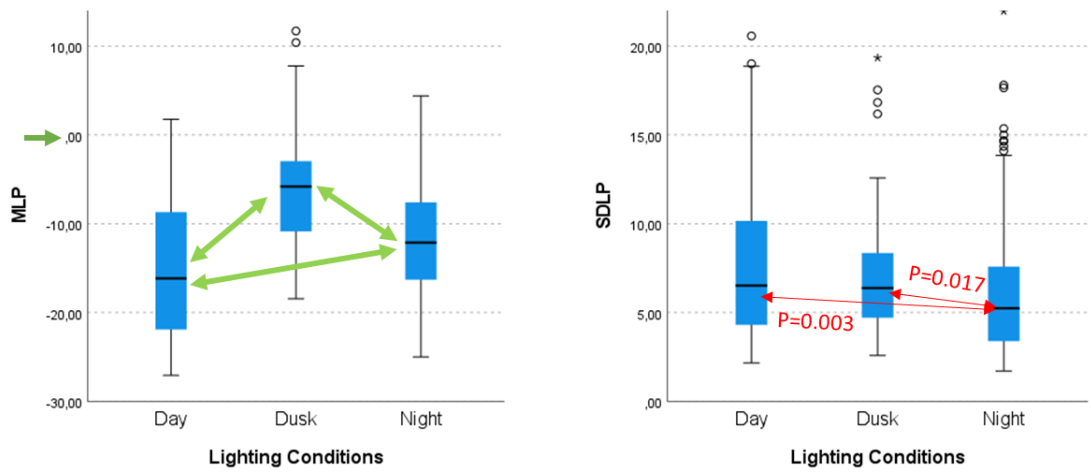


Figure 49 Effect of Lighting Conditions on Lane Positioning of Vehicle X

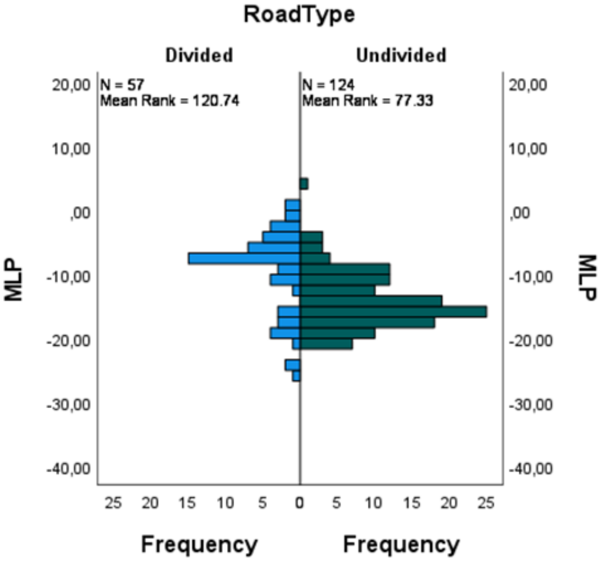


Figure 50 Mann Whitney test for Vehicle X Performance on Divided and Undivided Roads

