# DRIVING INTO THE FUTURE: HOW DATA SCIENCE POWERS AUTONOMOUS VEHICLES


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# 1. ABSTRACT

As reported in numerous studies and industry reports, data science has an indisputably substantial impact on a wide range of industries. Making educated judgements and increasing efficiency, it is essential in altering industries including healthcare, banking, manufacturing, retail, and e-commerce. This revolutionary force is also present in the automobile industry, which everyday deals with massive data influxes. The automobile industry uses data science in a number of areas, including product development, marketing and sales, manufacturing, supply chain management, and financing and insurance. However, the focus of this article will be on the innovative fields of autonomous vehicles, where data science and artificial intelligence collaborate to orchestrate these astounding advancement in the automotive industry. We will examine the advantages, these technologies claim to offer, from improved user experiences and higher safety to more efficiency. We will also discuss any possible concerns these technologies could pose. This thorough investigation will shed light on the complex issue of how data science is being used in autonomous car technologies, which is a double-edged sword.

# 2. INTRODUCTION

Data science employs a range of tools, algorithms, and machine learning techniques to uncover hidden patterns in raw data. In order to improve comprehension of various factors and have an impact on decision-making, these patterns can then be utilised. The "why" underlying a data is revealed via data science, which goes beyond simple number crunching. Utilising vast amounts of data to anticipate behaviours and derive meaning from meaningfully connecting facts, data science is the key to turning knowledge into action. Data science is assisting businesses in maximising creativity by helping them do anything from identify the best clients and set the proper rates to effectively allocate resources and reduce work-in-progress and inventory [1]. Data science provides great prospects for companies to flourish as a result of the proliferation of information. Through data science, firms in health care, finance, energy, media, and other industries are uncovering insights from huge data that help them make strategic choices and optimise results. Data science is transforming various sectors. Revenue margins are improving as operational efficiency rise [2]. The automobile industry, too, has embraced this transformation, harnessing the data collected on a daily basis to effect huge changes in the landscape of the business. Every stage of the automobile product life cycle involves data science [3][4][5]. Data mining and artificial intelligence are progressively influencing every element of development, procurement, logistics, and manufacturing. This also includes marketing, sales, after-sales retail, and the future notions of connected customers and autonomous vehicles [6]. This article concentrates on autonomous vehicles—to examine the advantages they provide and to provide a balanced discussion, we simultaneously bring to light possible problems these technologies can cause.

## 3. AUTONOMOUS VEHICLES

Autonomous vehicles are those that can move and comprehend their surroundings without the assistance of a human driver [7][8]. Other names for these vehicles include self-driving, robotic, unmanned, and driverless [7][9]. There is no denying the growing interest in autonomous vehicles. In a 2015 survey, the Boston Consulting Group found that 44% of prospective car buyers would be interested in purchasing a completely autonomous vehicle and 55% of respondents stated they would be interested in purchasing a semi-autonomous vehicle [10]. To accommodate this demand, almost all of the major automakers are engaged in production. An international research firm called HIS estimates that the market share of 4th and 5th level autonomous vehicles will be 0.004% (4,200 cars) in 2020, which will increase up to 0.5% (578,000 cars) in 2025, and 3.8% (4,503,000 cars) in 2030 [11].

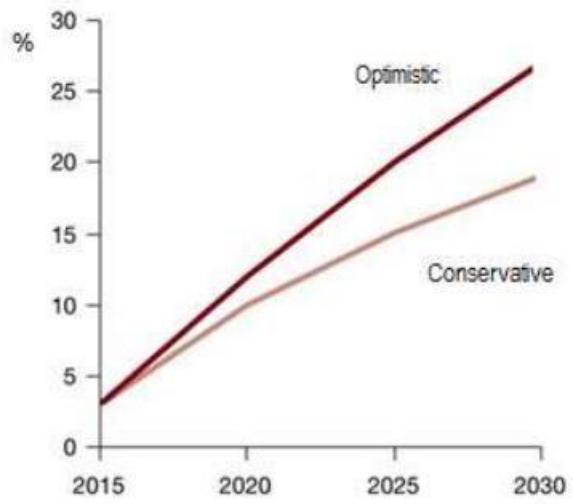


Figure 1. Market penetration of automated vehicles [7][11].

**3.1 Levels of Autonomous Driving:** In 2016 The Society of Automotive Engineers (SAE) International updated its terminology for autonomous cars originally released in 2014 and specified their levels in relation to their automation grade (figure 2)[12]. A 0–5 scale for assessing vehicle automation is introduced by the SAE J3016 standard [13]. Basic driving assistance is offered by vehicles with lower SAE Levels, and completely autonomous vehicles are the goal of higher SAE Levels. Level 5 vehicles are those that don't even need a steering wheel or foot pedals and don't even require any human input.

