Synthetic Worlds for Improving Driver Assistance Systems

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Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

Saad Sajid Minhas
November 2022

Acknowledgements

'Nothing is possible without the blessings of almighty Allah' My PhD journey started back in 2010 as a simple conversation with my head of department and teacher Eddie Horn at Glasgow Caledonian University when I was finishing my Masters in 3d Design for virtual environments. The possibility of initiating and completing this enormous goal after getting married and having two beautiful kids was always a challenge and it has proven over the past 7 years that it requires more then just setting out specific hours in a day and weekends. The amount of concentration and external support required to achieve this goal was immense and would not have been possible without the key contributors.

And I would like to acknowledge the unwavering support provided by the School of Computer Science and Electrical Engineering for believing in me in times that I really needed their support especially during the Covid period 2020-2021. In particular my supervisors Prof. Klaus McDonald-Maier, Dr. Shoaib Ehsan & Hernández-Sabaté without them I would not be any where near where I am right now. During times when I was about to give up and was close to failure, they guided me and made sure that I kept on moving towards my end goal. I have indulged in a number of fruitful discussions with my peers and supervisors with regards to Advanced Driver Assistance Systems and the contributions towards experiments is immensely valued. Also the fact that difference in time zones had no adverse effect on the communication throughout this research.

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Last but not least, I am grateful to the University of Essex for providing me with a productive environment to conduct my research in a an efficient manner.

Abstract

The automotive industry is evolving at a rapid pace, new technologies and techniques are being introduced in order to make the driving experience more pleasant and safer as compared to a few decades ago. But as with any new technology and methodology, there will always be new challenges to overcome. Advanced Driver Assistance systems has attracted a considerable amount of interest in the research community over the past few decades. This research dives into greater depths of how synthetic world simulations can be used to train the next generation of Advanced Driver Assistance Systems in order to detect and alert the driver of any possible risks and dangers during autonomous driving sessions. As Autonomous driving is still in the process of rolling out, we are far away from the point where Cars can truly be autonomous in any given environment and scenario and there are still quite a fair number of challenges to overcome. A number of semi autonomous cars are already on the road for a number of years. These include likes of Tesla, BMW & Mercedes. But even more recently some of these cars have been involved in accidents which could have been avoided if a driver had control of the vehicle instead of the autonomous systems. This raises the question why are these cars of the future so prone to accidents and whats the best way to over come this problem. The answer lies in the use of synthetic worlds for designing more efficient ADAS in the least amount of time for the automobile of the future.

This thesis explores a number of research areas starting from the development of an open source driver simulator that when compared to the state-of-the art is cheaper and efficient to deploy at almost any location. A typical driver simulator can cost between £10,000 to as much as £500,000 [1] [2]. Our approach has brought this cost down to less than £2,000 while providing the same visual fidelity and accuracy of the more expensive simulators in the market. On the hardware side, our simulator consist of only 4 main components namely, CPU case, monitors Steering/pedal and webcams. This allows the simulator to be shipped to any location without the need of any complicated setup. When compared to other state-of-the-art simulators [3], the setup and programming time is quite low, if a PRT based setup requires 10 days on state-of-the-art simulators [3] [4] then the same aspect can be programmed on our simulator in as little as 15 minutes as the simulator is designed from the ground up to be able to record accurate PRT.

The simulator is then successfully used to record accurate Perception Reaction Times among 40 subjects under different driving conditions. The results highlight the fact that not all secondary tasks result in higher reaction times. Moreover, the overall reaction times for hands were recorded at 3.51 seconds whereas the feet were recorded at 2.47 seconds. The study highlights the importance of mental workloads during autonomous driving which is a vastly important aspect for designing ADAS. The novelty from this study resulted in the generation of a new dataset comprising of 1.44 million images targeted at driver vehicular interactions that can be used by researchers and engineers to develop advanced driver assistance systems. The simulator is then further modified to generate hi fidelity weather simulations which when compared to simulators like CARLA [3] provide more control over how the cloud formations giving the researchers more variables to test during simulations and image generation.

The resulting synthetic weather dataset called Weather Drive Dataset is unique and novel in nature as its the largest synthetic weather dataset currently available to researchers comprising of 108,333 images with varying weather conditions. Most of the state-of-the-art datasets only have non automotive based images or is not synthetic at all. The proposed dataset has been evaluated against Berkeley Deep Drive dataset which resulted in 74% accuracy. This proved that synthetic nature of datasets are valid in training the next generation of vision based weather classifiers for autonomous driving.

The studies performed will prove to be vital in progressing the Advanced Driver Assistance systems research forward in a number of different ways. The experiments take into account the necessary state of the art methods to compare and differentiate between the proposed methodologies. Most efficient approaches and best practices are also explained in detail which can provide the necessary support to other researchers to set up similar systems to aid in designing synthetic simulations for other research areas.

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Abbreviations

ADAS	*Advanced Driver Assistance Systems*
AI	*Artificial Intelligence*
CNN	*Convolutional Neural Networks*
DLN	*Deep Learning Networks*
LEE	*Low − Cost Extendable Easy − to − use*
LiDAR	*Light Detection and Ranging*
NDR	*Non Driver Related Tasks*
PRT	*Perception Reaction Times*
SAE	*Society Automotive Engineers*
TOF	*Time Of Flight*
WDD	*Weather Drive Dataset*

Chapter 1

Introduction

1.1 Motivation

Transportation is the absolute pinnacle of human superiority and necessity. The 21st century has proven to be vital in aggressive advancements within the automotive industry. It's hard to believe that just over a hundred years ago, we were still relying heavily on horses and steam trains for the bulk of our transportation needs. But with the advent of technology and new combustion techniques, we were quickly able to travel long distances with relative ease. But with new methods of transport comes with greater risks to human life. US Department of Transportation's Data has shown that deaths by car crash has always been in the range of 40,000 annually[5]. Although new safety standards had been introduced over time but they are still not enough to get the number of deaths down to a manageable factor. The report also states that in 2019 out of 50,000 drivers that lost their lives in fatal crashes, 3,008 of those were distracted[5]. Hence a human's ability to loose concentration during long driving sessions is quite concerning. Present day advancements pose a greater challenge because automobiles are getting smarter and their systems are getting more complex. Ideally removing the driver completely from the driver's seat is a viable option and can reduce the rate of fatalities by a huge margin. But these autonomous systems are far from perfect. There are just too many obstacles that need to be navigated with extreme caution. Recently a Tesla autonomous car crashed into an overturned Lorry on a Taiwanese highway [6]. It is speculated that if the human driver had control instead of the autonomous car, this crash could have been avoided. Moreover, this is not the only crash that has caused speculation around the use of autonomous cars on the public roads [7]. Hence there is alot of room for improvement and this is what motivates us to conduct our research into the challenges that are being faced by the automotive industry in this new era of autonomous driving.

1.2 Background

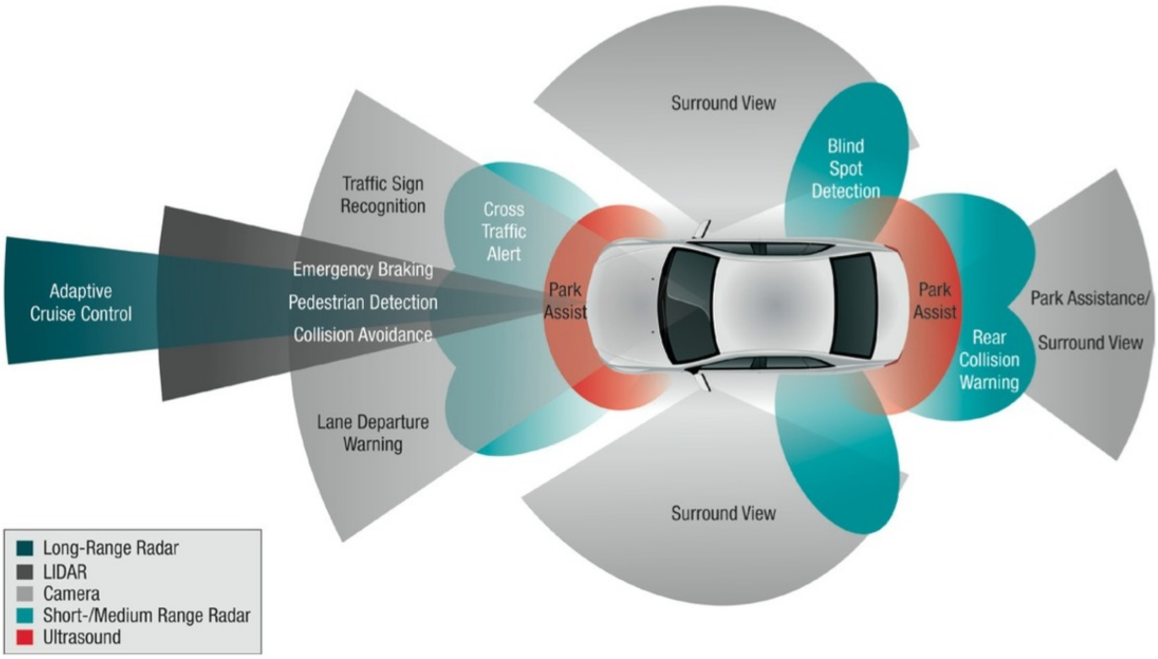


Fig. 1.1 ADAS - Advanced Driver Assistance Systems

The automotive industry is moving at a very fast phase; new and upgraded technologies are being introduced day in and day out. A particular sector of automotive industry, where a considerable amount of research is being done is the Advanced Driver Assistance Systems (ADAS). ADAS refers to a collection of necessary equipment and sensors as shown in figure 1.1. These instruments and sensors make sure that the driver gets the necessary information and assistance in due course which in return will aid the driver in making the right decision while on the road. These systems are highly complex in nature and once implemented and used to their fullest extent, they have the capacity to revolutionize the automotive industry. Coupled with advance AI (Artificial Intelligence), ADAS can provide a creative and effective way to project data and information at the moment when it is required.

The automotive industry has been shocked recently by a number of car crashes involving autonomous cars. A few of these incidents had involved Tesla cars and the authorities have blamed the car's Autopilot mode [6, 7]. At least one death occurred during these crashes. This resulted in a significant change in the marketing strategy by Tesla which now stresses on the fact that the drivers should always keep their hands on the wheels at all times during Autonomous Mode. As the world is being introduced to the age of Autonomous vehicles, accidents are bound to happen. This particular instant also opens up doors for researchers around the world to find an efficient method to streamline the transition from manual driven cars to Autonomous vehicles. More companies are now adapting to the changing landscape brought forward by the the Autonomous revolution, namely Ford, Mercedes, BMW, Volvo, Uber etc. Some of these manufactures have already launched their driverless fleet of cars in major cities in 2021.

SAE (Society of Automotive Engineers) which is a U.S -based, globally active professional association has defined five different levels of Autonomous Driving Technology. Namely, Level 1 to 5 [8].

Level 0 is the baseline with no assistance at all. This is what resembles the average car nowadays, whereas Level 1 supports systems such as automatic braking if a potential imminent collision is detected. This type of Automation has already been implemented in most of the big brand cars that went into production in 2020. Level 2 includes semi-autonomous modes which involve acceleration, braking and basic steering assistance, this also involves variable speed cruise control systems. Level 3 extends the autonomous driving mode to a step further. This results in the car handling the driving tasks in a given parameter like on the freeway and during clear day times, this type of Autonomous system can allow the driver to take back control if he wishes. Level 4 further extends the autonomous tasks and is able to handle all driving responsibilities even if the driver is present or not. Level 5 is the ultimate Autonomous Driving mode, which can handle complex driving tasks in any sort of road surface and weather conditions. It is also noted that Level 5 is still at a hypothesis stages, some vehicle manufacturers believe that the level 5 is a pure myth at present.

1.3 Problem Statement and Challenges

There are a number of research challenges involved in designing an effective Driver Assistance System. Most of the variables revolve around finding the quickest way to test algorithms and make the necessary adjustments in the next iterations of the design. There is a reason why the automotive industry has been quite slow in recognizing these challenges due to complex manufacturing processes and costing issues. Moreover, it took quite some time for highway safety standards to be recognized and implemented during the second half of 20th century. In short, the problem is that the automotive industry cannot rely on full scale real simulators anymore due to the time and budget constraints attached to them, Moreover, the hypothesis needs to be tested thoroughly to identify whether fully synthetic data is a viable option to design the next generation of ADAS in the least amount of budget and time hence empowering the researchers with the tools necessary to push forth the development of new safety standards. This is the fundamental problem statement which helps to connect all the chapters in this thesis. This sub-section identifies some of the most crucial challenges that will be targeted in this thesis and are addressed in later chapters.

1.3.1 Synthetic Environments

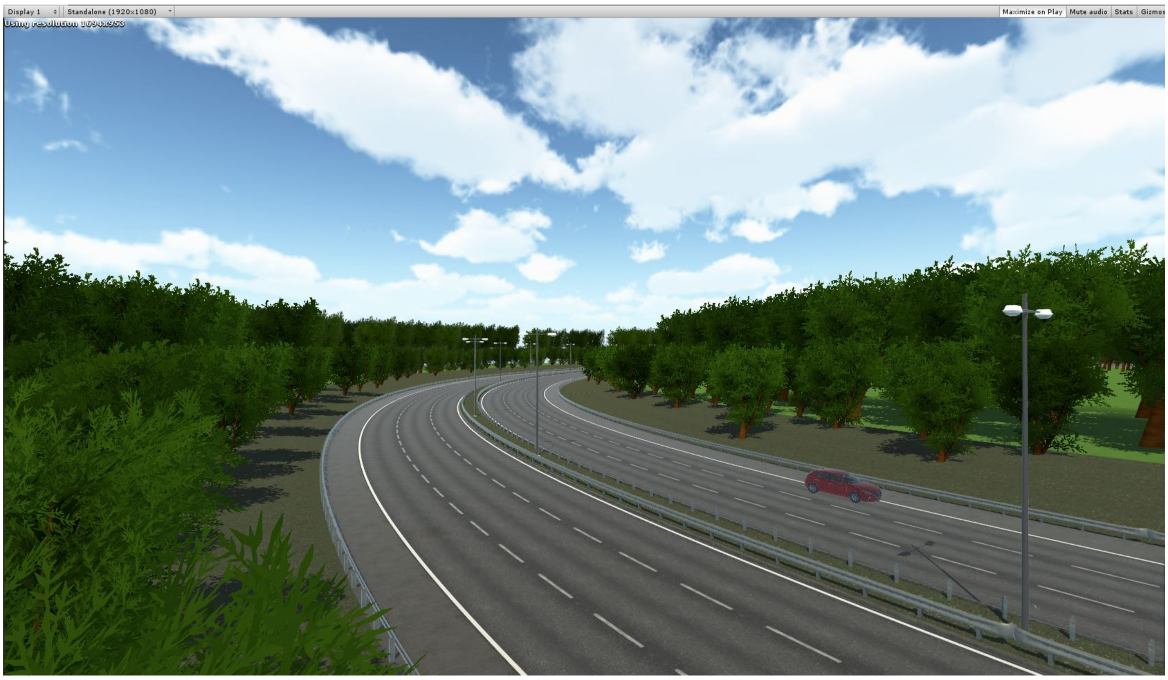


Fig. 1.2 Synthetic World View

In order to test the validity of complex algorithms, it is considered a more productive approach to test them out in a closed and controlled environment before releasing them into the wild. The concept of Synthetic Environments is not new but using them for the development of ADAS is quite a challenge on its own. A synthetic environment can be termed as a digital twin of it's real world counterpart, closely reflecting the physical properties such as materials, shading, lighting and weather conditions. Since the advancements made in computer graphics in the early 2000's, it is now possible to build virtual worlds than can simulate almost all the necessary physical properties closing the gap between real and synthetic worlds even further.

1.3.2 Driver Simulator

Although big car maker companies such as Ford & BMW do have huge test facilities where they can perform relative experiments but the iteration times between when an issue is identified to when it is resolved can be quite high when it involves physical production.

This is where virtual simulations can play an important part in reducing the time between production iterations. Moreover, an unlimited amount of datasets can be generated from this simulations. Chapter 3 deals with the approach and best practices necessary to develop low-cost and mobile simulation systems that can efficiently simulate their real-world counter parts.

Fig. 1.3 Driver Simulator

1.3.3 Perception Reaction Time

Perception Reaction Time or PRT is quite crucial in highlighting a potential crash and subsequent solution to avoid it within a plausible time frame. On average, 1.1 second is the typical time for when the driver sees an issue on the road to when he reacts to it with evasive maneuvers [9]. But these times can vary heavily when the car is in autonomous mode and the driver is distracted by other tasks. This is due to the fact that drivers do not pay the same amount of attention as compared to when the car is in manual mode. This has resulted in quite a few crashes and fines over the recent years. Main challenge is to know exactly how much time is required for the driver to safely navigate through the potential collision ahead. Chapter 4 will investigate this issue further in detail within this thesis. Experiment setups and detailed result analysis are performed to answer the problem statements. Figure 1.4 shows glimpses of the recorded data used for perception reaction time experiments.

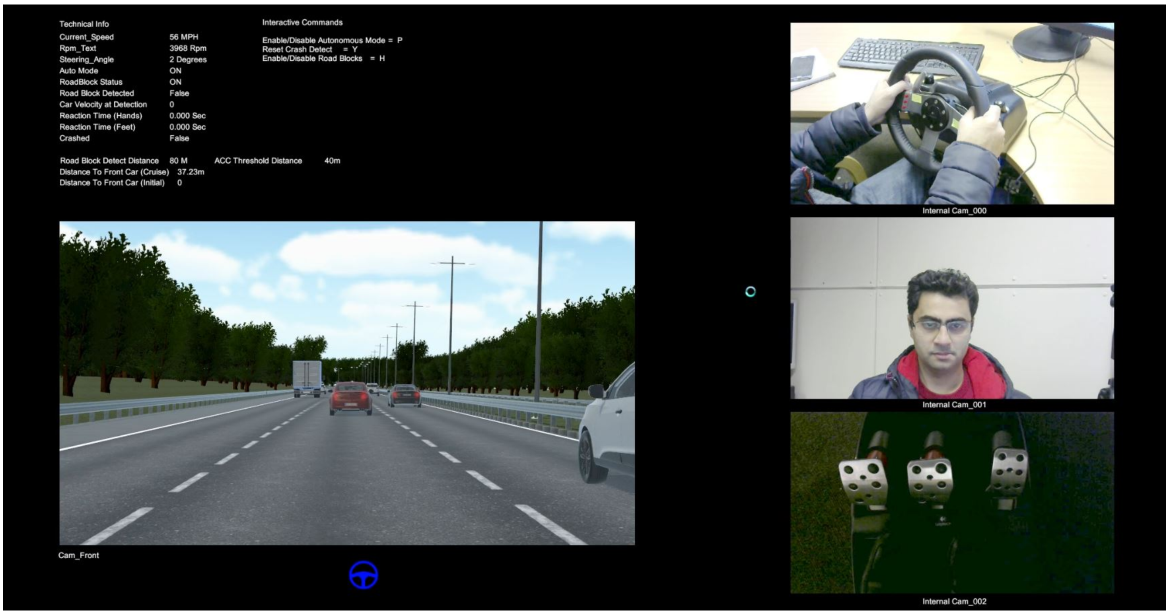


Fig. 1.4 Driver Simulator Recorded Data

1.3.4 Weather Classification

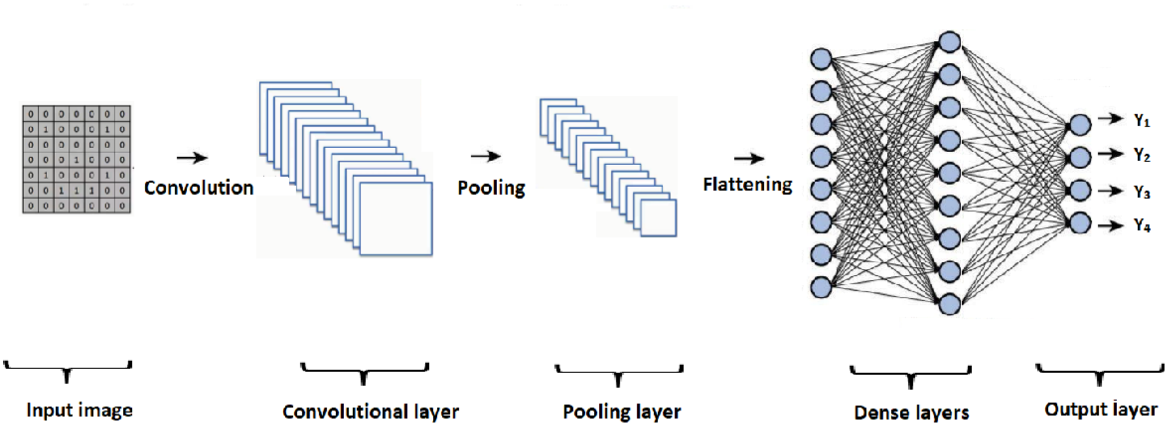


Fig. 1.5 Weather Classification Cnns

Effective Weather Classification is one of the most challenging problems faced by vehicle manufacturers today. Knowing the severity of localized weather and then amending the driving attributes of a vehicle can substantially decrease the chances of a potential crash. The other issue to note is that weather is made of up many unique factors like color, visibility, shadows & highlights and it is quite common to confuse certain weather conditions with others which can be dangerous for self driving cars if perceived incorrectly. Moreover, multiple variables can be used to provide absolute classification for weather. Chapter 5 investigates this issue in more detail and will outline an approach that can classify weather images at a respectable success rate by using only synthetic images generated on a custom built simulator. This newly generated dataset can play a vital role in training pretrained deep learning networks for better performance and accuracy in varied weather classification scenarios. A number of Deep learning networks are used to test out the feasibility of the recorded synthetic dataset.

1.4 Contributions

The contributions of this thesis for the problem statements as mentioned in section 1.3 vary significantly in scope and can be broken down into the following points.

1. The first contribution of this work is the development of a driver simulator called LEE Driver Simulator that is able to record important aspects of a driver during a variety of autonomous driving scenarios. The simulator was designed specifically to be easy to use and extendable which provides researchers with the freedom to simulate and test with out being bound to any physical restrictions. The easy to use aspect is comparable to other simulators in the market like CARLA [3] which might require 10 days of programming in order to set it up for driver reaction control whereas Our approach is build from the ground up to target driver reactions and hence can be deployed in less than 15 minutes. Our simulator is also designed to be light weight meaning it only has 4 main components namely CPU Case, monitors, Steering/pedal and webcams. Hence, it can be transported to a target location without any specific physical setup unlike other state-of-the-art simulators [4] [10]. The low cost aspect of the hardware also makes sure that it is accessible by even the smallest of organizations and research teams. A typical physical driver simulator can cost between £10,000 to as much as £500,000 [4] [1] [2] [10]. Our approach has brought this cost down to less than £2,000 while providing the same visual fidelity and accuracy of the more expensive simulators in the market.

2. The second contribution involves Testing the hypothesis that a driver behind the wheels of an autonomous car can quickly lose focus on the road which results in increased reaction times resulting in possible fatal outcomes. The driver simulator introduced in the previous contribution is used to it’s fullest extent, resulting in accurate time recording for PRT (Perception Reaction Time). The results show that not all secondary tasks result in high Perception Reaction Times. Moreover, the global reaction times for hands was recorded to be 3.51 seconds whereas the feet were recorded at 2.47 seconds

which implied that drivers are always prioritise the feet over the hands. Our approach also sheds light on the relationship between Perception Reaction times and mental workload, although fatigue was not the outstanding entity, the study finds that reaction times do suffer by approx 20% when secondary tasks are introduced during driving.

3. The third contribution is the generation of a new dataset of images which captures the driver from three different viewpoints within an autonomous virtual car. This dataset is generated form the PRT (Perception Reaction Time) experiments as discussed in the previous contribution. The dataset comprises of a number of different scenarios, each driver is subjected to a number of tasks during autonomous mode. The dataset sheds light on a number of interesting facts with regards to where the driver rests his/her arms, legs and eyes during the targeted scenarios. Moreover, important variables like the velocity, distance and reaction times of feet as well as hands are also recorded separately which gives a detailed insight into how drivers behave in an emergency situation behind the wheel of an autonomous vehicle. The dataset is currently sized at over 100 GB and contains over 1.44 million images. According to the literature review, a dataset of such scale is not available freely. Hence the proposed dataset is vital for researchers and engineers who are striving to design the next generation of ADAS.

4. The fourth contribution involves the generation of a new weather dataset comprising of synthetic images with varying weather conditions known as Weather Drive Dataset or WDD. This includes hi fidelity images produced for four different weather conditions, Clear, Cloudy, Foggy and Rainy. The feasibility of these images is tested in deep learning methods and when used with VGG it is able to attain an efficiency of 74% which is unprecedented for a synthetic only dataset which is being tested on real world images. These images were generated by our custom built simulator which was developed ontop of the LEE simulator. It provides great ease of use meaning that a number of different weather scenarios can be setup in a fraction of time as compared to state-of-the art simulators like Carla [3]. Moreover our approach allows for wider range of controls over the cloud visual fidelity making it one of the best weather based simulators in the field and it is designed for a quick launch and record approach meaning that very little setup is required to generate complex weather scenarios. Moreover, the simulator is the only one of its kind whose purpose is to generate high fidelity synthetic weather simulations for autonomous driving research. The Weather Drive Dataset is novel in nature as it is the largest synthetic dataset for weather classification comprising of 108,333 images in total.

1.5 Thesis Structure

The thesis is divided into the following 5 Chapters:

In **Chapter 2** we provide a detailed literature review of the existing research in the field of Advanced Driver Assistance Systems. It covers a vast majority of the topics related to synthetic worlds, Perception Reaction Times, Driver Behavior & Deep learning Networks.

In **Chapter 3** we present a detailed development overview of the LEE driver simulator which was designed specifically for recording Driver vehicular interactions in self-driving mode. It sheds light onto many aspects of the development methodology and provides a fair guide to what to look out for when developing a specialized simulator from scratch. It also explores how the proposed simulator is suitable for assessing driver vehicular interactions within a Level 3 autonomous vehicle.

In **Chapter 4** dives deeper into recording usable data from the driver simulator introduced in chapter 3. Major modifications were implemented in terms of camera setup and driver input recorders. This resulted in an upgraded system that is able to perform well and can simulate autonomous scenarios in a much more expansive detail. This particular chapter also deals with the recording of Perception times of drivers behind an autonomous car, the significance of the problem is provided in detail and statistical analysis techniques such as ANOVA are also explained in detail. The experiments that were performed on human subjects is also outlined providing details with regards to the way the subjects were introduced into this experiment. The chapter also covers the dataset that was generated as a result of this study which sheds more light into how the proposed simulator can be used to record important driver behavior data that can be used in further research into other related fields.

In **Chapter 5** we explain how the driver simulator that was introduced in the previous chapter is further enhanced and modified to produce hi-fidelity synthetic images specifically for weather classification research. The resulting images were then used to retrain CNNs (Convolutional Neural Networks) which resulted in 74% accuracy which is of great importance because it shows the significance of synthetic only data which is capable of plausible accuracy when tested on real world data. The chapter also highlights the important methodology changes that were performed to conform the driver simulator to this specific task of weather images. Deep Learning Models are also discussed in detail including the setup of layers as compared to state-of-the-art.

Finally **Chapter 6** deals with the concluding remarks and future directions related to synthetic worlds for driver assistance systems, the limitations that the current approach possesses and potential workarounds for highlighted issues. The chapter effectively leaves the door open for future researchers to build on top of the experiments and results provided in this thesis.

1.6 List of Publications

The following contributions were made during the course of this PhD Doctor of Philosophy:

1. Minhas, Saad & Hernàndez, Aura & Ehsan, Shoaib & Díaz-Chito, Katerine & Leonardis, Ales & López, Antonio & McDonald-Maier, Klaus. (2016). LEE: A Photorealistic Virtual Environment for Assessing Driver-Vehicle Interactions in Self-Driving Mode. CVPR 2016

2. Minhas, Saad & Ehsan, Shoaib & Hernàndez, Aura & McDonald-Maier, Klaus. (2020). Effects of Non-Driving Related Tasks During Self-Driving Mode. IEEE Transactions on Intelligent Transportation Systems. 10.1109/TITS.2020.3025542.

3. Minhas, Saad & Khanam, Zeba & Ehsan, Shoaib & Hernàndez, Aura & McDonald-Maier, Klaus. (2022). Weather Classification by Utilizing Synthetic Data. MDPI Sensors 2022

Chapter 2

Literature Review

This chapter provides a detailed overview of the literature within the use of simulators and synthetic worlds for the purpose of improving Driver Assistance Systems. A breakdown of the most used techniques and methodologies is performed to give a better understanding of the current state-of-the-art. The author also presents a detailed insight into datasets that are currently available to further compare it to the datasets that were produced during this study. This chapter provides a strong base to compare against the contributions highlighted in the previous chapter.

