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AI-Driven Innovations in Automotive Safety: High-level Analysis

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Abstract
Safety in the transportation sector has been of particular concern to policymakers, industry participants, and the scholarly community. The continued steady progress in scientific knowledge and technological progress has resulted in a decrease in fatal accidents. The ever-decreasing cost of computing power has created the preconditions for a new round of innovative solutions that use AI-driven technologies to enhance automotive safety. In this study, we provide a scientific-technical survey of AI-driven innovations in vehicle safety, underscore potential barriers to large-scale implementation, and provide policy recommendations. The results are intended to assist policymakers, researchers, and practitioners in a wide range of domains in understanding the potential effects of AI-driven technologies on vehicle safety.

Keywords: AI-Driven Innovations in Automotive Safety, 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

Artificial intelligence (AI) and autonomous systems are driving innovation and enhancing the efficiency of an extensive array of industries. However, AI has also transformed the risk landscape as it is vulnerable to attacks. Moreover, AI-driven autonomous systems are highly sensitive, have a weak regulatory framework, and are nearly impossible to insure. In the realm of automobiles, AI-driven autonomous systems have paved the way for several favorable developments, particularly for vehicle safety. It has the potential to save billions of dollars and hundreds of thousands of lives. Despite these merits, AI-driven autonomous vehicle systems are not without their demerits and deficiencies. This manuscript elaborates on the merits and demerits of AI-driven innovations in vehicle safety and assesses the concerned regulatory frameworks, followed by presenting some conclusive discussions.

1.1. Background of AI in the Automotive Industry

The automotive industry is the "new internet" where connectivity, autonomous driving, and smart mobility concepts are continuously shifting the industry landscape. The convergence of physical and cyber worlds creates myriad untapped data treasure chests spread across vehicular, infrastructure, and client-specific origins. AI technologies, such as machine learning (ML) and deep learning (DL), are part of a select group capable of unraveling vehicular data with transformative socioeconomic, scientific, and human safety ripple effects. These technologies also embed countless inherent technical, operational, and performance challenges that have, thus far, hindered AI's widespread adoption. Carefully designed experiments and computational simulations help mitigate the risks of AI technologies before they are inserted into critical missions and/or human-in-theloop environments that are routinely encountered in the automotive sector. While the progress of AI technologies is unprecedented, there is a paucity of in-depth foundational reviews that unravel, document, and categorize the myriad enabling elements, AI-based methods, and their academics' desiderata within the automotive domain, as our manuscript aims to achieve.

The Edge Computing and Internet of Things (IoT) design paradigms capitalize on extending the cloud conservation of resources notion to the far edge of the IoT, thereby minimizing the data boomerang effect of raw data source IoT end-point to cloud server processing architectural choices, and improving various performance aspects including latency, reliability, security, data communication costs, and scalability. To that end, the hybrid LSTM-based model for edge computing reduces the video surveillance system monitoring latency; likewise, AI-powered IoT at the network edge enhances the training scenarios and the performance of the vehicle-dynamic and power-health models while minimizing the impact of migrating these computationally complex AI models to the cloud. The cornerstone of these innovative AI-driven projects rests on improving the quality, speed, and efficacy of the considered decision-making applications operating near the edge, where sensor-rich databases trigger the deployment of cost-effective predictive and insights models with real-time monitoring, tracking, prediction, and anomaly detection roles. Moreover, the simultaneous embrace of edge computing and AI is made possible by task allocation expansion LSTM models that engage AI models for demand prediction and energy forecasting, thereby lowering the operational cost and energy consumption, and bolstering grid resiliency by dynamically optimizing edge AI-load sharing across IoT, edge computing, and cloud computing resources.

1.2. Significance of Automotive Safety Innovations

The automotive industry has long been a leader in technological innovation. As technologies of artificial intelligence mature, innovative vehicles are being developed, making the automotive industry a driving force in AI development alongside major tech innovation companies. AI technologies have already been widely applied in various aspects related to transport industries, including vehicle intelligent driving, smart monitoring and regulation, smart system design for traffic control in intelligent expressway systems, and airport intelligent stereo garage dispatch systems. Among them, intelligent vehicle safety-assisted transportation is improving automotive safety. The development of AI technologies is changing the manufacturing model of smarter, more adaptive, and more personalized vehicles, and promoting the transition from "passive" automobile safety features to "active" automobile safety designs.