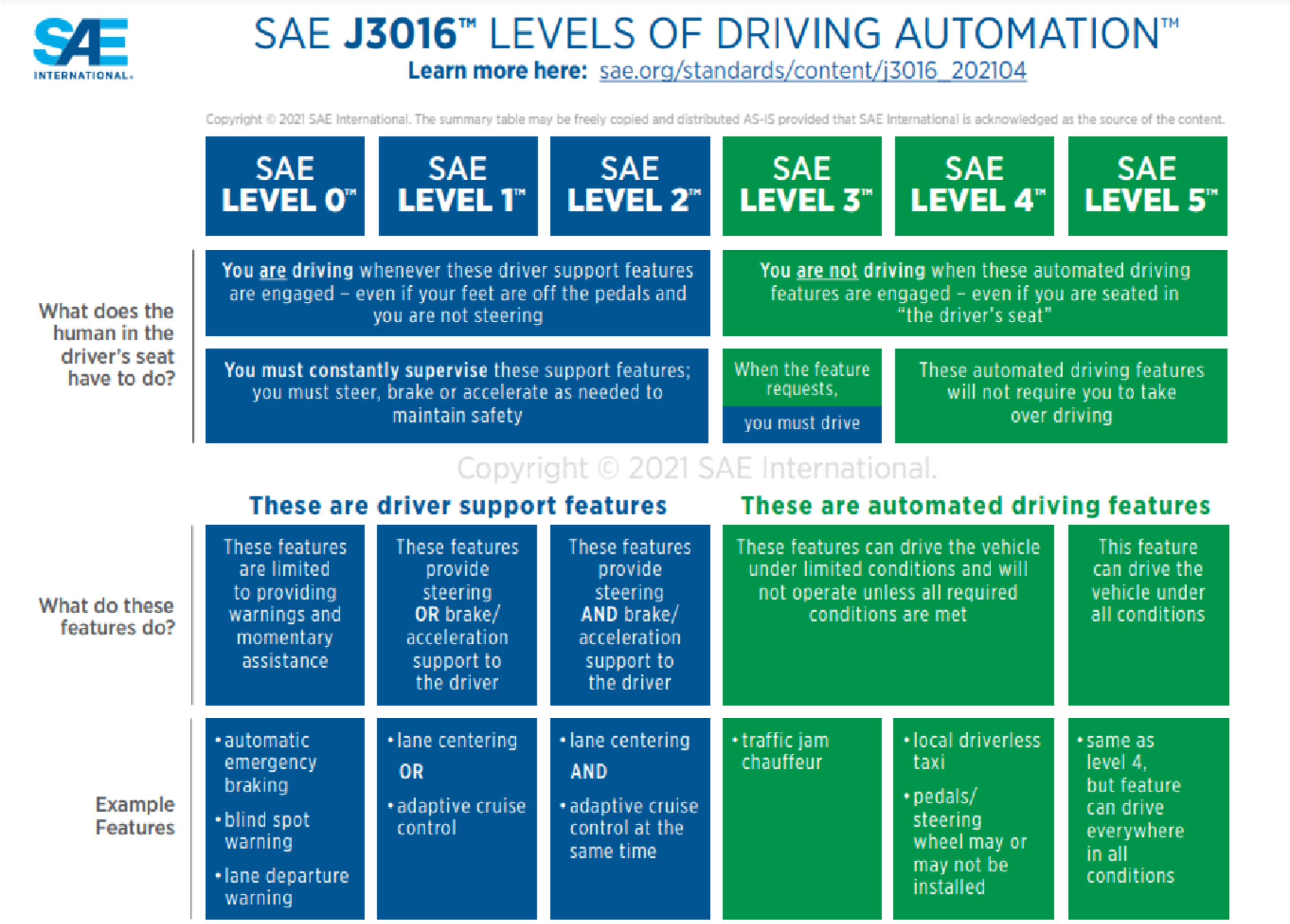


Figure 2. SAE Levels of Driving Automation [12].

**3.2 Role of Data Science and Deep Learning**: The research and testing of autonomous vehicles (AVs) and self-driving vehicles began in laboratories, but they have already moved to actual road use. Their implementation in the environment enables a reduction in traffic jams and accidents, as well as an enhancement of mobility in crowded cities [14]. In the 1980s, Ernst Dickmanns [15] created one of the earliest autonomous cars. Streams of observations from various on-board sources, such as cameras, radars, LiDARs, ultrasonic sensors, GPS units, and/or inertial sensors, are processed by autonomous decision-making systems in self-driving cars. The car's computer makes driving judgements based on these observations [14].