2.1 Overview

When it comes to major literature review regarding Advanced Driver Assistance Systems research, there are numerous publications in exceptional journals and conferences, some of them deal with the effective use of cheap mobile devices as HUD systems while others are researching on more complex systems like achieving collision Avoidance through HUD and LIDAR systems. The overall aim is to address the problem of how an electronic device can help to prevent road accidents in order to save human lives. Recent study[11] has shown that most of major accidents are caused due to negligence and frequently leads to fatal accidents on the motorways especially during lane switching maneuvers. Most of the factors include recognition failure, lack of awareness and fatigue.

Moreover, researchers are also working closely with designers and engineers to work out the most efficient implementation of Driver Visual Guidance Systems by using Heads Up Displays. On the hardware side, researchers are looking into different optical designs in order to efficiently implement HUD systems onto full windshield areas. Other research areas include intelligent headlights [12] and lane changing assistance [13] which are quickly becoming a standard for modern automotive assistance systems. A study was carried out recently where 16 participants were instructed to drive in a parking lot with a monoscopic heads up display warning them of a possible collision with a pedestrian in front. The experiment reflected the benefits of AR displays and conformable graphics such as the ability to guide drivers attention and their positive consequences [14]. Moreover, Coleman [15] did another study which involved 24 drivers and used fixed and animated AR graphics to find out how the driver's reacted in both cases. Results showed that the animated graphics can produce some driving gains like goal-directed navigation tasks but often come at the cost of response time and distance.

Our research also specifically deals with the fact that computer-generated virtual worlds can play a vital role in designing and implementing new algorithms that can make driving experiences more secure and efficient. The proposed research not only deals with manual human factors involved in driving but also computer vision based components that can help the autonomous cars of the future to better understand their surroundings and make efficient decisions accordingly.

2.2 Autonomous Driving Levels

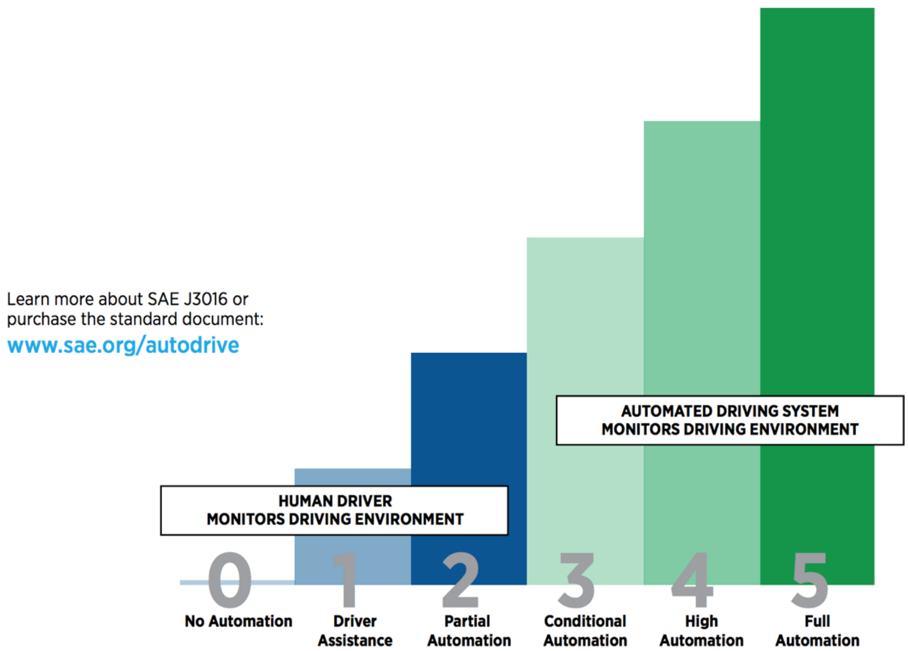


Fig. 2.1 SAE Levels of Autonomy

Before we dive deep into Advanced Driver Assistance Systems during autonomous driving, first we have to understand what constitutes and can be termed as autonomous driving. SAE (Society of Automotive Engineers) which is a U.S -based, globally active professional association has defined five different levels of Autonomous Driving Technology. Namely, Level 0 to 5 [8].

Level 0 is the baseline with no advance assistance at all. This is what resembles the average car nowadays with no electronics that can help a driver to drive more efficiently and safely. This level can contain systems such as tyre pressure monitors and sensors that can show and alert the driver of potential mechanical problems such as engine oil change warning indicators. SAE has termed this level as if the driver is driving the car even if the feet are off the pedals and there is no steering input from the driver. The driver should continuously supervise the controls such as steering, braking and acceleration. So the total features in this level are limited to providing warnings and momentary assistance like automatic emergency braking, blind spot warning and lane departure warning.

Level 1 is the next level of autonomous driving. It supports steering or brake / acceleration support to the driver which include lane centering and adaptive cruise control. Most of the new cars built after 2020 have these features as standard. So instances where a vehicle can be kept at a safe distance behind the other car, qualifies as Level 1 because the driver only has to monitor the other aspects such as steering and braking.

Level 2 further steps up the driver assistance above level 1 as it supports both steering as well as braking / acceleration at the same time. So effectively it provides the ability of lane centering and Adaptive cruise control at the same time. This feature is particularly common in cars built after 2021 making it a standard throughout the industry.

Tesla by far has been the first to develop autonomous vehicles. Tesla unveiled the famous Level 2 Autopilot system 5 years back, which made headlines worldwide, it was the first true autonomous system of its kind. It involved systems like Auto Steer, Auto Lane Change, Traffic-Aware Cruise Control, Side Collision Warning and Auto Park.

BMW has been a major player within the Autonomous vehicles industry. They had rolled out Level 2 Autonomous cars in late 2016. This included systems such as Traffic jam assist. The system is able to detect the car ahead and can read lane markings, the car can correct it's heading by steering into the correct direction. Unfortunately, the system works up to 43 mph. which is way lower than the standard highway speeds. The European version of the cars have self-driving features which does not require the driver to be present behind the wheel.

Level 3 extends the autonomous driving mode to a step further. The driver is practically not driving when Level 3 features are enabled. But when the feature requests, the driver must take back control. The car is able to drive itself under limited conditions and will not operate unless all required conditions are met. examples include features such as traffic jam chauffeur in which car would gently keep a safe distance from another car in a traffic jam scenario. Other scenarios include the car handling the driving tasks in a given parameter like on the motorway and during clear day times.

Major car companies are spending a large portion of their research and development budget to bring Level 3 Autonomous modes to the roads worldwide. Audi was one of the first manufacturers to bring a fully functional level 3 autonomous car onto the roads with its A8 models. It comprised of unique features like Traffic Jam Pilot System. It was able to handle acceleration, braking and steering at 40 mph. However, such systems have their own set of limitations, For example the system needs at least 2 cars in front to decide whether the traffic is heavy or light, the system is also bound to specific weather conditions, and as a result the feature is unable to perform efficiently on a snowy road. Moreover, the car also features a driver detection system which detects whether the driver is looking down the road or not, also it will be able to tell if the driver is incapacitated or not.

After the successful roll out of level 3 system, Audi initially had plans to launch Level 3 plus close to the end of 2021 but was put on hold due to performance issues. This was supposed to be a refined version of their level 3 Traffic Jam Pilot system, which would have allowed the car to operate at standard highway speed such as 60 to 70 mph but the system still requires the successful detection of a freeway environment by using the GPD and on board camera systems. Moreover, the system was also planned to include a data recorder system which would collect real-time driving data during a driving sessions, it almost acts as an airplane black box, which collects vital data just before a crash.

Honda might be the most affordable option for Autonomous Driving Suites. They have features like Adaptive Cruise Control and Lane Keep Assist, which uses a forward facing camera to determine the distance and hence control the speed and direction. Honda cars can also include Forward Collision warning, Collision Mitigation Braking, Lane Departure Warning and Road Departure Mitigation systems. Honda plans to launch its Level 3 cars in the next few years which will have car to car communication build in. This helps to share the necessary road data with other Honda cars in effect making the autonomous driving more accurate and efficient. Moreover, Honda has also made a bold claim of No crashes after 2040.

The Mercedes Drive pilot system is far the most resilient than the company allows it to be under its current stage. Also the E-class was the first car ever to introduce V2V technology which like Honda's planned cars are able to communicate necessary road data with other cars and this particular data is not bound to just Mercedes specific cars but it is a global shared data pool to which every other car company can contribute effectively making it an open source communication model for transmitting vital road data and information.

Level 4 further extends the autonomous tasks and is able to handle all driving responsibilities even if the driver is present or not. Examples can include local driver less taxis and by design the vehicle can include or not include pedals or steering wheels. This level would in theory bring about the biggest change in automotive industry but is still limited by specific conditions.

Audi is also pushing the Level 4 Autonomous systems by 2030. This will allow the cars to drive autonomously anywhere as long as the car is within a geo-fenced area. This system will allow the car to travel from London to Paris, provided the road is already mapped into the system. In total Audi would require at least 24 sensors to make Level 4 Autonomous driving a reality, this includes sensors such as GPS, LIDAR (Light Imaging, Detection and Ranging), short and long range radar system, and at least two different digital cameras for computer vision based input.

Apart from Audi, BMW is planning to launch level 4 Autonomous cars in the next few years and are planning to tackle Level 3 to 5 cars in the next 10 years.

Fig. 2.2 Level 5 Autonomy Concept

Level 5 is the ultimate Autonomous Driving mode, which can handle complex driving tasks in any sort of road surface and weather conditions. It is also noted that Level 5 is still at a hypothesis stages, One Audi representative recently described the level 5 as a pure myth but that is surely bound to change with the progression of technology.

The pioneering technologies do have their own set of limitations. As discussed before, Tesla autopilot system has been involved in quite a few crashes since it's debut which resulted in at least one death.[16] [6] Tesla has always maintained that the users should have their hands on the wheels at all times even in Autopilot mode, until there is a stricter procedure in place to force the users to comply with the guidelines, these accidents are bound to happen again and again until the automotive industry reaches level 5 Autonomous modes.

The above levels highlight the fact that in order to reach the Level 5 Autonomous Level, researchers and designers require systems and simulators which can aid in reducing the iteration times between algorithms. The author presents a number of solutions which are vital in achieving this goal.

2.3 Synthetic Worlds

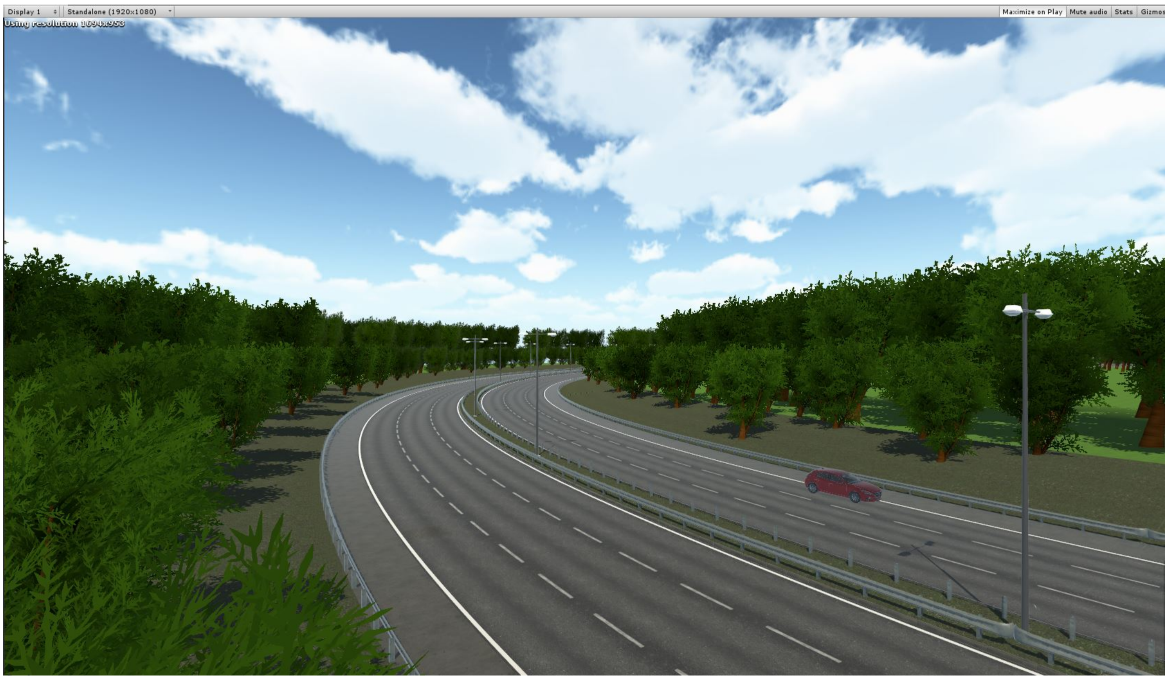


Fig. 2.3 Driver Simulator Synthetic View

Synthetic worlds are becoming very useful in the research community for the purpose of iterating quickly and efficiently with regards to testing new algorithms. There are alot of advantages and disadvantages for using synthetic data for deep learning applications. One of the limitations of deep learning networks is the data-hungry nature of using such systems, they just require too much data to train and test. This limitation can be overcome by using virtually created data that can be generated easily and efficiently in great numbers without having to step outside into the real-world. The artificially generated data can help to improve the performance of deep learning methods by meeting their data demands [17]. A report created by Gartner agrees to this notion that artificially created data will surpass real data usage for AI by mid 2030's as shown in the figure 2.4[18]

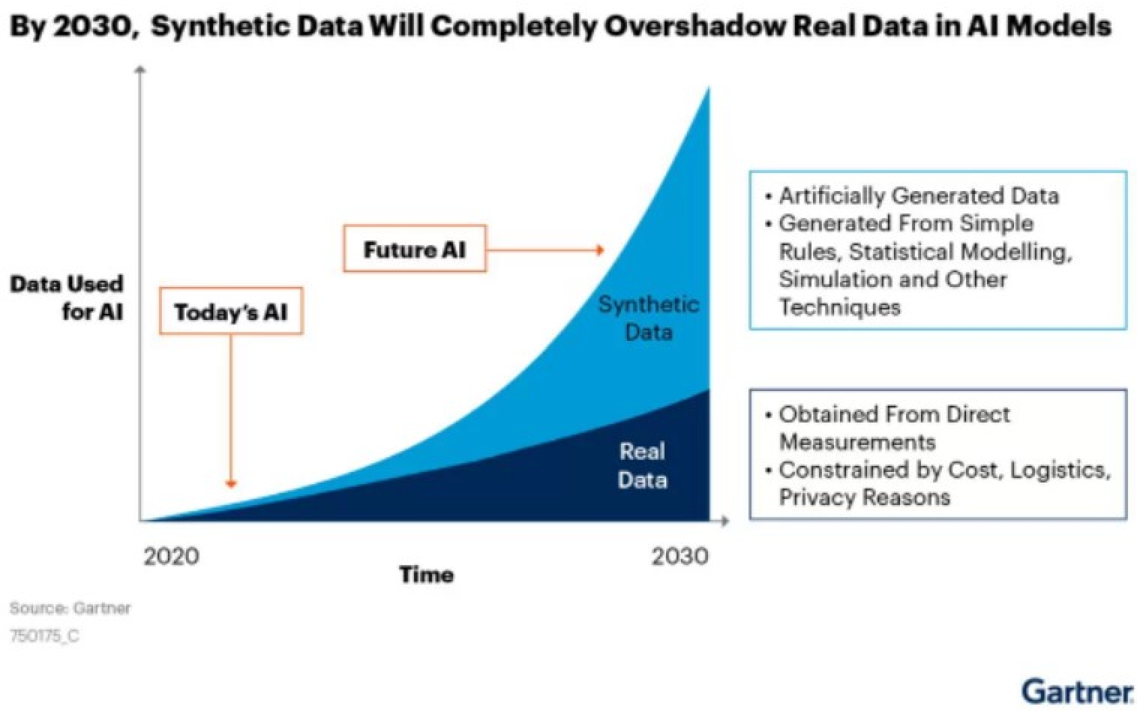


Fig. 2.4 Gartner 2021 Report

Driving simulators are proving to be vital in automotive research and are used heavily in other fields as well such as military and construction. The overall premise has changed so much that it is safe to say that the research community cannot proceed without them. They can primarily be broken down into 2 categories.

1. Physical Simulators

2. Virtual Simulators

2.3.1 Physical Simulators

The first interactive simulator was introduced in the 1960 [19] which paved the way forward for other physical simulators like TRAFFIS which is an industrial grade simulator relying specifically on a re-configurable approach [20]. Another recent research was carried out at

The University of Auckland, New Zealand [21], It deals with recording the facial expression of the driver to detect if the driver is paying attention towards the road or not with respect to what exists in front of the road. The research proposes an advanced driver-assistance system that correlates the driver's head pose and hazards by analysing both simultaneously. They also propose three novel ideas, Asymmetric appearance-modelling, 2D to 3D pose estimation enhanced by the introduced Fermat-point transform, and adaptation of Global Haar classifiers for vehicle detection under challenging lighting conditions. The system is capable to detecting the driver's direction of attention, it can also detect yaw and head nodding as well as vehicular detection in front of the driver. Having both road and the driver's data and implementation of a fuzzy system, they had successfully managed to develop an All in one system to detect driver's attention and point of concentration. Moreover, the system is also stable enough to provide real-time performance analysis for real-world driving scenarios.

Our approach demystifies the notion that physical simulators are better at performing complex experiments than virtual simulators. The later chapters in this thesis will show that virtual simulators are just as effective and accurate as their physical counterparts while reducing the setup and iteration times by a huge factor.

2.3.2 Virtual Simulators

The complexities and setup times of physical simulators has a drastic effect on efficiency and reusable data. A good example would be a specific weather condition would not be the same next time a physical simulator is used. The environmental aspects are not controlable enough, these issues can be solved by opting for a virtual simulator instead. which can provide complete control over all aspects of driving while still maintaining the accuracy of experiments performed.

Virtual Simulators are by far becoming more robust and cost effective, examples include a research that was carried out at Stanford University which looks into ways of anticipating manoeuvres via learning Temporal Driving Models [22]. A real car is fitted with cameras and computing device that captures driver actions along a road, the research then proposes an Auto-regressive Input-Output HMM to model the contextual information along with the manoeuvres. The captured data is then evaluated against a diverse dataset of 180 miles of real-world motorway and city driving. The results have shown that the system can anticipate manoeuvres 3.5 seconds before they occur with over 80 percent F1-score in real-time. As the above result reflects, this particular research is quite fascinating as it paves a way to have a quick peek just over a few seconds into the future to detect what will happen next. This type of approach would generously support new algorithms and applications that can detect and avoid particular automotive accidents.

An enormous amount of interest is being generated regarding the use of Virtual or synthetic Worlds to test algorithms that will eventually make their way into the real world applications [23]. Image-based detection of humans and automobiles is of vital importance when it comes to AR and HUD development. The detection of non-occluded standing humans has always remained a challenge for intensive research. One such approach involves the training of data set that involves 3d animated humanoid models from a game engine [24]. The training dataset still requires a lot of human input to pave the way for Convolutional Neural Networks to work effectively in identifying the humanoids. The results are quite promising, the research presents a solution to a problem namely the acquisition at a low cost of good samples to train. In short, subjects were instructed to play an open-world video game which consisted of an urban environment full of cars, buildings and humanoid characters. Whereas in the background vital data is being recorded, the captured data is then subjected to a classifier which isolates humanoids from the background. As the data being used is virtual, the game engine can automatically classify the humanoids from the background. Also later the researchers introduce an active learning technique thereby using the virtual world data in conjunction with the real-world data. They then also provide quantitative results showing the validity of the approach.

Fig. 2.5 VR Simulator setup

Another crucial study was performed by Chen-Ruei et al [25]. The experiment proposes a new methodology to carry out 3d pose estimation of an object by assuming a single lens camera environment and then uses a synthetic virtual world dataset to assist the deep learning model. By using only the synthetic dataset to conduct the training the efficiency achieved was close to 85% with 30 million parameters. The study increases the confidence in the synthetic worlds by a huge margin as it provides insights into how virtual worlds can be used to test and train deep learning models with plausible efficiency.

Tozman et al [26] A study was performed on a virtual simulator to understand the relationship between flow and heart rate variability. 18 subjects took part in a driving scenario that projected them to boredom, flow and anxiety. Heart rate variability or HRV differed significantly between the three mental states.

Another study was performed by Yimen et all [27] studies the effects of driver vehicular control switch between manual and autonomous driving systems. The subjects found it challenging because they were not used to that system. the study proposes a robust controller to assist human drivers in the handover scenarios. A virtual simulator was used equipped with a VR headset.The results showed that the driver steering loads and vehicle lateral deviations can be reduced by the designed controller hence improving the driver safety in the handover process.

Virtual simulators can also be used in conjunction with the real world by using augmented reality to overlay virtual information on top of the real one. We also have quite a lot of examples relating to an effective AR in real-world scenarios, these include the use of AR systems within Military equipment, like a fighter pilots visor display system. It effectively helps the pilot to acquire targets on a battlefield by just looking in the direction of the target. Examples like that can also be implemented within the automotive version of AR displays. A typical scenario would involve the driver looking in a certain direction. By doing so the AR systems would project data and information containing famous landmarks in the bespoke direction, without having to need to stop on the side of the road or even the driver taking out his phone to look for the required information, as a result making the driving more effective and safer at the same time. Moreover, an effective design and composition theory is also necessary for the projection of the above information. Because according to a recent study from Toronto University, the HUD systems can have a negative effect on the driving if the information being transmitted is too overwhelming. We believe such problems can be overcome by using an effective design methodology while creating the AR systems. The perfect example of such a scenario would be a driver being bombarded with unwanted data and information at the wrong time. The design methodology may involve the colour of the fonts as well as the contrast ratio with the background elements. This approach is also beneficial to the psychological researchers as well, who are willing to see how a driver responds to such scenarios. Which will result in a broader range of possible research scenarios.

Tracking and Registration are also quite important in delivering an effective driving experience; The importance of VANETS (Vehicular Ad Hoc Network Systems) is crucial under such circumstances [28]. It is a system that allows cars on the road to share vital information regarding their surroundings, effectively allowing information to be transmitted from one edge of the road to the other. This can involve an accident alert down the road. This system has the ability to make the roads much safer and less crowded by relaying accident info the incoming cars and effectively giving diversions before the bespoke point on the road.

Another challenge for an effective ADAS system is to assist the driver in all weather conditions. This can be quite challenging for the ADAS of the future. A particular system would work just as well as it's military counterpart. Armies around the world are using the Thermal and night vision system vigorously in everyday combat situations. The same can be true for an automotive display system, a system that can operate in varying weather helping the driver to overcome nature's constraints. The scenarios can involve driving in a heavy storm, extreme fog or pitch-black night [29].

In this section, we have seen how the virtual simulators have a decisive edge over the physical simulators and that they can save enormous amount of time and budget when designing advanced driver assistance systems. Moreover, the virtual simulators that are available do require enormous amount of setup time and hence can be improved further specifically towards the area of driver vehicular interaction and visual place recognition.

2.4 State-of-the-art Simulators

As discussed in the previous section, simulators have been part of the research community for a number of decades, it is a plausible proving ground for testing new systems but only a decade ago the visual fidelity was quite far behind. With the advent of technology this is rapidly changing and the simulations are becoming more reflective of their real-world counterparts. The challenge is to bring the cost down and design better scenarios that can reflect the real world problems as close as possible.

Another study used 30 drivers strapped with a heart rate sensor to detect the increase in heart rate of drivers during a scenario that simulated a critical situation which as a result increased the driver's heart rate. the Wahoo Tickr X chest strap was used to measure the heart rate. [30]

Alexander and Neville [31] did an experiment on 26 drivers in two different scenarios. The subjects were asked to read a newspaper while waiting for the car to give back control from an automated scenario. The results showed that the lane positioning was unaffected in both automated and manual conditions. However, a significant increase in the standard

Table 2.1 LEE General Comparison for PRT and Weather classification with State-of-the-art Simulators

	Costing	**Learning Curve**	**Extendable**	**Visual Fidility**
Our Work (LEE)	Low	Low	High	High
CARLA	Low	High	Mid	High
STISM	High	High	Low	Low

deviation of the steering wheel was noted. In short, drivers performed better in the self-paced transfer as compared to system paced transitions. Another study showed that a prior familiarization with takeover requests affected the driver's takeover performance and automation trust, hence the first take-over performance is the most relevant whereas it slowly lowers driver's automation trust [32]. Regarding the use of simulators to gather such scientific results is concerned, it was found that the ADAS simulations contributed significantly to enhance the data that would mean better ADAS for future auto-motives [33] [34].

Soleymanpour et al [4] performed a study by using a desktop driving simulator known as STISIM Drive, the simulator was programmed with night driving for atleast 70 minutes on a two way highway with no turns, fourteen healthy volunteers aged 18 were selected to perform this experiment. The main purpose of the study was to detect drowsiness among the drivers. The novel algorithm was able to show an accuracy of 78.79% and a detection rate of 95% by comparison with KSS based drowsiness. This shows that a lot of time can be saved and iterations of experiments can be performed without the need to spend huge sums of time and budget by using a virtual simulator. As shown in Table 2.1 STISIM is quite expensive and requires special setup, and transporting issues can arise as well due to the bulky nature of the hardware. Although the developer support is quite reasonable, the system still has a steep learning curve which adds to the overall budget and time. The biggest issues if the Low visual fidelity, STISIM is quite a respectable simulator when it comes to driver research but for computer vision tasks it lacks the visual quality for efficient dataset generation.

Carla is another simulator which works really well in simulating an urban environment for autonomous driving vision research, it is able to mimic Lidar camera outputs and also generates dynamic weather conditions, but the issue is the setup which is quite cumbersome. [3] Another extension of CARLA simulator came in the form of a bus modification. Xiang et al [35] managed to modify the standard CARLA simulator to a Bus simulator. CARLA is perhaps the only simulator that is closely comparable to LEE but the high learning curve when it comes to accessing external hardware communication and scenario setups makes it harder for researchers to adapt to it quickly. Same can be said for the extend-ability because the users would need to access the API specifically for altering the virtual environment. The image quality is comparable to LEE as it provides a comparable visual fidelity especially in the recent builds releases of CARLA. As we can see from the above that the gaps that our approach can fill is in the area of affordability, easy usage and scalability which can provide the researchers, a simulator that can provide the usage and feedback as efficiently and accurately as the real-world counterparts. However the simulators discussed in this section have one thing in common, although they are all significant in performance, but they lack in setup times, plug and play and visual fidelity. Our approach will aim to solve these issues in more detail in Chapter 3.

The above literature is enough to motivate that there is a plausible need for synthetic or virtual simulator utilising synthetic worlds to help answer some of the problem statements raised in the previous chapter. There is also a need for generating usable datasets that can be used to test and train the next generation of deep learning models to assist in designing better driver assistance systems. Chapter 3 introduces the development of a specialized low-cost simulator called LEE that has proven to be beneficial in recording usable data and experiments which have resulted in a publications of a journal paper as well as a conference paper.

2.5 PRT: Perception Reaction Time

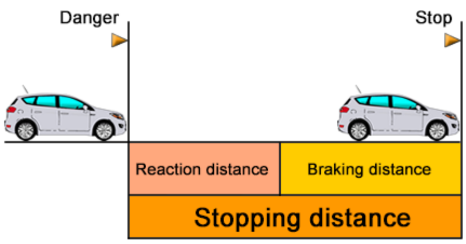


Fig. 2.6 Perception Reaction Time

PRT of human drivers is an active research area within the driving performance domain, where it plays an important role in road incidents [36] - [37]. Green [36] highlights that the most important variable is the driver's expectation. Jurecki [37] Confirms that reaction time is approximately a linear function of Time To Collision (TTC). Svetina [38] concludes that mean reaction time and inter-individual variability progressively increases with age. It is worth mentioning here that all these studies are carried out on active users while actually driving a real vehicle.

Regarding the average reaction times in emergency situations, it has been studies that the average time is 5 seconds [39]. Another interesting study shows that human reaction time can increase by 40 to 87 percent due to increased fatigue levels. [40] The problematic side of transferring control from autonomous to manual driving results in a jitter effect no matter how smooth the transfer is, Takahiro [41] proposes a shared authority approach for this type of control transfer which results in increased driving control during simulator trials.

Regarding driver distraction studies, Saifuzzaman et al [42] investigated the impact of mobile phone use on drivers within a car following scenario, interestingly it was found that drivers tend to select lower speeds, large vehicle spacing and longer time headways as risk compensation behaviour, Cognitive distraction and visual distraction was also one of the focus points in that study.

