

The Evolution of Autonomous Driving Technology and Its Ethical Challenges: A Pedestrian-First Perspective

Mohan Wang ^a

Faculty of Computing and Data Science, Boston University, 15 N Beacon St, Unit 428, Allston, U.S.A.


Keywords: Machine Learning and Deep Learning, Sensor Integration, Data Collection and Processing, Pedestrian Safety, Ethical Frameworks.

Abstract: This essay examines the progression of autonomous driving technology, explores its core technical components such as data collection, sensor integration, and real-time decision-making. By integrating cameras, LiDAR, and radar with sophisticated algorithms, modern autonomous vehicles demonstrate markedly enhanced perception and navigation capabilities. However, widespread adoption also raises profound ethical questions. Central to these debates is the dilemma of whether passenger or pedestrian safety should take precedence, especially when accidents pose life-threatening risks. Drawing on utilitarian, deontological, and social contract ethical frameworks, the essay contends that protecting pedestrians represents not only a logical policy choice but also a moral imperative. The discussion underscores the importance of maintaining the inherent dignity of all individuals and ensuring legal and societal acceptance for future implementation. By balancing technological development with robust ethical considerations, autonomous vehicles can move toward broader acceptance and enduring success. Ultimately, the evolution of autonomous driving will be shaped by both technological progress and the ethical principles that guide its adoption. As innovation continues, ongoing discussions and thoughtful decision-making will play a crucial role in shaping its impact on society.

1 INTRODUCTION

In an era of rapid development in artificial intelligence, autonomous driving technology has emerged as an innovative advancement, gradually entering the public eye and becoming a new industry that major automobile manufacturers are actively investing in. Through the use of sensors, artificial intelligence algorithms, data fusion, and high-performance computing, autonomous driving technology enables vehicles to perceive their surroundings, plan routes, and operate safely with little or no human intervention. In its early stages, this technology primarily relied on relatively simple environmental sensing methods and rule-based algorithms, and its functionality was often limited to specific environments or structured roads (Chen et al., 2022; Dhanasingaraja et al., 2014). However, with the emergence of new technologies, such as using high-precision sensors, lidar, and cameras to collect data in real time, autonomous vehicles are now able to

continuously gather information about their surroundings. In addition, the integration of machine learning, deep learning, and path-planning algorithms (including path-based decision-making) enables swift and accurate recognition of, and response to, complex road conditions and rapidly changing external environments (Gerdes & Thornton, 2015; Bimbray, 2015). As autonomous driving technology begins to satisfy most travel needs, merely following traffic regulations is no longer sufficient to ensure its widespread application. Rather, possessing the ability to carry out independent analysis, risk assessment, and optimal decision-making represents the greatest challenge for this technology (Liang, Liu, & Wang, 2024; Martinho, Silva, & Cunha, 2021; Kabir et al., 2025). When accidents endanger the safety of pedestrians, passengers, other vehicles, the environment, surrounding property, or even the autonomous vehicle itself, people are forced to ask: by what standard does the system decide whose interests, or even whose life, should take priority? It

^a <https://orcid.org/0009-0006-6113-0804>

is precisely this profound ethical consideration that underscores the complexity of autonomous driving technology. Against this backdrop, drawing on utilitarianism, deontological ethics, and social contract theory, this essay proposes that the safety of the pedestrian should take priority.

2 HISTORY AND DEVELOPMENT

Tracing back to the mid-20th century, some automobile manufacturers had already begun experimenting with sensing cables, radar, and other methods to achieve simple automated driving functions. In the 1920s, the first radio-controlled car was designed, opening the door to the development of autonomous vehicles. Over the following decades, vehicles with similar electronic guidance systems gradually moved toward the ideal of full automation. "1980s saw vision guided autonomous vehicles, which was a major milestone in technology and till date we use similar or modified forms of vision and radio guided technologies" (Bimbraw, 2015). Entering the 21st century, major companies such as Tesla, Google, Baidu, and other general automobile manufacturers began conducting autonomous driving tests on public roads, accelerating the commercialization of this technology and gradually bringing it to the public and the market. "While there were about 31 million machines with some level of automation in operation around the world in 2019, that number is predicted to rise to 54 million by 2024" (Ignatious, Karthikeyan, & Kumar, 2022). Over the span of five years, this increase of 23 million vehicles fully illustrates the rapid growth of autonomous vehicle market penetration, indicating an expanding consumer demand. Moreover, the positive market conditions have generated highly favorable social impacts. "Although the market dropped by roughly 3% in 2020 because of the economic slowdown induced by the Covid-19 epidemic, the market is expected to rise by about 60% between 2020 and 2023" (Ignatious et al., 2022). This comparison of data shows that the prospects for the autonomous vehicle industry remain very promising. Even in the face of global economic challenges, the industry continues to demonstrate remarkable competitiveness and strong market demand, suggesting that its potential is immeasurable. Furthermore, the post-pandemic economic recovery may introduce a new group of consumers to autonomous vehicle technology, thereby spurring further technological

innovation and creating a positive cycle of development.