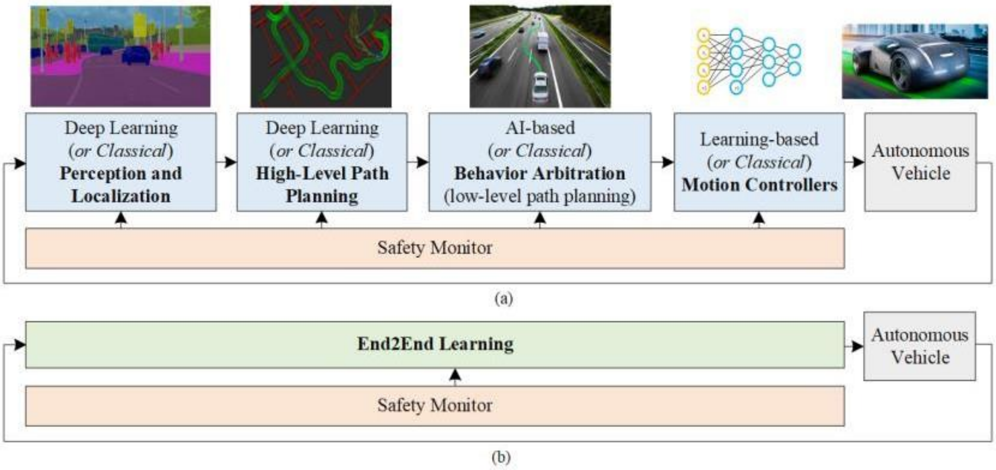


Figure 3. Deep Learning based autonomous vehicle. Either a sequential perception-planing-action pipeline (a) or an End-to-End system (b) can be used to achieve the design. When designing components for a sequential pipeline, one may choose between applying AI and deep learning procedures or more traditional non-learning ones. Deep learning techniques provide the basis of most end-to-end learning systems. To assure each module's safety, a safety monitor is often created. [14].

The main elements of this strategy are the many sensors that collect data from the environment. Examining the four key components is necessary to comprehend how self-driving carsfunction.

They are Perception, Localization, Prediction and Decision Making – under decision making there are modern controllers, behaviour arbitration and high-level path planning

## Perception

A fundamental pillar for ensuring the functioning of an autonomous vehicle is the capacity to extract pertinent knowledge from the immediate environment. As a result, humans must develop and manage the associations in the immediate environment. An automobile can recognise other cars thanks to its perceptive abilities to detect possible hazards and track their movements using cameras and other equipment continuously. Both moving and stationary objects may be detected and followed by the driving vehicle. The vehicle has an expandable 360° field of view. The computational process begins with perception a safety pipeline to guarantee a self-driving automobile operates safely. As soon as the machine can gather the necessary data from its surroundings It will prepare the way ahead and fully operate without human interference [15a, 16]. Autonomous cars create three-dimensional maps of their environment using sensors like LiDAR, radar, ultrasonic, and cameras to navigate their surroundings. The car can interact securely with its surroundings thanks to these sensors, which gather essential environmental data [17].

## Cameras

In the modern day, cameras are a need for any vehicle that wants to go on the roads [18]. They are principally in charge of four crucial tasks: lane classification and detection, road sign recognition and detection [19], traffic light detection and identification, and object detection, classification, and tracking [20]. Cameras are less adept at determining near proximity to objects than they are at determining distance, despite their high resolution, compact size, and low cost. However, what sets them apart from conventional sensors is their capacity to recognise optical characters and detect colour and contrast. Their range and performance suffer in dim light and situations when it is extremely bright, which is a negative. Speed detection is possible using digital signal processing, albeit it is not as precise as radar or LIDAR devices.[21].

## Radars

To compensate for the limitations of cameras, radar, lidar, and ultrasonic sensors are highly helpful. These sensors may be used to measure depth information, or the distance to objects, and can obtain 3D data without being impacted by lighting conditions. The sensors, however, are active.Radio waves are emitted by radars, which track the times of each bounce as they are reflected back from various objects. Other systems may be hampered by the emissions from active sensors. The well-known technology of radar is portable and reasonably priced. As an illustration, side-mirrors may accommodate radars.Although lidars are more accurate, radars are more affordable and can detect things at a farther distance [22].

## Lidars

Infrared light rays rather than radio waves are emitted by lidar, which functions on a similar concept to radar. Under 200 metres, it is far more accurate than radar. Lidar's effectiveness is negatively impacted by weather conditions like snow and fog. Another factor is the sensor size: smaller sensors are desired on the vehicle due to space constraints and aerodynamic limits, whereas lidars are often bigger than radars [22]. [23] compares automated driving systems to humans in terms of sensing performance. One of the main conclusions of this research is that, despite the fact that human drivers are still better at reasoning in general, Automated Driving Systems with sensor fusion may see objects more accurately than humans, particularly in poor lighting situations.

