Autonomous Vehicles Safety

CS 4390/5390

Project Documentation

Students Name:

Aidan Tobar & Daisy Nevarez

Alexander Gintz & Nick Laviano & Thad Drees

Academic Supervisor:

Dr. Hassan Rajaei

Fall 2025

Department of Computer Science

Bowling Green State University, Ohio

Autonomous Vehicles Safety

Students:
Aidan Tobar & Daisy Nevarez
Alexander Gintz & Nick Laviano & Thaddeus Drees
Supervisor: Dr. Rajaei
Dept. of Computer Science
Bowling Green State University, Ohio
Reporting date: 12/05/2025

Abstract
Autonomous vehicle (AV) safety relies heavily on communication networks as well as reliable perception systems. However, both face significant challenges under adverse weather conditions and complex traffic conditions. Investigating how modern network-based communication architectures, such as Internet of Vehicles (IoV), Vehicle-to-Everything (V2X) systems, and 5G/6G-enabled edge computing, can enhance safety and the decision-making performance of AVs is crucial in creating safer environments on the road when visibility and sensor reliability are degraded. Examining current literature, case studies, and recent advances in sensor fusion, low-latency networking, and cooperative perception assists in identifying the mechanisms, limitations, and design considerations that support resilient AV operation in dynamic environments. A consolidated framework describing how communication architecture, edge intelligence, and multi-sensor integration interact to maintain AV safety is contributed to enabling more reliable performance in real-world adverse scenarios.

Table of Contents

This page is left intentionally blank

1. Introduction

Autonomous vehicles rely on a combination of onboard sensing, intelligent decision-making algorithms, as well as network-based communication in order to safely navigate various real-world environments. Under ideal weather and traffic conditions, many AV systems are able to perform in a reliable manner. When adding rain, fog, snow, and dense or unpredictable traffic patterns, major challenges arise. Adverse weather reduces visibility, degrades sensor accuracy, and also increases perception uncertainty. Similarly, heavy traffic that changes rapidly requires faster and more reliable communication among vehicles and infrastructure to aid in the prevention of collisions and to maintain situational awareness.

As vehicle automation advances, communication technologies such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Network (V2N), and IoV systems have become essential components of AV safety. Emerging 5G and 6G networks, along with multi-access edge computing (MEC), enable low-latency data exchange and distributed intelligence that can support AV decision-making during sensor degradation. At the same time, cooperative perception and sensor fusion frameworks allow vehicles to share information to mitigate the effects of occlusions and weather-related visibility loss.

Addressing AV safety in various environments is critical for mitigating risk in real-world scenarios. To be able to deploy AVs, reliability is required across all conditions. Adverse weather is a leading cause of sensor failure within current systems. Additionally, network-based safety mechanisms can assist with reducing dependence on local sensors. V2X allows vehicles to share perception data and warnings even when the visibility is limited. Low-latency communications assist with improving reaction time, as 5G/6G, and edge computing enables near real-time updates that aid in preventing collisions in dynamic environments. Overall, understanding system limitations supports creating safer designs. Examining vulnerabilities in sensors, communication networks, and traffic coordination helps identify the gaps that must be resolved for full autonomy.

This project is aimed at better understanding, communicating, and helping AV manufacturers to design their vehicles to navigate adverse weather conditions and road construction in the safest manner possible. We will explore the technology and ideologies that can create a safer and more reliable Autonomous Vehicle experience when traveling in adverse weather or high construction areas. To do so, we will explore different research that includes predictive models from human-drivers, case studies from AV manufacturers like Waymo and Tesla, V2X systems, multiple types of sensors, and the inclusion of all sensors in one AV architecture.

Key Questions:

1. How can predictive modeling of extreme weather hazards aid real-time navigation decisions for AV safety?
2. How do 5G/6G networks and edge computing improve safety through low-latency communication, and what delays remain problematic in adverse conditions?
3. How can V2X communication assist safety amongst autonomous vehicles when weather reduces sensor performance?
4. How do autonomous vehicles safely handle detours and work zones?

5. What are the most critical design features and technologies that enhance passenger and driver safety in modern vehicles?

2. Related Work

[4] U. Yusuf, S. Khan, and R. Souissi, "Vehicle-to-everything (V2X) in the autonomous vehicle domain – A technical review of communication, sensor, and AI technologies for road user safety," Transportation Safety and Environment, 2024.

This article is an extensive review of V2X technologies and highlights the important role of low-latency communication for autonomous vehicle safety. It focuses on how 5G and the upcoming 6G networks enable cooperative perception, real-time hazard sharing, and reliable communication between vehicles, infrastructure, and people who are driving. The authors emphasize that safety for critical applications needs very reliable, low-delay messaging, which 5G NR-V2X and edge computing architectures are specially designed to support. These applications include emergency braking alerts, VRU warnings, intersection collision avoidance, etc. However, the review also shows reoccurring challenges such as non-line-of-sight (NLOS) signal obstructions, adverse weather conditions that force automated vehicles to rely heavily on network-assisted sensing, channel congestion in dense traffic, and increasing latency budgets. These limitations identify that unresolved delay sources continue to be a problem for consistent real-time decision-making, even with 5G/MEC technologies very enhanced in AV safety. This article directly answers the research questions: "How do 5G/6G networks and edge computing improve safety through low-latency communication, and what delays remain problematic in adverse conditions?"

[11] Chen, P., Shi, L., Wang, H., & Xu, J. (2021). *Predicting traffic accident risks under extreme weather conditions using machine learning methods.* Accident Analysis & Prevention, 162, 106358.

This paper studies how machine learning can predict accident risk when under extreme weather conditions. The authors' idea is to incorporate historical crash data with different weather conditions. The study looks at different methods/algorithms of combining crash data and weather conditions like random forests, gradient boosting, and neural networks. Random forests are used as a learning method for the models to create a relationship between weather conditions and accident likelihood, gradient boosting is an iterative learning method that uses the errors of previous trees to improve predictions, and neural networks are used to analyze and encapsulate patterns in the crash and weather condition combined dataset. The authors use these algorithms in their models and discover that those using weather conditions as well as date and time data. The results they find show that weather conditions play a significant role in accident likelihood, and ML-based prediction systems can be utilized to better traffic management and safety alerts. This helps to answers the research question: "How can predictive modeling of extreme weather hazards aid real-time navigation decisions for AV safety?"

[13] Luo, H., Wang, X., Yin, X., Sun, L., Xie, Y., Peng, X., ... & Hu, J. (2023). *Multi-modal learning for AV perception in adverse weather.* Sensors, 23(18), 7693.

This paper studies how multi-modal learning techniques can be designed to aid AV perception in adverse weather. The authors' proposed approach is to create a fusion framework that integrates LiDAR, radar, cameras, and thermal data with deep neural networks (like those talked about in [11]) to accommodate the weaknesses of each sensor type. The results show that in fog, rain, and snow the multi-modal models improve object detection accuracy and range in comparison to single-modal sensors. This helps to answers the research question: "How can predictive modeling of extreme weather hazards aid real-time navigation decisions for AV safety?"