Perception Reaction Time (PRT) and mental workload have proven to be crucial in manual driving [43–45]. Meanwhile, in highly automated cars, Take-Over Performance (TOP) is an addition variable to take into account for road safety [46]. In these cases, the mental workload is closely related to immersing the driver in NDR-tasks (s)he is performing while the car is driving autonomously [47]. Previous studies found impairments in take-over performance while engaged in NDR-tasks, but little is known about the impact of specific task characteristics [48, 49].

To summarize the above literature review, Chapter 4 aims to explore how the immersion in NDR-tasks affects the success of TOP of drivers in a highway critical situation and evaluate the influence of several variables, such as PRT, on this success.

2.6 Classification of Weather

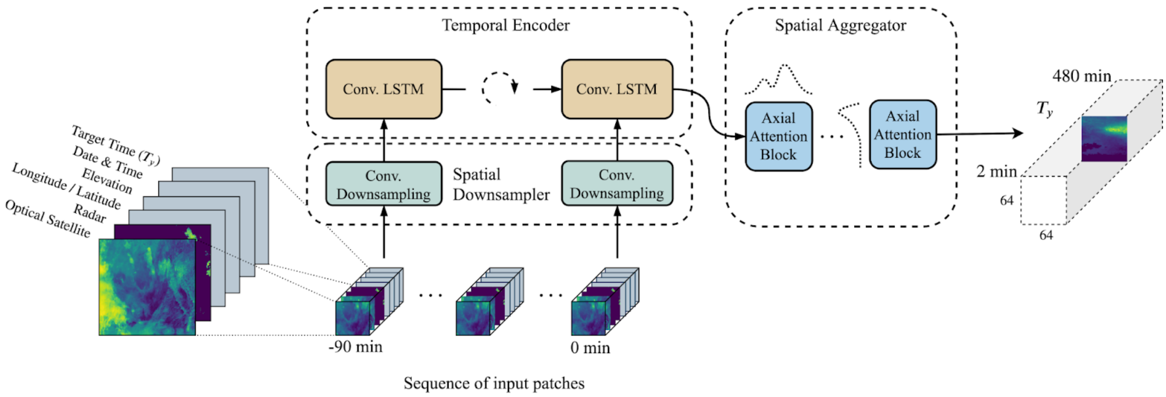


Fig. 2.7 Weather Classification CNN

Weather is one of the most important variables that can affect the transportation industry as a whole. If left unnoticed it can trigger car crashes, train derailments and numerous other accidents that can cripple the logistics operations of a particular area. Numerous studies have been carried out which have tried to expose the vulnerability of transportation services due to adverse weather conditions [50]. Current systems rely on expensive sensor arrays which try to detect present weather [51]. Trying to get an autonomous car to detect weather is quite a challenging endeavour on its own. the recent advancements in computing power have paved the way for machine learning to classify images and features. Lu et al, [52] proposed a two-class weather classifier which can differentiate between images based upon five features, namely, Sky, Haze, Contrast, Reflection and Shadow.

There is a rise in the use of Convolutional Neural Networks for the purpose of image classification. Works by Krizhevsky et al [53] consisted of a CNN architecture which takes considerable advantage of the improved computing power to train and improve the overall performance. The system utilises a built-in feature extractor based on supervised learning, which is more efficient as compared to manual feature extraction used in other machine learning systems.

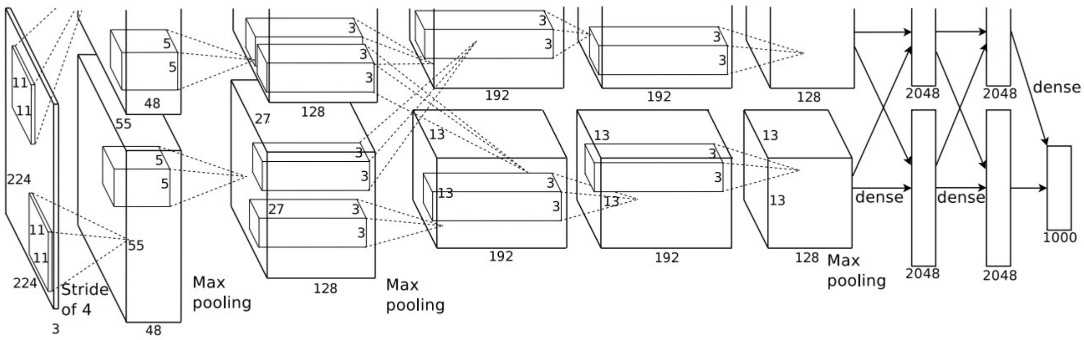


Fig. 2.8 Krizhevsky Weather classifier Architecture

Other CNN systems have been designed around Krizhevsky et al [54] model such as [55] are a good example. Elhoseiny et al [53] network is designed around Krizhevsky's weather classifier and is able to categorize between two possible classes, proving that a technology used for general-purpose categorization can be used for highly specific applications while achieving exceptional results. [56] resulted in an architecture which is quite successful when it comes to image classification known as GoogLeNet, which was further explored later [57].

Another study performed by Di Lin et al [58] proposed a deep learning framework named region selection and concurrency model (RSCM)which used regional cues to predict the weather conditions.

Recent study [59] proposes a new open-source dataset comprising of three classes namely Rainy, Foggy and Snowy. Each class contains 1100 images and uses a novel algorithm which

Fig. 2.9 RFS Dataset

uses superpixels delimiting masks as a form of data augmentation, leading to reasonable results with respect to ten convolutional neural network architectures.

A recent study performed by Mazin et al [60] which studies the detection efficiency of road elements during a rainy weather, indicates that the performance of image detectors trained on clear weather images can significantly degrade during rainy images. This implies that better training datasets are required to overcome the issue of not enough images for a particular weather class.

Most of the previous research includes the use of polarized and infrared cameras, the use of these cameras can give some plausible data but the installation costs can easily be substantial. [61] In order to combat this, the use of RGB cameras is much more simple and cost-effective, hence making it viable for mass release.

Most of the studies aimed toward driver assistance systems have been performed towards Rainy weather classifications [62] [63]. A study performed by Lu et al [64] deals with two class weather classification which includes Sunny and Cloudy. In that study, the authors proposed a new data augmentation scheme to substantially enrich the training data, which is then used to train a latent SVM framework to make the solution insensitive to global intensity transfer. Another study [65] deals with multi-class weather classification which only deals with fixed camera point only.

The above literature review proves the fact that weather classification in autonomous cars is a significant problem and needs to be solved in order for cars to provide a safe and stable driving experience within any weather condition, especially for Level 3 to Level 5 autonomous cars. Experiments and dataset generated in chapter 5 sheds more light into probable solutions for the autonomous cars to classify the weather conditions more efficiently.

2.7 Summary

In this chapter, readers were provided with an overview of the research being performed on Advanced Driver Assistance Systems. Moreover, a detailed insight is provided into Driver simulators, Perception Reaction times & Weather classification. A more in-depth literature review is provided within each of the upcoming chapters as well. We also looked into the different data sets that are currently available for Deep Learning model research which will be explored in further detail in the next chapters and hence challenged. Our data sets are further tested and analysed in later chapters as well.

Chapter 3

Driver Simulator

3.1 Background

The last few decades have seen a dramatic increase in the number of vehicles utilizing ADAS, such as intelligent head- lights [12], lane change assistance [41], and even the first attempts of automatic driving systems [66][67][6]. Although currently far from having feasible completely automated driving systems, there are several intermediate levels of driving automation for on-road vehicles, according to the SAE international standard J30164 [8], based on the system core functionality. Its level 3 specifies that the automated driving system performs all aspects of dynamic driving task with the expectation that the driver will recover the car's control when required. Thus, the human driver can perform other activities while the system is driving autonomously. This gives rise to an important question: At which moment and how can the automated driving system return the control to the driver?

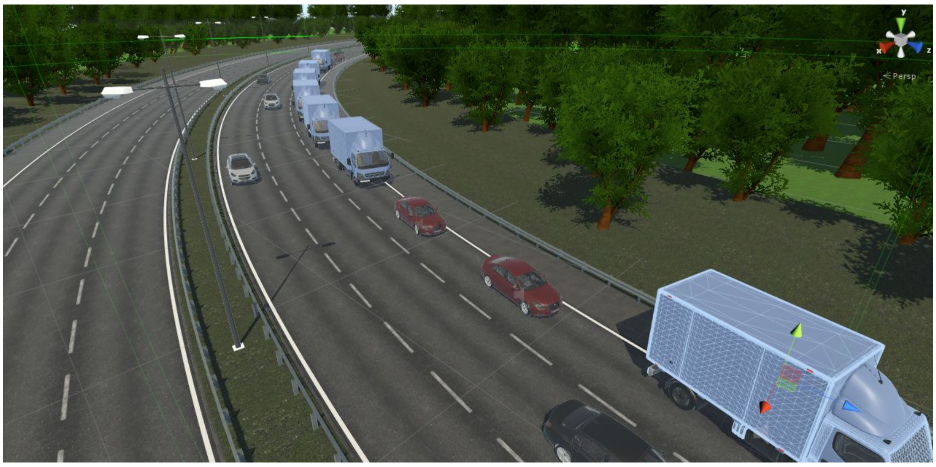
The answer to this question depends on several aspects, such as the activity of the driver, his/her general state and possible reaction, the particular state of the environment and the current state of the car. All these aspects should be carefully analyzed without compromising road security, and hence require a simulated environment for research, development and testing purposes so that greater number of iterations can be performed to get the most amount of data without going on a real road.

This is where the idea of a custom built driver simulator comes into the picture. The main objective of the driver simulator was to be light, inexpensive and portable means to test different driving scenarios involving driver interactions and most importantly to generate usable datasets for future research. The hardware assets that were required involved a reasonably powered workstation, steering and pedal set and a web camera that is able to capture the subject's interactions with the hardware during different trials. The software side is broken down into two parts, namely the assets and programming. The assets created involved vehicular 3d models and environmental props. The vehicle model was a pre-made modelled bought from an online 3d model store. Moreover, the supplementary traffic car models are also bought from 3rd party vendors to further enhance and populate virtual environments. The models were then processed to optimize them for real-time renderings. This included stripping down any unwanted details on the 3d models, in particular, the interiors of the traffic vehicles were reduced quite substantially as they are never seen in the actual simulation. The Main simulation car interior is also optimized to a point where it can be interactive in the final simulation.

3.2 Development

Decision was made right at the beginning to follow an agile development approach, meaning the simulator development followed many design iterations during which more enhancements were made in order to get the required outputs and functionality. It was necessary to draw attention to physical attributes on the virtual environment like virtual gravity and plausible weights of the cars and other movable objects within the environment, car acceleration systems were to be closely resemble the real world model, in our case it was the Mazda 3 which can reach 0-60 mph in 5.9 seconds. This was important as the absence of it would make the experiment void. In other aspects of the virtual environment. the road surface was to have a considerable amount of friction so that car tyres would adhere to it as close as possible to the real road surface. This allowed the cars to drift if a certain amount of centrifugal force was in action. on the other hand, collisions were planned in so that cars would behave physically accurate if they hit the barrier of the neighbouring cars.

3.2.1 Foundations



(a) Virtual Motorway View

(b) Driver Simulator Synthetic View

Fig. 3.1 Driver Simulator

The most important premise was to keep the development process represent a plug and play design so that any new features could be added easily without too many issues. This allowed us to incorporate new and upgraded features with ease like dynamic weather conditions and advanced lighting controls which includes complete day/night cycle with atmospheric features like distant fog and ozone layer system. These will be discussed more in detail in this chapter. The main advantage is the portability of the whole setup, it can be transported to almost any location. Apart from that a number of scenarios can be prepared and evaluated in a short amount of time. The simulations can be executed unlimited number of times and for as long as required, this was plausible by implementing efficient garbage collector systems within the high level code which allows the simulator to keep operating under the most stress full scenarios.

3.2.2 Hardware

In order to keep the costs down and the entire setup mobile in nature, a typical desktop setup was used. A custom workstation equipped with an efficient Intel i7 processor, an NVIDIA GTX Titan Graphics card with 12GB of usable VRAM, two HD monitors, a HD Webcam which was further increased to three webcams later in the study in order to record more detailed driver behaviors and a Logitech G27 Wheel and pedal Set were used as input devices for the drivers. The input devices were then evaluated to make sure that they adhere with the input accuracy required for the complex simulations that will be planned in the next chapter. This allowed the simulator to be as cost effective as possible as compared to other state-of-the-art simulators.

3.2.3 Software

On the software side, Autodesk 3DS Max was used to model and develop the virtual assets for the driver simulator. This includes the driver's car, other traffic cars as well as road surfaces. Adobe Photoshop was used in the creation of 2D elements, which includes detailing on the modelled cars as well as the road sections. Finally, Unity3D was used to tackle the interactive challenges of the simulator.

3.2.4 Assets Prep

A standardized game development workflow was used to make sure that the projected simulation scenarios would not be effected by graphical performance dropouts. The method included

1. **3d Modelling**

   The road surface was modelled in 3dsmax by using reference imagery from the internet. It is loosely based on a three lane section of M25 motorway around London. In order to keep the modular aspect of the environment intact, only two road sections are modelled, a straight road section consisting of 100 meters and an angular portion of 25 degrees. These two road sections help in creating different looking road environments within Unity3D. Basic poly modelling techniques were used and additional polygons and vertices were kept to a minimum in order to adhere with the real time engine rendering requirements.

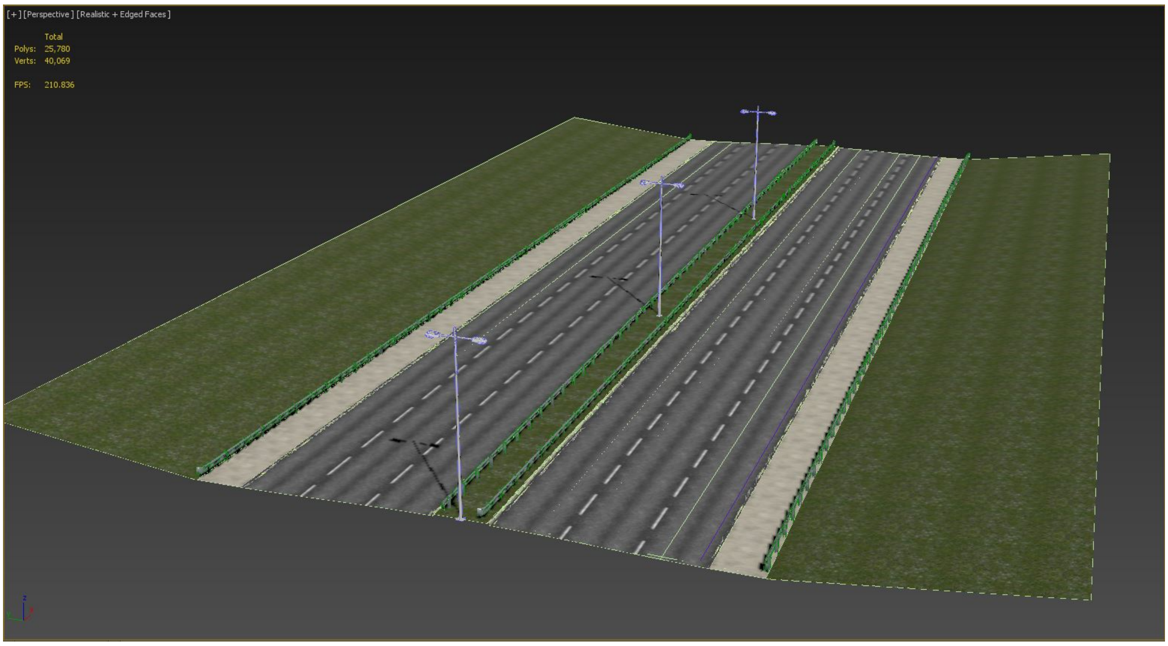


Fig. 3.2 Road surface Straight Section

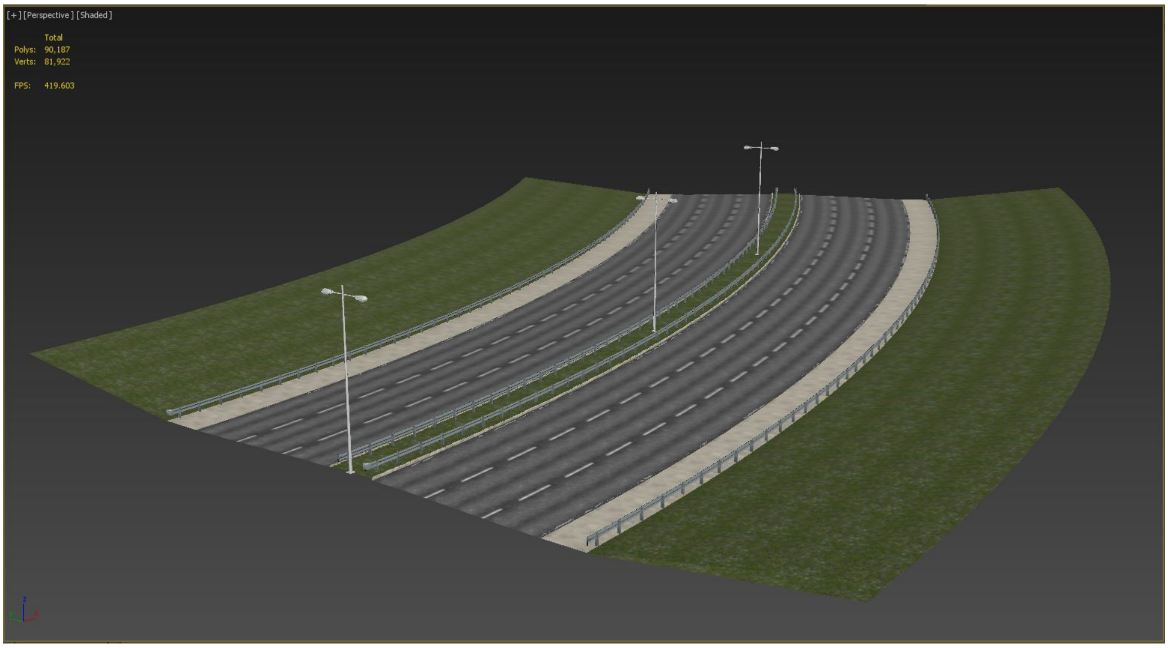


Fig. 3.3 Road surface Curve Section

2. **Texturing**

   In order to keep the export process as smooth as possible, It was decided to go for a more linear texturing path as shown in 3.4 instead of advanced procedural maps.

Advanced UVW mapping was avoided to keep the development time to the minimum. Only Box and Planner UV mapping were used for all the textures. The texture sizes were kept under 2048 x 2048 and were kept to a multiple of two for optimal memory and GPU performance because memory usage would go up significantly once traffic cars are spawned in the virtual world. Moreover, standard compression techniques were also used to reduce the texture file sizes to a manageable limit. Mip Map techniques were also Incorporated within unity3d for extra flexibility during run-time.

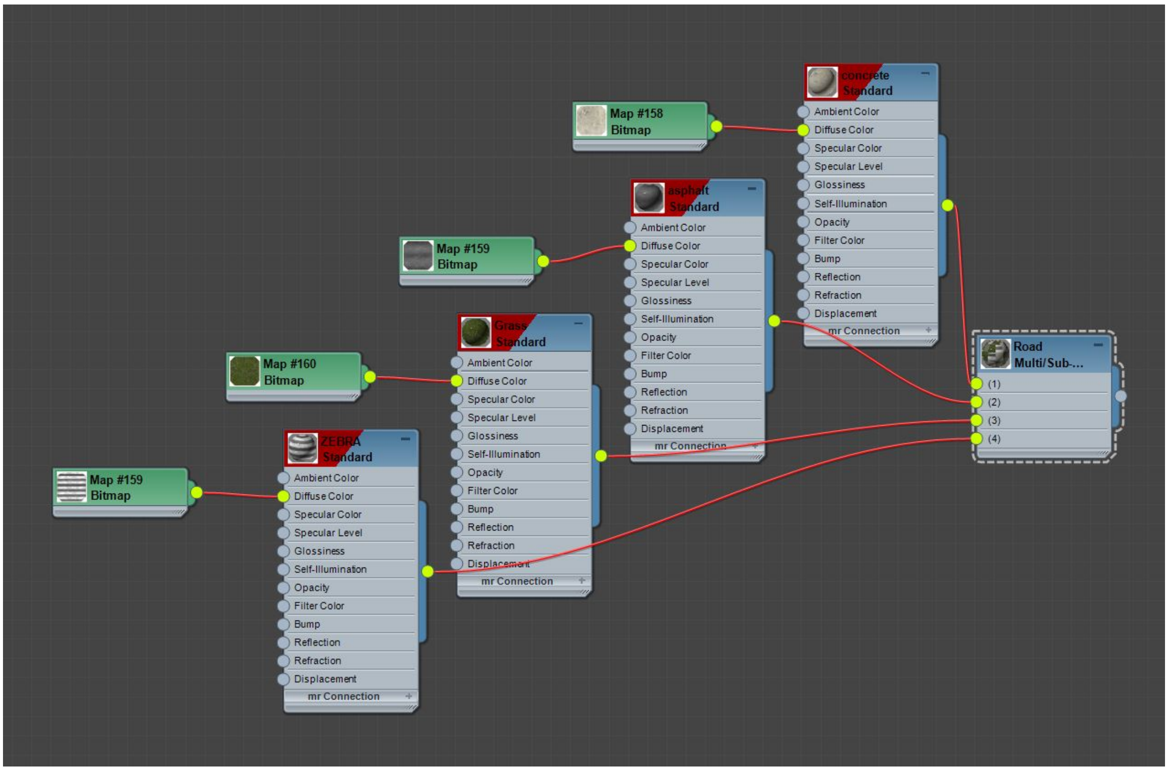


Fig. 3.4 Road Material Setup

3. **Optimization**

Optimization has to be the most important part of the simulator development process. In theory we could have added as much geometry and textures as possible but without optimization the graphical performance would have suffered significantly, rendering the whole simulator useless. In order to keep the memory counts low and frames per seconds high, more time was spend on cleaning and deleting the edges and polygons that were not required at the current viewing distance. As an example, the main car model as shown in 3.5 was originally consisted of more than 1 million polygons. By using 3dsmax's build in optimization tools such as ProOptimizer, we were able to bring down the poly count to a respectable 370,000 polygons for the complete model. Moreover, similar objects that had the same material and shader applied were connected together to keep the draw calls down, this resulted in the introduction of SUb-Object material setup which applies multiple materials to the same geometry based on surface IDs.

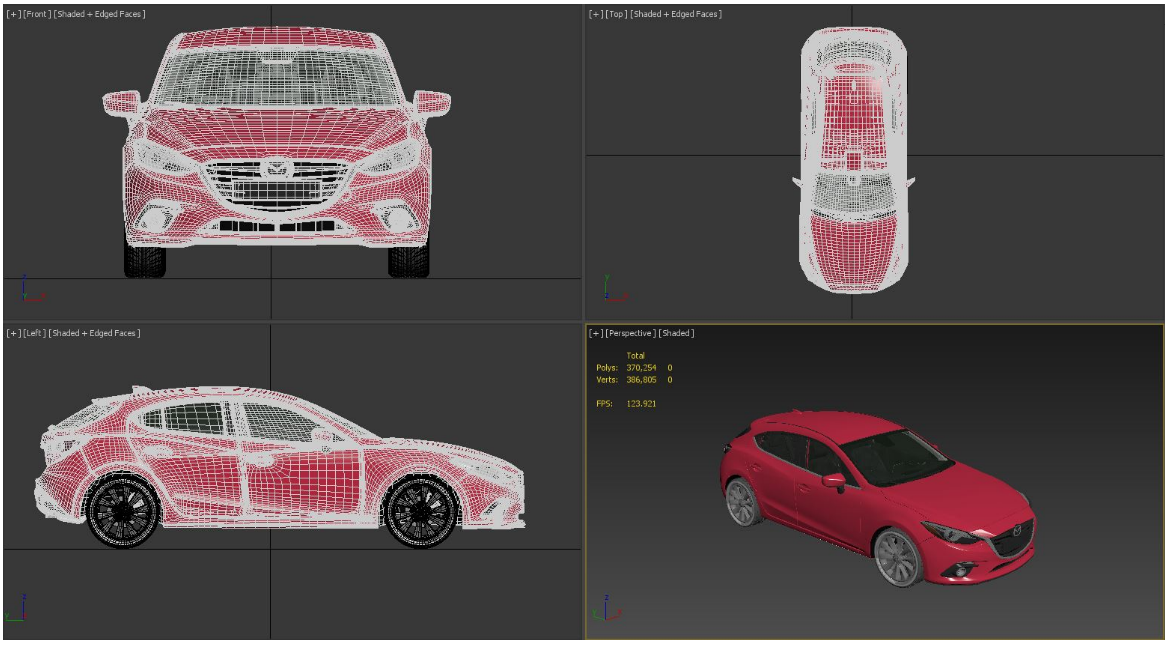


Fig. 3.5 Main Virtual Car Model

4. **Export**

   Once the models are prepped in 3dsmax, the next step was bringing them into Unity3d for real-time rendering. This process either makes or breaks the 3d models but good results can be achieved if done properly. FBX was used as the preferred format for all exports to unity3d. 3dsmax's built in FBX exporter provides all the necessary options to bring in geometry, materials as well as textures that already linked up to the 3d model. This is one of the main advantages of using FBX over other formats like .3ds and .obj. Moreover, the exporter provides useful options such as the options to export keyframe animations, axis conversion because some game engine support y- axis as vertical and some support z-axis, it also has the ability to do unit conversions. In our case the units were set to Meters in order to target the default unit scale in Unity3d i-e 1 Unit in unity is equal to 1 Meter. with regards to material/shader export from 3dsmax, care was taken as not to use unsupported maps, hence most of the textures and maps were kept to RGB jpegs in order to boost compatibility.

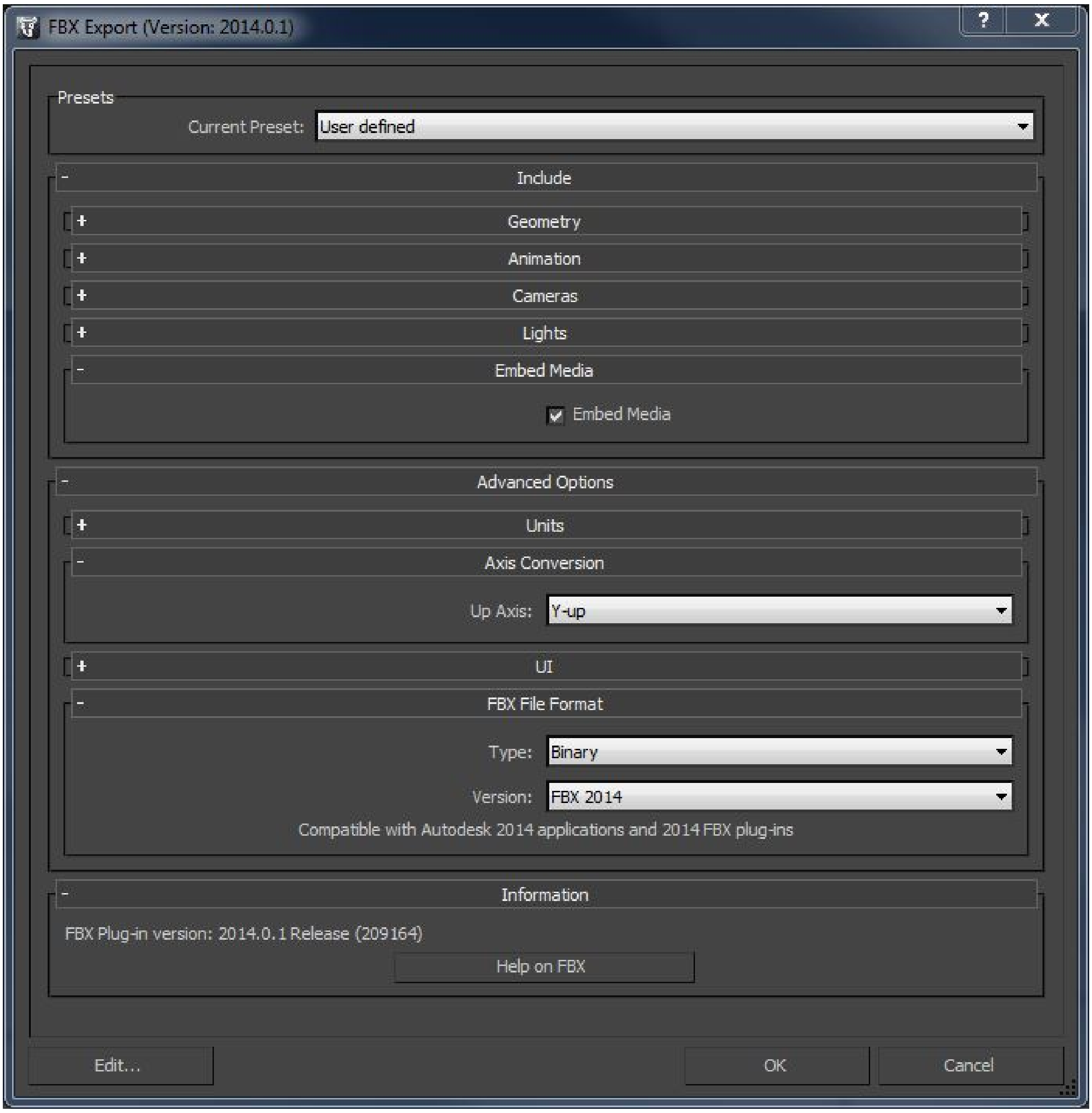


Fig. 3.6 FBX Export Window - 3dsmax

5. **Shader Optimization**

   Once the 3d models and materials were exported from 3dsmax, they always show up as standard shaders with diffuse channel textures attached. The next step is to amend the shader's specular and metalicness values to get the desired look of the shader within unity3d. Normal Bump maps were also created to give the illusion of high quality mesh. The advantages of using Normal Maps is the fact that it runs from a single jpeg texture but it gives the illusion of a hi resolution 3d model effectively adding more detail to the 3d model without affecting the memory usage too much.