In terms of technical thinking, AI-driven innovations in the automotive industry can change the traditional means of safety testing and verification of vehicles. Differing from the existing research on AI-driven innovations in R&D automotive technologies, we focus on technological innovations in "automotive safety" and their influence on industry development. In particular, it is the continuous updating of the safety assurance system, which includes the safety system design, safety testing, and verification. When an Automotive Safety Critical Event (SCE) happens, the car is trying to drive itself safely, which is considered the core function of a self-driving car. The AI design that helps the car handle this event is the AI function concerned with autonomy. Although such a categorization is generally accepted in the academic world, the boundaries between these three levels of automation are not well defined, and the presence of AI technologies in vehicles used for point-to-point commercial car-hailing service may make these boundaries even less perceivable by customers.

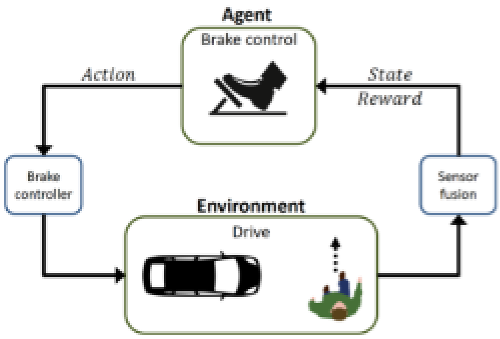

Fig 1: The proposed DRL-based autonomous braking systems.

2. AI Applications in Automotive Safety

Artificial Intelligence (AI) encompasses a group of technologies that can perform tasks that would normally require human perception, cognition, decision-making, and manipulation. In this chapter, the innovations driven by AI in automotive safety are analyzed. AI offers a mechanism to process various vehicle systems data captured around the vehicles and provides or assists recognition of potential risks caused by future unintended events, errors, or malfunctions in such systems. The current vehicle generation contains hundreds of different sensors and infrastructure capabilities. At the same time, AI can make very fast and accurate localized decisions. This is an ideal environment where AI systems are well-suited to improve automotive safety. This chapter discusses only advanced driver assistance systems (ADAS) and autonomous vehicles (AV).

A new generation of AI-powered safety systems is increasingly used in advanced driver-assistance systems to prevent collisions with objects, vehicles, and unprotected road users. The timing for AI usage in safety-critical areas in AV was good because there is so much sensor data around AVs and infrastructure that can be employed to identify potential risks. This chapter covers the most popular AI architectures and methods and AI applications in AV from SAE levels 1-5 which are complex enough to bring safety to cars in many private and professional use cases. The possible ways to develop, test, verify, validate, and operate the most popular safety features will be clarified as it is seen by the industry. Finally, the chapter gives the most widespread ways for accident reconstruction using AI technologies in the field of automotive safety.

2.1. Advanced Driver Assistance Systems (ADAS)

Current and near-future vehicle global standard features will be Advanced Driver Assistance Systems (ADAS). We can divide them into three bigger groups according to their benefits. The first and most important one is the safety features – like Halogen, Xenon, or LED lighting, Adaptive front lighting systems, emergency braking systems, Anti-lock brakes, Traction control, Electronic stability control, Adaptive cruise control (ACC), Blind spot detection, lane departure warning, Traffic sign recognition, Head-up display (HUD), Wildlife and pedestrian detection, Automatic parking, and others. Second important, but mainly for comfort usually also are Night vision, Collision Avoidance Systems, Object and Vision Recognition, Intelligent Speed Adaptation, Alcohol detection, and Traffic Congestion Assistance. The third group of entertainment or infotainment features includes Touch Screen Media, DVD, MP3 player or smartphone integration, GPS Navigation, Sound System, Wi-Fi, Bluetooth, Satellite Radio, Internet access, Games, and Telematics Services. Thanks to these innovations and connected vehicle technology, not only the human body, but the vehicle itself gets an additional barrier to crash avoidance. Be aware that even if ADAS is included in every future car, it is not a 100% guarantee for avoiding road accidents but can endanger traffic safety because of driver addiction. More complex systems for the prevention of accidents must be developed with time and the introduction of reliable AI technologies. Such ADAS devices could be implemented in globally standard car equipment using their implementation strategy and actions originating from global vehicle producers.