[14] Han, K., & Twumasi-Boakye, R. (2024). ***Deep learning for weather prediction: A comprehensive review.*** **Artificial Intelligence Review, 57(3), 4381–4412.**
This paper establishes a review of deep learning methods applied to weather prediction. The review covers deep learning models that use CNN-based approaches to models using transformer architectures and neural networks based on physics. The paper covers how modern AI models outperform normal numerical weather prediction methods. It also mentions challenges like lack of sufficient data, the ability to generalize across different areas and regions, computational limitations, etc. This helps to answers the research question: "How can predictive modeling of extreme weather hazards aid real-time navigation decisions for AV safety?"

[17] Li, M., Song, T., Chen, R., & Sun, J. (2023). ***AI-powered object detection and trajectory prediction for AV navigation in poor weather.*** **IEEE Access, 11, 12345–12357.**

This paper studies how AI-driven object detection and trajectory prediction methods can help aid AVs navigate through adverse weather conditions. The authors create a deep learning framework that improves detection when there is low visibility as well as incorporating trajectory predictions to help anticipate what the other vehicles on the road are going to do. Their framework uses multiple features to do so, including image enhancement, feature extraction, and motion modeling to maintain the accuracy needed in adverse weather conditions. The results show that there is improved accuracy in the AI-powered models in comparison to normal models which shows that AI-powered models are effective in their predictions and insight even in adverse weather. This helps to answer the research question: "How can predictive modeling of extreme weather hazards aid real-time navigation decisions for AV safety?"

[18] Singh, P., & Islam, M. (2020). Movement of autonomous vehicles in work zone using new pavement marking: A new approach. Journal of Transportation Technologies, 10(3), 183–197.
The authors investigate how new pavement marking designs are able to support safer AVs in hazardous and unpredictable environments called works zones. Within the article, there is emphasis on how AVs depend heavily on lane markings and road-surface cues to aid in navigation. However, work zones are often considered disruptive to the cues due to the additions of temporary lanes, construction signs, and additional factors such as faded markings. There are several issues mentioned, such as AV vulnerability to ambiguous lane markings, as work zones contain irregularities within markings or the addition of temporary markings, which confuse AV perception systems, increasing collision risk. To mitigate risk, a new pavement-marking system is introduced to enhance visibility with the intention of improving AV detection under disrupted road conditions. The high contrast within the markings also improves visibility under rain, low light, or partial occlusion. Regarding research questions, the article assists in answering "how do autonomous vehicles safely handle detours and work zones?"

[22] I. F. Akyildiz, S.-C. Lin, and P. Wang, "Wireless software-defined networks (W-SDNs) and network function virtualization (NFV) for 5G cellular systems: An overview and qualitative evaluation," Computer Networks, vol. 93, pp. 66–79, 2015.

This paper explains how 5G cellular systems rely on Wireless Software Defined Networking (W-SDN) and Network Function Virtualization (NFV) to achieve ultra-low latency, high reliability, and flexible network control, all of these are required for critical safety applications such as autonomous driving. The authors describe how SDN separates the control and data planes, which creates faster routing decisions, dynamic bandwidth allocation, and immediate network configuration during high mobility. These are all key factors that help minimize communication delays. NFV better improves performance by virtualizing network functions and deploying them closer to end users, which is an early conceptual model of modern mobile edge computing (MEC). This paper also finds many unresolved sources of latency, which includes synchronization overhead across virtualized functions, congestion in ultra-dense 5G deployments, signaling delays from centralized SDN controllers, and delay spiked during handover or rapid user mobility. Overall, this literature helps answer the research question "How do 5G/6G networks and edge computing improve safety through low-latency communication, and what delays remain problematic in adverse conditions?".

[23] C. Flores-Moyano and E. Grampín, "SDN and NFV in 5G mobile networks: Advancements and challenges," in Proc. IEEE Latin America Transactions, 2017.

This paper reviews how Software-Defined Networking (SDN) and Network Function Virtualization (NFV) help 5G networks achieve lower latency and higher flexibility, which is very important for critical safety applications such as autonomous vehicles. The authors explain that SND allows faster routing decisions through centralized control, which NFV moves important network functions closer to users, reducing the time it takes for data to travel across network. They also highlight many challenges that still make delays, which includes contoller-switch communication overhead, virtualization processing time, congestion in dense areas, and delays during mobility events such as handovers. Overall, this article helps answer the research question "How do 5G/6G networks and edge computing improve safety through low-latency communication, and what delays remain problematic in adverse conditions?".

[24] M. Ray and S. Kumar, "A systematic review on SDN/NFV-based edge–cloud IoT architectures: Challenges and future directions," Future Generation Computer Systems, 2021.

This paper reviews how combining SDN, NFV, and edge computing can reduce latency in loT and connected systems by computing and network functions closer to end devices. The authors explain that SND provides centralized traffic control and faster route adjustments, while NFV allows key services to run virtualized edge nodes instead of distant cloud servers, which results in shorter response times. The authors also go over challenges that still make delays, such as high traffic loads, synchronization issues across distributed nodes, limited edge resources, and perfromance drops during network congestion or rapid mobility. The paper focuses on loT very broadly, but these ideas apply directly to autonomous vehicles that depend on how low-latency edge processing is for safety. Overall, the article supports the research question "How do 5G/6G networks and edge computing improve safety through low-latency communication, and what delays remain problematic in adverse conditions? “.

3. Safety Centric Design for Autonomous Vehicles

The safety of Autonomous Vehicles (AVs) is a drastically important and constantly evolving issue within the world of AVs. The more you analyze the idea of a fully autonomous vehicle, the more issues and challenges that arise. Unlike a normal vehicle, AVs do not have a driver that can physically see the road ahead of them and act accordingly to the road. When a human driver is driving during adverse weather conditions, they are more likely to take the precautions to be able to create the safest driving experience as possible, like turning their windshield wipers on, slowing down, or increase following distance. AVs must rely on sensors, cameras, and radars so how can we decrease the chances of the equipment failing during these harsh conditions. AVs also must be able to detect and act on obstacles in the road. Humans can see the pothole or traffic cone on the road, but how can AVs ensure they detect an obstacle quickly and accurately avoid the obstacle while still ensuring safety? There are many different safety considerations when designing an autonomous vehicle that are drastically important to ensure the safety of the car and the passengers riding inside. This section will analyze some of the key aspects and considerations that are necessary to build and implement a safe and reliable vehicle.

3.1. Special Key Considerations for Safety of the Car and Passengers

Autonomous Vehicle (AV) systems require IoVT and V2X to communicate, allowing them to operate safely and correctly. This opens these vehicles to outside attack as well. This includes attacks such as intruder vehicles feeding false information to the network causing issues and accidents [21]. Communication between vehicles also always involves malicious agents to interrupt communication between vehicles and/or infrastructure. These attacks include message modification, GPS spoofing, and Sybil’s assault [21]. Another key security issue is Overhead. As ITS systems must be very fast and accurate, security measures may slow down the system. There is also the issue of security vulnerabilities that are a result of different manufacturers' standards [21].