6. **Virtual World Setup**

   Basic tree models were populated on either side of the road and a suitable sky environment is added to further enhance the realism of the virtual environment. The finished 3D assets including the vehicles and the road sections were then imported into Unity3D. The two road sections are cloned into multiple instances and are carefully put together to form a looping M25 environment, which is approximately 4 miles long and is used as a base for the synthetic world experiments. 3.1 shows the road surface, including the two road sections at the top, the complete environment within Unity3D in the middle and the complete road model dimensions at the bottom.

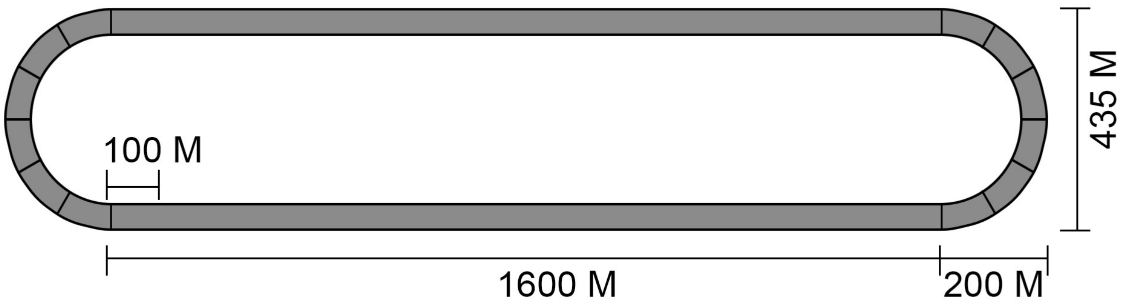


Fig. 3.7 Road Structure Dimensions

3.2.5 Programming

After the completion of the initial layout of the virtual environment, the next challenge comes in the form of adding interactivity and simulating the virtual environment as close as possible to the real world counter part. Traffic cars are populated by using a third party unity plugin called ITS (Intelligent Traffic System) utilising the 3d modeled traffic cars by using the same steps as described in 3.2.4. This allows the traffic cars to behave closely to their real-life counterparts, the cars are able to move in and out of lanes and they can respect the particular speed limits of each individual lane. The advantage of using this type of system is that it provides a vast amount of random behaviour for traffic cars. Moreover, each new execution of the simulator results in a different traffic structure which further adds to the realism and unpredictability of the virtual world. In addition to that when the cars detect a particular blockage on the road, they can stop to avoid it accordingly.

Additional controls include, Lane linking for Traffic cars, Tag system for traffic vehicles which can be used to set properties for each vehicle to either be of a specific type i-e Taxi, Bus, Lorry, etc. The system also supports pedestrian spawning which will become quite useful for future iterations of the driver simulator. The main car model is then rigged to reflect the moving parts like the steering wheel, RPM needle, pedals, rear view mirror reflections and the adaptive cruise control system. This part requires the most amount of time as it involves the programming of various components that helps to reflect the final car movement. The basic physics car model is based on the standard Unity3d car model. This is chosen so that more complex physics models can be refined on a proven physics model in the future. The main car also has a fully functional Autonomous Driving Mode which allows it to maintain a specific distance from the car in front by the use of proximity zones. The Autonomous Mode is also able to brake hard when the car in front enters a secondary proximity zone as shown in 3.8.

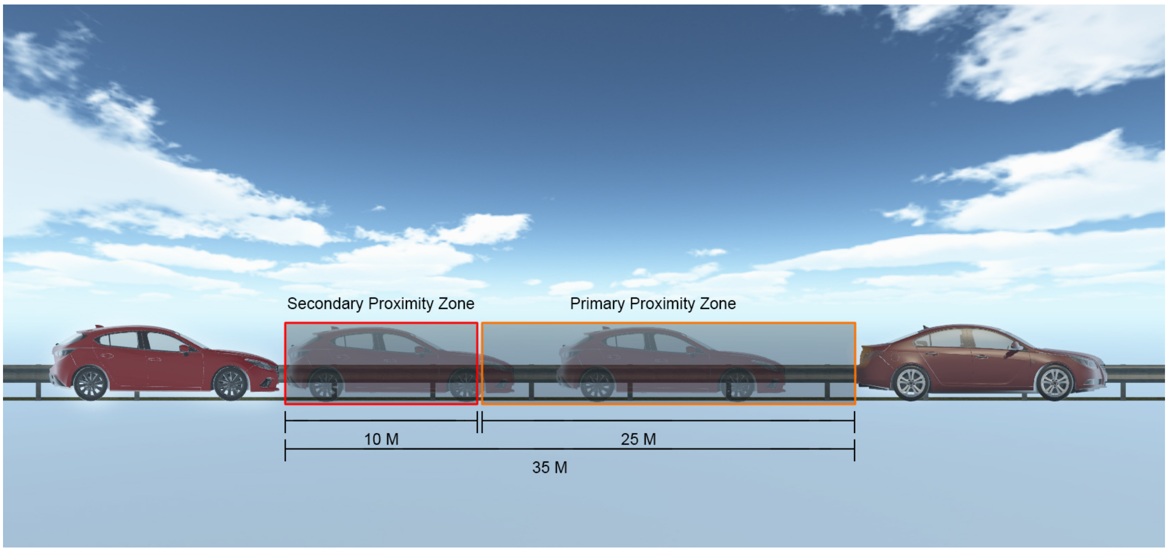


Fig. 3.8 Autonomous Mode Proximity Model

The initial version of LEE simulator only consisted of 1 driver facing camera, which recorded features such as head position, eye position and general arrangement of driver's sitting position as shown in 3.9. It also shows other useful information such as:

1. Current Speed
2. Engine RPM
3. Steering Angle
4. Autonomous Mode Toggle
5. Car Velocity at first road block detection
6. Distance to front car once the Main car is stopped

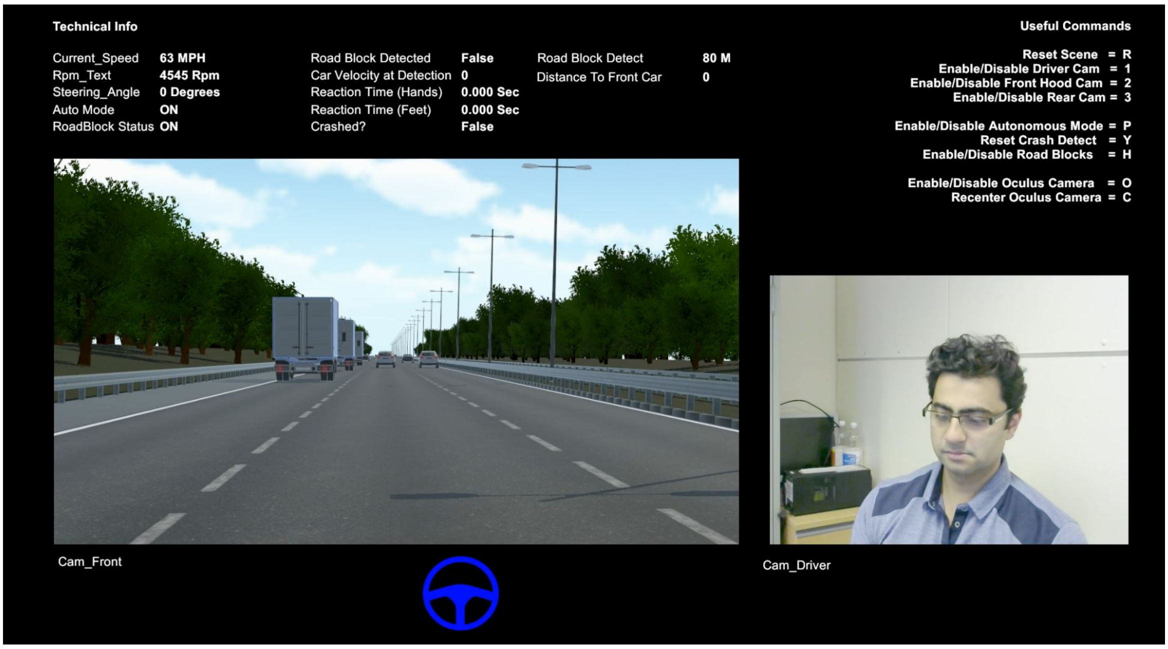


Fig. 3.9 LEE Driver Sim Data Screen V1

The above data was enough for evaluating the performance of LEE simulator which will be discussed in detail in initial sub sections of Chapter 4. The next version of LEE simulator required a more robust upgrade to tackle PRT with NDR (Non-Driver Related) tasks in more detail which will be discussed in the second half of Chapter 4. The upgraded LEE simulator could now support as many as 3 separate cameras which recorded almost every aspect of the driver's behavior during a test session. the cameras could now record portrait view of the driver, hand positioning on the steering wheel and foot positioning on the pedals as show in 3.10.

Theoretically it is now possible to use recorded data to train and test Deep learning models aimed specifically at Driver Behavior based computer vision tasks. The updated data screen was now able to output additional variables such as Reaction Times for Hands and Feet as two separate variables instead of just one as was the case in the previous version of LEE. Other variables included distance to front car while in autonomous cruise, distance to front car after the main car comes to stop and car velocity at first detection of a road block. These variables will be addressed in more detail in the next chapter.

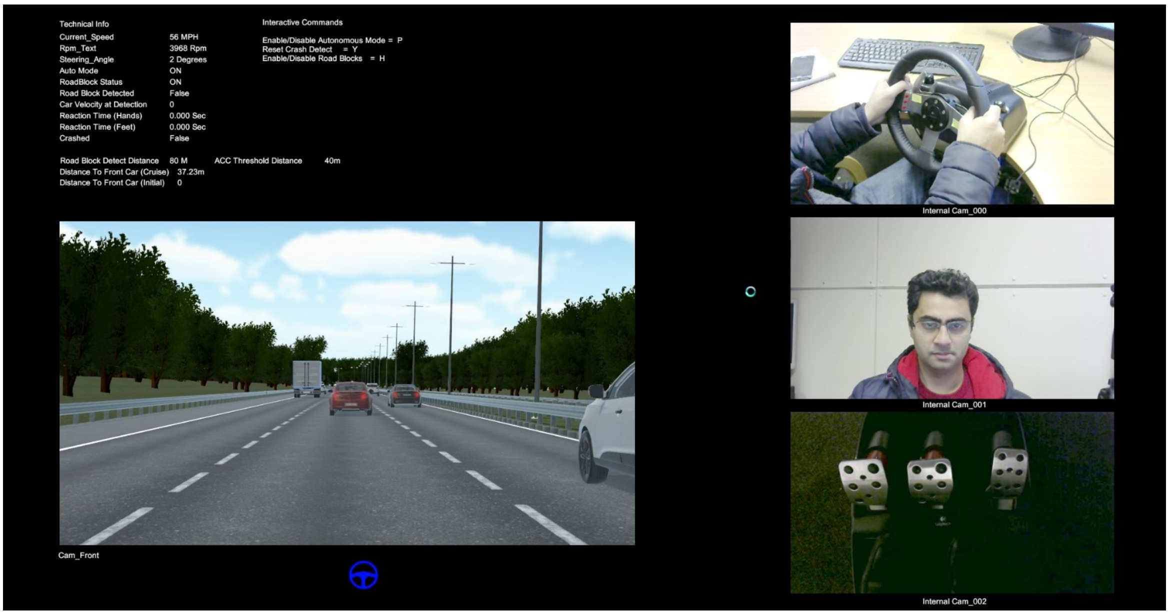


Fig. 3.10 LEE Driver Sim Data Screen V2

3.3 Cost effectiveness, Easy to use and Highly mobile

Typical virtual simulators can cost between the ranges of £10,000 to as much as £500,000 [4] [1]. Our cost saving approach brings the budget down to less than £2000 which makes our proposed simulator accessible to vast majority of researchers and engineers making it a viable option for quickly testing reaction times under different driving conditions. As compared to state-of-the-art simulators [10], our approach only consists of 4 main parts, CPU Case, 2 monitors, sterring/padel set and webcams. And it needs to be noted that these peripherals have not been modified in any way and hence rely on a standard plug and play protocols. The advantage of using such system is that no alteration is required for the initial setup hence saving time and budget in the process. The build code can also be executed on any specific windows machine provided that it has a reasonable GPU like an RTX 3080 installed, making it highly mobile as compared to other state-of-the-art simulators. The ease of use aspect consists of developer friendly approach which allows our simulator to be highly customizable as compared to CARLA [3]. As the LEE system has been developed from the ground up as a simulator that can record reaction times, it is far simpler for researchers to setup custom scenarios for recording PRT.

3.4 Additional Notable Problem Statement

In the previous chapter we learned about how depth perception actually works and what are the main cues to detect depth in images. We now move forward and find the problem and challenges involved in acquiring an efficient depth perception detection system. Existing implementations for depth estimation are quite varied, some rely on stereo cameras [68] while others rely on LiDAR sensors to detect the surrounding obstacles [69]. The main problem arises during the manufacturing process and cost effectiveness. A LiDAR sensor and a stereo sensor would always be more expensive as compared to a single mono camera lens [70] due to their higher production requirements.

3.5 Possible Solution

A plausible solution can be the introduction of optimized synthetic dataset generated from the virtual simulator introduced in chapter 3. The simulator has the ability to generate depth data parallel to RGB data at respectable resolutions of upto 1920 x 1080 or even 4k resolutions if required. But most of the times for deep learning model based studies, it is always prefer to introduce a lower resolution images for test/train.It is also plausible to introduce a mix and match approach with other state-of-the-art simulators like Carla [3] to further enhance the variation of input images.

3.6 Summary

This chapter can be summarized in the following manner:

- This chapter specifies the technical specifications needed to design and implement a functioning driver simulator. This can have implications when HCI systems are designed by using the results introduced above. Hence the implications of the results are important in understanding the criteria needed for designing Human Machine Interfaces for autonomous driving vehicles. This can include entities such as Driver's awareness to his/her surroundings which can be monitored by ADAS resulting in a more enhanced driving experience.

- Successfully developed a custom driver simulator that is Open Source, easy to use meaning the system is quite intuitive with a low learning curve for researchers to modify for their needs and is highly mobile in nature which means that the system only uses 4 main hardware parts namely, CPU case, 2 monitors, steering/pedal sets and webcams. None of the peripherals are modified in anyway and hence can be transported and used via the standard Plug and Play protocols. Moreover, the code and software are of a manageable file size which is less than 1 GB and can be transferable to any windows based machine with little to no setup required.

- Successfully implemented a diverse traffic system that generates random vehicles when a new session is loaded which is ideal for the procedural nature of the simulated sessions, this also works in favour of a controlled environment where drivers can be tested as close as possible to their real environment.

- Successful implementation of synced camera recording for all aspects of driver's behavior during autonomous driving sessions. This is highly practical for researchers who require the monitoring of all the main aspects of the drivers sitting position and head direction analysis.

Chapter 4

Perception Reaction Time and Effects of NDR tasks

4.1 Background

After the successful development of the driver simulator as described in the previous chapter, the next challenge was to evaluate the performance of the simulator for driver assessment experiments.

The state of the art can be broken down in to the following three categories.

4.1.1 Perception Reaction Time

PRT of human drivers is an active research area within the manual driving performance domain because it plays a central role in different road incidents.

Several studies have been carried out to deepen the comprehension of PRT's role in crash risks [43, 71, 72, 38, 36]. The methodologies range from proposing accident situations involving surprise factor to examine the reaction times of drivers and also analyzing reaction times as a factor to take into account within crash surrogate indicators.

The main results found in these studies are that the reaction time of drivers seem to be approximately a linear function of Time To Collision (TTC), and the mean reaction time and inter-individual variability progressively increases with age although some other factors such as driver gender, cognitive load, and urgency might influence in human perception-brake reaction time. However, the most influential factor is driver expectation.

All of the above studies were conducted under manual driving conditions, so they do not take into account the PRT when the driver is carrying NDR-tasks.

4.1.2 Mental Workload

Other studies have been centred on the influence of mental workload as a crash risk factor [73–77]. Mental workload is not only related to being stressed, fatigued or drowsy but performing a divided-attention task causes an increase of mental workload and task demands can exceed the driver's attention resources. These studies explore several indicators from many external sensors, such as pulse rate, skin electric potential activity or surface temperature, to better determine the physical and psychological state under different provoked circumstances. Although the general workload is not well defined psychometrically [78], all of them coincide that excessive (related to stress) or too low (related to vigilance) mental workload could derail the quality of driving [79].

Besides, human performance can either deteriorate or improve depending on the degree of automation which is introduced in that particular environment [80], so that mental workload should also be taken into account in highly automated cars. Indeed, PRT and mental workload can be closely related [9, 81], since increasing workload of the driver reduces the driver's ability to process information at different distances and thus deteriorates driving performances and increases reaction times. The first study shows that mental calculations increase the average reaction time for each age group, while the second one suggests that reaction times can increase by 40%-87% due to increased fatigue levels, giving valuable insight into how reaction times are taken into account via visual perception.

The above studies do appear to be invaluable in assessing the relationship between PRT and mental workload but assessing these variables under a controlled simulated autonomous car environment is quite crucial in exploring their effects further.

4.1.3 Control Switching

Last but not least, in highly automated cars, the process of getting the driver back into the loop is very important. In this fashion, some authors [82–84] explore different ways to get the driver back to the driving task in a safe manner, either focusing on signal modalities [82] or designing complete human-machine interfaces [83, 84]. But still, the automated system needs to know how far in advance and under which circumstances it has to warn the driver, depending on the NDR-tasks the driver is doing or can do, so that the analysis of drivers' take-over performance is crucial. Concerning the lead time to safely allow the driver to regain control. Eriksson et al. [85] review several papers exploring driver control transitions, although they not take into account secondary tasks, and carry on an experiment involving secondary tasks. On one hand, they claim that the reviewed results differ depending on the emergency the driver perceives (s)he has to cover on, and, on the other one, they find significant differences when drivers are engaged in secondary tasks.

Besides, [86] suggests that a take-over request with lead time at 10–60 s led to lower crash rate, greater minimum TTC, and lower lateral acceleration. However, both studies do not account for critical control transitions. Some other experiments [87, 48] exposed drivers to critical take-over situations and showed evidence that cognitive load on its own might not influence takeover time but have effects on the takeover quality. As well, reaction times might be in line with the driver's perception of emergency.

In case of being behind the wheel of an autonomous car such as Tesla S [88], although the drivers were also told that they were responsible for the safe operations of the vehicle regardless of it's driving mode, the recorded data demonstrated behaviour indicative of complacency and over-trust.

Still, prospectively evaluate the expected limitations caused by NDR tasks on the driver's ability to take control of an autonomous vehicle [89], more research is needed so that different aspects of NDR tasks can be translated into a modelling of a framework to predict takeover time or quality. This makes our present article more relevant as we explore in detail the different effects that the NDR tasks have on reaction times of drivers in an autonomous scenario.

4.2 Assessment of Driver Vehicular Interactions in Self Driving Mode

4.2.1 Methodology

It should be noted that the use of virtual worlds has changed significantly during the recent years for research purposes. Due to the progression being made in graphical processing units, the visual fidelity of virtual worlds is increasing quite rapidly, this favours the use of synthetic worlds as it increases the visual fidelity of data generated and in some cases can match up quite closely to their real-world counter parts.

The first successful trial of our Low cost, extendable and easy to use driver simulator allowed us to tackle a major issue of recording Perception Reaction Times [43] of drivers in a given scenario.

4.2.2 Experiment Setup

While the car is running in autonomous mode, two different scenarios are defined in this experiment using LEE (Low-Cost, Extendable & Easy-to-use) simulator which was introduced in Chapter 3:

1. The subject is not looking at the road, but attentive with hands on the wheel, which serves as a baseline so that other scenarios can be used to compare the results for evaluation.

2. The subject is on the phone checking social media. In both cases, once the car detects a road block at a random distance ahead, it triggers an alarm, at which point the subject has to take back control in order to avoid a crash.

LEE records the video of the subject, and several variables involved in the process, such as Hands/Feet PRT and the speed at which the alarm was triggered. A total of 10 subjects aged between 26 and 62 years were involved in the experiment. Each trial contains 12 sessions, 6 for each scenario. The distance at which the road block is detected is set to 60 meters in 3 sessions and 80 meters in the other 3. We have compared the hands and feet PRT by means of the computation of their ranges (mean std) and have also explored the influence of some of the variables recorded such as Hands/Feet PRT and speed. Hence three trials for each distance gave an average Perception Reaction Time per distance trials. The second scenario involved the same 6 trials at 60 meters and 80 meters, the only difference was the subjects were now bound to look down on their phones at all times in order to simulate a diversion of attention. They were free to roam around in their phones in applications like WhatsApp and Facebook. The reaction times were recorded accordingly.

4.2.3 Results and Analysis

The subjects were found to keep the wheel in a static position unchanged from the Autonomous mode was in, thus in this context, the driver appears to concentrate on control of the pedals first. This result is also evident when we compare the Hands/Feet PRT of both the scenarios, in which Hands PRT are significantly greater than Feet PRT. 4.1 summarizes the ranges for Hands/Feet PRT in both scenarios. 4.1 shows the influence of three variables, Hands/Feet PRT and speed, where blue and red colors show crash/no crash results, respectively. Dots and circles represent results for scenario 1 and scenario 2, respectively. It can be observed that the speed of the car when the alarm was triggered is a determinant variable in both scenarios since we can appreciate two separate clusters in the speed direction. As opposed to this, two separate clusters in the direction of feet or hands PRT cannot be seen.

	Hands	Feet	p-value
1st scenario	1.67 ± 1.61	1.26 ± 0.45	0.0034
2nd scenario	2.71 ± 1.91	1.42 ± 0.34	8.41 x 10^{-8}

Table 4.1 PRT Results

This was a proper reflection of what might have happened during the recent Tesla crashes where the drivers were feeling so much relaxed by the Autopilot system that they were not paying enough attention down the road while the car was in Autonomous mode which resulted in those inevitable crashes.

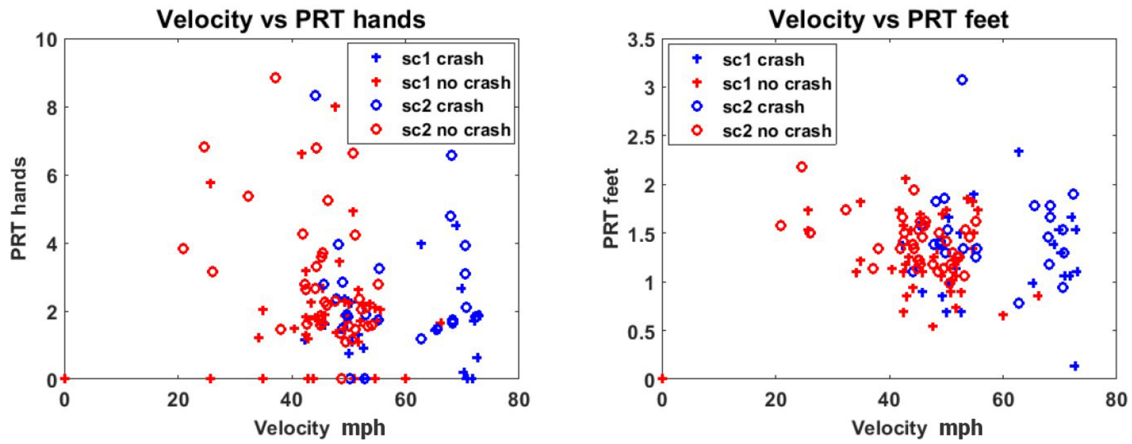


Fig. 4.1 Velocity vs PRT Hands and PRT Feet

The results were quite alarming, the Perception reaction time from the first scene came in at approximately 1.67 seconds for the hands and 1.26 seconds for the feet. Whereas the perception reaction times for the second scenario came in at approximately 2.71 seconds for the hands and 1.46 seconds on the feet, which proved the fact that drivers were treading a very thin line when it came to taking back control from an autonomous car in case of an emergency [90].

The fact is that the Autonomous cars still have a long way to go before they can fully understand the road ahead. The work discussed above was successfully published at the ECCV 2016 (European Conference on Computer Vision). The aim of the paper involved the use of the photo realistic virtual environment for assessing driver-vehicle interactions in self-driving mode. As a result, the driver simulator was an ideal candidate for performing experiments in the above particular scenario. It can be fair to say that this particular goal of a low cost driver simulator was achieved successfully, not only that but the simulator also proved its worth by successfully becoming a part of a research paper that was accepted in one of the top computer vision conferences in the world (ECCV16).

4.3 Enhanced Driver Vehicular Interactions

Moving forward from the first version of the driver simulator, the driver simulator was further enhanced to support more cameras to capture the driver's actions in more detail. The system already had one camera that was pointing towards the driver's face, capturing the details like if the driver is paying attention or not, or whether the subject is busy in secondary tasks apart from driving. The second additional camera was directed towards the subject's hand position on the steering wheel, this can further help to develop more Advanced Driver Assistance System (ADAS). Which can pave way for analyzing whether the subject is positioning his/her hands in the optimal driving position? The third additional camera focuses on the position of the feet. This data can be quite useful in assessing if the subject had his feet positioned correctly or not, also it can help to diagnose if the subject had accidentally pressed the accelerator instead of the brake pedal during an accident scenario.

4.3.1 Methodology

The second trial of the driver simulator was a more enhanced version as compared to the first one, Forty participants (10 female, 30 male) between 19 and 45 years old (*mean* = 30.73, *std* = 7.086) were recruited. All of them held a valid driver's license at the time of the experiment with a seniority of at least 1 year and at most 26 years (*mean* = 9.725, *std* = 7.66). Moreover, a consent form was prepared for the subjects which asked for their name age and years of driver's license held. It also contained useful information like if the subject felt uncomfortable at any stage of the trial, he/she would be free to quit. Safety and well being of the subjects were of great importance throughout the entire trial sessions. The trail consisted of 3 main scenarios namely Default Scenario, Social Media and Immersive Questions and Answers. Each scenario was further split into 4 separate runs, each run consisted of a change in the distance which the Autonomous car would keep which was 40 meters and 80 meters respectively. Whereas the other two runs consisted of the distance at which the alarm was triggered upon successful detection of the roadblock ahead which was also 40 meters and 80 meters. This gave us a diverse set of tests that would be beneficial in the data analysis stage. It has been noted that older drivers can solve critical traffic events as well as young drivers yet their methods of operation differs [81].

4.3.2 Simulated Situation

The simulated situation consisted of an infinite three-lane motorway of 4 miles loop, as explained in the subsection above. The car was driving in autonomous mode and, suddenly, the vehicle detected an invisible obstacle, an alarm was triggered and all the cars in front of it stopped. The detection time for obstacles randomly varies from trial to trial but usually, it happens between 2-5 minutes during a trial. At that moment, all the cars in front stopped and the driver had to take over the control of the car in order to avoid a collision. The average distance and the standard deviation of the main car to the car in front at the time the alarm was triggered was 40.64 ± 13.34 meters and the velocity of the car was 45.2 ± 10.97 mph. The traffic can be turned ON on both sides of the road, but this was not a requirement for the current experimental setup. Moreover, the drivers had the instruction of only braking or dodging if needed, depending on the situation.