However, it is mainly the final customer, namely the car buyer, who can influence how advanced the car will be in the ADAS area.

ADAS architecture should be flexible, open, and user-friendly for control, configuration, and operation both onboard and remotely. Producers of these intelligent vehicle devices should implement strict self-imposed rules of transparency, openness, integrity, and customer care. However, they should also remember security and privacy requirements for the implementation of ADAS and AI (Artificial Intelligence) technologies. It may be time for generic side node creation for vehicles able to attach more future advanced onboard systems, such as some kind of car Open Digital Platform which could be equipped with advanced plug-ins, with the possibility of new intelligent functions to be installed in the vehicle. We watch with interest the automotive projects which are mainly the results of automotive industrial and scientific cooperation, like Apollo Program, created by Chinese search engine Baidu with an open-plans strategy to provide automobiles with driverless capabilities shortly, or the Drive Me project by a possible global-leader in hybrid vehicles and also in car safety systems Volvo – at the same time, quite big and informative announcement by Tesla, USA and IBM Corporation probably gives the tone for future orientations of car developers – improvements by AI. But in conclusion, good, rare, and incredibly expensive cars must be safe even in the most difficult circumstances of usage. People in these cars demand not to be distracted by usual safe car operations, they want to convince themselves that also in rare dangerous situations, they are surely protected. High investments for future ADAS devices and AI inclusion by car developers reflect high quality for demanding customers. In addition, cars with excellent safety features are also communicators of one important feature of their owners – care of life and health of human beings. And safety should dominate all other car parameters in the future because people buy cars to move from one place to another. This is a basic functionality that demands constant safety paramount to be fulfilled before any other requirements. Car safety is designed for life. But life is also supposed to be happiness now and for the future.

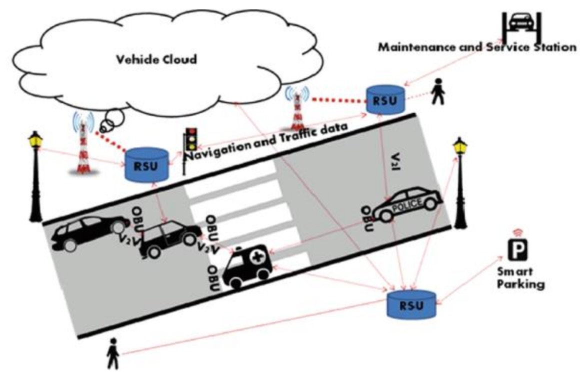

Fig 2: Enabling Technologies for Internet of Vehicles

2.2.Autonomous Vehicles

All the developments in automotive safety today are related to autonomous vehicles: fully self-driving vehicles. Level 5 of automation means the vehicle needs zero human intervention for the full duration of the trip, with the minimum constraint being that the driver does not need to drive and is therefore free to perform secondary activities. Vehicles that are not independent are not considered autonomous, but only "automated." At present, manufacturers can offer the ability to automate everything except that which is required to avoid accidents without being responsible for causing them. Moreover, the driver must be ready to take control and assume all responsibility if such a situation arises. Fully autonomous vehicles, on the other hand, not only learn all the inherent driving skills of the driver but also reach a higher level of intelligence.

