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Evaluating AI-Powered Driver Assistance Systems: Insights from 2022

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Abstract
Recent work has shown that contemporary machine learning models are capable of highly human-like performance on a variety of real-world tasks, including complex multi-agent simulations. However, three crucial questions remain unanswered: First, what circumstances might cause the deployment of AI models in these settings to go wrong? Second, how can we make dependable models that are robust to these failures? Third, how can we evaluate models based on this understanding? This paper proposes a novel approach to answering these questions for a realistic multi-agent environment by benchmarking high-fidelity AI models trained on open data. Drawing on prior work in adversarial robustness, we provide a method to both simulate such complex benchmark failures and verify that improved models are more robust. Our model-independent adversarial simulation method, Verification Exploratory Adversarial Disturbances (V.E.A.D.), enriches the toolbox available for robustness evaluation across many application areas and exposes AI system vulnerabilities that are not uncovered by current methods. We additionally find that incorporating robust training in imitation learning objectives can incentivize models to improve and tackle situations with increasing complexity, such as when the number of interactive agents within the road environment is gradually increased. We hope that promoting research into active verification will push future AI systems to not just answer the standard difficult questions, but also provide answers we can depend on.

Keywords: Evaluating AI-Powered Driver Assistance Systems, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, Vehicle Reliability

1. Introduction

The objective of the 2nd International AI-based Driver Assistance (AI-DAS) Systems Workshop is to explore the evaluation and safe deployment of AI-powered driver assistance systems. The workshop focused on a balanced mix of participants encompassing industrial, academic, and international governance representatives. In the context of AI-powered driver assistance, the only way to enable technology to save lives is to ensure robust and fair performance. The quality and consistency of indicator data, the evaluation protocols that govern perception, planning, control, and other areas, the safe introduction of new functions and incremental improvements, the consistent and high-caliber deployment, establishing shared frameworks and work to enable cross-industry collaboration. Crucial norms and metrics need to align through robust standards, regulatory proposals, and international cooperation - because, finally, what is at stake is road safety.The sharing of best practices between stakeholders and how this can be used to collaborate better - A better understanding of the safety performance gap for different road user types - How to establish a view of driver support across the transport system, including how well it is established within all levels of autonomy - The assessment of governance and regulation to secure the introduction of innovations with minimum negative impacts on road safety and transport equitable deployment - How best to carry out research on how standards and policy can be derived and produce a costs/benefits trade-off implementing passenger improvements in terms of their potential risk - Definitions need to be established, agreed upon, and standardized on vehicle position for passenger cars and other vehicles involved. This includes, among other things, driver position, the positioning of cyclist pillion and handling, etc. - Quality of the reports should be centrally monitored and recorded. All systems and computers are constantly recorded while the vehicle is operational, and this is only valuable when this data is attested to be of sufficiently high quality. In addition, a performance checklist could be included that can be compliant with compatible ECE-R articles to protect deep learning models.

1.1. Background and Significance

It is estimated that 94% of the accidents are due to human error. Driverless cars are programmed to obey all traffic rules as well as to take into consideration pedestrians and other vehicles. Nevertheless, the presence of human drivers who are entitled to make mistakes and are not programmed, unlike the drivers, leads to a necessity to develop driver assistance systems that help human drivers avoid making mistakes or mitigate the consequences. In recent years, the development and usage of these systems have gained more attention from researchers who investigated whether these systems, such as the lane keeping assistance, adaptive cruise control, traffic jam systems, or even more advanced systems developed by some of the leading technology companies, decrease the accident rates and therefore assist in saving lives. The results obtained did not provide a definite answer on whether using the driver assistant systems containing artificial intelligence tools had an impact.