To carry out the experiment, a series of plausible scenarios were needed that a driver would find behind the wheel of an autonomous car. Following a previous experiment performed by Eriksson et al. [31], in which he used a newspaper reading scenario while the car was in autonomous mode, the challenge was to enable the driver to lose focus on the road ahead while engaging in secondary tasks inside the car. Secondary tasks were selected in such a way that they resembled real-life situations as closely as possible. Hence keeping that in mind, three different scenarios for the driver were posed while the car was in autonomous driving mode. The first scenario, henceforth Default, is termed as the base scenario in which the driver was aware to the road with the hands and feet ready to react (hands on the wheel but without touching them and feet on a marked place very close to the pedals). The second scenario, henceforth Social, deals with the fact that the driver was not paying attention down the road, but was freely immersed in social media activities on her/his smartphone. Since immersion to social media could be total and the system is automatically driving, to suppress the variable off-road glance time, the driver was not allowed to look at the road. In the third scenario, namely Immersive Question and Answers (IMQA), the driver was answering a list of questions via a smartphone. These were relatively basic questions consisting of the driver's name, age, hobbies, etc and more cognitive loaded ones such as some basic mathematical addition and subtraction questions. Strict guidelines were provided to the drivers so that they won't even peek at the road ahead while the car was driving automatically and the driver is indulging in secondary tasks (second and third scenarios), the penalty for which was to start the trial again if the driver looked at the road during specific scenarios.

Each driver performed the experiment four times in each scenario under different circumstances, that is a combination of enabling to dodge or not and a threshold on the initial distance to the car in front during the autonomous driving (the approximate distance that the car would keep from the car in front in autonomous mode). Thus, there are a total of 12 trials that were carried out on each subject, although we group the four trials per driver and scenario as 4 different samples. There are a number of variables that are being recorded: Hands/feet PRT, cruise distance threshold to the front car, distance to the front car at which the alarm is triggered, final distance to the front car after the car comes to a stop, the speed at which the alarm is triggered, any traffic cars to the left and right side of the driver's car, crashed or not, and if the driver tried to dodge and save himself. The experiment also includes other basic variables like the age and gender of the driver and the seniority of his/her license.

4.3.3 Experimental Design

After a brief introduction to the driver simulator, the participants were given a trial run with the autonomous mode disabled just so that they could get the feel and sensitivity of the steering wheel as well as the pedals. Afterwards, the autonomous mode was turned on and the participants were told to take back control as soon as the audio/visual alarm was triggered by the simulator. Moreover, the participants were also instructed to place their hands and feet in a neutral position during this time. This gave them the initial confidence in tackling the simulated event and the baseline scenario (Default). For the next scenario, Social Media, the participants were briefed to indulge themselves in social media activities on their smartphones while behind the wheel of the virtual autonomous car. For the Immersive Question and Answers scenario, the participants were only given a short briefing regarding the type of questions that would be asked for this part of the experiment. All the data recorded during the trials was used in an anonymous form.

4.3.4 Objective measures

During the experiment, we recorded several objective variables to be explored under different scenarios.

1. PRT: We understand the PRT as the time that elapses from the instant that the driver recognizes the existence of a hazard on the road to the instant that the driver takes appropriate action. The hazard can result from traffic cars in front of the driver's car suddenly stopping and queuing up, which would alert the driver of a possible hazard. In this case, the hazard recognition is perceived thanks to an acoustic alarm. Since we do not have a tool to measure the time from when the alarm is triggered until the driver perceives it and the time elapsed from when the driver perceives it until (s)he acts, we can only measure the elapsed time from the moment the alarm is triggered until the moment when the driver reacts.

(a) PRT of hands (PRTH): The appropriate action for hands is steering the wheel. The system only records the reaction times of the steering once it receives at least 1 degree of input in either direction from the driver. Notice that the alarm is only triggered during straight road sections, so that normal steering inputs on a curve are absent.

(b) PRT of feet (PRTF): The appropriate action for feet is braking, so that, the system records the reaction time as soon as it detects pressure on the brake pedal.

2. Velocity of the car at the time the alarm is triggered.
3. Distance of the car to the one in front at the time the alarm is triggered.
4. Success of TOP: We consider a success when the car does not crash.

To answer how the immersion in NDR-tasks affects the TOP of drivers we analyze the PRTH and PRTF as soon as the alarm is triggered across different scenarios. As well, we explore the relationship between the velocity and distance at the moment the alarm is triggered.

4.3.5 Statistical Analysis

According to the objective variables explained in the above subsection notice that success of TOP can be considered as a dependent variable, while the remaining ones are independent, so that we analyze how such independent variables can influence on the success of TOP. Also, since the scenario can influence on the performance of the driver, PRTH and PRTF can be analyzed across the scenarios to explore if they are affected by the current scenario.

To decide if PRTH and PRT are affected by the scenario, a one-way ANOVA should be computed for each variable. This test is usually used to detect significant differences between the distributions of more than two factors (in this case the different scenarios). That is, its hypothesis test associated considers as null hypothesis H_0 meaning the factor has no effect, and as an alternative that it does. In terms of parameters, the ANOVA test can be written as follows:

$$\begin{cases} H_0: & \mu_1 = \mu_2 = \mu_3 \\ H_1: & \exists\ \mu_i \text{ s.t. } \mu_i \neq \mu_j \text{ for some } j = 1, \ldots, 3 \end{cases}$$

where $\mu_i, i = 1,2,3$ corresponds to the mean of the objective variable for each scenario.

A requirement for applying an ANOVA is that data is normally distributed, which can be contrasted by means of a Kolmogorov–Smirnov test. In particular, the Lilliefors test is a normality test based on the Kolmogorov–Smirnov one that compares the empirical distribution of the data with a normal distribution without any expected value and variance of the distribution [91]. In case the data does not follow a normal distribution we can use a non-parametric statistical test, instead of a parametric one, which analyzes differences among group medians instead of means. In particular, since each subject repeats the test for all scenarios in our experimental design, we can consider a repeated measure one way ANOVA, so that we use a Friedman test [92].

To measure the strength of agreement between subjects (effect size) we also compute Kendall's W, defined as $W = \chi^2/N(k-1)$, where χ^2 is the test statistic, N the number of samples (160) and k the number of scenarios (3). The results can be categorized as small, medium and large, which in our case will be $[0, 0.10)$, $[0.10, 0.30)$ and $[0.30, 1]$, respectively.

To analyze the influence of an objective variable on the TOP success in each scenario, we also need to compute a non-parametric test in case the data does not follow a normal distribution. In this case the Wilcoxon rank-sum test [93] is an alternative to the Student's t-test for independent (unpaired) samples and the effect size is computed as $r = \|Z/N^{0.5}\|$, where Z is the Z-statistic, and N is the number of participants. In this case, the results are categorized as small effect = $[0.10, 0.30)$, medium effect = $[0.30, 0.50)$ and large effect = $[0.50, 1]$.

4.4 Results

For each variable recorded there is a total of 480 samples (40 participants x 4 trials x 3 scenarios). In all tests, the significance level is 0.05. As well, none of the variables follow a normal distribution because the null hypothesis of the Lilliefors test is rejected with a p-value less than 0.05.

To have a visual idea of the distributions of PRT on each scenario, Figure 4.2 shows the boxplots of the 3 global scenarios (Default, Social and IMQA) for PRT of hands and feet. The first observation is that the hands reaction times are higher as compared to their feet counterpart in all scenarios. Outliers, in this case are reflecting the non-normality of the data. One plausible explanation about this non-normality is that there were some instances where the drivers failed to input any motion within the steering or the feet resulting in a crash, the reaction times were recorded only after the user performed any input, this caused the system to record higher than normal reaction times, hence the outliers.

The corresponding measures of central tendency are reported in Table 4.4. For each scenario we report the ranges (mean $\pm$ std), medians and p-values of the Wilcoxon Signed-rank test, which is the same as Wilcoxon rank-sum test, but for paired data.

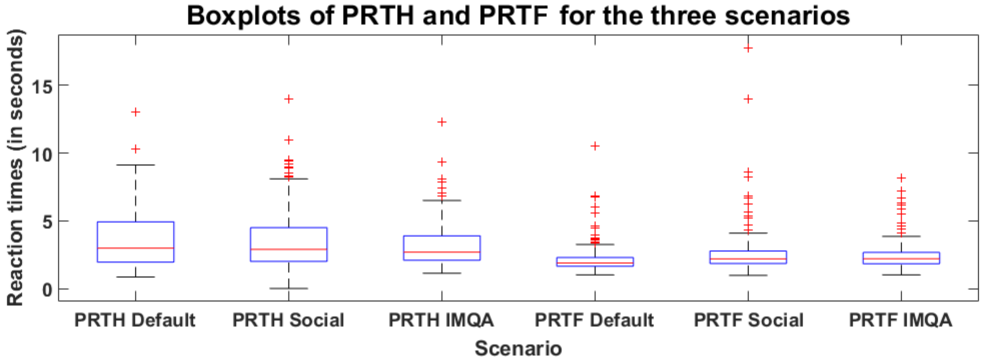


Fig. 4.2 BoxPlots of PRTH and PRTF among the three scenarios

Table 4.2 Mean ± std, median (in Seconds) and p-values for PRTH and PRTF

		PRTH		PRTF		p-value
		$\mu \pm \sigma$	median	$\mu \pm \sigma$	median	
Scenario	Default	3.645 ± 2.212	2.99	2.211 ± 1.158	1.90	$7.88e-14$
	Social	3.632 ± 2.326	2.9	2.723 ± 1.967	2.2	$1.81e-11$
	IMQA	3.247 ± 1.716	2.7	2.485 ± 1.139	2.21	$6.75e-11$

The results of the test verify the above visual observation with a global p-value of 6.2954e-33, ensuring the significant difference between PRT for hands and feet. This is due to the fact that drivers, when suddenly encountering an obstacle, tend to prioritize to use the brake pedal before putting any input into the steering wheel hence resulting in the above higher reaction times for hands.

Still, the global average reaction time was 3.51 seconds for hands and 2.47 seconds for feet which coincides with the minimum amount of time described in [39] in which drivers can take over the control of vehicle safely and comfortably in this situation.

The results of Friedman test for PRTH show that there are no significant effects among the 3 scenarios, $\chi^2(2, N = 160) = 3.6904$, $p = 0.1580$, $W = 0.0115$, although the strength of agreement among drivers is very small. That means that drivers take more or less the same time to steer the wheel in both scenarios. However, in the case of feet there are significant differences between at least one of the scenarios, with a medium strength of agreement: $\chi^2(2, N = 160) = 44.3974$, $p = 2.2868e-10$, $W = 0.1387$. To know what scenario is different from the rest, a multiple comparison test has been computed using the output of the Friedman test and shown in Figure 4.3. Two means are significantly different if their intervals are disjoint, and are not significantly different if their intervals overlap, so that the significant difference in PRTF is on the default scenario against the other two.

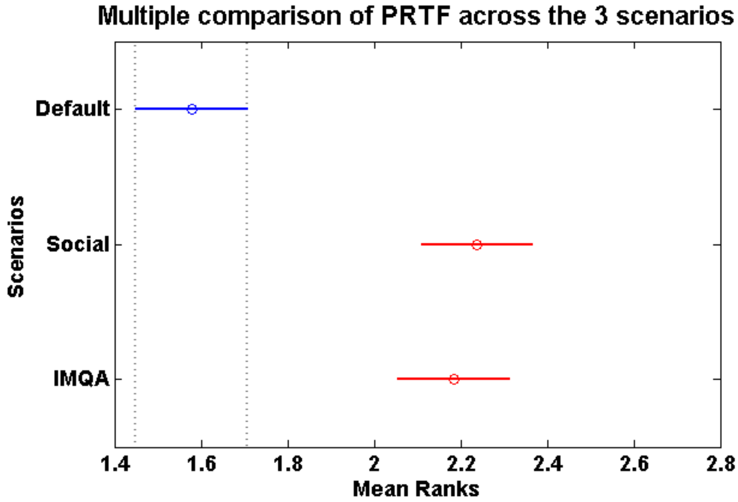


Fig. 4.3 Multiple comparison test of PRTF among the three scenarios

These results make sense from the point of view that drivers have to avoid a sudden hazard on the road, so probably the first instinctive action would be braking, taking into account that the alarm is triggered at the same time the cars in the front stop. In this way, as we pointed out before, the reaction time of hands is not relevant in any scenario, but drivers' reaction time of feet might be slower in NDR-tasks scenarios due to their cognitive processing [94], and the driver's lack of attention to the road.

Still, another interesting point is the success of the TOP action by itself, which is reflected in table 4.3.

Table 4.3 Percentage of Successes of TOP among the 3 global scenarios

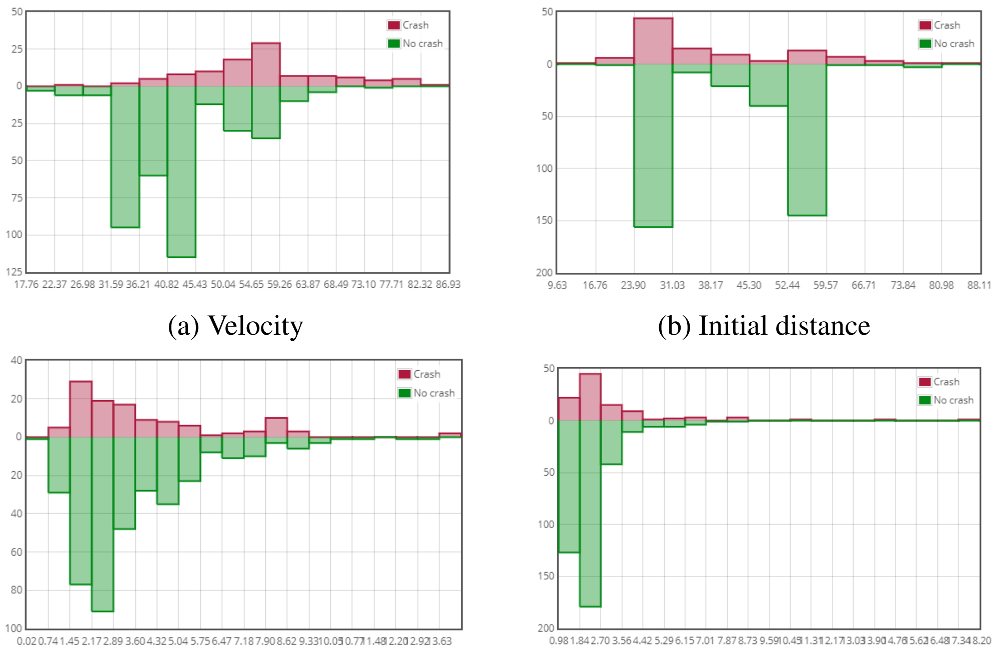
	Default	Social	IMQA	global
Failure	18.75	26.25	19.38	21.46
Success	81.25	73.75	80.63	78.54

We can appreciate a slight peak of failures in the Social scenario, although it is not significant (Pearson's chi-squared test [95]: $\chi^2 = 3.2881$, $p - value = 0.193$ at significant level of 0.05). There are no significant differences in PRT among Social and IMQA scenarios either, but probably social activities provokes a deepen immersion than questions and answers, so that there are more crashes. If we separate by gender, we can observe that the peak in social scenario remains, as table 4.4 suggest. As well, we can notice that females have less crashes than male, although these data could be biased since the number of females is $\frac{1}{3}$ than males.

Table 4.4 Percentage of Successes of TOP by gender among the 3 global scenarios

	Default	Social	IMQA
Female	85	67.5	85
Male	80	75.84	79.17

As well, we can assess the relationship between variables such as velocity, distance or PRTH and PRTF and the success of TOP in each scenario. Global descriptive statistics from Figure 4.4 show that the clearest variable that has significant differences between crashing or not is the velocity. Other variables like Occlusion and aggressive traffic cars had little part to play because the experiment was targeted towards a controlled study of driver's perceptions in a given scenario. That is, the bihistogram of velocity is the most asymmetric one, having most of the no-crash samples lower velocity than most of the crash ones.



(a) Velocity

(b) Initial distance

(c) PRTH

(d) PRTF

Fig. 4.4 Bihistograms of the distributions of the different variables about their success of TOP

This fact is proved by means of the Wilcoxon rank-sum test, summarized in table 4.5. In all the scenarios we can reject the null hypothesis so that we have evidence that the medians of the velocity when crashing or not differ.

Table 4.5 Wilcoxon rank-sum test for the relationship between velocity and crashing

	Crash	No crash	z-score	r	p-value
Default	55.55	41.01	6.103	0.482	< 0.001
Social	54.88	42.09	6.121	0.484	< 0.001
IMQA	55.16	40.95	5.744	0.454	< 0.001
global	55.34	41.09	10.436	0.476	< 0.001

Table 4.6 for the variable of the initial distance of the car to the one in front at the time the alarm is triggered shows that, depending on the scenario, their medians when crashing or not significantly differ, although p-value is very close to the significant level. If we do not take into account the scenario, the p-value obtained rejects the null hypothesis, but we can appreciate that the effect size is small, unlike in the case of velocity.

Table 4.6 Wilcoxon rank-sum test for the relationship between initial distance and crashing

	Crash	No crash	z-score	r	p-value
Default	31.5	45.99	−0.560	−0.044	0.576
Social	31.44	48.11	−1.871	−0.148	0.061
IMQA	28.34	47.53	−2.046	−0.162	0.041
global	31.15	47.55	−2.553	−0.117	0.011

If we focus on the relationship between PRT and success of TOP we can observe that PRTH maintain the little relevance they already had across the scenarios. Table 4.7 shows that p-values are much greater than the significance level. It makes sense in the light of the foregoing. On the contrary, PRTF seems to impact on the success of TOP, since there are significant differences between crashing or not in most of the scenarios, with a medium effect size. In the case of Social scenario, the null hypothesis can not be rejected. but the p-value is very close to the significance level.

Table 4.7 Wilcoxon rank-sum test for the relationship between PRTH and crashing

	Crash	No crash	z-score	r	p-value
Default	2.870	2.990	−0.981	−0.078	0.326
Social	3.100	2.820	1.256	0.099	0.209
IMQA	2.660	2.740	−0.052	−0.004	0.959
global	3.100	2.760	1.1017	0.046	0.309

Table 4.8 Wilcoxon rank-sum test for the relationship between PRTF and crashing

	Crash	No crash	z-score	r	p-value
Default	2.290	1.900	2.018	0.159	0.044
Social	2.380	2.14	1.943	0.154	0.052
IMQA	2.620	2.100	3.104	0.245	0.002
global	2.420	2.060	4.403	0.201	< 0.001

4.5 Summary

This chapter can be summarized in the following manner:

- Experiment shows that not all secondary tasks result in higher Perception Reaction Times. The experiment clearly shows that the subjects who were busy on their phones indulged in social media activities recorded a higher reaction time of 2.72 seconds on the feet as compared to when they were answering IMQA's at 2.48 seconds.
- Experiment shows that the Perception Reaction Times have a global average of 3.51 seconds for hands and 2.47 seconds for feet.
- The chapter shows that any secondary tasks while driving result in deterioration of quality of driving. Also the results of Friedman test for PRTH show that there are no significant effects among the 3 scenarios, $\chi^2(2, N = 160) = 3.6904$, $p = 0.1580$, $W = 0.0115$, although the strength of agreement among drivers is very small. That means that drivers take more or less the same time to steer the wheel in both scenarios. However, in the case of feet there are significant differences between at least one of the scenarios, with a medium strength of agreement: $\chi^2(2, N = 160) = 44.3974$, $p = 2.2868e-10$, $W = 0.1387$.
- The chapter also highlights the fact that the true self-driving cars can be hazardous if they lack the proper systems that can observe the driver's behavior in a timely manner.
- Generation of a more enhanced dataset with an extended data capture system, that contains all possible positions of driver's Hands, Feet and Face. This is specifically useful for Computer vision research area as it is necessary to monitor the driver in a real car. The dataset comprises of a number of different scenarios, each driver is subjected to a number of tasks during autonomous mode. Moreover, important variables like the velocity, distance and reaction times of feet as well as hands are also recorded

separately which gives a detailed insight into how drivers behave in an emergency situation behind the wheel of an autonomous vehicle. The dataset is currently sized at over 100 GB and contains over 1.44 million images. According to the literature review, a dataset of such scale is not available freely. Hence the proposed dataset is vital for researchers and engineers who are striving to design the next generation of ADAS (Advanced Driver Assistance Systems).

- Perception Reaction Time trials have shown that the driver's reaction times are reduced when they are answering challenging questions while behind the wheel of an autonomous car. Whereas the reaction times are increased when the driver is busy in social media activities during the same scenario.

Chapter 5

Weather Classification

5.1 Background

Road accidents related to adverse weather conditions play a huge part in disrupting the flow of traffic in a busy city environment [96–98]. The data available at present contains a large amount of variation. Figuring out a particular weather condition is a straight forward task for a normal human being but can be quite challenging for a computer vision system [99–101]. To overcome the challenges neural networks, in the last decades, have revolutionised computer vision systems to detect the weather condition using images as an input. Indeed, Convolutional Neural Networks (CNN) have been deployed in various fields like ship detection [102–107], object tracking in endoscopic vision [108, 109], nuclear plant inspection [110–112], transport systems [113, 114] and other complex engineering tasks [115, 116]. Yet there is still a lot of ground to cover.

5.2 Why weather classification?

After the successful experiment for PRT in the previous chapter, it was certain to find the next problem to solve, as LEE had a fairly decent visual quality aspect, the next challenge certainly needed to be a vision based issue. There were alot of problems to choose from like place recognition systems or even traffic detection systems. Weather classification is one field which has it's own set of variables. No one distinct weather is equal to the other and deep learning systems should be accurate enough to distinguish between different weathers. It is a complex matrix of light, color, shadows and different sun angles at any given time. This proved to be an ideal candidate to test out the flexibility of LEE. Hence, weather classification was identified as the next target to tackle the issue of hi-fidelity dataset for training deep learning models. The Detection of weather conditions based on visual data is a crucial research area with regards to the autonomous driving research, Presently there is not enough work being done to tackle this problem, the vision based system currently available in the market tend to work well under certain weather conditions like sunny day, whereas they struggle to keep up when it comes to the harsh weather conditions like heavy rain, fog and snow. The problems is that there is a certain lack of accessible datasets that can be used to train the deep network frameworks to successfully detect varying weather scenarios. This can be achieved if the datasets were recorded on the same location, with the same camera positions but with different varying weather conditions. Achieving that target in real-life is quite cumbersome and time consuming. This is where Synthetic datasets can play a vital role in bridging the gap between input data and scene understanding. We already know that the use of synthetic data can greatly increase the performance and accuracy of Convolutional Neural Network systems [117].

In the case of weather recognition on road the main challenges are: variability in elements such as camera placement and road layouts [118] and the machine learning methods such as CNN. Under such circumstances there is a need to explore more methods of filling the gaps left from using real world images, ideally a set of images recorded in the same location but with different weather conditions would be ideal in maximising the efficiency of machine learning system. This is the main reason why the use of synthetic data can be more productive as compared to the real-world counter part. In this chapter, two main objectives are approached: firstly to assess the modifications made to the driver simulator which was previously used for driver vehicular interactions [119]. The second objective is to test the performance of the generated dataset with other comparable ground truth datasets.

A custom-built virtual simulator that specializes in varying weather systems is implemented [120]. It utilizes Unity3d to simulate the weather with accurate lighting effects. The simulator environment is based on a real-world location of central Colchester, United Kingdom. It features a good mix of wide-open road and inner-city roads. An autonomous car is driven at different hours of the day in weather conditions ranging from sunny, cloudy, rainy and foggy with different camera angles. The final dataset recorded comprises of 108,333 images, approx 35,000 images per class The results show that state-of-the the art CNN architectures trained on synthetic dataset were able to achieve an accuracy as high as 74% when tested on real-world dataset [121].

5.3 Related Work

Previous research work has shown that the use of synthetic images can greatly increase the performance of 2d pose estimation of humans by using automatically annotated 3d pose dataset.[122] Also the use of single step frameworks for training convolutional neural networks that can differentiate instances, estimate masks and categorize objects is of a great interest. [123] Another paper discusses the usefulness of generating synthetic flying chairs showed that the networks trained on this unrealistic data still generalized very well to existing datasets such as sintel and KITTI, achieving a competitive accuracy at frames rates of 5 to 10 fps. [124]. Real-world datasets like KITTI are of great importance and can be enhanced by enhancing the existing datasets with synthetic clones. [117][125] Moreover, Synthetic datasets have also proved invaluable when it comes to text detection, dataset images were generated procedurally containing texts in cluttered environments, the resulting CNN outperformed the current methods for text detection. [125] Another interesting use of synthetic data came about in the form of generating 3d human models positioned correctly over a CCTV footage for training convolutional neural networks for detecting pedestrians, the proposed approach outperformed the classical pedestrian detection methods as well as real world specific data. [126] Hassan went for another noval approach for training cnns for car segmentation, he was able to augment real world datasets with synthetic data to generate a varying traffic density in the prepared images. [127] Scott [128] used a data driven approach in which he developed a framework for rendering 3d models from a given viewpoint and than comparing the 3d model with an input image for a better scene understanding. Rendering of Entire synthetic environments have been proposed for training convolutional neural networks for stereo disperity and scene flow estimation [129]. Also SYNTHIA [23] is another dataset which is fully synthetic and contains pixel-perfect annotations. The dataset contains approximately 200,000 images recorded with pixel perfect annotations which results in a decent training material for CNN's. Results showed that using synthetic dataset such as SYNTHIA can greatly improve the performance of Deep Learning Networks.

Most of the previous research includes the use of polarized and infrared cameras. The use of such cameras can give some plausible data but the installation costs can easily be substantial [130]. In order to overcome this issue, the use of RGB cameras is preferred because they are much more simple and cost-effective, hence making them viable for mass production.

A study performed by Omer & Fu [131] used Color cues to add illumination variance, however, their approach requires the detection of white road lines for the detection of road area which can be quite challenging in severe winter weather conditions.

Most of the studies aimed toward driver assistance systems have been performed towards Rainy weather classifications [132, 133]. A study performed by Lu et al. [134] deals with two class weather classification which includes Sunny and Cloudy. In that study, the authors proposed a new data augmentation scheme to substantially enrich the training data, which is then used to train a latent SVM framework to make the solution insensitive to global intensity transfer. Another study [135] deals with multi-class weather classification which only deals with fixed camera point only.

With regards to synthetic datasets, there is alot of research being carried out with a goal to fill the gaps between real world data with synthetic data. There are some driver simulators that can fill in the void by generating synthetic datasets for weather classification. CARLA [136] is one such simulator that aides in autonomous research. It comprises of a built in weather system that can be used to generate weather classification datasets. Synthia dataset [137] is another example which comprises of 200,000 plus images comprising of varying dynamic seasons like clear sky, rain & night time. Hao et al. [138] developed a weather simulator that could replicated the weather at a given time in a virtual environment. But it lacks in visual fidelity for our experiments. The current chapter also has specific requirements that require the camera position to be from the location on the driver's car.

Another plausible direction of research for weather monitoring has been use of microwave based Synthetic Aperture Radar (SAR) imaging. Unlinke, optical sensors, this tool is unaffected by weather conditions. This is the main reason that they have been used for high speed ship detection [139, 140]. The SAR images are used as input to a grid convolutional neural network (G-CNN) to detect ship while considering their speed. Another prominent work has used depthwise separable convolution neural network (DS-CNN) to detect high speed ship [141]. Other direction of research has focused on small sized of ships [142] and unperceived imbalance problem [143]. However, connection to the satellite is not always possible, thus in this research, optical sensors have been considered.

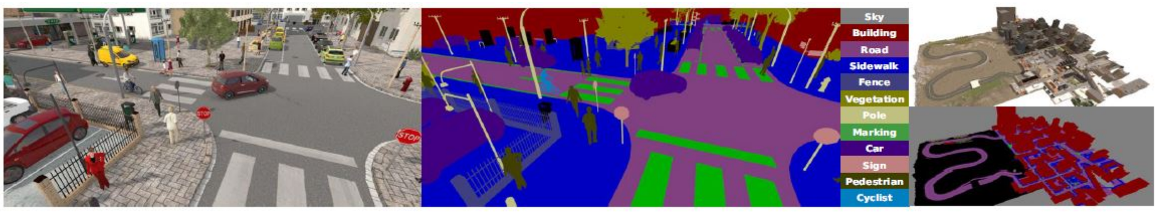


Fig. 5.1 SYNTHIA Dataset

Ros [63] proposed a new approach for detecting weather conditions based on images captured via in-vehicle vision system that takes into account the histogram of gradient amplitude, HSV color histogram and road information, and employ an algorithm based on real AdaBoost making use of category structure to achieve the task of classification. the experiments showed superior performance. Elhoseiny [53] showed some very promising results when he trained the convolutional neural networks for weather classification, an overall accuracy of 82.2% was achieved when compared to state-of-the-art's 53.1%.