Today, autonomous vehicles, especially Level 5, represent the sum of the AI-driven innovations discussed in the previous section. We are not confronted, in this case, with one or two primary solutions. On the contrary, everything seen earlier can be applied to bring such vehicles to the commercial stage. From sensor systems that allow the vehicle to sense its environment, derived from experience and perception models and tested specifically for safe behavior, to the constraints capable of monitoring it, algorithms that allow for decision processes that are designed to make decisions to counteract the events that perception perceives; all these elements interact in the autonomous vehicle development pipeline, as shown. Several other elements of a non-deep learning nature could also be used by Artificial Intelligence to attain higher values of performance. For example, as mentioned earlier, the algorithms that create cellular statistical models are required to assess the vehicles' system behavior in terms of recognition of images and graphics collected by the sensor system.

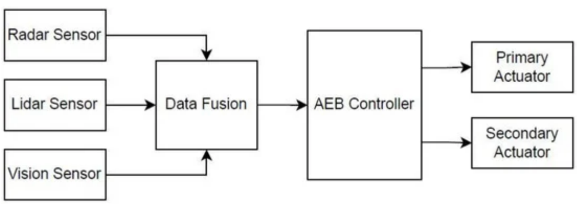

Fig 3: Block Diagram of AEB with Sensor Fusion

3. Challenges and Limitations

Some of the main limitations and challenges of the paper presented herein regard the relatively small number of identified cases. Of particular note are the few signals referring to public policy and the fact that there are few sources in English about the Asian region. Importantly, the findings of this paper are based on public information, rather than on previously classified government data. The method presented here could be used to survey a further range of academic articles beyond the scope of this exploratory study. In addition, the cases were collected and reviewed at a specific time frame, so there may be new cases of interest for this study, that present themselves post-collection.

Further, in the literature reviewed - although there is an emphasis on public health - little attention is given to innovations in the automobile safety industry that deal with a pandemic or an event of a comparable nature. Finally, it is important to emphasize that some technologies - such as blockchain, big data, and robotics - while having the ability to make a significant contribution to the public sector, were only recently developed. Consequently, there are not as many mature implementations that represent a meaningful part of public administration's current activities, needs, and priorities.

3.1.Ethical and Legal Implications

Ensuring public safety and user well-being is of the utmost importance for developers and policymakers when integrating AI-driven technologies into automated and self-driving cars. The two most important concerns relate to a possible misuse of the technology in car design or through its operation and to a possible unfair distribution of benefits. It is important to find the right balance between ensuring overall public safety and user well-being, on the one hand, and creating a level playing field for new entrants facing established, traditional car manufacturers, on the other hand. The mechanisms for safety assurance clamor for public-private partnerships to work effectively. Legal barriers encompass privacy rights, product liability, and consumer protection as well as questions of data sharing and ownership.

These concerns must be addressed at multiple junctions: (a) public encouragement to mitigate externalities and to exploit promised positive transformational impacts by, for example, adapting the road infrastructure to self-driving cars; (b) strict safety conformity regulations to promote early improvements and innovative technologies; (c) institutional rules to shield against opportunistic behavior, in particular at the testing stage of the technology use; (d) broad data access and usage rights to reap the social benefits from novel technologies developed through data analysis; and (e) other rules and regulations pertinent to the socio-technical challenges of AI-driven self-driving cars.

Establishing a desirable level of government intervention responds to the following questions: what are the associated objectives? Who should distribute and allocate those benefits? Who should operate under the regulatory envelope? What is the optimal regulatory envelope itself? And, should regulations, penalties, and other elements of the political economy incentivize external agents to behave in socially acceptable ways?

3.2. Technological Constraints

Active safety features, such as ADAS systems in cars today, continuously monitor the surroundings and kick in if any anomaly is detected. Most of the perception is now done by cameras, and any bad weather condition would massively impact the performance of the whole ADAS system. Also, sources of noise present in both the raw sensory data and all the potential feature extraction steps may have a significant impact on the operational performance of ADAS systems because of false detections by the inferencing operation. Engineers today have to report high false-negative detection rates to ensure autonomous vehicles are very cautious and do not cause any accidents, while this also negatively affects the comfort and adoption of the technology. However, increasing the safety threshold for the vehicles (from 60% to 99%) would optimize for the correct class predictability, but the system performance would drop from 89% to just 75%.