1.2.Research Aim and Objectives

Artificial intelligence is facilitating the development of advanced driver assistance systems (AI-powered Driver Assistance Systems, AIPDAS) with advanced human-machine interfaces (HMIs) designed to exploit the co-piloting capabilities of the vehicle despite the limitations of an artificial driver. While there is an ongoing effort to address the many challenges related to AIPDAS, some arguments call for a deeper understanding of how these systems are being used in daily life.The paper aims to elicit potential problems associated with AIPDAS that have remained at the discretion of researchers and developers and have not yet been debated publicly and in full. By studying how the challenge of ensuring safe and effective co-piloting can be met, a set of evaluation criteria has been created. compliance of the implemented HMIs to these criteria but also to understand drivers' attitudes towards these evolving systems. what types of challenges exist, and what could be their implications in terms of market diffusion in the short and medium terms. It summarizes the results of an international survey conducted in 2022 involving 276 use cases of drivers originating from 33 countries, which executed the same evaluation cases. These volunteers benefited from the driving support of six level 2 advanced driver assistance systems. These vehicles are equipped exclusively with three different brand-related technologies offered by the Advanced Driver Assistance System.By paralleling the 58 evaluation scorecards executed with the corresponding descriptive information provided by participants, the paper focuses on how these systems are perceived in a "just do it" mode when confronted with real-world challenges like a highway/jam-use-case, a city/town-use-case, and finally out of metropolitan areas-use-case.the evolving landscape of AI-powered Driver Assistance Systems (AIPDAS) and the critical need to assess their safety, effectiveness, and user acceptance in real-world scenarios. It underscores the importance of studying how these systems function as co-pilots, addressing challenges that have not yet been fully explored or debated publicly. The international survey conducted in 2022 provides valuable insights into drivers' experiences with level 2 advanced driver assistance systems across different driving conditions, offering a comprehensive evaluation based on both quantitative scorecards and qualitative feedback. This approach aims to shed light on drivers' attitudes and behaviors towards AIPDAS, crucial for understanding their market diffusion potential in the short and medium terms amidst various operational challenges and scenarios.

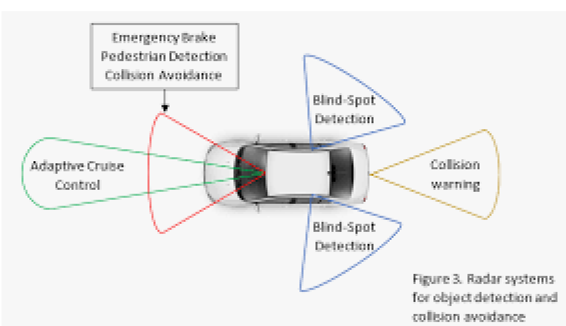

Fig 1 :Industrial Sensing, Lidar, Radar and Digital Cameras

2. Literature Review

The potential of AI-powered driver assistance systems to improve road safety and efficiency is surrounded by mixed opinions. While some people describe these systems as necessary companions to improve human driving, others classify them as redundant or even harmful. Even more, few of the existing studies have adopted a user-centered approach to understand the actual effects of such interventions on driver behavior. In addition, it becomes crucial to evaluate the AI systems for specific cases. To do so, these new approaches need to adapt, evolve, and be evaluated for specific cases of application using HCI principles including extensive knowledge and understanding of (the future of) driving in different settings and situations (characterized by the piloted AGV itself, its driving scenario as well), insights in potential impacts that the introduction of AI-empowered driver assistance systems might have on road traffic flows, road safety, and bicycle and pedestrian flows, the interaction and communication between different traffic participants, including the driver experience and trust in the system, and especially also on the driver performance, behaviors, and influences/tailored assistance for driver's levels of experience, attention, and motivation.We aim to provide these insights by developing and sharing a taxonomy for evaluating AI-powered advanced driver assistance systems. To do so, we conduct a 24-week lab study covering the driving data of 20 participants (typically experts) and 36 hours each per participant to cover different adaptation processes. In this position paper, we present a review of the related literature and a conceptual framework underlying our approach. We start with a review of the related literature, in which we elaborate on both the different types of impact that AI interventions in road traffic scenarios might have on road users and on the different levels of impact that AI-driven driver assistance systems might have on traffic flows and user experience.