Autonomous vehicles look to reduce the number of automotive accidents; however, accidents will still happen, and post-accident safety is considered less. A key example of this is Cruise taxis in San Francisco. In 2023, a Cruise vehicle was involved in an accident where it dragged a pedestrian 20 feet due to its post-accident procedure [27]. The vehicle also had no system to communicate with law enforcement and had no system to check for a person under the vehicle [27]. The AV also only began communicating with its handler following the incident and continued to drag the pedestrian for several seconds afterwards [27].

AV will reduce the human component of driving to increase safety. This, however, brings up problems with human machine interactions. Human drivers may drive in ways that disrupt AVs and cause delays and problems with traffic flow [34]. Pedestrians also present a problem as they can act in unpredictable ways, not follow laws, and appear suddenly from blindspots[34]. Vehicles to pedestrian communication are also important. It is relatively easy for a pedestrian to identify signals from another human, but AVs don’t communicate the same information to pedestrians [34]. This can cause problems with pedestrians misunderstanding an AVs behavior [34].

3.2. Detecting, Avoiding, and Mitigating Obstacles on the Roads

A main piece of designing the safety for Autonomous Vehicles is making sure they can detect, avoid, and mitigate any obstacles on the road. A lot of research has a strong foundation for knowing how 5G networks, SDN/NFV architectures, and edge computing can improve communication performance, but there still is a lack of studies that connects these technologies to autonomous vehicle safety under adverse conditions. An example of this is from the V2X review by Yusuf et al. [4] talks about how 5G/6G and cooperative communication improve safety message delivery and reduce latency, but the study does no evaluate how these systems respond when visibility is bad or when sensors become unreliable due to weather. Similarly, the foundational 5G architecture work by Akyildiz et al. [22] discusses how SDN and NFV help 5G networks achieve lower latency, but the paper shows results in ideal networking scenarios and does not consider sensor degradation, vehicle mobility, or environmental disruptions. Additionally, the literature on SDN/NFV in 5G mobile networks by Flores-Moyano and Grampín [23] finds important delay sources such as handovers, congestion, and controller overhead, yet it does not apply these challenges to critical safety AV scenarios where delays are completely affecting collision avoidance and hazard detection. Also, the SDN/NFV edge cloud IoT architecture review by Ray and Kumar [24] elaborates on how distributing computation to edge nodes can reduce latency, but it does not study how well these systems perform in quick changing, weather heavy environments or under high traffic which is very common in AV applications.

Across these four papers, the discussion focuses on theoretical network improvements instead of practical safety performance during adverse conditions such as rain, fog, or non-line-of-sight situations. None of the works consider the combined delay around communication, sensing, fast decision making, and edge process. All of these are critical for autonomous vehicle safety, and because of this, there is a limited understanding of whether 5G/6G and edge computing can maintain the necessary reliability and low latency during real-world conditions that bring unpredictable obstacles and constant interference. Our project addresses this gap by examining how these technologies behave under these adverse conditions and finding which sources of delay continue to pose safety risks for autonomous vehicles.

3.3. Extreme Weather Navigation Control for Safety of AV

Extreme weather navigation control focuses on how AVs safely drive through adverse weather conditions like pouring rain, snow, fog, and ice. This topic is important because adverse weather can hinder the performance of the sensors and systems in place in AVs that allow them to operate safely. Common AV sensors like cameras, LiDAR, and radar will lose reliability when weather blocks signals or introduces unwanted or incorrect signals and information in the sensor data. With this in mind, extreme and adverse weather conditions are consistently one of the leading challenges for autonomous vehicles. This challenge must be addressed for AVs to be released to the public and ensure full reliability of the vehicle. This is because if the AV cannot make accurate predictions and real-time decisions during adverse weather like those mentioned previously, then the AV cannot be trusted on the road as these conditions are sometimes unpredictable. For example, in Florida, random points of heavy rainfall are common when driving throughout the state, and the AVs must be able to handle these conditions on the spot.

With this issue in mind, there has been a multitude of research that aims to create a more versatile and accurate prediction and perception system for AVs. One study shows that uncertainty-aware domain adaptation allows AVs to recognize when their sensors are unreliable because of weather changes [10]. This uncertainty-aware adaptation approach allows AVs to adapt to the weather changes by making the correct corresponding safety actions like increasing following distance. Another study found that multi-modal learning or combining multiple sensors helps AVs keep consistent awareness even in adverse weather conditions since the sensors can help each other if one of them fails [13].

Adverse and extreme weather creates and increases driving hazards and risks normally, so having the sensors and prediction systems that AVs hold can actually provide a benefit to passengers. A 2021 study showed that machine learning models can predict the chances of accidents during extreme weather by using historical accident data across environmental conditions [11]. This study can be further backed up with the findings and methods from Han et al. [14] who found that using modern AI deep learning techniques on real weather patterns can create a prediction technology better than normal weather predictions. Using these findings and results, we can utilize this method so that AVs can make real-time decisions about what roads and paths to take during the inclement weather. These routing decisions during inclement weather is also supported by another study that used real-time and data on past weather patterns to help AVs avoid roads and places that will have low visibility or icy and nonideal road surfaces [15]. Another viable solution found by Zeng et al. [16] was training the AV perception systems on synthetic weather data which found that when adding synthetic rain, fog, and snow data to training images the model can detect obstacles in the road when visibility is low. These methods combined could create a reliable and safe navigation system that can handle adverse and extreme weather conditions.

Our contribution is to analyze, summarize, and connect different methods of providing a safer and reliable navigation system for autonomous vehicles when exposed to inclement and extreme weather. There are several methods described in this section, 3.3, that describe how sensor reliability, uncertainty-aware perception systems, combining multiple sensors (multi-modal), risk of accident prediction and avoidance, as well as real-time decisions on route choices to minimize the risk of an accident. All these systems, training techniques, and methods can be used in unison with each other to create a safer and more reliable AV system when proposed with extreme weather.

3.4. Instructions Damage Protections for the Car on the Roads

Damage protection refers to the set of features and design strategies that help a vehicle prevent, withstand, and reduce physical damage during real-world driving. For autonomous vehicles, this involves not only the traditional safety structures found in all modern cars, such as crumple zones, bumpers, and reinforced side frames, but also protections that maintain the functionality of the sensing systems that autonomous vehicles rely on to interpret their surroundings. Damage and failure for things such as radar sensors, LiDAR sensors, and ultrasonic sensors which are all integral parts of autonomous vehicle functionality, potentially have catastrophic effects on safety (Matos, Francisco et al, 2024). Therefore, “damage protections” for autonomous vehicles must address both vehicle body integrity and sensor survivability.

Damage protections for autonomous vehicles sensors include a wide variety of things. As with all things, sensors in autonomous vehicles don’t only wear down with use but wear down with time. There are many ways in which AVs protect their sensors, so vehicles remain safe overtime, First, is the software approach. In AV design, research has extensively targeted the idea of “sensor fusion” and algorithmic approaches. The idea of sensor fusion is that by combining the characteristics of AVs sensors, AVs are able to get a better idea of its surroundings and make better decisions (Matos, Francisco et al, 2024). As relating to damage protections, sensor fusion is useful, because as sensors degrade performance worsens, or loss of functionality entirely, instead of just losing functionality of sensing, it is able to use fusion algorithms to work with other sensors in order for the AV to maintain a safe and operable state, until maintenance on sensors is achievable. AVs also provide physical damage protections for cars. These are things like special lens covers for cameras, which help to mitigate damage from ultraviolet light, or covers for radar and lidar sensors which make help prevent them from damage from debris on the road, dust, and regular wear and tear from driving conditions, as well as potential accidents.