Despite all the potential issues, autonomous driving will leverage ADAS to build a structural policy for higher-level AD driving systems. This will be done based on end-to-end overlapping TD and FSD functionalities. Indeed, the ADAS will accomplish a few vital facilitating functions on behalf of the driver in case of inadequate readiness. Thus, conditional acceleration towards Level 3 and conditional both acceleration and lateral control will occur later. Finally, the AC will deal with the only operational performance functions to manage the transition to L5 while ensuring the safety level of these vehicles.

Currently, HD maps are fundamental to bridge the gap towards end-to-end functioning, integrating users and road providers as part of the automated mobility ecosystem. This is because the outstanding denominator aspects (the properties of Powered Road Infrastructure) are valuable complements to DNN-based image classification methods, especially in the inference operation. Indeed, for Level-3+ AC, accurate structural delineation is pivotal for understanding two key denominators: lane boundaries and traffic signal locations. Currently, at the core of most FSD DNN methods, there are only enhanced perception pathfinders capable of recognizing traffic signs, traffic signals, lanes, vehicles, or pedestrians (e.g., boosted CNNs). The latter devices, however, are major contributors to the uncertainty challenge in the performance of these driving systems because a minimal change or perturbation during the driving task could hinder the abilities of the car and the safety of its passengers. This scenario can be further aggravated if, as likely to happen, the availability of the supporting device changes during the pattern of inference.

4. Case Studies

4.1. Enforcement and Vigilance: A Safety System for Autonomous Vehicles We propose a controller capable of enforcing any velocity and safety constraints provided that they are feasible. The impact of uncertainty is twofold: speed importance and discretization into simple constraints. If the parameters are progressively defined, the optimization benefits all the parameters. Furthermore, by definition, the mismatch between the optimization values and the real values underperforms the dynamics of the system. A possible application of the proposed controller involves the autonomous car. The proposed model has several controllers, one for each required objective, used according to the characteristics of the external environment and the availability of the vehicle actuators. It provides a set of inertial, elastic, virtual, and supervisory forces resolved in the coordinates of the cinematic path by a vehicle reference model and acting on the vehicle. For the implementation of the proposed controller, we present a simulation of the artificial intelligence model SAE control logic together with the "safety rules" for the California Intelligent Speed Adaptation system.

4.2. Automotive Safety Applications Driven by Artificial Inclinations Analyzing the spatial orientation angles of the anterior and posterior parts of the vehicle using the AI methods on the roll test bench, a jerking effect is revealed, which, in emergencies, appears in a roll direction. It is determined by the forced reaction of the vehicle structure to the effect of the side wind. The revealed vehicle spatial orientation angle κ expresses readiness to control skidding and preserve vehicle stability. A reciprocal increase of the examined spatial orientation angles κ of the front and rear vehicle parts is proposed, defining the maximum safe limit in the relationship between the vehicle weight, height/width length, and the height of its object for the road. Material from computer experiments achieved by AI methods on the vehicle roll test bench is presented testifying that the vehicle roll stiffness increases with the enlargement of the side wind. Using photo informatics and the experimental vehicle orientation relation arrived at by AI methods, an experimental vehicle roll angle κ is determined.

4.1. Tesla's Autopilot Syst

Tesla's system, the Autopilot, uses detectors such as radar and ultrasonic sensors to transfer information to the vehicle's actuators by analyzing the environment and surroundings. In this way, this type of system can function as a semi-autonomous vehicle in nearly all types of situations. It is an advanced driver's assistance system designed to inform the driver when loss of attention could result in a dangerous situation.

Although the controlled automation level has made significant strides in the automotive sector, it is known that the objective of achieving a fully autonomous vehicle is not an easy one. The TM/DSAD classification problem aims to prove the maturity of a system that can handle real-time dynamic scenarios by testing it over four vehicle maneuvers: maintaining lane conditions and the subject vehicle, as well as the defended area, induction of an initial move between two lanes, lane change maneuver between two detected lanes, and departure conditions observing the following vehicle. This fact is verified in this paper's discussion and analysis of the different levels of automation of autonomous vehicle systems.