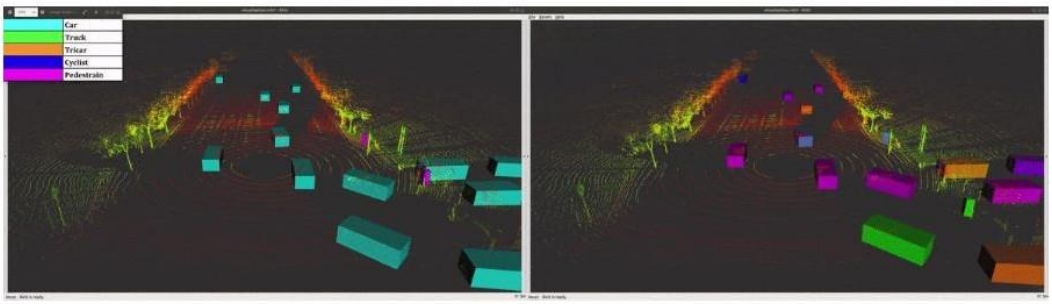


Figure 4. 3D Object Detection using Lidar [24].

Each autonomous vehicle sensor, including the cameras, radar, and lidar, has certain advantages and disadvantages. In excellent lighting, cameras provide the finest range and detail; nevertheless, in poor lighting or bad weather, cameras suffer. Radar is less detailed but yet maintains dependable performance under different circumstances making it beneficial for high-speed detection in challenging conditions. In clear weather, LiDAR excels at producing 3D maps with high resolution, but it struggles in conditions like fog, snow, or torrential rain. Since driving circumstances vary, no one sensor can be said to be the best; rather, a combination of all three provides the best performance [21].

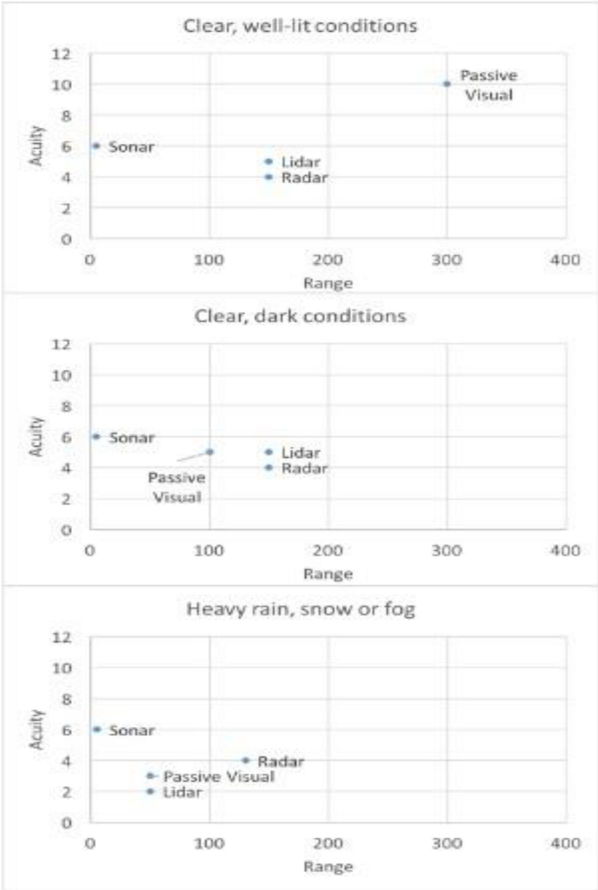


Figure 5. Comparison between all sensors [21].

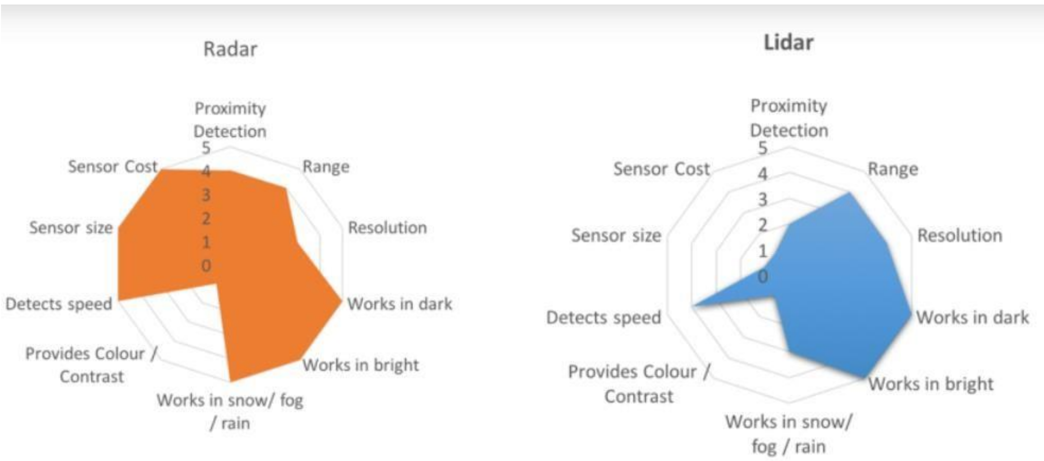


Figure 6. Comparison between Radar and Lidar [21].

