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Review Article

# Drawbacks of Employing Self-driving Automobiles

[1]Danladi King Garba, [2]Muhammad Baballe Ahmad*, [3]Aminu Hussein, [4]Nuhu Adam Sulaiman

[1]Department of Mechanical Engineering, Nigerian Defence Academy (NDA), Kaduna, Nigeria.
[2]Department of Mechatronic Engineering, Nigerian Defence Academy (NDA), Kaduna, Nigeria
[3]Department of Mechanical Engineering, Kano State Polytechnic, School of Technology, Kano, Nigeria.
[4]Department of Mechatronics Engineering, Kano State Polytechnic, School of Technology, Kano, Nigeria.

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***Corresponding author:** Muhammad Baballe Ahmad
Department of Mechatronic Engineering, Nigerian Defence Academy (NDA), Kaduna, Nigeria
**ORCID:** 0000-0001-9441-7023

## Abstract
An autonomous car (AC), driverless car (DC), robotic car, or self-driving car is a vehicle that can operate with little to no human input. All aspects of driving, such as observing the surroundings, keeping an eye on critical systems, and operating the vehicle including navigating from one place to another are handled by self-driving cars.

**Keywords:** Navigating, Detection, Traffic, Obstacles, Autonomous Cars.

## I. INTRODUCTION

The automotive industry is undergoing significant changes due to the swift advancement of self-driving car technology, which has the potential to completely transform transportation. A nation's progress and prosperity are reflected in its transportation system. But it also leads to a number of major issues, like traffic congestion [18] and accidents [15–17]. In the first quarter of 2021, there were 3,206 traffic accidents nationwide, resulting in 1672 fatalities. Intoxication, exhaustion, and imprecise vehicle control are subjective factors that affect drivers of motor vehicles. One of the most important functions for smart cars is the detection of obstacles [19–29] and lane recognition. They have a direct impact on how people drive. When a driver uses a smart vehicle that uses lane recognition to determine its exact location on a road, they can steer it effectively. The efficiency and safety of driving are greatly increased by obstacle recognition [29], which includes information about the location and separation from other intelligent cars or animals on the road, as well as object recognition [18], which includes traffic lights and signs. Radio, sound, and light sensors like LiDAR and RADAR are used to do these tasks. A prototype vehicle that is capable of autonomous movement within its surroundings is called a self-driving car. Road-based image processing is required to accomplish the goal. In addition to kinematic modeling for car mathematical approaches [1-3], several research groups have demonstrated methods for determining the turning angle of the car prototype and have achieved impressive results on this task [1-6]. This research delves deeper into the direction control design, which is designed with greater simplicity, as per the explanation provided in the aforementioned paper and journal. The purpose of direction control in a car prototype is to ascertain its direction of motion. The turning angle of a car prototype toward the trajectory determined by the image processing technique is the outcome of the direction control.


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**Fig. 1: A model of Self-driving Car**