3 DATA COLLECTION AND ANALYSIS

3.1 Data Collection

After examining the history of autonomous driving technology, this paper will discuss how autonomous driving technology acquires, processes, and utilizes data to achieve safe and efficient driving. The first step in autonomous driving is data collection; only after gathering data does the process move on to analysis, computation, and other steps. As the foundation of this technology, the architecture of autonomous driving is generally described from two perspectives: a technical perspective and a functional perspective. These respectively refer to the hardware and software layers of the technology, as well as the processes required for analysis and decision-making. Tools familiar to the public, such as cameras and radar, can be classified as sensors, which detect events or changes in the environment and convert them into measurable data. Sensors are often categorized by their transmission range into three types: short-range, medium-range, and long-range. Achieving near-perfect detection typically requires the combined use of multiple sensors. Based on their operating principles, sensors can be divided into two major categories: internal state sensors (such as IMUs, encoders, and GNSS receivers), which measure forces, wheel loads, and vehicle orientation, and external state sensors (such as cameras, radar, and LiDAR), which collect information about the surrounding environment. Passive sensors (e.g., cameras) gather existing energy from the environment, while active sensors (e.g., LiDAR and radar) emit signals and measure their reflections.

Three of the most common and widely adopted external environment sensors are cameras, LiDAR, and radar. Cameras, as one of the most extensively applied technologies for environmental observation, are used not only in autonomous vehicles but also in everyday cars—for example, in rearview systems, 360-degree surround-view systems, and dashcams. The operating principle of a camera is: "A camera produces crisp images of the surrounding by detecting lights emitted from the surroundings on a photosensitive surface (image plane) using a camera lens (placed in front of the sensor)" (Ignatious et al., 2022). This technology boasts low cost and can

recognize both static and dynamic obstacles simultaneously, although the data acquired may sometimes experience relatively higher latency. The second technology is LiDAR, first developed in the 1960s, which estimates the distance between the reflected objects and the sensor by emitting infrared or laser pulses. Its advantages include the ability to conduct detection and estimation in three dimensions, as well as providing intensity information about the reflected objects. Radar operates on principles similar to those of LiDAR, emitting electromagnetic waves toward a target area and determining the target's relative speed and position by receiving the reflected waves. It's easy to see that combining the functions of these three types of sensors creates a solid framework for detecting obstacles and gathering related information. By integrating sensor data with advanced software and computing systems, autonomous driving technology can reduce reliance on human input while enhancing overall efficiency and safety. As a prerequisite and foundation for all subsequent calculations and processes, data collection, along with robust and reliable environmental evaluation and detection, warrants significant attention. After all, one of the highest potential risk factors to others on the road is the presence of other vehicles. The ability to accurately and promptly perceive and identify the surrounding environment is critical to ensuring the safety of passengers, pedestrians, and the vehicles themselves. Only by predicting potential danger can the system respond accordingly based on given instructions. Equipping an autonomous vehicle with a comprehensive data-capturing system can greatly reduce safety risks, earn greater public trust, and ultimately expand its marketing potential.

3.2 Target Detection

After discussing the data collection techniques in autonomous vehicles, another critical aspect is object detection. Vision-based object detection can generally be categorized into three types: traditional techniques, machine learning, and deep learning. This paper focuses on the roles of machine learning and deep learning in autonomous driving. As a highly popular topic in artificial intelligence and computer science in recent years, machine learning primarily operates by using data and algorithms to split data into training and testing sets, thereby emulating human learning processes and gradually reaching minimal error through continual learning and training. When applied to autonomous vehicles, machine learning typically involves two key steps:

first, inputting and processing images to obtain a region of interest (ROI), and then transforming and encoding the extracted images, converting high-dimensional image-space data into lower-dimensional data, all while continuously refining this process through training and optimization.