4.2. Waymo's Self-Driving Cars

Waymo is an American autonomous subsidiary of Google's parent company, Alphabet Inc. It spent millions to develop autonomous systems that hold unrivaled expertise in driverless technologies. Waymo's self-driving vehicles employ AI and high-resolution 3D maps. The acquired images are cleaned and annotated by specialized teams before the training stage. Datasets contain the removed moving objects to prevent models from learning the wrong patterns. The main challenge of relying on prebuilt 3D maps is the compatibility issue since the use of lidar depends on the environment. Waymo, in partnership with vehicle manufacturers, spent millions on developing sensors and robots, several iterations of LiDAR while continuing to work to reduce the costs and enlarge the volume of production for sensors and robots.

Using lidar was proven to be important for diverse datasets that promote safety. The creation of labeled 3D data that includes the removal of static objects is costly, since collecting and cleaning the images takes a substantial amount of time, and annotating objects is required, especially after ensuring that the models are not learning unwanted behavior. Also, there is a plethora of problems that can impact the perception algorithm. For example, fog, rain, dust, snow, and wet pavement can impair depth perception, and many interesting areas like autonomy-in-the-understanding or estimation errors are still open for development. Waymo was denounced for partially relying on high-definition 3D maps processed by professional teams and for flaws that include the fact that the vehicle's operation autonomy is almost exclusive by design to a small subset of U.S. cities.

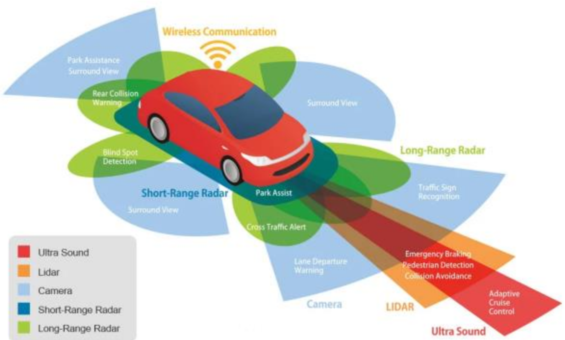

Fig 4: Different Types ADAS Sensors Used in Today's Autonomous Vehicle

5. Future Directions

Prototyping the combined usage of AI-driven systems of both car and infrastructure could, on the one hand, allow us to create multifaceted safety layers, each more reliable on its own (vehicle-based and infrastructure-based). On the other hand, it could give rise to systems whose components and the whole can be executed interchangeably by smart transport terminals, driverless cars, and any electro-mechanical vehicles. Since today, no high-tech transport terminal is represented on the automotive scene yet, each innovative AI transcription of the transport system's relevant functions, being promising and theoretically well-founded, still needs to be validated.

Interconnected control of cars and infrastructure should be tactile in the first place due to the reasons outlined above. What device can implement tactile control? It must be something with kaleidoscopic functions in a transport system. When turned on, it must represent a car control component. If necessary, it must seamlessly take over the function of an intelligent transport terminal. The magic gadget must approach the terminal's possibilities while driving close to it since a distance must be treated as a limit of constraint. When in the embodiment of a transport terminal, a single device (or a group of devices) should project control signals outside (the commands for the car and, if necessary, for other traffic participants). When gaining the status of a car controller, the device should get its information from infrastructure (say, a specialized element of road marking, organized by a standard car maker), then process it and pass the command to the car's control elements.