3.5. Fault-Tolerant Measures: Preventive & Reactive On-Roads

As of 2023, 40,990 fatalities occurred regarding motor vehicle crashes [37]. AVs have the potential to lessen fatality rates through preventive and reactive safety measures and creating systems that are fault tolerant.

Fault tolerance within AVs is defined as the ability of the system to be able to maintain safe behavior despite faults in one or more areas such as sensors, software, actuators, or the environment itself. Regarding on-road operation, this becomes critical as traffic hazards or adverse weather can degrade perception and reduce control performance.

Many preventive measures originate in the development of the AV and the mechanisms to create a safe system before allowing the AV to go on the road, creating a safer environment and a decrease in projected errors rates. Preventive measures implemented to enhance AV safety include several mechanisms and sensors such as light detection and ranging (LIDAR), which uses pulses of lasers to create models of the surrounding environment in 3D [38]. Systems also developed for integration within the AV is AI to enhance decision-making on the road, further preventing accidents and additional hazards. Cybersecurity protocols are also put in place prior to allowing the AV on the road to mitigate unauthorized users from tampering with the safety of the AV as well as the safety of the objects interacting with the AV. In addition to developing several mechanisms, systems are tested on to ensure validation before on-road implementation.

Reactive measures refer to how the AV reacts to a current event and the response being taken afterward. Rather than a prevention response, a reactive response includes active decision-making. For example, traffic hazards are random events requiring the AV to have a reactive response through robust decision-making. Weather can also introduce a level of randomness such as heavy rain, snow, or fog that can reduce sensor visibility or road traction, prompting the AV to adjust driving behavior by lowering speed, and increasing following distance. Reactive capabilities ensure that, even when unexpected conditions arise, the AV maintains safe operation through adaptive planning and real-time risk assessment [39].

3.6. How AI Can Improve Safety of AV

Artificial Intelligence (AI) significantly improves the safety and reliability of AVs through a multitude of factors, such as enhancing perception, prediction, and decision-making. Many safety challenges such as adverse weather and traffic hazards have prompted the development of AI-driven methods in order to assist AVs in maintaining safe operation even through uncertainties.

AI strengthens safety through trajectory prediction as well as behavioral modeling as machine learning models train on large-scale data to anticipate future events. The predictive ability gives AVs valuable milliseconds to adjust speed or lane position to reduce errors, such as collision risks. In complex road environments such as crowded intersections or work zones, AI prediction models assist in helping the AV understand what is currently occurring and what is likely to occur next.

Another key safety component is the ability of AI to make decisions in real-time as well as plan adaptively. AVs must choose safe driving actions in situations involving uncertainty or insufficient sensor information. AI-based planning systems allow AVs to adjust their behavior dynamically, such as decreasing speed during rainy conditions or increasing following distances. Adaptive behaviors help ensure that AVs maintain safe operation even when unexpected situations arise. AI also improves fault detection and self-monitoring, which assist in early identification of sensor failures or system abnormalities.

Overall, AI improves AV safety by providing enhanced perception, better anticipation of risk, and adaptive decision-making. When combined with robust hardware systems and communication architectures, AI allows autonomous vehicles to operate more safely across a wide range of environments.

3.7. Strengths and Limitations

AV safety systems offer several strengths that significantly enhance reliability on the road. One major strength is the use of redundant sensing and AI-driven perception, which allows AVs to maintain awareness even when certain sensors are degraded by environmental conditions, such as varying weather. Sensor fusion and predictive modeling improve obstacle detection and help the vehicle anticipate the behavior of other road users. AVs also benefit from extensive simulation testing and V2X communication, both of which increase situational awareness and reduce reaction time in critical safety events.

However, limitations still remain. For example, AV performance can degrade when multiple sensors fail simultaneously, such as during heavy rain, fog, or snow, where even fusion algorithms may struggle to produce reliable outputs. Edge cases, particularly those involving unpredictable pedestrian behavior or temporary construction layout, continue to challenge AI models that have limited exposure to specific scenarios. Additionally, AV safety is constrained by data quality and environmental variability, as models trained in one region may not generalize well to new conditions. External dependencies, such as communication networks, can also create vulnerabilities during congestion or outages.

Overall, while AVs incorporate strong safety mechanisms, the limitations highlight that further development in sensing, AI robustness, and system redundancy is required before fully autonomous operation can be consistently safe across all environments.

4. Case Studies, Examples, and Analysis

4.1. Case Studies

This section provides a few strong case studies from the top markets in autonomous vehicles including Tesla, Waymo, and Cruise by General Motors. These case studies provide detailed statistical safety data that can be analyzed to get a better picture of what is needed to make safe

AVs. This section will explore how Tesla and Cruise tackle general safety issues within their AV systems and how Waymo is handling extreme weather navigation as well as general safety. These leading companies and innovators in the AV industry can provide a great synopsis of how the current technology can be used in real world applications to provide a safe riding experience for users as well as where the companies are trying to expand involving the safety of their passengers.

4.1.1. Case Study 1

This case study examines Tesla's approach to autonomous vehicle safety. It has a focus on system limitations in adverse conditions, perception, and documented safety issues. Tesla's Full Self-Driving (FSD) and Autopilot systems mainly rely on cameras for perception, which is known as Tesla Vision. According to Tesla's FSD Safety Overview, the system is designed to use neural networks trained on real-world driving data to detect lanes, vehicles, pedestrians, and traffic controls, with frequent over-the-air updates to improve performance over time [35]. The Autopilot Support page further describes that these driver assistance systems are intended to assist an attentive driver, and the driver must be ready to always take over [36]. On the other hand, the camera design means that Tesla's safety performance is very dependent on visibility and the sensor being clean.

Tesla's documents understand the important limitations in challenging environments. The Model 3 Owner's Manuel talks about how the Autopilot may not operate as expected when the cameras are obstructed, dirty, or affected by weather conditions such as fog, rain, snow, or direct sunlight that brings a glare. It also states that drivers should not rely on the system under these circumstances [41]. These limitations directly affect object detection, speed control, and lane recognition. When vision is poor, the system may not work properly to detect obstacles or interpret road markings in time for a safe reaction. Tesla's warnings are made to ensure that drivers understand the system is not designed to handle all weather conditions and scenarios because the cameras may not work properly in these environments [41].

There are crash investigations that highlight how these limitations can contribute to safety failures. The NTSB's detailed investigation of the Culver City crash, in which a Tesla Model S on Autopilot collided with a stationary fire truck. This case found that the Autopilot did not properly detect or respond to the stopped emergency vehicle ahead [39]. The report stated that the system continued tracking a vehicle that changed lanes, and once that vehicle moved, the Autopilot did not identify the fire truck in time, which caused the accident. NHTSA's Autopilot crash investigation EA22-002 includes similar cases where Tesla's with Autopilot engaged struck stationary vehicles on highways, which suggests that there is a recurring pattern of difficulty recognizing stopped or slow obstacles under certain environmental or roadway conditions [40]. These investigations show that even when the system is working as intended, detection delays and misinterpretations can still happen.