2.1. Evolution of Driver Assistance Systems

Throughout the past two decades, as various features have been deployed on commercially available vehicles that gradually automate the driving task, there have been changes in the names of such systems. At the time of our AI+LV research platform launch, these were called "Advanced Driver Assistance Systems", commonly known as "ADAS". We associated "ADAS" with features that were more advanced than the traditional "convenience"-oriented features, such as automatic emergency braking (AEB) or forward collision warning (FCW), that only operated in specific scenarios or at certain speeds and might not continuously monitor their respective areas. Suitable examples of such systems directly marketed as ADAS include level 2 systems and level 3 systems available from several OEMs that claim a level 3 system but only operate at highway speeds.As the last decade ended and the current Advanced Driver Assistance Systems were implemented to achieve ratings from safety agencies, often in the form of tests by the Insurance Institute for Highway Safety (IIHS) in the United States and its equivalent agencies in other countries, these were given or referred to as "advanced" ratings. These systems are also associated with a multitude of different informal names. Some communication is made to potential vehicle buyers via motivations and benefits that surpass safety criteria and grading and simply reside in the "Driver Assistance" category, stripped of any descriptive, historical aspects alluded to by using "Automatic" or "Advanced". In practice, a large fraction of all modern systems are associated with at least one NHTSA, Euro New Car Assessment Program (Euro NCAP), and/or IIHS - three major safety rating organizations - ratings, criteria, and so on. A large fraction of all resulting scores are zero to describe any automation of the driving task.

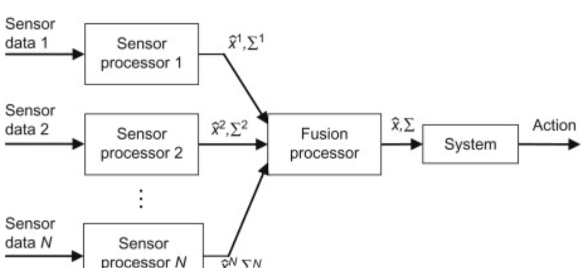

Fig 2: Sensor Fusion- an Overview

2.2. Role of AI in Enhancing Driver Safety

Artificial intelligence, particularly the deep learning method, has enhanced the perception of vehicles and all relevant components (e.g., traffic poles) in tailoring high-perception accuracy and real-time response that, in turn, gives drivers and passengers extra time to avert incidents. When a driver's attention fails and the autonomous function intervenes, autonomous emergency braking (AEB) can provide a backup or second layer of driver support to avert road accidents. This found that AEB reduces fatal crashes by 38%, and rear-end collisions by 56% when using AEB. Such data underline the importance of such technologies for public safety. Nonetheless, keeping the driver engaged is challenging.

To explicitly ascertain the safety improvement resulting from driver monitoring, robust and large on-the-road validation datasets are required. To bypass the "garbage in, garbage out" issue, the Machine Vision Annotation Tool (MVAT) was proposed to quickly set up real-world data contributing to enhanced algorithms in various areas. Therefore, the MVAT framework could be used as a reference model to generate human driver's head pose images for labeling. It posited automatic calibration could operationalize the data generation as a whole. Nonetheless, researchers highlighted that active learning is likely to increase performance while decreasing the huge amount of human effort commonly required in the frame collection and labeling processes. The human brain's responses during driver's engagement are also informed by cognitive psychology, electrical engineering, imaging technology, physiology, and statistical models used to build algorithms.