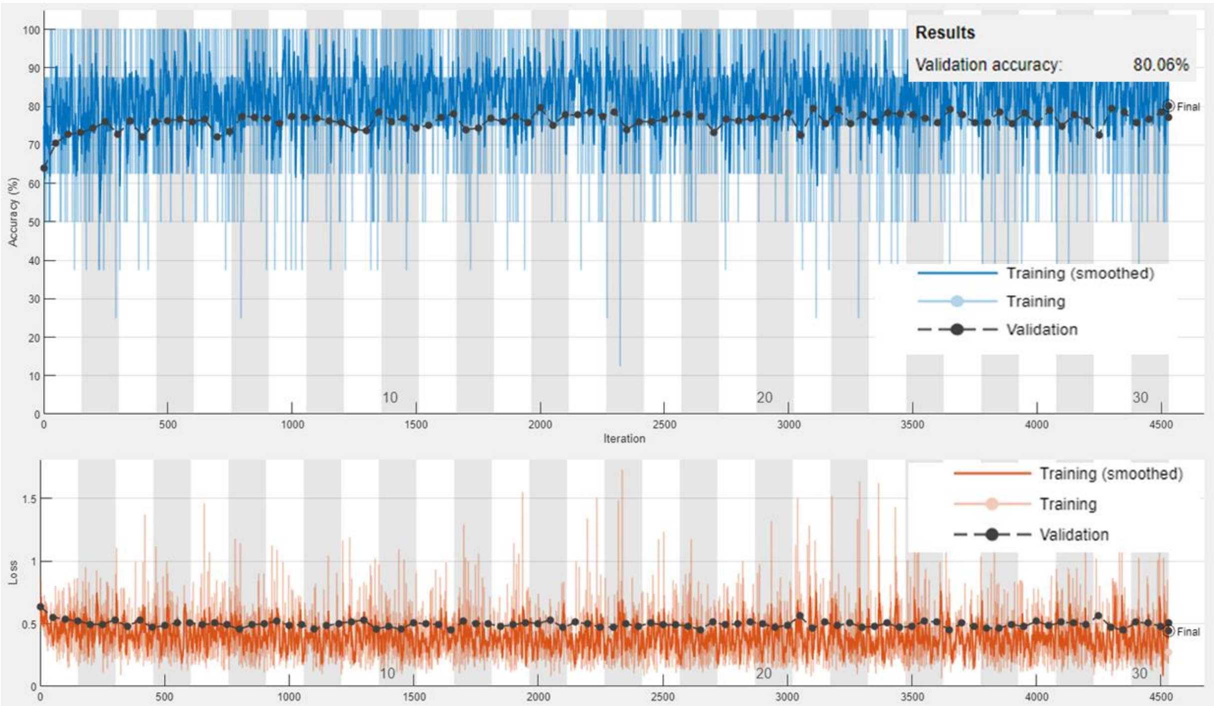


Figure 51 Training loss and accuracy for MV prediction model (Vehicle Y)