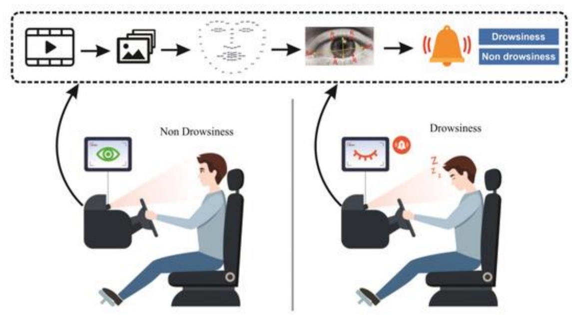

Fig 5: General Model of The Drowsy Detection System

5.1. Emerging AI Technologies in Automotive Safety

The next generation of automotive safety technologies will marry classical rule-based modern constraints to machine-learning-based perception algorithms and will use predictive analytics and context understanding to anticipate and execute optimal trajectories for vehicles and occupants. Efficient GPU-driven inference and optimization will make it possible to realize these innovations in mass-market electronics platforms, making automotive safety an exemplar of the rapid democratization of AI innovation. In contrast with automated driving, whose highly directional deployment is concentrated in much smaller areas of the world, safety innovations will bring the democratized benefits of AI to a higher percentage of the world's citizens.

Driver drowsiness causes at least 90,000 police-reported crashes per year, many of which involve fatalities or serious injuries. Current drowsiness-detection systems in mass production, including those developed by the authors, use vision and steering feedback sensors to detect the early warning signs or onset of drowsiness, and then provide visual and/or audio alerts, demand driver interactions, or even level-1 vehicle control to awaken the driver and avoid a crash. AI can significantly improve these capabilities by using state-of-the-art visual object detection, motion detection, sleep-state detection, and optical-flow models developed for ADAS and AD, and adapting the alerts and control strategy to minimize detrimental interactions. We can also use the same model to identify signs of drowsiness in electronic data collected from the actions of long-haul truck drivers or other operators of potentially dangerous equipment. This technology can use novel alerting and control paradigms, for example, providing alarms to the relevant dispatch and operations managers, or in the case of road infrastructure or traffic accidents, directly to emergency services.

6. Conclusion

We exploit new automotive accident datasets and provide empirical evidence that AI-driven innovations introduce substantial safety benefits. These innovations result in significantly lower realized accident rates. We also provide a framework to understand potential accidents enabled by these innovations. The estimates imply that AI-driven innovations do not introduce excessive risk. They imply that establishing a regime where insurance companies are made to act collectively as data custodians can be beneficial. Even without such a regime, key findings provide important implications for usage substitution and product liability litigation regulation. The insights are also useful for designing incentive-based optimal inspection mechanisms.

AI-driven innovations and safety are not just limited to the air travel industry. The advent of new cars, especially autonomous vehicles, is expected to bring about substantial safety improvements. To give a flavor, consider the following similar discussions that are found in news articles and activist websites: "This brings us to the final and perhaps most important selling point of autonomous vehicles: the fact that they cannot be driven while distracted. Data models and human-machine interfaces may grow immeasurably smarter, augmenting driver performance in ways not yet imagined... Furthermore, the steps necessary to bring AVs to market may inadvertently foster the development of safer conventional passenger vehicles." Our exploratory analysis in this paper connects such discussions to the data and provides empirical evidence that AI-driven innovations in automobiles are substantially improving safety.

6.1 Future Trends

AI-driven innovations in automotive safety, which benefit from vision cameras, are extremely dynamic. Innovations are continuously introduced, creating a large momentum. Moreover, the pace of technological innovation is increasing. Commercially available ADAS on the market today has been developed for only a few model years. The rate of introduction and the development of novel functionality are milestones to watch. Techniques and methods that are state-of-the-art will continue to exist, and new solution approaches will play an increasing role in product development.

The current level 2 technologies (Complex ADAS) will be developed further in terms of both additional functions and functionalities, as well as higher performance. A broad spectrum of features could be realized, leading from the development of specific ADAS fine-tuning the SAF to the improvement of perception algorithms. This may ultimately lead to increased robustness of the driving function under adverse conditions (e.g., fog, sun, animals in the road, road signs affected by snow) or motion states (e.g., partially blocked roads). An increasing number of sensors will be integrated into the vehicle to enhance its perception capabilities and its situational awareness. The key technology trend will be the use of AI/ML-based methods and the utilization of higher bandwidth available communication technology. The amount of edge computing and onboard storage will increase to accommodate the growing amount of processed data and increasing complexity of algorithms. All this will increase efficiency, safety, and comfort delivered to the vehicle occupants.

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