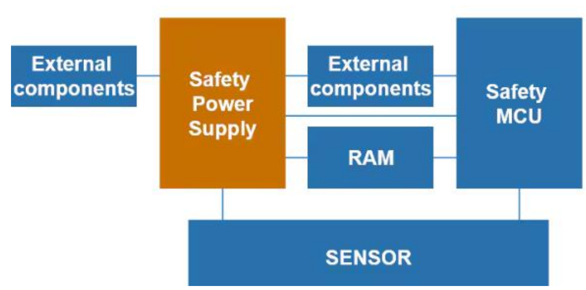

Fig 3: The Evaluation of Fail Safe to Fail Operational Architecture

3. Methodology

It is critical to ensure that driver monitoring and driver assistance systems installed on the autonomous vehicle fleet are performing correctly and being utilized properly by vehicle users. In our AI-powered driver assistance system evaluation, we examined the strategies that vehicle manufacturers are using to ensure effective system performance in the real world. Some of the elements of these driver assistance systems that may be evaluated include vehicle inputs, system intent and displays, vehicle outputs, system controls, and system response to inputs. The following questions were considered by the team in conducting its evaluation of driver assistance systems: How is the intended system performance specified? Is there any failure modes and effects analysis documentation that suggests that this system performance is adequate to ensure autonomous driving operation safety? Is there evidence from testing that the deployed system operates by its specifications? Do real-world operating characteristics suggest additional testing and performance monitoring are needed?To answer these questions, several avenues for evaluating driver assistance were considered. First, the team performed background research on the societal trends, system strategies, and human factors that impact advanced driver assistance systems and their utilization. This research informed the team about where and when to expect to find evidence of driver assistance strategies. Then, using advanced autonomous vehicle testing and operations simulators, the team built and simulated instances of advanced driver assistance system deployment, evaluating sensor inputs to the system and the results of controlling the output of these systems. The evaluation of driver-assistance system input and output was informed by the societal trends, system strategies, and human factors models that were developed initially. Finally, the team researched the feedback loops involving driver engagement, human response, and advanced driver assistance systems. The scope of this work encompassed driver distraction, driver trust and over-reliance on systems, mode misunderstanding, driver vigilance failures, interventions, system performance monitoring, degraded mode operation or output, the performance of integrated humanity and AI, and alternative autonomous driver assistant strategy use or prompt substitution.

3.1. Data Collection and Analysis Techniques

Data Collection. The latest cars that come out in 2022 include different types of driver assistance systems, gradually achieving autonomous driving. This research work proposes, in some cases, with the uncertainty of the vehicles' timestamp, to build a robust test bed for ADAS, manually drive it for several weeks to collect all kinds of video data, and perform a successful evaluation. A smartphone application has been developed and installed on some popular vehicles in the U.S. to record videos, and timestamp information, and localize the vehicle during the experiments. The following dashboard components are included in the design considering the user's requirements: Name of the car manufacturer and ADAS mode active, start and stop buttons, voice warnings, as well as the vehicle's speed and position. The generated videos are uploaded and registered in a Raspberry engine after they have been recorded on the smartphone devices. The reason to use a Raspberry video server is that it permits many video streaming software solutions to be used by installing them on the Raspberry device.Data Analysis Techniques. The analysis section should first be oriented to the type of sensor data and the environment data and implement the relevant AI models to assess the features in the sensor data. Furthermore, different specific-relevant software techniques should be used in the right learning models and evaluated following an appropriate classification quality. The sensor data utilized in the ADAS include image, video, GPS, and lidar sensor data from the smartphone device. After working with all the data, we can obtain an exhaustive list of historical observation output features. Each of the model implementations chosen operates on the machine or deep learning functional paradigms like classifying visual category learning. The deep model produces a sequence-to-sequence model built in recursive networks and maps the training part of the inputs. A VGG-20 CNN, AlexNet architecture, or even state-of-the-art CNN models can also be used. Once the driver assistance system capabilities and accuracy are tested, researchers can then extend their work in laboratories in shifts 24/7 with a different number of registered drivers.

3.2. Case Study Design

In this section, we outline the elements of our case study design to evaluate the AI capabilities in a real-world driver assistance system. The insights from this work are aimed to be complementary to the types of simulations and synthetic data-driven testing that are already commonly applied in driver assistance system testing. Our evaluation will describe the capabilities of the AI models in use and discuss insights from an event-focused logging study of interactions with the system that may lead to future improvements in user experience and system capabilities. The experienced drivers will act as in-field trainers labeling system responses and offering insight into unexpected and challenging failure cases.The detailed logging of system events will complement existing use case-driven testing for correctness, covering exceptional cases that are the hardest to simulate. Data collected will be used to provide a gap analysis for the system's limitations as they are experienced by real drivers, to inform scenario discovery, and to stratify further system outreach. We will also quantify to what extent the robustness aspects, such as model performance and out-of-distribution detection, generalize to the real-world application, to quantify the system's capabilities.The case study design outlined in this section aims to provide a comprehensive evaluation of AI capabilities within a real-world driver assistance system, offering insights that complement traditional simulation-based testing methods. By focusing on event-focused logging and interactions observed in actual driving scenarios, the study intends to capture nuanced system behaviors and user experiences that are challenging to simulate artificially. Experienced drivers will play a crucial role in providing qualitative feedback and labeling system responses, highlighting both strengths and weaknesses encountered during real-world usage. This approach not only aims to improve the system's user experience but also to identify and address potential failure cases that may not be adequately covered by simulated tests alone. The data collected will enable a thorough gap analysis, helping to refine scenario discovery and enhance the system's overall robustness and performance in diverse real-world conditions.