Making accurate conclusions and forecasts requires the clean-up of the RADAR data. Data that is based on points is transmitted by RADAR and LiDAR. In order to be easily comprehended, this data has to be clustered. To accomplish this, clustering techniques like DBSCAN (Density-Based

Spatial Clustering of Applications with Noise) are utilized [25].

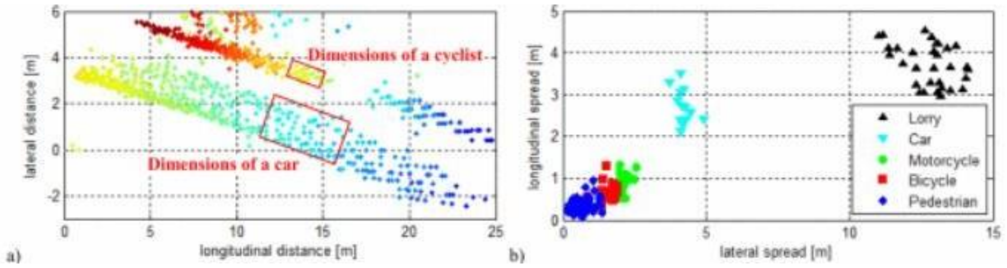


Figure 7. a) aerial image of the detections of a situation where a bicycle is being passed by a faster-moving automobile, coloured according to their measurement time. b) a comparison of the lateral and longitudinal spatial dispersion derived from radar readings of various road users. [25].

## Localization

By matching keypoint landmarks in succeeding video frames, the deep learning-based Visual Odometry (VO), also known as Visual Localization, improves vehicle posture (position and orientation) [26]. By learning important point distractors that help with outlier rejection, a neural network increases VO accuracy. The environment is then gradually mapped using SLAM (Simultaneous Localization and Mapping) methods [27]. PoseNet [28], VLocNet++ [29], and other neural networks [30][31][32][33][34] use image data for scene semantics derivation and 3D camera pose prediction, respectively. Through Convolutional matching using deep learning LiDAR intensity maps aid in real-time vehicle localisation [35]. Urban and natural environment localisation is supported by laser scanning with deep neural networks [36]. Deep learning architectures are increasingly being used to understand scene flow (motion estimation of surroundings), which replaces manually created features [37].

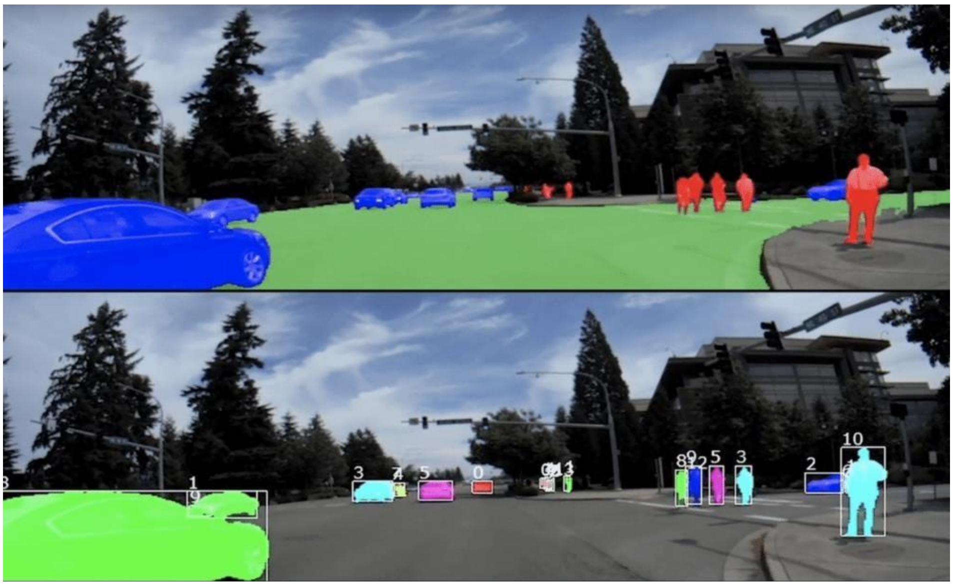

Figure 8. In comparison to only using bounding boxes, Panoptic segmentation deep neural network provides greater detail for visual perception [38].

## Prediction

Involving both logical reasoning and emotional responses, predicting human driving behaviour is difficult. Autonomous vehicles using deep learning systems analyse and forecast possible actions of other road users using a 360-degree picture of the surroundings. Using sensor-generated training data, the system completes tasks such as object recognition, segmentation, and location. As a result, it foretells behaviours like lane changes or braking during inference, assuring commuter safety and effectiveness. Making the best decision from a variety of options is the difficult part [22].