Overall, Tesla shows both the strengths and limitations of heavy perception autonomous driving systems. While its neural-network-based approach is helped through continuous data collection and frequent updates, the system's reliance on camera visibility and its lack of sensing redundancy make vulnerability in adverse weather and complex visual environments. The combination of Tesla's own documented findings and limitations from federal crash investigations indicates that environmental conditions and detection latency remain significant safety challenges. This case study supports the research objective by showing how autonomous vehicle safety depends on not only local perception, but also the possible role of complementary systems, such as low-latency communication or additional sensing, in improving reliability under dangerous conditions.

4.1.2. Case Study 2

This case study will examine and analyze Waymo's general safety techniques, the handling of extreme weather, and how Waymo aims to provide riders with a safe and reliable trip under these adverse conditions. Waymo's general safety framework creates a foundation for its extreme weather handling to be built upon. Waymo is one of the largest fully autonomous vehicle systems which allows them to be able to obtain detailed data on different traffic patterns, road constructions, as well as human driving behaviors. Waymo often makes the comparison of performance between the Waymo's automated drive and human driver data across a multitude of fully autonomous driving miles, showing reductions in serious injury crashes and low rates of significant collisions shown in **Figure 1** [29]. They also consistently use independent analyses, performance comparison, and accident review processes to ensure that their safety models are up to date and refined. This structure that they have in place is a strong foundation for constantly improving and expanding their safety model to handle different scenarios, one of which being navigating through extreme weather conditions.

Waymo has done a multitude of research, tests, and continuous brainstorming to ensure that their AVs are using the safest and most reliable approach for handling extreme weather. Their approach starts with transforming every AV into a mobile sensing node by using cameras, LiDAR, and radar signals which allows the AV to predict and understand different weather conditions like fog density, visibility levels, and precipitation levels [31]. This data is used to cross-reference with other weather prediction tools to ensure that the AVs prediction is precise and accurate [31]. The weather prediction maps that the AVs generated provide the vehicles with a better analysis that, allowing Waymo's engineers to understand how perception systems work in even minor environmental changes. This same data is given to hyper-realistic simulations to give the Waymo team the ability to repeat and analyze different harsh precipitation weather conditions to continuously refine the perception and navigation technology in their AVs [32].

Waymo also studies and ensures that their hardware advancements can support safer driving experiences in difficult environments. Better and vaster environmental coverage, thermal management, and protective design considerations are key factors in maintaining sensor reliability in difficult weather conditions like heavy rain, dense fog, cold temperatures, and snow [32]. The hardware improvements Waymo implements all go through closed-course stress tests and various large-scale simulations before being released on public roads which allows engineers to show reliability under unexpected conditions [32].

The most important effort for navigating in extreme weather environments that Waymo is studying and working on is their all-weather autonomous driver. This is especially important for those areas in the world that have heavy winters that create harsh driving environments. Right now, Waymo has released vehicles in US locations, Michigan and Upstate New York, because conditions like snow, sleet, slush, and black ice are common and can all happen in one season which creates a rigorous testing environment for Waymo's vehicles [33]. Waymo also has invested in closed-course facilities that can be used to recreate safe and repeatable tests under extreme weather scenarios like losing traction on black ice and heavy snow causing extremely low levels of visibility [33]. These facilities are also used by the Waymo team to create winter conditions during different seasons, allowing them to be constantly testing and refining their all-weather AV [33].

Overall, Waymo and their team of engineers are constantly evolving, improving, and refining their AV models to ensure the safety of their riders in any condition. They create rigorous and thorough tests and simulations under multiple different weather conditions prior to releasing them into the real world for exposure to the elements of real time traffic during these weather conditions. The combination of these methods allows Waymo to be constantly approaching the end goal of providing a safe and reliable, but fully autonomous, driving experience even under extreme weather conditions.

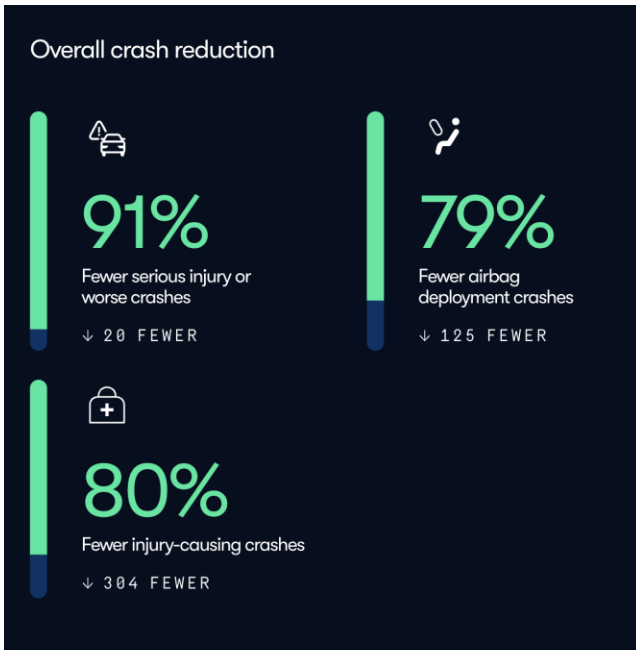
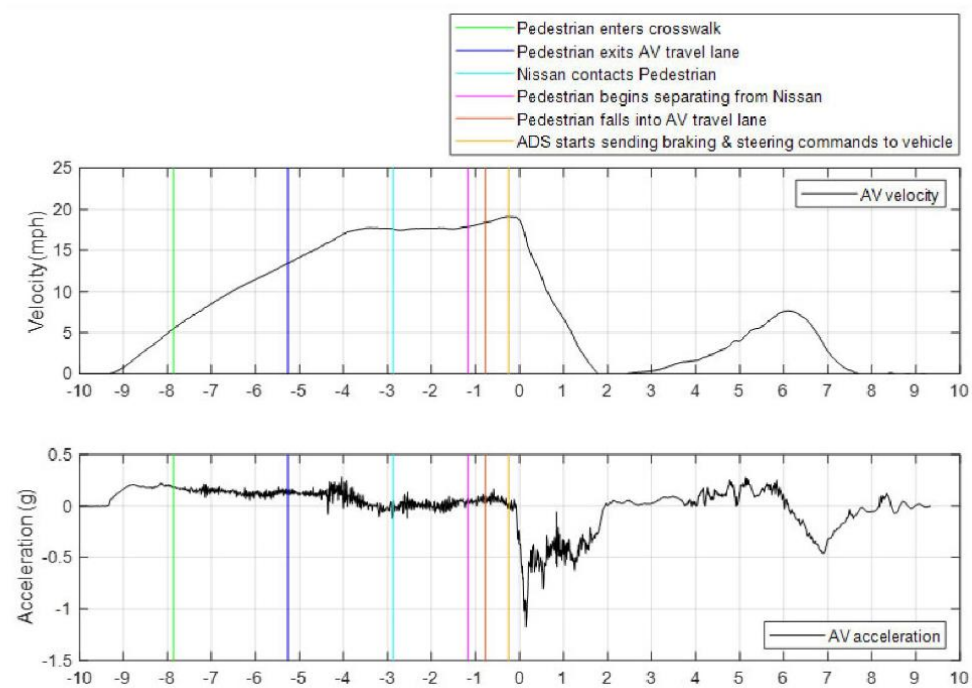