First, during the feature extraction step, various methods, such as Histogram of Oriented Gradients (HOG), Haar-like descriptors, Local Binary Patterns (LBP), Gabor filters, and Speeded-Up Robust Features (SURF), are commonly used to capture recognizable vehicle traits. These approaches help identify consistent patterns that remain reliable when the vehicle's orientation or model changes. Some techniques, like the Deformable Part Model (DPM), further refine HOG features to deal with more complex shapes. In the classification stage, algorithms like AdaBoost, K-Nearest Neighbors (KNN), Naive Bayes, Support Vector Machines (SVM), and Decision Trees are often employed. Each classifier must balance how well it fits its training data with how effectively it adapts to new inputs. Ensemble learning, which merges multiple classifiers, can enhance overall detection performance. A key challenge is the high computational cost of searching the entire image for potential vehicles. To address this, many systems focus on areas of interest, such as identifying shadows or other cues, before running feature extraction and classification. This targeted approach can significantly reduce processing time while maintaining reliable detection.

Another object detection algorithm is deep learning. Because machine learning's reliance on feature extractors and classifiers can limit a model's capabilities in certain scenarios, the rise of convolutional neural networks brought significant attention to deep learning algorithms, making them more suitable for object detection methods in the field of computer vision. Typically, deep learning-based object detection methods are divided into object detection-based approaches and segmentation-based approaches. First, the object detection-based approach can be categorized into three types: anchor-based detectors, anchor-free detectors, and end-to-end detectors. The key difference between anchor-based and anchor-free detectors is that anchor-based detectors predefine bounding boxes to detect objects by partitioning and categorizing vehicles in proposed regions, then predicting the vehicle's center and bounding box. Anchor-free detectors directly predict the object's center point and then cluster them into a single entity to obtain the bounding box. Some models derived from YOLO play a crucial role in

both anchor-based and anchor-free detectors, while others like FSAF and FCOS use different detection methods. End-to-end detectors can be viewed as a derivative and evolution of anchor-based detectors, but they operate more directly. They do not require complex preprocessing or postprocessing and only need to analyze the input image to determine the target's category and location. The second approach is the segmentation-based method. Compared to simpler target-level detection, semantic segmentation assigns a category to every pixel in an image, giving a more precise representation of vehicles' positions and shapes—crucial for autonomous driving. Traditionally, vehicle segmentation has followed a region-based approach that mirrors two-stage object detectors: first, candidate areas are proposed, and then a classifier labels the pixels within those regions. Models like DeepMask, SharpMask, MultipathNet, and Mask R-CNN exemplify this process by refining region proposals before creating segmentation masks. Although this can produce high-quality results, it also increases computation time, making real-time deployment more challenging. Consequently, ongoing research aims to balance accuracy with faster processing, ensuring that segmentation can meet the demands of autonomous systems on the road.

4 ETHICAL PROBLEMS

4.1 Utilitarianism

After analyzing the basic operation of autonomous vehicles, the next important factor is the ethical problem arising with it. Given the significant potential risk and direct involvement of human life in both situations, the most contentious issue is whether pedestrian or passenger safety should come first. "An ethical theory that is based on the principle that our policies and laws should be such that they produce the greatest good (happiness) for the greatest number of people" (Tavani, 2016), which also implies to minimize the total harms, is how Tavani describes it from a utilitarian standpoint. Pedestrians are usually the most vulnerable individuals in an accident. They are much more likely to suffer severe injuries or die without any kind of protection, such as seat belts, airbags, or a car frame, and the level of damage they endure is greater than that experienced by someone inside a car. Pedestrians are therefore the most vulnerable population in these situations, with the greatest risk of suffering serious injury. Prioritizing pedestrian safety reduces total suffering by

preventing fatalities, according to the utilitarian ethical framework.

Additionally, rule utilitarianism calls for the analysis of broader societal ramifications and rule-based requirements, both of which are strongly backed by the field of legal accountability. For example, Massachusetts law clearly states that cars have an obligation to stop for pedestrians using a crosswalk in order to safeguard them. Therefore, adhering to these regulatory requirements is consistent with building autonomous cars using the "pedestrians-first" approach. The concern that robots may prioritize passenger safety over the protection of innocent pedestrians is a common source of public anxiety about autonomous driving. Since there are generally more pedestrians than passengers on the road, putting pedestrian safety first would greatly allay public concerns and skepticism. It would increase the long-term potential for autonomous vehicle development, improve traffic flow efficiency, and save public resources, which are essential to maximizing overall benefits.