## II. RELATED WORKS

The performance evaluation of real-time object detection in YOLOv8 models—a cutting-edge deep learning framework for autonomous vehicles operating in mixed traffic environments—is presented in this paper. The aim of this study is to evaluate the potential applications of YOLOv8's object detection capabilities for self-driving cars in intricate real-world traffic situations. According to the experimental results, YOLOv8's accuracy in typical daylight scenarios ranges from 0.60 to 0.80. The accuracy values found in nighttime scenarios, on the other hand, range from 0.15 to 0.25. In a similar vein, the YOLOv8 models' F-measure in daylight conditions varies from 0.75 to 0.87. On the other hand, the F-measure during the night ranges from 0.27 to 0.46. Our extensive evaluation results show that YOLOv8 is robust when it comes to object detection. To properly handle the difficulties faced by autonomous vehicles' object detection systems in mixed traffic, including different object classifications, small-scale objects, objects moving quickly, blur, glare, and low-light illumination, especially at night, the algorithm needs to be improved [7]. Semantic segmentation and object detection were the two main tasks that this paper focused on while reviewing the recent literature on autonomous vehicle perception (AVP). Both jobs are essential to the functioning of the car's navigation system. A thorough review of deep learning for perception is presented, along with an explanation of how it makes decisions using point clouds from LiDAR and images. We talked about the sensors, benchmark datasets, and simulation tools that are frequently used for tasks related to object detection and semantic segmentation, particularly in autonomous driving. This work serves as a roadmap for both present and upcoming AVP research, emphasizing models, evaluation, and field obstacles [8]. This paper offers several metrics to assess the classification performance in different environmental conditions and introduces a new approach for analyzing the robustness of semantic segmentation models. To increase system integrity and automate the process, a lidar sensor is added, which removes the need for tedious manual validation data labeling. The experimental results are shown based on several datasets that were gathered in various environmental conditions and at various times of the year. To illustrate the ideas, we extract the Road class using the lidar; however, this could be extended to other classes using different feature detection algorithms. These findings demonstrate how different weather conditions, camera settings, and shadow presence affect semantic segmentation performance. The outcomes also show how metrics can be used to evaluate and compare performance following model modifications and to compare the effectiveness of various networks [9]. In this work, we present the application of semantic image segmentation to improve object perception and classification, as well as road and lane marking detection, for an autonomous ground vehicle based on LiDAR data. In order to accomplish this, we used a Formula SAE Electric car equipped with LIDAR as our test bench, and we mounted and calibrated a cheap monocular camera on it. To confirm the viability of semantic segmentation, tests were first conducted on local road video recordings. Later, tests were conducted on the Formula-SAE car using LIDAR readings. The road areas in every video frame were correctly segmented, and the classification of road edges and lane markers was validated by the semantic segmentation results. By combining this information with LIDAR measurements for road edges and obstacles, distance measurements for each segmented object can be obtained, thereby allowing the vehicle to be programmed to drive autonomously within the road lanes and away from road edges [10]. In the future, mixed-flow traffic will unavoidably result from the coexistence of human-driven vehicles (HDVs) and connected and autonomous vehicles (CAVs) on the roads. The diverse car-following (CF) conduct exhibited by HDVs has the potential to deteriorate the control efficacy of CAVs and introduce operational inefficiencies. It is essential to understand HDV CF behavior in mixed-flow traffic in order to address these issues. This study examines the behavior of HDV CF in mixedflow traffic under three different CAV control settings (string-stable, string-unstable, and HDV-like), using a driving simulator. Demographic traits and the degree of traffic congestion have an impact on CF behavior as well. To investigate the effects of these factors on string stability, traffic efficiency, and safety, statistical analysis and CF model calibration are carried out using trajectory data gathered from 72 participants in driving simulator experiments. Next,