Figure 1: Statistics showing accident and collision rates of Waymo drivers in comparison to Human drivers [29]

4.1.3. Case Study 3

This case study will examine General Motors autonomous vehicles (AVs) subsidiary Cruise and an accident that was caused due to unaccounted for edge cases. Cruise was founded in 2013 and with a focus on autonomous vehicle technology [26]. In 2022 Cruise deployed a fleet of AVs taxis that were available for use in San Francisco for testing purposes. A key safety idea they employed their AVs to operate safely was Operational Design Domains (ODD), a set of conditions in which their autonomous vehicles are designed to function. In the 2022 taxi deployment the vehicles were restricted to a certain area they could operate in, there were also constraints for certain traffic elements such as roundabouts that can present issues to an AV, and specific times to avoid time specific traffic elements [26]. The weather was also a major safety concern, San Francisco was chosen because it receives low amounts of sleet, snow, and sand. Even then AV were designed to return to the main facility or safely exit traffic in poor weather conditions. ODD is used to avoid worse/edge cases that can decrease safety of AVs. Cruise also implements several backups for important systems in case of malfunction or errors; this keeps single part failure from causing catastrophic failures like how planes are designed [26]. Even with these constraints Cruise AVs were removed from San Francisco following several accidents. One of these accidents shows several issues that come with Cruise's safety implementation. On October 2, 2023, a pedestrian was hit by a human operated vehicle then dragged 20 feet by one of Cruise's AVs [27]. The pedestrian entered a crosswalk while they were signaled not to and was hit by a Nissan vehicle and thrown into the pathway of a Cruise Taxi. The taxi failed to properly detect collision location and attempted to enter a Minimal Risk Condition (MRC) [27] defined by Cruise as "a state in which the Cruise AV has minimized safety risks to the extent possible within the driving context" [26]. In doing so It dragged the pedestrian 20 feet before stopping due to vehicle motion abnormality and not due to the pedestrian [27]. Below is a timeline of the vehicle's velocity and acceleration



. *Figure 2. AV velocity and acceleration profiles from EXPR 43.*

Figure 2: AV velocity and acceleration profiles from EXPR 43. [27]

This incident was mostly due to poor implementation of safety. The AV successfully tracked the pedestrian and determined a collision was likely between the Nissan and the pedestrian but did not change behavior due to this prediction [27]. The AV also accelerated into the intersection falling to adhere to California law [27]. Following the collision, the vehicle stopped temporarily and proceeded forward, dragging the pedestrian. A key safety failure here is not fully considering pedestrian behavior. This is especially problematic because the vehicle's prediction did not consider an interruption that would cause the pedestrian to stop and thus accelerated towards the pedestrian. Another key issue is the focus on entering an MRC. After the collision was detected, the vehicle's only focus was to attempt to enter an MRC. This shows that there are less safety considerations following an accident than there are before an accident. Specifically, the vehicle did not consider what it had hit even though it tracked the before and during the accident [27]. Another key issue was the lack of a human overview. The Cruise taxi had no human operation and took 5 seconds to connect to a human operator at which point it was already dragging the pedestrian. This incident also presents an issue with ODD-focused vehicles. Using ODD work to reduce edge cases and make the vehicles more efficient, however, edge cases will still come up and in this case the design response causes untoward harm to a pedestrian. Even if you can constrain so much, there will be unconsidered edge cases that cause accidents like this.

4.2. Examples

There are many examples that could be included in the subject of autonomous vehicle safety. Examples are important as they can paint a concrete and short example that is easier to grasp than an entire case study. These examples still showcase some potential safety challenges and risks an AV could face.

An example of AVs avoiding obstacles on the road is: During rainfall, a pothole in the road fills up with water and causes the camera to believe it is a puddle and will not avoid it which in turn causes a significant bump in the ride and could cause damage to the vehicle.

An example of extreme weather navigation control is: During a drive in Florida, a sudden heavy downpour comes out of nowhere, which causes the sensors and cameras to not be able to adjust quickly enough, but an uncertainty-aware perception system causes the vehicle to immediately increase its following distance and decrease traveling speeds. This example shows the real-time uncertainty-aware adjustment system Majoros et al. [10] introduces.

An example of damage protection for an AV on the road is: During a drive on less maintained back roads loose rocks are skipping up and hitting the sides of the AV, but the AV uses a tough scratch-resistant sensor and camera lenses which blocks the rocks from damaging any of the hardware.

An example showing a key safety consideration for the passengers and the car is: While on a typical drive someone sends a fake GPS signal near a busy intersection making the AV believe the intersection is further than it actually is, causing a potential collision when the AV doesn't stop. This shows the risk of GPS spoofing and how it can increase the risk of an accident.

An example involving fault-tolerant measures is: During a drive the AV senses that the breaking is not as responsive as it should be, as soon as this is detected the AV safely pulls over to the side of the road and alerts the passenger and the AV's operator.

An example of how AI improves safety of AVs is: During a drive on the highway, there is a car in the lane to the right of the AV that is hovering over the lane's marking, AI predicts that the vehicle is going to merge without a blinker, so to improve safety the AV reacts by increasing the gap between the AV and the other vehicle to allow them to merge.

4.3. Discussions and Analysis

Across the three case studies and examples shown in section 4.2, a clear pattern with autonomous vehicles is that they struggle when perception becomes unreliable. Waymo is shown to handle this the best with its multiple sensors and heavy simulation to maintain accuracy in rain, fog, and snow. Cruise limits where the vehicle can operate, but its case study shows that even strict boundaries, unexpected events can still lead to failures. Tesla, which relies on mainly

cameras, shows the most sensitivity to poor visibility. This is shown through several investigations that document late detections of vehicles that are at a complete stop.
The examples of section 4.2 support this trend even more. Fog, traffic congestion, and sensor obstruction all create delays in how fast a vehicle can detect hazards. When detection is delayed, the vehicle has less time to mitigate or avoid obstacles, increasing the change of unsafe events. The overall analysis recommends that autonomous vehicles need stronger support systems when weather or road conditions reduce sensor reliability. Through additional sensing, improved prediction models, or external information sources, AVs must be able to compensate when local visibility and perception become limited. This relates to the project's goals by showing why improving communication and reducing delay is very important for critical AV safety in real-world conditions.