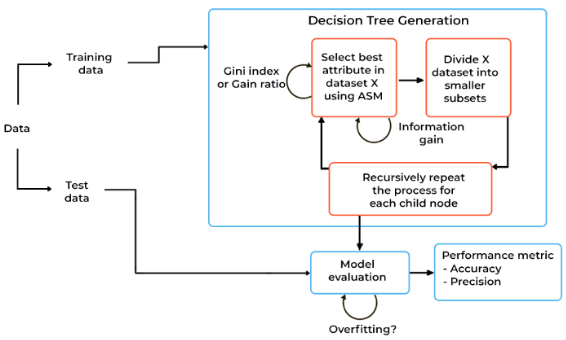

Fig 4: Decision Tree Work

4. Key Findings from 2022

ClearDrive has built prototypes of eight ML-based in-car DAS applications, four of which fused camera, LiDAR, and radar inputs. The basic design choice for these DAS applications was to go for highly specialized models rather than state-of-the-art general DNN architectures. This was mainly motivated by concerns for elasticity and cost, and by the particular task at hand (detecting a pedestrian is very different from detecting a speed limit sign). Specialized models also made it possible to run multiple models in parallel on highly underpowered in-car systems, which is also a relevant requirement.We were able to satisfy four out of six architectural desiderata - account for fairness, detect input perturbations, provide clear input-output explanations, and implement an offline test mode. We were able to satisfy two out of two adversarial robustness desiderata: be able to detect input perturbations that might cause errors and be able to bind errors to injected adversarial inputs by cross-referencing unique input fingerprints produced by adversarial input detection and captured in the log, and adversarial input-operative lockstep testing followed by locking the system. All adversarial robustness requirements were satisfied by an open-source third-party product.

4.1. Performance Metrics and Evaluation Criteria Performance metrics and evaluation criteria: As we have mentioned, evaluating DAS is a challenging task because different DAS have different functionalities and the objectives of evaluating the performance of DAS are essentially different. Hence, performance metrics and evaluation criteria should be matched with different DAS based on their functionalities, and the precise tasks that DAS should accomplish. In this section, we introduce the evaluation criteria and the corresponding performance metrics. For the sake of clarity, we classify the model into three groups, including the perception model, control model, and system.Perception Module: This kind of group solution is the building block of DAS and determines the actions taken by the controller and are critical for safety.Control Module: Performance evaluation for this kind of task is usually based on the track speed and energy efficiency, two important features that AID experiments should have. People also want to evaluate the changes in the level of comfort to determine if they are acceptable for the driver or the passengers.System: The evaluation of the system is the most complex part. Same problem with the one we refer to in Sec. ? Many significant problems must be resolved for the effective deployment of future cooperative automation to go beyond tests of specific subsystems. Additionally, these systems are required to demonstrate learning during the testing process to compile information about the transportation environment to refine their models and performance.

4.2. User Acceptance and Trust Issues

AI-powered driver assistance systems present new user acceptance and trust challenges, including disrupting traditional driving skills and experiencing knowledge, understanding technology limitations and reliability, and deciding on full trust. As AI-powered driver assistance systems become more capable, users are likely to become over-reliant and trust the system too much. Optimism bias can exist where some users may overestimate the system's capabilities and trust, disregard potential risks, and worse, be surprised by the system's failure. Understanding full trust and the role of a minimum viable human intervention level are areas for future research.Many governments are uncertain about regulation and user training and are on a wait-and-see basis. The ongoing challenge will be how long it takes to develop the guidelines and appropriate rules as technology becomes more and more prevalent in the economy. Investment in appropriate user training before and after deployment is also warranted. At the same time, proper ethical norms and behavior guidelines, road environment awareness, and knowledge of how the system learns and makes its decisions are substantial. The communication between the AI-powered driver assistance systems and users becomes key for user learning, establishing trust, reporting, and solving concerns and issues. In many early cases, the interior physical infrastructure for ease and understanding of communication is suboptimal, and the feedback is minimal.