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online parameter estimation is carried out to show the sensitivity to spacing and speed variations and the time-varying desired time headway (i.e., CF behavior evolution). Further analysis of eye-tracking data and post-experiment interview results reveals that most HDV drivers prefer the string-stable CAV control setting, which can cause driver distraction. The results also provide insights for CF behavior prediction and the optimal mixed platoon formation to enhance CAV benefits for traffic flow [11]. The development of a cooperative control approach for autonomous vehicles enables them to execute various intricate traffic manoeuvres, such as double lane switching or intersection scenarios. In order to make the problem computationally feasible in real-time, the distributed approach is used to formulate the problem as a distributed optimal control problem for a system of multiple autonomous vehicles. The problem is then solved using a nonlinear Model Predictive Control (MPC) technique. A collision avoidance constraint is introduced, likewise distributedly, to ensure safety. According to the suggested approach, each car uses the estimated states of nearby vehicles to calculate its own control inputs. Furthermore, a compatibility constraint that balances collision avoidance with preventing each vehicle from substantially deviating from what other vehicles expect of it is defined. We can create a cost function for a variety of traffic scenarios using this method. If there are no uncertainties or disturbances, the system's asymptotic convergence to the intended destination is demonstrated for a small enough MPC control horizon. The distributed algorithm scales well with an increasing number of vehicles, according to simulation results [12]. The measured turning angle range of 60 degrees to 120 degrees is made possible by the direction control design. The average angle read on the 90-degree lane is 90.4198 degrees, with an average error of 1,086 degrees, based on the turning angle test for the straight, right, and left turn lanes. With an average error of 3.03727, 3.62493, and 3.0636296 degrees, the average angles that are read on the 100-, 110-, and 120-degree lanes are 99.5502, 112.96973, and 117.0711 degrees, respectively. With average errors of 1.61674, 1.88093, and 1.48696 degrees, the average angles that are read on lanes 60, 70, and 80 degrees are 58.7540333, 71.218, and 80.1277667 degrees, respectively [13]. In this regard, the current study uses vehicle trajectory data based on relative speed and position to segment vehicular response into driving regimes. Formulating acceleration models involves incorporating driving regimes and how they interact with various traffic attributes. The following behavioral differences between cars and two-wheelers are studied using these models. The suggested models produce a much better fit and more accurate depiction of mixed traffic since they capture the asymmetric behavior and take into consideration variations across driving regimes [14]. The study discusses two primary issues: using image processing algorithms to detect obstacles (such as traffic lights, road signs, oncoming cars, etc.) and lanes. Lane and object detection algorithm barriers for smart traffic are proposed as solutions to issues like low detection accuracy of traditional image processing methods and poor real-time performance of methods based on deep learning methods. Prior to applying a threshold algorithm for the lane detection algorithm, we convert the camera-caused image distortion. Then, a region of interest is extracted, and an inverse perspective transformation is applied to determine the image with a top-down view. In order to identify the pixels that belong to each lane, we finally apply the sliding window method and modify it to fit a quadratic equation. Numerous kinds of obstacles can be identified by the YOLO algorithm for identification problems. Lastly, we run simulations for the suggested algorithm using real-time videos and the TuSimple dataset. Based on the simulation results, the proposed method has a 97.91% accuracy rate in lane detection and a processing time of 0.0021 seconds. The proposal has an 81.90% accuracy rate in detecting obstacles, and it takes 0.022 seconds to process. The suggested method has a strong anti-noise ability; when compared to the traditional image processing method, its average accuracy and execution time are 89.90% and 0.024 seconds, respectively. The outcomes demonstrate that the suggested algorithm can be used for advanced network systems with high processing speeds, such as self-driving car systems [15]. The answer lies in autonomous cars that can drive themselves, strengthening the mobility intelligence that comes with using them. This project offers a practical means of implementing a self-driving car. Neural networks, computer vision, and artificial intelligence form the main foundation of the proposed work. We're using a lot of features in our assignment, including planning, monitoring, and mapping. We can effectively construct a car that can exhibit correct lane changes, parking, and U-activate its own. Our unique improvements include street car tracking, barriers and reduction detection methods, and monitoring traffic conditions at unique sites. This will result in a strong, unbiased, self-propelled car. It will successfully display automated U-turns, lane changes, and appropriate parking allocation. The obstacle and various diminish detection methods, like the car tracker, can be used to achieve that. In order to comprehend their surroundings, self-driving motors incorporate a variety of sensors, such as GPS, lidar, sonar, radar, odometry, and inertial length devices. Cutting-edge management systems decipher sensory statistics to pinpoint suitable navigation routes, obstacles, and relevant signage. It is evident that long-distance trucking is at the forefront of implementing and embracing the technology. We employ artificial intelligence to identify and display the path that the autonomous vehicle must traverse in order to function properly. Furthermore, because an autonomous car will take the shortest route possible and avoid traffic, it can arrive at its destination faster. It is possible to prevent human error and allow people with disabilities—including the blind—to own their own car [30]. The goal of this research is to increase vehicle efficiency and safety. Although the idea of self-driving cars has been around for a while, the lack of full intelligence in the vehicle has prevented it from being used in many countries. Certain contemporary cars have partially automated features like speed limits, lane-keeping assistance, and emergency braking. Statistics show that failure to react quickly enough to traffic signs and impending obstacles is the main cause of accidents. This issue can be solved in the case of a self-driving car by employing a high-end camera to detect traffic signals. By recognizing traffic signals and obstructions, the real-time traffic sign detection model achieves its goal. To accurately detect the signals, an open