4.2 Deontology

Next, Tavani then discusses Kant's categorical imperative from the perspective of rule deontology, saying: "Adhere always to that maxim or principle (or rule) that guarantees that all individuals will be treated as ends-in-themselves and never merely as a means to an end" (Tavani, 2016). Kant's other version of the categorical imperative, which states, "Act always on that maxim or principle (or rule) that can be universally binding, without exception, for all human beings" (Tavani, 2016), fully addresses the idea that an action is just if it respects each person's autonomy and treats them as an end in and of themselves rather than as a means. In the event that an autonomous vehicle is configured to put the safety of its passengers first, the risk is unintentionally transferred to pedestrians, who never agreed to take that risk. The fundamental tenet of rule deontology is violated when potential injustice is created.

A similar example may be found in commercial aviation, where planes frequently fly for large portions of the journey on a quasi-autopilot system. In fact, accidents caused by this technology have happened in the past. It is completely legitimate for someone to choose a slower or less convenient form of transportation over an autonomous system in order to lessen personal danger. Going back to autonomous cars, people who believe the manufacturer's safety assurances can travel more conveniently, but they also have to accept the potential for increased risk that

comes with new technology. If manufacturers allow a "passenger-first" policy, people who trust the technology will benefit from its ease while simultaneously shifting the risk of the system on those who are less sure and have avoided it. Since each person should be seen as an independent creature with inherent dignity, this effectively gives the technology a kind of supremacy, breaking the deontological necessity that prohibits using others just as a means. Therefore, rather than shifting risks on uncooperative bystanders or exploiting the safety of others for profit, the people can only force automakers to improve the technology itself by prioritizing pedestrian safety.

5 CONCLUSIONS

In summary, autonomous driving technology has advanced from early rule-based trials to complex systems that combine deep learning, machine learning, and high-precision sensors. Data collection and processing, which are crucial for perception and decision-making in real time while driving, are at the heart of this evolution. With the help of sophisticated algorithms, cameras, LiDAR, and radar combine to provide cars the ability to recognize and react to challenging driving situations more accurately than ever before. However, ethical issues inevitably arise as the technology advances and becomes more well-known. The crucial issue is how to put safety first, especially for vulnerable pedestrians and the occupants of the car, without violating people's rights or placing unwarranted risk on onlookers. Using ethical frameworks like utilitarianism and Kant's rule deontology, this essay emphasizes how prioritizing pedestrian safety maintains both the inherent dignity of every person and more general societal norms and legal requirements. By doing this, autonomous driving may keep moving forward toward broader acceptance and financial success while preserving a fair balance between the welfare of the general population and technological growth.

REFERENCES

- Bimbraw, K. 2015, July. Autonomous cars: Past, present and future a review of the developments in the last century, the present scenario and the expected future of autonomous vehicle technology. In 2015 12th International Conference on Informatics in Control, Automation and Robotics (ICINCO) (Vol. 1, pp. 191-198). IEEE.
- Chen, R., Hu, J., & Xu, W. 2022. An RRT-Dijkstra-based path planning strategy for autonomous vehicles. *Applied Sciences*, 12(23), 11982.
- Dhanasingaraja, R., Kalaimagal, S., & Muralidharan, G. 2014. Autonomous vehicle navigation and mapping system. *International Journal of Innovative Research in Science, Engineering and Technology*, 3(8), 15468–15474.
- Gerdes, J. C., & Thornton, S. M. 2015. Implementable ethics for autonomous vehicles. In M. Maurer, J. C. Gerdes, B. Lenz, & H. Winner (Eds.), *Autonomous Fahren* (pp. 87–102). Springer Vieweg.
- Ignatious, H. A., Karthikeyan, P., & Kumar, R. 2022. An overview of sensors in autonomous vehicles. *Procedia Computer Science*, 198, 736–741.
- Kabir, M. M., Kaur, M., & Kassim, A. A. 2025. Terrain detection and segmentation for autonomous vehicle navigation: A state-of-the-art systematic review. *Information Fusion*, 113, 102644.
- Liang, L., Liu, Y., & Wang, Y. 2024. Vehicle detection algorithms for autonomous driving: A review. *Sensors*, 24(10), 3088.
- Martinho, A., Silva, J. A., & Cunha, J. F. 2021. Ethical issues in focus by the autonomous vehicles industry. *Transport Reviews*, 41(5), 556–577.
- Tavani, H. T. 2016. *Ethics and technology: Controversies, questions, and strategies for ethical computing* (5th ed.). Wiley.