## Decision Making

Using rule-based or learning-based methodologies, autonomous vehicles' decision-making processes navigate complicated landscapes and traffic dynamics [39]. Key research in autonomous vehicle decision-making includes the following: effective traffic control with time-frequency rules [40], predictive control models for improved accuracy and vehicle stability in uncertain environments [41][42][43], advanced decision-making in complex scenarios using Markov models and deep reinforcement learning [44][45][46][47], successful prediction of varying traffic flows [48], rule-based decision models for real-time responses [49][50], and improved trajectory finding via reinforcement learning [51], and real-time decisions at intersections with map information [52]. The use of hierarchical finite state machines facilitates decision-making, with subdivided vehicle behaviors [53], layered state machines [54], and improved state transitions in real-world uncertainties [55].

The decision-making process for self-driving cars follows a four-tier hierarchical structure. The first phase is **route planning**, in which the automobile plots the best route from its current location to the destination. Through probabilistic planning algorithms like MDPs (Markov decision processes), the second phase, **behaviour arbitration**, addresses the unpredictable nature of other road users. By coordinating vehicle movements like speed and lane changes in accordance with the surroundings, the third layer, **motion planning**, assures passenger comfort and viability. The motion planning system's calculated course is put into practise in the final phase, **vehicle control** [56].

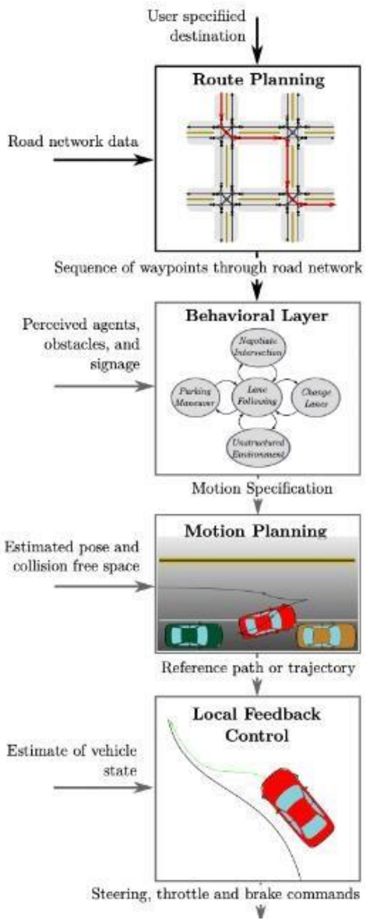


Figure 9. A decision-making process hierarchy. A route planner receives a destination to create a path via the road system. The motion specification for moving along the chosen path is produced by a behavioural layer after it considers the surroundings. The specification is then solved for by a motion planner using a workable motion. When the reference path is executed incorrectly, actuation variables are changed via a feedback control [56].

## Convolutional neural networks (CNN)

In a variety of computer vision tasks, particularly those related to autonomous vehicle technology, convolutional neural networks (CNNs), a form of machine learning algorithm inspired by biological visual perception, have become a dominant force. CNNs have proven to perform very well in tasks including image segmentation, classification, detection, and retrieval, making them one of the top deep learning algorithms for identifying image content, according to [57]. Convolution, pooling, and fully connected layers are the three fundamental processes that make up CNNs. Multiple filters are used by convolution layers to extract features, pooling layers are used to reduce the dimensionality of feature maps, and fully connected layers are used for classification. Backpropagation is used for error correction [58]. The experiment described in the publication [58] involved using CNNs in a set-up similar to an autonomous vehicle with three cameras. In order to anticipate steering orders, the CNN analysed the camera's captured pictures. About 16,000 photos were gathered and pre-processed as part of the study's training of the CNN utilising a simulator with a range of real-world driving scenarios. The outcomes demonstrated that in the simulation, the CNN was able to drive the automobile on its own. Future research will incorporate more challenging elements like obstructions and changing weather. According to the study, CNNs can considerably advance and improve the design of autonomous cars.