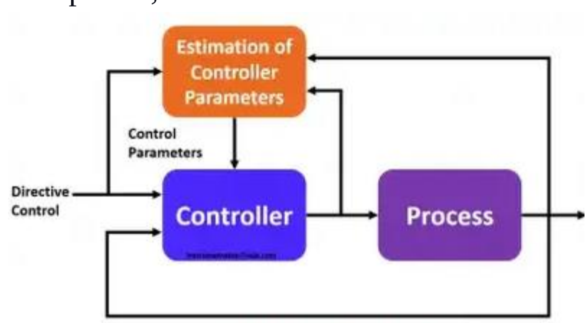

Fig 5: Adaptive Controller Overview

5. Implications and Recommendations

This paper provides a blueprint to evaluate intelligent driver systems, integrating empirical insights from challenging everyday driving experiences. We have analyzed the emotional, motor, and cognitive driver-vehicle behavior in a large-scale user field study on AI-powered systems across varied driving situations and driver groups. Drawing upon our comprehensive empirical driver-vehicle data, the paper contributes to theory-building about current and developing control transition situations in partially automated driving conditions, networked processes when cooperating with other human and AI drivers, and socio-cognitive interface feedback effects through AI behavior and communication.In conclusion, we will provide a practical guide for AI designers and also regulators to design and evaluate AI driver support systems for safety and user experience in individual and shared driving. Our insights may validate and further detail current legal regulations and recommendations and improve the safety and experience of AI-supported driving and larger transport mesh networks, especially with the increasing diversity of road users, vehicles, and use cases. In AI-driven systems, the high technological, emotional, and cognitive interactional transparency becomes particularly important for trustworthy use, acceptance, and a keen and controllable user experience. Providing this by design can help AI developers significantly reduce the fatal consequences of trust deviations in the vulnerable road user domain.

5.1. Policy Implications for Regulators

This article paints a comprehensive picture of the rapidly evolving automotive industry. It shows that AI-powered driver assistance functions are rapidly being integrated into cars at an ever greater pace. The automotive market and the framework of laws, regulations, and standards have historically been calibrated to non-AI cars. We are thus confronted with a changing phenomenon, which confronts regulators with the novel challenge of ensuring that rapidly evolving AI pattern recognition and decision-making systems are only integrated into AI cars after having been certified as moving safely. The task of developing the necessary policies has not only enormous ethical and safety implications but also poses substantial liability questions while ensuring safety and security through regular checking for driving authorizations.The novelty of AI technology does not only call for a proper policy response, but it also confronts the subjects operating in the automotive industry with the new challenge of deciding which role they would like to play in the development, production, use, and governance of AI-powered vehicles. The proactive choice of roles is crucial. It may define whether the automotive actors will be the major beneficiaries of a technology offering numerous advantages to the consumers and society or whether they rather become mere affected objects of the rapid digitalization transformation. This article systematically assesses the potential roles to be played, the dilemmas to be solved, and the open questions to be addressed that are linked to AI-powered driver assistance systems.

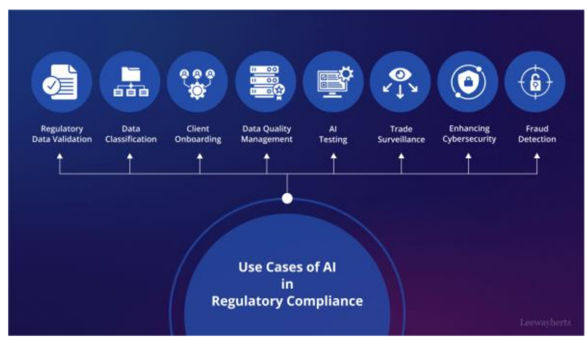

Fig 6: AI For Regulatory Compliance- Use Cases, Technologies, Benefits Solution and Implementation