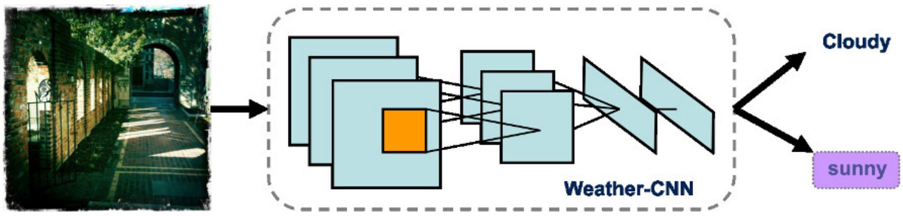


Fig. 5.2 Weather Classification using CNN

5.4 Significance of the Problem

The problem being faced at present is the lack of datasets for efficiently training CNNs. Training a Deep Learning network requires exponential amount of image data in order to get the best possible result. The present datasets are mostly real life images captured throughout the world, the problem arises with specific requirements for weather classification. In order to acquire a good data one needs to record the same visual image from the same angle with different weather conditions which will give the CNN layers important features to compare and differentiate between weather conditions. We intend to solve this problem by incorporating and modifying our Driver simulator to generate varying photo-realistic images of a known real world urban environment. As discussed above synthetic datasets provide a means of enhancing the training process of deep learning networks and in some cases even exceed their real-world counterparts when it comes to overall accuracy. The main advantage is the absolute control over how and when weather can change in the virtual environment. Since there are not enough synthetic datasets available in the wild which can assist in training deep learning networks, it is evident that we solve this issue with the help of our simulator by generating a large dataset of varying weather based images from the perspective of an autonomous car. Therefore streamlining the pathway for other researchers to further enhance the ADAS for the car of the future.

5.4.1 Research Questions and Hypothesis

The hypothesis states that the use of synthetically generated datasets comprising of different weather conditions will greatly increase the accuracy of the resulting CNNs. This can include mixed training models which will consist of a collection of real images coupled with synthetically generated images. Is it possible to achieve the same performance when you team up a synthetic with a non synthetic dataset? Our research will try to answer these questions in this chapter.

5.4.2 Methodology

Previous two driver simulator Experiments as described in Chapter 3 relied on a motorway track for recording Perceptional Reaction times of the drivers. In order to test the capabilities of the driver simulator further, more complex environments were needed. For this purpose we moved towards urban environments because they are more demanding when it comes to complex driving scenarios. We had 3 options of possible road layouts to test out, namely, Colchester High Street, North Station Road, Essex University route and Cowdry Avenue.

1. **Colchester High Street** provided a busy urban environment full of parked cars and pedestrian movements. It also consisted of not too wide streets which provided a challenge for the development due to time constraints. Ideally this environment will eventually be required in the future to further enhance capabilities of the simulator providing exceptional challenges to test and train car of the future.

2. **North Station Road** provided a good balance of urban and wide roads which were inline with the goals of this version of the simulator. There were 4 roundabouts int he entire circuit which meant a complex mix of traffic simulations. Moreover, future versions of this environment would add more detail to make sure the deep learning methods get all the necessary details for test/train purposes.

3. **Essex University Route and Cowdry Avenue** provided a more quiet environment with open fields and long straight roads with minimal traffic, probably not the best mix for the current goals.This type of environment is good for entry level autonomous vehicle training but as we had already done a version of the simulator with straight roads in the previous version, it was probably not the best fir for current purpose.

In the end, after careful consideration it was decided to move forward with Colchester North Station Road route as shown in figure 5.3, due to it's plausible mix of straight and urban roads.

The selected route provided a good balance between 2 lane A-Road and two way urban road. The route also has a good collection of Retail, Commercial and Residential areas. This provides the basics for testing out a complex synthetic environment for the next iteration

Fig. 5.3 Colchester North Station Road Route

of the driver simulator. The novelty is to test if we can get better performance if we train Convolutional Neural Network models with a mix of Real world data [144] and the above Synthetic data. The above proposed synthetic environment would also include varying weather simulation as well, which would pave the way for not only training deep models for autonomous vehicles but also for weather classification in general. This will be helpful in further branching out the research into image classification territory. Previous studies have shown that including synthetically generated weather conditions actually deteriorates the deep models for tracking. [117] The total preparation time for the above environment was no more than 3 months and included methodologies as discussed previously in chapter 3. In theory, the updated simulator can generate a million images with varying weather conditions. Google maps and street views was be used as a guide to match the synthetic data to the real world data as close as possible. The goal was to make our synthetic data more realistic as compared to the state of the art synthetic dataset i-e Virtual Kitti. This will provide clues to whether a more realistic data actually results in better training performance or not. After the successful preparation of the images, the next step was to record the images in varying weather conditions. The approach has some similarities with what Stephen [128] did, he used the popular Grand Theft Auto 5 Game for recording twenty five thousand images with pixel perfect annotation, the difference between his and our approach is the fact that we have more control over what we can create. Moreover, Using an already released game for research purposes without asking the developers of the game first can lead to illegal use of the software which we defiantly wanted to avoid. In the end the generated dataset would prove invaluable for training future deep learning models. Kunming [145] recently used advanced computer graphics techniques to produce synthetic virtual environments for evaluating weather conditions. In edition they also benchmarked recent de-hazing methods. This will be useful in our Analysis as well, But the drawback of Kunming's approach [145] is that it only takes in to consideration fog environments whereas we are generating cloudy, rainy and Fog conditions. Once fully recorded our dataset would be one of the most comprehensive synthetic datasets available any where.

After the initial production of the synthetic environment, we were able to generate close to 650,000 images comprising of three weather classes namely, Cloudy, Foggy and Rainy. The number of images is targeted to go well beyond 1 Million in the near future. The novelty in our a recorded dataset is that it includes images that were generated from only three different vantage points (C1,C2,C3). Below are the some of the images from the generated data-set. More vantage points are planned to be added in order to avoid over fitting.

(a) Cloudy

(b) Foggy

(c) Rainy

Fig. 5.4 Three class data-set

Figure 5.5 shows a Mosaic generated from the cloudy class images, Note the amount of variation achieved between the cloud formations. This is what makes our dataset quite unique in terms of weather formations. To explain this further, it is to be noted that the cloudy class alone contains 3 different cloud variations recorded at 3 different day time intervals

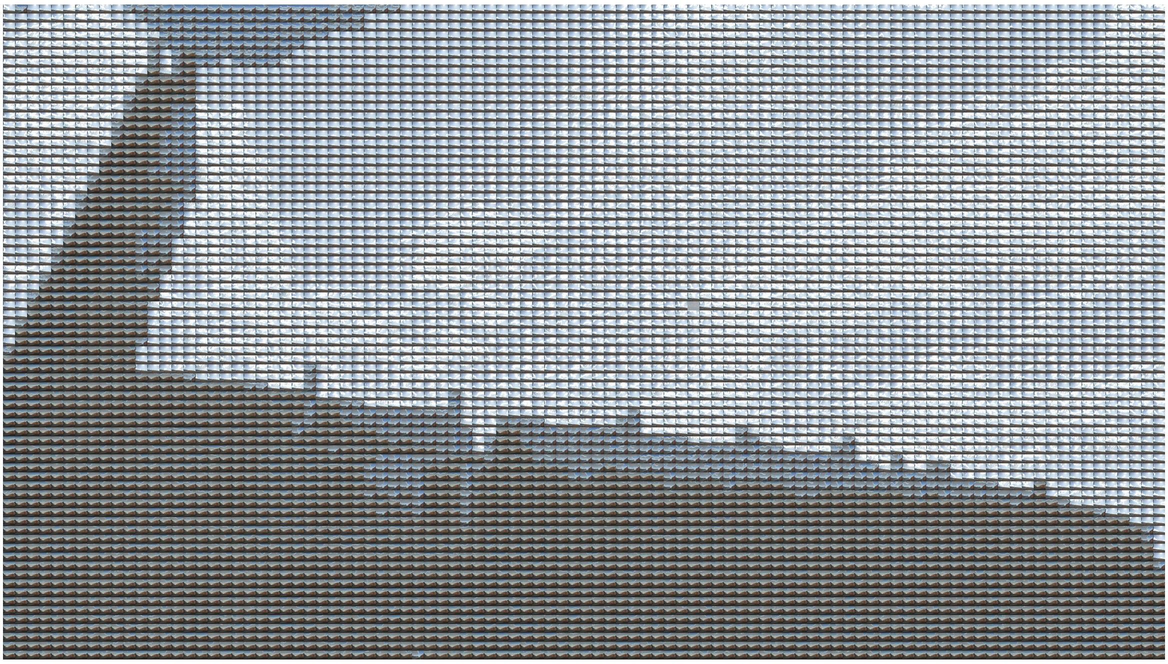


Fig. 5.5 Cloudy Class Mosaic

(10:00am, 12:00pm, 2:00pm, 4:00pm)and each interval contains 10,000 images comprising of unique cloud formations. The system is capable of generating random formation of clouds with varying wind speeds at any given instance.

After this successful generation of synthetic images from limited vantage point, it was then decided to better utilize the extent at which the images can be produced. Instead of static vantage points, the virtual camera was attached to an autonomous car and was then let to drive throughout the circuit. The figure 5.6 below shows the virtual car ready for the simulation. The virtual environment required some further treatment in order to fill the gaps on the areas that might potentially be visible to the camera.

(a) Virtual Car

(b) Environment

Fig. 5.6 Virtual Environment

Each session of the simulation lasted for approximately 2500 images. initially the footage was captured at +1 hour instances from 9:00 AM to 4:00PM for each weather condition. The images below shows the car in different weather conditions.

Further adjustments were made in order to get a better overall lighting and atmosphere.

5.5 WDD: Weather Drive Dataset

The generated dataset provides a plausible amount of varied weather conditions. The main classes include Sunny, Cloudy, Foggy and Rainy. Each class then contains further sub classes involving the same class captured every hour from 9 AM to 4 PM. This methodology provides the most efficient learning material for CNN's and deep learning algorithms as it provides the same location within varied lighting and weather conditions. For each recording session the virtual car was allowed to run through the circuit which resulted in the capture of approximately 2600 images. Each session was recorded on a one hour difference basis, i-e for a clear day weather each session driving was captured at 9, 10, 11, 12, 1, 2, 3 and 4 o clock. This provided a much needed variation in the overall shadow and lighting conditions for a varied data-set generation. Figure 5.7 shows the 4 main classes captured at various locations through different sessions.

Class	Training	Testing
Clear	9,613	1,764
Cloudy	38,949	1,677
Foggy	29,914	5
Rainy	29,857	396
Total	108,333	3,842

Table 5.1 No. of Training images(Our dataset) & Testing images(BDD) per class distribution

Moreover, extensive care was taken to simulate secondary imperfections like water droplets on the camera lens for distortion, Traffic Car signal bloom effects, water shower behind traffic car wheels. Additional camera angles such as left view, right view & back view were also captured to meet the challenge of diverse nature task and absence of discriminate features among various weather conditions. Table 5.1 shows the distribution of images per class. The resolution of each image was recorded at 1280 x 720, the channels used were Red, Green & Blue. Notice that the validation images for Foggy class only consist of 5 images, this is because a foggy image is by far the most specific in color tone and channel information. Moreover, the quantity of validation images is set by the creators of Berkeley Deep Drive dataset.

(a) Clear

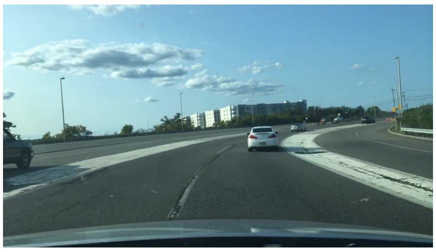
(b) Cloudy

(c) Rainy

(d) Foggy

Fig. 5.7 WDD: Weather Drive Dataset

Our synthetic dataset has been evaluated on the Berkeley Deepdrive dataset[121] because it provides a considerable variation of varying weather conditions in a fairly balanced annotated pattern as shown in the Figure below.



(a) Clear

(b) Cloudy

(c) Rainy

(d) Foggy

Fig. 5.8 BDD (Berkeley Deep Dive) Dataset

5.6 Deep Learning Networks

The state-of-the-art Deep learning frameworks include weather classification CNN based on AlexNet [53]. where the weather is classified between sunny and cloudy, the dataset used comprised of ten thousand images. Our initial results were not very promising as there was quite alot of over fitting detected and the accuracy was not more then 50%, which was partially due to corrupted data, once the data was edited we approached the training via AlexNet model as done by [53]. The current state involves the replacement of final layers with our target classes which includes Cloudy, Foggy and Rainy weather.

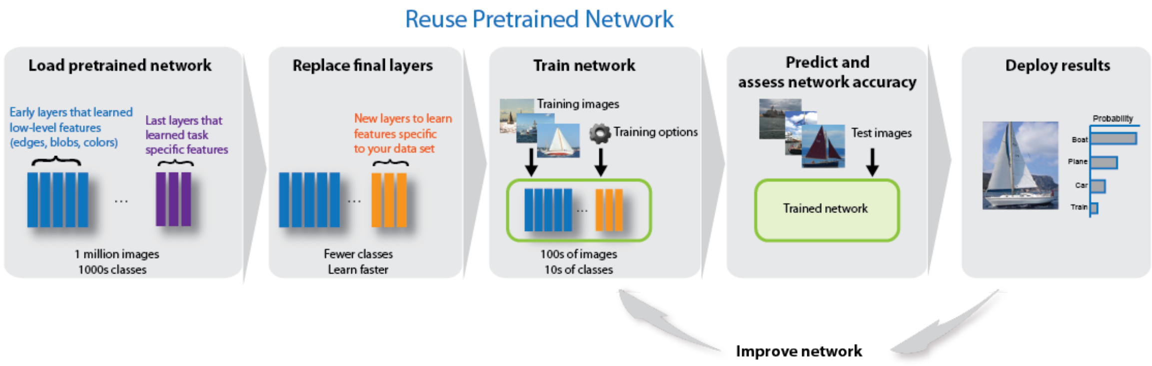


Fig. 5.9 AlexNet Transfer Learning

The figure 5.10 shows the initial training progress that was recorded. Already the accuracy started from above 60% and started to stabilize close to the 65% to 70% mark. It should be noted that the training cycle is still in the 1st Epoch, also the fact that the training is being performed on a single Nvidia Tesla GPU, hence the timed required to train such a model is quite substantial.

The table 5.2 below shows the total number images trained and tested so far from the generated data-set. The next approach would be to train the model with datasets captured from multiple cameras and test the model with a dataset involving a camera angle that was not used in the training process.

Table 5.2 Total Images Trained and Tested

Class	Test (No. of Images)	Train (No. of Images)
Cloudy	160311	240567
Rainy	80127	161218
Foggy	8032	16079

The important to know that training deep learning models with this amount of data requires exceptional amount of time and resources, It can easily take somewhere between 3

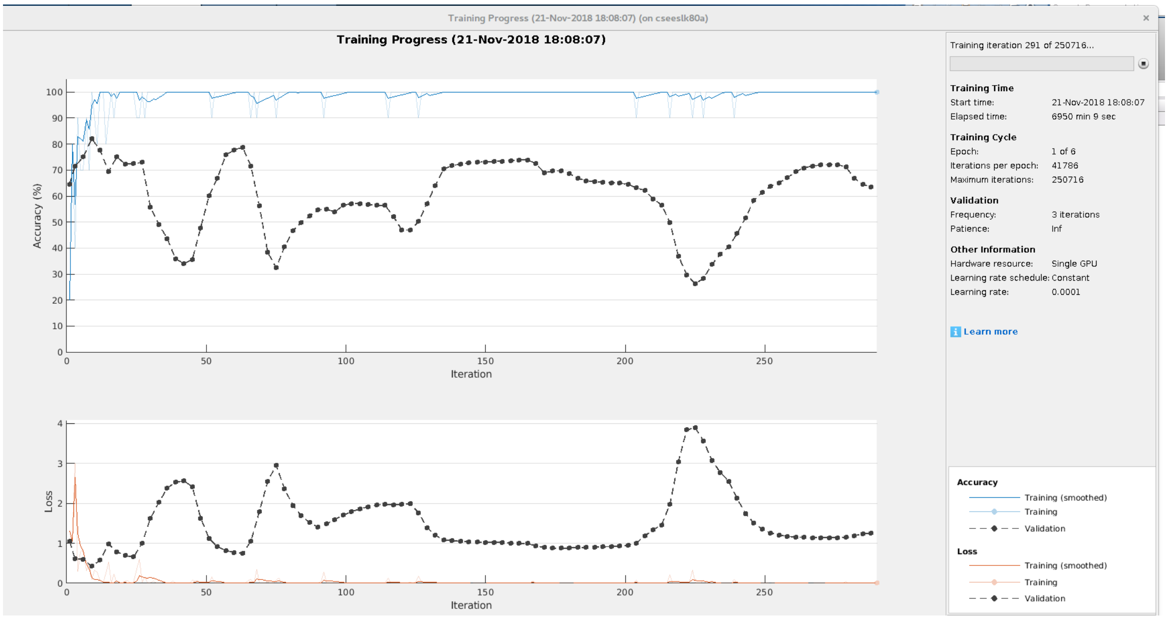


Fig. 5.10 AlexNet initial Results

to 4 months to train an efficiently working model. Thee training performed for this study averages between 2 to 3 weeks per learning model. Moreover, the results indicate the use of just AlexNet training model. It is a necessity to train our weather classifier with atleast another state of the art model, like ResNet which performed well in another recent study [59]. This will be done later in the chapter.

The field of weather classification is still evolving and applying new techniques can never guarantee the best of results, Weather is a very complex phenomenon and segmentation of such images can be a problematic task in complexity. Rutkowski [146] lays down the fact that different techniques of computer science when combined can constitute to new and better proposals. So it can be said that tackling uncertainty as an opportunity rather then a problem is a very important step towards tackling efficient weather classification [59].

Further training of the CNN was performed with the newly generated WDD Weather Drive Dataset, this time the testing images from the RFS(Rain, Fog, Sunny) dataset were used, this resulted in an accuracy of only 42% which was not a plausible result.

It was further noted that perhaps the non road environments of the RFS dataset might have played a part in the lower accuracy. Hence we decided to go for a road oriented dataset for testing our CNN. BDD Berkeley Deep Drive is one of the most extensive real world driving datasets available. [147] and this particular dataset also has carefully labelled images with respect to time of day and weather conditions. This works perfectly for testing our CNN. As expected the results produced far better accuracy then the RFS dataset.

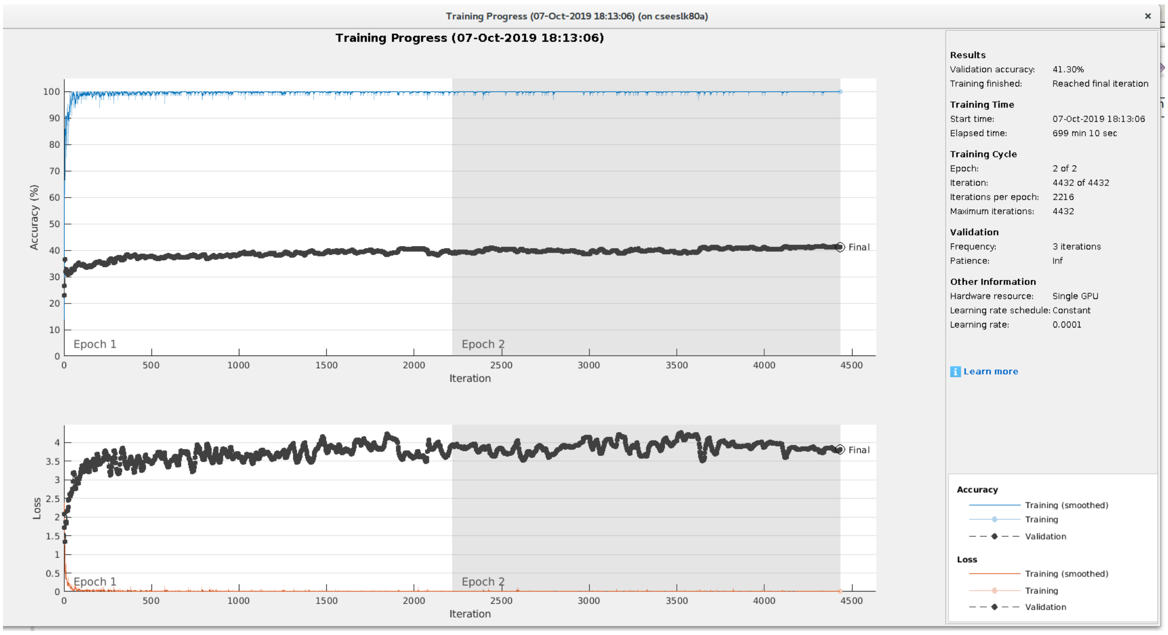


Fig. 5.11 RFS Test

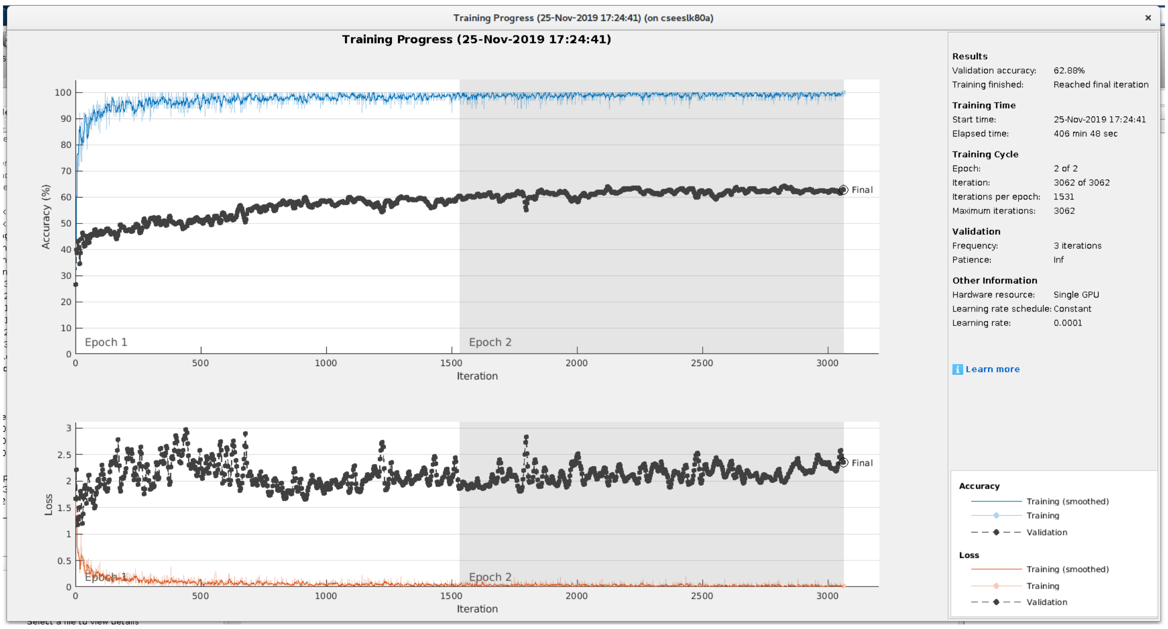


Fig. 5.12 BDD Test

62% is a much welcomed starting point, at this stage some issues were identified within the generated images, especially the rainy class. The rainy class was lacking some of the visual aspects like reflective water puddles and wet surfaces in general. Also it is further planned to introduce a new weather classification category like snowy conditions to further enhance the dataset. we also managed to try out Mappilary dataset which has a generous amount of 25,000 images [148]. Although the dataset has been advertised as containing variety of different weather and seasons. However the dataset images are not labelled according to the weather which is the case with most of the state of the art datasets. This is one instance where our WDD(Weather Drive Dataset) contributes heavily to the research community as it provides the only Synthetic set of images specifically aimed toward weather classification.

5.7 Weather Classification Methodology adjustment

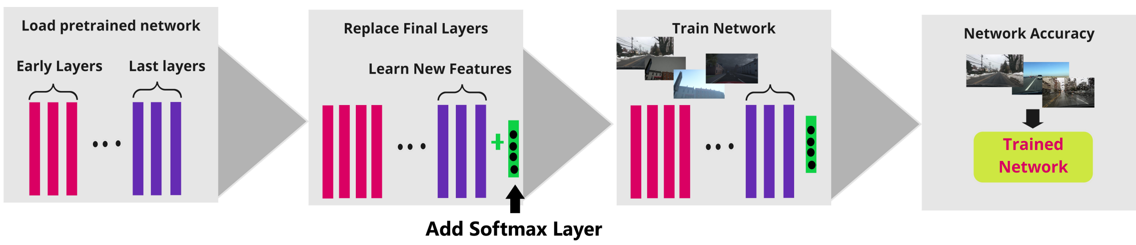


Fig. 5.13 Pipeline: Step 1: The pre-trained network is loaded, Step 2: unfreeze classification layers and add softmax layer (4,1), Step 3: Train the weights of classification layers with synthetic dataset, Step 4: Test the network accuracy with real time test dataset.

To check to what extent our synthetic dataset is useful for weather classification, we propose to apply a number of deep learning networks to test the dataset. One of the most famous deep learning architecture, Convolutional Neural Networks (CNN) have been able to perform various vision tasks with capabilities comparable to humans. However, CNNs performance is highly dependent upon the large size of training data. This problem intensifies for the weather classification task as the real time weather variation data availability for self-driving cars is difficult [149]. Based on this problem, we try to gauge whether different CNN architectures trained using synthetic data are good enough to classify the weather captured in real time.

Transfer learning is a powerful machine learning technique which allows re-usage of model for different tasks. It has gained immense popularity for computer vision tasks where pre-trained CNN architectures are used as the standard starting point given the vast resources in terms of computation and time required to develop CNNs from scratch.

The pipeline used for the work described in this paper is visually represented in Figure 5.13. The pipeline operates in a fashion where the weights of entire pre-trained network are frozen except the classification layers in the end. The softmax layer is added for multi weather classification. The softmax layer (4,1) is added because the number of classes is 4. The classifier layers of the pre-trained networks are re-trained on the proposed synthetic weather dataset. The test real-time images are passed through re-trained CNN models to extract predict the network's accuracy.

The classifier layers are trained on the synthetic images and tested on real-world dataset Berkeley DeepDrive [121]. After performing set of the experiment, the mean Average Precision (mAP) was calculated for each of the models.

5.7.1 Pre-trained Models

The pre-trained Models used for predicting weather have been described in depth in the following subsections:

1. **AlexNet**

   AlexNet [150] can easily be considered as a breakthrough network that has popularized deep learning approaches against traditional machine learning approaches. With eight layers, AlexNet won the famous object recognition challenge known as called the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012. It is a variants of artificial neural networks where the hidden layers comprise of convolutional layers, pooling layers, fully connected layers, and normalization layers. Few of its standout features were addition of non-linearity, use of dropout to overcome overfitting and reduction in network size due to overfiting.

2. **VGGNET** VGGNET [151], a 19 layer network, was proposed as a step to the AlexNet and was a runner up of ILSVRC- 2014 challenge. As an improvement, the large kernal size of the first and second convolutional layer of AlexNet net were replaced by multiple 3 x 3 size kernal filters. The small-size filters allows the network to have a large number of weight layers. Non-linearity in decision making was incremented by adding 1x1 convolution layer.

3. **GoogleLeNet**

   GoogleLeNet [152], a 22 layer network, was the winner of ILSVRC- 2014 challenge. It was proposed as a variant of inception network to reduce the compuational complexity of traditional CNNs.The inspection layer had a variable receptive fields to capture sparse correlation patterns in the feature map.

4. **Residual Network**

   Residual Network [153] was the winner of ILSVRC-2015 challenge. It was proposed with the aim of overcoming the problem of vanishing gradient in ultra-deep CNN by introducing residual blocks. Various versions of Residual Network (ResNet) were developed by varying the number of layers as 34, 50,101, 152, and 1202. The popular Residual Networks ResNet50 and ResNet101 are used in our experiment.