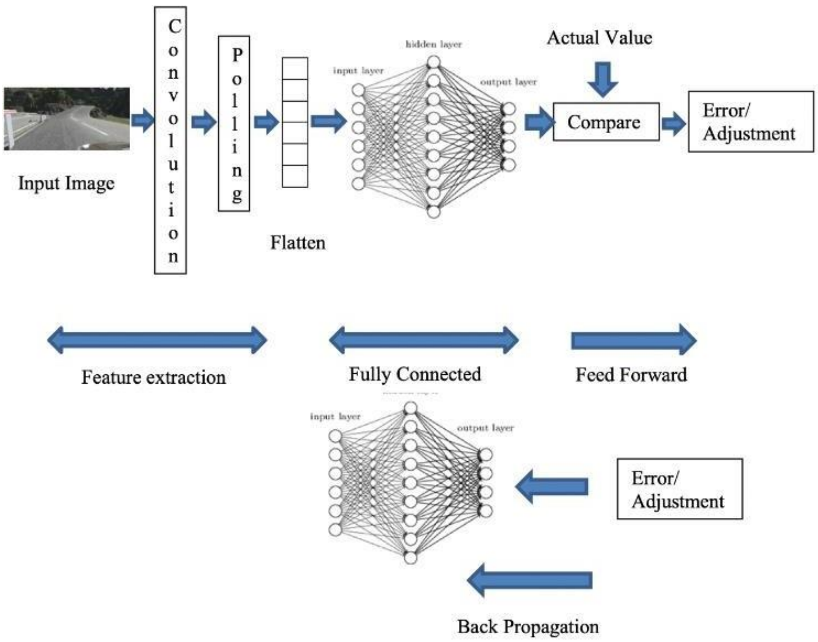


Figure 10. CNN architecture [58].

## Reinforcement learning

A self-driving automobile (the agent) may learn from its interactions with the environment and make judgements using the machine learning approach known as deep reinforcement learning (DRL). State (present position on the road), Action (all potential moves), and Reward (feedback for each action done) are the three fundamental factors on which DRL is based. DRL learns differently from supervised learning because it maximises the cumulative rewards from environment exploration. Convolutional Neural Networks (CNNs) are used by the network, which was trained on perceptual data, to effectively extract low-dimensional representations from higher-dimensional input. DRL algorithms are trained using these representations, which aid in decision-making efficiency. Self-driving automobiles are taught in risk-free simulators like CARLA, AirSim, etc. because training them on actual roads would be risky. The automobile adjusts its decision-making rule or "policy" in accordance with what it learns from each action-reward combination over the course of thousands of training epochs. In order to avoid receiving unfavourable rewards, policy defines the agent's behaviour at a certain period. A state-value function that uses the Bellman Expectation Equation is used to gauge the quality of an action. In order to ensure that judgements are made based on observations from the perception data and not only on the underlying state, DRL in self-driving cars requires a Partially Observable Markov Decision Process (POMDP) [59][60][61].

## Partially Observable Markov Decision Process used for self-driving cars

In order to make consecutive decisions, Deep Reinforcement Learning (DRL) uses the Markov Decision Process (MDP). This involves an agent interacting with its surroundings throughout time, determining what to do in response to the present situation, moving from one state to another, and being rewarded. To maximise overall benefits is the goal. According to how this happens: The environment is in the state "St" during the specified period "t". The agent observes 'St', decides on 'At', and changes the environment to 'St+1' while obtaining 'Rt' as reward. The agent, after processing perception input, makes decisions based on observed states and is rewarded. This is known as a partially observable Markov decision process (POMDP). The POMDP model is written as POMDP M:=(I, S, A, R, P, ), where 'I' stands for observations, 'S' for a finite set of states, 'A' for a finite set of actions, 'R' for a reward function, 'P' for a transition probability function, and 'y' for a discounting factor for future rewards. Finding the best value-action function (Q-function) is the main goal of DRL, that is identify the best policy that maximises reward at each timestep [62].

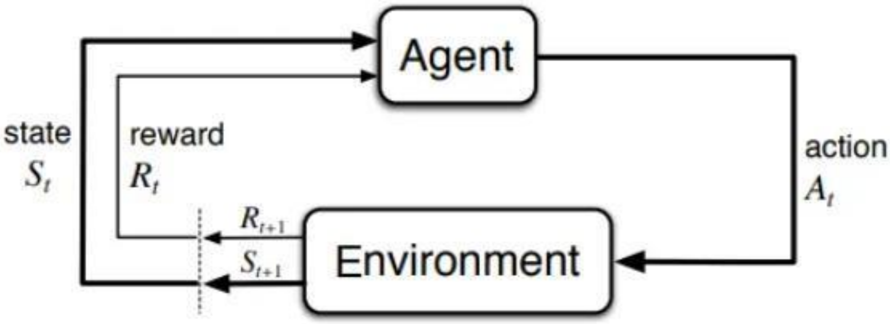


Figure 11. Typical Reinforcement Learning cycle [62].

### Q-learning

In self-driving automobiles, the Deep Reinforcement Learning (DRL) algorithm Q-learning frequently employed. It operates within the context of model-free learning, where the agent approximations ideal state-action pairings. In order to discover the best course of action through interactions with the environment and subsequent corrections when an error occurs, the learning policy directs the updating and visiting of these Q-values. Assuming unlimited availability of all actions across all states, Q-learning may, with a high degree of probability, converge to the ideal state-action values of a Markov Decision Process (MDP), given enough data. Through trial and error, one learns to differentiate between appropriate and inappropriate behaviour. It is important to recognise the significance of the learning rate, alpha, which regulates the amount of Q-value updates at a specific time t and has a range between [0,1]. Due to its capacity to promote the best decision-making in autonomous cars, Q-learning, is essential in the self-driving car area.