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computer vision library is utilized to process the image and find patterns in it, using a high-end camera for image capture and a Raspberry Pi 3 for hardware. To detect obstacles, an ultrasonic distance sensor is employed [31]. This thorough analysis examines the most recent developments in autonomous vehicle prototypes, primarily concentrating on their realworld performance, hardware, and software. After a thorough analysis of the body of literature, we pinpoint critical issues and identify gaps in the state of the art for autonomous vehicle research. From a methodological perspective, we give a thorough explanation of the steps taken to design and test a novel self-driving car prototype, including the incorporation of cutting-edge sensors, algorithms, and data sources. We talk about extensive testing and validation protocols while adhering to the ethical principles that are fundamental to the development of autonomous vehicles. The results of our research provide important new information about the limitations and capabilities of the developed self-driving car prototype. We provide an in-depth understanding of the prototype's practical performance through a thorough analysis supported by data, graphs, and performance metrics. In the following discussion, we assess the importance of these results by comparing the performance of our prototype with well-known solutions. We discuss the constraints and difficulties that arose during the development stage and outline a path forward for further study, emphasizing the wide range of possible uses for self-driving car technology. This work makes a significant contribution to the constantly expanding body of knowledge in the field of autonomous vehicles. It creates a crucial point of reference for researchers, industry experts, and legislators to use when navigating the ever-changing landscape of autonomous vehicle technology [32].

## III. Cons of Self-Driving Cars

### 1. SECURITY ISSUES

Potential hacking is one of the drawbacks of self-driving cars. Automated vehicles would need to use the same network protocol in order to communicate and work together. However, if a lot of cars are connected to the same network, they could be hacked. On busy roads, even a tiny hack could cause major damage by causing accidents and traffic jams.

### 2. JOB LOSSES

The advent of self-driving cars may render driving as a means of employment obsolete for those who rely on it. All truck drivers, including bus and taxi drivers, will need to look for new jobs. Automated cars would also replace Uber drivers and people who deliver fast food.

### 3. INITIAL COSTS

Long-term cost savings for society could be substantial from self-driving cars, but their initial cost could be enormous. According to some experts, owning a fully autonomous car could cost an extra $250,000 per vehicle. Of course, costs should decrease as new technology develops. However, the initial entry barrier might be too great for the majority of people.

### 4. MORAL MACHINE DILEMMA

An additional drawback of autonomous vehicles is their incapacity to distinguish between various undesirable consequences. What would happen, for instance, if a self-driving car was faced with only two options:

Veering to the left and striking a pedestrian.

or

Veering to the right and hitting a tree, potentially injuring passengers inside your vehicle.

Which option would the autonomous car pick if both were undesirable? By gathering information on actual people's decisions, a team at MIT is attempting to address this problem with the Moral Machine. Nevertheless, the data gathered reveals wide variations across various demographic groups, making it challenging to program a conclusive solution for driverless vehicles.

### 5. MACHINE ERROR

A consideration of machine error is necessary when weighing the benefits and drawbacks of autonomous vehicles. Even though most people believe that self-driving cars will probably reduce the number of accidents that occur, machine error-related accidents are still a possibility. Furthermore, an autonomous vehicle may put the driver in greater danger than if the driver took manual control of the vehicle if the software or any other component of the vehicle malfunctions [34].

## Conclusion

Numerous articles about self-driving cars were reviewed for this study. The benefits of using technology and its advancements have been shown by our review of the literature [33]. A list of the advantages of driverless cars can be found in [35]. Also covered in-depth are the drawbacks of employing self-driving automobiles.

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