5.8 Results

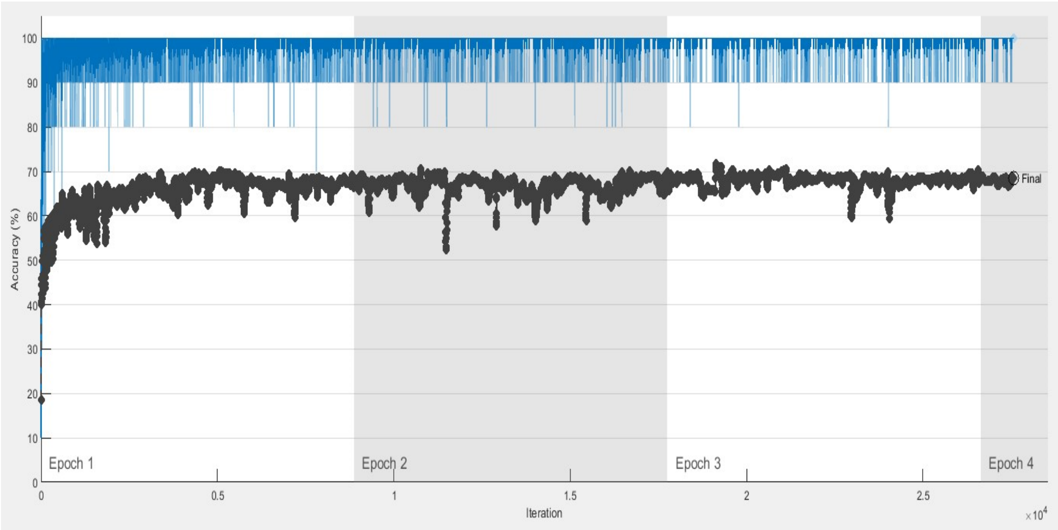
In this section, we evaluate various CNN models trained on our proposed synthetic dataset and compare their performance on BDD dataset. The synthetic dataset contains images annotated with 4 weather classes. The number of epochs is set to be 500. The learning rate of stochastic gradient descent (SGD) optimizer for cross-entropy minimization was set to be 0.0001. These parameters were deduced empirically by analyzing the training loss. As a regularization strategy during training phase, two data augmentation techniques were used for all architectures. The first technique took random crops of training images and second technique applied rotation to the training images. All the algorithms are implemented using MATLAB, and the experiments are performed on a Tesla K80 with 12GB GPU memory and 916.77GB storage.

Architecture	mAP	Trainable Parameter	Time (min)
AlexNet	0.6856 $\pm$0.012	61M	986
VGGNET	0.7334 $\pm$0.023	138M	2930
GoogleLeNet	0.6034 $\pm$0.009	7M	618
ResNet50	0.6183 $\pm$0.025	26M	1020
ResNet101	0.63 $\pm$0.006	44M	1242

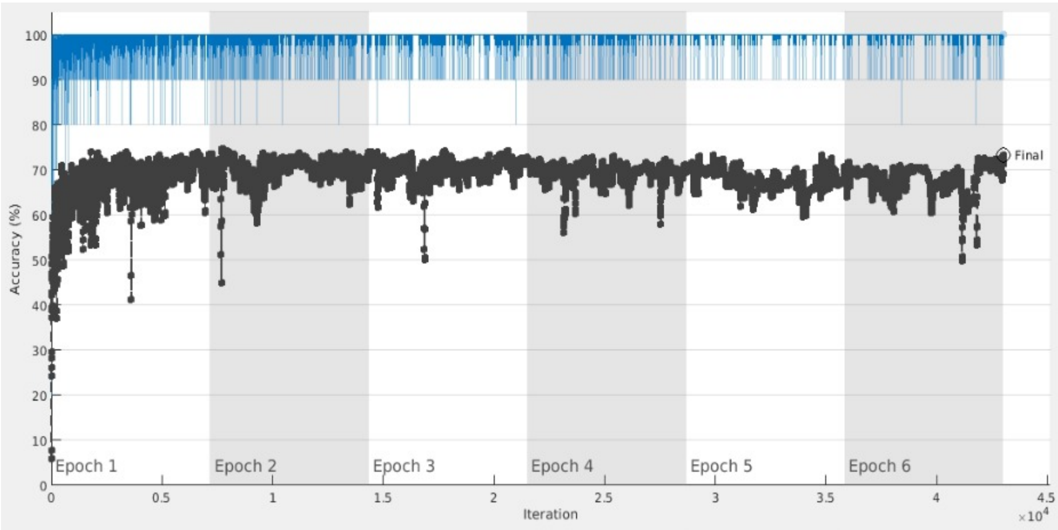
Table 5.3 Results from CNN evaluations

Each experiment of calculating accuracy for any given pre-trained model on testing dataset is conducted 10 times. Then average accuracy for any given model is calculated and denoted as mean Average Precision (mAP). The results tabulated in Table 5.3 show that mAP for all the architectures vary between 60% to 74%. The accuracy variation over each epoch has been shown in Figure 7 and 8.

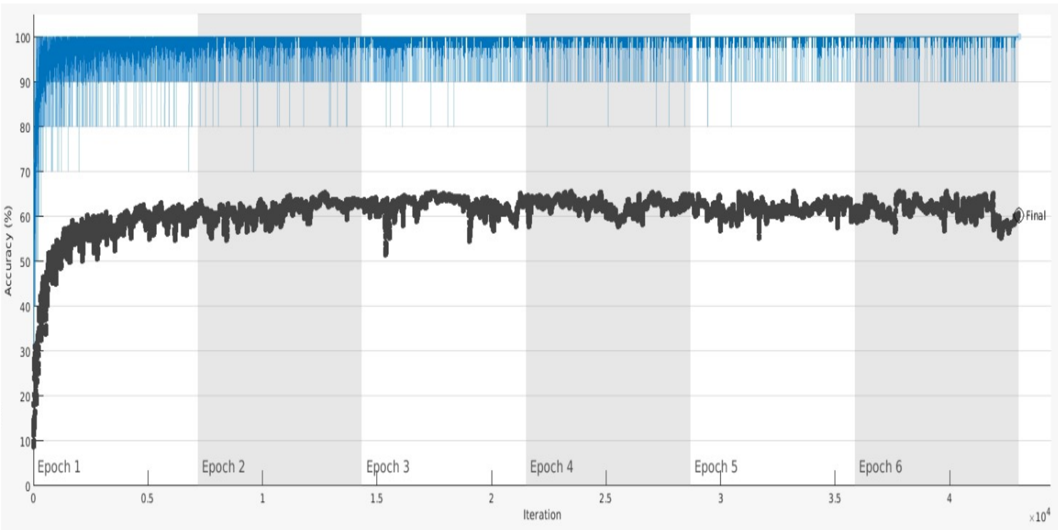
ResNet architectures achieve lowest accuracy due to their complicated multi-branch designs, i.e., residual addition in ResNet, as the fine tuning of hyper-parameters and other customisation becomes difficult. Given the constraint of hardware in self driving cars, the inference is slowed down along with the reduction in memory utilization [154].



(a) AlexNet

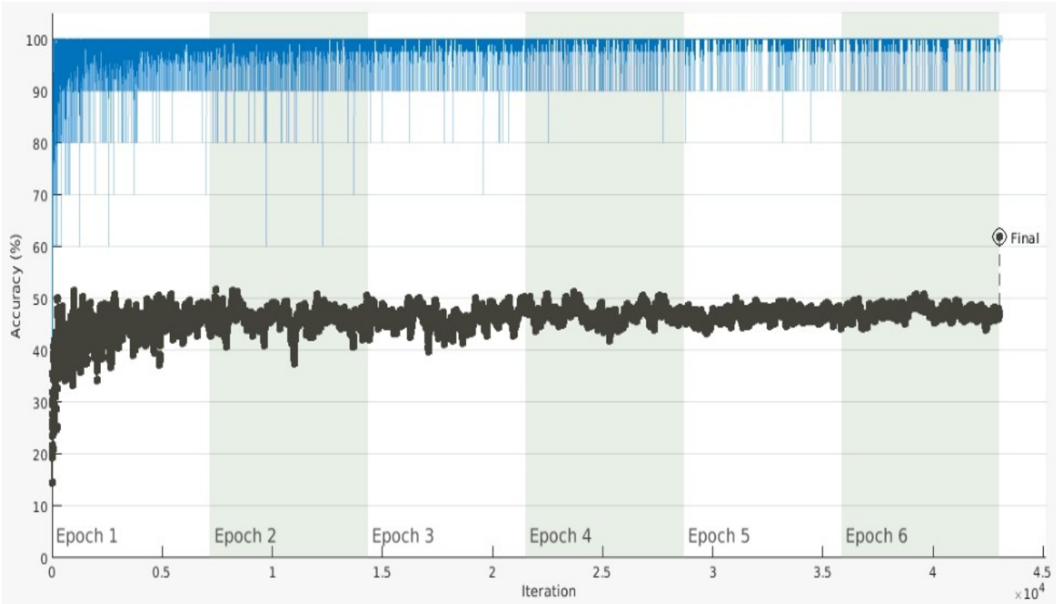


(b) VGG

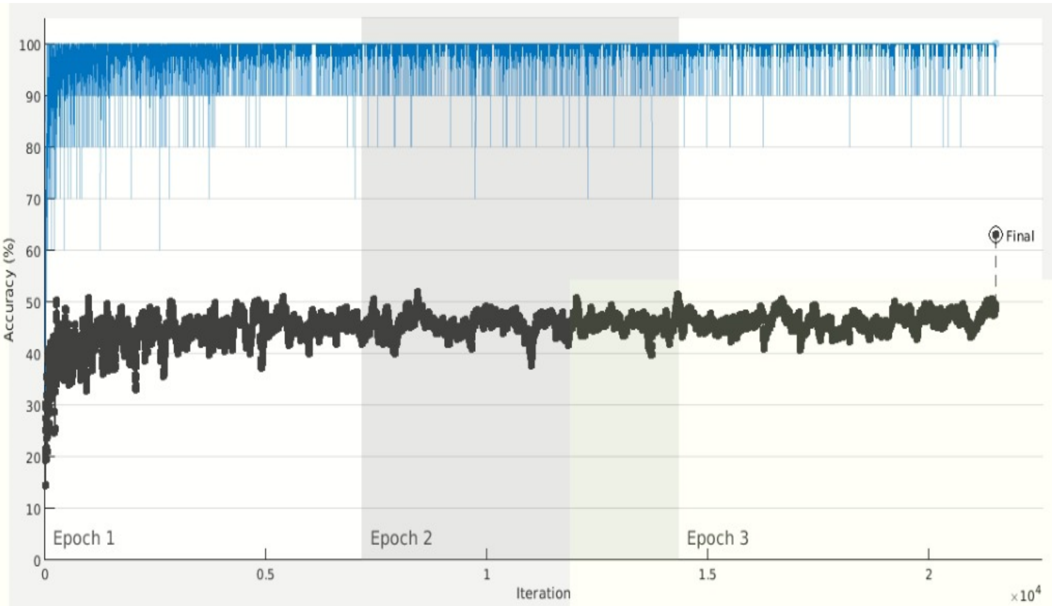


(c) GoogleNet

Fig. 5.14 Accuracy variation over each epoch for (a) AlexNet (b) VGG (c) GoogleLeNet model



(a) ResNet50



(b) ResNet101

Fig. 5.15 Accuracy variation over each epoch for Residual Networks (a) ResNet50 (b) ResNet101

The most efficient weather classification accuracy on testing dataset was achieved by the VGGNet architecture. These results indicate that the optimisation achieved by the inclusion of smaller kernel filters at the initial convolutional layers has a positive effect in the overall task of weather classification. The universal effectiveness of performance of VGGnet to extract deep features has also been affirmed previously by state-of-the-art PFGFE-Net [107] that use VGGNet as a backbone.

The training time from Table 5.3 reveal that it is directly proportional to the parameter due to the back propagation process to retrain the weights of classification layers. However, a closer look at the task at hand, one can conclude the training of weather classification process for self driving cars will be performed at cloud and it is one time process. In the particular case of VGG, training is time intense but is a one time task. The testing time for determining weather from single image on average using VGG is 15.67 fps that is real-time efficient. Concluding the potential of this type of architecture on classification task with paucity of dataset, draws attention for the possibility of more experimentation by training on larger synthetic dataset with more diverse classes.

5.9 Summary

1. This chapter highlights the modification of the custom driver simulator first introduced in chapter 3 that is now able to produce complex weather scenarios in immaculate detail. The simulator is designed to be highly user friendly and uses a launch and record approach towards generating different weather conditions within a virtual road environment.

2. The chapter also highlights the newly generated synthetic dataset called WDD (Weather Drive Dataset) to train a classifier in the context of weather classification and provides a synthetic dataset validated with the real world Berkeley DeepDrive [121]. WDD comprises of 108,333 images and consists four different weather conditions namely, Clear, Cloudy, Foggy & Rainy. The evaluation of this dataset has been tested as mentioned in the last point. The study shows that the use of synthetic data set can result in accuracy of upto 74% which opens up further room for research in the future.

3. The weather classification accuracy is derived by testing classifiers on different real time dataset which allows the persistent problem of bias in vision datasets to be tackled. The study proves that a persistent visual fidelity is important in generating realistic datasets for computer vision based datasets. In other words, details like lighting, color, shadow , form and depth are paramount when generating a realistic synthetic images for weather classification. Furthermore, with advent of computer graphics it will be possible to achieve advanced photo-realism in the virtual environments, game engines like Unity & Unreal are embedding new visualization techniques to further enable the data-scientists to generate accurate synthetic data for vision based tasks.

Chapter 6

Conclusion and Future Directions

Use of Synthetic worlds for Advanced Driver Assistance Systems is still quite a varied field for designers and engineers because there is no hard and fast framework for how a virtual world should be constructed. Moreover, these systems are vital for ensuring that car of tomorrow is able to safely transport it's passengers efficiently from one location to the other without any fatal collisions and accidents. Till we reach a point where the cars are totally autonomous, the researchers would still have to manage how the driver's interact with their semi-autonomous vehicles in a meaningful manner.

The application domains of using synthetic worlds for solving real world problems is quite broad, ranging from automotive related simulations to medical and even military simulations. The automotive industry still has a long road ahead before it reaches the Level 5 autonomous vehicles. But in order to reach that goal alot more research and problem and solving still needs to be done. The author has tried to answer the main questions and problem statements that were raised in **Chapter 1** to the best of his abilities followed by an extensive literature review introduced in **Chapter 2** which gives a detailed overview of the state-of-the-art related to the thesis chapters.

This thesis is a combination of various research gaps within the field of drivers assistance systems. As such the author's research work can be divided into three separate tracks, (a) Driver Simulator, as discussed in **Chapter 3** which goes through the complete process of developing an efficient and cost effective driver simulator from scratch - (b) **Chapter 4** Perception Reaction Time - which uses the LEE driver simulator developed previously and efficiently records the reaction times of drivers in a given scenario which in return highlights the potential risks of drivers ability to take back control of an autonomous car - (c) **Chapter 5** Weather Classification by using synthetic data from a modified version of the LEE simulator which shows effective use of computer generated images to train weather classifiers. All of these chapters are peer reviewed and have gone through extensive revisions. As these chapters are all linked to the overall objective of progressing the Advanced Driver Assistance Systems, they pose their own future directions in unique ways.

6.1 Initial Research Questions and Objectives

This thesis covers alot of ground in terms of simulators and synthetic datasets. The initial research questions can be listed as follows,

6.1.1 Driver Simulator

Can the use of virtual simulators in place of physical simulators decrease the time, budget and complexity required in terms of ADAS research? What are the technical specifications required for such a setup. The main objective was to find a plausible solution which would help researchers to program any specific scenario for the sole purpose of testing and improving ADAS of the future. This objective was achieved in the form of the successful development of a virtual Driver Simulator namely LEE that has the capacity to be open source, meaning the it is accessible by a broad range of Research community who can use it for solving not just ADAS related problems but also driver behavior related issues as well. It is Light-weight meaning, it only has 4 separate hardware parts namely, CPU Case, 2 monitors, steering/pedal and webcams and hence can be transferred from one Location to the other with out any complex setup processes. There are no modifications done to these hardware items and comply with plug and play protocols. The code is also transferable to any windows based machine provided that it has a decent Nvidia RTX 3 series GPU installed. The next headline feature of the driver simulator involves a procedural based traffic system which populates cars on the road in new locations every time a session is executed which makes it match closer to the real-world challenges on the road. Driver simulator also supports multiple webcams meaning a researcher can record almost all aspects of a drivers behavior during a session. The LEE driver simulator is of vital importance to the research community and when compared to the state-of-the-art it provides a good balance of accessibility and accuracy.

6.1.2 Perception Reaction Time

How much time is required for the driver to safely navigate through the potential collision ahead? This is quite a important research question that the researchers have been tackling with in the past. And what happens when the Drivers are busy in other non driver related tasks behind the wheel of an autonomous car? Does it have any specific implications on the reaction times if suddenly a crash is to be avoided on the road in front? these research questions are quite complex in nature and the main objective is to allow the researchers to be able to test different driving scenarios in which accurate reaction times can be recorded thus paving the way for the better ADAS. This objective was achieved by utilizing the LEE driver simulator to record accurate reaction times of drivers in different scenarios. This has implications on the HCI designs when the results are analysed.

Experiment shows that not all secondary tasks result in higher Perception Reaction Times. The experiment clearly shows that the subjects who were busy on their phones indulged in social media activities recorded a higher reaction time of 2.72 seconds on the feet as compared to when they were answering IMQA's at 2.48 seconds. The global average of 3.51 seconds for hands and 2.47 seconds for feet is recorded during the advanced perception reaction time experiments. Any secondary tasks while driving result in deterioration of quality of driving. Also the results of Friedman test for PRTH show that there are no significant effects among the 3 scenarios, $\chi^2(2, N = 160) = 3.6904$, $p = 0.1580$, $W = 0.0115$, although the strength of agreement among drivers is very small. That means that drivers take more or less the same time to steer the wheel in both scenarios. However, in the case of feet there are significant differences between at least one of the scenarios, with a medium strength of agreement: $\chi^2(2, N = 160) = 44.3974$, $p = 2.2868e - 10$, $W = 0.1387$.

6.1.3 Synthetic datasets

Can the virtual simulators be used to generate realistic images for the purpose of improving ADAS? synthetic worlds have come a long way since their inception a few decades ago. The advent of computer graphics now allows for more realistic images to be produced at real-time. This begs the question, how good are the dataset and can the help to improve driving experience of the future? This objective was achieved by successfully recording and generating a hybrid dataset consisting of virtual car environment images coupled with real footage of drivers interacting with the synthetic car, paving the way for the future ADAS research. The dataset is currently sized at over 100 GB and contains over 1.44 million images. According to the literature review, a dataset of such scale is not available freely.

6.1.4 Weather Classification

Can synthetically generated realistic weather images be used in classifying different weather conditions efficiently? This is a more complex question to answer as the weather itself is made up of alot of different entities such as shape of clouds, lighting, etc. This objective was achieved by modifying the LEE simulator and allowing it to produce a number of different weather conditions, the images are recorded with resulted in the formation of a new dataset called Weather Drive Dataset. The performance was analyzed against real world data and the research question was answered. WDD comprises of 108,333 images and consists four different weather conditions namely, Clear, Cloudy, Foggy & Rainy. The evaluation of this dataset has been tested as mentioned in the last point. The study shows that the use of synthetic data set can result in accuracy of upto 74% which opens up further room for research in the future. Yes, synthetic data can be used to train deep learning models to classify real world weather which opens up different avenues in the weather classification field.

6.2 Contributions Summary

This thesis presents the author's research performed during the path to satisfy the requirements for Doctor of Philosophy. The main contributions can be listed as follows:

1. Firstly, this thesis explains the concept of Advanced Driver Assistance Systems and their link to Synthetic Data. The major problem statements and challenges are also identified.

2. Secondly, A detailed literature review is presented which covers all the important aspects of existing research and state-of-the-arts.

3. Chapter 3, presents a detailed method for designing and developing an open source and extendable driver simulator known as LEE that is able to perform experiments to acquire results quicker and efficient iterations. The effectiveness of the driver simulator is evident as it provides the basis for almost all of the experiments within this thesis. Our simulator is also designed to be light weight meaning it only has 4 main components namely CPU Case, monitors, Steering/pedal and webcams. Hence, it can be transported to a target location without any specific physical setup unlike other state-of-the-art simulators [4] [10]. The low cost aspect of the hardware also makes sure that it is accessible by even the smallest of organizations and research teams. A typical physical driver simulator can cost between £10,000 to as much as £500,000 [4] [1] [2] [10]. Our approach has brought this cost down to less than £2,000 while providing the same visual fidelity and accuracy of the more expensive simulators in the market.

4. Using the driver simulator that was developed in Chapter 3, Chapter 4 covers the novel method of recording perception reaction times for the purpose of autonomous driver vehicular interaction research. The driver simulator is used extensively during this experiment and provides alarming results with regards to the time required before a

manageable action can be performed by the driver when an alarm is triggered. The driver simulator goes through some worthy upgrades during this time. The results show that not all secondary tasks result in high Perception Reaction Times. Moreover, the global reaction times for hands was recorded to be 3.51 seconds whereas the feet were recorded at 2.47 seconds which implied that drivers are always prioritise the feet over the hands. Our approach also sheds light on the relationship between Perception Reaction times and mental workload, although fatigue was not the outstanding entity, the study finds that reaction times do suffer by approx 20% when secondary tasks are introduced during driving.

5. During the experiments for Perception Reaction times, a new dataset was generated from all 40 participants resulting in recorded data that captures 4 different views of the virtual driving sessions (a) Driver's view of the road (b) portrait view of driver (c) steering view (d) pedal view. Future researchers can use this dataset to further test and train future ADAS systems based on computer vision. The dataset sheds light on a number of interesting facts with regards to where the driver rests his/her arms, legs and eyes during the targeted scenarios. Moreover, important variables like the velocity, distance and reaction times of feet as well as hands are also recorded separately which gives a detailed insight into how drivers behave in an emergency situation behind the wheel of an autonomous vehicle. The dataset is currently sized at over 100 GB and contains over 1.44 million images. According to the literature review, a dataset of such scale is not available freely. Hence the proposed dataset is vital for researchers and engineers who are striving to design the next generation of ADAS.

6. Building on top of the work done in Chapter 4, Chapter 5 deals with the complex problem of weather classification, after successful modification of the driver simulator we were able to produce hi fidelity weather classification images that were then used to train deep learning networks to efficiently classify weather in real-world images. This resulted in a the production of a novel dataset called Weather Drive Dataset, comprising specifically for synthetic weather images. This includes hi fidelity images produced for four different weather conditions, Clear, Cloudy, Foggy and Rainy. The feasibility of these images is tested in deep learning methods and when used with VGG it is able to attain an efficiency of 74% which is unprecedented for a synthetic only dataset which is being tested on real world images. These images were generated by our custom built simulator which was developed ontop of the LEE simulator. It provides great ease of use meaning that a number of different weather scenarios can be setup in a fraction of time as compared to state-of-the art simulators like Carla [3]. Moreover our approach

allows for wider range of controls over the cloud visual fidelity making it one of the best weather based simulators in the field and it is designed for a quick launch and record approach meaning that very little setup is required to generate complex weather scenarios. Moreover, the simulator is the only one of its kind whose purpose is to generate high fidelity synthetic weather simulations for autonomous driving research. The Weather Drive Dataset is novel in nature as it is the largest synthetic dataset for weather classification comprising of 108,333 images in total.

6.3 Future Directions

This thesis has been a culmination of so many different domains and the author hopes that it will provide insights into many solutions to the problematic statements concerning synthetic worlds for advanced driver assistance systems. The next question arises where can we go from here? The author acknowledges that the solutions provided in this research are not absolute in nature and better solutions will catch up in the near future building on top of what has been provided in this thesis. Some of the future directions are listed as follows:

1. The main purpose of the driver simulator was to bring the cost and iteration times down that normally took quite a huge amount of resources. There is significant room for improvement in the overall design and feature set of the LEE simulator. More sensors can be added in like eye tracking and heart rate sensor to increase the amount of variables that can be recorded at any specific time. Moreover, additional autonomous car scenarios can be added to further enhance the future experiments that can directly contribute to the design and testing of future autonomous car algorithms.

2. Additional datasets can be generated from the simulator to further aid the computer vision domain and explore further work frames of deep learning networks.

3. Some drawback to such a setup can include a lack of true real world connection. sure the simulations can be modelled as close as possible to the real counter part but the complexity and reliability of the real world exercise can not be taken lightly. So caution should be taken under such circumstances. but for the purpose of our research i-e recording perception Reaction Times, the simulator works flawlessly and the relationship between synthetic world and the real life counter part is quite close.

4. The simulator can be further modified to add pedestrian related data that can in theory simulate close to reality pedestrian movements within a given scenario. examples can

include an inner city pedestrian crossing in which an autonomous car has to make a decision to stop upon a successful detection of humanoids at the crossing.

5. This thesis leaves a lot of room open for future research into variables like lead times of NDR tasks (Non Drive Related Tasks). This can further aid in identifying which secondary tasks are more bound to increase perception reaction times which as a result can affect the quality of driving.

6. Weather classification dataset can be enhanced further by adding additional camera angles on the virtual car, which in turn can increase the number of generated images. this can have significant effect on the training of the pre training deep learning models, further more additional test/train ratio of the images can fine tune the accuracy of the models as well.

7. Depth Perception is a complex problem in it's own domain, the simulator lays the ground work for it to be used for depth estimation as well. After some minor code changes it will be able to generate datasets for depth estimation which can then be used to train deep learning networks. Evaluating these results would prove to be crucial in making the driver assistance systems of the future more reliable. It is crucial to get this data as efficiently as possible otherwise it can have drastic effects on the driving quality of the autonomous car. Over the years many different approaches have been used to detect depth and distance to other cars and obstacles like Radars, LiDARs and Stereo image sensing technology but most of these techniques use specialist hardware and can be quite expensive to manufacture resulting in high production costs to the car maker. The hypothesis is to use just one colour camera to detect depth and calculate the necessary distance between objects and cars. This can be achieved by using Convolutional Neural Networks and Deep Learning Networks to detect distance and depth. Furthermore, this approach can be further enhanced by using synthetic data to train these networks for acquiring better efficiency.

References

[1] curvrs, "Aston martin curvrs racing simulators," Available at https://www.curvrs.com/ (2022-11-02).

[2] vesaro, "Vesaro simulators," Available at http://www.vesaro.com/store/pc/Home.asp (2022-11-02).

[3] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, "Carla: An open urban driving simulator," 2017.

[4] R. Soleymanpour, H. H. Shishavan, J.-S. Heo, and I. Kim, "Novel driver's drowsiness detection system and its evaluation in a driving simulator environment," in *2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2021, pp. 1204–1208.

[5] U. D. of Transportation, "Aston martin curvrs racing simulators," Available at http://www.iihs.org/topics/fatality-statistics/detail/yearly-snapshot (2021-08-11).

[6] B. Templeton, "Tesla taiwan crash," Available at http://www.forbes.com/sites/bradtempleton/2020/06/02/tesla-in-taiwan-crashes-directly-into-overturned-truck-ignores-pedestrian-with-autopilot-on/ (2021-08-11).

[7] BBC, "Tesla autopilot involved in a crash," Available at http://www.bbc.com/news/technology-36783345 (2018-11-18).

[8] J. SAE, "Sae levels of driving automation," Available at https://www.sae.org/blog/sae-j3016-update (2022-04-05).

[9] H. Makishita and K. Matsunaga, "Differences of drivers reaction times according to age and mental workload," *Accident Analysis & Prevention*, vol. 40, no. 2, pp. 567–575, 2008.

[10] S. T. Inc, "Stism," Available at https://stisimdrive.com// (2022-11-05).

[11] M. Ahmed, "Factors affecting lane change crashes," *IATSS Research*, vol. 44, 2020.

[12] S. Eum and H. G. Jung, "Enhancing light blob detection for intelligent headlight control using lane detection," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 2, pp. 1003–1011, 2013.

[13] A. Bartels, M.-M. Meinecke, and S. Steinmeyer, "Lane change assistance," *Handbook of Intelligent Vehicles*, pp. 729–757, 2012.

[14] H. Kim, J. Gabbard, A. Anon, and T. Misu, "Driver behavior and performance with augmented reality pedestrian collision warning: An outdoor user study," *IEEE Transactions on Visualization and Computer Graphics*, vol. PP, pp. 1–1, 2018.

[15] C. Merenda, H. Kim, K. Tanous, J. Gabbard, B. Feichtl, T. Misu, and C. Suga, "Augmented reality interface design approaches for goal-directed and stimulus-driven driving tasks *best paper award honorable mention, ismar," *IEEE Transactions on Visualization and Computer Graphics*, vol. PP, pp. 1–1, 2018.

[16] D. Yadron and D. Tynan, "Tesla car crash," Available at https://www.theguardian.com/technology/2016/jun/30/tesla-autopilot-death-self-driving-car-elon-musk (2018-11-18).

[17] C. Dilmegani, "https://www.vesaro.com/store/pc/home.asp," Available at http://research.aimultiple.com/synthetic-data-for-deep-learning/ (2022-09-04).

[18] gartner, "Vesaro simulators," Available at http://www.gartner.com/document/4002912 (2022-09-04).

[19] R. van der horst and J. Hogema, "Driving simulator research on safe highway design and operation," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2248, pp. 87–95, 2011.

[20] K. Abdelgawad, M. Abdelkarim, B. Hassan, M. Grafe, and I. Gräßler, "A modular architecture of a pc-based driving simulator for advanced driver assistance systems development," in *Research and Education in Mechatronics (REM), 2014 15th International Workshop on*. IEEE, 2014, pp. 1–8.