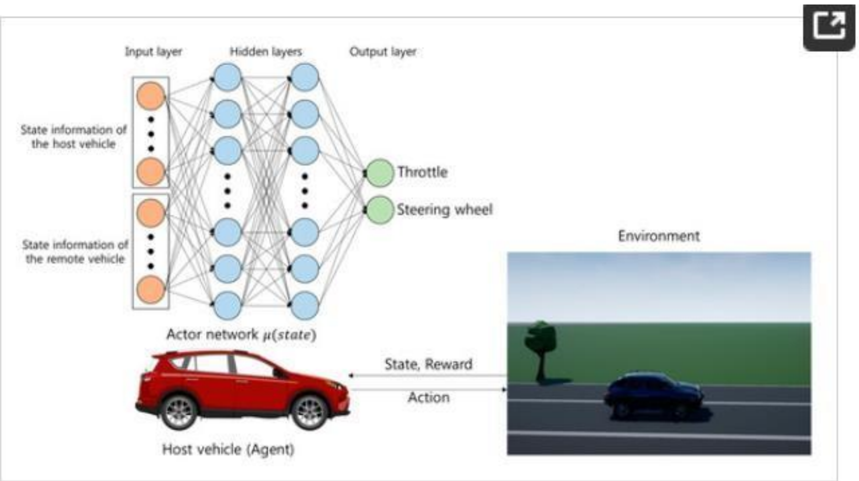


Figure 12. Architecture of proposed decision-making system. [63].

## 3.3 BENEFITS

Numerous potential advantages that might revolutionise our everyday lives and urban settings come with the widespread use of autonomous driving systems (ADS). First off, considering that human error, such as distraction, drunk driving, and speeding, is a big contributor to accidents [64], they show great potential in avoiding traffic accidents. We can anticipate a decrease in accident rates by removing these human shortcomings. Additionally, these devices may significantly reduce transportation congestion and consequently pollution. By optimising the vehicle's accelerating and braking motions, new technologies integrated with ADS can significantly reduce fuel consumption, cutting it by up to 60% [65]. Additionally, autonomous vehicles may be organised into platoons with regulated speed using vehicle-to-vehicle communication, which may result in a further 5-20% decrease in fuel usage [65]. By reallocating driving time and improving mobility for the elderly and other people with disabilities, autonomous driving technology can open up new possibilities. Growing this group's mobility with ADS can considerably enhance their quality of life and overall societal productivity because the global ageing population is expanding faster than the younger generation [66]. With the broad use of ADS, it's expected that emerging trends like the move away from personal car ownership and towards Mobility as a Service (MaaS) will gain momentum. Under 1000 km of yearly travel, ride-sharing is now less expensive than owning a car [67]. It is anticipated that by 2030, the proportion of privately owned to publicly owned cars may equal 50:50 [68]. This

tendency may accelerate with the broad-scale use of ADS, ushering in a revolutionary change in logistics. Aside from lowering accident risks and any wear on the vehicle's brakes or tyres, ADAS systems significantly save maintenance expenses of cars by up to 6% [69].
ADSs provide many benefits, but it's also important to think about any possible hazards. So we will move forward to check on potential risks.

### 3.4 RISKS

Despite the fact that Advanced Driver Assistance Systems (ADAS) provide major advantages in terms of convenience and safety, they have certain drawbacks. The necessity for advanced technology, such as sophisticated sensors and cameras, might make the initial pricing exorbitant. As a result of the delicate, essential components' fragility and complexity, maintenance can also be costly and difficult. Furthermore, the dependability of these systems may be jeopardised by the heavy reliance on sensors, which are susceptible to weather-related effects. Due to erroneous warnings or obtrusive assistance, some ADAS systems may cause drivers to become complacent. Additionally, these systems may have difficulty identifying less typical road conditions or traffic signals. It's critical to keep in mind that ADAS should support attentive driving rather than substitute for it, keeping a healthy dependence on both technology and core driving abilities. [70]

## 4. CONCLUSION

In conclusion, the study's findings demonstrate the transformational potential of autonomous driving assistance systems (ADAS) in the automobile sector, highlighting chances for improved safety, user experiences, and environmental effects. The path to complete ADAS deployment, however, is fraught with difficulties, including high prices, upkeep requirements, and problems with sensor dependability. These problems highlight the need for ongoing study, innovative strategic thinking, and legislative changes to reduce possible downsides. A well-rounded conversation is required because ADAS has effects that go beyond technology and raise moral, societal, and practical issues. Our objective is still to turn the promise of autonomous cars into practical advantages as we move through this period of automotive innovation. Future studies and innovations will surely improve our comprehension of ADAS's potential and hazards, assisting in the creation of effective implementation frameworks. In our quest for a future of more efficient and sustainable mobility, this study is an essential first step.

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