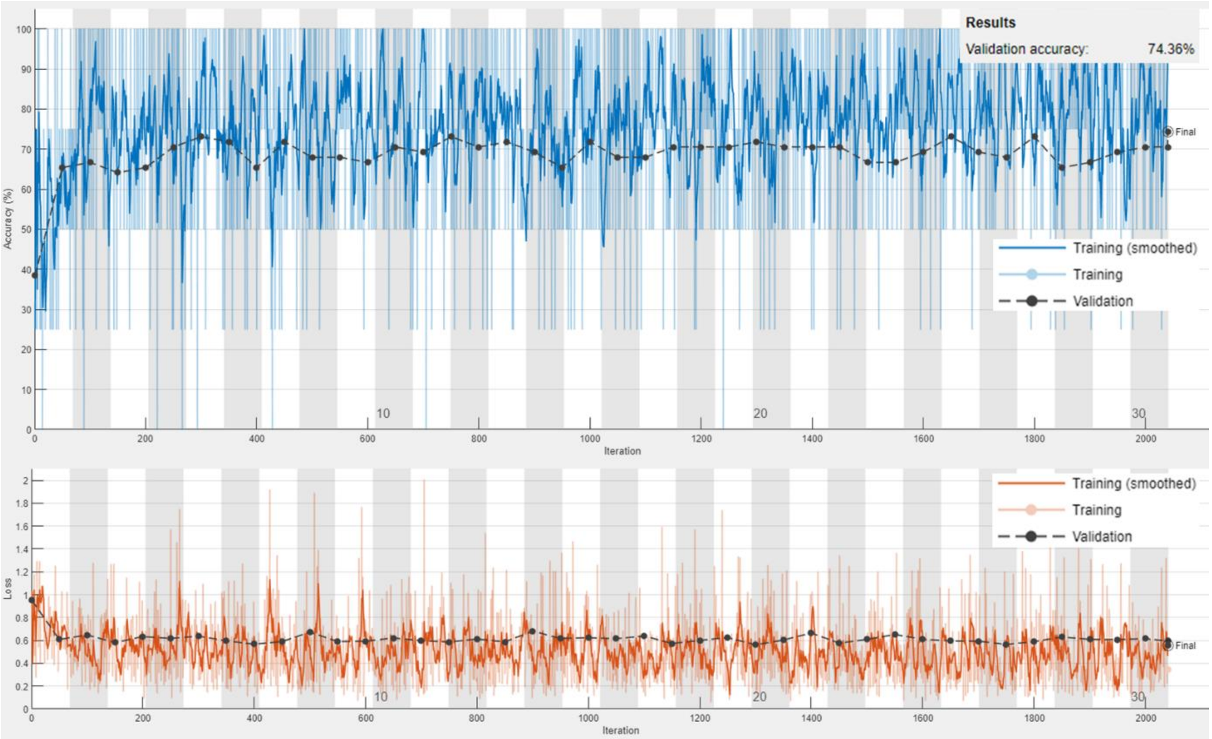


Figure 52 Training loss and accuracy for MLP prediction model (Vehicle X)

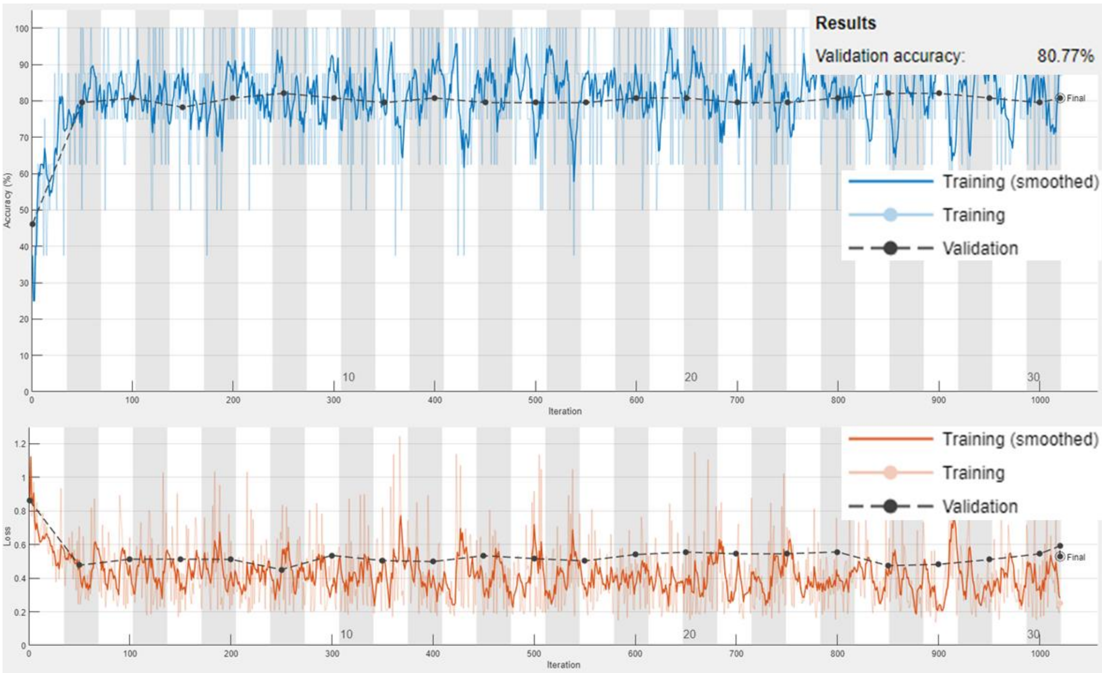


Figure 53 Training loss and accuracy for SDLP prediction model (Vehicle X)