5. Project Self-Evaluation

5.1. Phases and Efforts

This project when through four main phases. The first phase was team creation and organization. This phase focused on creating the team and developing a plan for moving forward and completing all deliverables in a reasonable time frame. The second phase was topic development and scope focusing. This phase focused on reducing the scope of our project and redefining our topic. The third and longest phases were literature review and further topic focusing. This phase focused entirely on gathering and reviewing academic material that would comprise the majority of the paper. This phase also further changed and focused on our topics. The final and shortest phase was paper writing and presentation creation. This phase distilled the information we obtained in the third phase and was when all deliverables were written

5.2. Project Learning Outcomes

Throughout the project, a deeper understanding of the technical environment and human-centered challenges involved in AV safety were gained. Topics such as how communication systems and sensor reliability give a comprehensive perspective into the interactions that support safe AV performance in real-world environments. The research process strengthened the ability to evaluate academic literature to compare approaches and identify gaps that still exist within current AV technology as well as to synthesize the gathered information into a clear analysis. Overall, the project enhanced technical knowledge of AV systems and improved various skills such as collaboration, research, and engineering communication.

5.3. Project Strengths and Limitation

The strength of this project is being able to cross reference and analyze multiple different papers and findings as well as compare them to what is currently being implemented in our case studies. This will allow us to give our contribution to the science and innovation of autonomous vehicles. This study takes in many different sources and combines them into a single place for those looking to find a hub that you can reference to find topics among AV safety that interest you, learn important details about them, understand how they have been implemented or could be implemented, and then further research on a more specific and narrowed down topic. This leads to the limitations of this project, where in this project it is difficult to have many details about one topic when the topic of autonomous vehicles is very broad. The scope was narrowed down, but it would be too much to put a full research focus on each specific topic as it may cause the reader to not be able to retain or finish the paper as that would too much information to be given at one time. To minimize this limitation, we ensure that each section has enough detail to inspire engineers or researchers to want to dive deeper into any of the topics covered.

6. Proposal for Future Work

There are many unanswered and untested questions that arose from this study that we either did not have the time to solve or did not have the resources and budget to test them. One of the most important questions that arose from this study is how to take down the cost of all the sensors, cameras, LiDAR, etc that is needed to create the safe environment that was talked about in previous sections. In section 3.3, we found that multi-modal AVs provide a much safer riding experience in adverse weather because if one of the cameras or sensors failed, there was another that could compensate for this and continue on safely. The issue with this is implementing a multi-modal system can because expensive, especially when trying to use the top-of-the-line and safest technology. Future work could be to find ways to combine different sensors or cameras together or how to manufacture this technology in the most efficient way possible to cut costs to make the product cheaper for consumers. This future work could be aimed to help consumers if AVs are going to be sold directly to consumers or could be aimed to help AV manufacturers and AV taxi services to provide the cheaper rides will still making great profit margins to continue their own research.

Another idea for future research can be researching how AVs can handle combined environments that we studied. The most important topic or combination topics would be how AVs are designed to handle construction and detours while there is heavy rain or snow. This is an important topic because there are many places where road work is common and can be ongoing while adverse weather conditions are also happening. In these situations, how are AVs and AV engineers working to ensure that the optimal detour path is still being followed while also ensuring that you are not putting the passengers at risk by taking a riskier road with less snow plowing or drainage. Also, what takes priority with this is it more important to stay on the shortest path to the destination or avoid back roads and staying on well-maintained roads more importantly. This topic and these questions are important and should be studied, but due to the scope of our research we were not able to fully dive into this hypothetical nor be able to run any type of test or simulation.

A third proposal for future work is researching the lifespan of sensors because this is a very important topic that we did not get to research due to time constraints. In many sections throughout this paper, there was talk about adding or improving different sensors, radars, and cameras, but there was no mention of how long these will last, are they built to withstand multiple years of life, how long will they still send correct signals and data, what happens when dirt builds up, does this affect their sensing ability? These are all questions that need to be answered and studied because technology does not have an infinite life span. Many pieces of technology, especially items like sensors, can start to give false readings and begin to send noise as they get older. So, researching how these sensors are built to withstand time as well as being able to handle dirty sensors efficiently is of the utmost importance. If this isn't researched, how will we know that older AVs with old sensors can be trusted on the roadways?

These are just a few potential options for future work that can evolve from this study. The world of AVs is constantly growing, and the topic of safety will be everlasting, so researching safety problems and finding solutions is very important for the future and AVs right now. As already mentioned, there are plenty of topics and we chose a few that were found throughout our own research, but there are many more that can be discovered.

7. Conclusions

This study was focused on autonomous vehicle safety measures and safety shortcomings. As AVs become more prevalent, these safety measures and shortcomings will become increasingly important. This study highlights important technology, safety concerns, and current problems. This study asked important questions about safety including fault tolerance measures, vehicle protection to reduce wear, extreme weather navigation, obstacle avoidance, potential improvement with applications, and others. This study looked at currently available AVs and their positive improvement and their failings. This study shows the improvement in safety technology for AVs but also showed that there was significgant room for improvement in safety systems.

8. References

1. Al-Sultan, S., Al-Doori, M. M., Al-Bayatti, A. H., & Zedan, H. (2021). A Survey of Autonomous Vehicles: Enabling Communication Technologies and Challenges. https://pmc.ncbi.nlm.nih.gov/articles/PMC7864337
2. Zhang, Y., Chen, M., Mao, S., Hu, L., & Leung, V. C. M. (2018). Networking and Communications in Autonomous Driving: A Survey. https://www.researchgate.net/publication/329820442_Networking_and_Communications_in_Autonomous_Driving_A_Survey
3. Ali, G., Khan, S., & Imran, M. (2021). A Comprehensive Survey on Vehicular Networking for Safe and Efficient Driving in Smart Transportation. https://www.sciencedirect.com/science/article/abs/pii/S2214209621000188
4. U. Yusuf, S. Khan, and R. Souissi, "Vehicle-to-everything (V2X) in the autonomous vehicle domain – A technical review of communication, sensor, and AI technologies for road user safety," *Transportation Safety and Environment*, 2024. https://www.sciencedirect.com/science/article/pii/S2590198223002270
5. Hassan, M., & Nur, R. (2023). Literature Review on the Future of V2X Communication in Connected and Autonomous Vehicles. https://www.researchgate.net/publication/370491938_Literature_Review_on_the_Future_of_V2X_Communication_in_Connected_and_Autonomous_Vehicles
6. Wang, T., & Zhao, Y. (2024). A Literature Review on V2X Communications Security: Threats, Vulnerabilities and Future Directions. https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/cmu2.12778

7. Vargas, J., Alsweiss, S., Toker, O., Razdan, R., & Santos, J. (2021). An overview of autonomous vehicles sensors and their vulnerability to weather conditions. *Sensors*, *21*(16), 5397.