[21] M. Rezaei and R. Klette, "Look at the driver, look at the road: No distraction! no accident!" in *2014 IEEE Conference on Computer Vision and Pattern Recognition*, 2014, pp. 129–136.

[22] A. Jain, H. Koppula, B. Raghavan, S. Soh, and A. Saxena, "Car that knows before you do: Anticipating maneuvers via learning temporal driving models," 2015, pp. 3182–3190.

[23] G. Ros, L. Sellart, J. Materzynska, D. Vázquez, and A. López, "The synthia dataset: A large collection of synthetic images for semantic segmentation of urban scenes," 2016, pp. 3234–3243.

[24] D. Vázquez, A. López, D. Ponsa, and J. Marín, "Virtual worlds and active learning for human detection," 2011, pp. 393–400.

[25] C.-R. Sin and W.-L. Lin, "3d pose estimation based on deep learning without real world data training," in *2020 IEEE International Conference on Consumer Electronics - Taiwan (ICCE-Taiwan)*, 2020, pp. 1–2.

[26] T. Tozman, E. Magdas, H. MacDougall, and R. Vollmeyer, "Understanding the psychophysiology of flow: A driving simulator experiment to investigate the relationship between flow and heart rate variability," *Computers in Human Behavior*, vol. 52, pp. 408–418, 2015.

[27] Y. Chen, X. Zhang, and J. Wang, “Robust vehicle driver assistance control for handover scenarios considering driving performances,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 7, pp. 4160–4170, 2021.

[28] N. Bansal, R. S. Bali, K. Jakhar, M. S. Obaidat, N. Kumar, S. Tanwark, and J. J. P. C. Rodrigues, “Htfm: Hybrid traffic-flow forecasting model for intelligent vehicular ad hoc networks,” in *ICC 2021 - IEEE International Conference on Communications*, 2021, pp. 1–6.

[29] J. Gabbard, G. Fitch, and H. Kim, “Behind the glass: Driver challenges and opportunities for ar automotive applications,” *Proceedings of the IEEE*, vol. 102, pp. 124–136, 2014.

[30] O. PAPRČKA, “Heart rate changes in critical situations in a vehicle simulator,” in *2021 Smart City Symposium Prague (SCSP)*, 2021, pp. 1–6.

[31] A. Eriksson and N. A. Stanton, “Driving performance after self-regulated control transitions in highly automated vehicles,” *Human factors*, vol. 59, no. 8, pp. 1233–1248, 2017.

[32] S. Hergeth, L. Lorenz, and J. Krems, “Prior familiarization with takeover requests affects drivers takeover performance and automation trust,” *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 59, 2016.

[33] T. Ogitsu and H. Mizoguchi, “A study on driver training on advanced driver assistance systems by using a driving simulator,” 2015, pp. 352–353.

[34] M. A. Raja, S. Ali, and A. Mahmood, “Simulators as drivers of cutting edge research,” in *Intelligent Systems, Modelling and Simulation (ISMS), 2016 7th International Conference on*. IEEE, 2016, pp. 114–119.

[35] Y. Xiang, S. Wang, T. Su, J. Li, S. S. Mao, and M. Geimer, “Kit bus: A shuttle model for carla simulator,” in *2021 IEEE Industrial Electronics and Applications Conference (IEACon)*, 2021, pp. 7–12.

[36] M. Green, “How long does it take to stop?" methodological analysis of driver perception-brake times,” *Transportation Human Factors*, vol. 2, no. 3, pp. 195–216, 2000.

[37] R. Jurecki and T. Stańczyk, “Driver reaction time to lateral entering pedestrian in a simulated crash traffic situation,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 27, p. 22–36, 2014.

[38] M. Svetina, “The reaction times of drivers aged 20 to 80 during a divided attention driving,” *Traffic Injury Prevention*, vol. in press, 2016.

[39] B. Mok, M. Johns, K. J. Lee, D. Miller, D. Sirkin, P. Ive, and W. Ju, “Emergency, automation off: unstructured transition timing for distracted drivers of automated vehicles,” in *Intelligent Transportation Systems (ITSC), 2015 IEEE 18th International Conference on*. IEEE, 2015, pp. 2458–2464.

[40] M. Körber, C. Gold, D. Lechner, and K. Bengler, "The influence of age on the take-over of vehicle control in highly automated driving," *Transportation Research Part F Traffic Psychology and Behaviour*, vol. 39, pp. 19–32, 03 2016.

[41] A. Bartels, M.-M. Meinecke, and S. Steinmeyer, "Lane change assistance," in *Handbook of Intelligent Vehicles*. Springer, 2012, pp. 729–757.

[42] M. Saifuzzaman, S. M. M. Haque, Z. Zheng, and S. Washington, "Impact of mobile phone use on car-following behaviour of young drivers," *Accident Analysis & Prevention*, vol. 82, pp. 10–19, 2015.

[43] Y. Kuang, X. Qu, J. Weng, and A. Etemad-Shahidi, "How does the driver's perception reaction time affect the performances of crash surrogate measures?" *PLoS one*, vol. 10, no. 9, p. e0138617, 2015.

[44] N. Lyu, L. Xie, C. Wu, Q. Fu, and C. Deng, "Drivers cognitive workload and driving performance under traffic sign information exposure in complex environments: a case study of the highways in china," *International journal of environmental research and public health*, vol. 14, no. 2, p. 203, 2017.

[45] C. Dijksterhuis, K. A. Brookhuis, and D. De Waard, "Effects of steering demand on lane keeping behaviour, self-reports, and physiology. a simulator study," *Accident Analysis & Prevention*, vol. 43, no. 3, pp. 1074–1081, 2011.

[46] C. Gold, D. Damböck, L. Lorenz, and K. Bengler, ""take over!" how long does it take to get the driver back into the loop?" in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 57, no. 1. SAGE Publications Sage CA: Los Angeles, CA, 2013, pp. 1938–1942.

[47] B. Wandtner, N. Schömig, and G. Schmidt, "Effects of non-driving related task modalities on takeover performance in highly automated driving," *Human factors*, vol. 60, no. 6, pp. 870–881, 2018.

[48] B. Wandtner, G. Schmidt, N. Schoemig, and W. Kunde, "Non-driving related tasks in highly automated driving-effects of task modalities and cognitive workload on take-over performance," in *AmE 2018-Automotive meets Electronics; 9th GMM-Symposium*. VDE, 2018, pp. 1–6.

[49] N. Merat, A. Jamson, F. Lai, M. Daly, and O. Carsten, "Transition to manual: Driver behaviour when resuming control from a highly automated vehicle," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 26, p. 1–9, 2014.

[50] J. Andrey, B. Mills, M. Leahy, and J. Suggett, "Weather as a chronic hazard for road transportation in canadian cities," *Natural Hazards*, vol. 28, pp. 319–343, 2003.

[51] J. Nystuen and H. Selsor, "Weather classification using passive acoustic drifters," *Journal of Atmospheric and Oceanic Technology - J ATMOS OCEAN TECHNOL*, vol. 14, 1997.

[52] C. Lu, D. Lin, J. Jia, and C.-K. Tang, "Two-class weather classification," 2014, pp. 3718–3725.

[53] M. Elhoseiny, S. Huang, and A. Elgammal, “Weather classification with deep convolutional neural networks,” 2015.

[54] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in *Advances in Neural Information Processing Systems*, F. Pereira, C. Burges, L. Bottou, and K. Weinberger, Eds., vol. 25. Curran Associates, Inc., 2012.

[55] A. Krizhevsky, I. Sutskever, and G. Hinton, “Imagenet classification with deep convolutional neural networks,” *Neural Information Processing Systems*, vol. 25, 2012.

[56] Z. Zhu, L. Zhuo, P. Qu, K. Zhou, and J. Zhang, “Extreme weather recognition using convolutional neural networks,” 2016, pp. 621–625.

[57] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, “Going deeper with convolutions,” 2015, pp. 1–9.

[58] D. Lin, C. Lu, H. Huang, and J. Jia, “Rscm: Region selection and concurrency model for multi-class weather classification,” *IEEE Transactions on Image Processing*, vol. PP, pp. 1–1, 2017.

[59] J. Guerra, Z. Khanam, S. Ehsan, R. Stolkin, and K. McDonald-Maier, “Weather classification: A new multi-class dataset, data augmentation approach and comprehensive evaluations of convolutional neural networks,” 2018, pp. 305–310.

[60] M. Hnewa and H. Radha, “Object detection under rainy conditions for autonomous vehicles: A review of state-of-the-art and emerging techniques,” *IEEE Signal Processing Magazine*, vol. 38, no. 1, pp. 53–67, 2021.

[61] S. Kawai, K. Takeuchi, K. Shibata, and Y. Horita, “A method to distinguish road surface conditions for car-mounted camera images at night-time,” 2012, pp. 668–672.

[62] H. Kurihata, T. Takahashi, I. Ide, Y. Mekada, H. Murase, Y. Tamatsu, and T. Miyahara, “Rainy weather recognition from in-vehicle camera images for driver assistance,” 2005, pp. 205– 210.

[63] X. Yan, Y. Luo, and X. Zheng, “Weather recognition based on images captured by vision system in vehicle,” vol. 5553, 2009, pp. 390–398.

[64] C. Lu, D. Lin, J. Jia, and C.-K. Tang, “Two-class weather classification,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PP, pp. 1–1, 2016.

[65] H. Song, Y. Chen, and Y. Gao, “Weather condition recognition based on feature extraction and k-nn,” *Advances in Intelligent Systems and Computing*, vol. 215, pp. 199–210, 2014.

[66] E. Jitsukata, S. Kobayashi, and K. Tamura, “Automatic driving system,” 2001, uS Patent 6,169,940.

[67] W. Zhang, T. Mei, H. Liang, B. Li, J. Huang, Z. Xu, Y. Ding, and W. Liu, “Research and development of automatic driving system for intelligent vehicles,” in *Foundations and Practical Applications of Cognitive Systems and Information Processing*. Springer, 2014, pp. 675–684.

[68] W. Mehringer, M. Wirth, D. Roth, G. Michelson, and B. M. Eskofier, “Stereopsis only: Validation of a monocular depth cues reduced gamified virtual reality with reaction time measurement,” *IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 5, pp. 2114–2124, 2022.

[69] J. Eom, G. Kim, and Y. Park, “Concurrent firing lidar for self-driving car,” in *2021 International Conference on Information and Communication Technology Convergence (ICTC)*, 2021, pp. 1226–1229.

[70] Al Root. (2021) https://www.barrons.com/articles/lidar-is-the-future-of-autonomous-driving-this-company-is-making-it-cheaper-and-better-51625405944.

[71] R. S. Jurecki and T. L. Stańczyk, “Driver reaction time to lateral entering pedestrian in a simulated crash traffic situation,” *Transportation research part F: traffic psychology and behaviour*, vol. 27, pp. 22–36, 2014.

[72] R. S. Jurecki, T. L. Stańczyk, and M. J. Jaśkiewicz, “Driver’s reaction time in a simulated, complex road incident,” *Transport*, pp. 1–11, 2014.

[73] J. Paxion, E. Galy, and C. Berthelon, “Mental workload and driving,” *Frontiers in psychology*, vol. 5, p. 1344, 2014.

[74] F. P. da Silva, “Mental workload, task demand and driving performance: What relation?” *Procedia-Social and Behavioral Sciences*, vol. 162, pp. 310–319, 2014.

[75] M. M. Moniri, D. Merkel, M. Feld, and C. Müller, “Incorporating the driver’s focus of attention into automotive applications in real traffic and in simulator setups,” in *Intelligent Environments (IE), 2016 12th International Conference on*. IEEE, 2016, pp. 198–201.

[76] G. J. Andersen, R. Ni, Z. Bian, and J. Kang, “Limits of spatial attention in three-dimensional space and dual-task driving performance,” *Accident Analysis & Prevention*, vol. 43, no. 1, pp. 381–390, 2011.

[77] G. Iizuka, Y. Saito, and M. Yamada, “Measurement of a driver’s mental state using a 4k driving simulator,” in *Computer Application Technologies (CCATS), 2015 International Conference on*. IEEE, 2015, pp. 66–71.

[78] G. Matthews, L. E. Reinerman-Jones, D. J. Barber, and J. Abich IV, “The psychometrics of mental workload: Multiple measures are sensitive but divergent,” *Human Factors*, vol. 57, no. 1, pp. 125–143, 2015.

[79] K. A. Brookhuis and D. De Waard, “Monitoring drivers’ mental workload in driving simulators using physiological measures,” *Accident Analysis & Prevention*, vol. 42, no. 3, pp. 898–903, 2010.

[80] R. Parasuraman, T. B. Sheridan, and C. D. Wickens, “Situation awareness, mental workload, and trust in automation: Viable, empirically supported cognitive engineering constructs,” *Journal of Cognitive Engineering and Decision Making*, vol. 2, no. 2, pp. 140–160, 2008. [Online]. Available: https://doi.org/10.1518/155534308X284417

[81] R. Abbasi-Kesbi, H. Memarzadeh-Tehran, and M. J. Deen, "Technique to estimate human reaction time based on visual perception," *Healthcare technology letters*, vol. 4, no. 2, p. 73, 2017.

[82] S. Petermeijer, P. Bazilinskyy, K. Bengler, and J. De Winter, "Take-over again: Investigating multimodal and directional tors to get the driver back into the loop," *Applied Ergonomics*, vol. 62, pp. 204–215, 2017.

[83] S. S. Borojeni, L. Chuang, W. Heuten, and S. Boll, "Assisting drivers with ambient take-over requests in highly automated driving," in *Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. ACM, 2016, pp. 237–244.

[84] A. Eriksson, S. M. Petermeijer, M. Zimmermann, J. C. de Winter, K. J. Bengler, and N. A. Stanton, "Rolling out the red (and green) carpet: supporting driver decision making in automation-to-manual transitions," *IEEE Transactions on Human-Machine Systems*, vol. 49, no. 1, pp. 20–31, 2019.

[85] A. Eriksson and N. A. Stanton, "Takeover time in highly automated vehicles: Non-critical transitions to and from manual control," *Human Factors*, vol. 59, no. 4, pp. 689–705, 2017, pMID: 28124573.

[86] J. Wan and C. Wu, "The effects of lead time of take-over request and nondriving tasks on taking-over control of automated vehicles," *IEEE Transactions on Human-Machine Systems*, vol. 48, no. 6, pp. 582–591, 2018.

[87] C. Gold, M. Körber, D. Lechner, and K. Bengler, "Taking over control from highly automated vehicles in complex traffic situations: the role of traffic density," *Human factors*, vol. 58, no. 4, pp. 642–652, 2016.

[88] V. Banks, A. Eriksson, J. O'donoghue, and N. Stanton, "Is partially automated driving a bad idea? observations from an on-road study," *Applied ergonomics*, vol. 68, pp. 138–145, 2018.

[89] F. Naujoks, D. Befelein, K. Wiedemann, and A. Neukum, "A review of non-driving-related tasks used in studies on automated driving," 2017, pp. 525–537.

[90] S. Minhas, A. Hernández-Sabaté, S. Ehsan, K. Díaz-Chito, A. Leonardis, A. M. López, and K. D. McDonald-Maier, "LEE: A photorealistic virtual environment for assessing driver-vehicle interactions in self-driving mode," in *European Conference on Computer Vision*. Springer, 2016, pp. 894–900.

[91] H. W. Lilliefors, "On the kolmogorov-smirnov test for normality with mean and variance unknown," *Journal of the American statistical Association*, vol. 62, no. 318, pp. 399–402, 1967.

[92] W. W. Daniel *et al.*, *Applied nonparametric statistics*. Houghton Mifflin, 1978.

[93] M. Hollander, D. A. Wolfe, and E. Chicken, *Nonparametric statistical methods*. John Wiley & Sons, 2013, vol. 751.

[94] K. Zeeb, A. Buchner, and M. Schrauf, "Is take-over time all that matters? the impact of visual-cognitive load on driver take-over quality after conditionally automated driving," *Accident Analysis & Prevention*, vol. 92, pp. 230–239, 2016.

[95] R. D'Agostino, *Goodness-of-fit-techniques*. Routledge, 2017.

[96] M. Cools, E. Moons, and G. Wets, "Assessing the impact of weather on traffic intensity," *Weather, Climate, and Society*, vol. 2, no. 1, pp. 60–68, 2010.

[97] V. P. S. Achari, Z. Khanam, A. K. Singh, A. Jindal, A. Prakash, and N. Kumar, "I 2 uts: An iot based intelligent urban traffic system," in *2021 IEEE 22nd International Conference on High Performance Switching and Routing (HPSR)*. IEEE, 2021, pp. 1–6.

[98] M. Kilpeläinen and H. Summala, "Effects of weather and weather forecasts on driver behaviour," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 10, pp. 288–299, 2007.

[99] C. Lu, D. Lin, J. Jia, and C.-K. Tang, "Two-class weather classification," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2014, pp. 3718–3725.

[100] M. Roser and F. Moosmann, "Classification of weather situations on single color images," in *2008 IEEE Intelligent Vehicles Symposium*. IEEE, 2008, pp. 798–803.

[101] Z. Zhang and H. Ma, "Multi-class weather classification on single images," in *2015 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2015, pp. 4396–4400.

[102] T. Zhang and X. Zhang, "Shipdenet-20: An only 20 convolution layers and< 1-mb lightweight sar ship detector," *IEEE Geoscience and Remote Sensing Letters*, vol. 18, no. 7, pp. 1234–1238, 2020.

[103] T. Zhang, X. Zhang, J. Shi, S. Wei, J. Wang, J. Li, H. Su, and Y. Zhou, "Balance scene learning mechanism for offshore and inshore ship detection in sar images," *IEEE Geoscience and Remote Sensing Letters*, vol. 19, pp. 1–5, 2020.

[104] T. Zhang, X. Zhang, X. Ke, C. Liu, X. Xu, X. Zhan, C. Wang, I. Ahmad, Y. Zhou, D. Pan, *et al.*, "Hog-shipclsnet: A novel deep learning network with hog feature fusion for sar ship classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–22, 2021.

[105] T. Zhang and X. Zhang, "Squeeze-and-excitation laplacian pyramid network with dual-polarization feature fusion for ship classification in sar images," *IEEE Geoscience and Remote Sensing Letters*, vol. 19, pp. 1–5, 2021.

[106] T. Zhang, X. Zhang, and X. Ke, "Quad-fpn: A novel quad feature pyramid network for sar ship detection," *Remote Sensing*, vol. 13, no. 14, p. 2771, 2021.

[107] T. Zhang and X. Zhang, "A polarization fusion network with geometric feature embedding for sar ship classification," *Pattern Recognition*, vol. 123, p. 108365, 2022.

[108] Z. Khanam, P. Soni, J. L. Raheja, *et al.*, "Development of 3d high definition endoscope system," in *Information Systems Design and Intelligent Applications*. Springer, 2016, pp. 181–189.

[109] Z. Khanam and J. L. Raheja, "Tracking of miniature-sized objects in 3d endoscopic vision," in *Algorithms and Applications*. Springer, 2018, pp. 77–88.

[110] B. Aslam, S. Saha, Z. Khanam, X. Zhai, S. Ehsan, R. Stolkin, and K. McDonald-Maier, "Gamma-induced degradation analysis of commercial off-the-shelf camera sensors," in *2019 IEEE SENSORS*. IEEE, 2019, pp. 1–4.

[111] Z. Khanam, S. Saha, B. Aslam, X. Zhai, S. Ehsan, C. Cazzaniga, C. Frost, R. Stolkin, and K. McDonald-Maier, "Degradation measurement of kinect sensor under fast neutron beamline," in *2019 IEEE Radiation Effects Data Workshop*. IEEE, 2019, pp. 1–5.

[112] Z. Khanam, B. Aslam, S. Saha, X. Zhai, S. Ehsan, R. Stolkin, and K. McDonald-Maier, "Gamma-induced image degradation analysis of robot vision sensor for autonomous inspection of nuclear sites," *IEEE Sensors Journal*, vol. 22, no. 18, pp. 17 378–17 390, 2022.

[113] D. Gil, A. Hernàndez-Sabaté, J. Enconniere, S. Asmayawati, P. Folch, J. Borrego-Carazo, and M. À. Piera, "E-pilots: A system to predict hard landing during the approach phase of commercial flights," *IEEE Access*, vol. 10, pp. 7489–7503, 2021.

[114] A. Hernández-Sabaté, J. Yauri, P. Folch, M. Piera, and D. Gil, "Recognition of the mental workloads of pilots in the cockpit using eeg signals," *Applied Sciences*, vol. 12, no. 5, 2022. [Online]. Available: https://www.mdpi.com/2076-3417/12/5/2298

[115] A. Yousefi, Y. Amidi, B. Nazari, and U. Eden, "Assessing goodness-of-fit in marked point process models of neural population coding via time and rate rescaling," *Neural computation*, vol. 32, pp. 1–42, 2020.

[116] A. Azizi, I. Tahmid, A. Waheed, J. Mangaokar, Neal amd Pu, M. Javed, C. K. Reddy, and B. Viswanath, "T-miner: A generative approach to defend against trojan attacks on dnn-based text classification," in *Proc. of USENIX Security*, 2021.

[117] A. Gaidon, Q. Wang, Y. Cabon, and E. Vig, "Virtualworlds as proxy for multi-object tracking analysis," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 4340–4349.

[118] Y. Qian, E. J. Almazan, and J. H. Elder, "Evaluating features and classifiers for road weather condition analysis," in *2016 IEEE International Conference on Image Processing (ICIP)*, 2016, pp. 4403–4407.

[119] S. Minhas, A. Hernández-Sabaté, S. Ehsan, and K. D. McDonald-Maier, "Effects of non-driving related tasks during self-driving mode," *IEEE transactions on intelligent transportation systems*, 2020.

[120] S. Minhas, A. Hernández-Sabaté, S. Ehsan, K. Díaz-Chito, A. Leonardis, A. M. López, and K. D. McDonald-Maier, "Lee: A photorealistic virtual environment for assessing driver-vehicle interactions in self-driving mode," in *Computer Vision – ECCV 2016 Workshops*, G. Hua and H. Jégou, Eds. Cham: Springer International Publishing, 2016, pp. 894–900.

[121] F. Yu, H. Chen, X. Wang, W. Xian, Y. Chen, F. Liu, V. Madhavan, and T. Darrell, "Bdd100k: A diverse driving dataset for heterogeneous multitask learning," 06 2020, pp. 2633–2642.

[122] C. Wenzheng, H. Wang, Y. Li, H. Su, Z. Wang, C. Tu, D. Lischinski, D. Cohen-Or, and B. Chen, "Synthesizing training images for boosting human 3d pose estimation," 2016, pp. 479–488.

[123] J. Dai, K. He, and J. Sun, "Instance-aware semantic segmentation via multi-task network cascades," 2016, pp. 3150–3158.

[124] P. Fischer, A. Dosovitskiy, E. Ilg, P. Häusser, C. Hazırbaş, V. Golkov, P. van der Smagt, D. Cremers, and T. Brox, "Flownet: Learning optical flow with convolutional networks," 2015.

[125] A. Geiger, P. Lenz, C. Stiller, and R. Urtasun, "Vision meets robotics: the kitti dataset," *The International Journal of Robotics Research*, vol. 32, pp. 1231–1237, 2013.

[126] H. Hattori, V. Boddeti, K. Kitani, and T. Kanade, "Learning scene-specific pedestrian detectors without real data," 2015, pp. 3819–3827.

[127] H. Abu, S. Mustikovela, L. Mescheder, A. Geiger, and C. Rother, "Augmented reality meets deep learning," 2017.

[128] S. Richter, V. Vineet, S. Roth, and V. Koltun, "Playing for data: Ground truth from computer games," vol. 9906, 2016.

[129] N. Mayer, E. Ilg, P. Hausser, P. Fischer, D. Cremers, A. Dosovitskiy, and T. Brox, "A large dataset to train convolutional networks for disparity, optical flow, and scene flow estimation," 2016, pp. 4040–4048.

[130] S.-H. Lim, S.-k. Ryu, and Y.-H. Yoon, "Image recognition of road surface conditions using polarization and wavelet transform," *Journal of The Korean Society of Civil Engineers*, vol. 27, 2007.

[131] S. Kawai, K. Takeuchi, K. Shibata, and Y. Horita, "A method to distinguish road surface conditions for car-mounted camera images at night-time," in *2012 12th International Conference on ITS Telecommunications*, 2012, pp. 668–672.

[132] H. Kurihata, T. Takahashi, I. Ide, Y. Mekada, H. Murase, Y. Tamatsu, and T. Miyahara, "Rainy weather recognition from in-vehicle camera images for driver assistance," in *IEEE Proceedings. Intelligent Vehicles Symposium, 2005.*, 2005, pp. 205–210.

[133] X. Yan, Y. Luo, and X. Zheng, "Weather recognition based on images captured by vision system in vehicle," in *Advances in Neural Networks – ISNN 2009*, W. Yu, H. He, and N. Zhang, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, pp. 390–398.

[134] C. Lu, D. Lin, J. Jia, and C. Tang, "Two-class weather classification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 12, pp. 2510–2524, 2017.

[135] H. Song, Y. Chen, and Y. Gao, "Weather condition recognition based on feature extraction and k-nn," in *Foundations and Practical Applications of Cognitive Systems and Information Processing*, F. Sun, D. Hu, and H. Liu, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2014, pp. 199–210.

[136] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, "CARLA: An open urban driving simulator," in *Proceedings of the 1st Annual Conference on Robot Learning*, 2017, pp. 1–16.

[137] G. Ros, L. Sellart, J. Materzynska, D. Vazquez, and A. M. Lopez, "The synthia dataset: A large collection of synthetic images for semantic segmentation of urban scenes," in *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 3234–3243.

[138] H. Feng and H. Fan, "3d weather simulation on 3d virtual earth," in *2012 IEEE International Geoscience and Remote Sensing Symposium*, 2012, pp. 543–545.

[139] T. Zhang and X. Zhang, "High-speed ship detection in sar images based on a grid convolutional neural network," *Remote Sensing*, vol. 11, no. 10, p. 1206, 2019.

[140] T. Zhang, X. Zhang, J. Shi, and S. Wei, "Hyperli-net: A hyper-light deep learning network for high-accurate and high-speed ship detection from synthetic aperture radar imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 167, pp. 123–153, 2020.

[141] T. Zhang, X. Zhang, J. Shi, and S. Wei, "Depthwise separable convolution neural network for high-speed sar ship detection," *Remote Sensing*, vol. 11, no. 21, p. 2483, 2019.

[142] T. Zhang, X. Zhang, X. Ke, X. Zhan, J. Shi, S. Wei, D. Pan, J. Li, H. Su, Y. Zhou, *et al.*, "Ls-ssdd-v1. 0: A deep learning dataset dedicated to small ship detection from large-scale sentinel-1 sar images," *Remote Sensing*, vol. 12, no. 18, p. 2997, 2020.

[143] T. Zhang, X. Zhang, C. Liu, J. Shi, S. Wei, I. Ahmad, X. Zhan, Y. Zhou, D. Pan, J. Li, *et al.*, "Balance learning for ship detection from synthetic aperture radar remote sensing imagery," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 182, pp. 190–207, 2021.

[144] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele, "The cityscapes dataset for semantic urban scene understanding," 2016.

[145] K. Li, L. Yu, S. You, and N. Barnes, "Photo-realistic simulation of road scene for data-driven methods in bad weather," 2017, pp. 491–500.

[146] L. Rutkowski and K. Cpalka, "Flexible neuro-fuzzy systems," *IEEE Transactions on Neural Networks*, vol. 14, no. 3, pp. 554–574, 2003.

[147] F. Yu, W. Xian, Y. Chen, F. Liu, M. Liao, V. Madhavan, and T. Darrell, “Bdd100k: A diverse driving video database with scalable annotation tooling,” 2018.

[148] G. Neuhold, T. Ollmann, S. Rota Bulò, and P. Kontschieder, “The mapillary vistas dataset for semantic understanding of street scenes,” 2017, pp. 5000–5009.

[149] J. C. V. Guerra, Z. Khanam, S. Ehsan, R. Stolkin, and K. McDonald-Maier, “Weather classification: A new multi-class dataset, data augmentation approach and comprehensive evaluations of convolutional neural networks,” in *2018 NASA/ESA Conference on Adaptive Hardware and Systems (AHS)*. IEEE, 2018, pp. 305–310.

[150] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” *Advances in neural information processing systems*, vol. 25, pp. 1097–1105, 2012.

[151] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” *arXiv preprint arXiv:1409.1556*, 2014.

[152] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, “Going deeper with convolutions,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 1–9.

[153] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[154] X. Ding, X. Zhang, N. Ma, J. Han, G. Ding, and J. Sun, “Repvgg: Making vgg-style convnets great again,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2021, pp. 13 733–13 742.