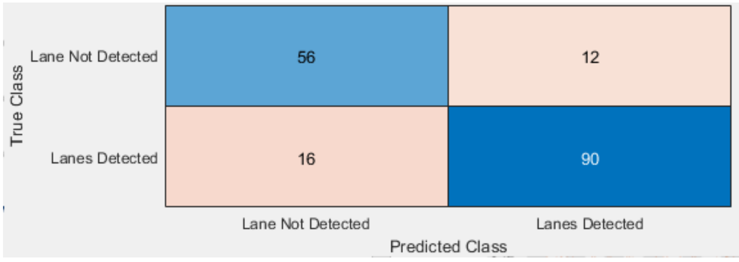


Figure 54 Confusion matrix for MV prediction model (Vehicle Y)

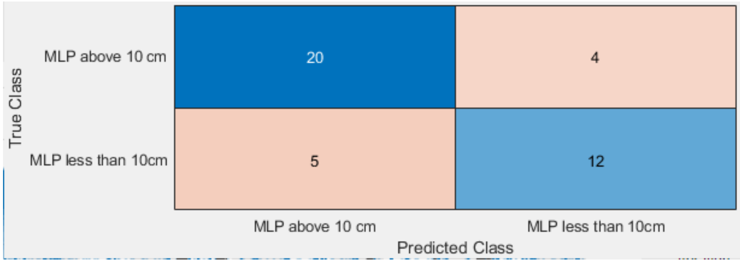


Figure 55 Confusion matrix for MLP prediction model (Vehicle X)

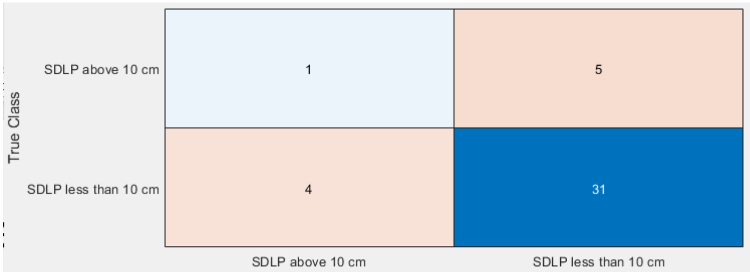


Figure 56 Confusion matrix for SDLP prediction model (Vehicle X)

APPENDIX K – VISUALIZATION OF RESULTS

Figure 57 Day 1 Level of Service for LKS (a) Vehicle Y (b) Vehicle X (confidential)

```
Command Window
Set 'VariableNamingRule' to 'preserve' to use the original column headers as
table variable names.
Do you want to change original test condition? Y/N [Y]: Y

Please enter the number (1 to 3)for the Weather condition
1 is Dry Road
2 is Wet Road
3 is Rain
Press enter if you don not want to change
Enter the number here ......
-------------------------


Please enter the number (1 to 3)for the Lighting condition
1 is Day
2 is Dusk
3 is Night
Press enter if you don not want to change
Enter the number here ......
-------------------------


Please enter the number (1 to 4)for the Lane Width
1 if Lane Width is less than 3m
2 if Lane Width is between than 3m and 3.5m
3 if Lane Width is between than 3.5m and 4m
4 if Lane Width is above 4m
Press enter if you don not want to change
Enter the number here ......2


Please enter the number (1 to 4)for the Line Marking Type
1 is Continuous - Continuous
2 is Continuous - Dashed
3 is Dashed - Continuous
4 is Dashed - Dashed
Press enter if you don not want to change
Enter the number here ......1
```

Figure 58 Interface to interact with Prediction Model

Figure 59 Prediction Model Output 1 (confidential)

APPENDIX L - CONFIDENTIAL

Figure 60 Example of dataset collected by Vehicle X fleet for training DL-based algorithms (confidential)

Figure 61 Using data from Vehicle X fleet for continuous training of Neural Networks (confidential)

Table 39 Different type of road classification in xx (confidential)

Table 40 Lane Width for different type of roads in xx (confidential)