5.2. Best Practices for Implementation

Best practice #1: Consult real-world state authorities While it is beneficial to consult the literature and other private sector bodies operating at the cutting edge of driver assistance systems, it is essential to dialogue with organizations that can administer, ratify, or enact changes upon the strategies developed. In the United States, this means engaging with the National Highway Traffic Safety Administration (NHTSA) - an agency operating at the administrative level of the United States Department of Transportation (USDOT). NHTSA is mandated to inform the public about recalls, initiate investigations, and drive forward national road safety standards. Identifying technical knowledge at this authoritative level can not only ground the system development in legal and ethical "red lines"; it can also move the needle in terms of selecting evaluation stimuli that are both useful and realistic.

Best practice #2: Adopt a cross-disciplinary, all-of-the-above, user-centered approach Chaplin (2021A) described a 5-domain approach to positively exposing and validating intelligent systems. The chief function of domain #1, real-world use, is exactly as it sounds - reflecting the interactive, symbiotic relationship between the road and the vehicle. Then comes the cyber domain - concerned with the flow of information and any potential vulnerability to network attacks. It is on the far side of the cyber domain that the control domain resides, encompassing issues of trust and human factors, as well as control, verification, and software safety. As the operator of information coming from and going to the road, cyber, and control domains, the human becomes the keystone/internal weakness to our 5-domain security "vault". Second to last is the regulation domain, reflecting everything and anything concerned with situational ethics, market trust, and commercial anti-competitive measures.

6. Conclusion

The development of advanced driver-assistance systems is directed to make driving safer, more reliable, and sustainable. Today's evaluation methods for such systems consider performance in typical and extreme real-world situations. This paper contributes a powerful tool that fills such gaps by an example evaluation combined with an AI model for driver-awareness monitoring. The following drivers and shareholders are likely to benefit most from a better understanding of AI-assisted driving scenarios: 1) vehicle manufacturers who can focus software testing, equipment, and setup on relevant driving scenarios, 2) insurance and contemporary inspection services that can enhance their decision-making processes, and 3) e-mobility providers who may solve complex logical steering behavior and autonomous driving dilemmas through car sharing.

Assessment of the results from an AI model to check the reasonability of the chosen set of driving scenarios carefully and see whether this scenario subset is indeed a good representation of the general driving behavior model and real-driving situations. These tests are crucial to estimate the potential performance of an AI model in vehicle situations that are not part of the model, or to estimate the performance of a different or new AI model. To avoid potential adversarial behavior in combination with surroundings and traffic situations, the AI model should be tested in combination with different sensors and the resulting closed-loop control. Considering the samples of the learned AI model during the training process is necessary to obtain a first insight into these questions at a potentially early stage without quality-related software-hardware interactions. The important graph of learned driving situations example can guard software debugging.

6.1 Future Trends

It may be helpful to identify high-level future research, like methodologies that will be explicitly leveraged to perform the analysis of future proposed systems, focusing on topic-specific developed methods designed to explicitly focus on topics within the system. Finally, the challenges section suggests future systems where machine learning researchers working in traffic security could apply their skills to advance the state-of-the-art in the domain. With the introduction of large-scale training data, speed video processing AI methods, as well as methods that combine various sensor modalities, these core visions are now more feasible than ever. These capabilities facilitate the development of advanced driver assistance systems and possibly systems that not only have driver comfort as a prime objective but can enable automated driving and cooperatively negotiate complex interaction patterns with other road users.The surveillance equipment is now available on the streets and the data generated could be leveraged to improve traffic security to a great extent. The automotive industry has been advancing vehicles' design to make them more automated over the years, with the main objective of improving the safety of individuals moving through the car. As consumers expect more comfort and better support in their daily traffic routine, new car models are released with more innovative and powerful cameras and LiDAR surrounding them. Collectively, the demands of modern traffic and the improvements in generation surveillance hardware have allowed us to collect and annotate a significant amount of interaction data about various traffic actors, which still do not enable immunizing the development of AI techniques. However, without forgetting counterattacks like adversarial learning, AI model fabrics may be capable of handling the proposed system's privacy challenges, and learning-based techniques should be used to the benefit of society by correctly sensing, understanding, and interpreting vehicle interactions.

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