8. Miao, L., Chen, S. F., Hsu, Y. L., & Hua, K. L. (2022). "How does C-V2X help autonomous driving to avoid accidents?" *Sensors*, *22*(2), 686. https://www.mdpi.com/1424-8220/22/2/686

9. Ahangar, M. N., Ahmed, Q. Z., Khan, F. A., & Hafeez, M. (2021). A survey of autonomous vehicles: Enabling communication technologies and challenges. *Sensors*, *21*(3), 706. https://www.mdpi.com/1424-8220/21/3/706

10. Majoros, A., Mühlegg, M., Tauscher, J., Rottmann, M., Dietmayer, K., & Schöneberg, T. (2021). *Uncertainty-aware domain adaptation for reliable all-weather perception.* IEEE Transactions on Intelligent Transportation Systems. https://arxiv.org/html/2508.18630v1

11. Chen, P., Shi, L., Wang, H., & Xu, J. (2021). *Predicting traffic accident risks under extreme weather conditions using machine learning methods.* Accident Analysis & Prevention, 162, 106358. https://doi.org/10.1016/j.aap.2021.106358

12. McCarthy, Z., Choudhury, S., Pertsch, K., Dai, H., Sadigh, D., & Dragan, A. (2020). *Game-theoretic interpretability for safety-critical machine learning.* Proceedings of the Conference on Robot Learning (CoRL), 1555–1570. https://proceedings.mlr.press/v155/mccarthy21a

13. Luo, H., Wang, X., Yin, X., Sun, L., Xie, Y., Peng, X., ... & Hu, J. (2023). *Multi-modal learning for AV perception in adverse weather.* Sensors, 23(18), 7693.

14. Han, K., & Twumasi-Boakye, R. (2024). *Deep learning for weather prediction: A comprehensive review.* Artificial Intelligence Review, 57(3), 4381–4412.

15. Wang, J., Li, Y., Duan, Y., & Qi, X. (2022). *Weather-aware route planning for unmanned vehicles using historical and real-time meteorological data.* IEEE Transactions on Intelligent Transportation Systems. https://doi.org/10.1109/TITS.2022.3142306

16. Zeng, X., Yu, T., & Lin, P. (2022). *Adversarial weather augmentation for robust semantic segmentation in autonomous driving*. Computer Vision and Image Understanding, 220, 103456. https://doi.org/10.1016/j.cviu.2022.103456

17. Li, M., Song, T., Chen, R., & Sun, J. (2023). *AI-powered object detection and trajectory prediction for AV navigation in poor weather.* IEEE Access, 11, 12345–12357. https://doi.org/10.1109/ACCESS.2023.3249532

18. Singh, P., & Islam, M. (2020). Movement of autonomous vehicles in work zone using new pavement marking: A new approach. Journal of Transportation Technologies, 10(3), 183–197. https://doi.org/10.4236/jtts.2020.103012

19. Ansarinejad, M., Ansarinejad, K., Lu, P., & Huang, Y. (2025). *User experience of navigating work zones with automated vehicles: Insights from YouTube on challenges and strengths.* Smart Cities, 8(4), 120. https://doi.org/10.3390/smartcities8040120

20. Cai, M., Kezierbieke, J., Zhong, X., & Chen, H. (2024). *Uncertainty-aware and class-balanced domain adaptation for object detection in driving scenes. IEEE Transactions on Intelligent Transportation Systems, 25*(11), 15977–15990. https://doi.org/10.1109/TITS.2024.3413813

21. G. Muhammad and M. Alhussein. (2022) *Security, Trust, and Privacy for the Internet of Vehicles: A Deep Learning Approach. IEEE Consumer Electronics Magazine*, 11(6), 49-55. https://doi.org/10.1109/MCE.2021.3089880.

22. I. F. Akyildiz, S.-C. Lin, and P. Wang, "Wireless software-defined networks (W-SDNs) and network function virtualization (NFV) for 5G cellular systems: An overview and qualitative evaluation," *Computer Networks,* vol. 93, pp. 66–79, 2015.

23. C. Flores-Moyano and E. Grampín, "SDN and NFV in 5G mobile networks: Advancements and challenges," in *IEEE Latin America Transactions*, 2017.

24. M. Ray and S. Kumar, "SDN/NFV-based edge–cloud IoT system architectures: A systematic review of challenges and future research directions," *Future Generation Computer Systems*, vol. 124, pp. 32–45, 2021.

25. "Cruise." *LinkedIn*, www.linkedin.com/company/getcruise. Accessed 9 Dec. 2025.

26. Cruise LLC. *2022 Cruise Safety Report*. Cruise, 2022, assets.ctfassets.net.

27. Koopman, P. (2024). Anatomy of a Robotaxi Crash: Lessons from the Cruise Pedestrian Dragging Mishap. In: Ceccarelli, A., Trapp, M., Bondavalli, A., Bitsch, F. (eds) Computer Safety, Reliability, and Security. SAFECOMP 2024. Lecture Notes in Computer Science, vol 14988. Springer, Cham. https://doi.org/10.1007/978-3-031-68606-1_8

28. Matos, F., Bernardino, A., & Santos, V. (2024). A survey on sensor failures in autonomous vehicles: Challenges and solutions. *Sensors, 24*(16), Article 5108. https://doi.org/10.3390/s24165108

29. **Waymo.** (n.d.). *Safety*. https://waymo.com/safety/

30. **Waymo.** (n.d.). *Safety impact*. https://waymo.com/safety/impact

31. **Rothenburg, D., James, M., Chen, R. .** (2022). *What's in the forecast: Using cutting-edge weather research to advance the Waymo Driver*. https://waymo.com/blog/2022/11/using-cutting-edge-weather-research-to-advance-the-waymo-driver

32. **Jeyachandran, S.** (2024). *Meet the 6th-generation Waymo Driver*. https://waymo.com/blog/2024/08/meet-the-6th-generation-waymo-driver

33. **Waymo.** (2025). *Creating an all-weather driver*. https://waymo.com/blog/2025/10/creating-an-all-weather-driver

34. P. Koopman and M. Wagner, "Autonomous Vehicle Safety: An Interdisciplinary Challenge," in *IEEE Intelligent Transportation Systems Magazine*, vol. 9, no. 1, pp. 90-96, Spring 2017, https://doi.org/10.1109/MITS.2016.2583491

35. Tesla. (2024). *Full Self-Driving (FSD) Safety Overview.* https://www.tesla.com/fsd/safety

36. Tesla. (2024). *Autopilot Support and System Overview.* https://www.tesla.com/support/autopilot

37. Barzin, R., & Heidari, M. (2023). *Autonomous vehicle perception and LiDAR-based environmental modeling*. https://pmc.ncbi.nlm.nih.gov/articles/PMC10051412/

38. Bai, X., Li, Y., & Guo, S., (2023). *Risk assessment and real-time decision-making for autonomous vehicles under hazardous conditions.* https://www.sciencedirect.com/science/article/abs/pii/S0925753523000334

39. National Transportation Safety Board (NTSB). (2019). *Collision Between a Tesla Model S Operating With Automated Vehicle Control Systems and a Fire Truck, Culver City, California. HAB1907.* https://www.ntsb.gov/investigations/AccidentReports/Reports/HAB1907.pdf

40. National Highway Traffic Safety Administration (NHTSA). (2022). *Autopilot Crash Investigation EA22-002 Supporting Documents.* https://static.nhtsa.gov/odi/inv/2022/INCR-EA22002-14496.pdf

41. Tesla. (2024). *Model 3 Owner's Manual – Autopilot Features and Limitations.* https://www.tesla.com/ownersmanual/model3/en_us/GUID-E5FF5E84-6AAC-43E6-B7ED-EC1E9AEB17B7.html